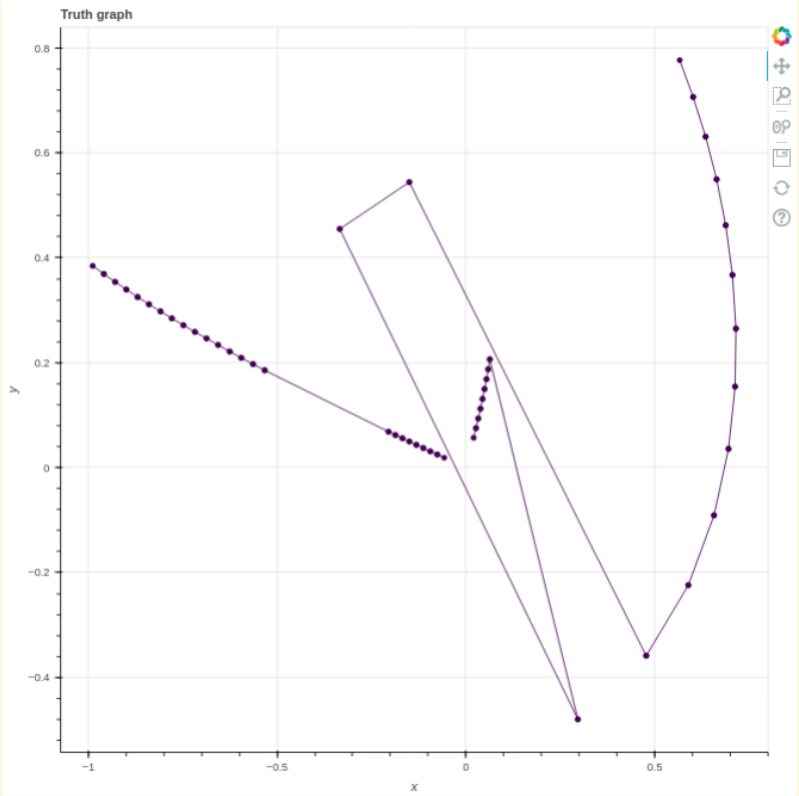
Dataset

- Change to 25 layers. (Because the layers of most dataset are around 30 layers.)



We focus on one simple category of quirk tracks initially (This is the first study for well-behaved quirks), so we do the simple selection on Quirk dataset:

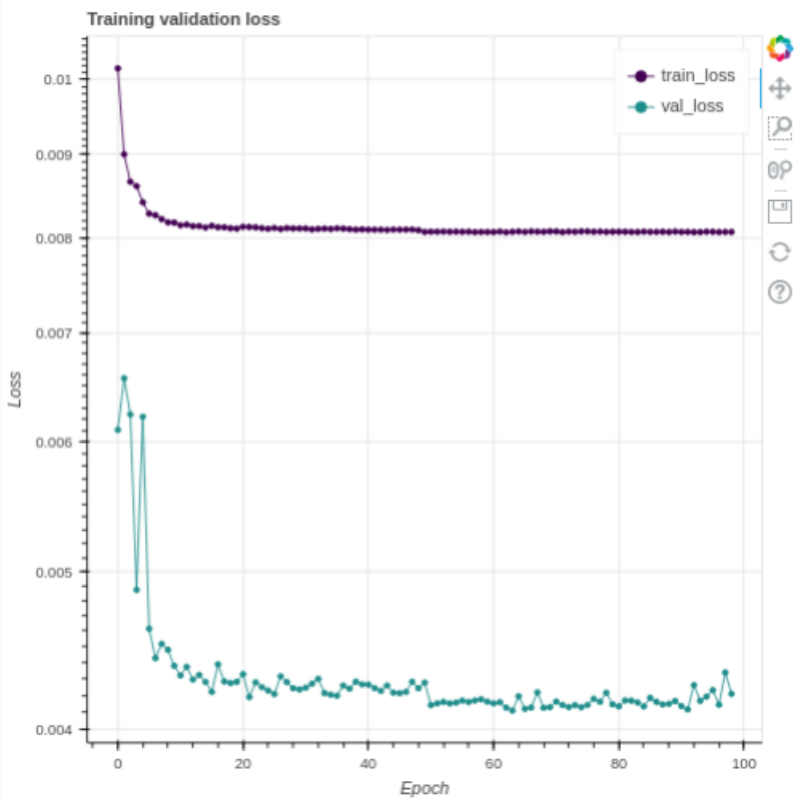
- No Opening angle selection
- $N_{hit} < 50$
- I found that open_angle have little impact when N_{hit} is limited.

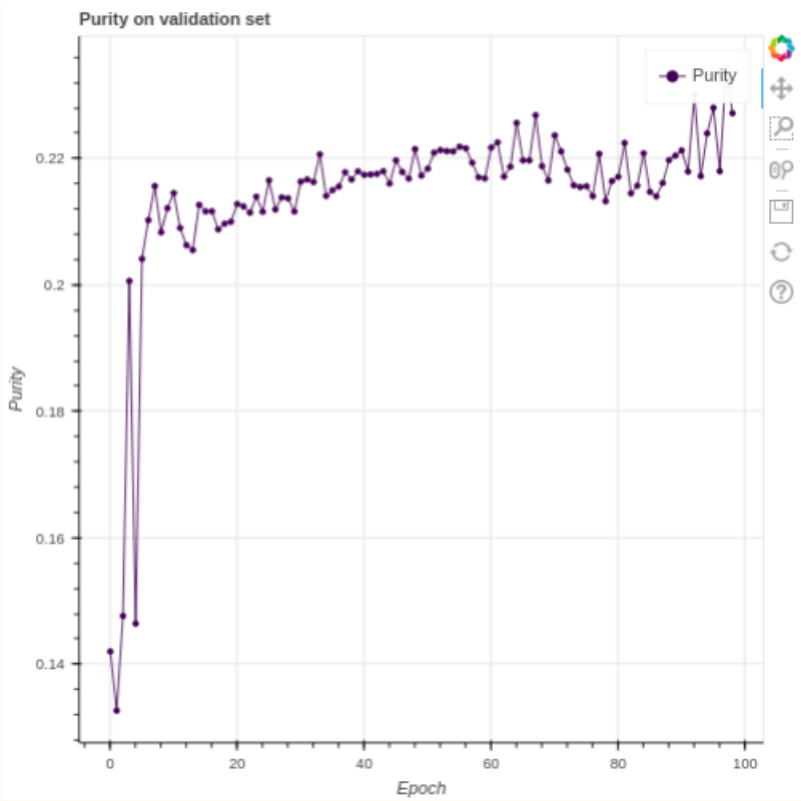
Separate the Background and Quirk dataset for analysis:

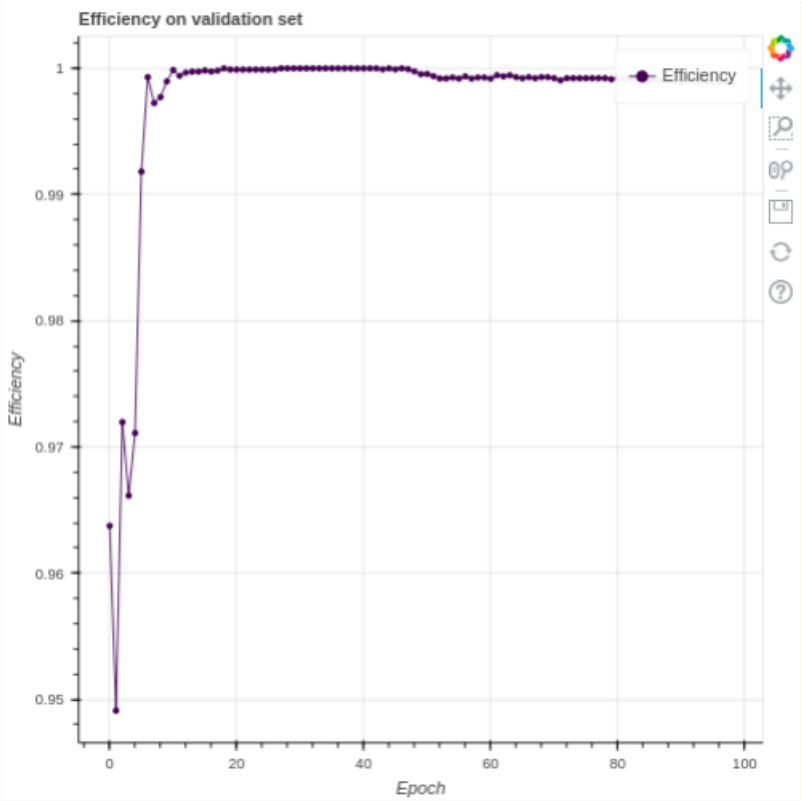
- Quirk training, quirk inference (1600 events to train on, 200+200 val/test)

Metric Learning : Well behaved Quirk training, quirk inference

Use metric learning to reduce the dimension: Embedding the space points on to graphs.

