# Flavor Identification of Atmospheric Neutrinos in JUNO with Machine Learning

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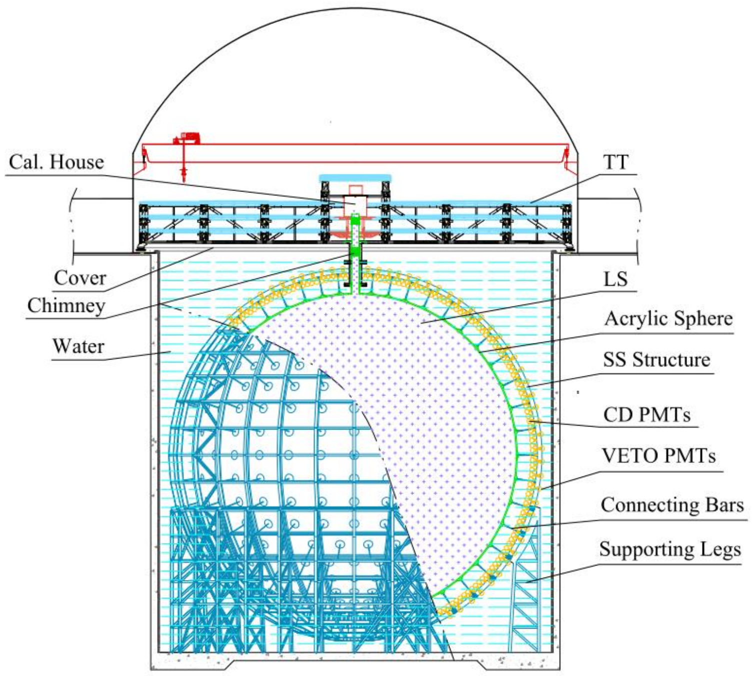
# Outline

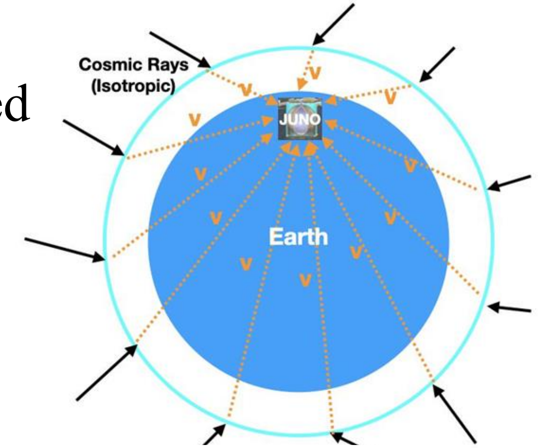
- **1. Introduction of JUNO**
- **2.Methodology**
- **3. Applications of Machine Learning in PID for Atmospheric Neutrinos**
  - **Cosmic Muon vs Atmospheric Neutrinos**
  - **3-class($\nu_{\mu}/\bar{\nu}_{\mu}$ vs $\nu_e/\bar{\nu}_e$ vs $NC$)**
  - **5-class**($\nu_{\mu}$ vs $\bar{\nu}_{\mu}$ vs $\nu_e$ vs $\bar{\nu}_e$ vs NC)
  - **3-class+2-class**($\nu_{\mu}$ vs $\bar{\nu}_{\mu}$ & $\nu_e$ vs $\bar{\nu}_e$)
- **4.Summary**

## ➢ JUNO Physics and Detector

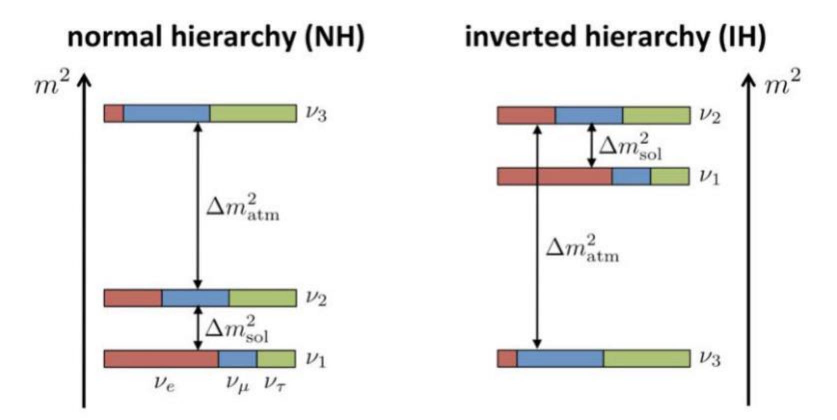



•Main physical goal: The JUNO experiment is designed to measure the neutrino mass order (NMO)

•The measurement of atmospheric neutrino oscillation has great potential to boost JUNO's NMO sensitivity








There are still two possibilities for neutrino mass order

•20 kton liquid scintillator detector
•700 m rock overburden
• PMTs coverage 75%
•53 km oscillation baseline

➢Precise reconstruction algorithms are critical, and challenging.

Particle incident direction (to calculate the oscillation baseline)

**Neutrino flavor (PID)**

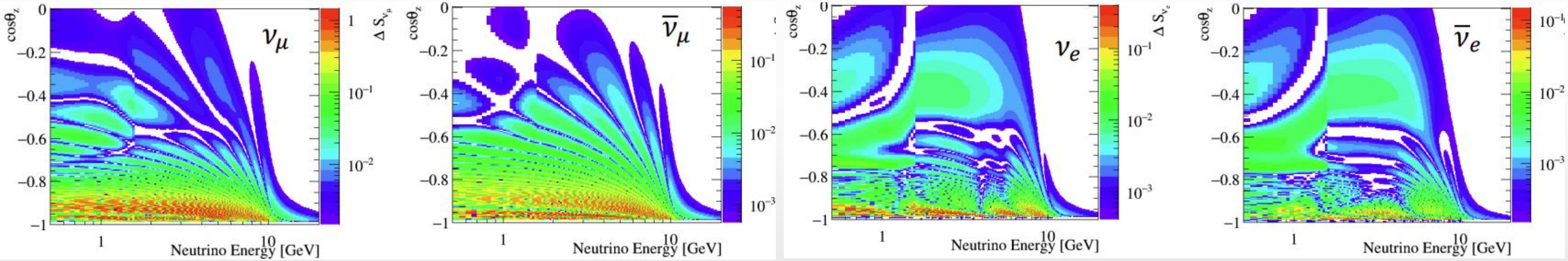
Neutrino energy

# Why PID?

➢ Measurements of atmospheric neutrinos require identification:

- Signal： $\nu_\mu/\bar{\nu}_\mu$CC, $\nu_e/\bar{\nu}_e$CC
- Background： NC ,cosmic muon

} Identification of final charged leptons produced by CC



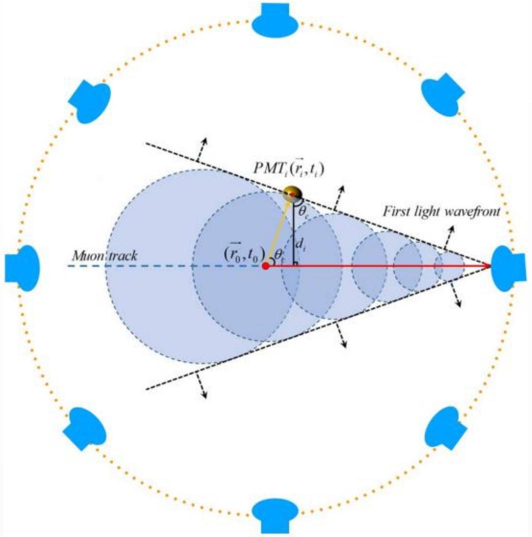

Differences between NO and IO in atmospheric neutrino oscillation spectrums

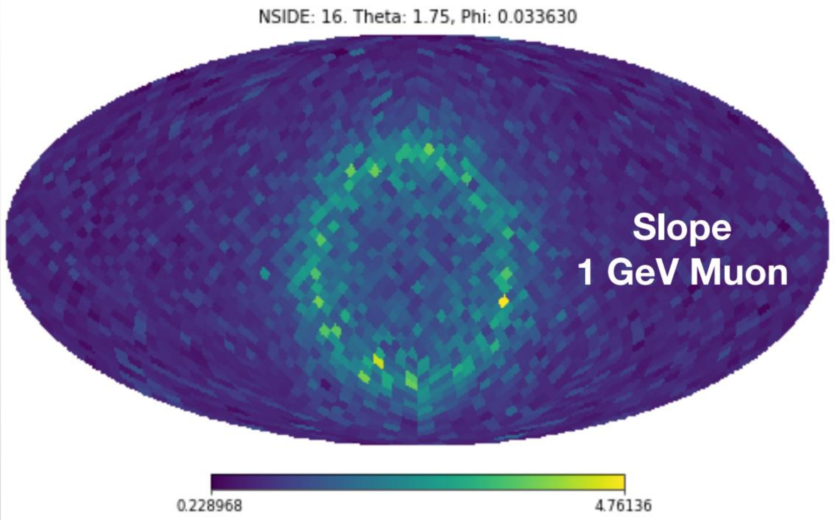
- **Flavor identification** is critical, including $\nu$ **vs** $\bar{\nu}$.

