Event Reconstruction in the NOvA Experiment

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Oscillation Analysis:

Sterile neutrinos search.

arXiv:1706.04592

\[ \sin^2 \theta_{23} \] at Near Detector

Exotics

Booster neutrinos etc..

Cross-section at Near Detector

Hongyue Duyang

NuINT 2017

\[ \Delta m_{21}^2 = 2.44 \times 10^{-3} \text{ eV}^2 \]
\[ \theta_{13} = 8.5^\circ, \theta_{23} = 45^\circ \]
\[ \Delta m_{31}^2 = 0.5 \text{ eV}^2 \]

Others...
NOvA is a long-baseline oscillation experiment
Uses NuMI muon neutrino beam from Fermilab

Both detectors are functionally identical.

**NOvA FD:**
- 15.5m X 15.5m X 60m
- 14 kton, 0.3M channels
- 896 planes

**NOvA ND:**
- 3.9m X 3.9m X 16m
- 300 ton, 20k channels
- 214 planes

**14.6 mrad off-axis peaked at 2 GeV Neutrino energy.**
- Basic unit of NOvA detector are cells made up of PVC with liquid scintillator (mostly Carbon).
- Wave length shifting fibre collects light from interaction of charge particle with liquid scintillator.
- Low-Z (nicely separation between long track and electromagnetic shower), 1 plane $\sim 0.15X_0$, highly active tracking calorimeter.
Data Events in Far Detector

An event (cosmic ray) within the 550 μs window of data in the Far Detector.
An event within the 10 µs window of data in the Near Detector
Isolating Neutrino Interaction

Far

In the Far Detector, located on the surface, the primary concern is separating 50-70 cosmic rays in a 550 microsecond window.

In the Far Detector, Time resolution is 10 ns

Near

For the Near Detector separating ∼5 neutrino interactions are expected in each 10 microsecond neutrino beam window.

In the Near Detector, Time resolution is 5 ns
Slicing
(coarse event level time-space clustering)
Reconstruction Chain in NOvA

2D guide line finding
(2-point Hough Transform)
Reconstruction Chain in NOvA

Interaction point (vertex) (Elastic Arms)
Reconstruction Chain in NOvA

Formation of Cluster (FuzzyK)
Event Reconstruction in the NOvA Experiment

Event Identification (CVN)
Accurately separate the signal hits from the noise hits and further separates the signal hits into clusters of hits that originate from different sources.

- Uses an expanding, density-based clustering algorithm called DBSCAN* which makes use of spatial and temporal information.

The neighbor score function determines whether or not two hits are to be considered neighbors.

\[
\text{neighbor score} = \left( \frac{\Delta T - \Delta \vec{r}/c}{T_{res}} \right)^2 + \left( \frac{\Delta Z}{D_{pen}} \right)^2 + \left( \frac{\Delta XY}{D_{pen}} \right)^2
\]

* M. Ester, et al., A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise (1996)
Identification of vertex is a two stage process.

First *Hough Algorithm makes line in each individual detector view separately by taking pairs of hits in the event.

* Fernandes & Oliveira, Pattern Recognition 41 (2008) 299-314
Identification of Vertex: Elastic Arm

Uses the output from the Multi-Hough algorithm as a seed for finding the global event vertex.

Optimum vertex candidate is chosen by minimizing an energy cost function

\[ E = \sum_{i=1}^{N} \sum_{a=1}^{M} V_{ia} M_{ia} + \lambda \sum_{i=1}^{N} \left( \sum_{a=1}^{M} V_{ia} - 1 \right)^2 + \frac{2}{\lambda \nu} \sum_{a=1}^{M} D_a \]

- \( E \): energy cost function
- \( N \): No. of hits
- \( M \): No. of arms
- \( V_{ia} \): strength of association between hit \( i \) and arm \( a \)
- \( M_{ia} \): distance between cell hit \( i \) and arm \( a \)
- \( \lambda \): noise penalty
- \( \lambda \nu \): distance scale of photon conversions
- \( D_a \): distance between the vertex and the first hit on arm \( a \)

References:
- 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.
FuzzyK Cluster Formation

• Assign a cluster membership to each cell hit within the event, with each cluster representing the hits from a single particle track or shower. This is accomplished with possibilistic fuzzy-k means algorithm.

• Possibilistic: The sum of each hit’s membership across all clusters is not forced to be one, which allows for isolated hits to be treated as noise.

• Fuzzy: Individual hits are allowed to have membership in multiple clusters.

Cluster Membership

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

Distance to cluster centers

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

- \( m \): Fuzzyness factor
- \( c \): number of cluster center
- \( \beta \): normalization factor

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.
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Clustering has done separately in each view of the detector and then matches views via topology and clusters dE/dx.

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BreakPoint Fitter (BPF)

• It takes input as FuzzyK cluster

• Starting with a cluster of hits and a vertex, a trajectory is approximated with a straight line fit, assuming zero kinetic energy at the end.

• The expected energy loss is added up, walking back from the end of the track to the vertex. Moving from the vertex back to the end of the track, scattering planes are inserted based on a multiple scattering model.

• The kinetic energy is added from the final trajectory, which is made by minimization.

