For the NOvA Collaboration

Electron Neutrino Energy Reconstruction in NOvA Using CNN Particle IDs

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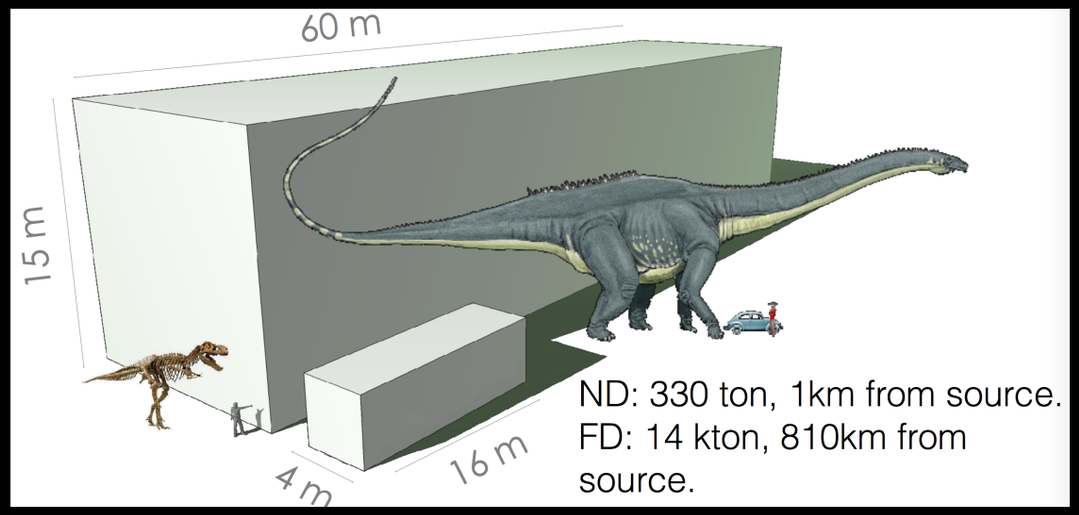
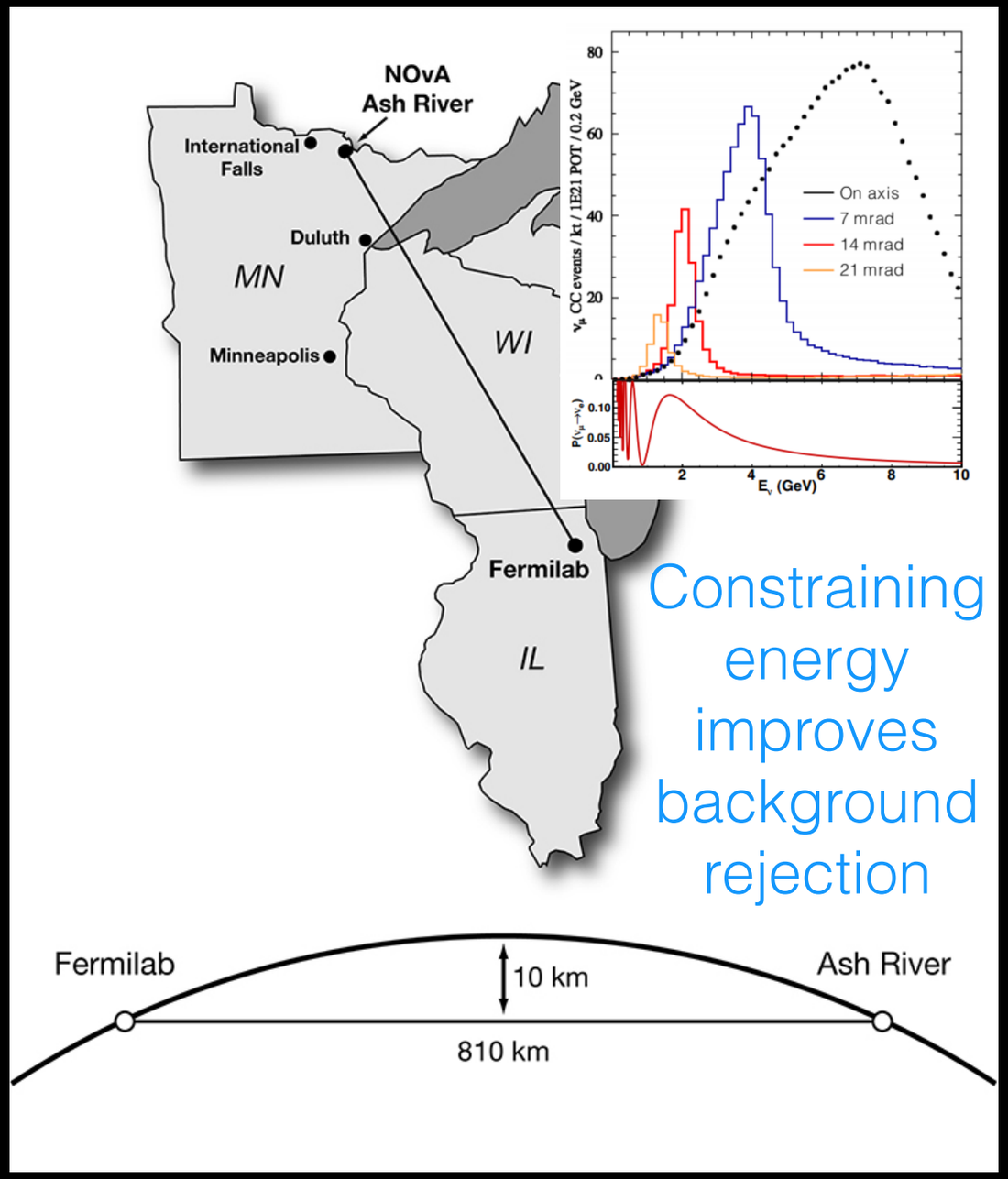
NuMI Off-axis ν_e Appearance

Studying oscillations over a 810km baseline with two functionally identical detectors and the world's most powerful muon neutrino beam, NuMI.





Constraining energy improves background rejection

NOvA Physics Goals

Precise measurements:

Δm_{32}^2 and $\sin^2(2\theta_{23})$ for neutrinos and antineutrinos

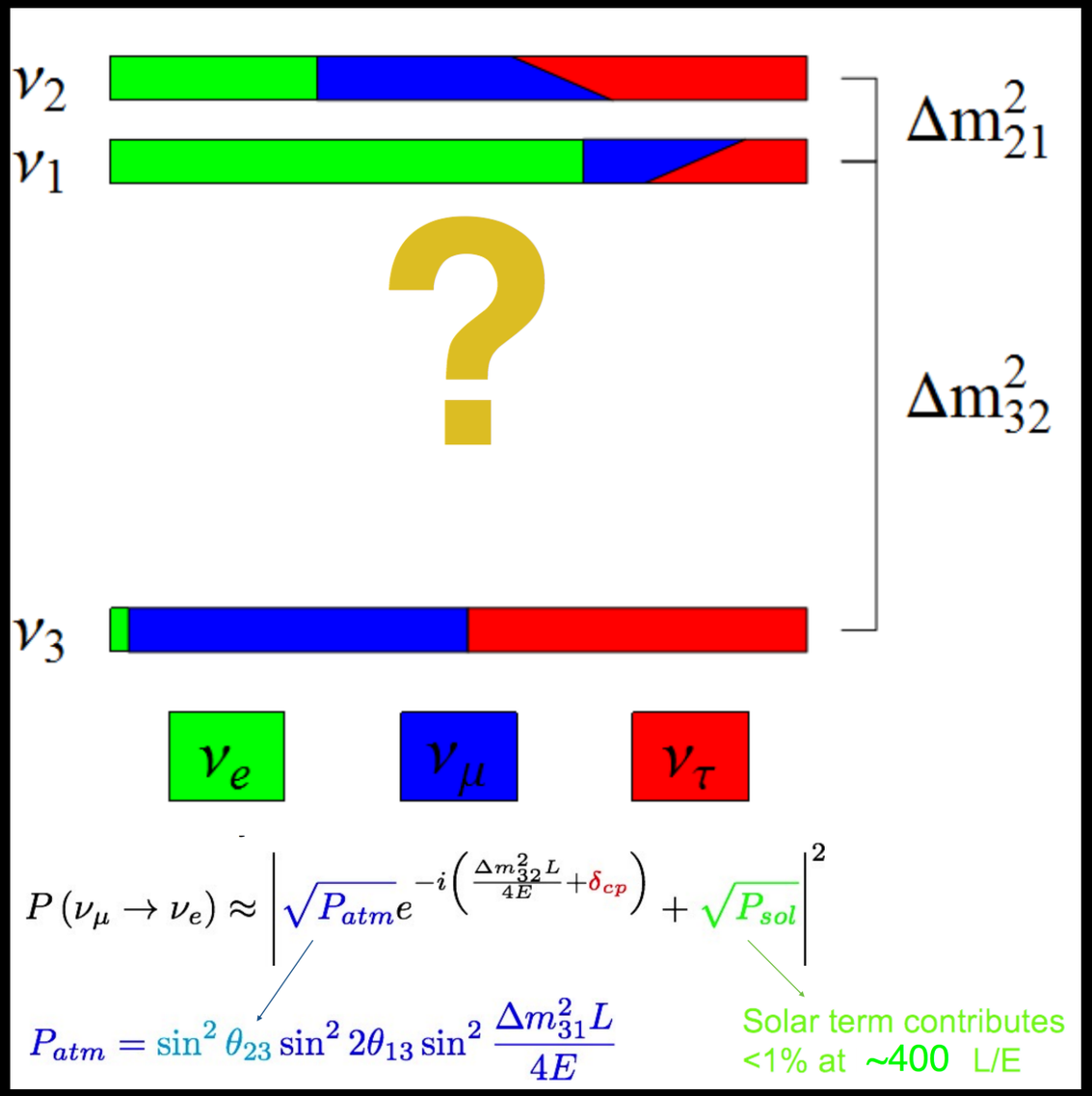
Strong constraints on:

θ_{23} octant

δ_{cp}

mass hierarchy

A precise energy reconstruction is important for accurate determination of oscillation parameters in NOvA



