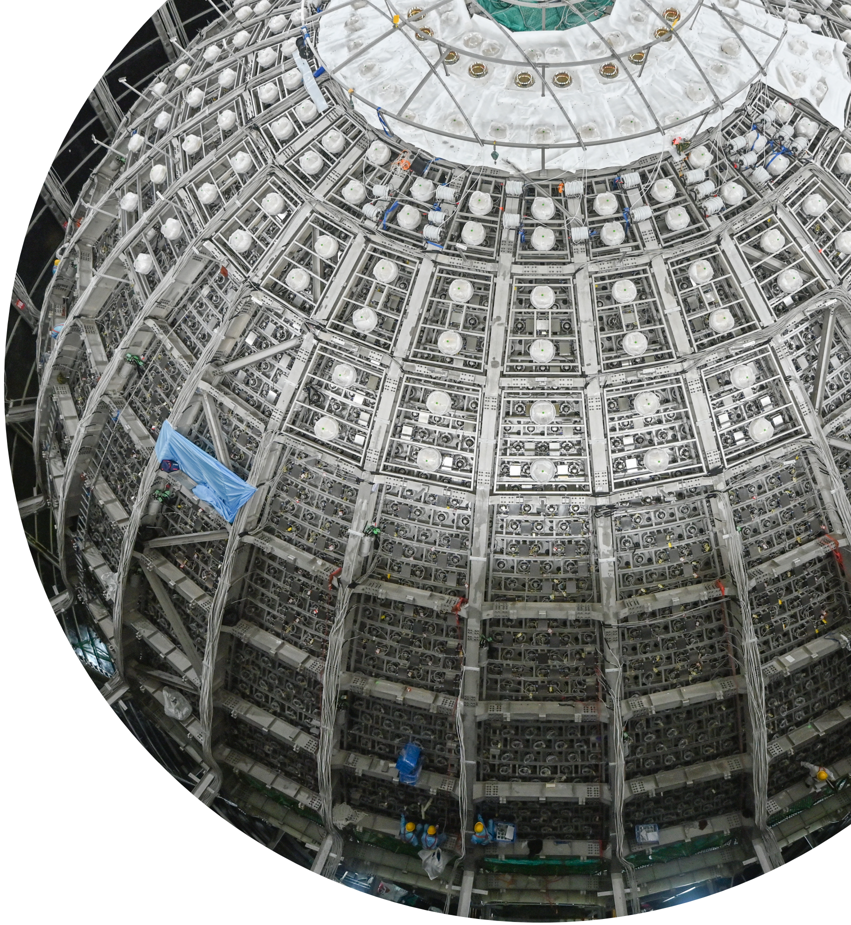
NNN23

22nd International Workshop on Next Generation Nucleon Decay and Neutrino Detectors

Procida October 11-13, 2023



Machine Learning Techniques for the Event Reconstruction: the JUNO Experiment

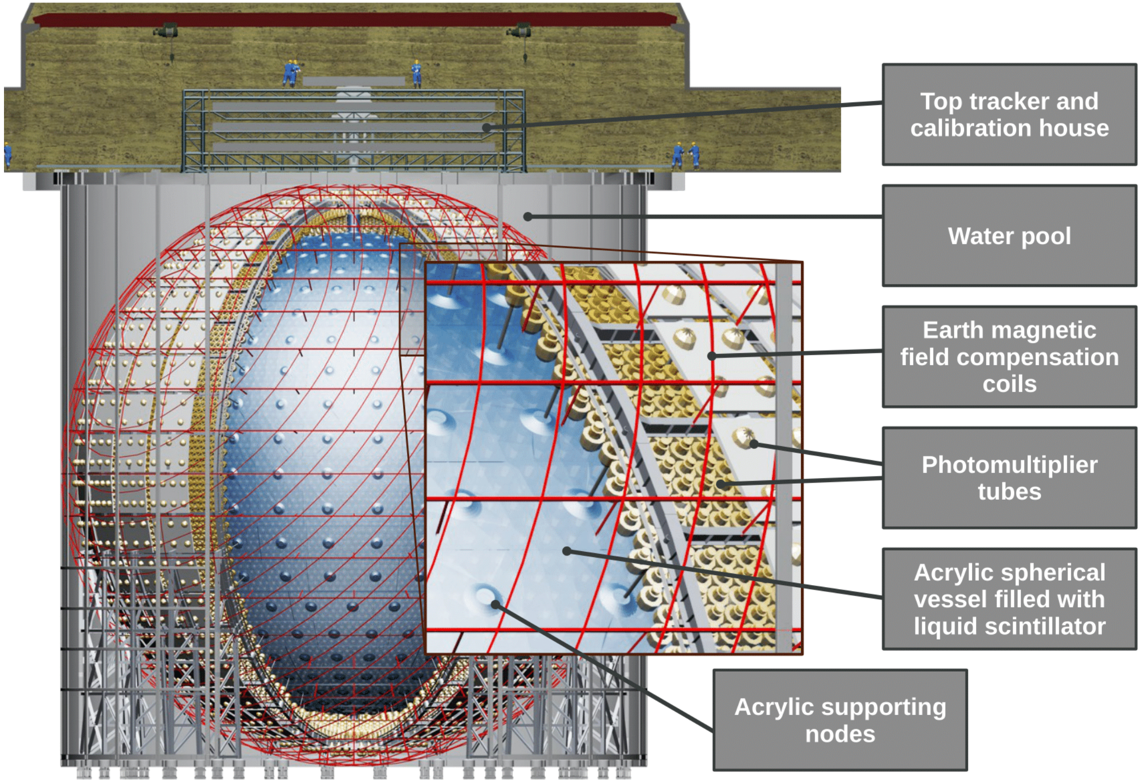
Arsenii Gavrikov[1] of behalf of the JUNO collaboration

