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2 μ/π separation using

3 Convolutional Neural Networks

4 for the MicroBooNE

5 Charged Current Inclusive Cross Section

6 Measurement

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DISSERTATION

Submitted in partial fulfillment
of the requirements for the degree
Doctor of Philosophy in Physics

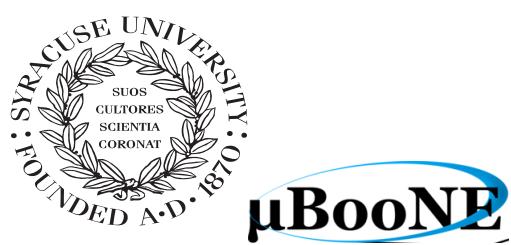
- * - DRAFT January 28, 2018 - * -

December, 2017
Syracuse University
Syracuse, New York

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μ BooNE



26

Abstract

27

The purpose of this thesis was to use Convolutional Neural Networks
28 (CNN) to separate μ' s and π' s for use in increasing the acceptance rate
29 of μ' s below the implemented 75cm track length cut in the Charged
30 Current Inclusive (CC-Inclusive) event selection for the CC-Inclusive
31 Cross-Section Measurement. In doing this, we increase acceptance
32 rate for CC-Inclusive events below a specific momentum range.

33

Dedication

34

I dedicate this dissertation to the two important women in my life; My
35 wife and my mom. Both have been there cheering me on giving me strength
36 and love as I worked towards the hardest accomplishment I've ever done.

37

Jessica Nicole Esquivel

38

Acknowledgements

39 Of the many people who deserve thanks, some are particularly prominent, such as
40 my supervisor...

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*"If they don't give you a seat at the table,
bring a folding chair."*

— Shirley Chisholm

⁴¹⁹ **Chapter 1**

⁴²⁰ **Introduction**

⁴²¹ This thesis will be a description of work done to further increase efficiency and purity
⁴²² of the charged current inclusive cross section measurement using the MicroBooNE
⁴²³ detector. It will also describe the MicroBooNE detector, what neutrinos are, the
⁴²⁴ charged current inclusive cross section measurement and its importance as well as
⁴²⁵ convolutional neural networks and how they can be used in μ/π separation. Chapter
⁴²⁶ 2 will talk about the background of neutrinos and the people and detectors that
⁴²⁷ discovered neutrinos as well as an in depth history of neutrino oscillation and the
⁴²⁸ discovery that neutrinos have mass.

⁴²⁹ Chapter 3 will discuss the MicroBooNE experiment, specifically, how Liquid
⁴³⁰ Argon Time Projection Chambers work, the Light Collection System and the Electronic
⁴³¹ and Readout Trigger systems. This chapter will also describe the Booster Neutrino
⁴³² Beam sationed at Fermilab.

⁴³³ Chapter 4 will discuss the work that was done to detect the first neutrinos seen in
⁴³⁴ the MicroBooNE detector and the software reconstruction efforts required to create an
⁴³⁵ automated neutrino ID filter that was used to find the first neutrinos and then was
⁴³⁶ later expanded on to create the charged current inclusive filter that will be discussed
⁴³⁷ in chapter 5

⁴³⁸ Chapter 6 will give a brief description of what Convolutional Neural Networks are
⁴³⁹ and how it will be used for μ/π separation in this selection. Chapter 7 will discuss
⁴⁴⁰ the hardware frameworks and training methods used to train multiple Convolutional
⁴⁴¹ Neural Networks for use in the charged current inclusive cross section measurement.
⁴⁴² Chapters 8 and ?? will discuss the results of using Convolutional Neural Networks on
⁴⁴³ monte-carlo and data to sift out charged current inclusive neutrino events.

⁴⁴⁴ Chapter 2

⁴⁴⁵ Neutrinos

⁴⁴⁶ 2.1 What are Neutrinos

⁴⁴⁷ Neutrinos are fundamental particles which help make up the universe. They are also
⁴⁴⁸ one of the least understood. Neutrinos are not affected by the electromagnetic force
⁴⁴⁹ because they do not have electric charge. Neutrinos are affected by a weak sub-atomic
⁴⁵⁰ force of much shorter range than electromagnetism, and are therefore able to pass
⁴⁵¹ through great distances in matter without much possibility of being affected by it.
⁴⁵² Until the late 1990's, neutrinos were thought to have no mass. Neutrinos are created
⁴⁵³ by radioactive decay such as the ones that happen in the sun, in nuclear reactors or
⁴⁵⁴ when cosmic rays hit atoms. There are three types of neutrinos, ν_e , ν_μ and ν_τ which
⁴⁵⁵ correspond to their charged lepton pairs.

⁴⁵⁶ As previously stated, neutrinos are very weakly interacting; in fact, neutrinos can
⁴⁵⁷ pass unscathed through a wall of lead several hundred light-years thick. Because
⁴⁵⁸ neutrinos interact so rarely, studying neutrinos requires a massive detector and a
⁴⁵⁹ powerful neutrino source. With that being said, we can only "see" a neutrino when
⁴⁶⁰ they interact in a detector. In a collision, distinct charged particles are produced with
⁴⁶¹ each type of neutrino because of the weak force. An electron neutrino will create an
⁴⁶² electron, a muon neutrino will create a muon, and a tau neutrino will create a tau. The
⁴⁶³ charged lepton track the particle leaves in the detector is how one figures out what
⁴⁶⁴ type of neutrino interaction was "seen". Liquid Argon Time Projection Chambers are
⁴⁶⁵ being used to study neutrinos due to their excellent imaging and particle identification
⁴⁶⁶ capabilities.

⁴⁶⁷ 2.2 History of Neutrinos

⁴⁶⁸ The neutrino was first postulated by Wolfgang Pauli in 1931 to explain how beta
⁴⁶⁹ decay could resolve the conservation of energy, momentum and angular momentum
⁴⁷⁰ problem. Pauli suggested that this missing energy might be carried off, unseen, by a
⁴⁷¹ neutral particle (he called neutron) which was escaping detection. James Chadwick
⁴⁷² discovered a much heavier nuclear particle in 1932 that he also named neutron, leaving
⁴⁷³ two particles with the same name. Enrico Fermi was the first person to coin the
⁴⁷⁴ term neutrino (which means little neutral one in latin) in 1933 to fix this confusion.
⁴⁷⁵ Fermi's paper, which was published in 1934, unified Pauli's neutrino with Paul Dirac's
⁴⁷⁶ positron and Werner Heisenberg's neutron-proton model and his theory accurately
⁴⁷⁷ explained many experimentally observed results. Wang Ganchang first proposed the
⁴⁷⁸ use of beta capture to experimentally detect neutrinos and in 1959 Clyde Cowan and
⁴⁷⁹ Frederick Reines published their work stating that they had detected the neutrino.
⁴⁸⁰ The experiment called for antineutrinos created in a nuclear reactor by beta decay that
⁴⁸¹ reacted with protons producing neutrons and positrons: $\nu_e + p^+ \rightarrow n^0 + e^+$. Once
⁴⁸² this happens, the positron finds an electron and they annihilate each other and the
⁴⁸³ resulting gamma rays are detectable. The neutron is detected by neutron capture and
⁴⁸⁴ the releasing of another gamma ray. In 1962 Leon M. Lenderman, Melvin Schwartz
⁴⁸⁵ and Jack Steinberger were the first to detect interactions of the muon neutrino. The
⁴⁸⁶ first detection of the tau neutrino was announced in the summer of 2000 by the
⁴⁸⁷ DONUT collaboration at Fermilab. In the late 1960s, many experiments found that the
⁴⁸⁸ number of electron neutrinos arriving from the sun was around 1/3 to 1/2 the number
⁴⁸⁹ predicted by the Standard Solar Model. This became known as the solar neutrino
⁴⁹⁰ problem and remained unresolved for around thirty years. This problem was resolved
⁴⁹¹ by the discovery of neutrino oscillation and mass. [1]

⁴⁹² 2.3 Neutrino Oscillations

⁴⁹³ Neutrino oscillation was first predicted by Bruno Pontecorvo. It describes the phe-
⁴⁹⁴ nomenon of a neutrino created with a specific lepton flavor (electron, muon or tau)
⁴⁹⁵ that is later measured to have a different flavor. Neutrino oscillation is important
⁴⁹⁶ theoretically and experimentally due to the fact that this observation implies that the
⁴⁹⁷ neutrino has a non-zero mass, which is not part of the original Standard Model of
⁴⁹⁸ particle physics. [2]

499 2.3.1 Solar Oscillations and the Solar Neutrino Problem

500 The solar neutrino flux derived from Bahcall's Standard Solar Model is shown in figure
 501 2.1. Nuclear fusion and decay processes produce an abundant amount of neutrinos.
 502 The standard solar model predicts that these reactions produce several groups of
 503 neutrinos, each with differing fluxes and energy spectra. The figure also shows the
 504 ranges of detection of existing solar neutrino experiments in different shades of blue
 505 to illustrate that they sample different portions of the solar neutrino energy spectrum.
 506 Three of these experiments, plus a new one, are discussed below.

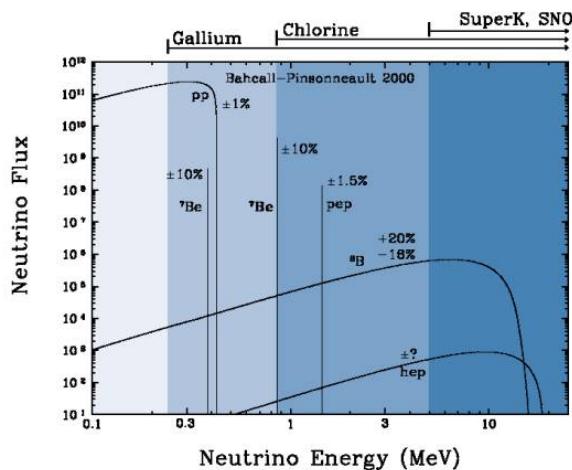


Figure 2.1: The Standard Solar Model

507 Since neutrinos rarely interact with matter, they pass through the sun and the earth
 508 undetected. About 65-billion neutrinos from the sun stream through every square
 509 centimeter on the Earth every second, yet we are oblivious to their passage in our
 510 every-day lives. [3]

511 The first experiment to detect the effects of neutrino oscillation was the Ray Davis's
 512 Homestake Experiment. The detector was stationed in the Homestake Gold Mine in
 513 Lead, South Dakota. It was 1,478 meters underground and was $380\ m^3$. The detector
 514 was filled with perchloroethylene. Perchloroethylene was chosen because of its high
 515 concentrations of chlorine. When an ν_e interacted with chlorine-37 atom, the atom
 516 would transform to argon-37 which was then extracted and counted. The neutrino
 517 capture reaction is shown in equation 2.1. Davis observed a deficit of about 1/3
 518 the flux of solar neutrinos that was predicted by Bahcall's Standard Solar Model.

- 519 The unexplained difference between the measured solar neutrino flux and model
 520 predictions lead to the Solar Neutrino Problem. [4]



521 While it is now known that the Homestake Experiment detected neutrinos, some
 522 physicist were weary of the results. Conclusive evidence of the Solar Neutrino Problem
 523 was provided by the Kamiokande-II experiment, a water Cherenkov detector with
 524 a low enough energy threshold to detect neutrinos through neutrino-electron elastic
 525 scattering. In the elastic scattering interaction the electrons coming out of the point of
 526 reaction strongly point in the direction that the neutrino was traveling, away from the
 527 sun. While the neutrinos observed in Kamiokande-II were clearly from the sun, there
 528 was still a discrepancy between Kamiokande-II and Homestake; The Kamiokande-
 529 II experiment measured about 1/2 the predicted flux, rather than the 1/3 that the
 530 Homestake Experiment saw.

531 The solution to the solar neutrino problem was finally experimentally determined
 532 by the Sudbury Neutrino Observatory(SNO). The Ray Davis's Homestake Experiment
 533 was only sensitive to electron neutrinos, and the Kamiokande-II Experiment was
 534 dominated by the electron neutrino signal. The SNO experiment had the capability to
 535 see all three neutrino flavors. Because of this, it was possible to measure the electron
 536 neutrinos and total neutrino flux. The experiment demonstrated that the deficit was
 537 due to the MSW effect, the conversion of electron neutrinos from their pure flavor
 538 state into the second neutrino mass eigenstate as they passed through a resonance
 539 due to the changing density of the sun. The resonance is energy dependent, and is
 540 visible near 2 MeV. The water cherenkov detectors only detect neutrinos above about 5
 541 MeV, while the radiochemical experiments were sensitive to lower energy (0.8 MeV for
 542 chlorine, 0.2 MeV for gallium), and this turned out to be the source of the difference
 543 in the observed neutrino rates at the two types of experiments. Figure 2.2 shows
 544 Homestake, Kamiokande-II and SNO experiments.

545 **MSW Effect**

546 The Mikheyev-Smirnov-Wolfenstein effect is a process which acts to modify neu-
 547 trino oscillations in matter. The presence of electrons in matter changes the energy

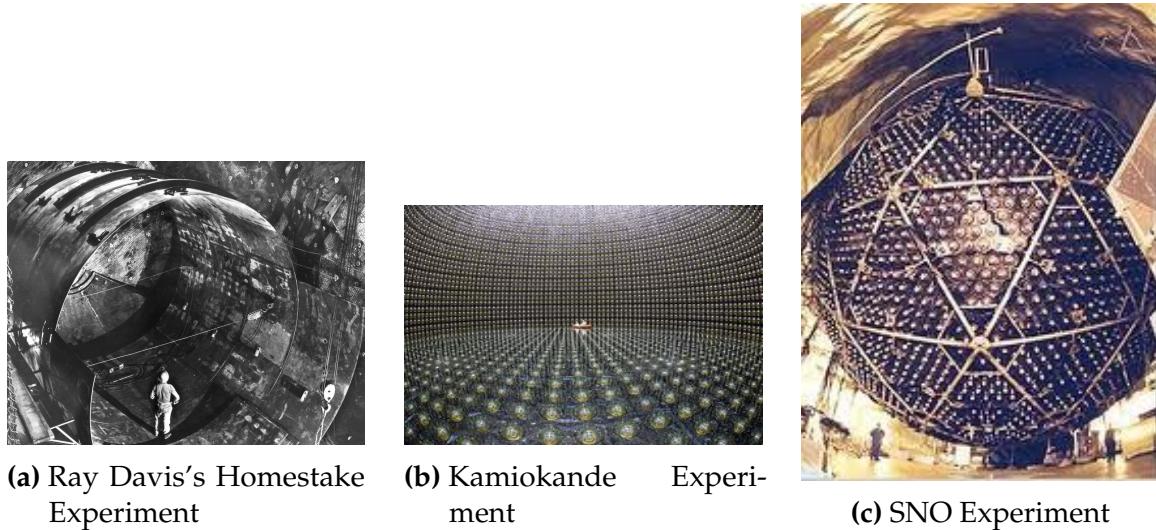


Figure 2.2: Solar Neutrino Experiments

548 levels of the mass eigenstates of neutrinos due to charged current coherent forward
 549 scattering of the electron neutrinos. This coherent forward scattering is similar to
 550 the electromagnetic process with respect to the refractive index of light in a medium.
 551 Because of this MSW Effect, neutrinos in vacuum have a different effective mass than
 552 neutrinos in matter and because neutrino oscillations depend on the squared mass
 553 difference of the neutrinos, the neutrino oscillations are different in matter than in
 554 vacuum. This effect is important at the sun where electron neutrinos are produced.
 555 The neutrinos of high energy leaving the sun are in a vacuum propagation eigenstate
 556 ν_2 that has a very small overlap with the electron neutrino $\nu_e = \nu_1 \cos(\theta) + \nu_2 \sin(\theta)$
 557 seen by the charged current reactions in Kamiokande-II and SNO. The discrepancy of
 558 the deficit between SNO, Kamiokande-II and Homestake is due to the energy of the
 559 solar neutrinos. The MSW effect "turns on" at about 2 MeV and at lower energies, this
 560 MSW effect is negligible. [5]

561 **2.3.2 Atmospheric Oscillations and the Atmospheric Neutrino 562 Anomaly**

563 Atmospheric neutrinos are neutrinos that stem from the decay hadrons coming from
 564 primary cosmic rays. The dominant part of the decay chain is shown in equations 2.2
 565 and 2.3

$$\pi^+ \rightarrow \mu^+ \nu_\mu \mu^+ \rightarrow e^+ \nu_e \bar{\nu}_\mu \quad (2.2)$$

566

$$\pi^- \rightarrow \mu^- \bar{\nu}_\mu \mu^- \rightarrow e^- \bar{\nu}_e \nu_\mu \quad (2.3)$$

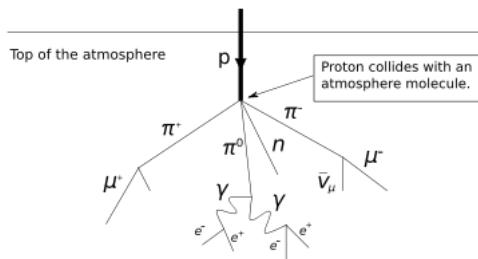


Figure 2.3: Cosmic Ray Shower

567 Figure 2.3 shows the cosmic ray shower. In general, these neutrinos have energies
 568 from 1 GeV to 100s of GeV and the ratio of ν_μ s to ν_e s equals to 2 (see equation 2.4)

$$R = \frac{(\nu_\mu + \bar{\nu}_\mu)}{(\nu_e + \bar{\nu}_e)} \quad (2.4)$$

569 There have been two types of detectors used to study atmospheric neutrinos: Water
 570 Cherenkov detectors and tracking calorimeters. Super-Kamiokande is the detector we
 571 will focus on. These atmospheric detector experiments measure the ratio of ν_μ to ν_e .
 572 They also measure the zenith angle distribution of the neutrinos. These experiments
 573 report a double ratio (shown in equation 2.5). This double ratio is the ratio measured
 574 in the detector to the ratio that's expected which is 2. If the double ratio equals to 1, the
 575 data agrees with the prediction. Various measurements from multiple experiments
 576 are shown in figure 2.4. Except for Frejus, all R measurements are less than 1. This
 577 discrepancy between the predicted R and the measured R became known as the
 578 Atmospheric Neutrino Anomaly.

$$R = \frac{(N_\mu / N_e)_{DATA}}{(N_\mu / N_e)_{SIM}} \quad (2.5)$$

579 Kamiokande-II has the the capability of measuring the direction of the incoming
 580 neutrinos. The expectation of atmospheric neutrino detection is that the flux be

Experiment	Type of experiment	R
Super-Kamiokande	Water Cerenkov	0.675 ± 0.085
Soudan2	Iron Tracking Calorimeter	0.69 ± 0.13
IMB	Water Cerenkov	0.54 ± 0.12
Kamiokande	Water Cerenkov	0.60 ± 0.07
Frejus	Iron Tracking Calorimeter	1.0 ± 0.15

Figure 2.4: Measurements of the double ratio for various atmospheric neutrino experiments

isotropic due to the fact that atmospheric neutrinos can reach the detector from all directions. Kamiokande-II noticed that muon-like data did not agree well with this expectation. At low energies approximately half of the ν_μ are missing over the full range of zenith angles. At high energies the number of ν_μ coming down from above the detector seems to agree with expectation, but half of the same ν_μ coming up from below the detector are missing. This anomaly can be easily explained by neutrino flavor oscillations. Due to the fact that the neutrino travels less distance coming straight down into the detector (about 15km) than coming up from the bottom of the detector(13000km) changes the probability of oscillation. The probability of oscillation for the muon neutrinos coming down into the detector is roughly zero, whereas for neutrinos coming up, the oscillation probability is $\sin^2(2\theta)$. Both the solar and atmospheric neutrino problems can be explained by neutrino oscillation so its fitting to derive this phenomenon mathematically. In the next two sections, two flavor and three flavor neutrino oscillation derivations will be explained.

2.3.3 Two Flavor Neutrino Oscillation Formulation

The flavor eigenstates can oscillate between each other because they are composed of an add-mixture of mass eigenstates(ν_1, ν_2). Figure 2.5 shows the mass and flavor eigenstates rotated by an angle θ which is the mixing angle.

In matrix form the wavefunctions are:

$$\begin{pmatrix} \nu_\mu \\ \nu_e \end{pmatrix} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} * \begin{pmatrix} \nu_1 \\ \nu_2 \end{pmatrix} \quad (2.6)$$

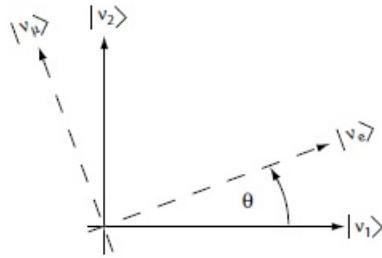


Figure 2.5: The flavor eigenstates are rotated by an angle θ with respect to the mass eigenstates

600 Applying the time evolution operator to ν_μ :

$$|\nu_\mu(t)\rangle = -\sin\theta|\nu_1\rangle e^{-i\frac{E_1 t}{\hbar}} + \cos\theta|\nu_2\rangle e^{-i\frac{E_2 t}{\hbar}} \quad (2.7)$$

601 where $E_1 = \sqrt{p^2 c^2 + m_1^2 c^4}$ and $E_2 = \sqrt{p^2 c^2 + m_2^2 c^4}$ and $p_1 = p_2$. For the time
 602 being, let us assume $\hbar = c = 1$. With this assumption: $E_1 = \sqrt{p^2 + m_1^2}$ and $E_2 =$
 603 $\sqrt{p^2 + m_2^2}$. The next modifications is to assume neutrinos are relativistic:

$$\gamma = \frac{E}{m_o c^2} = \frac{\sqrt{p^2 c^2 + m_o^2 c^4}}{m_o c^2} \gg 1 \quad (2.8)$$

604 because of this,

$$p \gg m_o \quad (2.9)$$

605

$$E = \sqrt{p^2 + m_o^2} = p\sqrt{1 + m_o^2/p^2} \simeq p + \frac{1}{2}\frac{m_o^2}{p} \quad (2.10)$$

606 where the binomial expansion is used. Now E_1 and E_2 can be written as:

$$E_1 \simeq p + \frac{1}{2}\frac{m_1^2}{p} \text{ and } E_2 \simeq p + \frac{1}{2}\frac{m_2^2}{p} \quad (2.11)$$

607 Now applying all these assumptions back into equation 2.7 gives us:

$$|\nu_\mu(t)\rangle = -\sin\theta|\nu_1\rangle e^{-i\left(p + \frac{1}{2}\frac{m_1^2}{p}\right)t} + \cos\theta|\nu_2\rangle e^{-i\left(p + \frac{1}{2}\frac{m_2^2}{p}\right)t} \quad (2.12)$$

$$|\nu_\mu(t)\rangle = e^{-i\left(p+\frac{1}{2}\frac{m_1^2-m_2^2}{p}\right)t} (-\sin\theta|\nu_1\rangle + \cos\theta|\nu_2\rangle) \quad (2.13)$$

608 Substituting $\Delta m^2 = m_1^2 - m_2^2$ and $t = \frac{x}{c} = x$ and $e^{-iz} = e^{-i\left(p+\frac{1}{2}\frac{m_1^2}{p}\right)t}$ gives us:

$$|\nu_\mu(t)\rangle = e^{-iz} \left(-\sin\theta|\nu_1\rangle + \cos\theta|\nu_2\rangle e^{+ix\left(\frac{1}{2}\frac{\Delta m^2}{p}\right)} \right) \quad (2.14)$$

609 Finding the Probability for a $\nu_\mu \rightarrow \nu_e$:

$$P(\nu_\mu \rightarrow \nu_e) = |\langle \nu_e | \nu_\mu(t) \rangle|^2 \quad (2.15)$$

610 Remembering that $\langle \nu_i | \nu_j \rangle = \delta_{ij}$

$$\langle \nu_e | \nu_\mu(t) \rangle = e^{-iz} \left(-\sin\theta\cos\theta + \sin\theta\cos\theta e^{\frac{i\Delta m^2 x}{p}} \right) \quad (2.16)$$

611 Taking the absolute value squared gives us:

$$P(\nu_\mu \rightarrow \nu_e) = |\langle \nu_e | \nu_\mu(t) \rangle|^2 = e^{+iz} e^{-iz} \sin^2\theta \cos^2\theta \left(-1 + e^{\frac{i\Delta m^2 x}{p}} \right) \left(-1 + e^{\frac{-i\Delta m^2 x}{p}} \right) \quad (2.17)$$

612 Since the neutrino is relativistic we can set $p = E_\nu$ and change $x = L$. Also 613 recognizing the trigonometric relation $(1 - \cos 2\theta)/2 = \sin^2\theta$ the above equation 614 becomes:

$$P(\nu_\mu \rightarrow \nu_e) = \sin^2 2\theta \sin^2 \left(\frac{\Delta m^2 L}{4E_\nu} \right) \quad (2.18)$$

615 All that's left to do now is re-introduce \hbar and c doing this we get:

$$P_{\nu_\mu \rightarrow \nu_e}(L, E) = \sin^2 2\theta \sin^2 \left(1.27 \Delta m^2 \frac{L}{E_\nu} \right) \quad (2.19)$$

616 This equations has three important variables.

- The angle θ : This angle, as mentioned before, is called the mixing angle. It defines the difference between the flavor and the mass eigenstates. When $\theta = 0$ the mass and flavor eigenstates are identical and now oscillations occur.
- The mass squared difference, Δm^2 : Again $\Delta m^2 = m_1^2 - m_2^2$. The reason this is an important variable is because it implies that for neutrinos to oscillate, neutrinos must have mass. Furthermore, the mass squared difference also tells us that the neutrino mass eigenstates must be different.
- L/E: This is the variable that is of most interest to experimental physicists due to the fact that it is the variable that we set. L is the distance between the source and detector and E is the energy of the neutrino. For a given Δm^2 , the probability of oscillation changes with respect to L/E.

2.3.4 Three Flavor Neutrino Oscillation Formulation

Seeing the quantum mechanics involved in deriving the probability of a two flavor neutrino oscillation, it is now possible to formulate the three flavor neutrino oscillation. The three flavor neutrino oscillation formulation begins similarly to the two flavor, but there is the Pontecorvo-Maki-Nakagawa-Sakata matrix (PMNS) instead of the 2X2 matrix in the previous section. The PMNS matrix is show below:

$$\begin{pmatrix} c_{12}c_{13} & s_{12}c_{13} & s_{13}e^{-i\delta} \\ -s_{12}c_{23} - c_{12}s_{23}s_{13}e^{i\delta} & c_{12}c_{23} - s_{12}s_{23}s_{13}e^{i\delta} & s_{23}c_{13} \\ s_{12}s_{23} - c_{12}c_{23}s_{13}e^{i\delta} & -c_{12}s_{23} - s_{12}c_{23}s_{13}e^{i\delta} & c_{23}c_{13} \end{pmatrix} * \begin{pmatrix} e^{i\alpha_1/2} & 0 & 0 \\ 0 & e^{i\alpha_2/2} & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (2.20)$$

where $c_{ij} = \cos\theta_{ij}$ and $s_{ij} = \sin\theta_{ij}$

Following the same steps as before we get:

$$P_{\alpha \rightarrow \beta} = \delta_{\alpha\beta} - 4\sum Re(U_{\alpha i}^* U_{\beta i} U_{\alpha j} U_{\beta j}^*) \sin^2\left(\frac{\Delta m_{ij}^2 L}{4E}\right) 2\sum Im(U_{\alpha i}^* U_{\beta i} U_{\alpha j} U_{\beta j}^*) \sin\left(\frac{\Delta m_{ij}^2 L}{2E}\right) \quad (2.21)$$

The main things to notice here are δ_{ij} which is the CP violating term and has not been measured yet, and θ_{13} which has just been measured. CP violation is a violation

638 of the postulated CP-symmetry. CP-symmetry states that the laws of physics should
639 be the same if a particle were to be exchanged with its antiparticle and then if the left
640 hand side of a decay were switched with the right hand side.

641 **2.3.5 Reactor Oscillation**

642 Many experiments have searched for oscillation of electron anti-neutrinos produced at
643 nuclear reactors. Such oscillations give the value of the parameter θ_{13} . The KamLAND
644 experiment, started in 2002, has made a high precision observation of reactor neutrino
645 oscillation. Neutrinos produced in nuclear reactors have energies similar to solar
646 neutrinos, a few MeV. The baselines of these experiments have ranged from tens
647 of meters to over 100 km. On 8 March 2012, the Daya Bay team announced a 5.2σ
648 discovery that $\theta_{13} \neq 0$.

649 **Chapter 3**

650 **The MicroBooNE Experiment**

651 The purpose of this chapter is to discuss and understand the details of the MicroBooNE
652 detector. A thorough understanding of MicroBooNE and the technology behind liquid
653 argon time projection chambers is important for understanding results as well as
654 understanding how images were made for use in deep learning efforts that will be
655 outlined in later chapters.

656 **3.1 Liquid argon time projection chambers**

657 Liquid Argon Time Projection Chambers (LArTPCs) are an exciting detector technol-
658 ogy that provide excellent imaging and particle identification, and are now being
659 used to study neutrinos. The Time Projection Chamber (TPC) was first invented by
660 Nygren in 1974 [?] and the proposal for a LArTPC for neutrino physics was made
661 by Rubbia [?] in 1977 with the ICARUS collaboration implementing this concept [?].
662 A LArTPC is a three-dimensional imaging detector that uses planes of wires at the
663 edge of an active volume to read out an interaction. When a neutrino interacts with an
664 argon atom, the charged particles that are produced ionize the LAr as they travel away
665 from the interaction. By placing a uniform electric field throughout the LAr volume,
666 the ionization is made to drift towards a set of anode planes, which consist of wires
667 spaced very closely together collecting the ionized charge, which is subsequently read
668 out by electronics connected to the anode wires. The collected ionization creates a
669 spatial image of what happened in the detector on each anode plane. The position
670 resolution of the interaction along the beam direction (perpendicular to drift direction)
671 relies on the wire pitch, while the resolution in drift direction is dependent on the

672 timing resolution of the electronics used and the longitudinal diffusion in the volume.
673 The drift time of the ionization relative to the time of the original signal allows the
674 signal to be projected back along the drift coordinate, hence the name LArTPC. Having
675 very small distances between each wire within an anode plane allows for very fine
676 granularity and detail to be captured, and having multiple wire planes at different
677 angles provides independent two-dimensional views that can be combined into a
678 three dimensional picture of the interaction. Once the charge signal is created on the
679 anode planes, software analysis packages identify particles in the detector by using
680 deposited energy on the wires along their track length. The 30 year development of the
681 ICARUS detector has led to LArTPCs being used as cosmic ray [?], solar neutrino [?]
682 and accelerator neutrino [?] detectors. The ArgoNeuT experiment at Fermilab was
683 the first United States based liquid argon neutrino program that has since produced
684 short-baseline $\nu - Ar$ cross-section measurements in the NUMI beamline [?]. The
685 MicroBooNE experiment is the second experiment in the US based LArTPC neutrino
686 program and will be discussed thoroughly in the next sections. The next phases of
687 the liquid argon neutrino program are under way and are the Fermilab Short Base-
688 line Neutrino (SBN) program [?] and the Deep Underground Neutrino Experiment
689 (DUNE) [6]. The SBN program will include three LArTPC detectors, including the
690 MicroBooNE detector, on the Booster Neutrino Beam (BNB) to do multiple-baseline
691 oscillation measurements. The detector closest to the beam will be the 40 ton Short
692 Baseline Neutrino Detector (SBND) [?] at 150 m and the detector furthest is the 600 ton
693 ICARUS T600 [?] detector positioned at 600 m. The DUNE collaboration will deliver
694 a 30 GeV neutrino beam 1300 km from Fermilab to a 34 kiloton LArTPC detector
695 at Homestake, SD. DUNE will study the leptonic CP phase, δ_{cp} , as well as measure
696 neutrino and antineutrino oscillations.

697 3.2 The MicroBooNE Time Projection Chamber

698 MicroBooNE (Micro Booster Neutrino Experiment) is a 89 ton active volume (180 ton
699 total mass) LArTPC which is then inserted into a cylindrical cryostat on axis of the
700 Booster Neutrino Beam (BNB) stationed at Fermilab in Batavia, Illinois. Understanding
701 LArTPC technology and detector physics is necessary to build a LArTPC the size of
702 DUNE, and MicroBooNE has made many advances in developing this technology [7]
703 [8].

