Overview of Machine Learning Applications in JUNO

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on behalf of JUNO

ICHEP 2024@prage

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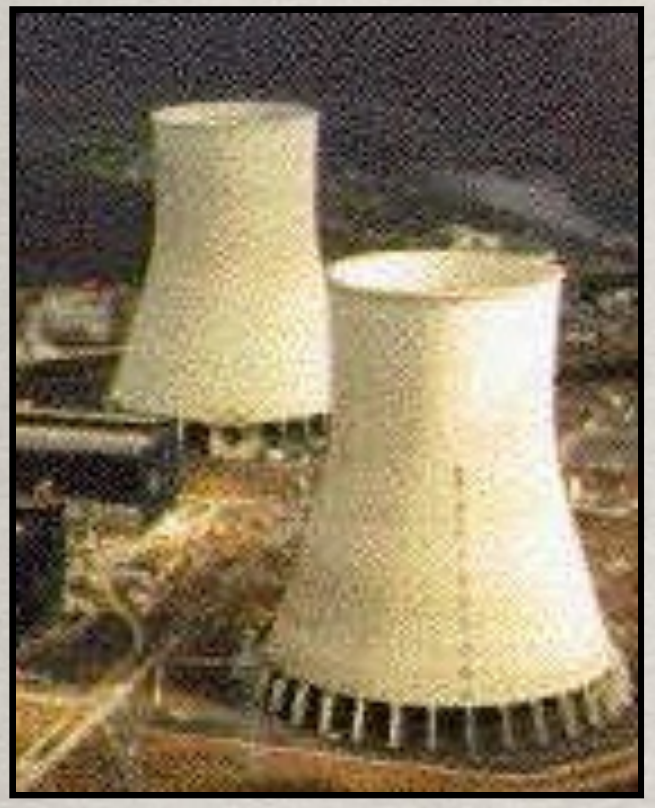
JUNO

OUTLINE

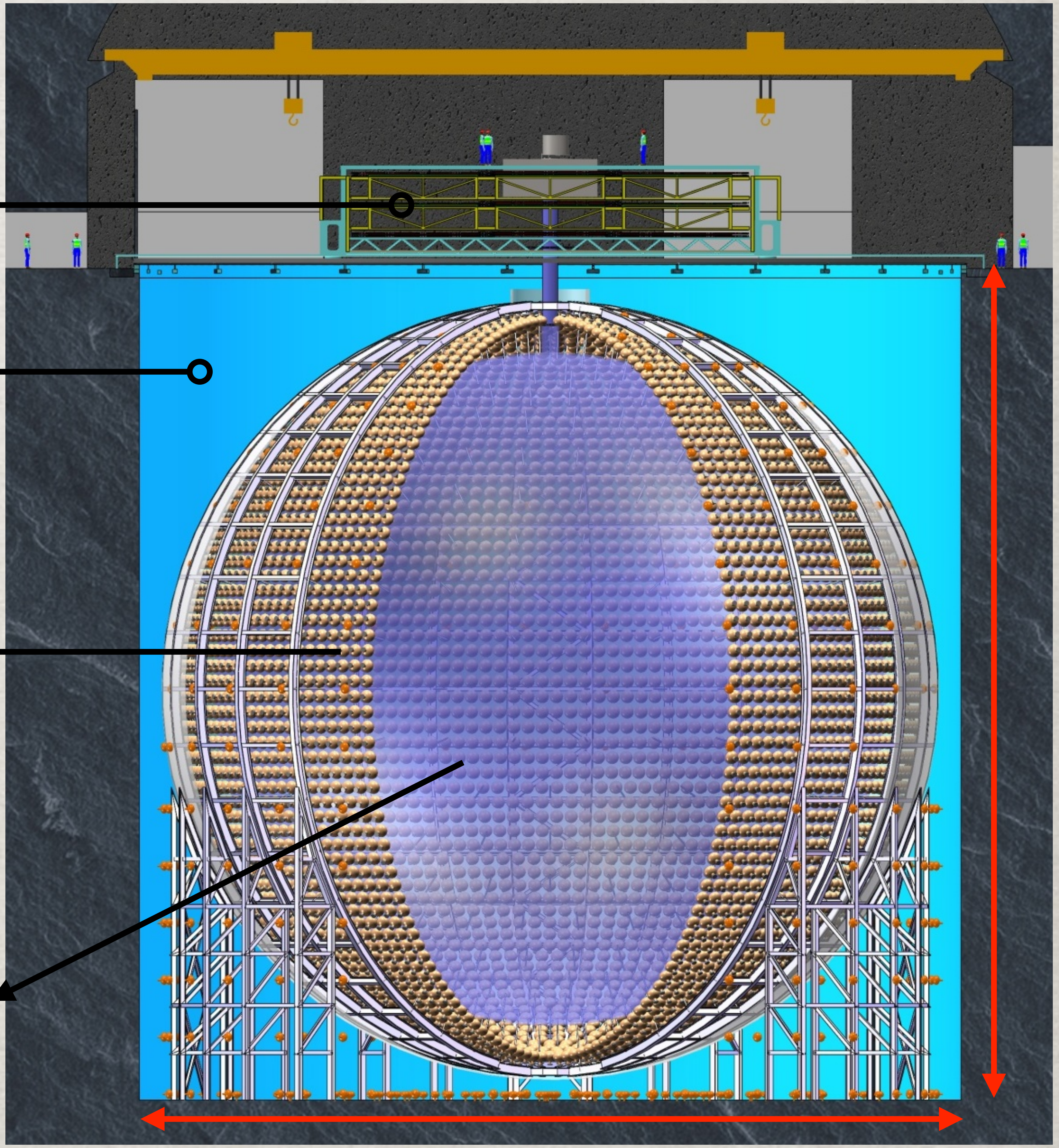
- Introduction of JUNO
- Applications of Deep Learning in MeV region
  - PMT waveform reco for reactor anti-neutrinos
  - Vertex/Energy reco for reactor anti-neutrinos
- Applications of Deep Learning in GeV region
  - Directionality for atmospheric neutrinos
  - Particle Identification for atmospheric neutrinos
- Summary

JUNO

- Jiangmen Underground Neutrino Observatory(JUNO):
  - Determine the neutrino mass ordering
  - Measure neutrino oscillation parameters to sub-percent level
  - SuperNova, Solar, Atm. Geo. etc



	DETECTOR TARGET MASS	ENERGY RESOLUTION
KamLAND	1000 t	6%@1MeV
D. Chooz	8+22 t	
RENO	16 t	8%@1MeV
Daya Bay	20 t	
Borexino	300 t	5%@1MeV
JUNO	**20000 t**	3%@1MeV



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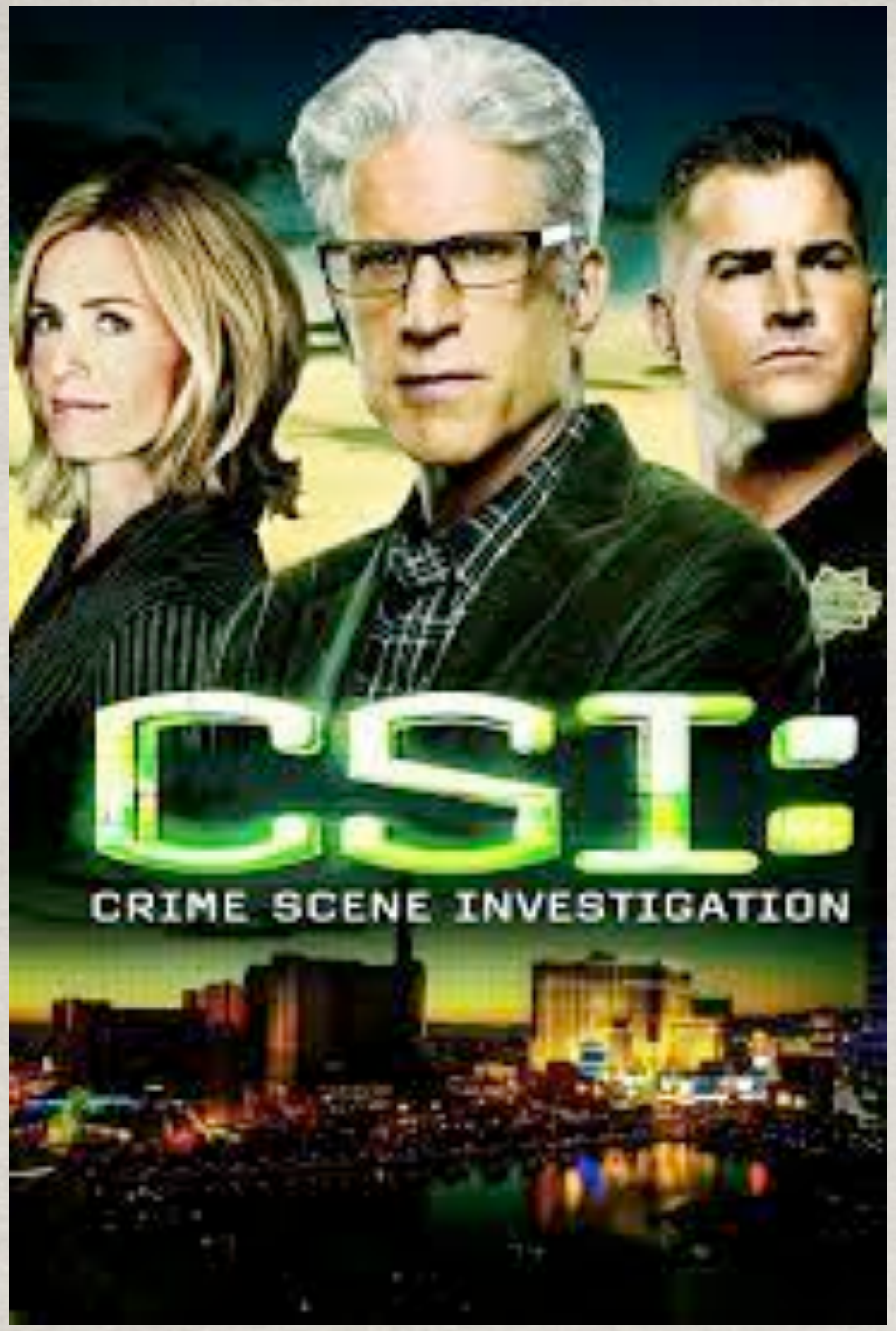
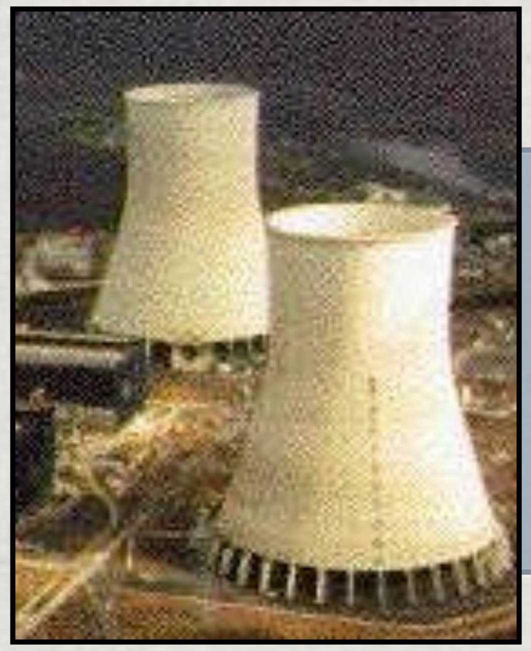


RECO IN JUNO

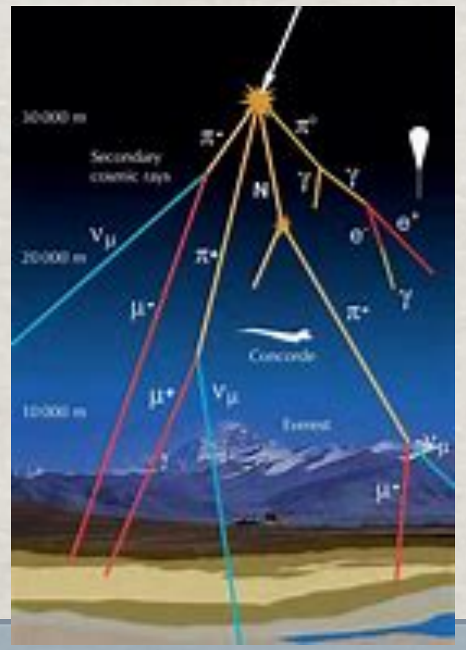


reactor $\bar{\nu}$
MeV

- PMT waveform
- energy
- vertex

- non-uniformity
- PMT dark noise
- PMT charge smear
- ^{14}C pileUp

Neutrino Mass Ordering



atm.ν
GeV

- Direction
- Particle ID
- Energy

- ν_μ vs ν_e vs NC
- ν vs $\bar{\nu}$

cosmic μ
GeV

- muon classification
- multi-detector combined reco
- track
- shower vertex

reactor $\bar{\nu}$

MeV

Neutrino Mass Ordering

PMT waveform

energy

vertex

non-uniformity

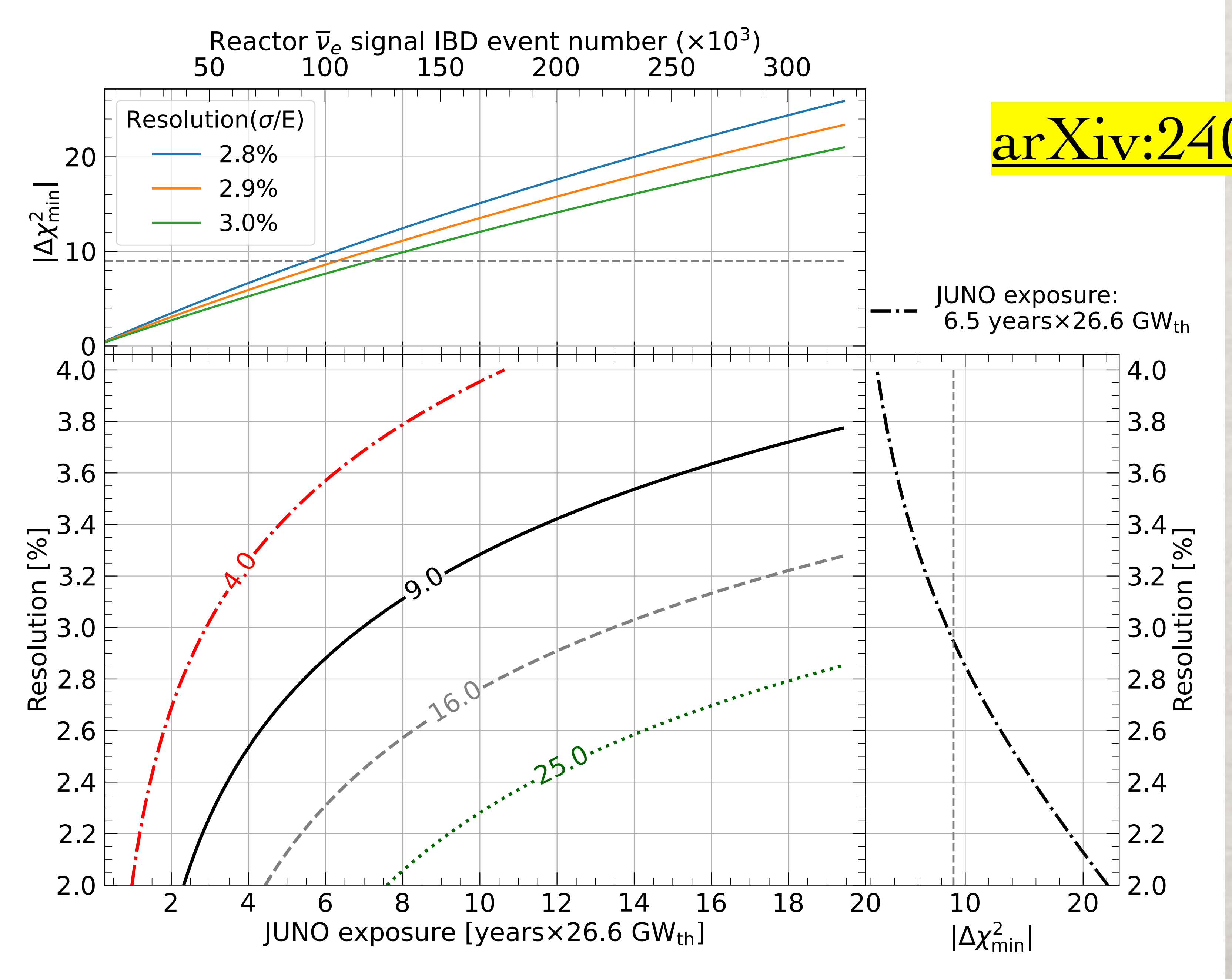
PMT dark noise

PMT charge smear

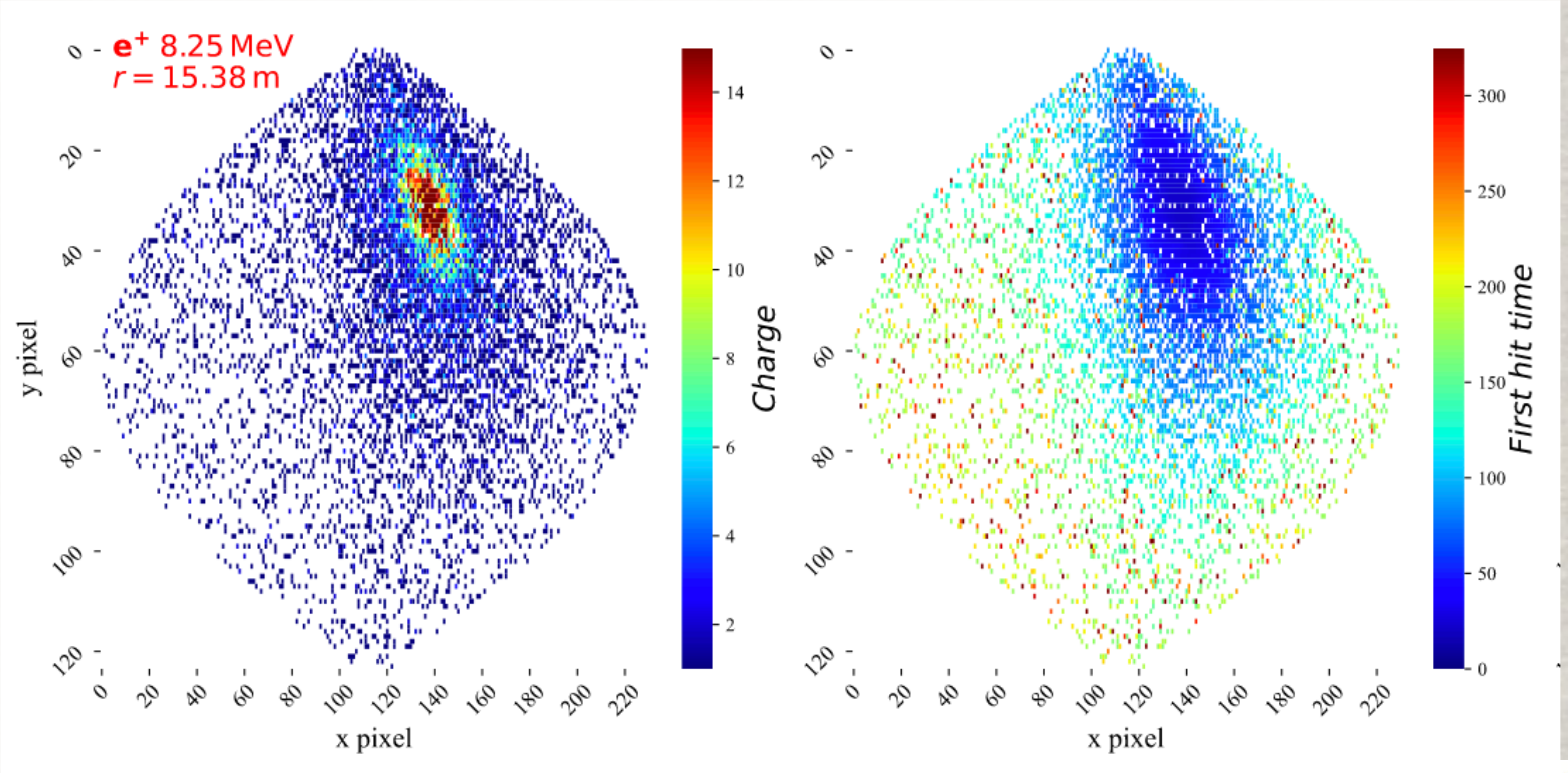
^{14}C pileUp

IMPORTANCE AND PRINCIPLES

- ❖ Large number of PMTs O(10^4) installed on a sphere
  - ❖ each PMT as a pixel —> JUNO as a Camera
  - ❖ ensemble of PMTs charge/time form an image
- ❖ Image is highly vertex and energy dependent
- ❖ Vertex/energy reconstruction <—> Image recognition



arXiv:2405.18008



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INPUTS

- ❖Large number of PMTs O(10^4) installed on a sphere
- ❖Method 1: projection to 2D plane —>Plane CNN
- ❖Method 2: HEALPix —> plane/spherical CNN
- ❖Method 3: 3D models such as pointNet++/Transformer

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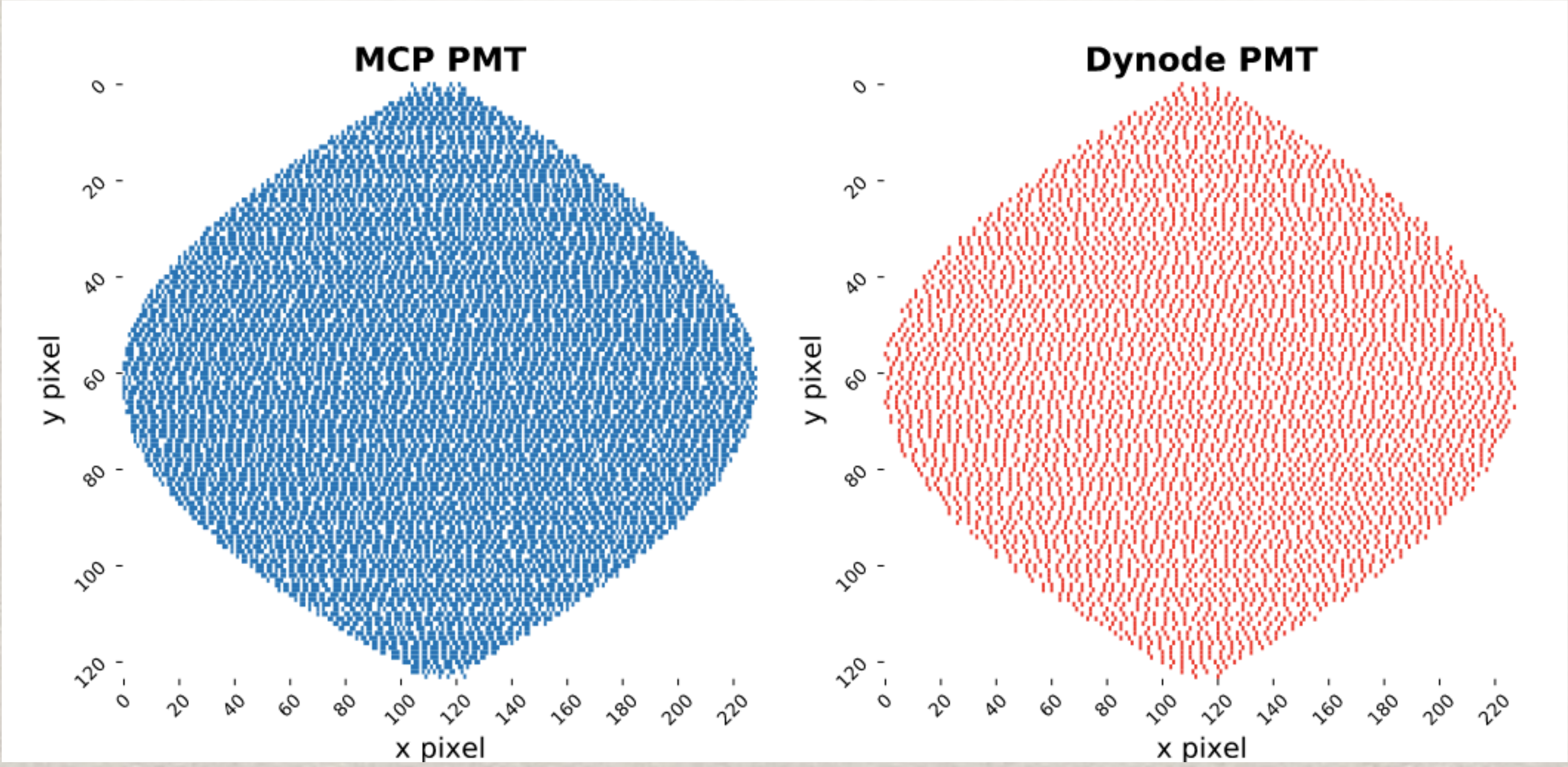

