Simultaneous Track Finding and Track Fitting with Deep Neural Network at BESIII

Yao ZHANG[1] , Ye YUAN[1,2] , Haiyong JIANG[2] , Zhibin YANG[1]

1. Institute of High Energy Physics, Chinese Academy of Sciences, Beijing

2. University of Chinese Academy of Sciences

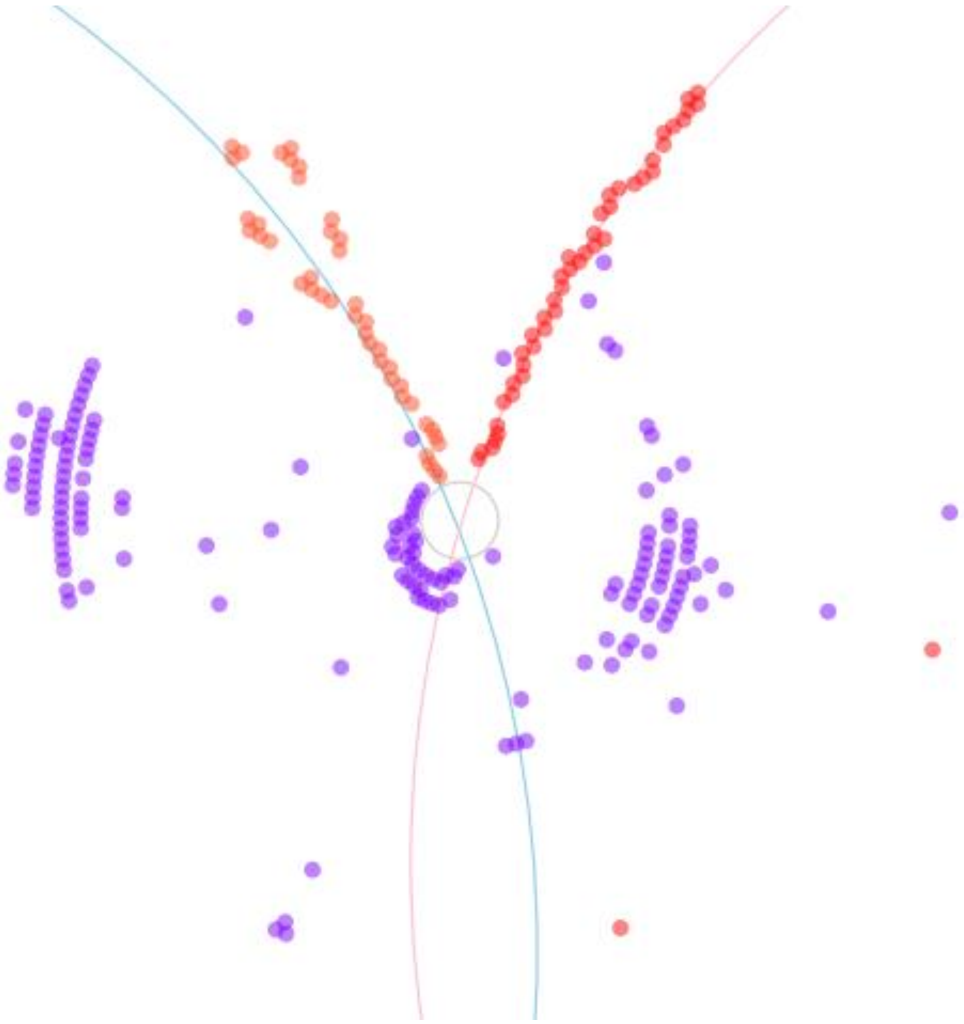
Workshop of Computing Software and Technologies in Particle Physics Experiments