MicroBooNE's Time Projection Chamber (TPC) is 10.3 m long (beamline direction), 2.3 m high and 2.5 m wide (which corresponds to the drift distance). The TPC is shown in figure ?? . MicroBooNE is the largest LArTPC currently running in the world [9]. This LArTPC has 3 wire planes: 1 plane that collects the ionization in the wires and is 0° to the vertical with 3456 wires spaced 3 mm apart, and 2 planes where the ionization drifts passed and induces a signal at $\pm 60^\circ$ to the vertical each with 2400 wires also spaced 3 mm apart. Each plane has a spacing also of 3 mm from eachother. The first two planes are the induction planes and the last is the collection. The 270 V/cm electric field of the TPC is created using 64 stainless steel tubes shaped into rectangles around the TPC and held in place by G10 to form a field cage. The cathode is charged at a high voltage of -70 kV and this voltage is stepped down across the field cage tubes using a voltage divider chain with an equivalent resistance of $240\text{ M}\Omega$ between the tubes. The field cage tubes are separated by 4 cm from center to center. The electron drift distance is 2.5 m in the x direction with a drift time of 2.3 ms. Maintaining high charge yield is done by continuously recirculating and purifying the argon. The purity is monitored using MicroBooNE's light collection system. Another use of the light collection system is initial timing and drift coordinate of the interaction.

MicroBooNE's light collection system is a crucial part for 3D reconstruction of all particle interactions in the LArTPC. The initial interaction time, t_0 , and initial drift coordinate, x_0 , are not known from the TPC alone. For beam events, the accelerator clock is used to determine t_0 of the interaction and the x_0 can be inferred using drift time. Non-beam events, however, do not have this capability, which is why scintillation light from an interaction is used. The $\nu - Ar$ interaction produces scintillation light which is collected by photomultiplier tubes (PMTs) which allows the exact time, t_0 of the neutrino interaction to be determined. The scintillation light created propagates within nanoseconds to the light collection system compared to the milliseconds it takes the ionized electrons from the interaction to reach the anode wire planes. Therefore we can precisely know where along the drift direction the particle interaction first took place. The scintillation light is also localized, so combining the PMT information with the wire plane information allows for cosmic background rejection happening outside the beam timing window.

The light collection system is made up of 32 Hamamatsu R5912-02mod cryogenic PMTs with a diameter of 8-inches. The PMTs are located behind the 3 wire anode planes and provides 0.85% photocathode coverage. Each PMT has an acrylic plate mounted in front of it that is coated with a wave-length shifting material called TPB.

⁷³⁹ The acrylic plates take in the scintillation light, at 128 nm, and re-emits it visible
⁷⁴⁰ wavelengths visible to the PMTs, with a peak at 425 nm.

⁷⁴¹ Both the light collection system and the TPC create analog signal that is read out and
⁷⁴² digitized by the electronics system. The process requires amplification and shaping of
⁷⁴³ the signal which then goes to the data acquisition (DAQ) software for writing of the
⁷⁴⁴ digitized data to disk. The anode plane wires are connected to detector specific circuit
⁷⁴⁵ boards (ASICS) that are submerged and operate inside the liquid argon volume. These
⁷⁴⁶ ASICS send amplified signal to 11 feed-throughs where further amplification of the
⁷⁴⁷ signal happens outside the cryostat. The signal is received by custom LArTPC readout
⁷⁴⁸ modules distributed over nine readout crates which do the digitization. The TPC wires
⁷⁴⁹ are digitized at 16 MHz then downsampled to 2 MHz. The TPC system reads out 4
⁷⁵⁰ frames of wire signal data per event, 1 frame before a trigger and 2 frames after the
⁷⁵¹ triggered frame. The four frames allows for identification of a neutrino interaction as
⁷⁵² well as cosmic background rejection. The process of digitization is similar for the light
⁷⁵³ collection system. Each PMT signal undergoes a shaping with a 60 ns peaking time
⁷⁵⁴ for digitization of multiple samples. The digitization occurs at 64 MHz but are not
⁷⁵⁵ read out continuously during the TPC readout time. Only shaped PMT signal samples
⁷⁵⁶ above a small threshold are read out and saved. Both the TPC and PMT readouts are
⁷⁵⁷ initiated via triggers on a separate trigger board located in a warm electronics crate.
⁷⁵⁸ The timing trigger is created by a timing signal from the BNB accelerator which is
⁷⁵⁹ shaped and sent to the trigger board. The PMT trigger is generated when the PMT
⁷⁶⁰ signal multiplicity is greater than 1 and the summed PMT pulse-height is more than 2
⁷⁶¹ photo-electrons summed up over all PMT channels. When the trigger board gets both
⁷⁶² a timing trigger and a PMT trigger in coincidence, at BNB trigger is then generated by
⁷⁶³ the board. This signal is then passed to all readout crates initiating the readout of data.
⁷⁶⁴ The data is then sent to the DAQ software which then saves the data to disk into one
⁷⁶⁵ event memory.

⁷⁶⁶ 3.3 MicroBooNE's Physics Goals

⁷⁶⁷ 3.3.1 The low-energy excess

⁷⁶⁸ The primary goal of the MicroBooNE experiment is to study and investigate the low-
⁷⁶⁹ energy excess seen in MiniBooNE 3.1. MicroBooNE has the capability of confirming or

denying this excess as electrons or photons due to the detector being in the same beam, having a similar baseline, and lastly the detector being able to clearly distinguish between electrons and photons. LArTPCs use the topology of events as well as energy loss near the vertex to differentiate between single e^- tracks and photon-induced induced pair production $\gamma \rightarrow e^+ e^-$, which wasn't possible in MiniBooNE, a Cherenkov detector. This technique has been shown in the ArogoNeuT detector [?] and a side by side comparison of both event types in a LArTPC can be seen in figure ???. An excess in electrons would point towards new oscillation physics beyond the standard model, while photons would be within the standard model. MicroBooNE will observe a $4-5\sigma$ signal.

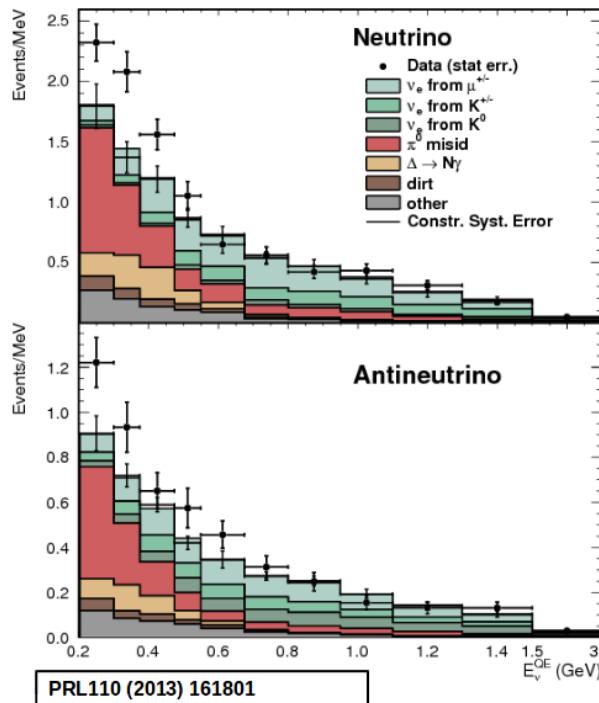


Figure 3.1: Low Energy excess seen in MiniBooNE

3.3.2 Cross sections

MicroBooNE's neutrino cross-section program will be the first $\nu - Ar$ cross-section in the 1 GeV energy range and one of only a few cross-section measurements of $\nu - Ar$ in the world. MicroBooNE is also the first liquid argon detector to collect the highest statistics sample of neutrino interactions. Investigating final-state-interactions in the 1GeV energy range provides information about short range nuclear correlations that affect the interpretations of neutrino oscillation experiment data.

One of the cross-section measurements MicroBooNE can make is an inclusive charged-current cross-section measurement (referred to as CC-inclusive). CC-inclusive events consist of a neutrino exchanging a W^\pm boson with an argon atom, producing a charged lepton and any number of other final state particles. In MicroBooNE's case, a CC-inclusive event will mostly have a defining muon track coming out of the vertex due to our neutrinos being predominately ν_μ s. A cross-section measurement is the energy dependent probability of $\nu - Ar$ interaction in the detector. Cross-sections however are independent of the intensity or focus of the particle beam so they can be compared among different experiments. A background for a CC-inclusive cross-section measurement are the neutral-current events that contain a pion. It is possible to have a neutral current interaction with a $\pi + p$ event signature that looks like a charged current $\mu + p$ event. Reconstruction tools implemented to date don't efficiently separate muons from pions. A common way to separate these two particles species is to implement a track length cut. On average, muons tend to have longer track lengths in LArTPCs so by requiring that the hypothesized lepton be above a threshold track length, it is possible to increase signal to background.

3.3.3 Liquid argon detector development

The last physics goal for the MicroBooNE collaboration is to provide important information regarding LArTPC technology. Being the first in large scare LArTPCs in the US, MicroBooNE will be able to provide improvements to High Voltage (HV) distribution, Noise Characterization [?], and Michel Electron Reconstruction [8].

3.4 The Booster Neutrino Beam

The MicroBooNE detector is stationed at Fermi National Accelerator Laboratory (FNAL) where it receives neutrinos from both the Booster Neutrino Beam (BNB) and Neutrinos from the Main Injector (NuMI) beams. MicroBooNE is on-axis for the BNB and off-axis by 135 mrad for NuMI. For the purpose of this analysis, only data from the BNB was used. This section will discuss how neutrinos are created using the BNB. How these neutrinos are produced as well as their flux through the MicroBooNE detector is necessary for any analysis because of the systematic uncertainties the beam

⁸¹⁶ introduces to a measurement. An aerial view of fermilab as well as the BNB is shown
⁸¹⁷ in figure 3.2

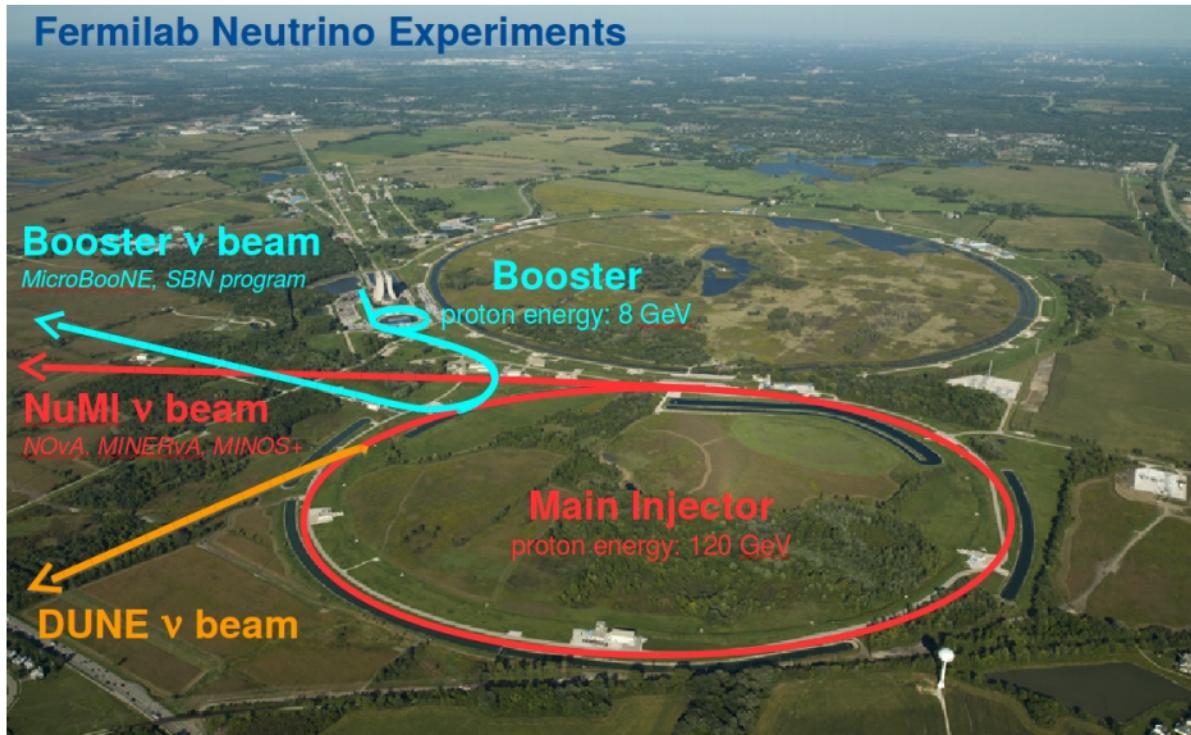


Figure 3.2: Arial view of the Main Injector and the Booster Neutrino Beam at Fermilab

⁸¹⁸ 3.4.1 Creating the Booster Neutrino Beam

⁸¹⁹ The BNB is a very pure ν_μ beam, with only 0.6% contamination from ν_e s. The energy
⁸²⁰ also peaks around 700 MeV which is desired based on the probability of oscillation
⁸²¹ equation which depends on the the value of L/E , where L is the distance of the
⁸²² detector from the neutrino beam and E is the energy of the neutrino beam. L/E was
⁸²³ chosen to increase the probability of seeing neutrino oscillations in the MiniBooNE
⁸²⁴ Low Energy Excess (LEE) range based on the probability of oscillation equation, which
⁸²⁵ is $P_{\nu_\mu \rightarrow \nu_e}(L, E) = \sin^2 2\theta \sin^2 \left(1.27 \Delta m^2 \frac{L}{E} \right)$. The BNB collides 8.9 GeV/c momentum
⁸²⁶ protons from the FNAL booster synchrotron into a beryllium target which produces a
⁸²⁷ high flux of neutrinos. The protons originate from H^2 gas molecules that are turned
⁸²⁸ into H^- ions by a Cockcroft-Walton generator shown in figure ???. The H^- initially are
⁸²⁹ accelerated to 1MeV kinetic energy and are then passed to a linear accelerator using
⁸³⁰ alternating electromagnetic fields to increase their energy to 400MeV. The ions are
⁸³¹ stripped of electrons by passing them through a carbon foil. The protons are bunched

832 into beam spills which contain $4 * 10^{12}$ protons in a $1.6 \mu\text{s}$ time window per spill. It's
833 at this point that the protons are directed towards the beryllium target. The amount
834 of protons directed towards the target (POT) is measured by two toroids upstream of
835 the target with an error of 2%. Beam intensity, timing, width, position, and direction
836 are monitored by beam position monitors, multi-wire chamber and resistive monitors.
837 The beryllium target is 71.1 cm long, 1.7 proton interaction lengths, and is 0.51 cm in
838 radius. The target is located inside a larger focusing electromagnet called the horn.
839 The horn is an aluminum alloy pulsed toroidal electromagnet. The pulsed current
840 peaks at 170 kA with a time-width of $143 \mu\text{s}$ which coincides with the protons arriving
841 on the target. The current flows from the inner conductor to the outer conductor
842 with a maximum magnetic field of 1.5 Tesla. The magnetic field focuses the charged
843 secondary particles produced by the p-Be interactions. The direction of current can be
844 switched to change the polarity of the secondary particles being focused creating a
845 beam of either primarily neutrinos, with positively charged secondary particles, or
846 antineutrinos.

847 Further down the beamline is a concrete collimator which absorbs particles not
848 necessary to the neutrino flux. The collimator is 214 cm long and 30 cm in radius.
849 After the collimator comes a 45 meter long, 1 meter radius, air-filled cylindrical decay
850 region which then ends in a beam-stop made of steel and concrete. The beam-stop
851 contains an array of gas proportional counters to detect muons. The BNB is shown in
852 figure 3.3.

853 **3.5 Event Reconstruction**

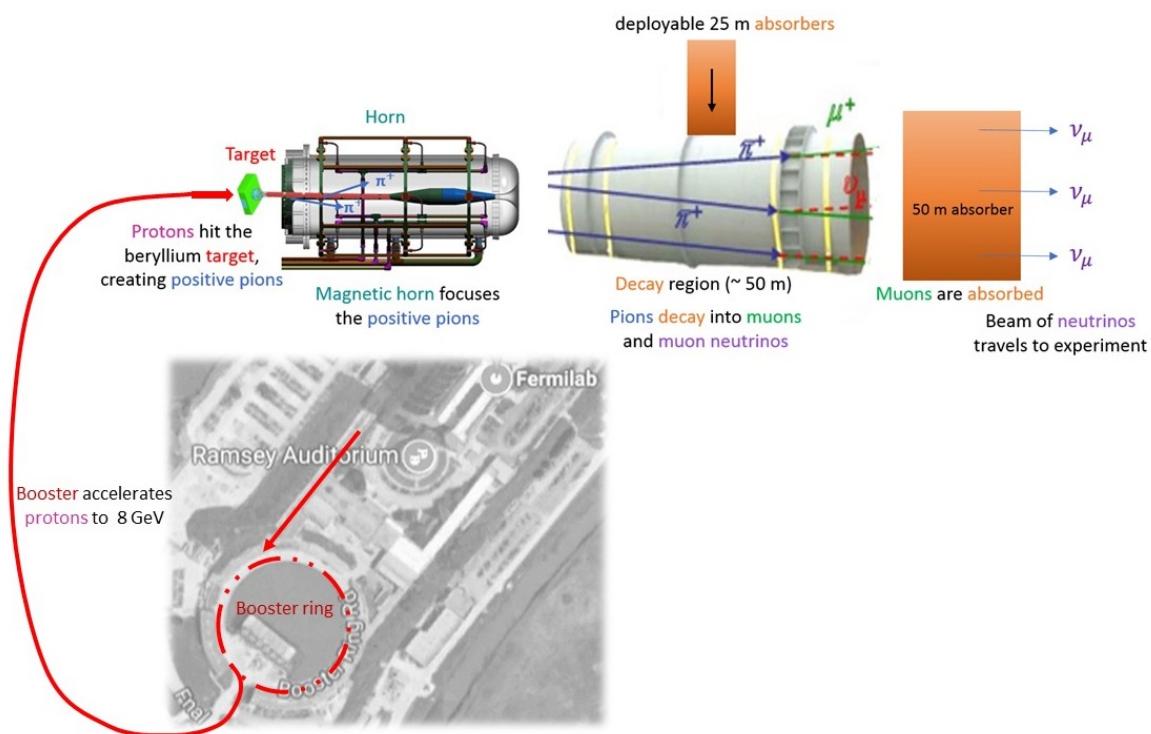


Figure 3.3: Aerial view of the Main Injector and the Booster Neutrino Beam at Fermilab

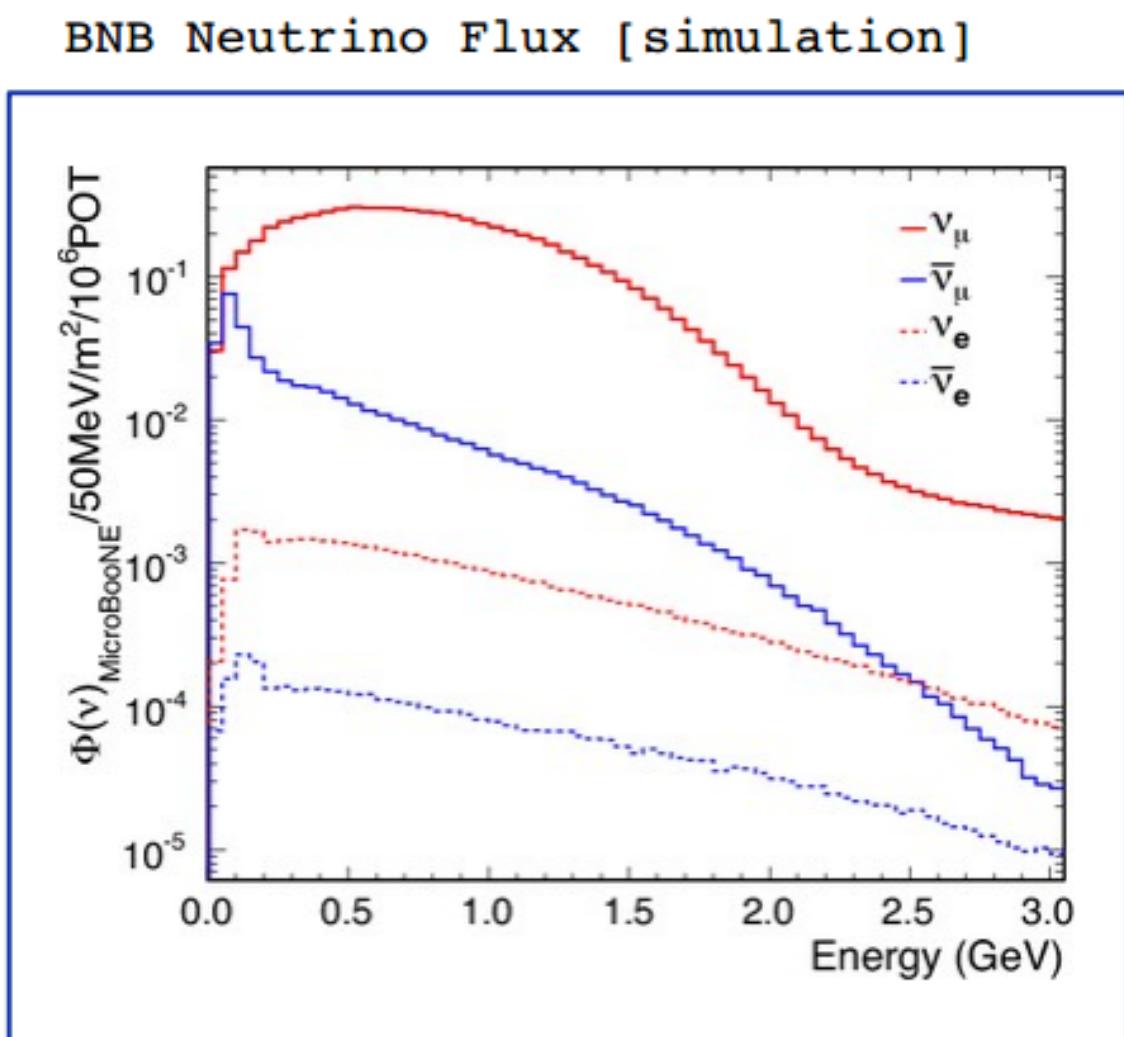


Figure 3.4: Energy spectrum of the Booster Neutrino Beam at Fermi National Laboratories

854 **Chapter 4**

855 **Neutrino Identification: Finding**
856 **MicroBooNE's first Neutrinos**

857 The goal of the Neutrino Identification analysis was to positively identify BNB neutrino
858 interactions in the MicroBooNE detector collected during the first days of running.
859 Neutrino event candidates were identified in part by using a cut on detected flash of
860 scintillation light during the $1.6 \mu\text{s}$ beam-spill length of the BNB as well as identifying
861 reconstructed object from the TPC that are neutrino like. After this selection, 2D
862 and 3D event displays were used for verification of the selection performance. This
863 selection was targeted to reduce the ratio of neutrino events to cosmic-only events from
864 the initial 1 neutrino to 675 cosmics to a ratio of 1 to 0.5 or better which is equivalent to
865 a background reduction by a factor of 1000 or more. These selected events were used
866 for MicroBooNE's public displays of neutrino interactions. A clearly visible neutrino
867 interaction with an identifiable vertex and at least 2 tracks originating from the vertex
868 was what the analysis focused on. This analysis wasn't optimized for high purity
869 or efficiency, but rather for very distinguishable neutrino interactions that could be
870 identified by the public.

871 **4.1 Flash Finding**

872 Flash finding is the first step used in finding neutrino interactions. This section will
873 detail how optical information is reconstructed as well as analysis scripts and event
874 filters were used.

875 **4.1.1 Flash Reconstruction**

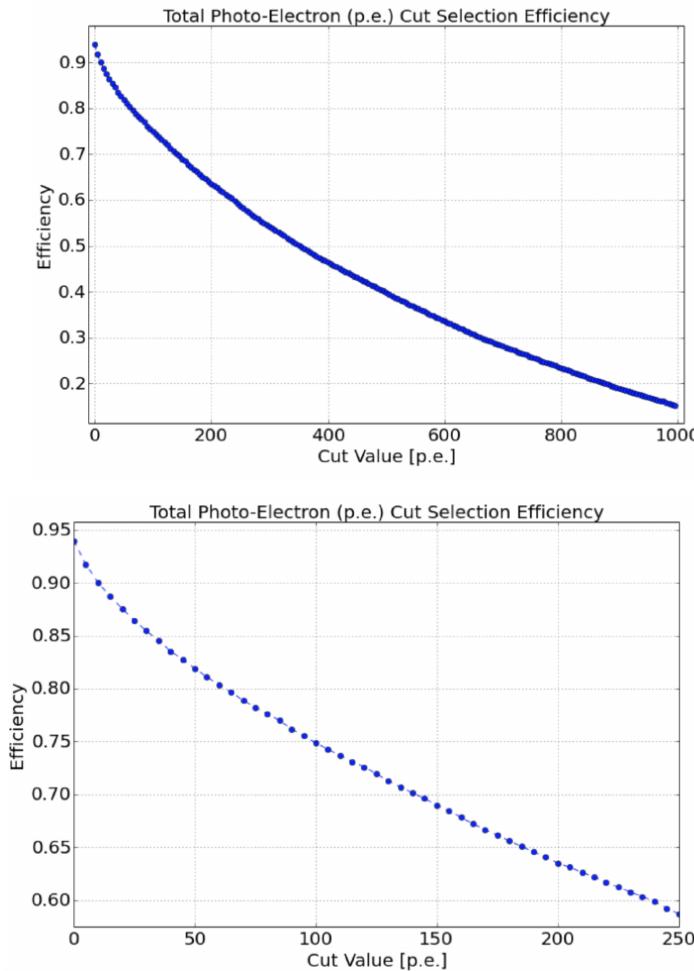
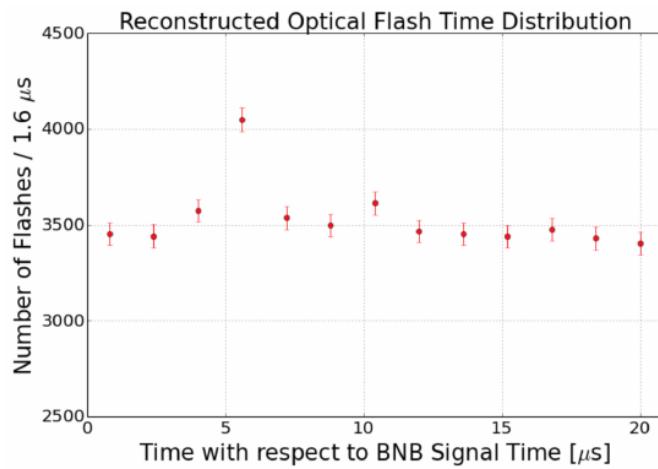


Figure 4.1: Efficiency for selecting beam events as a function of minimum total PE cut for all PE cuts as well as zoomed into interesting region.

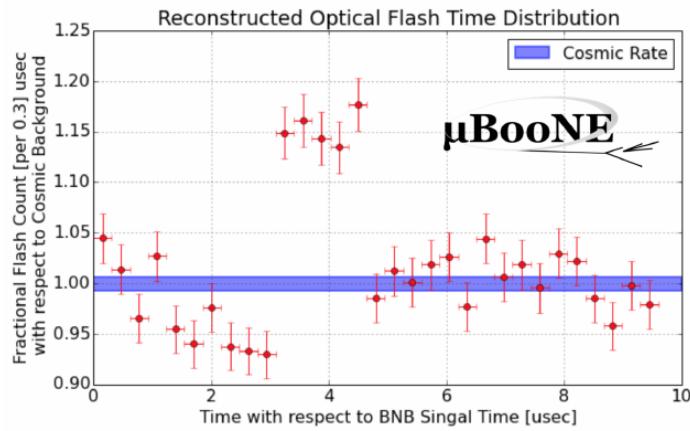
876 A flash is described as a collection of light seen at the same time within the detector.
877 They are then reconstructed by identifying signal from the PMTs above a specific
878 photoelectron (PE) threshold. These signals are called optical hits. Optical hits from
879 all the PMTs are then accumulated into $1\text{ }\mu\text{s}$ bins of time. If a specific bin is above a
880 set PE threshold, then the optical hits that overlap in time are the labeled as the hits
881 from the flash. All flash reconstructed properties like average time and x/y positions
882 are then found via the flash labeled optical hits. The total size of the flash is found by
883 summing up the total number of photoelectrons from all PMTs. Neutrino interactions
884 and cosmic muons will have a larger flash size compared to noise and other low-energy
885 backgrounds, therefore a total PE cut is used to reject these backgrounds. A total PE

886 cut of 50 PE was deemed sufficient for this analysis. Figure 4.1 show the total PE
887 versus the selection efficency of selecting neutrino beam events.

888 4.1.2 Beam Timing



(a) Predicted distribution of flash times with respect to trigger time for 1 day of data taking at nominal rate and intensity



(b) Measured distribution of flash times with a 50 PE threshold cut, with respect to trigger time. Shown as a ratio to the expected cosmic rate from off-beam data. A clear excess from neutrinos is visible between 3- 5 μ s after the trigger time.

889 It is necessary to get the specific time from flashes if one uses flashes to filter out
890 neutrino interactions coincident with the neutrino beam spill period and background.
891 Before a filter can be applied, an understanding of the timing of the trigger and PMT

892 readout with respect to the arrival of neutrinos from the BNB. To do this, a $1.6 \mu\text{s}$
 893 window near the expected beamtime was created and verified by finding that the
 894 number of flashes was significantly above the cosmic-ray background flashes. Beam
 895 data during the first week of running, October 16th 2016 through October 22nd 2016
 896 and were used for a timing measurement. The total POT uses corresponds to roughly
 897 24 hours of data taking at nominal intensity ($4 \times 10^{12} \text{ ppp}$) and a 5 Hz repetition rate.
 898 Figure 4.2a shows size of the expected neutrino signal in time using Monte Carlo
 899 predictions and figure 4.2b shows the neutrino signal in data. The intensity in data is
 900 lower, however there can still be seen a significant excess above data.

901 4.1.3 Event Rates

902 Applying a 50 PE threshold cut inside a $1.6 \mu\text{s}$ window reduces the cosmic-ray passing
 903 rate to 0.8%. With a 5 Hz beam rate, this corresponds to 135 cosmics passing per
 904 hour. The neutrino passing rate for this filter is about 22 events per hour. To further
 905 increase the neutrino to cosmic ratio, TPC topology cuts were implemented and will
 906 be discussed in the following section.

907 4.2 TPC Topology Selection

908 In order to further reduce the background of cosmic events, two independent selection
 909 streams using TPC wire data reconstruction was implemented. The first using 2D
 910 reconstructed clusters, and the second using 3D reconstructed tracks. Both streams
 911 look for neutrino interactions in the active TPC volume which are identifiable by two
 912 or more tracks originating from the same vertex.

913 Both 2D and 3D channels were optimized using monte carlo simulation which
 914 used a 128 kV cathode voltage. Passing rates were calculated using a 0.008 efficiency
 915 factor for cosmic events passing to simulate the flash finding described in section 4.1.
 916 This efficiency factor was an overestimation and was just used to get a general feel of
 917 what signal and background rates we would actually see in data.

918 **4.2.1 Cosmic Tagging**

919 The first step in TPC selection was based on the geometry of cosmic tracks in an event.
920 The cosmic ray muon geometry tagger runs on 3D tracks and assigns a score to each
921 reconstructed track on the likeliness of the track originating from a cosmic. The cosmic
922 scores are detailed below:

- 923 • 1: The track is tagged as entering or exiting the TPC
- 924 • 0.95: The track is a delta ray associated with a tagged track
- 925 • 0.5: The track is either entering or exiting, but not both
- 926 • 0.4: The track is entering or exiting through the Z boundary
- 927 • 0: The track isn't tagged

928 Clusters are assigned either a 0 or 1, 1 being a cosmic. In simulation, 90% of cosmics
929 are tagged as cosmics. These tracks are no longer considered when looking for a
930 neutrino topology. Requiring that the tracks be contained in turn affects the neutrino
931 efficiency by 20%. The algorithm checks that each track is contained within a boundary
932 region of 10 cm from all sides of the TPC. This boundary region was optimized via
933 handscanning of experimental data.

934 As can be expected, cosmic tagging is more efficient in the 3D channel (tracks) than
935 the 2D channel (clusters) because the reconstructed tracks can use the full 3D position
936 information of the entering and exiting points while the 2D channel mainly use the
937 reconstructed x position of the cluster which is associated to timing.

