Reconstruction of Atmospheric Neutrinos with Machine Learning Method in JUNO

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Outline

- Introduction to JUNO
- Methodology
- Introduction to ML models
- Performances
- Summary

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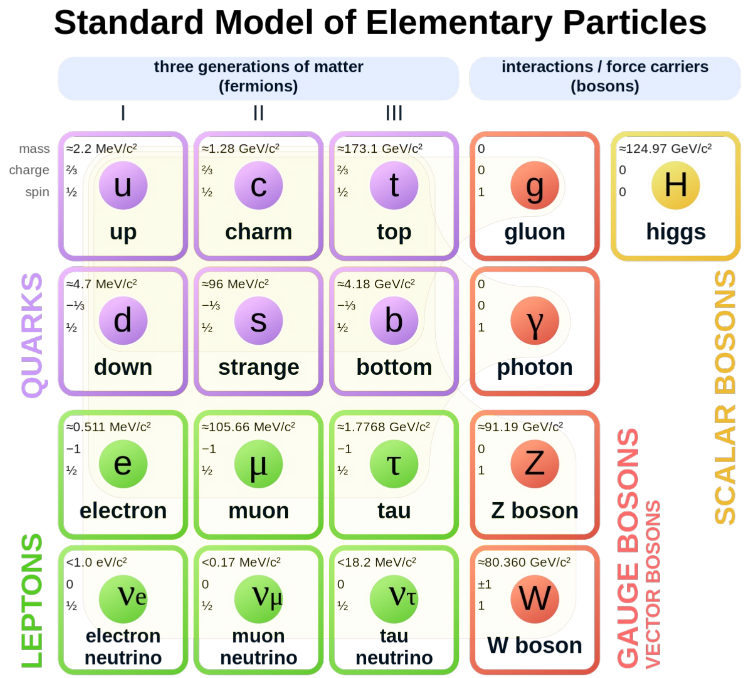
Introduction to JUNO: overview

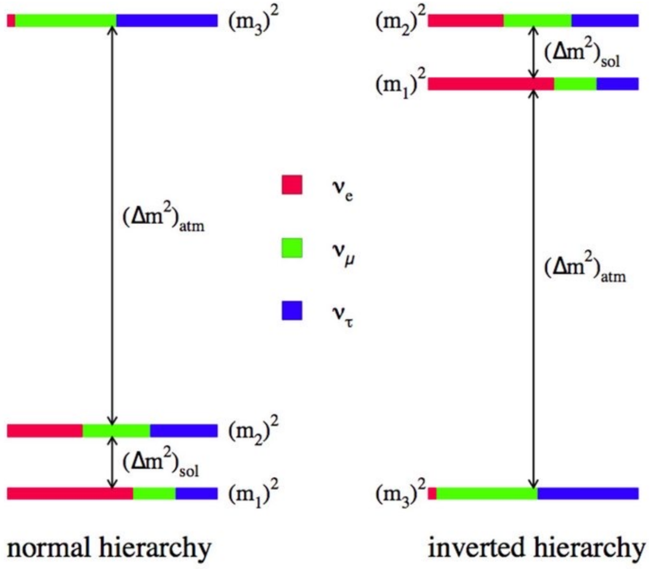
- Neutrino oscillation is of great theoretical and experimental interest.
- It implies that the neutrino has non-zero mass, which requires a modification to the Standard Model of particle physics.

$$P(\overline{\nu}_\alpha \to \overline{\nu}_\alpha) = P(\nu_\alpha \to \nu_\alpha) = 1 - 4|U_{\alpha1}|^2|U_{\alpha2}|^2 \sin^2\left(1.27\frac{\Delta m_{21}^2}{E}L\right)$$

$$U = \begin{bmatrix} U_{e1} & U_{e2} & U_{e3} \\ U_{\mu1} & U_{\mu2} & U_{\mu3} \\ U_{\tau1} & U_{\tau2} & U_{\tau3} \end{bmatrix} \qquad - 4|U_{\alpha1}|^2|U_{\alpha3}|^2 \sin^2\left(1.27\frac{\Delta m_{31}^2}{E}L\right)$$

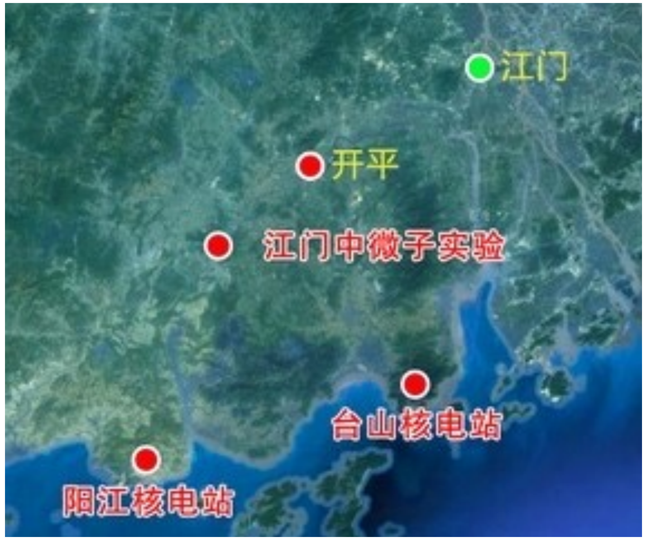
$$- 4|U_{\alpha2}|^2|U_{\alpha3}|^2 \sin^2\left(1.27\frac{\Delta m_{32}^2}{E}L\right)$$





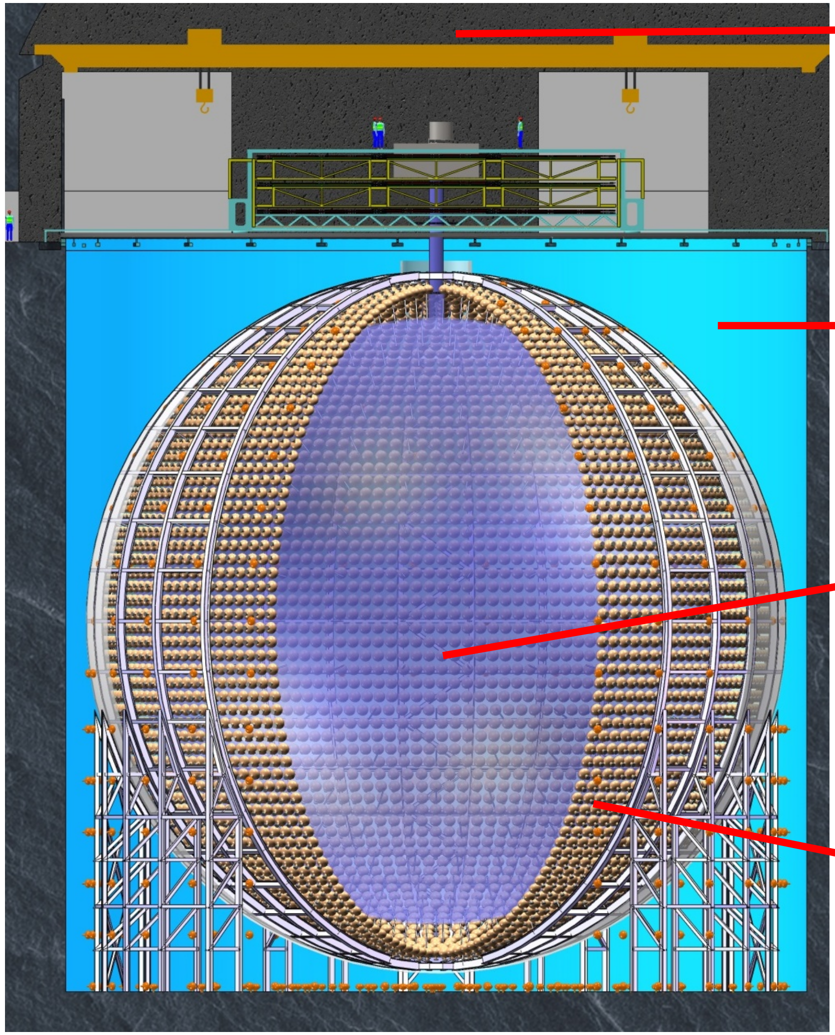
Introduction to JUNO: overview

- 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 bring 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:

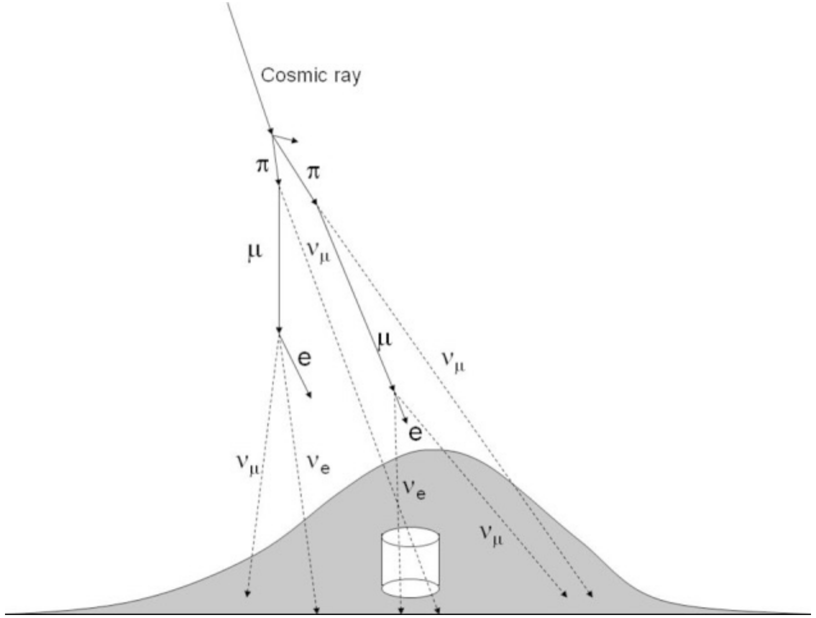
- 17,612 20-inch PMTs (used in this study);
- 25,600 3-inch PMTs.

75% PMT coverage.