June 11, 2023, Qingdao

Speaker: Zhibin Yang

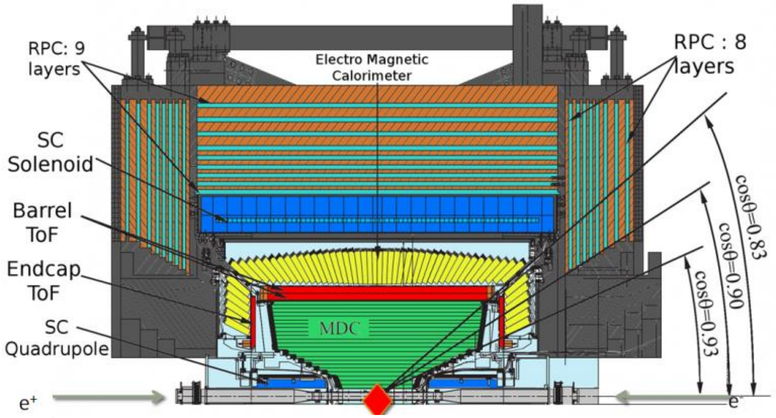
Outline

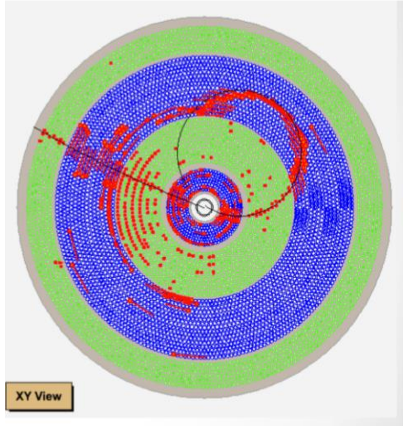
- **Background and motivation**
  - BESIII MDC Tracking
  - GNN approaches
- **Model structure**
  - Point cloud data
  - PointNet and PointNet++
  - Clustering and fitting network
- **Current results**
  - Performance
- **Next step**
  - Remain problems and future work
  - BESIII tracking dataset for ML
- **Summary**



BESIII MDC Track Reconstruction

- Track finding
  - Template matching
  - Mathematical transformation (Hough transform, Conformal mapping, Legendre transform)
- Track fitting
  - Least squares fitting
  - Kalman filter

