A Multi-purposed Reconstruction Method Based on Machine Learning for Atmospheric Neutrino at JUNO

Hongyue Duyang[1], Teng Li[1], Xiaohan Tan[1], Zekun Yang[1], Fanrui Zeng[1]

Jiaxi Liu[2], Zhen Liu[2]

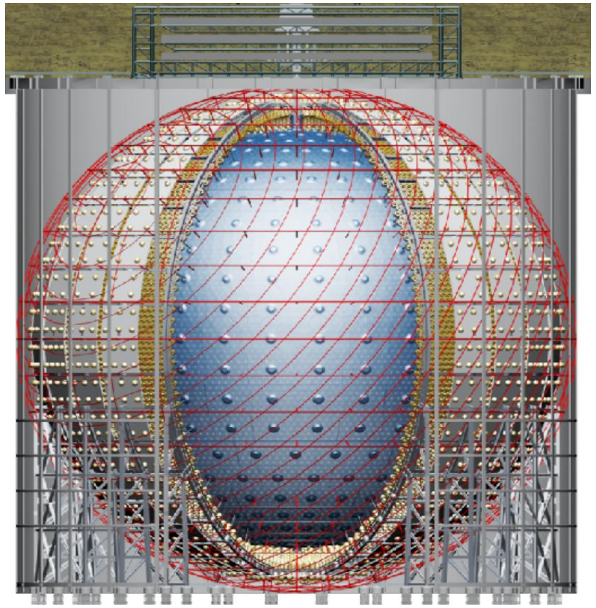
[1]Shandong University

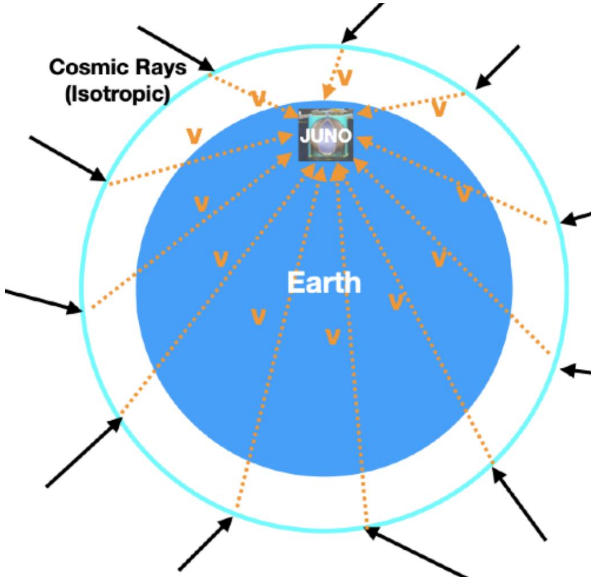
[2]Institute of High Energy Physics, CAS

2022.10 ACAT 2022

Motivation

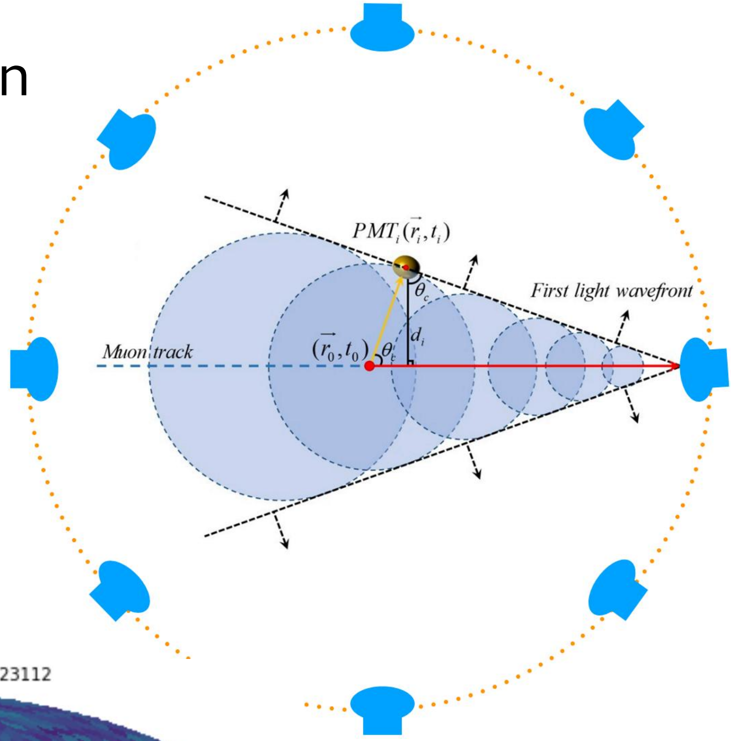
- JUNO Physics and Detector
  - The JUNO experiment is designed to measure the **neutrino mass order (NMO)** using a 20 kton liquid scintillator detector
  - The measurement of **atmospheric neutrino oscillation** has great potential to boost JUNO's NMO sensitivity
- Precise reconstruction algorithms are critical, and challenging due to complicated interactions
  - Particle incident angle (to calculate the oscillation baseline)
  - Neutrino flavor (PID)
  - Neutrino energy
- A noval, multi-purposed reconstruction method based on **machine learning** is introduced in this talk

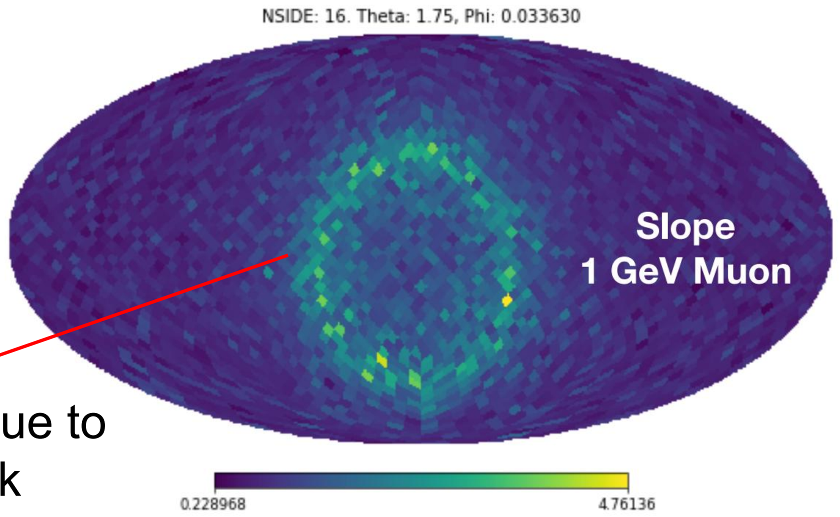




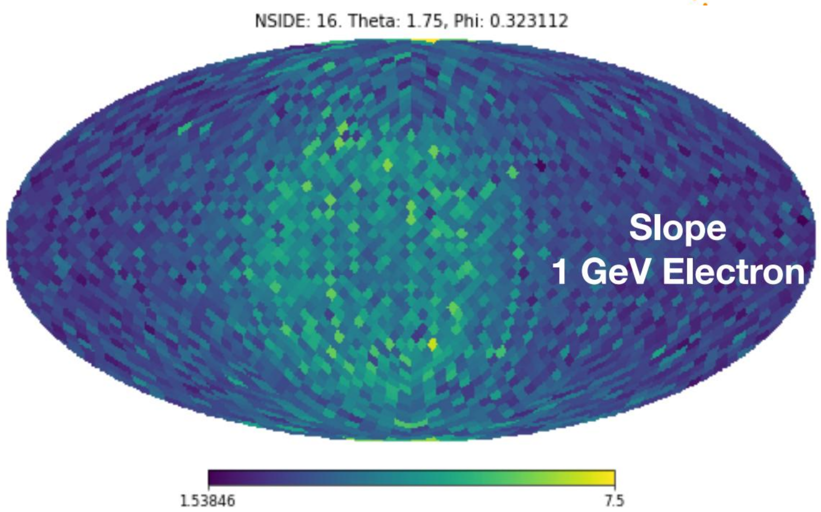
Methodology

- In the LS detector, the light received by a PMT is the superposition of the scintillation light from many points along the track.
- How the amount of light received by a PMT evolves as a function of time (waveform) depends upon
  - Its angle wrt to the track direction;
  - Distance from the track and its start/stop points;
  - Visible energy and dE/dx (particle ID).



