NOvA Reconstruction

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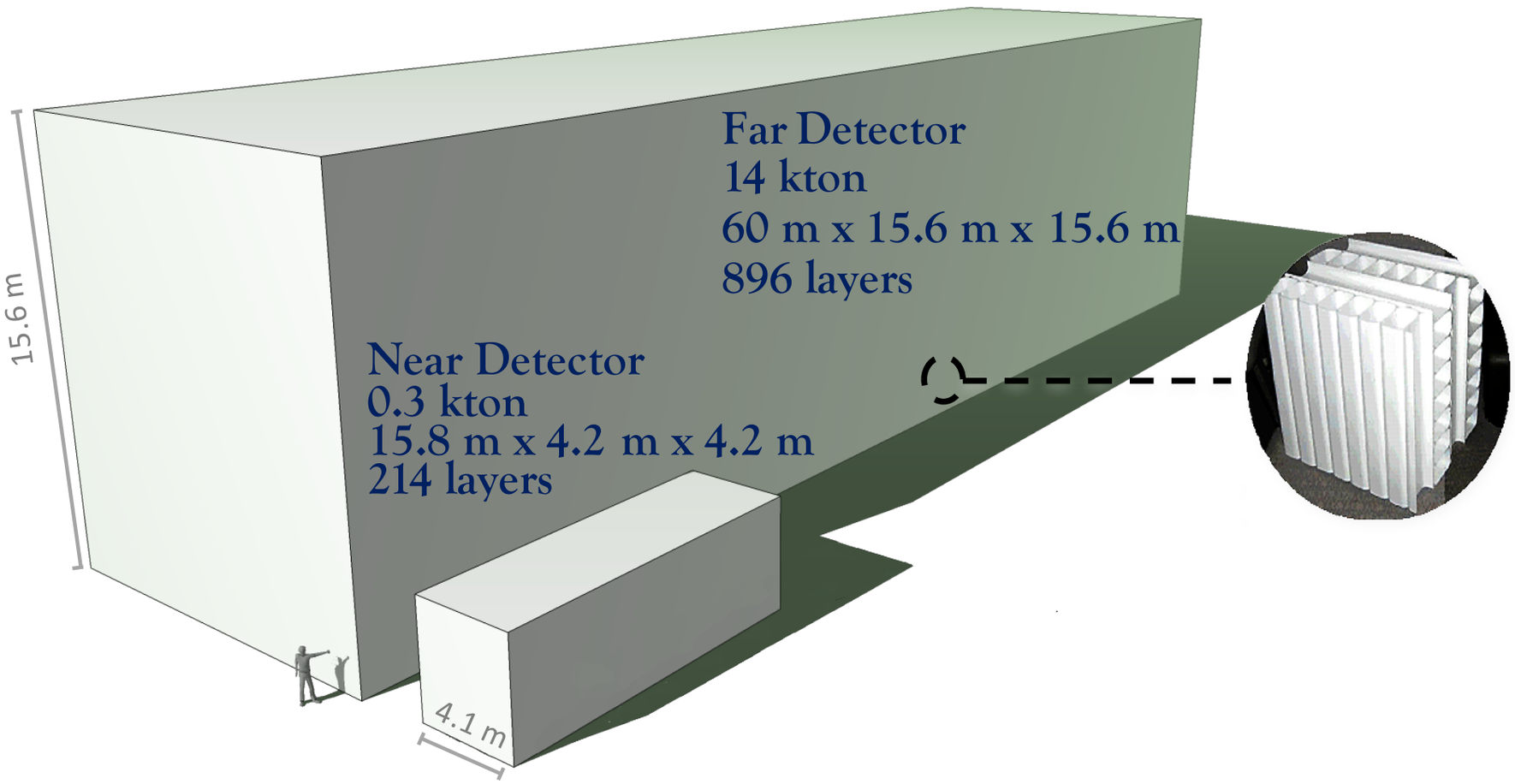
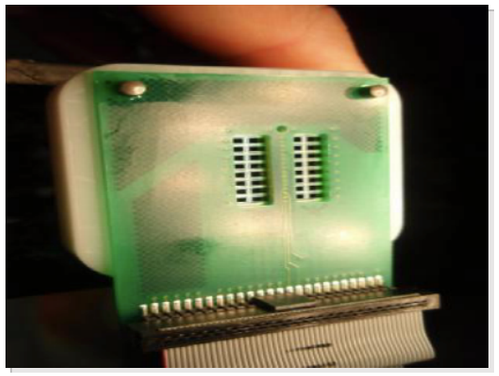
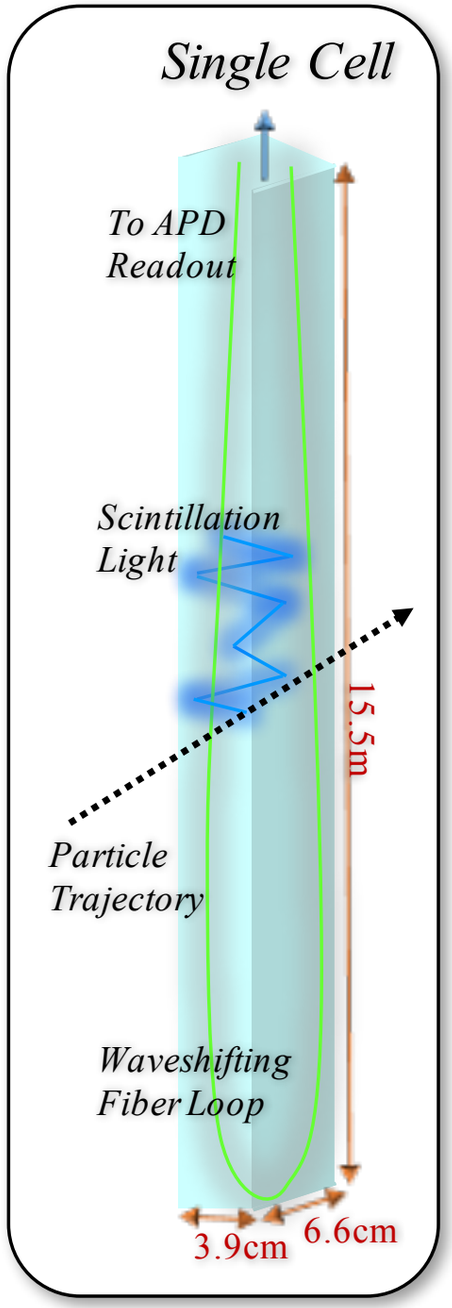
9/28/16

NOvA Overview



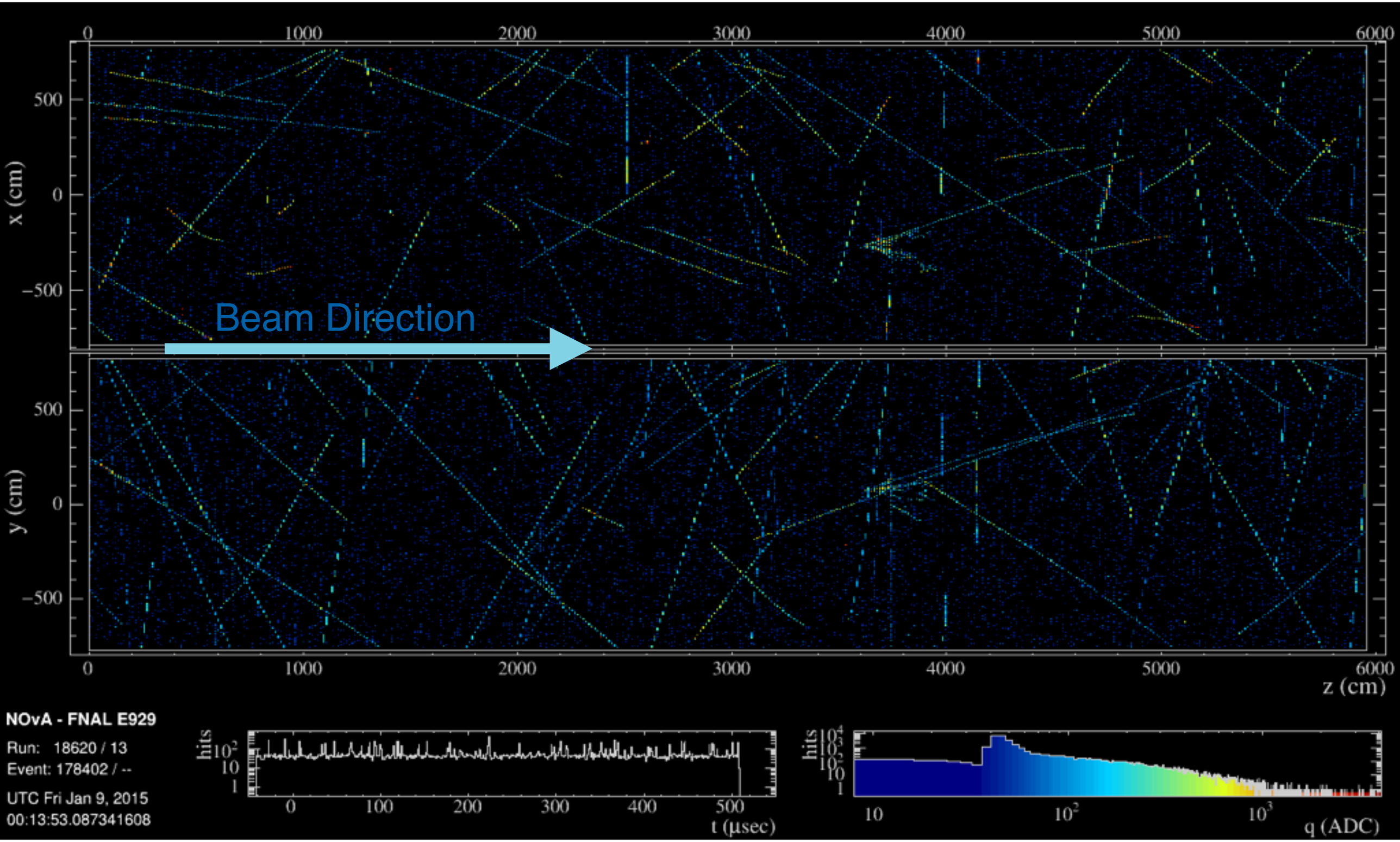




- Alternate horizontal and vertical planes of liquid scintillator filled cells
- radiation length of 38 cm (6 cell widths, 10 cell depths)
- read out 500 us windows, 10 microsecond NuMI beam
- ND 100 meters underground, FD on surface

