Improving Computational Performance of a GNN Track Reconstruction Pipeline for ATLAS

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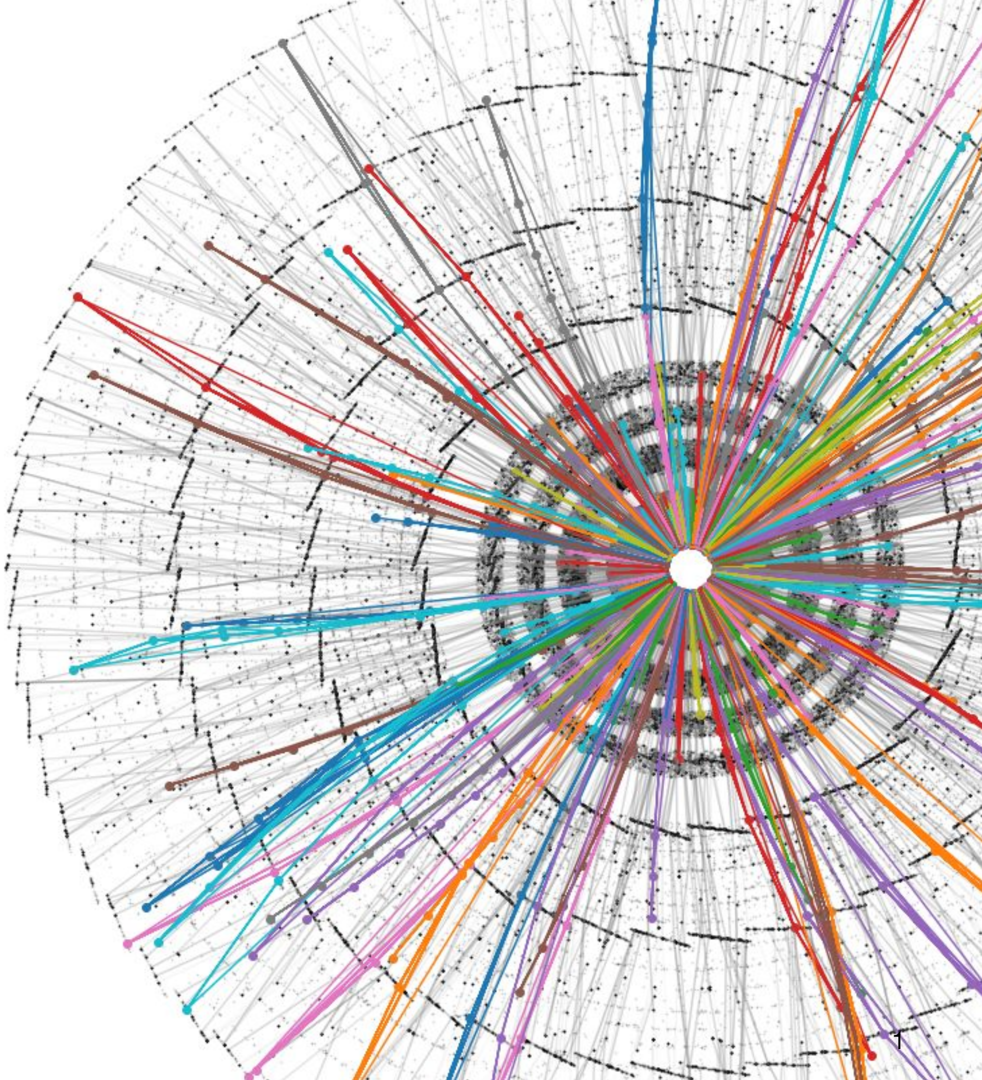
On behalf of the ATLAS GNN4ITk Group
and GNN Event Filter Group

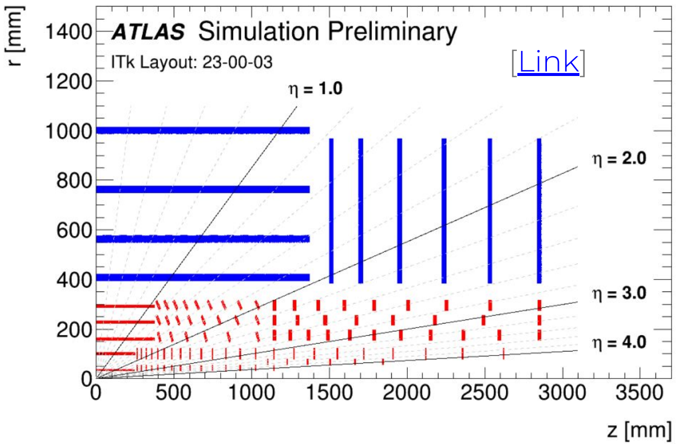


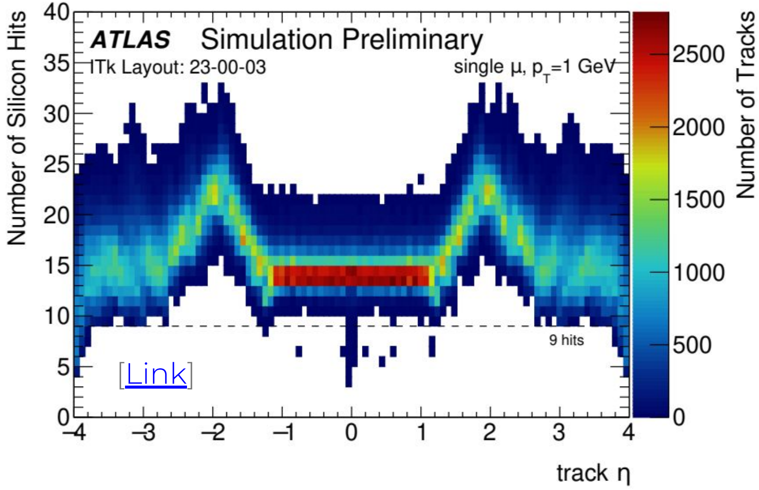
Outline

- Description of current pipeline
- Physics performance
- Acorn training, inference and evaluation framework
- Computational constraints for offline and online tracking
- Optimization research directions

