



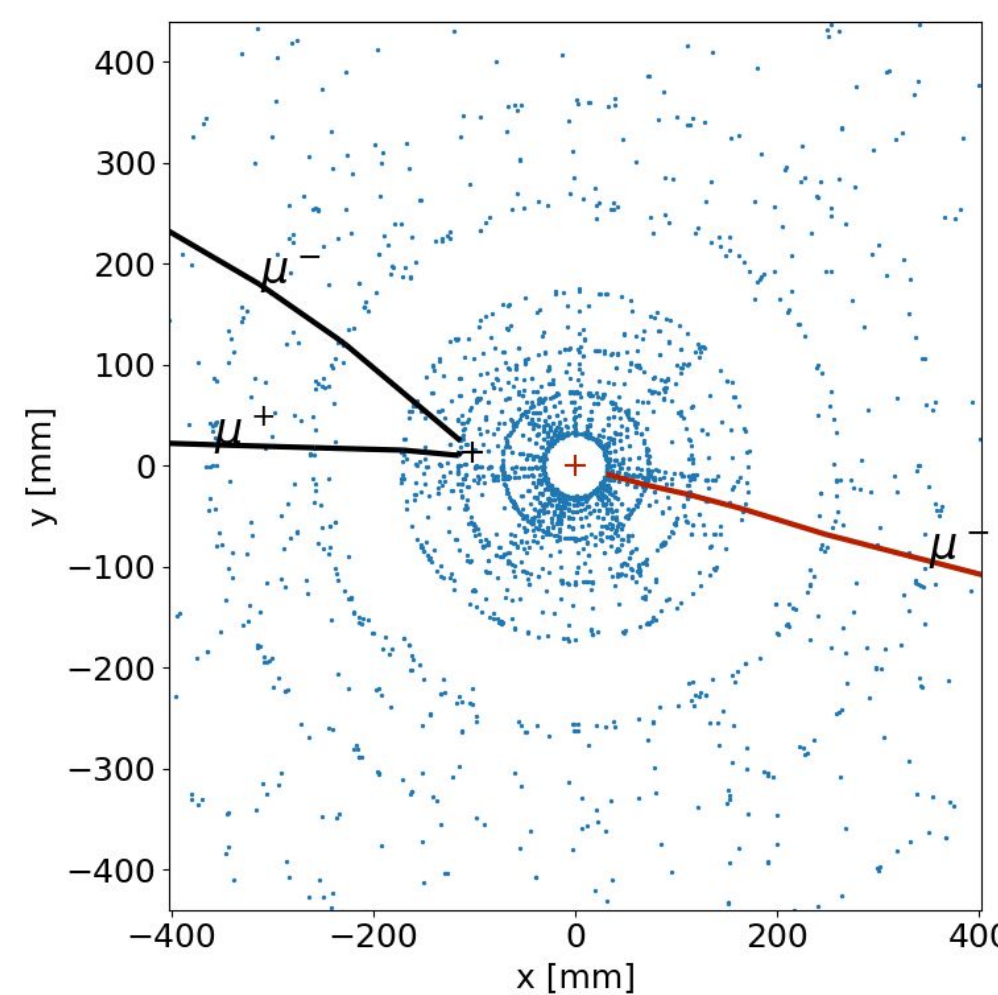
# Graph Neural Network for Large Radius Tracking

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## Long Lived Particles

Long-lived particles are predicted by many beyond Standard Model theories such as SUSY. They have relatively long lifetime, travel a distance before decaying to other particles, resulting in large radius tracks. Traditional algorithms based on the Kalman filter require a large computing cost and dedicated tuning for finding such type of tracks.

