ML at JUNO

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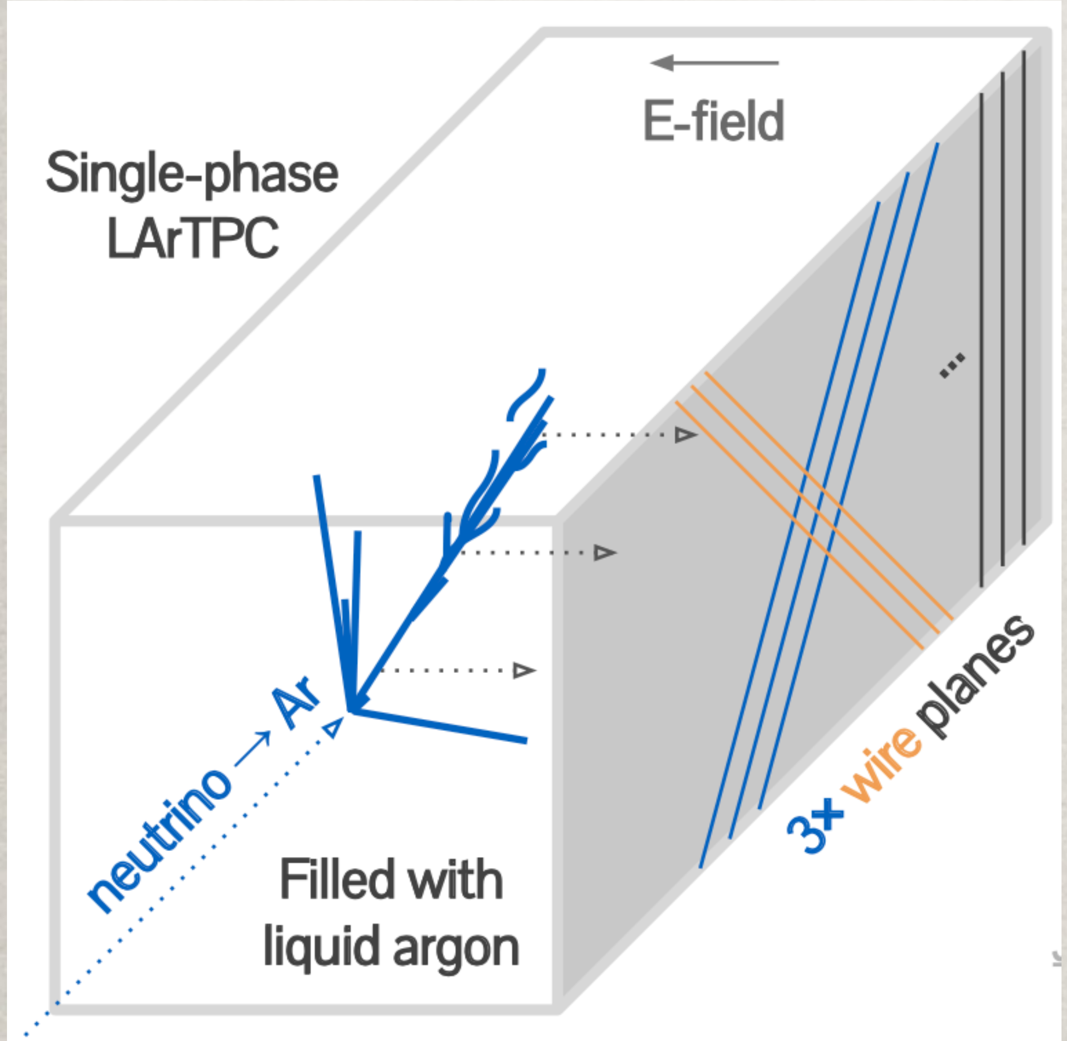
机器学习技术在高能物理中的应用研讨会

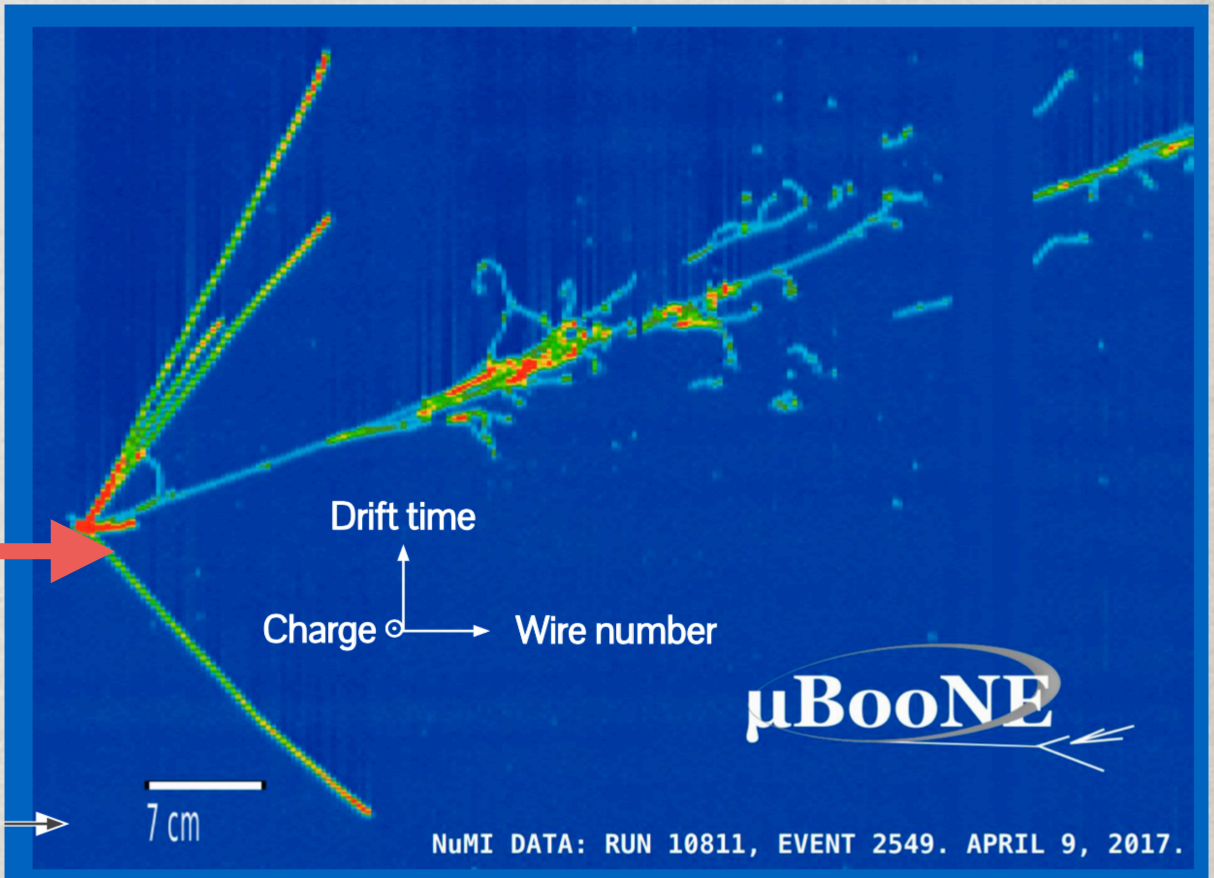
OUTLINE

- Status of ML in neutrino exp.
- ML applications in JUNO
- Manpower, issues, requests
- Summary

ML FOR NEUTRINO EXP.