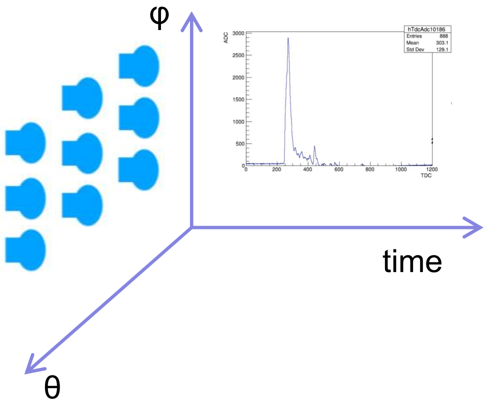


sharper ring due to straighter track

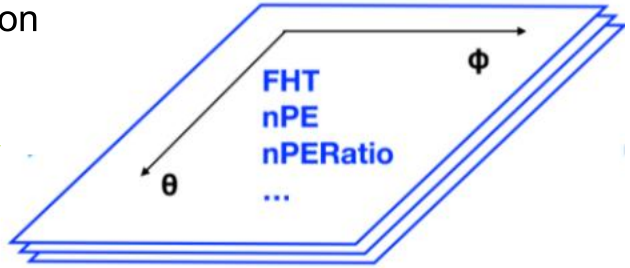


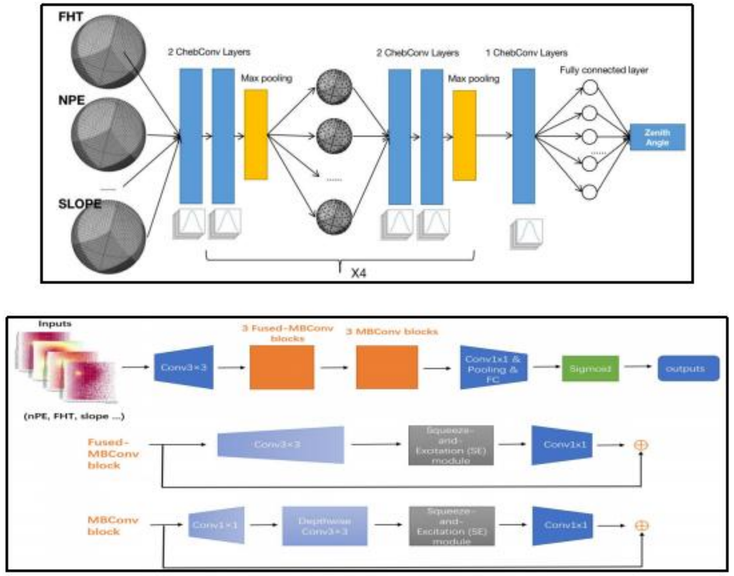
Methodology

- Due to the large number of PMTs (~18000 20'' and ~25000 3'') distributed on the sphere, directly feeding models with all waveforms is hard
- A few characteristic features that reflect event topology in the detector are extracted from the waveforms to reduce the data volume



manual/auto convolution



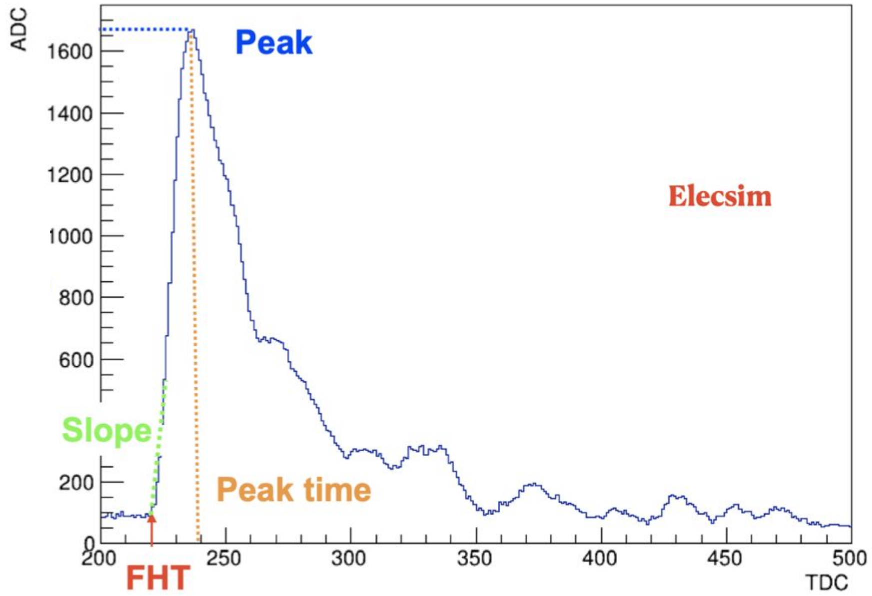


Three dimension input data

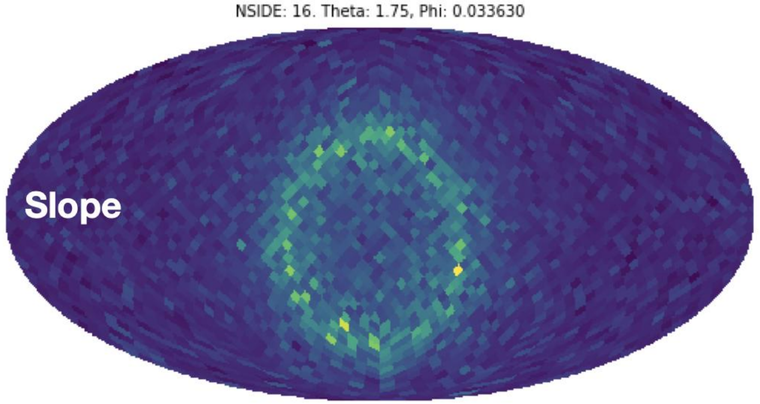
A few two dimension channels

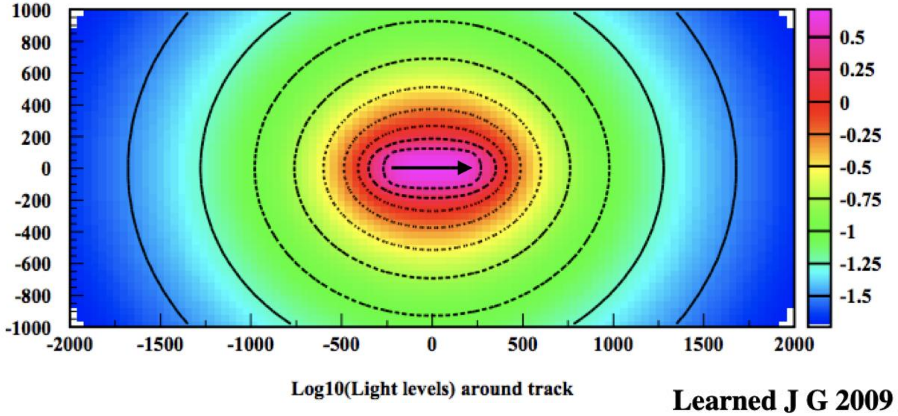
Feature Engineering

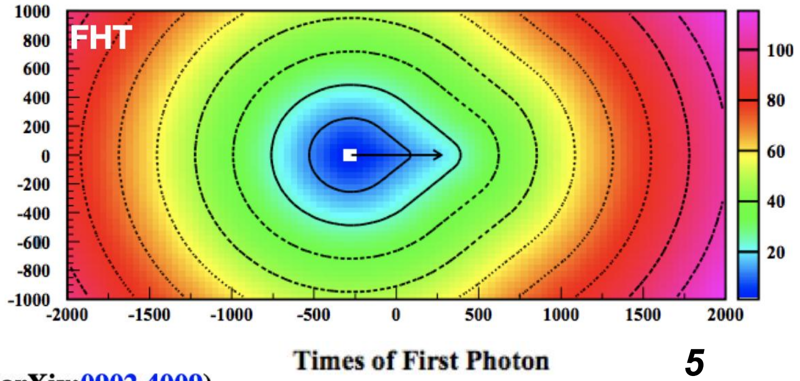
❖ Selected characteristic information (feature) from waveforms



- First hit time: distance between track and PMT, and angle information
- Slope: angle between track and PMT
- Peak time: track length
- Total nPE: Energy deposition topology
- ...







