Neutrino Physics with Deep Learning on NOvA

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Indiana University

On behalf of the
NOvA Collaboration

NOvA

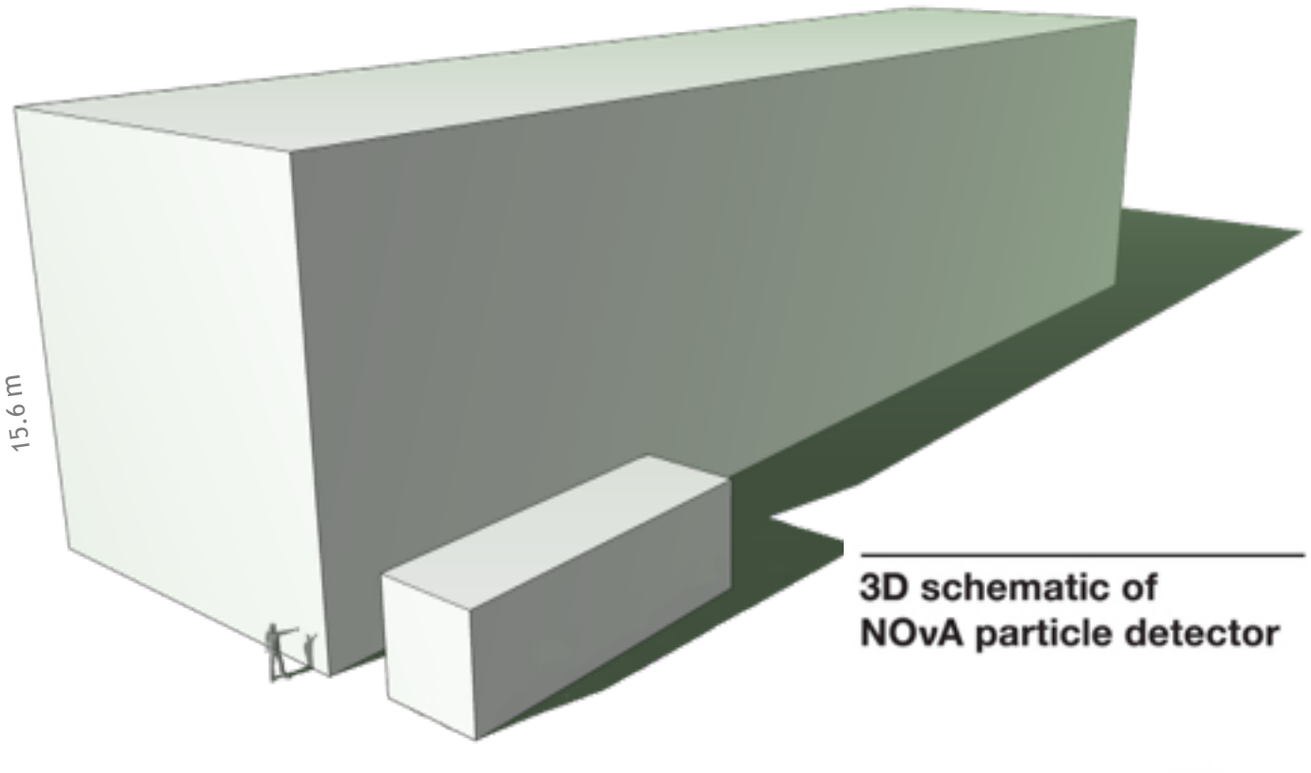
A long baseline neutrino oscillation experiment utilizing the NuMI beam at Fermilab.

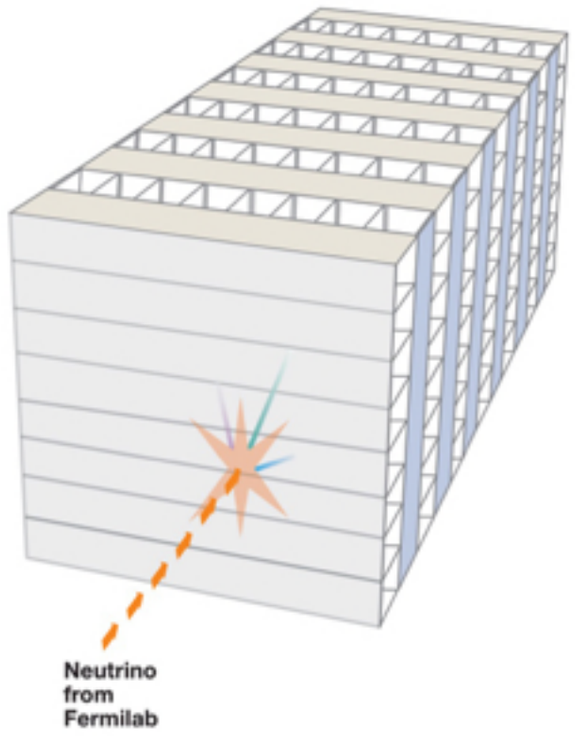
Physics Program:

- Neutrino Oscillations
- Neutrino Cross Sections
- Supernova Neutrinos
- Exotic Phenomena

Measurables are Neutrino Flavor and Energy

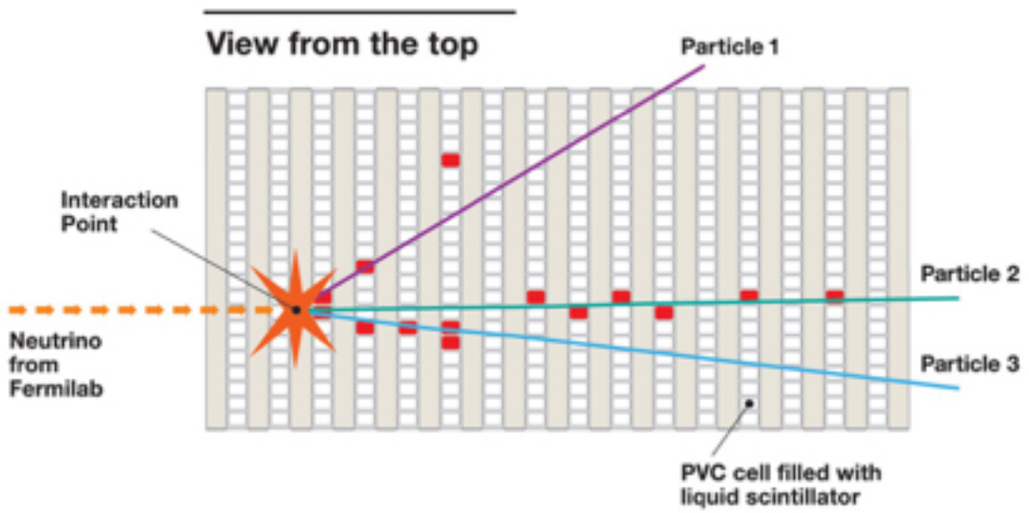
NOvA

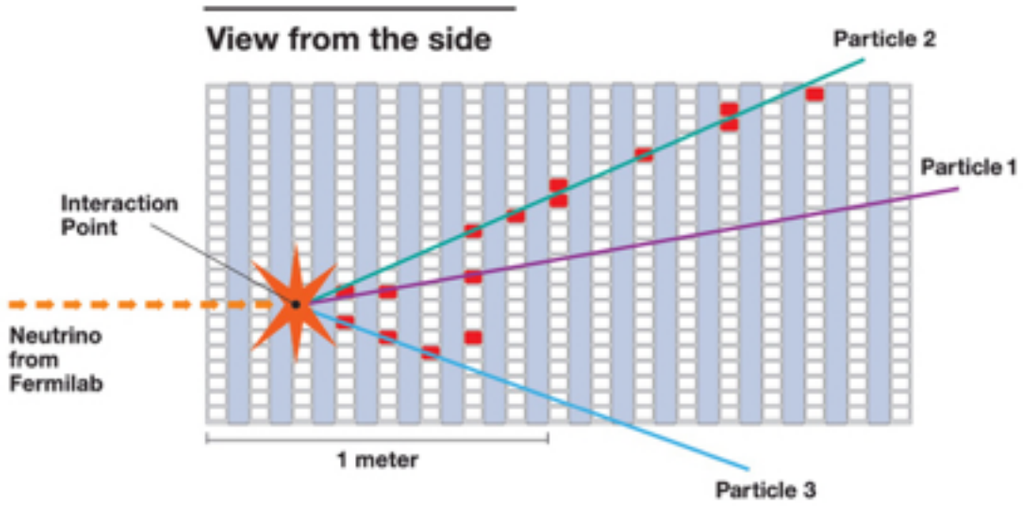




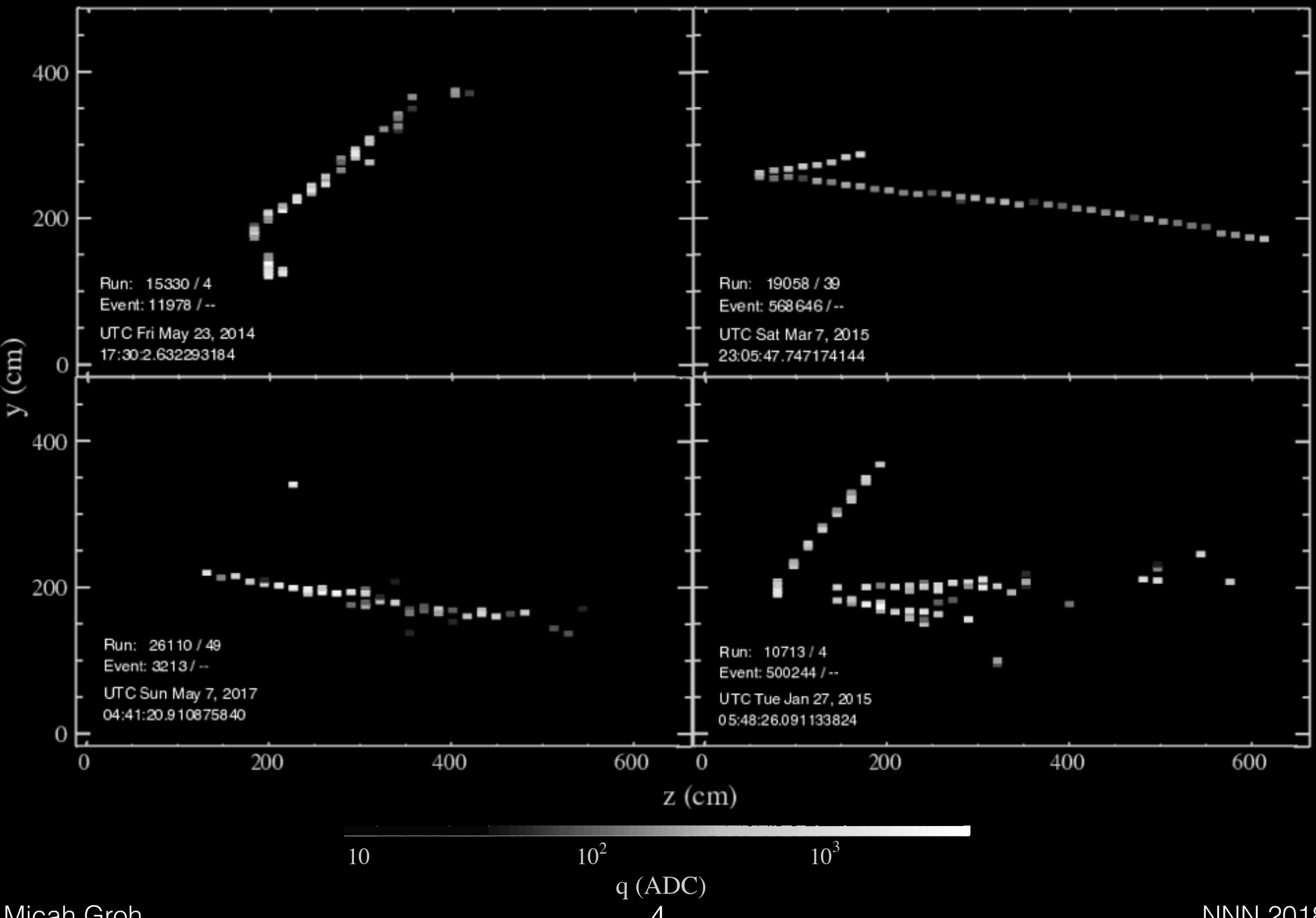
Both detectors are functionally equivalent sampling calorimeters.

Detect scintillation light from charged particles.

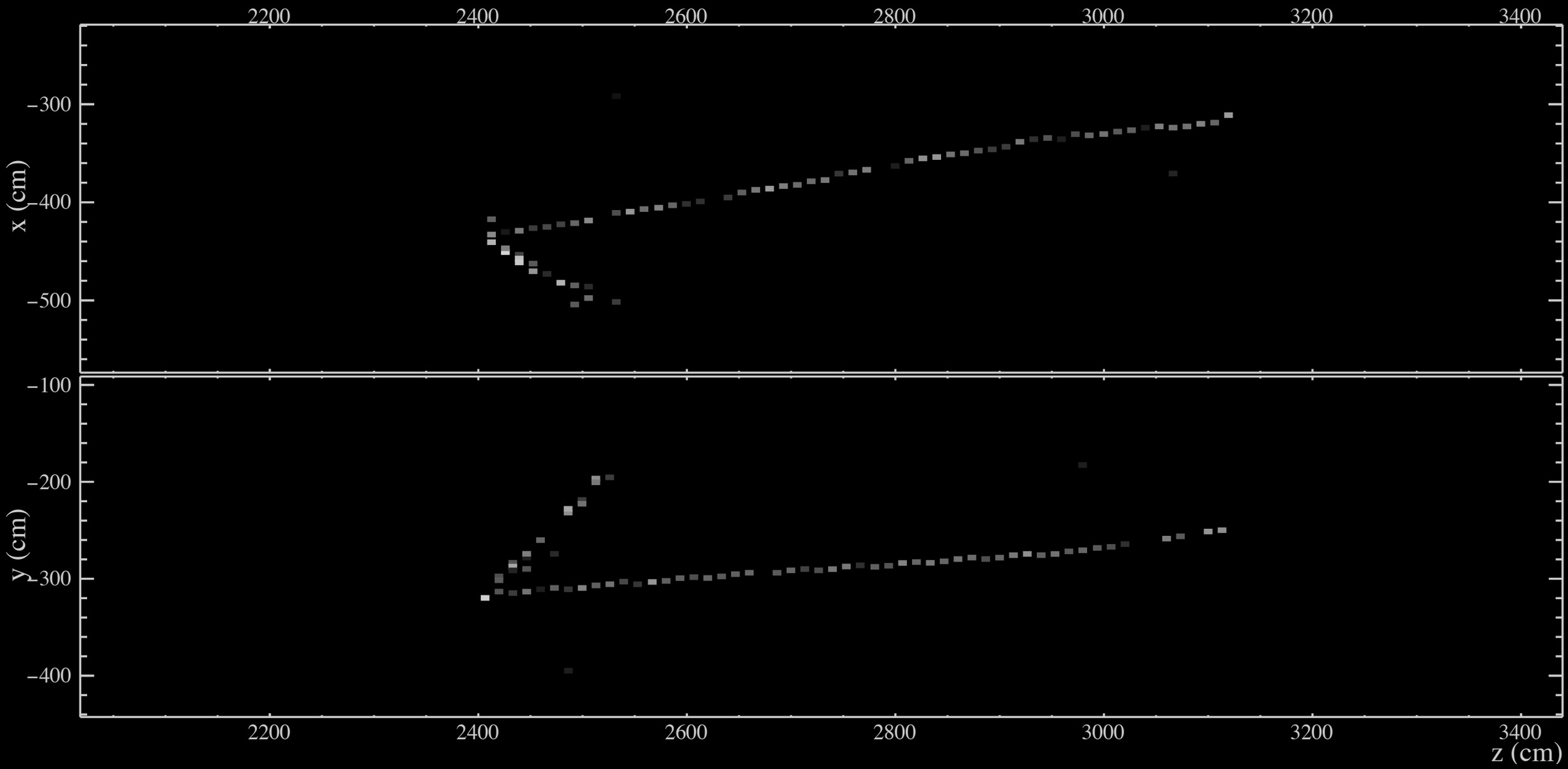




Signature Data Events



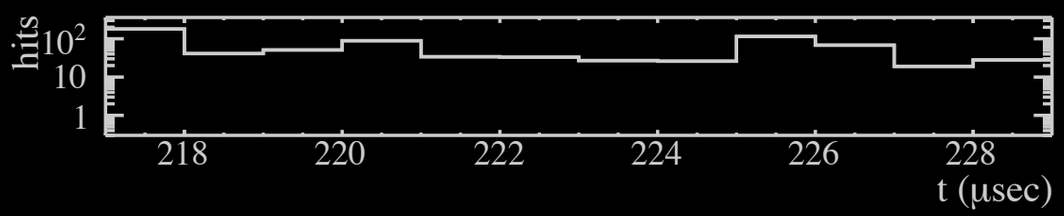
NOvA Events

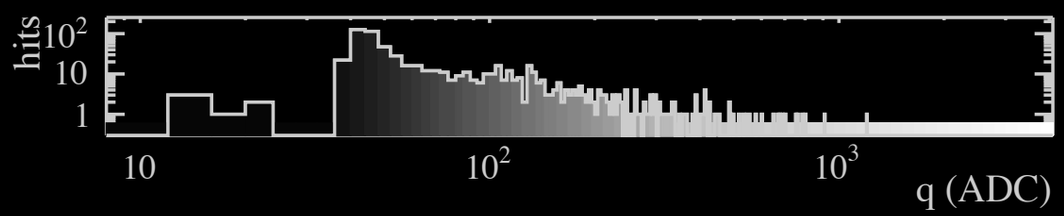


NOvA - FNAL E929

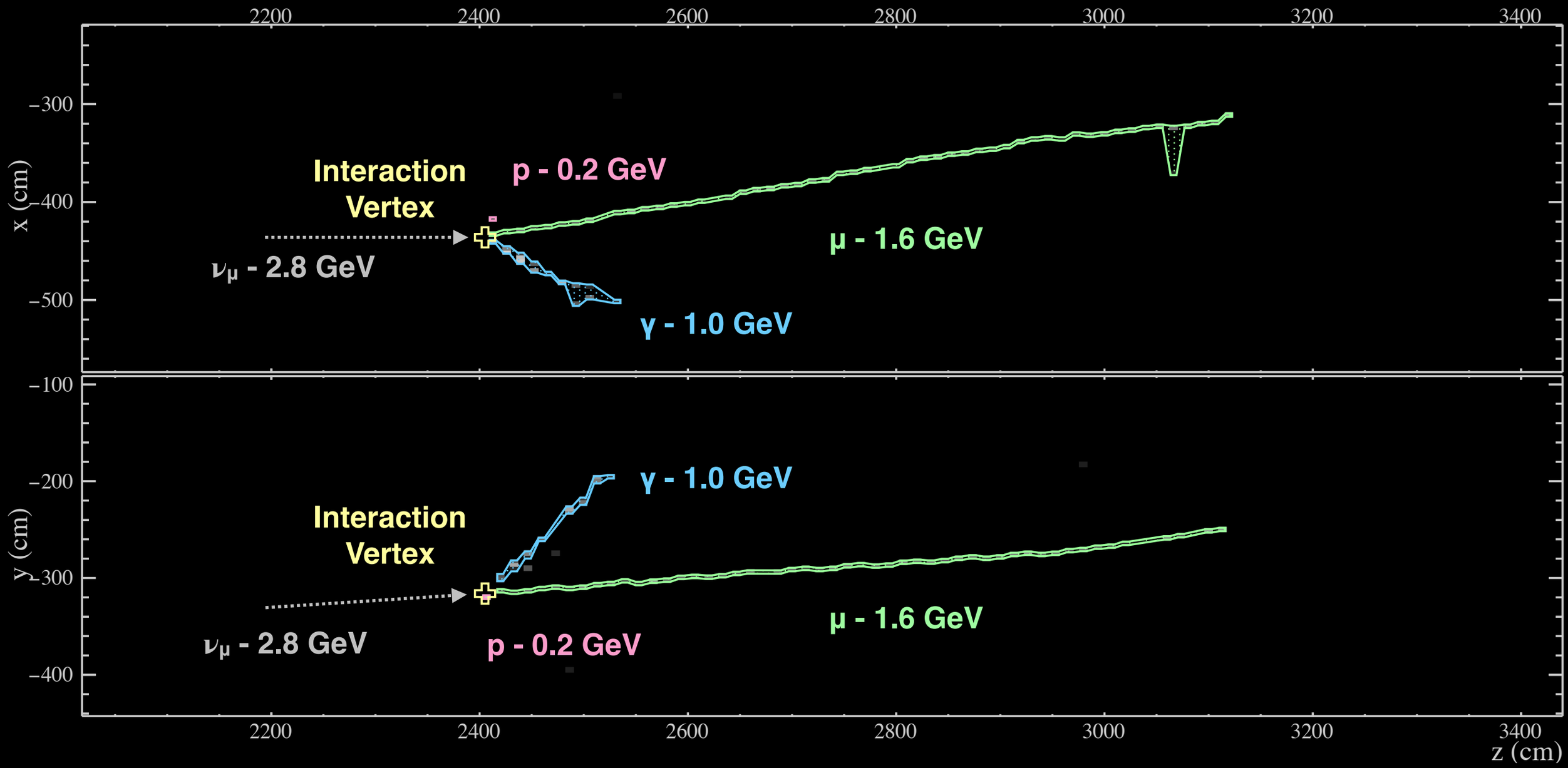
Run: 14828 / 38
Event: 192569 / --

UTC Tue Apr 22, 2014
21:41:51.422846016





Reconstruction



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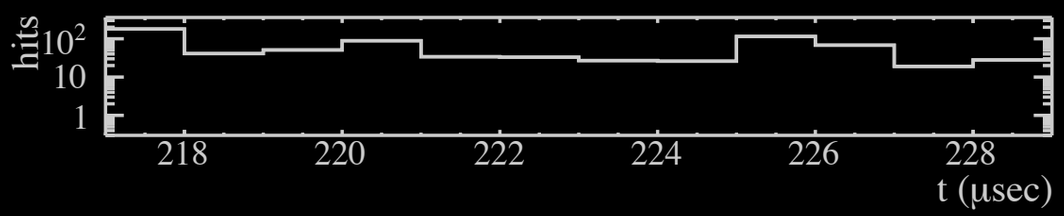
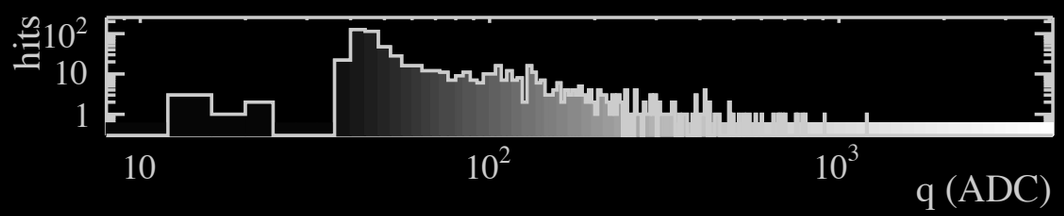
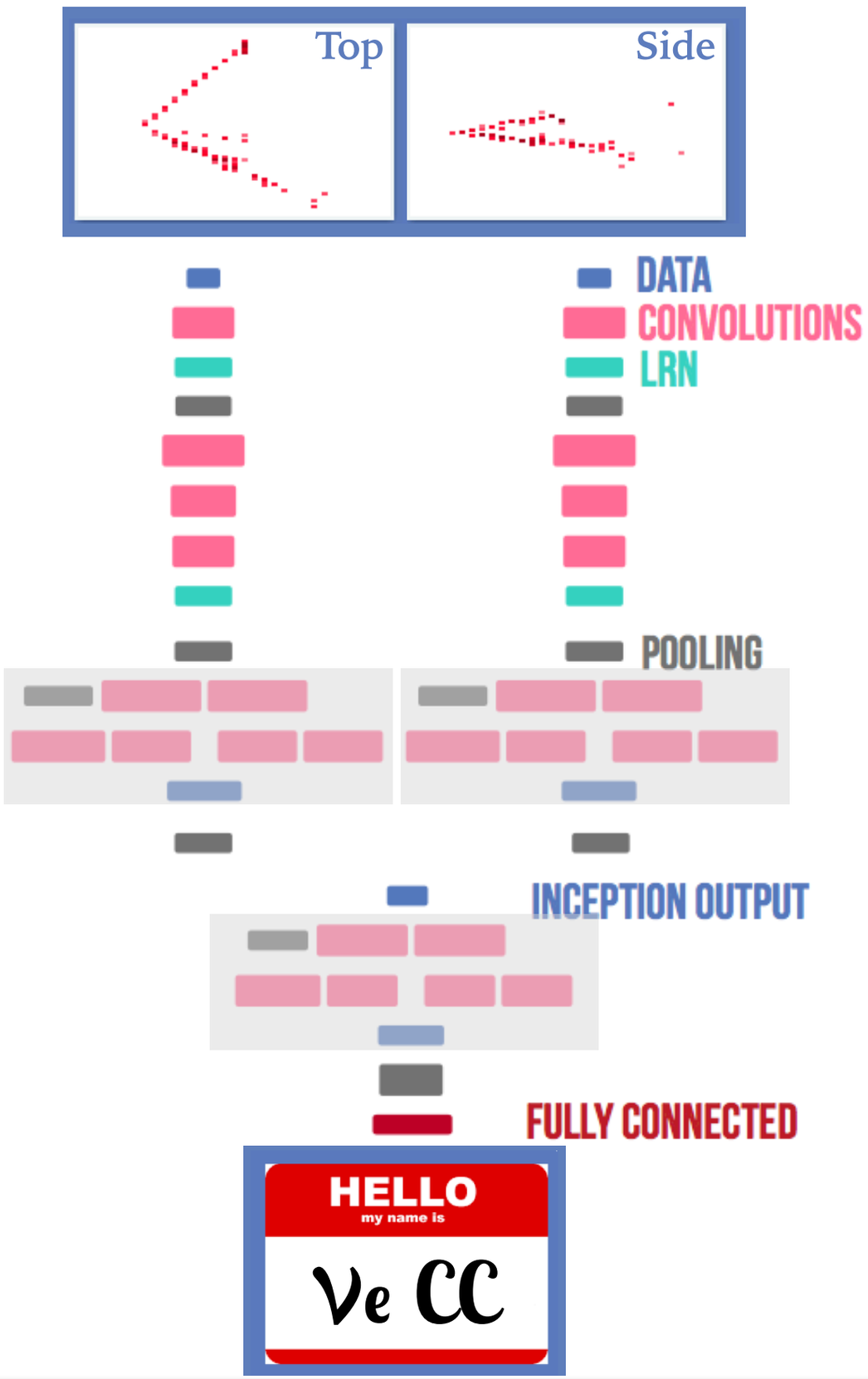




Event Classification



Classify neutrino events using two tower network, **Convolutional Visual Network**, based on googlenet.

