ML at JUNO

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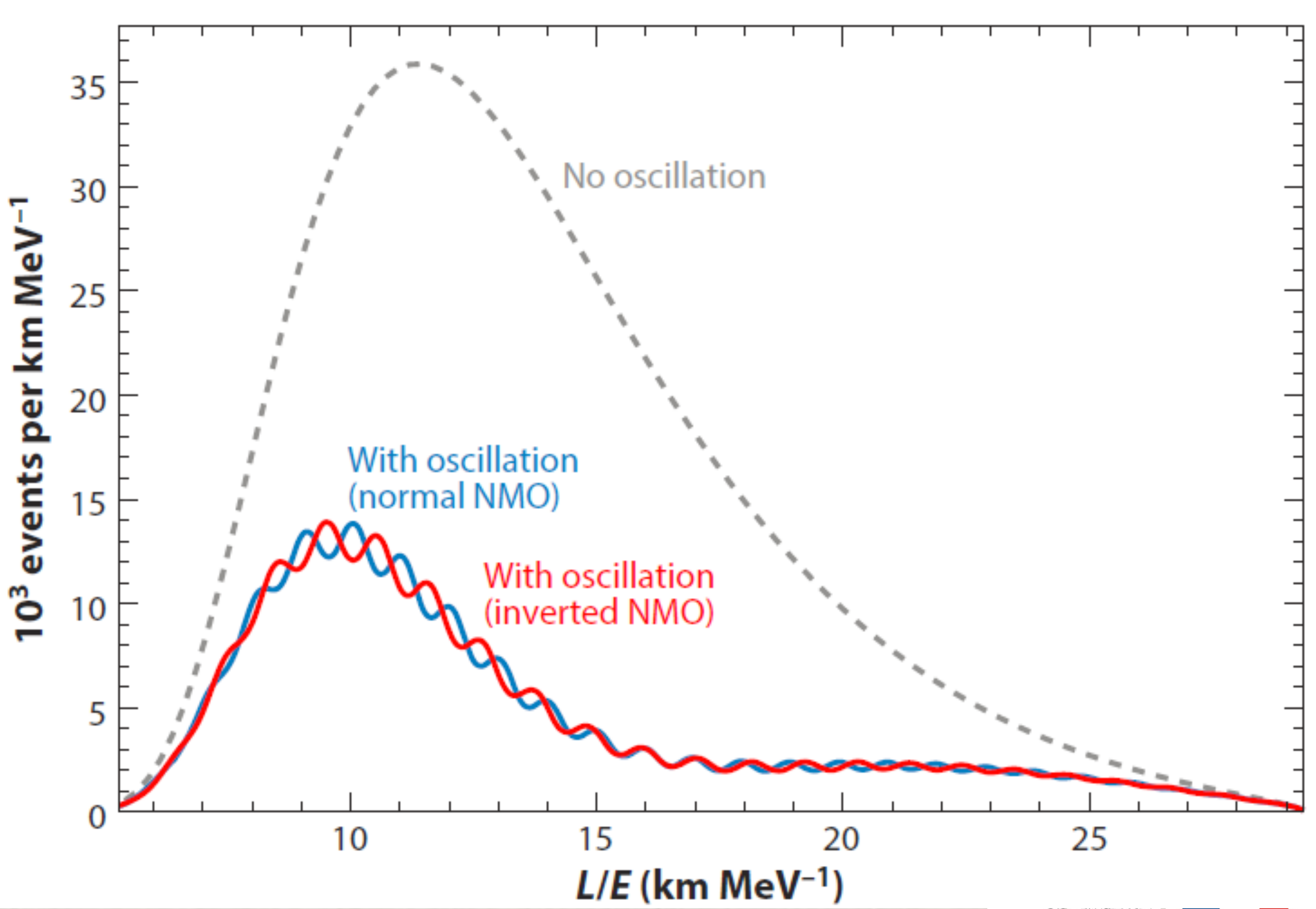
JUNO

- 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%/√E
D. Chooz	8+22 t	8%/√E
RENO	16 t	8%/√E
Daya Bay	20 t	8%/√E
Borexino	300 t	5%/√E
JUNO	**20000 t**	**3%/√E**

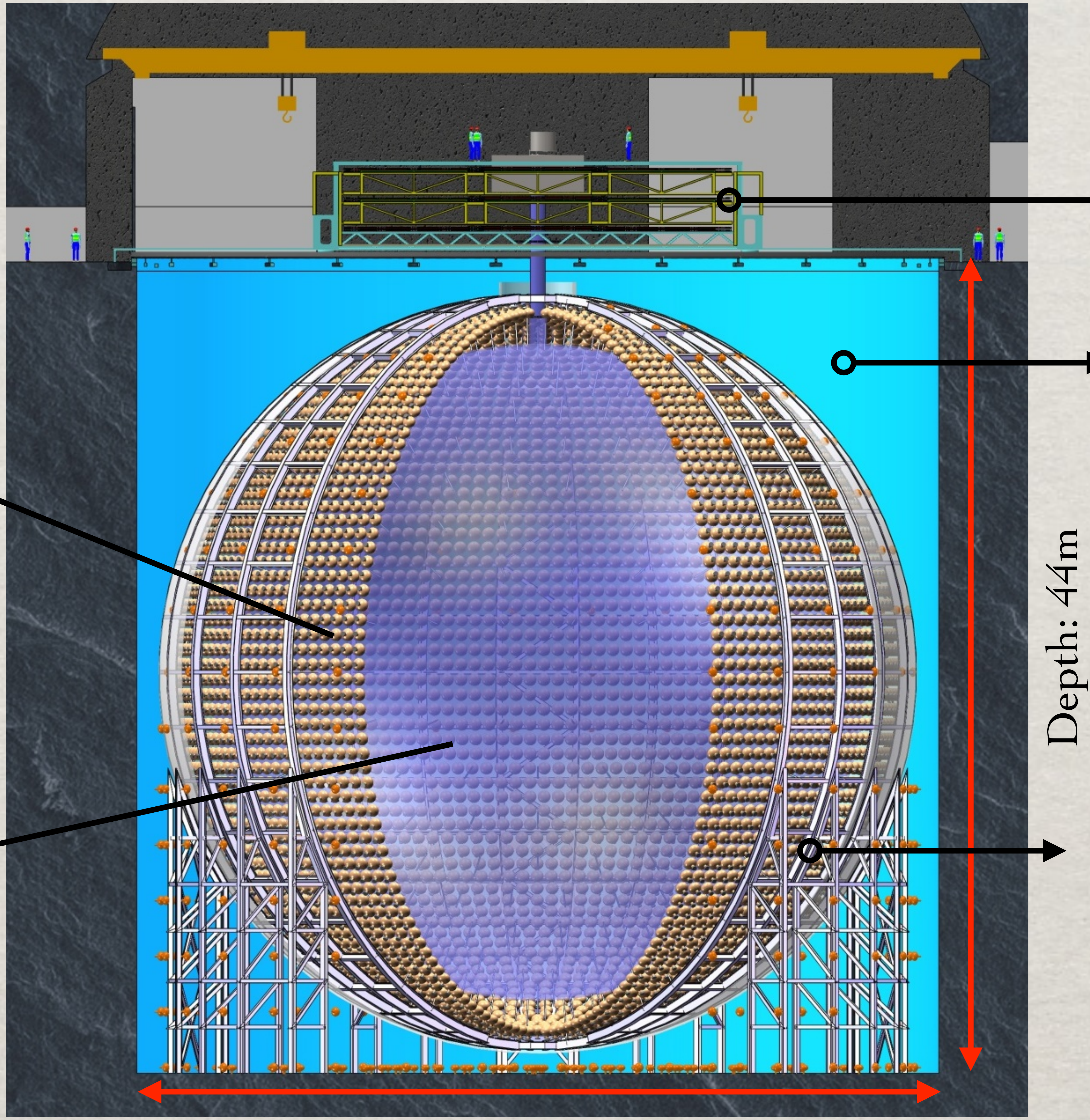


DETECTOR

Central Detector*

~17,612 20" PMTs

+ ~25,600 3" PMTs
+ ~75% coverage



Top Tracker

Water Pool

Central Detector*
Acrylic sphere
Stainless steel truss

Liquid Scintillator
20kton

ϕ: 43.5m

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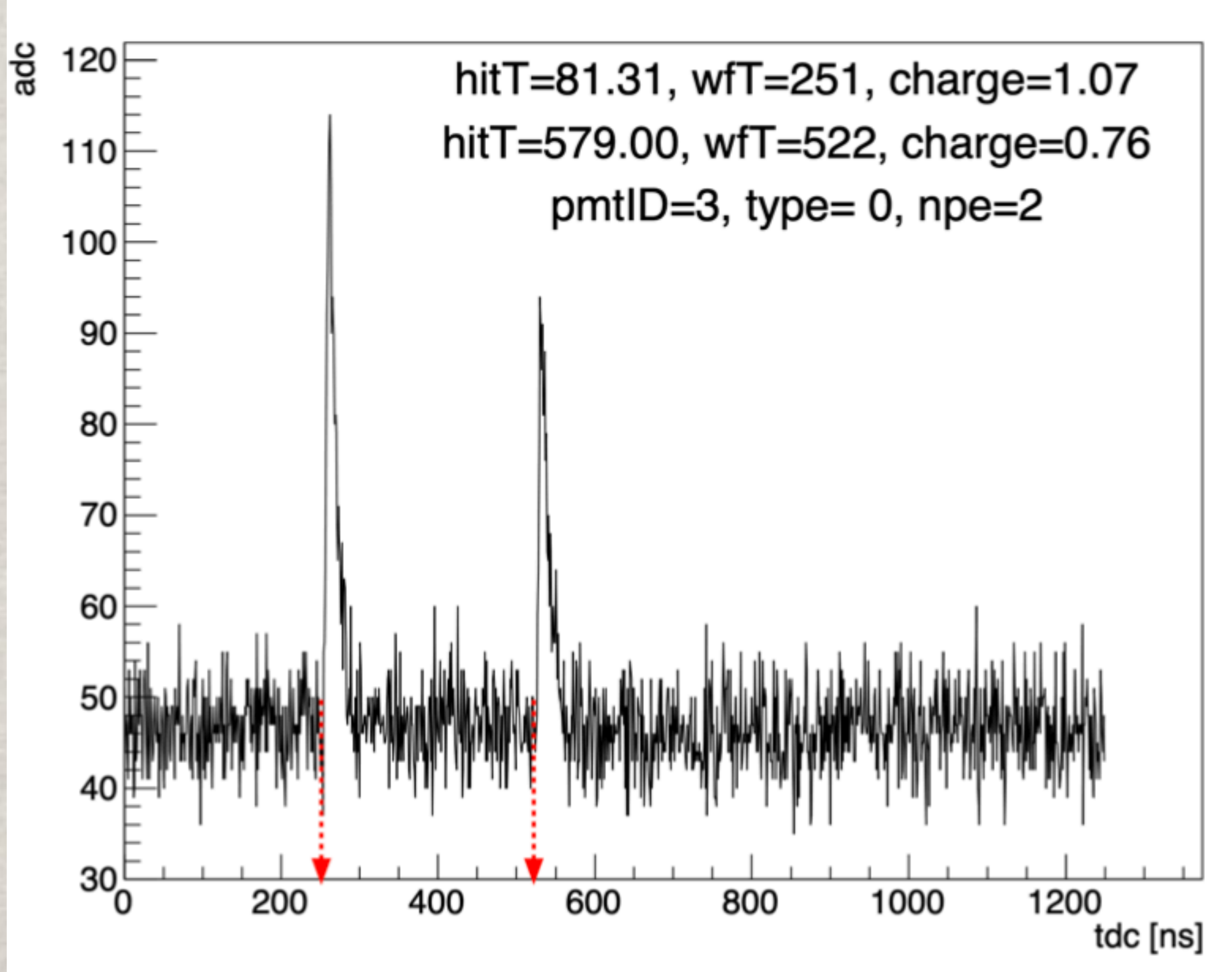
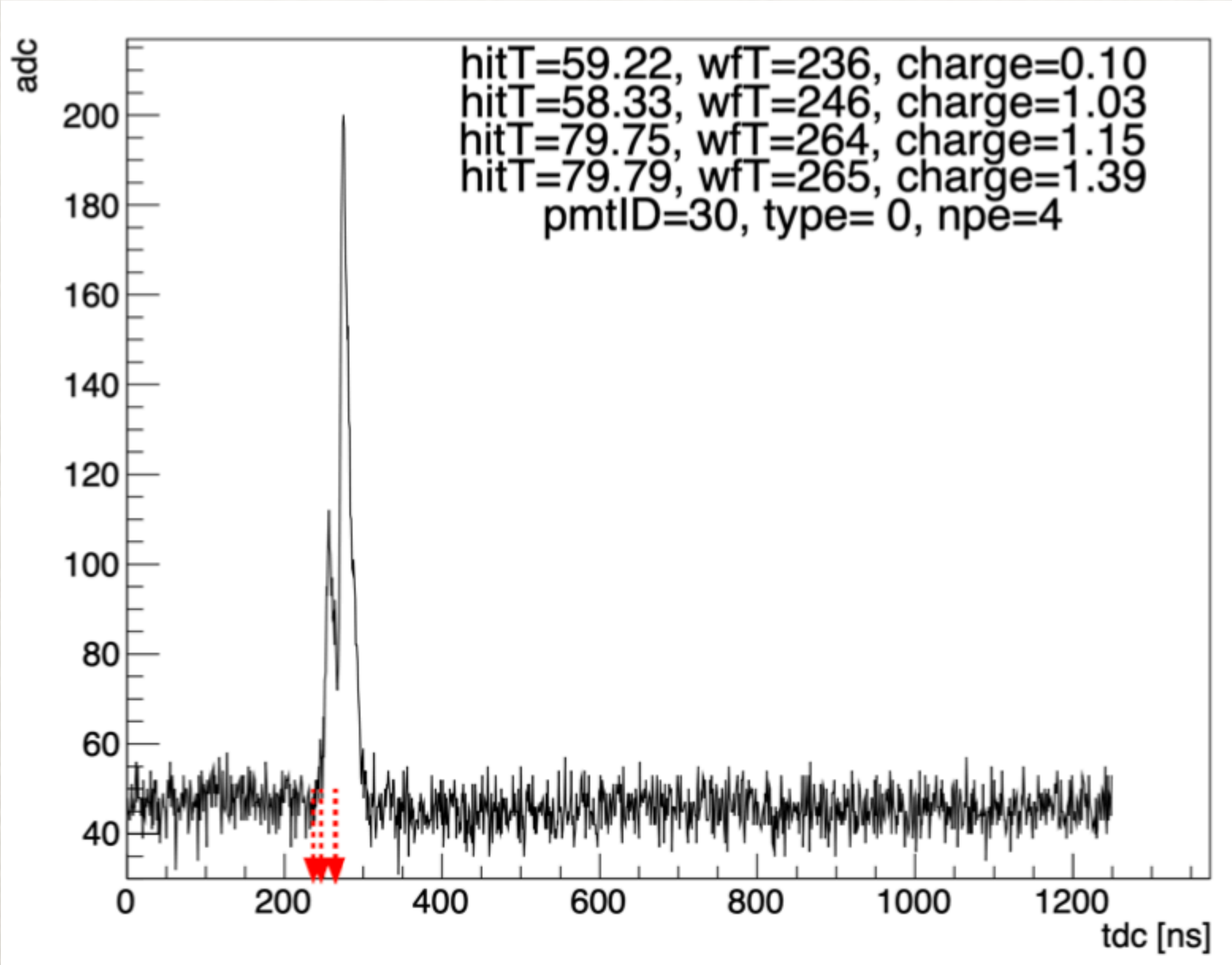
RECONSTRUCTION - PMT

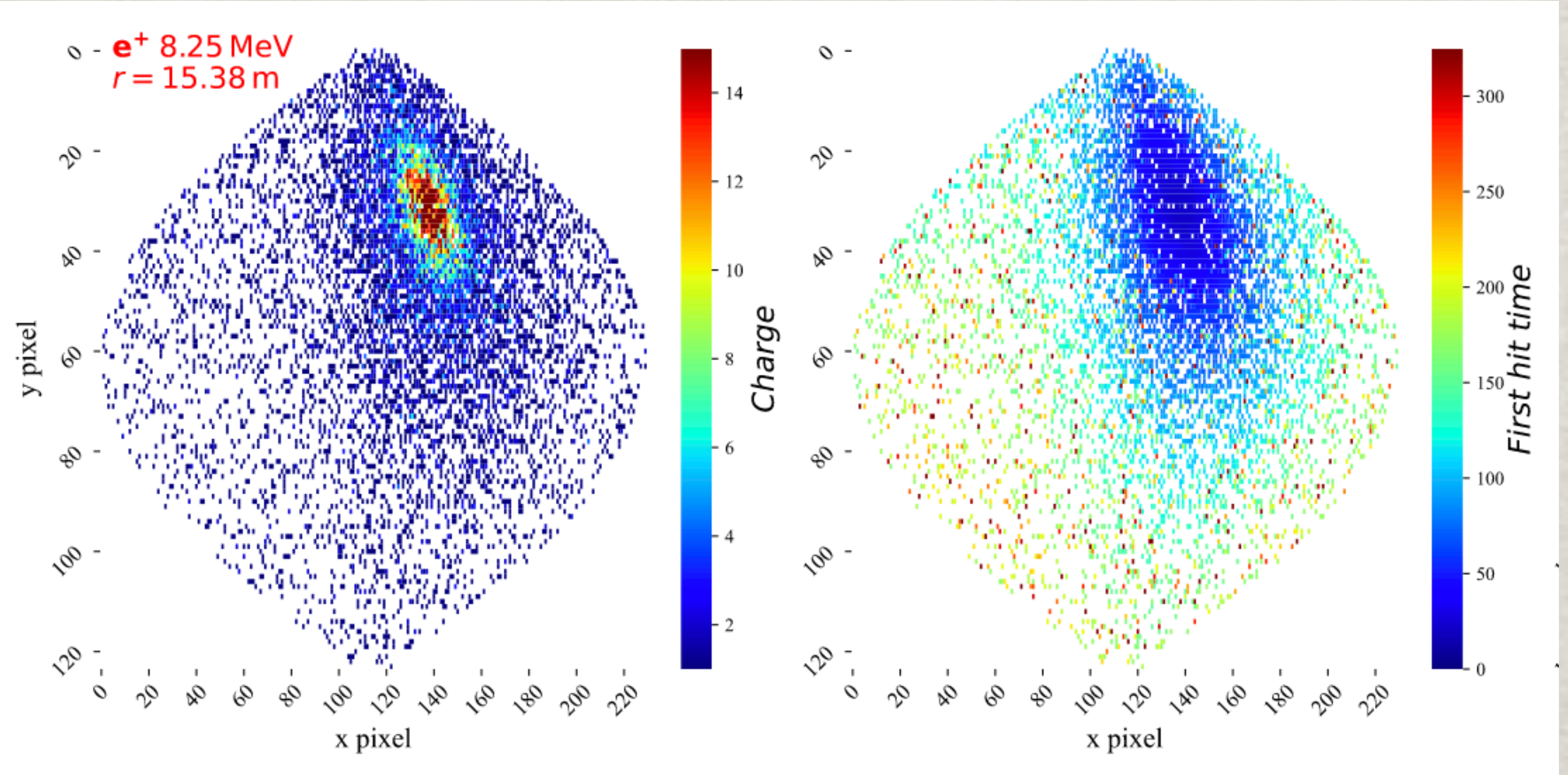
- PMT waveform reco (common issue for many exp.)
  - photon counting (classification)
  - time/charge reco (regression)
    - baseline: first_hit_time and total_charge
    - ideal: T/Q for every photon hit?

