Graph Neural Network for Large Radius Tracking

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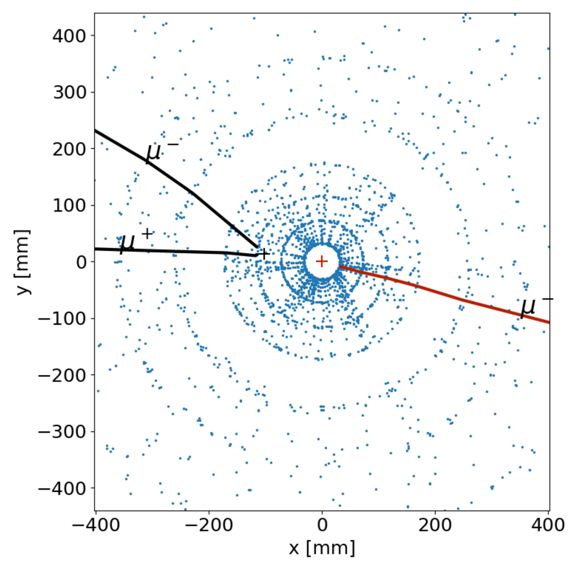
Long Lived Particles

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.

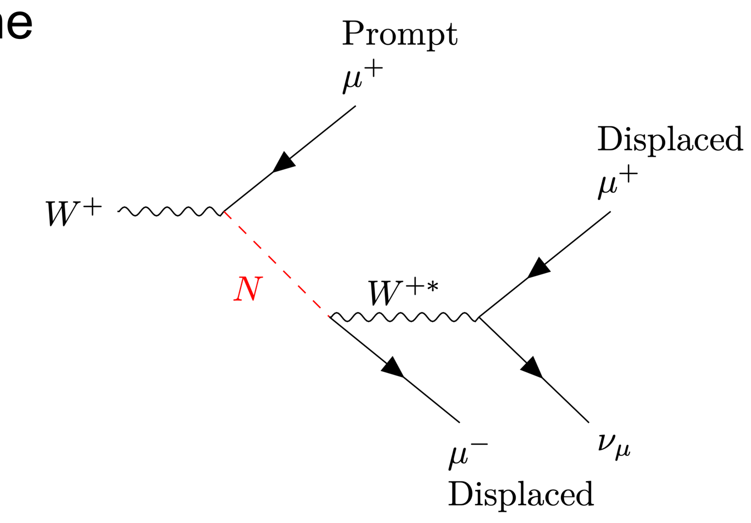


Physical Process and Dataset

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

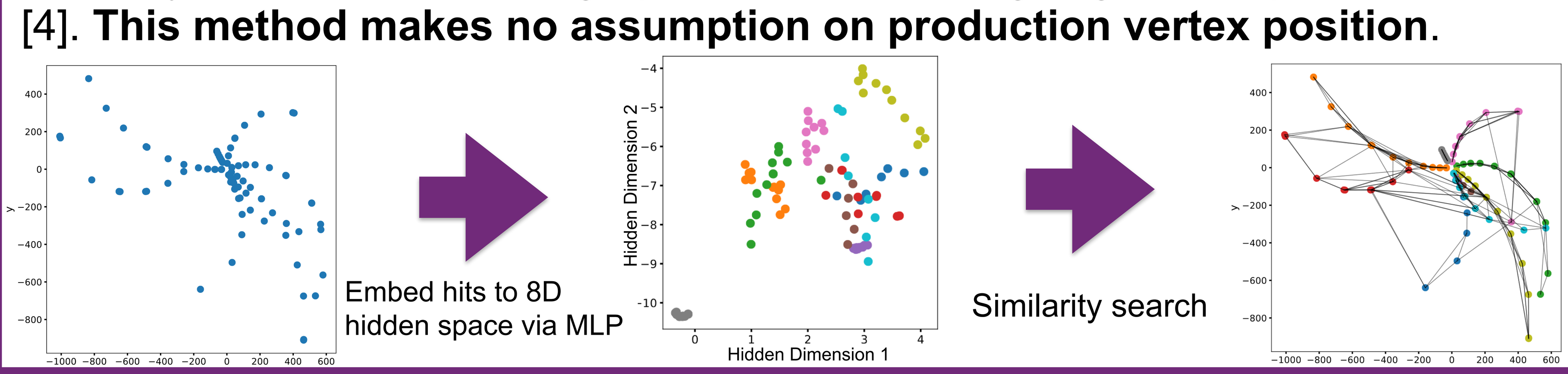
$$pp \to W \to \mu N, N \to \nu_\mu \mu^+ \mu^-$$

where N represent heavy neutral lepton (HNL) 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.



