

NOvA (NuMI Off-Axis v_e Appearance) Neutrino Experiment – Neural Network Analysis

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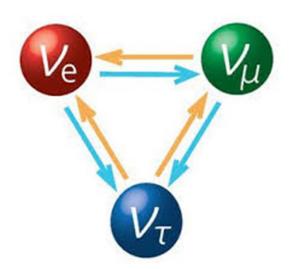
Outline

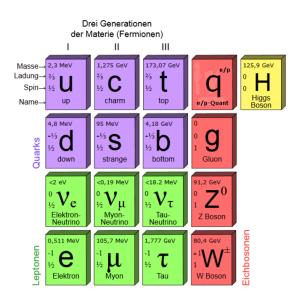
- Introduction and Theory
- The NOvA Experiment
- Project Goals
- Deep Learning and Convolutional Neural Networks
- Training
- Results and Analysis
- Conclusions



Properties of Neutrinos

- Come in three flavors electron, muon, and tau
- Oscillate into one of three different flavors
- Once thought to be massless extremely light
- Interact via the weak force mechanism

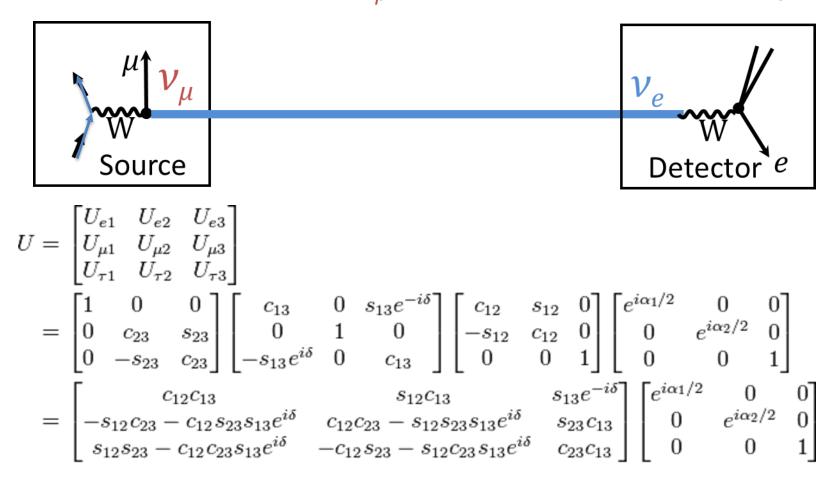






Neutrino Oscillations

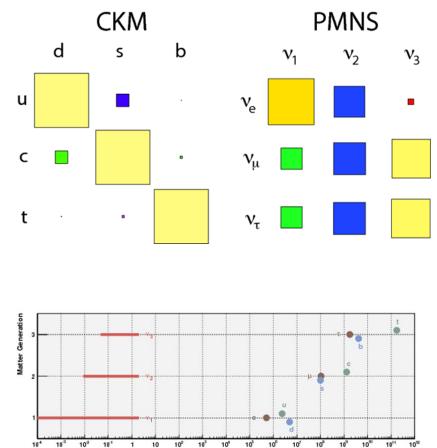
• Create in one flavor (v_{μ}) , but detect in another (v_{e})



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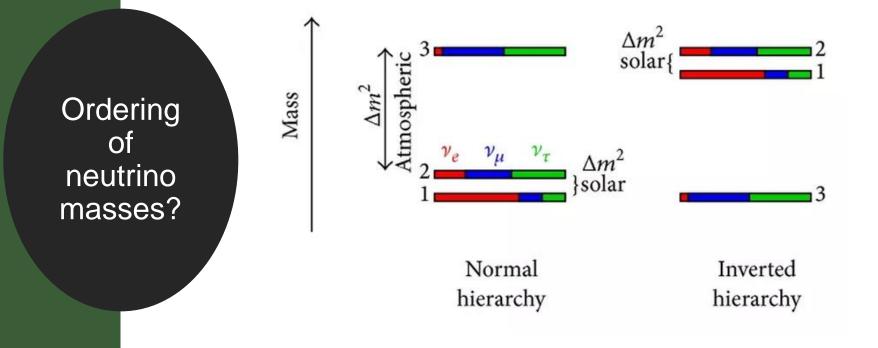
Why study neutrinos?

- Neutrinos are unique:
 - Neutrino mixing looks very different from CKM.
 - Neutrino masses are *really* small compared to the rest of the SM.
- Potentially *CP*-violating:
 - Might be a window into matterantimatter asymmetry.
- Physics beyond the standard model!
 - Oscillations are an interferometric effect – gives access to high-scale or unknown physics.



Mass (eV)

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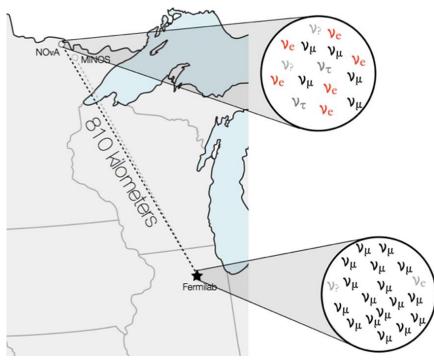
Matterantimatter asymmetry?