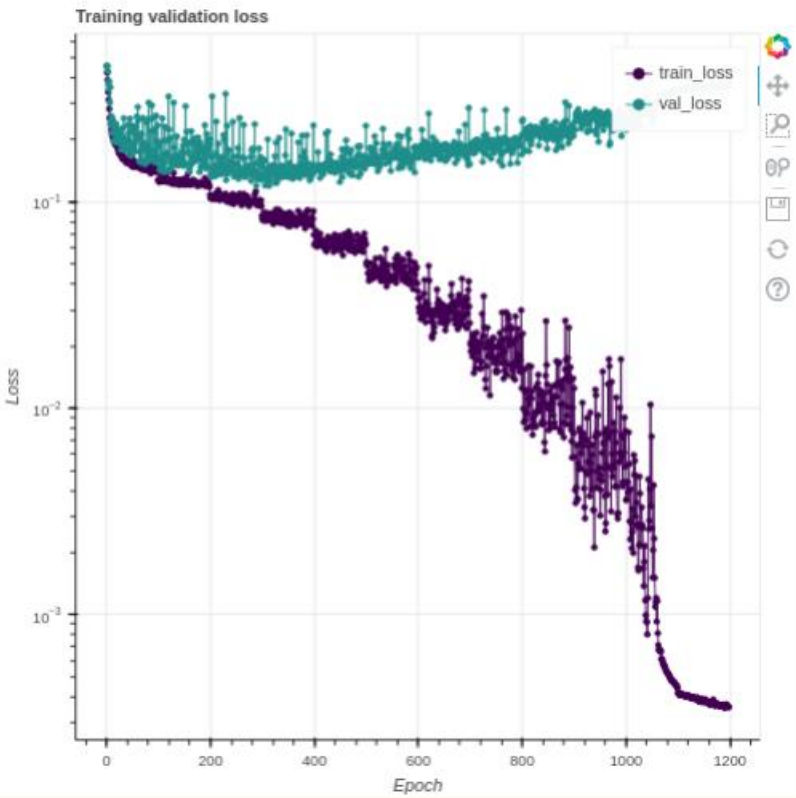


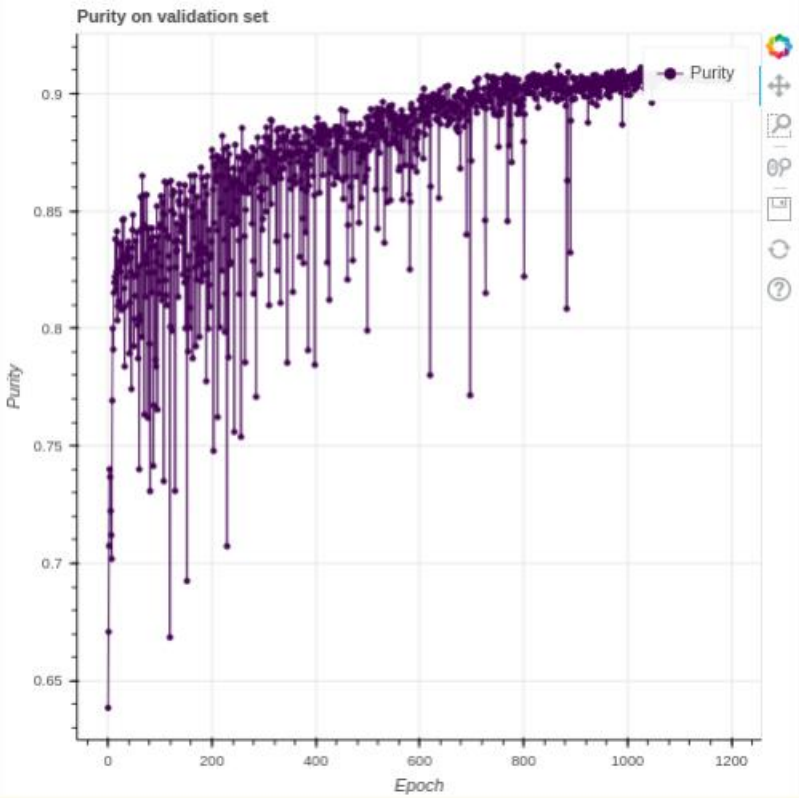


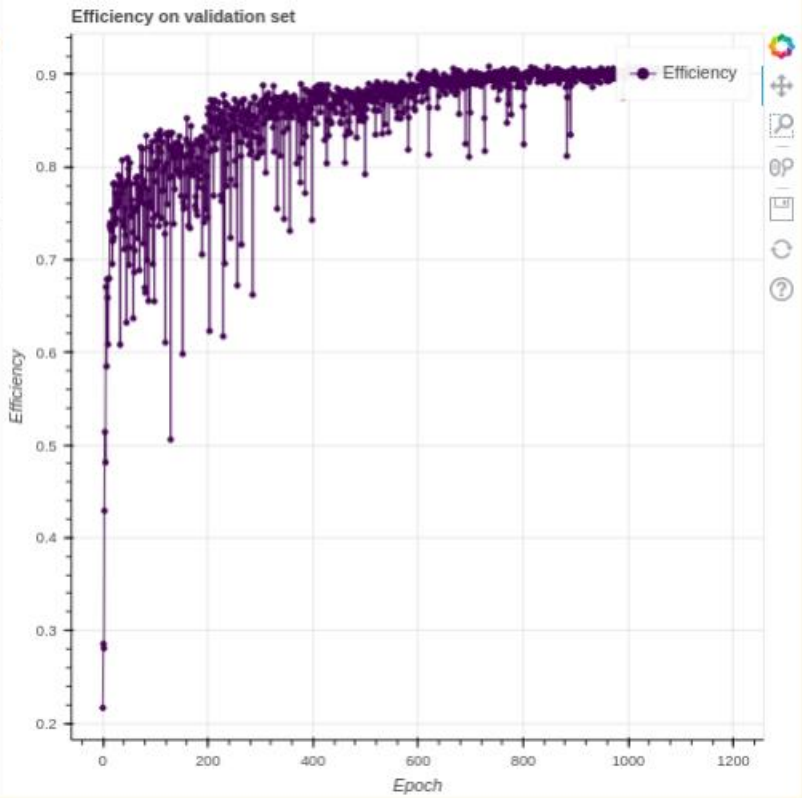


GNN : Well behaved Quirk training, quirk inference

Train GNN to classify edges as either “true” (belonging to the same track) or “false” (not belonging to the same track)

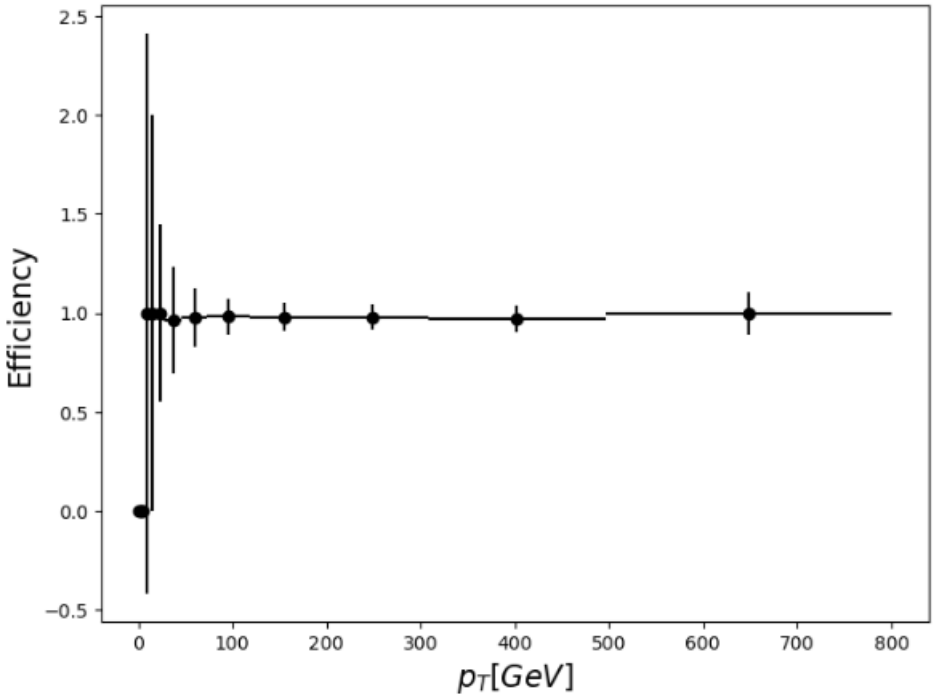


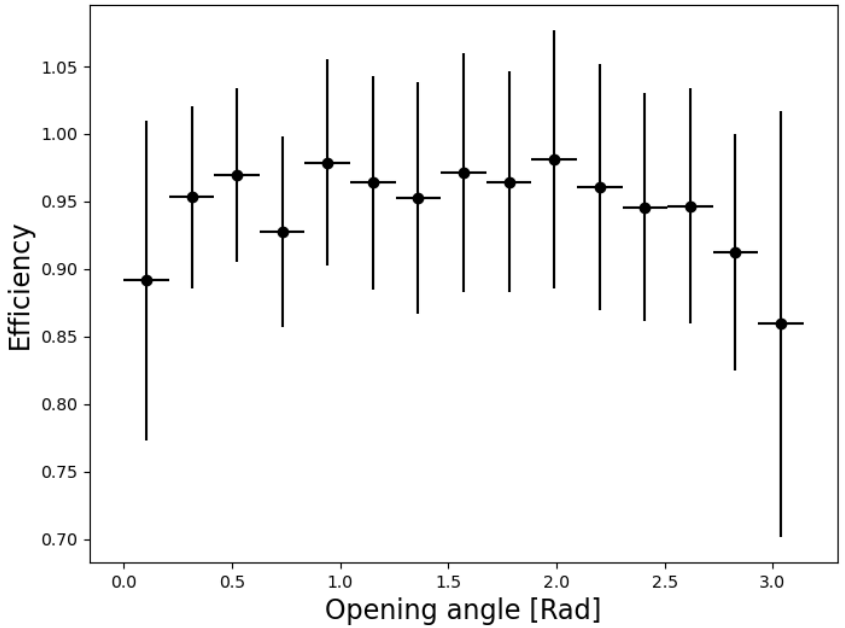




Results: Quirk training, quirk inference

Well-behaved Quirk training, quirk inference: 95.3% reconstructed efficiency (8layers: 92.8%)



