



Overview of Machine Learning Applications in JUNO

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Shandong University

2024.8.7

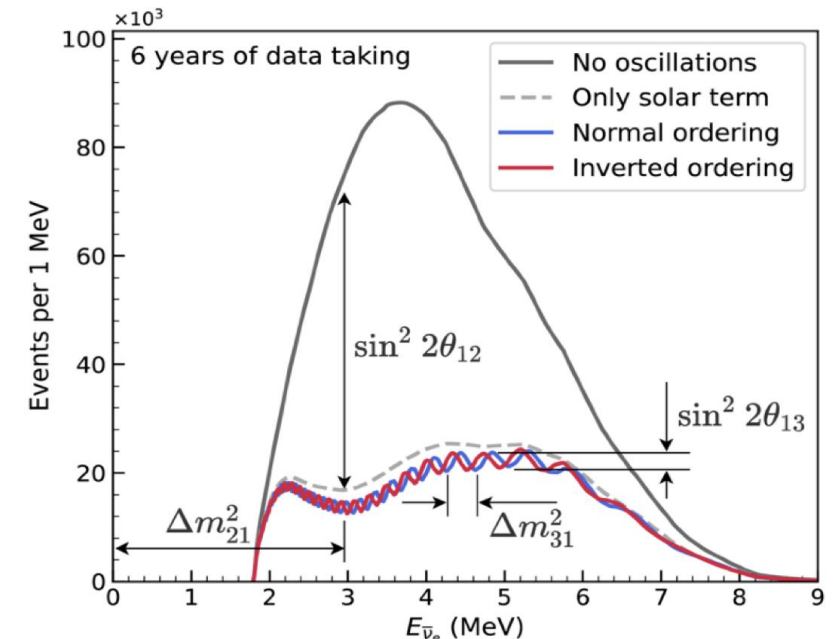
Changchun

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 (1% level) 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

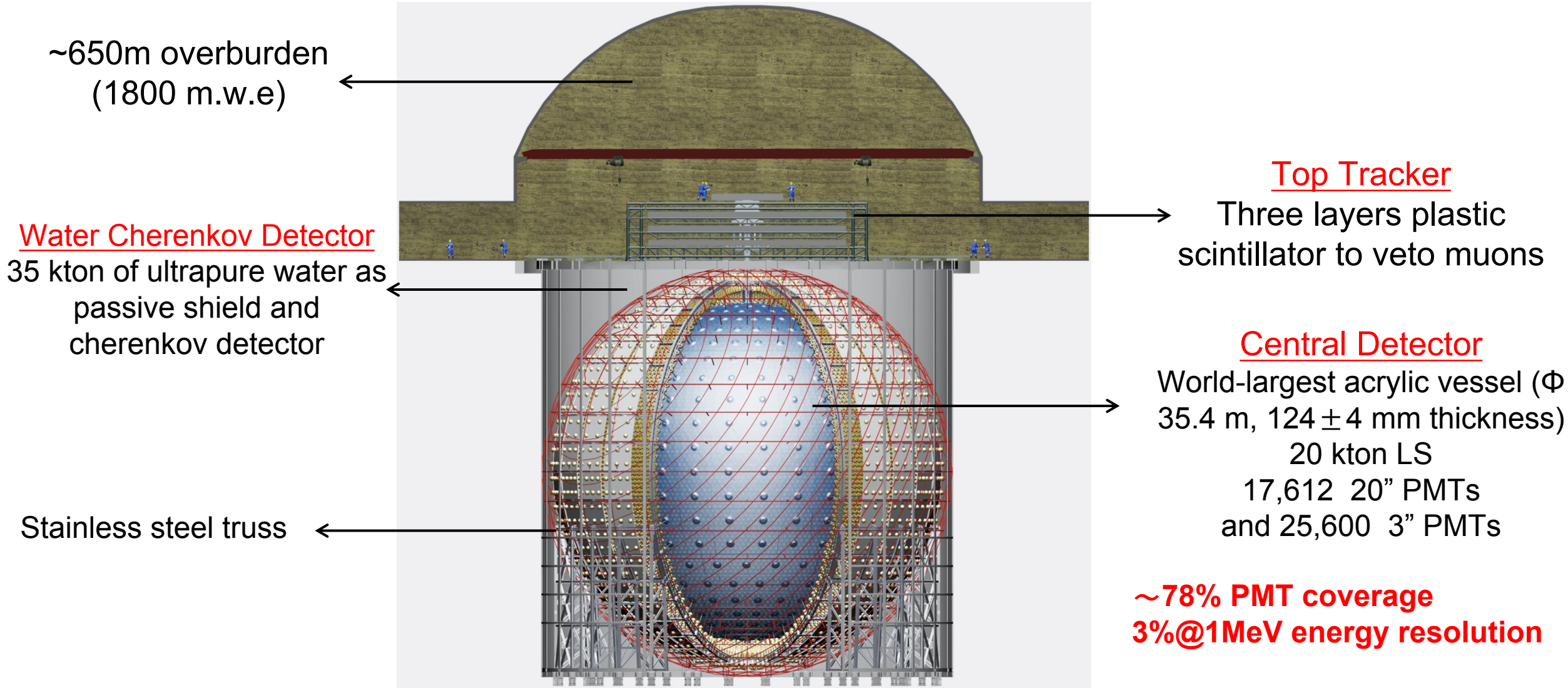
JUNO Site

Surface buildings / campus

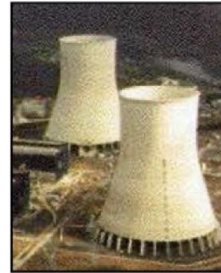
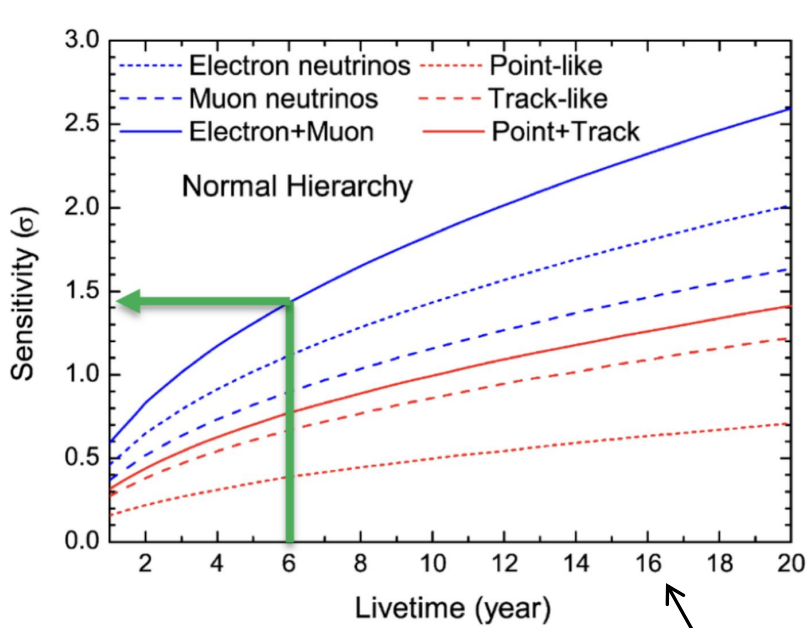
- Office / Dorm
- Surface Assembly Building
- LAB storage (5 kton)
- Water purification / Nitrogen
- Computing
- Power station
- Cable train



The JUNO Detector



JUNO Reconstruction Road-map (for NMO)

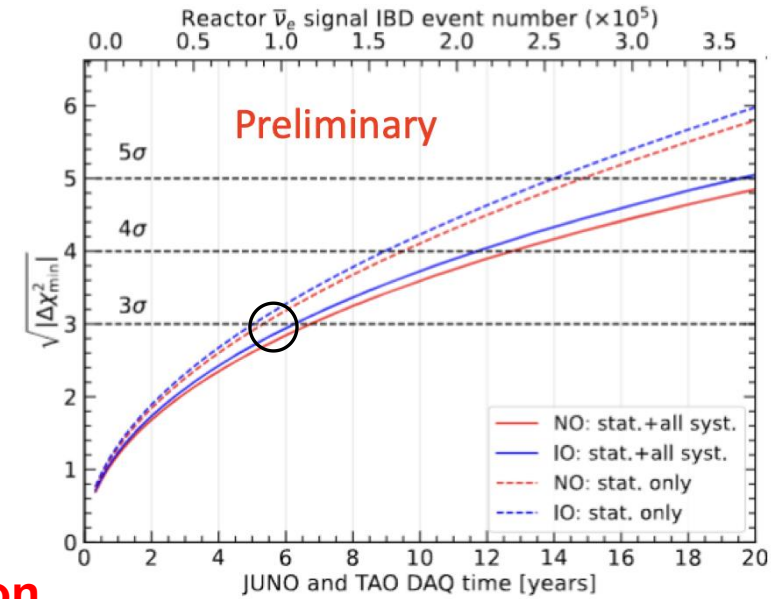


MeV
Reactor Neutrino

Vertex Rec.
Energy Rec.

