Identifying new Long-lived particles (LLPs) using Graph Neural Networks with the ATLAS detector

Winter Nuclear and Particle Physics Conference

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Search for new Physics?

- No strong indications of new physics at the modern collider experiments.
  - Indicate two possibilities: either the new physics is **above the energy scale accessible to LHC** - the largest particle collider, or we have been looking at the "wrong places”.
  - Wrong places?
    - Most BSM physics searches have been performed with the assumption that the particles decay (promptly) near the primary interaction point of collider experiments

Long Lived Particles (LLPs)

- LLPs: Particles that travel an observable distance from the primary collision point in particle detectors. Will have macroscopic proper lifetimes.

- Long-lived particle signatures : Unexplored phase space for BSM physics search, and requires a dedicated search

- As SM has LLPs (muons) no reason to exclude BSM searches with LLP signatures!

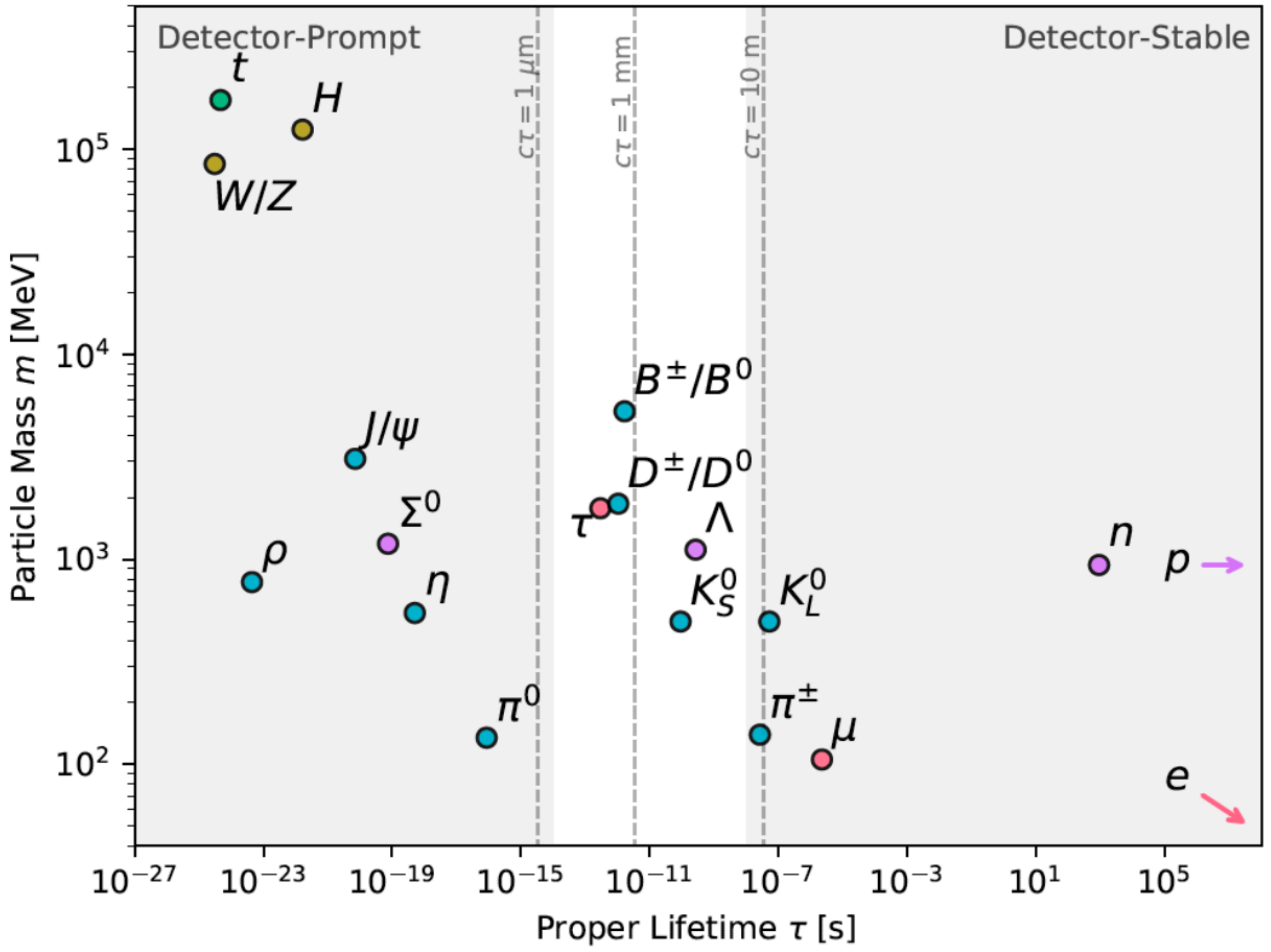
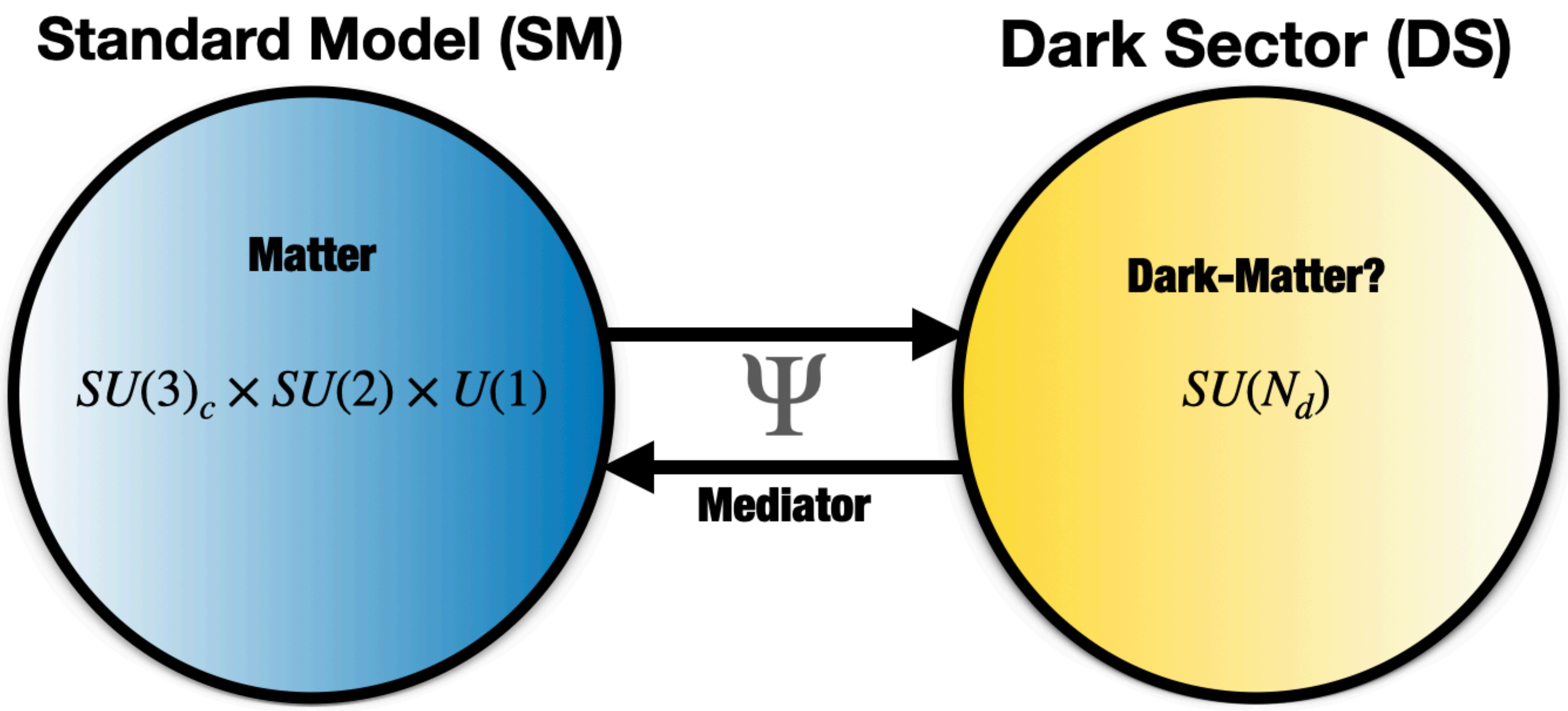


Image from Ref[1]

[1] Lawrence Lee, Christian Ohm, Abner Soffer, and Tien-Tien Yu. Collider searches or long-lived particles beyond the standard model. Progress in Particle and Nuclear Physics, 106:210–255, may 2019.65

Theoretical Motivation for BSM LLPs



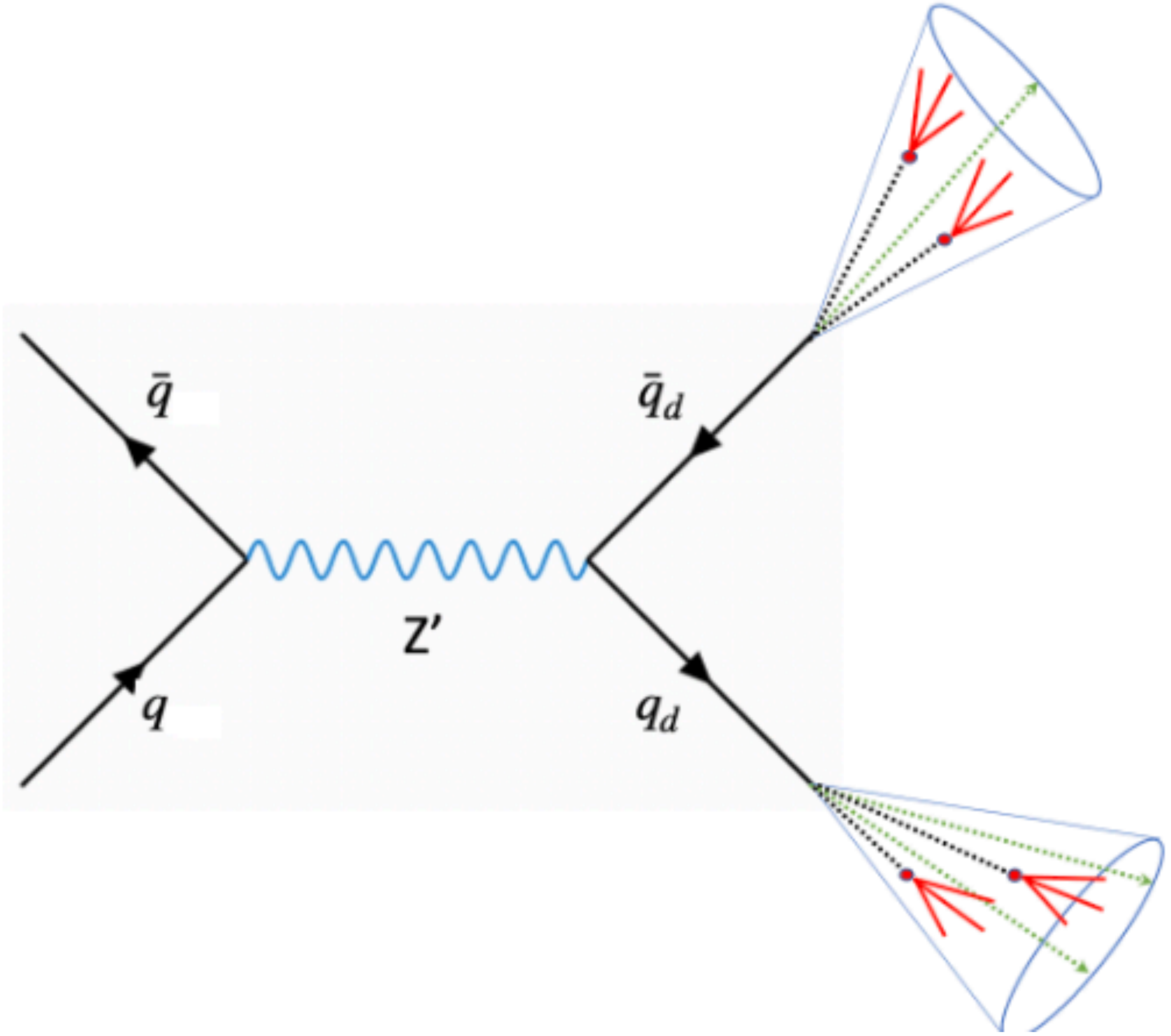
- Extended SM with additional particles and forces collectively referred as dark sector(DS).
- Weak coupling between SM and DS can give rise to LLPs

Benchmark Model

$$\mathcal{L}_{\text{med}} = -\frac{1}{4} Z'^{\mu\nu} Z'_{\mu\nu} - \frac{1}{2} M_{Z'}^2 Z'^{\mu} Z'_{\mu} + Z'_{\mu} (\bar{q}'_i \gamma^{\mu} q'_i + \bar{q}_j \gamma^{\mu} q_j)$$

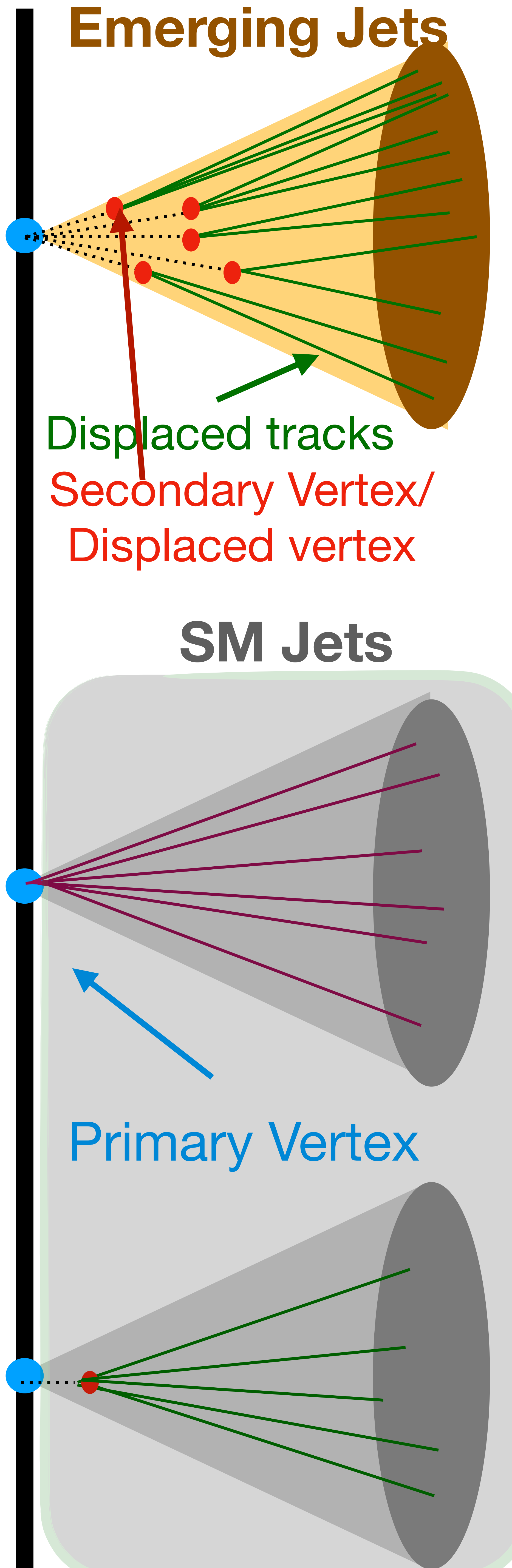
BSM physics processes that is considered

- Targeting s-channel production of dark quarks via Z' (vector) mediator.
- Dark mesons travel sizeable distances (5mm-50mm) before decaying back to SM
- Leads to exotic jet topologies known as Emerging Jets (EJs)



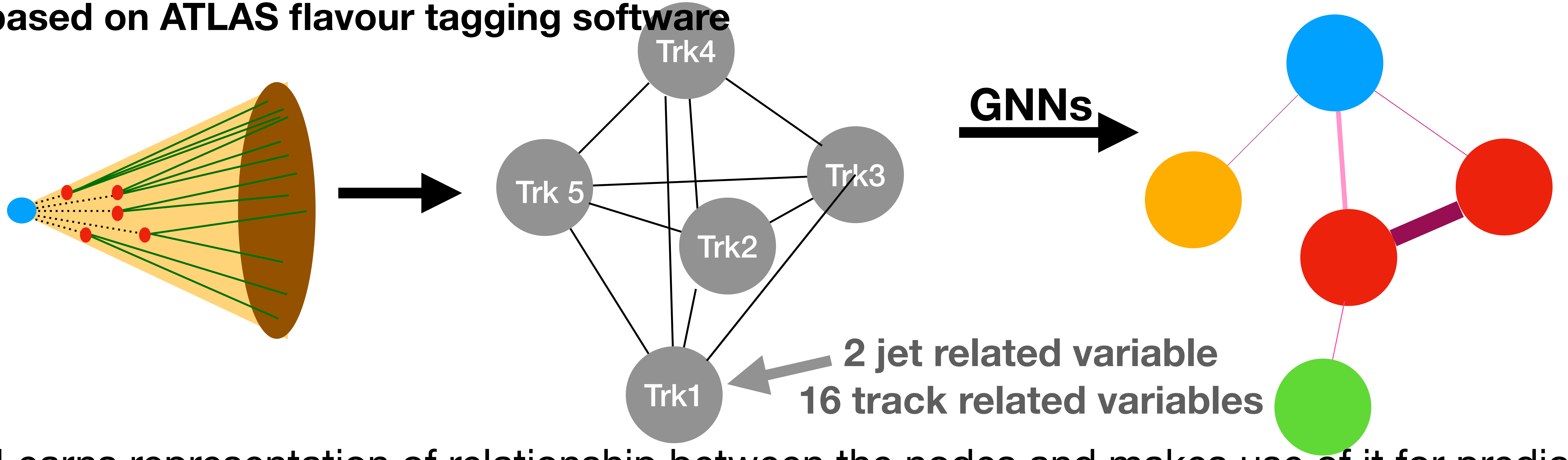
Emerging Jets (EJs) Signature!

