Machine Learning methods for JUNO Experiment

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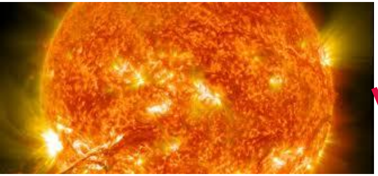
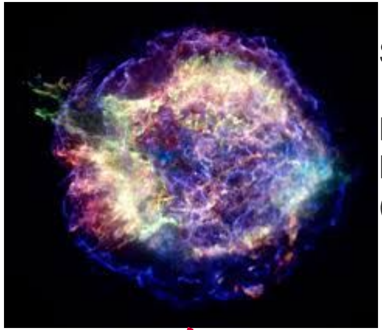
on behalf of JUNO collaboration

JUNO Physics Overview

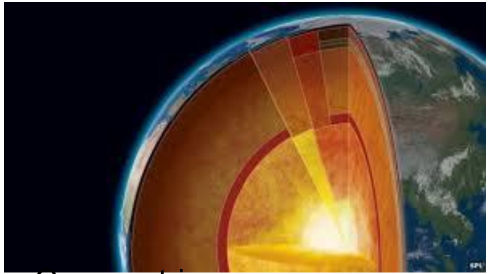


Solar neutrino



Supernova burst neutrino

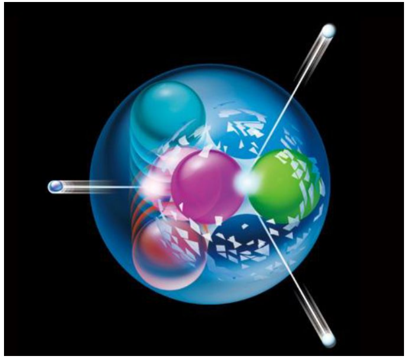
Diffuse Supernova Neutrino Background (DSNB)



