GNN for BESIII tracking

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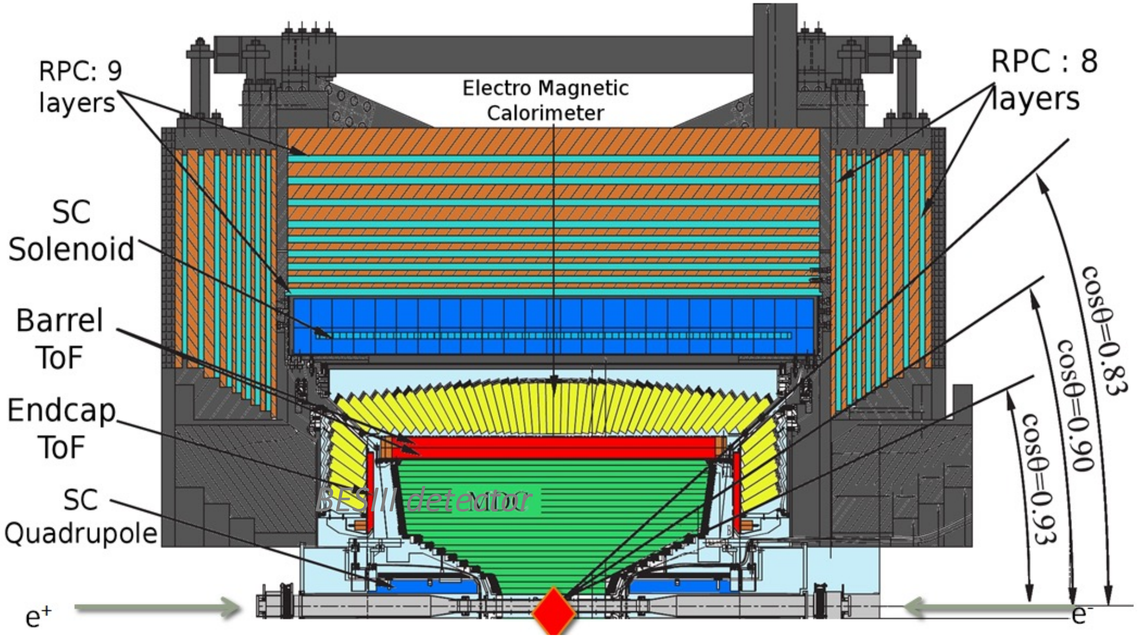
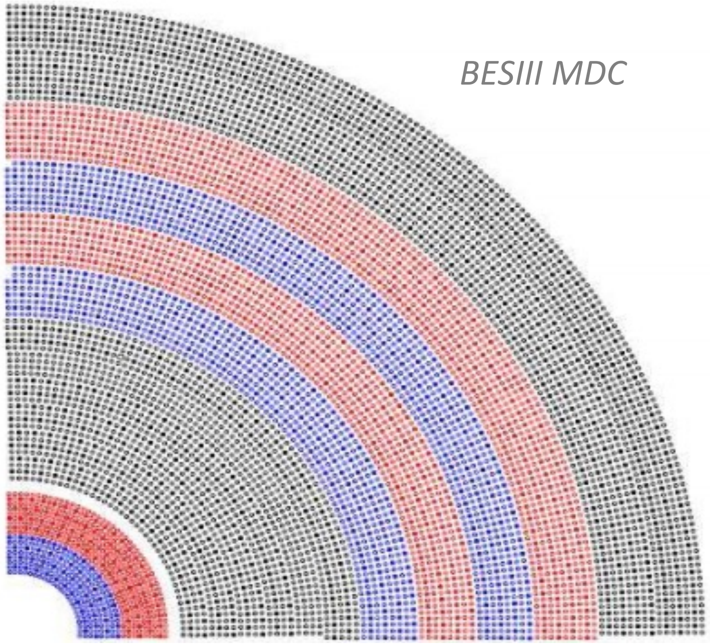
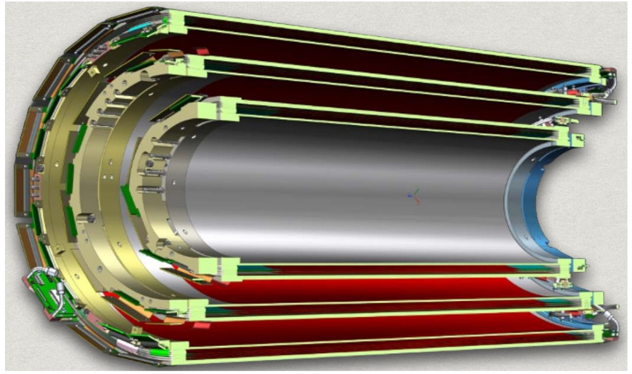
BESIII tracking system

- Beijing electron-positron collider (BEPCII)
  - Peak luminosity : $10^{33}\ cm^{-2}s^{-1}$
  - CMS: 2.0 - 4.95(5.6) GeV, τ-charm region
- Main Drift Chamber (MDC) at BESIII
  - 43 sense wire layers
  - 5 axial wire super-layers, 6 stereo wire super-layers
  - dE/dx resolution : 6%
  - Momentum resolution : 0.5%@1GeV/c







CGEM inner tracker

Traditional tracking in drift chamber

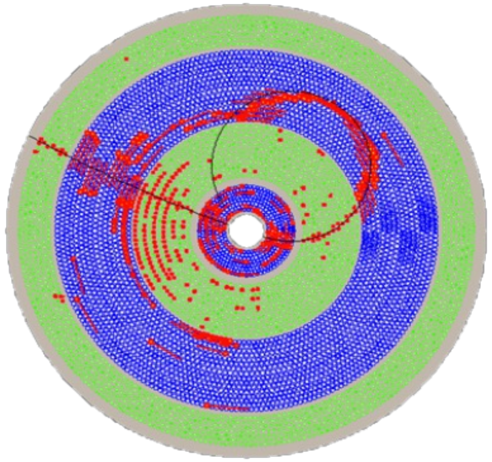
MDC hits produced by charged particles

Track finding

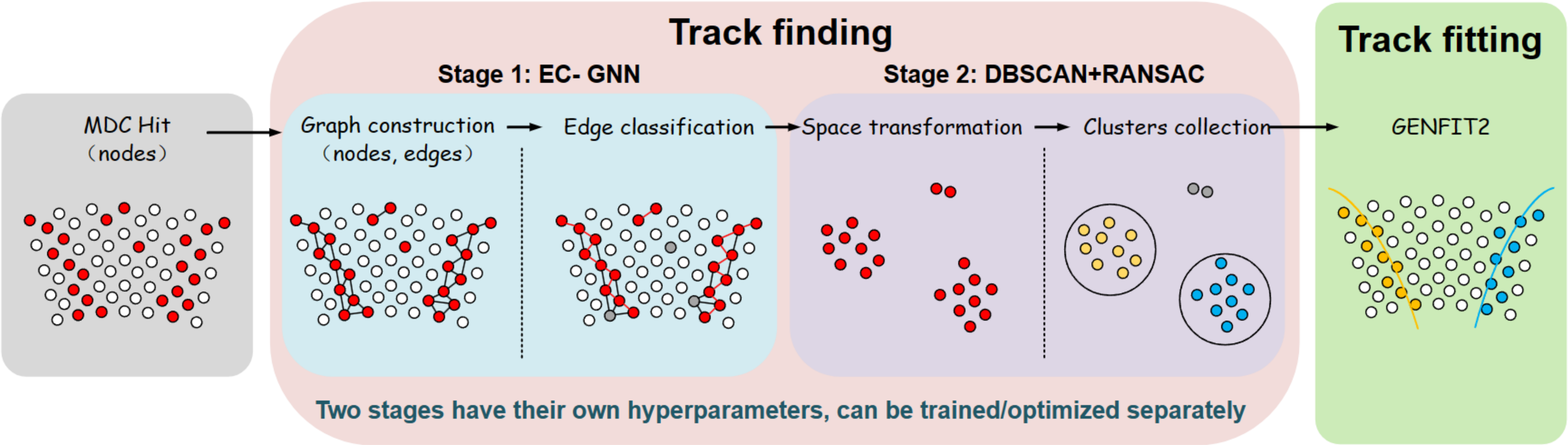
Track fitting

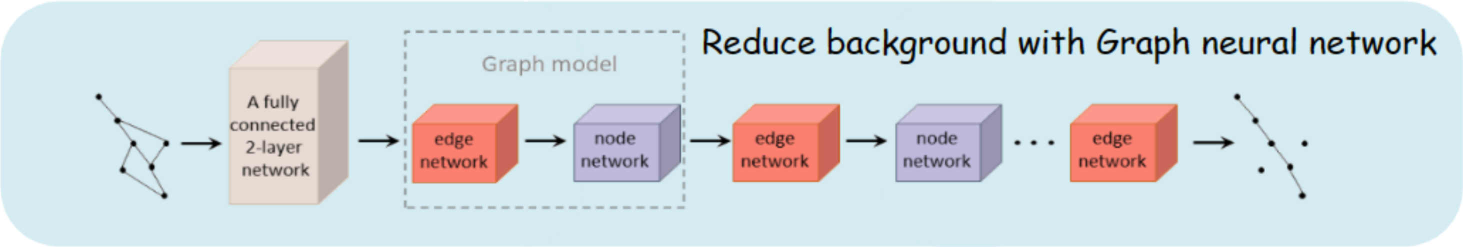
Vertex and physics object reconstruction