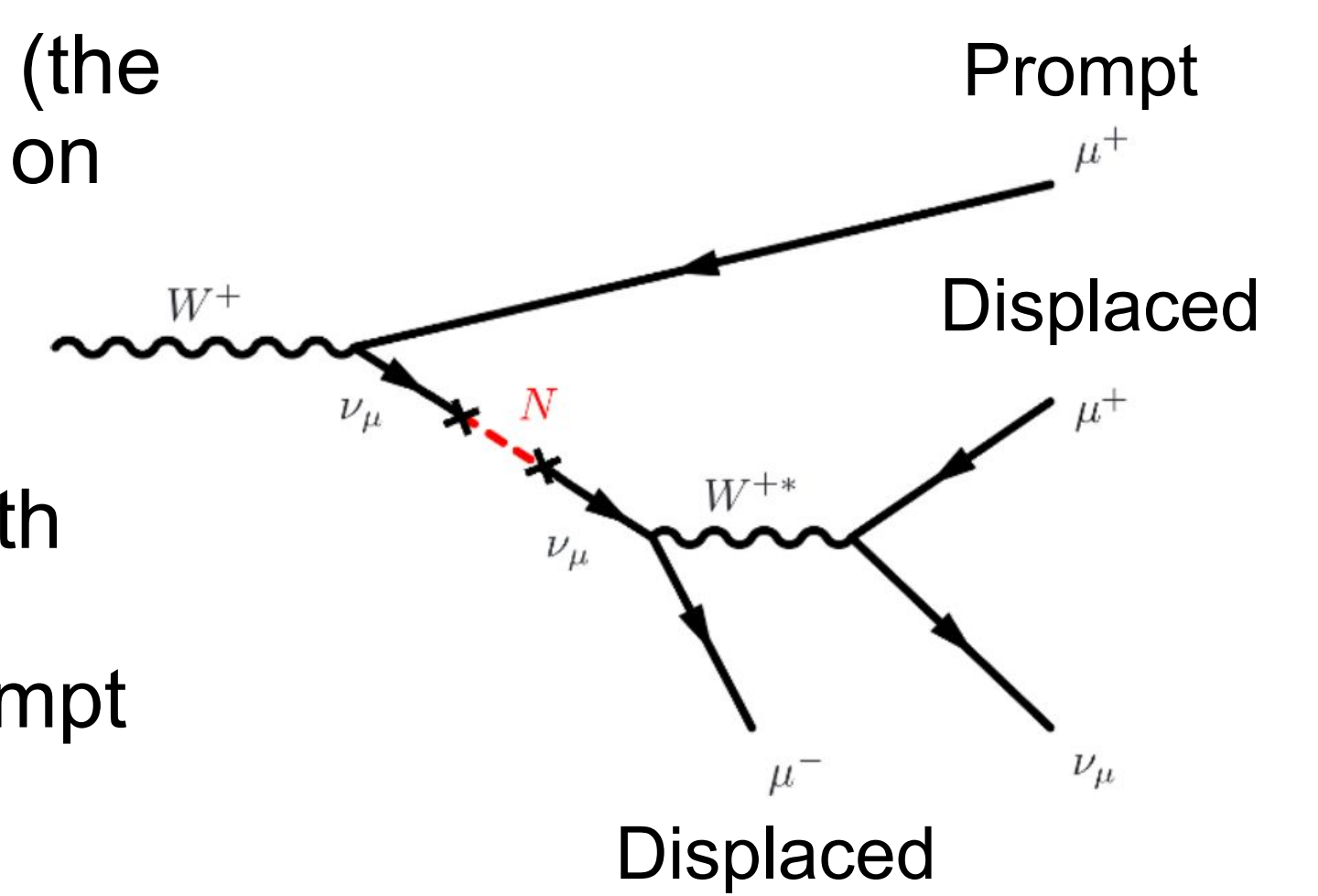


## Physical Process and Dataset

We generate simulated data with ACTS [1] (the TrackML geometry) without pileup focusing on the Heavy Neutral Lepton process [2]:

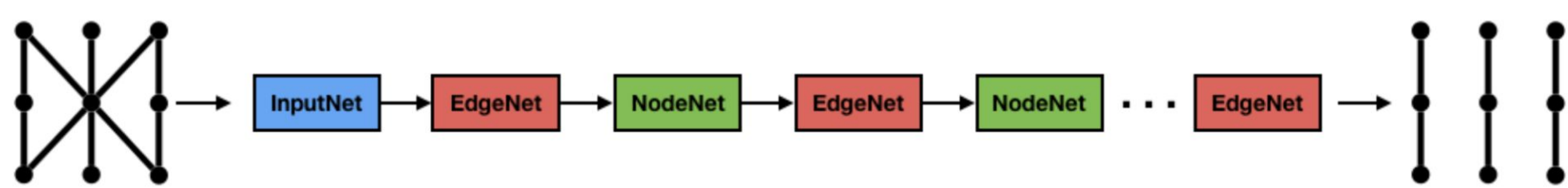
$$pp \rightarrow W \rightarrow \mu N, N \rightarrow \nu_{\mu} \mu^{+} \mu^{-}$$

where  $N$  represent heavy neutral particle with mass of 15 GeV and lifetime of 100 mm. All tracks are included in the training. Only prompt and displaced muons are included in the testing.



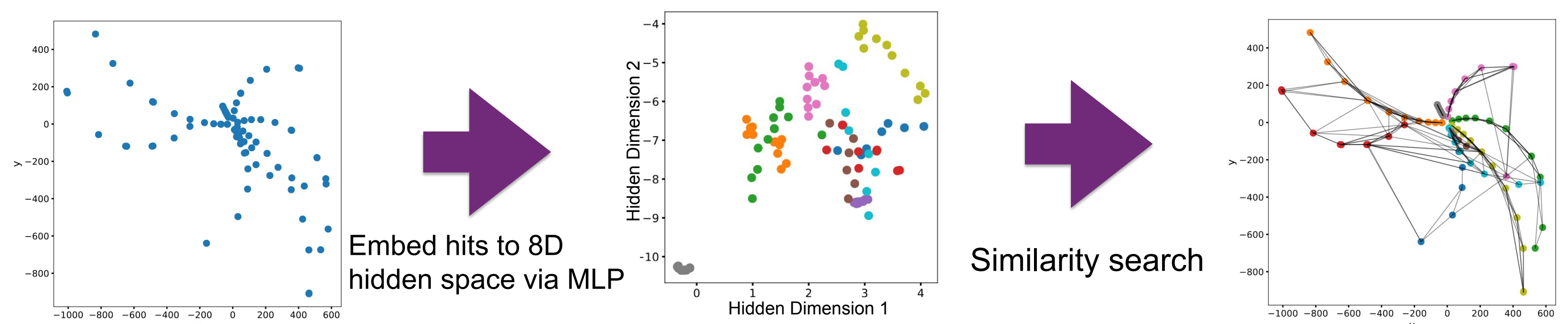
## Graph and Graph Neural Network

In a graph, nodes are hits recorded by the tracker, edges are connections between hits. True edges are those connecting hits from the same track. We use **Graph Attention Network** [3] to score those edges. EdgeNet outputs edge scores, which are then used to weight node features in message passing steps.



## Generic Graph Construction

We use an embedding model (Multilayer Perceptrons, MLPs) and similarity search to construct graphs, i.e. constructing edges from point clouds [4]. **This method makes no assumption on production vertex position.**



## The Exa.TrkX Pipeline

### Embedding

A MLP with 512 units and 6 layers is trained to embed input spacepoint features.



### Filter

A MLP with 512 units and 5 layers is trained to prune away fake edges.



### GNN

An attention GNN is trained to output a score for each edge.