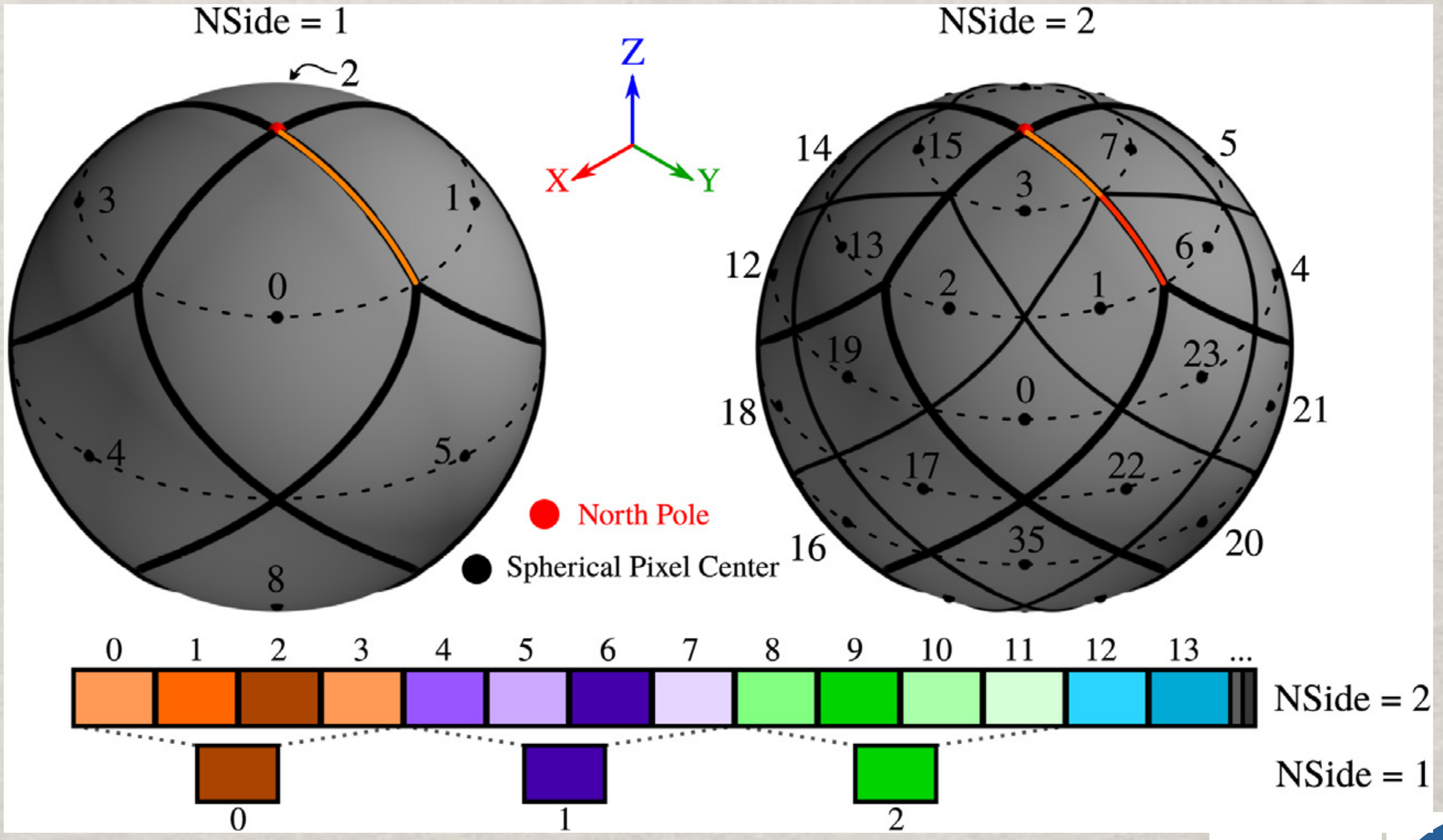

MODELS: VGG-J

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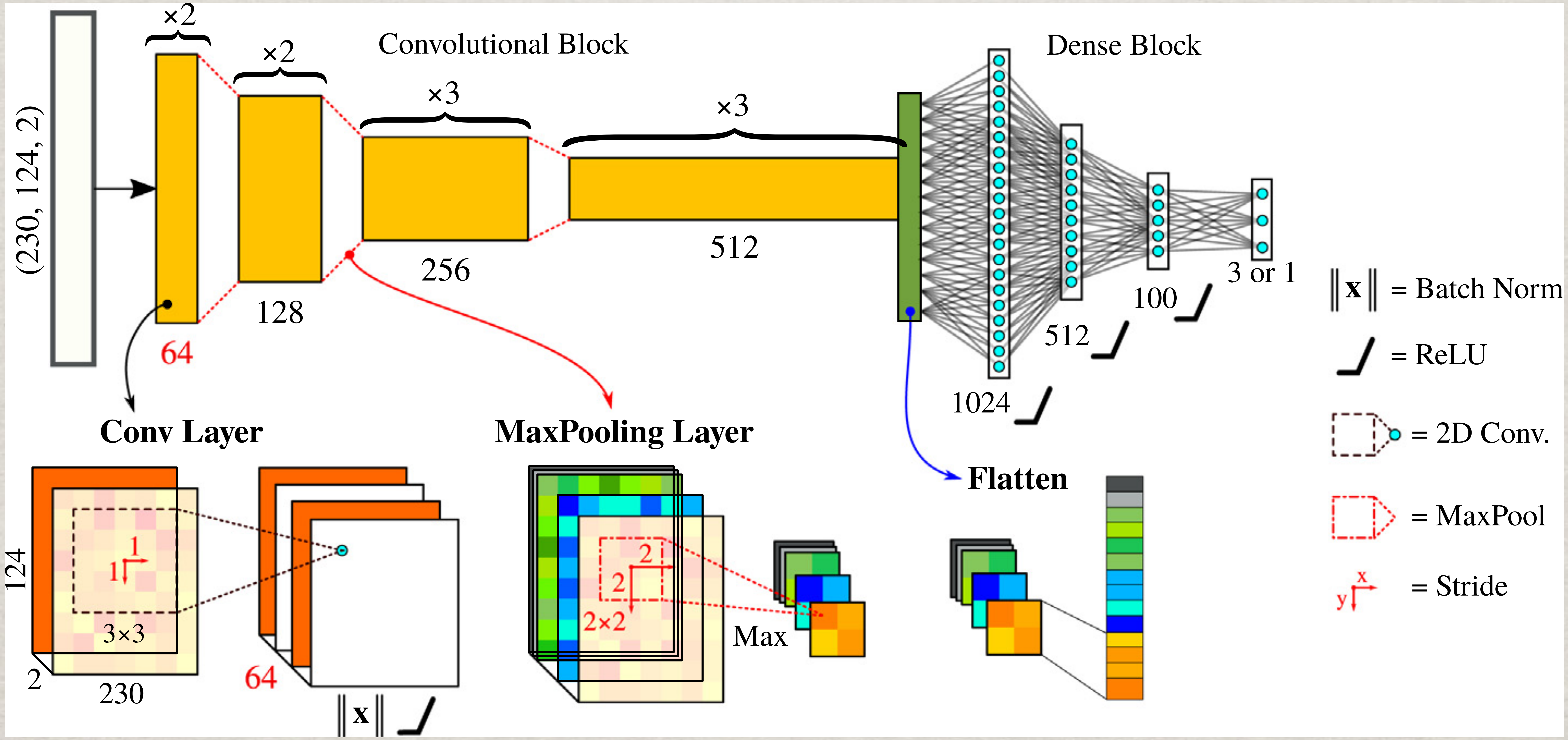

MODELS: RESNET-J

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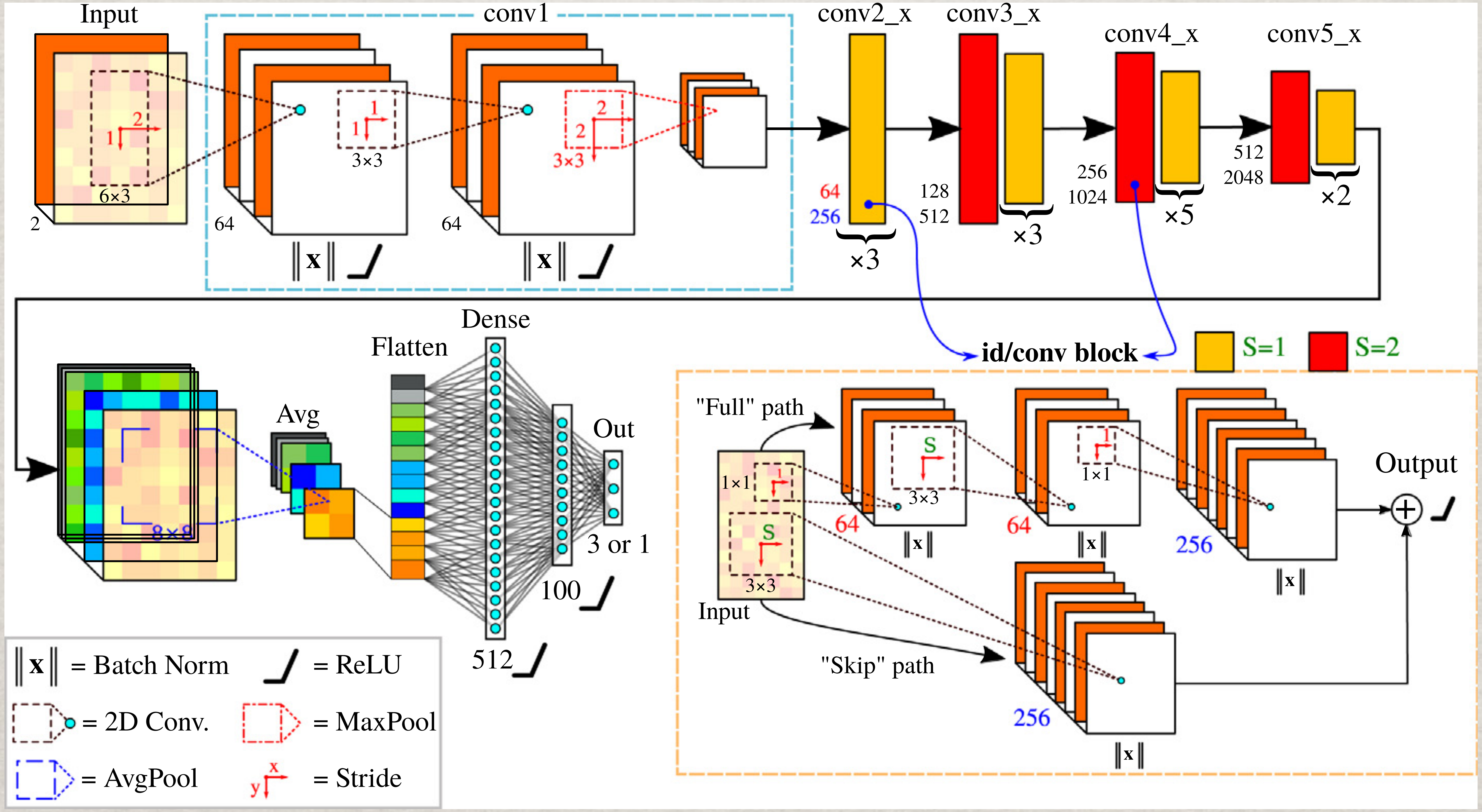

MODELS: GNN-J

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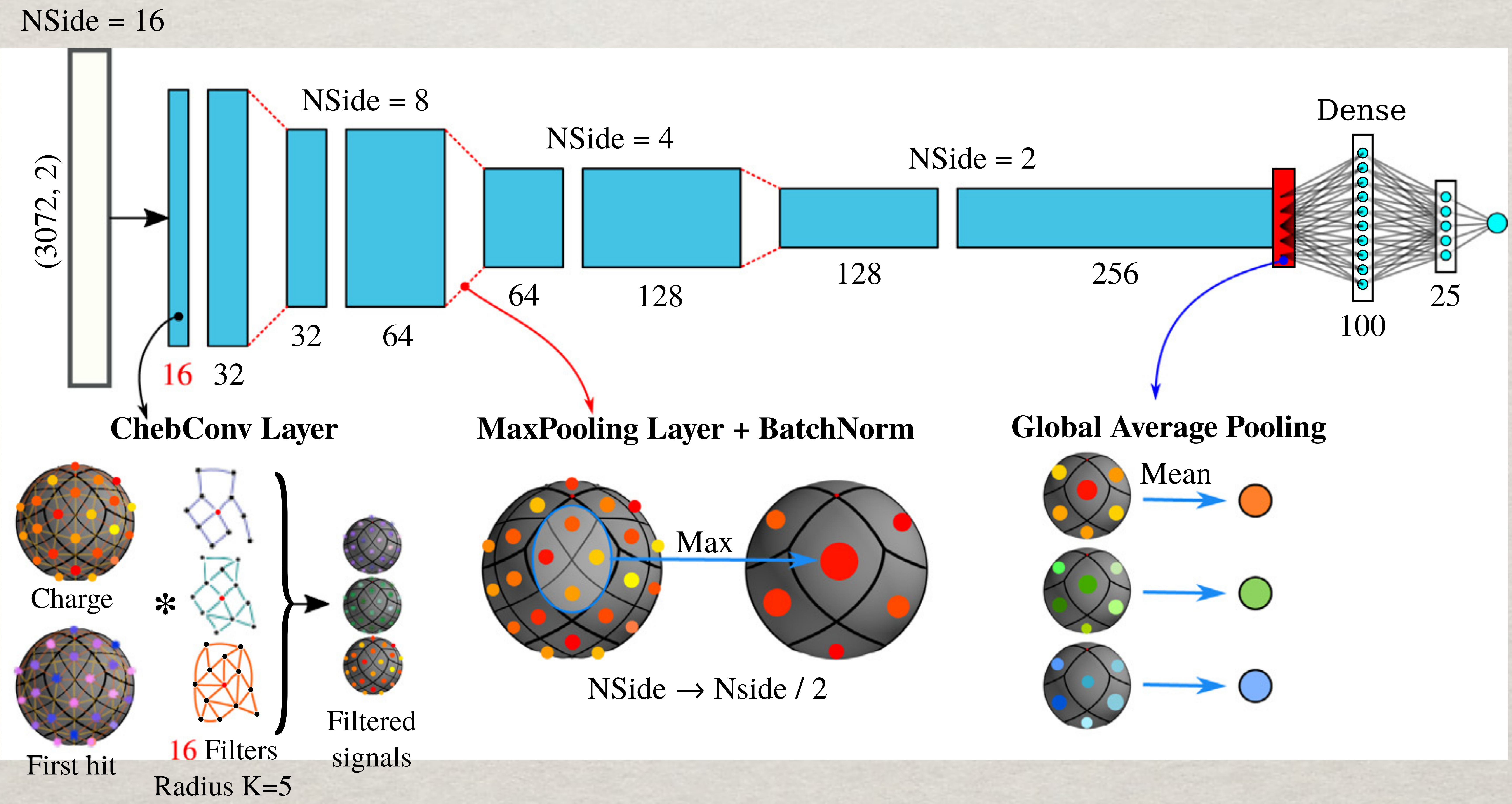

Vertex: Charge vs Time

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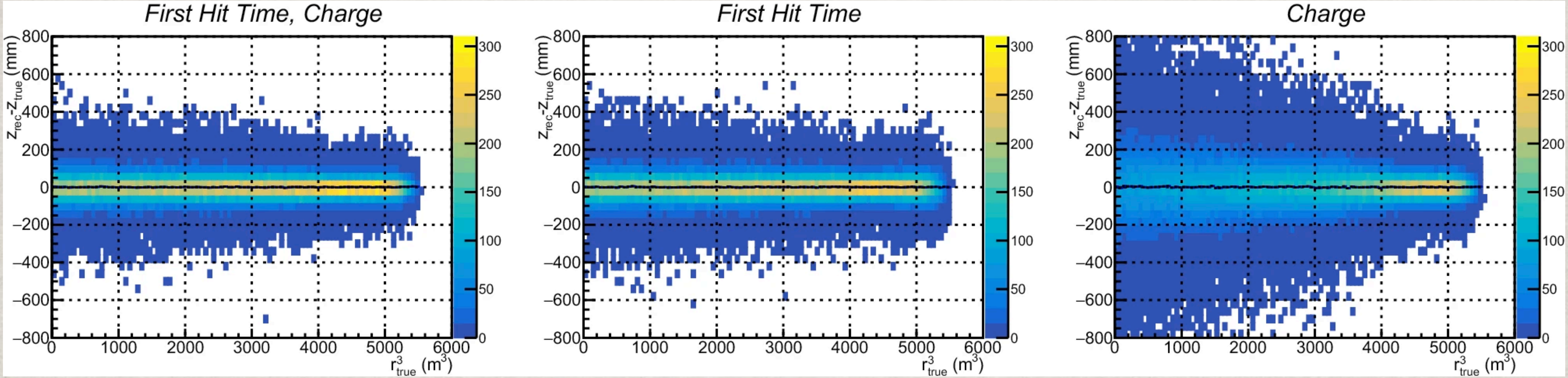
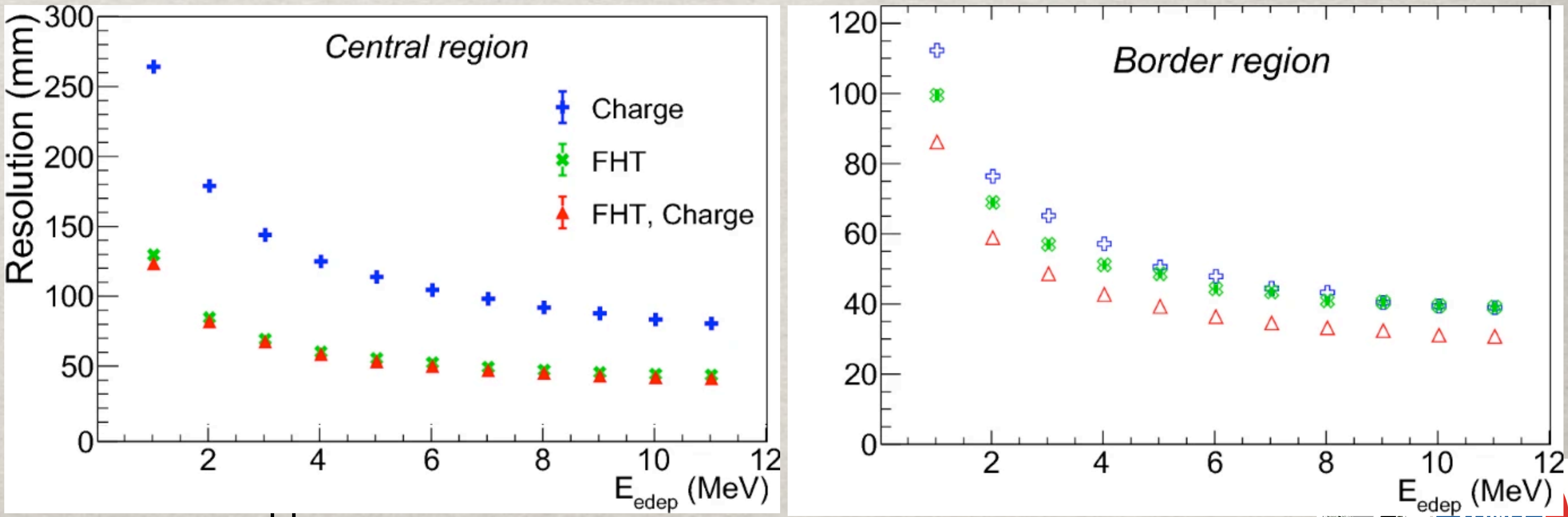
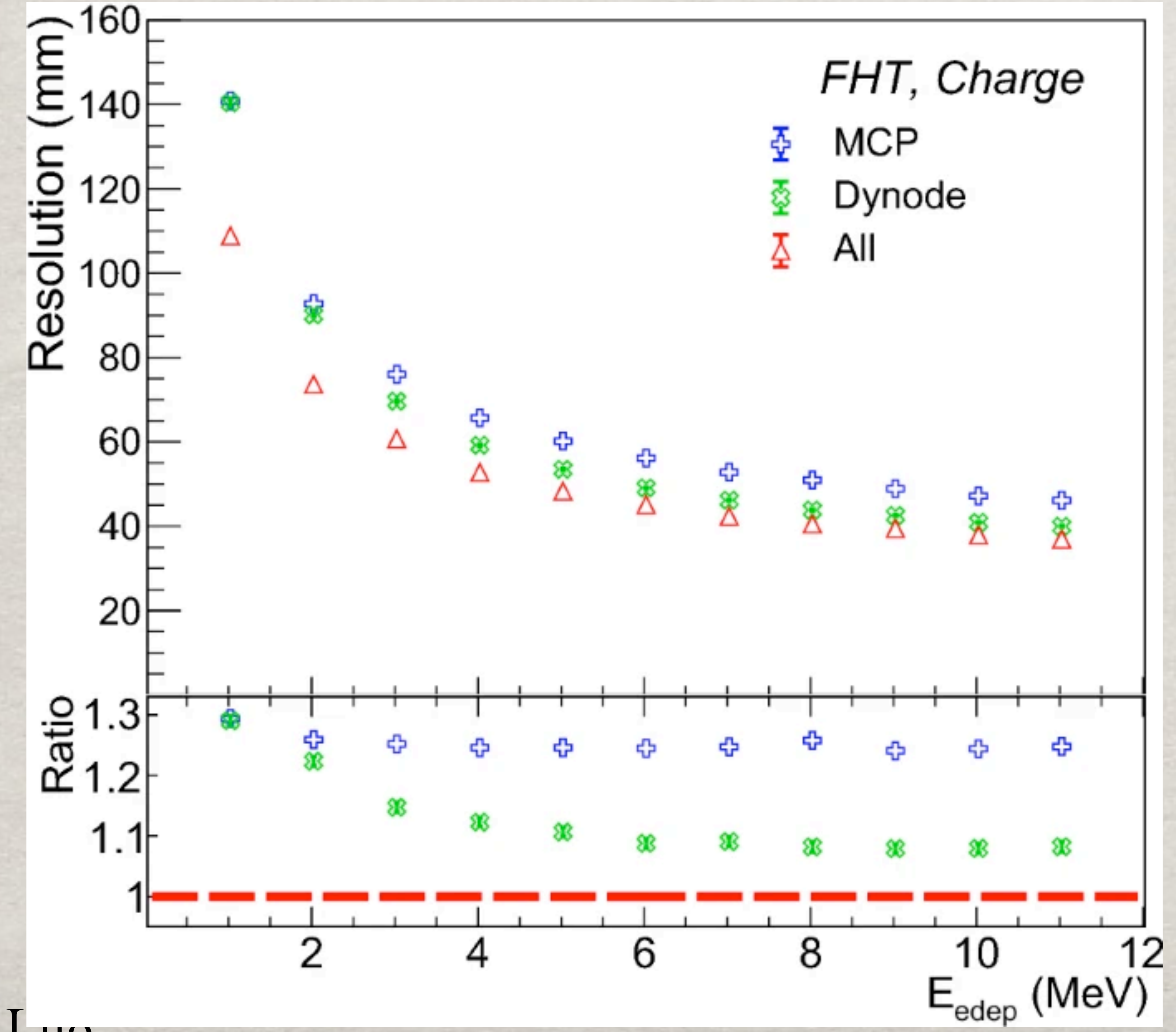


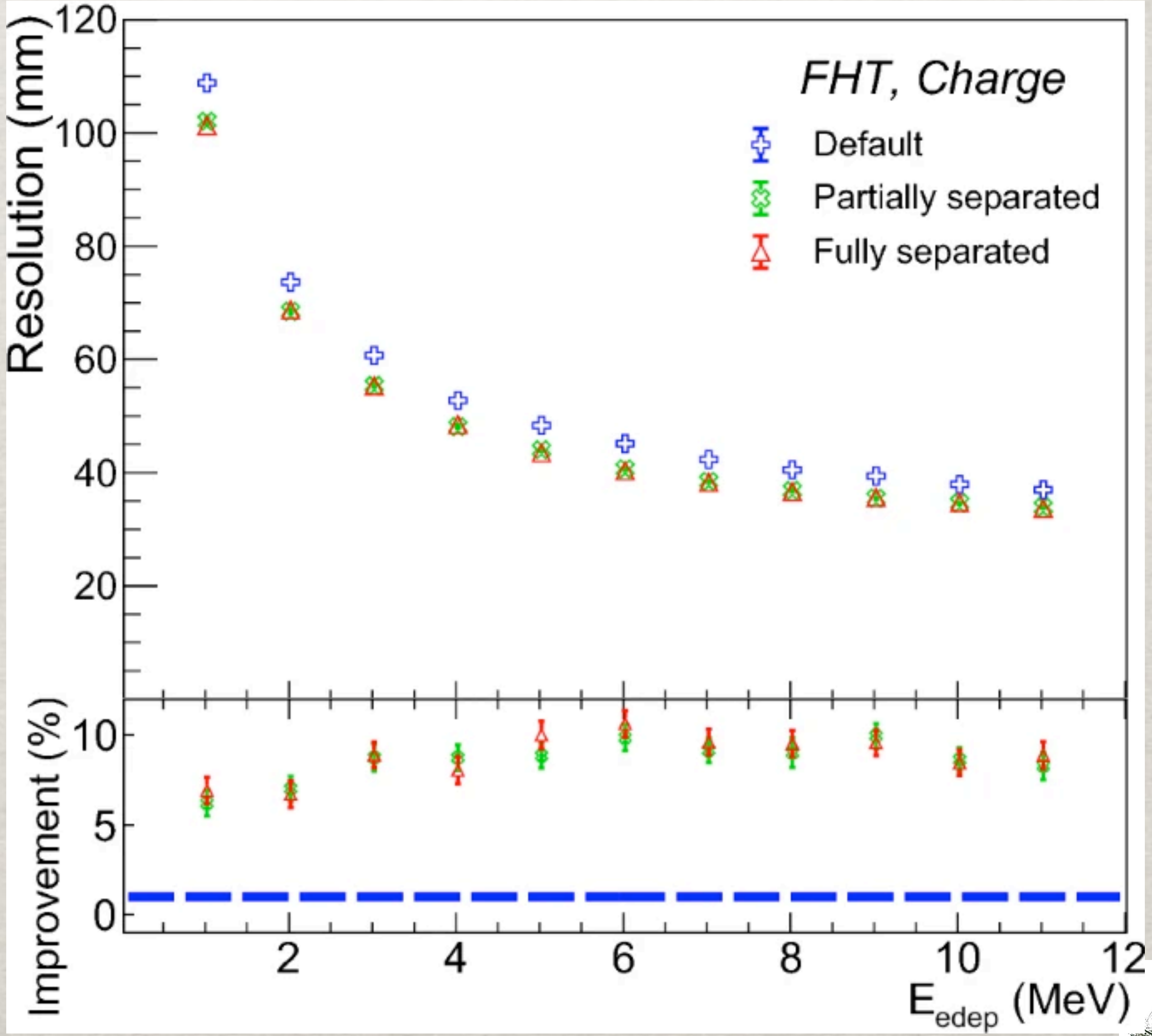
- ❖Charge also helps constrain the Vertex, especially in the border region



Vertex: MCP vs Dynode

- Comparison between MCP PMTs and Dynode PMTs Nucl.Sci.Tech. 33 (2022) 7, 93
  - Number: 12612 vs 5000; Time resolution(σ_{tts}): 12 ns vs 2.8 ns
- Separating charge/time info by PMT type gives the best performance