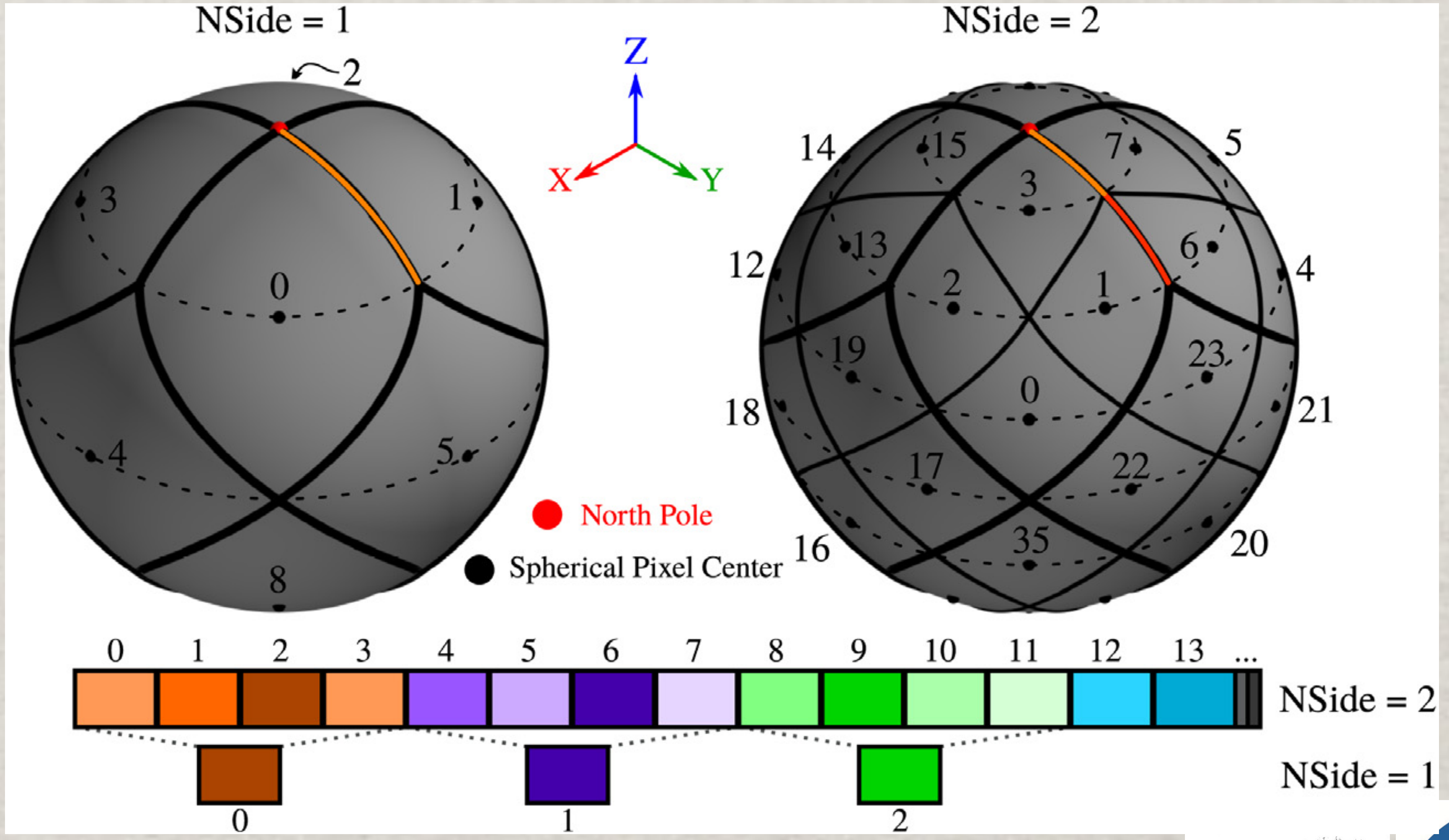




RECONSTRUCTION - MEV

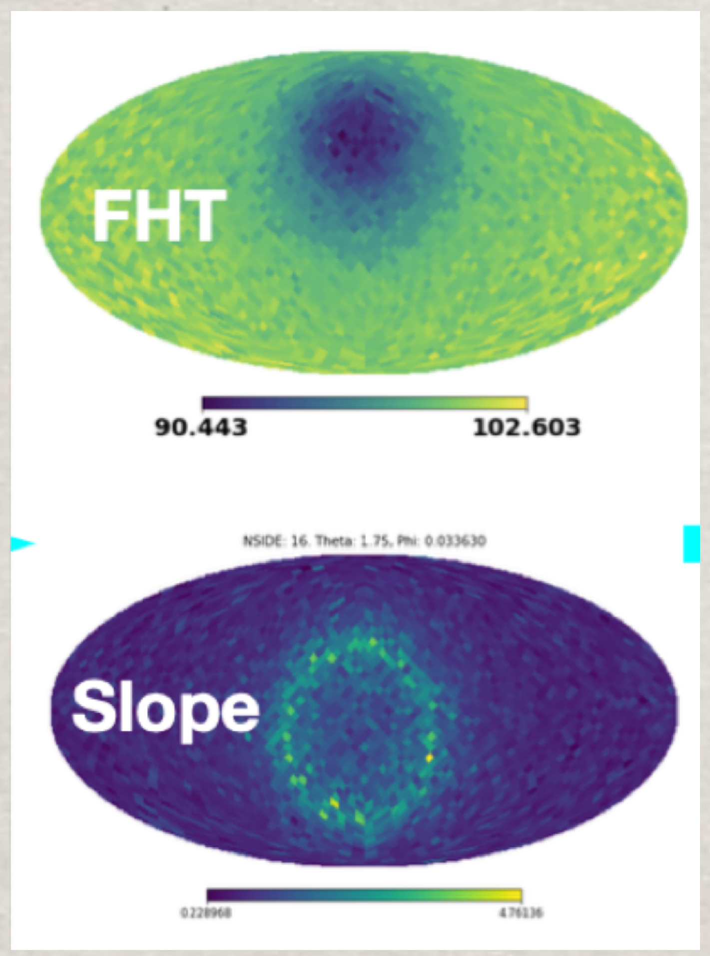
- High precision Vertex/Energy reco in MeV region
  - world leading energy resolution: 3%@1MeV
  - model/inputs/outputs optimization
  - universal challenges:
    - PMT dark noise de-noising, information segmentation…

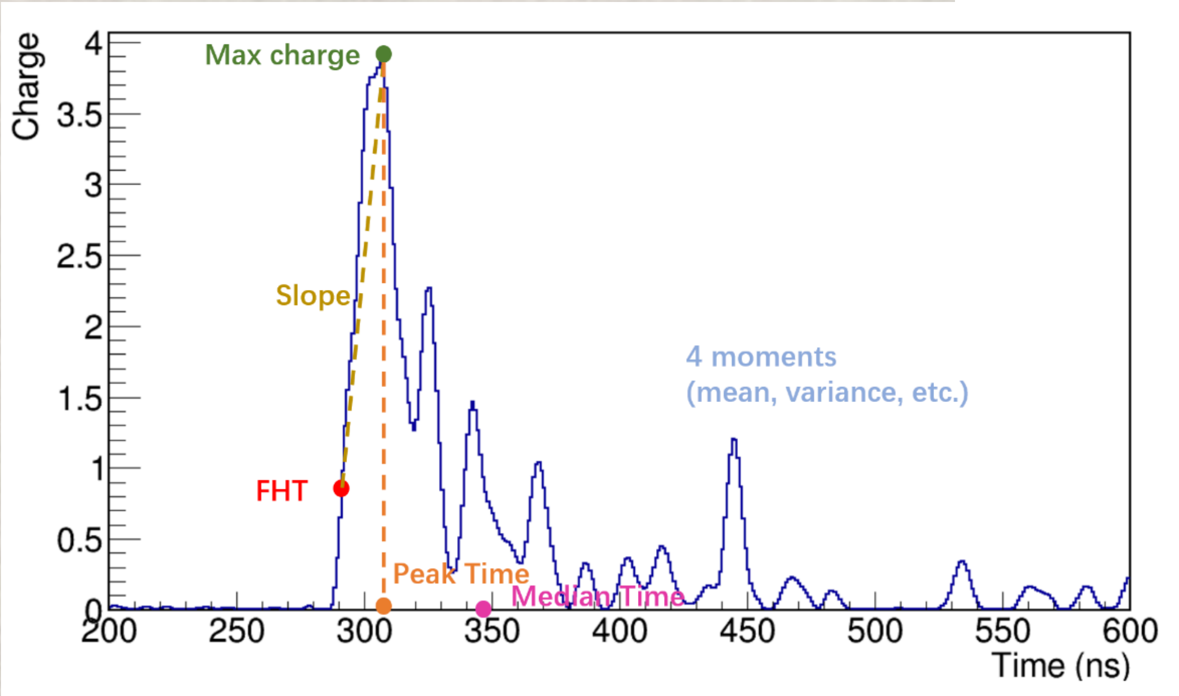


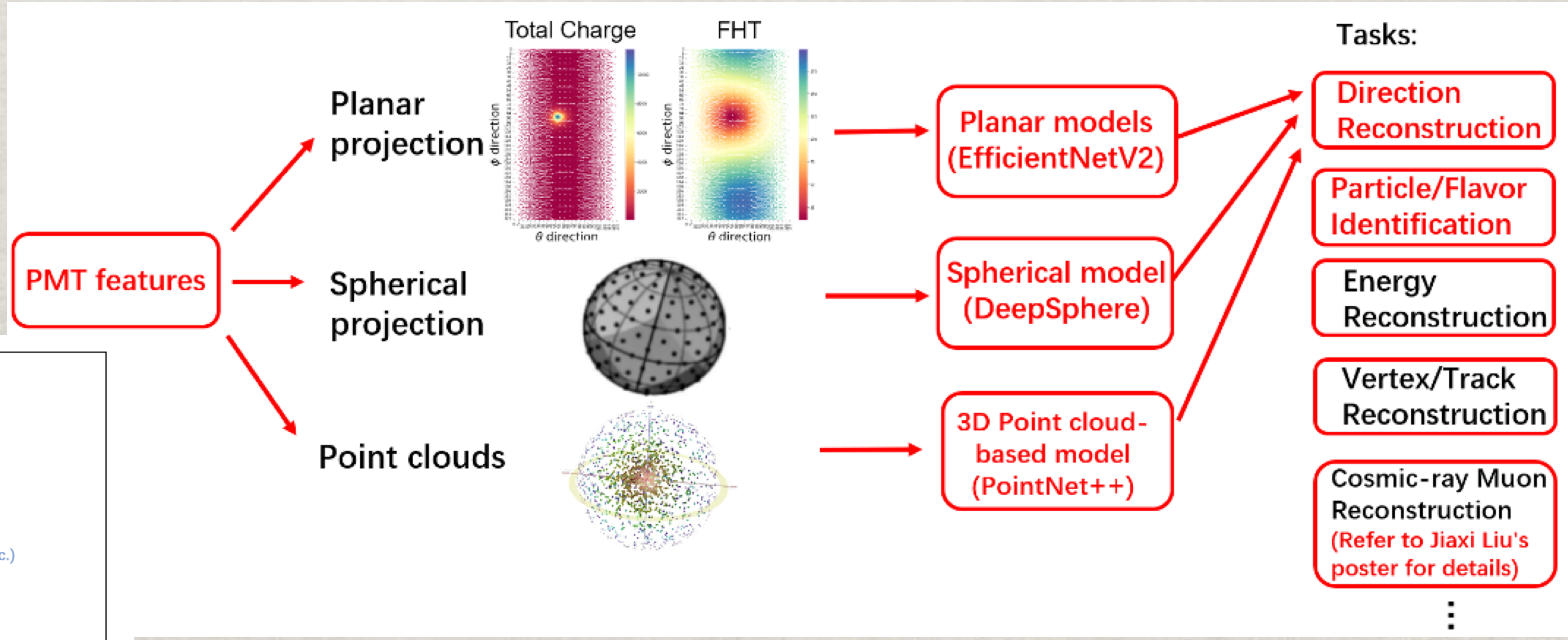


RECONSTRUCTION - GEV

- Muons:
  - classification, track reco
- Atmospheric neutrinos:
  - PID, direction/energy reco…







PHYSICS ANALYSES

- Signal/bkg separation
- Correlated signals selection
  - IBD prompt&delayed signals
  - muons & induced isotopes
- Parameter fitting
- More…

MORE...

- ML based fast&accurate simulation
- Hardware: ML waveform reco on FPGA
- Online: Event Classification (no triggers for JUNO)
  - different energy range, multiple categories for the same type of events (muons, atm. neutrinos…)
  - need to save different info (WaveForm, partial WF, T/Q)
- Detector monitoring
  - anomaly detection
  - rare signal detection (such as SuperNova)
- more…

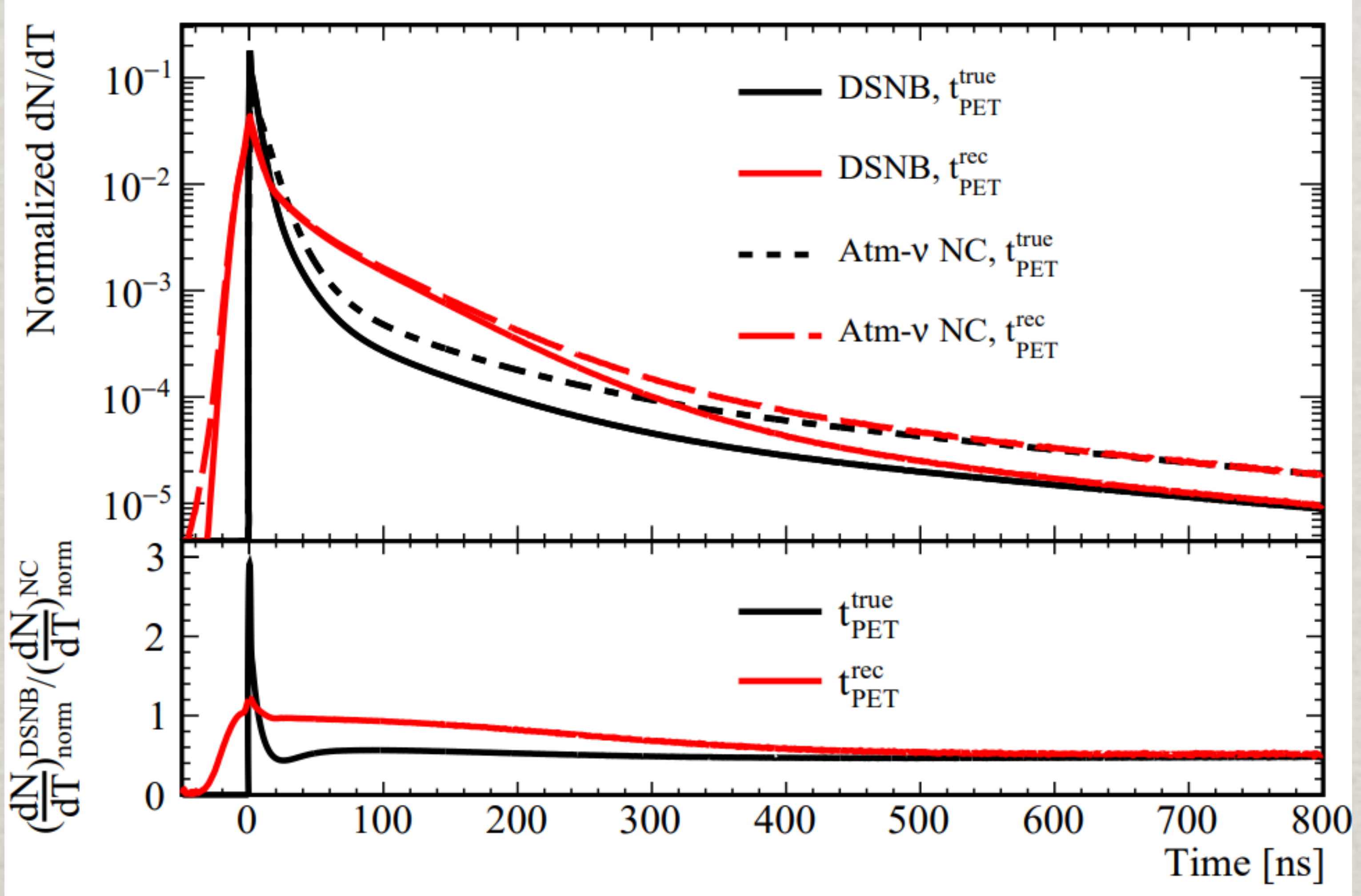
COMMON ISSUES

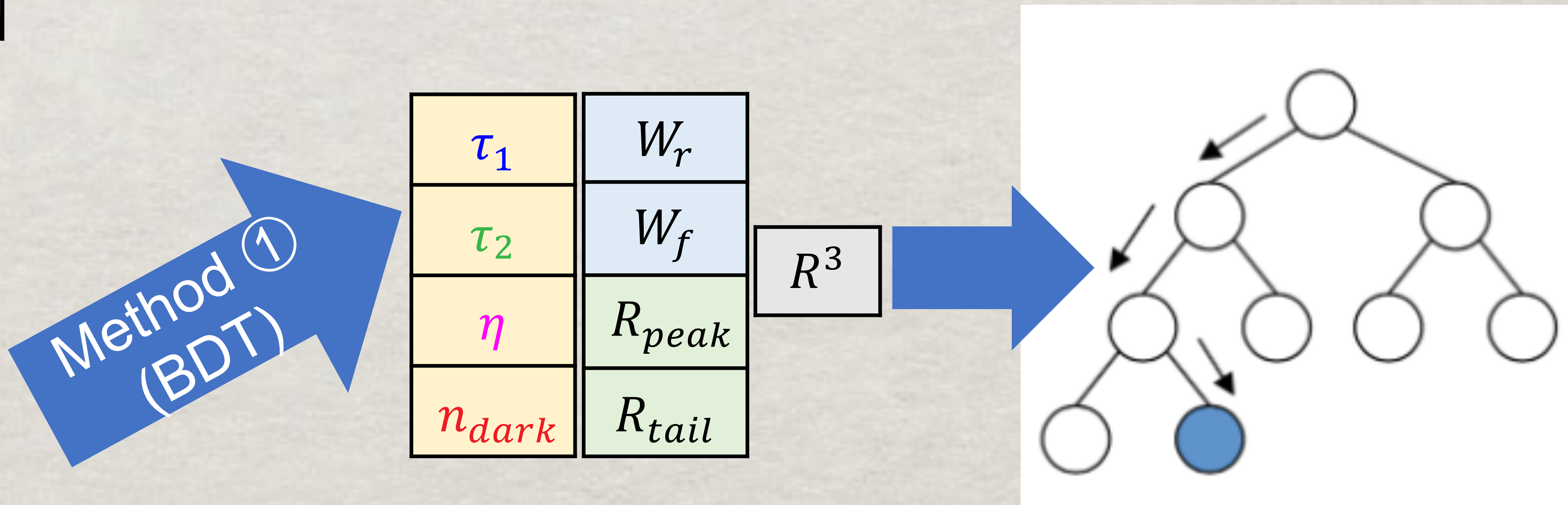
- Image vs video: how to use the temporal info
- Sparse data: lots of un-fired PMTs
- Spherical detector
- MC and data discrepancy
- ML related systematics uncertainties
- Information segmentation: multi-target reco
- Resource bottleneck for running Large Models such as Transformer(not enough GPU memory)
- And more…

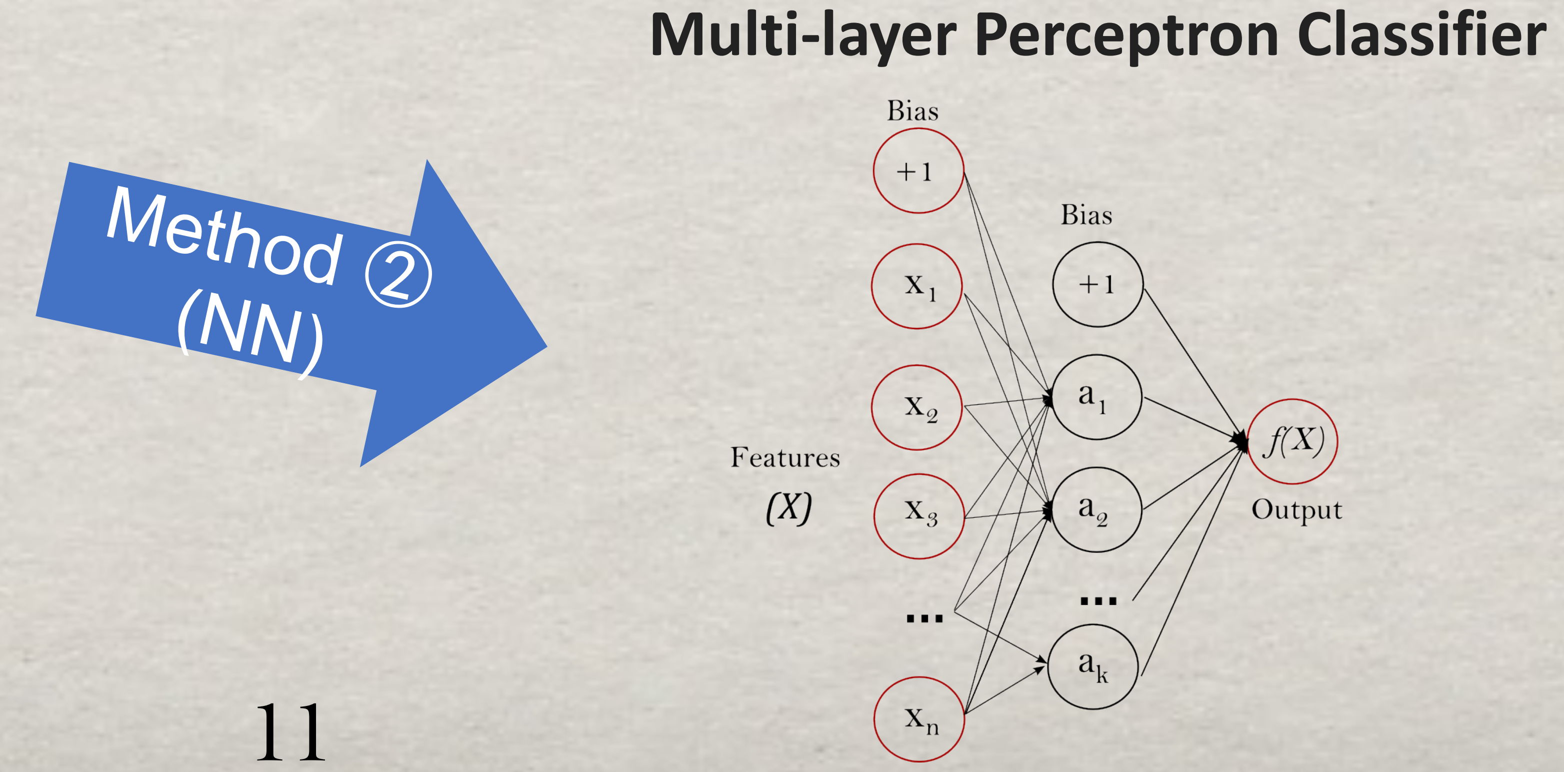
PID

PARTICLE IDENTIFICATION

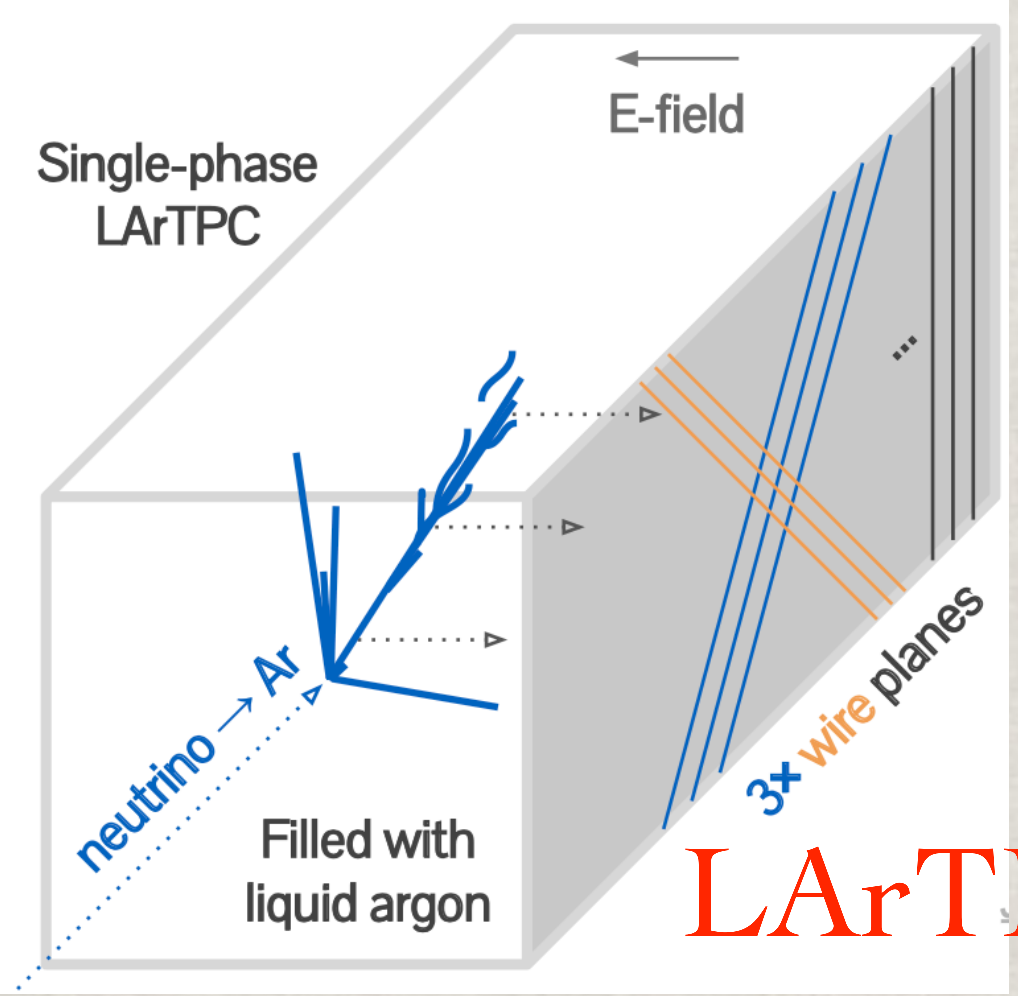
- Goal: Pulse Shape Discrimination (γ/e/e$^+$, vs proton/ neutron)
- Principle: different scintillation timing profile
- Method: BDT or NN