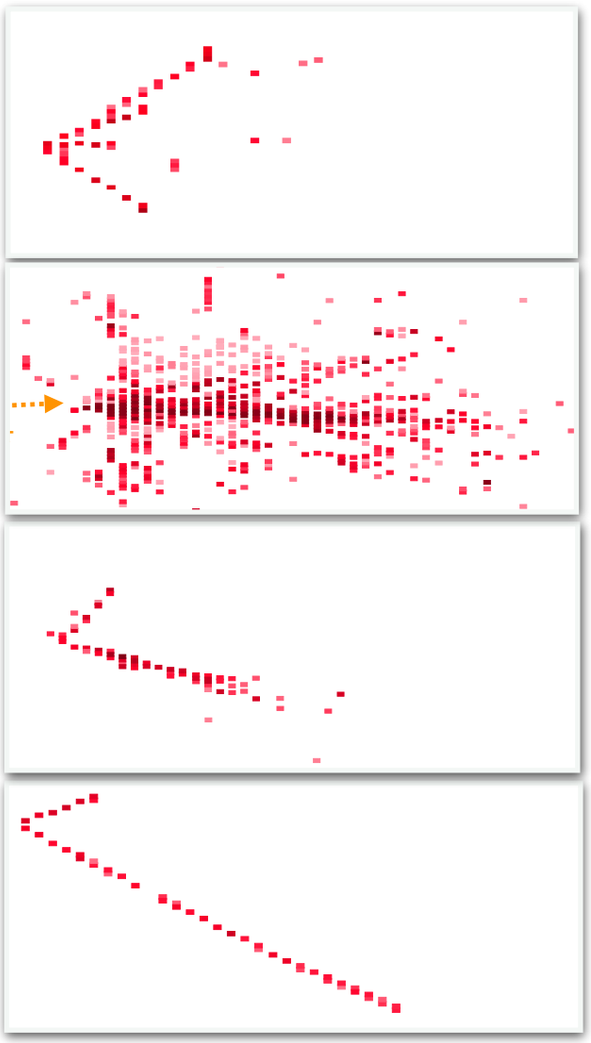
Each view of the event is examined separately for most of feature extraction.

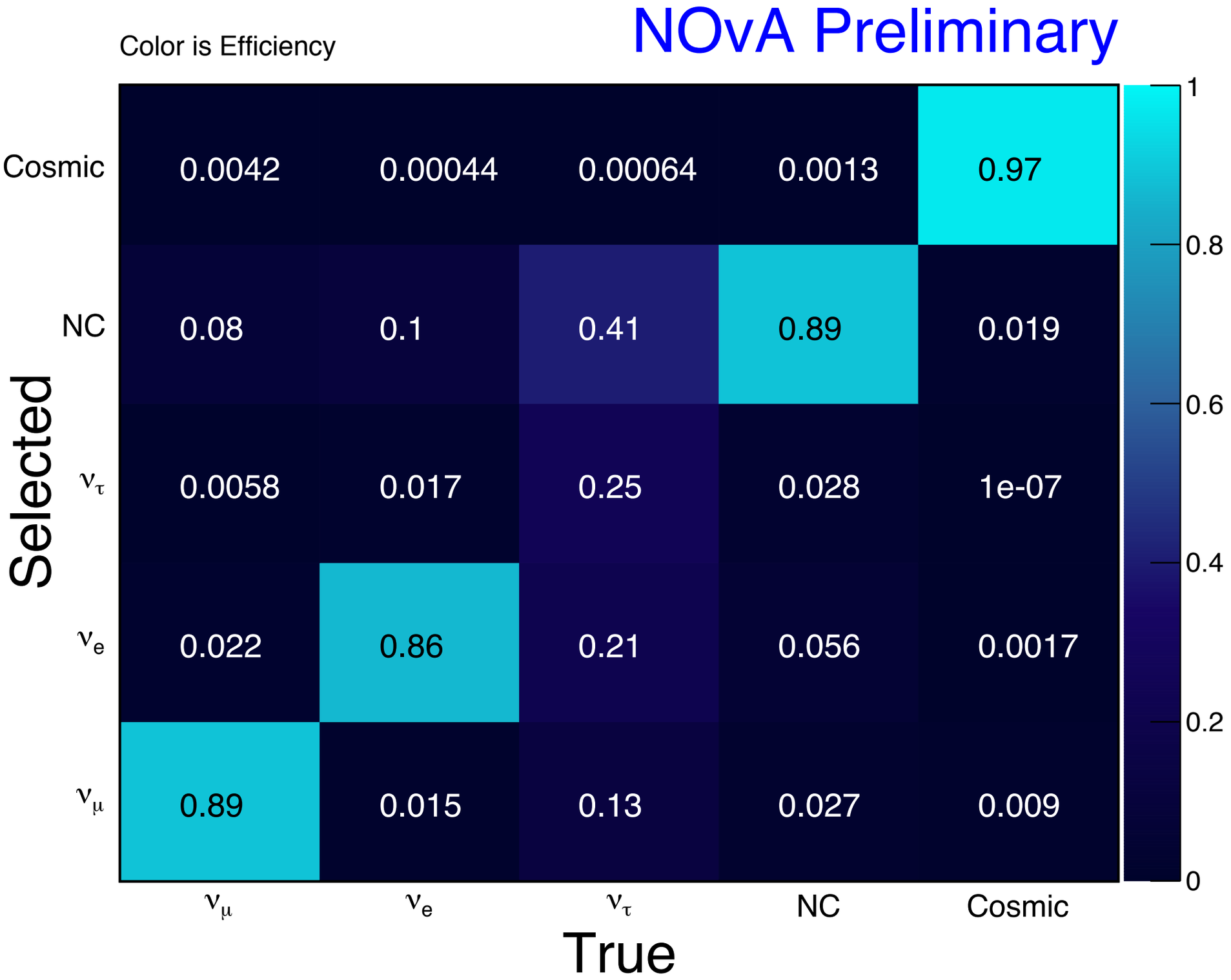
NOvA was the first experiment to apply CNNs to a HEP result in its 2016 analysis.

Yielded an effective **30%** increase in exposure.

Aurisano et al., "A Convolutional Neural Network Neutrino Event Classifier", JINST 11, P09001 (2016).

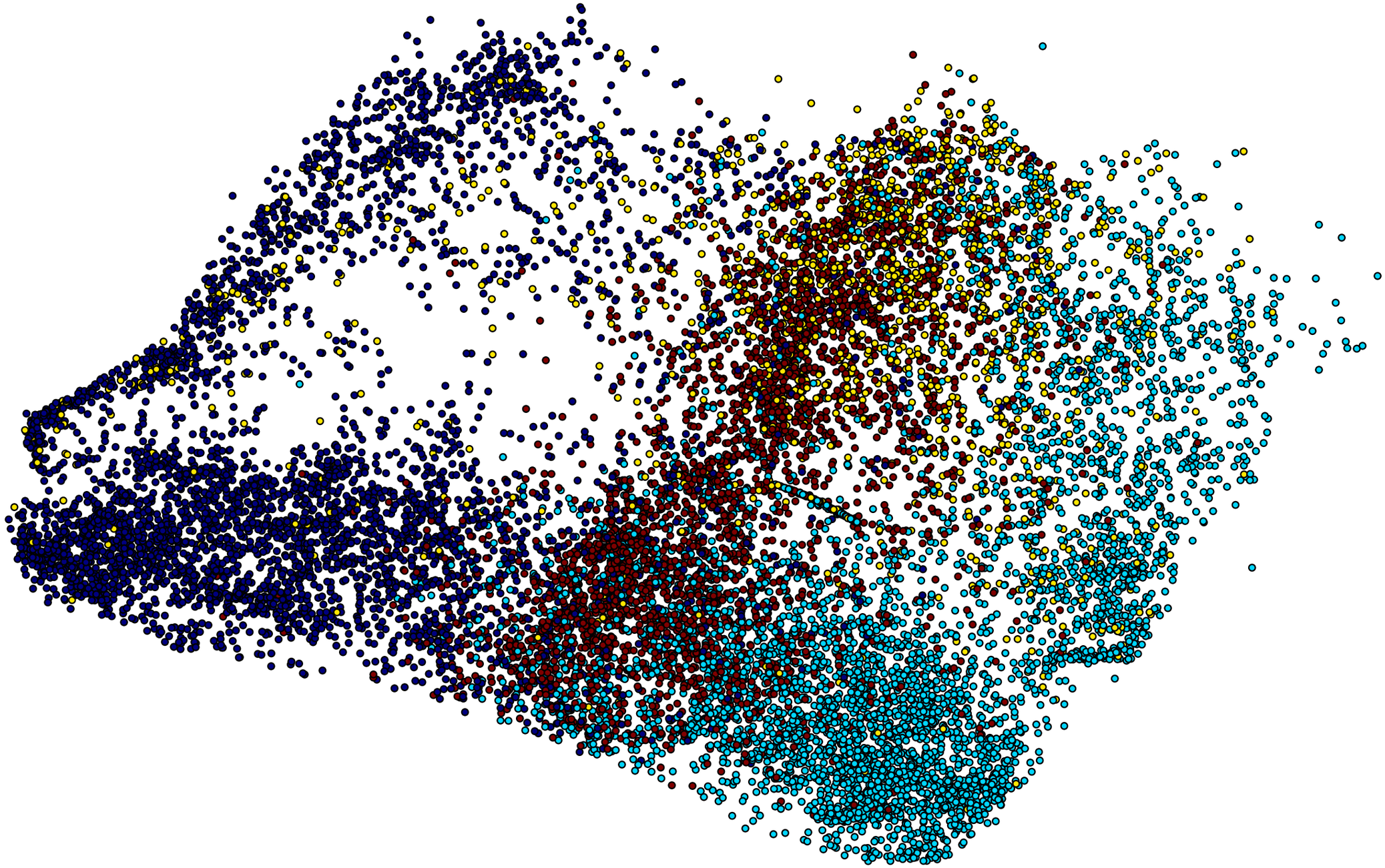
Event Classification





t-SNE

t-Distributed Stochastic Neighbor Embedding

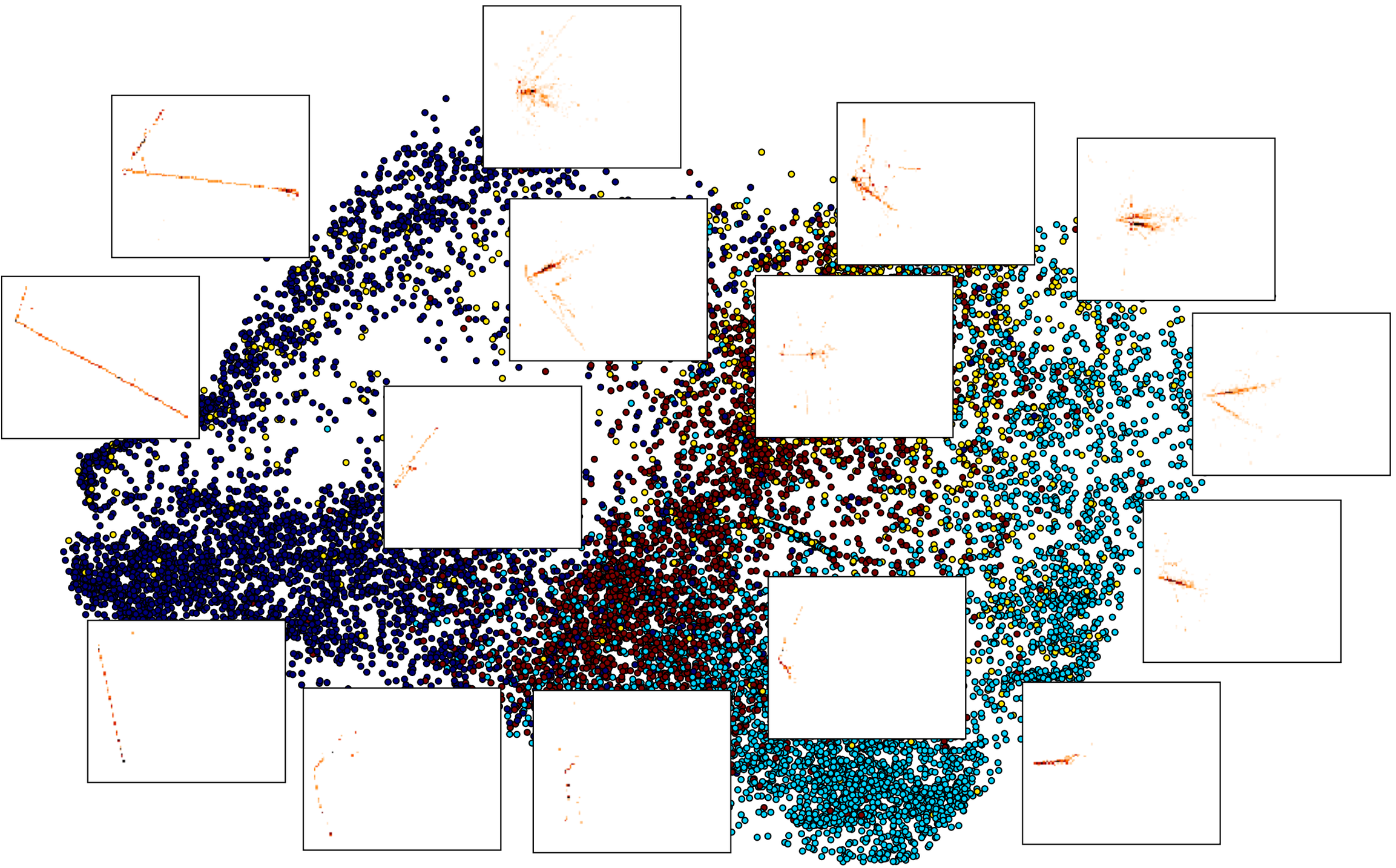


https://indico.io/blog/visualizing-with-t-sne/

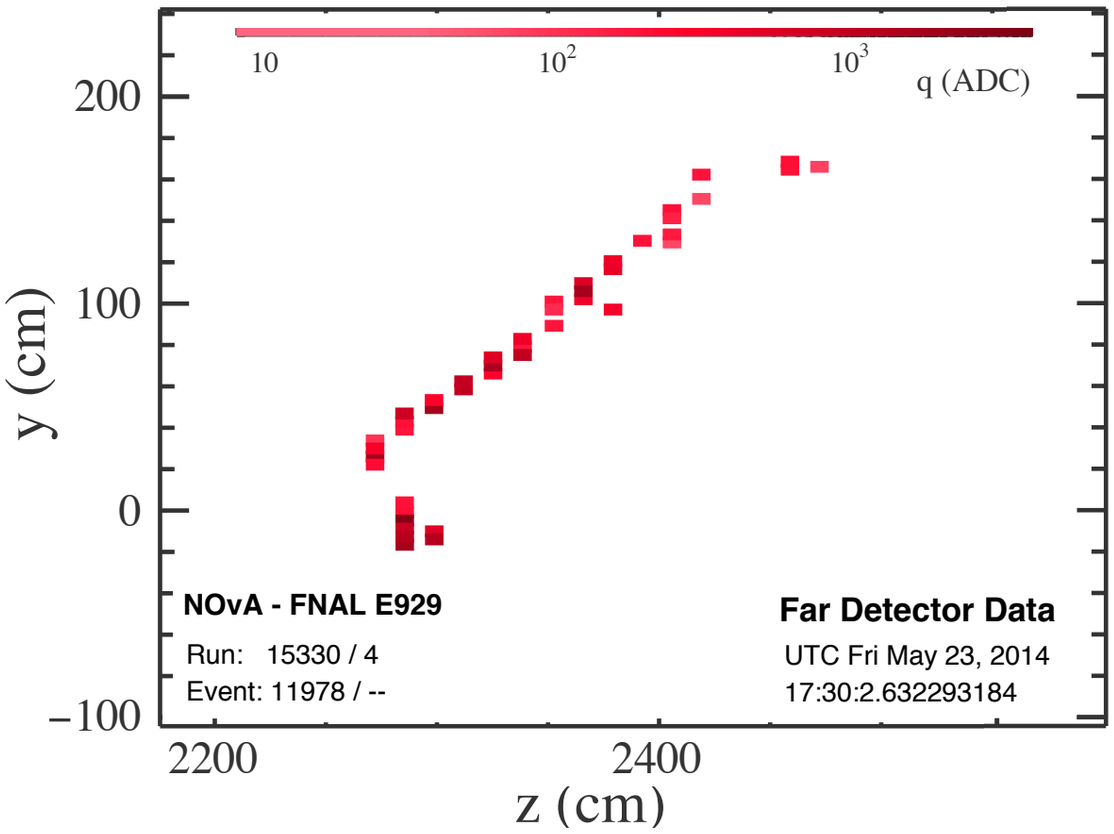
https://www.nature.com/articles/s41586-018-0361-2

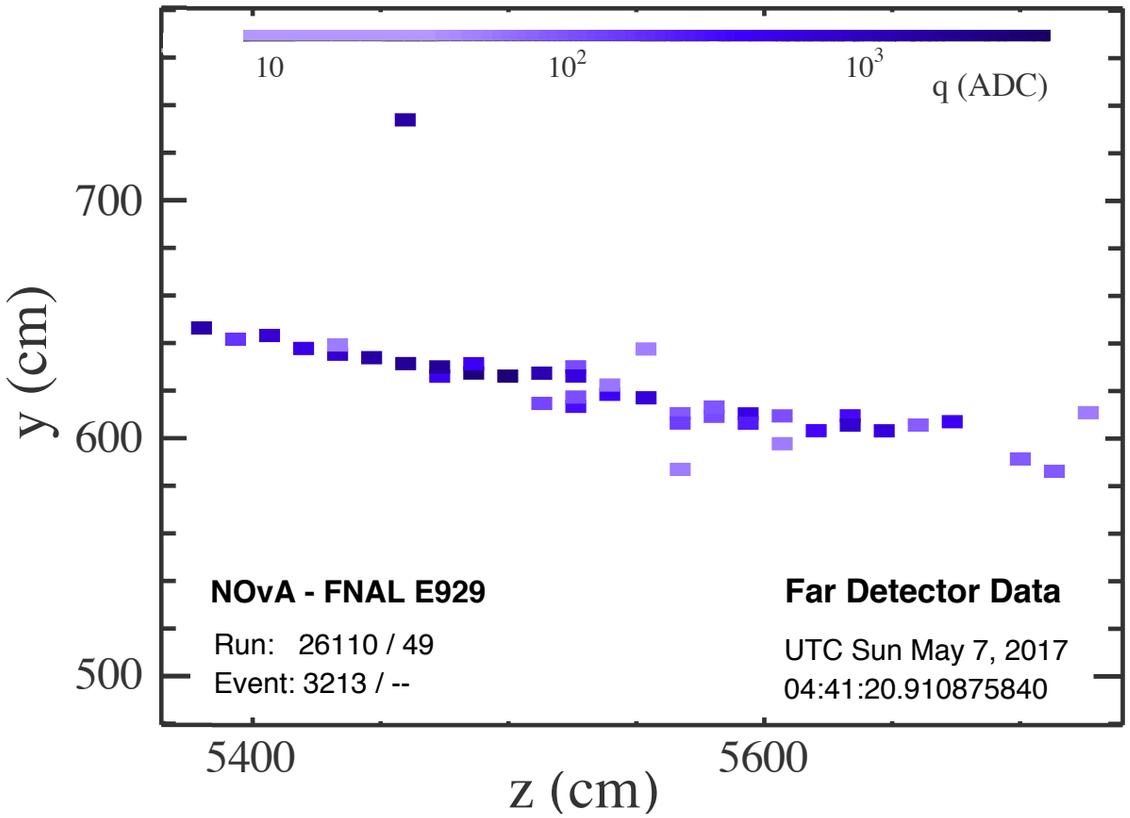
t-SNE

Example Event Topologies

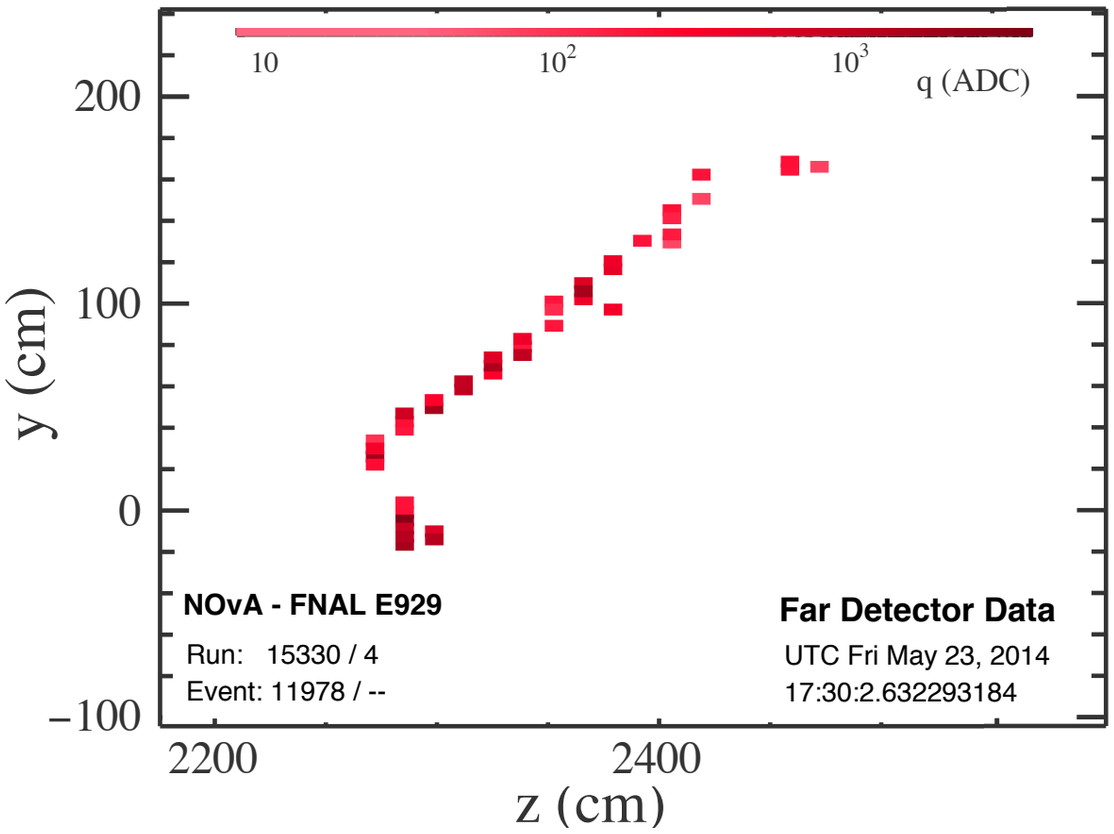


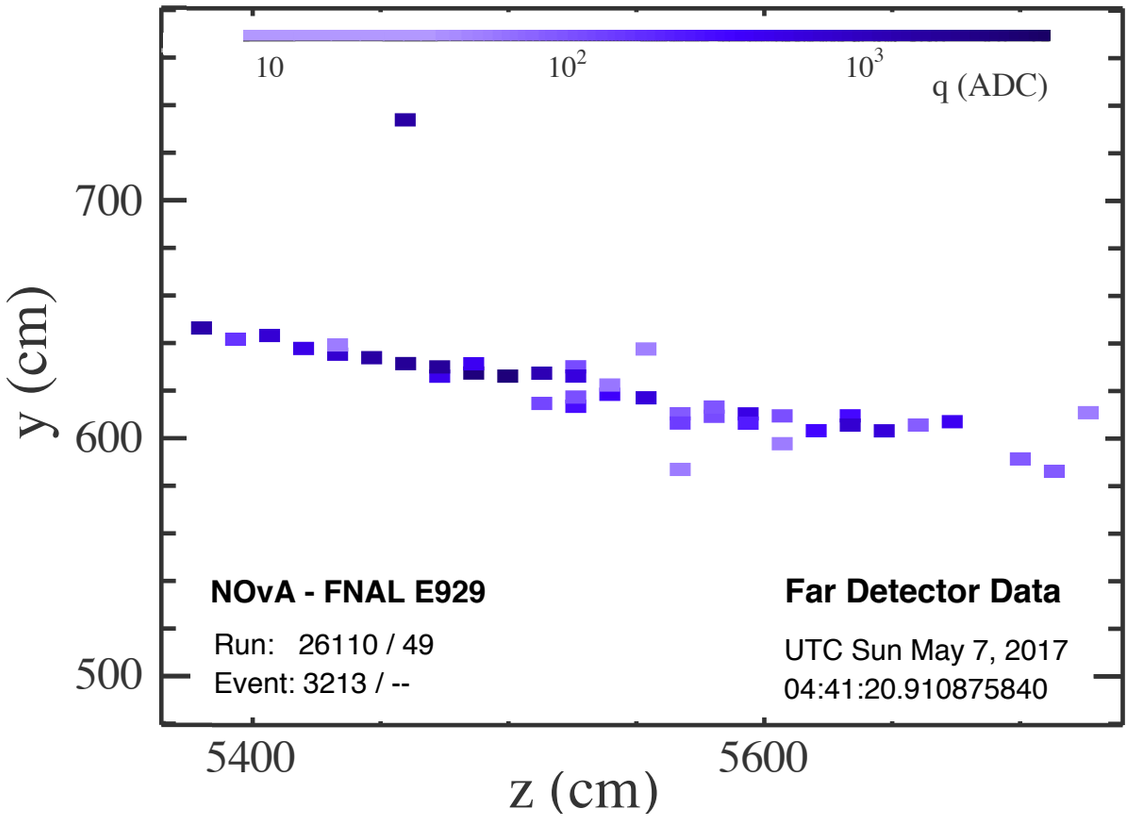
Neutrinos and Anti-Neutrinos





Neutrinos and Anti-Neutrinos



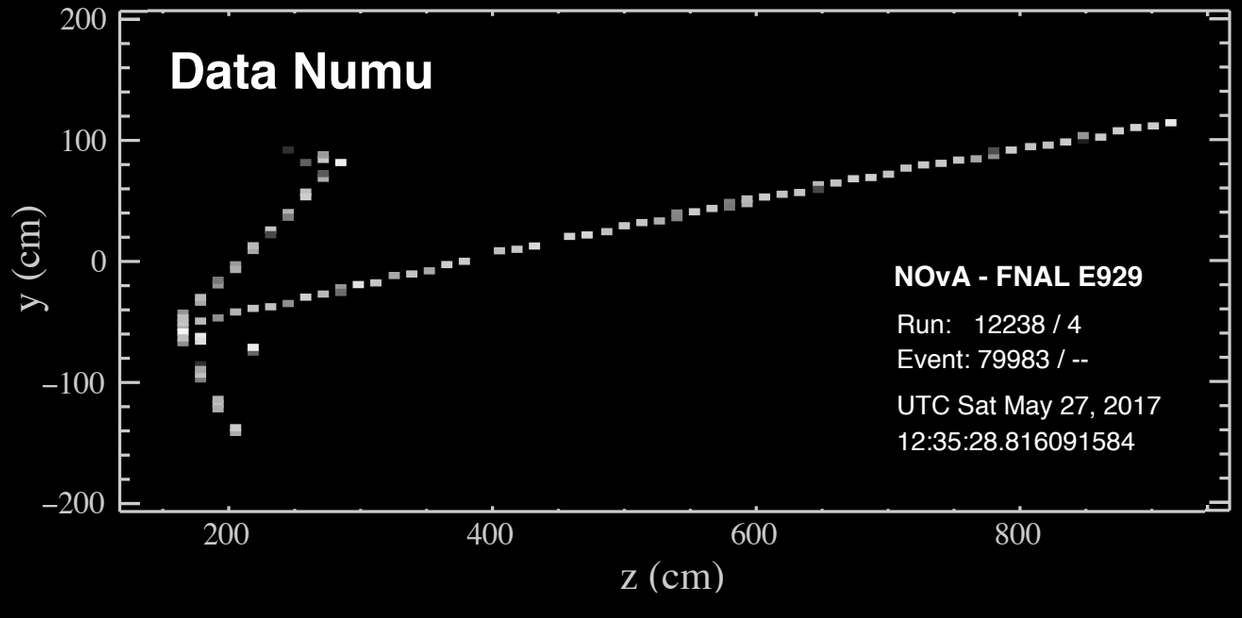


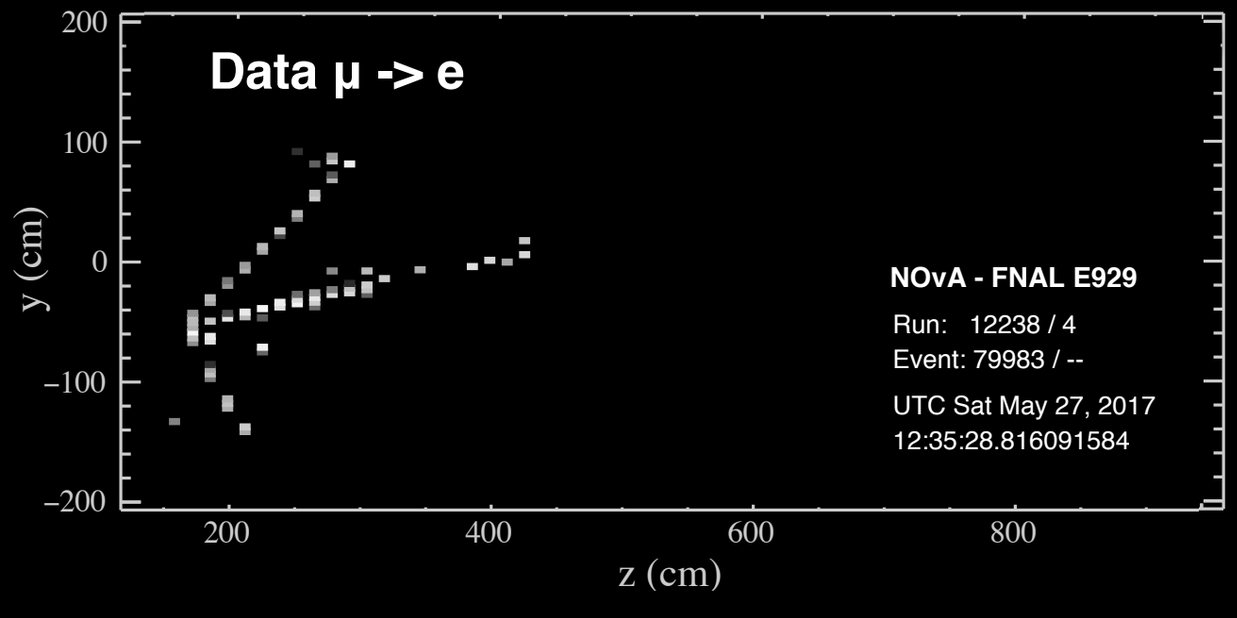
Train on **neutrino** beam and **anti-neutrino** beams separately.