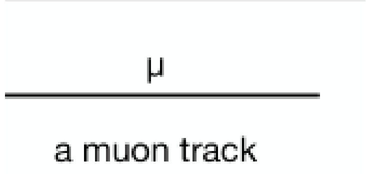
*tips： CC:charged current NC: neutral current*

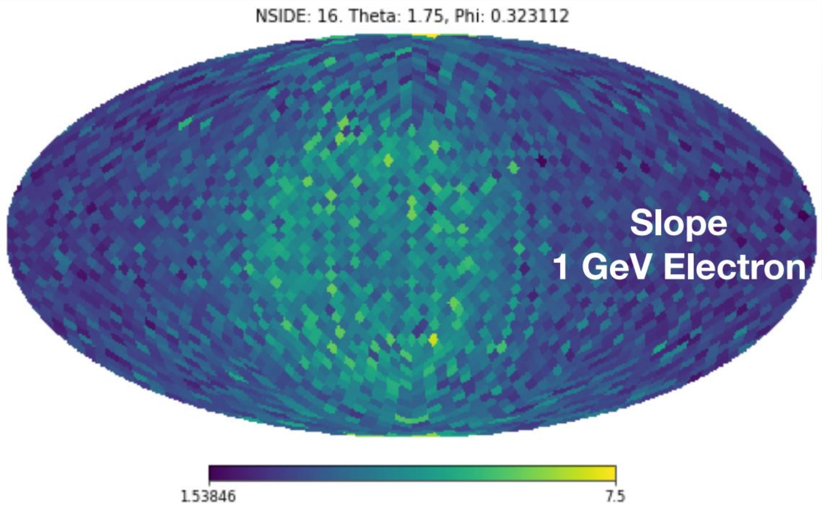
# Methodology

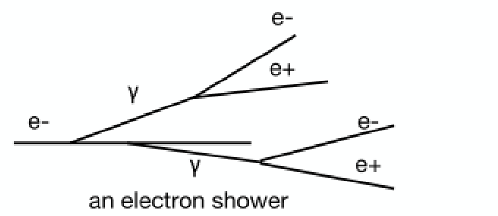
- In the LS detector, the light received by a PMT is the superposition of the scintillation light from many points along the track.
- How the amount of light received by a PMT evolves as a function of time depends upon its  angle wrt to the particle direction , position, visible energy and **PID**.
- These are reflected in the PMT waveforms, from which features are extracted and used as inputs to ML models.



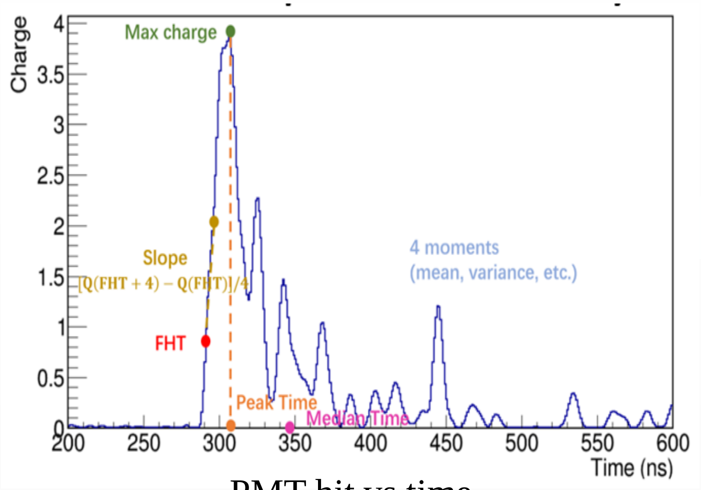



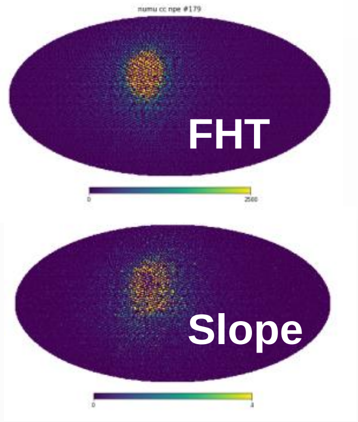




- Distribution of the slope of the ascending section of 1GeV muon /electron waveform on the pmt sphere of JUNO

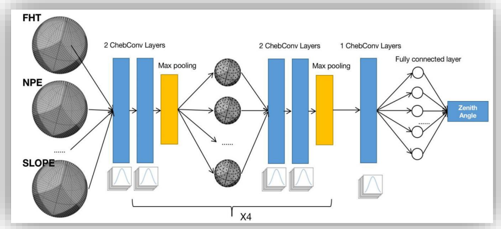
# Methodology



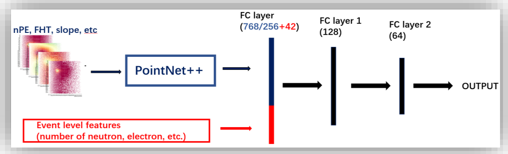

PMT hit vs time




Extract feature




DeepSphere




PointNet++

Direction

Energy

Flavor

Track

Vertex

- **FHT**: distance between track and PMT, and angle info
- **Slope**: angle between track and PMT
- **Peak time**: track length
- **Total nPE**: Energy deposition topology

- Due to the large PMT number distributed on the sphere, directly feeding models with all waveforms is hard

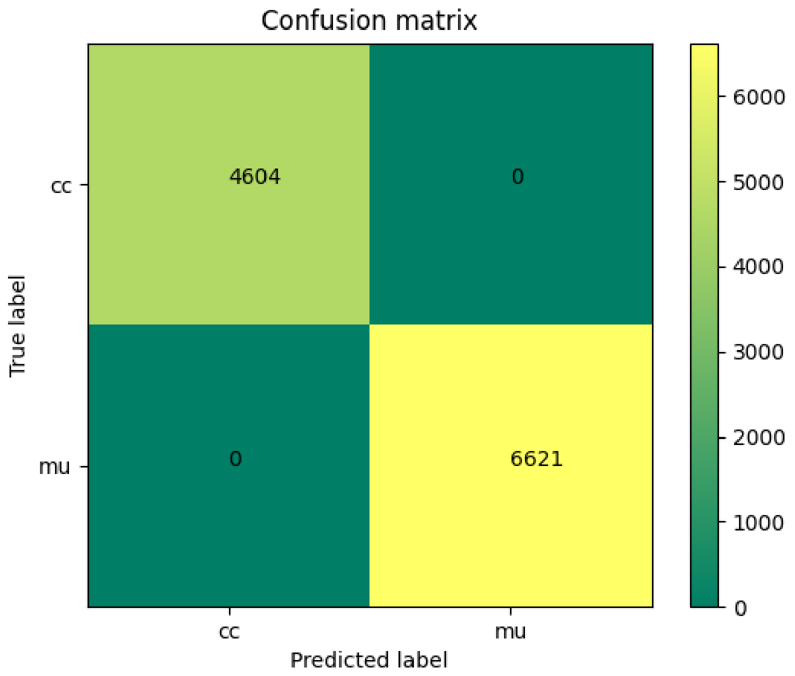
- Features are extracted from each PMT to mathematically describe the waveform, which reflect **event topology** in the detector