938 Cosmic tagging uses timing information to reject tracks and clusters that are outside
939 of drift window. The drift window for 128 kV is $1.6 \mu\text{s}$ while for 70 kV, the actual
940 voltage MicroBooNE is running at, is $2.3 \mu\text{s}$. Due to this variation between simulation
941 and data, we expect to see $2.3/1.6 = 1.44$ times more cosmic induced tracks or clusters
942 in the drift window.

943 **4.2.2 2D Cluster Selection**

944 This selection was spearheaded by myself and Katherine Woodruff. After looking at
945 experimental cosmics data, 2D clustering performs well, while 3D track reconstruction
946 is affected by more variations in simulation, for example noise filters. This was the

947 motivation for having a selection only on 2D clusters in the collection (Y) plane. As
 948 stated previously, the goal of this analysis was to find identifiable neutrino interactions
 949 for use in public event displays, in future analyses, the 3D track reconstruction has
 950 been modified to further increase the tracking efficiency and has more information
 951 that just the clusters. For this analysis, however, 2D cluster information was sufficient
 952 enough for neutrino selection.

953 **Primary Cuts**

954 The first cuts were used to select which clusters to consider. First the clusters must
 955 have at least ten hits on the collection plane and have a cosmic tagging score < 0.4.
 956 Only events that have at least two clusters that satisfy these primary cuts continue on.

957 After the initial cosmic tagging is applied, the following cuts are used to further
 958 separate identifiable neutrinos from background cosmics.

959 The next cut was to remove long, vertical clusters. This was applied after seeing
 960 that most cosmic induced clusters passing were long with high angles, while neutrino
 961 induced clusters were mainly forward going. We required a good cluster to either
 962 have a projected start angle less than 30 degrees from the z axis or be less than 200
 963 wires long. The length cut was added to make sure we don't cut any short high angle
 964 clusters that can correspond with a proton, or other highly ionizing particle associated
 965 with a long muon cluster. The 200 wire cut roughly equates to 0.6 m in the z direction,
 966 with a 3 mm wire pitch. Also, the projected angle is defined by $\tan \alpha = \Delta T / \Delta W$ where
 967 T is the time ticks and W is the wires.

968 The last cut requires the clusters to be either 30 time ticks or 30 wires. This cut was
 969 applied to reduce small delta rays associated with a cosmic without removing proton
 970 clusters associated with a long muon cluster, which saves ideal neutrino events that
 971 have both a long minimum ionizing muon like cluster and a short highly ionizing
 972 proton like cluster.

973 **Secondary Cuts**

974 The secondary cuts look to match long, low-angle clusters with short, high-charge
 975 clusters. Only clusters that have passed previous cuts are used. First clusters with
 976 length greater than 100 wires are chosen, which is approximately 0.3 m in the z

Cluster set	No Cuts	Primary Cuts	Secondary Cuts
Neutrinos only	570	303	32
Cosmics only (no flash)	308,016	291,879	602
Cosmics only (w/ flash)	2464	2335	5
Neutrinos/Cosmics	0.23	0.13	6.4

Table 4.1: Passing rates for 2D cluster cuts for neutrino on MC set and a cosmic only MC set. First column shows event rates with no cuts applied to both sets. Columns two and three show event rates after primary and secondary cuts are applied. Line three shows the second line scaled with the flash finding factor of 0.008. All events are normalized to per day assuming we are running at 5 Hz.

977 direction. Then we search for any cluster that is within approximately 3 cm (10 wires
 978 and 30 time ticks) away from the low-z end of the long cluster. This cluster must also
 979 be shorter than the first. In our reconstruction, the start and end point of a cluster can
 980 be swapped so both ends of the short cluster are compared to the long cluster.

981 Now that there is a vertex match, cuts based on charge and projected opening angle
 982 are implemented. We require the short cluster to have a higher start charge than the
 983 long cluster or the long cluster be longer than 500 wires. Start charge is defined as
 984 the charge on the first wire in ADC counts. The projected opening angle must also
 985 be between 11 and 90 degrees. This last cut is intended to remove clusters that are
 986 entirely overlapping or are part of the same long track. The resulting neutrino/cosmic
 987 event rate per day is shown in table 4.1. Figures 4.3 and 4.4 shows the percentages of
 988 clusters that pass each primary and secondary cuts.

989 4.2.3 3D Tracks and vertices Selection

990 The neutrino selection for the 3D channel was based on a reconstructed vertex and
 991 two tracks. All vertices and tracks were looped over that had a cosmic tag score < 0.4
 992 and the distances below were calculated:

- 993 • d : distance between the start points of the two tracks.
- 994 • d_1 : distance between vertex and start of track 1.
- 995 • d_2 : distance between vertex and start of track 2.

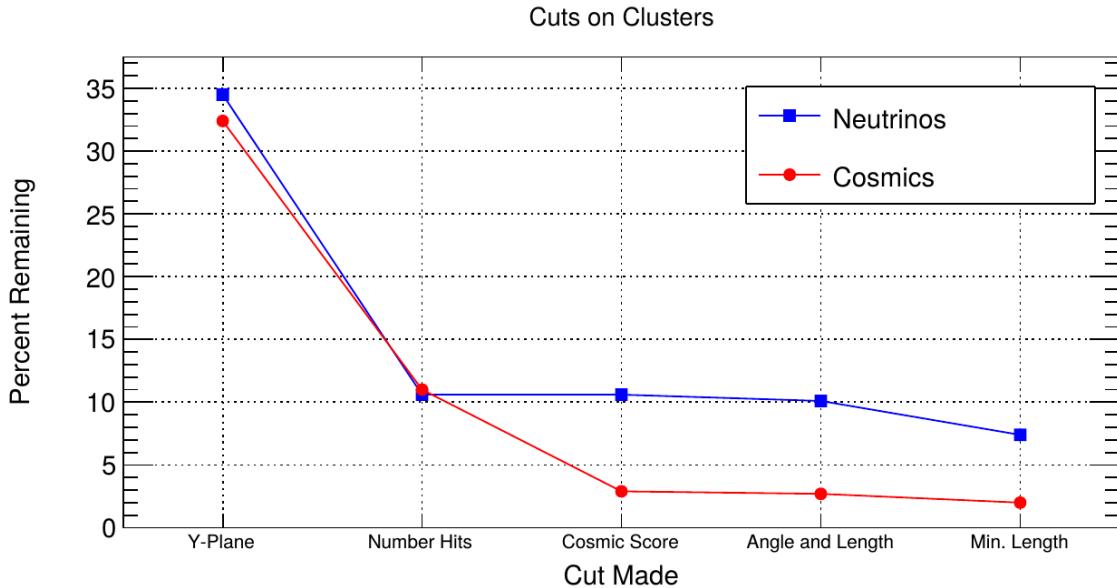


Figure 4.3: Percent of good clusters remaining for neutrinos and cosmics after the primary cuts were applied. This is relative to total number of initial clusters.

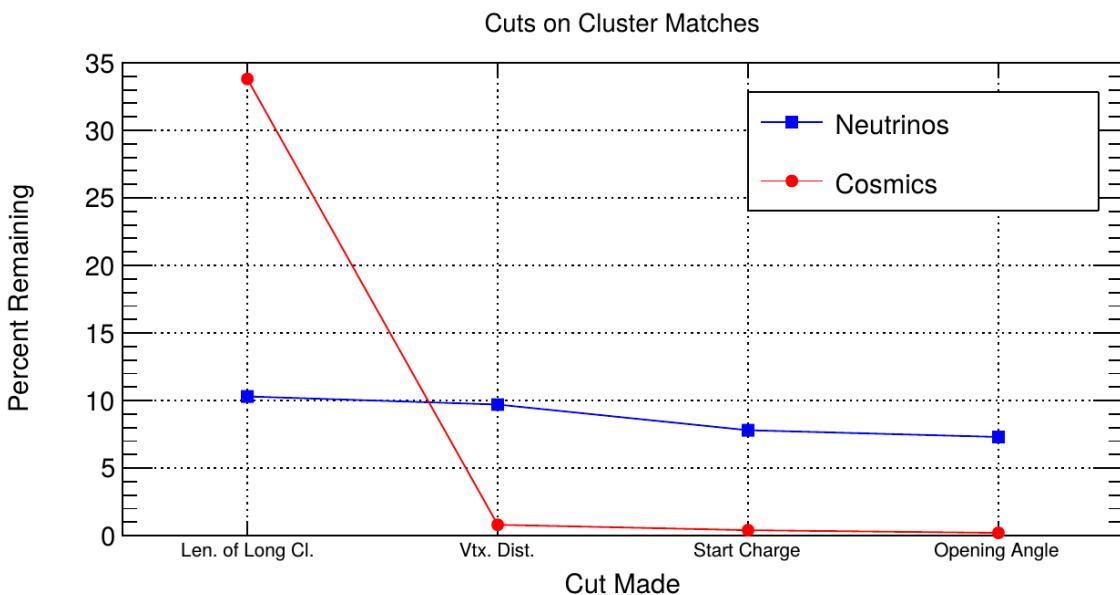


Figure 4.4: Percent matched cluster pairs remaining for neutrinos and cosmics after secondary cuts applied. This is relative to the number of events that contain clusters which pass the primary cuts.

996 The maximum distance of all three is then selected as the important characteristic per
997 trio. The best trio is the one that has the smallest maximum distance. The $\min(\max_d)$
998 for all trios in an event were plotted for BNB neutrino events and for cosmics to
999 find the best cut value for each tracking algorithm. The distribution of $\min(\max_{d,i})$
1000 is smaller for neutrinos than for cosmics. The cut values for different tracking and
1001 clustering algorithms are shown below. These cut values were chosen to minimize the
1002 cosmic background to 20%.

- 1003 • trackkalmanhit with cccluster $\min(\max_{d,i}) < 3$ cm.
1004 • trackkalmanhit with pandoraNu $\min(\max_{d,i}) < 4.5$ cm.
1005 • pandoraNu with cccluster $\min(\max_{d,i}) < 5$ cm.

1006 **4.2.4 TPC Updates**

1007 After doing a visual hand-scanning of the first beam data processed with the filters
1008 detailed above, the events passing had a larger contamination of background than
1009 expected. This was mainly in part due to the reconstruction performing better on
1010 simulation than on data. Due to this, additional cuts on both streams needed to be
1011 implemented in order to increase signal/background ratio. These cuts were added on
1012 top of the filters described above and further reduce the event count.

1013 **2D Filter Updates**

1014 The main background observed in the 2D filter were Michel events, where the muon
1015 and electron formed two connected clusters. These events were rejected by comparing
1016 the start and end charge deposition of the long cluster (i.e muon particle). The start
1017 charge deposition must be less than the end charge deposition. This cut is implemented
1018 because muons have a higher ionizaiton loss at the end.

1019 **3D Filter Updates**

1020 It was seen that cosmic tracks can often originate or end at the same point, therefore
1021 faking a signal. Cosmic tracks, however, are mostly vertical. By requiring the angle
1022 of the longer track have a cosine greater than 0.85 with respect to the z-axis as well

₁₀₂₃ as requiring the longer track to have a length greater than 10 cm, we can reduce this
₁₀₂₄ background.

₁₀₂₅ **4.3 Conclusion**

₁₀₂₆ After proccesing these filters in parallel, it was shown that the 3D filter had a higher
₁₀₂₇ purity than the 2D filter because of the higher cosmic rejection being used due to 3D
₁₀₂₈ reconstruction. The 2D filter is blind to track entering/exiting from the top or bottom
₁₀₂₉ of the TPC. Although the 3D filter had a higher purity, the 2D filter was still able to
₁₀₃₀ find identifiable events in data that were used as public event displays. A sample of
₁₀₃₁ event displays are shown in figures 4.5 and 4.6.

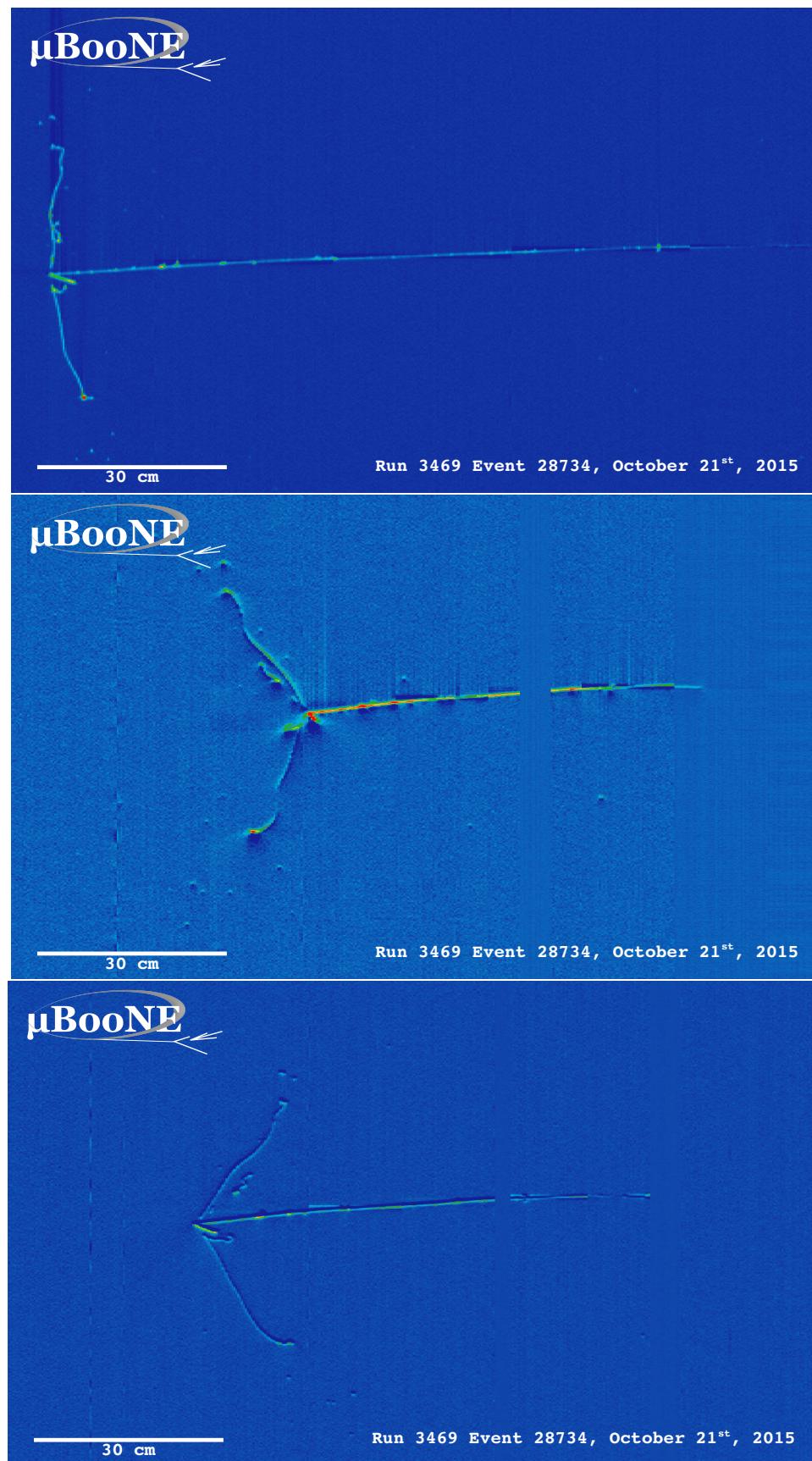


Figure 4.5: First Neutrino Interaction Candidate Events from MicroBooNE

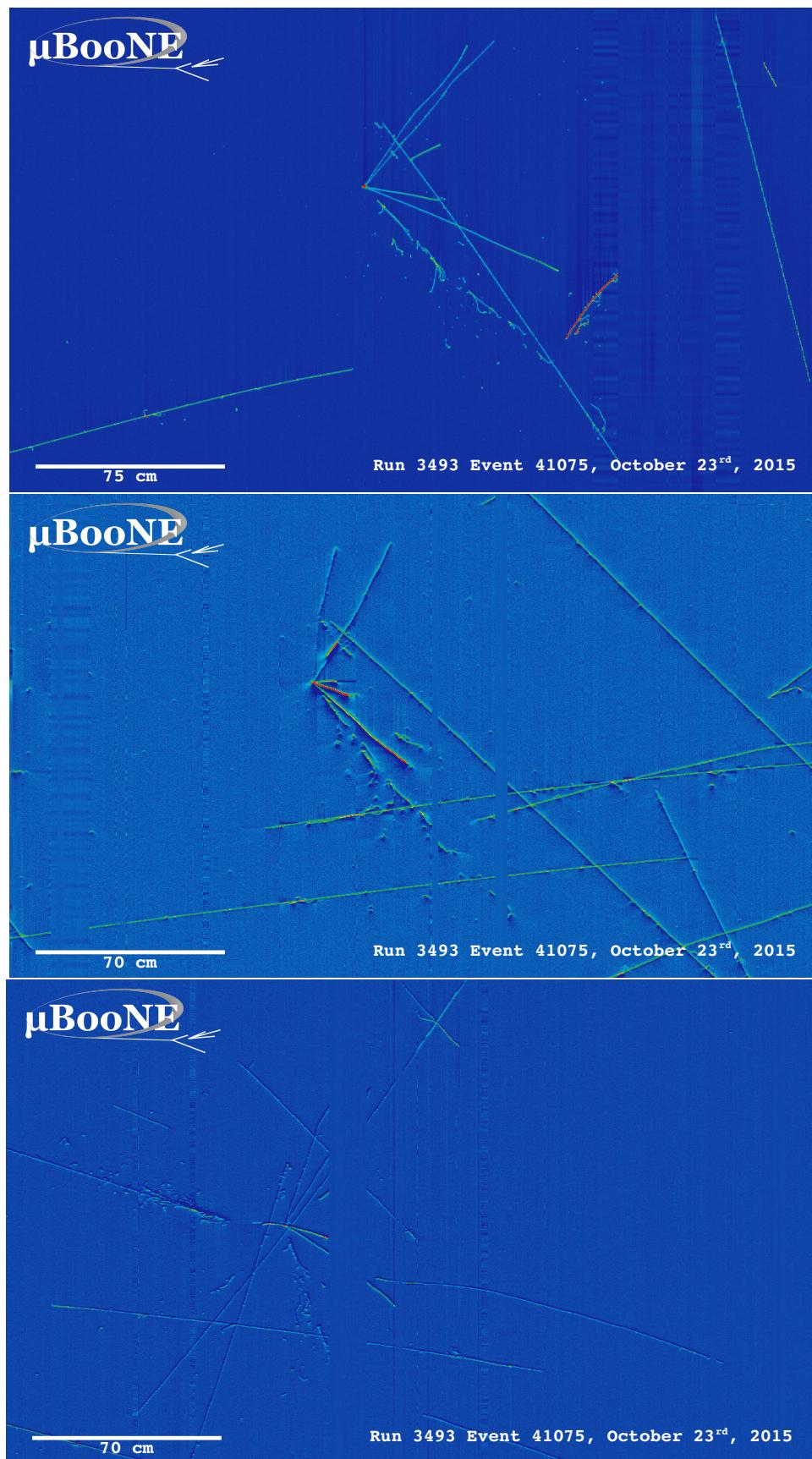


Figure 4.6: First Neutrino Interaction Candidate Events from MicroBooNE

1032 **Chapter 5**

1033 **CC-Inclusive Cross Section Selection
1034 Filter**

1035 The CC-Inclusive cross-section selection I and selection I modified filters used in this
1036 analysis will be described in the following sections below. These filters are an expan-
1037 sion of the Neutrino ID filter. The work done in this thesis was to further improve these
1038 selections by increasing both efficiency and purity as well as increasing acceptance
1039 without further affecting the kinematic distributions of the selected neutrino events.

1040 MicroBooNE requires fully automated event reconstruction and selection algo-
1041 rithms for use in the many physics measurements being worked on to date due to
1042 the large data rate MicroBooNE receives. Being able to automatically pluck out the
1043 neutrino interaction among a sea of cosmics proved to be challenging but was accom-
1044 plished. MicroBooNE has developed two complementary and preliminary selection
1045 algorithms to select charged-current $\nu_\mu - Ar$ interactions. Both are fully automated
1046 and cut based. The results of this thesis will focus on selection I and selection I modi-
1047 fied and will focus on further improving these algorithms using Convolutional Neural
1048 Network (CNN) implementations. These selections identify the muon from a neutrino
1049 interaction without biasing towards track multiplicity. To combat cosmic and neutral
1050 current background, the analysis is strongly biased towards forward-going long tracks
1051 which are contained. This limits phase space and reduces acceptance.

1052 5.1 Data and MC Processing Chain

1053 The data used for this analysis were based on hardware and software triggers. Events
1054 used came from the *BNB_INCLUSIVE* and *EXT_BNB_INCLUSIVE* streams and were
1055 used for signal and background. The *BNB_INCLUSIVE* stream is chosen by requiring
1056 that the hardware trigger bit is fired and that the event passed an optical software
1057 trigger within a BNB spill timing window. The *EXT_BNB_INCLUSIVE* stream requires
1058 the EXT hardware trigger to fire as well as pass the same optical software trigger
1059 within a BNB spill size timing window similar to the *BNB_INCLUSIVE*.

1060 The two MC samples used in this analysis and for determining selection efficiencies
1061 and purities were GENIE BNB neutrino interactions with CORSIKA cosmic ray overlay
1062 within the readout window and inTime CORSIKA cosmic rays. The MC samples
1063 generated used *uboonecode v04_36_00* and are based on the following packages:

- 1064 • larsoft v04_36_00
- 1065 • GEANT v04_09_06_p04d
- 1066 • GENIE v02_08_06d
- 1067 • GENIE xsec v02_08_06a
- 1068 • pandora v02_03_0a
- 1069 • CORSIKA v07_4003

1070 Both data and MC samples were processed using the same reconstruction release,
1071 *uboonecode v05_08_00* and the fcl files used for reconstruction are listed below:

- 1072 • MC fcl files
 - 1073 – reco_uboone_mcc7_driver_stage1.fcl
 - 1074 – reco_uboone_mcc7_driver_stage2.fcl
- 1075 • Data fcl files
 - 1076 • reco_uboone_data_Feb2016_driver_stage1.fcl
 - 1077 • reco_uboone_data_Feb2016_driver_stage2.fcl

1078 On top of the hardware and software triggers, the data also had to pass more
1079 criteria to be identified as part of the good run list. The criteria is detailed below.

- 1080 • **Detector conditions:** the detector has to be in a good operating condition. The
 1081 detector conditions are read from the slow monitoring database and are required
 1082 to be within the alarm thresholds. The variables of interest for events passing
 1083 the good run list criteria include DAQ, PMT, HV, Drift HV, wire bias, electron
 1084 lifetime and detector power. These conditions need to be met on a run-by-run
 1085 basis in order to pass the selection.
- 1086 • **Data quality:** normal and stable behavior for basic reconstruction quantities.
 1087 These reconstruction variables include average number of tracks, hits, and flashes
 1088 in each event, the average length of tracks, the average amplitude and area of
 1089 hits, the average PE and the average spread of each one of these quantities.
- 1090 • **Beam Conditions:** the BNB must be on and stable and the POT per spill needs
 1091 to above the intensity threshold. Beam quality conditions include checking the
 1092 fraction of proton beam interacting within the target, the horn current, and the
 1093 intensity of protons per spill. The final sample is $5 * 10^{19}$ and a per-spill intensity
 1094 of $4 * 10^{12}$
- 1095 • **Run processed:** the full run must be processed completely without missing
 1096 subruns or crashes in the data processing.

1097 5.2 Normalization of data and MC

1098 The off-beam sample is used to measure beam unrelated backgrounds. For normalization,
 1099 one needs the total number of BNB spills (N_{BNB}) and the total number of external
 1100 triggers. The BNB spills used need to pass the beam quality cuts. The normalization
 1101 factor is then N_{BNB}/N_{EXT} which is 1.23.

1102 To normalize generated BNB MC events to POT, we used the following:

- 1103 • $5 * 10^{19} POT = 41524.3$ generated events

1104 where this scaling factor only applies to mcc7 generated events. The inTime cosmic
 1105 sample is normalized with respect to the open cosmic sample so an understanding
 1106 of both is necessary. The POT per beam spill for mcc7 BNB samples is $5 * 10^{12}$. To
 1107 calculate how many spills are necessary to produce a specific POT one would multiply
 1108 the total POT by the average 1/POT per spill. For a total POT of $5 * 10^{19}$ the amount
 1109 of spills necessary is $\frac{5 * 10^{19}}{5 * 10^{12}} = 1 * 10^7$. This is only one in ~ 241 events therefore each

cosmic event needs to be scaled up by a factor of 240.8 when comparing to BNB MC. For inTime cosmics however, two filters are applied to reduce computing and processing time and only leave cosmics that will interact within the detector. The passing rate after these two filters is 0.02125, therefore the total inTime cosmic scaling factor to compare inTime cosmics to BNB is $0.02125 * 240.8 = 5.12$.

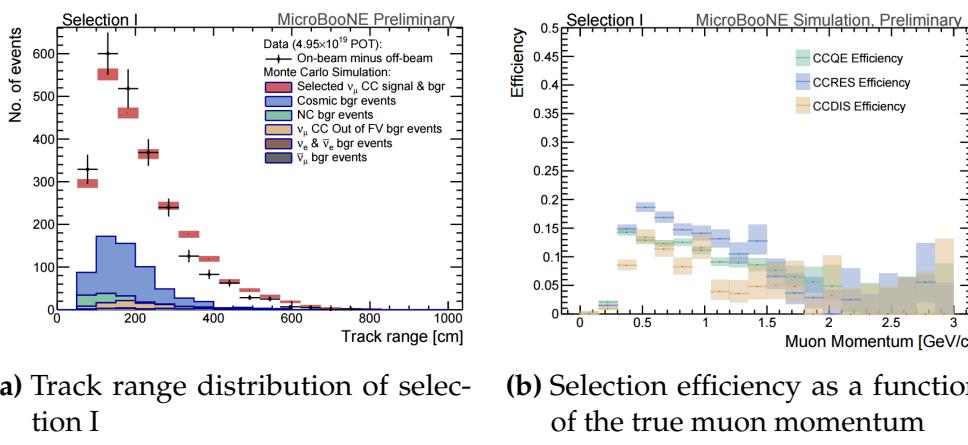


Figure 5.1: 5.1a Track range distribution for selection I. The track range is defined as the 3D distance between the start and end of the muon candidate track. No data is shown below 75 cm due to the track length cut described previously. 5.1b Efficiency of the selected events by process quasi-elastic (QE), resonant (RES), and deep-inelastic (DIS). Statistical uncertainty is shown in the bands and the distributions are a function of true muon momentum. The rise of the efficiency between 0 GeV and 0.5 GeV is due to the minimum track length cut and the decreasing efficiency for higher momentum tracks is caused by the containment requirement.

5.3 Optical Software Trigger and Reconstruction

5.3.1 Software Trigger

Most of the BNB spills from the accelerator do not have a neutrino interaction in MicroBooNE. To save computation resources and reduce data-rates, we require a burst of light in the light collection system in coincidence with the 1.6 μs beam spill. Requiring light activity in coincidence with the beam spill eliminates the vast majority of triggers with no neutrino interaction in the detector, however, it doesn't guarantee the activity in the detector is a neutrino interaction since a cosmic ray can interact in coincidence with the beam spill as well.

1124 To implement this, a software trigger was used on the PMT waveforms to decide
1125 whether or not to keep that event. The software trigger is implemented after the event
1126 builder combines data from the PMTs and triggers into a single event. The software
1127 trigger uses the digitized output of the 32 PMT channels in the light collection system.
1128 Only the waveform region in coincidence with the beam spill is used to search for
1129 possible triggers. For each PMT, a waveform is found by taking the difference of ADC
1130 values is calculated between t and $t + s$. This waveform is then scanned for ADC
1131 values above a threshold X_0 . Once an ADC is above this threshold, a discriminator
1132 window is opened for a fixed number of time ticks (W_0). If the ADC count within this
1133 window W_0 is greater than a second larger threshold X_3 , a final window of width W_3
1134 is opened. The max ADC value within this final window is set as the peak amplitude
1135 for the PMT and then summed across all 32 PMTs and set to the variable PHMAX. The
1136 software trigger places a final cut on the PHMAX variable to decide whether or not
1137 to keep the event. The thresholds were found by the Trigger task force using Monte
1138 Carlo Studies and are as follows:

- 1139 • $X_0 = 5$ ADC
- 1140 • $X_3 = 10$ ADC
- 1141 • $W_0 = 6$ Ticks
- 1142 • $W_3 = 6$ Ticks
- 1143 • PHMAX cut = 130 ADC

1144 5.3.2 Flash Reconstruction

1145 MicroBooNE collects light from each of the 32 PMTs either in a continuous readout
1146 window of $23.4 \mu\text{s}$ activated by a beam gate signal on the trigger board, or in discrimi-
1147 nated pulses of $\sim 1 \mu\text{s}$ duration activated if the ADC count for any PMT goes above 80
1148 ADC count. These two formats are saved as output waveforms and put onto an event.
1149 Additionally, each PMT can provide two output streams, high-gain (~ 20 ADC/PE)
1150 and low-gain (~ 2 ADC/PE) channels. The first step in the reconstruction is to merge
1151 both these channels into a “saturation corrected waveform” which uses information
1152 from the low-gain waveform to correct for saturating high-gain pulses.

1153 The saturation corrected waveform in the continuous readout window is used to
1154 reconstruct optical hits. Each PMT’s waveform is scanned for hits then a threshold

1155 based hit reconstruction algorithm is applied which requires pulses of a minimum
1156 area in order to be reconstructed. Each reconstructed hit is associated to a PMT, a time
1157 in μs , and a PE count.

1158 Once hits are reconstructed for all 32 PMTs, all PMT information is then combined
1159 into optical flashes which represent optical information seen by the PMTs from interac-
1160 tions in the detector. Each flash has information on total light seen per interaction, the
1161 distribution of the light across all 32 PMTs, the flash time with respect to the trigger
1162 time of the flash, and lastly, the spacial information of the flash in Y-Z plane of the
1163 detector. These flashes are reconstructed by requiring that there is a $\sim 1 \mu\text{s}$ coincidence
1164 between the reconstructed hits in all 32 PMTs. The total PE is summed up among
1165 all coincident hits across the PMTs and if the total PE is greater than 2 PE, a flash is
1166 reconstructed. There are also safe guards in place to take care of late scintillation light.

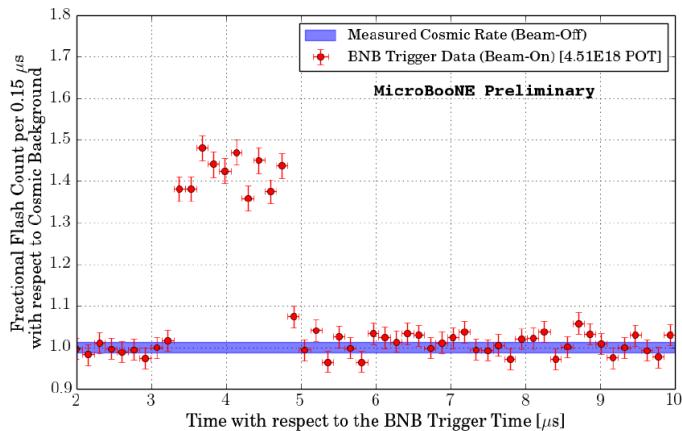


Figure 5.2: Time distribution of reconstructed optical flashes with a PE value of 50 or more for a sample of BNB unbiased triggered events.

1167 Figure 5.2 shows the time distribution of reconstructed optical flashes using the
1168 BNB continuous stream. You can see a clear excess in coincidence with the expected
1169 arrival time of neutrinos. The same flash reconstruction that was used in the cc-
1170 inclusive filter detailed here was used to create this plot in data.