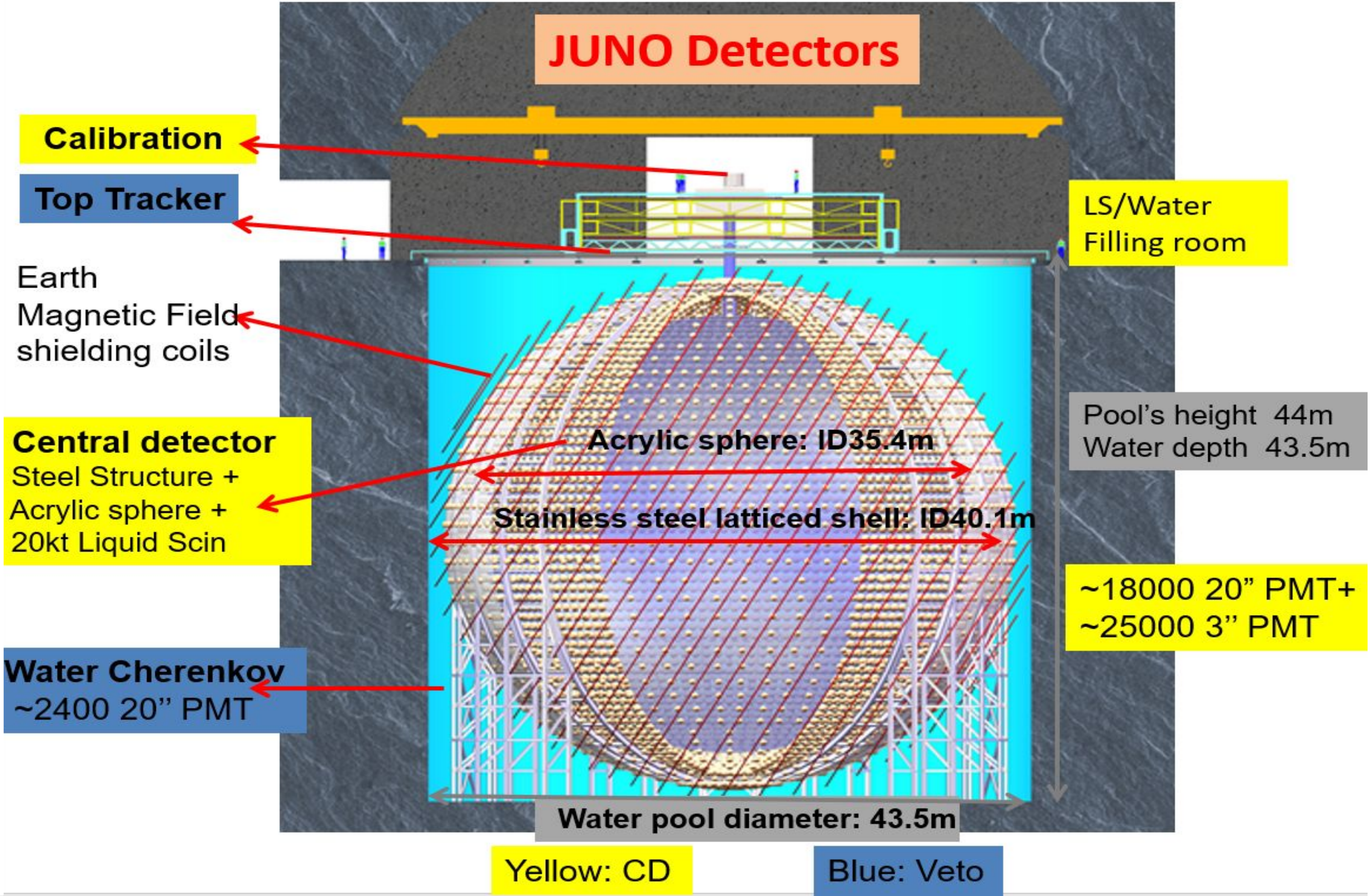
Geo-neutrino

Neutrino mass ordering

Precise measurement of neutrino parameters



Nucleon decay


JUNO Detectors
Calibration
Top Tracker
Earth
Magnetic Field
shielding coils
Central detector
Steel Structure +
Acrylic sphere +
20kt Liquid Scin
Water Cherenkov
~2400 20" PMT
LS/Water
Filling room
Pool's height 44m
Water depth 43.5m
~18000 20" PMT+
~25000 3" PMT
Acrylic sphere: ID35.4m
Stainless steel latticed shell: ID40.1m
Water pool diameter: 43.5m
Yellow: CD
Blue: Veto