- Do muon antineutrinos oscillate at a different rate than muon neutrinos?
 - Would imply broken symmetry between neutrinos and anti-flavors are broken
- If antineutrinos do not follow the same pattern as neutrinos when they change from one flavor to another - a signal of CP violation



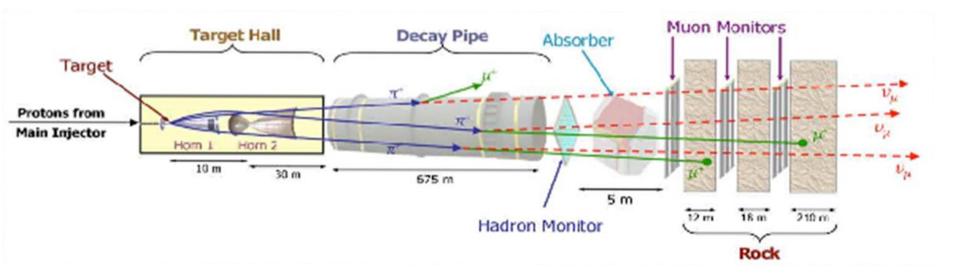
The NOvA Experiment

- Long-baseline neutrino oscillation experiment.
 - NuMI neutrino beam at Fermilab
 - Near Detector to measure the beam before oscillations
 - Far Detector measures the oscillated spectrum.
- Detectors located 14 mrad offaxis of the beam.
 - 2-body π decay gives narrow range of v energies
 - Tune peak energy for oscillations
 - More events at max oscillations
 - Fewer backgrounds



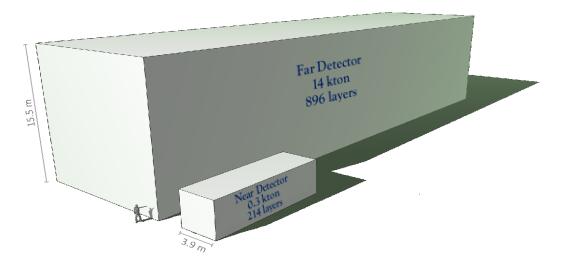


NuMI (Neutrinos at the Main Injector) Beam





The NOvA Detectors



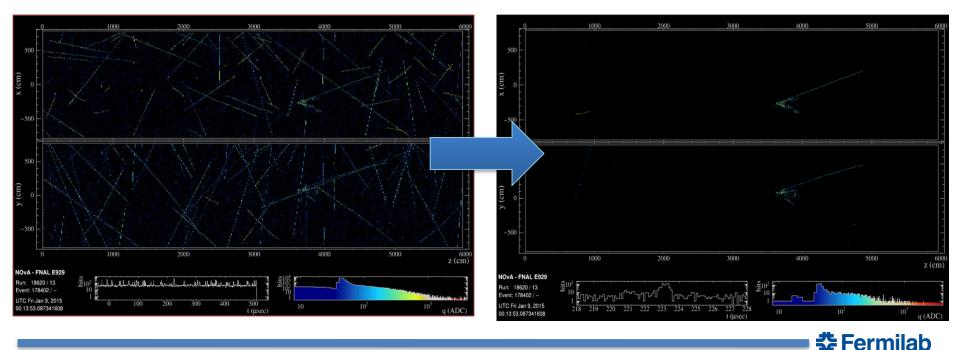
Large, 14 kTon at the Far Detector – 385,000 scintillator cells Consist of plastic cells filled with liquid scintillator Arranged in alternating directions for 3D reconstruction

- NOvA Measures:
 - *CP*-violating phase
 - θ_{23} octant
 - Sign of Δm_{32}^2 "Mass Hierarchy"



Project Goals

- The far detector is above ground
 - Subject to approximately 11 billion cosmic rays per day
 - Approximately 10⁷ events need to be rejected to process and reconstruct pixel maps
- Construct a cosmic rejection network via machine learning able to identify events based on event topology



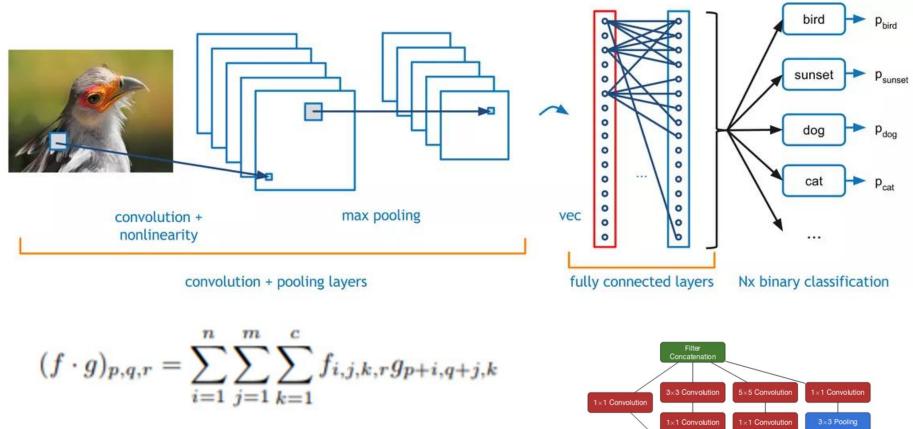
Deep Learning and Convolutional Neural Networks