Physics Performance of GNN4ITk Pipeline

Tracking in ATLAS HL-LHC Inner Tracker (ITk)



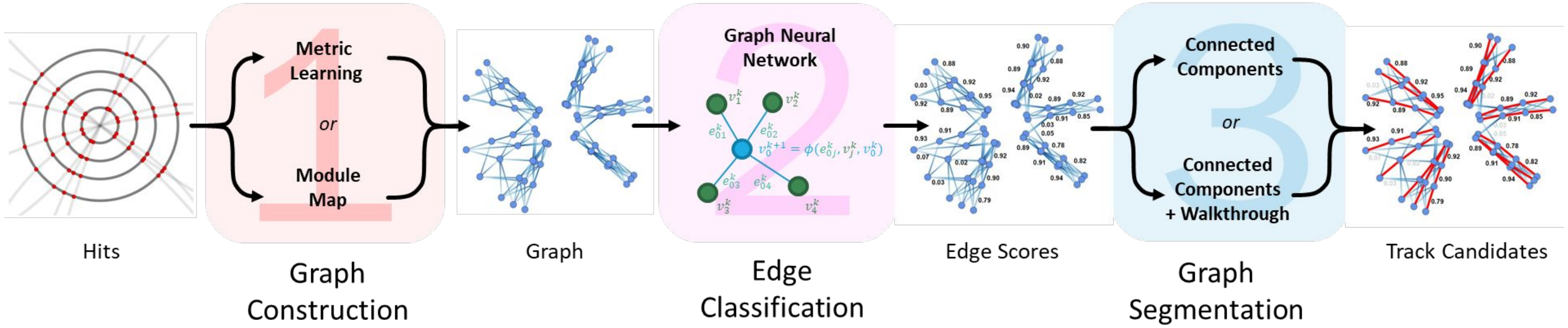


- Number of hits per ttbar ITk event: 311,000 +/- 35,000
- Number of particles per ttbar ITk event: 16,000 +/- 1,700
- Innermost pixel layer 25x100 micron^2, all other pixel layers 50x50micron^2

Layer	Radius [mm]	Channels in ϕ	Strip Pitch [μm]	Strip Length [mm]	Tilt Angle [°]
0	405	28×1280	75.5	24.1	11.5
1	562	40×1280	75.5	24.1	11.0
2	762	56×1280	75.5	48.2	10.0
3	1000	72×1280	75.5	48.2	10.0

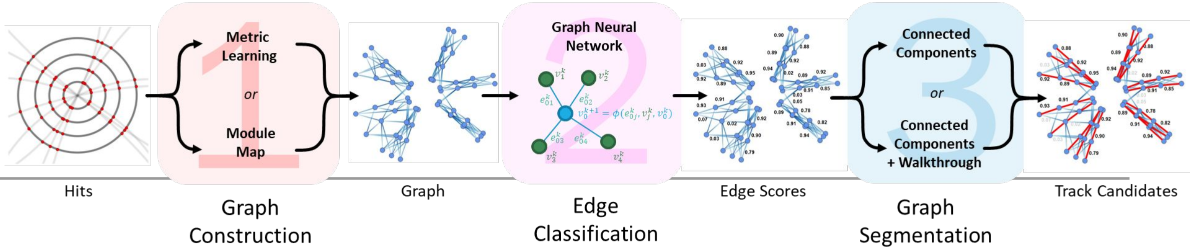
Barrel strip module dimensions[Link]

GNN4ITk Pipeline



- Pipeline receives clusters = collections of energy deposits on silicon. These are associated with 3D spacepoints, to be used as nodes for stage 1 onwards
- Out of stage 3 we obtain a set of track candidates, each is an unordered set of spacepoints
- For processing in Athena track fitting chain, we associate these back to the original clusters, and order in increasing distance from beamspot origin

