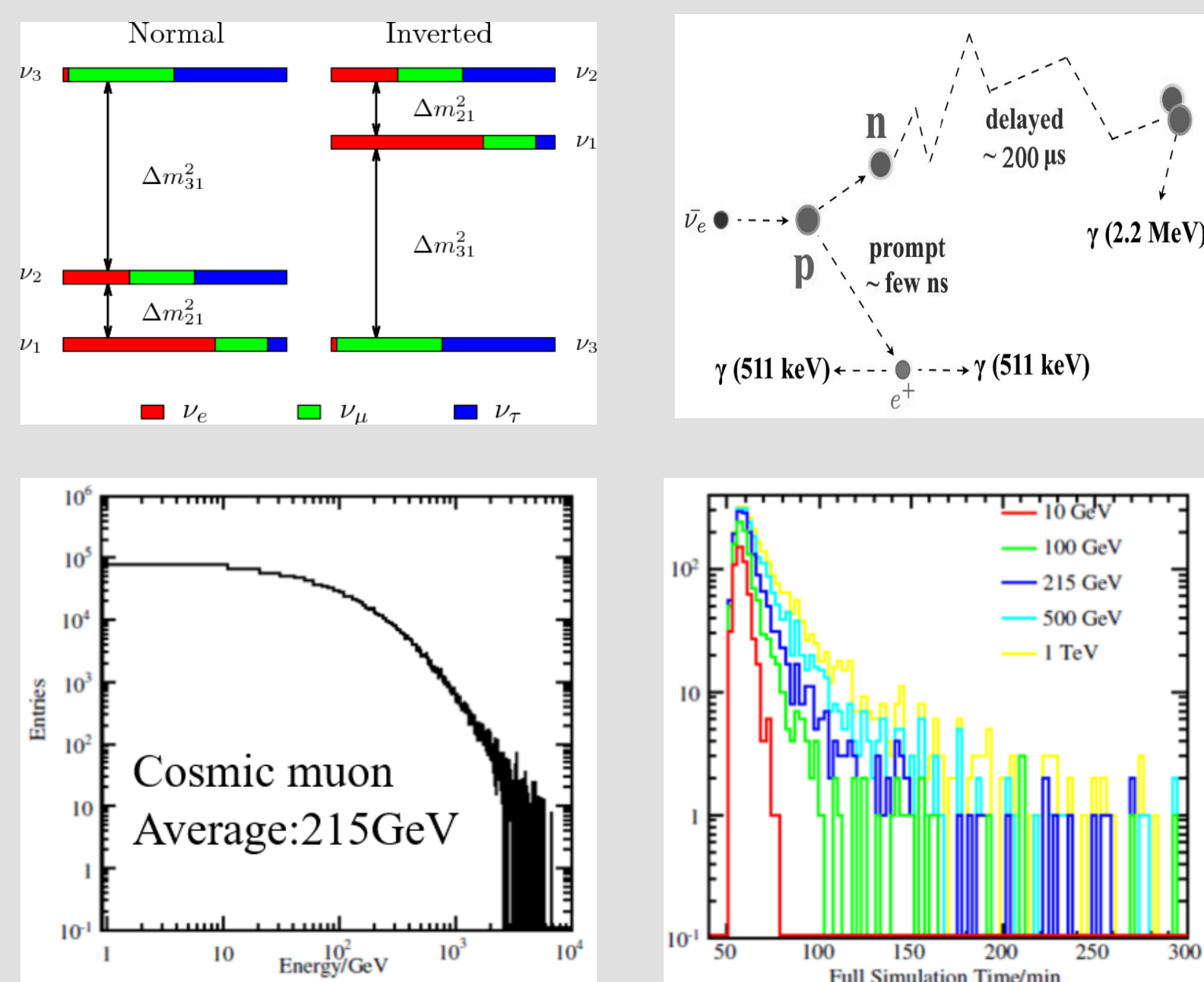


Fast muon simulation in the JUNO experiment with neural networks

Wenxing Fang, Weidong Li, Tao Lin (on behalf of the JUNO collaboration)
Institute of High Energy Physics, CAS / fangwx@ihep.ac.cn

