Simultaneous Track Finding and Track Fitting by the Deep Neural Network at BESIII

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BESIII

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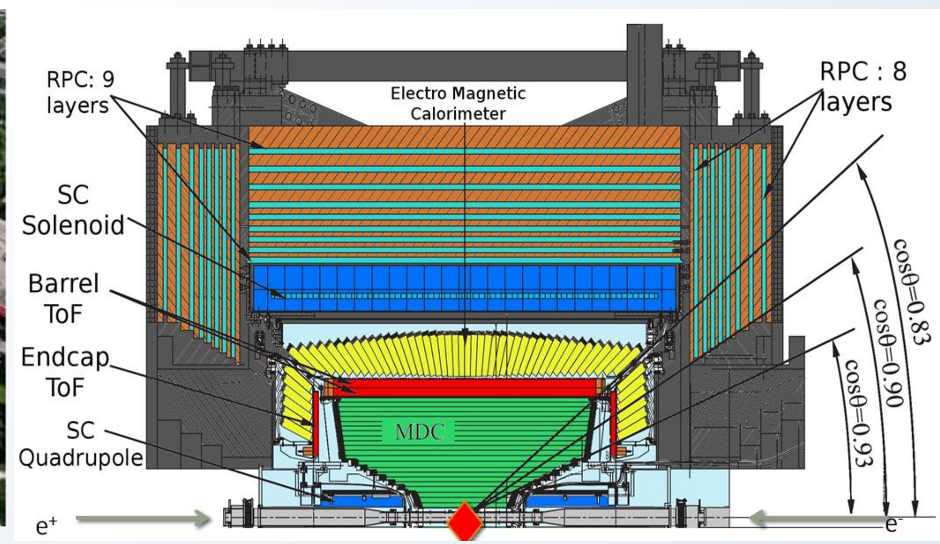
BEPCII and BESIII

- BEPCII is a double-ring e^+e^- collider running in the E_{cm}=2-5GeV in China
  - Highest luminosity : $10^{33}cm^{-2}s^{-1}$
- BESIII at the BEPCII is for the studies at hadron physics and τ-charm physics with the highest accuracy achieved until now
- World's largest J/ψ dataset : 10 billion

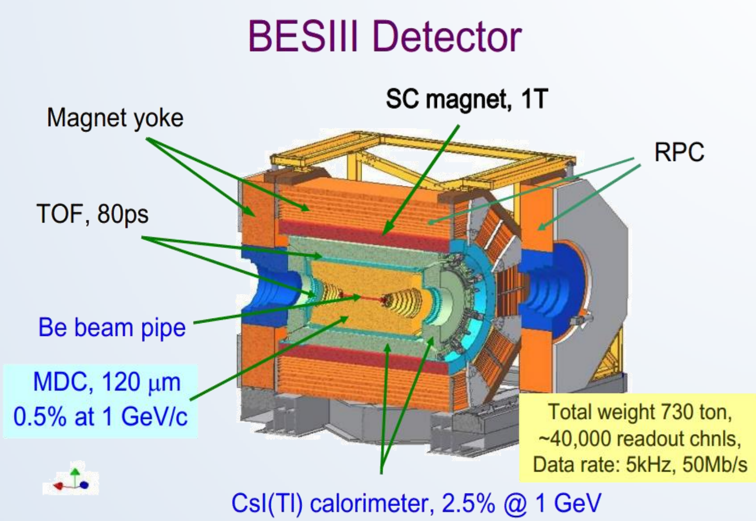
The Beijing Electron Positron Collider (BEPCII)

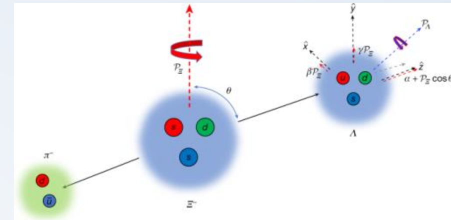


The BESIII detector

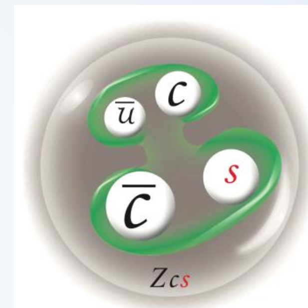
Detector and physics of BESIII

- Charged track reconstruction
  - A multi-layer drift chamber(MDC) for track momentum, position and secondary vertex
- Particle identification
  - A time-of-flight system (TOF)
  - An electromagnetic calorimeter (EMC)
- Muon-pion separation
  - Muon counter (MUC)

