



# LIGHTNING ROUND: MACHINE LEARNING IN NOVA

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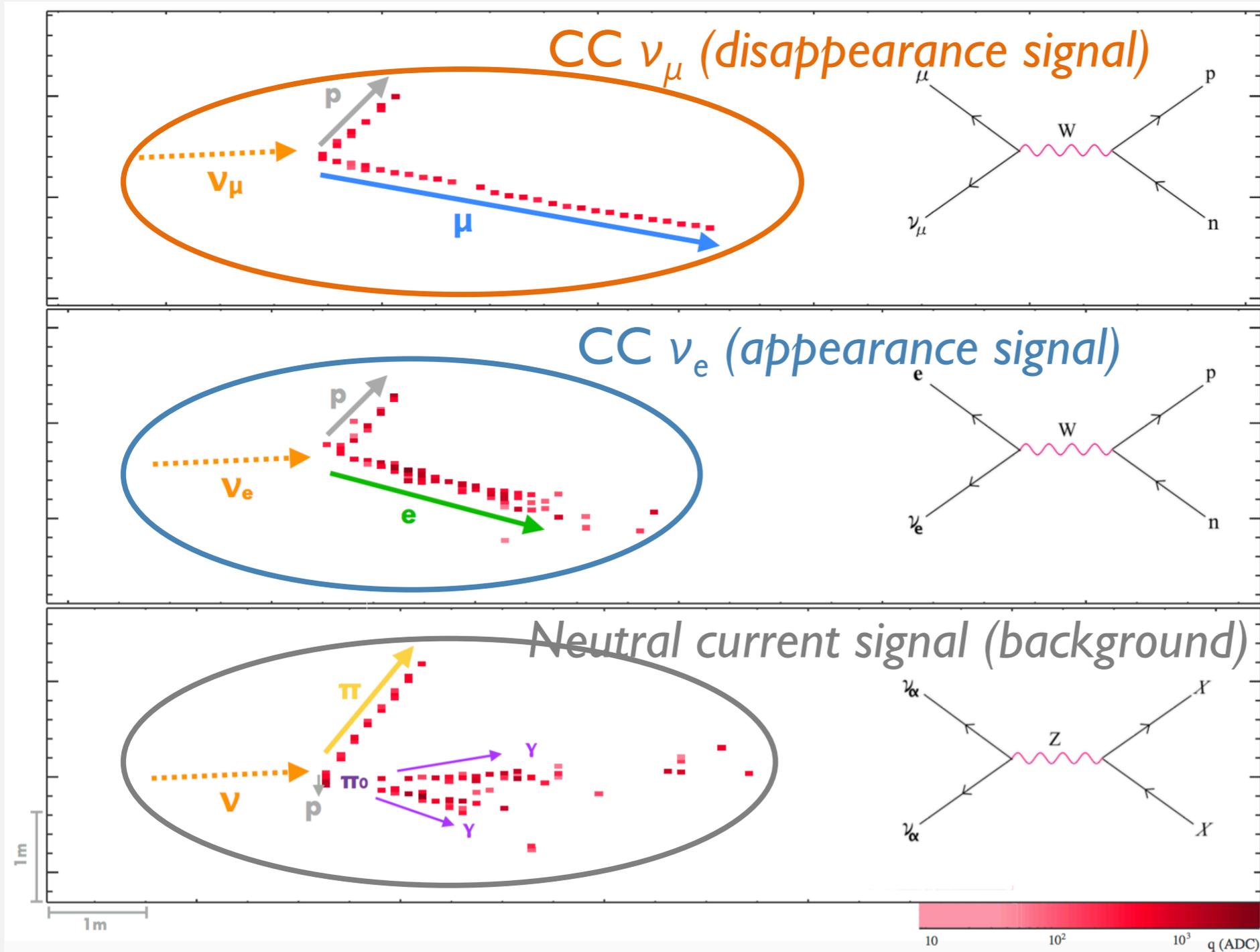
11<sup>th</sup> September 2019

# THE NOVA EXPERIMENT

- Long baseline neutrino experiment based at Fermilab in the NuMI beamline.
- Two homogenous, functionally identical, tracking calorimeters separated by a 810 km baseline.
  - Near detector is on-site at Fermilab.
  - Far detector is in Ash River, MN.
- Broad physics goals;
  - Neutrino oscillations
  - Cross-section measurements
  - Various other non-oscillation searches.