Learned J G 2009 (arXiv:0902.4009)

Spherical GNN Model: Deepsphere

- Graph construction: adjacency matrix defined as

$$W_{ij} = \begin{cases} \exp\left(-\frac{\|x_i - x_j\|_2^2}{\rho^2}\right) & \text{if pixels } i \text{ and } j \text{ are neighbors,} \\ 0 & \text{otherwise,} \end{cases}$$

$\mathbf{x}_i$ as the 3d coordinates, ρ as the averaged distance over all connected pixels

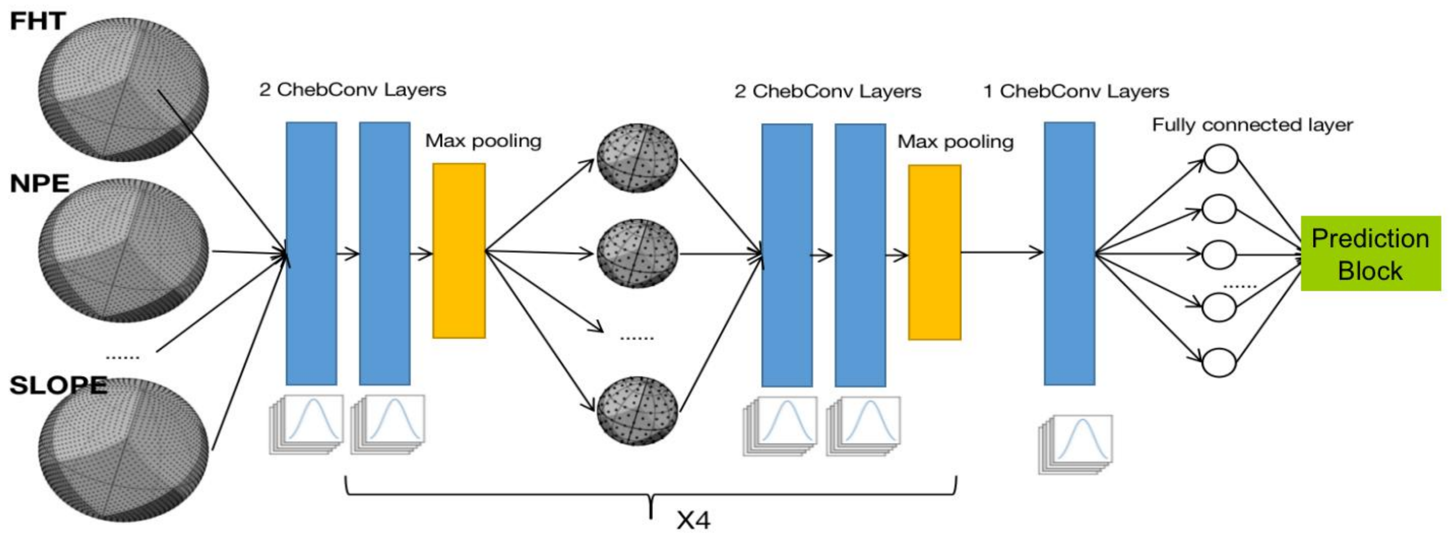
more details in backup

- Convolution: based on spherical harmonic transform

$$h(\boldsymbol{L})\boldsymbol{f} = \left(\sum_{i=0}^{P} \alpha_i \boldsymbol{L}^i\right)\boldsymbol{f},$$

α_i as the coefficient to be learnt; P as the polynomial order; L as the graph Laplacian; f as the graph signal

- Pooling: the data supported on the sub-pixels is summarized by **max()**, min() or avg()



Graphs are formed directly on the spherical detector

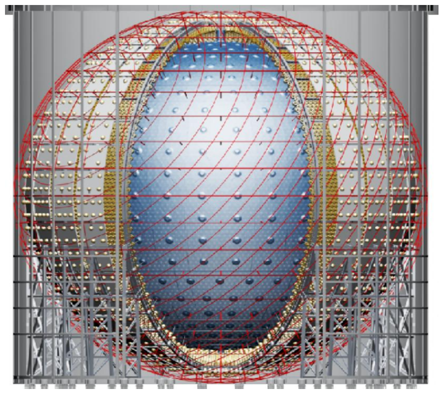
Rotation covariance is maintained to make the model easier to converge

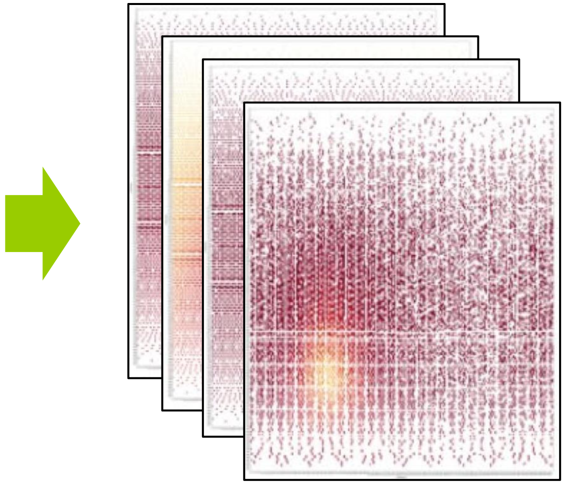
Flexible prediction block for:

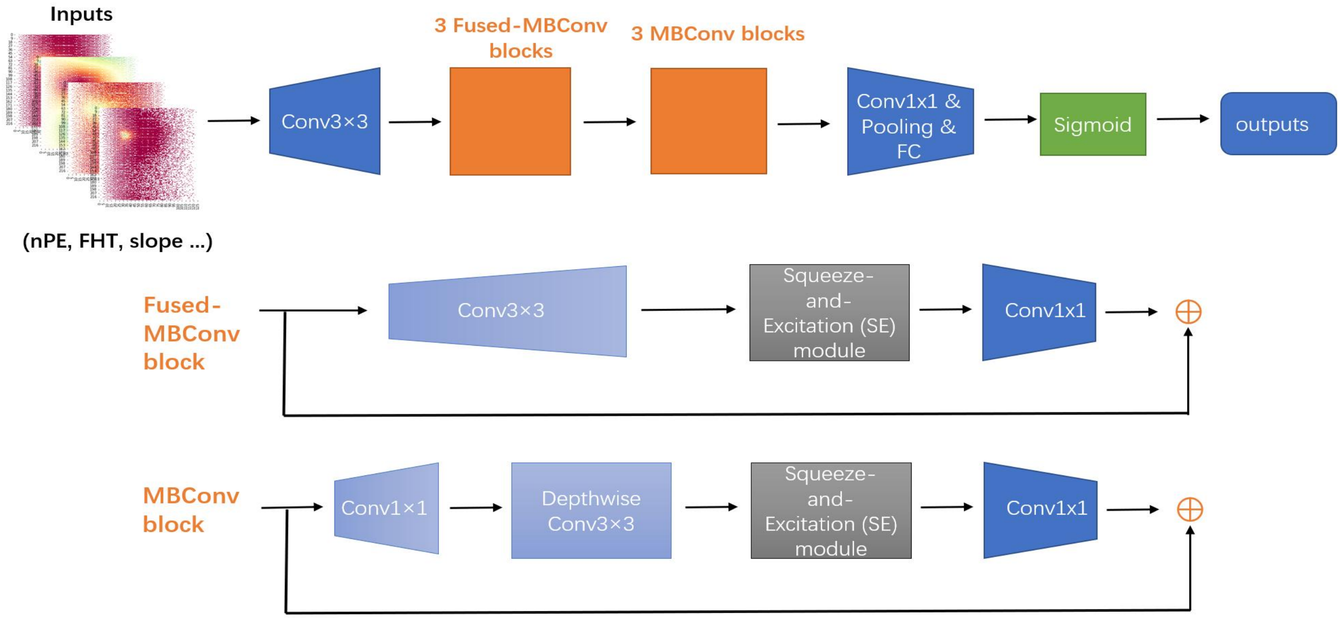
- **Angle**
- **PID**
- **Energy**

Planar CNN/Transformer Model

- PMTs are seen as pixels, with each feature projected from the sphere to the planar surface
- A few CNN/Transformer models are applied and cross-validated
  - EfficientNetV2-S: state-of-art performance among CNNs
  - CoAtNet: CNN + Transformer hybrid network



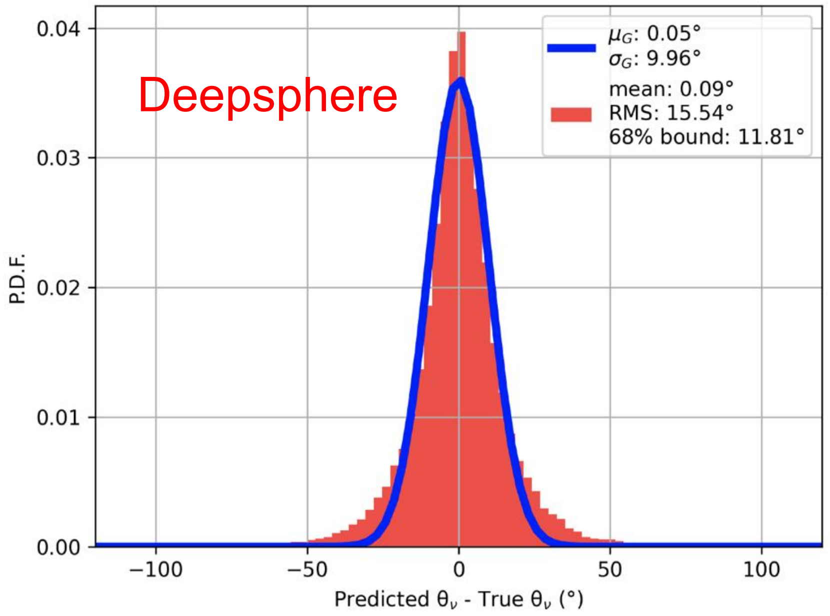


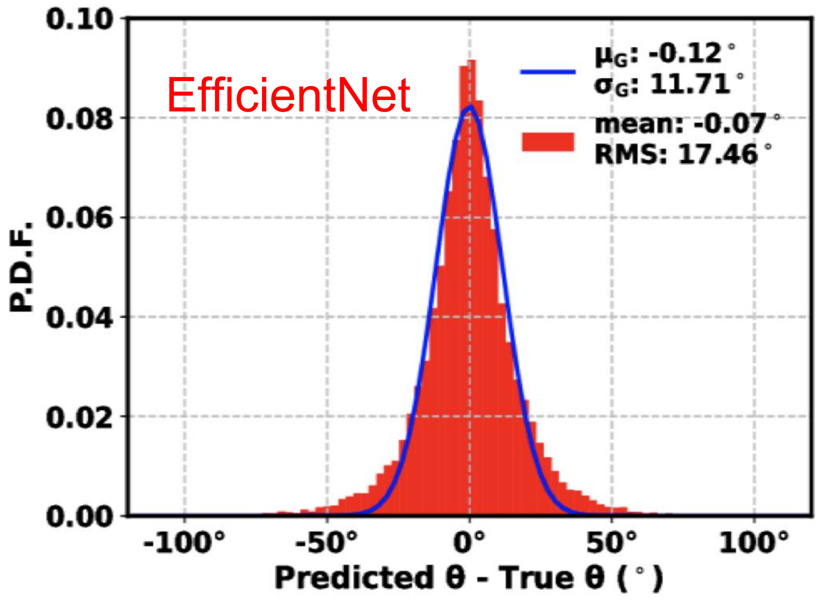


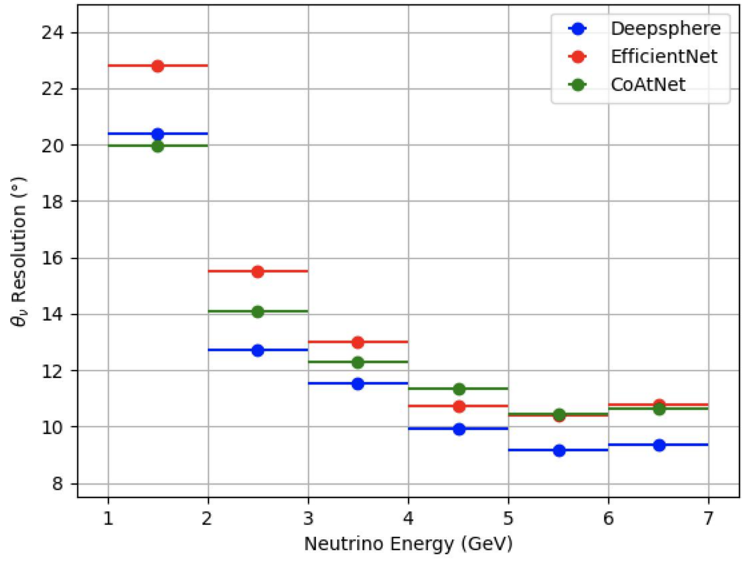
Direction Reconstruction

- MC sample: ~135k total $\nu_\mu/\bar{\nu}_\mu CC$ events. ~95k training events, 40k testing events (Honda flux)
  - Similar results are obtained from GNN/CNN models
  - Zenith angular resolution gets better as the neutrino energy increases as expected