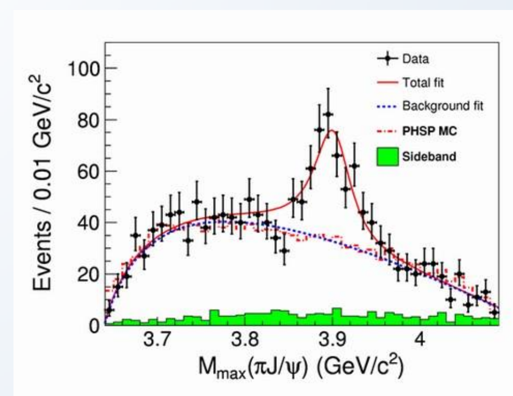




[Probing CP symmetry with Entangled Double-strange baryons]() @ nature



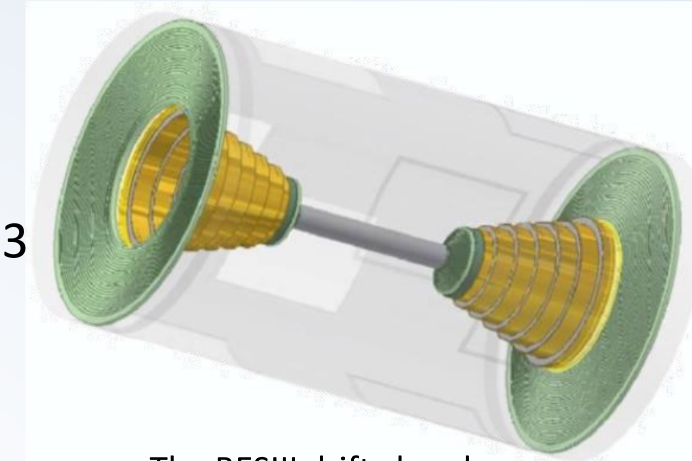
[Observation of the Zcs(3985) strange four-quark meson]()



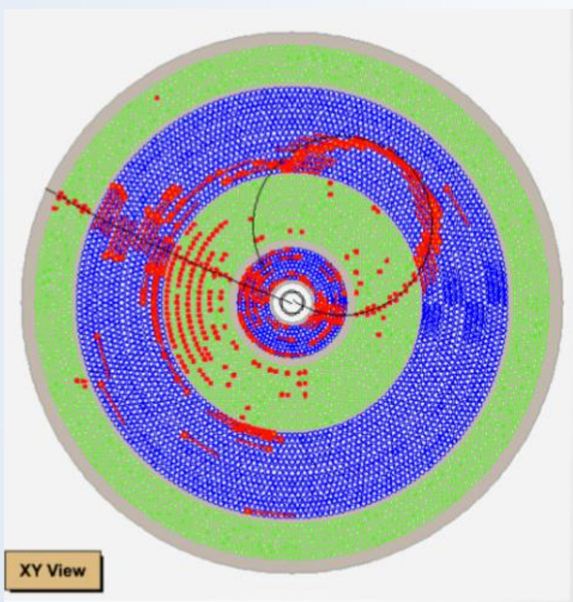
[Observation of a charged charmonium like structure at BESIII Zc(3900) is on the top of the "Highlights of the Year"]()

The BESIII Drift Chamber

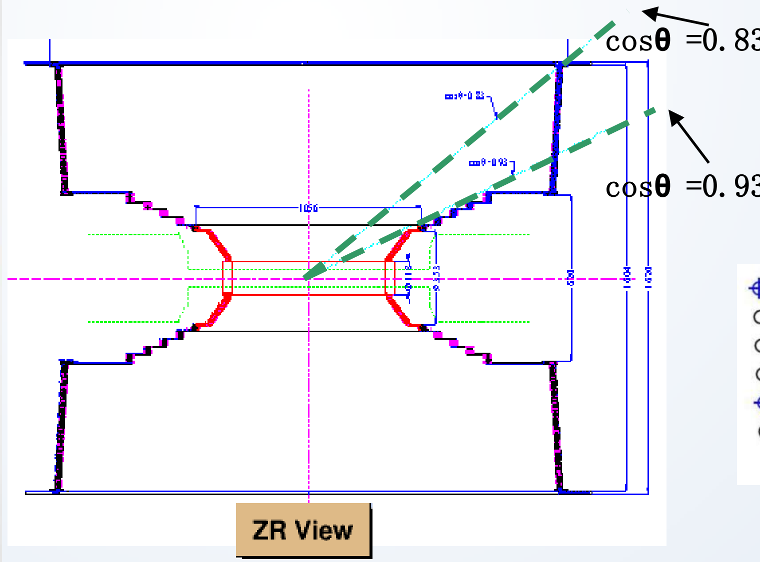
- Gaseous cylindrical drift chamber with |cosθ|<0.93
- 6796 wires arranged in 43 layers
- 3 or 4 layers are grouped to super-layers
- Axial and stereo super-layers alternatively