# IDENTIFYING PARTICLE INTERACTIONS IN NOVA

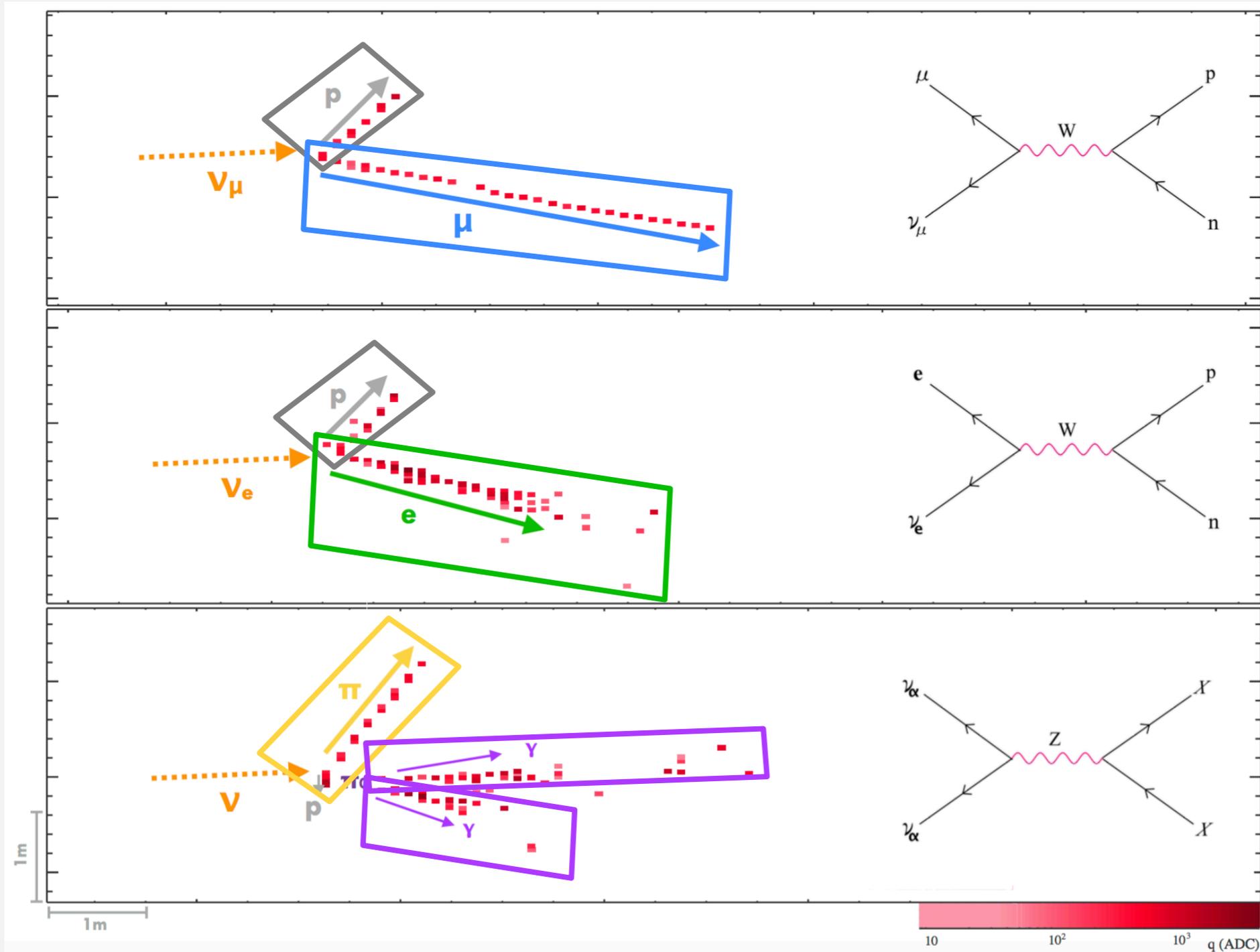


- NOvA was the first HEP experiment to use a CNN in a physics measurement to classify candidate neutrino interactions.
- Provide full interaction to CNN, the output is an event classifier.
- Trained separately on (anti)neutrino mode.

A Convolutional Neural Network Neutrino Event Classifier: <https://arxiv.org/abs/1604.01444>

Context-Enriched Identification of Particles with a Convolutional Network for Neutrino Events: <https://arxiv.org/abs/1906.00713>

# IDENTIFYING PARTICLE INTERACTIONS IN NOVA



- Another CNN has been developed to identify individual particles.
- Provide hits from individual clusters, which are made by geometrical reconstruction.
- By providing context of the interaction network performance increases.

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# THE CHALLENGES THAT WE FACE IN NOVA

- The environments in which we train and evaluate our Machine Learning (ML) algorithms are very different.
- To fully train a model takes on the order of a month. Only basic validation can be performed after training.
- To perform full validation, a new dedicated sample has to be produced on CPUs, which also took on the order of a month.
- Therefore, it was a very time consuming process to develop and improve upon our ML algorithms.

## Standard Reco File

- Run Preproc. Job (Month)

## LevelDB training files

- Train networks on GPUs (Week)

## Trained Network

- Make efficiency tables (Days)

## Network with limited val.

- Run reco on dedicated sample of validation files - CPU (Month)

## Files with analysis variables

- Run analysis validation scripts (Week)

# ADDRESSING CHALLENGES THAT WE FACE IN NOVA

## HDF5 File

- Produced by Reco. Chain
- Train Network on GPU (Day)

## Trained network

- Make efficiency tables (Day)
- Run analysis validation scripts (Day)

## Fully trained and validated network

- Complete in the order of a Week.
- All work done on GPUs

- With the help of sciDAC we have started using HDF5 files this summer to alleviate these limitations.
- Currently training / testing new networks for use in our upcoming analyses for 2020.
- This has required us to develop a new analysis framework to validate training results on the fly.
- We are also transitioning from using Caffe to using Keras/Tensorflow, and are seeing improvements in both CPU inference time (roughly a factor of 7) and overall network accuracy.

# VALIDATING A NEW ANALYSIS FRAMEWORK

- To fully utilise HDF5s, we had to develop a new Python based analysis framework (*PandAna*). This would complement our ROOT based framework (*CAFAna*).
- The main difference being switching from row based operations to column based operations.
- *PandAna* utilises pandas to do much of the heavy lifting.

