GNN Track Reconstruction of Non-helical BSM Signatures

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8TH INTERNATIONAL CONNECTING THE DOTS WORKSHOP

Quirk Introduction

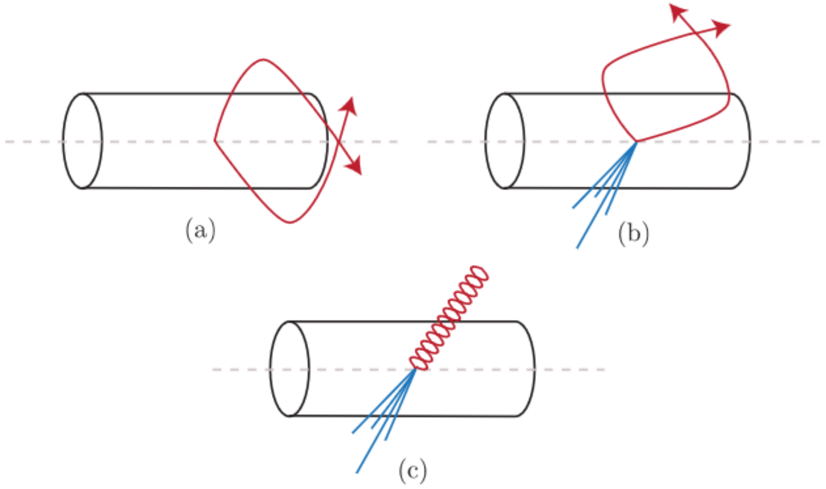
Quirks are stable BSM particles that are charged under an unbroken non-Abelian gauge force which confines at low energies:

- Used in models of dark matter, little Higgs scenarios, folded SUSY…

Quirks are characterized by a hidden QCD-like confinement scale $\boldsymbol{\Lambda}$ and mass m_Q with:

$$\boldsymbol{\Lambda} << m_Q$$

- Once produced quirks are separated by a QCD-like color-string which keep the quirk pair neutral
- But as opposed to the SM, the small energy stored in the string is insufficient to produce a quirk pair and thus preventing hadronization



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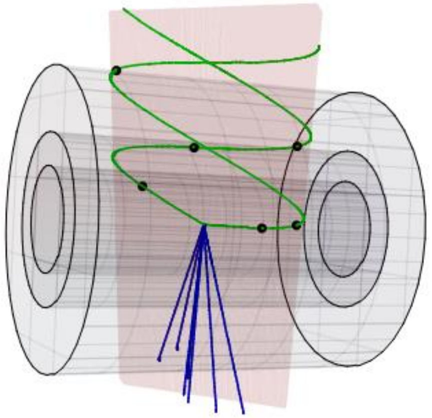
Quirks are subjected to a restoring force with the scale $\boldsymbol{\Lambda}^2$ and exhibit oscillations on the scale

$$d \sim 2 \text{ cm} \left(\frac{m_Q}{100\text{GeV}}\right)\left(\frac{\text{keV}}{\Lambda}\right)^2$$

Quirk Introduction

Some previous works include:

- Stopping Quirks at the LHC
  - Look for quirks that stop in the detector and produce hits that are out of time with any bunch crossing
- Tracking down Quirks at the LHC
  - Recognize that quirks are subject to a central force, and so their hits lie along the plane
- The Quirk Signal at FASER and FASER2
  - String tension forces quirks to be dominantly produced with a zero net pT → look in the forward direction



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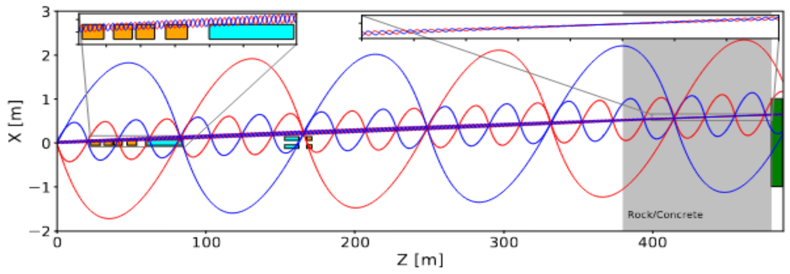

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While these explorations probe large regions of parameter space, they struggle when oscillations are on the scale of meters.

What’s the plan

We can’t use the standard tracking tools to find these quirk tracks because they are not helices, and writing a dedicated quirk tracker would require a complete rewrite.

- Use the more flexible ML-based tracking algorithm to learn maybe a good way to find quirks.

1. Does the GNN tracking work for non-helical tracks?
2. When it is trained on SM (i.e. mostly helical) tracks, can it work on non-helical?
3. When it is trained on non-helical, can it work on non-helical?

- Train on SM, validate on quirk
- Train on well-behaved quirks, validate on well-behaved quirks
- Train on all quirks, validate on all quirks

Dataset

- Use MG5 generate samples through pp $\rightarrow Q\bar{Q}$ + j:
  - Quirk: Collect Quirk and through a simplistic model of the ATLAS detector which consists of 8 layers of trackers.
    - A 500 GeV quirk pair with the string tension (Lambda) = 500 eV (The small Lambda don't have non-helical tracker)
  - Background: Jet (~100 particles for one event)

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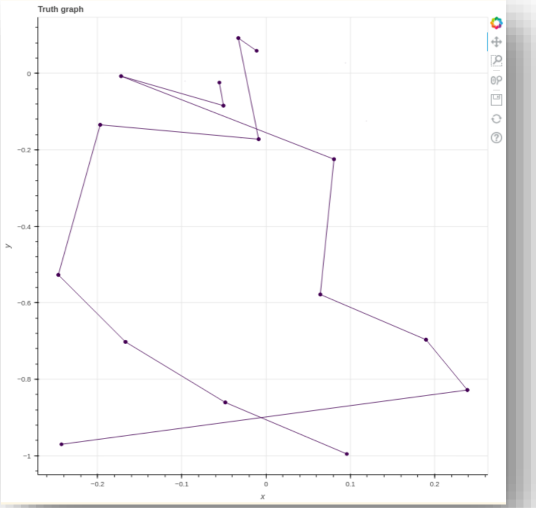
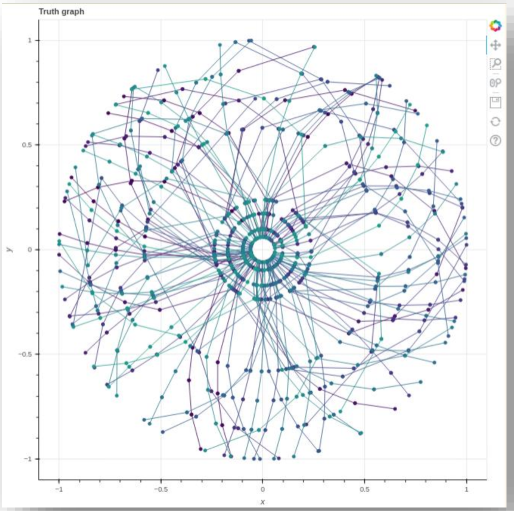
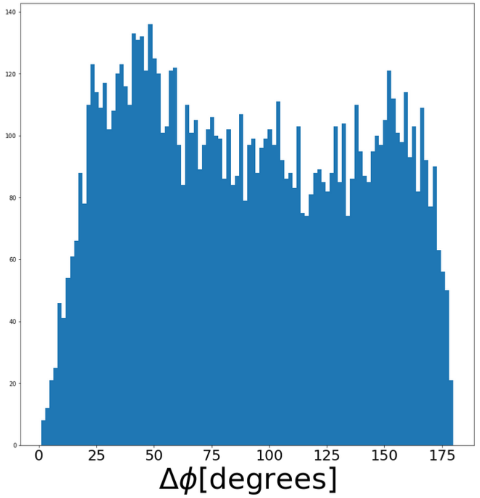
Quirk non-helical tracks:

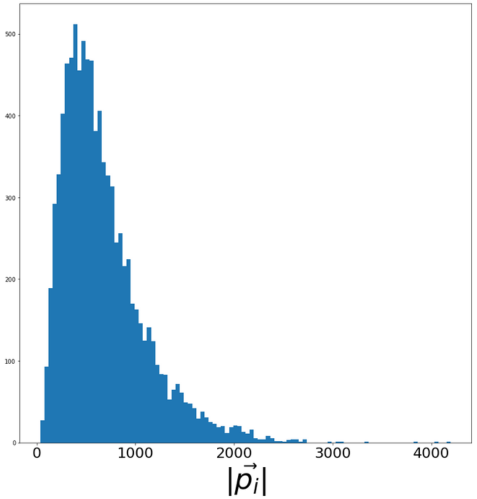


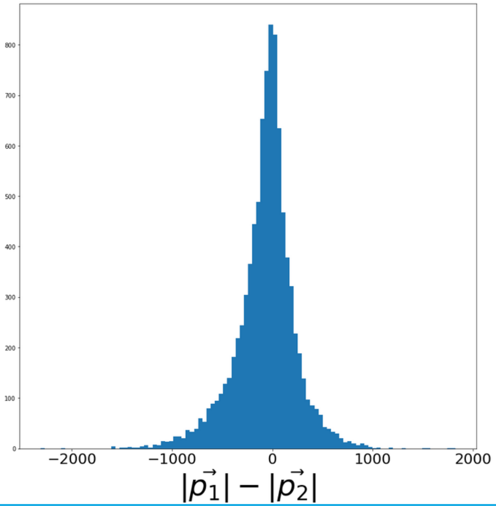
Bkg tracks:



- Check on the quirk dataset:
  - Uniform opening angle
  - ~500 GeV momenta
  - Some asymmetry, the typical case is $\overrightarrow{p_1} = \overrightarrow{p_2}$.





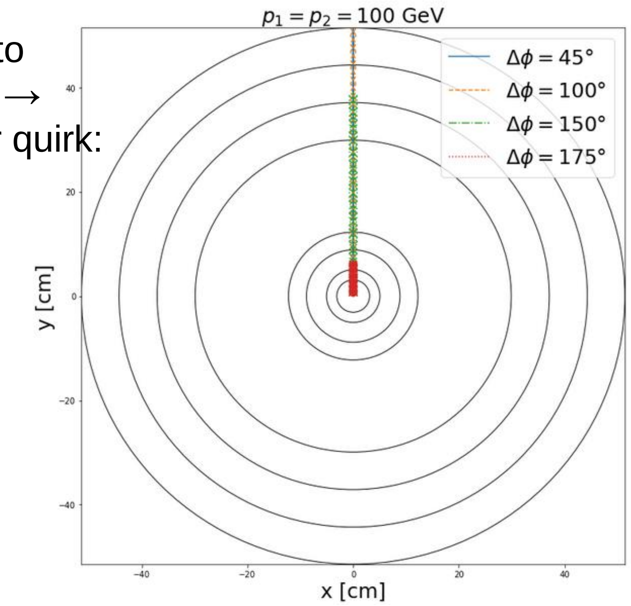


Quirk Dataset

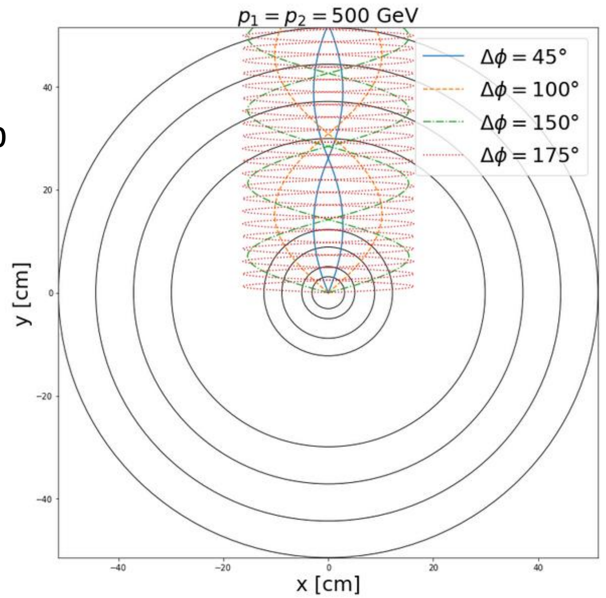
Quirks come out at a variety of momenta with different opening angles.

- Let's set $\overrightarrow{p_1} = \overrightarrow{p_2}$, and look at trajectories for different opening angles centered on y axis

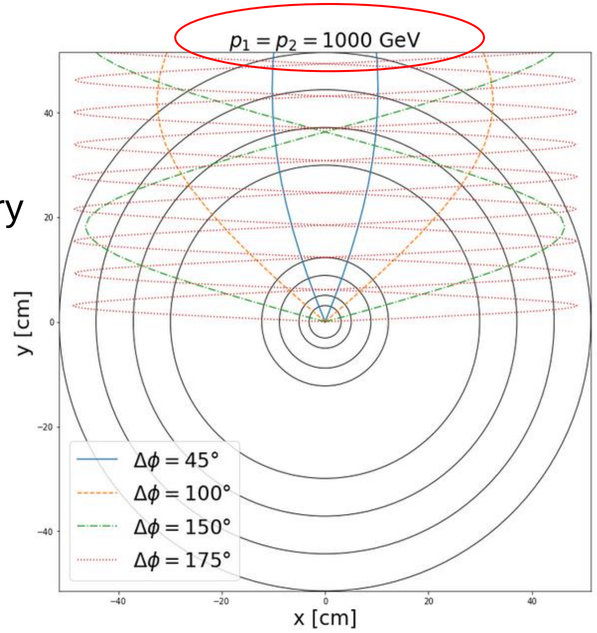
Too soft to separate → 8 hits per quirk:



Start to separate → Can rack up many hits:



For phi<100, can still have only 8 hits, otherwise very many:



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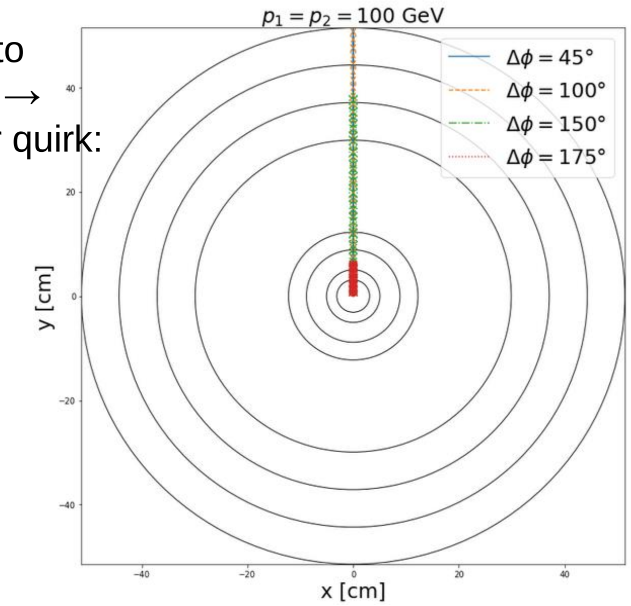