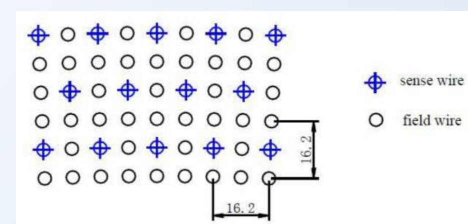
The BESIII drift chamber



Blue: stereo layers Green: axial layers



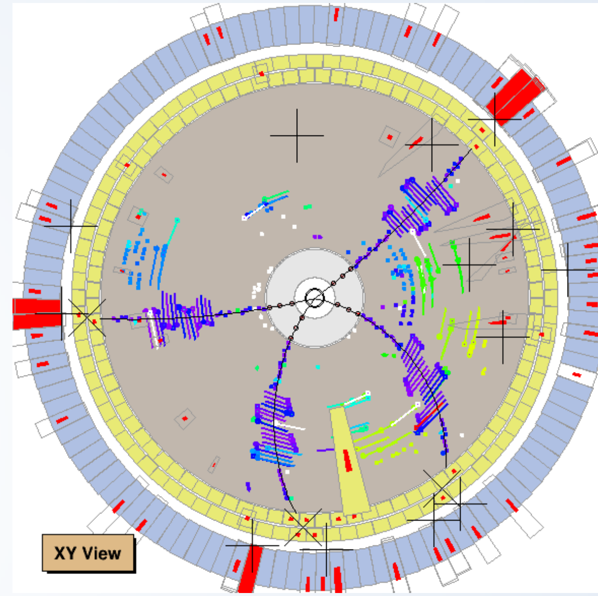
ZR view of drift chamber



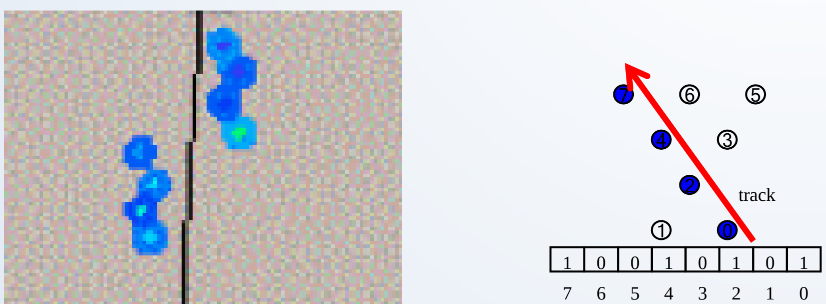
Cell structure

Traditional tracking of BESIII drift chamber

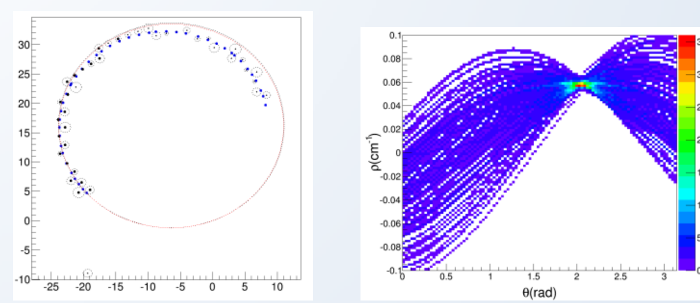
- Local method
  - Template matching for segment in super-layers
    Sensitive to wire inefficient, layer arrangement and momentum
  - Seeding and road following
    Affect by noise or background alone the track path
- Global method
  - Hough transform
    Affect by energy loss and overlapping track



An event display



Track segment finding in super-layers



Hough transform

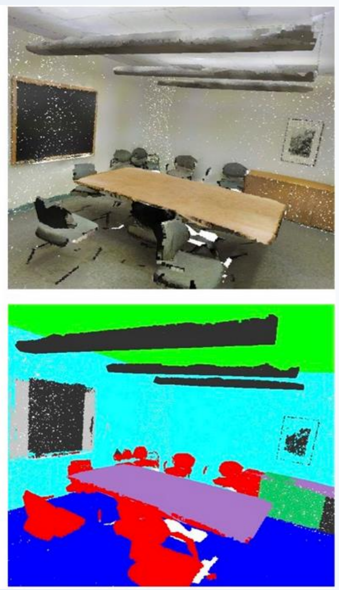
Motivation

- Increase the tracking efficiency and performance for special events
  - Low transverse momentum
  - Large dip angle
  - Secondary vertex
- Higher Background and noise with the upgrade of BEPCII
  - Noise hit resistance (another efforts please refer to Rostam's poster)
- The optimization of the tradition tracking algorithm could be risky and challenge