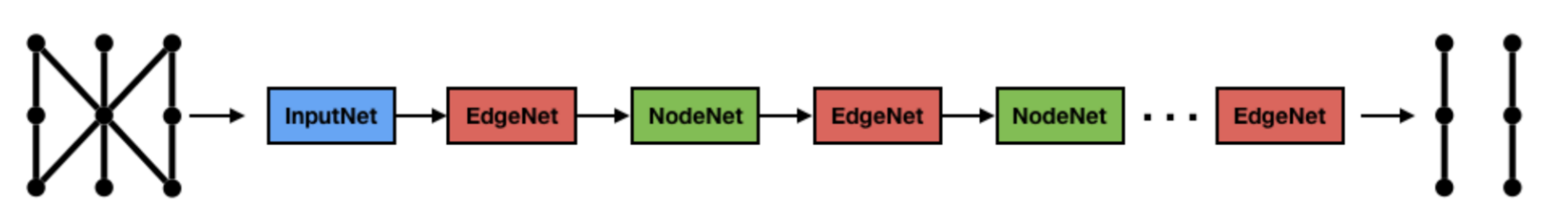
Generic Graph Construction

In a graph, nodes are hits recorded by the tracker, edges are connections between hits. 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**.



Graph Neural Network

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.



The Exa.TrkX Pipeline

Embedding

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

Edges

Filter

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