[1]The University of Padova + INFN-Padova

JUNO: a next-generation neutrino observatory[1]

- Jiangmen Underground Neutrino Observatory (JUNO):
  - a 20 kt **liquid scintillator (LS)** detector
  - 53 km away from **8 reactor cores**
  - ~650-meter deep underground
  - data taking expected in 2024

- The main goals of JUNO:
  - neutrino mass ordering (NMO) **3σ in ~6 years**
  - precise measure of oscillation parameters $\sin^2\theta_{12}, \Delta m^2_{21}, \Delta m^2_{31}$
  - more in the **talk of M. Grassi**



[1]JUNO Collaboration, PPNP **123**, (2022): 103927

JUNO collaboration

= 74 institutes

Country	Institute	Country	Institute	Country	Institute
Armenia	Yerevan Physics Institute	China	SYSU	Germany	U. Mainz
Belgium	Universite libre de Bruxelles	China	Tsinghua U.	Germany	U. Tuebingen
Brazil	PUC	China	UCAS	Italy	INFN Catania
Brazil	UEL	China	USTC	Italy	INFN di Frascati
Chile	PCUC	China	U. of South China	Italy	INFN-Ferrara
Chile	SAPHIR	China	Wu Yi U.	Italy	INFN-Milano
Chile	UNAB	China	Wuhan U.	Italy	INFN-Milano Bicocca
China	BISEE	China	Xi'an JT U.	Italy	INFN-Padova
China	Beijing Normal U.	China	Xiamen University	Italy	INFN-Perugia
China	CAGS	China	Zhengzhou U.	Italy	INFN-Roma 3
China	ChongQing University	China	NUDT	Pakistan	PINSTECH (PAEC)
China	CIAE	China	CUG-Beijing	Russia	INR Moscow
China	DGUT	China	ECUT-Nanchang City	Russia	JINR
China	Guangxi U.	China	CDUT-Chengdu	Russia	MSU
China	Harbin Institute of Technology	Czech	Charles U.	Slovakia	FMPICU
China	IHEP	Finland	University of Jyvaskyla	Taiwan-China	National Chiao-Tung U.
China	Jilin U.	France	IJCLab Orsay	Taiwan-China	National Taiwan U.
China	Jinan U.	France	LP2i Bordeaux	Taiwan-China	National United U.
China	Nanjing U.	France	CPPM Marseille	Thailand	NARIT
China	Nankai U.	France	IPHC Strasbourg	Thailand	PPRLCU
China	NCEPU	France	Subatech Nantes	Thailand	SUT
China	Pekin U.	Germany	RWTH Aachen U.	U.K.	U. Warwick
China	Shandong U.	Germany	TUM	USA	UMD-G
China	Shanghai JT U.	Germany	U. Hamburg	USA	UC Irvine
China	IGG-Beijing	Germany	FZJ-IKP		

+Observers: University of Liverpool

JUNO’s central detector

- The central detector:
  - **the largest** liquid scintillator detector: 20 kt
  - **~35 m** of diameter
- **77.9% photo-coverage** by photo-multiplier tubes (PMTs):

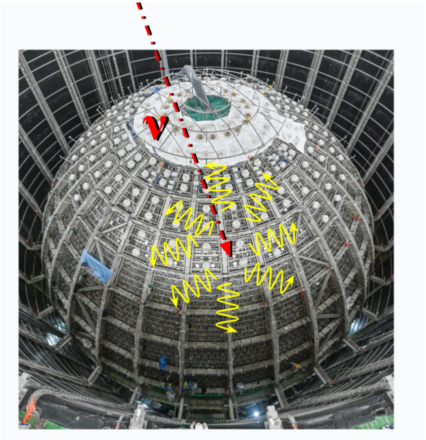
  1) 17612 **20’’ (LPMT)** 2) 25600 **3'' (SPMT)**

Large statistics

Energy resolution of 3%/√E

- **Challenges**:
  - non-linear energy response
  - detector’s spatial non-uniformity
  - account for all effects affecting the photon emission, propagation
  - etc.
- Can Machine Learning (ML) techniques help us **to solve** these issues?