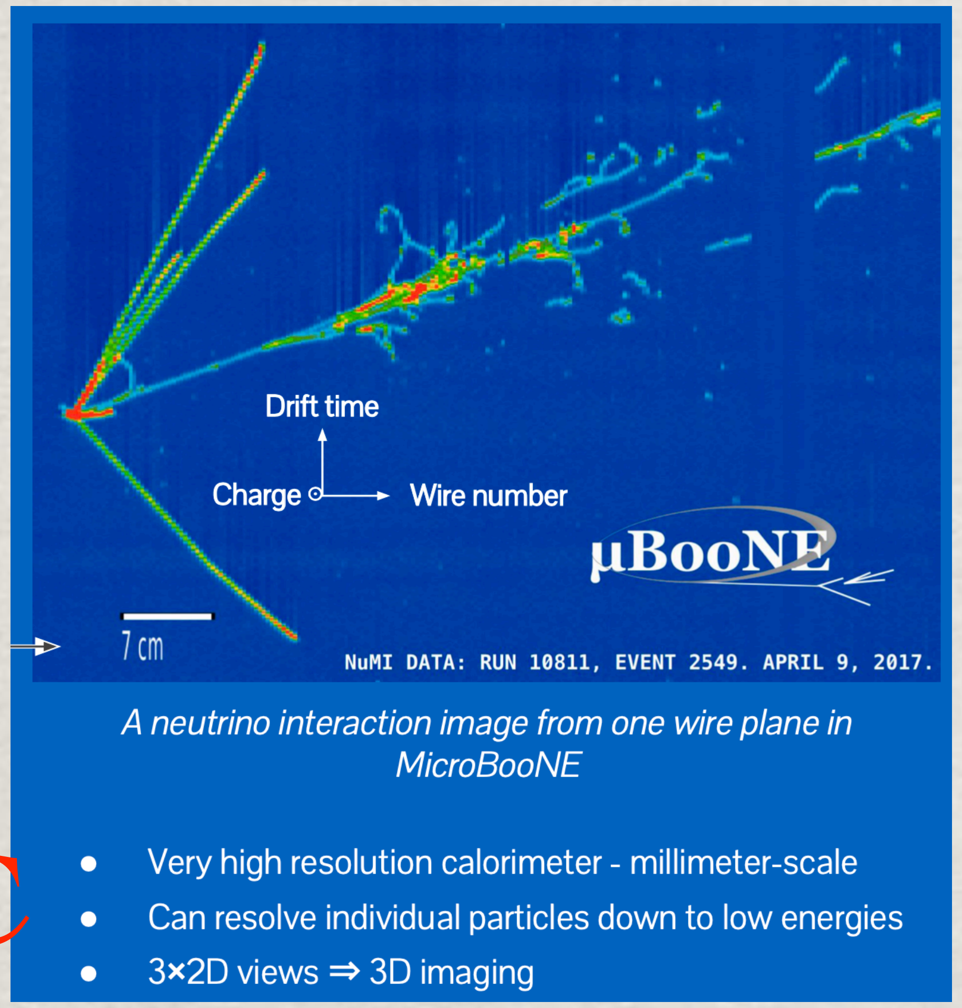




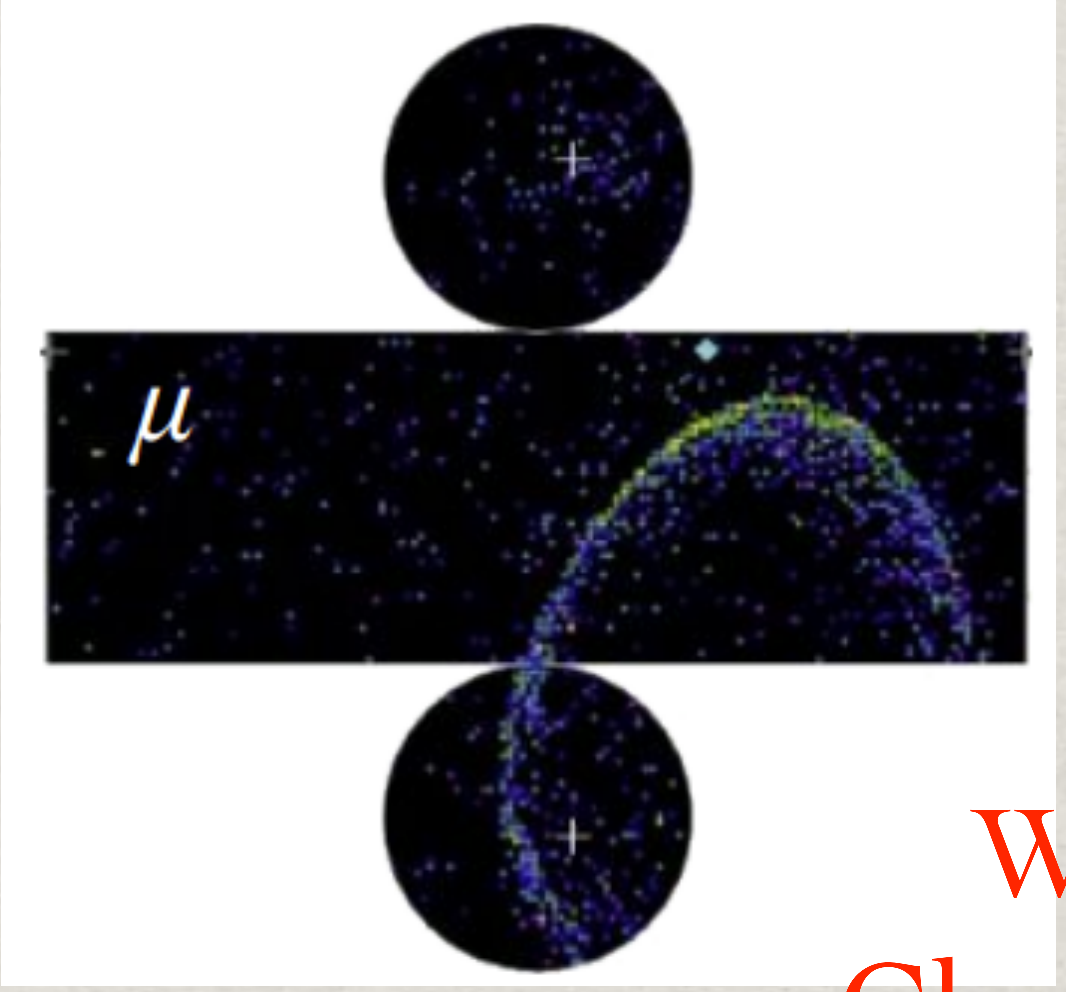


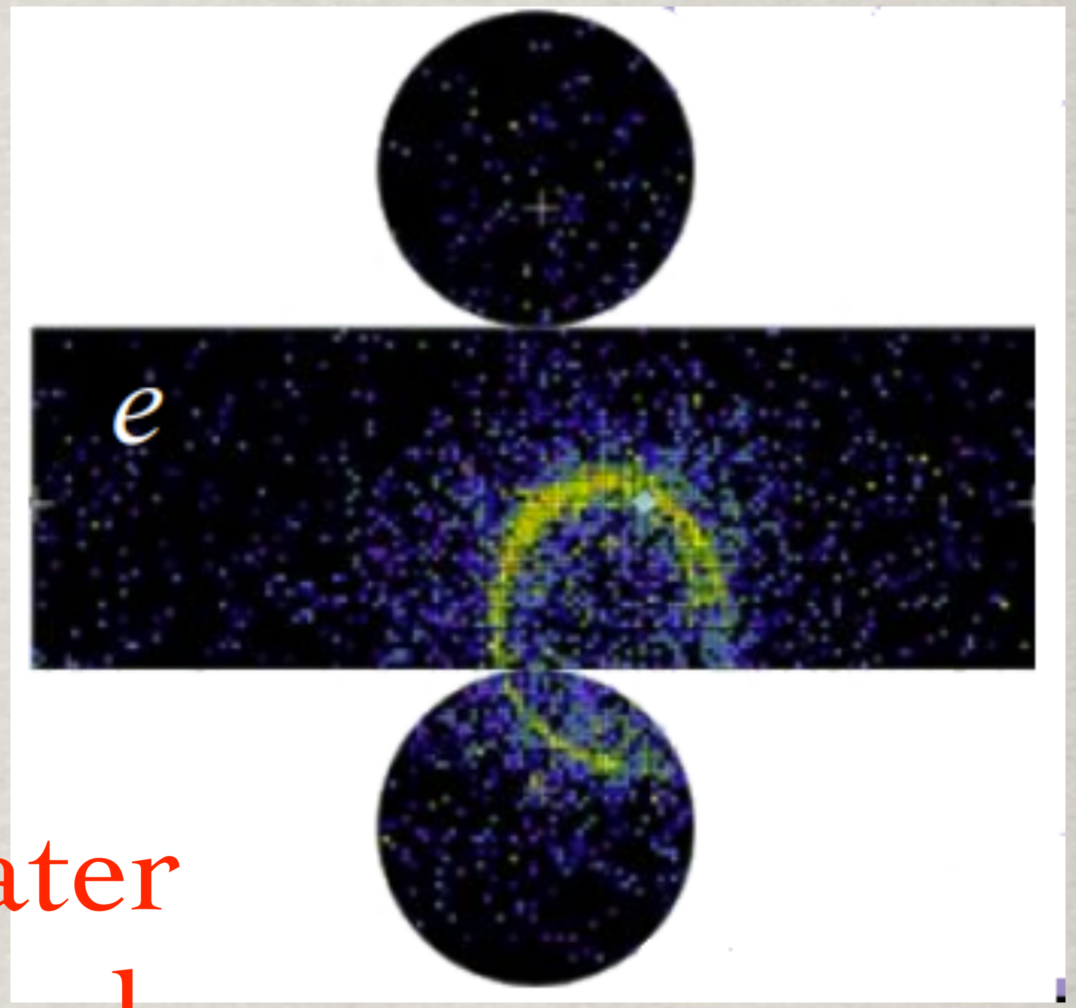
CHALLENGES AND OPPORTUNITIES





LArTPC





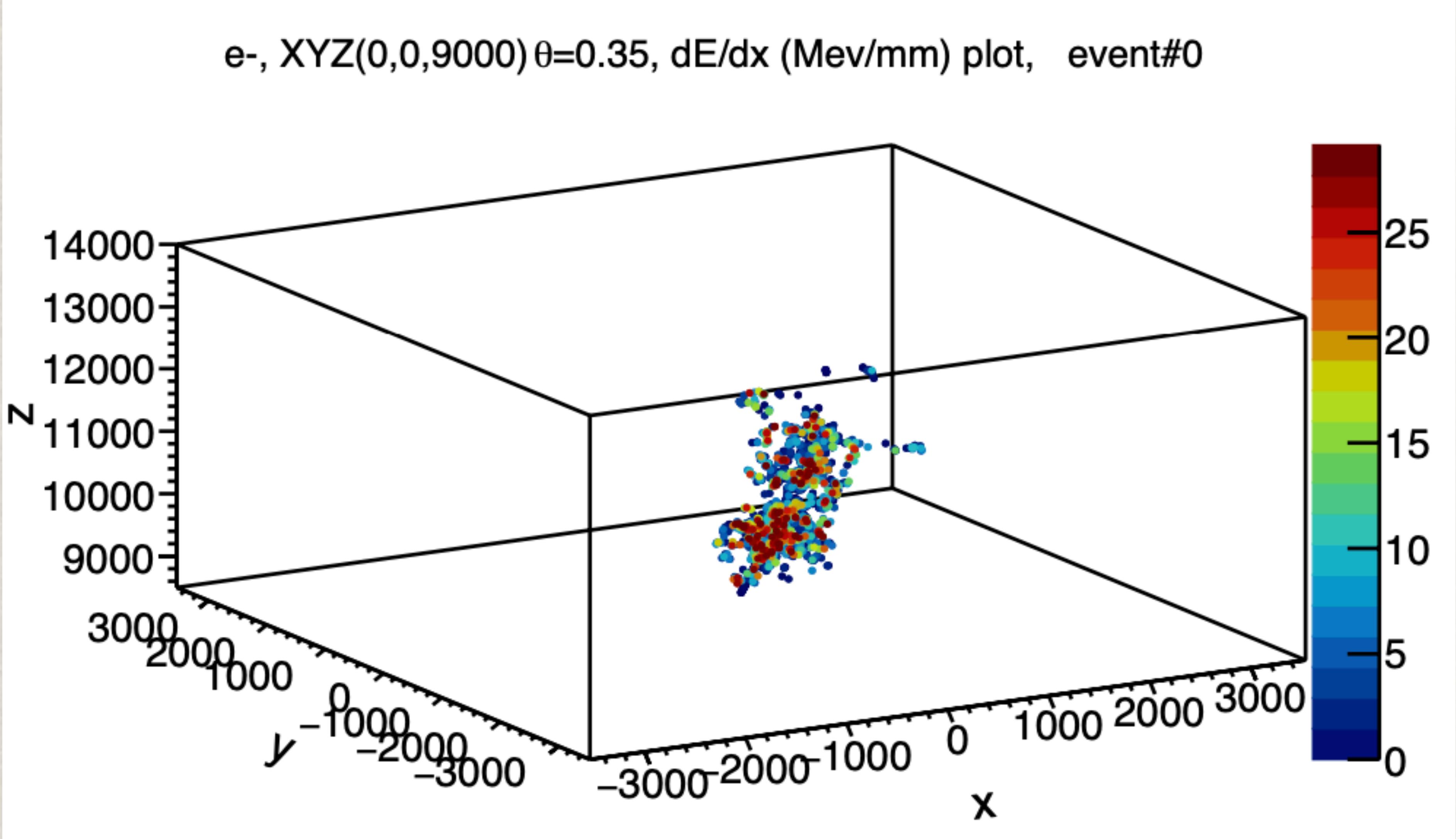
Water Cherenkov

- 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

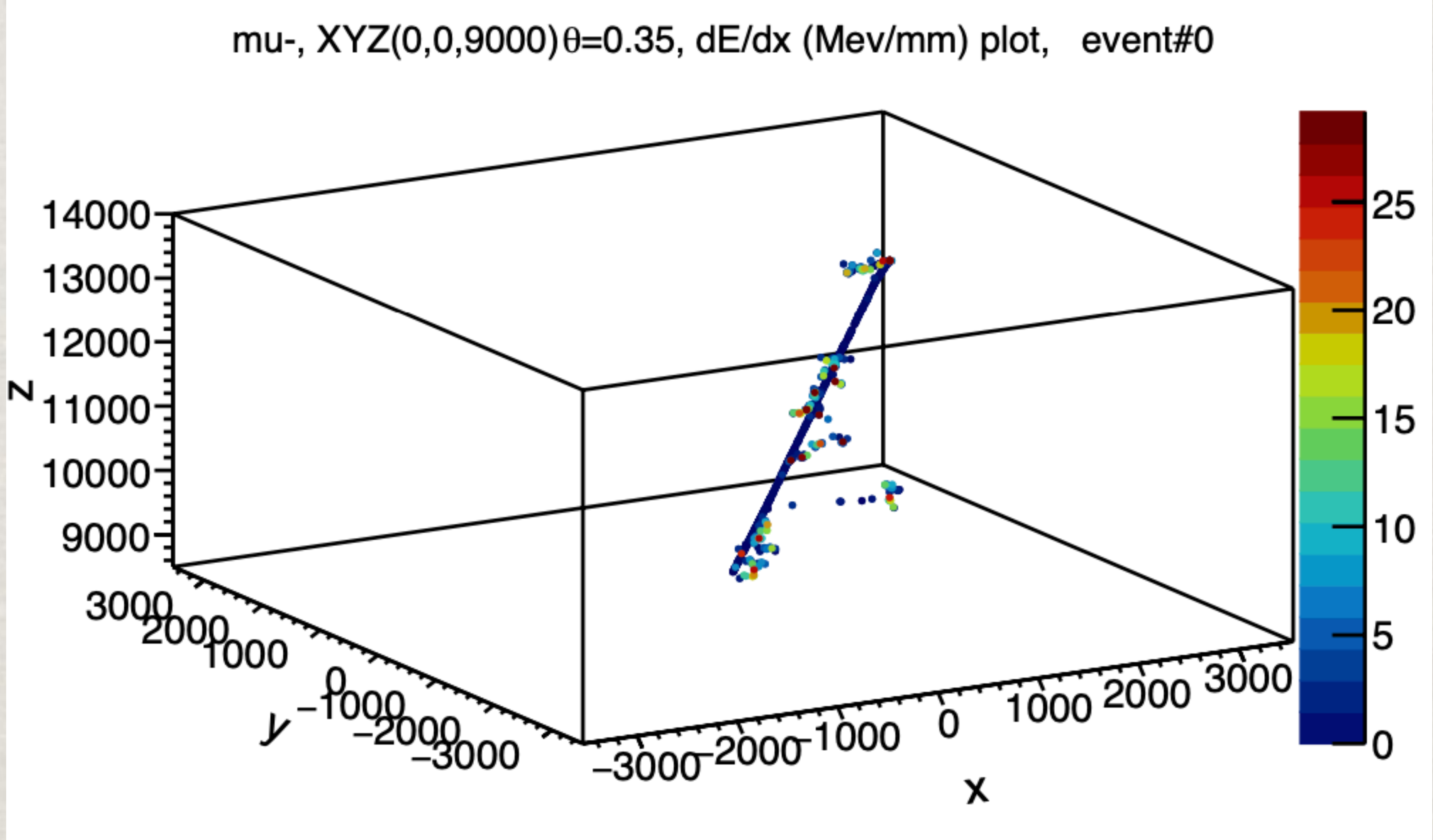
PARTICLE TOPOLOGY

Energy deposition topology in LS for different type of particles