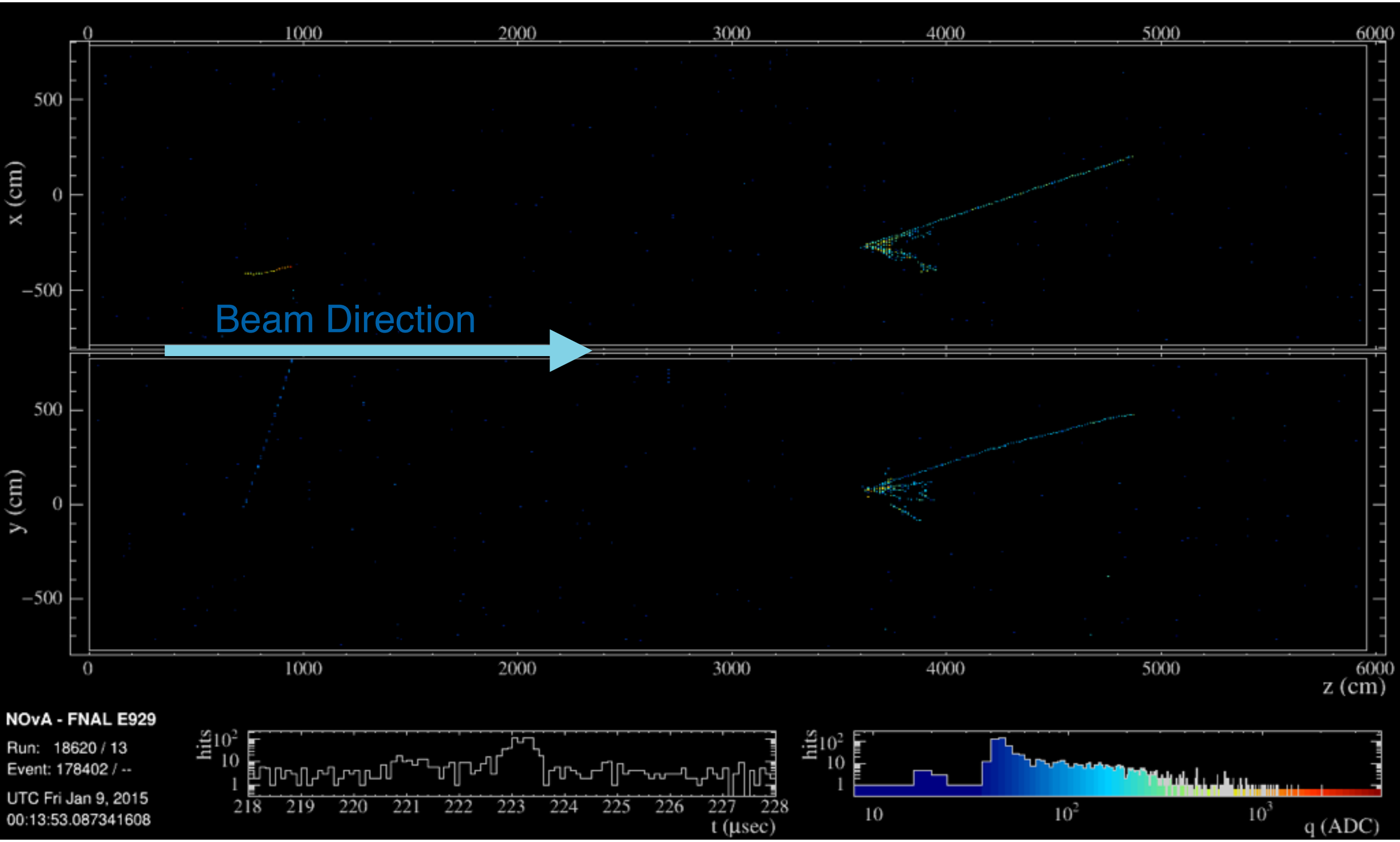
Far Detector 550 μs Readout Window

Cell hits colored by charge deposition



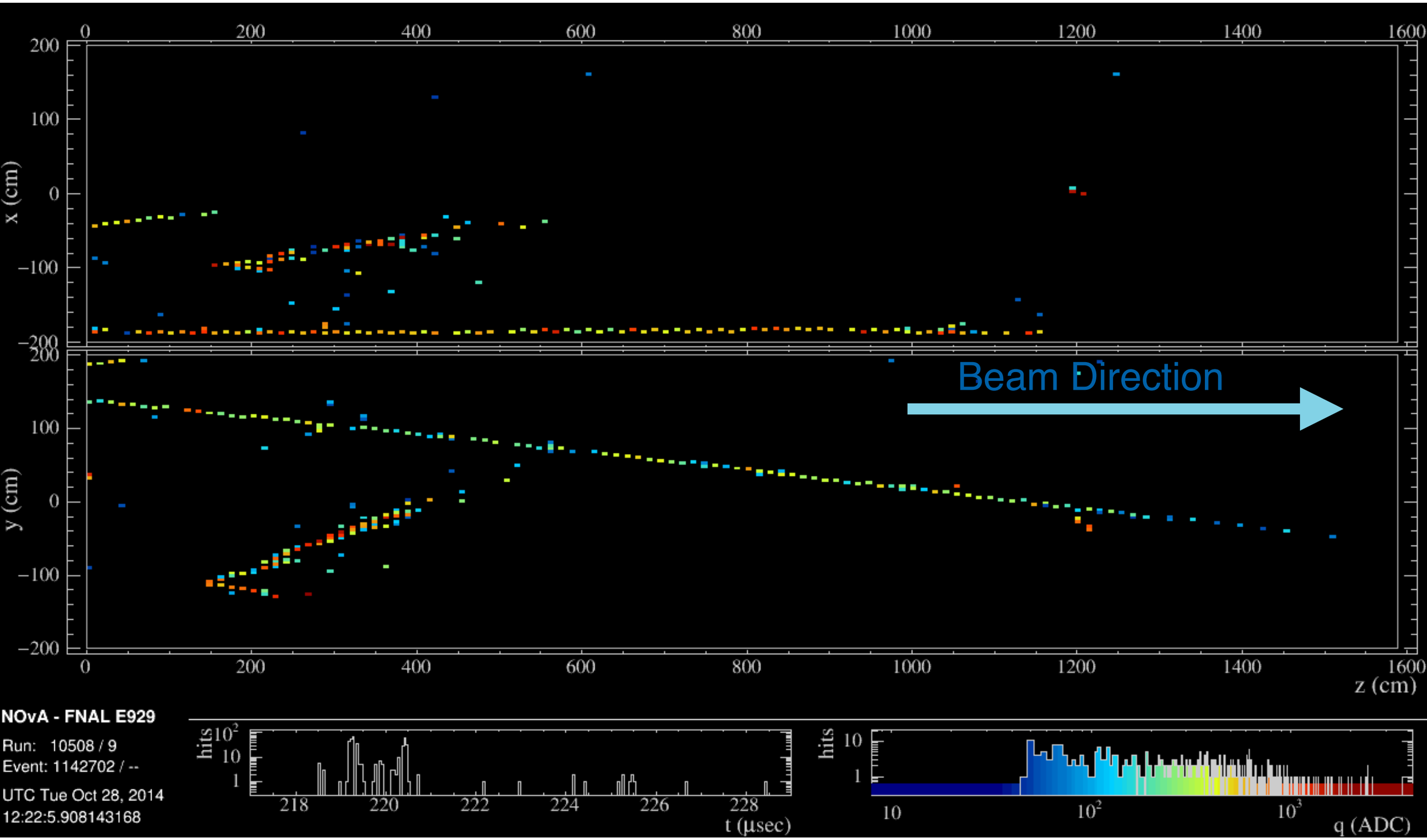
Far Detector 10 μs NuMI Beam Window

Cell hits colored by charge deposition

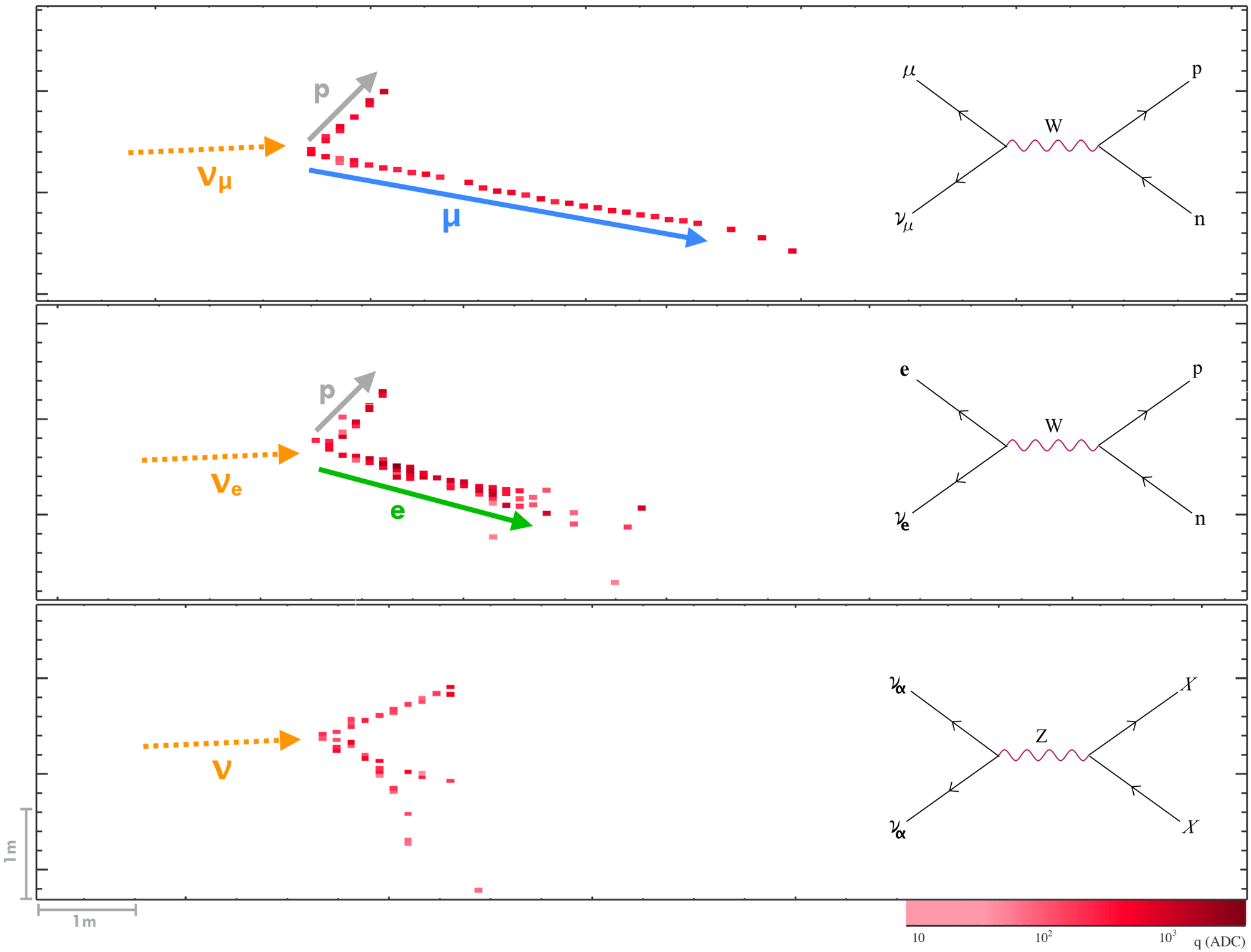


Near Detector 10 μs NuMI Beam Window