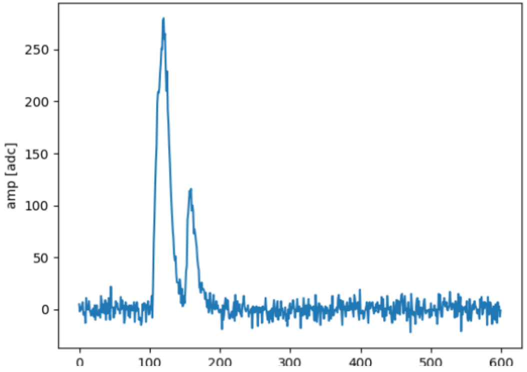
Reconstruction chain



Light production in LS

Light detection by PMTs

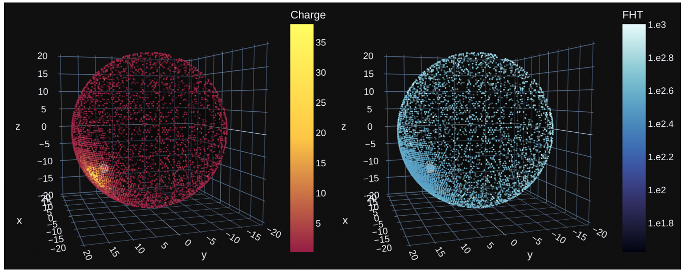
Readout electronics



PMT waveform reconstruction

Charge at PMT

First Hit Time (FHT) at PMT

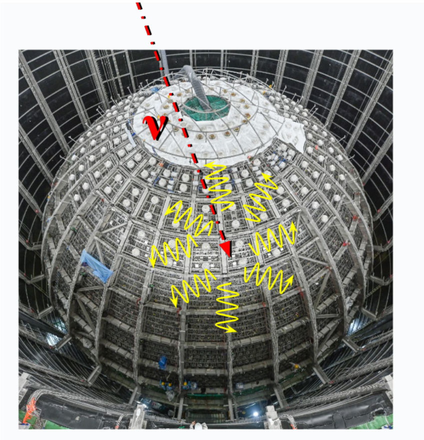


Energy reconstruction

Vertex reconstruction

Further analysis

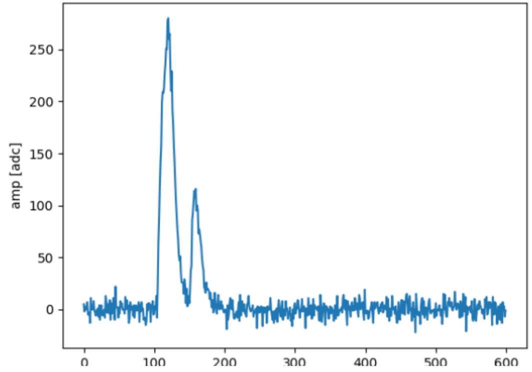
Reconstruction chain



Light production in LS

Light detection by PMTs

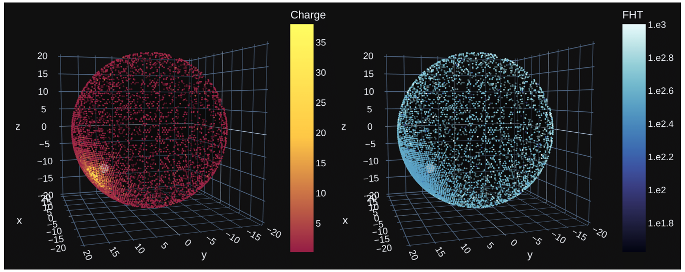
Readout electronics



PMT waveform reconstruction

Charge at PMT

First Hit Time (FHT) at PMT



Energy reconstruction

Vertex reconstruction

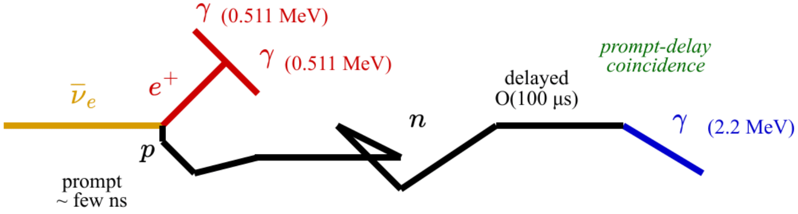
Further analysis

Neutrino detection in JUNO

- electron anti-neutrinos $\overline{\nu}_e$ from **the reactor cores**
- detected via Inverse Beta Decay (**IBD**):

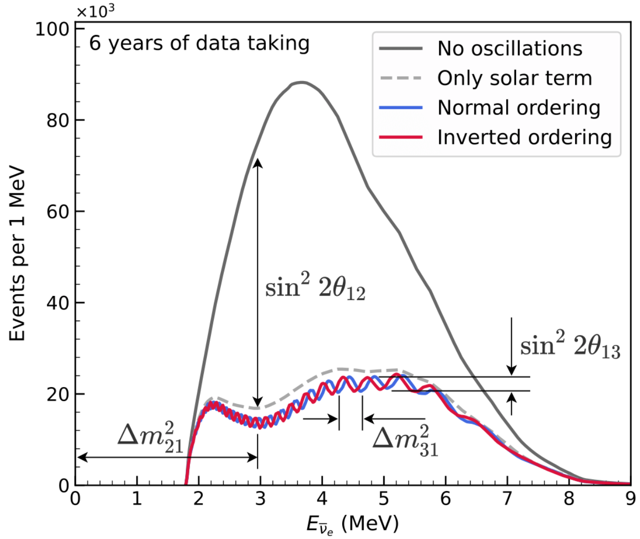
$$\overline{\nu}_e + p \rightarrow e^+ + n$$

- e^+ **takes** most of *the neutrino energy* =>
- => it can be **calculated** as follows: $E_{\tilde{\nu}_e} \approx E_{\mathrm{dep}} + 0.8\ \mathrm{MeV}$



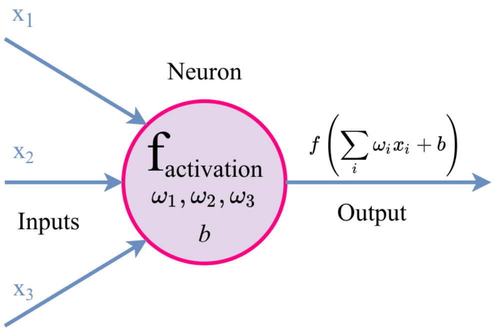
To ensure **resolving NMO**:

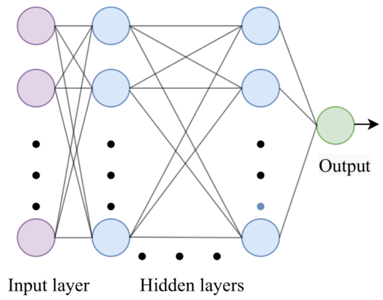
- energy reconstruction with resolution < **3% at 1 MeV**



Machine learning in particle physics

- **ML methods** are used at **all levels** of data processing in many experiments:
  - signal/background discrimination
  - event selection in a trigger
  - anomaly detection
  - particle identification, etc.