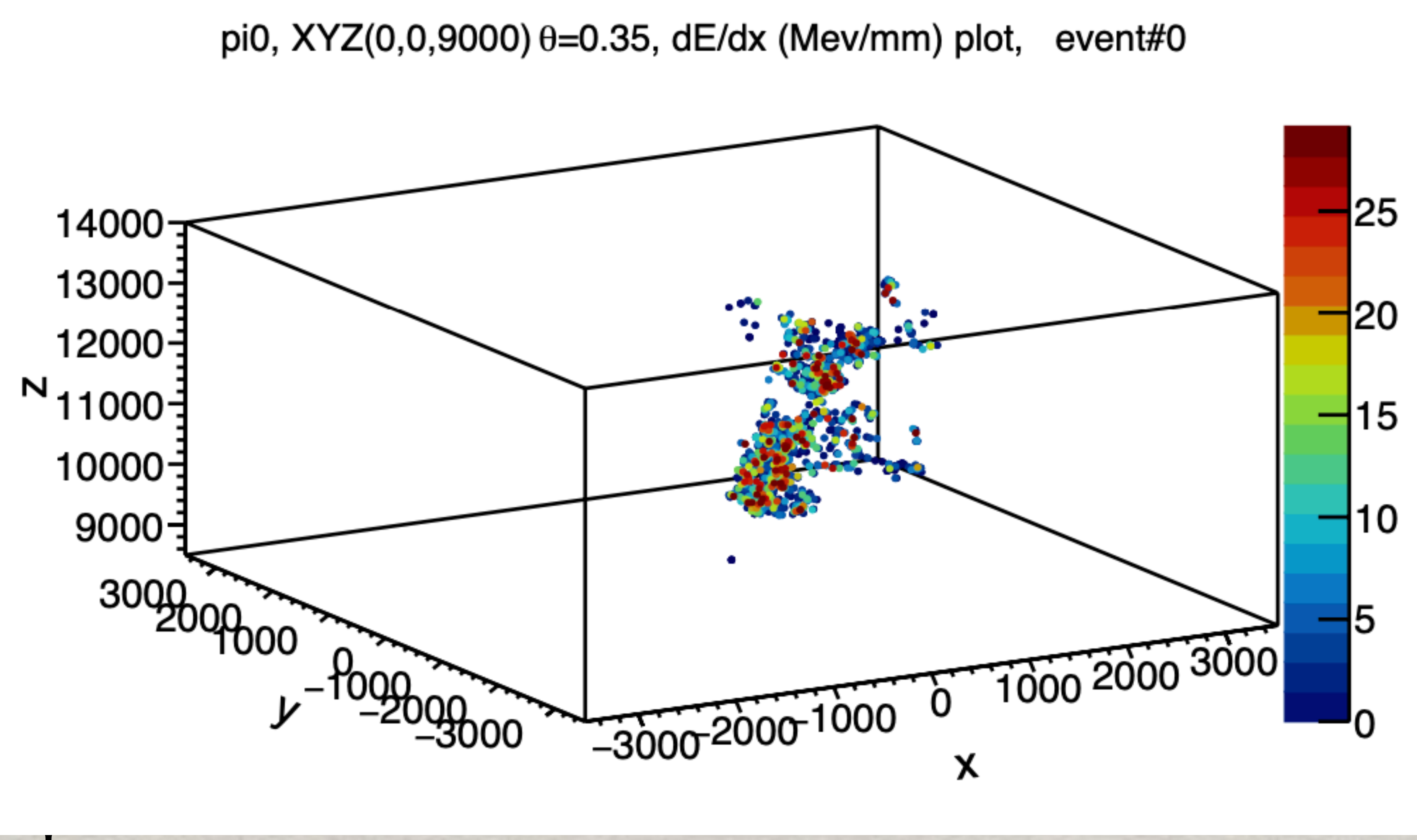
e



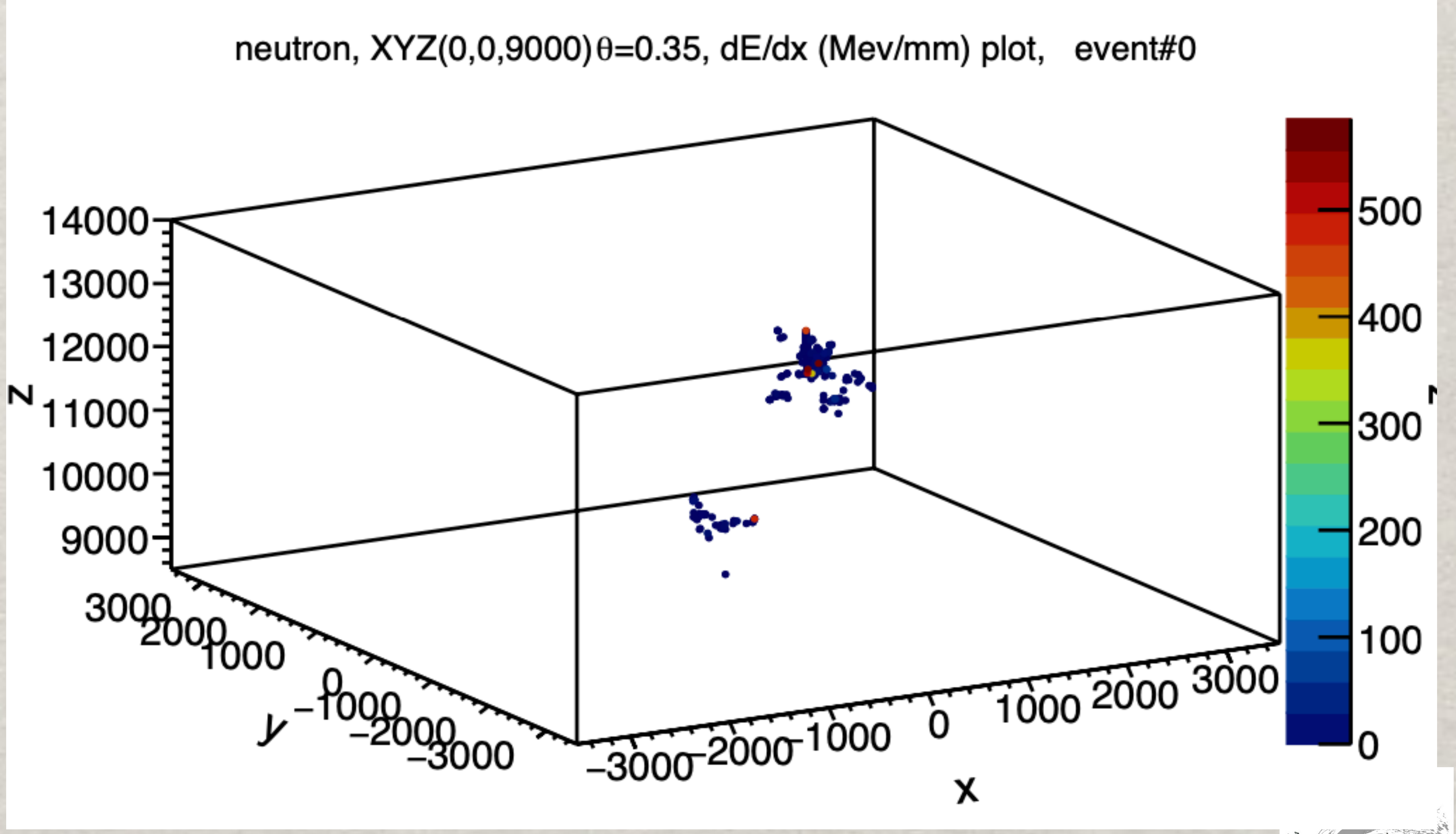
μ



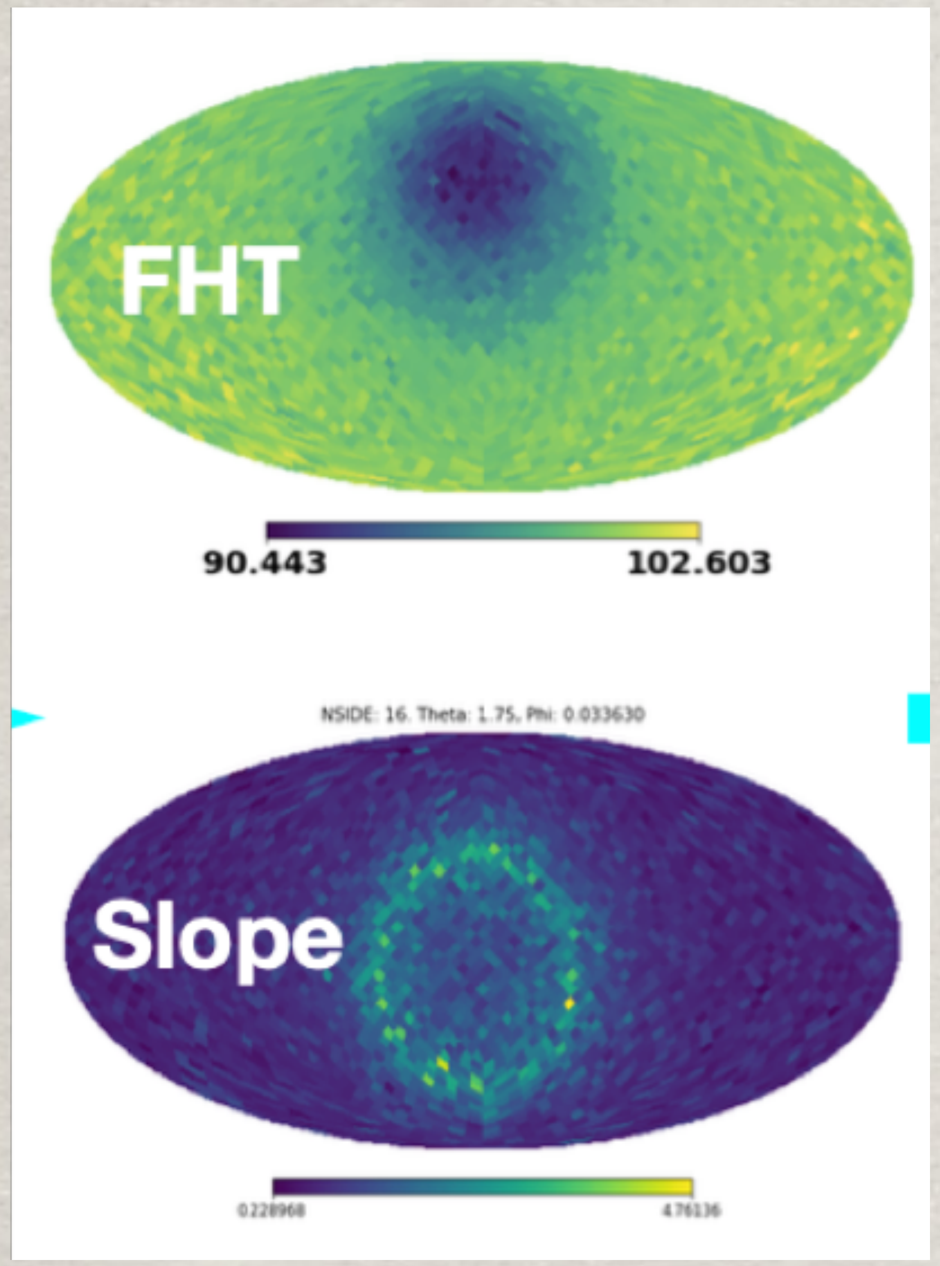
π^0



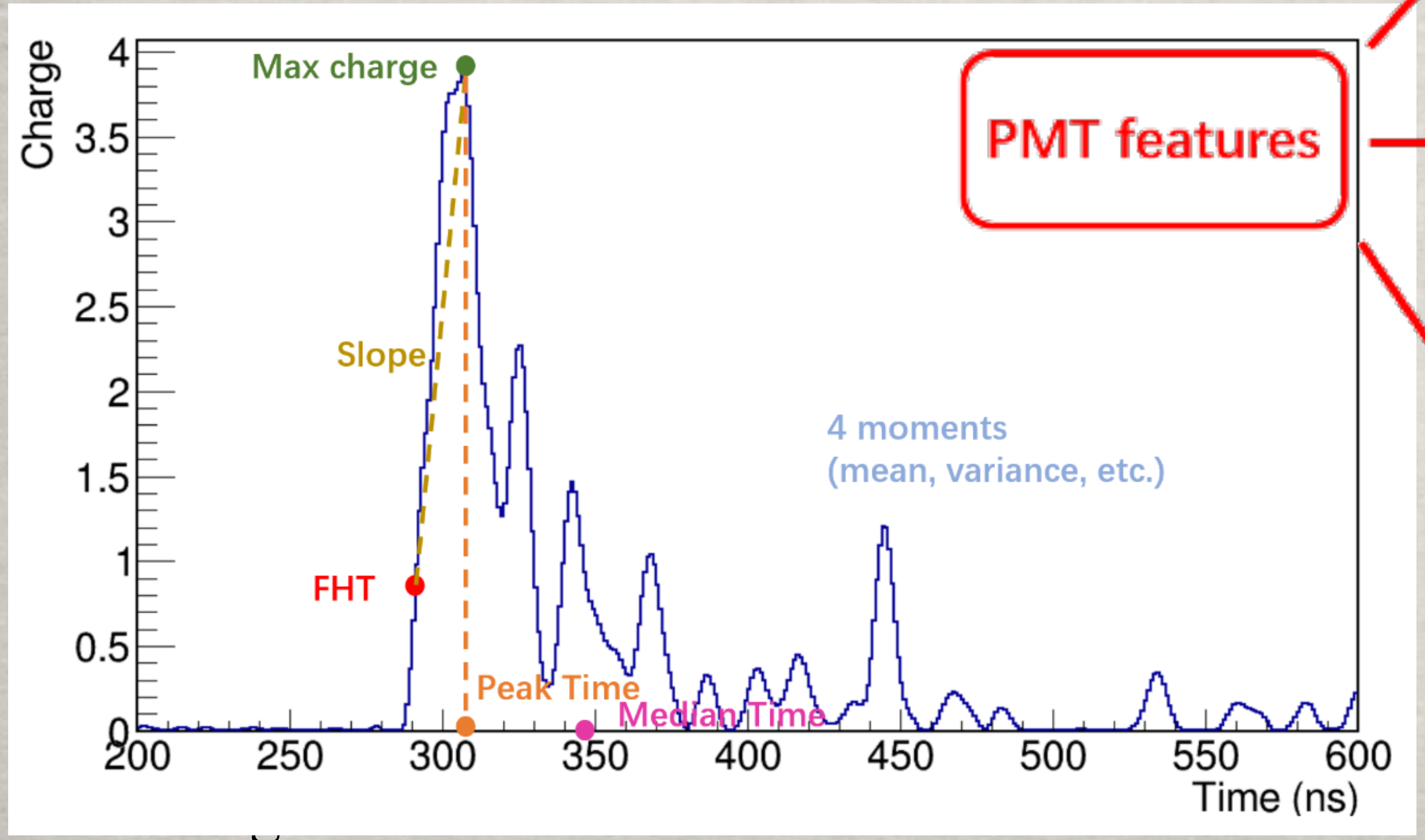
n

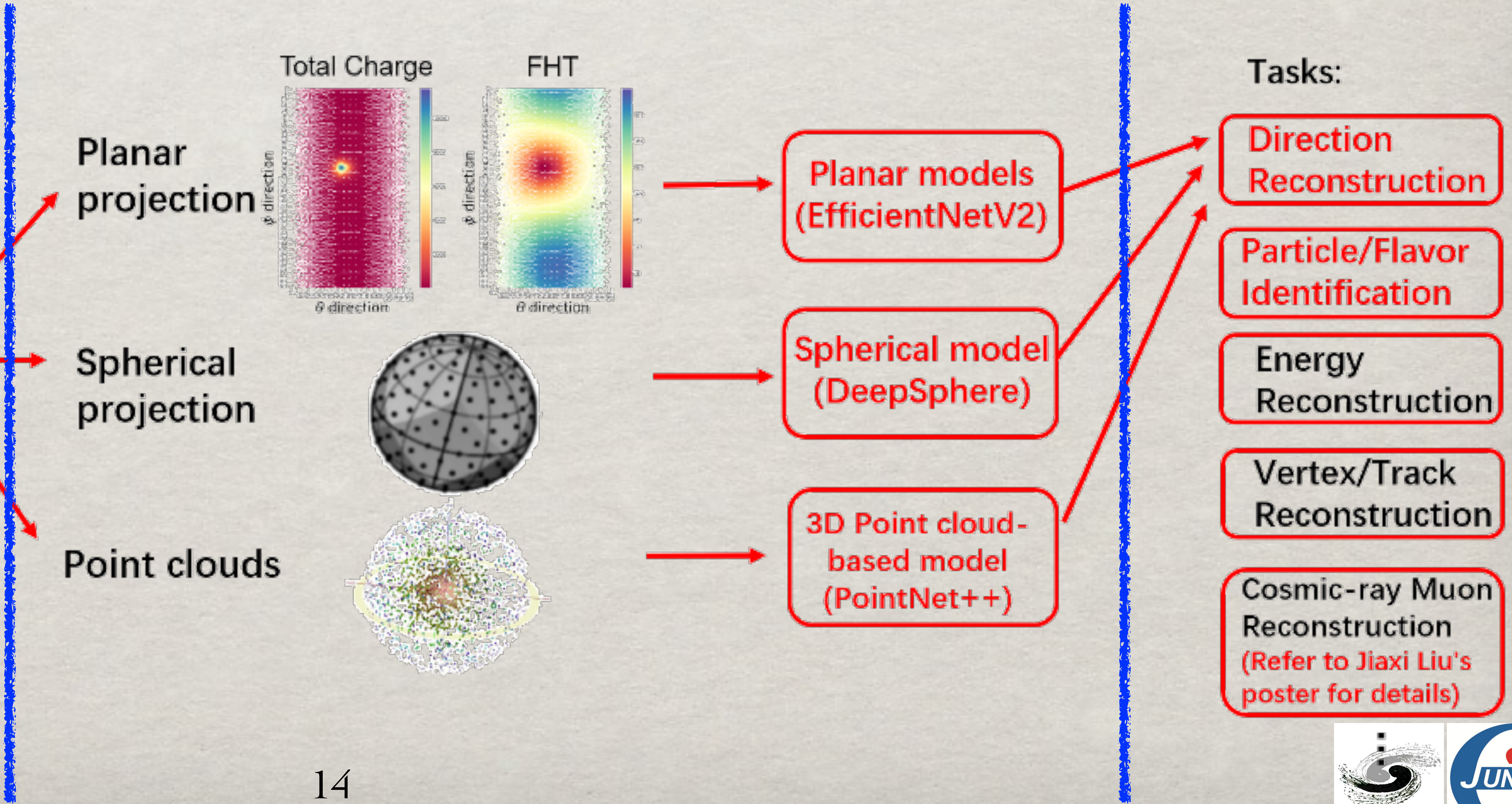


RECO/PID METHODOLOGY

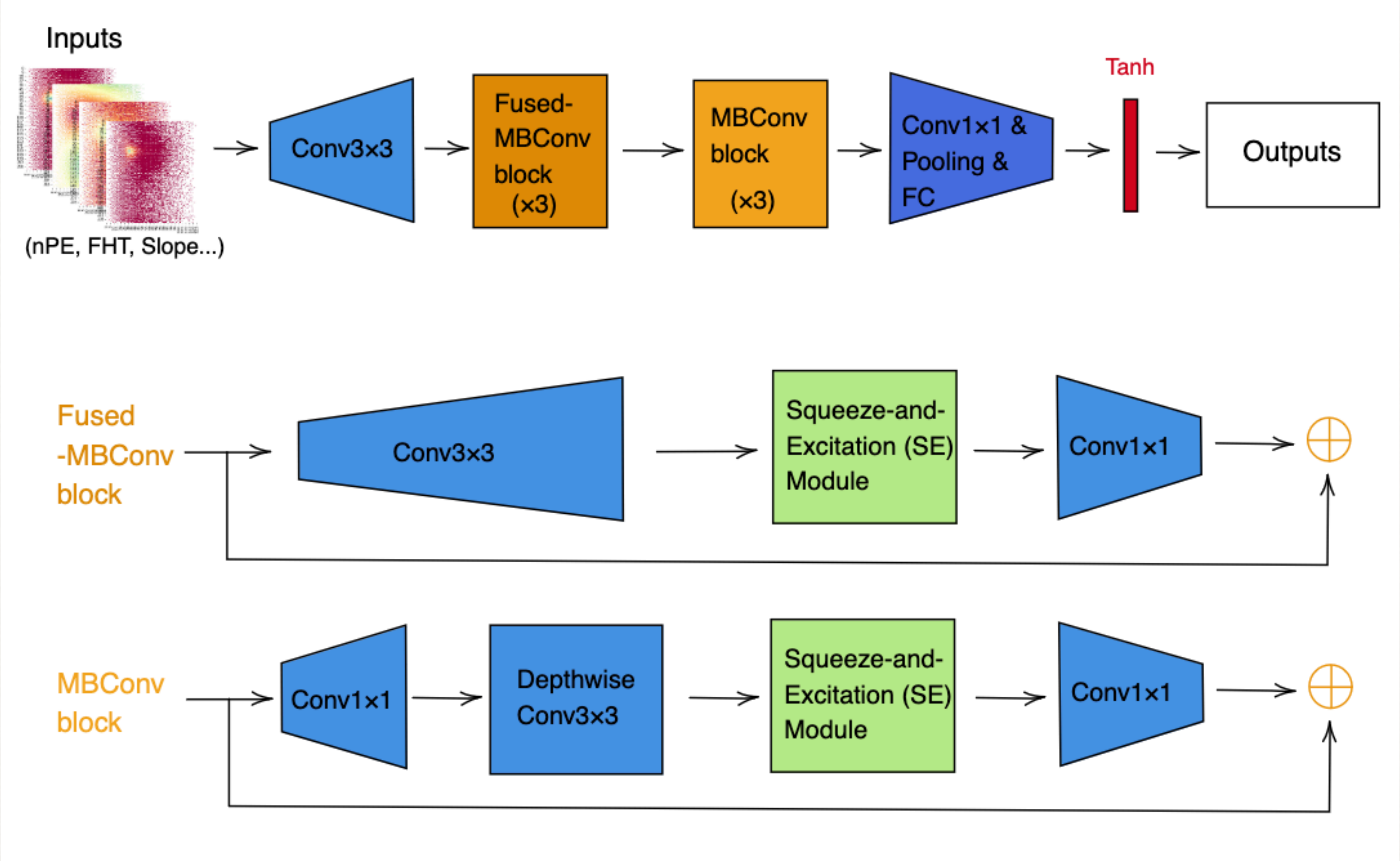


- Step 1: feature extraction from PMT waveforms
- Step 2: model building
- Step 3: optimization and validation