- The multilayer perceptron (MLP), or traditional neutral network- a machine learning algorithm
- Scales poorly to a large number of raw inputs.
- The number of nodes necessary in that hidden layer may approach infinity
- Large number of free parameters in a large network runs the risk of possibly overtraining





Convolutional Neural Network

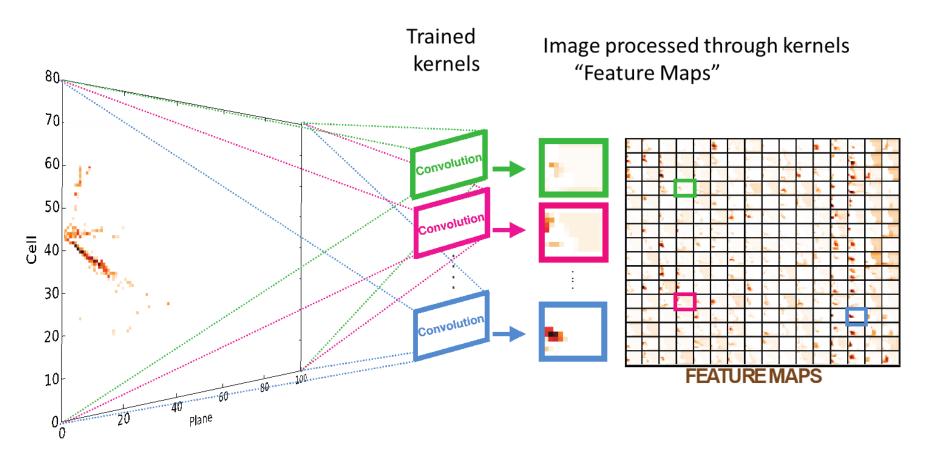


Previous Layer

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13

8/9/18

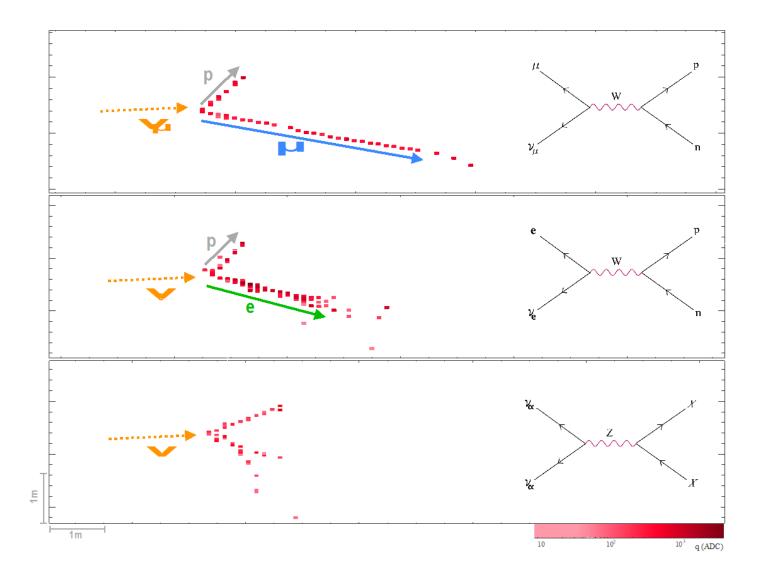




Identifying Events

- ν_μ CC A muon plus a hadronic component; long, low dE/dx track
- v_e CC An electron plus a hadronic component; is typically a wide shower
- ν_τ CC A tau plus a hadronic component. The tau is extremely short lived and not visible in the detector; may produce pions, electrons, muons, and neutrinos.
- v NC- The outgoing lepton in these interactions is a neutrino; will travel onward undetected; hadronic component only is visible
- Cosmic events (Usually) Long muon tracks entering tops or sides







Training

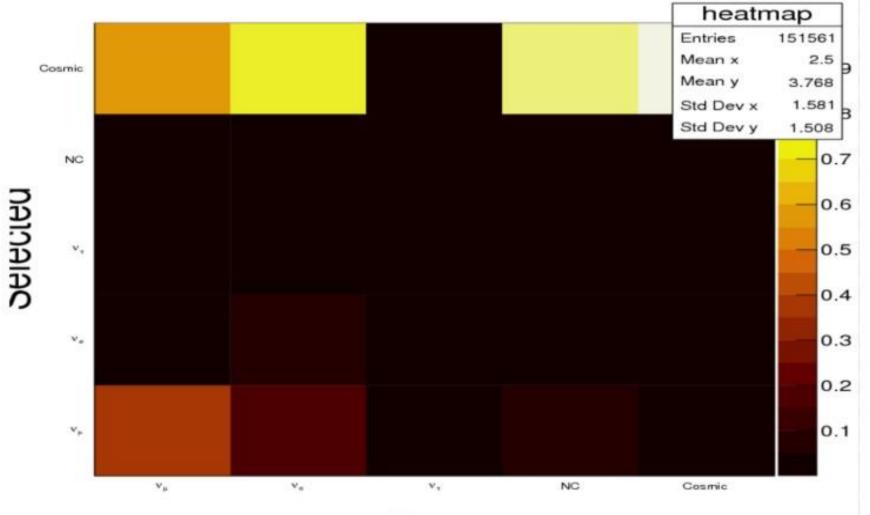
- Create Pixel Maps
 - Full FD events sliced in time to spill window width ~12 μS
 - Select one random window and the spill window
 - Cuts on empty windows and less than 10 interaction hits
- Create LevelDBs
 - Large LevelDBs needed to be "chunked"
 - 250 files per LevelDB = ~470k
 pixelmaps (over 12k files available)
 - 376k training / 94k testing (80/20)
 - Reduced Labeling







