



Overview of Machine Learning Applications in JUNO

Teng LI on behalf of JUNO

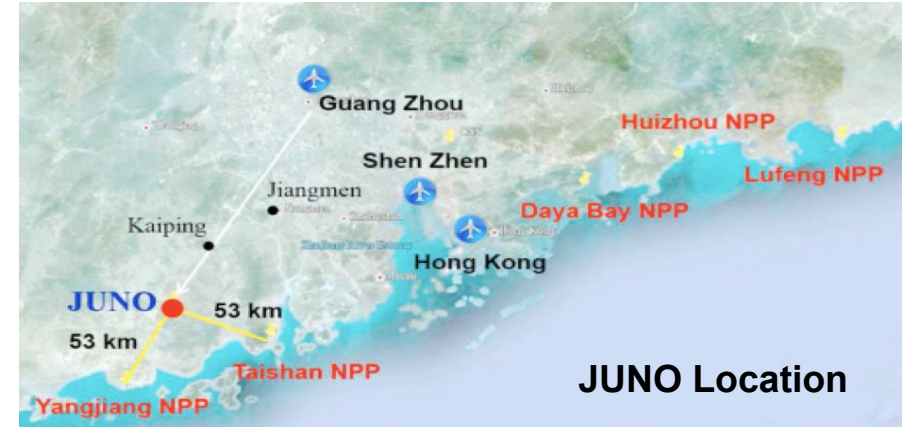
Shandong University

2024.6.25

NPML2024, ETH Zurich

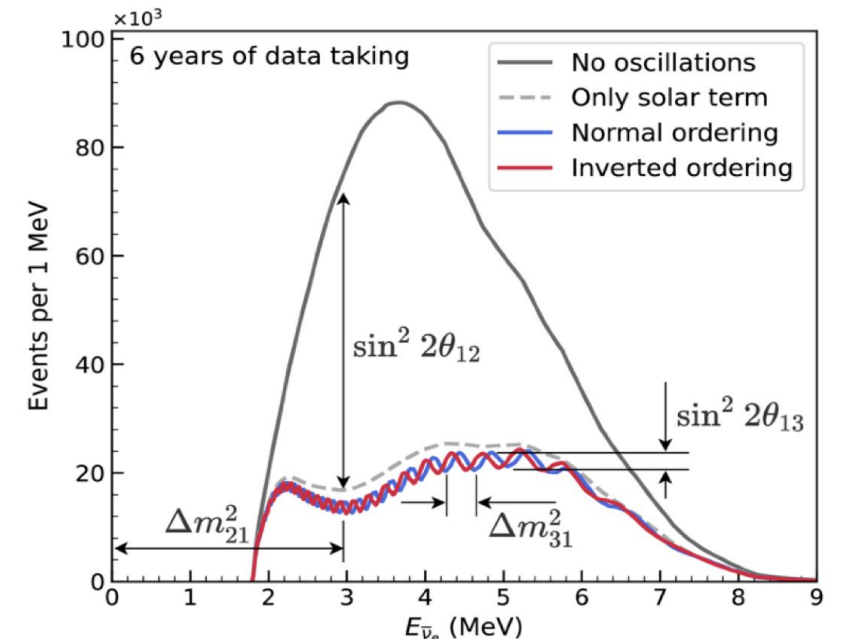
The JUNO Experiment

- ❖ Jiangmen **U**nderground **N**eutrino **O**bservatory
- ❖ Main physics goals
 - Determination of the mass ordering at the 3σ level in 6 years of data taking
 - Precise measurement of oscillation parameters, θ_{12} , Δm_{21}^2 and Δm_{31}^2



- ❖ JUNO also serves as an observatory detecting neutrinos from Supernova, Sun, Atmosphere and Earth etc.

Experiment	Target Mass	E Resolution
KamLAND	1000t	6%@1MeV
D. Chooz	8+22t	
RENO	16t	8%@1MeV
Daya Bay	20t	
Borexino	300t	5%@1MeV
JUNO	20000t	3%@1MeV



Reactor neutrino energy spectrum expected to be observed

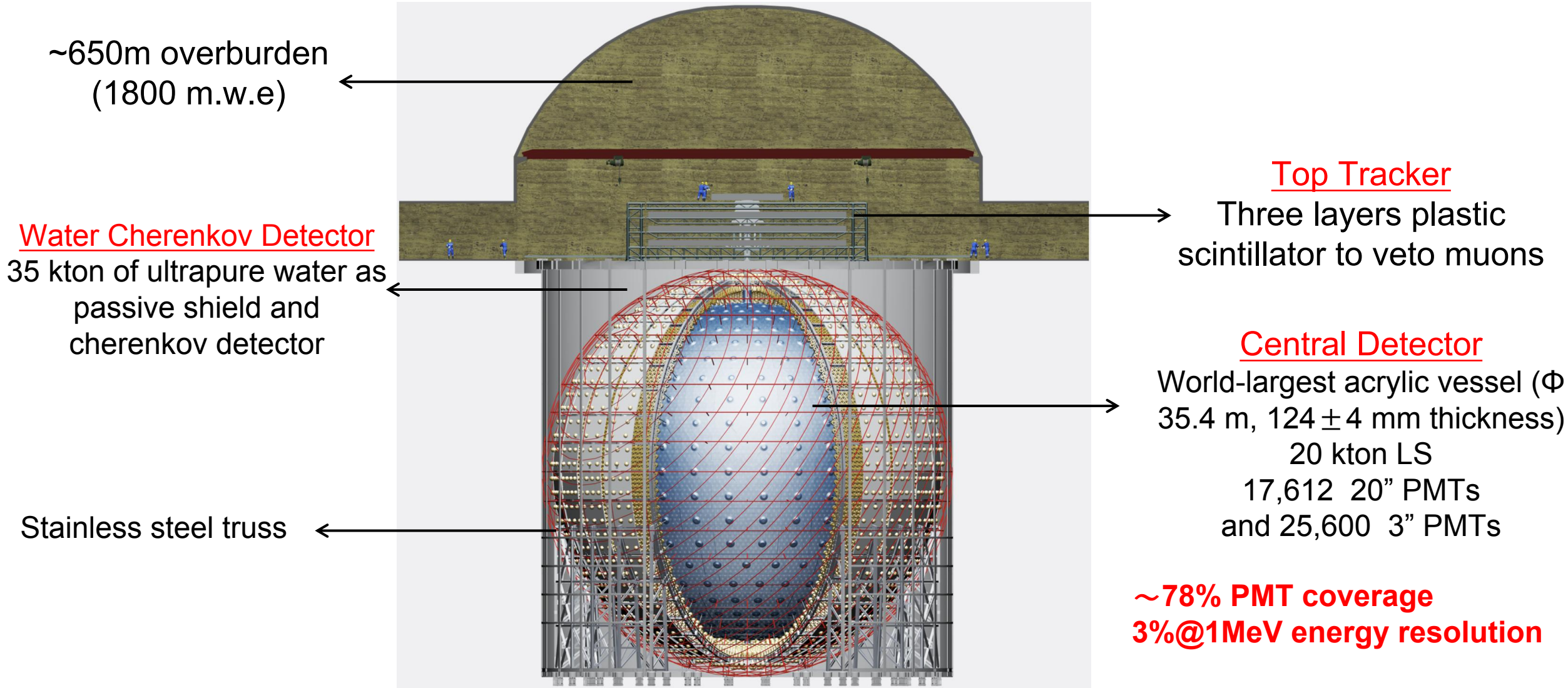
JUNO Site

Surface buildings / campus

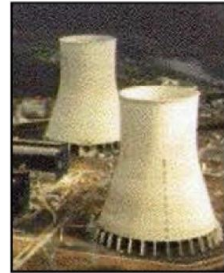
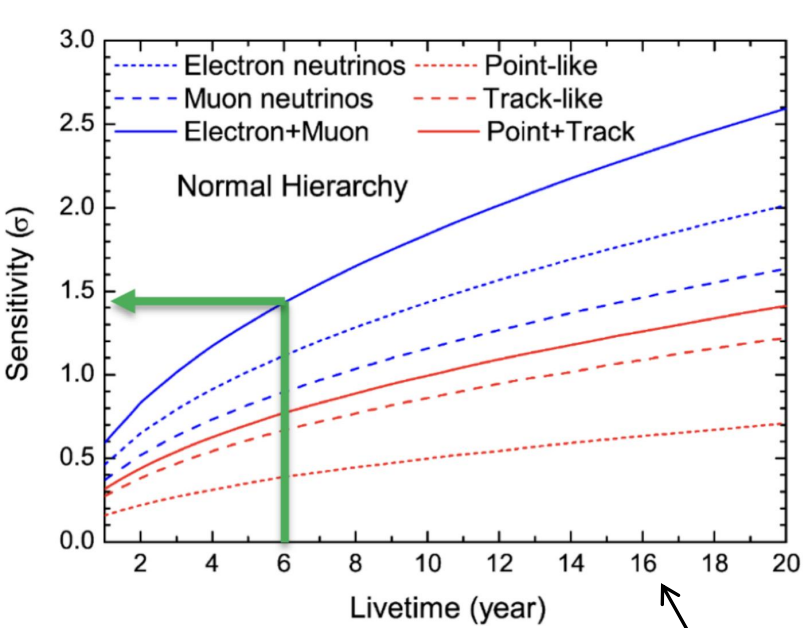
- Office / Dorm
- Surface Assembly Building
- LAB storage (5 kton)
- Water purification / Nitrogen
- Computing
- Power station
- Cable train



The JUNO Detector



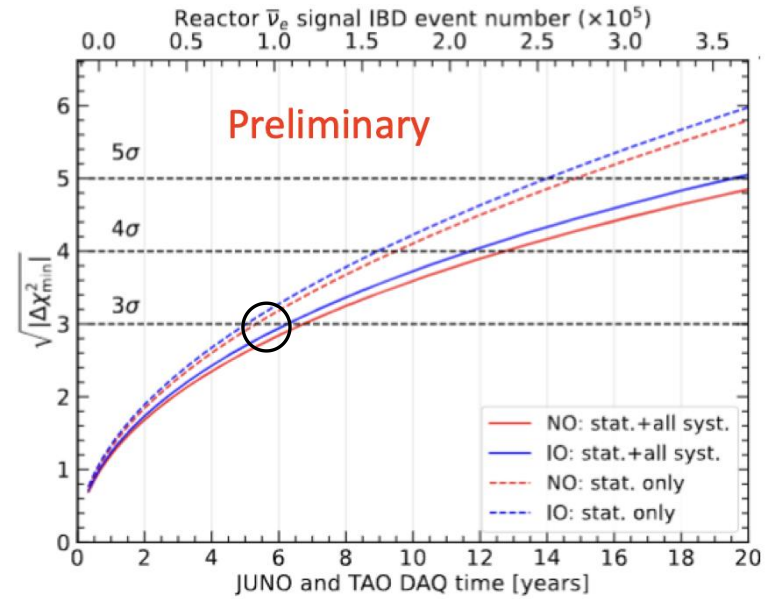
JUNO Reconstruction Road-map (for NMO)



MeV
Reactor Neutrino

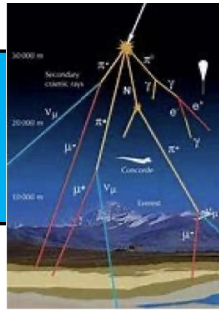
Vertex Rec.
Energy Rec.