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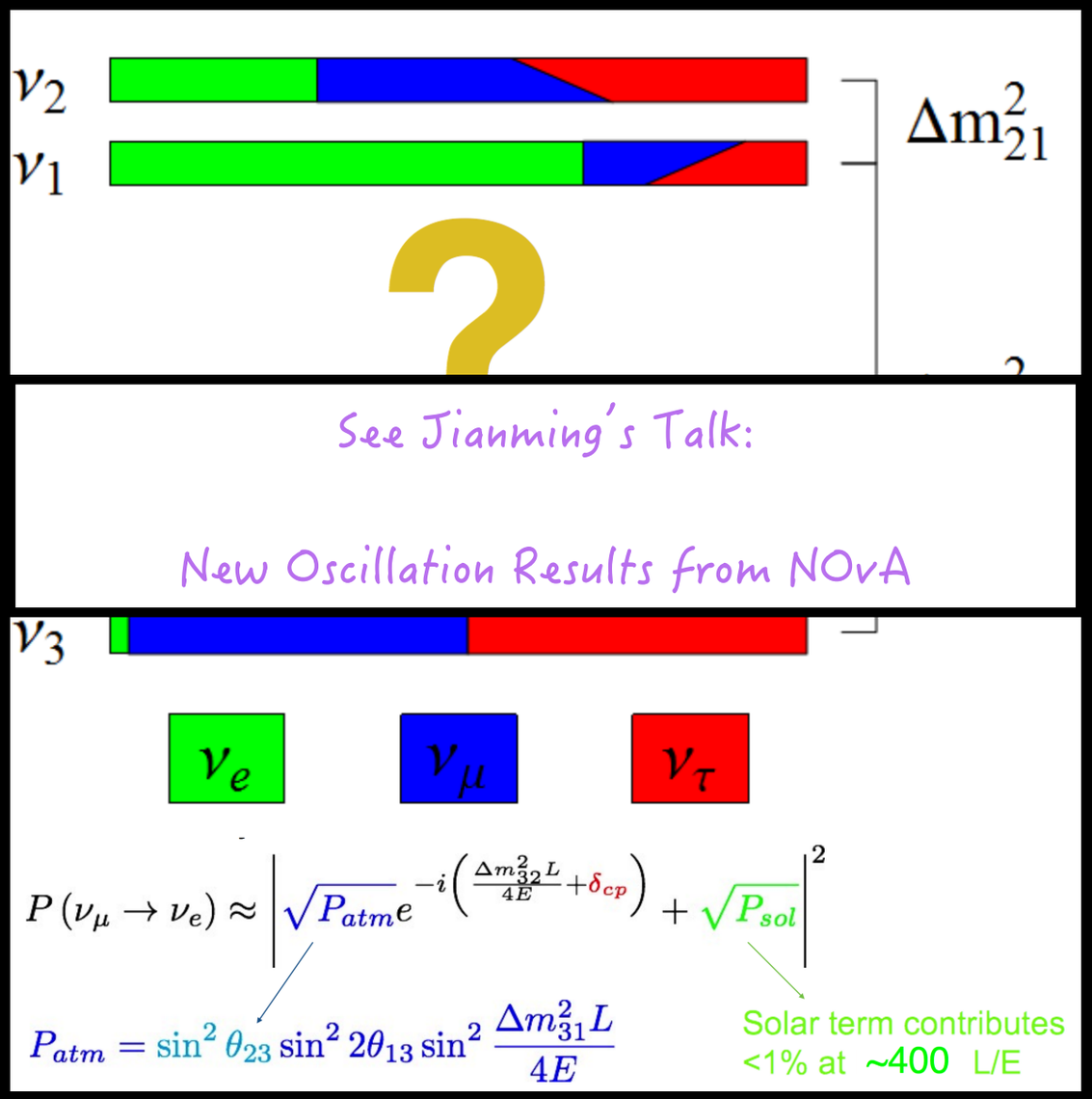
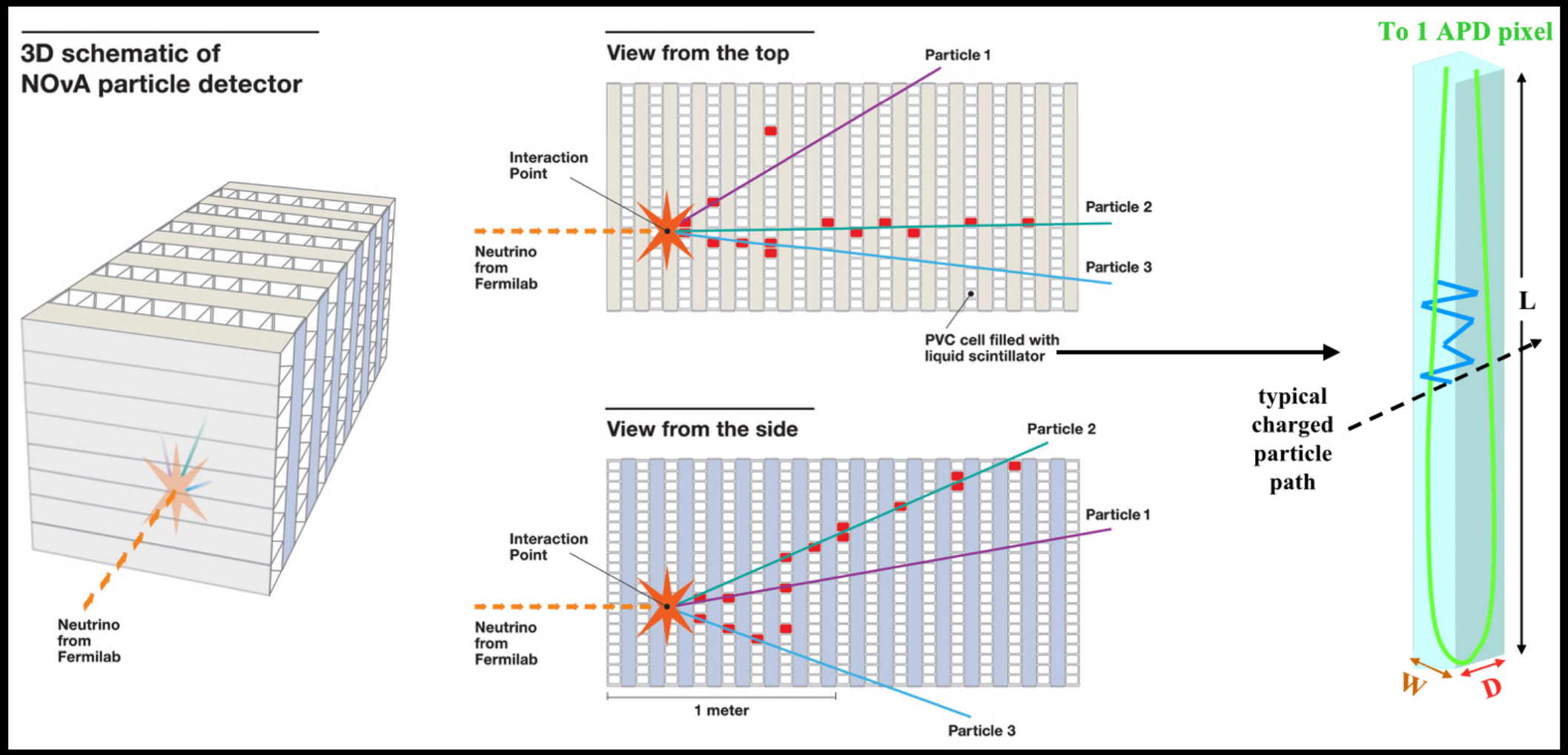
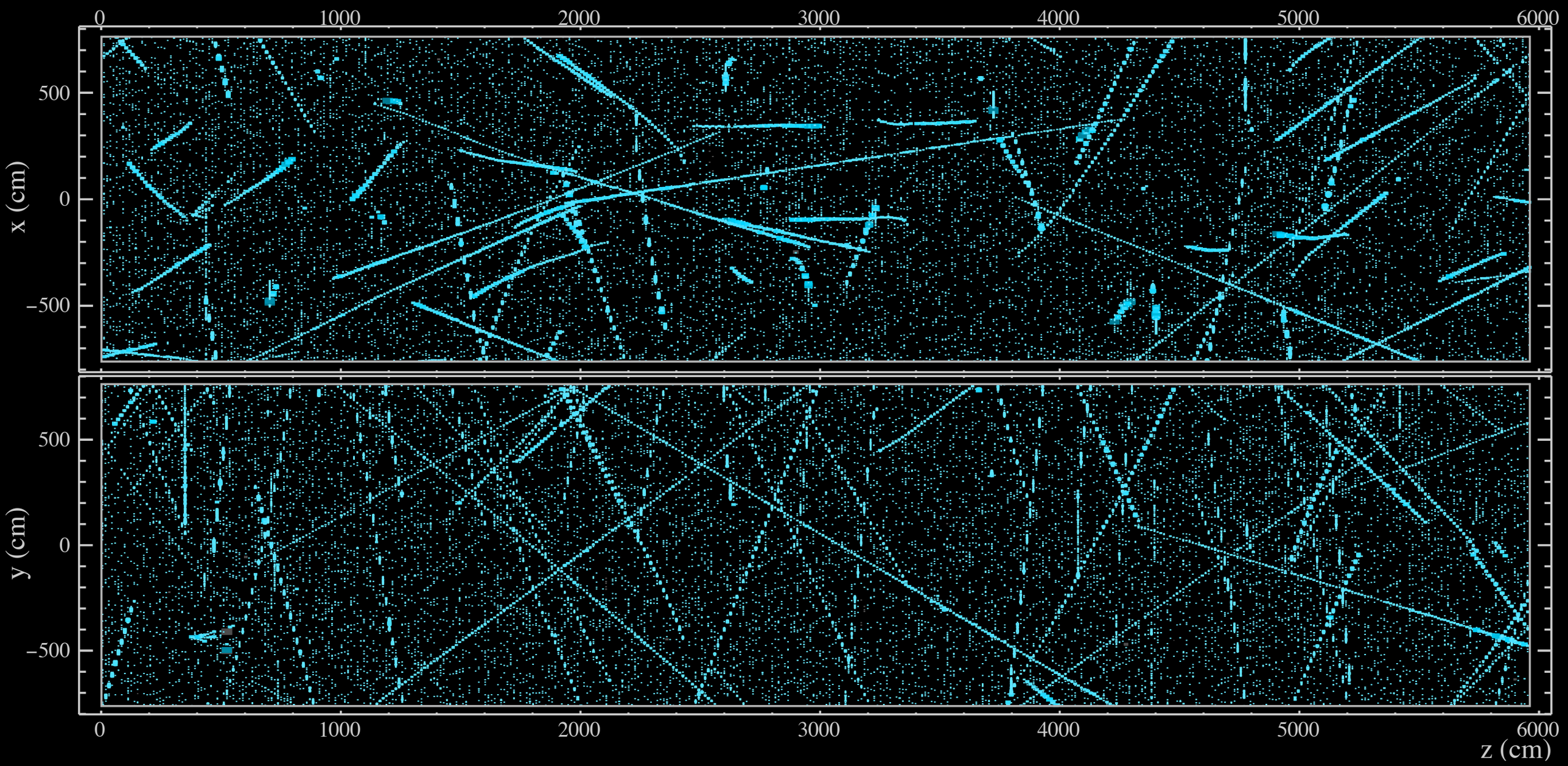


Detector Structure



Layered planes of orthogonal views allow 3D reconstruction. Charged particles are detected though the scintillation light produced in each cell.

