Reconstruction of Atmospheric Neutrinos and muon with Machine Learning Method in JUNO

X. Tan,[1] Z. Yang,[1] F.Zeng,[1] J. Liu,[2] H. Duyang,[1] T. Li,[1] W. Guo,[2] X. He,[2] Z. Liu,[2]
W. Luo,[2] X. Luo,[2] Y. Zhang[2]

[1] Shandong University

[2] Institute of High Energy

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Outline

- Introduction to JUNO
- Methodology
- Introduction to ML models
- Reconstruction methods and Performances
- Summary

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Introduction to JUNO: overview

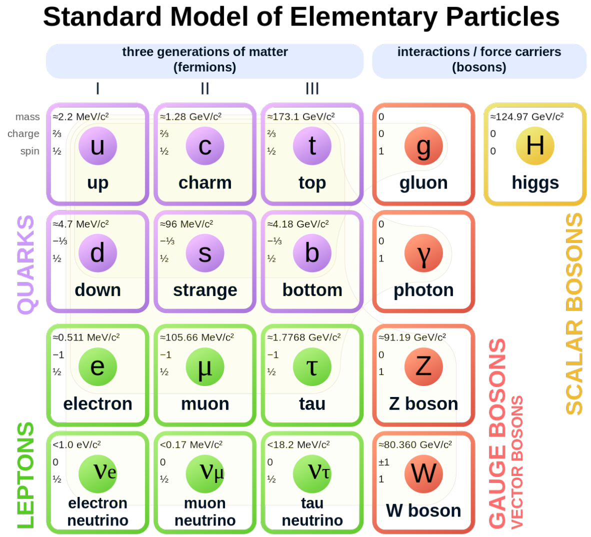
- Neutrino oscillation is of great theoretical and experimental interest.
- It implies that the neutrino has non-zero mass, which requires a modification to the Standard Model of particle physics.

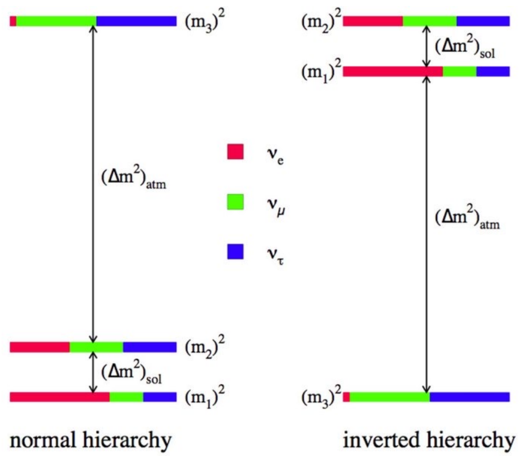
$$P(\overline{\nu}_\alpha \to \overline{\nu}_\alpha) = P(\nu_\alpha \to \nu_\alpha) = 1 - 4|U_{\alpha 1}|^2|U_{\alpha 2}|^2 \sin^2\left(1.27\frac{\Delta m_{21}^2}{E}L\right)$$

$$- 4|U_{\alpha 1}|^2|U_{\alpha 3}|^2 \sin^2\left(1.27\frac{\Delta m_{31}^2}{E}L\right)$$

$$- 4|U_{\alpha 2}|^2|U_{\alpha 3}|^2 \sin^2\left(1.27\frac{\Delta m_{32}^2}{E}L\right)$$

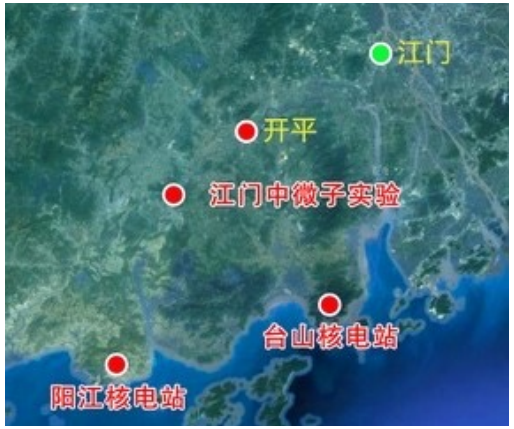
$$U = \begin{bmatrix} U_{e1} & U_{e2} & U_{e3} \\ U_{\mu 1} & U_{\mu 2} & U_{\mu 3} \\ U_{\tau 1} & U_{\tau 2} & U_{\tau 3} \end{bmatrix}$$





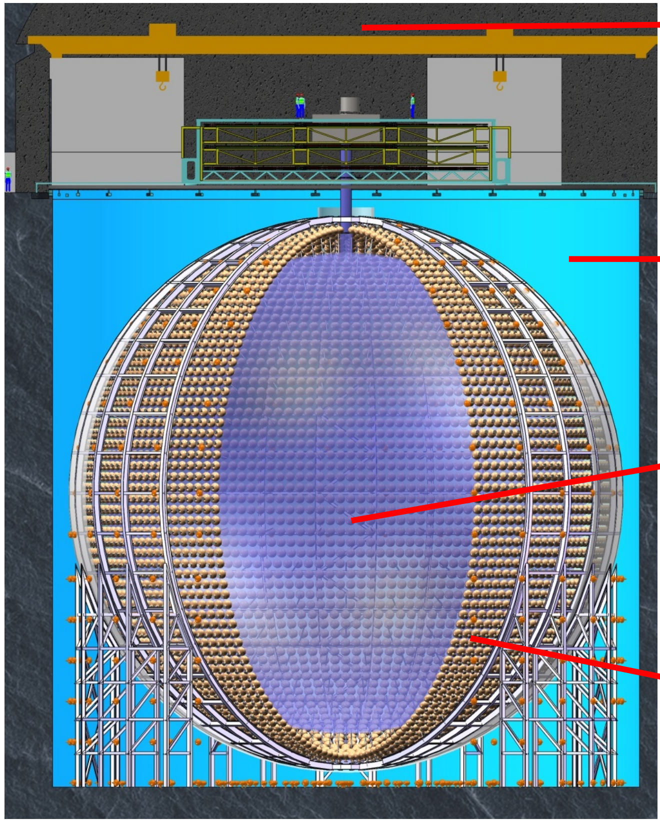
Introduction to JUNO: overview

- The Jiangmen Underground Neutrino Observatory (JUNO)
- A next-generation neutrino experiment.
- Scientific goals:
  - Determine the neutrino mass ordering (NMO);
  - Improve the precision of neutrino oscillation parameters;
  - SuperNova, Solar, Atm., Geo. etc
- Largest liquid scintillator detector and a superb energy resolution.



	DETECTOR TARGET MASS	ENERGY RESOLUTION
KamLAND	1000 t	6%@1MeV
D. Chooz	8+22 t	8%@1MeV
RENO	16 t	8%@1MeV
Daya Bay	20 t	8%@1MeV
Borexino	300 t	5%@1MeV
JUNO	**20000 t**	3%@1MeV

Introduction to JUNO: detector



700m underground, blocking cosmic rays through rocks.

More than 2 meters of water, vetoing external background.

20,000 tons of liquid scintillator (LS).

PMTs to detect and collect neutrino events:

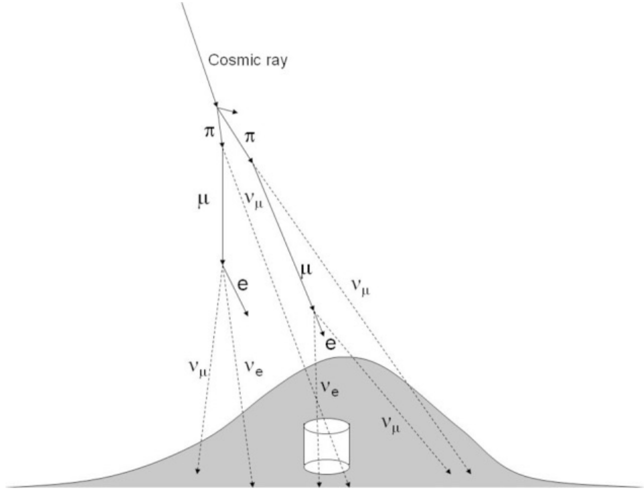
- 17,612 20-inch PMTs (used in this study);
- 25,600 3-inch PMTs.

78% PMT coverage.

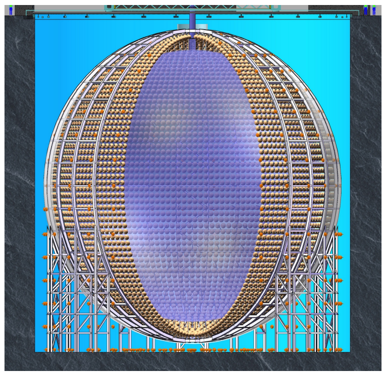
Introduction to JUNO: atmospheric neutrinos

- Atmospheric neutrinos are from cosmic rays interacting with upper atmosphere:

$$\begin{cases} p + N & \rightarrow N' + n(\pi) \\ \pi & \rightarrow \mu + \nu_\mu \\ \mu & \rightarrow e + \nu_\mu + \nu_e \end{cases}$$



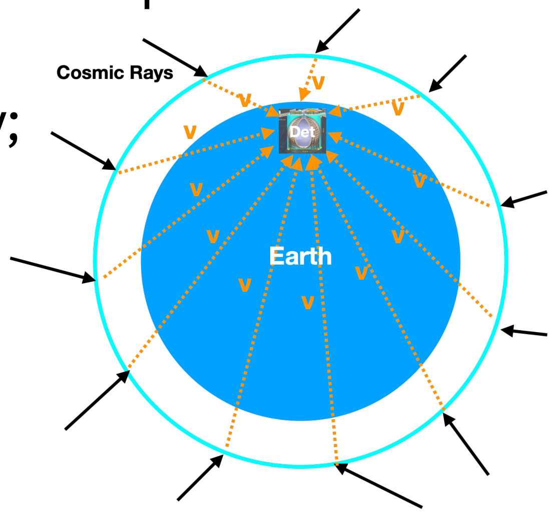
Reactor neutrinos: Sensitivity to NMO via oscillation in vacuum

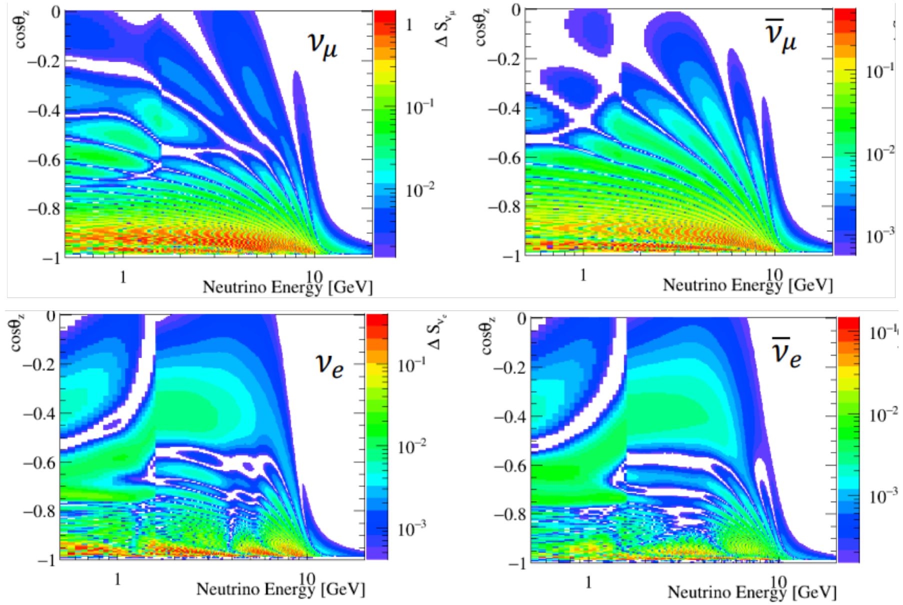


Atmospheric neutrinos: Sensitivity to NMO via oscillation with matter effect

Introduction to JUNO: atmospheric neutrinos

- The measure of atmospheric neutrino oscillations has great potential to enhance JUNO's NMO sensitivity.
- Neutrino oscillations probability $P = f(\frac{L}{E})$.
- Reconstruction of atmospheric neutrinos:
  - Zenith angle θ;
  - Neutrino energy;
  - Flavor (PID).