Cell hits colored by charge deposition



Events in NOvA



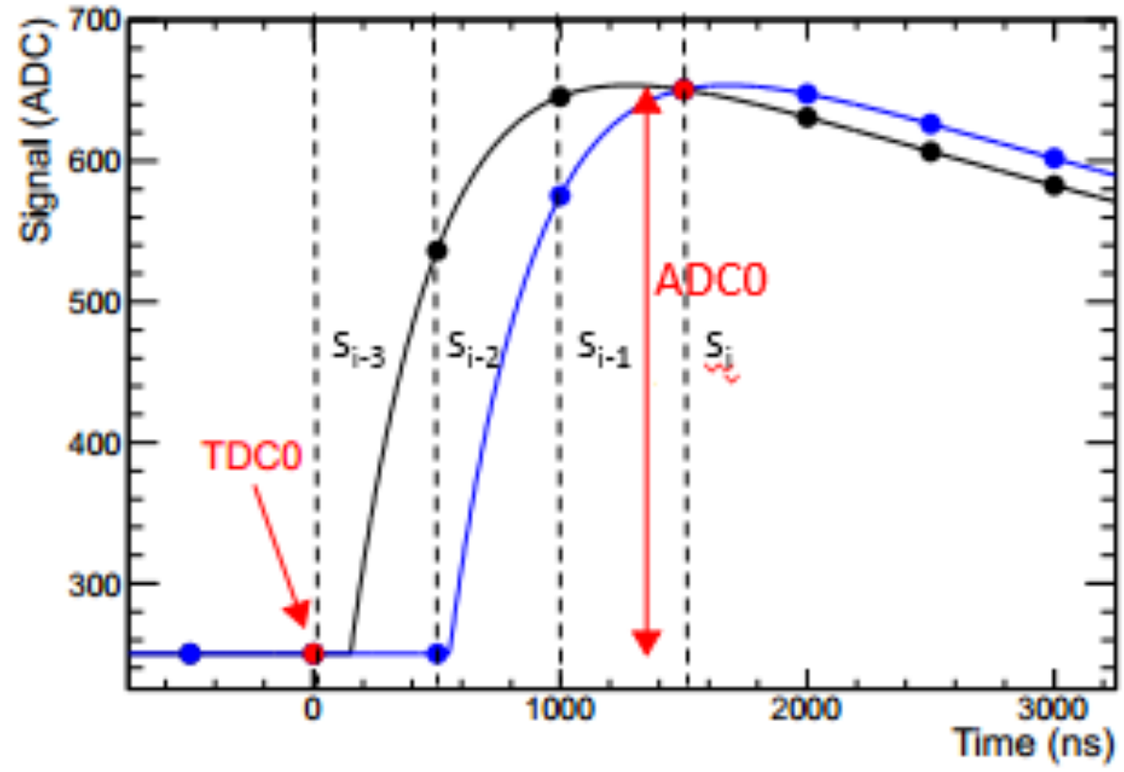
ν_μ CC

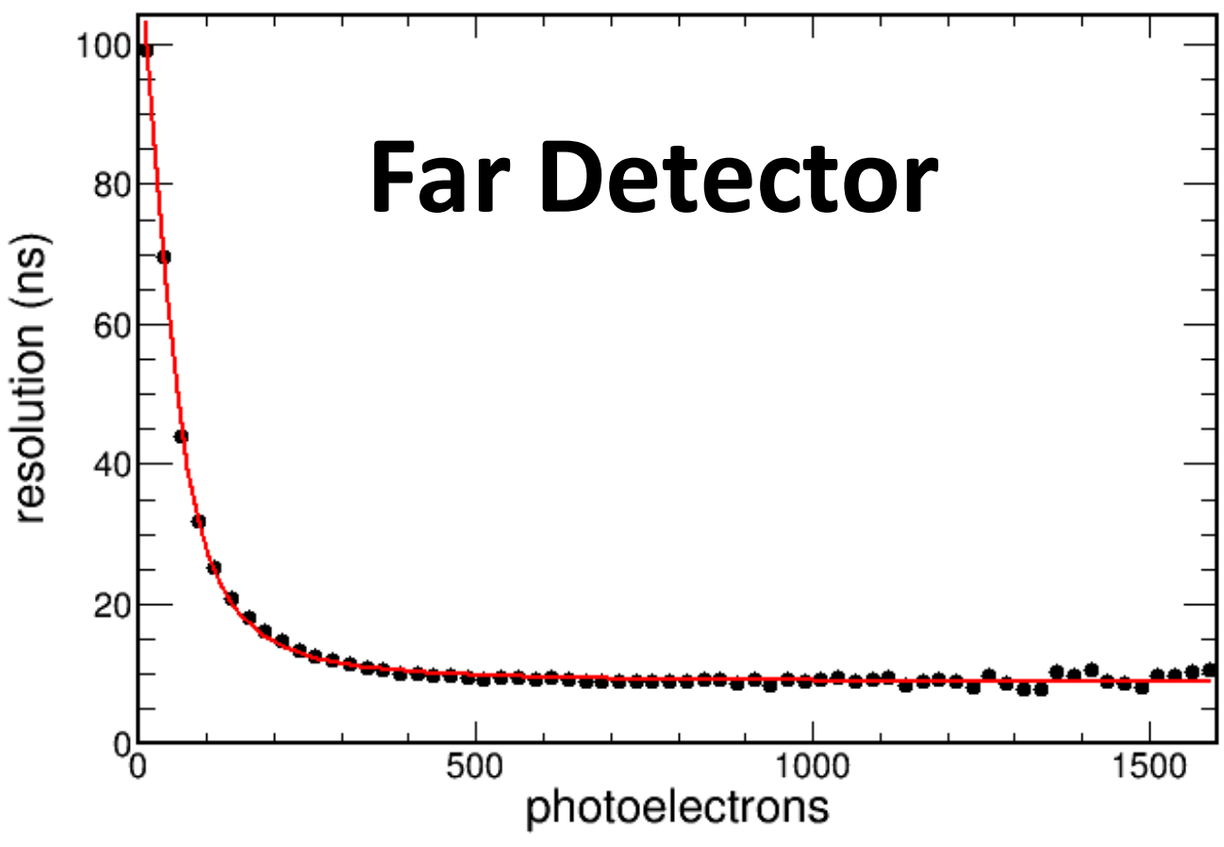
ν_e CC

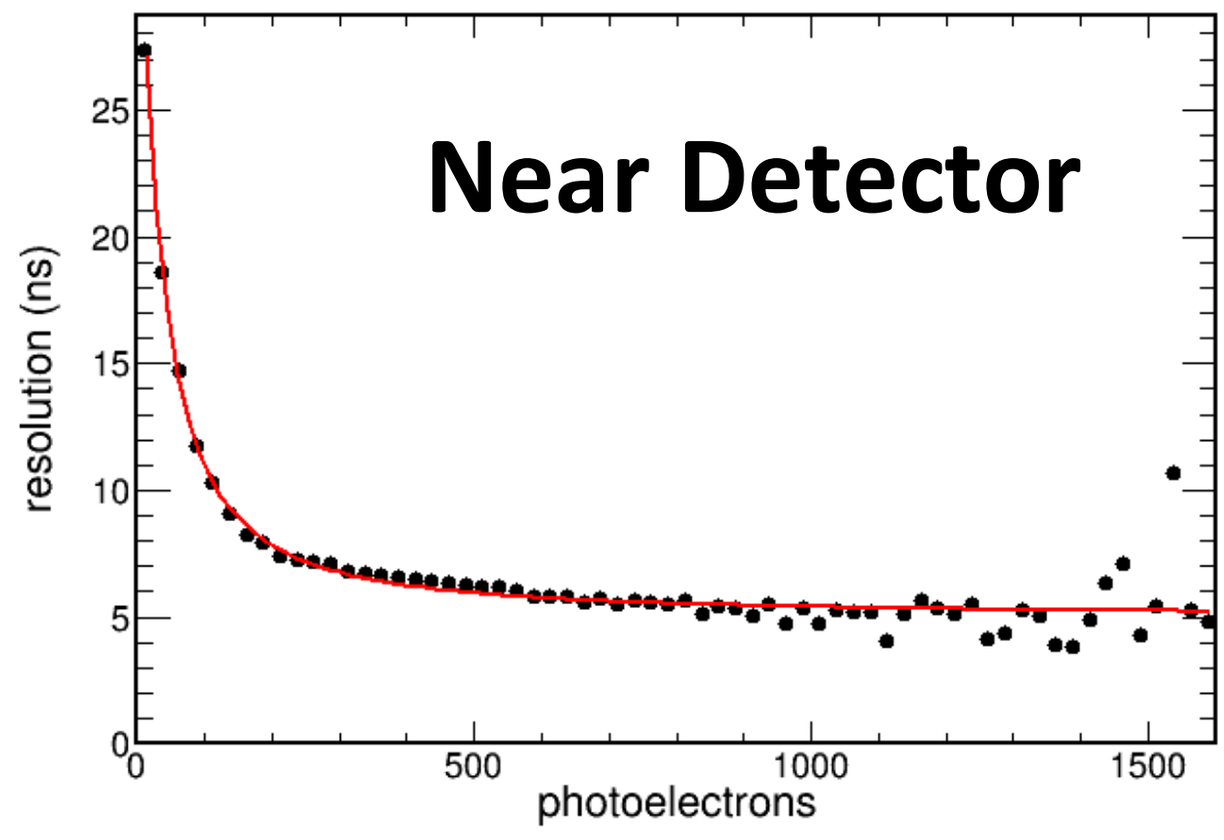
NC

NOvA Timing

- Sample APD at 2 MHz (FD) or 8 MHz ND)
- Read out four samples for hits over threshold, fit for pulse-height and time