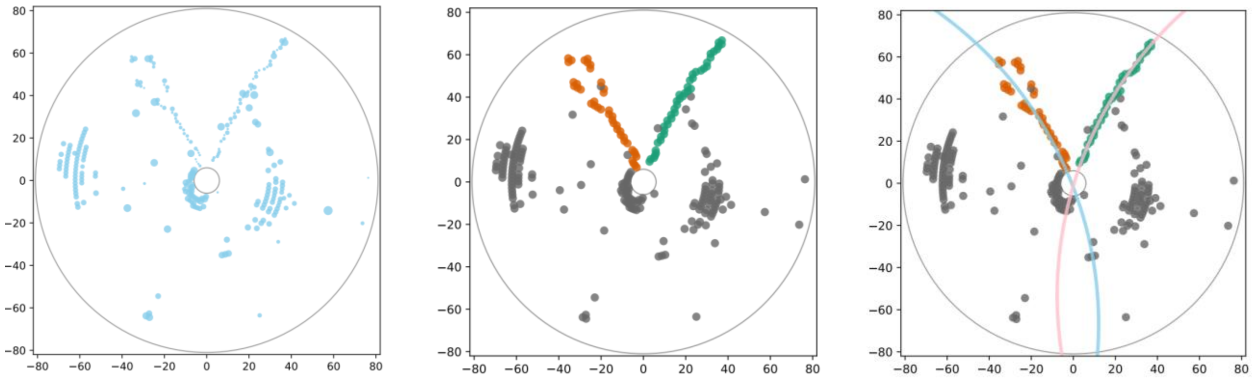




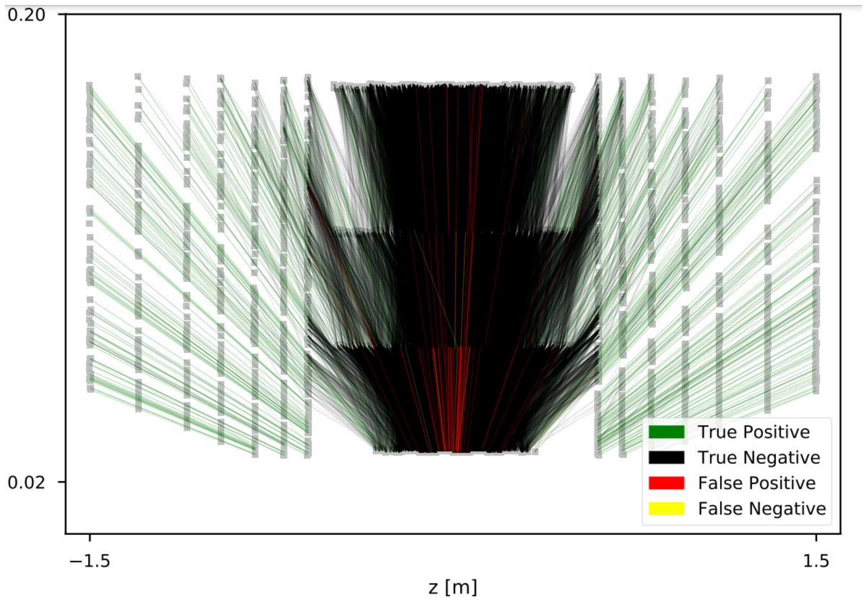
- Why Machine Learning
  - Limited computing resource
    - e.g. HL-LHC
  - Improve traditional tracking algorithms
    - Low transverse momentum
    - Large dip angle
    - …
  - Promising results have been shown [1]
    - Charged particle tracking
    - Secondary Vertex Reconstruction
    - Pileup Mitigation
    - Calorimeter Reconstruction
    - Particle-Flow Reconstruction

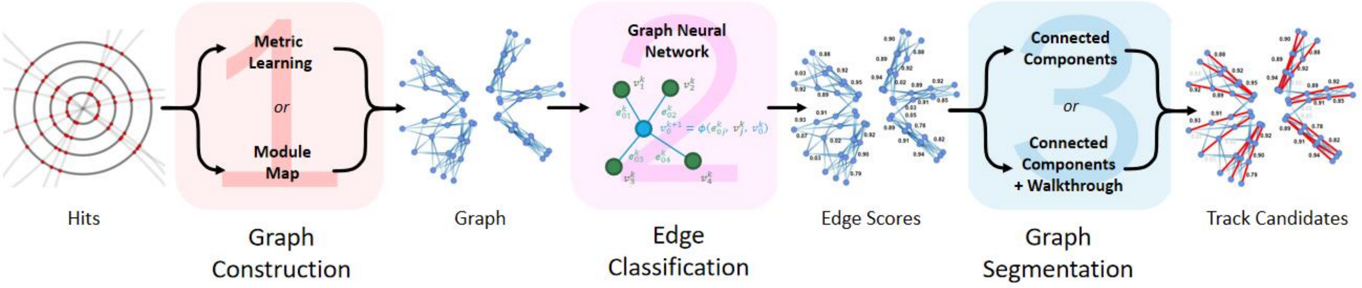
Graph Neural Networks on Track Reconstruction

- ML for tracking
  - **Classification** of signal and noise
  - **Clustering** of signal (track finding)
  - **Fitting** of tracks



- GNN pipeline [2]
  - Pros: Graphs can capture inherent sparsity of much physics data
  - Cons: Graph construction is needed, poor result on clustering, originally for pixel detector