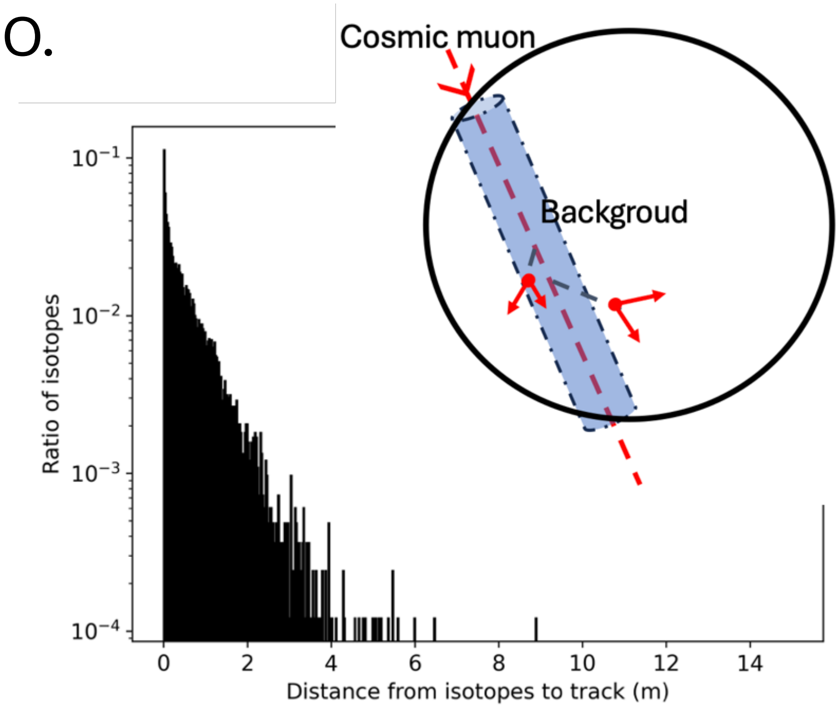




Introduction to JUNO: cosmic ray muon

Isotopes(9Li/8He etc.) produced by cosmic muons are the main background of IBD signal in JUNO.

- **Classification and track reconstruction:**
  - Spallation isotopes are short-lived and their spatial distribution follows an exponential decay profile relative to the parent muon trajectory
  - A straightforward veto strategy involves excluding events within a defined spatial-temporal window around the muon track.
- **Shower vertex reconstruction:**
  - Muons can shower, creating additional spallation isotopes. These contribute over 85% of the background, reducing neutrino oscillation sensitivity.



Introduction to JUNO: challenging

- Directionality and tracker measurement in large homogeneous LS detectors, however, are very challenging:
  1. LS detectors do not offer direct track information.
  2. Cherenkov light, while offering excellent directional information in Water detectors, is about two orders of magnitude weaker than scintillation light in a typical LS detector.
- So we turned to scintillation light for directionality, energy, pid, track, vertex

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- Introduction to JUNO
- **Methodology**
- Introduction to ML models
- Reconstruction methods and Performances
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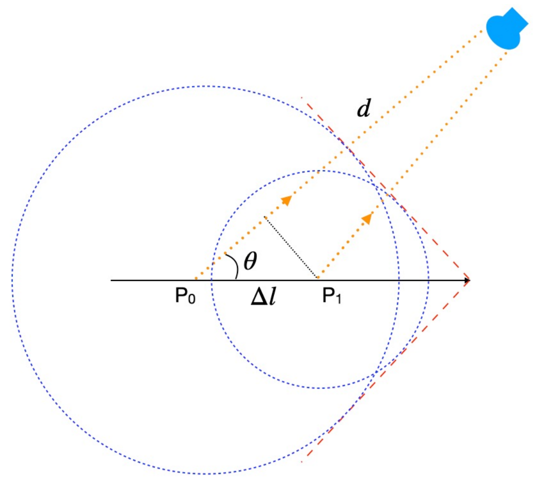
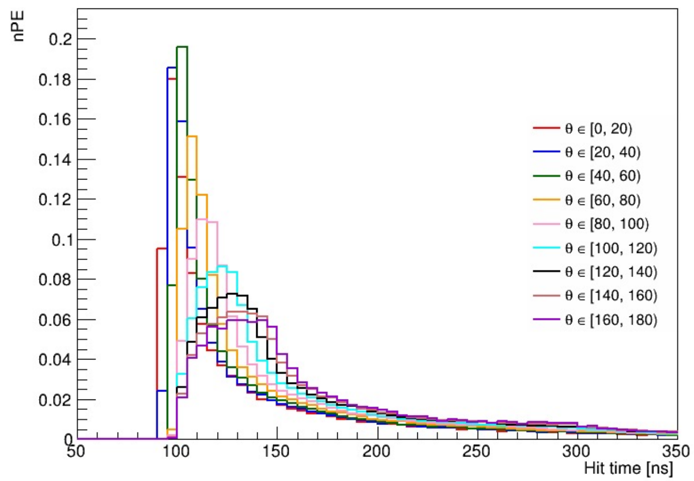
Methodology: physics process

- A particle's track depicts distict shape of nPE(t) for PMTs at different angles.
- Practically, the shape of nPE(t) depends on:
  - The angle between the track and PMT; → Direction
  - Track starting and stopping points;
  - $\mathrm{d}E/\mathrm{d}x$ etc.

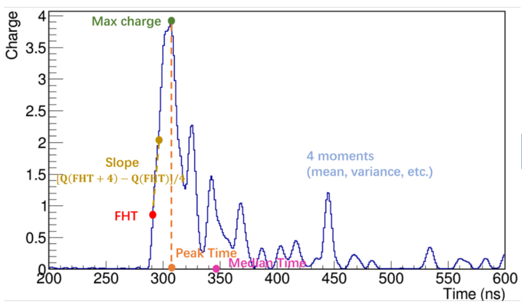
  } PID
- Therefore, the particle's information is reflected in nPE(t), and finally reflected in the waveform.



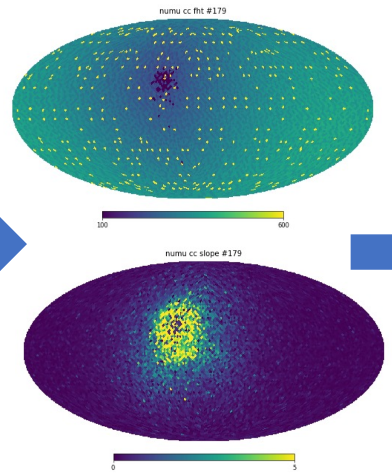


Methodology: PMT features

- It is too complex to use full waveform as inputs to ML. So, features are extracted from waveforms to keep only the useful information relevant to reconstructions.



PMT Waveform



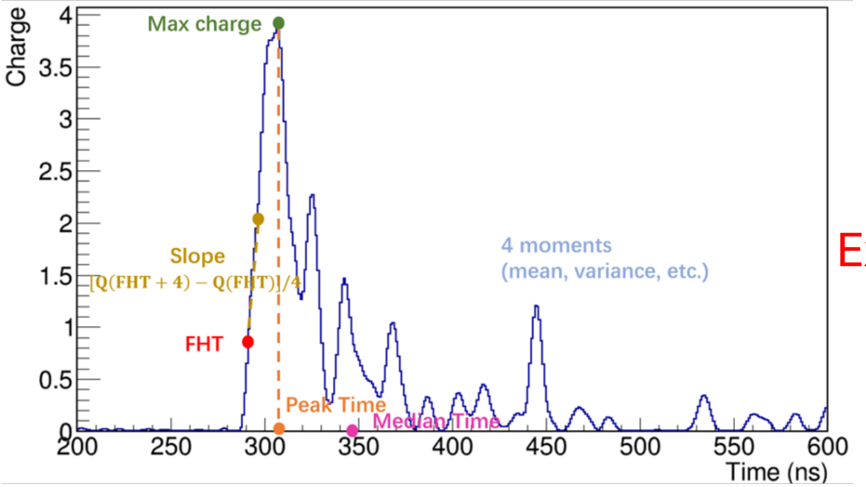
Pictures Features

Machine learning models

Reconstruction

- Directionality
- Energy
- PID
- Track
- Vertex

Methodology: PMT features



Extract feature

First Hit Time

Total charge: The charge integration over the entire readout time window.

Charge ratio: Charges in the first 4ns divided by the total.

Slope: Describes the average slope in the first 4ns.

Max charge, Peak Time

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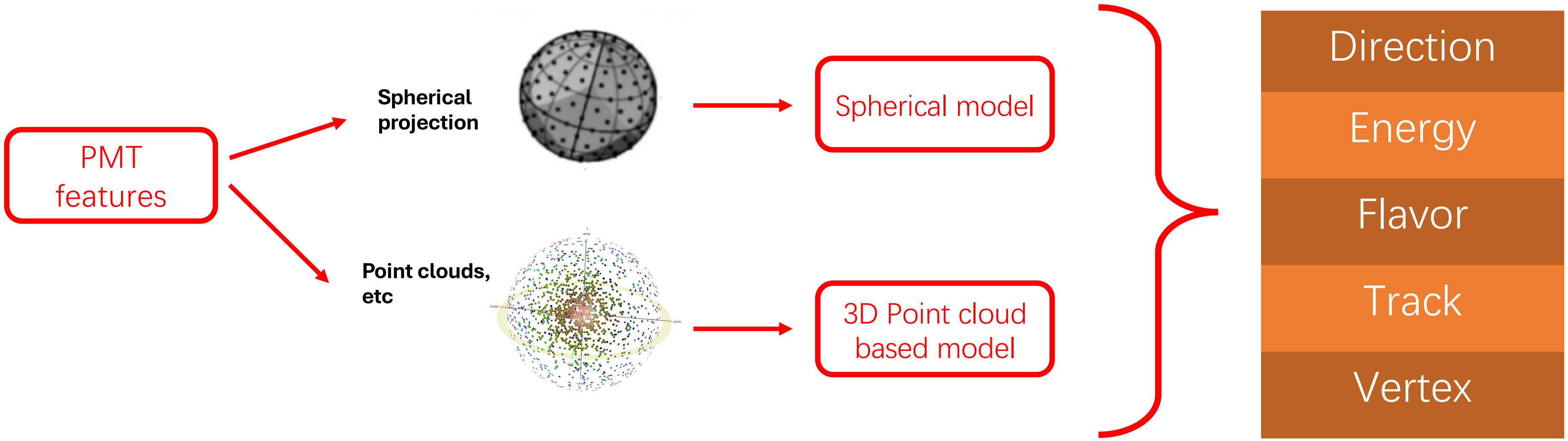
Introduction to models

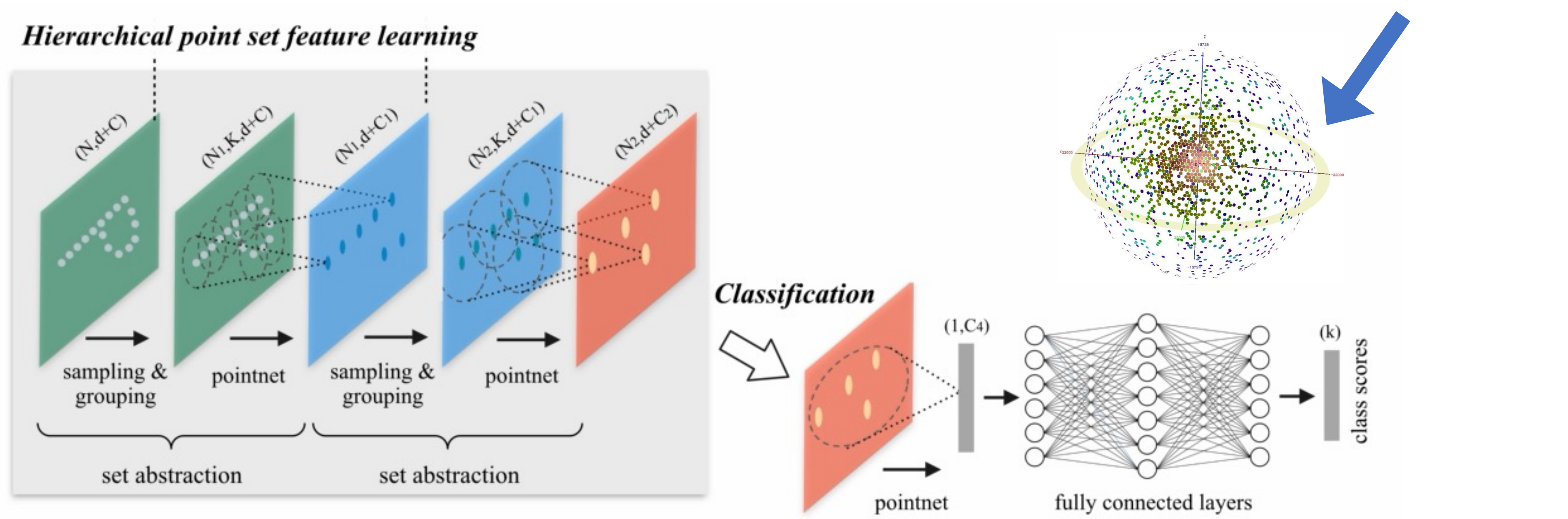
2 categories of machine learning method to deal with a spherical problem:

- Spherical-image-based method: DeepSphere
- 3D-based method: PointNet++



Introduction to models: PointNet++

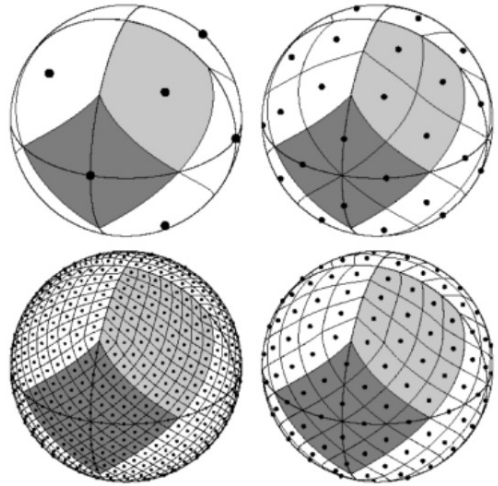
Directly taking 3D point clouds as input → JUNO signal more resembles point clouds.