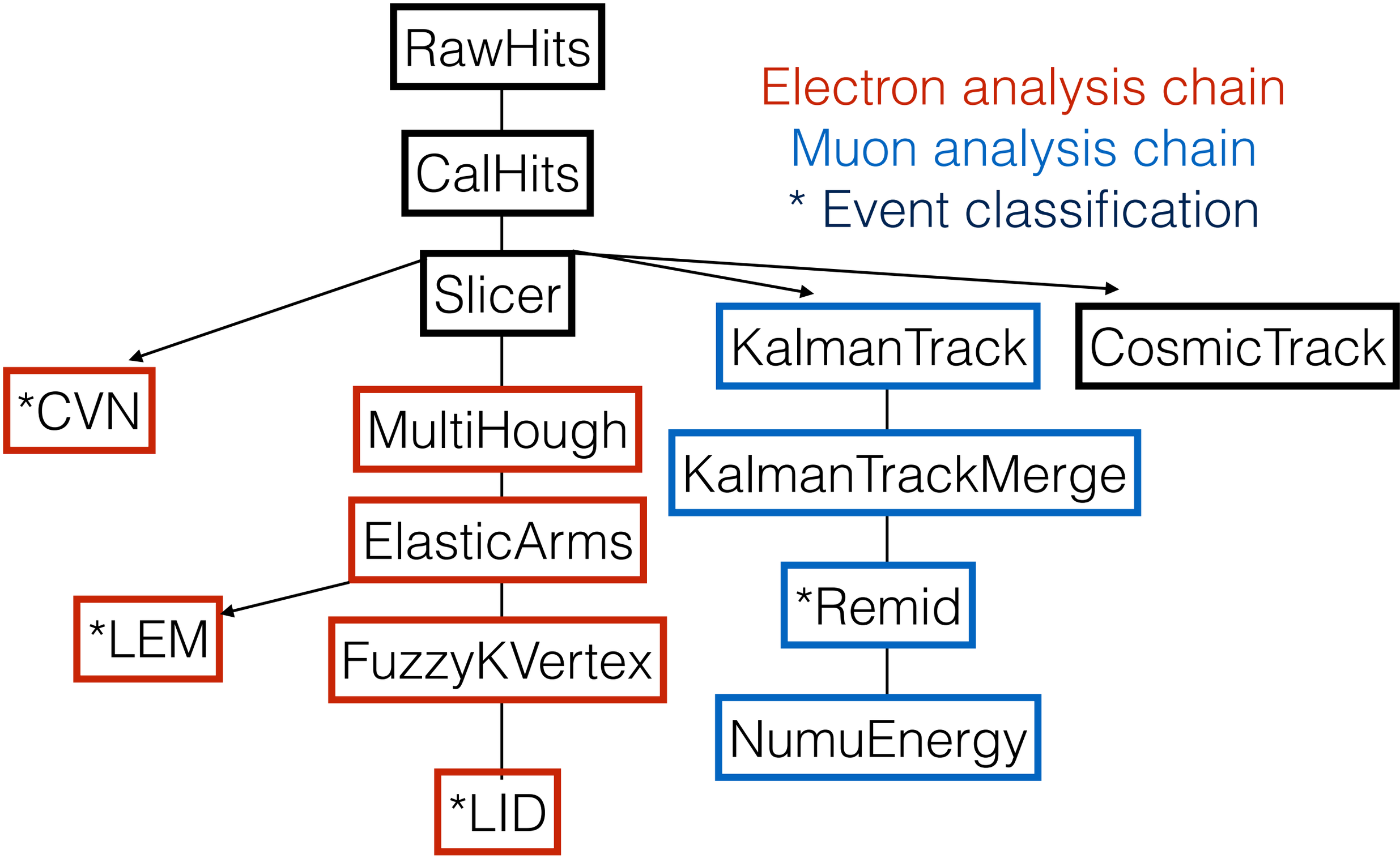




Reconstruction Challenges

- Far Detector is on the surface, sees 150 kHz of cosmics, need 10^7 cosmic rejection
- Near Detector sees 3-4 neutrino interactions per 10 microsecond beam spill.
- Our algorithms work well, have been through two analyses. Currently evaluating a few reconstruction improvements for the next cycle.

Reconstruction Chains



Slicing

- Reconstruction foundation. Downstream reco assumes each slice is one physics interaction

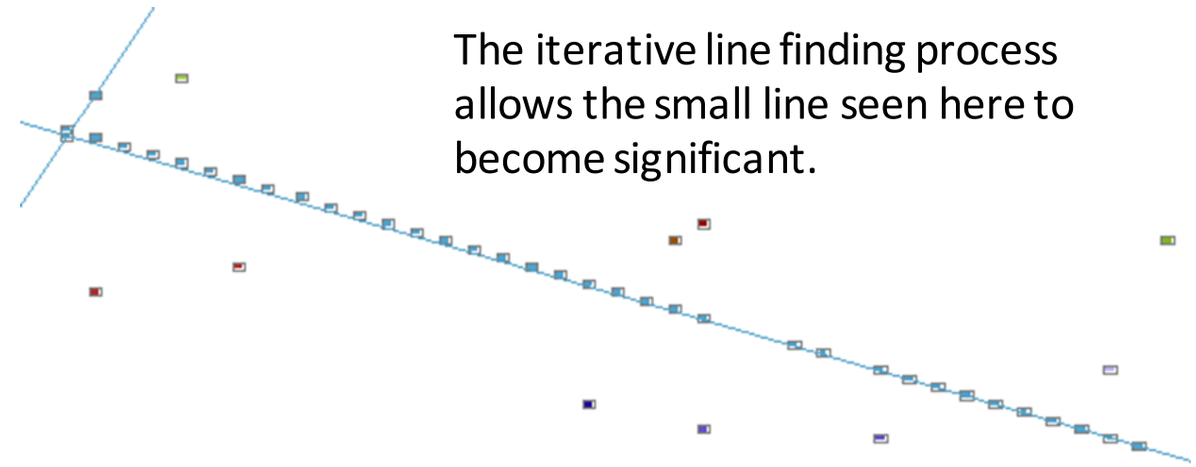
- Current: DBSCAN algorithm[1] clusters based on 4D space-time metric

$$D_n = \left(\frac{|\Delta T| - |\Delta \vec{r}|/c}{T_{res}} \right)^2 + \left(\frac{\Delta Z}{D_{pen}} \right)^2 + \left(\frac{\Delta XY}{D_{pen}} \right)^2$$

- Produces 3D clusters. Have seen a couple percent effect of multiple interactions being merged, largely due to triangle-inequality failures of the metric for slices aligned in time and Z, but spatially separated in X and Y.

[1]M. Ester, et. al., A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise (1996)

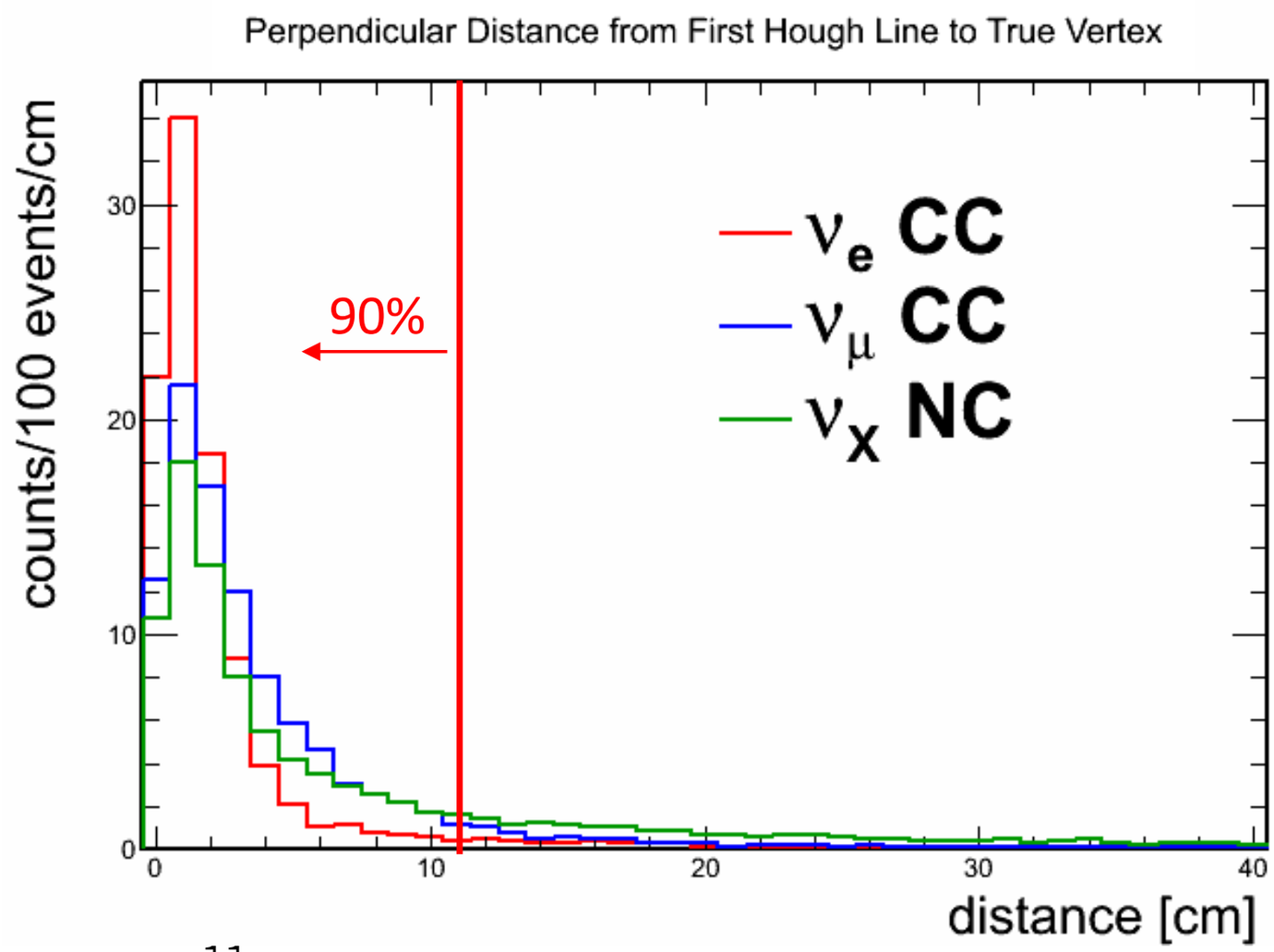
Hough Transform



The iterative line finding process allows the small line seen here to become significant.

- Modified algorithm where pairs of points are mapped into hough space, more robust against noise.
- Points near lines are removed in an iterative process in order to find finer structure.

In 90 % of all charged current events the prominent hough line comes within 11 cm of the event vertex.



Fernandes & Oliveira, Pattern Recognition 41 (2008) 299-314

Vertexing

- The algorithm fits a model of a single vertex and N "arms" to the event by minimizing the energy function below.

Least squares | Noise penalty | Displaced prong penalty

hits → K, arms → N

$$E = \sum_{i=1}^{K} \sum_{a=1}^{N} V_{ia} M_{ia} + \lambda \sum_{i=1}^{K} \left(\sum_{a=1}^{N} V_{ia} - 1 \right)^2 + \frac{2}{\lambda_v} \sum_{a=1}^{N} D_a$$

