PROCEEDINGS OF SCIENCE

Machine learning-based waveform reconstruction at JUNO

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The analysis of the waveforms of photo-multiplier tube (PMT) is essential for high precision measurement of position and energy of particles' interaction in liquid scintillator (LS) detectors. JUNO is a next-generation large volume liquid scintillator neutrino experiment with a designed energy resolution of 3% @1 MeV. The accuracy of the reconstruction of the number of photo-electron (nPE) is one important key of achieving the best energy resolution. This work introduces the machine learning-based nPE estimation methods, including supervised learning depended on electronic simulation and data-driven weakly supervised learning. The calibration parameters of LS and PMT responses are used to generate training waveforms for supervised learning. The photon counting performances of different methods will be presented.

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1. The JUNO experiment

The Jiangmen Underground Neutrino Observatory (JUNO) is a multi-purpose observatory for determining the neutrino mass ordering, precisely measuring $\sin^2 2\theta_{12}, \Delta m^2_{21}, \Delta m^2_{31}$, studying the solar neutrinos, supernova neutrinos, diffuse supernova neutrino background, etc [1]. It is constructed 650 meters underground in Jiangmen, China, and is located about 53 kilometers away from both Yangjiang and Taishan nuclear power plant, which is a perfect place to measure the Neutrino Mass Ordering (NMO) via the analysis of reactor neutrino oscillation. The detector consists of a Central Detector (CD) which acts as the main target, a Top Tracker (TT) for tagging muons, and a Water Cherenkov Detector (WCD) for tagging muons and shielding radioactivity. The CD is equipped with 20 kton LS, 17612 20-inch PMTs and 25600 3-inch PMTs, respectively. The WCD is equipped with 35 kton ultra-pure water and 2400 20-inch PMTs. The JUNO CD aims to achieve an unprecedented energy resolution of 3% or better at 1 MeV. So far, more than 6000 large PMTs and 6000 small PMTs were installed.

2. Motivation

Each photon induced by physical events in the LS has a probability of hitting the PMT and generating photoelectrons (PEs), then electronics reads the PMT current signal and converts it to a voltage signal and digitizes it into a waveform. The waveform reconstruction needs to restore the photoelectron information. The energy resolution of a LS detector is mainly determined by the total number of PEs, and secondarily determined by the accuracy of the estimation of total nPE, which depends on the channel-wise estimation of nPE. The basic method is to integrate the waveform to get the charge of nPE. However, charge has dispersion. Compared to using the true nPE for energy reconstruction, the energy resolution using charge-based energy reconstruction decreases by 0.6% at 1 MeV, as shown in Fig. 1. This study aims to optimize the accuracy of nPE estimation using machine learning (ML), which can improve the charge-based energy reconstruction [2].

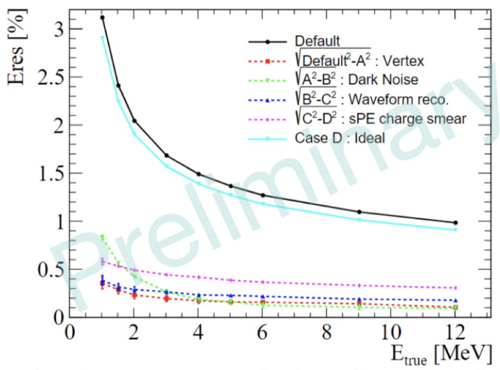


Figure 1: Energy resolution as a function of the deposited energy. The different curves indicate the single contributions to the global energy resolution. Charge smearing contributes about 0.6%@ 1 MeV to the energy resolution, which is one of the main factors currently limiting energy resolution.

3. Supervised method

The distribution of PMT waveforms are determined by the waveform template, the probability density function (PDF) of hit time, the PDF of hit charge and the noise spectrum of single PE. These detector responses can be extracted from calibration data and used to establish electronic simulation procedure. Supervised methods use simulation waveforms with known nPE to train neural network by minimizing the categorical crossing-entropy (CCE) between predicted nPE and true nPE. The classes are chosen as $0, 1, 2, ..., K$ p.e., where $K = 9$ in this study. Training waveforms are labeled with n_m p.e.: 0, 1, ..., 9 p.e.. The statistic of each set I_m is $\sim$ 1000000. The number of training data set is written as M.

For I_m calibration waveforms of n_m p.e., the output of neutral network is a $I_m \times (K+1)$ matrix y^m_{ik}, the CCE is given by $CCE_m = -\sum_{i=1}^{I_m} \log(y^m_{ik})$. The loss function of training data is defined as

$$L_{CCE} = \sum_{m=1}^{M} CCE_m. \tag{1}$$

4. Weakly supervised method

There have been studies on binary classification methods based on weakly supervised learning in the field of particle physics [3]. This work develops a multi-class classification method based on weakly supervised learning.