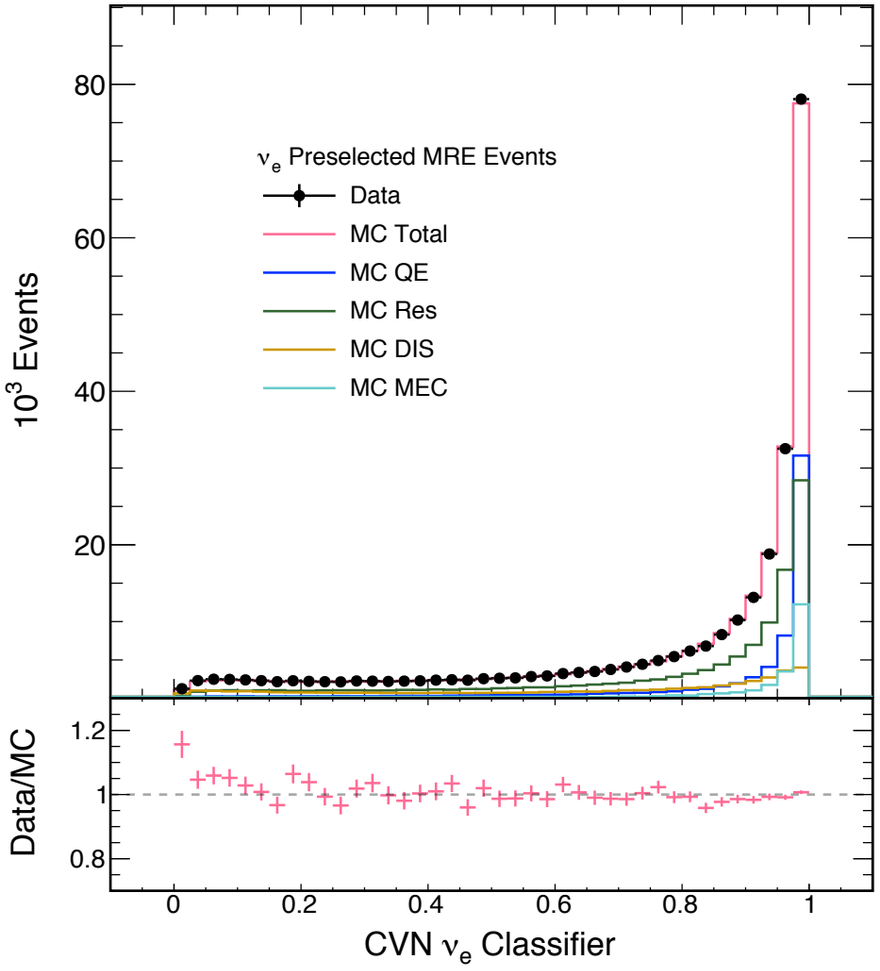
Utilize differences in event topology.

$\bar{\nu}$ **Efficiency Improvement** Training Sample (ID > 0.9)		
$\bar{\nu}_e$ CC Signal	$\bar{\nu}_\mu$ CC Signal	$\bar{\nu}$ NC Signal
14%	6%	10%

Example Data Check: MRE







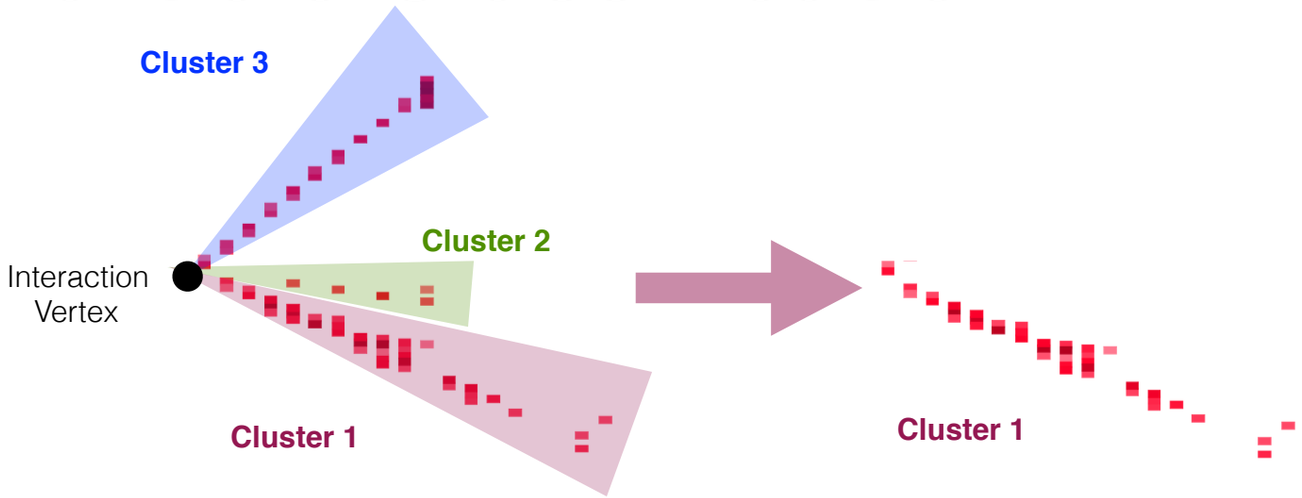
Muon Removed - Electron Added:

Select a muon neutrino interaction.

Remove the muon hits and replace with a simulated electron.

	Pre Selection	Full Selection	Efficiency
Data Events	486083	316009	0.6501
MC Events	511287	341119	0.6672

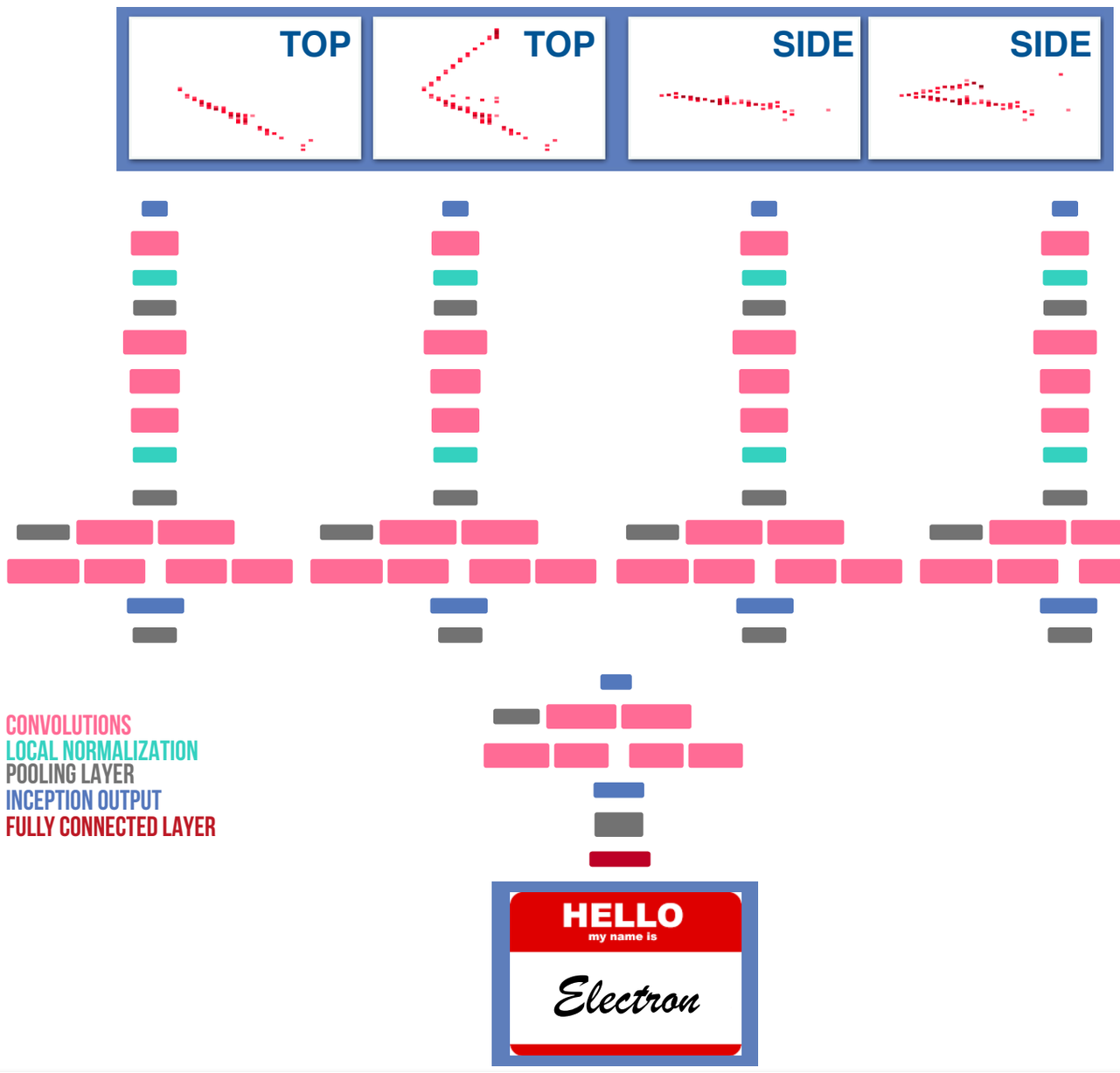
Particle Classification



Single particles are currently separated using geometric reconstruction methods.

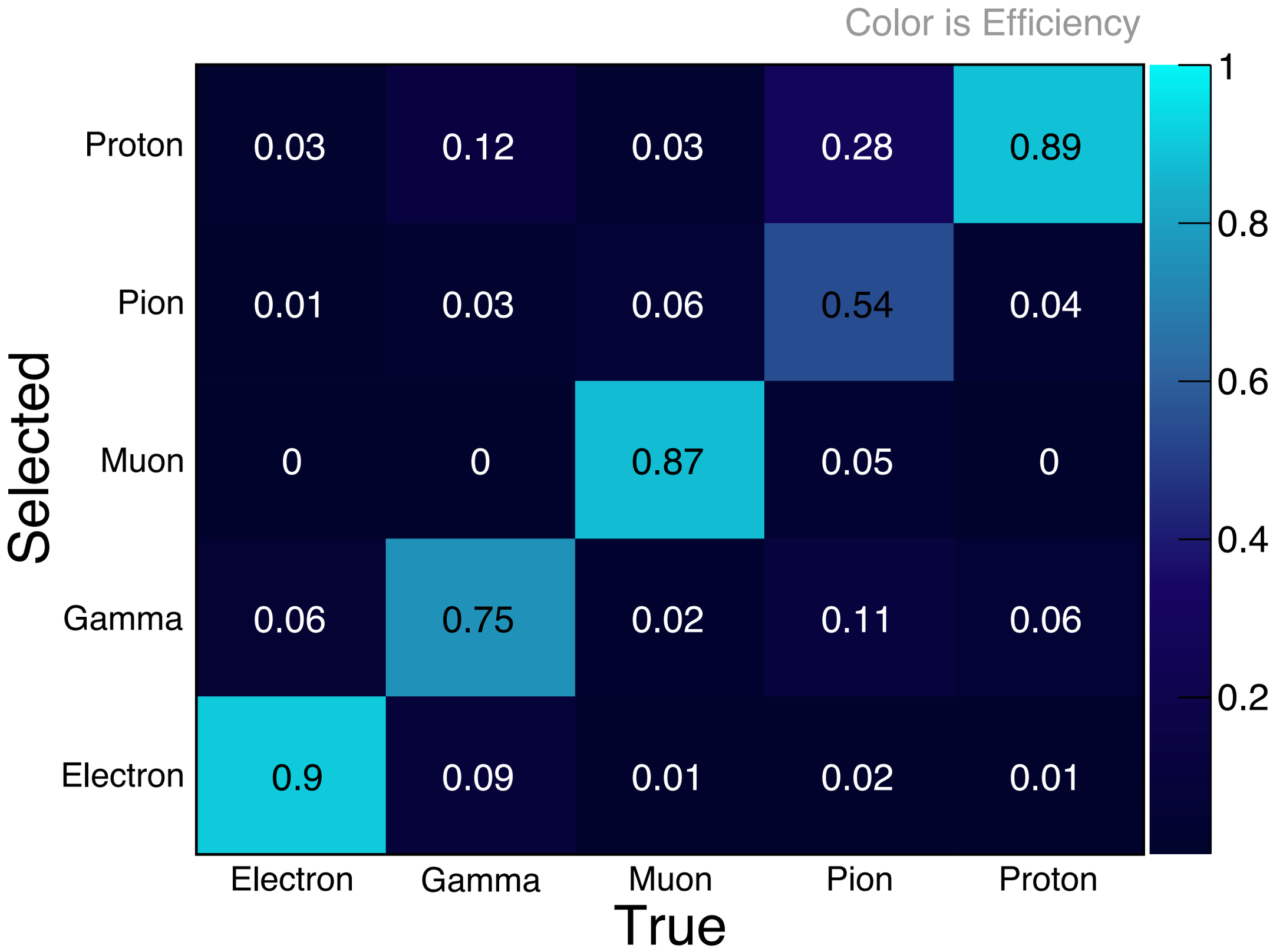
Classify particles using both views of the **particle** and both views of the entire **event**.

This shows the network **contextual information** about single particles.



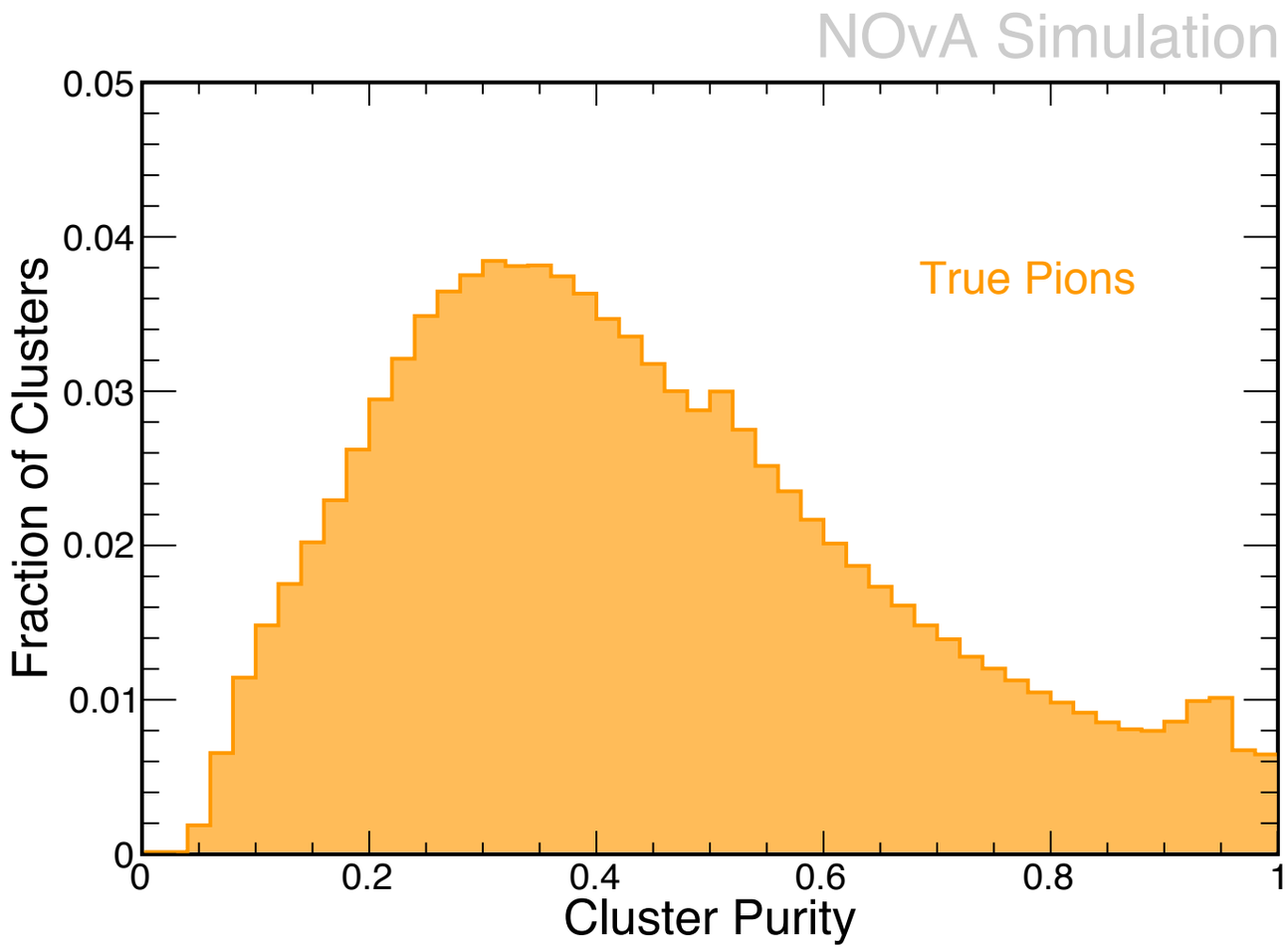
Paper in preparation.

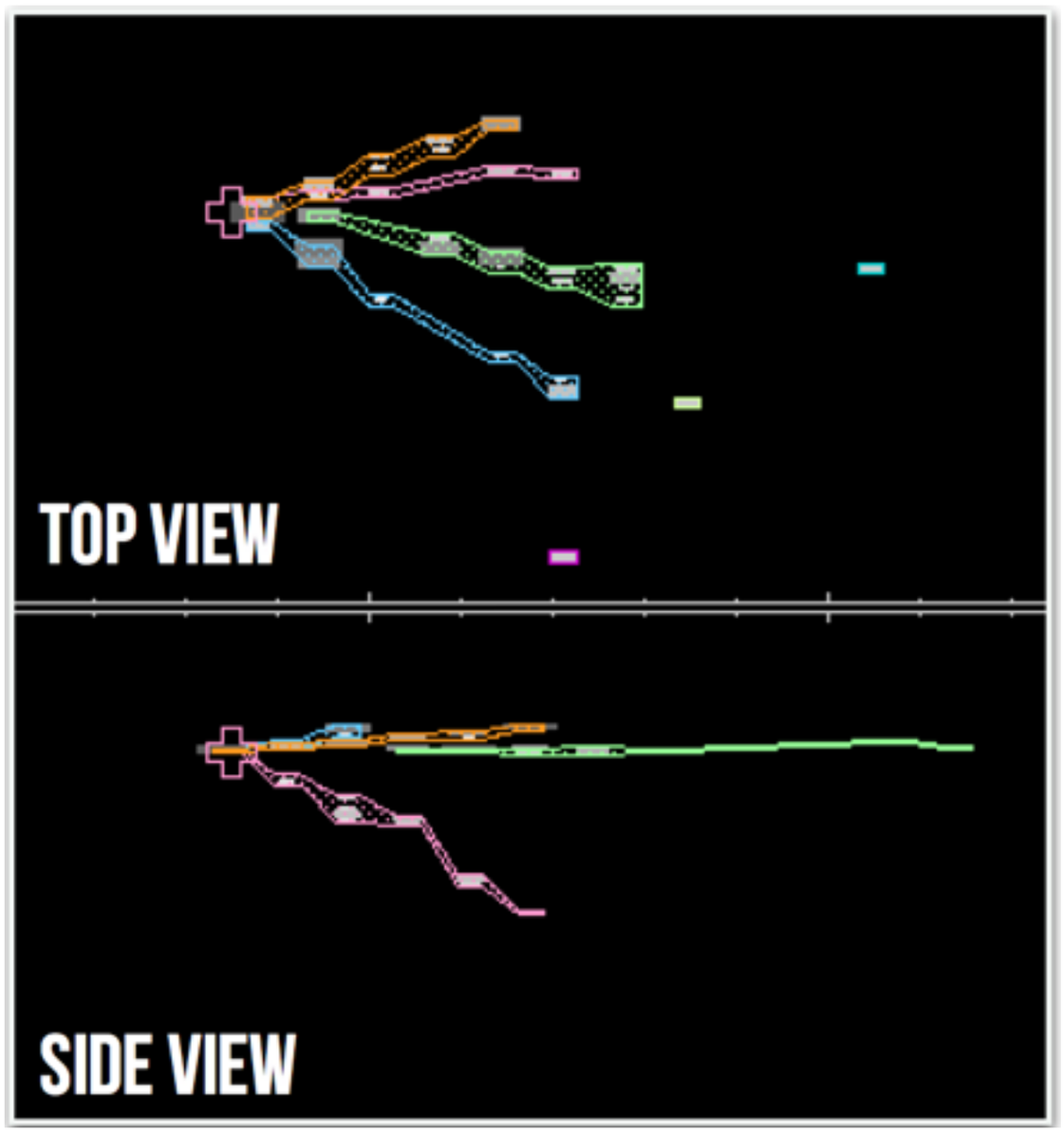
Particle Classification



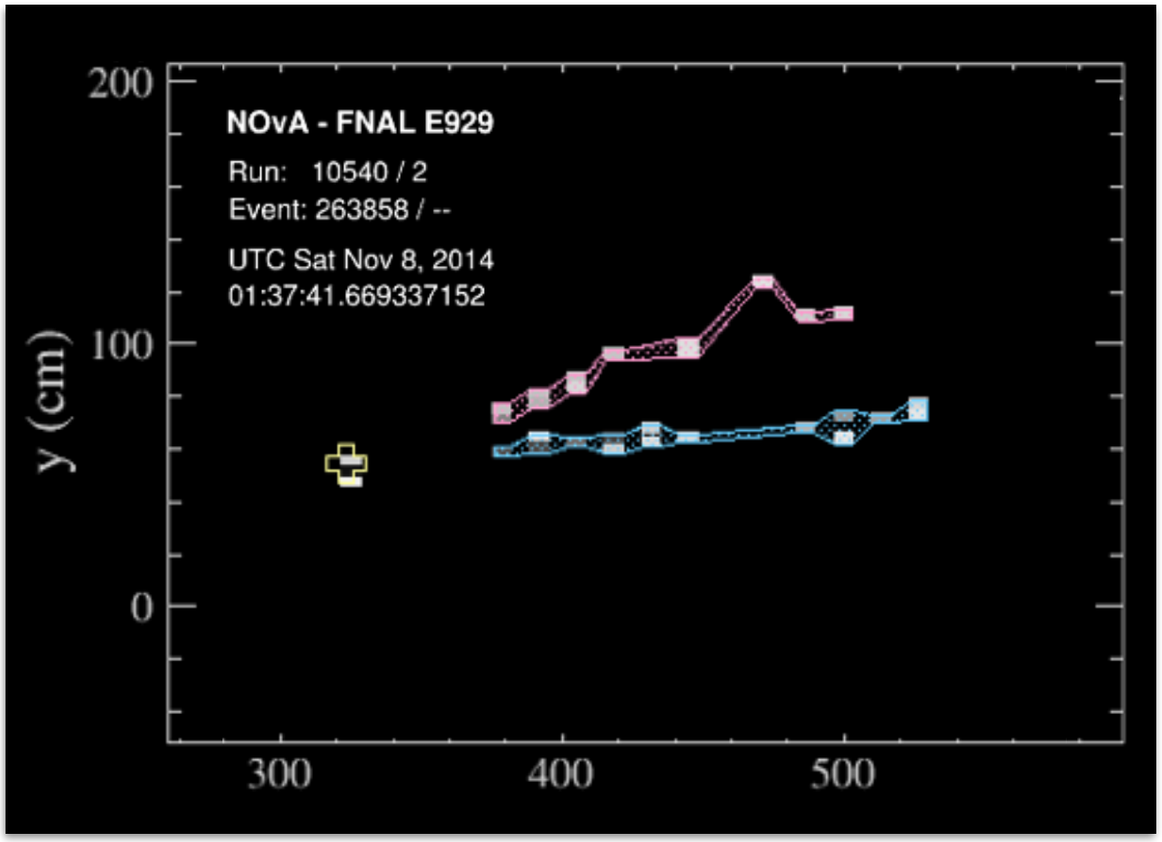
Reconstruction Caveats

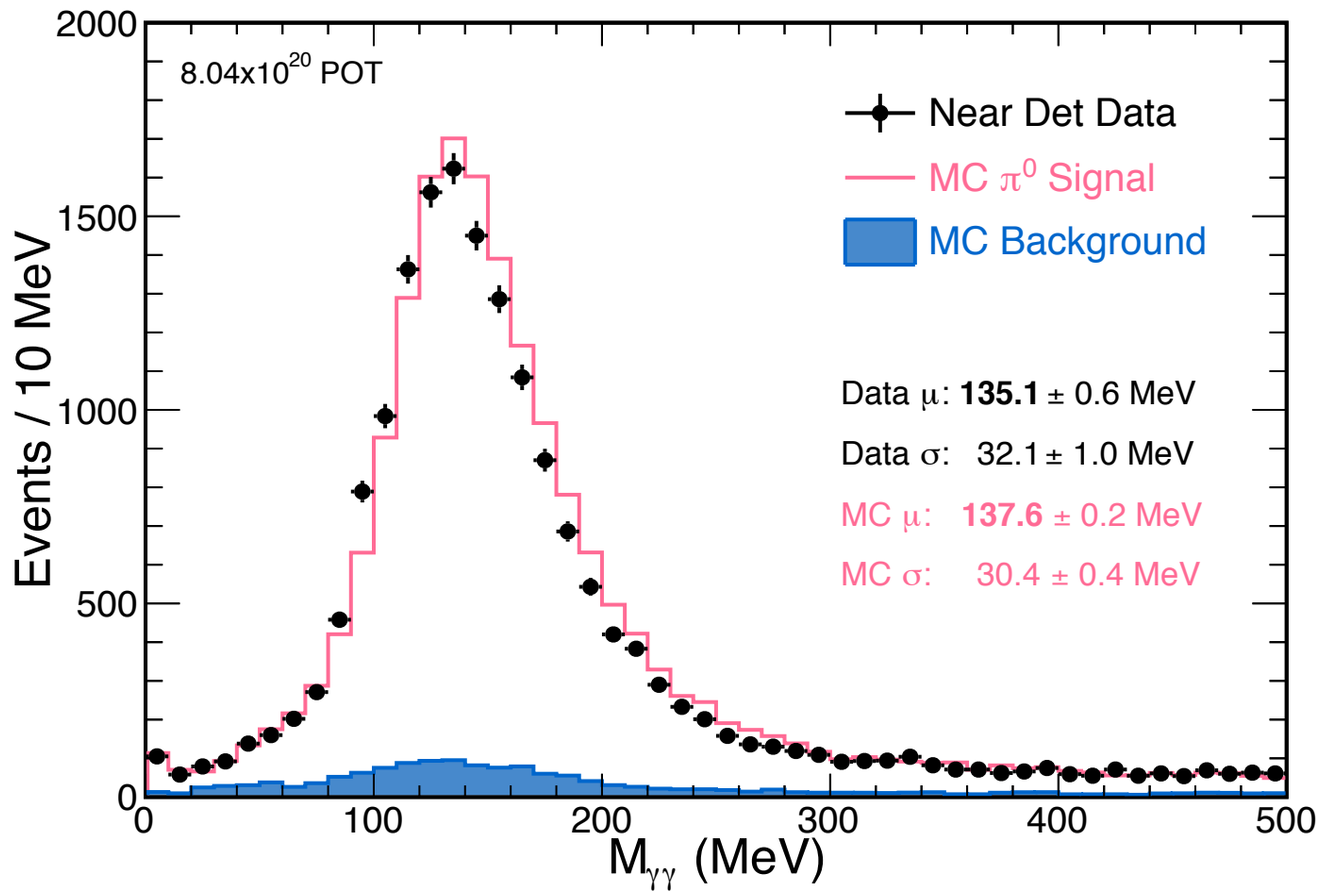
Single particle classifier is dependent on the quality of the already existing clusters.





