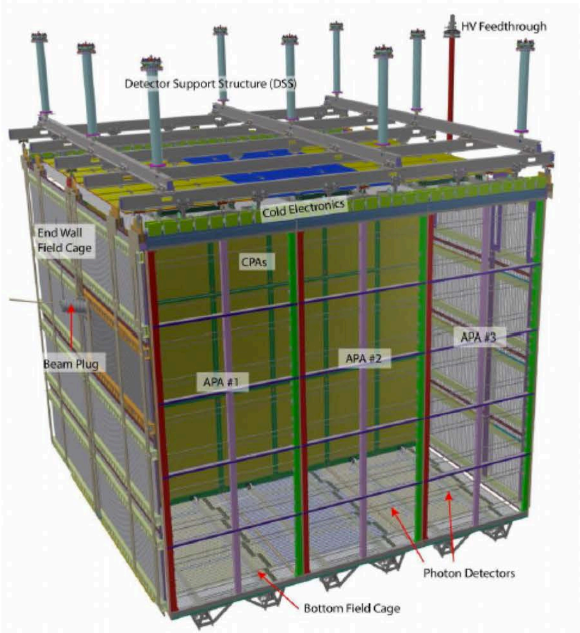
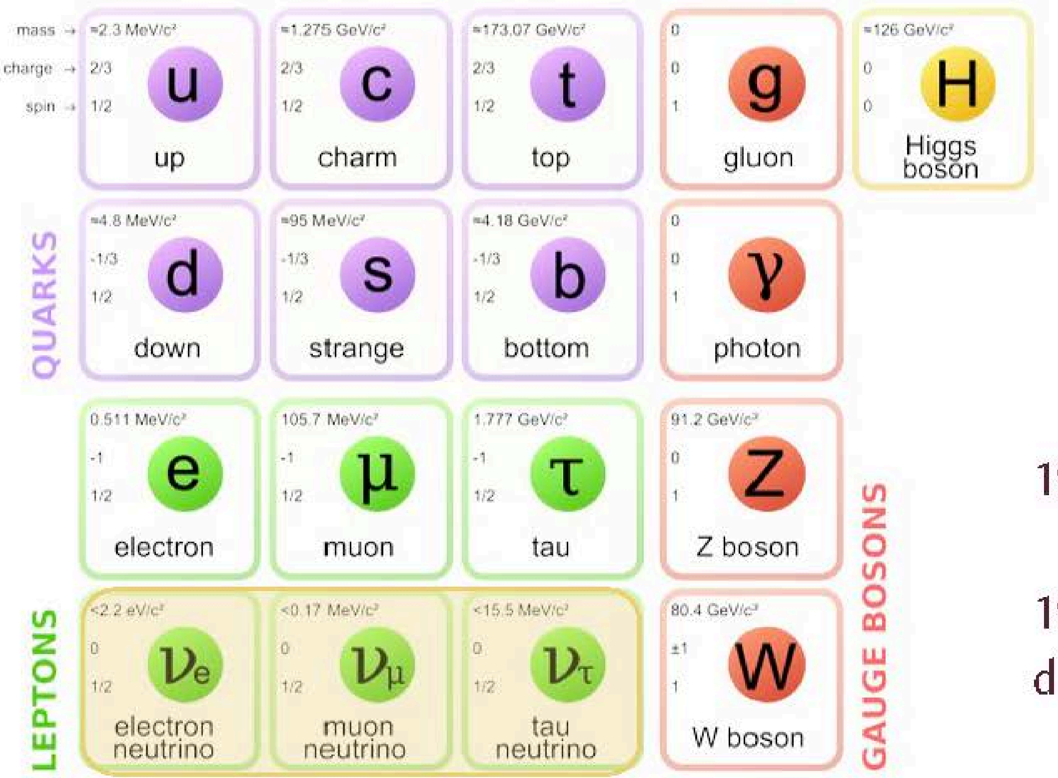
Understanding Neutrino Interactions Using Deep Learning



Adam Aurisano
University of Cincinnati

Physics Next: Machine Learning
8 October 2018

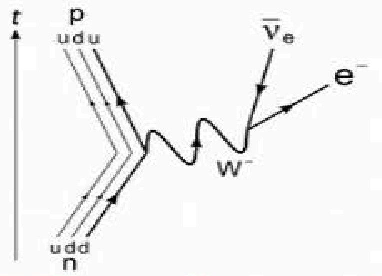
Neutrinos in the Standard Model



Neutrinos only feel the weak force

In the SM neutrinos are massless

1930: Wolfgang Pauli proposed neutrinos to make β decays conserve energy

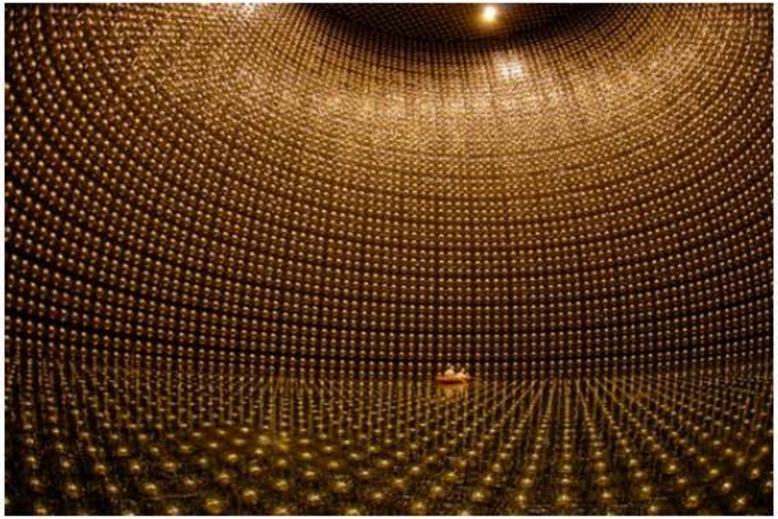


1956: Cowan and Reines discovered the ν_e

1962: Lederman, Schwartz, and Steinberger discovered the ν_μ

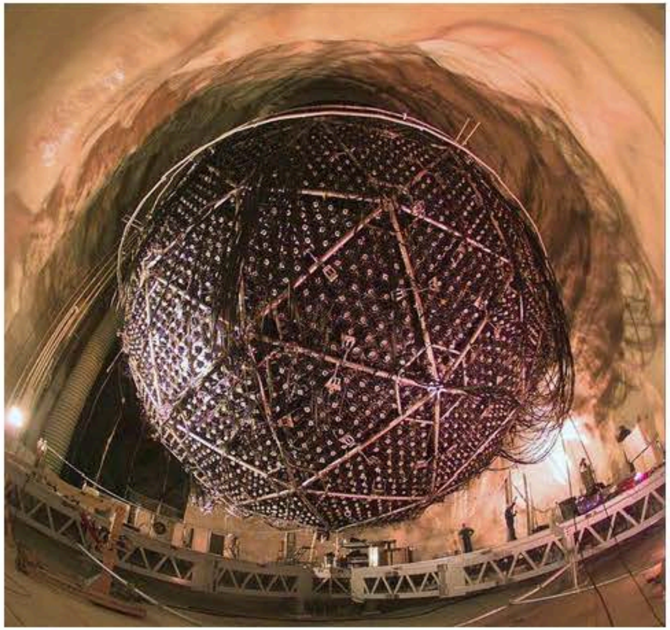
2000: DONUT collaboration discovered the ν_τ

The Plot Thickens…

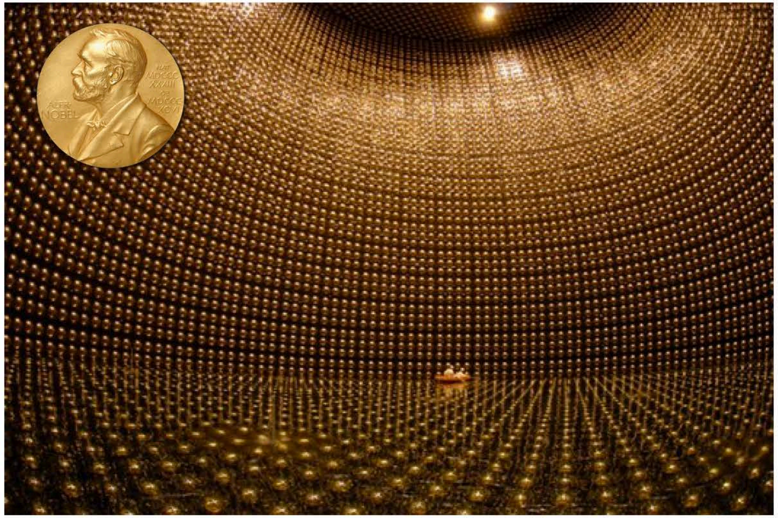


- Super-Kamiokande
  - Looked for ν_μ produced in the atmosphere by cosmic rays
  - Deficit of ν_μ going up through the earth compared to those coming down from the sky.

- SNO
  - Showed that ν_e from the sun less than expected
  - Total number of neutrinos agreed with expectations



The Plot Thickens… Oscillations!



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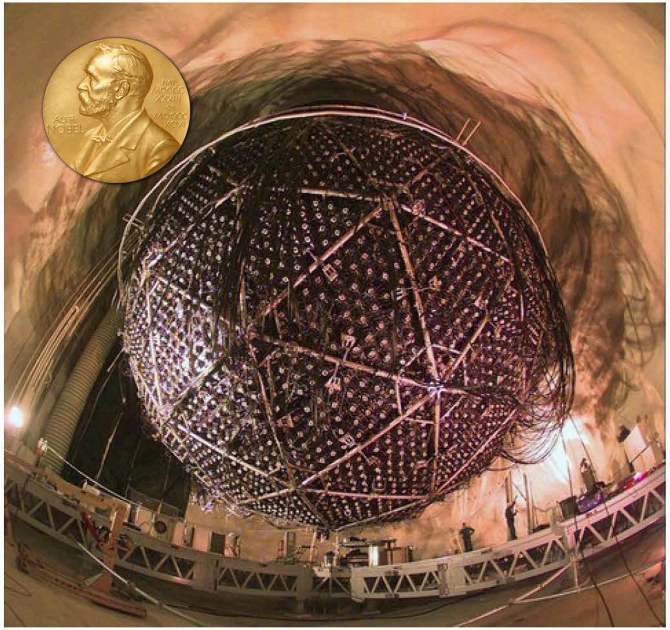
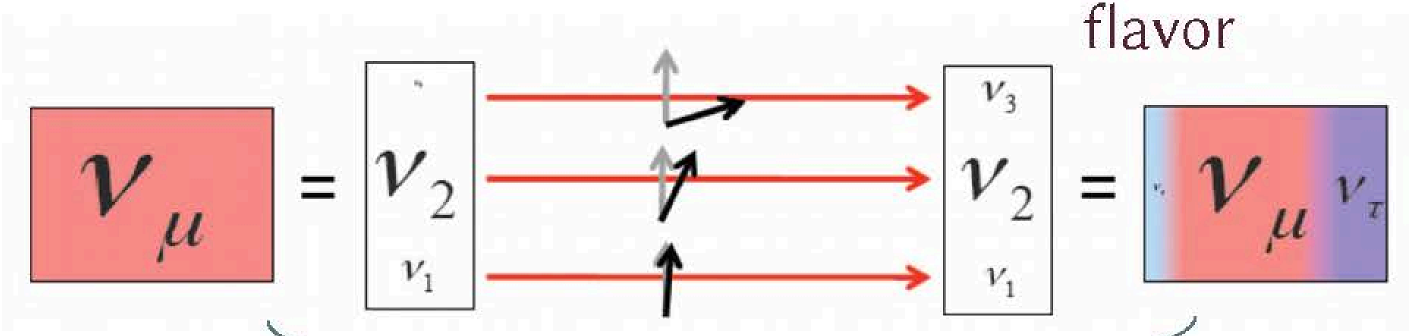


Neutrinos have Mass!

Neutrinos are produced with a definite flavor

They travel as a superposition of mass states

They interact with a definite flavor – maybe different than its starting flavor



L = baseline traveled

Neutrinos oscillations are only sensitive $\Delta m^2 = m_j^2 - m_i^2$

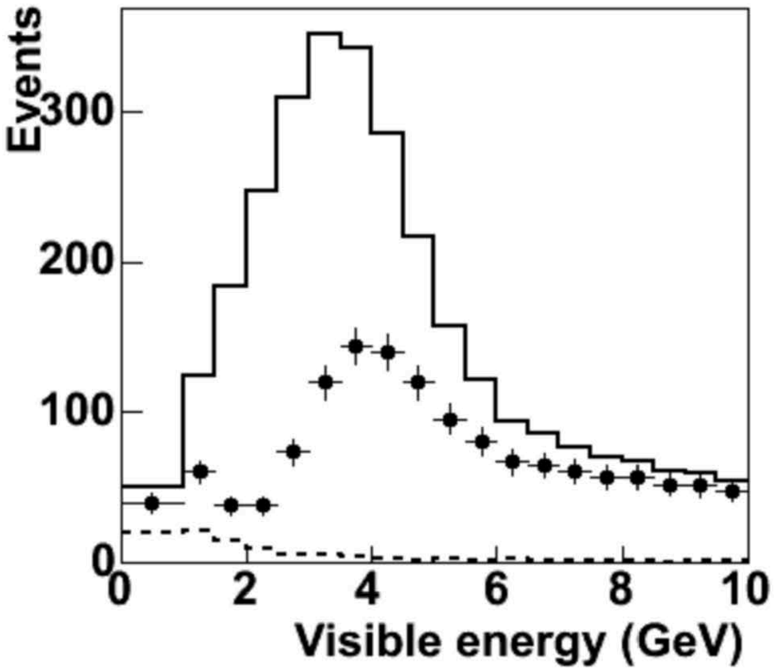
Not absolute masses!