- Build candidate tracks and perform hits assignment
  - Global approach : Hough Transform (HOUGH)
  - Local approach :
    - Template Matching (PAT)
    - Track Segment Finding (TSF)
    - Combinatorial Kalman Filter (CKF) (not yet used in BESIII)
- Estimate the track parameters
  - Global fit : Least Square Method, Runge-Kutta Method
  - Recursive fit : Kalman filter



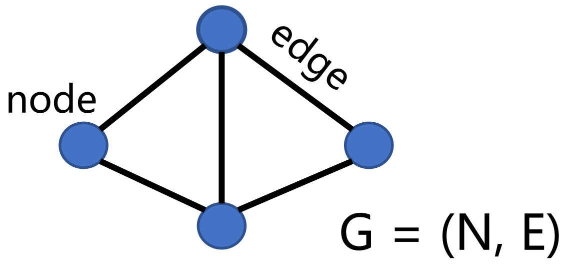
Methodology: GNN based tracking pipeline

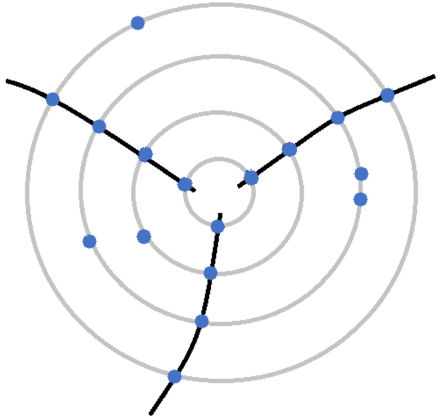




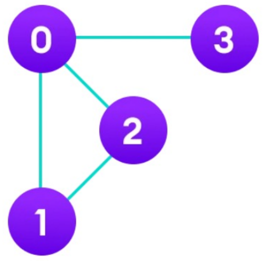
Graph representation

- ◆ A type of neural network that are specifically designed to operate on graph-structured data
- ◆ Graph elements: nodes, edges





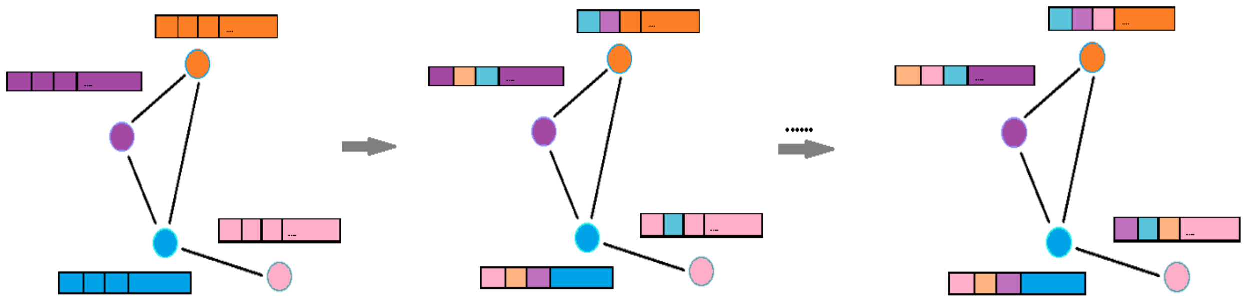
- ◆ From graph to track
  - nodes → hits
  - edges → track segments
- ◆ The storage structure of graphs
  - Adjacency matrix √
  - Adjacency table
  - Orthogonal list
  - Adjacency multiple table
  - Edge set array
  - ……



	0	1	2	3
0	0	1	1	1
1	1	0	1	0
2	1	1	0	0
3	1	0	0	0

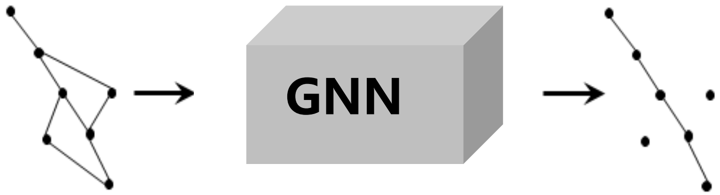
Graph Neural Network

- GNN key idea: propagate information across the graph using a set of learnable functions that operate on node and edge features



Message-passing

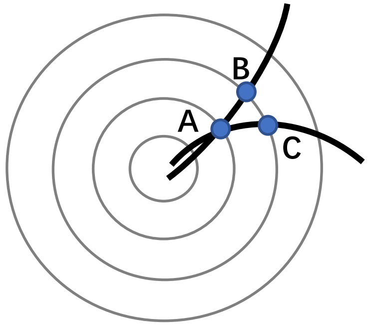
- Graph Neural Network edge classifier
  - High classification score
    - the edge belongs to a true particle track
  - Low classification score
    - it is a spurious or noise edge



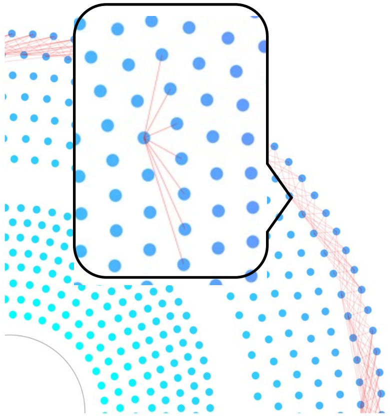
Graph construction

Reduce the number of fake edges during graph construction

Pattern Map based on MC simulation at BESIII



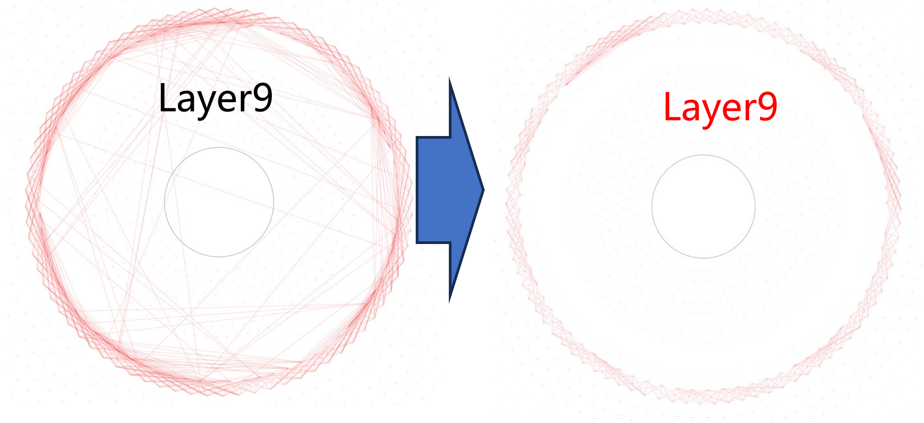
- Definition of valid neighbors
  - Hits on the same layer
    - Two adjacent sense wires on the left and right
  - Hits on the next layer
    - The collection of sense wires that could potentially represent two successive hits on a track
- Edge assignment based on Pattern Map
  - Hit with its neighbors on the same layer and next layer
  - Hit with its neighbors' neighbors on one layer apart
  - Edge label: two hits of this edge belongs to same track or not.
- Graph representation
  - Node features (raw time, position coordinates r, φ of the sense wires), adjacency matrices, edge labels

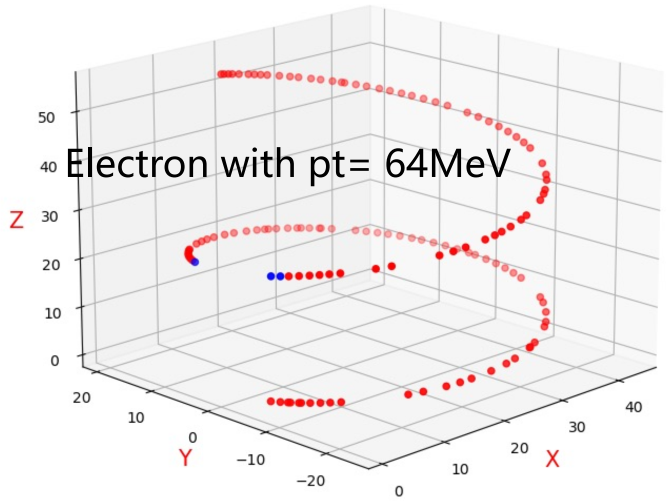


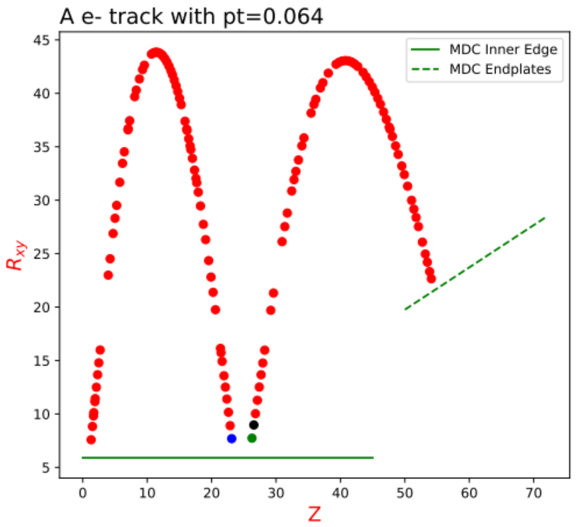
A wire on layer13 and its neighbors on layer14

