Machine learning for energy reconstruction in JUNO

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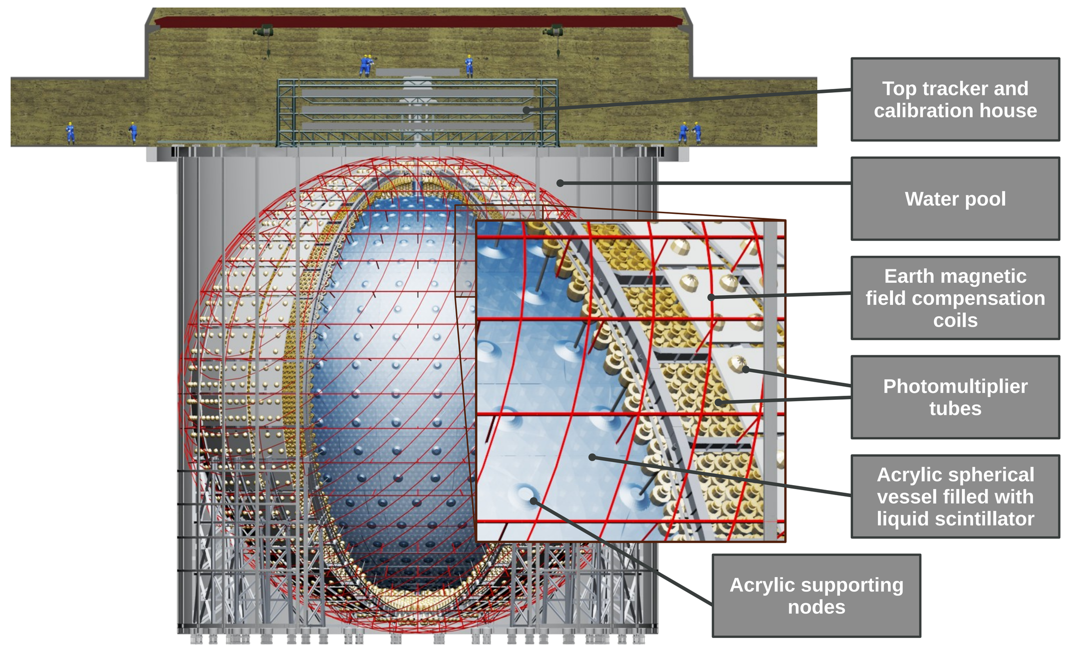
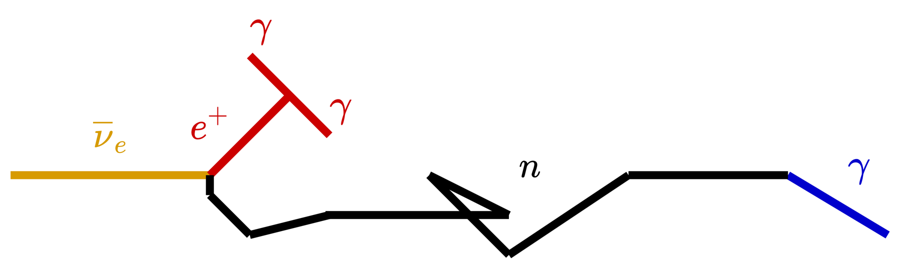
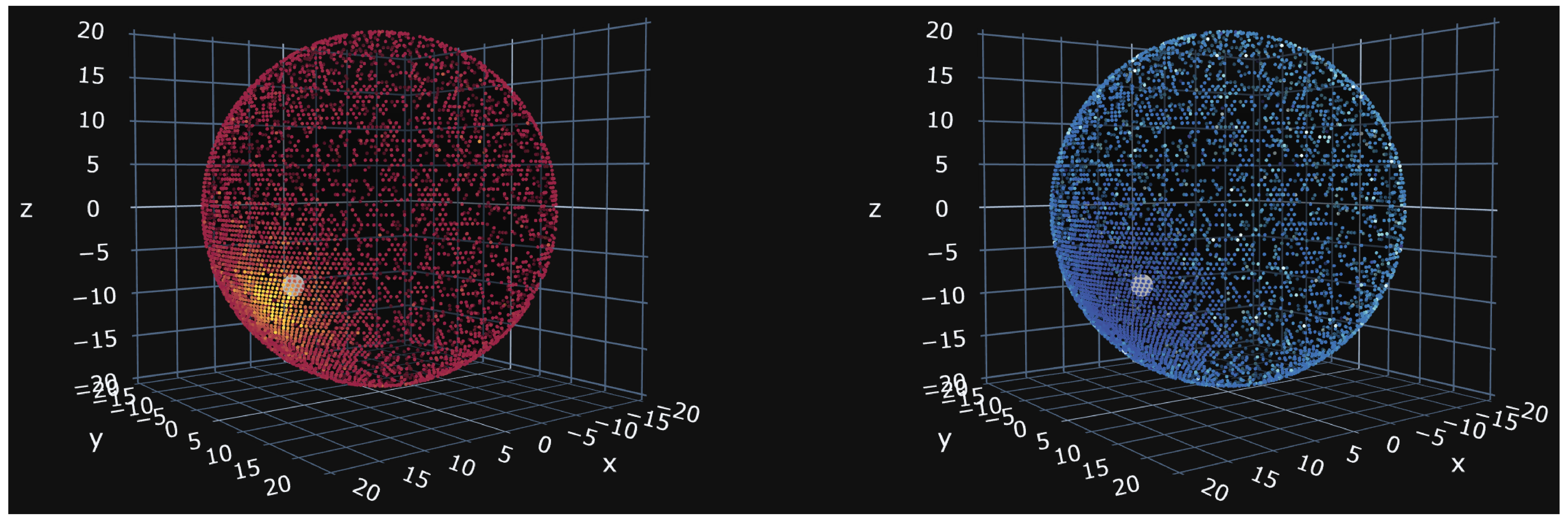
Introduction