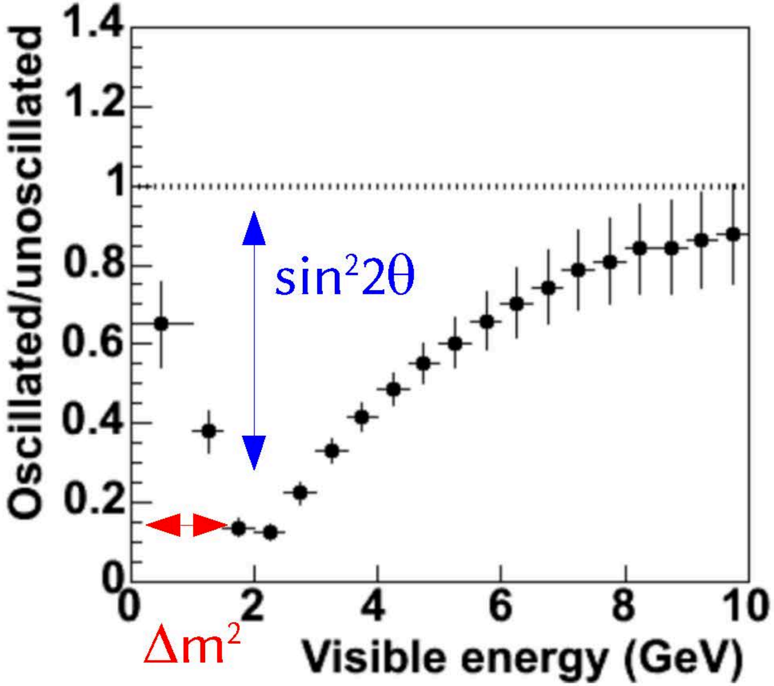
Neutrinos have Mass!

$$\begin{bmatrix}\nu_\alpha \\ \nu_\beta\end{bmatrix} = \begin{bmatrix}\cos\theta & \sin\theta \\ -\sin\theta & \cos\theta\end{bmatrix}\begin{bmatrix}\nu_1 \\ \nu_2\end{bmatrix}$$

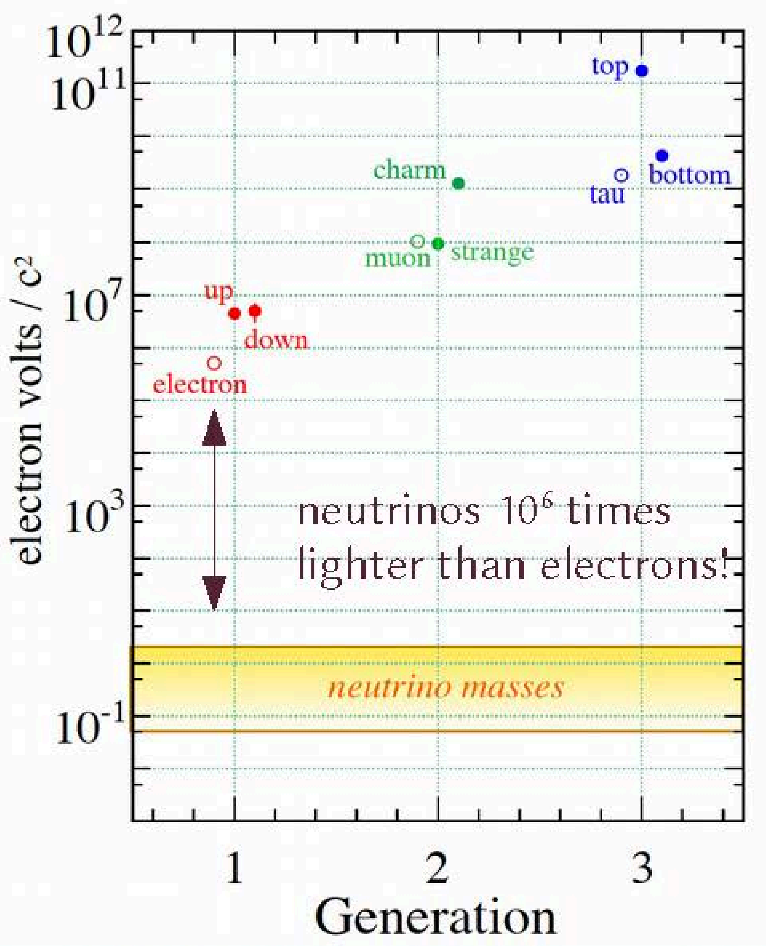
$$P(\nu_\alpha \to \nu_\alpha)$$

$$= 1 - \sin^2 2\theta \sin^2 \frac{\Delta m^2 L}{4E}$$

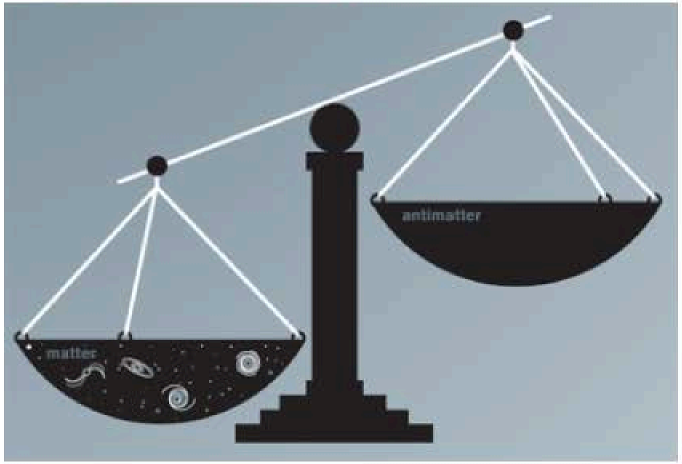




...But Not Much

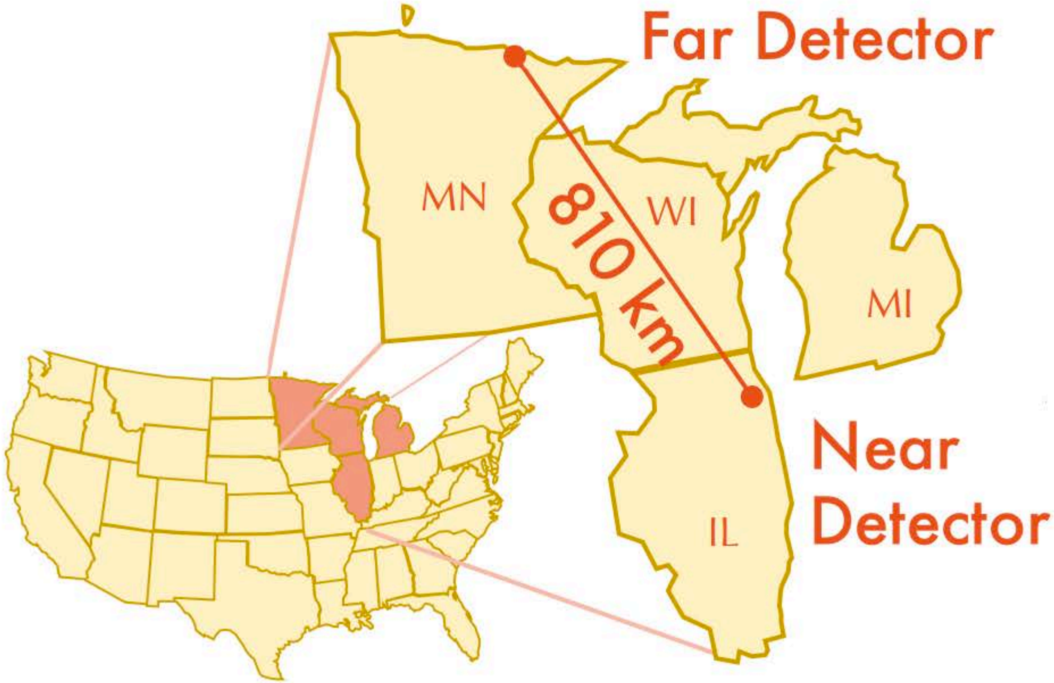


- Neutrino oscillations raise as many questions as they answer
  - Why are neutrinos so much lighter than every other particles?
  - Why is neutrino mixing so much larger than quark mixing?
  - Are neutrinos their own antiparticles?
  - Do they violate CP? By enough to explain the matter-antimatter asymmetry of the universe?
- Neutrino experiments can help, but it is crucial that we can:
  - Separate neutrino flavors efficiently and with high purity
  - Accurately estimate the neutrino's energy



NuMI Off-Axis ν_e Appearance Experiment

NOvA is a long-baseline neutrino oscillation experiment located 14 mrad off-axis from the NuMI beam designed to measure:



ν_e appearance

- Mass hierarchy
- CP violation
- θ_{23} octant

ν_μ disappearance

- Improved precision on $|\Delta m^2_{32}|$ and θ_{23}

NC disappearance

- Search for sterile neutrinos
- Constrain θ_{34} and θ_{24}

Others

- Short-baseline steriles
- Cross sections
- Supernovae
- Exotics

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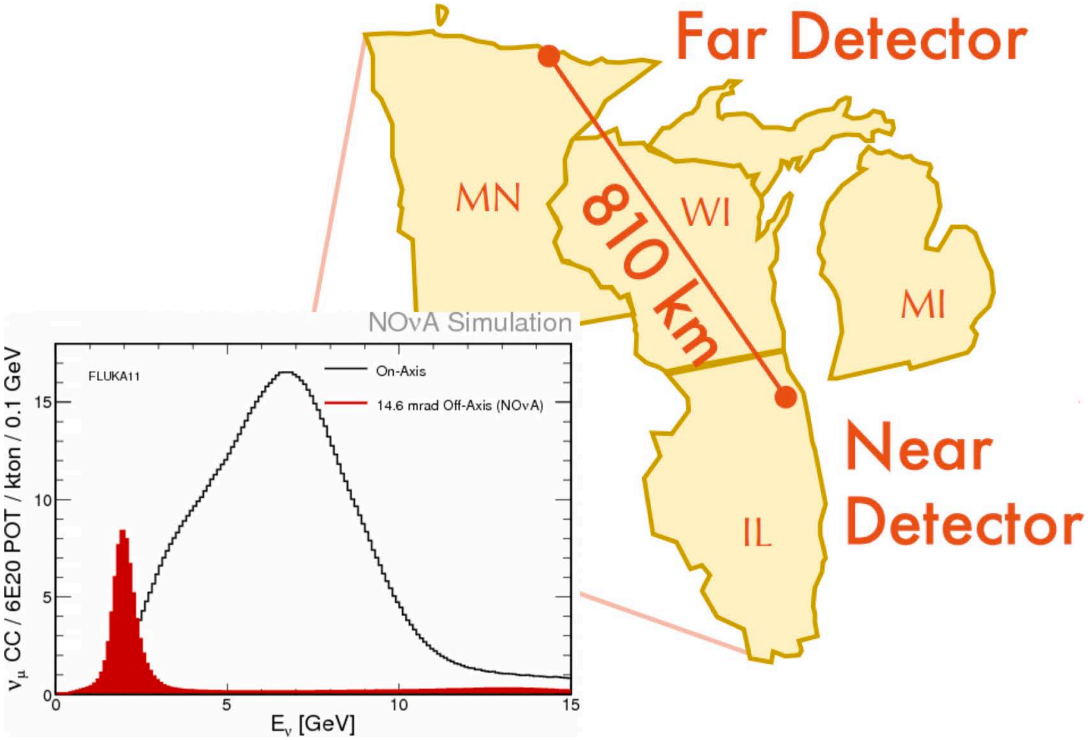

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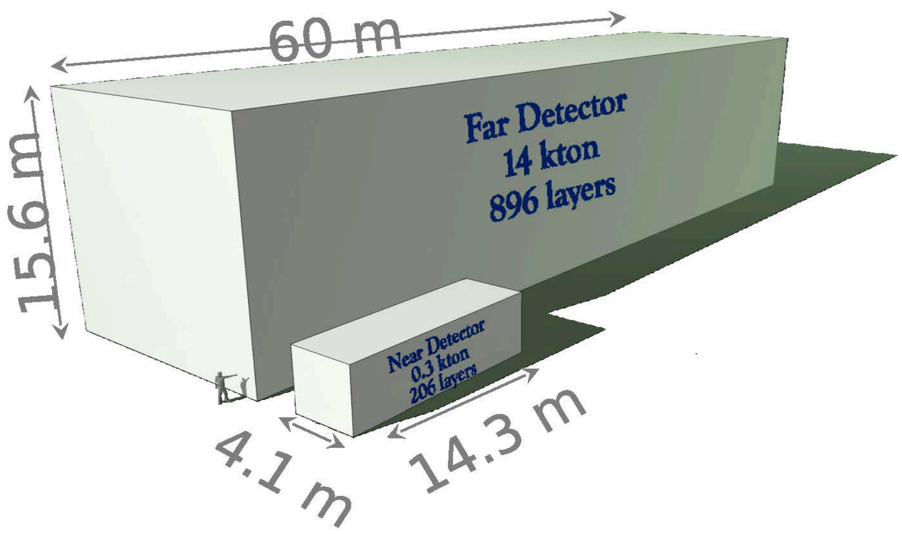
NOvA Detector Design

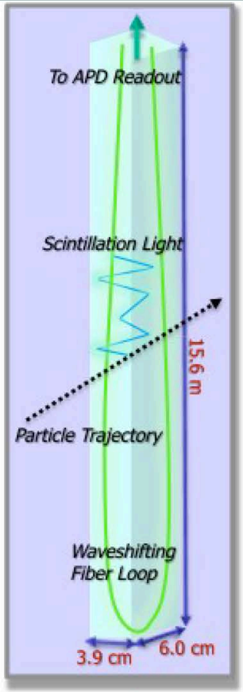


Far detector (FD)

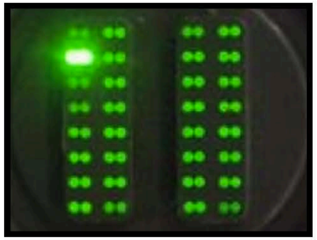
- 14 kton
- 65% active mass
- ~344,000 channels

