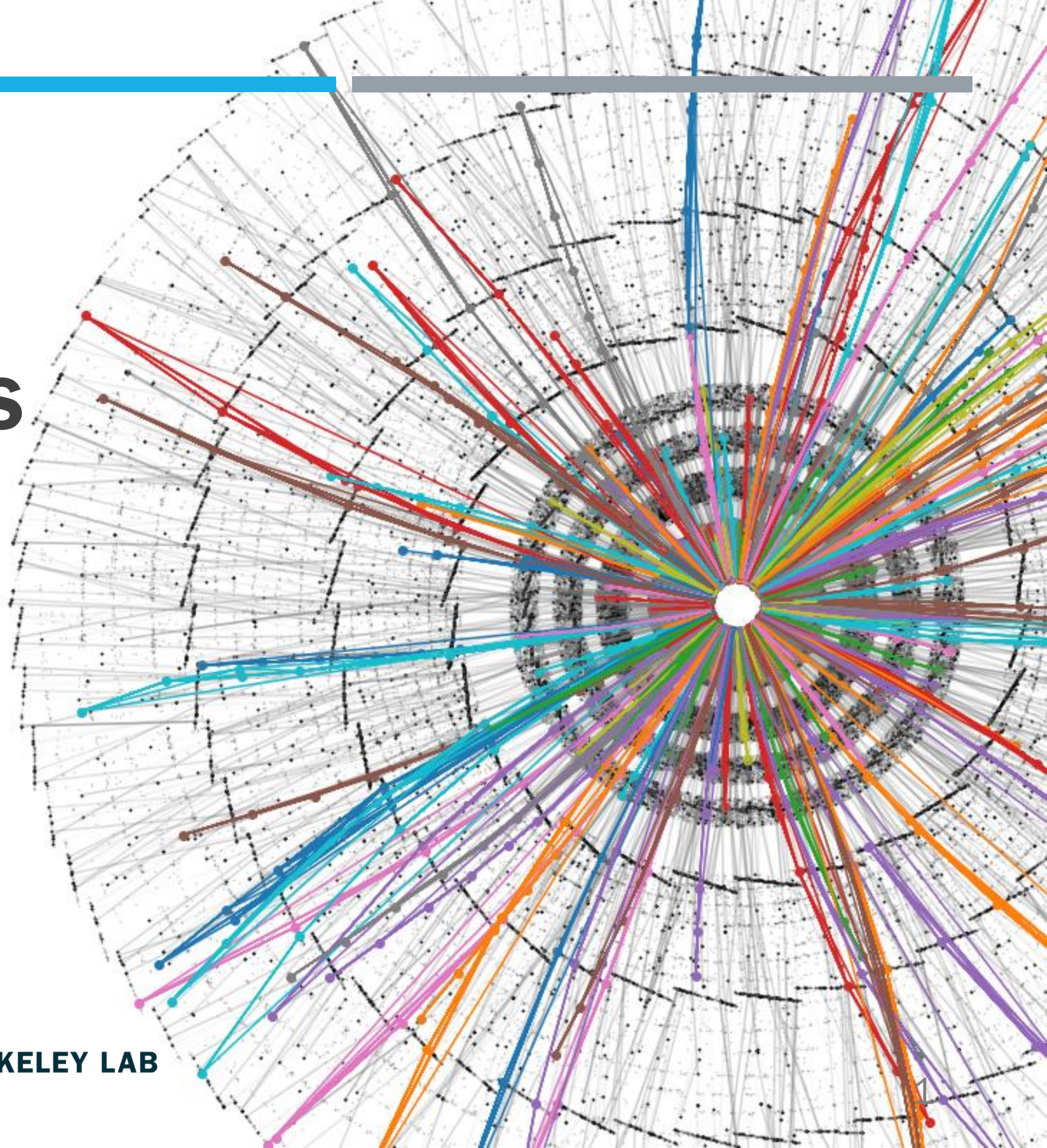
GRAPH NEURAL NETWORKS FOR HIGH LUMINOSITY TRACK RECONSTRUCTION

EP-IT DATA SCIENCE SEMINAR, CERN, 18 MAY 2022



DANIEL MURNANE

ON BEHALF OF THE EXATRKX AND L2IT PROJECTS

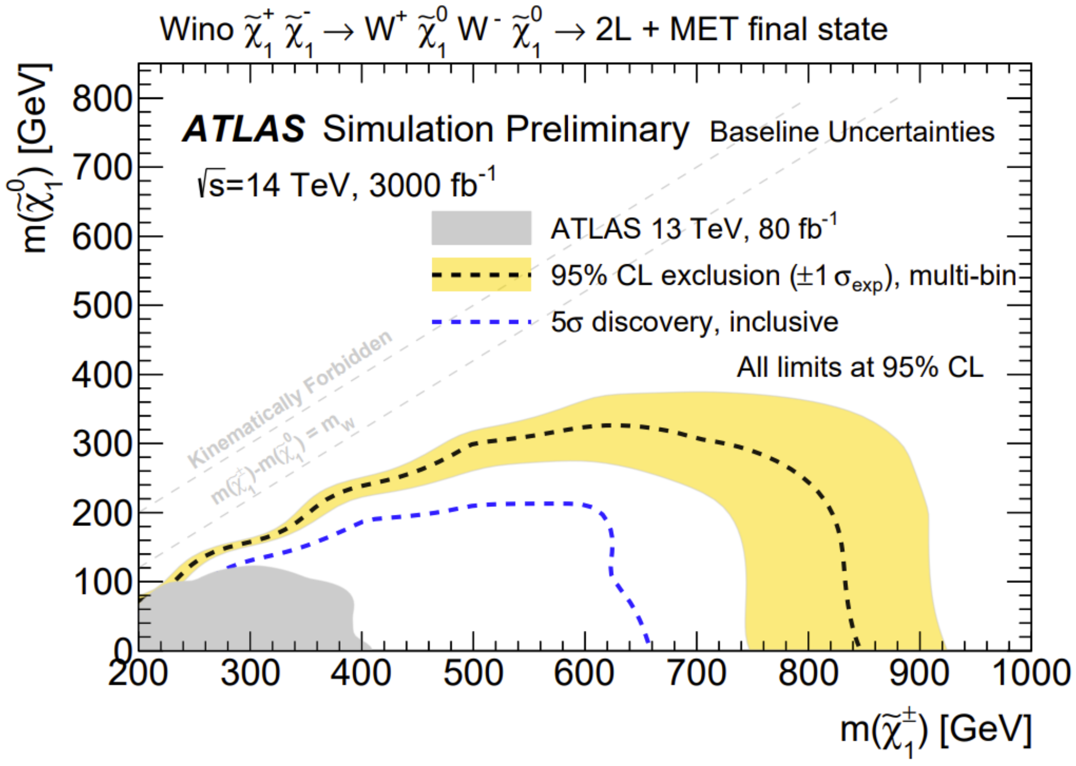
AND THE ATLAS COLLABORATION

ExaTrkX L2IT ATLAS EXPERIMENT BERKELEY LAB

HIGH LUMINOSITY TRACK RECONSTRUCTION

WHY HIGH LUMINOSITY PHYSICS?

1. Better reach for Supersymmetry discovery:
   a) Electroweakino particles produced by much greater range of chargino masses
   b) Gluino exclusion from channels across 0.7-2.0TeV to channels across 2.5-3.2TeV
2. Sensitive to resonances (W', Z') up to 6-8TeV
3. W mass precision improvement from $\pm$9.4MeV to $\pm$6MeV



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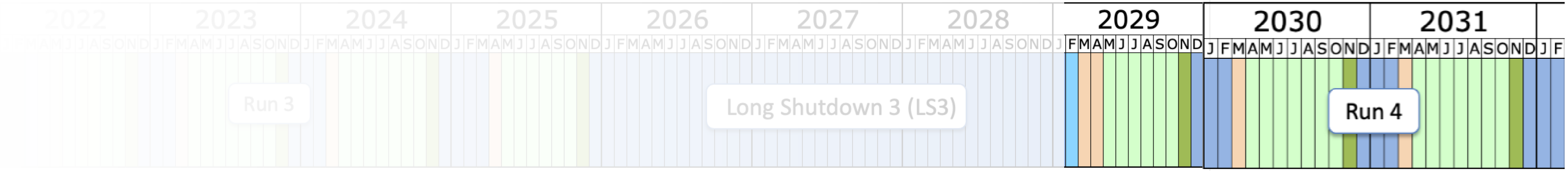
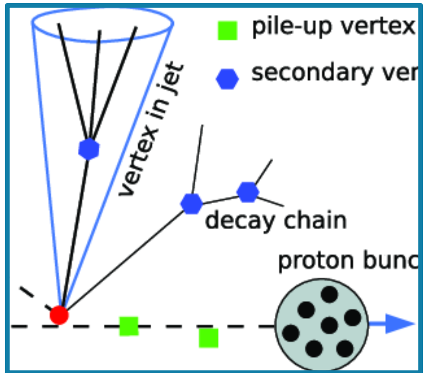


...

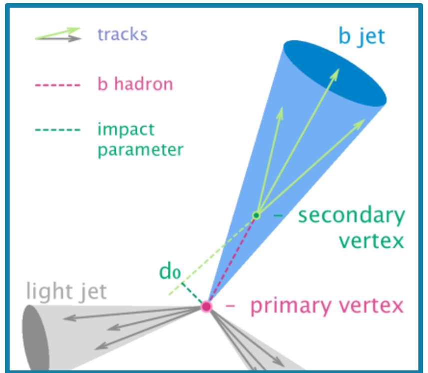
LHC Long Term

TASKS IN AN HL-LHC DETECTOR

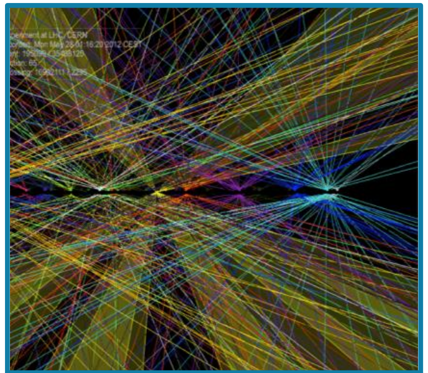
- In order to perform the analysis that leads to discovery (e.g. of dark matter, extra dimensions, SUSY, …), need to make sense of the detector read-out
- There are many tasks required to reconstruct the physics event behind the read-out

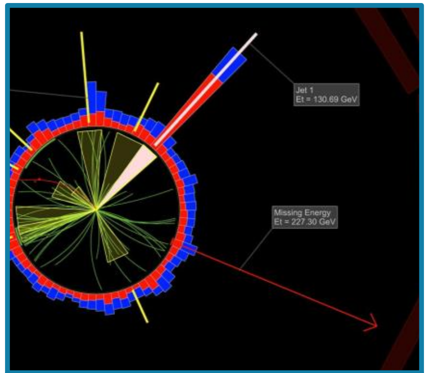


Vertex Reconstruction



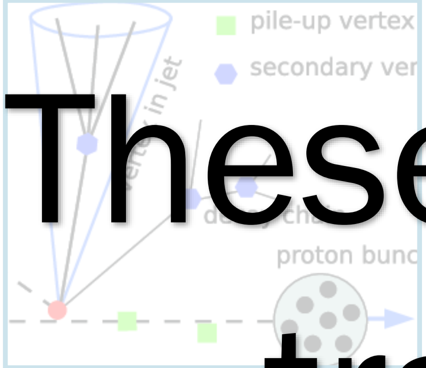
Jet Tagging


Pile-up Removal


Missing Energy Reconstruction

TASKS IN AN HL-LHC DETECTOR

- In order to perform the analysis that leads to discovery (e.g. of dark matter, extra dimensions, SUSY, …), need to make sense of the detector read-out
- There are many tasks required to reconstruct the physics event behind the read-out



Vertex Reconstruction

Jet Tagging


Pileup Removal


Missing Energy Reconstruction

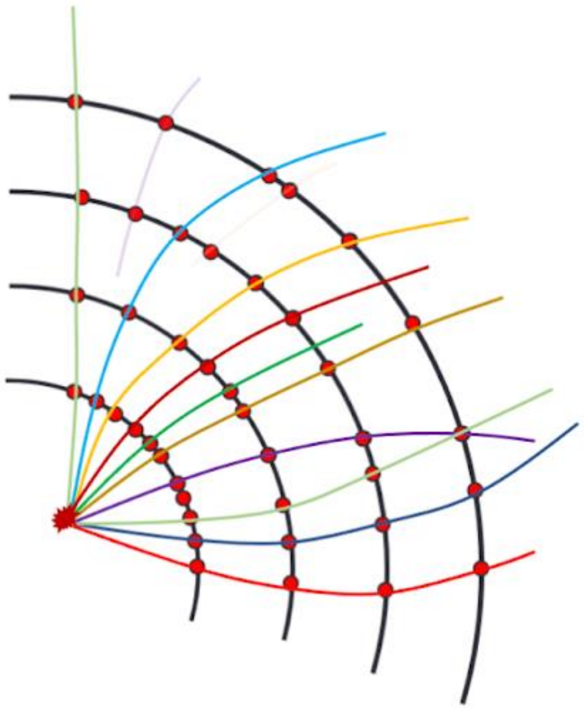
These all require accurate track reconstruction

TRACK RECONSTRUCTION

- Protons collide in center of detector, “shattering” into thousands of particles
- The *charged* particles travel in curved **tracks** through detector’s magnetic field (Lorentz force)
- A track is defined by the **hits** left as energy deposits in the detector material, when the particle interacts with material
- The goal of track reconstruction:

Given set of hits from particles in a detector, assign label(s) to each hit.

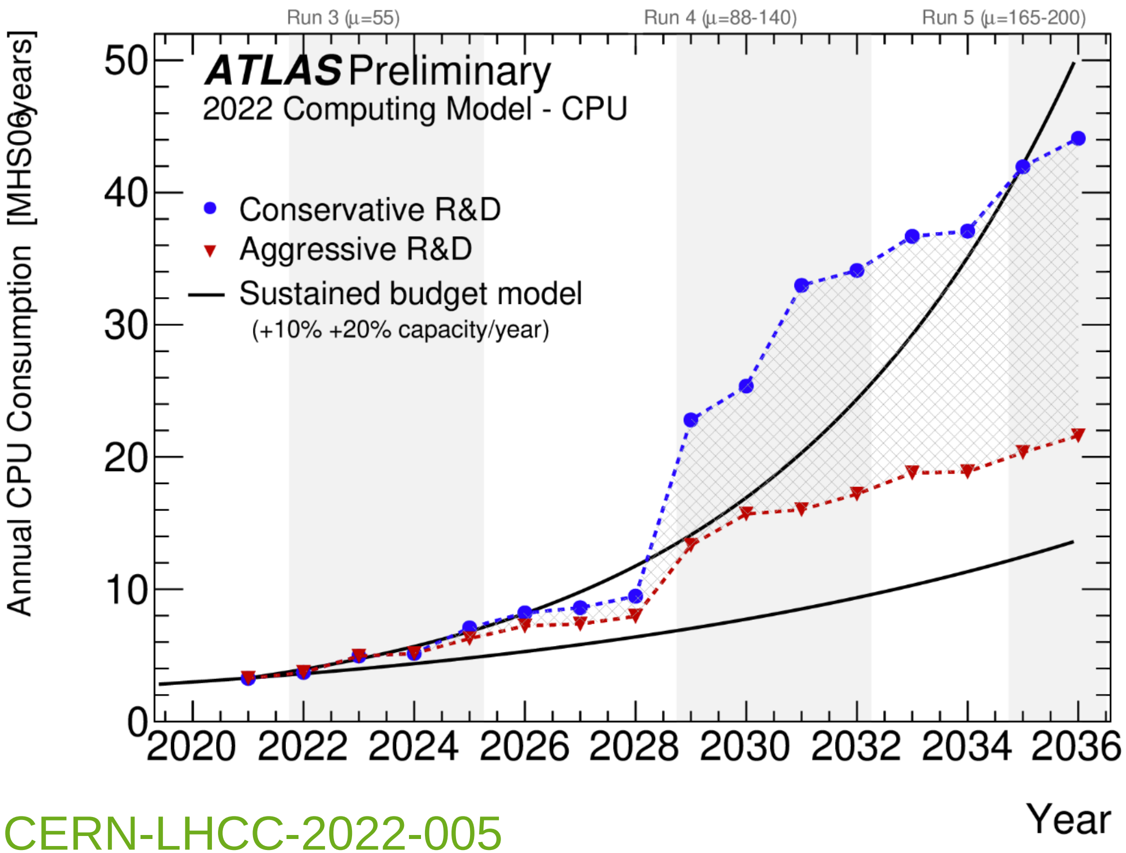
Perfect classification: All hits from a particle (*and only those hits)* share the same label



REPRESENTATION OF COLLISIONS

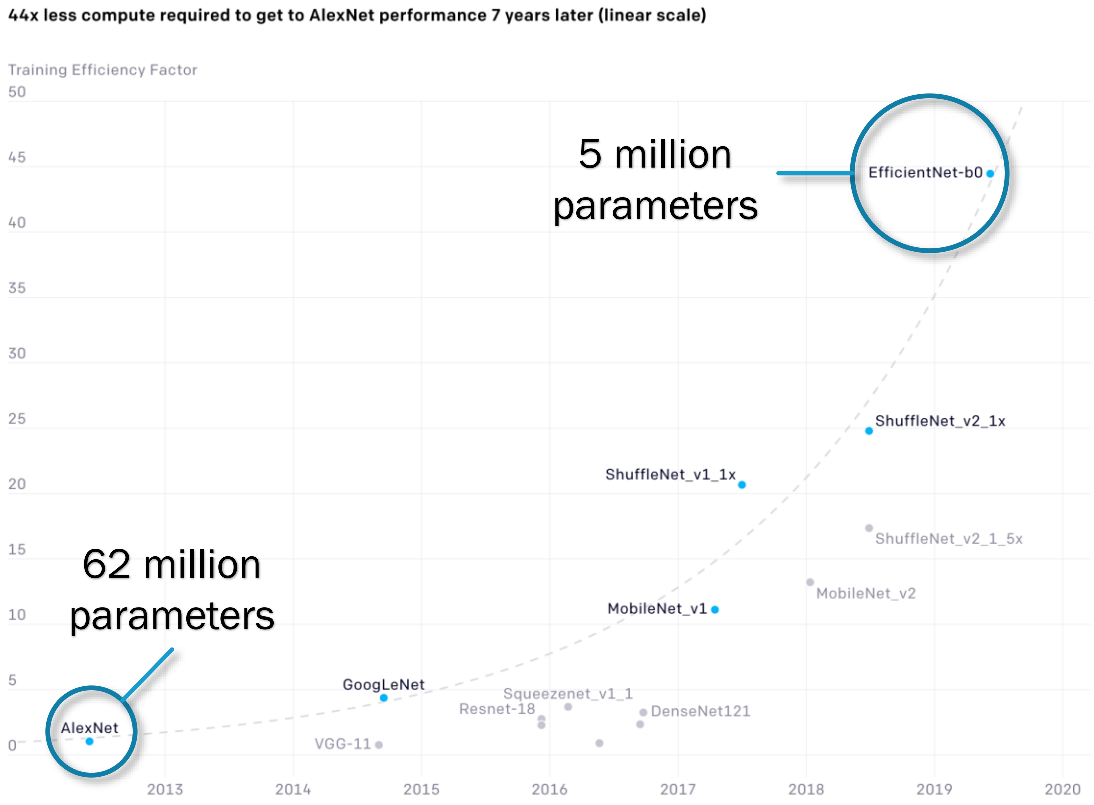
COMPUTE SCALING FOR HIGH LUMINOSITY

ATLAS Computing Requirements Over Time



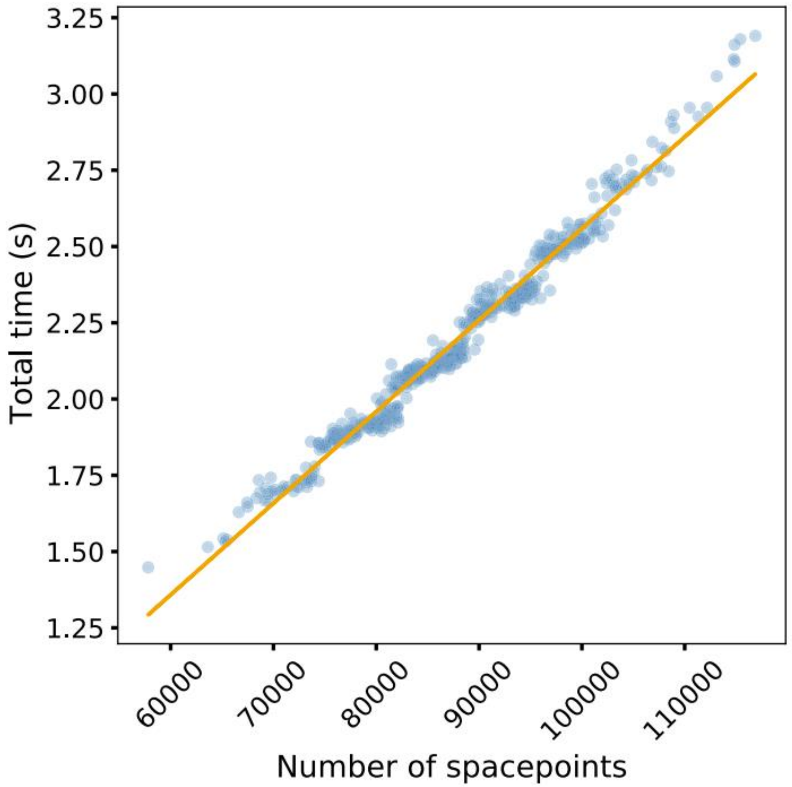
CERN-LHCC-2022-005

ML Image Classification Efficiency Over Time



TEASER: GRAPH-BASED PIPELINE FOR TRACK RECONSTRUCTION

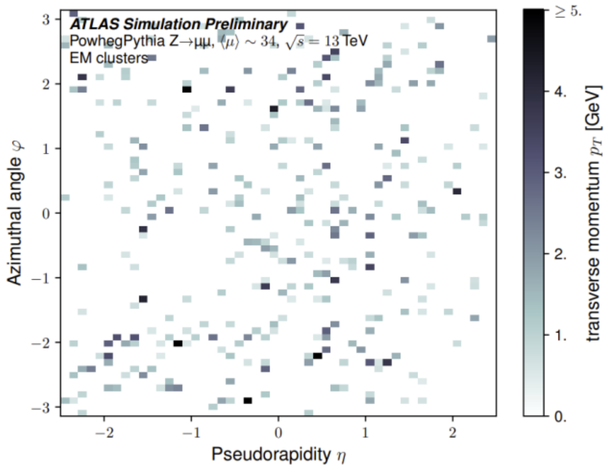
- Using **graph-based ML**, can perform track reconstruction on High Luminosity detector events
- Comparable efficiency and fake rates to traditional algorithms
- Scaling that is approximately linear in event size (on open-source TrackML dataset)



HOW SHOULD WE REPRESENT PARTICLE COLLISIONS?

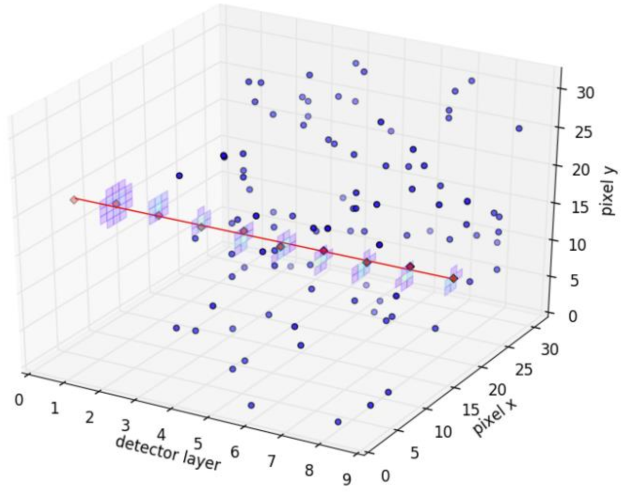
Assuming we want to use deep learning, how can we represent a particle collision?

Image?



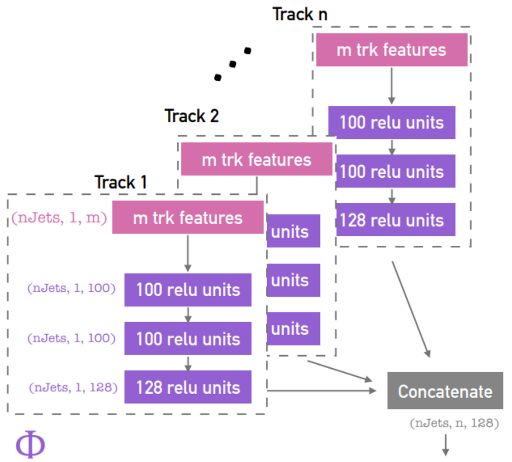
[Convolutional Neural Networks with Event Images..., ATLAS Collab.]

Sequence?



[Particle Track Reconstruction with Deep Learning, Farrell et al]

Set/Point Cloud?