Neutrino Mass Ordering

Waveform Reconstruction



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**

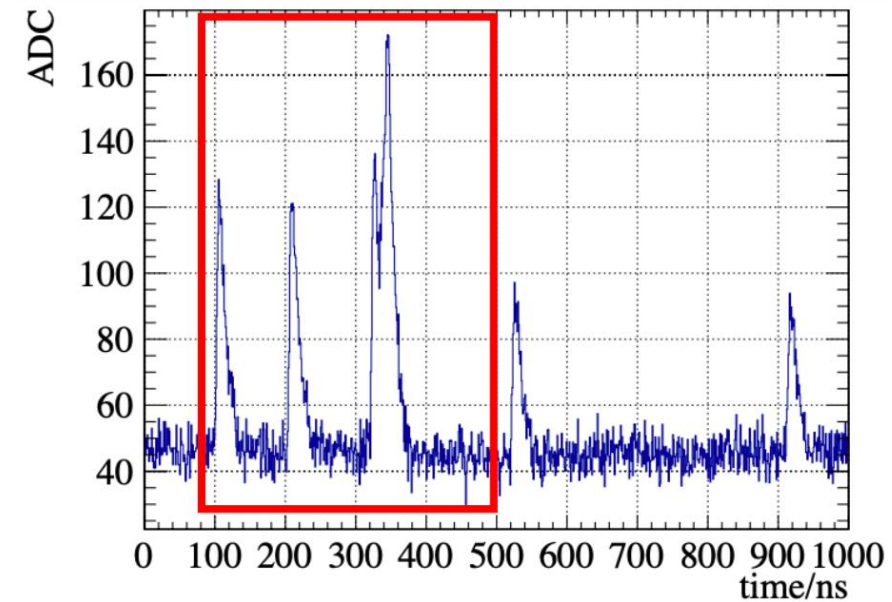
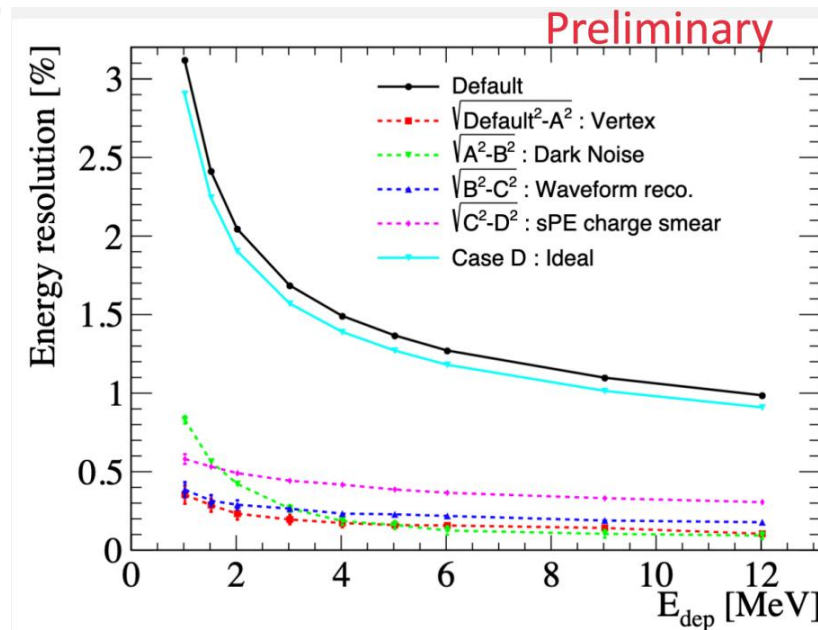
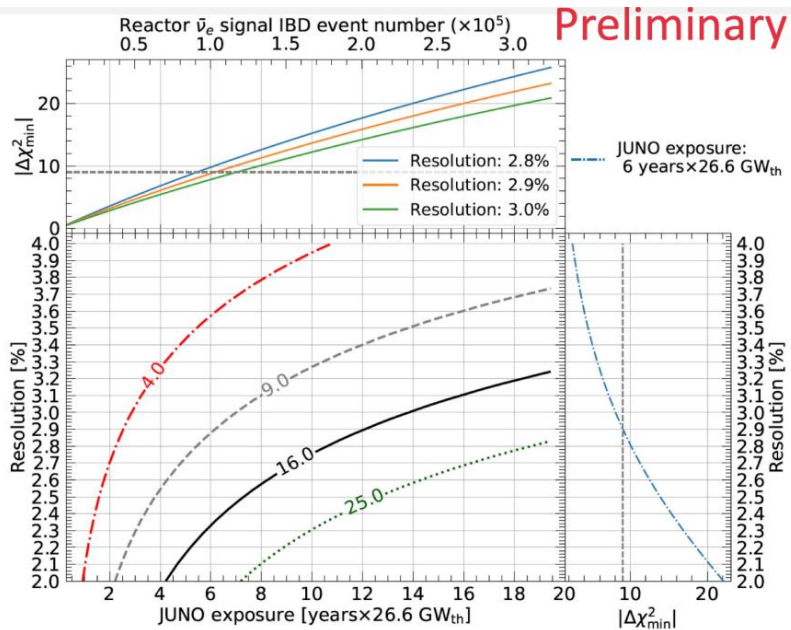
- Atmospheric neutrino directionality, PID and energy reconstruction
- Muon track reconstruction

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?

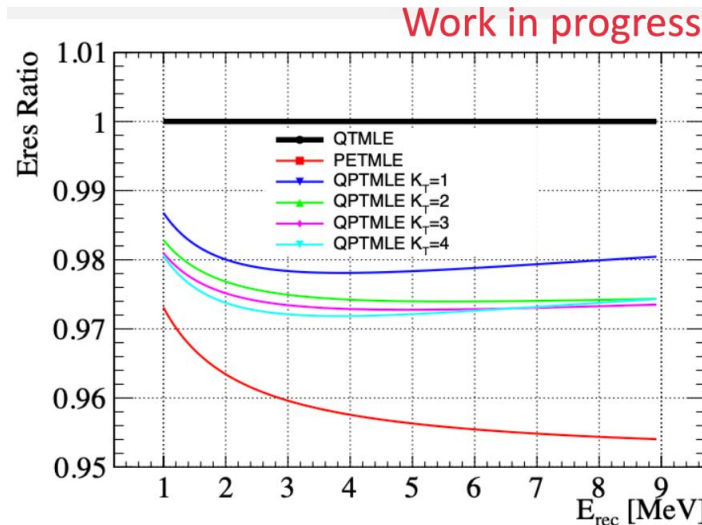
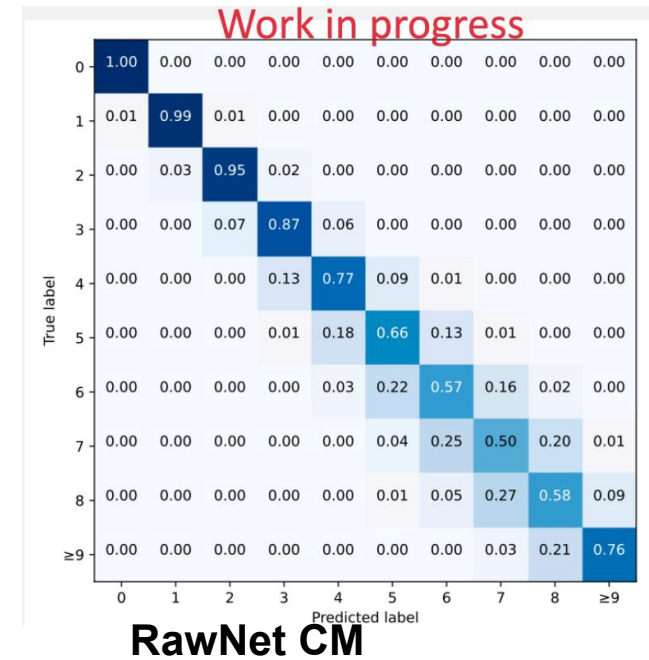
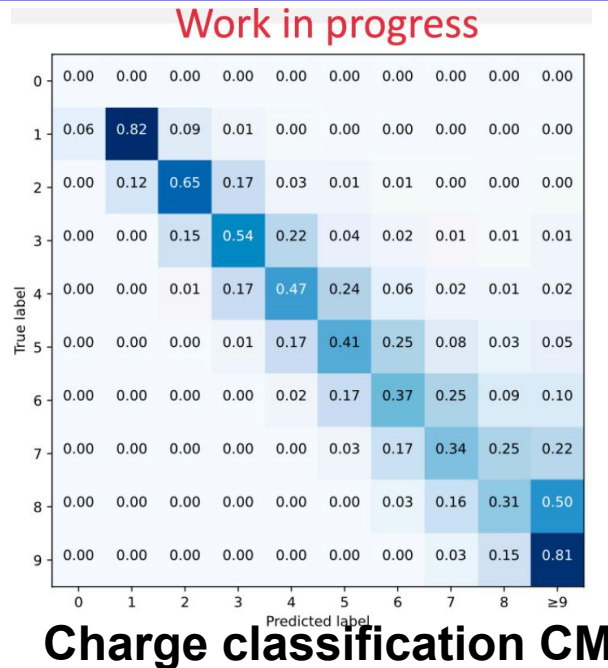
- Perform 1-D convolution on the raw waveform
- Use a classification model to “count the photons”

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)					
			$\left\{ \begin{array}{l} \text{Conv}(3,1,256) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{Conv}(3,1,256) \\ \text{BN} \\ \text{LeakyReLU} \\ \text{MaxPool}(3) \end{array} \right\} \times 2$	(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

