Developing and Testing a Convolutional Neural Network for Multi-Particle Neutrino Interaction Identification

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This paper describes the development and testing of a deep neural network for the identification of particles produced through neutrino interactions in the MicroBooNE detector, a liquid argon time projection chamber studying short baseline neutrino oscillations. I present an adjustment to previously used convolutional neural net architecture to allow for multiclass particle identification (PID), removing the constraint of exclusivity of particle types in an image for successful PID. Studies on validation data and low energy events containing one lepton and one proton indicate that the network can successfully recognize particle types in an image, and that network failure cases are primarily caused by inherent challenges of PID.

1 Neutrino Interactions and Oscillations

Neutrinos are both the lightest and most abundant known source of matter in the Standard Model of Particle Physics. Like all Standard Model fermions, there are three generations of neutrinos, $\nu_e$, $\nu_\mu$, and $\nu_\tau$, associated with the three generations of charged lepton, $e^-$, $\mu^-$, and $\tau^-$. These three known neutrino eigenstates are referred to as neutrino flavor and correspond to the charged lepton with which each neutrino couples to through weak force interactions (1).

Two channels through which neutrinos interact with matter are charged current (CC) interactions and neutral current (NC) interactions.

Figure 1: Charged current (left) and neutral current (right) interactions of a neutrino with deuteron, as depicted by (1)
Feynman diagrams for these two processes for electron neutrinos interacting with deuterons are depicted in Figure 1. In a neutral current interaction, a neutrino scatters off of a neutron, $\nu_l + n \rightarrow \nu_l + n$. For neutral current interactions, it is impossible to tell the flavor of the neutrino - that is, which charged lepton it is associated with. The concept of flavor becomes relevant to charged current interactions, where a neutrino interacts with a neutron to produce a proton and a charged lepton of its same flavor: $\nu_l + n \rightarrow l + p$. For instance, an electron flavored neutrino would produce an electron in a CC interaction, while a muon flavored neutrino would produce a muon ($l$).

In 1998-2001, results from the Super-Kamiokande Experiment in Japan and the Sudbury Neutrino Observatory (SNO) in Canada provided the first evidence that neutrino flavor is not a fixed property, but rather transforms through the phenomenon of neutrino oscillations. At the time of their creation and interaction, neutrinos are in measurable flavor eigenstates. However, these particles propagate in time not in flavor eigenstates, but in mass eigenstates, which time evolve as eigenstates of the free particle Hamiltonian: $\psi(x, t) = \phi(x)e^{iEt}$. Assuming three neutrino mass eigenstates, we can refer to them as $\nu_1, \nu_2$ and $\nu_3$. In the phenomenon of neutrino oscillations, these mass eigenstates do not align with the neutrino flavor eigenstates, $\nu_e, \nu_\mu$ and $\nu_\tau$. Rather, a CC interaction of known flavor produces a neutrino which is a superposition of the three mass eigenstates ($l$).

The neutrino mass and flavor eigenstates are related to each other through the unitary Pontecorvo-Maki-Nakagawa-Sakata (PMNS) matrix:

$$
\begin{pmatrix}
\nu_e \\
\nu_\mu \\
\nu_\tau
\end{pmatrix} = 
\begin{pmatrix}
U_{e1} & U_{e2} & U_{e3} \\
U_{\mu1} & U_{\mu2} & U_{\mu3} \\
U_{\tau1} & U_{\tau2} & U_{\tau3}
\end{pmatrix}
\begin{pmatrix}
\nu_1 \\
\nu_2 \\
\nu_3
\end{pmatrix}.
$$

The PMNS matrix can be expressed in terms of three neutrino mass mixing angles, $\theta_{13}, \theta_{23}$, and $\theta_{12}$, in addition to a single complex phase $\delta_{CP}$. With the introduction of these variables, the PMNS matrix can be factored into three mixing matrices

$$
U_{PMNS} = 
\begin{pmatrix}
1 & 0 & 0 \\
0 & \cos \theta_{23} & \sin \theta_{23} \\
0 & -\sin \theta_{23} & \cos \theta_{23}
\end{pmatrix}
\begin{pmatrix}
\cos \theta_{13} & 0 & \sin \theta_{13} e^{-i\delta} \\
0 & 1 & 0 \\
-\sin \theta_{13} e^{i\delta} & 0 & \cos \theta_{13}
\end{pmatrix}
\begin{pmatrix}
\cos \theta_{12} & \sin \theta_{12} & 0 \\
-\sin \theta_{12} & \cos \theta_{12} & 0 \\
0 & 0 & 1
\end{pmatrix}.
$$