Graph construction

- Continuity of track:
  - geometric structure of detector, track momentum.
- To reduce the size of the graphs, the Pattern Map is further reduced based on a probability cut (>1%)
- MC sample used to build pattern map
  - Two million single tracks produced with BESIII offline software (BOSS)
  - 5 types of charged particles ($e^{\pm}, \mu^{\pm}, \pi^{\pm}, K^{\pm}, p/\bar{p}$)
  - 0.05 GeV/c < p < 3 GeV/c

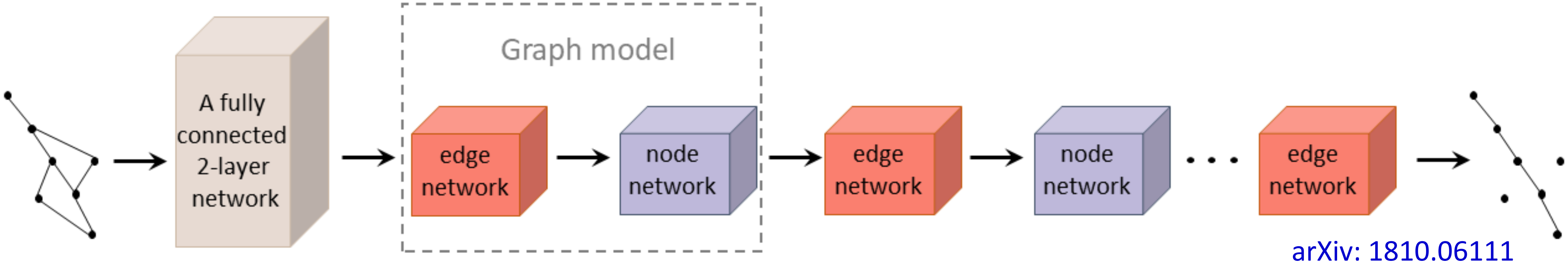






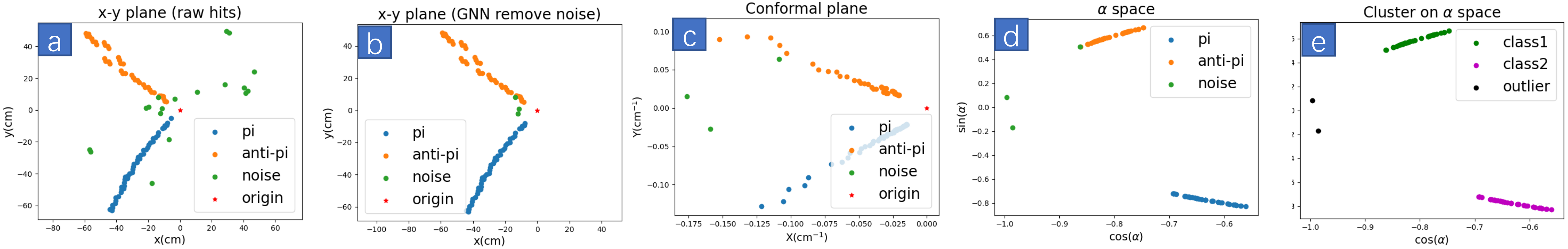
GNN edge classifier based on PyTorch

- Input network
  - Node features embedded in latent space
- Graph model
  - Edge network: computes weights for edges using the features of the start and end nodes
  - Node network: computes new node features using the edge weight aggregated features of the connected nodes and the nodes' current features
  - MLPs
  - 8 graph iterations
  - Strengthen important connections and weaken useless or spurious ones



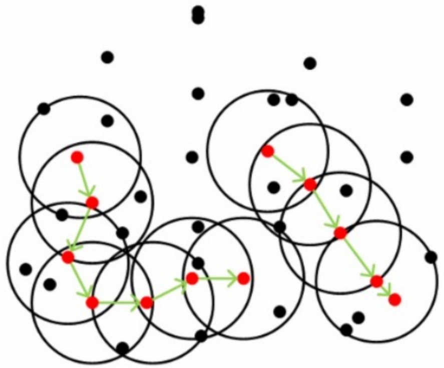
arXiv: 1810.06111

Clustering based on DBSCAN



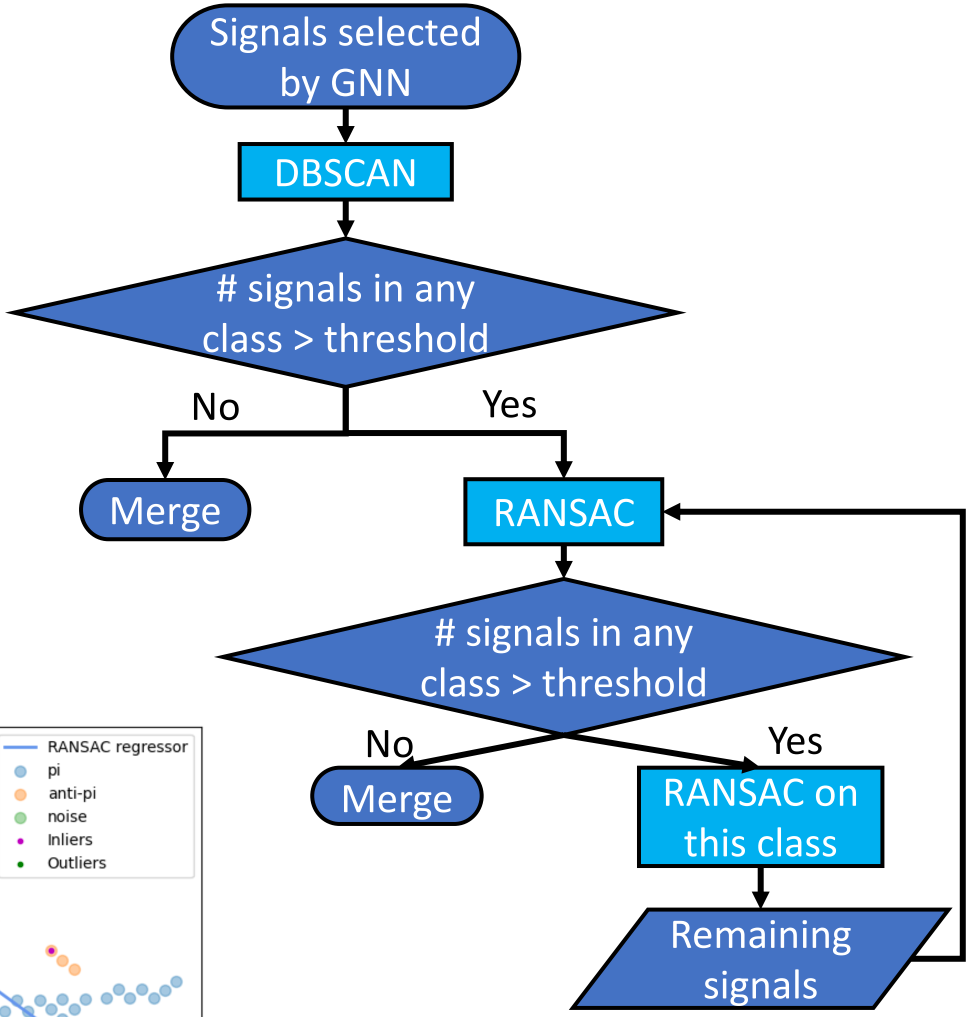
- Transform to Conformal plane
  - $X = \frac{2x}{x^2+y^2}$ $Y = \frac{2y}{X^2+y^2}$
  - Circle passing the origin
  - transform into a straight line
- Transform to ‘α’ parameter plane
  - Hits connected in the X-Y plane in a straight line
  - α as the angle between the straight line and X axis
  - The parameter space as cosα and sinα