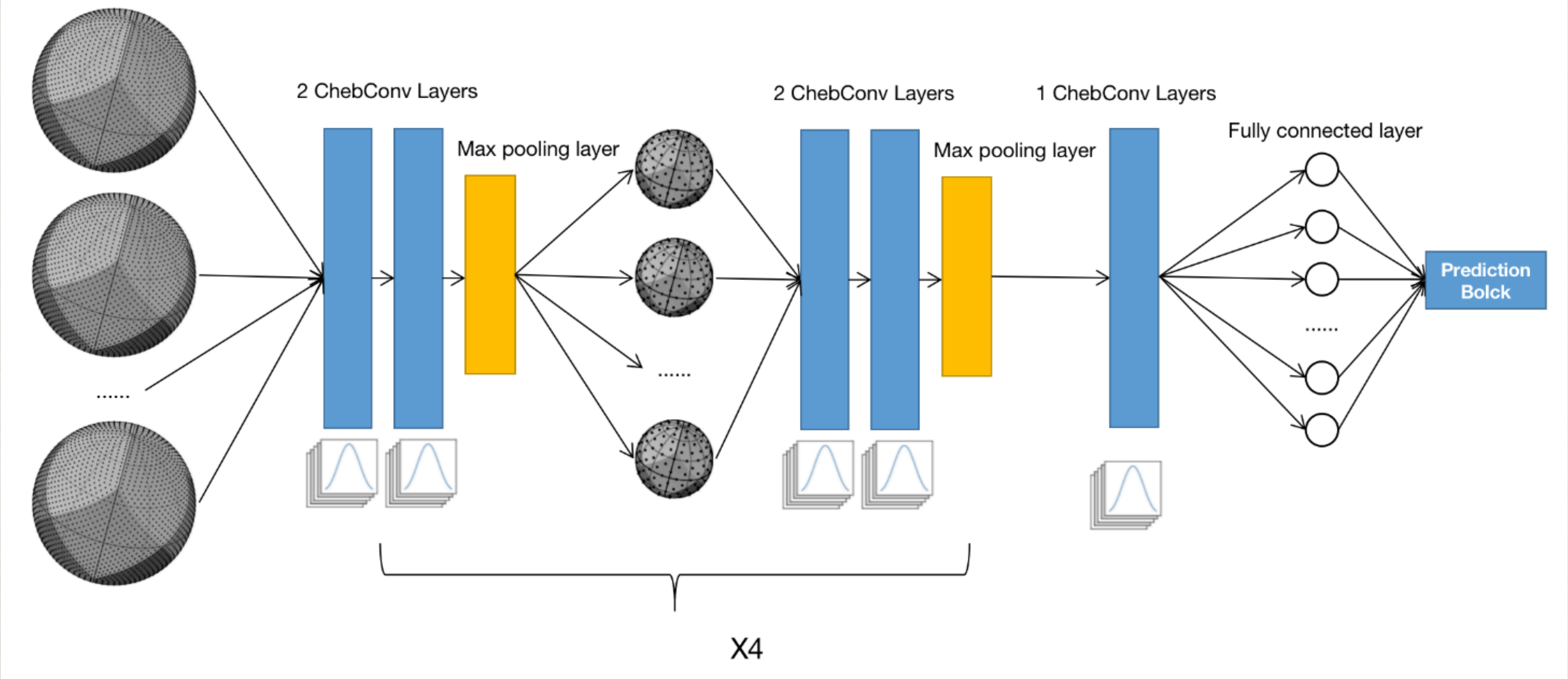




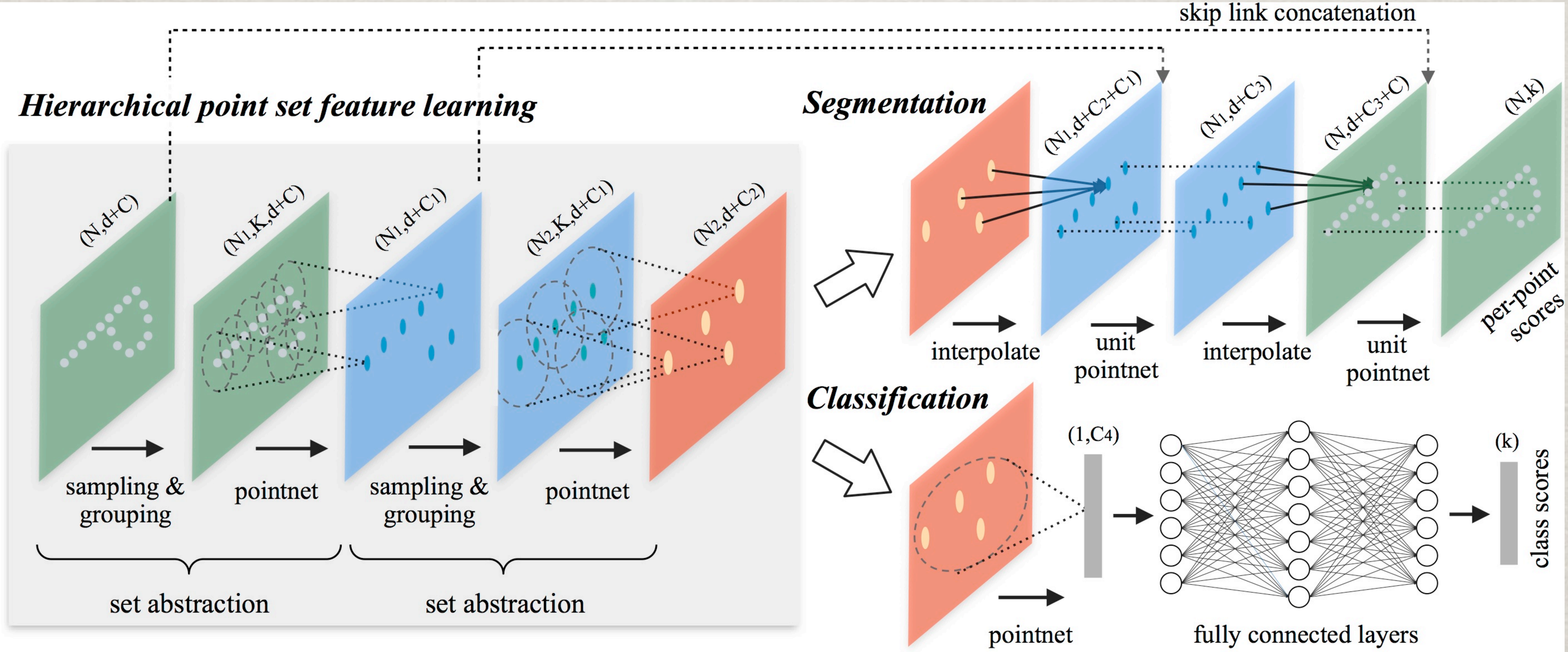
PLANE MODEL: EfficientNetV2-S



spherical model: Deepsphere



3D model: PointNet++



DIRECTIONALITY

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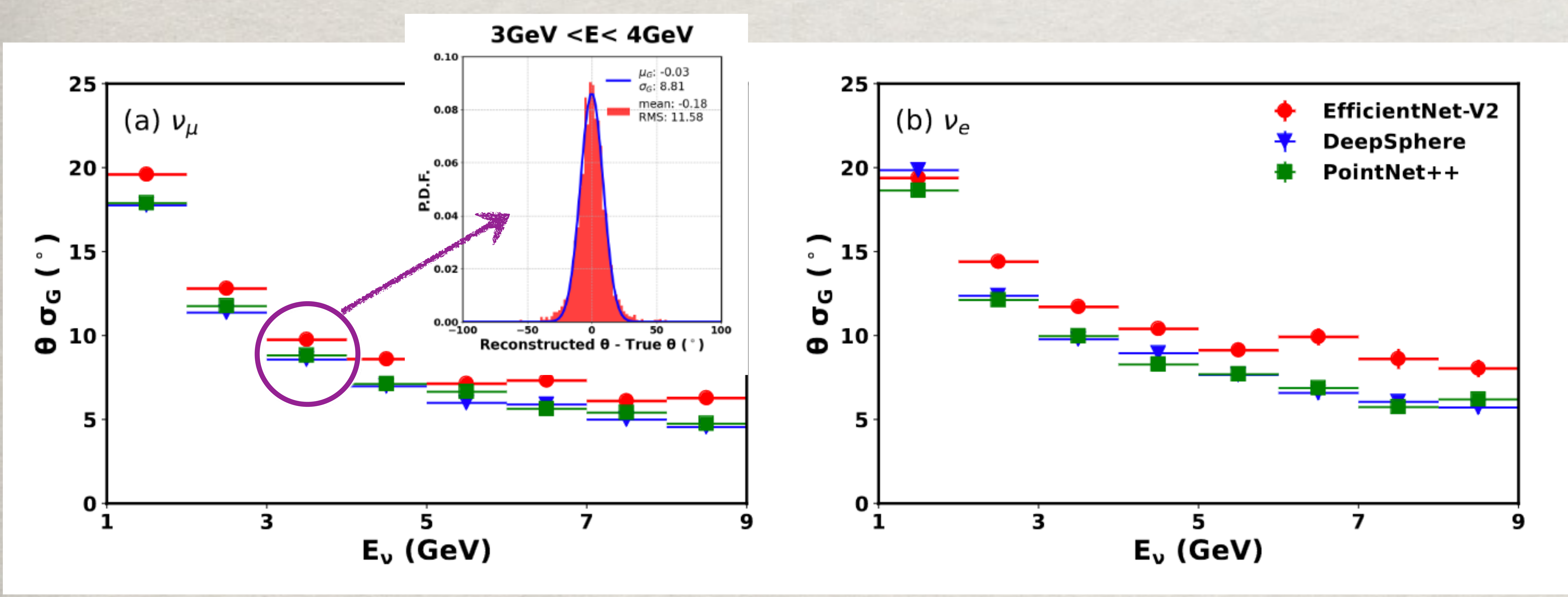
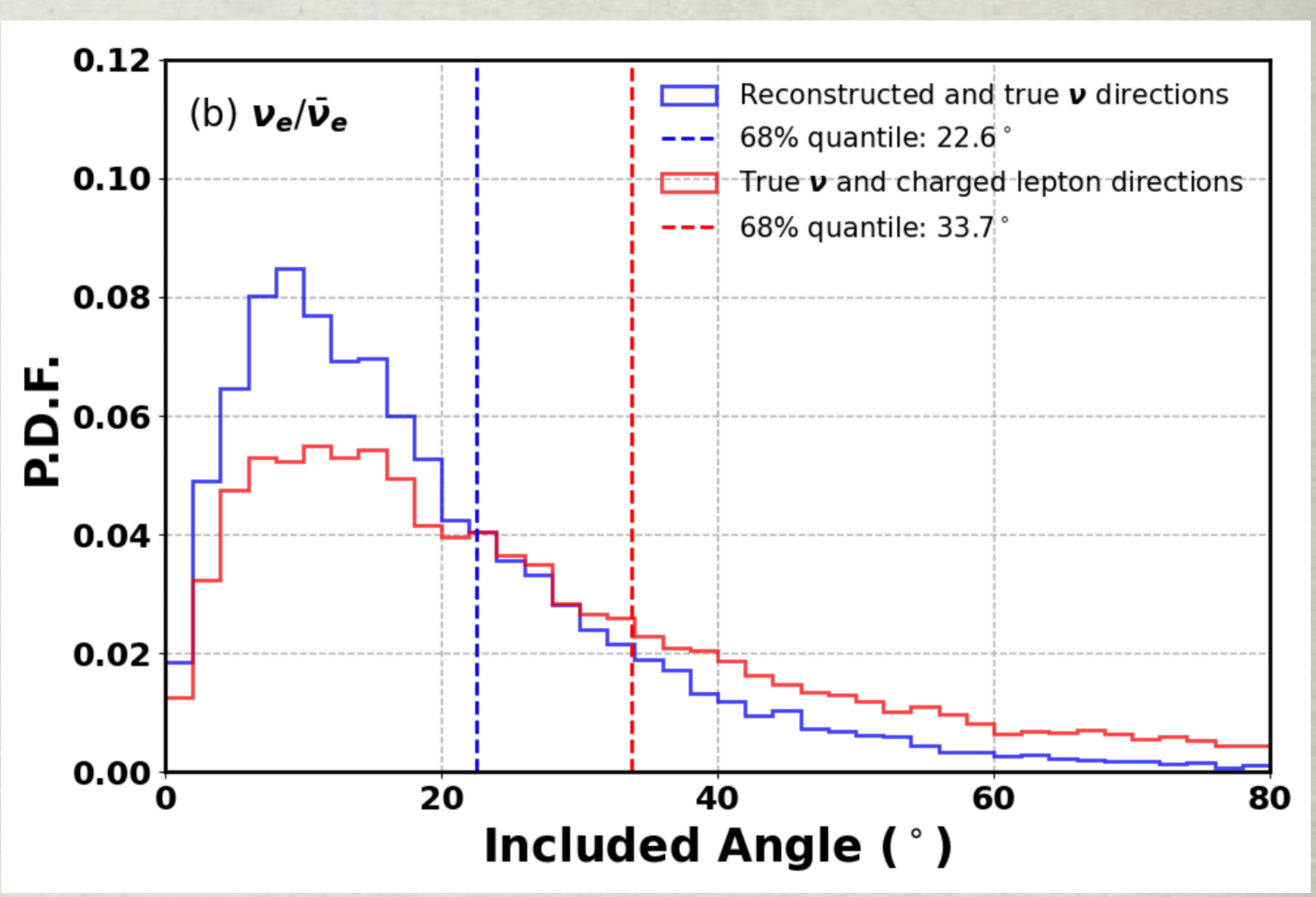




- Directly reconstruct the direction of ν instead of the charged lepton
  - mitigate the intrinsic large uncertainty between the two
  - hadronic component in LS also helps, advantageous w.r.t. Water Cerenkov
- Energy dependent Zenith Angle resolution, less than 10° for E>3GeV

J. Phys. G: 43 (2016) 030401

Yellow Book

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

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

PID STRATEGY

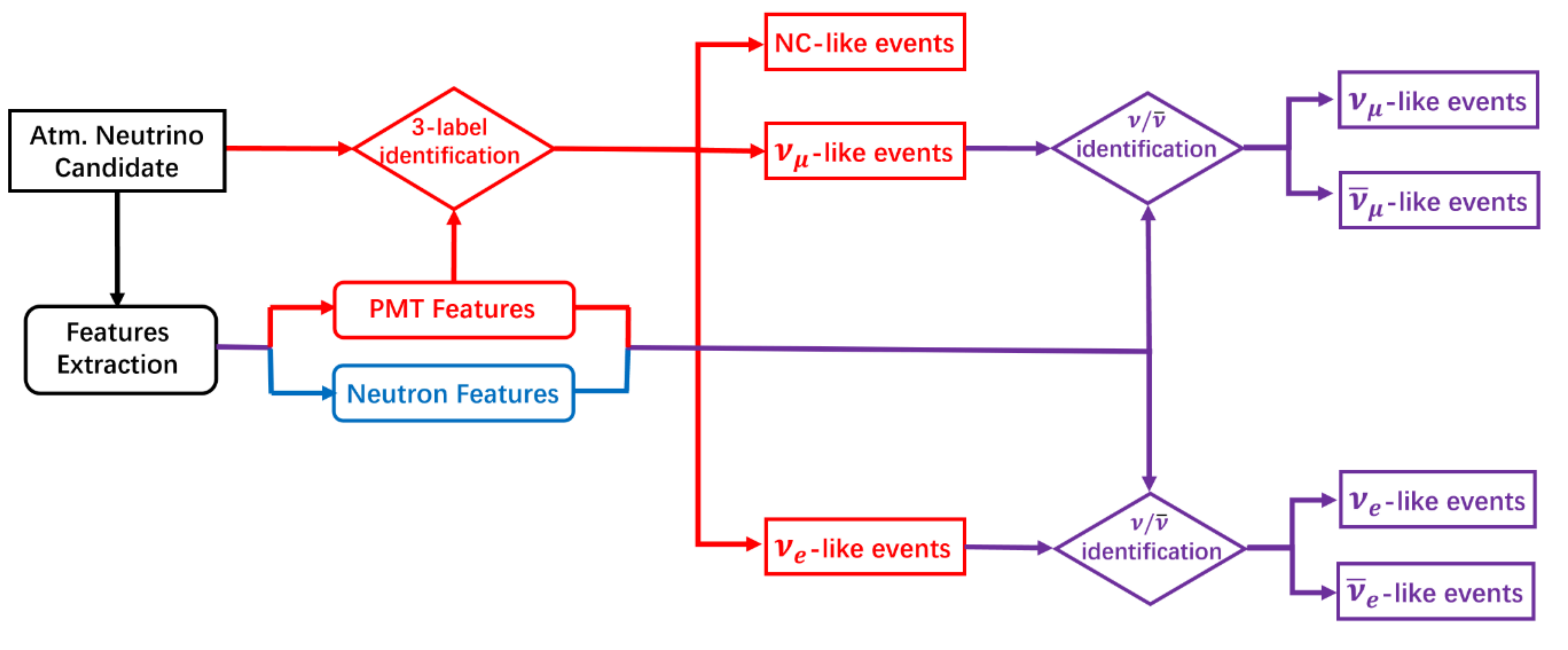
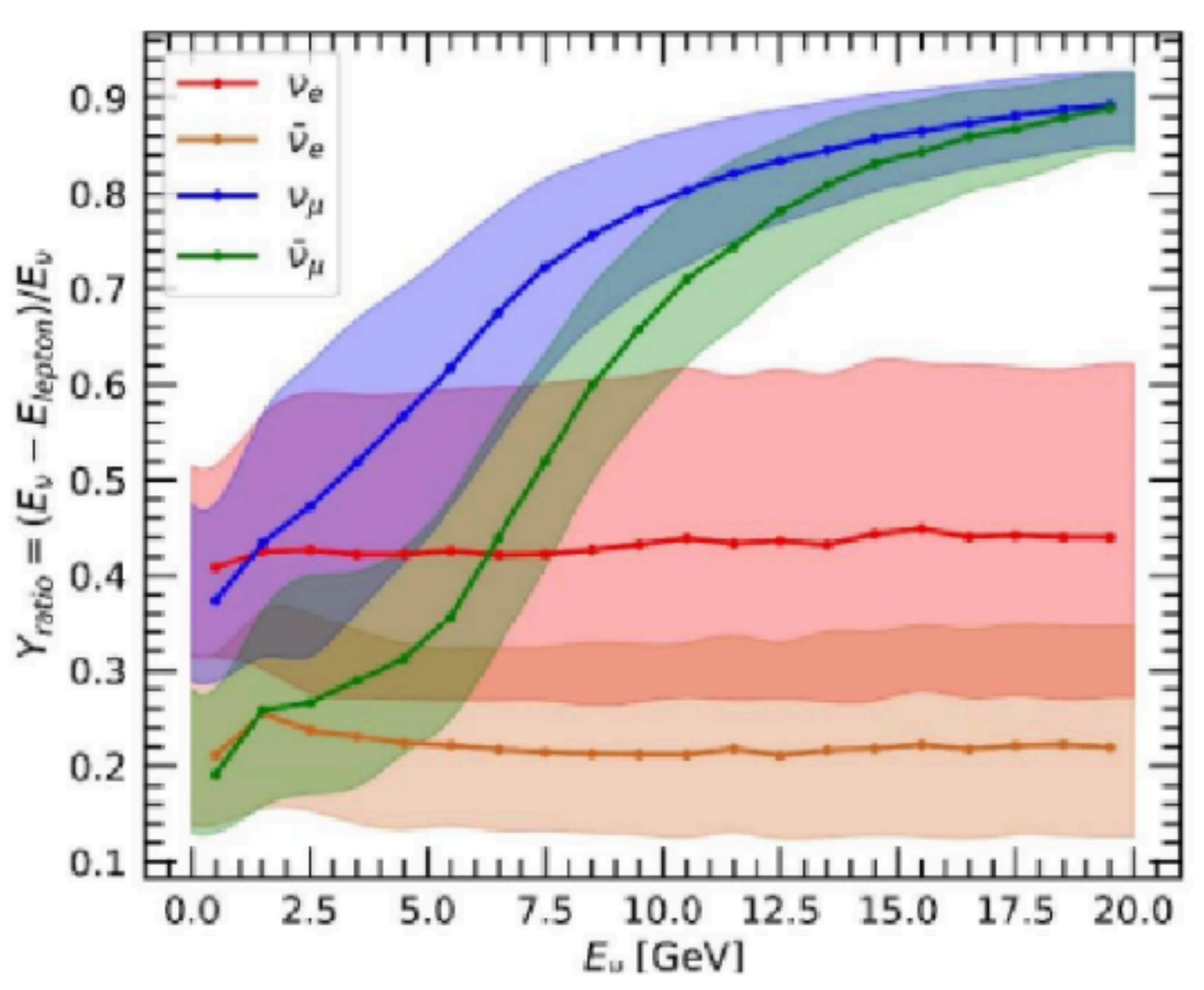
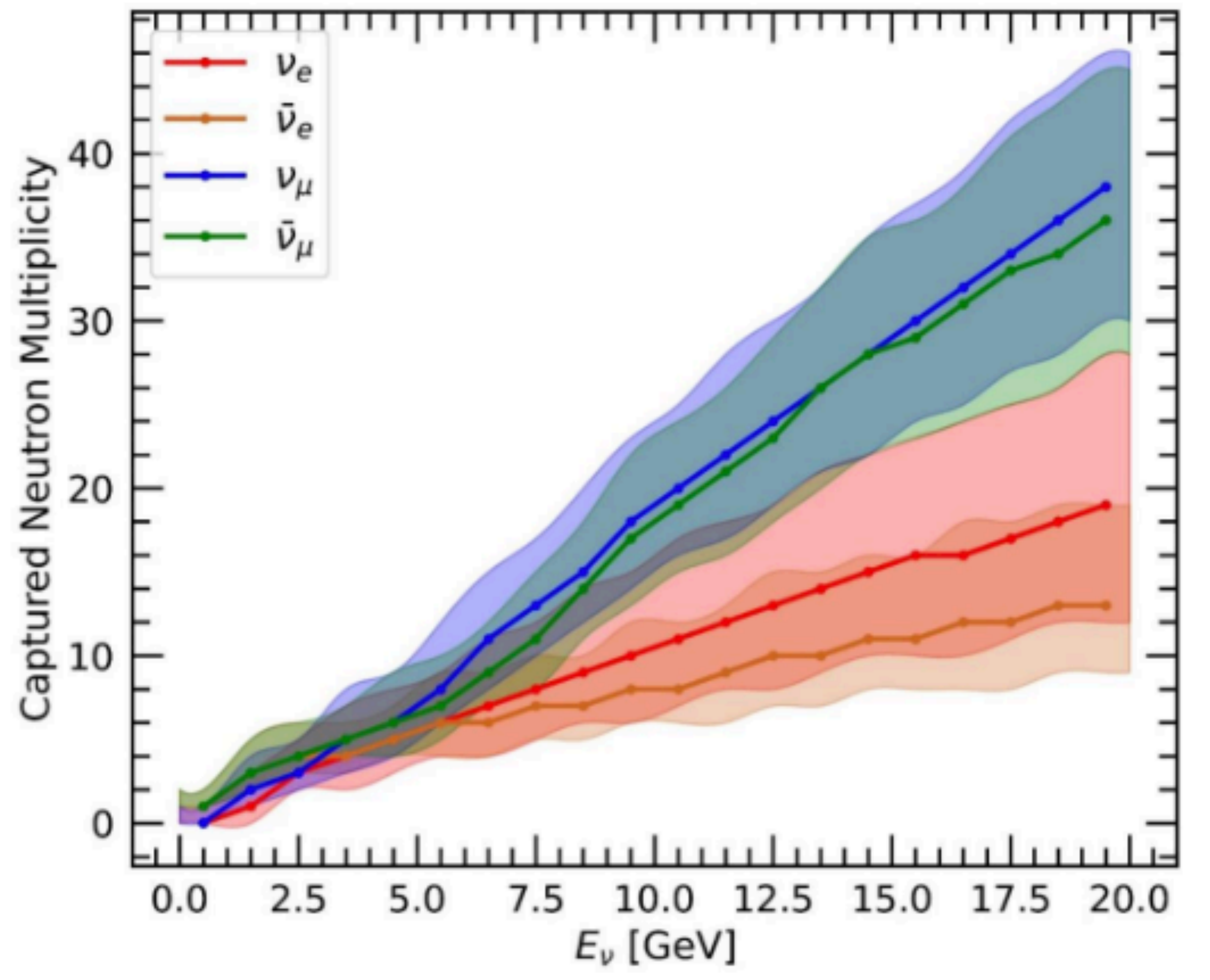


Figure 4. The schematic workflow of atmospheric neutrino classification.