- Jets are sprays of particles
- EJ's are BSM LLP signature!
- **EJs are jets with many displaced tracks and displaced vertices.**
- Difficult to identify!
    - Calorimeter signature looks similar to a QCD jet
    - Need to use the displaced tracks and vertices to identify the EJ using conventional methods



Graph Neural Network (GNNs)

Complex algorithm to identify intricate LLP signature: Emerging Jets(EJs) -architecture based on ATLAS flavour tagging software



- Learns representation of relationship between the nodes and makes use of it for prediction/ classification tasks.

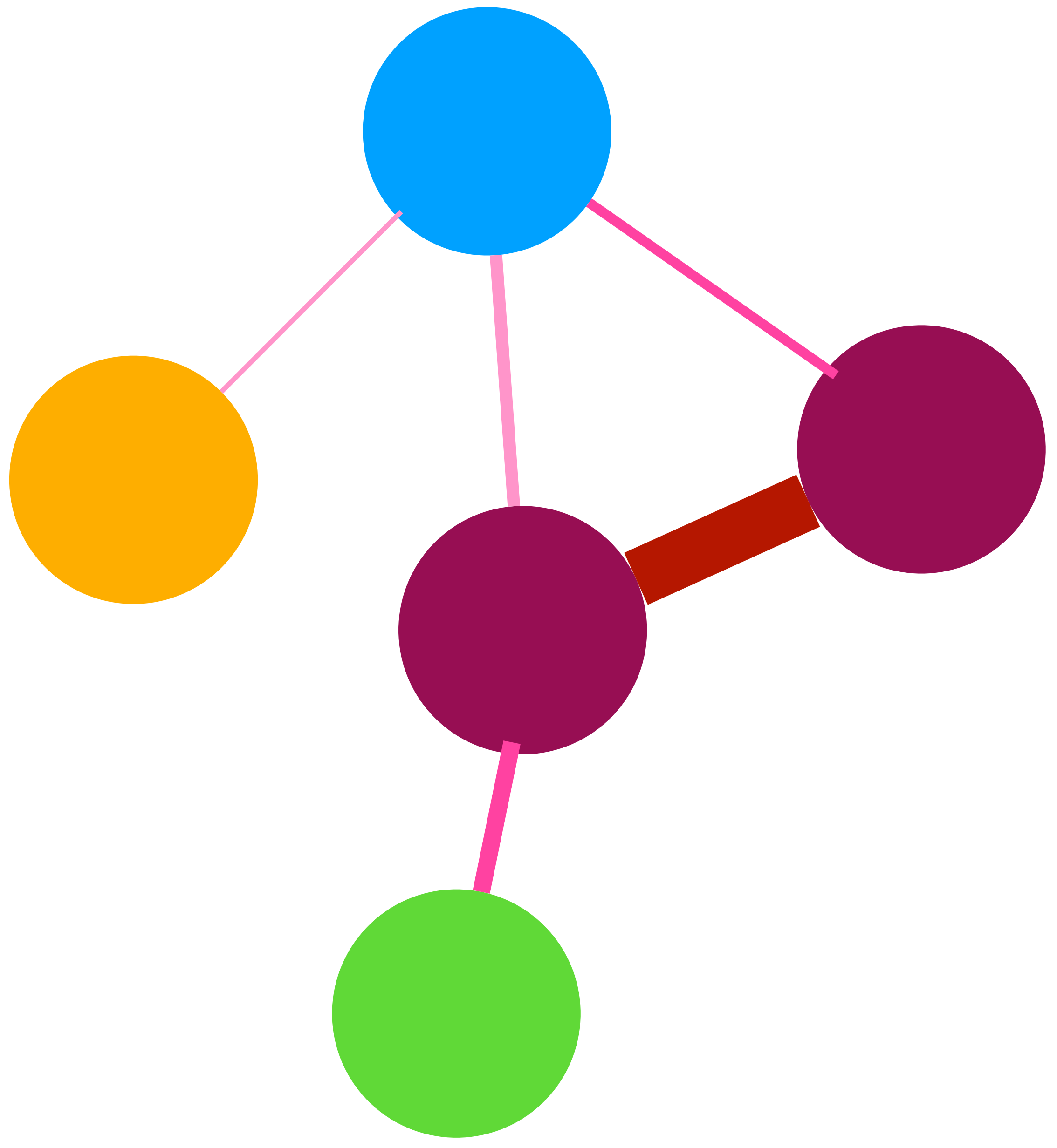
- Well suited for EJ tagging:

  - Can take large inputs. Inputs not fixed size

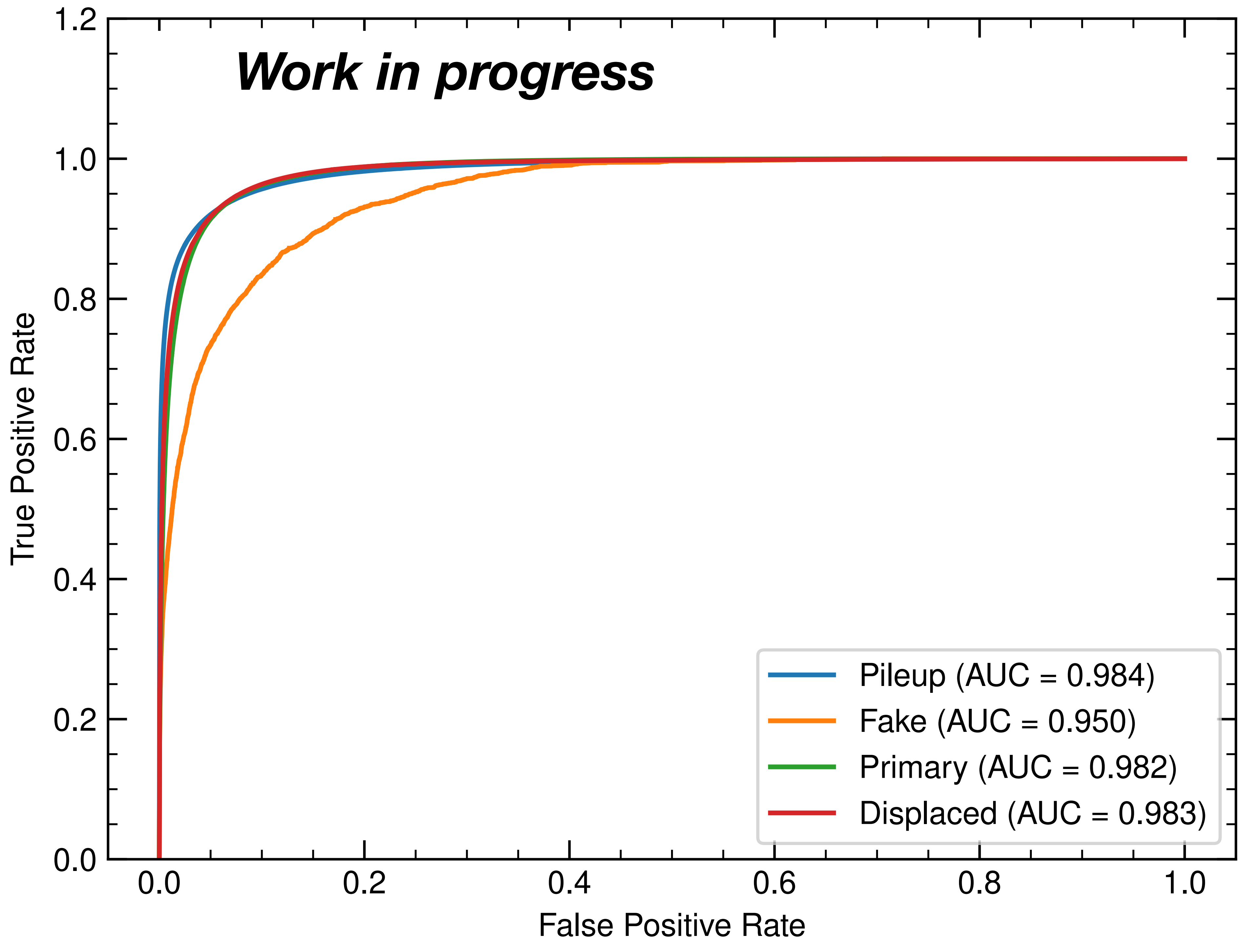
  - Good classifiers -> does not learn the ordering of the nodes (permutation invariant)

  - Learns relationships before classifying eg: if multiple displaced vertices, then emerging jet

GNNs Performance: Track Origin Classification (ROC)