Event	NHit	Max X	Max Y	Max Z
1	75	5.4	5.6	23.9
2	54	3.9	4.8	54.8
3	102	4.5	5.9	12.7
4	63	5.7	2.4	43.6

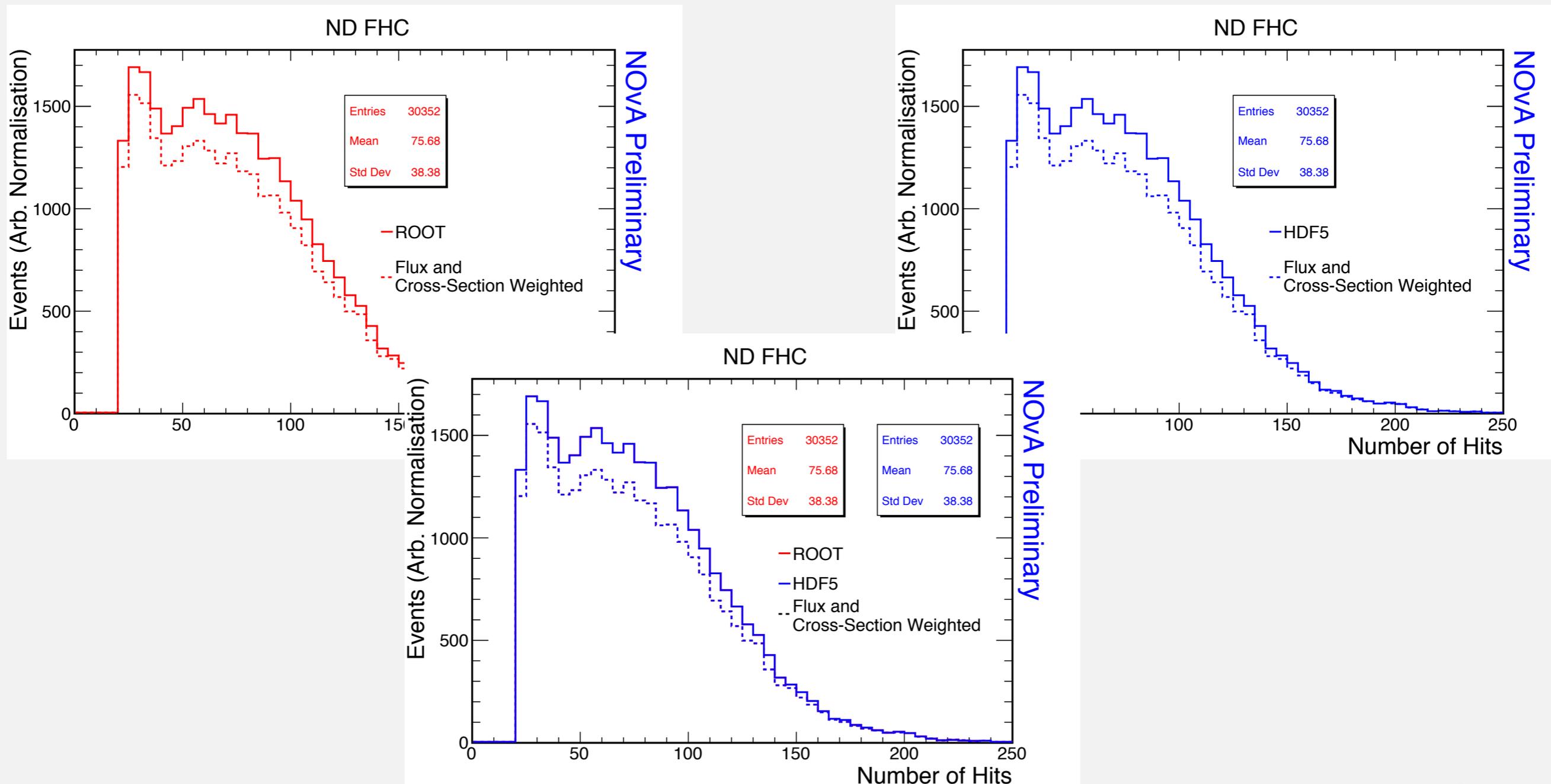
*CAFAna*

*PANDAna*



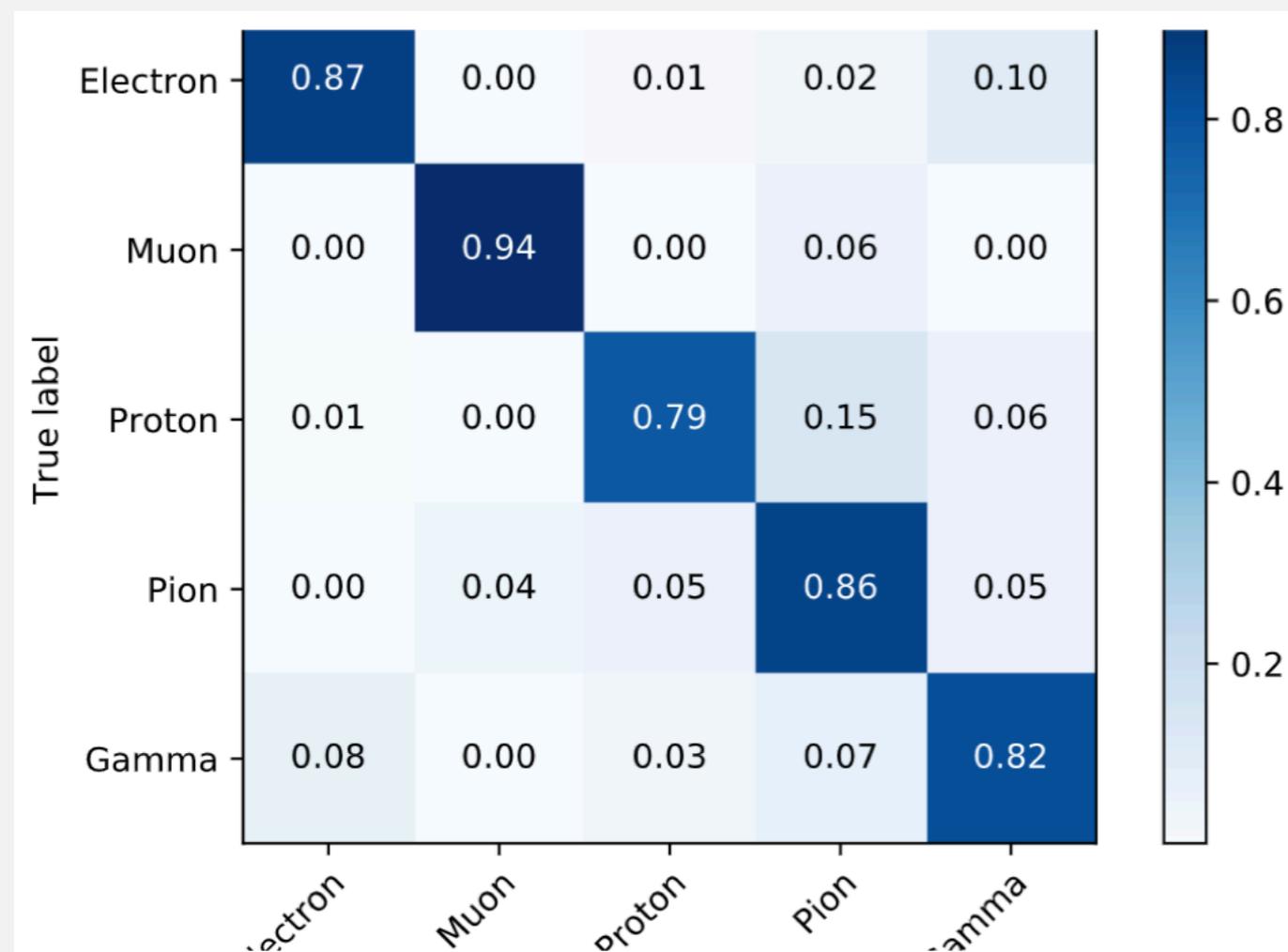
# VALIDATING A NEW ANALYSIS FRAMEWORK

- Extensive consistency checks were performed, ensuring that analysis variables were identical in the ROOT and HDF5 files, both before and after the application of analysis cuts and weights.

