Reconstruction of Cosmic Muon with Machine Learning in JUNO

Zekun Yang, Junya Wei, Hongyue Duyang
Shandong University

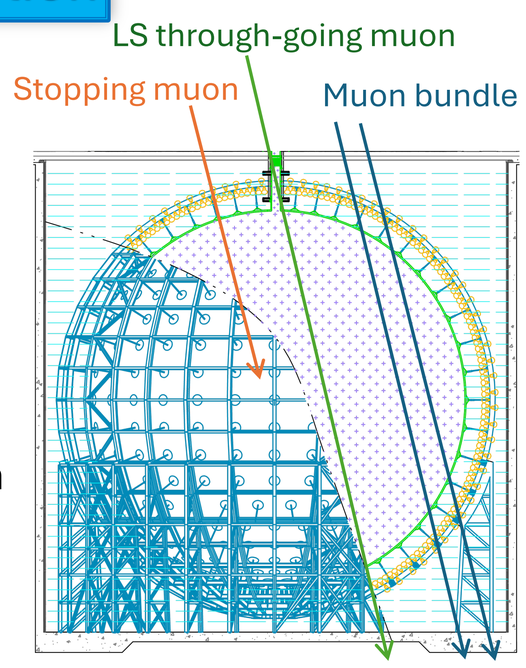
1. Overview

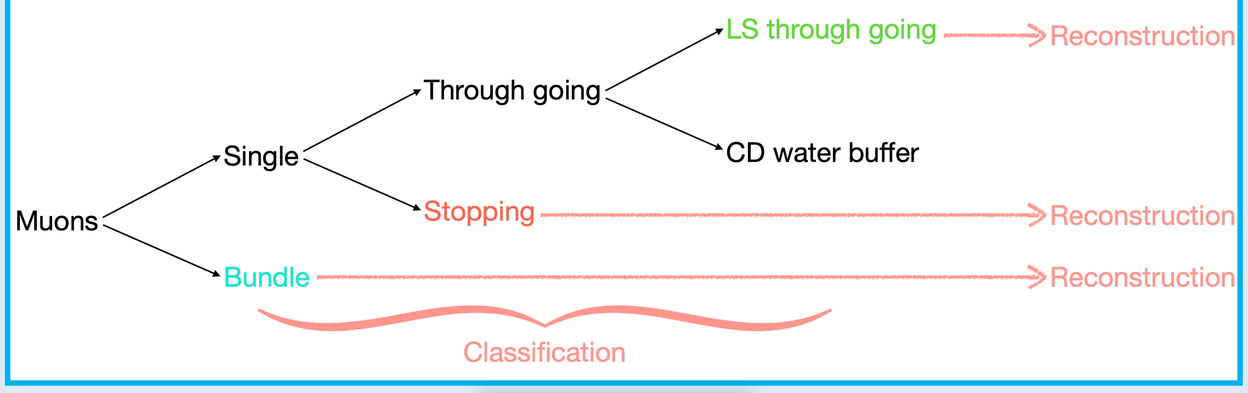
The Jiangmen Underground Neutrino Observatory (JUNO)

- A next-generation neutrino experiment that consists of a 20-kton liquid scintillator (LS) detector with ~78% PMT coverage.
- JUNO's Primary objective is to determine the neutrino mass ordering (NMO) via reactor neutrino oscillation measurements.

2. Motivation

- Cosmic muons contribute to one of the dominant background sources to reactor neutrinos by producing isotopes that mimic the inverse beta decay (IBD) signal.
- To maximize the efficiency of background rejection, a **classification** for observed muon events and suitable **track reconstruction** strategies for each muon types are needed.





