

# Neutrino Interactions and Deep Learning

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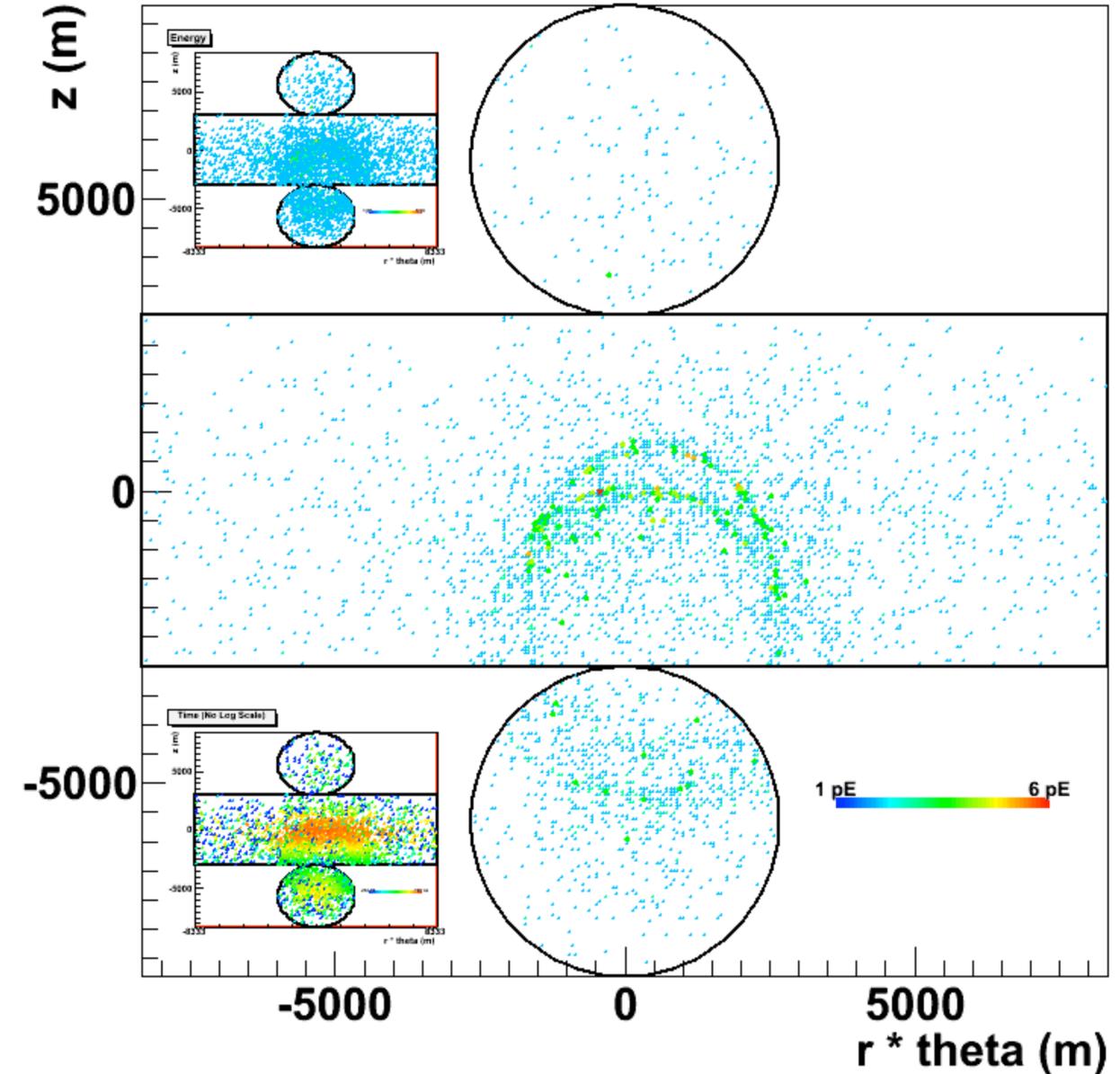
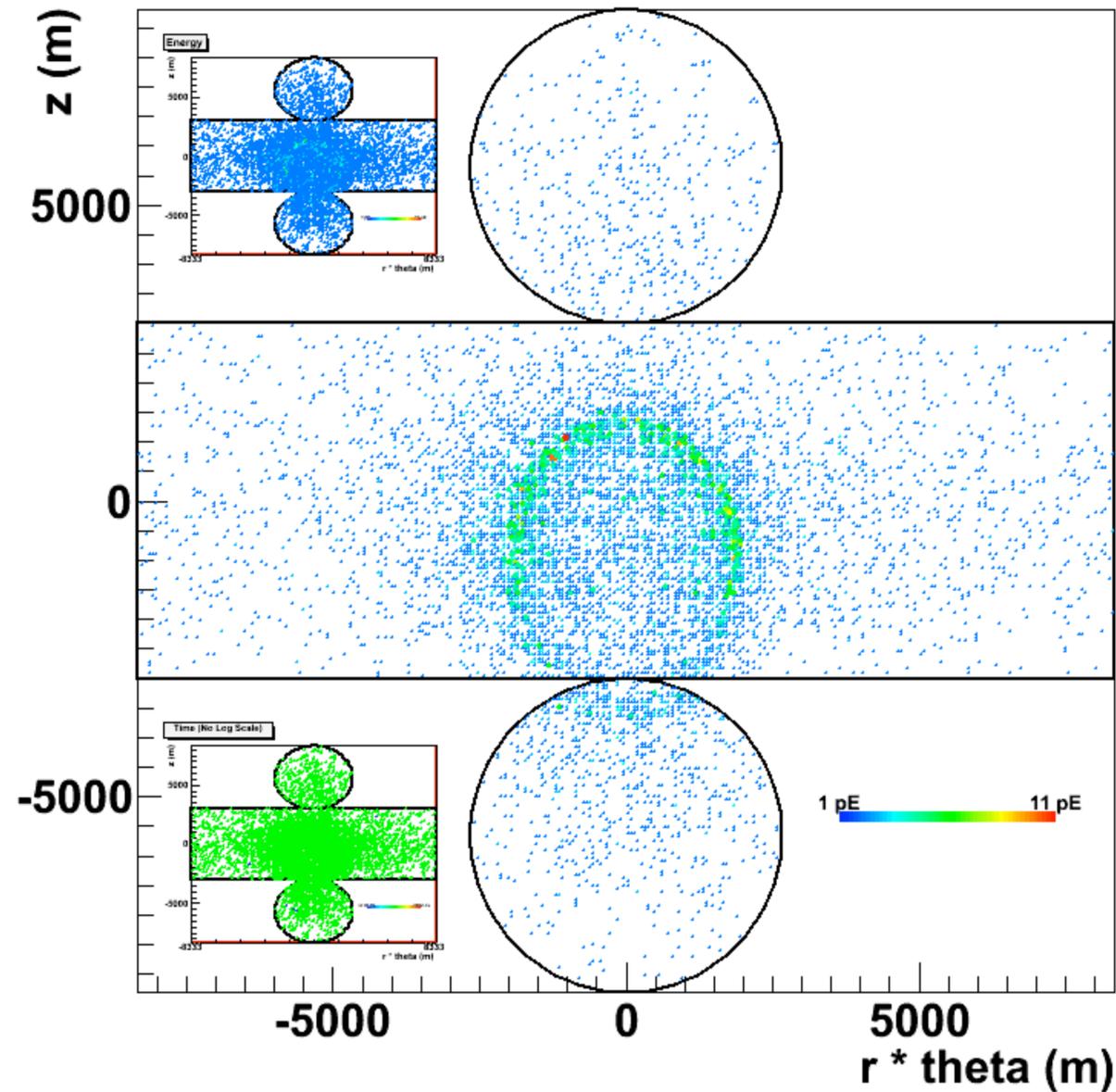
vSTEP2024 @ Hangzhou

# Disclaimer

- Limited and biased view based on personal experiences.
- More focusing on the needs for the neutrino-interaction side than deep learning.
- More focusing on the neutrino physics in few-GeV energy region.

# A little bit of History: “Hand Scan”

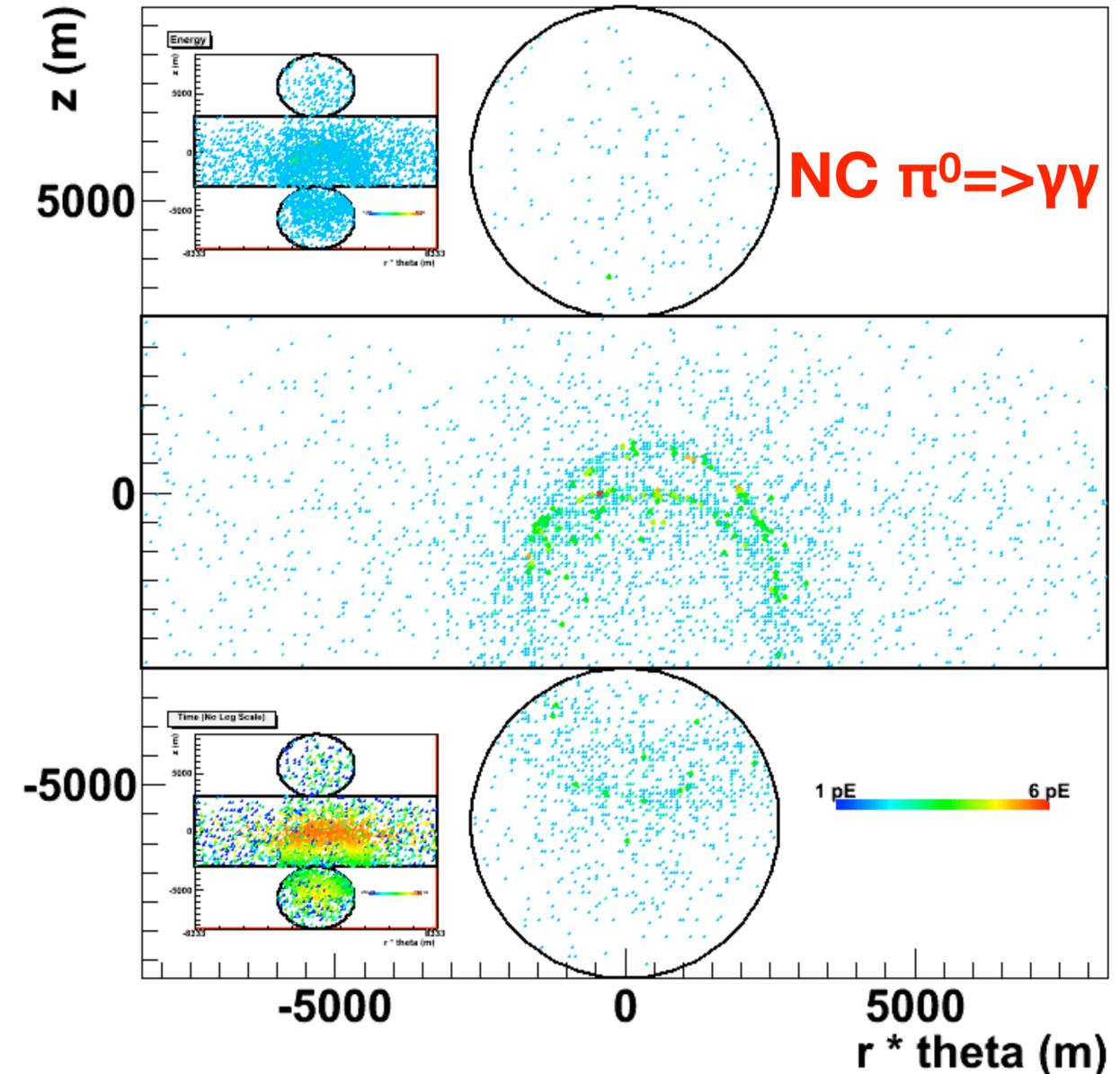
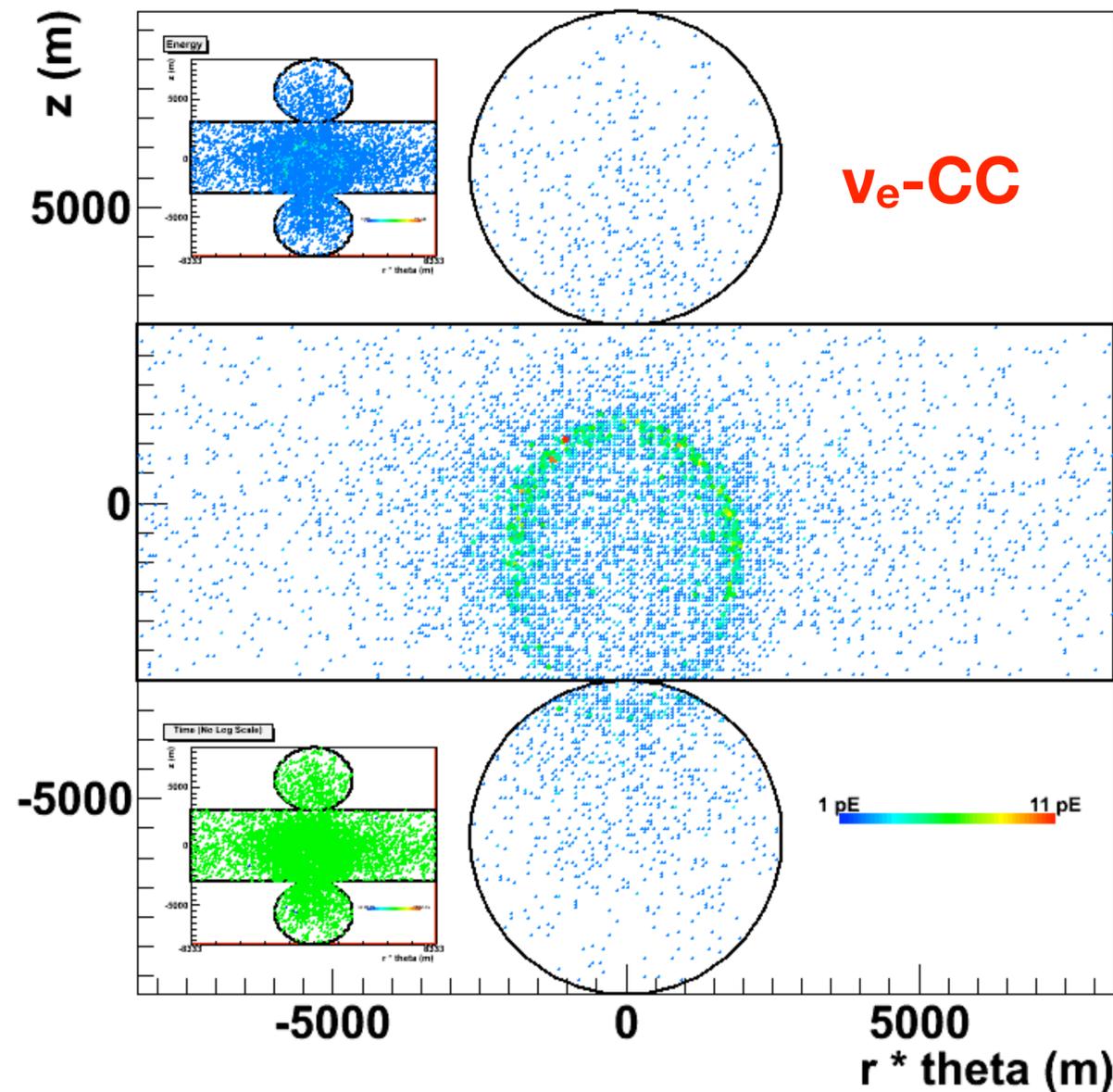
H. Duyang, TIPP 2011: “A Scan Study of  $\nu_e$ -CC and NC Event Simulated in the LBNE Water Cherenkov Detector”



- Question: which is a  $\nu_e$ -CC interaction and which is a NC?

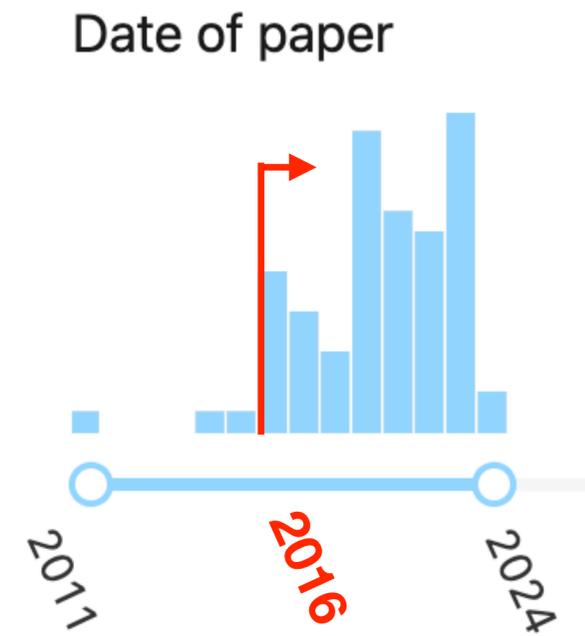
# A little bit of History: “Hand Scan”

H. Duyang, TIPP 2011: “A Scan Study of  $\nu_e$ -CC and NC Event Simulated in the LBNE Water Cherenkov Detector”



- Historically, large number of event display pictures are hand-scanned (by innocent students) to search for signal in data or estimate the detector’s performance at the early stage of detector design.
- I personally scanned tens of thousands of such pictures for the water Cherenkov design of FD for the LBNE experiment (now known as DUNE).

# “Neutrino interactions and deep learning” in Inspire

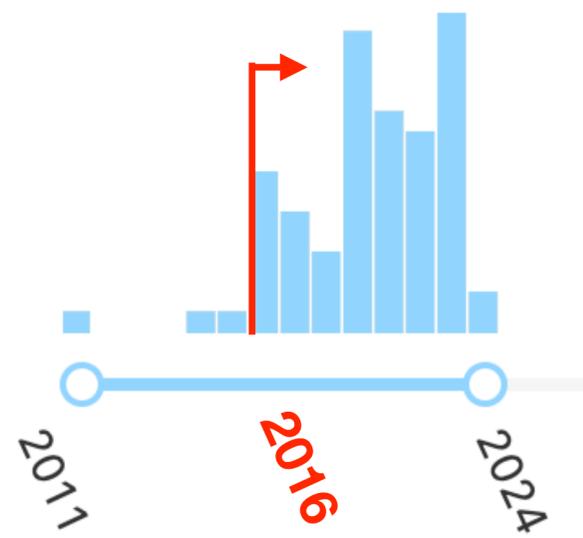


**Explosion of literatures since 2016**

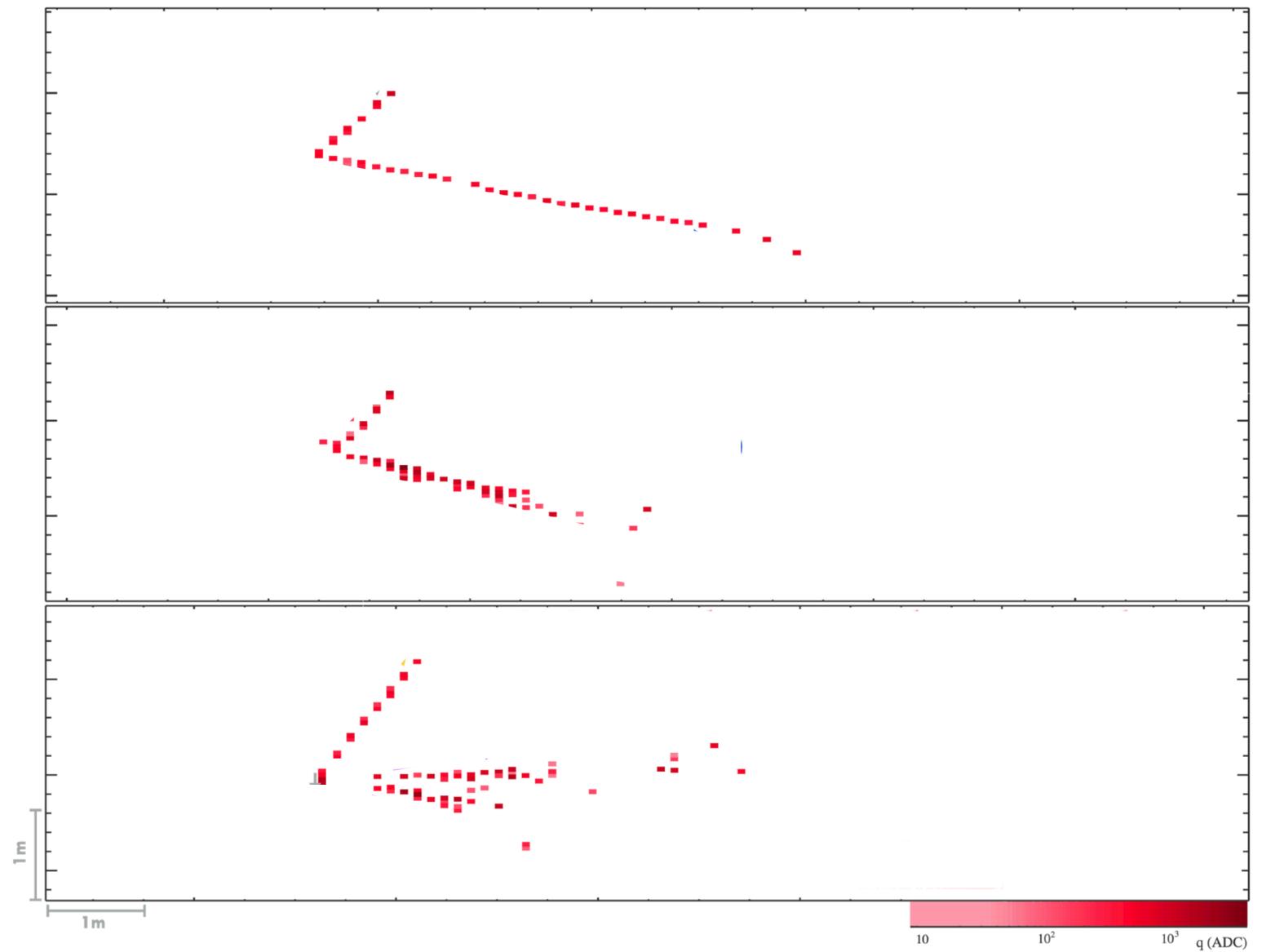
Searching result for “Neutrino interactions and deep learning” in inspire

# DL Applications in Neutrino Experiments: NOvA

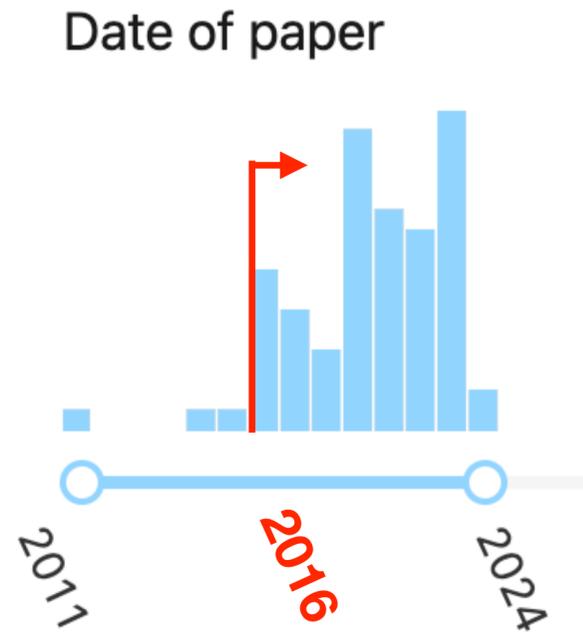
Date of paper



Searching result for “Neutrino interactions and deep learning” in inspire



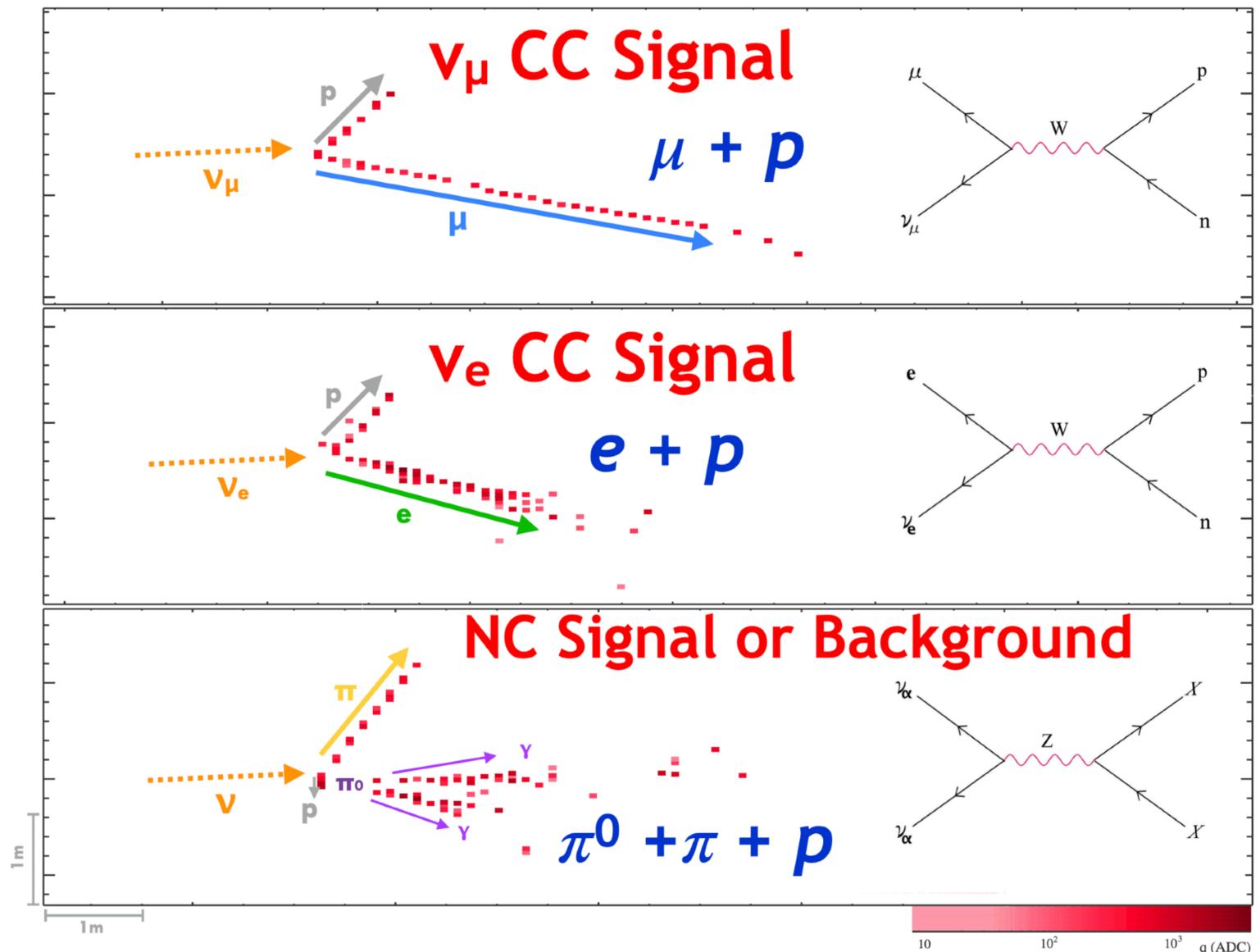
# DL Applications in Neutrino Experiments: NOvA