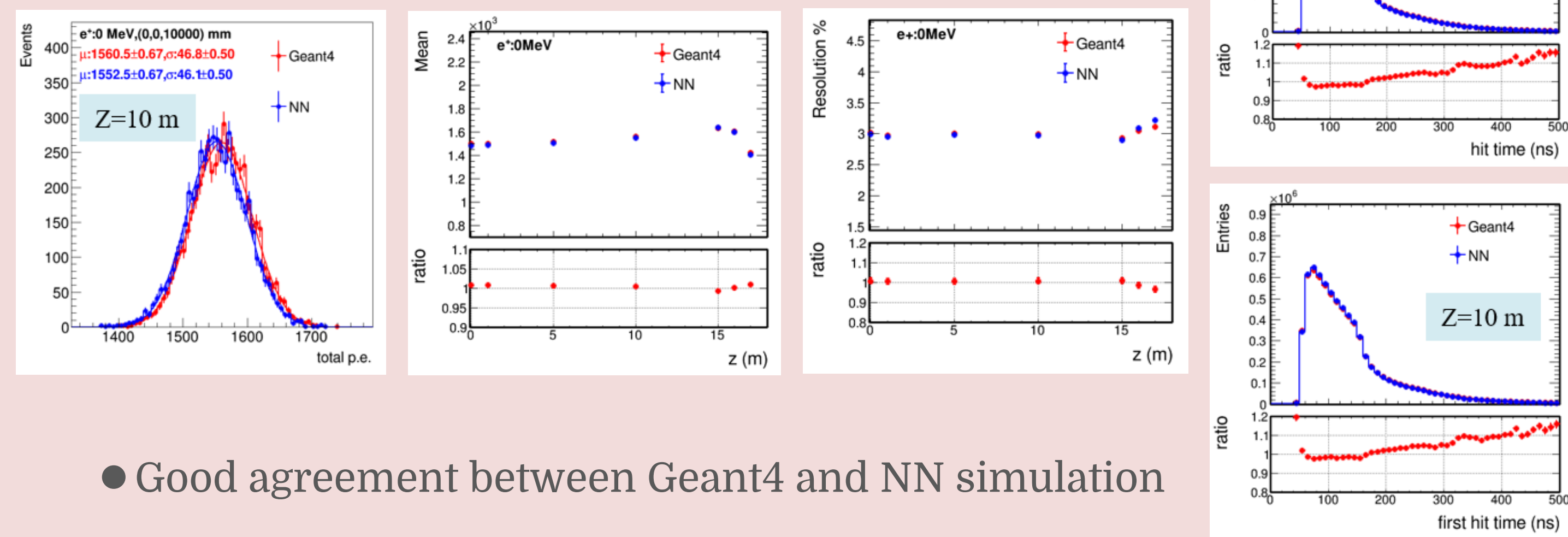
Introduction

- Jiangmen Underground Neutrino Observatory (JUNO) experiment mainly aims to determine the neutrino mass ordering [1]
- The signal is (inverse beta decay) IBD event
- Cosmic muon will interact with liquid scintillator and produce a nucleus like ${}^9\text{Li}$, ${}^8\text{He}$, which will give IBD-like events (important background)
- Muon simulation is needed
- Current Geant4 takes few hours to simulate one muon