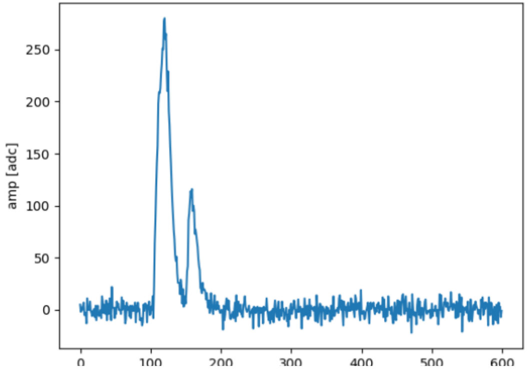


- Why is ML **useful** for particle physics?
  - **Faster.** More precisely, with proper training
  - **Adequate** for many purposes simultaneously: event simulation, analysis, reconstruction, identification, etc.
  - **GPU friendly** by construction, which is important for big data processing
- **Drawbacks**:
  - models are trained on simulation data – MC vs. real data discrepancy
  - stability, reliability & interpretability

Machine learning for IBDs in JUNO

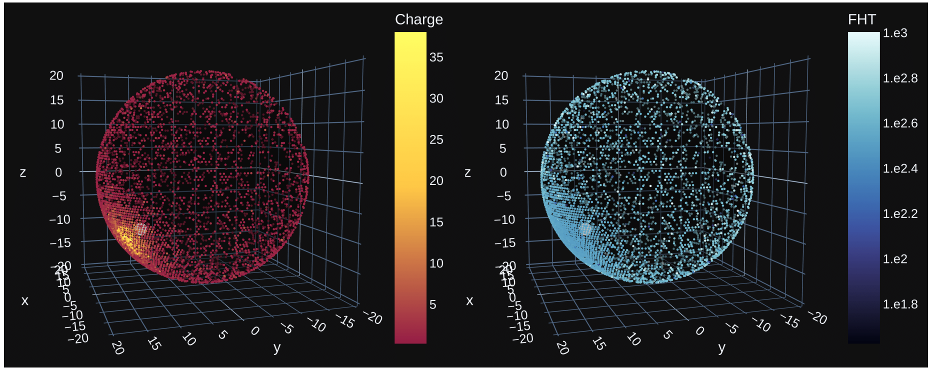
Single channel level

PMT waveform reconstruction



Event level

energy & vertex reconstruction



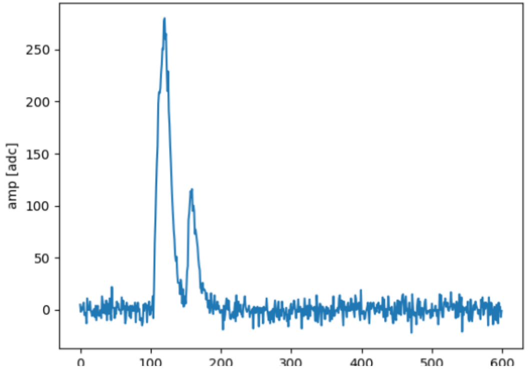
Machine learning for IBDs in JUNO

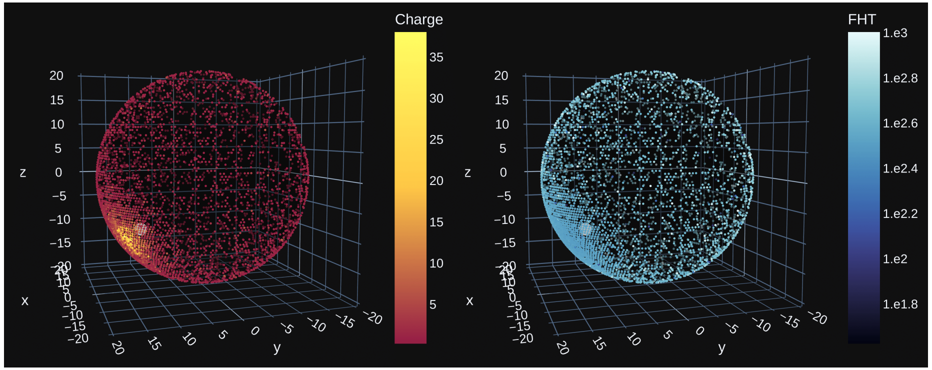
Single channel level

PMT waveform reconstruction

Event level

energy & vertex reconstruction

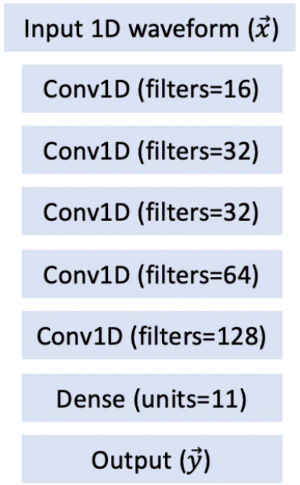


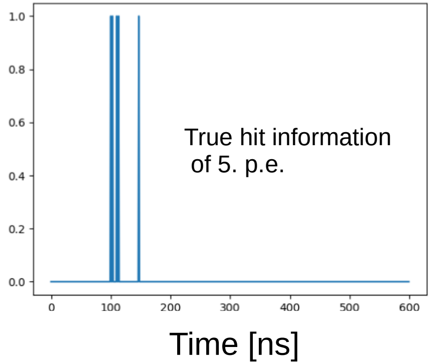


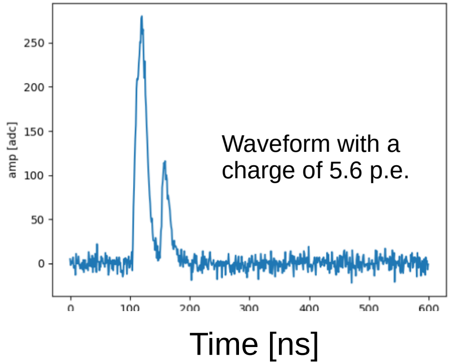
PMT waveform reconstruction with ML[1]