Example Data Check: π^0 Mass Peak





π^0 mass reconstructed using invariant mass of pairs of photons identified using the single particle classifier.

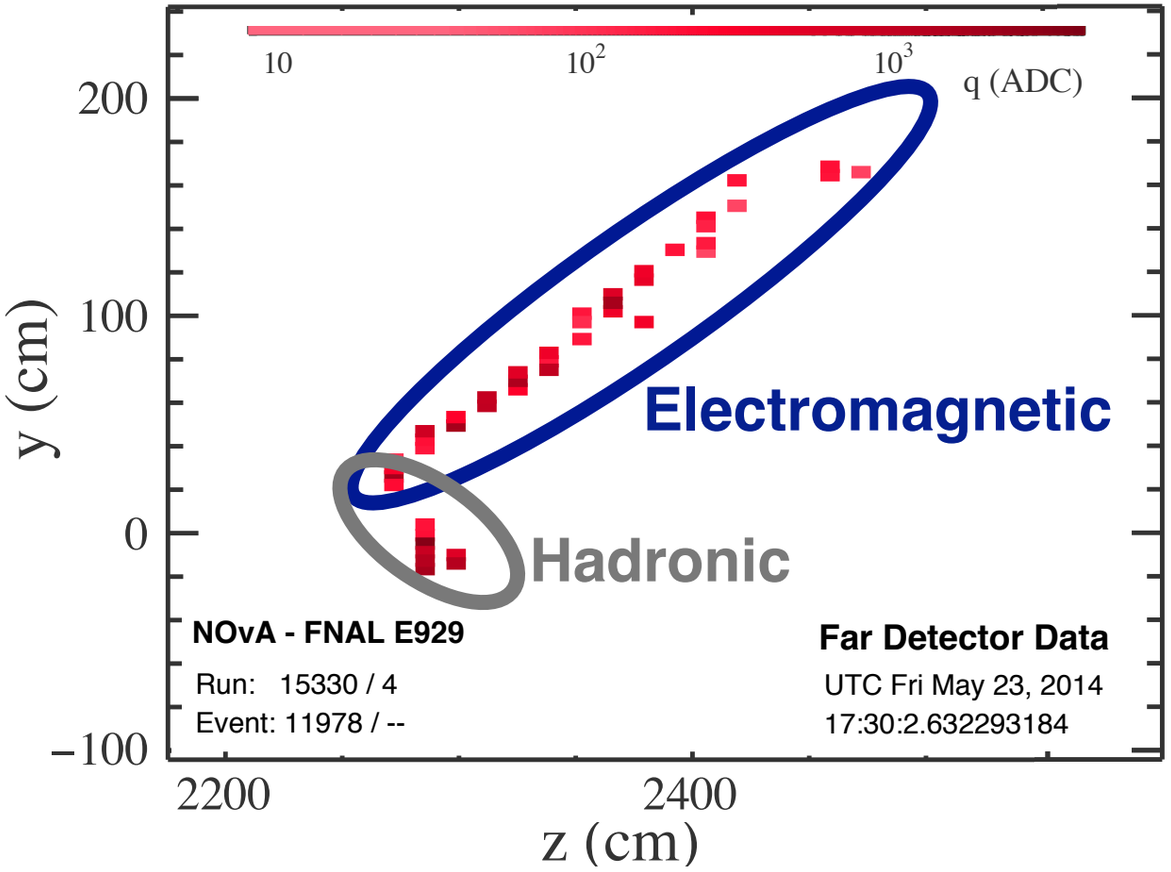
Shows a 60% reduction in backgrounds over previous techniques.

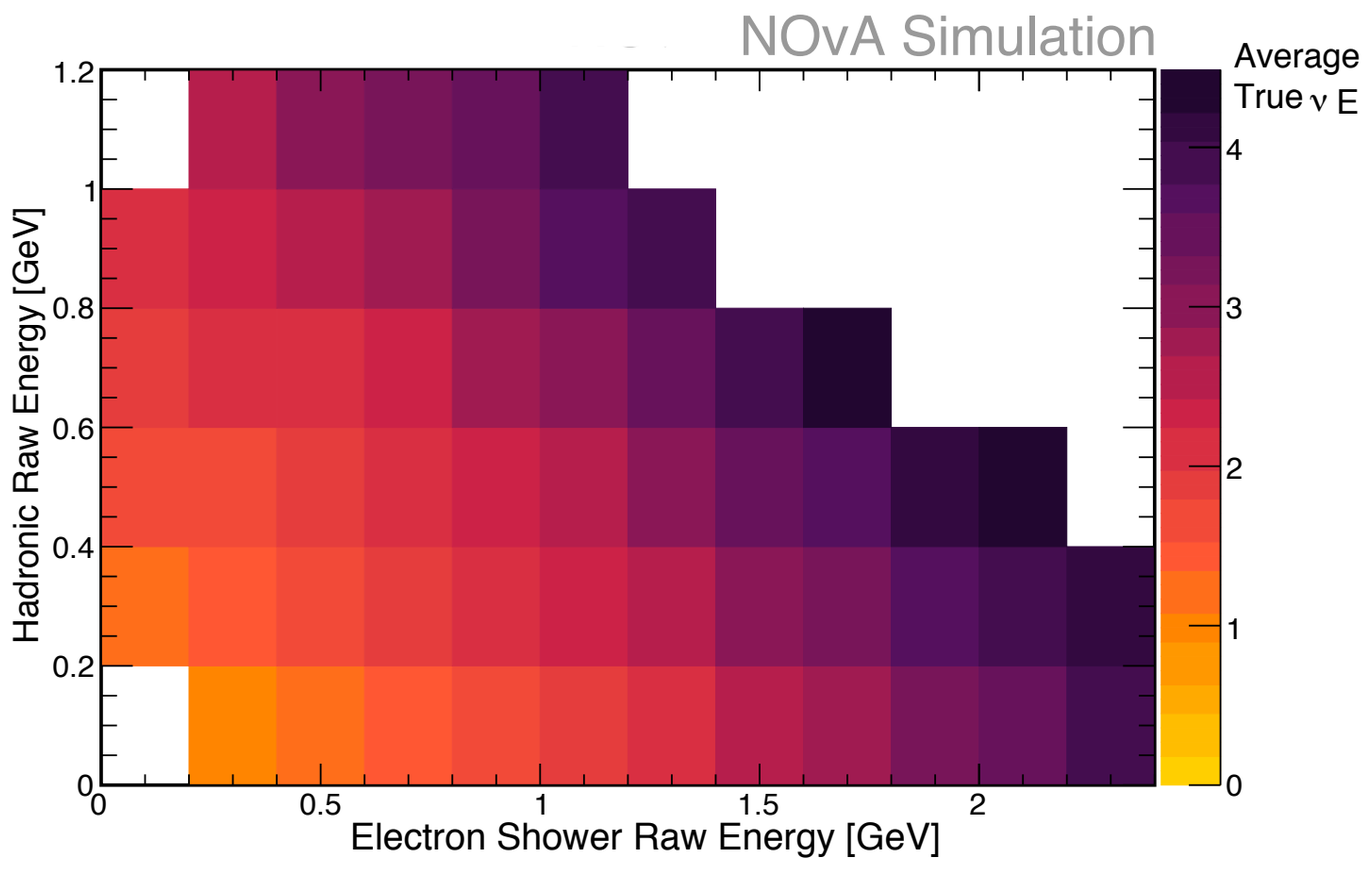
Energy Estimation

Each cluster is identified as hadronic or electromagnetic.

This method shows an energy resolution of 11%.

$$E_{reco} = f(E_{EM}, E_{had})$$





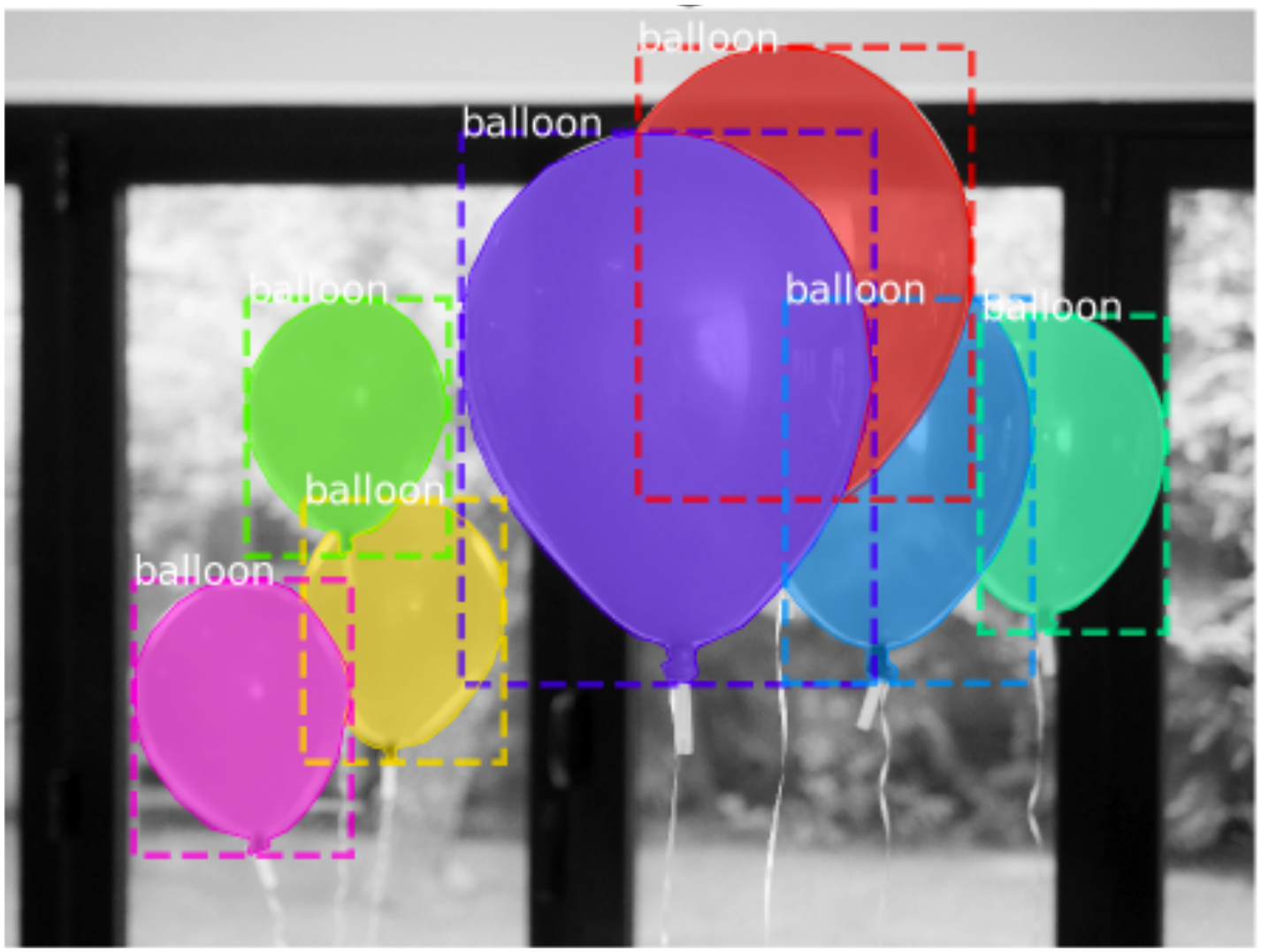
Full Event Reconstruction

Cluster and **classify** objects simultaneously using **instance aware semantic segmentation**.

Use machine learning to reconstruct an event **hit by hit**.

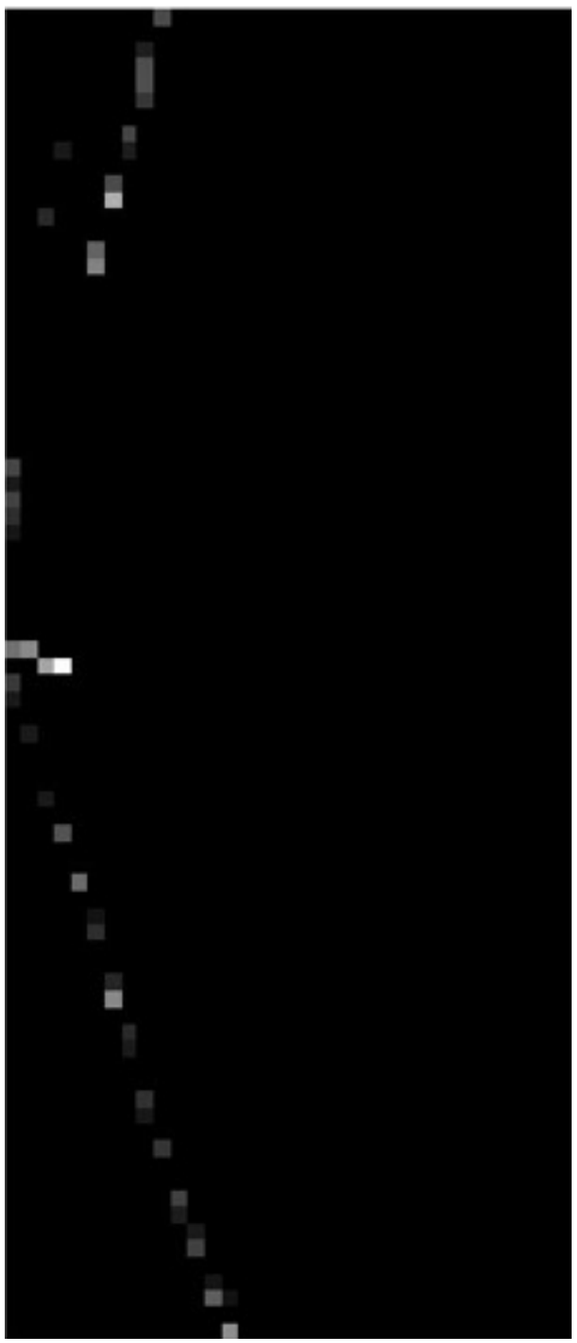
Three outputs:

1. **Bounds**
2. **ID Score**
3. **Clusters**



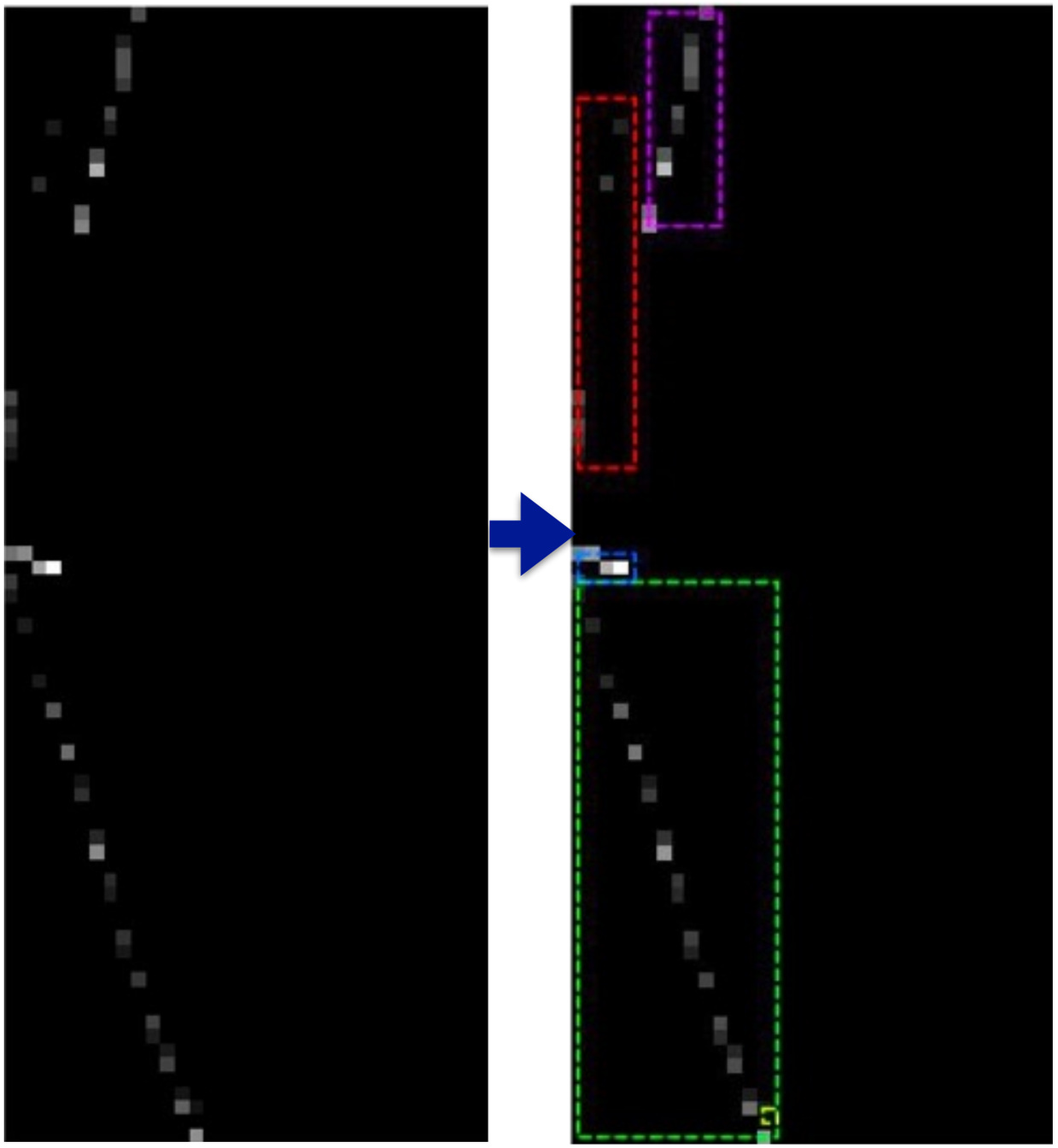
Using an implementation of Mask R-CNN:
K. He, G. Gkioxari, P. Dollar, and R. Girshick. Mask R-CNN. arXiv:1703.06870, 2017.

Full Event Reconstruction



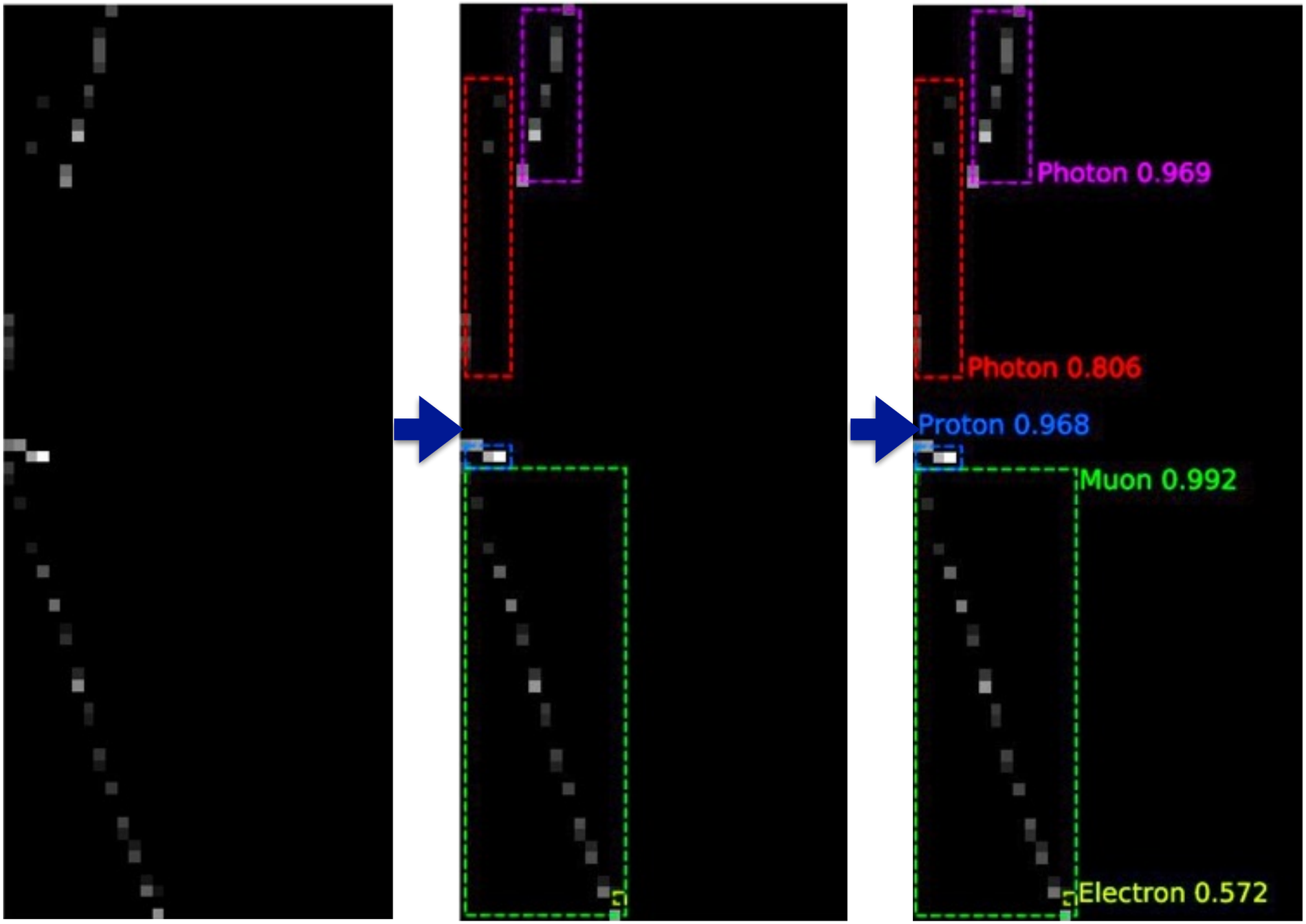
Full Event Reconstruction

Bounds - Look for individual particles within the event and construct bounding boxes containing each.



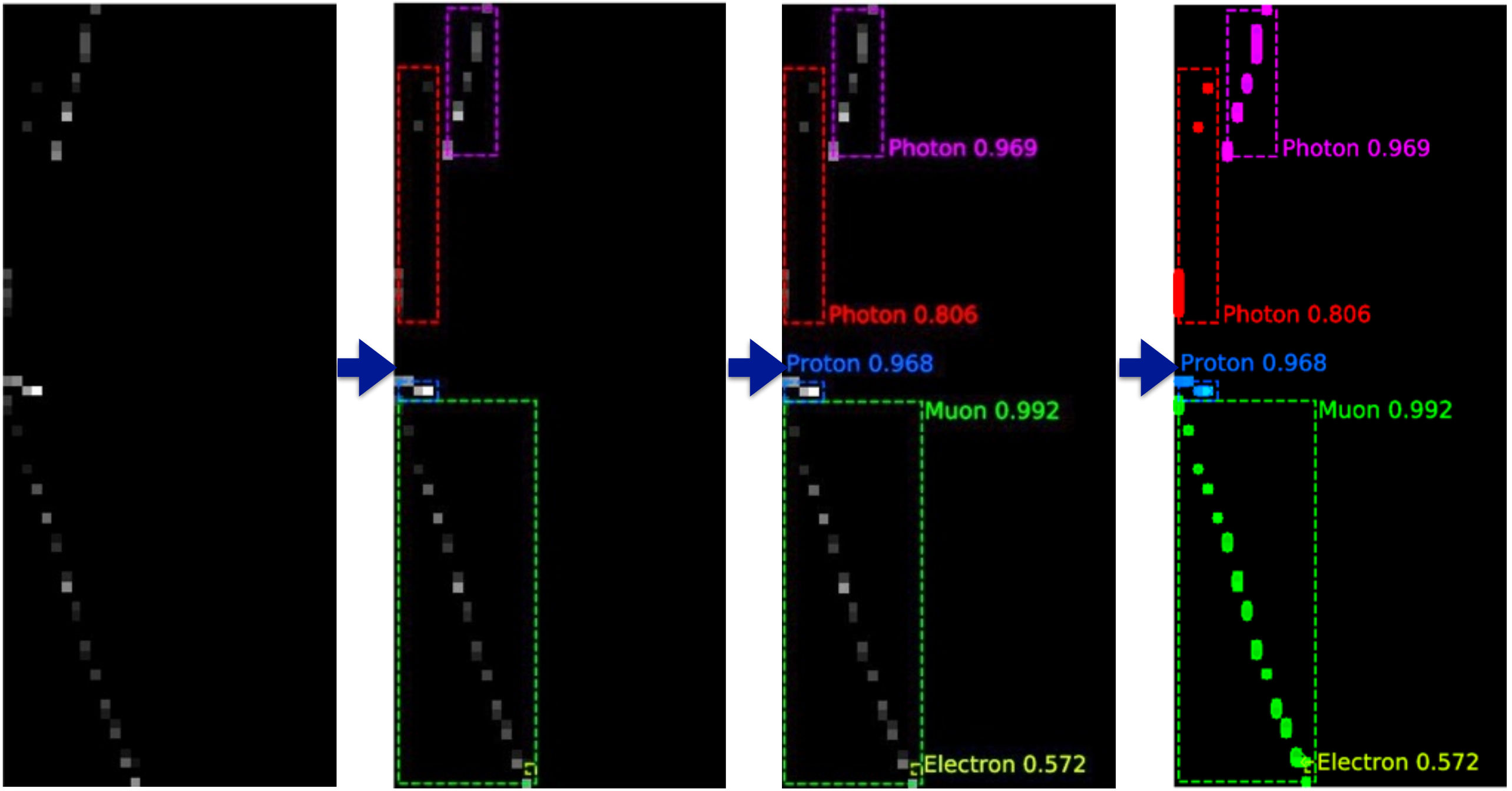
Full Event Reconstruction

ID Score - Use a softmax function to classify the particle contained within each box.