Neutrino Mass Ordering



Flavor Identification
Directionality
Energy

Atmospheric Neutrino



GeV

Cosmic Muon (Veto)

GeV

Muon Classification
Track Reconstruction
Shower/Vertex Rec. (dE/dx)

Work shown in this talk is non-exhaustive

Ref. W. Luo's talk @ NuFact23

Outline

❖ **PMT waveform reconstruction**

- Photon counting and calibration data based reconstruction

❖ **Particle reconstruction in MeV region**

- Reactor neutrino vertex and energy reconstruction

❖ **Particle reconstruction in GeV region**

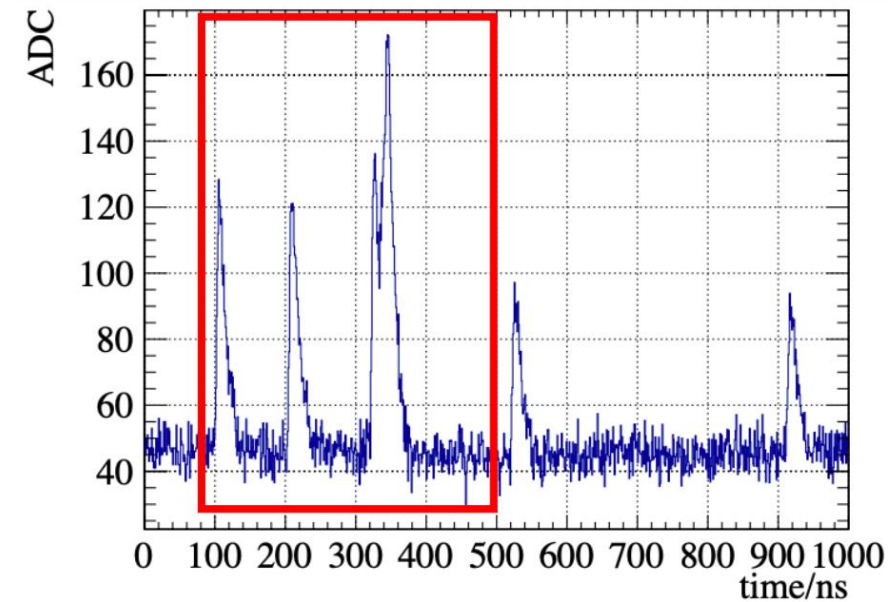
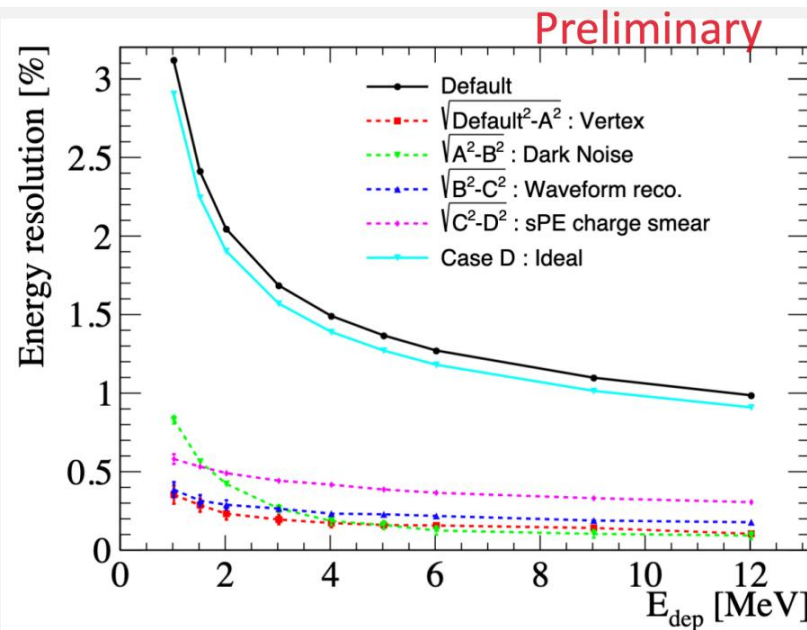
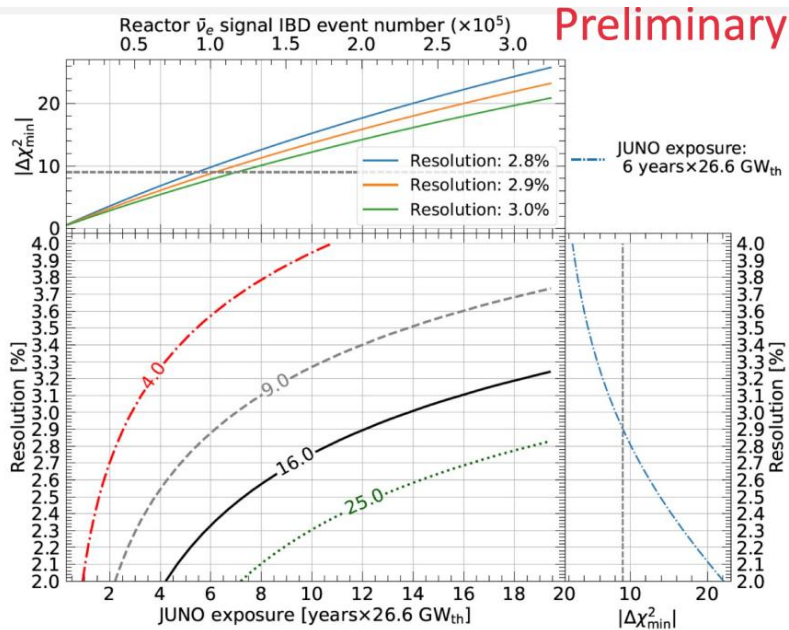
- Atmospheric neutrino directionality, PID and energy reconstruction
- Muon track reconstruction

PMT waveform reconstruction

Photon counting and calibration data based reconstruction

ML Based Photon Counting

- ❖ Energy resolution is crucial for NMO sensitivity in JUNO, where PMT charge smearing is one of the dominant factors



- ❖ Can we use ML to predict the number of received photons of each PMT?

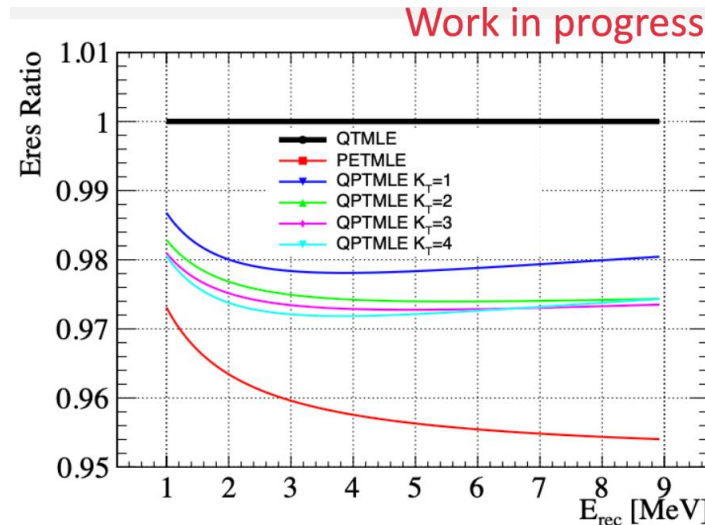
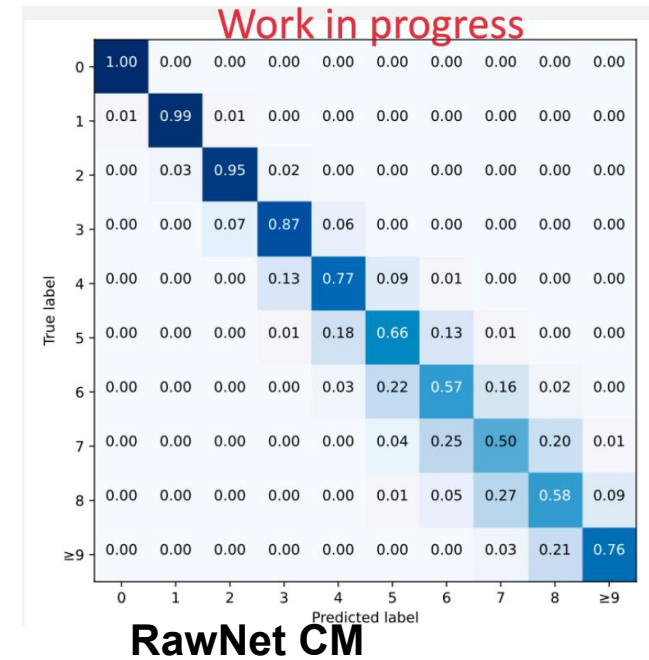
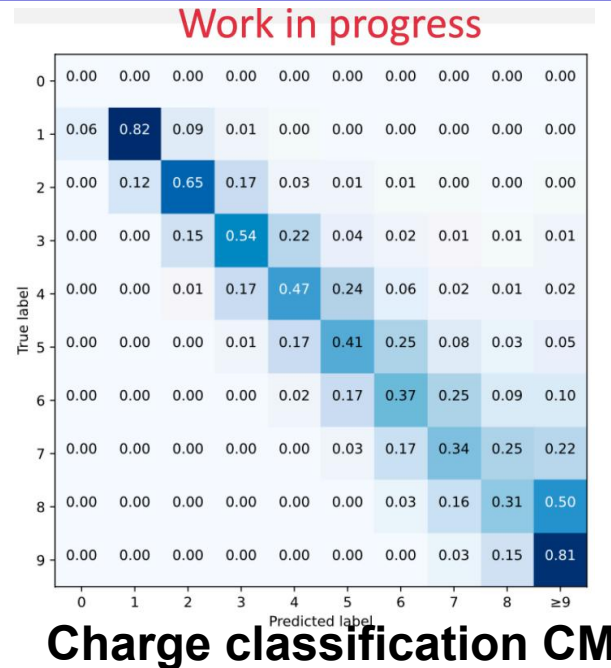
- Perform 1-D convolution on the raw waveform
- Use a classification model to “count the photons”

ML Based Photon Counting

Model: Customized RawNet

Table 2: Modified RawNet architecture. For convolutional layers, numbers inside parentheses refer to filter length, stride size, and number of filters. For gated recurrent unit (GRU) and fully-connected layers, numbers inside the parentheses indicate the number of nodes.