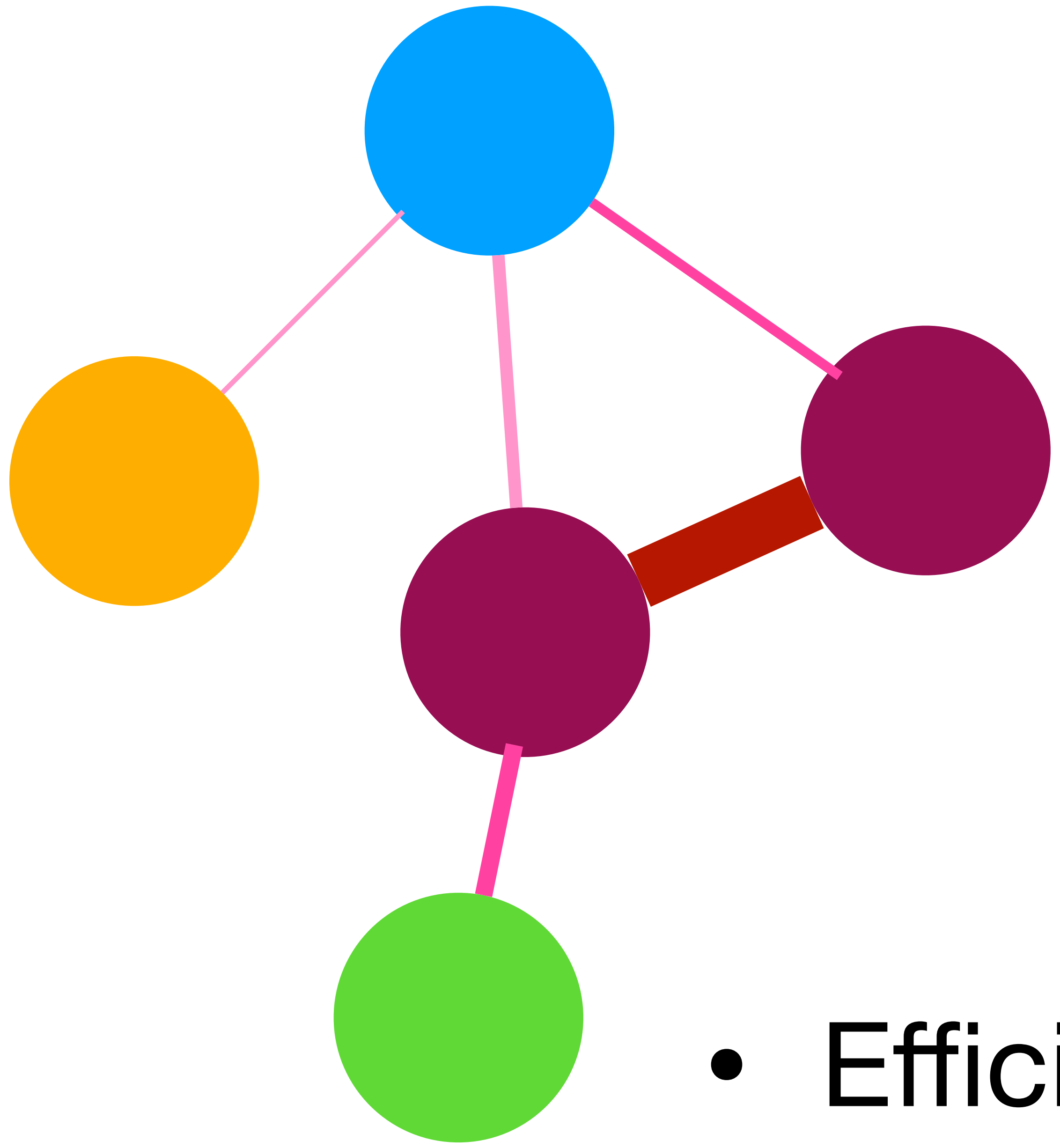
Pileup
Fake
Primary
Displaced

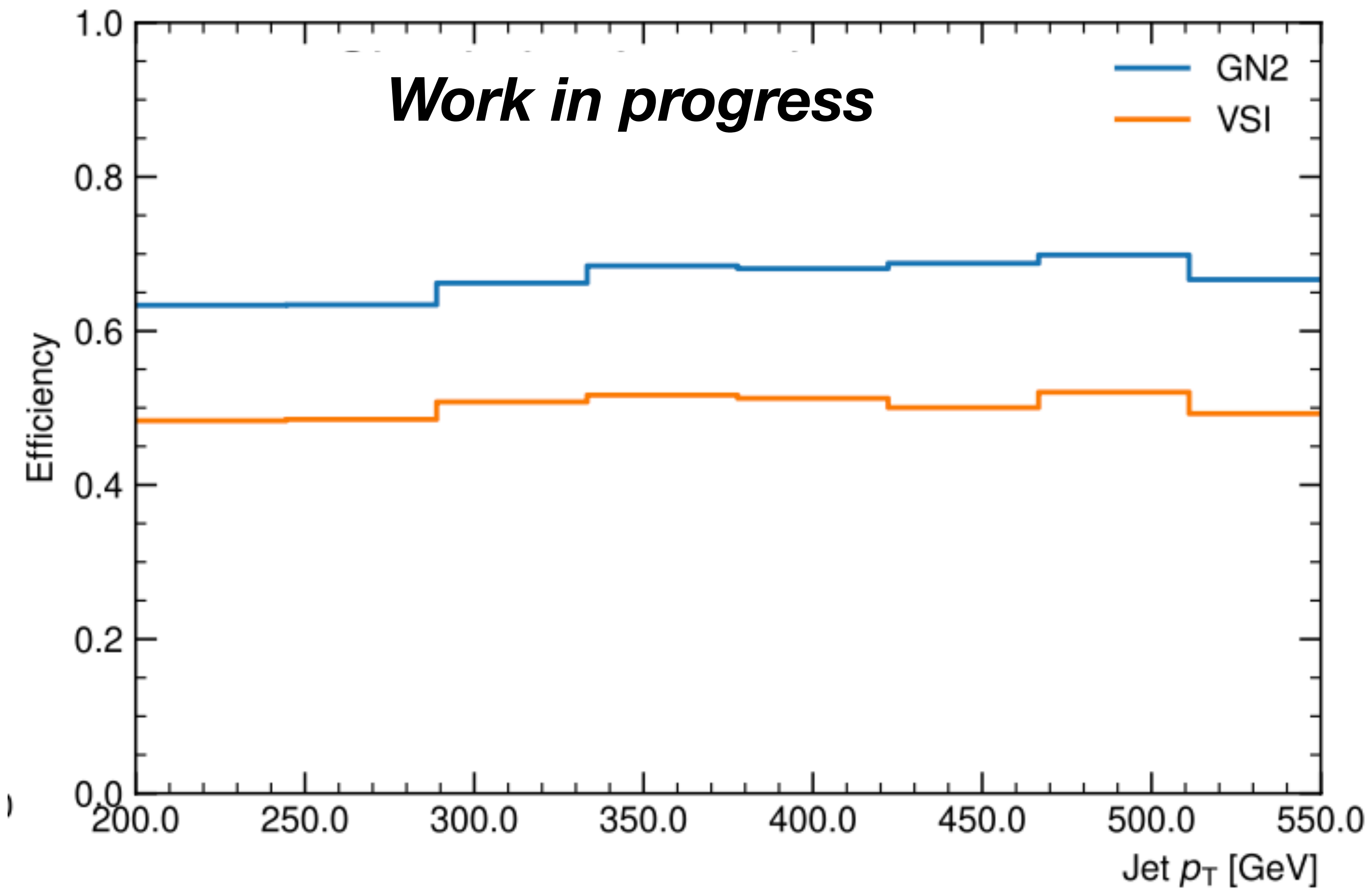


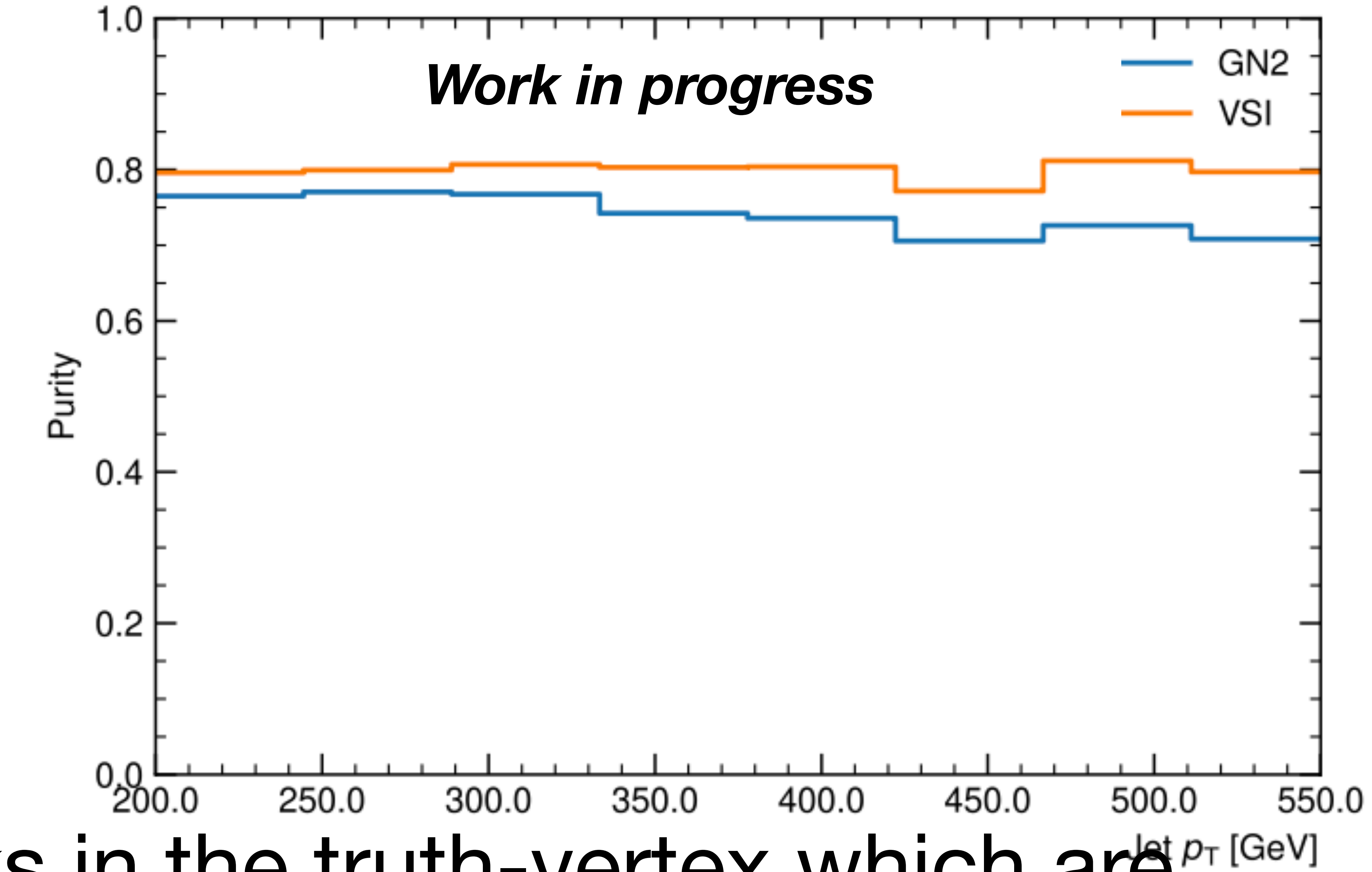
- Pileup: From additional proton-proton interactions that occur within the same bunch crossing
- Fake: From purely combinatorial collections of hits
- Primary: From Primary Vertex
- Displaced: From Secondary vertices

- FPR: proportion of actual negatives that are incorrectly identified as positives
- TPR: proportion of actual positives that are correctly identified

GNN Performance: Vertex Identification







- Efficiency: Per-vertex fraction of tracks in the truth-vertex which are included in a common reco-vertex!

- Purity: Per-vertex fraction of tracks in the reconstructed vertex which are from the same truth vertex.

- **GNN vertices have higher efficiency but have similar purity**

Jet Classification: Performance

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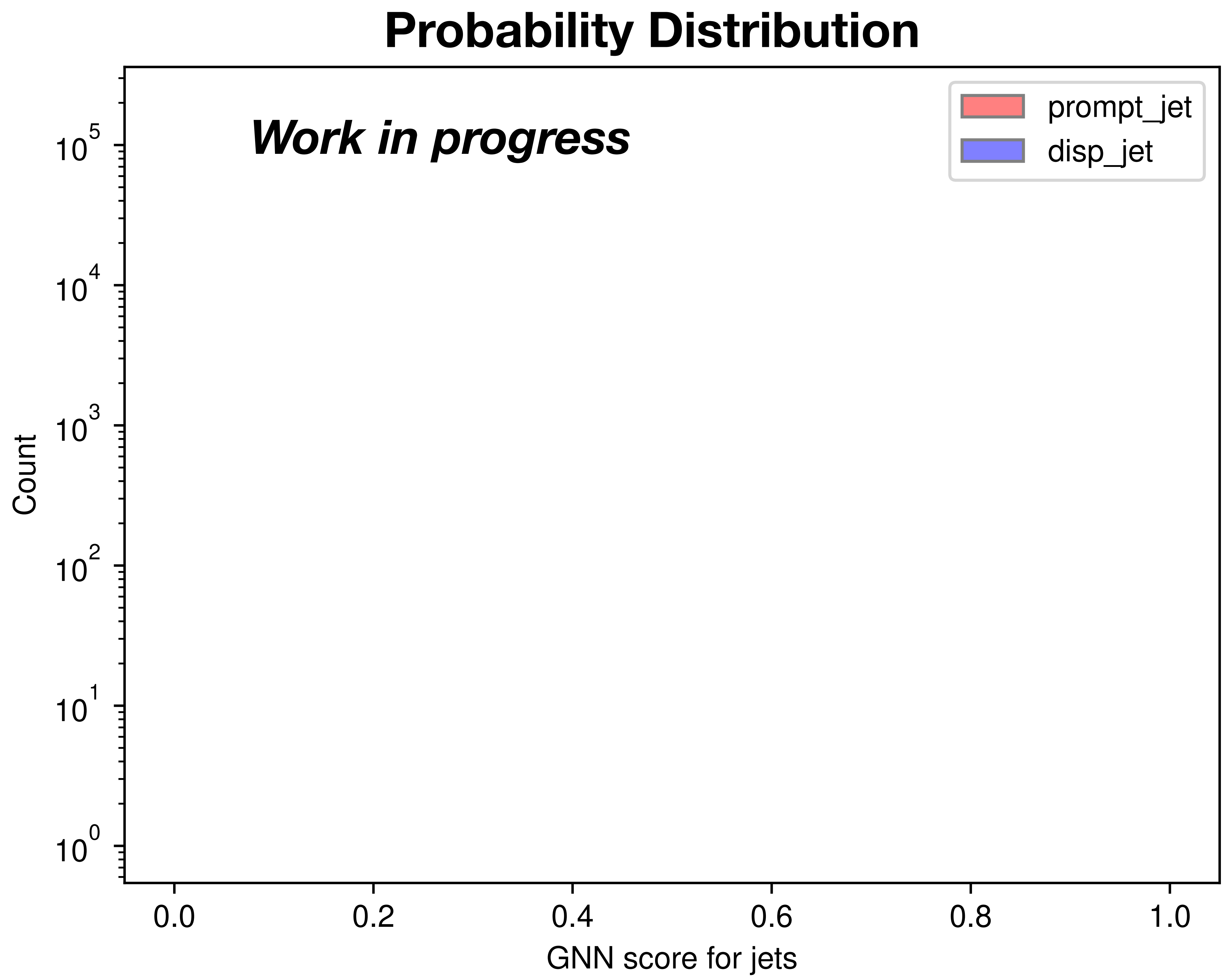
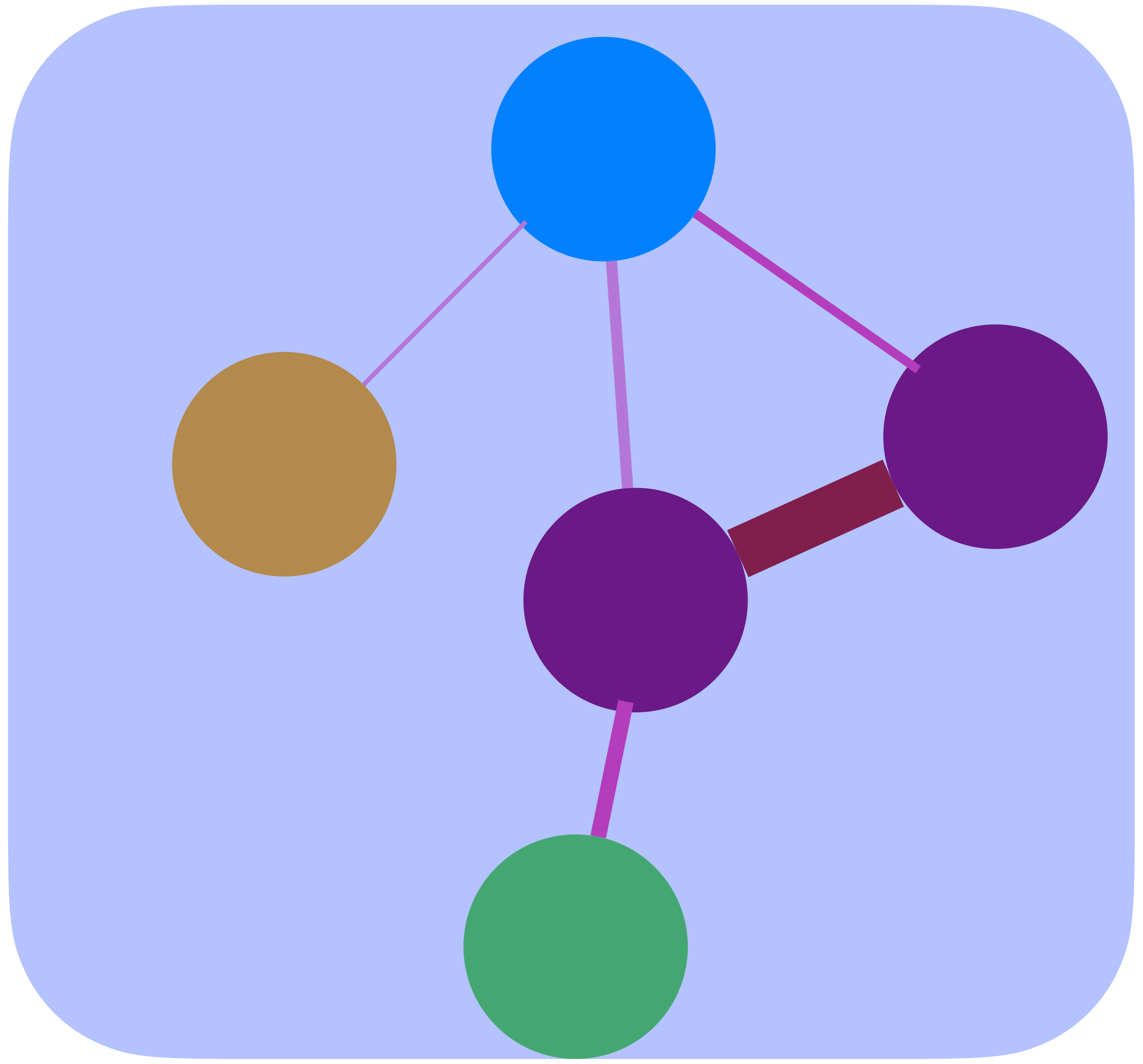
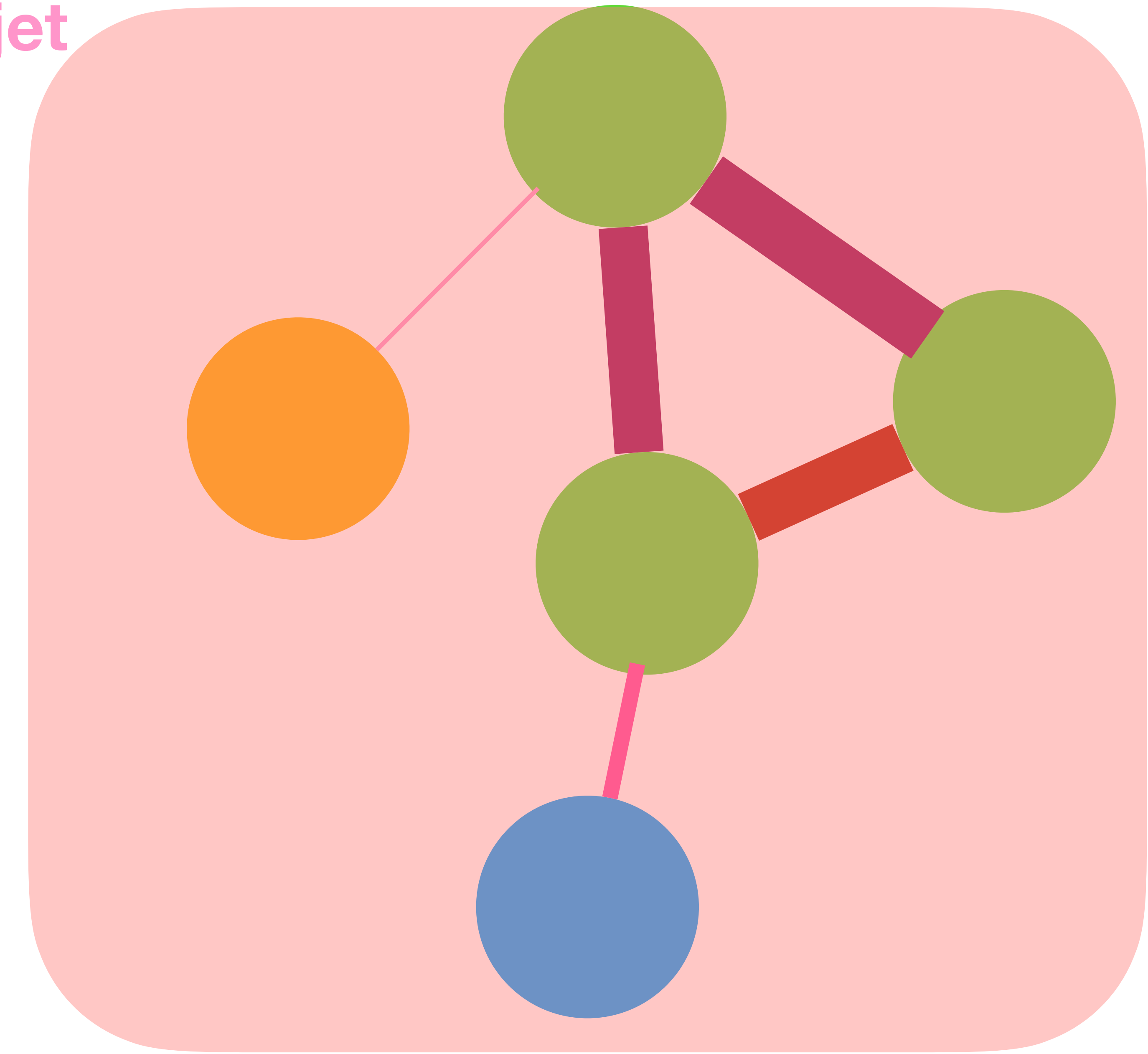