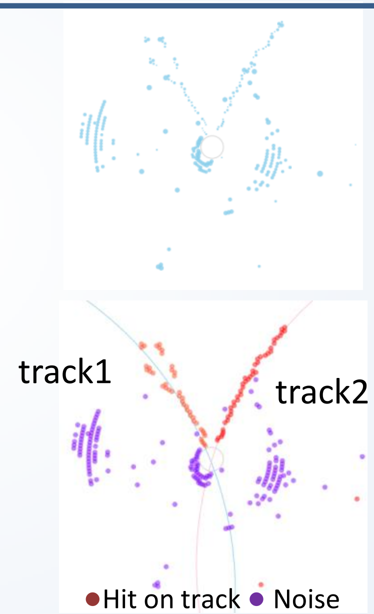
- Aim of our work
  - Explore the new tracking method with novel technics
  - Hit clustering with the auxiliary of the track parameter regression
    - Parallel "track finding and fitting" with neural network
  - Experiment independent tracking with 2-D measurement (drift chamber)

Neural network approach for track reconstruction

- Idea:
  1. Semantic segmentation of the point set –> track finding/hit clustering
  2. Extract local features –> track fitting/track parameter estimation



PointNet:Deep Learning on Point Sets for 3D Classification and Segmentation



Track reconstruction

Address track parameter estimation and hit clustering simultaneously in an end-to-end fashion

PointNet++:

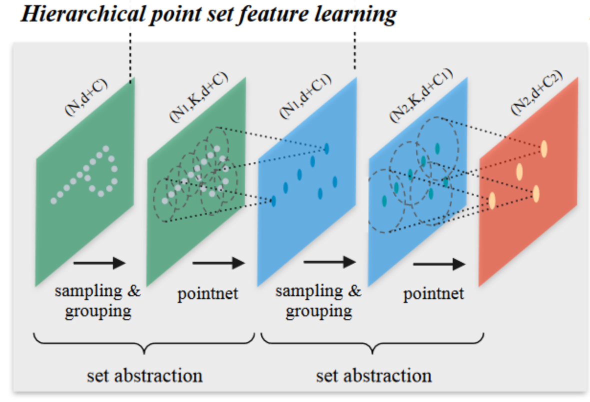
Point set segmentation for semantic scene labeling and feature extraction

Given an unordered point set $\{x_1, x_2, ..., x_n\}$ with $x_i \in \mathbb{R}^d$, one can define a set function $f : \mathcal{X} \rightarrow \mathbb{R}$ that maps a set of points to a vector:

$$f(x_1, x_2, ..., x_n) = \gamma \left(\underset{i=1,...,n}{\mathrm{MAX}} \{h(x_i)\} \right) \tag{1}$$

where γ and h are usually multi-layer perceptron (MLP) networks.

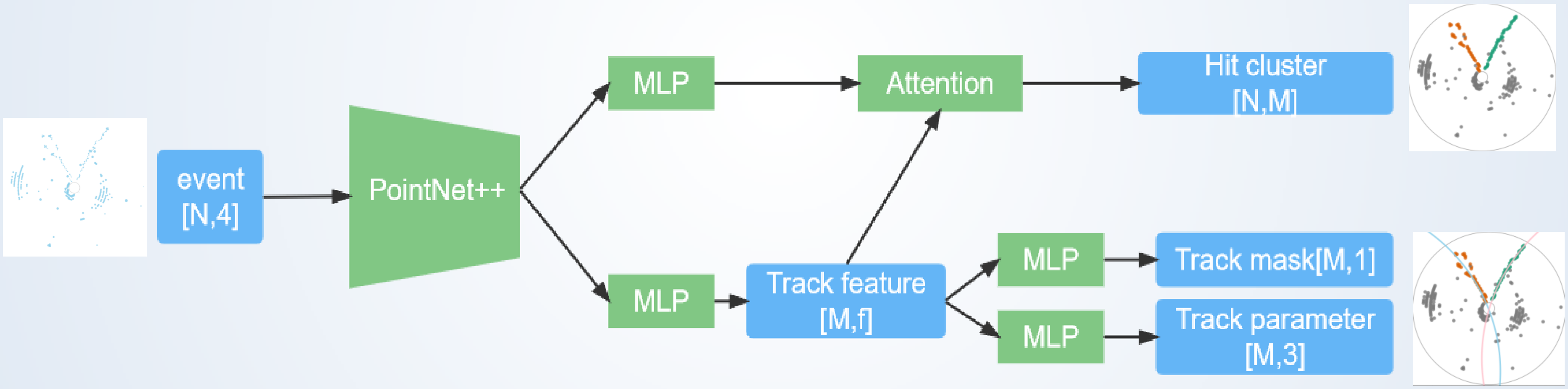
- The response of h can be interpreted as the spatial encoding of a point
- The set function f in Eq. 1 is invariant to input point permutations and can arbitrarily approximate any continuous set function