Understanding the mixing between the neutrino flavor generations - that is, the exact values of these mixing angles and phase - is a question at the forefront of modern particle physics. In particular, the complex phase $\delta_{CP}$ is of special interest, as it indicates that neutrinos and antineutrinos may oscillate differently. Finding CP violation in the PMNS mixing matrix could illuminate the cause of the matter-antimatter asymmetry in the universe (1) (4).
Figure 2: The energy distribution for neutrinos generated from quasi-elastic interactions as observed by MiniBooNE (3). Understanding the anomalous excess of electron-like neutrino events in the 200MeV-600MeV range is a primary physics goal of MicroBooNE.

2 Introduction to MicroBooNE

MicroBooNE (Micro Booster Neutrino Experiment) is a follow-up experiment to the MiniBooNE (Mini Booster Neutrino Experiment) experiment, and a part of the Short Baseline Neutrino (SBN) experiment at Fermi National Accelerator Laboratory (FNAL). The SBN program will eventually consist of three liquid argon time projection chambers (LArTPCs) along the Booster Neutrino Beam (BNB) line, which will study the short baseline oscillations of neutrinos.

2.1 The MiniBooNE Low Energy Excess

The MiniBooNE experiment is located at FNAL along the BNB, and previously conducted a study of short baseline $\nu_\mu \rightarrow \nu_e$ oscillations. In 2007, MiniBooNE published results indicating an excess of electron neutrino-like events with energy between 200 MeV and 600 MeV which deviated from the expected model by $3\sigma$. This anomalous result is depicted in Figure 2.

The primary physics goal of MicroBooNE and a major goal of SBN is to better understand the source of the low energy excess. Additionally, MicroBooNE aims to study the cross section of neutrinos in liquid argon and prototype LArTPC technology for future neutrino experiments.
2.2 The MicroBooNE Detector

The Fermilab booster synchotron produces protons with 8.89 GeV/c momentum, which the BNB collides with a beryllium target to produce a focused beam of pions, which decay into muons and eventually muon neutrinos. The MicroBooNE detector is located off-axis on the BNB, 470 meters downstream of the target (3).

The detector itself is a 60 ton fiducial volume rectangular prismatic LArTPC contained in a cylindrical cryostat. A rendering of the MicroBooNE detector is shown in Figure 3 (3). Neutrinos from the BNB interact with the liquid argon inside the TPC, producing charged particles. Charged particles in liquid argon produce both scintillation light and ionization electrons, which are measured by MicroBooNE’s two datataking systems.

Ionization electrons drift through the TPC due to the presence of a uniform electric field, produced by a field cage of 64 2.5 cm steel pipes connected to a high voltage cathode currently operating at 70 kV. The field drives these ionization electrons to three anode wire planes: two induction planes at angles of ±60° to the vertical, consisting of 2400 wires separated by 3mm, and one collection plane of 3456 wires with the same spacing, oriented parallel to the vertical. This geometry is depicted in the rightmost image in Figure 3. Ionization electrons deposit their charge on the three wire planes, and the waveform of this charge is digitized with a 2MHz frequency and corresponding 2 µs processing time. The the timing of the charge deposition allows for reconstruction of particle trajectories along the dimension of each plane, while 3D event reconstruction is possible when information across all three planes is combined. Calorimetric information is also retained from the collection plane so the charge deposited per path length, or dQ/dS, can be used to differentiate particle types (3) (2).

The drift time of ionization electrons is relatively slow, however, on the scale of several microseconds, depending on the distance between the interaction vertex and the anode plane. In
Figure 4: A sample MicroBooNE event display. The vertical axis corresponds to time ticks, while the horizontal axis corresponds to wire numbers (each separated by 3 mm).

