CVN A Convolutional Visual Network for Identification and Reconstruction of NOvA Events

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Abstract. In the past year, the NOvA experiment released results for the observation of neutrino oscillations in the $\nu_\mu$ and $\nu_e$ channels as well as $\nu_e$ cross section measurements using neutrinos from Fermilab’s NuMI beam. These and other measurements in progress rely on the accurate identification and reconstruction of the neutrino flavor and energy recorded by our detectors. This presentation describes the first application of convolutional neural network technology for event identification and reconstruction in particle detectors such as NOvA. The Convolutional Visual Network (CVN) Algorithm was developed for identification, categorization, and reconstruction of NOvA events. It increased the selection efficiency of the $\nu_e$ appearance signal by 40% and studies show potential impact to the $\nu_\mu$ disappearance analysis.

1. Introduction - NOvA Events

NOvA is a long baseline neutrino oscillations experiment which measures the neutrino signal close to its source, at Fermilab, as well as 810 km away, at Ash River, MN. Given that oscillation measurements rely on the identification of the neutrino flavor the detectors, two low-Z material sampling calorimeters, are designed to optimize electron identification. They are composed of alternating vertical and horizontal planes of liquid scintillation, an array which allows us to produce two views of the detector activity, which in detector coordinates are a view on the XZ plane (from the top) and one on the YZ plane (from the side).

Events can be classified by analyzing the topology and energy deposition profile of the hits from the interaction. The main approaches at signal identification employed for our first analyses,[1, 2] was done in two main steps. First, reconstruction algorithms make a geometrical separation of each particle’s contribution to the event$^1$. Then, identification algorithms extract physics information, i.e. dE/dx and projected trajectory, from each particle’s contribution (given as a cluster of hits) and attempt to identify the leptonic component of the interaction$^2$ by using neural networks trained on these features.

2. The CVN Convolutional Neural Network

Deep learning algorithms present several advantages with respect to the traditional identification methods described in section 1. Not only do traditional algorithms rely heavily on the efficiency of the geometrical separation of the components, they are also limited in that the features they

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$^1$ Before this step the group of hits have been previously correlated in time and space to separate them from the rest of the activity in the detector.

$^2$ As seen in Fig 1 the outgoing lepton carries the same flavor as the original neutrino by lepton conservation.
Figure 1. NOvA characteristic data events. Side views of 3x11 meter sections of the detector. The color of the hits indicates deposited charge (measured in ADC counts). The neutrino neutral current interactions, as well as the charged current interactions for muon and electron flavor are each the main signal on NOvA’s neutral current, \( \nu_\mu \) disappearance and \( \nu_e \) appearance analyses, respectively. The classification of these events is the crucial first step for their respective analyses.

Figure 2. Simulated \( \nu_\mu \) CC event. Some track activity is visible in one of the feature maps.

employ for identification are only those which have been previously selected by the designer, equally folded in with the efficiency of their extraction. In turn, convolutional neural networks, in their implementation for image classification[5], eliminate the need for both previous separation of the event into components and extraction of predefined features.

We have developed a Convolutional Visual Network (CVN) based on existing implementations of machine learning [3] which classifies neutrino interactions by categories. These categories can then be labeled as signal or background for each analysis independently. The CVN network is trained on pixel maps (analogous to images but constructed from the output of the detector) of simulated events and labels corresponding to the type of simulated interaction. The network combines different types of layers, each with its own purpose. The following is a brief explanation of the main components of our network architecture:

• Convolutional Layers: These employ the use of feature extraction kernels of various types to extract features from the image. Kernels operate on images to extract different features
Figure 3. Left: Signal efficiency an purity vs cvn output for $\nu e$ CC simulated events. Middle: Signal efficiency of different cuts for $\nu_\mu$ signal events. Red: Cuts used on NOvAs first analysis[6]. Cyan: CVN + quality cuts. Right: CVN pid event distribution for the new NOvA results**.

3. CVN for Reconstruction
While the current implementation of CVN focuses on event classification, it is possible to train a network for single particle identification through the clusters of hits it contributes to the event. Adding single cluster views to the network input allows it to combine features extracted from the particle signature itself and in context with the rest of the interaction. Currently the input clusters to our particle CVN classifier come from traditional cluster reconstruction[4] but there is ongoing work to disentangle the network from traditional reconstruction completely.

4. Performance of CVN
The CVN event classifier was implemented as a selector for the $\nu_e$ appearance analysis presented at this conference. It improved the efficiency of $\nu_eCC$ events by 40% with respect to the traditional algorithm [4] and a CVN-based $\nu_\mu$ disappearance analysis of NOvAs initial dataset reveals potential improvements on our sensitivities as well as signal efficiency.[6]. The CVN particle classifier is currently in development but initial studies already show promise, especially for electron/$\pi^0$ and $\mu$/proton discrimination, as seen by their respective efficiencies in figure 3.

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[2] P. Adamson et al. First measurement of muon-neutrino disappearance in NOvA. *Phys. Rev.*, D93(5):051104, 2016.
[3] A. et al. Aurisano. A Convolutional Neural Network Neutrino Event Classifier. *JINST*, 11(09):P09001, 2016.
[4] Baird et al. Event Reconstruction Techniques in NOvA. *J. Phys. Conf. Ser.*, 664(7):072035, 2015.
[5] Christian Szegedy et al. Going deeper with convolutions. *CoRR*, abs/1409.4842, 2014.
[6] Dominick Rosario Rocco. *Muon Neutrino Disappearance in NOvA with a Deep Convolutional Neural Network Classifier*. PhD thesis, Minnesota U., 2016.

3 The kernels also evolve through local response normalization as training progresses.