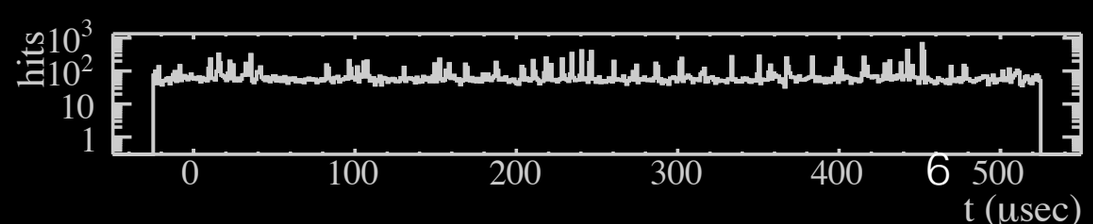
Far Detector View

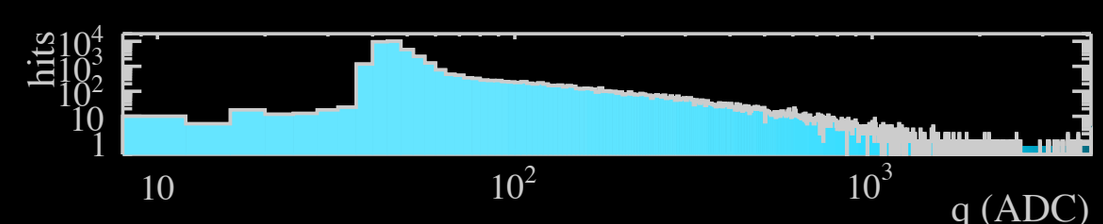


NOvA - FNAL E929

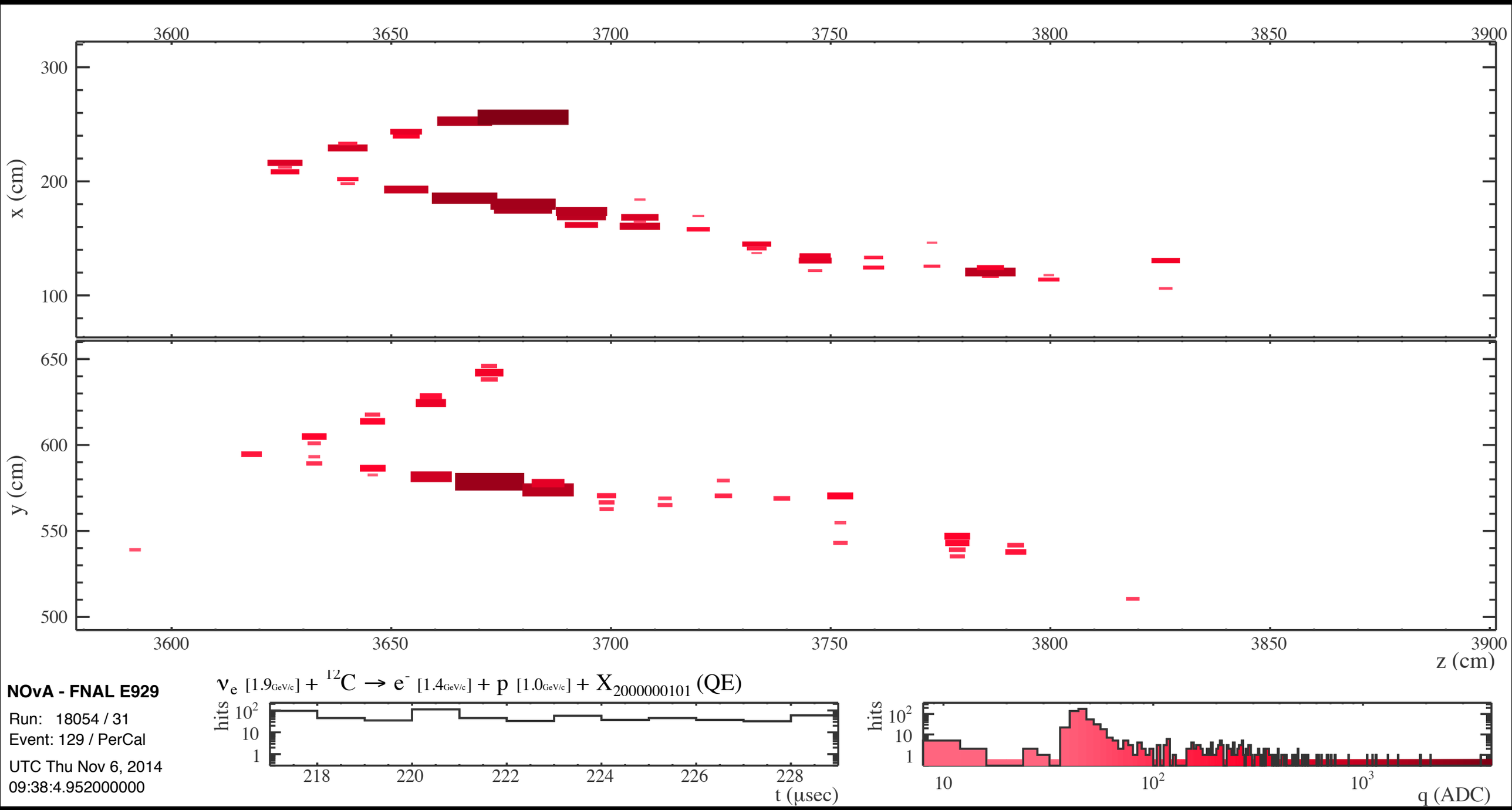
Run: 22357 / 1
Event: 16934 / --

UTC Sun Feb 28, 2016
14:44:25.490674976

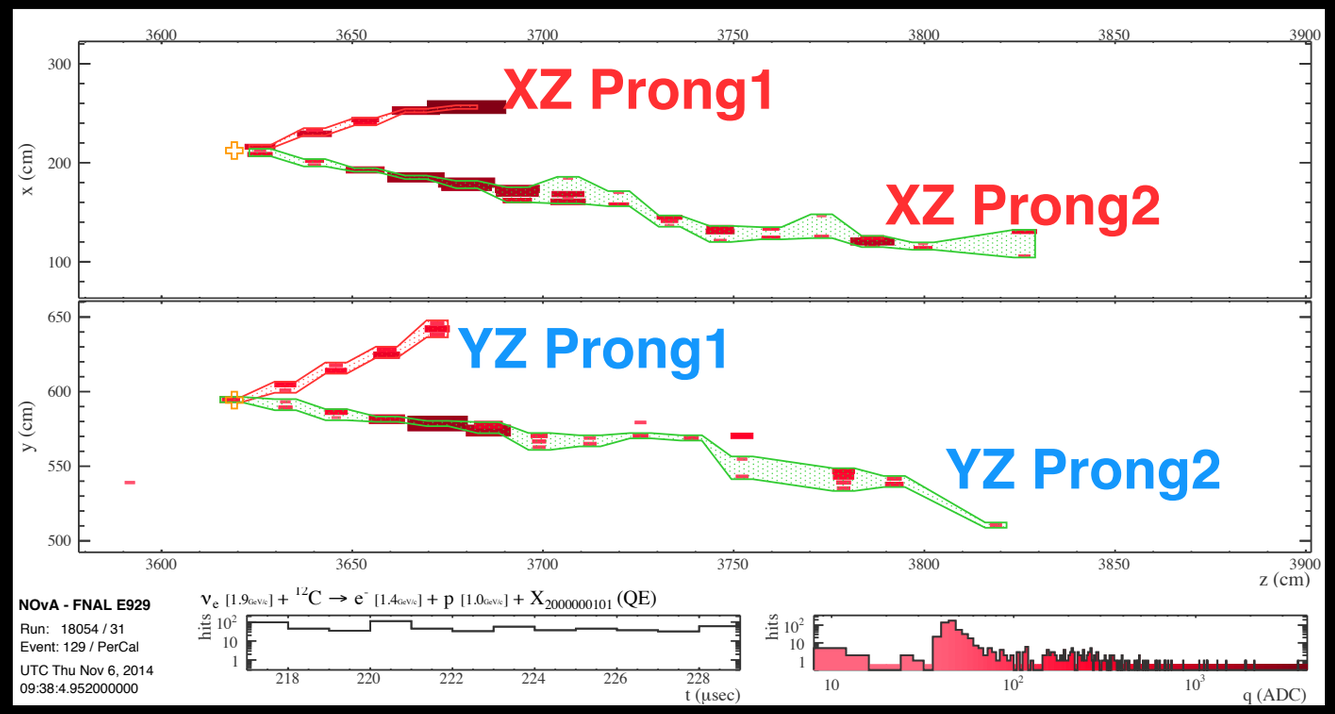




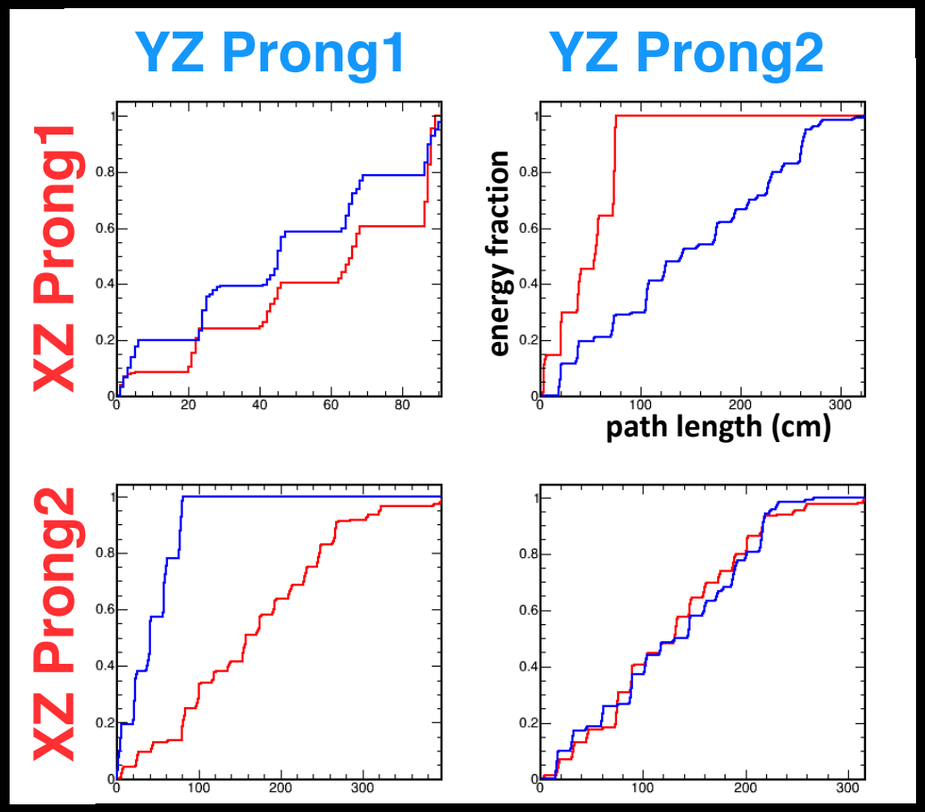
ν_e Signal Candidate



Prong: Fuzzy K-Mean Algorithm



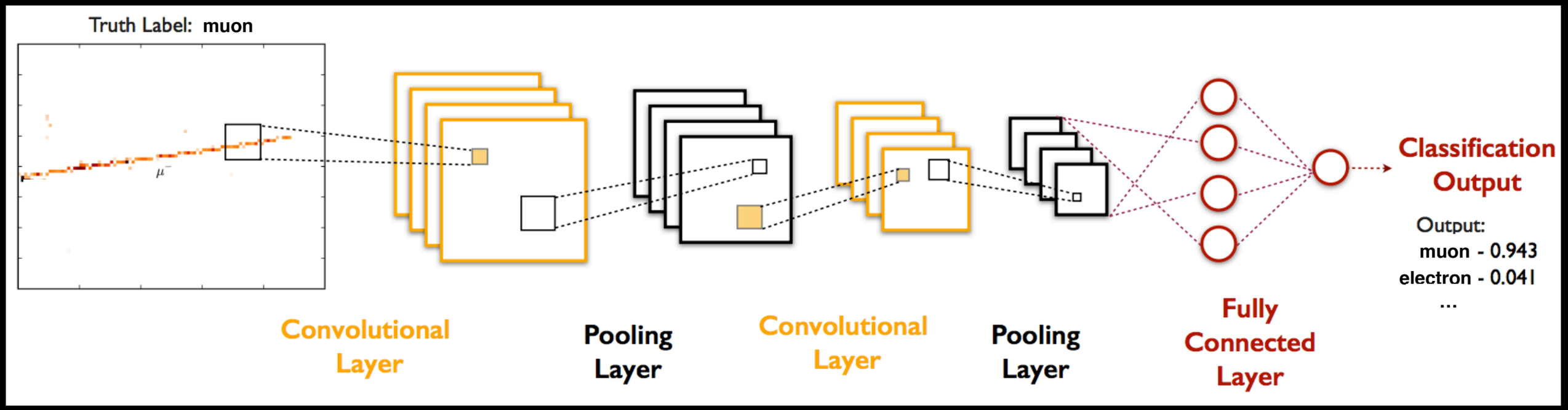
Cumulative energy profile as a function of path length along a prong for 3D match candidates



Cluster hits into track-like structure — Prongs:

- ★ In each of two detector views, compute distance between given hit and center of existing clusters;
- ★ A hit is added to the cluster if the overall distance is minimized.
- ★ 2D clusters are matched into 3D objects.