In order to reconstruct the absolute timing of events, MicroBooNE harnesses the faster propagation time of scintillation light, which moves through the detector on the nanosecond scale and is captured by an array of 32 8-inch photomultiplier tubes (PMTs) located behind the anode wire plane (3). This allows for the selection of data based on timing when the beam was present in the TPC, and the rejection of background events containing only cosmic rays.

### 2.3 MicroBooNE Data Representation

Data from the MicroBooNE detector is analyzed as event displays, which are the 2D projections of neutrino events on one of the three wire planes of the TPC. A sample event display of this sort is displayed in Figure 4. These images are generated by filling each column with the value of the reconstructed waveform of charge deposition on the wires in the plane, such that the two axes for such an image are wire number, displayed horizontally, and readout time, displayed vertically. As such, a single pixel corresponds to 0.55 mm. The pixel value, displayed in Figure 4 as color, contains the calorimetric information from the event: the analog-to-digital-converted (ADC) charge deposited on the wire (2).
Figure 5: A simulated event display for an interaction which has produced a proton, muon, pion and electron, as labeled in the image.

2.4 Identifying Particle Types in LArTPC

The final step of event reconstruction for MicroBooNE analysis is particle identification: for a given image, it is necessary to identify the particles produced by a neutrino interaction in order to understand both the flavor of the neutrino and the cross section of the interaction channel. Figure 5 displays a sample simulated MicroBooNE event display. The four particles in the image are distinguishable through both topological and calorimetric properties.

Charge deposited on the wire plane can have two different classes of event topology, depending on particle type. Muons, pions and protons appear as continuous tracks of ionization electrons, as shown in Figure 5. In comparison, gammas can irradiate electron/positron pairs, which come off of the particle trajectory in shower-like pixels of ionization electrons. Electrons similarly appear to be shower-like. In addition to the track/shower delineation, topological information from event displays can also illuminate particles stopping or decaying. The “kink” in the muon track in Figure 5 likely corresponds to a muon stopping, and the subsequent track is likely a low energy Michel electron produced by muon decay.

Calorimetric information from event displays can similarly aid in particle identification. This is especially clear in the case of protons: as shown in Figure 5, these particles typically appear as high dE/dx tracks. This calorimetric information is one of few ways to distinguish gammas from electrons: electromagnetic showers from gammas are produced by an electron/positron pair, and thus have a higher initial dE/dx than single electron showers. An important distinction with respect to single wire plane calorimetry such as this is the difference between dE/dx, the particle’s true energy deposition per unit length in three dimensions, and dQ/dS, the charge deposited by the particle per path length along the one dimensional projection of the wire plane. Event displays from a single wire plane only contain dQ/dS information,
and while the two values are correlated, a particle’s dQ/dS can appear artificially high along a particular dimension, depending upon its angle to the wire plane. This is one of several PID challenges.

3 Deep Neural Network for Particle ID

The primary task of MicroBooNE particle ID is thus parsing both the calorimetric and topological information contained in event displays containing interaction vertices, and discerning which particle types are present in the image. This type of object recognition task is extremely suitable to analysis via convolutional neural networks, or CNNs. A detailed discussion of CNNs is available in Appendix A. In 2016, the MicroBooNE collaboration first applied these deep neural networks to PID tasks on isolated particle tracks and showers, as discussed in Reference (2). However, end-state PID in the MicroBooNE analysis does not take single particle tracks and showers as an input, but rather entire neutrino interaction vertices. Bridging this gap requires a change in the architecture of the deep neural network used for analysis.

3.1 Loss Functions and Softmax Regression

The aspect of deep learning which allows neural networks to learn from training is a loss function, which measures unhappiness with the network output result. High loss function values correspond to poor network performance, and CNNs minimize this value throughout training (5).

The MicroBooNE collaboration has previously had success with CNN applications to particle identification using the loss function associated with the Softmax Classifier (2). This technique introduces some N number of classes (for example, five different particle types), and asks the network which of the N classes is most likely present in this image.