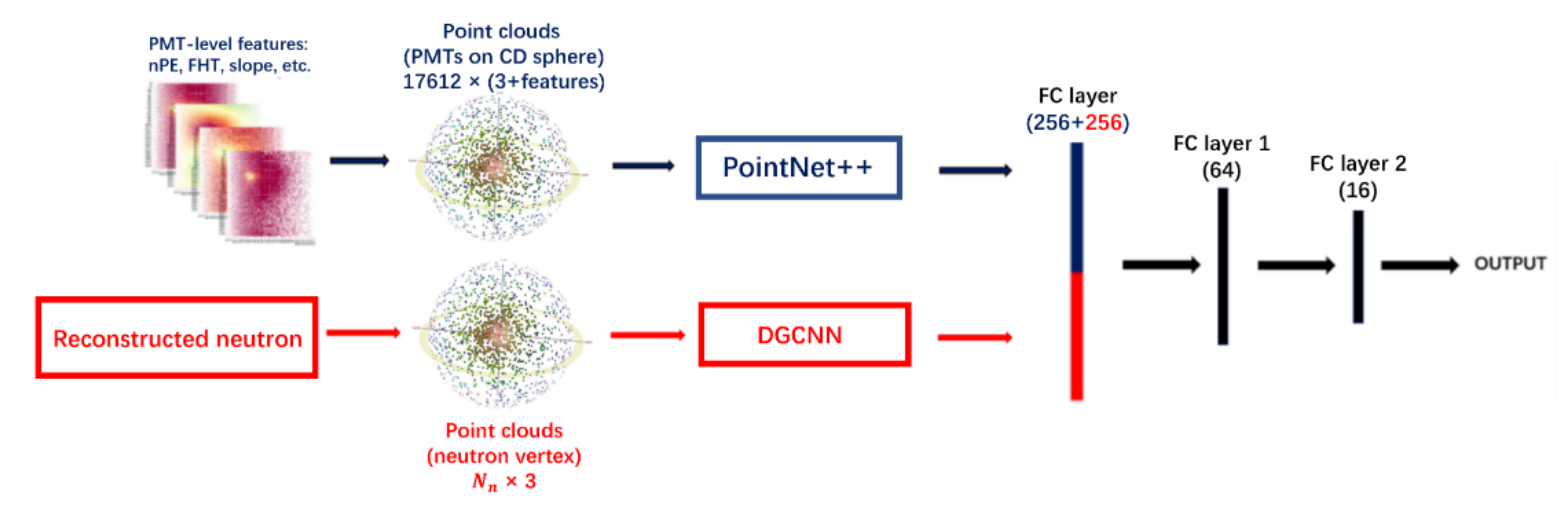
(a) Y_{ratio}



(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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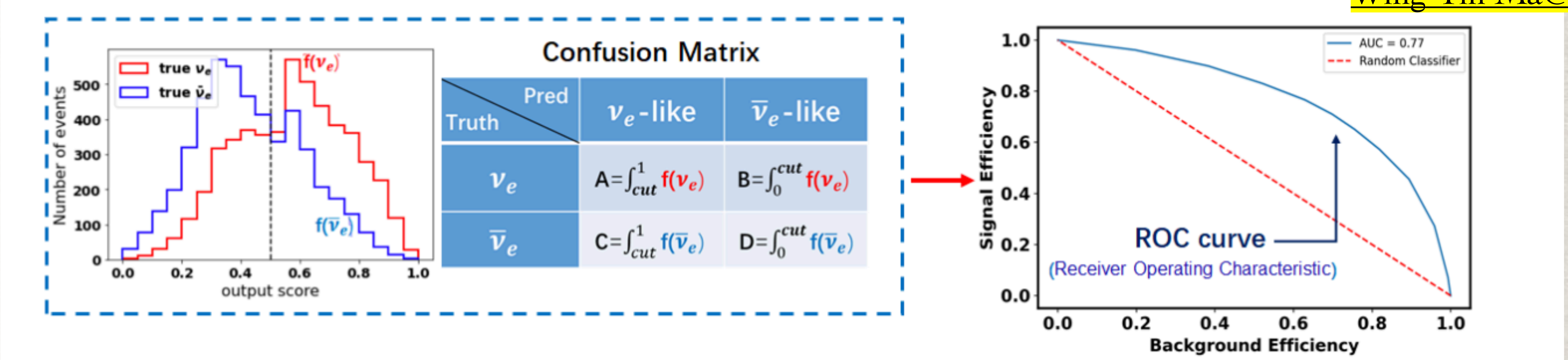
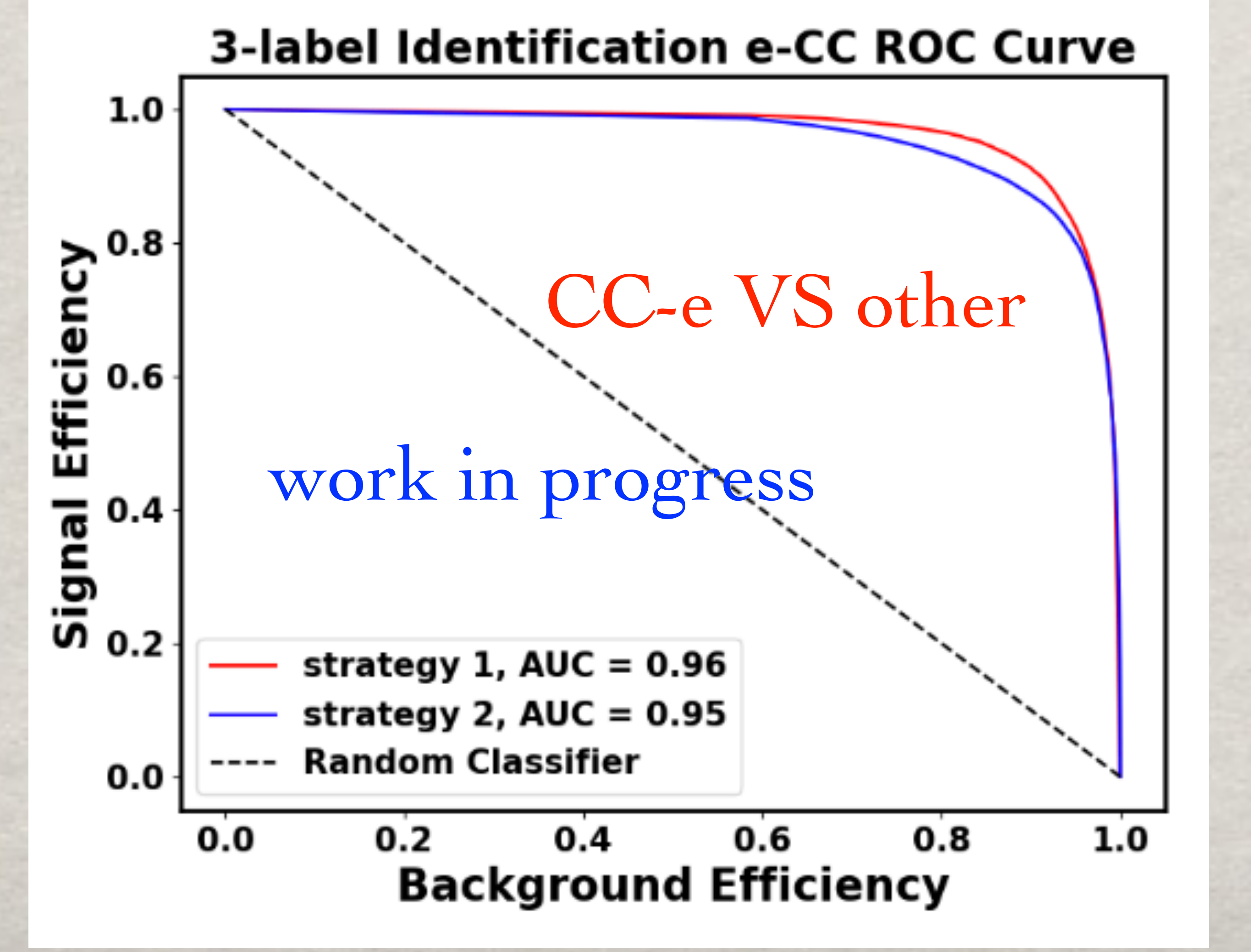
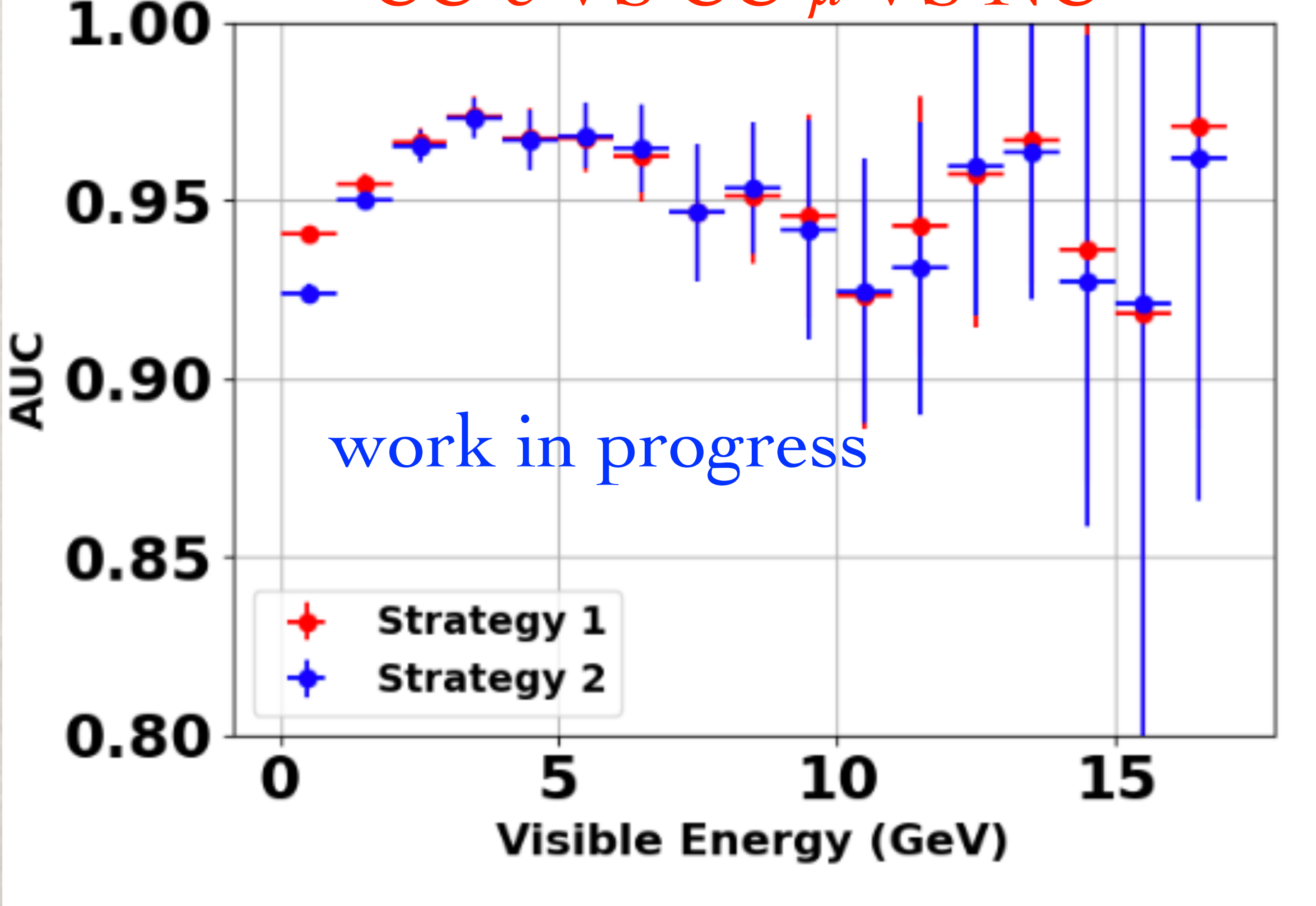


Fig. 8: Illustration of the AUC score using ν_e /$\bar{\nu}_e$ classification as an example. The AUC score can be viewed as an optimisation of ν_e /$\bar{\nu}_e$ efficiencies.



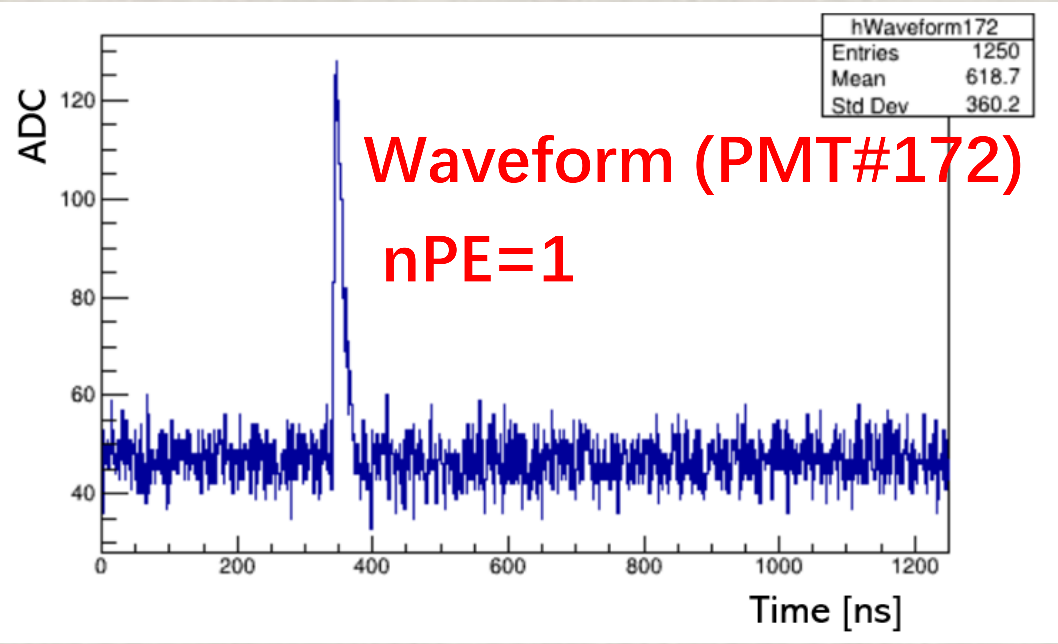


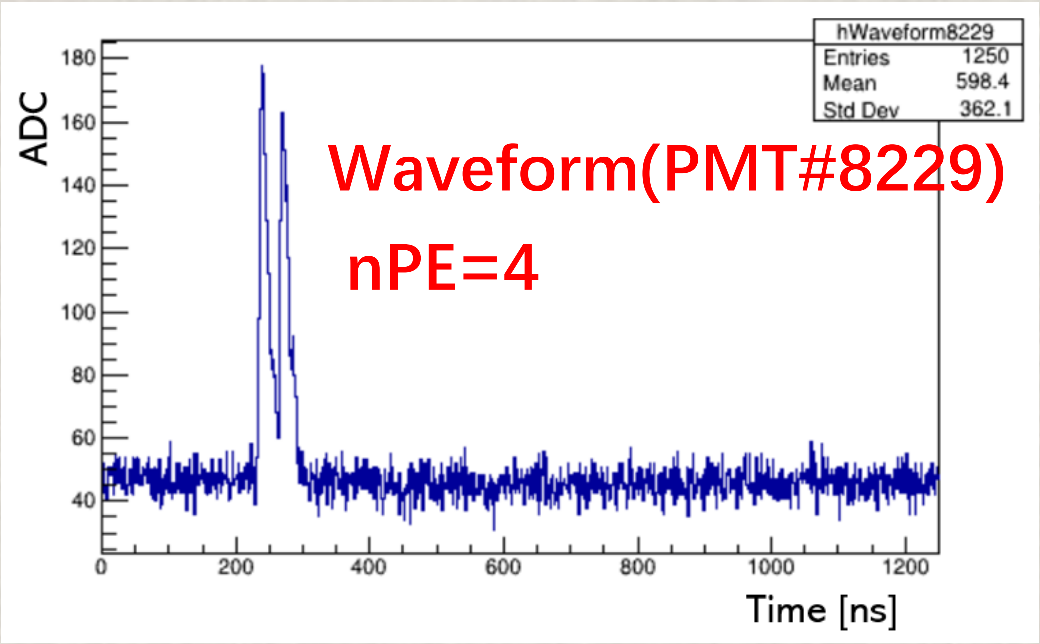
PMT

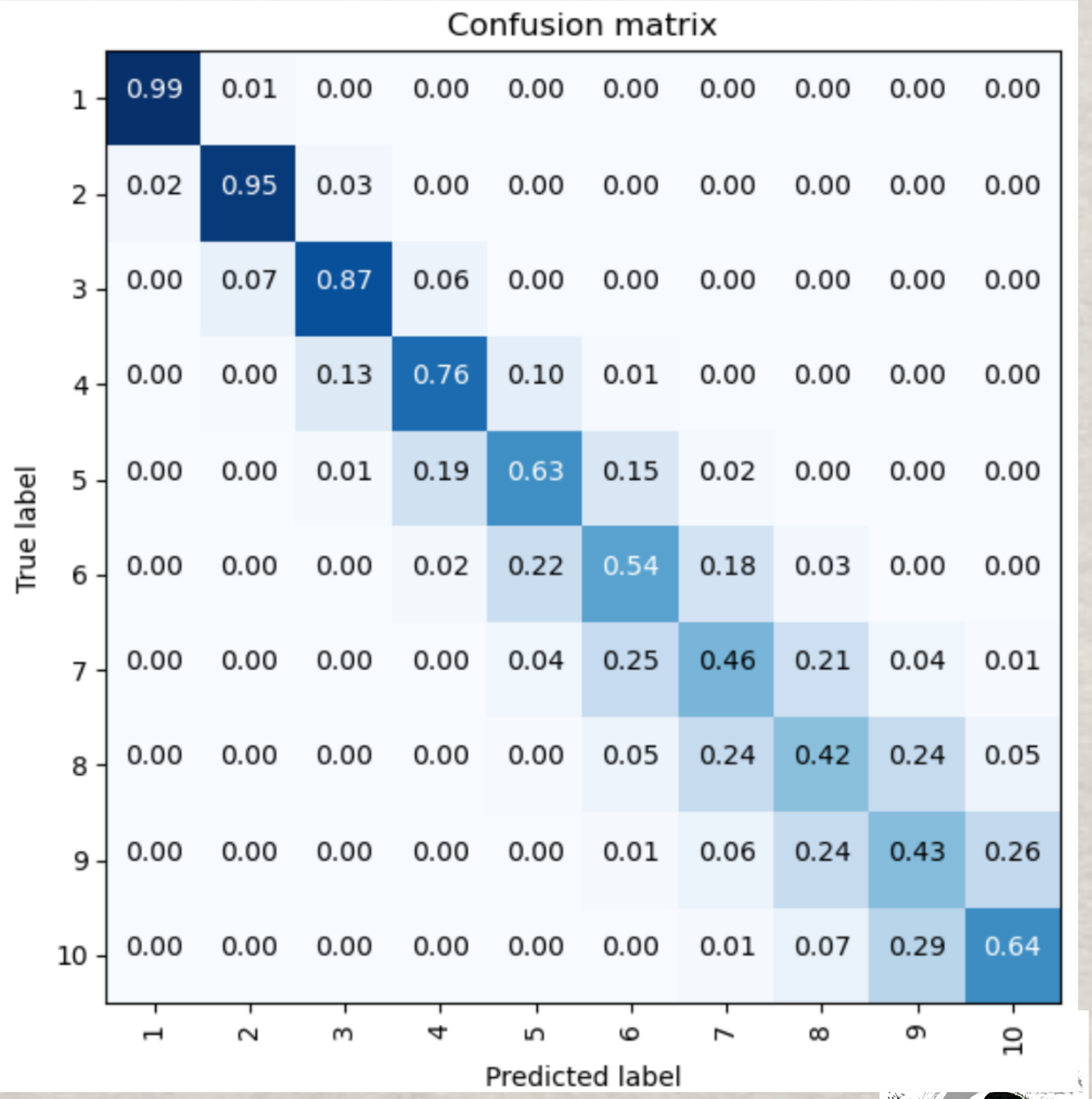
MeV Region

PMT WAVEFORM RECO I

- Classification: photon counting
- Model:
  - resembles speech recognition
  - **RawNet:** one of the most influential DNN model designed for speech recognition
  - takes 1D waveform as input

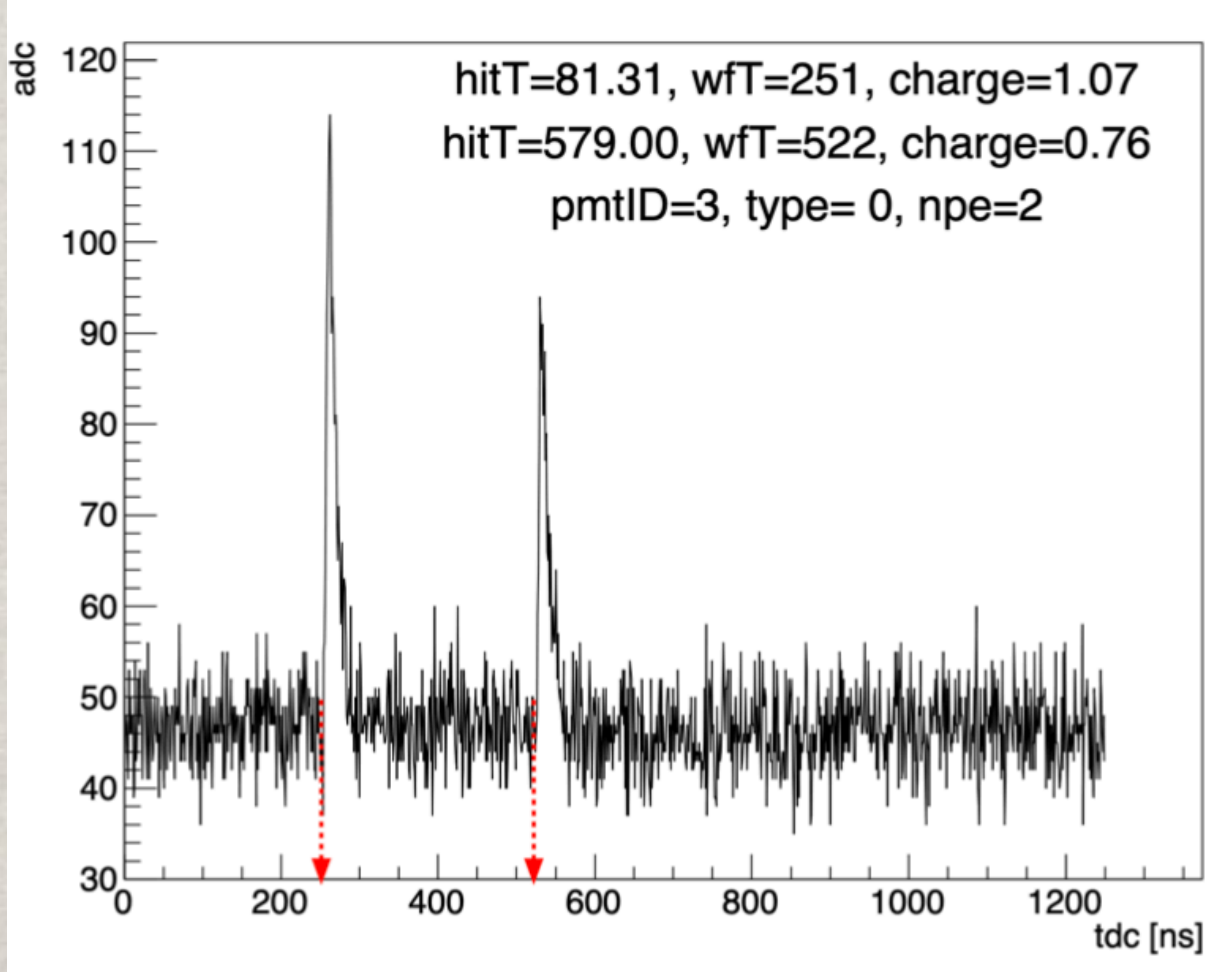


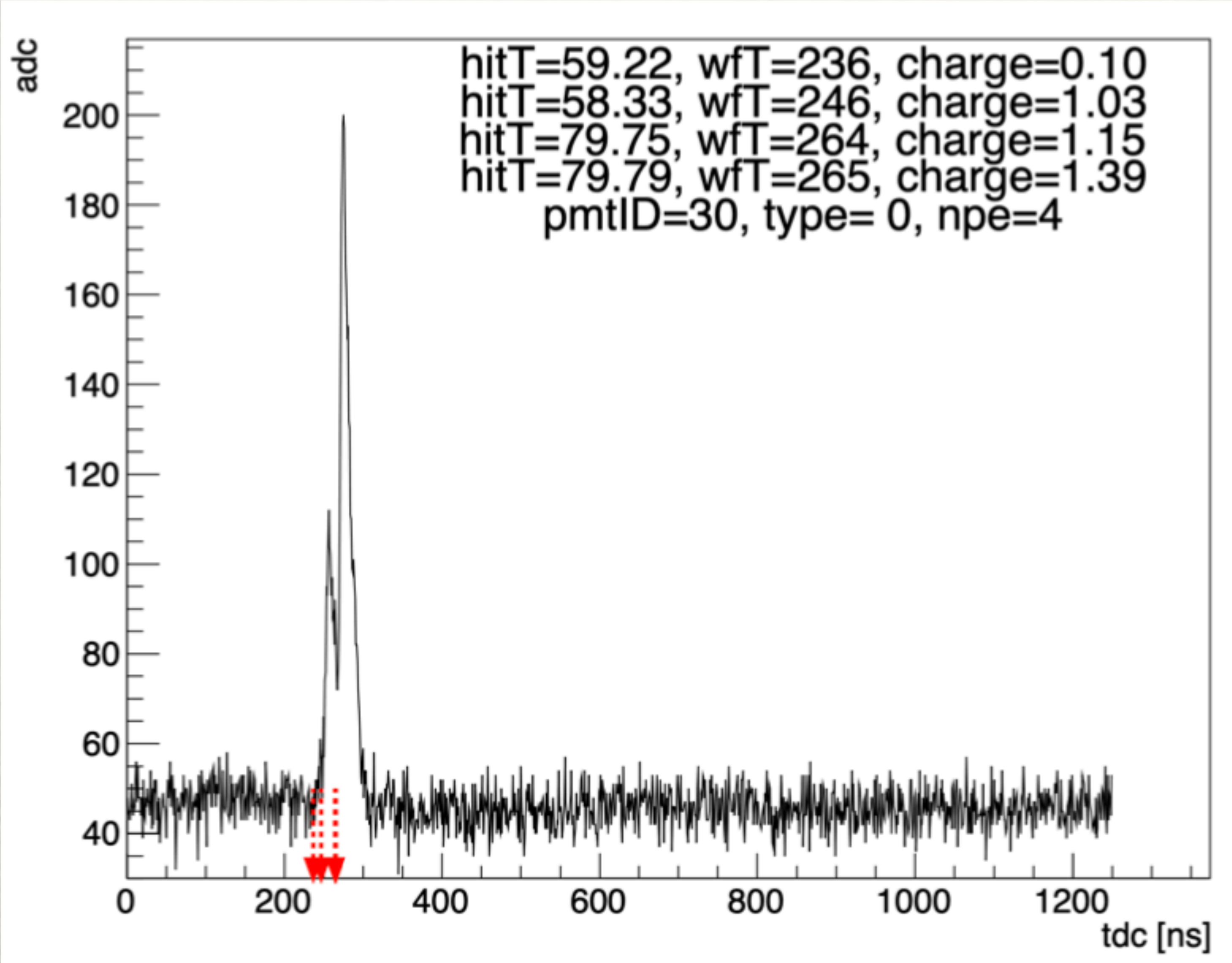




PMT WAVEFORM RECO II

- Regression:
  - easy: total charge or first hit time 😀
  - difficult: charge and time for the first 5 or 10 pulses 😵‍💫
  - super difficult: charge and time for each pulse 😱
- Method: 1D waveform + CNN