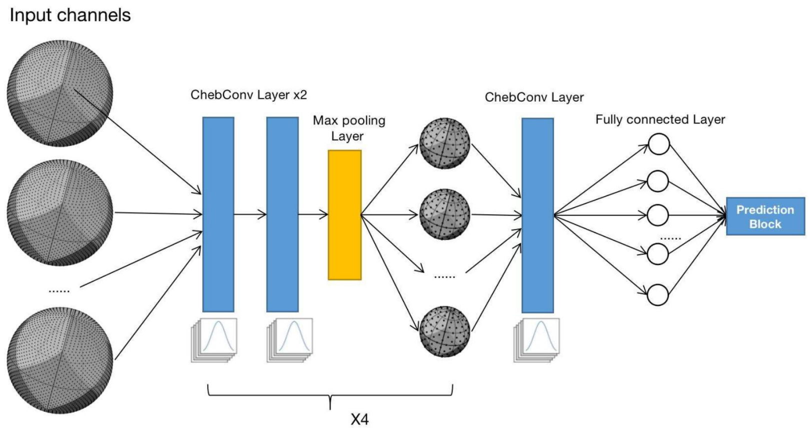


(N.B. PointNet++ input format: for each event, N(PMT)*[x, y, z, features, ..])

Introduction to models: DeepSphere

- DeepSphere: a popular tool processing spherical data originally developed for cosmology studies.
  - Maintain rotation covariance;
  - Avoid distortions caused by projection to a planar surface.





4 sets of convolution blocks, followed by one Chebyshev convolution layer, a fully connected layer and lastly a prediction block.

- $N_{side} = 32$
- $\text{Pixels}=12\times N_{side}^2 = 12288$
- If more than one PMTs are grouped into one pixel, information is merged:
  - First hit time: the earliest;
  - Totoal charge: the sum;
  - Slope and others: the average.

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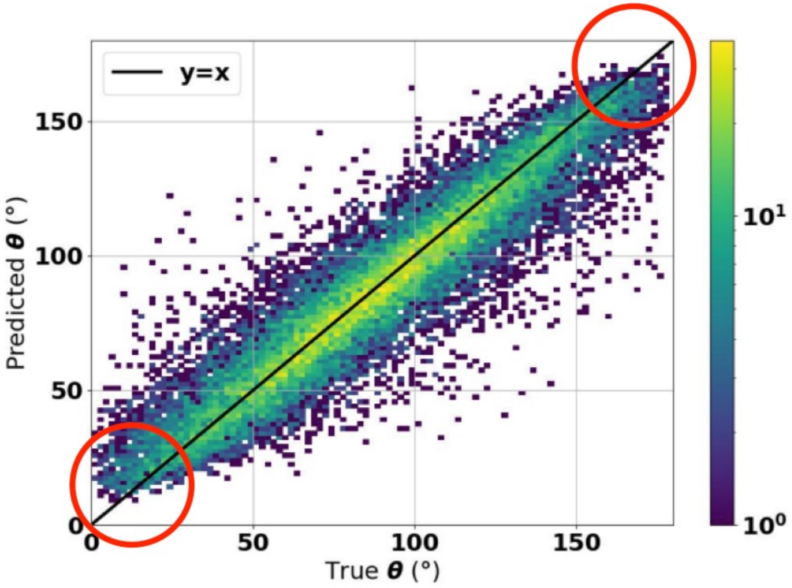
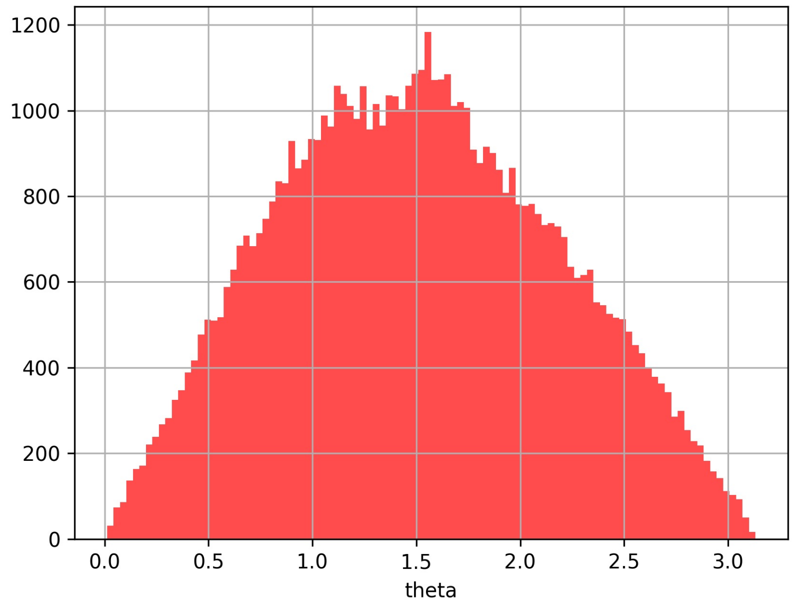
Reconstruction methods and Performances

- Atmospheric neutrino reconstruction
  - Directionality
  - Energy
  - PID
- Cosmic muon
  - Classification
  - Reconstruction

Directionality reconstruction method: Loss function

- Predict theta directly: The result is obviously biased, and the model seems to prefer value closer to 90°. This is because the distribution of theta is not uniform, and more events are distributed around 90°.

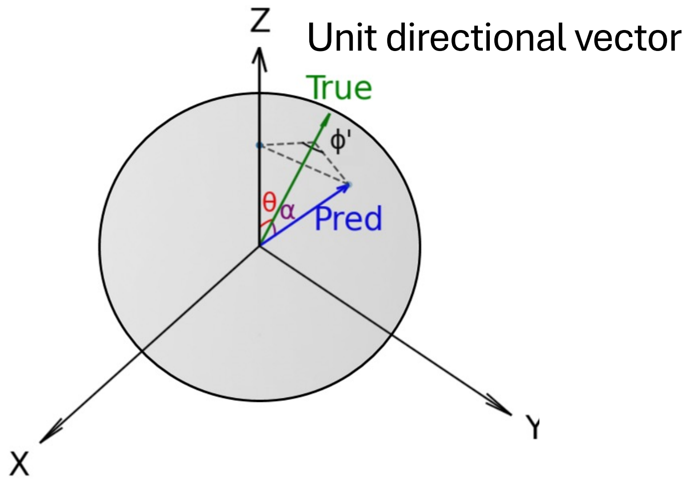


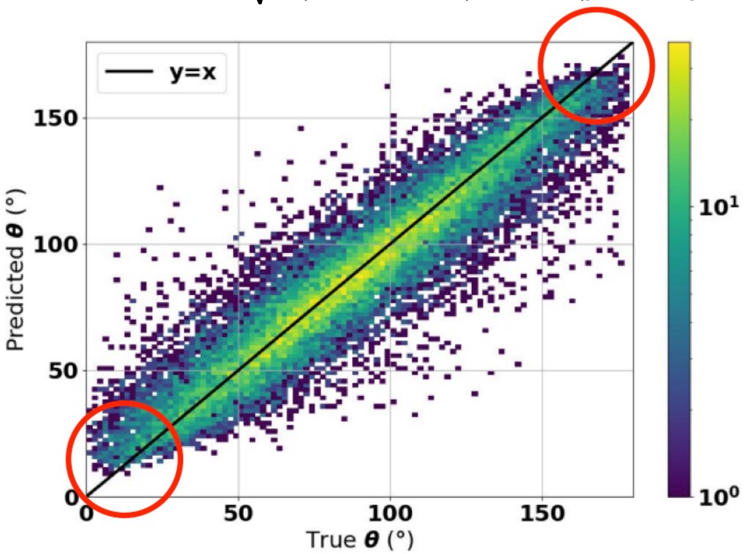


Directionality reconstruction method: Loss function

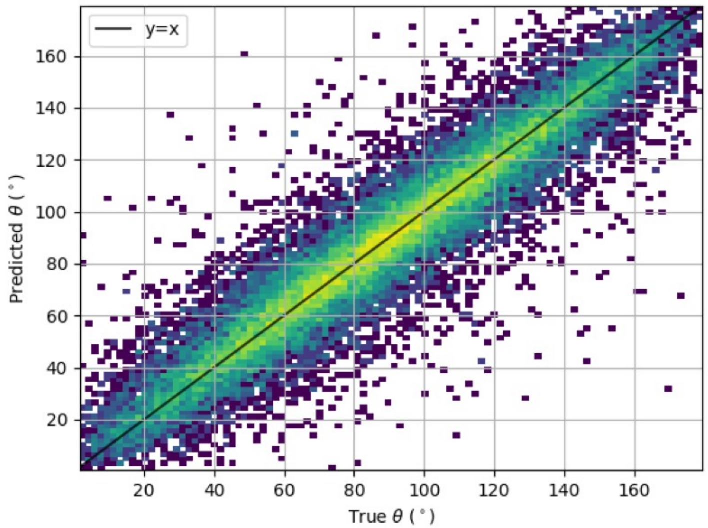
- Then try to reconstruct the directional vector (x, y, z) and update Loss Function (Rotation invariance):

$$\text{Loss} = \sqrt{(x - x')^2 + (y - y')^2 + (z - z')^2}$$



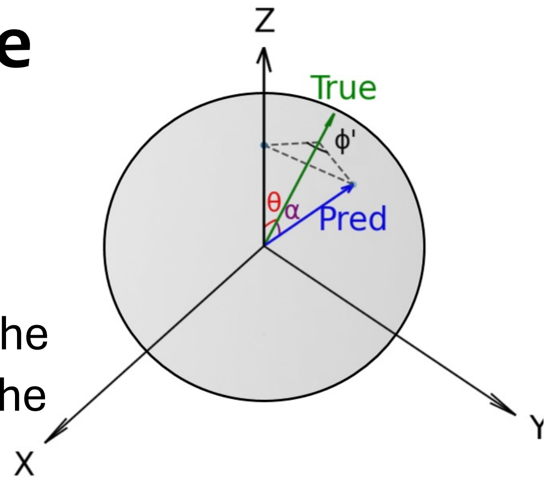


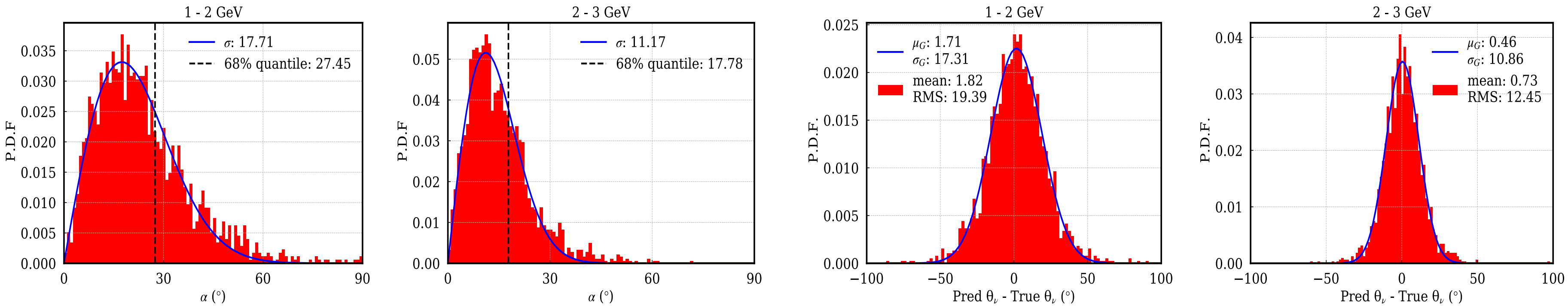
Bias is gone



Directionality reconstruction performance

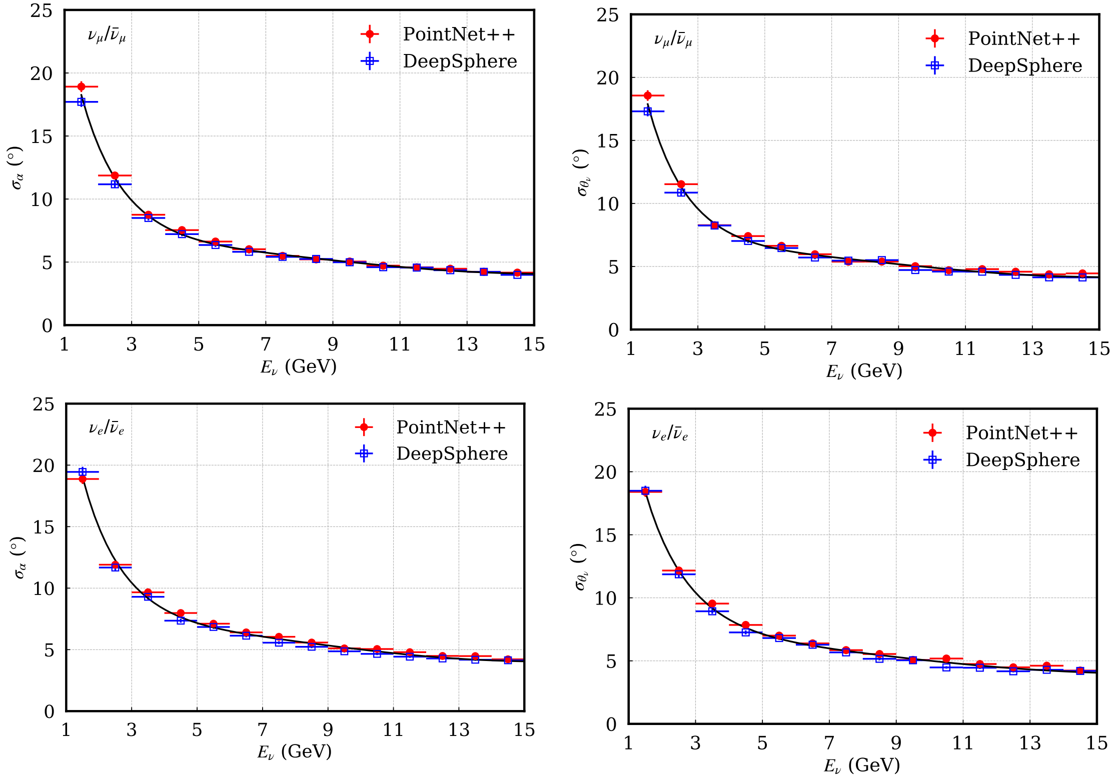
α: Angle between the true and reconstructed directional vector. Due to the range of α is 0 to 180°, 68% quantile is used to quantify the performance of α.
θ: Zenith angle of the true vector. Reconstructed θ - True θ reflect the resolution. Distribution in different E_ν bins can be well in line with the Gaussian distribution. σ_G is used as quantized resolution.