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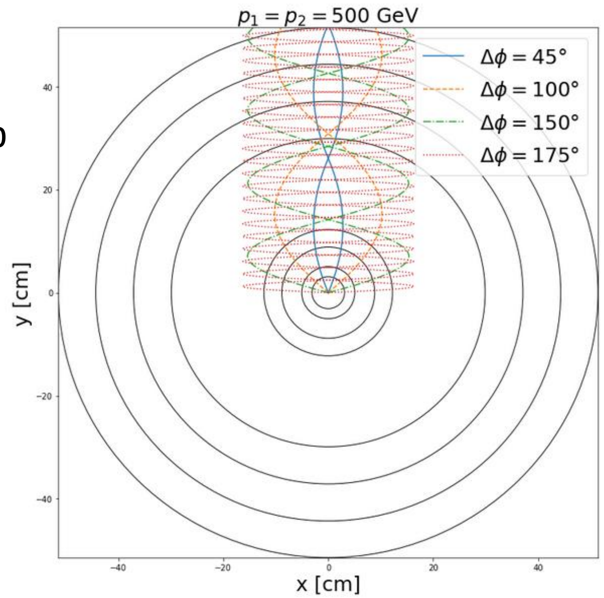

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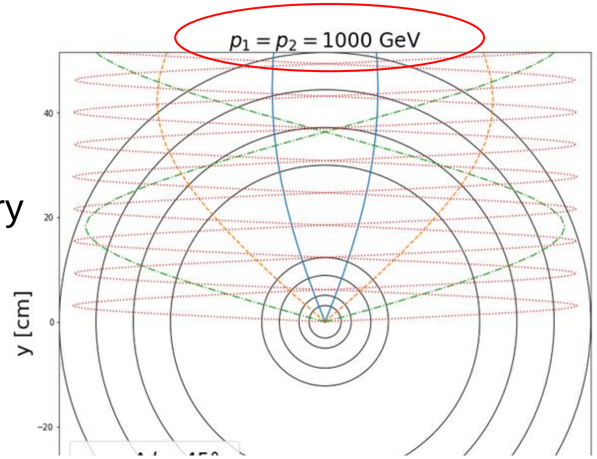
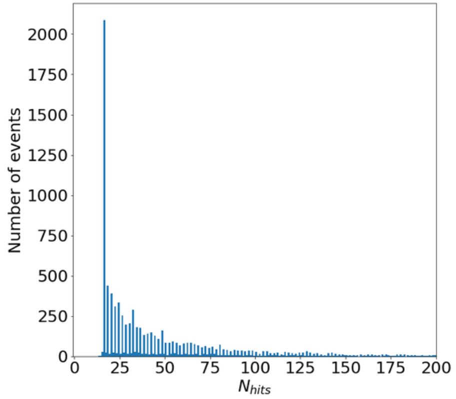
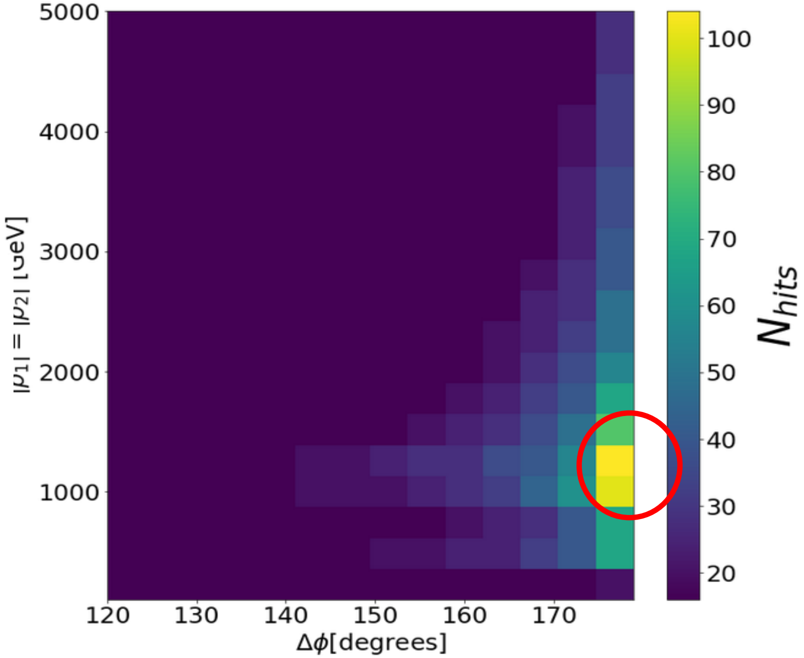


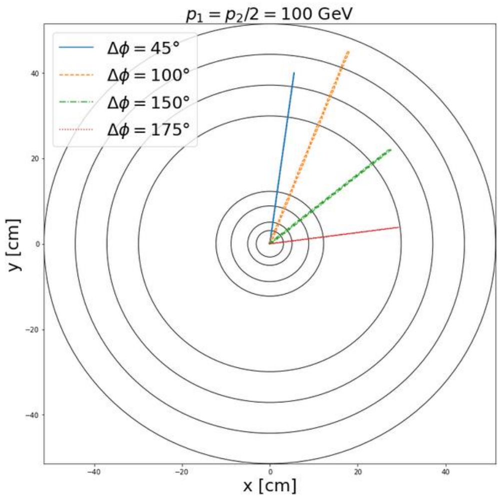
- We rack up many hits for only large opening angles, but typically get ~30+
- Looking at the actual data, median of 26 hits (13 for each quirk)

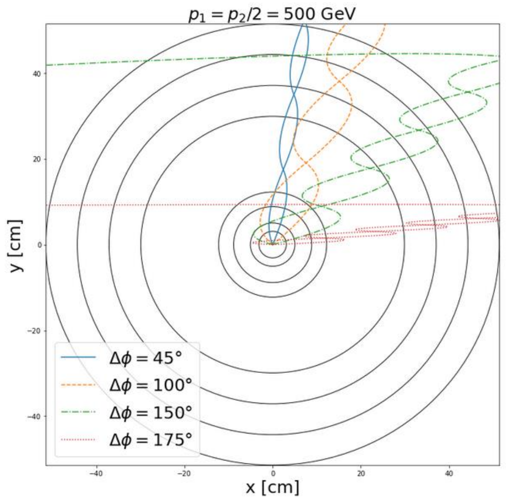


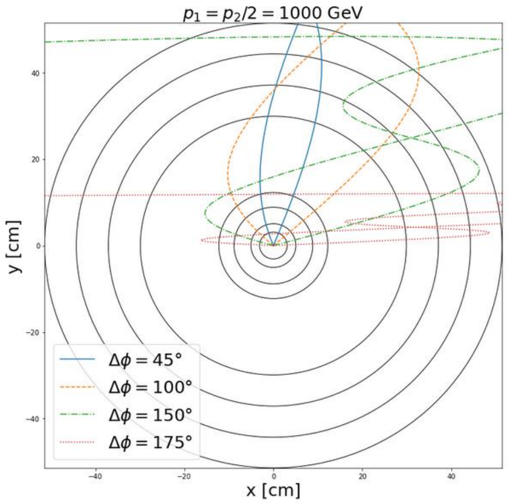


Dataset for training

Now let's study some asymmetry and set p1 = p2 /2 for example.
A coupled pendulum…Crazy tracks… Hard to reconstruct and training.







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:

- Opening angle < 50°
- N_{hit} < 20

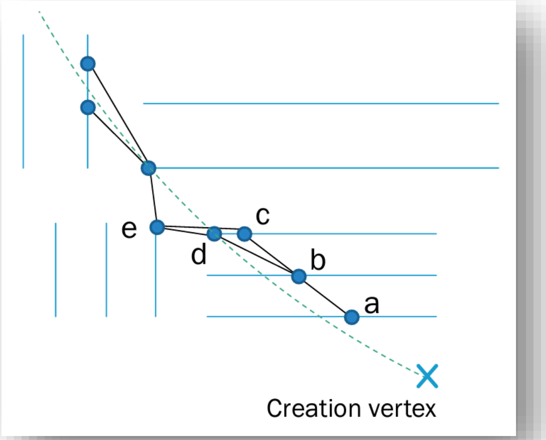
Separate the Background and Quirk dataset for analysis:

- Background training, quirk inference (1000 events to train on)
- Quirk training, quirk inference (800 events to train on)

Pipeline

Construct graph → Metric Learning → Classify edges → GNN → Identify connect components

Based on Exa.Trkx.



Defining “True neighbors”:

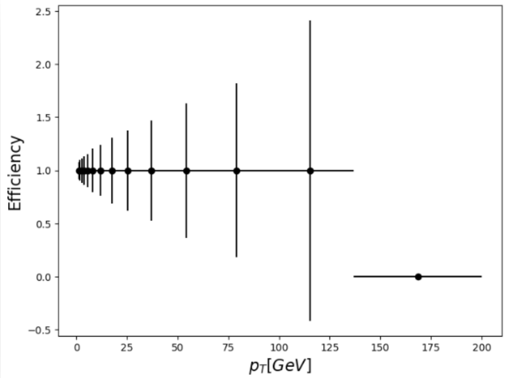
- For each particle, order hits by increasing the “hit_id”
- Group by shared module ID
- Connect all combinations from layer L_i to L_{i+1}

Metric Learning:

- For all hits in detector, embed features into N-dimensional space.
- Associate neighboring hits as close in N-dimensional distance.
- Score each “neighbour” hit within embedding neighborhood against the “target” hit at centre.

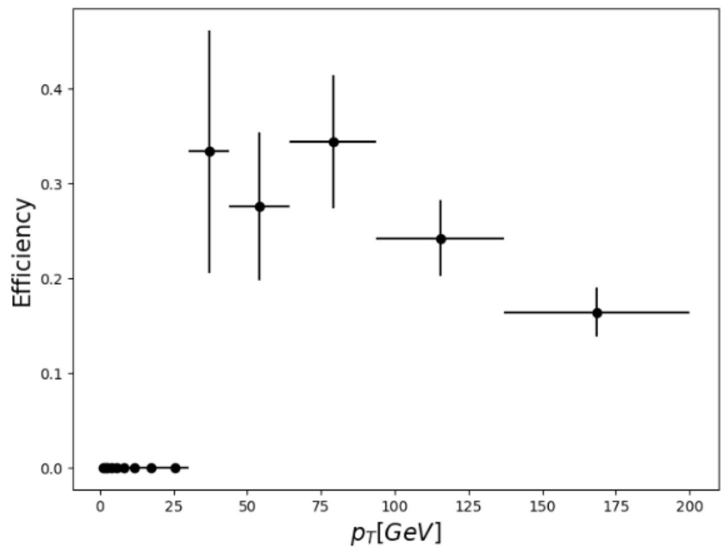
Results: Background training, quirk inference

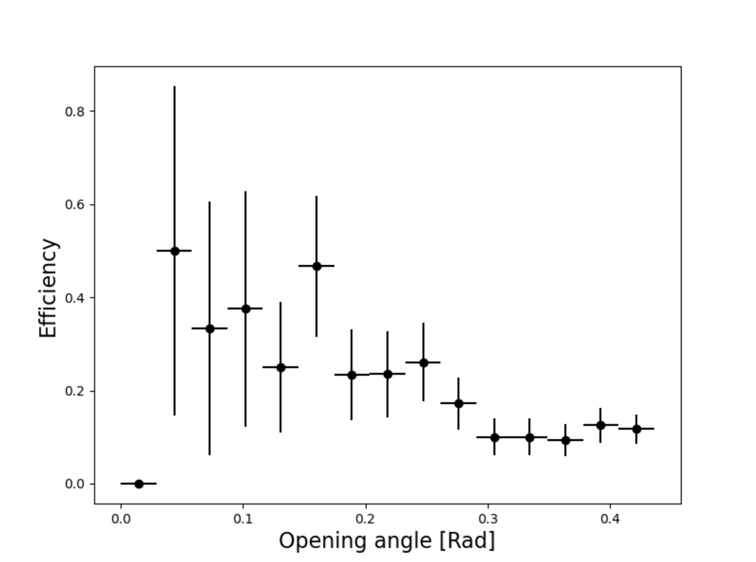
Background training, background inference: 97.9% reconstructed efficiency



The track definition
$\vert\eta\vert < 4$
$n_{track}^{hits} \geq 5$
$n_{particle}^{hits} \geq 7$
Double-majority matching