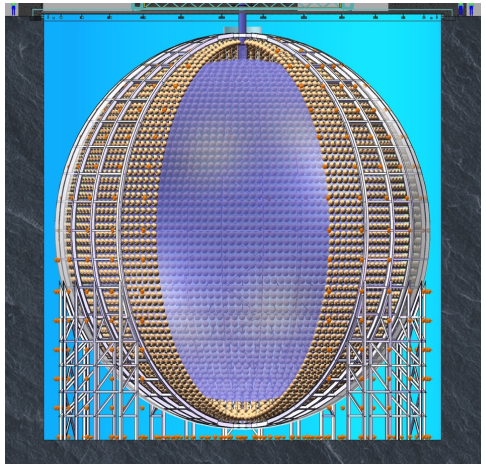
Introduction to JUNO: atmospheric neutrinos

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

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



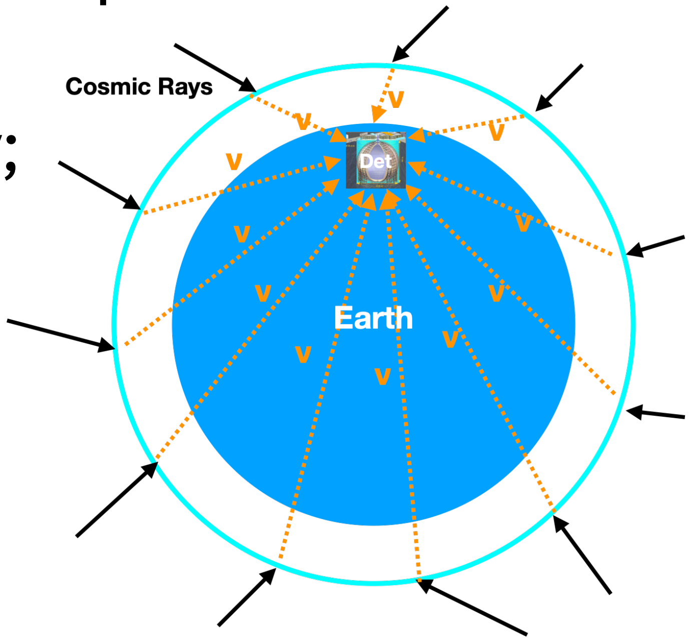
Reactor neutrinos:
Sensitivity to NMO via
oscillation in vacuum

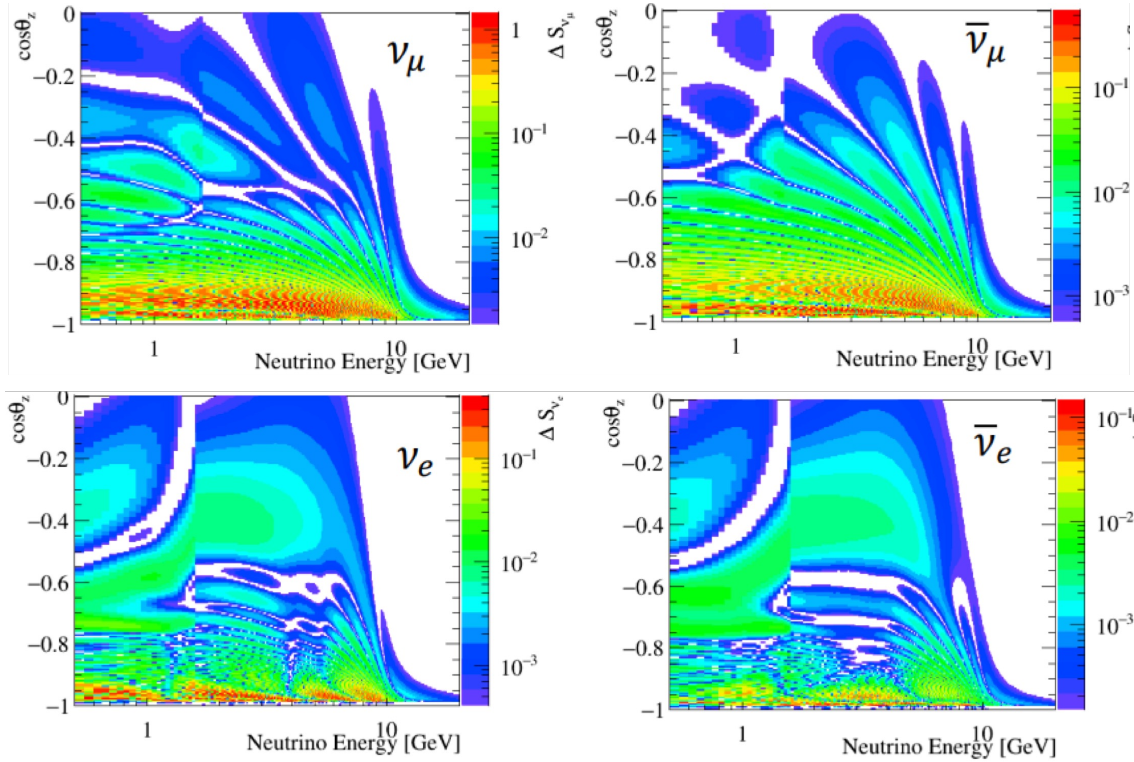


Atmospheric neutrinos:
Sensitivity to NMO via
oscillation with matter effect

Introduction to JUNO: atmospheric neutrinos

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





Introduction to JUNO: atmospheric neutrinos

- Directionality measurement in large homogeneous LS detectors, however, is 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

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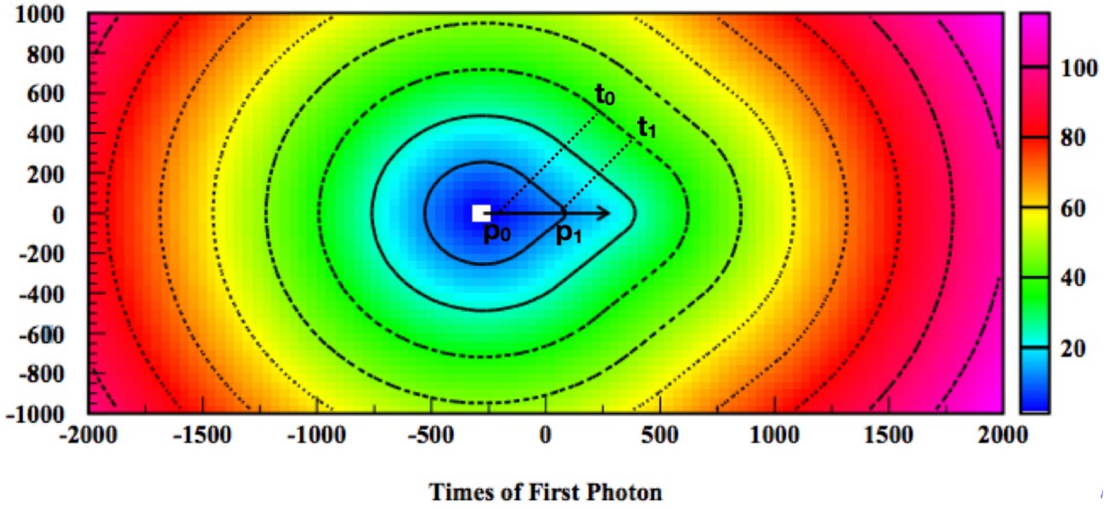
Methodology: physics process

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

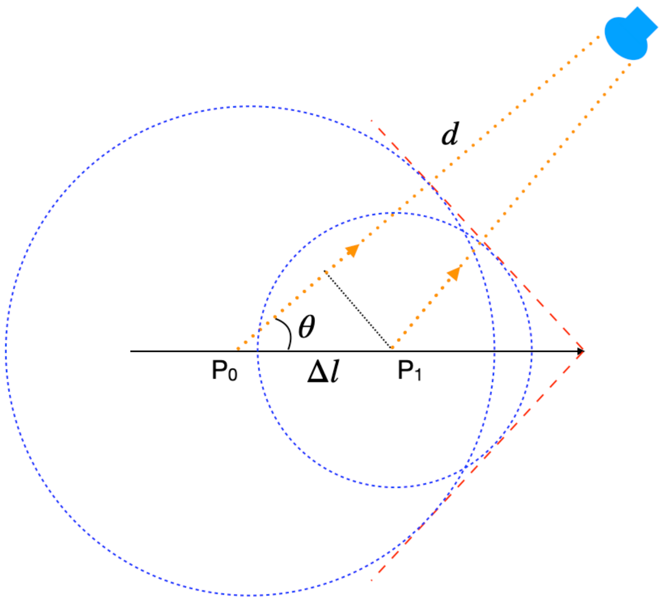


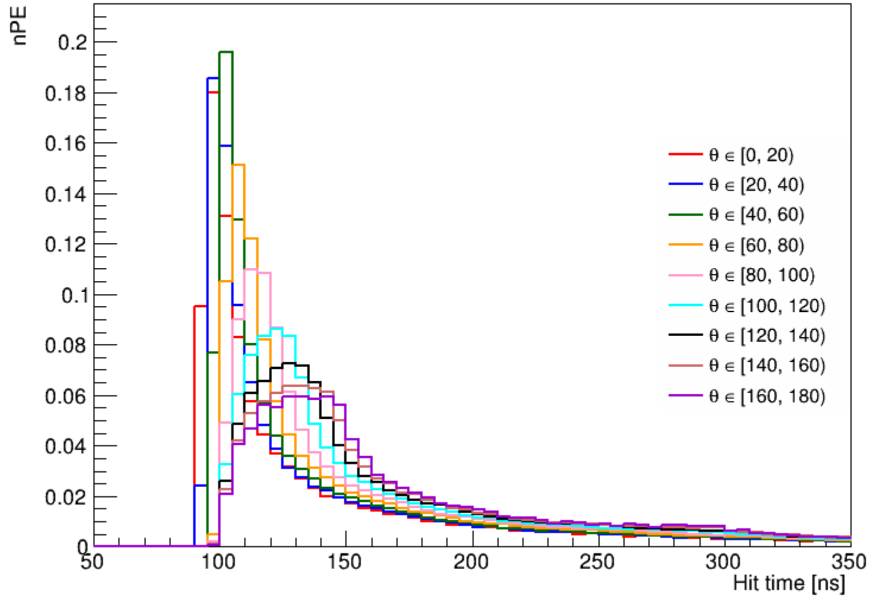
- The hit time of the earliest photon reaching a PMT (“first hit time”) therefore naturally offers information on the event directionality.

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.

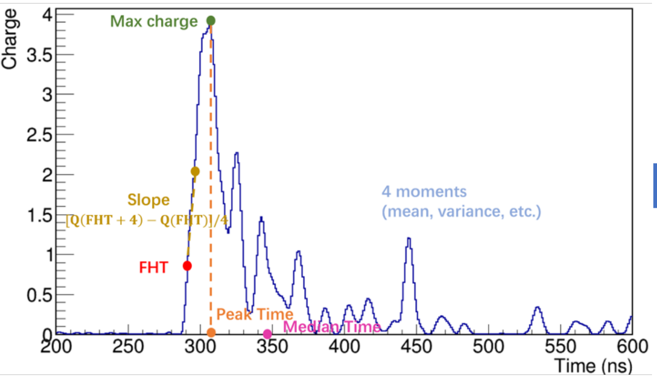
  } PID
- Therefore, the particle's information is reflected in nPE(t), and finally reflected in the waveform.