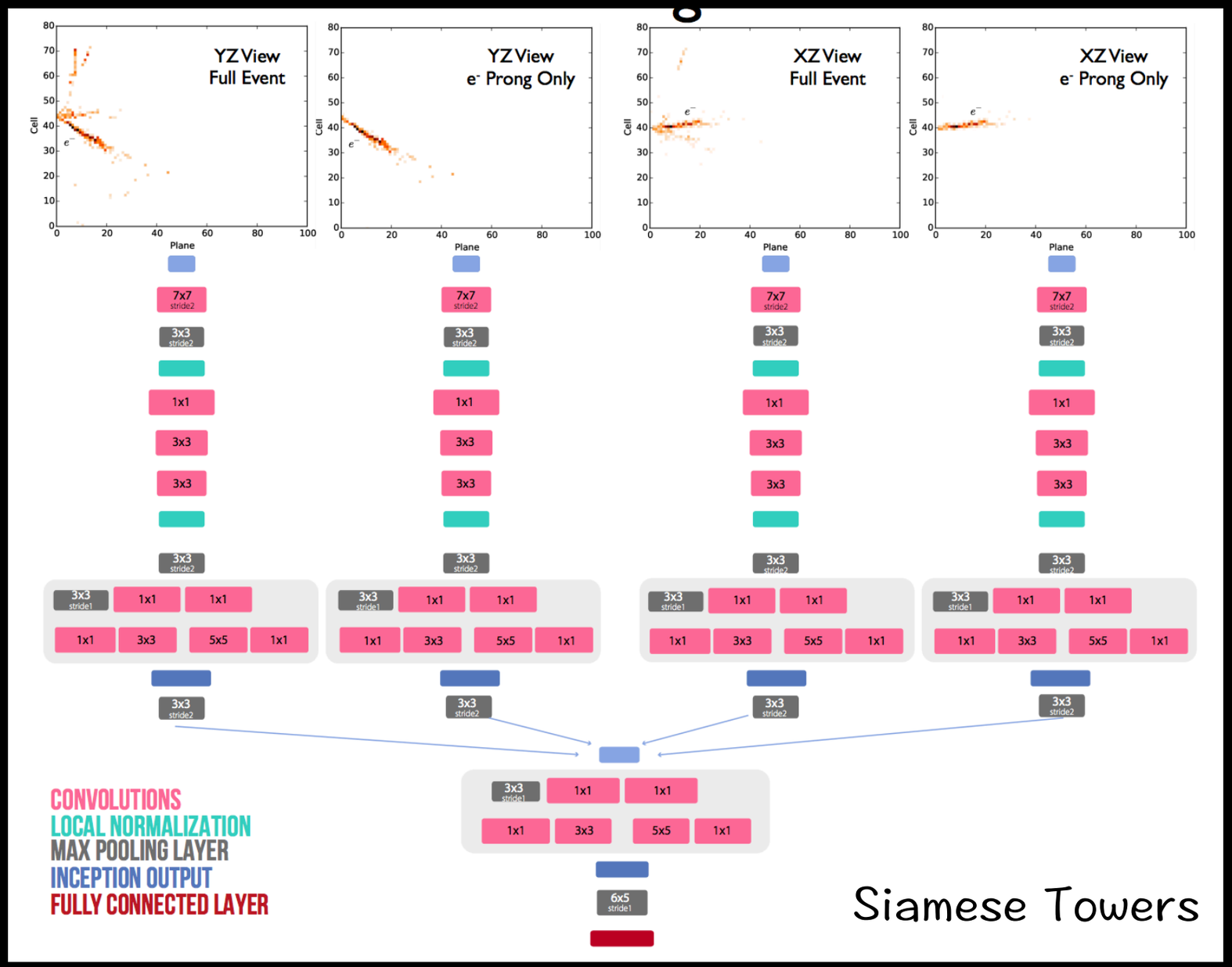
Convolutional Neural Network (CNN)



CNNs take images as input and process trough groups of layers to extract the abstract features from the inputs. Then the final layer compress the result into a vector of scores as predicted values corresponding to the labels that the CNN has been asked for.

arXiv:1906.00713

Prong CNN: Particle ID Classification



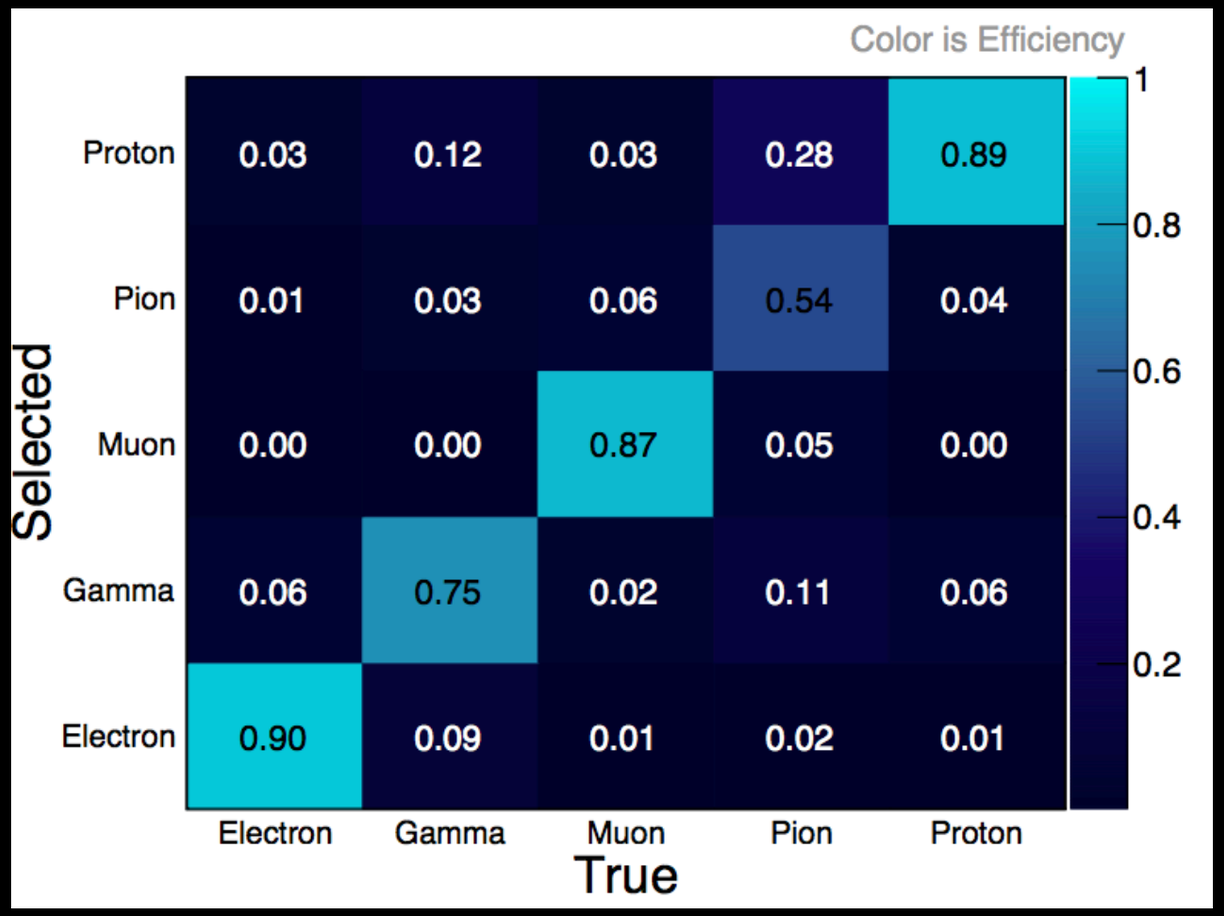
4 input pixel maps:

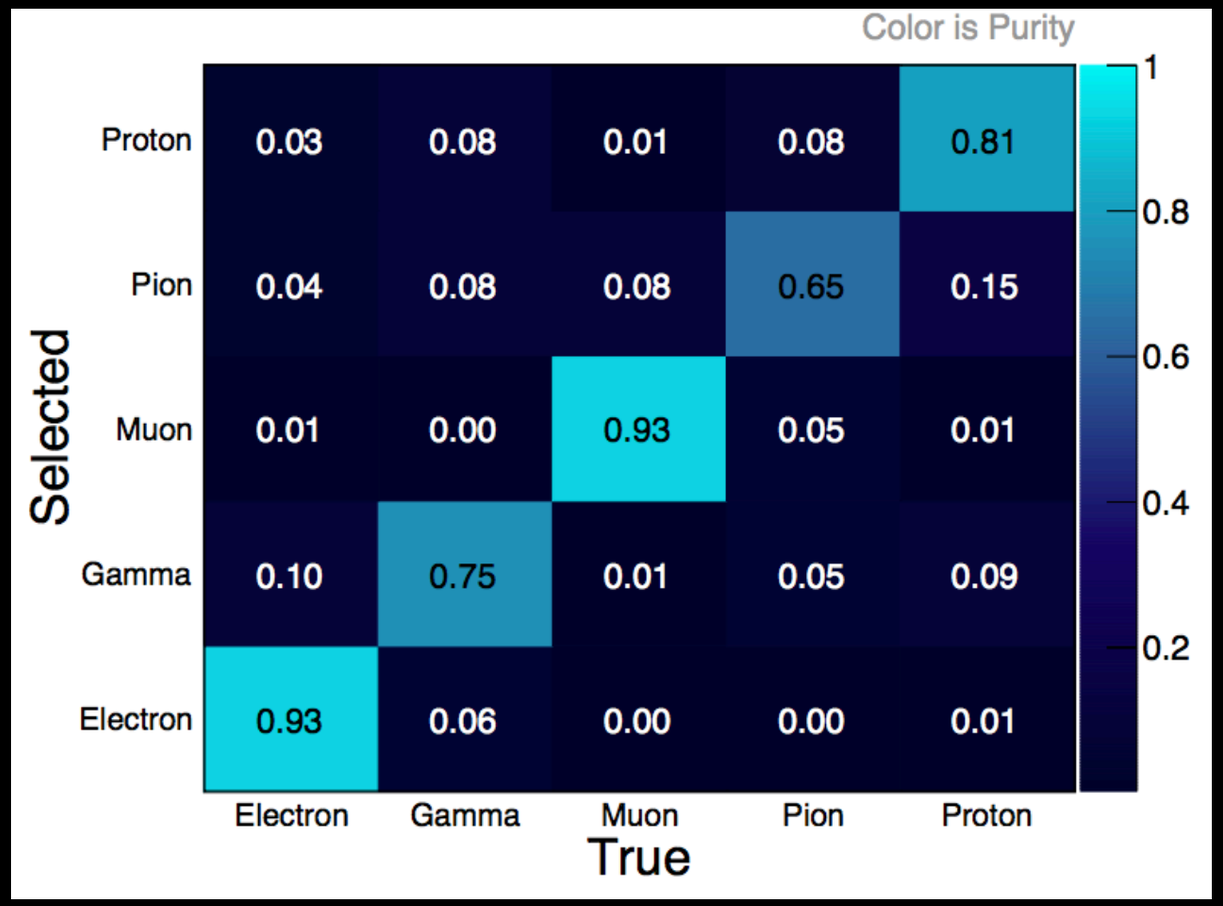
- 2 views of prongs
- 2 views of events

Output: a vector of predicted scores of each possible particle id for the 3D prong.

Prong CNN Performance

Classification Matrix





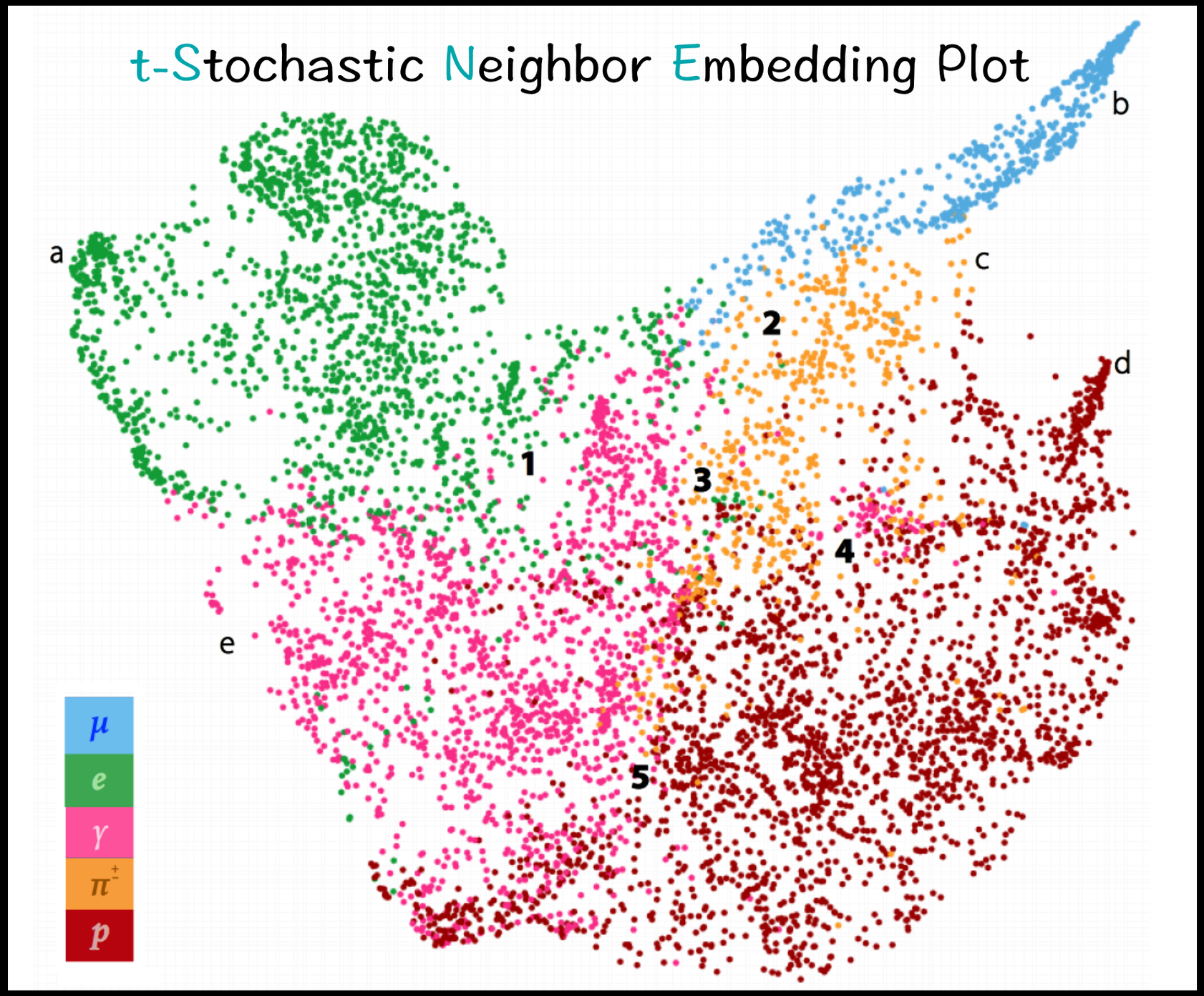
The diagonal shows the efficiency of the CNN predicting the label correctly and the rest are fractions of prongs being mislabeled.