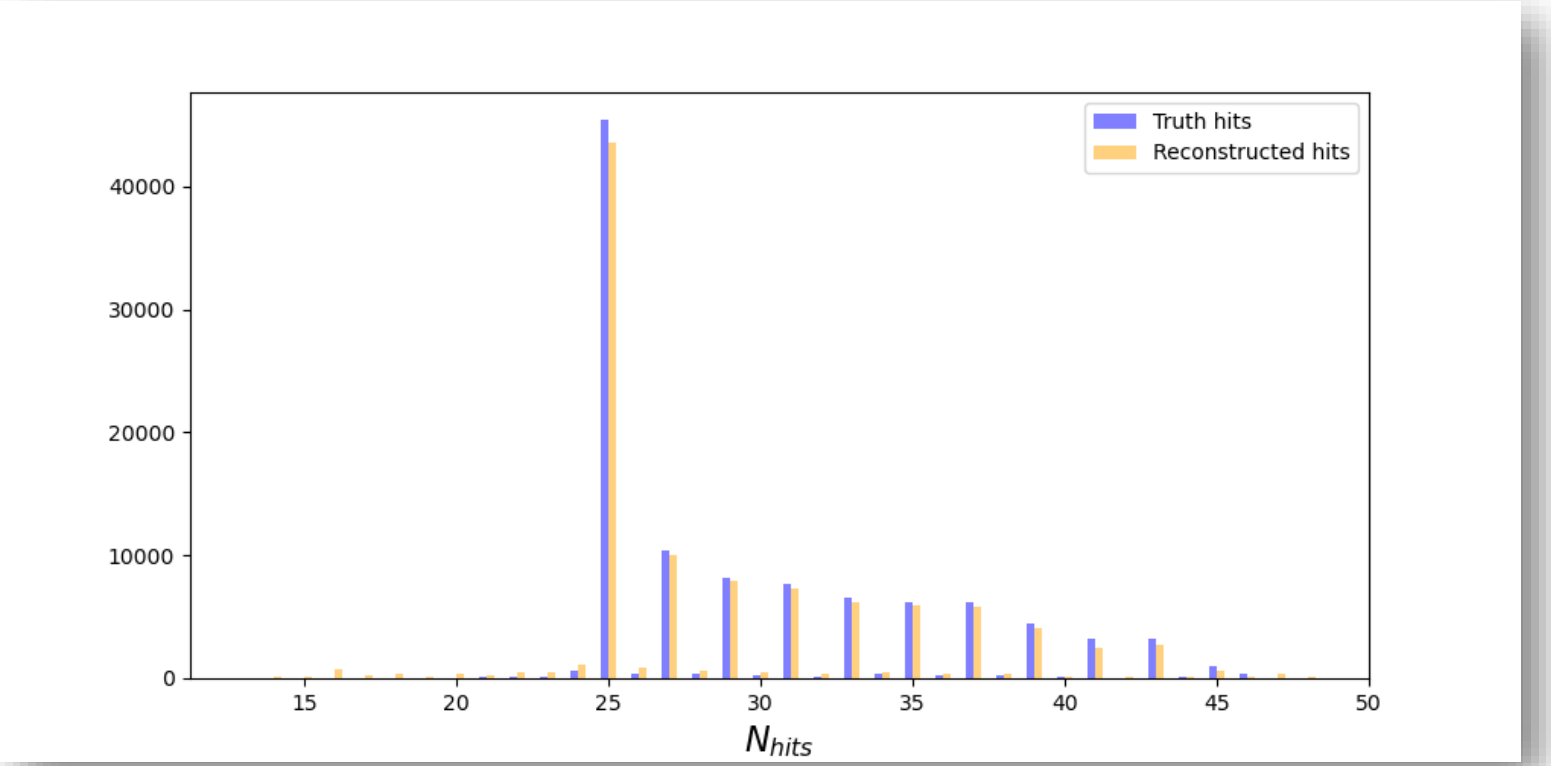


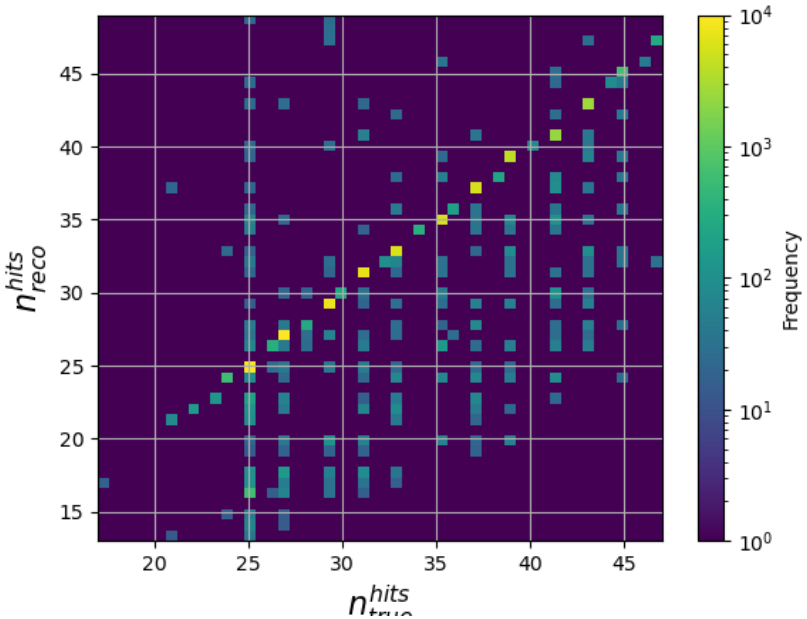
- The opening angle has no big impact on the Quirk reconstruction efficiency in well-behaved Quirk training.

Distribution of reconstructed quirks

The distribution of reconstructed quirks' information:

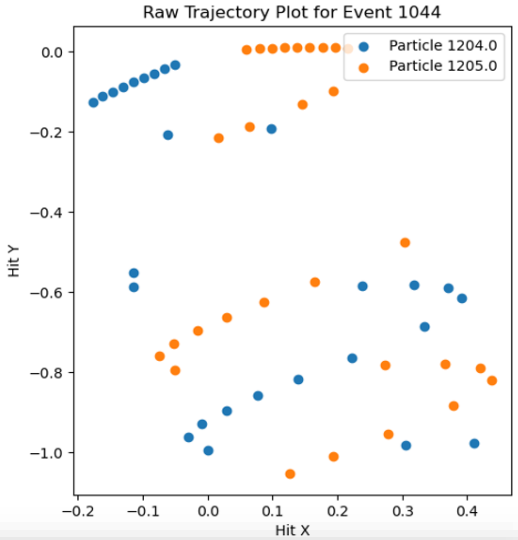
- $r, \phi, z(cm)$ are truth information of hits. r is scaled to (0,1). The plots are shown in the backup.
- n_{reco}^{hits} is the number of reconstructed hits, n_{truth}^{hits} is the number of truth hits.