The softmax regression works by assigning final network outputs each a value \( W \), so that for the \( i \)th test image

\[
 f_i = W x_i, \tag{3}
\]

where \( x_i \) refers to the image label returned by the network. These weighted values are interpreted as the un-normalized log probabilities that the image contains each class. The network then attempts to minimize the loss, a quantity known as the cross entropy:

\[
 L_i = -\log \left( \frac{e^{f_{y_i}}}{\sum_j^N e^{f_j}} \right), \tag{4}
\]

where \( L_i \) is the loss/cross-entropy, \( y_i \) is the truth label for the \( i \)th image, the index \( j \) refers to each of the N classes possible, and \( f_i \) is as defined in Equation 3 (5).

A network which employs the softmax regression will return an array of normalized scores for each class it knows. An important aspect of this network architecture is that the CNN must make a choice as to which class is present in the image: there is no way for the network to
indicate that multiple classes are present. This architecture is extremely suitable to problems where an image can be classified as a whole (for example, cases where it is applicable to say “the particle in this image is an electron”).

3.2 Limitations of Softmax Classification for PID

The 2016 MicroBooNE publication on CNNs for events in liquid argon applied the softmax regression to classify isolated particle tracks and showers (2). While promising as to the suitability of CNNs as a PID technique, this specific network alone is not capable of fully carrying out PID on true neutrino events: interaction vertices, once located, contain multiple particles, and can not be classified as containing one particle type only.

A possible approach to analyzing these multi-particle neutrino events would be to separate out each track and shower emerging from the nucleus, cluster the pixels, and show them individually to the softmax-based network for classification. While this approach is intuitive, it also requires near-perfect clustering of the track and shower pixels, an extremely non-trivial task. Rather than use imperfect clusters to train the network, we decided to implement a new network architecture for PID, capable of recognizing multiple particle tracks in a single image.

3.3 Implementation of Sigmoid Loss Minimization

In order to eliminate the normalization constraint of the softmax regression algorithm and train the network on identification of multiparticle events, we implemented the sigmoid multiclassification regression. This method makes use of the binomial logistic function, which calculates a score between 0 and 1 correlating to how certain the network is that a certain class (such as a particle type) is present, according to

\[ f_i = \frac{1}{1 + e^{-x_i}}, \]  

(5) where \( x_i \) again refers to the array of labels returned by the network. In this case, the network’s label corresponds to whether or not a class is present. This is reinforced through training with the modified logistic cross entropy loss function

\[ L_i = \max(x_i, 0) - x_i y_i + \log(f_i), \]  

(6) where \( x_i \) and \( f_i \) are as defined above and \( y_i \) is the truth label of the image (6).

A major advantage of this sigmoid approach with respect to PID applications is that it does not require exclusivity of particle types in an image. For a given image, a network using the sigmoid loss function will return an array of scores for the existence or lack thereof of each class of object it knows how to recognize, regardless of which other particles may be in the image. The normalization constraint is thus lifted. Figure 19 in Appendix B demonstrates an example of such scoring on toy data. Appendix B contains a discussion of a proof-of-
3.4 Network Training and Preliminary Performance on Validation Data

After implementing the sigmoid loss function architecture, we trained the CNN on a set of training images produced by a multi-particle generator, which produced event displays each containing one 3D interaction vertex located randomly throughout the TPC. Each of five particle types was introduced to the network: electron, gamma, muon, pion, and proton. For each particle type, multiplicities ranging from 0 to 4 were allowed. The training dataset was composed 80\% of events with allowed particle kinetic energy ranging from 100 MeV to 1000 MeV, with the exception of proton kinetic energy, which ranged from 100 MeV to 400 MeV. The remaining 20\% of training data was comprised of low energy events, with particle kinetic energy ranging from 30 MeV to 100 MeV (40 MeV to 100 MeV for protons). This training was conducted for 12 hours, or approximately 17000 training steps.
A preliminary test of network performance was conducted on a validation dataset containing a new set of images from the training data with the same distribution of energies and particle types. We did this in order to ensure that the network learned correctly during the training process, and did not simply memorize the training images.