True EJ



Probability EJ = 0.9

True QCD jet

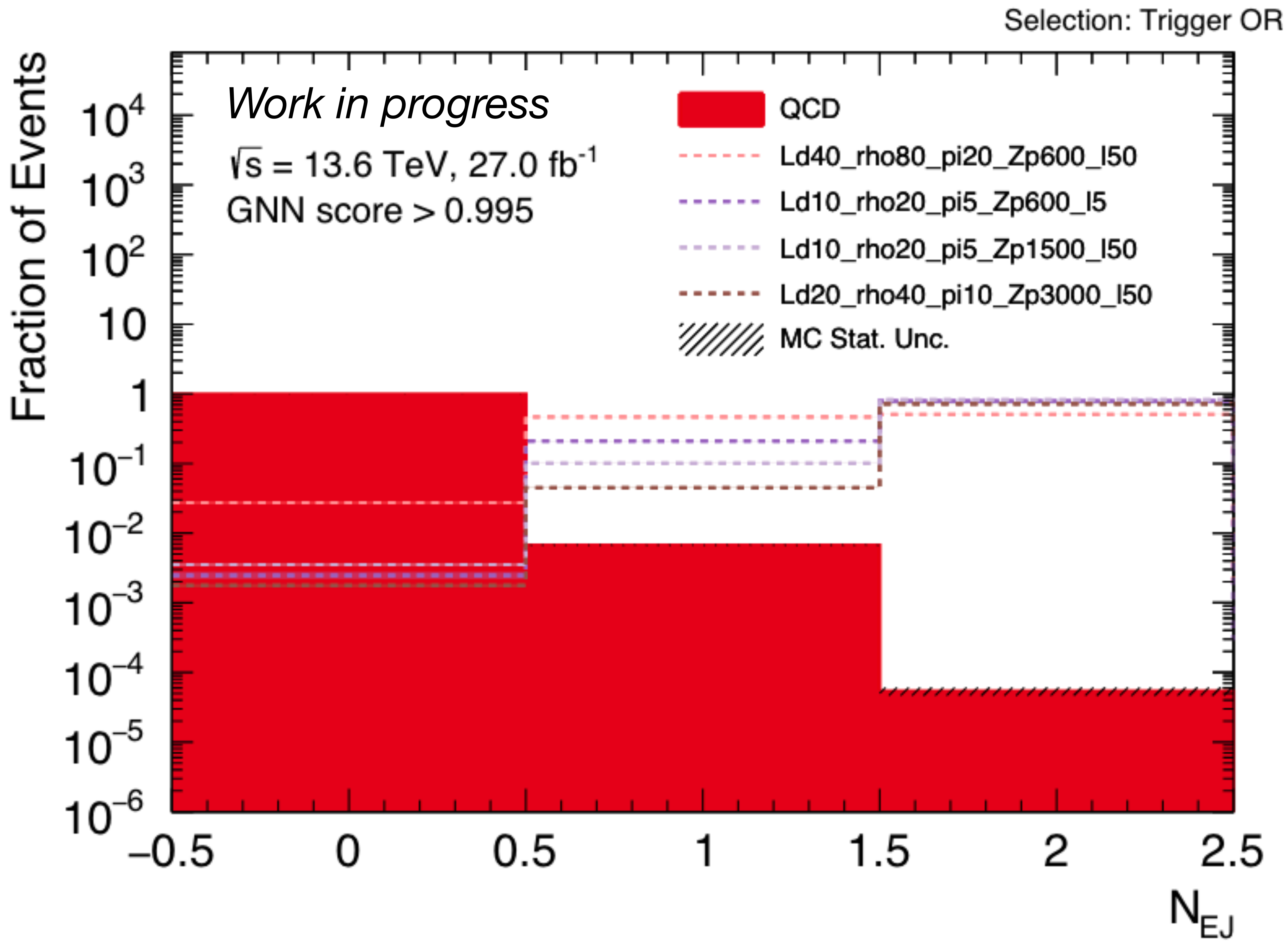


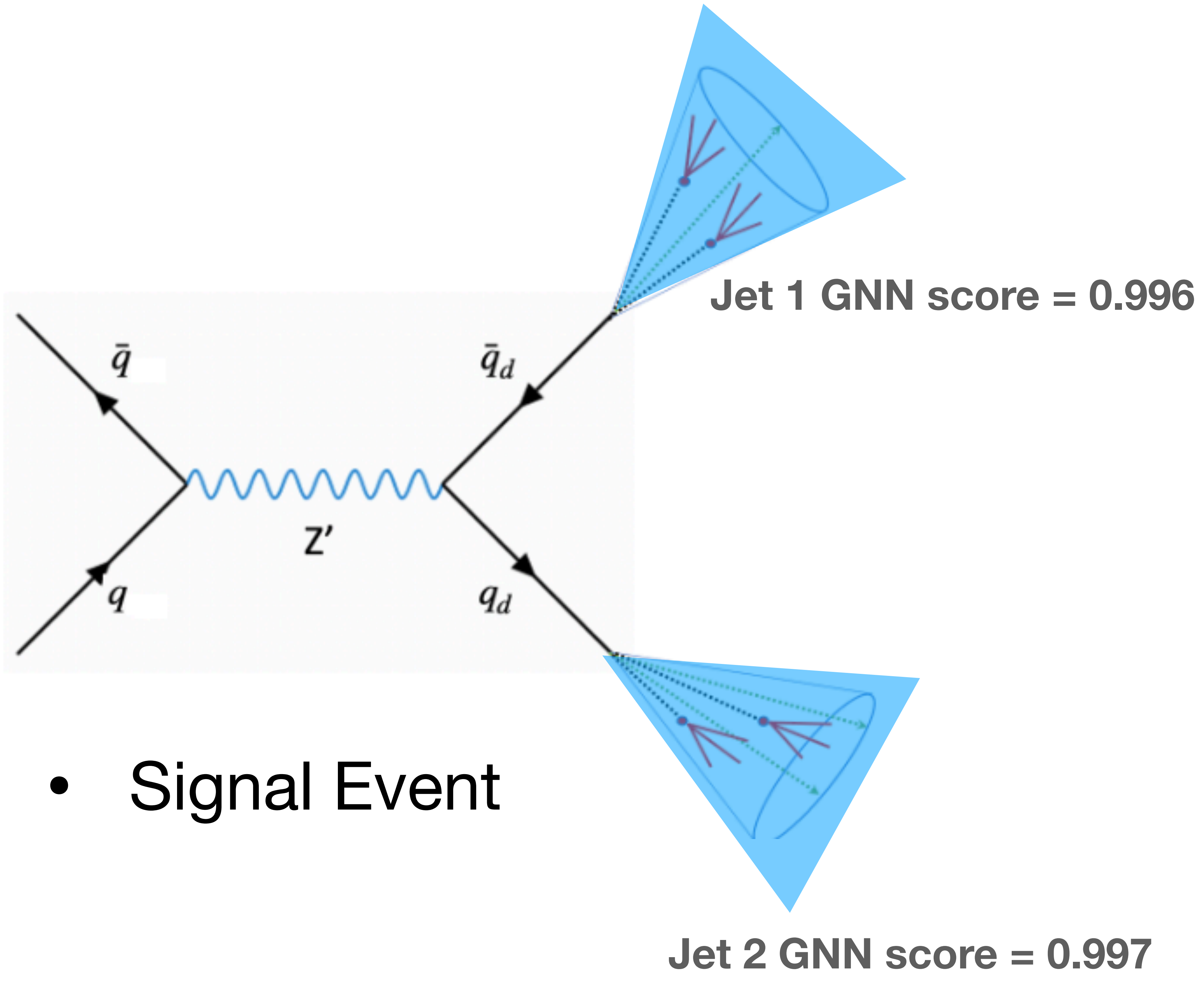
Probability EJ = 0.2

- Two categories: Signal Jets (***EJs)*** from long lived dark mesons and background Jets (***Prompt jets)*** from QCD background process!

- Signal jets peaks at last bin suggesting extremely high likelihood for majority of signal jets to be correctly identified!

GNN in EJ (Run 03) Analysis





- Signal Event

- Requiring two jets to have GNN score > 0.995 gives significant background reduction with high signal efficiency!

Conclusion

- GNNs can identify intricate long lived particle signatures: “Emerging Jets” with high efficiency.
- GNNs proven efficient in classifying displaced tracks as well as the identification of displaced vertices.

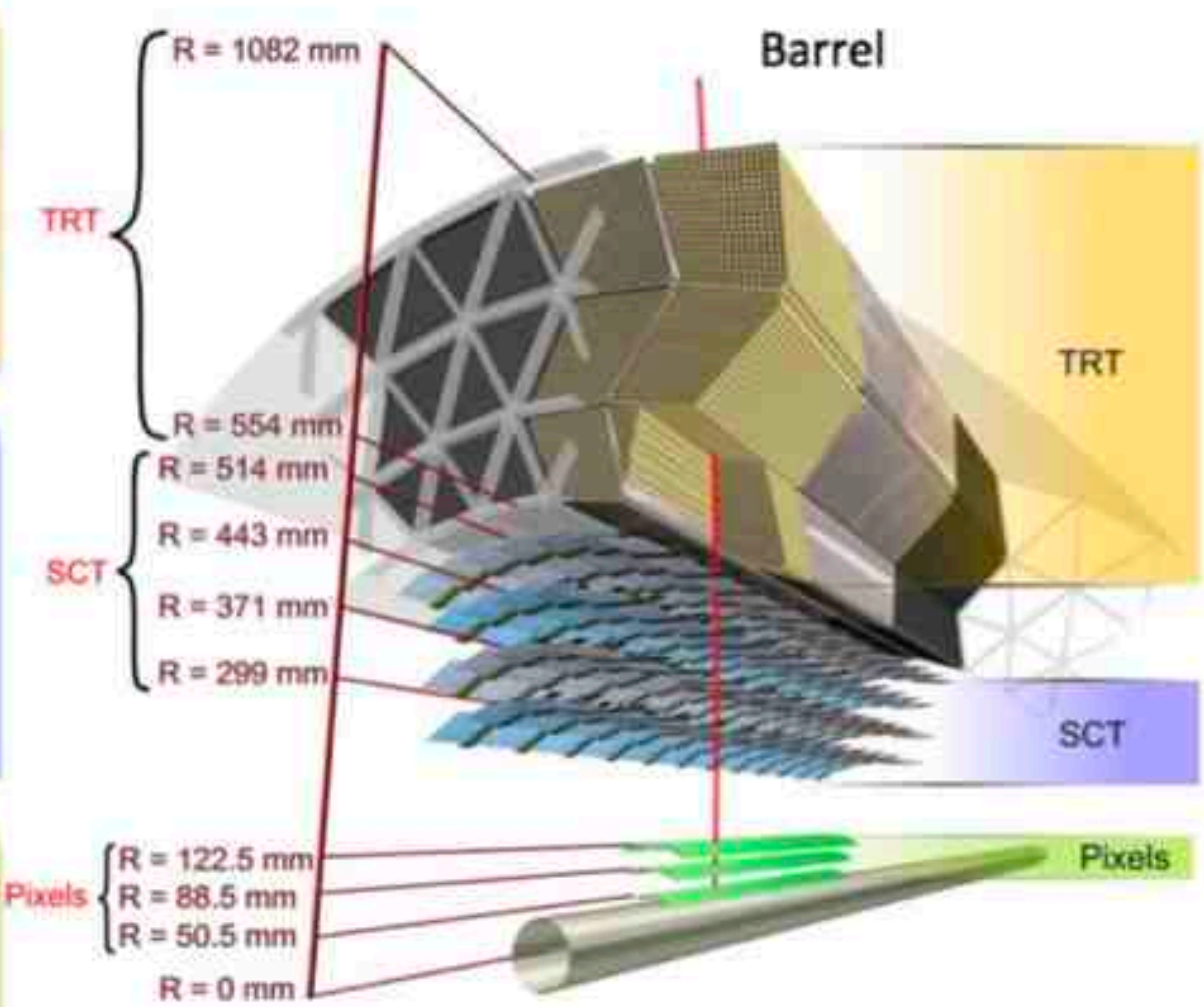
Backup

ATLAS Detector

- Straw tracker + Transition Radiation
- 4mm diameter straws with 35 μm anode wire
- Layers: 73 in Barrel (axial) 2x160 in Endcap (radial)

- 4(9) double layers in Barrel/Endcap
- 4088 modules, 6M chan., strips 80 μm
- Resolution 17 x 580 μm

- 3 layers in Barrel and Endcap
- Pixel size 50 x 400 μm
- Resolution 10 x110 μm
- 80 M channels



GNN Architecture

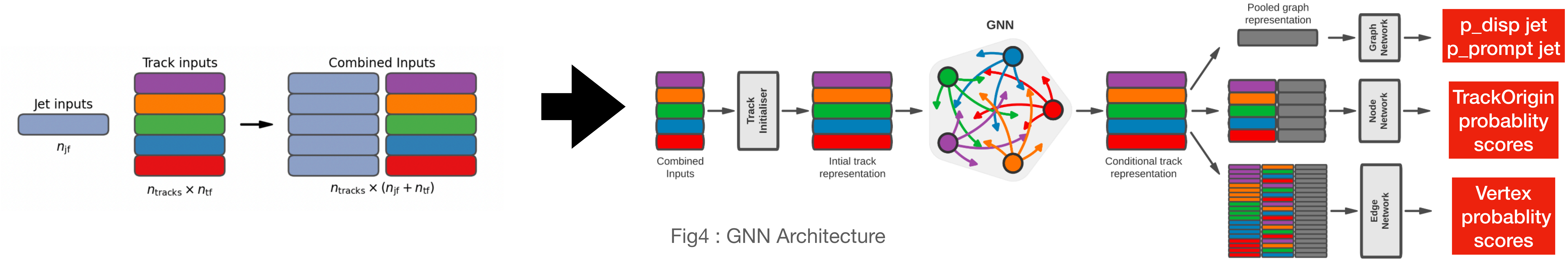


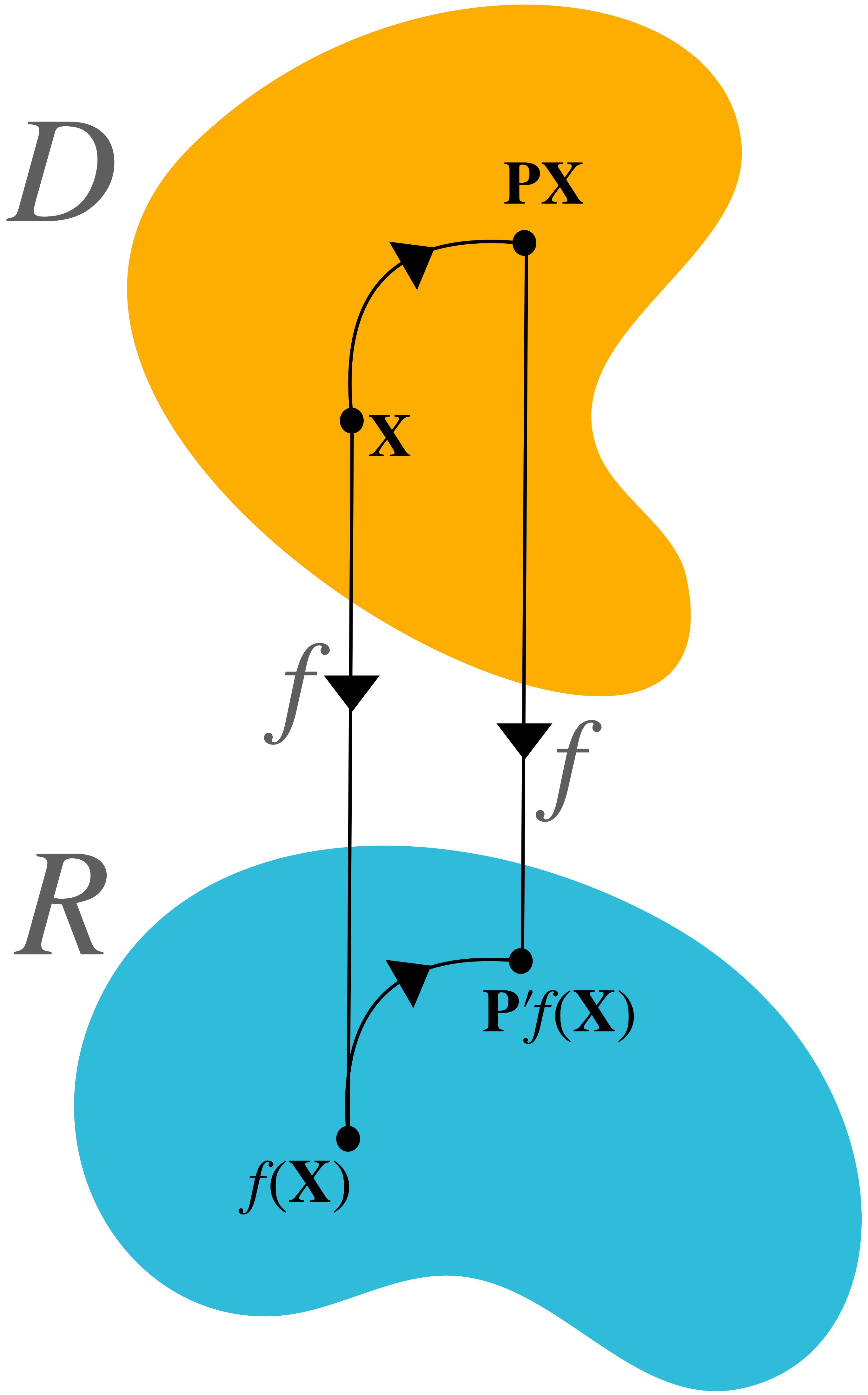
Fig4 : GNN Architecture

- Combined input prepared and fed into network architecture (2 jet variables 16 track variables)
- Initial latent representation for each track created. These representations are then used to populate the node features of a fully connected graph network
- Message passing graph neural network's loss function also accounts node and vertex classification loss function.
- After the graph network, the resulting node representations used to predict Track Label (truthOriginLabel), JetLabel (isDisplaced) probability score.
- Architecture based on the ATLAS Flavour tagging software!