Training Details



Dataset

- Run 4 ATLAS simulation, ttbar <mu>=200 pileup, ITk layout 23-00-03

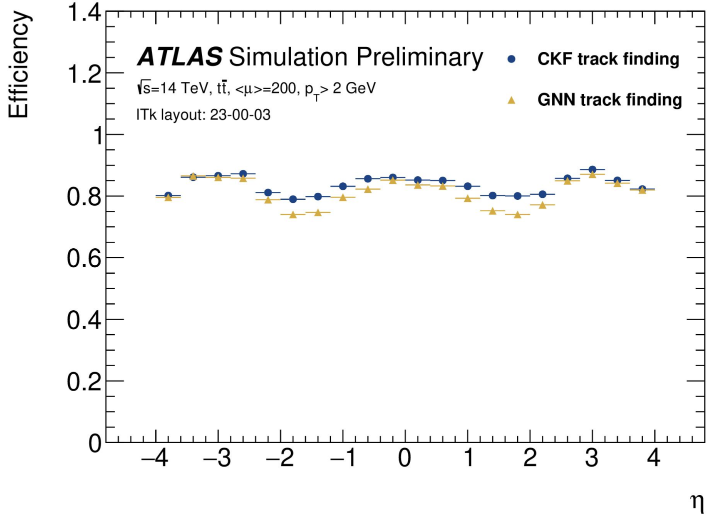
Truth

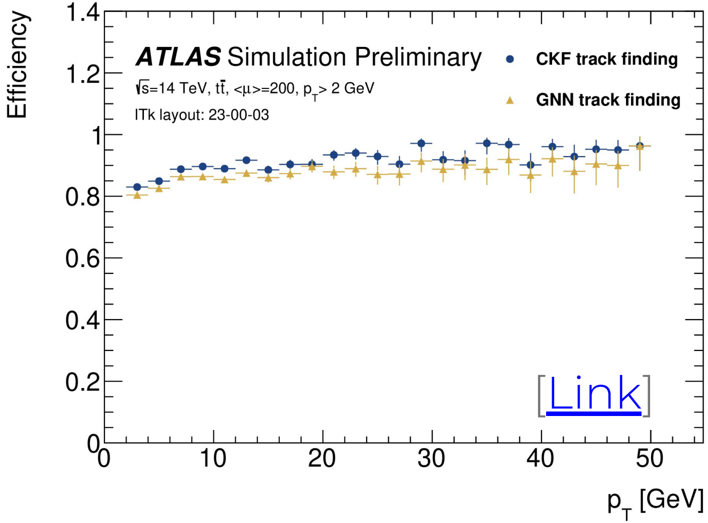
- Pairwise connections between *sequential* hits in *target tracks* treated as true
- A target track is primary, non-electron, pT>1GeV, and has at least 3 hits
- All other connections between all other tracks (or noise) considered fake

Loss Functions

- Contrastive hinge loss for metric learning
- Binary cross entropy for edge classification (GNN and edge filter)
- Data-driven adjacency matrix and geometric cuts for module map

Track Reconstruction Performance

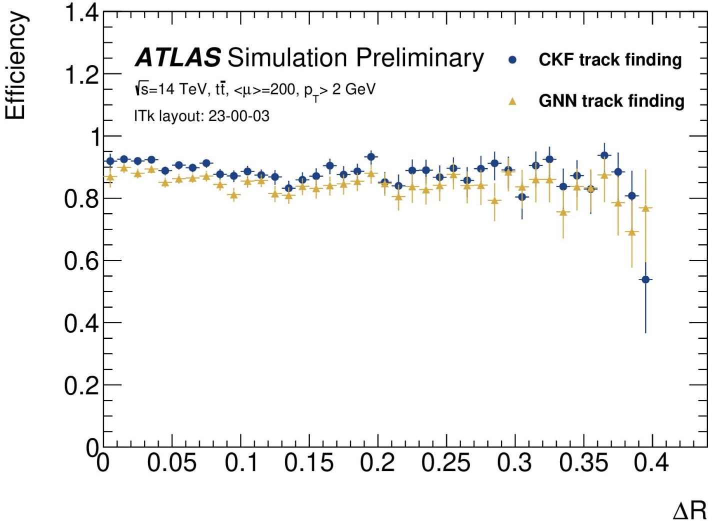


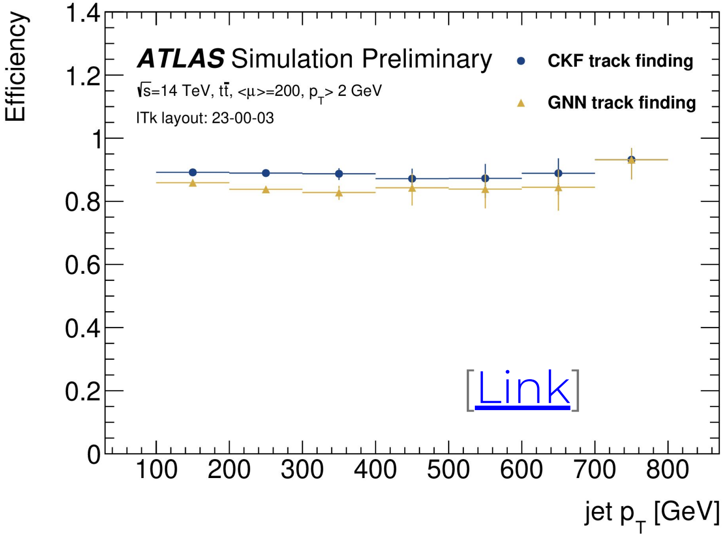


[Link]

- Tracking efficiency compared with current combinatorial kalman filter (CKF) technique
- Behaviour across eta and pT similar to CKF - good sanity check!