preliminary results



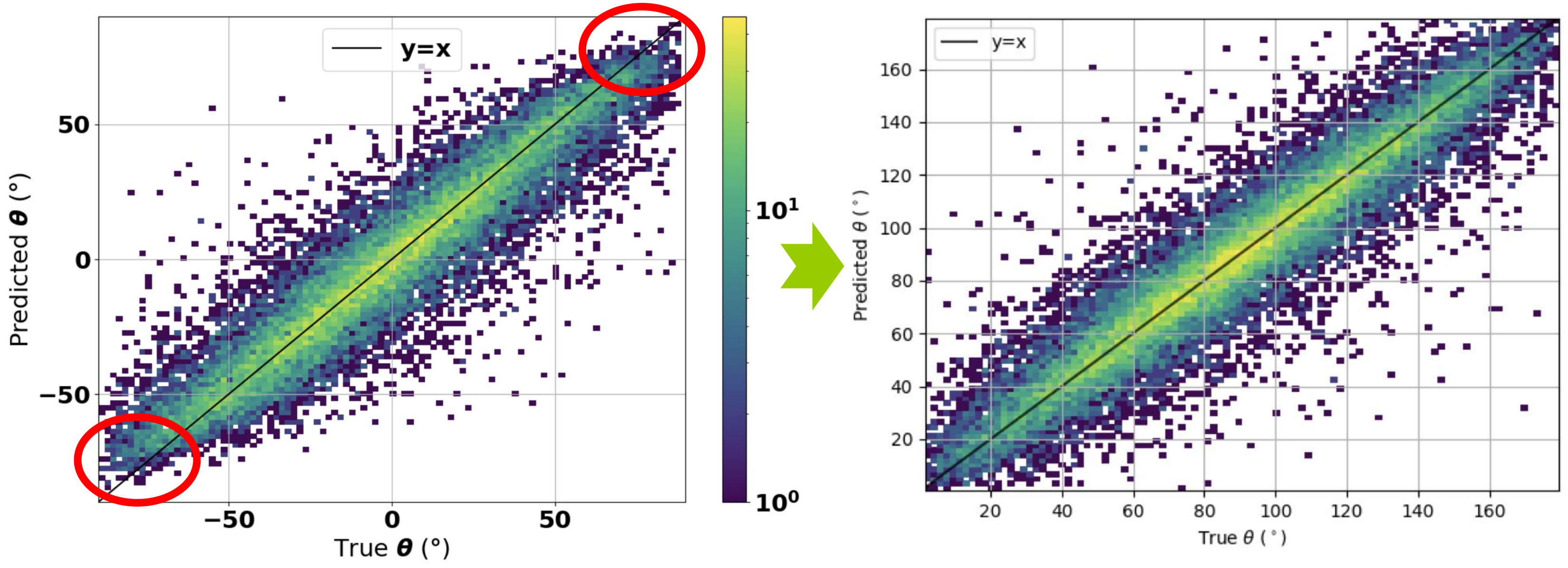




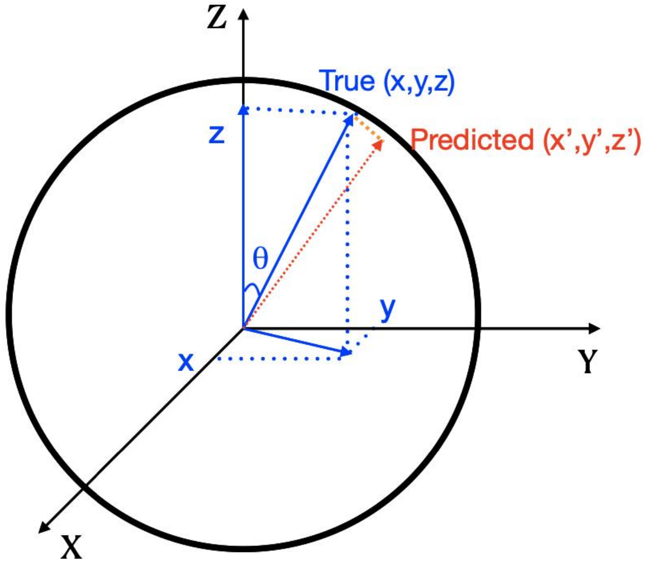
Eliminate Bias of Directionality Regression

The definition of θ/φ naturally causes uneven angular distribution

The ML models struggle to provide a unbiased prediction, in particular at north/south pole



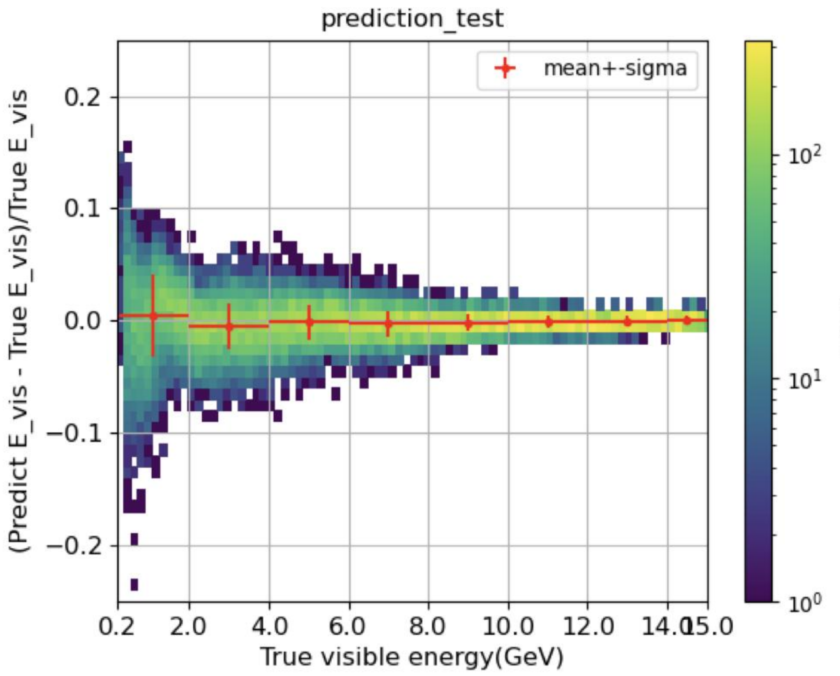
- Work-around is to predict (x,y,z) of the direction vector, then convert to zenith angle θ.
- The loss function is defined as the distance between the true and predicted vector endpoint
  - Rotation invariance can be remained
  - Get minimum bias, and slightly better performance