1171 5.3.3 Beam Window

1172 Figure 5.3 shows the distribution of flashes for on-beam, off-beam and various MC
1173 samples. The software trigger has been applied to these samples. The pile-up seen just
1174 after 0 μs is a feature of the flash finding algorithm and consists of low PE flashes and

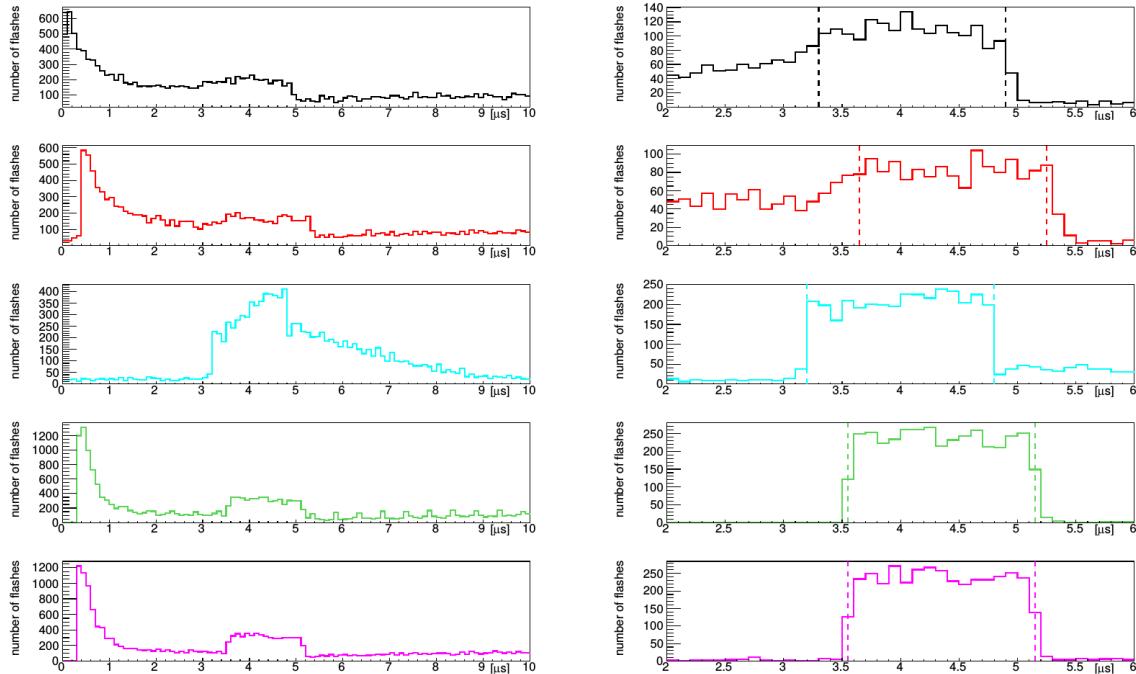


Figure 5.3: Flash time distribution for all flashes (left plot) and flashes $> 20\text{PE}$ (right plot). The different curves are as follows: on-beam data (black), off-beam data (red), CORSIKA inTime MC (light blue), BNB only MC (green), and BNB+Cosmic MC (purple). The dashed vertical lines mark the time window that was chosen for each sample

1175 is removed in the second column of distributions with a low 20 PE threshold cut. The
1176 plots show that the time window for the distributions are shifted a small amount from
1177 each-other. This is caused by different hardware configurations per sample. Using
1178 these distributions, the windows chosen per sample are as follows:

- 1179 • On-Beam: 3.3 to 4.9 μ s
 - 1180 • Off-Beam: 3.65 to 5.25 μ s
 - 1181 • CORSIKA inTime: 3.2 to 4.8 μ s
 - 1182 • BNB only: 3.55 to 5.15 μ s
 - 1183 • BNB+Cosmic: 3.55 to 5.15 μ s
- 1184 Each window has a width of 1.6 μ s.

1185 5.4 TPC Reconstruction

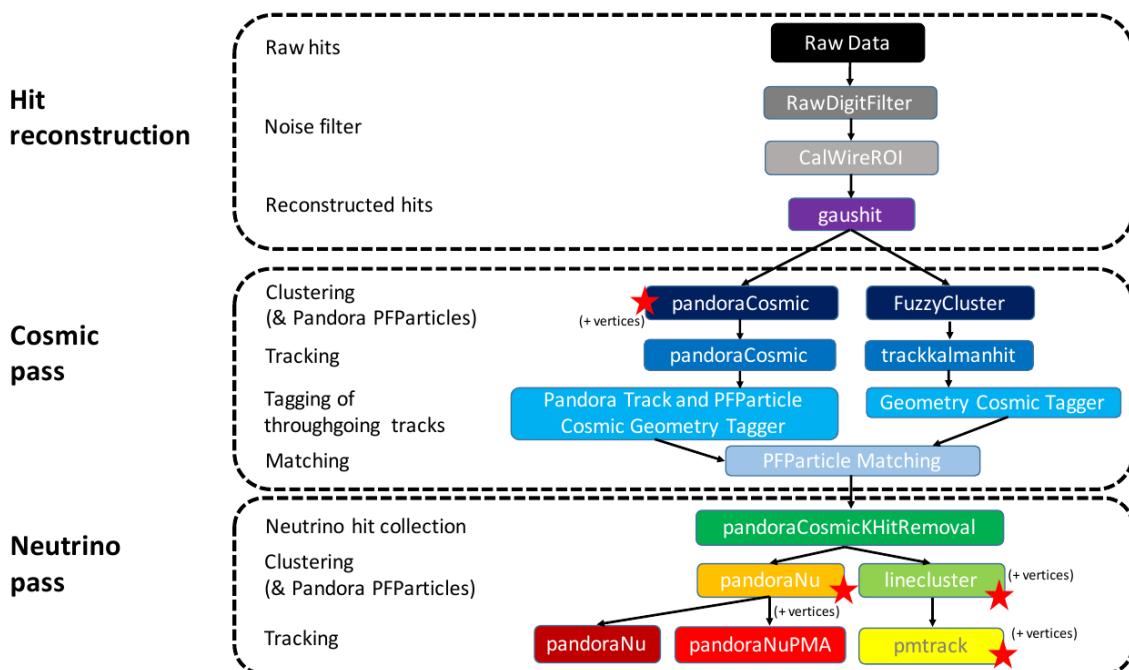


Figure 5.4: Reconstruction chain run on both data and MC. The red stars mean that the algorithm returns reconstructed 3D vertices.

1186 Figure 5.4 summarizes the reconstruction chain applied to both MC and data for
1187 this analysis. After the hit reconstruction, a cosmic pass is applied which removes all
1188 hits associated to through-going tracks. A description of these TPC reconstruction
1189 algorithms will be detailed below.

1190 **5.4.1 Hit Reconstruction**

1191 The waveforms used for hit reconstruction consist of charge deposited on the sense
1192 wire in drift time. The first step in hit reconstruction is to pass the waveforms through
1193 a filtering algorithm to filter out the noise introduced from the electronics. The input
1194 waveforms are also truncated from 9600 time ticks to 6400 time ticks in this first step
1195 to reduce the data footprint of these waveforms.

1196 Once noise filtering is complete, a deconvolution algorithm is applied to the wave-
1197 forms to remove the drift field and electronics response, therefore leaving only the
1198 ionized electrons kicked off the argon atoms by an incident track. During this process,
1199 Region of Interests (ROI) are identified and cut out of the waveforms to further reduce
1200 the data volume.

1201 The hit finding algorithm then finds candidate peaks in these ROI's and fits the
1202 peaks to Gaussian curves. These Gaussian shaped peaks are now called hits and
1203 represent the charge deposition on a wire by the incoming track. These hit objects
1204 have a peak time and width and are the basic object input to further algorithms down
1205 the reconstruction chain.

1206 **5.4.2 Clustering**

1207 There are multiple clustering algorithms used in this analysis. The main purpose of all
1208 the clustering algorithms is to associate hits together in 2D space to create objects like
1209 tracks, vertices and showers. For the fuzzy cluster algorithm, three steps are used to
1210 achieve this. The first step is to associate hits to each-other using a fuzzy clustering
1211 algorithm which gives each hit a degree of belonging to the cluster. Second, a Hough
1212 transform is used to find hits associated to candidate tracks and showers within each
1213 of the clusters found in the first step. The last step merges smaller candidate tracks
1214 and showers into large clusters. The last step also associates unclustered hits into

1215 nearby objects which helps shower reconstruction. The result is a set of clusters made
1216 up of associate hits that represent tracks or showers per plane.

1217 The pandora algorithm utilizes it's own clustering algorithm and will be detailed
1218 in the next section. The last clustering algorithm is called linecluster. The linecluster
1219 algorithm reconstructs 2D linear clusters per plane by fitting a line onto nearby hits
1220 which is then extrapolated to neighboring wires. 2D vertices are found per plane by
1221 using the intersection points of the ends of nearby clusters. These 2D vertices are then
1222 matched in time across all three planes to get a 3D vertex in space.

1223 5.4.3 Pandora

1224 5.4.4 Trackkalmanhit

1225 The trackkalmanhit algorithm takes 2D clusters returned from the fuzzy cluster algo-
1226 rithm and outputs track objects. There are no hierarchy structure as it is in pandora,
1227 each track is independent. There also is no vertex reconstruction with this algorithm
1228 as well.

1229 5.4.5 Cosmic Hit Removal

1230 The Pandora algorithm is applied to the events twice, the first to remove downward
1231 going tracks primarily from cosmic ray muon like particles. The second pass only runs
1232 on a subset of hits that aren't associated with cosmic ray muon tracks.

1233 After the first pass, the output of PFParticle hierarchy is then passed to a cosmic
1234 ray tagger to look through all hits to determine start and end points. If the start or
1235 end point trajectories are consistent with entering or exiting the TPC, then these hits
1236 are removed from the second pass. Hits are considered entering or exiting the TPC
1237 if the drift time are outside of the neutrino drift window or outside of the fiducial
1238 volume of the TPC. The fiducial volume was based on a montecarlo study and is 20
1239 cm from the top or bottom of the TPC and 10 cm from the TPC ends. Hits associated
1240 with candidate cosmic ray tracks are removed from the input hit collection and the
1241 remaining hits are passed to the neutrino optimized pass of Pandora.

1242 5.4.6 Projection Matching Algorithm

1243 The projection matching algorithm (PMA) was inherited from ICARUS and has been
1244 implemented in LArSoft. PMA differs from traditional LArSoft 3D reconstruction
1245 algorithms. Most 3D reconstruction attempts to match 2D objects from all three planes
1246 by drift time, while the PMA algorithm projects a track hypothesis on each plane
1247 then the distance between this projection and the hits on each plane is minimized
1248 simultaneously. More information can be found in [?].

1249 5.5 Event Selection

1250 The first requirement for selecting ν_μ CC events is that the event has at least one
1251 scintillation light flash in the beam trigger window with more than 50 PE on all PMTs
1252 combined. From the flashes that pass, the most intense is chosen and considered to be
1253 originating from a neutrino interaction and will be the only flash used in further cuts.

1254 Vertices are then required to have at least one reconstructed track start or endpoint
1255 within a 5 cm radius. Showers associated with a vertex do not pass this cut. All
1256 tracks associated with a vertex are then used to calculate a track length weighted
1257 average of the θ -angle. Of all the vertices that do pass, only the vertex with the most
1258 forward going θ -angle average of all associated tracks is considered the neutrino vertex
1259 candidate. The most forward going θ -angle average is chosen by picking the largest
1260 track range weighted average of $|\cos(\theta)|$, seeing as $\cos(\theta) = 1$ is the beam direction.
1261 Next, it is required that the reconstructed neutrino vertex candidate be within the
1262 fiducial volume as well as within the drift time starting at t_0 . The fiducial volume
1263 boundaries chosen are 10 cm from the edges of the TPC in x and z which is the drift
1264 direction and beam direction respectively, and 20 cm from the edges of the TPC in y
1265 which is the vertical direction. For all further cuts, only the longest track associated
1266 with the neutrino vertex candidate and this track is assumed to be the muon candidate
1267 of the neutrino event.

1268 The next cut requires the position of the flash in the z-direction and the track z-
1269 projection to be compared. This basic flash matching algorithm is rudimentary and a
1270 placeholder for a more sophisticated algorithm. The z-position of the flash needs to be
1271 within 80 cm to the z-positions of track start or endpoints. If the flash is between the
1272 track start and endpoint, the distance of the flash to the track is considered to be 0 cm.

1273 Lastly, the track needs to be fully contained within the fiducial volume and have a
 1274 track range greater than 75 cm. The range is the 3D distance between the track's start
 1275 and endpoint. The length cut was optimized to remove NC background that contain
 1276 a pion due to the pion interaction rate to be ~ 70 cm. A track that makes all the cuts
 1277 is considered to be the muon of a ν_μ CC event. The list of cuts for this selection is
 1278 described below:

- 1279 1. At least one flash > 50 PE within the beam gate.
- 1280 2. At least one track within 5 cm around a vertex.
- 1281 3. Vertex with flattest tracks is chosen to be vertex candidate.
- 1282 4. Vertex candidate in fiducial volume.
- 1283 5. Longest track associated with vertex candidate is chosen to be track candidate.
- 1284 6. Longest track is within 80 cm (z-axis only) of the flash.
- 1285 7. Longest track is fully contained.
- 1286 8. Longest track is greater than 75 cm.

1287 The event selection scheme can also be seen in figure 5.5. Table 5.1 lists the passing
 1288 rates for MC events for the selection scheme described above. Table 5.2 lists the passing
 1289 rates for on-beam and off-beam data for the selection scheme. The normalization
 1290 factors applied between on-beam and off-beam data are described in section 5.2.

1291 5.5.1 Expected Backgrounds

1292 Most of the selected background events will be of cosmic origin. There are two types
 1293 of cosmic background, one triggered by a cosmic-ray event occurring in the beam
 1294 gate time window, the other triggered by a beam induced interaction in the cryostat
 1295 followed by a misidentification of a cosmic event as a neutrino event. The first
 1296 cosmic background can be subtracted from the selected events using the off-beam
 1297 BNBEXT sample normalized to the on-beam. The second cosmic background events
 1298 are modeled by MC by using BNB+Cosmic MC sample.

1299 Other backgrounds originate from neutrino beam contaminants. A major contribu-
 1300 tion in this sector is by neutral current neutrino events for example a charged pion track
 1301 misidentified as a muon. Another contribution are ν_e -like and anti-muon-neutrino

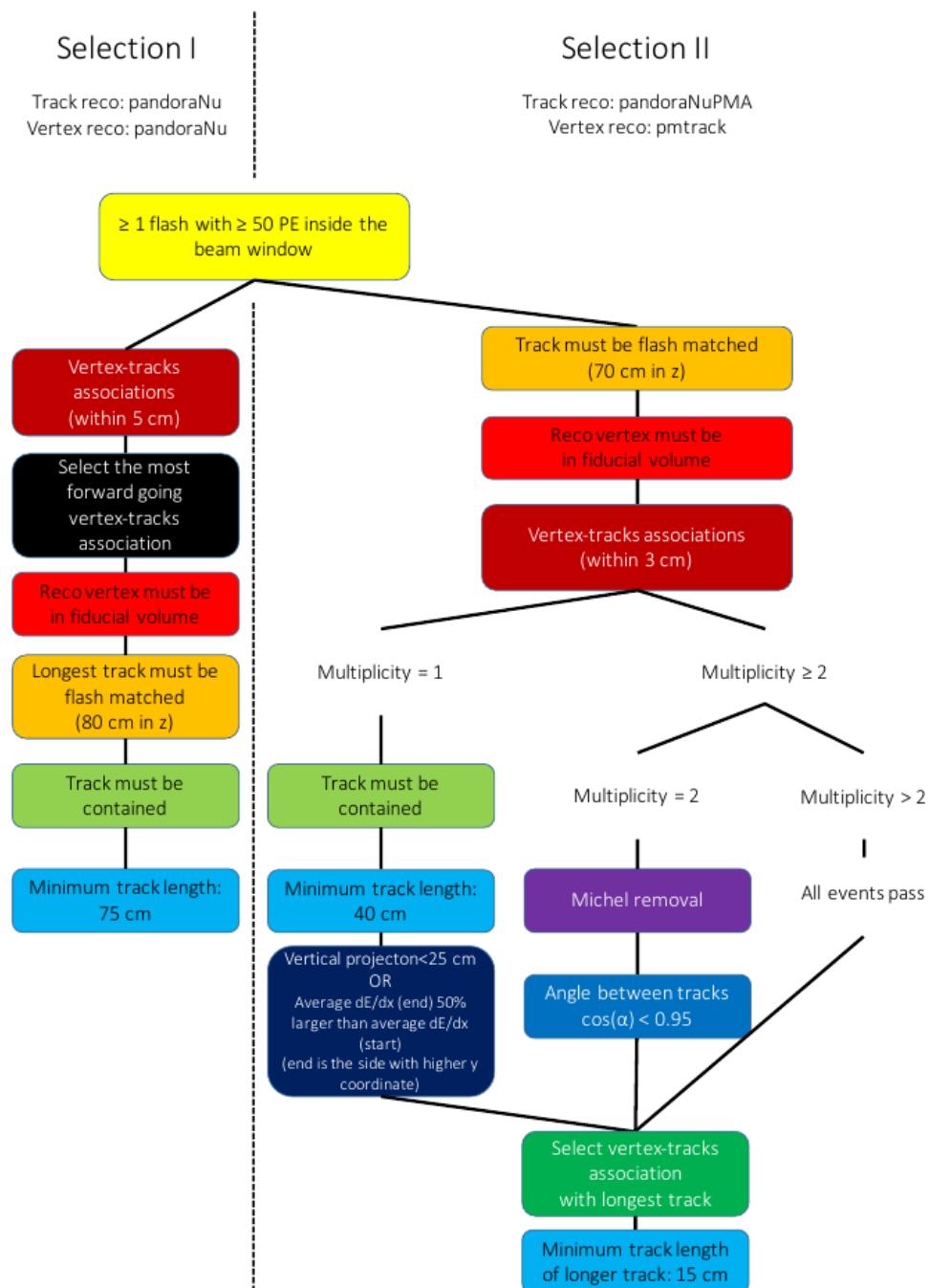


Figure 5.5: Event selection diagram for selection I and selection II. This analysis focused on optimizing selection I. Boxes with the same color across the two selections symbolize similar cuts.

	BNB+Cosmic Selection	BNB+ Cosmic MC-Truth	Cosmic Only	Signal:Cosmic Only
Generated Events	191362	45273	4804	1:22
≥ 1 flash with ≥ 50 PE	136219 (71%/71%)	44002 (97%/97%)	2970 (62%/62%)	1:14
≥ 1 track within 5 cm of vertex	135830 (99%/71%)	43974 (99%/97%)	2975 (99%/62%)	1:14
vertex candidate in FV	79112 (58%/41%)	34891 (79%/77%)	1482 (50%/31%)	1:8.9
flash matching of longest track	40267 (51%/21%)	25891 (74%/57%)	340 (23%/7.1%)	1:2.8
track containment	19391 (48%/10%)	11693 (45%/26%)	129 (38%/2.7%)	1:2.3
track ≥ 75 cm	6920 (36%/3.6%)	5780 (49%/13%)	17 (13%/0.4%)	1:0.6

Table 5.1: Passing rates of Selection I. Numbers are absolute event counts and cosmic background is not scaled. The BNB+Cosmic sample contains all events, not just ν_μ CC inclusive. The numbers in brackets give the passing rate wrt the step before (first percentage) and wrt total generated events (second percentage). The BNB+Cosmic MC-Truth column shows how many true ν_μ CC inclusive events are left in the sample. This number includes mis-identifications where a cosmic track is picked by the selection instead of the neutrino interaction in the same event. The cosmic only sample is used just to illustrate the cut efficiency. The last column Signal:Cosmic only gives an estimate of the ν_μ CC events wrt the cosmic only background at each step. For this number, the cosmic background has been scaled as described in section 5.2.

	on-beam	off-beam
Generated Events	546910	477819
≥ 1 flash with ≥ 50 PE	135923 (25%/25%)	96748 (20%/20%)
≥ 1 track within 5 cm of vertex	134744 (99%/25%)	95778 (99%/20%)
vertex candidate in FV	74827 (55%/14%)	51468 (54%/11%)
flash matching of longest track	22059 (29%/4.0%)	12234 (24%/2.6%)
track containment	10722 (49%/1.9%)	5283 (43%/1.1%)
track ≥ 75 cm	3213 (30%/0.6%)	1328 (25%/0.3%)

Table 5.2: Passing rates for Selection I selection applied to on-beam and off-beam data. The numbers in brackets give the passing rate wrt the step before (first percentage) and wrt the generated events (second percentage). Off-beam data has been scaled with a factor 1.23 to normalize to the on-beam data stream.

1302 events. These beam related backgrounds are an order of magnitude smaller than the
1303 cosmic misidentification backgrounds. These backgrounds can not be subtracted and
1304 are estimated using MC truth.

1305 The efficiency and purity of Selection I are calculated below:

- 1306 • Efficiency: Number of selected true ν_μ CC events divided by the number of
1307 expected true ν_μ CC events with interaction in the FV.

1308 – $(12.3 \pm 3.4) \%$

- 1309 • Purity: Number of selected true ν_μ CC events divided by the sum of itself and
1310 the number of all backgrounds.

1311 – $(53.8 \pm 4.4) \%$

1312 5.5.2 Truth Distributions

1313 The truth distributions of MC truth variables before and after the selection are detailed
1314 in this section. The overall efficiencies are calculated for all ν_μ CC signal events
1315 with a true interaction within the fiducial volume and a fully contained muon track
1316 originating from said vertex. Figures 5.6 through 5.8 detail the truth distributions for
1317 muon momentum, $\cos(\theta)$ and ϕ and figures 5.9 through 5.11 detail the total efficiency
1318 of the selection for charged current quasi elastic (CCQE) events, charged current
1319 resonant (CCRES) events, and charged current deep inelastic (CCDIS) events.

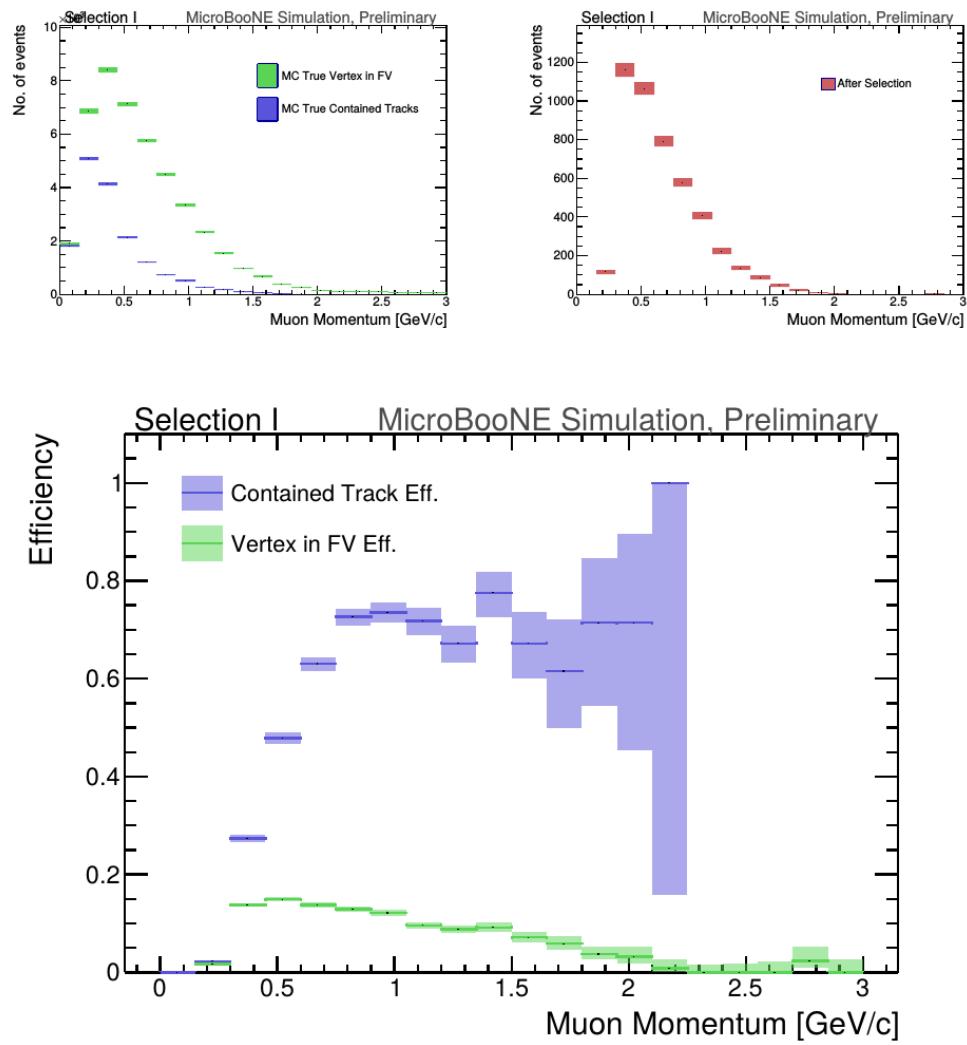


Figure 5.6: MC momentum distributions of the muon originating from a ν_μ CC interaction. Upper left is the momentum distributions of events with a vertex within the FV (green) and the events with a fully contained track (blue) before the selection. The upper right side is the momentum distribution after the selection (red). The lower plot is the selection efficiencies.

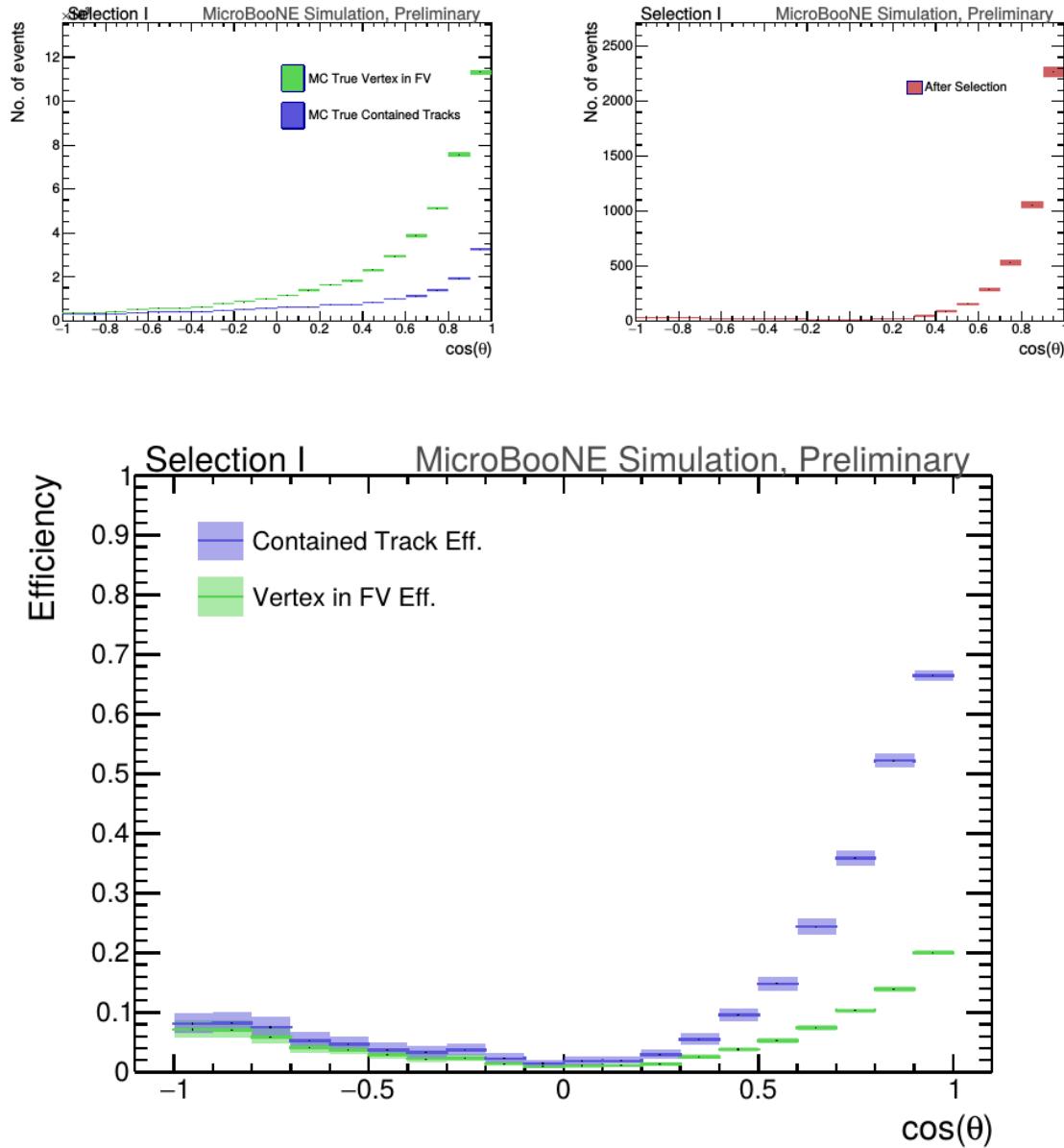


Figure 5.7: MC $\cos(\theta)$ distributions of the muon originating from a ν_μ CC interaction. Upper left is the $\cos(\theta)$ distributions of events with a vertex within the FV (green) and the events with a fully contained track (blue) before the selection. The upper right side is the $\cos(\theta)$ distribution after the selection (red). The lower plot is the selection efficiencies.

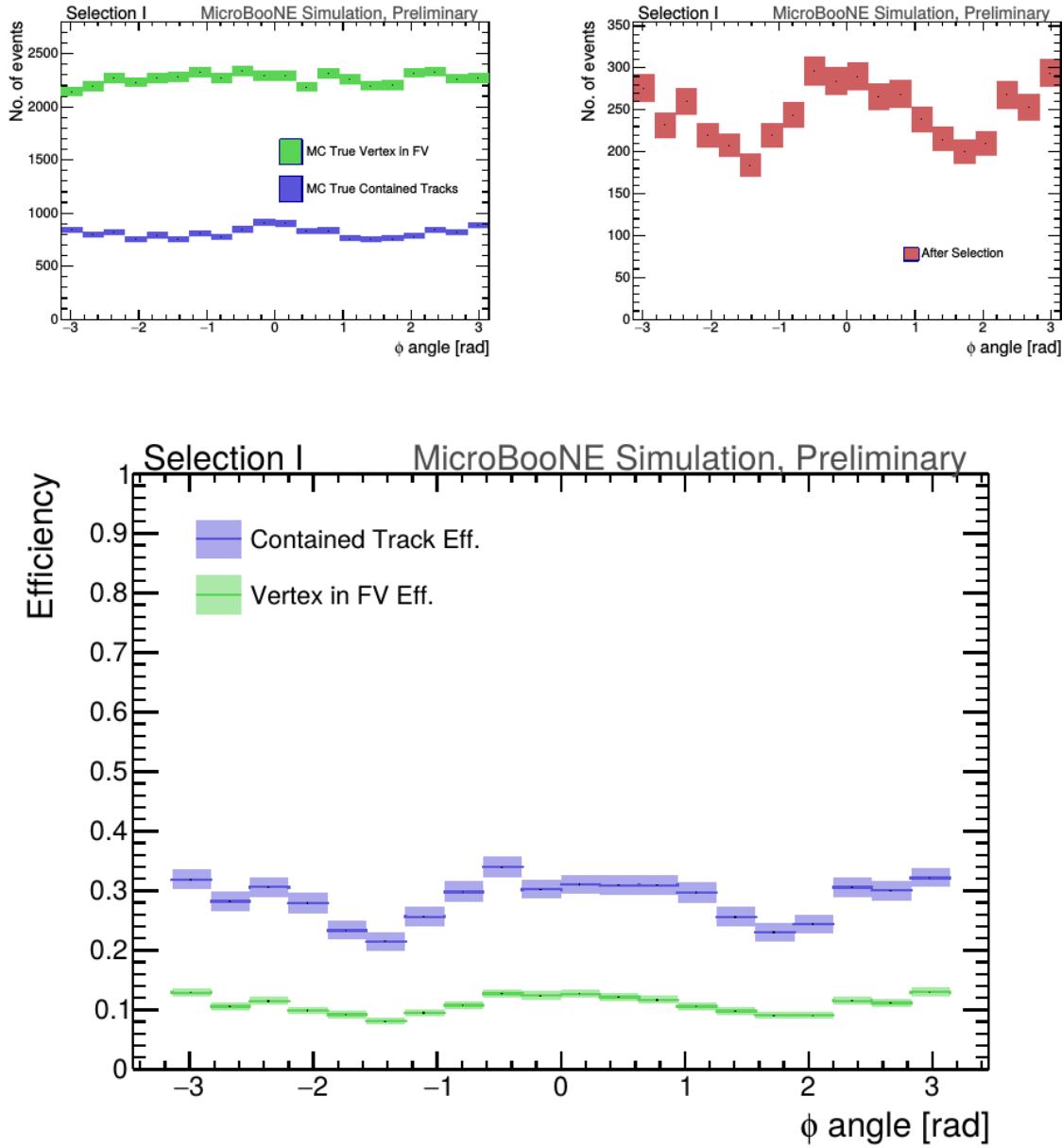


Figure 5.8: MC ϕ distributions of the muon originating from a ν_μ CC interaction. Upper left is the ϕ distributions of events with a vertex within the FV (green) and the events with a fully contained track (blue) before the selection. The upper right side is the ϕ distribution after the selection (red). The lower plot is the selection efficiencies.