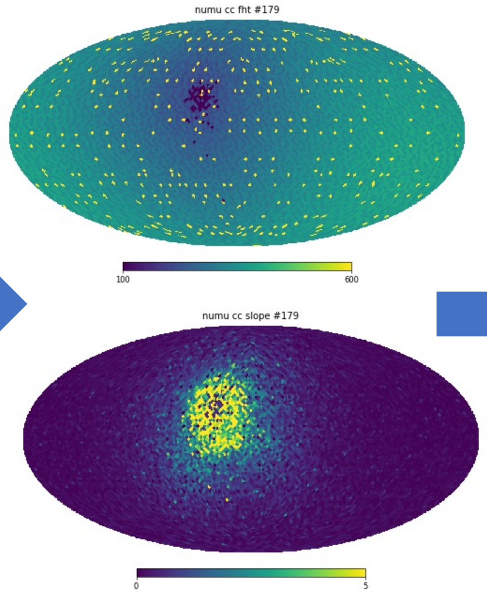


Methodology: PMT features

- 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



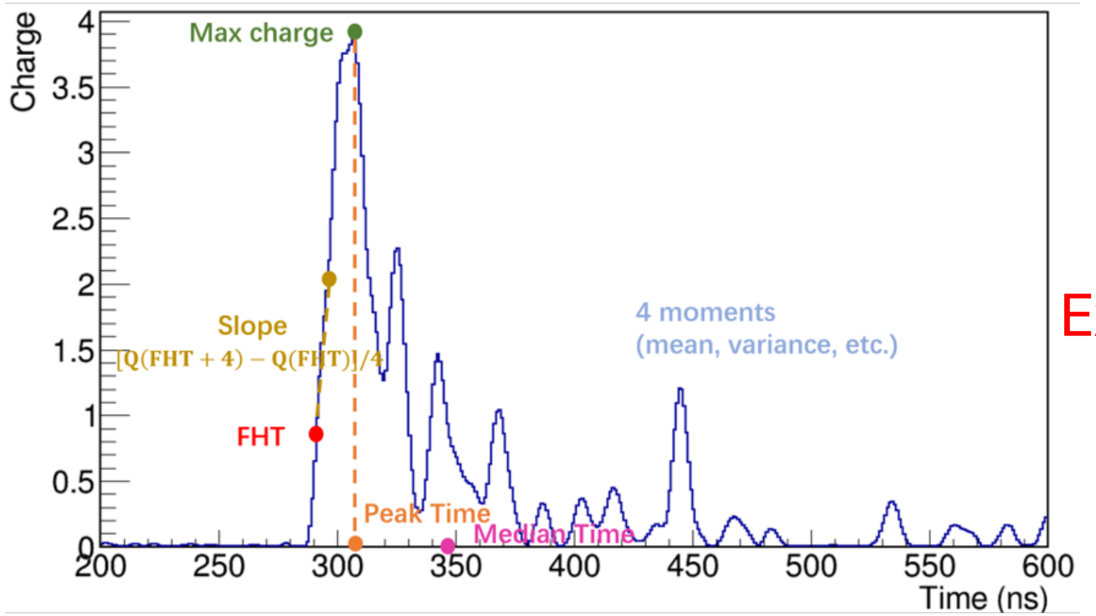
Pictures Features

Machine learning models

Reconstruction

- Directionality
- Energy
- PID
- Track
- Vertex

Methodology: PMT features



Extracte feature

- First Hit Time
- Total charge: The total number of PEs before electronic effects.
- 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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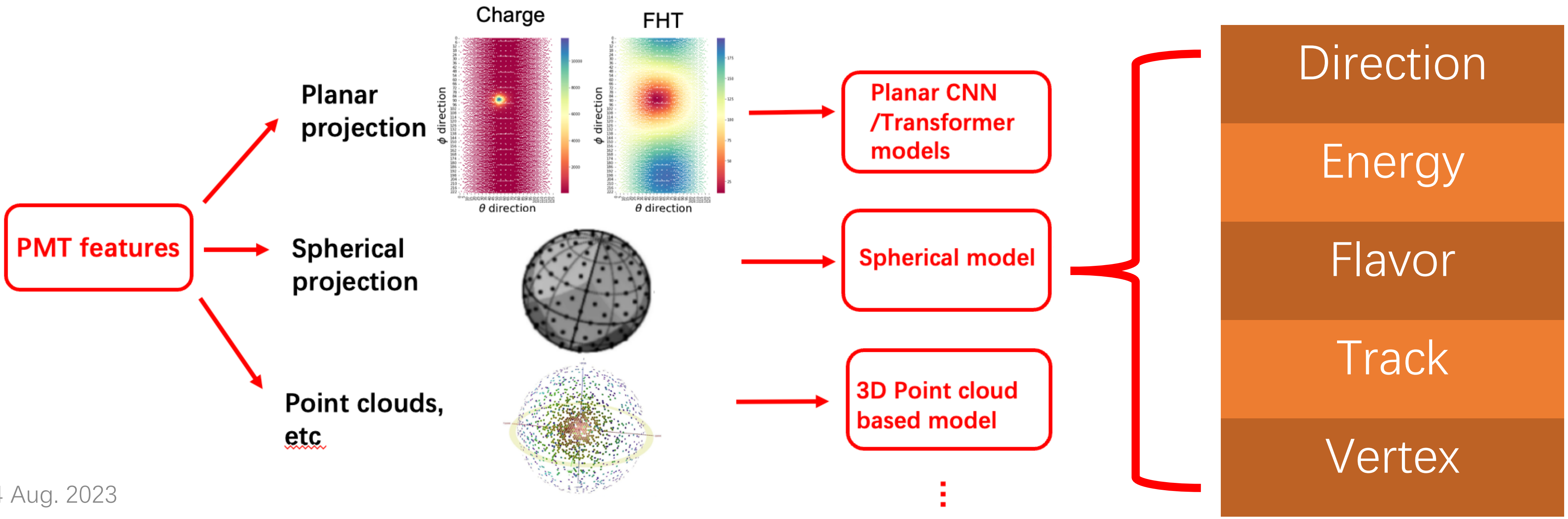
Introduction to models

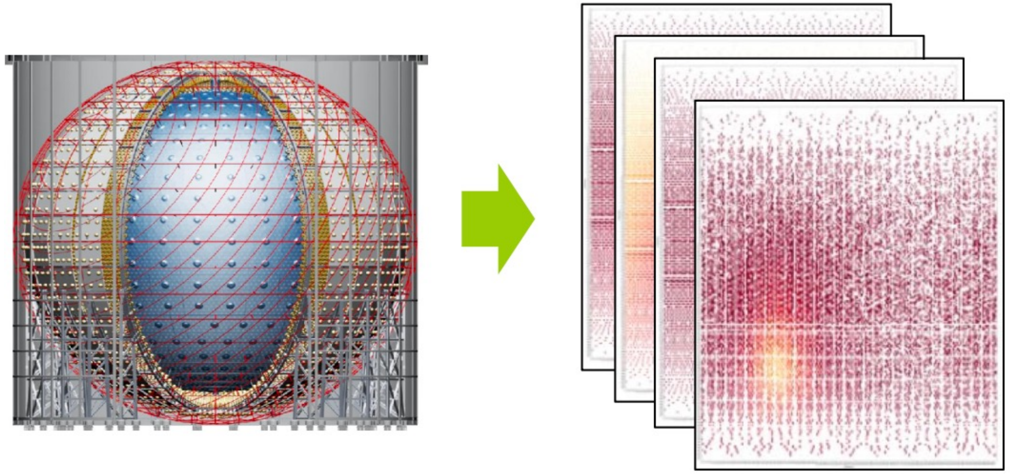
3 categories of machine learning method to deal with a spherical problem:

- Planar-image-based method: EfficientNetV2
- Spherical-image-based method: DeepSphere
- 3D-based method: PointNet++