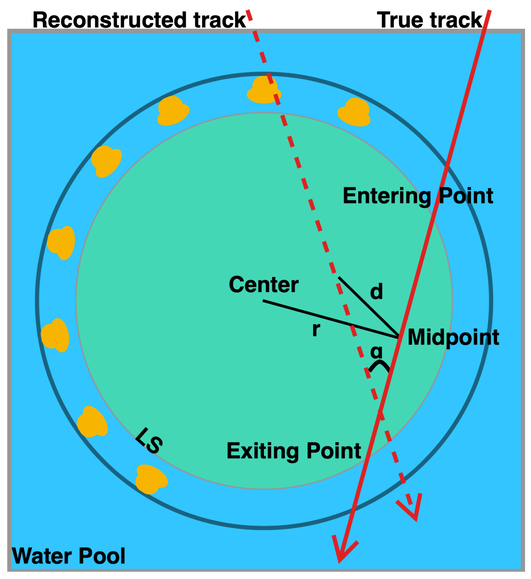
4. Results

Dataset: 8k each of three muon types for classification training; 83k LS through-going muons for track reconstruction training.

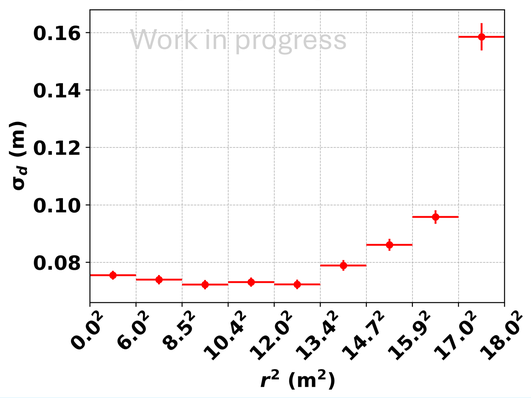
The **classification** performance:

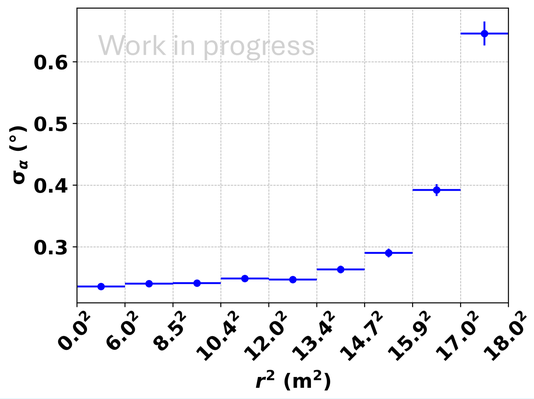
Muon types	Efficiency	Purity
Stopping muon	98.8%	99.2%
Through-going muon	98.3%	97.5%
Muon bundle	98.6%	99.0%
Total accuracy	98.6%	

A muon track is defined as the connection between entering and exiting points on the LS sphere.
r: distance from center to track
α: included angle between the true and reconstructed tracks
d: distance from midpoints of true to reconstructed tracks

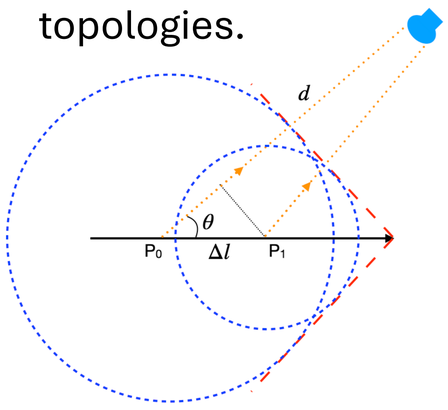


The **reconstruction** performance of LS through-going muon:

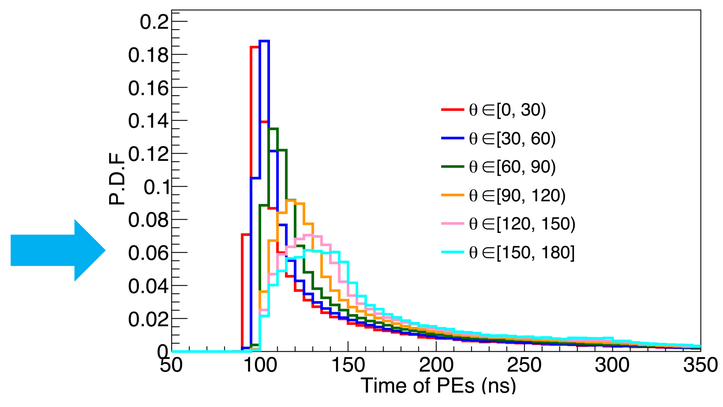




- Light received by a PMT in the LS detector is the superposition of light from points along the track.
- The distribution of number of PEs over time of each PMT contains the information of the particle's track and type, therefore the waveform of each PMT can reflect the event topologies.