Directionality reconstruction performance

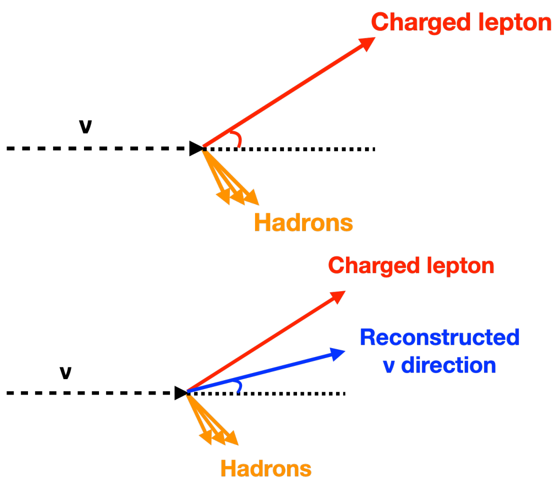
Cross-check with other models

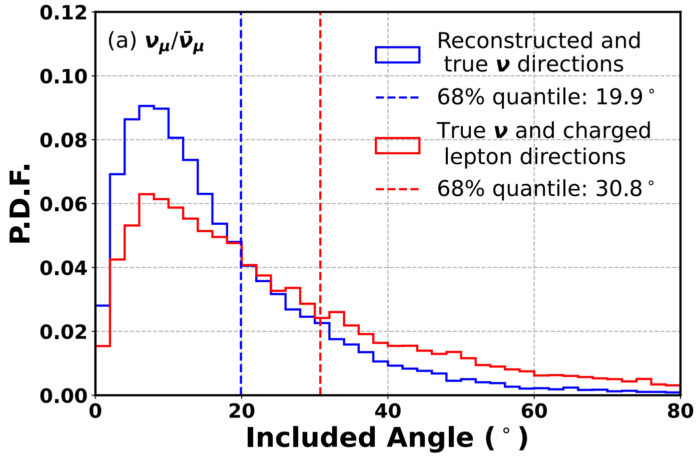


The blue and red line segments are the reconstruction results of the DeepSphere and PointNet++ models used by the high energy institute of the cooperative unit.

Overall, the inter-model differences in resolution are not much with 2°

Directionality reconstruction performance





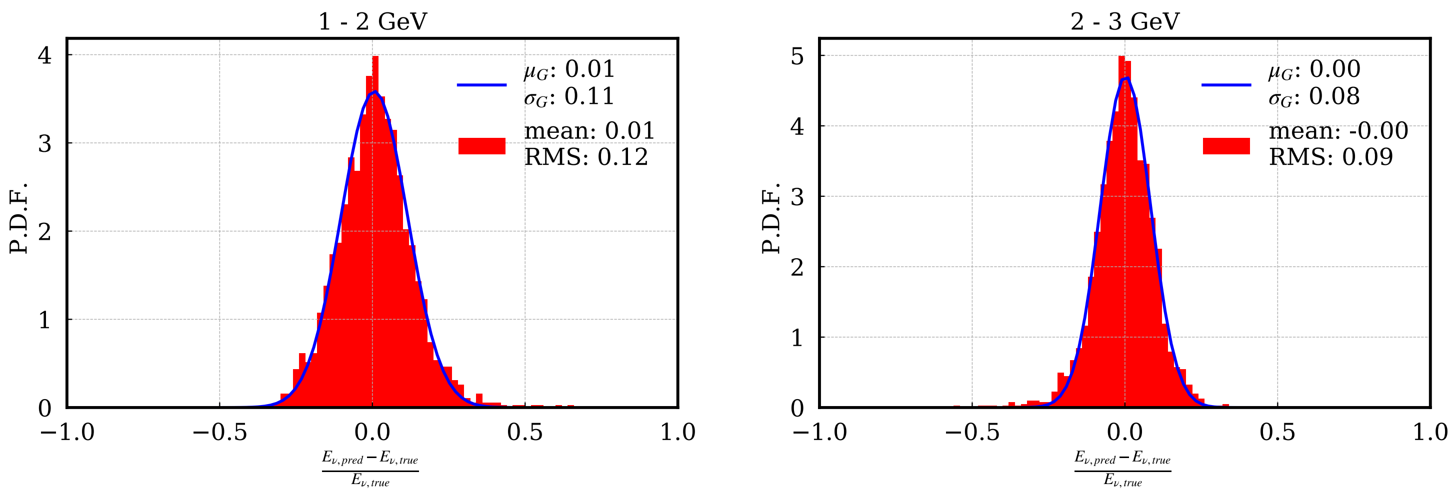
- Both lepton and hadron information are used in the directionality reconstruction.
  - Low-threshold in LS detectors allows for more information from hadrons.
- The reconstructed neutrino direction is less smeared from true neutrino direction compared with the charged lepton direction.
  - An advantage for an LS detector with this method.

Reconstruction methods and Performances

- Atmospheric neutrino reconstruction
  - Directionality
  - Energy
  - PID
- Cosmic muon
  - Classification
  - Reconstruction

Energy reconstruction performance:

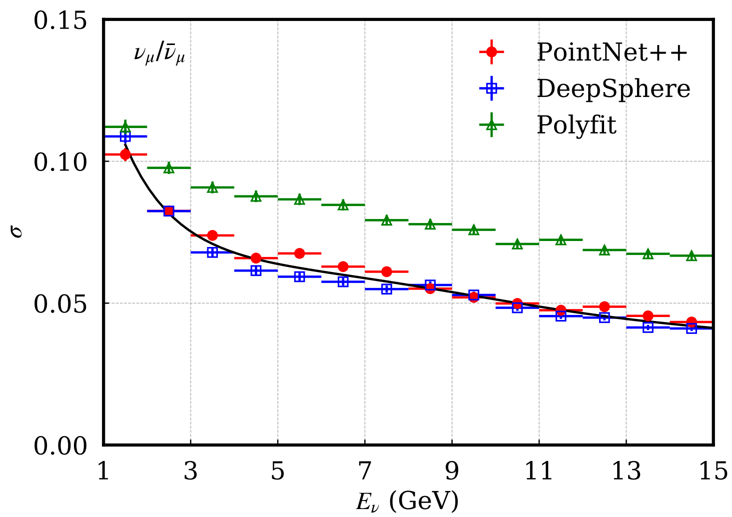
- Neutrino interaction → Secondary particles → Deposition energy → Visible energy.
- Performance benchmark:
  - (Reconstructed E - True E)/True E reflect the performance.
  - Distribution in different E_ν bins can be well in line with the Gaussian distribution. σ_G is used as quantized resolution.

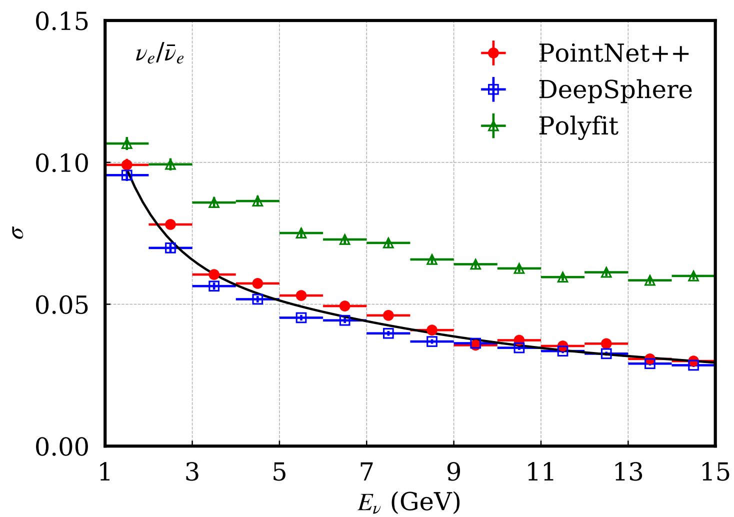


Energy reconstruction performance

Cross-check with other models

- The blue and red line segments are the reconstruction results of the DeepSphere and PointNet++ models used by the high energy institute of the cooperative unit.
- Green line means reconstruction by fitting the relationship between the total charge of the event and the neutrino energy with a polynomial function.





Reconstruction methods and Performances

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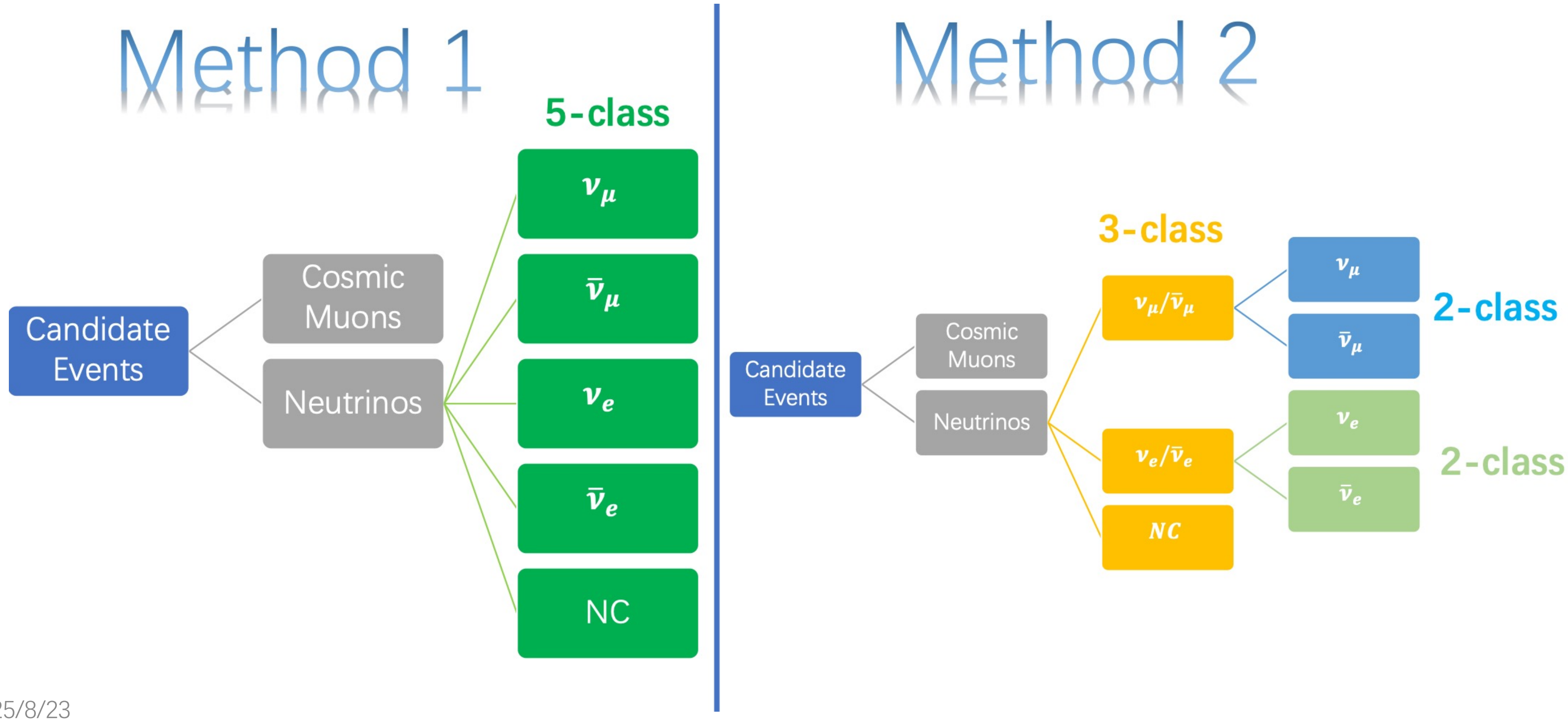
PID performance

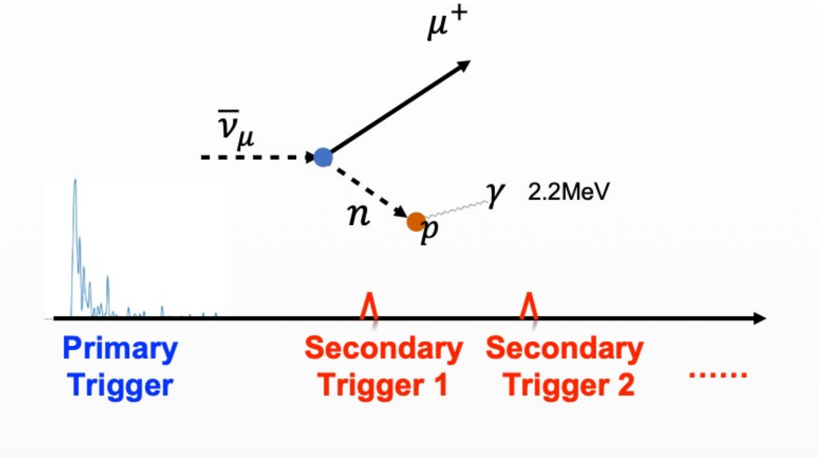
Two PID strategies:



PID method

The identification of $\nu/\bar{\nu}$ interactions relies on their differences in event kinematics, neutron multiplicity, and the spatial distribution of neutron-capture vertices.