The results of this validation test are displayed in Figure 3.4. Here accuracy for a given particle is defined as the score returned by the network for that particle for images which in truth contain it. In general, higher scores are extremely favored, which is promising as to the network’s ability to recognize different particle types. As multiplicity of a given particle type increases, the network’s ability to recognize it decreases, which is consistent with the increasing difficulty of PID as more particles are present in an image. This is especially noticeable in the case of the electron scores, which do not seem to favor higher recognition for multiplicities greater than 2. Of all the particle types the network is trained to identify, the electron showers are particularly made more difficult by increasing multiplicity. There is a significant likelihood of showers overlapping and obscuring one another, potentially causing the event display to appear to contain high dE/dx showers consistent with gammas.

This brief performance test is promising as to the network’s ability to recognize particle types, and also demonstrates the increasing difficulty of the PID task as multiplicity increases. This shows that the network is doing PID in an intuitive way.

4 Testing Network Performance on Low Energy Events

To better understand network performance and its applicability to the MicroBooNE analysis, we tested its ability to recognize the contents of images from low energy events containing one lepton and one proton (1L1p images). These events were chosen because the 1L1p signal is of particular interest to the MicroBooNE collaboration. As shown in Figure 2, the dominant interaction mode in the energy range of the MiniBooNE low energy excess is charged-current quasi elastic channel (CCQE). These interactions are consistent with a 1L1p event signal: $\nu_e$ candidate CCQE events will produce one electron and one proton, while the $\nu_\mu$ counterpart events will produce one muon and one proton. Identifying the particle types in 1L1p low energy events are thus of the utmost importance for discerning the flavor of low energy neutrinos interacting in the MicroBooNE detector. Understanding network performance in this energy range is a good preliminary indicator of its suitability to PID goals.

In testing network performance, there are two related goals: first, to discern how well the network is able to recognize the lepton and proton present in the image. Second, in the cases where the network fails to recognize particle types, it is important to understand whether or not these failures are rooted in legitimate PID challenges which can be potentially accounted for in analysis.
4.1 Performance on 1 Electron 1 Proton Events

Network performance was tested on 50,000 simulated events containing exactly one proton and one electron (1e1p), propagating from a shared vertex. Vertex location was distributed uniformly throughout the detector, and particle momentum was given isotropic momentum.

The electron kinetic energy was distributed uniformly between 30 MeV and 100 MeV, while proton kinetic energy ranged from 40 MeV to 100 MeV. The energy and momentum distributions for the particles of interest are shown in Figure 4.

4.1.1 Network Score Distributions

A preliminary way to understand network image recognition is to study the distribution of the scores returned for each of the five particle classes the network is trained to recognize. These distributions are shown in Figure 4.1.1.

The distributions for proton and electron scores show peaks at the very high end of the score range, close to 1. This indicates that a majority of the time, the network is confident that tracks from an electron and proton are present in the image, and correctly identifies its contents. In contrast, the score distributions for muons, pions and gammas show that higher scores are disfavored, which is consistent with the network correctly identifying that there are none of these particles present. However, the distributions for muon and gamma scores both show small peaks in the frequency of scores close to 1. This indicates that the network is occasionally very confident that a muon or gamma is present in the image. In order to understand network performance, these false-positives need to be explored.
4.1.2 Muon False Positives

Displayed in Figure 4.1.2 is the 2D histogram for electron and muon score distributions. This plot shows the population of high muon scored events are clustered where electron score for these images is very low. This indicates that high muon scores are caused when the network mistakes an electron for a muon. Examining the electron energy distribution for these false positive events illuminates the likely cause of this error. The right hand plot in Figure 4.1.2 shows the amplitude-normalized electron energy distributions for both all the test events and for only those with a muon score above 0.7. The distribution for these muon false positive events shows a skew towards lower energy events.

This indicates that the network’s misidentification of energy electrons is grounded in a difficult PID challenge: low energy electrons can appear tracklike in the detector, and produce event displays very similar to those from low energy muons. Two example events of this sort are depicted in Figure 10.
Figure 9: Left: A 2D histogram of the score distributions for electron and muon scores of 1e1p events. Right: Amplitude-normalized histograms for the electron kinetic energy of two different populations, illuminating a that potential cause of muon false positives is the PID challenge associated with low energy electrons.