Layer	Input	Output shape						
Strided -conv	Conv(3,3,128)	(128, 140)						
	BN							
	LeakyReLU							
Res block	$\left\{ \begin{array}{l} \text{Conv}(3,1,128) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{Conv}(3,1,128) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{MaxPool}(3) \end{array} \right\} \times 2$	(128, 46)						
			Res block	$\left\{ \begin{array}{l} \text{Conv}(3,1,256) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{Conv}(3,1,256) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{MaxPool}(3) \end{array} \right\} \times 2$	(256, 1)			
						GRU	GRU(1024)	(1024,)
						Speaker embedding	FC(128)	(128,)
						Output	FC(10)	(10,)



2% to 2.8% relative improvement on the energy resolution can be achieved

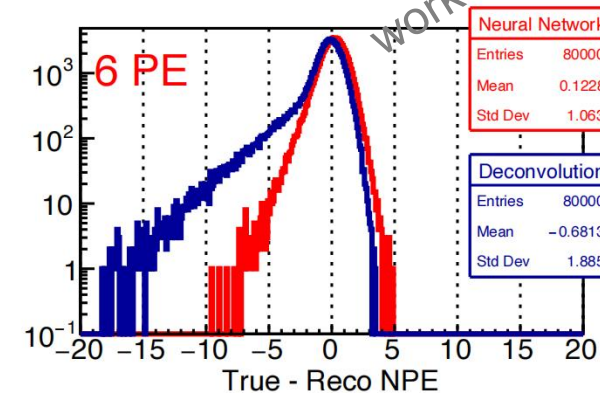
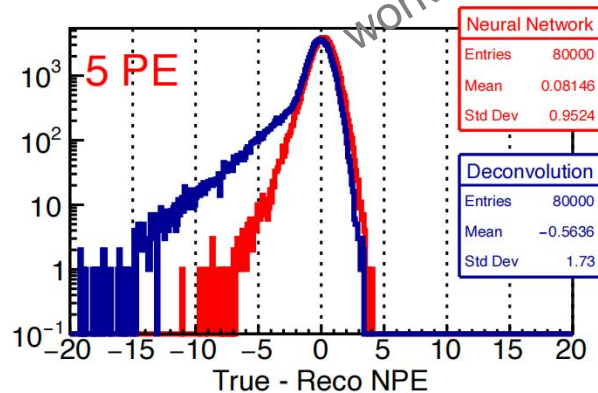
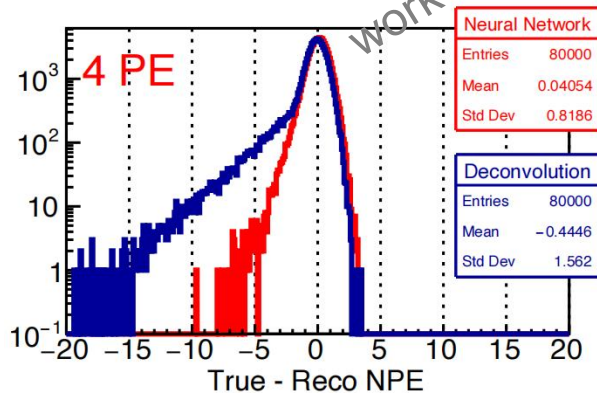
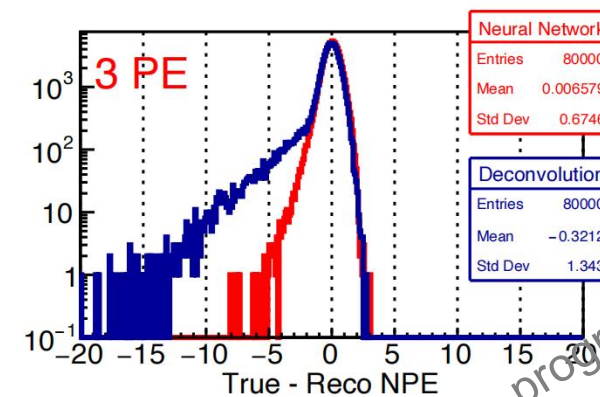
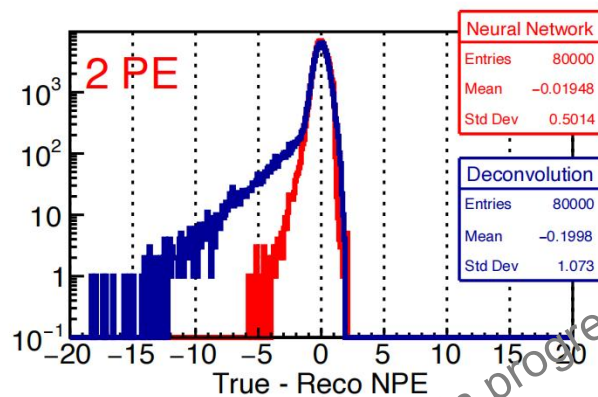
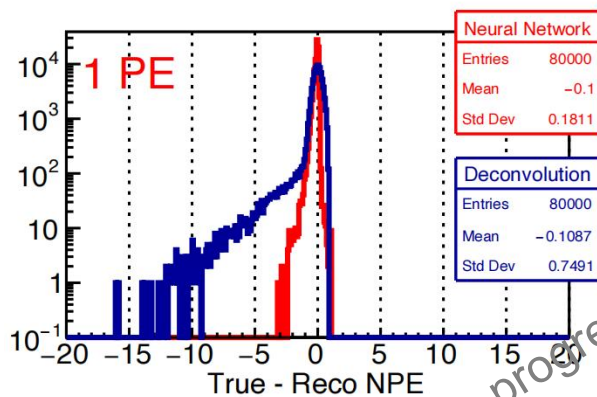
Details in Guihong's talk

Calibration-based Waveform Reconstruction

- ❖ Assemble “fake” waveform using calibration data, then train ML model (MLP) to learn from calibration data, and reconstruct number of PEs
 - Immune from the MC-data discrepancy problem
 - “Long tail” problem of the deconvolution-based waveform reconstruction algorithm is mitigated

- Input:
“Fake” waveform
- Model:
32*64 MLP network
- Output:
Number of PEs

Ref. Junting's poster
@Neutrino2024

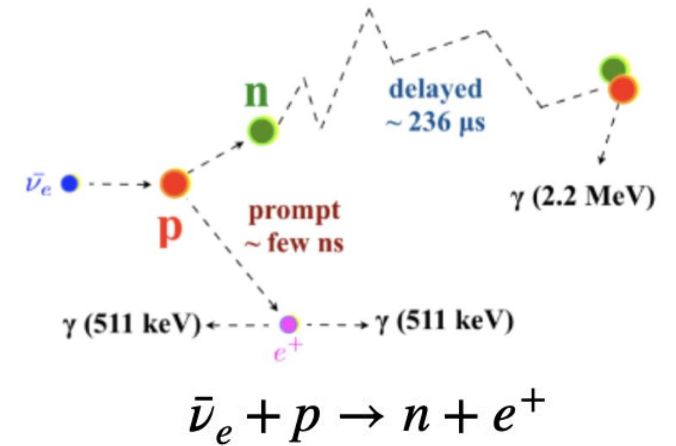


Particle reconstruction in MeV region

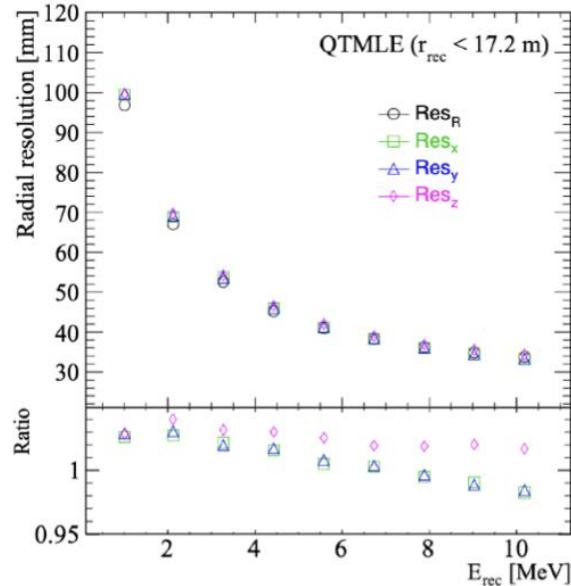
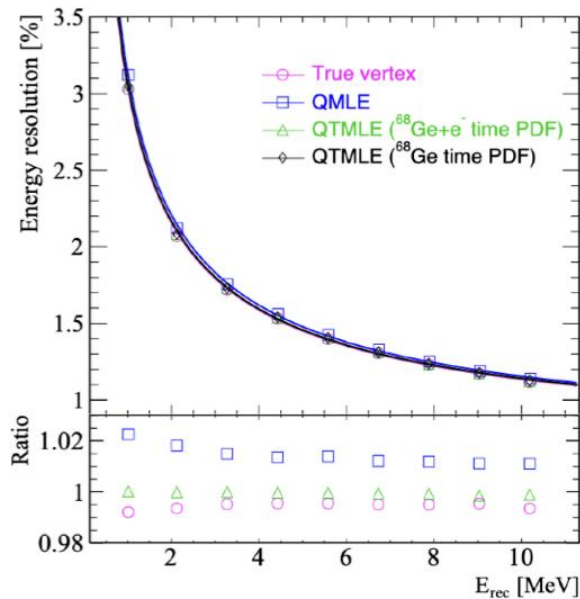
Reactor ν vertex and energy

Reactor Neutrino Reconstruction: Principle

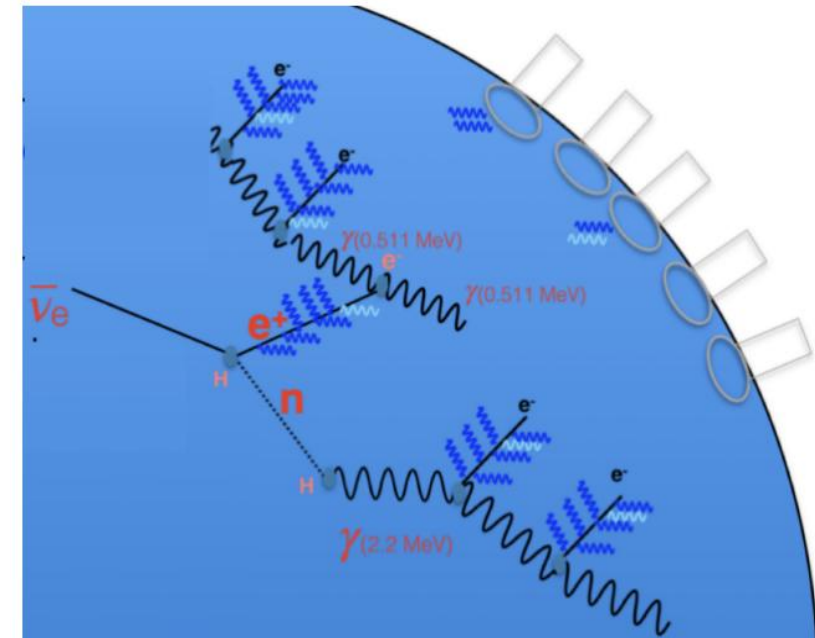
- ❖ Reactor neutrinos ($\bar{\nu}_e$) are detected via the inverse beta decay reaction in the CD
 - The e^+ generates a prompt signal in the CD
 - The neutron generates a delayed signal in the CD, with a 2.2 MeV gamma from the neutron capture process
 - Seek the coincidence between the detection of a positron and a neutron signal, with $\sim 200 \mu\text{s}$
- ❖ Classical methods are based on likelihood algorithms, taking
 - Charge, first hit time, position of each fired PMT



Energy and radial resolution of QTMLE



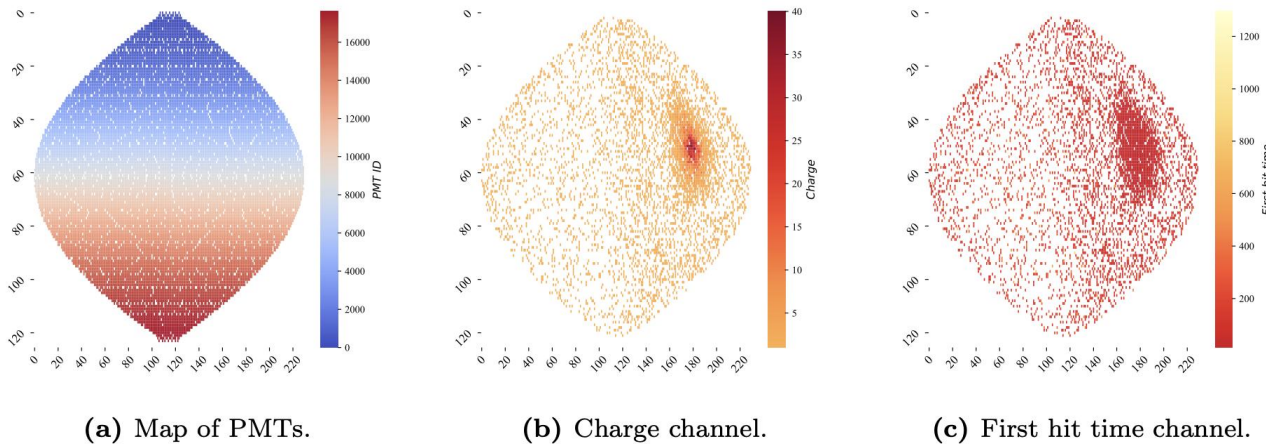
Can this be further improved using ML?