Pruned Edges

GNN

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

Classified Edges

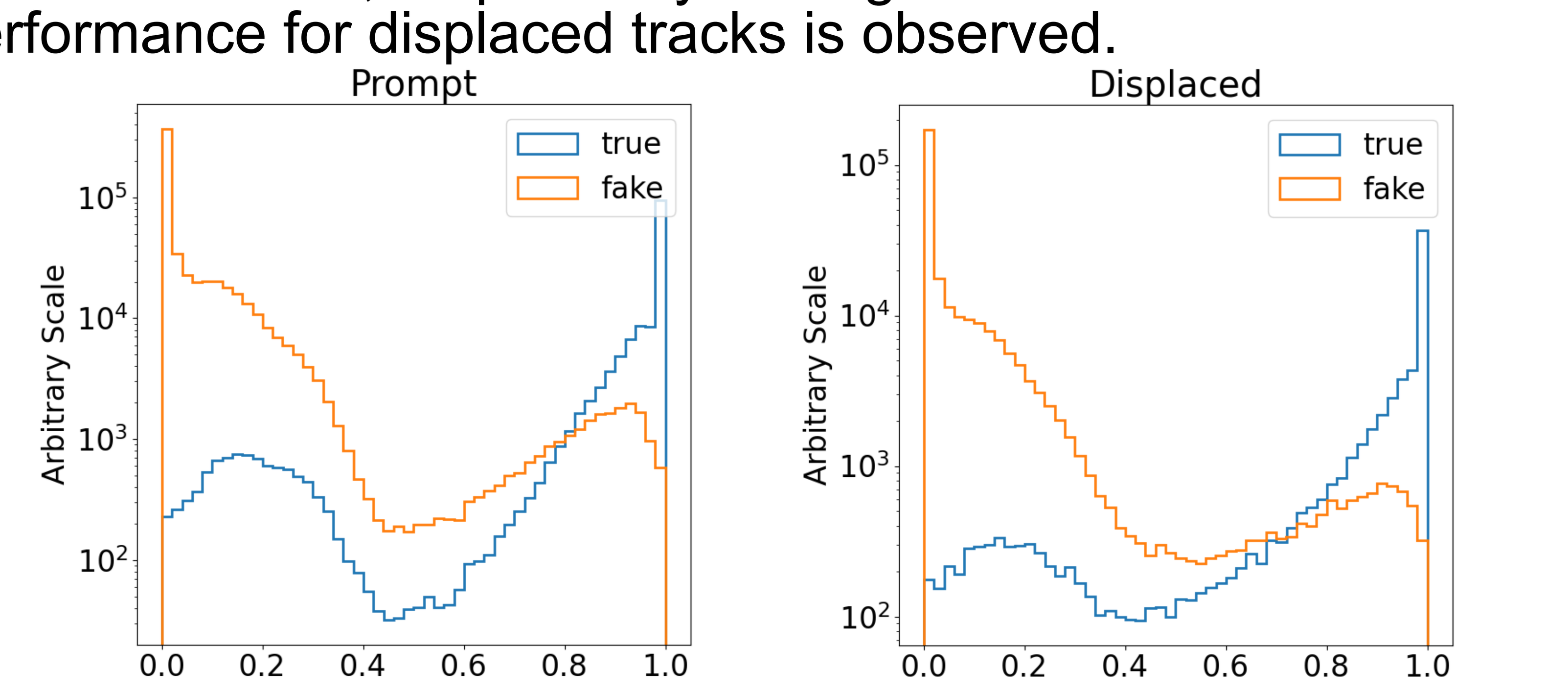
Track Reconstruction

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

Result

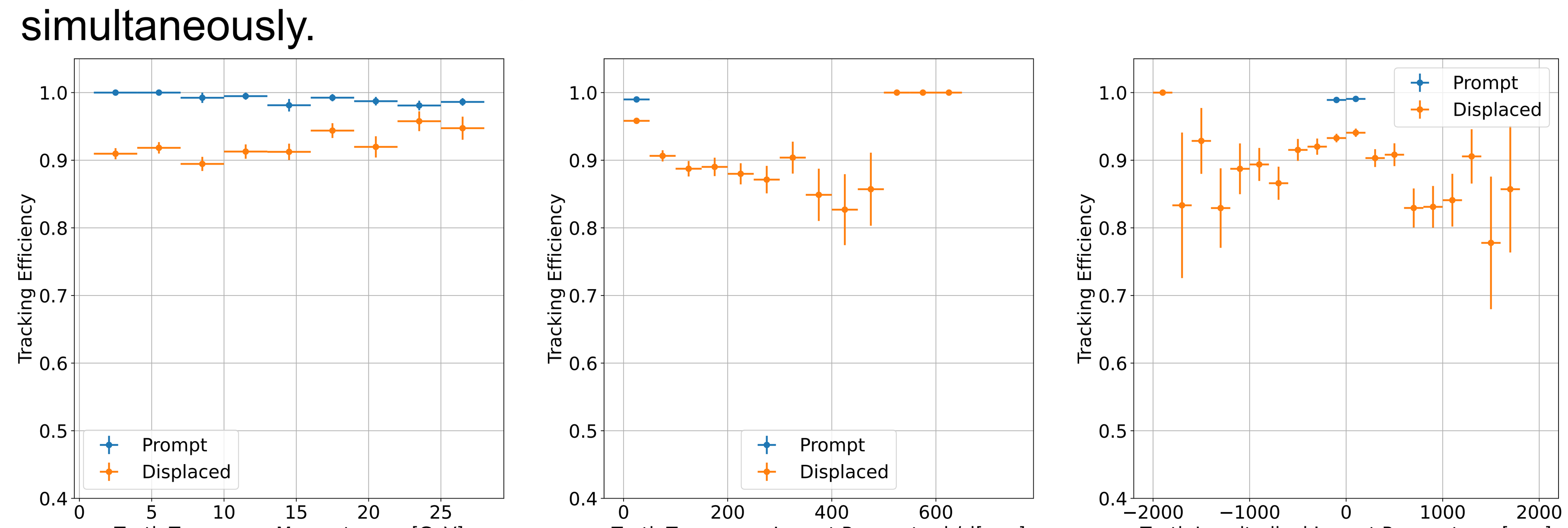
GNN Edge Score

GNN area under curve (AUC) for prompt and displaced tracks are 0.988 and 0.986, respectively. No significant reduce in performance for displaced tracks is observed.