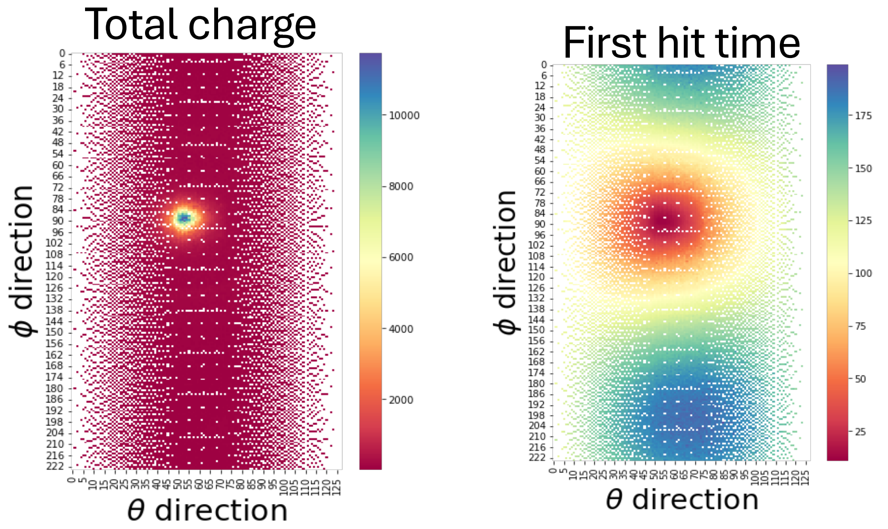
Introduction to models: EfficientNetV2

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



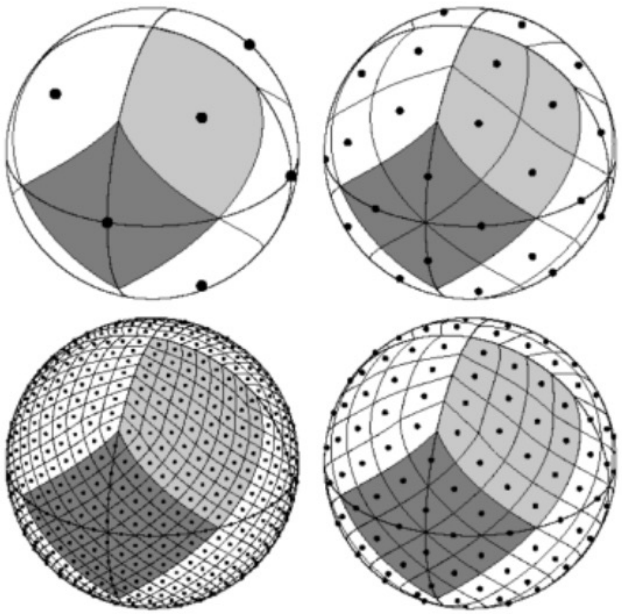
Model input: 2D grids

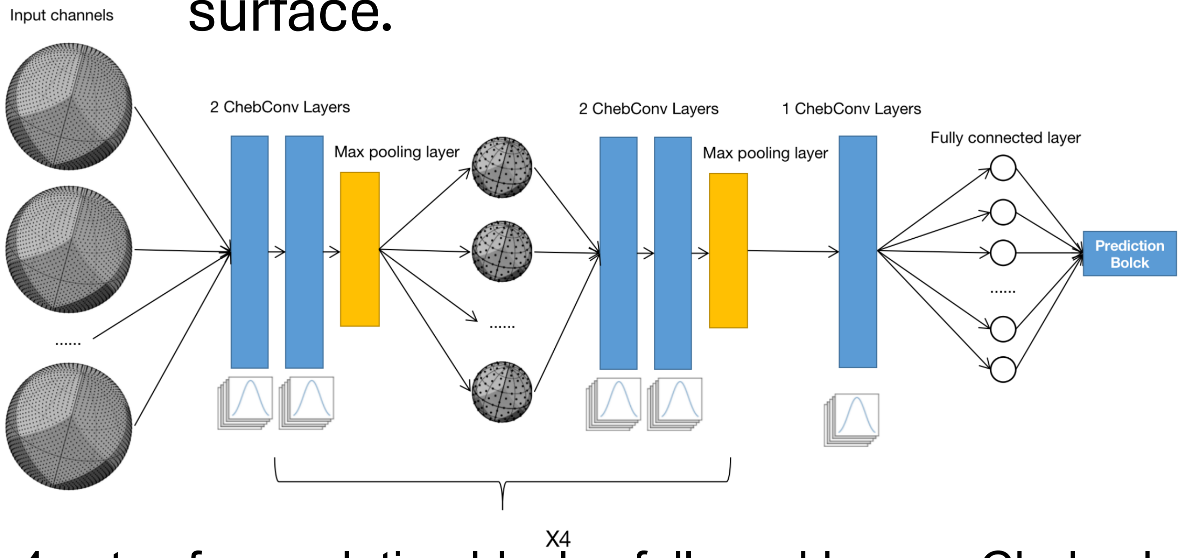
- The PMT map is projected onto a 2D θ−ϕ grid (according to PMT spherical coordinates);
- The grid size of 128×224 for Large PMTs is chosen to ensure each grid cell corresponds to at most one PMT.



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.



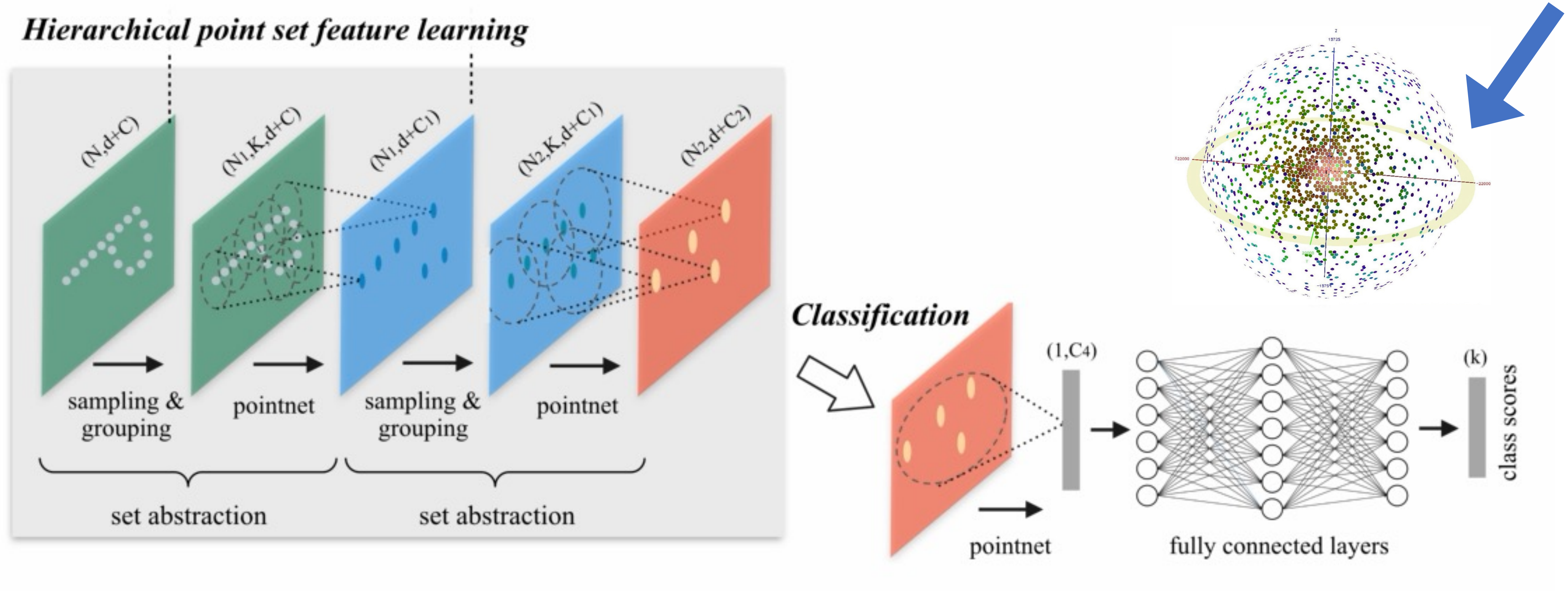


4 sets of convolution blocks, followed by one Chebyshev convolution layer, a fully connected layer and lastly a prediction block.

- $N_{side} = 32$
- 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.

Introduction to models: PointNet++

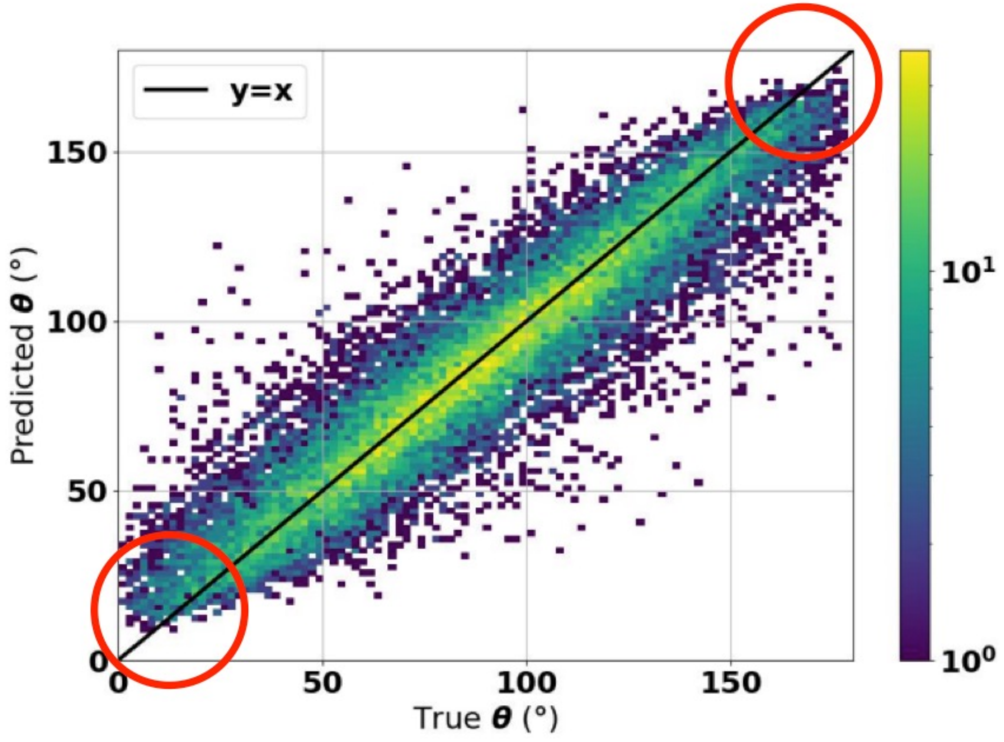
Directly taking 3D point clouds as input → JUNO signal more resembles point clouds.

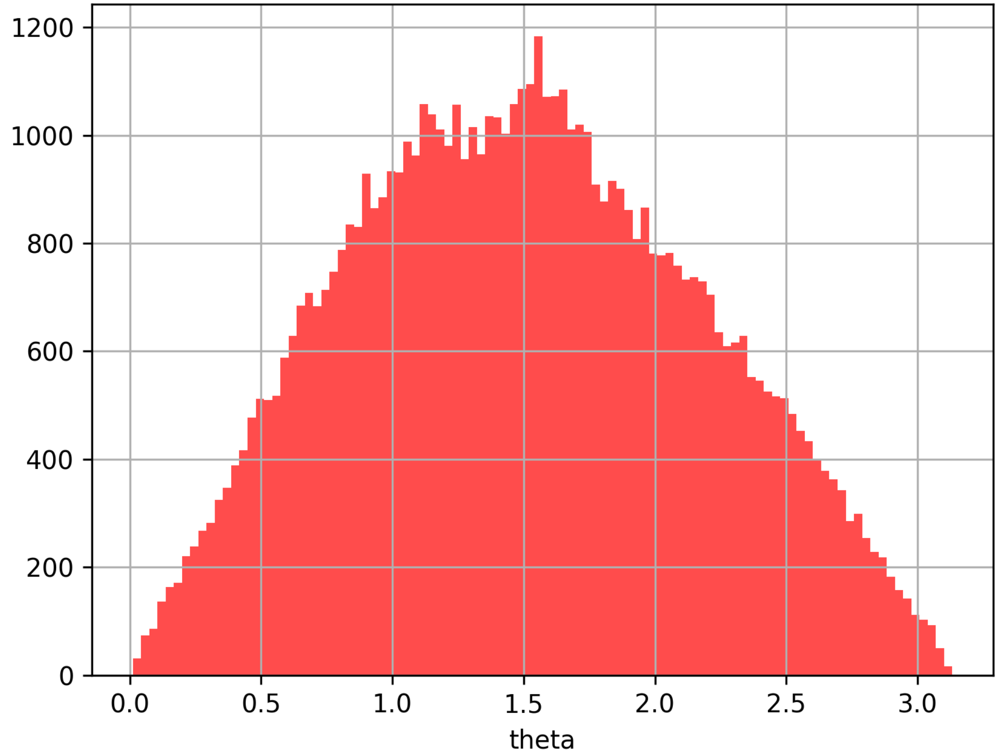


(N.B. PointNet++ input format: for each event, N(PMT)*[x, y, z, features, ..])

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°.