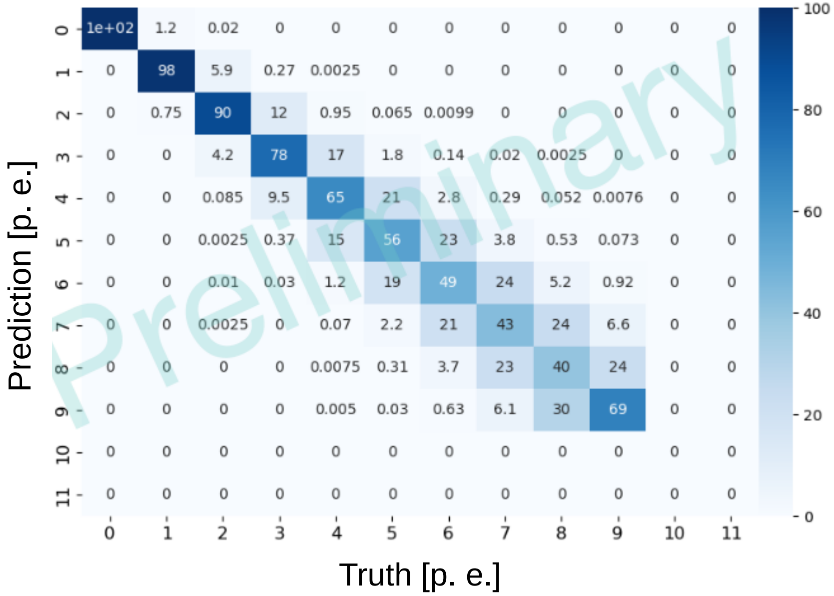
- Simulation waveforms with **known nPEs**
- **Classification**: photon counting
- 10 classes: {0, 1, 2, ..., 9} p.e.
- ~1 million of waveforms per class
- the **categorical crossing-entropy** as a loss function

- **ML approach**:
  - 1D waveform as input
  - 1D Convolutional Neural Network (CNN)









[1] G. Huang, TAUP 2023

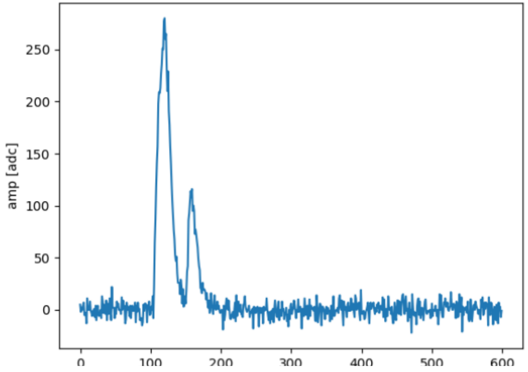
Machine learning for IBDs in JUNO

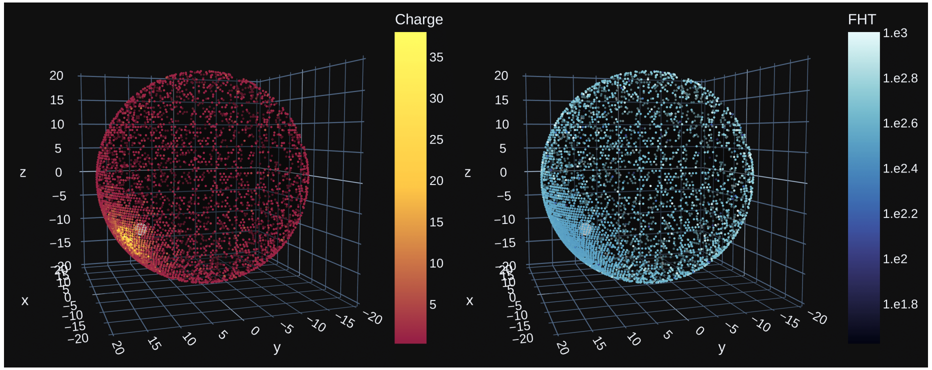
Single channel level

PMT waveform reconstruction

Event level

energy & vertex reconstruction





Datasets

- **Two datasets**: for training and for testing
- **Full** detector and electronics **simulation**[1]
- **Data description:**
  - positron events
  - uniformly spread in the volume of the central detector
  - $E_{kin} \in [0, 10]$ MeV. $E_{dep} = E_{kin} + 1.022$ MeV
- **Training dataset:**
  - 5 million events
  - **uniformly** distributed in kinetic energy E_{kin}
- **Testing dataset:**
  - subsets with **discrete** kinetic energies:
  - 0, 0.1, 0.3, 0.6, 1, 2, ..., 10 [MeV]
  - in total 140k events: each subset contains 10k

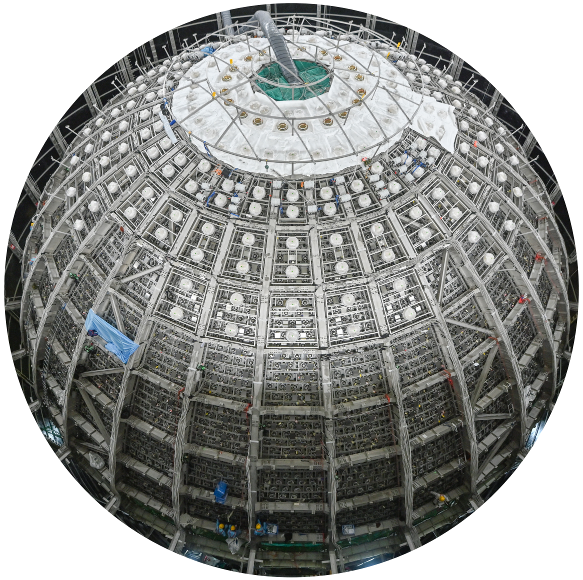
Charge at PMT

FHT at PMT

As **input** for ML models

[1]T. Lin et al. EPJ C **83**, 382 (2023)