Performance for 0 MeV e^+

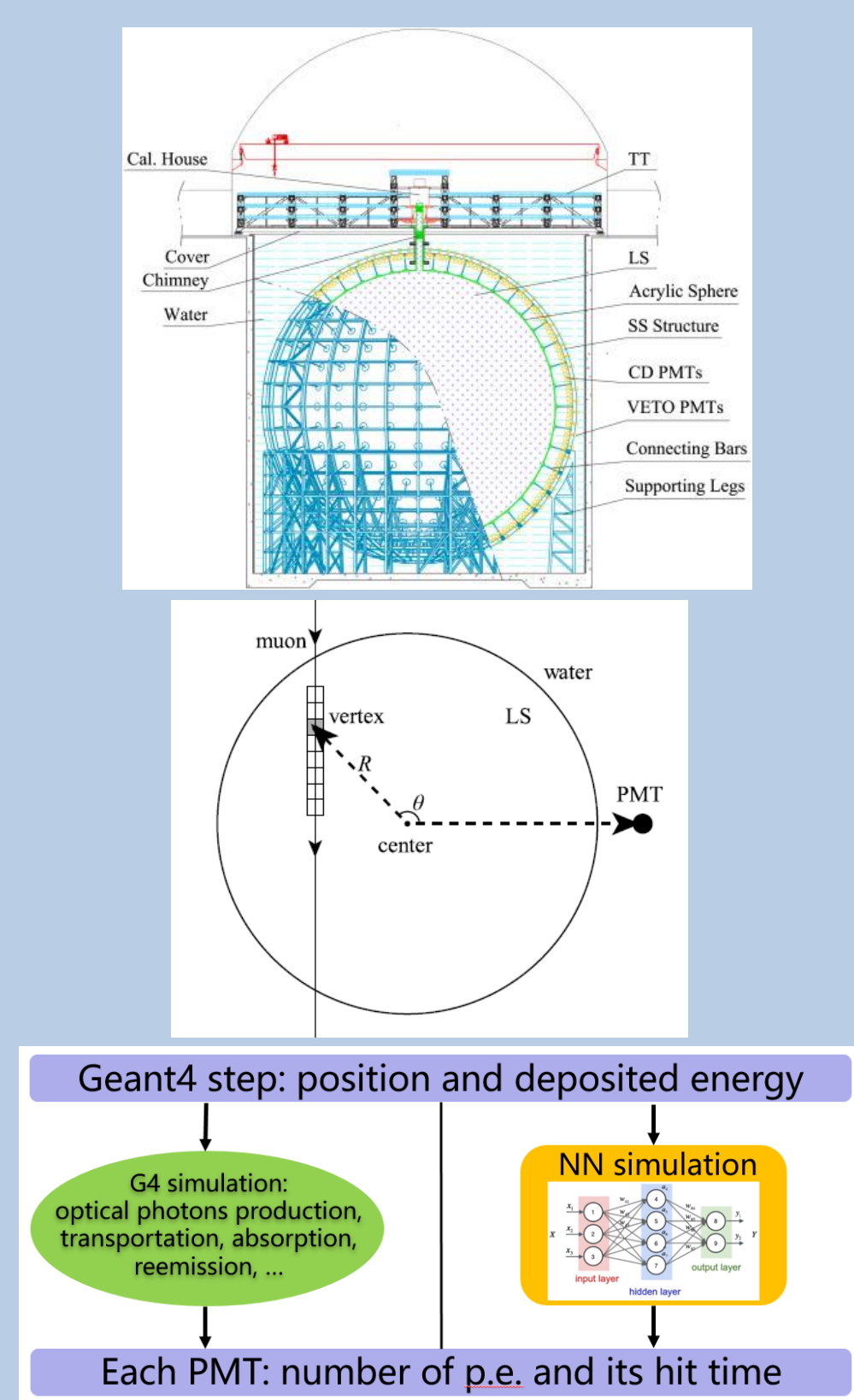
- Generating samples along with Z axis



- Good agreement between Geant4 and NN simulation

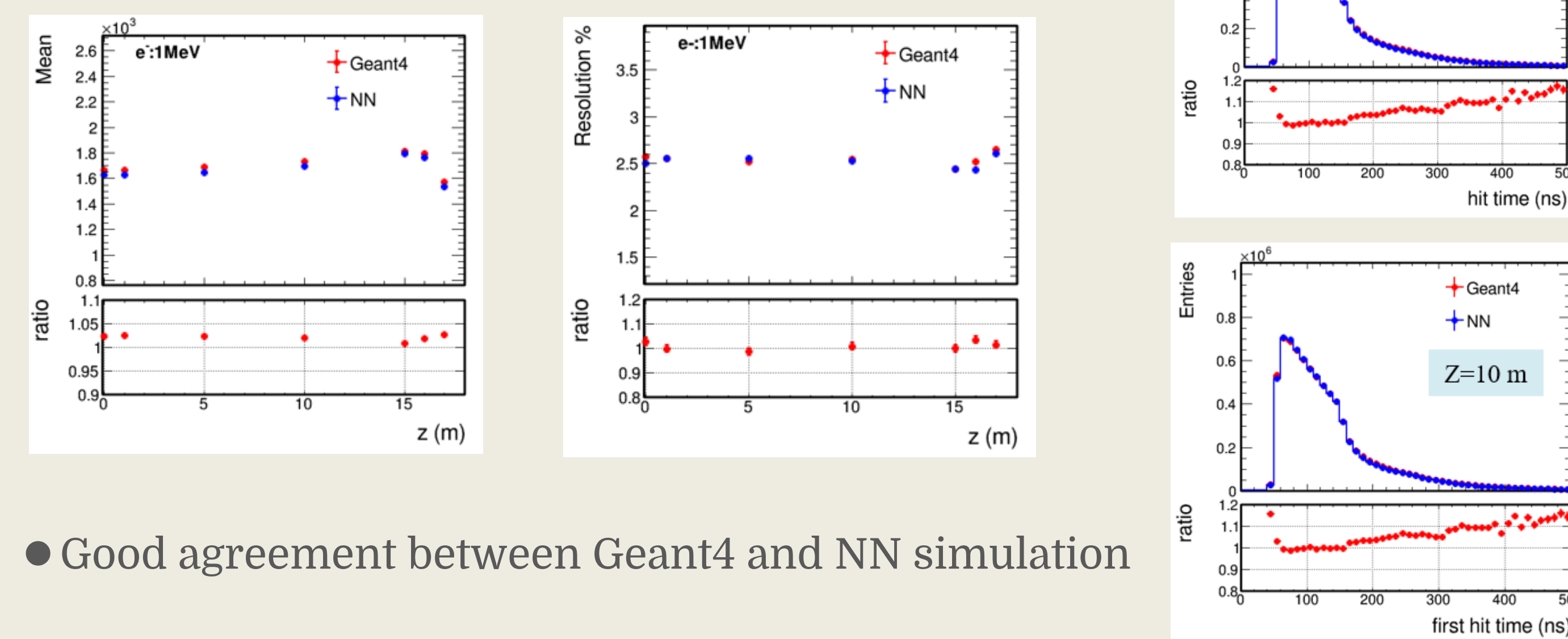
Methodology

- The center detector (CD) of JUNO is an acrylic ball filled with a 20kton liquid scintillator. It has approximate spherical symmetry
- Use similar ideas from the voxel method [2], but implemented with neural networks (NNs)