Distance from vertex to first hit in prong

Association strength of hit i to arm a

$\mathbf{X}^2$ distance from hit i to arm a

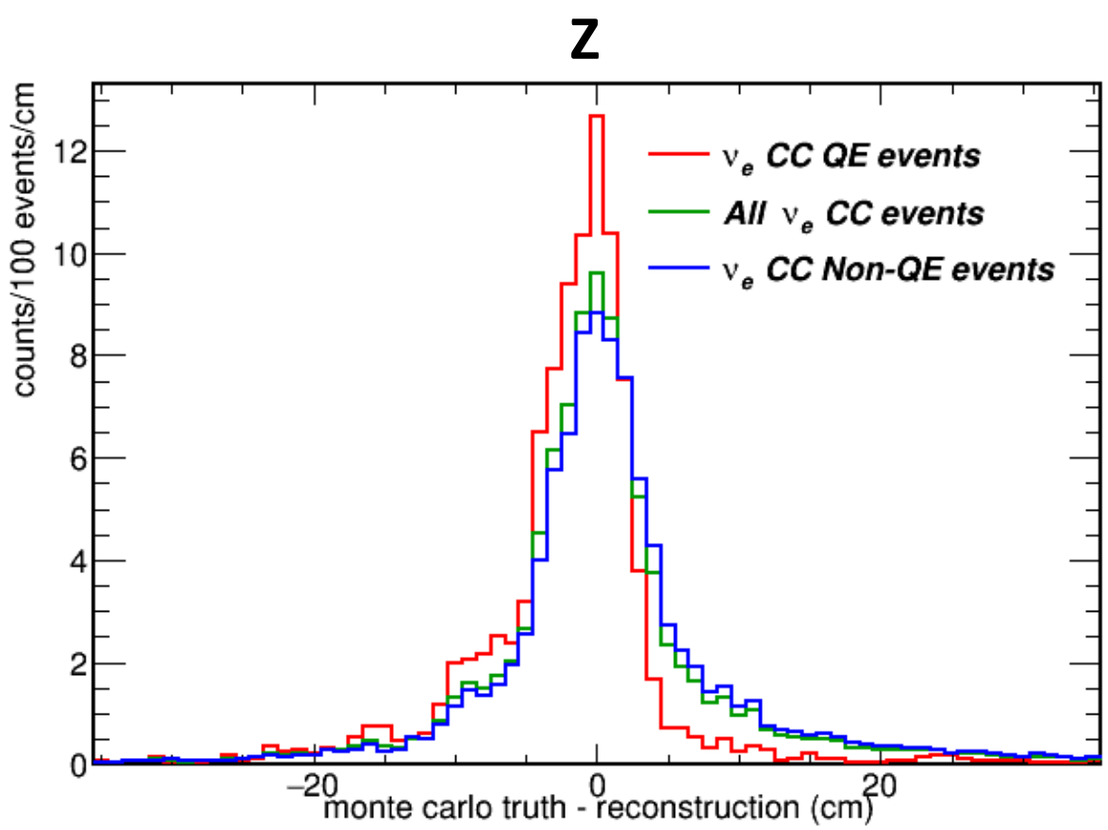
Photon conversion distance scale

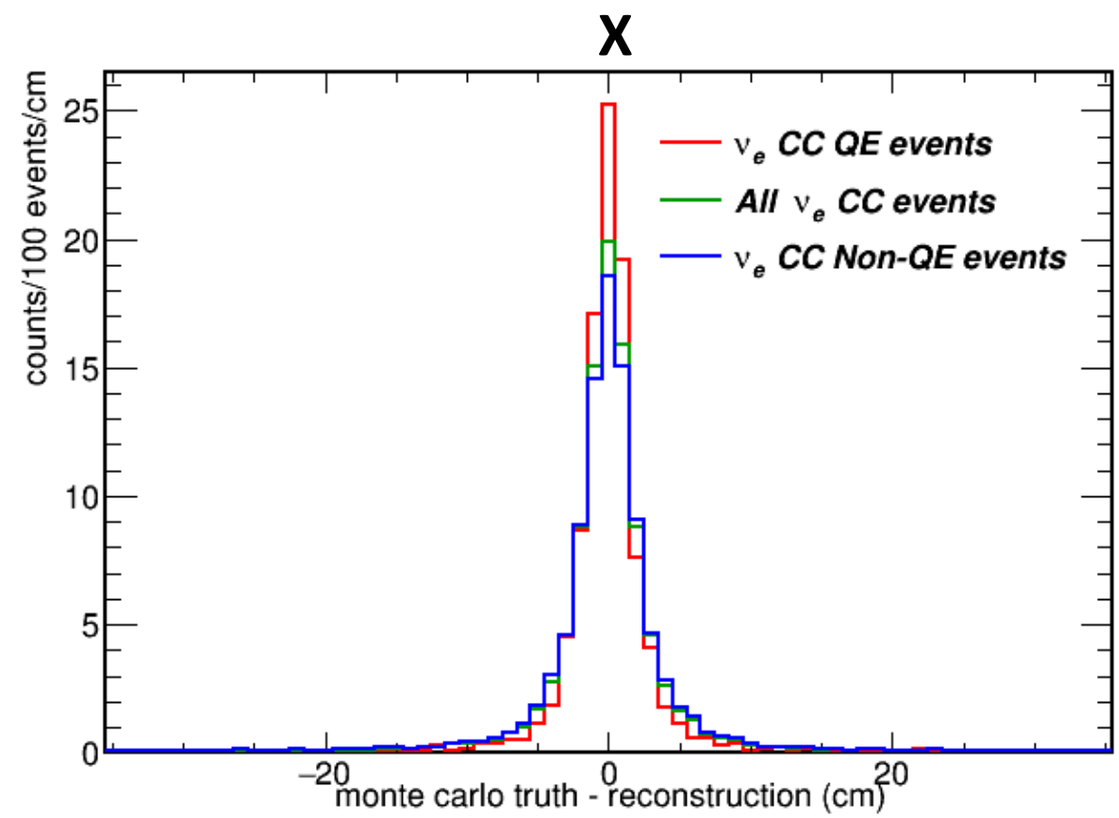
- Hough lines and intersections are used as seeds for arms and vertex.

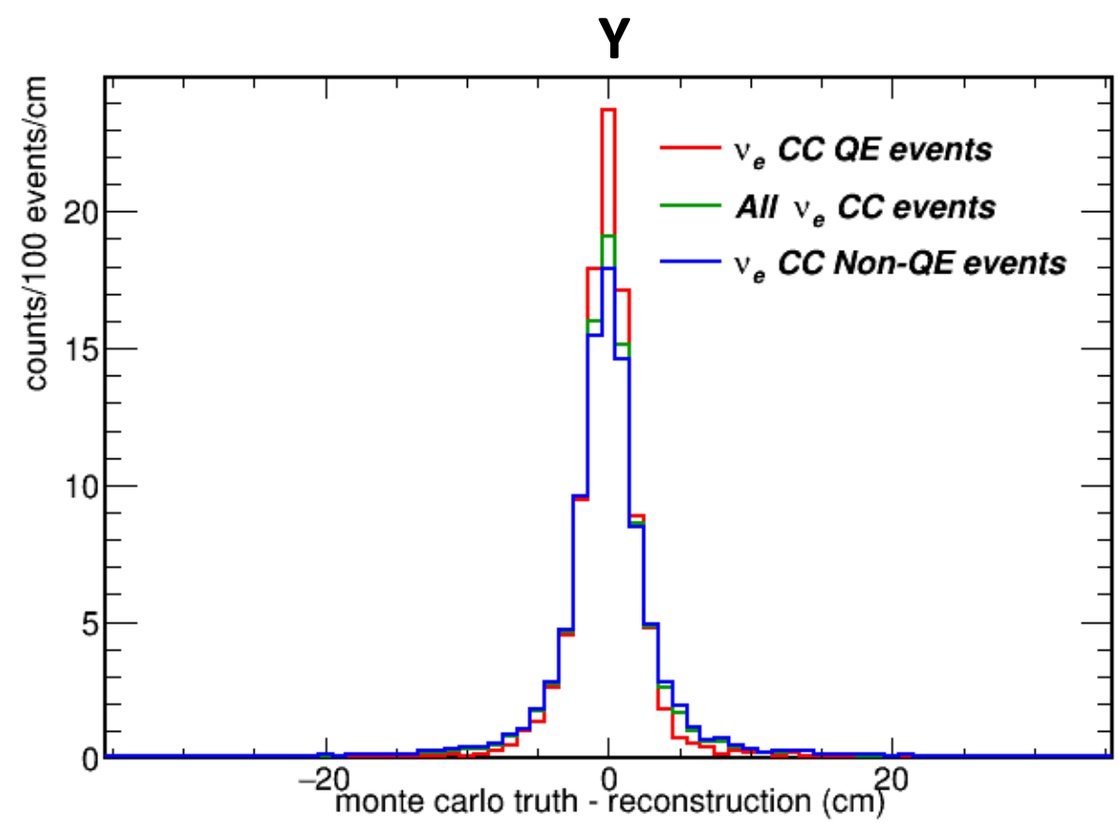
M. Gyulassy and M. Harlander, Computer Physics Communications, 66 (1991) 32-46.
M. Ohlsson, C. Peterson, Computer Physics Communications, 71 (1992) 77-98.
M. Ohlsson, Computer Physics Communications, 77 (1993) 19-32.
R. Fruwirth and A. Strandie, Computer Physics Communications, 120 (1999) 197-214.

Vertexing

Far Detector Simulation







The vertex resolution for all ν_e cc events is less than 5cm (one cell) in X and Y, and 8 cm in Z.

Shower Reconstruction: Possibilistic Fuzzy K-means clustering

- "Fuzzy": Individual hits are allowed to have membership in multiple clusters.
- "Possibilistic": A cells total membership cannot exceed one, but it is not normalized, allowing noise hits to be unclustered.
- Cluster number not known a priori, start with 1 cluster and iterate until all hits are accounted for.
- Clustering is done separately in each view of the detector and then matches are made based on cluster characteristics.

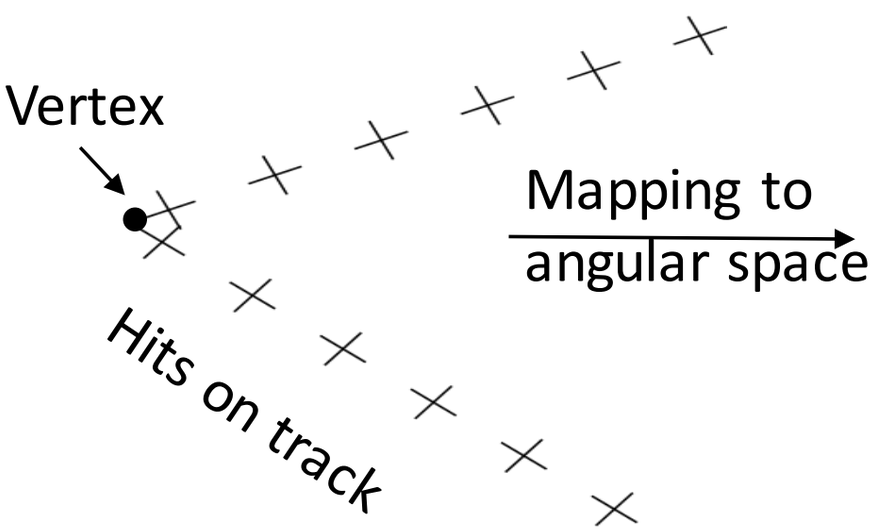
Distance to cluster centers

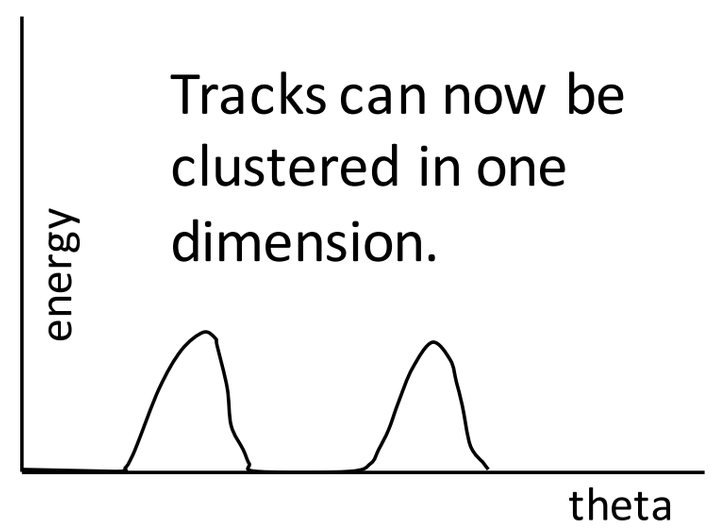
$$d_{ij} = \left(\frac{\theta_j - \bar{\theta}_i}{\sigma_j}\right)^2$$

Cell hit j

Cluster center i

Angular uncertainty, derived from simulation





Tracks can now be clustered in one dimension.