Before Training



Truo

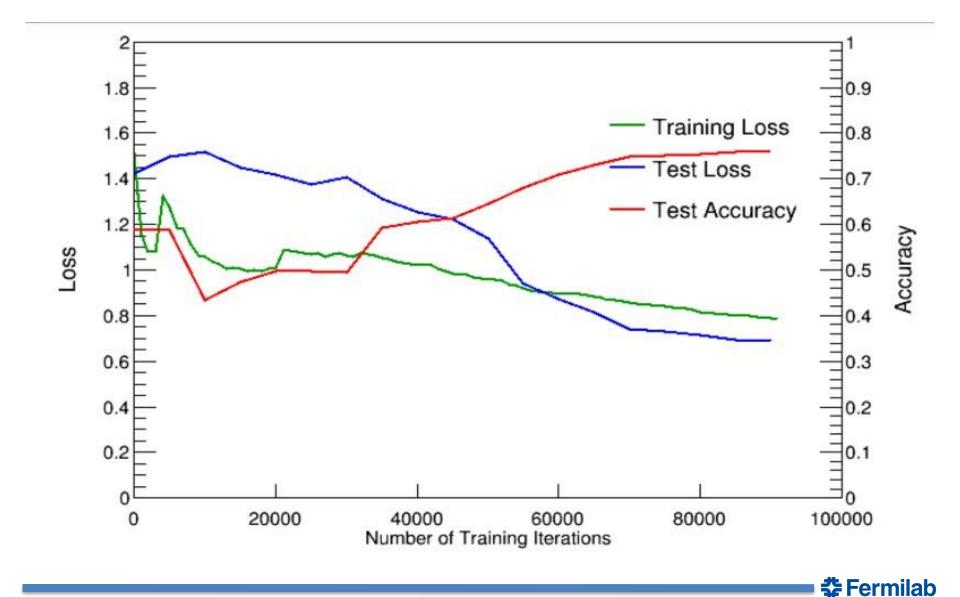
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Composition ration of 34:1 cosmics

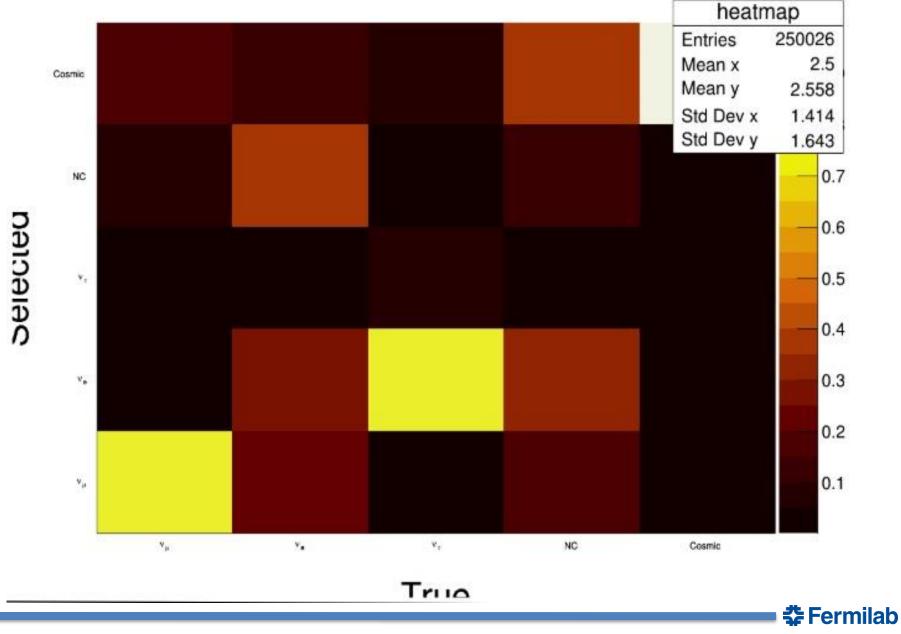
	$v_{\mu} CC$	v _e CC	$v_{\tau} CC$	v NC	cosmic	total
Chunk-05	13.0%	10.6%	3.4%	14.2%	58.8%	463708
Chunk-06	13.1%	11.4%	3.8%	15.9%	55.8%	460792