Track Reconstruction Performance



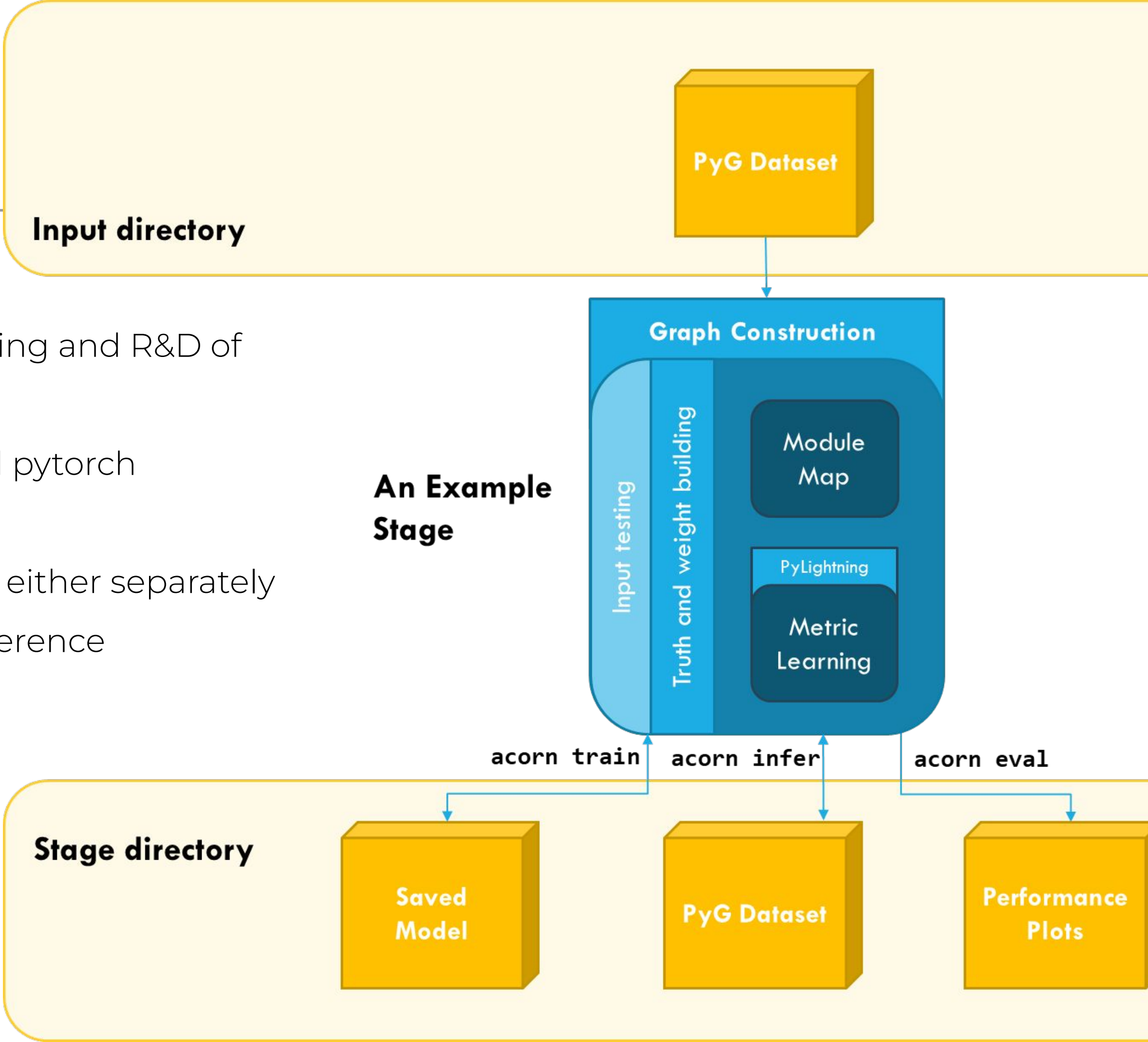


- Again, similar characteristics across deltaR and jet pT

ACORN: **A** **C**harged **O**bject **R**econstruction **N**etwork

acorn

- Framework design & goals
  - A modular framework for training and R&D of ML-based tracking
  - Runs on pytorch lightning and pytorch geometric
  - Each stage self-contained, run either separately or (newly built) multi-stage inference
- Integrations
  - ATLAS ITk
  - ACTS OpenData Detector
  - TrackML



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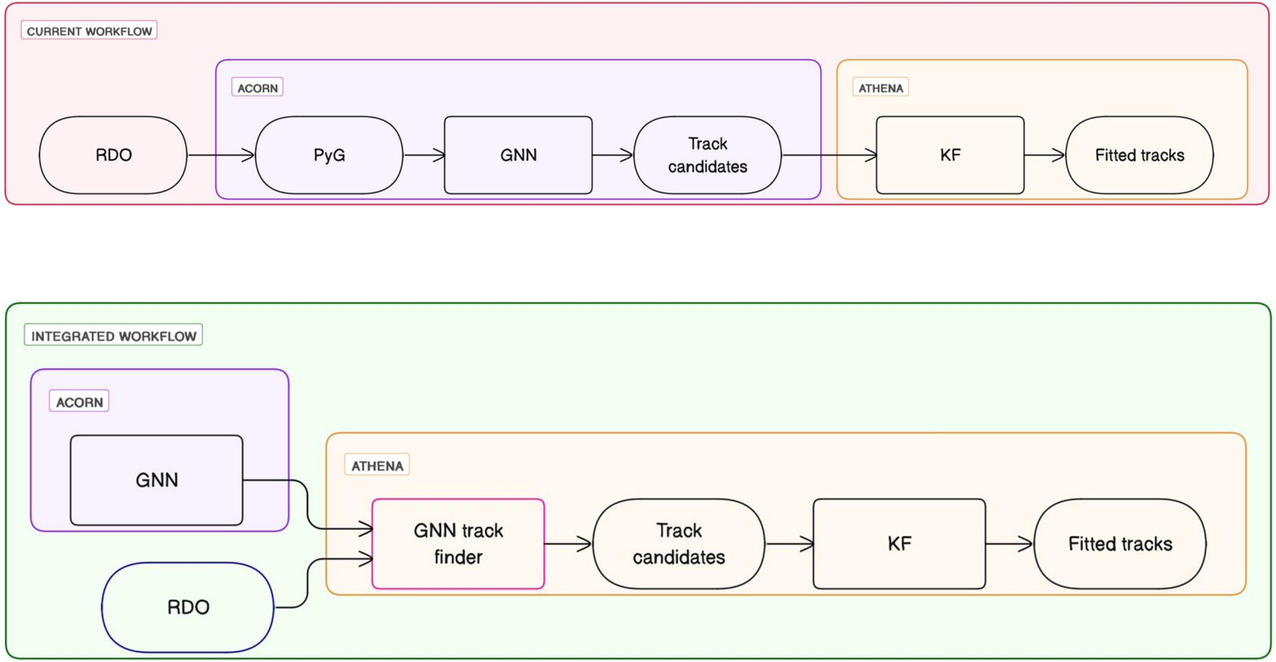
acorn → Athena



