Sparse Convolutional Neural Networks for particle classification in ProtoDUNE-SP events

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Abstract. Deep Learning (DL) methods and Computer Vision are becoming important tools for event reconstruction in particle physics detectors. In this work, we report on the use of submanifold sparse convolutional neural networks (SparseNets) for the classification of track and shower hits from a DUNE prototype liquid-argon detector at CERN (ProtoDUNE-SP). By taking advantage of the three-dimensional nature of the problem we use a set of nine input features to classify sparse and locally dense hits associated to track or shower particles. The SparseNet has been trained on a test sample and shows promising results: efficiencies and purities greater than 90%. This has also been achieved with a considerable speedup and substantially less resource utilization with respect to other DL networks such as graph neural networks. This method offers great scalability advantages for future large neutrino detectors such as the planned DUNE experiment.

1. Introduction

Neutrino event reconstruction represents a very important task in physics analysis. In Liquid argon time projection chamber detectors (LArTPC) event reconstruction is usually accomplished by combining multiple algorithms to achieve the most accurate result. One critical component of the event reconstruction chain is the separation between track and shower particles. Traditionally, the classification task of different particle types is done with Convolutional Neural Networks (CNNs) [1] where sections of the detector are converted into 2D images and then classified. However, one of the challenges of LArTPC detectors is that they produce a large amount of sparse and locally dense data which becomes difficult to handle for larger detector volumes. In this work we tested the usage of an innovative algorithm specifically designed to handle sparse data on three-dimensional space points.

Submanifold sparse convolutional neural networks (SparseNet) [2] are a class of Deep Learning methods primarily designed for 3D image reconstruction, image completion or semantic segmentation problems. The SparseNet has proven to be quite effective when dealing with sparse data and with potentially minimal resource utilization compared to other classes of CNNs. The three-dimensional hits produced in the LArTPC detector at CERN (ProtoDUNE-SP [3]) are well suited for the SparseNet algorithm as they are locally dense and sparsely located in the detector volume. Moreover, the computational benefit of utilizing the SparseNet may also be more relevant for larger LArTPC detectors such as the planned DUNE experiment [4].

In this work, we evaluate the performance of the SparseNet used for the classification task. First, we illustrate the architecture of the network and then we describe the results of the training

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and validation obtained for simulated ProtoDUNE-SP MC data. Ultimately, the SparseNet is also applied to a sample of real ProtoDUNE-SP data collected in 2018.

2. Network architecture

Submanifold sparse convolutional neural networks (SparseNet) is a class of Convolutional Neural Networks that use generalized convolution operations on sparse tensors. The architecture of the SparseNet implemented is a combination of both a U-Net and a Res-Net which are typical CNNs architectures used for semantic segmentation problems. In addition, the use of sparse tensors provides a reduction of the processing time compared to traditional CNNs which make the use of such networks interesting for problems where data is not dense.

For the purpose of this research, the SparseNet was used to perform the classification task of distinguishing between track hits and shower hits. A softmax activation function and a Stochastic gradient descent (SGD) optmizer have been used in the SparseNet. The output of the network is a score ranging from 0 for track objects and 1 for shower objects. In addition, the Minkoski Engine [5] was used to support the operations of convolution and pooling that are needed by the computation with sparse networks.

3. Data samples - MC and data

The MC data samples consist of ProtoDUNE-SP datasets. For the ML training and validation, more than 2M hits have been processed using a modified version of the code of the DUNE Convolutional Visual Network [1]. This was done in order to process the necessary features for the SparseNet. In total, 9 features were selected: charge deposition of each spacepoint; angle and dot product between two neighboring spacepoints; number of neighboring spacepoints as well as the total charge within a distance of 3 cm, 10 cm and 30 cm. Similarly, a smaller and independent inference data sample of 500k hits was also produced. Note that here a spacepoint refers to the 3D geometrical representation of the hits in the ProtoDUNE-SP detector.

The ProtoDUNE-SP dataset that was used for the evaluation consists in two runs from ProtoDUNE-SP run I: run 5387 and run 5809. A total of more than 300k hits were processed with the same features used for the MC datasets.

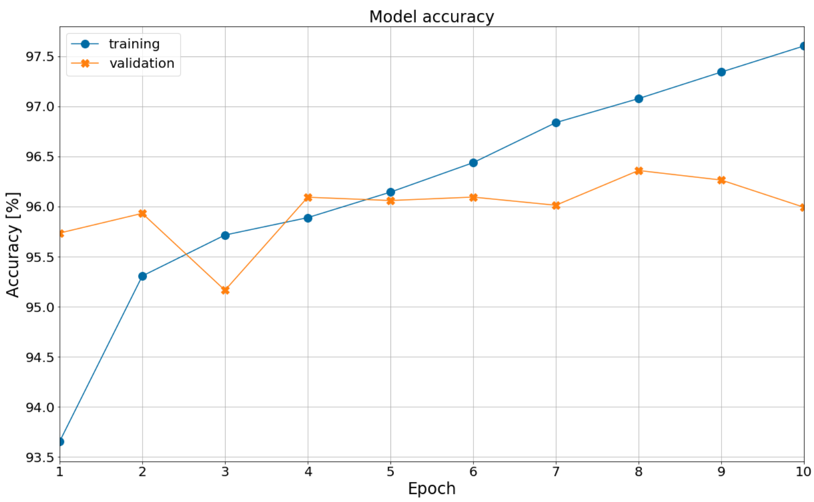

Figure 1. Accuracy as a function of the number of epochs for the SparseNet model.