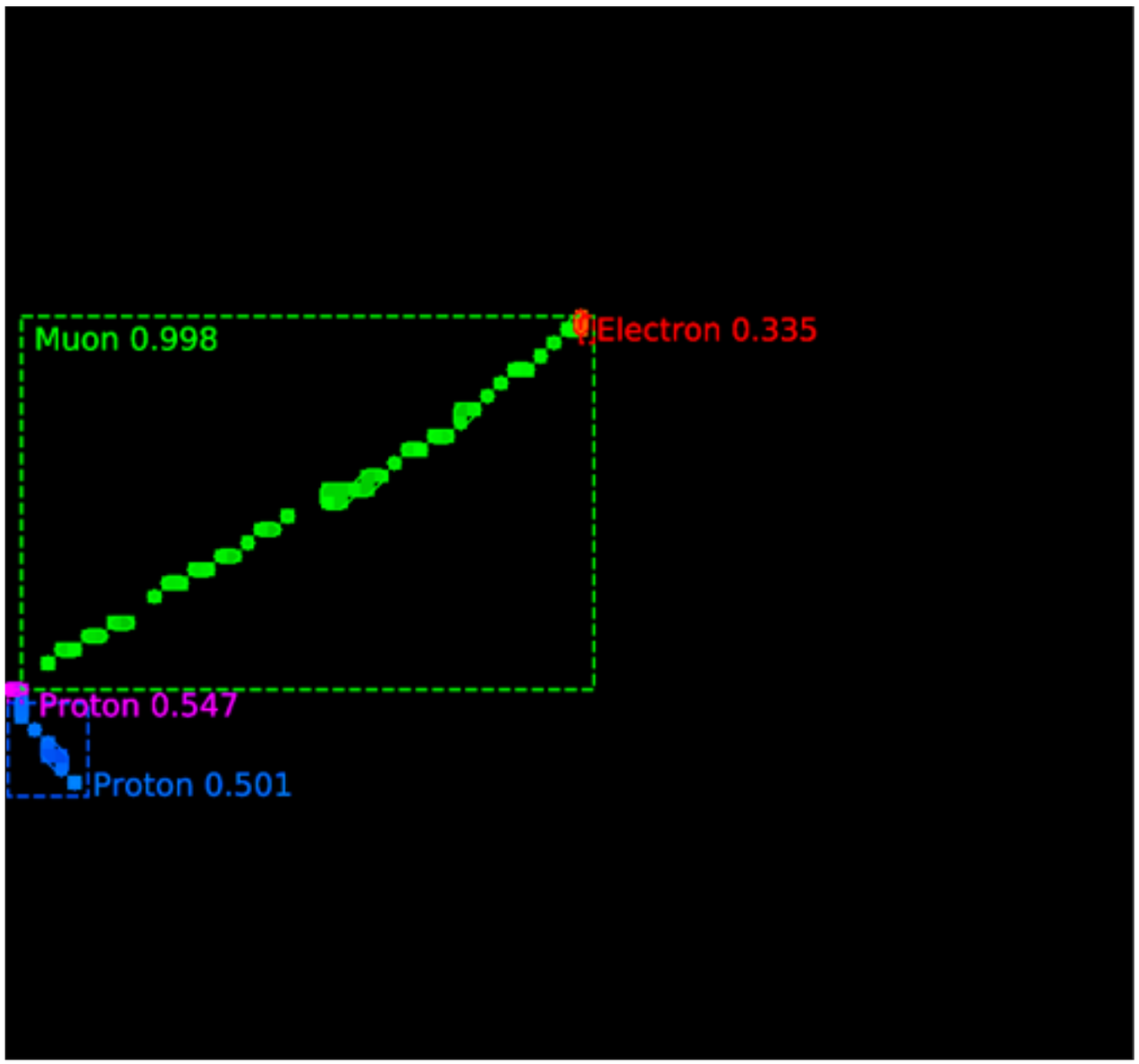


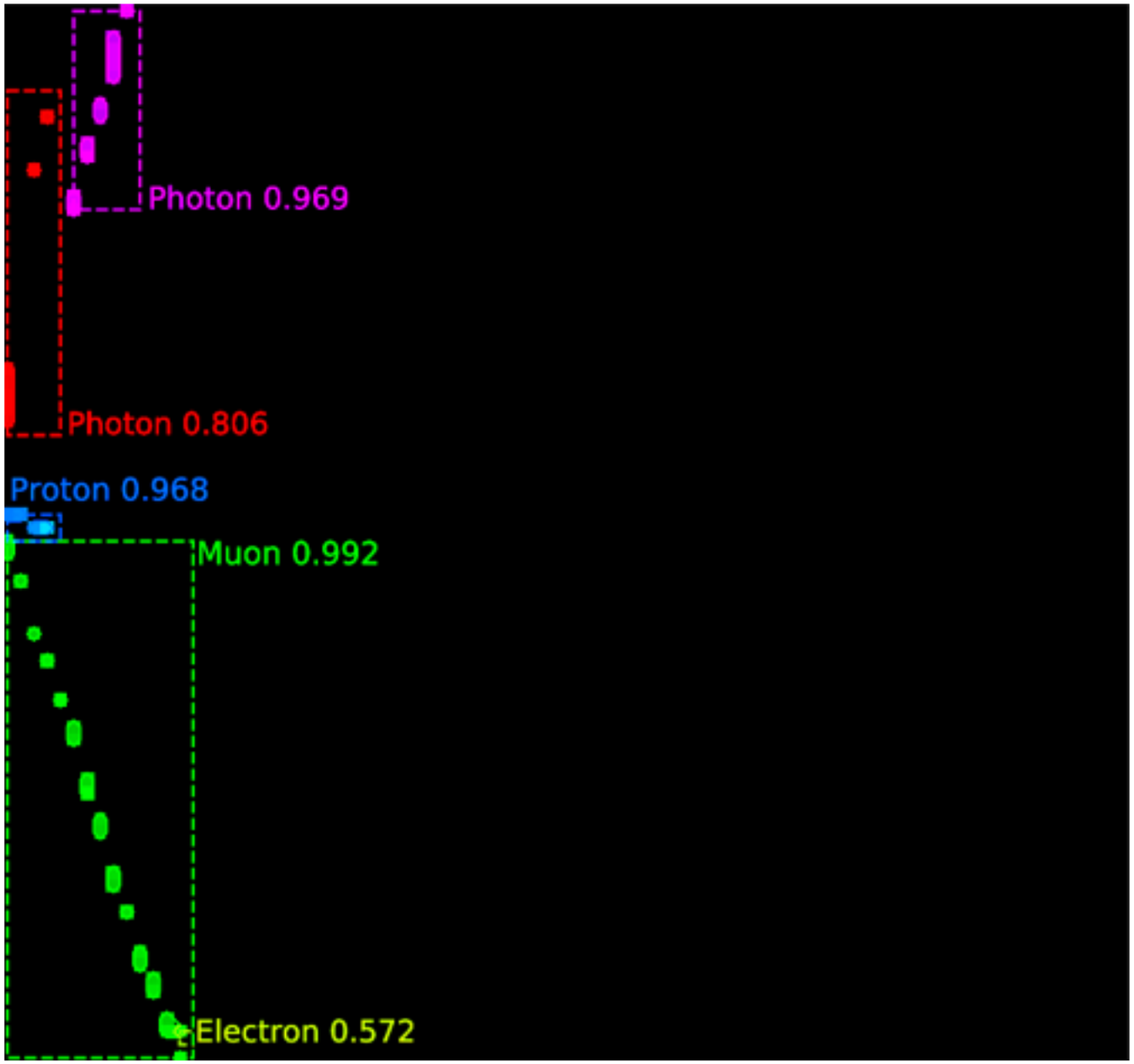
Full Event Reconstruction

Clusters - Group together hits within each box to make clusters for each particle.

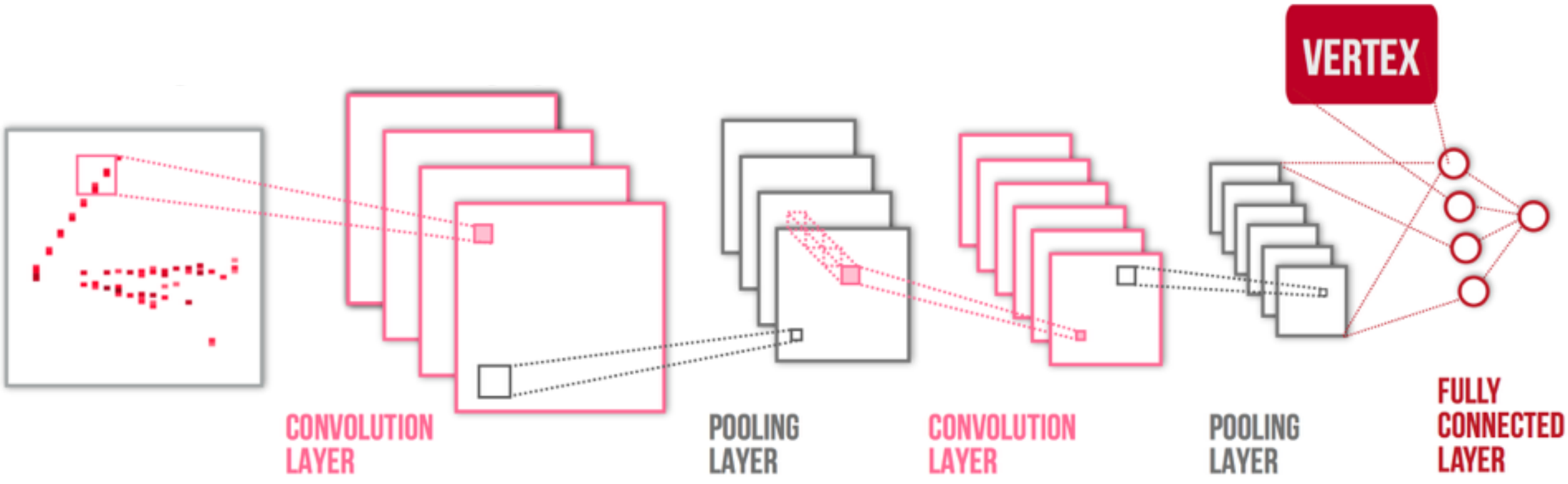


Full Event Reconstruction





Energy Regression

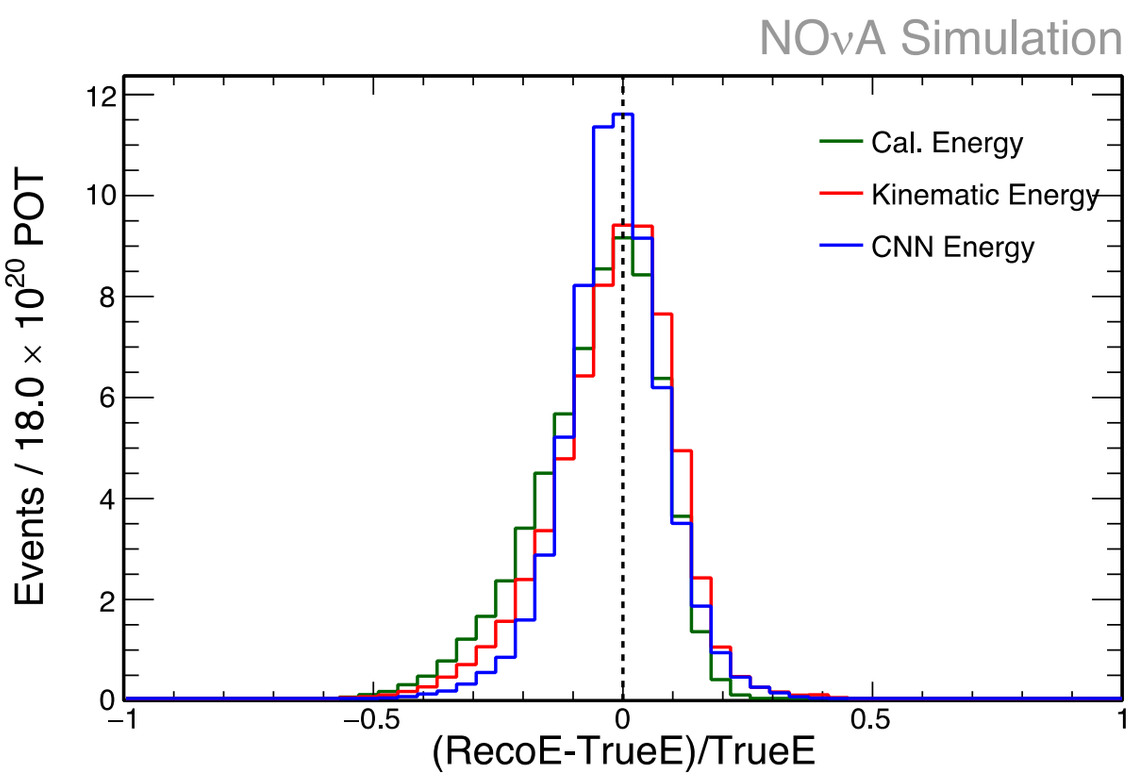


Use linear output rather than classification for continuous variables.

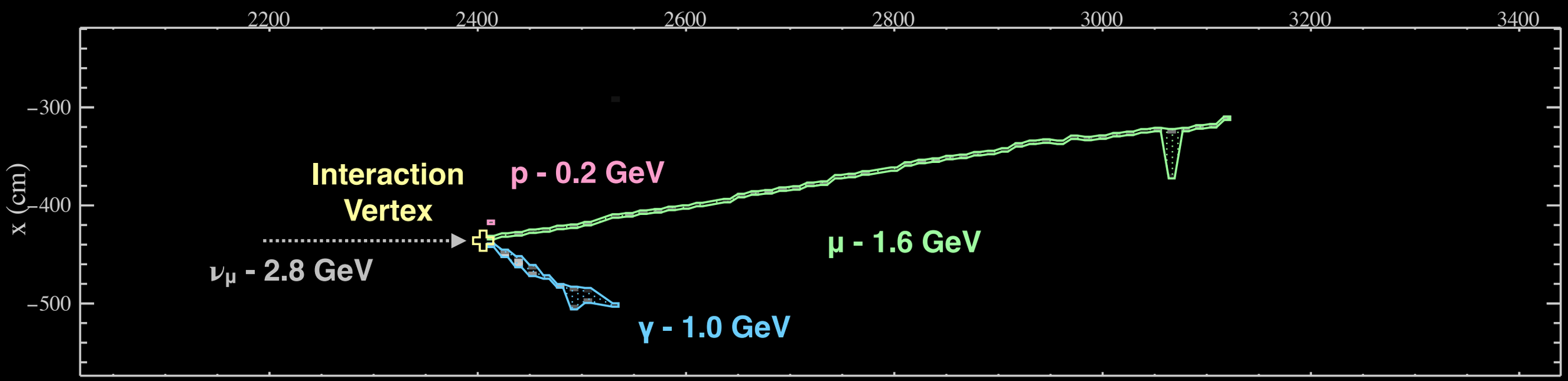
Shows better resolution and smaller dependence on interaction model.

See Jianming Bian's Poster!

Paper in final stages



Summary



NOvA uses deep learning for neutrino flavor and particle ID in our analyses.

Used to improve oscillation measurements since 2016, and now being incorporated into cross sections analyses.

Our deep learning program incorporates data driven cross checks from cosmic, neutrino, and soon test beam data!

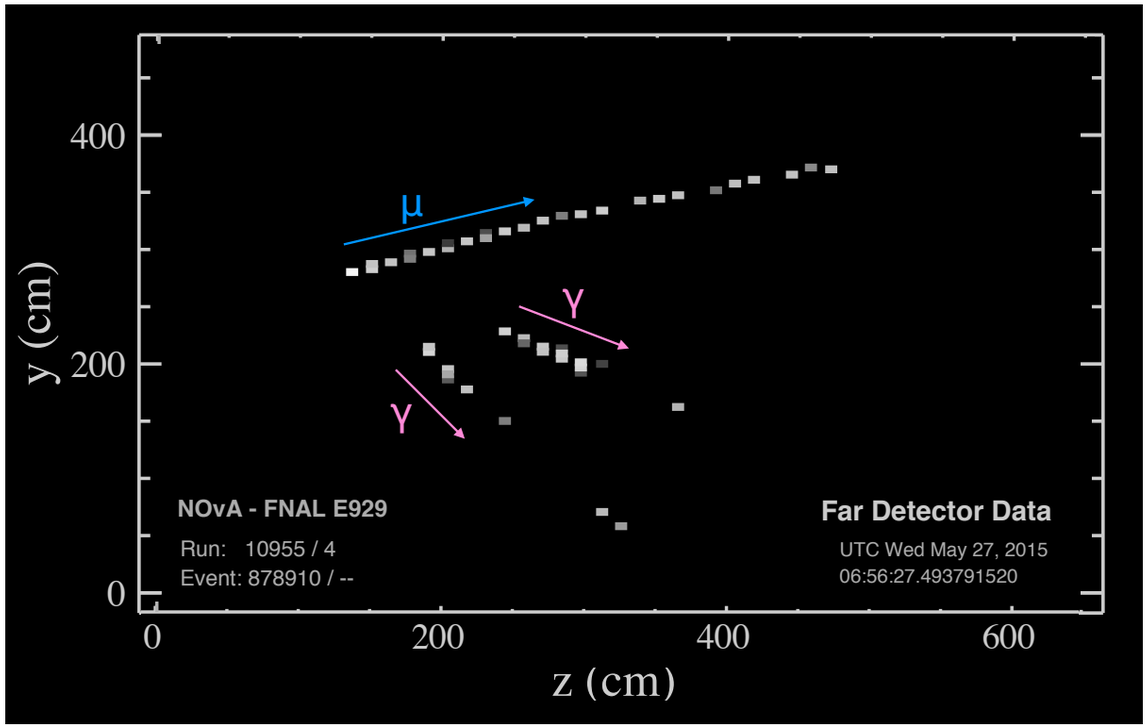
NOvA deep learning efforts are broad, including algorithms for identification, clustering, energy reconstruction, and more!

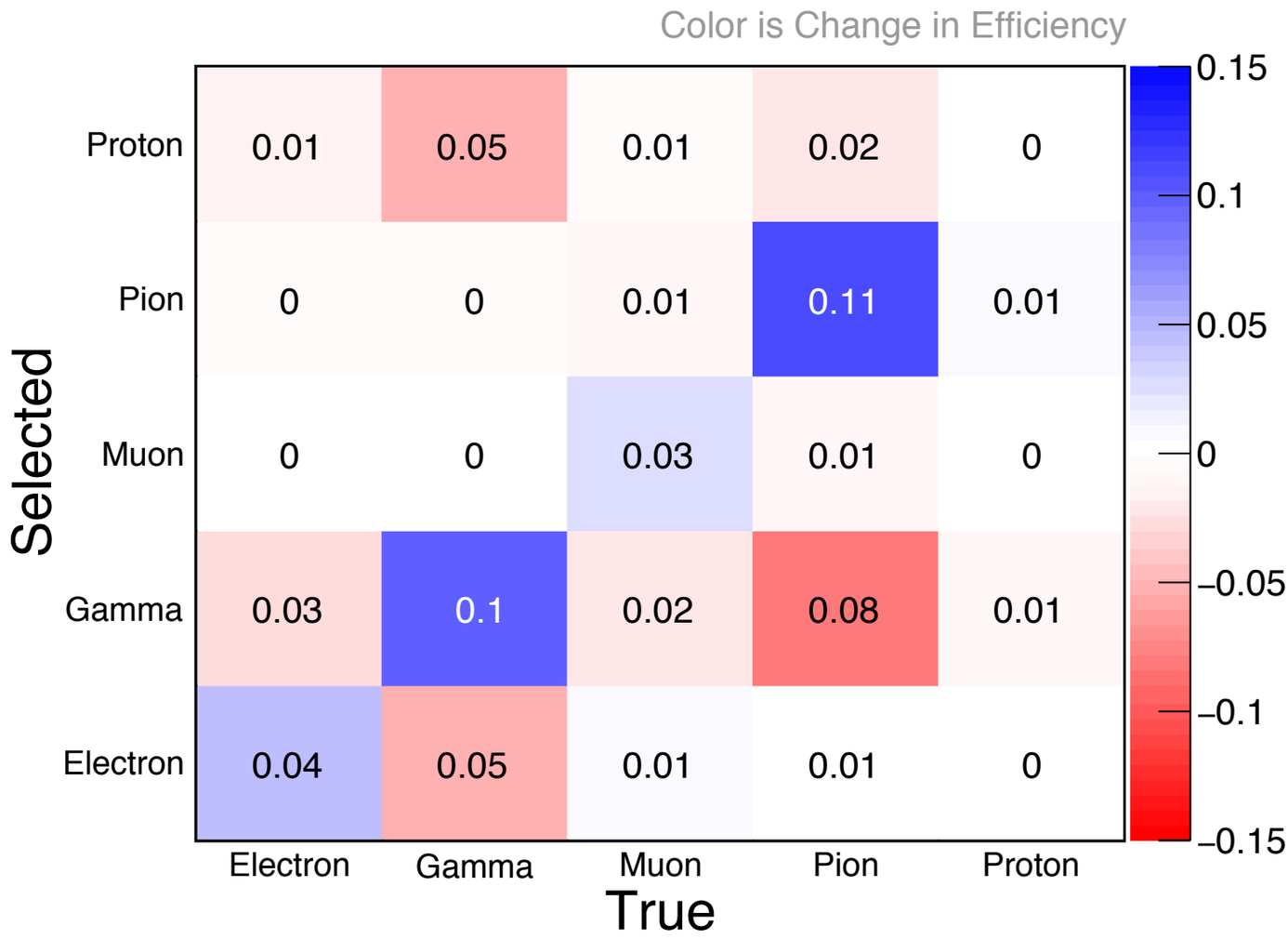
Backup

Utilizing Context

Showing the network the entire event teaches the network **contextual** information.

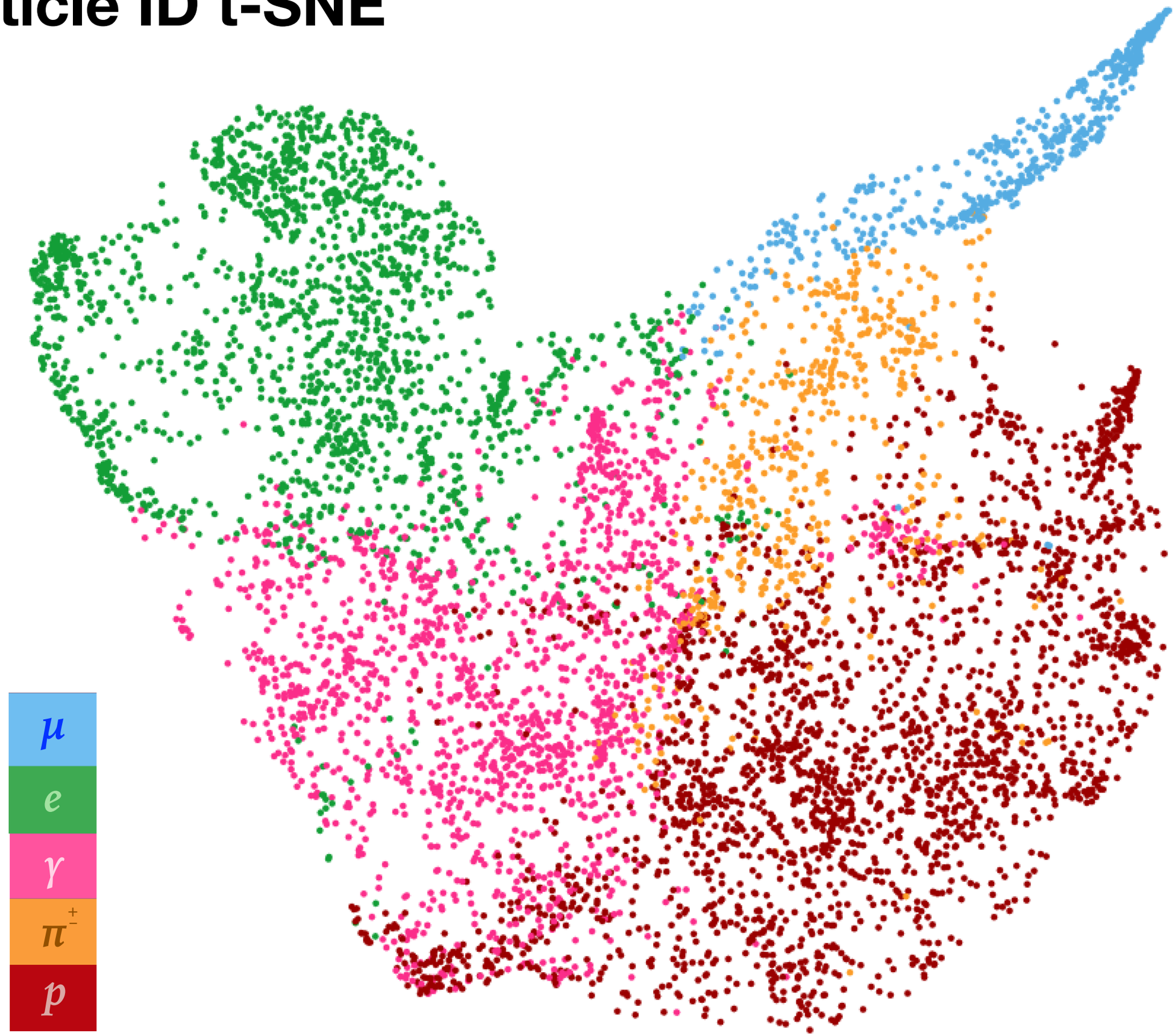
Particularly useful in the classification of photons.