Machine Learning Models

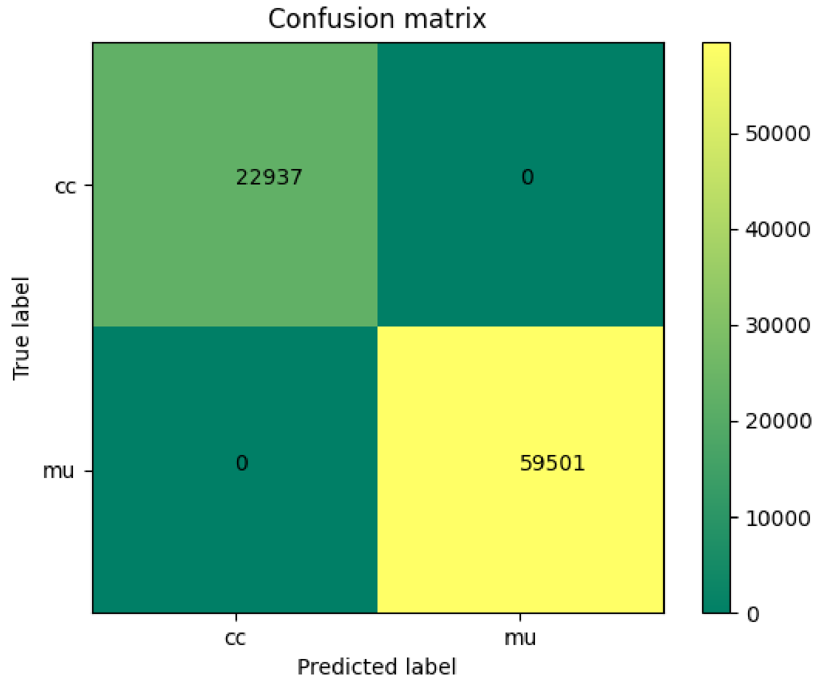
# Neutrinos vs Cosmic muons

- Features: nPE, fht, nperatio, peak and slope from CD PMTs
- Evis > 0.5GeV

Train : $\mu$: 33187   cc:22937



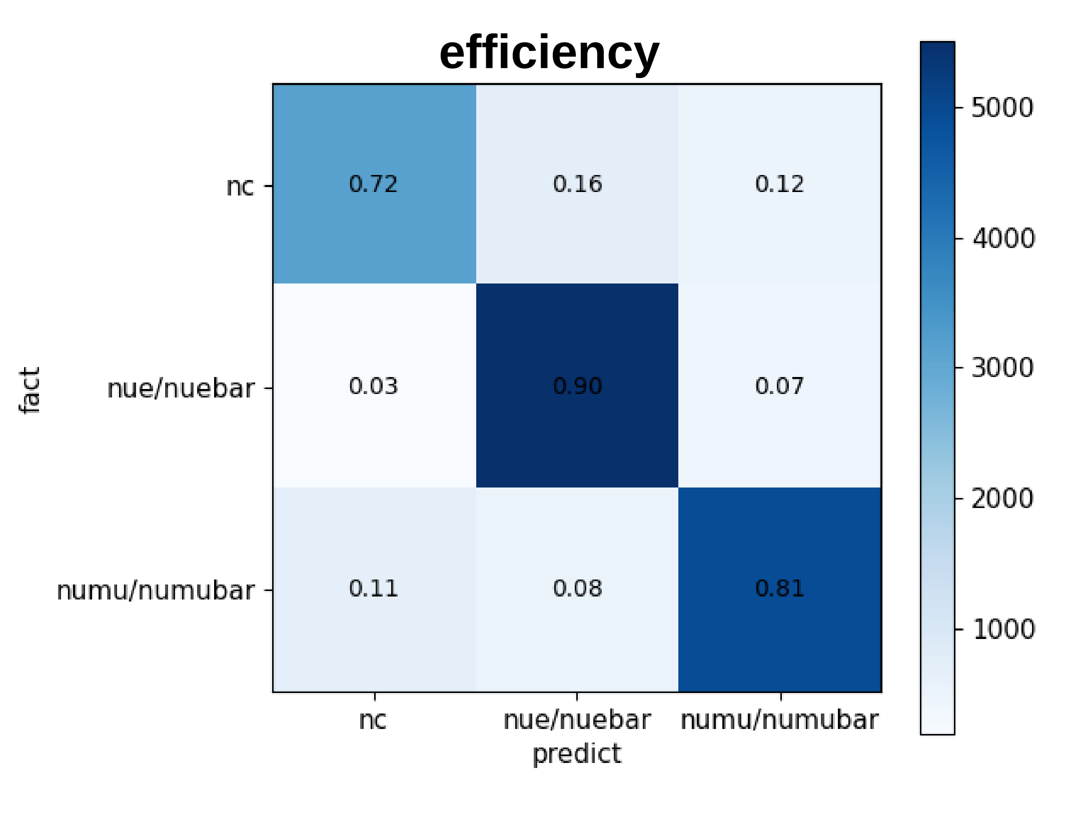

Test： $\mu$： 59501   cc:22937

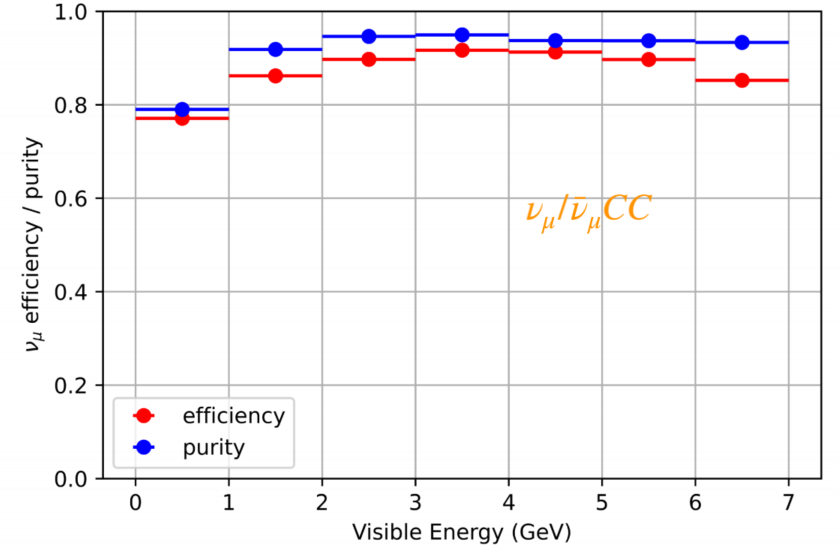



Mu efficiency: 100%; purity:  100%
CC efficiency: 100%; purity:  100%
No statistic uncertainty  take into account

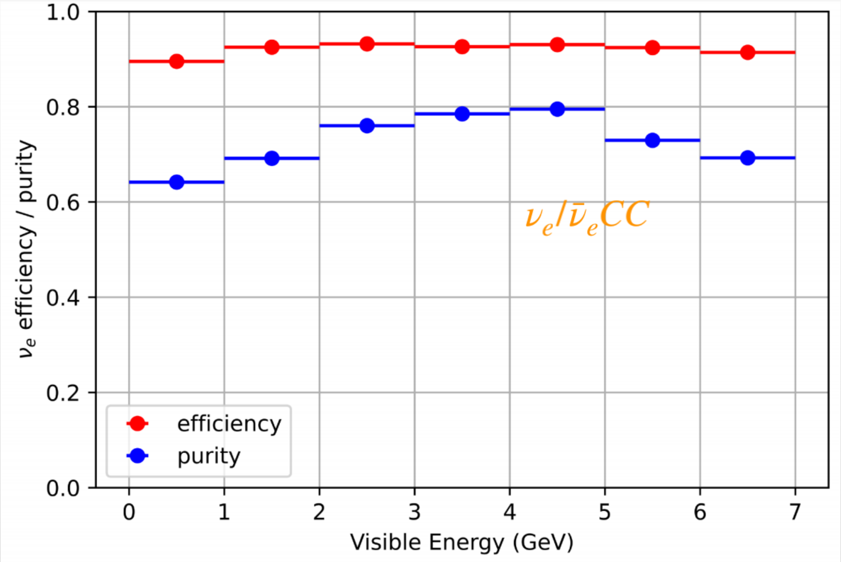
# 3-Label Classfication

- Samples: 500k Genie Sample(HONDA flux)
- Version: J21v2r0-Pre0
- Input features from PMT waveforms of ML models:
  fht, npe, slope,nperatio,mediantime