IBD Reconstruction: Planar CNN

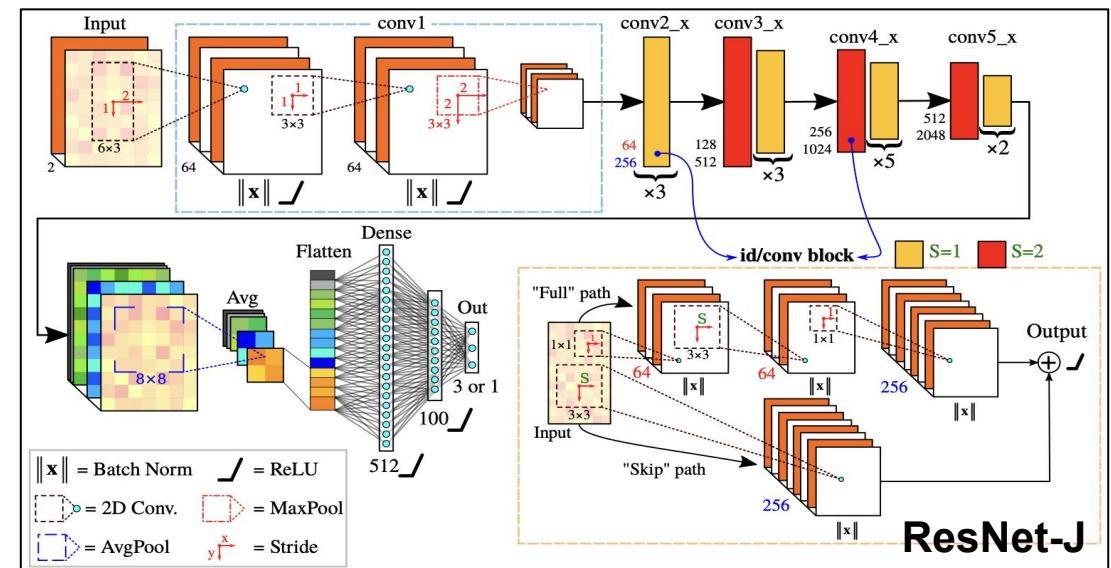
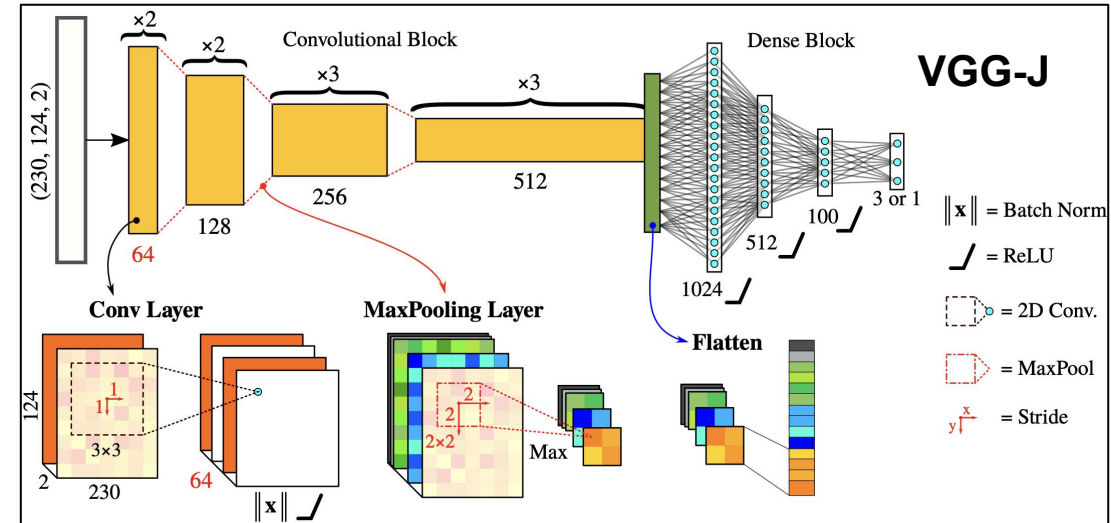
❖ Treating the JUNO detector as a camera and using the **image recognition** technique

- The PMT data is projected onto the planar surface, and fed into CNN models
- VGG and ResNet models are customized for JUNO



❖ Distortion, i.e. breaking of the $SO(3)$ symmetry is a potential problem

❖ Can we do better?

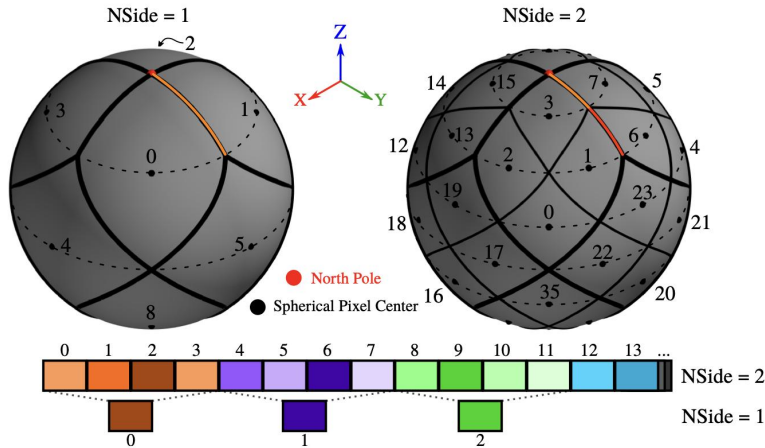


IBD Reconstruction: Spherical GNN

- ❖ The Spherical GNN method takes the $SO(3)$ symmetry of JUNO detector into account
 - Convolution is performed on the graph using spectral graph method
 - Convergence becomes easier compared to planar CNN

HEALPix Sampling Scheme to pixelise the detector

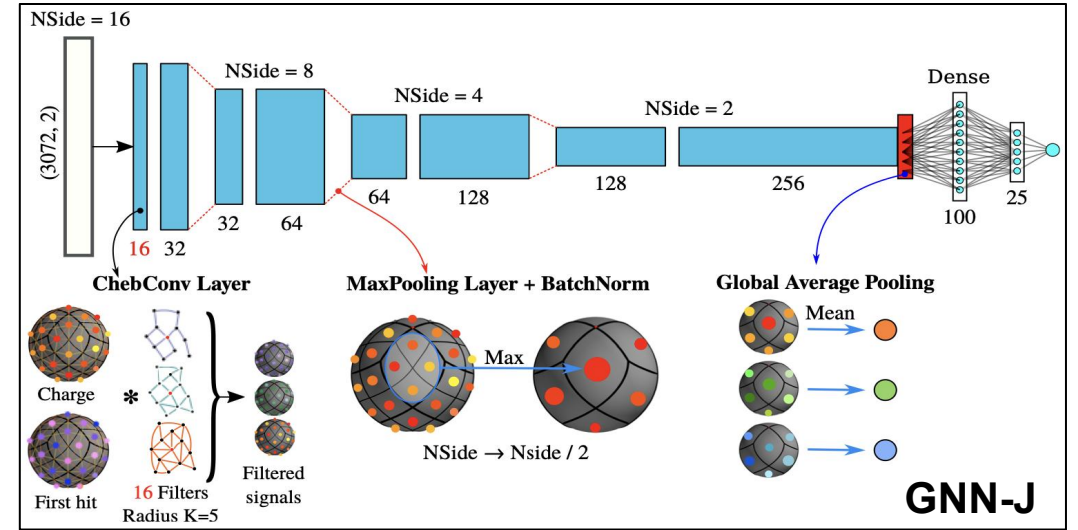
Then build Graph with adjacency matrix



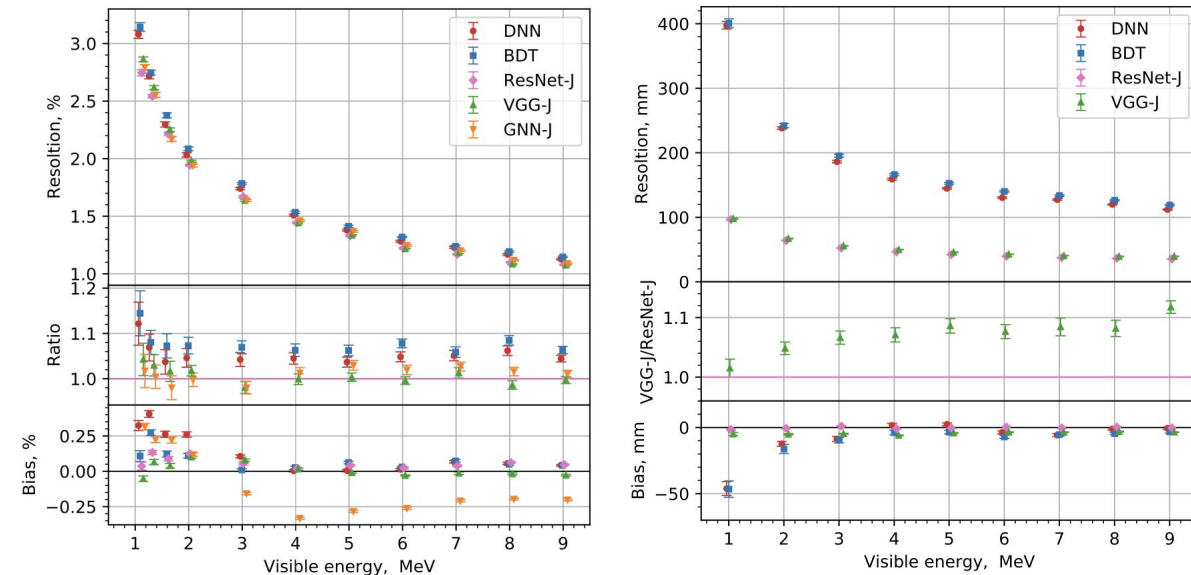
$$W_{ij} = \exp\left(-\frac{\|v_i - v_j\|_2^2}{2\bar{d}^2}\right)$$

$$\bar{d}^2 = \frac{1}{|\mathcal{E}|} \sum_{(v_i, v_j) \in \mathcal{E}} \|v_i - v_j\|_2^2$$