The diagonal shows the purity of each predicted label and the rest are the backgrounds in each type of prediction.

Prong CNN Performance

Transfer high dimensional features to 2D preserving separation.

Distances represent how well Prong CNN can distinguish different particles.



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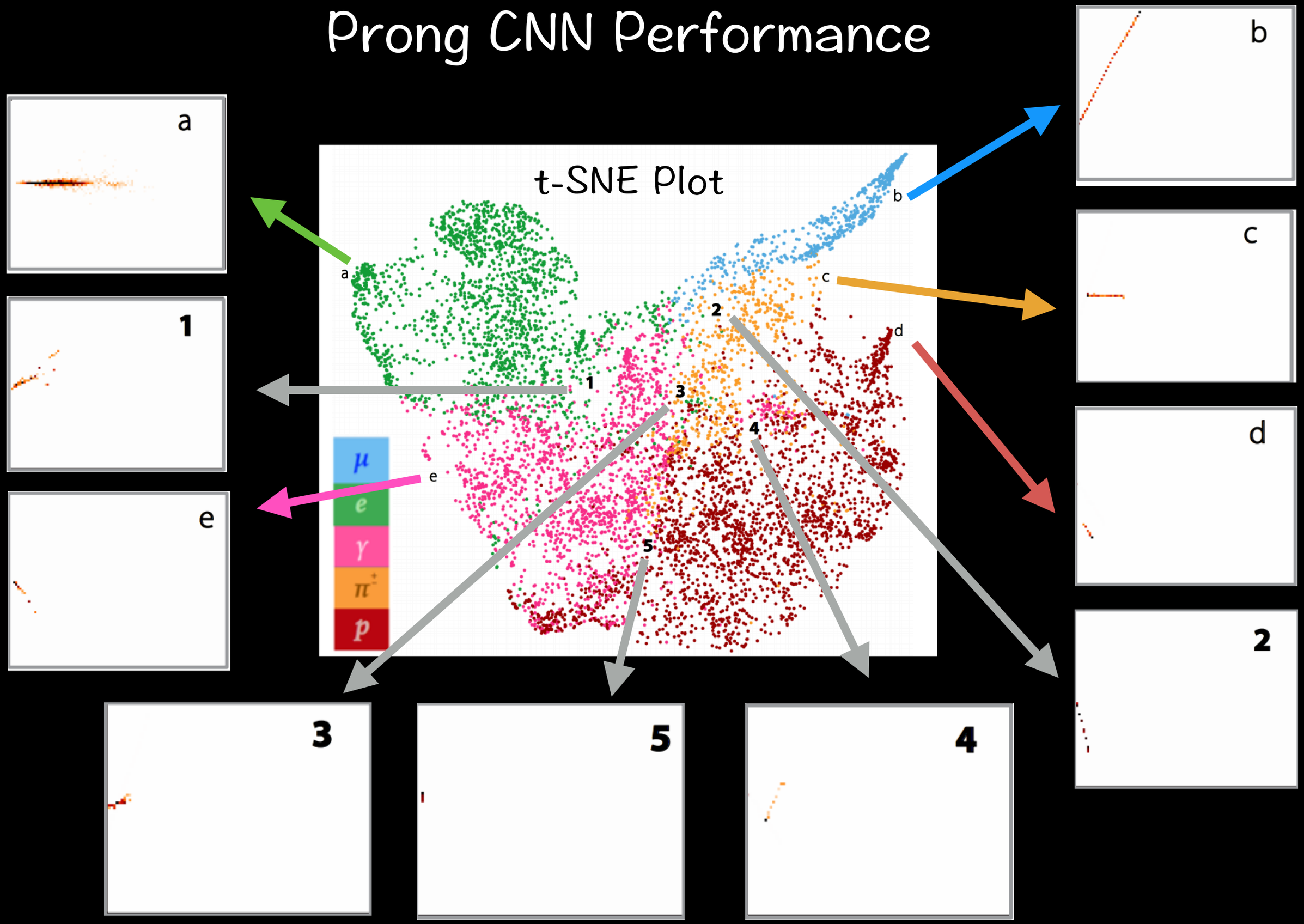


Energy Reconstruction

CNN_{EM} = electronID + photonID

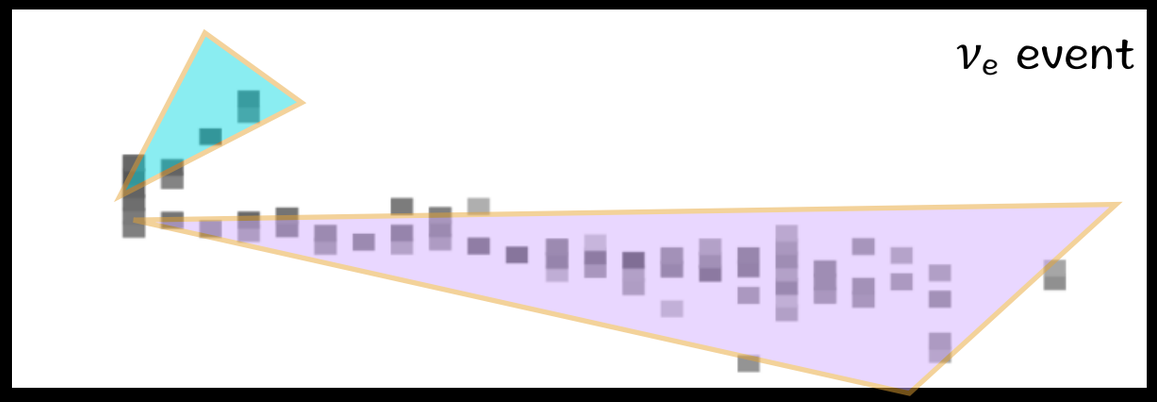
CNN_{HAD} = sum of the rest ID

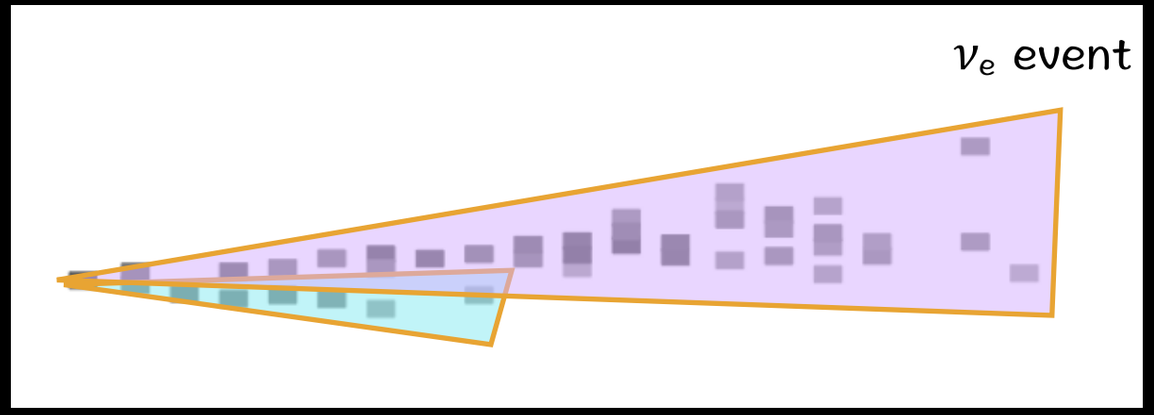
EM-like: $CNN_{EM} >= CNN_{HAD}$

EM Shower Energy:
Sum together energy of all EM-like prongs in the event.

Hadronic Energy:
Defined as the difference between the total hits energy and the EM Shower Energy.

Energy Reconstruction





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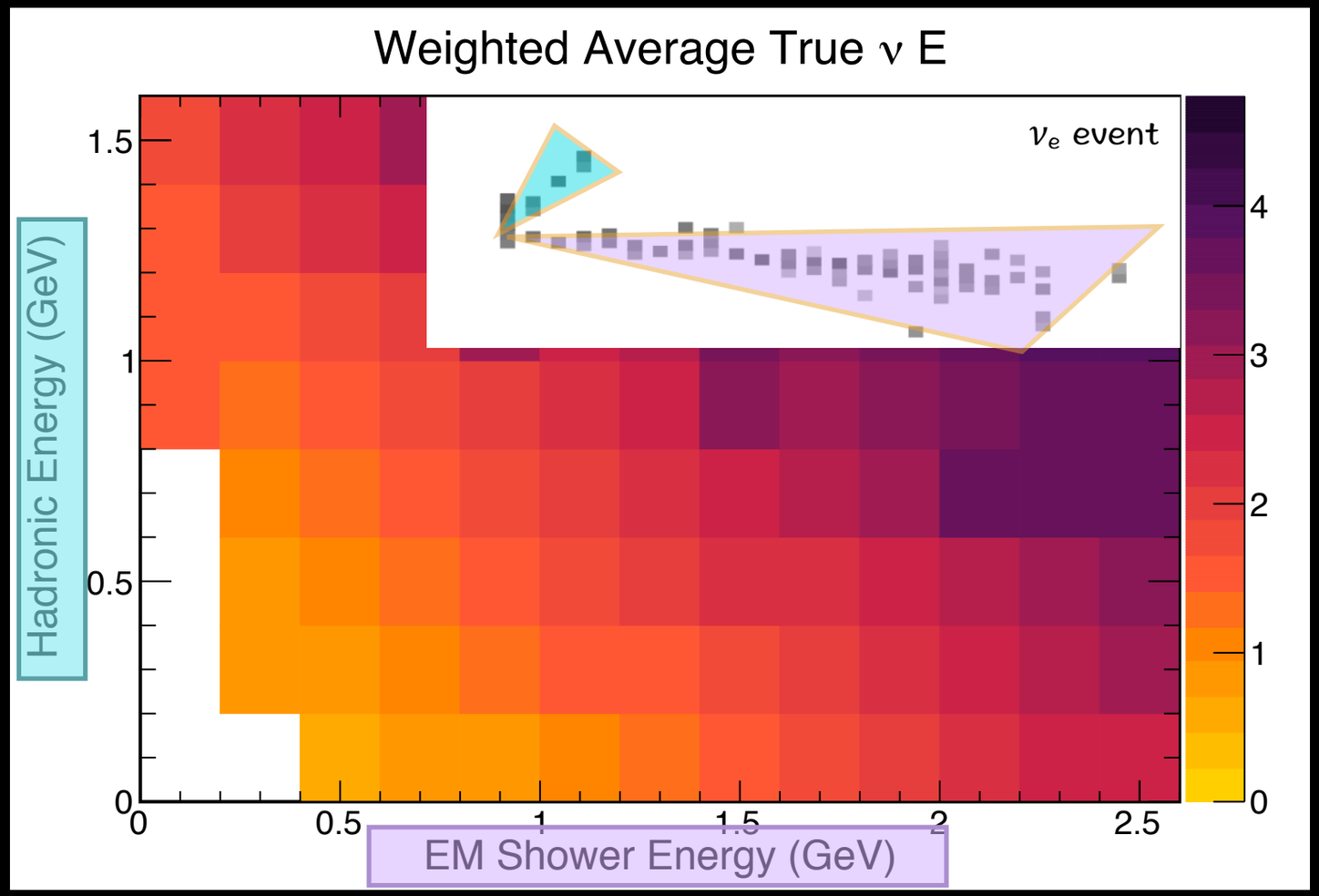