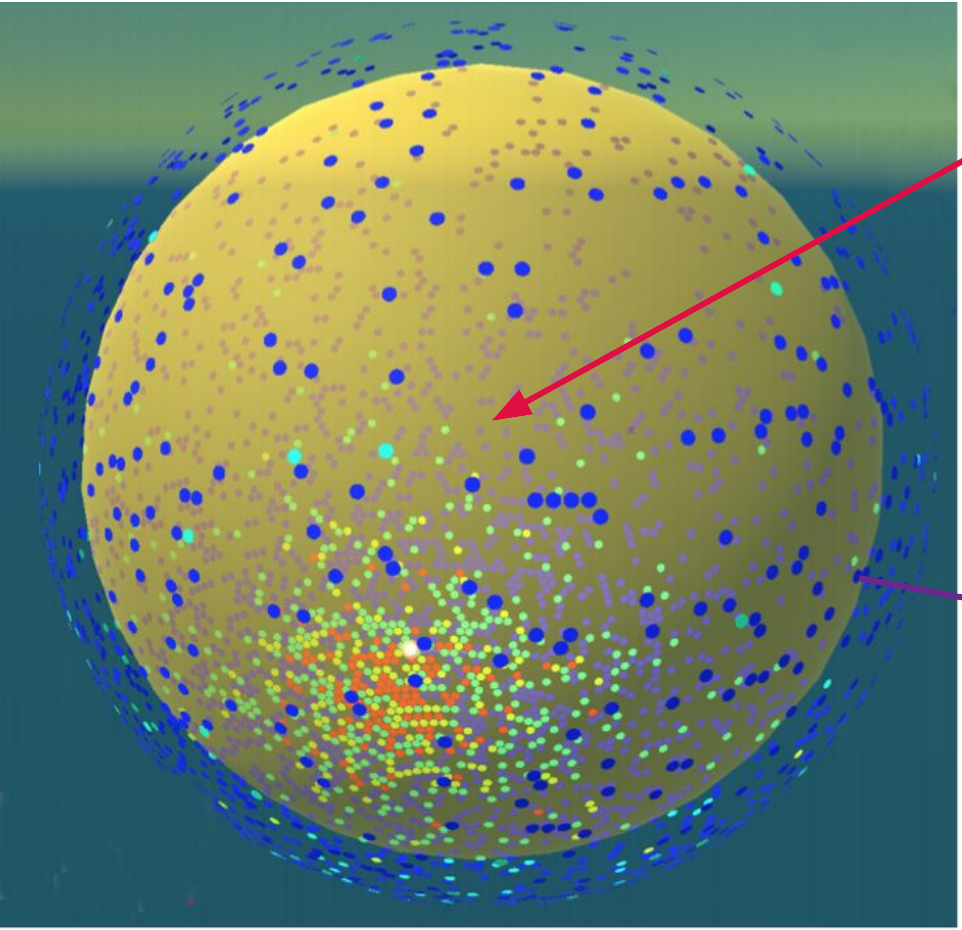
JUNO Collaboration

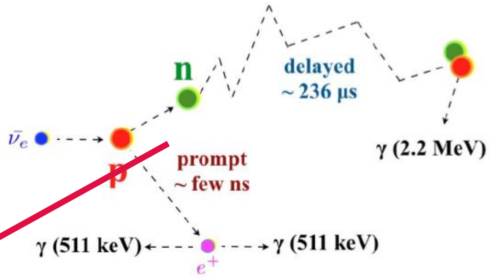
Collaboration established in 2014

17 country/regions, 77 institutions, ~600 collaborators by now

Country	Institute	Country	Institute	Country	Institute
Armenia	Yerevan Physics Institute	China	IMP-CAS	Germany	U. Mainz
Belgium	Universite libre de Bruxelles	China	SYSU	Germany	U. Tuebingen
Brazil	PUC	China	Tsinghua U.	Italy	INFN Catania
Brazil	UEL	China	UCAS	Italy	INFN di Frascati
Chile	PCUC	China	USTC	Italy	INFN-Ferrara
Chile	UTFSM	China	U. of South China	Italy	INFN-Milano
China	BISEE	China	Wu Yi U.	Italy	INFN-Milano Bicocca
China	Beijing Normal U.	China	Wuhan U.	Italy	INFN-Padova
China	CAGS	China	Xi'an JT U.	Italy	INFN-Perugia
China	ChongQing University	China	Xiamen University	Italy	INFN-Roma 3
China	CIAE	China	Zhengzhou U.	Latvia	IECS
China	DGUT	China	NUDT	Pakistan	PINSTECH (PAEC)
China	ECUST	China	CUG-Beijing	Russia	INR Moscow
China	Guangxi U.	China	ECUT-Nanchang City	Russia	JINR
China	Harbin Institute of Technology	Czech	Charles U.	Russia	MSU
China	IHEP	Finland	University of Jyvaskyla	Slovakia	FMPICU
China	Jilin U.	France	APC Paris	Taiwan-China	National Chiao-Tung U.
China	Jinan U.	France	CENBG	Taiwan-China	National Taiwan U.
China	Nanjing U.	France	CPPM Marseille	Taiwan-China	National United U.
China	Nankai U.	France	IPHC Strasbourg	Thailand	NARIT
China	NCEPU	France	Subatech Nantes	Thailand	PPRLCU
China	Pekin U.	Germany	FZJ-ZEA	Thailand	SUT
China	Shandong U.	Germany	RWTH Aachen U.	USA	UMD1
China	Shanghai JT U.	Germany	TUM	USA	UMD2
China	IGG-Beijing	Germany	U. Hamburg	USA	UC Irvine
China	IGG-Wuhan	Germany	FZJ-IKP		