Calibration-based Waveform Reconstruction

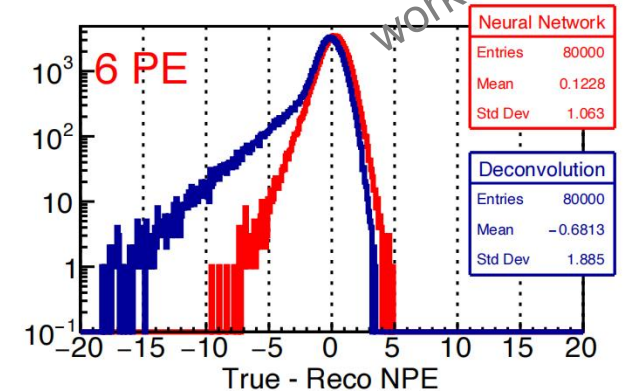
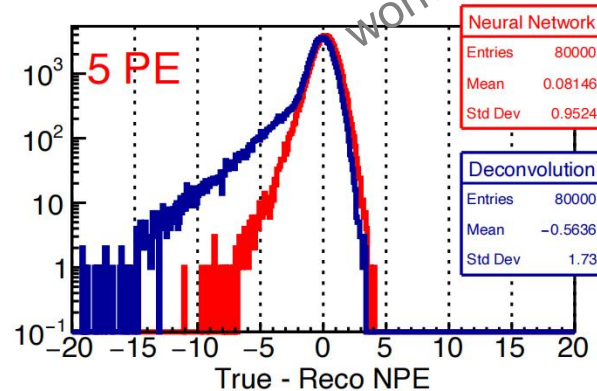
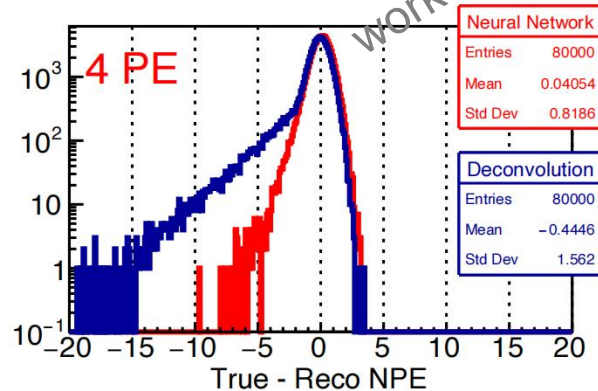
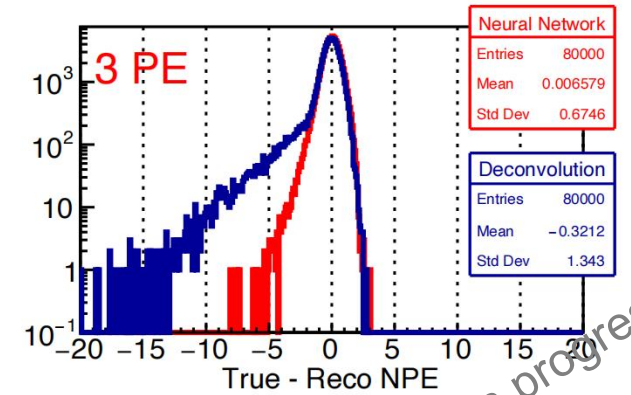
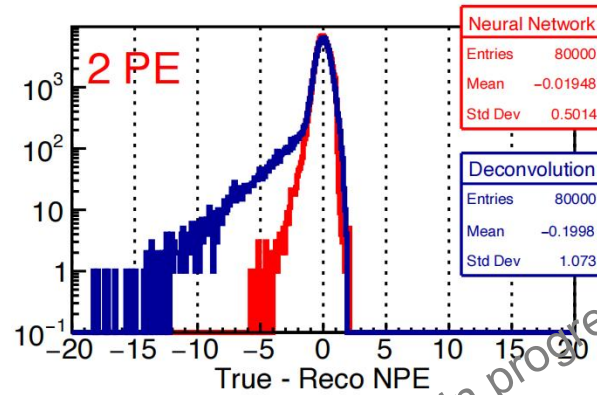
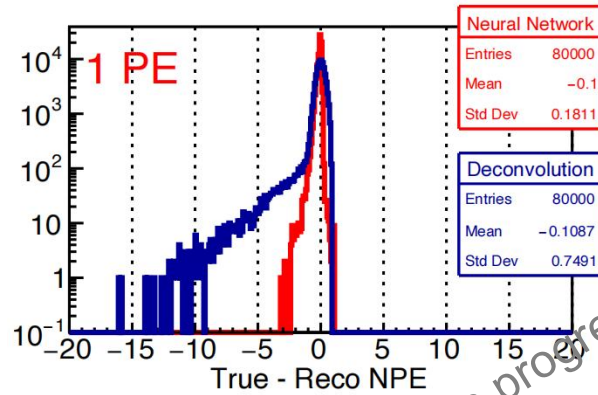
- ❖ Assemble “fake” waveform using calibration data, then train ML model (MLP) to learn from calibration data, and reconstruct number of PEs
 - Immune from the MC-data discrepancy problem
 - Deconvolution-based waveform reconstruction algorithm is improved

- Input:
“Fake” waveform

- Model:
32*64 MLP network

- Output:
Number of PEs

Ref. Junting's poster
@Neutrino2024

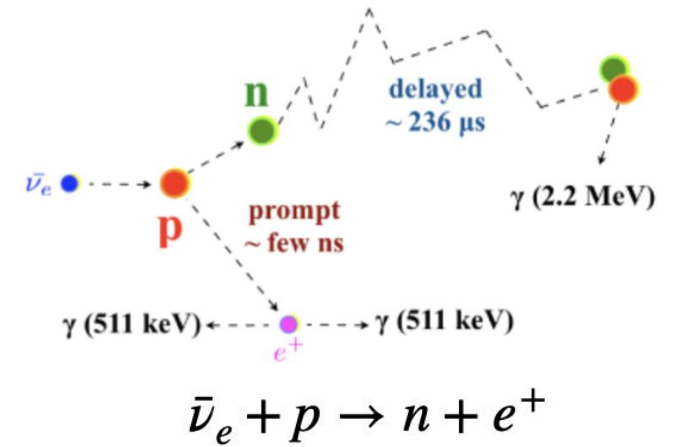


Particle reconstruction in MeV region

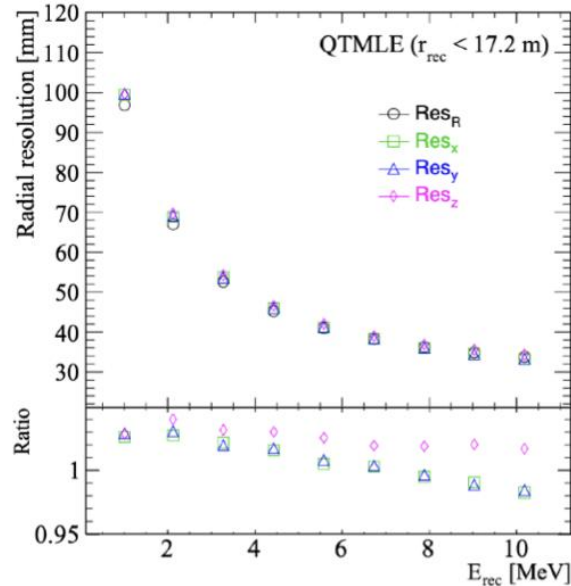
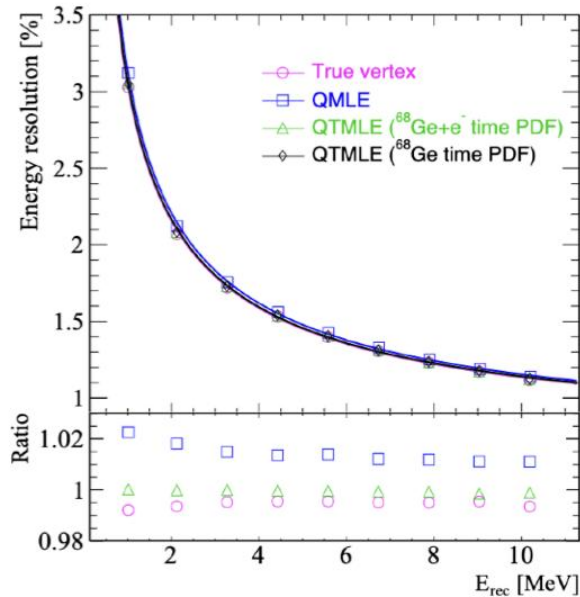
Reactor ν vertex and energy

Reactor Neutrino Reconstruction: Principle

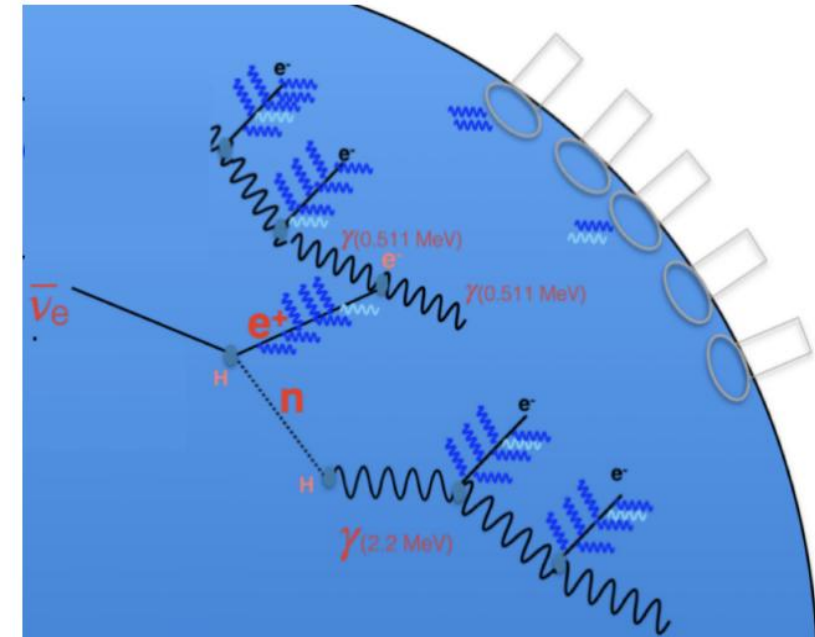
- ❖ Reactor neutrinos ($\bar{\nu}_e$) are detected via the inverse beta decay reaction in the CD
 - The e^+ generates a prompt signal in the CD
 - The neutron generates a delayed signal in the CD, with a 2.2 MeV gamma from the neutron capture process
 - Seek the coincidence between the detection of a 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



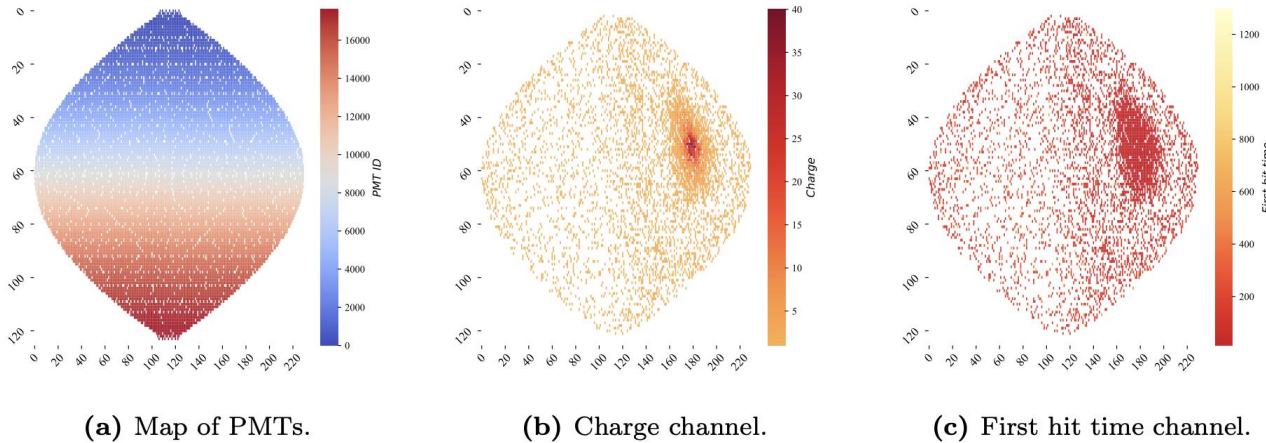
Can this be further improved using ML?