Methods



I) charge & FHT at each PMT

II) resulting in **35224*** channels

*only LPMT are used

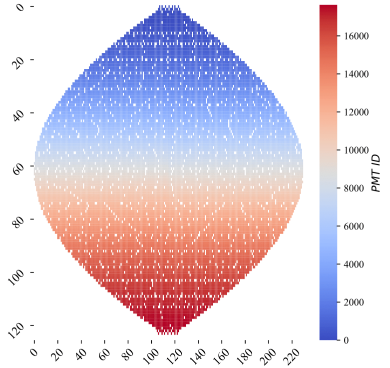
III) **dimensionality reduction** needed

IV) different methods to process the signals

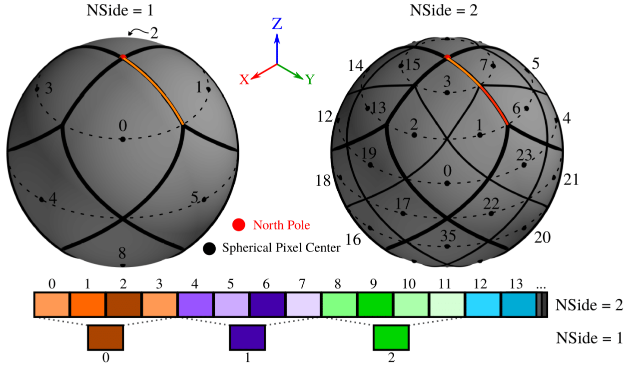
1) Aggregated features with
Boosted Desicion Trees (BDT)
Fully connected neural networks (FCDNN)

Description
Total accumulated charge
Number of fired PMTs
Center of charge
Charge distribution
Center of FHT
FHT distribution

2) Planar projection with
Convolutional Neural Networks (CNNs)

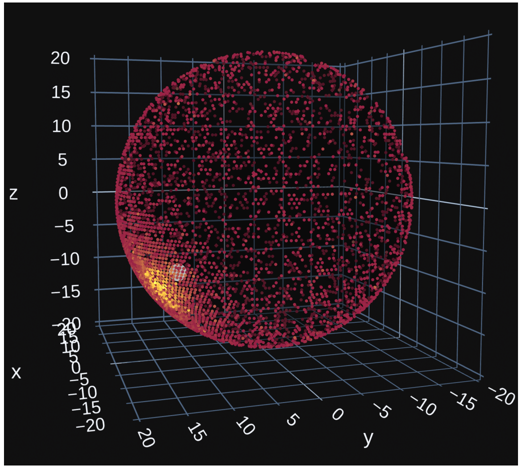


3) Graph neural networks (GNNs)



Complexity of the method

Aggregated features approach[1]

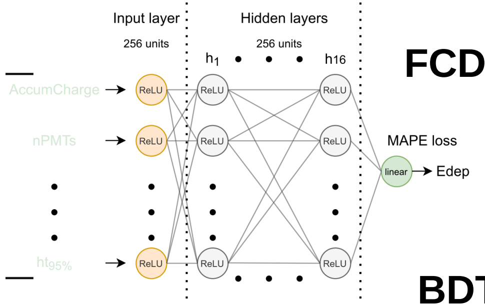


~35k channels

Aggregate information from the array of PMTs, using both **charge** and **FHT**

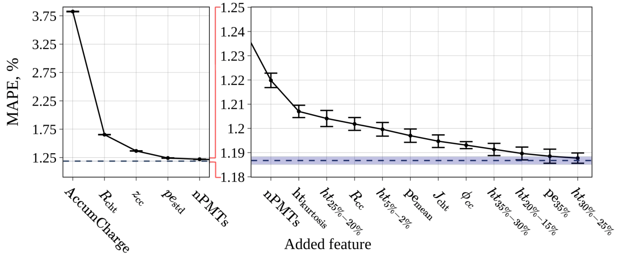
Notation	Description
AccumCharge	Total accumulated charge
nPMTs	Number of fired PMTs
$x_{cc}, y_{cc}, z_{cc}, R_{cc}, \theta_{cc}, \phi_{cc}, J_{cc}, \rho_{cc}, \gamma_z^{cc}, \gamma_y^{cc}, \gamma_x^{cc}$	Center of charge
$pe_{n\%}, pe_{mean}, pe_{std}, pe_{skew}, pe_{kurtosis}$	Charge distribution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

~100 features



FCDNN

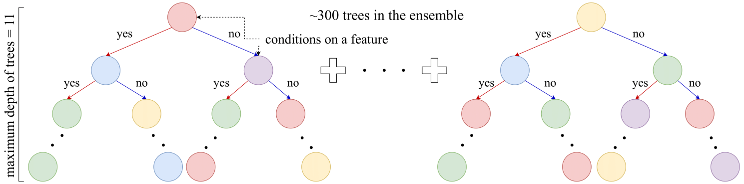
Further **feature selection** procedure performes with a greedy algorithm