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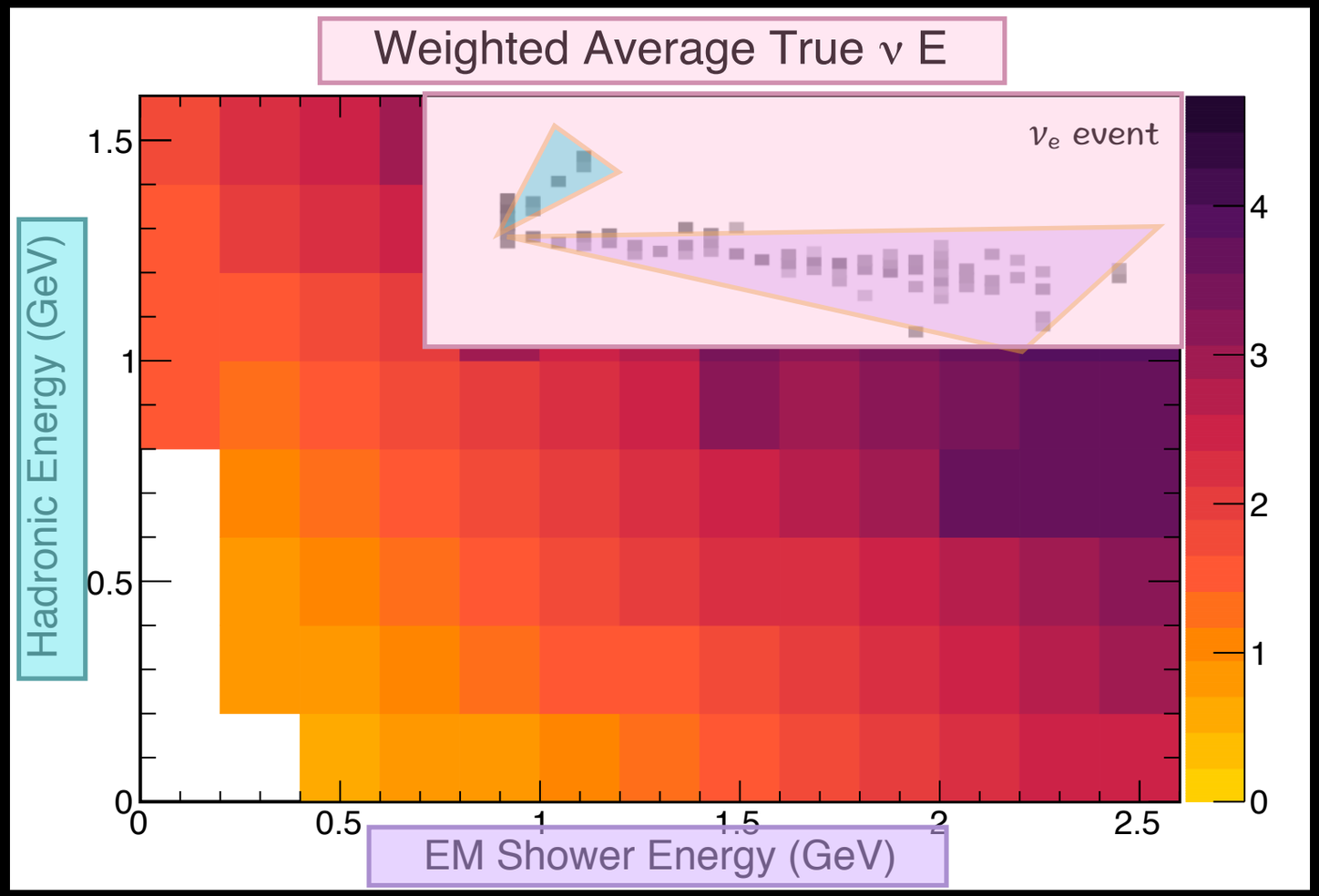
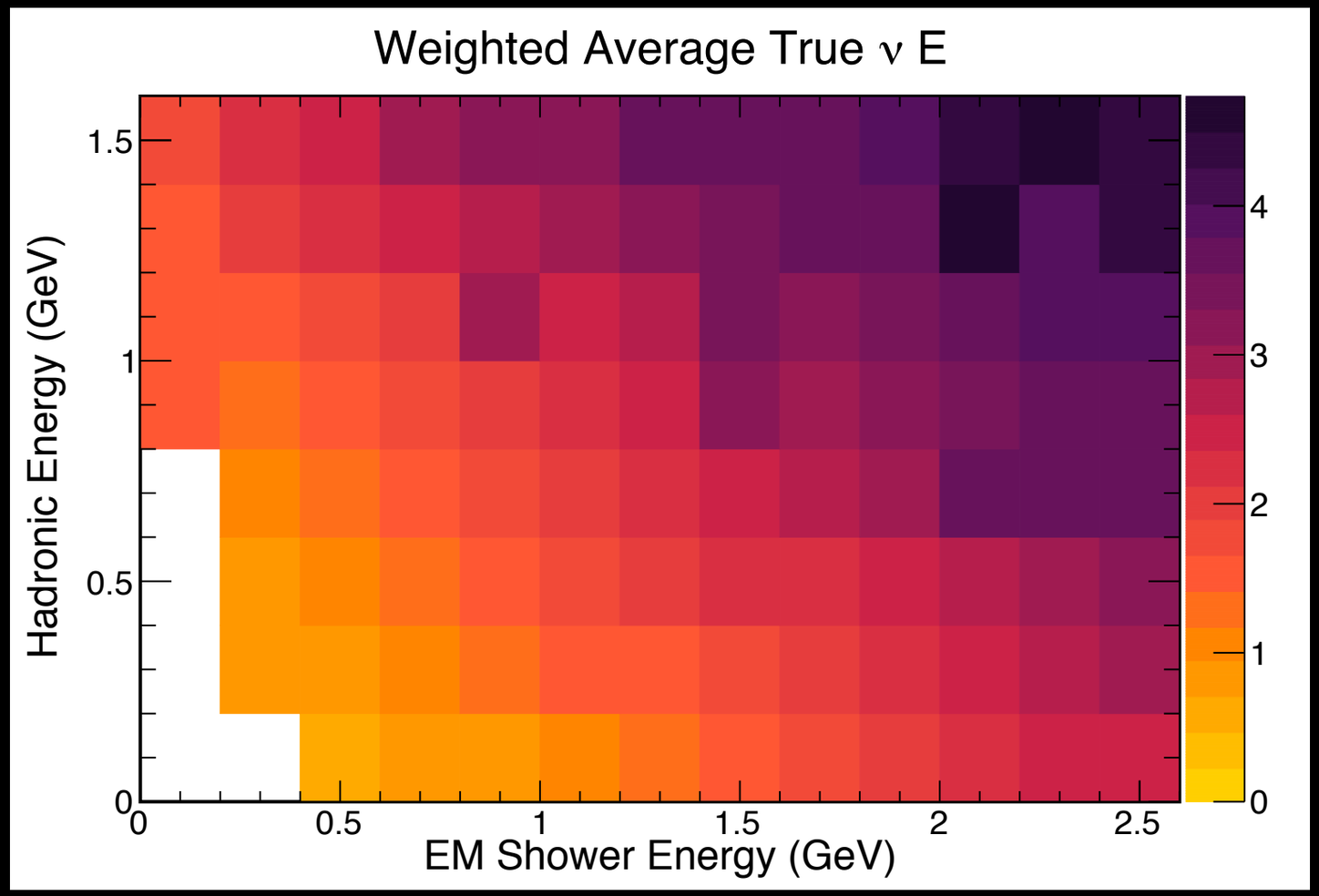


Each bin filled by weighted average true energy.

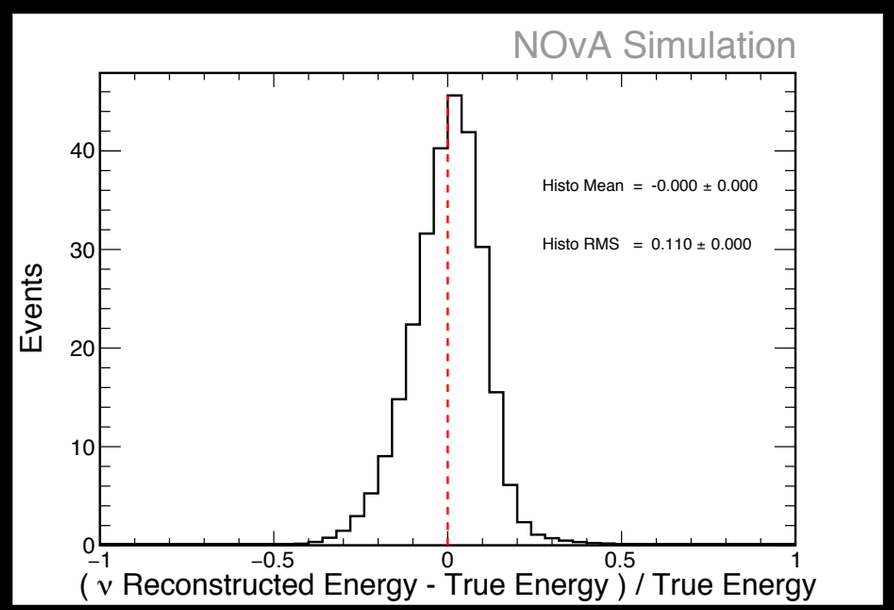
Energy Reconstruction



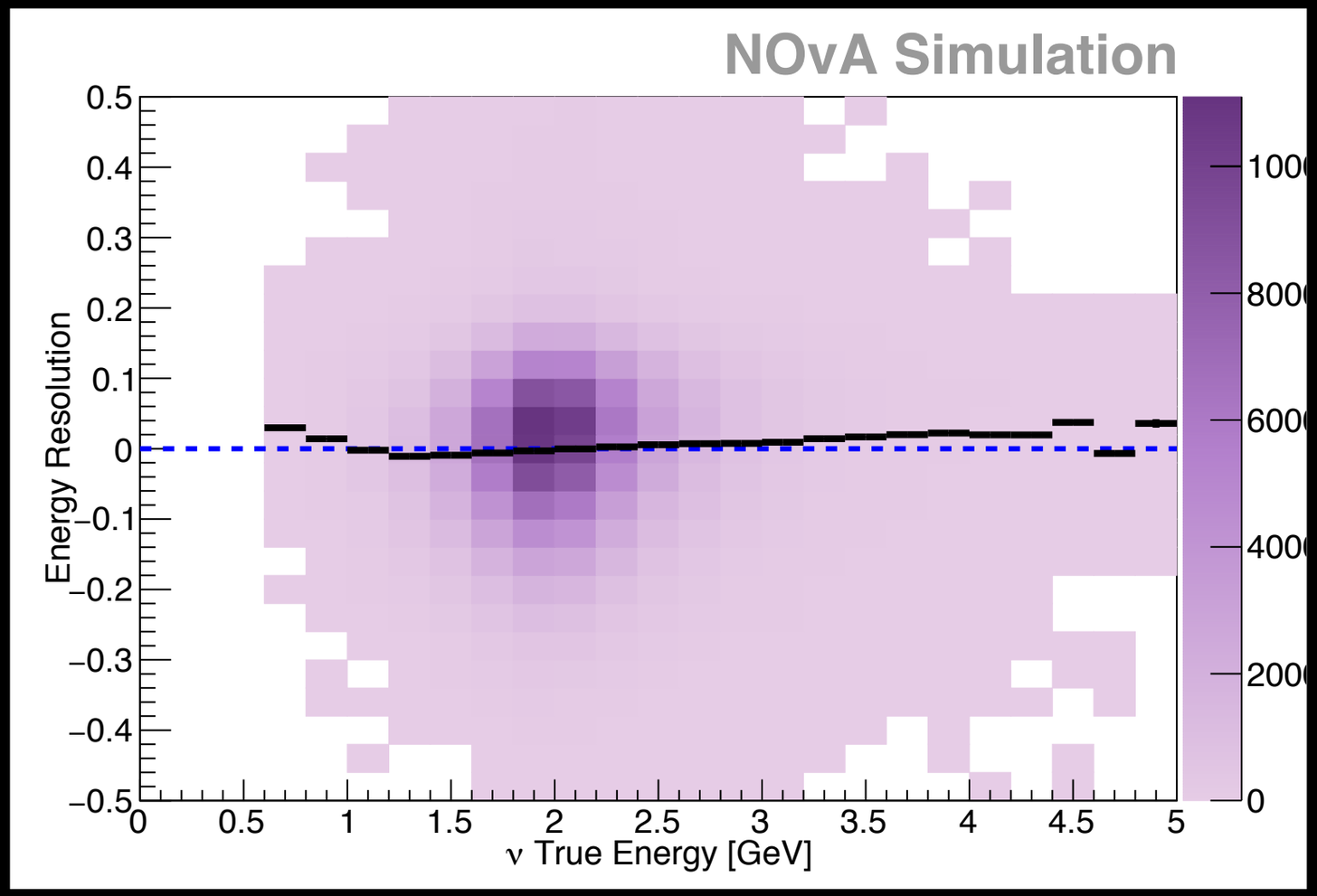
A quadratic fit to weighted average true energy as a function of EM Shower energy and Hadronic energy is used for estimation.