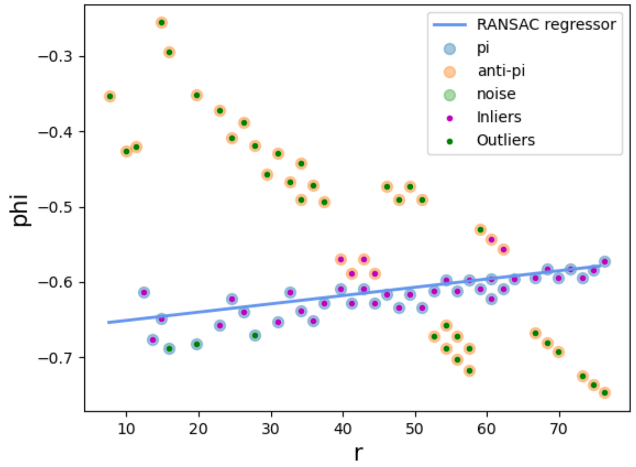
- DBSCAN clustering in ‘α’parameter plane
  - Density-Based Spatial Clustering of Application with Noise
  - Hits in a cluster are considered to be in the same track

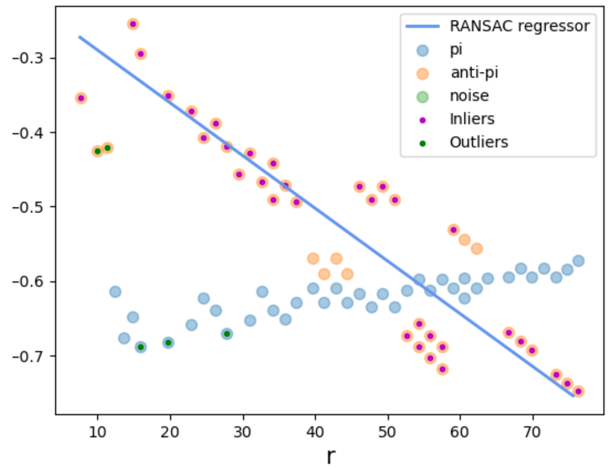


Clustering salvage algorithm RANSAC

- Random sample consensus (RANCAS)
  - Estimate a mathematical model from the data that contains outliers
  - Its good robustness to noise and outliers
  - Model can be specified
- RANCAS is triggered by the events when DBSCAN fails
  - Polar coordinate space
  - linear model
  - Inliers → a track , outliers → other tracks
  - Stop condition: outliers < threshold

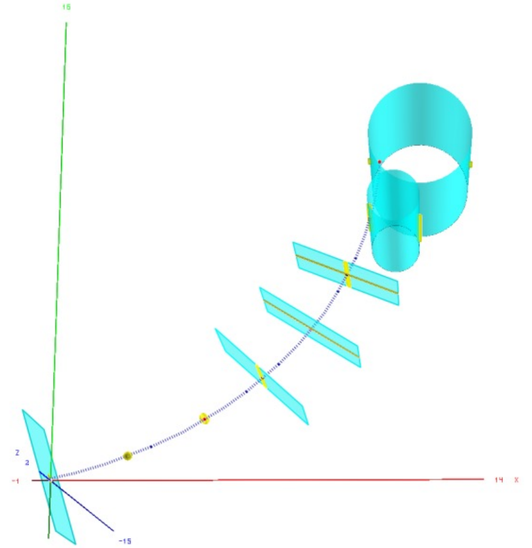


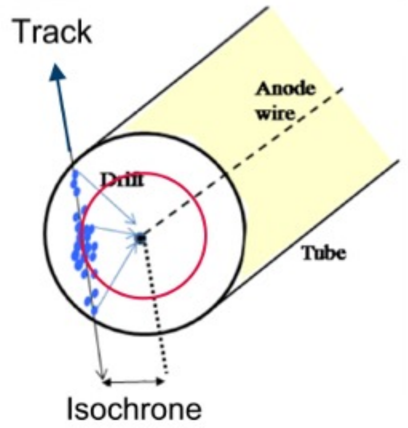




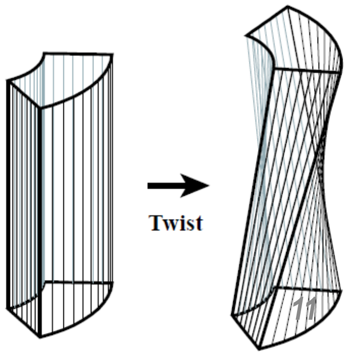
Track fitting

- Genfit2
  - A Generic Track-Fitting Toolkit
  - Experiment-independent framework
  - PANDA, Belle II, FOPI and other experiments
  - Deterministic annealing filter (DAF) to resolving the left-right ambiguities of wire measurements
- Configuration: Detector geometry and materials; TGeoManager
- Input :
  - Signal wire position, initial values of position and momentum
  - particle hypothesis for e, μ, π, k, p
- Fitting procedure:
  - Start 1st try: drift distance roughly estimated from TDC、ADC of sense wires
  - Iteration to update information of drift distance, left-right assignment, hit position on z direction and entrancing angle in the cell et al.



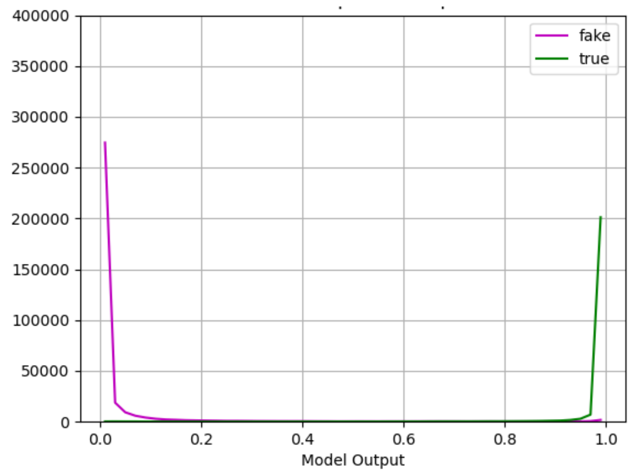


$$t_{\text{drift}} = t_{\text{TDC}} - t_{\text{EST}} - t_{\text{flight}} - t_{\text{wp}} - t_{\text{elec}}$$

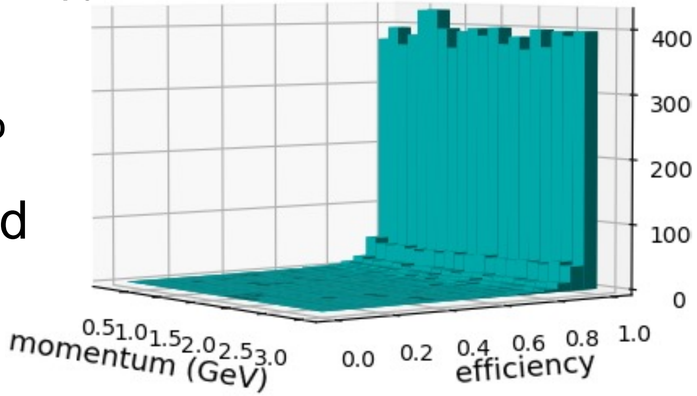


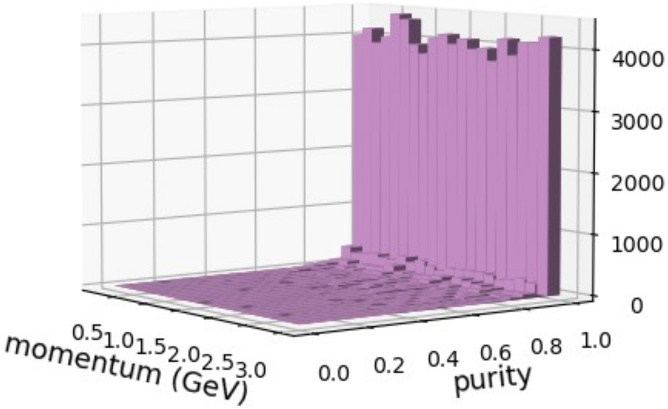
Performance of filtering noise at BESIII

- Datase
  - Single-particle ($e^{\pm}, \mu^{\pm}, \pi^{\pm}, K^{\pm}, p/\bar{p}$) MC sample
  - 0.2 GeV/c < p < 3.0 GeV/c
  - Mixed with BESIII random trigger data as background (~45% hits)
  - Train: Validation: Test = 4: 1: 1