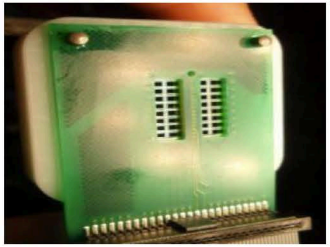
Near detector (ND)

- 0.3 kton
- Functionally equivalent to FD for systematic uncertainty reduction
  - Faster electronics
  - Muon catcher to contain muons
- ~20,000 channels



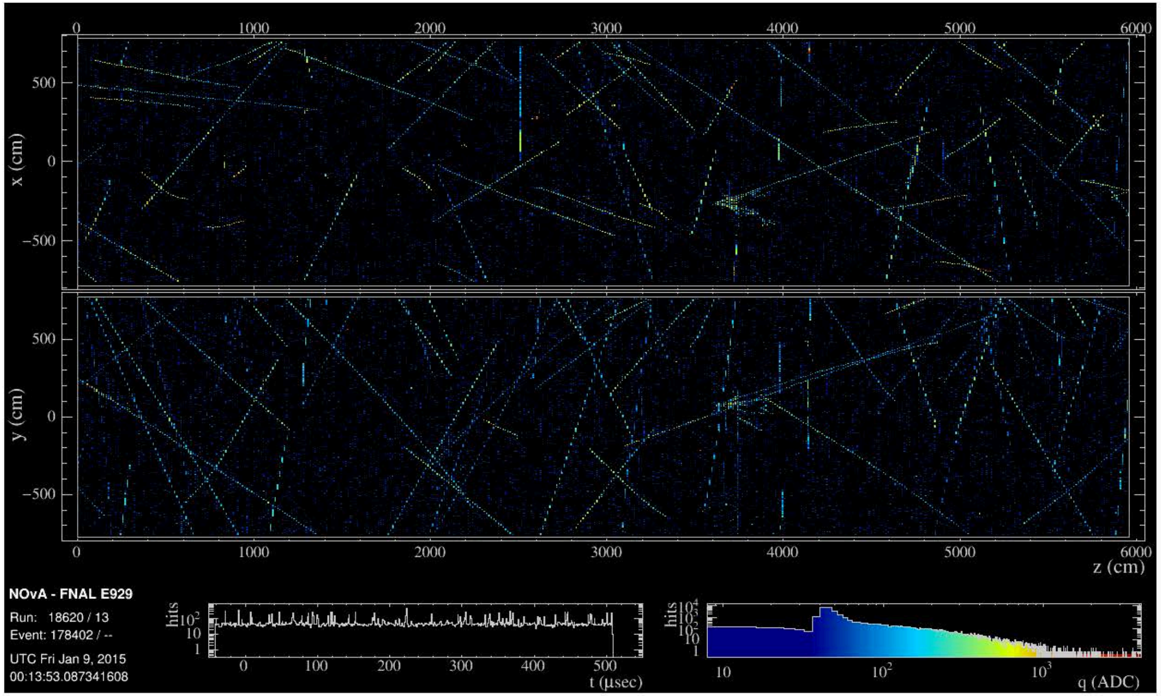
Low Z tracking calorimeter composed of alternating horizontal and vertical planes of liquid scintillator filled cells.





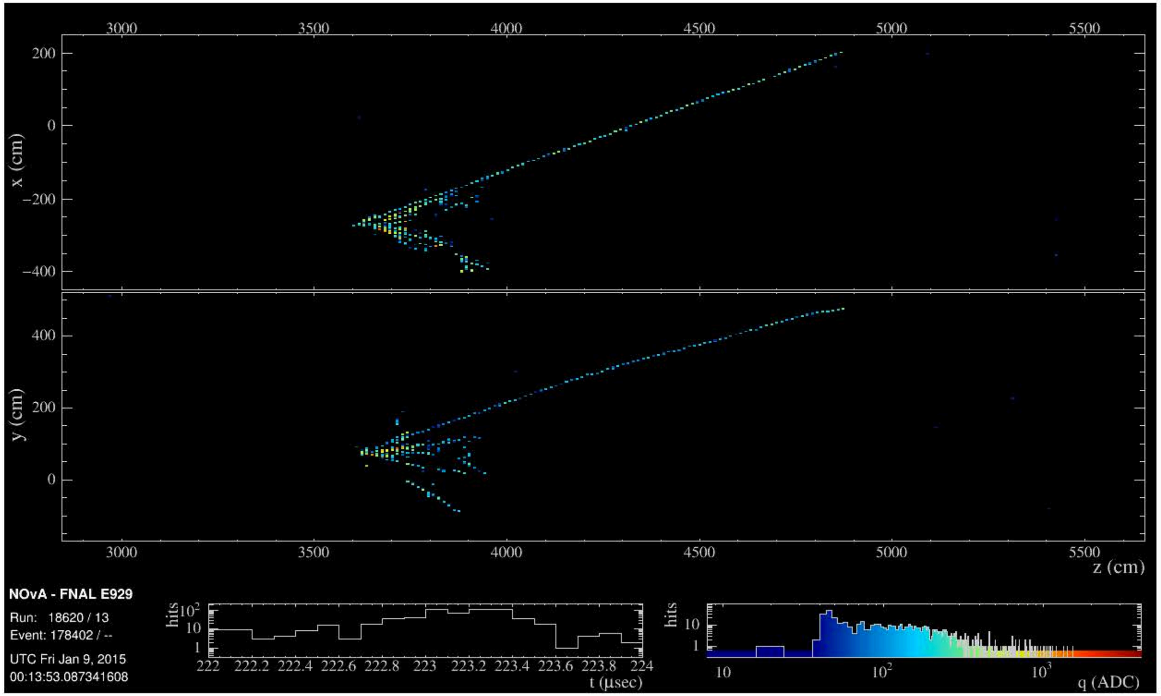
Wavelength shifting fibers carry light out of the cells to APDs.

Can You Find the Neutrino?



- NOvA takes data in 550 μs increments
- The FD is on the surface, so most activity is due to cosmic rays
  - 100,000s cosmic rays/second
  - 100s of ν_μ/year
  - 10s of ν_e/year

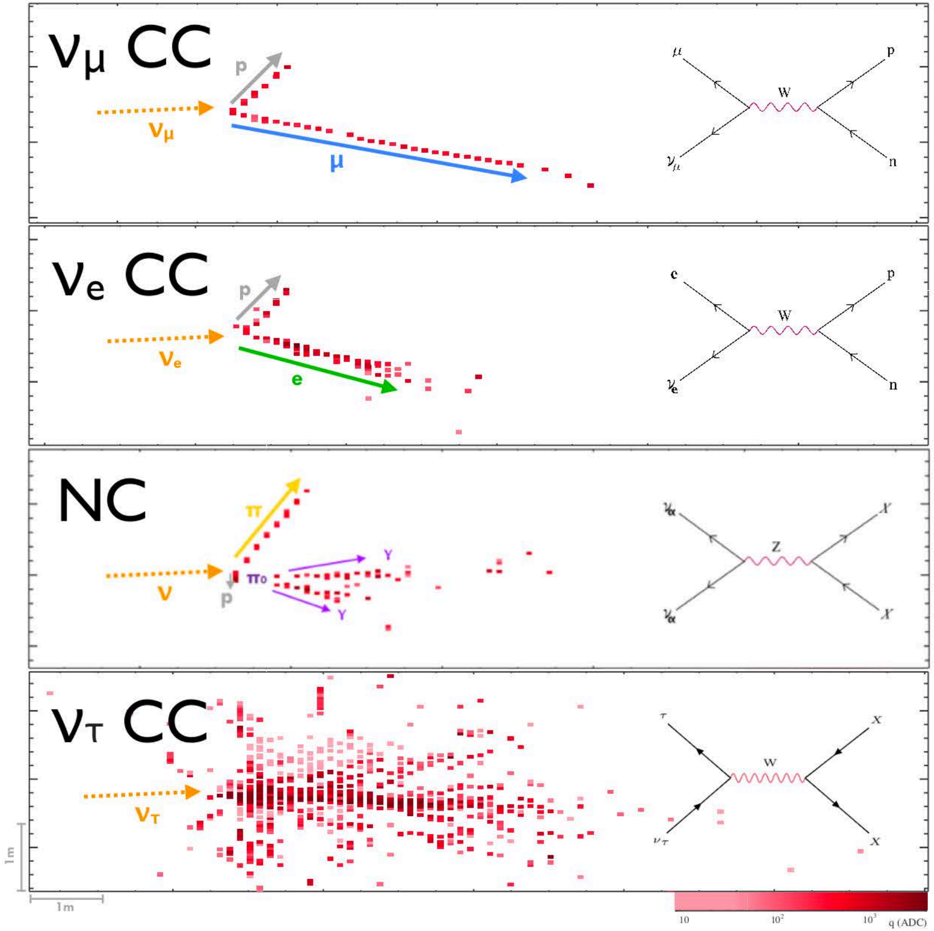
Zooming in…



- Cluster hits in space and time
  - Groups of hits likely to be causally related
  - Separates hits for neutrino events, cosmic rays, and noise
  - …but it doesn't tell us what they are

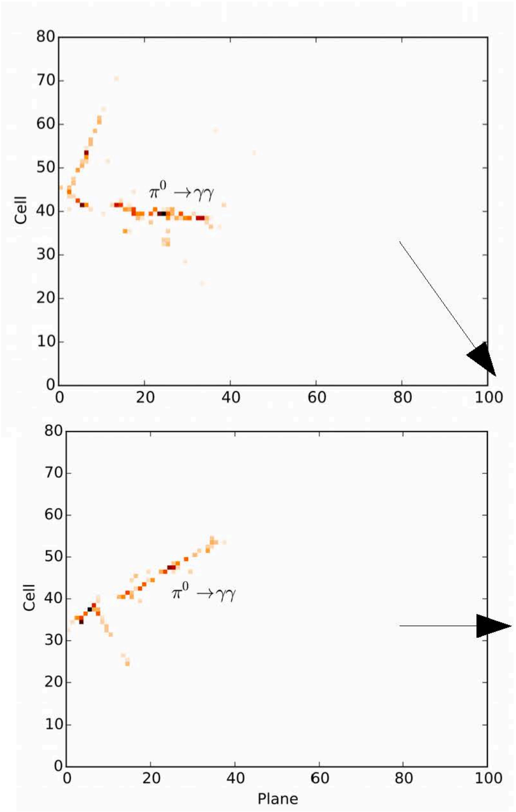
Event Topologies

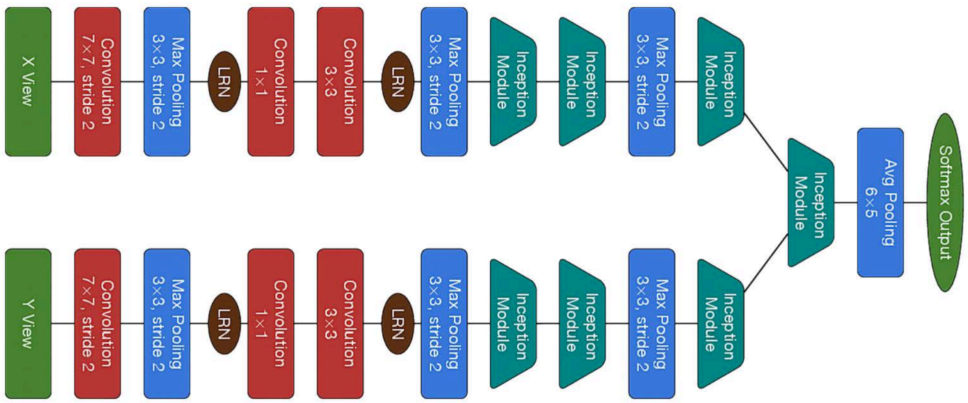
- Low Z detector materials lead to long tracks and well developed showers
- Key challenges
  - Discriminating between muons and charged pions
    - Both can produce long tracks, but muons are usually longer and interact less with nuclei
  - Discriminating between electrons and photons
    - Electrons start showering immediately, but photons travel a short distance before showering
      - Crucial since neutral pions decay into photons
- In the standard workflow, reconstruct particle content of the event and try to classify the neutrino flavor and interaction type
- Events in NOvA look like images
  - Try using convolutional neural networks for classifying



Convolutional Visual Network

- Detector is composed of alternating horizontal and vertical planes
  - Two views of the event- one from top and one from side
  - Resulting pixel maps are sparse
- Create a “siamese” GoogLeNet variant
  - Split the views early and extract parallel features
  - Merge together at the end before going through fully connected layers
  - 1024 features are used in the final layer for classification.