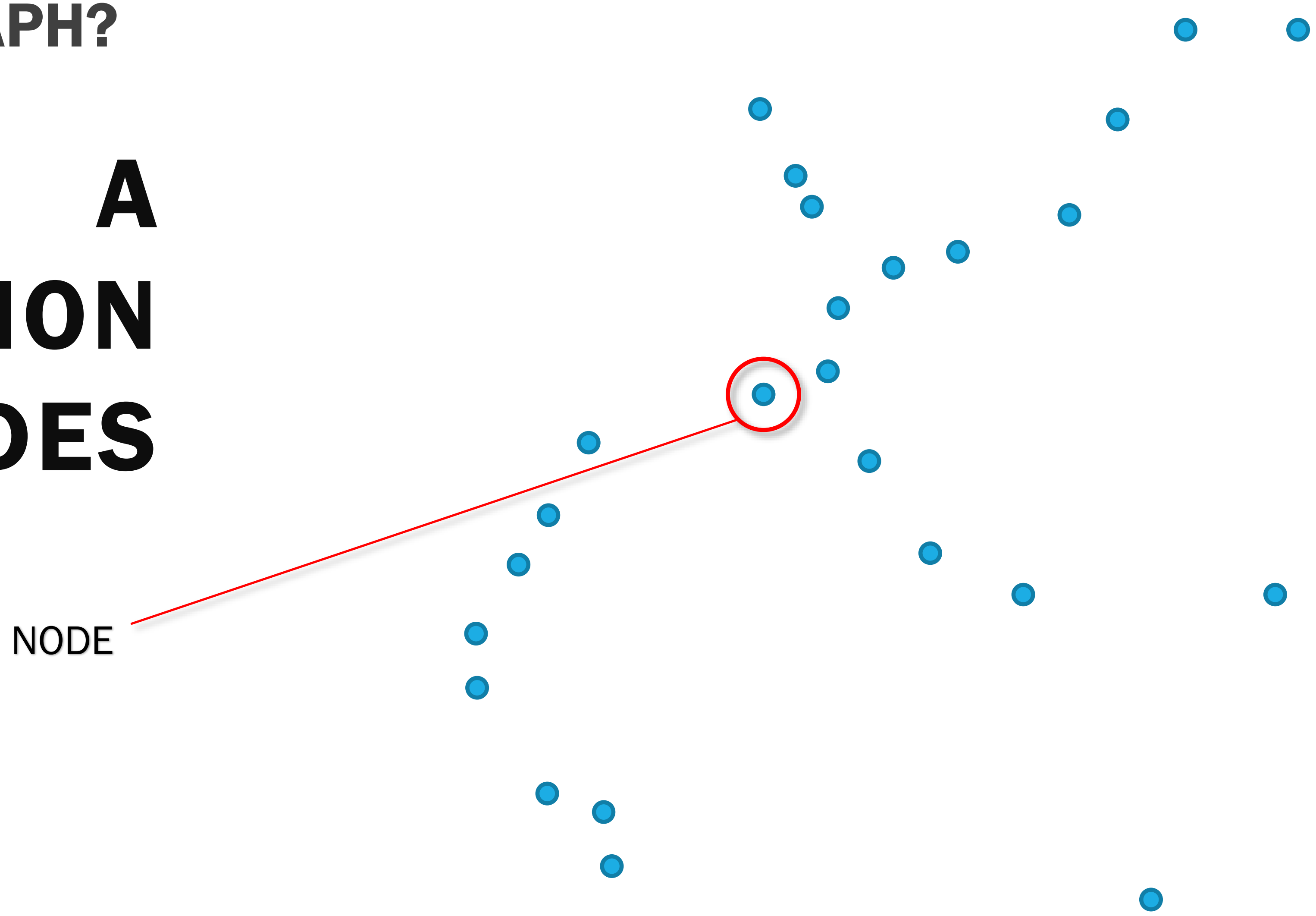


[Deep Sets based Neural Networks for Impact Parameter..., ATLAS Collab]

For event collision as point cloud, with relationships between points, this is a graph.

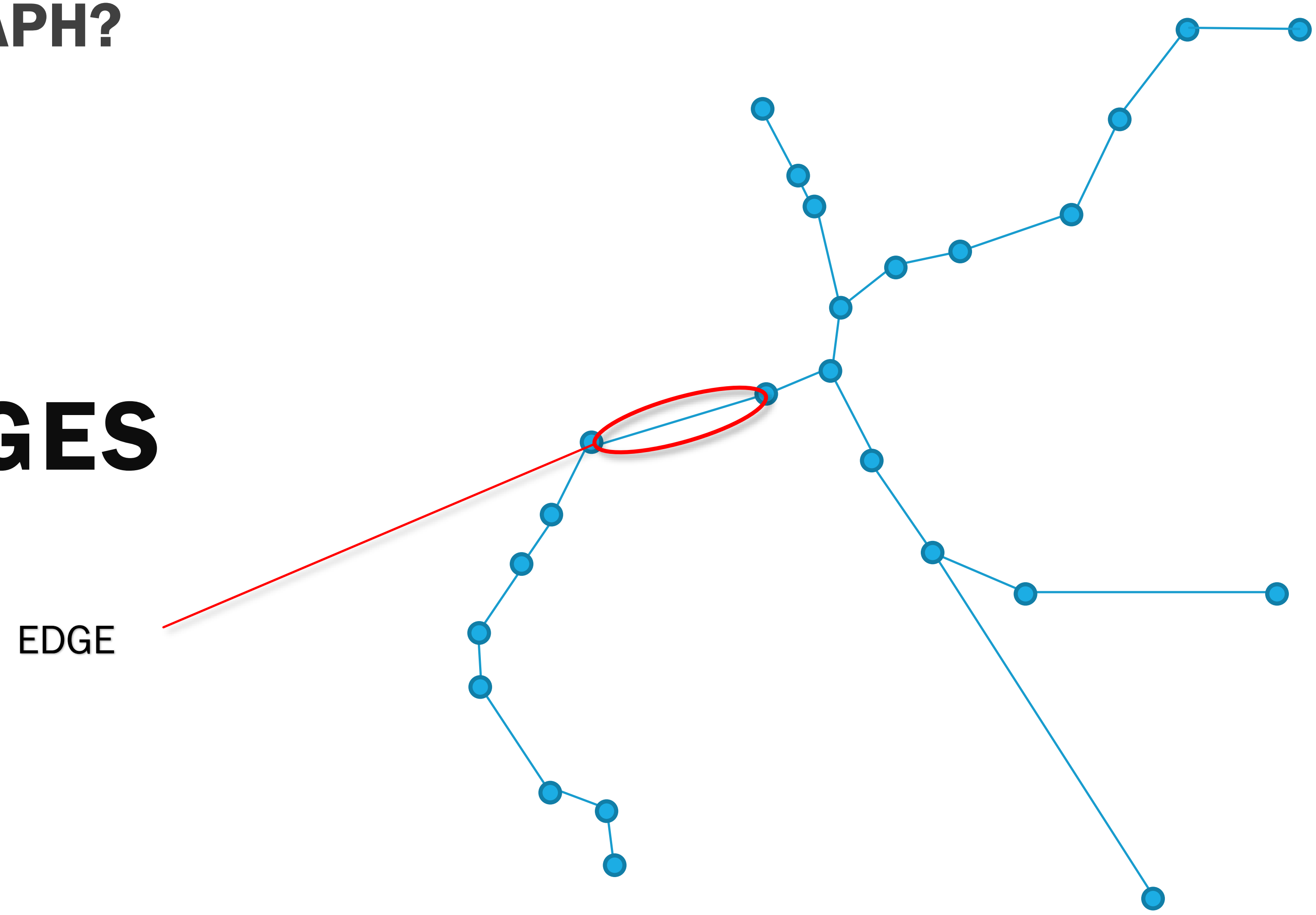
WHAT IS A GRAPH?

A COLLECTION OF NODES



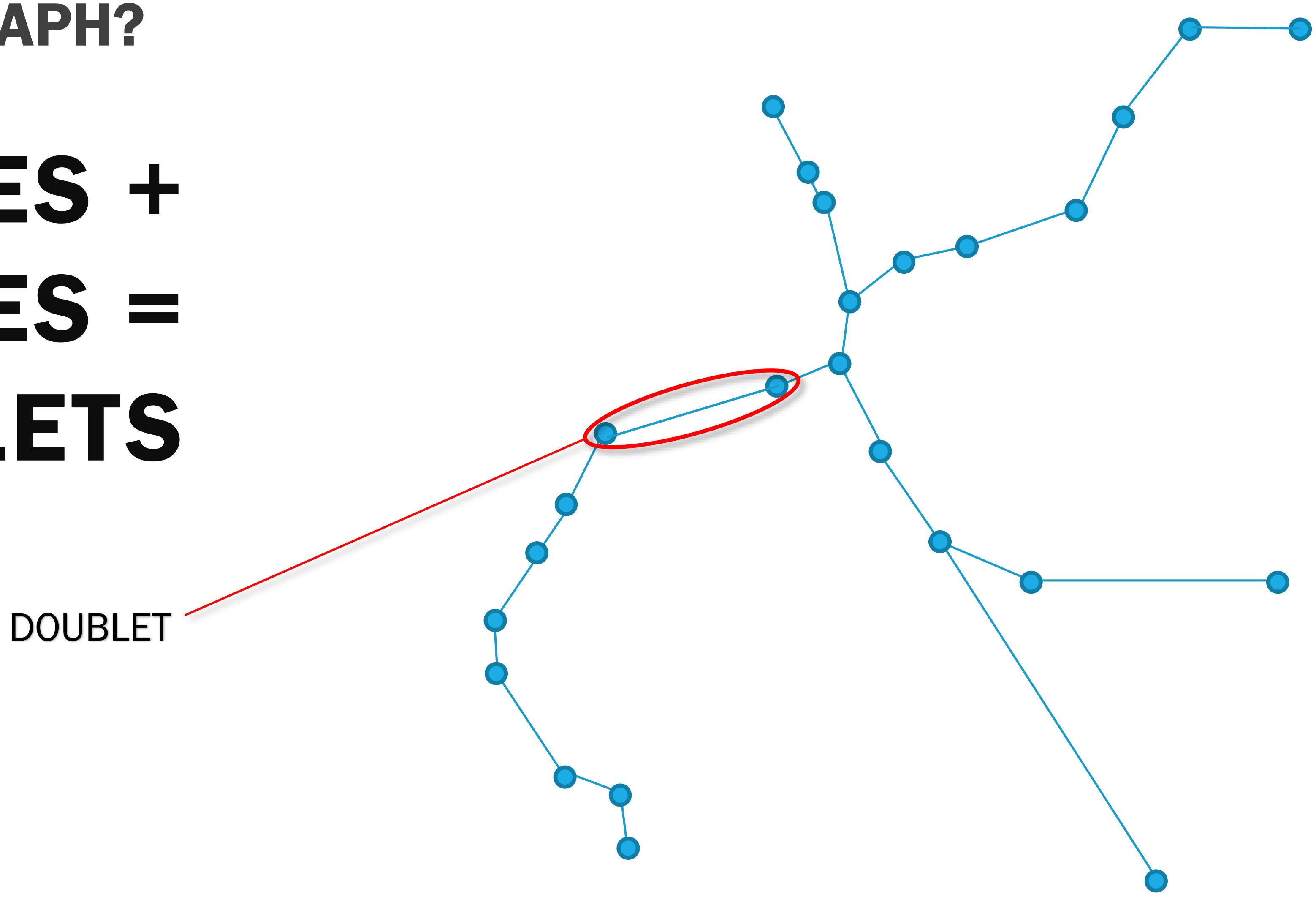
WHAT IS A GRAPH?

AND EDGES



WHAT IS A GRAPH?

NODES + EDGES = DOUBLETS



WHAT IS A GRAPH?

NODES CAN HAVE FEATURES

NODE FEATURE
e.g. “West Oakland”

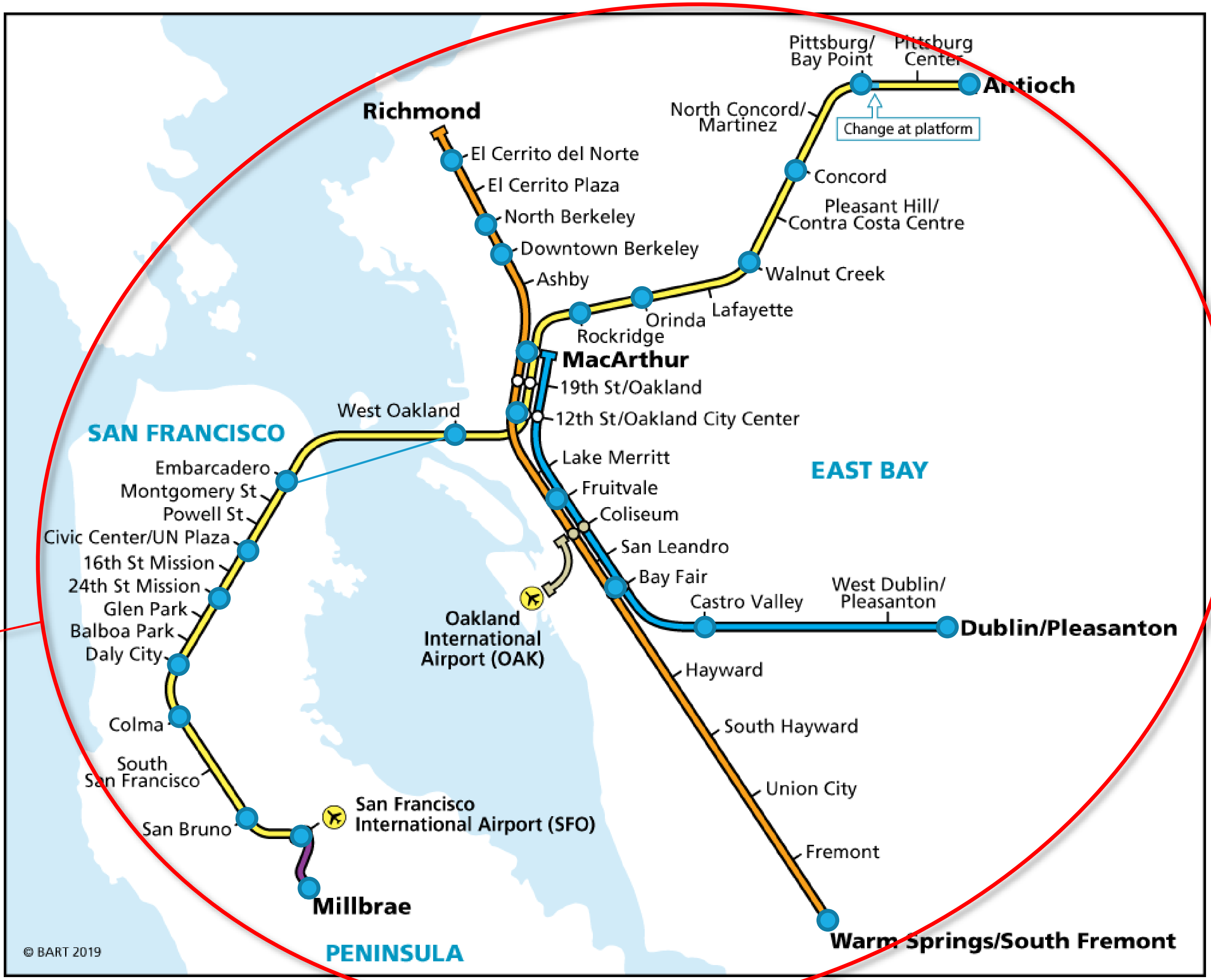
WHAT IS A GRAPH?

EDGES CAN HAVE FEATURES

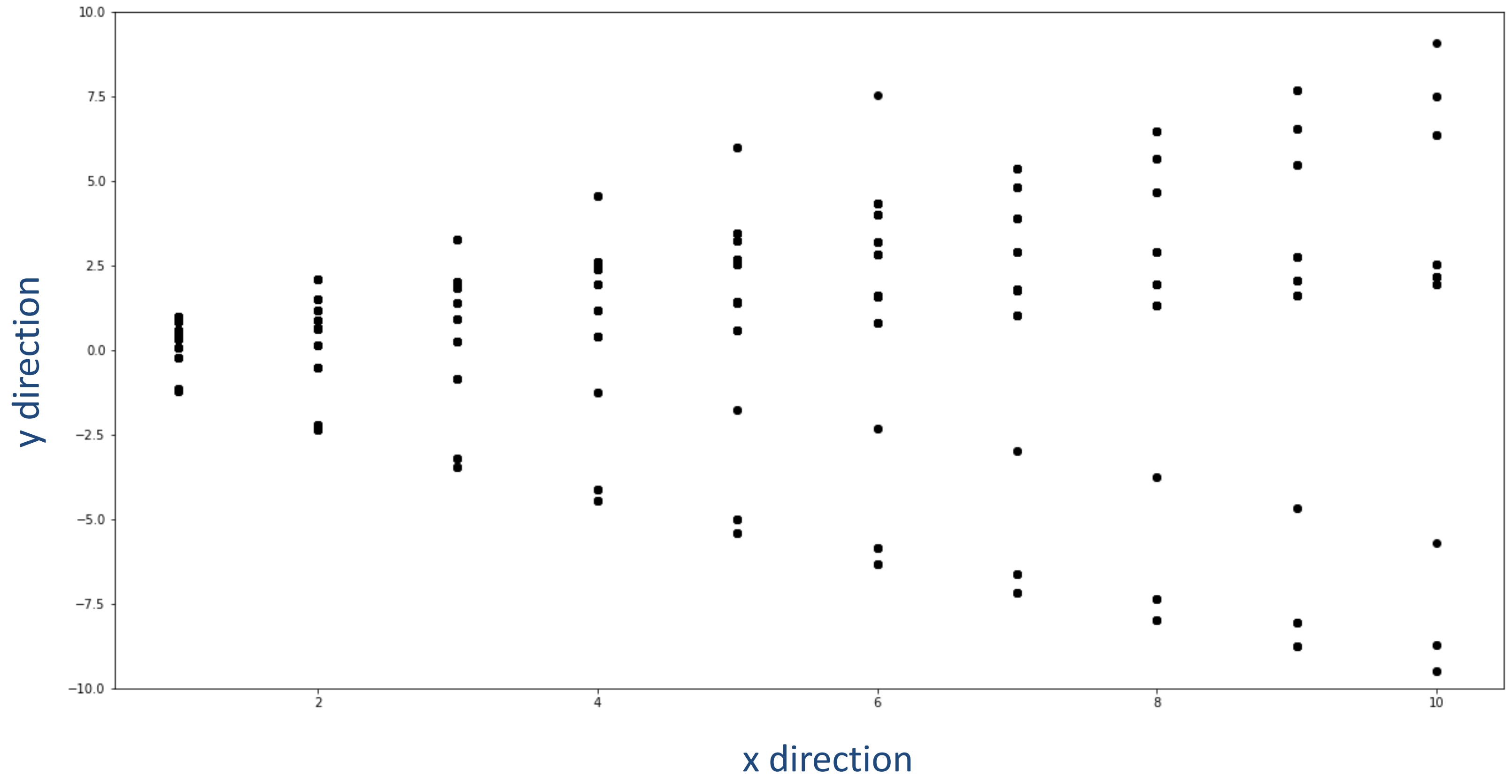
EDGE FEATURE
e.g. “Under Maintenance – Single Track”

THE WHOLE GRAPH CAN HAVE FEATURES

GRAPH FEATURE
e.g. "Sunday Timetable"

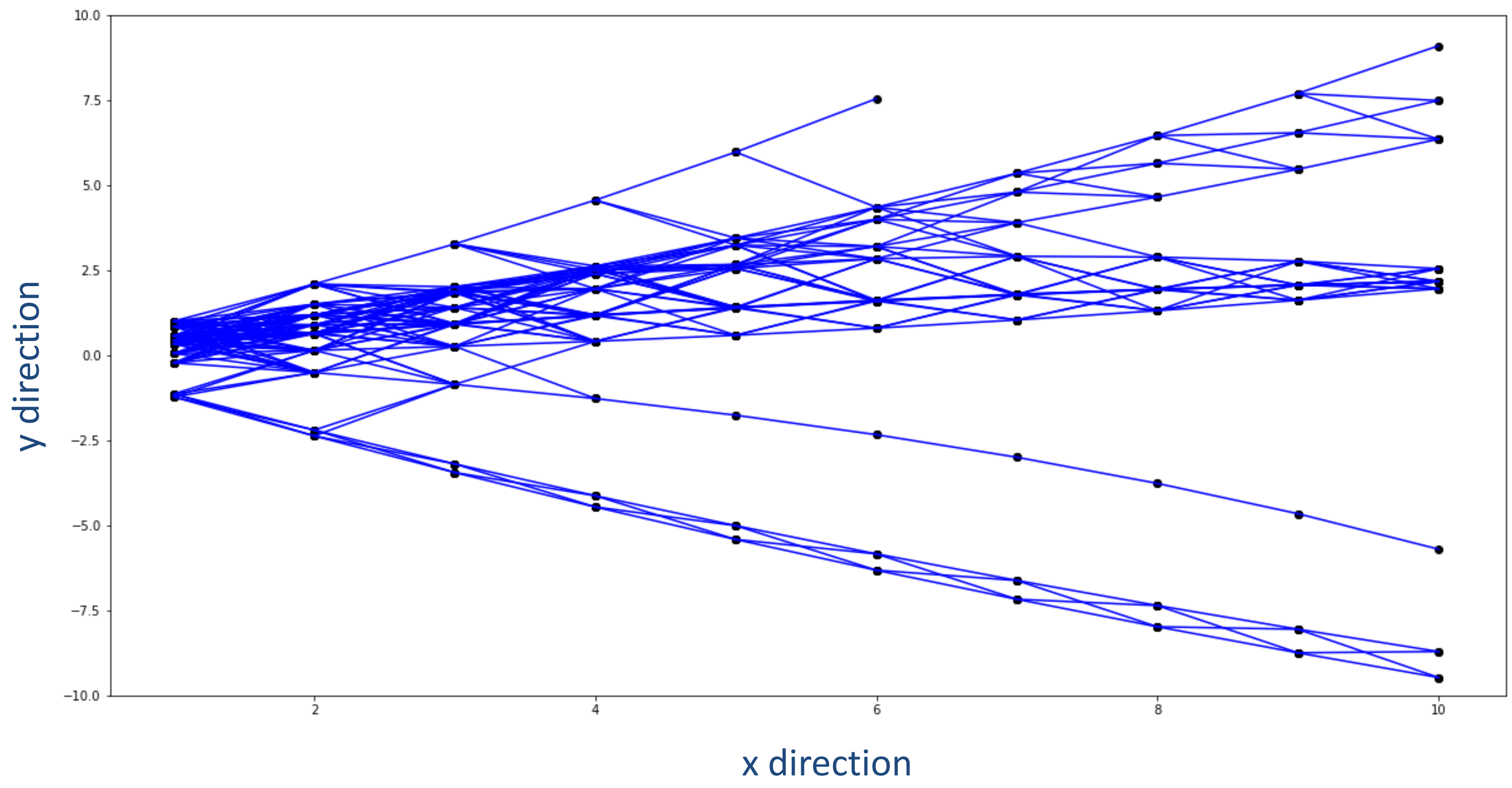


GRAPHS ARE A NATURAL WAY TO REPRESENT TRACKS



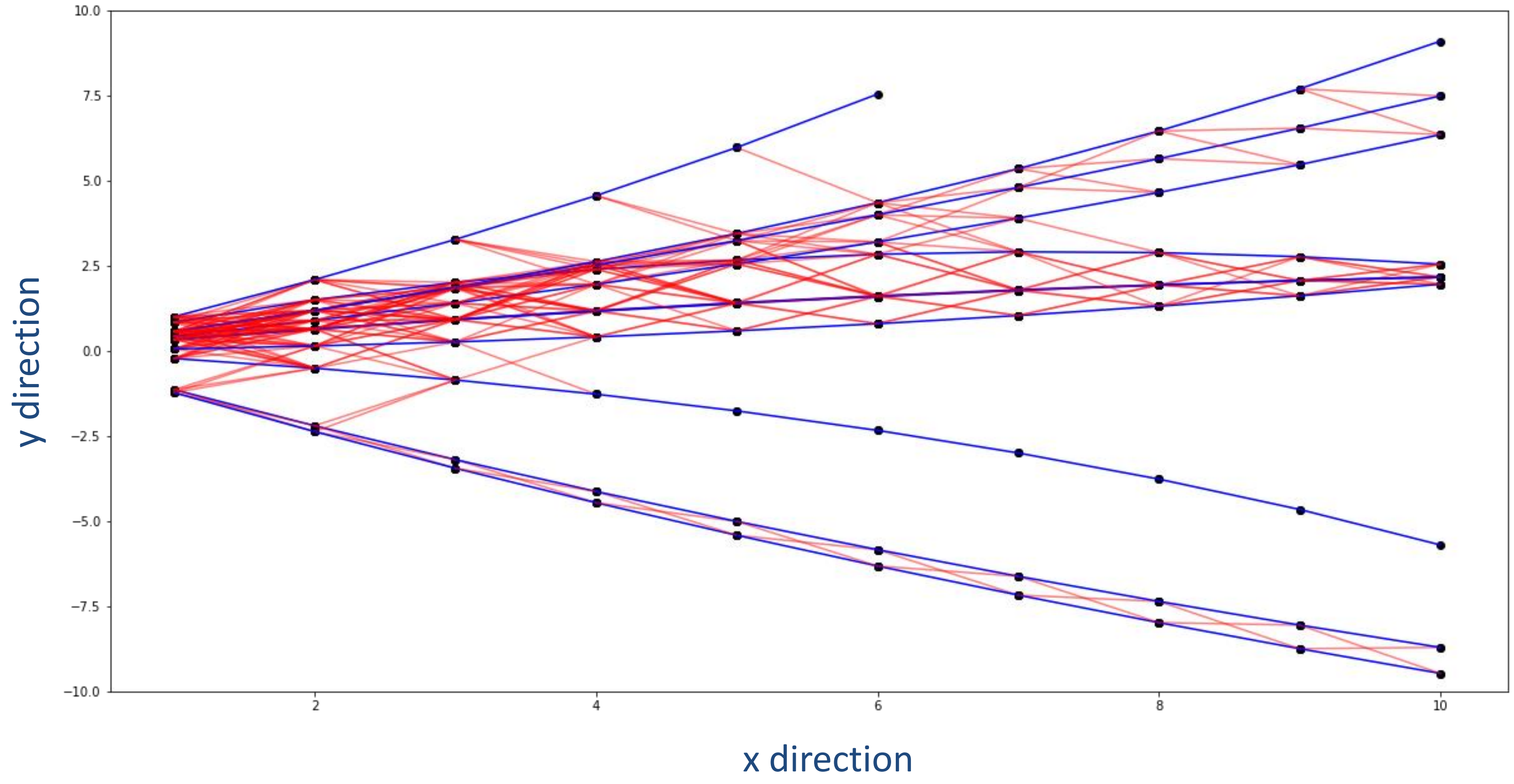
Given hits on layers of a detector

GRAPHS ARE A NATURAL WAY TO REPRESENT TRACKS



Connect the
hits in some way

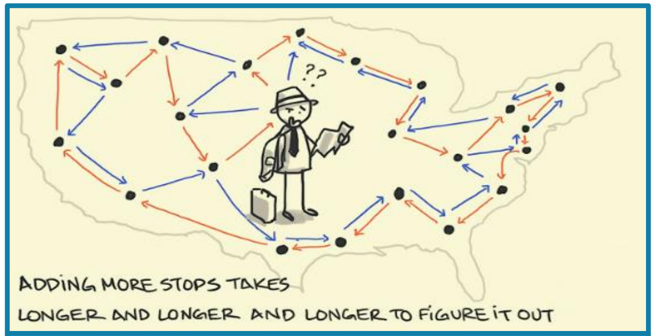
GRAPHS ARE A NATURAL WAY TO REPRESENT TRACKS



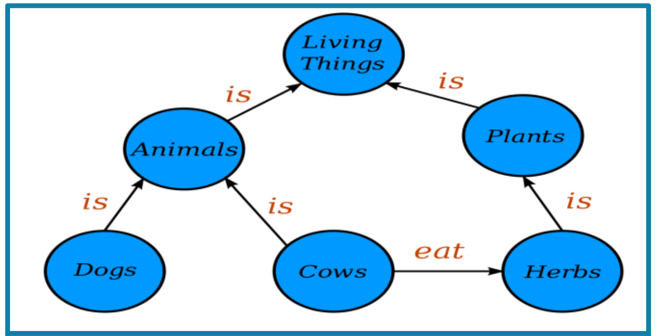
- Tracks should be found amongst the connected nodes.
- **Note the trade-off:** Rather than needing to classify or cluster nodes with many labels, we only need binary classification of edges
- However, introduce the extra step of building tracks from classified edges

