Tagging Emerging Jets Using Graph Neural Networks

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INTRODUCTION

Emerging Jet (EJ)

- A jet dominantly composed of displaced tracks and containing many displaced vertices within the jet cone.

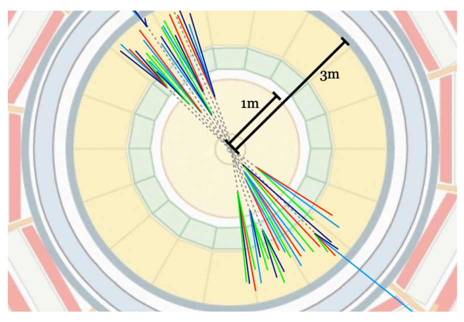

Figure 1: A schematic depiction of pair production of dark quarks forming two emerging jets [1]

Graph Neural Network(GNN)

- Special type of neural network designed to operate on graph-structured data
- Each node of the graph is populated with feature vectors.
- GNN propagates and updates the graph representations via the "message passaging" mechanism.

MOTIVATION

BSM search: Emerging Jet Analysis (Run 3)

- Extensions to Standard Model predict existence of strongly-interacting dark sectors.
- Depending upon the parameters of dark sector one potential signature could be "emerging jet"

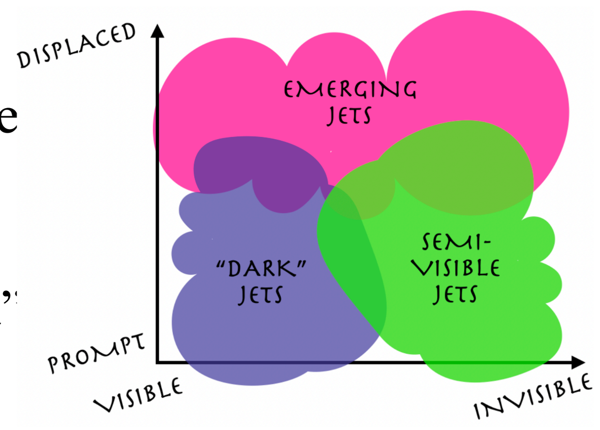

Figure 2: Displaced and Visibility nature of jets, Diagram credit - Caterina Doglioni and Hamza Hainf

GNN in particle physics

- Problems in particle physics involve data in the form of unordered sets with rich relations and interactions, which can naturally be represented as graphs!
- GN1 - GNN-based flavour tagging algorithm deployed in ATLAS and significantly outperforms previous taggers.

GNN in EJ Run-3

- Use the architecture of GN1, to tag emerging jets with intricate topology.
- Can also classify displaced tracks and vertex within the jet cone.

METHODOLOGY

Sample Preparation

- Signal: Mixture of models with emerging jets which are mostly "displaced"
- Background: Dijet samples (JZ2 - JZ9) with prompt jets.
- Input variables: 2 jet variables (p_T, η) and 16 other track variables.
- Framework: FTAG frameworks (UMAMI [2], Training Dataset Dumper) to create training, testing and validation files.