Figure 10: The event displays for two low energy events which the network mis-identified. On the left is a low energy electron and a proton, on the right a low energy muon and a proton. When the network was tested on these images, a high muon score was returned for the image containing an electron, while a high electron score was returned for the image containing a muon.
4.1.3 Gamma False Positives

Examining the 2D histogram for gamma scores and electron scores of the low energy 1e1p sample, as shown in Figure 4.1.3, shows three event populations.

The first and largest population has a high electron score and a low gamma score. These events are those which the network is able to correctly classify as electrons.

However, a second large population exists with moderate electron scores and gamma scores. Although in these cases the electron score is still higher than the gamma score, indicating that the network does not make an overt mistake, this event population likely contains some confusing features for the network and warrants exploration.

To study this population with moderate electron and gamma scores, a cut was performed to select the events where the electron score was greater than the gamma score, but less than the gamma score - 0.4. This population of events is depicted in the leftmost plot in Figure 4.1.3. Plotting the angle of the electrons in these events with respect to the wire plane shows that this population has a skew towards angles parallel to the direction of the wire plane. This indicates a likely cause of the network confusion: electrons moving parallel to the wire plane direction will deposit a higher dQ/dS upon the plane, making the electron appear more like the high dE/dX shower characteristic of a photon electromagnetic shower.

The final population of interest in Figure 4.1.3 is that with high gamma scores and low electron scores. Here, the network mistakes the electron it sees for a gamma. Studying the population of events with an electron score less than 0.05 and a gamma score greater than 0.95 illuminates several possible causes of this mis-identification.

From a qualitative study of these events, two dominant event types seem to give rise to very high gamma scores. First, the electron in the image has irradiated very early in its trajectory to produce a high energy gamma. In this case, the network is not making a mistake: it has been shown an image containing a proton and a gamma, and it correctly identifies the contents. In the second case, the electron and proton in the image have an open angle of either 0° or 180°, so that the particles are colinear. For these events, the network sees a high dE/dx track followed by an electromagnetic shower. The combination of these features often indicates the presence of a gamma, so it is understandable that the network could identify these event displays as gammas. Sample images of each of these classes of mistake are depicted in Figure 13. However, as shown in Figure 13, not all 1e1p gamma false positives fall into these two categories. Proton scattering...
Figure 12: Left: The 2D score network distributions for events with an electron score greater than gamma score and less than gamma score - 0.4 for low energy 1e1p events. Right: the normalized electron angle distributions for the entire 1e1p sample population (purple) and for only the population pictured in the lefthand plot (green). Note that angle is with respect to the perpendicular from the wire plane, such that 90° is parallel to the direction of the wire plane.

Figure 13: Three sample low energy 1e1p events for which the network returned an electron score below 0.05 and a gamma score above 0.95. Each illuminates a different type of network mistake. On the left, the electron has irradiated a gamma very early in its trajectory, producing majority gamma pixels. In the center image, the electron and proton are co-linear. For the third image, the cause of network confusion is not entirely clear - more network training may be required for the differentiation of this kind of shower.
or other rare events can confuse the network, while some errors are less easy to understand and could potentially be eliminated simply by training the network for a longer period of time.

4.2 Performance on 1 Muon 1 Proton Events

In addition to the 1e1p test conducted, the CNN was also tested on 50,000 simulated events containing one muon and one proton. Again, particles propagated from a shared vertex, distributed uniformly through the detector, and moved with isotropic momentum. For both protons and muons, particles were simulated with uniform momentum distributions, as shown in Figure 14. Muon kinetic energy ranged from 30MeV to 100MeV, while proton kinetic energy ranged from 40MeV to 100MeV.

4.2.1 Network Score Distributions

Plotting the distributions of the scores returned by the network for each particle type again shows that a majority of the time the network is confident that a muon and proton are present in the image, as shown in Figure 15. Similarly, the distributions for gammas, electrons and pions, which are not present in the sample images, shows that high scores are disfavored by several orders of magnitude. However, there is a slight peak in the electron score distribution in the high score region close to 1. This indicates that the network is occasionally very confident that an electron is present in the event display it sees.