INTRO TO GRAPH NEURAL NETWORKS

GRAPH NEURAL NETWORK APPLICATIONS



Travelling Salesman Problem



Knowledge Graph Comprehension

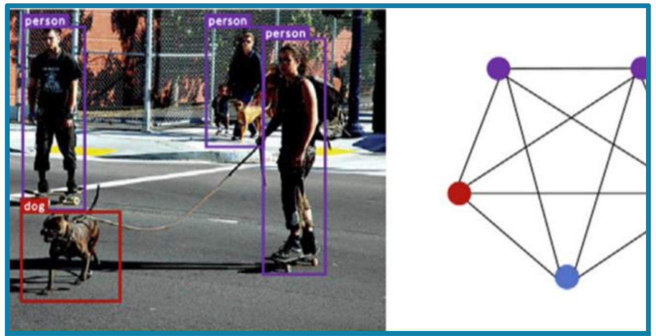
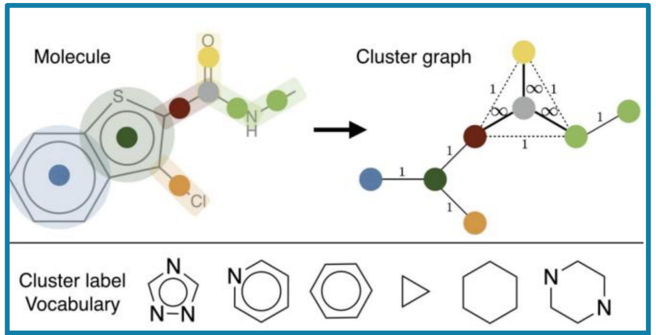
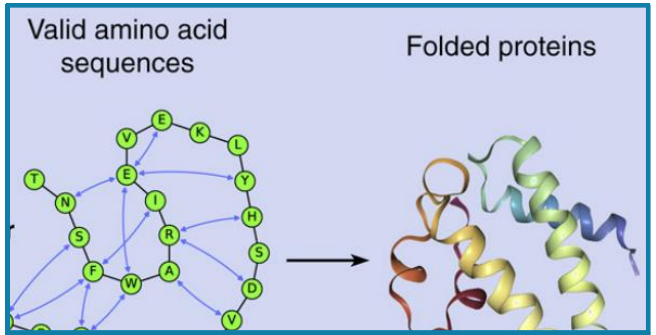


Image Comprehension

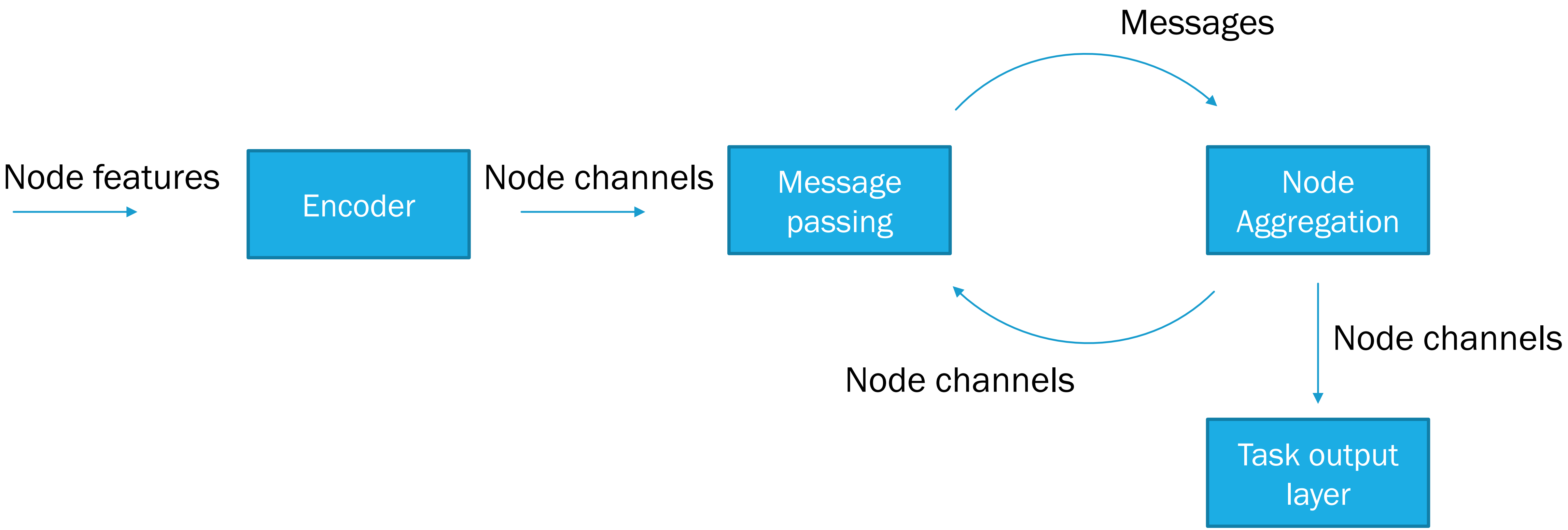


Molecular Chemistry



Protein Comprehension

GRAPH NEURAL NETWORK PROCEDURE



STEP 1: MESSAGE PASSING MECHANISM

For each node neighborhood:

a) Pass node channels through a multi-layer perceptron (MLP) encoder

b) Pass encoded channels along each edge to the central node of the neighborhood

Note: This is quite inexpensive since we store N_{nodes} for backpropagation

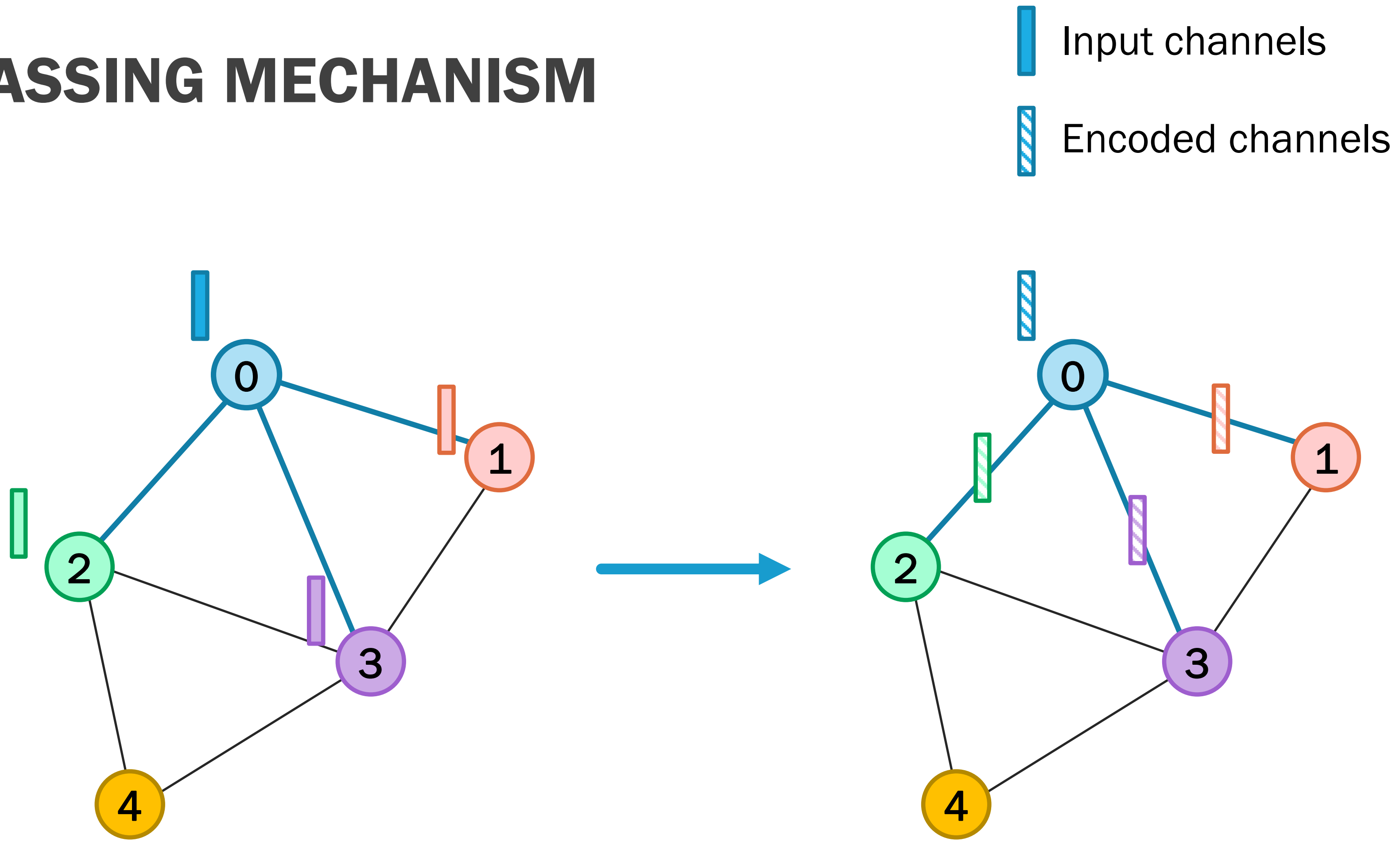


Figure inspired by Koshi et. al.

STEP 2: AGGREGATION

Input channels

Encoded channels

At each node:

Sum all messages

Note: Called *isotropic* message passing. Introduced as “Graph Convolution Network”

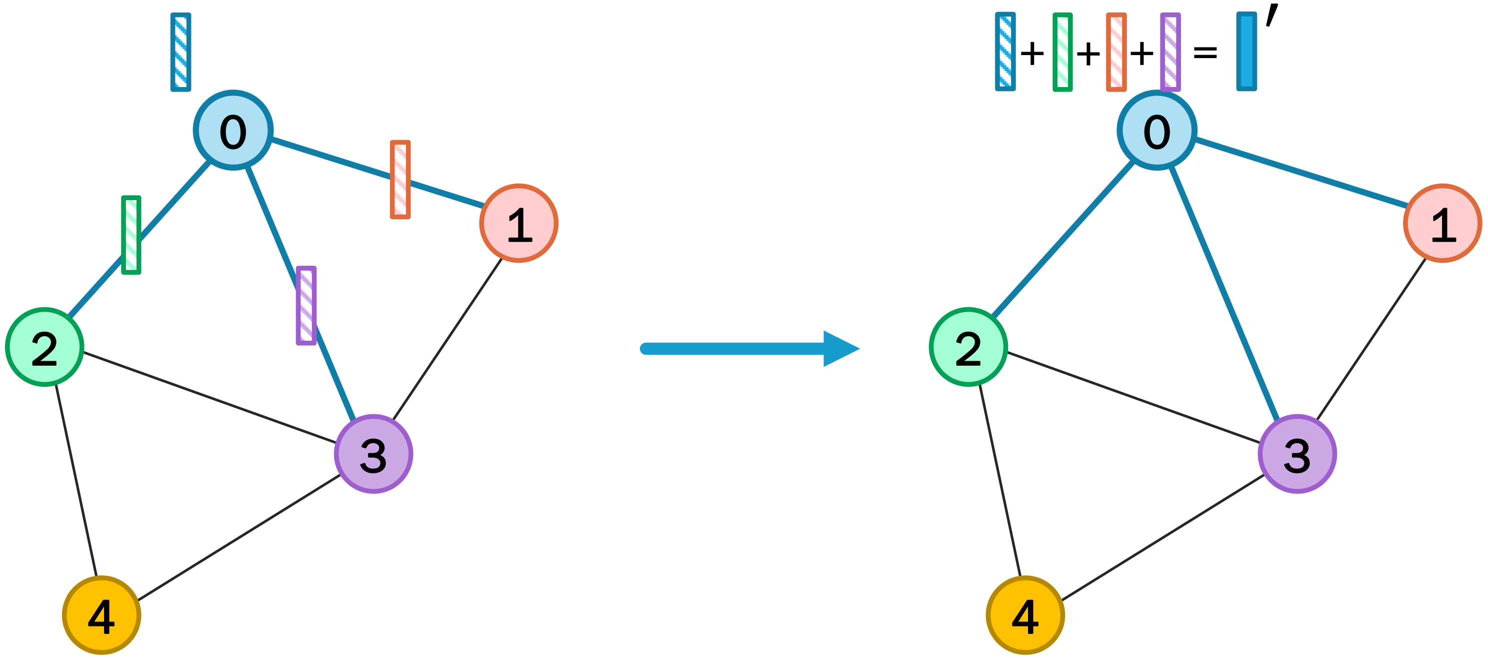
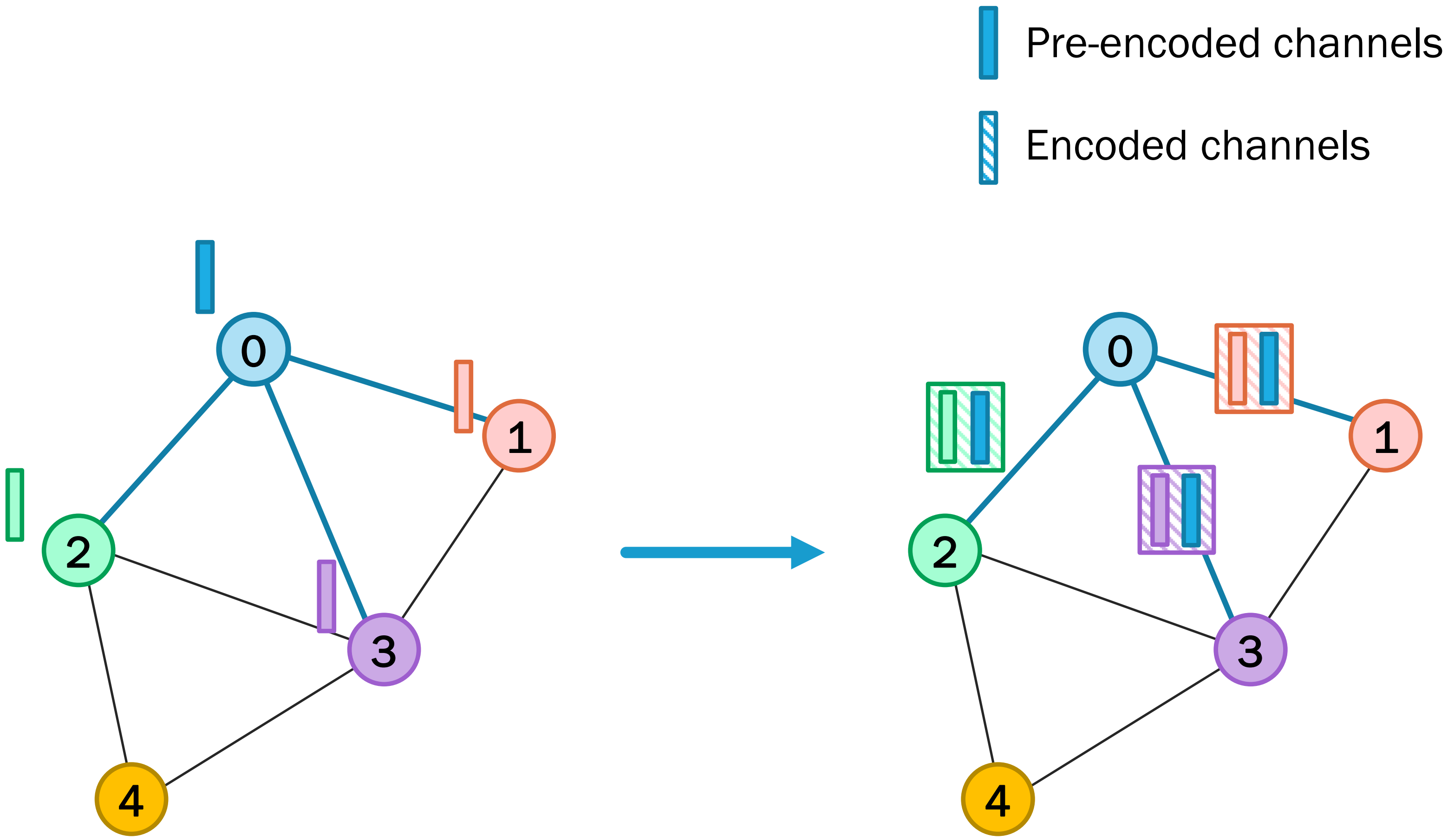


Figure inspired by Koshi et. al.

EDGE CHANNELS

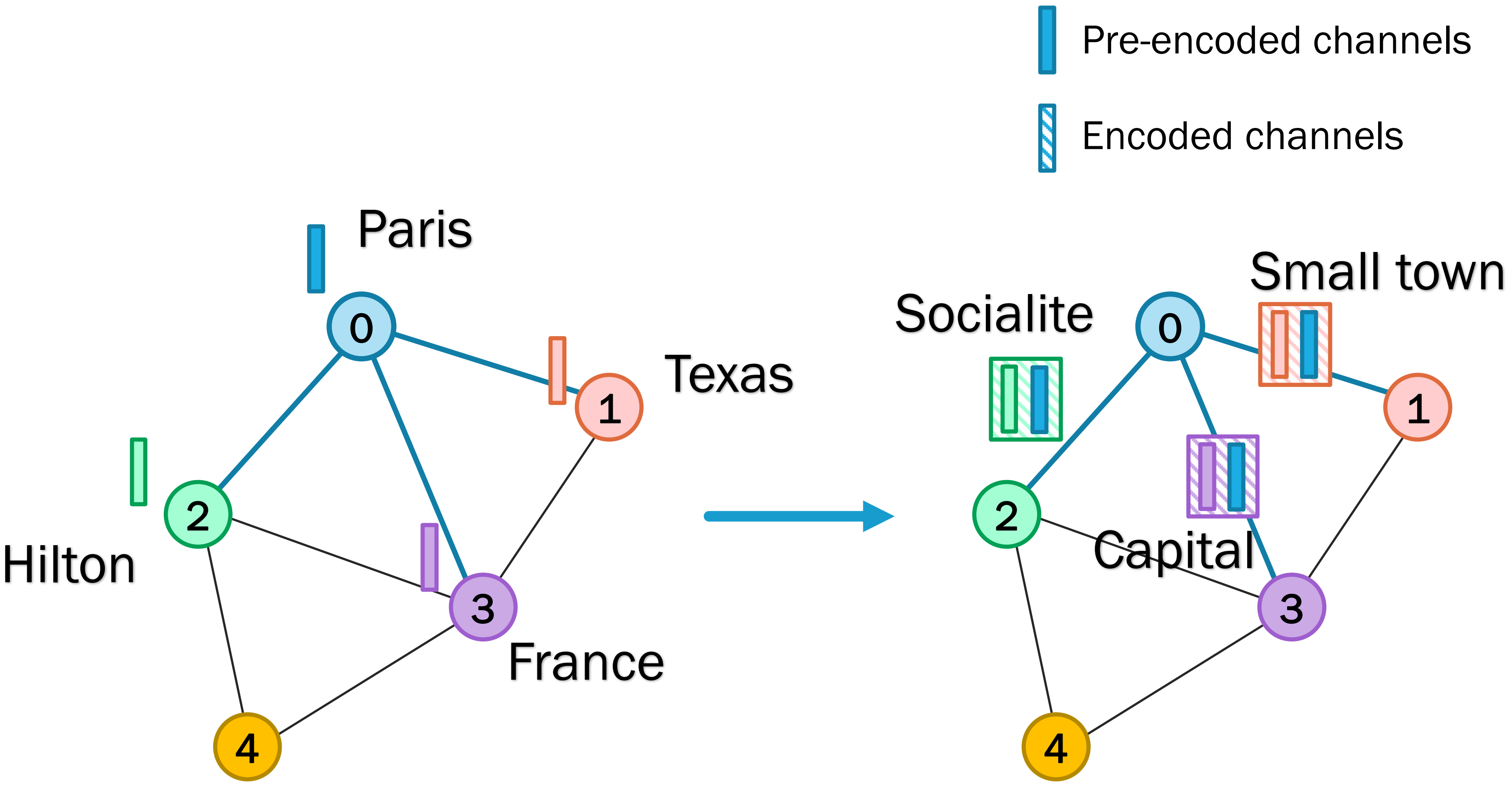
- Isotropic message passing can't differentiate importance of neighbors
- *An*isotropic message passing: encode a combination of node and neighbor along each edge
- Much more expensive – now need to store N_{edges} for backpropagation
- But much more powerful

Found in "Graph Attention Network" and "Interaction Network"