Graph Neural Netwrok

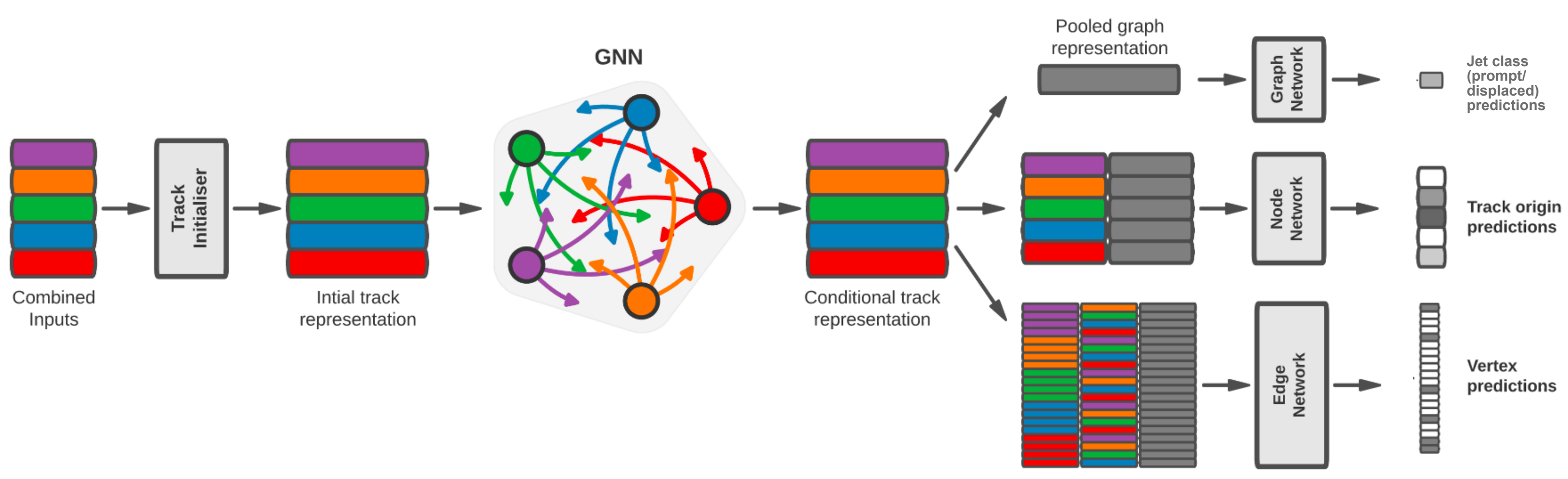

Figure 3: Network architecture of GNN

- Combined (track+jet variables) input is used to create an initial latent representation that populates node features of fully a connected graph [3].
- The neural network is trained (on SALT framework) by minimizing the total loss function $L_{total} = L_{jet} + \alpha L_{track} + \beta L_{vertex}$, where α, β are weight parameters, L_{jet} is jet classification loss, L_{track} is track origin identification loss and L_{vertex} is binary track-pair compatibility loss averaged over all tracks.
- After Graph Network, the resulting node representation is used to predict the jet class (Displaced/Prompt), track origins (Pileup, Fake, Primary, Displaced),and track-pair vertex compatibility.