The nPE of waveform is unknown, but the mean nPE (μ) of calibration data is known. This study uses μ labeled data to conduct weakly supervised training by minimizing the Kullback-Leibler (KL) divergence between predicted nPE distribution and true nPE distribution (Poisson distribution). The classes are chosen as $1, 2, ..., K+1$ p.e., where $K = 10$ in this study. Waveforms with nPE $> K$ p.e. are categorized as $K+1$ p.e.. Training waveforms are labeled with μ_m p.e.: 0.5, 1,..., 9.5 p.e.. The statistic of each set I_m is $\sim$ 1000000. Noise waveforms are excluded here.

For I_m calibration waveforms with known "μ_m", the output of neutral network is a $I_m \times (K+1)$ matrix y^m_{ik}. The probability of reconstructed k p.e is calculated by $Q_m(k) = \frac{1}{I_m}\sum_{i=1}^{I_m}(y^m_{ik})$. The probability of detected k p.e. is

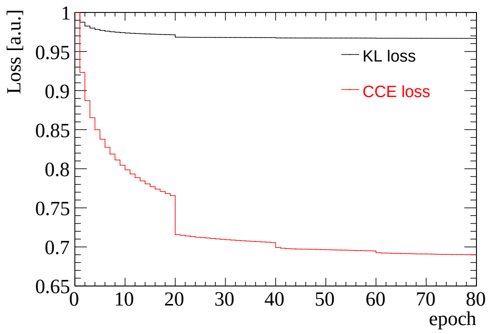
$$P_m(k) = \frac{e^{-\mu_m}\mu_m^k}{k!(1-e^{-\mu_m})}(k \le K), P_m(K+1) = 1 - \sum_{k=1}^{K} P_m(k). \tag{2}$$

The loss function of training data is defined as

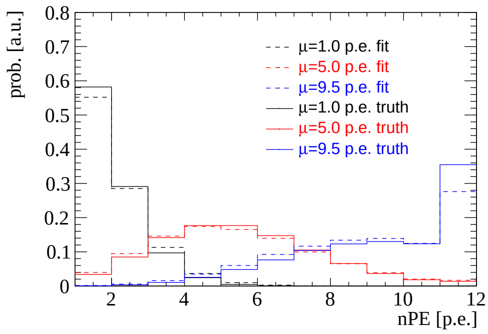
$$L_{KL} = \sum_{m=1}^{M}\sum_{k=1}^{K+1} P_m(k)\log\frac{P_m(k)}{Q_m(k)}. \tag{3}$$

5. Reconstruction performances

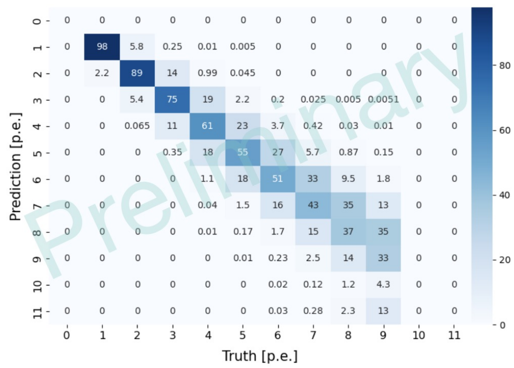
The neural network used by both the supervised method and the weakly supervised method consists of 5 convolutional layers and one dense layer. The testing data are labeled with n_m p.e.: 0, 1,..., 9 p.e.. The statistic of each set N_m is ~200000. The 0 p.e. waveforms are excluded for weakly supervised method. The training and testing results of the supervised method and weakly supervised method are shown in Fig. 2. Clearly, the CCE loss and KL loss of weakly supervised method both decrease as the number of training iterations increases, where CCE is merely a performance indicator, not a minimization target. The final distribution of the predicted nPE is close to the target Poisson distribution. Weakly supervised method achieves 100%, 99%, 96%, 94%, 98% efficiency of the supervised method in the case of 1, 2, 3, 4, 5 p.e., respectively.



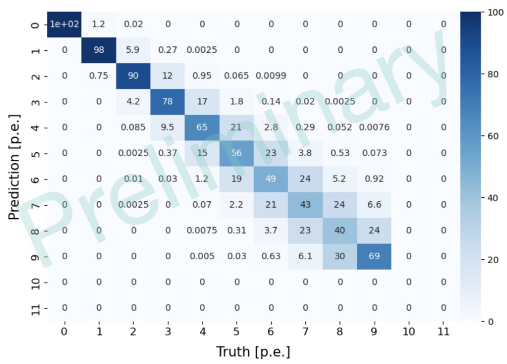
(a) KL loss and CCE loss vs. epoch of weakly supervised method.



(b) Poisson-fitting results of weakly supervised method.



(c) Confusion matrix of weakly supervised method.



(d) Confusion matrix of supervised method.

Figure 2: The training and testing results of the supervised method and weakly supervised method.

6. Conclusion

The nPE information is essential for the energy reconstruction. Machine learning has potential to extract accurate nPE information. Supervised method depends on electronic simulation. Weakly supervised method is data-driven. The weakly supervised method and supervised method has similar nPE accuracy in the case of small pe. Optimizations are on going.

7. Acknowledgements

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