PMT WAVEFORM PHOTON COUNTING

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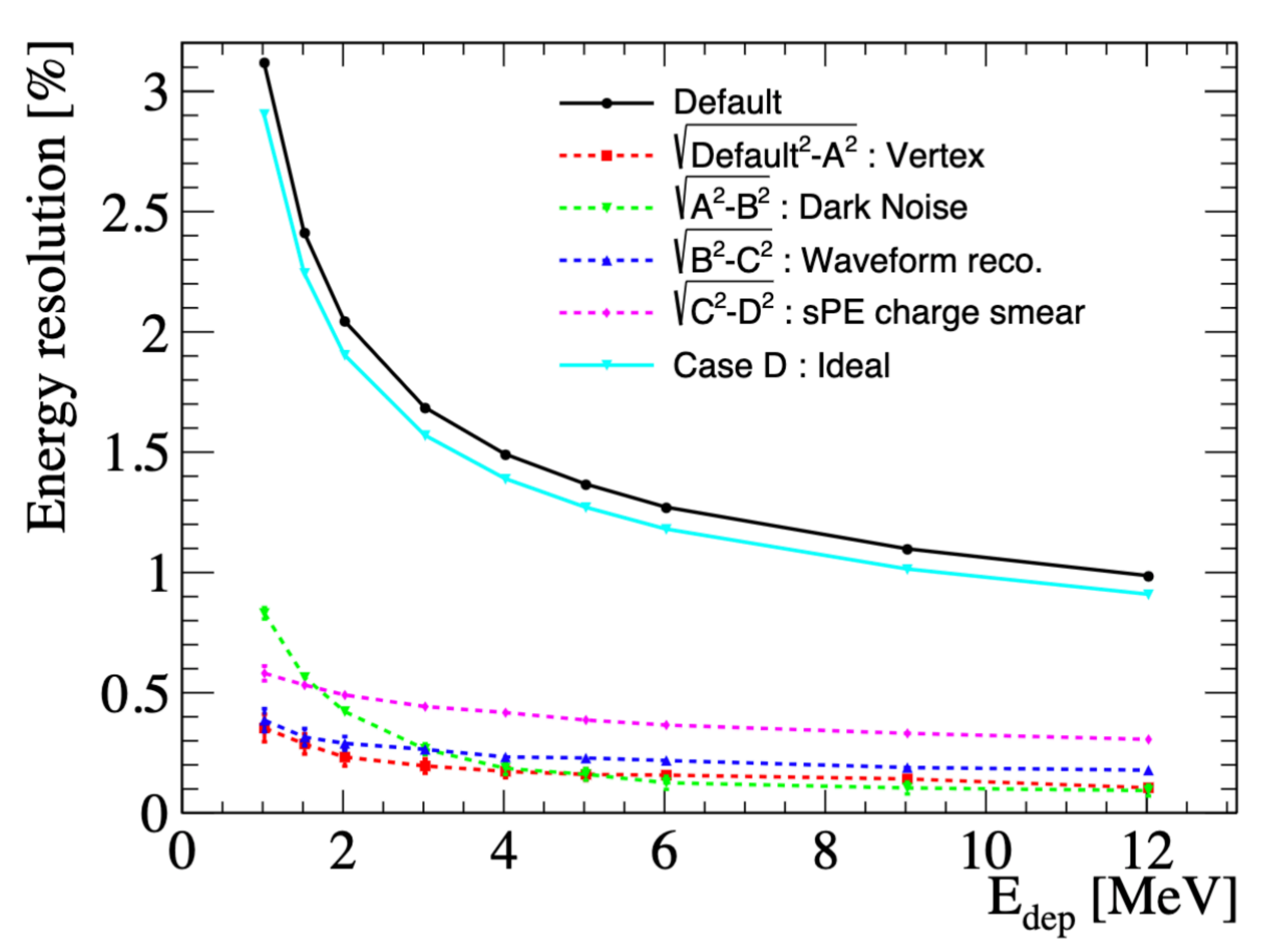


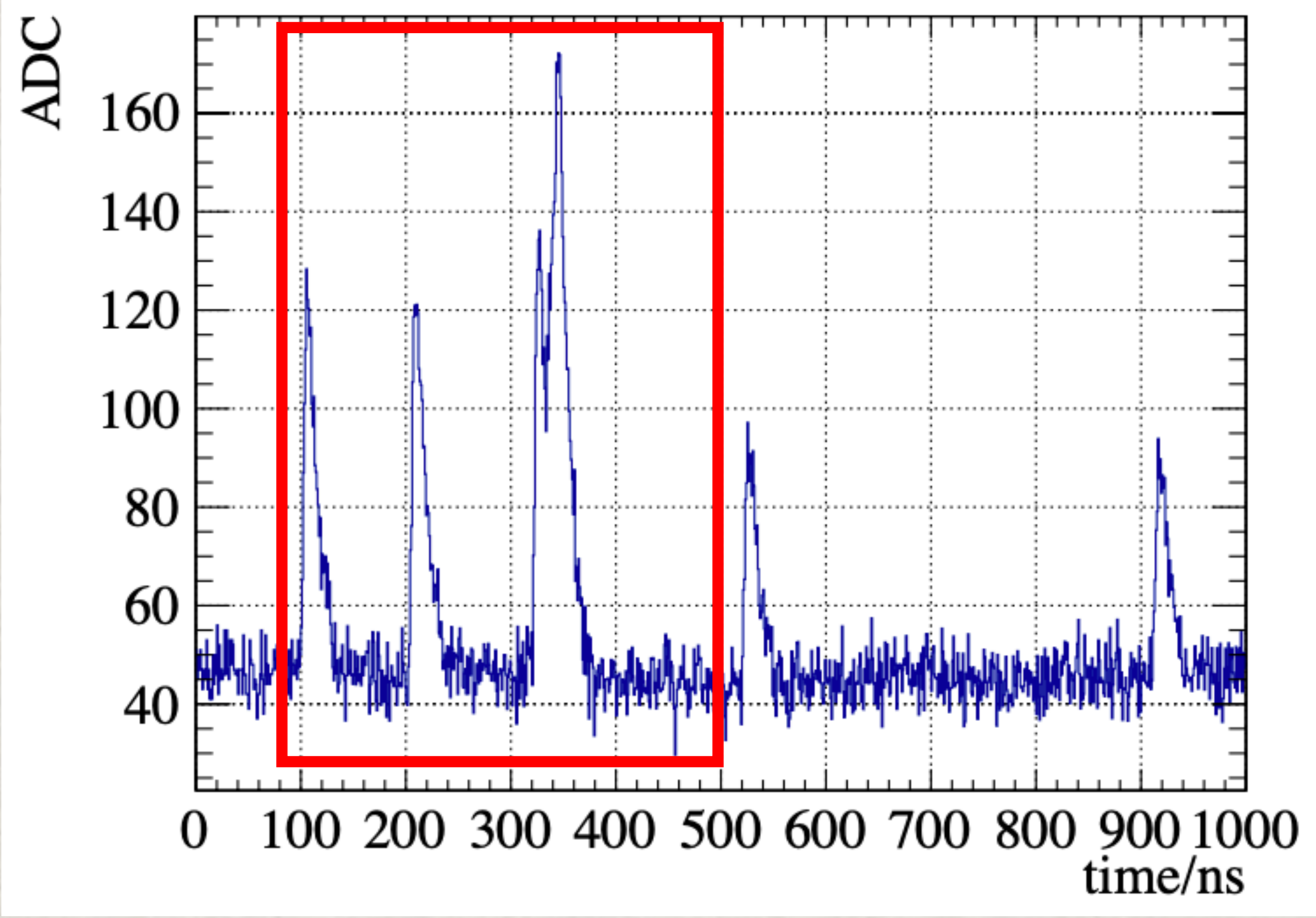
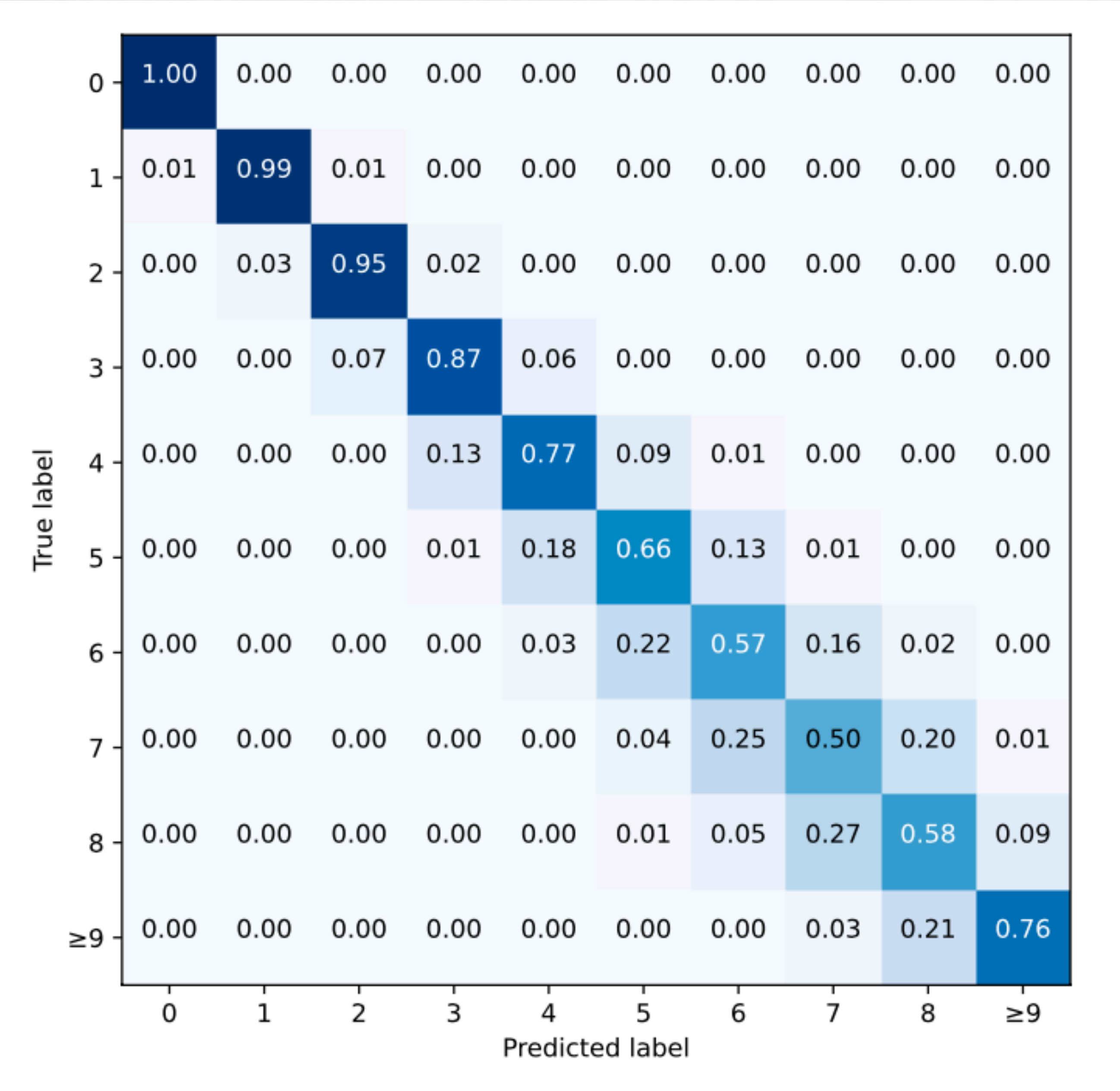


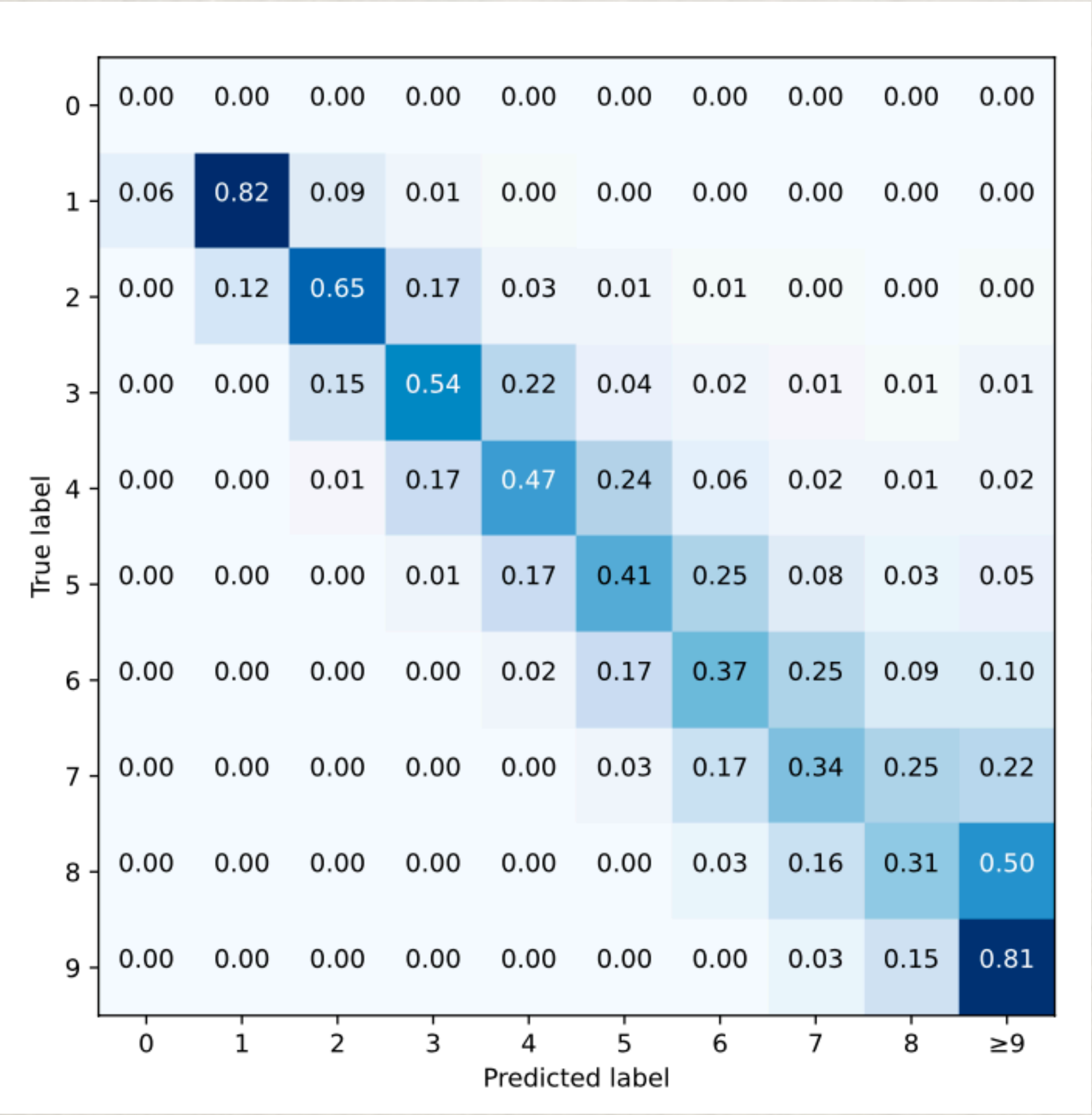
Table 2: Modified RawNet architecture. For convolutional layers, numbers inside parentheses refer to filter length, stride size, and number of filters. For gated recurrent unit (GRU) and fully-connected layers, numbers inside the parentheses indicate the number of nodes.

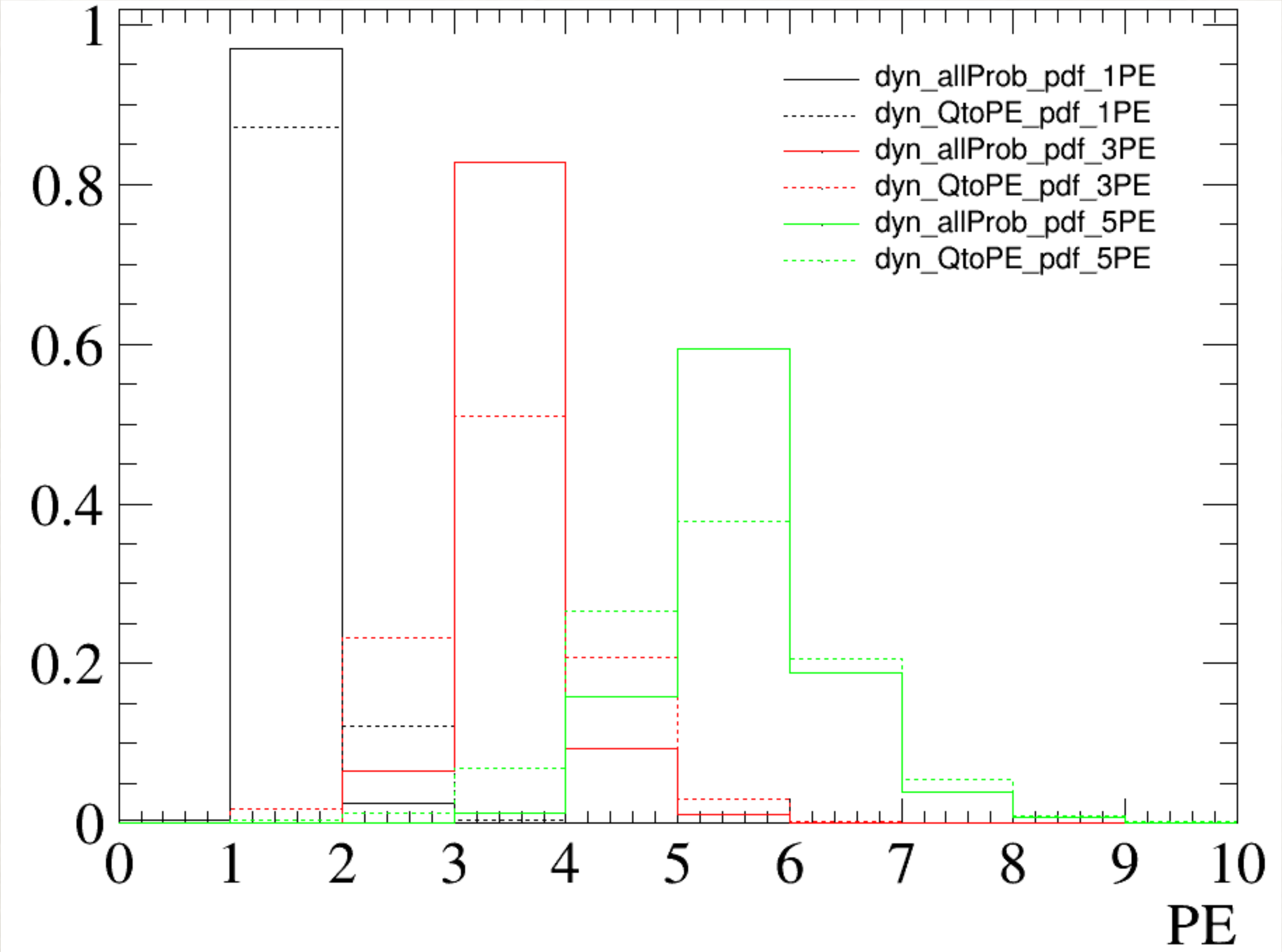
Layer	Input	Output shape
Strided -conv	Conv(3,3,128) BN LeakyReLU	(128, 140)
Res block	{ Conv(3,1,128) BN LeakyReLU Conv(3,1,128) BN - - - - - - - - LeakyReLU MaxPool(3) } ×2	(128, 46)
Res block	{ Conv(3,1,256) BN LeakyReLU Conv(3,1,256) BN - - - - - - - - LeakyReLU MaxPool(3) } ×2	(256, 1)
GRU	GRU(1024)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