- LArTPC(DUNE, μBooNE)
- Very advanced and mature application of ML



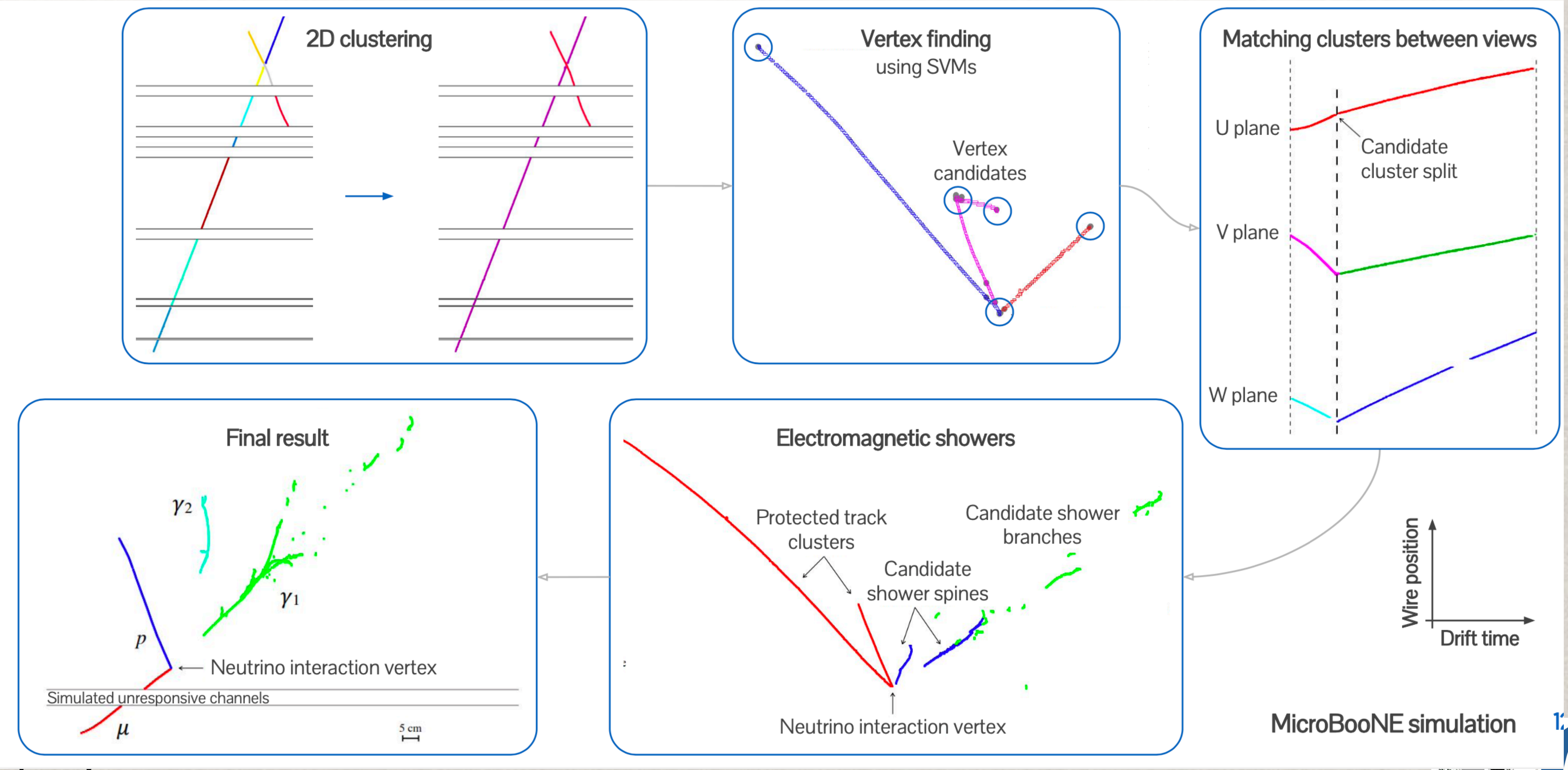


A neutrino interaction image from one wire plane in MicroBooNE

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

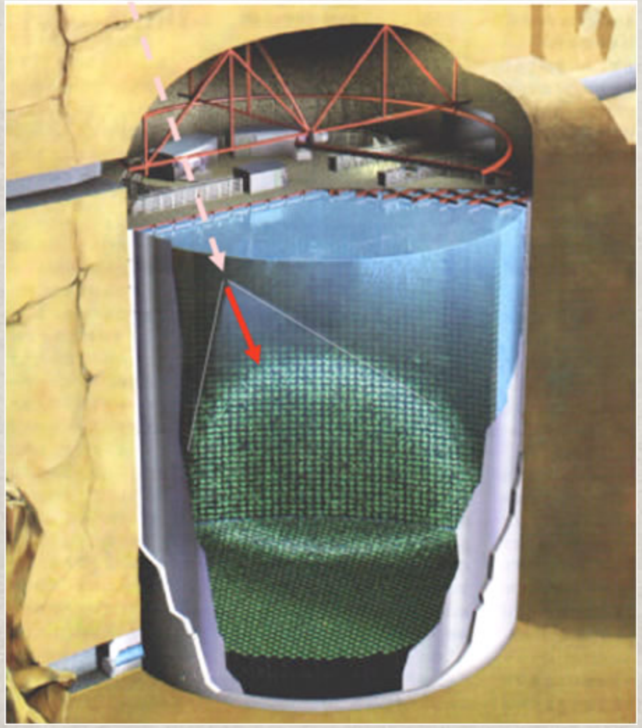
ML FOR NEUTRINO EXP.

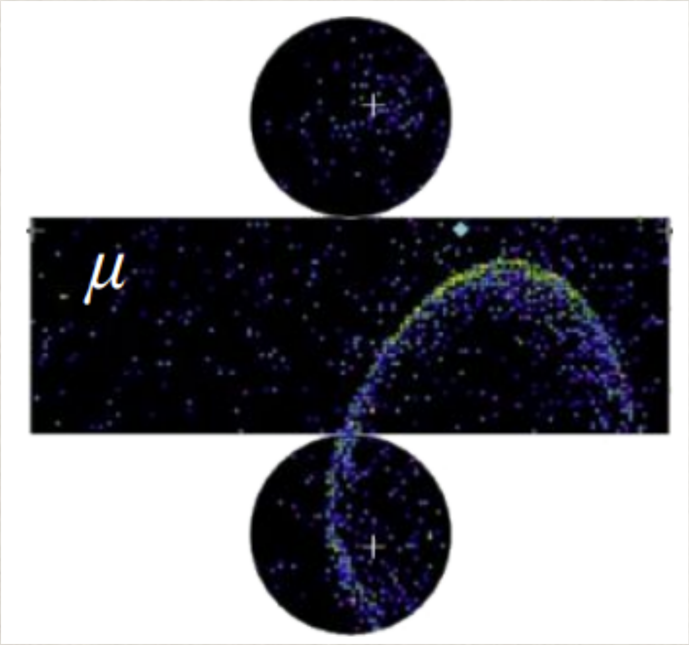
- End to end reconstruction, explainability, reusability

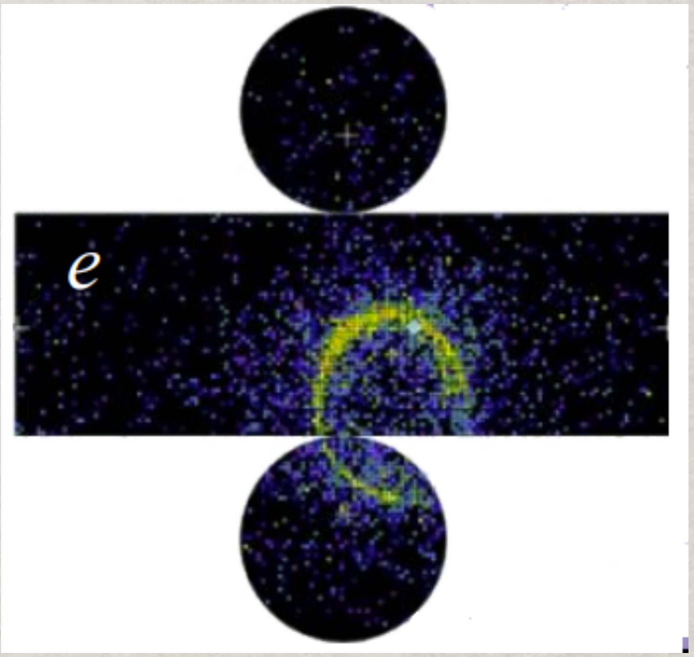


ML FOR NEUTRINO EXP.

- Water Cherenkov (Super-K/Hyper-K)
- Particle Identification: e/μ/γ/π
  - Challenges: cylindrical detector, sparse data
  - Models: CNN, PointNet, DGCNN