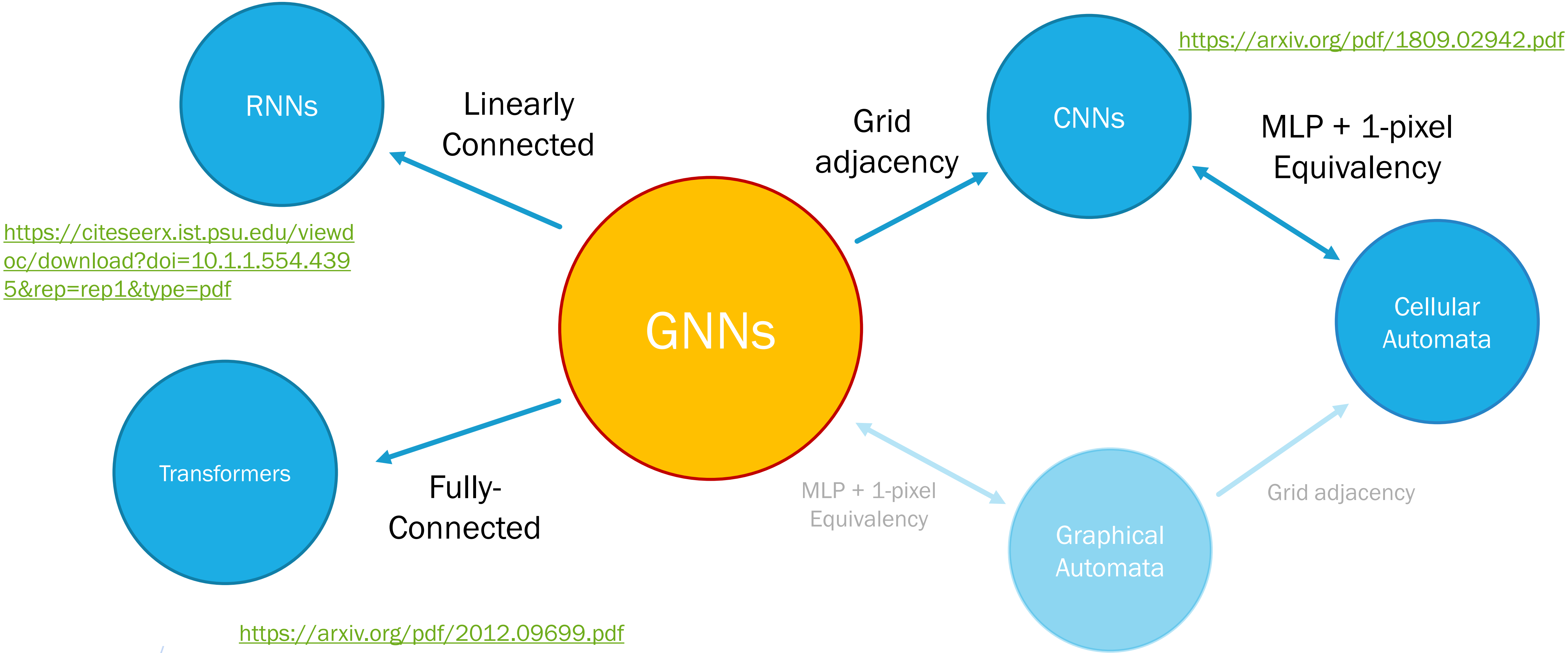
EDGE CHANNELS

- Can access *contextual* relationships

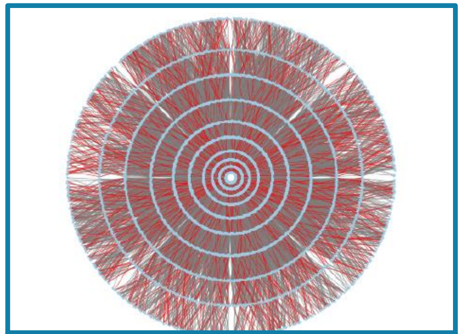


THE LANDSCAPE OF GNNS

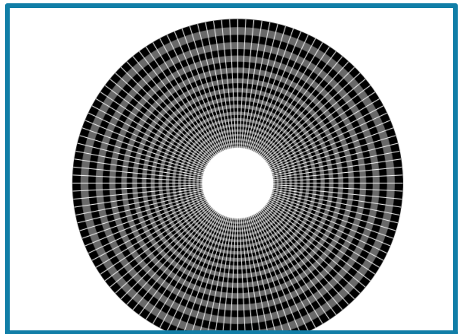
= reduces to



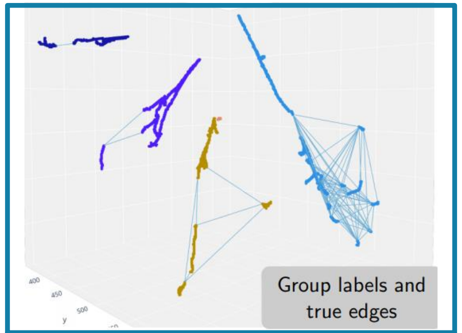
GNNS ELSEWHERE IN PARTICLE PHYSICS



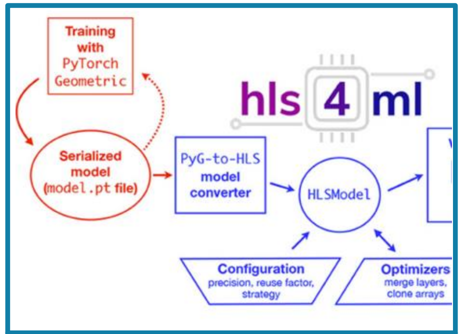
[High Lumi Generic Tracking]



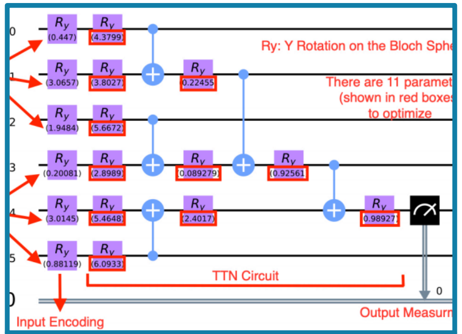
[High Lumi CMS Calorimetry]



[LArTPC Particle Reconstruction]



[FPGA-based Track Reconstruction]



[Quantum Track Reconstruction]

- Very large and active field of study!
- Comprehensive review of GNNs for Track Reconstruction - arXiv:2012.01249
- White paper on progress and future of the field – arXiv:2203.12852

GRAPH-BASED TRACK RECONSTRUCTION

WHO IS INVOLVED?

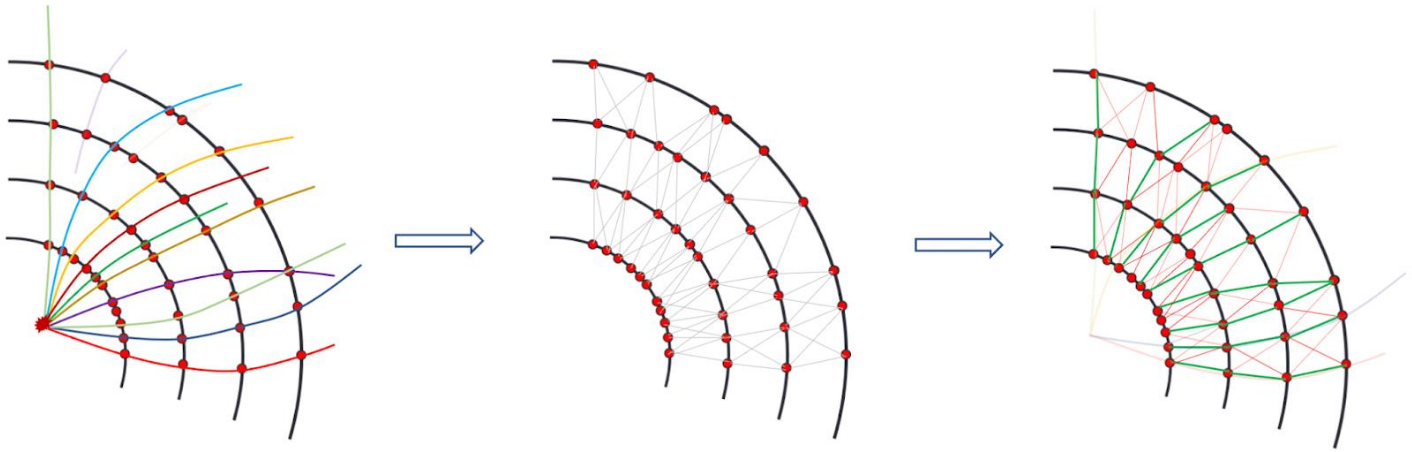
- Two groups worked on the results in this presentation, and both first tested methods on TrackML, based on the GNN-based reconstruction introduced in arxiv:2003.11603
- L2IT: Laboratoire des deux Infinis, institute based at the University of Toulouse, within the Institute of Nuclear Physics and Particle Physics
- Exa.Trkx: A DoE Office of Science-funded collaboration of LBNL, Caltech, FNAL, SLAC and a collaboration of US institutions including Cincinnati, Princeton, Urbana-Champaign, Youngstown State, and others

GRAPH REPRESENTATION OF AN EVENT

- The goal of track reconstruction:

Given set of hits in a detector from particles, assign label(s) to each hit.

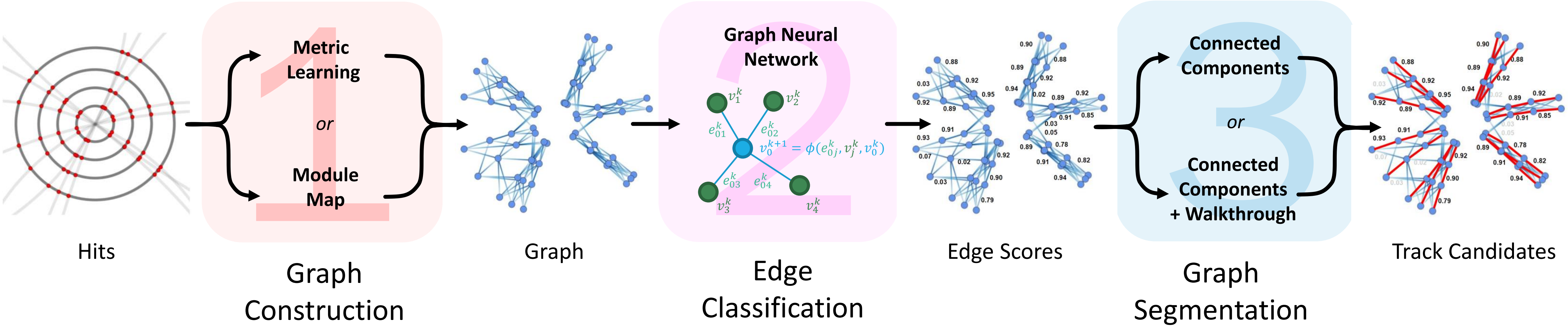
Perfect classification: All hits from a particle (*and only those hits*) share the same label



- What does it mean to represent an event with a graph?
  - Treat each hit as a **node**
  - A node can have features (e.g. position, energy deposit, etc.)
  - Nodes can be connected by **edges**, that represent the possibility of belonging to the same track
- Goal: **Use ML and/or graph techniques to segment or cluster the nodes to match particle tracks**
- **Proof-of-concept:** TrackML community challenge dataset with simplified simulation

PIPELINE OVERVIEW

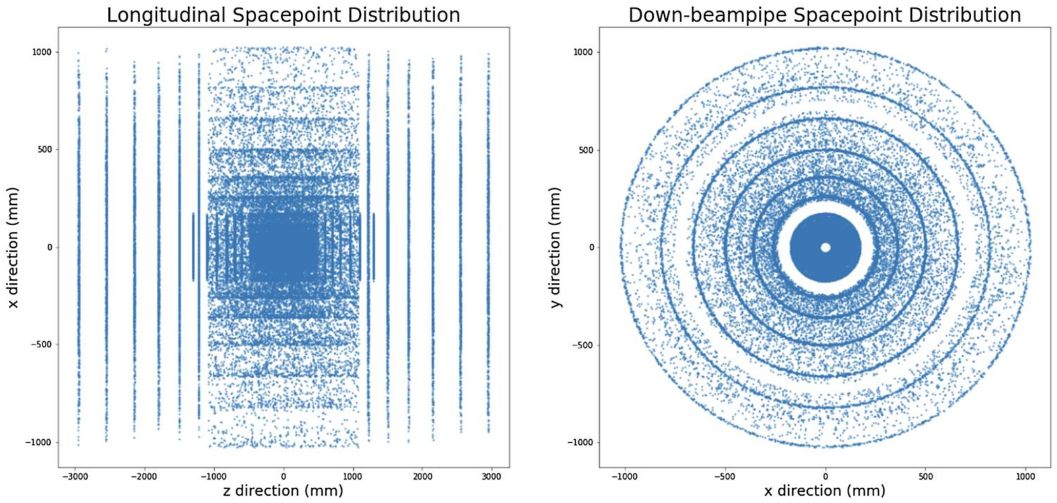
- Current pipeline of the L2IT-Exatrkx collaborative effort
- Each stage offers multiple independent choices, depending on hardware and time constraints



DATASETS

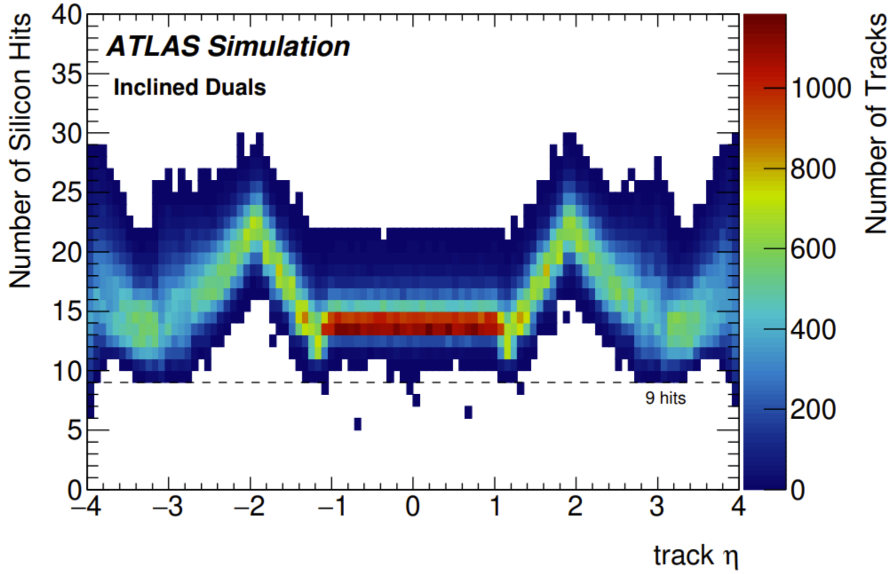
- Two datasets used to study this pipeline. For absolute clarity, when citing a result specific to one dataset, will place the badge of TrackML or ATLAS ITk on slide:

TrackML



- Mean number of spacepoints: 110k
- Simplified simulation: No secondaries and optimistic charge information

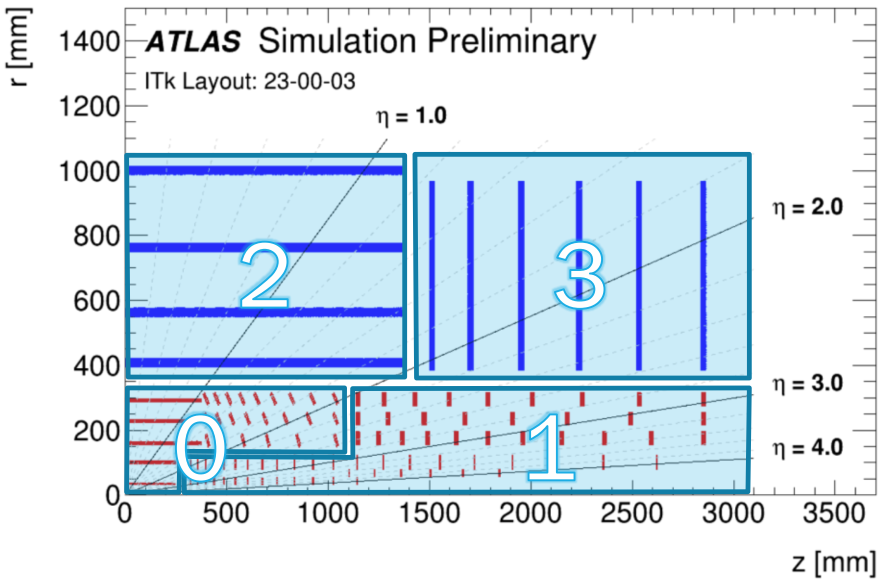
ATLAS ITk



- Mean number of spacepoints: 310k
- Full simulation

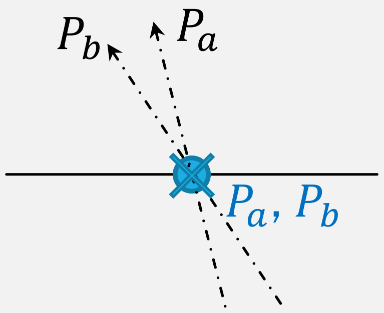
ATLAS ITK GEOMETRY

- Generation script* using Athena, $t\bar{t}$ at $\mu = \langle 200 \rangle$: with statistics dominated by soft interactions
- ITk consists of barrel and endcap, each with pixels and strips:

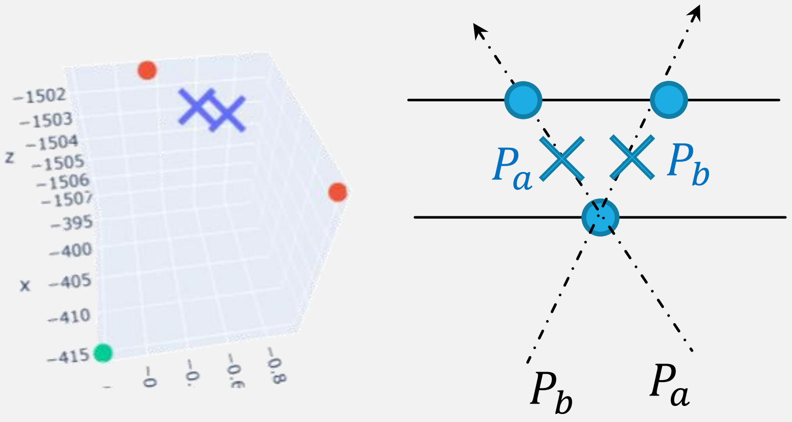


0: Pixel barrel
1: Pixel endcap
2: Strip barrel
3: Strip endcap

- Spacepoints (3D representations of track hits) are defined depending on strip or pixel:



Pixel is trivial: Each spacepoint maps to one cluster, which can map to many particles

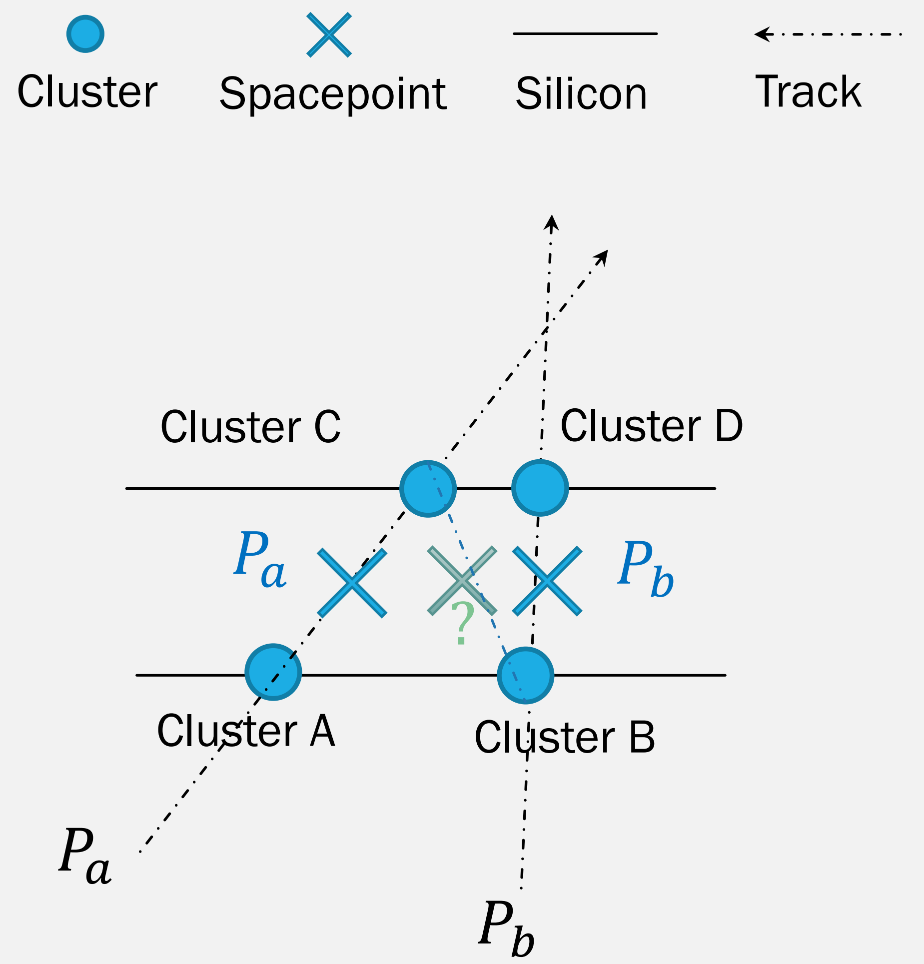


Strip: Each spacepoint maps to two clusters – one on either side of strip, which can map to many particles

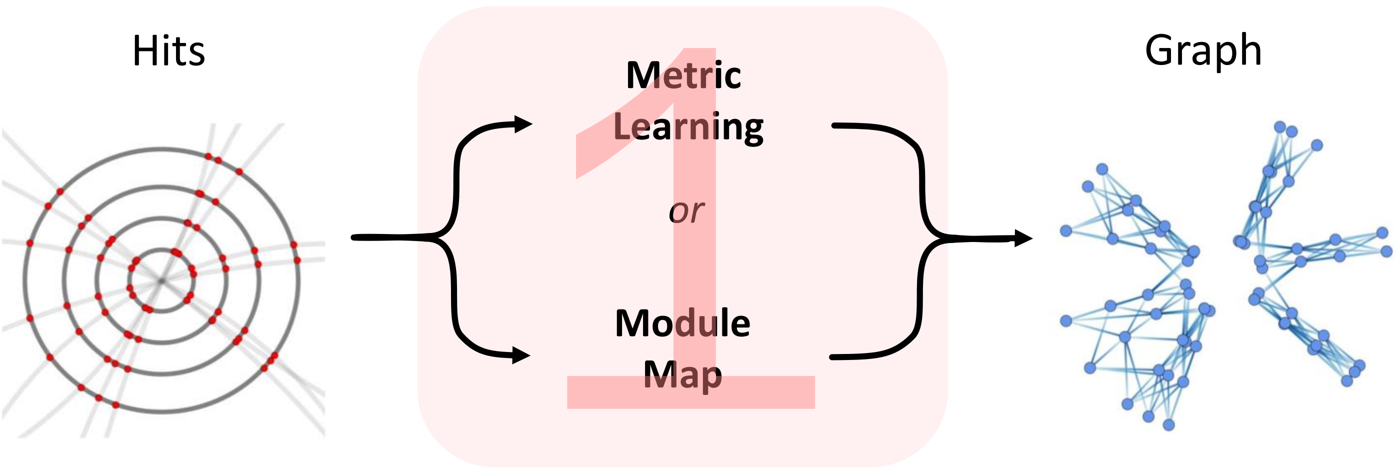
*Thanks Noemi Calace

ATLAS ITK GEOMETRY

- Fiducial particles are **charged, with $\eta \in [-4, 4]$, and production radius < 260mm**
- Each event has O(15k) fiducial particles, O(300k) spacepoints
- We define **background** spacepoints as including:
  - Those left by non-fiducial or intermediate particles (i.e. any particle barcodes not retained during simulation), or
  - Those mis-constructed in the strip regions as **ghost** spacepoints
- An event has O(170k) background spacepoints



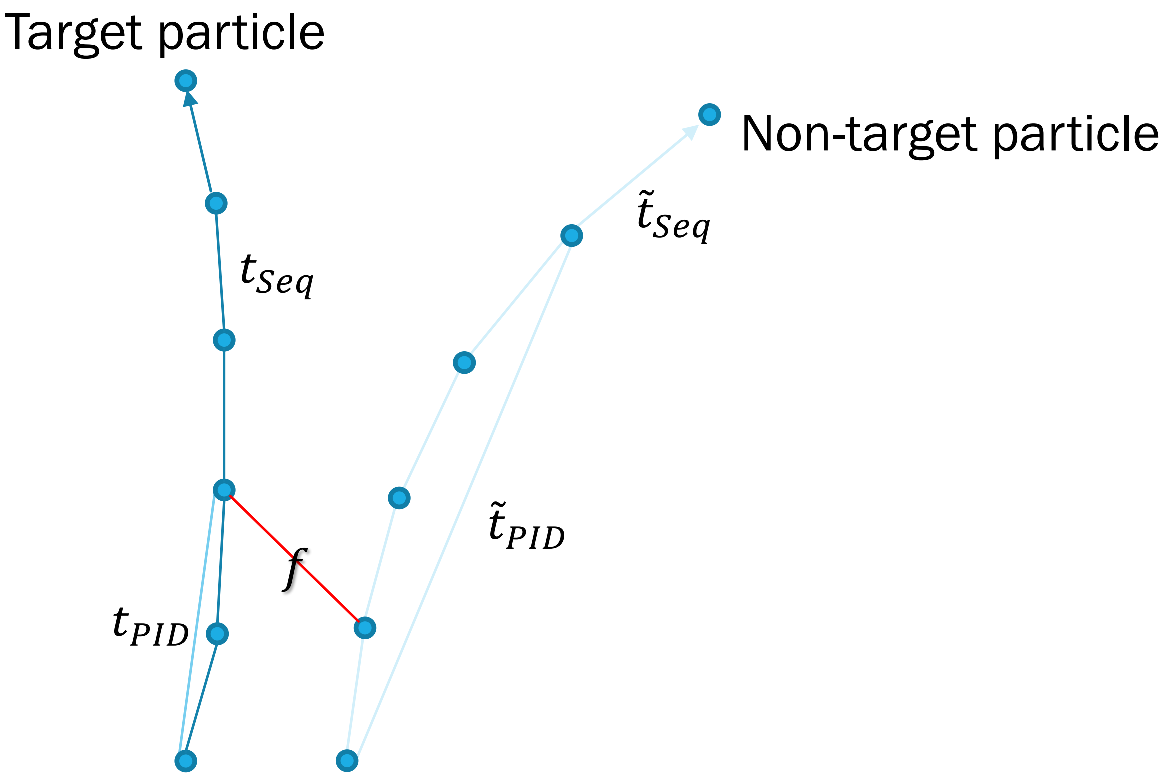
Ghost spacepoint: Incorrectly constructed from clusters left by different particles