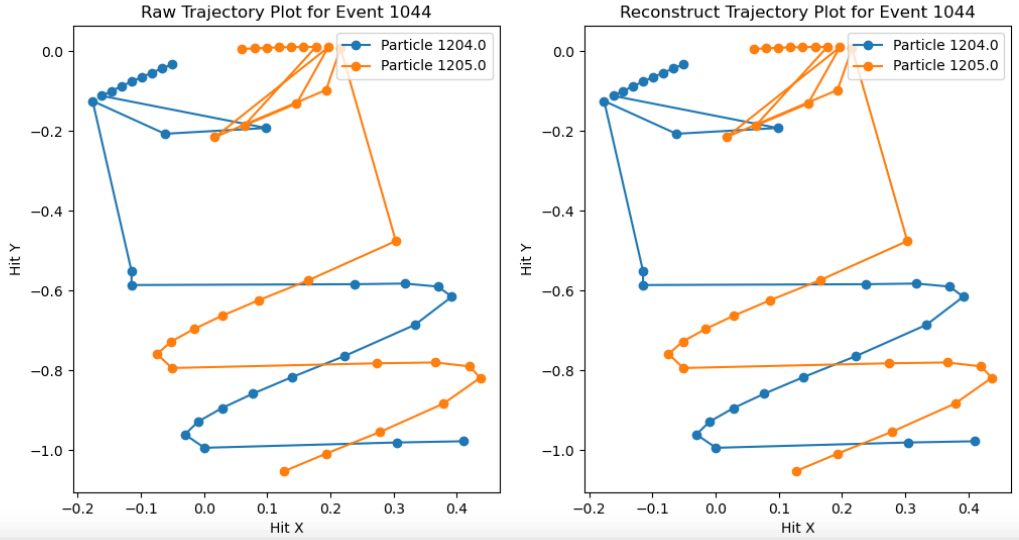


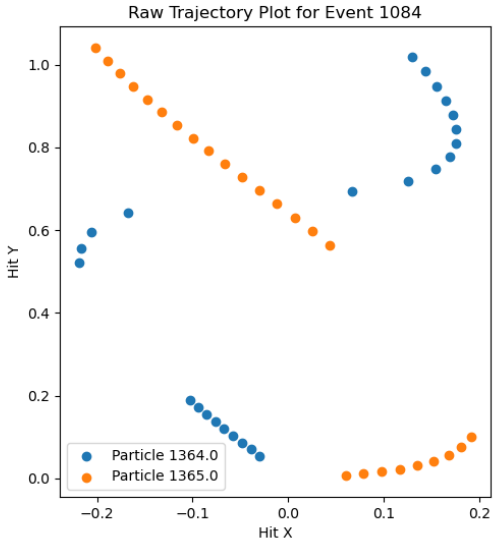


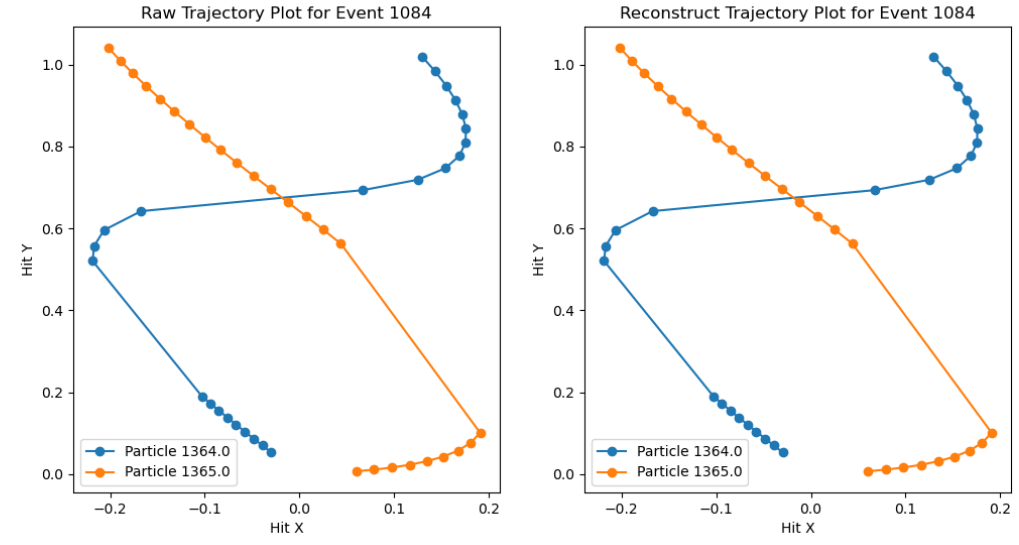
Reconstructed hits of quirk

All of well-behaved quirks are reconstructed well even though the dot plot looks chaos:



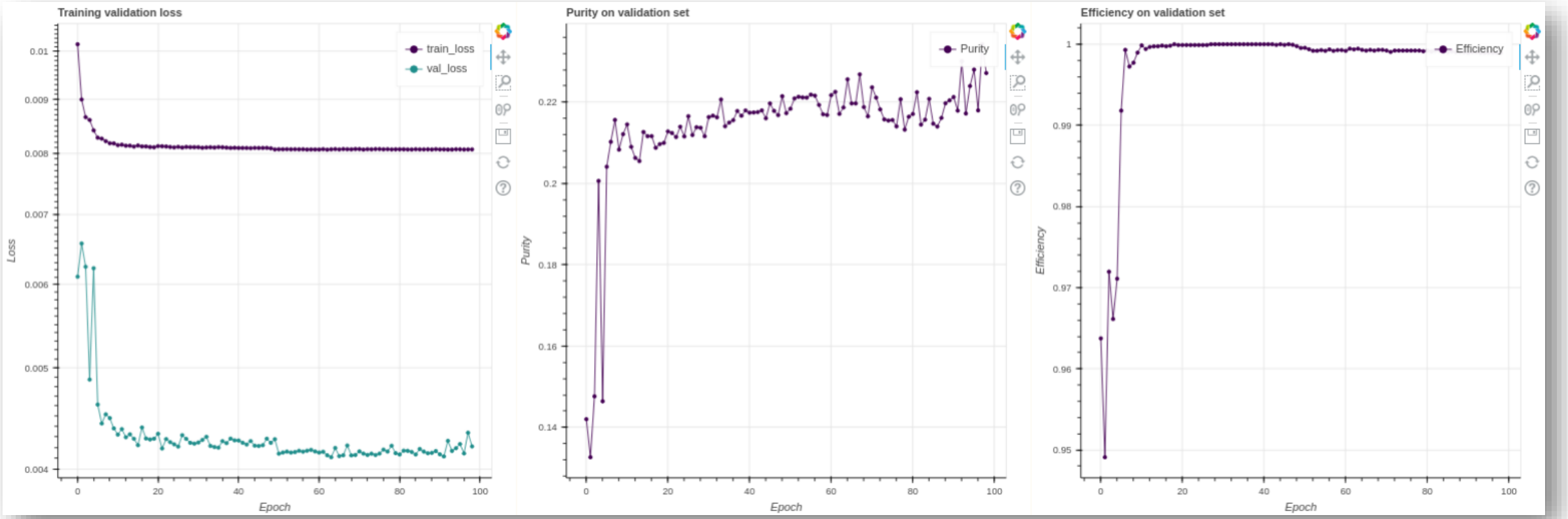






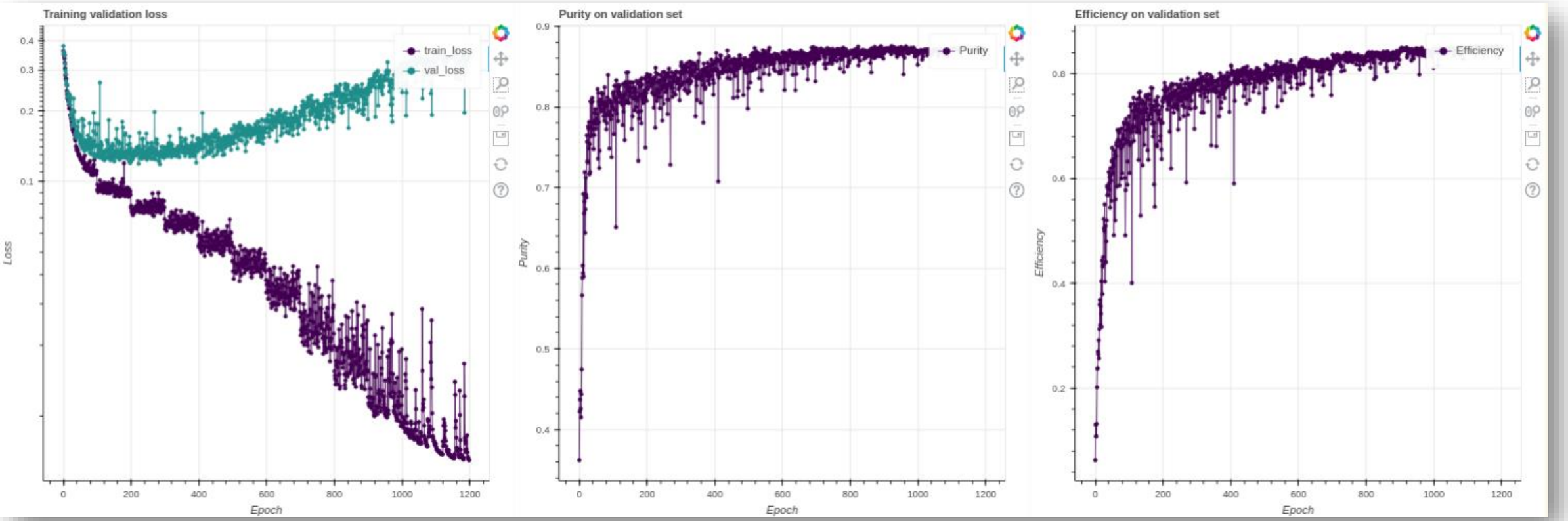
Metric Learning : All Quirk training, quirk inference

Use metric learning to reduce the dimension: Embedding the space points on to graphs.