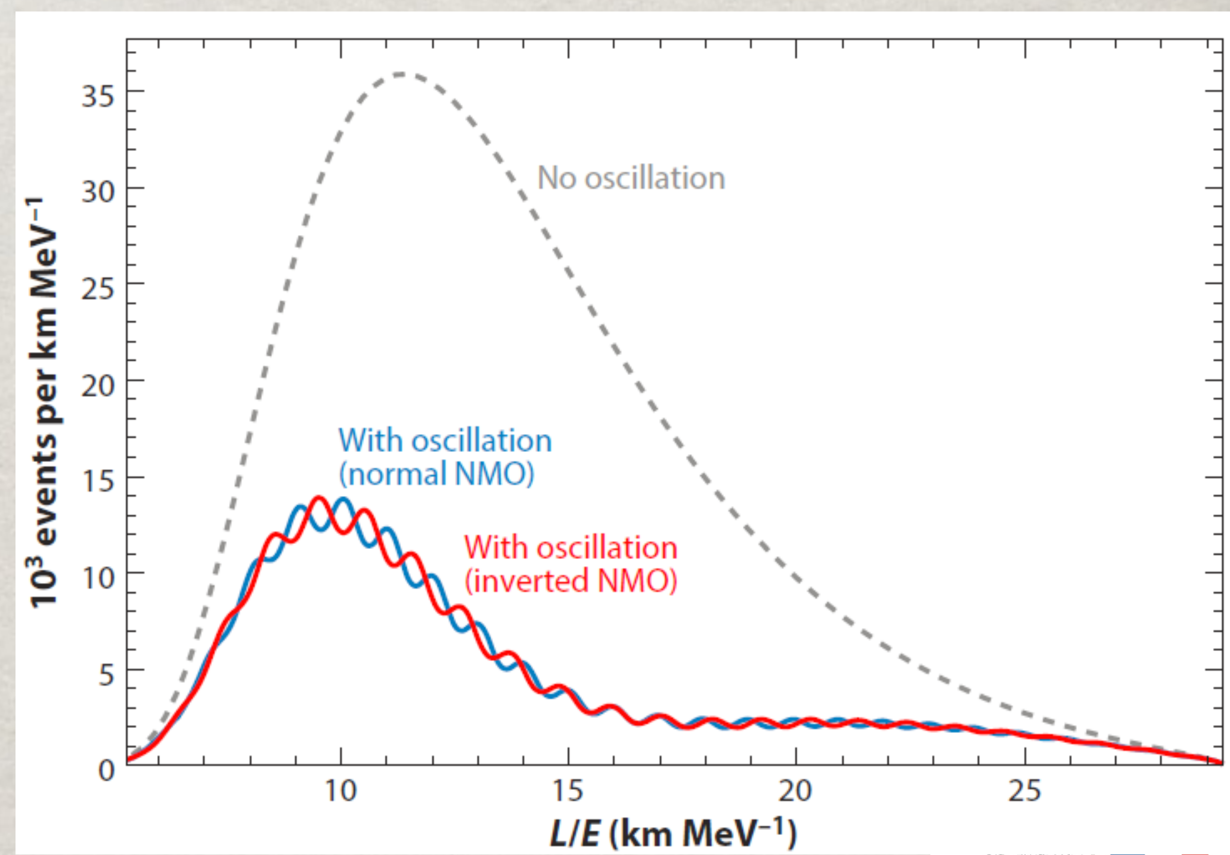




JUNO

- 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

Top Tracker

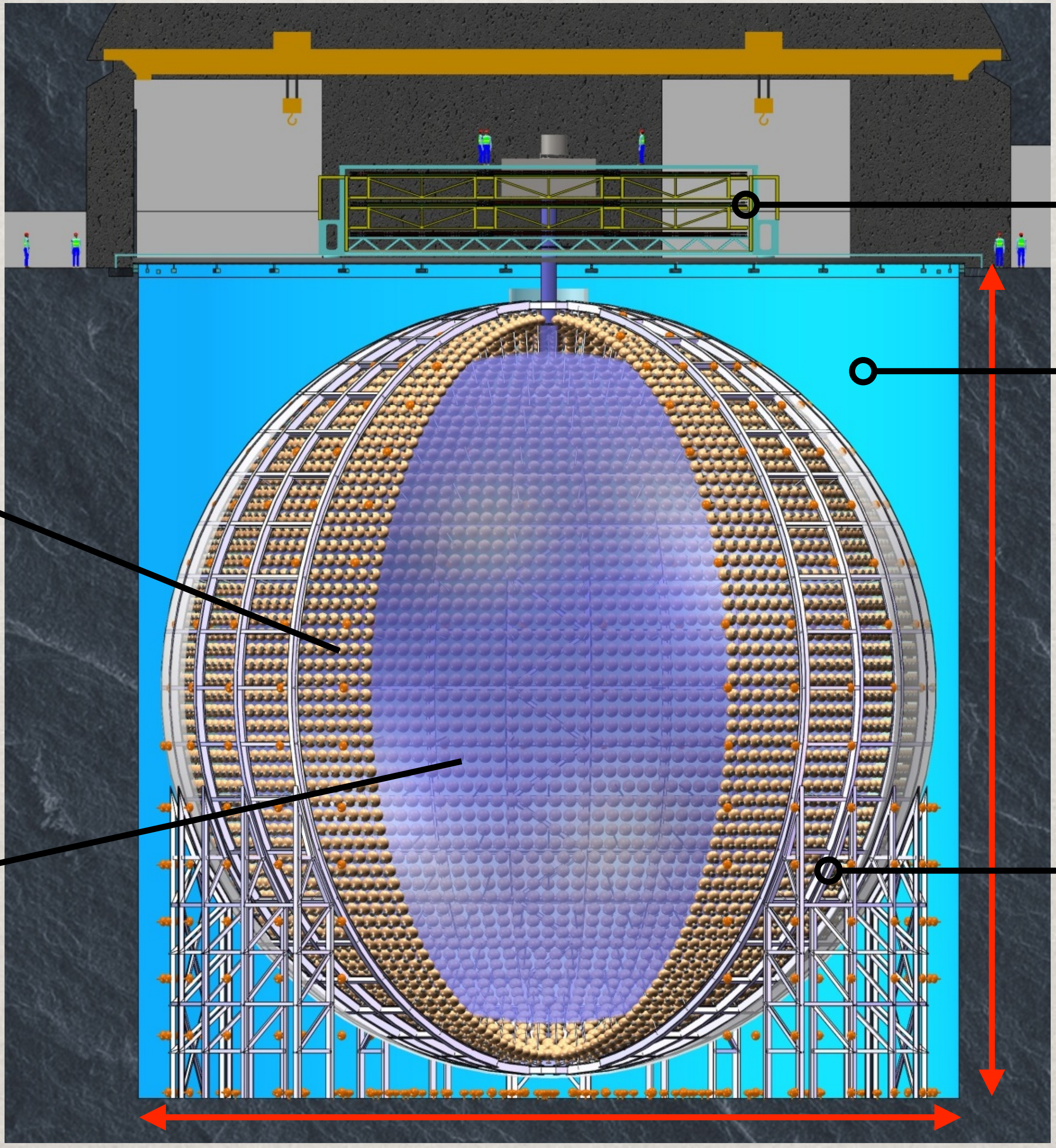
Central Detector*

~17,612 20" PMTs

+ ~25,600 3" PMTs

+ ~75% coverage

Water Pool



Depth: 44m

Liquid Scintillator

20kton

Central Detector*

Acrylic sphere

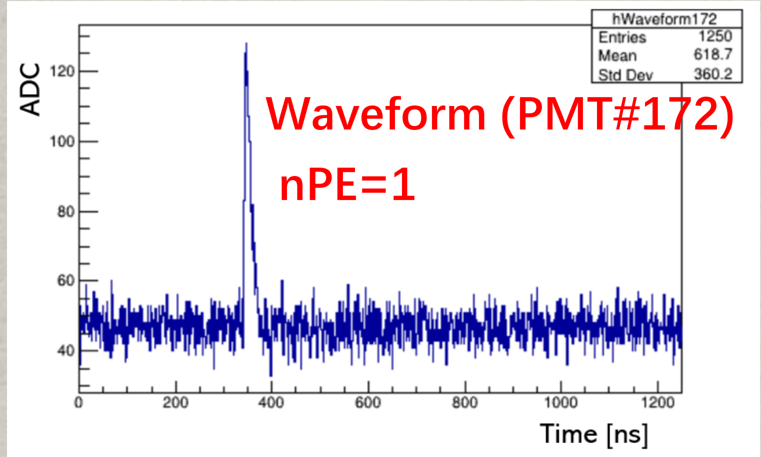
Stainless steel truss

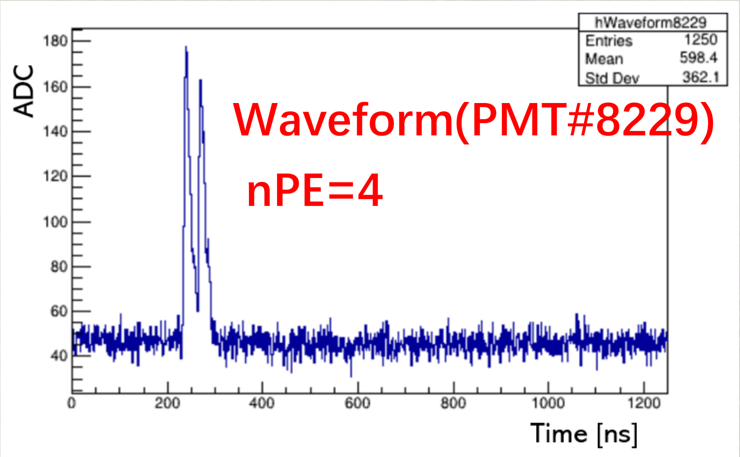