4.2.2 Causes of High Electron Scores

To better understand the cause of these disagreements between the image label and network label, we can study the 2D distribution of electron score in comparison to muon score, as shown

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Figure 14: Momentum distributions for simulated muons and protons in 50,000 1µ1p images which the network was tested on.
Figure 15: Network score distributions for each particle class it was trained on for low energy $1\mu1p$ test events.

Figure 16: Left: the 2D distribution of electron scores and muon scores returned by the network for low energy $1\mu1p$ events. Right: The amplitude-normalized muon energy distributions for two event populations: in cyan, the entire set of $1\mu1p$ test images, in purple those events with an electron score greater than 0.7.
Figure 17: Zoomed-in interaction vertices from $1\mu 1p$ truth labeled events which the CNN mislabeled as containing an electron. Both images displayed here in fact contain Michel electrons. Note that the muon in the leftmost image in fact decays in a region where ionization electrons are deposited on wires for which the electronics have malfunctioned, as shown by the blank region in the event display.

in Figure 4.2.2. This distribution shows that events with high electron scores are clustered in the region where muon scores are low: the network mistakes muons for electrons. Plotting the energy distribution of events with an electron score greater than 0.7 shows that the false positives are overwhelmingly caused by low energy muons.

One possible explanation for these false positives is that low energy muons appear very similar to low energy electrons, as discussed previously and displayed in Figure 10. However, studying the images which the network identifies as electrons reveals a second case of events: low energy muons can decay through the path

$$\mu^- \rightarrow e^- + \nu_\mu + \bar{\nu}_e.$$ 

Electrons produced by this decay, called Michel electrons, can thus be present in the event display seen by the network. Sample events of this variety are shown in Figure 17.

5 Conclusions and Next Steps

Overall, preliminary validation testing and performance on low energy $1L1p$ events indicates that deep neural network architecture using the sigmoid loss function is capable of performing PID for multi-particle events containing neutrino interactions. The contributions of this work is as follows:
• The development of a deep neural network for multiclass particle identification, which does not rely on the exclusivity of particle types in an image.

• Validation testing of the neural network on a dataset with the same composition as training data, which shows that the network is largely able to recognize the presence of each particle class, but is affected by the difficulties of PID for events with very high multiplicities.

• Testing of network performance on low energy 1L1p events consistent with the MicroBooNE low energy excess analysis signal of CCQE candidate $\nu_e$ and $\nu_\mu$ interactions indicates the following:
  
  – Network is largely able to recognize the presence of both low energy lepton and proton
  – Network mistakes are consistent with legitimate PID challenges and can be understood

• The development of toy data generator for proof of principle testing for multiclass and classification network architectures (see Appendix B).

The following aspects of multiclass deep neural network development for PID still need to be explored:

• Adjust network training time and dataset in order to minimize PID mistakes.

• Analyze network performance on more general simulated $\nu_e$ and $\nu_\mu$ events, not solely those containing one lepton and one proton, in order to understand its capacity for cross section analysis.

• Test network performance on MicroBooNE data.

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A Convolutional Neural Networks

Convolutional neural nets, or CNNs, are a type of neural network suitable for image recognition. Historical attempts to apply deep learning techniques such as this to high energy physics analysis have struggled due to the challenges of a fully connected neural network type known as a Feed-Forward Neural Network (FFNN). CNNs are an improvement on FFNN design, and were successfully implemented for recognition of single particles in liquid argon for MicroBooNE event displays in 2016 (2). Both CNNs and FFNNs rely on a set of features to classify images into categories (such as the particle types which may be present in an event display). For FFNNs, these features must be selected and taught to the network, a process which is difficult to successfully implement for HEP datasets and can introduce bias into image analysis. A major advantage of CNNs is their ability to learn these features automatically while training on provided data. This difference is due to adjustments in the architecture of CNNs.

