Fast modelling of scintillation light transport in a LArTPC experiment

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Abstract

An important feature for the liquid argon time projection chambers of the DUNE experiment to have is the capability to determine interaction region and deposited energy of low energy particle interactions occurring in their sensitive volumes. A machine learning study based on regression tasks using feedforward neural network models was developed using as input data obtained from a simplified Geant4 Monte Carlo simulation of the vertical drift large scale prototype being installed at CERN in order to make a rough first order evaluation on the reconstruction performance of these quantities obtained through the use of its photon detection system only.

Keywords: ProtoDUNE. Neural Network. Geant4.

1 Introdução

The ProtoDUNE (ABUD et al., 2023) are large scale prototypes for the Deep Underground Neutrino Experiment (DUNE) (ABI et al., 2020), designed to test and validate the technologies and methods to be used in the far detector modules of DUNE experiment. Located at CERN, each protoDUNE consists of a massive cryostat that is internally instrumented with a liquid argon time projection chamber (LArTPC) and a photon detector system (PDS) as its main detecting components. These systems allow to measure free ionization electrons (TPC) and scintillation light (PDS) both produced on the passage of charged particles through LAr. These prototypes are crucial for ensuring the success of DUNE, which aims to explore fundamental questions about the behaviour of neutrinos.

Another crucial component designed to shape and ensure a uniform electric field within the boundaries of the LArTPC sensitive volume is the so-called field cage (FC). The electric field is essential for guiding ionization charges towards the anode planes for detection. The field cage consists of a series of parallel conductive rings or strips connected by resistors, creating a potential gradient from the cathode to the anode. It also affects the observed amount of light received by the PDS sensors some placed on the cathode and others outside the FC. Figure 1 (left) illustrates protoDUNE's main components: top and bottom horizontal anode planes; horizontal cathode with 8 PDS detector modules; and 8 external PDS detectors installed vertically on the cryostat membrane. Figure 1 (right) shows a picture of the actual cathode and its detecting modules installed inside the FC of ProtoDUNE-VD.

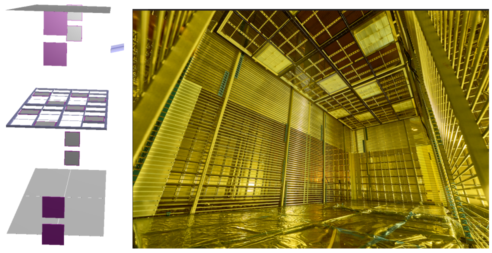

Figure 1 – ProtoDUNE-VD main components. Simulation model visualization (left) and internal picture of the cathode at x=0 within installed field cage at the cryostat (right).

A machine learning study based on regression tasks using feedforward neural network models (GéRON, 2022) was developed using as input Geant4 (ALLISON et al., 2016) simulated data representing the number of photon-electrons conversions detected in each of the 16 PDS modules due to a single interaction point event. Optical characteristics of the materials and scintillation light propagation parameters were taken into account. A total of 10k events randomly sampled in the LAr volume were simulated to produce our data base.

A feedforward neural network consists of a set of neurons organised in layers in which the neurons in adjacent layers are connected. Its layers are usually separated into three groups: the input layer, which refers to the first layer, the output layer, which is the model's final layer, and the hidden layers, which gather all the other layers. The number of neurons in the first layer is determined by the dimension of the dataset used. The first layer's number of neurons must match the number of features used, while the last layer's number of neurons must match the number of labels used.

The main goal of this work is to verify if it is possible, with enough precision and accuracy, to determine the three spatial coordinates and the total energy of low energy interaction events inside the protoDUNE-VD using the number of photo-electrons detected by each one of the sixteen receptors installed inside its cryostat, using feedforward neural networks.

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2 Methods

The first step of this study was to decide the type of neuron network model that could be used for each one of the four labels studied (x, y, z, E). For that purpose, a short study of different models and their results after training was realized and were compared in order to determine the best activation and optimizer functions to be used (CHOLLET, 2015). The loss function used for all the labels was the mean absolute error, since there would not be big differences on the kind of error in this context if the predicted value was higher or lower than the actual target, and also because this error type is expressed in the same units of the respective label trained, making it easier to interpret.

Training and testing procedures consisted in picking the whole dataset and using 80% of its rows for training, while the remaining lines were used for testing. Graphs comparing the corresponding label's predictions and their true values were plot to allow analysis of the trained network's performance.

3 Results and Discussion

It was shown that the network model using the activation function ReLU and the Adam optimizer performed some of the best results among all the combinations of functions tested. As they're also widely used for regression tasks using neural networks, they were selected to take place in the current work.

The training and posterior test predictions for the entire dataset was carried out using the functions mentioned. Nevertheless, it seemed that the fitting process had some difficulties describing the quantities of interest in the region outside of the FC. Therefore, it was decided to pre select data within FC boundaries and reproduce the training and testing procedures.

Regarding the training and testing procedures using only the data from the field cage's internal part, the general results for each one of the labels were better than the previously obtained, as already expected, since factors such as its separating metallic grid and the discontinuity of the electric field outside it have the potential to change drastically the scintillation light throughout protoDUNE-VD's volume.

Figure 2 shows the results obtained from the predictions. The two top row panels show a satisfactory agreement for the x and y coordinates estimates with respect to the true values set in the simulation. Only a few outliers are observed around $x = 0$ and $x = \pm 3.3$m due to the physical boundaries imposed by the materials in these regions. Such behavior was also noticed when the first anaylis was performed with the full date set. One can observe that among the three position labels analysed, the z trained model has given the worst result, which was also already expected, since none of the PDS modules face the protoDUNE-VD's z axis, which increases the difficulty to establish this coordinate of the events.

Furthermore, it's also noticeable that the energy deposited estimates provided were also not satisfactory results. In order to improve the results of the energy prediction, one could first train the networks to obtain all the three coordinates and then train the energy model using the predicted coordinates as features of this new model, since this method would be offering more information to the energy training part.

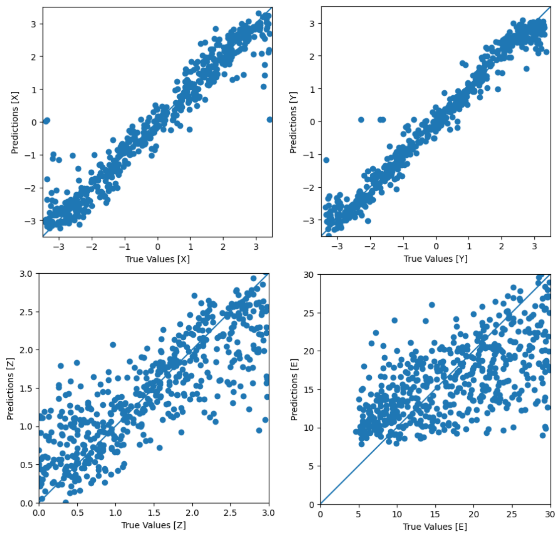

Figure 2 – The four labels predictions for the test dataset compared to its true values using only the data corresponding to events inside the field cage.

4 Conclusion

The estimates obtained for the x and y indicate that the use of neural networks can be an interesting approach as it is easy to implement as a fast calculation tool with satisfactory resolution and accuracy. The other quantities still need further development, however, physics informed models accounting for boundaries and particularities of the experiment geometry can be implemented.

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