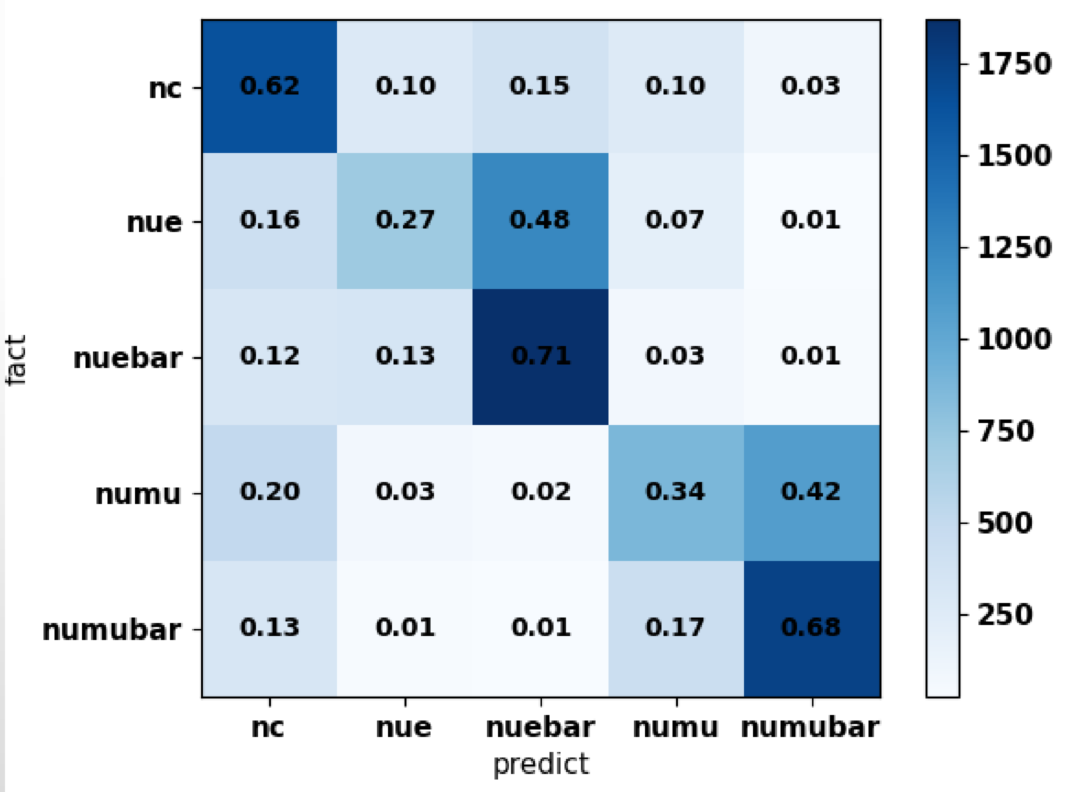




Efficiency/purity as functions of visible energy



# 5-Label Classfication

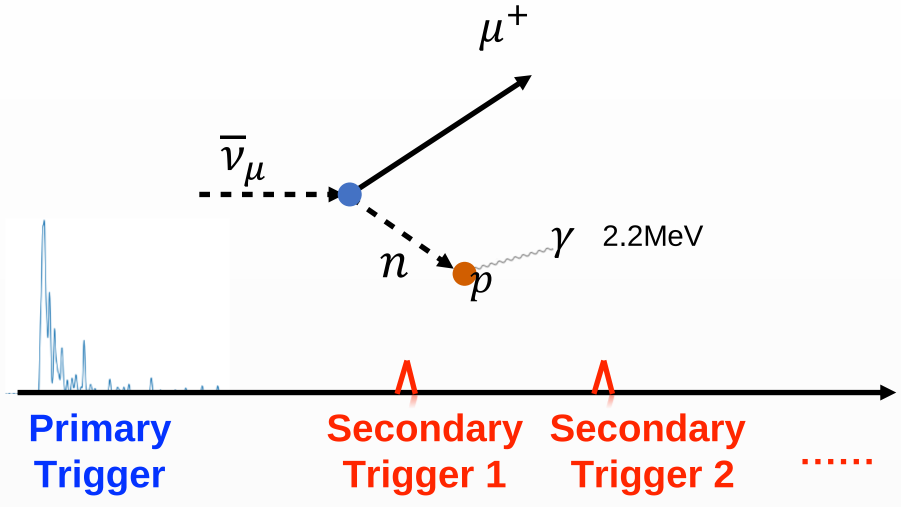
- Samples: 500k Genie Sample(HONDA flux)
- Version: J21v2r0-Pre0
- Input features from PMT waveforms of ML models: fht, npe, slope,nperatio,mediantime

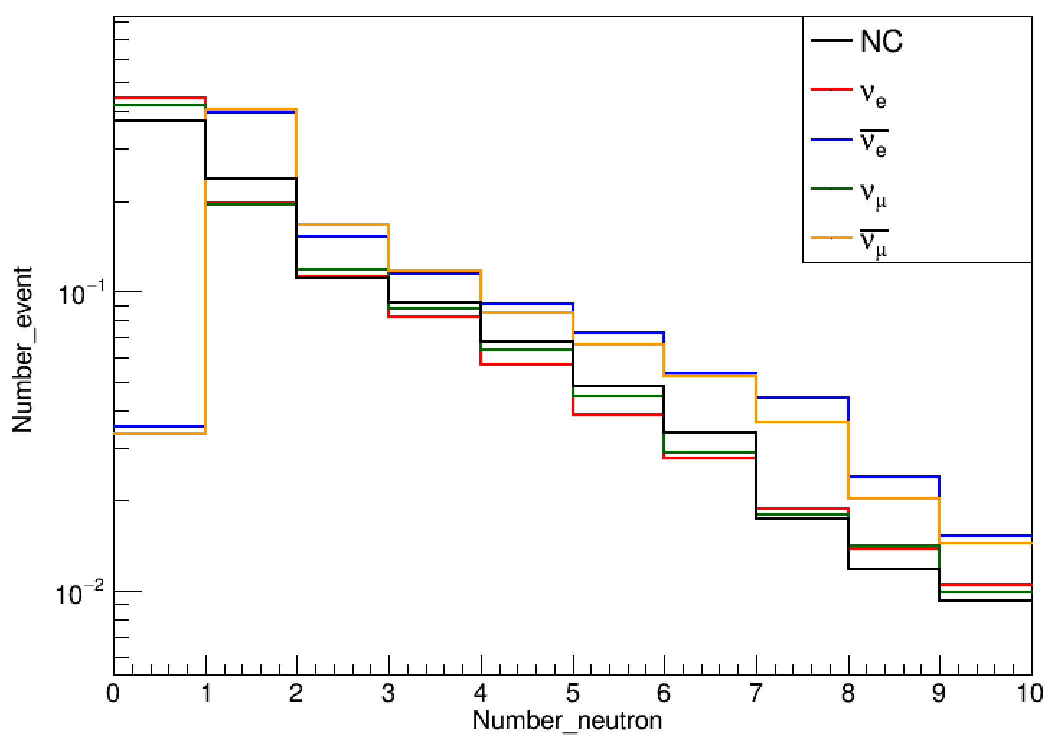



**Atm $\nu$ and $\bar{\nu}$ are hard to identify**

# Neutron vs Neutrino

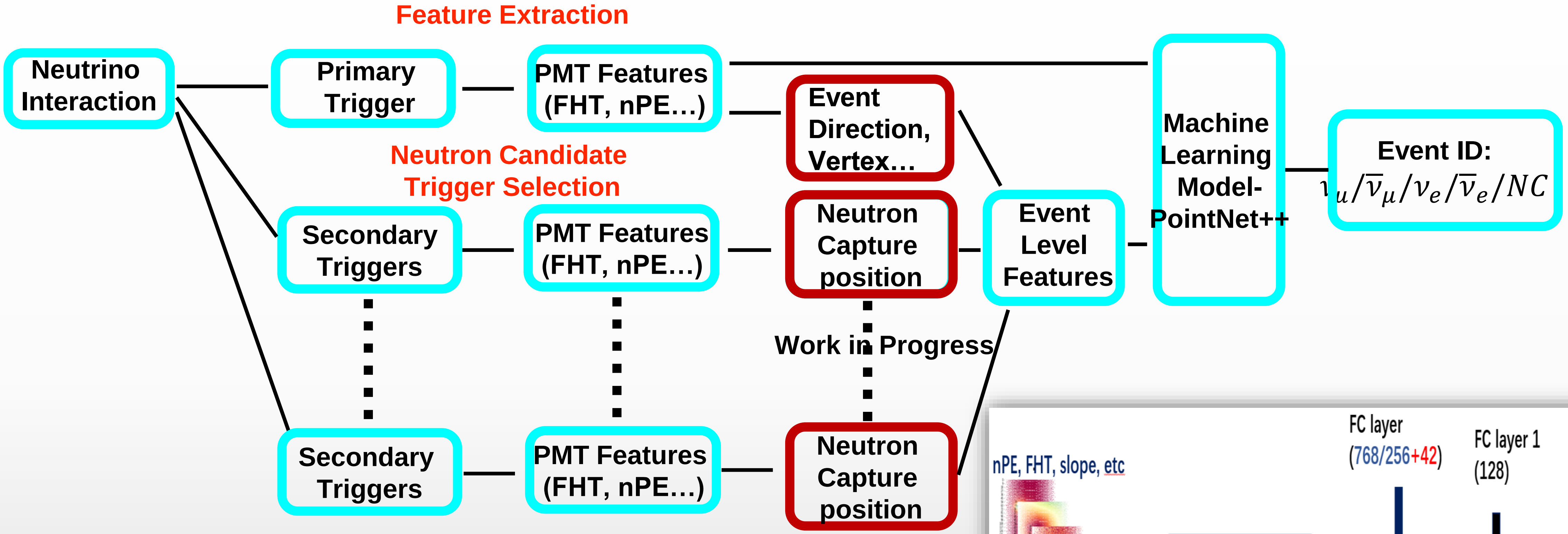
- Using only the primary trigger is difficult to identify $\nu/\bar{\nu}$
- The difference in neutrons produced by Atm $\nu/\bar{\nu}$ helps to identify
- Neutrons create Atm $\nu/\bar{\nu}$ events' secondary triggers