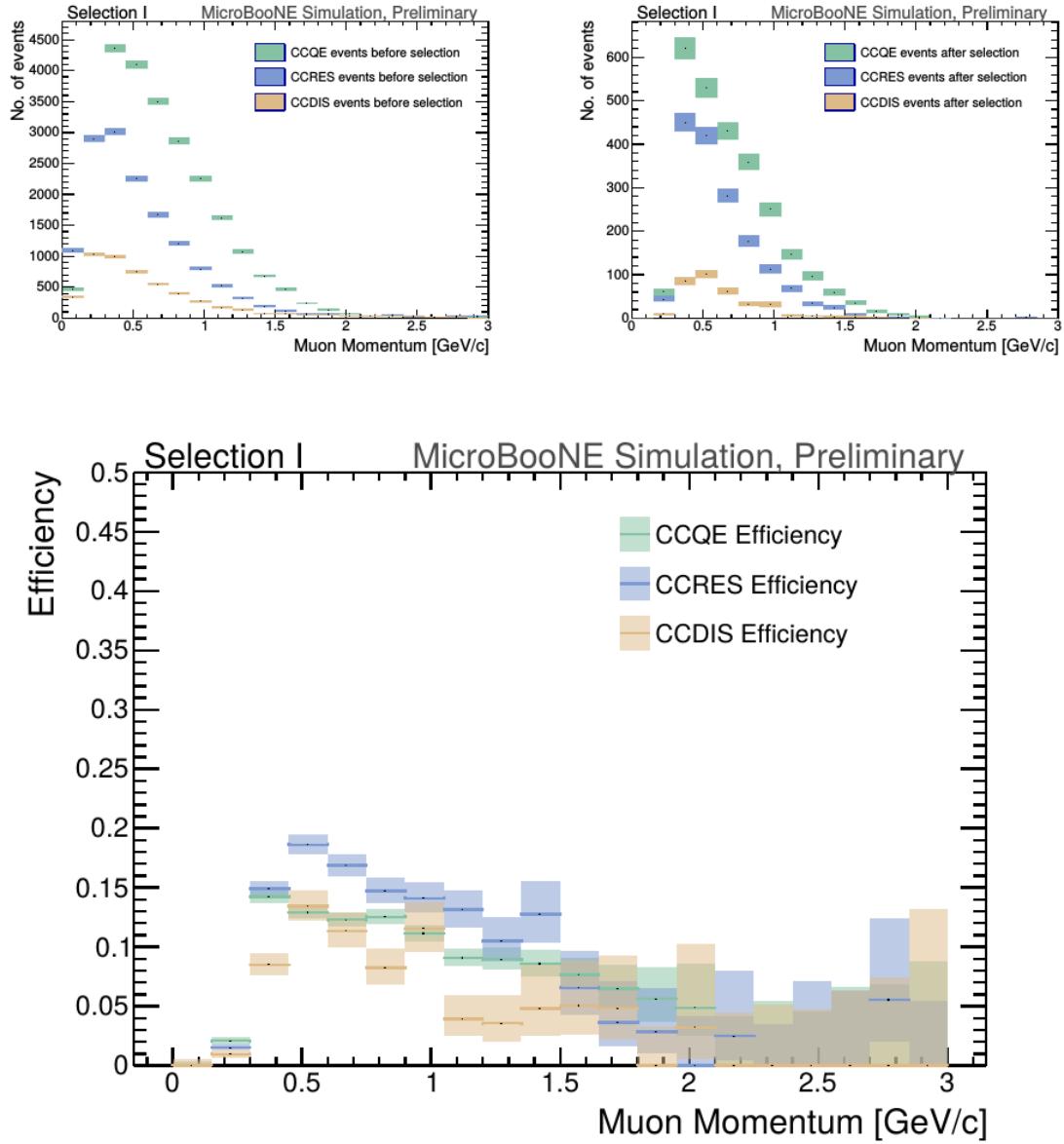


Figure 5.9: MC momentum distributions of the muon originating from a ν_μ CC interaction. Upper left is the momentum distributions of events with a vertex within the FV split up into CCQE (red), CCRES (yellow), and CCDIS (green) before selection. The upper right side is the momentum distribution after the selection with the same color schemes. The lower plot is the selection efficiencies for all three interaction types. The definition of QE, RES, and DIS is based on GENIE.

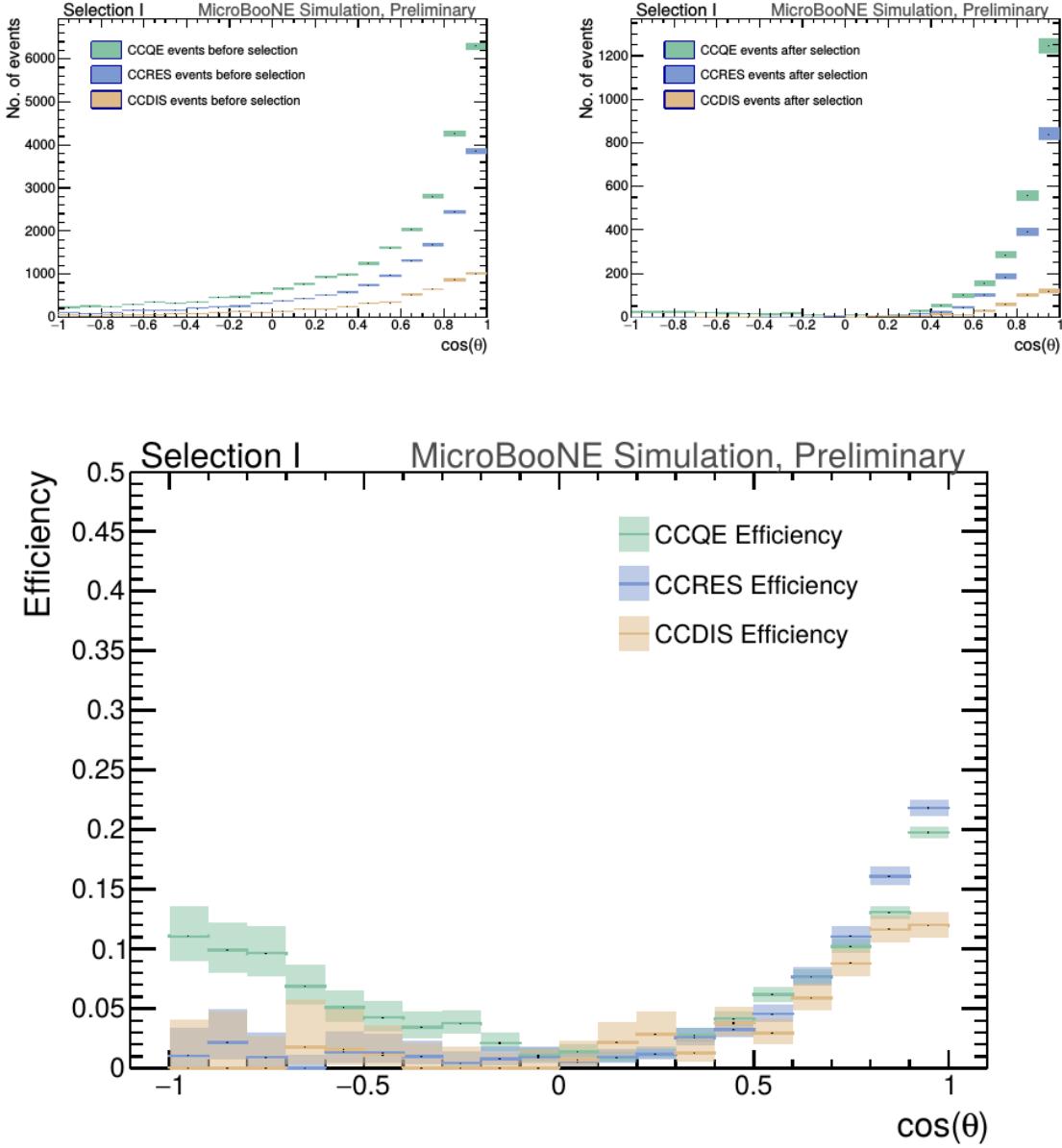


Figure 5.10: MC $\cos(\theta)$ distributions of the muon originating from a ν_μ CC interaction. Upper left is the $\cos(\theta)$ distributions of events with a vertex within the FV split up into CCQE (red), CCRES (yellow), and CCDIS (green) before selection. The upper right side is the $\cos(\theta)$ distribution after the selection with the same color schemes. The lower plot is the selection efficiencies for all three interaction types. The definition of QE, RES, and DIS is based on GENIE.

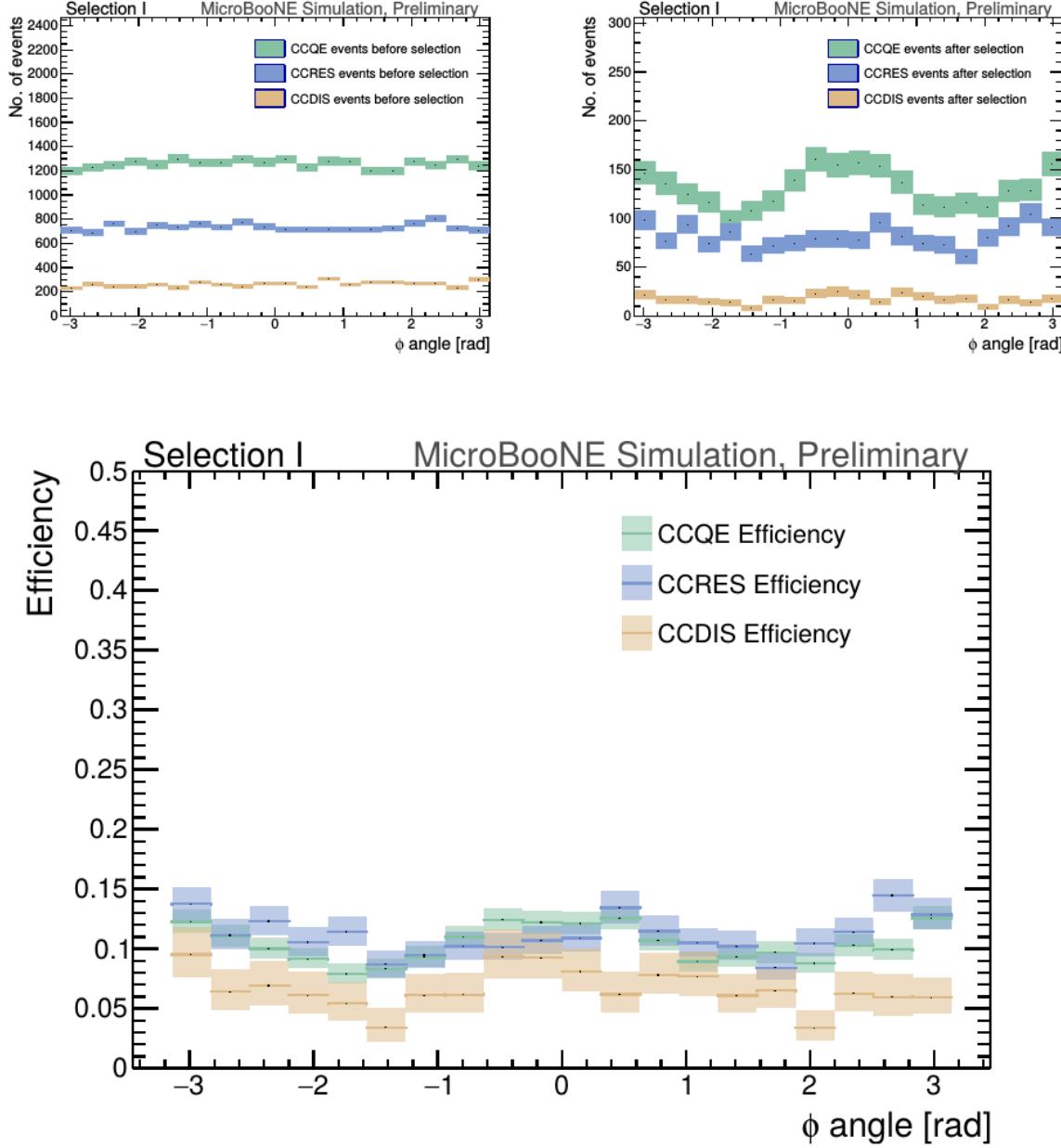


Figure 5.11: MC ϕ distributions of the muon originating from a ν_μ CC interaction. Upper left is the ϕ distributions of events with a vertex within the FV split up into CCQE (red), CCRES (yellow), and CCDIS (green) before selection. The upper right side is the ϕ distribution after the selection with the same color schemes. The lower plot is the selection efficiencies for all three interaction types. The definition of QE, RES, and DIS is based on GENIE.

1320 **Chapter 6**

1321 **Background on Convolutional Neural
1322 Networks**

1323 Convolutional neural networks (CNNs) have been one of the most influential inno-
1324 vations in the field of computer vision. Neural networks became popular in 2012
1325 when Alex Krizhevsky used them to win that year's ImageNet competition [?] by
1326 dropping the error from 26% to 15%. Since then, many companies are using deep
1327 learning including Facebook's tagging algorithms, Google for their photo search and
1328 Amazon for product recommendations. For the purpose of this thesis CNNs were
1329 used for image classification, specifically, images of varying particles created using
1330 LArTPC data.

1331 **6.1 Image Classification**

1332 Image classification is the process of inputting an image into the CNN and receiving a
1333 probability of classes that best describes what is happening in the image. As humans,
1334 image classification is something that is learned at a very young age and is easy to
1335 do without much effort. This is also apparent when hand-scanning LArTPC images.
1336 After learning what a neutrino event looks like in MicroBooNE, it is relatively easy
1337 to recognize simple neutrino events from cosmic ray background as well as highly
1338 ionizing particles like protons from minimum ionizing particles like muons. The very
1339 detailed images LArTPC detectors output are prime candidates for input images into
1340 a CNN. CNNs mimic a human's ability to classify objects by creating an architecture
1341 that can learn differences between all the images it's given as well as figure out the

unique features that make up each object. CNNs are modeled after the visual cortex. Hubel and Wiesel [?] found that there are small regions of neuronal cells in the brain that respond to specific regions of the visual field. They saw that some neurons fired when exposed to vertical edges while others fired when shown horizontal or diagonal edges. They also saw that these neurons were organized in columns. The idea of specific neurons inside of the brain firing to specific characteristics is the basis behind CNNs.

6.2 CNN Structure

When used for image recognition, convolutional neural networks consist of multiple layers that extract different information on small portions of the input image. How many layers is tunable to increase the accuracy. The output of these collections are then tiled so that they overlap to gain a better representation of the original image and allow for translation. The first of these layers is always a convolution layer. To the CNN, an image is an array of pixel values. For a RGB color image with width and height equal to 32x32 the corresponding array is 32x32x3. Filters, also known as neurons, of any size set by the user is then convolved with the receptive field of the image. If the filter is 5x5, the receptive field will be a patch of 5x5 on the input image. The filter is also an array of numbers called weights. The convolution of the filter and image are matrix multiplications of the weights and the pixel values. By stepping the receptive field by 1 unit, for an input image of 32x32x3 and a filter of 5x5x3 you'd get an output array of 28x28x1. This output array is called an activation map or feature map. The use of more filters preserves the spatial dimensions better. The filters can be described as feature identifiers. Examples of features in an image consist of edges, curves, and changes in colors. The first filters in a CNN will primarily be straight line and curve feature identifiers. An example of a curve filter is shown in figure 6.2. When a curve in the same concavity is found in the input image, the corresponding pixel in the output feature map will be activated. Going back to our example of a 32x32 input image and a 5x5 filter, if there were to be a curve in the top left corner of the input image, our output feature map would have a high pixel value in the top left. Therefore, feature maps tell us where a specific feature is located in the original image. Figure ?? shows a visualization of filters found in the first layers of many CNN architectures. These filters in the first layer convolve around the image and activate when the specific feature it is looking for is in the receptive field.

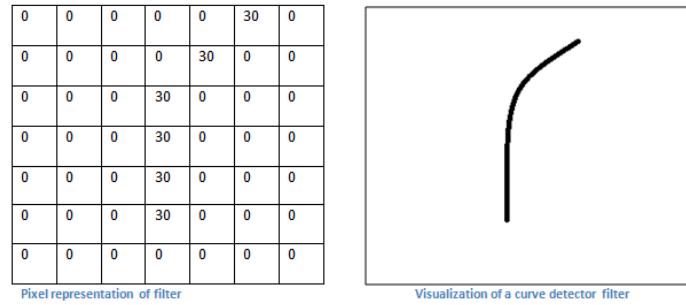


Figure 6.1: Pixel representation and visualization of a curve detector filter. As you can see, in the pixel representation, the weights of this filter are greater along a curve we are trying to find in the input image

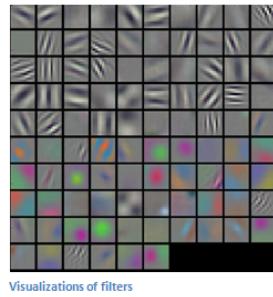


Figure 6.2: Visualization of filters found in first layer of a CNN.

In figure 6.3 you can see how an edge detection filter is used to save only necessary information for recognizing different types of clothes. You can also see by having multiple filters you can get more detail or less detail from an image which can then simplify or complicate the object recognition task. Being able to distinguish between a shirt or a leg garment is as much information you want, having a filter that extracts outline edge or shape information would be all that you need. But if instead you wanted to distinguish between a formal cocktail dress or a summer dress, more information would need to be saved equating to many more filters for one image. Rather than trying to come up with how many filters and what features are important for detection, CNNs do this automatically. CNNs take input parameters, called hyperparameters, for example number of layers, number of filters per layers, number of weights per filter, and uses these to create the output feature maps. The layers build upon each-other, for example if we were creating a CNN for facial recognition the convolutional layers will start learning feature combinations off of the previous layers. The low level features like edges, gradients, and corners of the first layers become high level features like eyes, noses, and hairs. This process is visualized in figure 6.4



Figure 6.3: Applying a feature mask over a set of fashion items to extract necessary information for auto-encoding. Unnecessary information for example color or brand emblems are not saved. This feature map is an edge detection mask that leaves only shape information which helps to distinguish between different types of clothes.

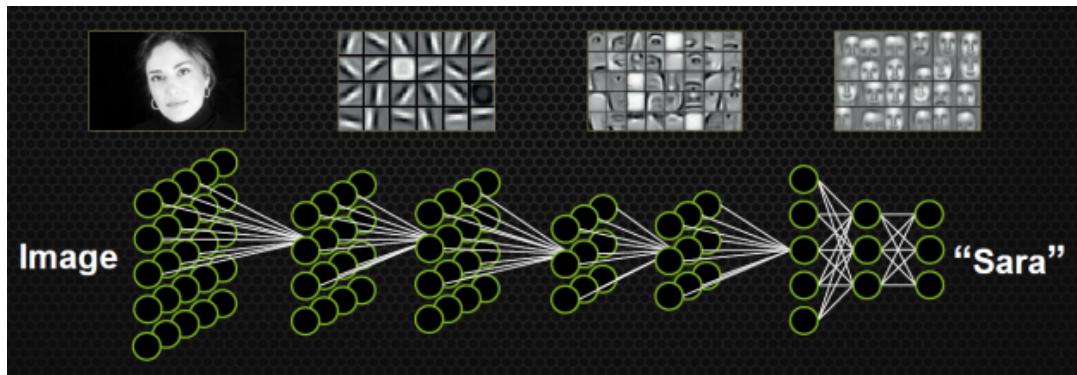


Figure 6.4: Pictorial Representation of Convolutional Neural Networks as well as a visual representation on CNN's complexity of layer feature extraction

1391 There are other layers in a CNN architecture that will not be covered in the scope
 1392 of this thesis but in a general sense, these layers are interspersed between convolution
 1393 layers to preserve dimensionality and control overfitting of the network. The last layer
 1394 is called a fully connected layer and it's job is to output an N dimensional vector where
 1395 N is the number of classes the network has been trained on. Each number in this vector
 1396 represents the probability that the input image is a certain class. Fully connected layers
 1397 use the feature maps of the high level features to compute the products between the
 1398 weights of the previous layer to get the probabilities of each class. These weights are
 1399 then adjusted through the training process using backpropagation.

1400 6.2.1 Backpropagation

1401 A CNN at it's onset has weights that are randomized. The filters themselves don't
 1402 know how to pull out identifying information per class. For a neural network to learn,
 1403 it must be trained on a training set that is labeled. Backpropagation has four seperate
 1404 steps: foward pass, loss function, backward pass and updating weights. In the forward
 1405 pass, a training image is passed through the whole network. All of our weights at this
 1406 time are randomly initialized so the output for the first image will have no preference
 1407 to a specific class. A common loss function is mean squared error (MSE):

$$E_{total} = \sum \frac{1}{2} (actualclass - predictedclass)^2 \quad (6.1)$$

1408 If we assume that the MSE is the loss of our CNN, the goal would be that our
 1409 predicted label (output of CNN) is the same as our training label. To do this, we need
 1410 to minimize the loss function. To do this, it is necessary to find out which weights most
 1411 directly affect the loss of the network i.e $\frac{dL}{dW}$ where L is our loss function and W are
 1412 the weights of a specific layer. The next step is the backward pass which determines
 1413 which weights contribute the most to the loss and finds ways to adjust these weights
 1414 so that the loss decreases. After the derivative is computed, the last step updates the
 1415 weights in the opposite direction of the gradient.

$$w = w_i - \eta \frac{dL}{dW} \quad (6.2)$$

$$w = \text{Weight} \quad (6.3)$$

$$w_i = \text{Initial Weight} \quad (6.4)$$

$$\eta = \text{Learning Rate} \quad (6.5)$$

1416 The learning rate is a parameter given to the CNN and it describes the steps the
 1417 network takes to update the weights. Higher learning rate equals large steps and a
 1418 lower training time, but a learning rate that is too large can mean the CNN never
 1419 converges.

1420 Going through backpropagation consists of one training iteration. Once the net-
 1421 work completes a specific number of iterations, another parameter given, and runs
 1422 over all training images that are split up into batches, the process is considered com-
 1423 plete. User input parameters, called hyperparameters, help the network converge to

1424 optimal weights for each layer. Batch size, learning rate, and training iteration are just
1425 some of the user input hyperparameters that help. Lastly, to check if the network has
1426 learned, a different set of labeled images are fed to the CNN iteratively through the
1427 training process to see how well it's learning. This process is especially important to
1428 make sure the network architecture isn't being affected by overfitting (memorizing
1429 training input rather than learning).

1430 6.3 Choosing Hyperparameters

1431 Convolutional neural networks are a relatively new tools in computer vision. Choosing
1432 hyperparameters for your specific dataset is a non-trivial task. Hyperparameters can
1433 range from the amount of layers and filters per layer in an CNN architecture to the
1434 stride the receptive field of a filter takes, not to mention training hyperparameters
1435 such as learning rate and batch size described above. They're ways to optimize these
1436 hyperparameters via hyperparameter optimization using Bayesian Optimization [?]
1437 but as you can imagine, optimizing an CNN architecture from scratch can be very
1438 computationally intensive. For the purpose of this thesis, two well known CNN
1439 architectures were used, AlexNet [?], which won the ImageNet Large-Scale Visual
1440 Recognition Challenge (ILSVRC) in 2012 and therefore bringing awareness of CNNs,
1441 and GoogleNet [?], which won the ILSVRC in 2014, giving rise to deep networks. Both
1442 AlexNet and GoogleNet architectures were used to train on LArTPC images and their
1443 low level filter weights. Higher level filter weights were randomly initialized before
1444 training so the network can learn high level features of LArTPC image classes. The
1445 AlexNet architecture is shown in figure 6.5 and the GoogleNet architecture is shown
1446 in figure 6.6

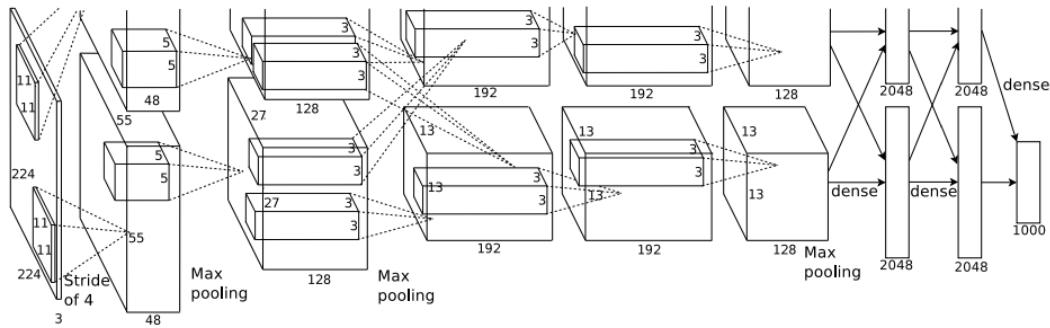


Figure 6.5: Pictoral representation of the AlexNet model. The AlexNet model consists of 5 convolution layers and 3 fully connected layers.

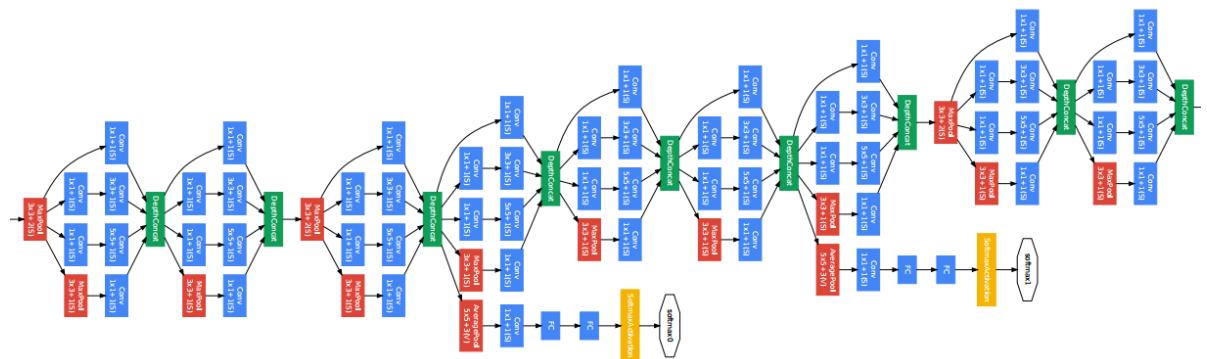


Figure 6.6: Pictoral representation of the GoogleNet model. The GoogleNet model consists of 22 layers. The model implements 9 Inception modules which performs covolution and pooling in parallel and strays away from the basis that CNN layers need to be stacked up sequentially. The GoogleNet model also doesn't use fully connected layers, instead it uses average pooling which greatly reduces the amount of parameters. GoogleNet has 12x fewer parameters than AlexNet.

¹⁴⁴⁷ Chapter 7

¹⁴⁴⁸ Training process of Convolutional ¹⁴⁴⁹ Neural Networks

¹⁴⁵⁰ Three Convolutional Neural Networks (CNNs) were trained throughout this analysis.
¹⁴⁵¹ There are differences to each CNN and will be described fully in the next sections but
¹⁴⁵² the main difference are the amount of particle images used for training and validation.
¹⁴⁵³ CNN1075 used 1,075 muons and 1,075 pions for training and the same amount of each
¹⁴⁵⁴ particle for validation. CNN10000 used 10,000 muons and 10,000 pions split in half
¹⁴⁵⁵ for testing and training. Lastly CNN100000 had muons, pions, protons, electrons,
¹⁴⁵⁶ and gammas in its training and validation set. Each particle had 20,000 images and
¹⁴⁵⁷ training and validation was split 90% training, 10% validation. This chapter will also
¹⁴⁵⁸ describe the different hardware frameworks used for training beginning on a CPU
¹⁴⁵⁹ and ending on a GPU cluster.

¹⁴⁶⁰ 7.1 Hardware Configurations for Convolutional Neural ¹⁴⁶¹ Network Training

¹⁴⁶² The first training iteration, CNN1075, was a proof of concept. This CNN was trained
¹⁴⁶³ on my local machine for ~4-5 weeks. The batch size had to be very small as well as the
¹⁴⁶⁴ image size due to the lack of computation resources. The second iteration of training,
¹⁴⁶⁵ CNN10000, was trained on a Fermilab stationed Syracuse University machine. This
¹⁴⁶⁶ machine had 6 TB of disk space, 6 cores at 2.1 GHz and 32 GB of RAM. The use of
¹⁴⁶⁷ this machine allowed me to increase the training sample as well as the batch size and
¹⁴⁶⁸ hence further increase the accuracy of the neural network. Lastly, the CNN100000 was

¹⁴⁶⁹ trained using two GTX 1080 Ti GPUs with 11GB of memory on a node on the Syracuse
¹⁴⁷⁰ University GPU cluster, SUrge, that has 8 cores and 16GB of memory. This increase in
¹⁴⁷¹ memory as well as the capability to use 2 GPUs drastically cut down on training time
¹⁴⁷² from \sim 4-5 weeks to \sim 8 hours. SUrge also allowed for hyperparameter optimization
¹⁴⁷³ by being able to run multiple training iterations over the two GPUs. Lastly, SUrge
¹⁴⁷⁴ allowed for training over higher resolution images and a larger particle class of 5
¹⁴⁷⁵ particles vs 2 particles.

¹⁴⁷⁶ **7.2 Creating images using LArTPC data for**
¹⁴⁷⁷ **training/validation of CNNs**

¹⁴⁷⁸ The μ/π image dataset used to train and validate CNN1075 was created using single
¹⁴⁷⁹ generated isotropic muons and pions from 0-2 GeV energy range. 2,150 muons and
¹⁴⁸⁰ 2,150 pions were used for training and testing split 50%. The images were created
¹⁴⁸¹ using LArSoft, a liquid argon software, and were based on wire number and time
¹⁴⁸² tick in the collection plane. Uboonecode reconstruction version v05_08_00 was used.
¹⁴⁸³ The raw ADC value after noise filtering was the wire signal. Each collection plane
¹⁴⁸⁴ greyscale image was 3456x1600x1 where 6 time ticks were pooled into 1 bin.

¹⁴⁸⁵ After the image was created, the region of interest (ROI) in the image was found by
¹⁴⁸⁶ using Open CV, a image processing open source software package, to scan the image
¹⁴⁸⁷ starting from the edges and stopping once a bright pixel is encountered. At this step,
¹⁴⁸⁸ the ROI can be larger or smaller than the necessary size of a training image and the XY
¹⁴⁸⁹ ratio of the image is not kept. This ROI is then resized to an image of 224x224x1.

¹⁴⁹⁰ The greyscale color standard is 8bit therefore the ADC value of wire and time tick
¹⁴⁹¹ was also downsampled due to the 12bit ADC value MicroBooNE has. To do this,
¹⁴⁹² the highest ADC pixel in the image was found and then this was divided by the rest
¹⁴⁹³ placing all pixel values between 0-1. From there, all pixel values are then multiplied
¹⁴⁹⁴ by 255.

¹⁴⁹⁵ The μ/π image dataset used to train and validate the CNN10000 was also created
¹⁴⁹⁶ using single generated isotropic muons and pions from 0-2 GeV energy range. 10,000
¹⁴⁹⁷ muons and 10,000 pions were used for training and testing split 50%. Uboonecode
¹⁴⁹⁸ v06_23_00 was used instead of v05_08_00. Each collection plane greyscale image was
¹⁴⁹⁹ 3456x1280x1 where 5 time ticks were pooled into 1 bin which is different than the

1500 previous dataset and was implemented due to the fact that the time ticks of an event
1501 went from 9400 to 6400 with the change of uboonecode version. Issues that arose in
1502 CNN1075 that were fixed in CNN10000 include zero-padding images in X and Y that
1503 are smaller than 224X224 to eliminate over-zooming effect and fixing a bug that shifted
1504 pixels separated by a dead-wire region.

1505 The $\mu/\pi/p/e/\gamma$ image dataset used to train and validate the CNN100000 were
1506 created using single generated isotropic particles with energy range from 0-2 GeV.
1507 20,000 of each particle were used for training and were split 90/10 between training
1508 and testing sets. Uboonecode v06_23_00 was used for these images. The collection
1509 plane greyscale iamge had the same dimensions as CNN10000, 3456x1280x1 and the
1510 ROI algorithm was the same except for resizing these images to 576x576.