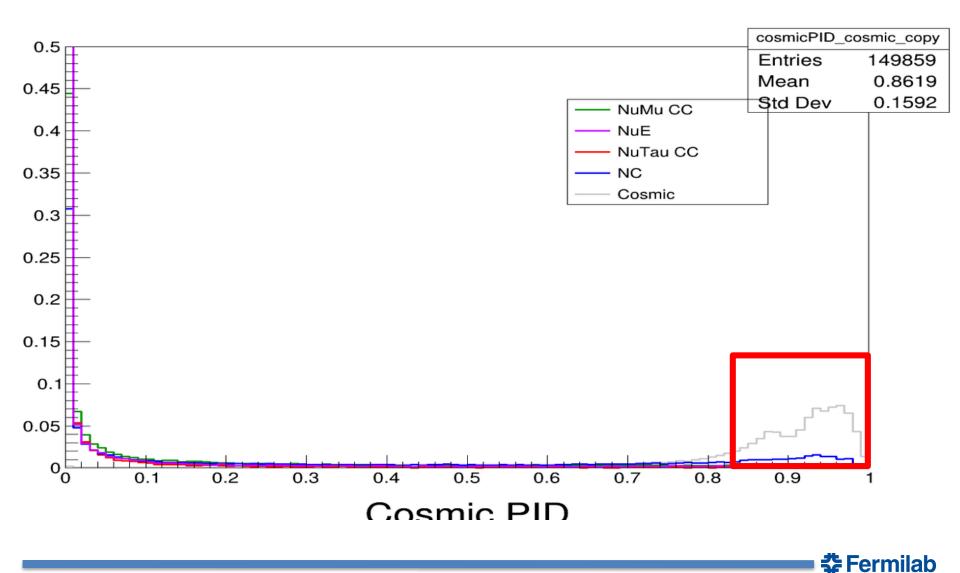
First Training (1st chunk)



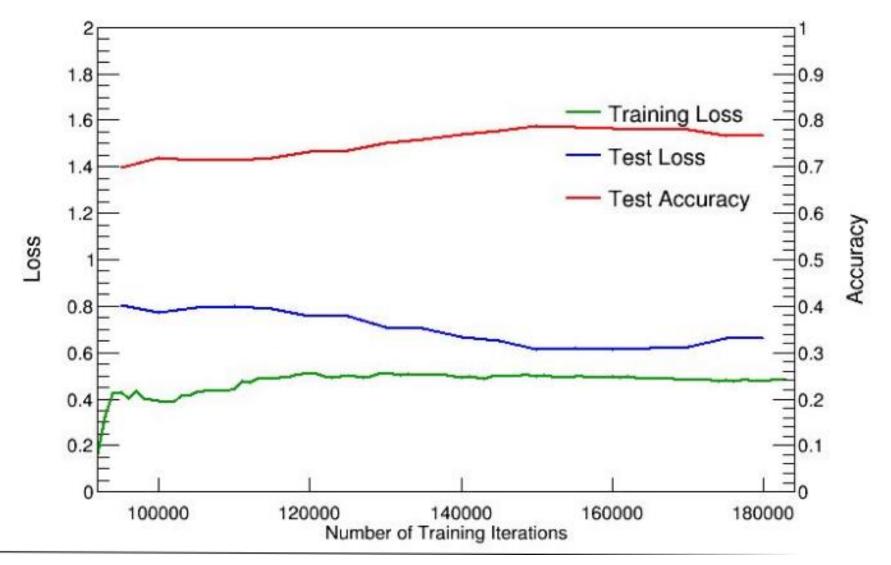
First Training – Confusion Matrix



First Training – PID Plot (Cosmic)

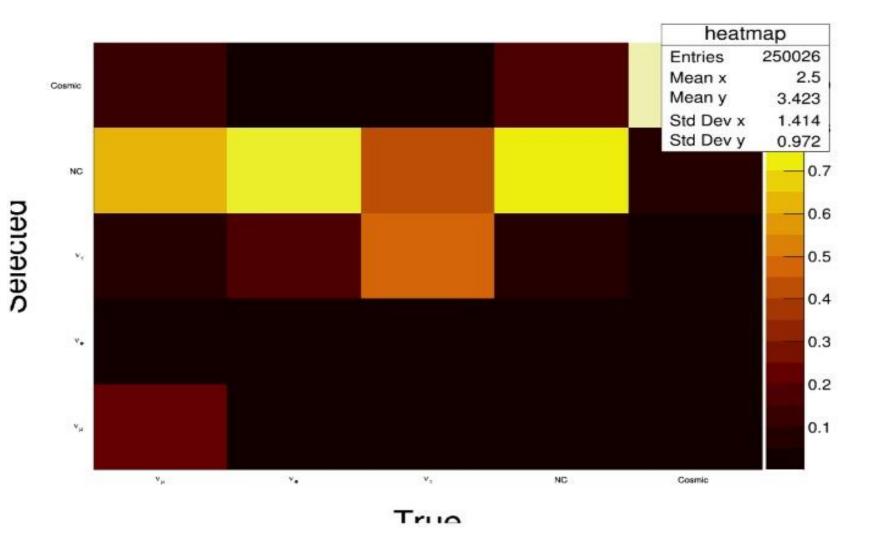


Second Training(2nd chunk)