Track parameter estimated by learning the local feature of hit cluster

PointNet++ based tracking network

- End-to-end hit clustering with track parameter estimation
  1. Hit clustering for each hit
  2. track parameters for each predicted group of hits



PointNet++ based tracking network

Loss function

- Clustering loss
  - Cross entropy loss for hits clustering

$$\ell(x,y) = L = \{l_1,\dots,l_N\}^\top, \quad l_n = -w_{y_n} \log \frac{\exp(x_{n,y_n})}{\sum_{c=1}^{C} \exp(x_{n,c})} \cdot 1\{y_n \neq \text{ignore\_index}\}$$

where x is the input, y is the target, w is the weight, C is the number of classes, and N spans the minibatch

  - Binary loss of the classification for default clusters

$$\ell(x,y) = L = \{l_1,\dots,l_N\}^\top, \quad l_n = -w_n \left[y_n \cdot \log x_n + (1-y_n) \cdot \log(1-x_n)\right],$$

where N is the batch size. If `reduction` is not `'none'` (default `'mean'`), then

- Track parameters loss
  - Frobenius Norm Loss

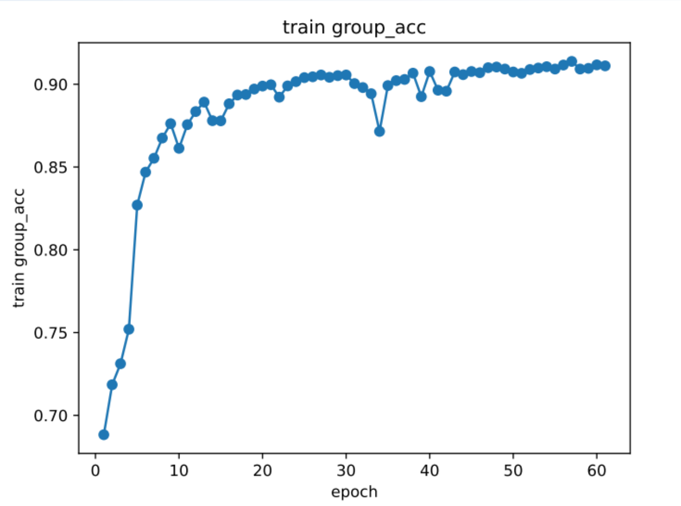
$$L_{Frob} = \| A_{pred} - A_{gnd} \|_F = \sqrt{\sum_i^m \sum_j^n |a_{ij}^{pred} - a_{ij}^{gnd}|^2}$$

Training

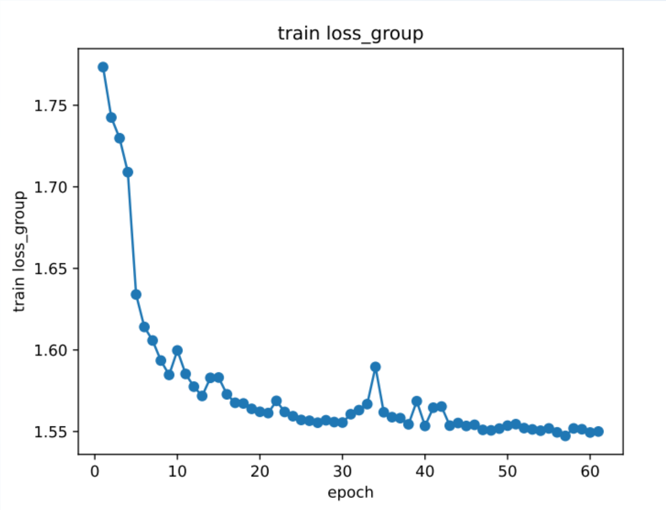
- Dataset
  - $J/\psi \to \rho\pi$ with one or two tracks as final state
  - Training/validation/test: 120k/15k/15k events
- Pre-processing
  1. Initial layer < 8
  2. Number of gap layers < 5
  3. Total number of hits >= 10
  4. Total number of layers >= 8
- GPU environment
  - Tesla V100