Fits each FuzzyK cluster under three different particle assumptions:
muon, charged pion and proton.

\[
\chi^2 = \chi^2(a, b, \alpha_1, ..., \alpha_N) = \sum_{i=1}^{n} \frac{(\xi_i - x_i)^2}{\sigma_{x_i}^2} + \sum_{j=1}^{N} \frac{(\beta_j - \alpha_j)^2}{\sigma_{j}^2}
\]

\[
x_i = a + b z_i + \sum_{j} \alpha_j (z_i - Z_j) \ast \Theta(z_i - Z_j)
\]
• Tracks are reconstructed on individual slices.

• The goal of the tracking is to trace the trajectory of individual particles that deposit energy in the detector.

• This is especially useful in identifying particles that do not create large electromagnetic or hadronic showers, such as muons.

• Tracking is based on multiple scattering model and Kalman Filter Algorithm.
NOvA classifies events based on Deep Neural Network.

NOvA’s nue appearance analysis is the first implementation of a CNN in a HEP result.

• 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.
**Event Classifier Using Convolutional Visual Network (CVN)**

**NOvA Paper**: “A Convolutional Neural Network Neutrino Event Classifier”  
A. Aurisano et. al., JINST 11 (2016) no.09, P09001

| Topic                                                                 | Speaker                                    | Time          |
|----------------------------------------------------------------------|--------------------------------------------|---------------|
| Deep Neural Networks for HEP Images                                  | Benjamin Nachman                           | 13:30 - 13:55 |
| Applying Deep Learning in MicroBooNE                                | Taritree Wongjirad                         | 13:55 - 14:20 |
| Deep Learning and DUNE                                               | Dr. Alexander Radovic                      | 14:20 - 14:45 |
| Advanced machine-learning solutions in LHCb operations and data analysis | Dr. Fedor Ratnikov                         | 14:45 - 15:10 |
| Exploration of Deep Convolutional and Domain Adversarial Neural Networks in MINERvA. | Jonathan Miller                           | 10:45 - 11:10 |
| Deep Learning Applications in the NOvA Experiment                    | Ms. Fernanda Psihas                       | 11:10 - 11:35 |
| Exploring Computing Methods for Improved Cosmic Background Rejection in NOvA's Sterile Neutrino Searches | Mr. Shaokai Yang                           | 11:35 - 11:55 |
Event Topology in NOvA

Muon Neutrino

Electron Neutrino

NC

Event Reconstruction in the NOvA Experiment
Event Topology in NOvA

23  Biswaranjan Behera  IIT Hyderabad / Fermilab  Event Reconstruction in the NOvA Experiment
NOvA classifies events based on Deep Neural Network.

- 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.
- Identify clusters of hits as particles. CVN is trained on 2 views of the cluster and 2 views of the full event.
Classify Clusters by particle ID using CVN

Using the existing reconstruction.
Classify clusters by particle ID

Cluster quality depends on view matching and vertex reconstruction.

| cvnID    | Electron  | Gamma    | Muon     | Pion     | Proton  |
|----------|-----------|----------|----------|----------|---------|
| Proton   | 0.14      | 0.15     | 0.096    | 0.35     | 0.83    |
| Pion     | 0.074     | 0.033    | 0.1      | 0.45     | 0.04    |
| Muon     | 0.013     | 0.0014   | 0.74     | 0.026    | 0.0025  |
| Gamma    | 0.12      | 0.73     | 0.037    | 0.15     | 0.11    |
| Electron | 0.65      | 0.088    | 0.023    | 0.026    | 0.019   |

side view

top view
Ongoing Efforts and Future Plan...

- We are doing very good job in all the traditional reconstruction chain from slicer to particle identification.

- Lot of improvements and brand new techniques are going on in NOvA

- **New Slicer Algorithm.**

- **CVN based Vertex reconstruction.**

- **Particle cluster level energy estimator.**

- **Particle Identification using final state particles.**

Stay tuned for new developments ....
Thank You!

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Event Reconstruction in the NOvA Experiment
Isolating Neutrino Interactions

An event (cosmic ray) within the 500 $\mu$s window of data in the Far Detector. These are reconstructed slices.
The vertex resolution for all νₑ cc events is less than 5cm (one cell) in X and Y, and 8 cm in Z.
Multi-Hough (1)

X Hough Map

Y Hough Map

Event Reconstruction in the NOvA Experiment
NOvA Reconstruction

Multi-Hough (2)

X Hough Map

Y Hough Map

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Multi-Hough (3)

X Hough Map

Y Hough Map

NOvA - FNAL E929
Run: 1 / 0
Event: 57 / NuMI
UTC Thu Jan 1, 1970
00:00:0 286000000

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Multi-Hough (4)

X Hough Map

Y Hough Map

Event Reconstruction in the NOvA Experiment
2 Point Hough Transform

Event Reconstruction in the NOvA Experiment
Match by minimizing the Kuiper metric, $K = \min(D^+ + D^-)$.
Where $D^+$ and $D^-$ are the largest positive and negative distances between energy profiles.
Timing resolution derived in data by calculating the time difference between pairs of hits on well reconstructed cosmic tracks after correcting for detector location and time-of-flight.

**Far Detector**

10 ns timing resolution

**Near Detector**

Faster ND clocking yields 5 ns timing resolution which reduces pile-up.