## Searching result for “Neutrino interactions and deep learning” in inspire

The selection criteria are chosen to maximize the figure of merit defined as  $S/\sqrt{S+B}$ , where  $S$  and  $B$  are the number of signal and background events, respectively. **The final  $\nu_e$  selection criteria select a contained appearance signal with 73.5% efficiency and 75.5% purity, representing a gain in sensitivity of 30% compared to the  $\nu_e$  classifiers used in the previously reported results [1].** These criteria also reject 97.6% of the NC and 99.0% of the  $\nu_\mu$  CC beam backgrounds. The cosmic ray backgrounds are suppressed by 7 orders of magnitude, and only  $0.53 \pm 0.14$  cosmic events are estimated to be selected in the final  $\nu_e$  appearance sample based on the performance of  $\nu_e$  selection criteria on cosmic data. Of the beam backgrounds that pass all  $\nu_e$  selection, 91% contain some form of

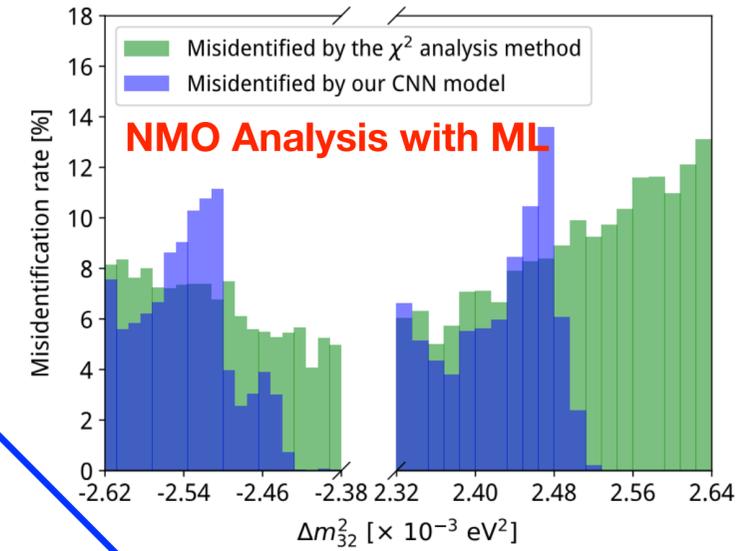
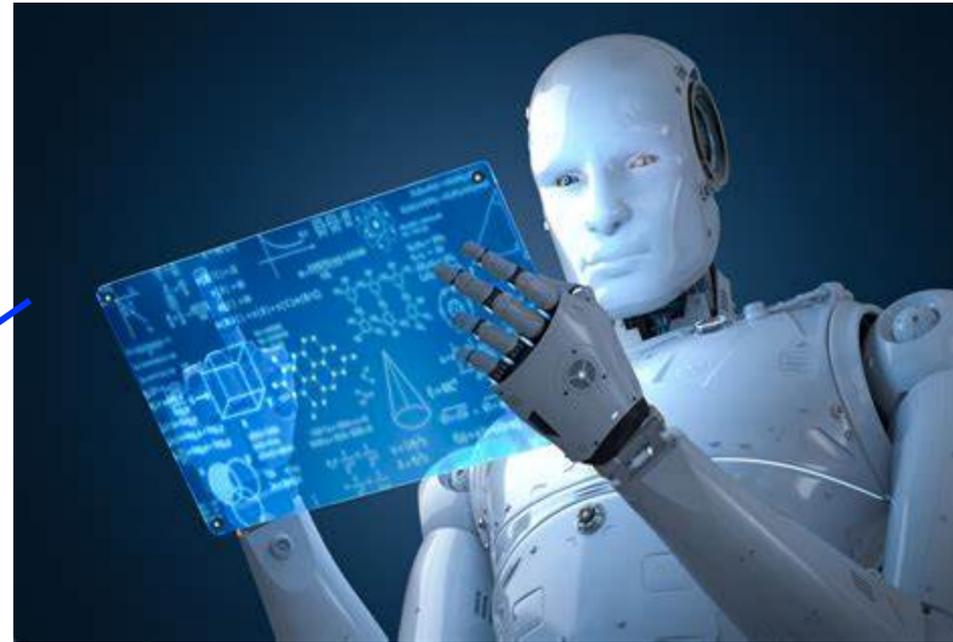
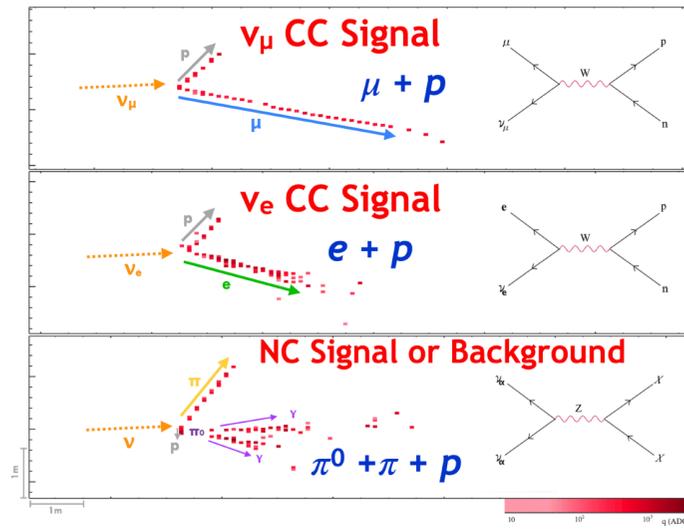
**PRL 118, 231801 (2017)**



- In 2016, NOvA pioneers in the application of **convolutional neural networks** in event classification in neutrino experiments for its  $\nu_e$ -CC appearance analysis.

# ML Applications in Neutrino Experiments

## NOvA event identification



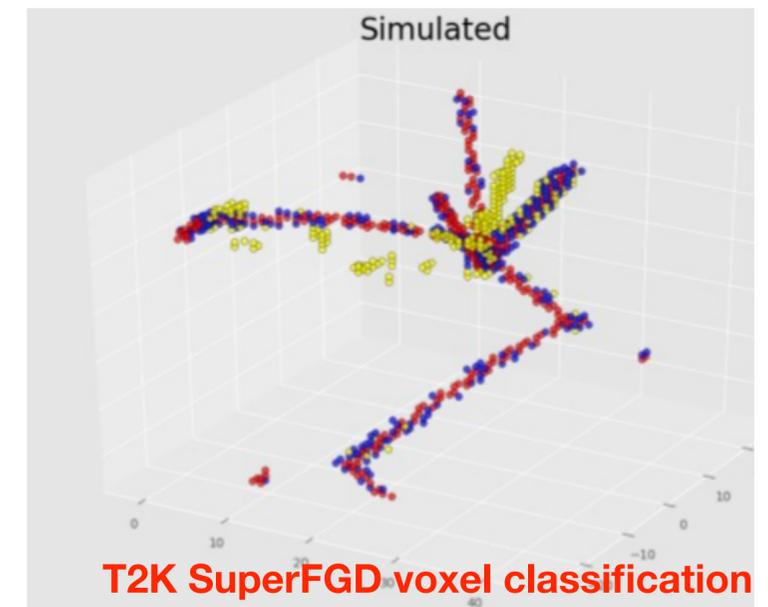
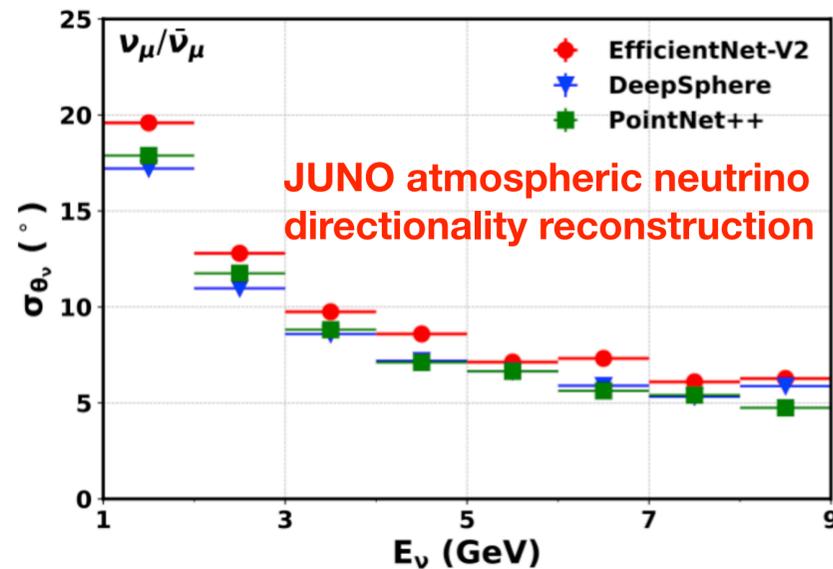
- Event/particle identification, rare event search

- Analysis

- Generative models: simulation

- Regression: Energy/momentum, direction reconstruction etc.

- clustering/tracking

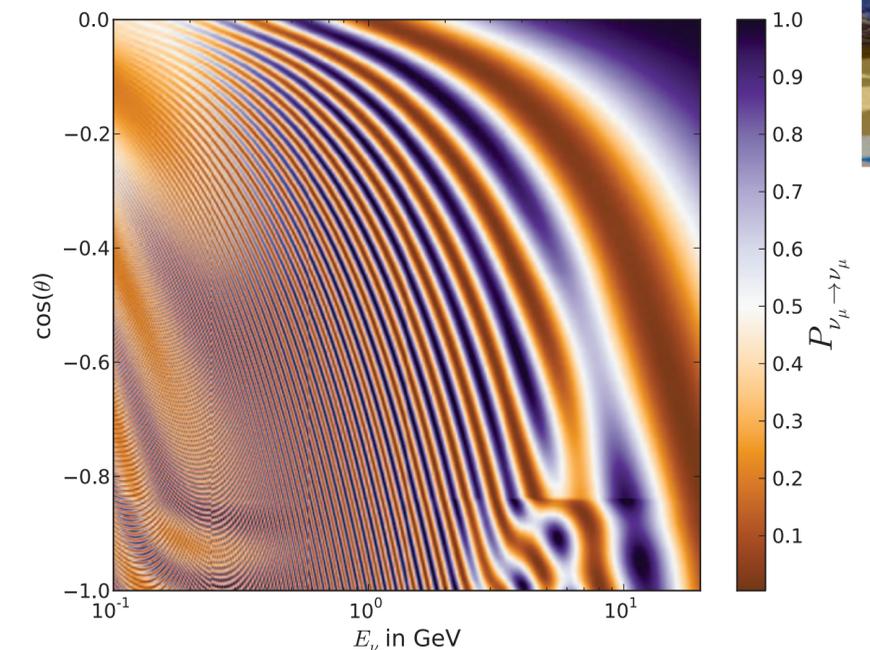
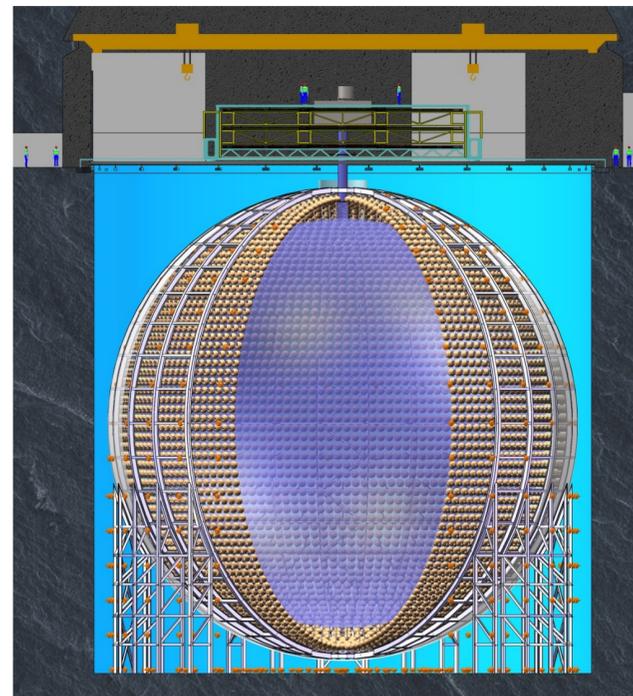
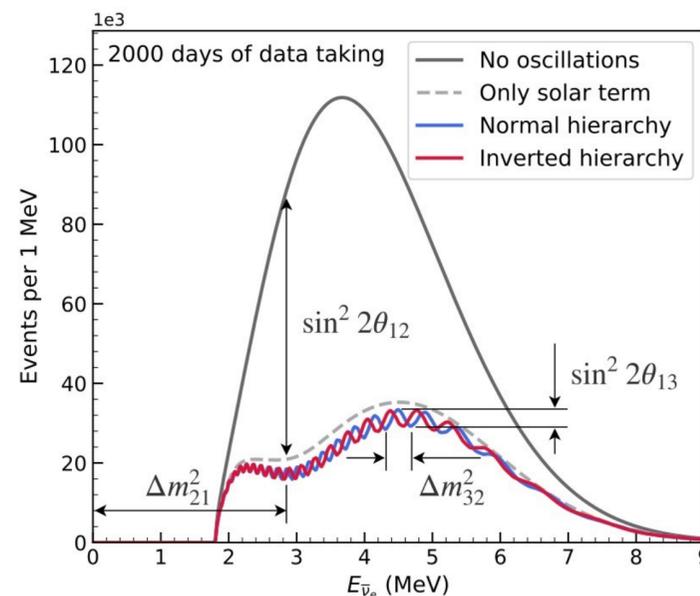
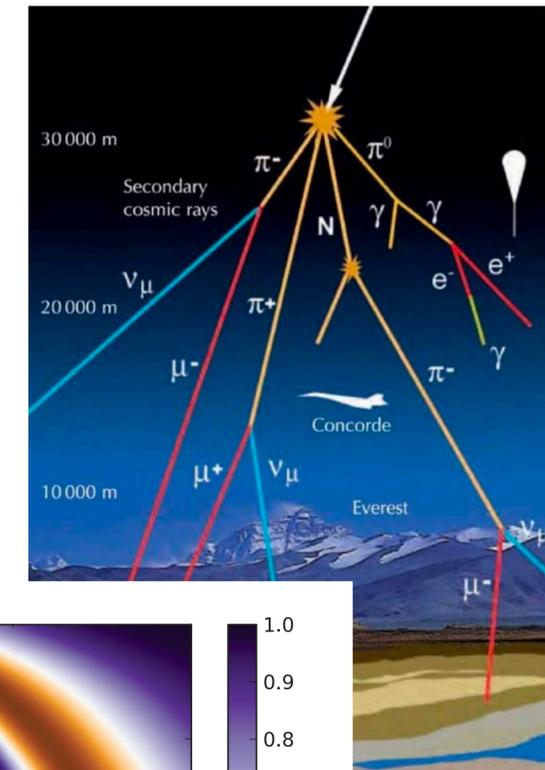


# ML Applications: JUNO Atmospheric Neutrinos



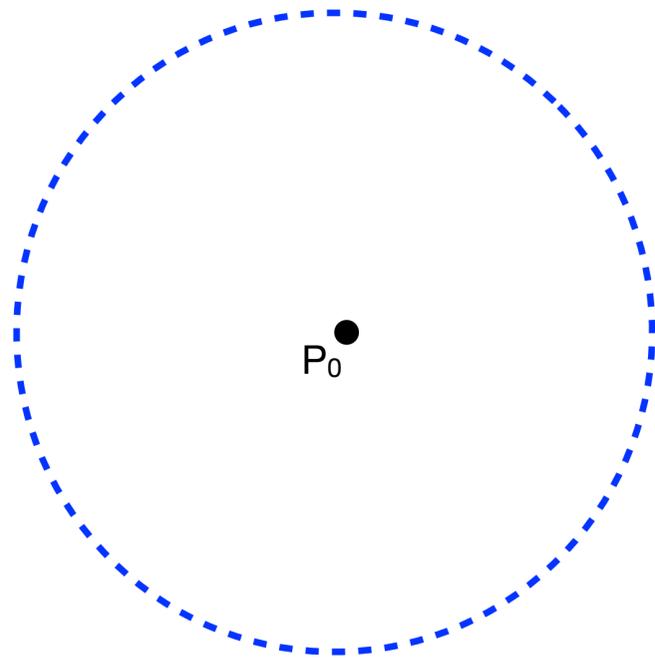
**Reactor neutrinos:  
Sensitivity to NMO via  
oscillation in vacuum**

**Atmospheric neutrinos:  
Sensitivity to NMO via  
matter effects**



- **Atmospheric neutrinos** provide independent sensitivity to NMO via matter effects (directionality and flavor identification are mandatory).
- But LS detectors have never been used for atmospheric neutrino oscillations before.
- No direct tracking or directional information.

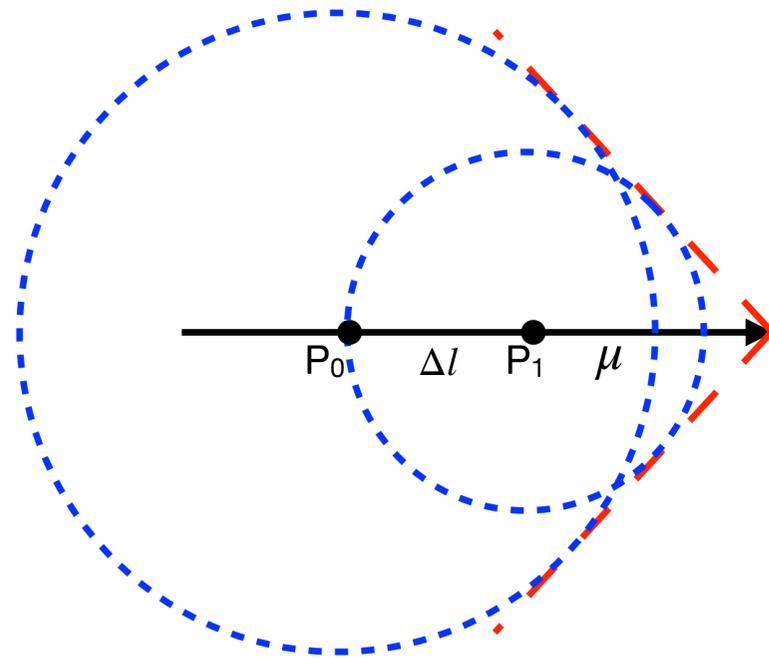
# Event Topology in PMT Waveforms



**Scintillation light from a point source is isotropic**

- PMTs at different angles wrt the track see distinct shapes of  $nPE(t)$
- Exactly how  $nPE(t)$  looks depends on:
  - Track direction;
  - Track starting and stopping points;
  - Track  $dE/dx$ ...
- Event topology information in the PMT waveform.

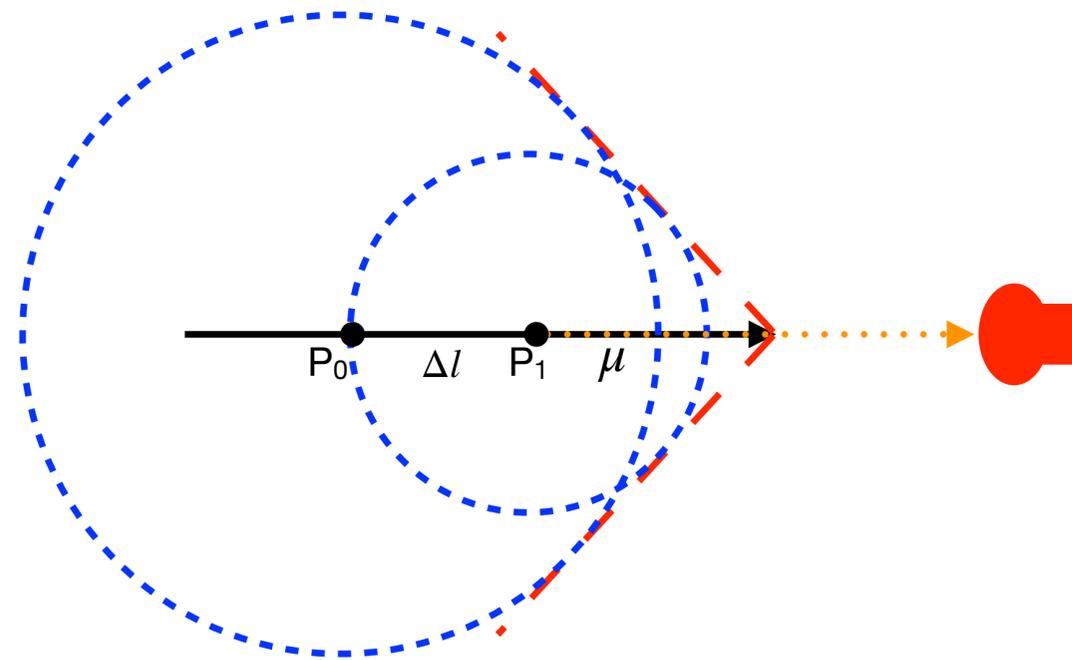
# Event Topology in PMT Waveforms



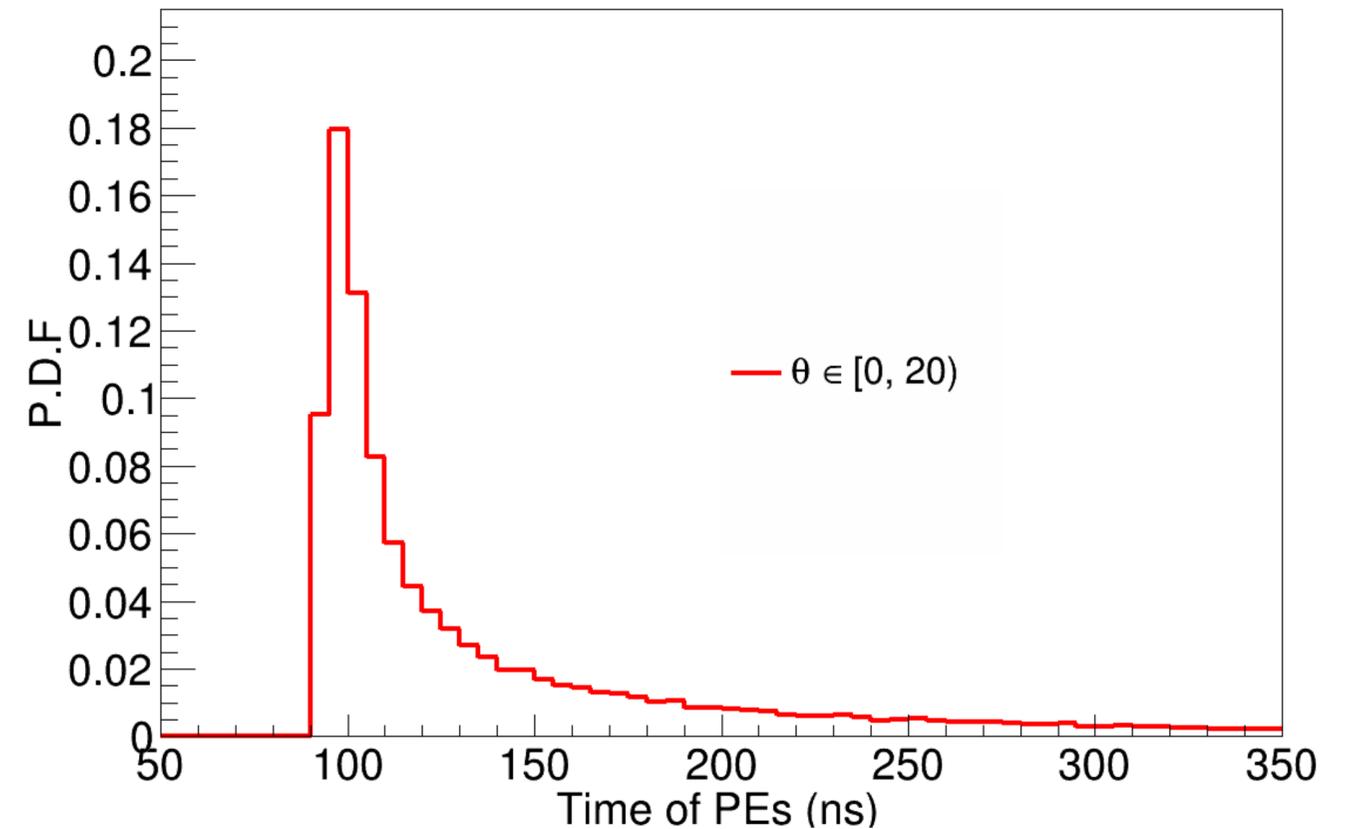
**Scintillation light photon distribution from a charged particle track in space and time is not isotropic**

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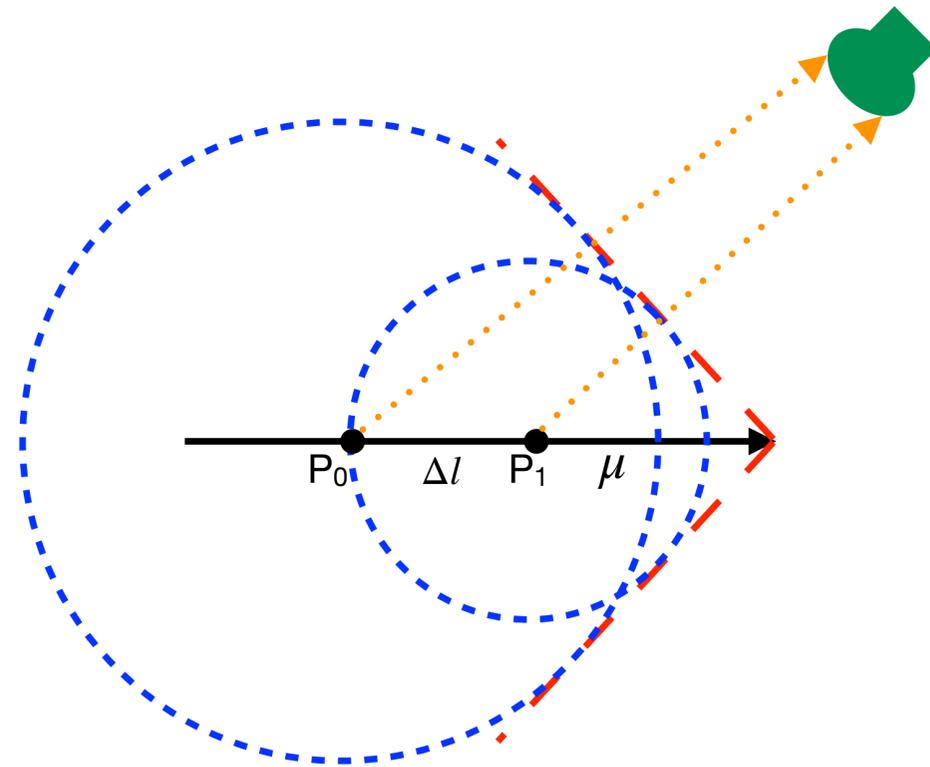