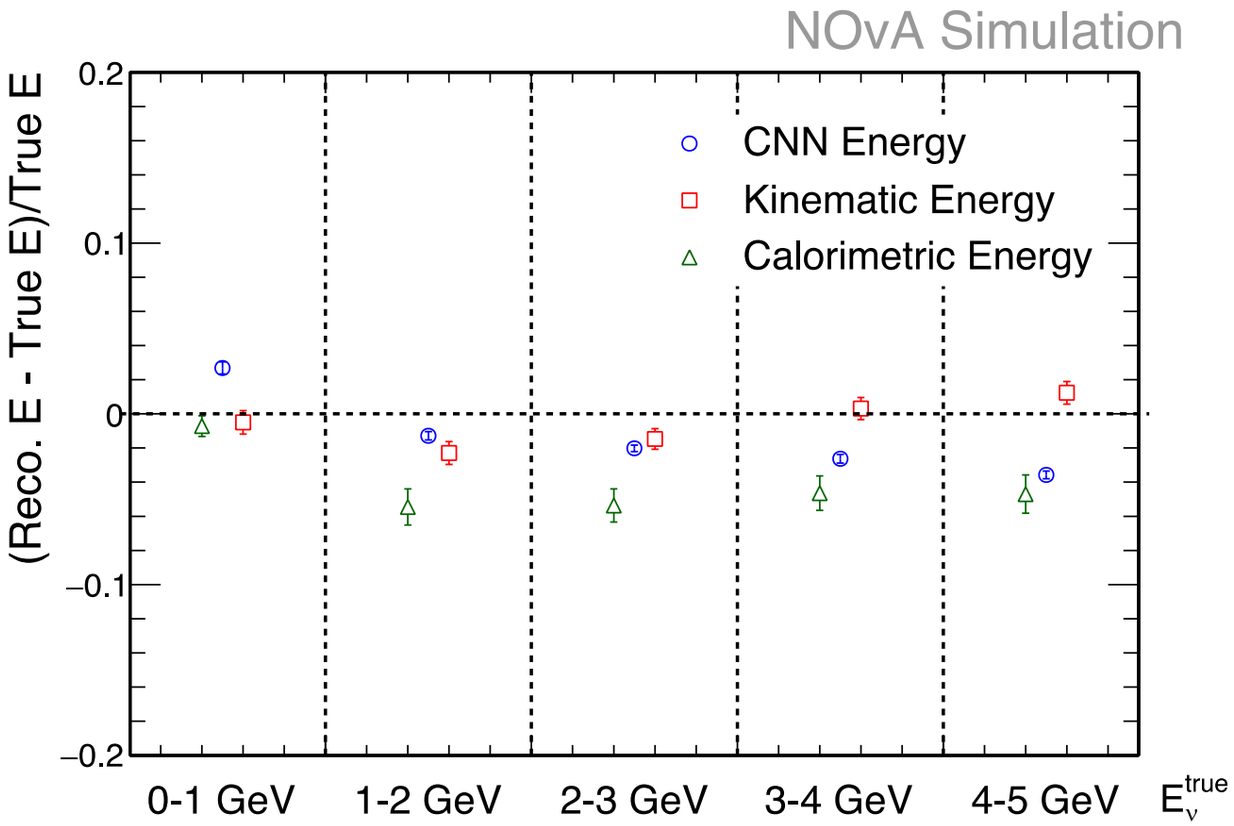
The change in efficiency for each category from inclusion of context information.

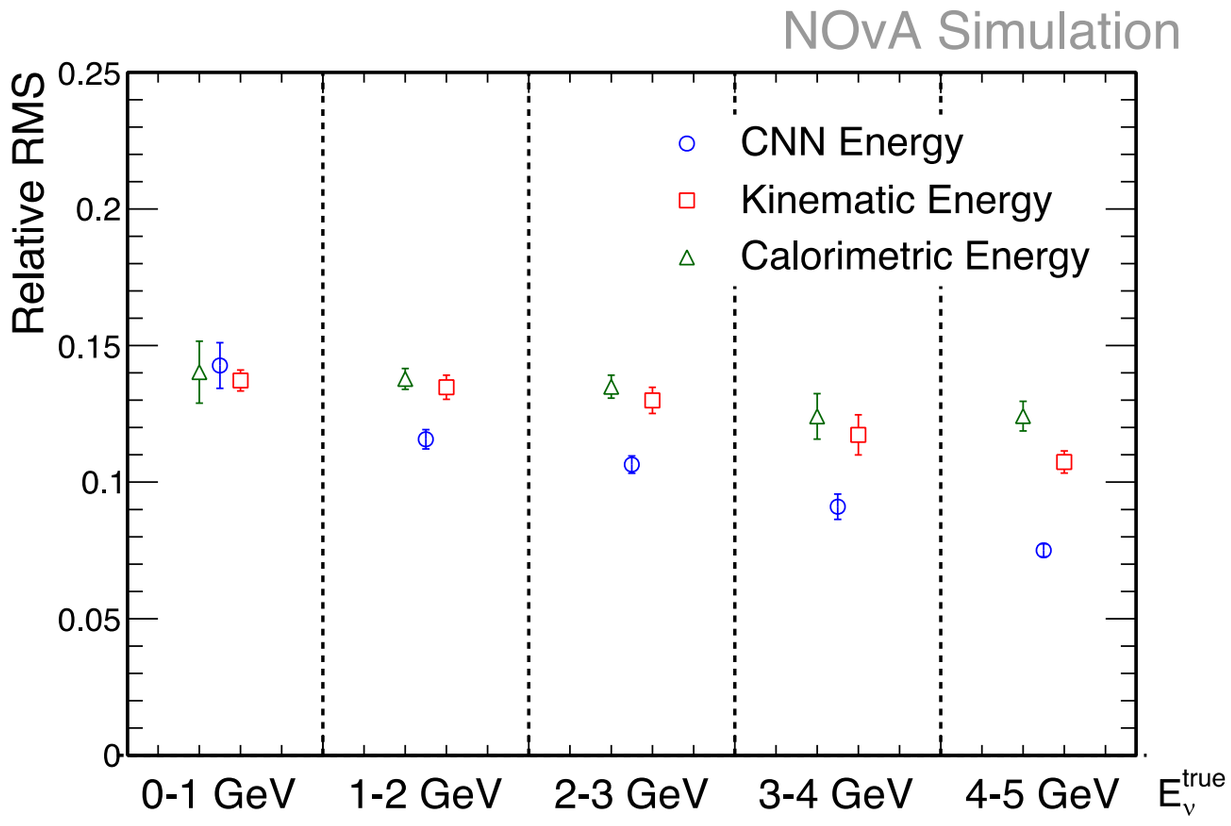
Particle ID t-SNE



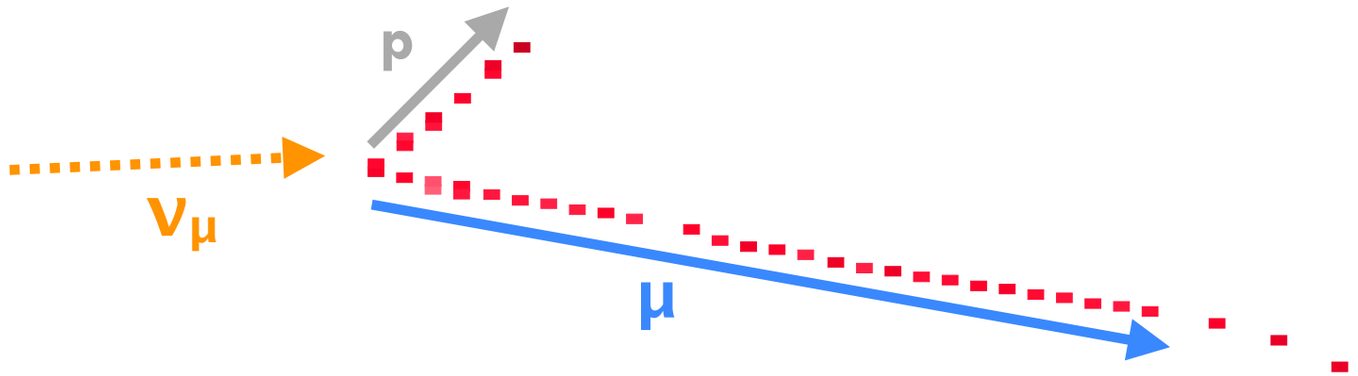
Regression CNN

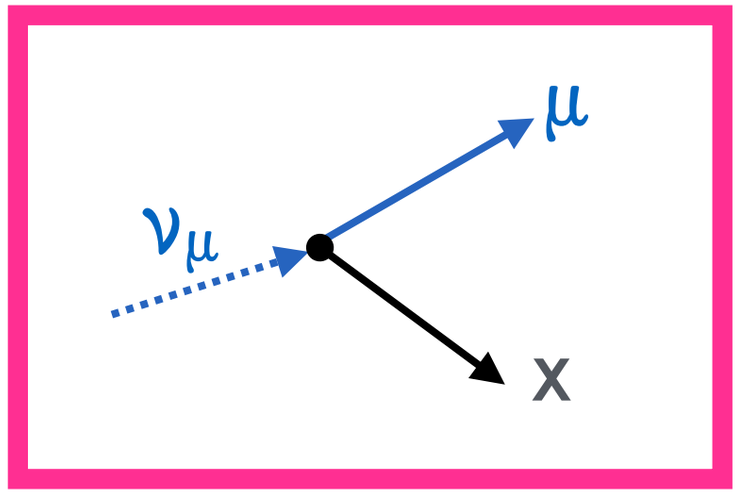
Bias against true energy.

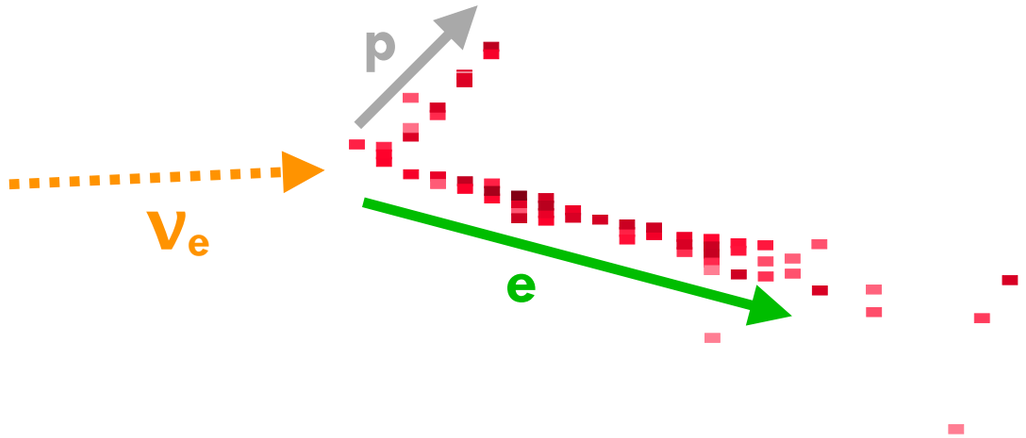


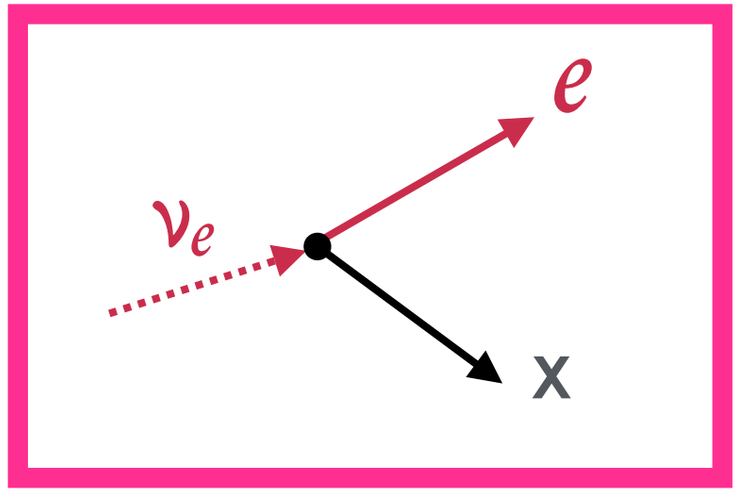


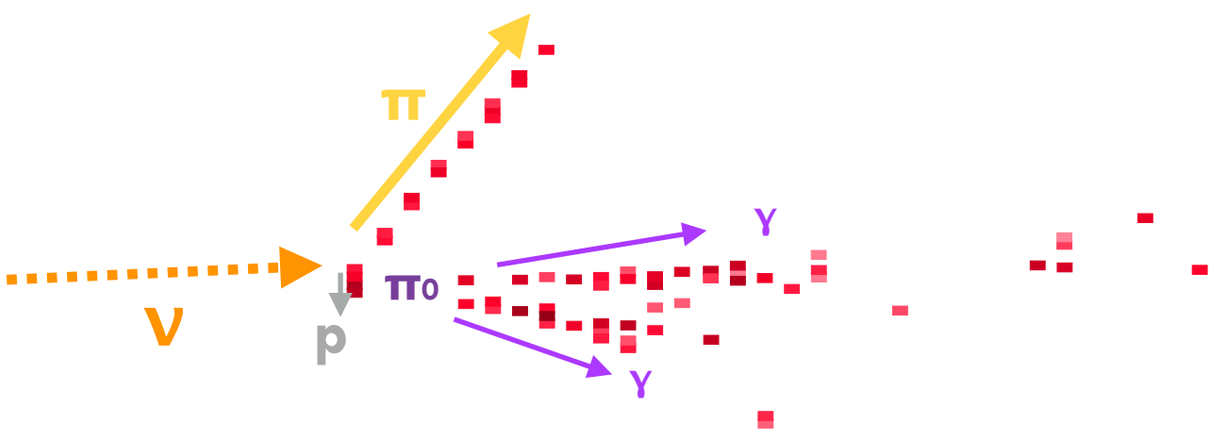
Signature Data Events

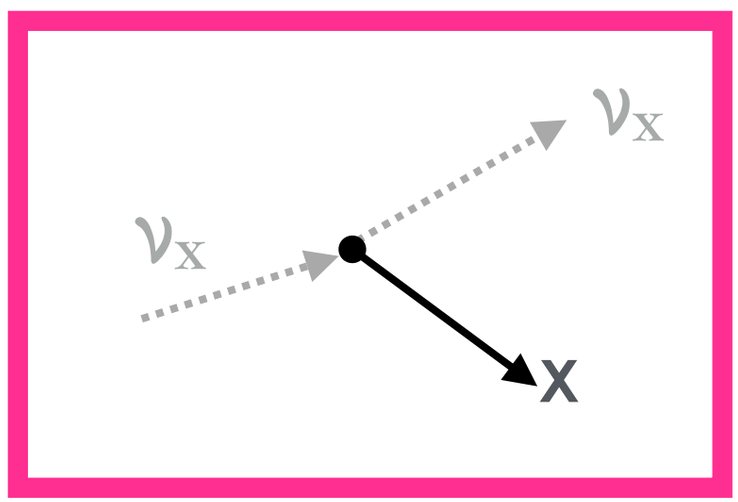


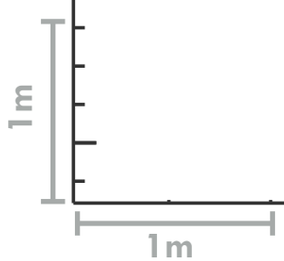


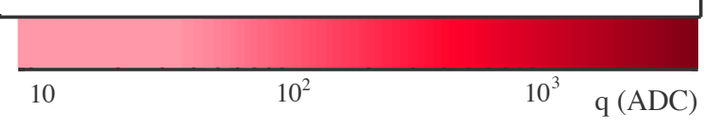


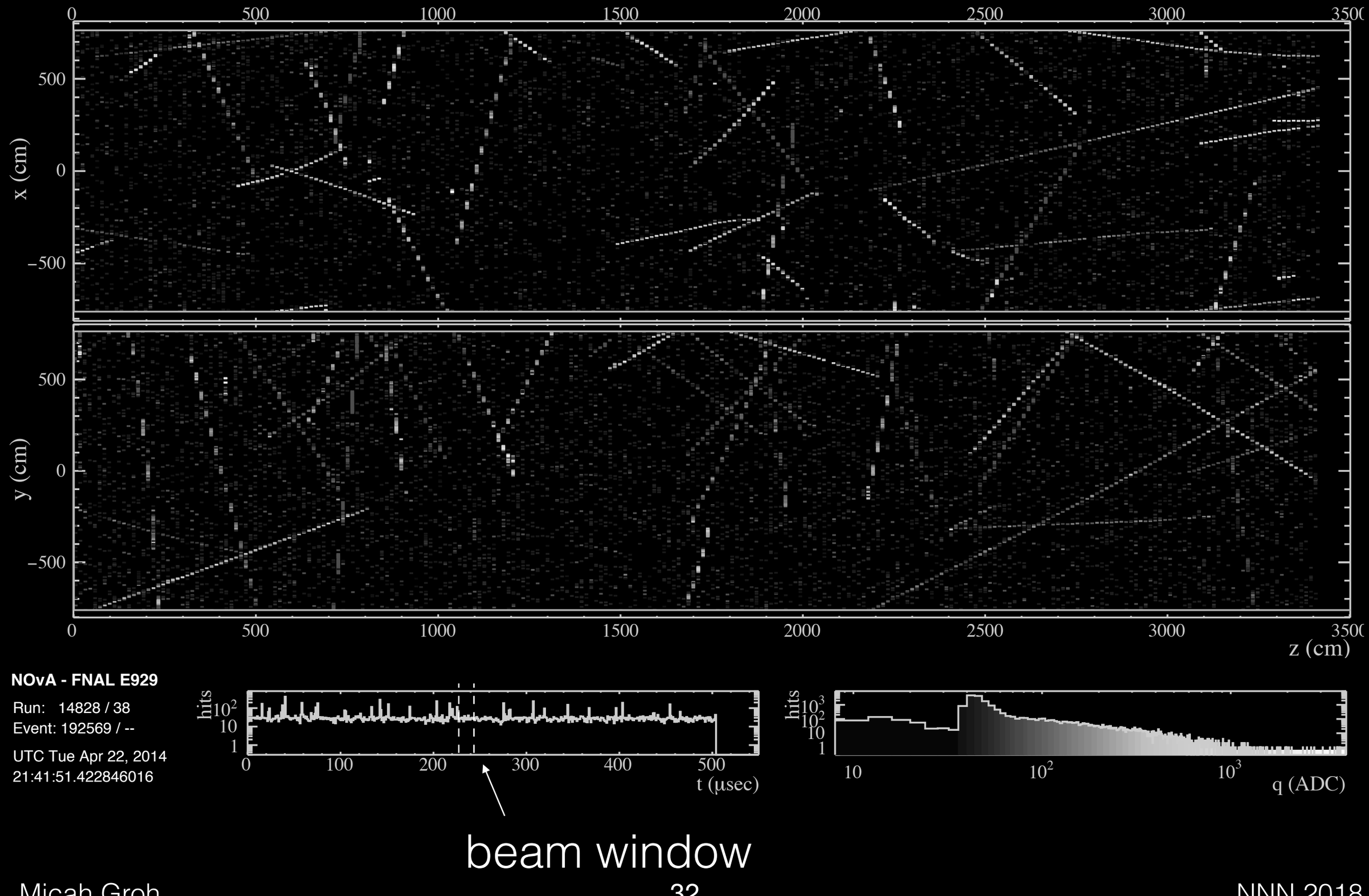






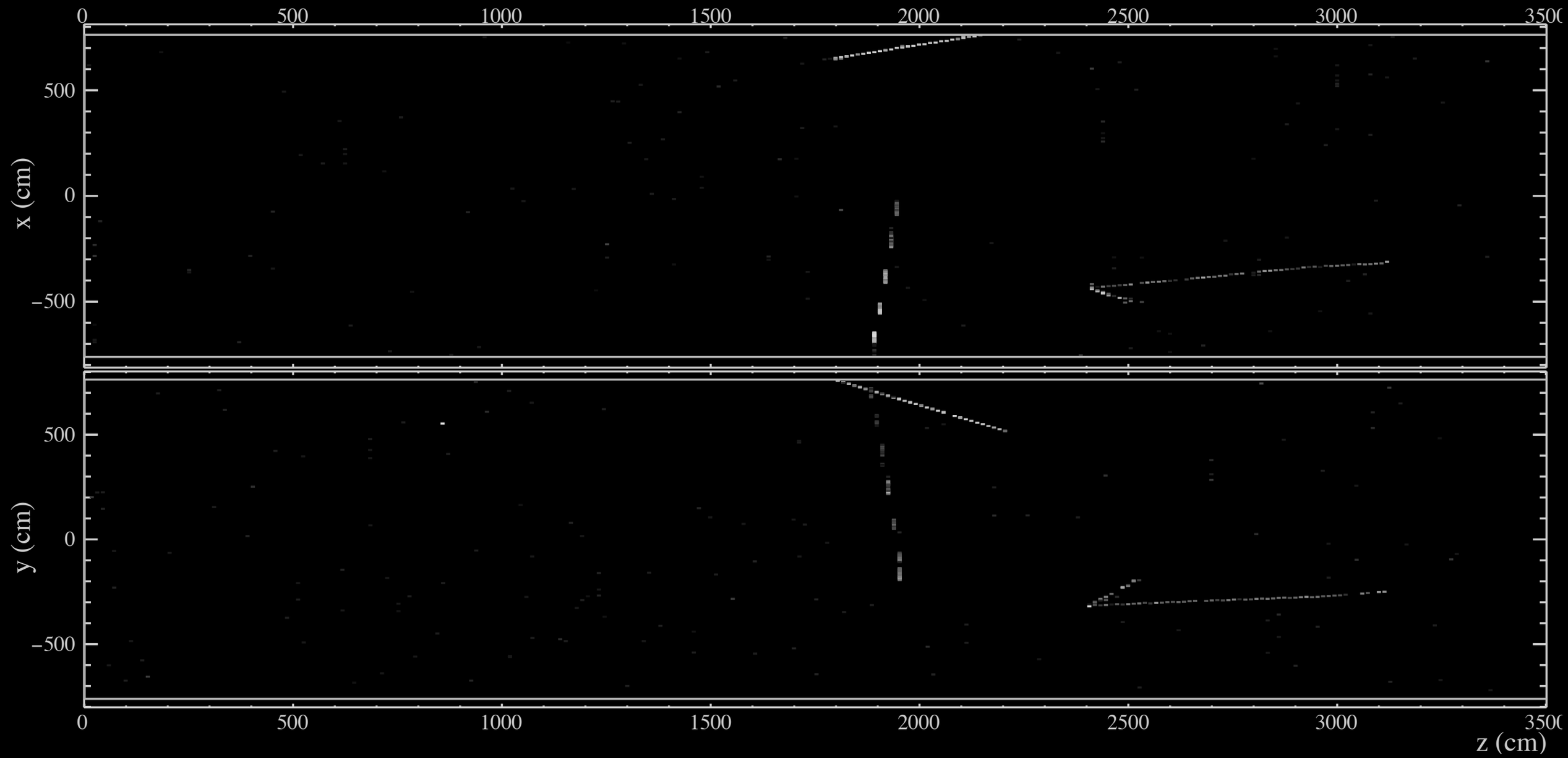





0
500
1000
1500
2000
2500
3000
3500
x (cm)
y (cm)
z (cm)
NOvA - FNAL E929
Run: 14828 / 38
Event: 192569 / --
UTC Tue Apr 22, 2014
21:41:51.422846016
hits
t (μsec)
q (ADC)
beam window

NOvA Events

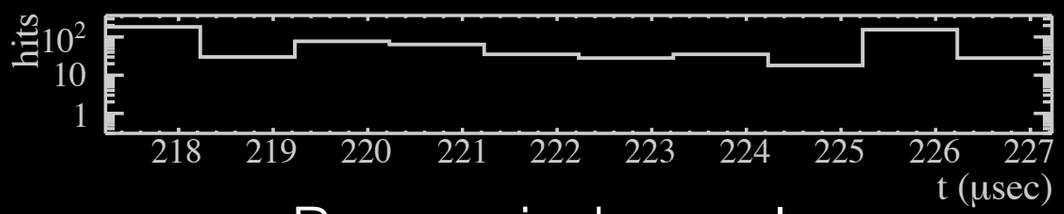
Separate hits by time and space

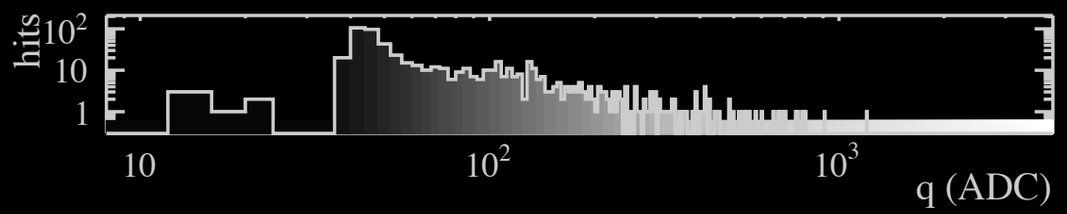


NOvA - FNAL E929

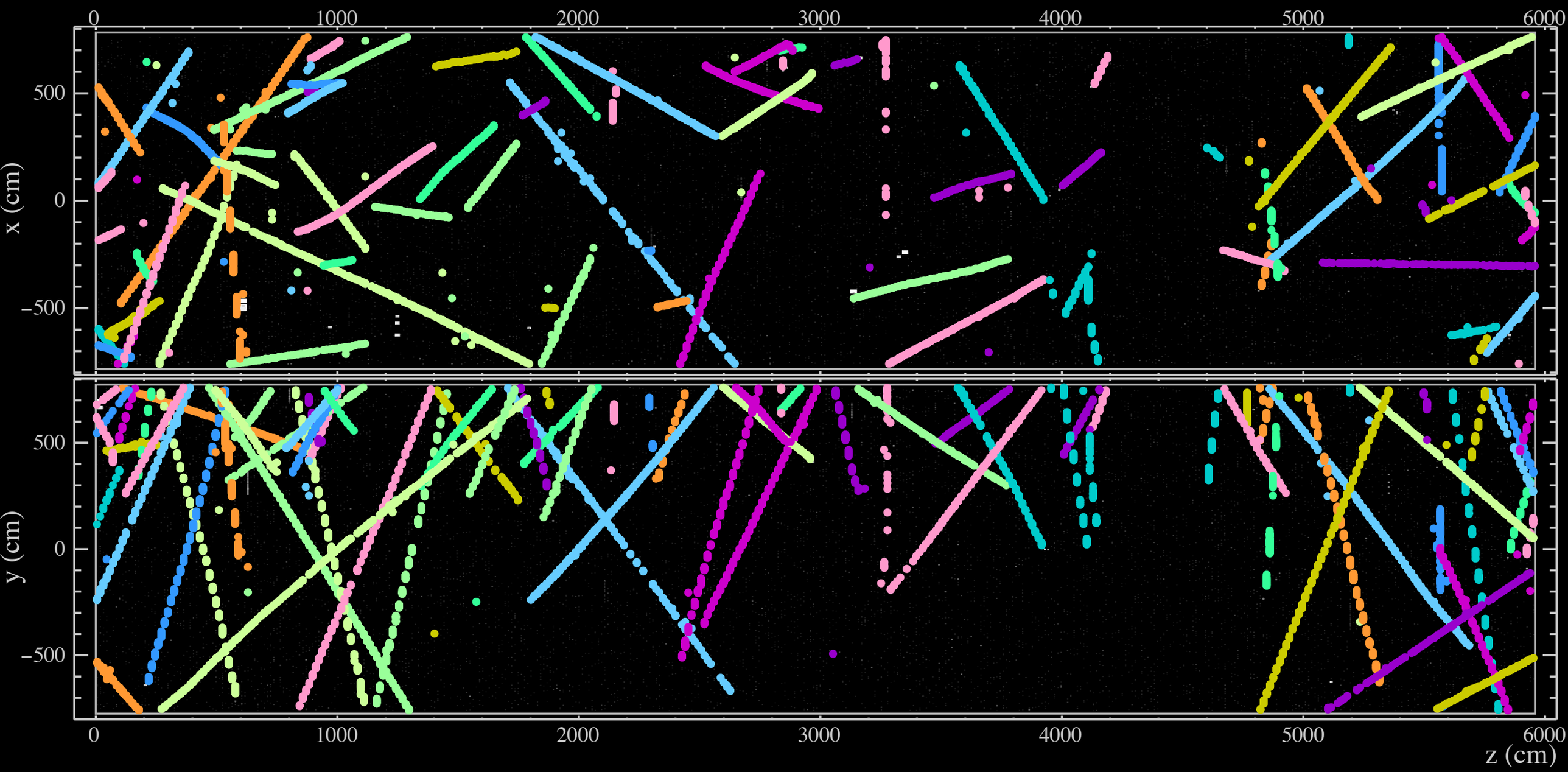
Run: 14828 / 38
Event: 192569 / --

UTC Tue Apr 22, 2014
21:41:51.422846016





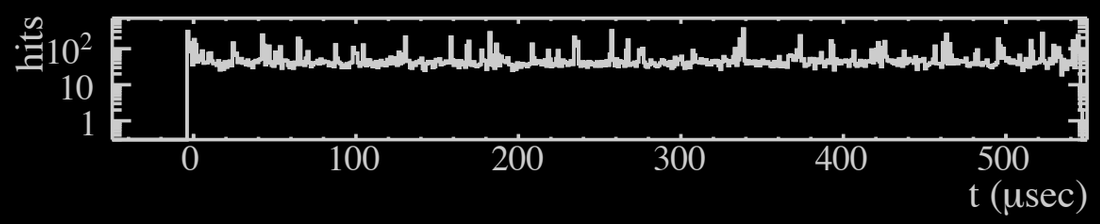
Beam window only.