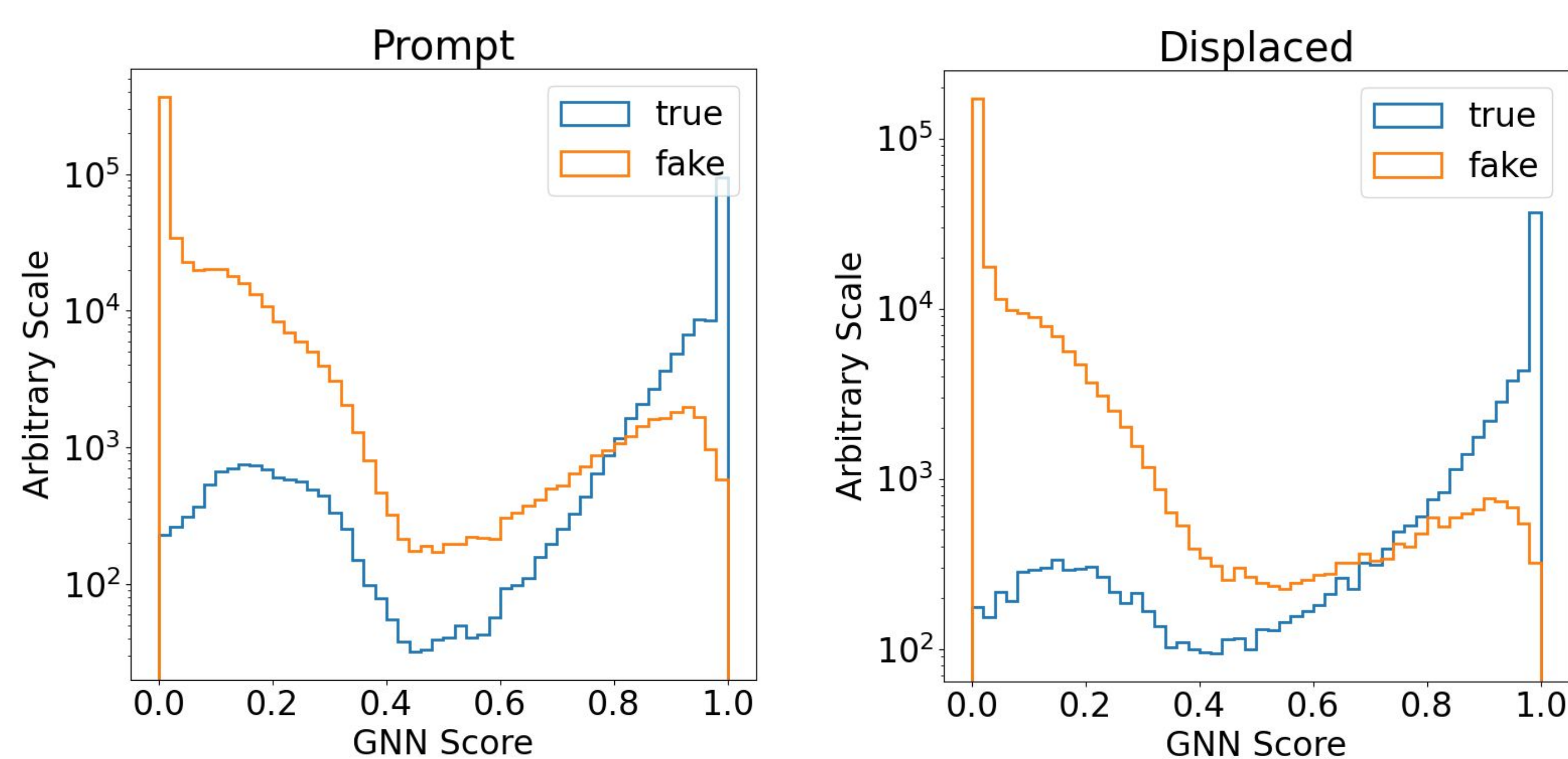
### Track Reconstruction

Mark (1 - edge score) as distance and perform DBSCAN [5] to get track candidates.