Where we start





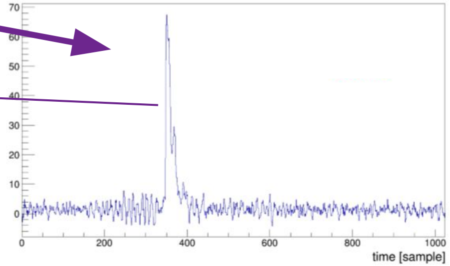
init particles deposite energy

photons

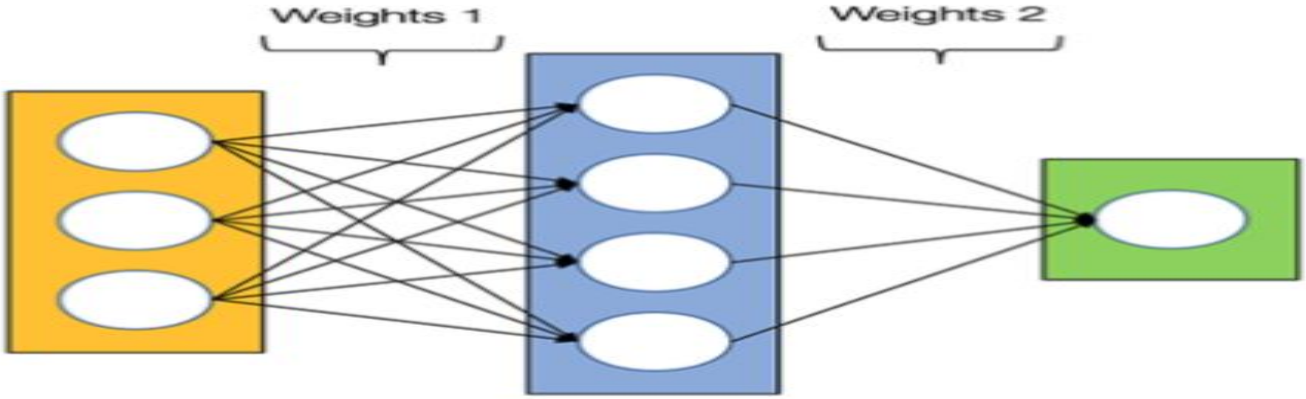
PMT pulse

PMT hit time and charge

Time
Charge



Principle of Neural Network: Structure



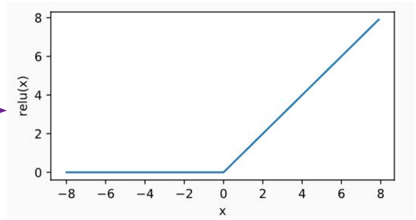
weights $\mathbf{W_1}$ bias $\mathbf{b_1}$ weights $\mathbf{W_2}$ bias $\mathbf{b_2}$

input $\mathbf{X}$ → hidden layer $\mathbf{H}$ → output $\mathbf{Y}$

$$\mathbf{H} = \sigma(\mathbf{W_1 X + b_1})$$
$$\mathbf{Y} = \sigma(\mathbf{W_2 H + b_2})$$