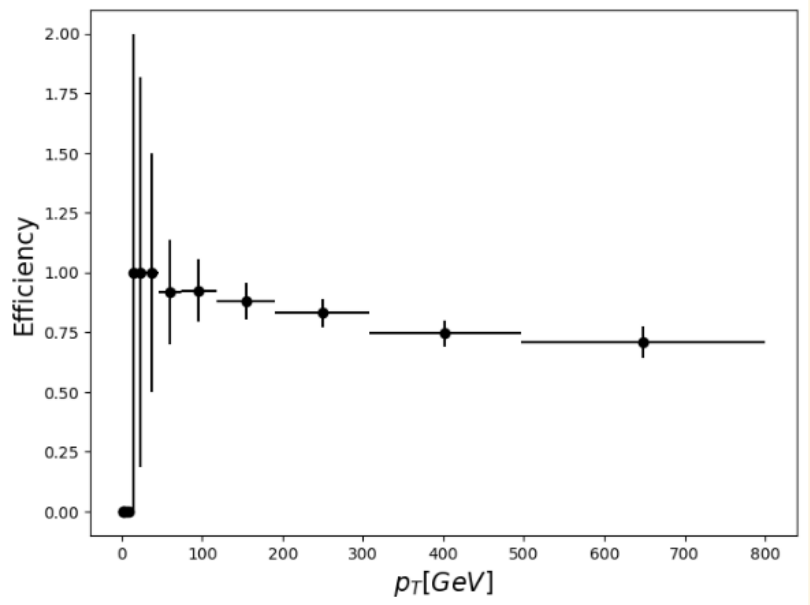
GNN : All Quirk training, quirk inference

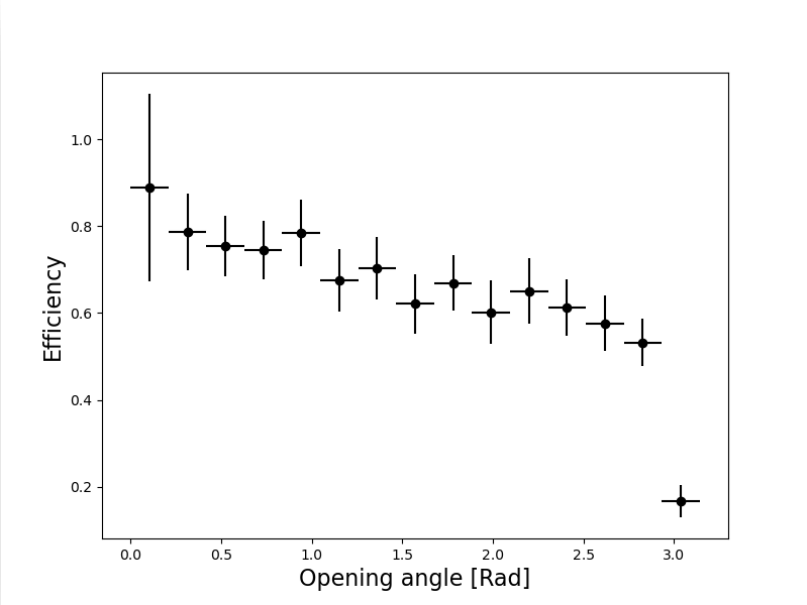
Train GNN to classify edges as either “true” (belonging to the same track) or “false” (not belonging to the same track)



Results: All Quirk training, quirk inference

When we training on all quirks without pre-selection, the performance has dropped significantly:
65.1% reconstructed efficiency (8layers: 56.3%)

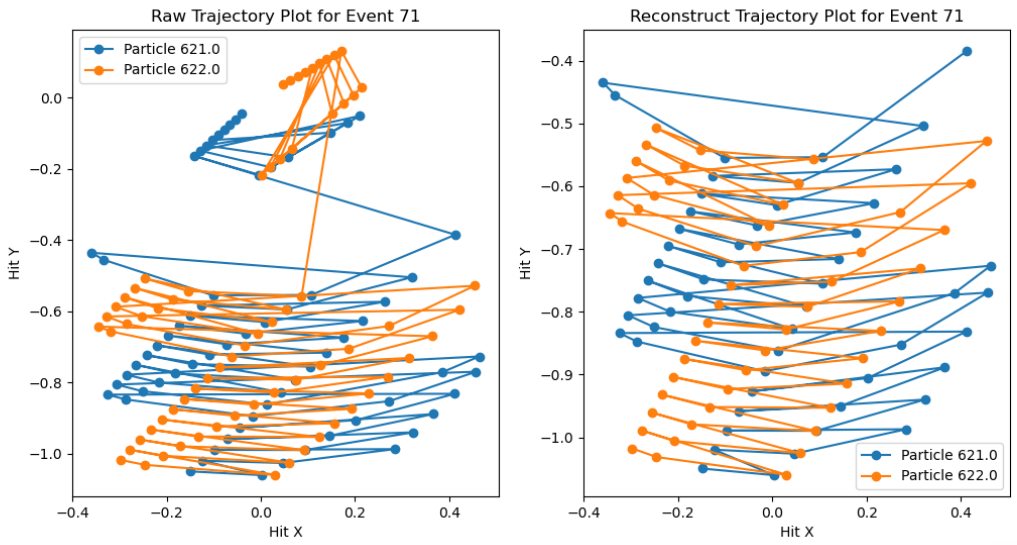


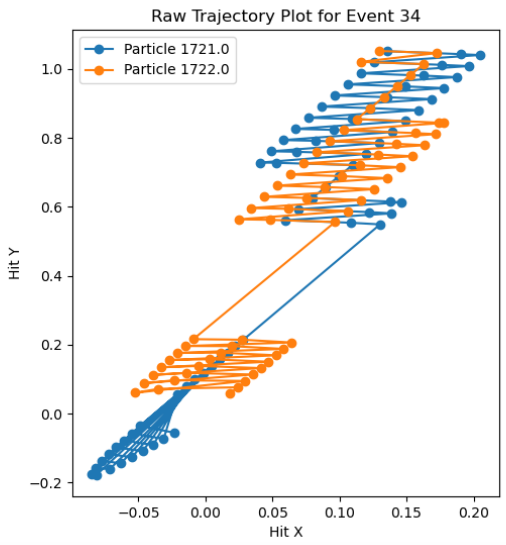


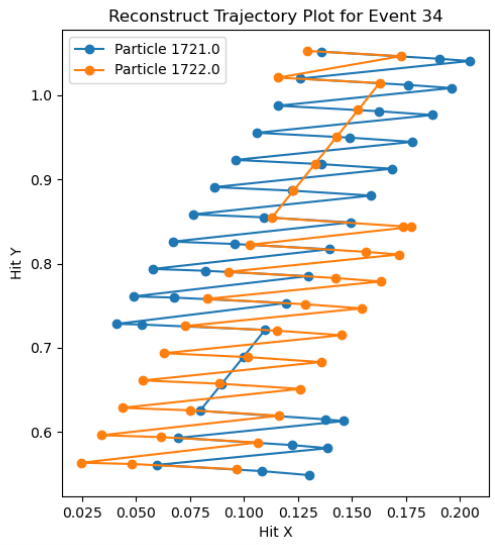
- Reconstruction efficiency decreases as the opening angle increases.

Reconstructed hits of quirk

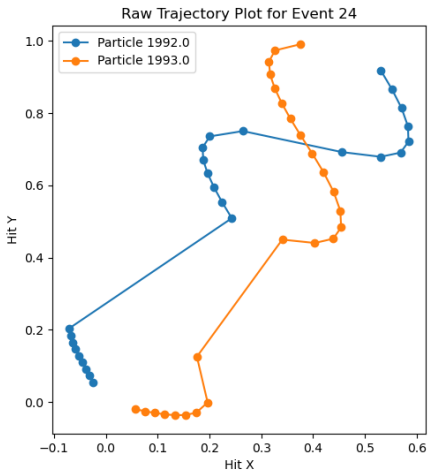
When tracks become crazy with lots of hits and in-out layers, the reconstructed performance is bad:

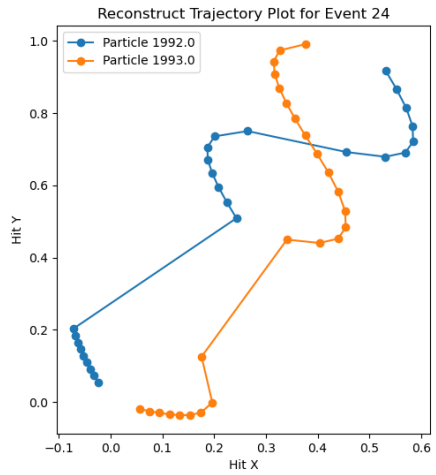






Well-behaved quirks (small n_{hits}) are still reconstructed well:





Conclusion and future work

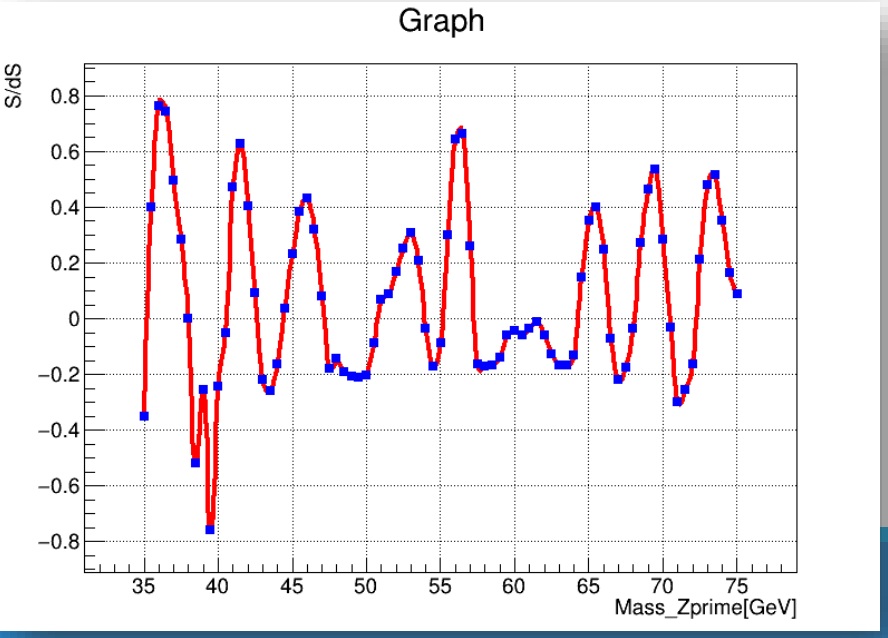
- Prepare the paper framework.
- Plan to training on dataset with more (m_Q, lambda) combination.
- Add noise in the training.