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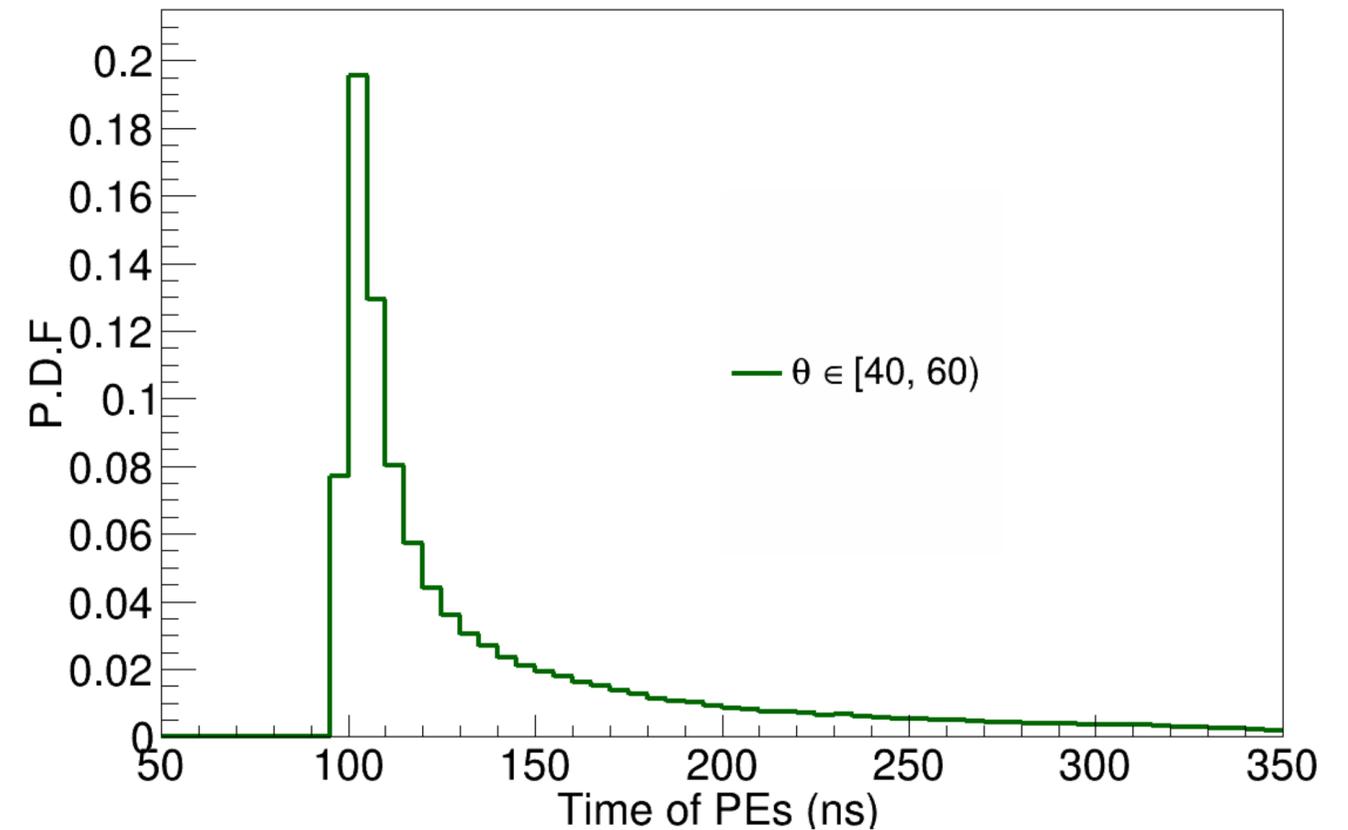


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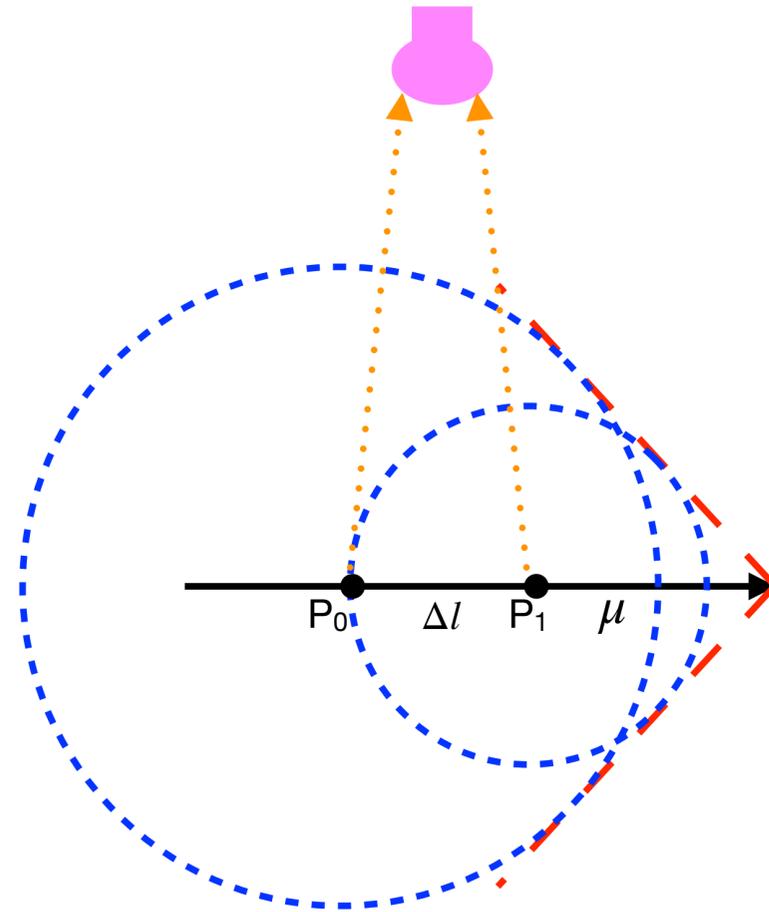


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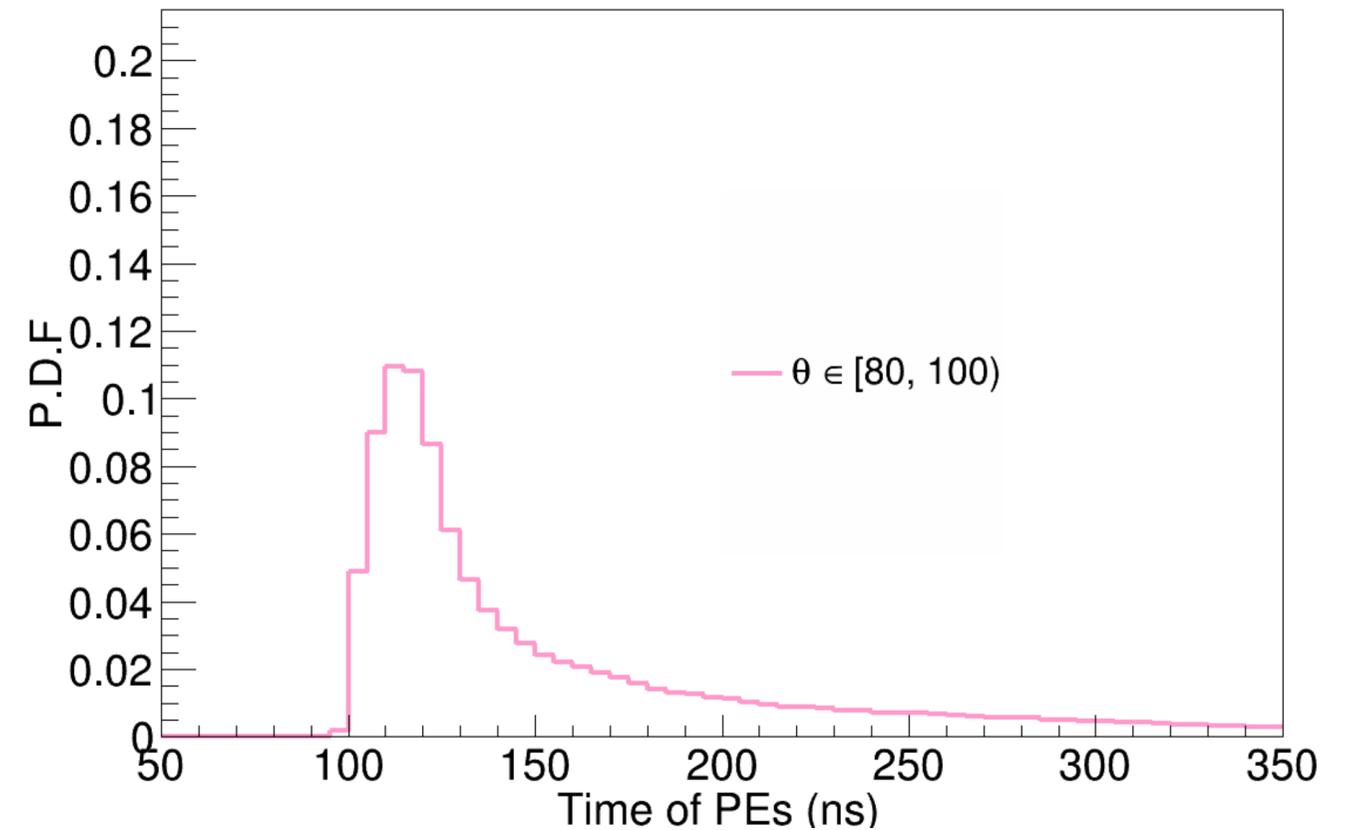


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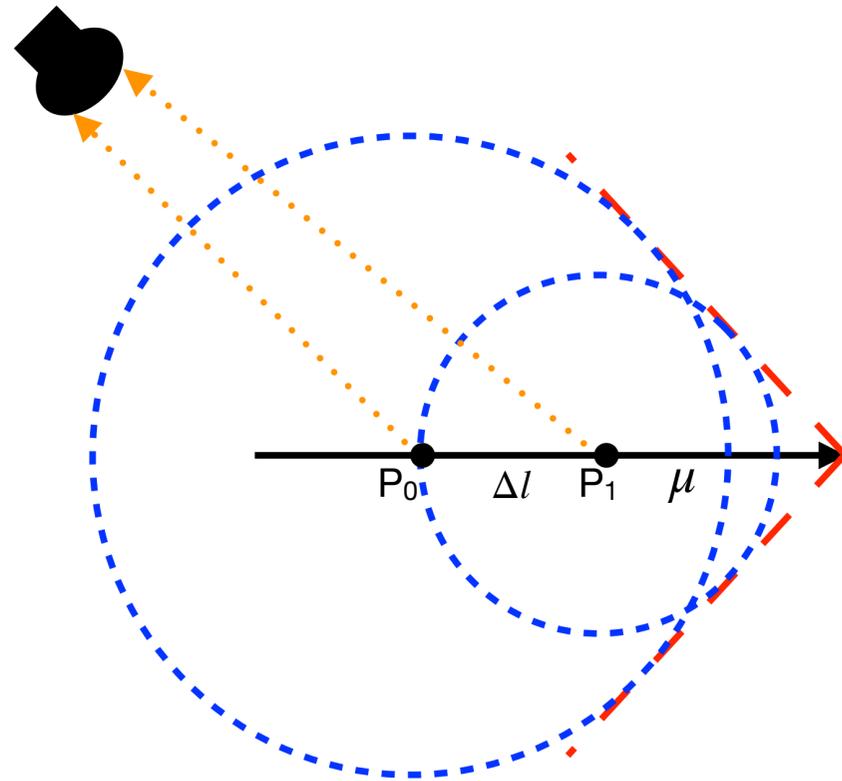


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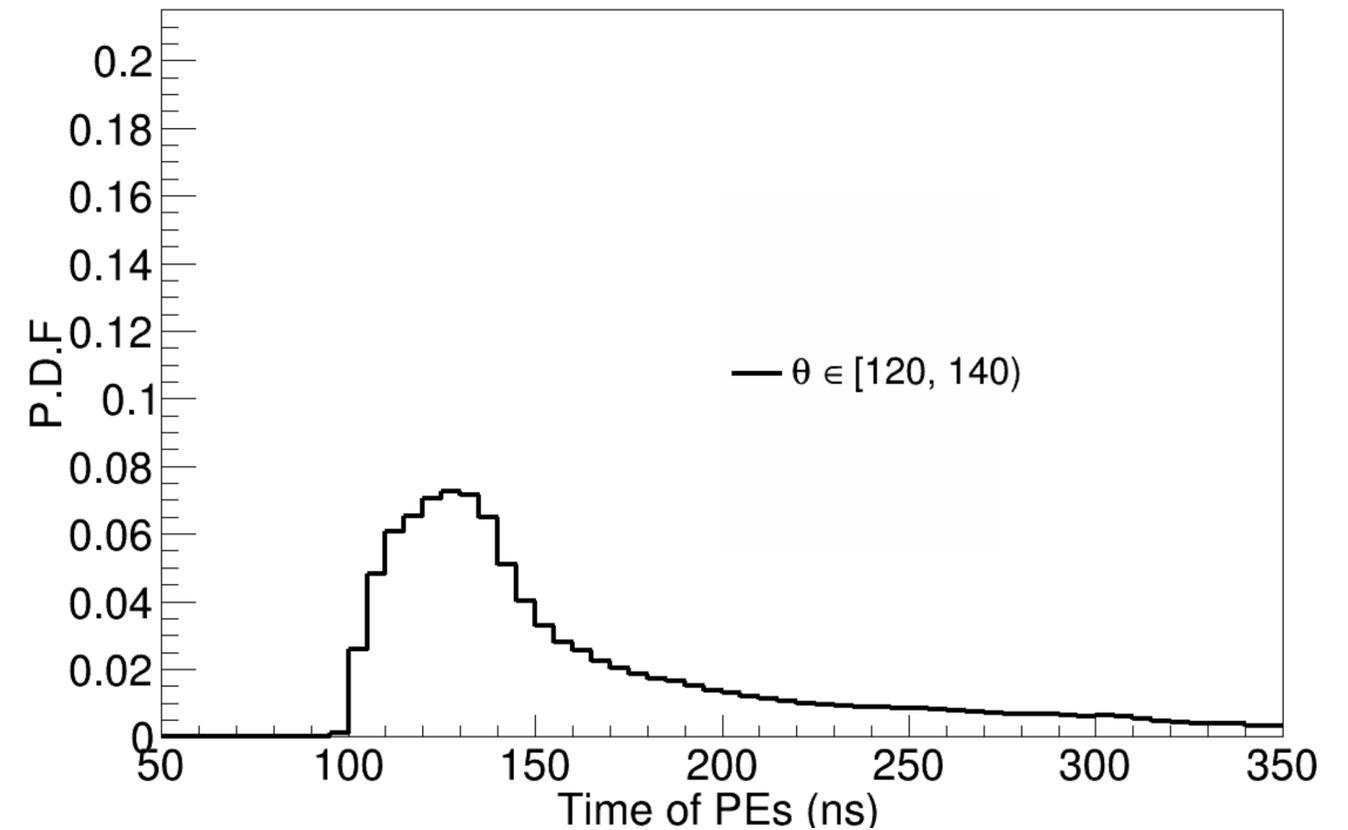


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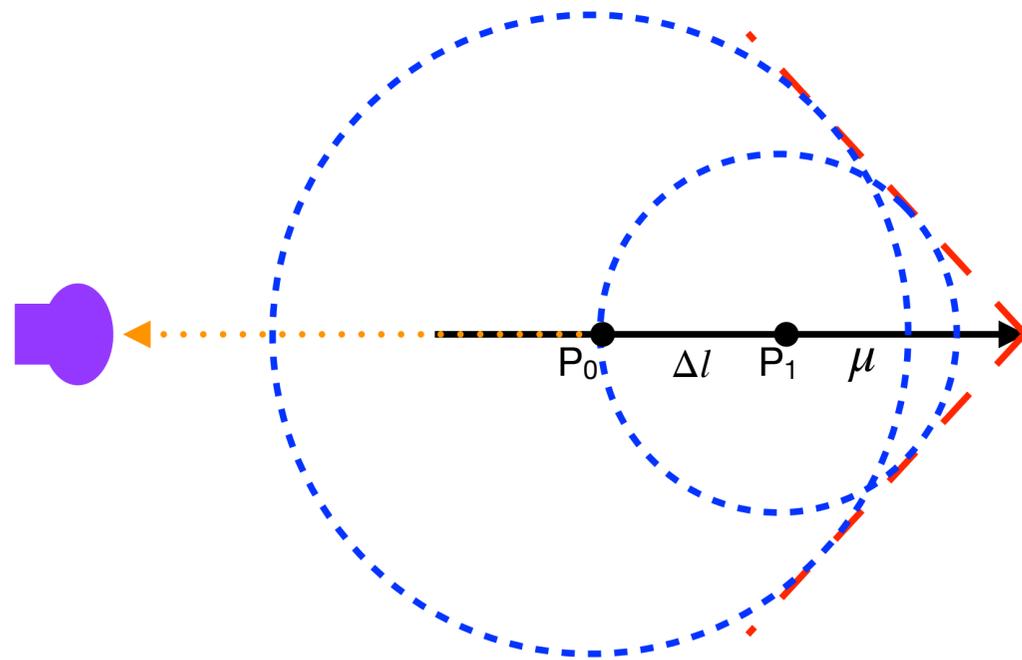


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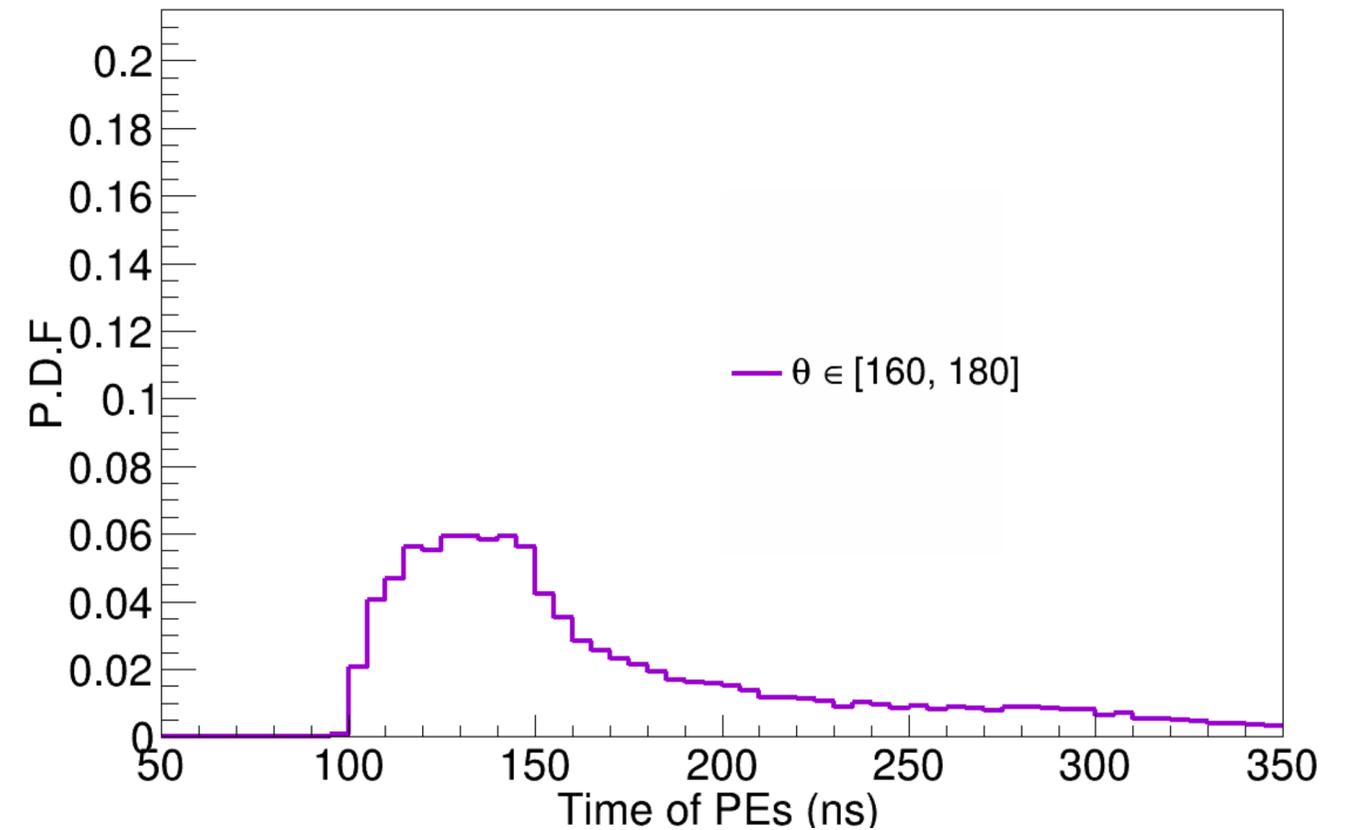


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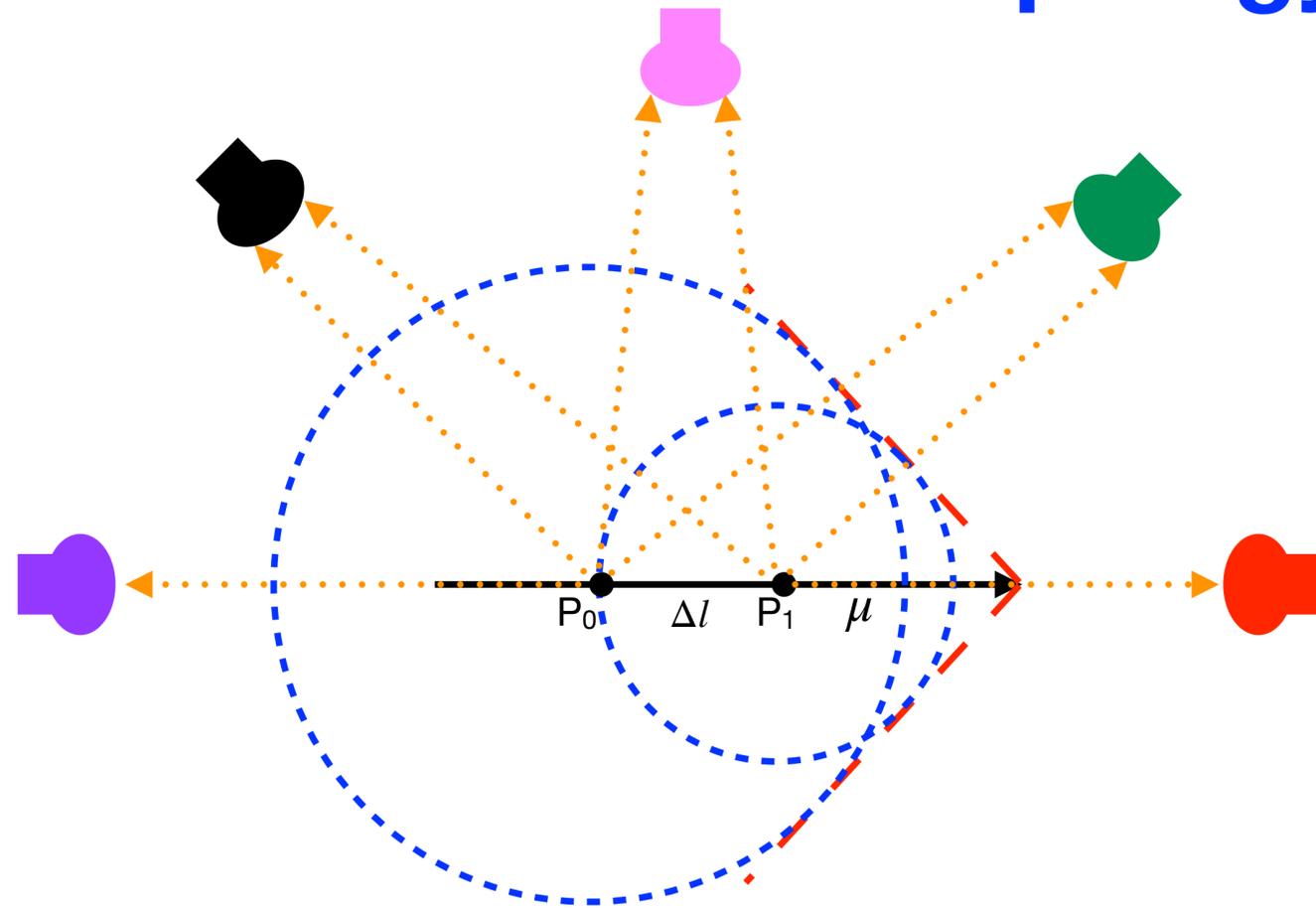