$$E\nu_e = A*E_{EM} + B*E_{HAD} + C*E_{EM}^2 + D*E_{HAD}^2$$

Energy Reconstruction

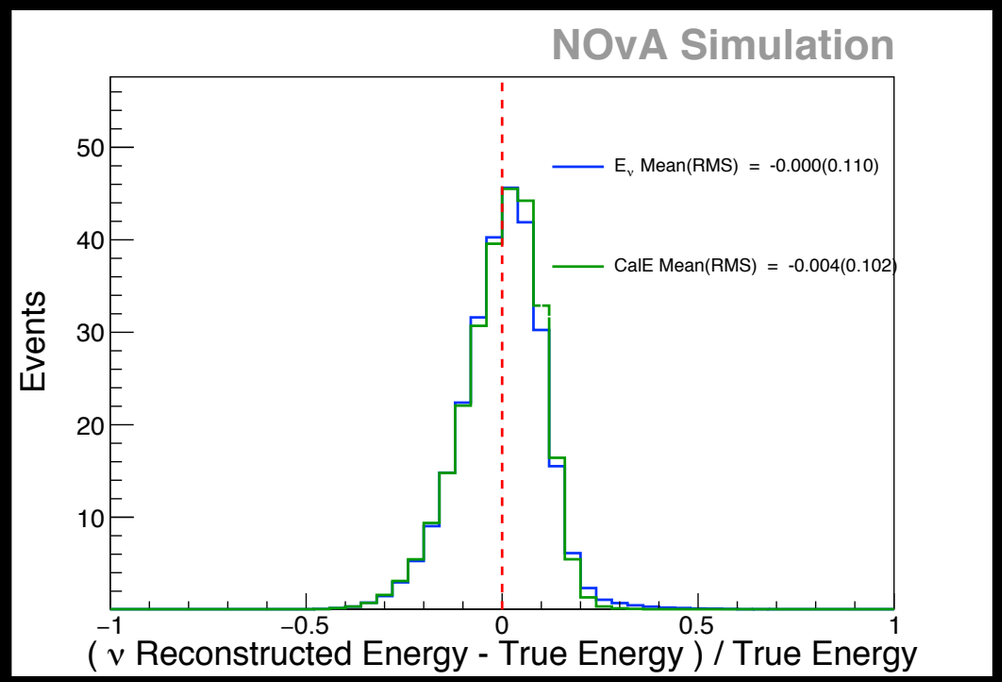


A flat resolution distribution along true energy between 1 and 4GeV.

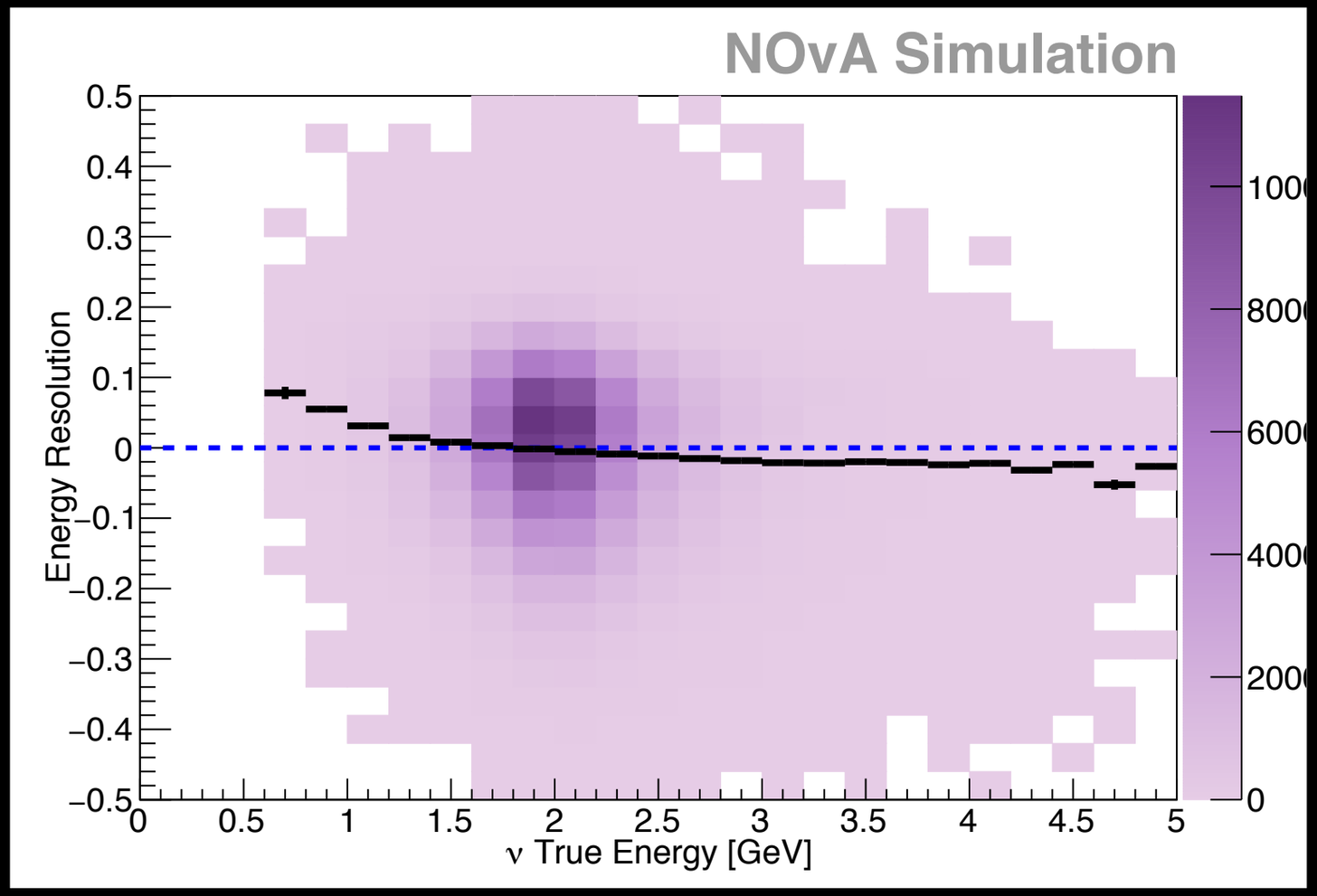


Energy resolution is 11%.

Energy Reconstruction



Comparing to sum of total hits energy.
Bias along true Energy is improved.



Energy resolution is 11%.

Summary of Energy Reconstruction

- ★ A precise energy reconstruction is important for many aspects of the NOvA analysis, for e.g. backgrounds rejection and determination of oscillation parameters.

- ★ We use a CNN-based classifier to sort prongs into EM-like or hadronic components and use them for energy reconstruction.

- ★ In the ν_e Appearance Analysis, energy resolution is 11% for signal events.

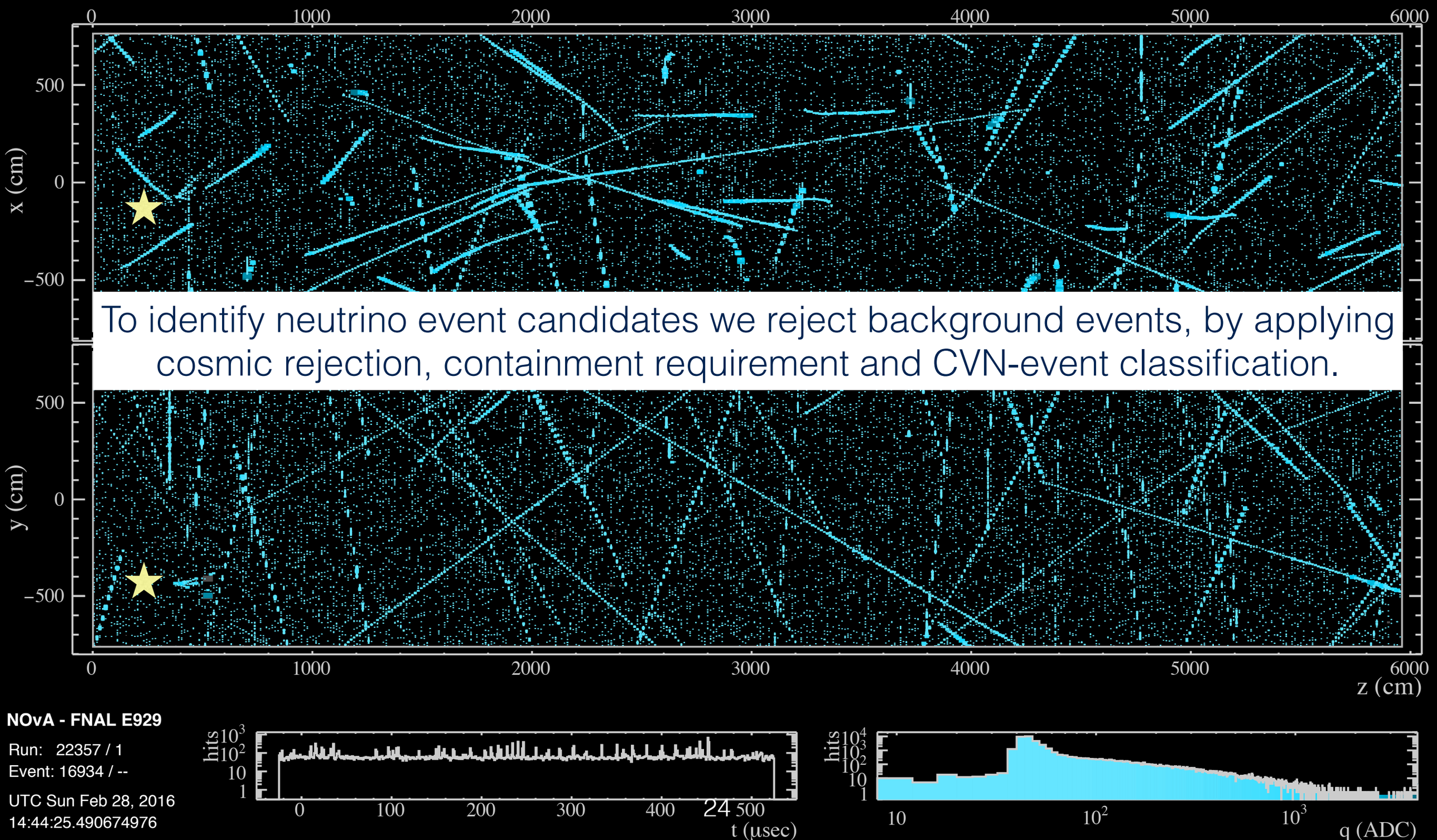
- ★ There are other works and publications using RNN and CNN to reconstruct energy which is different from this official method.