Vertex: Addition of 2nd Hit

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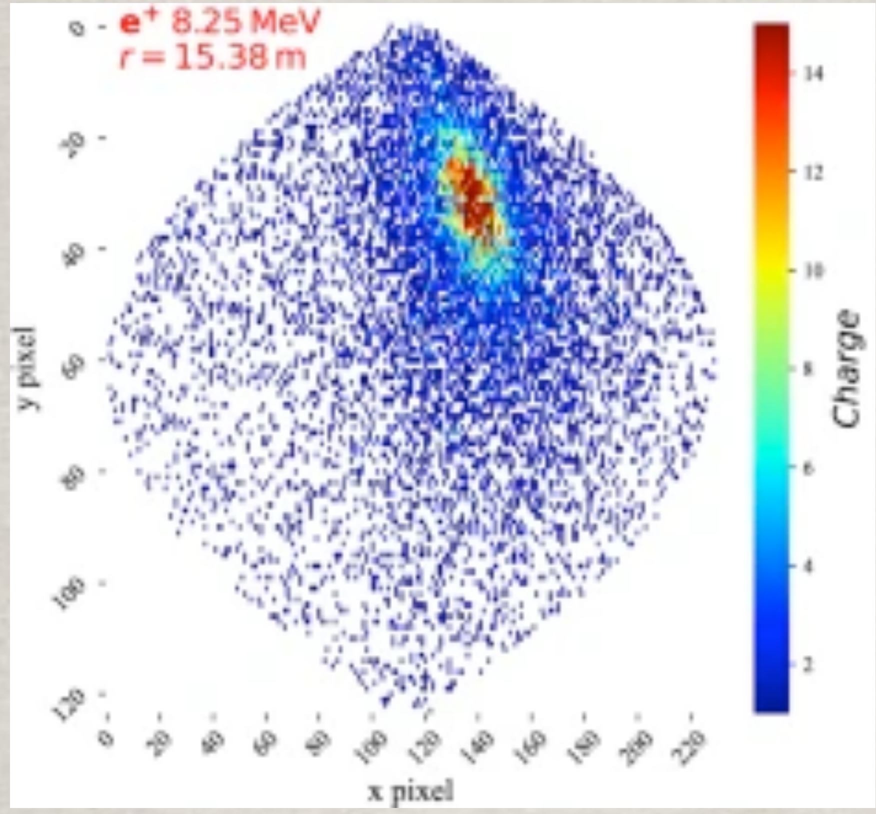
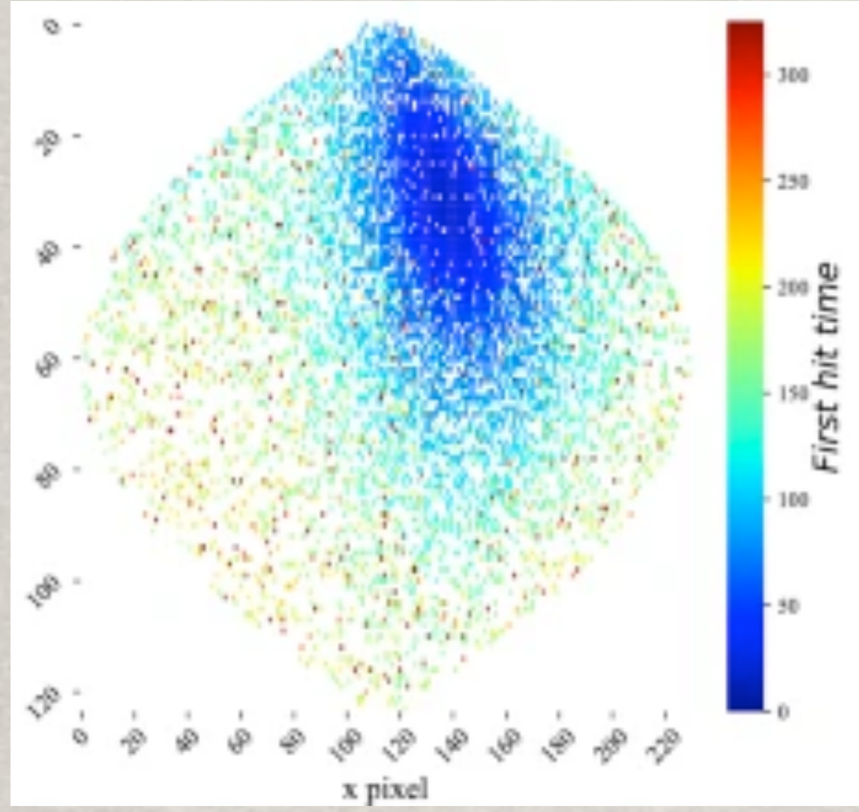
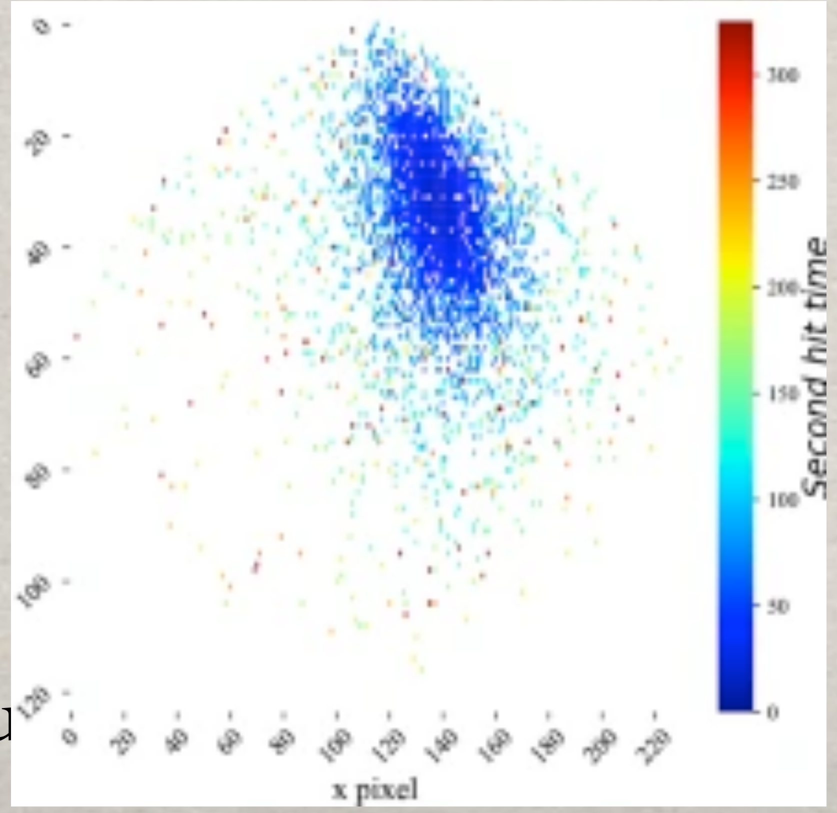


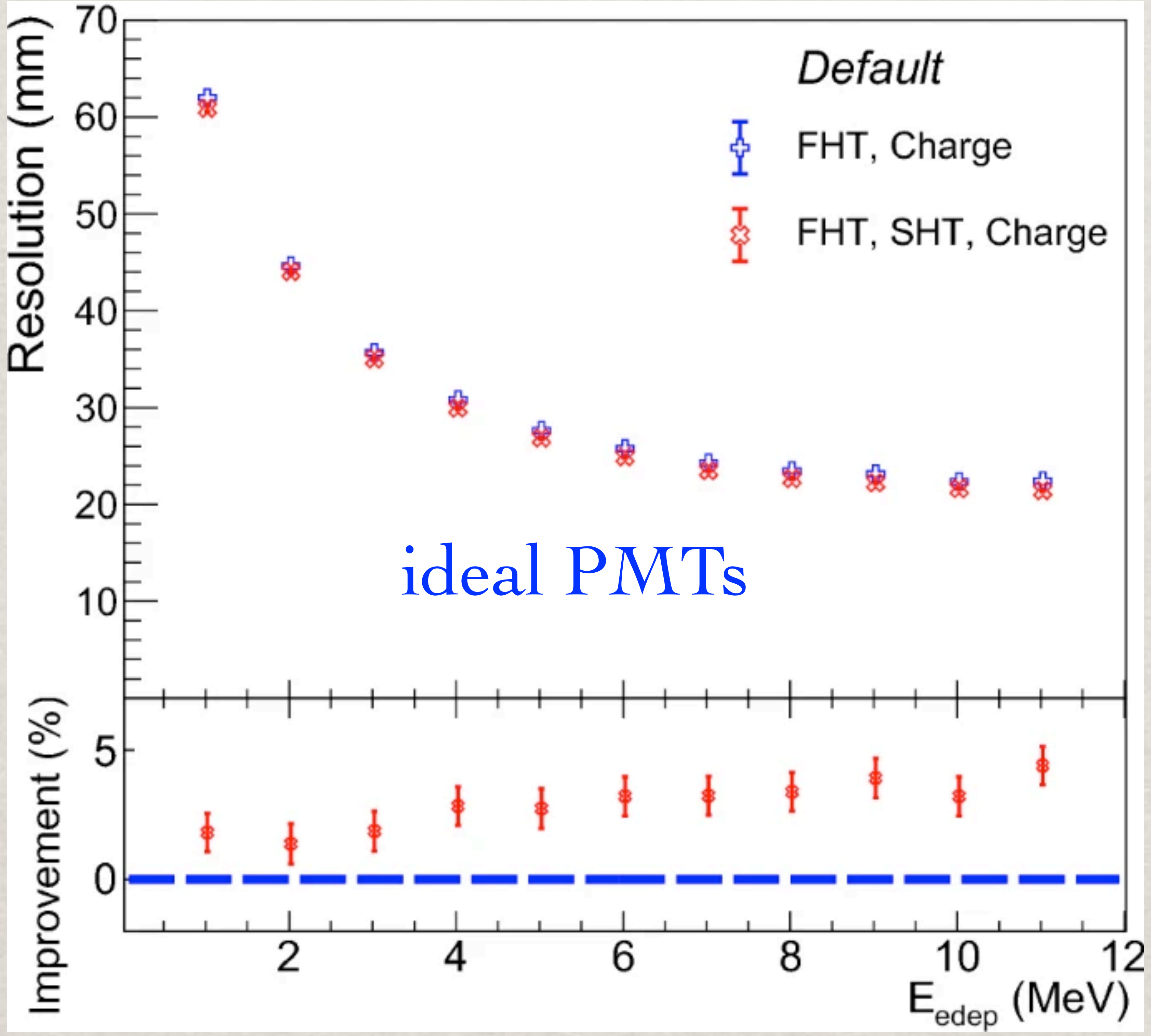
Charge



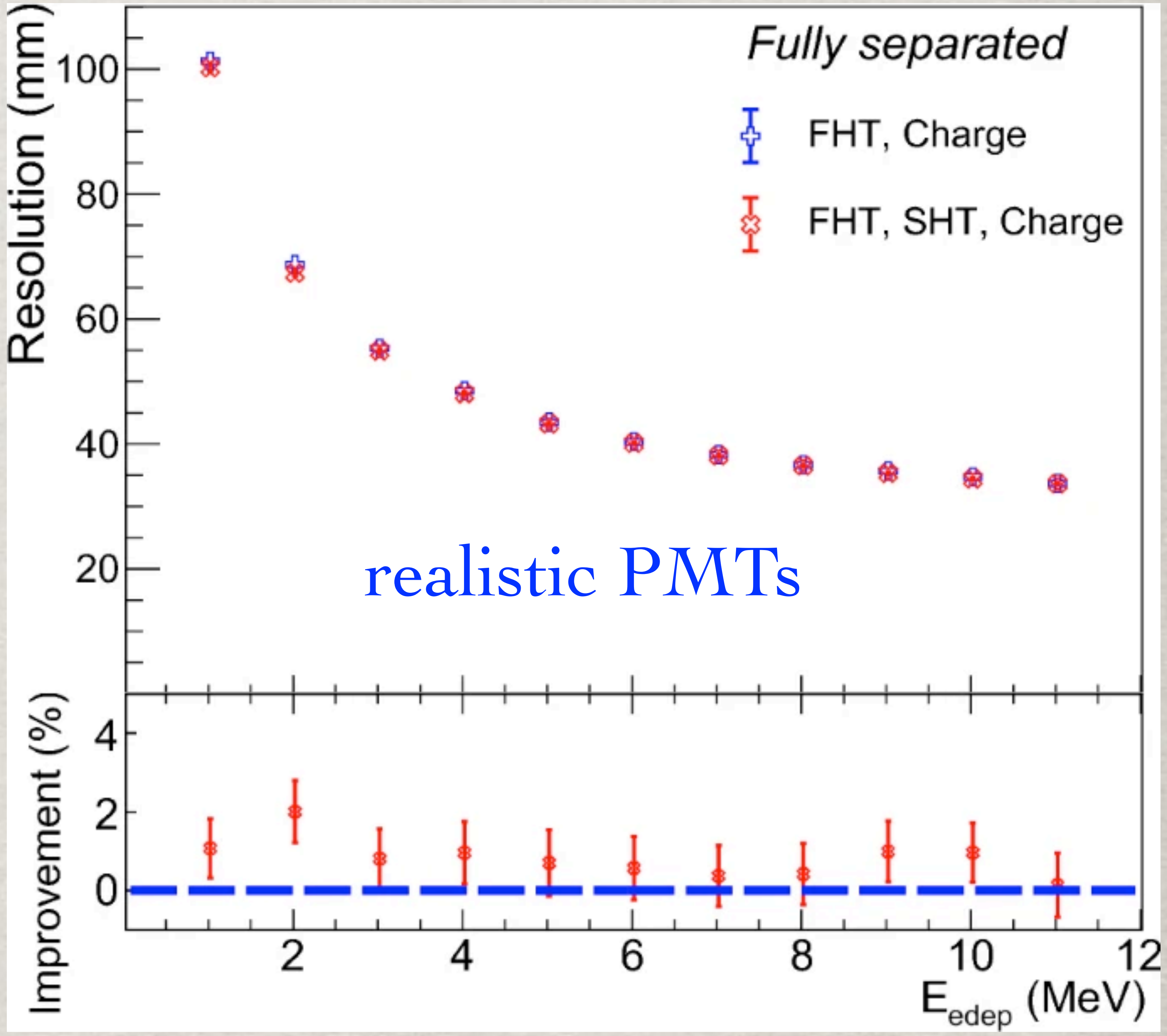
FHT: t(1st Hit)



SHT: t(2nd Hit)



ideal PMTs



realistic PMTs

- ❖Later hits are also useful in principle
- ❖PMT Time resolution is the key

ENERGY: BDT/FCDNN

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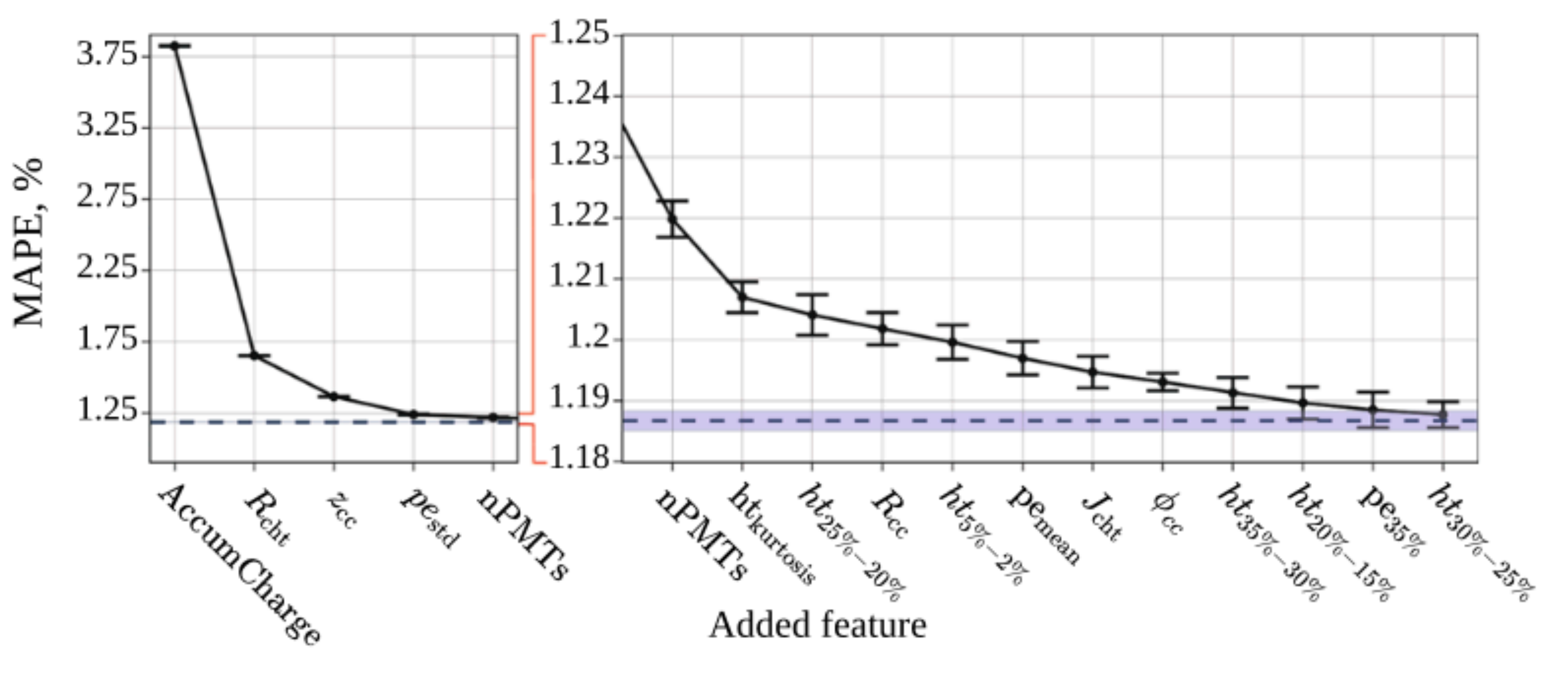
- Inputs: feature engineering
- Models: BDT or FCDNN
- Optimization:
  - hyper-parameters
  - feature selection

Notation	Description
AccumCharge	Total accumulated charge
nPMTs	Number of fired PMTs
$x_{cc}, y_{cc}, z_{cc}, R_{cc}, \theta_{cc}, \phi_{cc}, J_{cc}, \rho_{cc}, \gamma_z^{cc}, \gamma_y^{cc}, \gamma_x^{cc}$	Center of charge
$pe_{n\%}, pe_{mean}, pe_{std}, pe_{skew}, pe_{kurtosis}$	Charge distribution
$x_{cht}, y_{cht}, z_{cht}, R_{cht}, \theta_{cht}, \phi_{cht}, J_{cht}, \rho_{cht}, \gamma_z^{cht}, \gamma_y^{cht}, \gamma_x^{cht}$	Center of FHT
$ht_{n\%}, ht_{n_{i+1}\%-n_i\%}, ht_{mean}, ht_{std}, ht_{skew}, ht_{kurtosis}$	FHT distribution



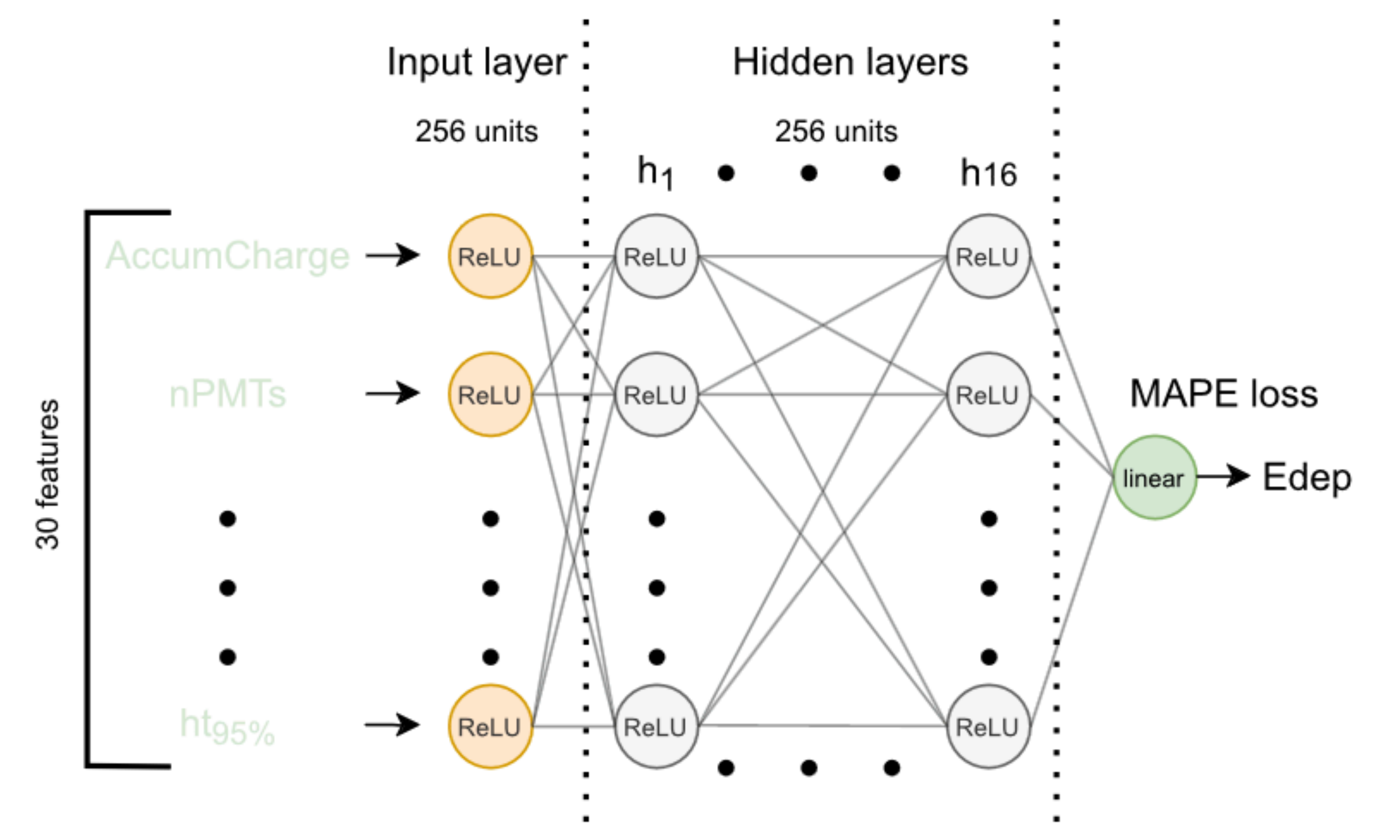


Fig. 12 Selected FCDNN architecture and its main selected hyperparameters

PMT WAVEFORM PHOTON COUNTING

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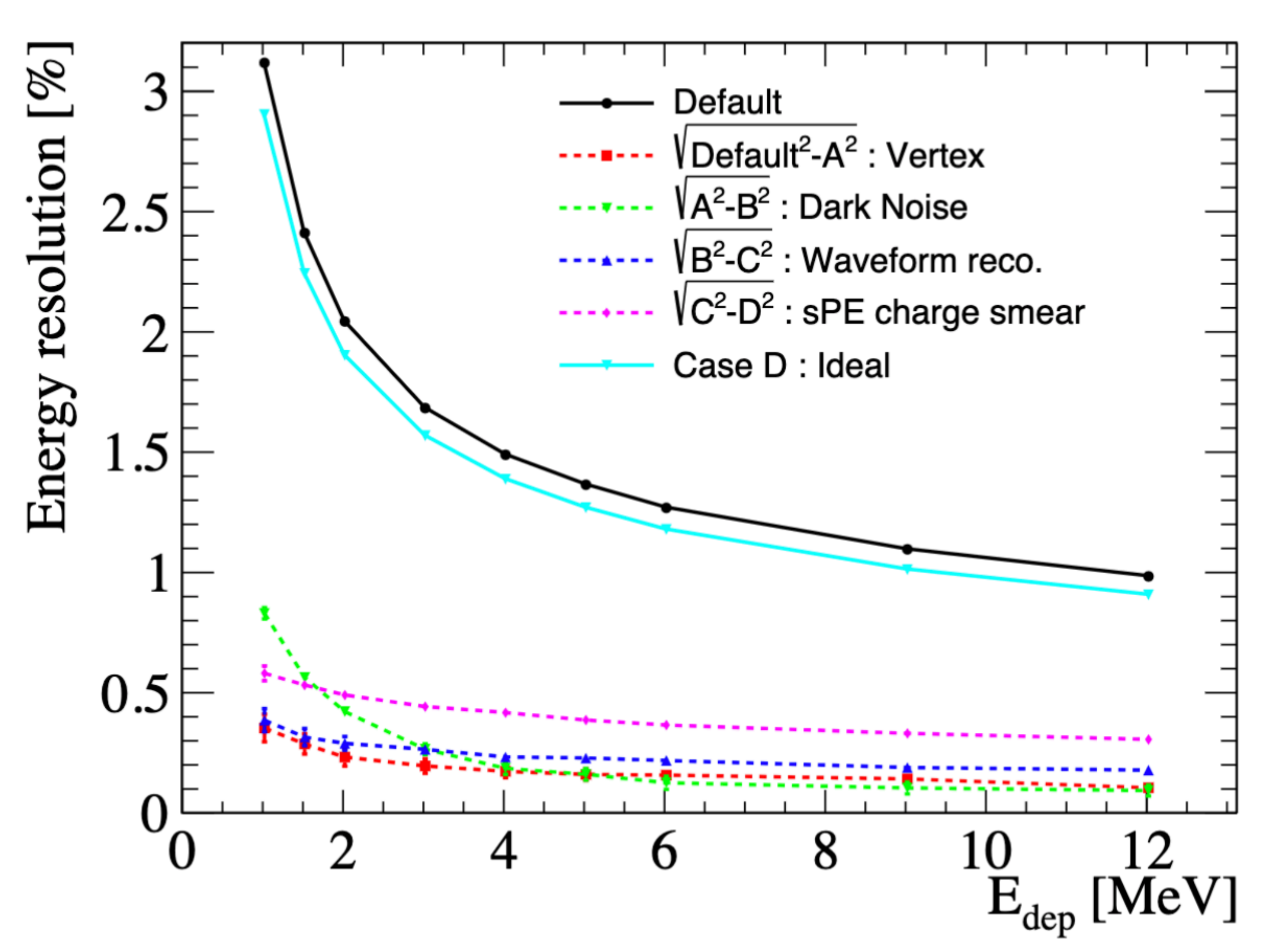


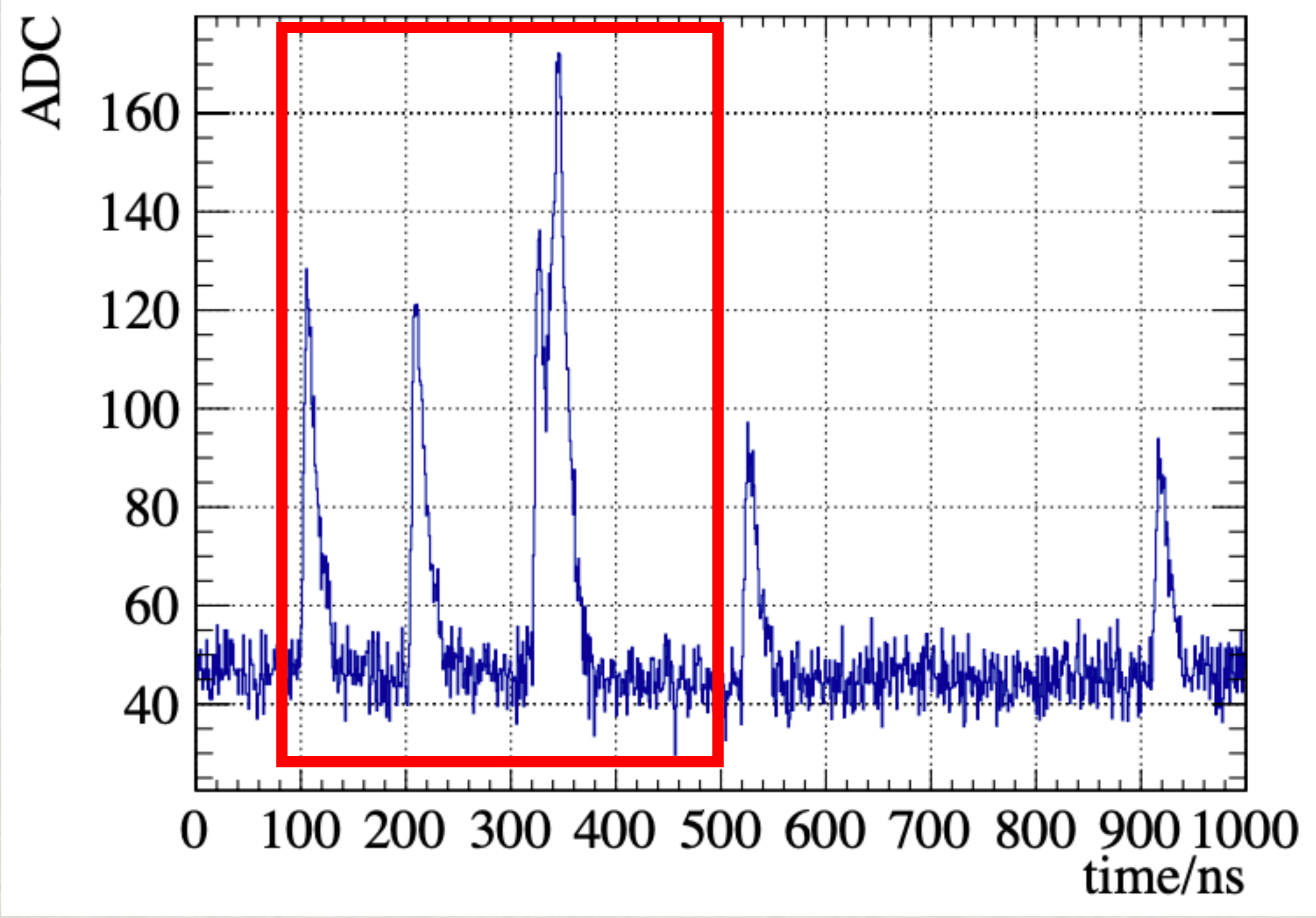


Table 2: Modified RawNet architecture. For convolutional layers, numbers inside parentheses refer to filter length, stride size, and number of filters. For gated recurrent unit (GRU) and fully-connected layers, numbers inside the parentheses indicate the number of nodes.