VERTEX RECO

- Goal: vertex reco for e^+ in [0–10] MeV region
- Principle: PMTs charge&time (both highly vertex dependent) —> vertex
- ML based Methods:
  - inputs: each PMT as a pixel —> images
  - models: Plane or Spherical CNN

1. PLANE MODELS

2D projection of PMTs

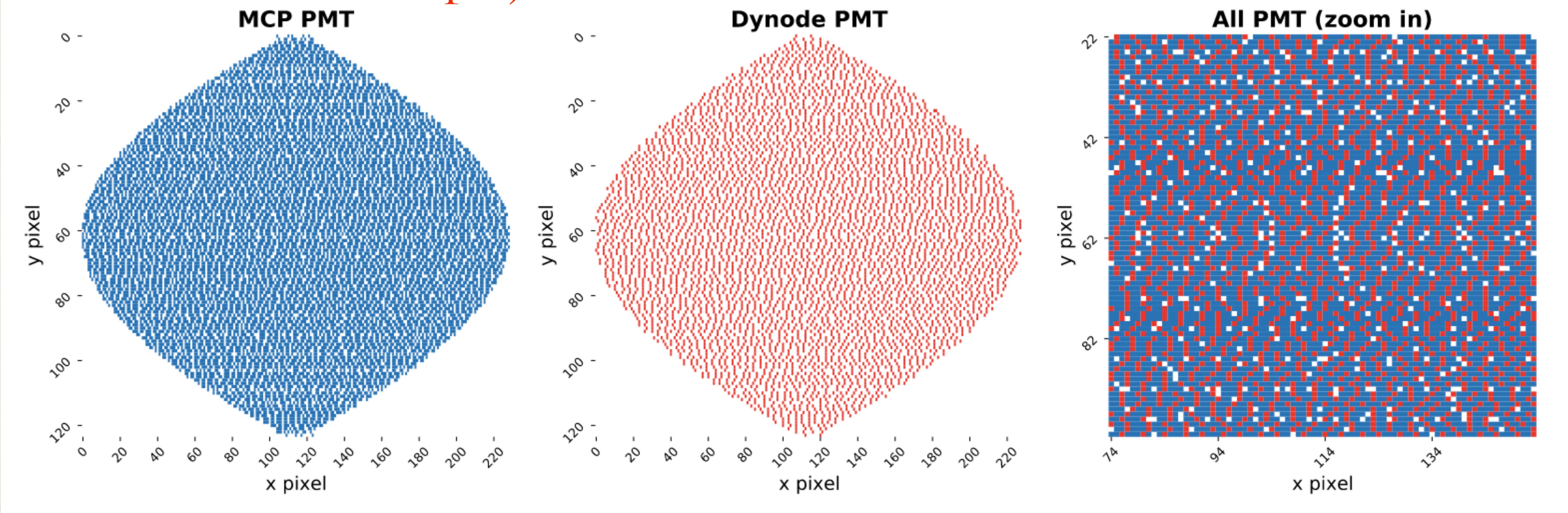
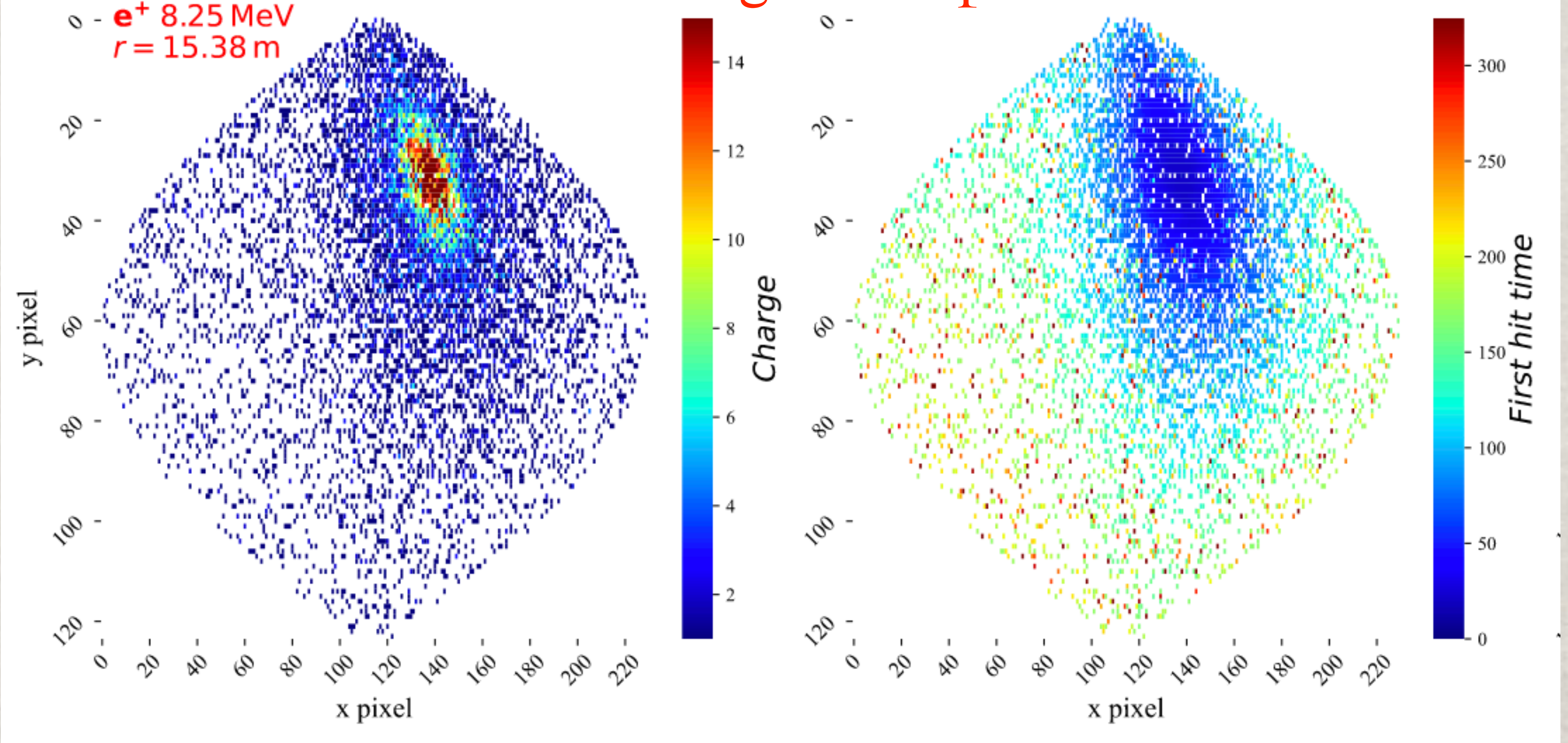


Image examples

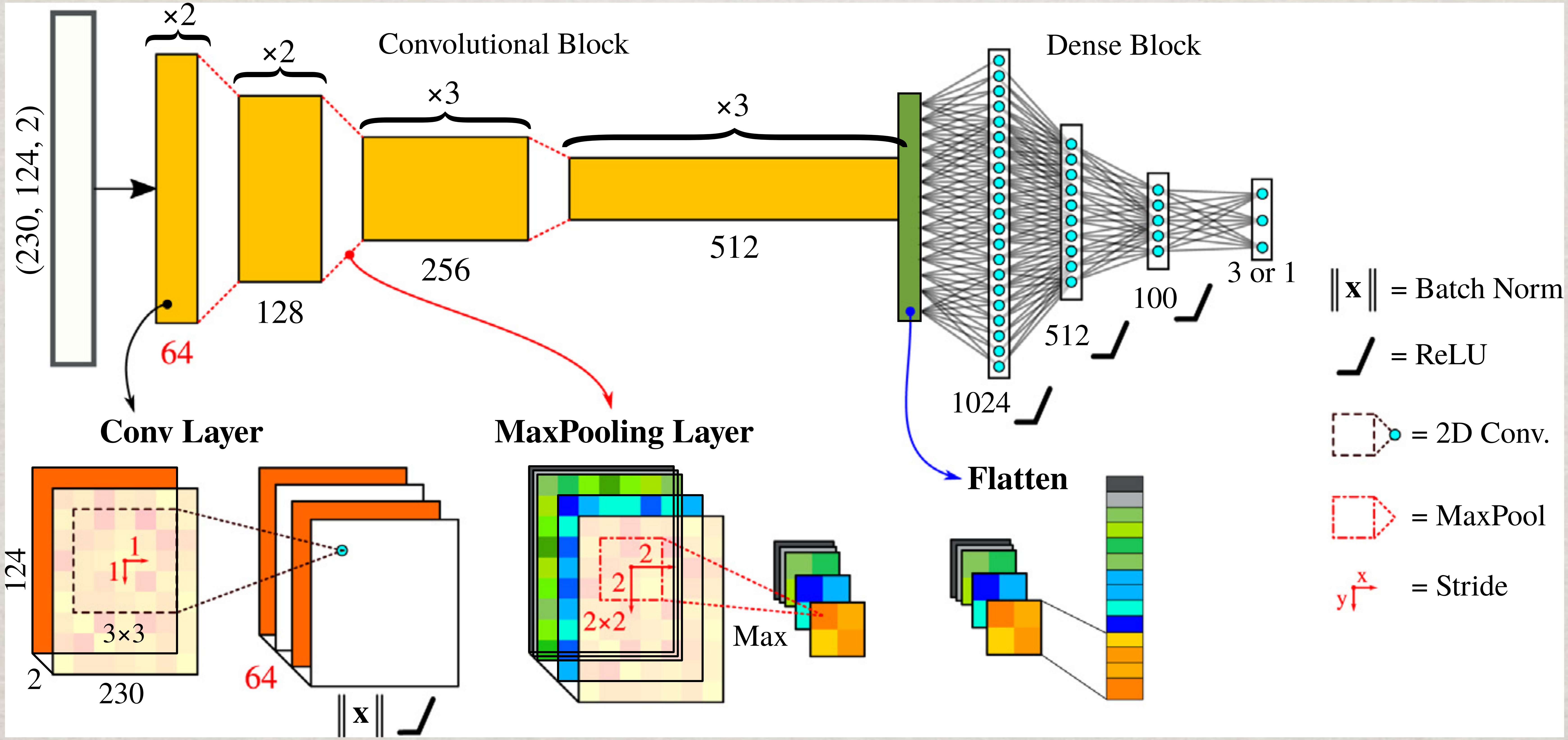


Remarks: inputs optimization

1. separate different types of PMTs
2. add info of later hits

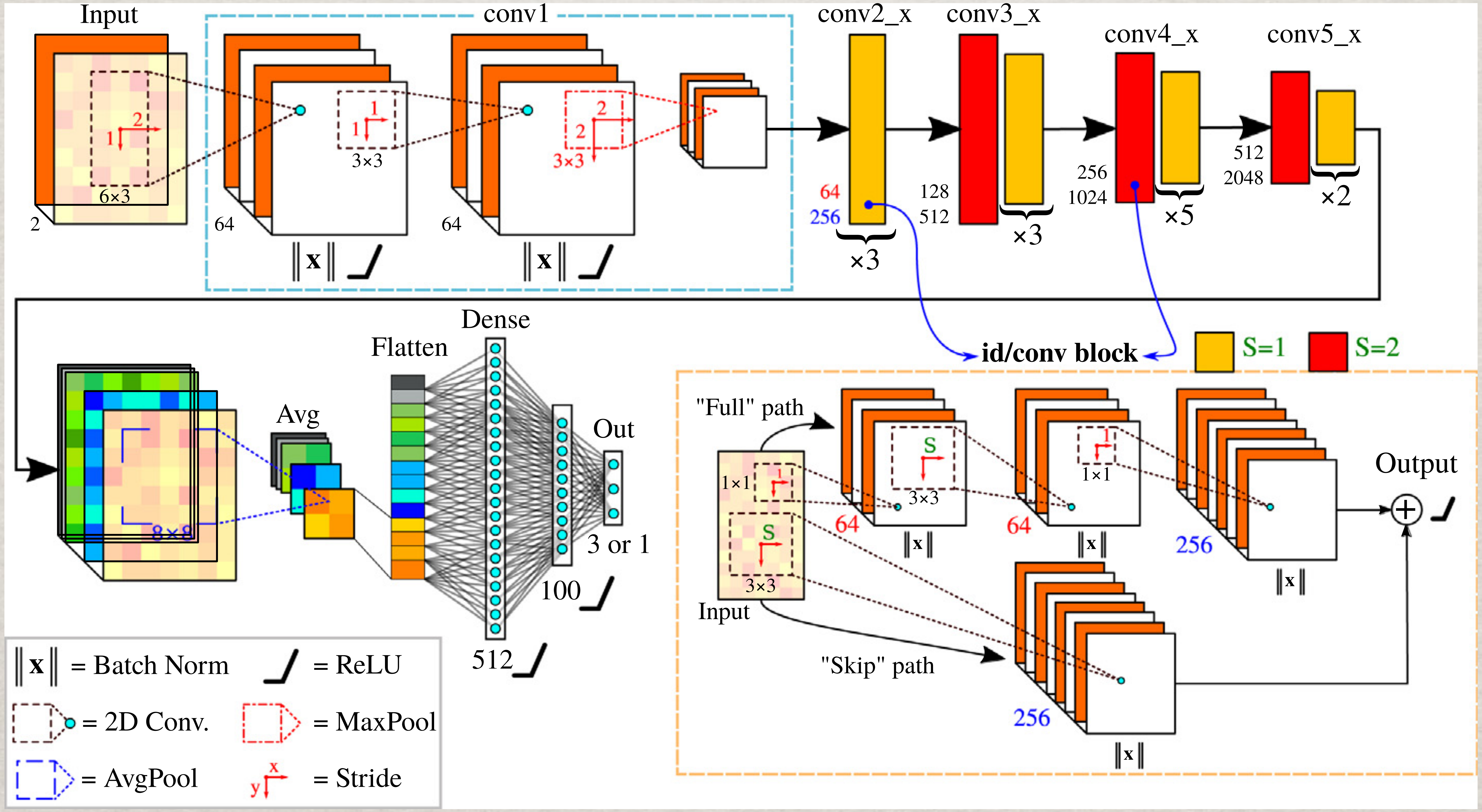
Pros and Cons

MODELS: VGG-J



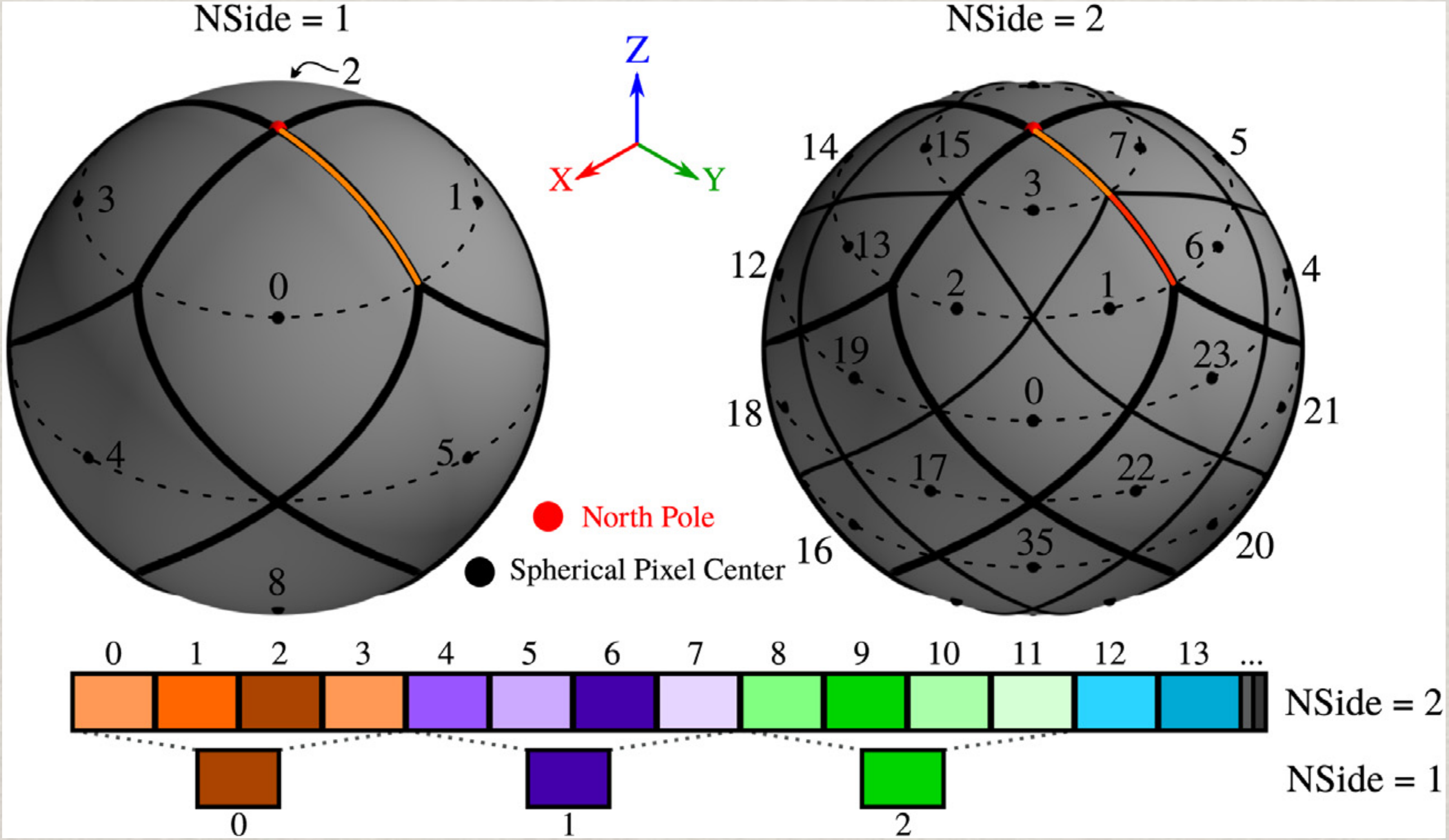
(230, 124, 2)
×2
×2
Convolutional Block
×3
×3
Dense Block
64
128
256
512
1024
512
100
3 or 1
= Batch Norm
= ReLU
= 2D Conv.
= MaxPool
= Stride
Conv Layer
MaxPooling Layer
Flatten
124
3×3
2
230
64
2×2
Max

MODELS: RESNET-J



2. SPHERICAL MODELS

- HEALPix —> spherical CNN
  - Borrowed from Astro. Phys.
  - Pixelization of a sphere
- Many other spherical models…



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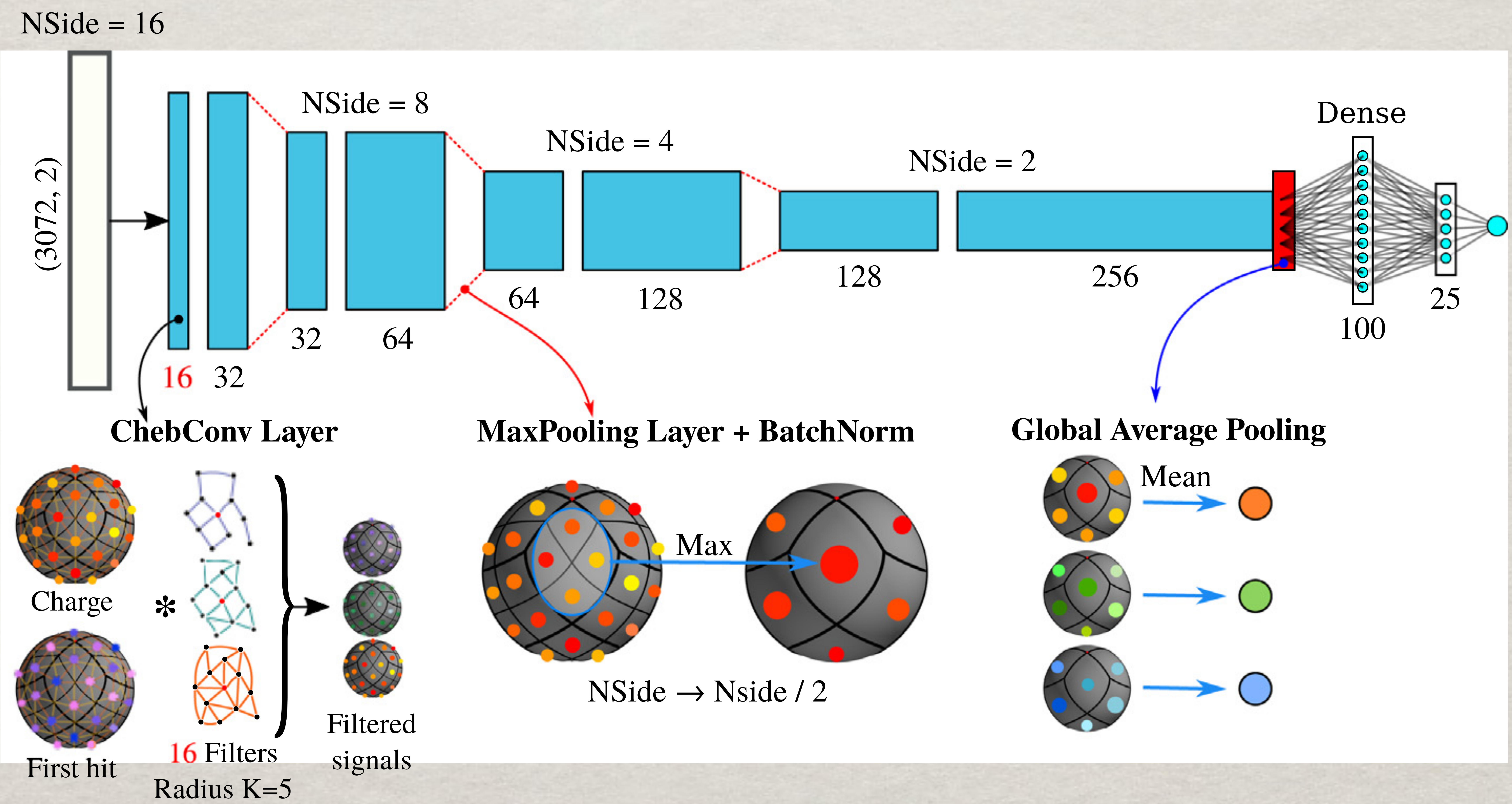
MODELS: GNN-J


NSide = 16
(3072, 2)
16
32
NSide = 8
32
64
NSide = 4
64
128
NSide = 2
128
256
Dense
100
25
ChebConv Layer
MaxPooling Layer + BatchNorm
Global Average Pooling
Charge
*
First hit
16 Filters
Radius K=5
Filtered signals
Max
NSide → Nside / 2
Mean