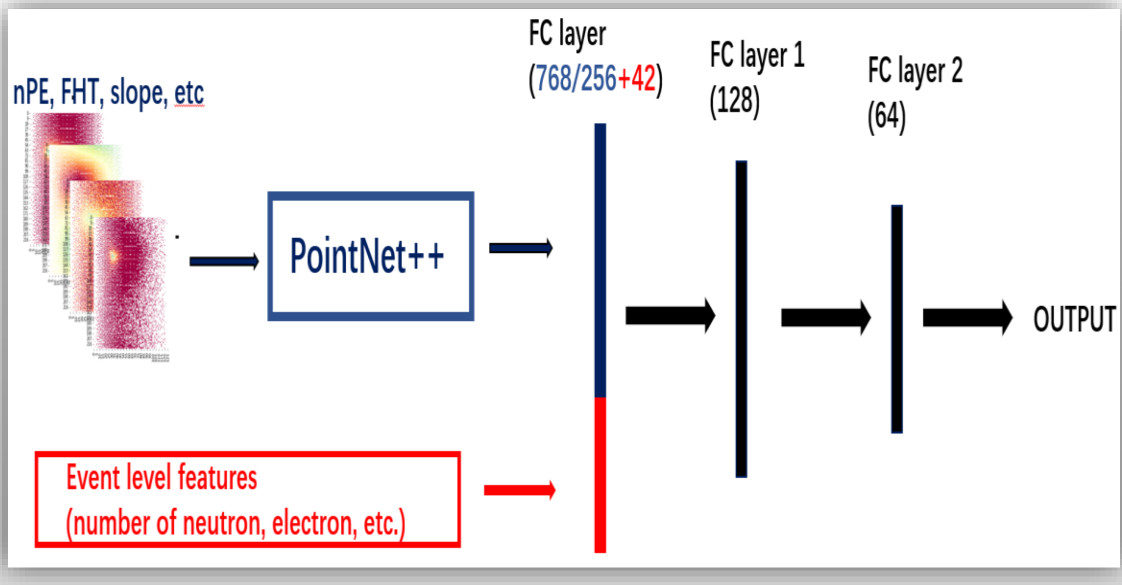




Number of neutrons in different type

# Method1



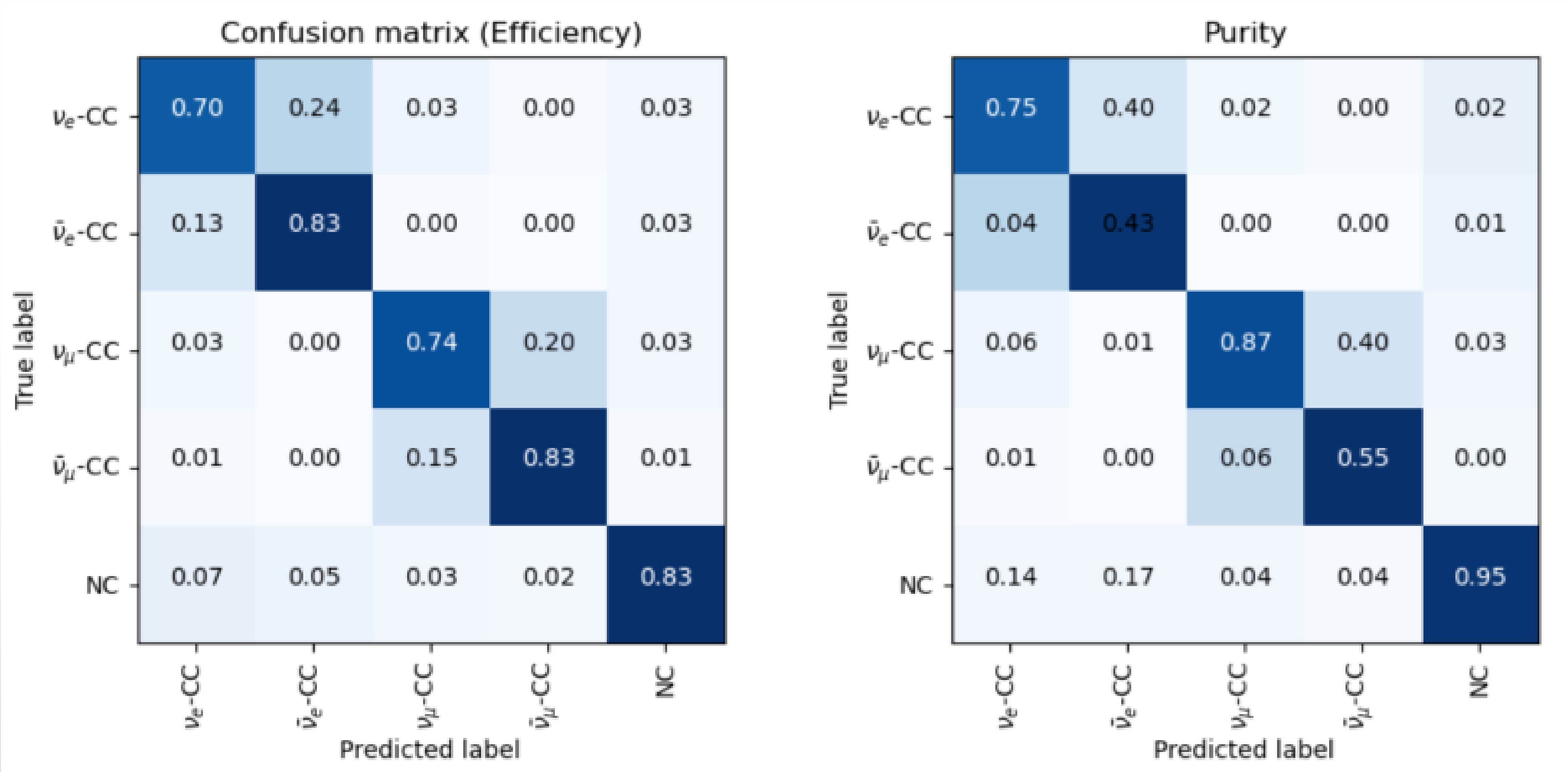

- **Method 1**: Combine the PMT-level features with event-level features (neutron-multiplicity, relative positions of neutrons to event vertex/directions, etc. ).




PointNet++

# 5 classification

- PointNet+




(inputs: PMT features +truth neutron variables)

# Method2

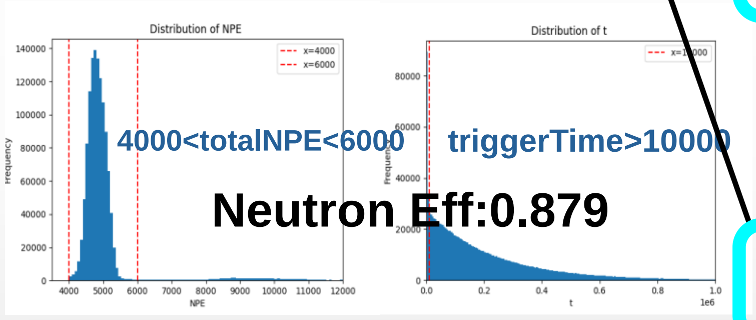
**Feature Extraction**

Neutrino Interaction — Primary Trigger — PMT Features (FHT, nPE…) — Machine Learning Model-DeepSphere — Event ID: $\nu_\mu/\bar{\nu}_\mu/\nu_e/\bar{\nu}_e/NC$

**Neutron Candidate Trigger Selection**

Neutrino Interaction — Secondary Triggers — PMT Features (FHT, nPE…) — Machine Learning Model-DeepSphere

