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Flavor Identification of Atmospheric Neutrinos in JUNO with Machine Learning

Fanrui Zeng,[a,*] **Hongyue Duyang,**[a] **Teng Li,**[a] **Jiaxi Liu,**[b] **Wuming Luo**[b] **and Wing Yan Ma**[a]

[a] *Shandong University, Binhai Road 72, Jimo district, Qingdao 266237, P. R. China*

[b] *Institute of High Energy Physics, Chinese Academy of Sciences, Beijing 100049, P. R. China*

E-mail: fr.zeng@mail.sdu.edu.cn

The Jiangmen Underground Neutrino Observatory (JUNO) is a next-generation large (20 kton) liquid-scintillator neutrino detector, which is designed to determine the neutrino mass ordering from its precise reactor neutrino spectrum measurement. Moreover, high-energy (GeV-level) atmospheric neutrino measurements could also improve its sensitivity to mass ordering via matter effects on oscillations, which depend on the capability to identify electron (anti-)neutrinos and muon (anti-)neutrinos against each other and against neutral current background, as well as to identify neutrinos against antineutrinos. However, this flavor identification task has never been attempted in large homogeneous liquid scintillator detectors like JUNO. This poster presents a machine-learning approach for the flavor identification of atmospheric neutrinos in JUNO. In this method, several features relevant to event topology are extracted from PMT waveforms and used as inputs to machine learning models. Moreover, the features from captured neutrons provide additional capability of neutrinos versus anti-neutrinos identification. Two independent strategies are developed to utilize the primary interaction and neutron-capture information with different machine-learning models. Preliminary results based on Monte Carlo simulations show promising potential for this approach.

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[*]Speaker

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1. Introduction

The Jiangmen Underground Neutrino Observatory (JUNO)[1, 2] aims to determine the Neutrino Mass Ordering (NMO) by measuring the oscillations of reactor electron antineutrinos ($\bar{\nu}_e$) with a large liquid scintillator (LS) detector. JUNO's overall sensitivity to NMO can be enhanced through a combined analysis of reactor and atmospheric neutrino oscillations. A crucial aspect of atmospheric neutrino oscillation measurements is the identification of neutrino flavors, including distinguishing between muon (anti)neutrinos, electron (anti)neutrinos, and neutral current (NC) events, as well as between neutrinos and antineutrinos ($\nu/\bar{\nu}$).

2. Methodology

Neutrino flavors can be determined by the outgoing charged leptons from charge current (CC) interactions. As detailed in the previous study on reconstructing the directionality of atmospheric neutrinos [3], the light received by PMTs in an LS detector is the superposition of light from points along the particle track. The number of photo-electrons (nPEs) collected by a PMT evolves over time and is determined by the angle relative to the particle's direction, position, visible energy, and the particle type (dE/dx). Therefore PMT waveforms contain all the information about the event topology. Various features are extracted from the PMT waveforms of the prompt trigger, including first hit time (FHT), nPEs, peak charge, peak time, and others like median time and four moments of the waveform distributions.

The distinction between ν and $\bar{\nu}$ arises from differences in their interactions, particularly in the hadronic energy fraction $y_{vis} = E_{had,vis}/E_{vis}$, where $E_{had,vis}$ is the visible energy cause by hadrons and E_{vis} is the total visible energy of the event, which is also reflected in the PMT waveforms of the prompt trigger. Additionally, neutrinos and antineutrinos differ in their average neutron multiplicities. Final state neutrons are captured by hydrogen nuclei in the LS. This process emits a 2.2 MeV photon in $\sim 200\,\mu$s, generating delayed triggers.

To process prompt and delayed triggers, two strategies using different deep learning models are developed. Strategy 1 utilizes a point cloud-based model, incorporating PointNet++ and DGCNN. Features extracted from the prompt triggers are fed into the PointNet++, while the reconstructed vertices of neutron capture candidates are input into a separate DGCNN model as a point cloud to preserve neutron multiplicity and spatial distributions, minimizing information loss. Strategy 2 employs a spherical image-based model, DeepSphere, designed for rotational covariance. Here, features for the same PMT from different neutron-candidate triggers are merged into one, which is then fed into the model together with the prompt trigger features. All features remain at the PMT level, enabling fast and efficient input handling. Both strategies leverage prompt and delayed trigger features in a 2-step approach: a 3-label classification (NC, $\nu_\mu/\bar{\nu}_\mu$-CC, $\nu_e/\bar{\nu}_e$-CC) followed by $\nu/\bar{\nu}$ classification.

3. Performance

The Area Under the Receiver operating characteristic(ROC) Curve (AUC) is used to assess models' performances, as it is independent of the score cut selection and is not affected by class imbalances in the dataset. The AUC score as a function of visible energy (Figure 1) demonstrates consistency across all three classification tasks in both strategies. Figure 2 shows the final selected sample as functions of L/E. For the upcoming NMO study, the efficiency and purity of each label will be tuned to obtain the best sensitivity.

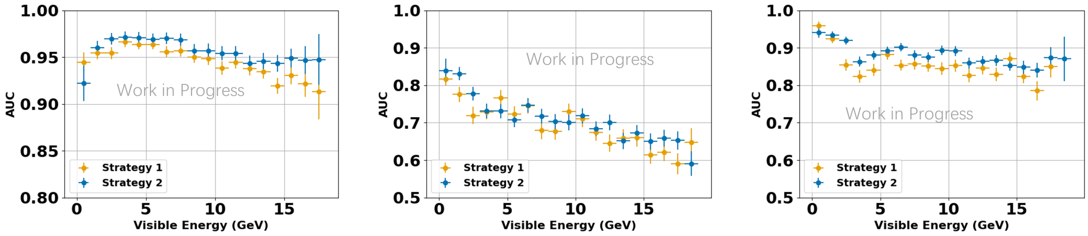
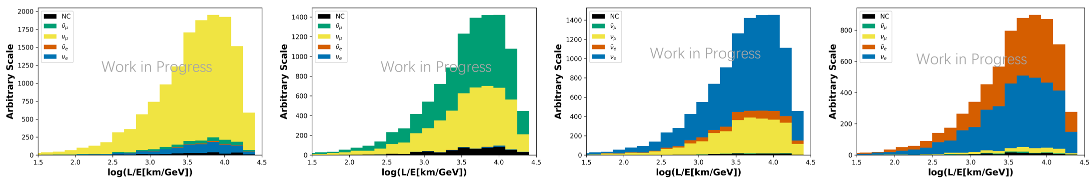


Figure 1: Comparison of AUC scores as a function of visible energy for 3-label classification (left), $\nu_e/\bar{\nu}_e$ classification (center), $\nu_\mu/\bar{\nu}_\mu$ classification (right) using a flat spectrum sample.



(a) ν_μ-like **(b)** $\bar{\nu}_\mu$-like **(c)** ν_e-like **(d)** $\bar{\nu}_e$-like

Figure 2: The distribution of L/E for the upward-going events in the selected neutrino subsamples with Honda flux spectrum. Contributions from true event categories are shown in different colors.

4. Summary

In this study, we introduce a general machine-learning approach for atmospheric neutrino identification, utilizing features extracted from PMT waveforms in the prompt trigger, along with the information from captured neutron candidates. Two different particle identification strategies employing different machine-learning models and ways of handling neutron-capture information were developed. Preliminary results based on Monte Carlo simulations demonstrate promising potential for this method. The performance of atmospheric neutrino identification can be further optimized to maximize JUNO's sensitivity to NMO. This technique can also be applied to other large LS detectors, making them strong candidates for future atmospheric neutrino oscillation studies.

References

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