Vertex Reconstruction in JUNO-TAO Using Deep Learning

On behalf of the JUNO collaboration

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Introduction

❖ Taishan Antineutrino Observatory :

- A ton-level liquid scintillator detector
- Full coverage of Silicon PhotoMultipliers
- Operates at -50℃ hence eliminates the dark noise
- Photoelectron yield : 4500 p.e./Mev
- High energy resolution: ~ 2% at 1 MeV

❖ Physics Goals :

- Provide model-independent reference spectrum for JUNO
- Provide a benchmark measurement to examine nuclear database
- Search for light sterile neutrinos with a mass scale around 1 eV
- Verification of the detector technology for reactor monitoring

TAO Detector

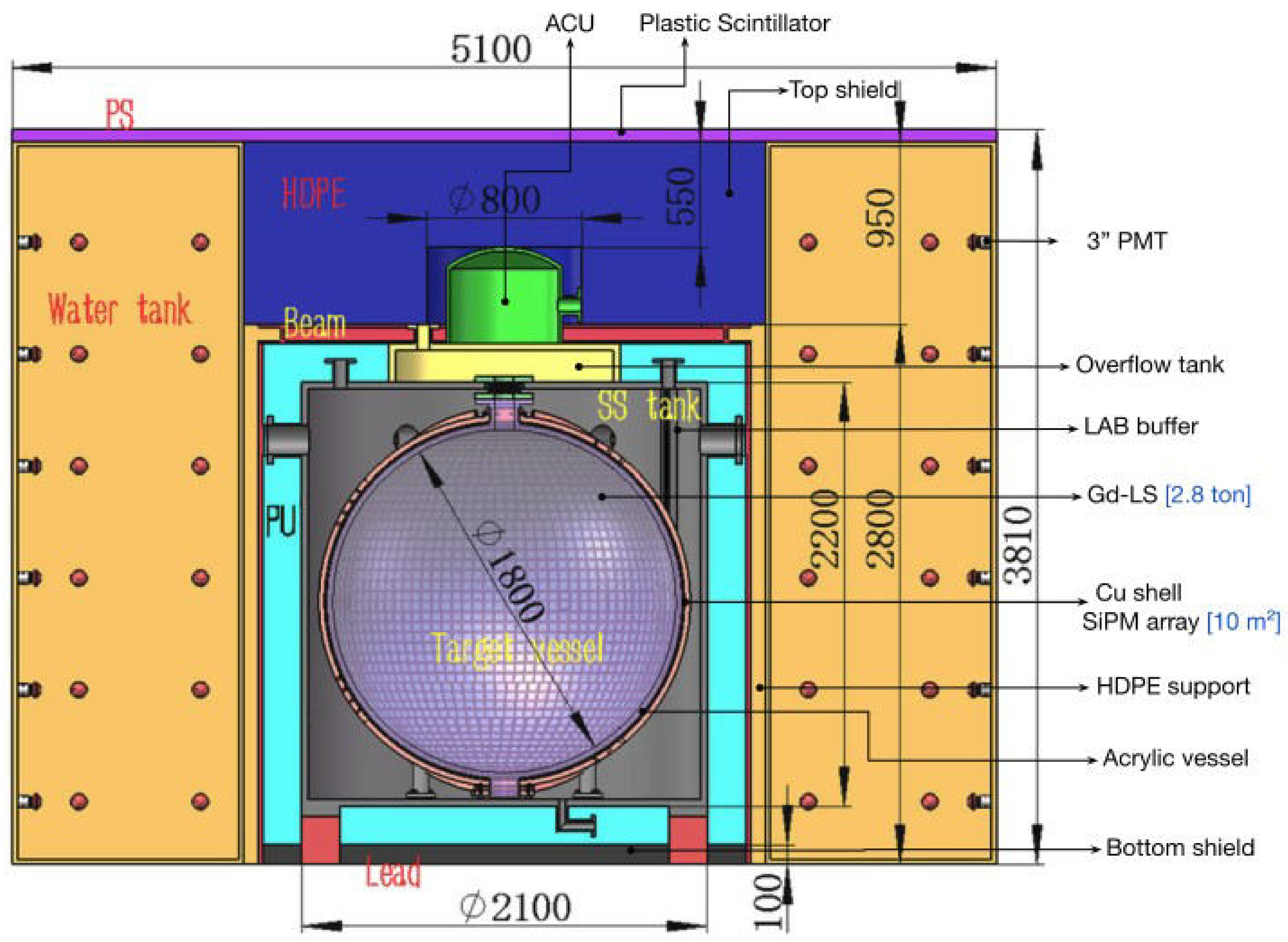
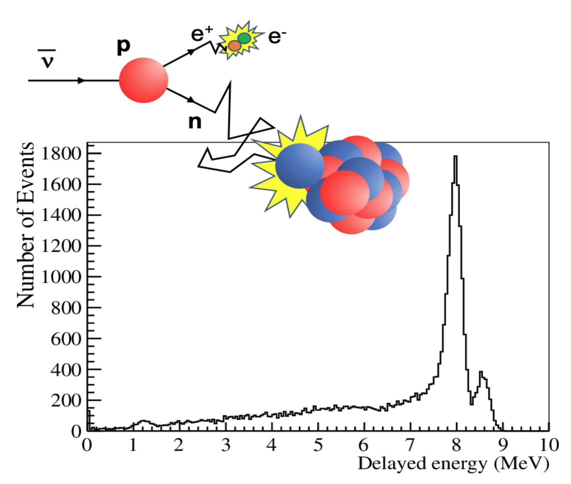