Cluster Membership

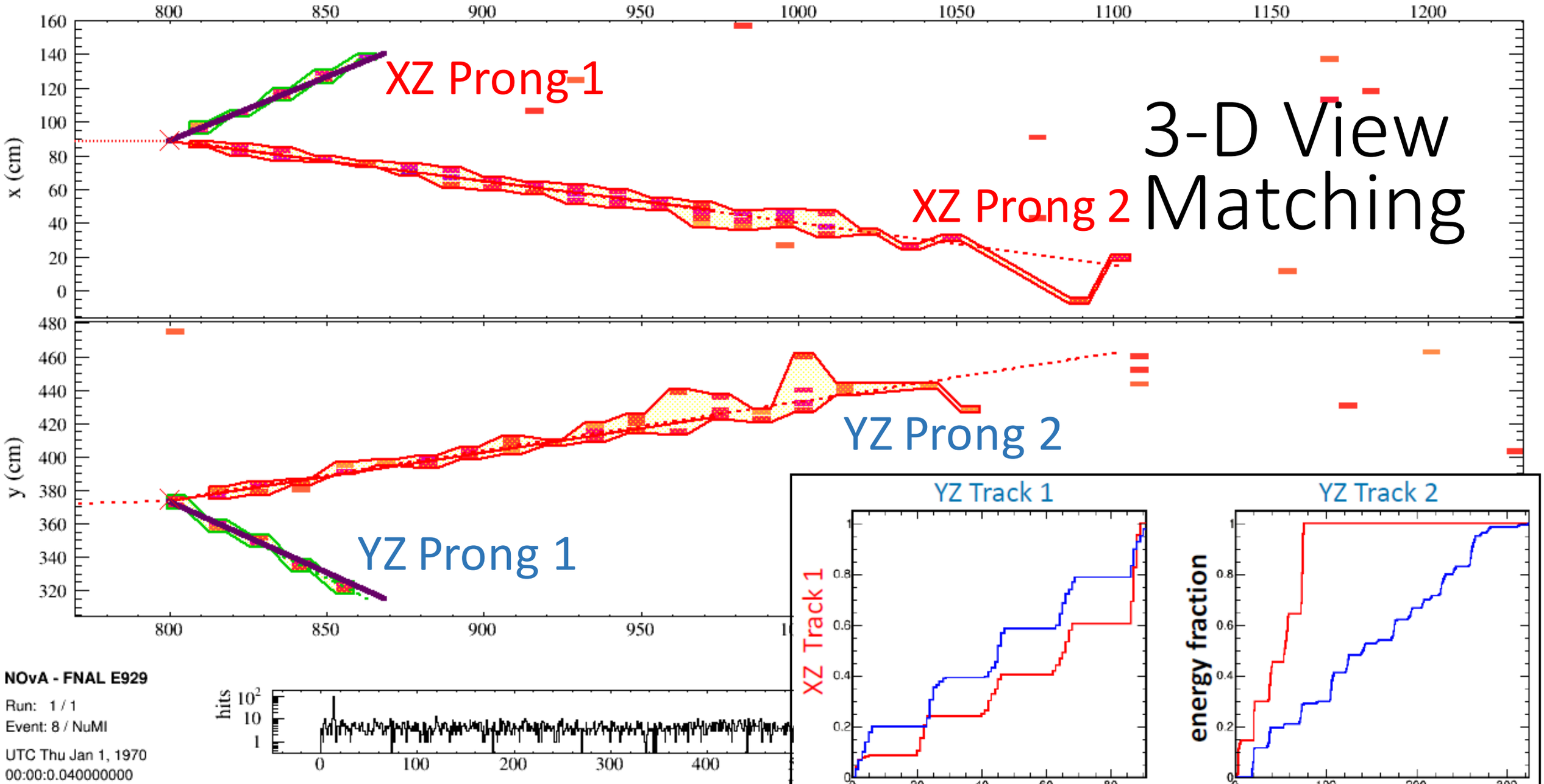
$$U_{ij} = e^{-\frac{m\sqrt{c}d_{ij}}{\beta}}$$

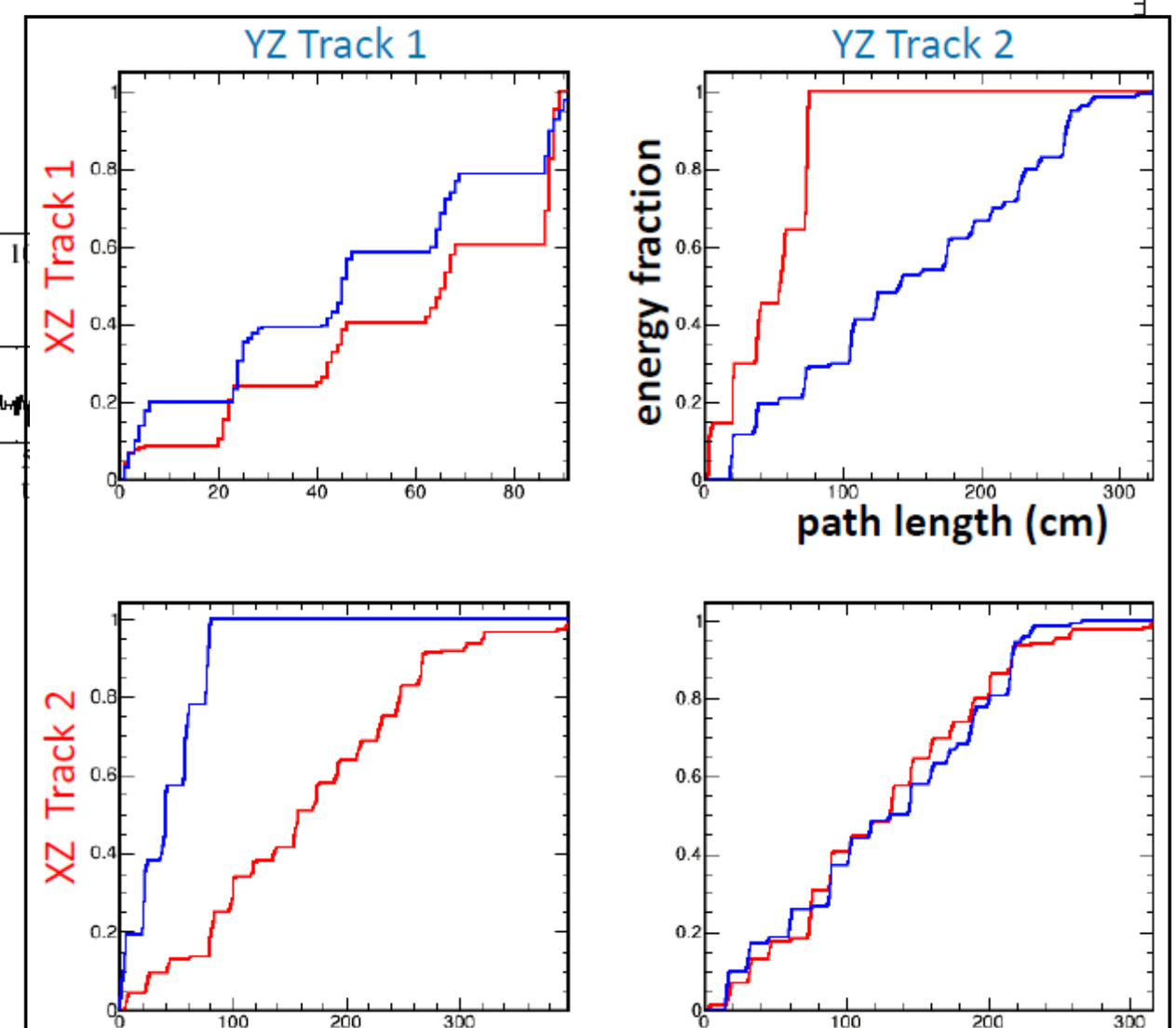
Updating cluster centers

$$\bar{\theta}_i' = \bar{\theta}_i + \frac{\sum_{j=1}^{K} \frac{U_{ij}^m}{\sigma_j^2}\left(\theta_j - \bar{\theta}_i\right)}{\sum_{j=1}^{K} \frac{U_{ij}^m}{\sigma_j^2}}$$

R. Krishnapuram, J.M. Keller, A possibilistic approach to clustering, IEEE Trans. Fuzzy Syst. 1 (1993) 98110.
M.-S. Yang, K.-L. Wu, Unsupervised possibilistic clustering, Pattern Recognition, 39 (2006), pp. 521.