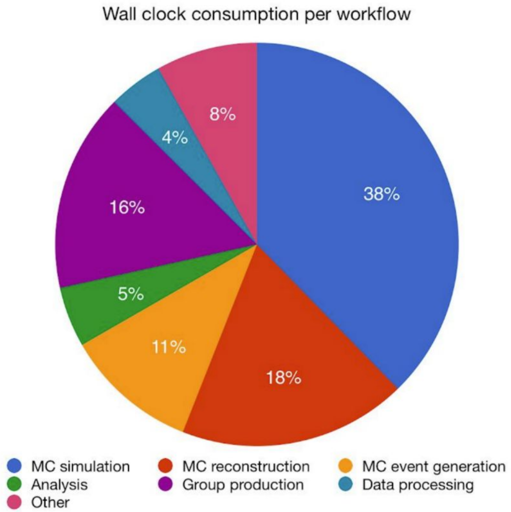
- Previously, Acorn used to build tracks, which were passed back into Athena for fitting
- Now, models trained in Acorn, translated to Onnx and TorchScript
- Loaded into Athena Component (c++) as part of tracking chain

Tracking Computational Requirements

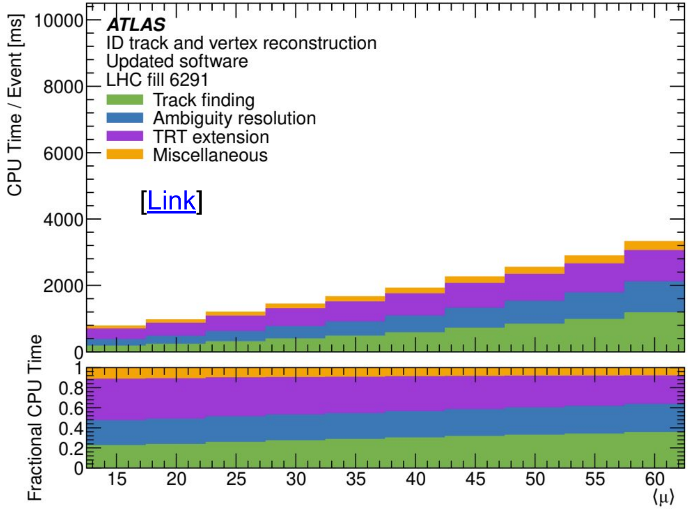
ATLAS Computing Budget

[Link]

Detector	$\langle\mu\rangle$	inner tracking	muon spectrometer and calorimeter	combined reconstruction	monitoring	total
Run 2	90	1137	149	301	106	1693



- (Top right) Average CPU usage in 2008: Reconstruction significant piece
- (Above) Reconstruction timings for run 2 (seconds): Tracking takes majority of time
- (Right) Run 3 track reconstruction timings: Track finding and ambiguity resolution take ~2s for <mu>=60



HL-LHC Offline & Online Track Reconstruction Needs

	LHC Run 3	**HL-LHC**
L0 trigger accept	100 kHz	**1 MHz**
Event Filter accept	1 kHz	**10 kHz**
Event size	1.5 MB	**4.6 MB**

- Event filter (high level trigger) contains tracking
- Regional tracking @ 1MHz
- Full event tracking @ 150kHz

- Current CPU proposed algorithm is optimized Fast Tracking
- 23.2 s/event single-core CPU, small drop in track efficiency: 1-2% on average, 5% for pT in [1,1.5]GeV

$\langle\mu\rangle$	Tracking	Release	Byte Stream Decoding	Cluster Finding	Space Points	Si Track Finding	Ambiguity Resolution	Total ITk
140	default	21.9	2.2	6.4	3.5	31.6	43.4	87.1
	fast			6.1	1.0	13.4	-	22.7
200	default	21.9	3.2	8.3	4.9	66.1	64.1	146.6
	fast			8.1	1.2	23.2	-	35.7

Fast tracking vs Default tracking timing (s) [Link]

$\langle\mu\rangle$	Tracking	Byte Stream Decoding	Cluster Finding	Space Points	Si Track Finding	Total ITk
140	full-scan	2.2	6.1	1.0	13.4	22.7
	regional	0.33	0.90	0.15	1.11	2.49
200	full-scan	3.2	8.1	1.2	23.2	35.7
	regional	0.48	1.23	0.18	1.92	3.81

Fast tracking timing (s) for regional vs full-scan [Link]