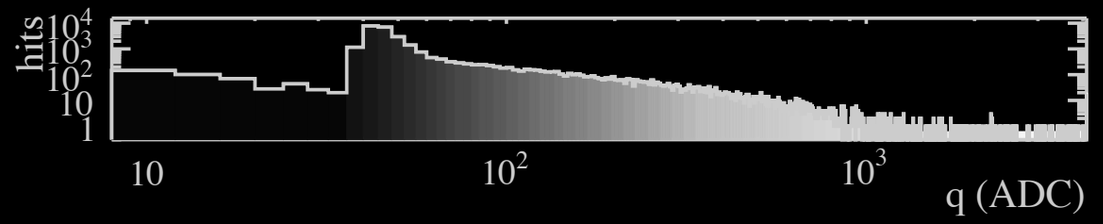


NOvA - FNAL E929

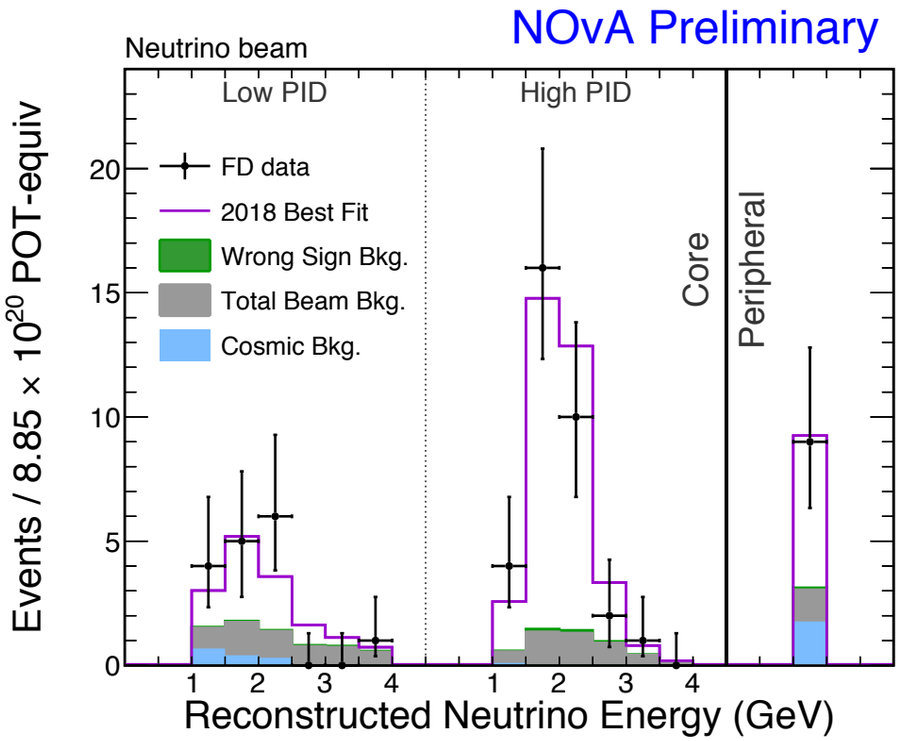
Run: 19193 / 13
Event: 188331 / --

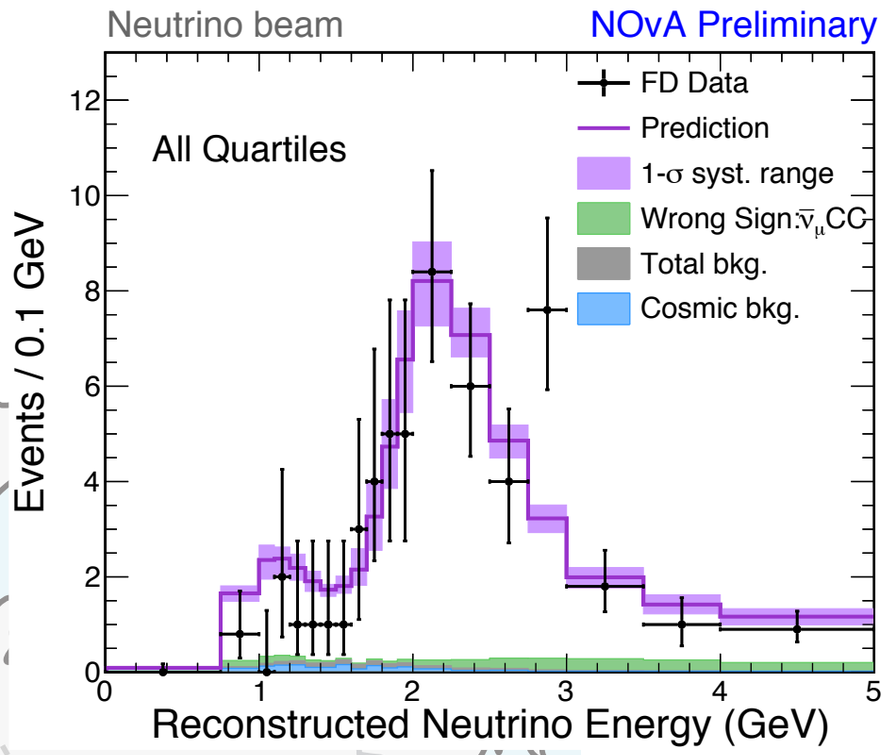
UTC Fri Mar 27, 2015
09:44:53.281953920

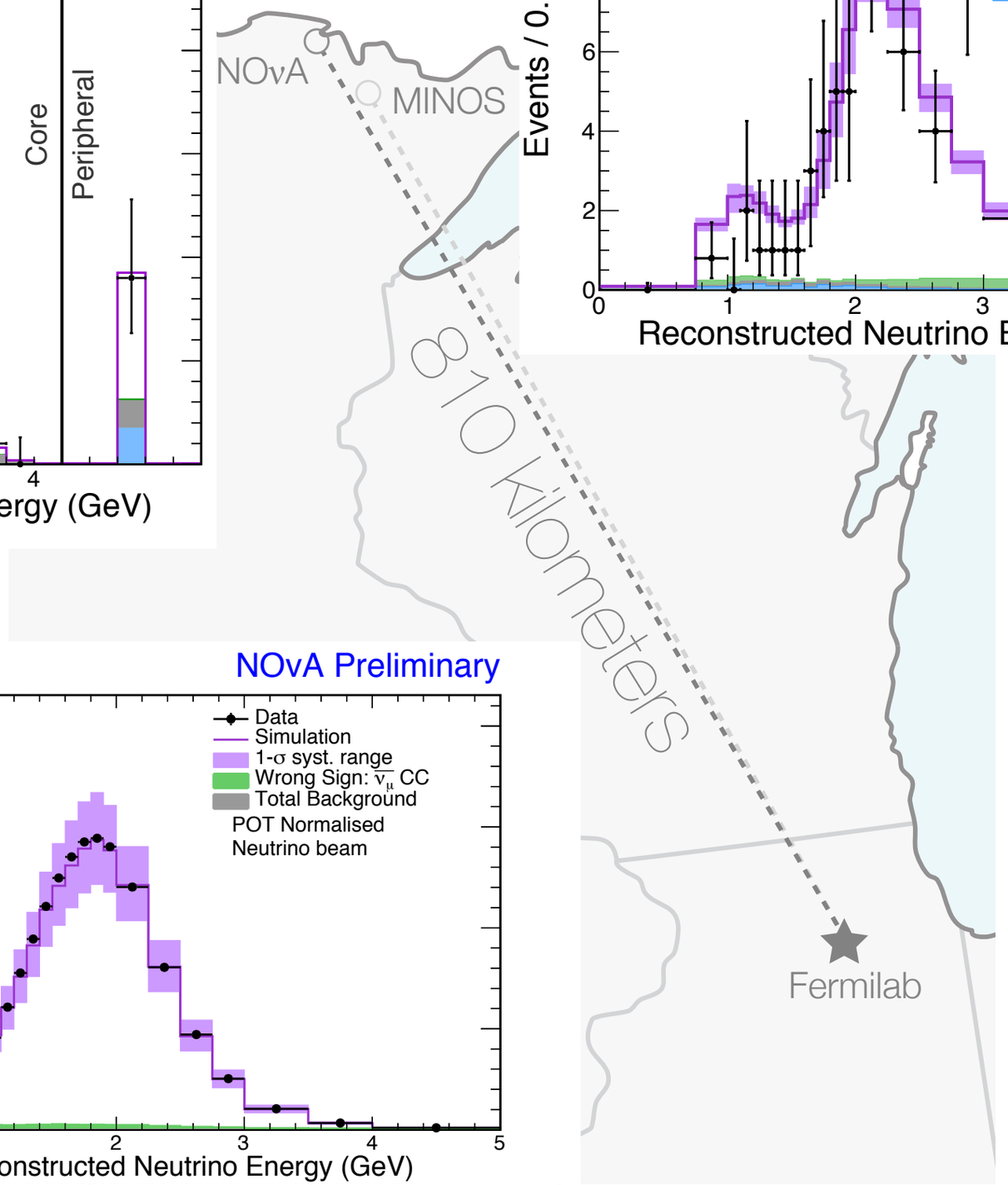




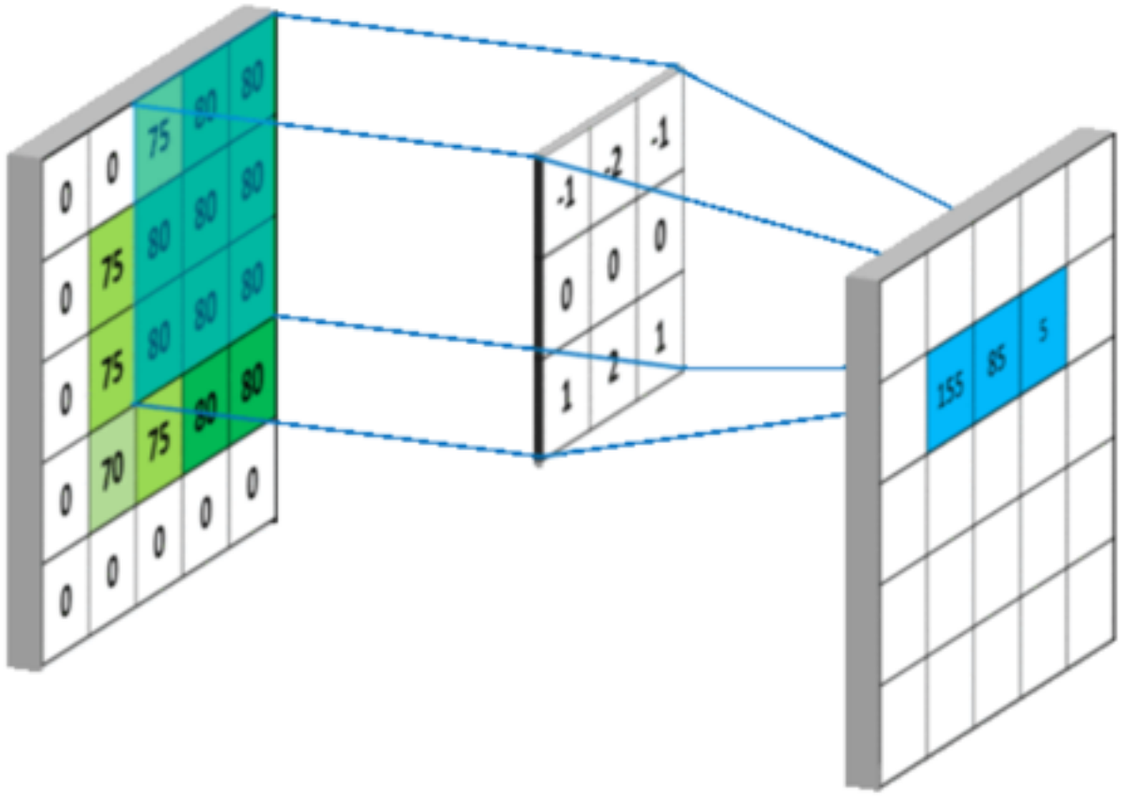
NOvA Analysis

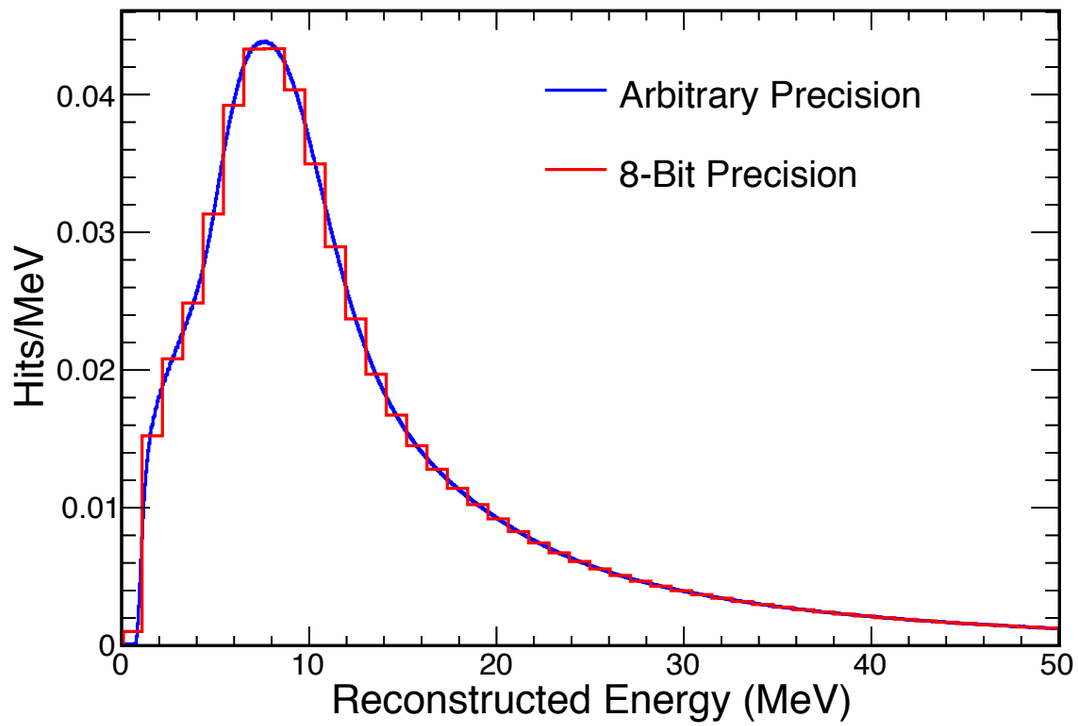


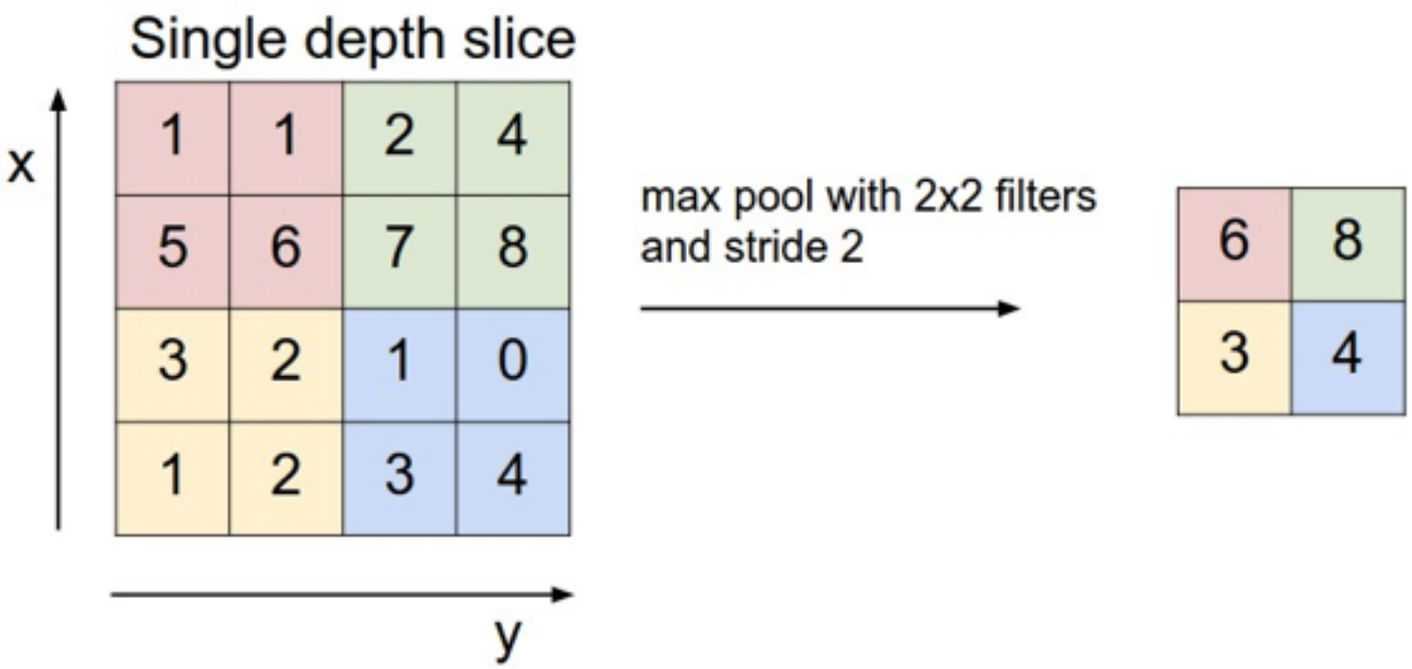




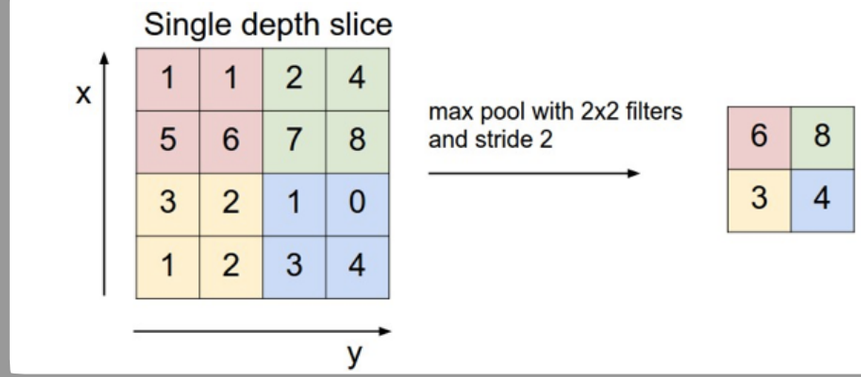
Convolutions and Pooling



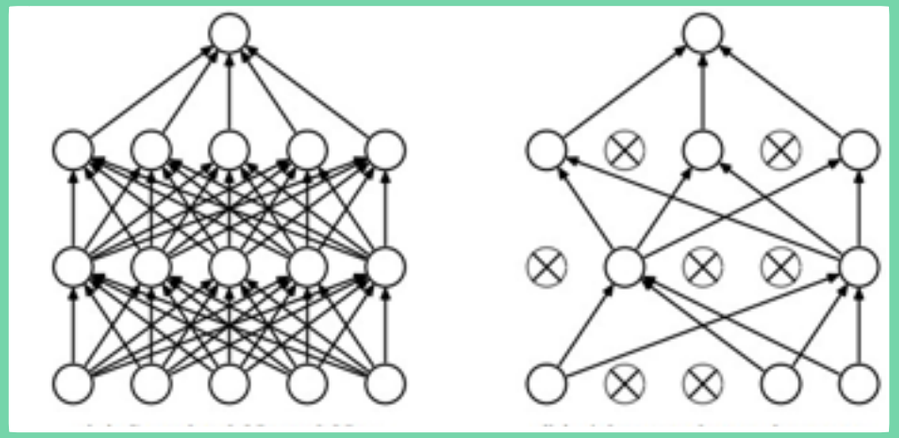




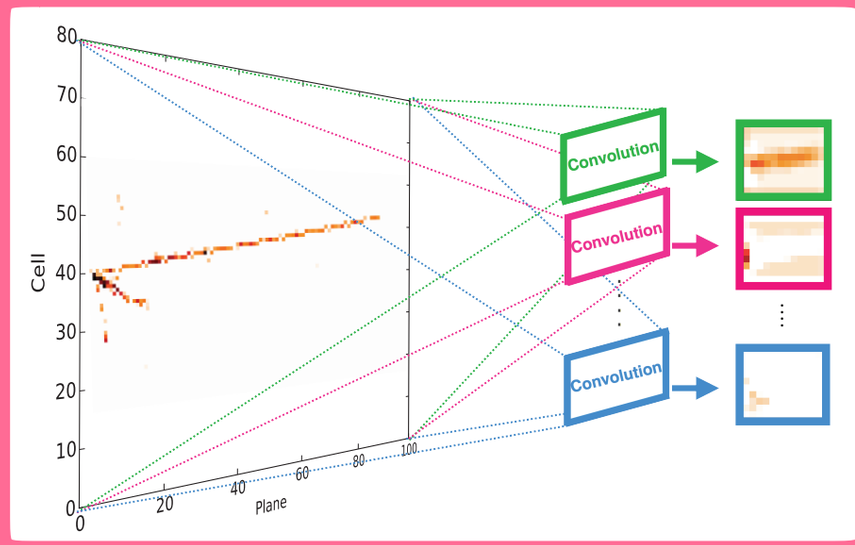
Pooling



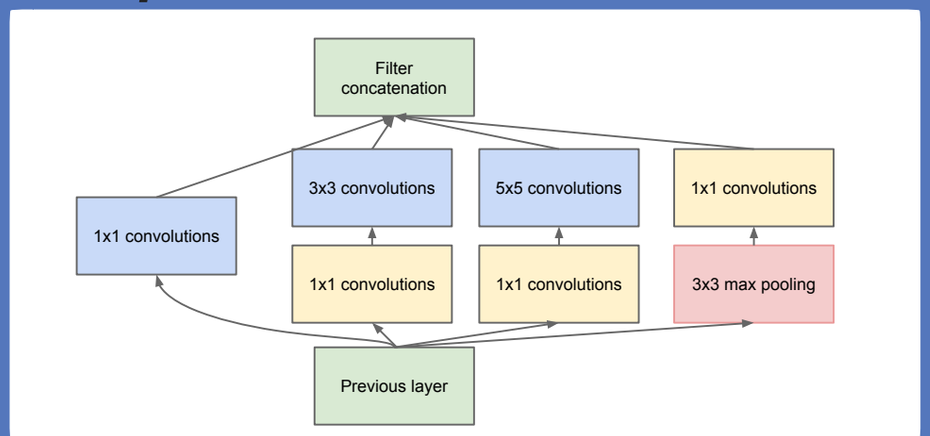
Dropout



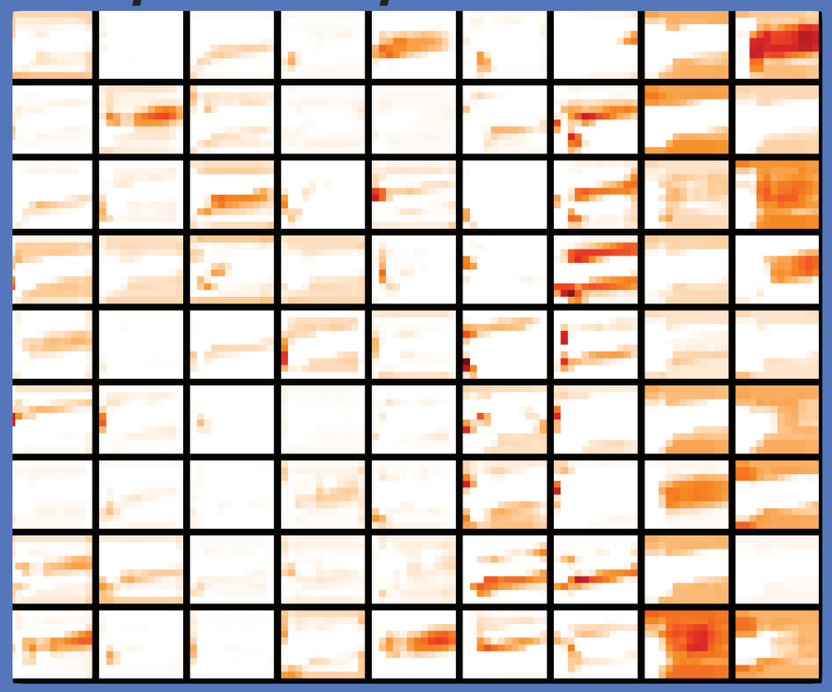
Convolution



Inception module



Inception output



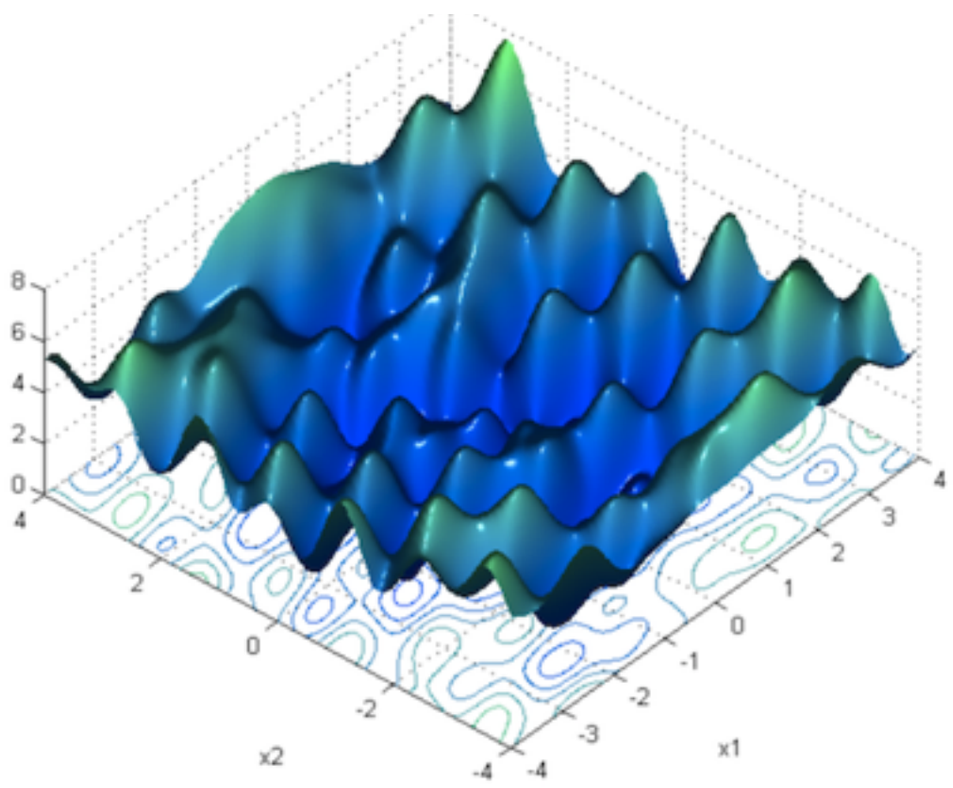
Training

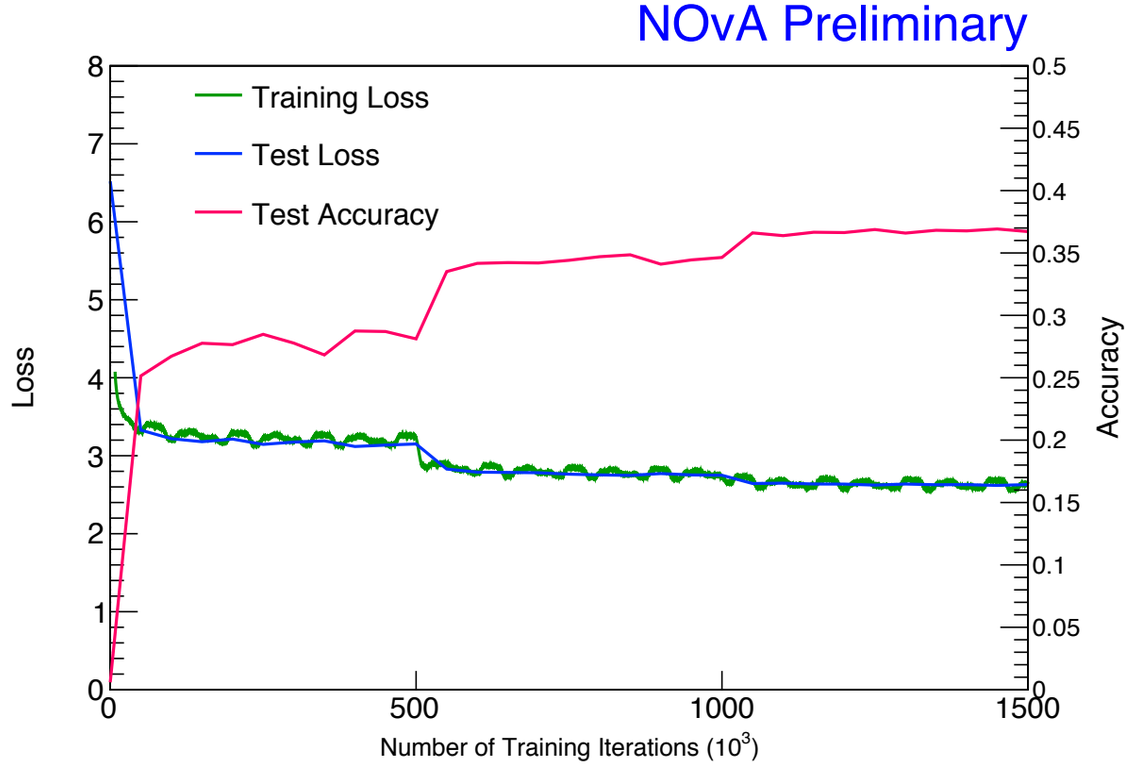
x4.7 million

Training Sample

Test Sample

Weights are learned through a process to minimize the loss function.





Traditional Reconstruction