1. Jiangmen Underground Neutrino Observatory (JUNO):
   - multipurpose experiment;
   - 53 km away from 8 reactor cores in China;
   - ~600-meter deep underground;
   - data taking expected in ~2023.
2. The main goals of JUNO:
   - neutrino mass ordering (3σ in 6 years);
   - precise measure of oscillation parameters $\sin^2\theta_{12}, \Delta m^2_{21}, \Delta m^2_{31}$.
3. The Central Detector:
   - detection channel: $\overline{\nu}_e + p \to e^+ + n$;
   - deposited energy converts to optical light.
   - the largest liquid scintillator detector: 20 kt;
   - 77.9% photo-coverage: 18k 20", 26k 3" photo-multiplier tubes (PMTs);





Problem statement



Example of an event seen by 20" PMTs for a positron of 6.165 MeV deposited energy. The color represents the accumulated charge in PMTs (left) and PMT activation time (right). The gray sphere: the primary vertex.

Avaliable information:
- Charge at each PMT;
- First Hit Time (FHT) at each PMT;
- PMT position.

We want to provide:

Deposited energy E_{dep} with resolution 3% @ 1 MeV

Data description

To train model and to evaluate model performance we prepared two datasets generated by the full detector Monte Carlo method using the official JUNO software:

1. **Training dataset:**
   - 5 million positron events;
   - uniformly distributed in kinetic energy E_{kin};
   - uniformly spread in the volume of the central detector (in LS);
   - $E_{\text{kin}} \in [0, 10]$ MeV. $E_{\text{dep}} = E_{\text{kin}} + 1.022$ MeV.
2. **Testing dataset:**
   - subsets with discrete kinetic energies;
   - 0 MeV, 0.1 MeV, 0.3 MeV, 0.6 MeV, 1 MeV, 2 MeV, ..., 10 MeV;
   - uniform spatial distribution;
   - each subset contains about 100 thousand events.