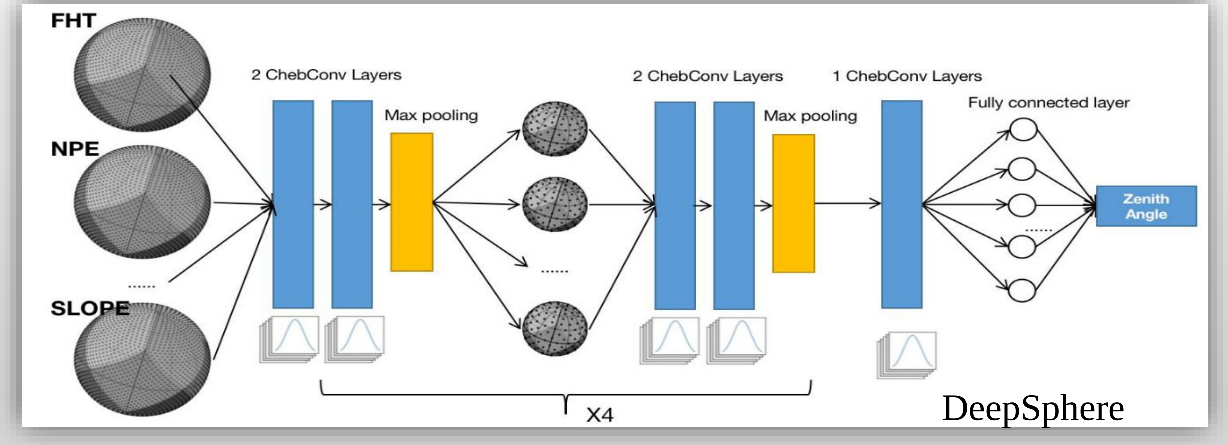
Neutrino Interaction — Secondary Triggers — PMT Features (FHT, nPE…)

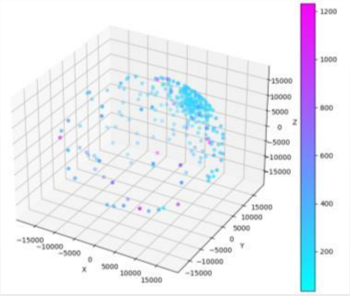


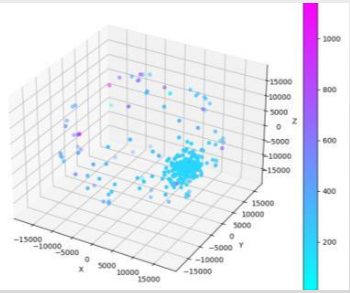

4000<totalNPE<6000

triggerTime>10000

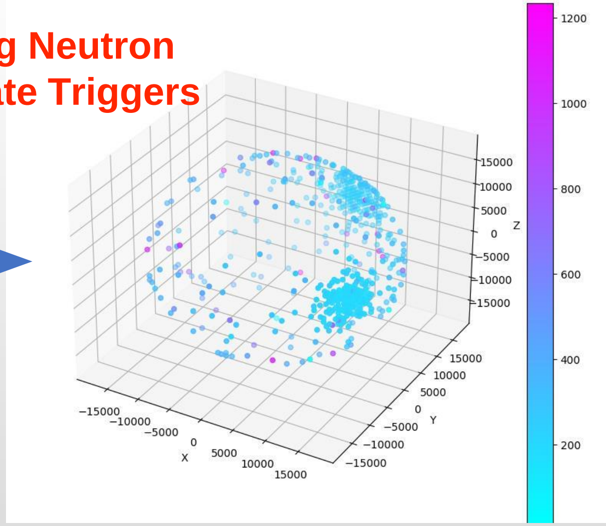
**Neutron Eff:0.879**



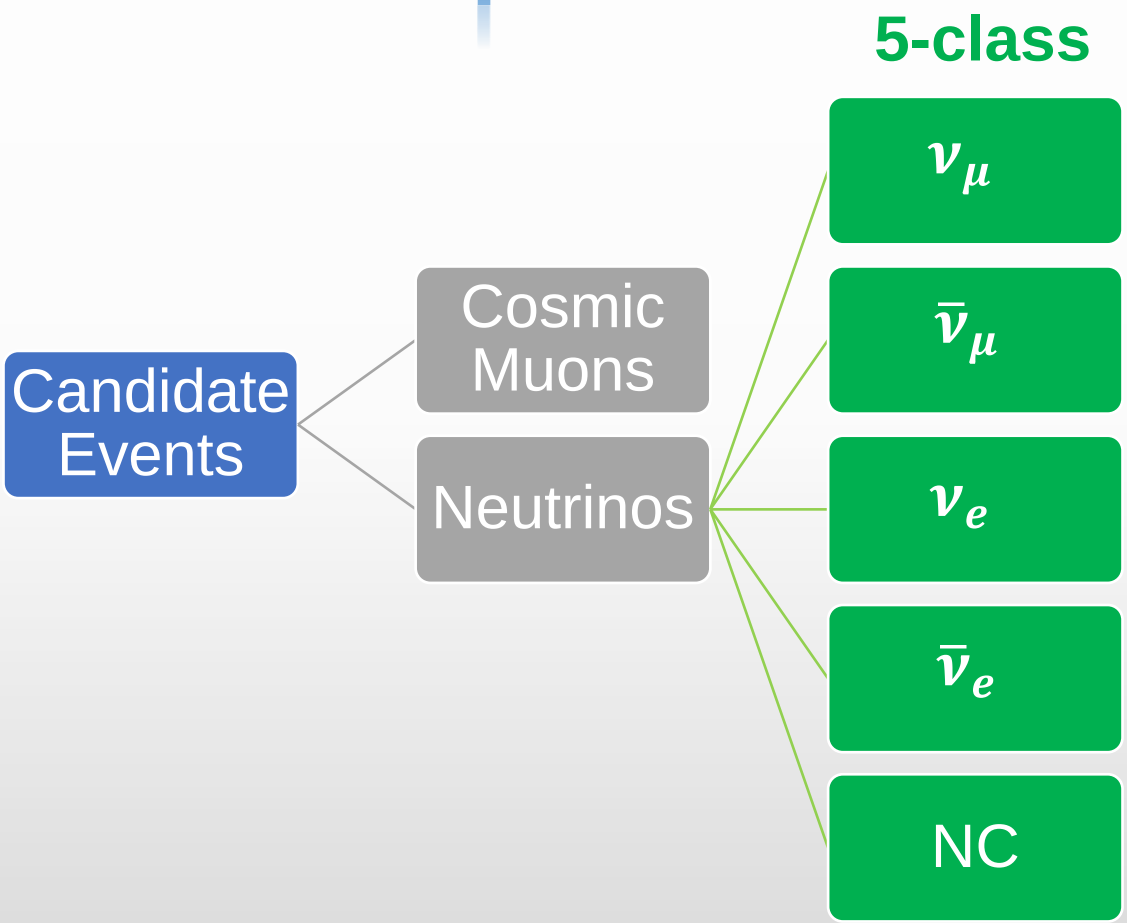


**Merging Neutron Candidate Triggers**

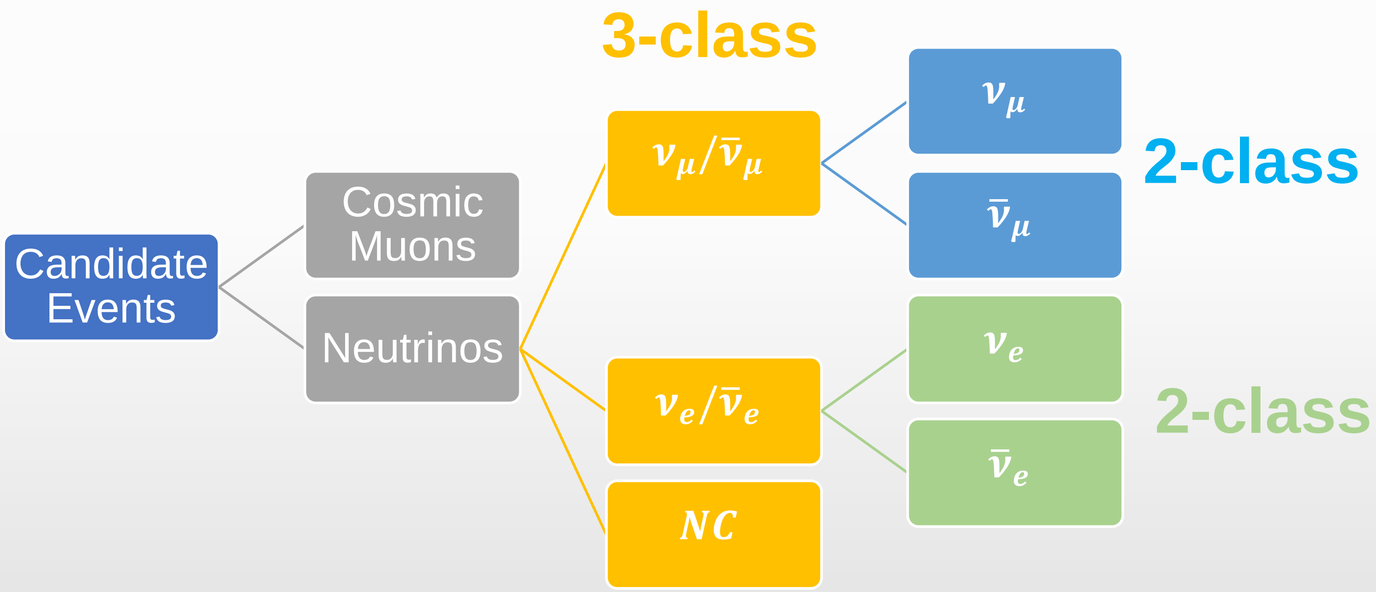


# Method2

1


5-class
$\nu_\mu$
$\bar{\nu}_\mu$
$\nu_e$
$\bar{\nu}_e$
NC
Candidate Events
Cosmic Muons
Neutrinos