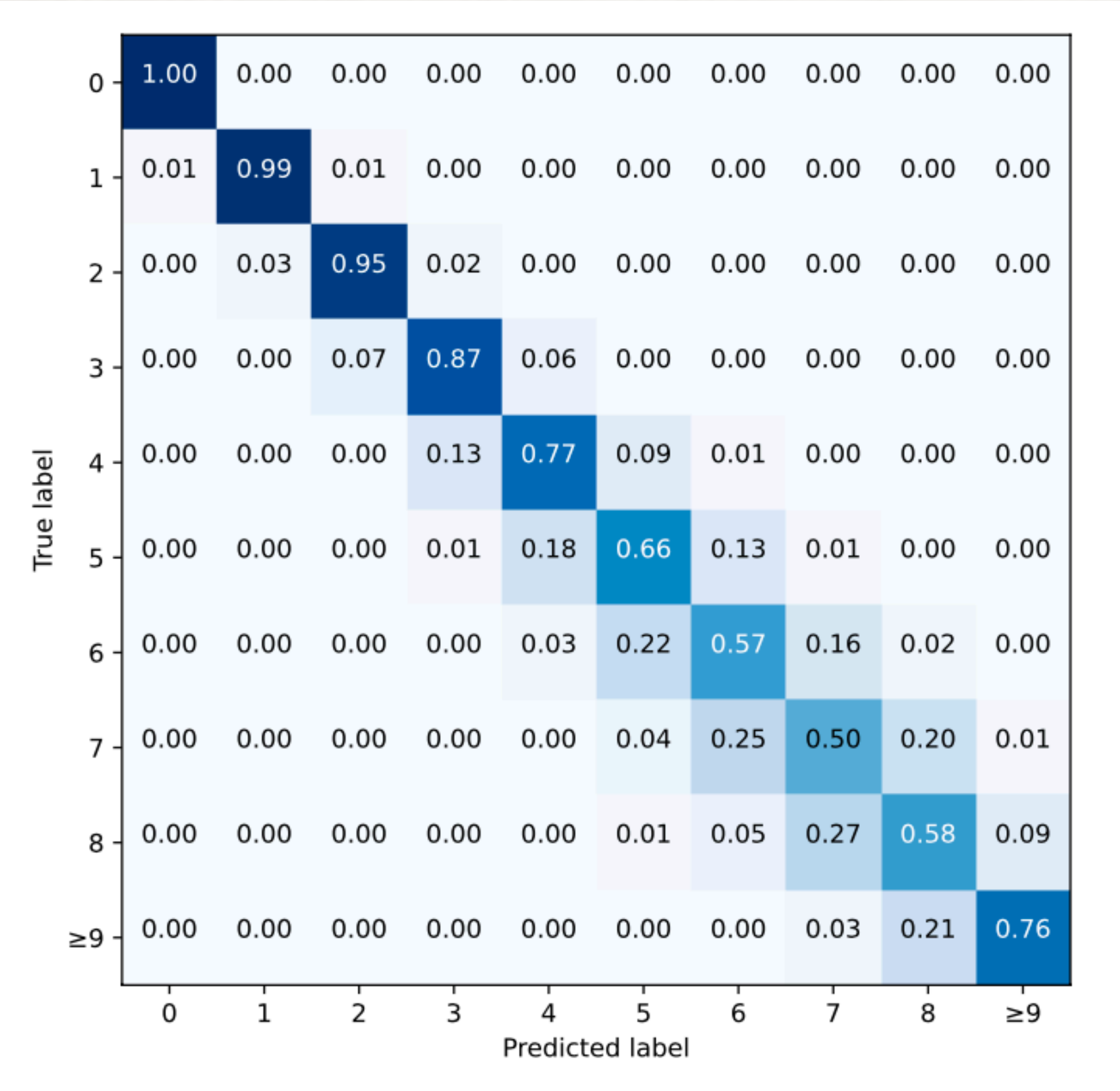
Layer	**Input**	**Output shape**
Strided -conv	Conv(3,3,128) BN LeakyReLU	(128, 140)
Res block	{ Conv(3,1,128) BN LeakyReLU Conv(3,1,128) BN LeakyReLU MaxPool(3) } ×2	(128, 46)
Res block	{ Conv(3,1,256) BN LeakyReLU Conv(3,1,256) BN LeakyReLU MaxPool(3) } ×2	(256, 1)
GRU	GRU(1024)	(1024,)
Speaker embedding	FC(128)	(128,)
Output	FC(10)	(10,)

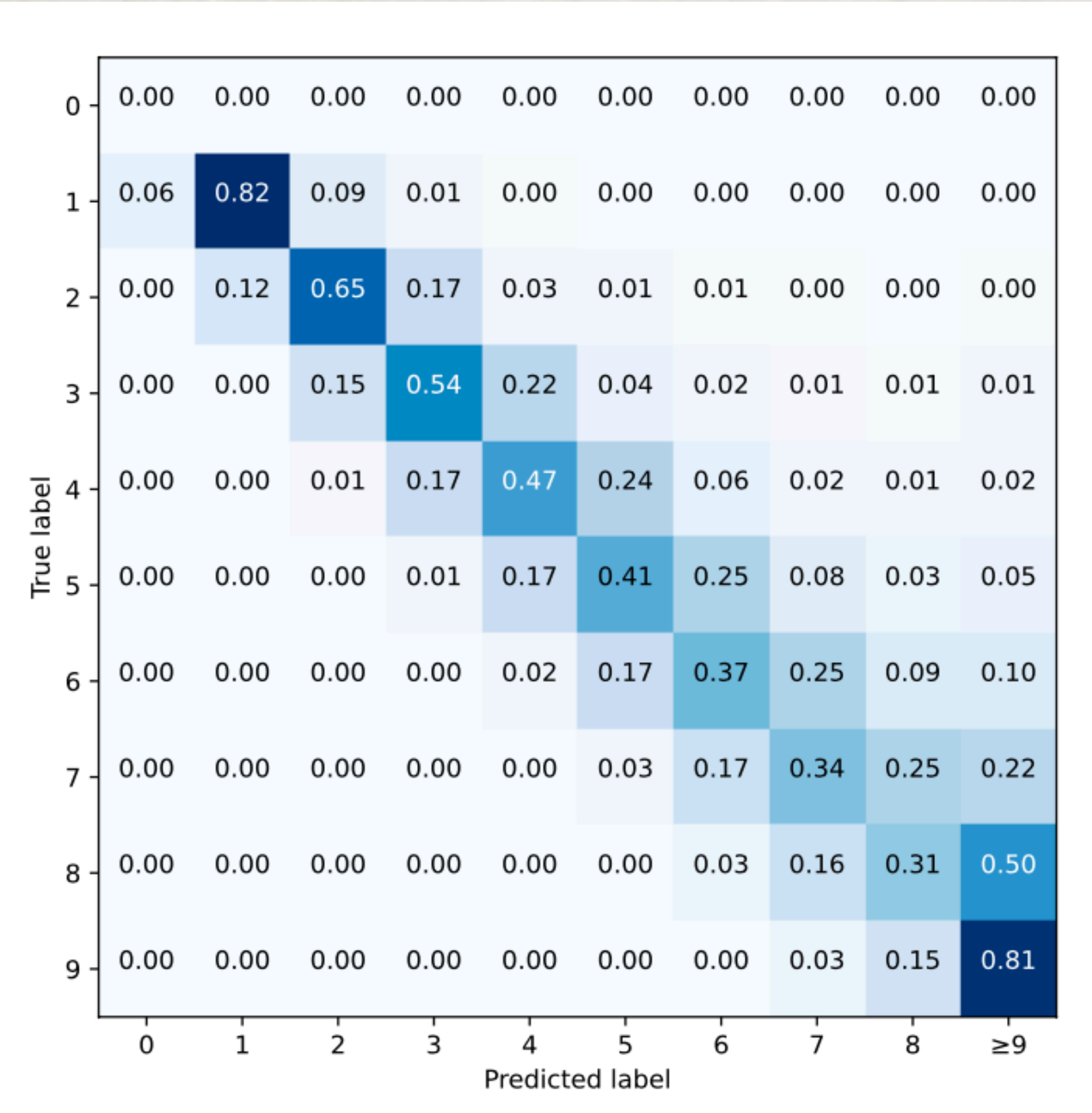
❖*Input*: pre-processed PMT waveform within 420ns signal window

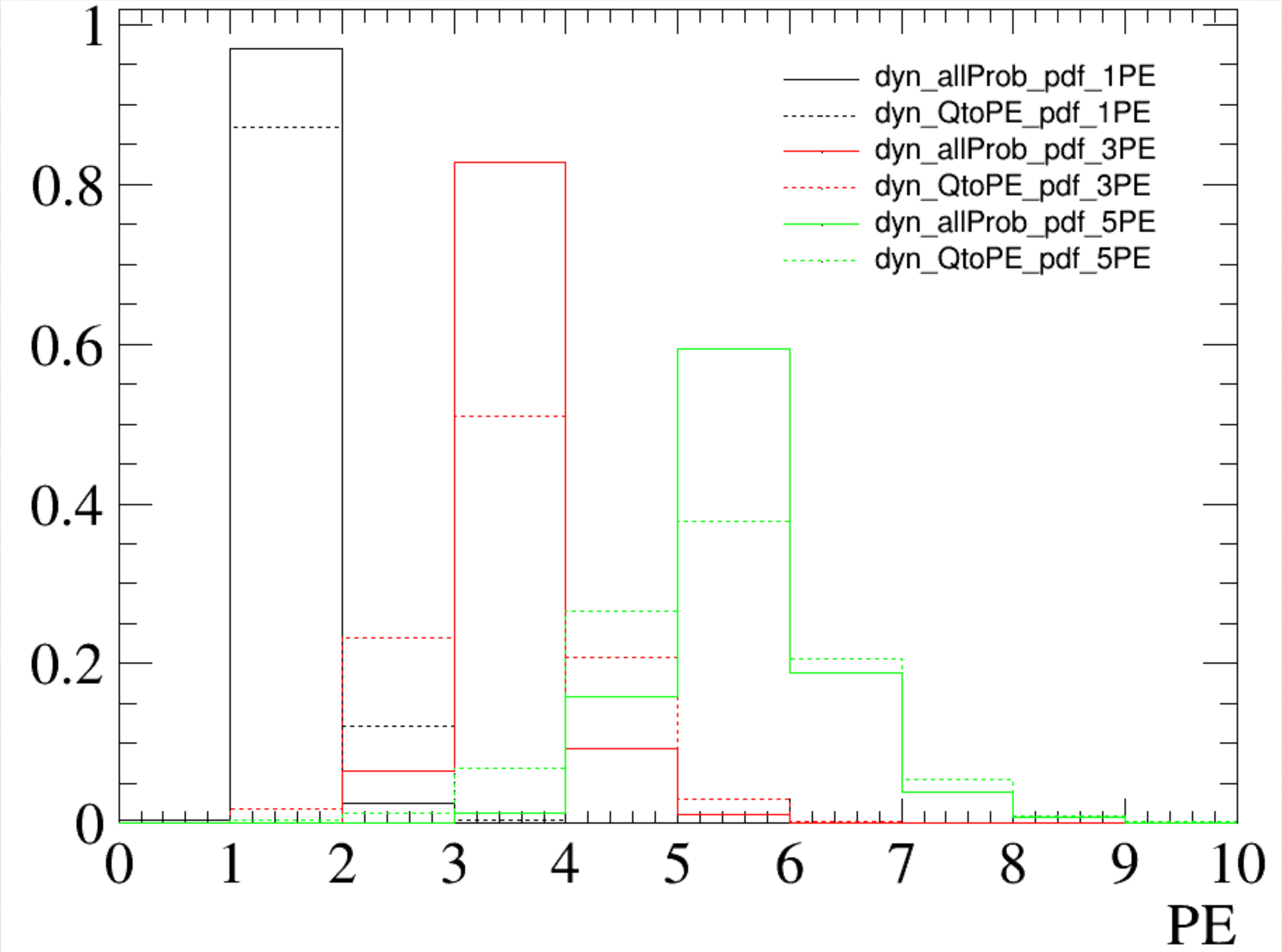
❖*Model*: Customized RawNet

❖*Output*: $\{p_k\}$ the probability for predicting ($k=0,1, \ldots \geq 9$) PEs

PHOTON COUNTING PERFORMANCE







- ❖Left: Confusion matrix of RawNet
  - ❖99% (95%, 87%) accuracy for 1PE (2PEs, 3PEs)
  - ❖Accuracy decreases rapidly as nPEs increases
- ❖Right: Confusion matrix based on charge classification
  - ❖The accuracy is markedly inferior to that of RawNet

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ENERGY RECONSTRUCTION

Note	Algo. Name	Observable	Likelihood: $\kappa \le K_T$	Likelihood: $\kappa > K_T$
Charge,Time, Maximum Likelihood Estimation	QTMLE (reference)	q (charge)	$\mathcal{L}(q_i\|\mu_i) = \sum_{k=1}^{+\infty} P_Q(q_i\|k)P(k,\mu_i)$	
PE,Time, Maximum Likelihood Estimation	PETMLE (ideal)	k (true PEs)	$\mathcal{L}(k_i\|\mu_i) = P(k_i,\mu_i)$	
Charge,Probability, Time, Maximum Likelihood Estimation	QPTMLE (realistic)	$\{p_k\}$, q	$\mathcal{L}(\{p_k^i\}\|\mu_i) = \sum_{k=0}^{9} R_{K_T k} p_k^i P(k,\mu_i)$,	$\mathcal{L}(q_i\|\mu_i) = \sum_{k=1}^{+\infty} P_Q(q_i\|k)P(k,\mu_i)$
Charge,PE, Time, Maximum Likelihood Estimation	QPETMLE (100% accuracy)	$k(p_k=1)$, q	$\mathcal{L}(k_i\|\mu_i) = P(k_i,\mu_i)$	
Charge,Confusion Matrix, Time, Maximum Likelihood Estimation	QCTMLE	κ (p_κ:max), q	$) = \sum_{k=0}^{9} C_{k\kappa_i} \times P(k,\mu_i)$	

where μ_i is the expected nPEs for the i-th PMT, $P(k,\mu_i)$ is just the Poission probability of observing k p.e. given μ_i and $P_Q(q_i|k)$ is the charge pdf for k p.e..

$$R_{K_T k} = \sum_{\kappa=0}^{K_T} C_{k\kappa},$$

confusion matrix $C_{kk'}$

RELATIVE IMPROVEMENT

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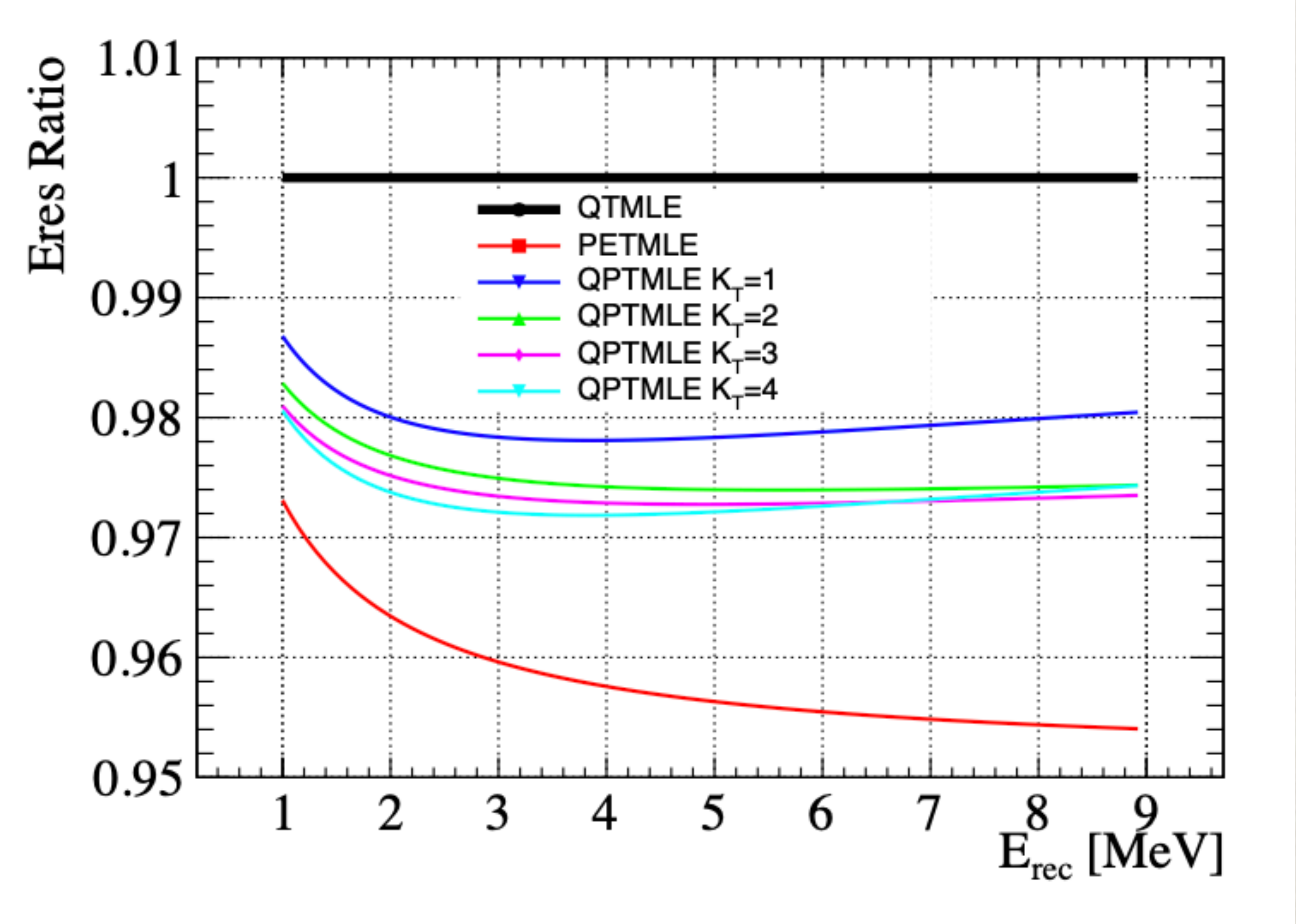
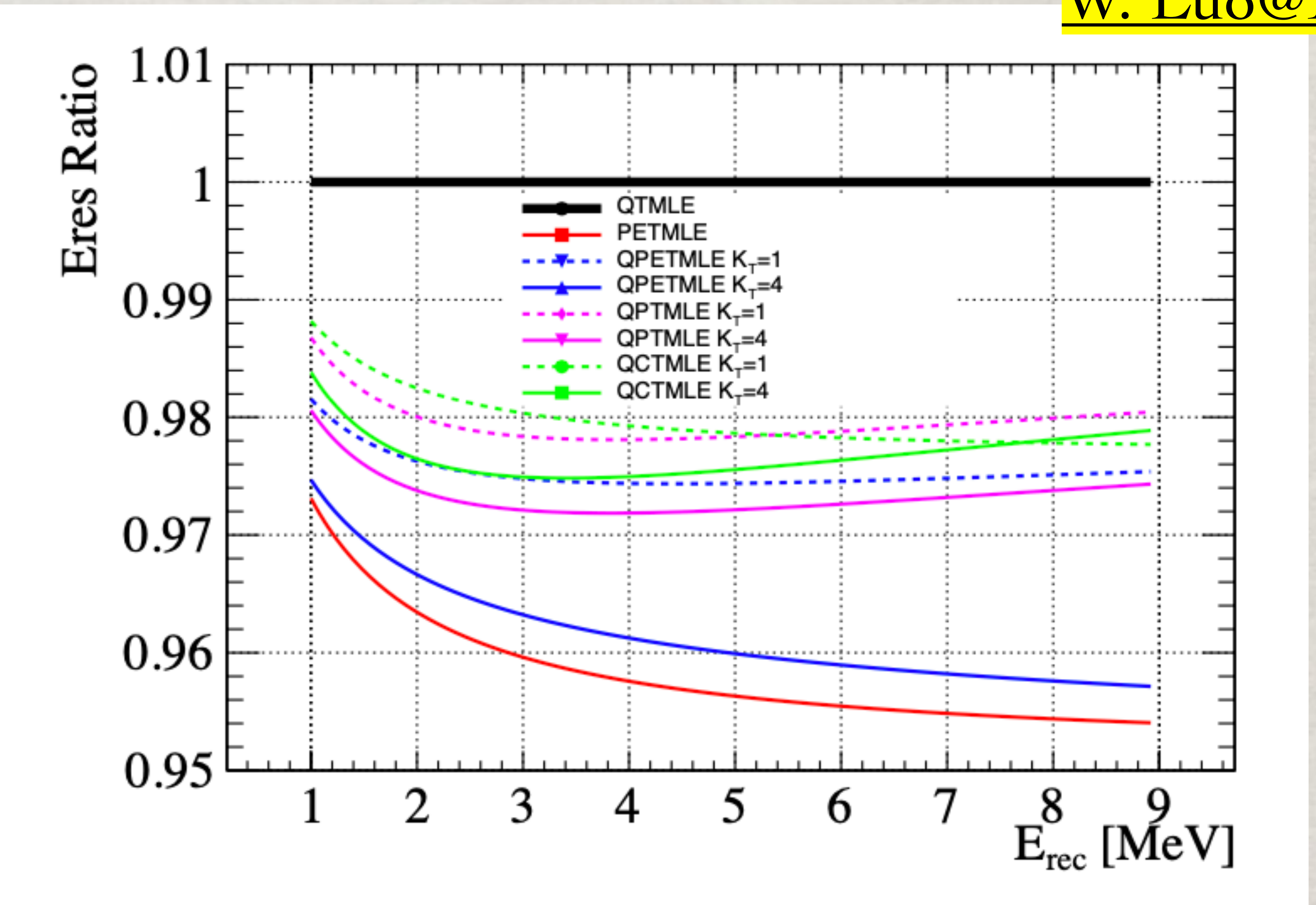
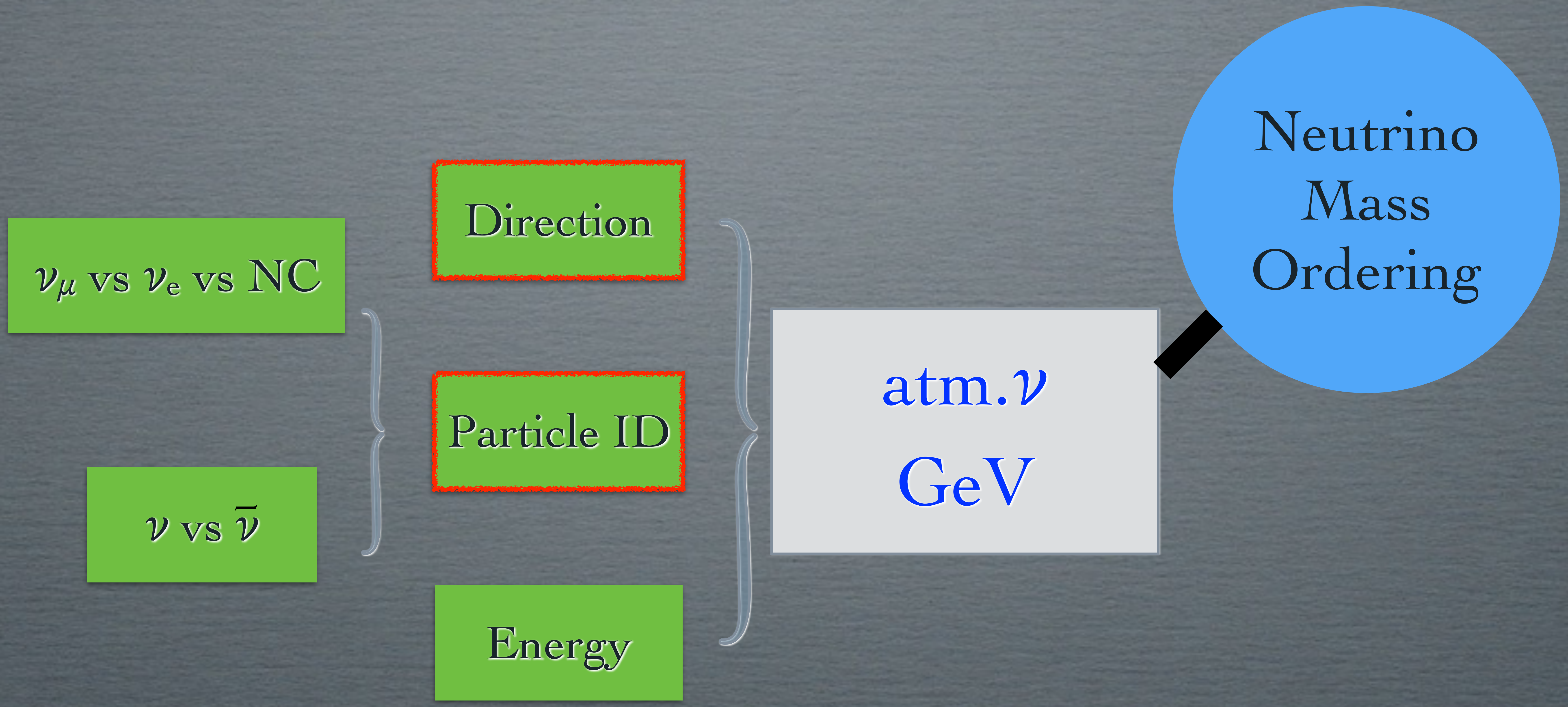