~20 features

Result is **an input** for simple models: BDT & FCDNN

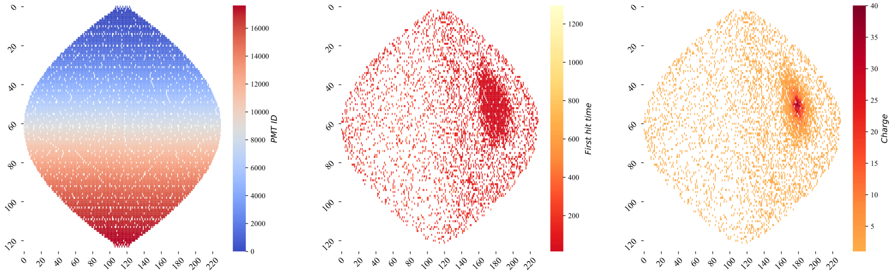
BDT



A. Gavrikov

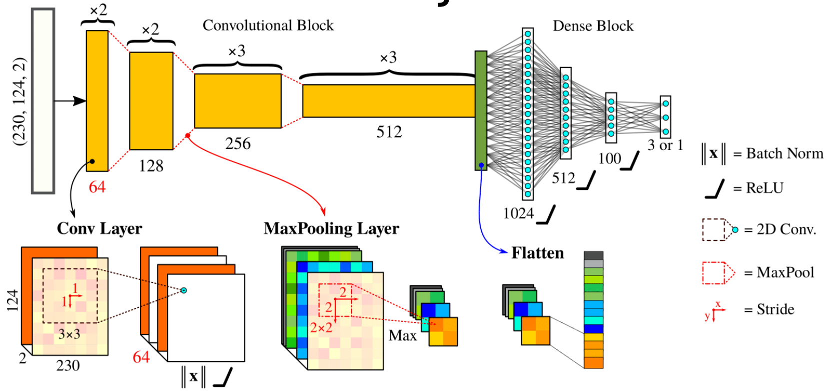
[1]A. Gavrikov et al. EPJ C **82**, 11 (2022): 1021

Planar projections with CNN[1]

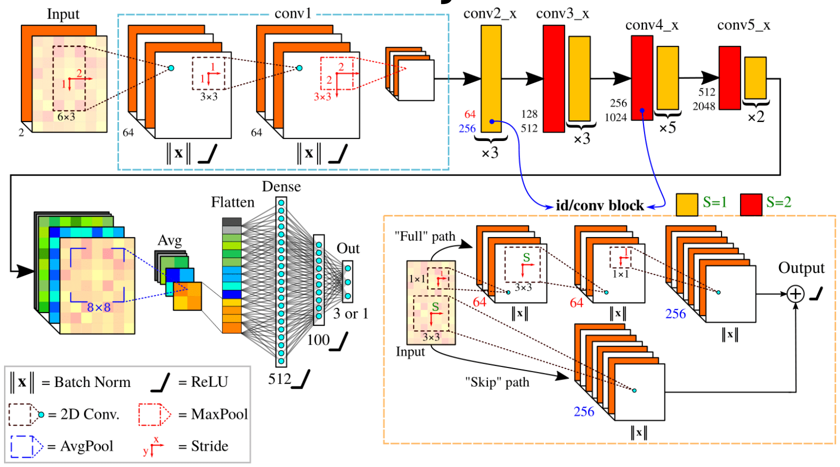


PMT id FHT Charge

VGG-J



ResNet-J



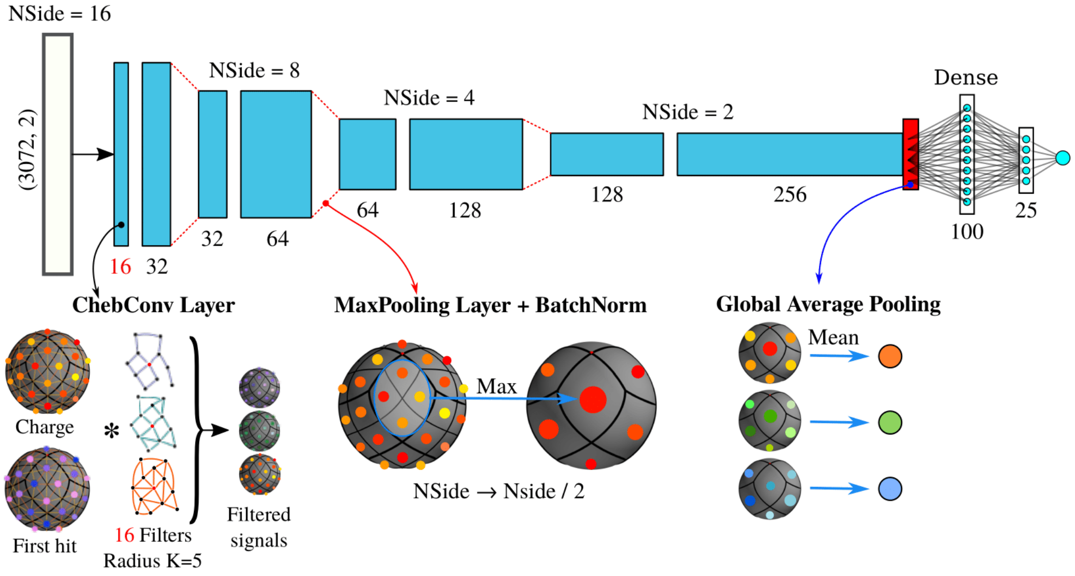
- **PMT-wise information** as input
- Planar projection for both FHT and charge
- Each PMT as **a pixel**
- Classical **convolution neural network** architectures:
  - **VGG**
  - **ResNet**
- Main **hyperparameters**

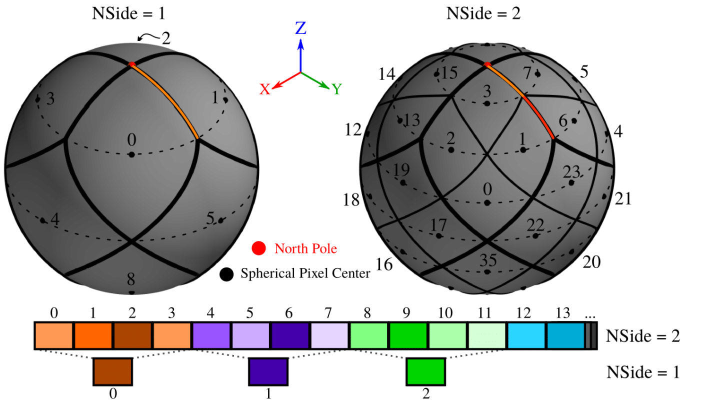
Parameter	Value
Loss	Mean Squared Error
Optimizer	Adam ($\beta_1 = 0.9$, $\beta_2 = 0.999$)
Learning rate	Linearly increasing from 0 to 10^{-3} during the first epoch, then exponential decay to 10^{-8}.
Batch size	64
N. Epochs	15