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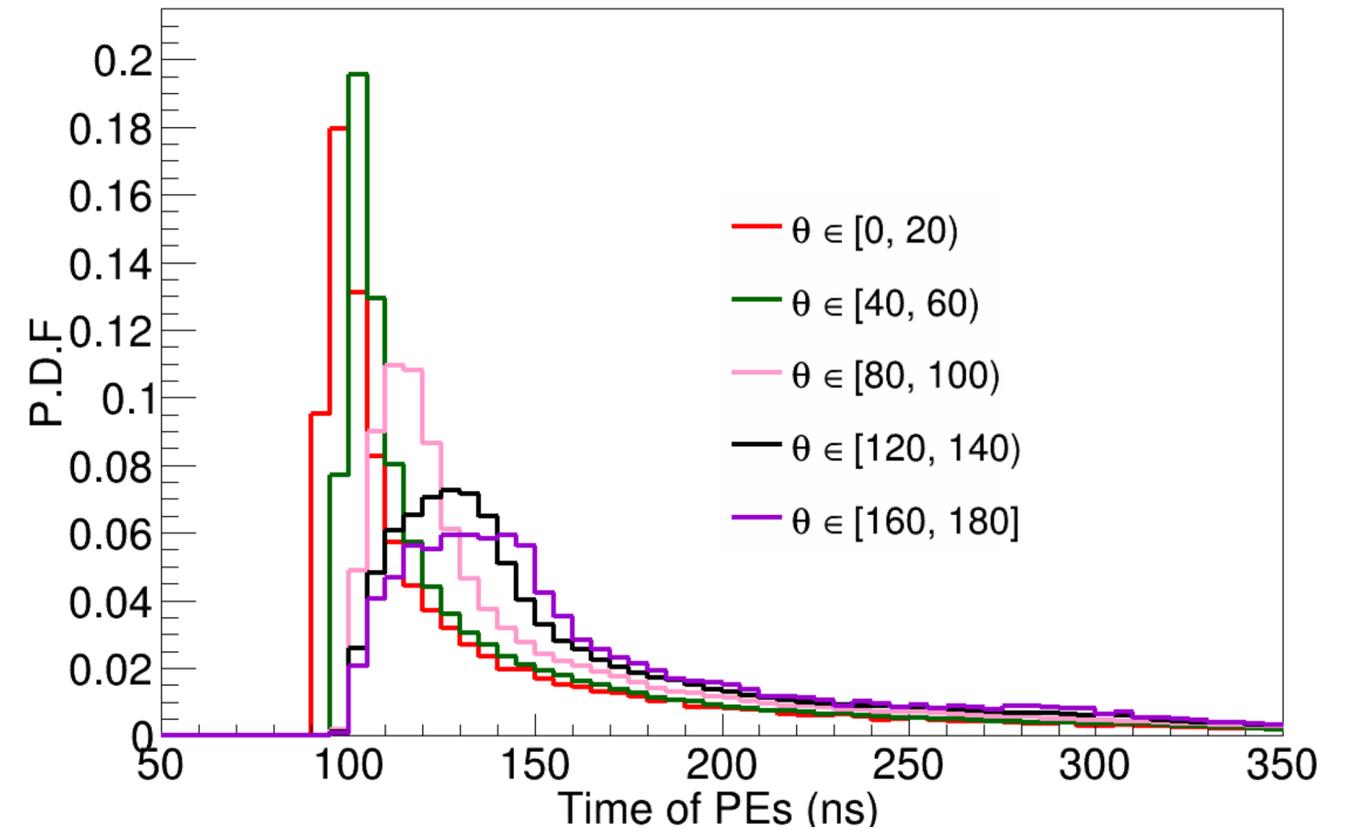


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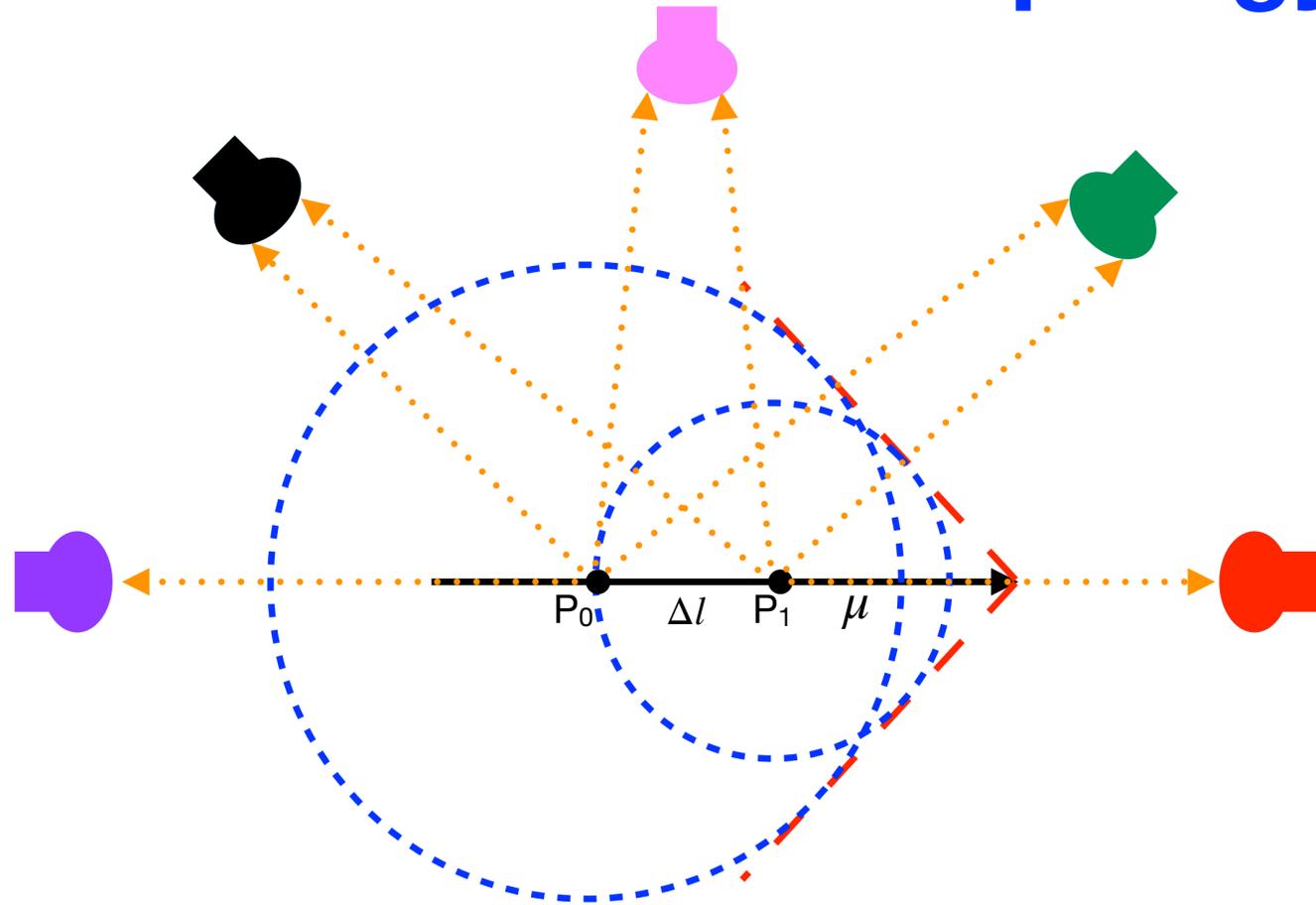


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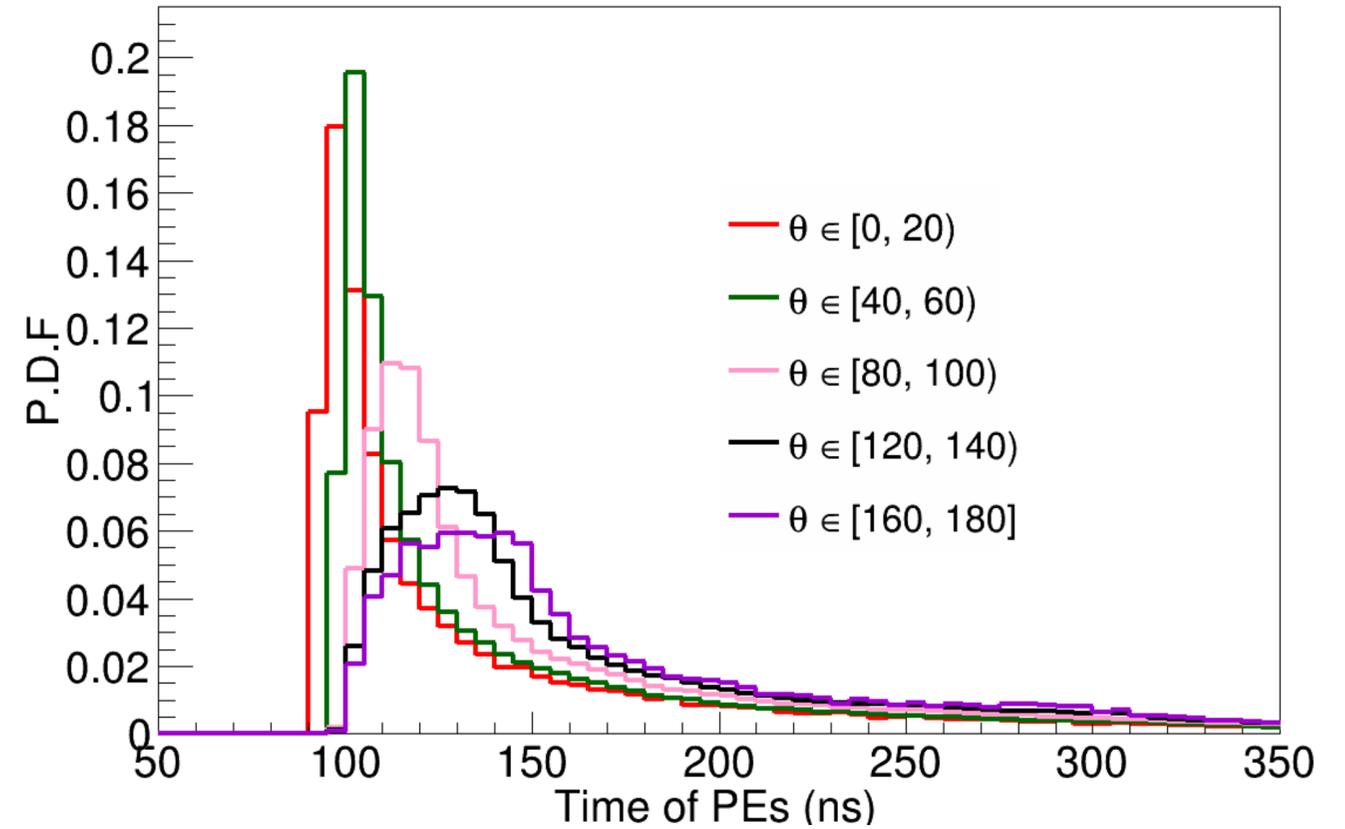


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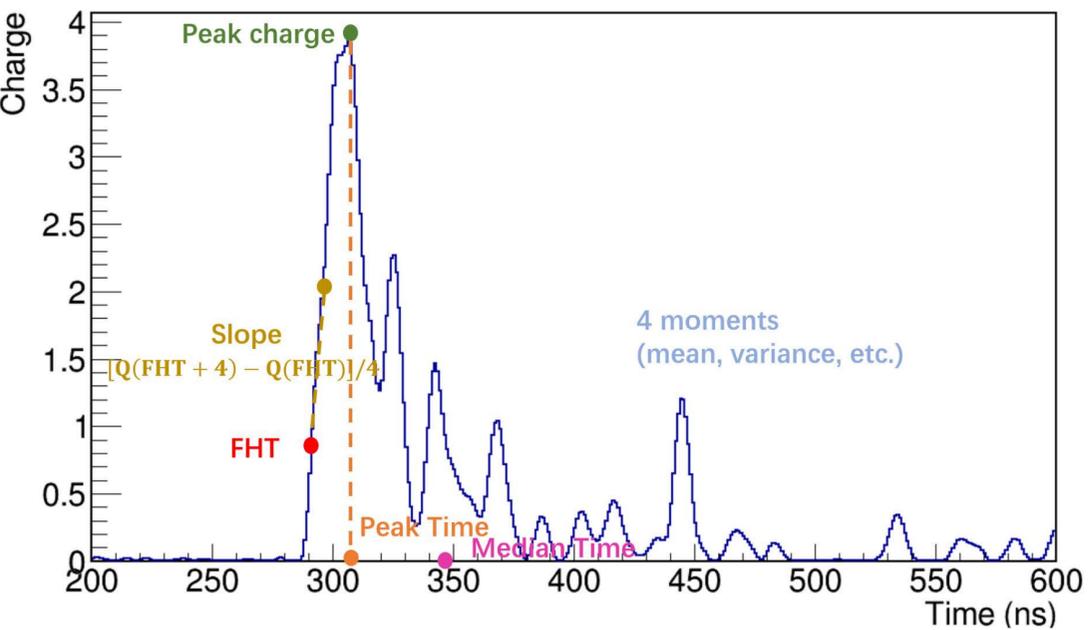
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Directionality  
Energy  
PID...

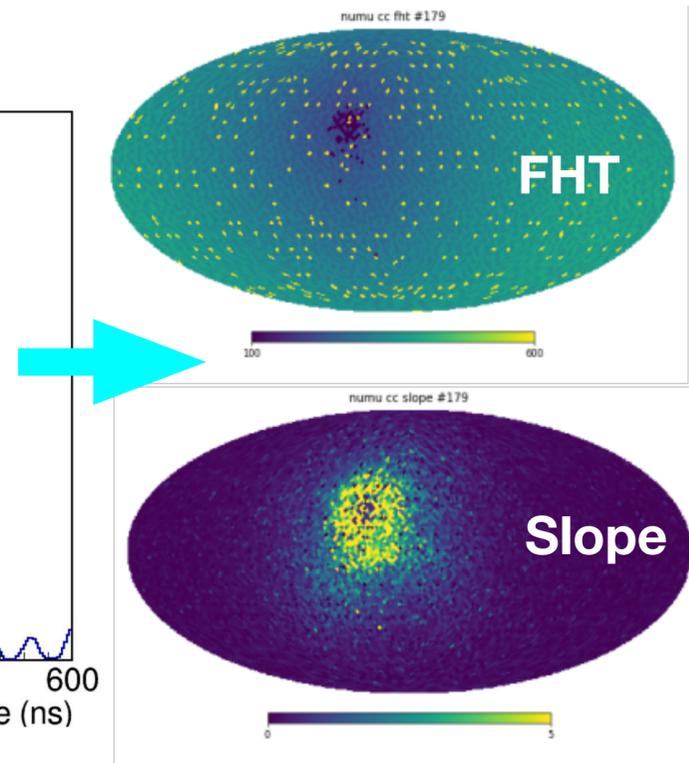
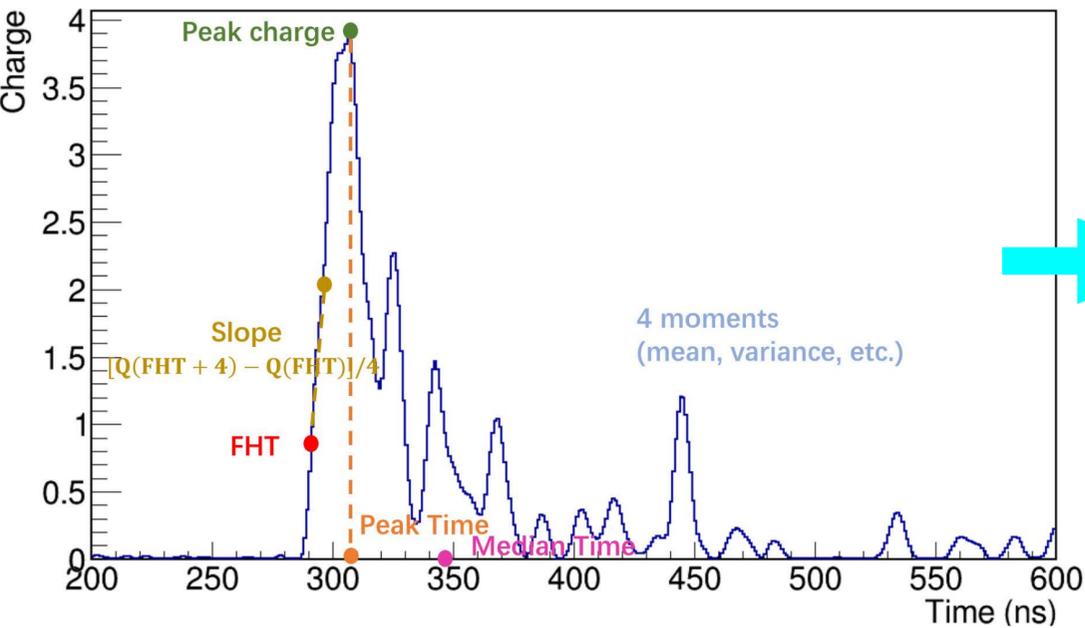
# A Multipurpose Machine Learning Solution



## PMT Waveforms (After deconvolution and noise-removing)

- Models are trained with large number of PMT feature pictures and learn to find direction/energy/ flavor/vertex etc. from the feature patterns.

# A Multipurpose Machine Learning Solution



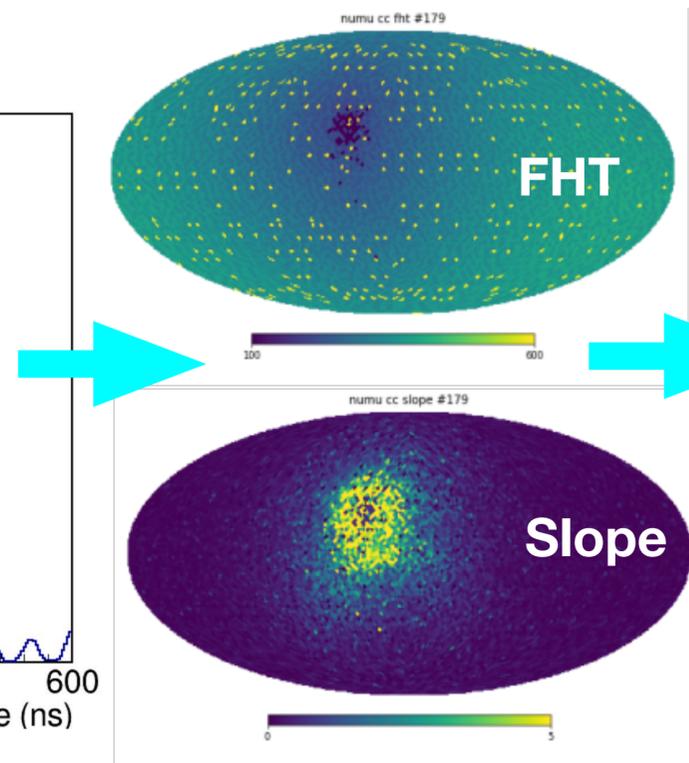
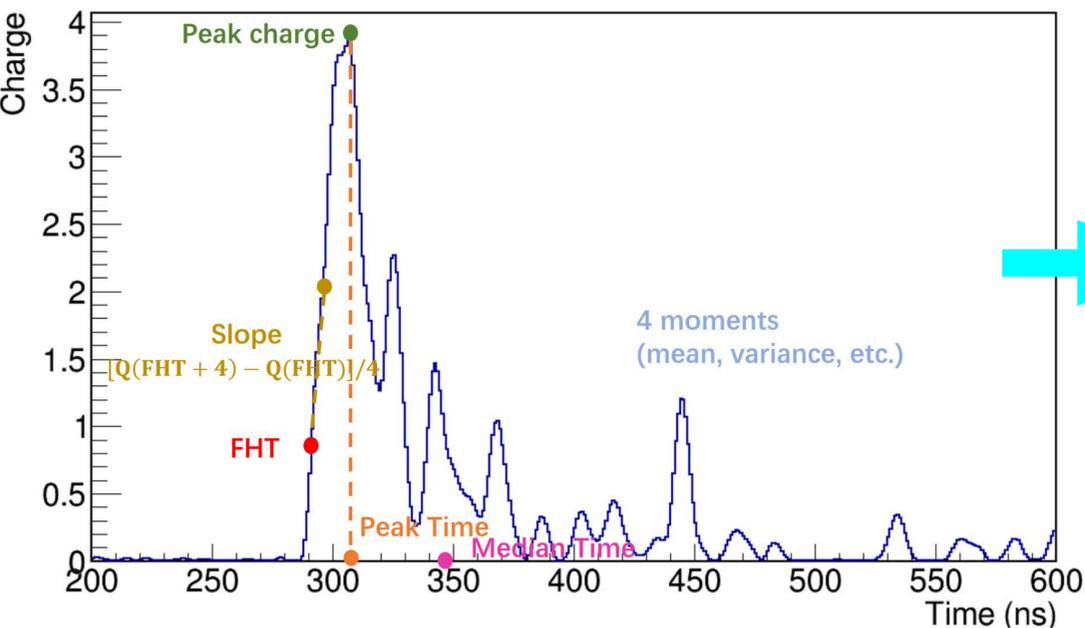
And more features... ..

**PMT Waveforms  
(After deconvolution  
and noise-removing)**

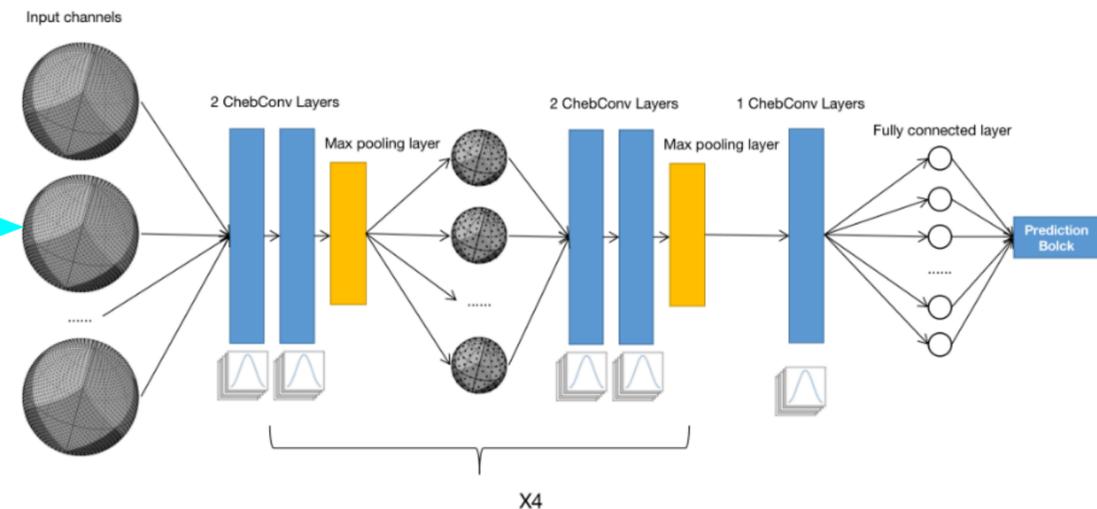
**Pictures of PMT  
Features**

- Models are trained with large number of PMT feature pictures and learn to find direction/energy/ flavor/vertex etc. from the feature patterns.

# A Multipurpose Machine Learning Solution



And more features... ..



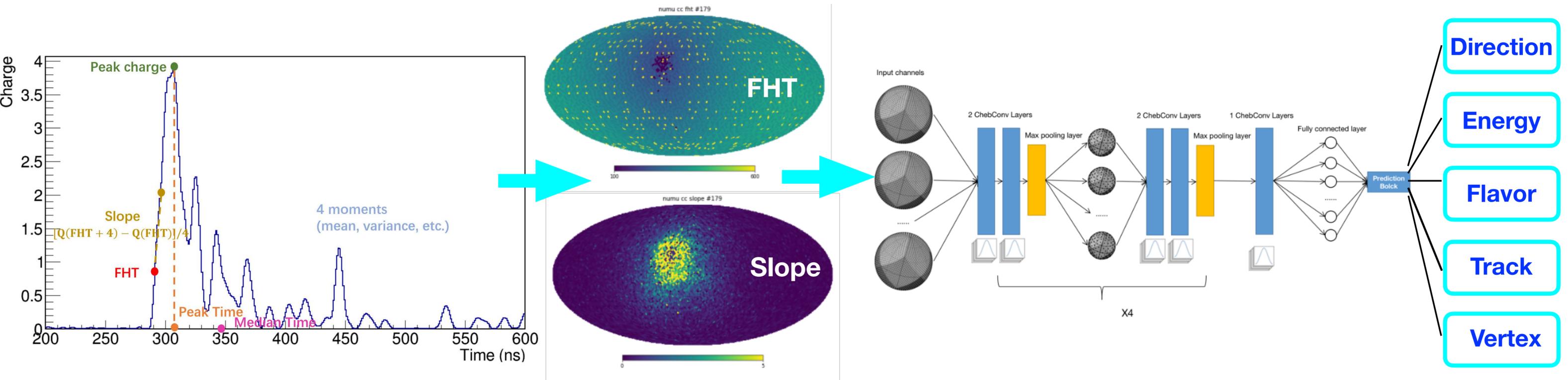
**Pictures of PMT Features**

**Machine Learning Models**

(Planer: EfficientNetV2;  
Spherical: Deepsphere;  
3D: PointNet++)

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# A Multipurpose Machine Learning Solution



**PMT Waveforms  
(After deconvolution  
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And more features... ..

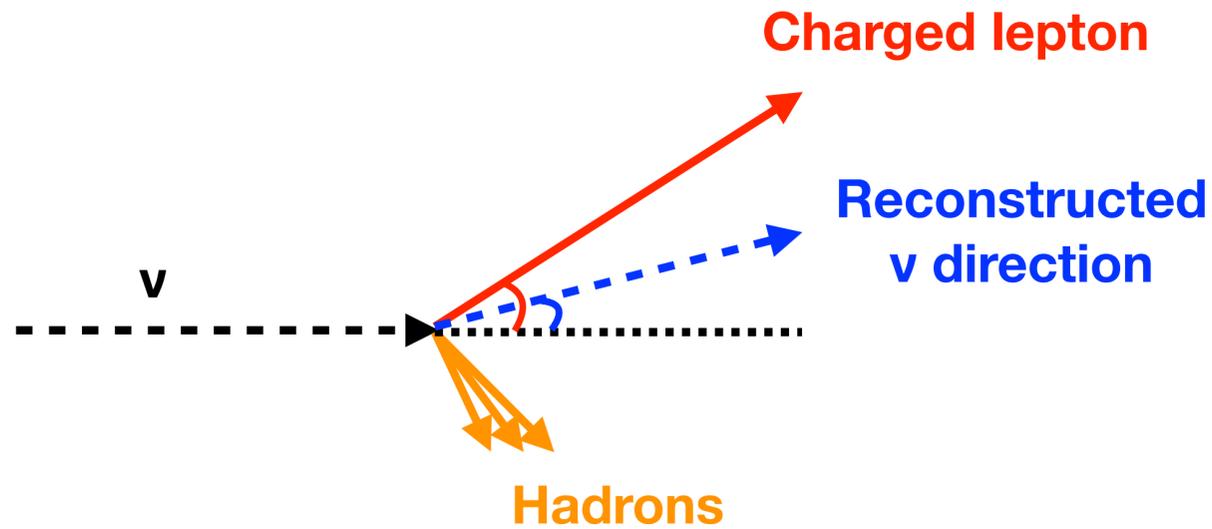
**Pictures of PMT  
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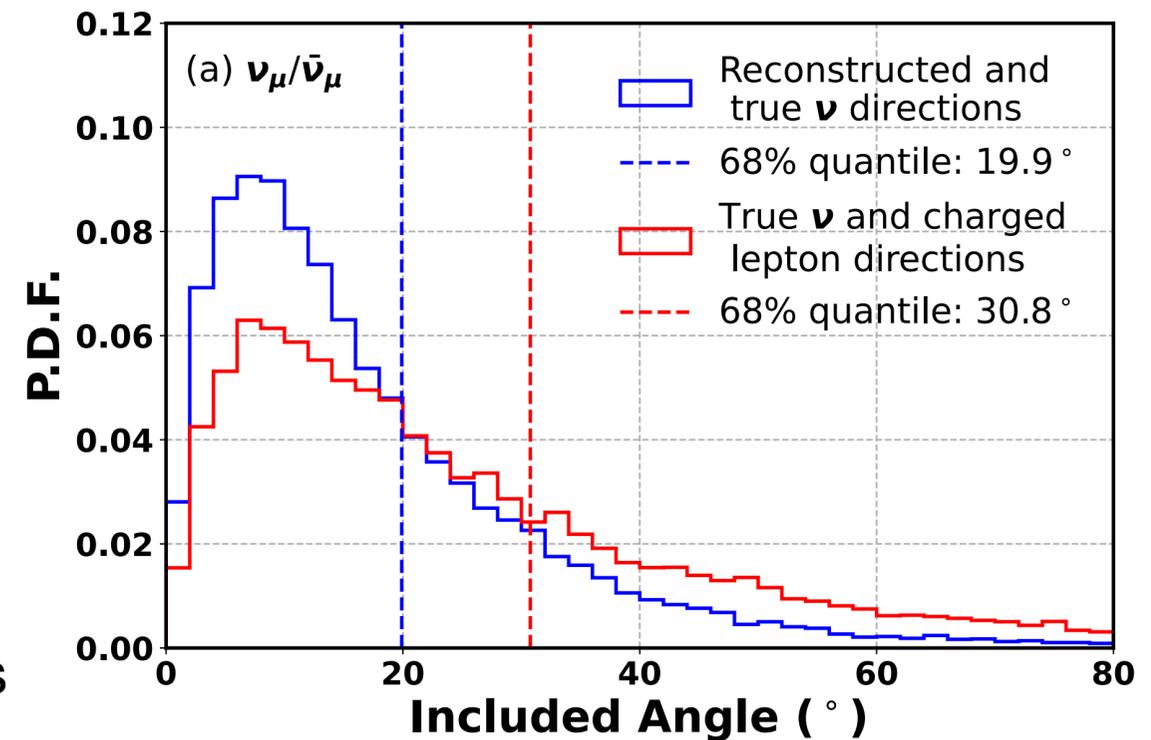
**Outputs**

- Models are trained with large number of PMT feature pictures and learn to find direction/energy/ flavor/vertex etc. from the feature patterns.