ϕ: 43.5m

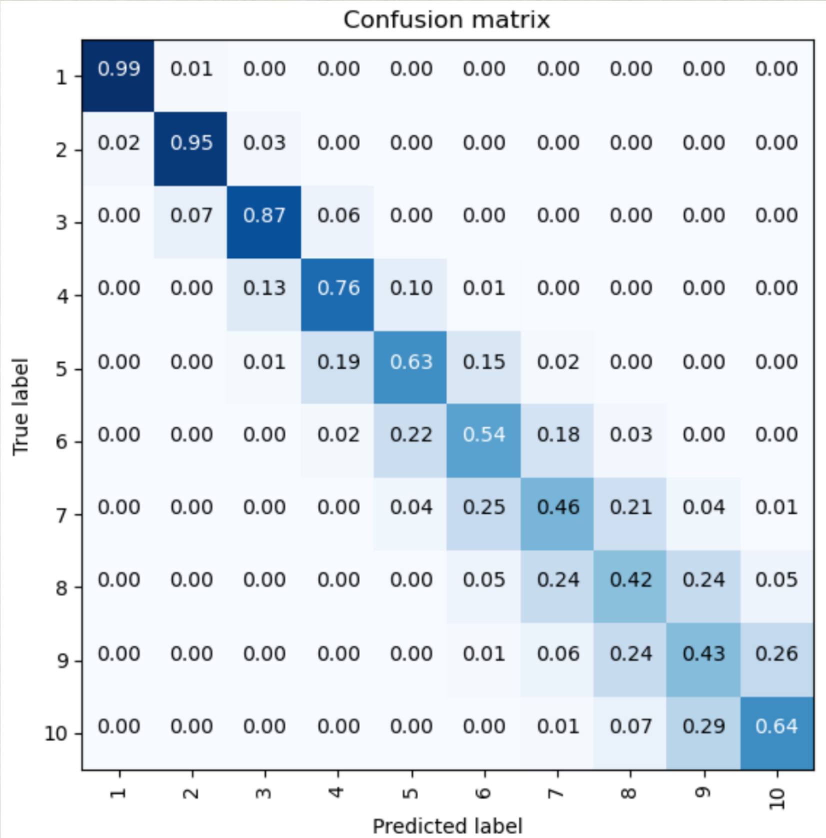
MeV Region

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

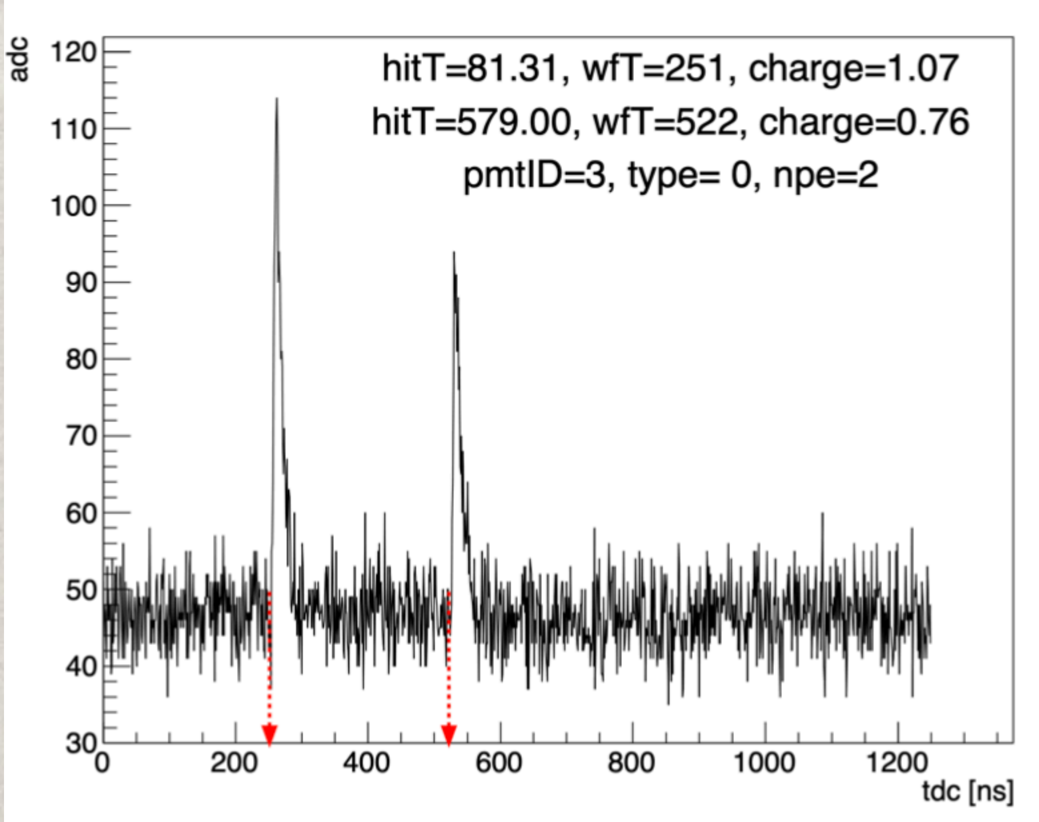


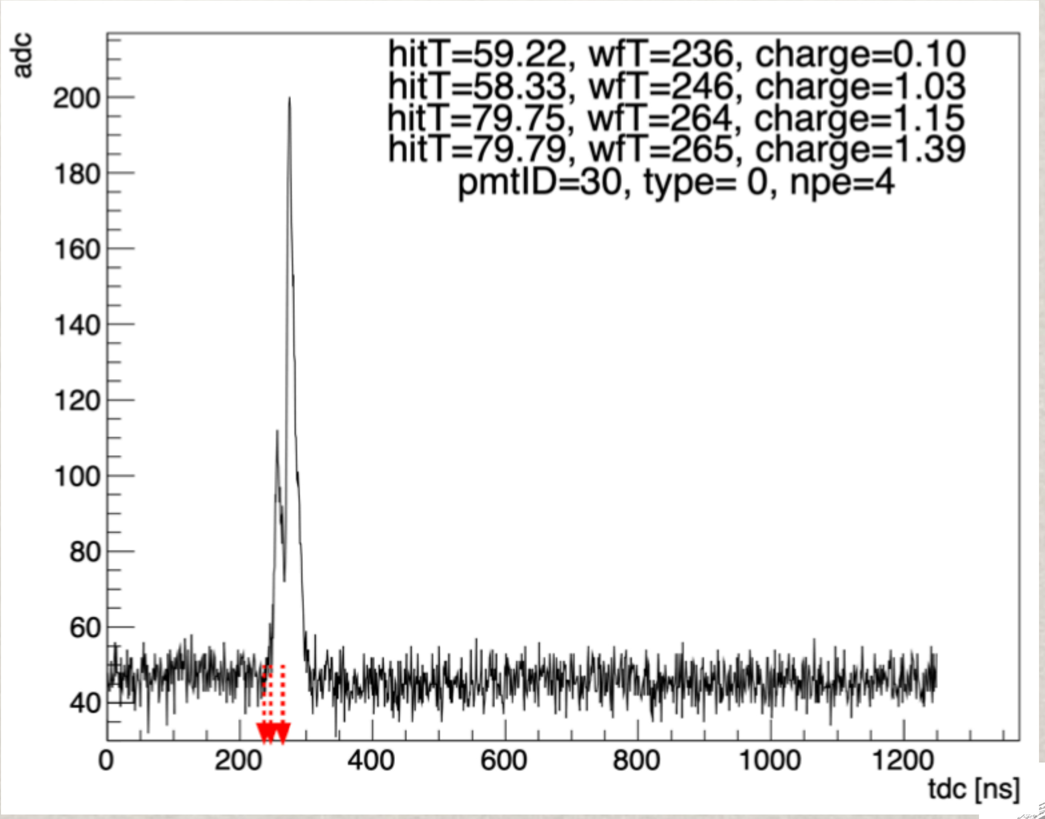




PMT WAVEFORM RECO II

- 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





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

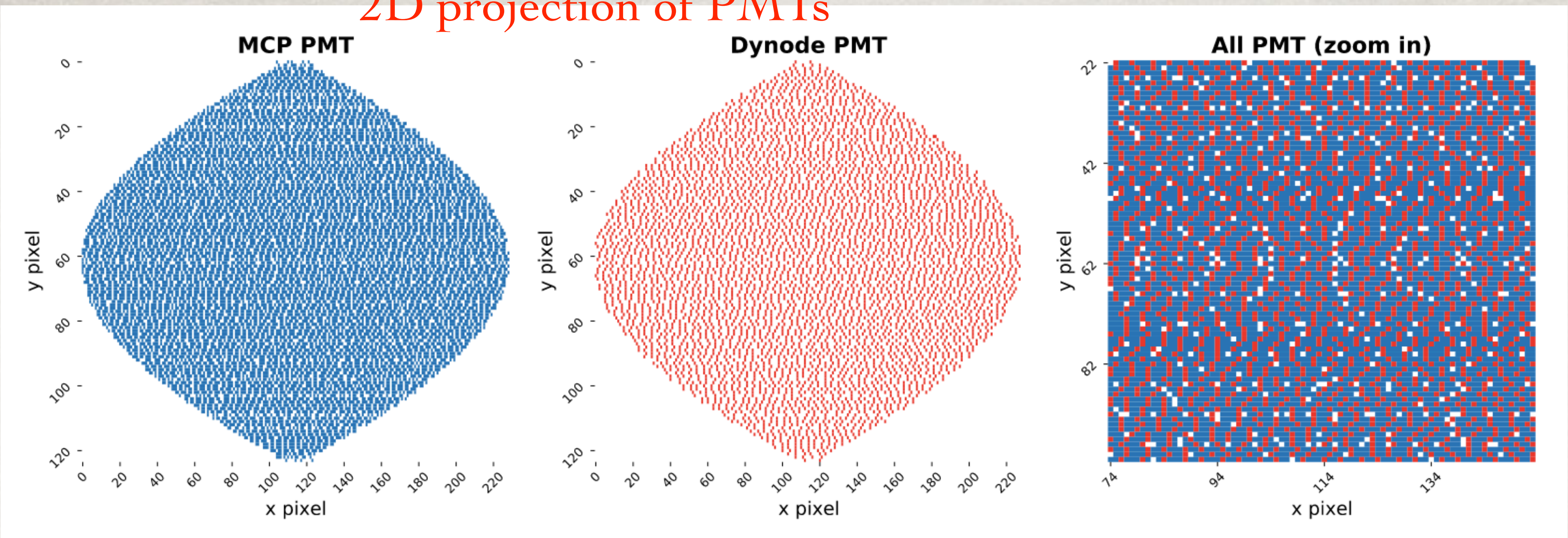
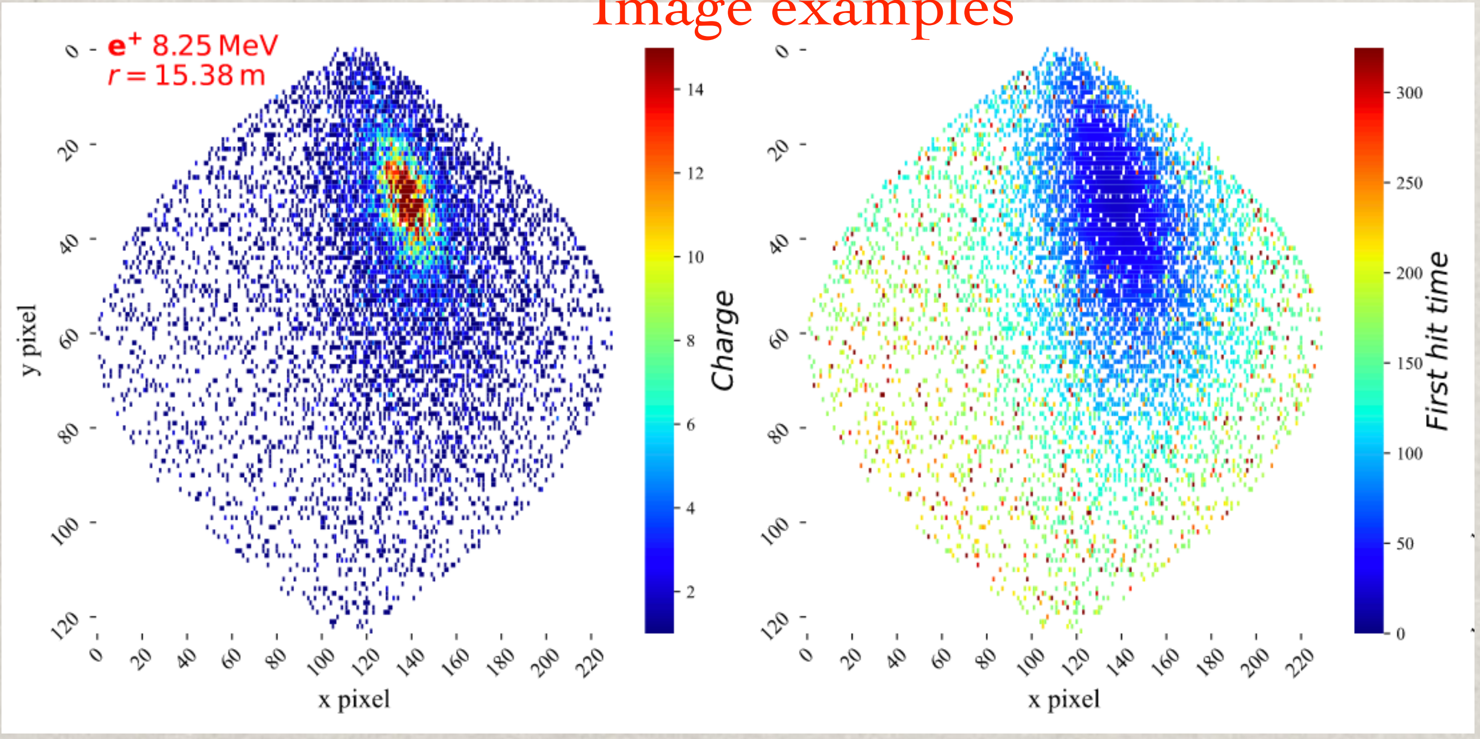