- **Issues** of the planar projection:
  - **no regular grid** can be constructed **on the sphere**
  - stretches or shrinks certain areas => **breaking translational invariance**
  - features that are close on the sphere can be far in the 2D projection

[1] Z. Qian et al. NIMA **1010** (2021): 165527

Graph neural network[1]





- **HEALPix** algorithm to divide the surface into **spherical pixels**
- N_{side} **controls** the discretization resolution
- N_{side} set to 16 => **3072** regions

- **Only neighboring** pixels *i*, *j* have **non-zero weights** W_{ij} defined as follows:

$$\mathrm{W}_{ij} = \exp\left(-\frac{\|\boldsymbol{v_i} - \boldsymbol{v_j}\|_2^2}{2\overline{d^2}}\right), \qquad \overline{d^2} = \frac{1}{|\mathcal{E}|}\sum_{(\boldsymbol{v_i},\boldsymbol{v_j})\in\mathcal{E}} \|\boldsymbol{v_i} - \boldsymbol{v_j}\|_2^2$$

- Main **hyperparameters**

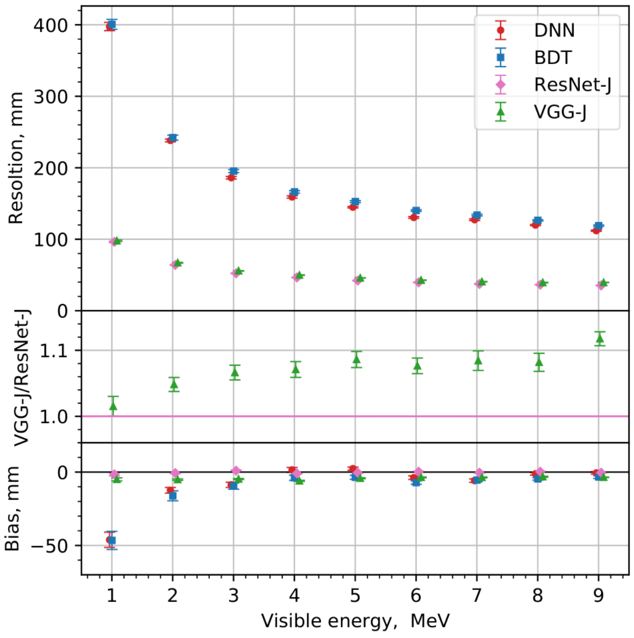
Parameter	Value
Loss	Mean Absolute Percentage Error
Optimizer	Adam ($\beta_1 = 0.8$, $\beta_2 = 0.9$)
Learning rate	Fixed at 0.001 for $N_{\text{epoch}} < 3$, then exponential decay at rate -0.1.
Batch size	64
N. Epochs	10

[1] Z. Qian et al. NIMA **1010** (2021): 165527

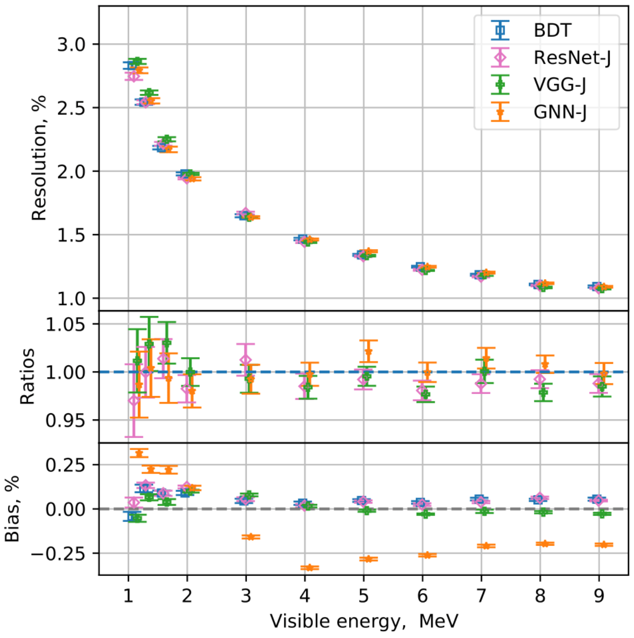
Results and comparisons[1,2,3]

- **Energy:**
  - **Similar performance of** both the **simple** models (aggregated features based)
  - and the **complex** ones (GNN and CNNs)
  - PMT-wise information **is not essential**
  - Simple models perform *faster*
- **Vertex:**
  - The **complex** models perform **better**
  - Signal granularities **are essential**
  - PMT-wise information **needed**

Vertex reconstruction



Energy reconstruction



[1]Z. Qian et al. NIMA **1010** (2021): 165527
[2]A. Gavrikov, et al. EPJ Web Conf. **251** (2021): 03014
[3]A. Gavrikov et al. EPJ C **82**, 11 (2022): 1021

Conclusions

- **JUNO** is at **the latest stage** of its construction
- **Many tools** are being developed to be prepared for **the first data**, including **ML** techniques
- This talk covered only the part related to **reactor anti-neutrinos**

- ML shows **good** and **promising** results for JUNO
- But still, there are **challenges to be addressed**:
  - adaptation to the real data
  - stability and reliability
  - interpretability
- **Calibration sources** data for fine-tuning and to test the models