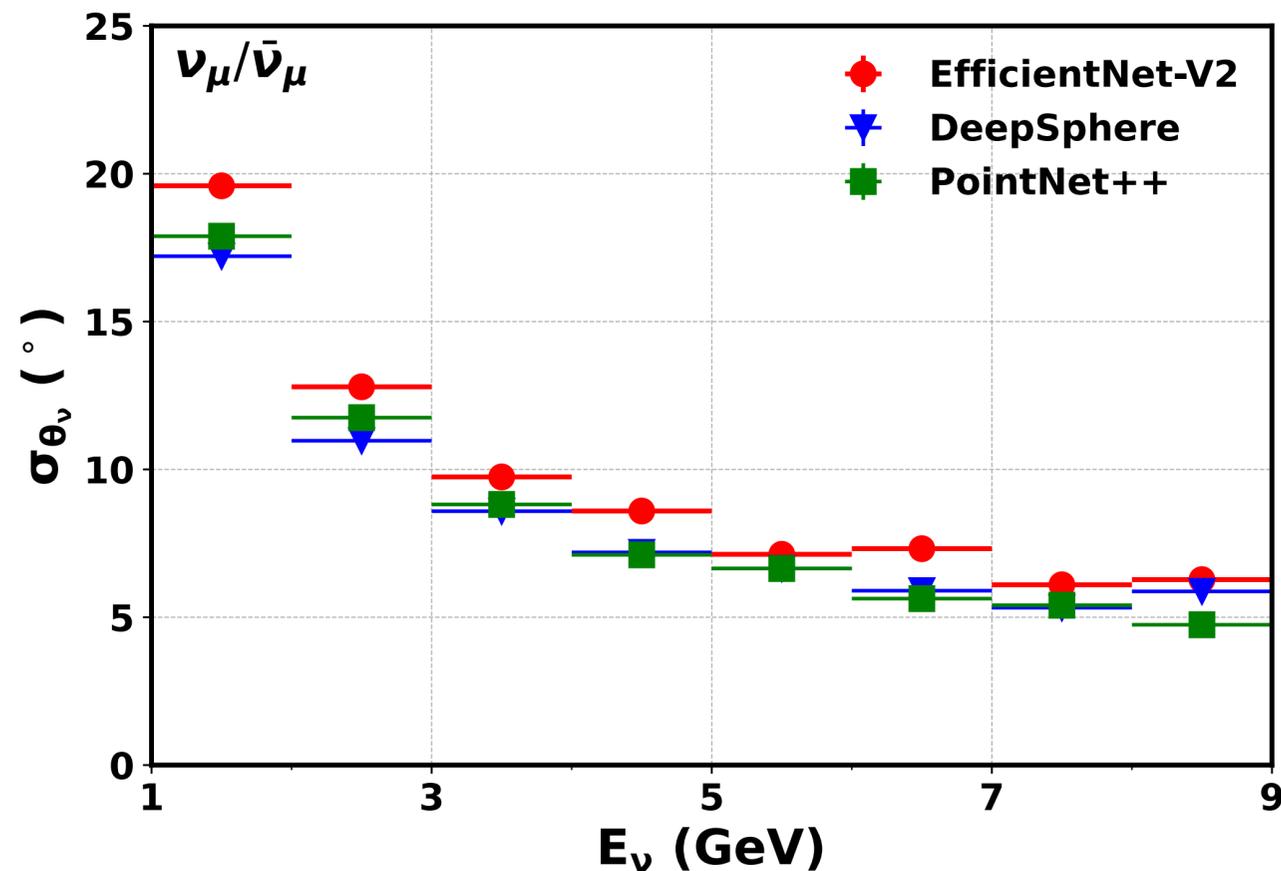
# JUNO Atmospheric $\nu$ : Directionality Reconstruction



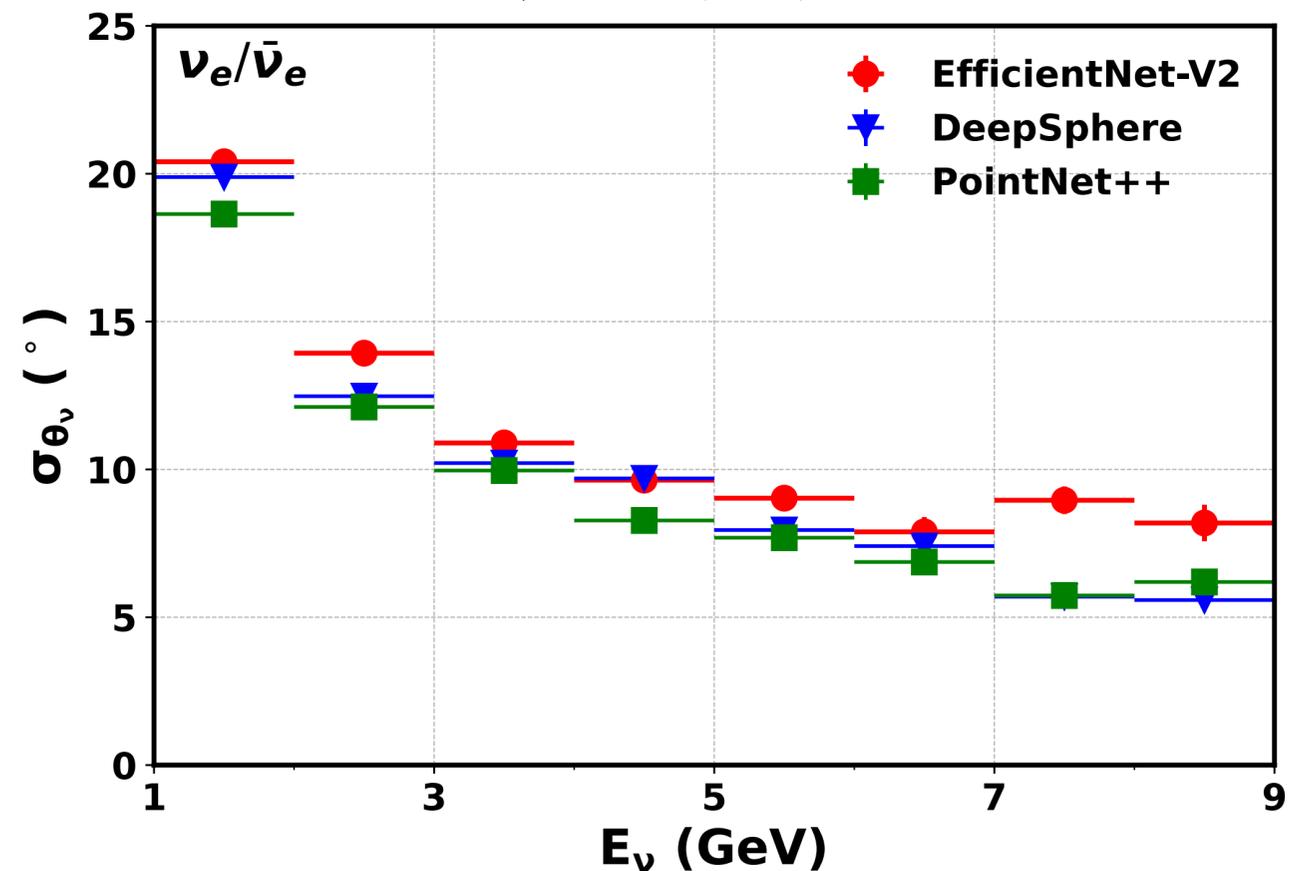
Reconstructing neutrino direction has better physics potential than reconstructing charged leptons



## Directional resolution of atmo $\nu$ in JUNO

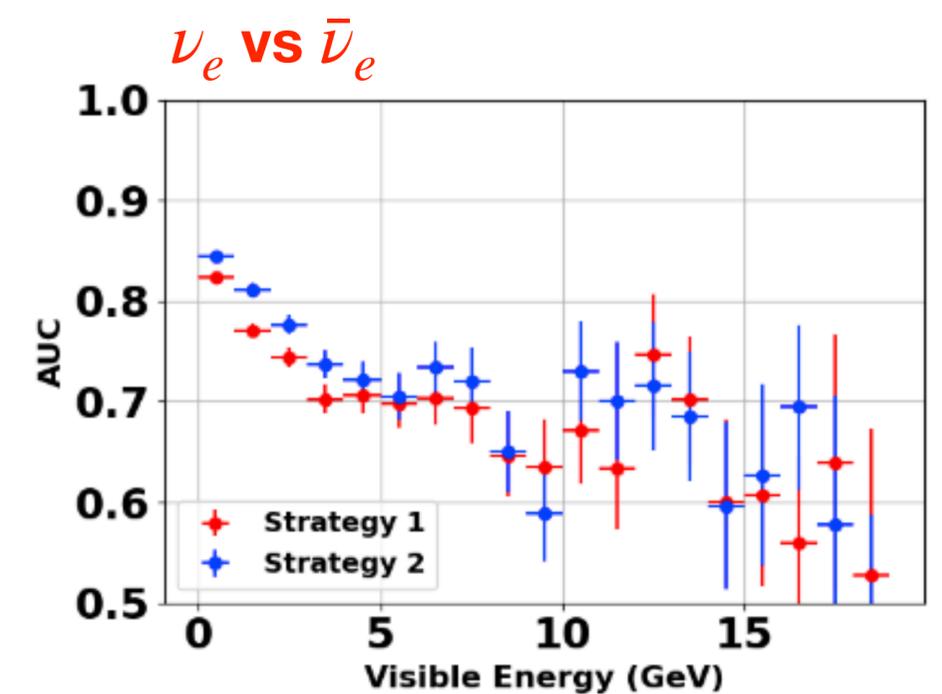
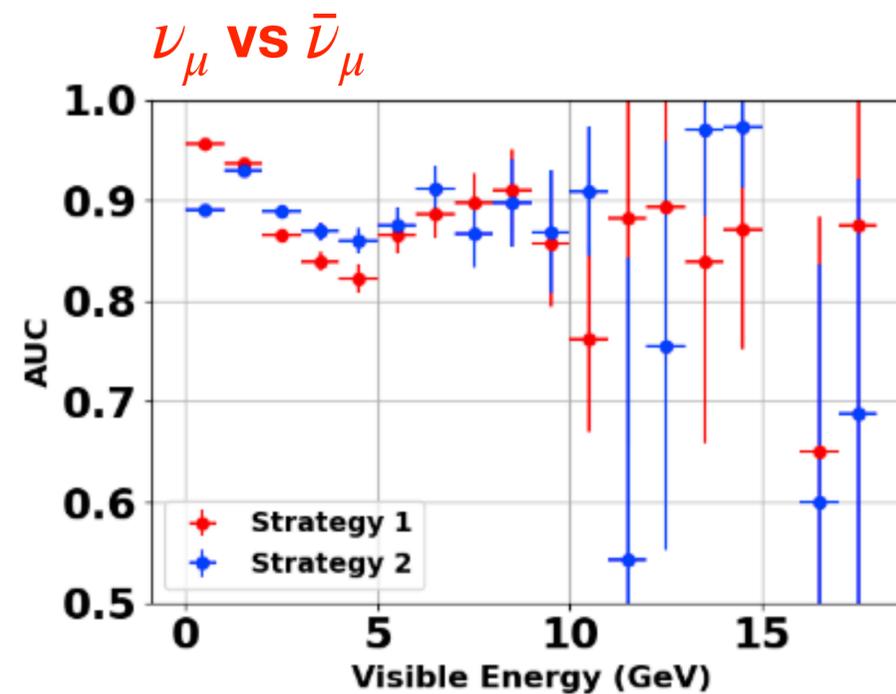
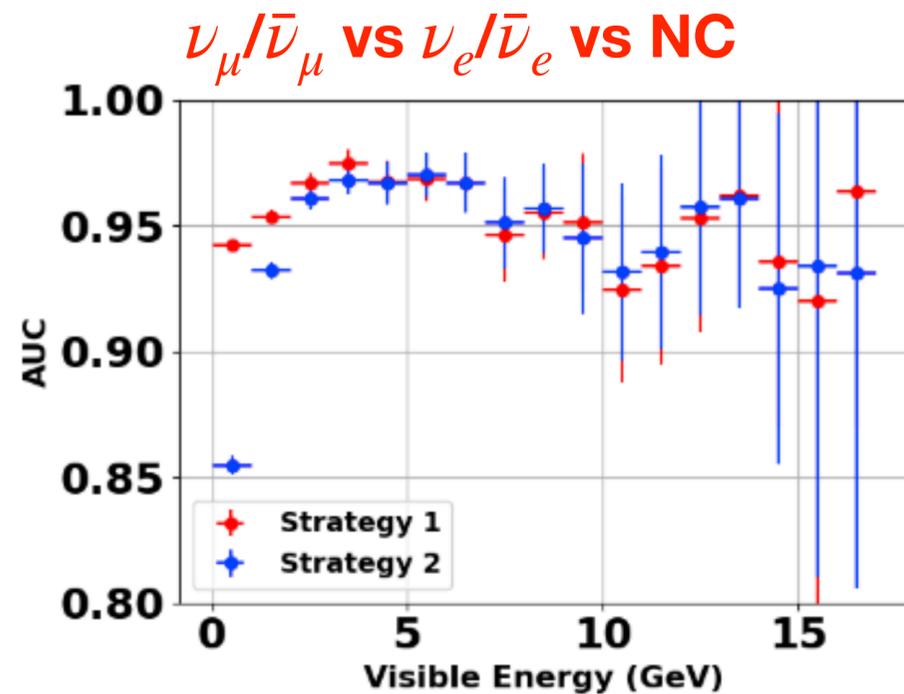
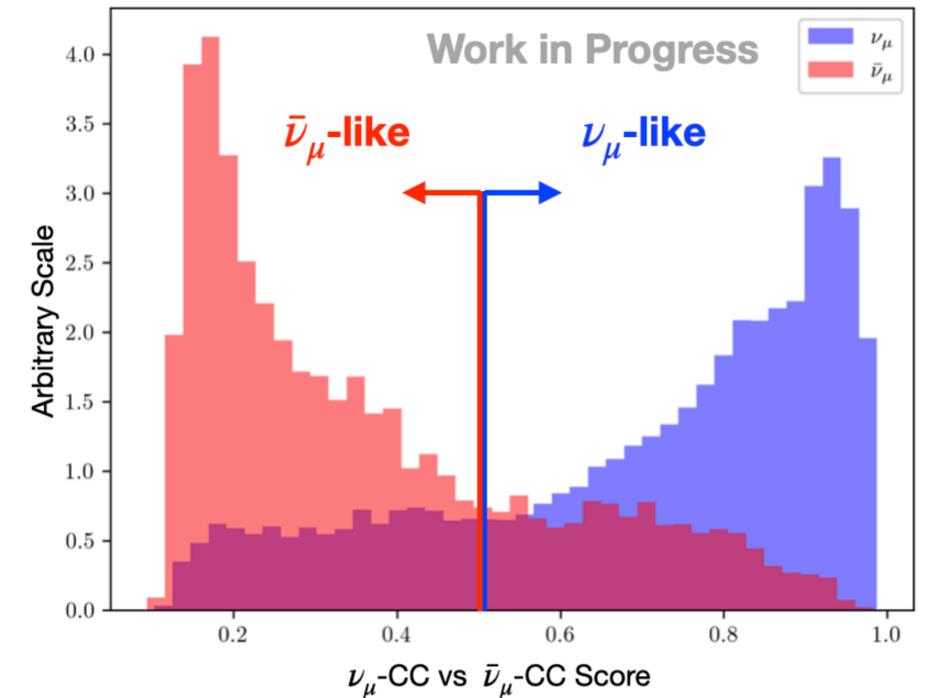


PHYS. REV. D 109, 052005 (2024)



# JUNO Atmospheric $\nu$ : PID Performance

- Input features from both the prompt trigger and delayed triggers into ML.
- $\nu$  and  $\bar{\nu}$  can be statistically separated with the help from neutron-capture and Michel electron informations.
- **In summary, ML significantly improves JUNO's capability to atmospheric neutrinos.**



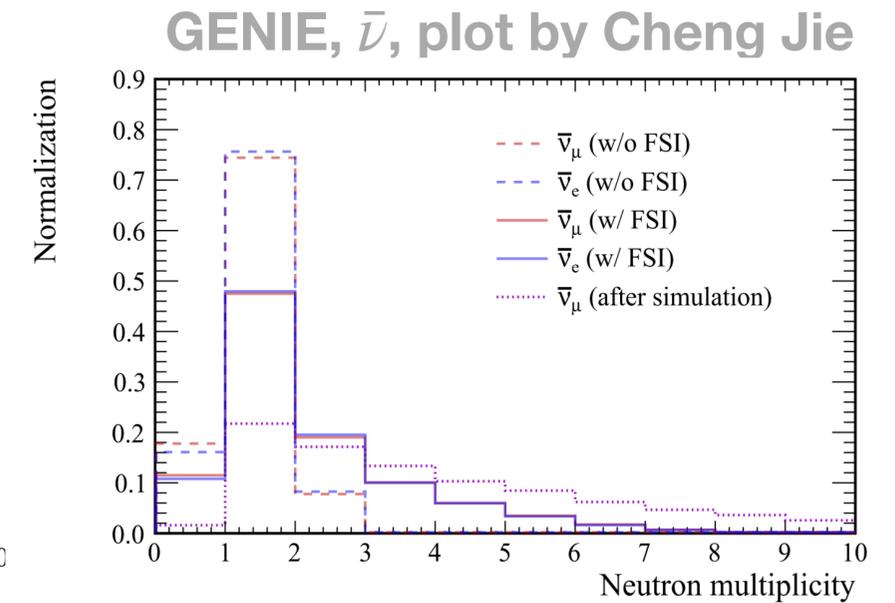
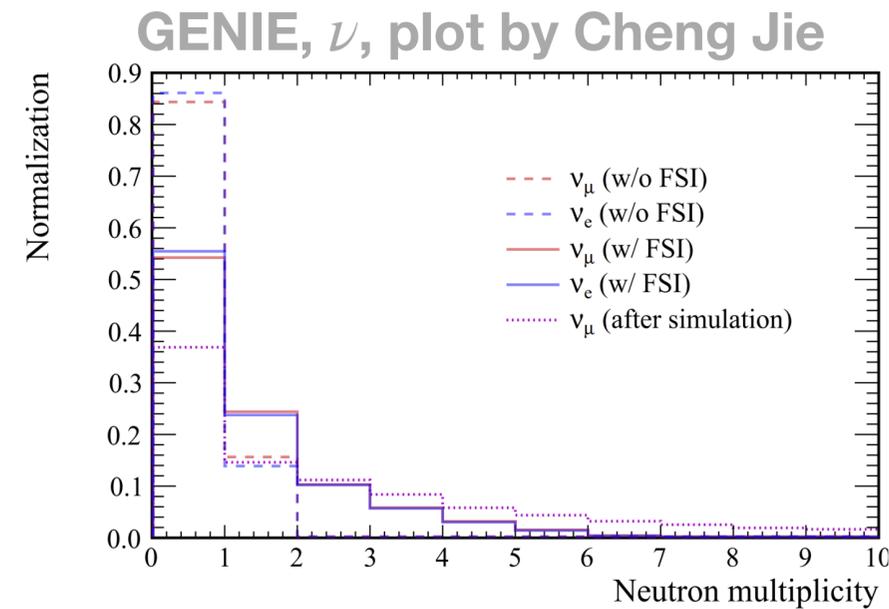
# Deep-learning in the Precision Era of Neutrino Physics: Gains and Questions

- Gains:

- More effective signal recognition.
- More precise measurements.
- Turn impossible into possible.

- Questions:

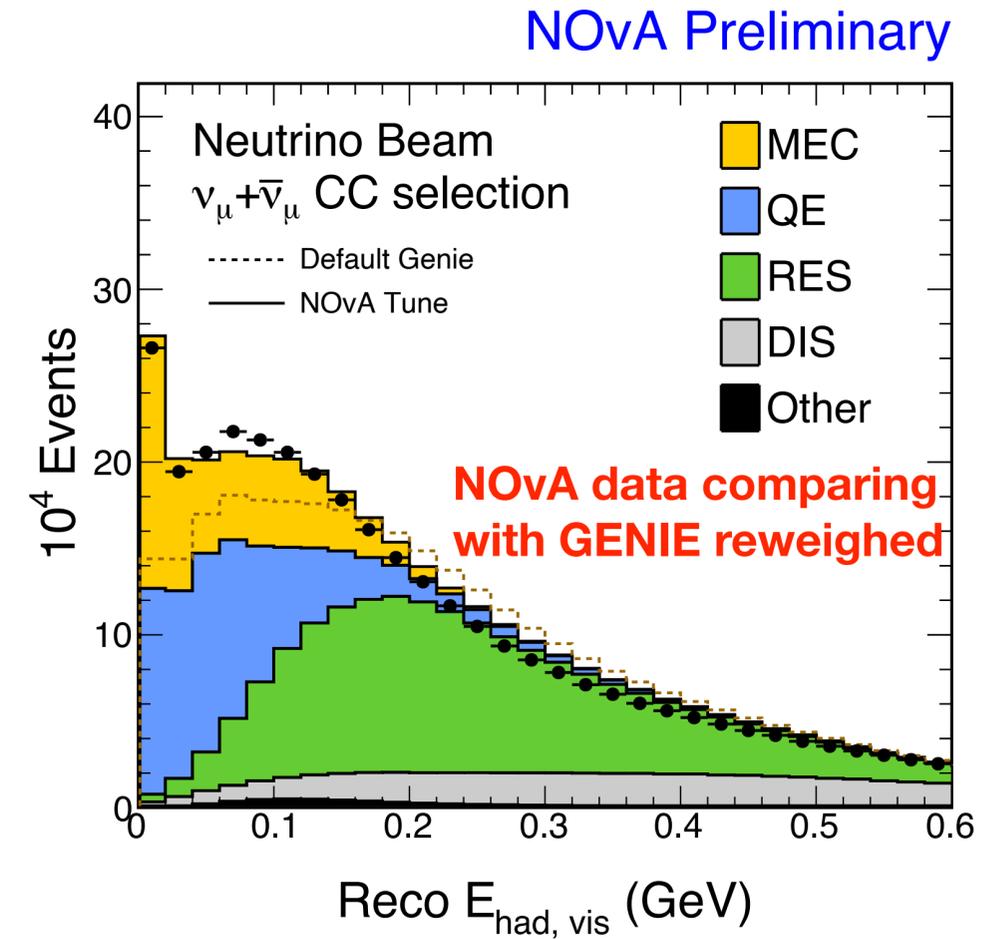
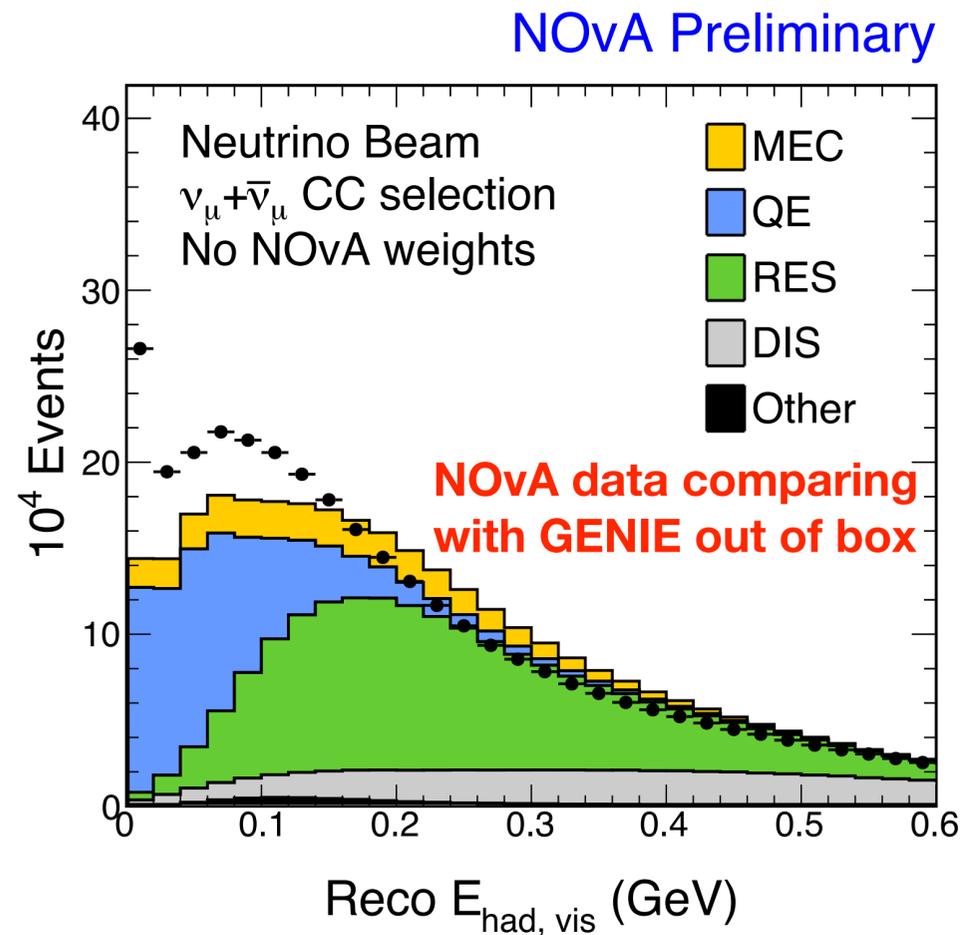
- Can we trust it?
- A black box trained with MC.
- Largely depends on our understanding of exactly what happens in the detector
  - Neutrino interactions + detector response.
- Ultimate solution: improving the quality of training datasets.