HL-LHC Offline & Online Track Reconstruction Needs

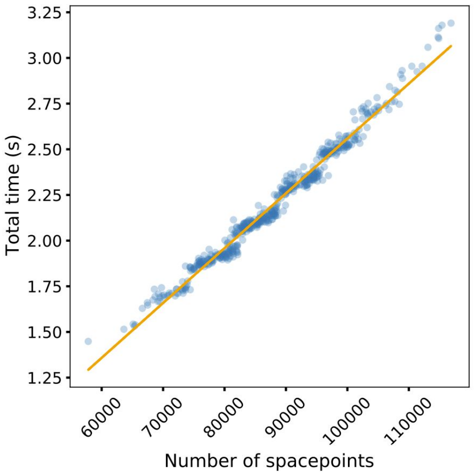
- Goal is to use GNN4ITk pipeline to perform offline tracking in <1s
- Target regional and full event online tracking in 10-100ms
- Starting with right-hand column below (TrackML ~90k hits)
- Optimizing for ITk (~300k hits)
- Need improvements in all stages

	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

TrackML Inference time - Seconds/event [Link]

TrackML

TrackML



[Link]

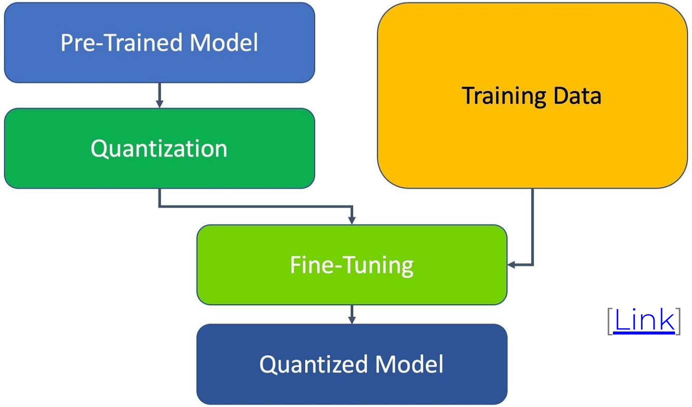
Graph Construction Optimizations

Quantization and Pruning

Optimizations for FPGA and GPU studied on embedding (metric learning) stage

1. Quantization Aware Training
- Fine-tune quantized model with differentiable notion of quantization
- FPGA can use arbitrary quantization
- GPU can exploit 8-bit quantization

2. Iterative (Learning Rate Rewind) Pruning
- During training, iteratively prune model
- After each iteration, restart learning rate



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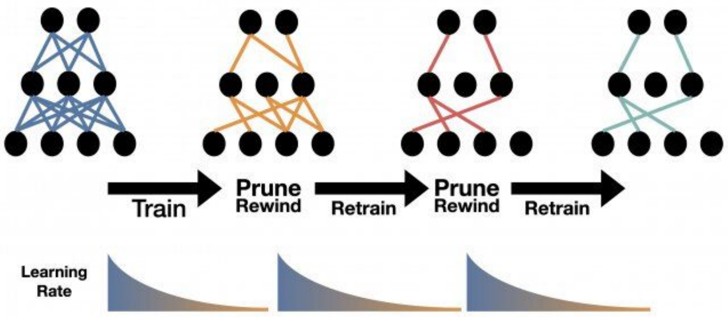
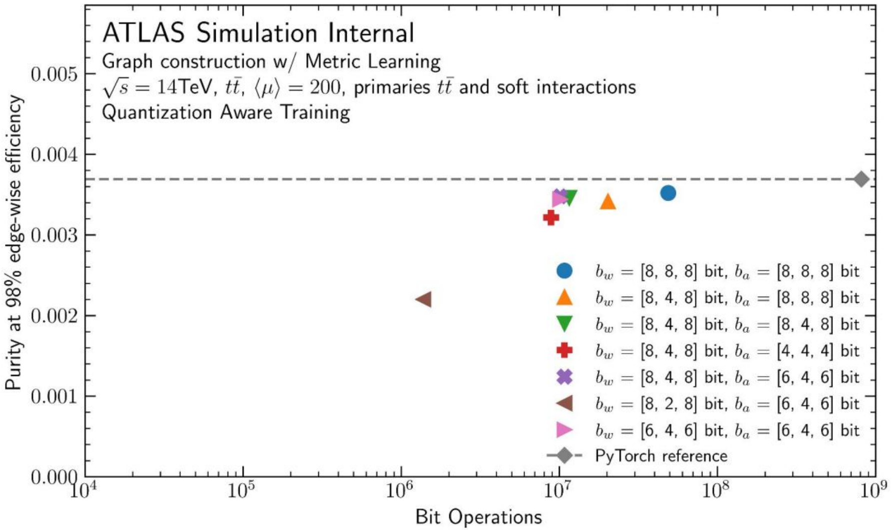
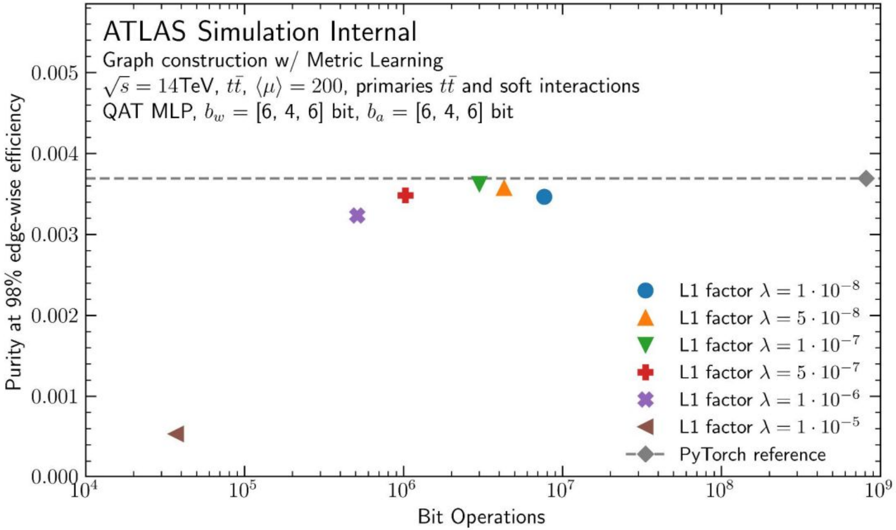