IBD Reconstruction: Planar CNN

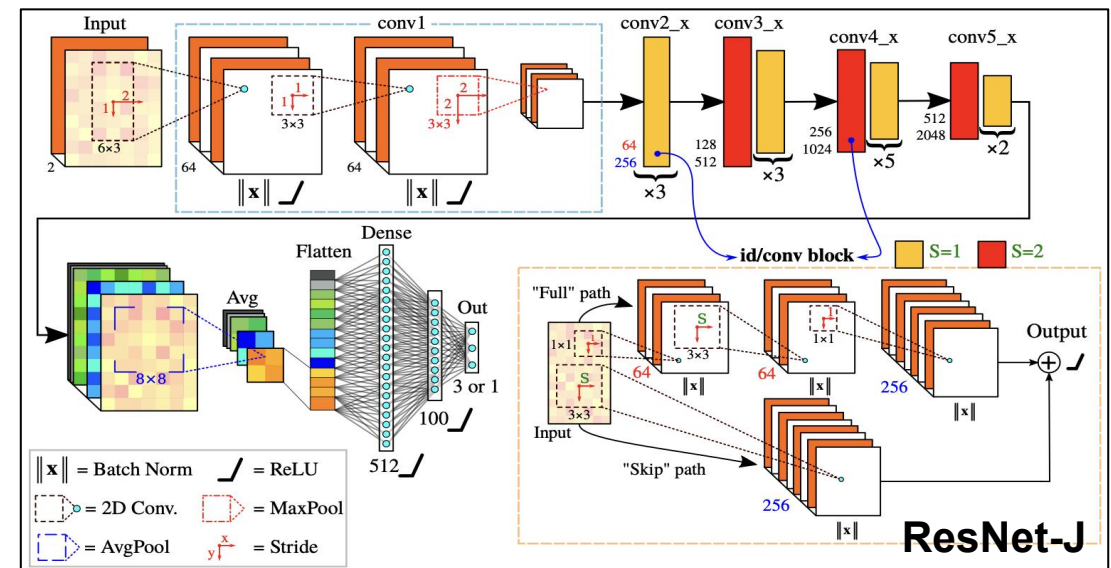
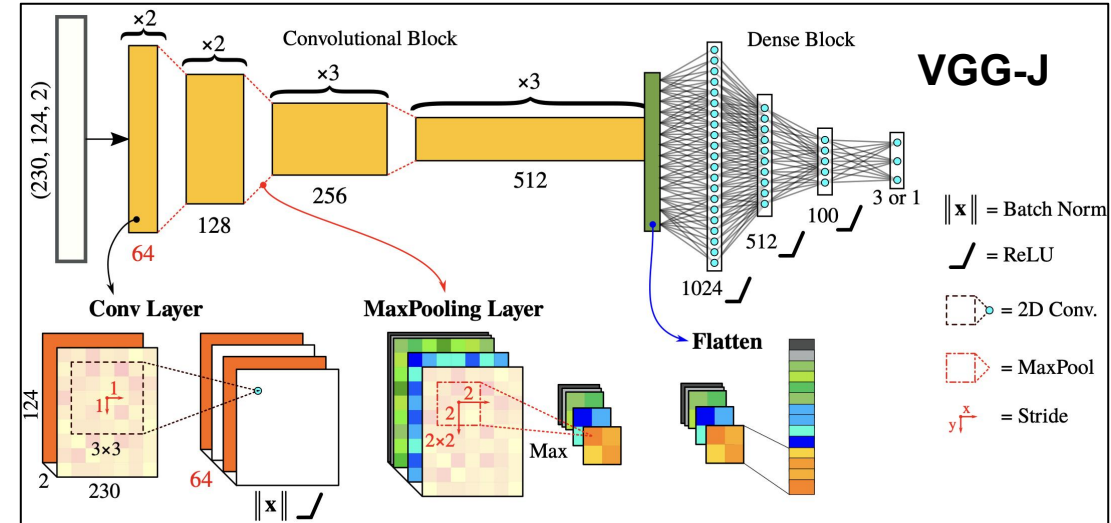
❖ Treating the JUNO detector as a camera and using the **image recognition** technique

- 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

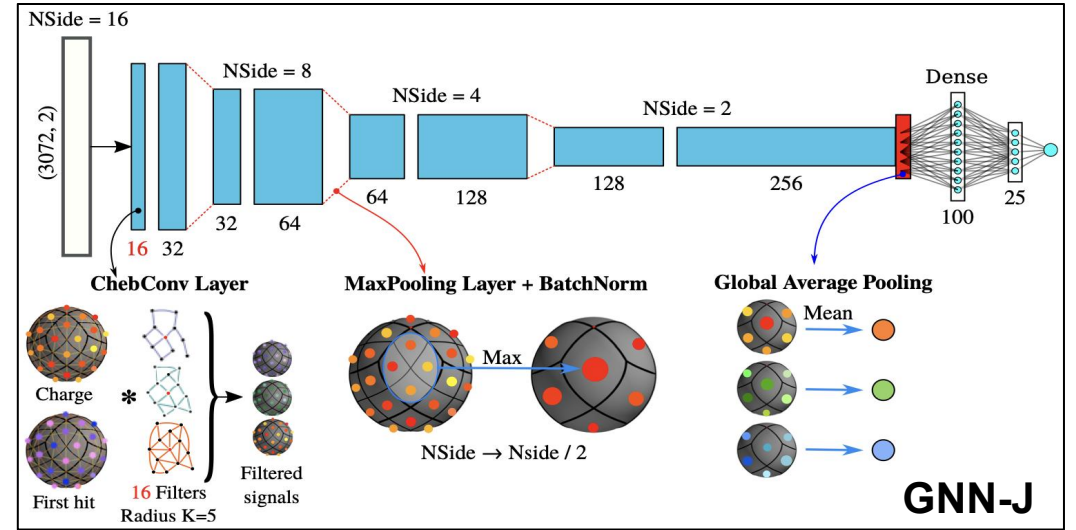
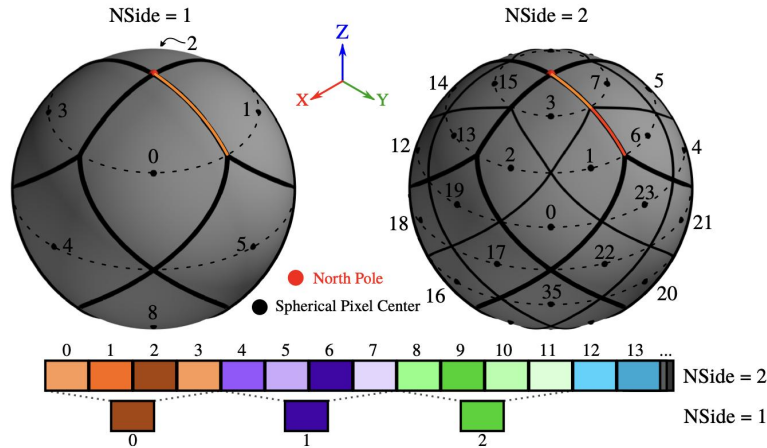
HEALPix Sampling Scheme to pixelise the detector

Then build Graph with adjacency matrix

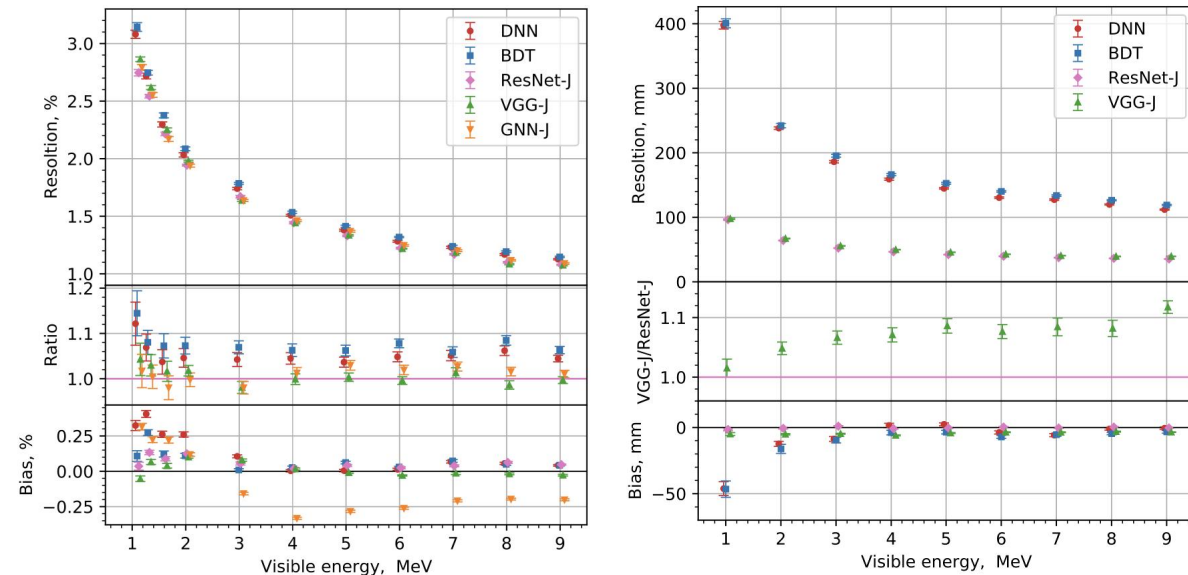
$$W_{ij} = \exp\left(-\frac{\|v_i - v_j\|_2^2}{2d^2}\right)$$

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

- ❖ Both methods gives similar resolution as classical methods



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



Particle reconstruction in GeV region

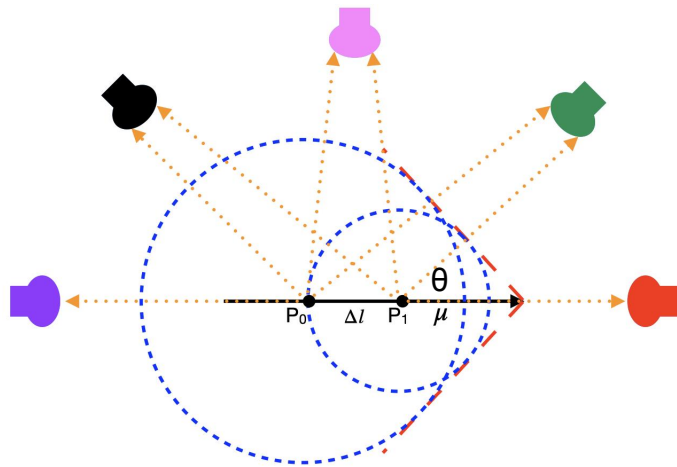
Atm. ν directionality, PID, energy and muon track