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4. Training and validation results

Figure 1 shows the accuracy of the model as a function of the number of epochs for both the training and validation steps. The overall accuracy reached after the training processes is more than 95 % which demonstrates the good discrimination power between track and shower events. Note that the network was trained for a total of 10 epochs to avoid overfitting the model.

The results obtained when the network is applied to MC inference dataset are summarized in Table 1 which shows the purity and the efficiency of the SparseNet of both the track and shower classes. The results show that the purity of the two classes is above 90 %, indicating that the percentage of misidentified hits belonging to a track (or shower) object is low. In addition, having an efficiency of over 90 % also suggests that the algorithm is able to select most of the relevant hits belonging to a track (or shower) class. Therefore, the SparseNet model is a promising algorithm to further investigate: the preliminary results obtained for the efficiencies and purities show higher values compared to the ones obtained with the currently adopted ProtoDUNE CNN [1].

Table 1. Table summarizing both the purity and the efficiency of the SparseNet on the MC inference dataset.

Class	Purity [%]	Efficiency [%]
Track	96.8	97.8
Shower	93.5	90.7

5. Evaluation of the DL network in ProtoDUNE-SP events

The performance of the SparseNet was evaluated for hits originating from different particle types: charged pions, muons, protons, positrons. In fact, each of these particles produce either a track or a shower and, therefore, they provide means to understand the response of the network. Charged pions, muons and protons have a detector signature of a track whereas positrons produce showers in the detector. Figure 2 shows the SparseNet score for the shower class for hits originating from pions, muons, protons and positrons. As an example, the distribution of the shower score for positron hits (violet curve) is peaked at a score of 1 which is the network representation of a shower. This is also approximately two orders of magnitude higher than the score at 0 which is the network representation of a track. On the other hand, the distribution of the SparseNet score for hits coming from pions, muons and protons have the opposite behaviour. They are all peaked at zero and are three orders of magnitude higher than the peak at a score of 1.

In addition, a cut value of 0.5 was chosen for the network after performing a careful evaluation in order to reduce the number of misidentified track and shower hits. As an example, from Figure 2 it can be noted that the number of track hits (e.g pions) that have been mis-classified as a shower (i.e. with a shower score of 1) are more than three orders of magnitude lower than the peak at 0.

5.1. Track and shower scores

An average score was also computed by grouping all the hits that belong to a single track or to a single shower object. In this way it is possible to compute how well the network is able to correctly classify tracks (or showers) rather than relying solely on the hit classification. The average track and shower scores are computed as following:

(i) Identify all the hits belonging to a single track (or shower)
(ii) Count the number of hits correctly identified by the network
(iii) Compute the efficiency by taking the ratio between the number of correctly identified hits and the total number of expected hits for a given track (or shower)

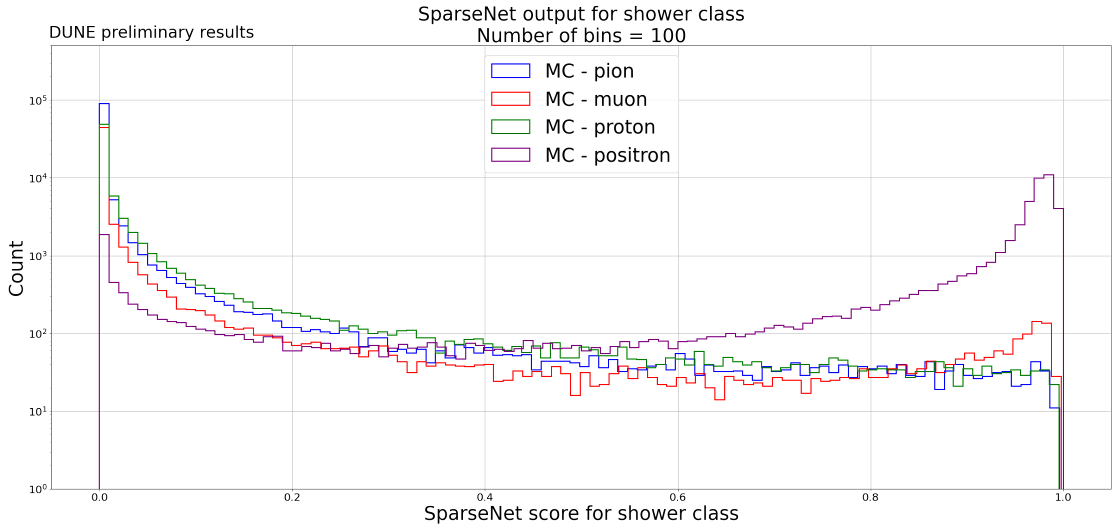

Figure 2. SparseNet score for the shower class different particle types (pion, muon, proton, positron).