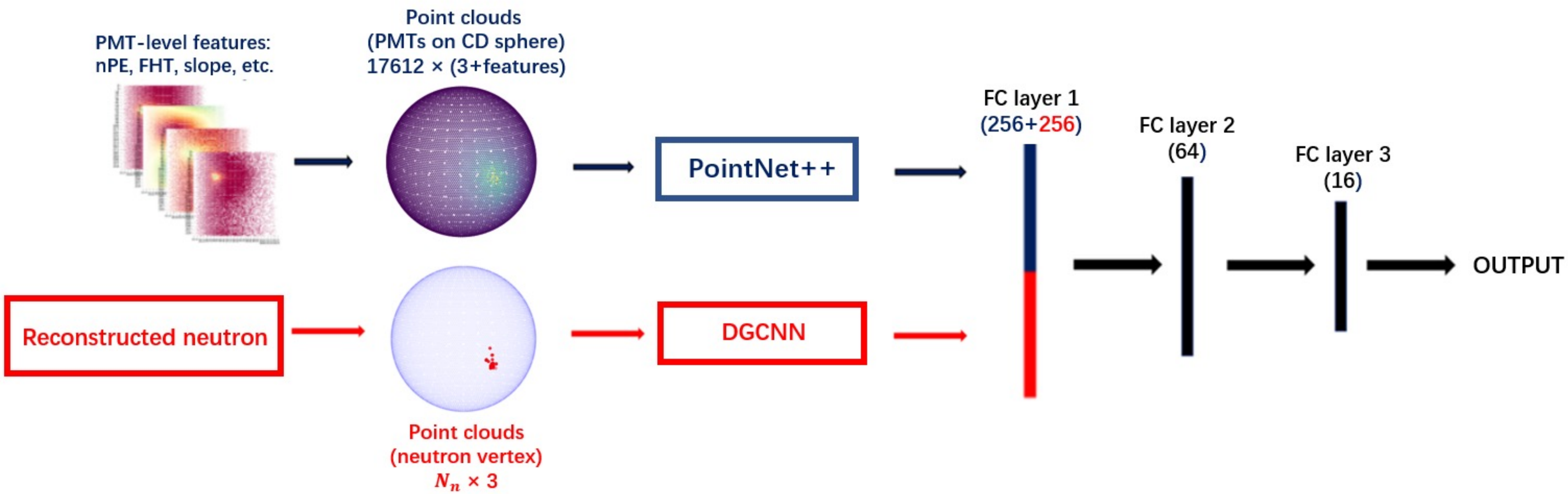
- Event kinematics: contained in the PMT primary trigger features;
- Neutron information: reflected in the delayed triggers, and two strategies on handling delayed trigger (neutron captures) information for $\nu/\bar{\nu}$ discrimination.



PID method -- Strategy 1

Reconstructed neutron-capture vertices taken as point clouds

The reconstructed vertices from multiple selected delayed triggers form a new 3D point cloud that is input to the ML model together with the one formed by PMT waveform features from the prompt trigger.



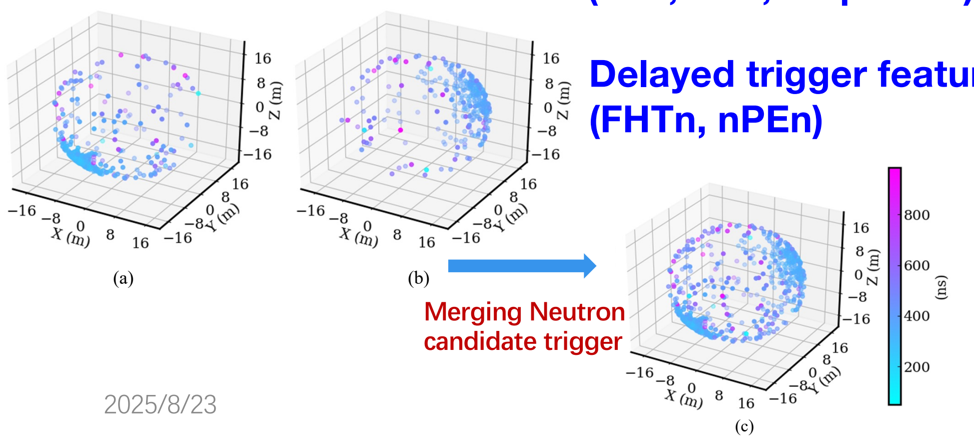
PID method -- Strategy 2

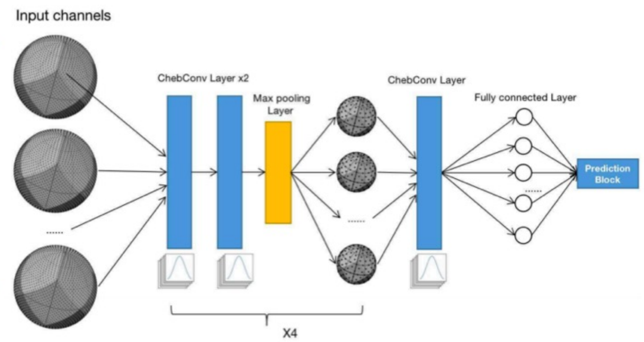
Neutron-capture triggers merged into one as additional features

- This strategy merges multiple delayed triggers into one by summing up the charges from multiple selected delayed triggers for each PMT, and taking the FHT value as the earliest among them.
- nPEn and FHTn used as extra features to the ML model together with features from the prompt trigger.

Primary trigger features (FHT, nPE, Slope etc.)

Delayed trigger features (FHTn, nPEn)



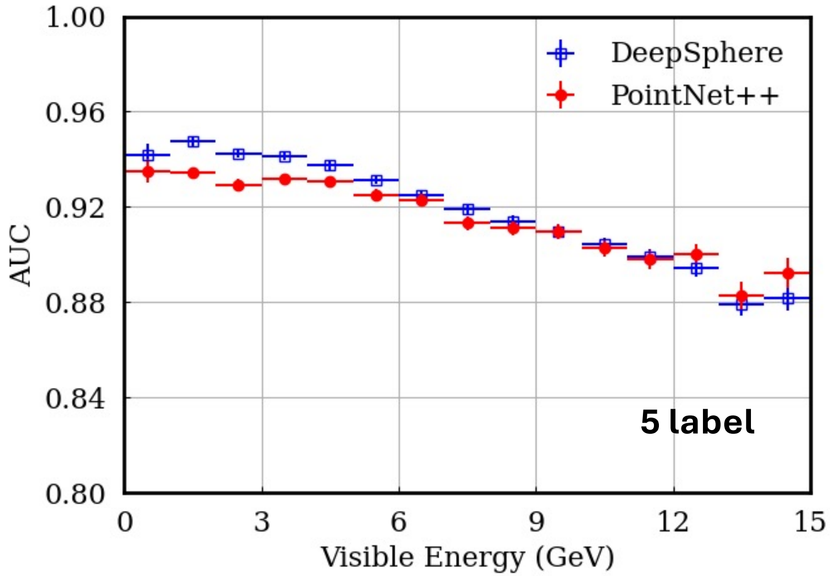


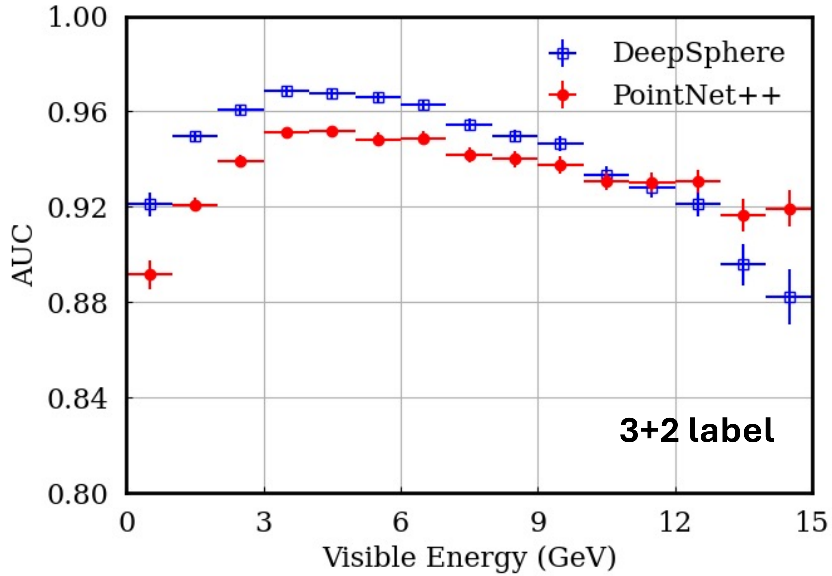
DeepSphere

PID performance

Cross-check with other models

- AUC for performance evaluation of 5 label and 3+2 label



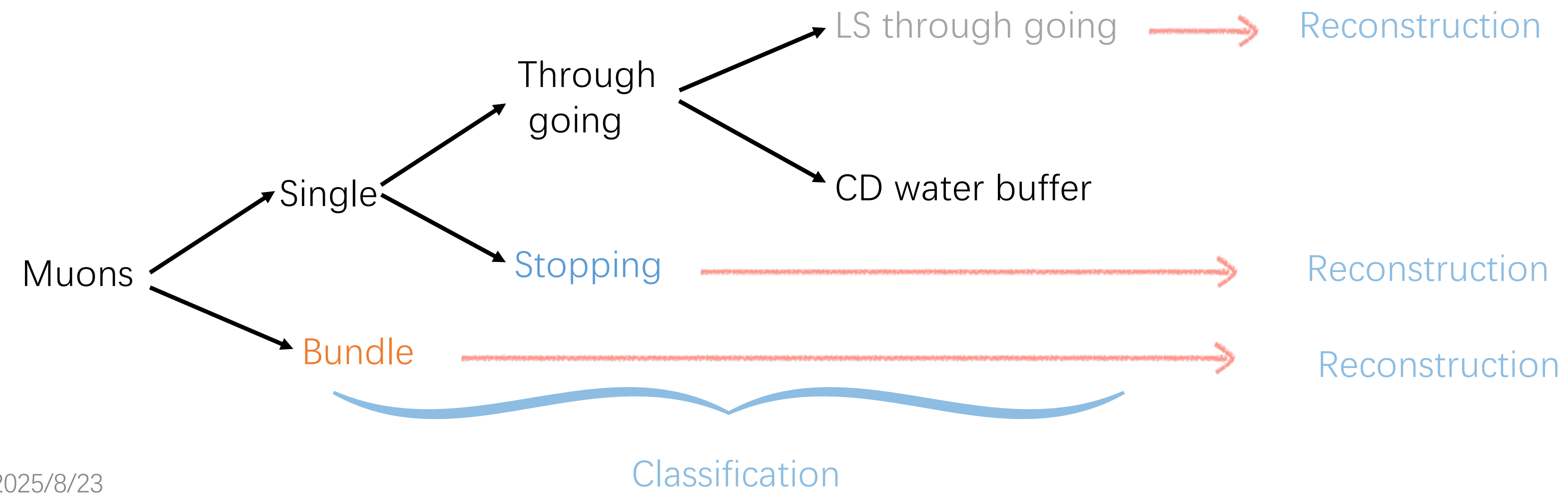


Reconstruction methods and Performances

- Atmospheric neutrino reconstruction
  - Directionality
  - Energy
  - PID
- Cosmic muon
  - Classification
  - Reconstruction

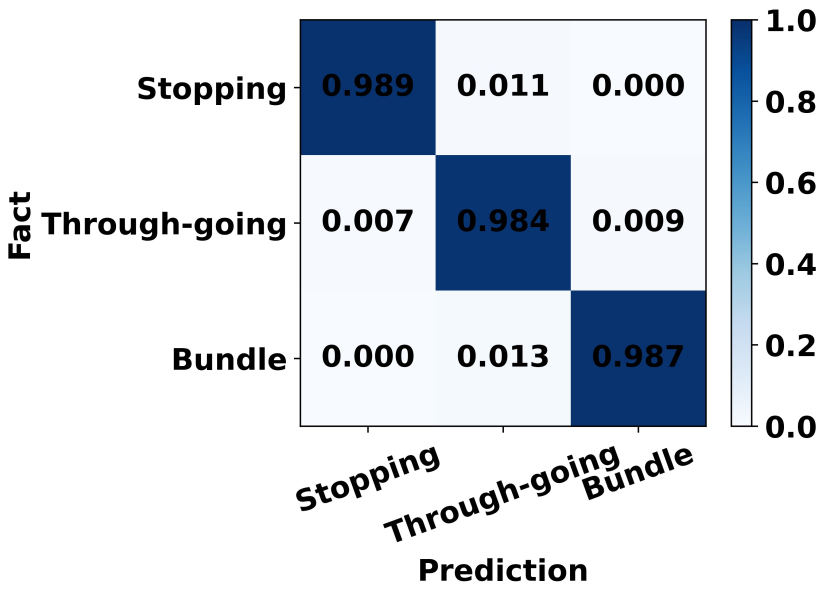
Cosmic ray muon reconstruction method

- To maximize the efficiency of background rejection, a classification for observed muon events and suitable reconstruction strategies for each muon types should be done.
- This work aims to develop a comprehensive process from muon classification to track reconstructions for all muon types.