1511 A major change other than the higher resolution images was the treatment of the
1512 ADC values. In the first two image making schemes, the highest pixel value was found
1513 per image and the image was then normalized by that. The issue arising from this
1514 ADC normalization wasn't inherent in μ/π training due to the fact that both particles
1515 are minimum ionizing particles in liquid argon, however, when dealing with a larger
1516 particle class, it was necessary to try and make sure energy deposition by each particle
1517 was preserved. The energy deposition in a particle image corresponds to the ADC
1518 value or pixel brightness. To preserve energy deposition, the ADC float value was
1519 passed straight to the image rather than doing any image normalization. This then
1520 makes sure that minimum ionizing particles like muons and pions appear dimmer
1521 than highly ionizing particles like protons.

1522 Images were also made from BNB+Cosmic events that passed the cc-inclusive
1523 selection 1 filter right before the 75 cm track length cut and were classified using
1524 the CNN10000. The dataset used to create these images is the same one used in
1525 [?], *prodgenie_bnb_nu_cosmic_uboone_mcc7_reco2*. These images were created using
1526 information from the track candidate that passed the filter. Only wire number and
1527 time ticks associated to the track candidate were drawn on the image to mimic a single
1528 particle generated image.

1529 These images were then classified using CNN10000. Two approaches were taken
1530 in making these images. The first was using the image normalization above where
1531 the maximum pixel in each image is used as a normalization constant to get all pixels
1532 between 0-1 then multiply all pixels by 255. As described above, this is the incorrect

way to normalize. The second way the images were created was by passing the ADC float to the image. The results of CNN10000 performance are shown in section 7.1.

1535 Lastly, multiple BNB+Cosmic images per event were made for CNN100000 by
1536 reducing many of selection I cuts to try and let the CNN do particle as well as event
1537 identification. This image making scheme used for CNN100000 will be described in
1538 more detail in later sections.

1539 7.3 Convolutional Neural Network Training

1540 7.3.1 Training CNN1075

The results of CNN1075 are described in this section. The accuracy is how well CNN1075 is doing by epoch and was 74.5%. The loss is gradient descent or minimization of the error of the weights and biases used in each neuron of each layer of CNN1075 and was 58% with a trend sloping downwards on the loss curve as well as a trend sloping upward in the accuracy curve. The accuracy and loss of CNN1075 are shown in figure 7.1. Due to the depth of the neural network framework, it was necessary to train with a larger dataset and for more epochs, however, the downward slope of the loss curve is an indication that once trained for longer with a higher training sample, neural networks can be used for μ/π separation. The hyperparameters used to train CNN1075 are detailed below:

- *train_batch_size*: 50
 - *test_batch_size*: 50
 - *test_iter*: 50
 - *test_interval*: 50
 - *base_lr*: 0.01
 - *lr_policy*: "step"
 - *gamma*: 0.1
 - *stepsize*: 200
 - *display*: 50
 - *max_iter*: 5000
 - *momentum*: 0.9
 - *weight_decay*: 0.0005
 - *snapshot*: 100

1564 The confusion matrices shown in figure 7.2 show the accuracy for both the training
1565 and testing datasets. The fact that these two have similar accuracies is important

Loss/Accuracy of CNN trained on 2150 images

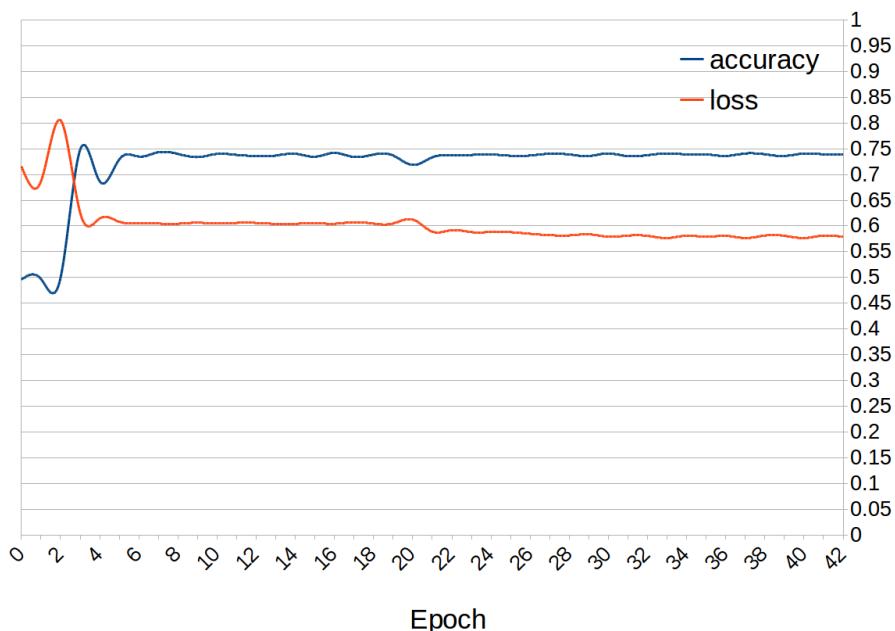


Figure 7.1: Accuracy vs. Loss of AlexNet 2-output μ/π sample consisting of 2,150 images each.

because if the training dataset had a much higher accuracy, that indicates an over-training of the training sample which means the neural network didn't learn features to separate muons from pions, it just memorized what was in the training dataset. Also note that the neural network does a better job of identifying muons than pions. This can be attributed to the more complex event scenes pions tend to leave in the detector due to pion interacting more in LAr than muons do. The CNN may do better at identifying pions with a larger training sample.

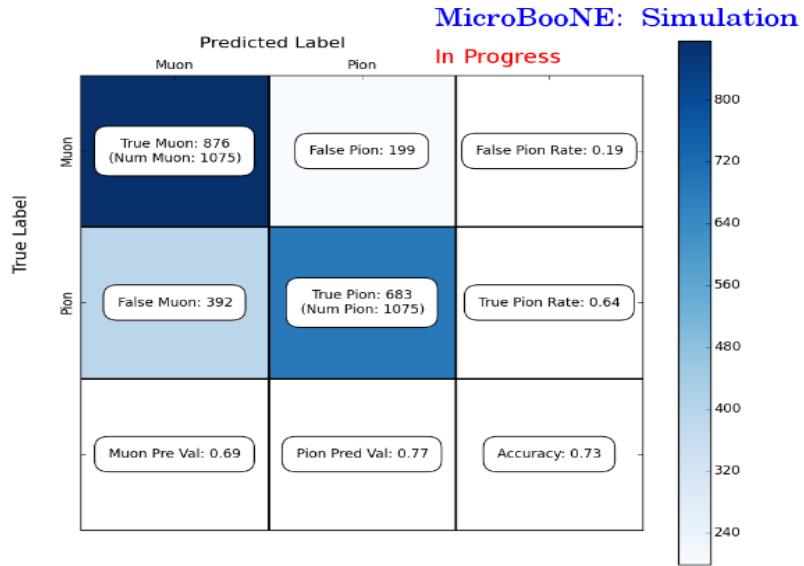
1573 7.3.2 Training CNN10000

1574 The hyperparameters used for CNN10000 are shown below. The batch size for the
1575 training and testing as well as the test_iter were chosen to encompass the whole
1576 training/testing image set when doing accuracy/loss calculations. To do this, multi-
1577 plying the test_iter by the test batch size gives you the amount of images used when
1578 calculating accuracy/loss curves.

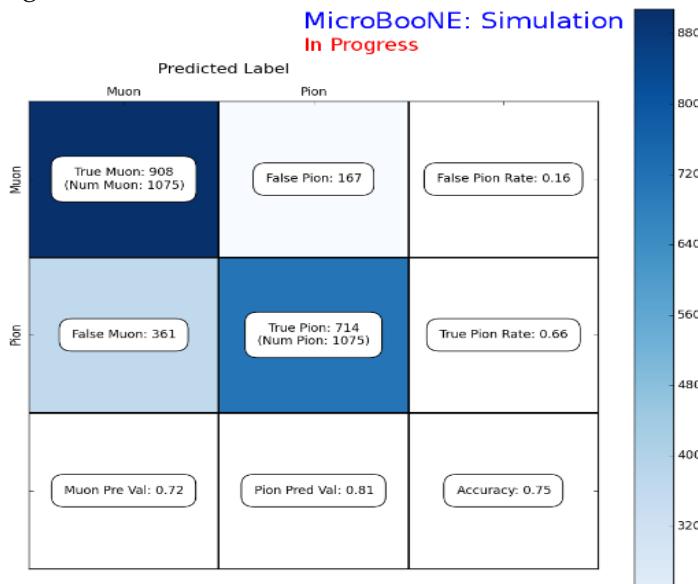
- *train_batch_size*: 100
 - *test_batch_size*: 100
 - *test_iter*: 100
 - *test_interval*: 100
 - *base_lr*: 0.001
 - *lr_policy*: "step"
 - *gamma*: 0.1
 - *stepsize*: 1000
 - *display*: 100
 - *max_iter*: 10000
 - *momentum*: 0.99
 - *weight_decay*: 0.0005
 - *snapshot*: 100

The same architecture that was used to train CNN1075 was employed on CNN10000, AlexNet. Caffe [?] was the software package used for both CNNs. The differences include batch size and test_iter and momentum to account for the larger dataset. Figure 7.3 shows the loss and accuracy of CNN10000. There is around a 10% increase in accuracy from CNN1075 to CNN10000, 85%, and around a 20% decrease in loss, 36%.

Figure 7.4 show a breakdown of μ/π separation for CNN10000. It also shows the network is not being overtrained due to the Accuracy of both the training and testing datasets being within .01% of eachother. The CNN is doing a very good job of



(a) Confusion Matrix showing Accuracy of CNN1075 using training MC data



(b) Confusion Matrix showing Accuracy of CNN1075 using testing MC data

Figure 7.2: Description of confusion matrix variables: False pion rate = $false\pi / total\pi$ True pion rate = $true\pi / total\pi$ Accuracy = $(true\pi rate + true\mu rate) / 2$ Pion prediction value = $true\pi / (true\pi + false\pi)$ Muon prediction value = $true\mu / (true\mu + false\mu)$

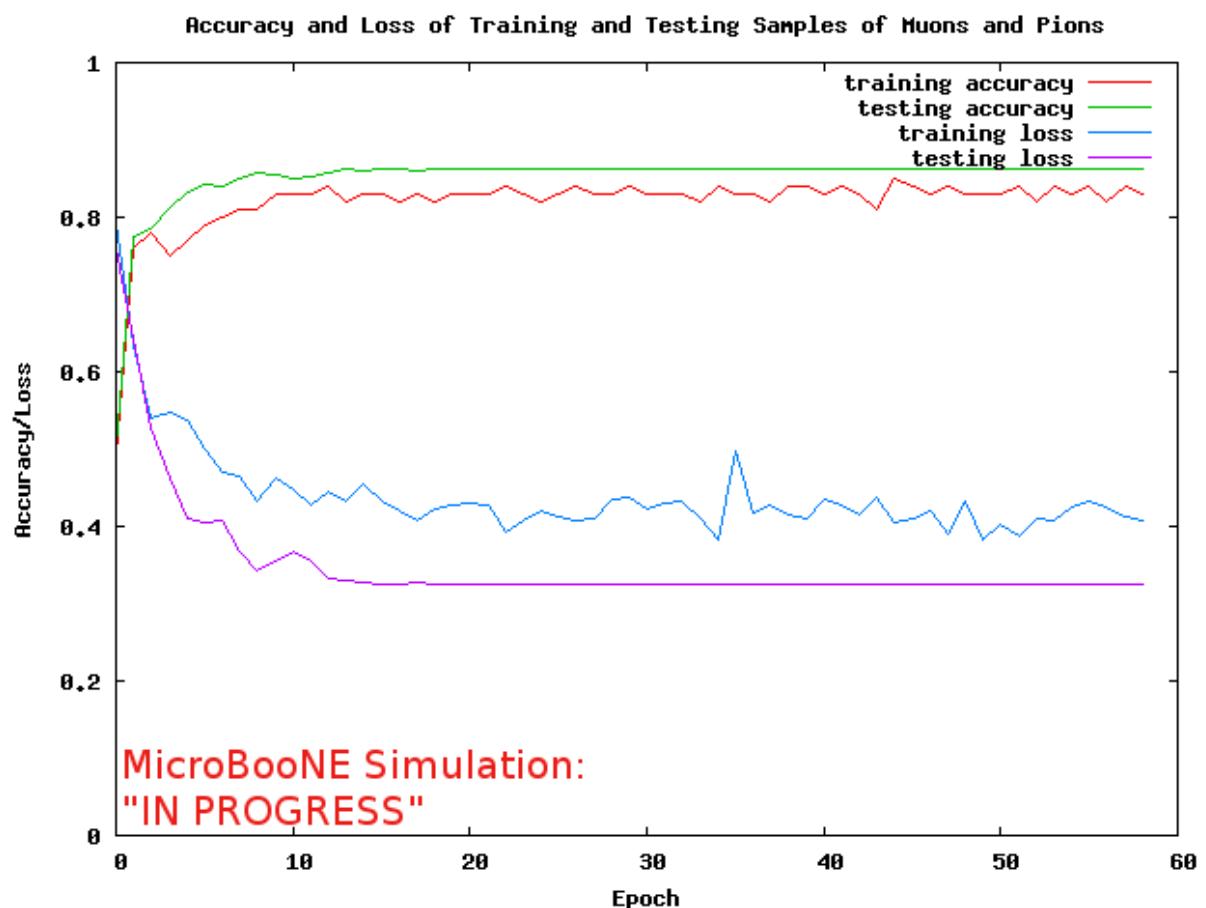
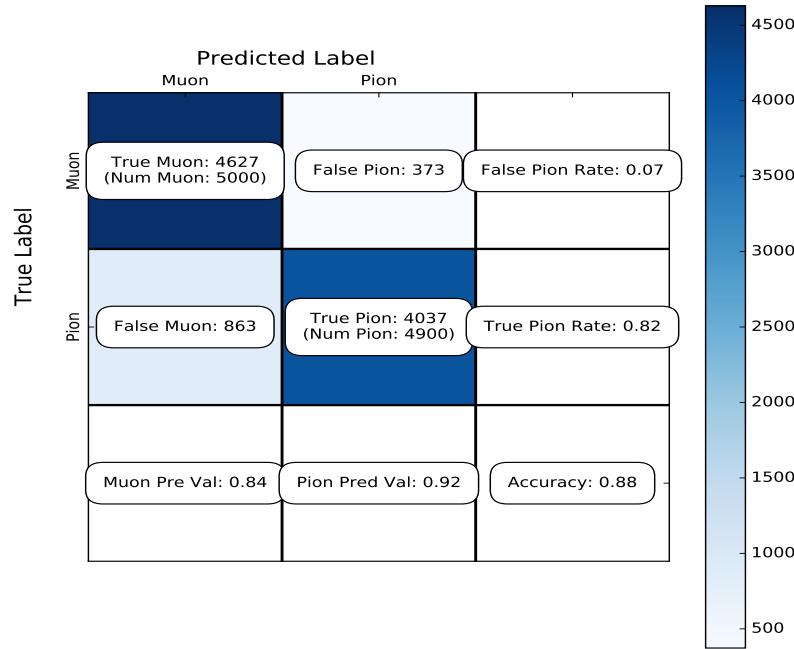
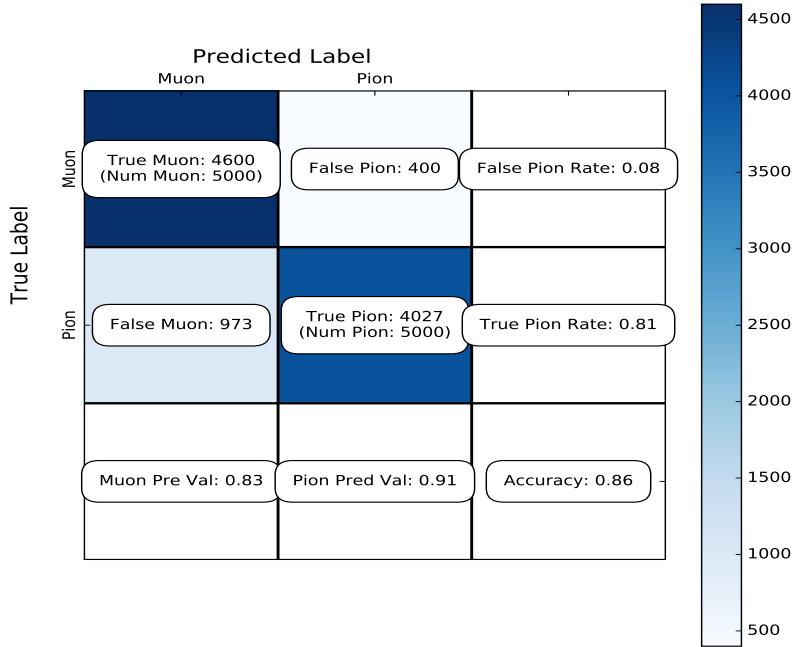


Figure 7.3: Accuracy vs. Loss of AlexNet 2-output μ/π sample consisting of 10,000 images each.



(a) Confusion Matrix showing Accuracy of CNN10000 using training MC data



(b) Confusion Matrix showing Accuracy of CNN10000 using testing MC data

Figure 7.4: Description of confusion matrix variables:
 False pion rate = $\text{false}\pi/\text{total}\pi$
 True pion rate = $\text{true}\pi/\text{total}\pi$
 Accuracy = $(\text{true}\pi\text{rate} + \text{true}\mu\text{rate})/2$
 Pion prediction value = $\text{true}\pi/(\text{true}\pi + \text{false}\pi)$
 Muon prediction value = $\text{true}\mu/(\text{true}\mu + \text{false}\mu)$

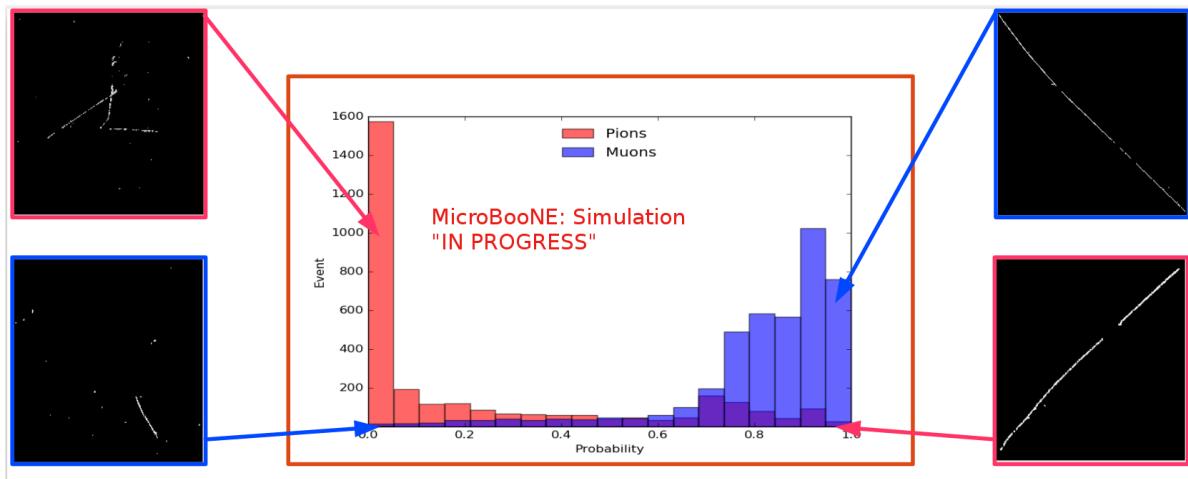


Figure 7.5: Probability plot of muons and pions from testing set. Images surrounding histogram are a random event from lowest bin and highest bin for each particle.

1601 classifying true muons as muons, and our loss increase from CNN1075 is due to the
1602 increase in accurately classifying pions as pions.

1603 7.3.3 Training CNN100000

1604 CNN100000 used the GoogleNet architecture rather than the AlexNet architecture
1605 used in the two previous trained CNNs. This is the first time the neural network was
1606 trained on a larger particle class, $\mu/\pi/p/\gamma/e$, and on higher resolution images. This
1607 CNN also employed GPUs during the training process. The hyperparameters are
1608 shown below:

- *train_batch_size*: 18
 - *test_batch_size*: 2
 - *test_iter*: 2000
 - *test_interval*: 2000
 - *base_lr*: 0.001
 - *lr_policy*: "step"
 - *gamma*: 0.96
 - *stepsize*: 10000
 - *average_loss*: 40
 - *display*: 40
 - *max_iter*: 10000
 - *momentum*: 0.99
 - *weight_decay*: 0.0002
 - *snapshot*: 50000

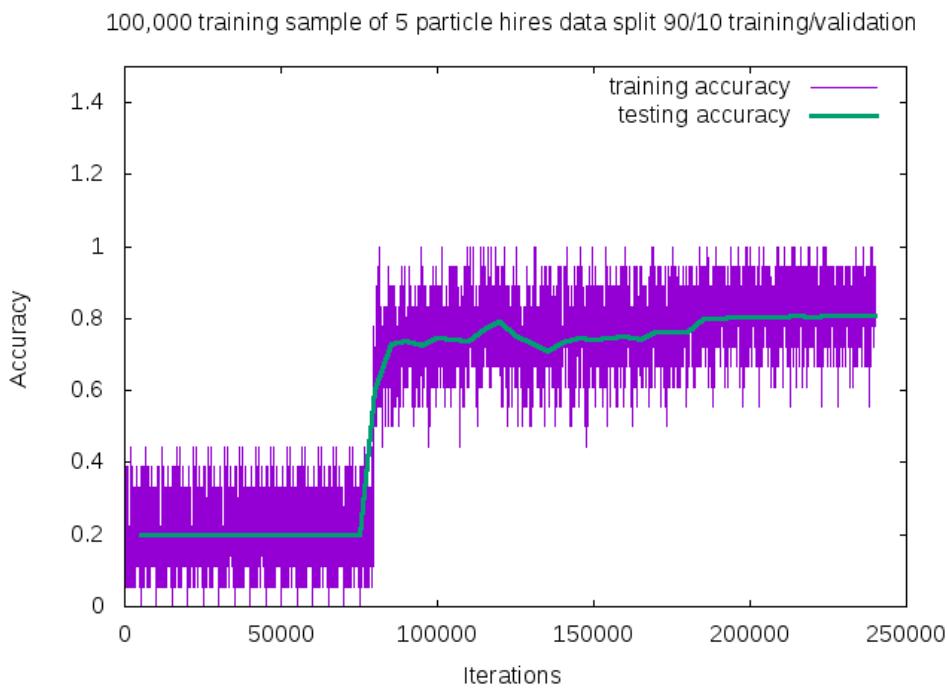


Figure 7.6: Training and testing accuracy of CNN trained on 100,000 images of $\mu/\pi/p/\gamma/e$ with 20,000 images of each particle. Each image was a size of 576x576 and the images per particle were split 90% use for training and 10% used for testing the network

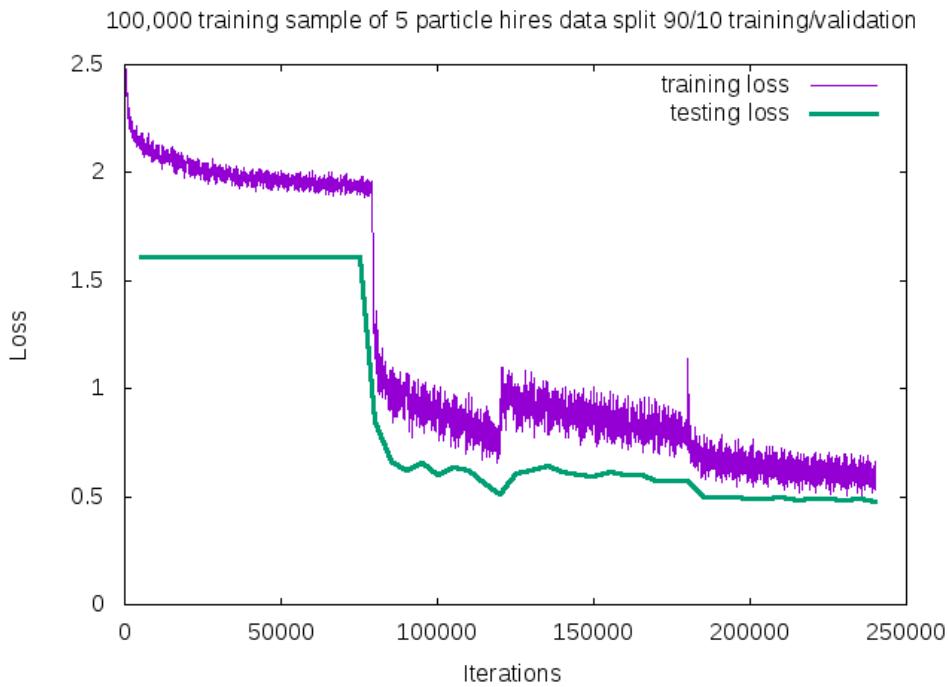


Figure 7.7: Training and testing loss of CNN trained on 100,000 images of $\mu/\pi/p/\gamma/e$

1623 The accuracy and loss for CNN100000 are shown in figures 7.6 and 7.7. The jumps
 1624 shown in both figures are when the training was stopped to fine-tune the weight decay
 1625 and the learning rate. The accuracy leveled off at $\sim 80\%$ and the loss was at ~ 0.48 .

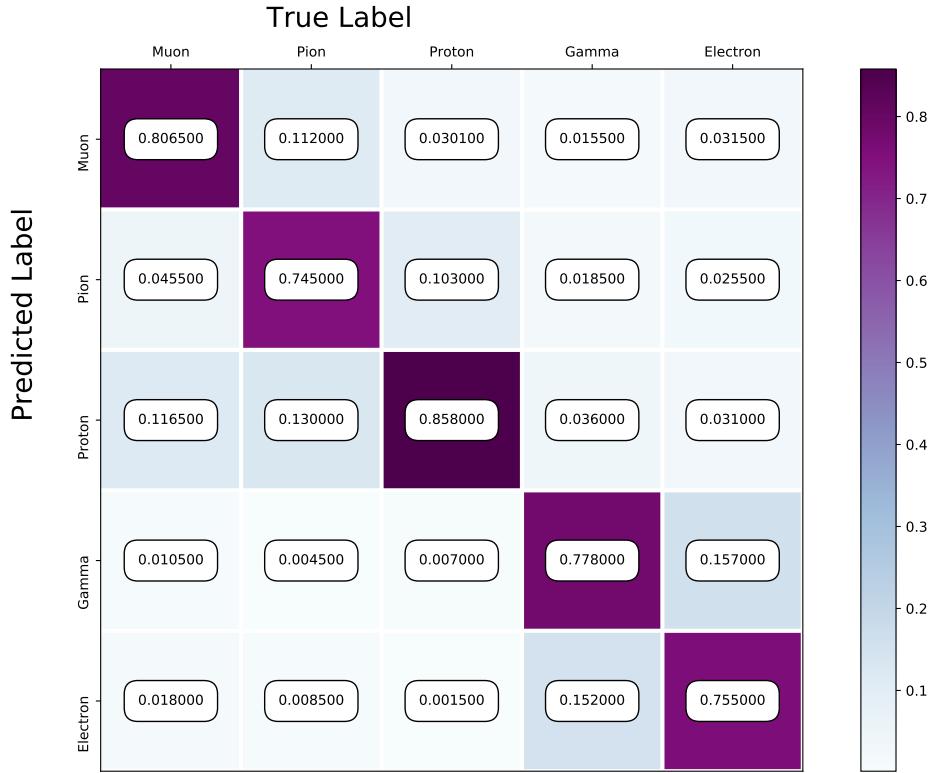


Figure 7.8: Confusion Matrix of all five particles

1626 Figure 7.8 shows the confusion matrix of CNN100000. The proton identification of
 1627 the neural network is at 85% and the highest out of all five particles. One thing to note
 1628 is clear separation between particles that leave track like objects in the MicroBooNE
 1629 detector, $\mu/\pi/p$, versus particles that leave shower like objects in MicroBooNE, e/γ .

1630 Another visualization of how the neural network is learning is shown in 7.9. t-
 1631 SNEs [?] is a technique used for dimensionality reduction developed for use in vi-
 1632 sualizing high-dimensional datasets. Each datapoint is given a location in a two
 1633 or three-dimensional map by using stochastic neighbor embedding to convert high-
 1634 dimensional euclidean distances between datapoints into conditional probabilities that
 1635 represent the similarities between these datapoints. For datapoints close together on
 1636 the map, their conditional probabilities are high, for datapoints with a wide separation
 1637 between them, their conditional probabilities are very small. Figure 7.9 is a t-SNE of
 1638 the final training iteration of a subset of the training sample used in CNN100000. You

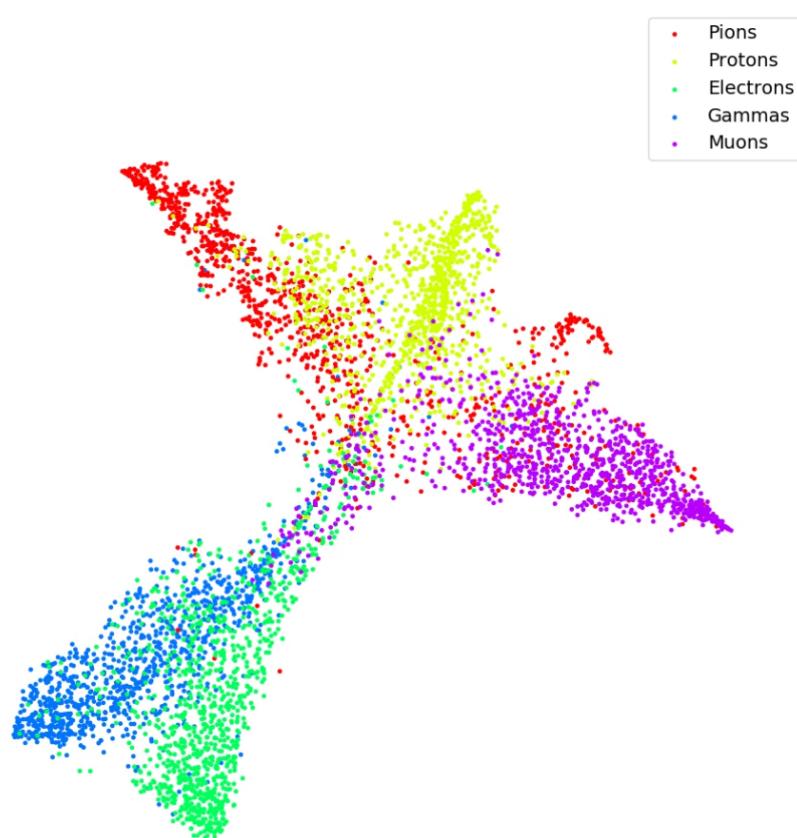


Figure 7.9: t-SNE of CNN

1639 can see a clear separation between track like objects and shower like objects. You can
1640 also see that electrons and gammas are not as separated as muons, pions, and protons.
1641 For the purpose of this thesis, this isn't an issue but later iterations of training could
1642 include more images for the gamma and electron classes to help the CNN further
1643 separate these classes.

1644 Figure 7.10 shows the probability of each particle class and the highest probability
1645 misidentification for each class. For muons, the largest misidentification is from
1646 protons. For pions, both protons and muons get misidentified as pions at around the
1647 same probability. Similar behavior is also seen for proton identification. Electrons and
1648 gammas are misidentified as each-other with similar probabilities.

1649 To see what type of background contamination one would be dealing with when
1650 doing muon identification, muon probabilities for each particle class was plotted
1651 against the probability of true muons to see how well muon signal vs other particle
1652 background separation can be done with CNN100000. Figure 7.11 is showing the
1653 true muon probability for true muons, versus the rest of the particle classes. This plot
1654 describes which muon probability value should be chosen for the least amount of
1655 other particle contamination. For electrons and gammas, a muon probability of $\sim 75\%$
1656 would eliminate e/γ contamination. For pions and protons, there is contamination at
1657 all values of muon probability, but the contamination is drastically reduced at a muon
1658 probability $\geq 75\%$.