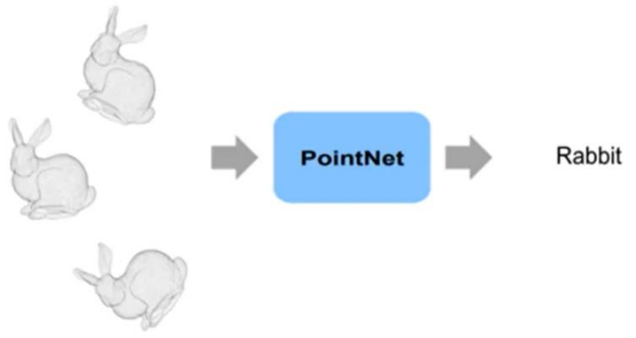




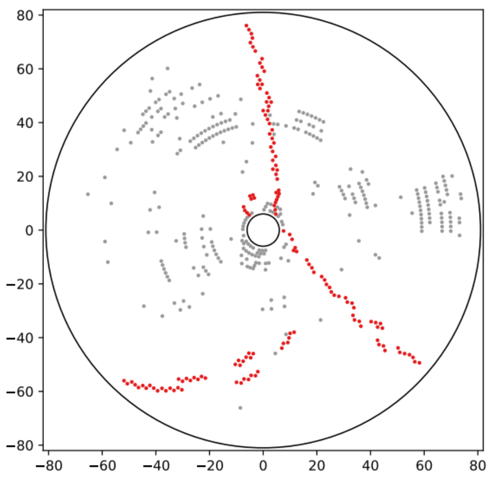
Point Cloud and Graph

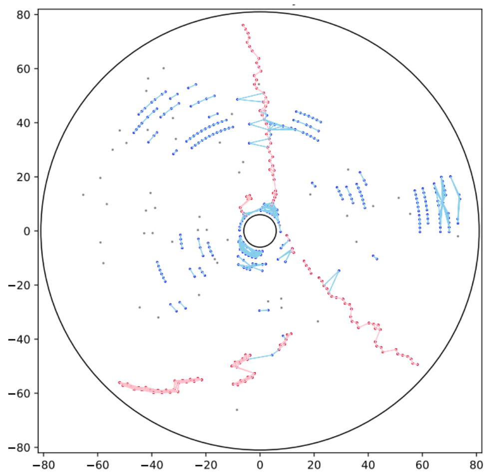
BESIII

- Point cloud data
  - Unordered point set as input
  - Invariance under geometric transformations
- Graph data
  - particle tracking data is naturally represented as a graph by identifying hits as nodes and particle trajectories as edges.



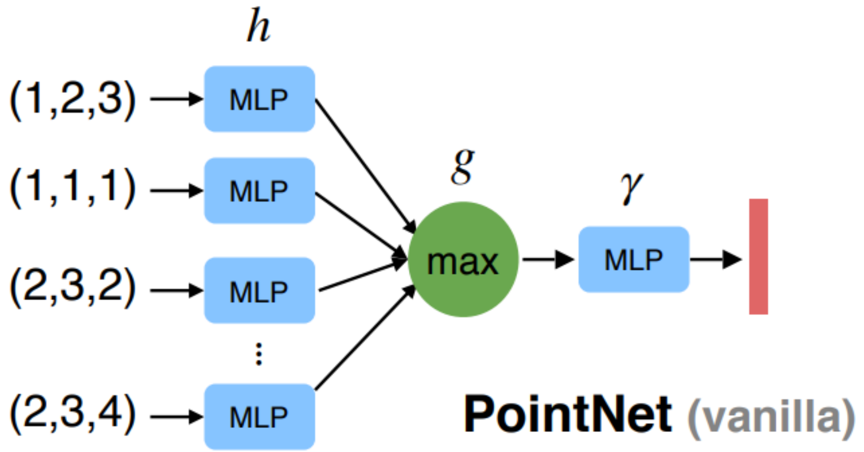
High Energy Physics Data	Papers	Classification ML Method
Jet image	3.57%	Deep neural networks
Event image	10.71%	Convolutional neural networks
Sequences	7.14%	Recurrent neural networks
Trees	3.57%	Recursive neural networks
Graphs	59.52%	Graph neural networks
Sets	15.48%	Point clouds base networks





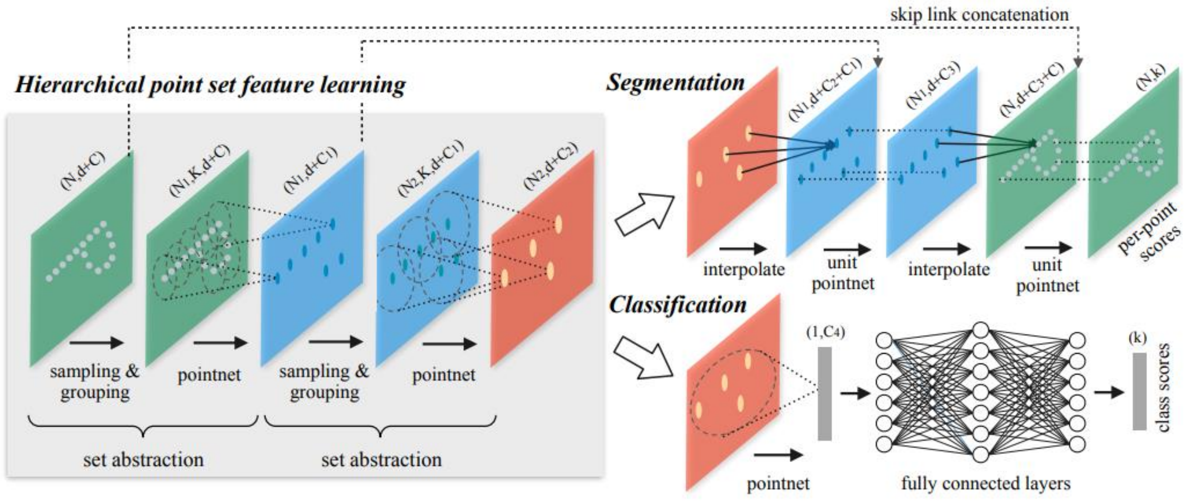
PointNet

- Point cloud data
  - Unordered point set as input
  - Invariance under geometric transformations