Methodology

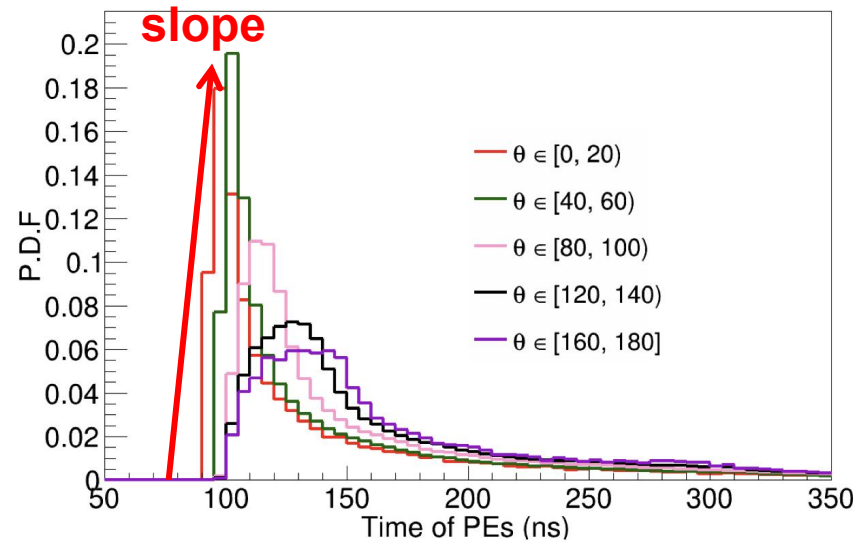
- ❖ Light received by a PMT is the superposition of light from many points on tracks in the detector
- ❖ The number of photo-electrons (PEs) seen by a PMT as a function of time is determined by the event topology
- ❖ Features related to event topology can be extracted from deconvoluted PMT waveform to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

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

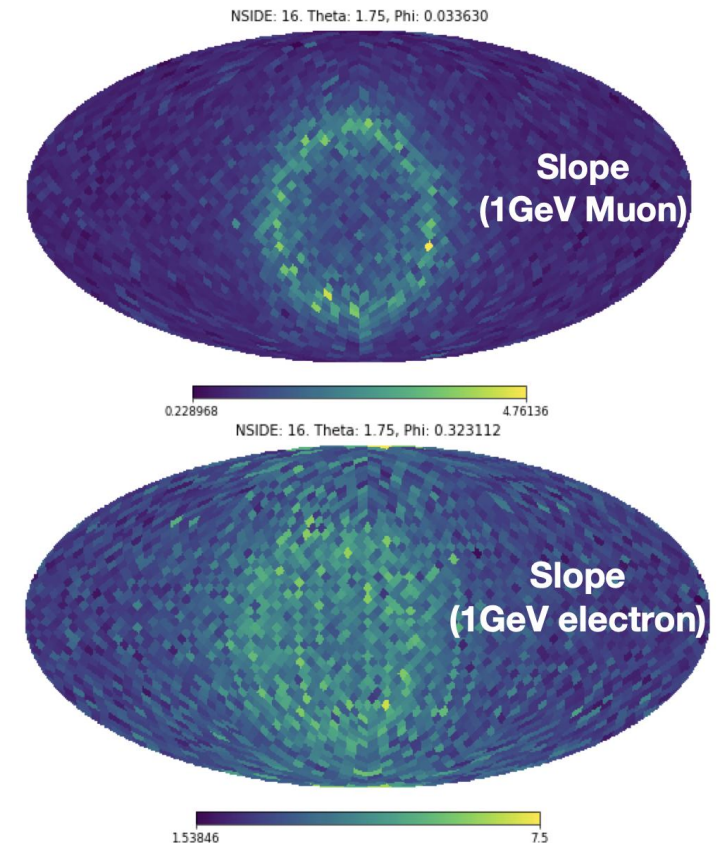
Directionality
Energy
PID



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

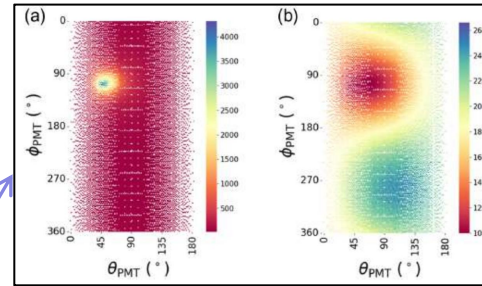
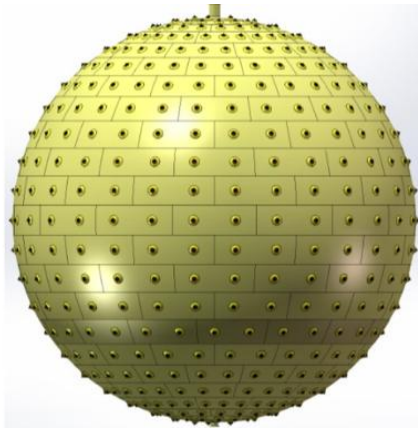


Ref. Duyang's talk @TIPP2023

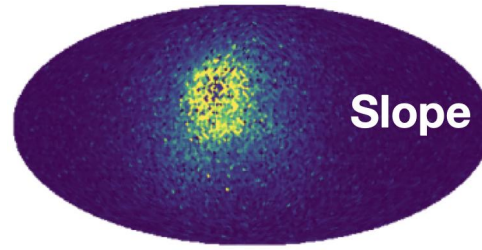


Methodology

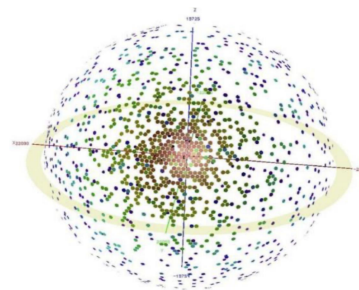
❖ Event reconstruction with **D**eep-learning and **W**aveform **I**nformation (**EDWIN**)



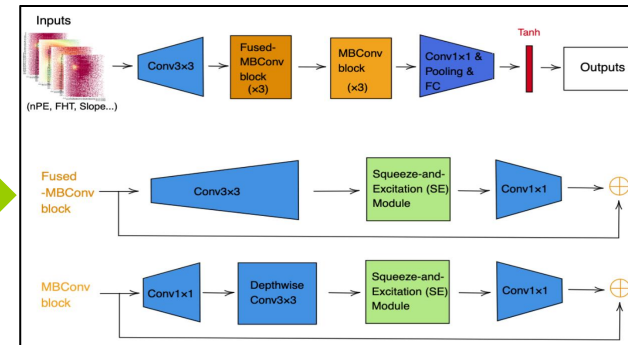
Planer Projection



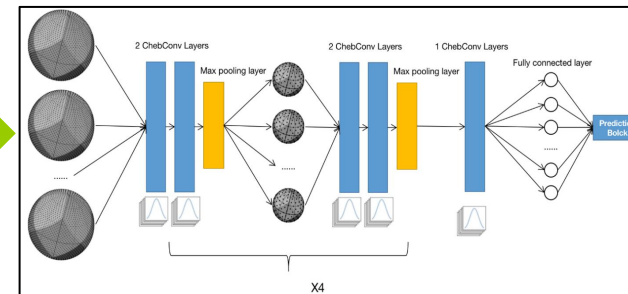
Spherical Projection



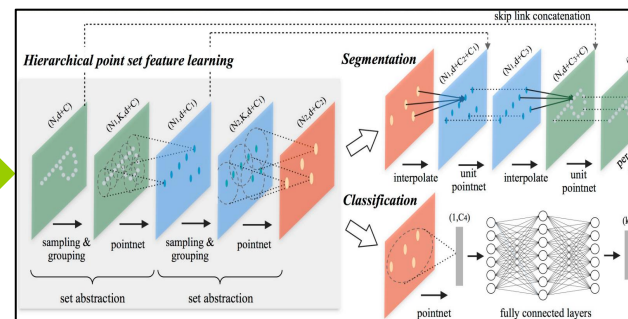
Point Clouds



EfficientNetV2



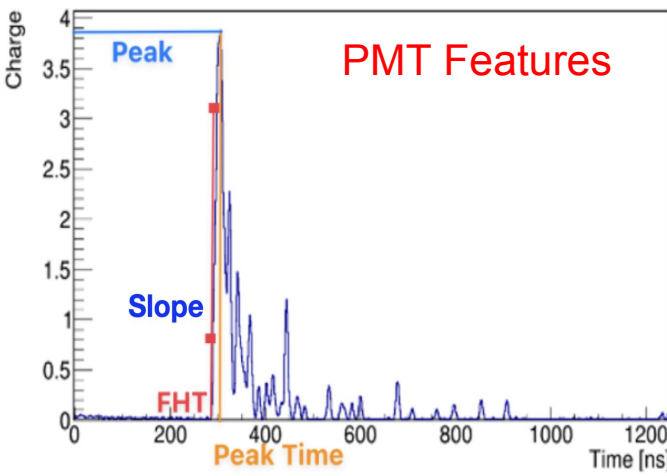
DeepSphere



PointNet++

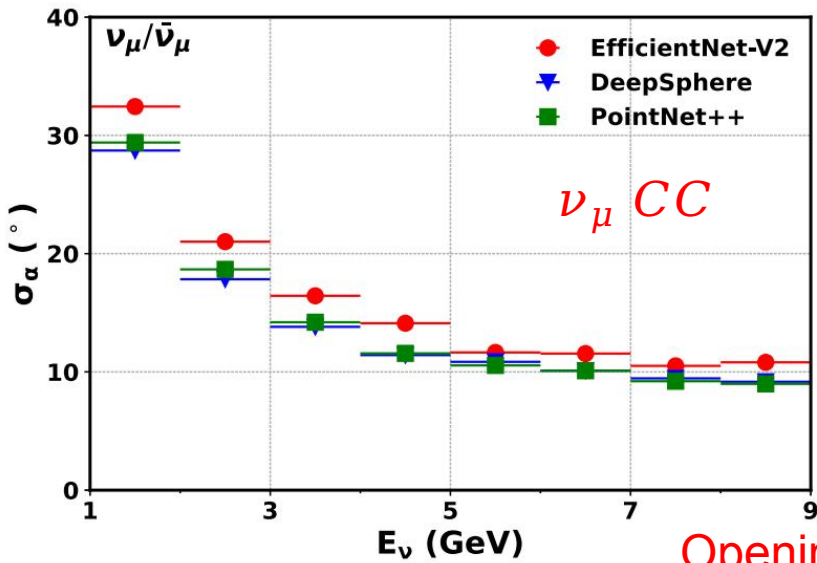
Direction
Energy
Flavor
Vertex
Track
Others...