Group all hits with a common origin, the same neutrino interaction or cosmic.

↓

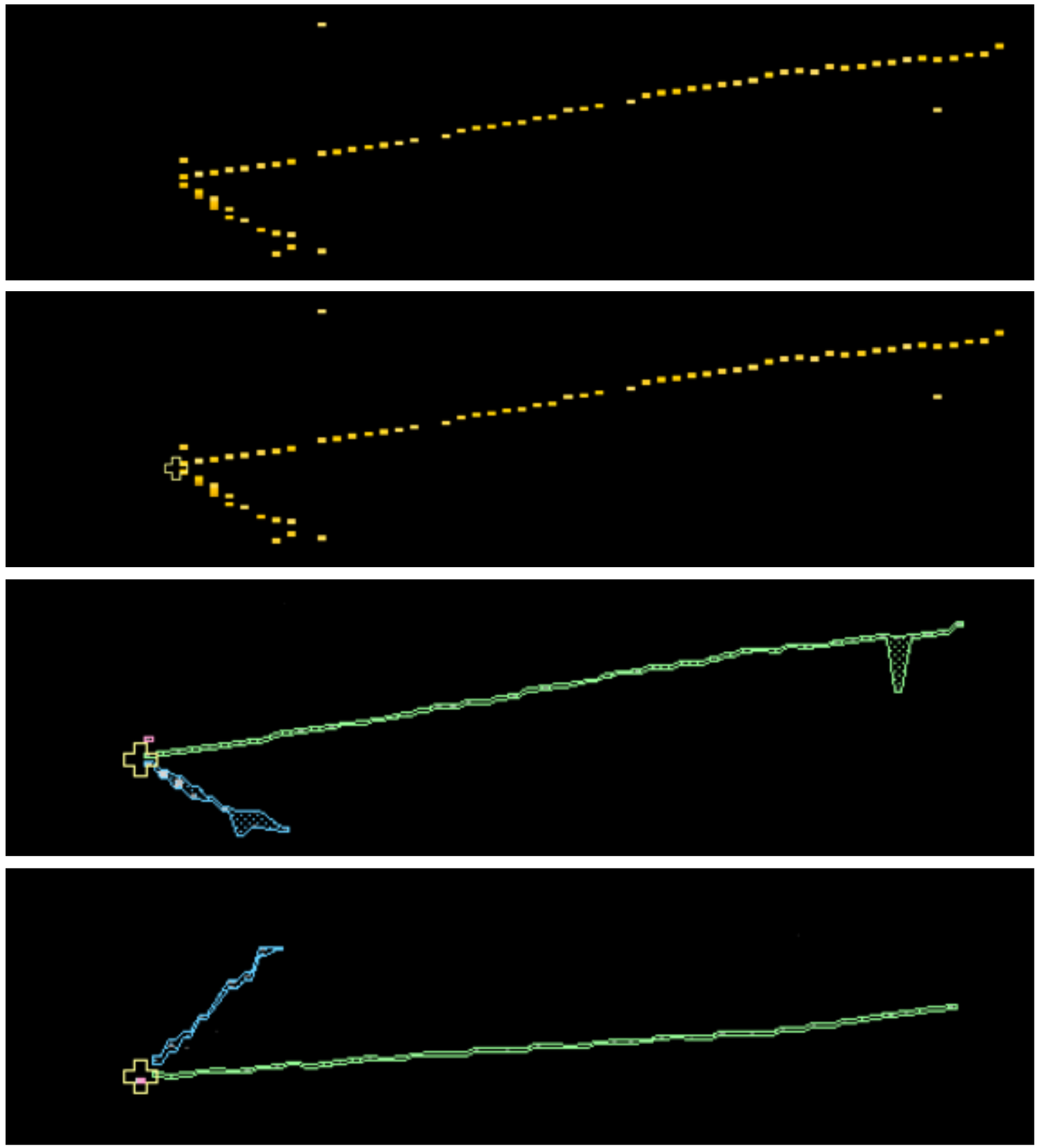
Reconstruct the global interaction vertex.

↓

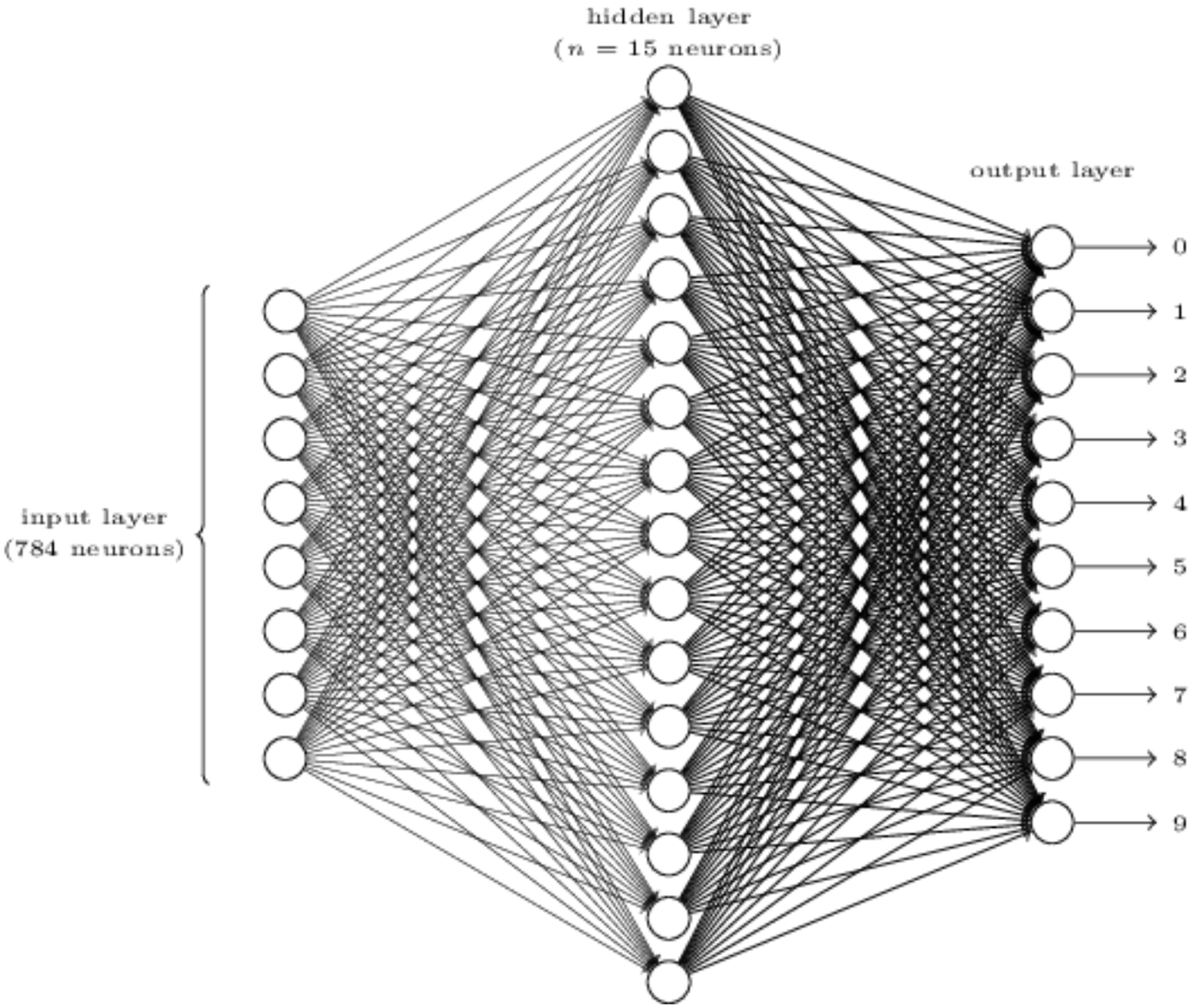
Cluster hits belonging to the same particle.

↓

Match clusters across views to make 3D prongs



Neural Networks



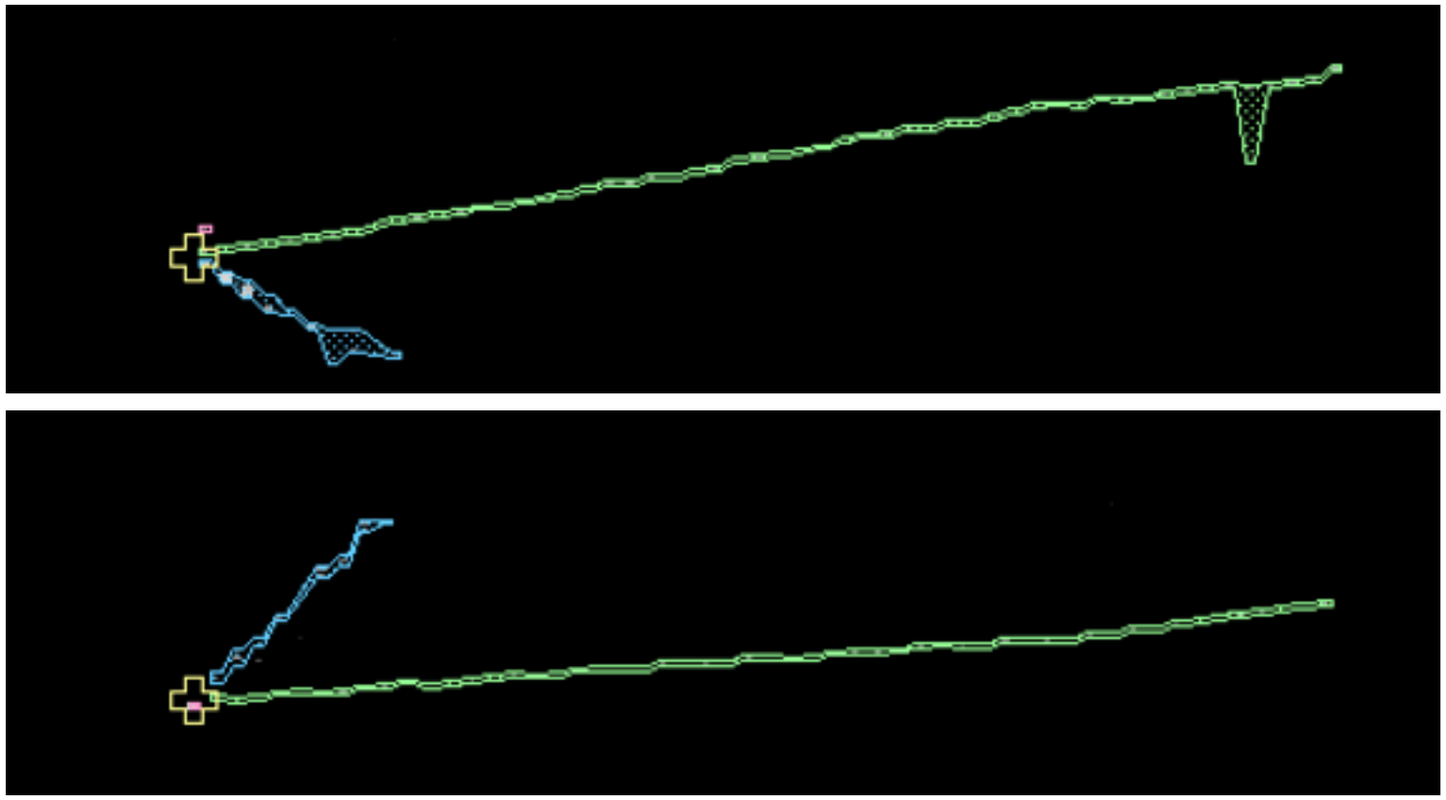
Identify neutrino flavor using neural networks.

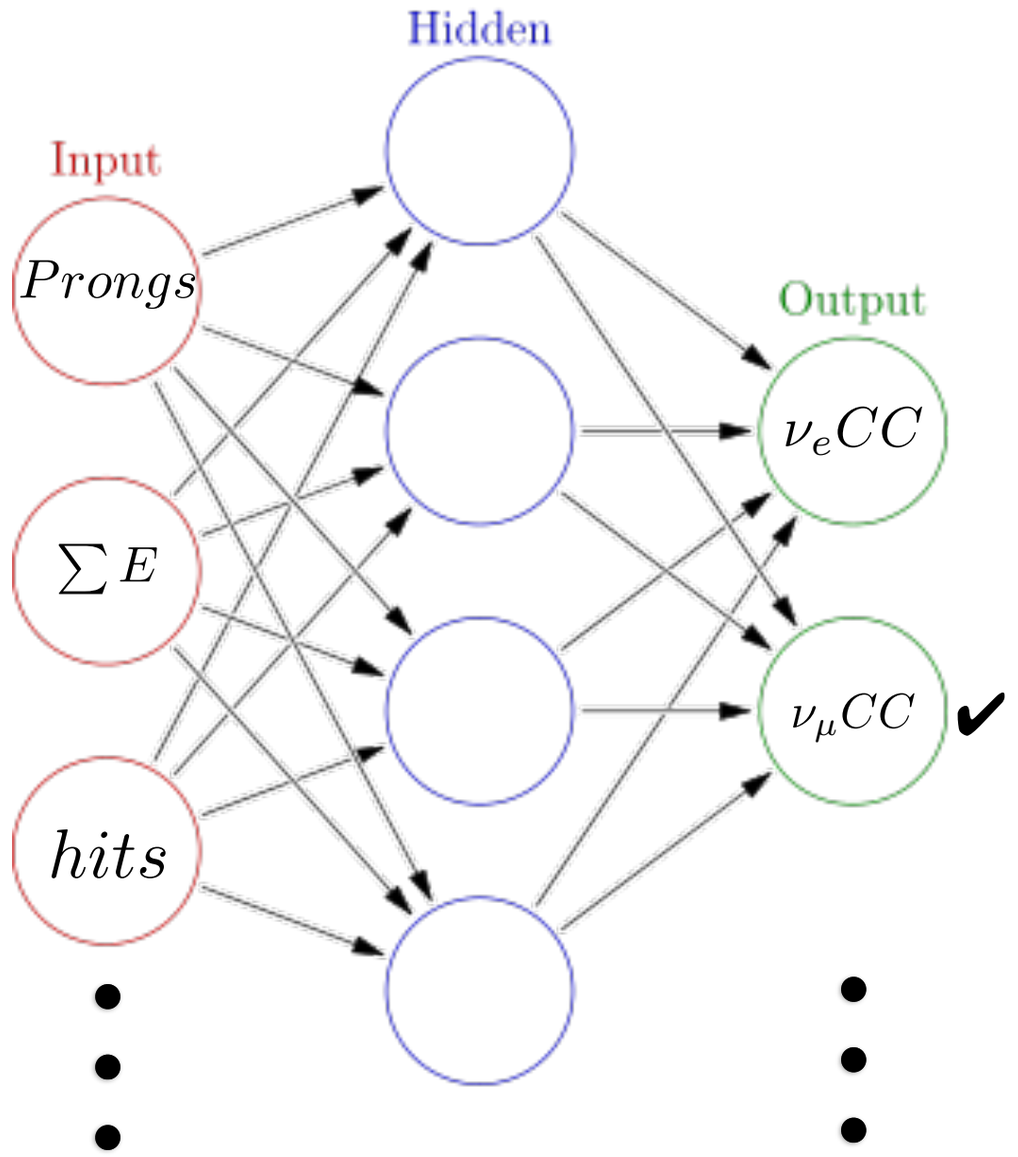
Artificial Neural Network (ANN) consists of multiple layers of neurons.

Each neuron represents a function using the values from the previous layer.

Output layer has scores for each category.

Event Identification

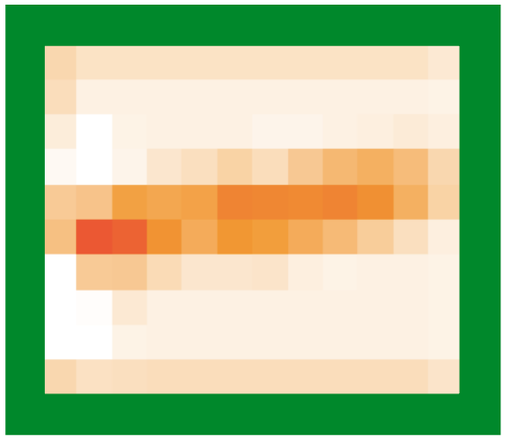


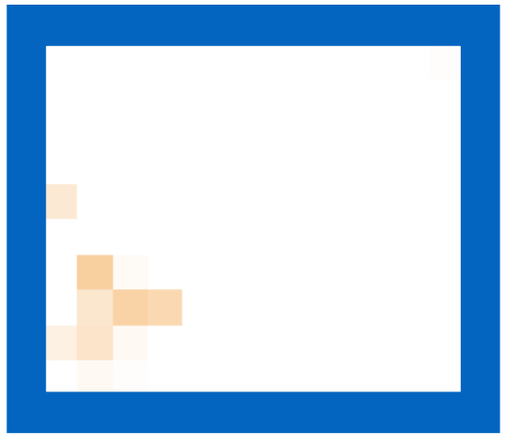


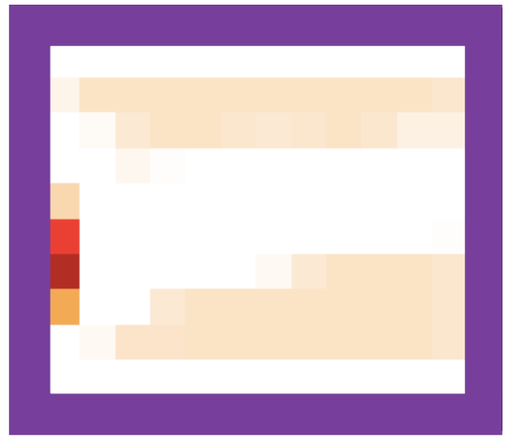
Extracted features from geometrical reconstruction used in a neural net.

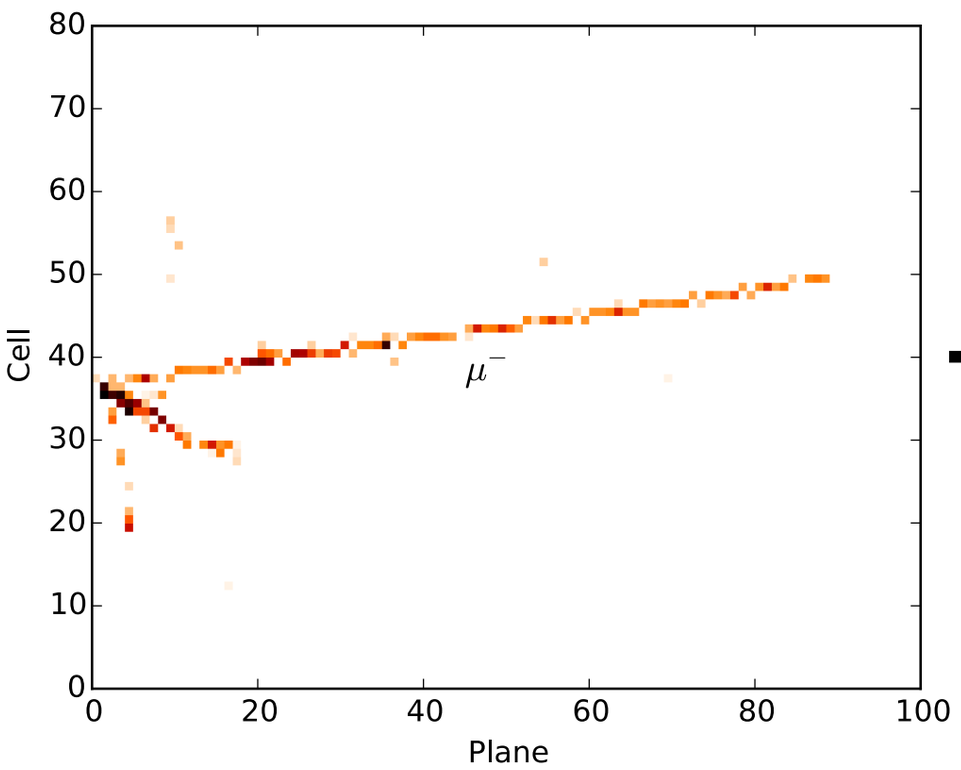
Output is the interaction type.

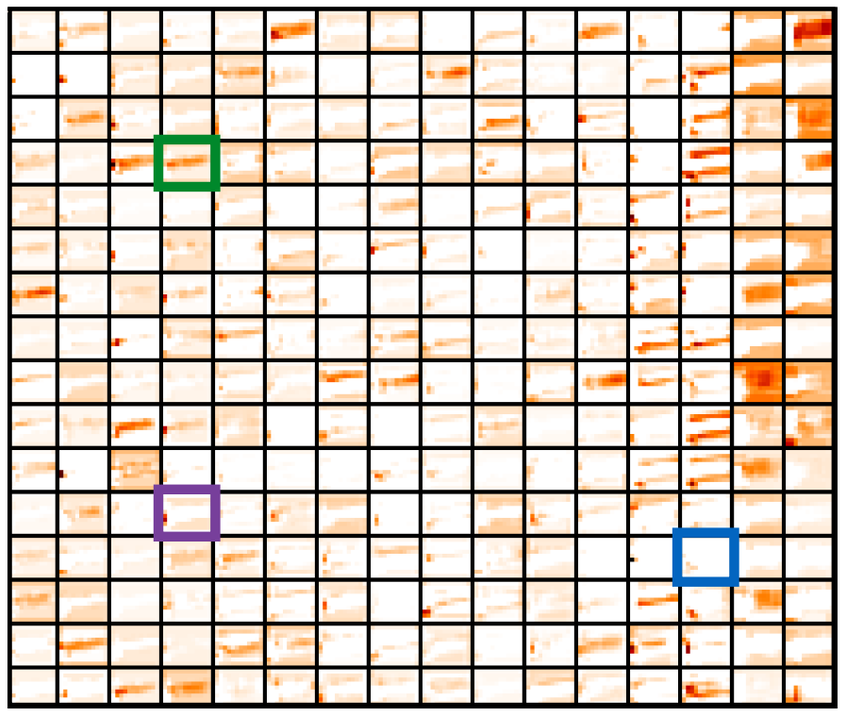
NOvA Features











NOvA Features