[Link]

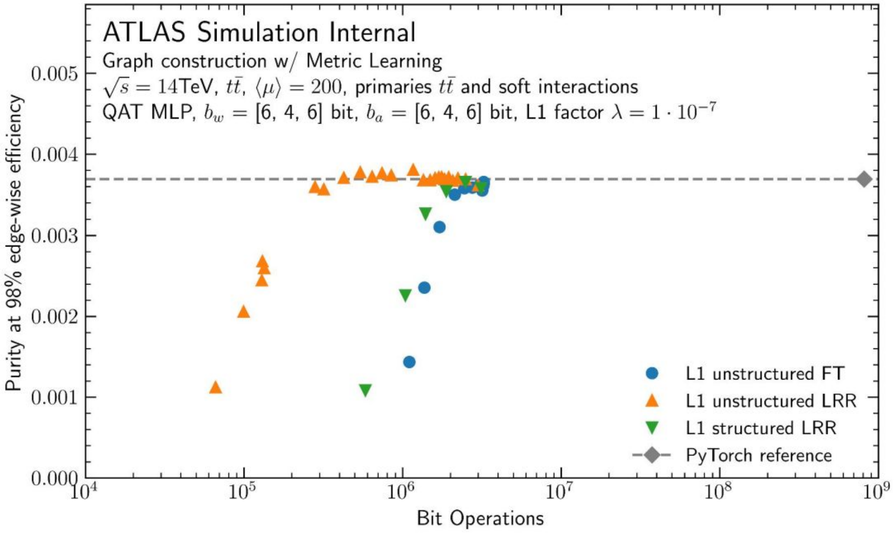
Quantization Aware Pruning Results

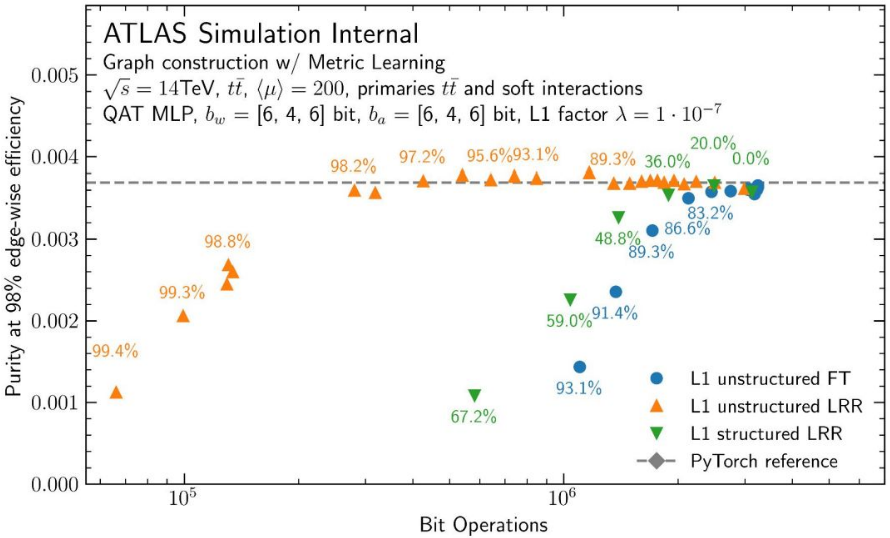




- Can shrink to [6,4,6] bits without significant loss of purity [Link]

Iterative Pruning Results





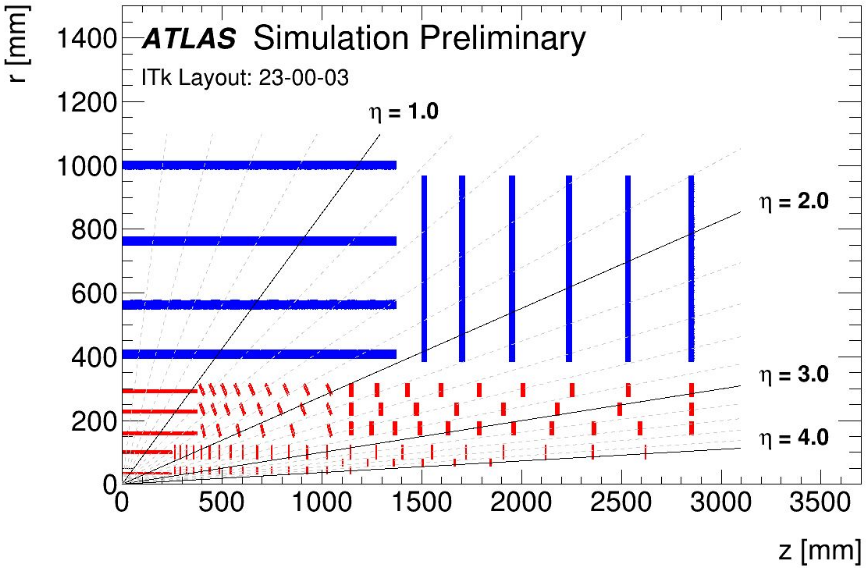
- Can prune model to 1/56 the size and maintain purity at fixed efficiency, using learning rate rewind training (LRR)