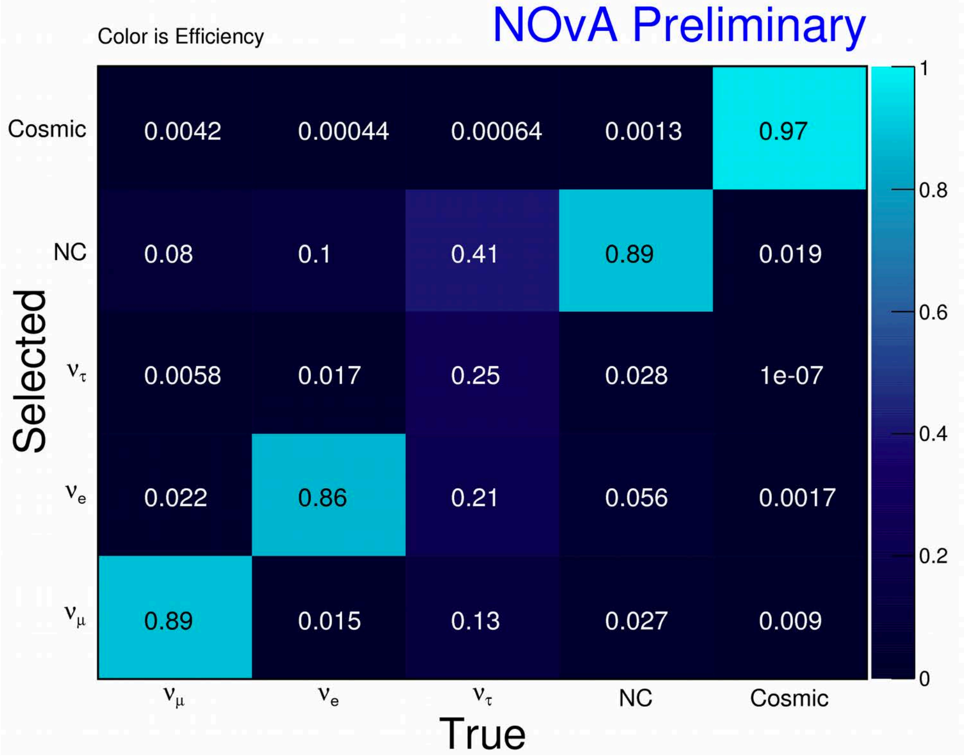




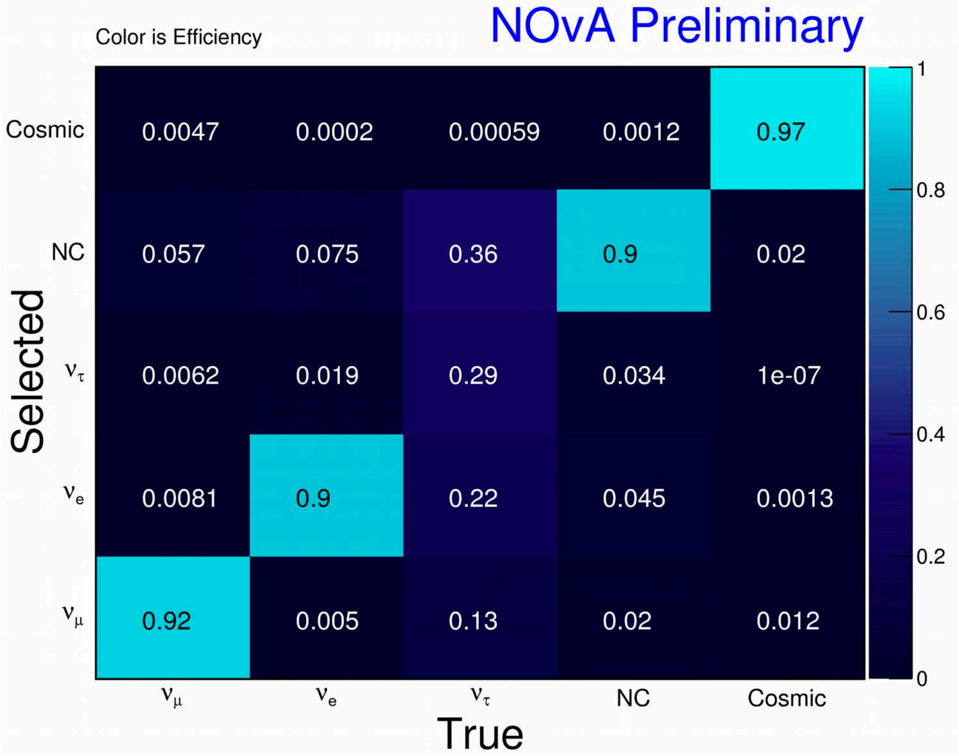
- The architecture is a multi-classifier
  - Neutrino flavor
  - Type of interaction with the nucleus
- In principle, this architecture is a universal neutrino classifier

Training

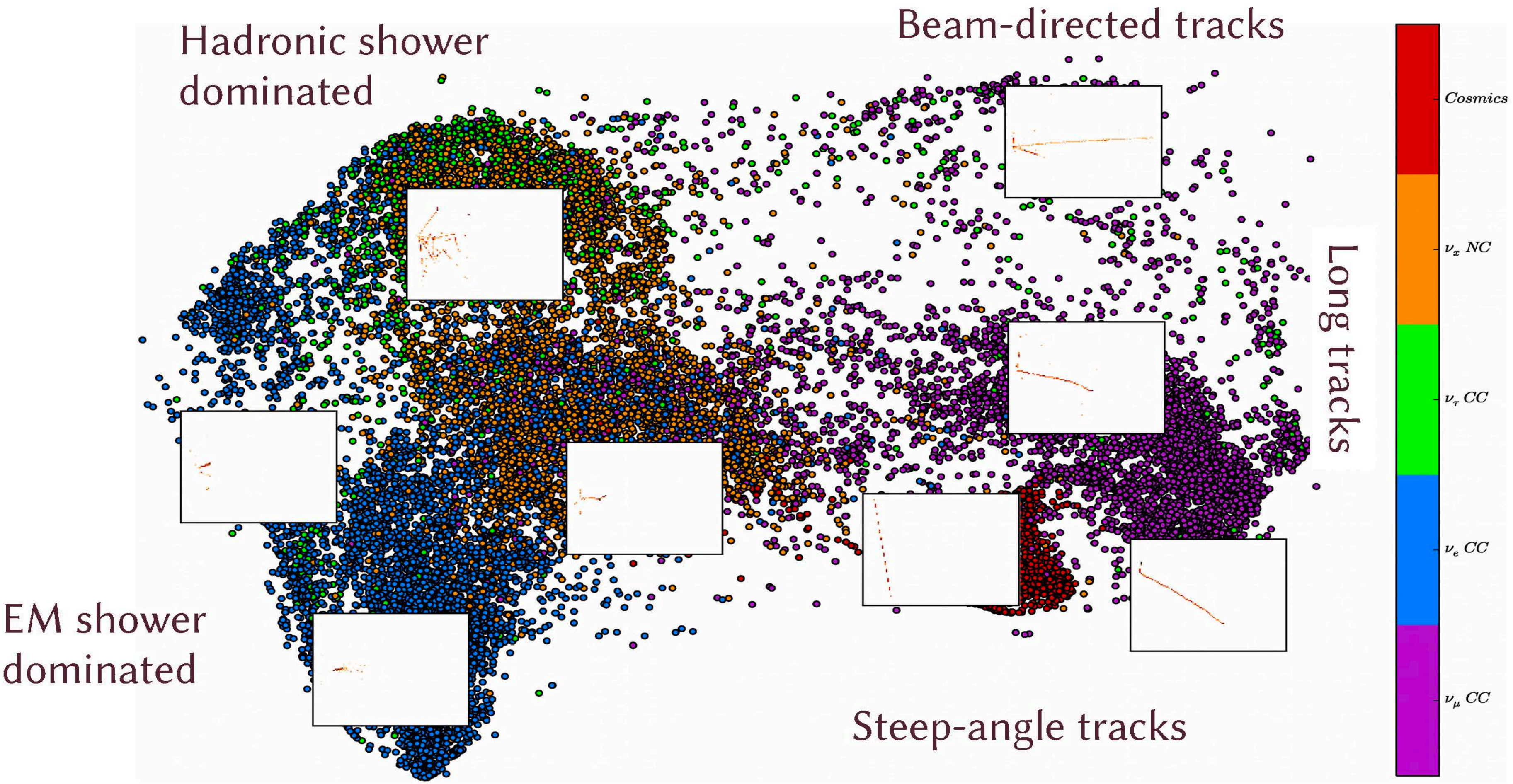
Neutrino mode



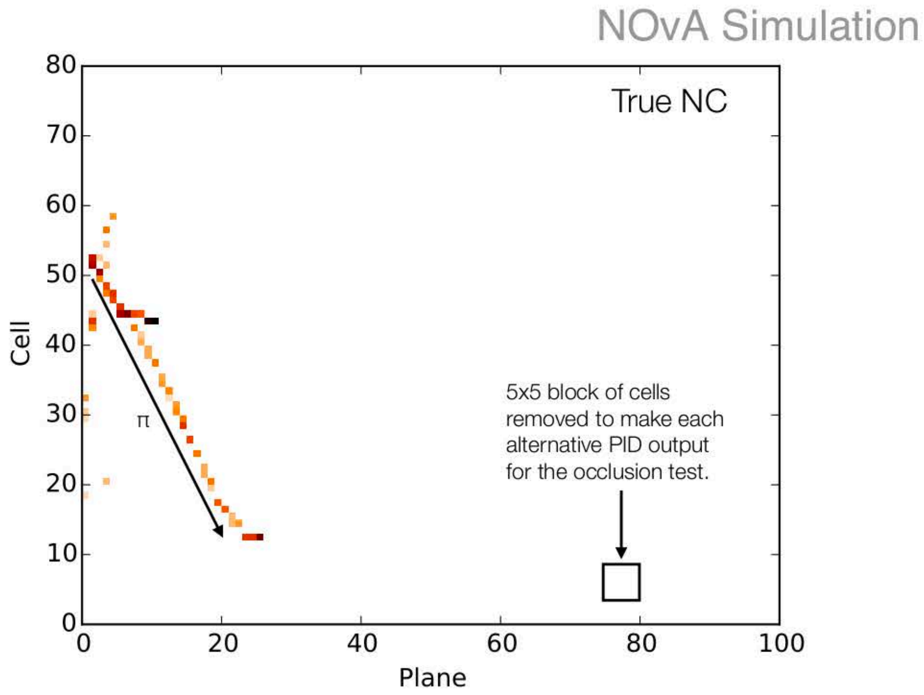
Antineutrino mode

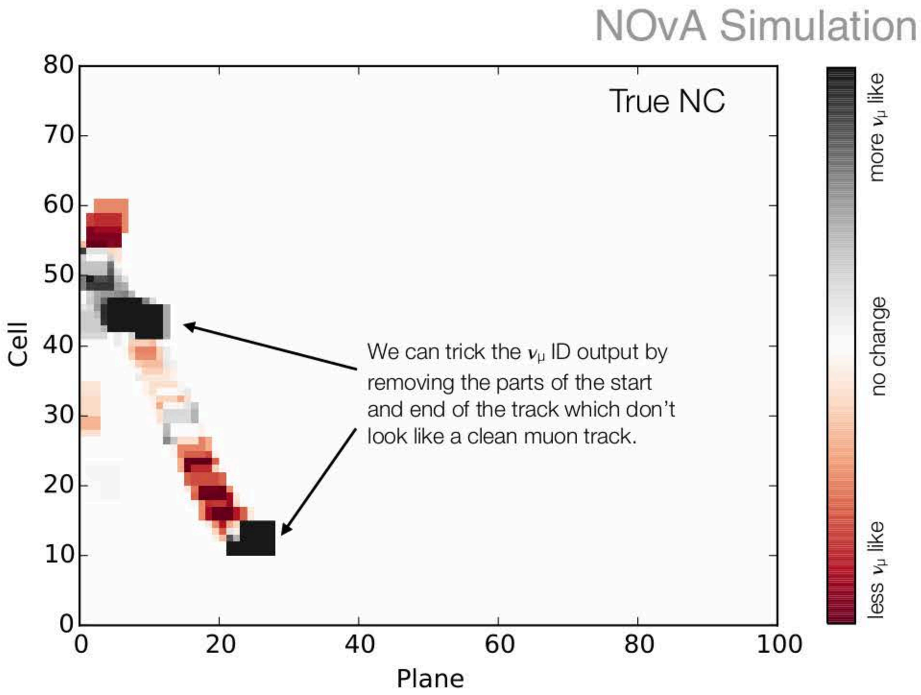


Understanding the Network: Feature Embedding with t-SNE



Understanding the Network: Occlusion Tests





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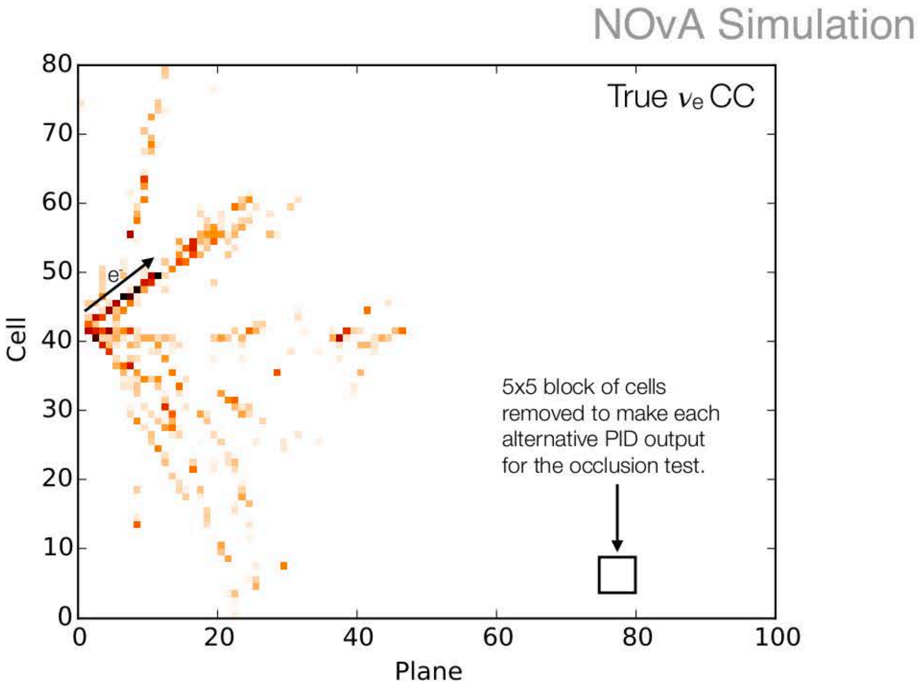
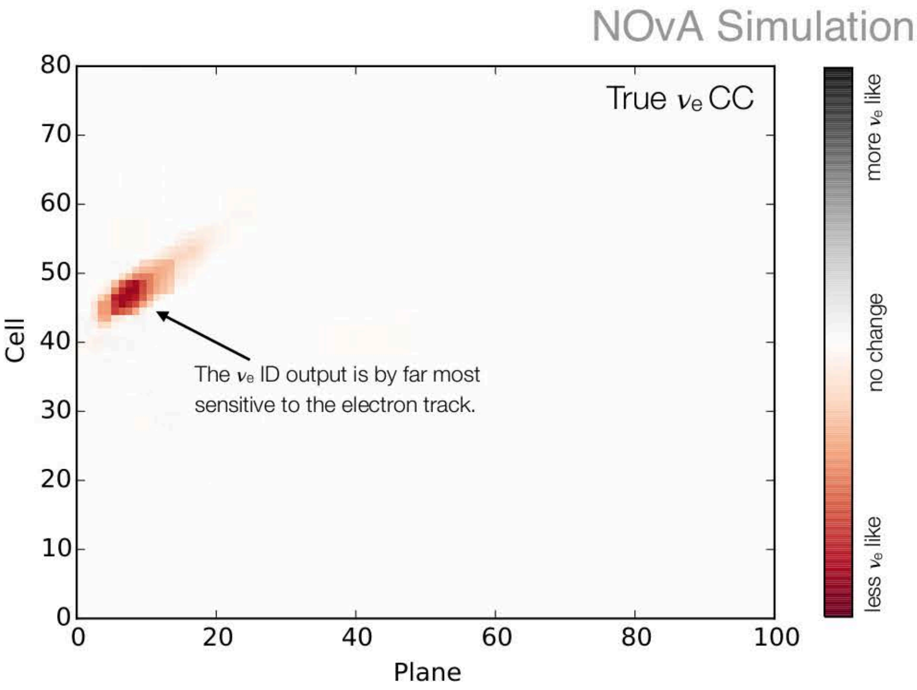
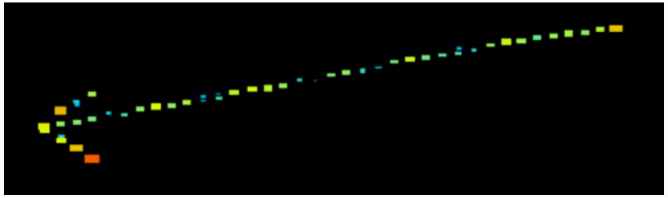