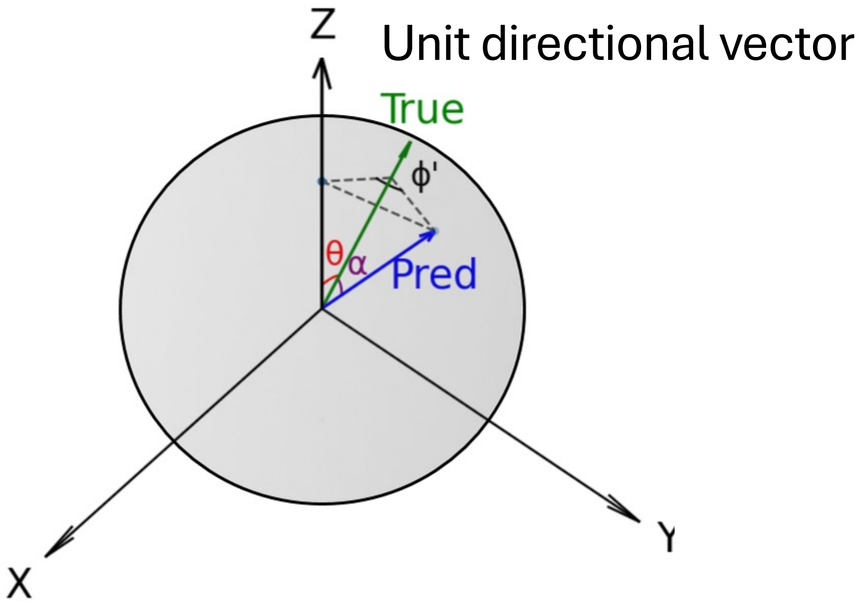


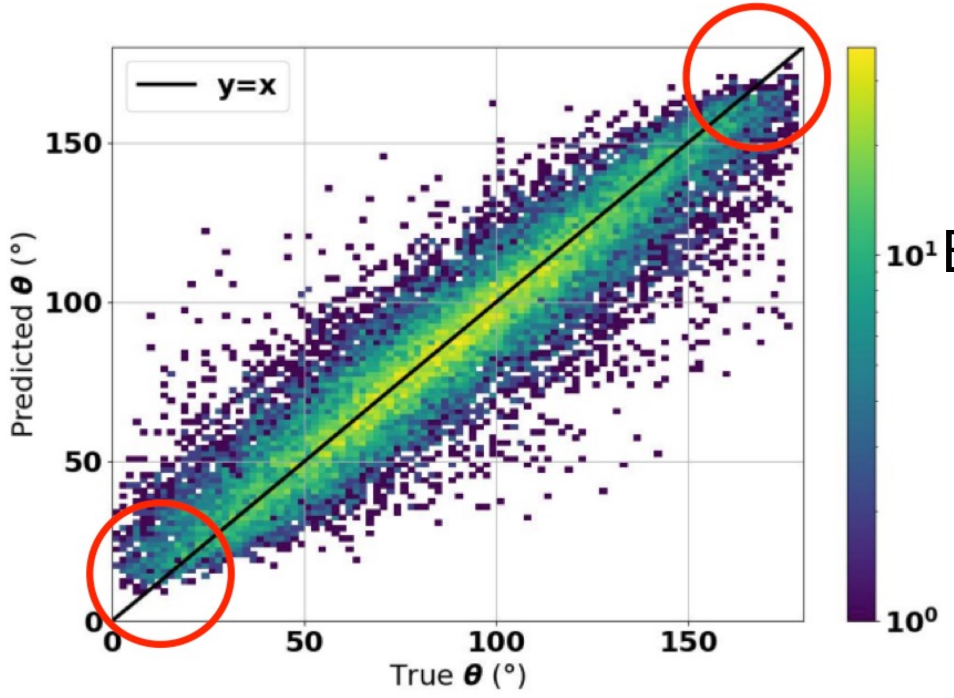


Loss function

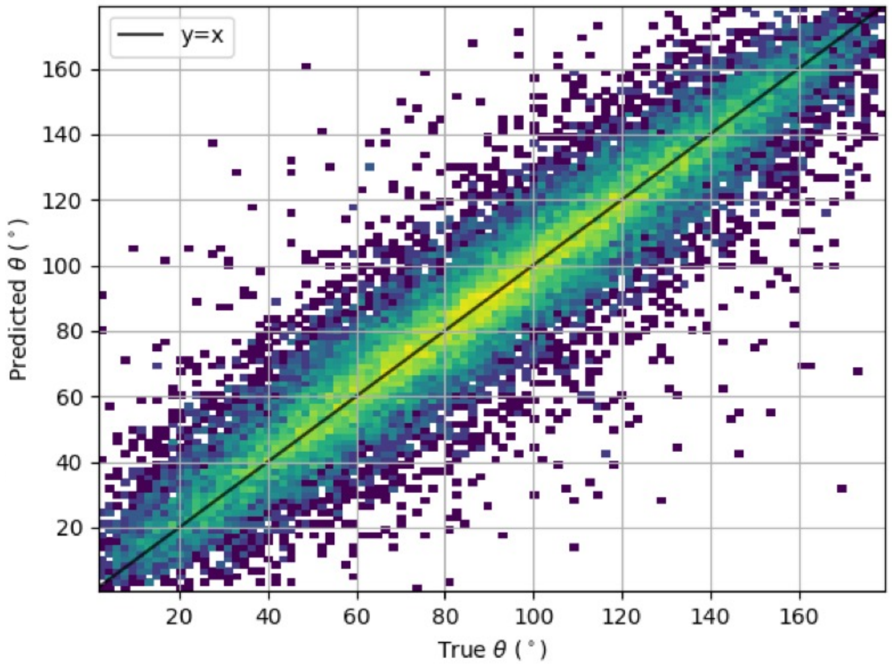
- Then try to reconstruct the directional vector (x, y, z) and update Loss Function (Rotation invariance):

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





Bias is gone



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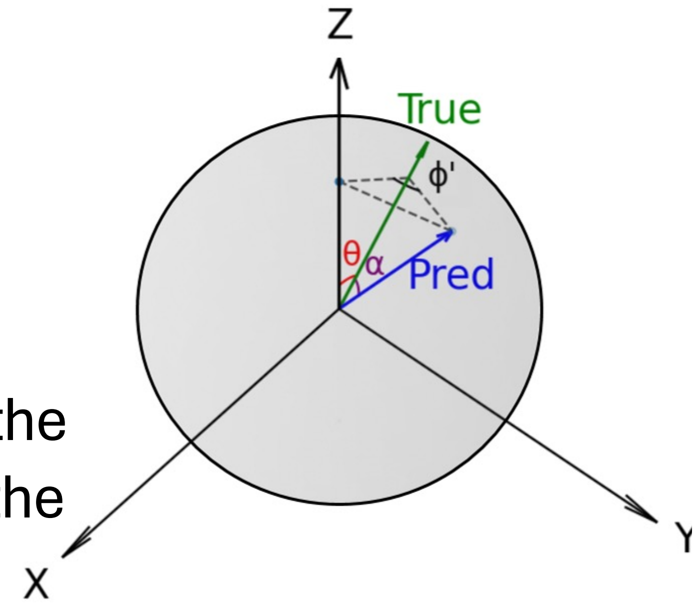
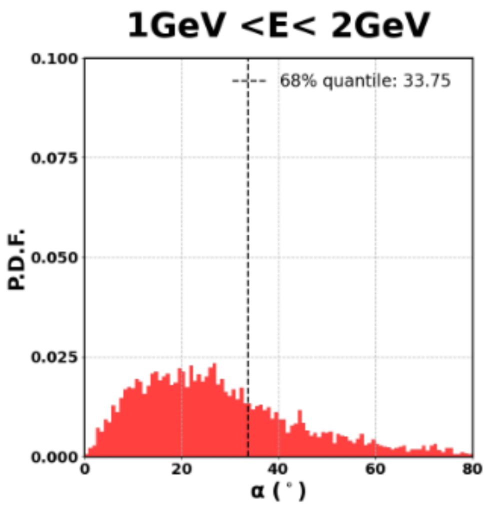
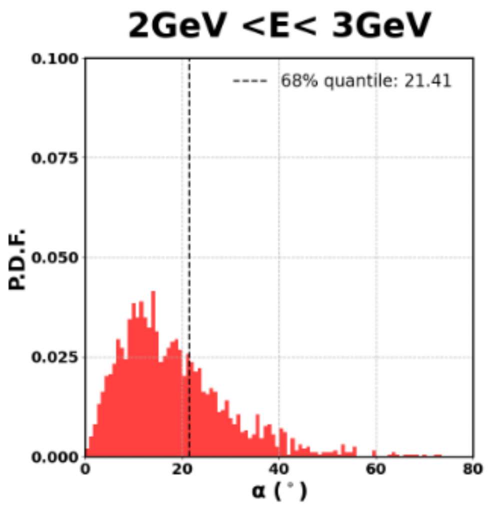
Directionality reconstrction performance

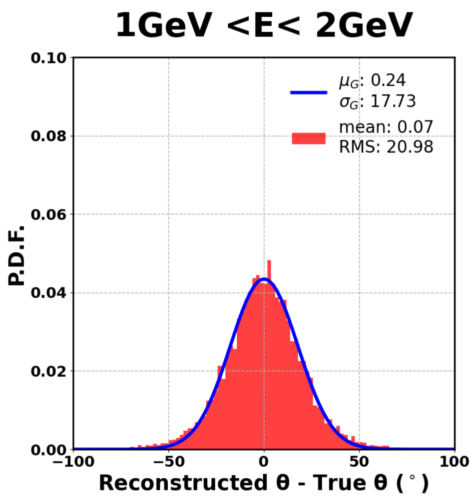
α: Angle between the true and reconstructed directional vector. Due to the range of α is 0 to 180°, 68% quantile is used to quantify the performance of α.

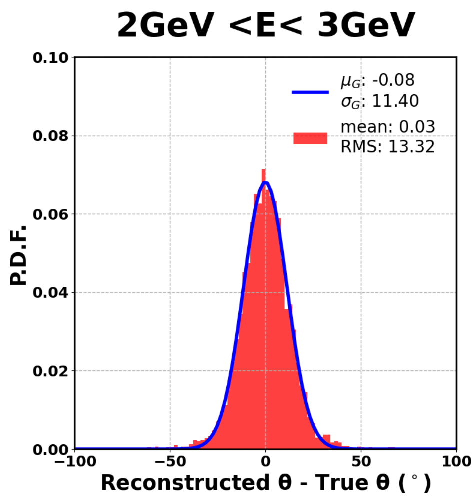
θ: Zenith angle of the true vector. Reconstructed θ - True θ reflect the resolution. Distribution in different E_ν bins can be well in line with the Gaussian distribution. σ_G is used as quantized resolution.