$$\frac{\mathrm{d}l}{\mathrm{d}t} = \frac{v}{|1 - n\beta\cos\theta|}.$$



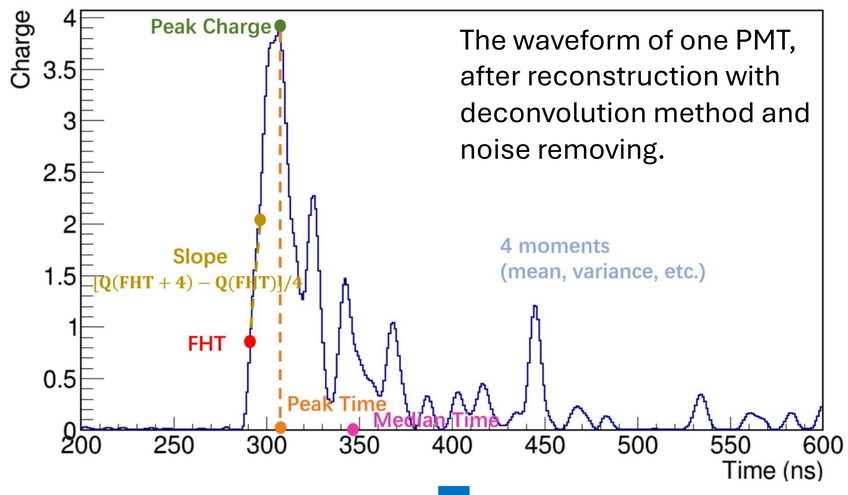
Distribution of the number of photoelectrons (PEs) over time for PMTs with different angles θ to the particle track of a 1 GeV muon

3. Machine Learning Approach

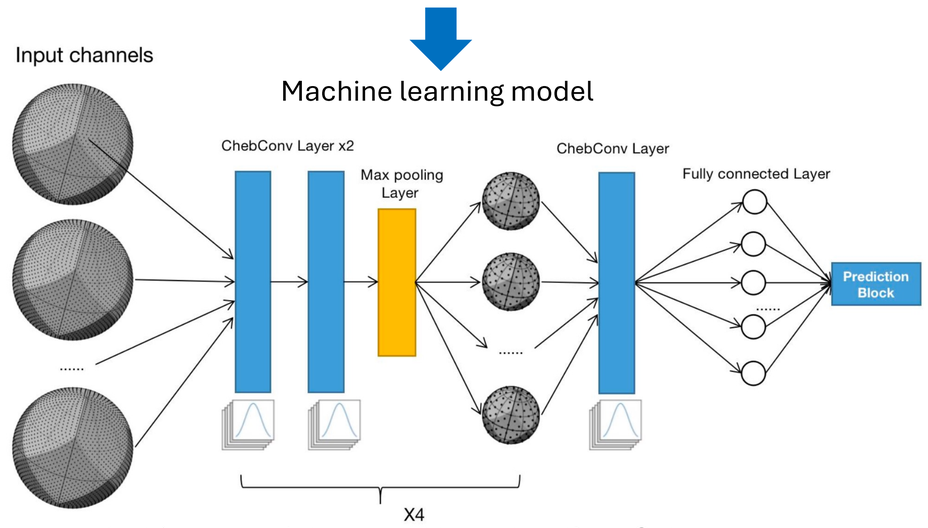
Only key features are extracted from each PMT's waveform to keep the most useful information relevent to muon track and type, including (more details in Ref. [1]):

- FHT: first hit time for each PMT
- Total Charge: the total charge in the first readout window
- 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

These features of each PMTs will be grouped into **Healpix pixels** based on their positions and then fed into a graph-based spherical machine learning model: **DeepSphere**.



Examples of feature's images of total charge. Red points indicate true entering positions into LS, as blue points indicate true exiting positions.



Architecture of the model based on DeepSphere.

References

[1] Zekun Yang et al. "First attempt of directionality reconstruction for atmospheric neutrinos in a large homogeneous liquid scintillator detector". Phys. Rev. D 109.5 (2024)