Training loss and accuracy

- Converged after ~30 epoch

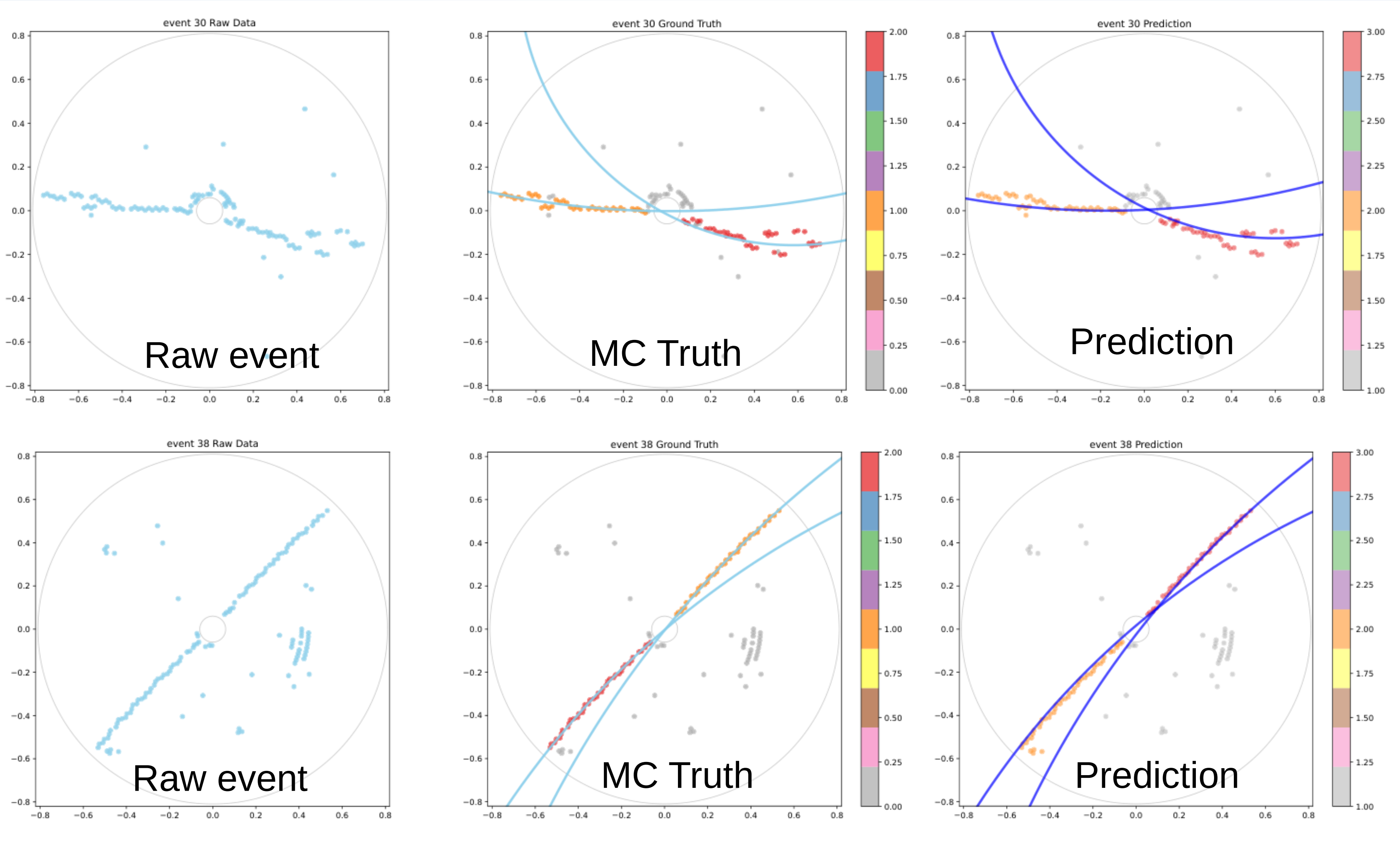


Training loss v.s. epoch



Training accuracy v.s. epoch

Prediction of the events



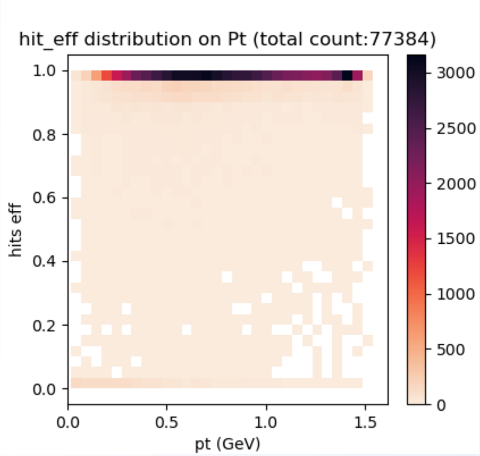
Hit clustering and track parameter performance