Image examples

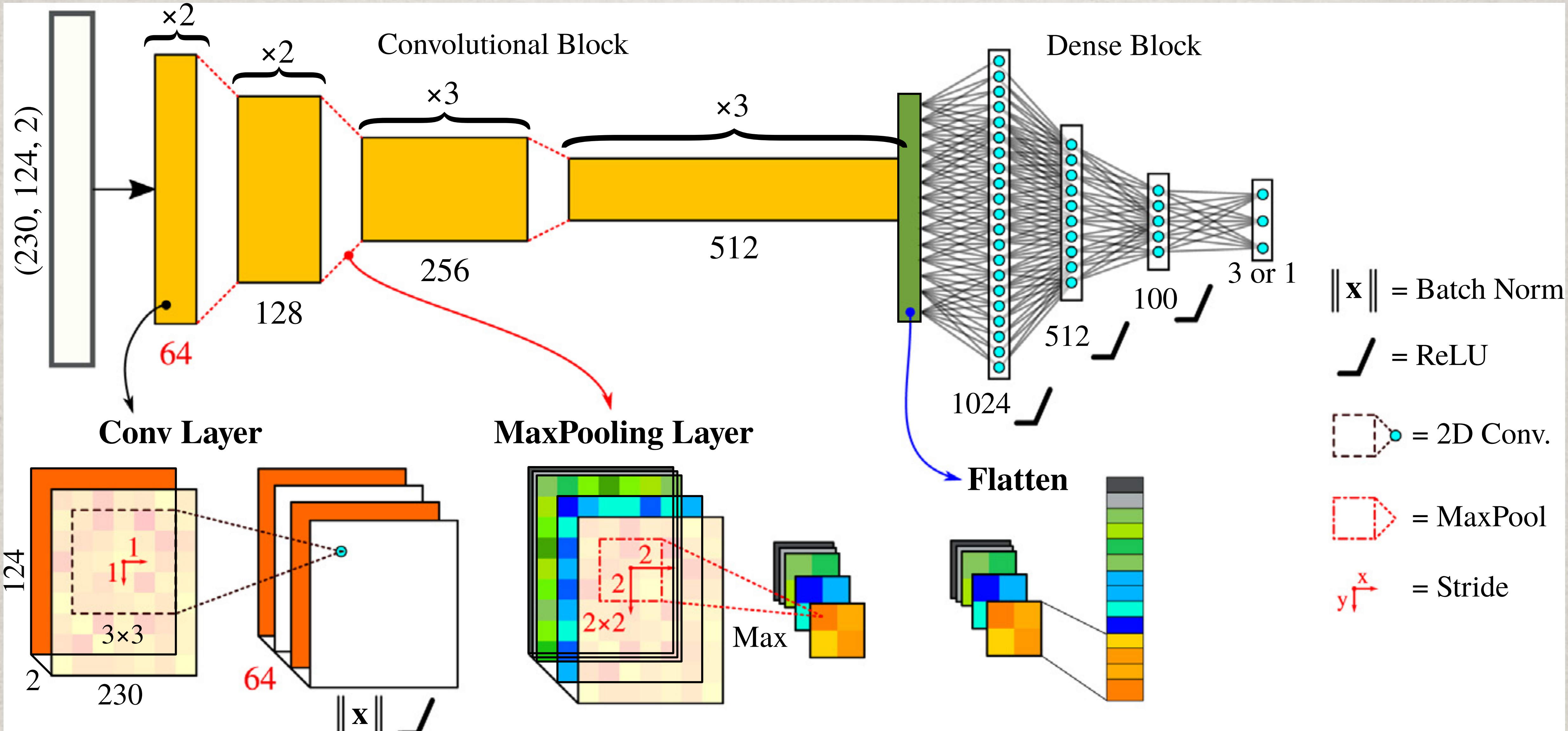


Remarks: inputs optimization

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

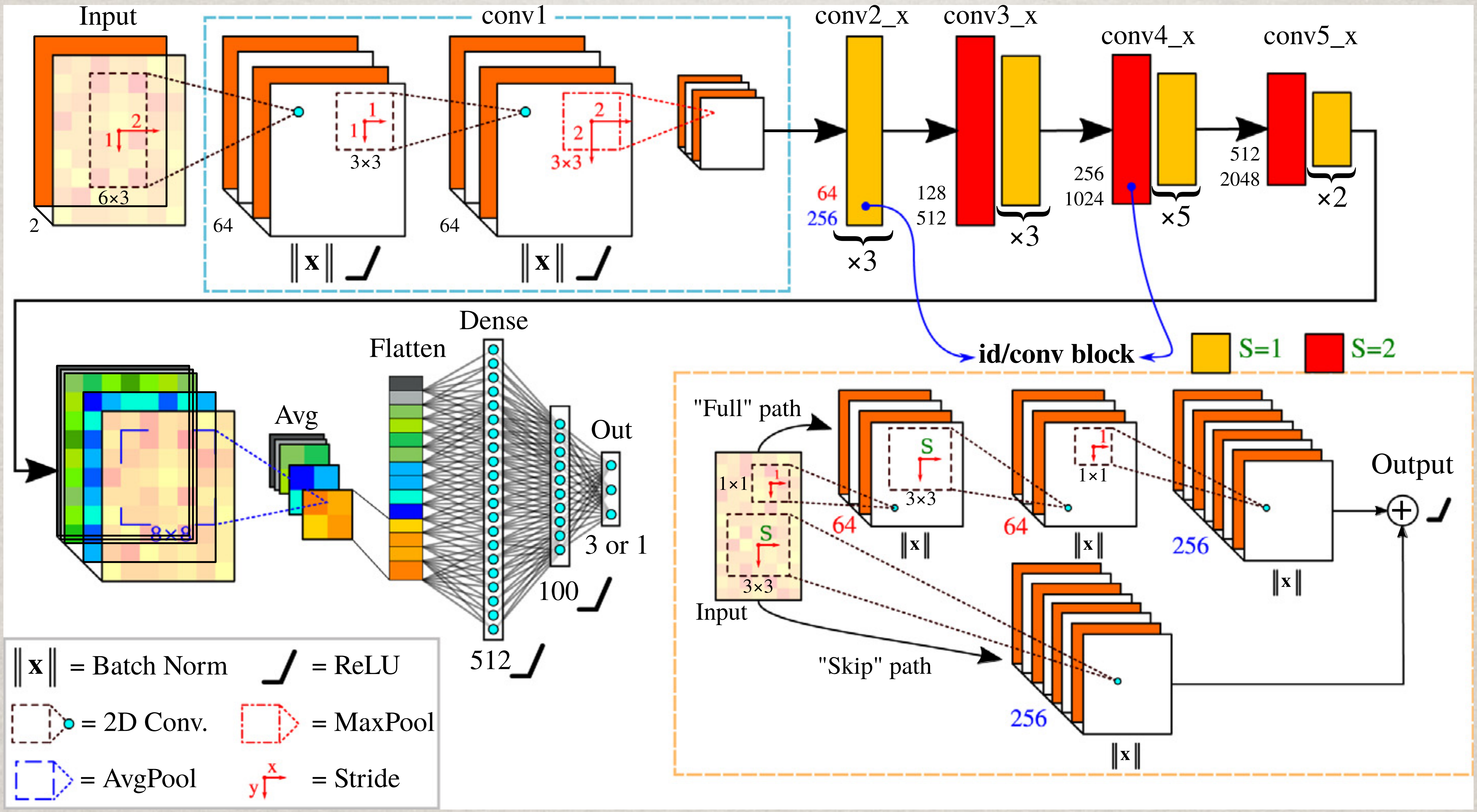
Pros and Cons

MODELS: VGG-J



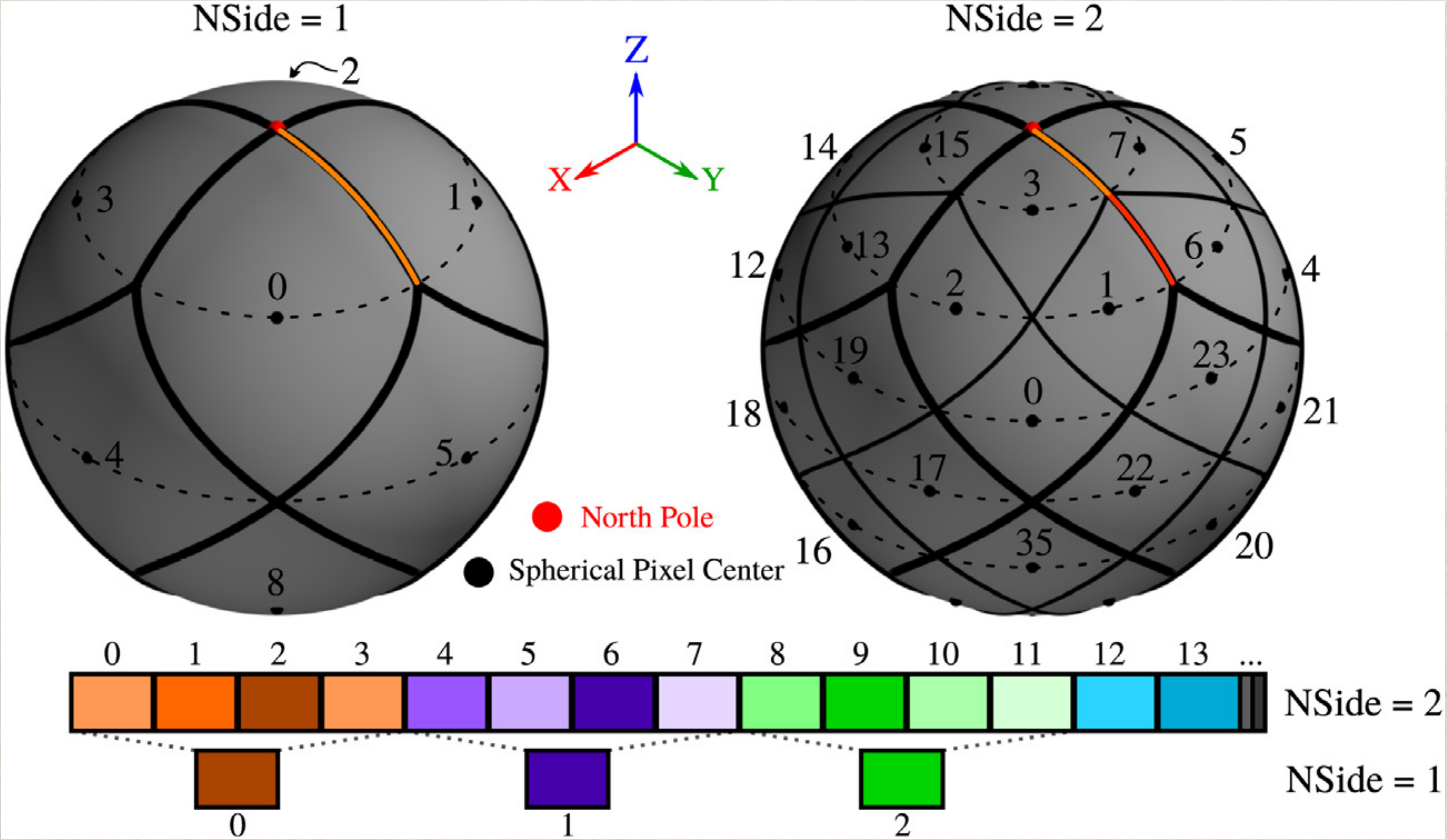
(230, 124, 2)
×2
×2
Convolutional Block
×3
×3
Dense Block
64
128
256
512
1024
512
100
3 or 1
= Batch Norm
= ReLU
= 2D Conv.
= MaxPool
= Stride
Conv Layer
MaxPooling Layer
Flatten
124
3×3
2
230
64
2×2
Max