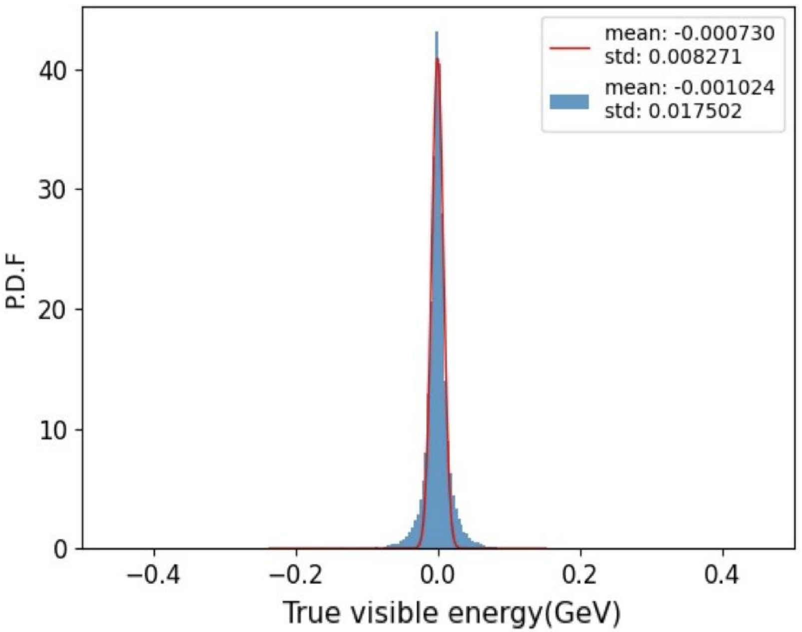


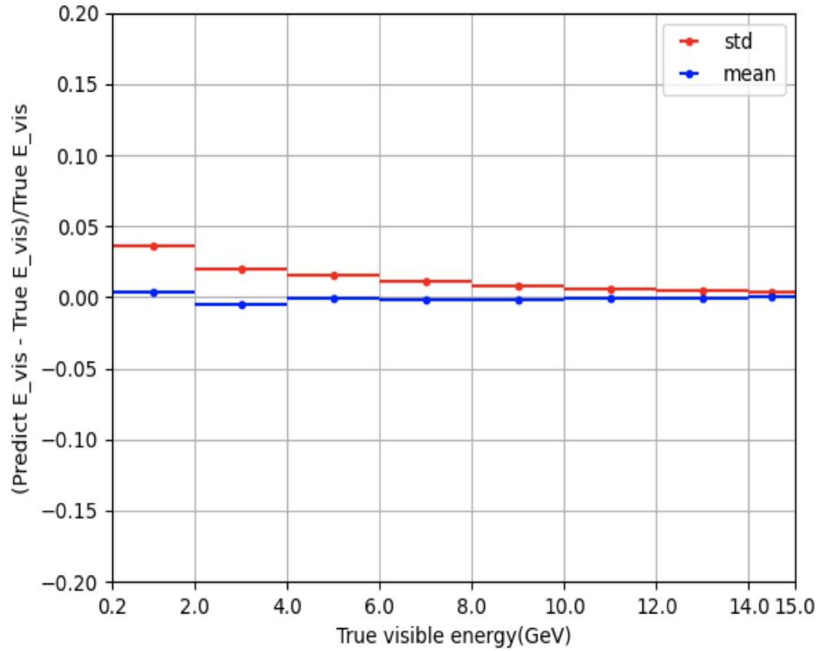
Energy Reconstruction

- Energy reconstruction based on the Deepsphere model
  - Results with ~135k $\nu_\mu/\bar{\nu}_\mu CC$ events
  - Trained with data collected in the first trigger readout window
  - Three features (nPE, FHT and slope) are used to reconstruct the visible energy