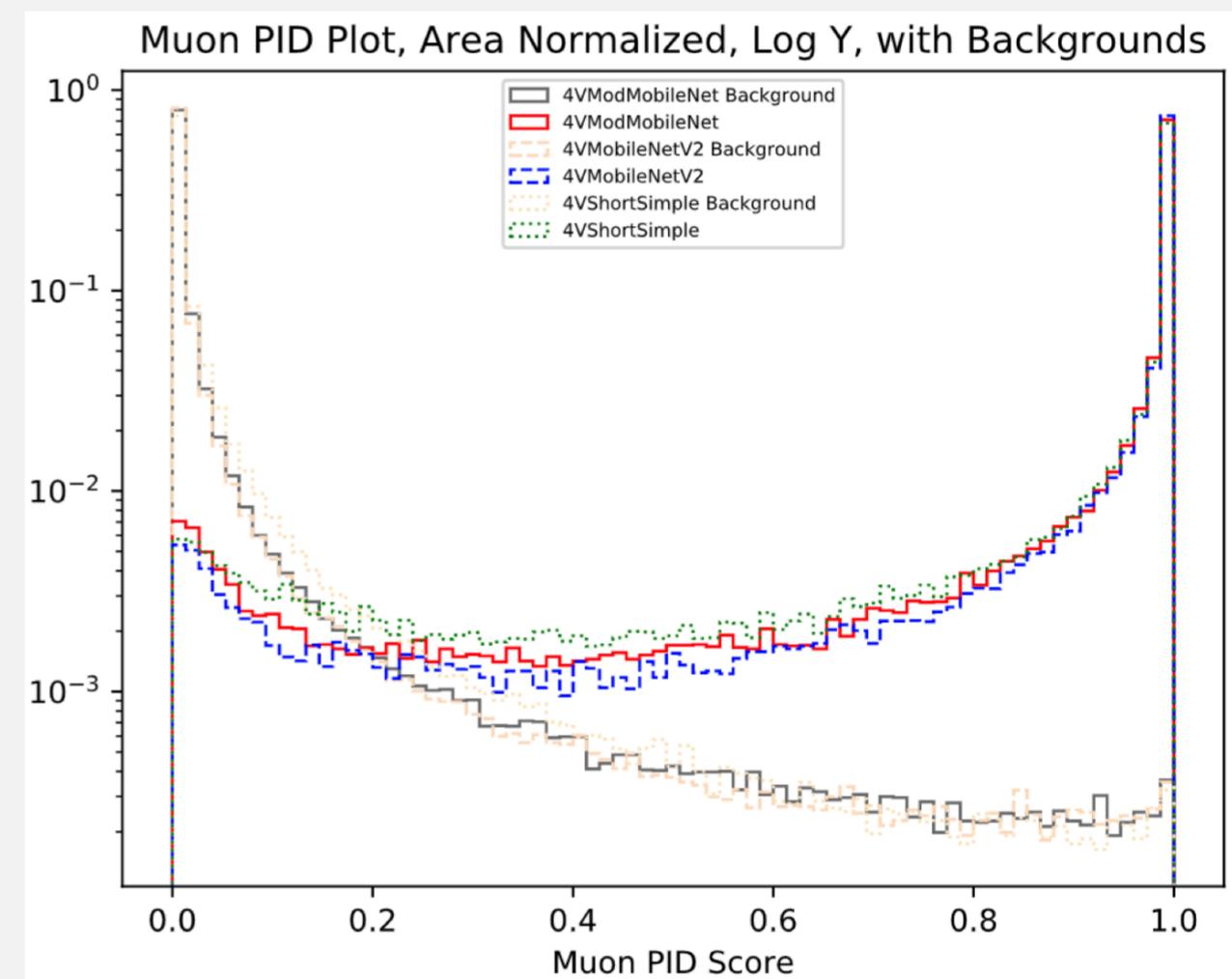


# PRELIMINARY RESULTS USING THE NEW FRAMEWORK

- Still fine tuning the exact training parameters, however we have verified that we are able to train and evaluate networks on the order of days, compared to months previously.



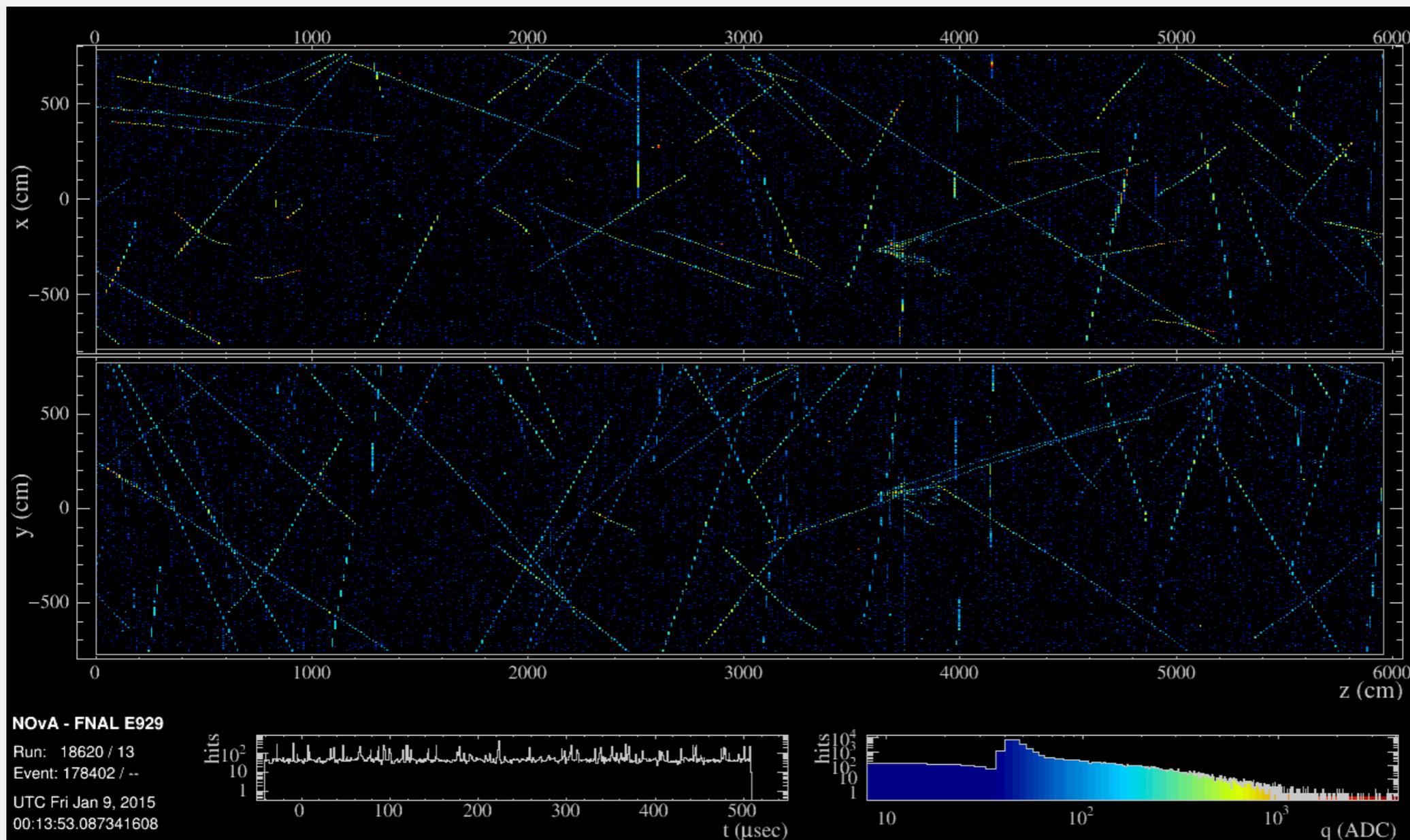
Identification efficiency of one of our newly trained "Prong CVN" networks.



Muon PID score of a newly trained "Prong CVN" network, evaluated on a GPU.

# REJECTION OF COSMIC RAYS USING ML

- NOvA sees only a handful of neutrino interactions per day, whilst as a surface detector, we have a huge cosmic flux.
- Therefore we record many terabytes of cosmic data each year.