Fig. 1: Schematic view of TAO detector

Signal

- $\bar{\nu}_e$ signature = prompt scintillation ($e^+ e^-$) + delayed neutron capture
- $E_{\bar{\nu}_e} \approx E_{e^+} + (m_n - m_p + m_e)$

TAO ~ 2000 inverse β-decay (IBD) events/day



Data Preparation

Dataset : Monte Carlo (MC) samples from TAO offline software

Events : Uniformly distributed within the central detector (CD)

Momentum : 0 - 10 MeV Training : 80k MC e^+ Testing : 20k MC e^+

Table 1: Data Structure of a single event

Parameter	Name	Type [x size]
True information		
Event ID	evtID	int
Average position of energy deposition	GdLSEdepX GdLSEdepY GdLSEdepZ	float x 3
Model input		
Total number of hits	nHits	int
First hit time	firstHitTime	float
SiPM-wise information		
SiPM ID of the Hits	SiPMHitID	int
Hit timings of detected photons	SiPMHitT	float
Position		float x 3

Graph Neural Netwok (GNN) Architecture

GNNs are complex models that are able to deal with more granular input, providing better precision by processing the full information.

- The detector topology is encoded into graph (No.of nodes = 4024)
- The input data: graph + node features are passed onto residual blocks in between every convolutional layer.
- The features are then flattened and sent to a Fully Connected Network (FCN) that predicts the vertices.

The hyperparameters used in the model are summarized in table 2.