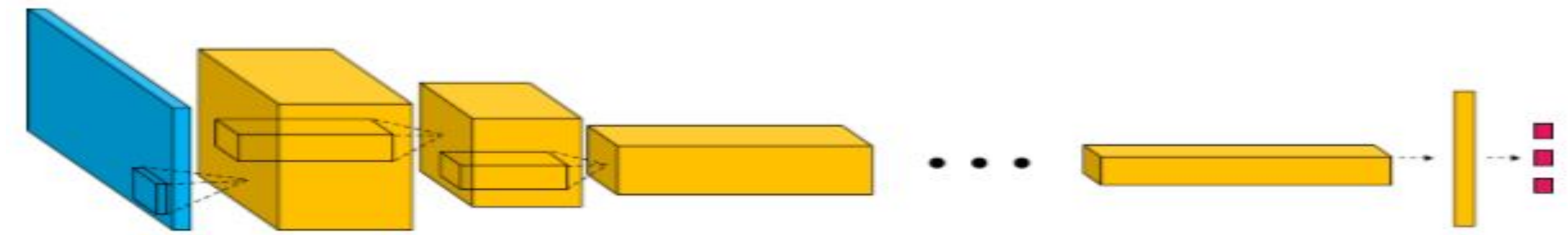
$$\mathbf{Y} = \mathbf{F}(\mathbf{X};\ \mathbf{W_1}, \mathbf{W_2}, \mathbf{b_1}, \mathbf{b_2})$$

σ: activation function,
provide non-linearity,
usually we use ‘ReLU’



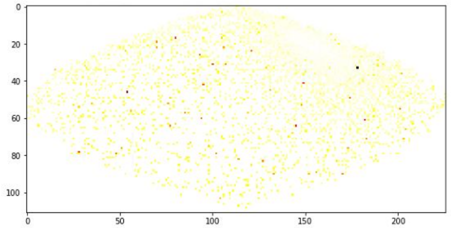
Usually we have much more than one hidden layer, and use some special layers (CNN,RNN,etc)

Principle of Neural Network: Feed Forward

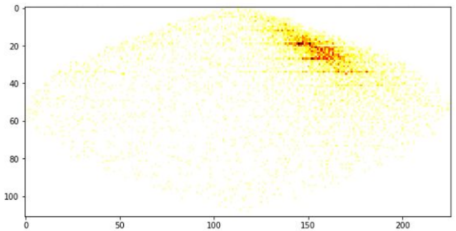


initialize parameters $\mathbf{W_1,W_2...b_1,b_2...}$

time



charge



f(time, charge, PMT position;**W**,**b**)

(0.0079,-0.0012, 0.0042)m

initial parameters not good. We need to improve them

position: (-3.3, 8.8, 11.6) m
energy: 4.56MeV

Principle of Neural Network: Loss Function

Real position: **Y**

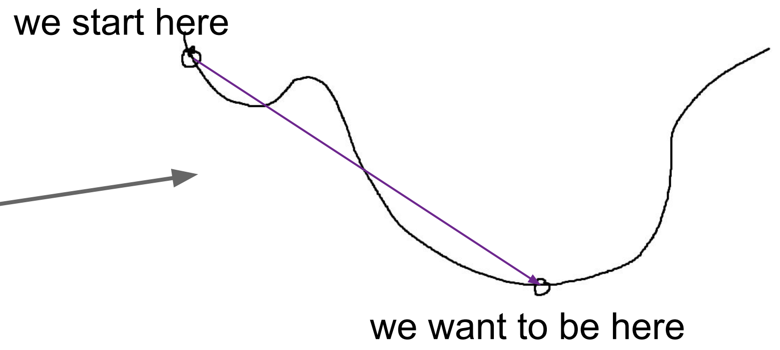
Neural network output: $\mathbf{F(X;W_1...W_i,b_1...b_i)}$

How to evaluate the network output:

$L = ||\mathbf{F(X;W_1...W_i,b_1...b_i) - Y}||^2$

$\Downarrow$

minimize L



$\Downarrow$

gradient descent:

$$\theta = \theta - \alpha \frac{\partial L}{\partial \theta}$$

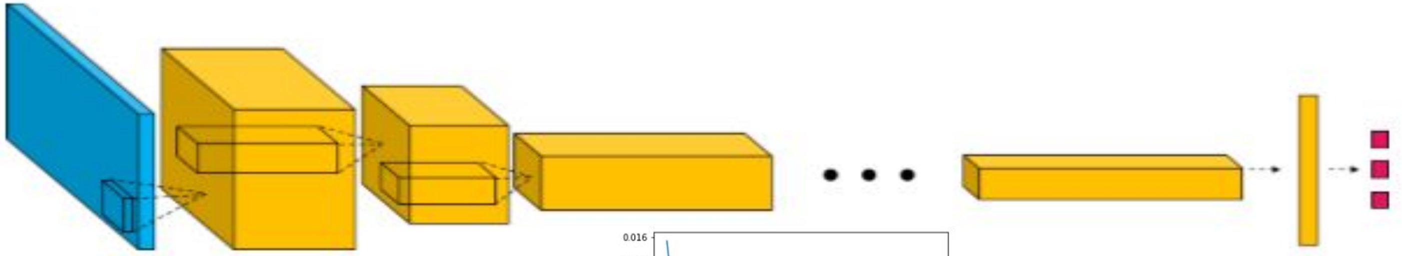
$$\theta = W_1, \ldots b_1, \ldots$$

Principle of Neural Network: Back Propagation

forward prop

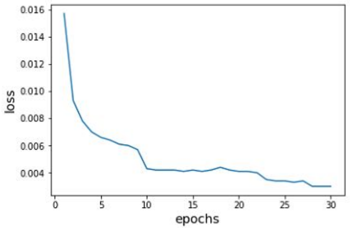
$\sigma(\mathbf{W_1 X + b_1})$ ...... $\sigma(\mathbf{W_i H_i + b_i})$

X



F(X) ⇒ L(F(X),Y)

$$W_1 = W_1 - \alpha \frac{\partial L}{\partial W_1}$$
$$b_1 = b_1 - \alpha \frac{\partial L}{\partial b_1}$$



$$W_i = W_i - \alpha \frac{\partial L}{\partial W_i}$$
$$b_i = b_i - \alpha \frac{\partial L}{\partial b_i}$$

back prop

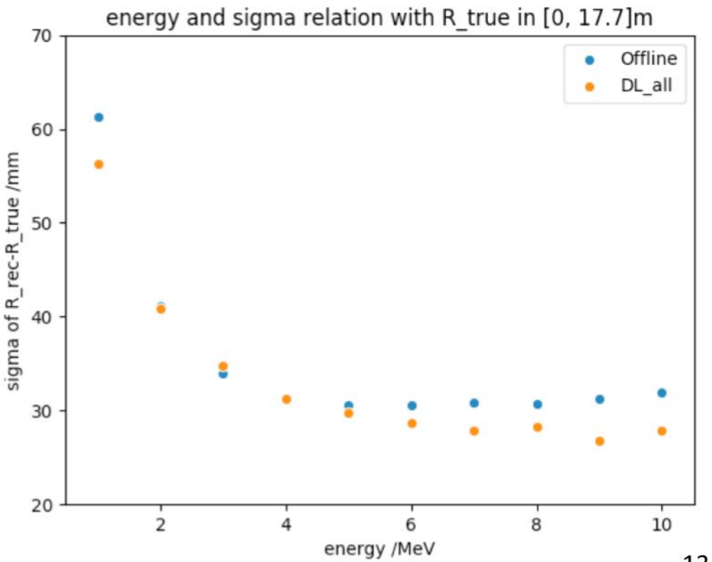
Vertex and Energy Reconstruction (low energy)

- Training data sample: 2M e^+ uniform in the detector, kinetic enegy continuous in (1,10) MeV
- Test data sample: 10k e^+ events at each discrete energy points
- No TTS, no dark noise