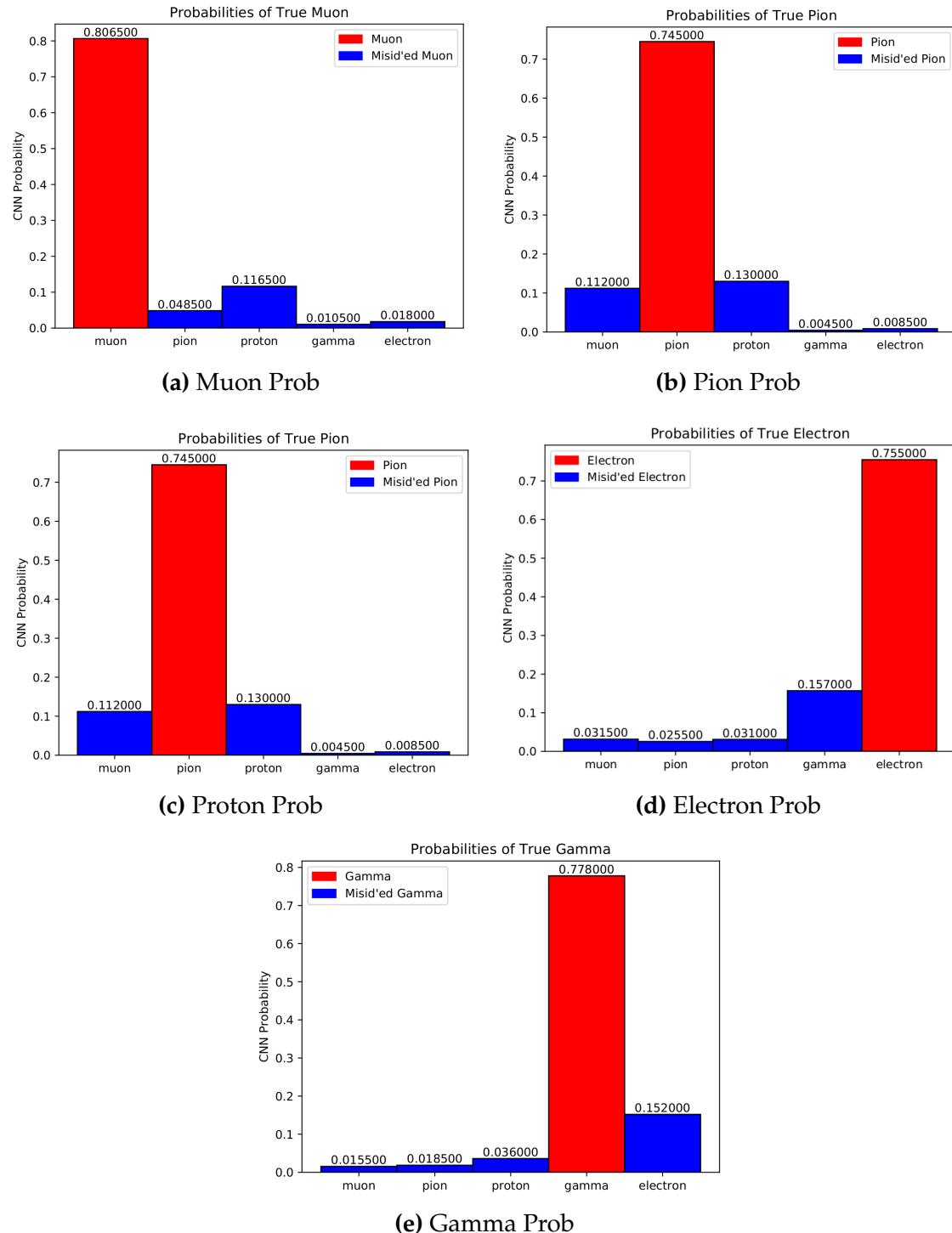


Figure 7.10: Probabilities of different particle classes as well as their contamination from other classes

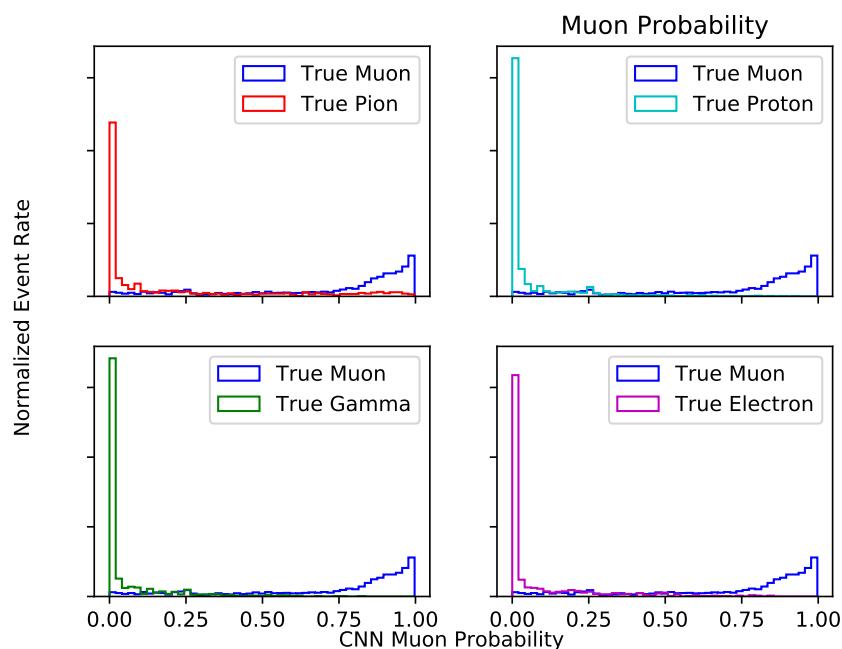
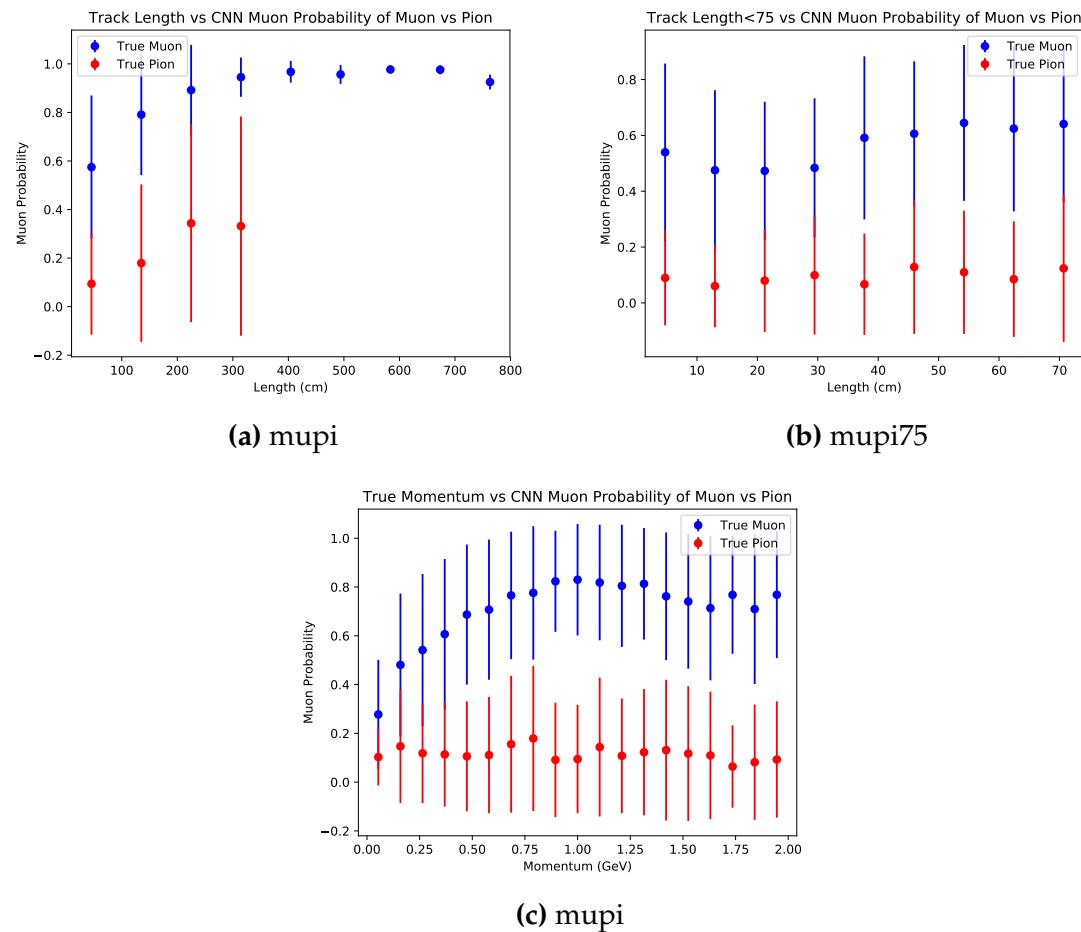
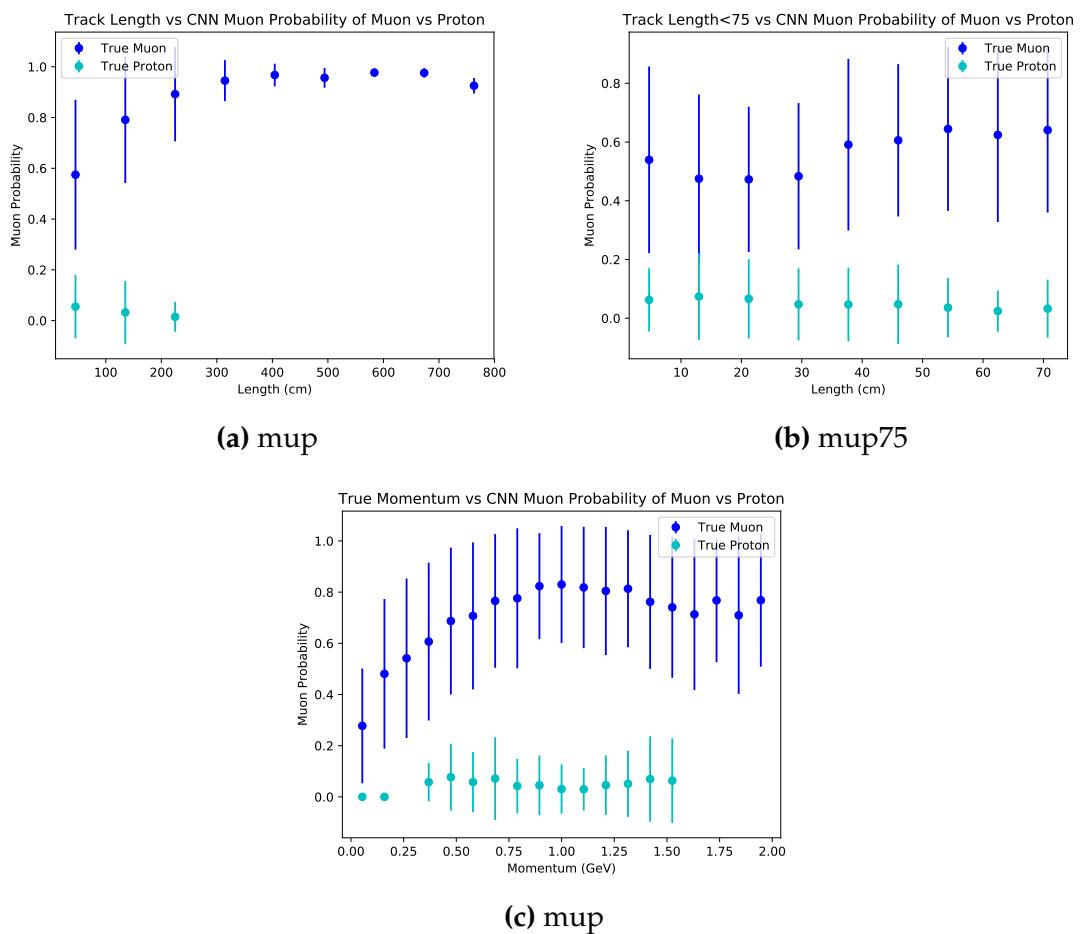
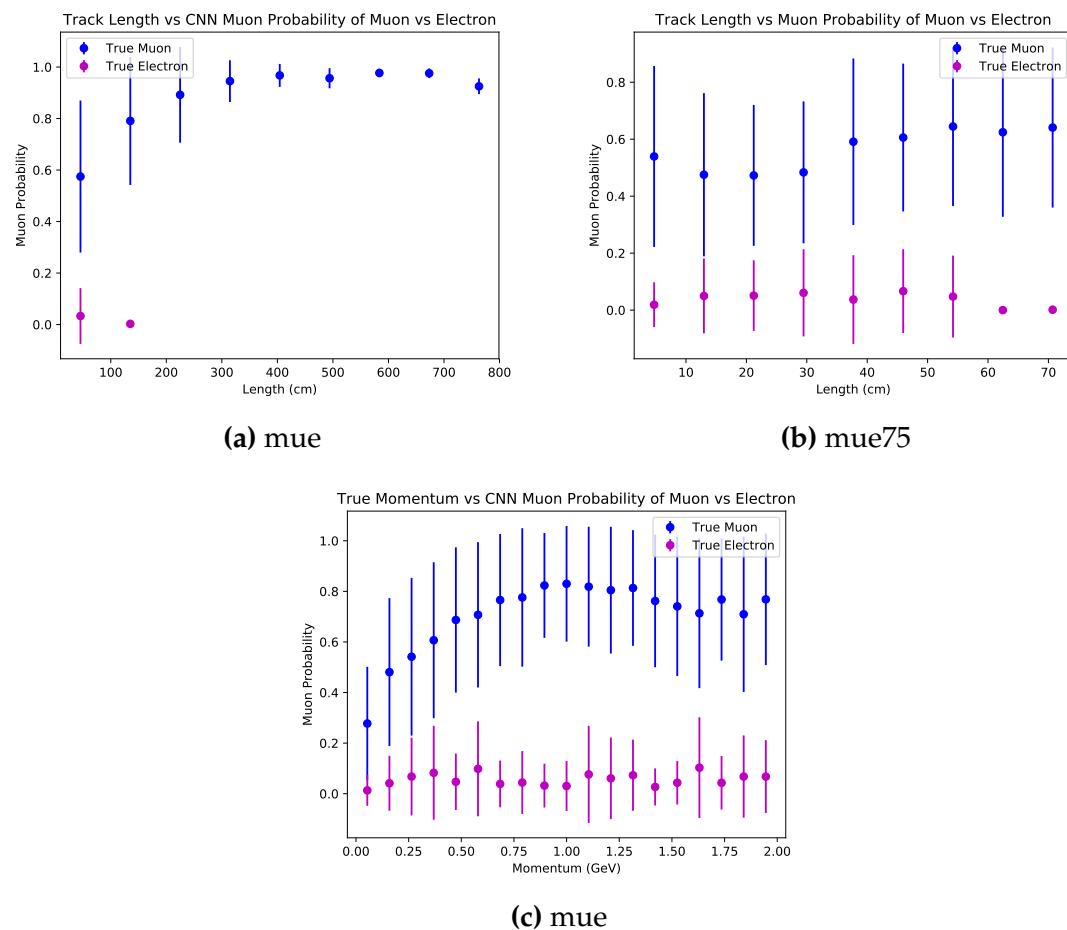


Figure 7.11: Muon probability of true muons (blue) versus pions (red), protons (cyan), gammas (green) and electrons (magenta).

**Figure 7.12**

**Figure 7.13**

**Figure 7.14**

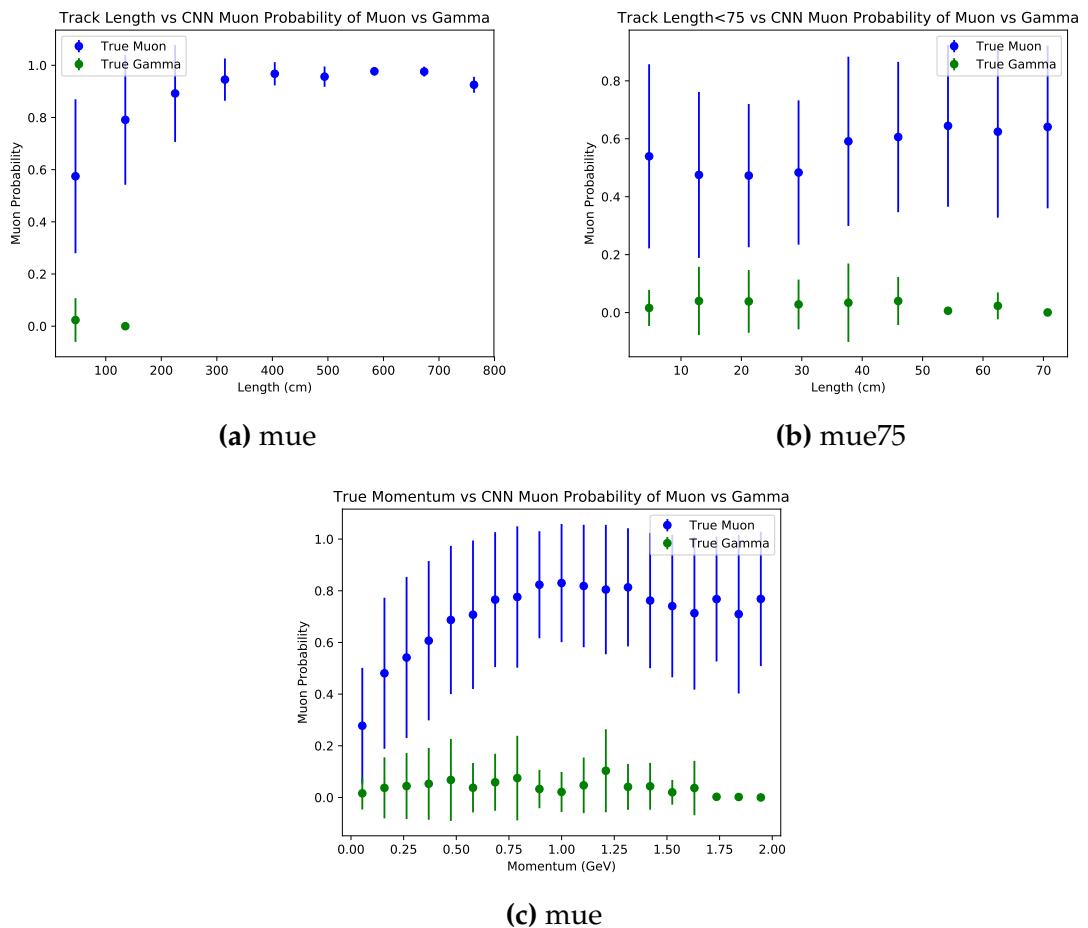


Figure 7.15

1659 **Chapter 8**

1660 **Results of Convolutional Neural
1661 Networks on particles WORKING
1662 TITLE**

1663 **8.1 Classification using CNN10000**

1664 **8.1.1 Classification of MC data using Selection I Original
1665 CC-Inclusive Filter**

1666 The next step that was taken was to use CNN10000 to classify track candidate images
1667 that were identified by the selection I original cc-inclusive filter described in [?].
1668 Passing rates for each cut in cc-inclusive filter are show in figure 8.1. For the incorrect
1669 image making normalization dataset, out of 188,880 events, 7438 passed the cut right
1670 before 75 cm track length cut which is 3.9% of total data. Discrepancies in passing rates
1671 are due to grid submission issues, however, this dataset is used to check if changes
1672 in image making normalization affects μ/π separation probability due to CNN10000
1673 being trained with incorrectly image making normalized data. For the second dataset
1674 with correct image making normalization, out of 188,880 events, 9552 events passed the
1675 cut right before the 75 cm track length cut which is 5.1% passing rate and is comparable
1676 to figure 8.1. In time cosmics were also run over for efficiency and purity calculations.
1677 Out of 14395 in time cosmic events, 175 passed the cut right before the 75 cm track
1678 length cut which is a passing rate of 1.2% compared to 1.3% shown in figure 8.1.

Table 3: **Selection I: Original** The table shows passing rates for the above described event selection. Numbers are absolute event counts and Cosmic background is not scaled appropriately. The BNB+Cosmic sample contains all events, not just ν_μ CC inclusive. The selected events are further broken up in the following subsection. The numbers in brackets give the passing rate wrt the step before (first percentage) and wrt the generated events (second percentage). In the BNB+Cosmic MC Truth column shows how many true ν_μ CC inclusive events (in FV) are left in the sample. This number includes possible mis-identifications where a cosmic track is picked by the selection instead of the neutrino interaction in the same event. The cosmic only sample has low statistics, but please note that it is not used in any plots, it is just for illustrating the cut efficiency. The last column Signal:Cosmic only gives an estimate of the ν_μ CC events wrt the cosmic only background at each step. For this number, the cosmic background has been scaled as described in chapter 2. Note that this numbers is not a purity, since other backgrounds can't be determined at this step.

	BNB + Cosmic Selection	MC-Truth	Cosmic only	Signal: Cosmic only
Generated events	191362	45273	4804	1:22
≥ 1 flash with ≥ 50 PE	136219 (71%/71%)	44002 (97%/97%)	2979 (62%/62%)	1:14
≥ 1 vertex in FV	131170 (96%/69%)	43794 (99%/97%)	2805 (94%/58%)	1:13
≥ 1 track within 5 cm of vertex	129784 (99%/68%)	43689 (99%/97%)	2756 (98%/58%)	1:13
flash matching of longest track	44775 (34%/23%)	23647 (54%/52%)	647 (23%/13%)	1:5.7
track containment	10114 (23%/5.3%)	6882 (29%/15%)	61 (9.4%/1.3%)	1:1.9
track ≥ 75 cm	7358 (73%/3.8%)	5801 (84%/13%)	31 (51%/0.6%)	1:1.1

Figure 8.1: Snapshot of passing rates of Selection I from CC-Inclusive Filter

Figures 8.2a, 8.2b, 8.2c and 8.2d show the accuracy and μ/π separation of both the correct and incorrect normalized images. The confusion matrices are only composed of μ/π data. Other particles passed the cc-inclusive filter before the 75 cm track length cut and were all mis-id'ed as muons. Since CNN10000 has not seen any particles other than muons and pions, it makes sense that those get mis-id'ed. Figures 8.2b and 8.2d don't have μ/π separation comparable to 7.5, but 8.2b does skew to higher probabilities compared to 8.2d. This is to be expected and further work on quantifying the performance of CNN10000 should use the incorrect image making normalization. It is also expected that the separation isn't as defined as the testing dataset for CNN10000. CNN10000 was trained and tested using single particle muons and pions and the track candidate dataset come from BNB+Cosmic events, not to mentions all track candidates have passed the cc-inclusive filter that tags "muon-like" tracks therefore the pions in this sample look much closer in muon topology than the network has seen. Also, these images were made from wire and time ticks associated to hits from the track candidate that passed the cc-inclusive filter. This is different from the training images where a bounding box was drawn over the total μ or π interaction. Spurious energy deposition from a $\pi - Ar$ interaction is most likely not included in the BNB+Cosmic images due to the tracking algorithm. To remedy this, the neural network needs to see more "muon-like" pions and muons and pions from a neutrino interaction passing the cc-inclusive filter as well as a larger particle variety including protons, photons

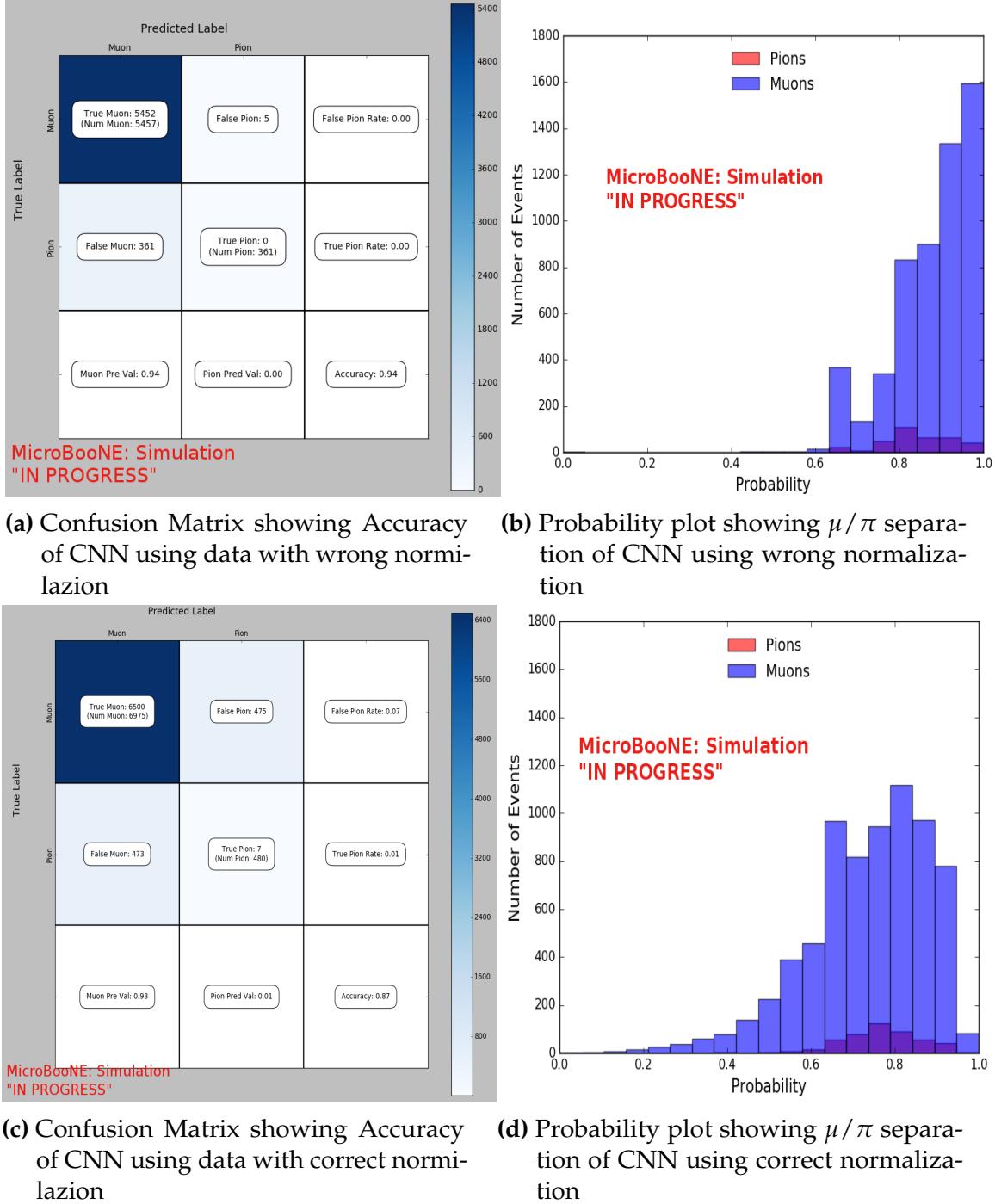


Figure 8.2: Results of CNN10000 classification of track candidate images output from cc-inclusive filter.

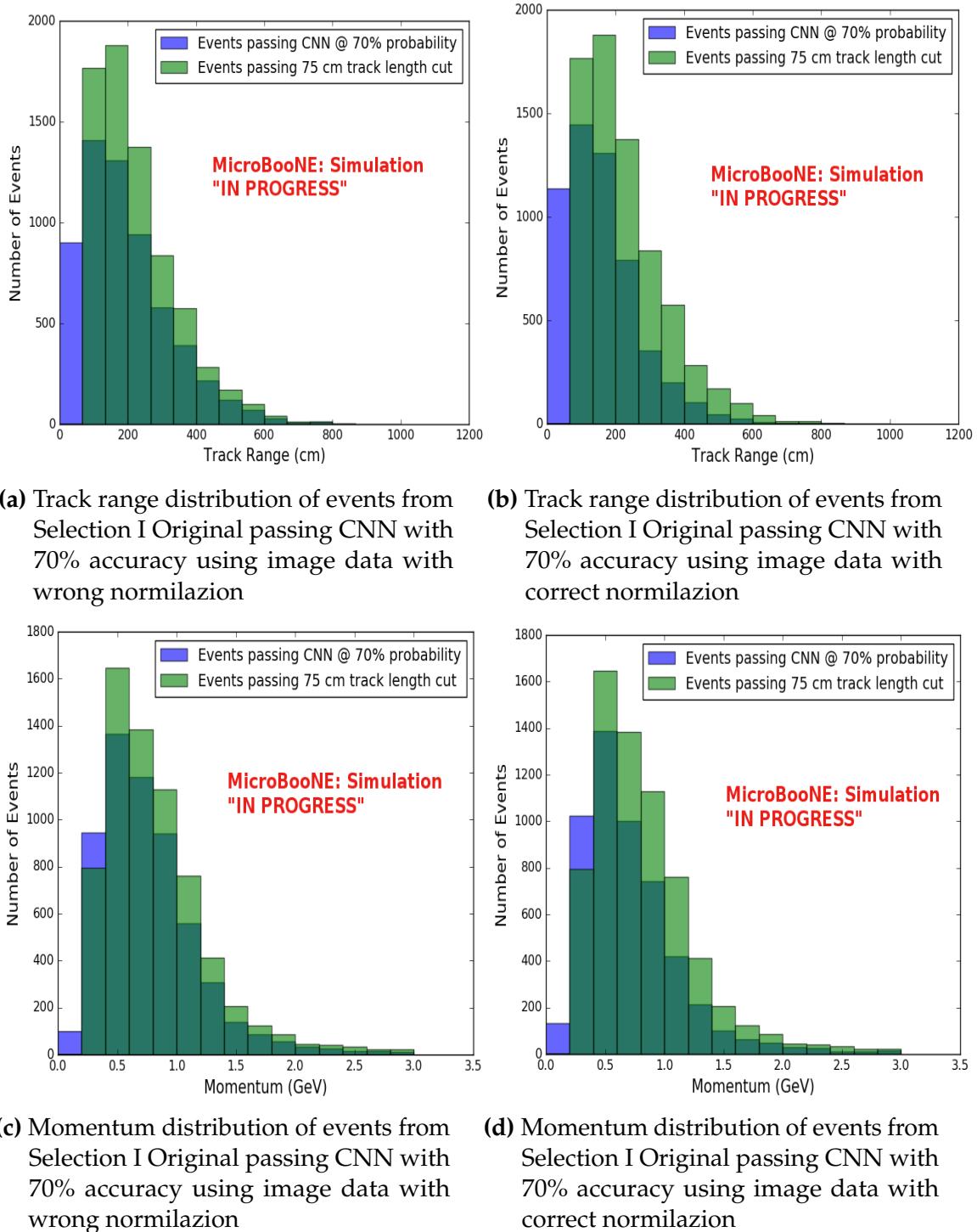


Figure 8.3: CNN10000 distributions of track candidate images output from Selection I Original cc-inclusive filter with different image data normalizations

and electrons. Although μ/π separation is lacking, CNN10000 does an excellent job of classifying muons and using higher CNN probability can increase purity. Figures 8.3a, 8.3b, 8.3c and 8.3d show the track and momentum distributions for these two datasets. In both sets you have an increase in data in the bin below 75 cm and at bins below 0.5 GeV. These distributions were made with events classified with 70% probability of being a muon regardless of true particle type.

8.1.2 Classification of MC data using Selection I Modified CC-Inclusive Filter

Table 5: **Selection I: Modified** The table shows passing rates for the above described event selection. Numbers are absolute event counts and Cosmic background is not scaled appropriately. The BNB+Cosmic sample contains all events, not just ν_μ CC inclusive. The selected events are further broken up in the following subsection. The numbers in brackets give the passing rate wrt the step before (first percentage) and wrt the generated events (second percentage). In the BNB+Cosmic Mc Truth column shows how many true ν_μ CC inclusive events (in FV) are left in the sample. This number includes possible mis-identifications where a cosmic track is picked by the selection instead of the neutrino interaction in the same event. The cosmic only sample has low statistics, but please note that it is not used in any plots, it is just for illustrating the cut efficiency. The last column Signal:Cosmic only gives an estimate of the ν_μ CC events wrt the cosmic only background at each step. For this number, the cosmic background has been scaled as described in chapter 2. Note that this numbers is not a purity, since other backgrounds can't be determined at this step.