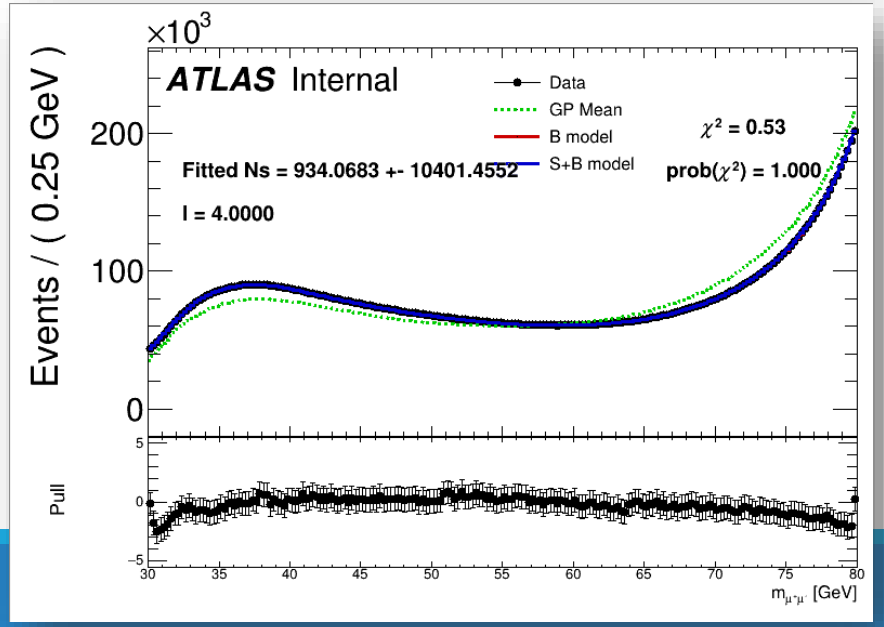
Zprime

- Extend the fit range to (30-80).
- Optimize the GP function for bkg modelling
- SS test and signal injection test.

$$G(\mathbf{y}|\boldsymbol{\mu}(\mathbf{x}), C) = \frac{1}{(2\pi)^{n/2}|C|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{y}-\boldsymbol{\mu}(\mathbf{x}))^T C^{-1}(\mathbf{y}-\boldsymbol{\mu}(\mathbf{x}))\right)$$

- The best results until now:
  - Bern order 9 as mean function.
  - K = 1e9, l = 4.0
  - SS uncertainties between -0.8 – 0.8 (plan to optimize to -0.5-0.5)
  - Signal injection test: The GP fitting demonstrates good fitting performance and excellent linearity, with signal bias within 1% of the injected signal yields. (√)





HH yyML

- Update plots to 140fb-1
- Finished the DAOD and MxAOD sample with parent pdgid information, will fill the table this week.

Backup

Distribution of well behaved reconstructed quirks

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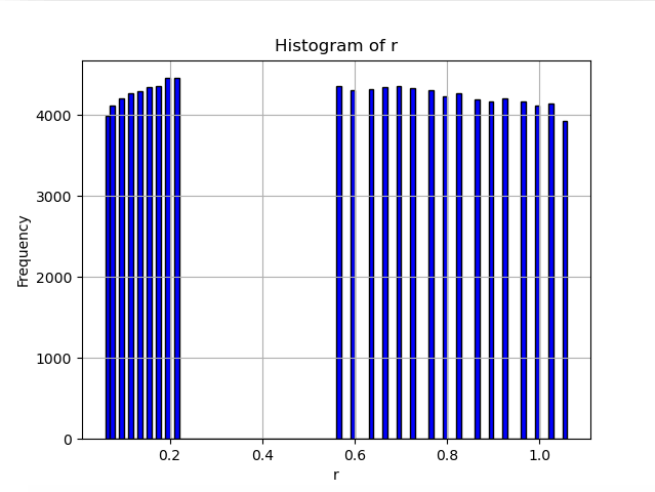