Cosmic ray muon classification performance

- Sample: through-going, stopping and bundle muons, each 6400 events.
- Features: FHT, nPE

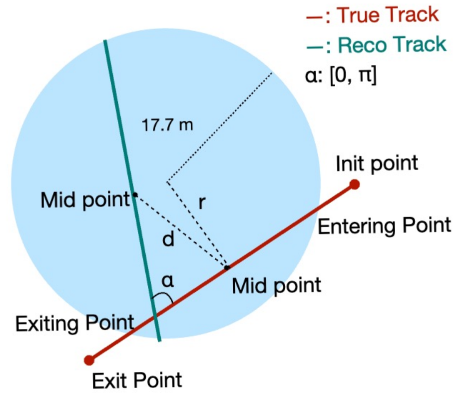


Performance:

- Through-going muons
  - Efficiency: 98.4%, Purity: 97.6%;
- Stopping muons
  - Efficiency: 98.9%, Purity: 99.3%;
- Muon bundles
  - Efficiency: 98.7%, Purity: 99.0%;
- Total accuracy: 98.6%.

Separation between muon bundles and single muons is great, because comprehensive information, like Edep, is reflected by features.

Cosmic ray muon reconstruction performance



Definition

A muon track is defined as the connection between init point and exit point in the simulation volume based on the MC truth.

Evaluation method

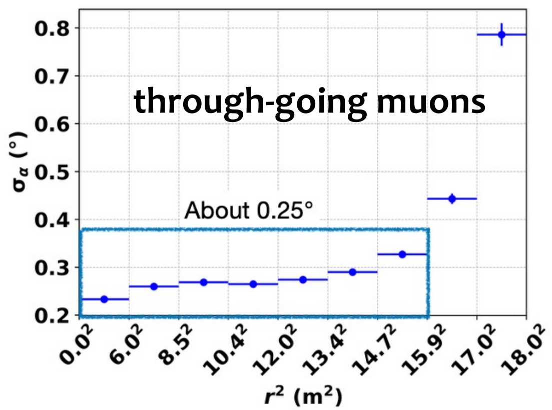
The usual method: α, d are used to quantify the results.

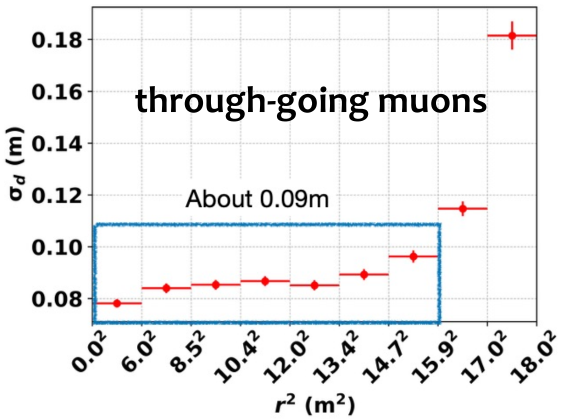
α: the included angle between true and reconstructed tracks. [0, π]

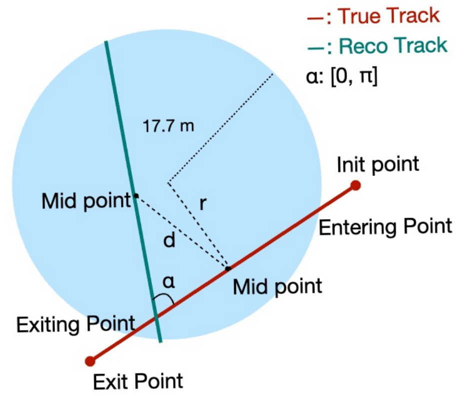
d: the distance between midpoints of true and reconstructed tracks.

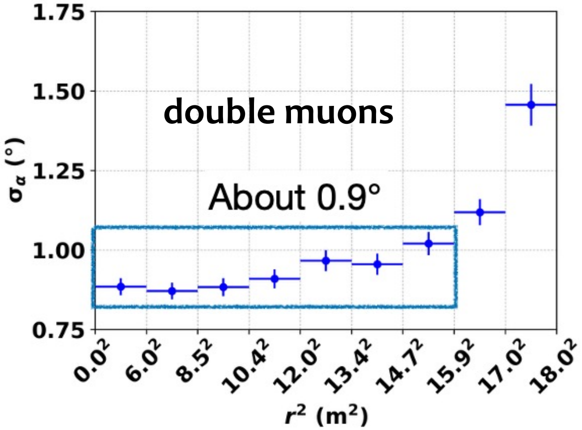
Resolutions as functions of r^2 (r: distance from center to the true track).

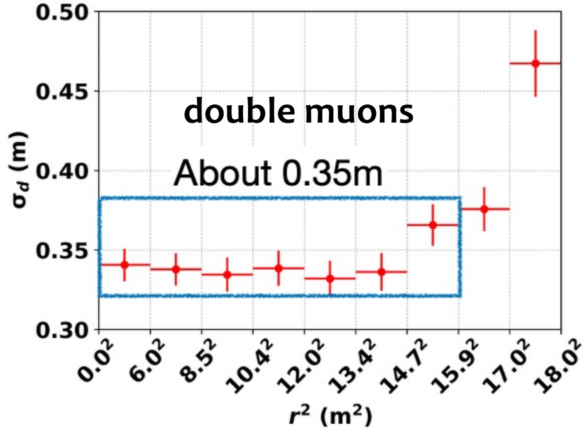
Cosmic ray muon reconstruction performance







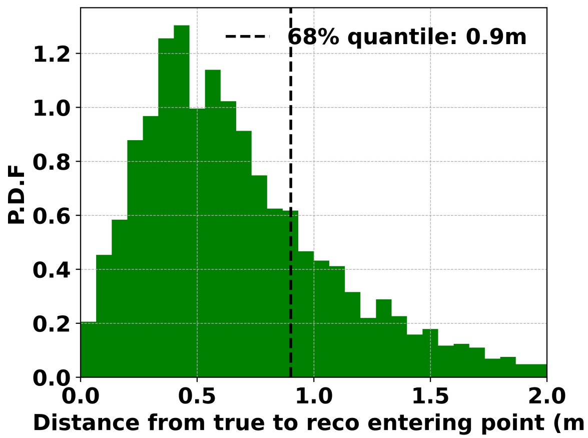


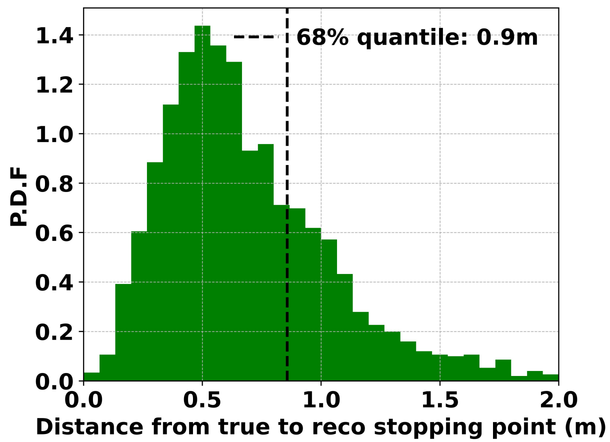


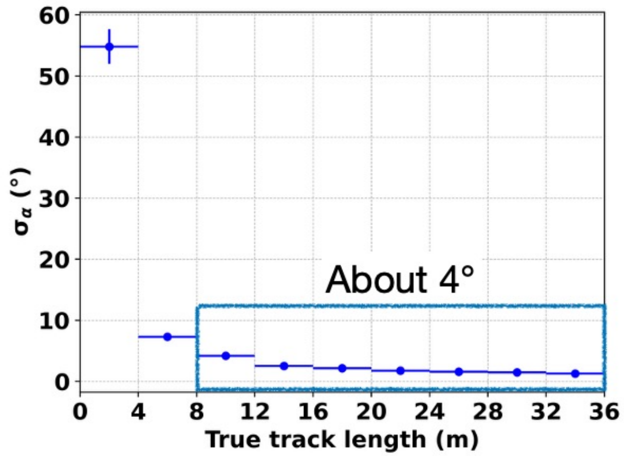
through-going muons:
The entering point to the LS and the direction of the track are the model output.
double muons:
The entering point of each track and the mean direction from two tracks are the model output.

Cosmic ray muon reconstruction performance stopping muons

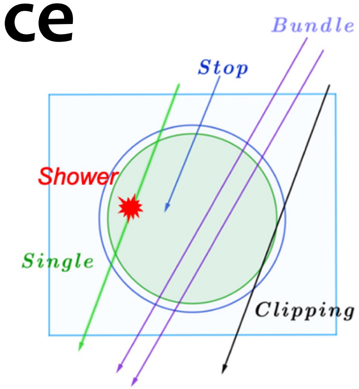
Entering point and direction cannot describe a stopping muon track. To minimize the number of parameters, the entering point and the stopping point of a track are the model output for a stopping muon



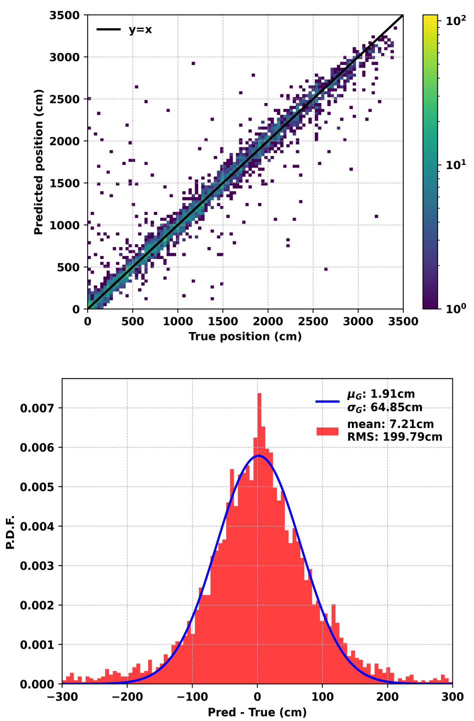




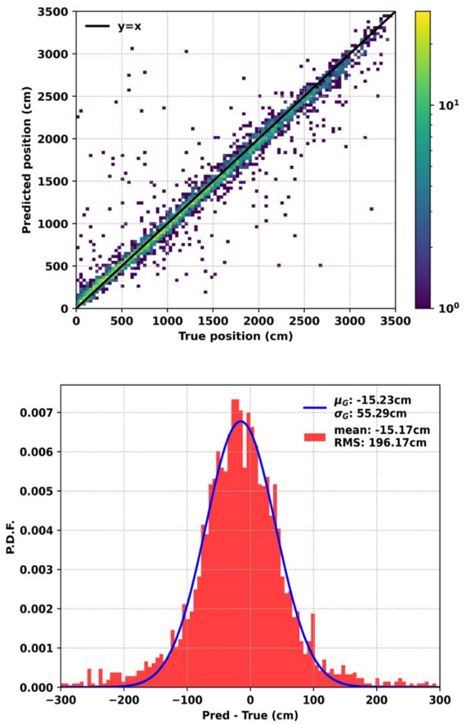
Cosmic ray muon reconstruction performance muon shower



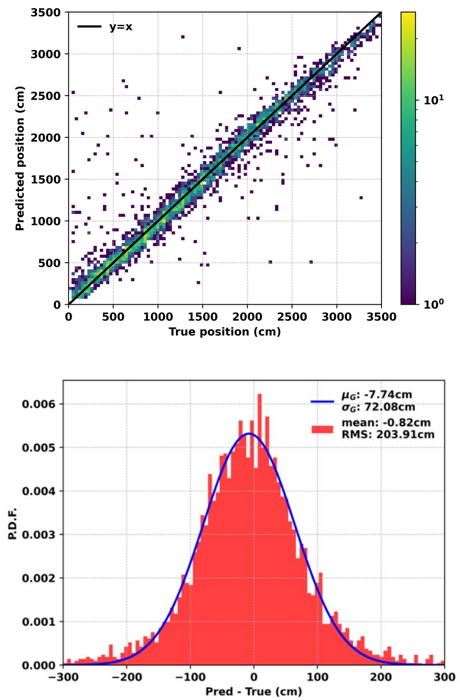
Reconstruction of start, end and center of showers



Start Position



Center Position



End position

- Well resolution (σ_G): 64cm on Start, 72cm on End, 55cm on Center.
- But some events are reconstructed much badly makes the RMS not very well. And there is bias when the true values are large.