$$hit\ efficiency = \frac{N_{hit\ predicted\ correctly}}{N_{truth\ hit\ on\ track}}$$

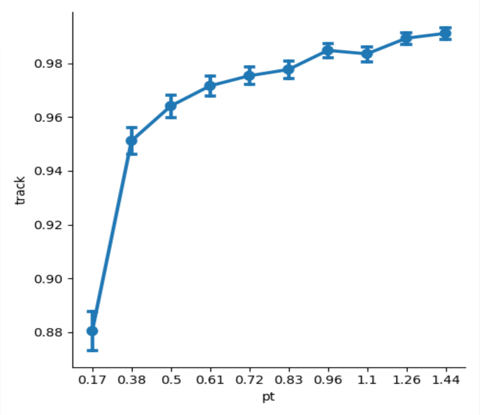
$$hit\ purity = \frac{N_{hit\ predicted\ correctly}}{N_{predicted\ hit\ on\ track}}$$

$$track\ efficiency = \frac{N_{predicted\ track}}{N_{truth\ track}}$$

- J/ψ–>ρπ
  - Hit efficiency: 93.2%
  - Hit purity: 91.9%
  - Track efficiency for high p_T tracks > 96%



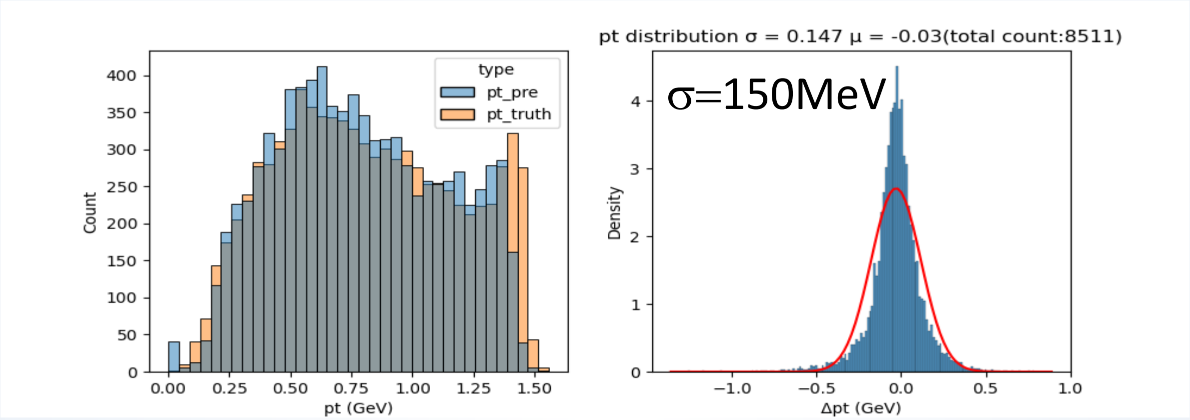
Hit efficiency vs p_T



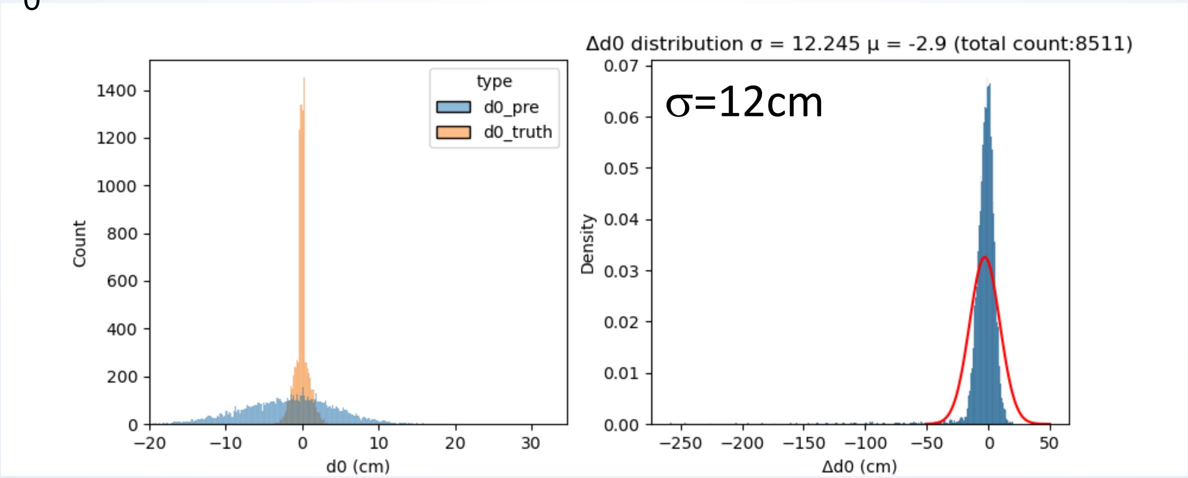
Track efficiency vs p_T

Performance of track parameter

- p_T distribution



- d_0 distribution



The performance of track parameter estimation is promising

Further approach

- Optimize current model considering physical mechanic
  - Use dice-loss to evaluate the hit efficiency
  - Distance between track and hits
  - Axial and stereo layers separately
  - Put kinematics and track model