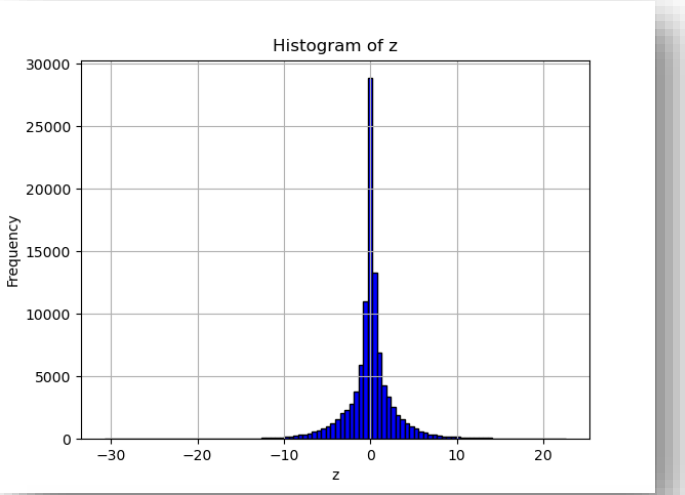

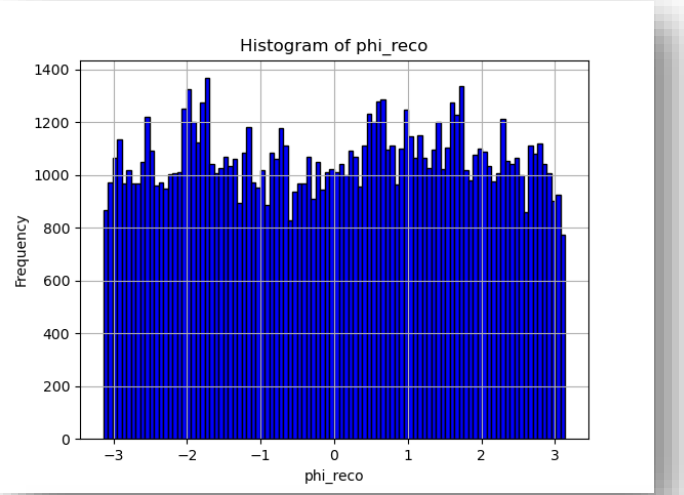

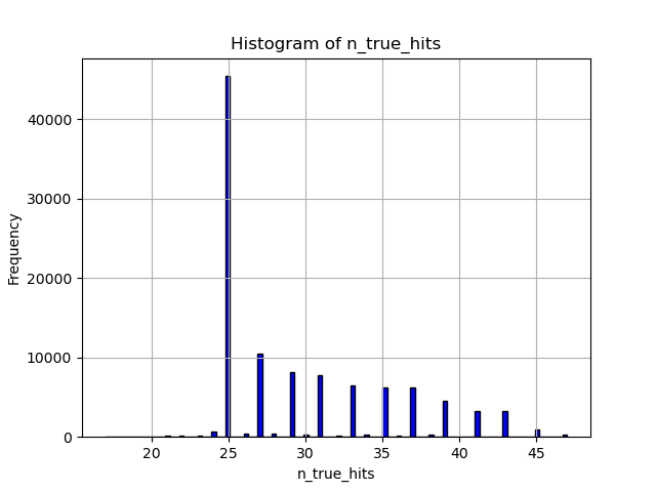

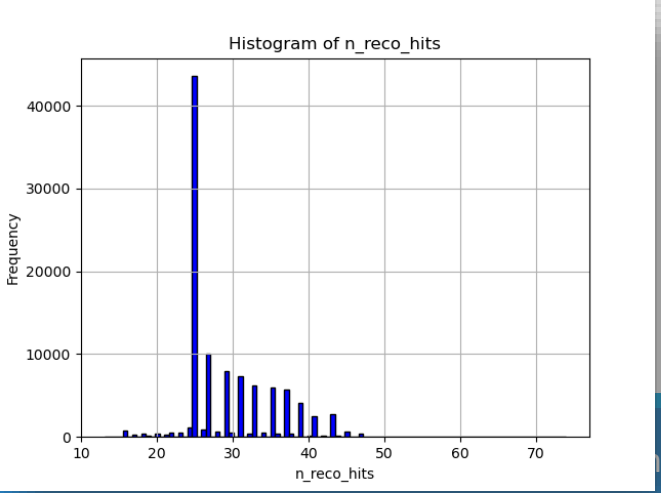

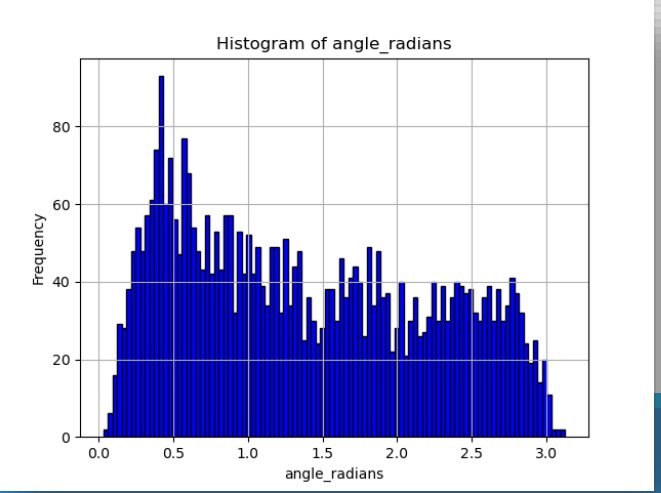

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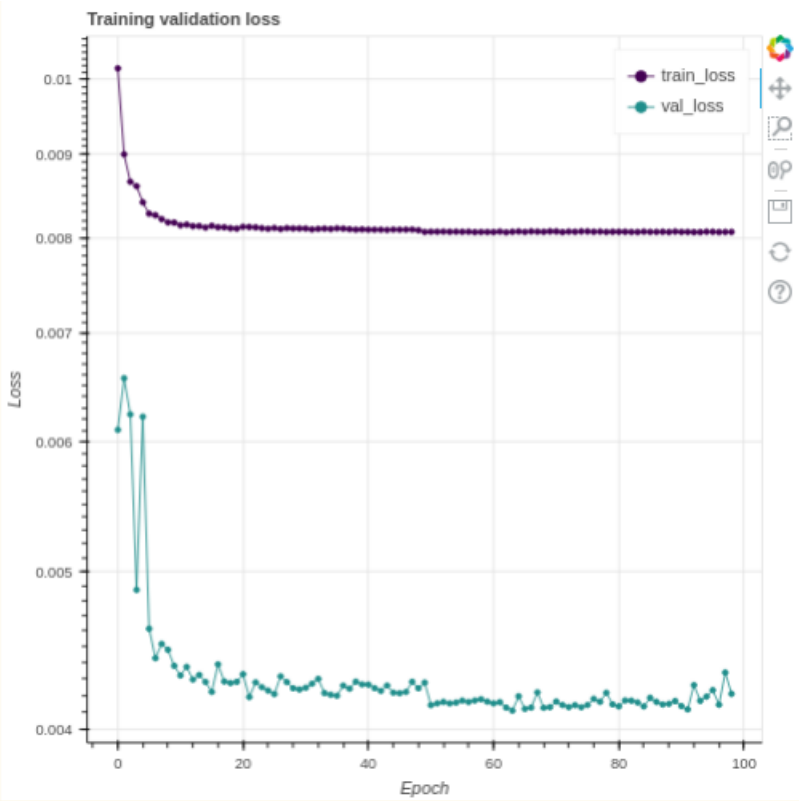