Outline

- Introduction to JUNO
- Methodology
- Introduction to ML models
- Reconstruction methods and Performances
- Summary

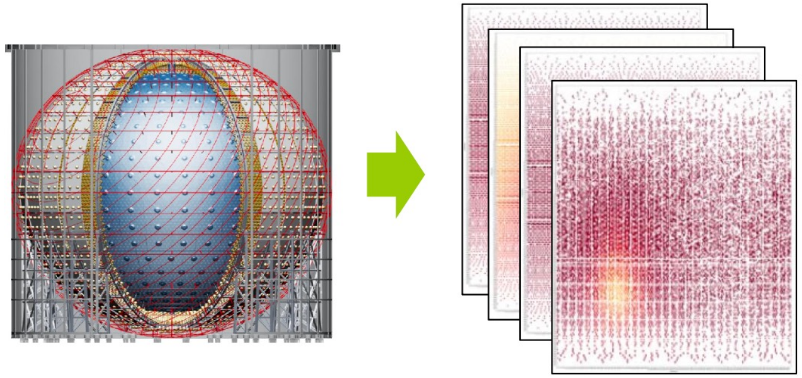
Summary

1. In this talk, we present a multi-purpose machine learning approach for the reconstruction and identification of high energy events in large homogeneous LS detectors.
2. We aim to perform the first atmospheric neutrino oscillation measurement in an LS detector in the world, and increase JUNO's total sensitivity to NMO.
3. Develop a comprehensive process from muon classification to track reconstructions for all muon types.

Back up

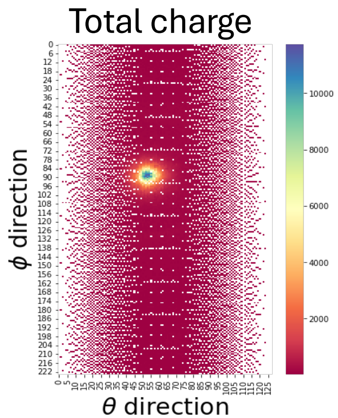
Introduction to models: EfficientNetV2

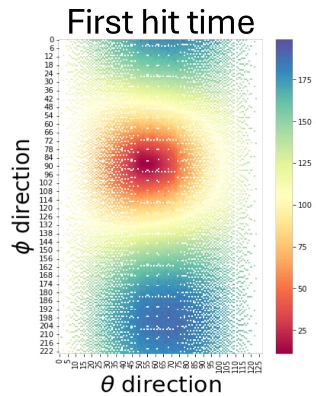
- State-of-the-art performance among CNNs;
- Smaller model size and fast training;



Model input: 2D grids

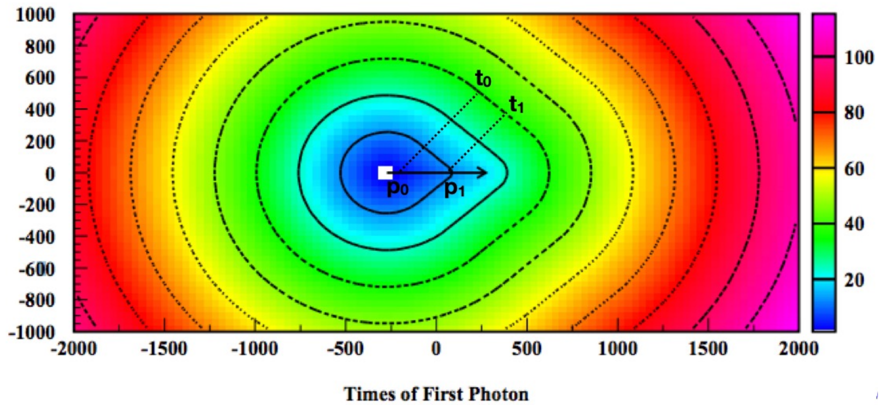
- The PMT map is projected onto a 2D θ−ϕ grid (according to PMT spherical coordinates);
- The grid size of 128 × 224 for Large PMTs is chosen to ensure each grid cell corresponds to at most one PMT.



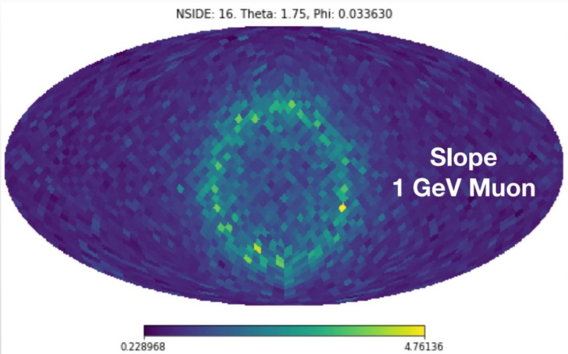


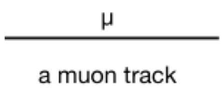
Methodology: physics process

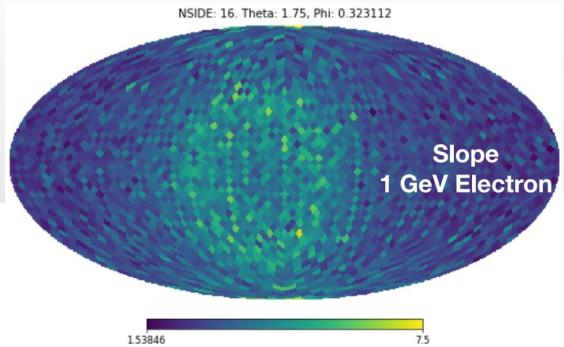
- If particles travel at a speed faster than the speed of light in LS, scintillation light forms a cone-like front structure.

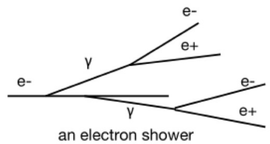


- The hit time of the earliest photon reaching a PMT ("first hit time") therefore naturally offers information on the event directionality.





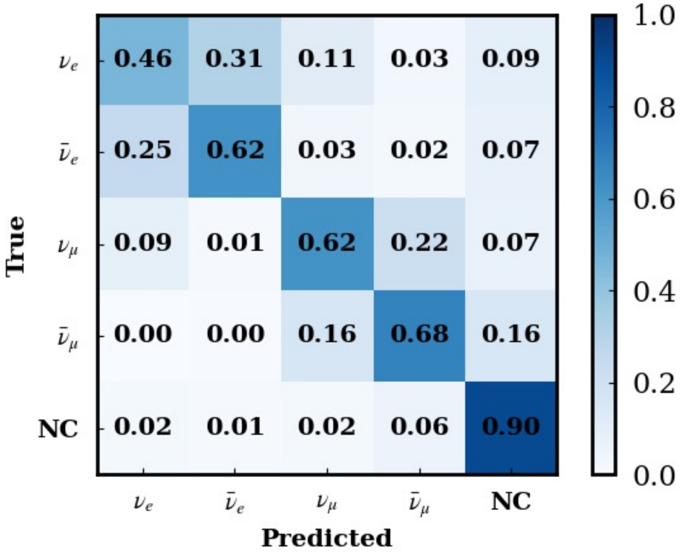




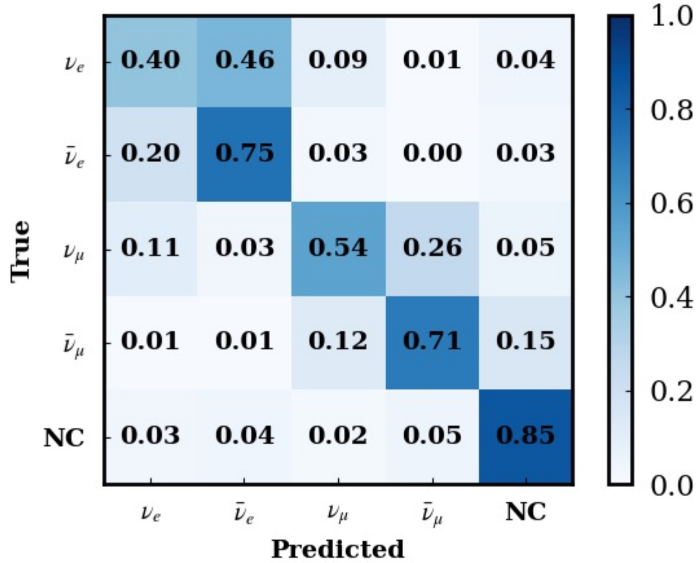
- Distribution of the slope of the ascending section of 1GeV muon /electron waveform on the pmt sphere of JUNO