- ❖ Both methods gives similar resolution as classical methods



Nucl.Instrum.Meth.A 1010 (2021) 165527



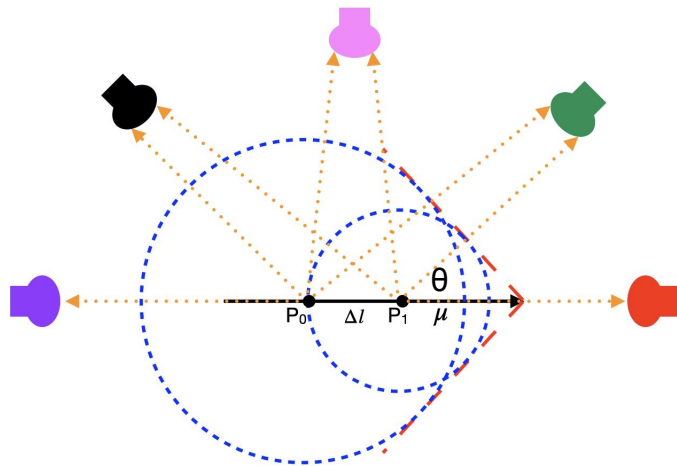
Particle reconstruction in GeV region

Atm. ν directionality, PID, energy and muon track

Methodology

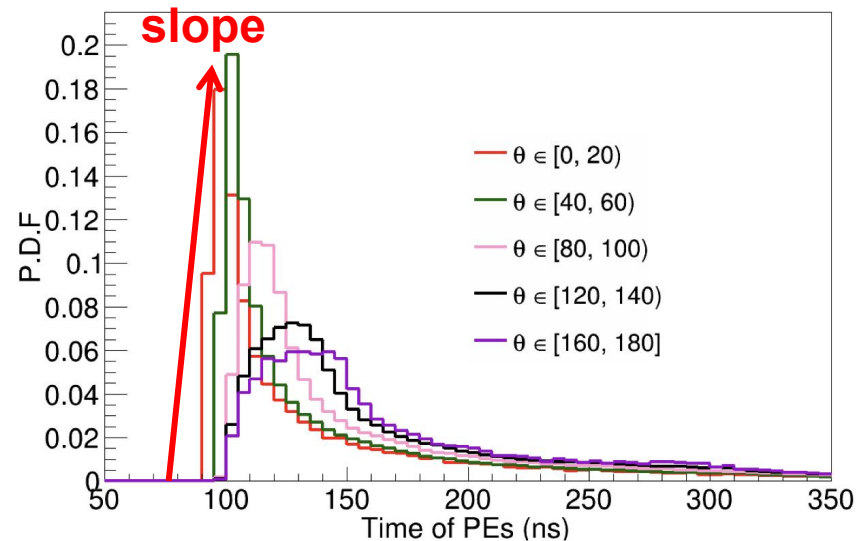
- ❖ Light received by a PMT is the superposition of light from many points on tracks in the detector
- ❖ The number of photo-electrons (PEs) seen by a PMT as a function of time is determined by the event topology
- ❖ Features related to event topology can be extracted from deconvoluted PMT waveform to get:

- Track direction
- Track starting and stopping points
- Track dE/dx

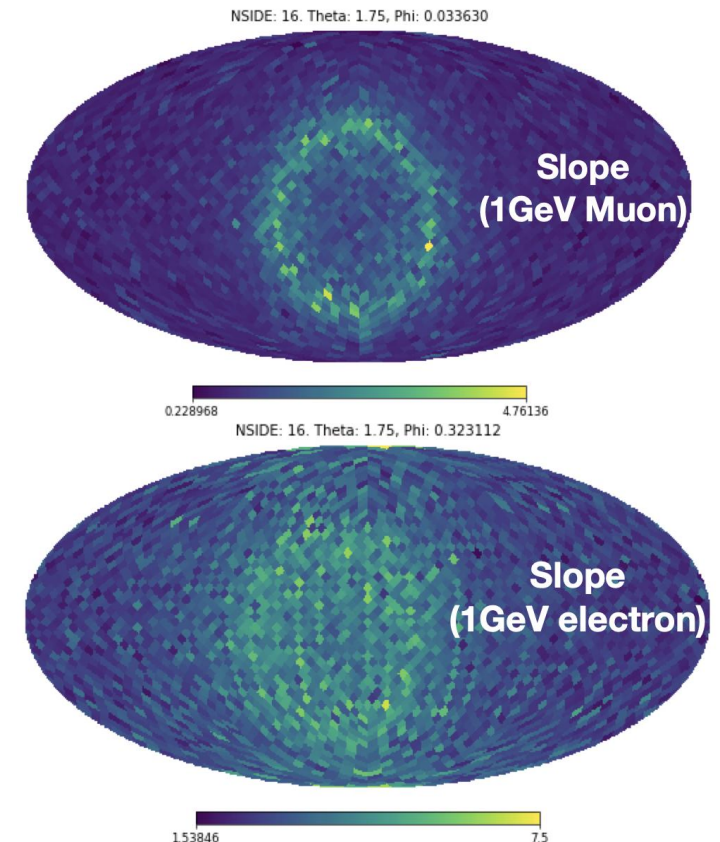


PMTs at different angles wrt the track see distinct shapes of $nPE(t)$

Directionality
Energy
PID

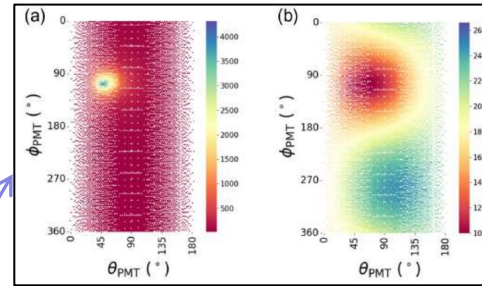
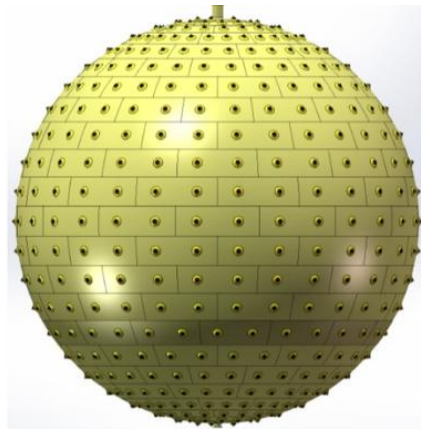


Ref. Duyang's talk @TIPP2023

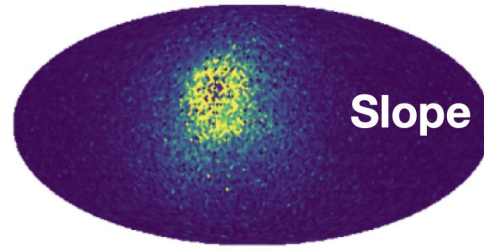


Methodology

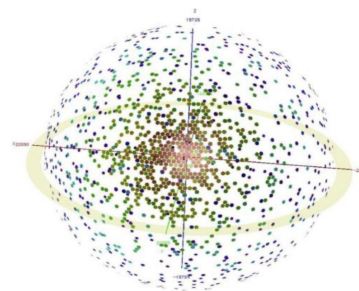
❖ Event reconstruction with **D**eep-learning and **W**aveform **I**nformation (**EDWIN**)



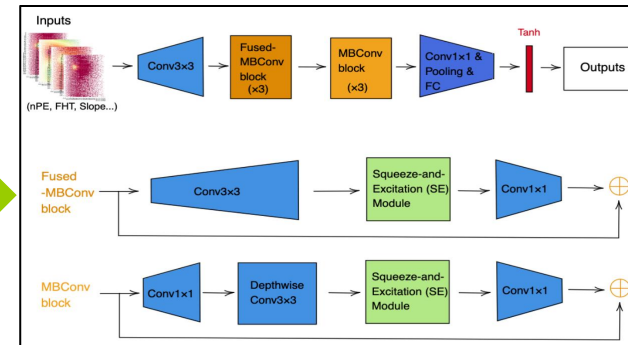
Planer Projection



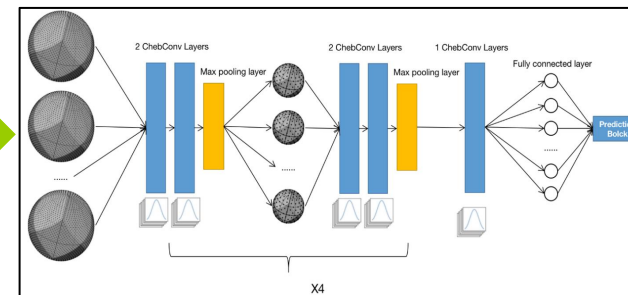
Spherical Projection



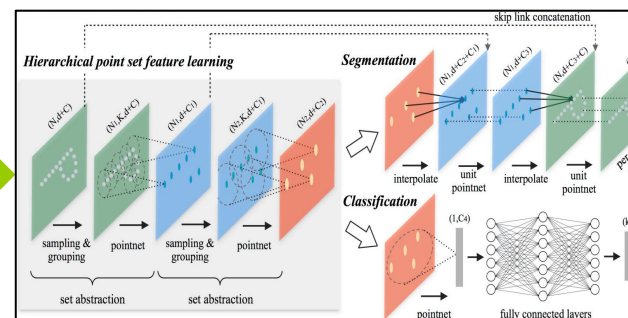
Point Clouds



EfficientNetV2



DeepSphere

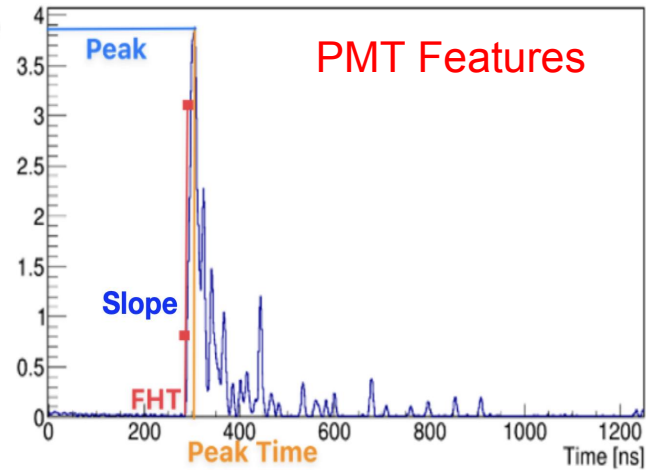


PointNet++

Direction
Energy
Flavor
Vertex
Track
Others...