Output

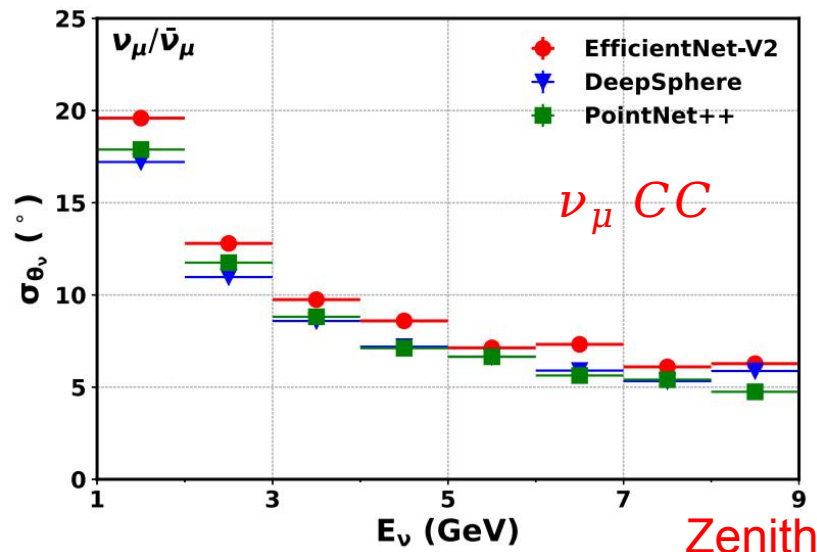
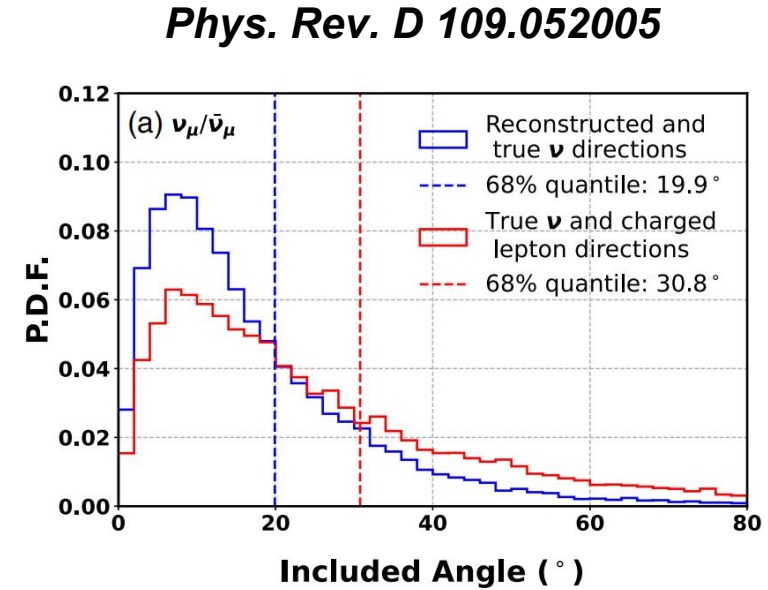
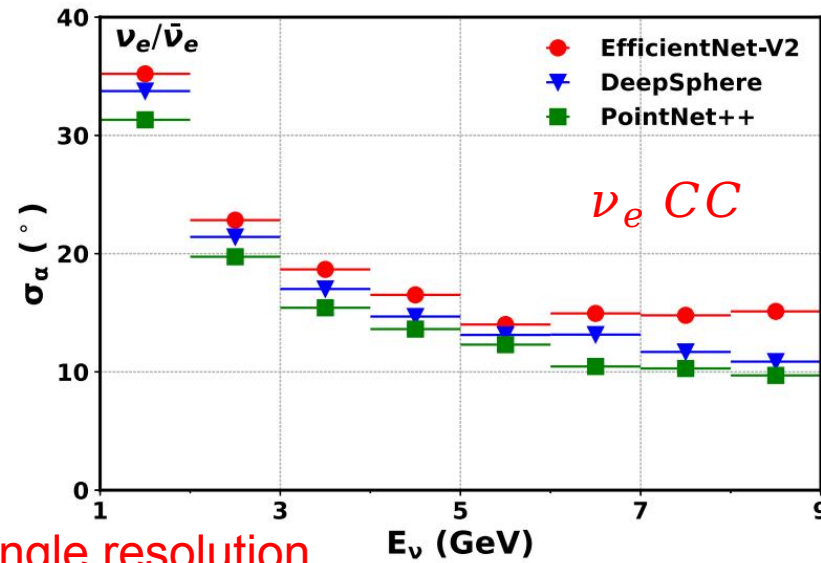


Deconvoluted PMT Waveform

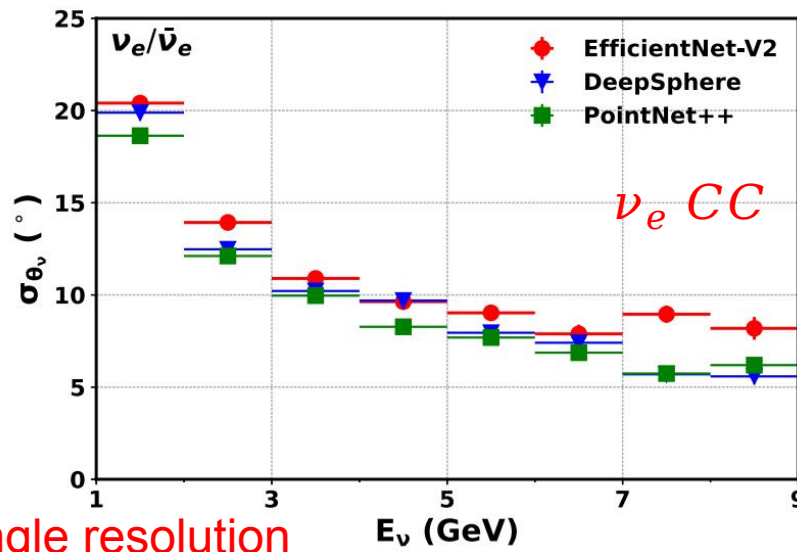
Atmospheric Neutrino Directionality Reconstruction



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

3-label classification:

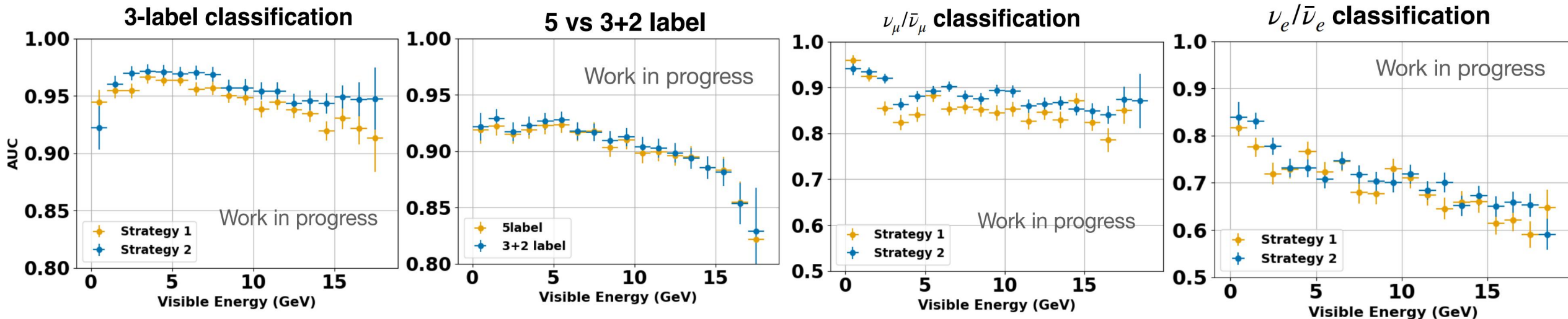
- Discriminate ν_e *CC*, ν_μ *CC* and *NC*

2-label classification:

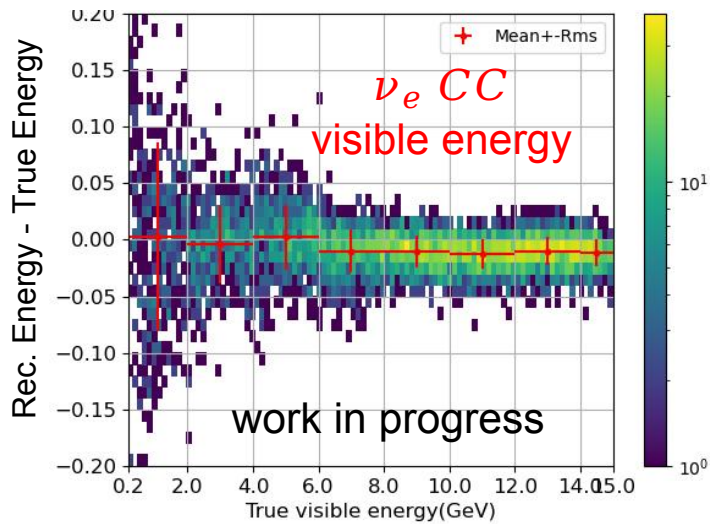
- Discriminate $\bar{\nu}/\nu$

3+2 label classification:

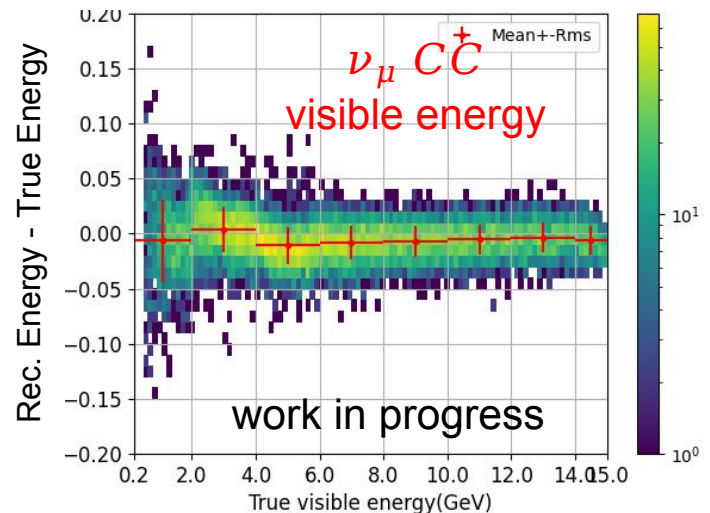
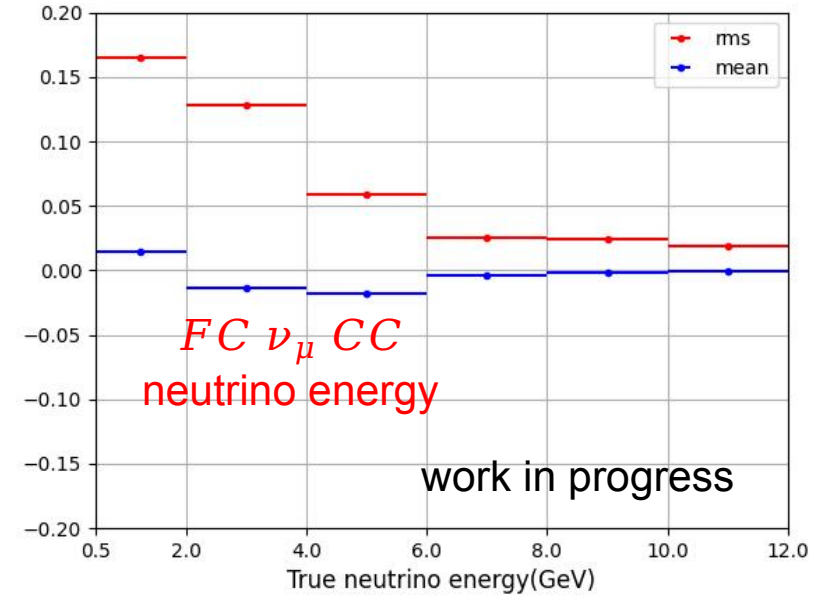
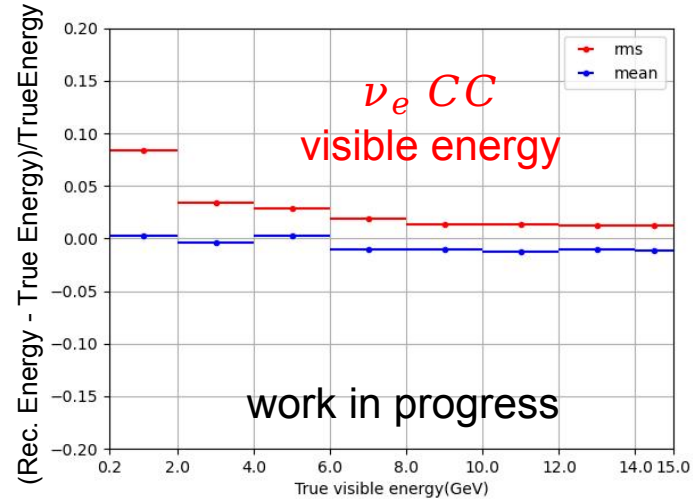
- Combine the 3-label and 2-label models to achieve 5-label classification (roughly consistent)



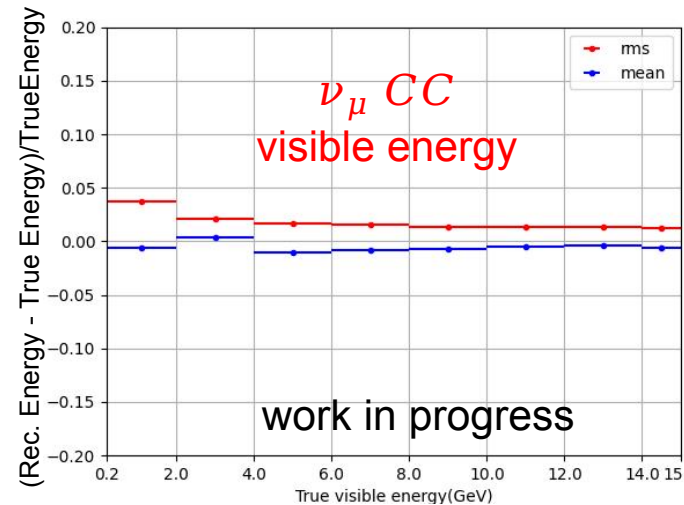
Atmospheric Neutrino Energy Reconstruction



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



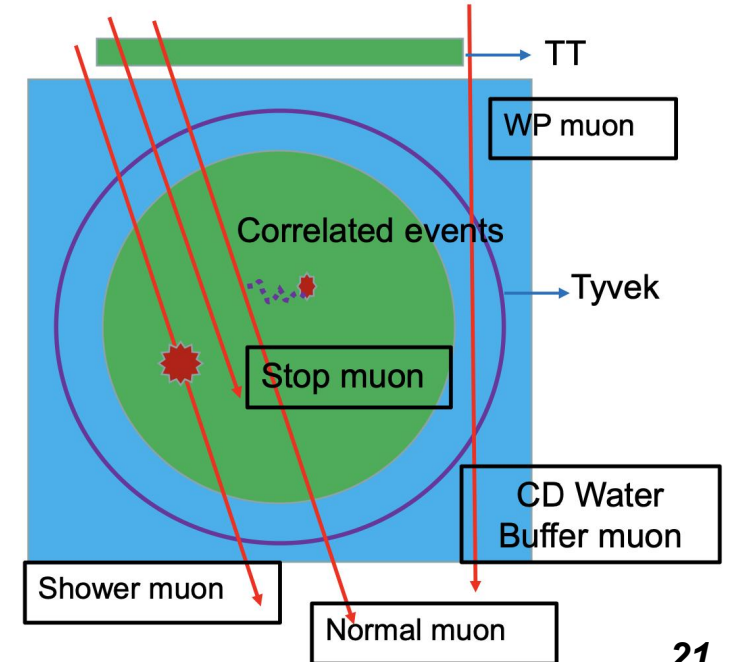
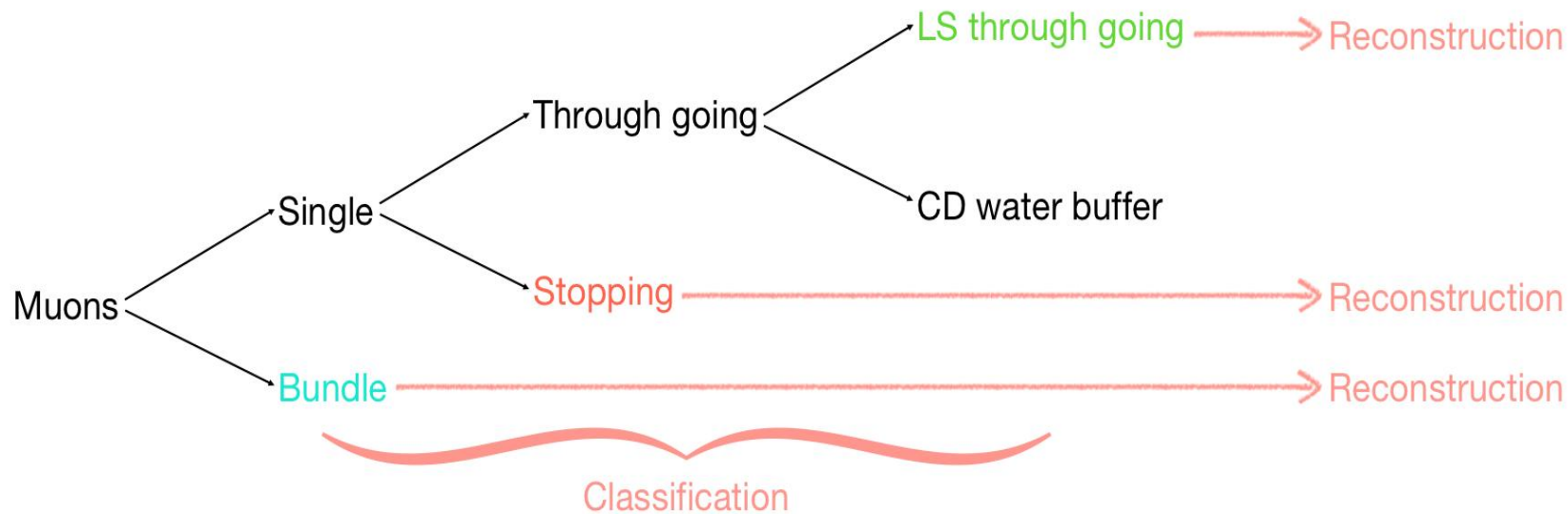
1% - 5% visible energy resolution for ν_μ CC from 0.2-15GeV



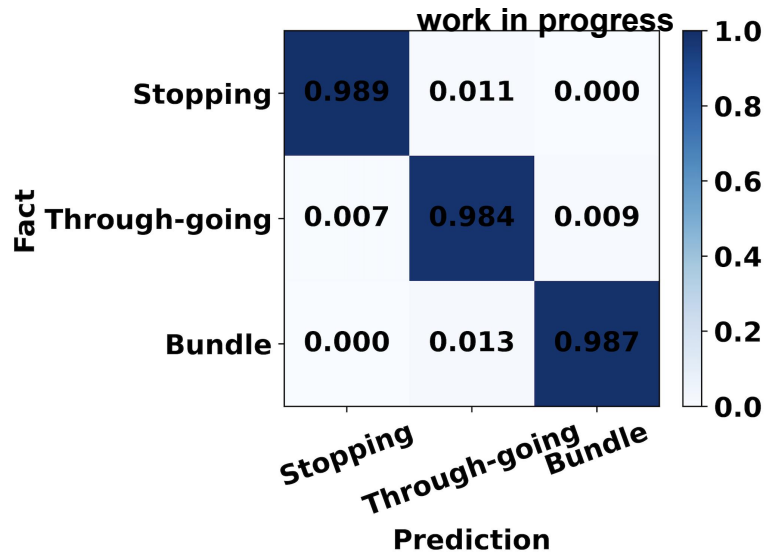
- Results based on the Spherical GNN
- Visible energy resolution is promising
- Neutrino energy resolution for fully contained neutrinos is sub-optimal, but still provides better sensitivity with preliminary NMO analysis