(iv) Repeat the steps above for all the particle objects in the dataset

(v) The score is given by computing the arithmetic mean of the efficiencies obtained for all the track (or shower) particles

The average track and shower scores obtained for the inference dataset:

$$\text{Track score: } 0.852 \pm 0.008; \text{ Shower score: } 0.739 \pm 0.002$$

Note that the average track and shower scores were computed for only the MC datasets. These average scores provide a useful indicator of how the network is performing in the classification of track/shower objects: if the score is closer to 1 then the network has correctly identified most of the hits belonging to a track or a shower particle. The track and shower scores are lower than the efficiency and purity obtained in Table 1 because the SparseNet is applied to single hits. For example, the model will not likely identify all the hits that belong to a shower that has many hits. In that case, the efficiency may be high but the shower score suffers from the reduced efficiency.

5.2. Network on ProtoDUNE data

Preliminary results show excellent performance for the SparseNet model when applied to ProtoDUNE-SP data (runs 5387 and 5809). In this case, the prediction of the network is compared with results from the event reconstruction software since the truth information is missing in the ProtoDUNE dataset. Nonetheless, the purities and efficiencies for both the track and shower clases are above 90 % for the ProtoDUNE data. An analysis of the output of the network was also performed to fully understand the performance of the SparseNet. Figure 3 shows the SparseNet shower score when the network is applied to the ProtoDUNE-SP data (runs 5387 and 5809). As it can be noted the network has a good discrimination power for both the track and shower hits. The two peaks where the SparseNet score is zero (red curve) and one (blue curve) showcase that the majority of the hits have been correctly classified by the network: track hits are associated with a score of 0 whereas shower hits are associated with a score of 1. In this case the truth of the hits is originating from the result of the event reconstruction software which gives an indication whether the hit is originating from a track or shower particle.

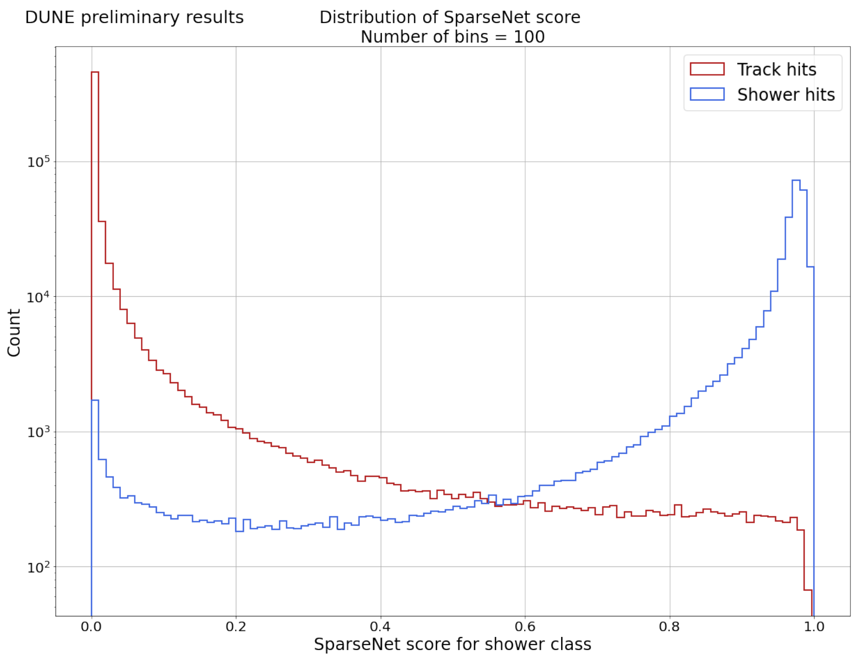

Figure 3. SparseNet score for the shower class for ProtoDUNE-SP data (runs 5387 and 5809).

6. Conclusion

The results obtained for SparseNet when applied to ProtoDUNE-SP events show excellent performance. Purities and efficiencies are both higher than 90 % for both MC and Data runs. The ML scores give also an indication of the good discrimination power of the network for hits belonging to a track or a shower particle. The immediate next steps of the SparseNet validation consist in a more in-depth evaluation of the performance of the network on ProtoDUNE runs as well as a comparison with the MC results.

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