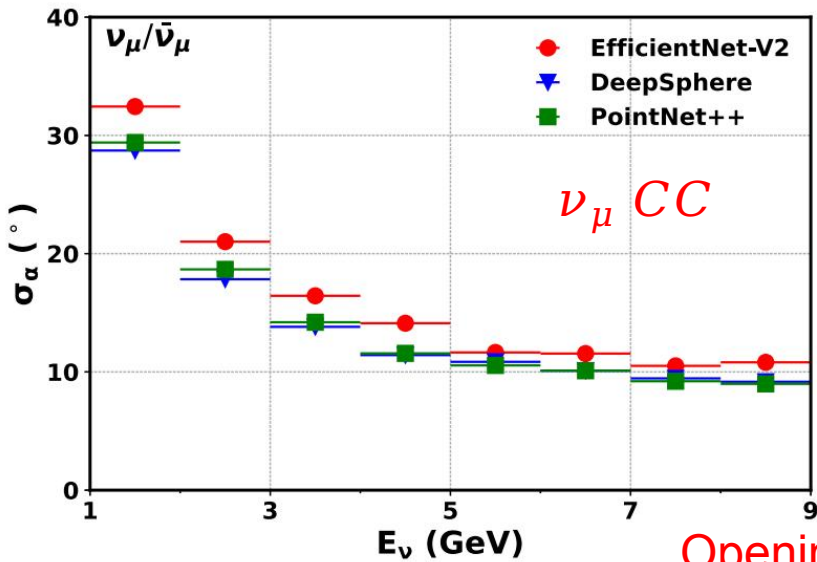
Output

PMT Features

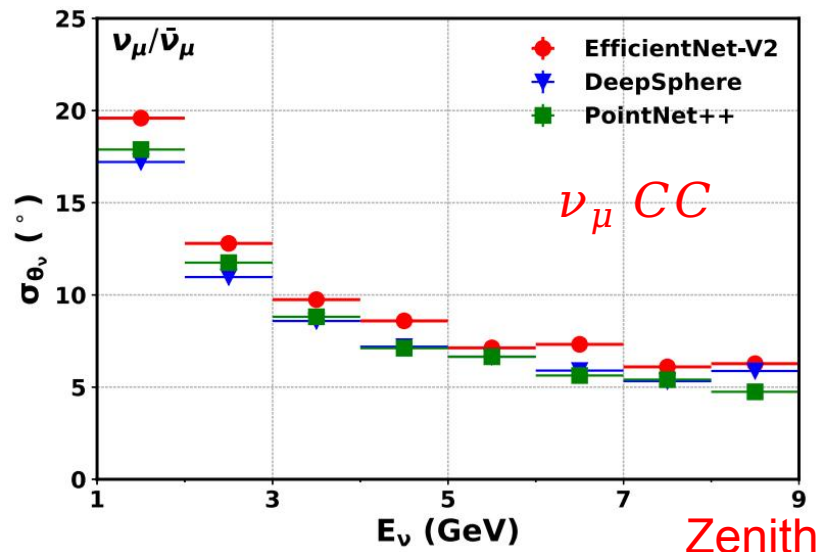
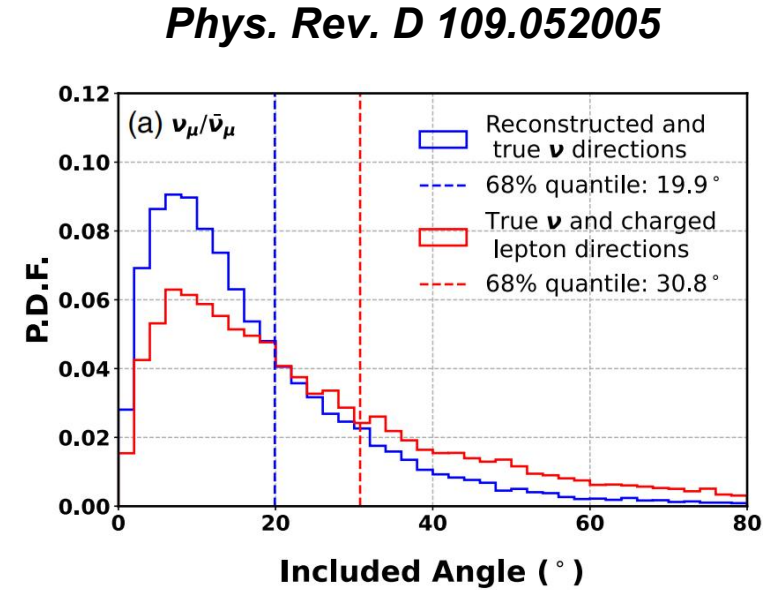
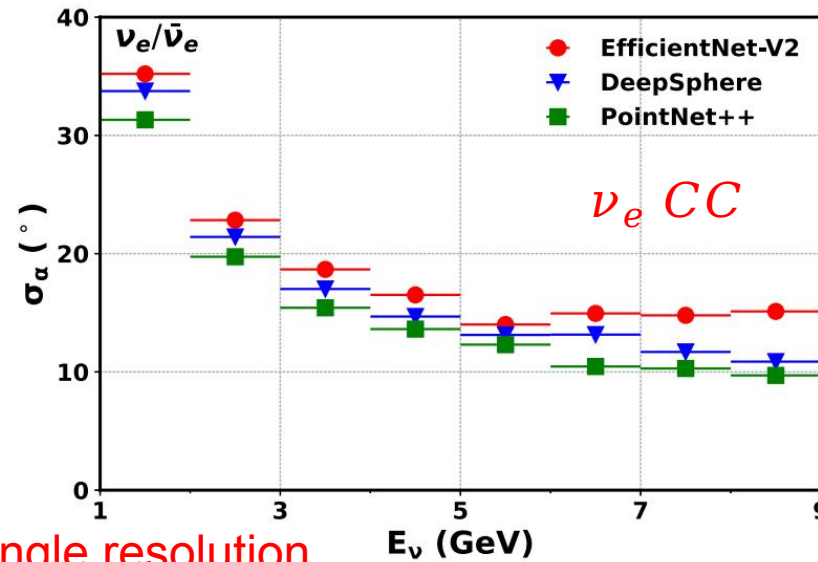


Deconvoluted PMT Waveform

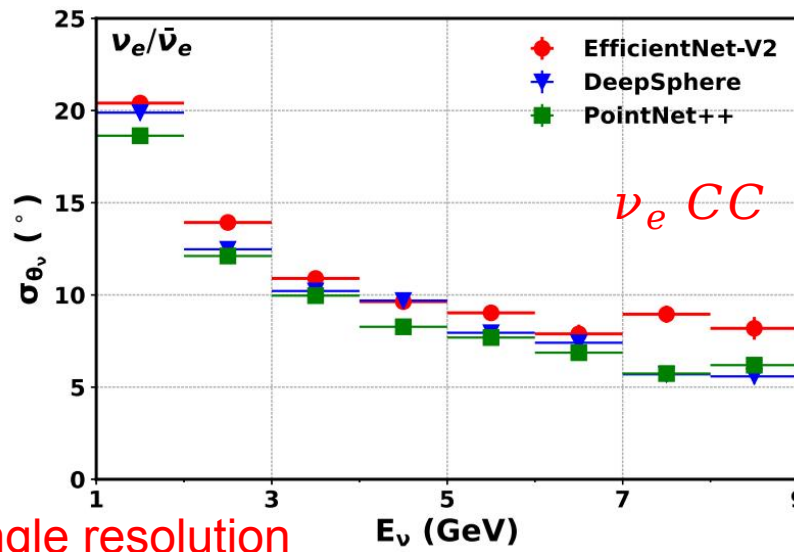
Atmospheric Neutrino Directionality Reconstruction



Opening angle resolution



Zenith angle resolution



- Neutrino direction is directly reconstructed rather than the final-state charged lepton direction, with good angular resolution.
- World's first attempt to reconstruct atmospheric neutrinos' directionality in a large homogeneous LS detector.

Atmospheric Neutrino Flavor Identification

Strategy 1:

- Hybrid model: [PointNet++](#) and [DGCNN](#)
- PMT features from primary trigger fed into PointNet++
- Scalar neutron capture features fed into DGCNN

Strategy 2:

- Spherical image-based model: [DeepSphere](#)
- Multiple neutron-candidate triggers are fed together with the primary trigger
- All features are at the PMT-level

Details in Jiaxi's and Wing's talks

3-label classification:

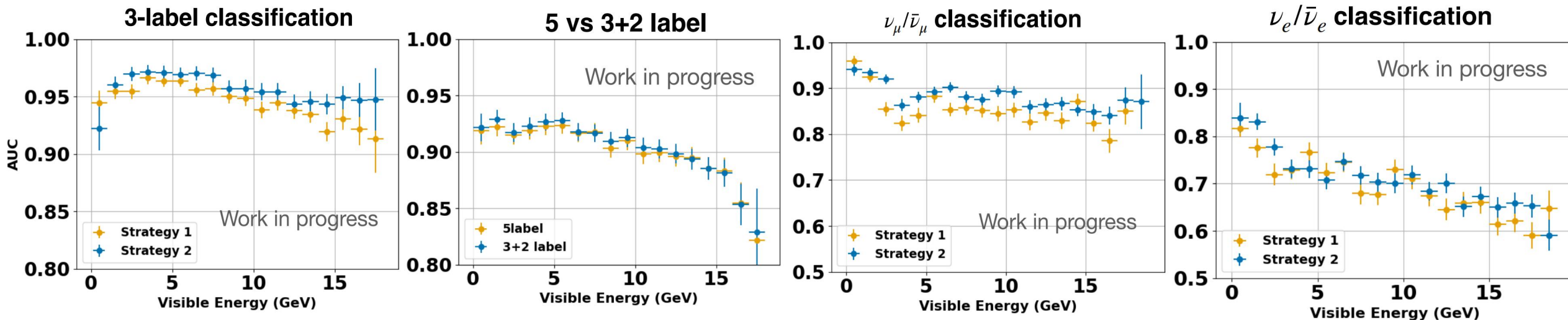
- Discriminate ν_e CC, ν_μ CC and NC

2-label classification:

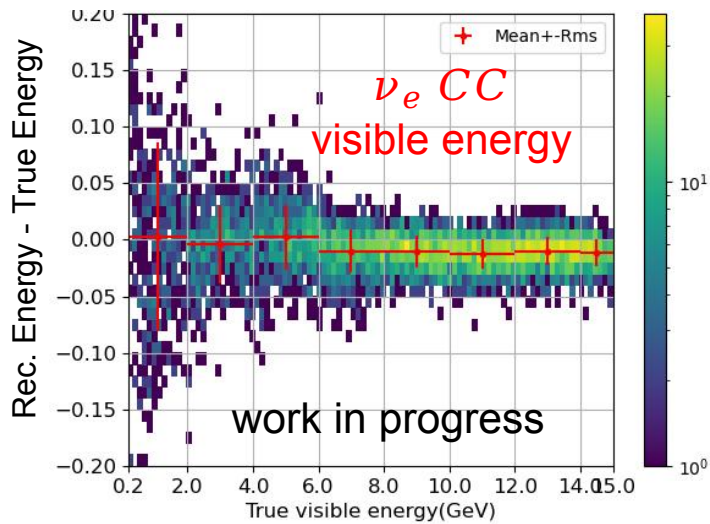
- Discriminate $\bar{\nu}/\nu$

3+2 label classification:

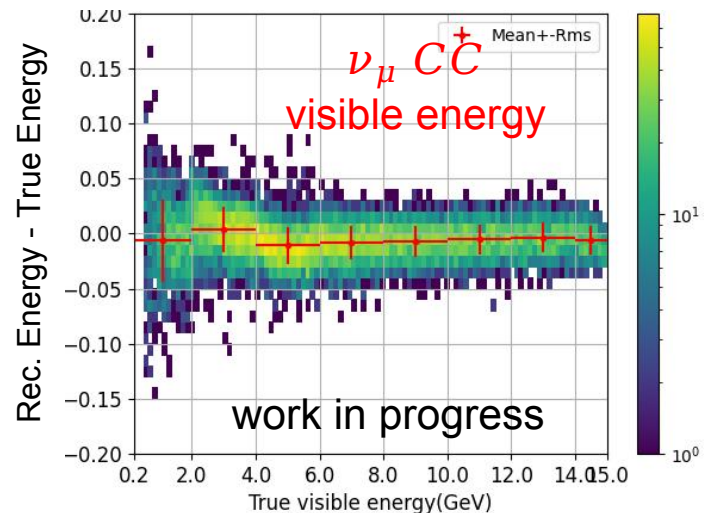
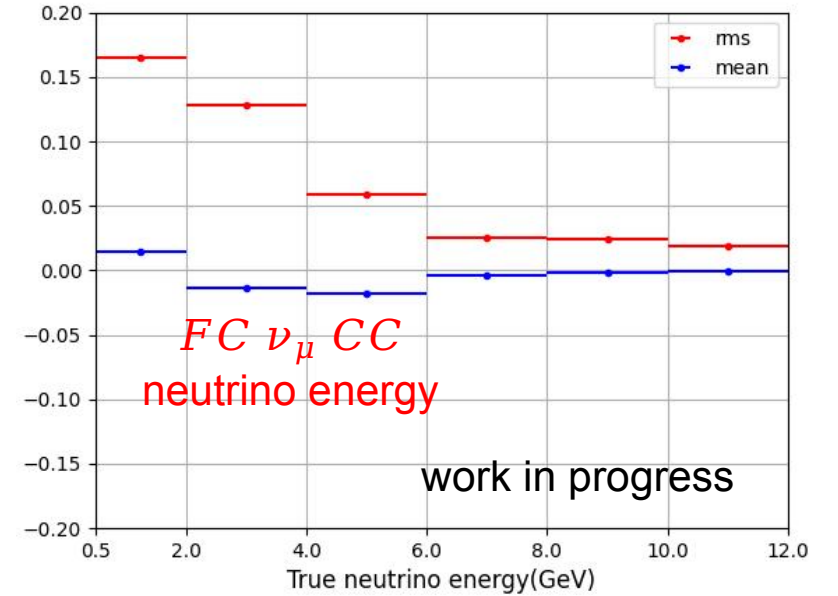
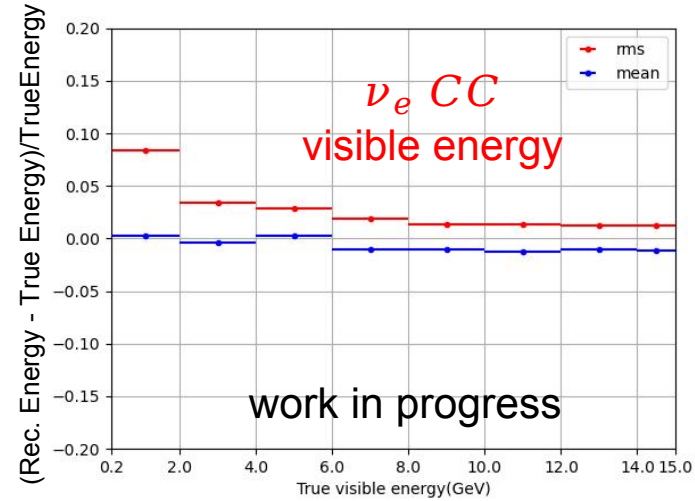
- Combine the 3-label and 2-label models to achieve 5-label classification (roughly consistent)



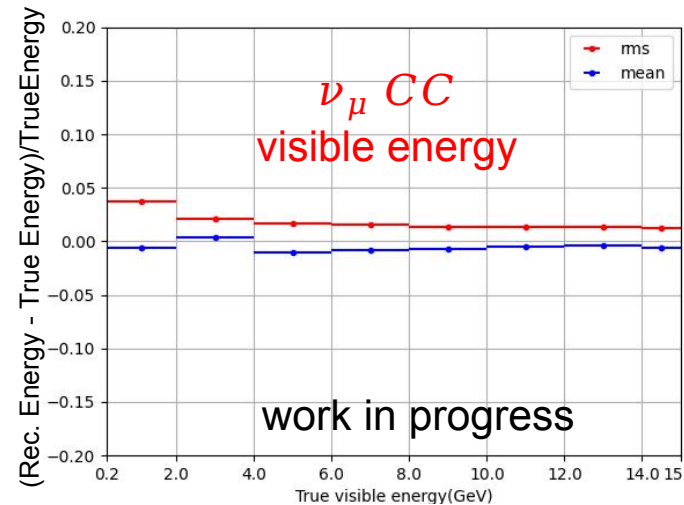
Atmospheric Neutrino Energy Reconstruction



1% - 8% visible energy resolution for ν_e CC from 0.2-15GeV



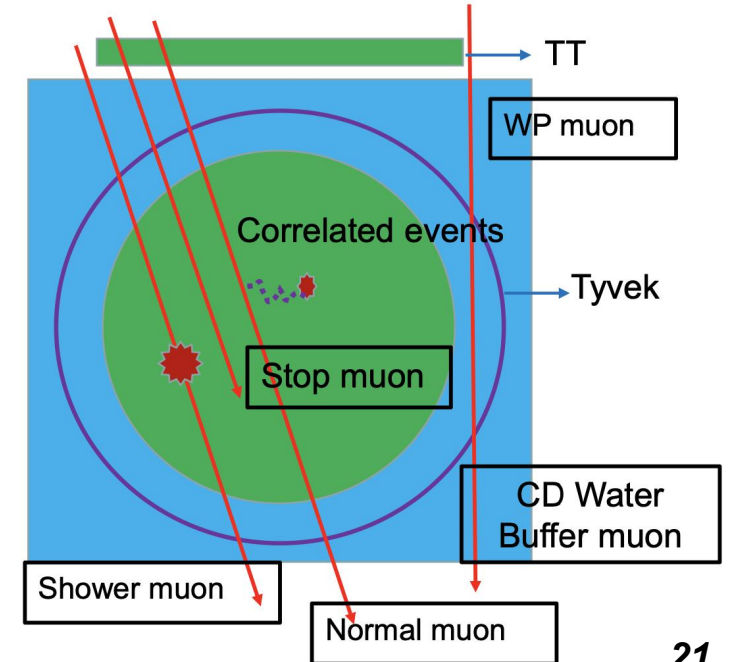
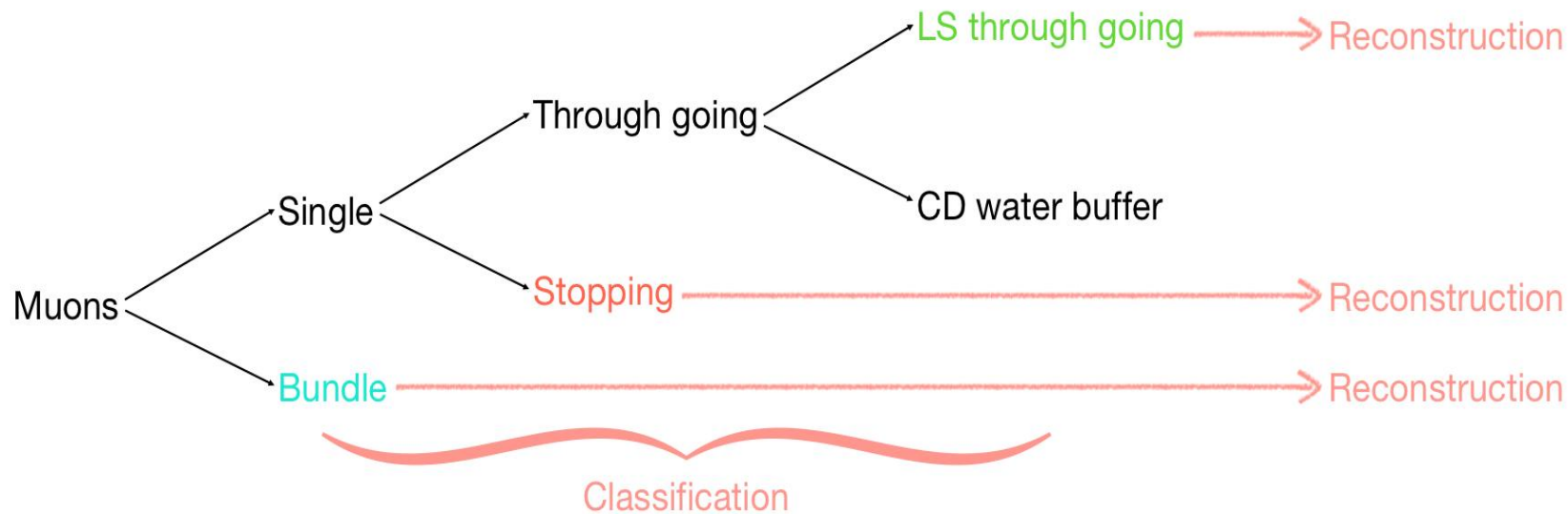
1% - 5% visible energy resolution for ν_μ CC from 0.2-15GeV



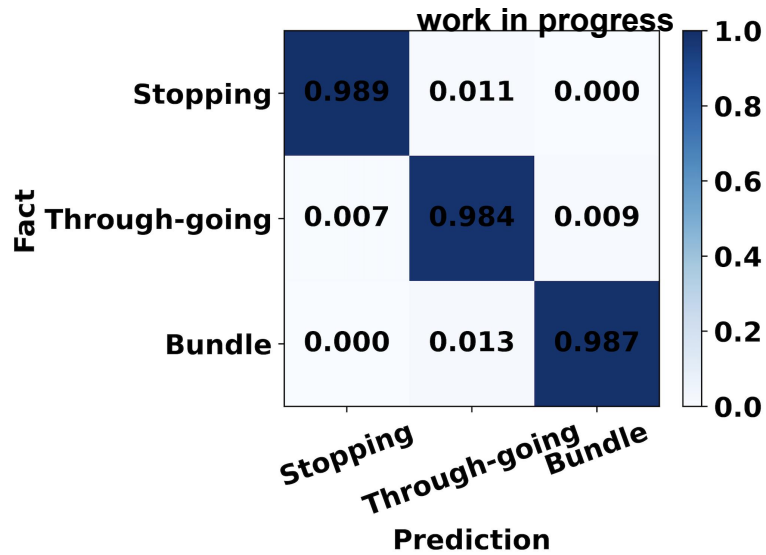
- Results based on the Spherical GNN
- Visible energy resolution is promising
- Neutrino energy resolution for fully contained neutrinos is sub-optimal, but still provides better sensitivity with preliminary NMO analysis