## Result

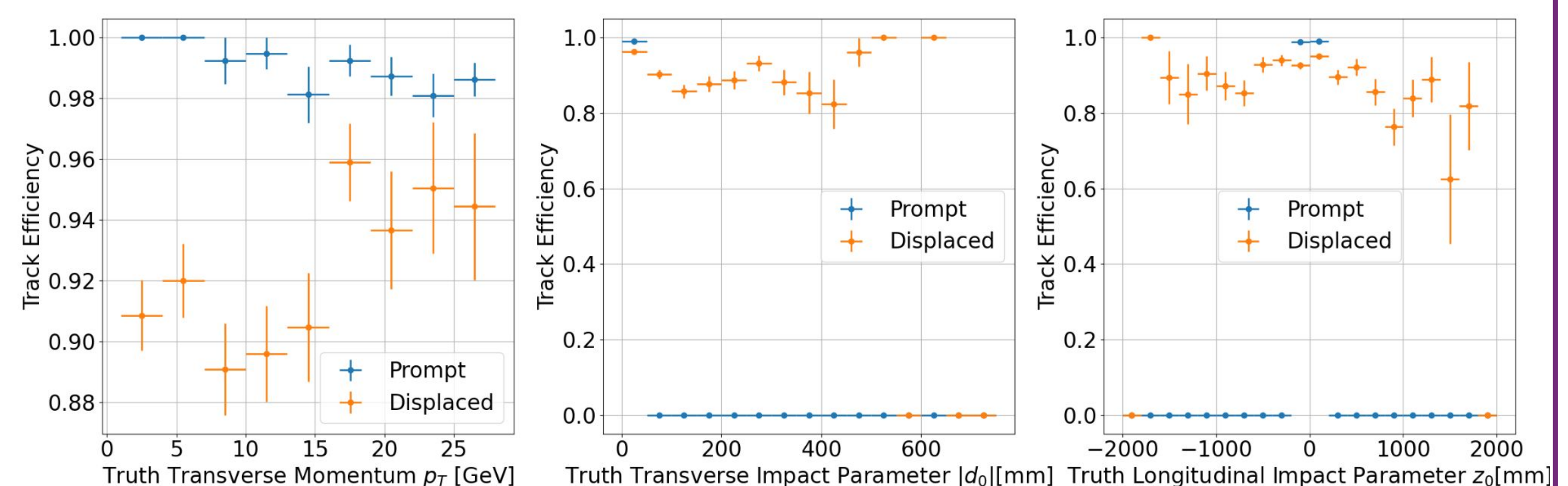
### GNN Edge Score

GNN area under curve (AUC) for prompt and displaced tracks are 0.988 and 0.985, respectively. No significant reduce in performance for displaced tracks is observed.



### Tracking Efficiency

True muon tracks containing a number of hits larger than five are considered as reconstructable. The tracking efficiency is defined as the ratio of reconstructable true tracks being matched (50% of double majority [6]) to at least one reconstructed track. Prompt and displaced muons are reconstructed simultaneously.



## Conclusion

In this study, we apply a GNN-based tracking algorithm on large radius tracks dataset. Our pipeline reconstructs prompt and displaced tracks simultaneously. We obtained a high tracking efficiency as a function of  $|z_0|$  and  $|d_0|$ . We will further improve the pipeline by exploring different GNN architectures and study its robustness with different physical processes.

## Reference

- Xiaocong Ai et al., "A Common Tracking Software Project," arXiv: 2106.13593.
- ATLAS Collaboration, "Search for heavy neutral leptons in decays of W bosons produced in 13 TeV pp collisions using prompt and displaced signatures with the ATLAS detector," JHEP 10 (2019) 265
- S. Farrell et al., "Novel deep learning method for track reconstruction" arXiv: 1810.06111
- X. Ju et al., "Performance of a Geometric Deep Learning Pipeline for HL-LHC Particle Tracking," EPJC, 81, 876 (2021), Exa.TrkX. <https://exatrkx.github.io/>
- M. Ester et al., "A density-based algorithm for discovering clusters in large spatial databases with noise", AAAI. KDD-96, 226 (1996)
- The criteria is the same as the one used in TrackML challenge, <https://www.kaggle.com/c/trackml-particle-identification/overview/evaluation>