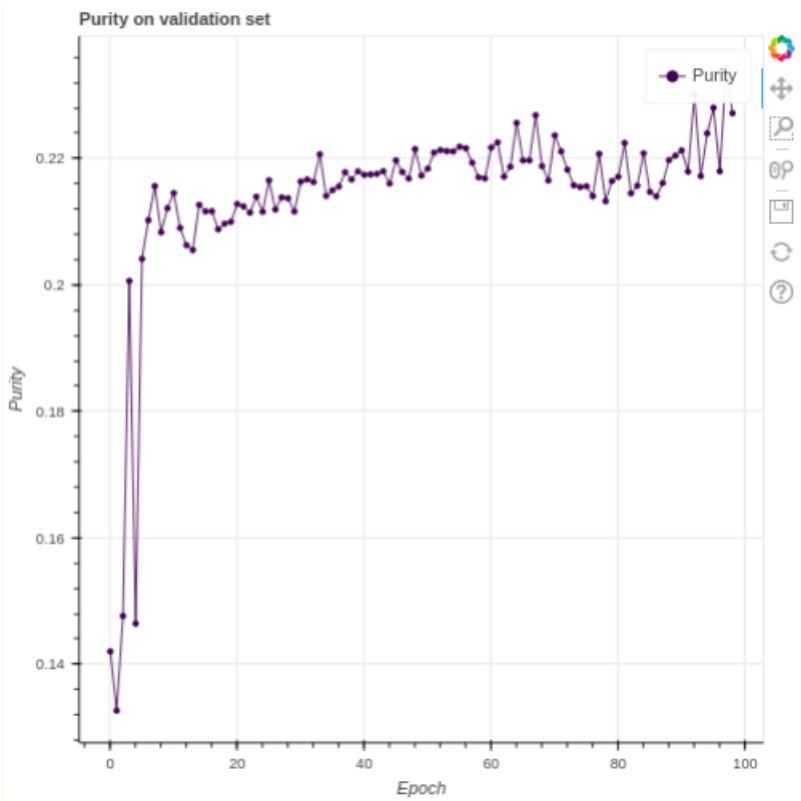

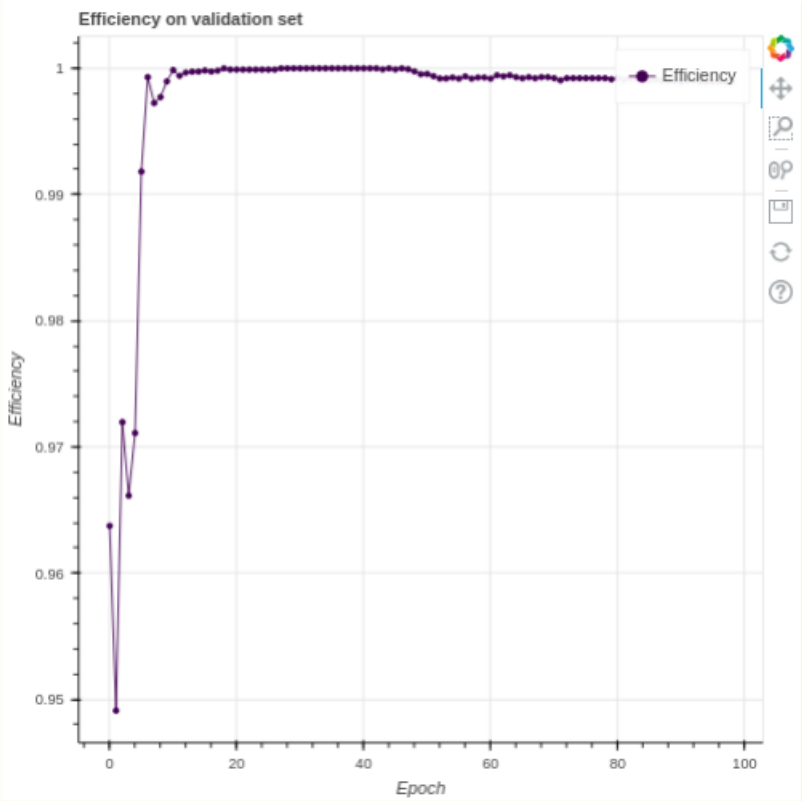

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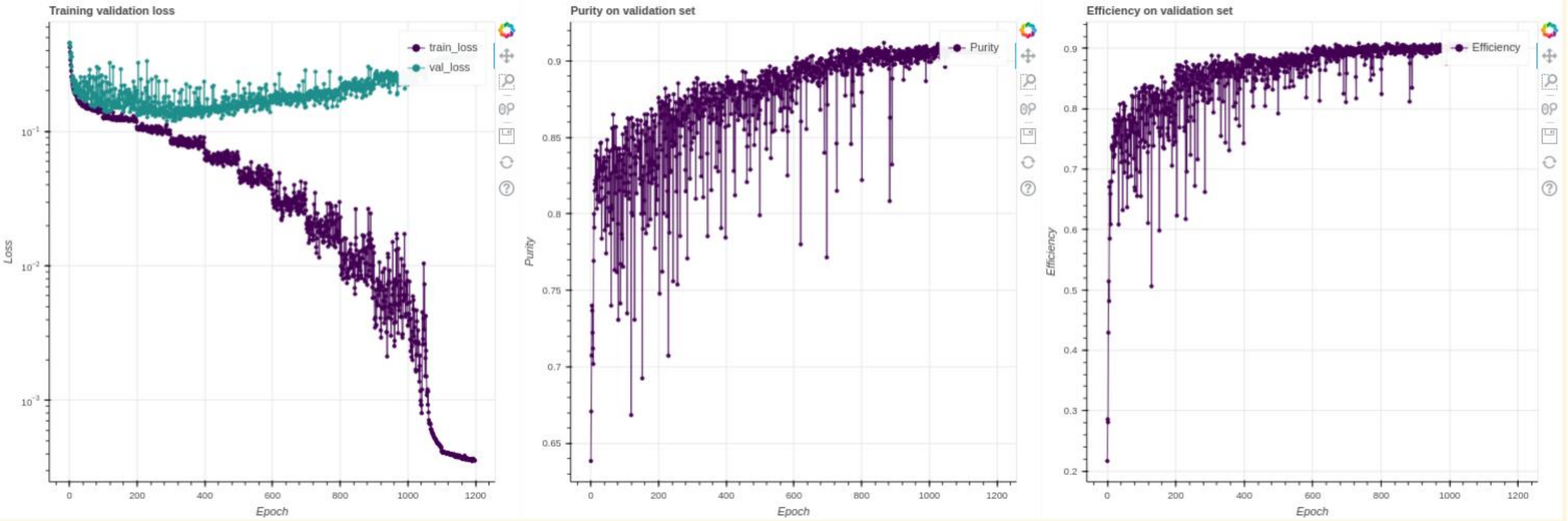
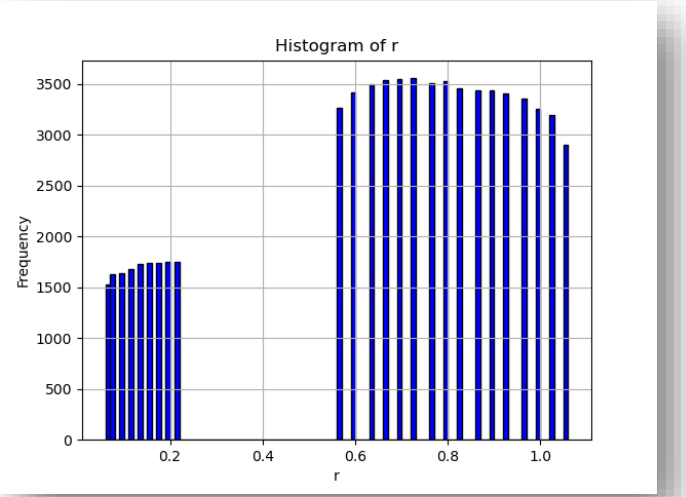
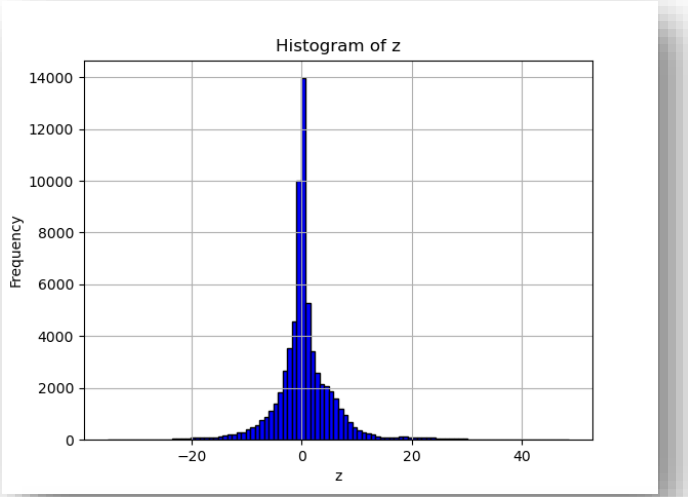
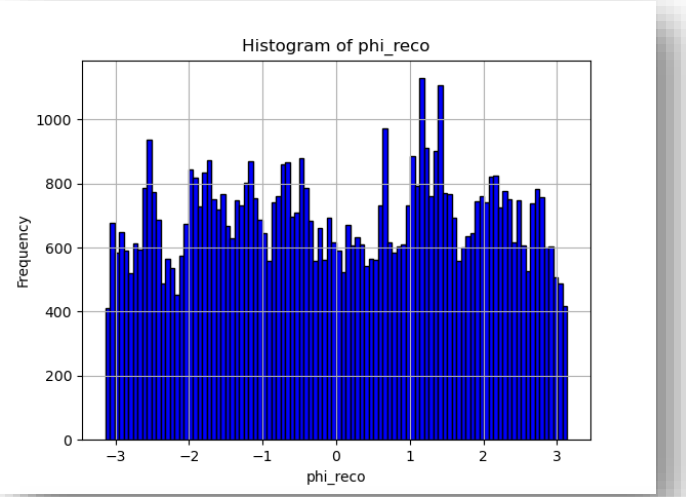


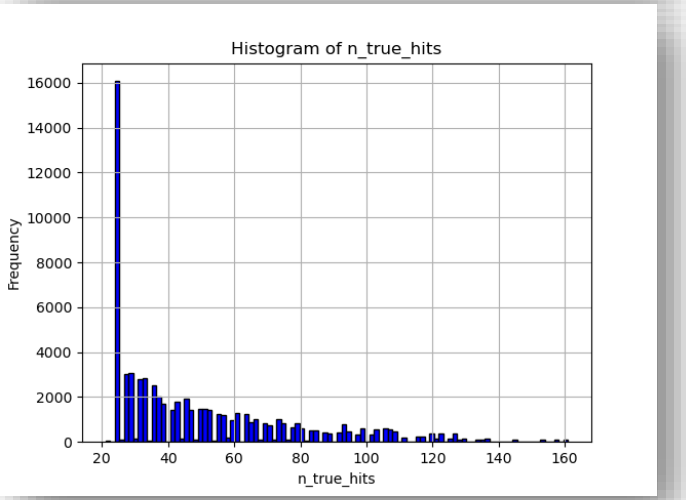
Results: All Quirk training, quirk inference

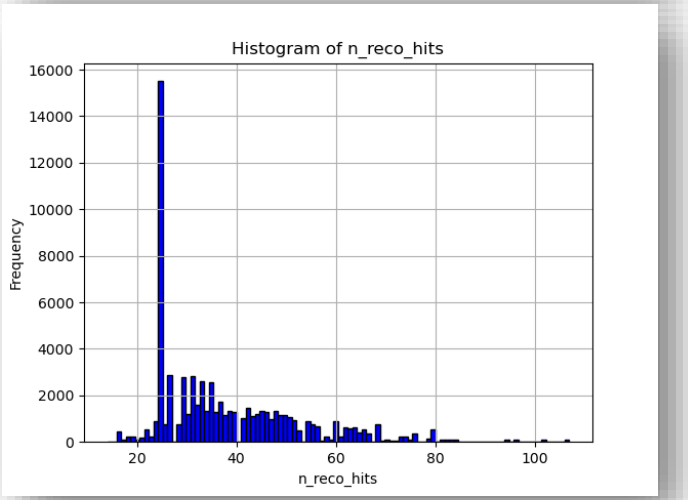
Distribution of reconstructed quirks:

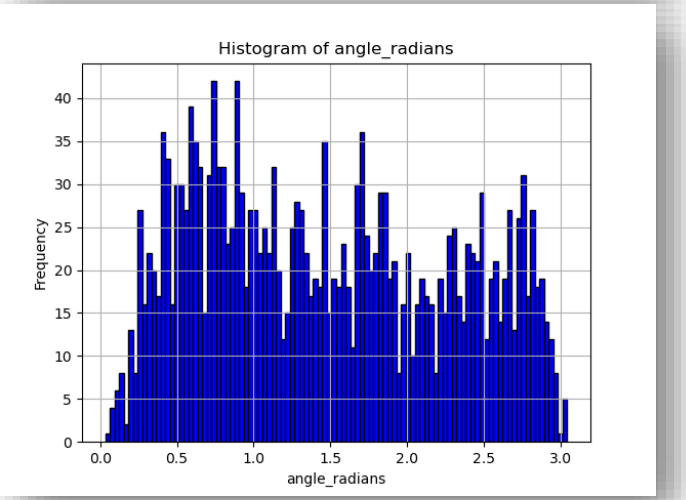












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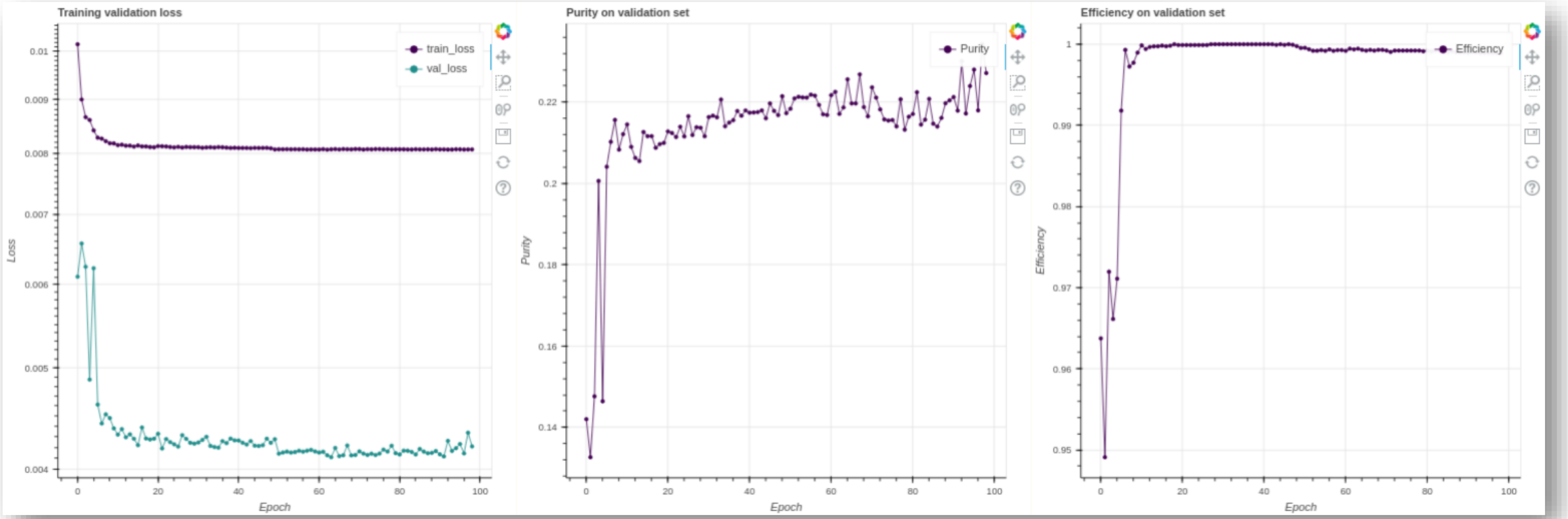

GNN : All Quirk training, quirk inference

Train GNN to classify edges as either “true” (belonging to the same track) or “false” (not belonging to the same track)