4: http://cds.cern.ch/record/2811135/files/ATL-PHYS-PUB-2022-027.pdf

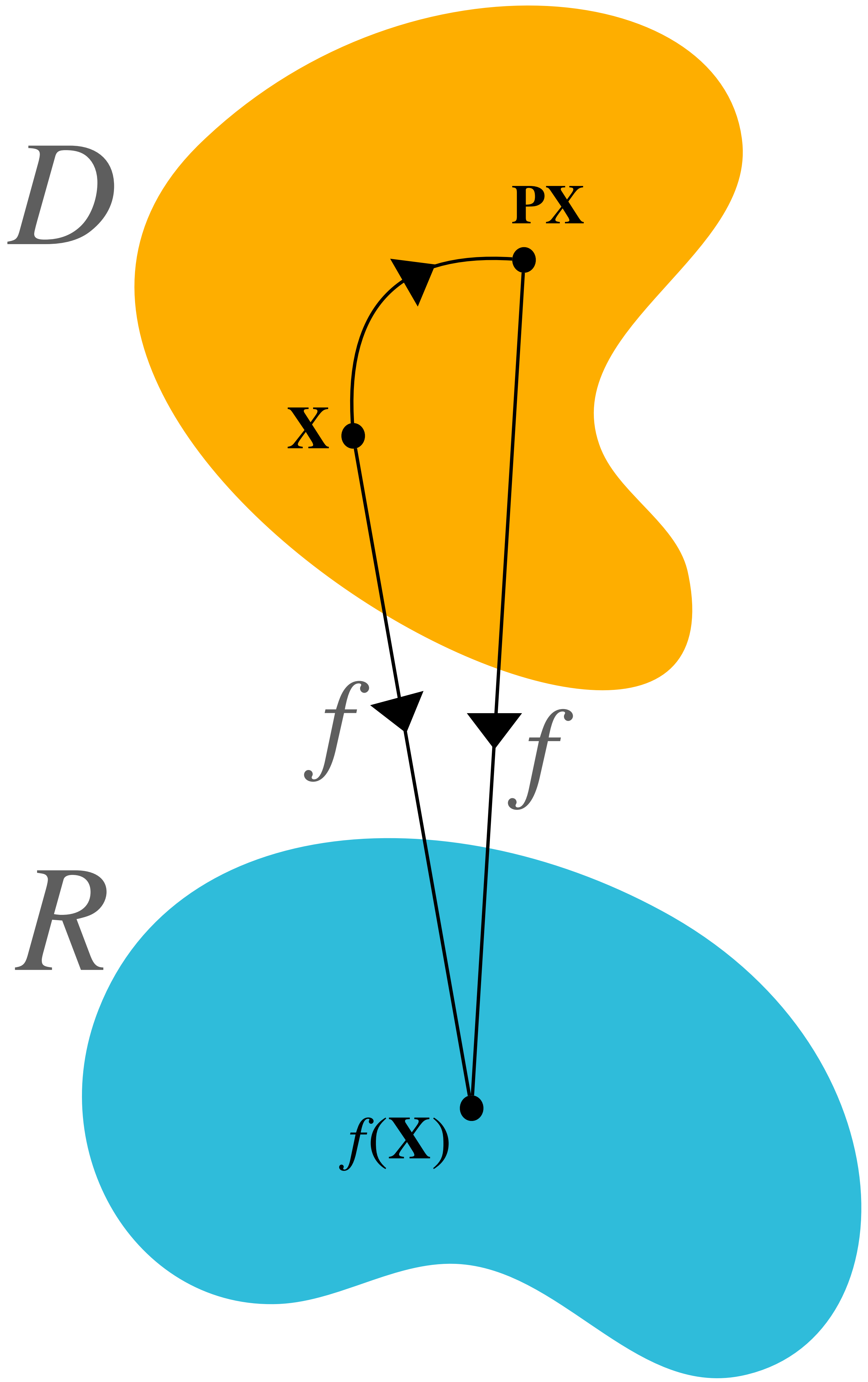
Equivariance

$$f(\mathbf{PX}) = \mathbf{P}'f(\mathbf{X})$$



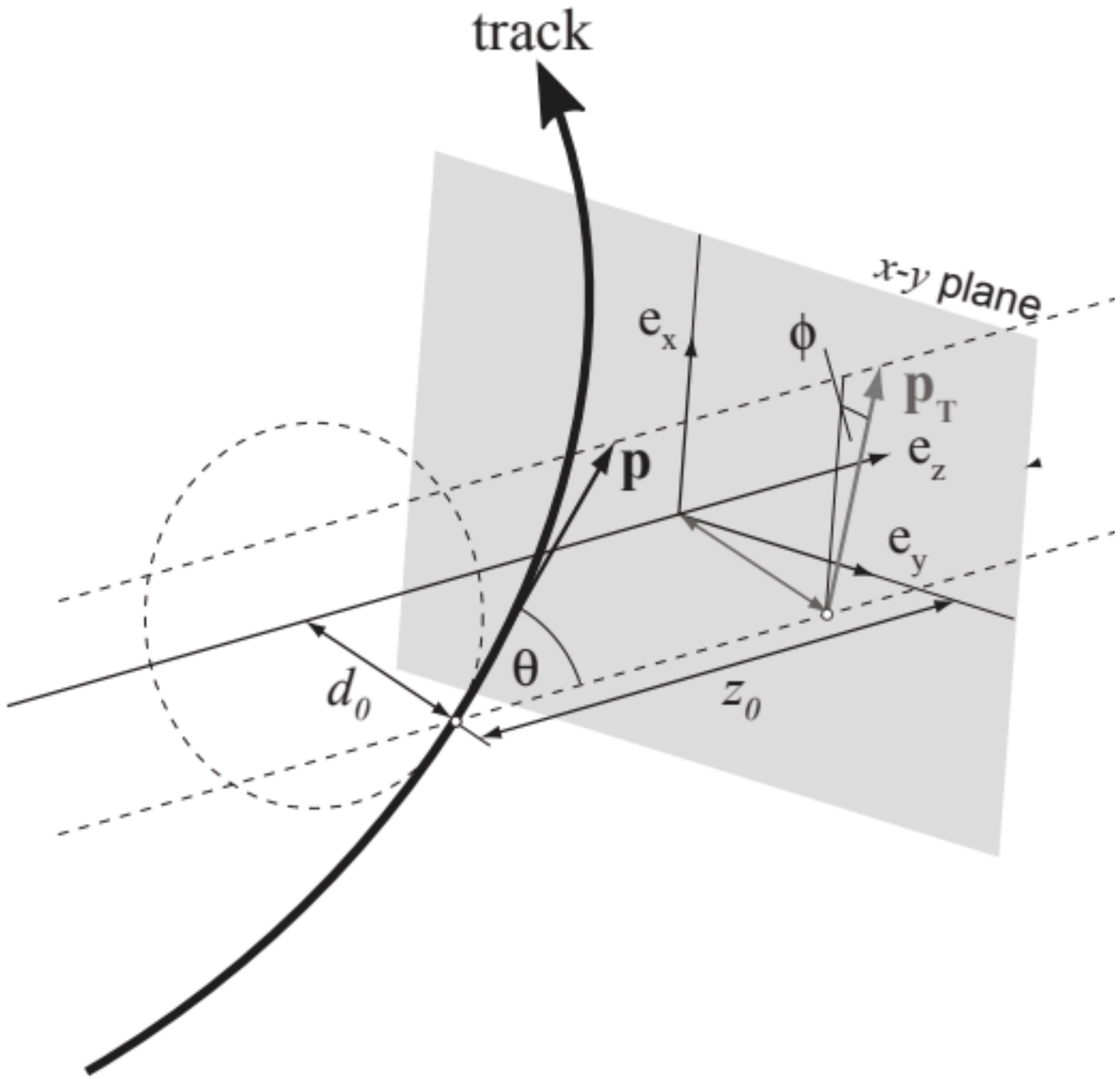
Invariance

$$f(\mathbf{PX}) = f(\mathbf{X})$$

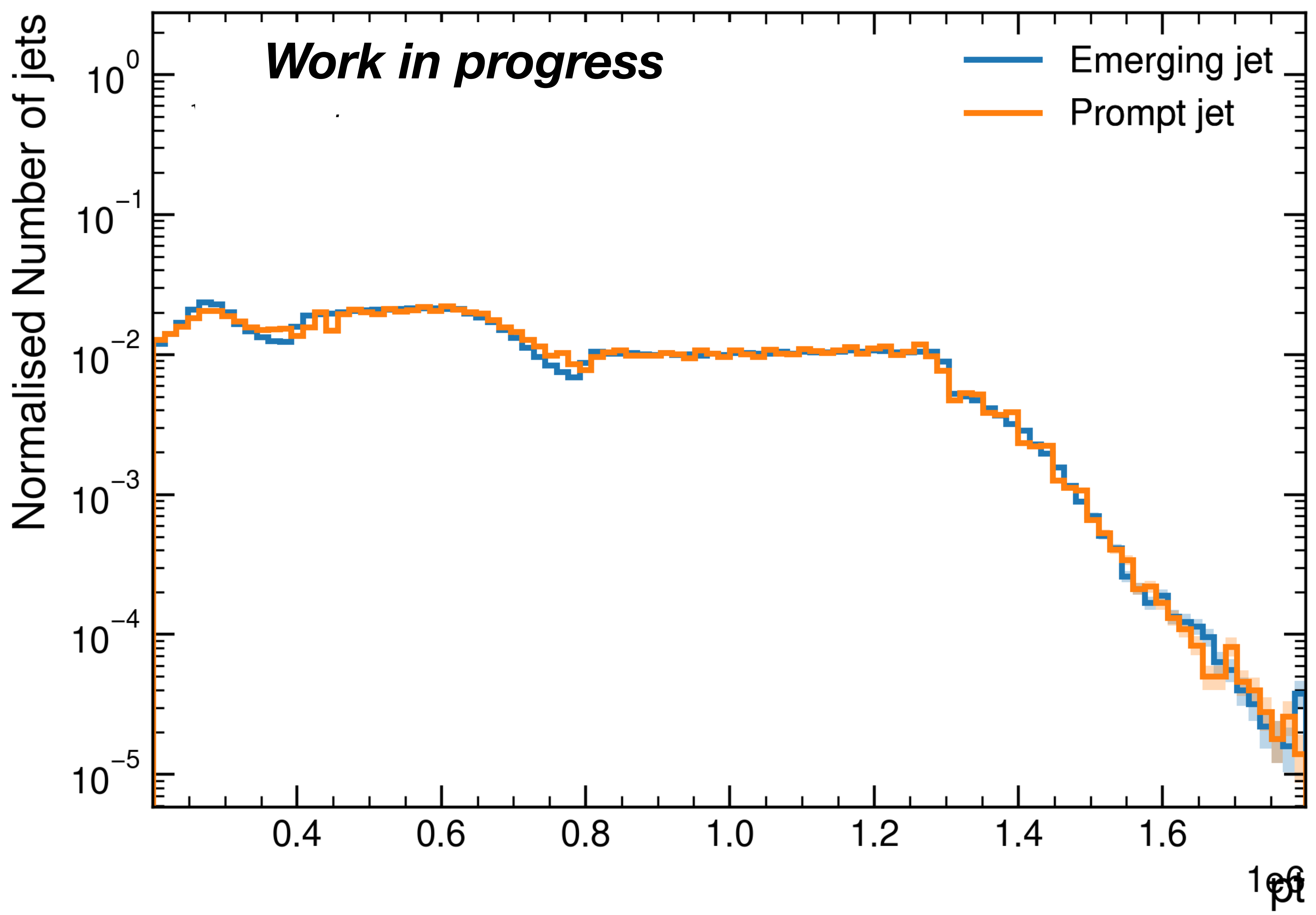


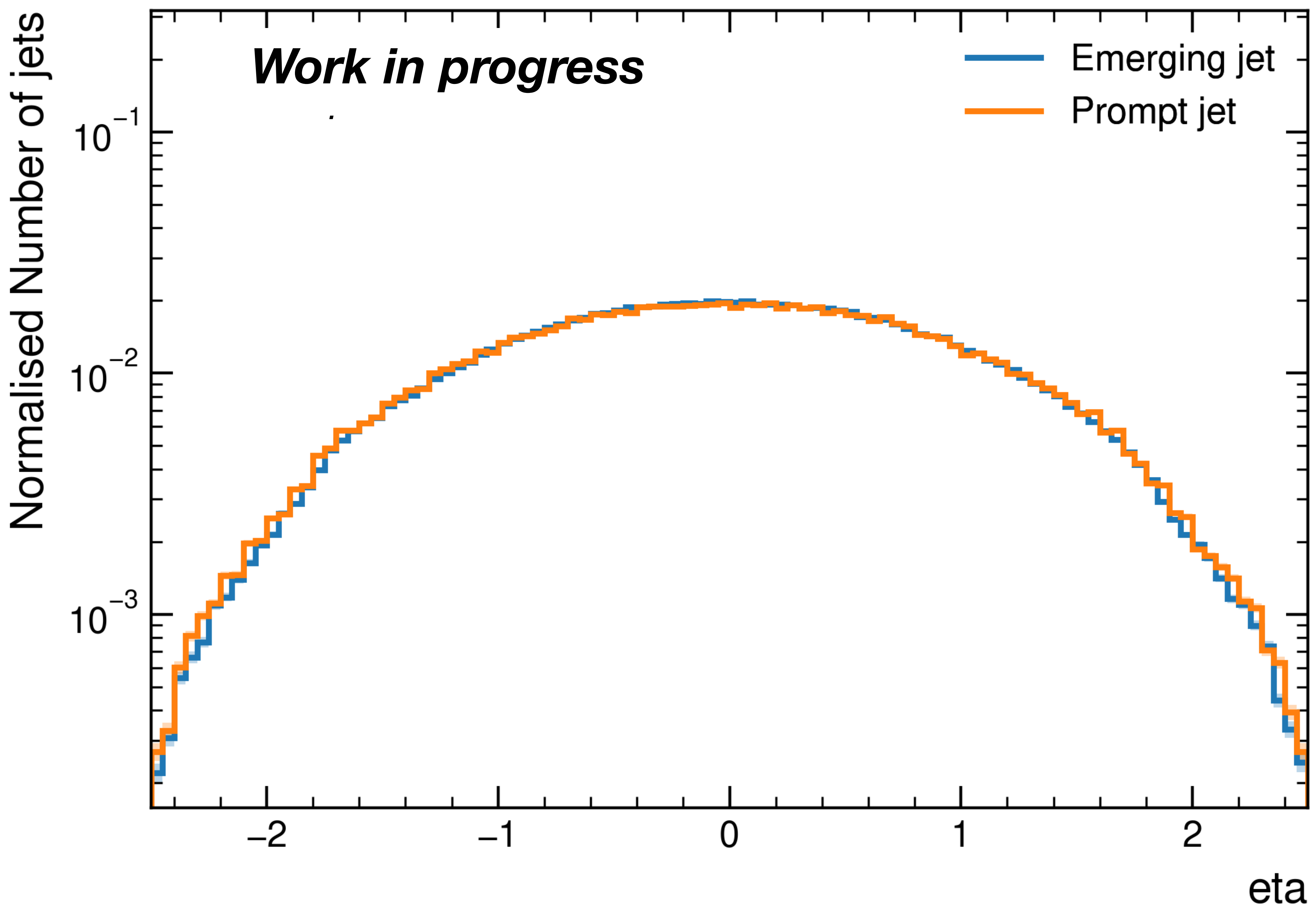
Jet-Track Inputs

```yaml
variables:
  jet:
  - pt
  - eta
  track:
  - d0
  - z0SinTheta
  - dphi
  - deta
  - qOverP
  - IP3D_signed_d0_significance
  - IP3D_signed_z0_significance
  - phiUncertainty
  - thetaUncertainty
  - qOverPUncertainty
  - numberOfPixelHits
  - numberOfSCTHits
  - numberOfPixelSharedHits
  - numberOfSCTSharedHits
  - numberOfPixelHoles
  - numberOfSCTHoles
```