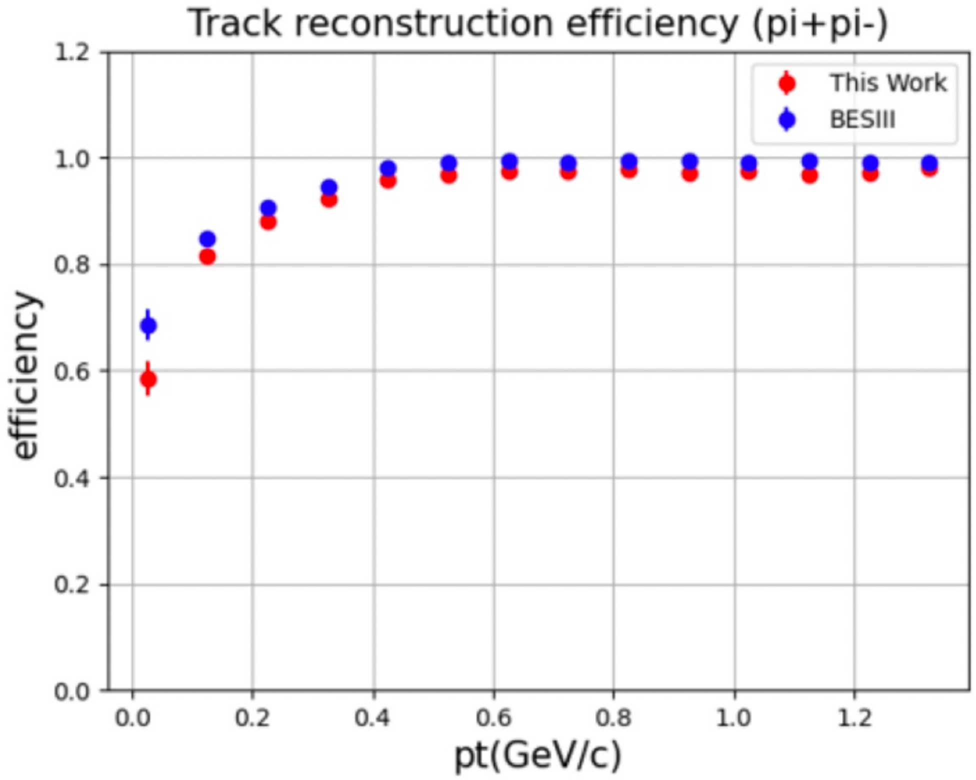
- Hit selection performance
  - The preliminary results show that GNN provides high efficiency and purity of hits selection
  - Hit selection Efficiency : $\frac{N_{signal}^{\text{predicted}}}{N_{signal}^{real}}$ 98.7%
  - Hit selection Purity : $\frac{N_{signal}^{\text{predicted}}}{N_{all}^{predicted}}$ 96.5%
  - Efficiency and purity can be balanced by adjusting the model parameter

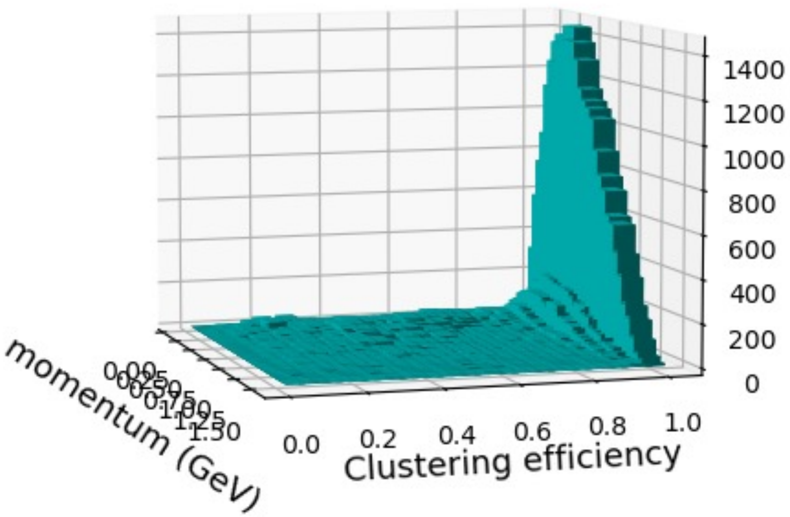


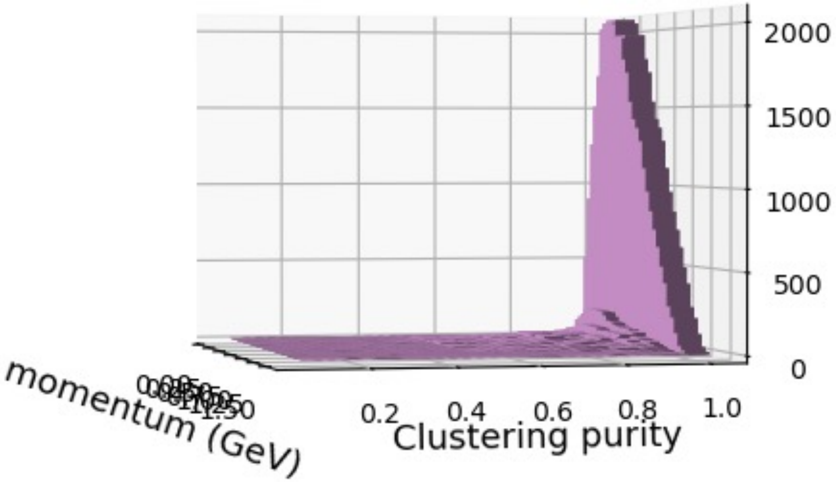


Preliminary tracking performance at BESIII

- Particle reconstructed performance
  - $J/\psi \to \rho^0\pi^0 \to \gamma\gamma\pi^+\pi^-$ from MC simulation
  - track eff = $\frac{N_{\text{rec tracks}}}{N_{\text{total tracks}}}$

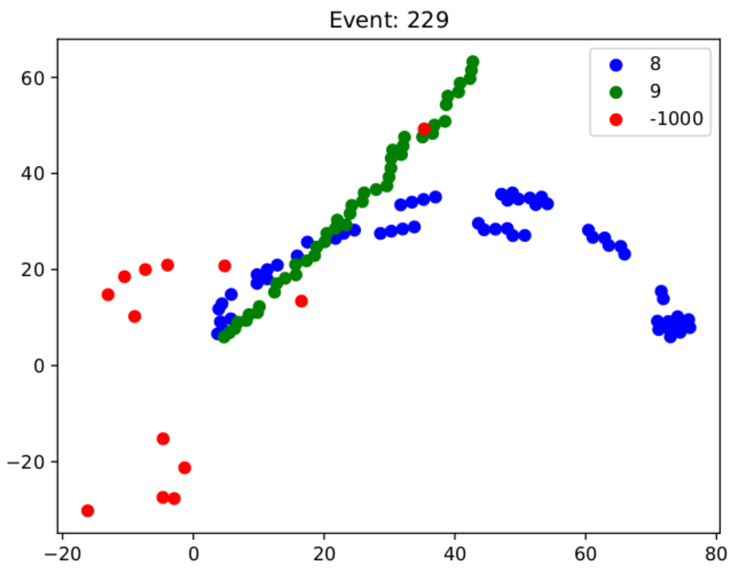


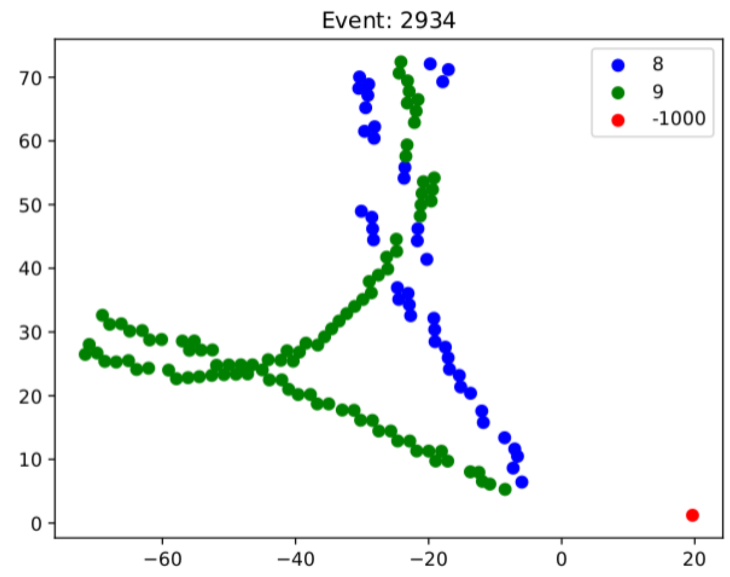


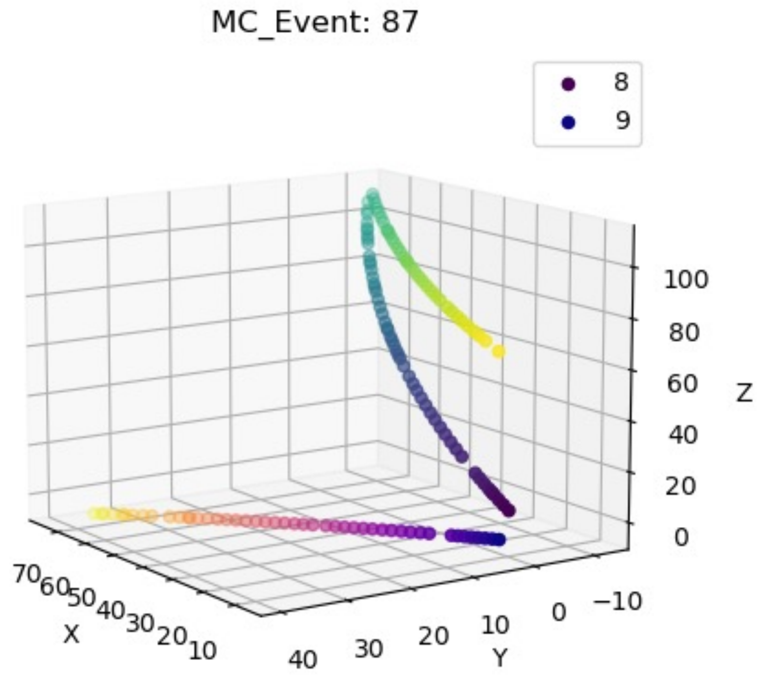


Sources of efficiency loss

- Efficiency loss during track finding(clustering):
  - multi-circular, decays,
  - interaction with detector boundary/material, scattering
  - 2D crossing tracks or too close to each other