Background training, quirk inference: 10.2% reconstructed efficiency

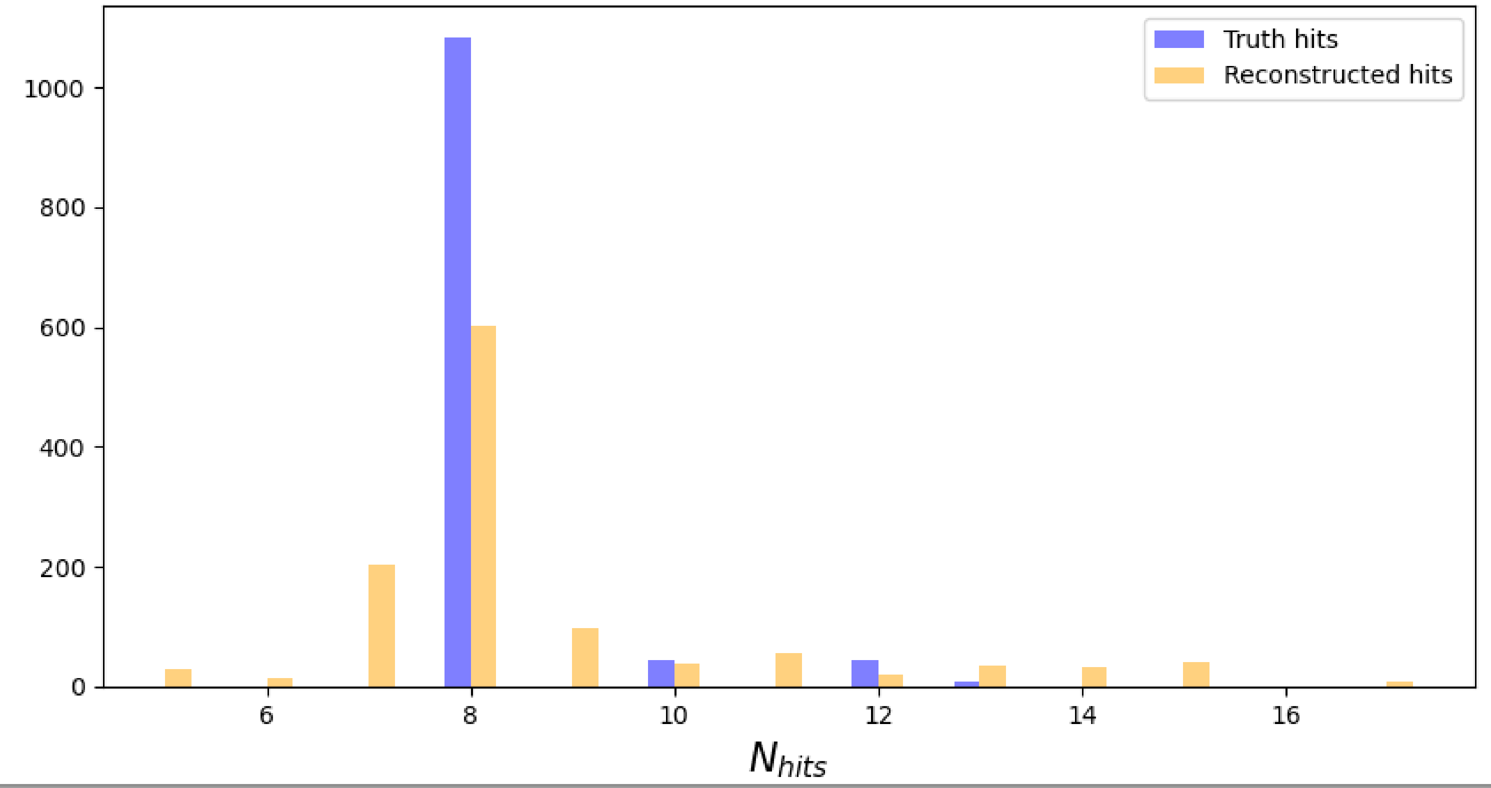




Distribution of reconstructed quirks

The distribution of reconstructed quirks' information:

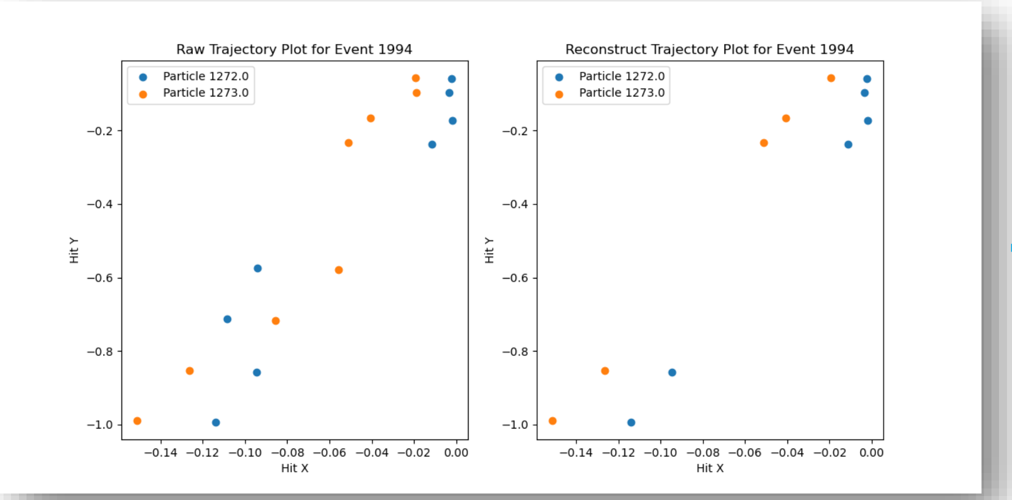
- $r, \phi, z(cm)$ are truth information of hits. r is scaled to (0,1). The plots are shown in the backup.
- n^{hits}_{reco} is the number of reconstructed hits, n^{hits}_{truth} is the number of truth hits.

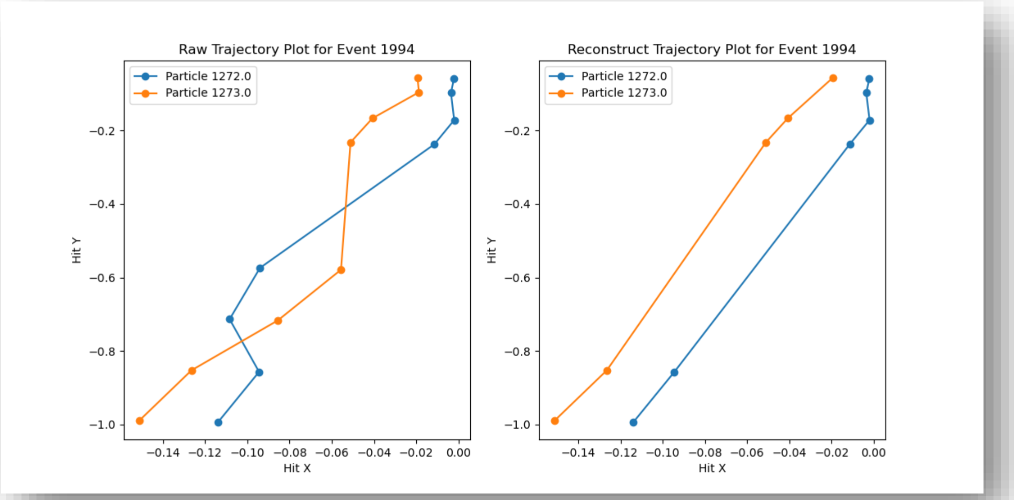


Reconstructed hits of quirk

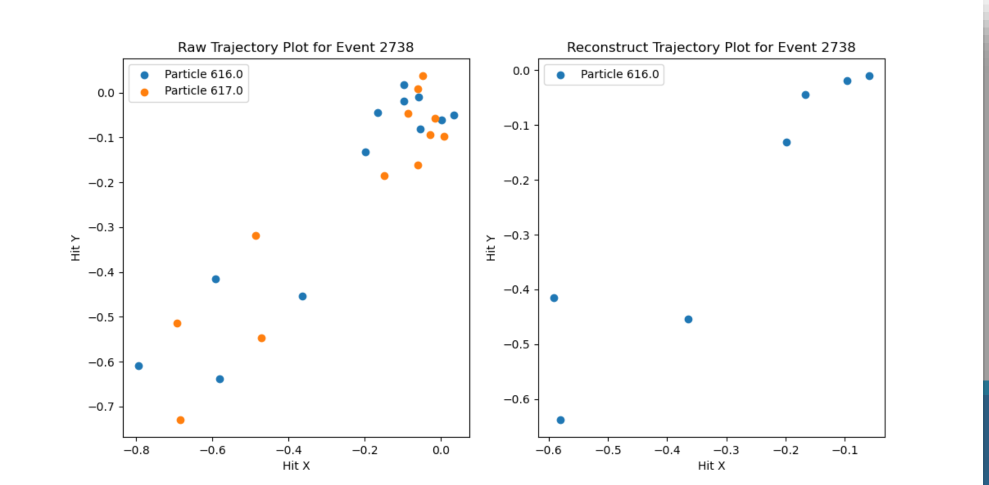
With same event (use the reconstructed event information):

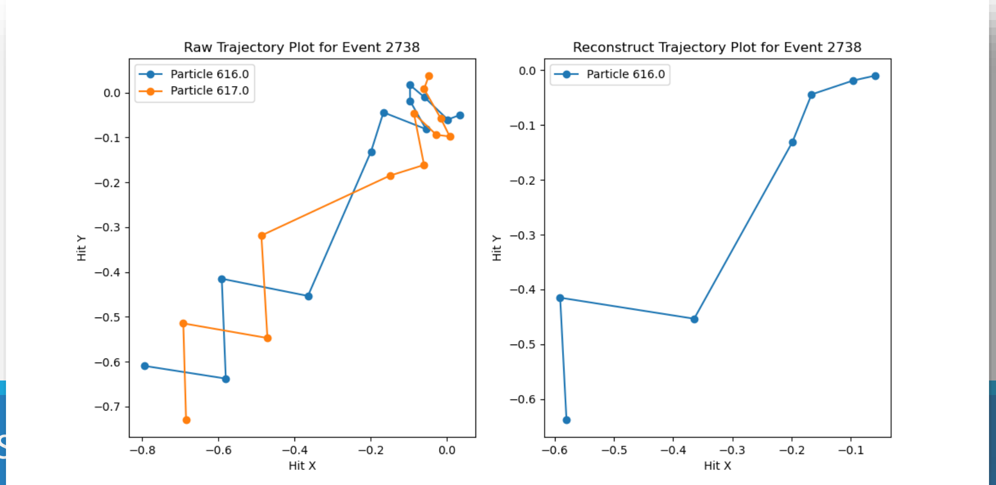
- Some $\text{hits}_{\text{reco}}$ are the part of truth quirk track.





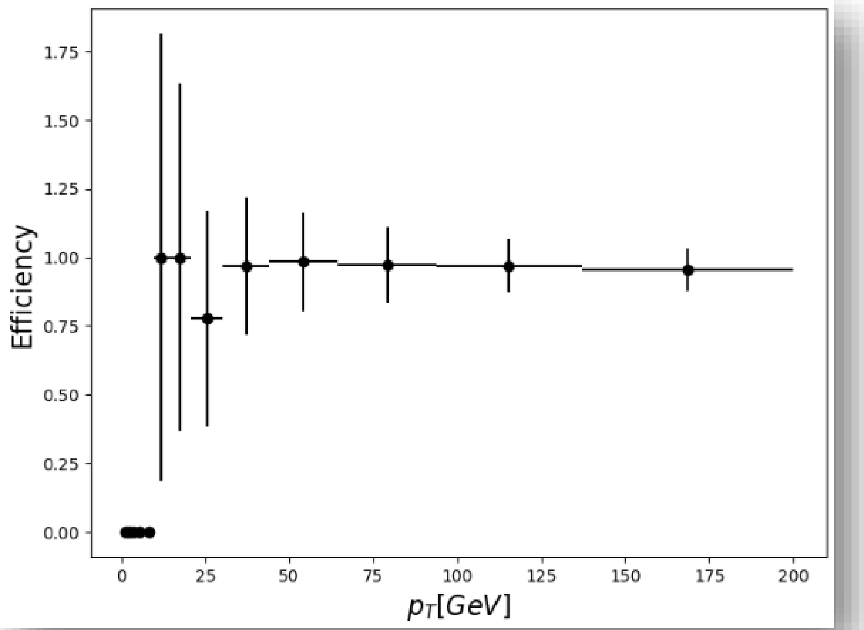
- Only reconstruct simple and smooth track. (The particle 617 is failed to be reconstructed)

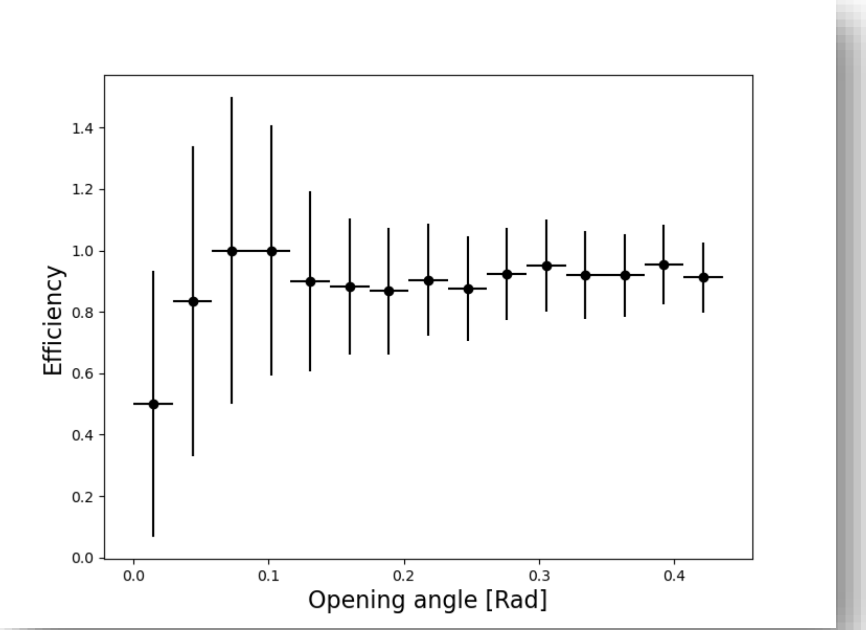




Results: Quirk training, quirk inference

Well-behaved Quirk training, quirk inference: 92.8% reconstructed efficiency



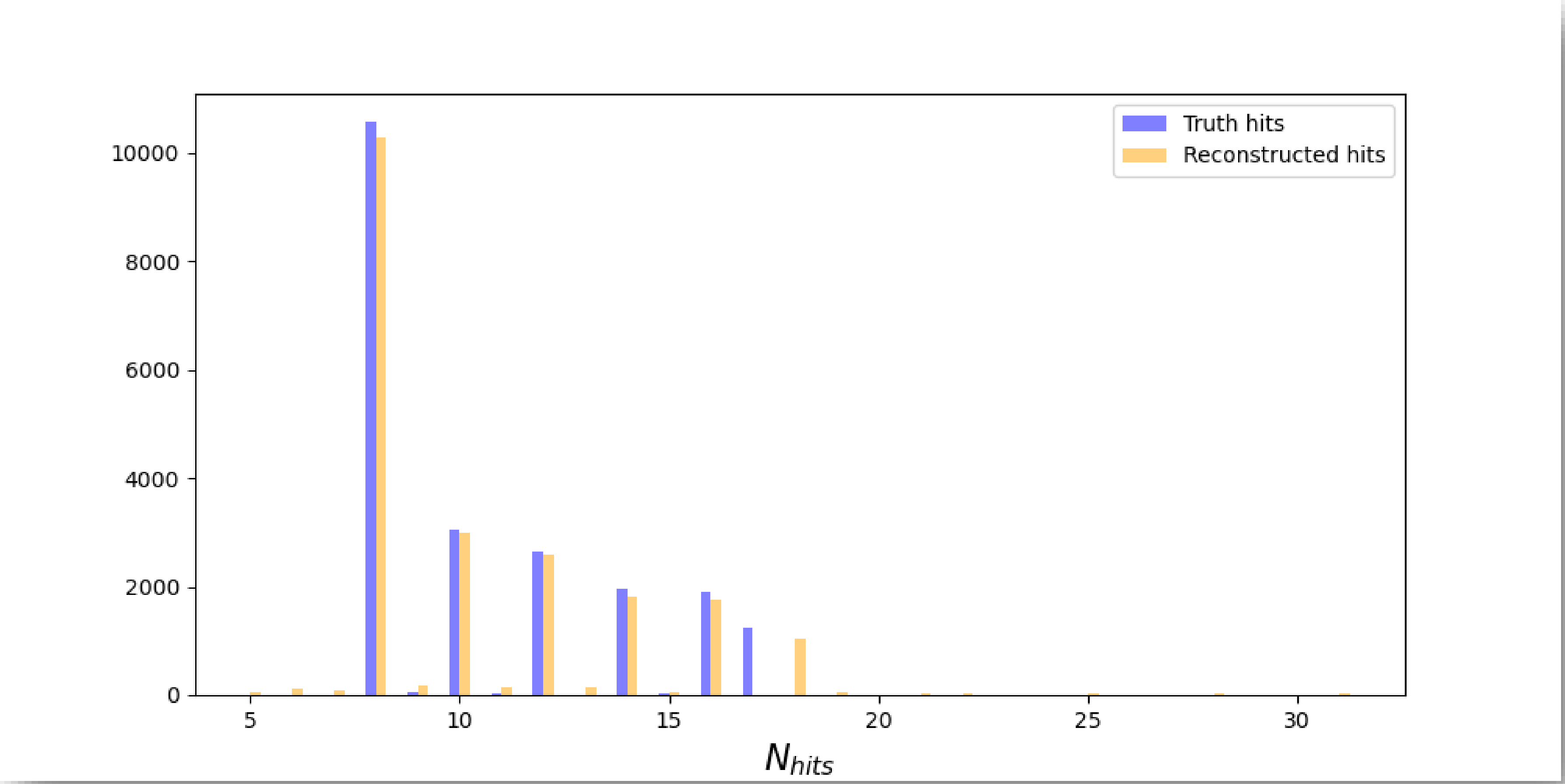


- The opening angle has no impact on the Quirk reconstruction efficiency in well-behaved Quirk training.