- For each Geant4 simulation step: First simulate the number of photon electrons for each PMT according to the deposited energy and position of the step. Then simulate the hit time of each photon electron for each PMT
- JUNO uses three types of large PMTs, including Hamamatsu, NNVT, and HighQENNV
- Two NNs will be trained for each type of PMT. One for N p.e. simulation, another for hit time simulation



Performance for 1 MeV e^-

- Generating samples along with Z axis



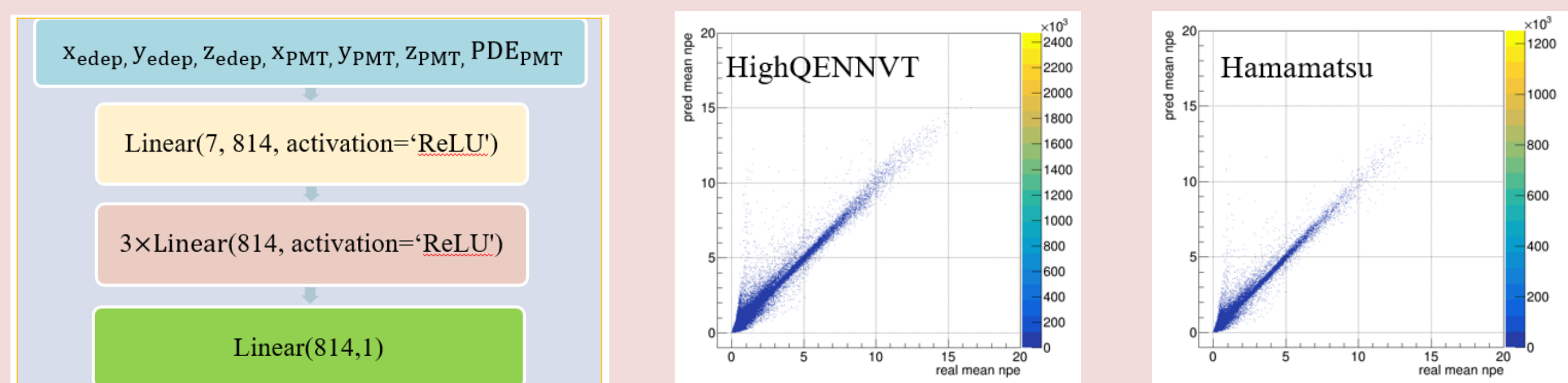
- Good agreement between Geant4 and NN simulation