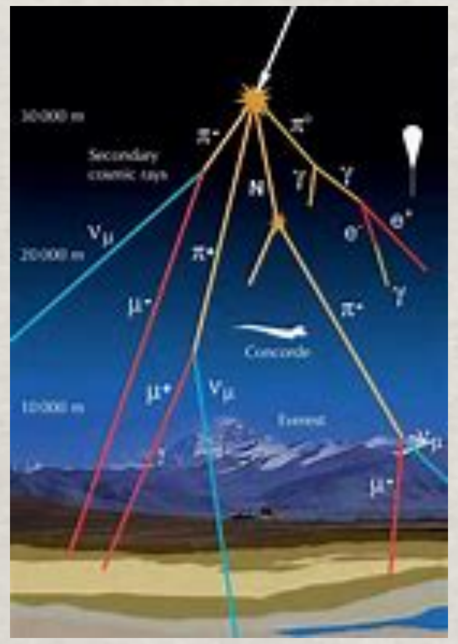
- ❖Using the photon counting information for PMTs with ($\kappa \leq K_T$) PEs can improve the energy resolution
- ❖The improvement becomes smaller as K_T increases due to the dropping accuracy for high PEs
- ❖Additional checks were done to validate the results


ν_μ vs ν_e vs NC
ν vs $\bar{\nu}$
Direction
Particle ID
Energy
atm.ν
GeV
Neutrino
Mass
Ordering

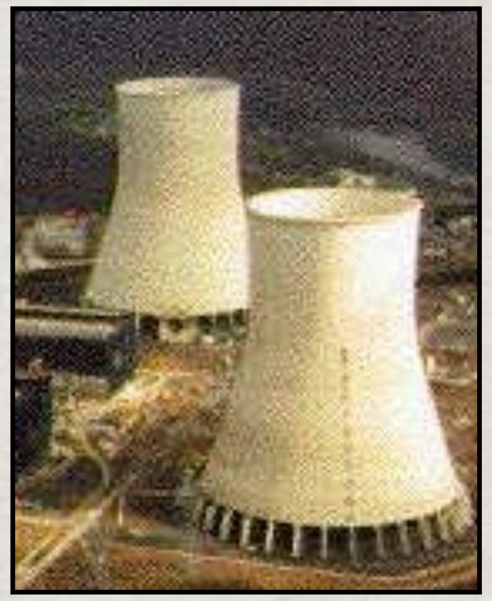
JUNO NMO SYNERGY

- NMO @ 6years $\Delta\chi^2$: Reactor(~ 9), atm.(~ 1.96), $|\Delta m^2_{ee}|$(4|1.5% or 9|1%)
- 1.96 of atm. was estimated with assumptions
- Can we do better than Yellow Book?

	Yellow Book assumptions
Event Selection $\nu_e/\overline{\nu}_e$	E_{vis} > 1GeV $Y_{vis}=E_h/E_{vis}$ < 0.5
Directionality	$\sigma_{\theta\mu}=1^\circ$ $\sigma_{\theta\nu}=10^\circ$
Classification	CC-e vs CC-μ vs NC: 100% eff.
	ν vs $\overline{\nu}$: Ne, Y_{vis},
Energy	σ_{Evis} = 1%/√E



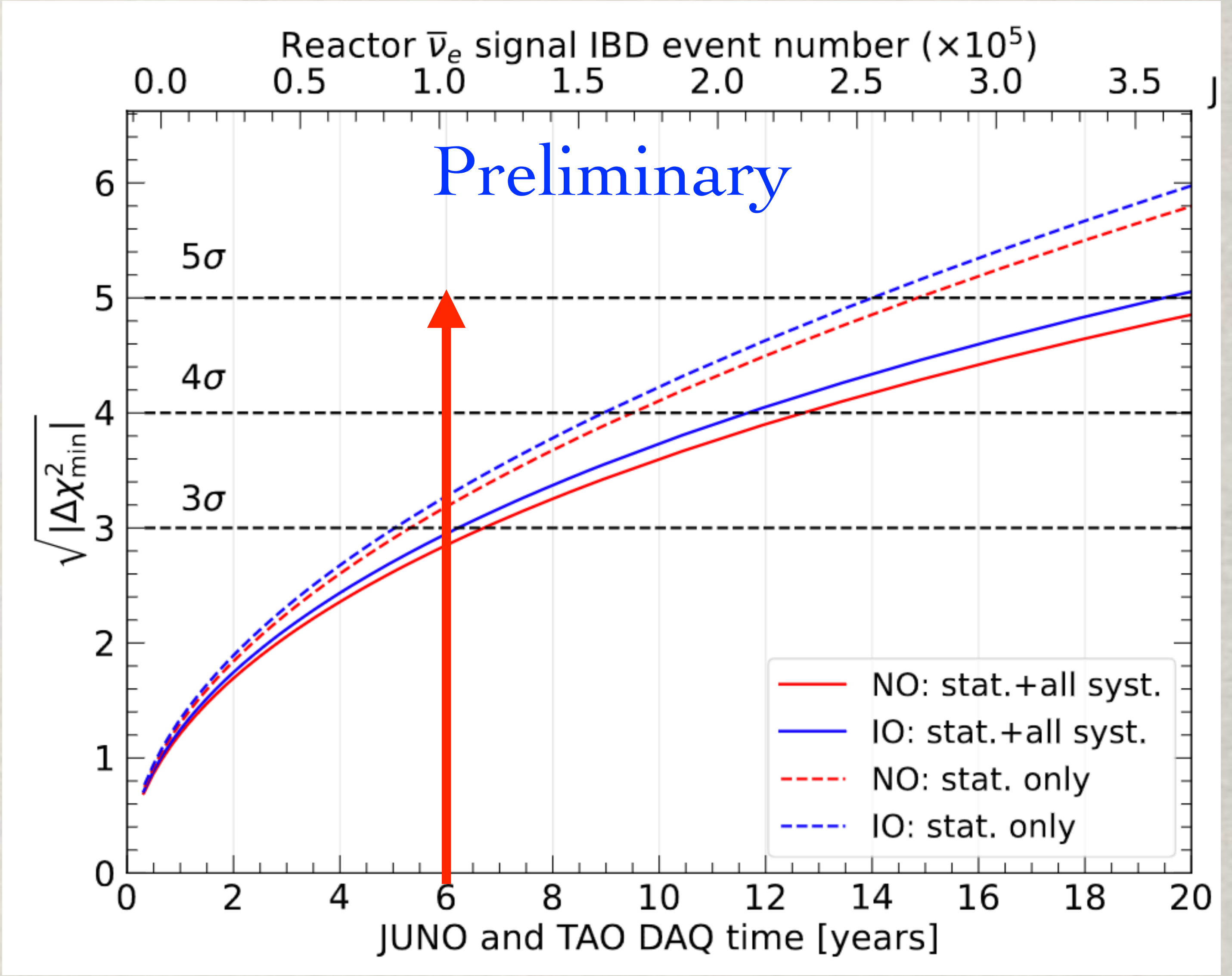
reactor ν
MeV



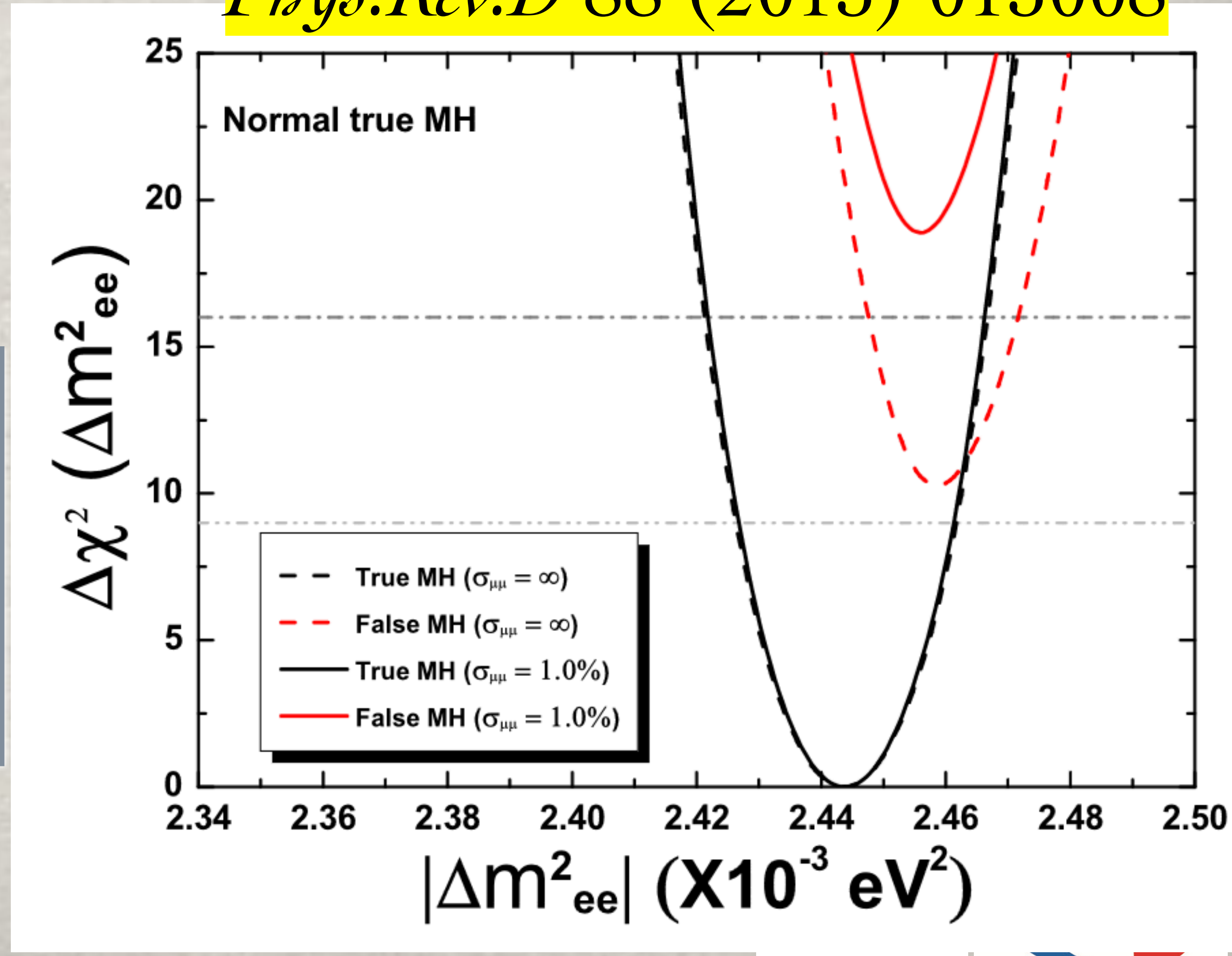
Neutrino Mass Ordering

atm.ν
GeV

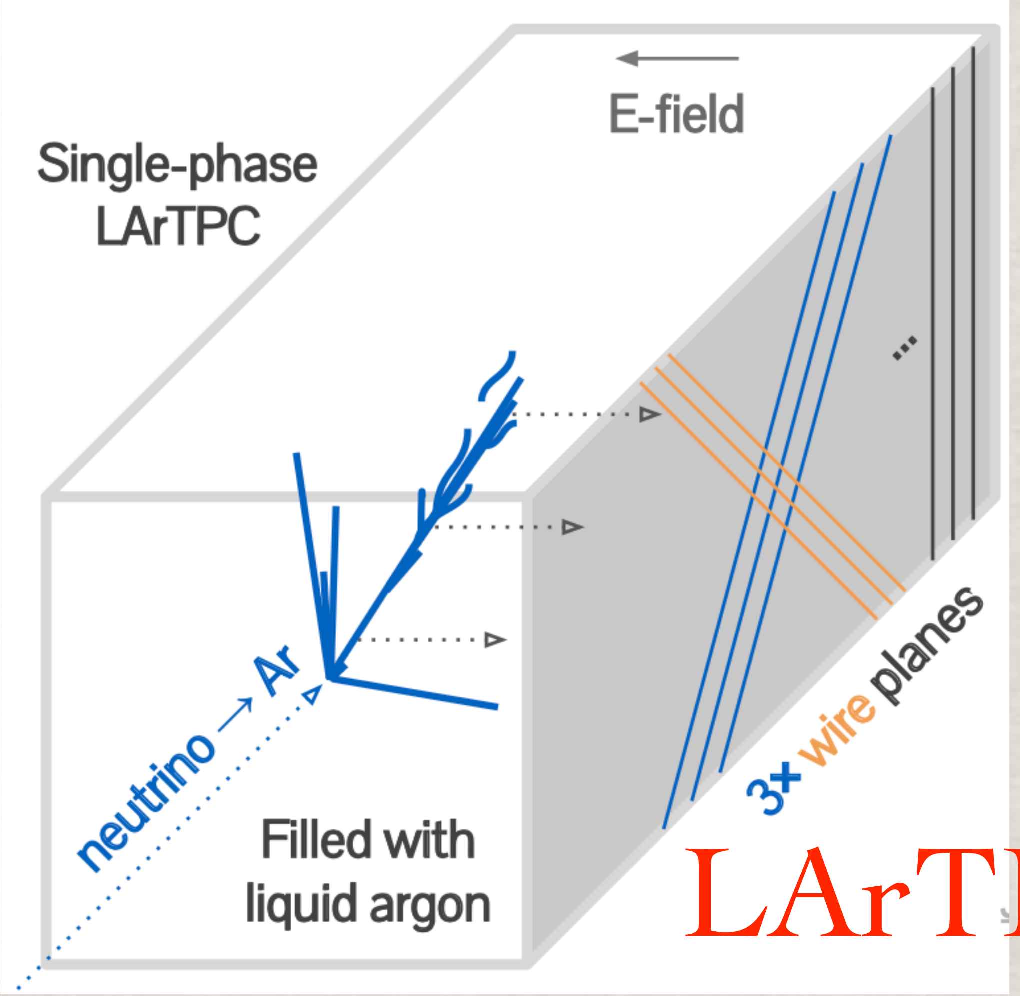
$|\Delta m^2_{\alpha\alpha}|$

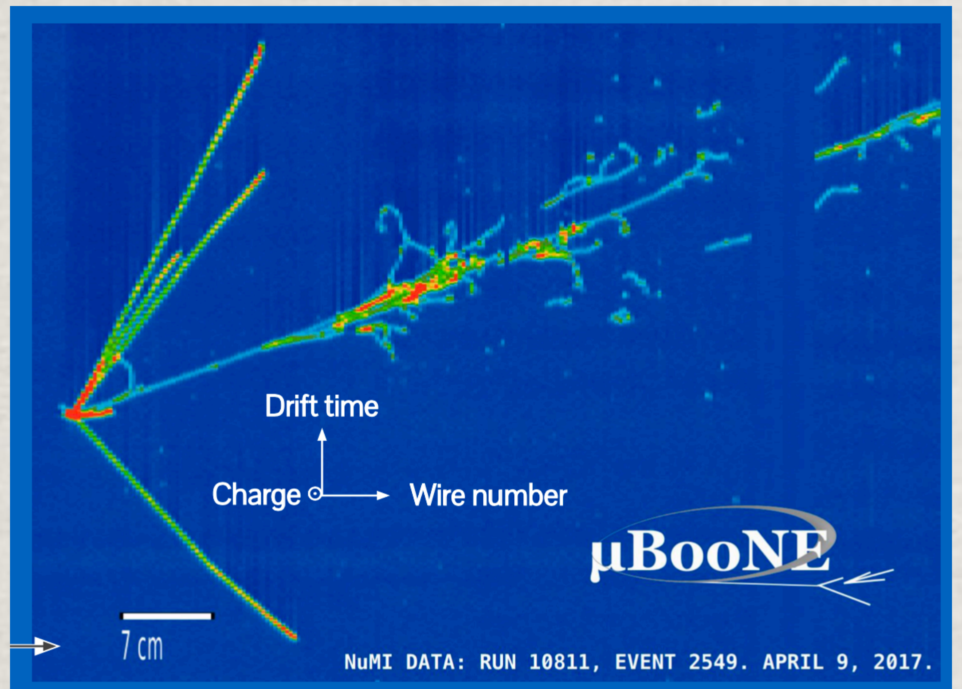


Yufeng Li et al.
Phys.Rev.D 88 (2013) 013008



CHALLENGES AND OPPORTUNITIES

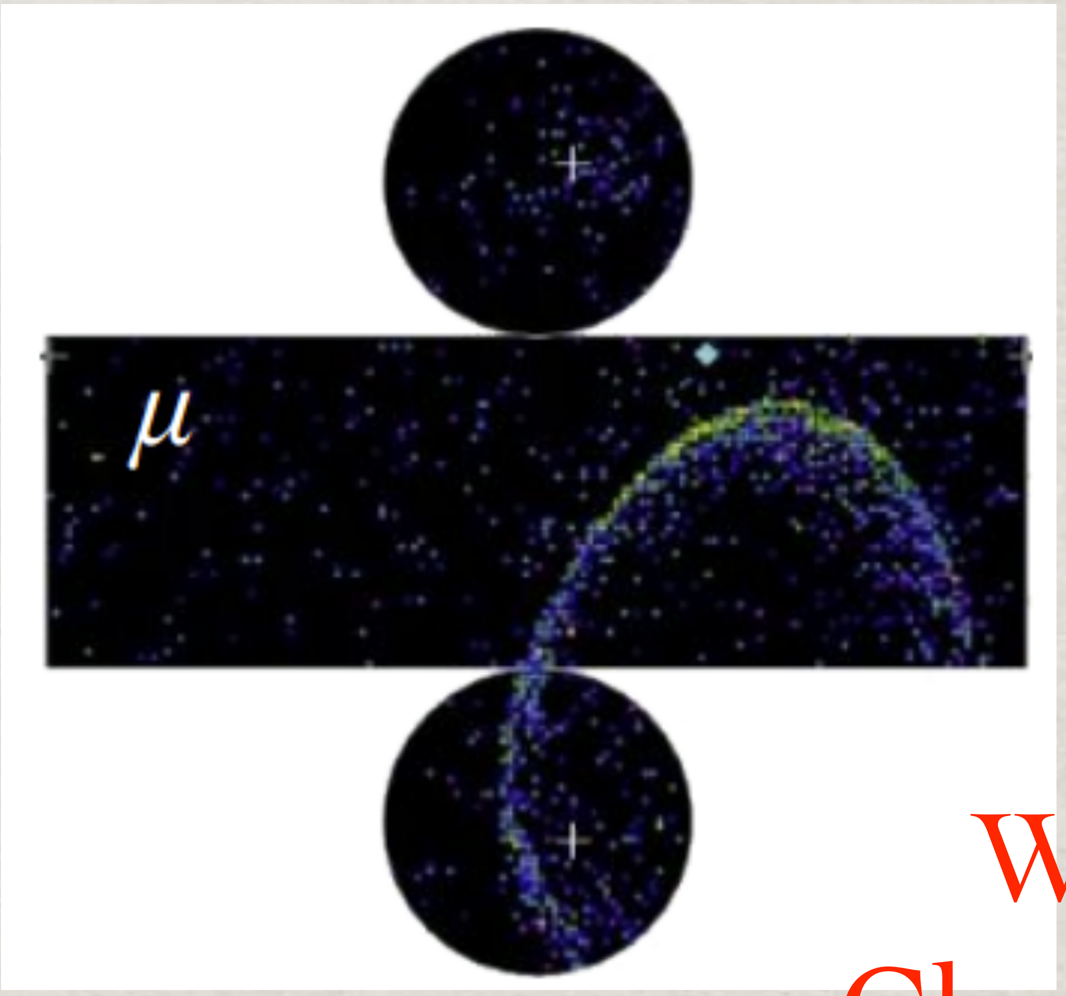


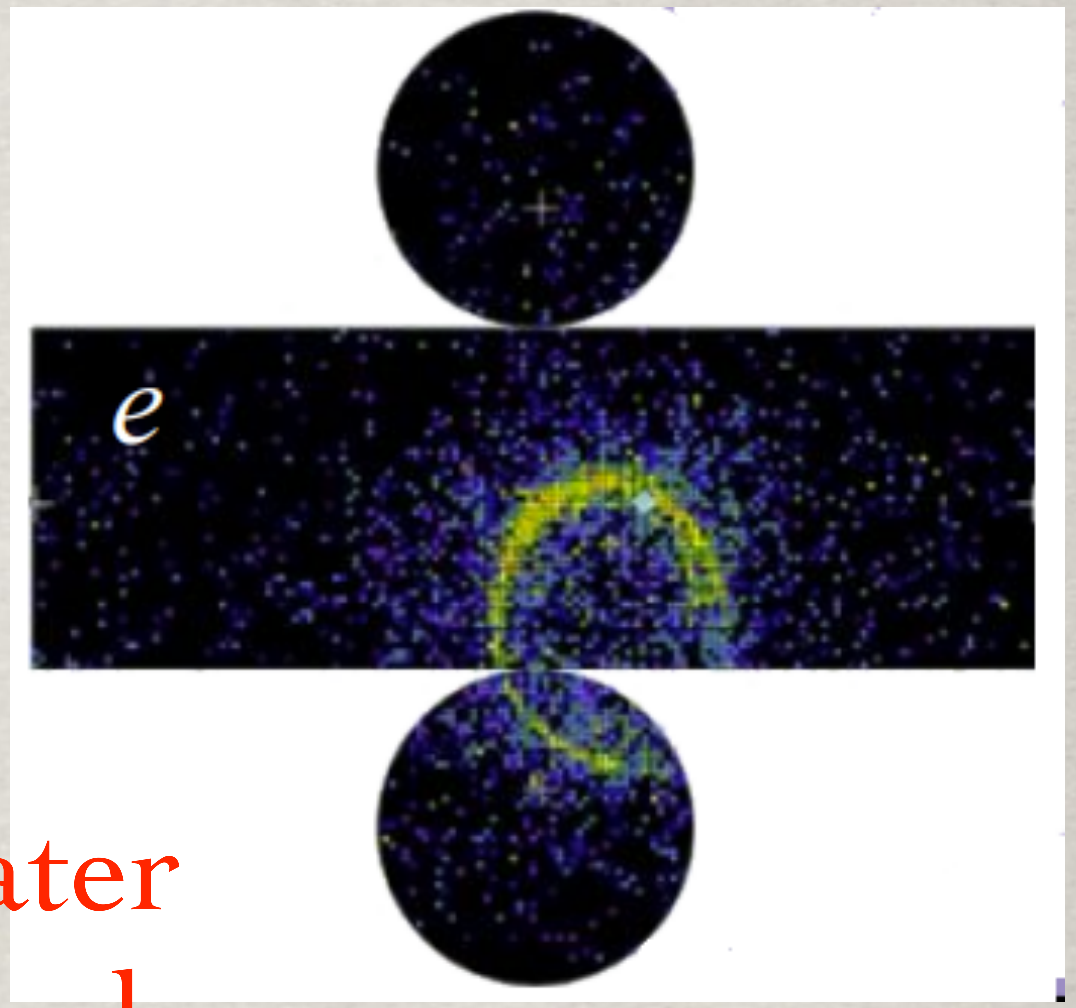


A neutrino interaction image from one wire plane in MicroBooNE

- Very high resolution calorimeter - millimeter-scale
- Can resolve individual particles down to low energies
- 3×2D views ⇒ 3D imaging