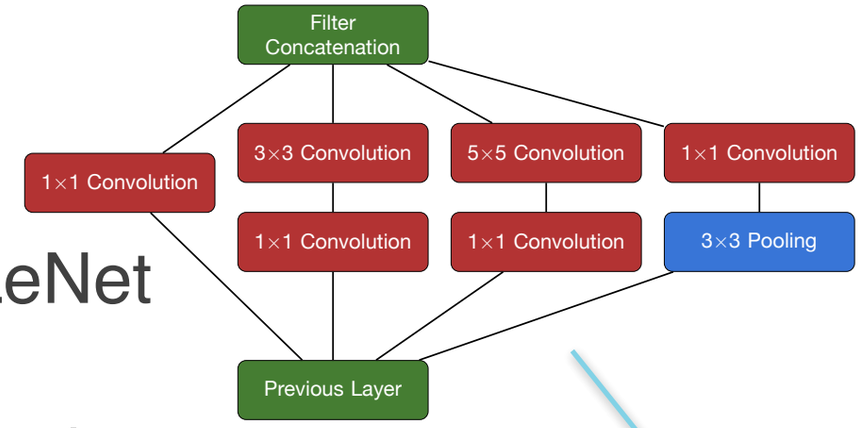
3-D View Matching



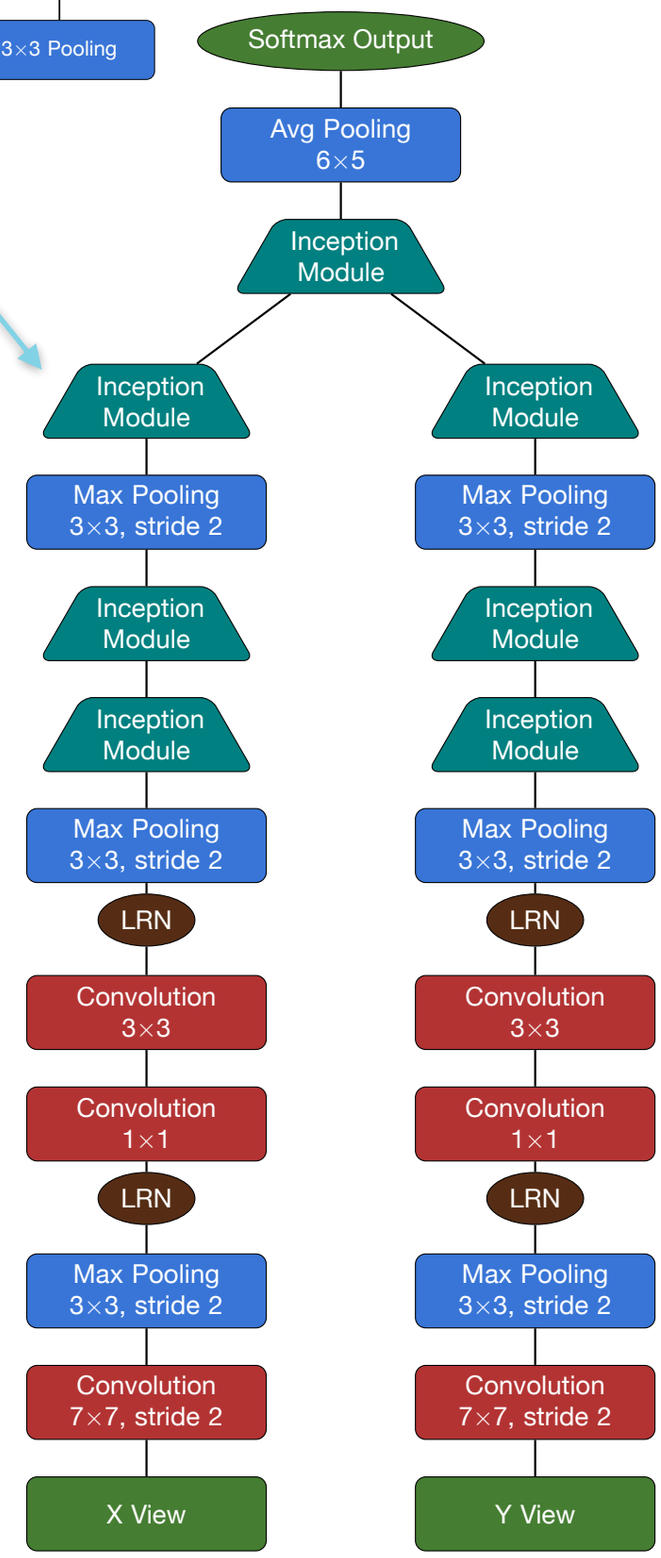


Algorithm does not yet support many-to-one matching between views

CVN



- Architecture adapted from GoogLeNet
  - C. Szegedy et al., arXiv:1409.4842
  - Input is 80 cell x 200 plane detector pixel map
  - Each event view processed separately and then merged



- Network implemented and trained in the Caffe Framework (Y. Jia et al., arXiv:1408.5093)
- Trained on 4.7 million simulated events on Fermilab GPU cluster

- Output classifies neutrino interaction type (ν_μ,ν_τ,ν_e,NC)
- Used in electron neutrino analysis and neutral current.
  - Performance gain over previous classifiers equivalent to adding 30% more detector mass
- Caffe framework available on Scisoft, experiment independent
- We have deployed our Caffe networks in ART framework for evaluation

A. Aurisano and A. Radovic and D. Rocco et. al, JINST **11** P09001 (2016)

CVN Plans

- Developing Prong-based network. ID each individual prong as a particle
- Go one step further with semantic segmentation. ID each pixel by particle and then reconstruct objects
- Exploring network speed optimizations
- Adding timing information to network (upward-going muons, michel tagging, information from other slices).
- and more

What are we working on?

- Evaluating new slicing algorithm. 2D temporal clustering, followed by spatial clustering and view matching to reduce some pile-up effects

- New vertex algorithm (algebraic hough transform, improves speed and resolution, reduces 2-step process to one)

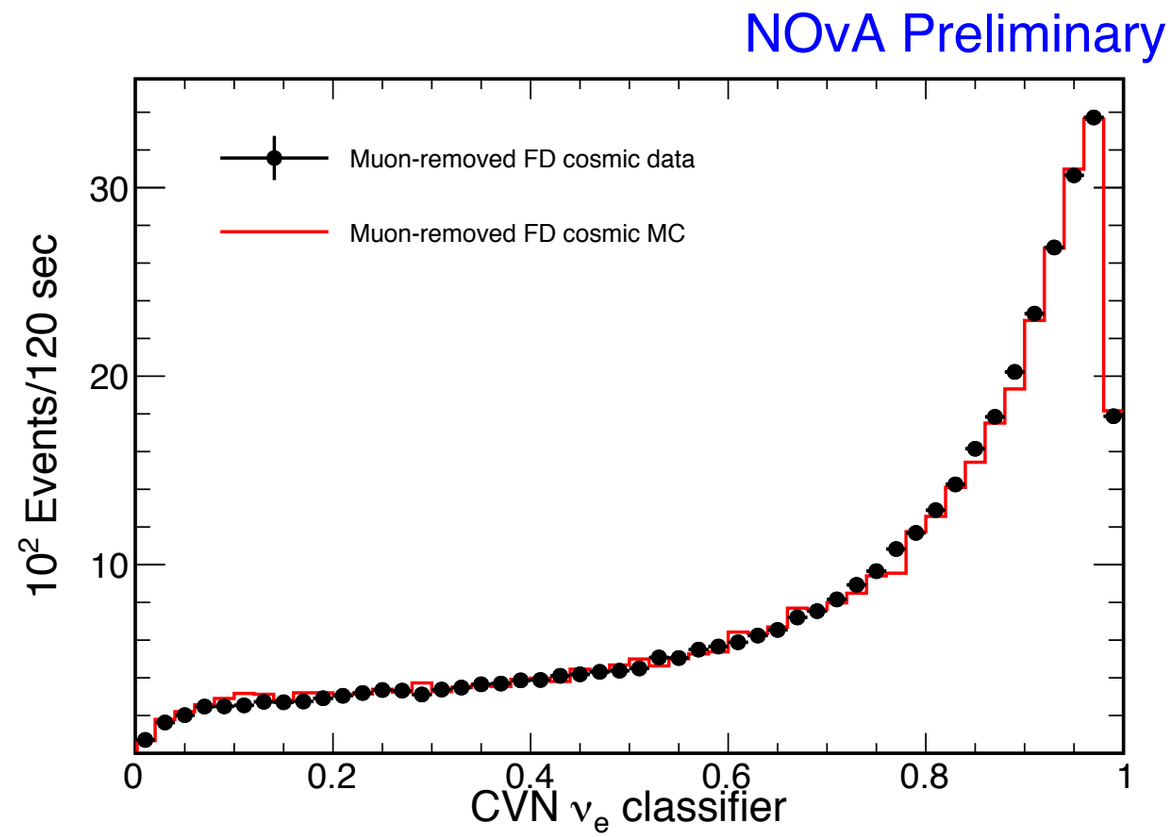
- Improve 2D->3D merging of showers (allow multiple-to-one matching, consider 3D from the start)

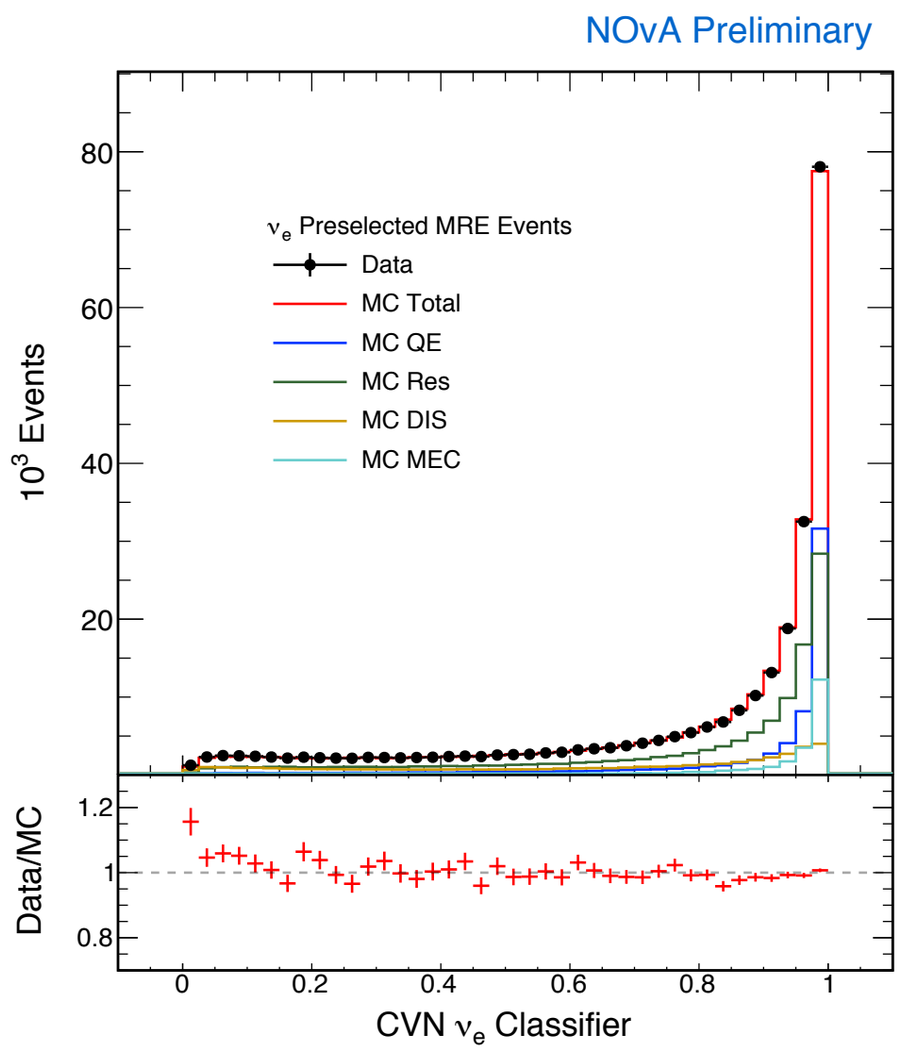
- CVN developments

Backup

Evaluating Signal Efficiency

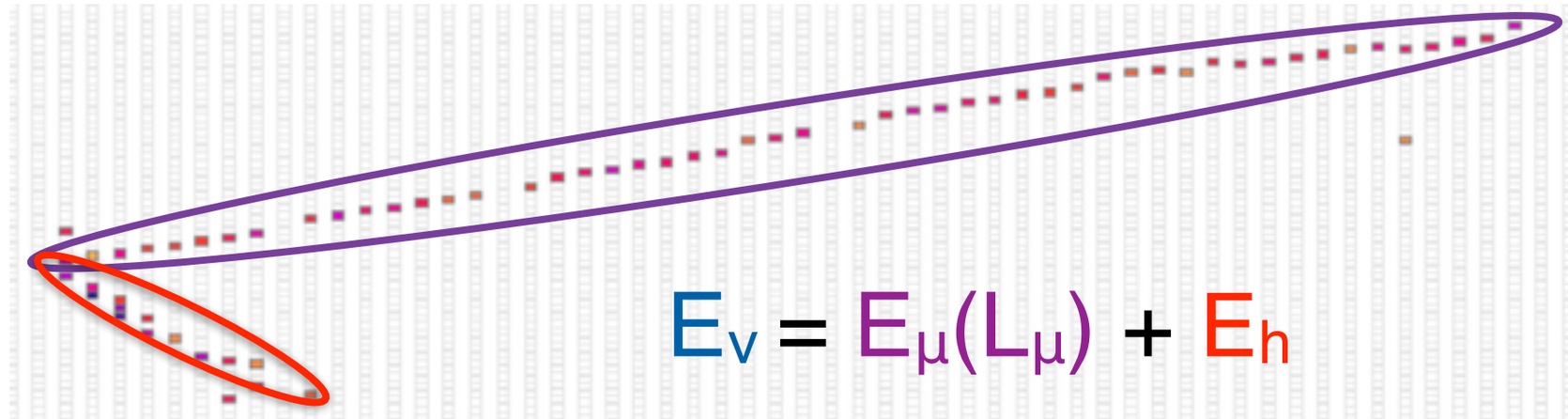
- Remove cosmic ray muon from FD events in data and simulation
- Apply selection to remaining bremstrahlung shower to benchmark simulation of electron selection