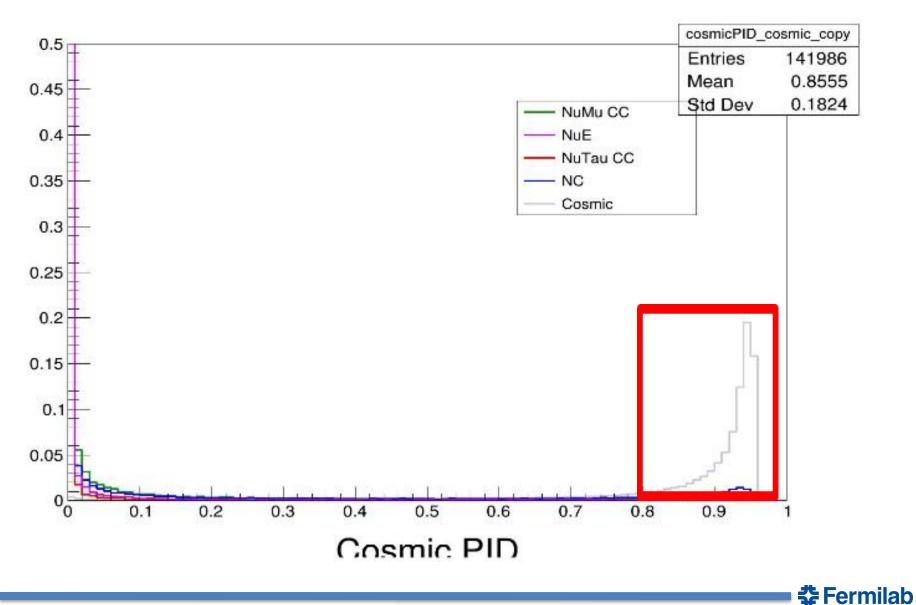
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Second Training – Confusion Matrix

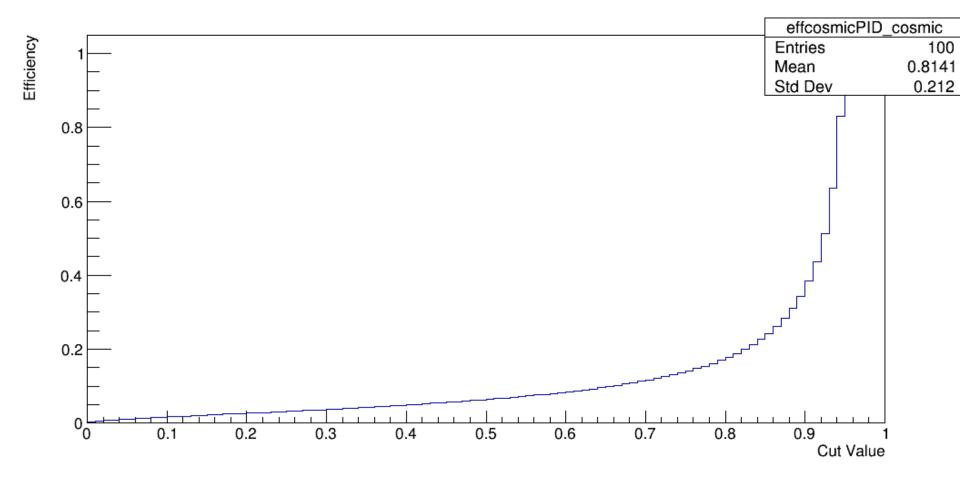


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Second Training – PID Plots (Cosmic)

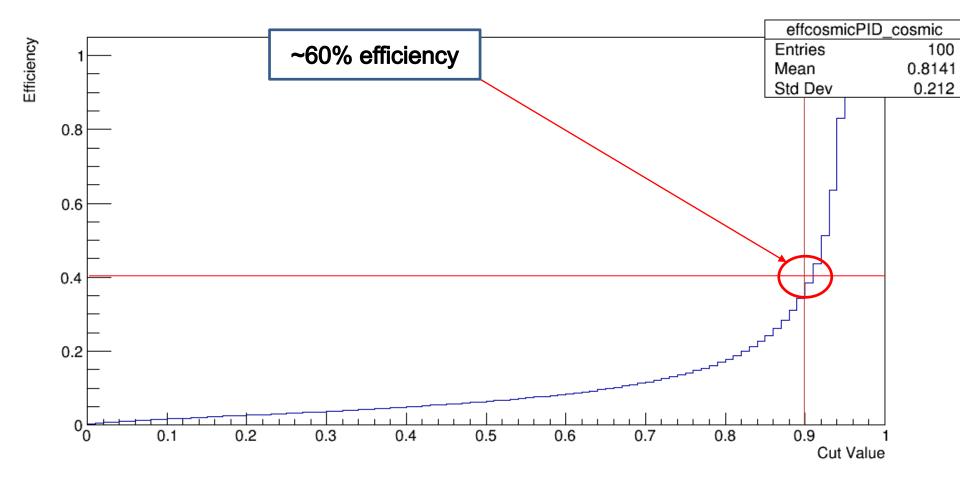


Efficiency vs. Cut(Cosmic)



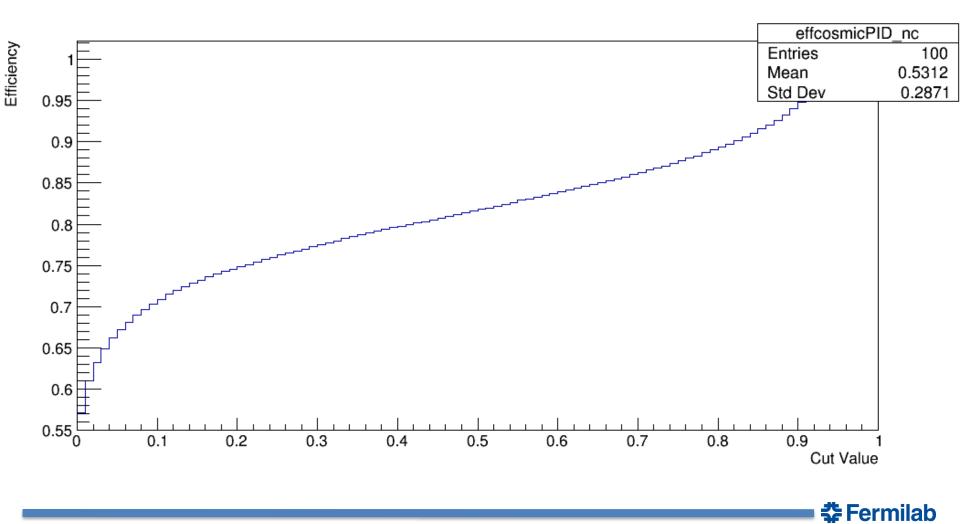
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Efficiency vs. Cut(Cosmic)