RESULTS

Jet Tagging

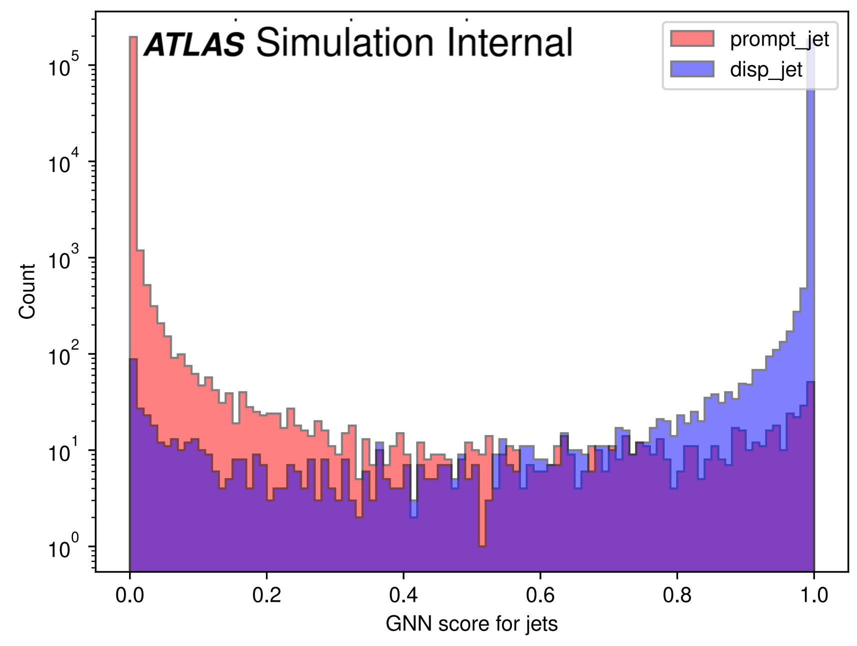

Figure 4: Distribution GNN score for prompt and displaced jets

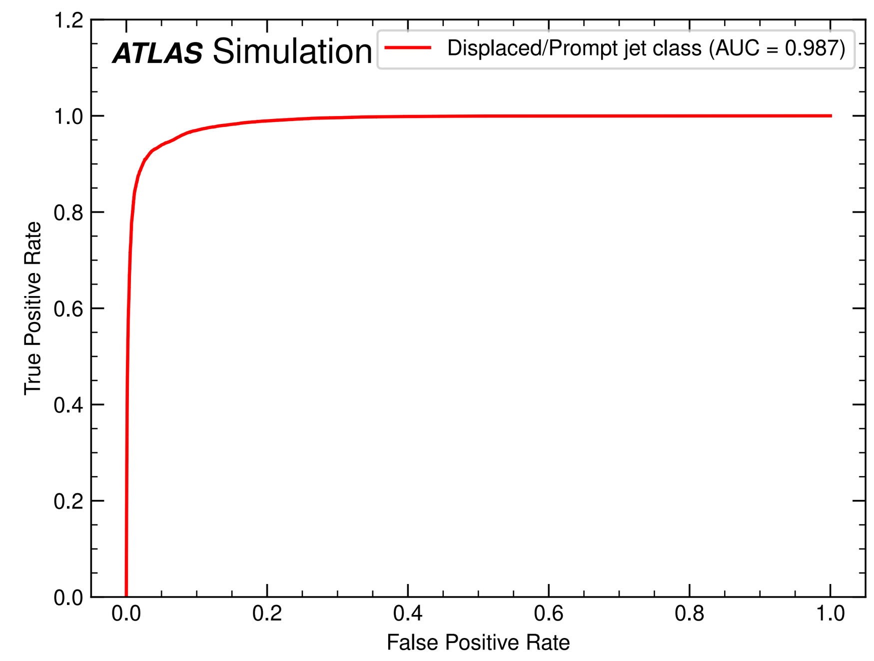

Figure 5: ROC curve for jet classification

- Clear separation between signal and background jets with high efficiency.