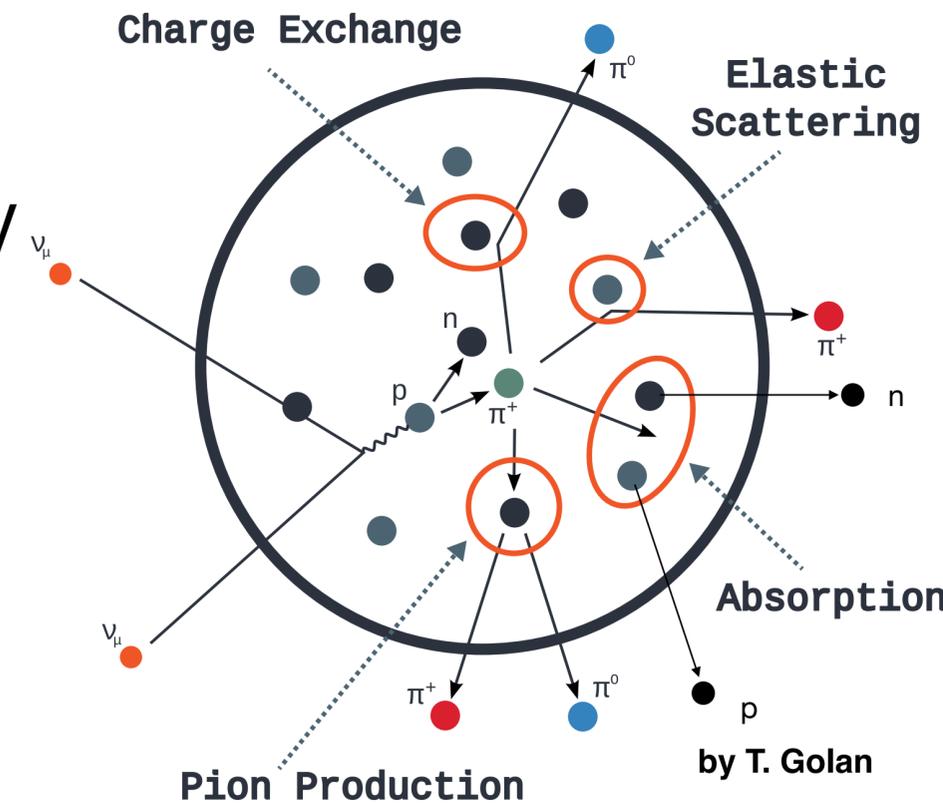
**Atmospheric neutrinos' neutron multiplicity predicted by GENIE**



# Problems with Neutrino Interactions

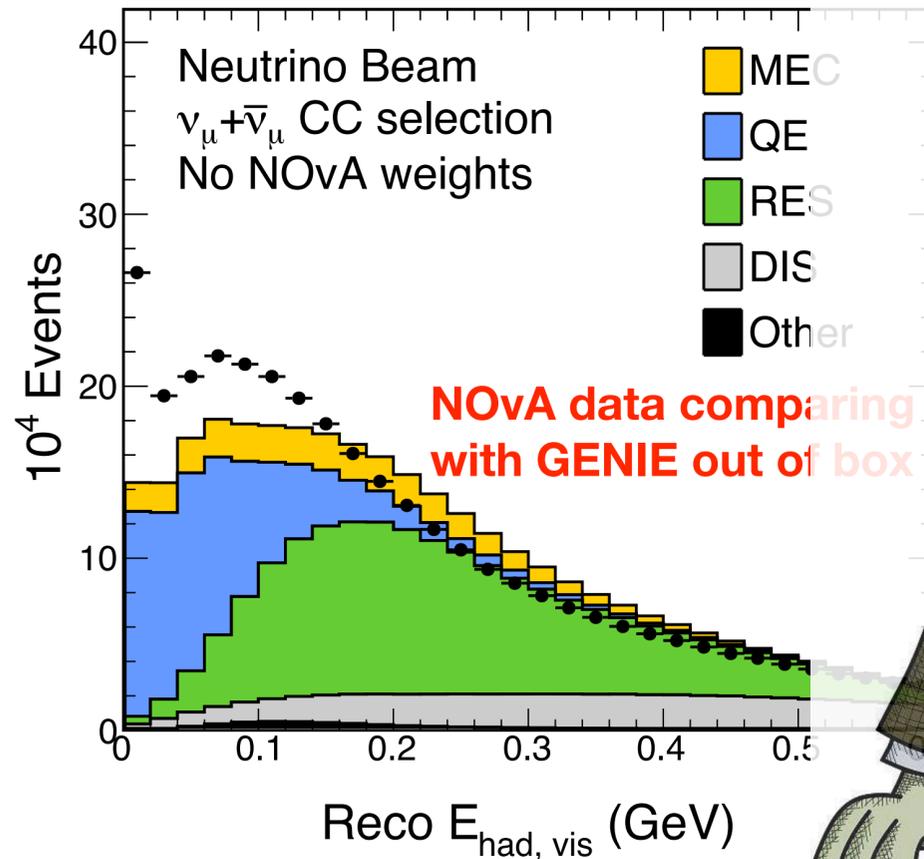


- Unfortunately current neutrino interaction modeling does not describe data well.
- Neutrino scattering on heavy targets like argon at the few-GeV neutrino energy range is complex
- Most generators are many models glued together
  - Initial states + (QE + RES + DIS + COH + 2p2h...) + FSI
  - Some of the models are pretty old (40+ years)

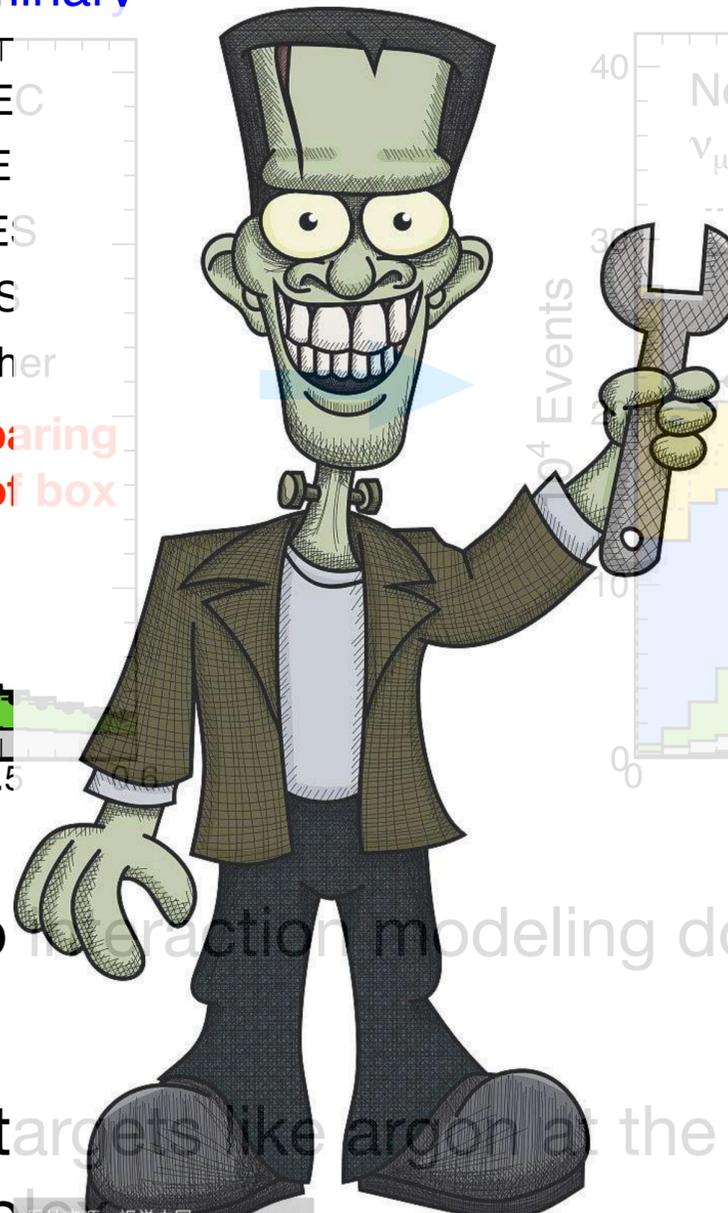
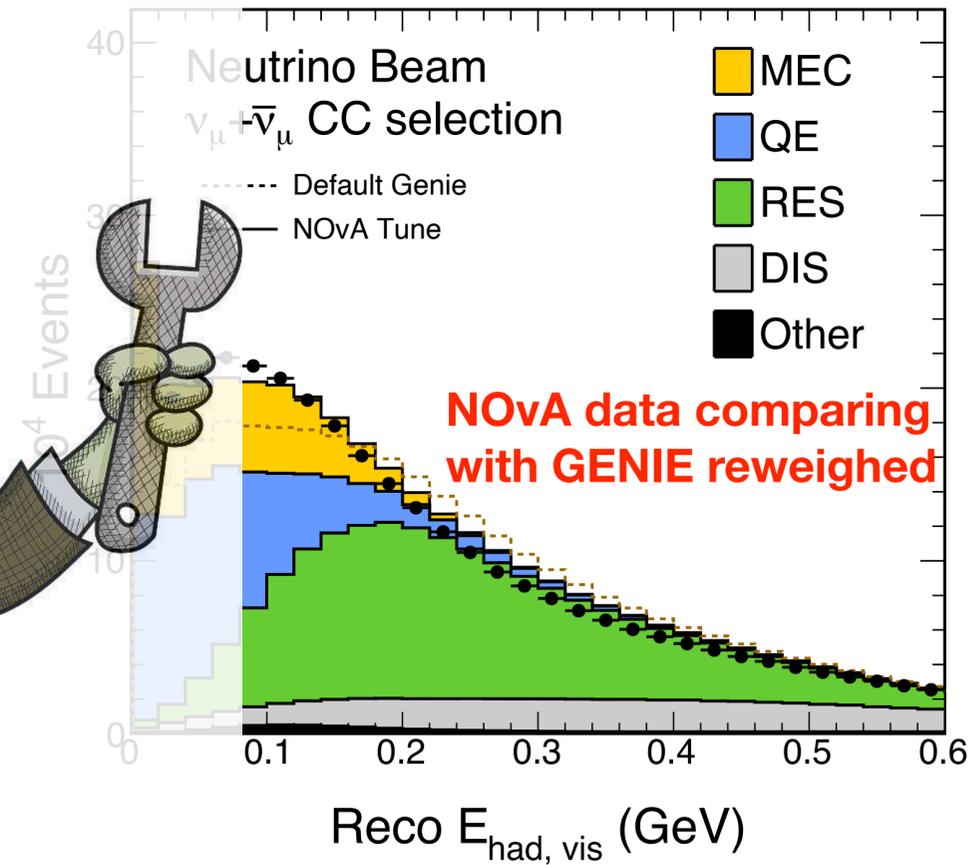


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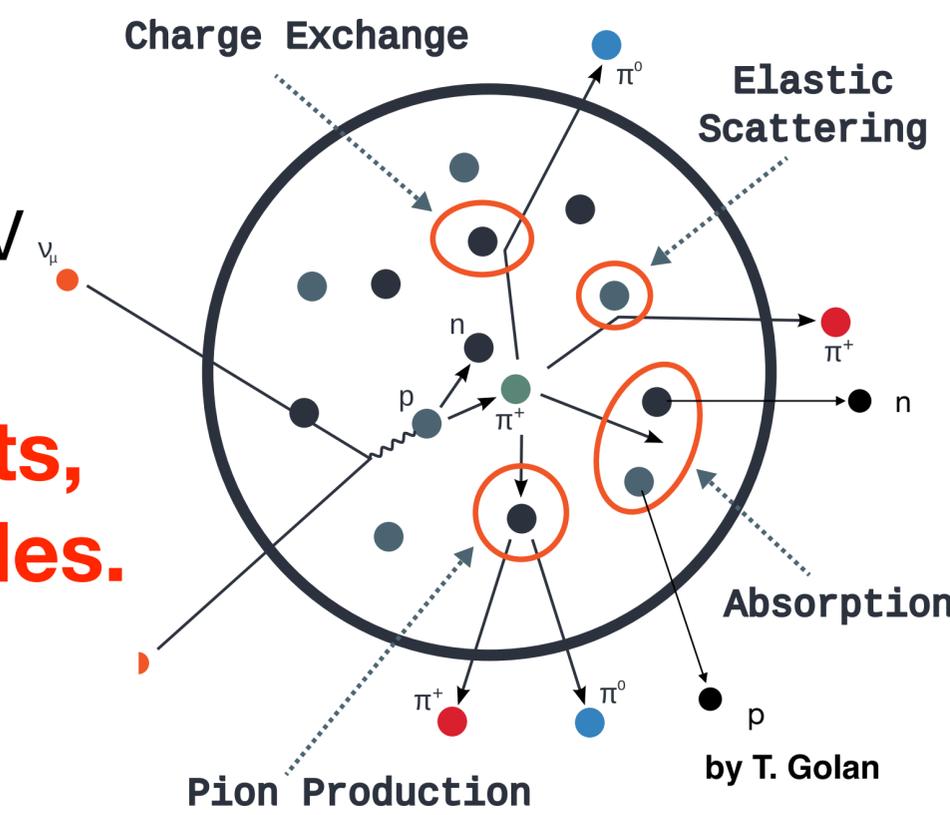
NOvA Preliminary



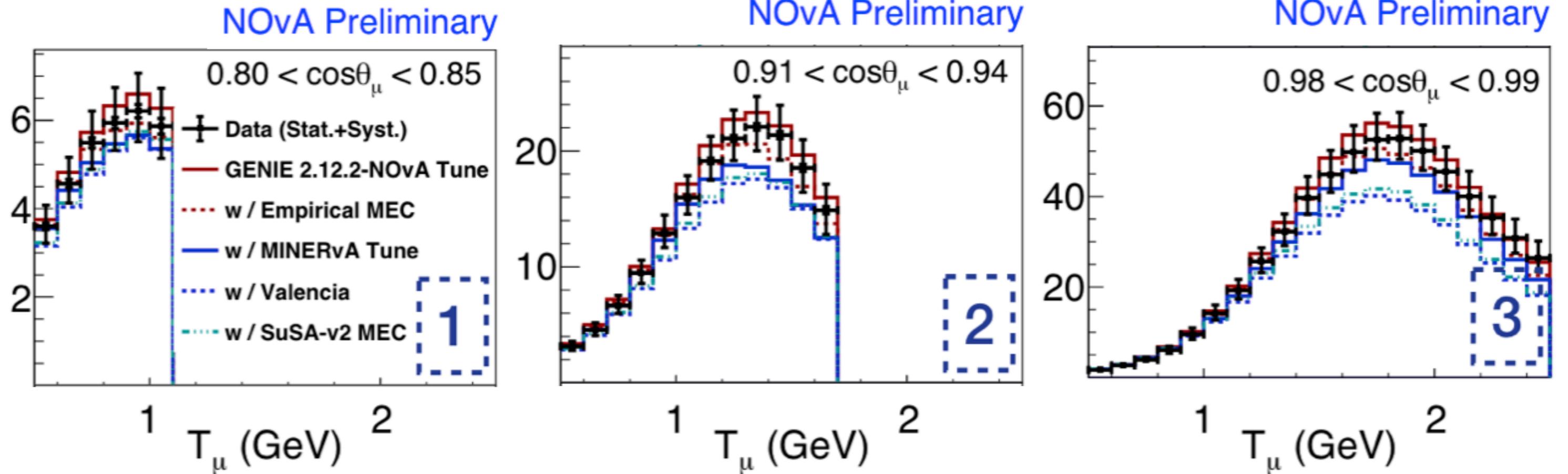
NOvA Preliminary



- Unfortunately current neutrino interaction modeling does not describe data well.
- Neutrino scattering on heavy targets like argon at the few-GeV neutrino energy range is complex.
- Most generators **Too many pieces in the experiments, but too limited number of observables. (Degeneracy!)**
  - Initial state
  - Some of th



# Problems with Neutrino Interactions



- Unfortunately the current tunings are very unlikely to be completely correct.
- **Data may not agree with data even with large uncertainties.**

# A Near Detector for the Solution?

**FD:**  $N(E_{rec}) = \int_{E_\nu} dE_\nu \Phi(E_\nu) P_{osc}(E_\nu) \sigma(E_\nu) R_{det}(E_\nu, E_{rec})$

**Number of events observed in the FD**

**Neutrino flux**

**Oscillation probability**

**Cross section**

**Detector response**

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Need to reconstruct  $E_\nu$  correctly!

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**ND:**

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Number of events  
observed in the ND

Not exactly the same  
neutrino flux

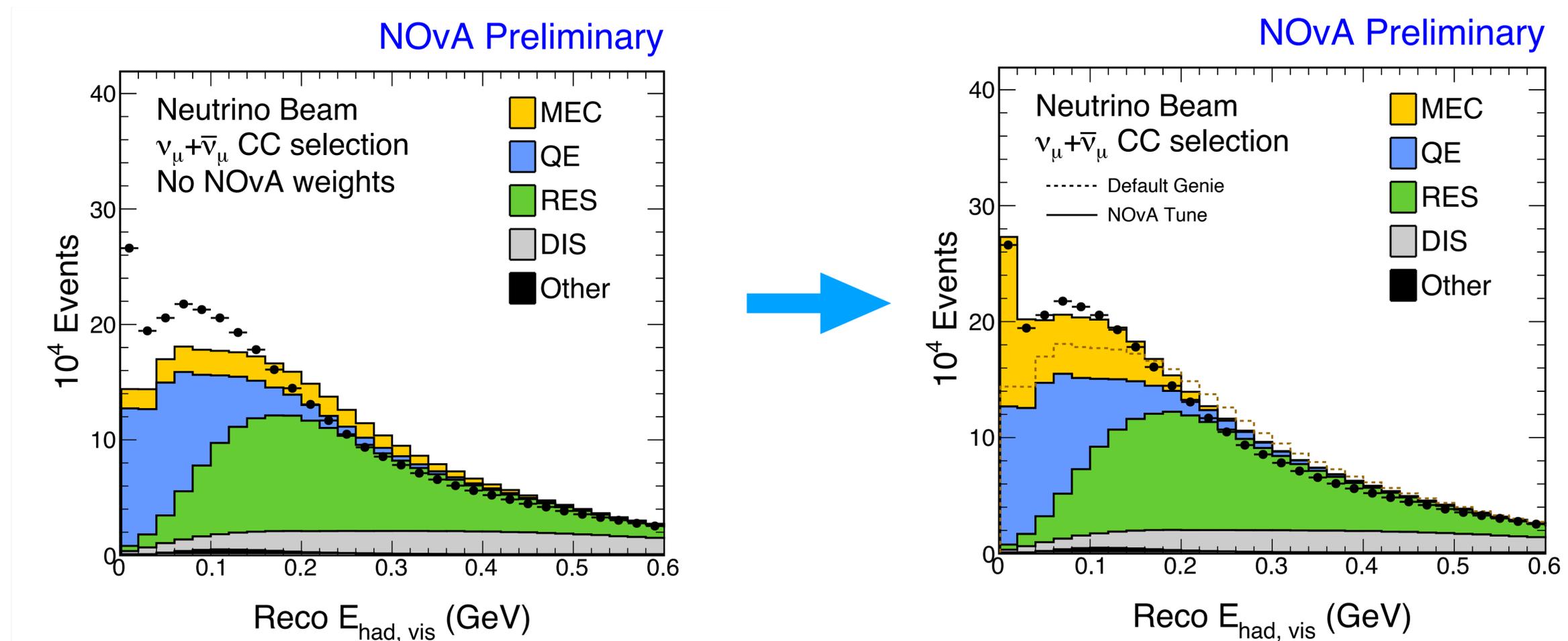
Oscillation probability  
(zero in the ND)

Not the same  
Detector response

Cross sections?  
Need Ar target

Need ways to disentangle those factors!

# A Near Detector for the Solution?



**ND:** 
$$N(E_{rec}) = \int_{E_\nu} dE_\nu \Phi(E_\nu) \cancel{P_{osc}(E_\nu)} \sigma(E_\nu) R_{det}(E_\nu, E_{rec})$$

Number of events  
observed in the ND

Not exactly the same  
neutrino flux

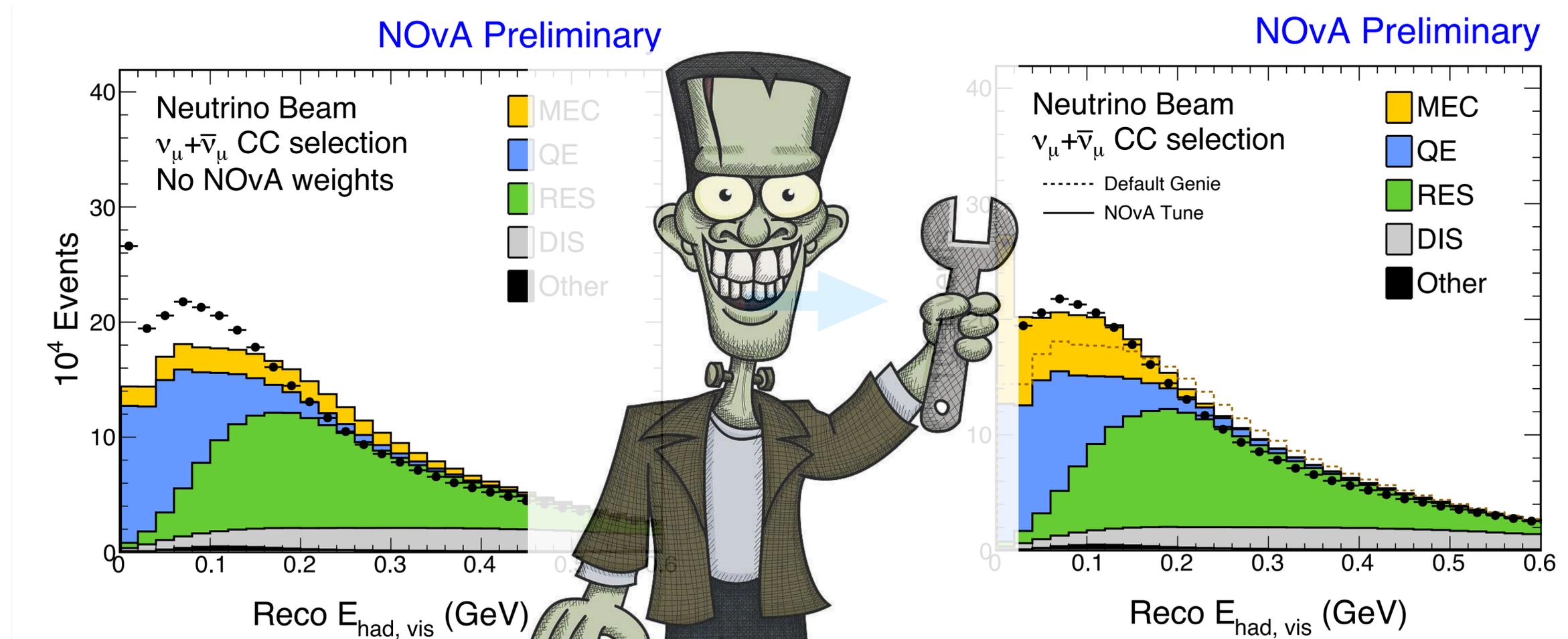
Oscillation probability  
(zero in the ND)

Not the same  
Detector response

Cross sections?  
Need Ar target

- Question: is this really because of cross sections? nuclear effects? flux? detector simulation/calibration?

# A Near Detector for the Solution?



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Number of events observed in the ND

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Not the same Detector response

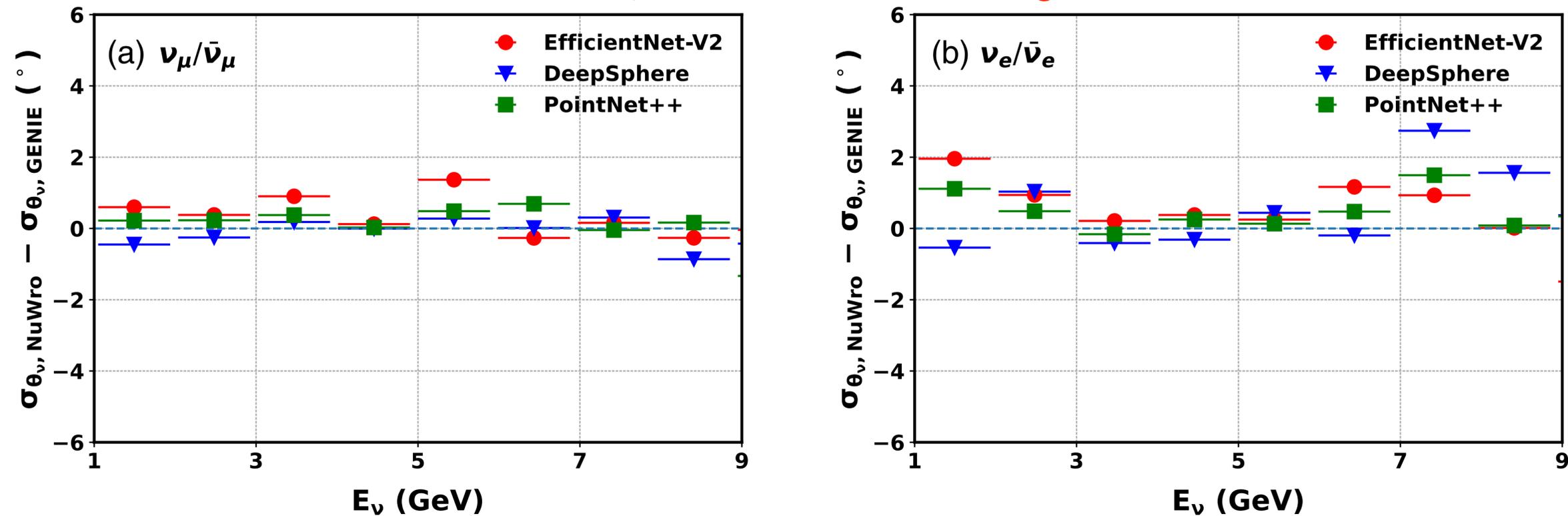
**Too many pieces in the experiments, but too limited number of observables. (Degeneracy!)**

sections?  
Ar target

- Question... is the really because of cross sections... nuclear effects? flux? detector simulation/calibration?