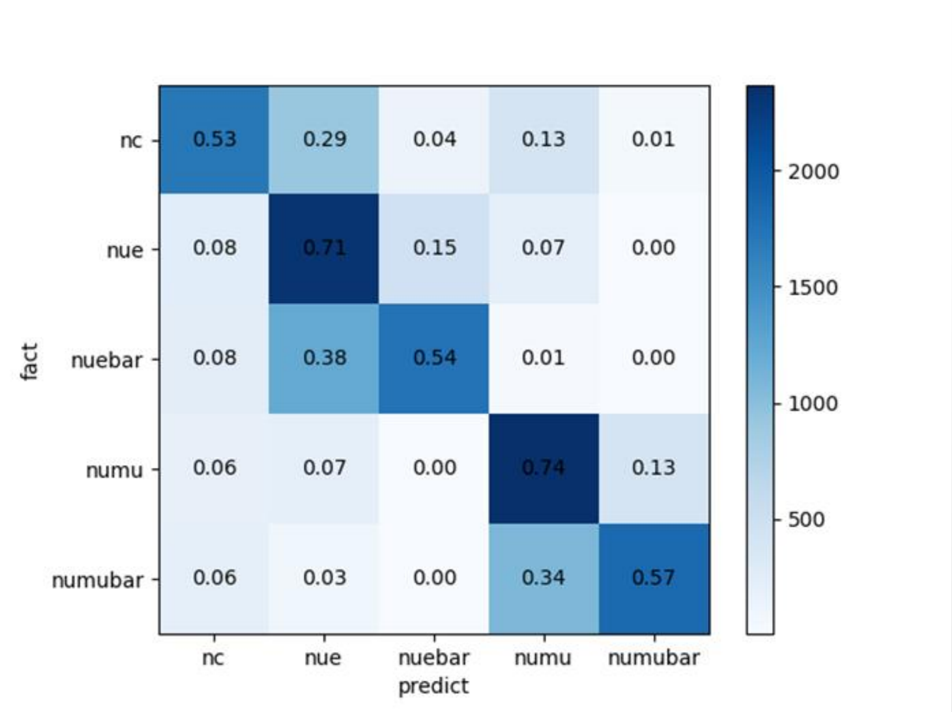
2


3-class
Candidate Events
Cosmic Muons
Neutrinos
$\nu_\mu/\bar{\nu}_\mu$
$\nu_e/\bar{\nu}_e$
$NC$
$\nu_\mu$
$\bar{\nu}_\mu$
2-class
$\nu_e$
$\bar{\nu}_e$
2-class

# Results: 5 classfication

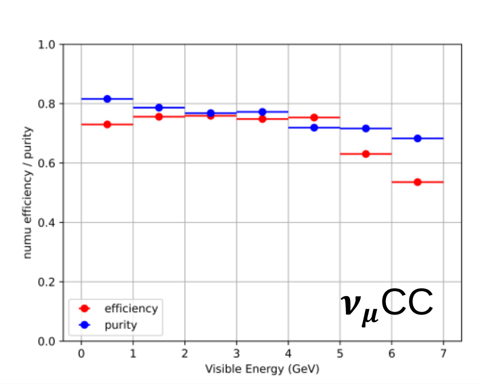
- ➢ Evis>0.5,TotalPE>7*10^5
- ➢ Feature:fht,npe,slope,nperatio,mediantime

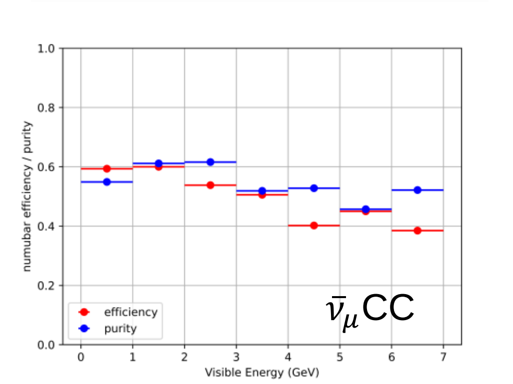
**fhtn,npen**

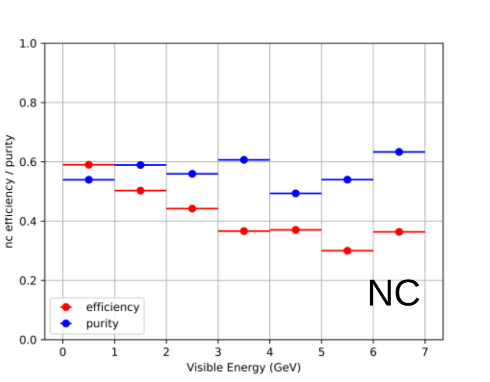


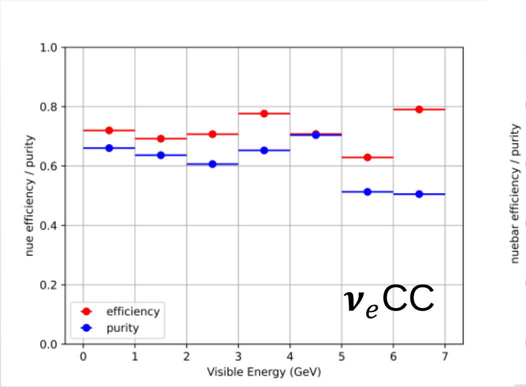

**efficiency**

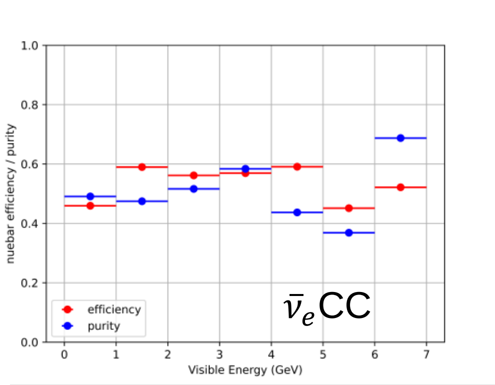
➢ Efficiency/Purity vs Visible Energy



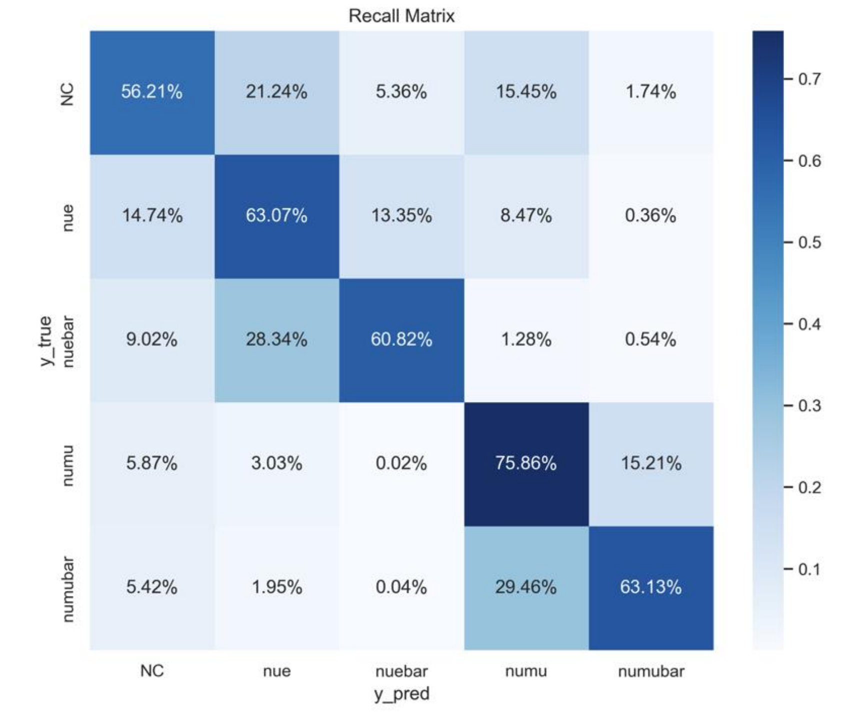




- Overall $\nu_\mu$ efficiency: 74%; purity: 79%
- Overall $\bar{\nu}_\mu$ efficiency: 57%; purity 58%
- Overall $\nu_e$ efficiency: 71%; purity: 64%
- Overall $\bar{\nu}_e$ efficiency: 54%; purity 49%