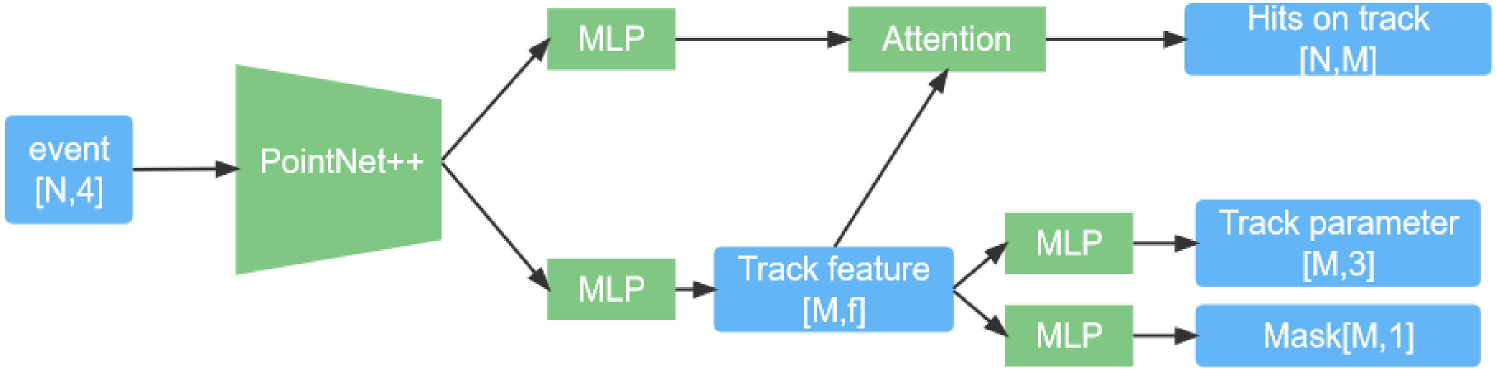
- PointNet [3] drawbacks: does not capture local structures

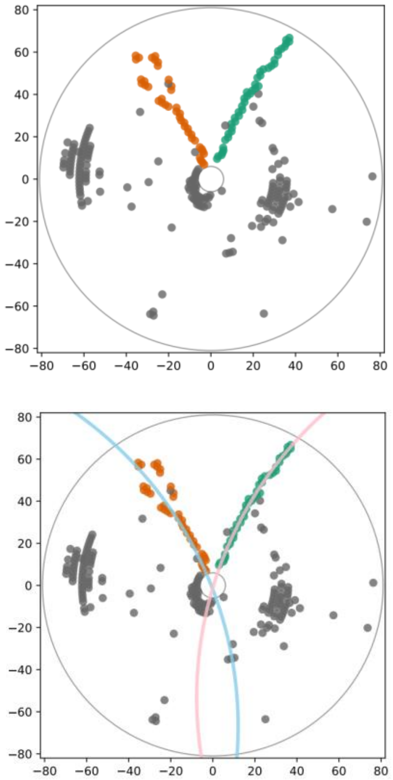
- PointNet++ [4]: added hierarchical structure to capture local features



Track Finding and Track Fitting Neural Network

- PointNet model on BESIII (Main Drift Chamber data)
  - Input data： Hits(wirePos_r, wirePos_phi, rawDriftTime)
  - Output:
  - 1. track index prediction for each hit (clustering)
  - 2. track parameters for each predicted track (fitting)
- Model:





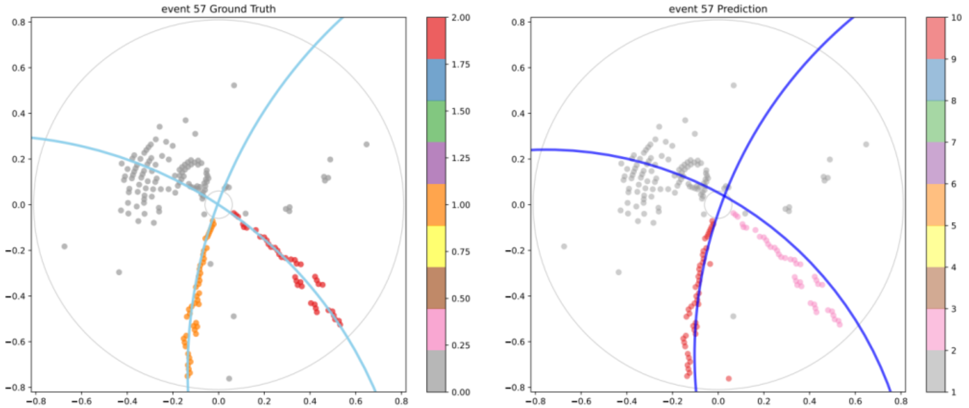
Performance – Track Finding

- Clustering evaluation:

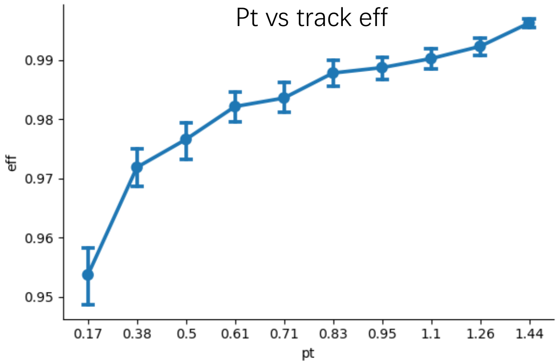
$$hit\ efficiency = \frac{N_{accurately\ predicted\ hits}}{N_{total\ hits\ in\ one\ physical\ track}}$$

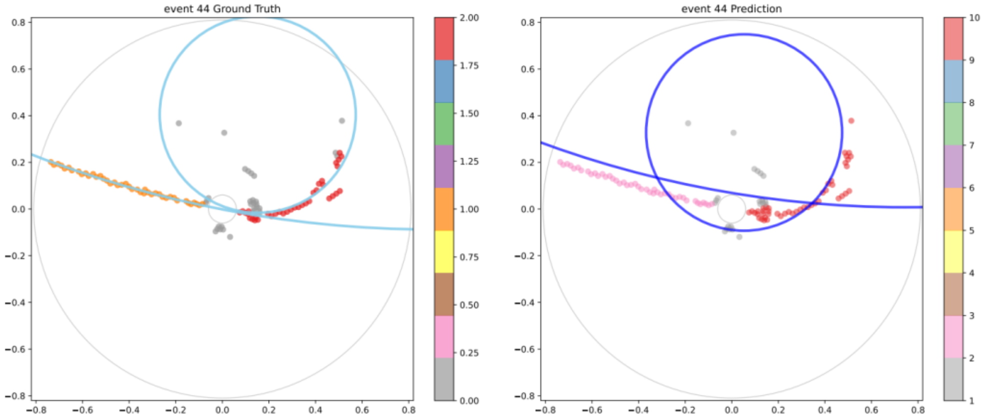
$$hit\ purity = \frac{N_{accurately\ predicted\ hits}}{N_{total\ hits\ on\ one\ predicted\ track}}$$

$$track\ efficiency = \frac{N_{tracks\ reconstructed}}{N_{total\ physical\ tracks}}$$