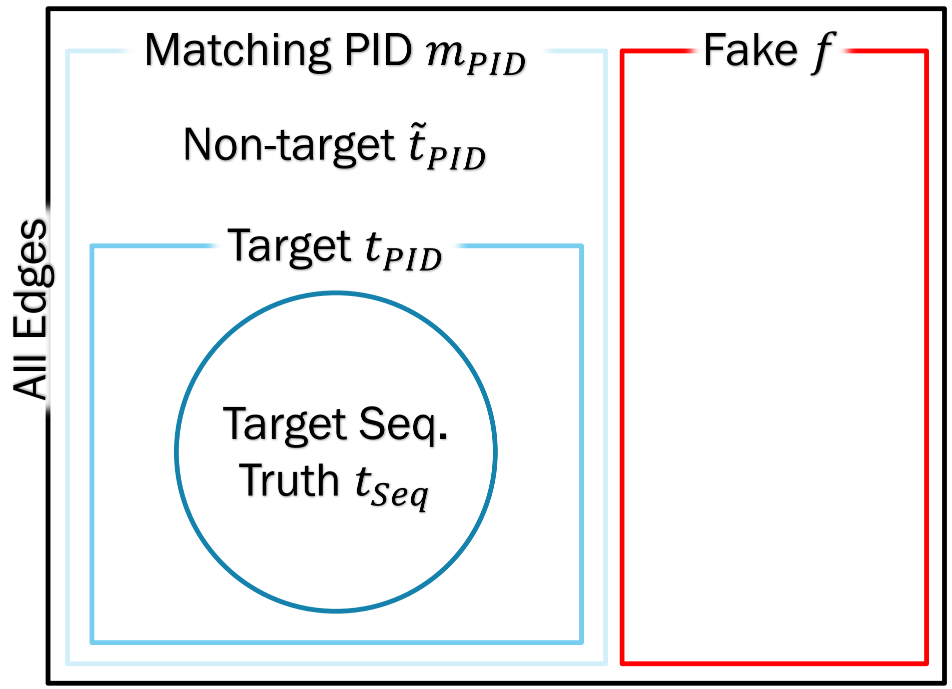


Graph Construction

EDGE TRUTH DEFINITIONS

ATLAS ITk



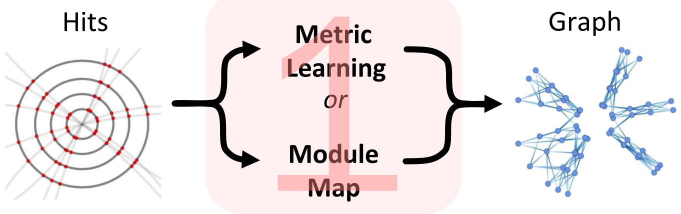


Target particle:

- $p_T > 1$ GeV, and
- At least 3 SP on different modules, and
- Primary

Therefore, define efficiency and purity (note that we mask out sequential non-target) for a graph with edges e

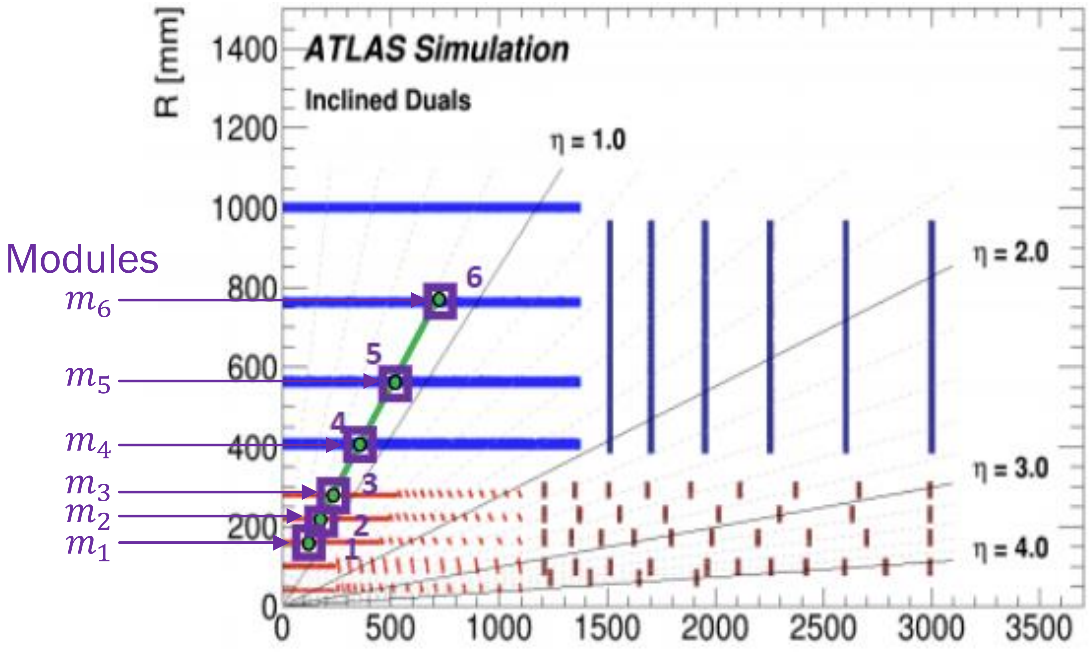
$$\text{Efficiency} = \frac{|e \cap t_{Seq}|}{|t_{Seq}|}, \quad \text{Purity} = \frac{|e \cap t_{Seq} - \tilde{t}_{Seq}|}{|e - \tilde{t}_{Seq}|}$$



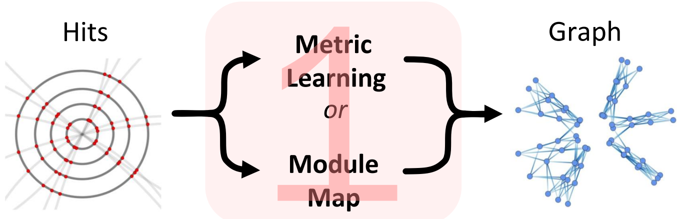
Graph Construction

MODULE MAP - DOUBLETS

- **The idea**: Build a map of detector modules, where a connection *from* module A
  to module B means that at least one true track has passed sequentially through A to B
- **Step 1**: Build all combinations of sequential doublets for an event, register an A-to-B entry if a doublet passes through. O(90k) events used to build these combinations
- **Step 2**: For *each* A-to-B entry, also register/update the max and min values of a set of geometric observables. Apply these cuts when building the graph in inference



$$\text{Map} = \{m_1\!: m_2, m_2\!: m_3, \dots, m_5\!: m_6\}$$

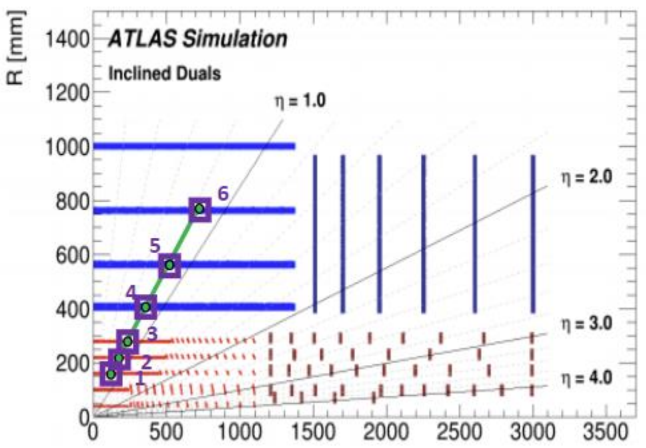


Graph Construction

MODULE MAP – TRIPLETS

- **The idea**: Build a map of detector modules, where a connection *from* module A *to* module B *to* module C means that at least one true track has passed sequentially through A to B to C
- Step 1: Build all combinations of sequential triplets for an event, register an A-to-B-to-C entry if a triplet passes through
- Step 2: For *each* A-to-B-to-C entry, also register/update the max and min values of a set of geometric observables. Apply these cuts when building the graph in inference

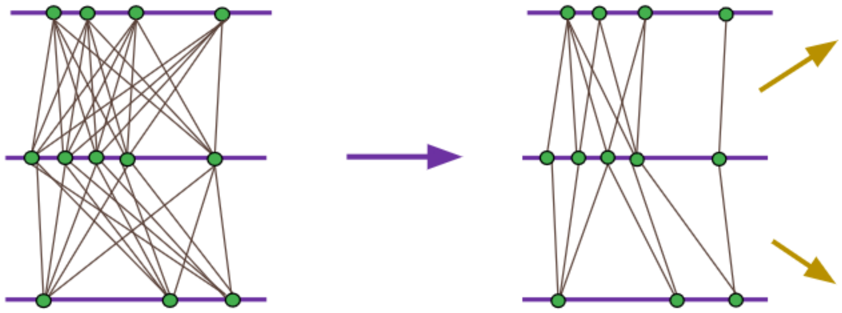
Step 1



Connections added:

1 -> 2 -> 3
2 -> 3 -> 4
3 -> 4 -> 5
4 -> 5 -> 6

Step 2



- $z_0 = z_{h1} - r_{h1} \times \left(\frac{\Delta z}{\Delta r}\right)$
- $\phi_{slope} = \frac{\Delta\phi}{\Delta r}$
- $\Delta\phi = \phi_{h2} - \phi_{h1}$
- $\Delta\eta = \eta_{h2} - \eta_{h1}$

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- $\Delta\phi = \phi_{h2} - \phi_{h1}$
- $\Delta\eta = \eta_{h2} - \eta_{h1}$

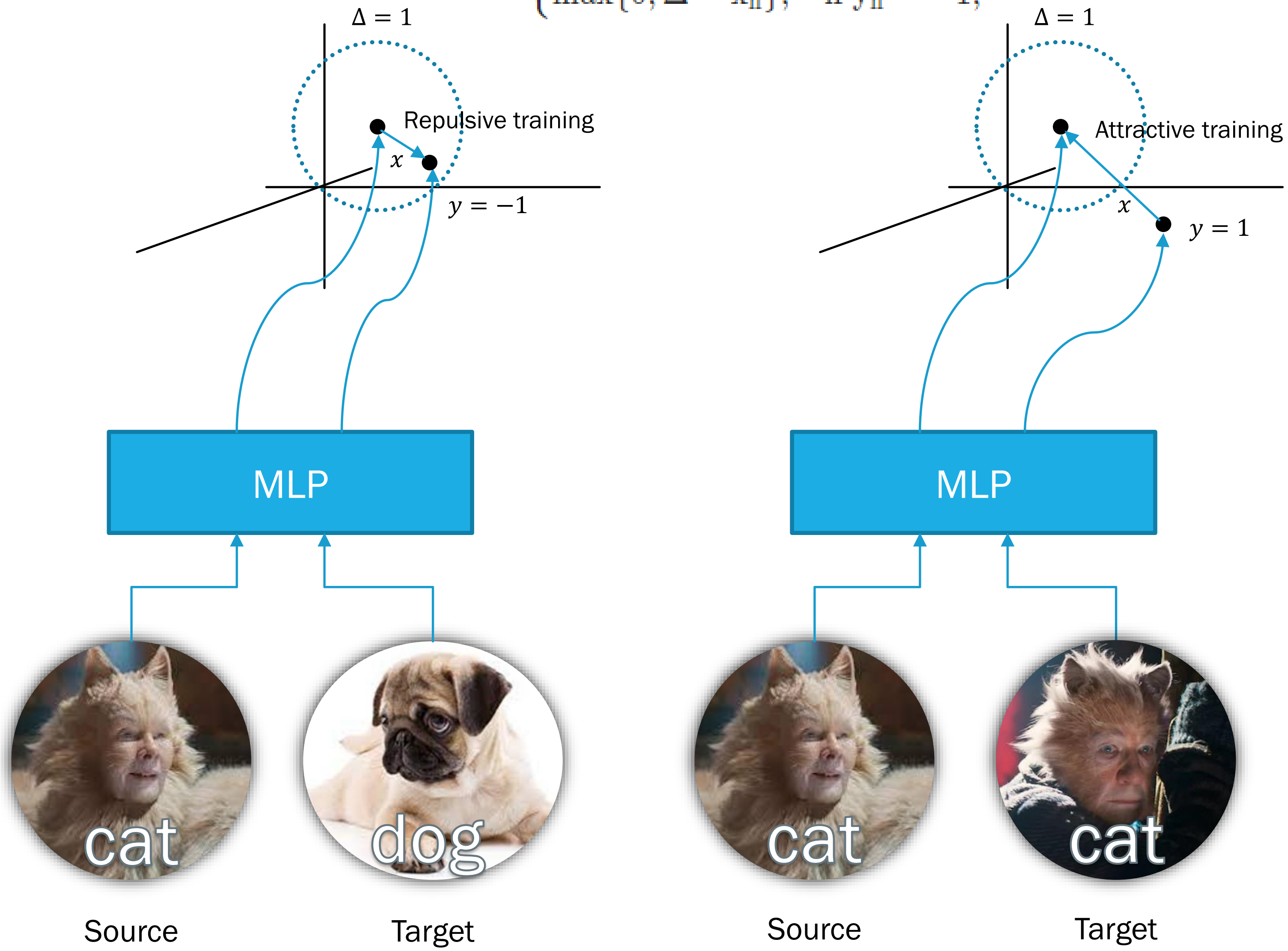
- $\Delta \frac{\Delta y}{\Delta x} = \frac{\Delta y_{12}}{\Delta x_{12}} - \frac{\Delta y_{23}}{\Delta x_{23}}$
- $\Delta \frac{\Delta z}{\Delta r} = \frac{\Delta z_{12}}{\Delta r_{12}} - \frac{\Delta z_{23}}{\Delta r_{23}}$

METRIC LEARNING INTUITION

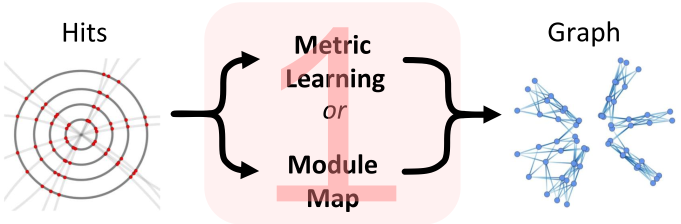
- Encode / embed input into N-dimensional space
- Reward (low loss) matching pairs within unit distance
- Punish (high loss) mismatching pairs within unit distance
- Repeat for many pairs

“Contrastive” hinge loss

$$l_n = \begin{cases} x_n, & \text{if } y_n = 1, \\ \max\{0, \Delta - x_n\}, & \text{if } y_n = -1, \end{cases}$$



METRIC LEARNING



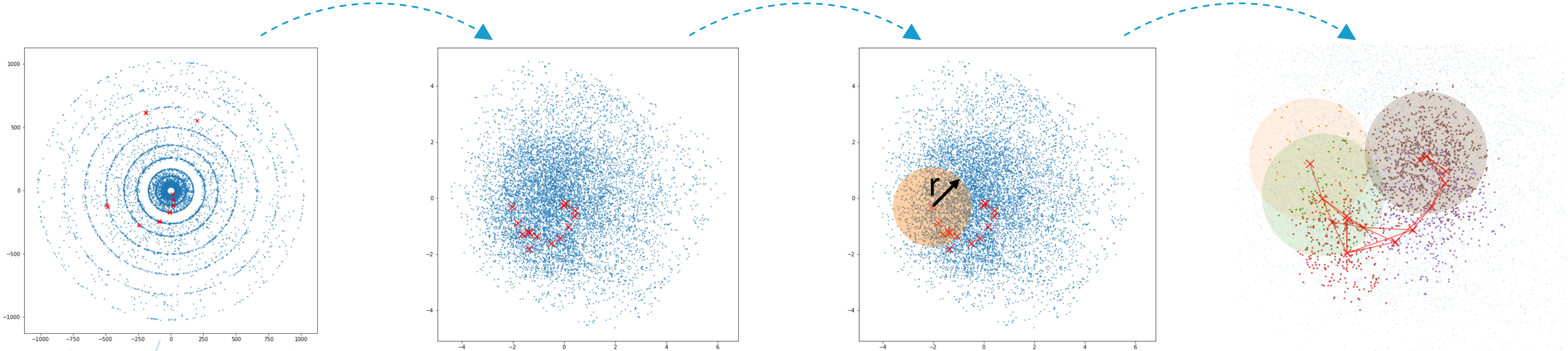
Graph Construction

- **The idea:** Teach an MLP to embed spacepoint features (spatial and cell information)
- In this embedded space, all doublets in a given particle track are **trained to be near each other (Euclidean distance x)**, using a contrastive loss function L:

$$L = \begin{cases} x, & \text{if true pair} \\ \max(0, r - x), & \text{if false pair} \end{cases}$$

- A hit in a track is trained to be **closest** to its preceeding and succeeding track hits

Embed into learned latent space — **Connect all spacepoints within radius r** — **All spacepoint pairs joined into graph**

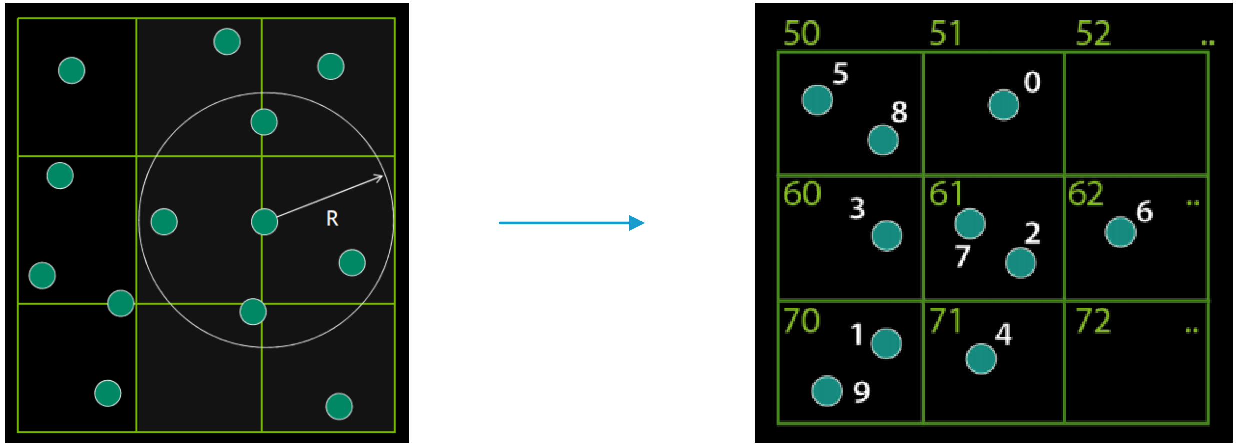


FAST GRAPH CONSTRUCTION

TrackML

- Nearest neighbor search is a **bottleneck** of the graph construction stage
- FAISS finding K=500 for N=100,000 ~ 700ms
- KNN is overkill – we don't need explicit list of K sorted neighbours
- Built custom library on **Fixed Radius Nearest Neighbour (FRNN)** search algorithm
- Cell-by-cell grid search is *much* faster: [*The complexity of finding fixed-radius near neighbors*. Bentley, et al 1977]

Fast fixed-radius nearest neighbors: Interactive Million-particle Fluids, Hoetzlein (NVIDIA), 2014

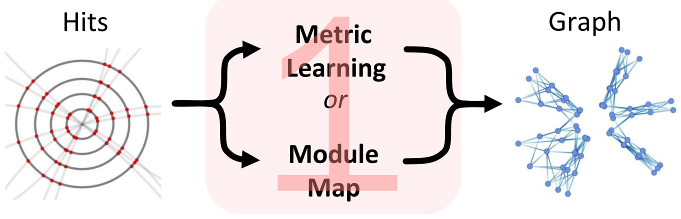


- Fixed Radius NN Search vs Pytorch3D's KNN

172974 points ~16x speed up | 543652 points ~12x speed up | 437645 points ~15x speed up | 100000 points ~30x speed up

Accelerating NN Search on CUDA for Learning Point Clouds, Xue 2020

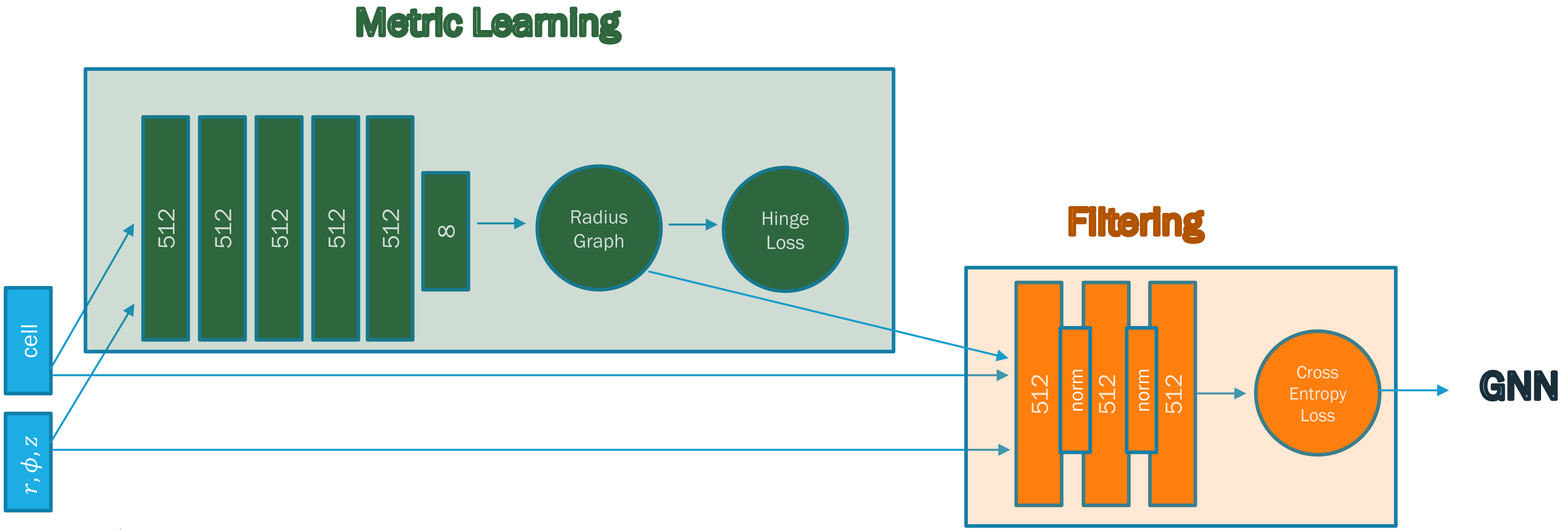
METRIC LEARNING - FILTERING



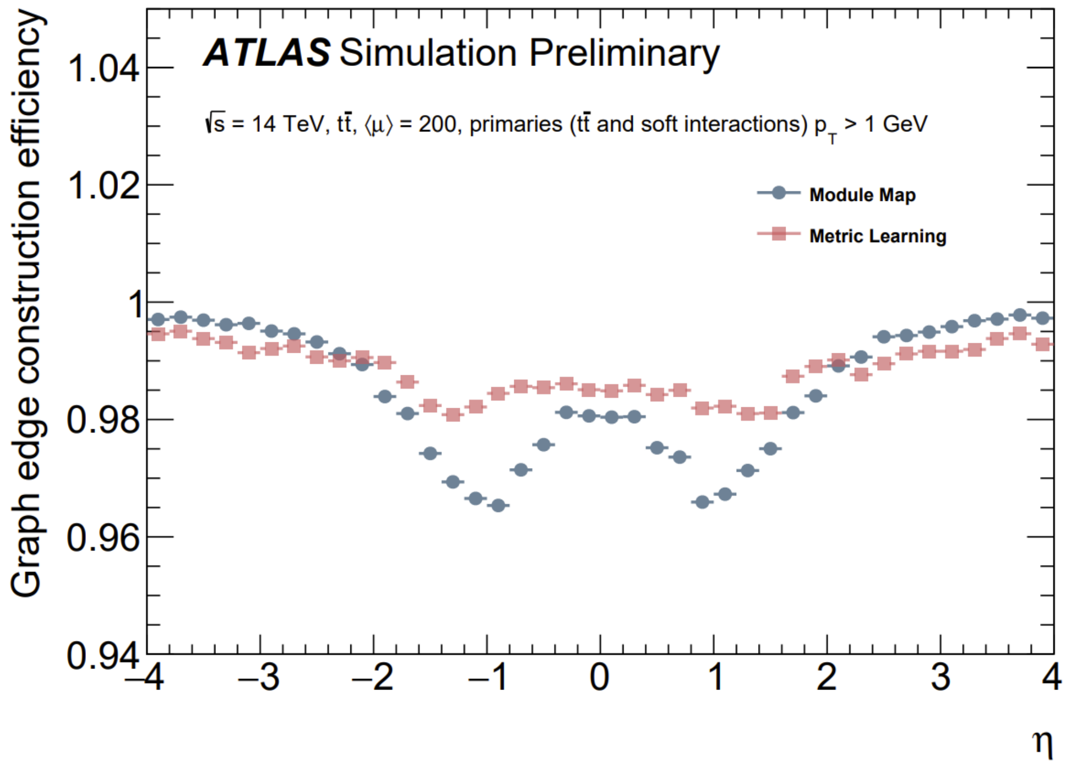
Graph Construction

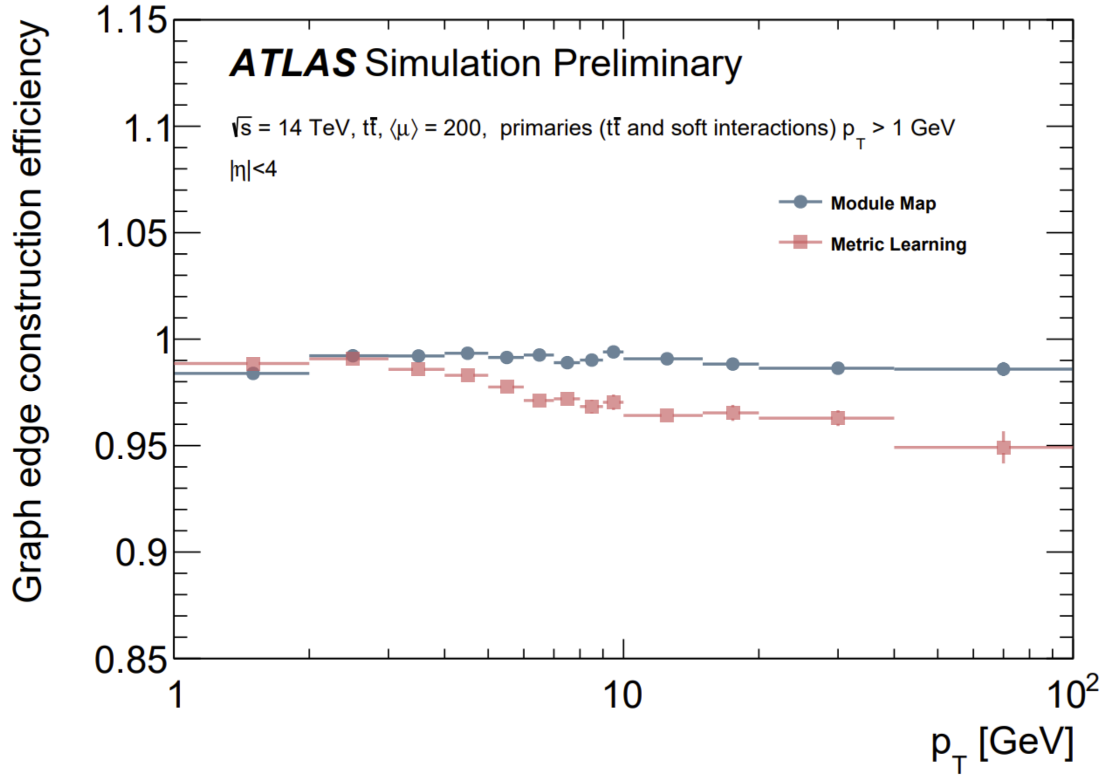
ATLAS ITk

- Output graph of metric learning is impure: 0.2%
- Can pass edges through a simple MLP filter to filter out the easy fakes
- Improves purity to 2%, so graph can be trained entirely on a single GPU



GRAPH CONSTRUCTION RESULTS

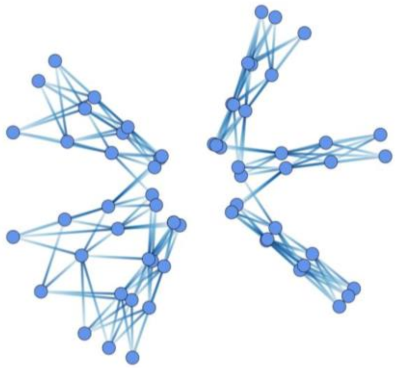




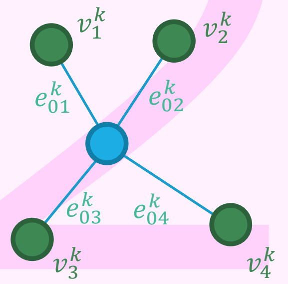
- Drop in efficiency at low η due to poor barrel strip resolution (will discuss further!)