  - Add an refinement of the track

- More efforts
  - DeepFit: 3D Surface Fitting via Neural Network Weighted Least Squares
  - Attention mechanism with transformers

DeepFit

Conclusions

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

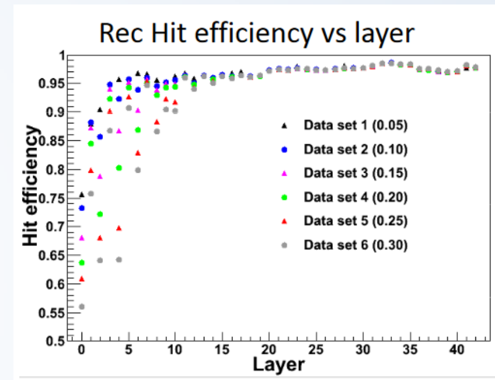
- More approach is under investigate such as
  - The combination of least-square fit
  - Attention mechanism with transformers

Thank you for your attention!

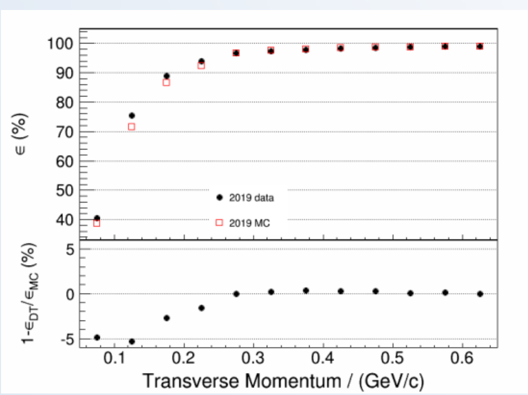
Backup

Challenge for BESIII tracking

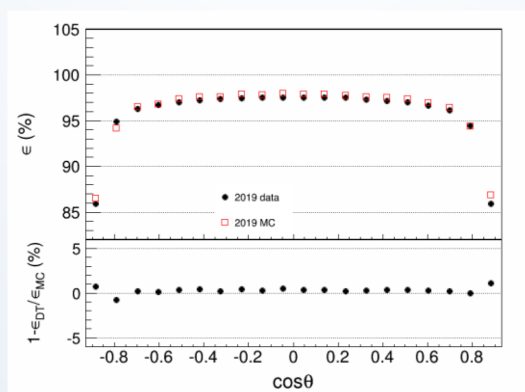
- Tracking quality need to improve for following situation
  - Noise resistance
  - Low momentum
  - Large dip angle
  - Secondary vertex



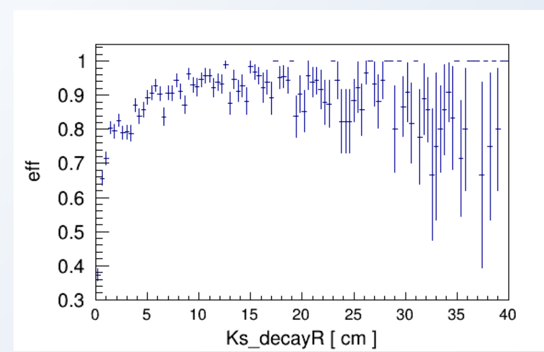
Hit efficiency vs noise level



Pion tracking efficiency vs p_T



Pion tracking efficiency vs $\cos\theta$



Ks tracking efficiency decay length