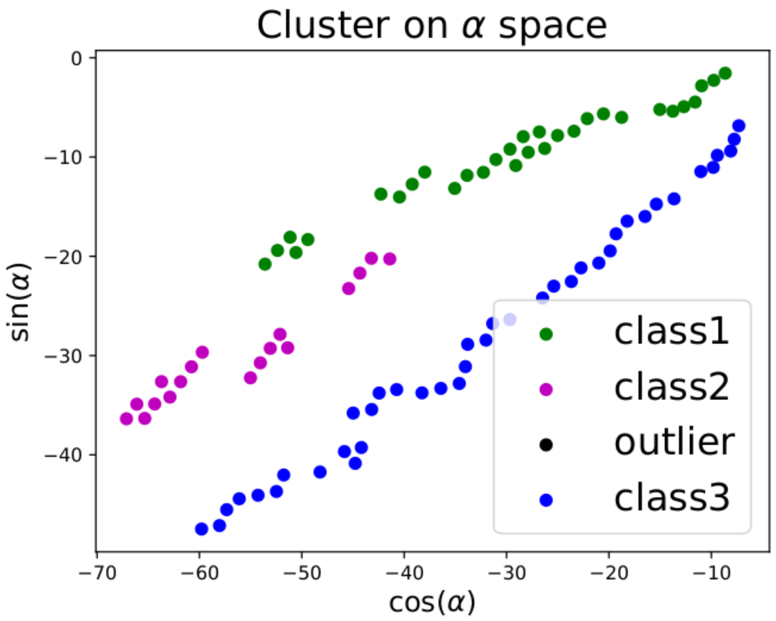


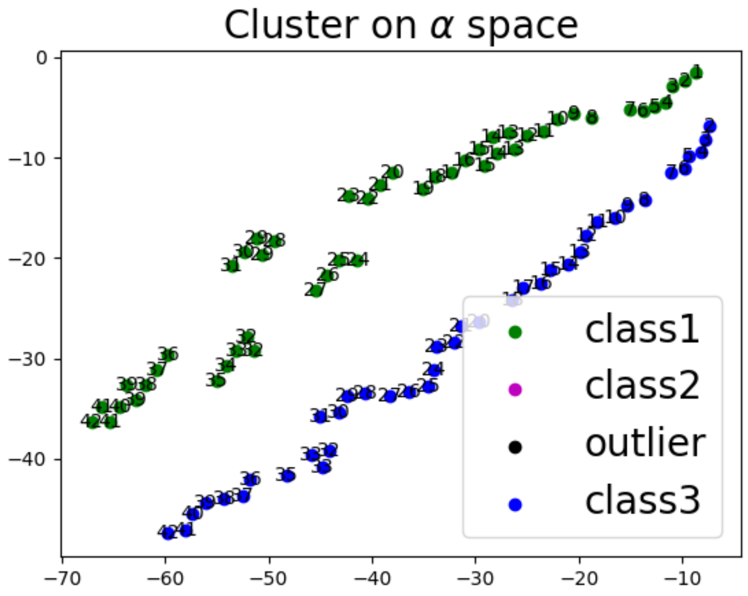




Further optimization of track finding

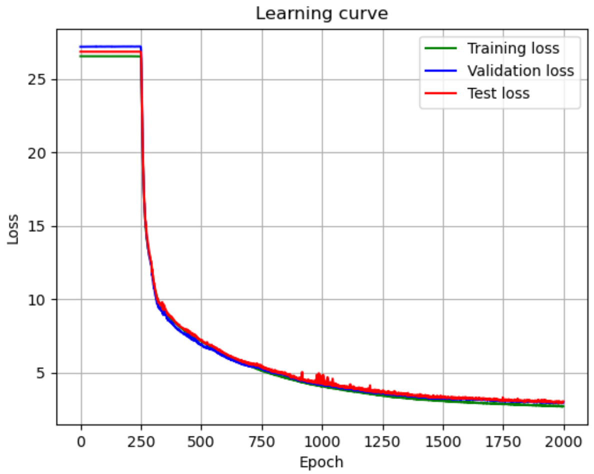
- ◆Since z position of hits is unknown, 2D information has large deviation for stereo wires
- ◆Break into parts especially for tracks with large polar angle
- ◆Re-combination at super layers level

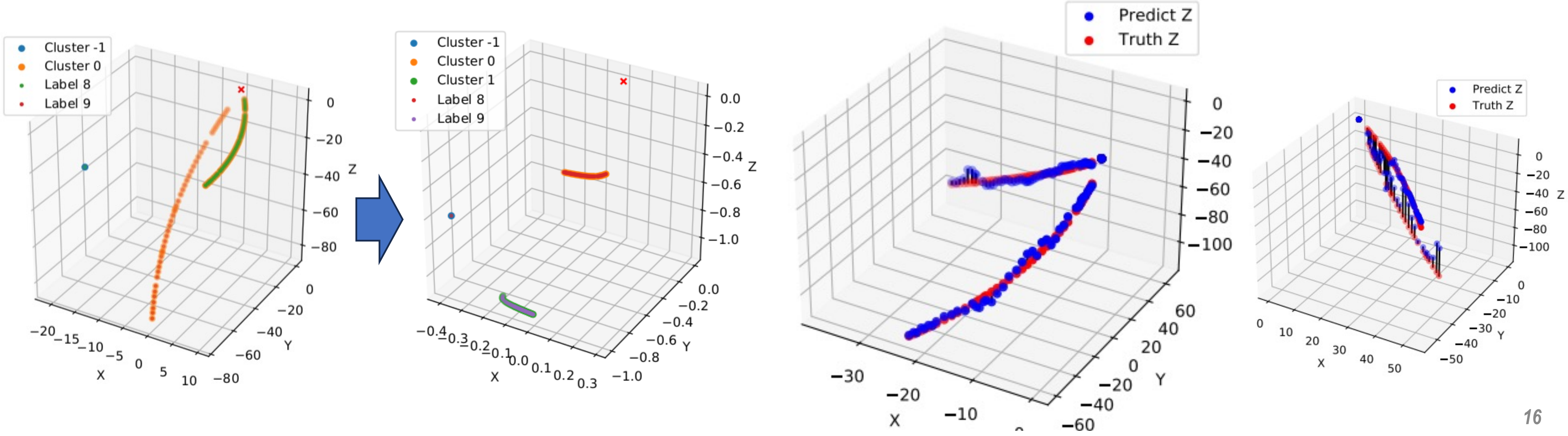




Z regression and 3D clustering

- GNN regression for z coordinate prediction
  - structure similar as edge classification GNN
  - Lost function:
    - averaged distance between predicted and real position
- Clustering:
  - 3D parameter space: sinα， cosα， z/r





Potential of 3D clustering

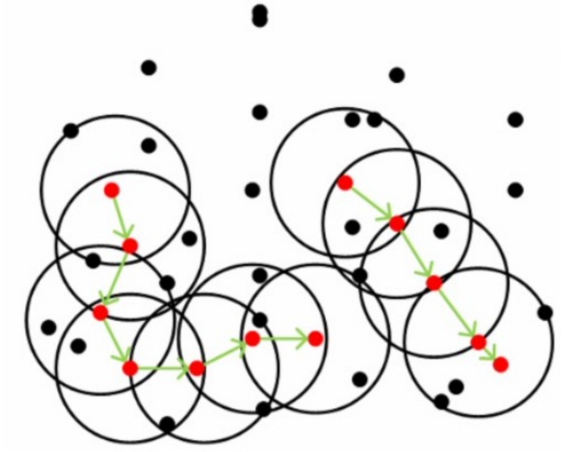
- Parameter space clustering is better than original coordinate space.
- Potential track finding efficiency can reach 97.5% via 3d parameter space clustering
- Good event definition: #hits per track is between 5 and 50, might get rid of circular and large angle scattering