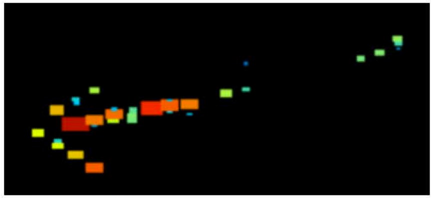
Hybrid Event Testing

- Select likely ν_μ events in the Near Detector

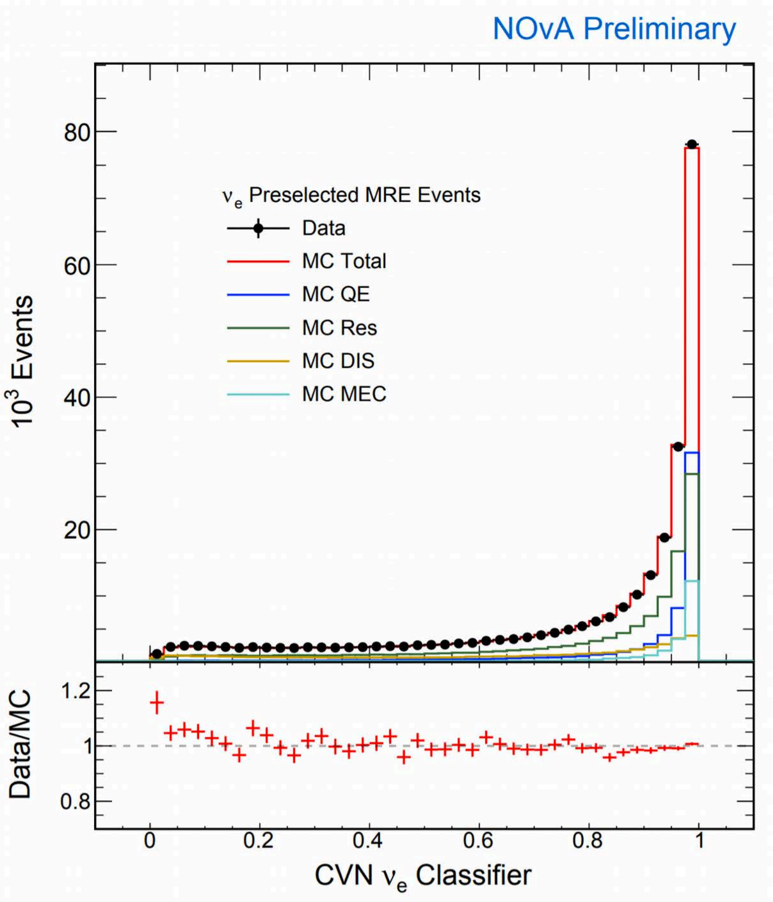


- Remove hits from the identified muon track

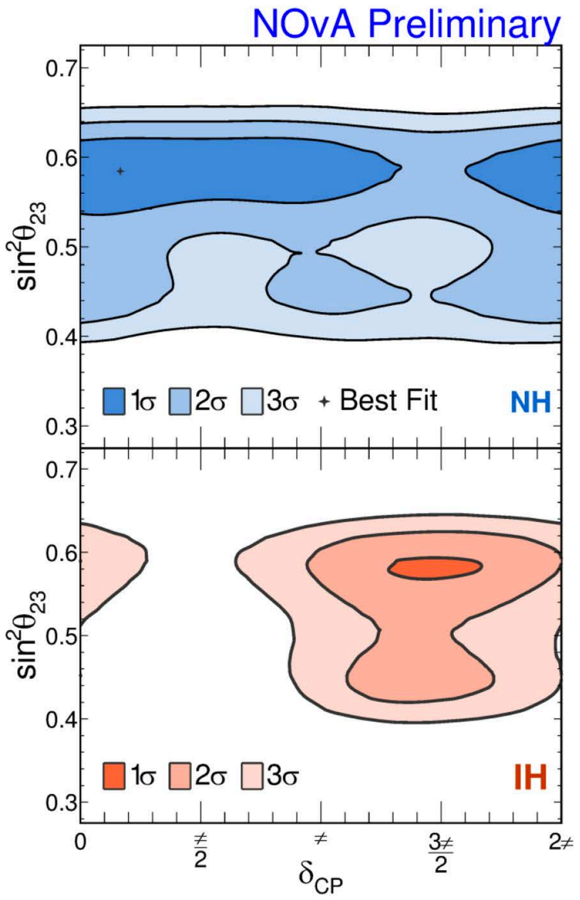
- Insert a simulated electron of the same momentum as the removed muon



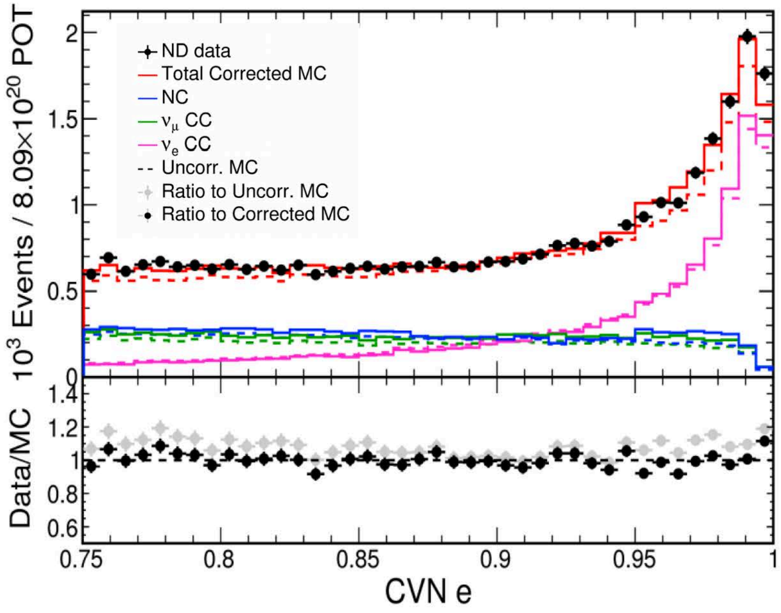
- Data and MC efficiency agree to better than 1%



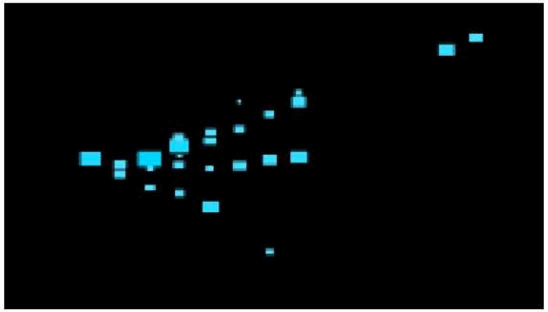
Use Case: ν_e Appearance



- CVN selected ν_e sample is 73% efficient and 76% pure
  - Improvement of traditional selection techniques equivalent to a 30% increase in detector mass
- Excellent data/MC agreement in the Near Detector

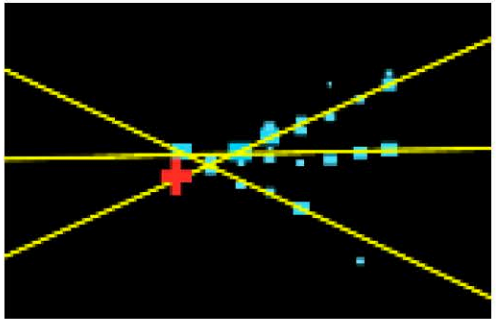


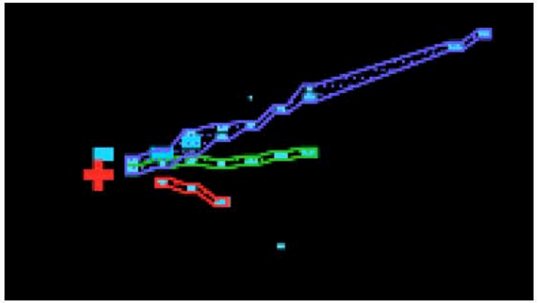
Traditional Reconstruction Methods



Event Separation: Coarse event-level time-space clustering (slicing) using the DBSCAN algorithm.

Vertexing: Find lines of energy deposition using the Hough transform. Find the best point line radiate from.