preliminary results



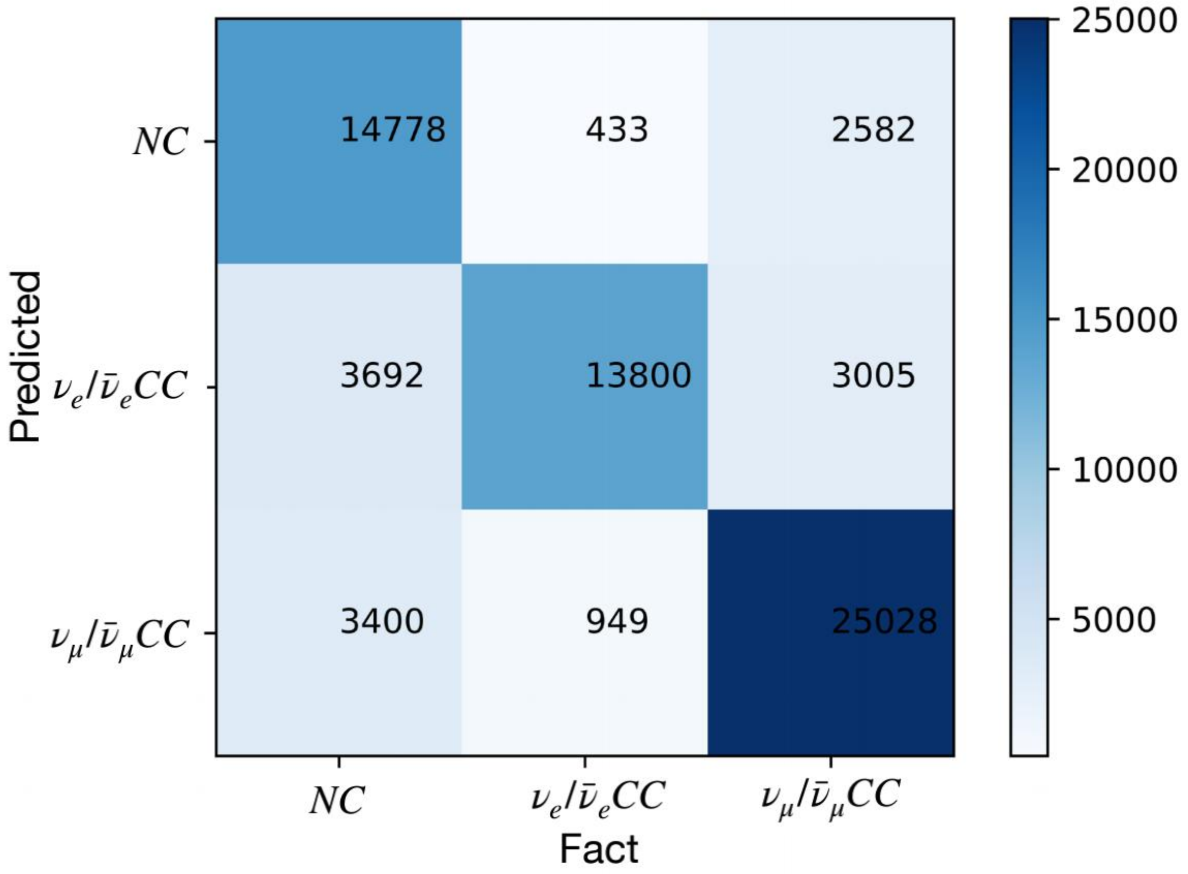




Event Identification

- Use deepsphere to identify event types: ν_μ CC, ν_e CC and NC neutrino

preliminary results

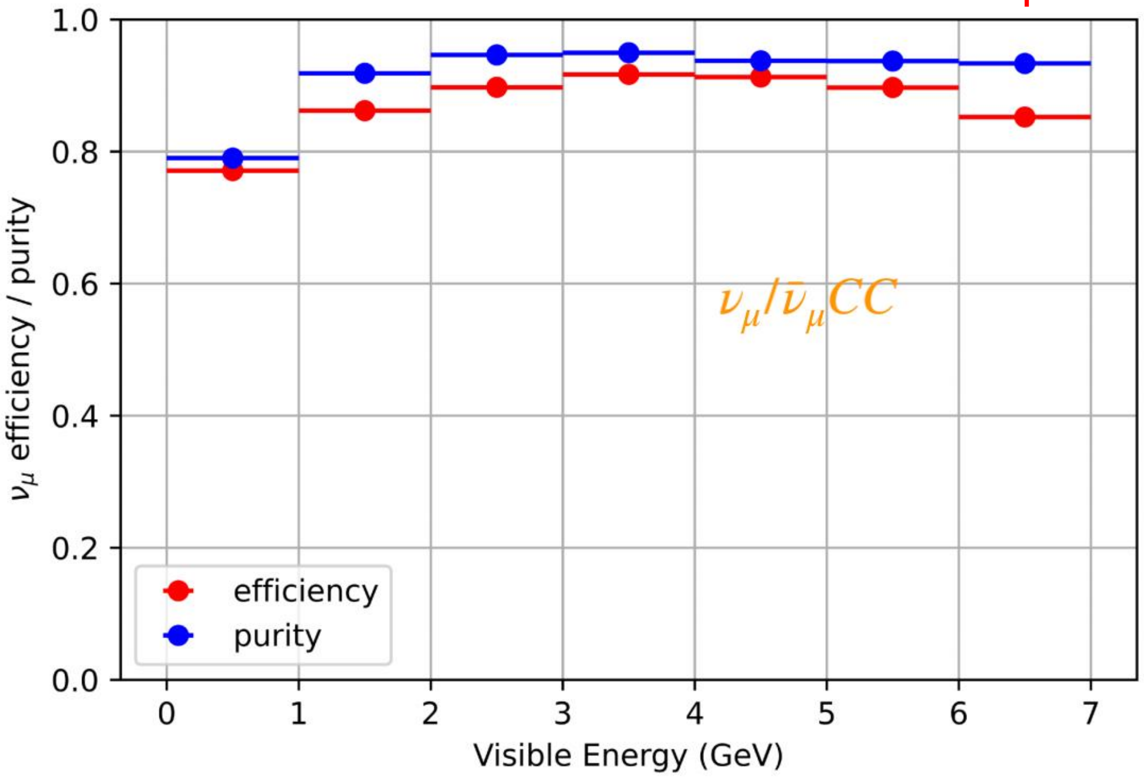


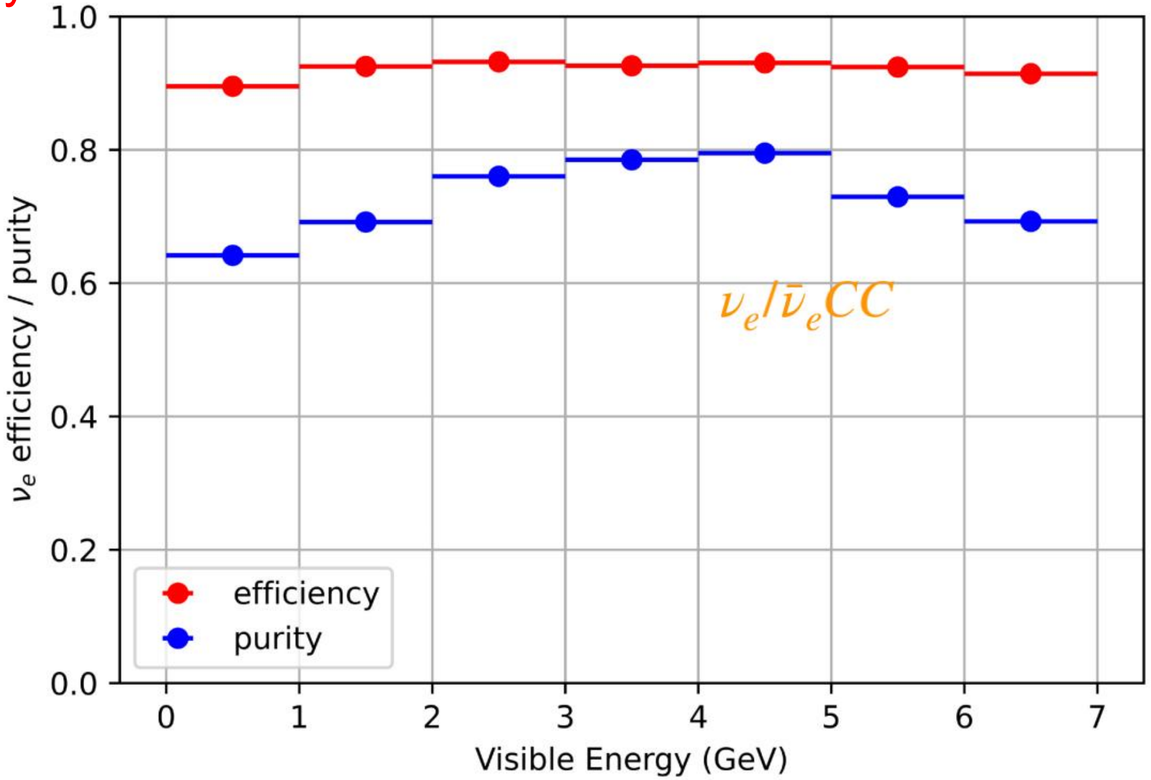
- Overall $\nu_\mu/\bar{\nu}_\mu CC$ efficiency: 82%; purity: 85%
- Overall $\nu_e/\bar{\nu}_e CC$ efficiency: 91%; purity 67%
- Default score cut is used here:

  Score cuts can be further optimized for efficiency/purity tradeoff

Event Identification

preliminary results

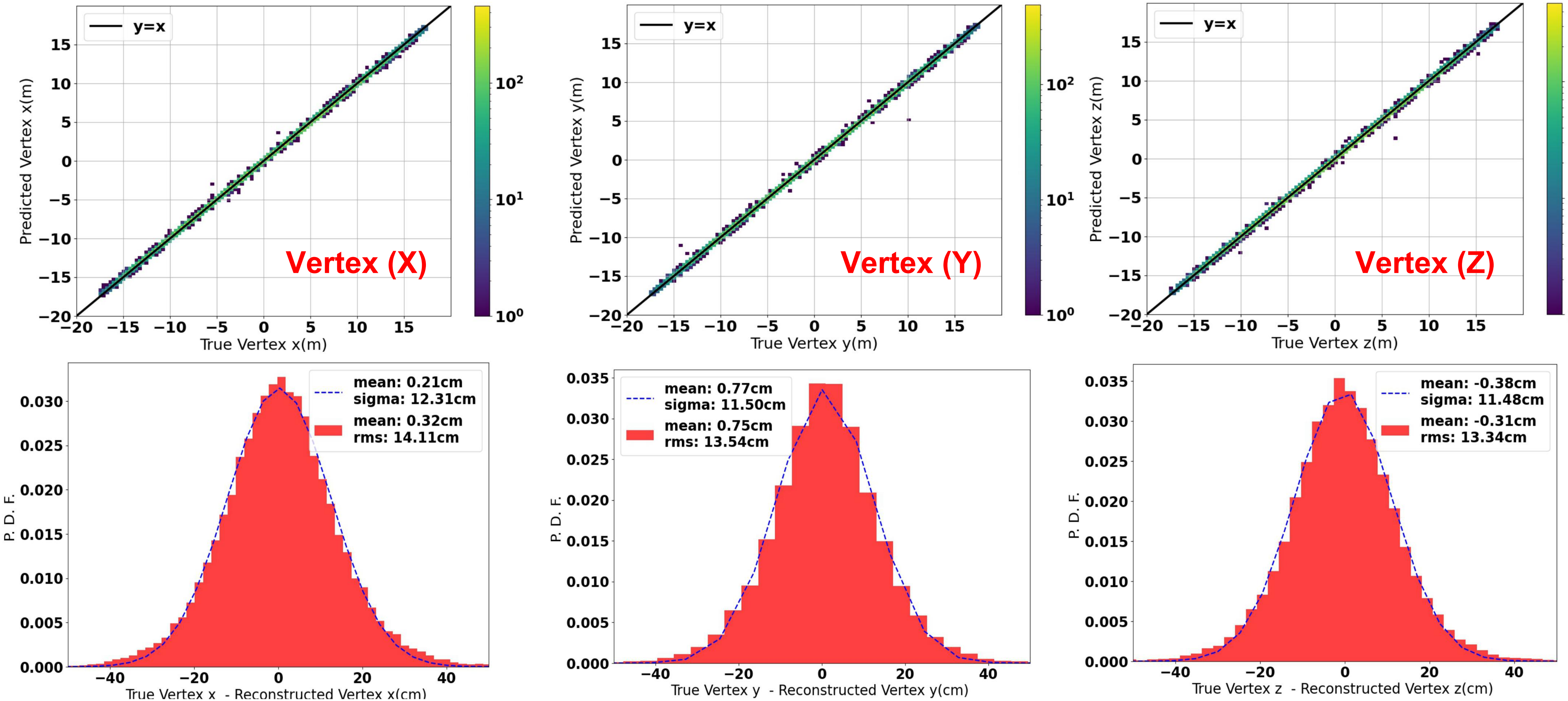




- Efficiency/purity increases and then decrease as functions of visible energy
- At lower energy, it is harder to distinguish electron from muon given short track length
- At higher energy, it is more likely for background NC events to create energetic $\pi^+/\pi^-/\pi^0$ which mimics μ/e in ν_μ/ν_e CC events