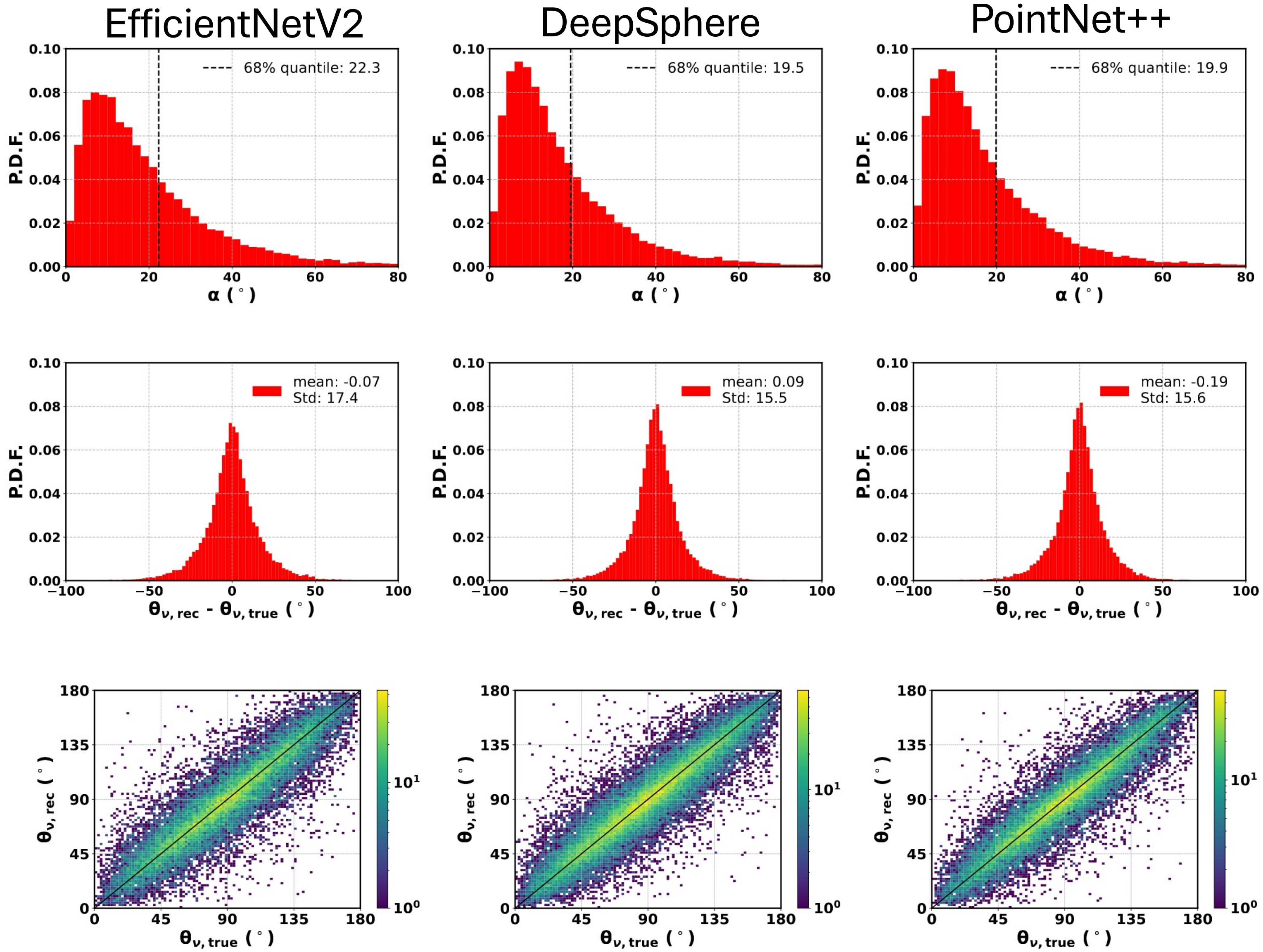






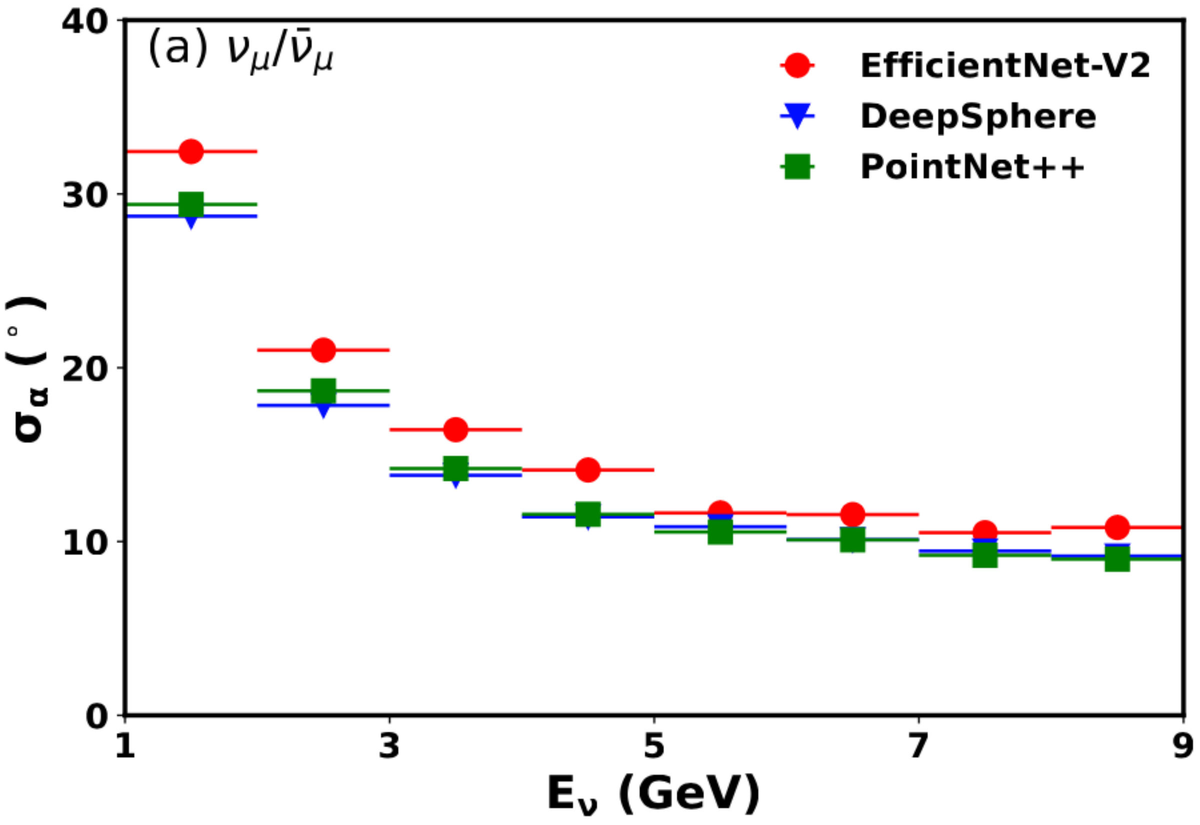


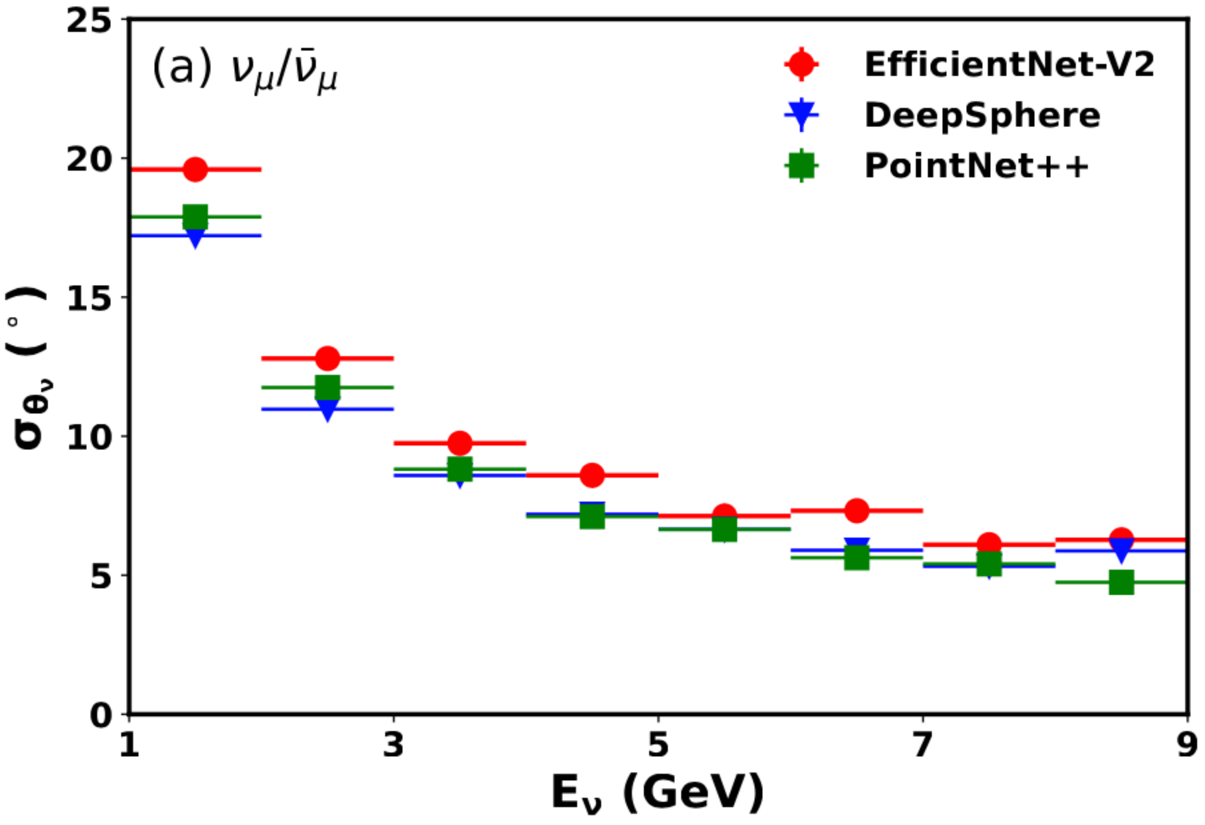
Directionality reconstrction performance: ν_μ-CC