MODELS: ResNet-J

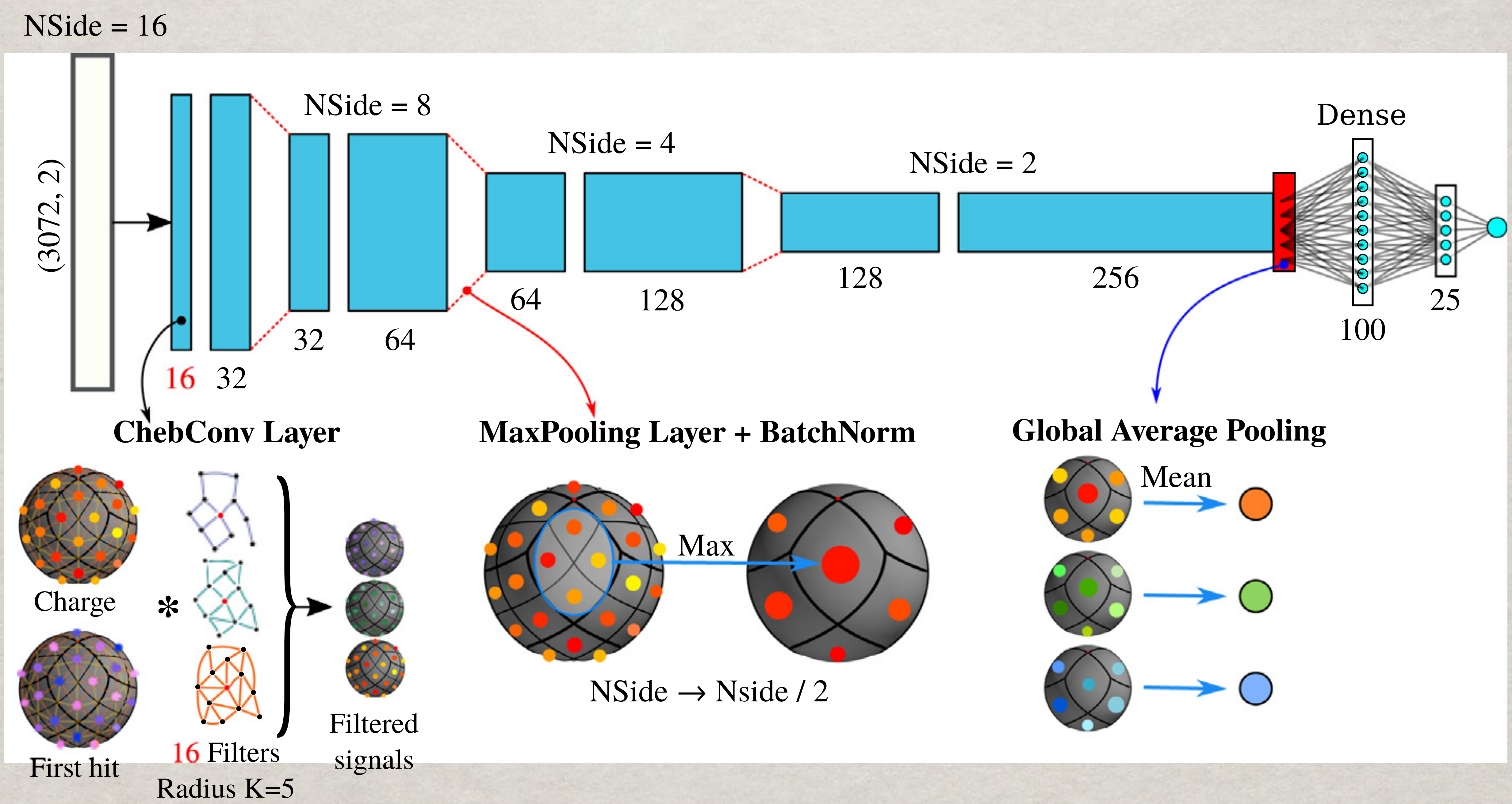


2. SPHERICAL MODELS

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



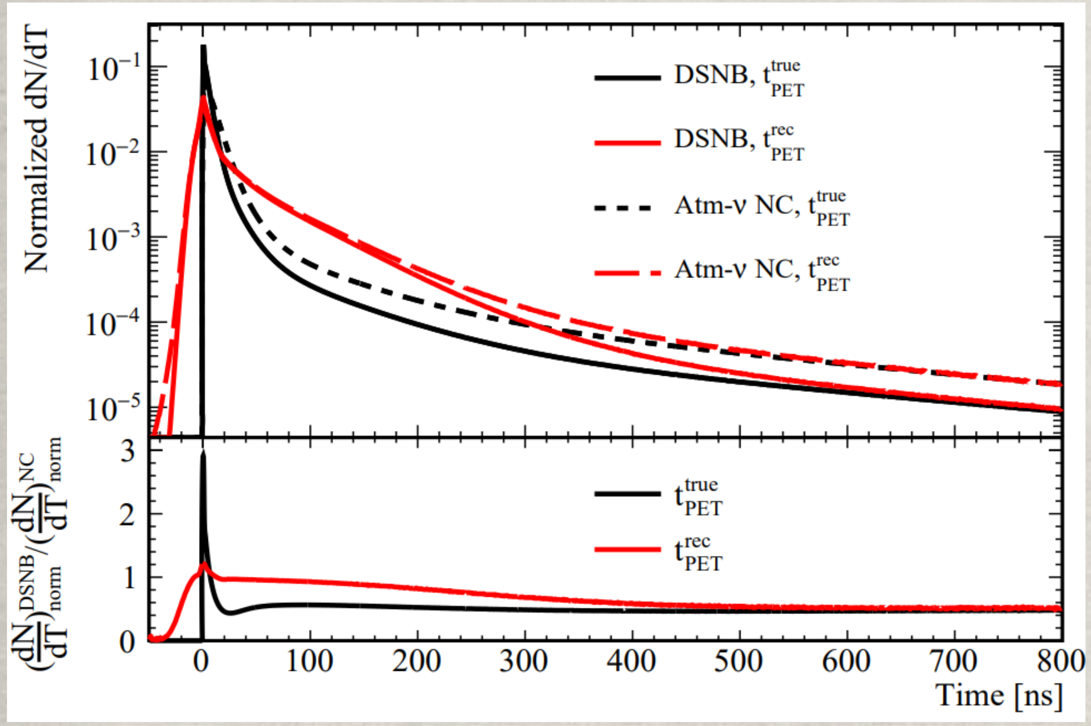
MODELS: GNN-J

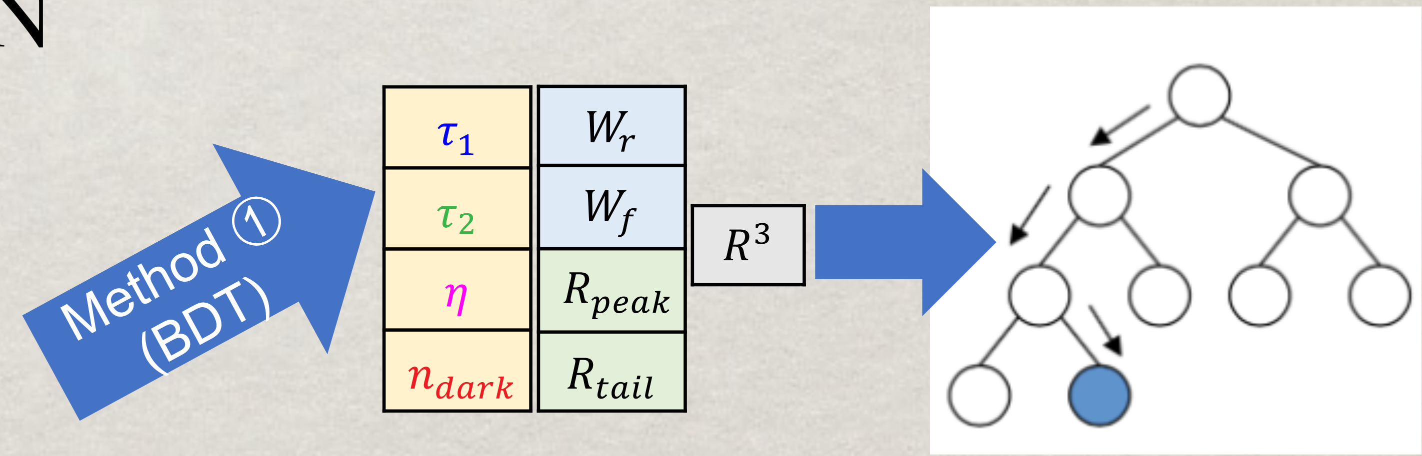


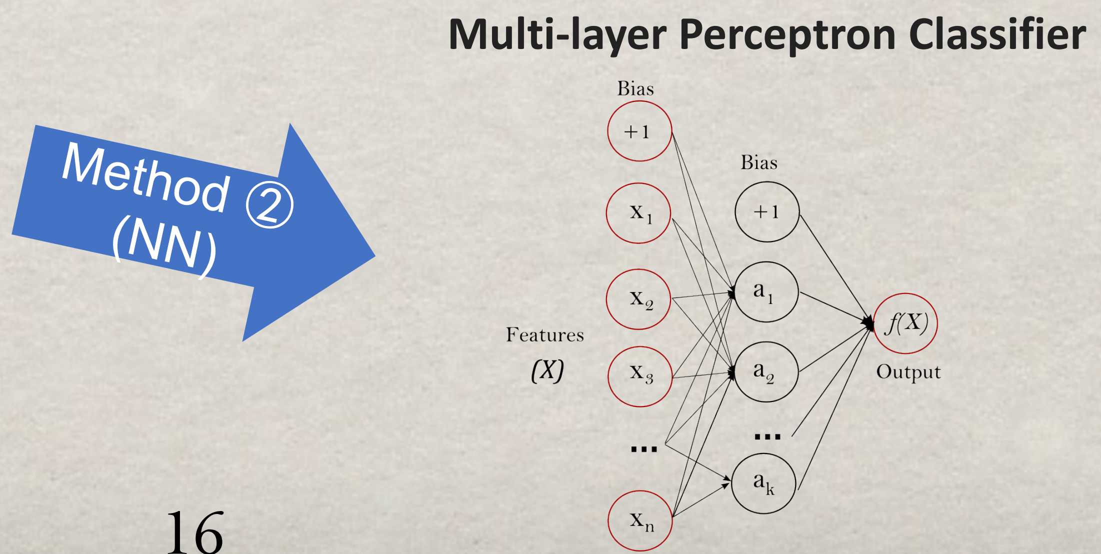
NSide = 16
(3072, 2)
16
32
NSide = 8
32
64
NSide = 4
64
128
NSide = 2
128
256
Dense
100
25
ChebConv Layer
Charge
First hit
*
16 Filters
Radius K=5
Filtered signals
MaxPooling Layer + BatchNorm
Max
NSide → Nside / 2
Global Average Pooling
Mean