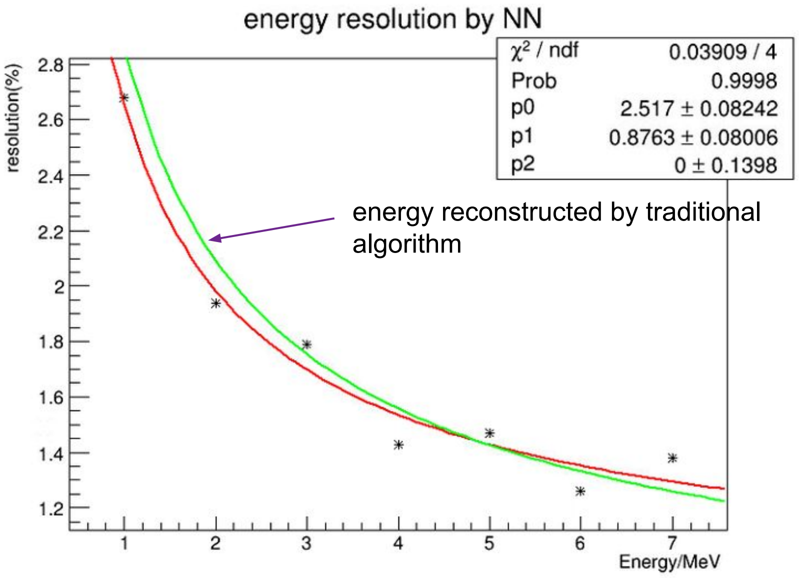
- Vertex resolution: 5.6cm@1MeV
- Energy resolution: $\sqrt{a^2 + (1.6b)^2} = 2.88\%$

$$\sqrt{\left(\frac{a}{\sqrt{E}}\right)^2 + b^2 + \left(\frac{c}{E}\right)^2} \simeq \sqrt{\left(\frac{a}{\sqrt{E}}\right)^2 + \left(\frac{1.6\,b}{\sqrt{E}}\right)^2 + \left(\frac{c}{1.6\,\sqrt{E}}\right)^2}, \quad (2.12)$$

Ref: An, et al. "Neutrino Physics with JUNO."



Sigma is fitted with the $R_{rec} - R_{true}$ in range [-250, 250] mm

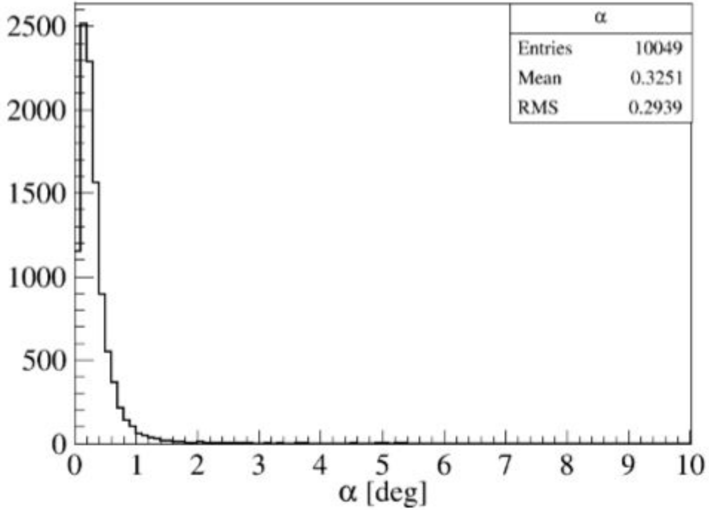


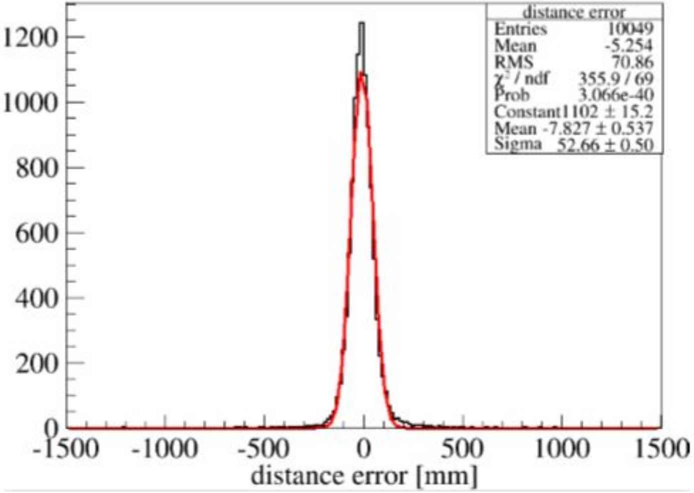
Muon Reconstruction

- Cosmic muon is one of the main source of background in JUNO, so we want to reconstruct the muon track with high accuracy and efficiency