- Drop in efficiency at high p_T due to low training statistics

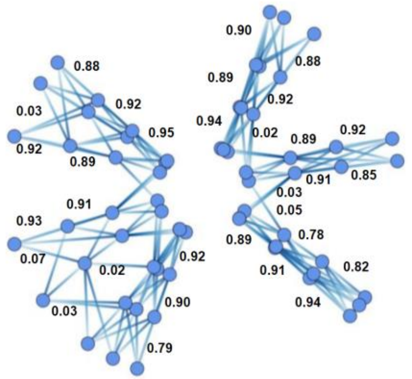
Graph



Graph Neural Network



Edge Scores



Edge Labeling

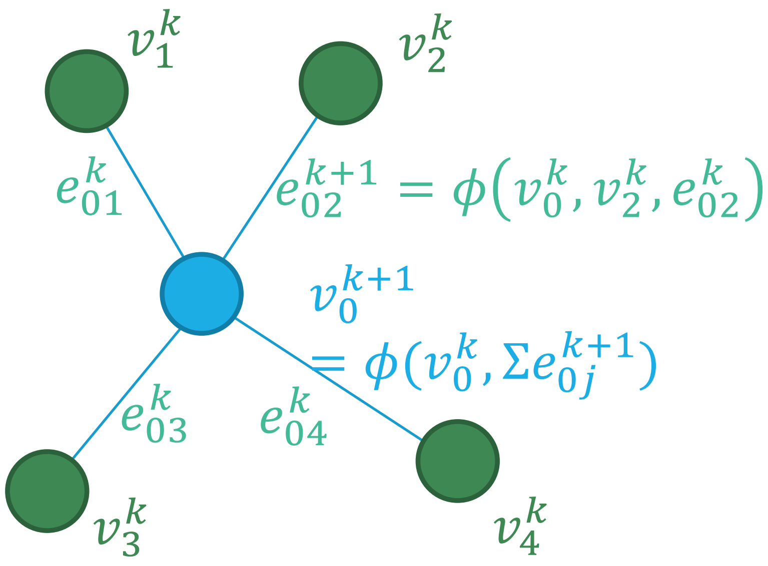
EDGE CLASSIFICATION WITH GRAPH NEURAL NETWORK

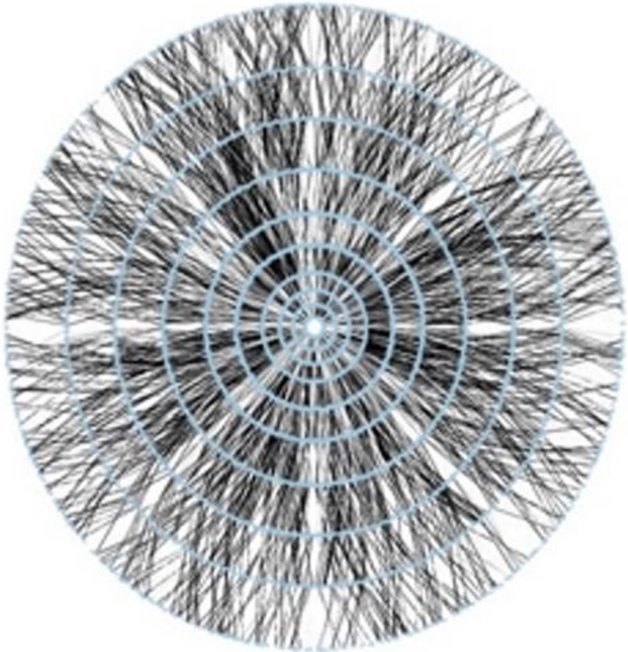
1. Node features (spatial position) are encoded
2. Encoded features are concatenated and encoded to create edge features
3. Edge features are aggregated around nodes to create next round of encoded node features (i.e. message passing)
4. Each iteration of message passing improves discrimination power

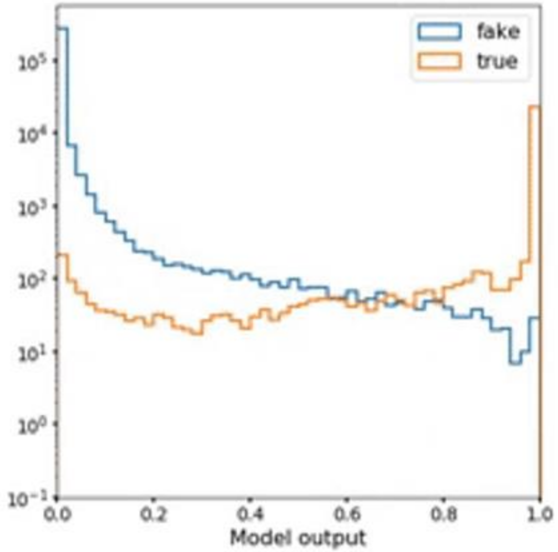
v_i^k node features
e_{ij}^k edge features
at iteration k

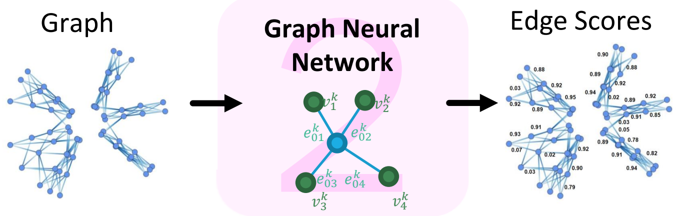
Battaglia, Peter, et al. "Interaction networks for learning about objects, relations and physics." 2016.

INTERACTION NETWORK







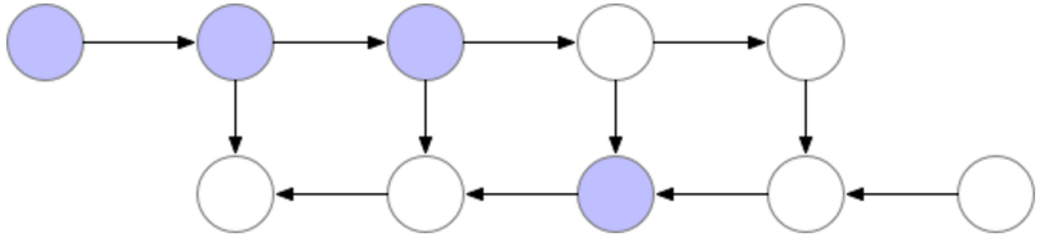


Edge Labeling

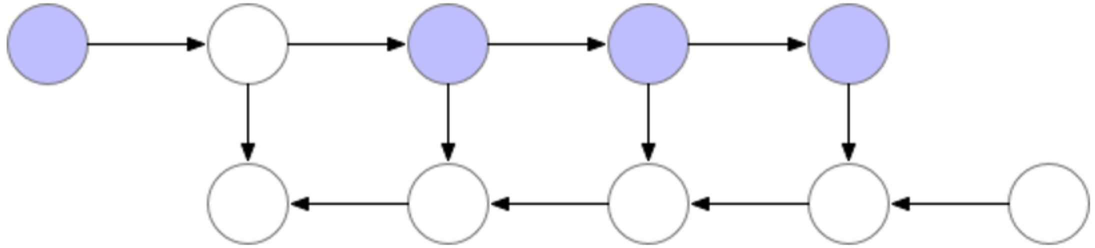
MEMORY MANAGEMENT

- Graph construction leads to very large graphs O(1m) edges, cannot fit training on A100 GPU with 32Gb memory
- Should not split the graphs up (leads to lower GNN accuracy)
- **Solution A:** Were previously using a compromising form of **"gradient checkpointing"** – reduced memory by 4x
- Now using maximal checkpointing, reduce memory further by 2x – just fits on A100

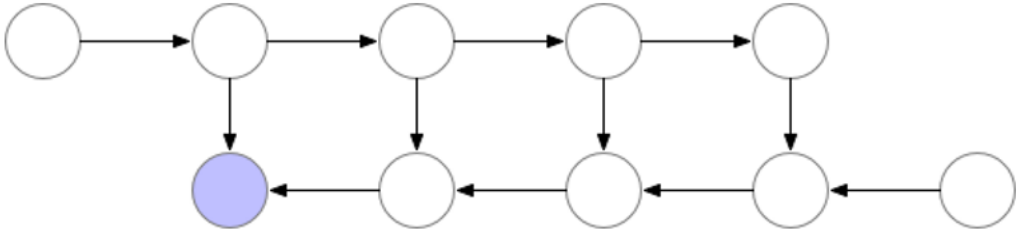
No checkpointing

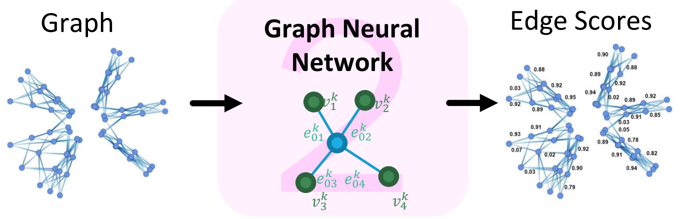


Partial checkpointing



Maximal checkpointing

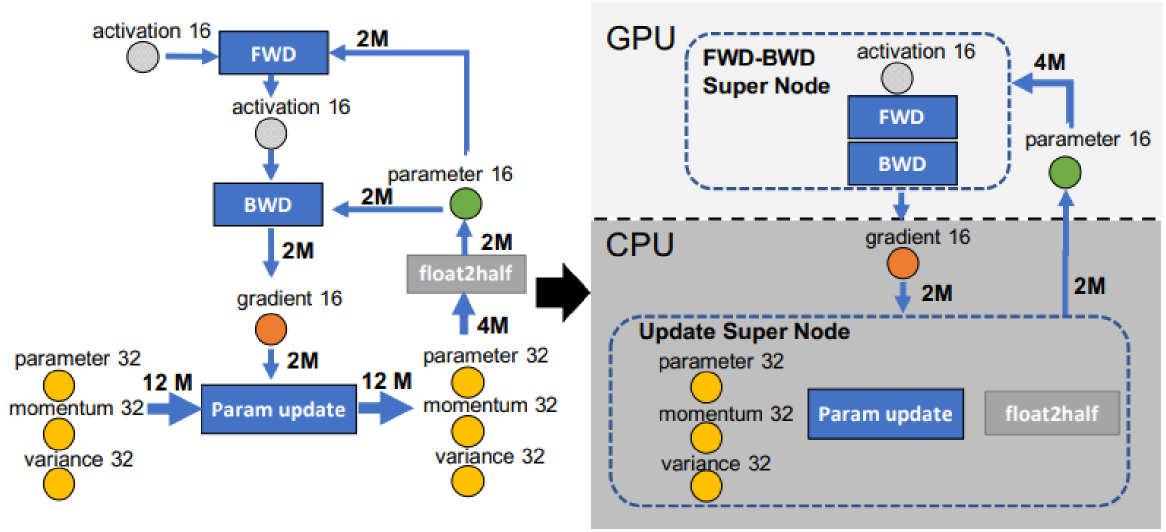




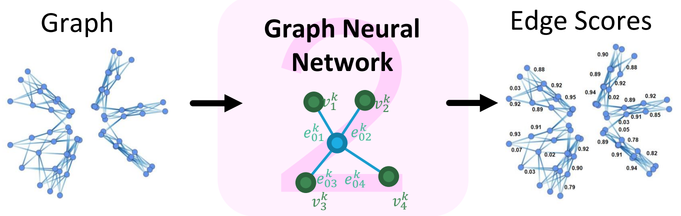
Edge Labeling

TRAINING SOLUTIONS

- **Solution B:** Model offloading
- Each layer of GNN placed on GPU for forward and backward pass, but held on CPU otherwise
- Works well with TensorFlow, enabling training of O(1m) edge graphs
- Unable to integrate with Pytorch pipeline



ZeRO-Offload: Democratizing Billion-Scale Model Training
arXiv: 2101.06840



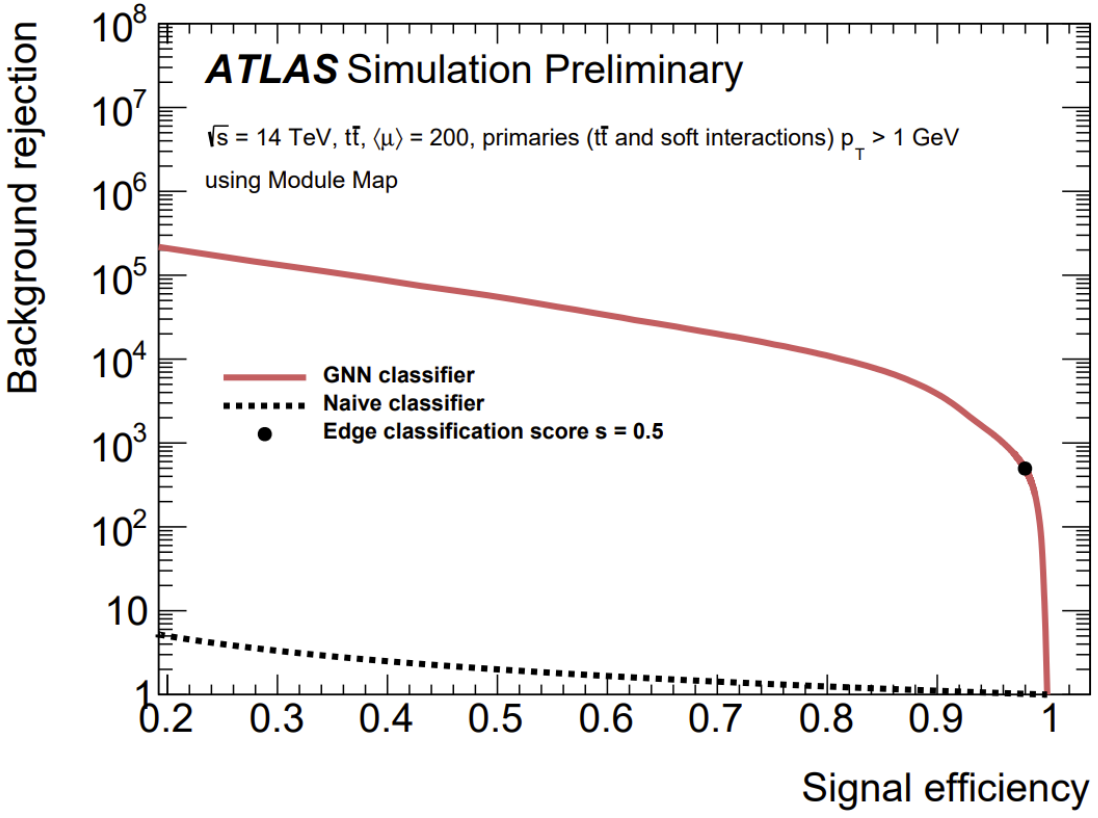
Edge Labeling

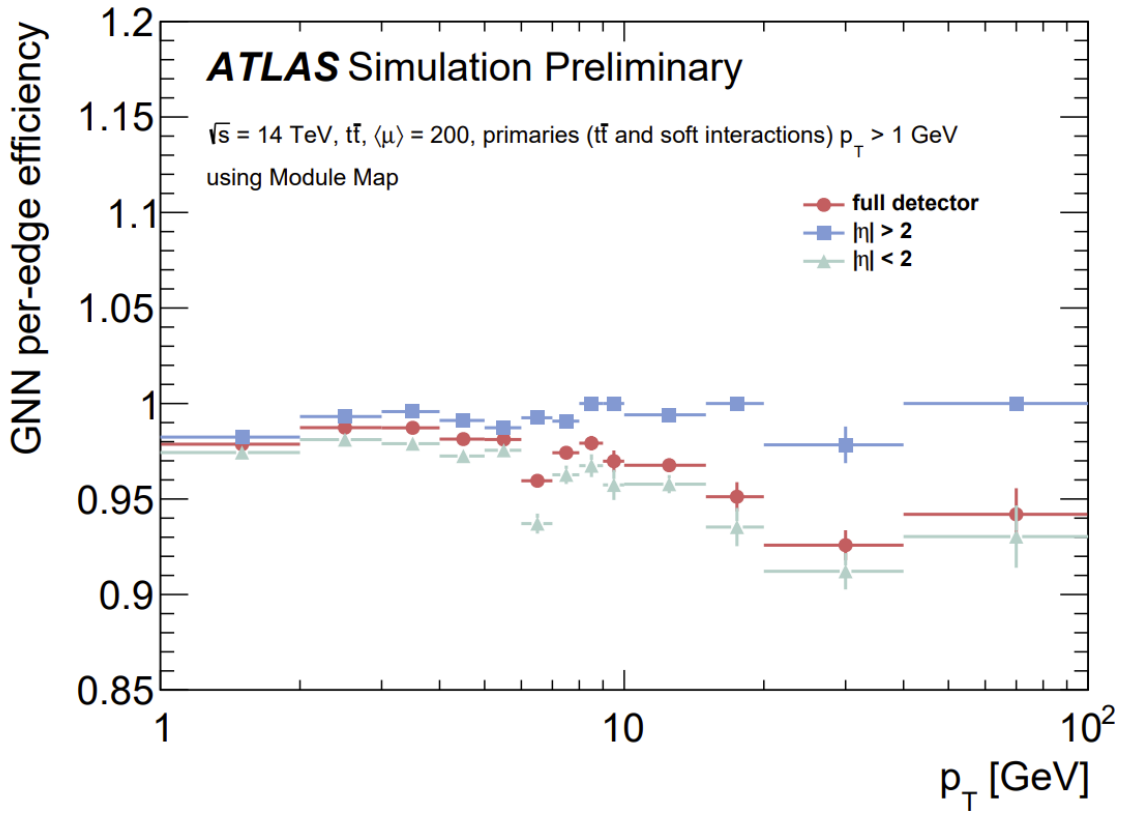
LOSS FUNCTION DESIGN

- The **target** of the GNN and track reconstruction is edges from primary particles with pT>1 GeV that have left at least 3 hits on different modules in the detector (see slide 12)
- Have very small set of target edges (1-2% of edges are true target t_{Seq})
- **Solution:** t_{Seq} $y = 1$ weighted up by $\times 10$, sequential background $\tilde{t}_{Seq}$ masked, all others $y = 0$
- Weighting gives much better performance at high-efficiency
- Masking gives much better performance around the 1 GeV cutoff