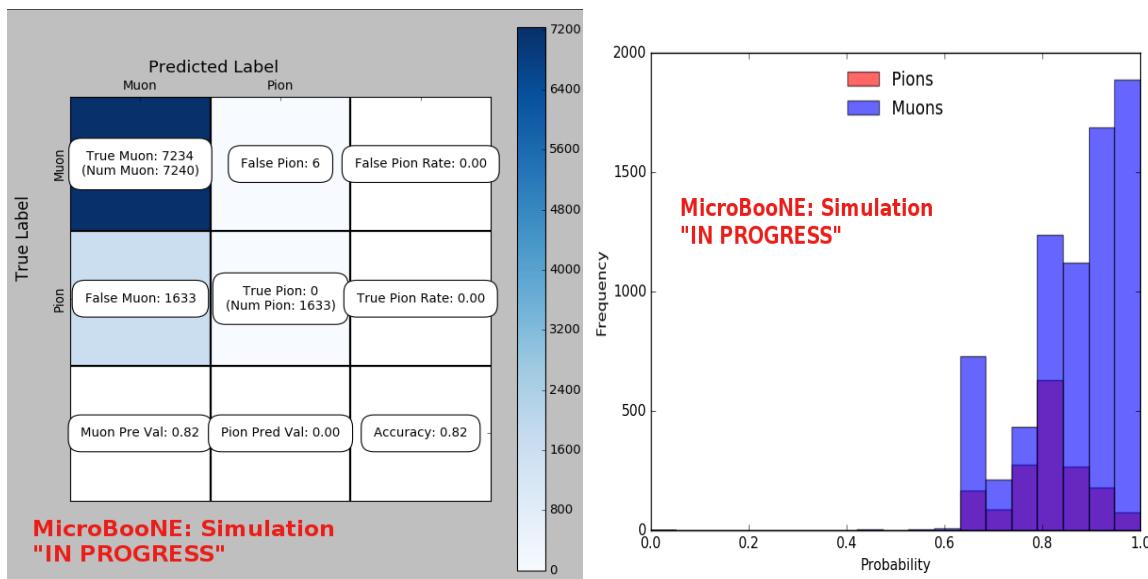
	BNB + Cosmic Selection		Cosmic only	Signal: Cosmic only
	MC-Truth			
Generated events	191362	45273	4804	1:22
≥ 1 flash with ≥ 50 PE	136219 (71%/71%)	44002 (97%/97%)	2979 (62%/62%)	1:14
≥ 1 track within 5 cm of vertex vertex candidate in FV	135830 (99%/71%)	43974 (99%/97%)	2975 (99%/62%)	1:14
flash matching of longest track	79112 (58%/41%)	34891 (79%/77%)	1482 (50%/31%)	1:8.9
track containment	40267 (51%/21%)	25891 (74%/57%)	340 (23%/7.1%)	1:2.8
track ≥ 75 cm	19391 (48%/10%)	11693 (45%/26%)	129 (38%/2.7%)	1:2.3
	6920 (36%/3.6%)	5780 (49%/13%)	17 (13%/0.4%)	1:0.6

Figure 8.4: Snapshot of passing rates of all cuts from Selection I Modified cc-inclusive filter

CNN10000 was also used to classify track candidate images that were identified by the selection I modified cc-inclusive filter described in [?]. Passing rates for each cut in this filter are shown in figure 8.4. As seen in section 8.1.1, wrong image normalization had a higher muon classification probability so all work done using selection I modified cc-inclusive filter was done using this normalization. Out of 188,880 events, 19,112 passed the cut right before the 75 cm track length cut which is a 10.1% passing rate and comparable to the 10% passing rate shown in figure 8.4. In time cosmics were also run over, out of 14,606 in time cosmics events, 302 passed the cut right before the 75 cm track length cut which is a 2.1% passing rate comparable to the 2.7% passing rate in the cc-inclusive tech-note. Figures 8.5a and 8.5b show the accuracy and μ/π separation. Both plots are only composed of muons and pions and like selection I original data,

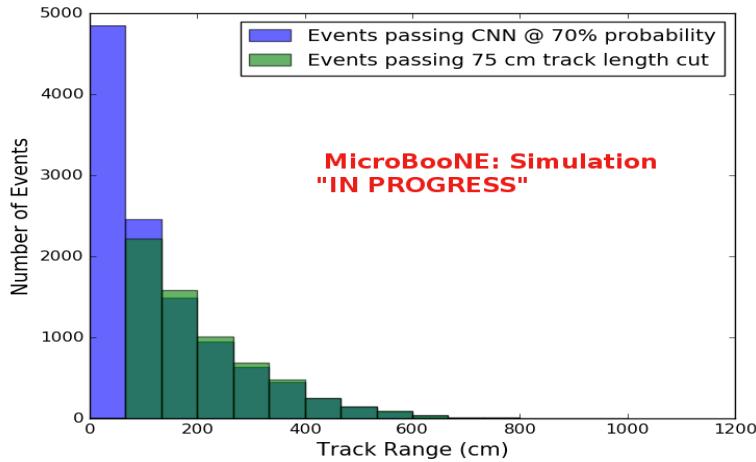
1718 all other particles were id'ed as muons. Also like selection I original data, muons are
 1719 being identified at a very high rate. Figure 8.6a shows the track range distributions
 1720 of all events from selection I modified being classified by the CNN as a muon with a
 1721 probability of 70% regardless of true particle type. We get entries for the CNN curve
 1722 in the lowest bin and none for the 75 cm curve. To see how many true CC events
 1723 were identified by CNN10000 breaking down figure 8.6a by event type was necessary.
 1724 Figures 8.6b and 8.6c show track range distributions separated by signal and various
 1725 backgrounds. Particle type was not taken into consideration in these plots so true CC
 1726 event images can be any track candidate particle passing selection I modified cut right
 1727 before track length cut including pions and protons.

1728 To gain an even deeper understanding on how CNN10000 is performing, plotting
 1729 these distributions with only muons and pions was done due to the fact that CNN10000
 1730 was trained with only those particles for μ/π separation. Figures 8.6d-8.7d show the
 1731 stacked histograms of signal and background of the track range distributions with
 1732 varying CNN probabilities starting from 70% and ending at 90% probability. With
 1733 higher probabilities we get a purer sample in the lower bin but we end up losing
 1734 events as well. Momentum distributions for all signal/background events are shown
 1735 in figure 8.8.

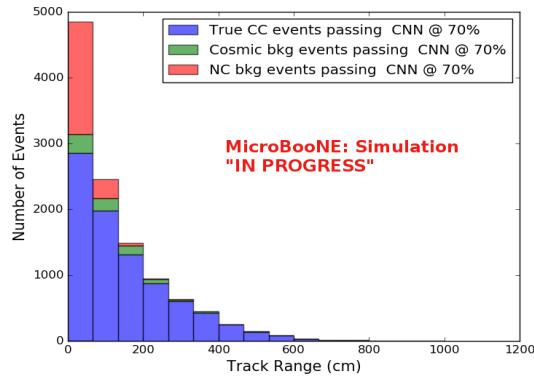


(a) Confusion Matrix for CNN10000 classified events from selection I modified (b) Probability plot for CNN10000 classified events from selection I modified

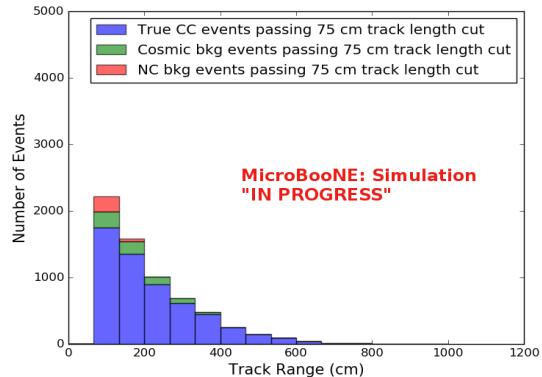
Figure 8.5: Confusion matrix and probability plot of events passing selection I modified cc-inclusive cuts right before 75cm track length cut



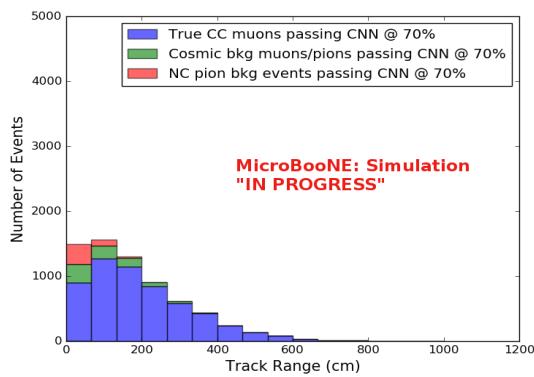
(a) Track range distribution of events from Selection I Modified passing CNN with 70% accuracy



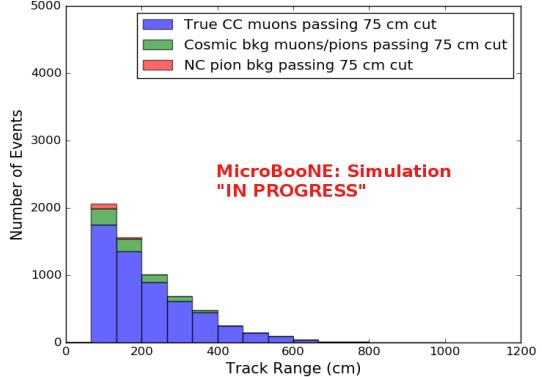
(b) Stacked signal and background track range distributions from Selection I Modified passing CNN with 70% accuracy



(c) Stacked signal and background track range distributions from Selection I Modified passing 75 cm track length cut



(d) Stacked signal muons and background muons/pions of track range distributions from Selection I Modified passing CNN with 70% accuracy



(e) Stacked signal muons and background muons/pions of track range distributions from Selection I Modified passing 75 cm track length cut

Figure 8.6: CNN10000 distributions of track candidate images output from Selection I Modified cc-inclusive filter

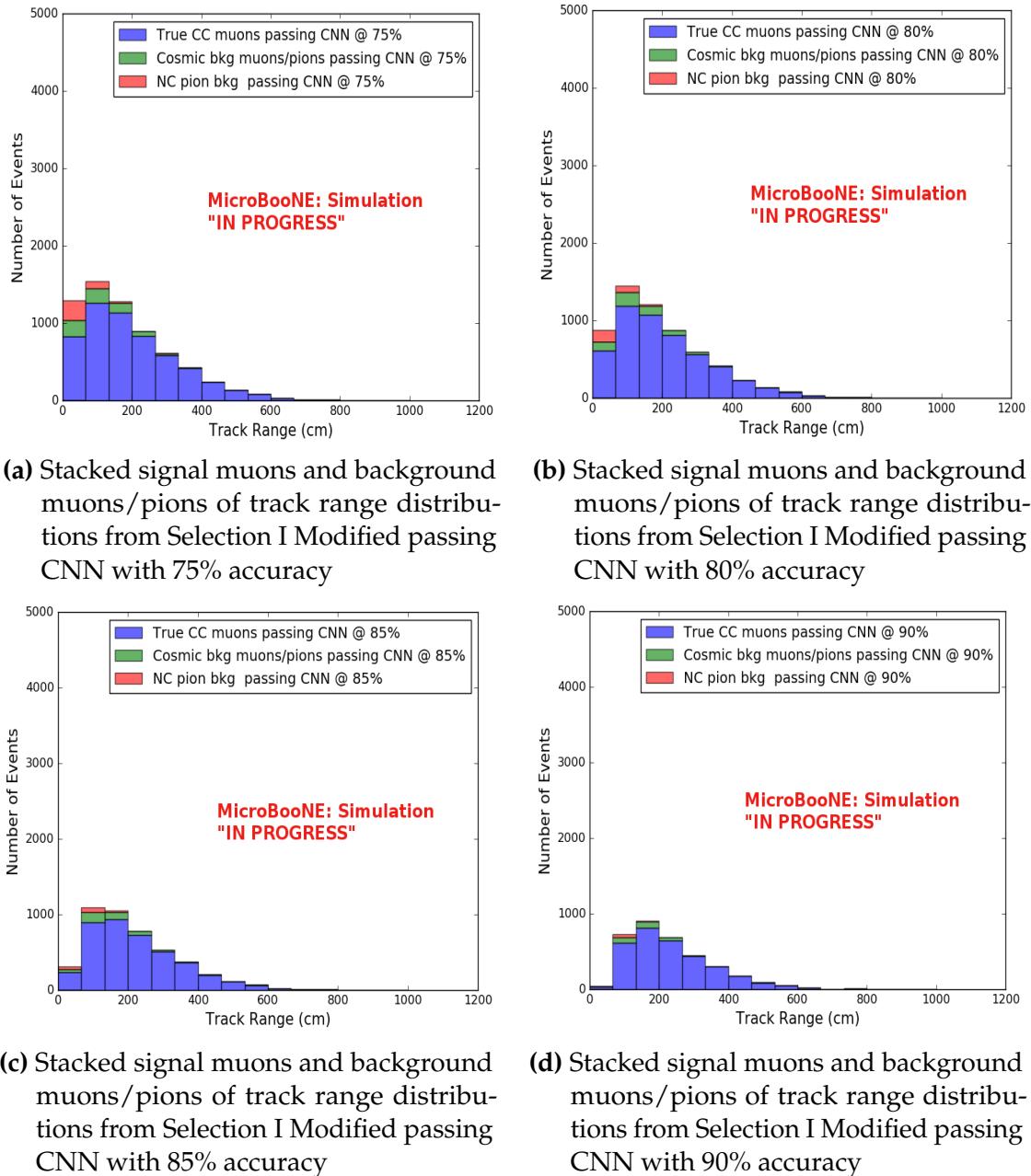
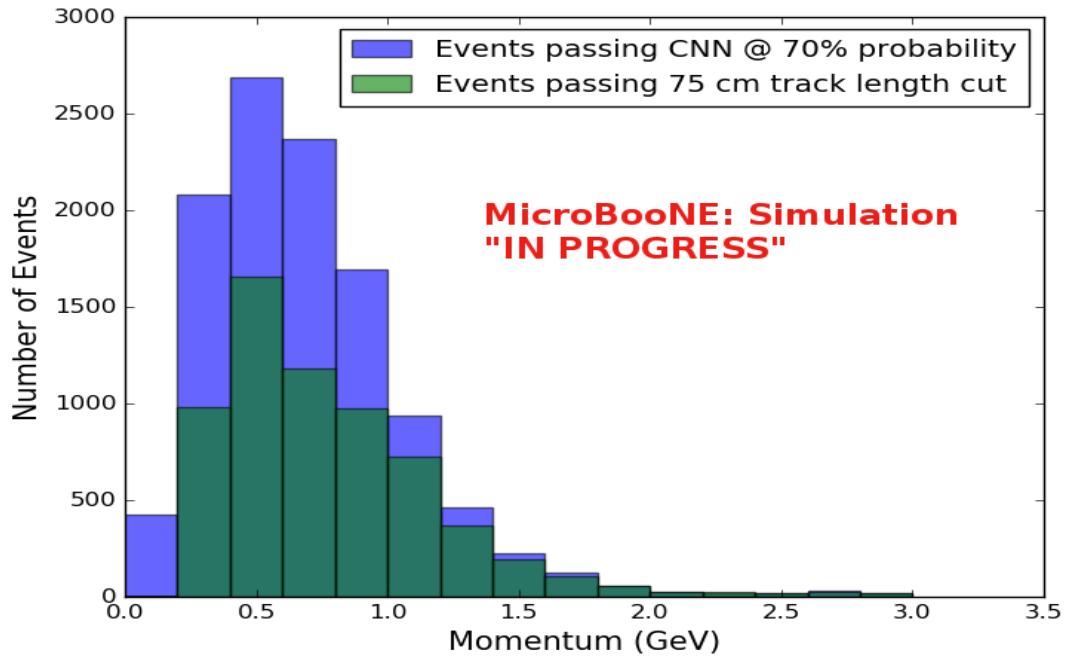
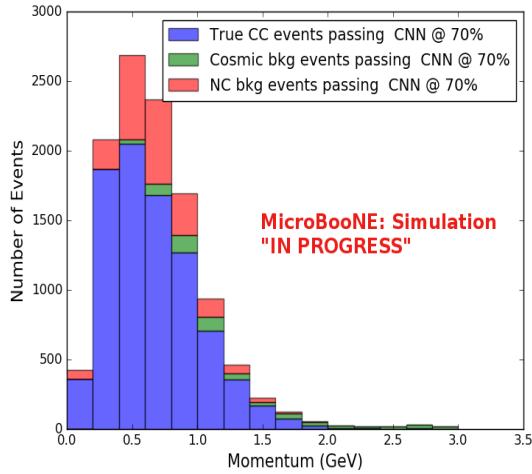


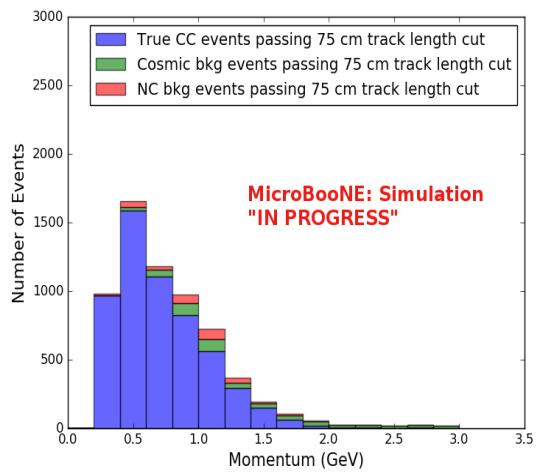
Figure 8.7: CNN10000 stacked signal/background track range distributions of track candidate images output from Selection I Modified cc-inclusive filter



(a) Momentum distribution of events from Selection I Modified passing CNN with 70% accuracy



(b) Stacked signal and background momentum distributions from Selection I Modified passing CNN with 70% accuracy



(c) Stacked signal and background momentum distributions from Selection I Modified passing 75 cm track length cut

Figure 8.8: CNN10000 momentum distributions of track candidate images output from Selection I Modified cc-inclusive filter

Another check was to see if any true CC pions were passing through the cut right before the 75 cm track length cut. Figure 8.9 shows the comparison of the stacked track range distribution with only true CC muon signal versus the stacked distribution with true CC muons and pions signal. As you can see, we gain more events when plotting CC events with a particle type of either muons or pions due to the CNN classifying all pions in this dataset as muons. This is an interesting scenario and a sample of topologies of these images are represented in figure 8.10, at least 3 tracks are coming out of the vertex for these types of events. With the 75 cm track length cut, the selection is cutting event topologies like this where the pion is the tagged track candidate. Figure 8.10a has a defined longer muon track, but because of dead wires through the track, the reconstructed range is 1. less than 75 cm and 2. shorter than the reconstructed pion whose length is also less than 75 cm. This is a very interesting event, but because of issues with the tracking algorithm, the 75 cm cut would get rid of this event. The CNN was able to recover this event only because it has classified all pions as muons. Figure 8.10b shows the second case to think about, the pion, while still less than 75 cm has a reconstructed track length longer than the muon. Again, the CNN recovered this event due to pions being classified as muons. Lastly, figure 8.10c shows a pion with a reconstructed track length greater than 75 cm and the muon. These three cases show that a broader question must be asked when training the network other than is it a muon or pion. There are different routes to recover interesting events like these. One route is to ask the network “Is it a CC event or is it an NC event?” and obtain an image dataset consisting of whole CC/NC events that will train the network to answer this question. The other route is to ask the network “Is this a $\mu/\pi/p/$ from a CC event or NC event and obtain an image dataset consisting of primary particles from a CC/NC event. Both these paths will be explored in future work.

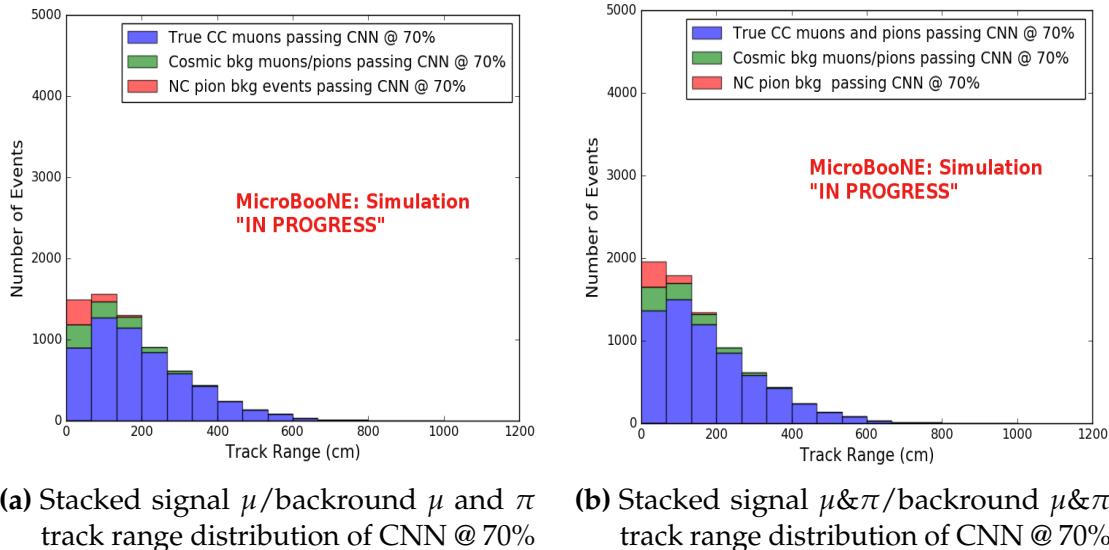


Figure 8.9: Track distribution comparisons of true CC muons plotted vs true CC muons and pions plotted

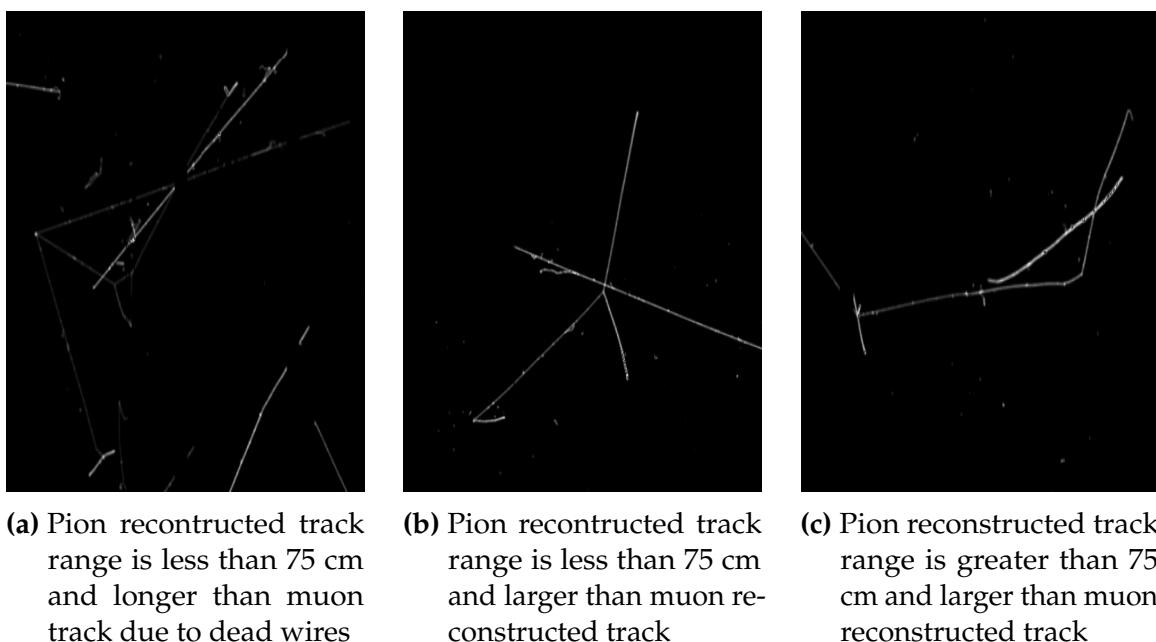


Figure 8.10: Images of true CC events where the pion was the tagged track candidate

		BNB + Cosmics		Cosmic Only	Signal: Cosmic Only
		Selection	MC Truth		
75 cm Cut passing rates	Generated Events	191362	45723	4804	1:22
	Track Containment	19391 (48%/10%)	11693 (45%/26%)	129 (38%/2.7%)	1:2.3
	track \geq 75 cm	6920 (36%/3.6%)	5780 (49%/13%)	17 (13%/0.4%)	1:0.6
CNN passing rates	Generated Events	188880	44689	14606	1:21
	Track Containment	19112 (/10%)	11554 (/26%)	302 (/2.1%)	1:1.73
	CNN cut @ 70% Probability	16502 (86%/8.7%)	10605 (92%/23%)	205 (68%/14%)	1:1.28
	CNN cut @ 83% Probability	7511 (46%/4.0%)	6142 (58%/14%)	32 (16%/0.2%)	1:0.4

Table 8.1: Comparing passing rates of CNN at different probabilities versus 75 cm track length cut: Numbers are absolute event counts and Cosmic background is not scaled appropriately. The BNB+Cosmic sample contains all events. The numbers in brackets give the passing rate wrt the step before (first percentage) and wrt the generated events (second percentage). In the BNB+Cosmic MC Truth column shows how many true ν_μ CC-inclusive events (in FV) are left in the sample. This number includes possible mis-identifications where a cosmic track is picked by the selection instead of the neutrino interaction in the same event. The CNN MC True generated events were scaled wrt the MC True generated events for the 75 cm cut passing rates due to only running over 188,880 generated events versus the 191362 generated events. The last column Signal:Cosmic only gives an estimate of the ν_μ CC events wrt the cosmic only background at each step. For this number, the cosmic background has been scaled as described in [?]. Note that these numbers are not a purity, since other backgrounds can't be determined at this step.

Signal	ν_μ CC events with true vertex in FV	#Events(Fraction)	#Events(Fraction)
		passing CNN @ 70% Probability	
		10605(35%)	6142(61%)
Backgrounds	Cosmics Only Events	13573(45%)	2582(26%)
	Cosmics in BNB Events	2249(7.4%)	492(4.9%)
	NC Events	3412(11%)	778(7.7%)
	ν_e and $\bar{\nu}_e$ Events	139(0.5%)	32(0.3%)
	$\bar{\nu}_\mu$ Events	97(0.3%)	67(0.7%)

Table 8.2: Signal and background event numbers at modified selection level with CNN cut estimated from a BNB+Cosmic sample and Cosmic only sample normalized to $5 * 10^{19}$ PoT. The last column gives the fraction of this signal or background type to the total selected events per CNN probability.

Table 8.1 shows the passing rates for the 75 cm track length cut and the CNN cut at 70% and 83%. The passing rates at the track containment level for the 75 cm track length cut compared to the CNN are comparable with only a 0.6% difference in the in time cosmic bin which may be due in part to the larger in time cosmic statistics used for the CNN dataset. These passing rates need to be comparable to then be able to compare the passing rates after the CNN cut to the 75 cm cut. Again, the same BNB+Cosmic sample was used for both selection I modified with 75 cm cut and selection I modified with CNN cut. As it stands, a CNN cut at 83% probability has

¹⁷⁶⁹ a MC true CC event passing rate of 14% compared to the 13% passing rate of the 75
¹⁷⁷⁰ cm track length cut. The Signal:Cosmic Only background is also reduced from 1:0.6
¹⁷⁷¹ to 1:0.4 The total passing rate is also higher than the 75 cm cut, 3.6% vs 4.0%. Table
¹⁷⁷² 8.2 shows the breakdown of signal and backgrounds for the CNN at the different
¹⁷⁷³ probabilities. We have a 61% signal passing rate with the CNN cut @ 83% versus the
¹⁷⁷⁴ 53.8% signal passing rate of the 75 cm cut.

¹⁷⁷⁵ Based on these numbers, the following performance values of the modified selec-
¹⁷⁷⁶ tion with 75 cm cut versus modified selection with CNN @ 83% probability cut were
¹⁷⁷⁷ calculated:

- ¹⁷⁷⁸ • Efficiency: Number of selected true ν_μ CC events divided by the number of
¹⁷⁷⁹ expected true ν_μ CC events with interaction in the FV.
 - ¹⁷⁸⁰ – Selection I modified: 13%
 - ¹⁷⁸¹ – Selection I modified with CNN cut @ 83% probability: 14%
- ¹⁷⁸² • Purity: Number of selected true ν_μ CC events divided by sum of itself and the
¹⁷⁸³ number of all backgrounds.
 - ¹⁷⁸⁴ – Selection I modified: 53.8%
 - ¹⁷⁸⁵ – Selection I modified with CNN cut @ 83% probability: 61%

¹⁷⁸⁶ Lastly, figure 8.12 shows a more representative performance of the CNN. Due to
¹⁷⁸⁷ the fact that the CNN was trained on muons and pions, showing the performance
¹⁷⁸⁸ of CC muon events versus NC pion events with respect to CNN probability gives a
¹⁷⁸⁹ better picture of how the network is performing. Figure 8.12 shows that at 83% we
¹⁷⁹⁰ are below the 75 cm cut NC pion threshold and still above the CC muon threshold.
¹⁷⁹¹ Using 83% probability not only reduced the NC pion background, it also dramatically
¹⁷⁹² reduced the in time cosmics and cosmics in the BNB.

¹⁷⁹³ 8.1.3 Conclusions and Future Work

¹⁷⁹⁴ It was shown that even though CNN10000 was trained with single particle generated
¹⁷⁹⁵ muons and pions, it performs fairly well at classifying track candidate images from
¹⁷⁹⁶ BNB+Cosmic events. Events have been regained below the 75 cm track length cut and
¹⁷⁹⁷ the momentum and track range distributions have similar shapes to the distributions of
¹⁷⁹⁸ Selection I original and modified. Efficiencies and purities were calculated for selection

Table 8: **Selection I: Modified** Signal and background event numbers at modified selection level estimated from a BNB+Cosmic sample and Cosmic only sample normalized to 5×10^{19} PoT. The last column gives the fraction of this signal or background type to the total 2189 selected events.

Signal	#Events	
ν_μ CC events with true vertex in FV	1168	53.8%
Backgrounds		
Cosmics only events	725	33.4%
Cosmics in BNB events	144	6.6%
NC events	75	3.5%
ν_e and $\bar{\nu}_e$ events	4	0.2%
$\bar{\nu}_\mu$ events	15	0.7%
ν_μ CC events with true vertex outside FV	40	1.8%

Figure 8.11: Snapshot of signal and background event numbers of Selection I modified from cc-inclusive note [?]

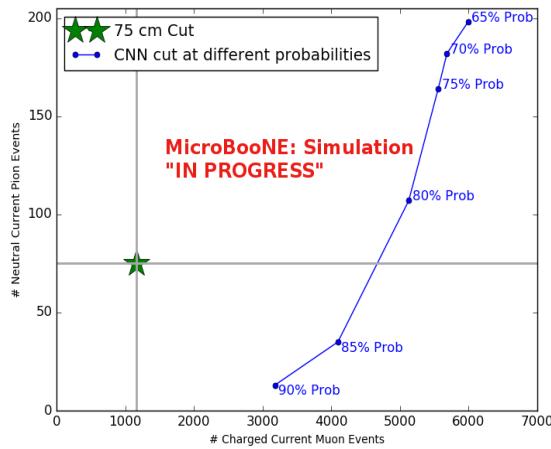


Figure 8.12: CNN performance of classified muons and pions compared to the already implemented 75 cm track length cut

1799 I modified events before 75 cm track length cut with the CNN at 83% probability and
1800 are 14% and 62% respectively. Although the CNN doesn't have separation between
1801 muons and pions and although all particles passing CNN are classified as muon,
1802 increasing CNN probability allows us to increase the purity as well as maintain an
1803 efficiency comparable to the 75 cm track length cut all while recovering events below
1804 that 75 cm cut. Out of the 6142 events that passed the CNN @ 83% 1470 events were
1805 below the 75 cm cut, a recovery of 3.3% of data with a purity of 15%. Although
1806 these numbers are low, it is an improvement from the selection I modified in both total
1807 efficiency and purity and an increase in phase space by recovering these events.

1808 **8.2 Classification using CNN100000**

1809 All future classifications will be done using Selection I Modified CC-Inclusive Filter
1810 because it has a higher efficiency and purity than Selection I Original CC-Inclusive
1811 Filter. To reiterate, CNN100000 was trained using 20,000 images of each $\mu/\pi/p/\gamma/e$.
1812 The results of using CNN100000 to classify BNB+Cosmics will be outlined below.

1813 **8.2.1 Classification of MC data using Selection I Modified
1814 CC-Inclusive Filter**

1815 **8.2.2 Classification of MicroBooNE data using Selection I Modified
1816 CC-Inclusive Filter**

1817 **8.2.3 Comparing two CC-Inclusive Cross Section Selection Filters**

¹⁸¹⁸ **Chapter 9**

¹⁸¹⁹ **Conclusion**

¹⁸²⁰ Your Conclusions here.

¹⁸²¹

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