Track Origin Identification

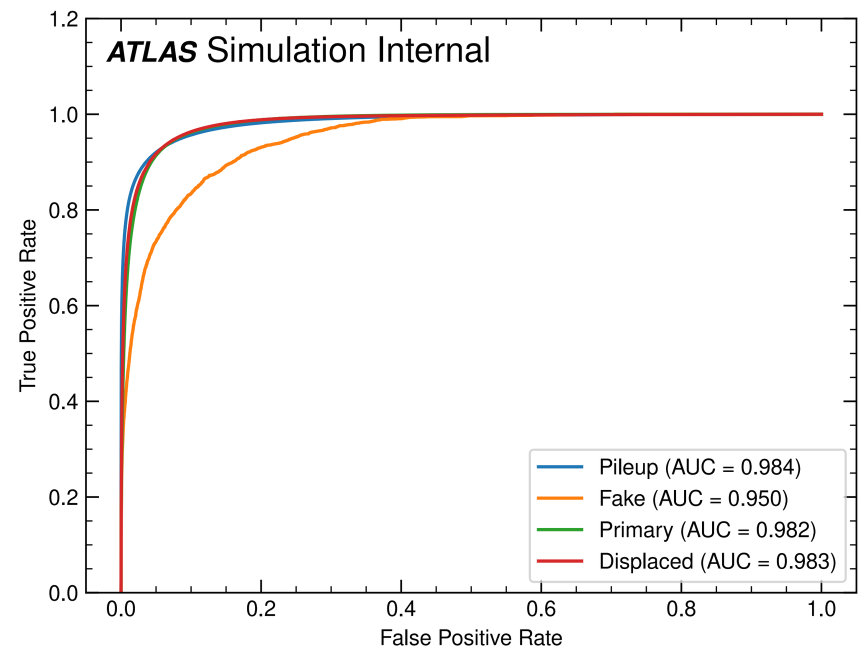

Figure 6: ROC curve for track origin identification

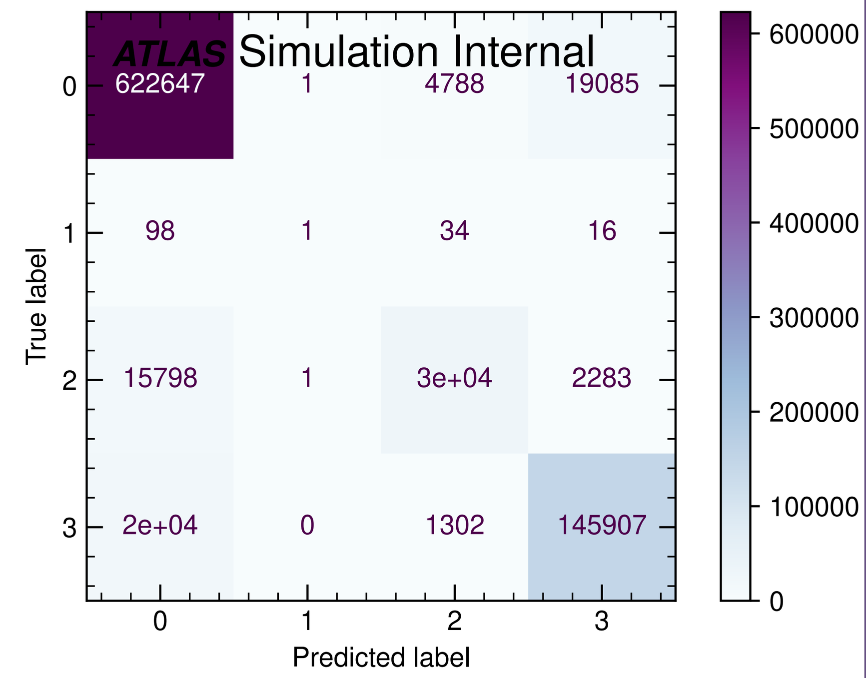

Figure 7: Confusion matrix of track origin. Track labels are: Displaced - 3, Primary - 2, Fake - 1, Pileup - 0.

- Displaced tracks in the jet were identified efficiently!

Vertex Identification

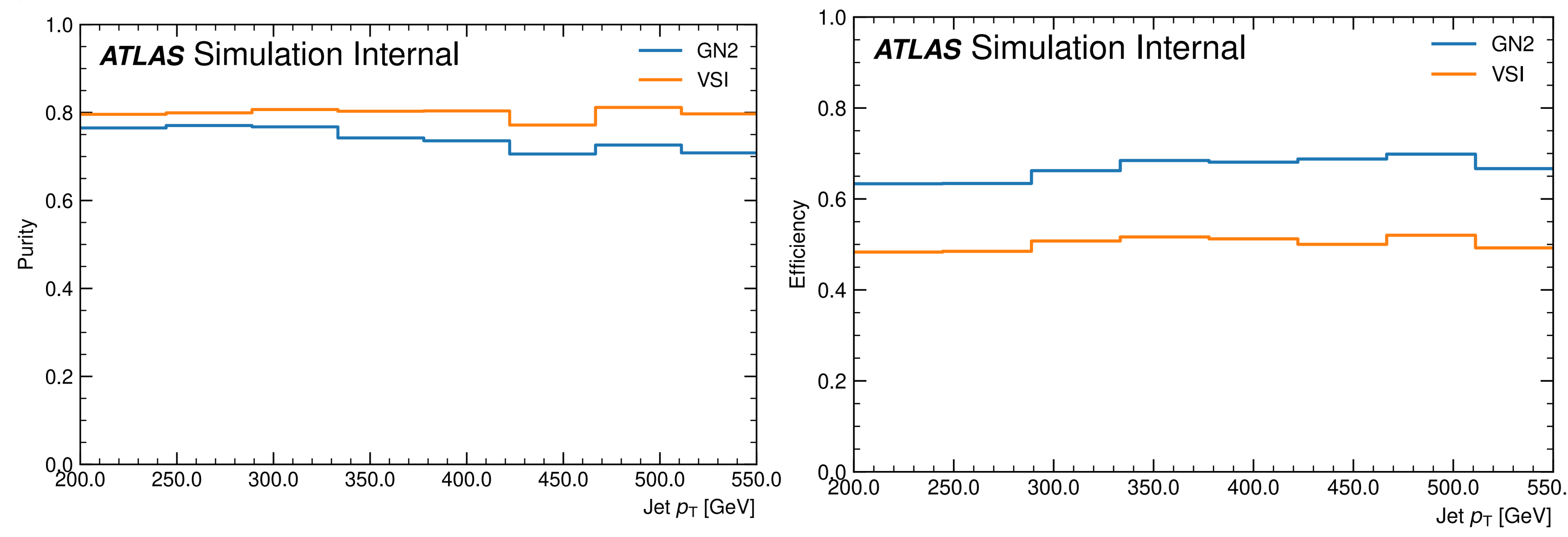

Figure 8 : Comparison of GNN (GN2) with VSI (VertSecInlcusive) algorithm on various performance metrics

Note: Results are based on vertex-finding and not vertex-fitting

Purity

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

Efficiency

- Per-vertex fraction of tracks in the truth-vertex which are included in a common reco-vertex.
- GNN has higher vertex reconstruction efficiency for similar purity.

