Vertex and Energy Reconstruction in JUNO with Machine Learning Methods

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Introduction

The ability to accurately reconstruct events in JUNO is critical to the success of the experiment: the energy resolution is expected to be $3\%/\sqrt{E(\mathrm{MeV})}$, and the vertex resolution is expected to better than 10 cm.

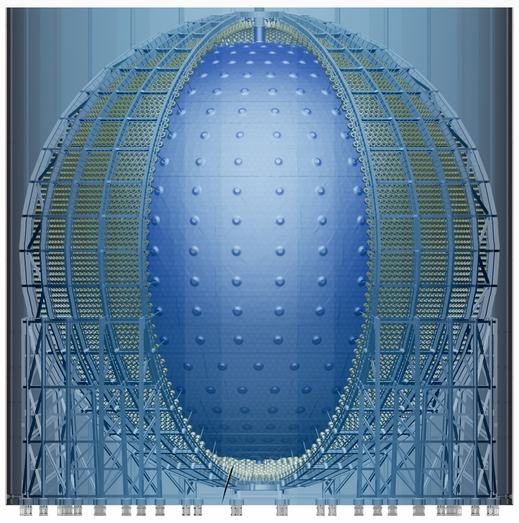

Fig. 1: Schematic view of JUNO detector.

In this poster, four machine learning (ML) methods applied to the vertex and the energy reconstruction will be presented, including Boosted Decision Trees (BDT), Deep Neural Networks (DNN), Convolution Neural Networks (CNN), and Graph Neural Networks (GNN).

Data Preparation

The training and testing of neural networks has been performed on Monte Carlo (MC) samples generated with the official JUNO software and further processed to include the most relevant effects of the electronics response.
Training: 5 million MC e^+, momentum from 0-10 MeV, uniformly distributed within the central detector (CD).
Testing: MC e^+, momentum (0, 1, ..., 10) MeV, 11 * 10k events, uniformly distributed within the CD.

Parameter	Name	Type [×size]
True information		
Event ID	int	
Deposited energy	`Edep`	float
Average position of the energy deposition	`x_edep`, `y_edep`, `z_edep`	float × 3
Aggregated information		
Total number of hits	`nHits`	int
Center of charge coordinates	`x_cc`, `y_cc`, `z_cc`	float × 3
Radial component of center of charge	`r_cc`	float
Average of the first hit time	`ht_mean`	float
Standard deviation of the first hit time	`ht_std`	float
PMT-wise measured information		
Number of hits (photoelectrons)	`npe`	int
Hit time of the first detected photon	`hittime`	float
Position		float × 3
Type		20″ Hamamatsu / 20″ NNVT

Fig. 2: Data structure of a single event.

Simple models : BDT and DNN

The models of BDT and DNN are trained with aggregated information, pre-calculated from PMT signal, which allows getting reasonable predictions at a very low computational cost.

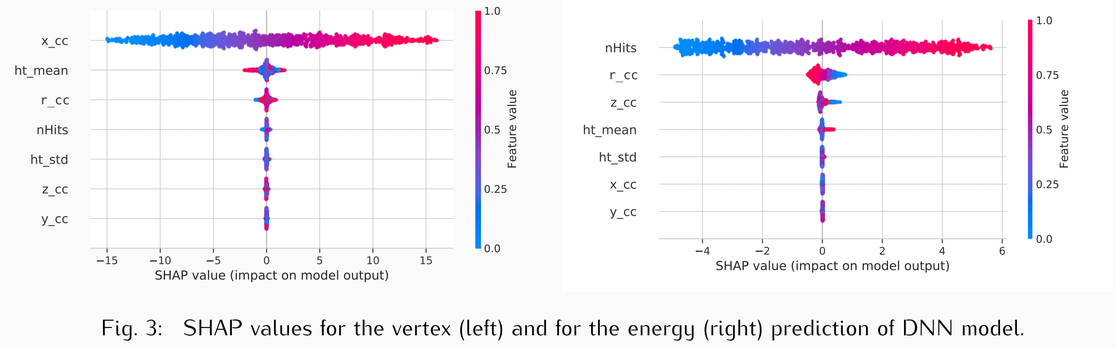

Fig. 3: SHAP values for the vertex (left) and for the energy (right) prediction of DNN model.

Both BDT and DNN have beed tuned for JUNO.

Complex models : CNN and GNN

The CNN and GNN are more complex and able to deal with more granular input, therefore provide better precision by processing the full information.

CNN
- Project CD and build a 230×124×2 matrix;
- Both VGG and ResNet networks architecture have been tuned for JUNO.

GNN
- Encode the topology of the input domain in a graph structure;
- Adapt the DeepSphere model.