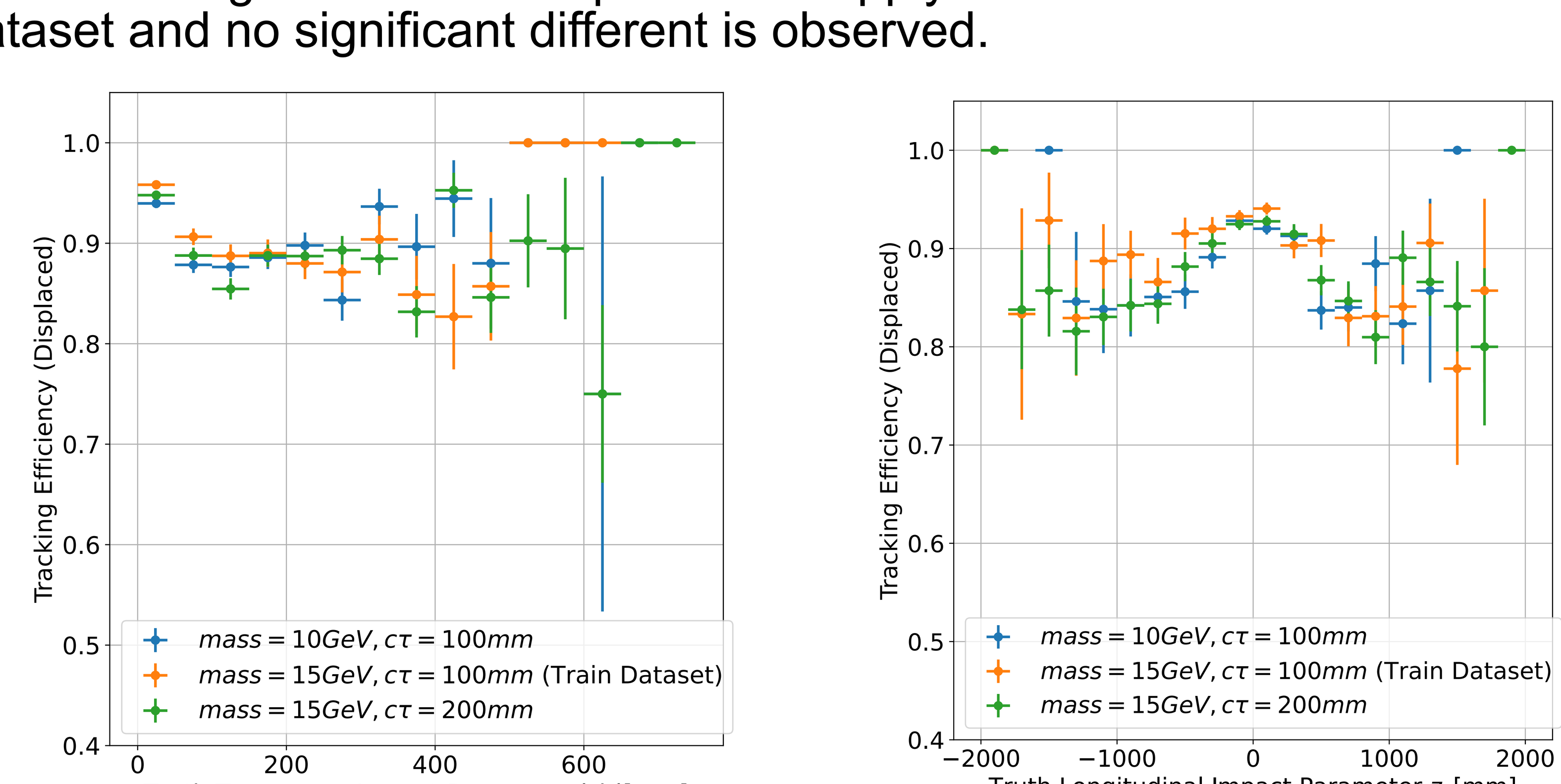
Tracking Efficiency

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.



Robustness

To search HNLs using the pipeline, robustness of different HNL mass and lifetime configurations are required. We apply trained model on different HNL dataset and no significant different is observed.



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 $|d_0|$ and $|z_0|$. We will further improve the pipeline by exploring different GNN architectures and study its robustness with different physical processes.

Reference

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3. S. Farrell et al., "Novel deep learning method for track reconstruction" arXiv: 1810.06111
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6. The criteria is the same as the one used in TrackML challenge, https://www.kaggle.com/c/trackml-particle-identification/overview/evaluation