PARTICLE IDENTIFICATION

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





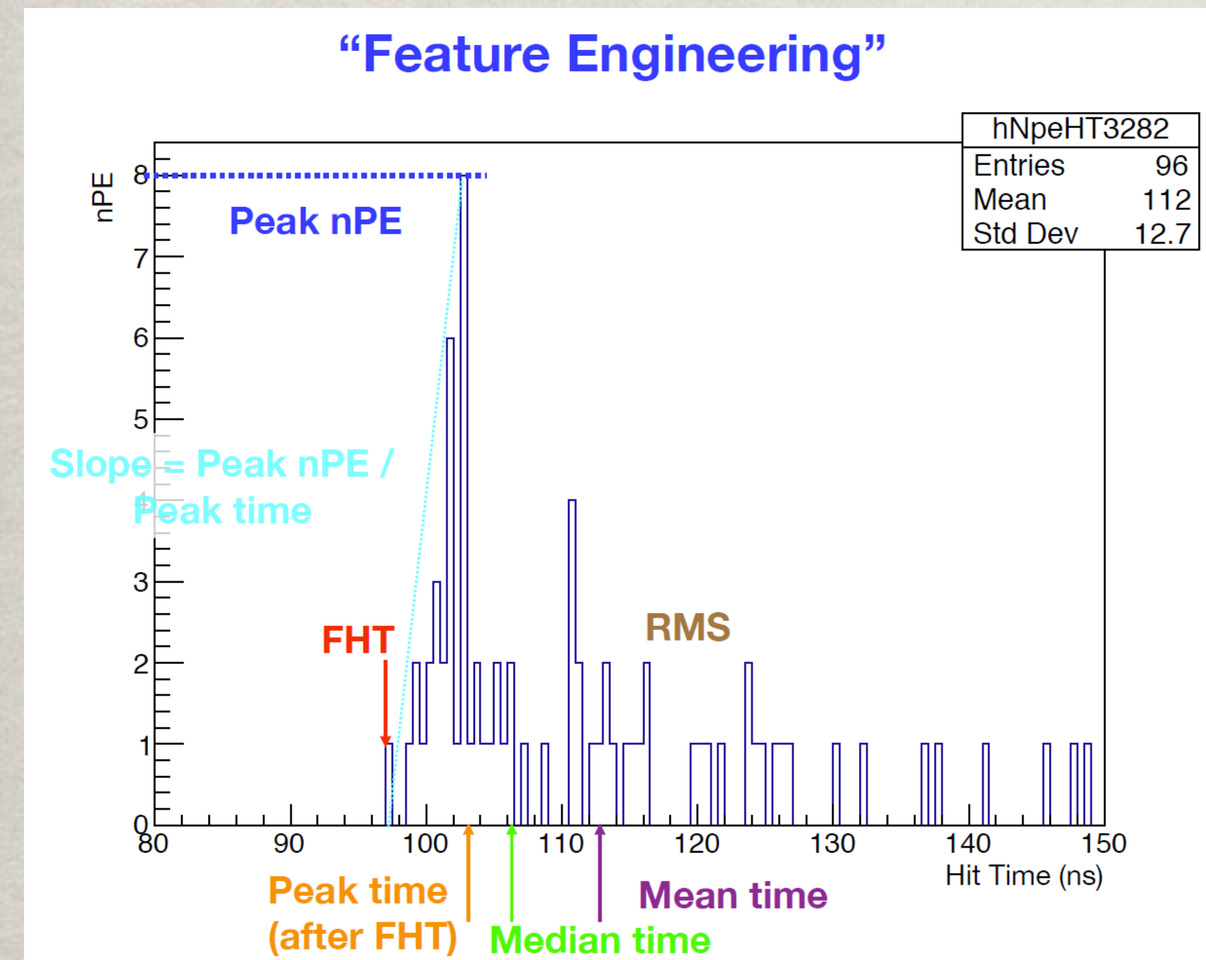


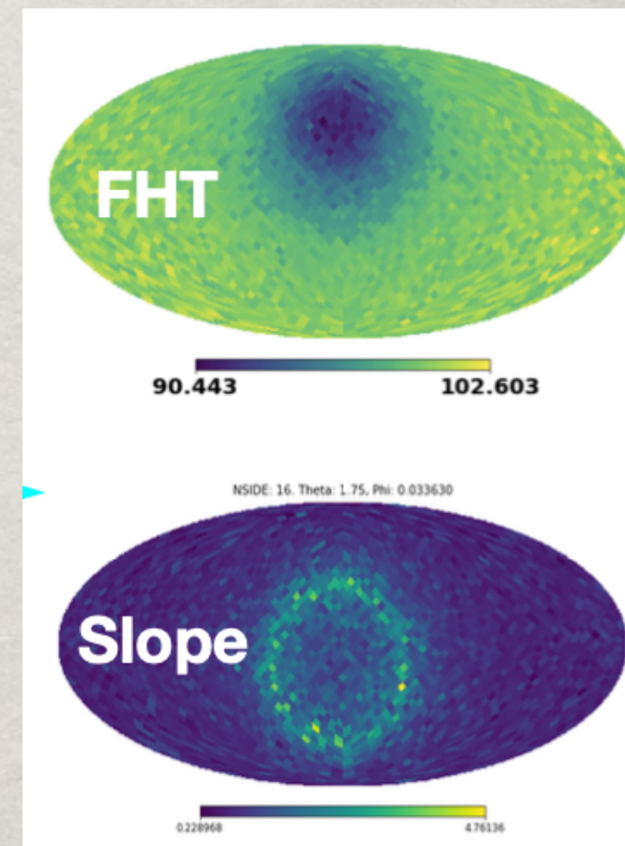
ATMOSPHERIC ν - I

- Detector signatures for Atm. ν in LS
  - Prompt signal: high energy μ/e/π/p…
    - track or shower
  - Delayed signals: neutron capture, Micheal electrons…
- Goal: directionality reconstruction
- Principle: event info hidden in PMT waveforms
- Methodology
  - Step1: feature extraction from PMT waveforms
  - Step2: feed features into ML models