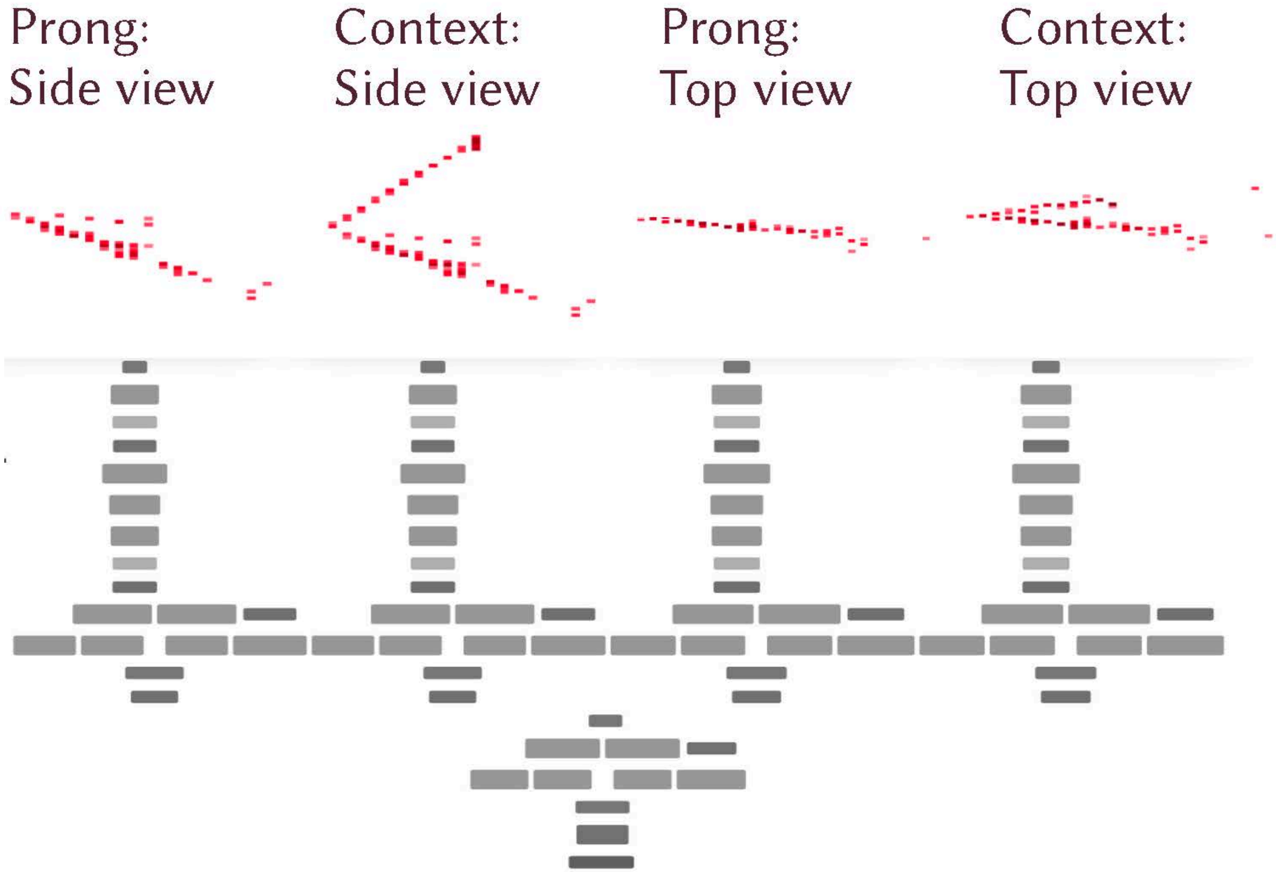




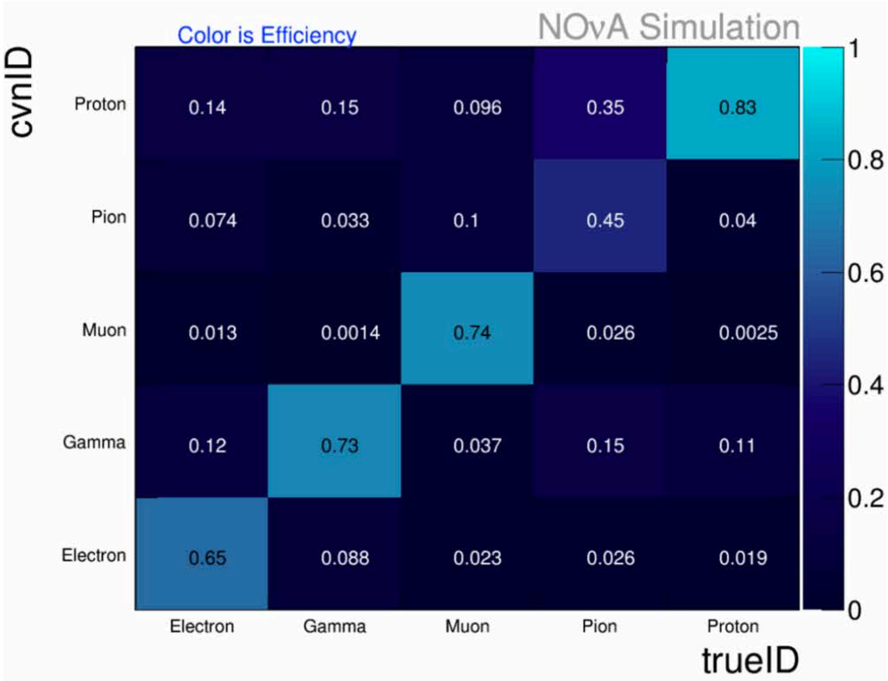
Prong Clustering: Find clusters in angular space around the vertex in each view. Merge views using topology and prong dE/dx.

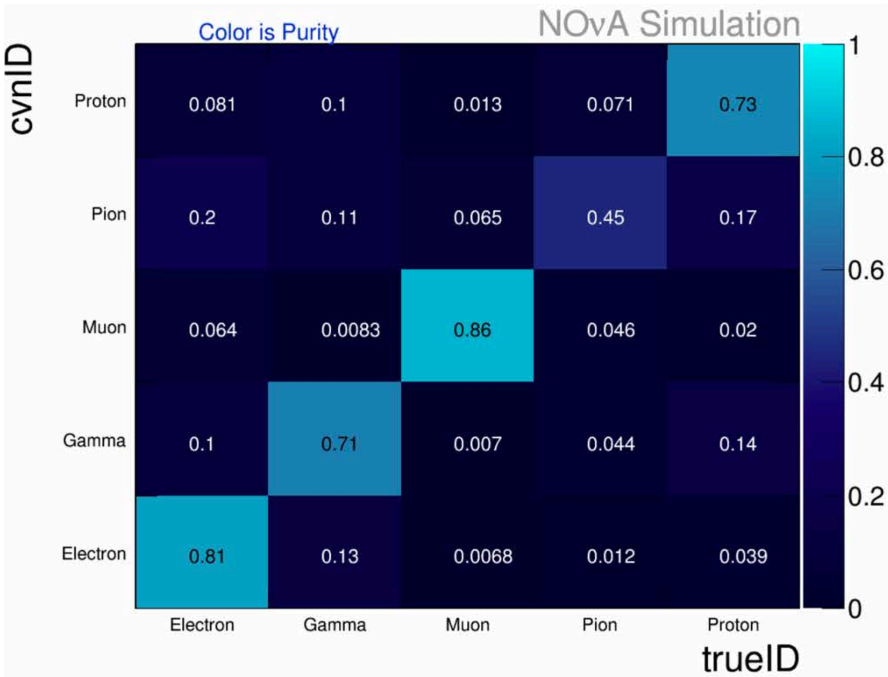
Prong CVN

- Full reconstruction is the dream
  - Still in the future, though instance-aware semantic segmentation is actively being developed
- Attempt to categorize prongs reconstructed using traditional methods to determine the type of particle that created it
- Modify CVN to take 4 views
  - Two prong-only views
  - Two context views
- Depends heavily on the quality of the reconstructed prong
  - This method cannot fix if prong matching between views failed



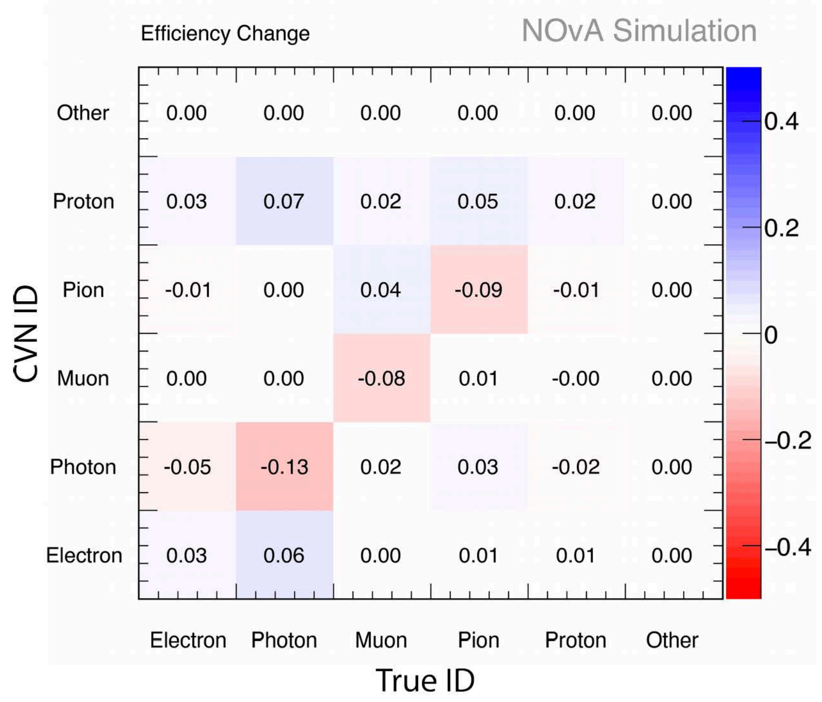
Confusion Matrices



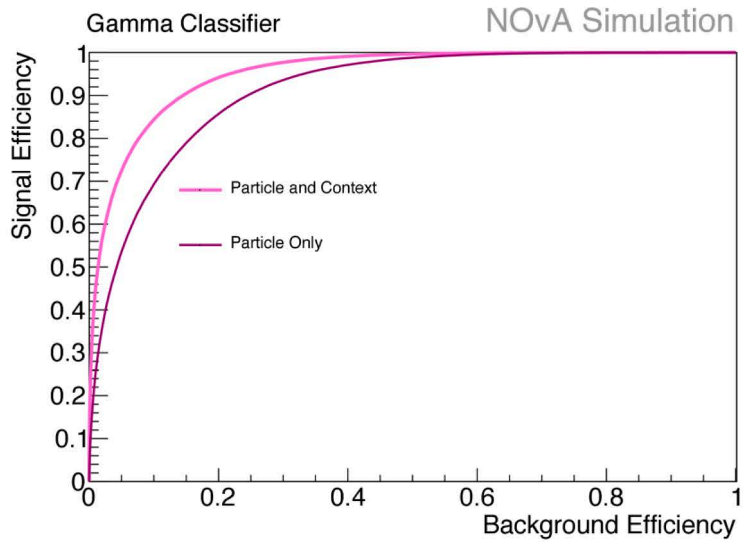


All particles are identified with high efficiency and purity except for pions

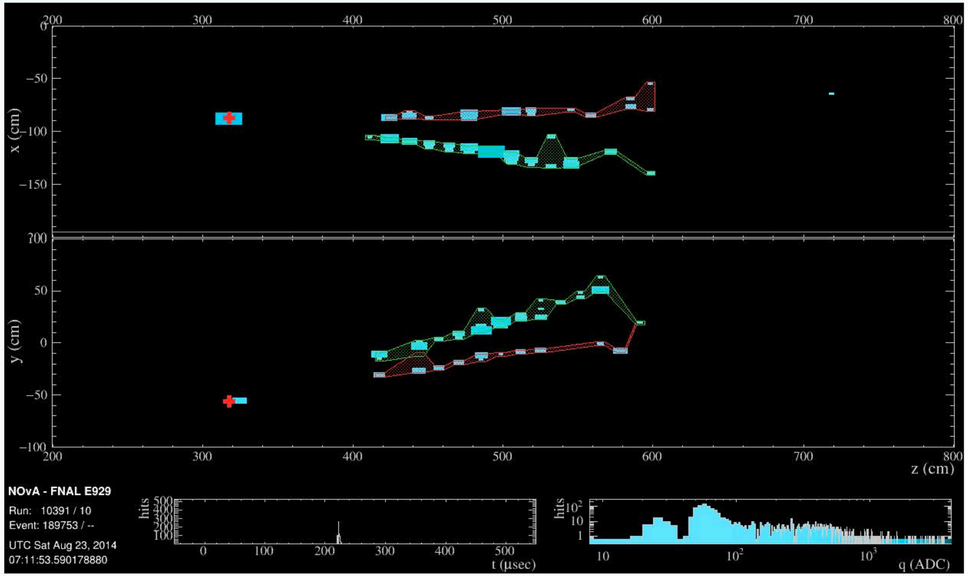
Context Matters



- Adding in full event context introduces dependence on GENIE interaction model
- What happens if context is removed?
- Without context:
  - Muons are more likely to be mis-identified as pions
  - Photons are more likely to be mis-identified as electrons
    - Vertex information is particularly important here

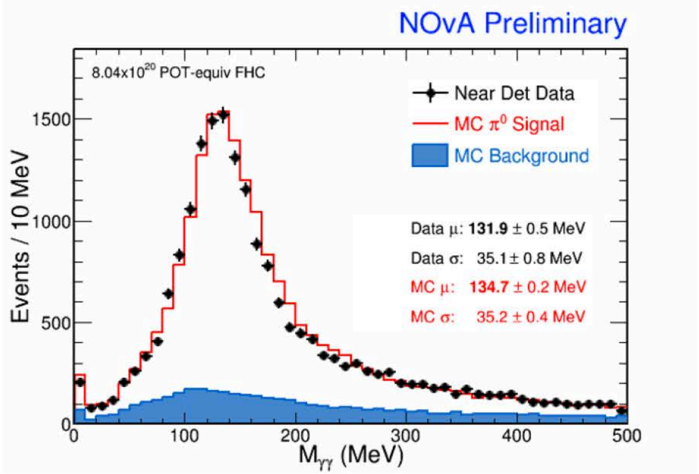


Use Case: π^0 Mass Peak

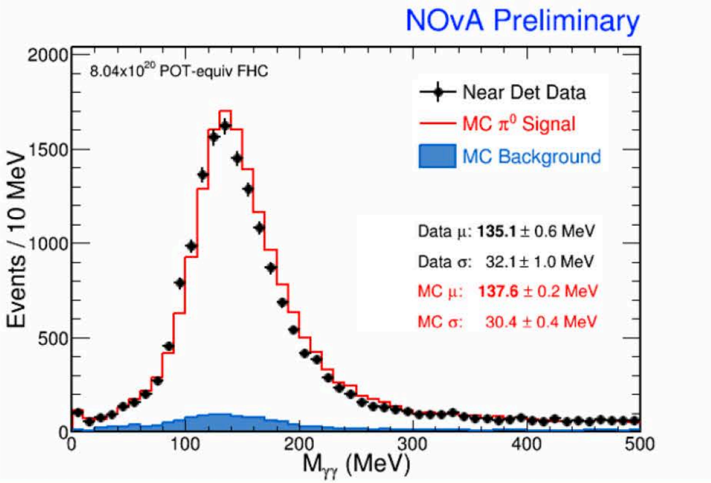


- The π^0 mass peak provides a way to test the ND energy response in data and MC
- Look for two photons emerging from a common vertex
- Prong CVN produces a 12% improvement in selection purity with similar efficiency to traditional methods.