Distribution of reconstructed quirks

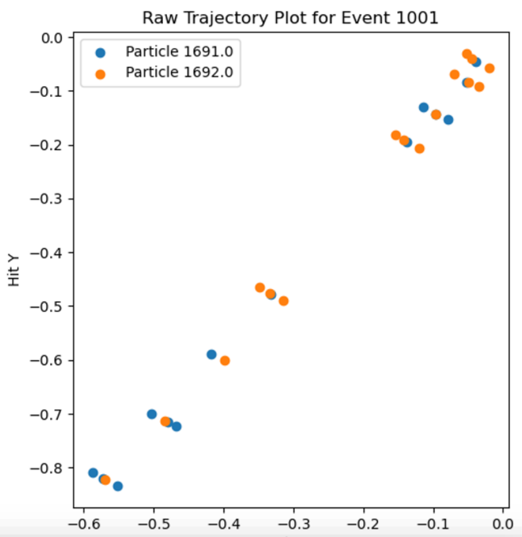
The distribution of reconstructed quirks' information:

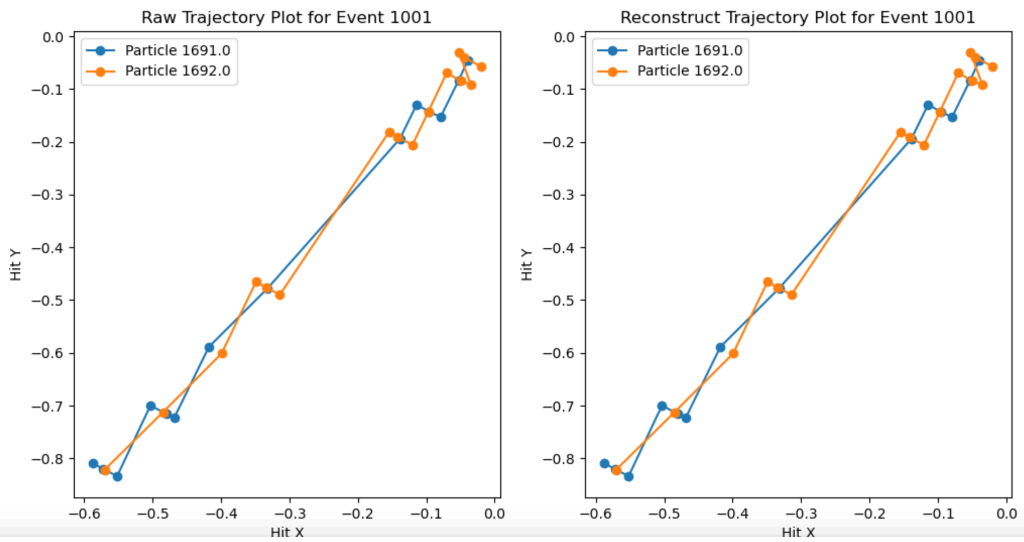
- $r, \phi, z(cm)$ are truth information of hits. r is scaled to (0,1). The plots are shown in the backup.
- n_{reco}^{hits} is the number of reconstructed hits, n_{truth}^{hits} is the number of truth hits.

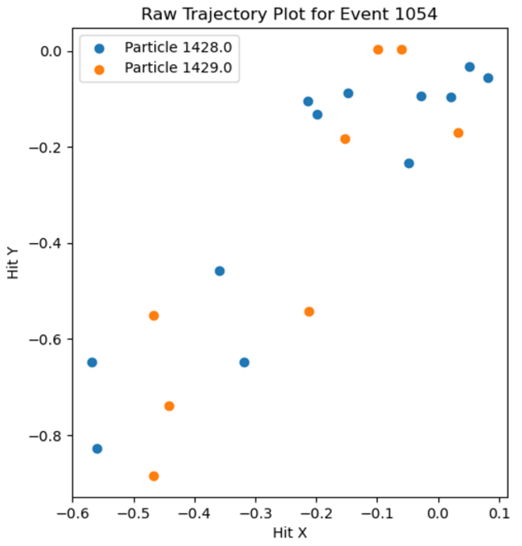


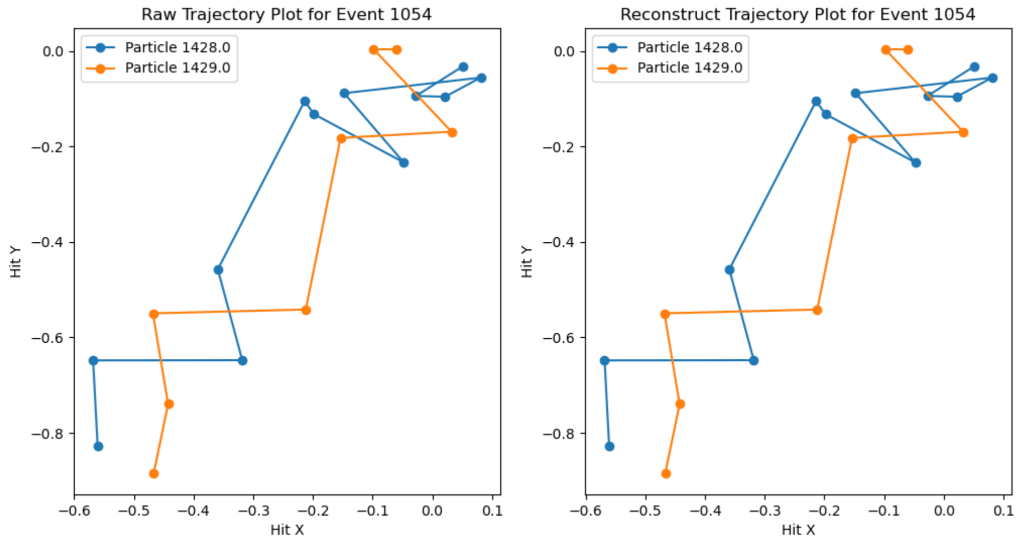
Reconstructed hits of quirk

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



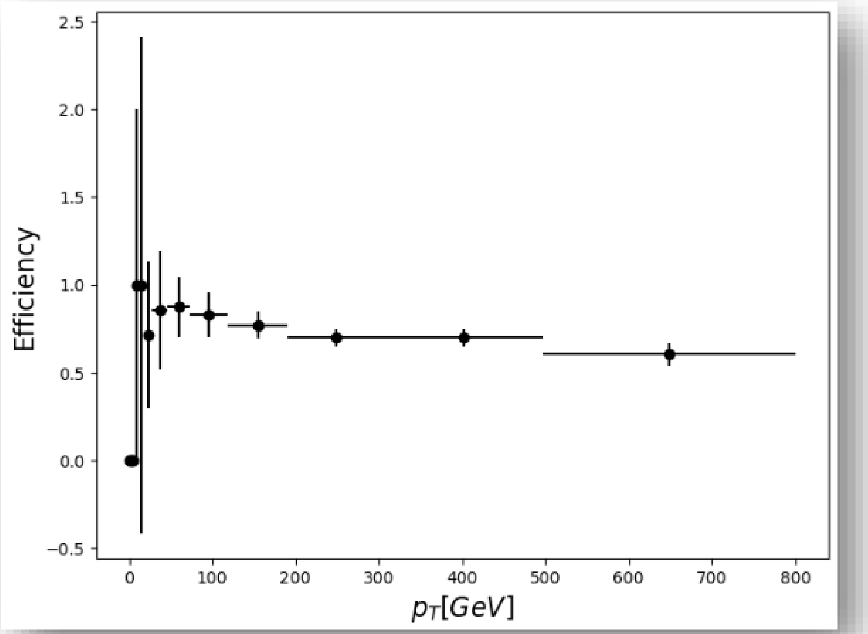


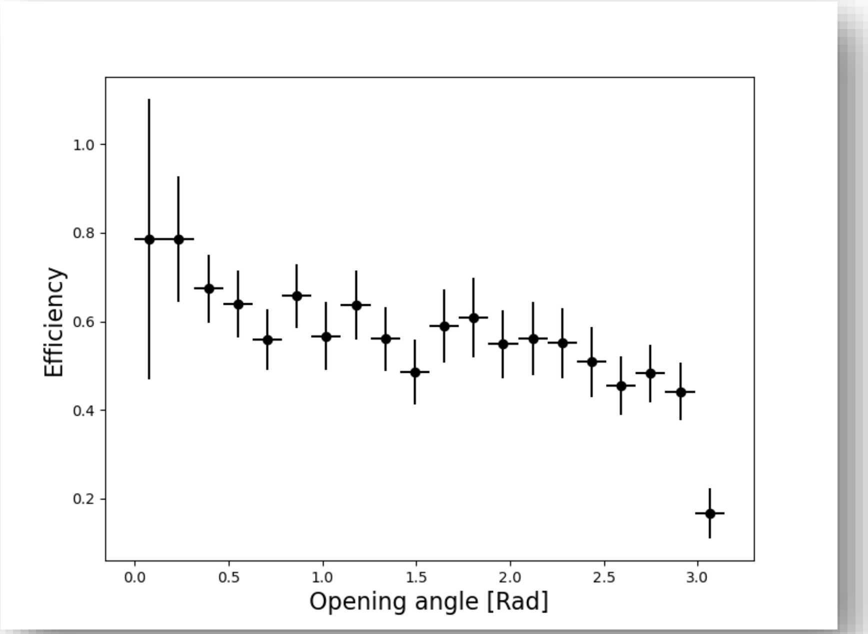




Results: All Quirk training, quirk inference

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

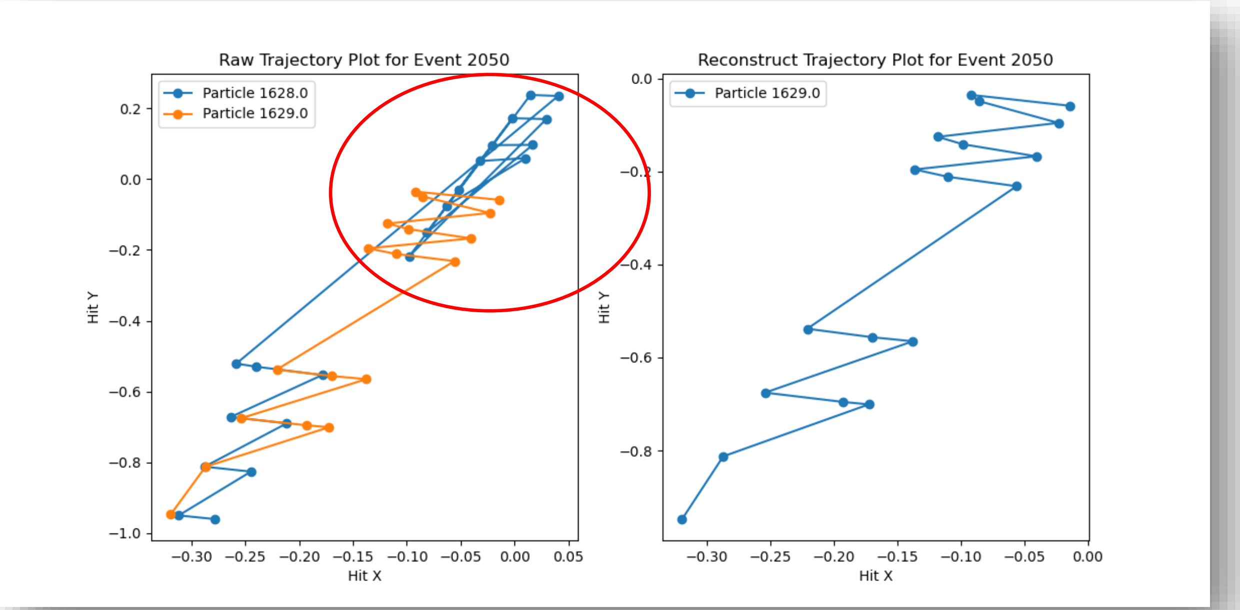


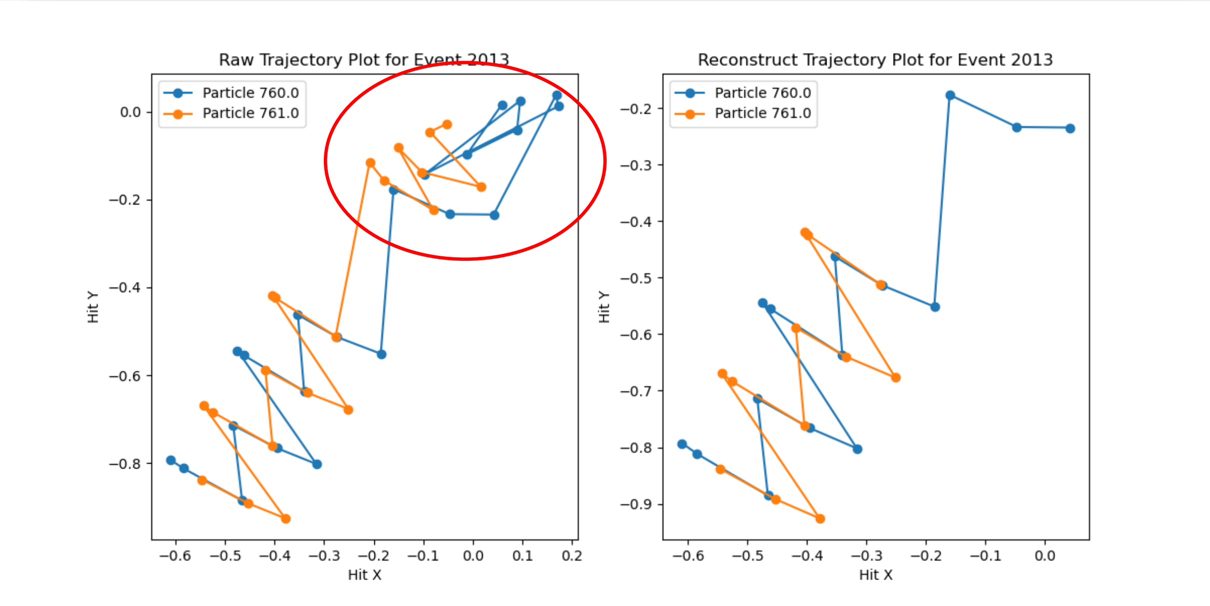


- Reconstruction efficiency decreases as the opening angle increases.