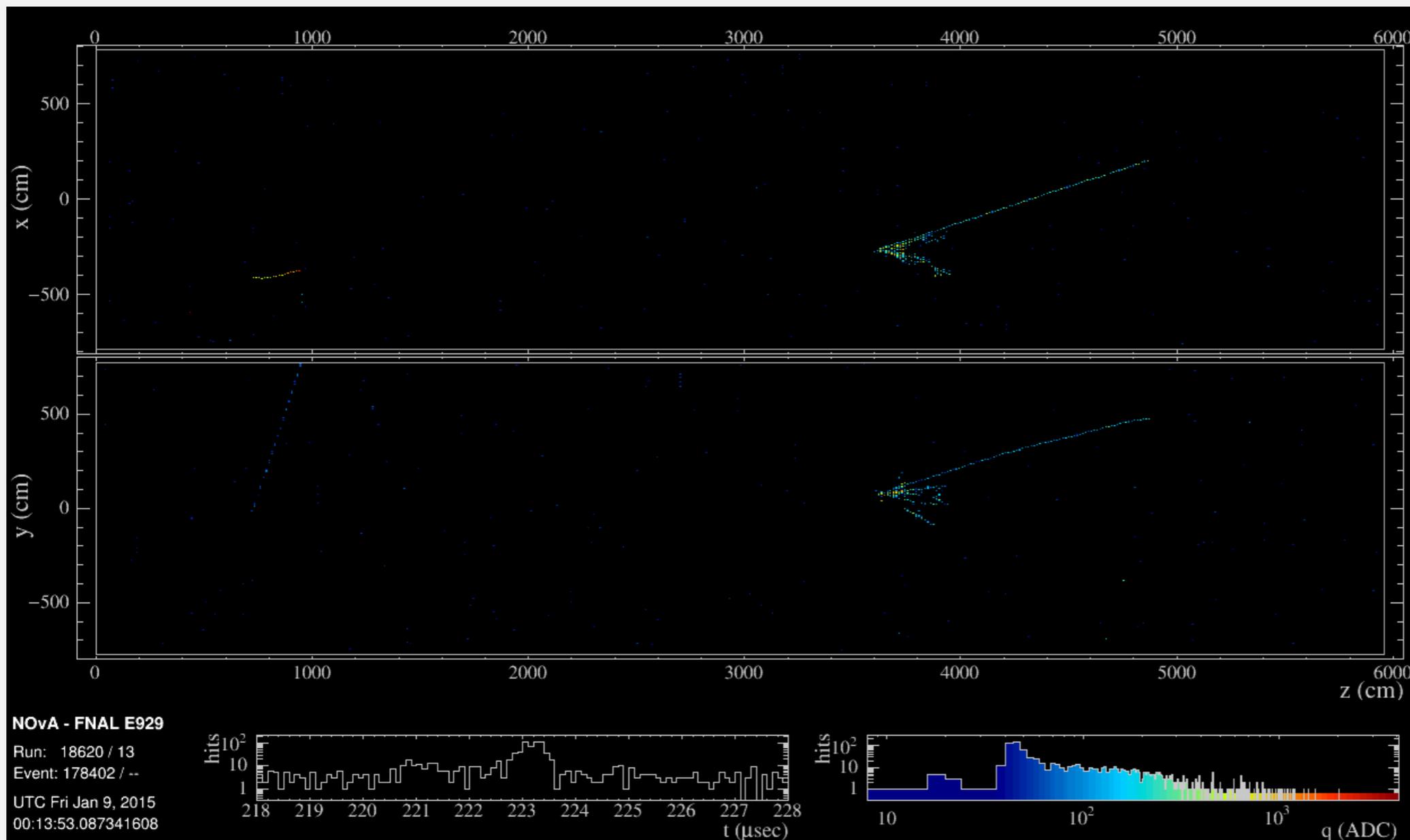
A 550  $\mu\text{s}$  exposure in the FD is dominated by cosmic rays.

# REJECTION OF COSMIC RAYS USING ML

- Much of the cosmic data could be readily rejected, as background events which pass our analysis cuts are rare.
- Previously this was done at the start of the reconstruction chain, however a more efficient method is to perform a pre-filter to the reconstruction.
  - This has been developed over the summer.
- We are currently in the process of back-processing over 6 years worth of cosmic data.
  - This represents over  $10^9$  events.
- The time to process each event is on the order of 2 s.
  - This represents a total of  $\sim 1$  M GPU hours to backprocess our cosmics.
  - In the future we will run these jobs as part of our data keepup.

# FINDING NEUTRINO CANDIDATES IN DATA

- Determine if there is a candidate interaction within a narrow time slice.
- If there is no such interaction, then remove all hits, as only cosmic rays are present.



A neutrino candidate is clearly visible when focusing on a  $10 \mu\text{s}$  exposure around the beam peak from the previous image.

# SUMMARY

- NOvA has been actively using machine learning techniques since 2016.
- The use of HDF5 files is allowing us to train and evaluate our machine learning algorithms more efficiently.
- A new analysis framework has been developed to do this over the summer.
- The use of machine learning algorithms to significantly reduce computational load, in the form of rejecting cosmics, is being performed.