Traditional selection



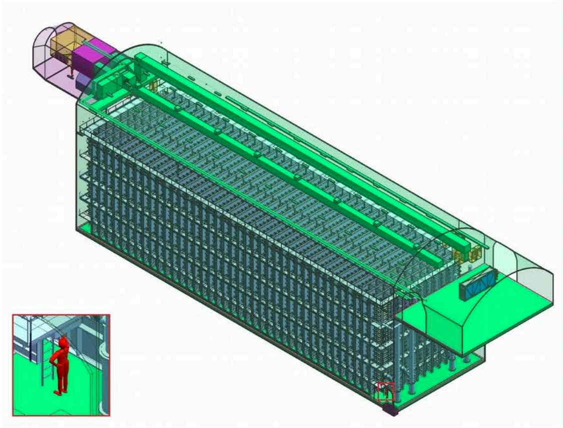
Prong CVN selection

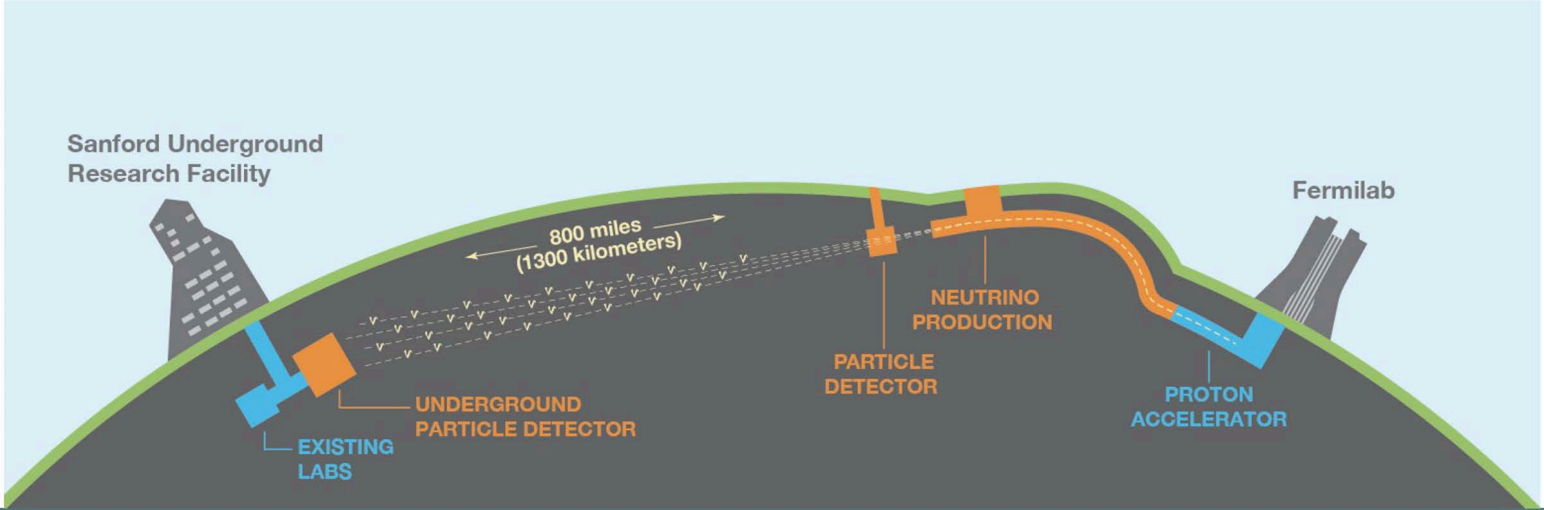


DUNE

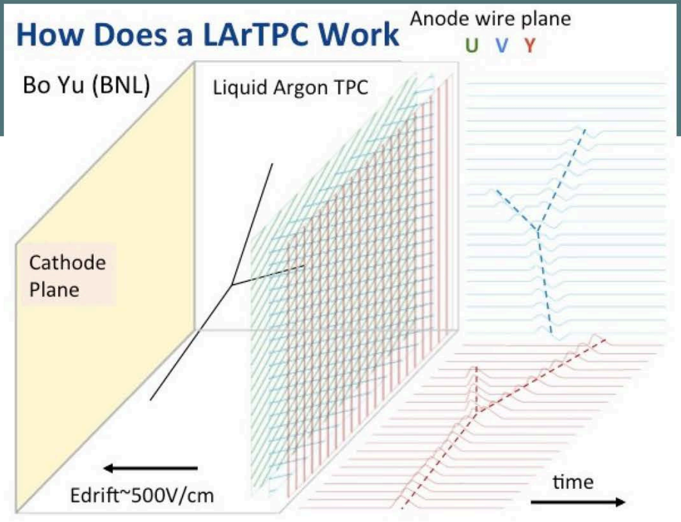
- Future flagship long-baseline neutrino experiment
- Goals:
  - Observe ν_e appearance and ν_μ disappearance in a wideband beam
  - Measure mass hierarchy, CP-violating phase, and atmospheric parameters with high precision
- Ancillary program: sterile neutrinos, ν_τ appearance, solar neutrinos, dark matter, and more

- Near Detector 575 m from target
- Far Detector 1,300 km from target, 1.5 km underground
  - Liquid argon time projection chamber technology for high resolution imaging
  - 4 modules, each with at least 10 kton fiducial mass

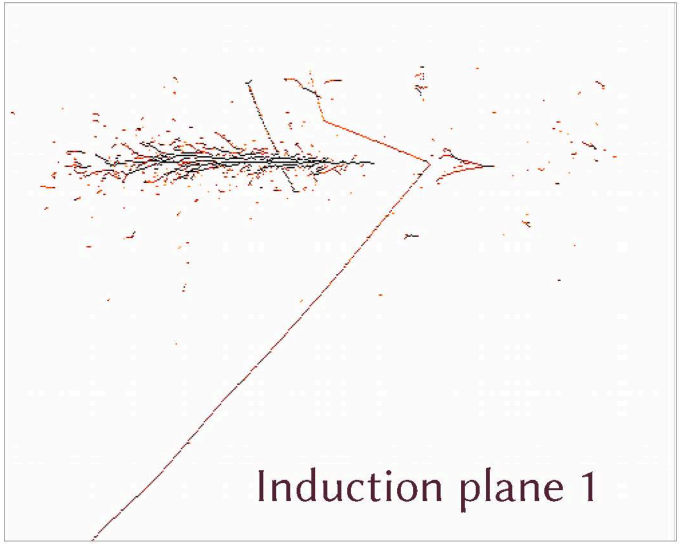


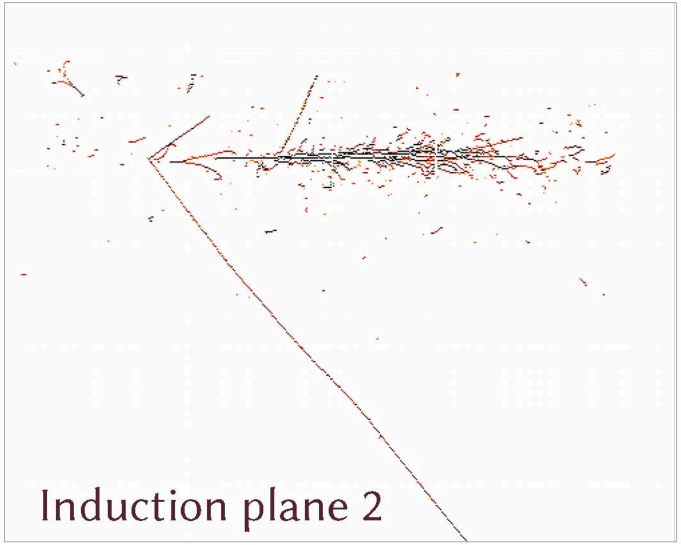


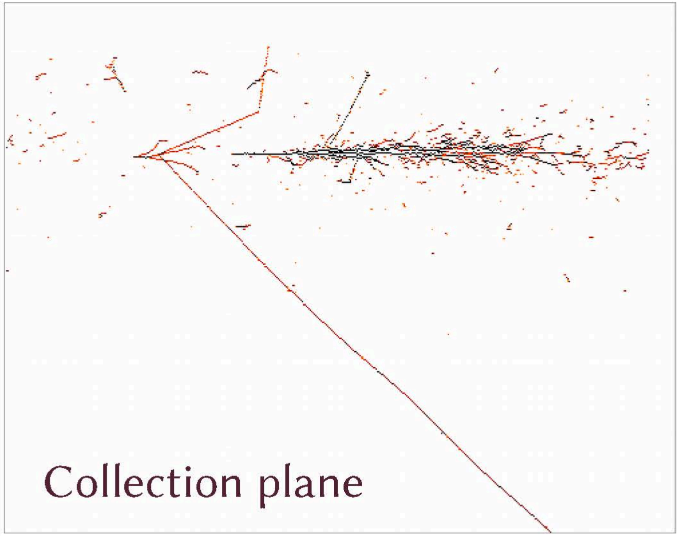
Promise of LArTPC Technology



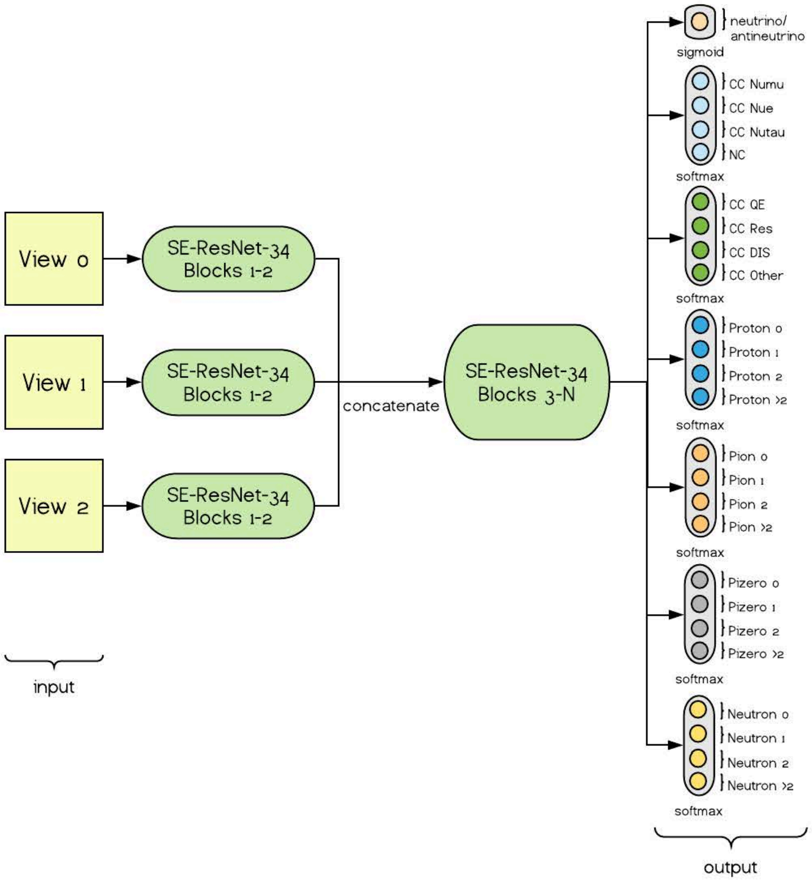
- Wire planes have a 3 mm spacing
- Drift field is 500V/cm
- Maximum drift length is 3.53 m
- Spatial resolution is good enough to distinguish individual electron-positron pairs in an EM shower!
  - Blessing and curse – high resolution images are hard to automatically reconstruct
- For classification, use regions 500 wires long and 1.2 ms wide (in 500 time slices)





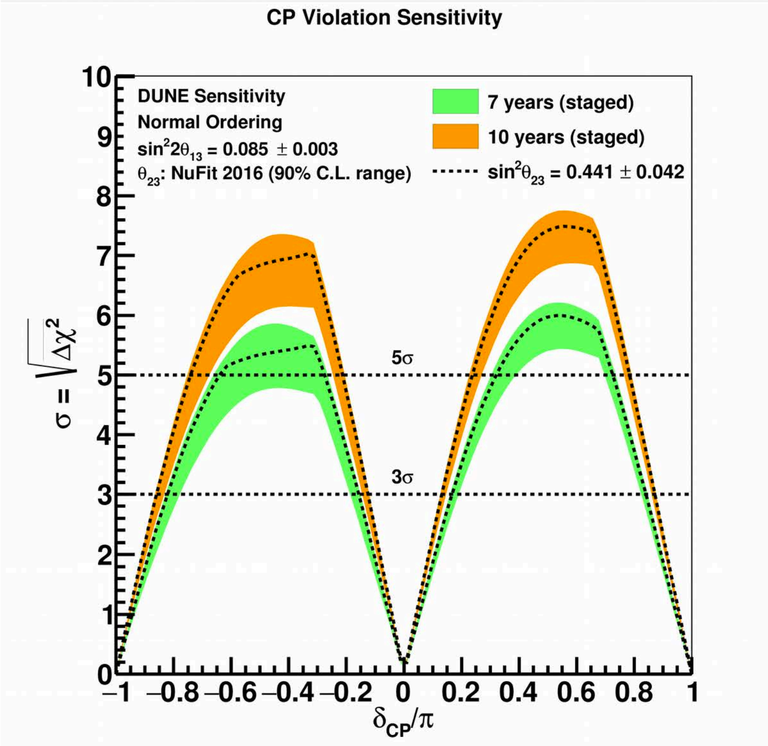


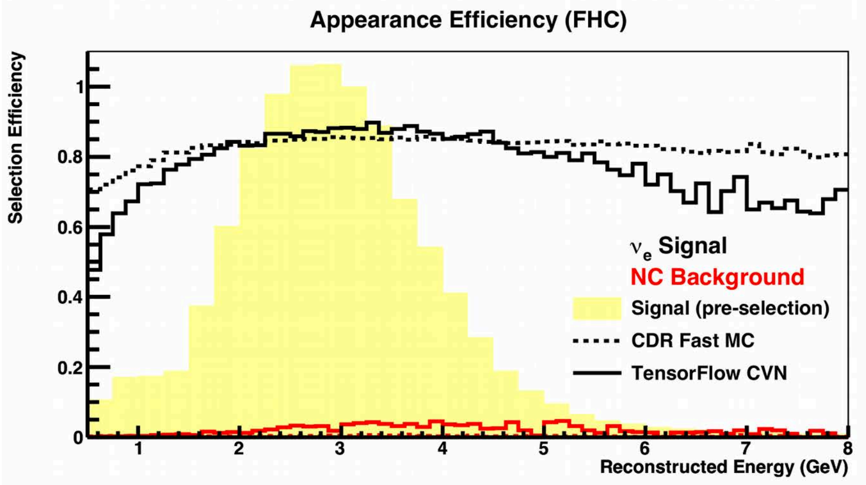
Multi-target Network



- Network is inspired by the NOvA network, but with a few key differences
- Underlying architecture:
  - GoogLeNet → SE-ResNet-34 (arXiv:1709.01507v2)
- Three views separately fed into first two blocks of SE-ResNet-34, then concatenated and fed into remaining blocks
- Multi-target outputs allow for learning many characteristics of the neutrino interaction in one pass
  - Neutrino/Antineutrino
  - Flavor
  - Interaction type
  - Proton multiplicity
  - Charged pion multiplicity
  - Neutral pion multiplicity
  - Neutron multiplicity

