Machine learning approach for the directional reconstruction of atmospheric neutrinos in JUNO

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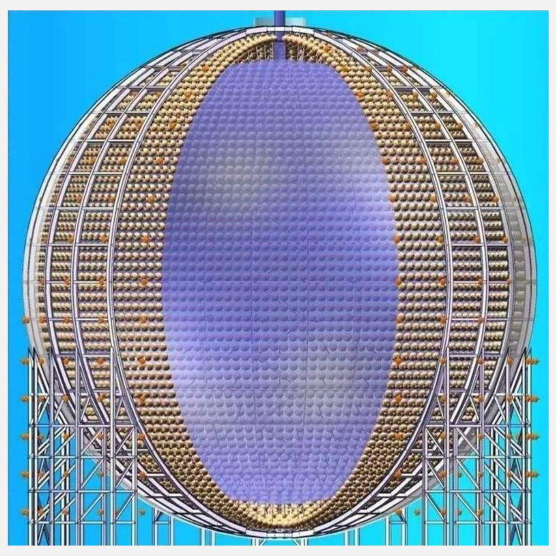
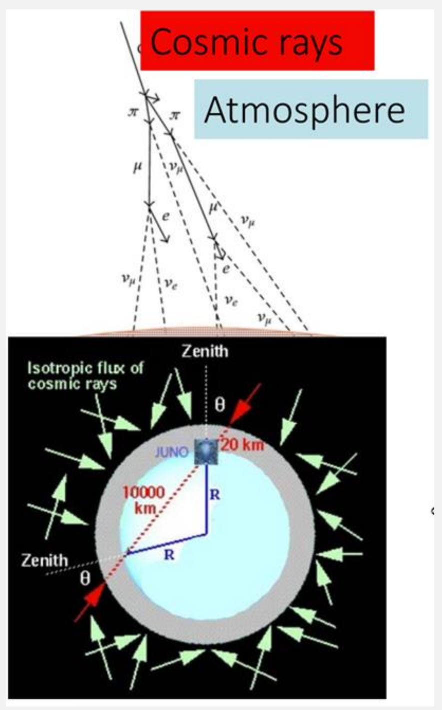
I. Background



JUNO Central Detector design

- JUNO is a next-generation large liquid-scintillator neutrino detector, designed to determine the neutrino mass ordering (NMO) from its reactor neutrino measurement.
- Its Central Detector (CD) is a 20 kton liquid scintillator detector that uses 17,612 20-inch large PMTs and 25,600 3-inch small PMTs as photosensors.

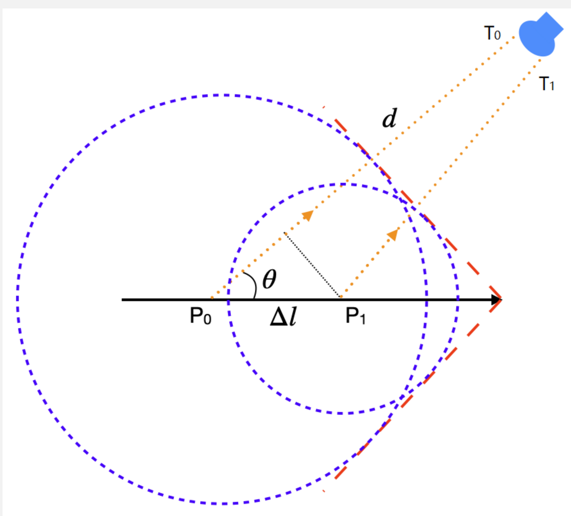
II. Motivation



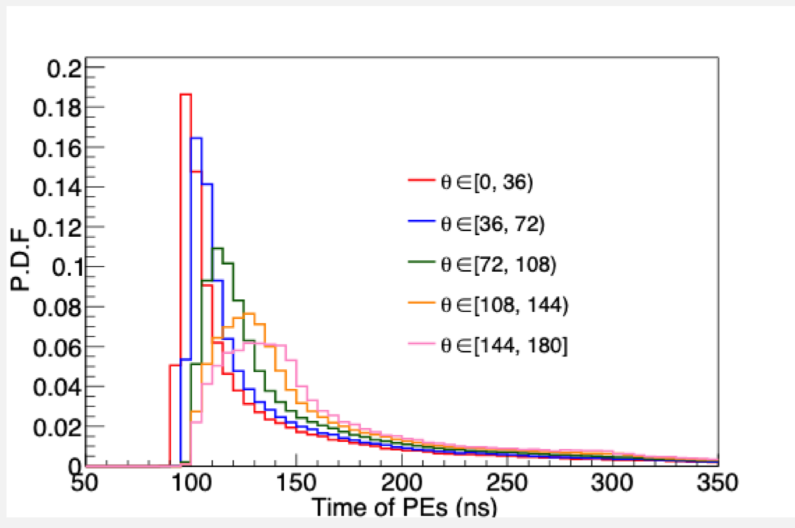
- Besides the reactor neutrino, the measurement of atmospheric neutrino oscillations can enhance JUNO's NMO sensitivity.
- Matter effects on oscillations are dependent on zenith angle since it is directly related to the oscillation baseline length.