LArTPC





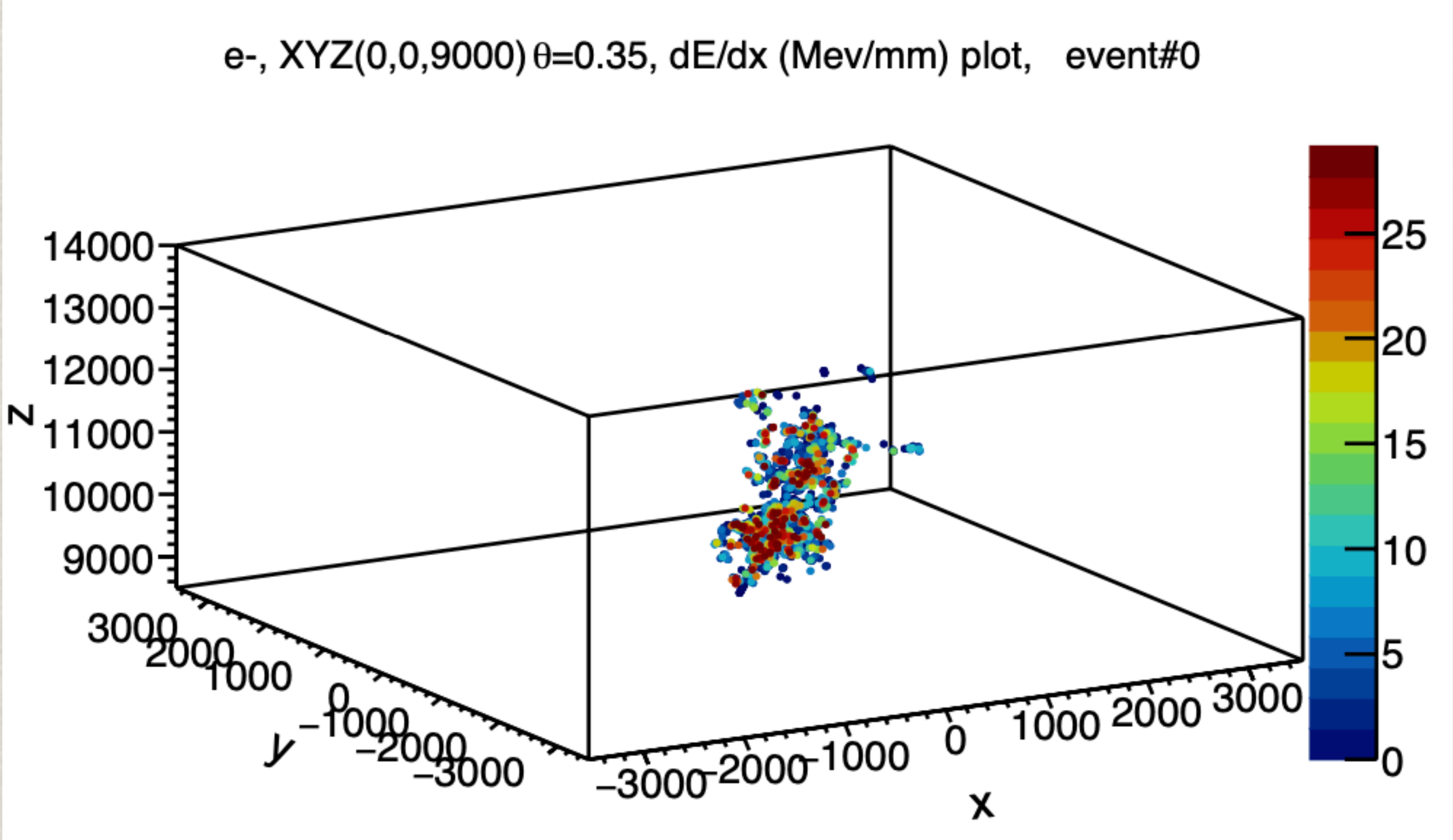
Water Cherenkov

- Neither track information, nor Cherenkov rings for JUNO
- Advantages of JUNO: 1. large PMT coverage(78%), large volume; 2. excellent neutron tagging; 3. hadronic component visible in LS; 4. can measure distinctive isotopes

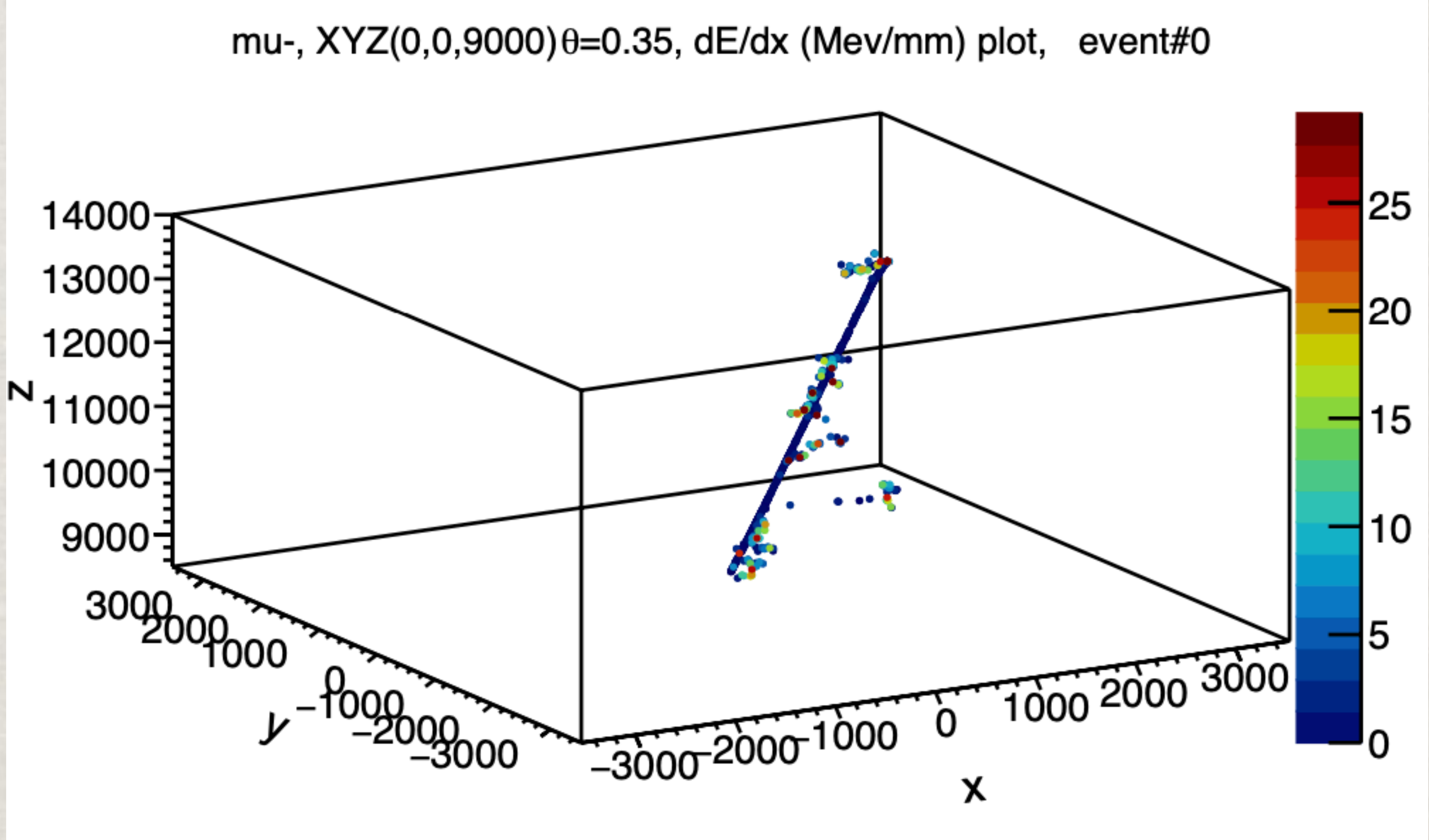
PARTICLE TOPOLOGY

Energy deposition topology in LS for different type of particles

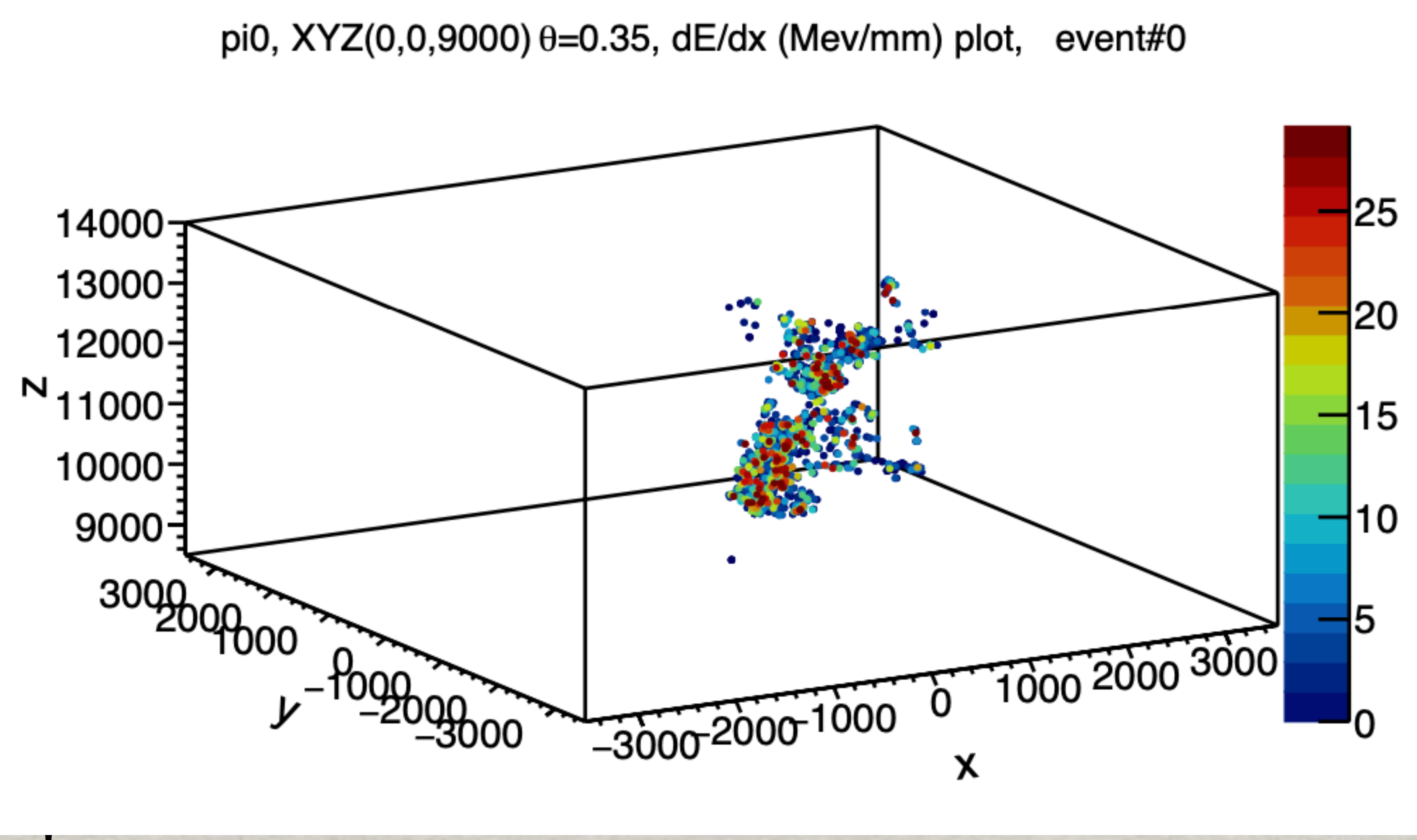
e



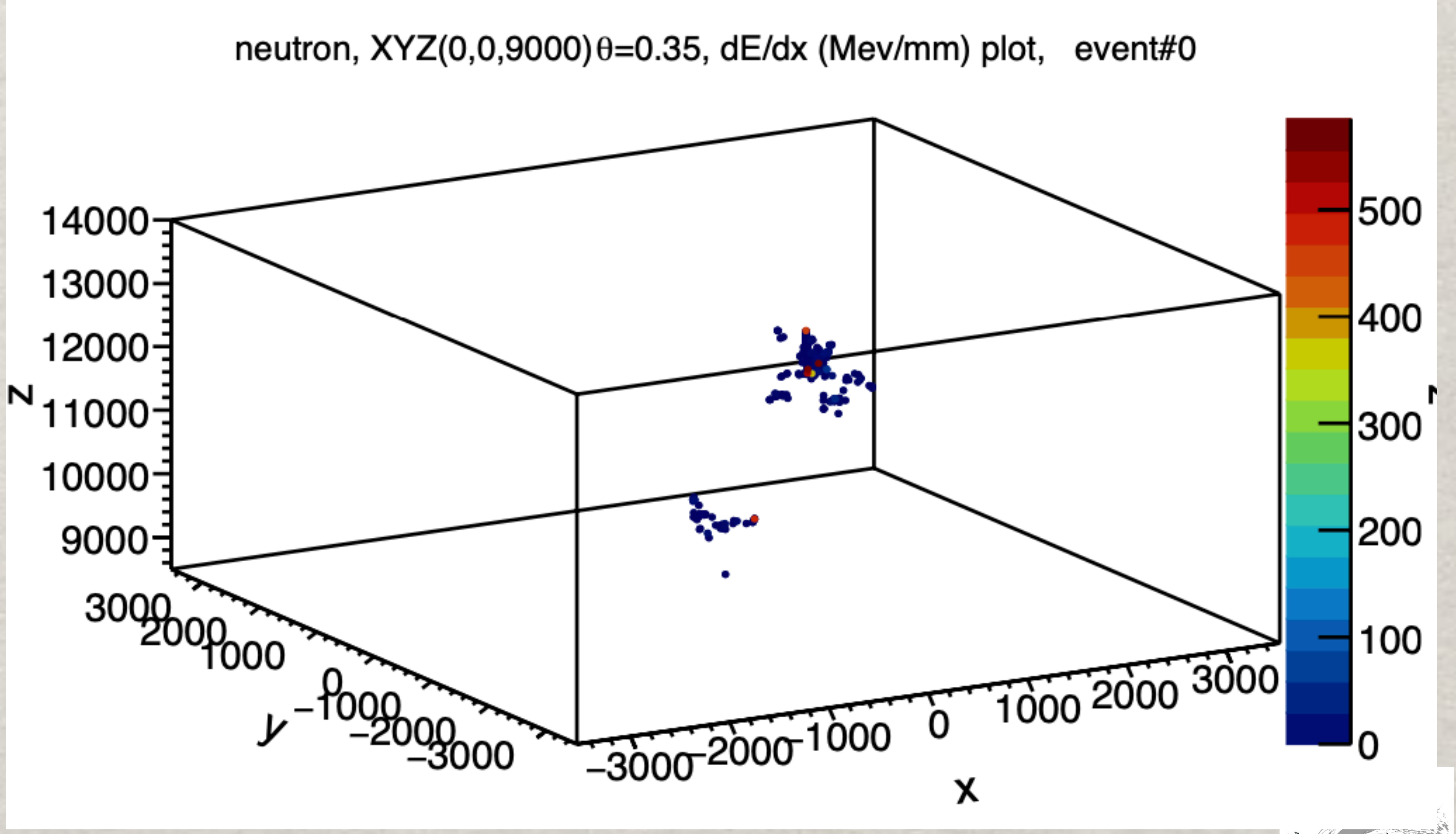
μ



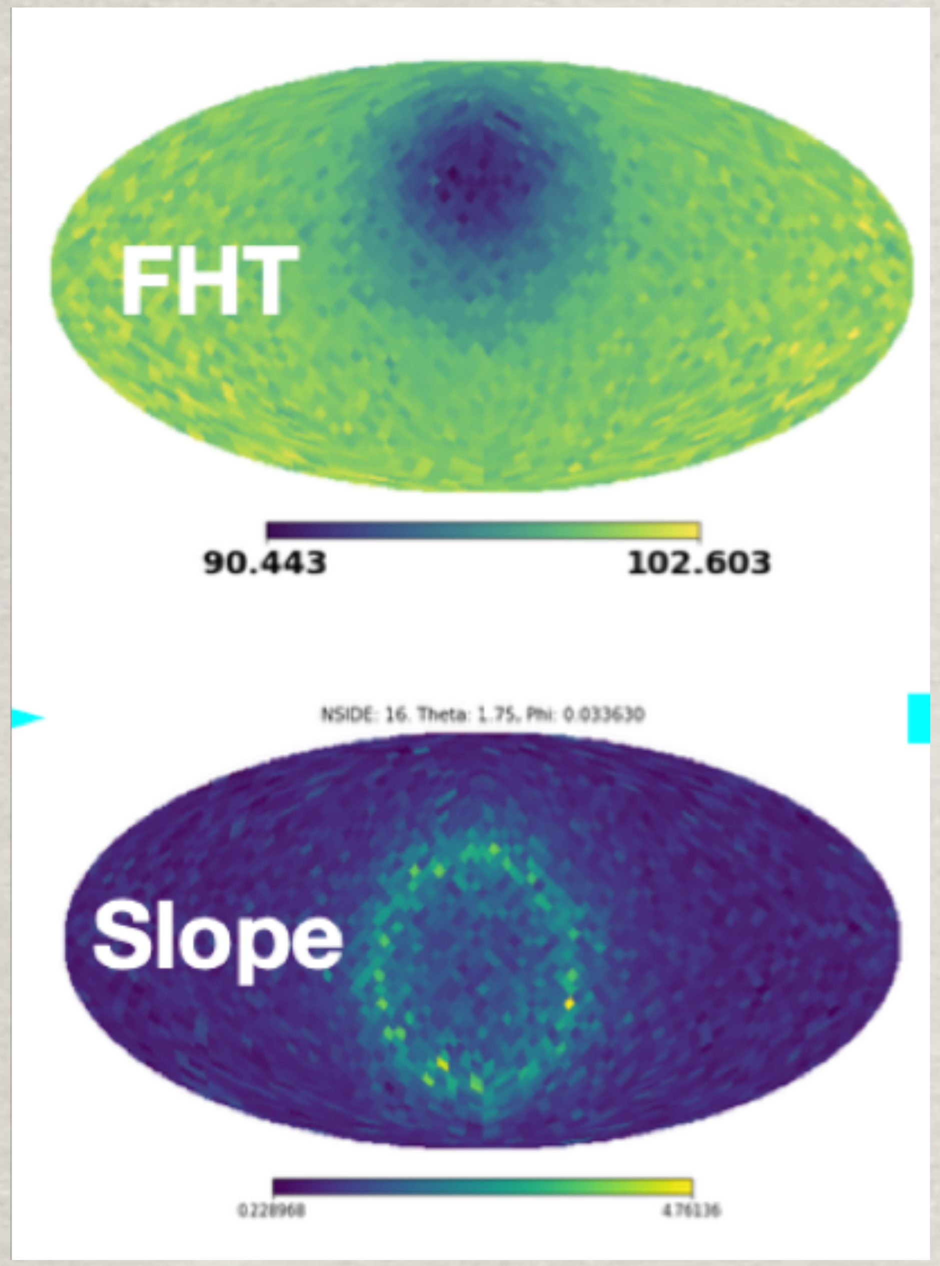
π^0



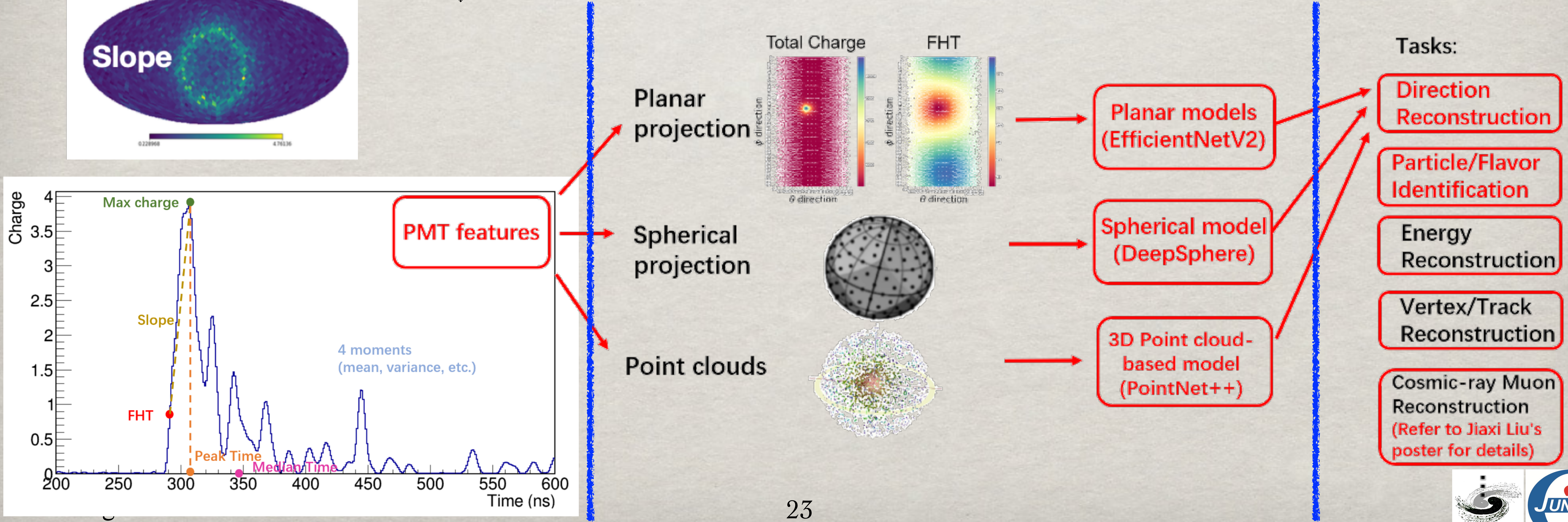
n



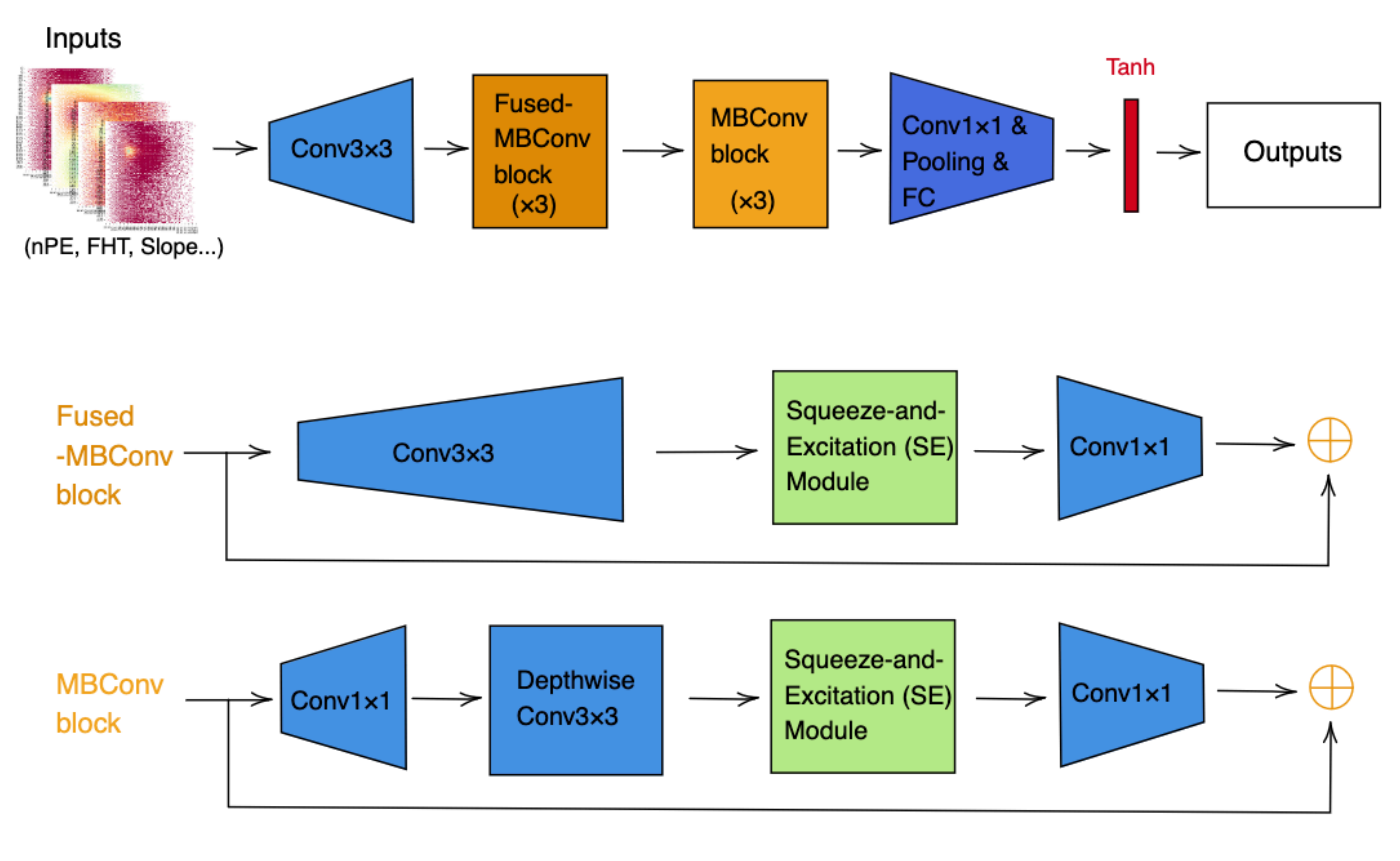
RECO/PID METHODOLOGY



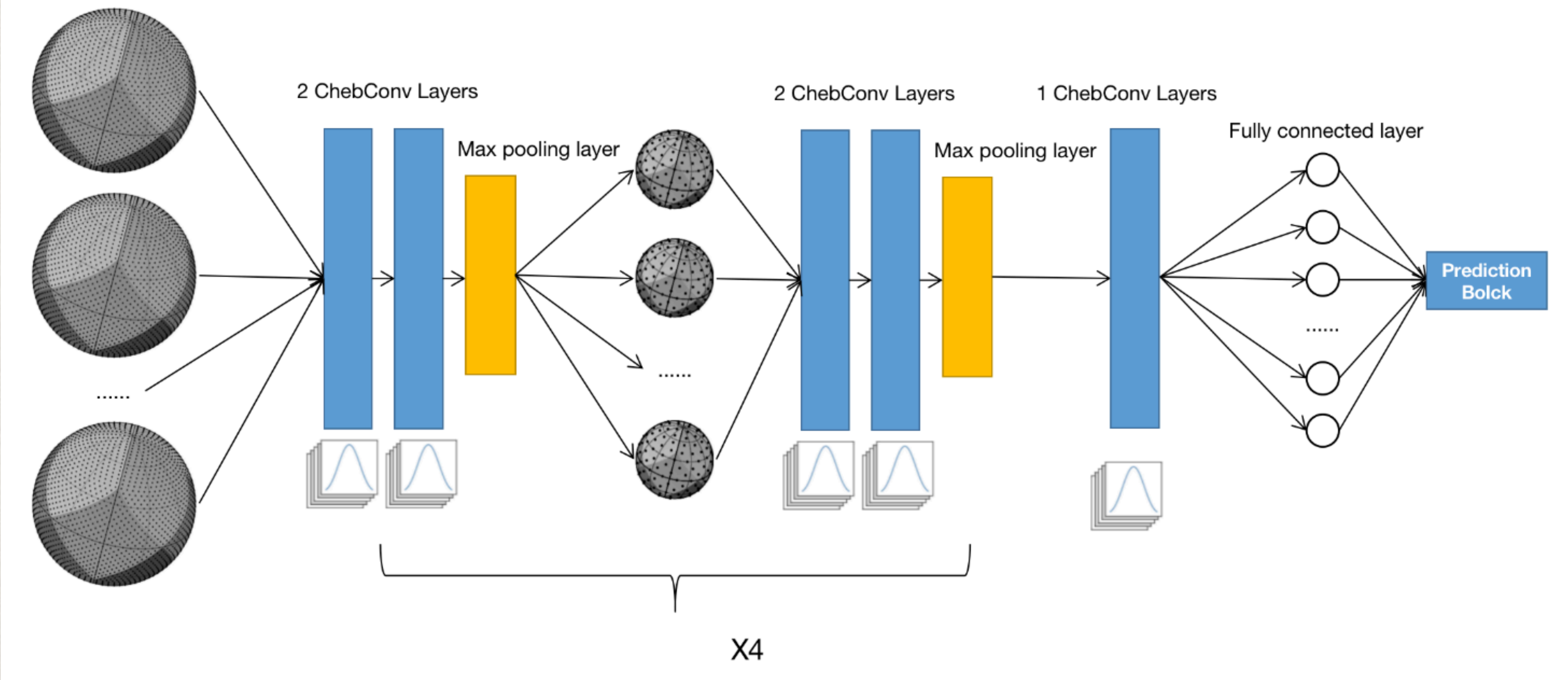
- Step 1: feature extraction from PMT waveforms
- Step 2: model building
- Step 3: optimization and validation