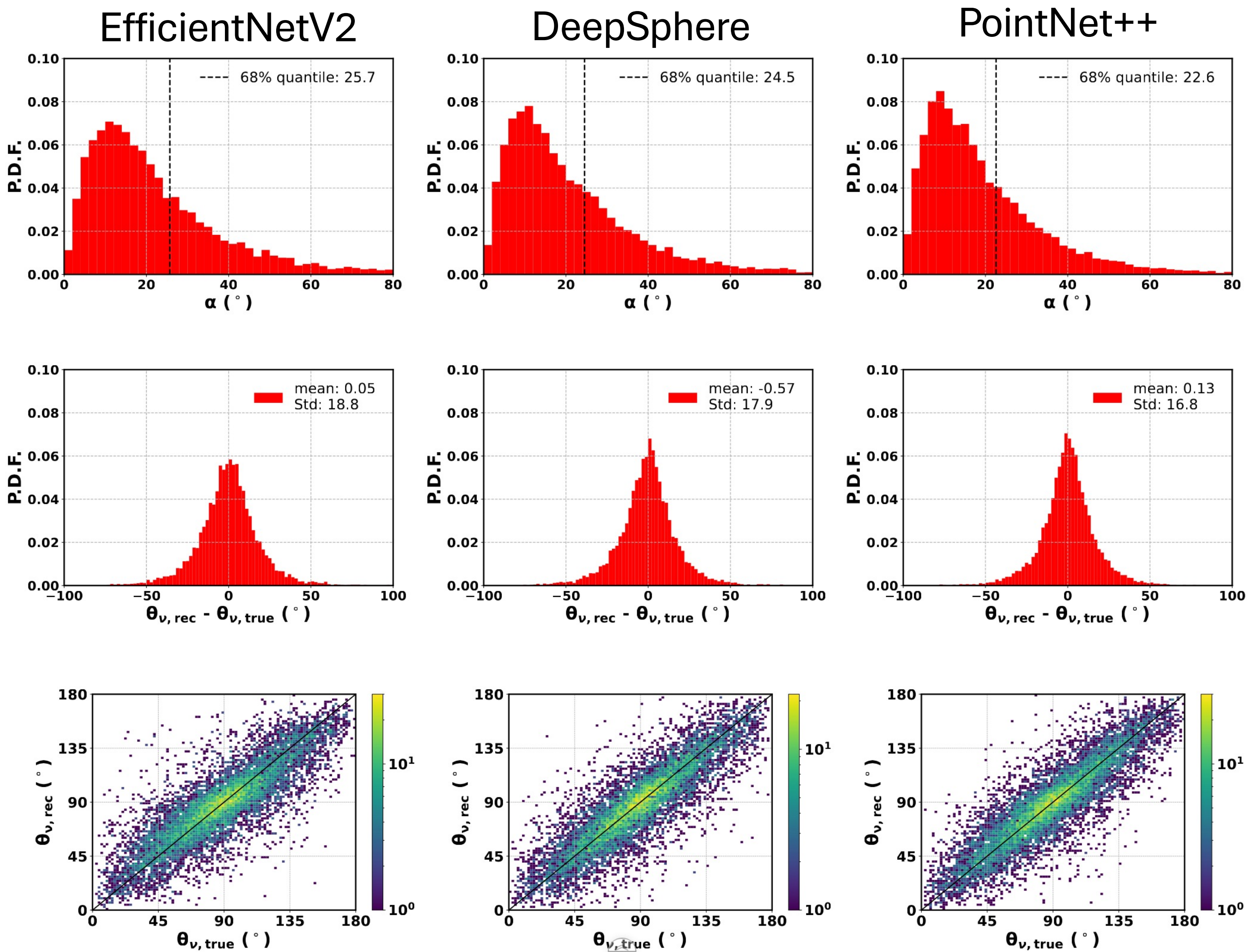
Directionality reconstrction performance: ν_μ-CC

Resolution gets better as energy increase.



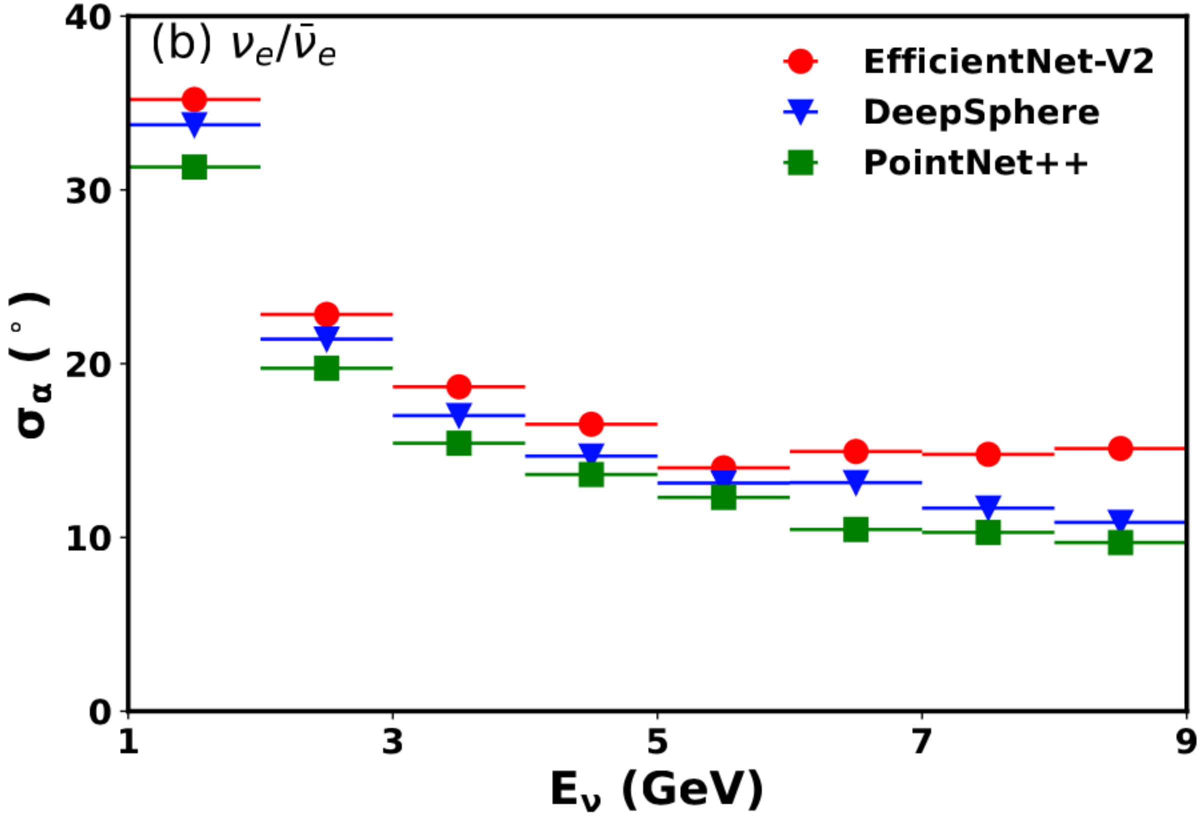


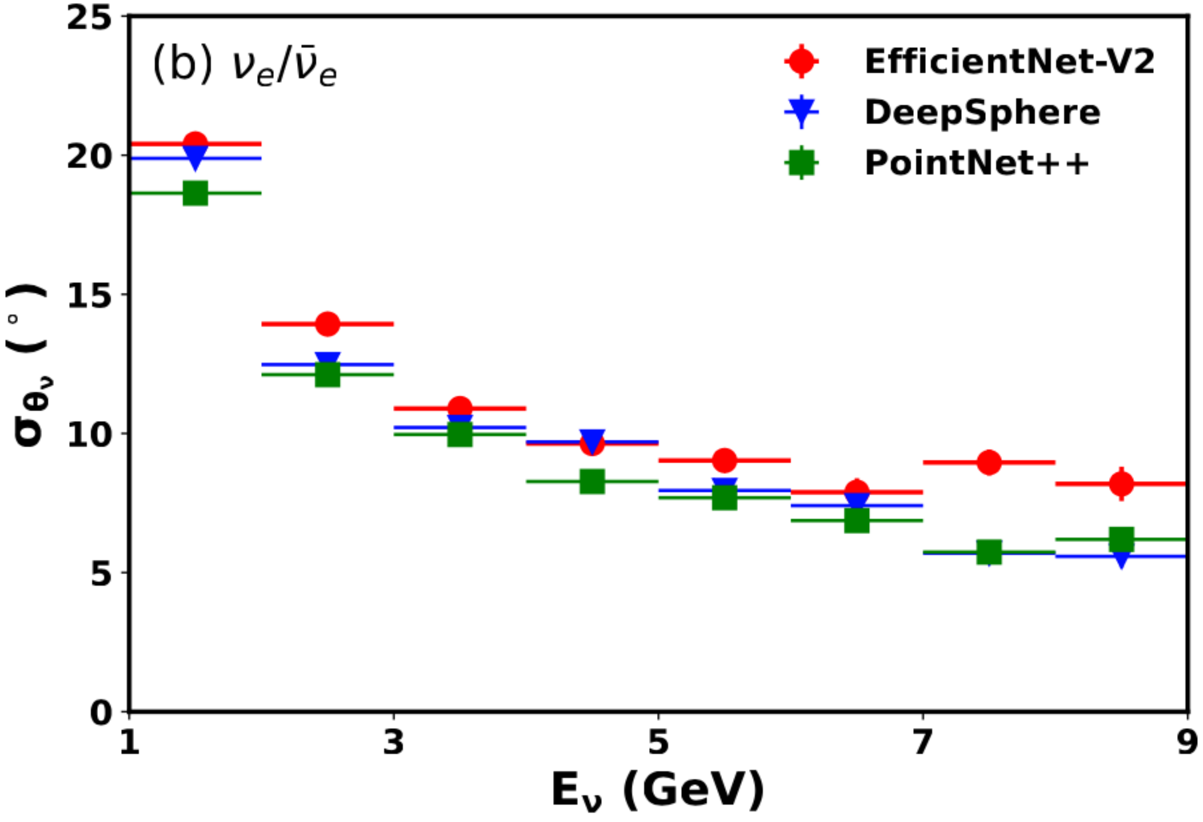
Directionality reconstrction performance: ν_e-CC



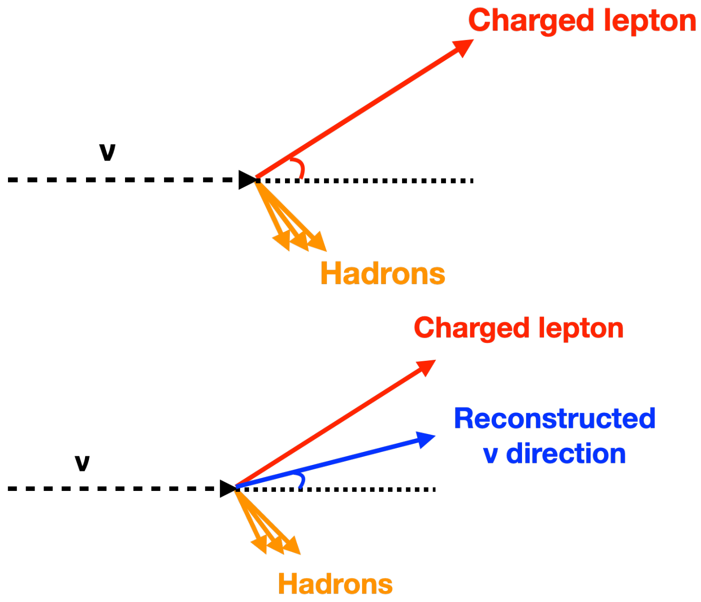
Directionality reconstrction performance: ν_e-CC