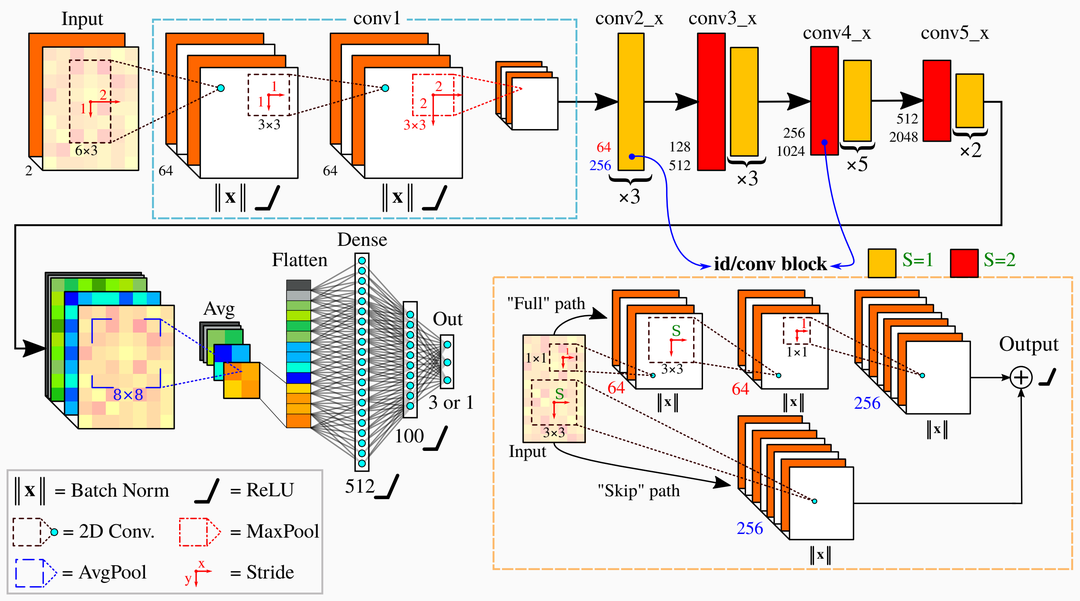

Fig. 4: ResNet network architecture for CNN reconstruction with 53 weight layers.

Reconstruction Performance

Architecture	BDT	DNN	Planar CNN ResNet-J	Planar CNN VGG-J	Spherical GNN-J
Prediction time, sec/100k events	<1	<1	235	155	110
Prediction batch size	10^5	10^5	100	100	10^4
Number of weights		6625	3.8×10^7	2.6×10^7	3.5×10^5
Memory occupied by weights, MB	17	0.073	146	100	4.2
Training time, min/1M events	5	1000	1543	840	265
Training batch size		700	64	64	64

Fig. 5: Prediction time and memory usage for different models.

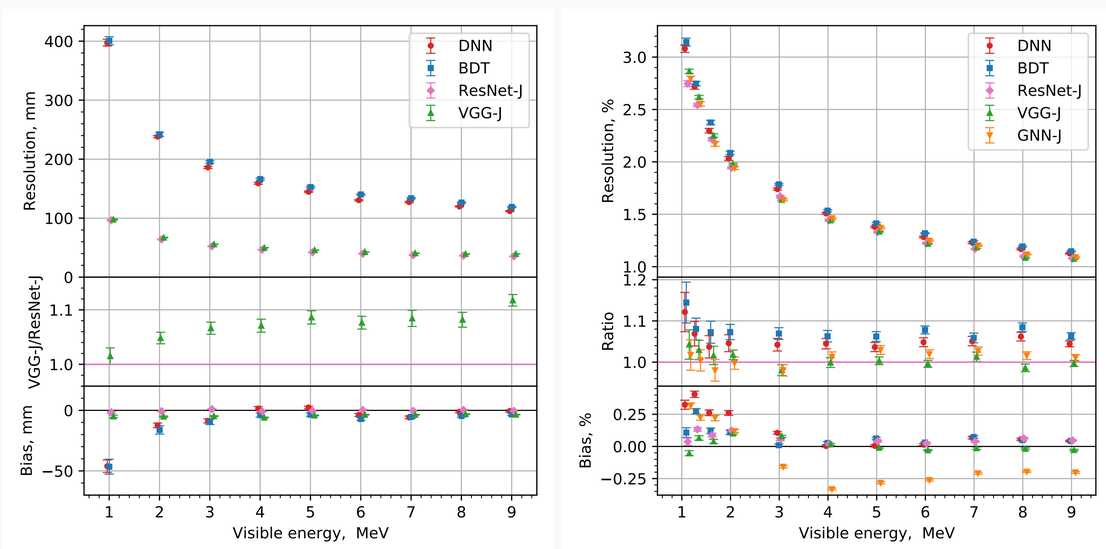

Fig. 6: Vertex (left) and energy (right) reconstruction performance for different models.

Conclusion We demonstrate that ML approaches achieve the necessary level of accuracy for reaching the physical goals of JUNO.

- For the first time, ML has been applied to event reconstruction of large liquid scintillator detectors with a large number of PMTs, and the results look very promising.
- PMT-wise information is crucial for vertex reconstruction, the best resolution is around $\sigma_{x,y,z} = 10$ cm at $E_{\mathrm{vis}} = 1$ MeV ;
- Simple models (BDT, DNN), using much less input, exhibit not much worse energy resolution when compared to the complex models (CNN, GNN).
- The simple models are much faster and are advised to be used for the tasks not requiring the finest possible resolution.
- The results are preliminary and more studies are needed.

More detail can be found in **arXiv:2101.04839**.

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