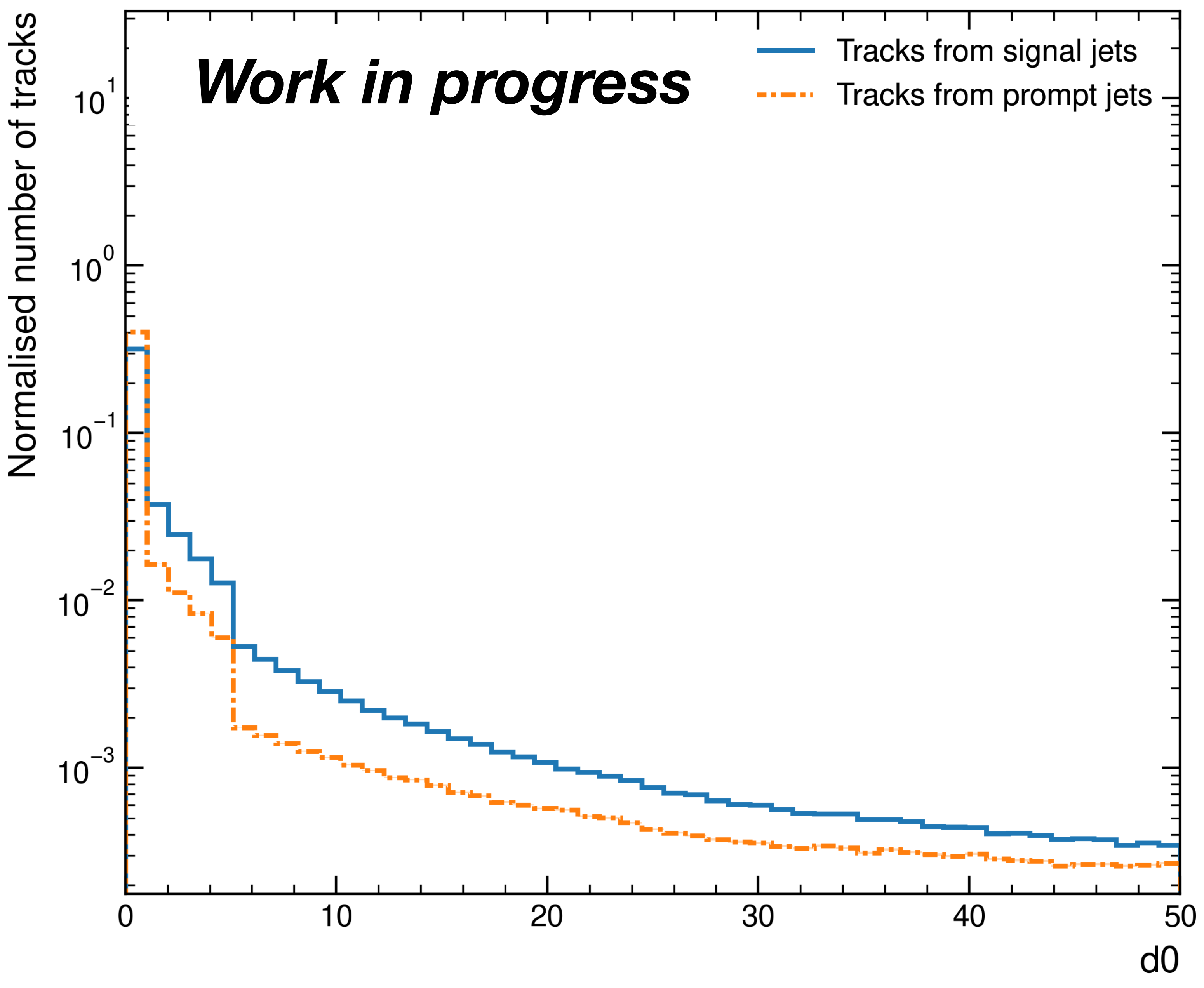
Input Variables: Jets

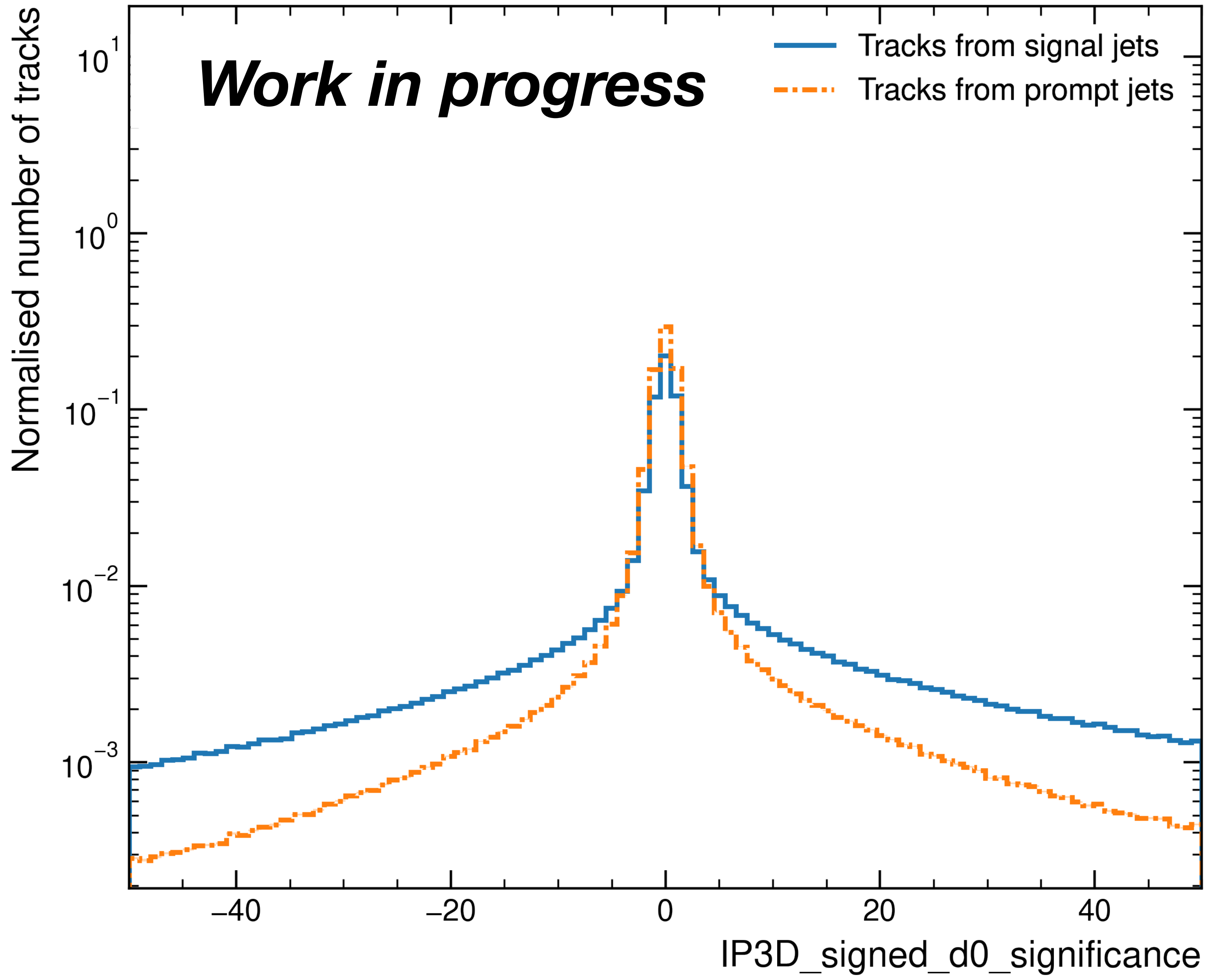


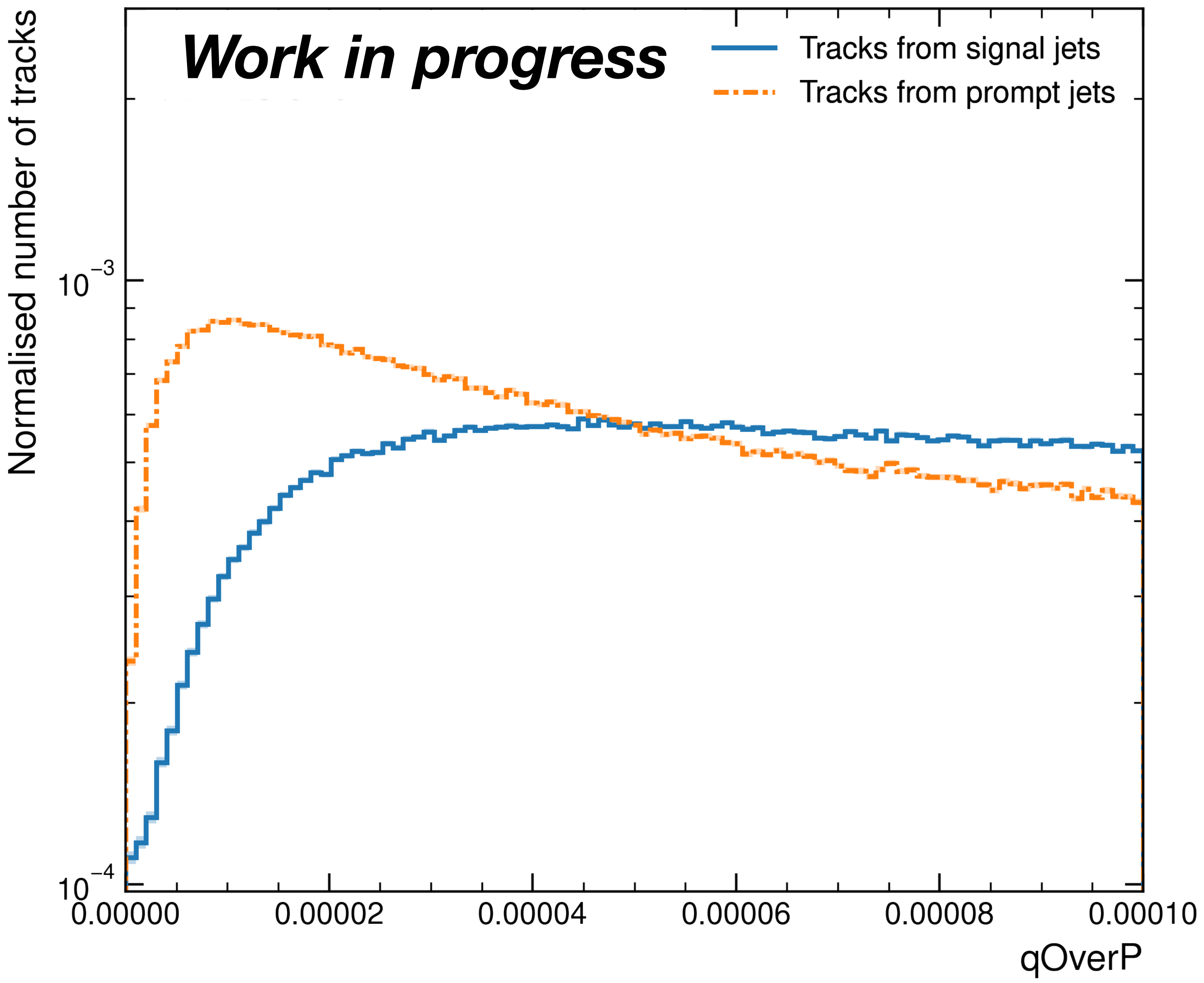


- Two jet variables that constitute the basic kinematics of a jet p_T, η
- To avoid avoid kinematic biases for jet tagger, the distributions are "resampled", i.e ensure uniformity in the kinetic distribution!

Input Variables: Tracks



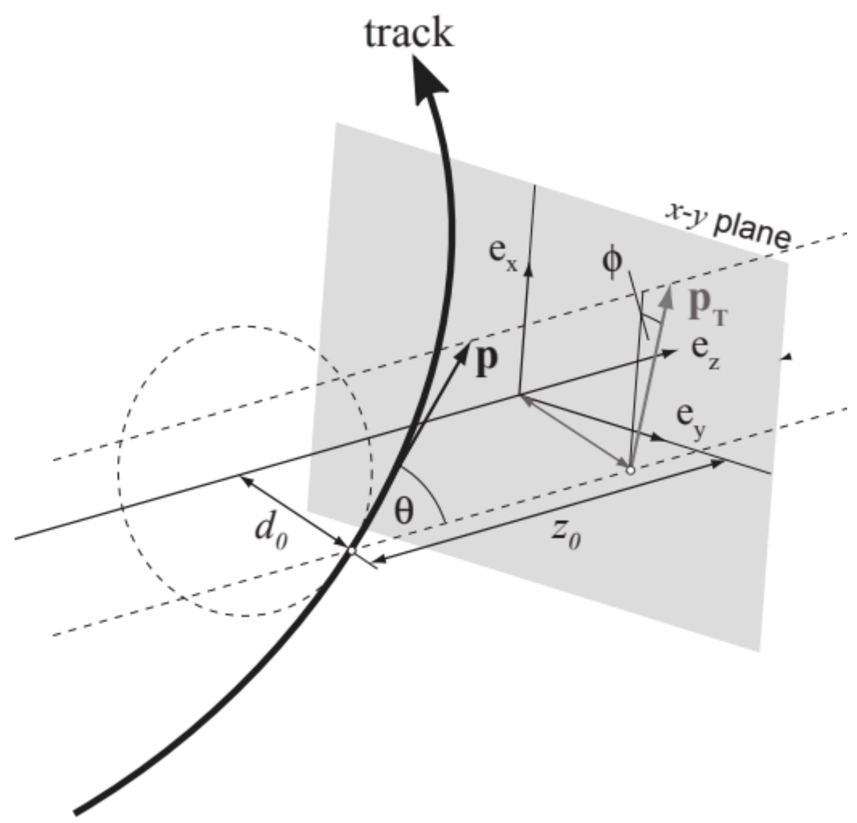




- 16 track variables including track parameters in ATLAS tracking system, detector hits and holes variables, uncertainty in track parameters … (detailed in backup slides)

- Most discriminating ones include

- - d_0: Distances of closest approach between the track
  - IP3D_signed_d0_significance: Ratio of d_0 and $\sigma(d_0)$ defined for both positive and negative scale with reference to the primary interaction point of the ATLAS detector
  - $\frac{q}{p}$ Track charge divided by momentum (measure of curvature)



Input Distribution (Tracks)

Samples Used for Training EJ classifier

QCD

Ld40_rho80_pi20_Zp600_l50

Ld10_rho20_pi5_Zp600_l5

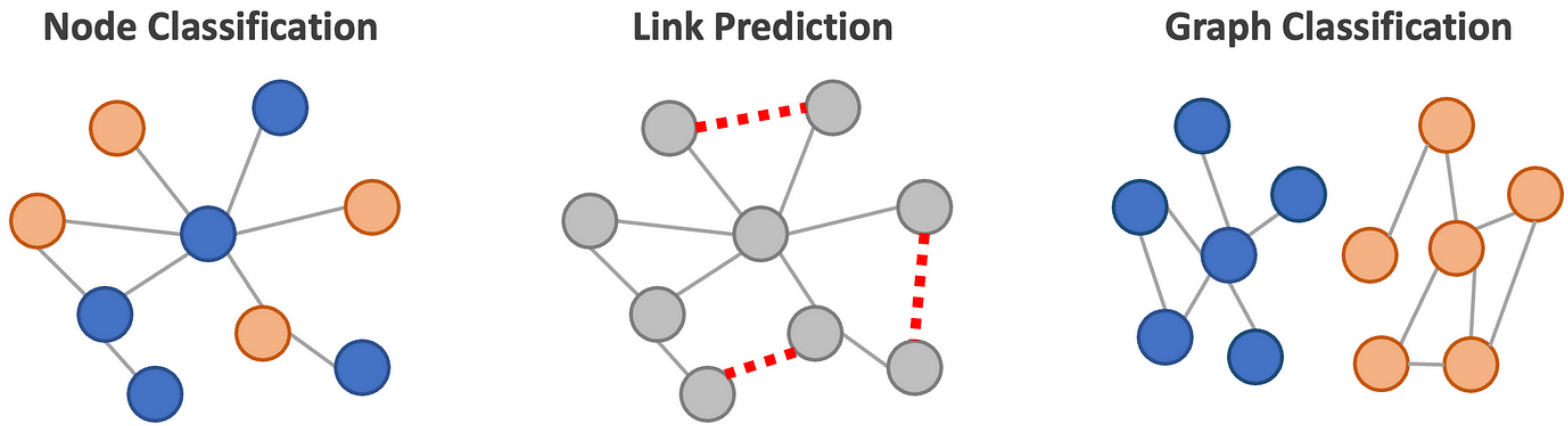
Ld10_rho20_pi5_Zp1500_l50

Ld20_rho40_pi10_Zp3000_l50

- Ld = dark confinement scale [GeV]
- rho = mass of rho meson [GeV]
- pi = mass of dark pion [GeV]
- Zp = mass of Z' [GeV]
- l = lifetime [mm]