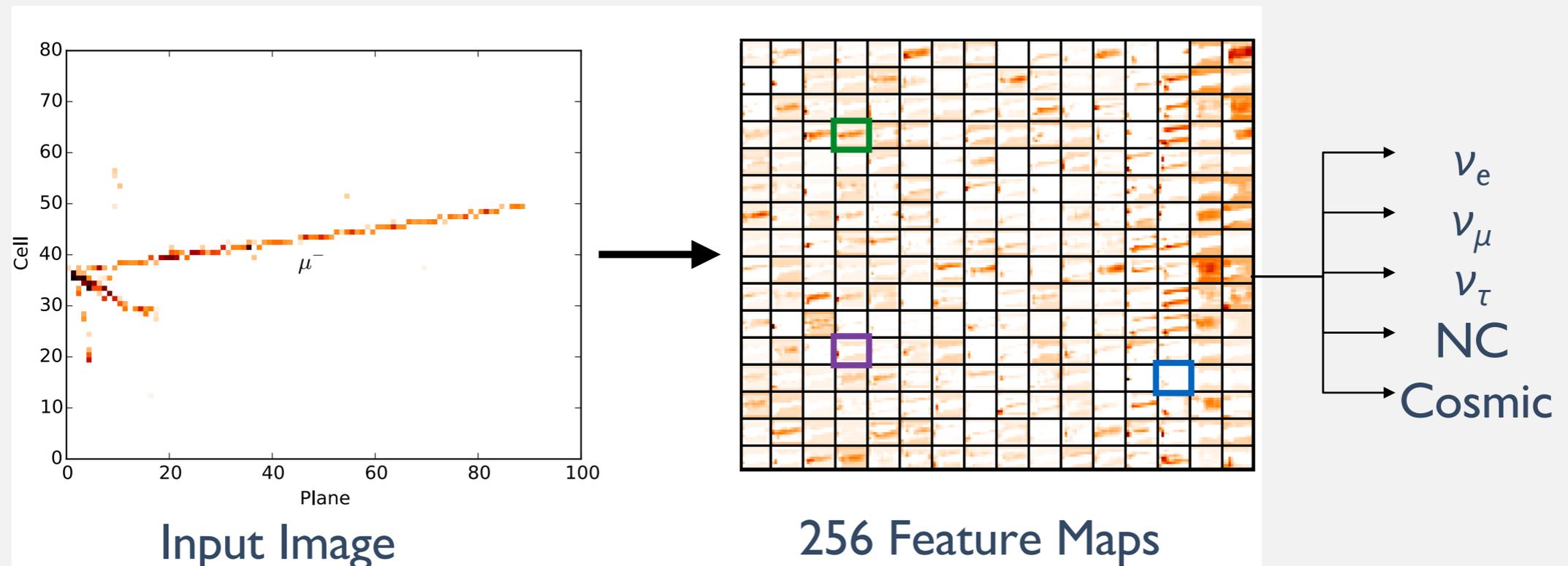
Can you beat our [neural nets?](#)