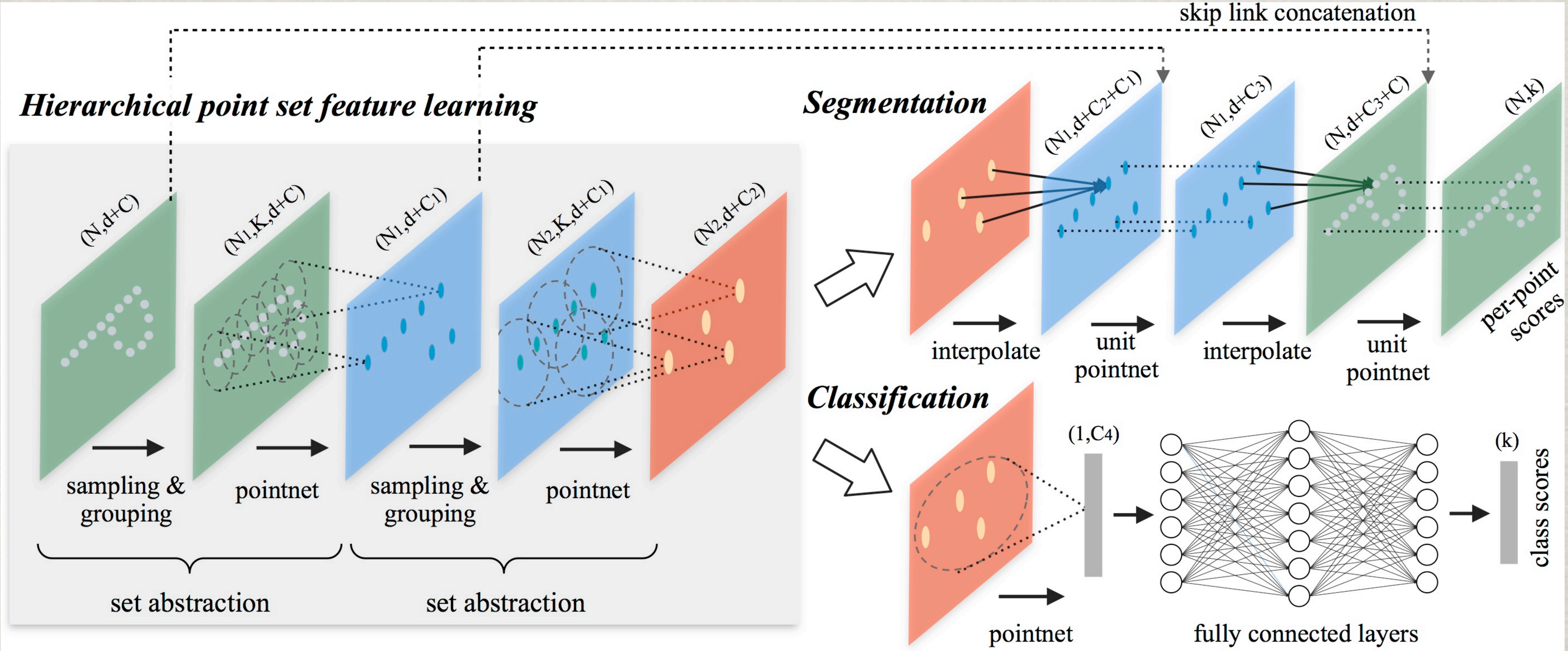
PLANE MODEL: EFFICIENTNETV2-S



spherical model: Deepsphere



3D model: PointNet++



DIRECTIONALITY

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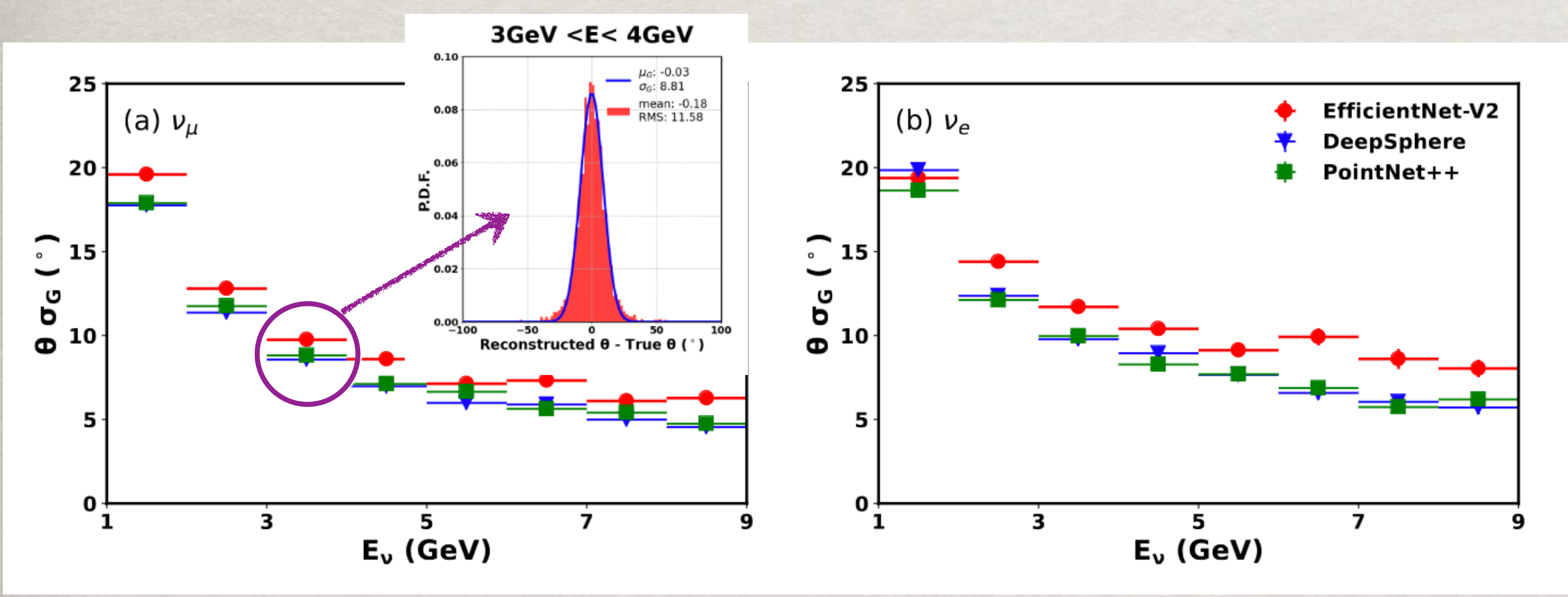

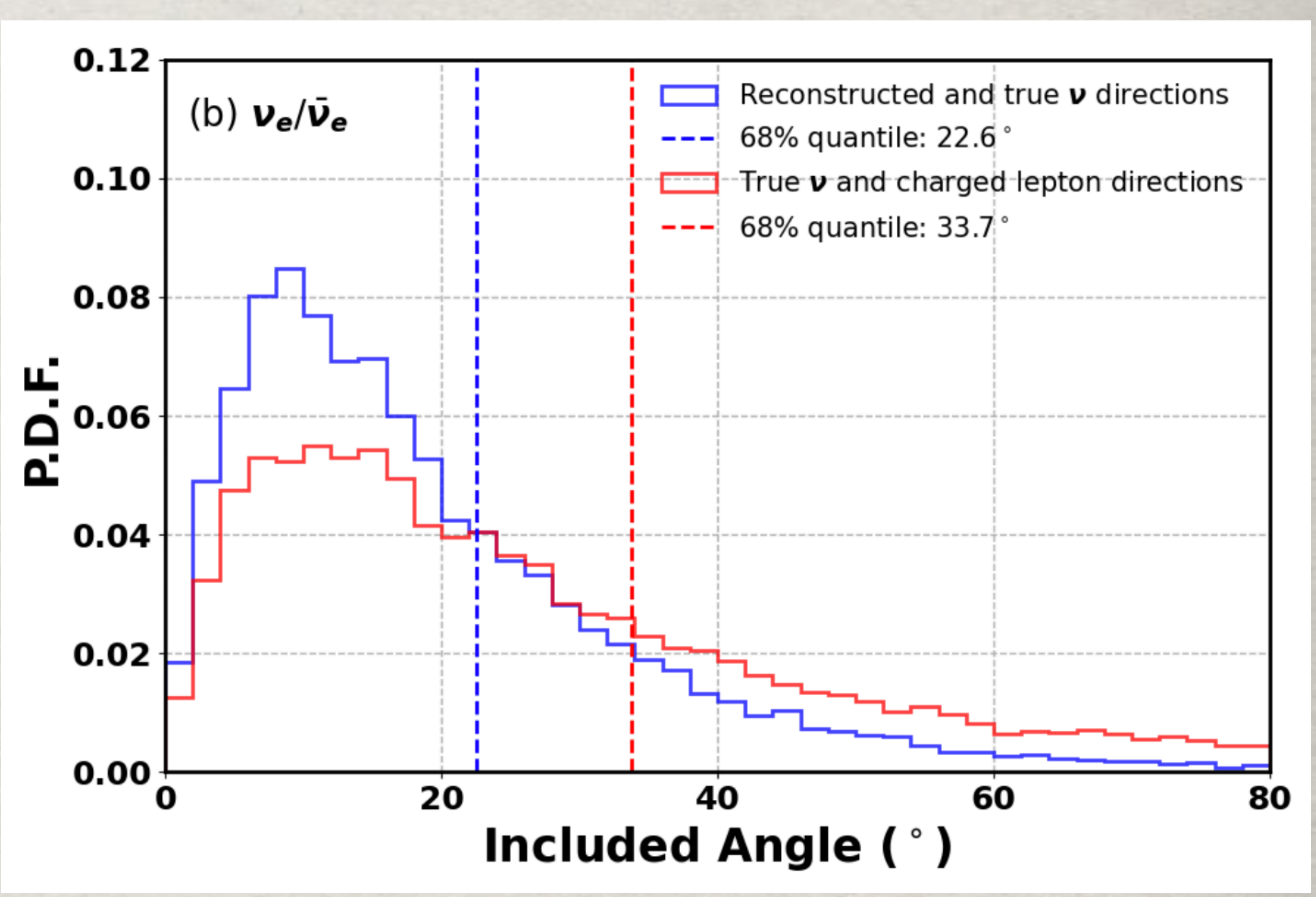

- Directly reconstruct the direction of ν instead of the charged lepton
  - mitigate the intrinsic large uncertainty between the two
  - hadronic component in LS also helps, advantageous w.r.t. Water Cerenkov
- Energy dependent Zenith Angle resolution, less than 10° for E>3GeV

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Yellow Book

$\sigma_{\theta\mu} = 1^\circ$

$\sigma_{\theta\nu} = 10^\circ$

PID STRATEGY

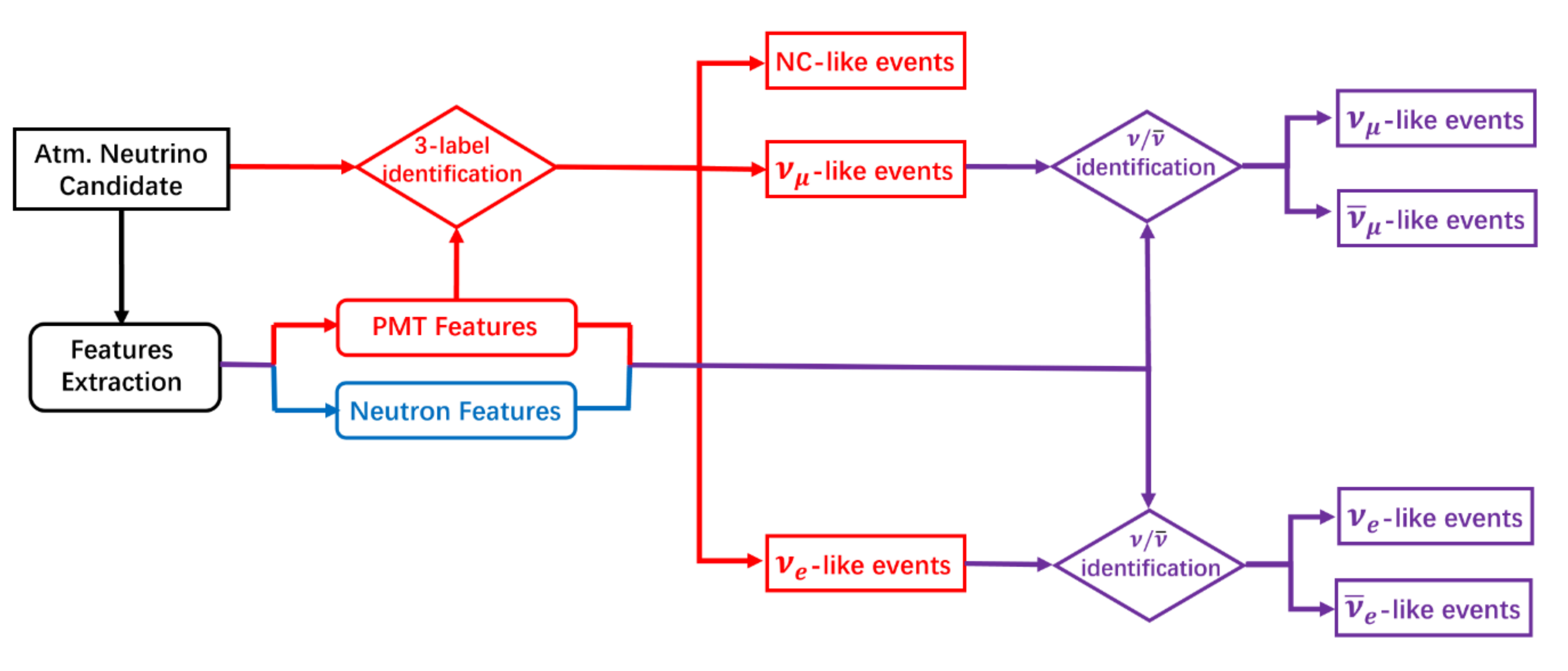
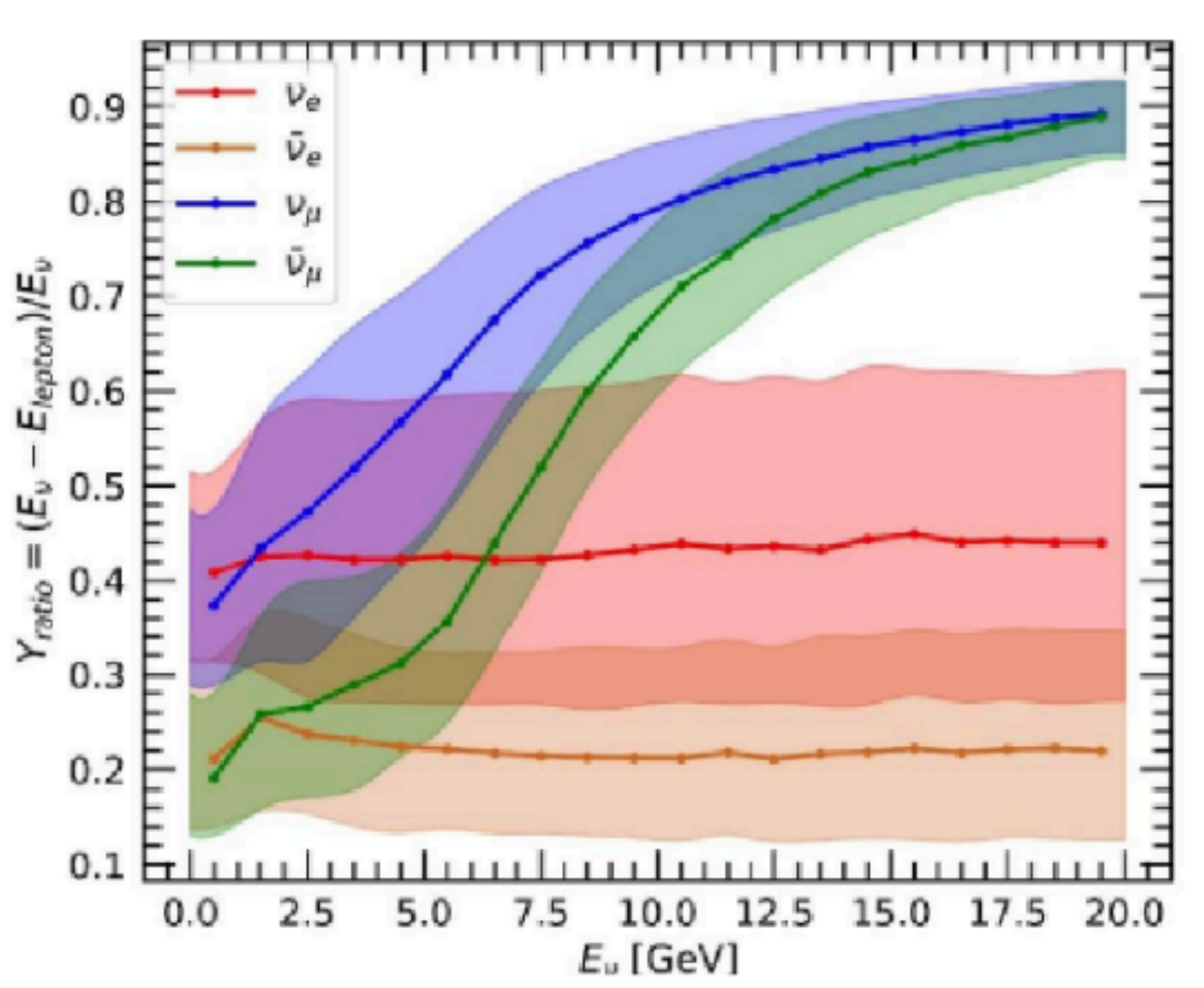
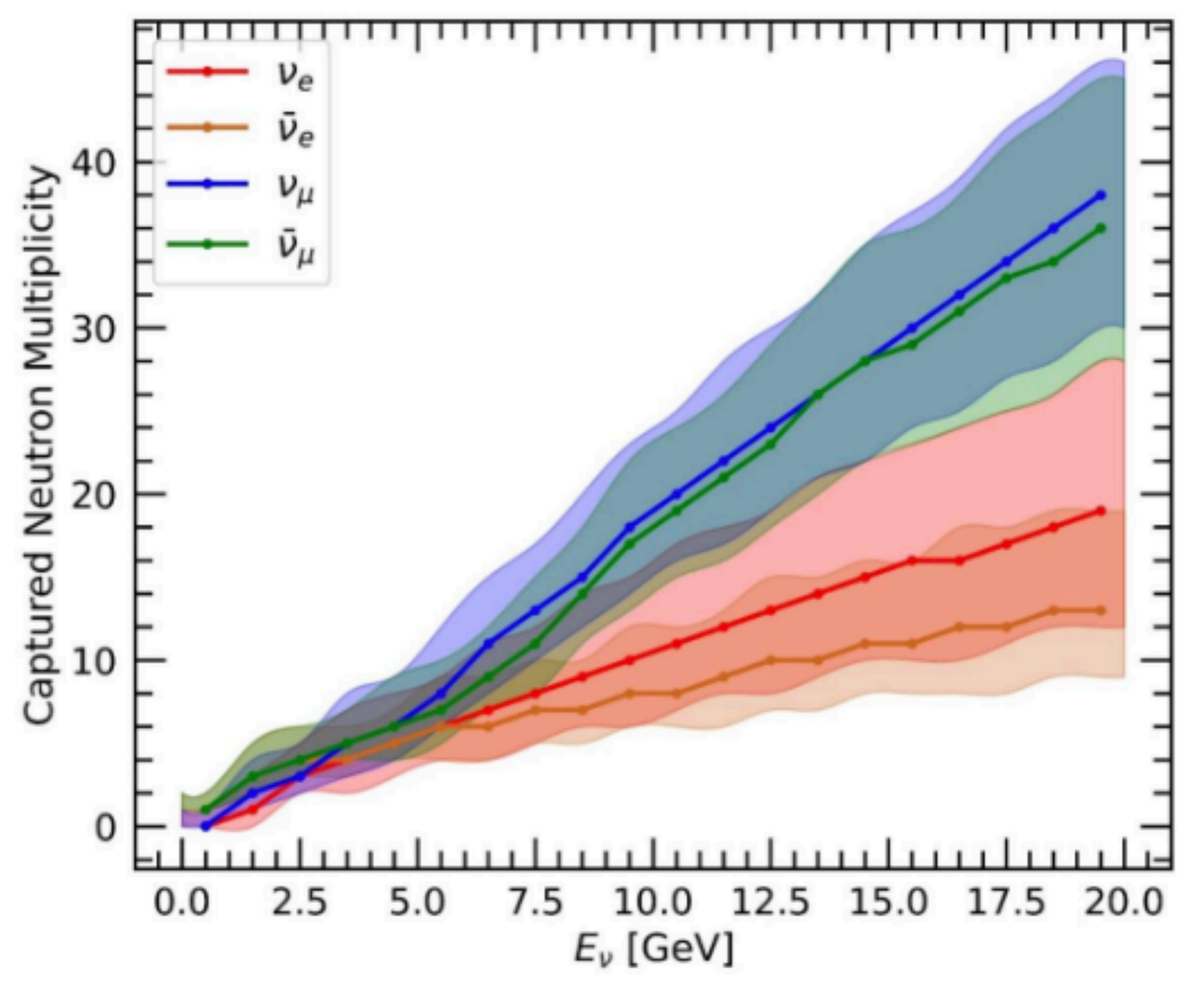


Figure 4. The schematic workflow of atmospheric neutrino classification.



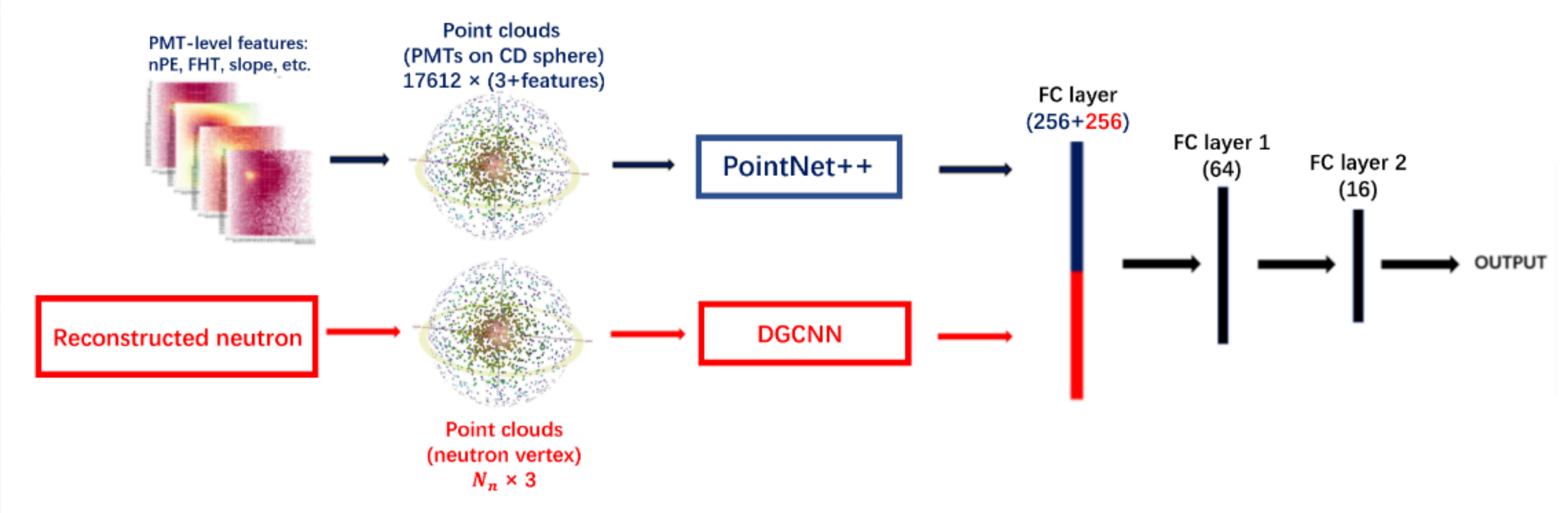
(a) Y_{ratio}



(b) Neutron multiplicity

- ❖ Both leptons&hadrons visible, different topology
- ❖ step1: CC-e/CC-mu/NC classification
- ❖ step2: $\bar{\nu}$ vs ν

PID ML INPUT & MODEL



- ❖PMT features —> PointNet++ (x, y, z, feature_i…)
- ❖Neutron candidates —> DGCNN (x, y, z)