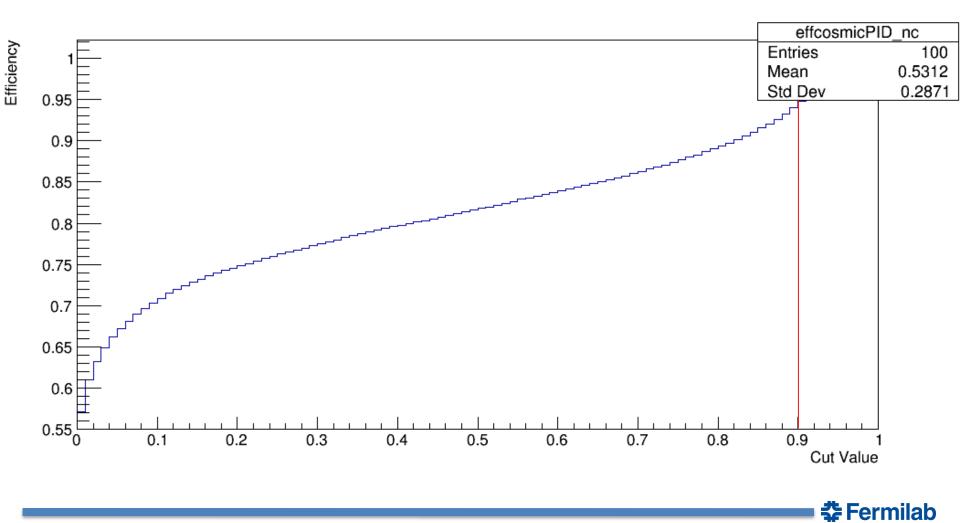


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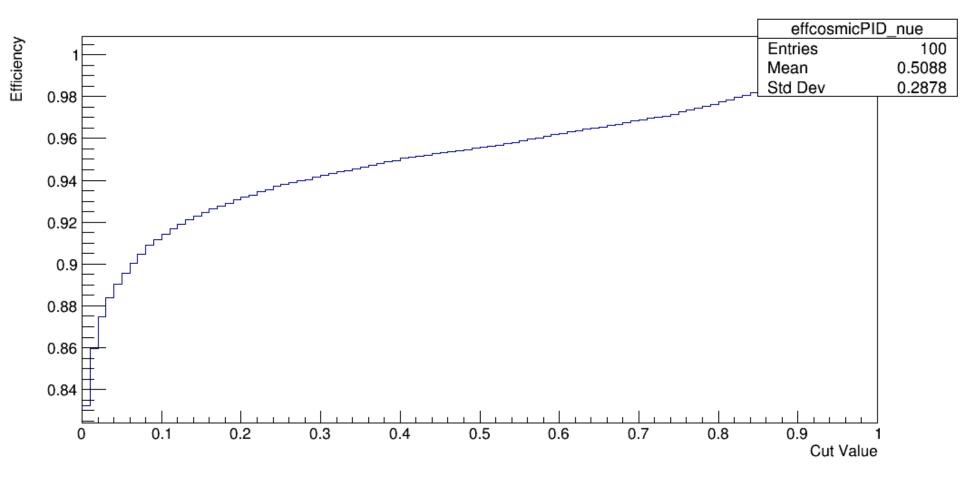
Efficiency vs. Cut(NC)



Efficiency vs. Cut(NC)

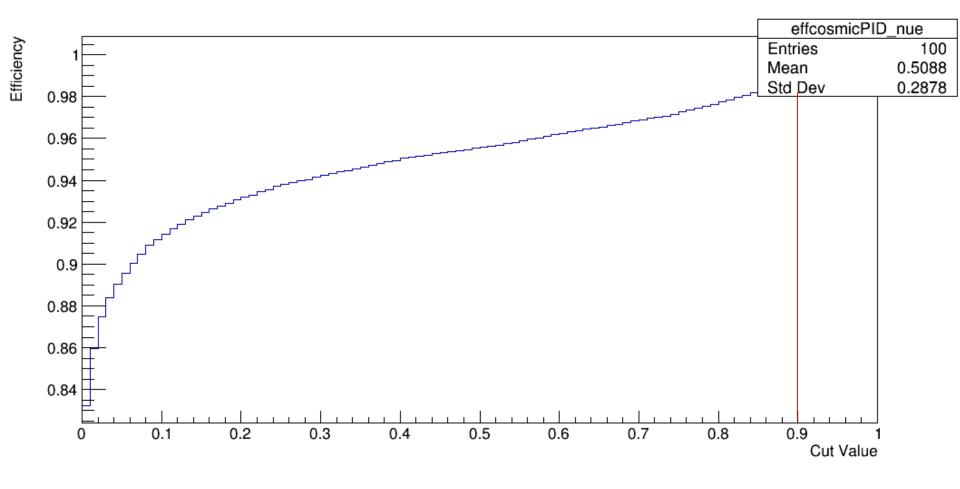


Efficiency vs. Cut(v_e)