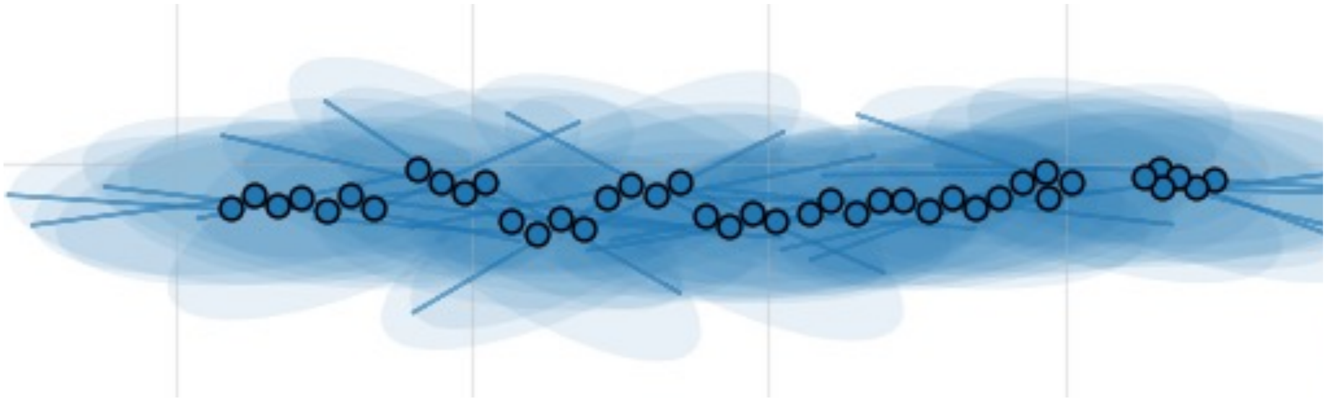
D+R	2D		3D				
	wire XY	Truth XY good event	PredZ wire XY good event	TruthZ wire XY good event	Truth XYZ good event	Truth parameter space	Truth parameter space good event
Efficiency (%)	97.3	98.3	98.1	97.9	98.1	98.2	98.3
Purity (%)	96.8	97.6	96.1	96.7	98.0	99.1	99.2
Finding Success rate (%)	83.3	90.2	71.6	84.3	91.8	92.0	97.5

DBSCAN using elliptical neighborhood

- Circular neighborhood is replaced with an elliptical neighborhood
- Local orientation of each point is determined based on PCA considering points within its neighborhood

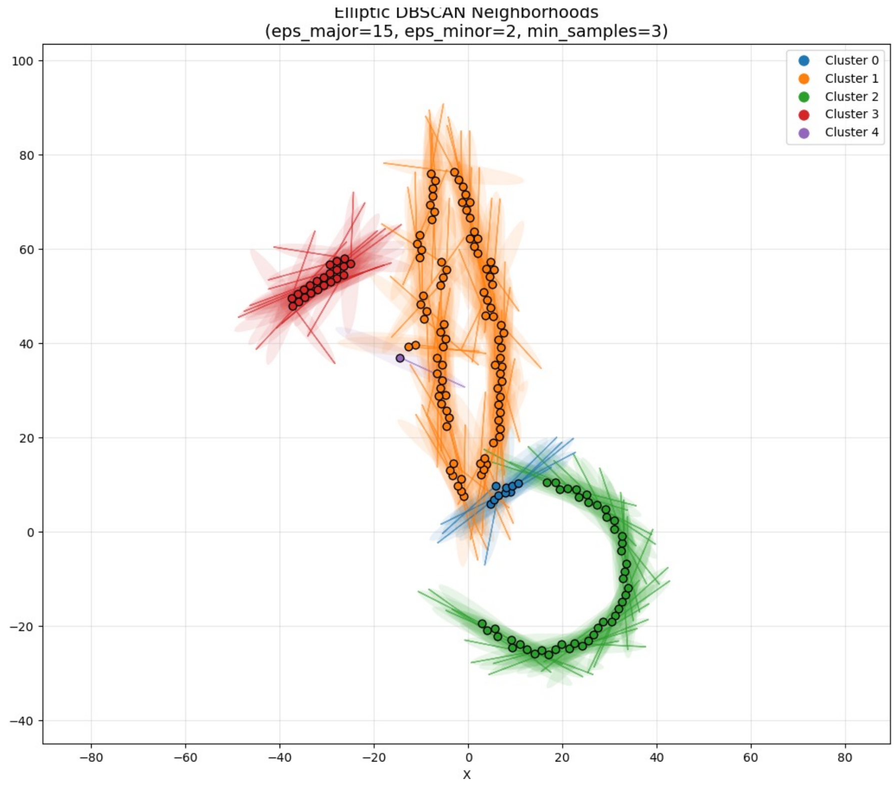
Parameters	Meaning	value
eps_major	long axis	15cm
eps_minor	short axis	10cm
min_samples	min neighbors	3
k (orientation calculation)	neighbors for PCA	5

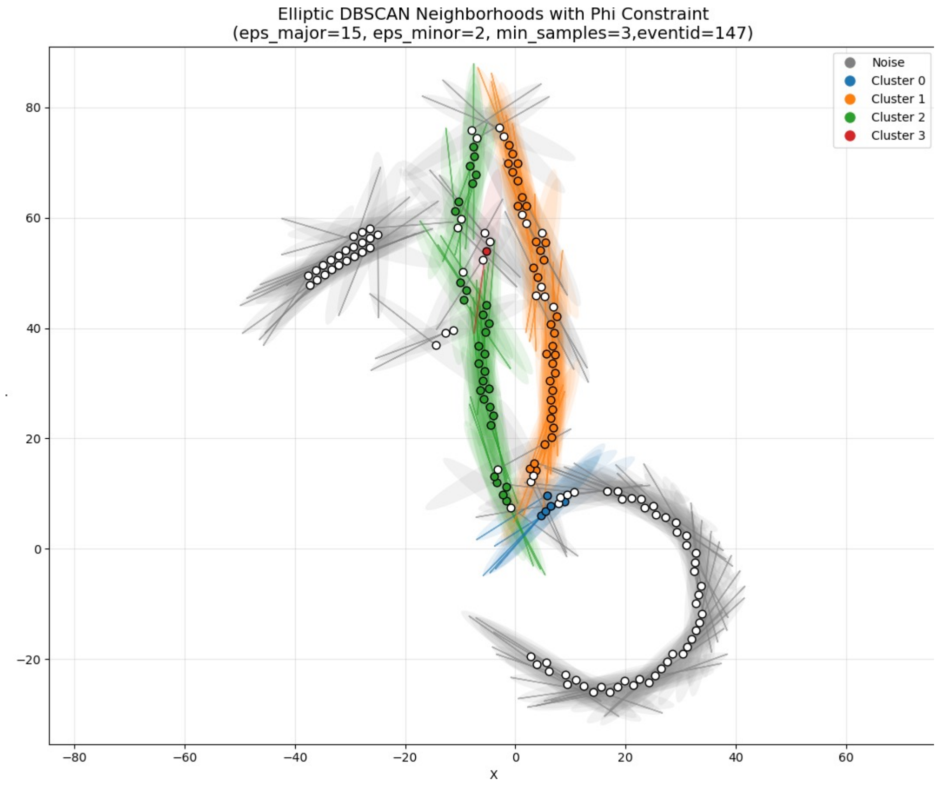




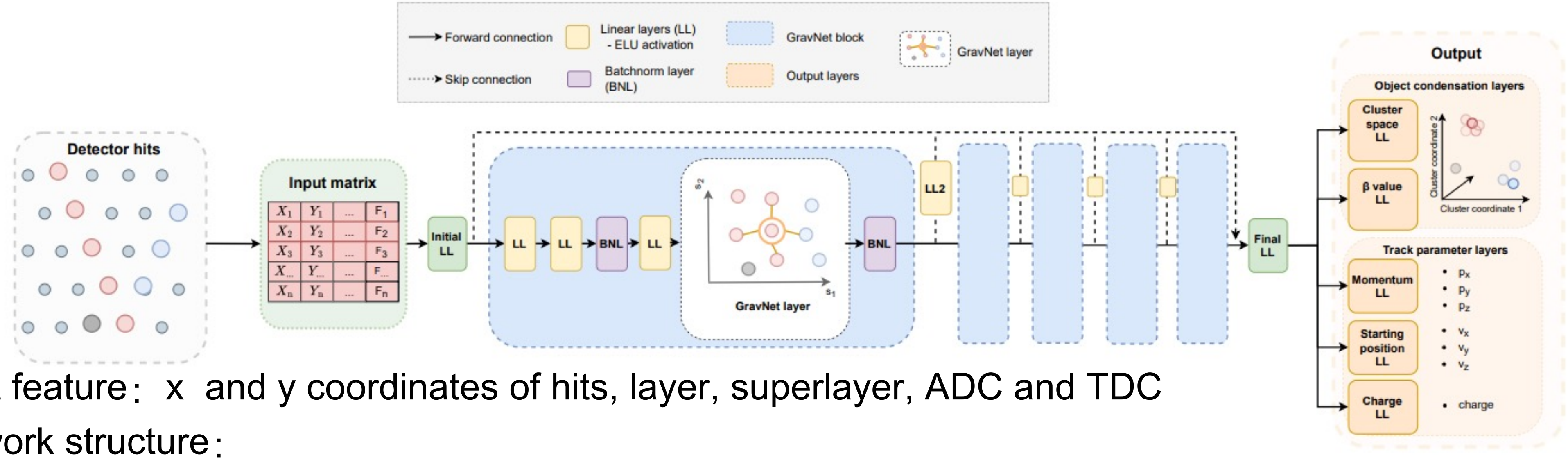
Split cluster via abnormal point

- Abnormal point detection:
  - large di-angle between direction of PCA and direction to the IP
- Further attempts:
  - assign large weight for hits in the same superlayer
  - veto hits in the same payer, same superlayer but another group