Interaction Vertex Reconstruction

preliminary results



Summary

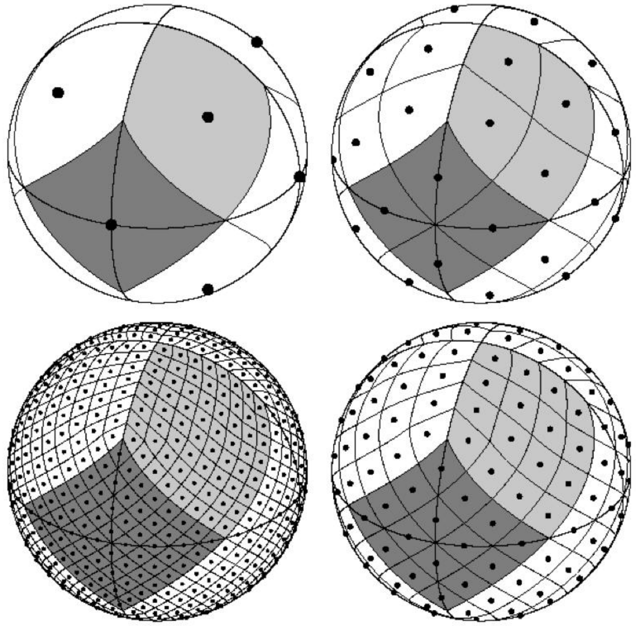
- In this talk, a general reconstruction approach for LS detector is introduced
- Multiple machine learning models (Spherical GNN/CNN/Transformer) are developed to cross validate the method
- By using MC sample produced by JUNO, multiple properties (directionality/ energy/ PID) of atmospheric neutrinos are reconstructed precisely
- For non-trivial reconstruction tasks (neutrino directionality), the performance is unprecedent
- As the next step, the method could be further improved and validated
  - Remove model dependent factor
  - Automatic extration of features

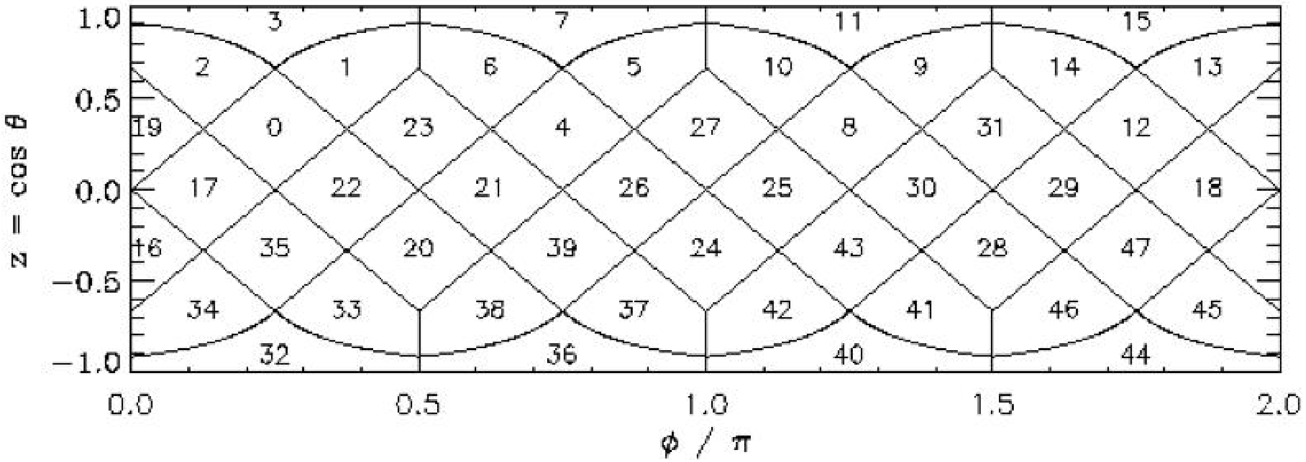
  ...

Backup

Deepsphere: Graph-CNN for Spherical Data

- Use healpix sampling to define vertices
  - Equally divide the sphere into 12 parts
  - Further divide each part into N_{side} parts ($N_{side}=2^n$).
  - Total number of pixels is $12X2^n$
  - If more than one PMTs are in one pixel, info is merged





Evolution of Light Received by PMTs

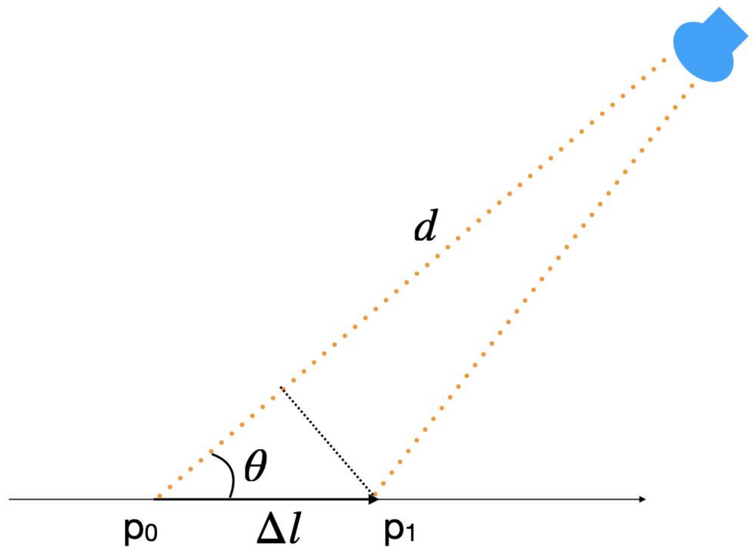
- Time for scintillation light from points on a track to reach a PMT

$$t_0 = \frac{d}{c/n} \qquad t_1 = \frac{\Delta l}{v} + \frac{d - \Delta l cos\theta}{c/n}, (\Delta l << d)$$

$$\Delta t = |t_1 - t_0| = \Delta l |(\frac{1}{v} - \frac{cos\theta}{c/n})|$$

$$\boxed{\frac{dl}{dt} = \frac{1}{|\frac{1}{v} - \frac{cos\theta}{c/n}|} = \frac{v}{|1 - n\beta cos\theta|}}$$

(Length of the track visible to a PMT as a function of time)



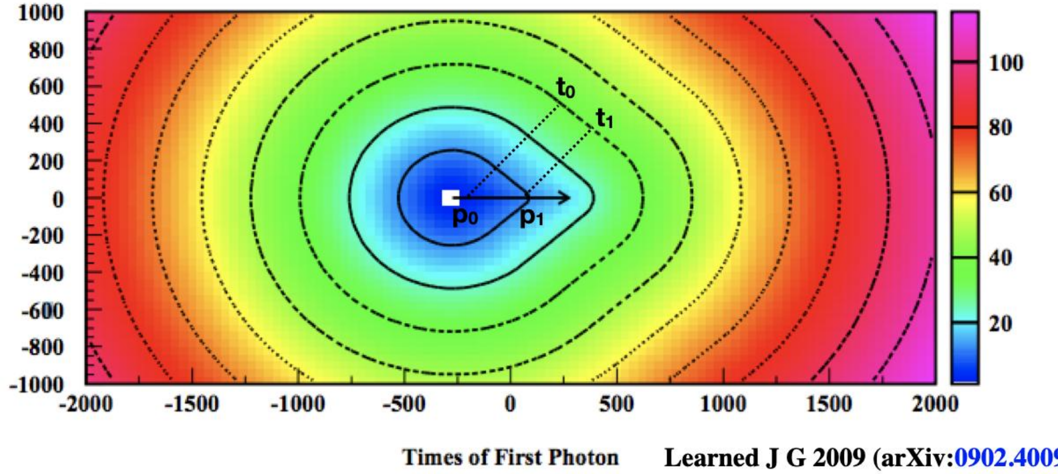
$\frac{dl}{dt}$ is a a function of θ, also depends on where the track starts and stops.

The amount of light emitted depends on l and particle type (*dE/dx*).

The amount of light received by a PMT evolves as a function of time according to the event topology in the detector.

Maximum light rising slope at $cos\theta = \frac{1}{n\beta}$ if $\beta > 1/n$

(the same angle as CKV)



Learned J G 2009 (arXiv:0902.4009)

Benchmarking Reconstruction Bias

- The reconstruction performance should be unbiased for all theta values
- Benchmark the reconstruction bias by Checking the φ' angle of predicted vector wrt z around the true vector
- Flat φ' distribution over all theta around 90 degree with small fluctuation means the bias is minimum