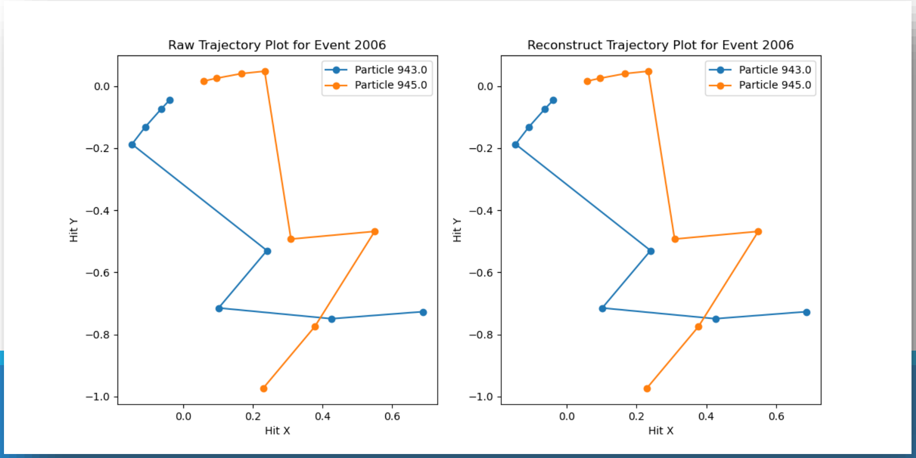
Reconstructed hits of quirk

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





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



Conclusion and future work

- We show that ML-based tracking can learn to reconstruct non-helical tracks with high efficiency when training on non-helical tracks. That will allow for powerful new quirk searches and open the door to other weird-track searches
- Could use non-helical tracks as a tool to understand GNN reconstruction on helical tracks, or hard-to-reconstruct SM particles

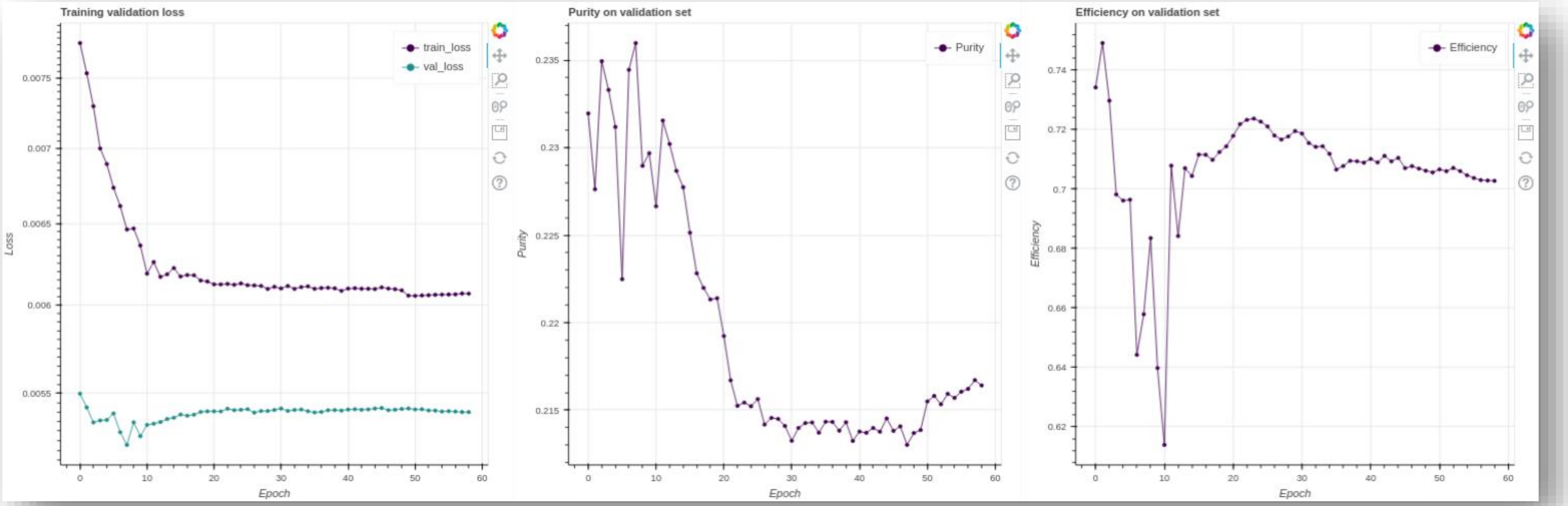
Next step:

- Generate more events and add more layers.
- Modify the pipeline to improve the results.
- Considering noise.

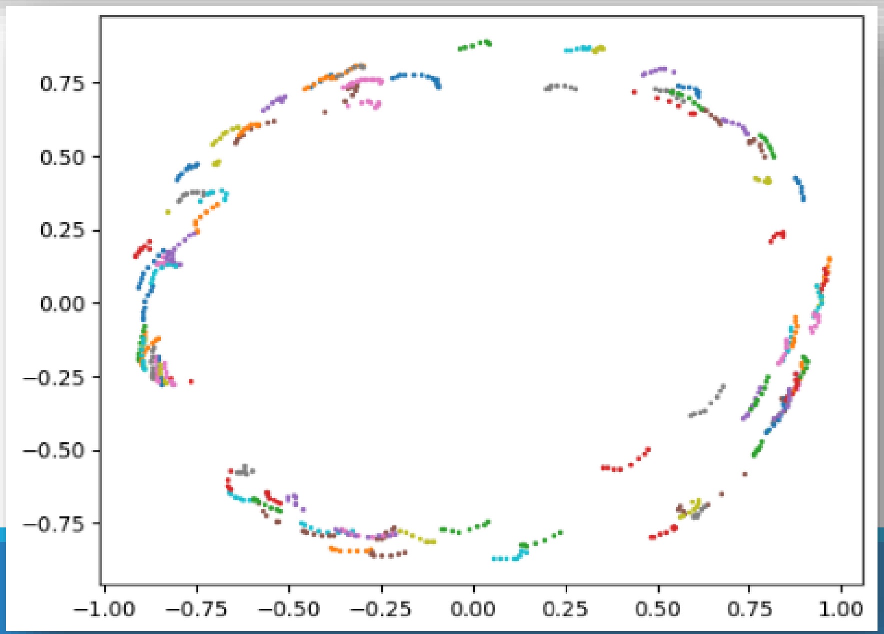
Backup

Metric Learning: Background training, quirk inference

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

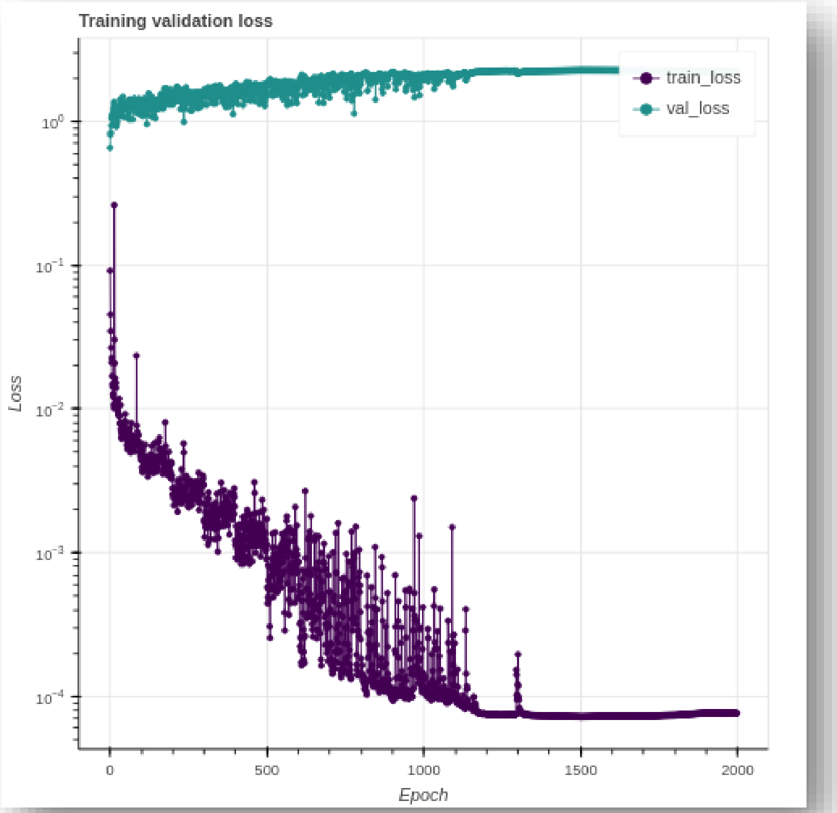


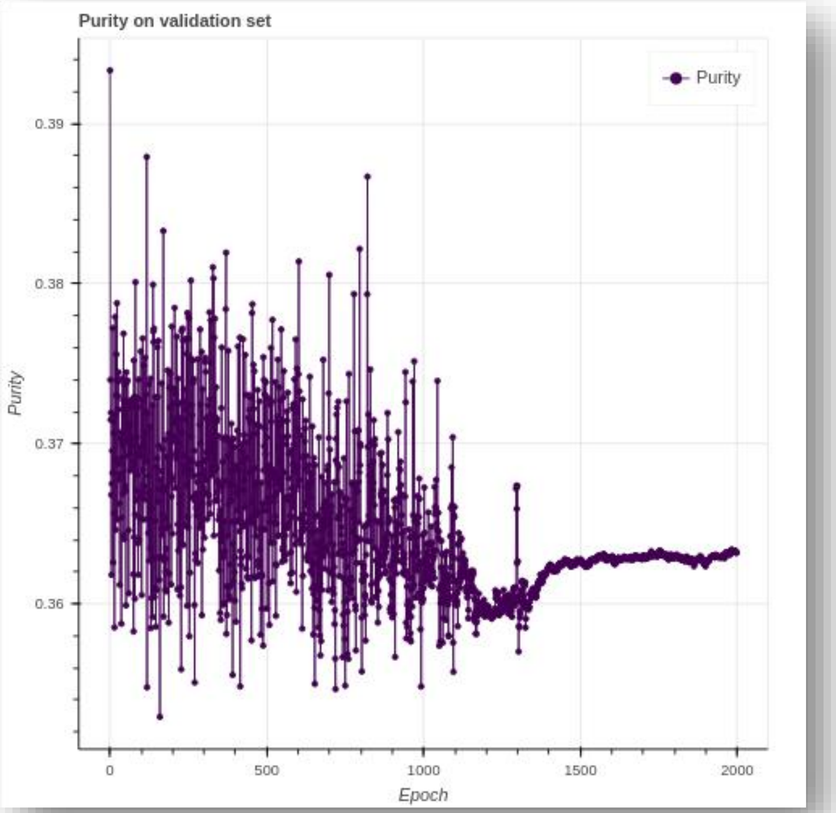
After Embedding:

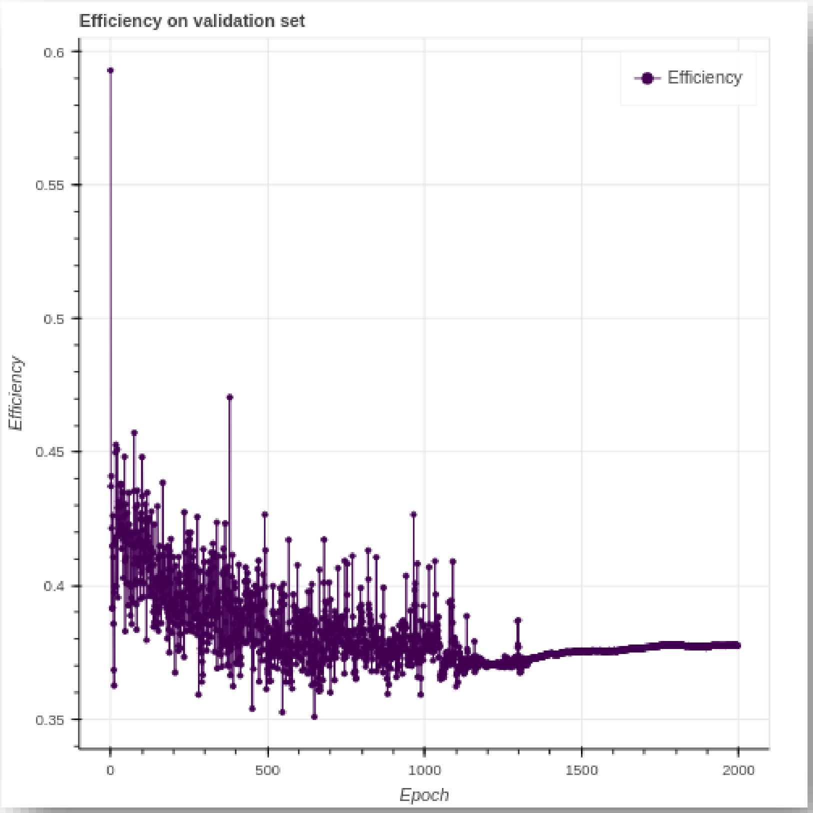


GNN: Background training, quirk inference

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







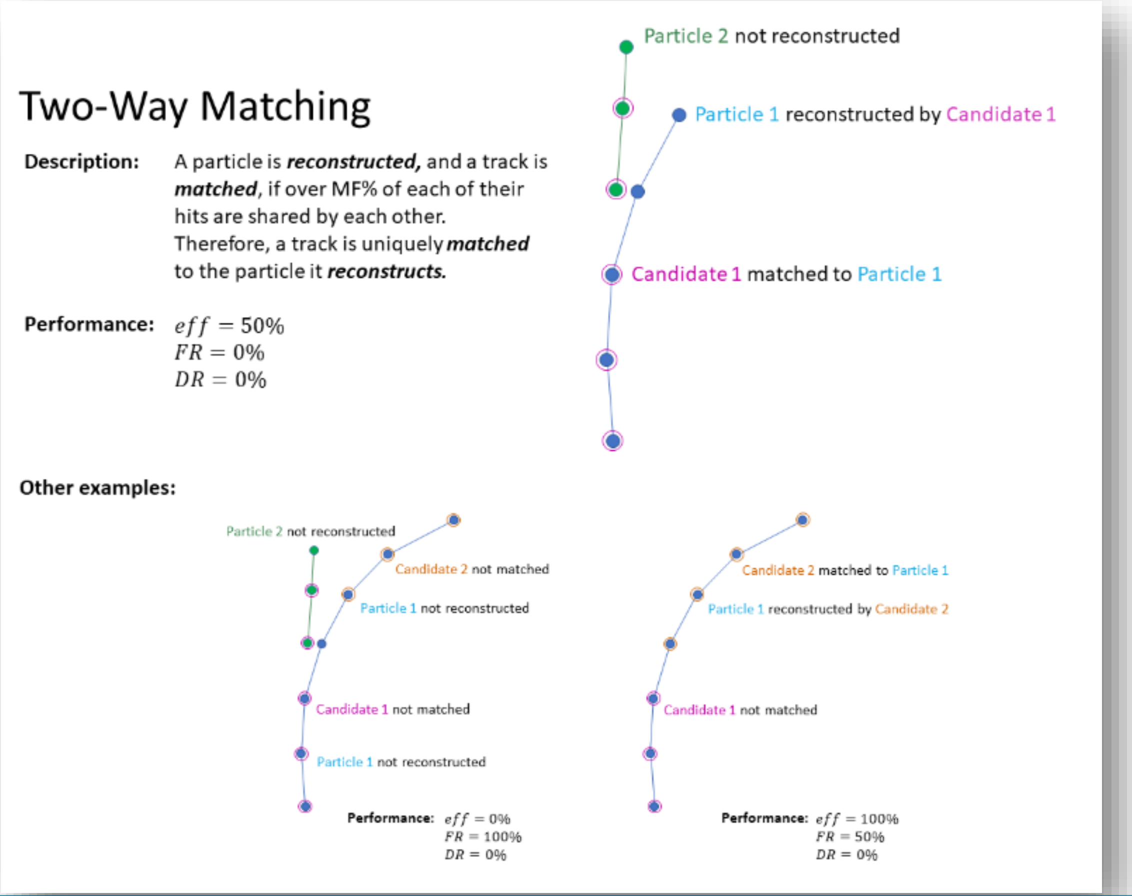
Performance – Tracking definitions

Physics cuts: {$|\eta| < 4$}

Some selection for reconstructed particles: For bkg, we have 8 true hits for each particles, for quirk, we have ≥ 8 true hits.

- min_reco_length: 5 (Reconstructable)
- min_truth_length: 7

- Matching style: Two_way



Distribution of reconstructed quirks

The distribution of reconstructed quirks' information:

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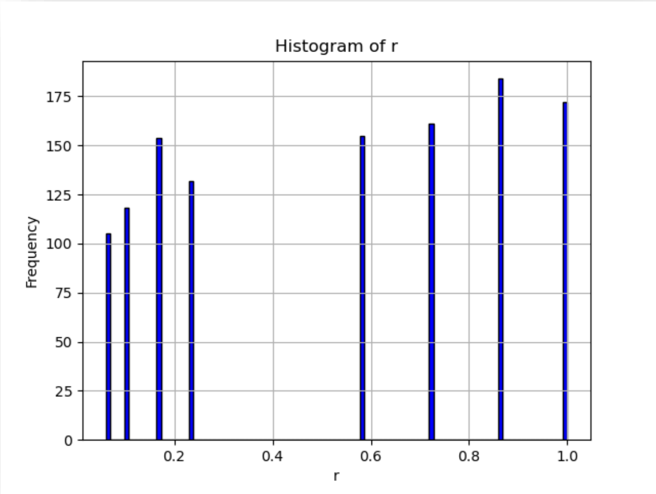
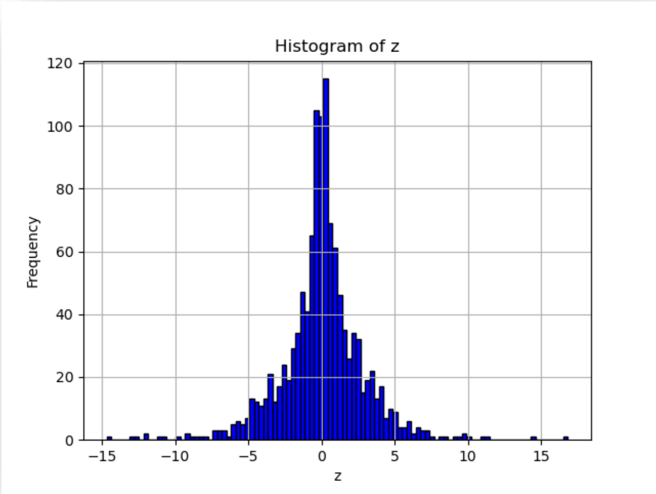
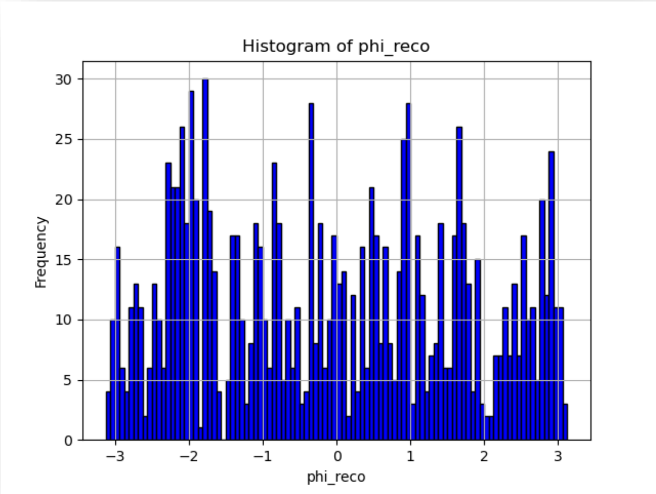
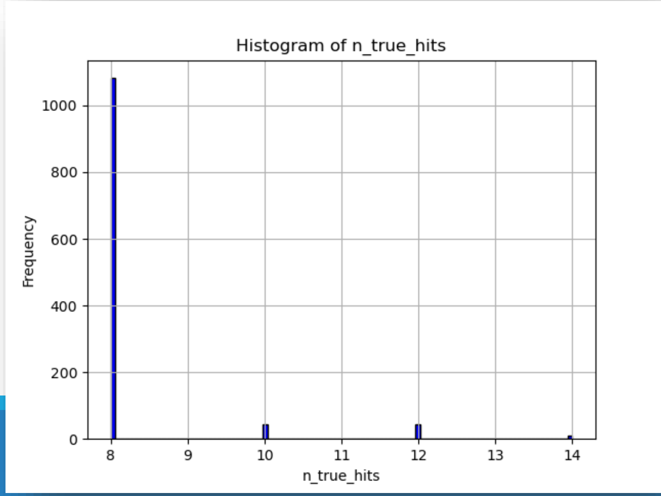
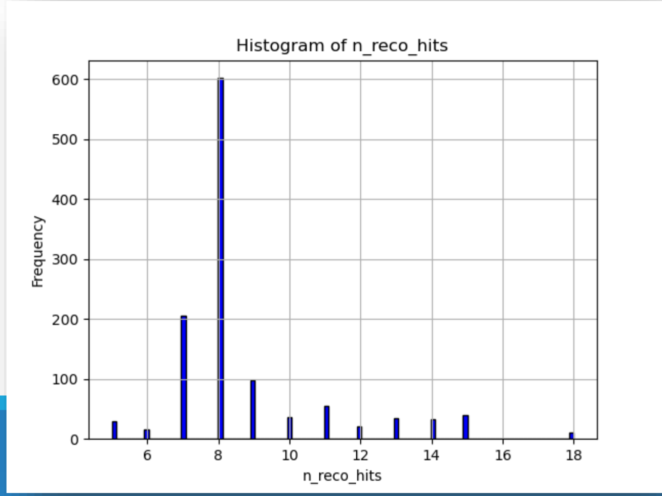
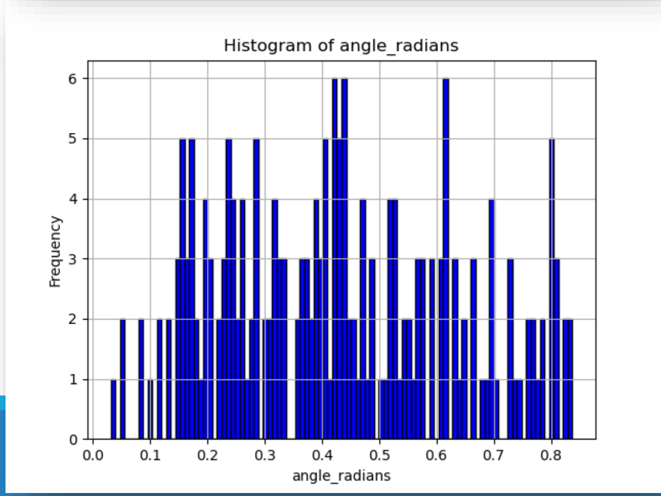








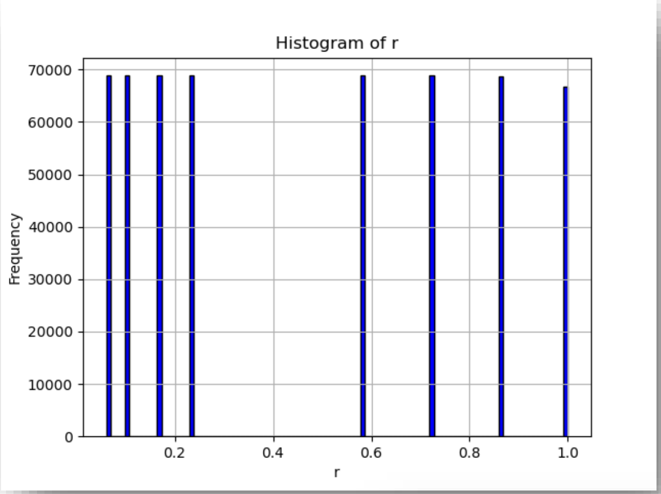


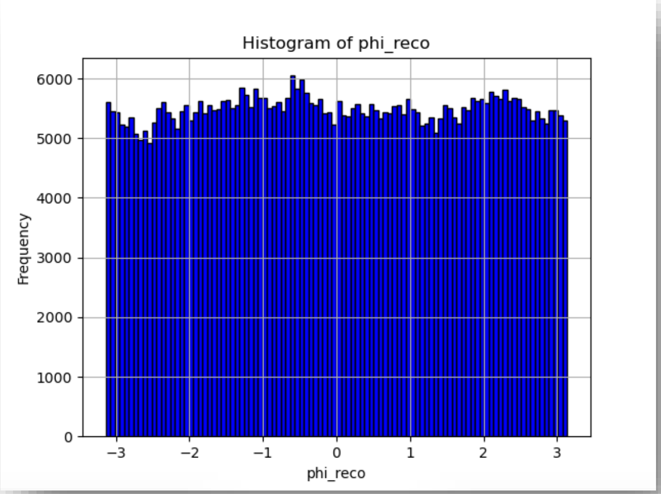


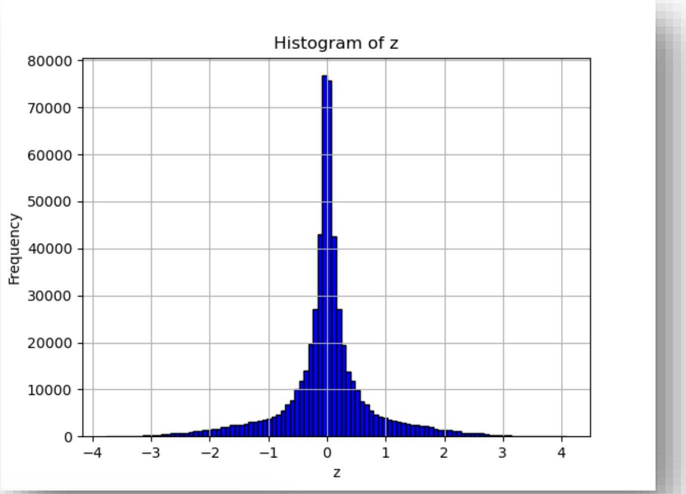
Distribution of reconstructed background

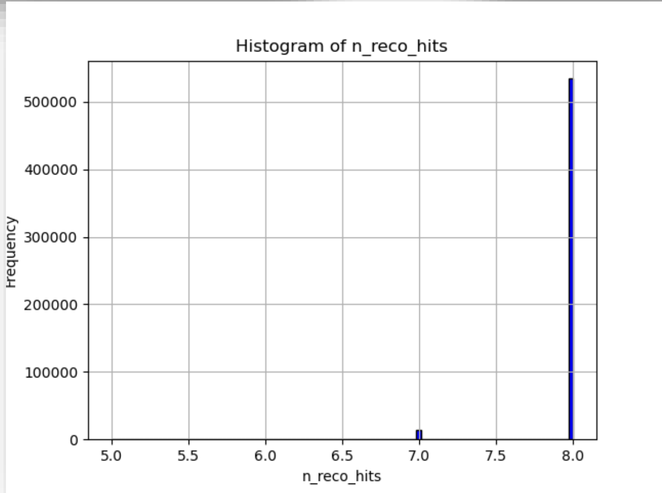
The distribution of reconstructed bkg(SM)s' information:

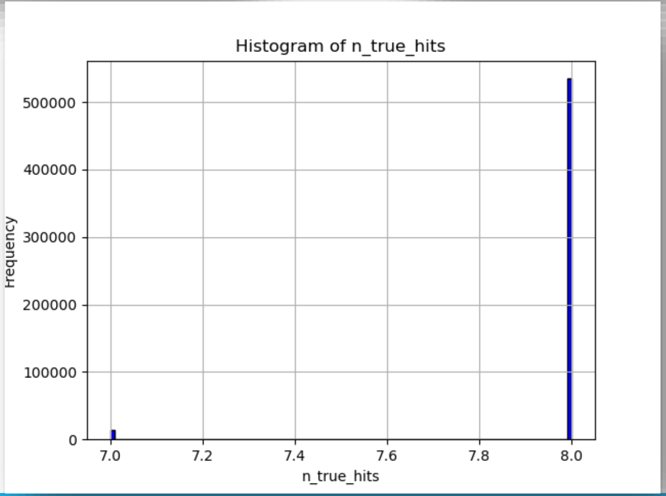
- The reconstructed information is similar as the truth information (n_hits)







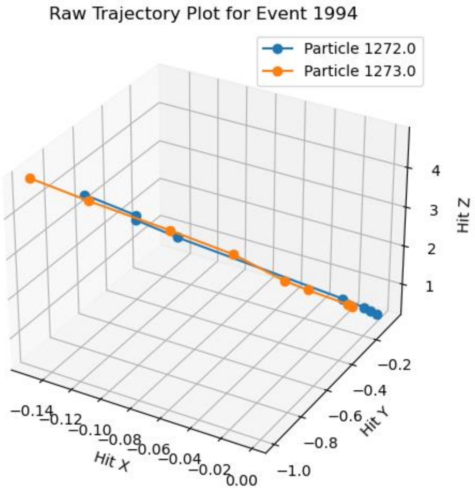


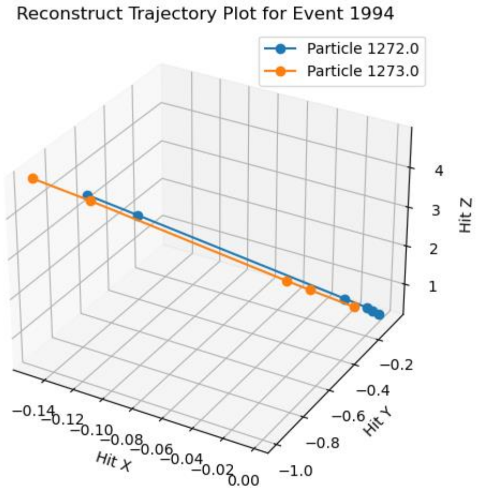


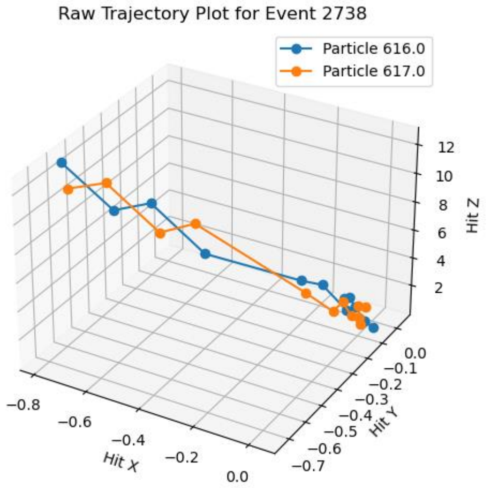
Reconstructed hits of quirk

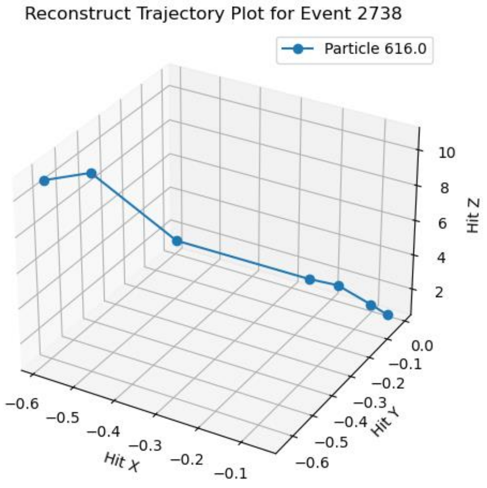
With same event (use the reconstructed event information):

- Some $\mathrm{hits}_{\mathrm{reco}}$ are the part of truth quirk track.
- Only reconstruct simple and smooth track.



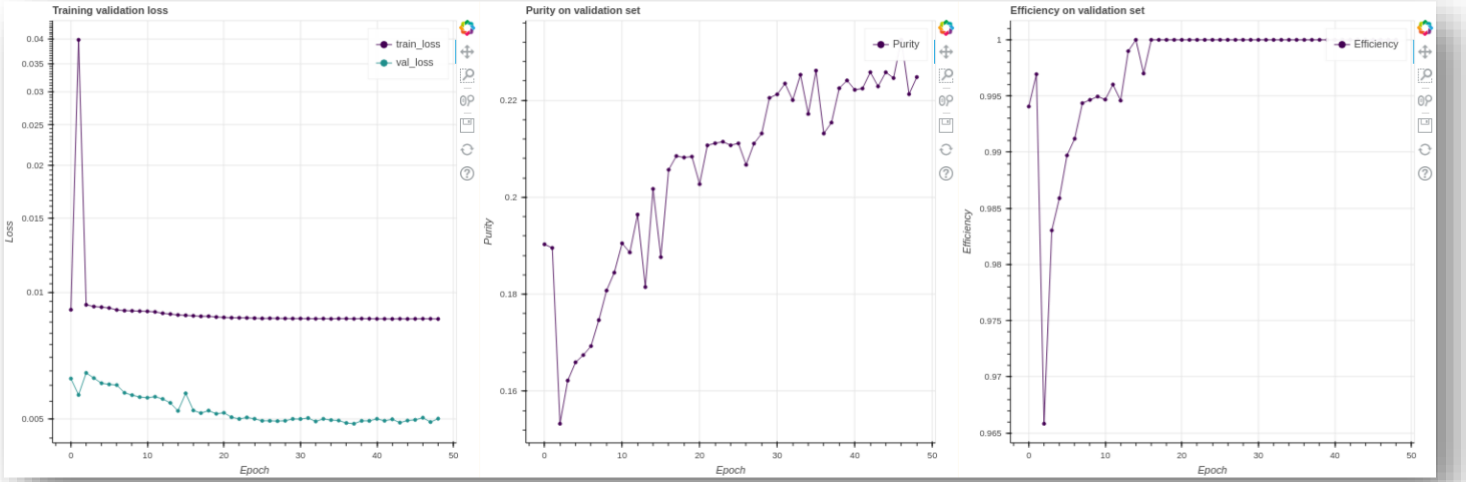




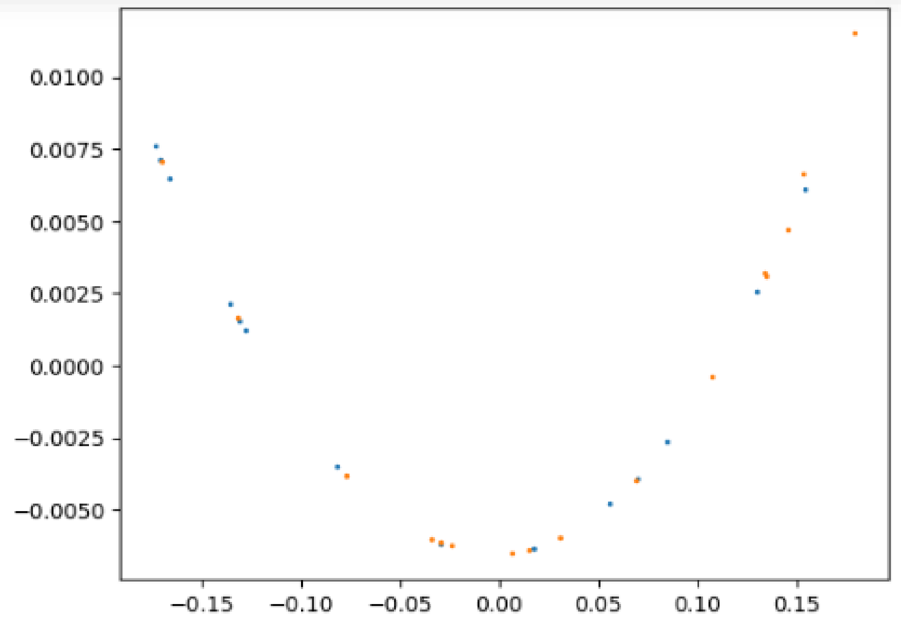


Metric Learning : Quirk training, quirk inference

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

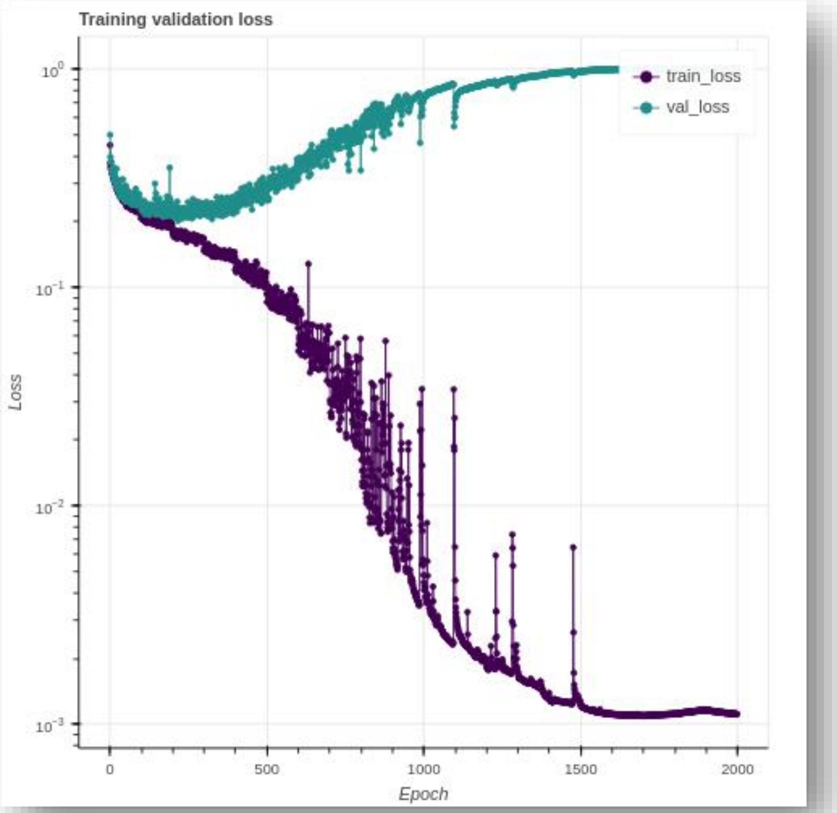


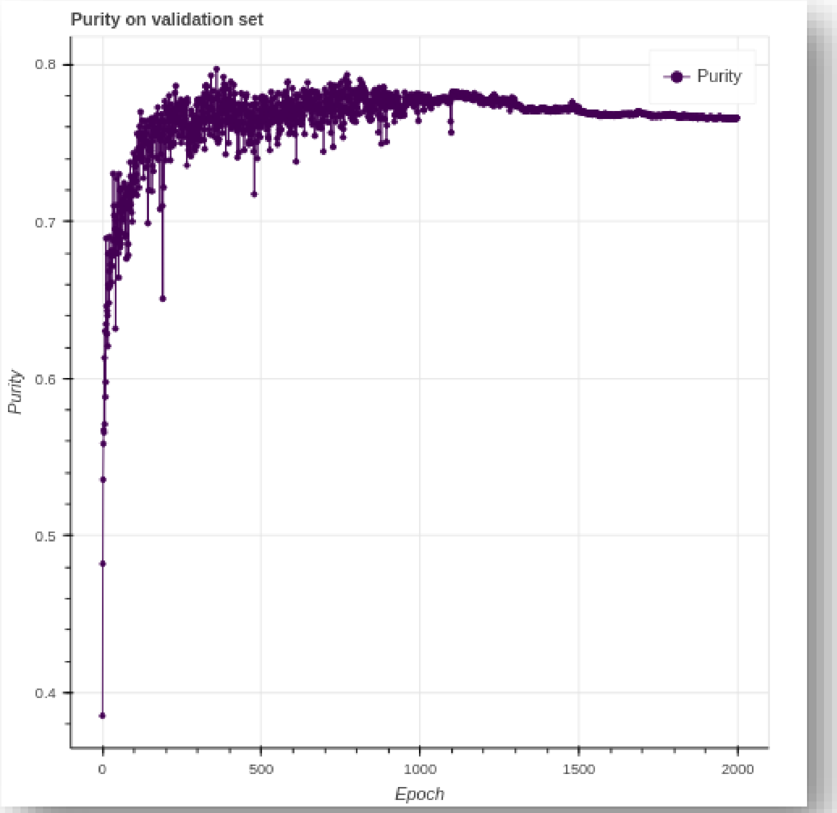
After Embedding:

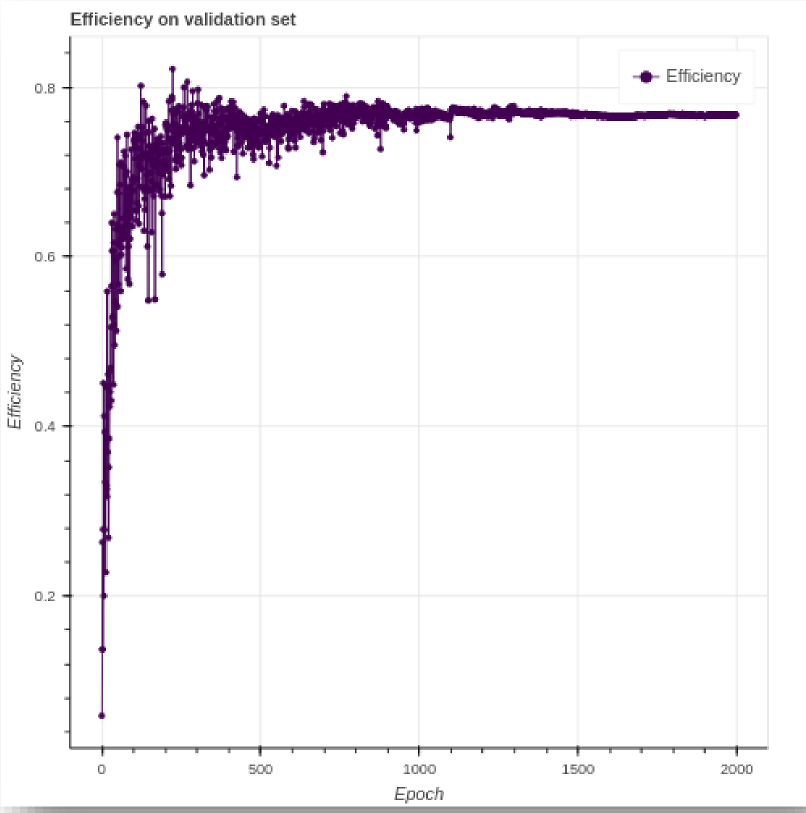


GNN : Quirk training, quirk inference

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

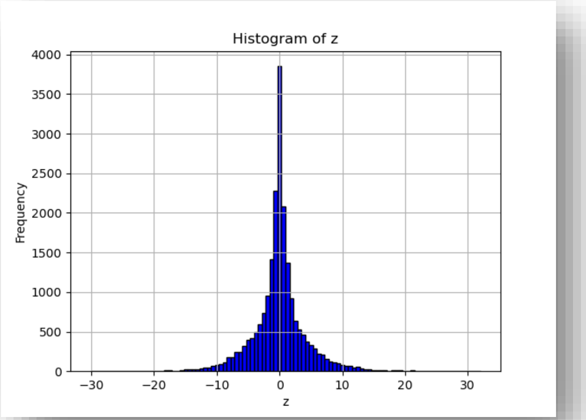


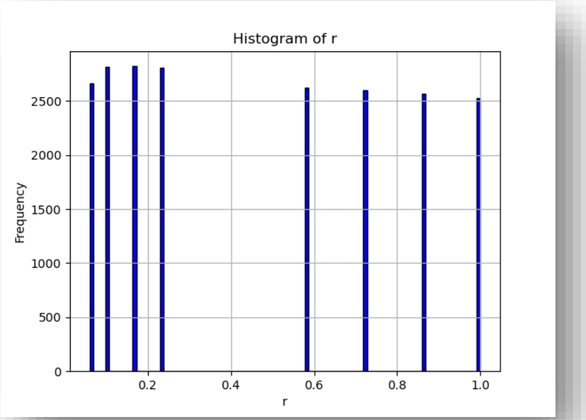


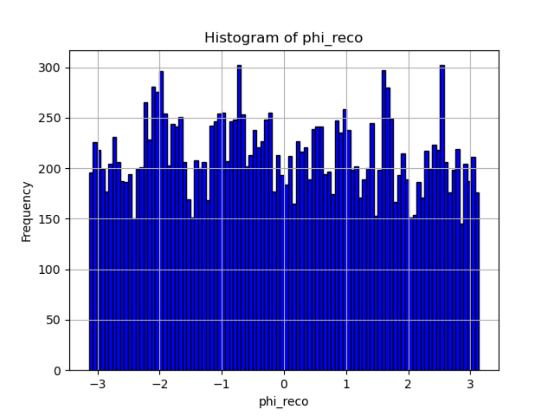


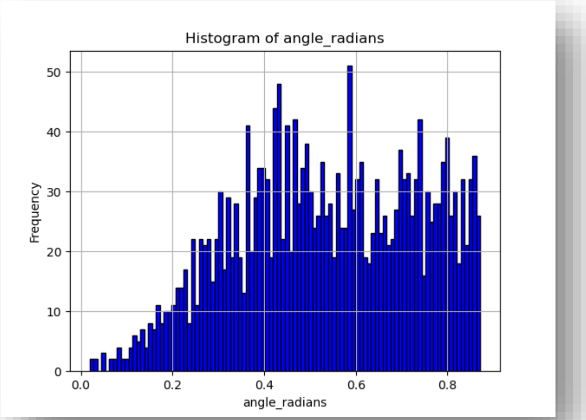
Results: Quirk training, quirk inference

Distribution of reconstructed quirks:





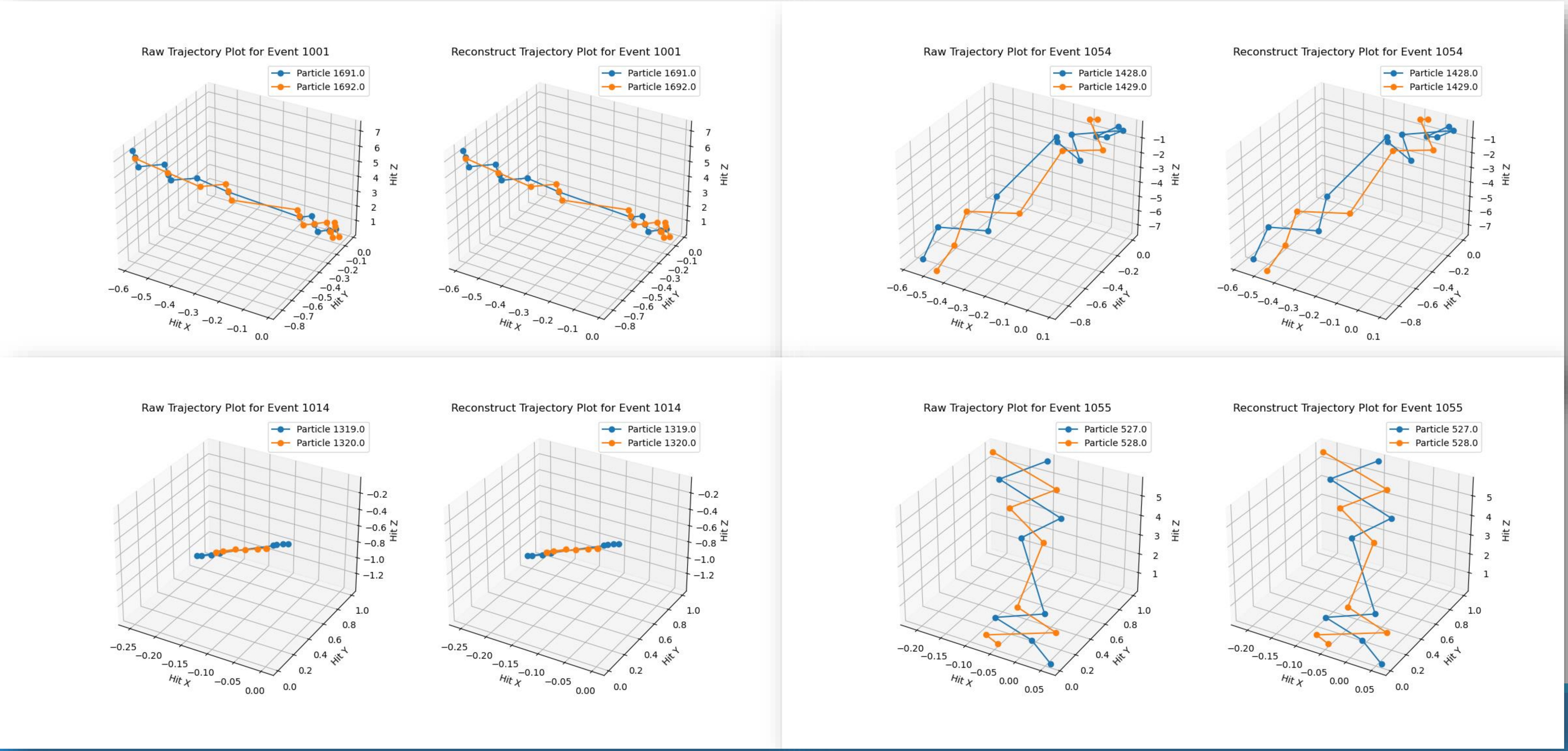




Qiyu Sha qsha@cern.cn

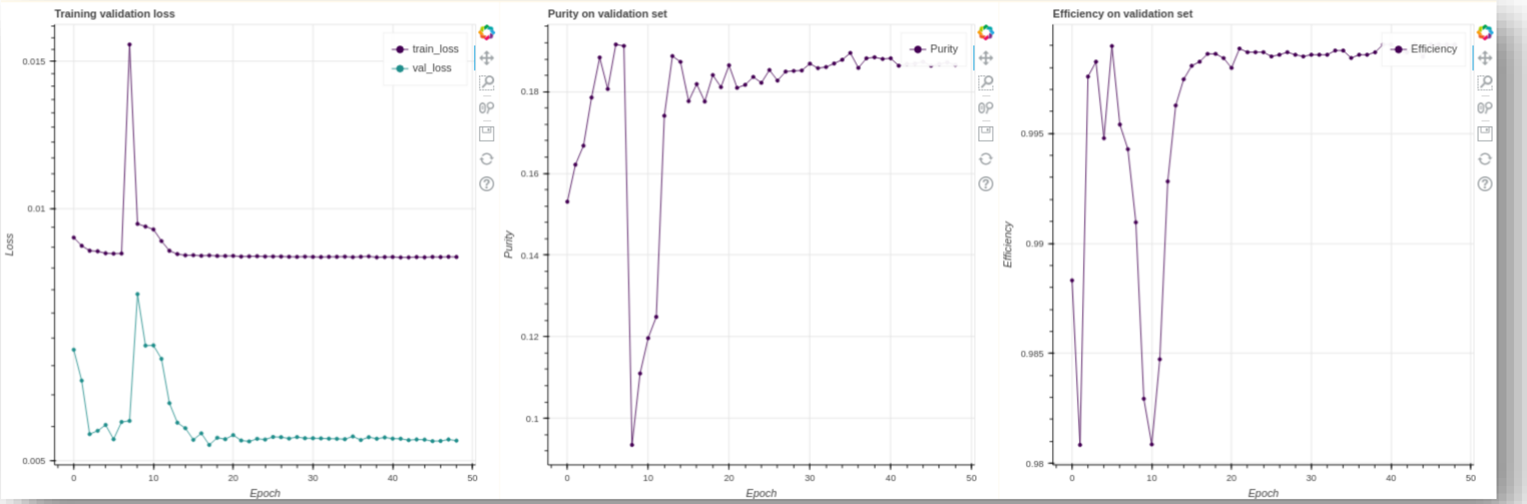
Reconstructed hits of quirk

All of well-behaved quirks are reconstructed well:

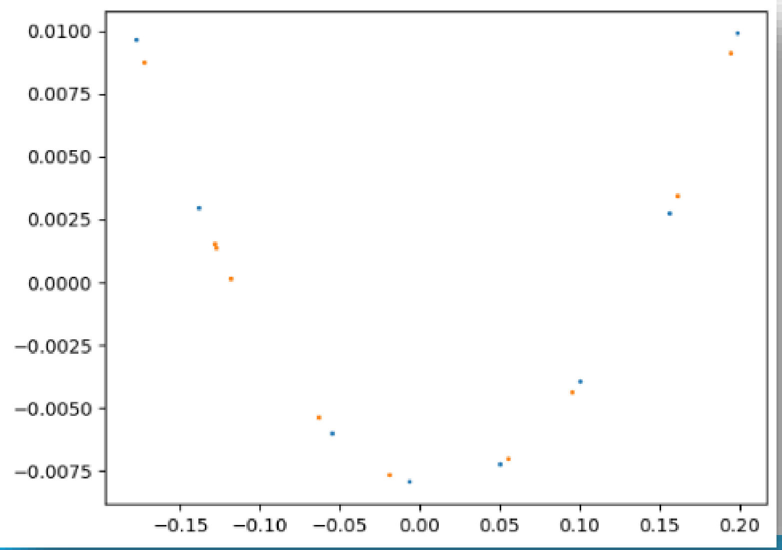


Metric Learning : All Quirk training, quirk inference

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

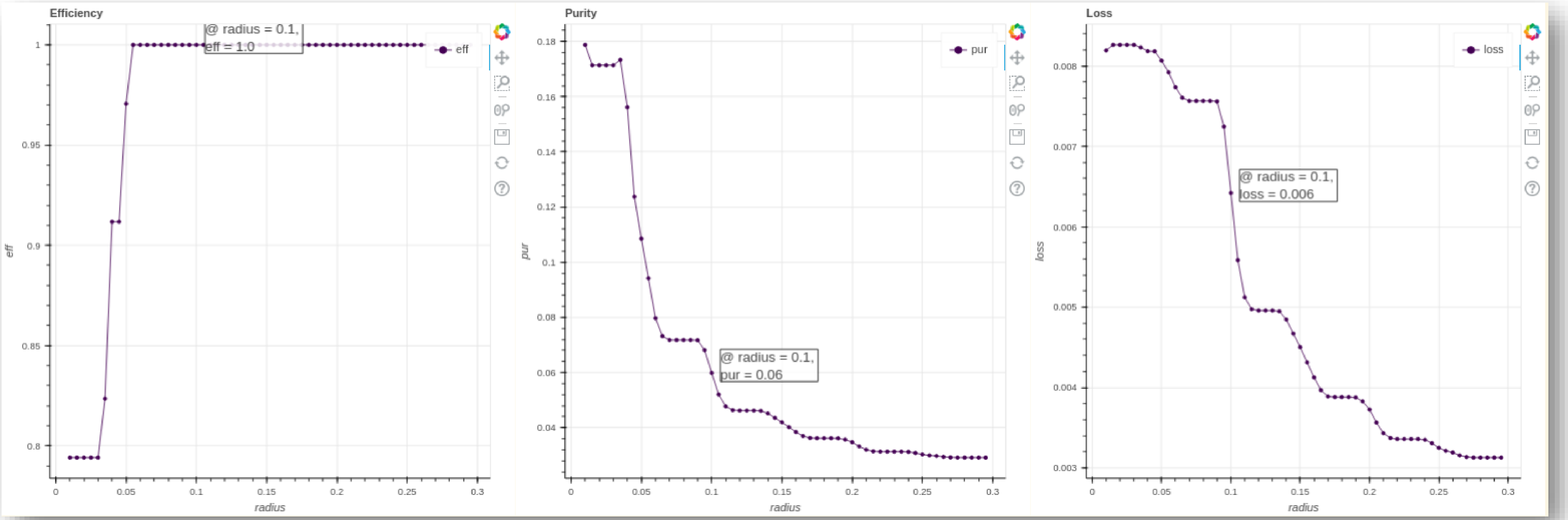


After Embedding:



Metric Learning : All Quirk training, quirk inference

Evaluate the model performance on one test data sample to see how the efficiency and purity change with the embedding radius.



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)