Number of photon electron simulation

- The N p.e. distribution for each PMT follows the Poisson distribution $\frac{e^{-\lambda}\lambda^k}{k!}$
- Using NN to predict the λ for each PMT
- For simplicity, one can train a NN to predict $\lambda_{\text{PMT}}^{1\text{MeV}}$ (for 1 MeV quenched energy)

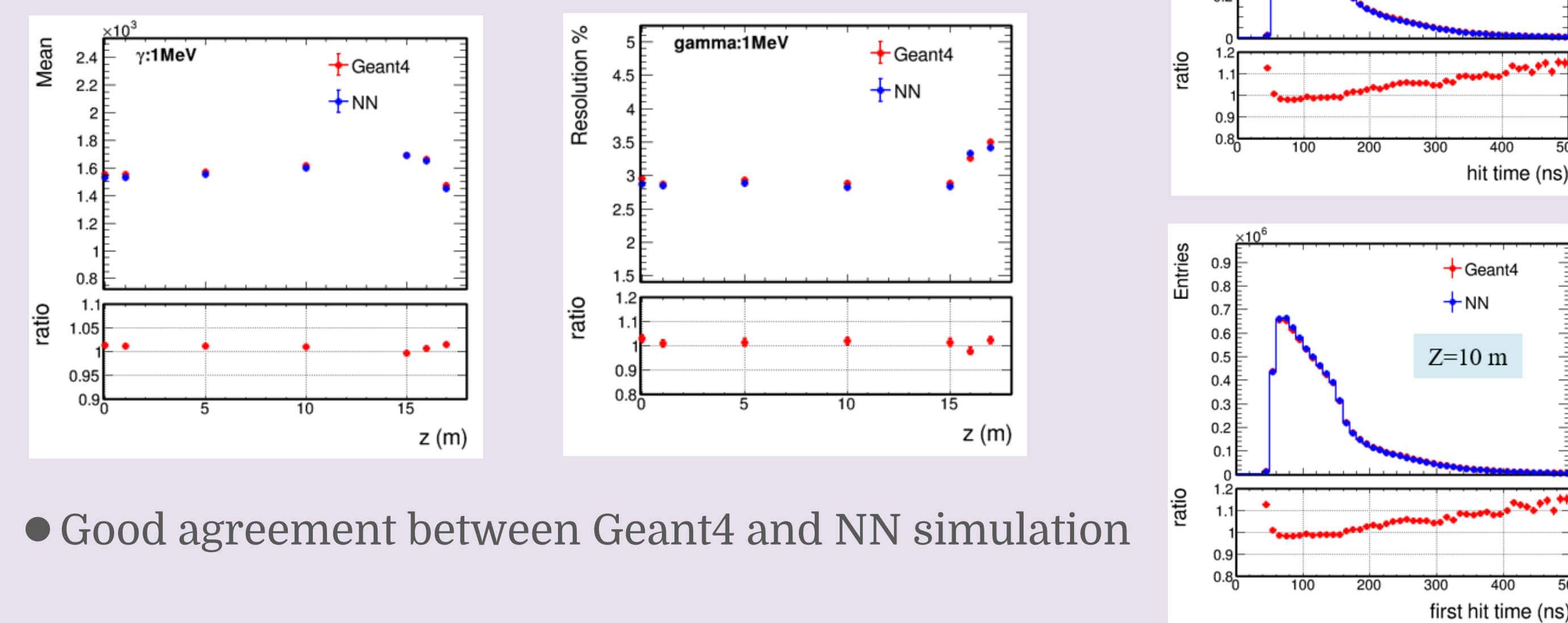
$$\lambda_{\text{PMT}}^{1\text{MeV}} = \text{NN}(x_{\text{dep}}, y_{\text{dep}}, z_{\text{dep}}, x_{\text{PMT}}, y_{\text{PMT}}, z_{\text{PMT}}, \text{PDE}_{\text{PMT}})$$