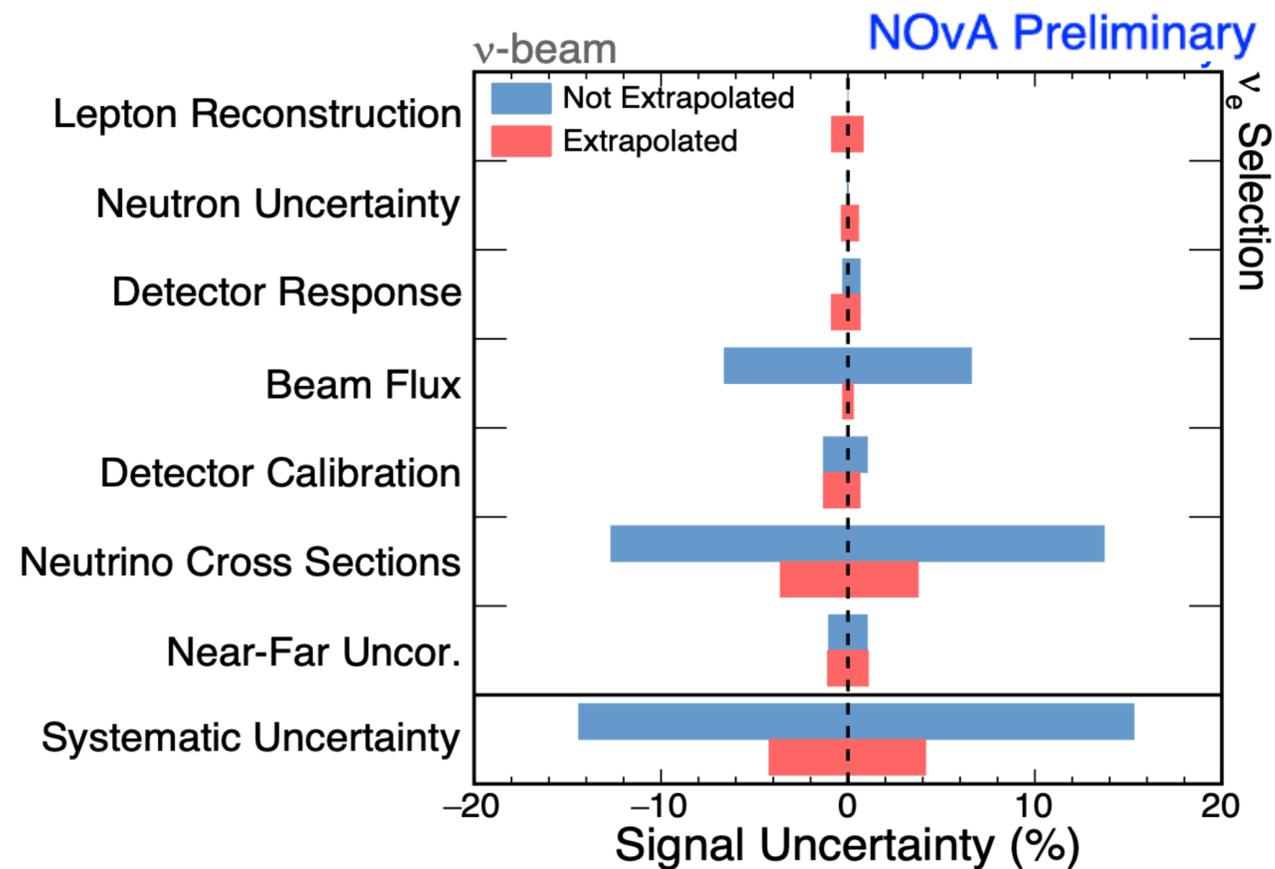
# How to deal with interaction uncertainties?

## JUNO directional reconstruction, checked with different generators



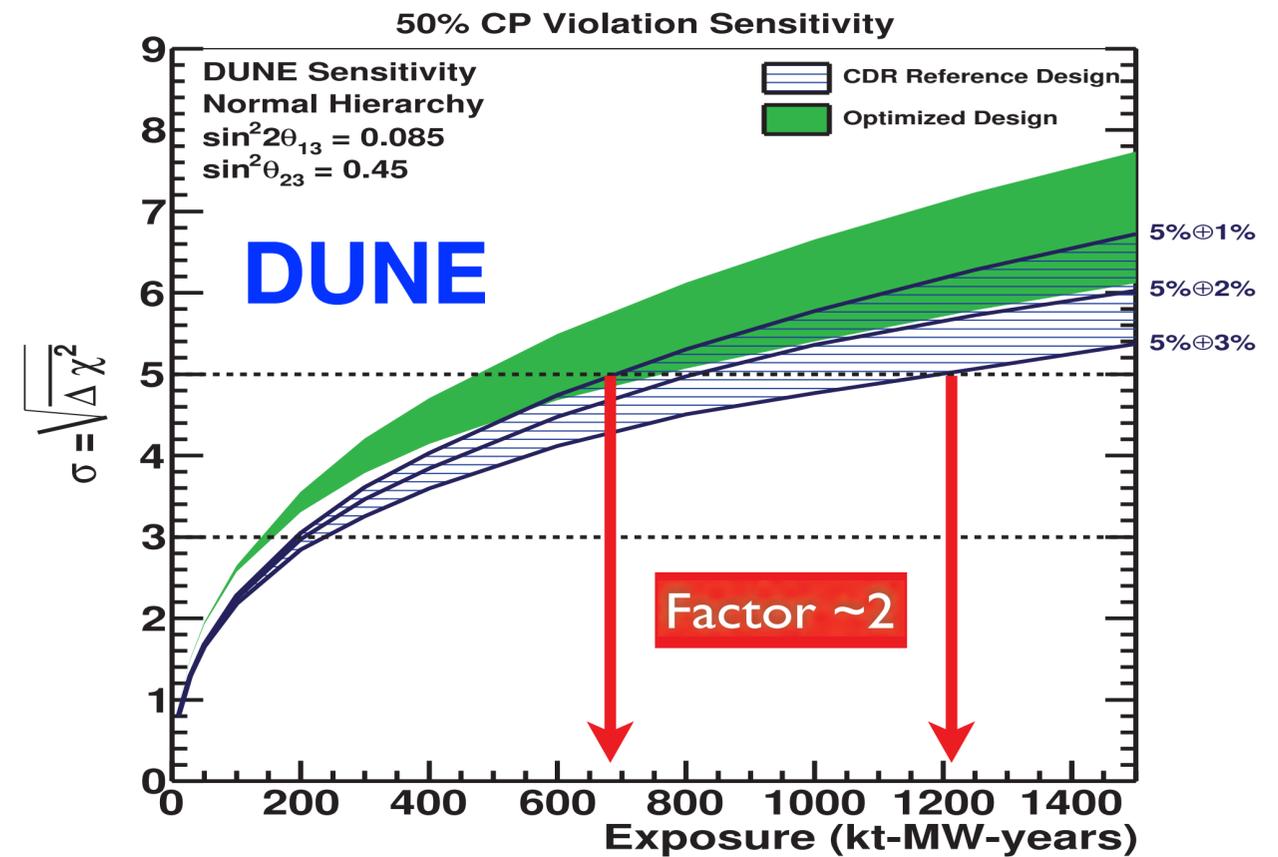
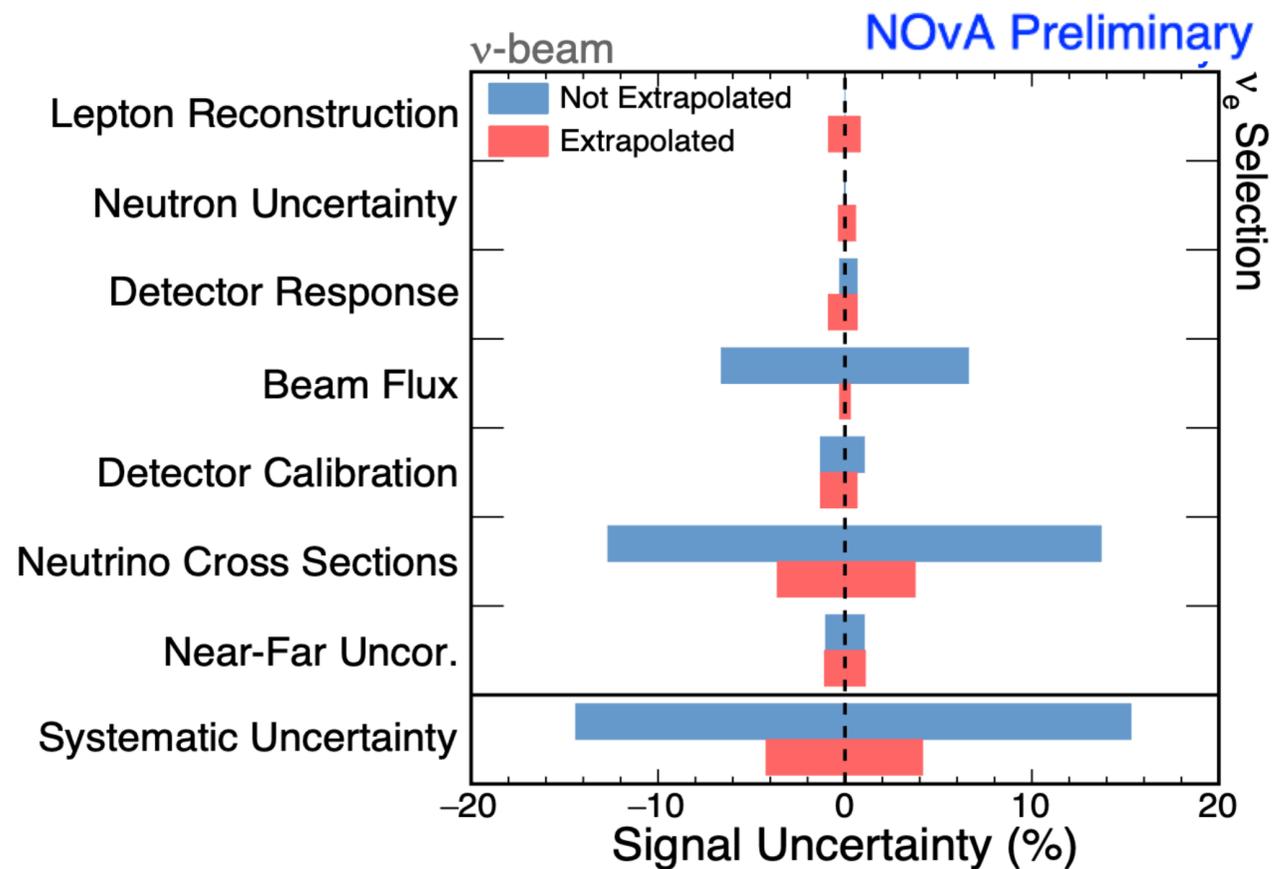
- Conventional approach is to vary the models/simulation parameters (GENIE “knobs” for example) to evaluate the uncertainties from  $\nu$ -interactions.

# Neutrino Interaction Model Uncertainties



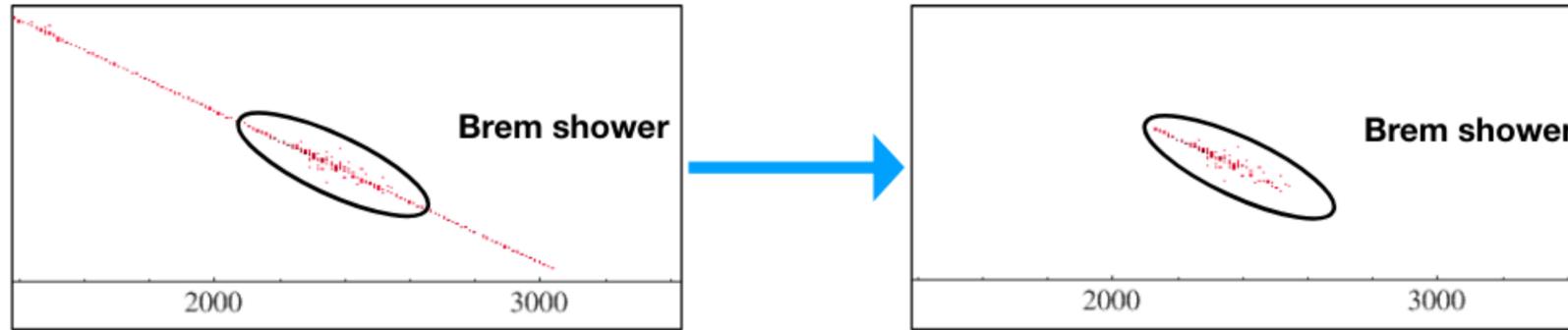
- Neutrino interaction models contribute one of the largest systematic sources
- Impossible to be completely cancelled by NDs.
- A too large uncertainty for precision measurement such as DUNE.

# Neutrino Interaction Model Uncertainties



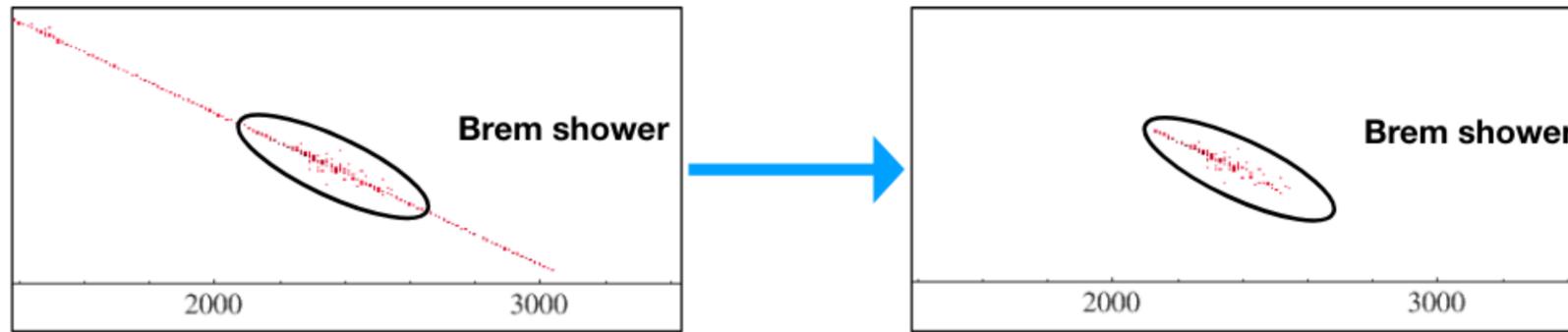
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# Data Driven Approaches: “Data-simulator”

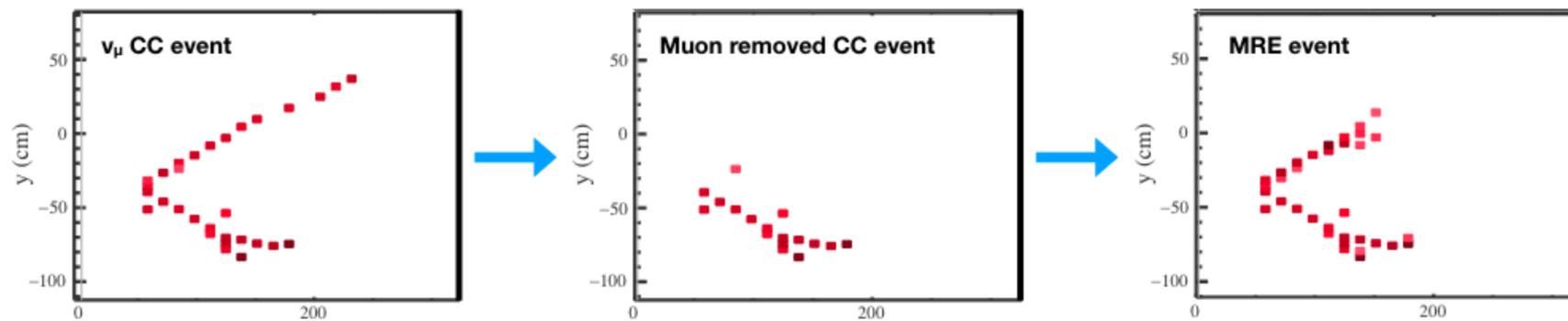


- Cosmic-muon induced bremsstrahlung showers are identified, muons are then removed to create pure electron-like EM showers from data to check the detector's response to electrons.

# Data Driven Approaches: “Data-simulator”

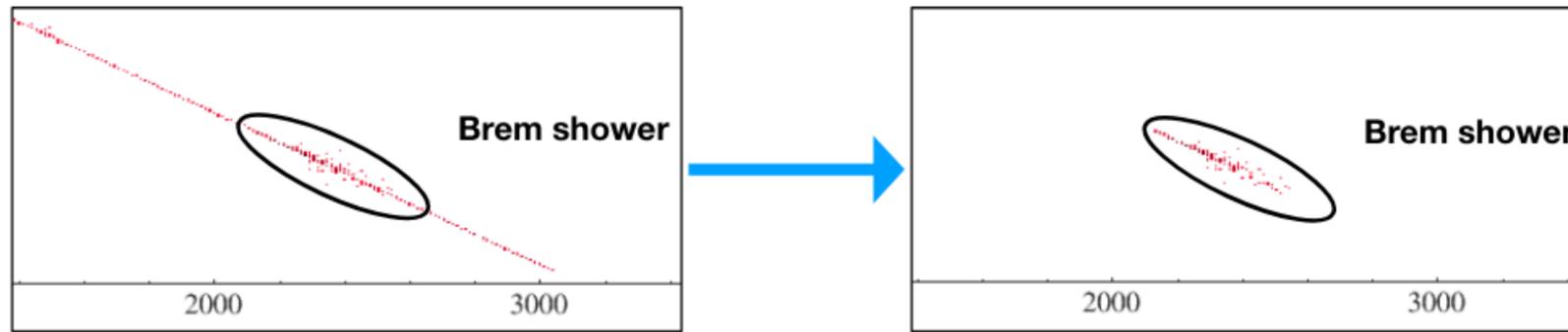


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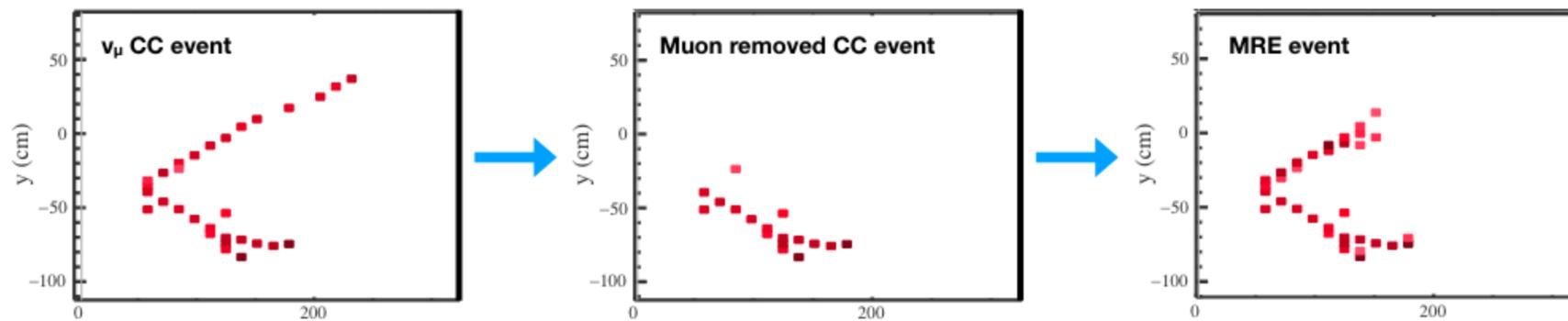


- $\nu_\mu$ -CC events are identified with traditional methods from data, muons are then removed and replaced with a simulated electron to check the detector's response to  $\nu_e$ -CC.

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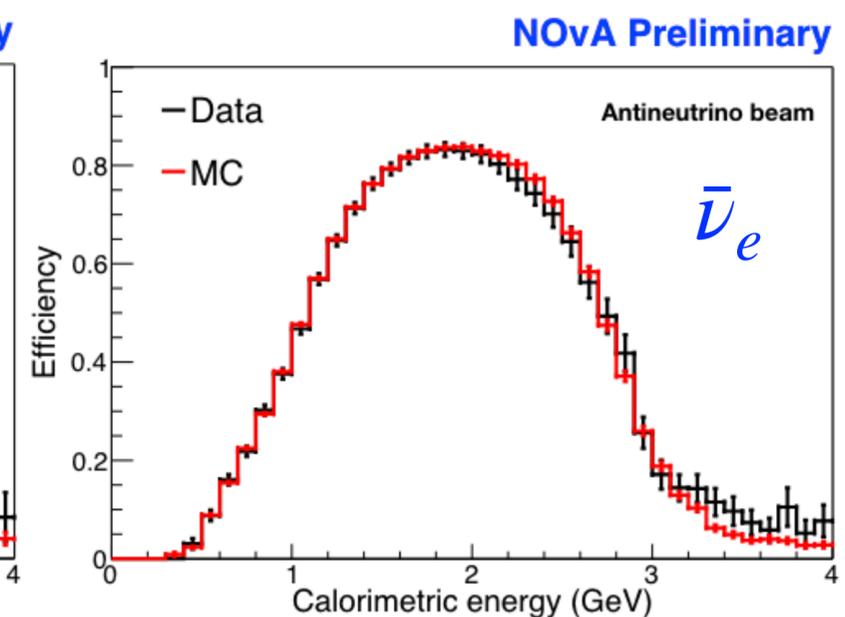
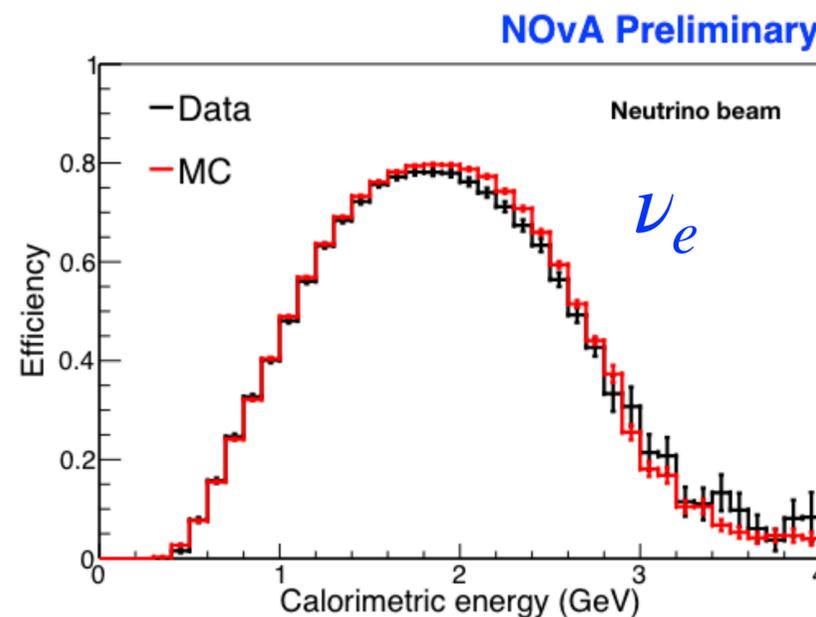


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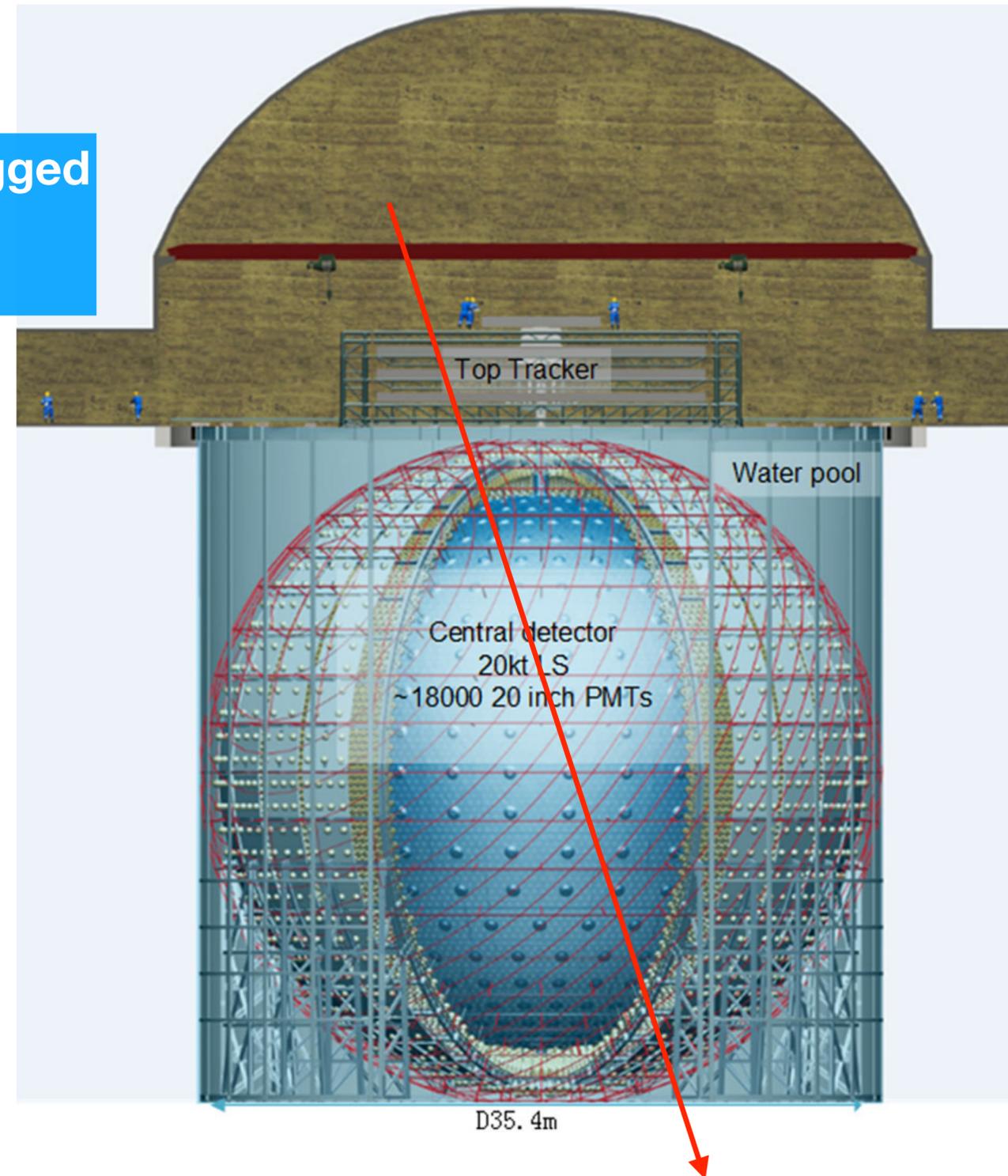
- $\nu_\mu$ -CC events are identified with traditional methods from data, muons are then removed and replaced with a simulated electron to check the detector’s response to  $\nu_e$ -CC.