[Link]

Graph Neural Network Optimizations

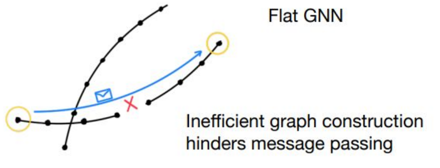
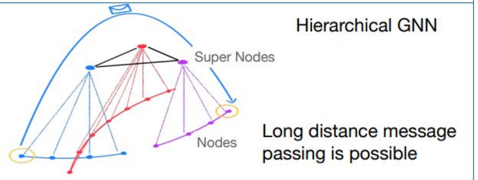
Regional Tracking

- To handle 150kHz-1MHz EF trigger rate, can parallelize across O(100) regions in event, or reconstruct only specific regions
- For highest flexibility, would like to train *one model* and infer on various topologies
- Initial tests performed very poorly, due to **batch normalization** in model
- Reimplementing with **layer normalization**, recover both original performance, and equal performance in regional track reconstruction



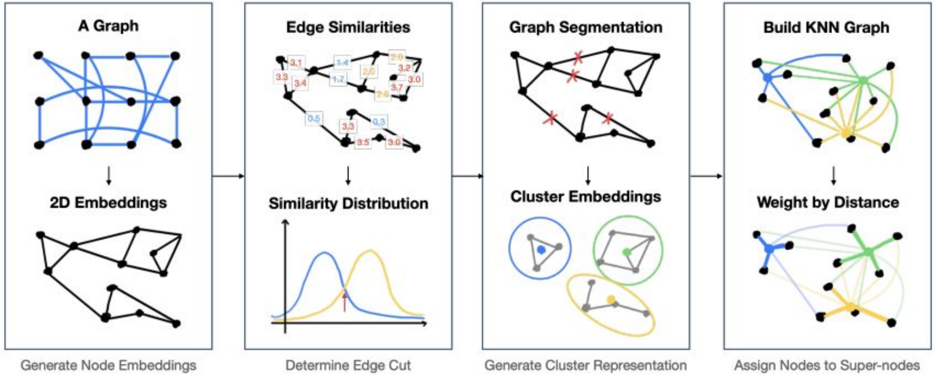
Graph Segmentation Optimizations

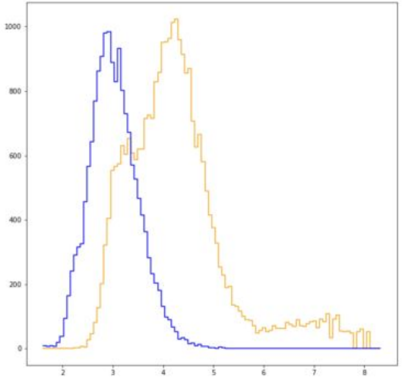
Hierarchical Graph Neural Network: Overview

Current Problem	Proposed Solutions
Performance limited by input graph	Make predictions less graph-dependent
Message passing obstructed by inefficiencies	Construct hierarchical structure
	

Tracking Goal	Feature	DiffPool	SAGPool	EdgePool	GMPool (ours)
Subquadratic scaling	Sparse	✗	✓	✓	✓
End-to-end trainable	Differentiable	✓	✓	✓	✓
Variable event size	Adaptive number of clusters	✗	✗	✓	✓
Many hits to many particles relationship	Soft assignment	✓	✗	✗	✓

How it works:





Hierarchical Graph Neural Network: Results

- The highest physics performance comes from HGNN with O(1) second inference
- Fastest inference still from connected components
- Latest ITk HGNN model combines both for high efficiency / high throughput
- We see robustness of HGNN to edge construction inefficiencies in earlier stages of pipeline

TrackML

Models	E-GNN	E-HGNN	BC-HGNN	EC-GNN	Truth-CC
Efficiency	94.61%	95.60%	**97.86%**	96.35%	97.75%
Fake Rate	47.31%	47.45%	**36.71%**	55.58 %	57.67%
Time (sec.)	2.17	2.64	1.07	**0.22**	0.07

Percent Edge Removed	0%	10%	20%	30%	40%	50%
BC Efficiency	98.55%	98.39%	97.68%	96.63%	95.10%	92.79%
BC Fake Rate	1.23%	1.55%	2.13%	3.10%	4.75%	7.31%
Truth-CC Efficiency	98.72%	96.21%	92.31%	85.81%	77.26%	64.81%
Truth-CC Fake Rate	5.87%	15.53%	24.40%	33.48%	42.99%	53.12%

Summary

- GNN4ITk pipeline:
  - Stable and converged
  - Available in open-source via the acorn framework
  - Out-of-the-box (i.e. not yet properly tuned) produces small drop in physics performance compared with Athena CKF algorithm
- HGNN, optimized module map, quantization, pruning and regional tracking all promising directions that show speed-ups with little/no drop in physics performance