Object Condensation(OC) using GNN



- Input feature： x and y coordinates of hits, layer, superlayer, ADC and TDC
- Network structure：
  - Initial LL with ELU activation and batch normalization.
  - Multiple stacked GravNet blocks with skip connections. Each block includes ：
    - A GravNet layer(GNN layer) that learns a latent space to determine neighborhood relationships and pass message.
    - Linear layers (LL) and batch normalization layers (BNL).
  - Final LL to generate output representations
- Output：
  - Object condensation layers ：
    - Cluster coordinates (for grouping hits belonging to the same track).
    - β-values (confidence scores for cluster centers).
  - Track parameter prediction layers： $q, p_x, p_y, p_z, v_x, p_y, v_z$

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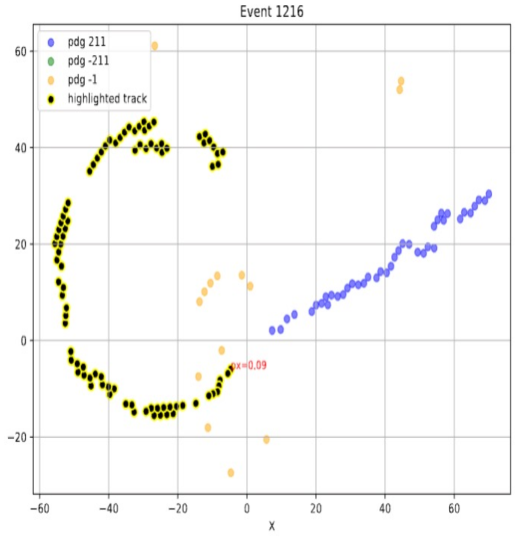
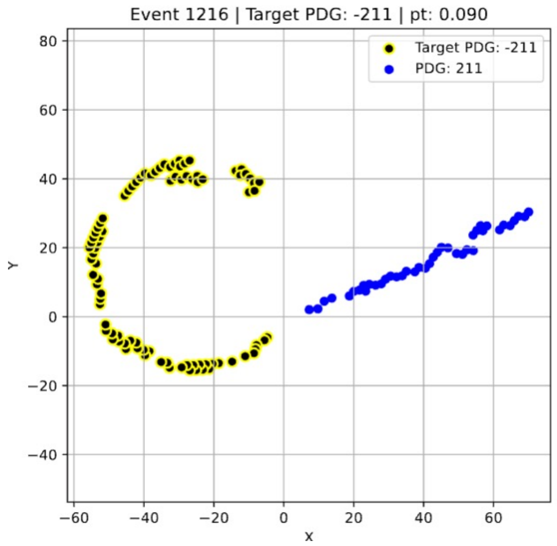
Track finding result via OC

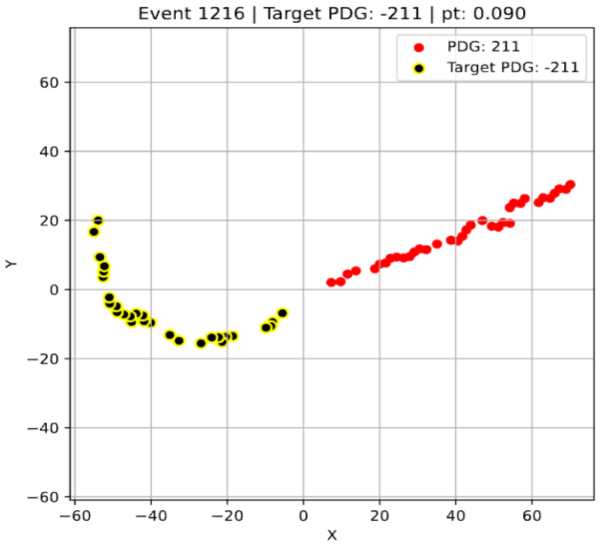
- ☐ circling track



truth

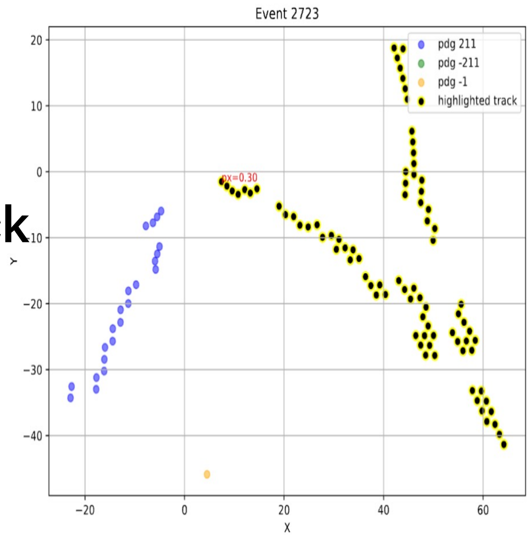


OC clustering results



BESIII PATTSF

- ☐ scattered track



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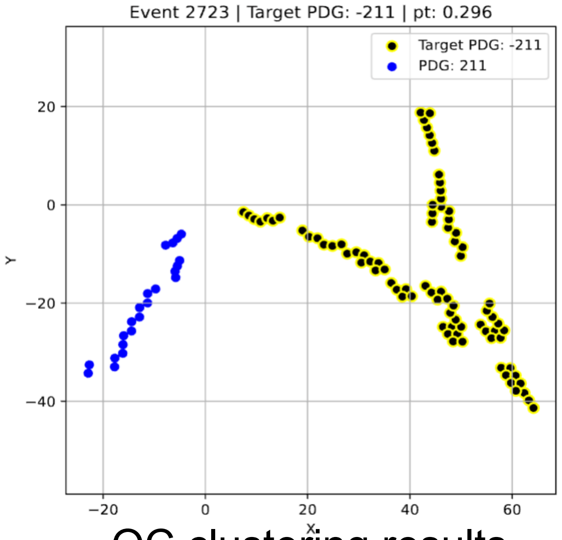
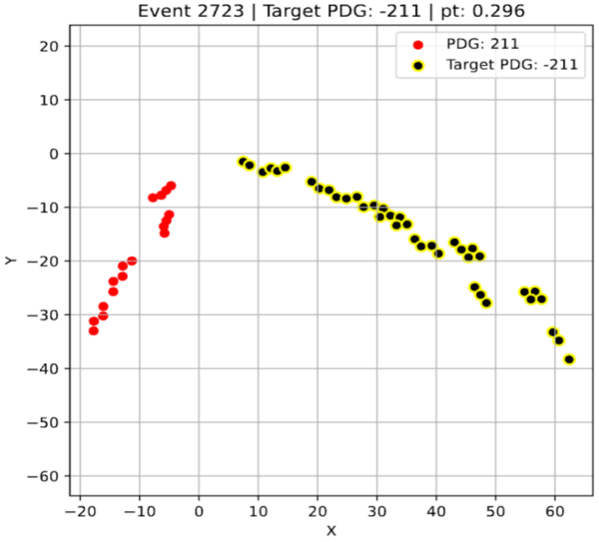


OC clustering results



BESIII PATTSF

Comparison of GNN and OC

- OC clustering efficiency is higher than GNN
- Attempts to improve fitting rate: keep 1^{st} circle or the part before scattering

	GNN	OC
low momentum (pt<200MeV)	circling track event: bad clustering quality	better short track reconstruction than BESIII circling track event: good clustering efficiency but might fail in fitting
high momentum	large angle scattering fail in clustering，2%-3% crossing tracks fail in clustering，1%	large angle scattering fail in fitting，3%-4%

Summary

- A novel tracking algorithm prototype based on machine learning method at BESIII is under development
  - GNN to distinguish the hit-on-track from noise hits.
  - Clustering method based on DBSCAN and RANSAC to cluster hits from multiple tracks
- Preliminary results on MC data shows promising performance

- Outlook
  - Further optimization: circular, scattering..
  - Performance verification concerning events with more tracks and long lived particle
  - Check the reconstruction time consumption

Thank you!