PID PRELIMINARY PERFORMANCE

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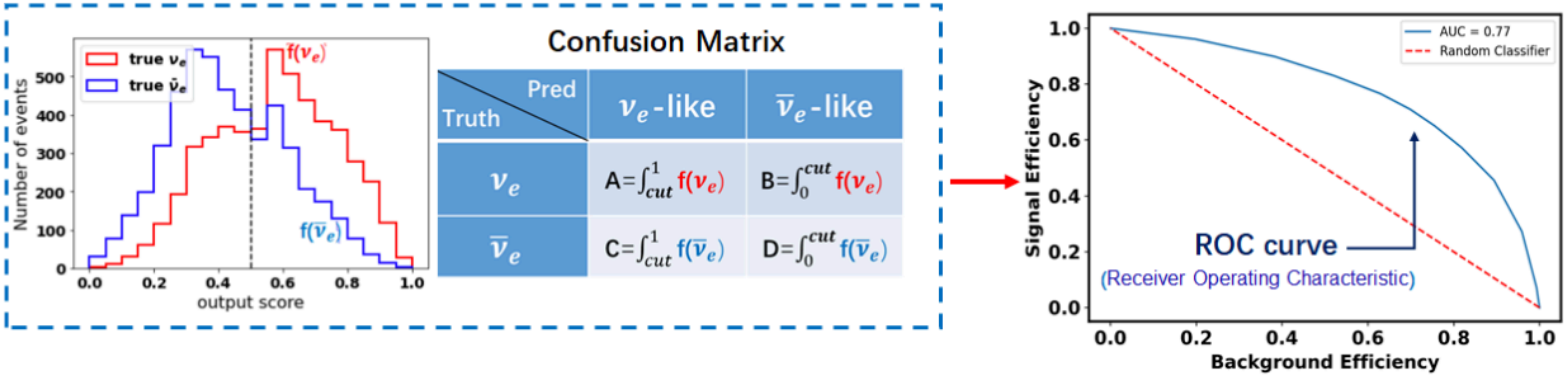
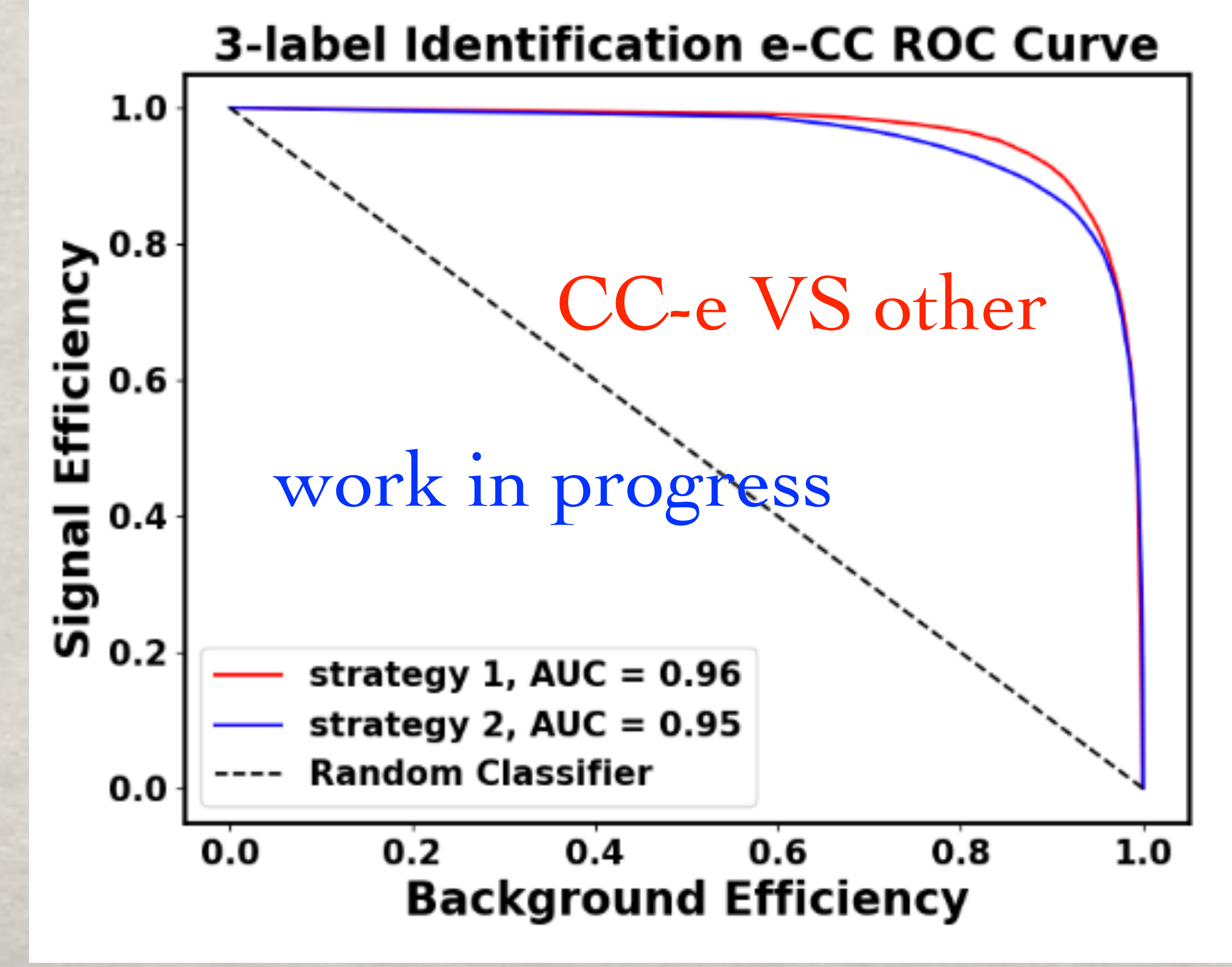
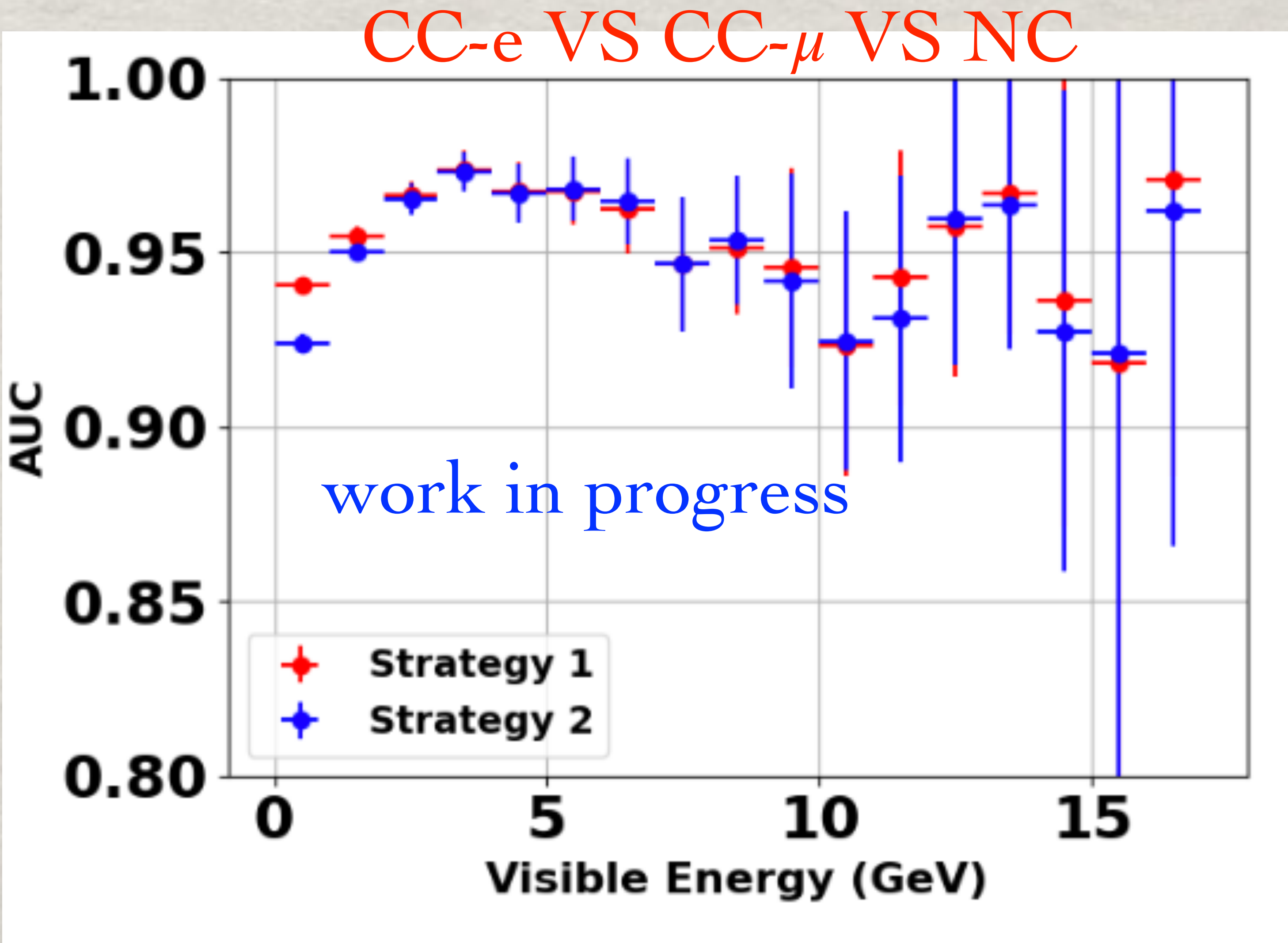


Fig. 8: Illustration of the AUC score using $\nu_e\,/\bar{\nu}_e$ classification as an example. The AUC score can be viewed as an optimisation of $\nu_e\,/\bar{\nu}_e$ efficiencies.





PID PRELIMINARY PERFORMANCE

Wing Yin Ma@Neutrino2024

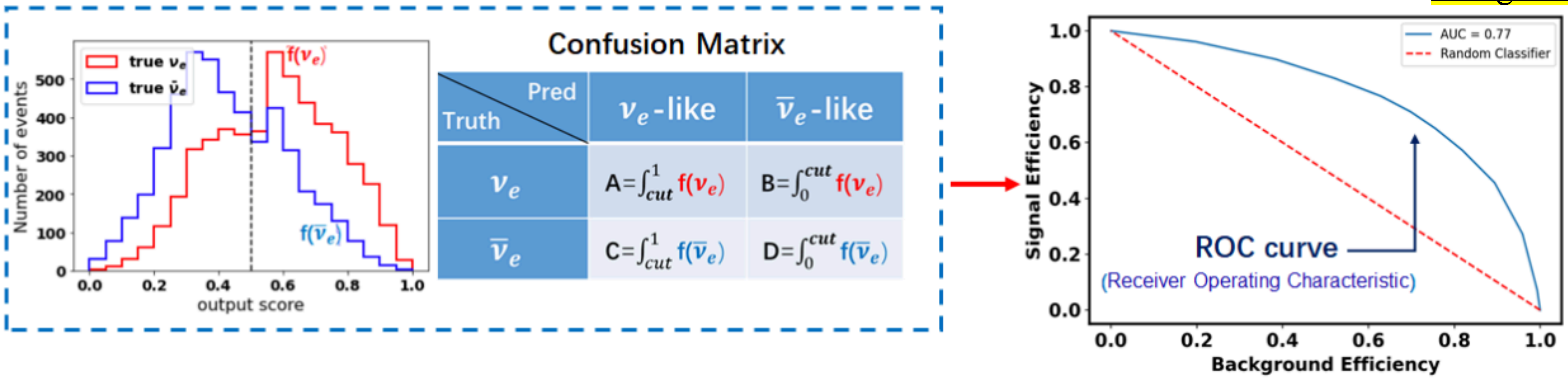
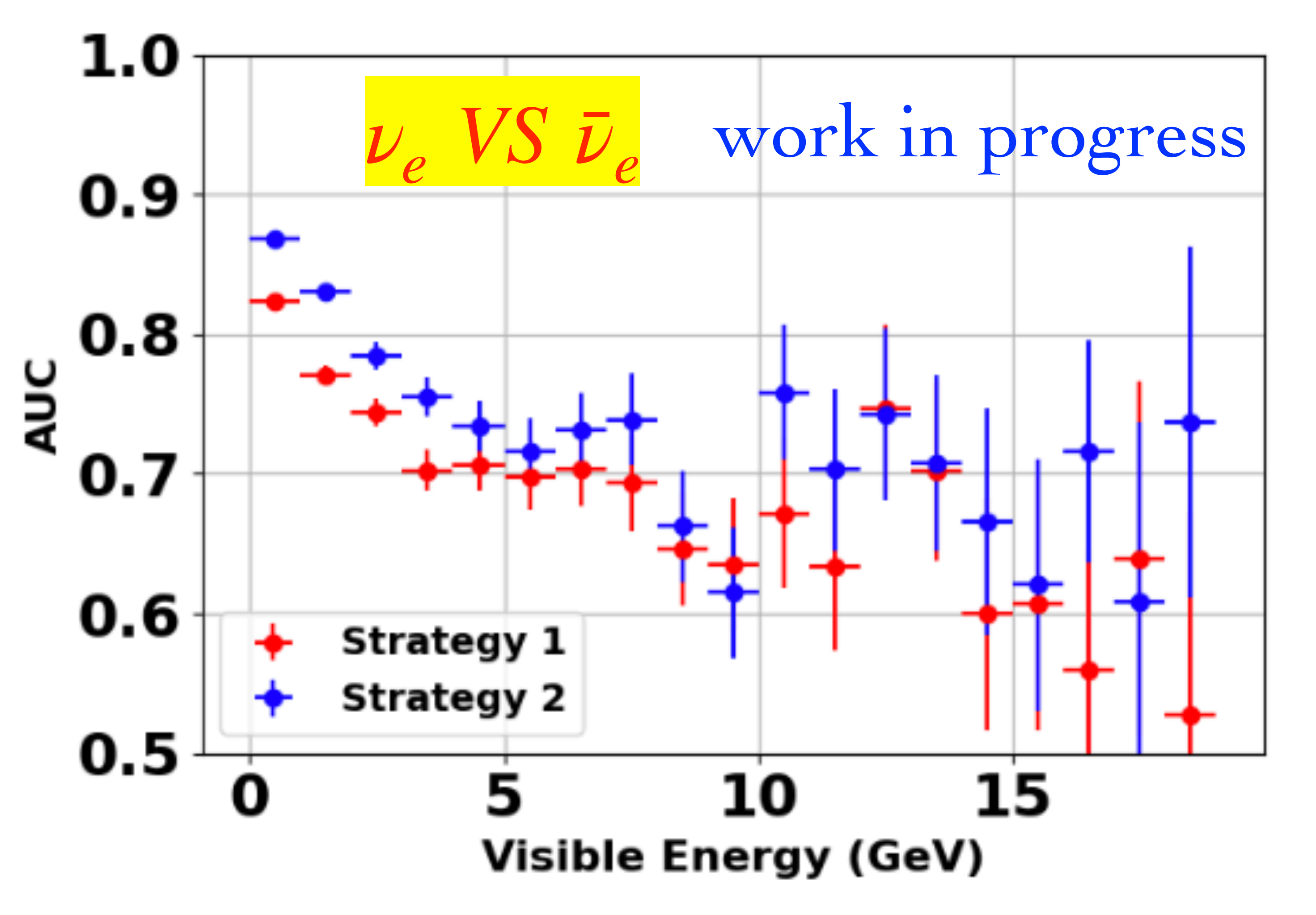
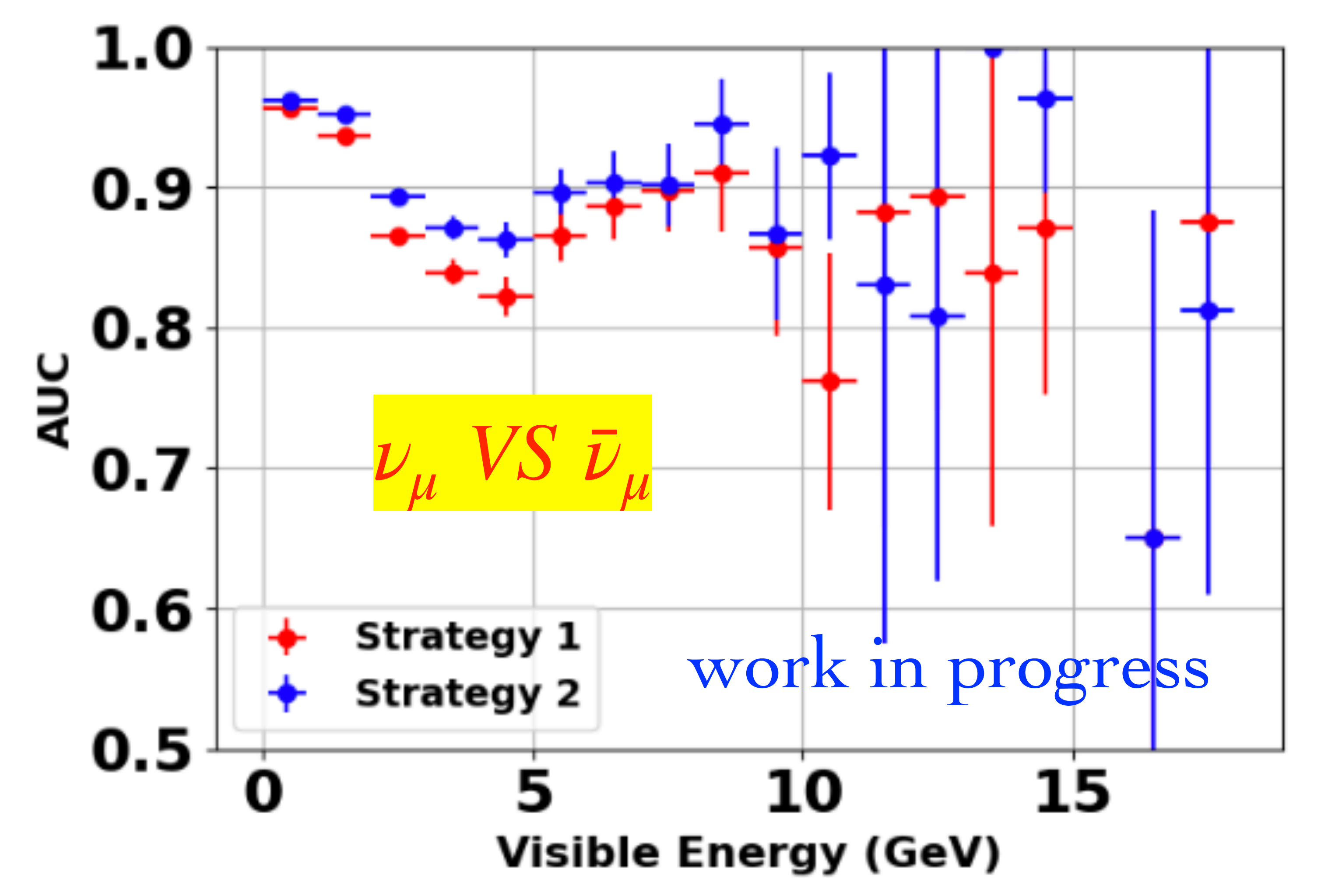
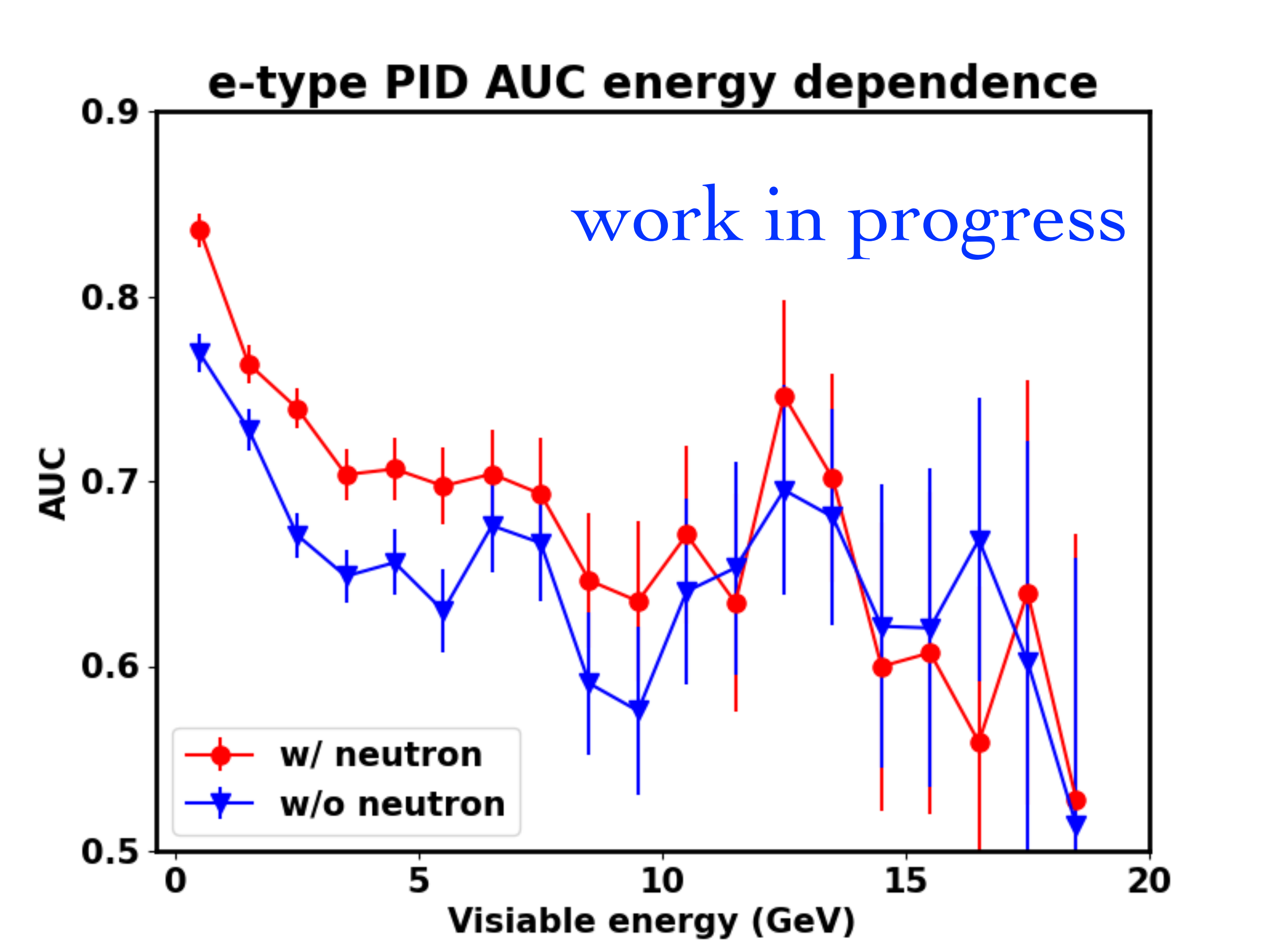


Fig. 8: Illustration of the AUC score using $\nu_e / \bar{\nu}_e$ classification as an example. The AUC score can be viewed as an optimisation of $\nu_e / \bar{\nu}_e$ efficiencies.







MORE INTERESTING TOPICS

- PMT de-noising, waveform reco
- ^{14}C pileUp identification
- Muon classification/combined reco
- Seperation of Scintillation and Cherenkov photons?
- Multi-target reco?
- And more…

SUMMARY

- With $O(10^4)$ PMTs and 20kton LS, JUNO provides a perfect scenario for Machine Learning applications
- A few examples were presented
  - MeV reactor ν: PMT waveform/vertex/energy reco
  - GeV atm. ν: directionality reco and PID
- More interesting and challenging problems…
- ML can further enhance the capability of the detector, yielding faster, better results

THANK YOU!

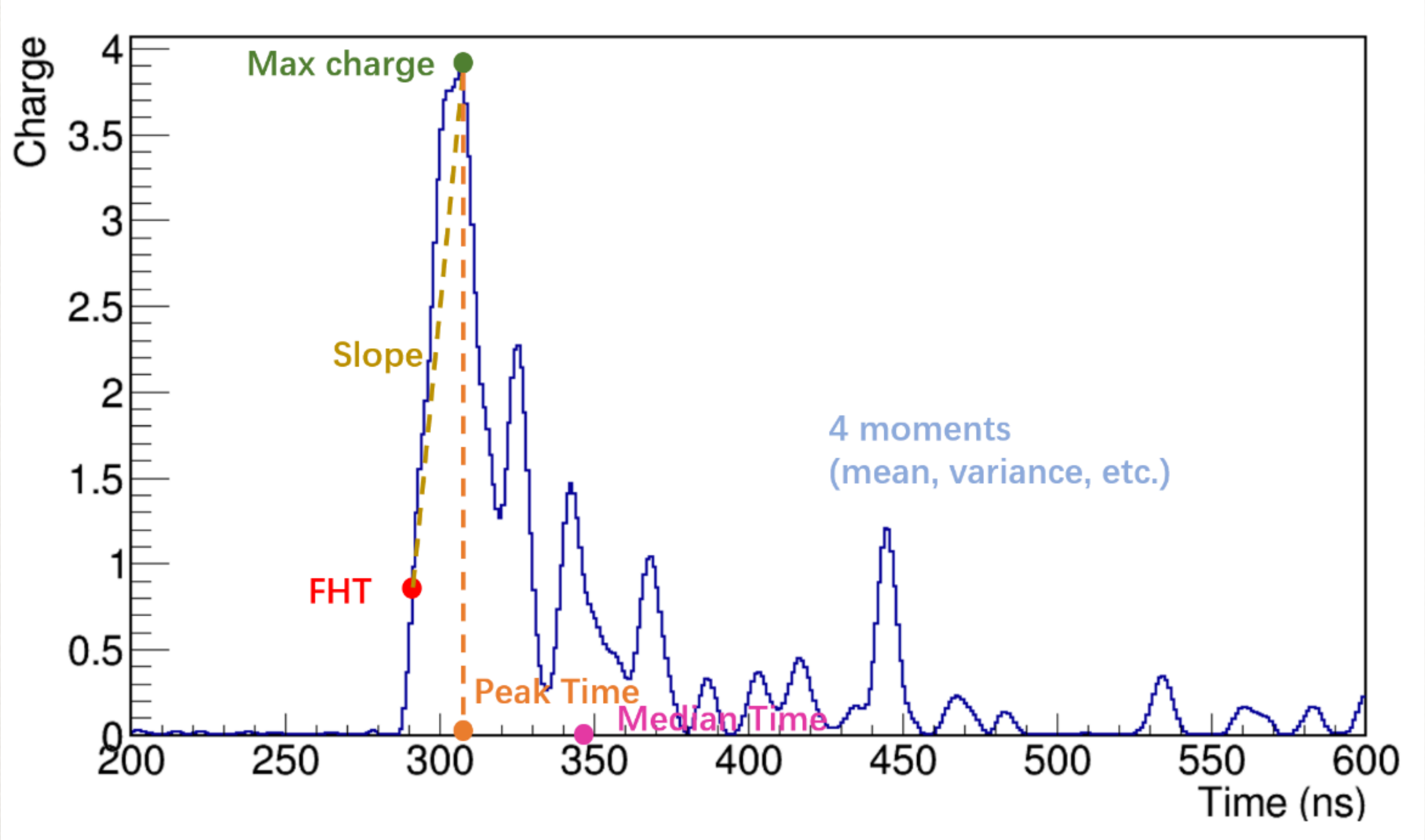
WE ARE HIRING

- Several postDoc openings at JUNO
- Commissioning, Reconstruction, Physics Analysis and more…
- Competitive salary!
- Email: **luowm@ihep.ac.cn**

BACK UP

INPUTS: PMT FEATURES

❖Feature variables extracted from PMT waveforms



ATM. NEUTRINOS: DIRECTIONALITY