Fermilab
Fermilab
Fermilab
Fermilab
NORMAN F. RAMSEY
AUDITORIUM
AISLE 1
AISLE 2

Thank you

Backup

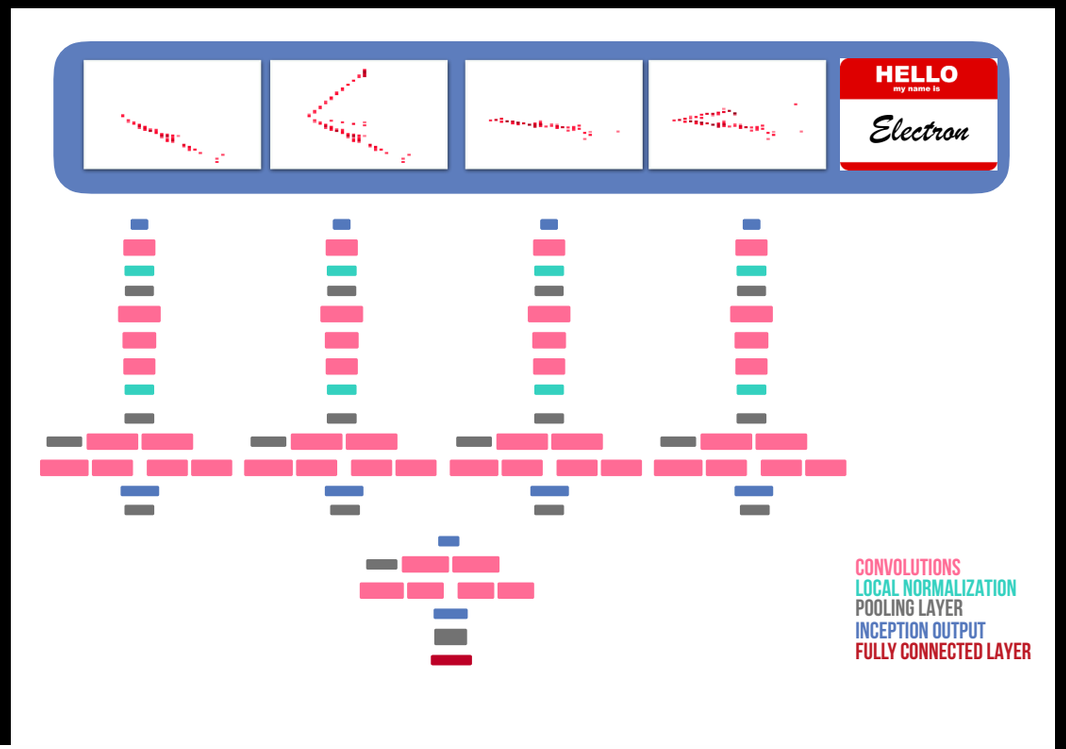
Far Detector View

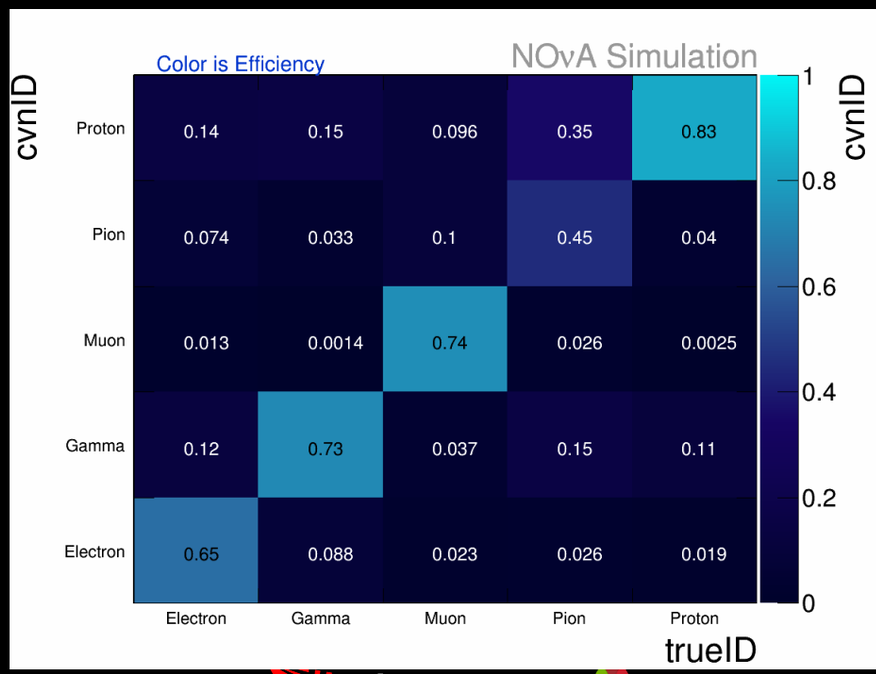


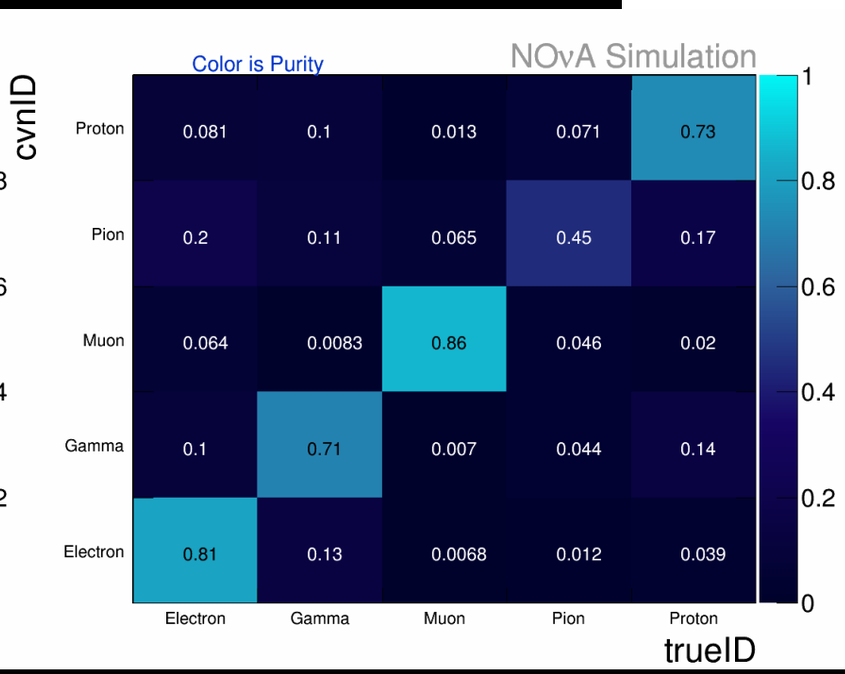
To identify neutrino event candidates we reject background events, by applying cosmic rejection, containment requirement and CVN-event classification.

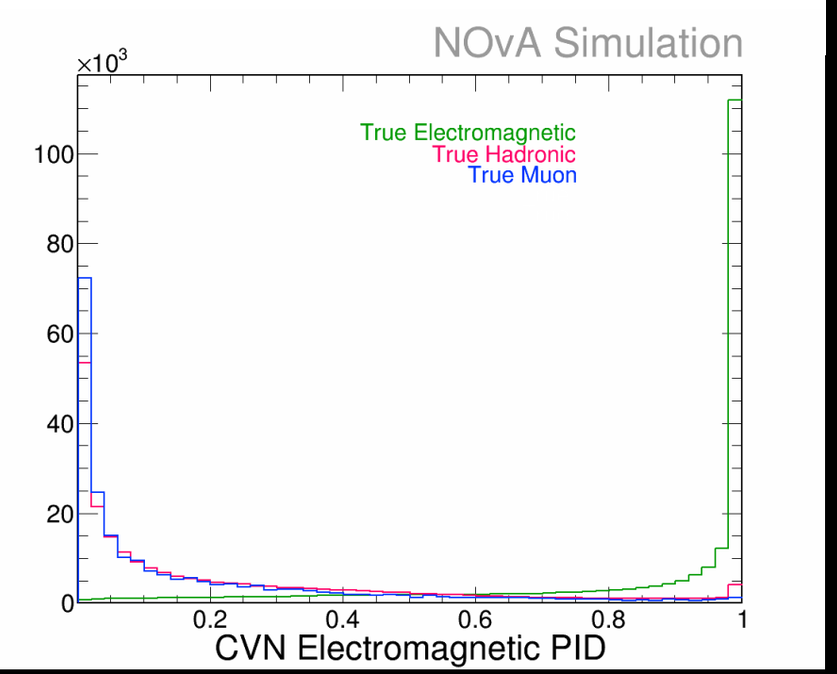
Prong Convolutional Neural Network Identifier

Siamese towers similar to event CVN but 4 input pixel maps: 2 views of prongs and 2 views of events. 3M @ 8:2









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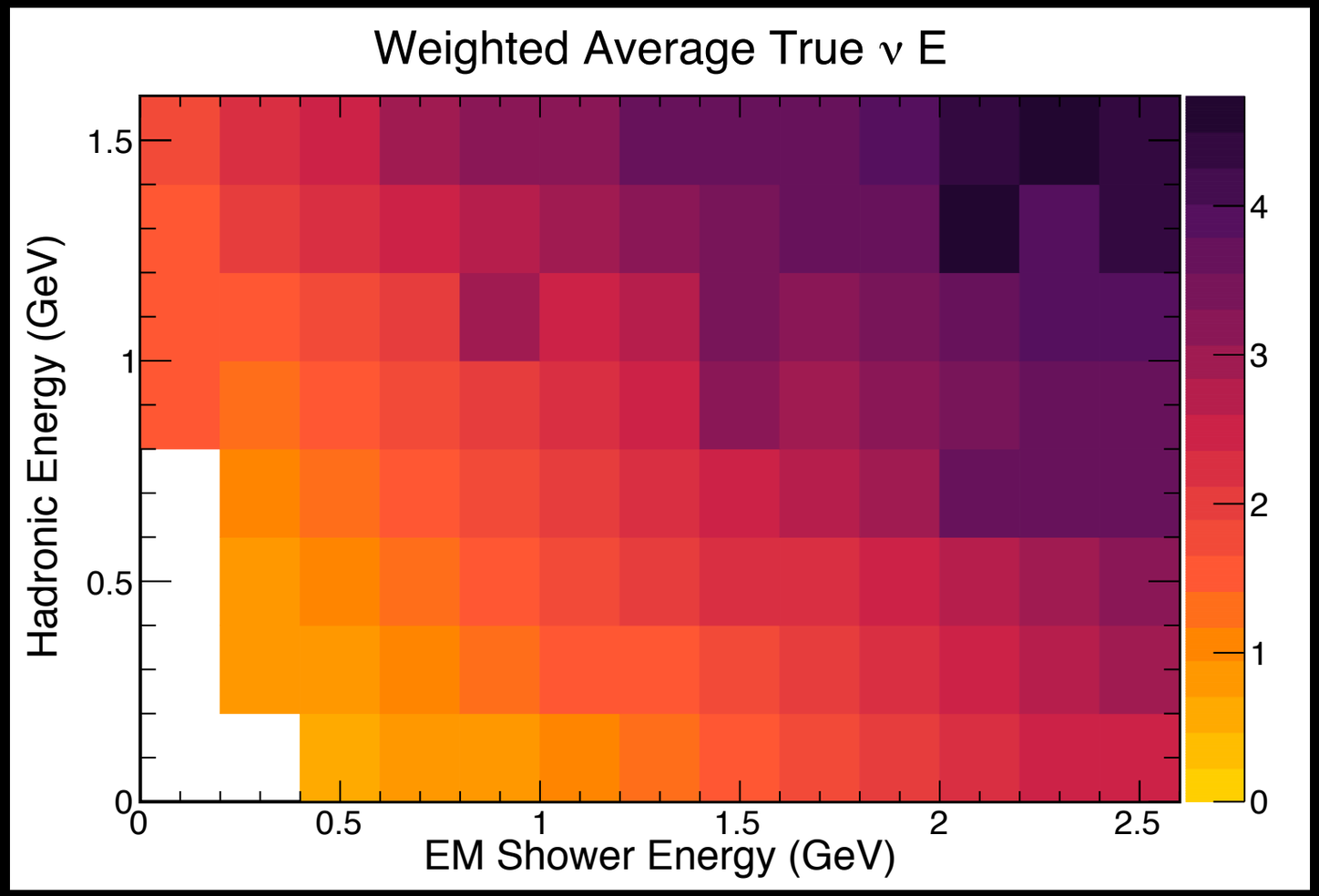

A quadratic fit to weighted average true energy as a function of EM Shower energy and Hadronic energy is used for estimation.

$$E\nu_e = 1/(1+0.057) * (0.996E_{EM} + 0.869\,E_{HAD} + 0.025E_{EM}^2 + 0.054\,E_{HAD}^2)$$