PID performance

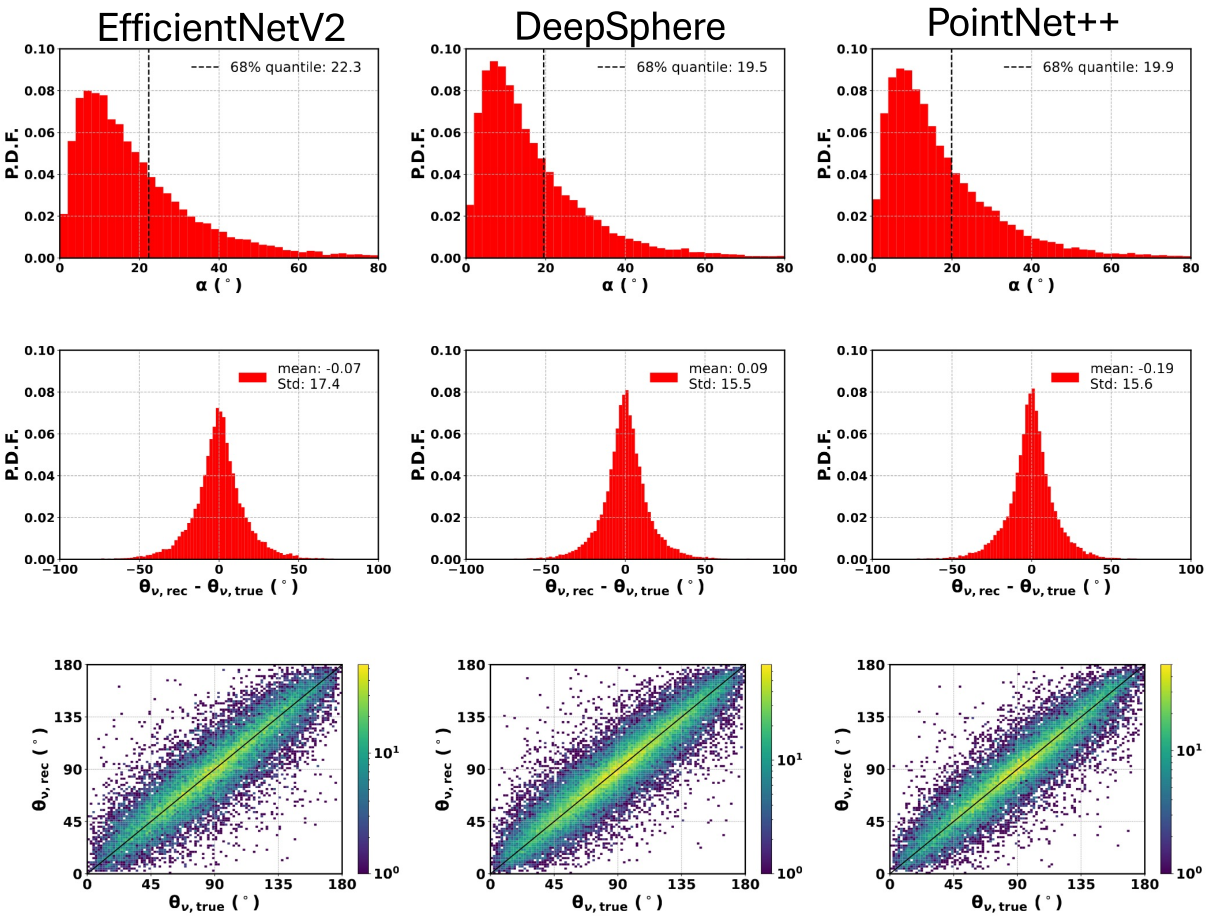
5 label



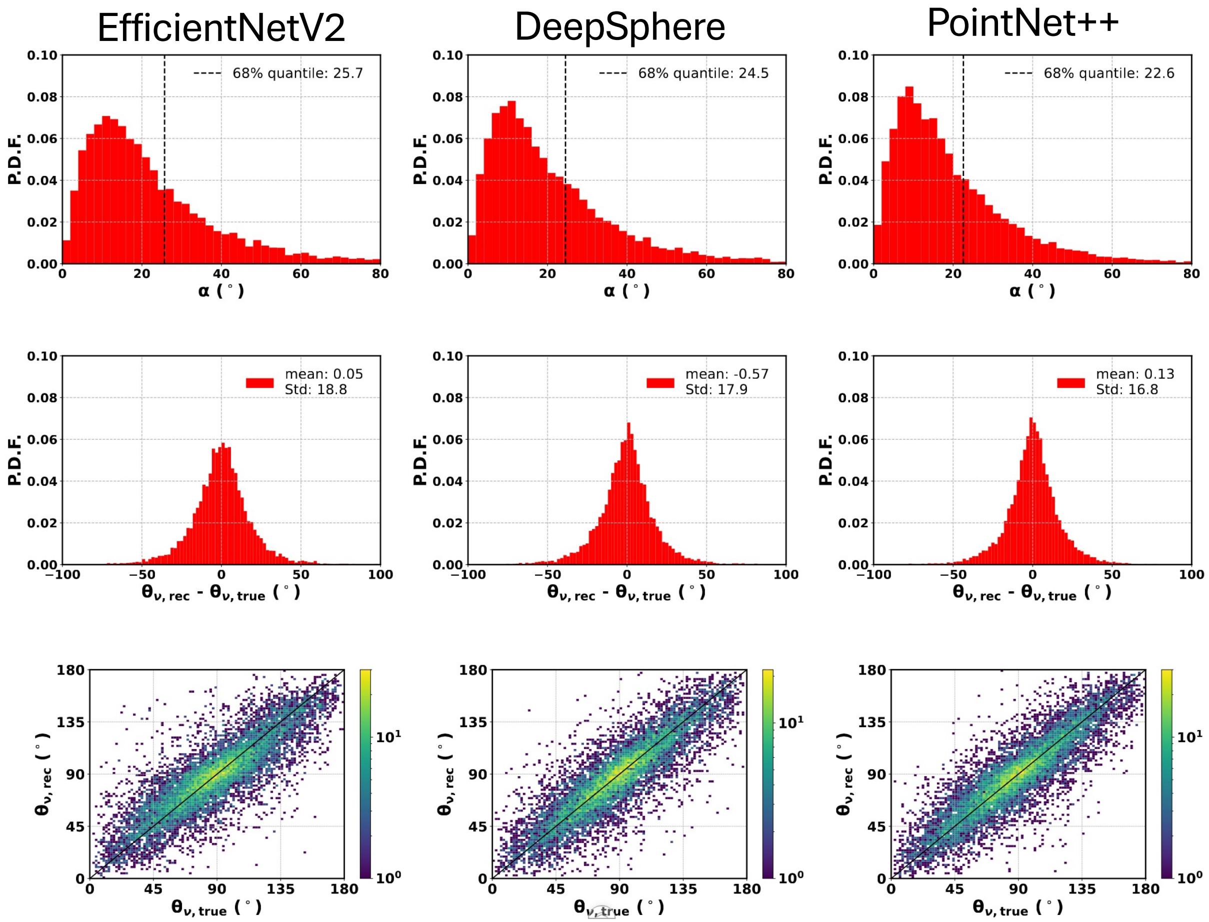
3+2 label



Directionality reconstrction performance: ν_μ-CC

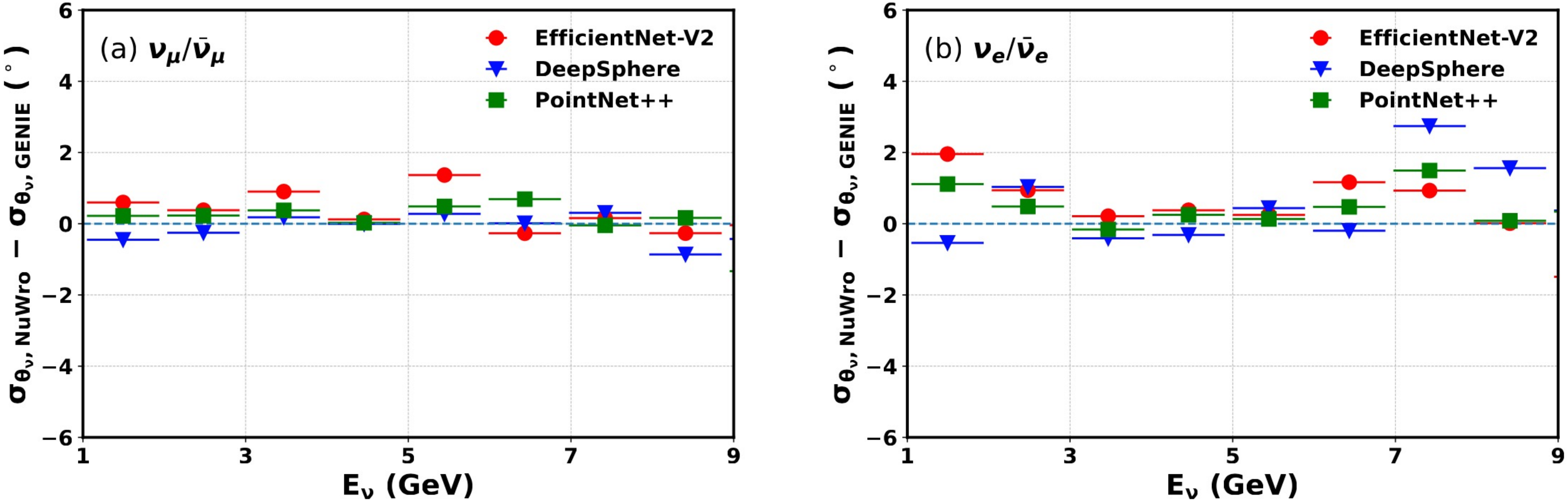


Directionality reconstrction performance: ν_e-CC



Directionality reconstrction performance: Validation

To check models' robustness and estimate systematic uncertainties, a different generator, NuWro, is used for validation:

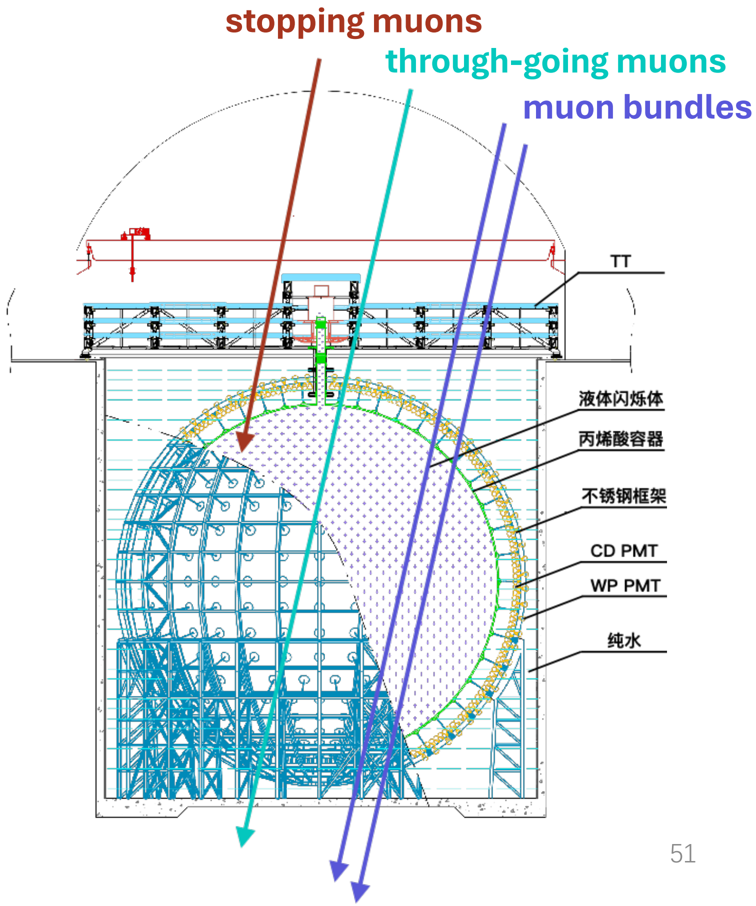


The result of GENIE and NuWro are consistent.

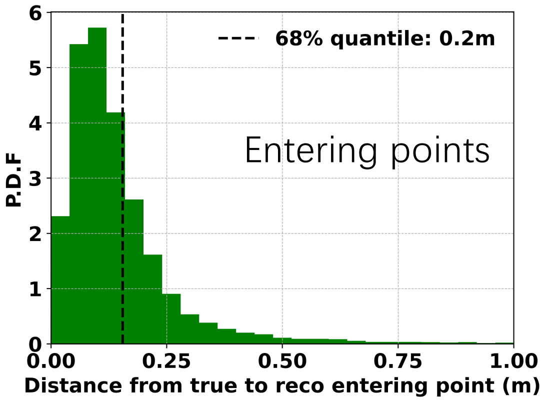
Introduction to JUNO: cosmic ray muon

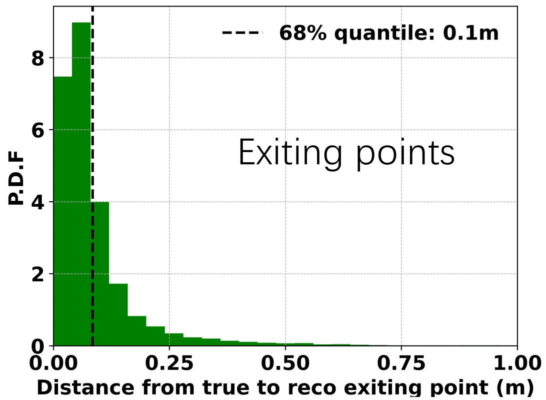
- Cosmic muons can be classified into many types, such as muon bundles, through-going muons, stopping muons and so on.

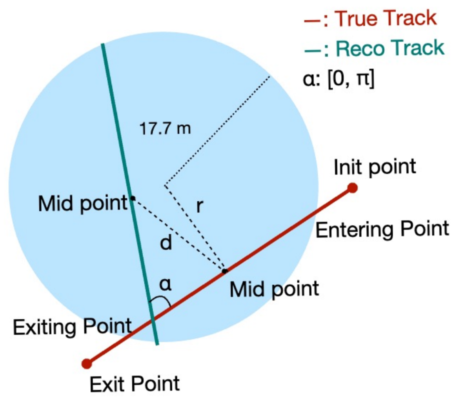
- To maximize the efficiency of background rejection, a classification for observed muon events and suitable reconstruction strategies for each muon types should be done.

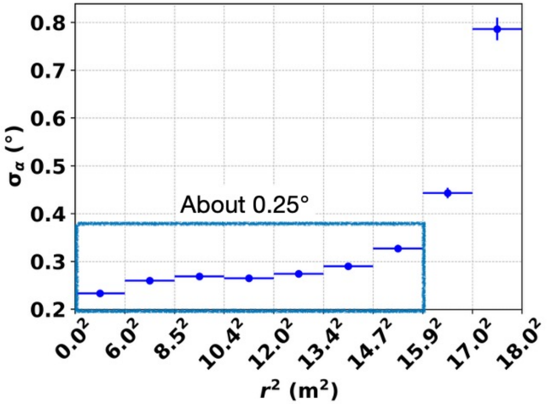


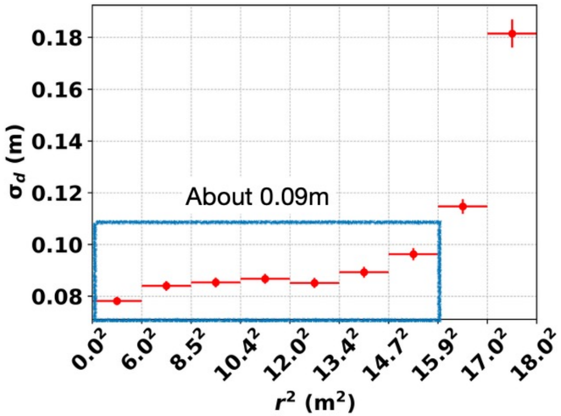
Cosmic ray muon reconstruction performance
1. through-going muons











(r: distance from cd center to the true track).

The entering point to the LS and the direction of the track are the model output.

Cosmic ray muon reconstruction performance
3. double muons

- Track No.1 is defined as the track which is most closest to the center. The reco muon tracks are marked by the distance to the center too.
- The entering point of each track and the mean direction from two tracks are the model output.

Output =

$(x_{enter1}, y_{enter1}, z_{enter1}, x_{enter2}, y_{enter2}, z_{enter2}, x_{mean\_direc}, y_{mean\_direc}, z_{mean\_direc})$

$$mean\ direction = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2}, \frac{z_1 + z_2}{2}\right)$$