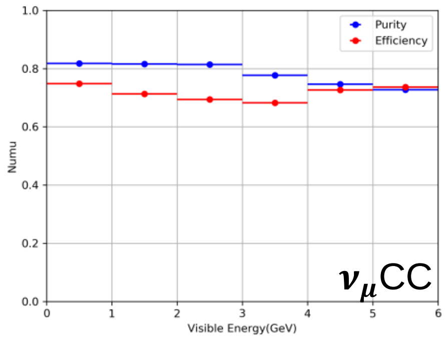
# Results:3+2+2 classfication

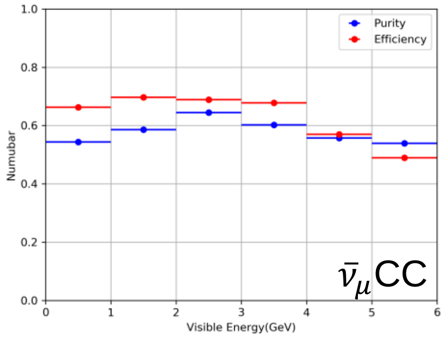
- Evis>0.5
- Feature:fht,npe,slope,nperatio,mediantime
  **fhtn,npen**

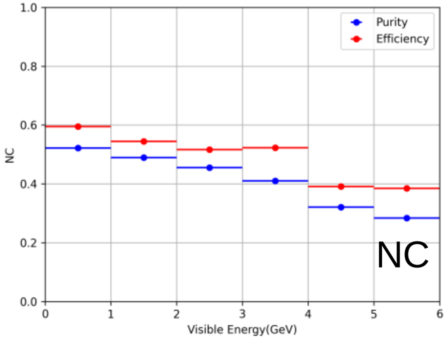
**efficiency**

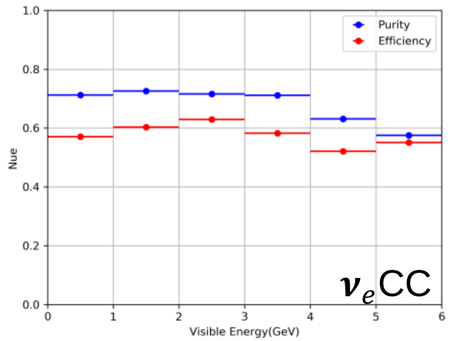


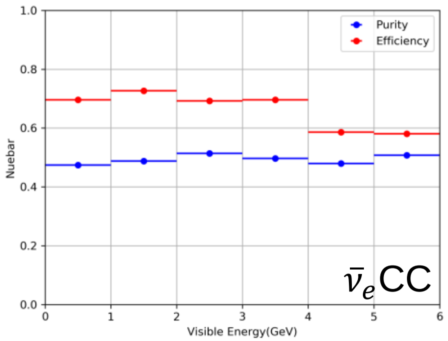

- Efficiency/Purity vs Visible Energy



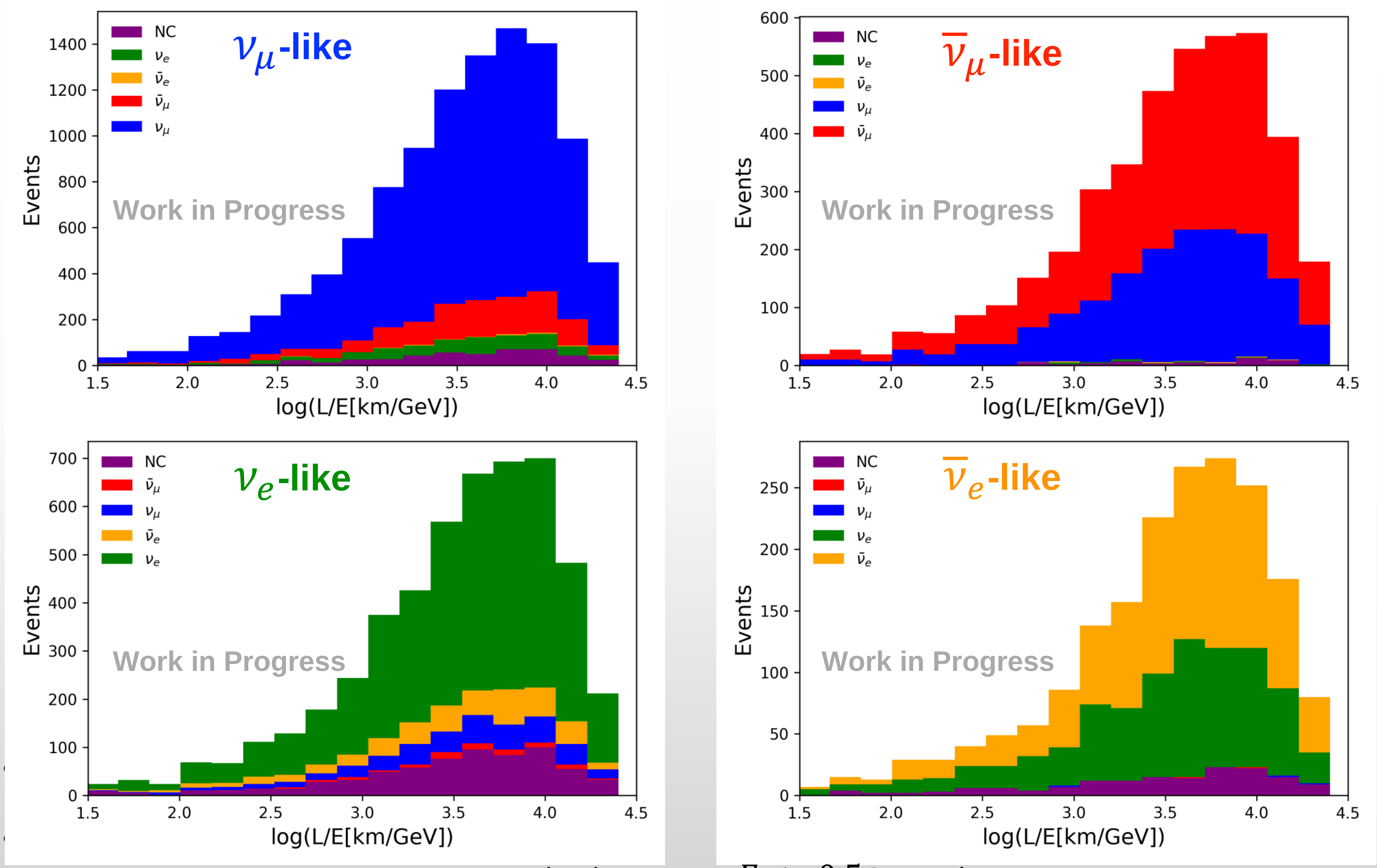




- Overall $\nu_\mu$ efficiency: 76%; purity: 79%
- Overall $\bar{\nu}_\mu$ efficiency: 63%; purity 59%
- Overall $\nu_e$ efficiency: 63%; purity: 69%
- Overall $\bar{\nu}_e$ efficiency: 61%; purity 53%

# Results




Upward-going events, $E_\nu > 0.5$GeV only

# Summary

- ✓ **In this talk, we presented a multi-purpose machine learning approach for the identification of atmosphere neutrino events in large unsegmented LS detectors**
- ✓ **Flavors of atmospheric neutrinos are identified with good efficiency and purity**
- ✓ **Combined with directionality and energy reconstruction, we aim to perform the first atmospheric neutrino oscillation measurement in an LS detector in the world, and increase JUNO's total sensitivity to NMO**

- **Next:**
- Further model optimization needed

Thanks!

# BACKUPS

3+2+2 classification with optimization

efficiency

purity