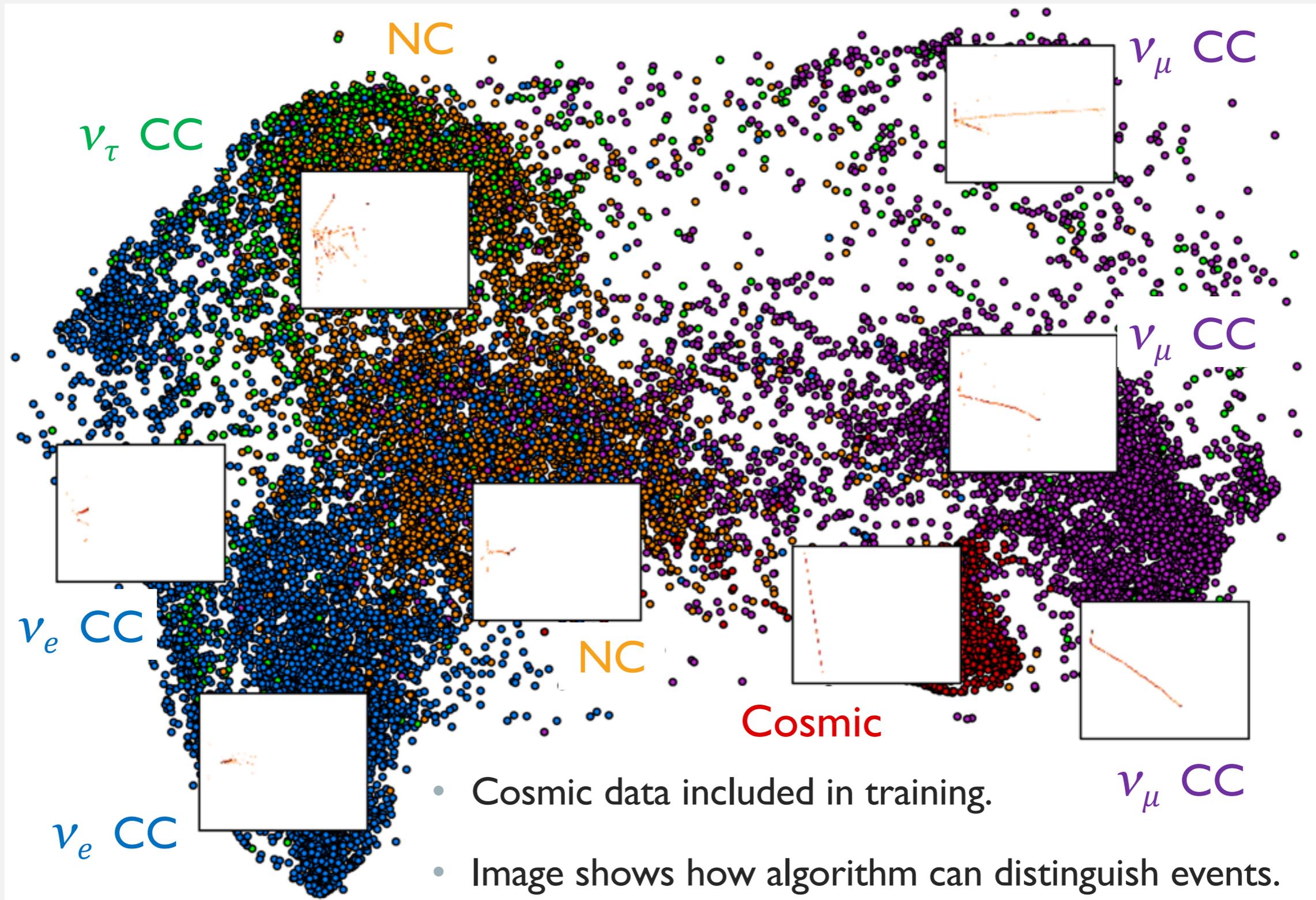
# BACKUP SLIDES

# CLASSIFYING NEUTRINO INTERACTIONS

- Signal identification is done by our CVN (Convolutional Visual Network).
- CVN is an event classifier which employs a Deep Convolutional Network in the "image recognition" style.
- The network is trained on two dimensional views of the event's calibrated hits.
- The information of each view is then combined in the final layers of the network.