In FFNN architecture the network takes in an input feature vector $\vec{x}$. Each element in the vector passes through every neuron in the first layer of the FFNN. The number of neurons in the FFNN layer corresponds to the number of features being tested for in the image, and has its own weight $w$ and bias $b$, which the FFNN learns through training. The output of the $i$th neuron in an FFNN layer can thus be expressed as a vector function

$$f_i(\vec{x}) = \sigma(\vec{x} \cdot \vec{w}_i + \vec{b}_i).$$

(8)

Here $\sigma$ is the activation function of the neuron, where the neuron is only activated when the input vector shows the presence of a given feature. A commonly used activation function is shown in Equation 9:

$$\sigma = \begin{cases} \vec{x} \cdot \vec{w}_i + \vec{b}_i & \vec{x} \cdot \vec{w}_i + \vec{b}_i > 0 \\ 0 & \vec{x} \cdot \vec{w}_i + \vec{b}_i \leq 0 \end{cases}. \quad (9)$$

The outputs of neurons from a given layer then become the input vectors for the subsequent layer of neurons. The FFNN “learns” by adjusting the weights and biases on each neuron such that the output of the final layer is equal to some truth label $\vec{y}$ (5) (2).

In addition to the difficulty of specifying features, FFNNs have several other limitations which make HEP applications difficult. First, in a FFNN every neuron in one layer connects directly to every neuron in a subsequent layer. This is known as a fully connected layer, and requires an unrealistic amount of computing power, which limits how many layers (how “deep”) a network can be. FFNNs are also not sensitive to translated objects in an image: recognizing an electron shower in an event display, for example, would be an entirely different question to ask the FFNN if the electron were in a different location. Both of these limitations make FFNNs impractical for analysis of MicroBooNE event displays, but are resolved by the architectural differences of CNNs.

A CNN is actually a limited version of a FFNN, where neurons in a given layer only receive information from a localized region of neurons in the previous layer, rather than the traditional fully connected layer structure. A given neuron scans each region of pixels in the image and
returns a score as calculated by Equation 8. For each neuron, a grid of these scores is pro-
duced, known as a feature map. The feature maps for each neuron are then combined into a
3D array of values, which is input to the subsequent layer. The feature parameters for these
neurons, also called filters, are learned by the network while it trains, providing a major ad-
vantage over FFNN architecture. Additionally, this type of feature scanning makes the network
sensitive to translation-invariant features in objects, and requires much less computation than
fully connected layers (2).

B  Proof-of-Principle Test using Toy Data

Before testing the multiclass architecture described in Section 3.3 on particle interactions, we
conducted a proof of principle test on a simpler case in order to determine if the sigmoid loss
function could be implemented successfully. To conduct this test we wrote a python package to
generate toy data, and developed sample scripts for the testing of deep neural networks for both
classification and multiclass architectures.

This data takes the form of images of variable size (default 28 pixels by 28 pixels) which
contain four possible classes of simple geometric shapes: square, triangle, horizontal line and
vertical line. Allowed multiplicities and types of the shapes can be adjusted by this data gen-
erator, and labeling options for multiclass and classification images are present. The proof-of-
principle test was conducted on images which could contain 0-4 of each class of shape. Over 12
hours of training, the network was able to learn to identify the contents of these images using
the sigmoid regression. Figure B depicts the accuracy and loss curves of the network over the
course of training: the network was able to minimize loss throughout the training steps, as is
consistent with learning.

Performance on test images was further promising as to the effectiveness of this multiclass
architecture. The network was overwhelmingly able to identify the contents of test images. A
sample toy data image shown to the network and its returned score are depicted in Figure B.
Overall, network performance on this simple multiclass identification question was extremely
promising as to the potential success of this same architecture for PID applications.

The generator used for this test is available for use in a github repository (7), along with
sample python scripts for developing and training deep neural networks using the Tensorflow
open source software library.

References and Notes


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Figure 18: The loss curve (left) and accuracy curve (right) for the training of a deep neural network with multiclass architecture training on toy data. Over the course of 800 training steps, loss decreases and accuracy increases, as is consistent with the network learning. Images are produced through the tensorboard tool for visualizing network training for tensorflow-based networks.


Figure 19: A sample toy data image used to test the success of the sigmoid loss function architecture. The truth label of this image is [1, 1, 0, 1], with indices corresponding to the existence of [triangle, square, horizontal line, vertical line]. The network returned label for this image is [0.999, 1., 0.004, 0.998]: not only is the neural net very confident that the image contains a triangle, square and vertical line, but it also is confident that the image does not contain a horizontal line.