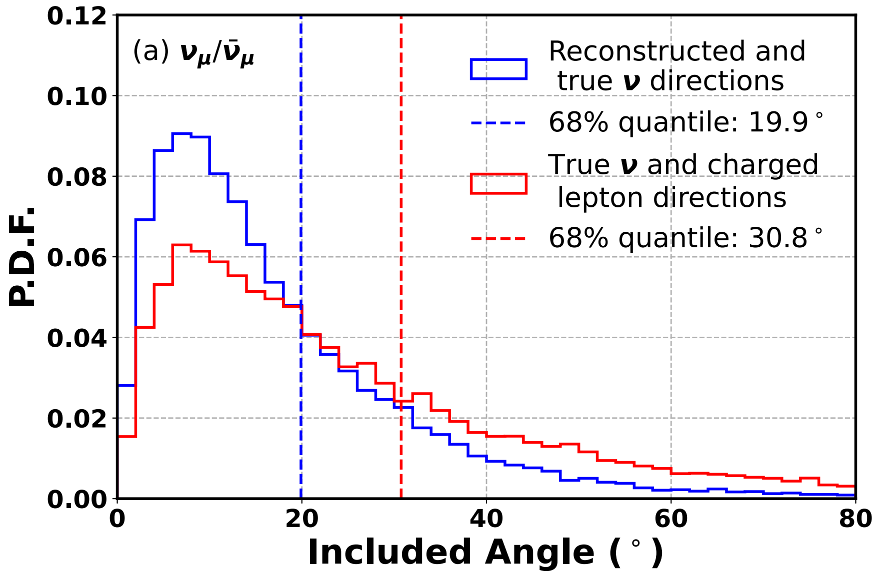
Resolution gets better as energy increase.





Directionality reconstrction performance

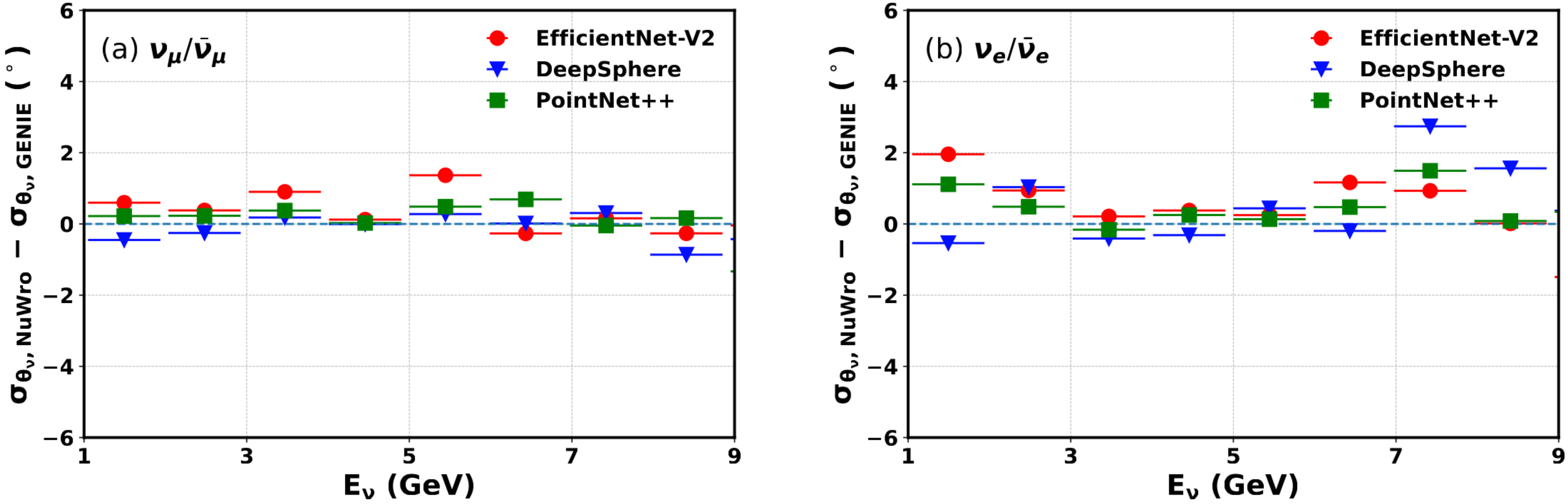




- Both lepton and hadron informations are used in the directionality reconstruction.
    - Low-threshold in LS detectors allows for more information from hadrons.
- The reconstructed neutrino direction is less smeared from true neutrino direction compared with the charged lepton direction.
    - An advantage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

Directionality reconstrction performance: Validation

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



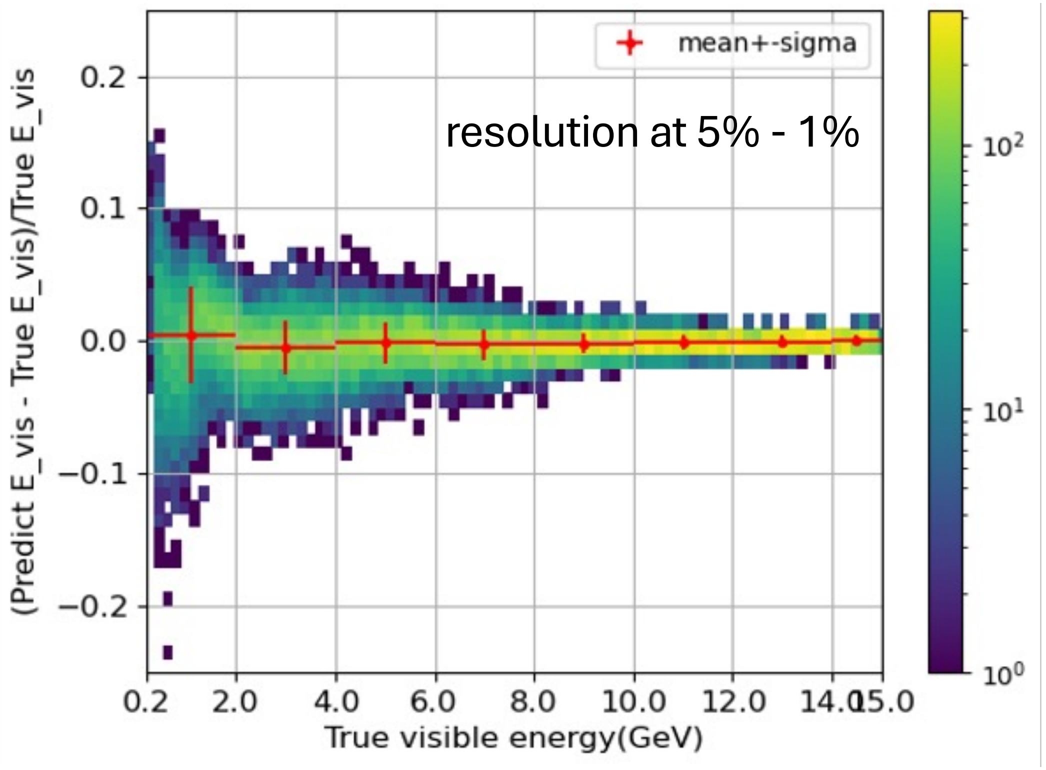
The result of GENIE and NuWro are consistent.

Energy reconstrction performance: ν_μ-CC

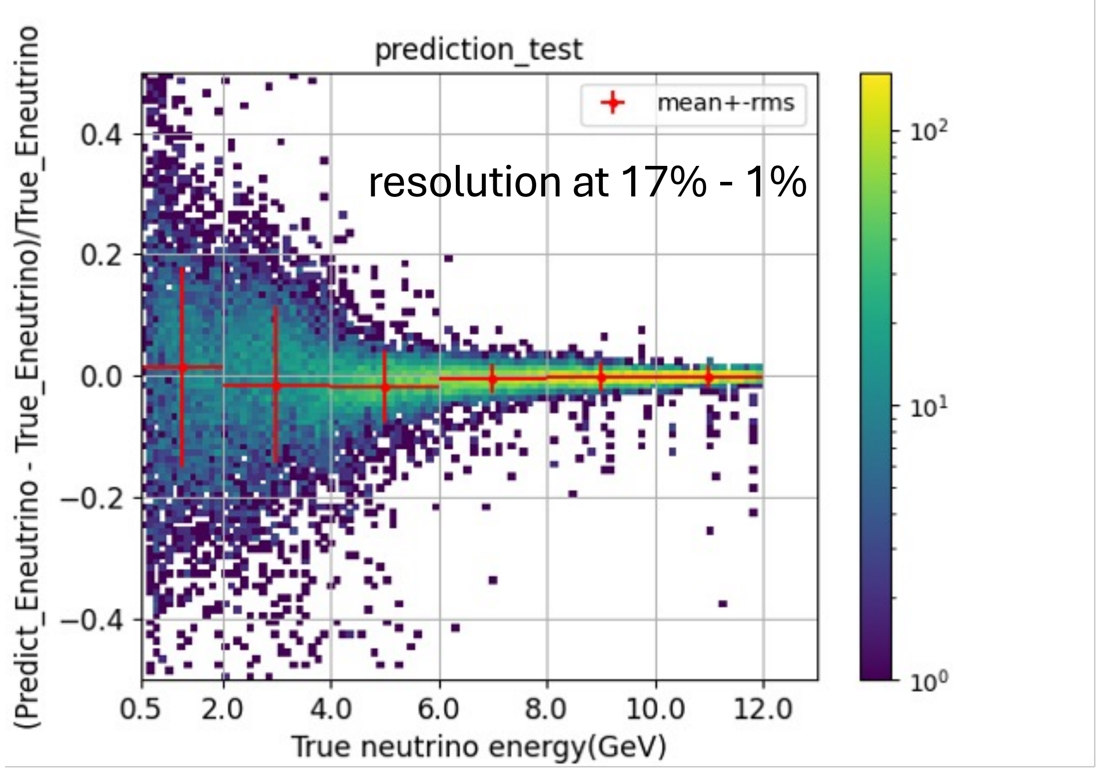
Neutrino interaction → Secondary particles → Deposition energy → Visible energy.

Two strategies on energy reconstruct: visable energy and neutrino energy.

Reconstruct the visible energy (after quenching in the LS).



Reconstruct the neutrino energy (For fully-contained events only).



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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 demonstrated the feasibility of atmospheric neutrinos' directionality reconstruction for the first time in an LS detector using this approach.
3. We also show that the results of directionality reconstruction obtained using different machine learning models and neutrino event generators are consistent.