- The network is trained separately on neutrinos and anti-neutrinos.

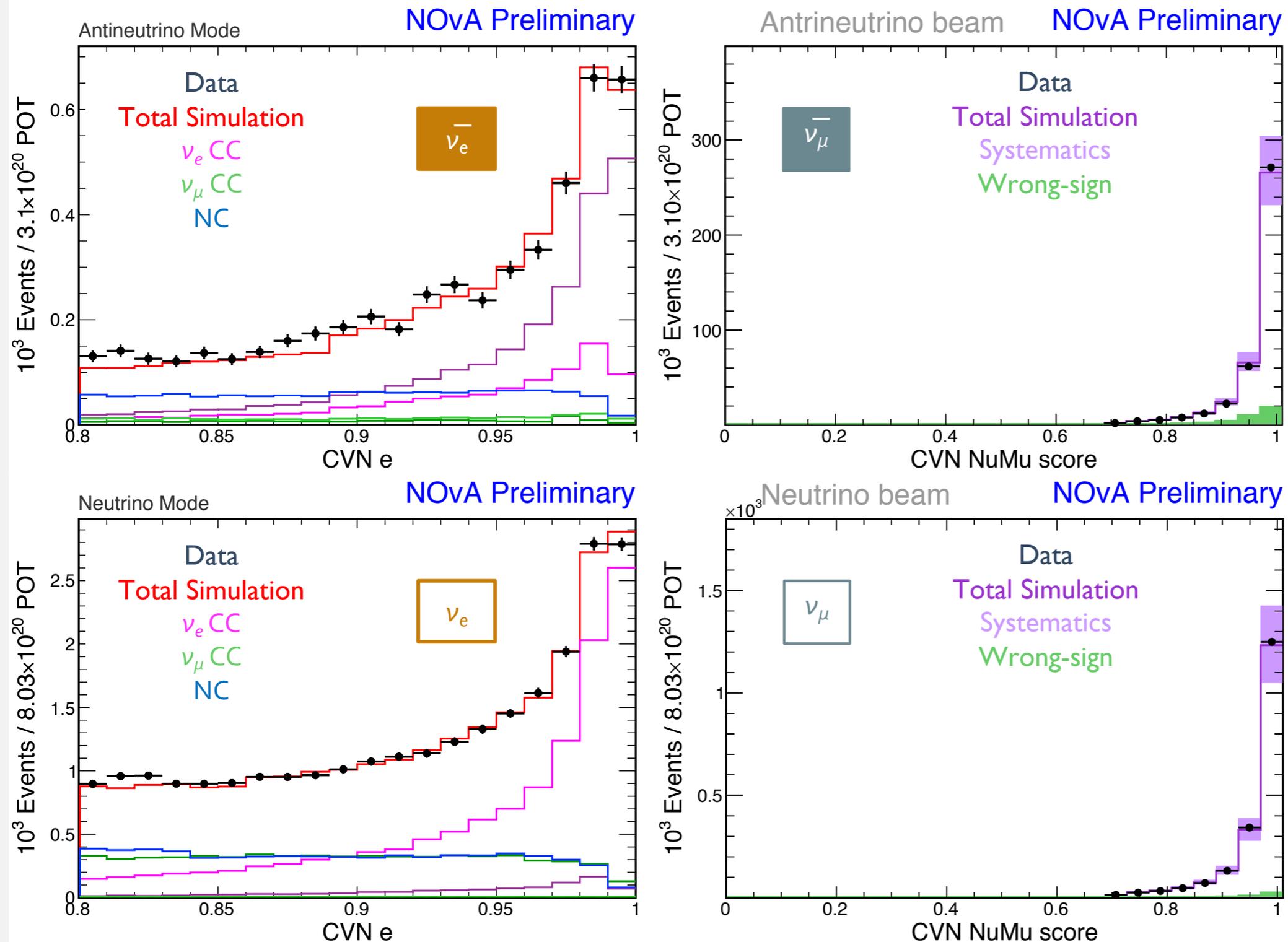


# CLASSIFYING NEUTRINO INTERACTIONS



- Cosmic data included in training.
- Image shows how algorithm can distinguish events.

# CVN VALIDATION



- Genie truth labels replaced with final state labels.
- Separate training for the neutrino and antineutrino beams.
- Wrong-sign treated as signal in training.
- 14% better efficiency for  $\bar{\nu}_e$  with a dedicated network.