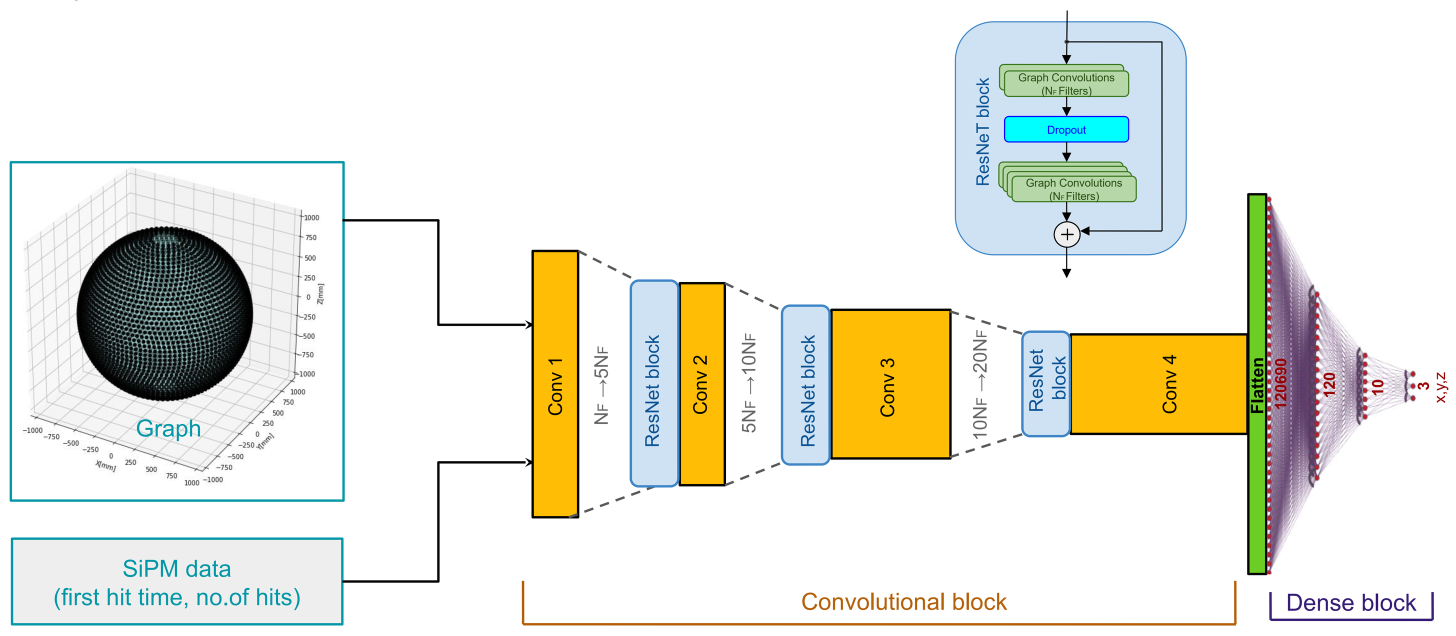


Fig. 2: GNN Architecture

Parameter	Values
Loss	Mean Squared Error
Optimizer	Adam
Learning rate	0.0005
Batch size	10
N.Epochs	20

Table 2: Hyperparameters of GNN

Results

- The reconstructed event positions and the deposited energy positions are compared (Fig 3.).
- The vertex resolution in each direction is estimated from the gaussian fit (Fig 4).
- The observed mean values are consistent with zero and the resolutions are similar in the three directions.