Muon Track Reconstruction: Methodology

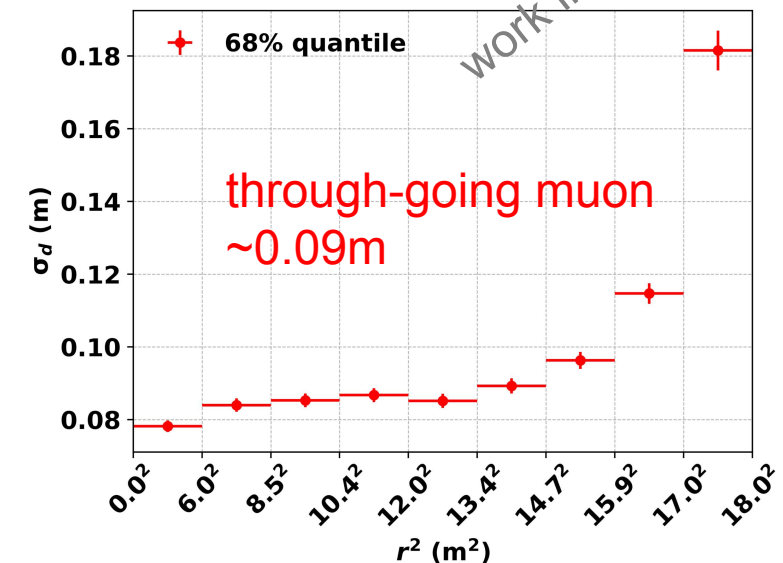
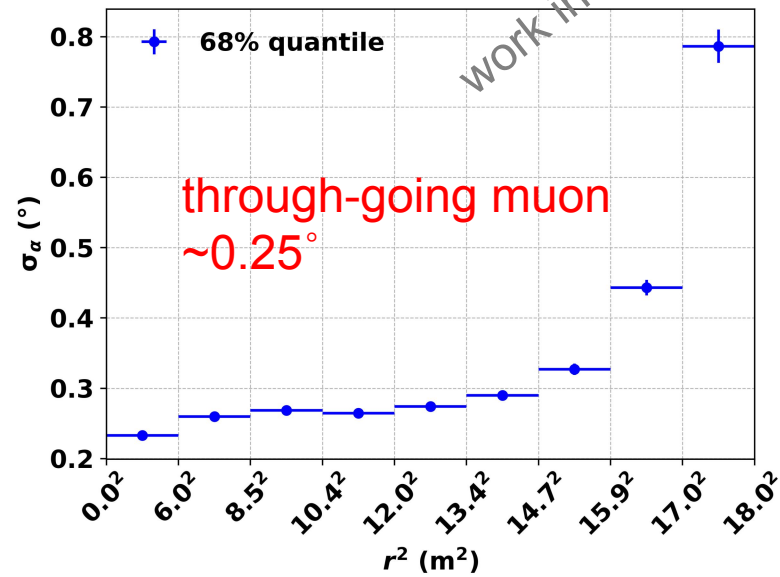
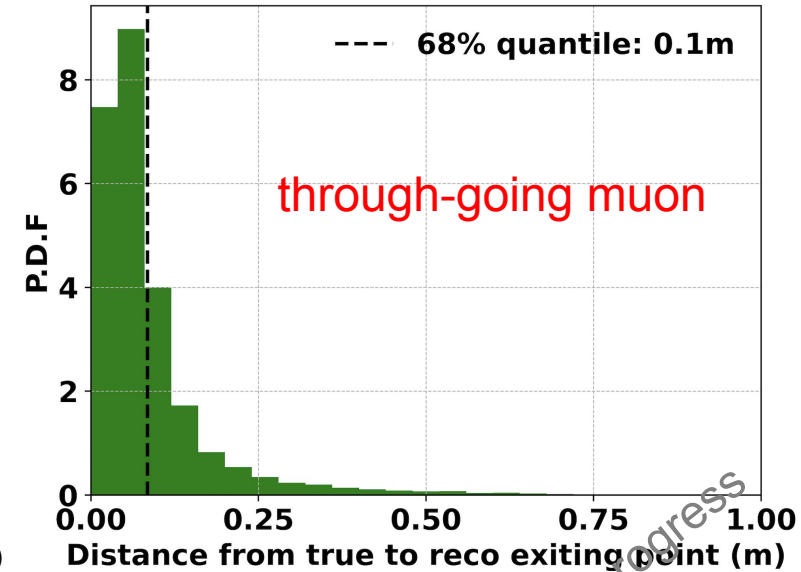
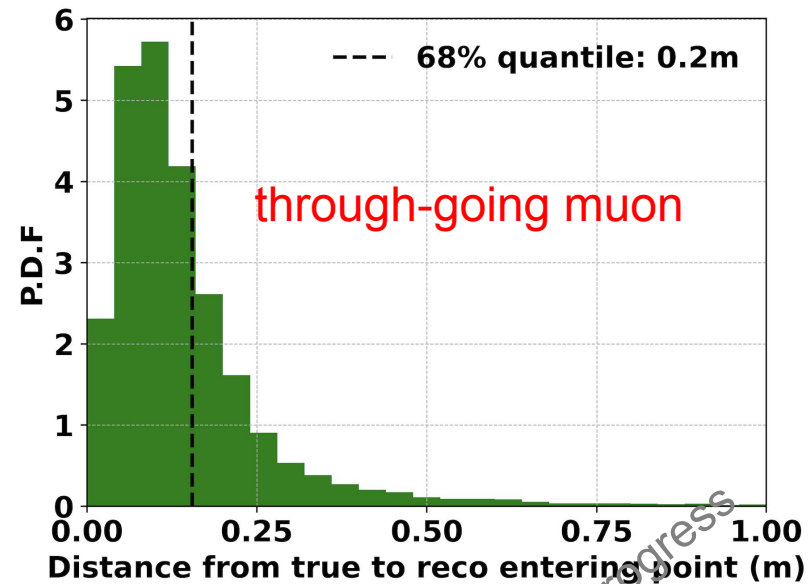
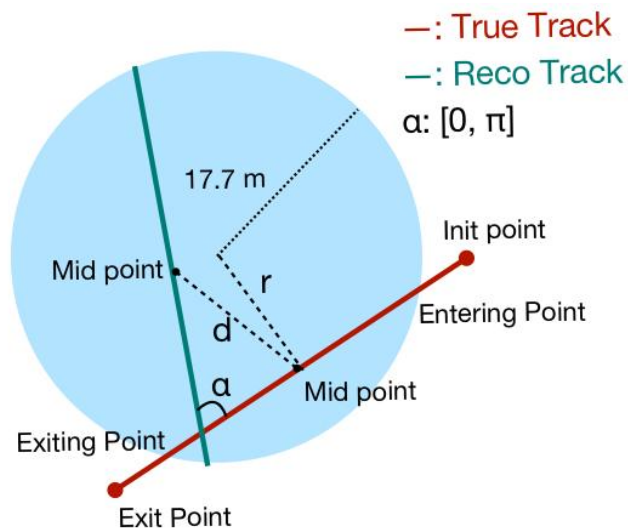
- ❖ Isotopes produced by cosmic muons are the main background of IBD signals
- ❖ Precise reconstruction of muon tracks is critical to veto major backgrounds
- ❖ Current ML-based reconstruction strategy for muons:
 - Classify through-going, stop and bundle muons
 - Reconstruct the entry point and exit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



Muon Track Reconstruction: Performance

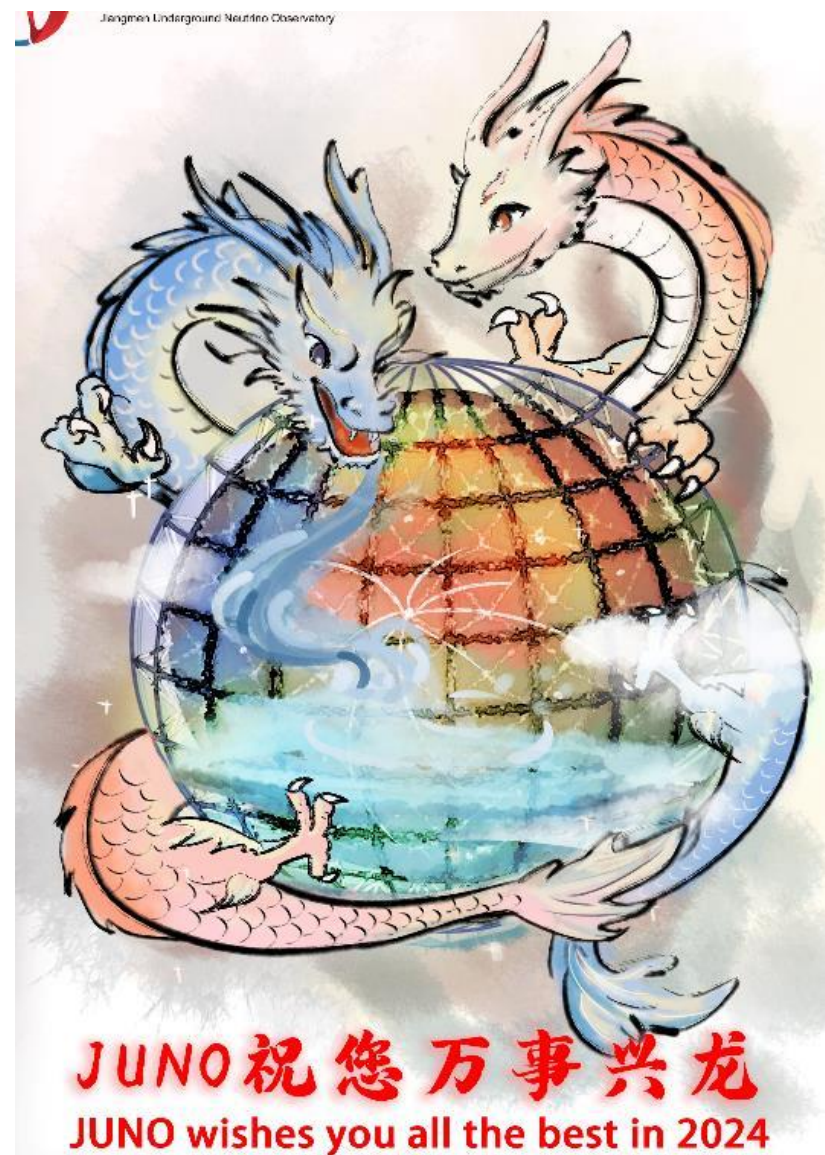


Muon Classification CM
Classification is precise



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