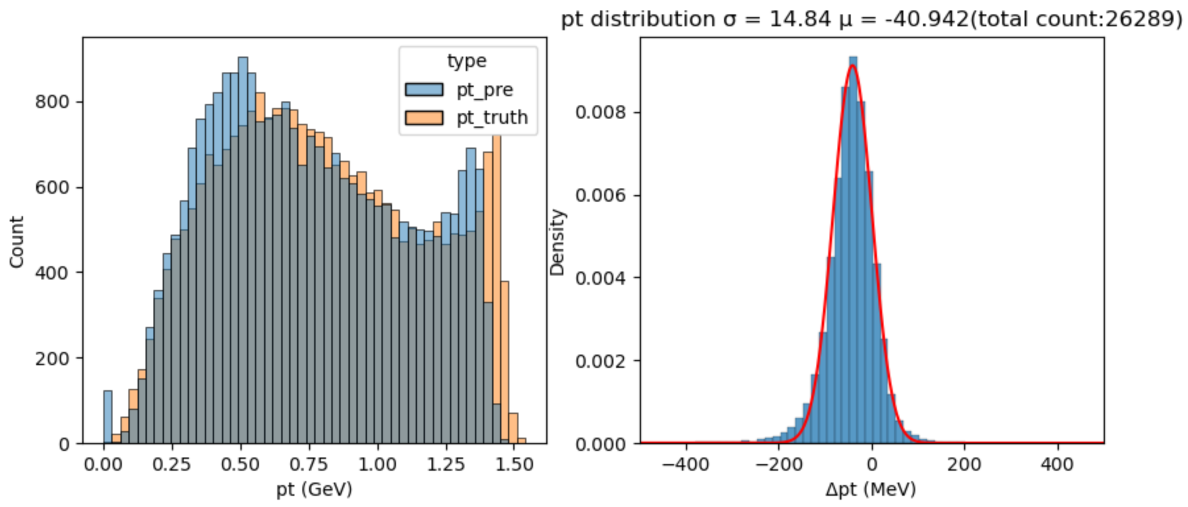
- Clustering results (Model No.: baseline_polar):
  - Training data set: 120k events (J/ψ–>ρπ)
  - Test set (15k events)：
    - Hit eff: 96.41%
    - Hit purity: 94.7%
    - Track eff: 97.17%

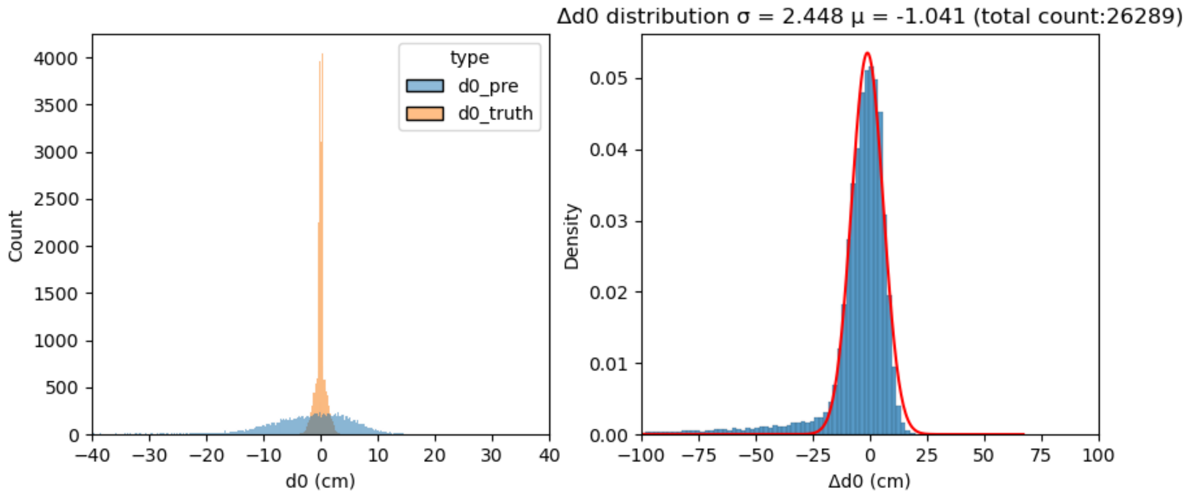




Performance – Track Fitting

- Resolution:
  - Transverse momentum: 14.84 MeV
  - Spatial resolution: 2.448 cm





Next Step

- Remain problems and future work
  - Clustering problem
  - Physics Inform
  - Integrate into BESIII Offline Software System
  - Network Structure Optimization
- BESIII tracking dataset for Machine Learning
  - Inspired by TrackML dataset[5]
  - Goals:
    - Easier development for different ML methods
    - Performance evaluation under the same dataset
  - Suggestion and try out are welcome!

Summary

- We propose a novel neural network approach for drift chamber tracking
  - An end-to-end multi-trajectory tracking
  - Hit clustering and track estimation simultaneously
- Preliminary performance of this work is promising