III. Methodology

Neutrino directional information reflects in each PMT's waveform by the scintillation light generated on the particle track:



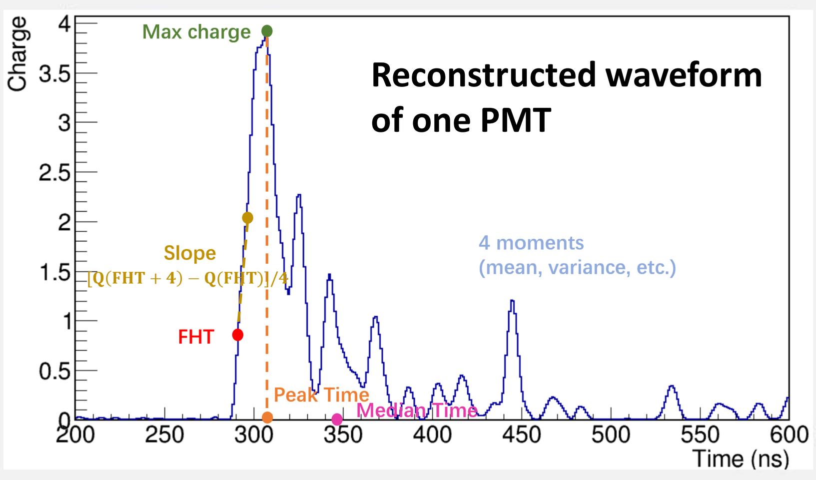
$$\frac{\Delta l}{\Delta t} \propto \frac{1}{|1 - n\beta\cos\theta|}$$



Distribution of the number of photoelectrons (PEs) over time for PMTs with different angles θ to the particle track

IV. Features Extraction

The key features are extracted from each PMT's waveform to keep only the useful information relevant to the event directionality:

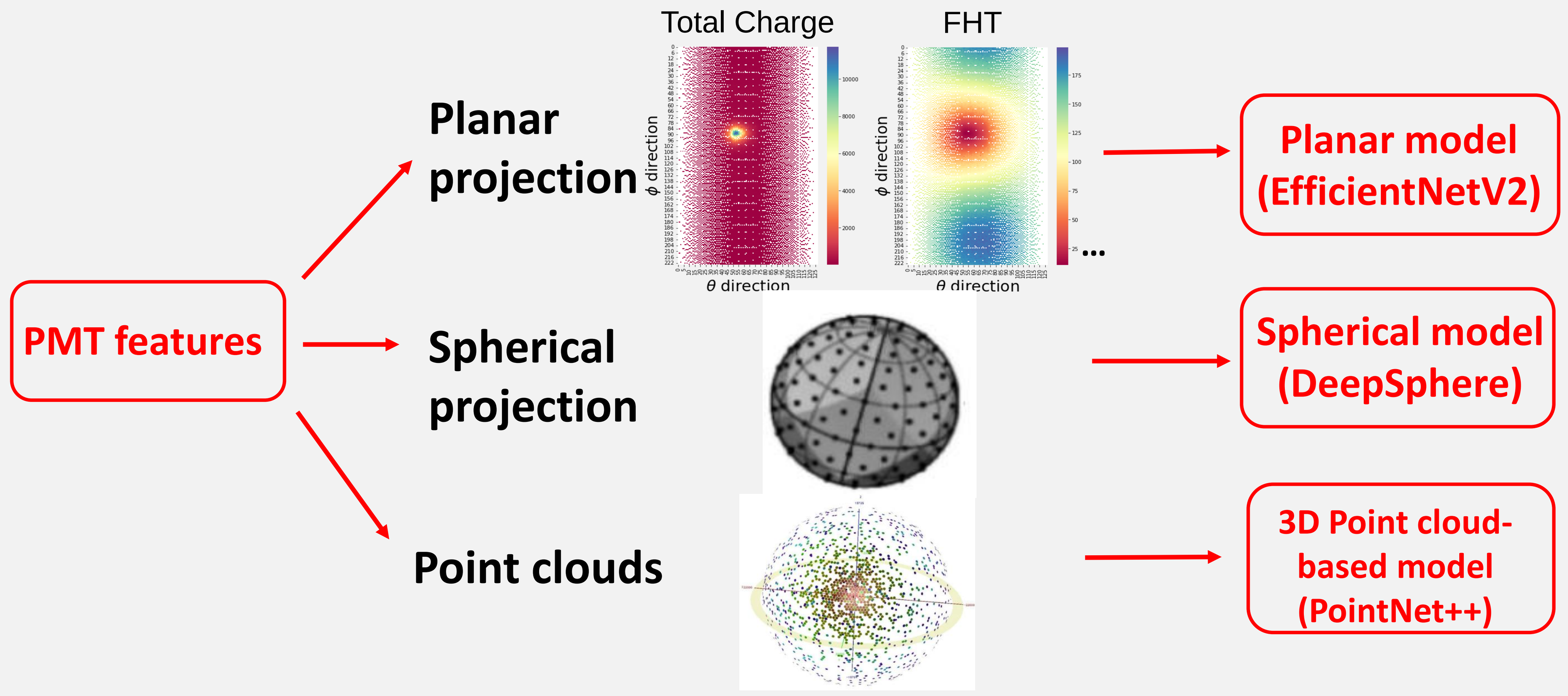


The waveform of one PMT, after reconstruction with deconvolution method and noise removing

- **FHT**: first hit time for each PMT
- **Total Charge**: the total charge in the first readout window
- **Peak Charge**: the maximum number of charges per ns
- **Peak Time**: the time when peak charge occurs
- **Slope**: the average slope of the waveform in the first 4ns after FHT
- **charge ratio**: The ratio of charges in the first 4ns after FHT to the total charge

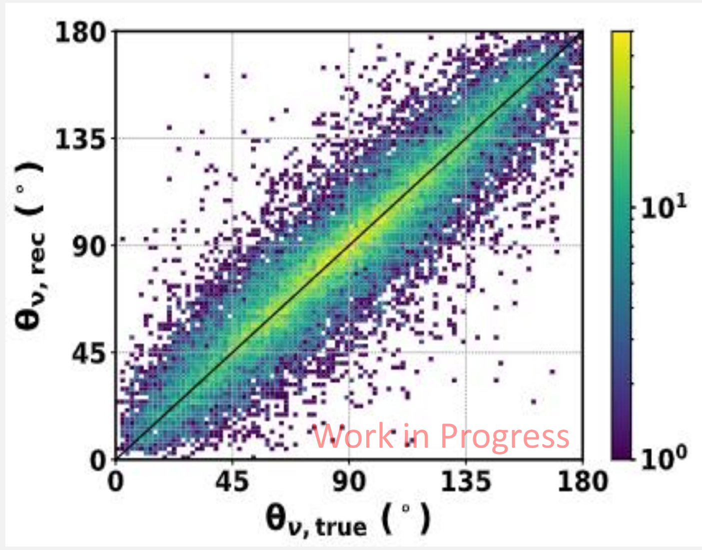
V. Machine Learning Approach

Three different approaches are developed to deal with the PMT features on CD's spherical surface:

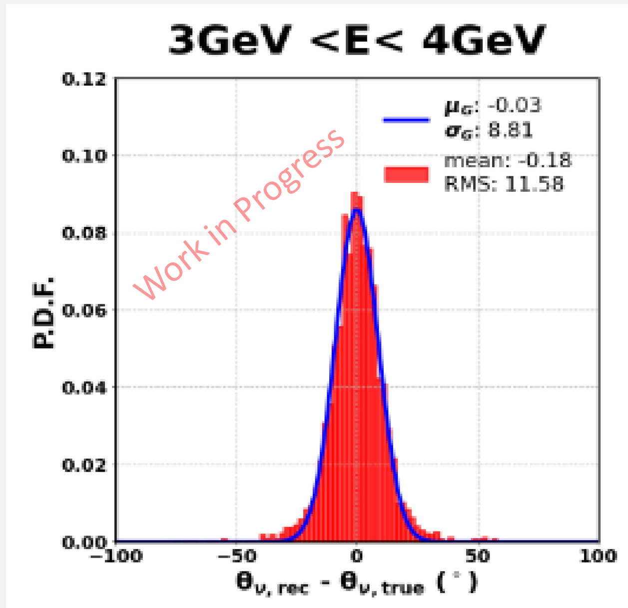


VI. Reconstruction Performance

Zenith angle (θ_ν) reconstruction performance, $\nu_\mu/\bar{\nu}_\mu$ PointNet++ result:

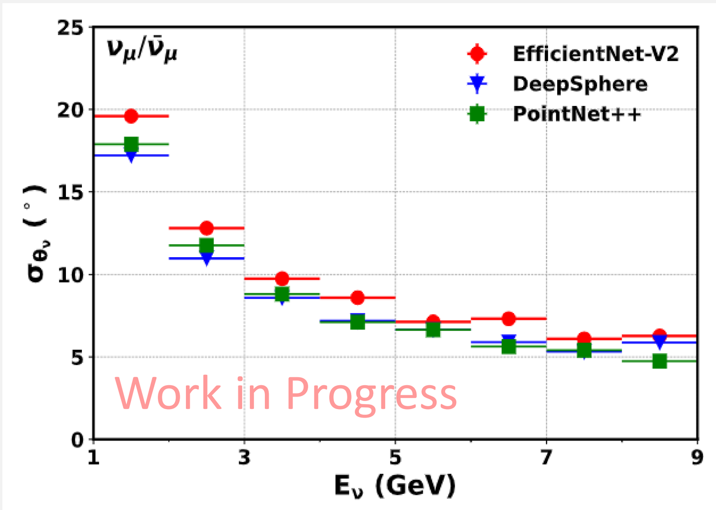


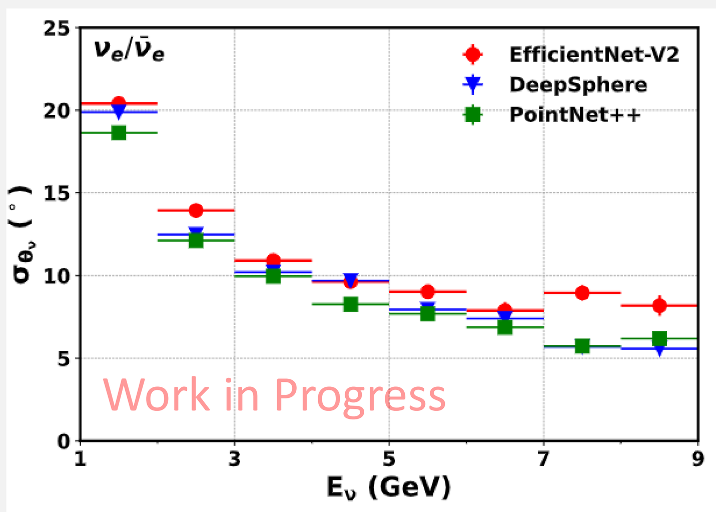
2D distribution of Reconstructed θ_ν VS True θ_ν over the energy range [1, 20] GeV



Angular uncertainty ($\theta_{\nu,\mathrm{rec}}$ - $\theta_{\nu,\mathrm{true}}$) in the energy range [3, 4] GeV

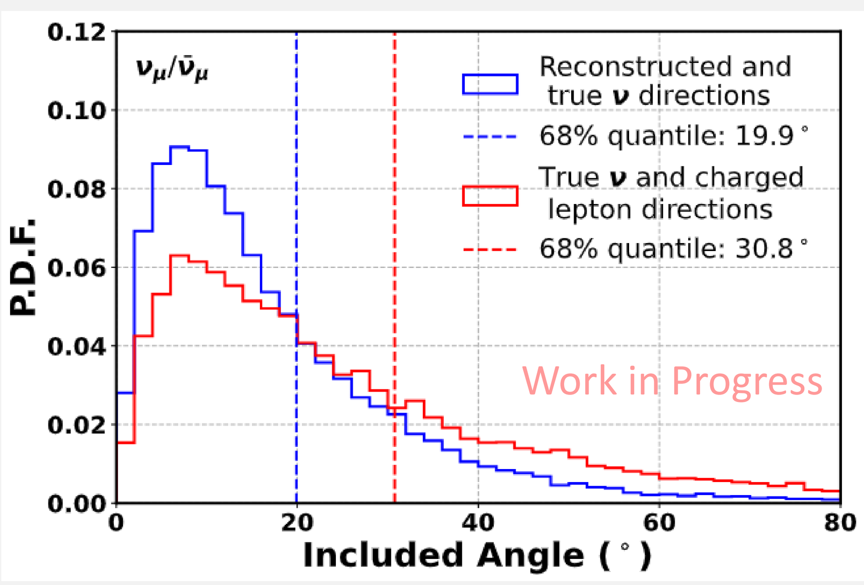
The energy-dependent θ_ν **reconstruction resolution** for $\nu_\mu/\bar{\nu}_\mu$ and $\nu_e/\bar{\nu}_e$, obtained from **three different types** of machine learning models:





VII. Summary

- We present a machine learning approach for the directional reconstruction of atmospheric neutrinos in JUNO. The resulting angular resolution based on simulations shows great potential.



- We reconstruct the incident neutrino direction instead of the charged lepton, because JUNO can capture scintillation light from primary leptons and hadrons, and get all the information for neutrino directionality.

References

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