Effect on CP-Violation Analysis





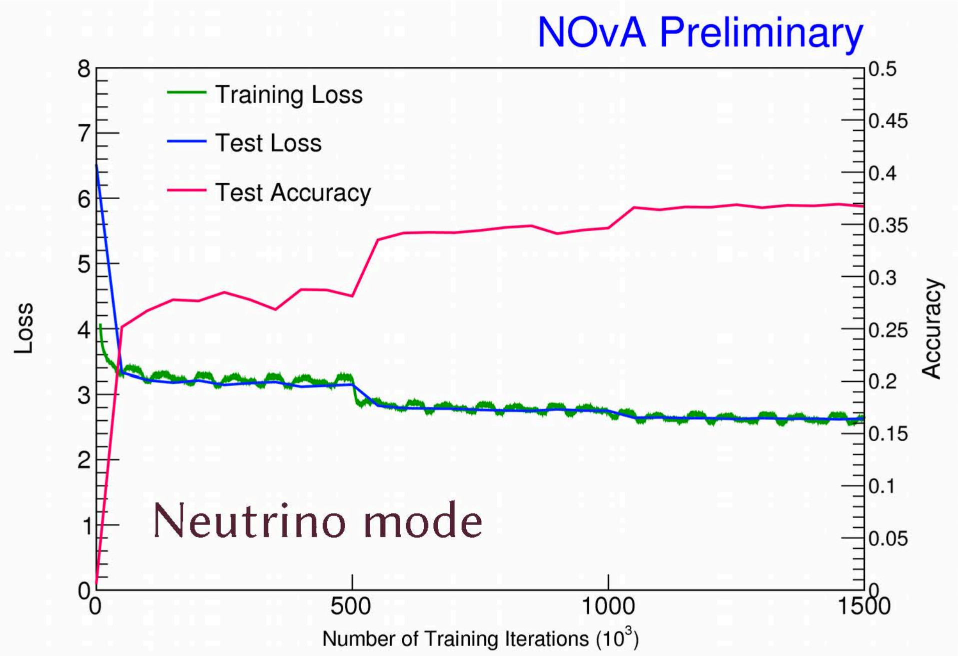
- CDR assumptions of the power of LAr technology implied significant discovery potential over most of the parameter space
- Traditional reconstruction and shallow machine learning methods could not reproduce CDR expectations
- CVN is the first method that exceeds CDR expectations in the most important energy range
  - It does not appear that we have exhausted potential improvements yet

Summary

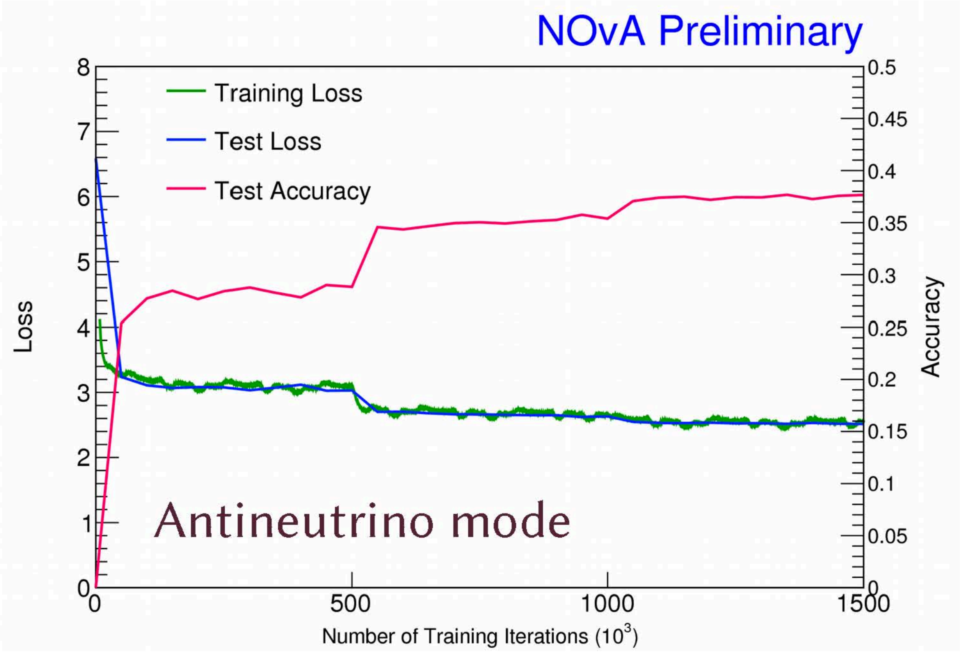
- Modern deep learning techniques are very powerful and are an excellent fit for neutrino experiments
- Using a modified GoogLeNet architecture, it is possible to create a universal neutrino interaction classifier that
  - Uses minimal reconstruction
  - Significantly increased our ν_e selection efficiency
    - Equivalent to a 30% increase in detector mass
- CVN was central to the ν_e appearance analysis
- In wide use throughout NOvA and is critical for the NC disappearance analysis
- Efforts to develop reconstruction methods using deep learning are underway
  - Prong CVN classifies prongs according to the particle that created them with high efficiency and purity
  - Full reconstruction based on instance aware semantic segmentation is being actively developed
- CNNs were critical for DUNE to achieve design sensitivities with realistic simulation and reconstruction
  - Multi-target outputs provide a fine grained view into neutrino interactions

Thank You!

Training

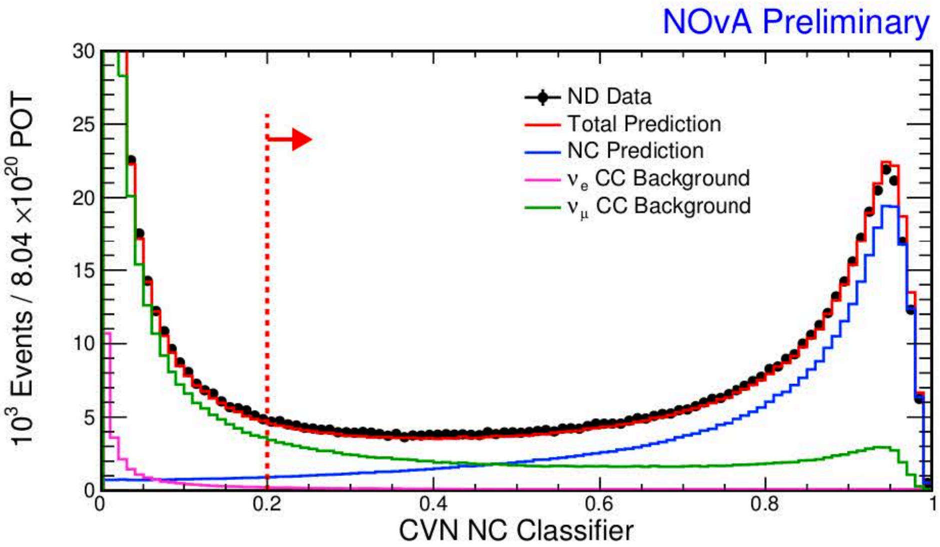


NOvA Preliminary
Training Loss
Test Loss
Test Accuracy
Neutrino mode
Loss
Accuracy
Number of Training Iterations (10^3)

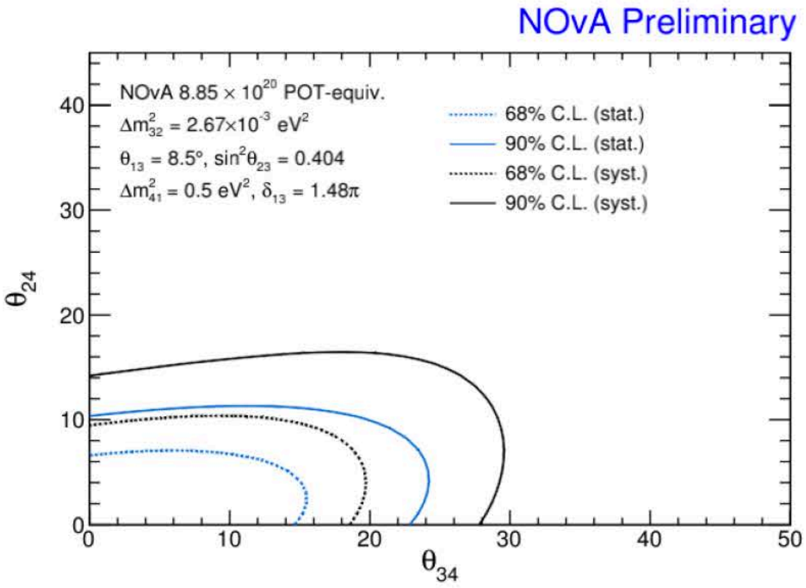


NOvA Preliminary
Training Loss
Test Loss
Test Accuracy
Antineutrino mode
Loss
Accuracy
Number of Training Iterations (10^3)

Use Case: Sterile NC Disappearance

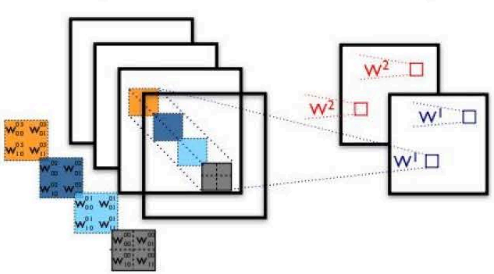


- CVN provides CC/NC separation
- Good data/MC agreement in the ND
- No evidence of sterile neutrinos

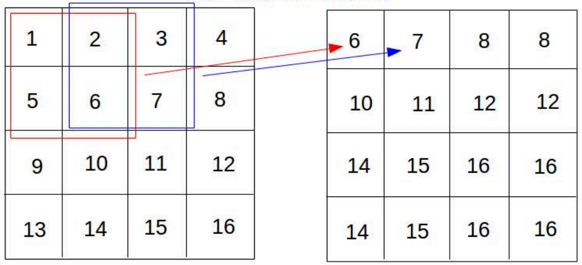


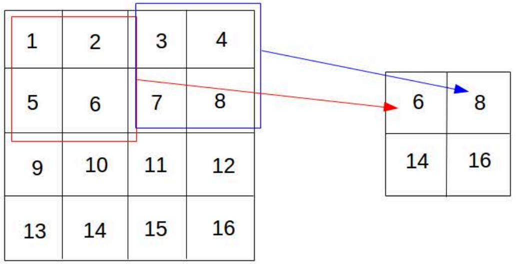
Convolutional Neural Networks

- X and Y views can be interpreted as pictures of a neutrino interaction from the top and the side
- Convolutional neural networks have been highly successful at image recognition tasks
- Two basic type of layers:
  - Convolutional layers – apply discrete convolutions using learned kernels to extract features from the image.
  - Pooling layers – down sample the image and increase translational invariance in the final output.
- Stacked structure of convolutional and pooling layers extract increasingly abstract features from the input raw data encoding both local and global structure.



2x2 MaxPool Stride 1

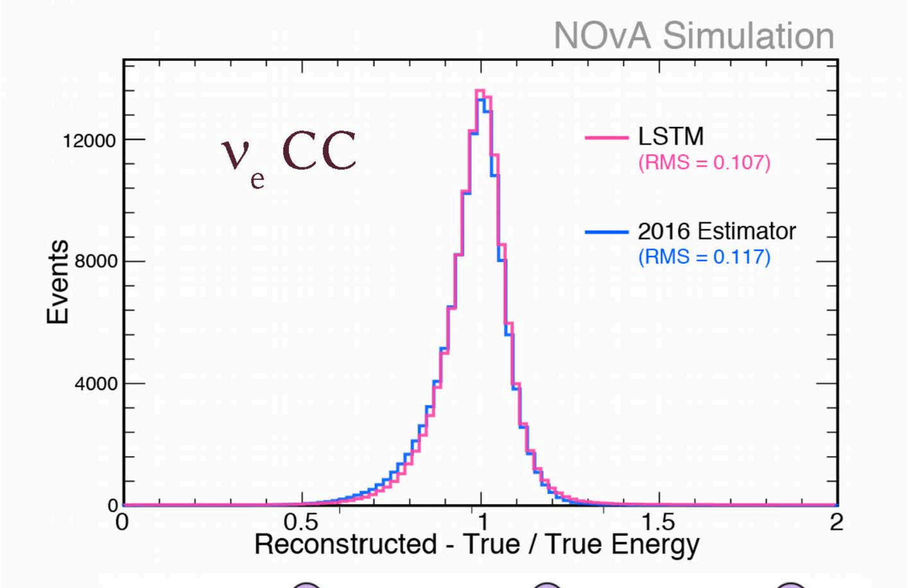


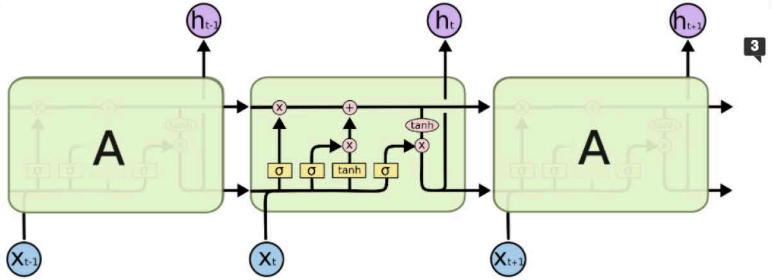


2x2 MaxPool Stride 2

LSTM Energy Estimation

- Recurrent neural networks and LSTMs provide a way to accept sequences as NN input
- Current neutrino energy estimators use coarse-grained energy information
  - Calorimetric energy of full hadronic system is usually used as a single input
- Use an LSTM network to accept variable length list of prongs with particle hypotheses and energy and momentum estimates
- Method builds up a representation of the event that models particle kinematics
- First results show improved energy estimation





http://colah.github.io/posts/2015-08-Understanding-LSTMs/

CNN Energy Estimation

- Also attempts to estimate energy directly from pixel maps with minimal reconstruction
- A variant of the CVN architecture
  - Adds in extra reconstructed vertex information into the fully connected layer