Aggregated features

We use 30 different aggregated features, which summarizing information from PMTs:

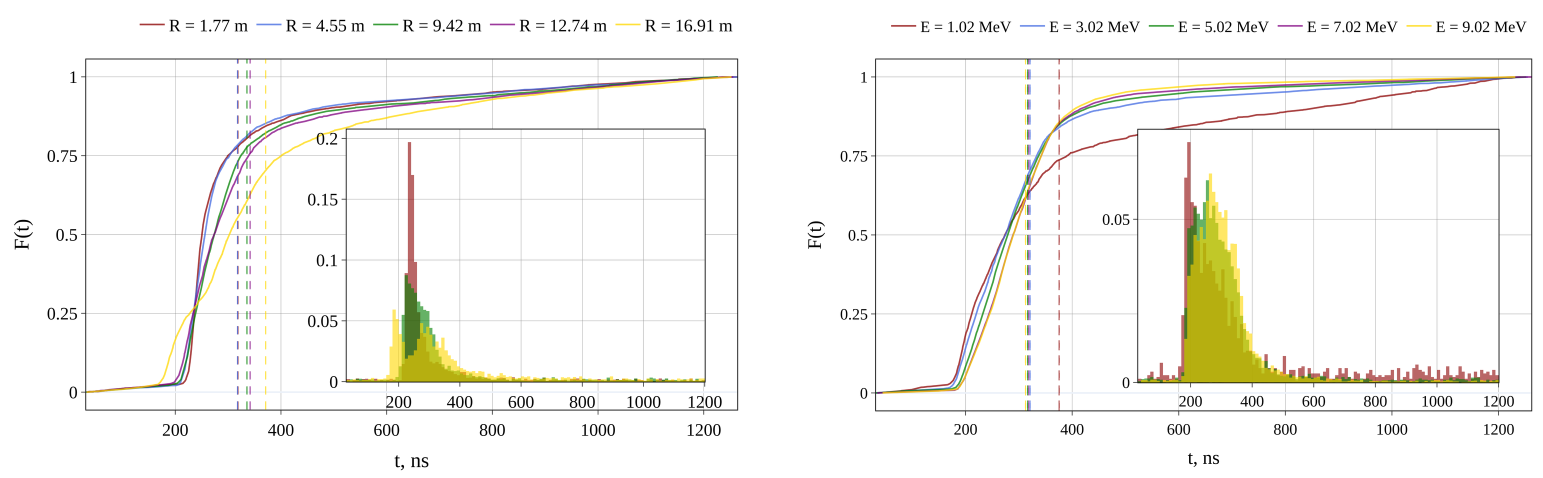
1. `AccumCharge` — the accumulated charge on fired PMT (roughly proportional to deposited energy);
2. `nPMTs` — the total number of fired PMTs;
3. $R_{cc} = \sqrt{x^2_{cc} + y^2_{cc} + z^2_{cc}}$;
4. $R_{cht} = \sqrt{x^2_{cht} + y^2_{cht} + z^2_{cht}}$;
5. $\rho_{cc} = \sqrt{x^2_{cc} + y^2_{cc}}$;
6. $\rho_{cht} = \sqrt{x^2_{cht} + y^2_{cht}}$;
7. `pe_mean` — mean of charge distribution (CD);
8. `pe_std` — standard deviation of CD;
9. `pe_skew` — skewness of CD;
10. `pe_kurtosis` — kurtosis of CD;
11. Percentiles of FHT distribution: {2%, 5%, 10%, ..., 95%}.

Where $(x_{\text{cc}}, y_{\text{cc}}, z_{\text{cc}})$ and $(x_{\text{cht}}, y_{\text{cht}}, z_{\text{cht}})$ defined as follows:

$$(x_{\text{cc}}, y_{\text{cc}}, z_{\text{cc}}) = \mathbf{r}_{\text{cc}} = \frac{\sum_i^{N_{\text{PMTs}}} \mathbf{r}_{\text{PMT}_i} n_{\text{p.e.},i}}{\sum_i^{N_{\text{PMTs}}} n_{\text{p.e.},i}}$$

$$(x_{\text{cht}}, y_{\text{cht}}, z_{\text{cht}}) = \mathbf{r}_{\text{cht}} = \frac{1}{\sum_i^{N_{\text{PMTs}}} \frac{1}{t_{\text{ht},i}+c}} \sum_i^{N_{\text{PMTs}}} \frac{\mathbf{r}_{\text{PMT}_i}}{t_{\text{ht},i}+c},$$

Examples of cumulative distribution functions and probability density functions for FHT distribution:

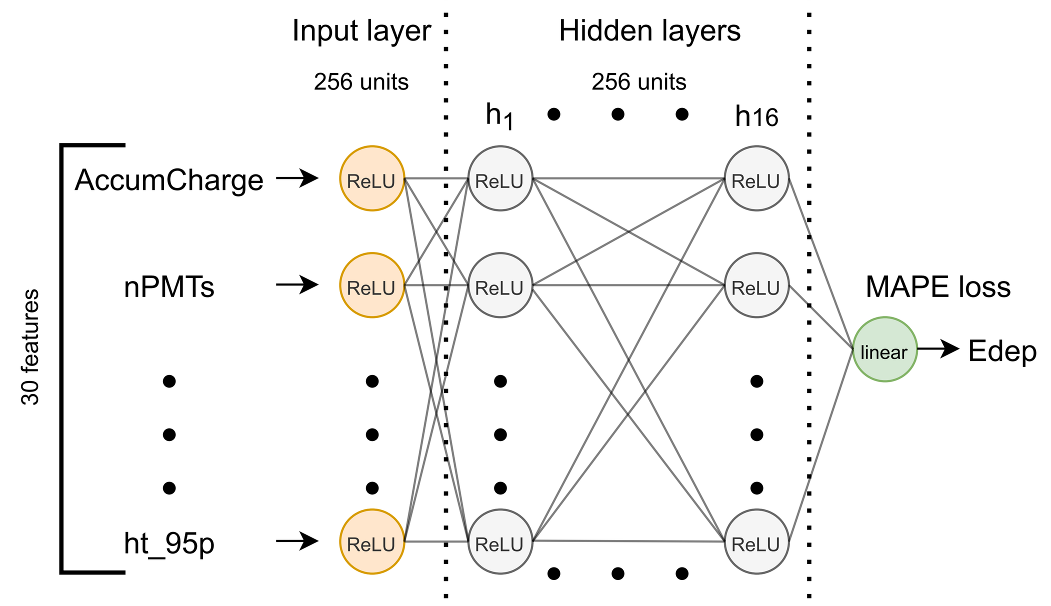


(a) $E_{\text{kin}} = 1$ MeV, R varied. (b) $R = 16$ m, E_{kin} varied.

Dashes lines illustrate mean values.

Model description

Fully Connected Deep Neural Network (FCDNN):



- Optimizer: adam;
- Training with early stopping;
- Validation dataset: 400k events;
- Learning rate scheduler: expon. decay.

Results

<u>Metrics</u>:

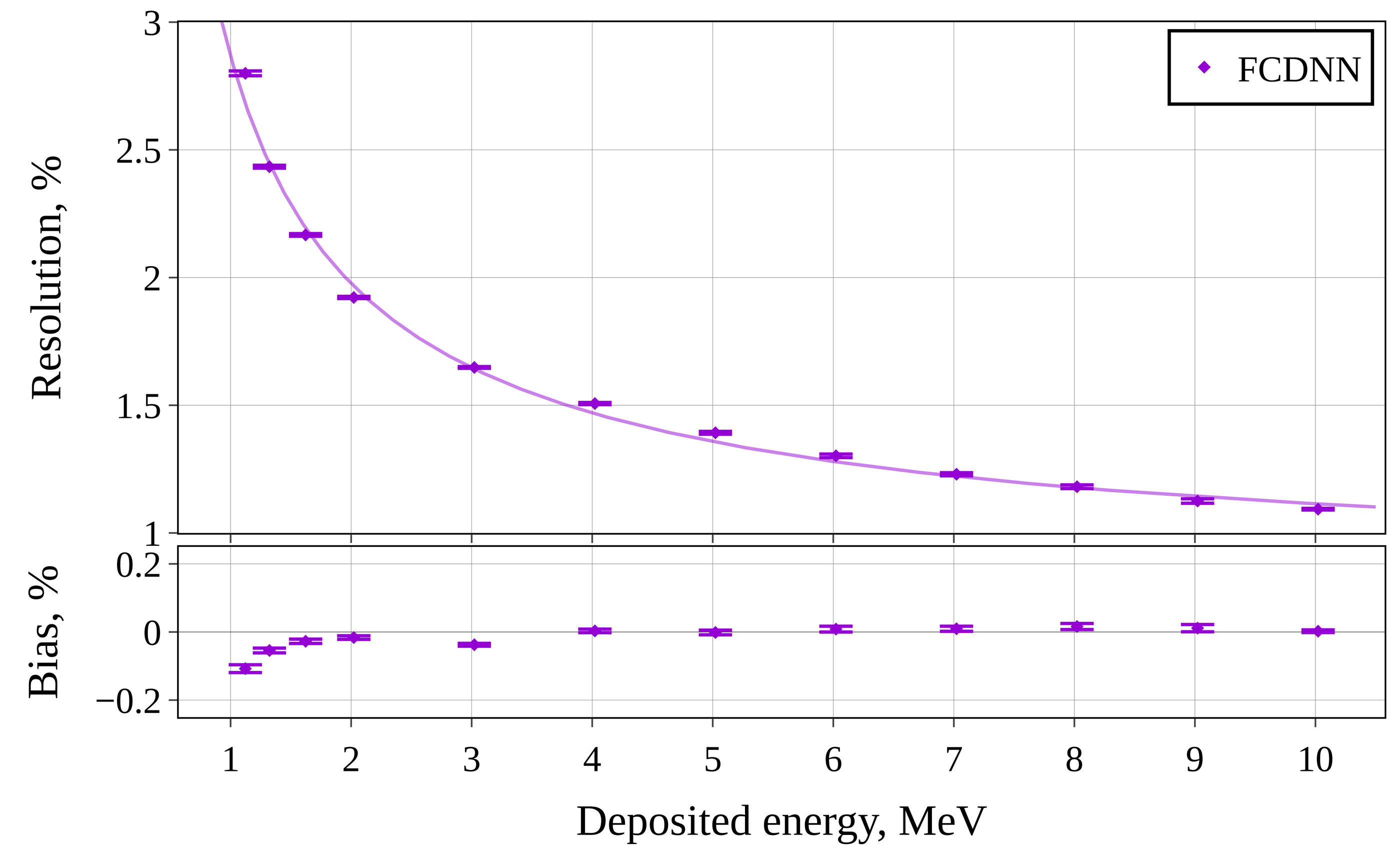
1. Defined by a Gaussian fit of the $E_{\text{predicted}} - E_{\text{dep}}$ distributions;
2. Resolution: σ / E_{dep}, where σ — standard deviation of the fit;
3. Bias μ / E_{dep}, where μ — mean of the fit.

<u>Parameterization</u>:

$$\frac{\sigma}{E_{\text{dep}}} = \sqrt{\left(\frac{a}{\sqrt{E_{\text{dep}}}}\right)^2 + b^2 + \left(\frac{c}{E_{\text{dep}}}\right)^2}$$

The JUNO requirement to the determination of neutrino mass ordering could be translated into a convenient requirement on an effective resolution $\tilde{a}$ as:

$$\tilde{a} \equiv \sqrt{(a)^2 + (1.6 \times b)^2 + \left(\frac{c}{1.6}\right)^2} \leq 3\%$$



Model	$a \pm \Delta a$	$b \pm \Delta b$	$c \pm \Delta c$	$\tilde{a} \pm \Delta\tilde{a}$
FCDNN	2.32 ± 0.14	0.83 ± 0.05	1.47 ± 0.29	2.82 ± 0.03

Summary

FCDNN with aggregated features:
- required $\tilde{a} \leq 3\%$ achieved;
- great computation speed.

References

[1] F. An *et al.*, *Neutrino Physics with JUNO*, J. Phys. G **43** (2016) no.3, 030401.
[2] A. Abusleme *et al.*, *JUNO Physics and Detector*, arXiv:2104.02565.
[3] Z. Qian, V. Belavin, V. Bokov, R. Brugnera, A. Compagnucci, *et al.*, *Vertex and energy reconstruction in JUNO with machine learning methods*, Nucl. Instrum. Meth. A **1010** (2021), 165527.
[4] A. Gavrikov, F. Ratnikov, *The use of Boosted Decision Trees for Energy Reconstruction in JUNO experiment*, EPJ Web Conf. **251** (2021), 03014.