Performance of Graph Neural Networks

Trained for 37 epochs for 3 classification tasks



Track Origin Identification

Vertex Finding

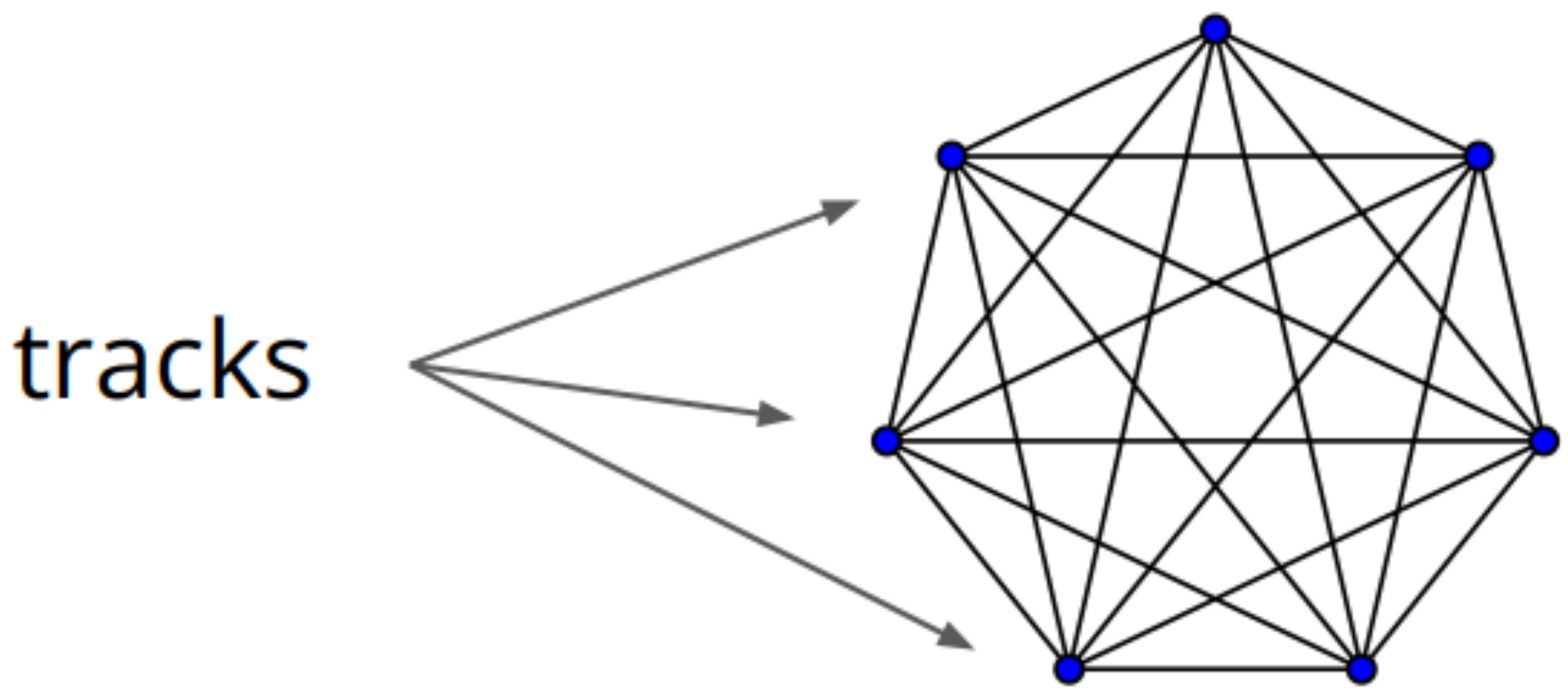
Jet Classification

Vertex Identification

Brief Introduction

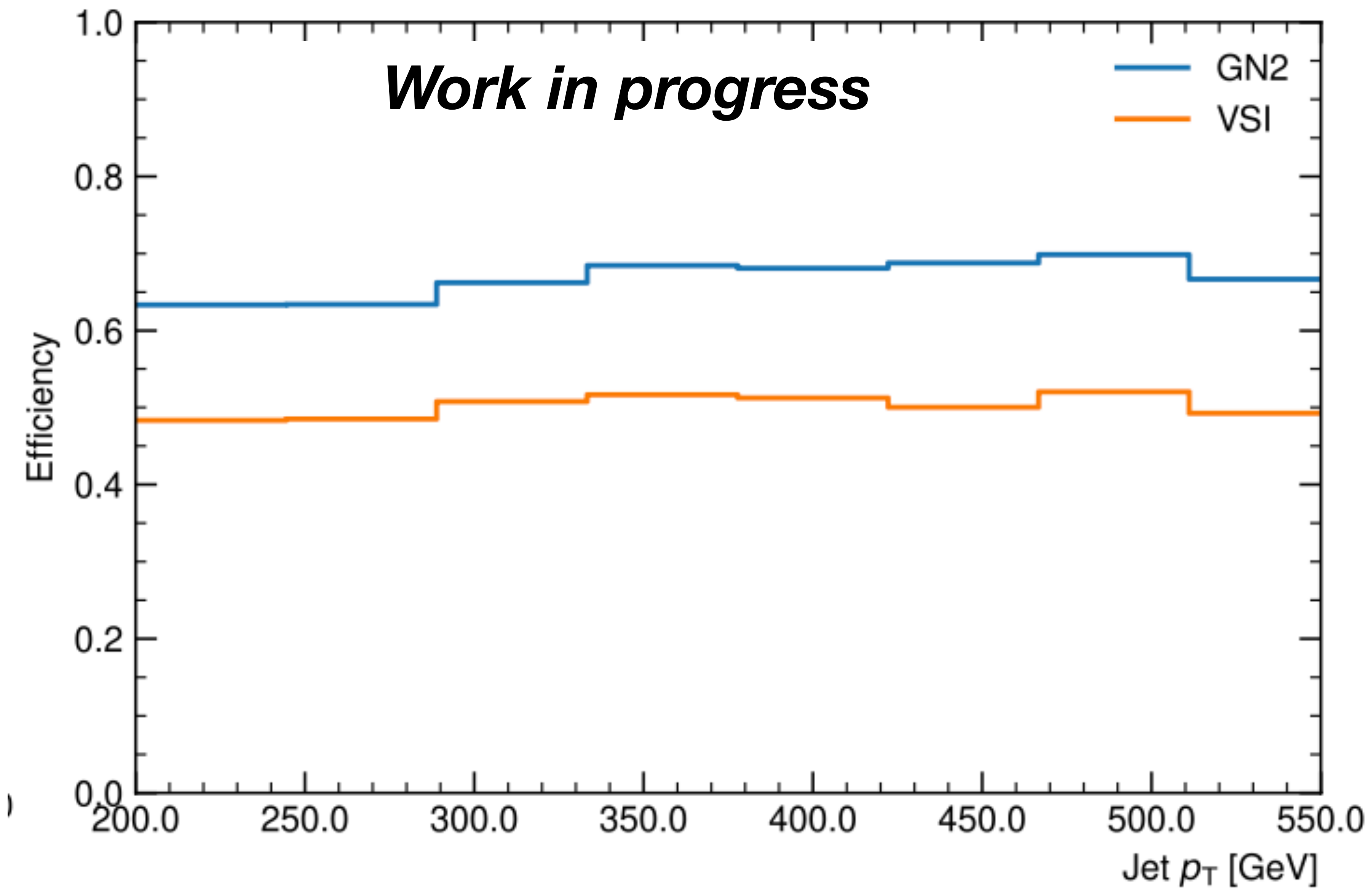
More on backup slides

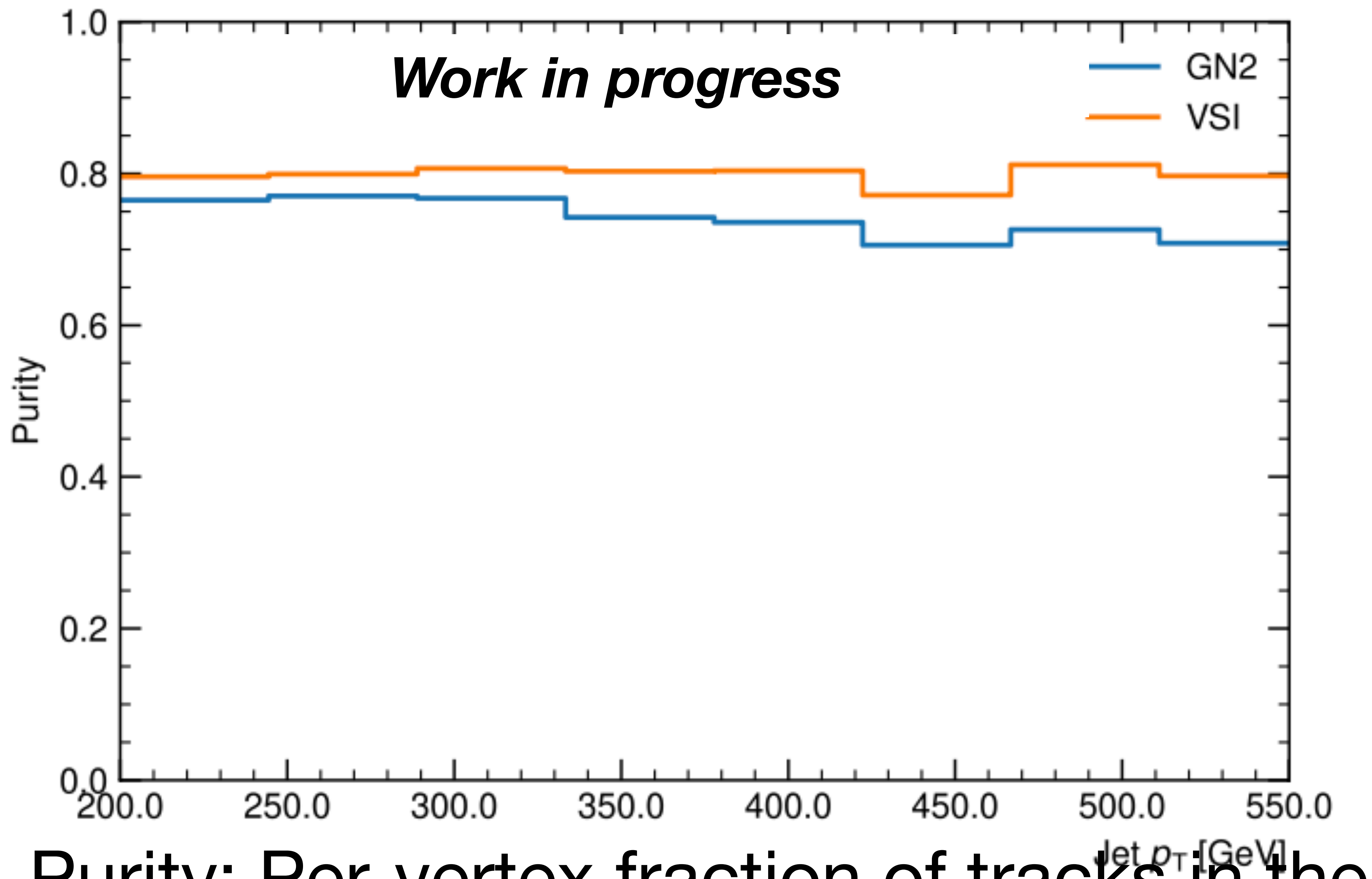
- Use jet-graph representation of the ATLAS simulation EJ sample and perform edge classification task to predict vertex compatibility for each track-pair!
    - Node = 2 jet variables + 16 track variables to form a node feature matrix!



- Only *vertex-finding* and not *vertex fitting*!
- Performance compared to other ATLAS secondary vertex reconstruction method, namely VSI.

Vertex Identification: Performance





- Efficiency: Per-vertex fraction of tracks in the truth-vertex which are included in a common reco-vertex!
- For example, TruthVertexTrackIDs = [1,2,3,4,5, PredictVertexTrackIDs=[1,2,3] , then efficiency = 3/5. GNN vertices have higher efficiency than VSI!

- Purity: Per-vertex fraction of tracks in the reconstructed vertex which are from the same truth vertex.
- For example: TruthVertexTrackIDs = [1,2,3,4,5]. PredictVertexTrackIDs=[1,2,3], Purity = 3/3

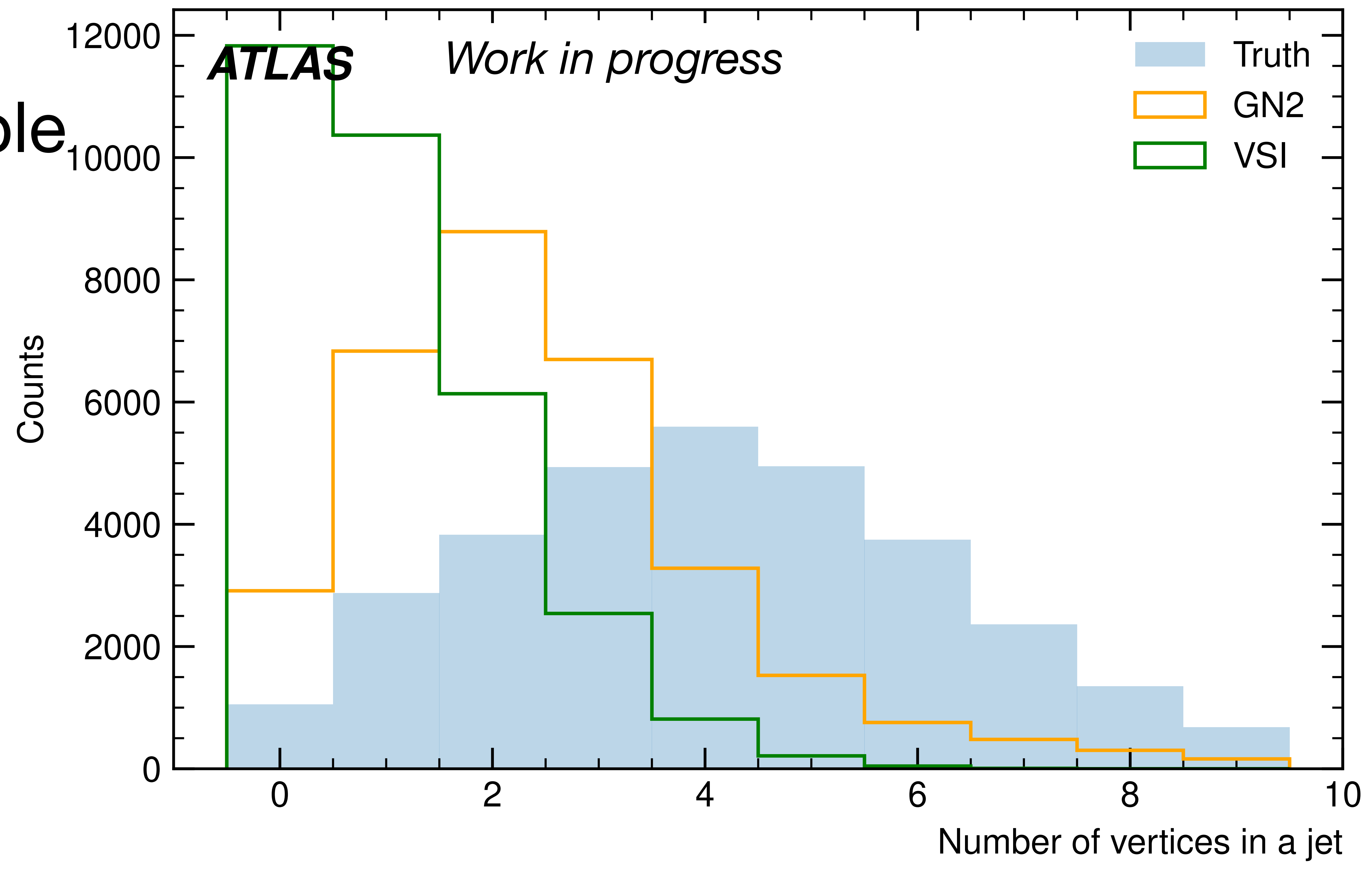
- **GNN vertices have higher efficiency but have similar purity**

Vetex Identification: Performance

NumVertex Distribution

- Emerging jets, by definition, has multiple vertices in a jet.
- #Vertex in per jet distribution
    - GNN dist. closer to truth dist.

GNN captures jet topology better!