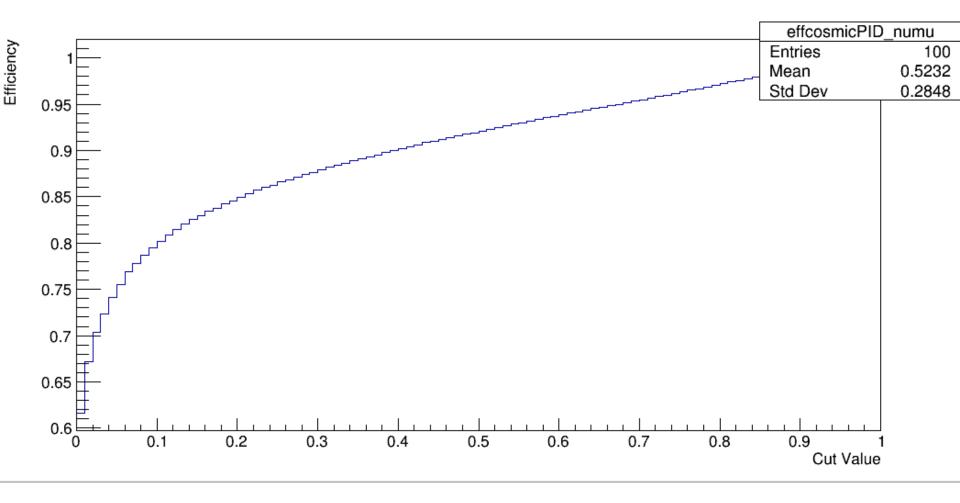
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Efficiency vs. Cut(v_e)



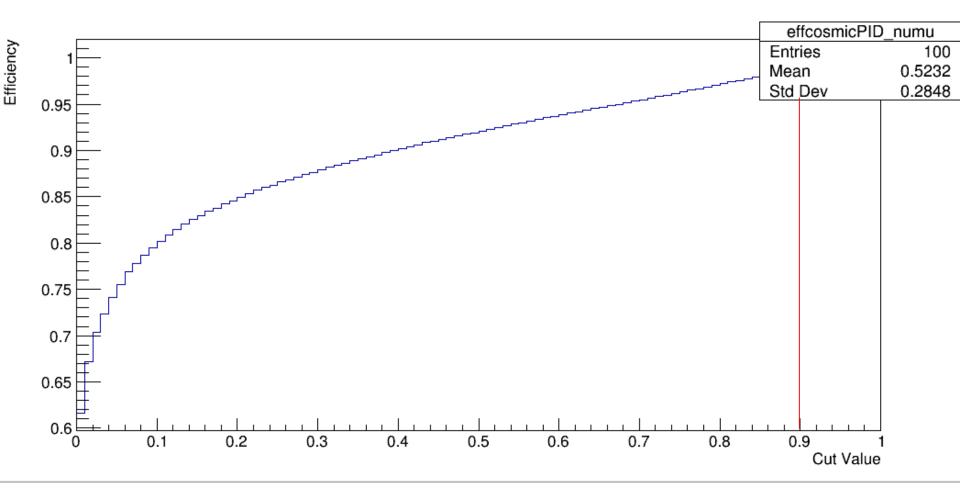
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Efficiency vs. Cut (v_{μ})



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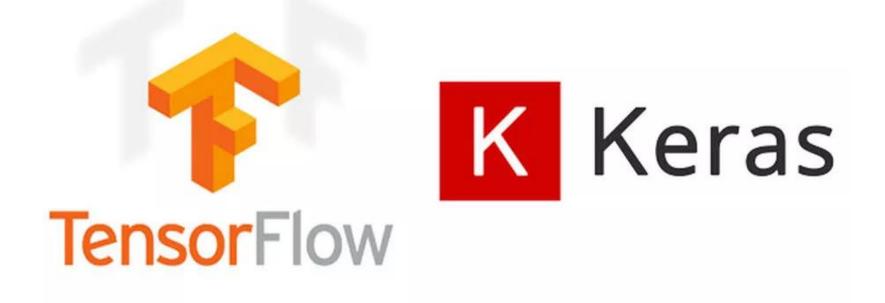
Efficiency vs. Cut (v_{μ})



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Conclusions and Future Work

- Cosmic rejection network has potential for implementation
- Continue to tune/train the networks
- Utilize multi-access DBs
- Move to Keras/TensorFlow





References

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Acknowledgements

- Fermi National Accelerator Laboratory for offering this research opportunity through funding and opportunities made possible by the National GEM Consortium.
- Dr. Alex Himmel, Dr. Evan Niner, Adam Moren, and Ryan Murphy for their continued support, guidance, and tutelage that made this project possible,
- I would also like to thank the U.S. Department of Energy for its continued support and funding of STEM-based pursuits.
- The SIST Committee for their guidance, support, and direction