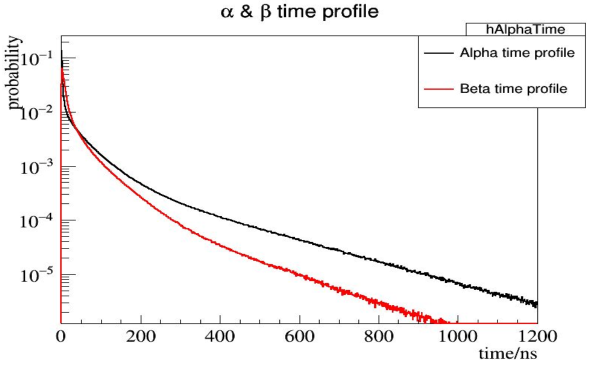
- Angle error α: RMS ~ 0.3 degree
  - The angle between reconstructed direction and real direction
- Distance error: ~60 mm
  - Distance means the distance from the trajectory line to the center of the detector
  - Distance error = $\text{distance}_{\text{reconstructed}} - \text{distance}_{\text{real}}$

- Reconstruction efficiency > 99%



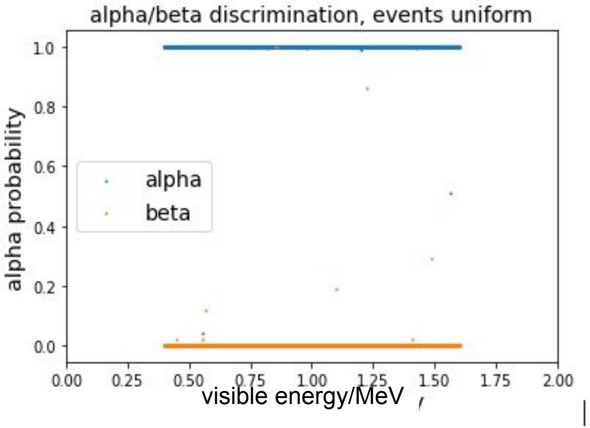


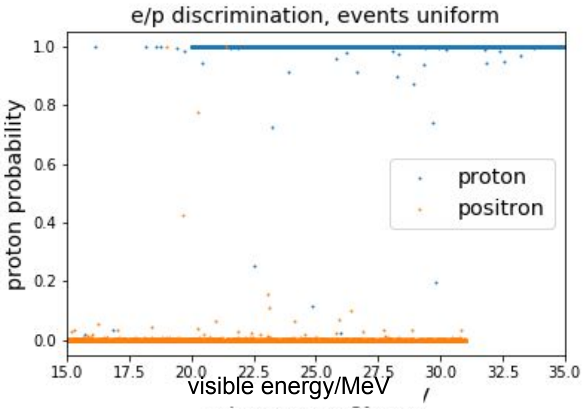
Pulse Shape Discrimination



- Here we use time profile of one event as input, instead of time & charge image
- alpha/beta:
  - 0.1M samples
  - study the probability to identify alphas in U/Th chain
- e/p discrimination:
  - 0.1M samples
  - study the performance in DSNB energy window

- Almost 100% discrimination for alpha/bata and e/p





Some discussion

- We train the neural network with MC data
- We need to reconstruct real data
- There is always a gap between simulation and reality.
- Calibration data is limited, can’t meet the requirement to train the network.

- a new idea:
  - Refer to the idea of transfer learning
  - We can use MC data to train our network, then use calibration data to fine tune the network.

Summary

- Machine learning method is proved to be helpful in the JUNO experiment
- Wide applications:
  - low energy event reconstruction
  - muon reconstruction
  - particle identification
- Some issues:
  - Still some information lose: Spherical symmetry, PMT pulse information, etc
  - Bias between MC and real data

Back Up