INPUTS

- Extract “features” from PMT waveforms

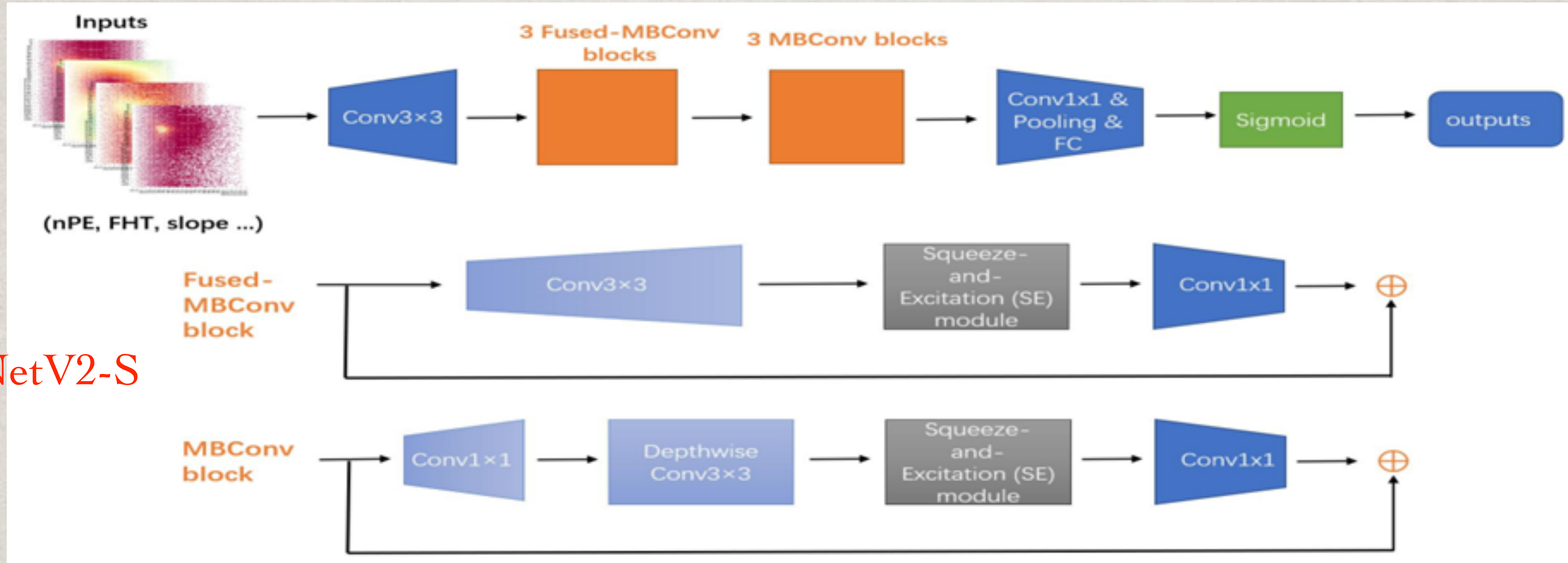




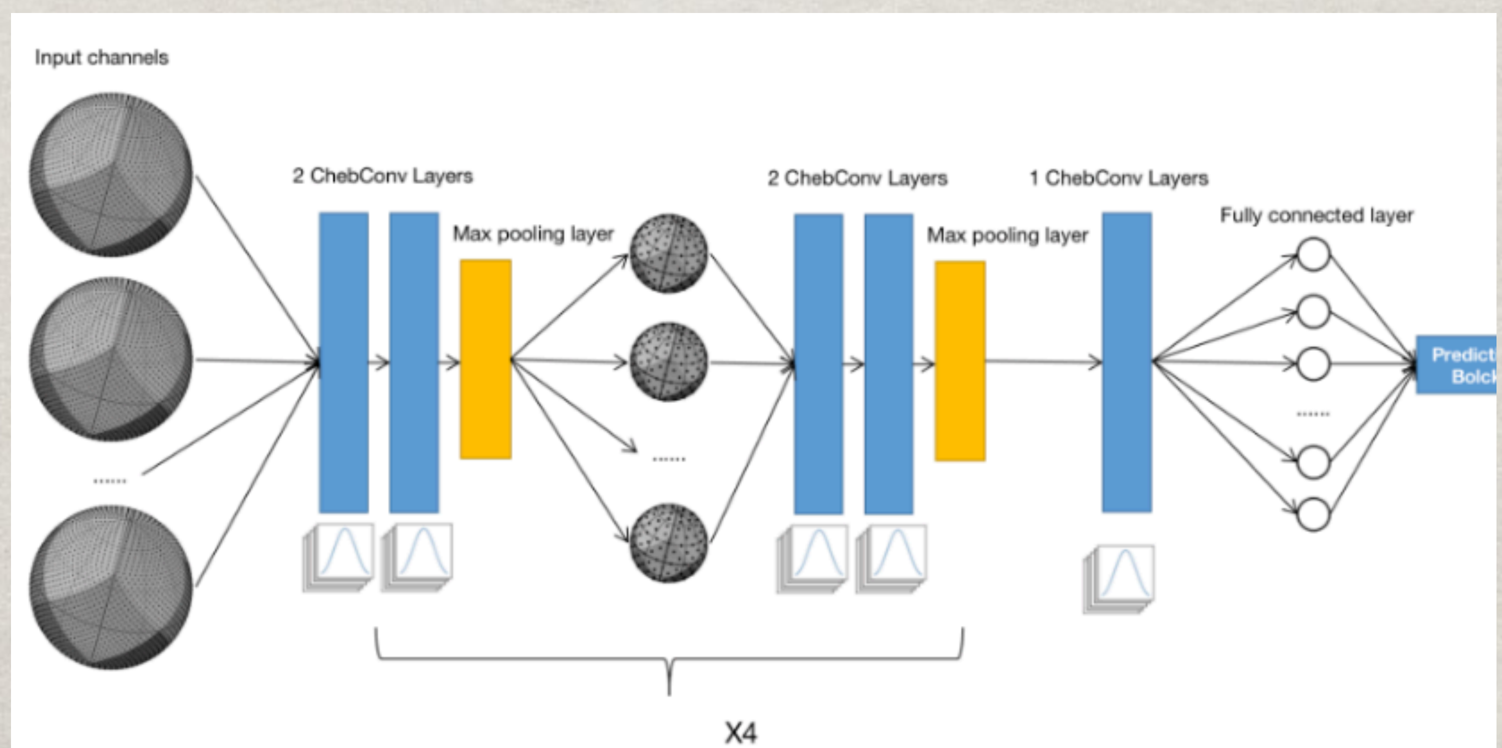
+ more…

MODELS

EfficientNetV2-S



DeepSphere



ATMOSPHERIC ν - II

- Goal: Particle Identification, ν_μ vs ν_e vs NC; ν vs ν
- Principle: different event topology
  - track or shower for prompt signal
  - different particles in delayed signals: neutrons, Michael electrons
- Method: mixed model
  - features + variables

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
- Multi-target reco, 如何信息分割
- And more…

MANPOWER

- 职工：罗武鸣（50%），方文兴（40%）
- 博后：刘震（100%），未来再招1人
- 学生若干

REQUESTS???

- GPU 资源
- 业界机器学习最新动态和最优模型
  - e.g. 语音/图像识别，降噪，视频处理etc
- 其他高能实验/探测器最新进展
  - 组织学习/借鉴
- 人力，基金

PLAN

- 底层重建/鉴别
- Cosmic muon track & shower point reco
- 多点鉴别/重建, 信息分割
  - 14C & e+
  - PMT dark noise de-noising
  - annihilation & kinetic energy separation
  - Cherenkov & Scintillation photons separation

PLAN CONT.

- 物理分析方面
- 快速事例分类： cosmic muons, atm. neutrinos
- 关联事例挑选: e.g. encoder—decoder
  - IBD快慢信号符合
  - Cosmic Muon & induced isotopes
- 信号/本底的TMVA fitting
- More…

SUMMARY

- ML at JUNO is in the early stage
- Lots of applications as well as challenges
- Look forward to all the activities in this ML@IHEP forum

REFERENCES

- Vertex and energy reconstruction in JUNO with machine learning methods
  - https://www.sciencedirect.com/science/article/pii/S016890022100512X?via%3Dihub
- Improvement of machine learning-based vertex reconstruction for large liquid scintillator detectors with multiple types of PMTs
  - https://link.springer.com/article/10.1007/s41365-022-01078-y
- RawNet: https://arxiv.org/abs/1904.08104