GNN EDGE CLASSIFICATION RESULTS

ROC CURVE & EDGEWISE PERFORMANCE VS. p_T

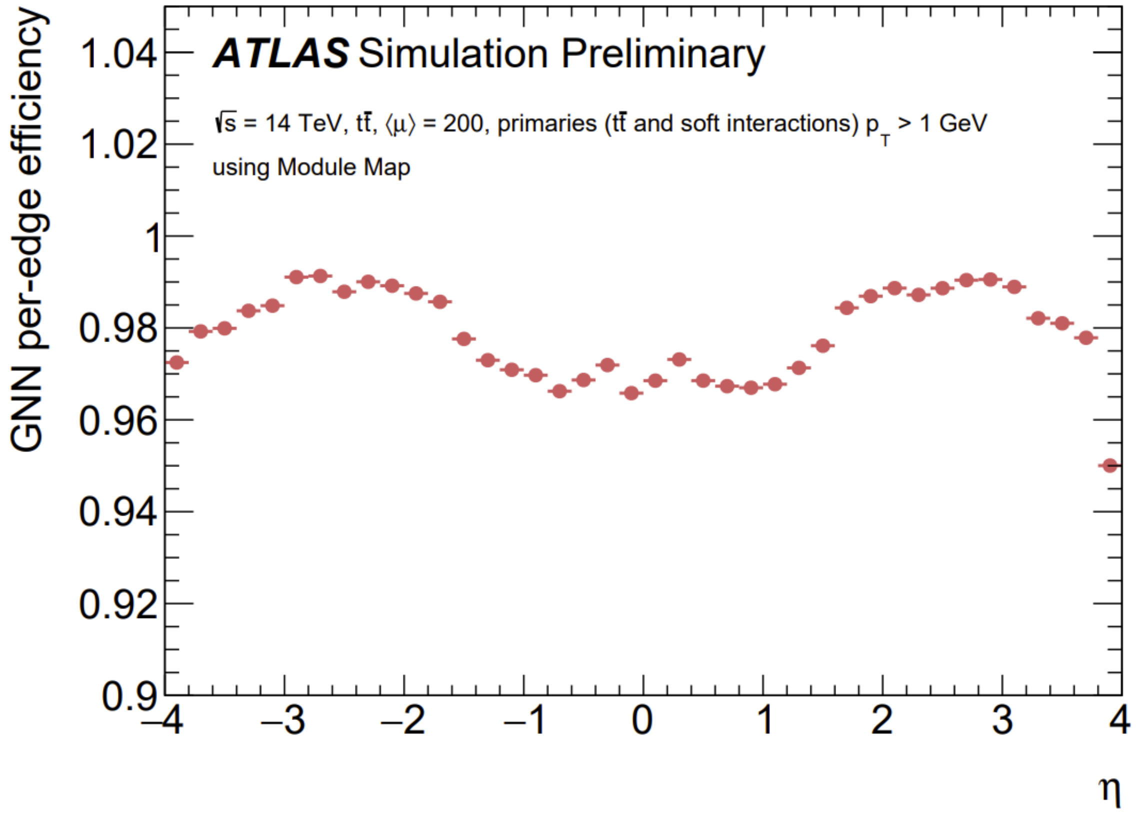


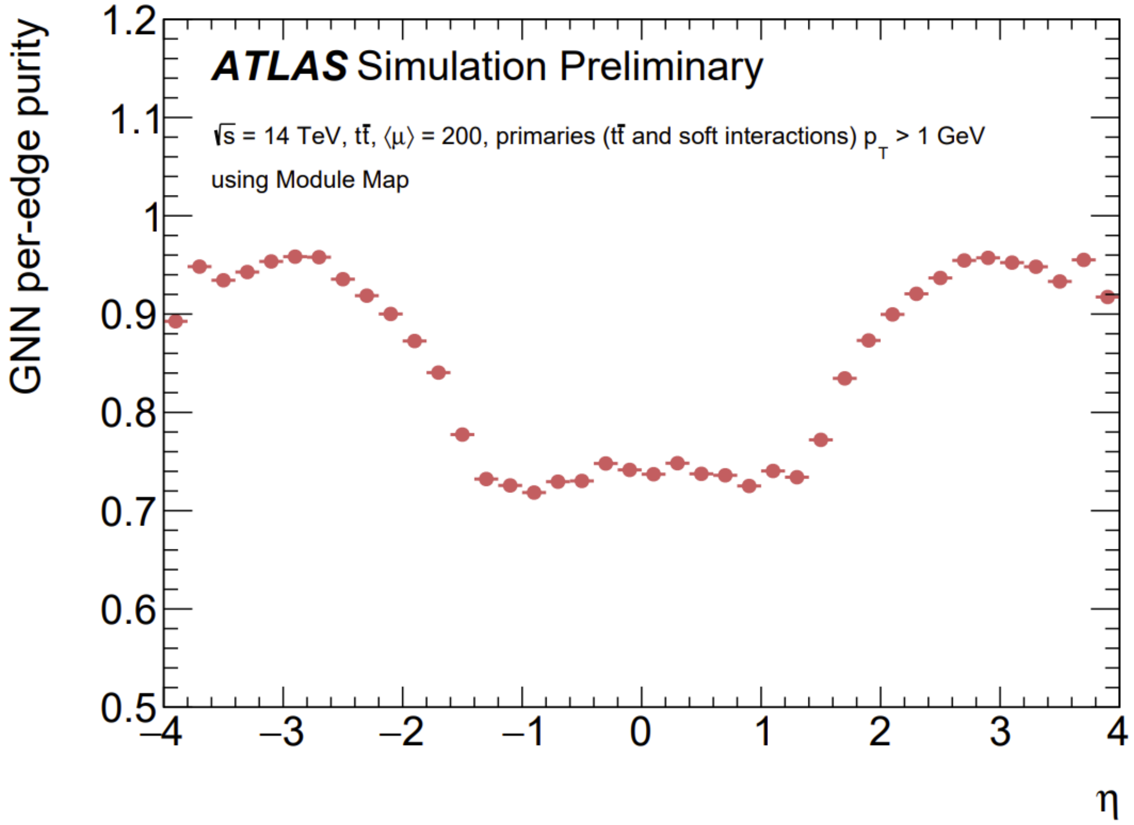


- Edge cut of 0.5 on output of GNN edge classifier

GNN EDGE CLASSIFICATION RESULTS

EDGEWISE PERFORMANCE VS. η

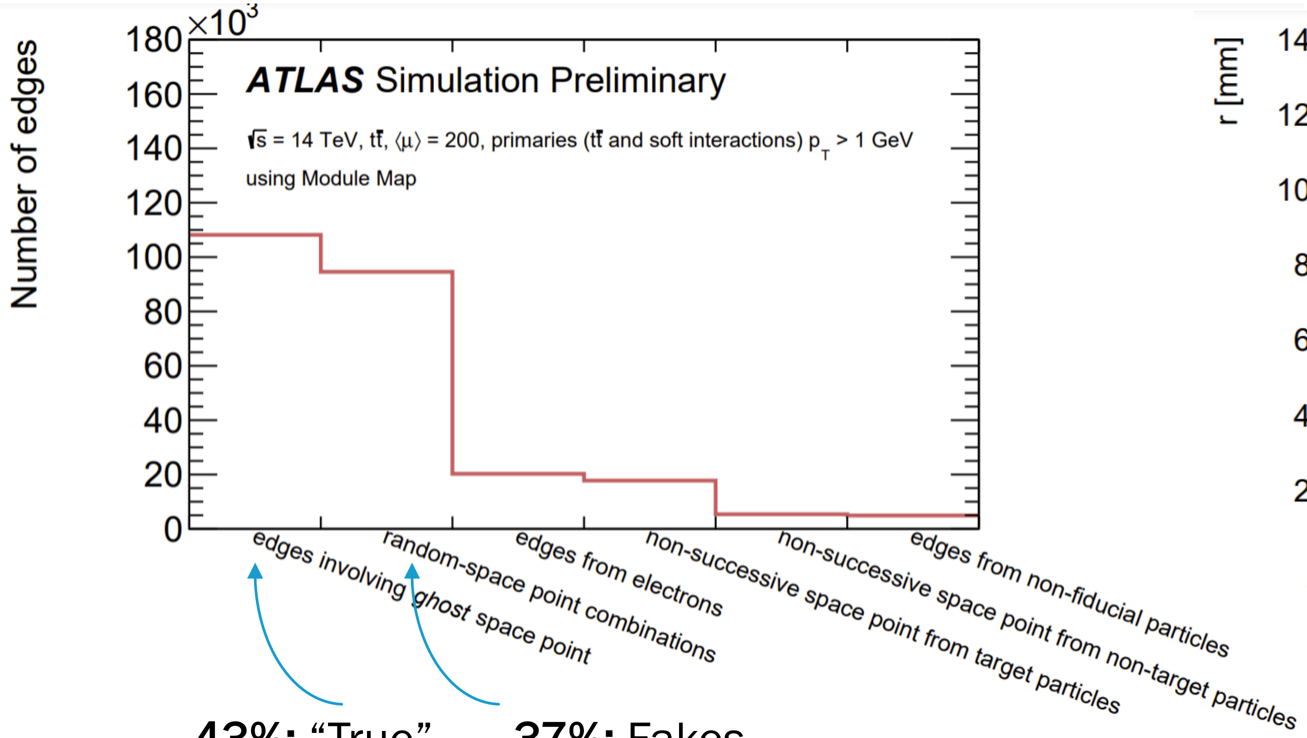




- Again, see a drop in performance at low η

BARREL STRIP MISCLASSIFICATION

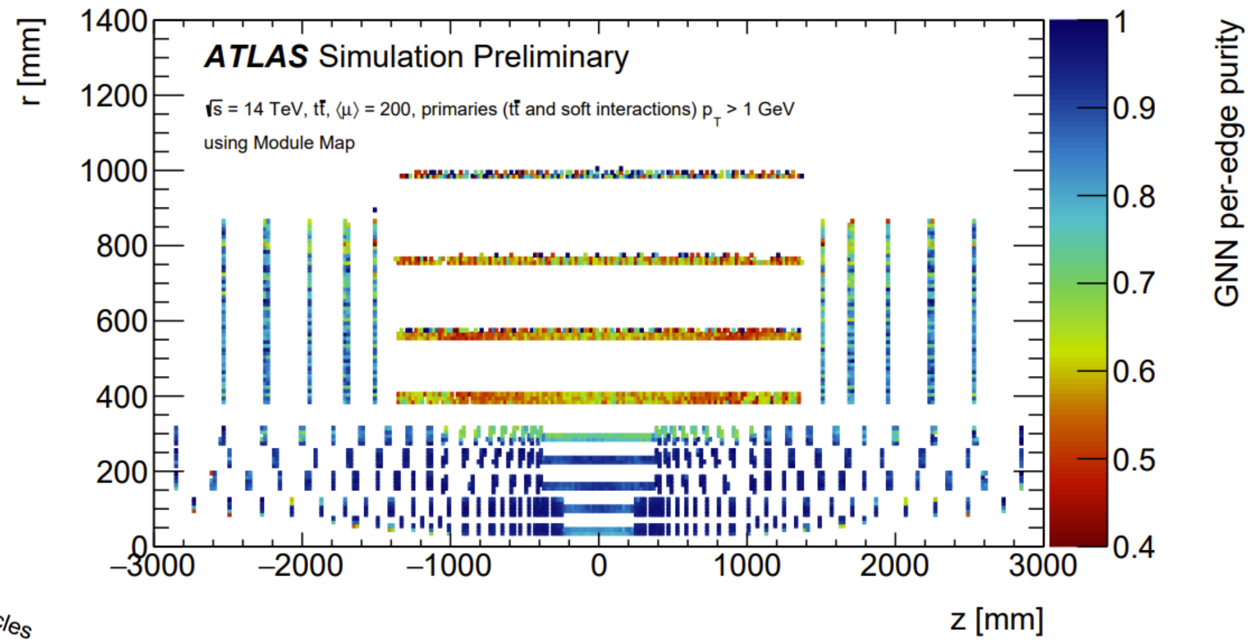
Nature of false positive edges



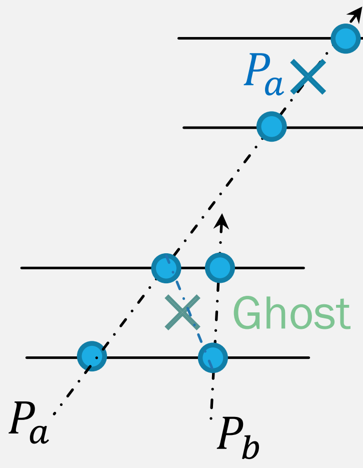
43%: "True" ghosts

37%: Fakes

Location of false positive edges



BARREL STRIP MISCLASSIFICATION



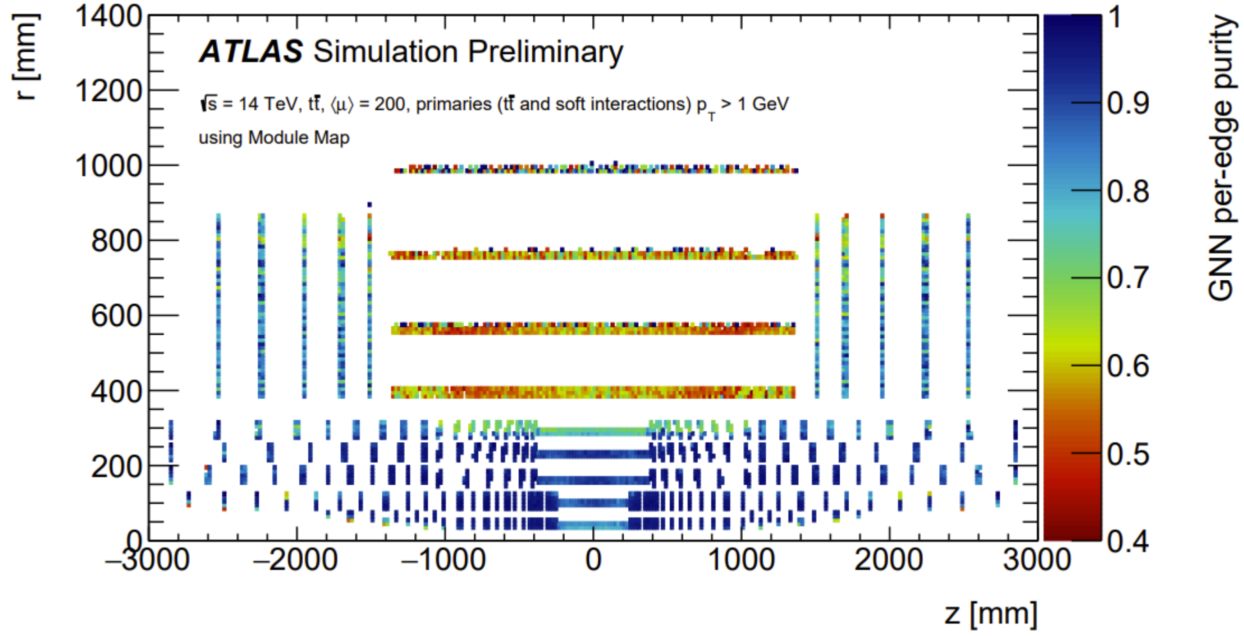
"True" ghost edges: 43%

Edges between SP from particle A, and a ghost SP of clusters from particle A and particle B. I.e. The GNN is "right", the construction is "wrong"

Fake edges: 37%

Edges between SP from particle A and particle B. i.e. The GNN is "wrong"

Location of false positive edges



STRIP MODULES: GHOSTS AND Z-RESOLUTION

- Since spacepoints are constructed from pairs of clusters in the strip, could mis-construct and form a ghost
- These ghosts can be cleaned up in later stages of the reconstruction chain
- *However,* even for correctly matched clusters, there remains low z-resolution
- Consider this example
- Easily confuses GNN!
- Could fix by including underlying cluster information somehow... (e.g. heterogeneous node features)

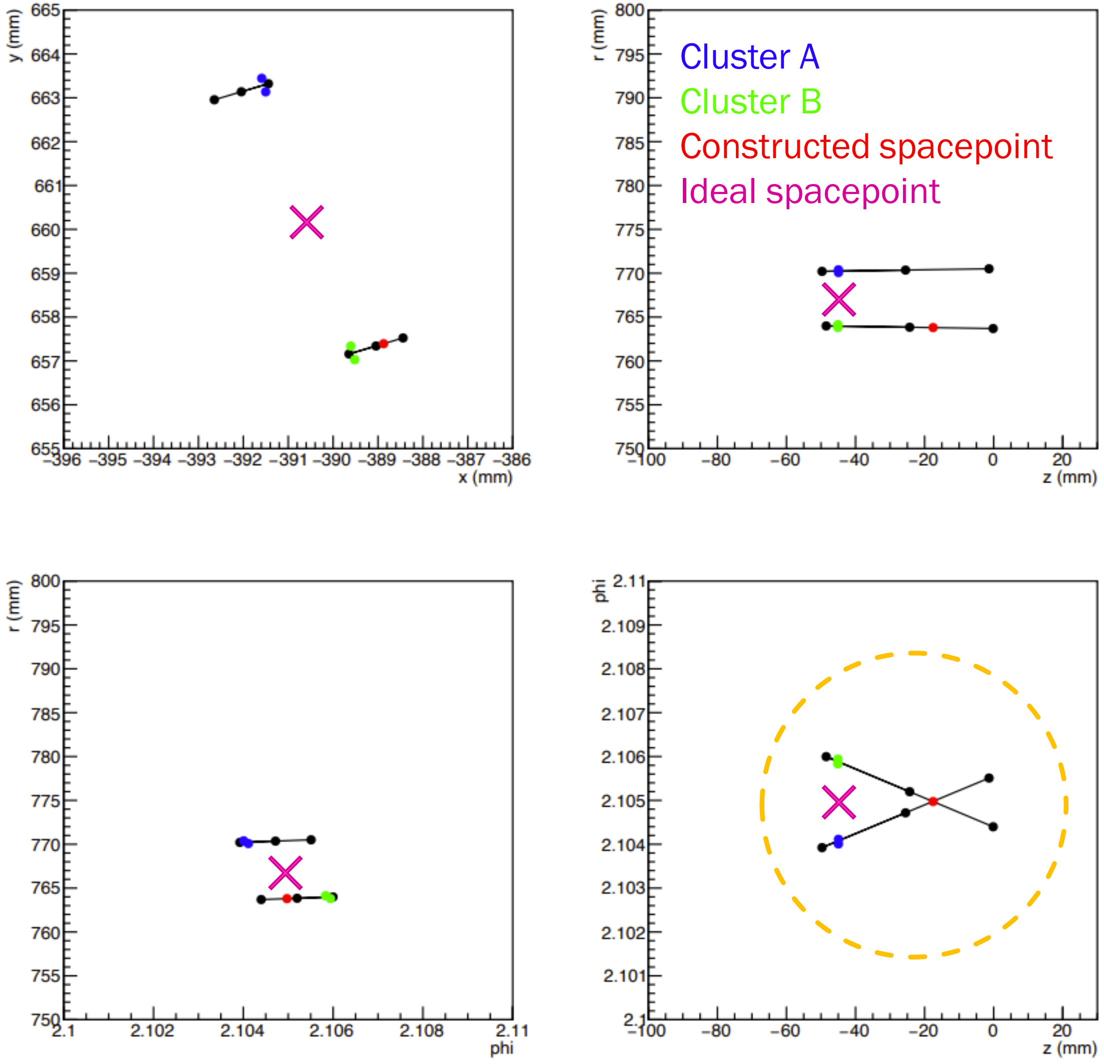
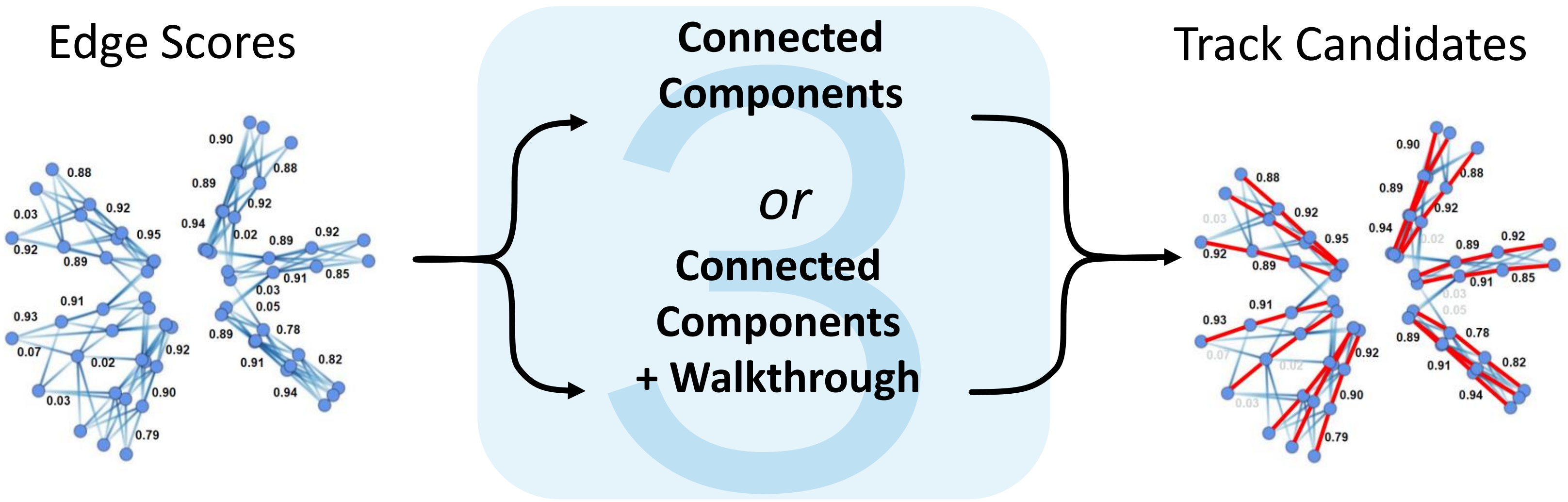
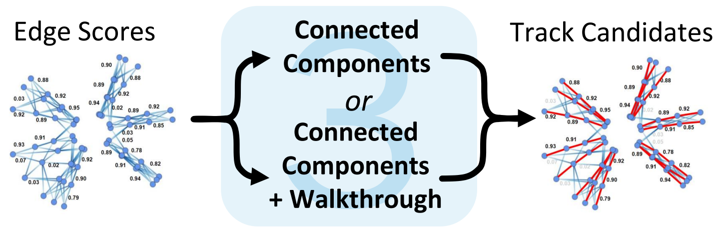


Image courtesy of Jan Stark – thanks!



Graph Segmentation



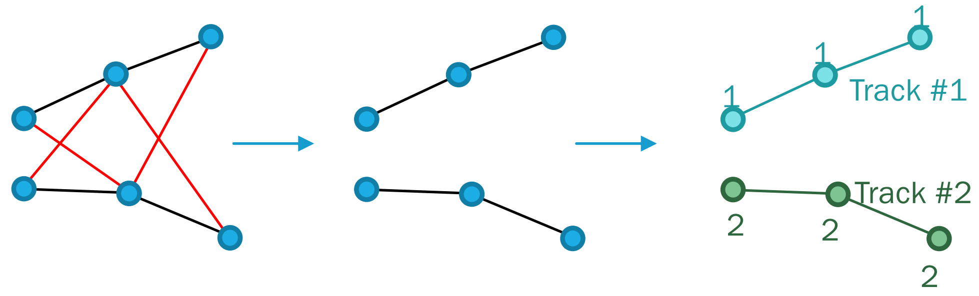
Graph Segmentation

TRACK CANDIDATES CONSTRUCTION

- We now have labelled edges. Want to now label each *node* depending on connectivity.
- Two distinct approaches: **component-based** segmentation, or **path-based** segmentation.

Component-based

E.g. connected components algorithm:

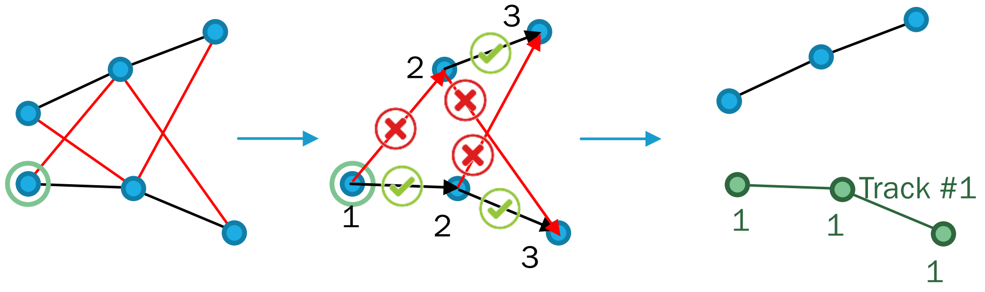


Classified edges | Ignore cut edges | Label connected components

- Pros: Fast - $O(N_{nodes})$
- Cons: Can merge tracks into one candidate

Path-based

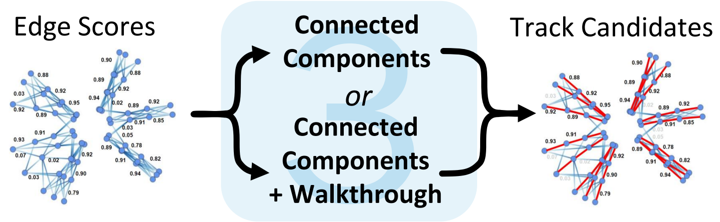
E.g. walkthrough algorithm:



Classified edges, Starting node | Choose high score junctions | Remove a high-scoring path

- Pros: Handles hits as a sequence, as a track should be
- Cons: Potentially slow - $O(N_{edges})$, needs a *directed* graph

TRACK CANDIDATES CONSTRUCTION



Graph Segmentation

- We now have labelled edges. Want to now label each *node* depending on connectivity.
- Two distinct approaches: **component-based** segmentation, or **path-based** segmentation.

Component-based

E.g. connected components algorithm:

- Pros: Fast - $O(N_{nodes})$
- Cons: Can merge tracks into one candidate

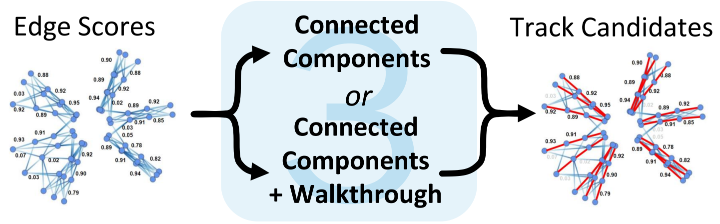
Path-based

E.g. walkthrough algorithm:

- Pros: Handles hits as a sequence, as a track should be
- Cons: Potentially slow - $O(N_{edges})$, needs a *directed* graph

Both methods <u>by construction</u> associate <u>each hit</u> with only <u>one track</u>

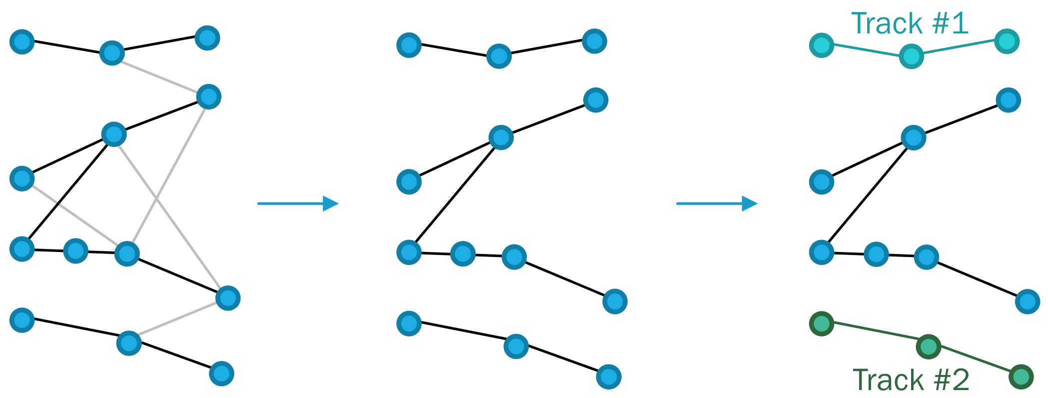
TRACK CANDIDATES CONSTRUCTION



Graph Segmentation

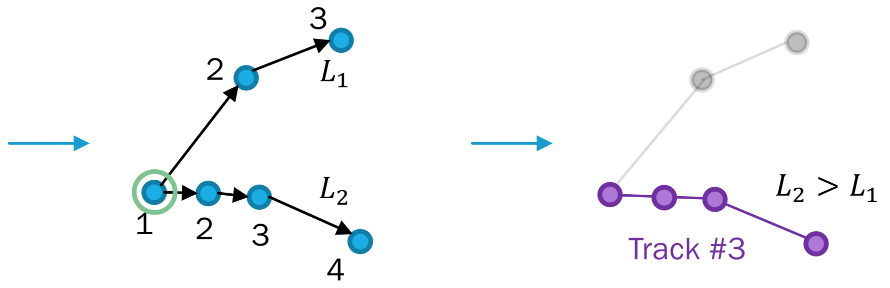
- Our specific algorithm combines the good features of each approach:

1. Connected Components



Classified edges | Cut score < 0.2 | Label simple candidates

2. Walkthrough, a.k.a "Wrangler"



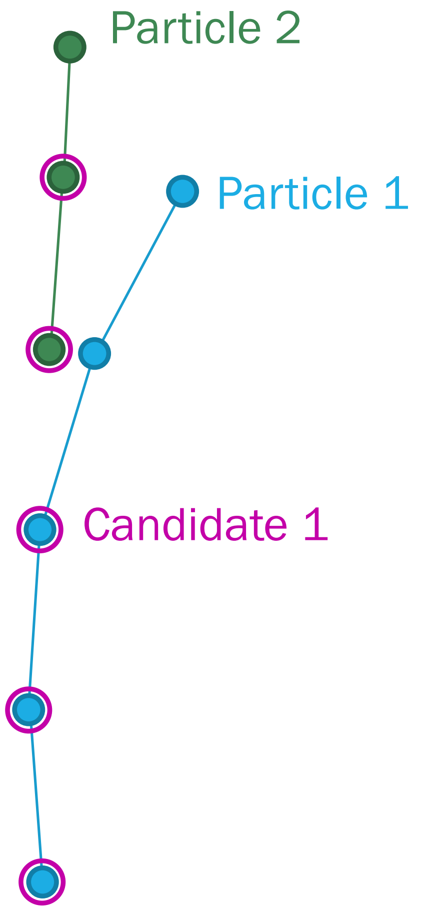
Walk through paths from starting node, count length L