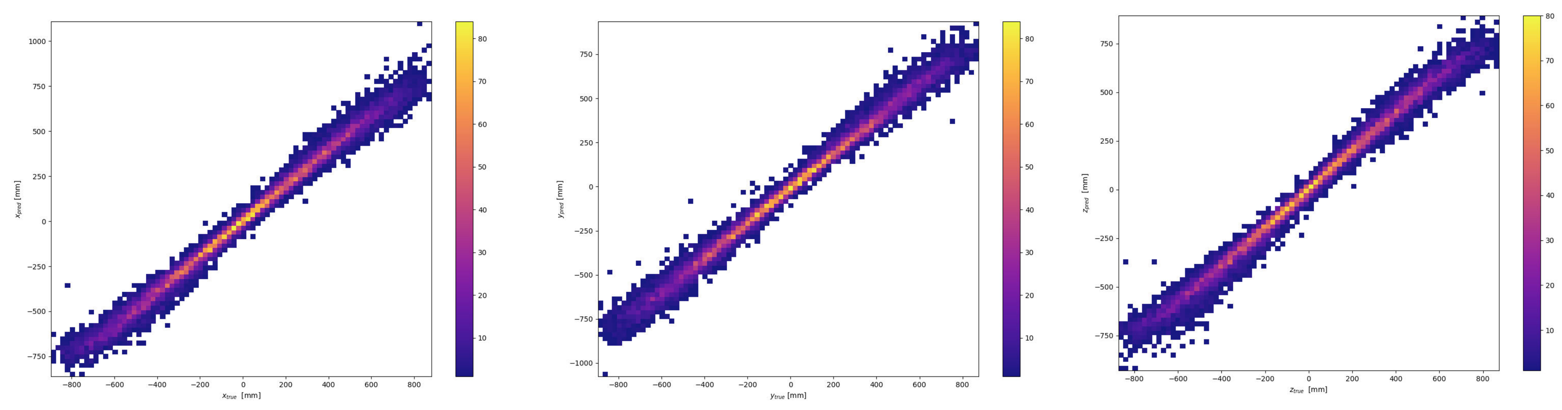


Fig. 3: True vs predicted positions

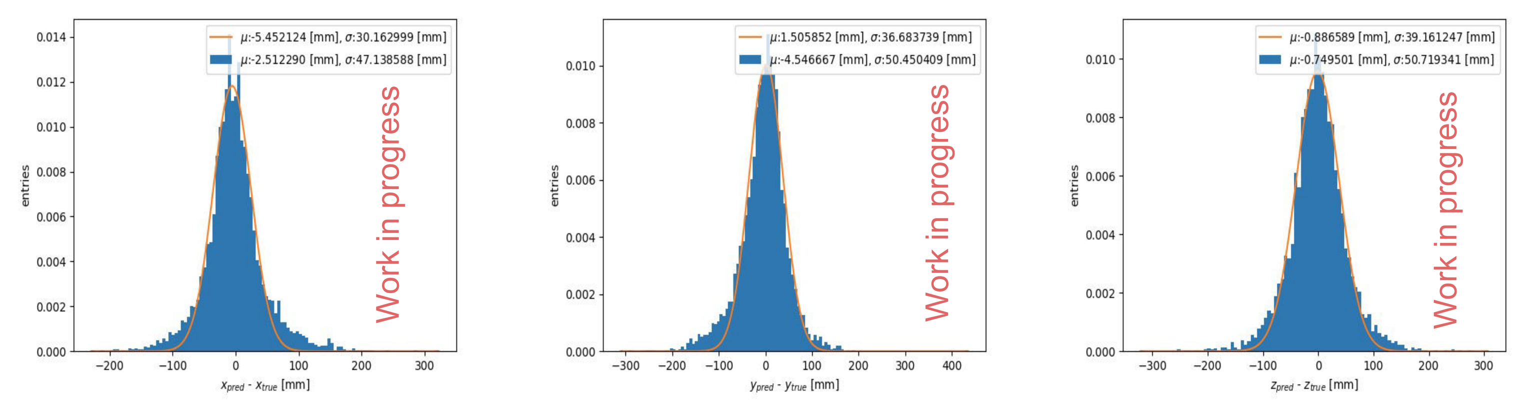


Fig. 4: Vertex resolution in each direction at 1 MeV

Conclusions

The work demonstrates the general applicability of Deep Learning techniques for vertex reconstruction.

- GNN incorporates the detailed detector topography, the SiPM-wise information is very crucial for vertex reconstruction.
- Resolution achieved by the model @1 MeV :
  σ_x = 30.16 mm, σ_y = 36.68 mm, σ_z = 39.16 mm

References

[1] Fengpeng An et al. Improved Measurement of the Reactor Antineutrino Flux and Spectrum at Daya Bay. Chin. Phys., C41(1):013002, 2017.

[2] A. Abusleme et al. TAO Conceptual Design Report: A Precision Measurement of the Reactor Antineutrino Spectrum with Sub-percent Energy Res-olution. 5 2020.

[3] Zhou, J., Cui, G., Zhang, Z., Yang, C., Liu, Z. & Sun, M. (2018). Graph Neural Networks: A Review of Methods and Applications (cite arxiv:1812.08434).

[4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015. arXiv:1512.03385.