Track Origin Identification

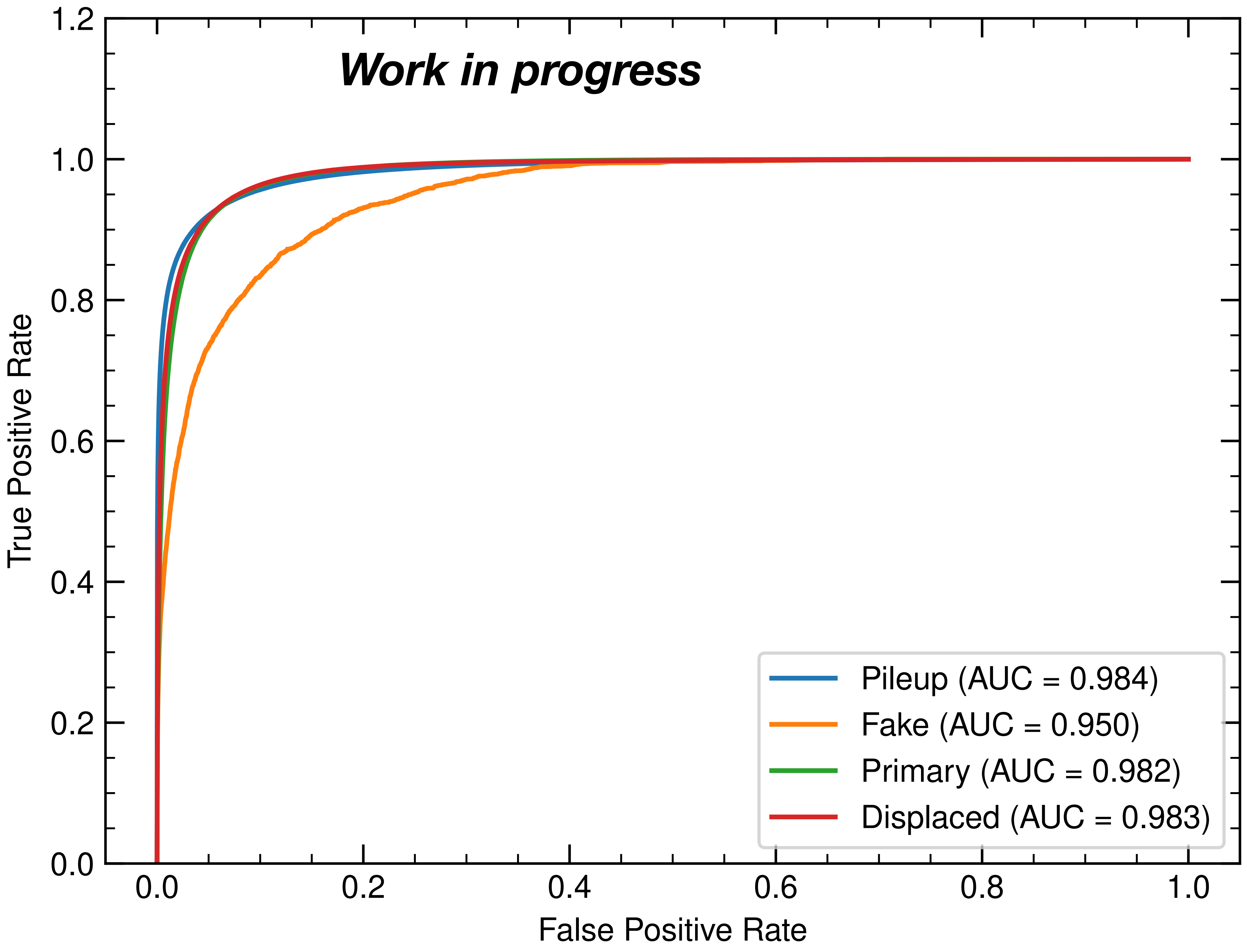
Brief Introduction

- Ultimately, studying the properties of *long-lived* dark-matter requires precise identification of the “origin” of tracks associated with emerging jet!
- Track classifier based on “node classification task” of GNN into 4 track classes based on truth origin labels!
    - Pileup: From additional proton-proton interactions that occur within the same bunch crossing
    - Fake: From purely combinatorial collections of hits
    - Primary: From Primary Vertex
    - Displaced: From Secondary vertices

Track Origin Identification: Performance

ROC

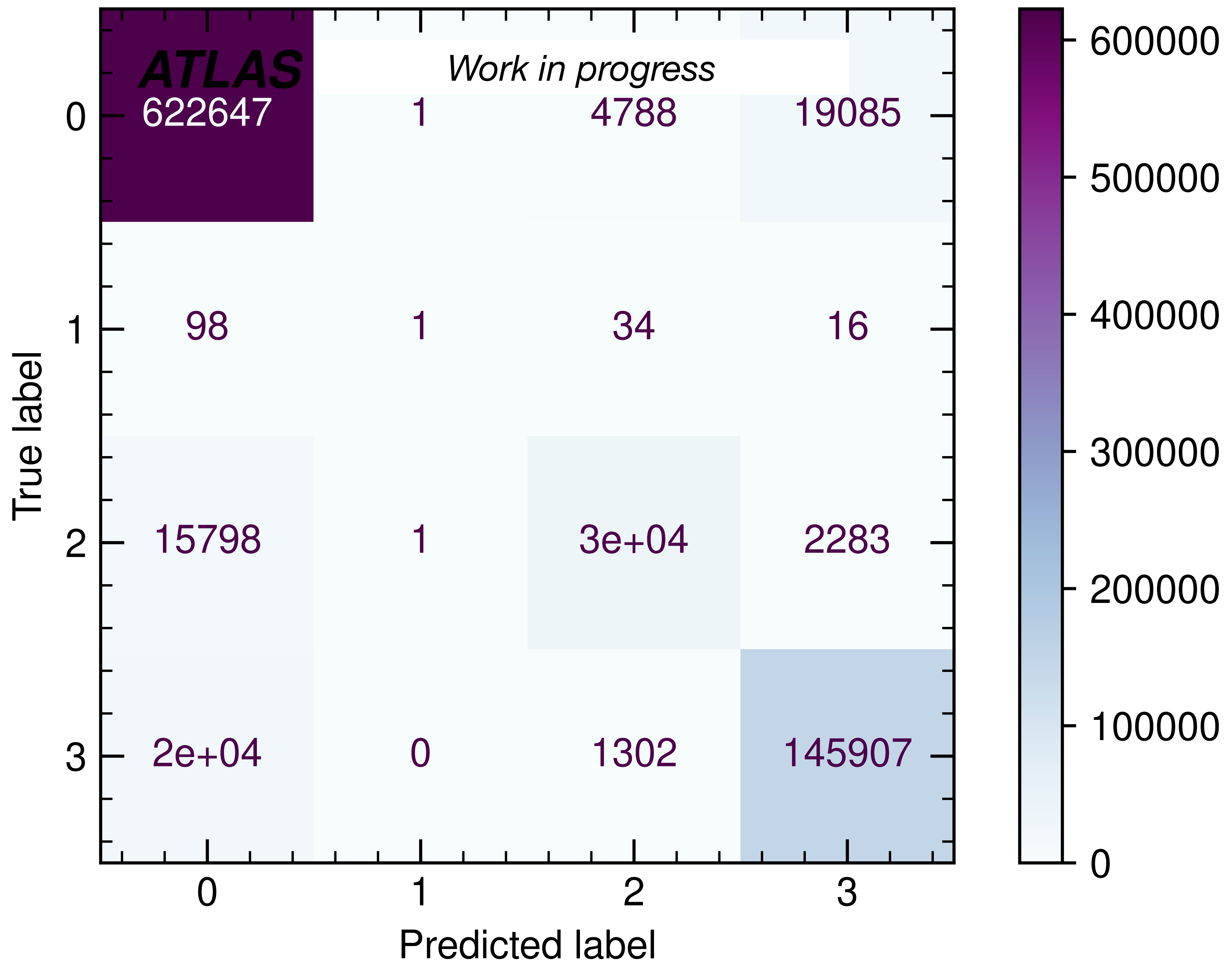
- Highly effective in classifying tracks!
- Displaced tracks classification AUC: 0.983!



Track Origin Identification: Performance

Confusion Matrix

- The diagonal elements of the matrix represent correct classification!
  - Pileups and Displaced tracks most accurately classified
  - ~20k “true” displaced tracks classified as pileups and vice versa!
  - ~16k “true” primary tracks classified as pileups



JetMatrixView

- 40 tracks x 40 tracks confusion matrix
  - Instead of being sorted by trackID’s its sorted by truthVertexId of each track
  - For example {TrackId(VertexId)} in a Jet is {2223(1),2224(3),2225(1),2226(2)}

Track ID Based Sort

	2223	**2224**	**2225**	**2226**
2223	1	0	1	0
2224	0	1	0	0
2225	1	0	1	0
2226	0	0	0	1

VertexID Based Sort

	2223	**2225**	**2226**	**2224**
2223	1	1	0	0
2225	1	1	0	0
2226	0	0	0	0
2224	0	0	0	0

Jet View from Classifiers!

Use GNN to classify events?

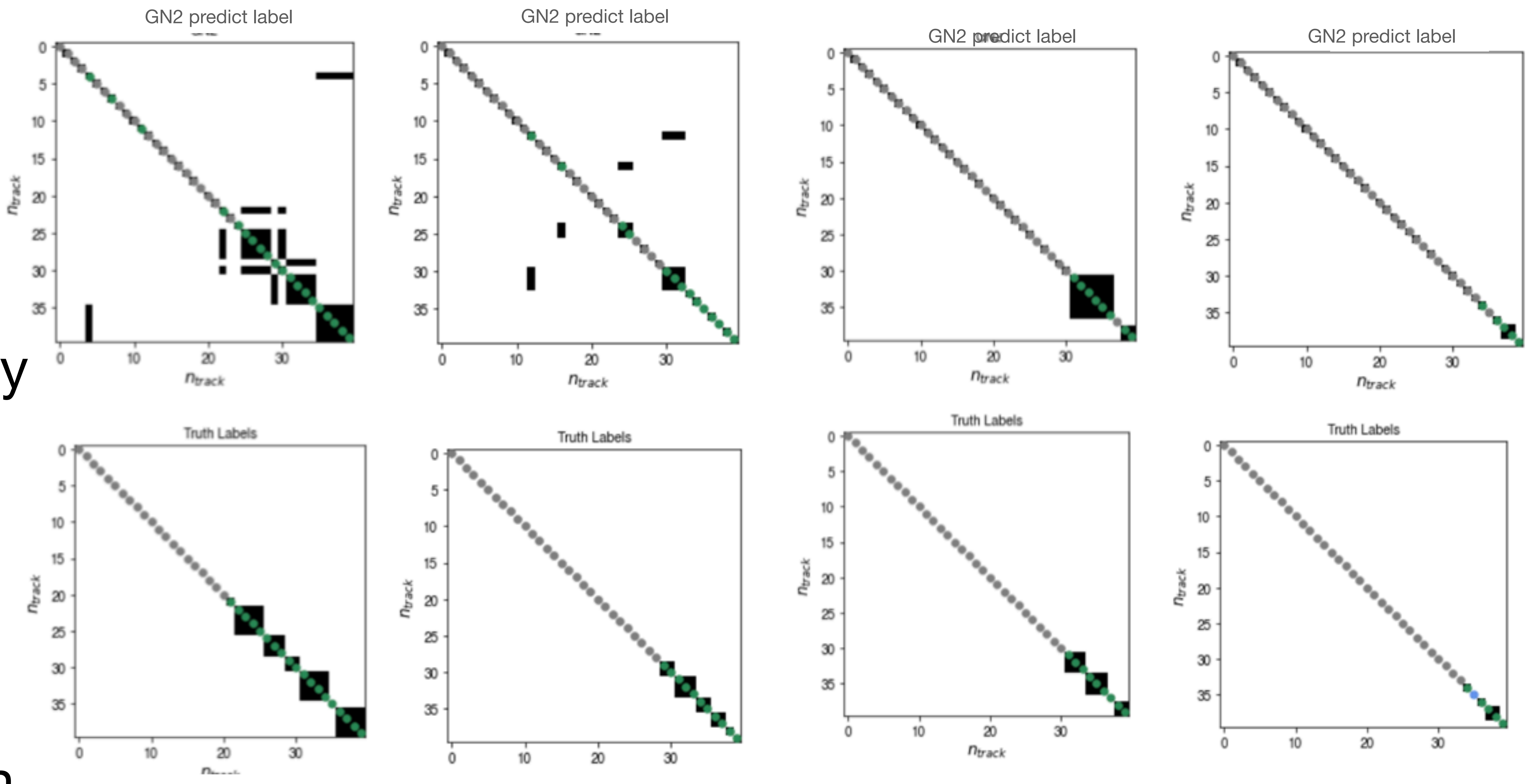
- True labels vs GNN predicted labels visualization for jet, track and vertex prediction

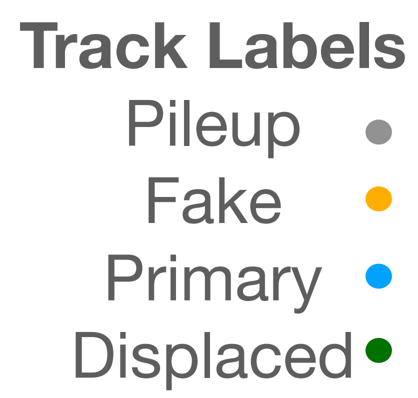
- $n_{trk} \times n_{trk}$ matrix sorted by TruthVertID

  - 1 (Black) if two tracks share the same vertex

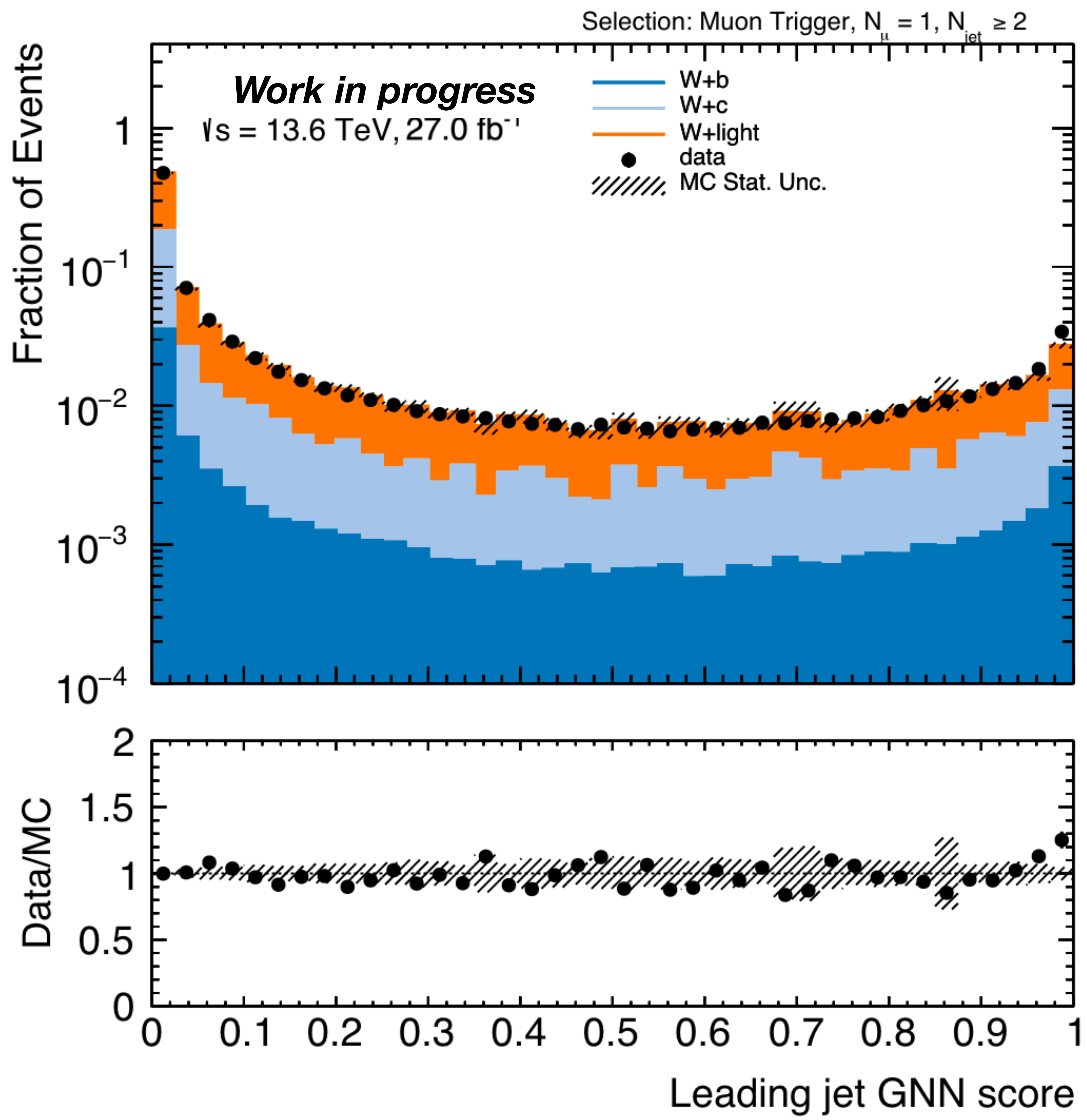
  - 0 (White) if two tracks do not share a common vertex

ATLAS *Work in progress*





GNN Validation



- First looks at 2022 data validate GNN performance on real data!

Jet Classification: Performance

Probability Distribution

- Classify jets into 2 categories.Signal Jets (*Displaced-jets)* from long lived dark mesons and background Jets (*Prompt jets)* from QCD background process!
- GNN score: Softmax probability for jets to be signal jets!
- Signal jets peaks at last bin suggesting extremely high likelihood for majority of signal jets to be correctly identified!
- CLEAR separation between signal and background jets with high AUC = 0.987