Assign longest path as candidate

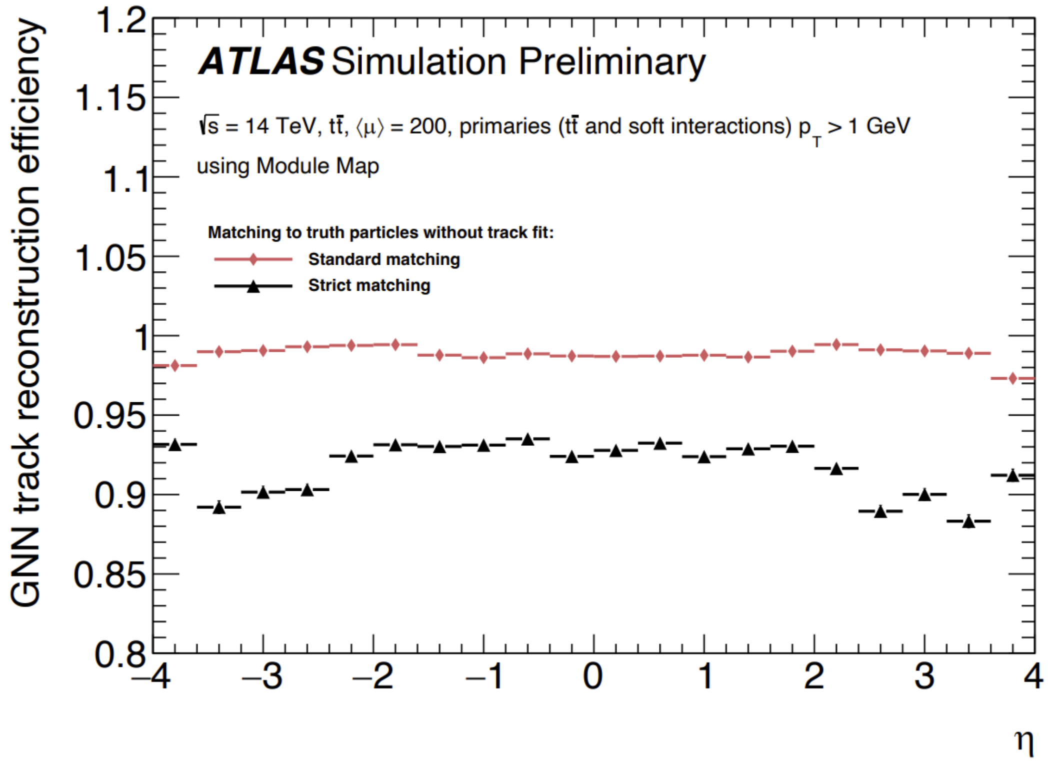
TRACK MATCHING DEFINITIONS

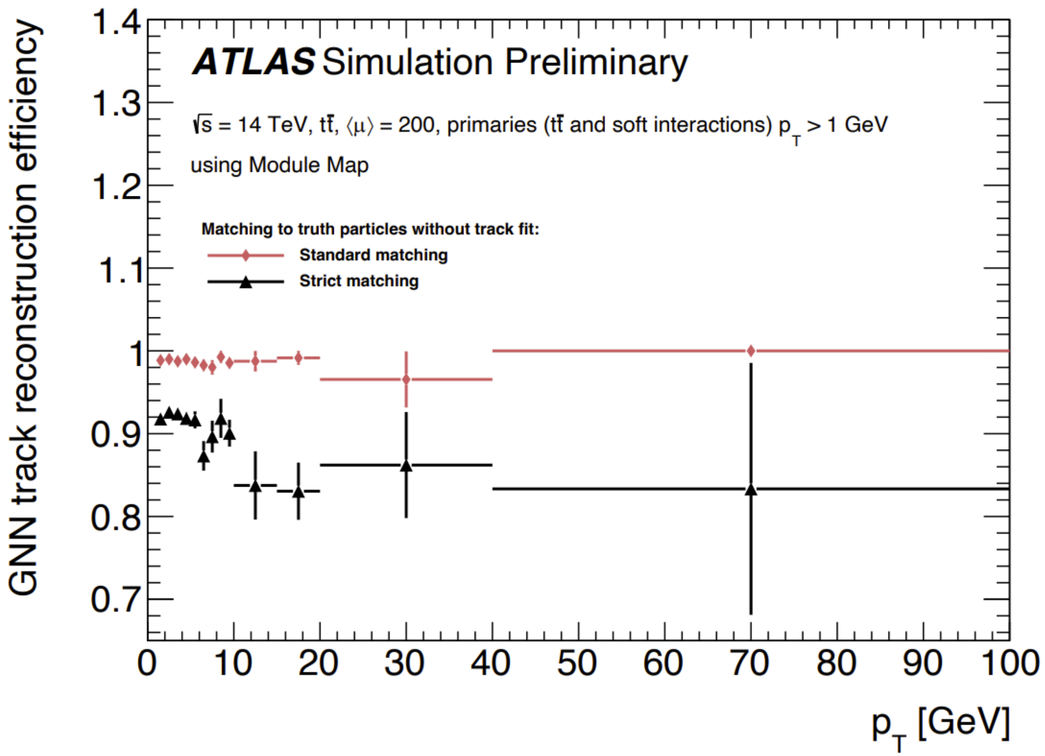
- $N(P_i, C_j)$ is the number of spacepoints shared by particle i and candidate j
- Particle i is called "matched" if, for some j, $\frac{N(P_i,C_j)}{N(P_i)} > f_{truth}$
- Candidate j is called "matched" if, for some i, $\frac{N(P_i,C_j)}{N(C_j)} > f_{reco}$
- Particle i and candidate j are called "double matched" if, for some i and j, $\frac{N(P_i,C_j)}{N(P_i)} > f_{truth}$ and $\frac{N(P_i,C_j)}{N(C_j)} > f_{reco}$
- $eff = \frac{\sum_i P_i(matching\ condition)}{\sum_i P_i}$, $pur = \frac{\sum_j C_j(matching\ condition)}{\sum_j C_j}$

Standard matching: single-matched particles with $f_{truth} = 0.5$
Strict matching: double-matched particles with $f_{reco} = 1.0$



TRACK RECONSTRUCTION RESULTS

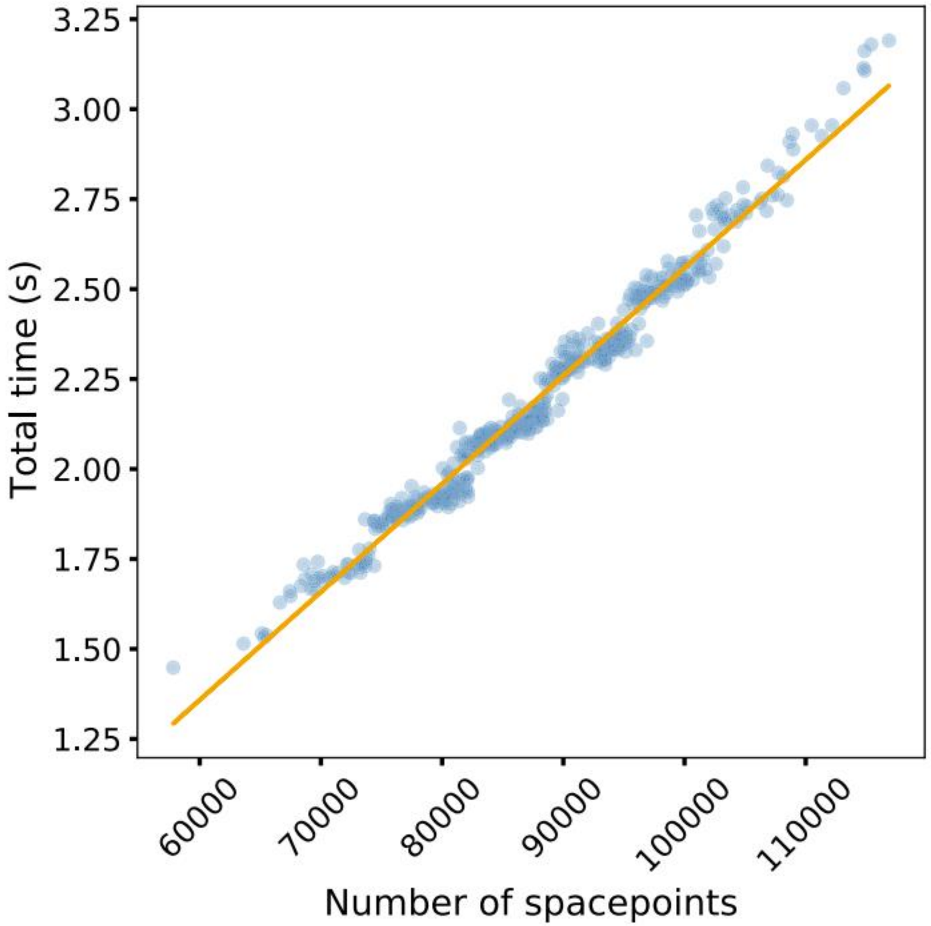




Standard matching: single-matched particles with $f_{truth} = 0.5$
Strict matching: double-matched particles with $f_{reco} = 1.0$

- Fake rate is $O(10^{-3})$ using standard truth matching

TIMING AND SCALING PERFORMANCE

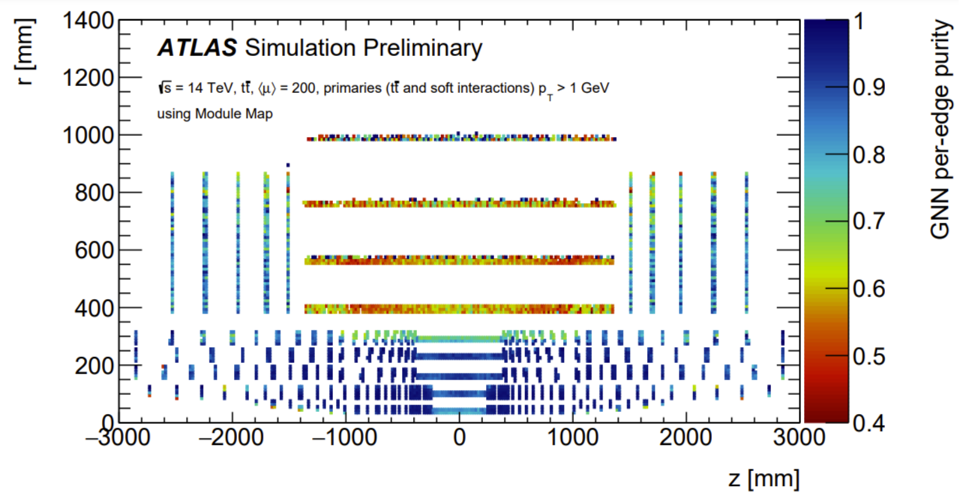


	Baseline	Faiss	cuGraph	AMP	FRNN
Data Loading	0.0022 ± 0.0003	0.0021 ± 0.0003	0.0023 ± 0.0003	0.0022 ± 0.0003	0.0022 ± 0.0003
Embedding	0.02 ± 0.003	0.02 ± 0.003	0.02 ± 0.003	0.0067 ± 0.0007	0.0067 ± 0.0007
Build Edges	12 ± 2.64	0.54 ± 0.07	0.53 ± 0.07	0.53 ± 0.07	0.04 ± 0.01
Filtering	0.7 ± 0.15	0.7 ± 0.15	0.7 ± 0.15	0.37 ± 0.08	0.37 ± 0.08
GNN	0.17 ± 0.03	0.17 ± 0.03	0.17 ± 0.03	0.17 ± 0.03	0.17 ± 0.03
Labeling	2.2 ± 0.3	2.1 ± 0.3	0.11 ± 0.01	0.09 ± 0.008	0.09 ± 0.008
Total time	$15 \pm 3.$	3.6 ± 0.6	1.6 ± 0.3	1.2 ± 0.2	0.7 ± 0.1

- Physics is important, but GNNs shine in scaling behavior
- When development began, graph-based pipeline started required 15 sec for TrackML
- Implemented custom Fixed Radius Nearest Neighbor (FRNN) algo., cuGraph Connected Components algo., and Mixed Precision inference
- Now have sub-second TrackML inference on 16Gb V100 GPU
- Inference time scales approximately linearly across size of event, in TrackML

ONGOING WORK

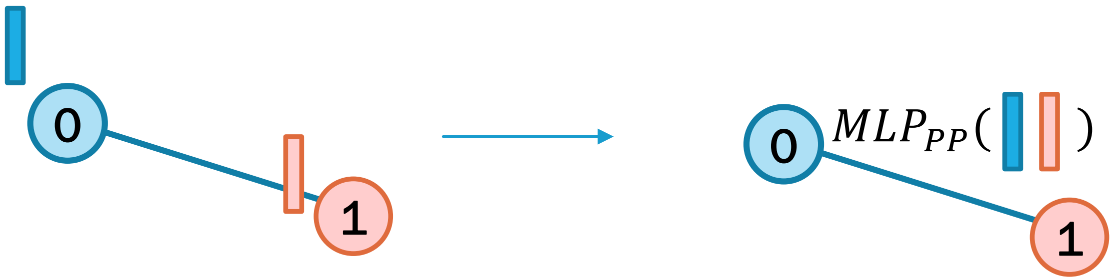
ONGOING WORK: HETEROGENEOUS NODE FEATURES



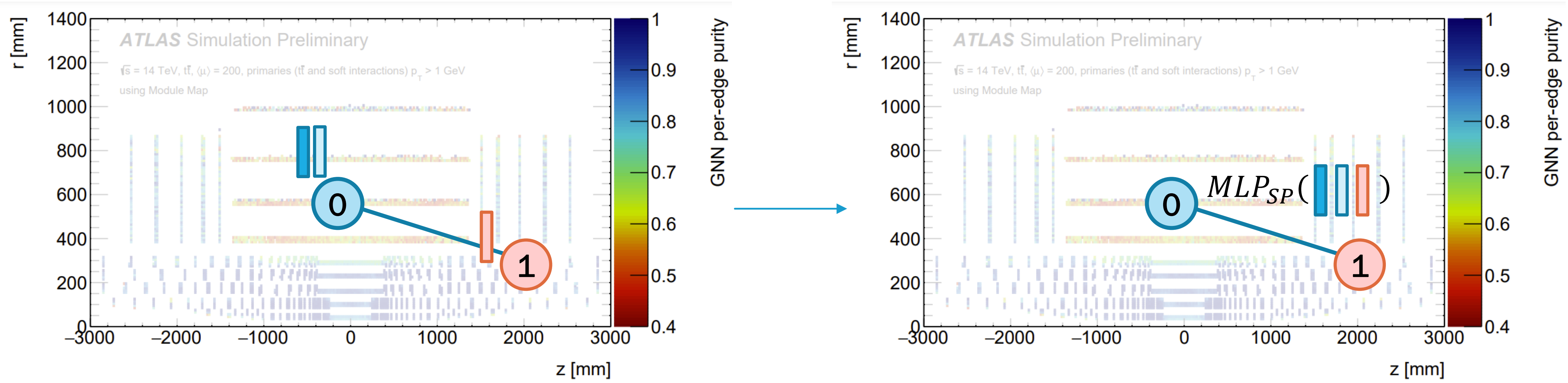
- Motivated by inconsistent performance across detector:
- Currently each node in graph uses same input feature set – spacepoint $s = (r, \phi, z)$
- We could imagine using cluster-level information, e.g. position and shape of energy deposit
- *But:* this is not consistent across detector. Need different node and edge networks depending on detector region

ONGOING WORK: HETEROGENEOUS NODE FEATURES

- To get intuition, consider simple filter MLP applied to two pixel nodes:



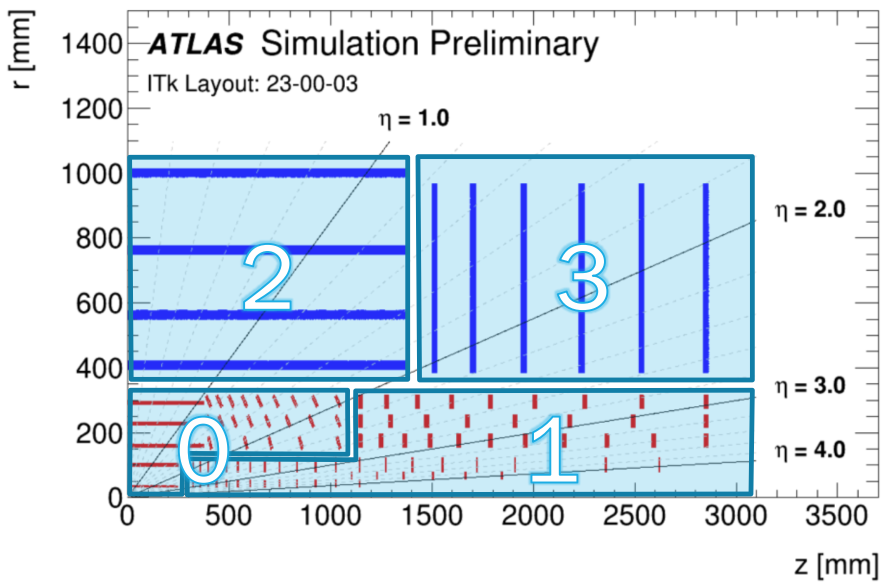
- To apply a filter MLP to a pixel (single cluster) and strip (double cluster) node combination, need a *different* MLP:

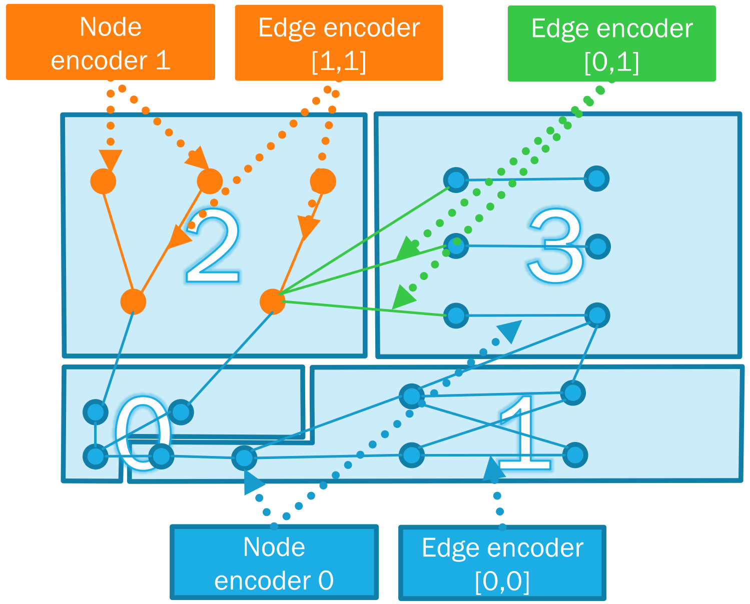


- Already gives better than homogeneous filter MLP (~2x construction purity)

ONGOING WORK: HETEROGENEOUS GRAPH NEURAL NETWORK

- Exact same logic applies to GNN networks
- For a four-region heterogeneous GNN, we have four node encoders/networks (N_0, N_1, N_2, N_3) and ten edge encoders/networks $(E_{00}, E_{01}, E_{02}, E_{03}, E_{11}, \ldots, E_{34}, E_{44})$
- Thus, is a larger model and takes longer to train
- But reduces GNN inefficiency and fake rate by approximately half





ONGOING WORK: ACTS & ATHENA INTEGRATION

A. Salzburger, et al.

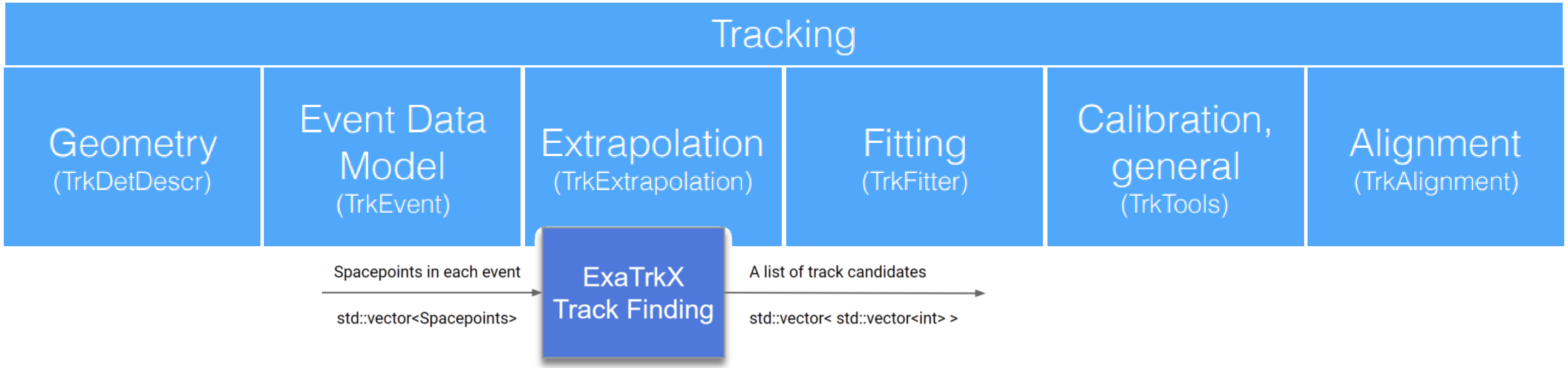
Tracking					
Geometry (TrkDetDescr)	Event Data Model (TrkEvent)	Extrapolation (TrkExtrapolation)	Fitting (TrkFitter)	Calibration, general (TrkTools)	Alignment (TrkAlignment)

ACTS (A Common Tracking Software)

- A library for tracking that is independent of particular experiment or geometry
- Written in highly performant c++ and parallelized

ONGOING WORK: ACTS & ATHENA INTEGRATION

A. Salzburger, et al.



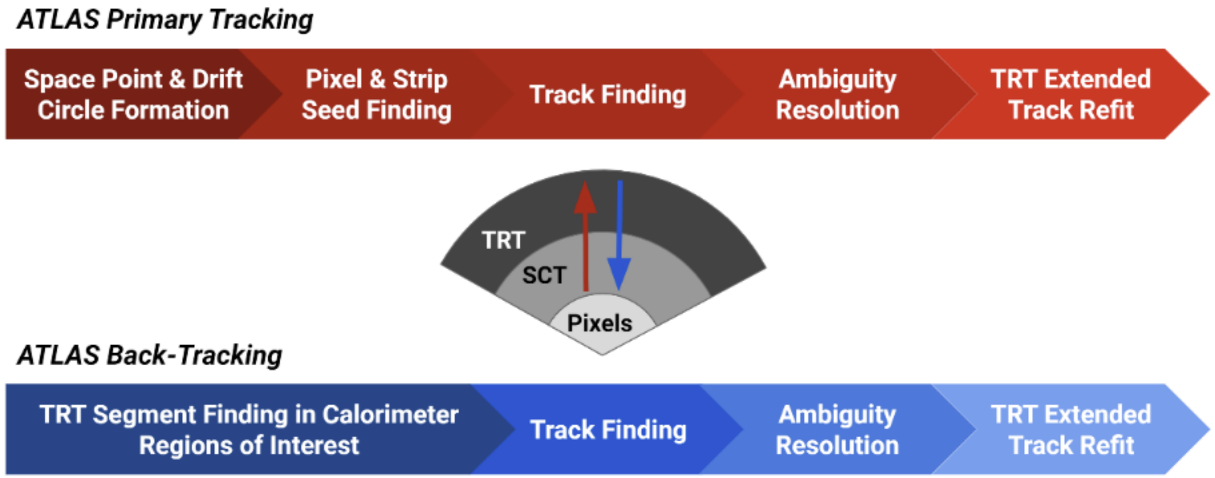
Integration of GNN pipeline with ACTS

- Integration complete, with generic **TrackFindingMLBased** interface
- Uses TorchScript to call ML models (OnnxRuntime not yet fully compatible with GNN methods)
- Replaces seeding and track finding stages, produces protoTracks

ONGOING WORK: ACTS & ATHENA INTEGRATION

Athena

- Framework for ATLAS event generation, simulation, digitization, reconstruction and analysis



Integration of GNN pipeline with Athena:

- This is ongoing!

OTHER ONGOING WORK

- Extending TrackML inference timing and scaling studies to ATLAS ITk
- Investigating training and inference performance on lower p_T tracks (i.e. < 1 GeV) and high p_T tracks (i.e. > 10 GeV)
- Investigating performance on large radius tracks and dense track environments
- Direct comparison with combinatorial Kalman filter (current algorithm) efficiency and track parameter resolution

CONCLUSION

- A graph-based representation of particle collisions is intuitive and rich
- GNNs and other graph techniques are well-suited even to high luminosity events
- Produced first public results on official ATLAS ITk geometry using GNN-based track reconstruction pipeline
- Promising reconstruction performance, well-positioned for comparison with traditional algorithms
- This is very early in development – many more improvements are in progress within Exatrkx+L2IT
- Also new techniques being invented in GNN/ML community every day

THANKS FOR TUNING IN!

Links

ExaTrkx website • L2IT website • ExaTrkx paper • L2IT paper • Codebase