- Can be easily scaled for other deposited energy situations
- Dataset: 10k positions uniformly distributed in the CD. Each position has 2k events. 70% for training, 10% for validation, and 20% for testing



Performance for 1 MeV γ

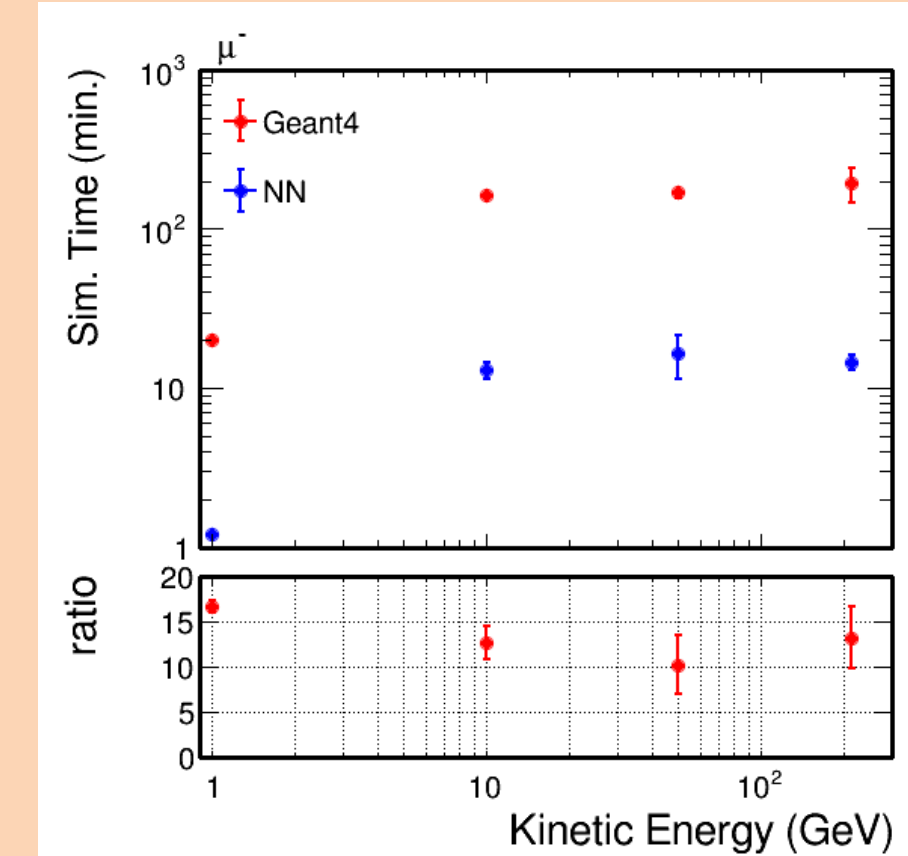
- Generating samples along with Z axis



- Good agreement between Geant4 and NN simulation

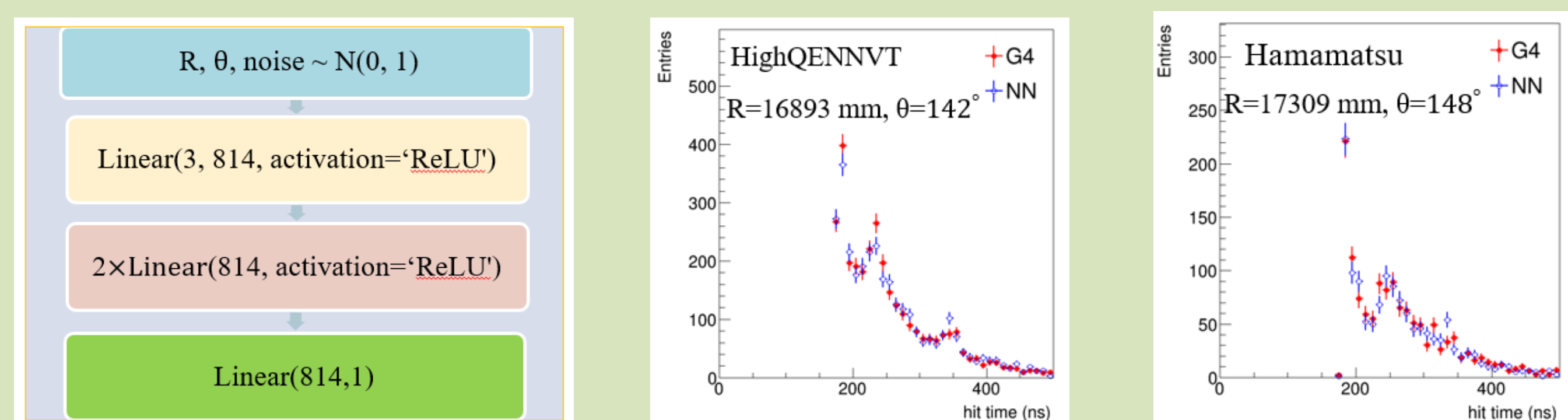
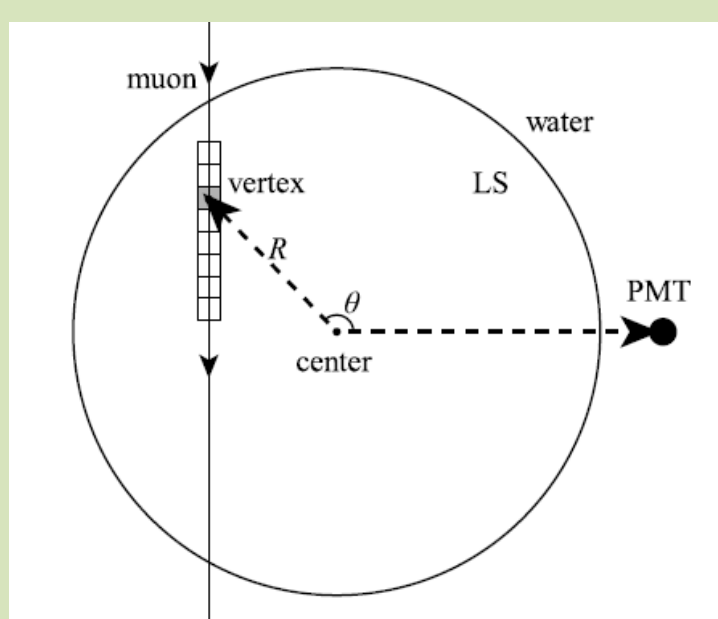
Muon simulation time

- Tested muon simulation time with energy
- The muon's start position is (0,0,19000), direction is (0,0,-1)
- For NN simulation, one GPU card (V100) is used
- On average, more than one magnitude speed-up can be reached



Photon electron's hit time simulation

- Use the spherical symmetry of the CD detector
- Simulating the hit time according to the R and θ values
- The dataset is the same as the N p.e. simulation
- To get the loss value between the simulated hit time distribution and truth hit time distribution, a differentiable two-sample test statistics [3] is used



Conclusion

- Muon simulation is very important for JUNO
- Traditional Geant4 simulation is very time-consuming
- Based on the idea from the voxel method, fast muon simulation using NNs is performed
- The physics performances (e.g. N p.e. and hit time) of the NN simulation method are checked using e^+ , e^- , and γ events. In general, the agreement between Geant4 simulation and NN simulation is good
- For muon simulation, by using NN simulation method, the speed-up can be greater than one magnitude

Reference

- [1] JUNO Collaboration, "JUNO physics and detector", Progress in Particle and Nuclear Physics, Volume 123, March 2022, 103927
- [2] Tao Lin *et al.*, "Fast muon simulation in the JUNO central detector", 2016 Chinese Phys. C 40 086201
- [3] Josip Djolonga *et al.*, "Learning Implicit Generative Models Using Differentiable Graph Tests", arXiv:1709.01006