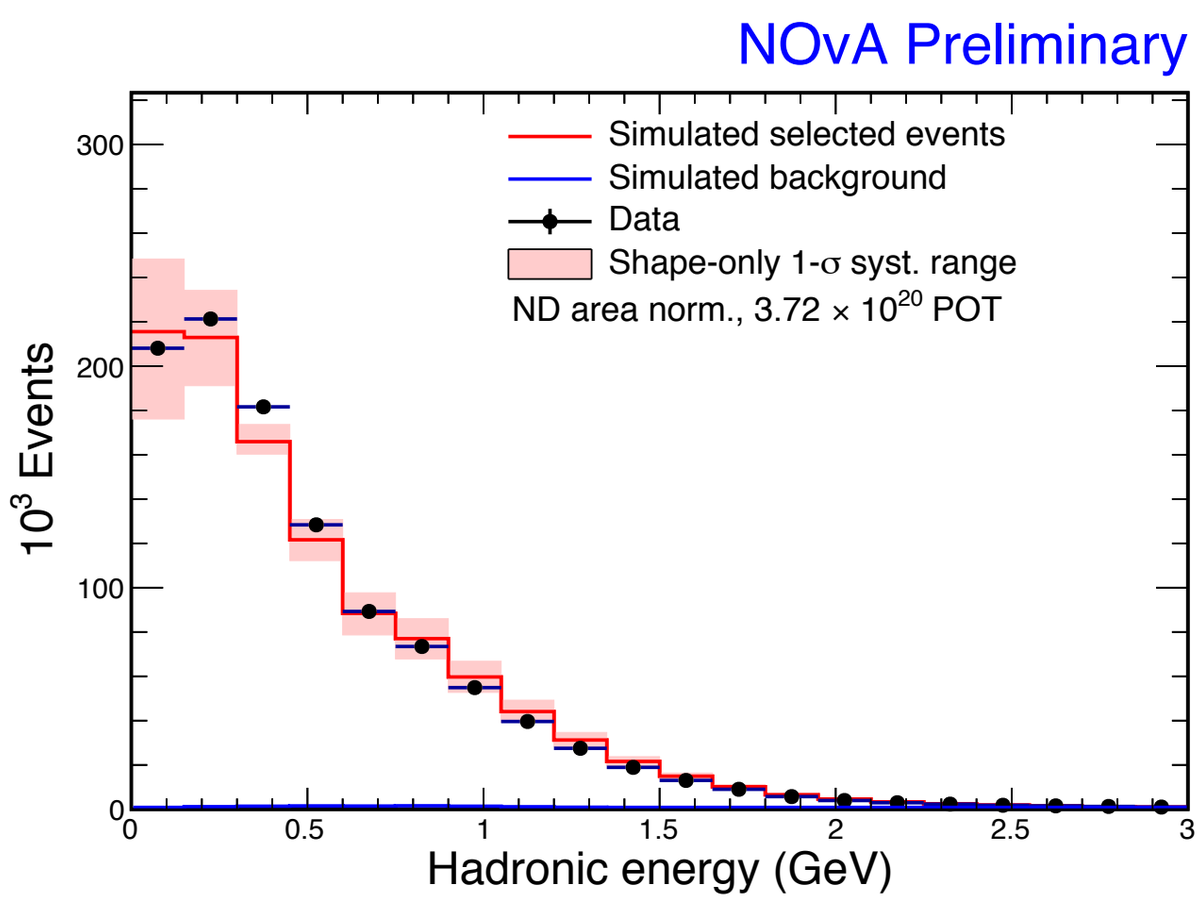


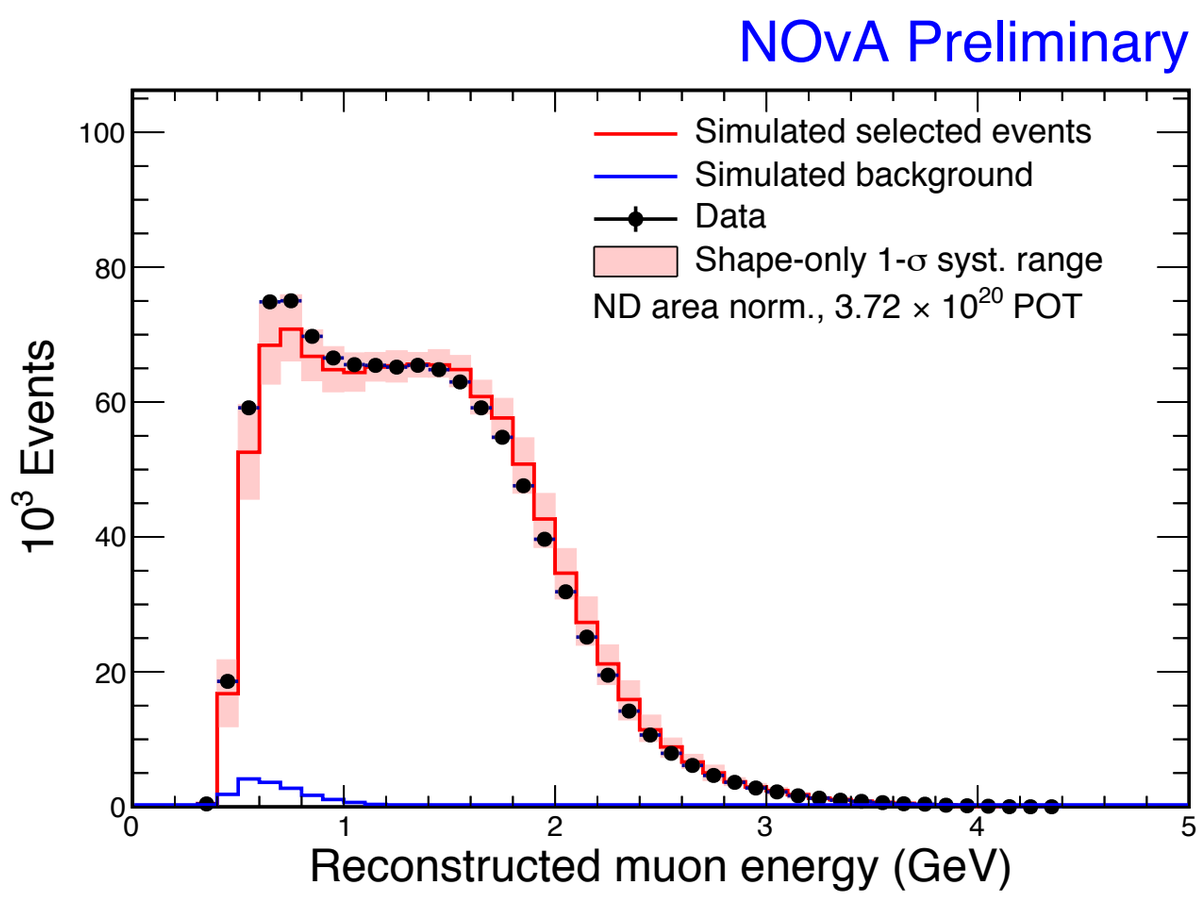
- EM showers should be well modeled, check if selection efficiency differences come from hadronic side
- Remove reconstructed muons from selected ν_μ events, replace with simulated electron (MRE)
  - better than 1% agreement between efficiency for selecting data MRE events and efficiency for selecting MC MRE events

Energy Estimation



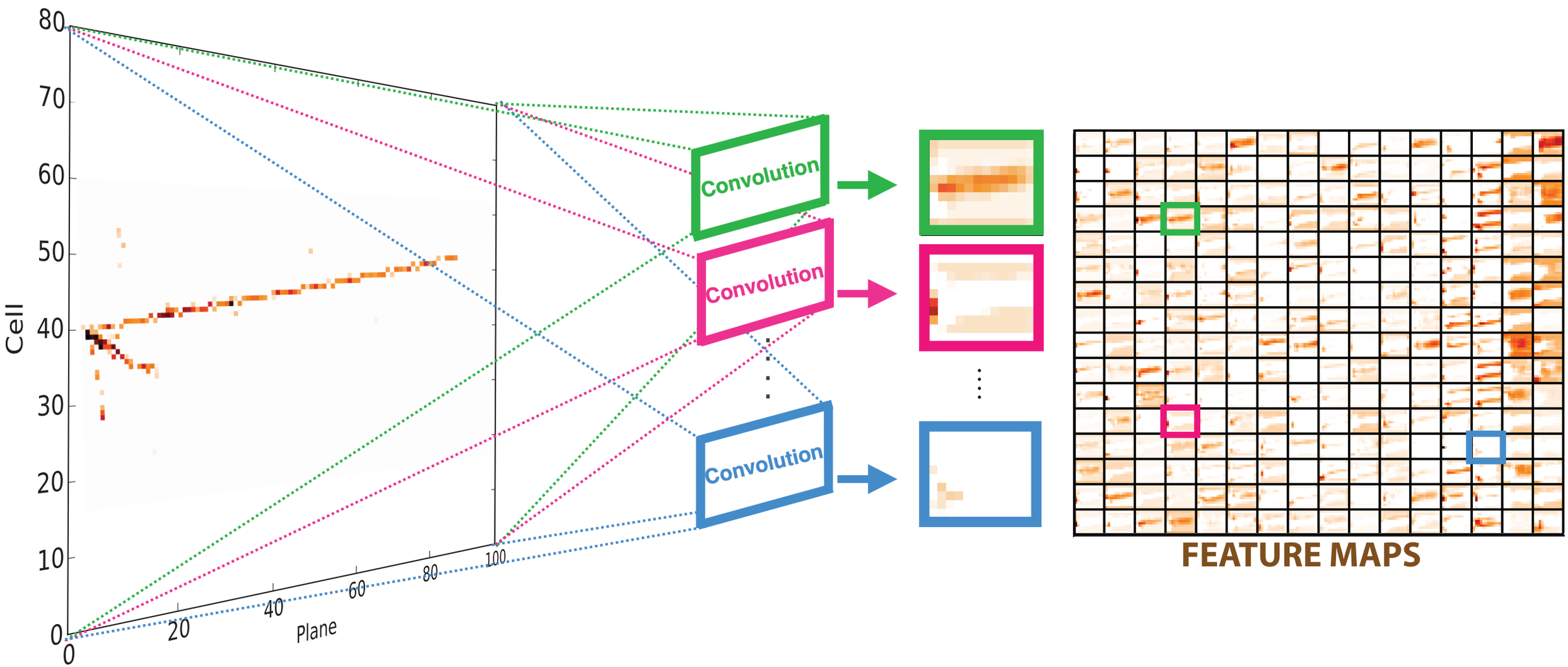
- Muon dE/dx used in length-to-energy conversion
- Hadronic energy estimated calorimetrically from off-track hits
- ~7% resolution on neutrino energy





Convolutional Neural Networks

- Showing a muon neutrino interaction and the first layer of feature maps extracted from the convolutional kernels



Convolutional Neural Networks

- Showing a electron neutrino interaction and the first layer of feature maps extracted from the convolutional kernels
- The strong features extracted are the shower as opposed to the muon track