- CNN-based PID (trained with MC) is applied to the “simulated data” to check the selection efficiency.



# Data Driven Approaches: “Data-simulator”

Select cosmic muons tagged by the Top Tracker with direction well-measured



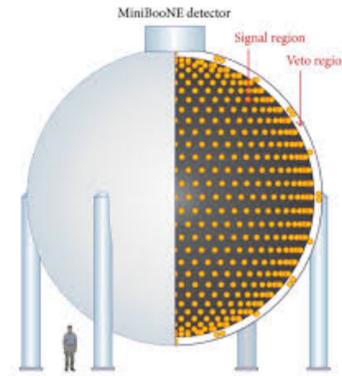
Use cosmic muon data to train/validate the DL models for direction/track reconstruction

Liu, Y., Li, WD., Lin, T. et al. *Radiat Detect Technol Methods* 5, 364–372 (2021).

# Previous/Current/Future $\nu$ -Int Experiments



Bubble Chambers



MiniBooNE



MINERvA



MicroBooNE



NOvA



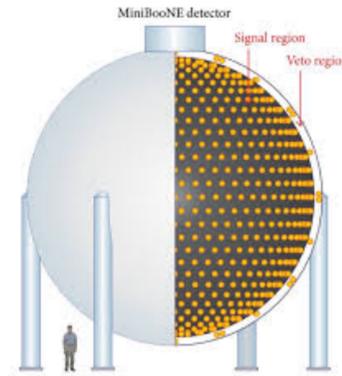
T2K

- Current data suffer from low-statistics/low-resolution/tensions.
- Future experiments are expected to give much stronger constraints.

# Previous/Current/Future $\nu$ -Int Experiments



Bubble Chambers



MiniBooNE



MINERvA



MicroBooNE



NOvA

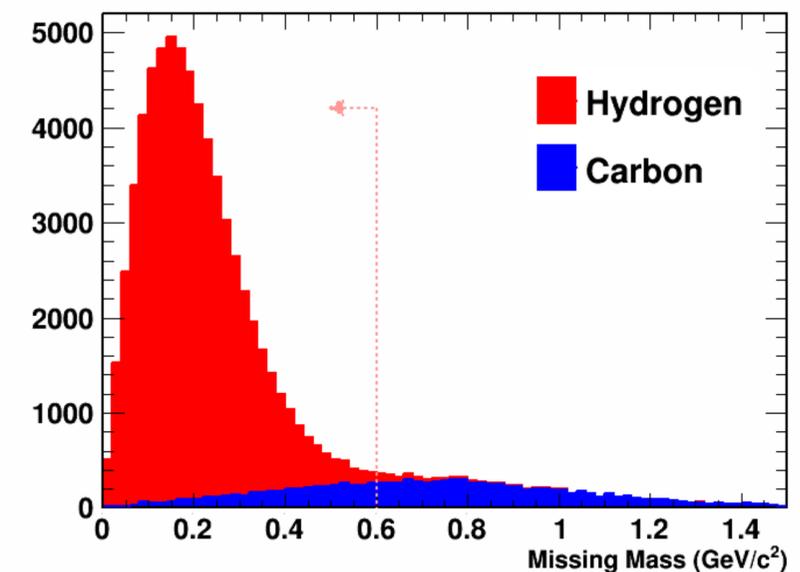
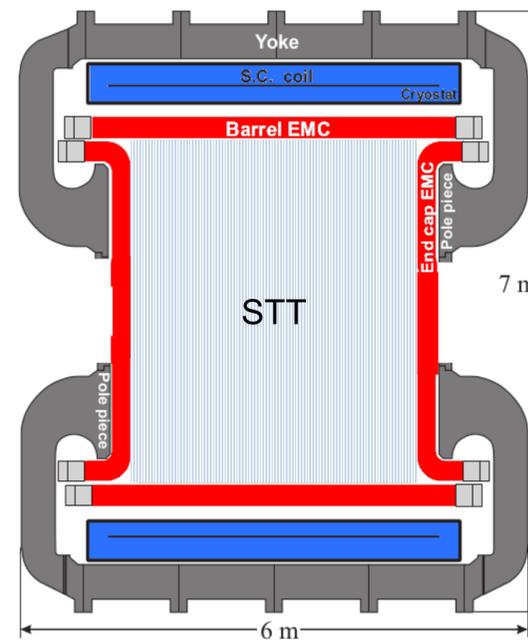
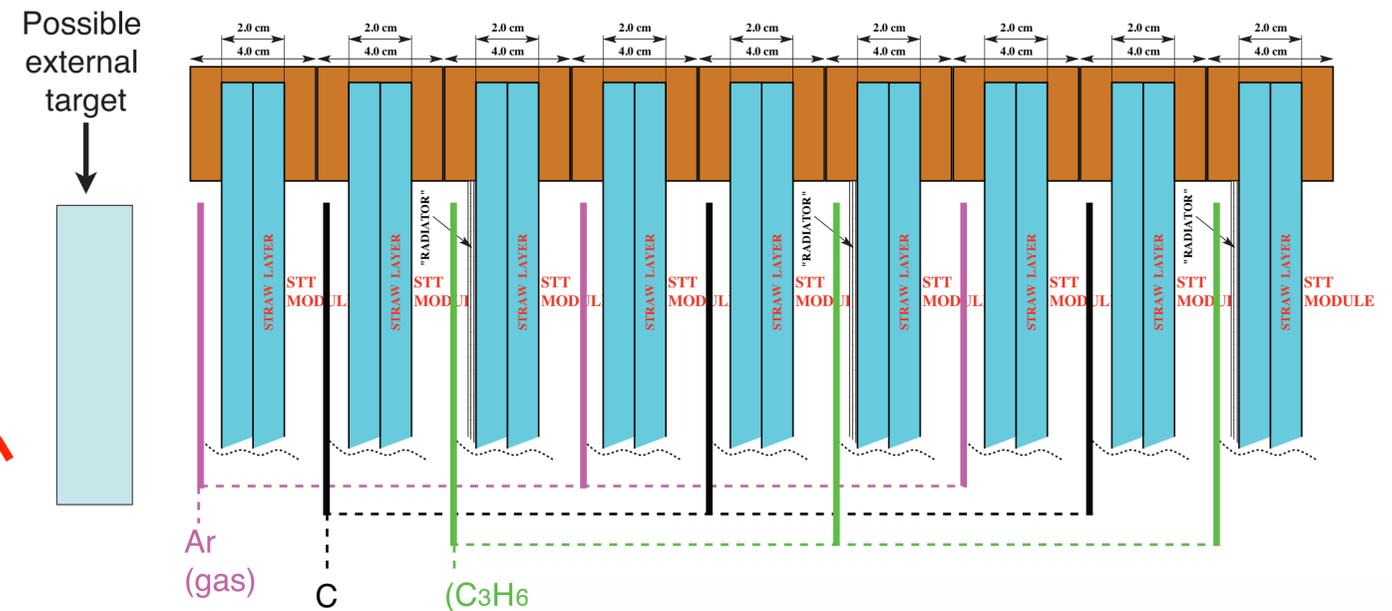
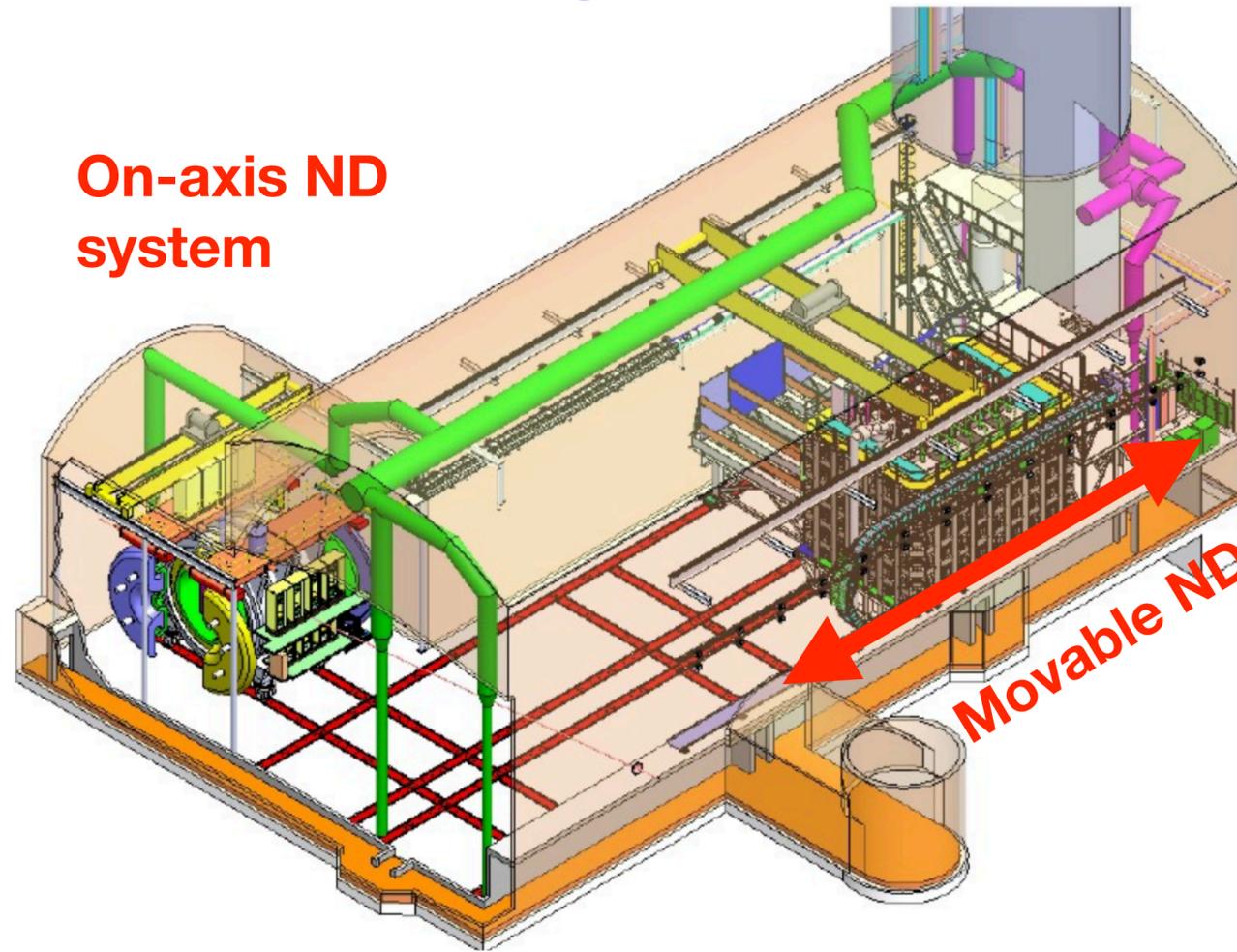


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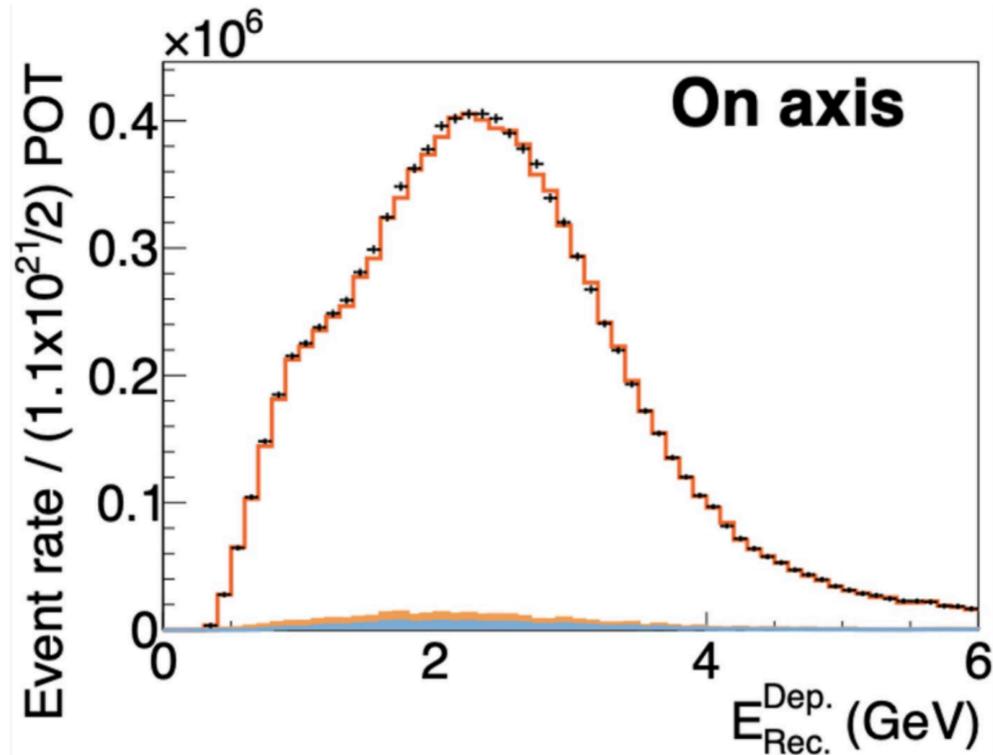
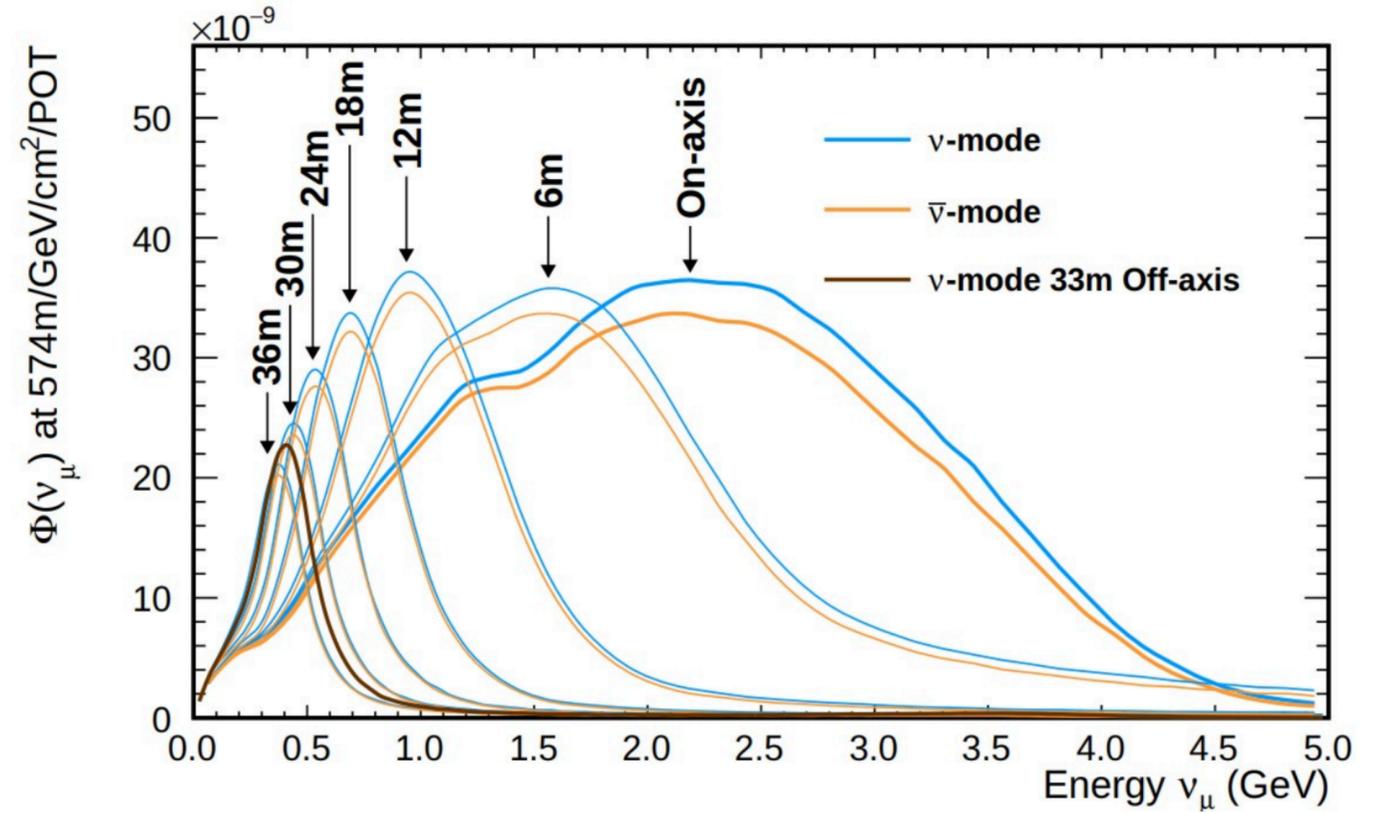
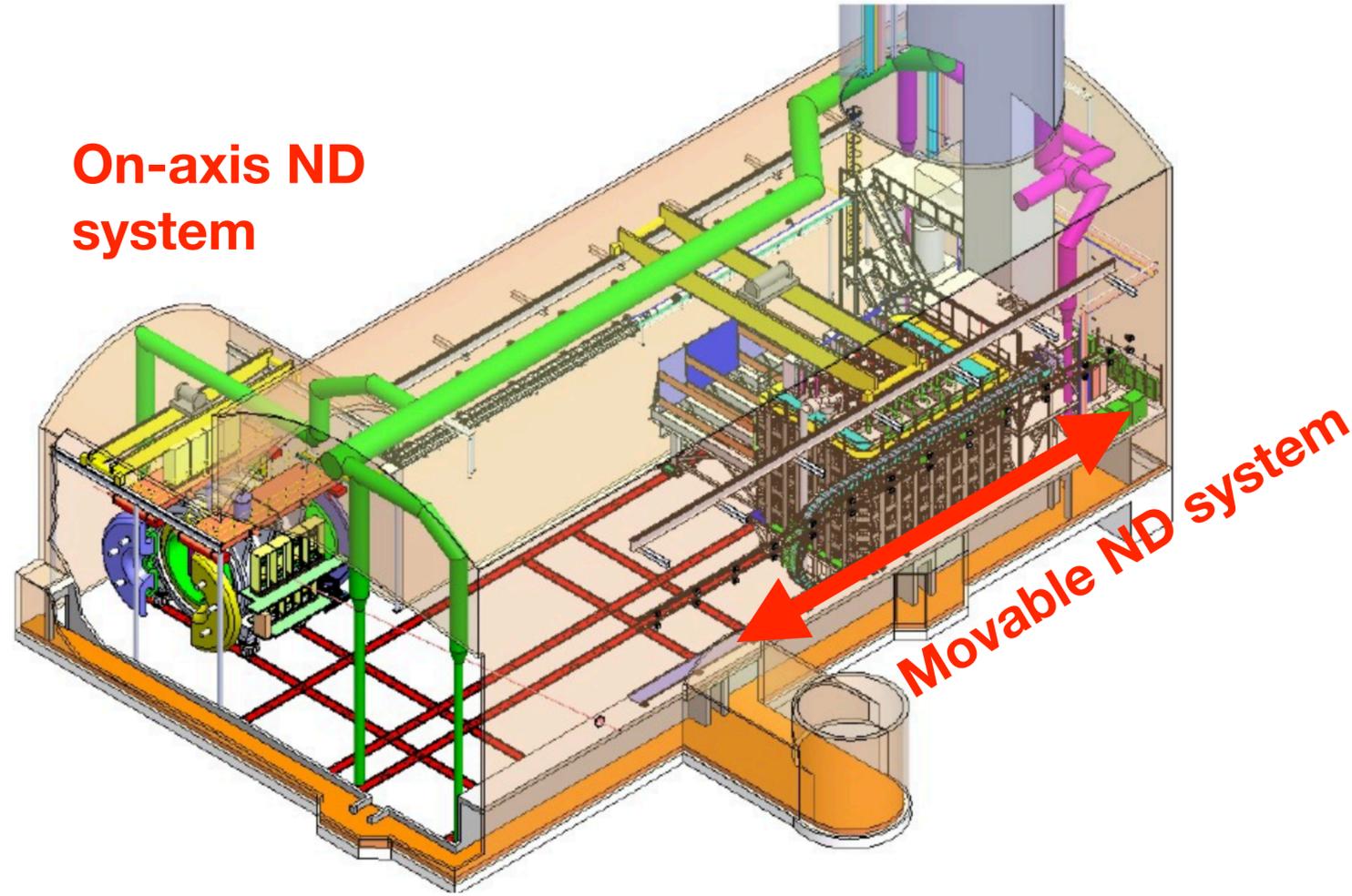
# Next generation of $\nu$ -interaction measurements



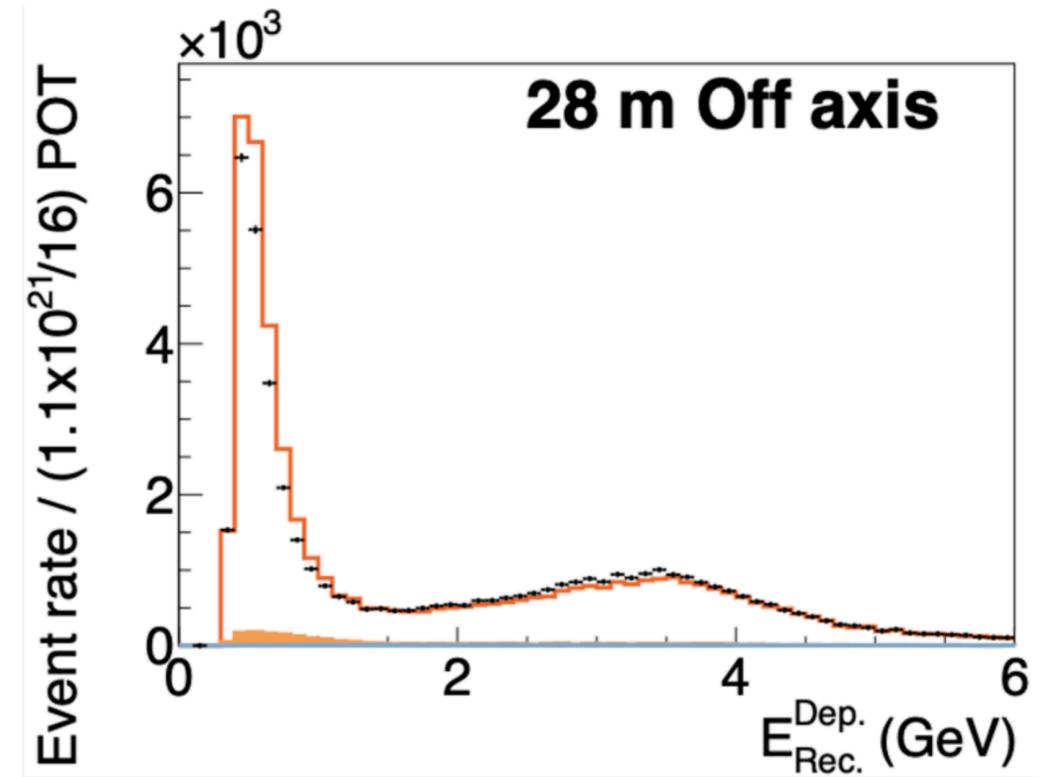
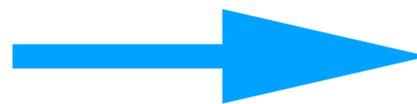
• [Phys.Lett. B795 \(2019\) 424-431](#)

- **The DUNE ND complex.**
- **SAND:** System for on-axis neutrino detection.
- Multiple nuclear targets in a low-density straw tube tracker.
  - CH<sub>2</sub> target and pure carbon target enables  $\nu$ -H interaction measurements by statistically subtract carbon backgrounds.
  - Precise flux measurements with  $\nu$ -H interactions and low- $\nu$  method.

# Next generation of $\nu$ -interaction measurements



De-coupling  $\nu$ -int and flux effects by varying the flux by going different off-axis locations

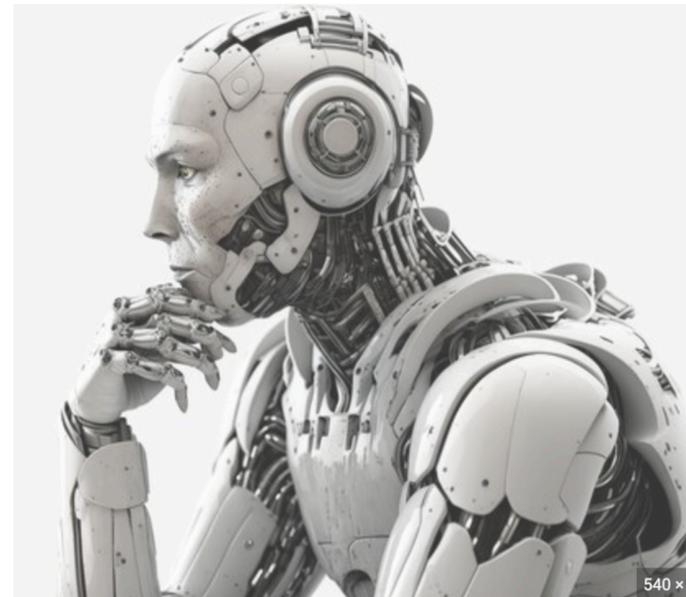


# Summary

- We are entering a precision era of neutrino physics, theoretically and experimentally.
- The applications of deep learning techniques greatly enhance detectors' capability
  - More effective signal recognition.
  - Higher resolution measurements.
  - Turn impossible into possible.
- **In the same time requires better understanding of neutrino interactions!**
  - Data-driven approaches may ease but not completely solve the problem.
  - Both theoretical and experimental efforts are needed.



Frankenstein's monster of v-int



Deep-learning