CONCLUSION

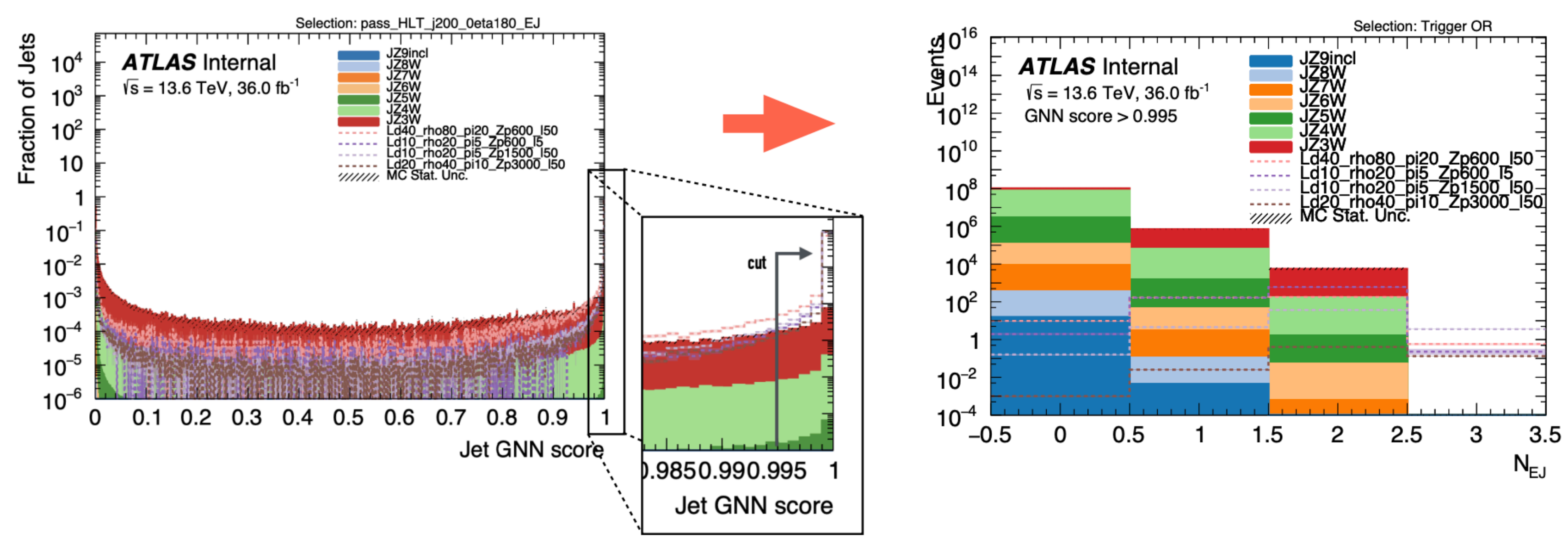

Figure 9: Distribution of jet GNN score in signal and background (Left), Number of jets with GNN score > 0.995 (Right)

- Using GNN score, it's possible to have significant background reduction. In particular, requiring 2 jets to have GNN score > 0.995 yields near 100% signal efficiency for some model.
- GNN can also efficiently reconstruct displaced vertices inside EJ's.

REFERENCE

[1] P. Schwaller, D. Stolarski, and A. Weiler, "Emerging Jets," J. High Energ. Phys. **2015**

[2] J. Barr et al., "Umami: A Python toolkit for jet flavour tagging in the ATLAS experiment"

[3] ATLAS Collaboration, "Graph Neural Network Jet Flavour Tagging with the ATLAS Detector", ATL-PHYS-PUB-2022-027 (2022).