Muon Track Reconstruction: Methodology

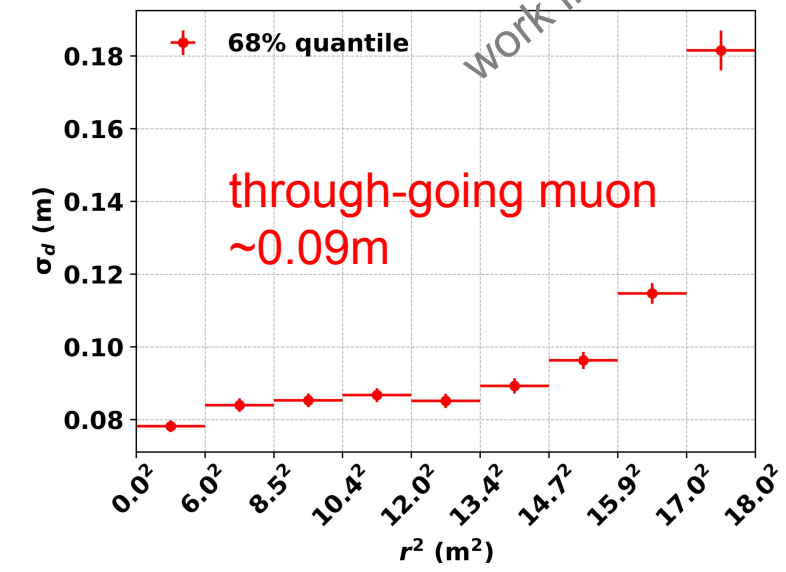
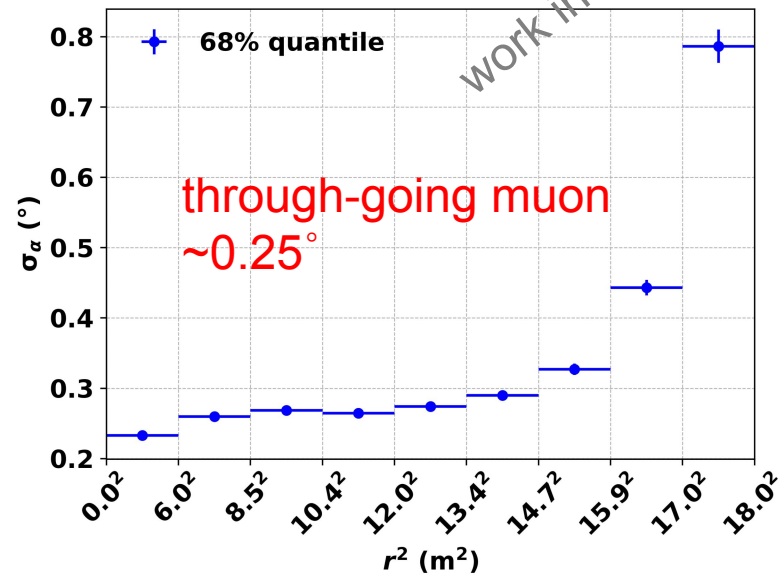
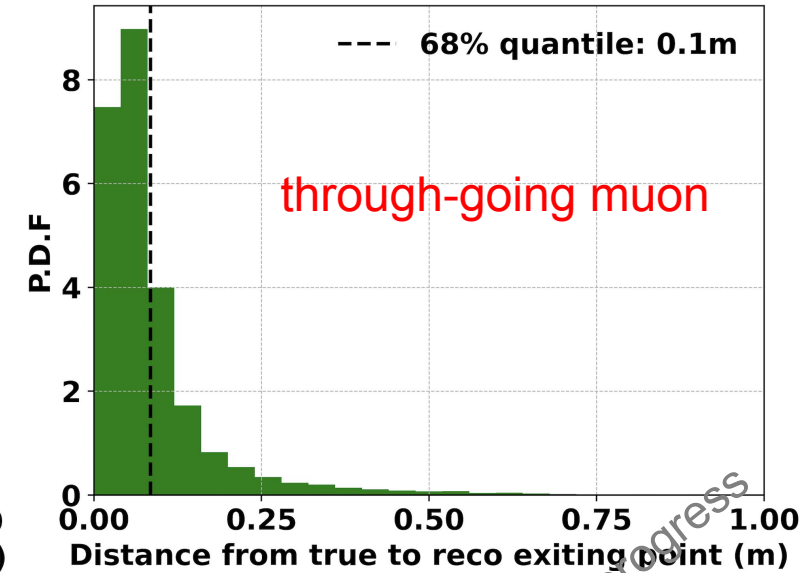
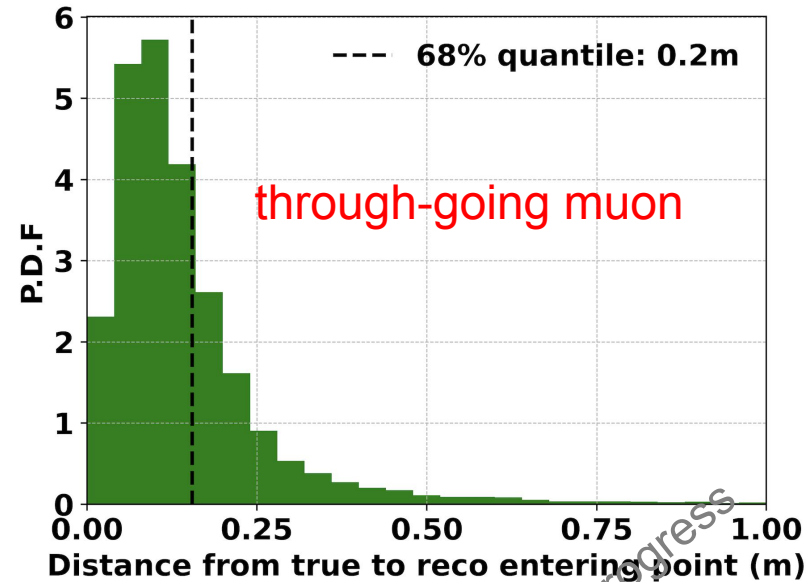
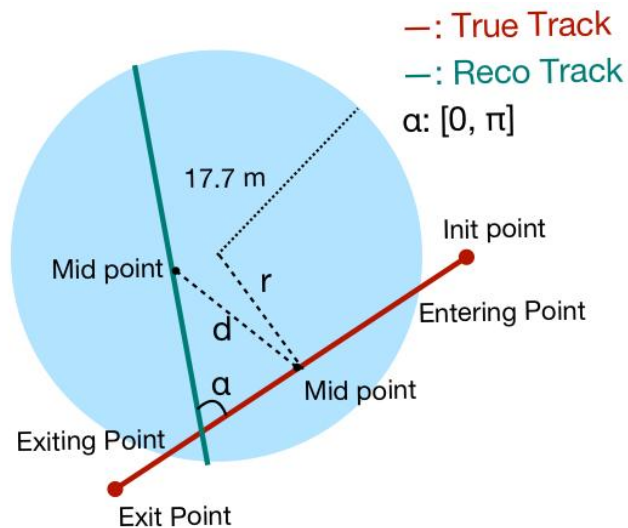
- ❖ Isotopes produced by cosmic muons are the main background of IBD signals
- ❖ Precise reconstruction of muon tracks is critical to veto major backgrounds
- ❖ Current ML-based reconstruction strategy for muons:
 - Classify through-going, stop and bundle muons
 - Reconstruct the entry point and exit point of LS through going, stop and bundle muons



Muon Track Reconstruction: Performance

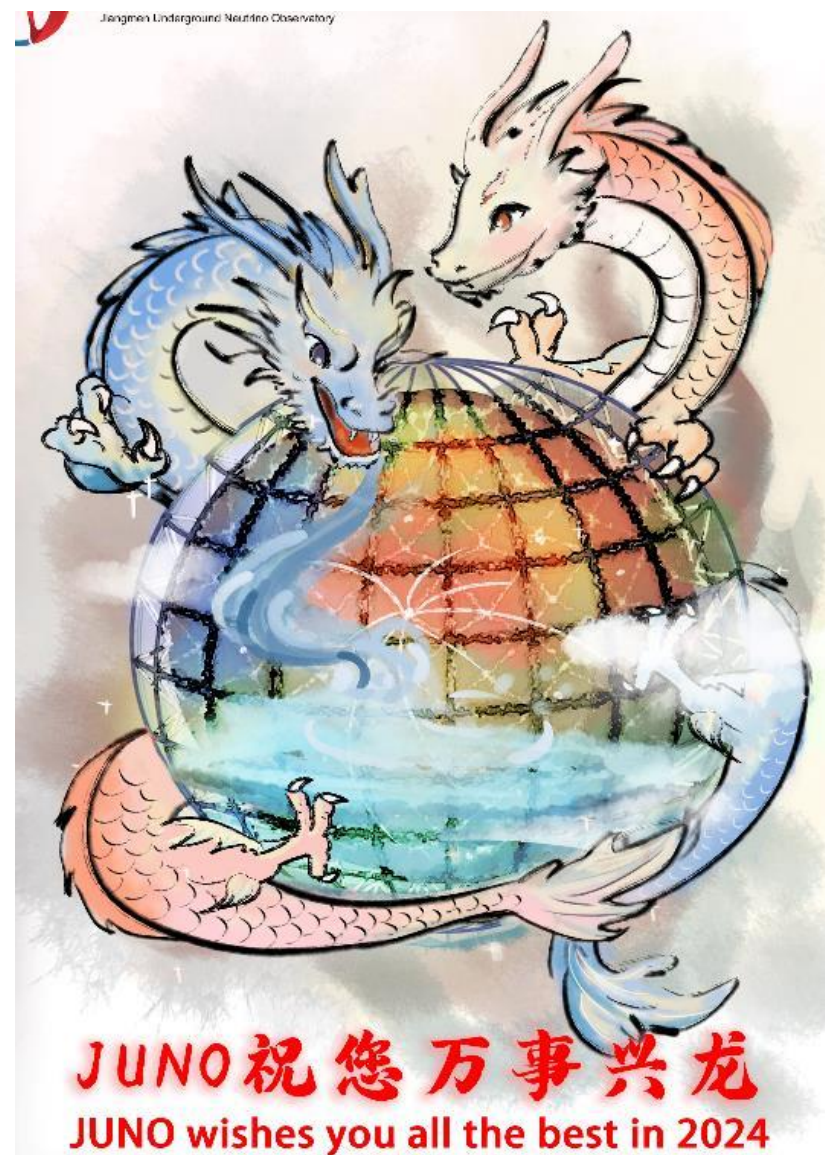


Muon Classification CM
Classification is precise



Summary

- ❖ Numerous ML models are (being) developed in JUNO (this talk shows only a sub-set)
- ❖ Even more exciting work is ongoing
- ❖ In general, comparable or superior performance can be achieved using ML, enhancing the NMO sensitivity
- ❖ Challenges ahead:
 - JUNO is a big detector, bringing challenges due to large quantities of data, sophisticated geometry and readout (training speed, GPU memory, ...)
 - MC-Data discrepancy is the major challenge damaging the reliability of ML models
 - Studies making use of calibration data have started





Thanks for your attention