Improvements and New Applications of Machine Learning Tools for NOvA

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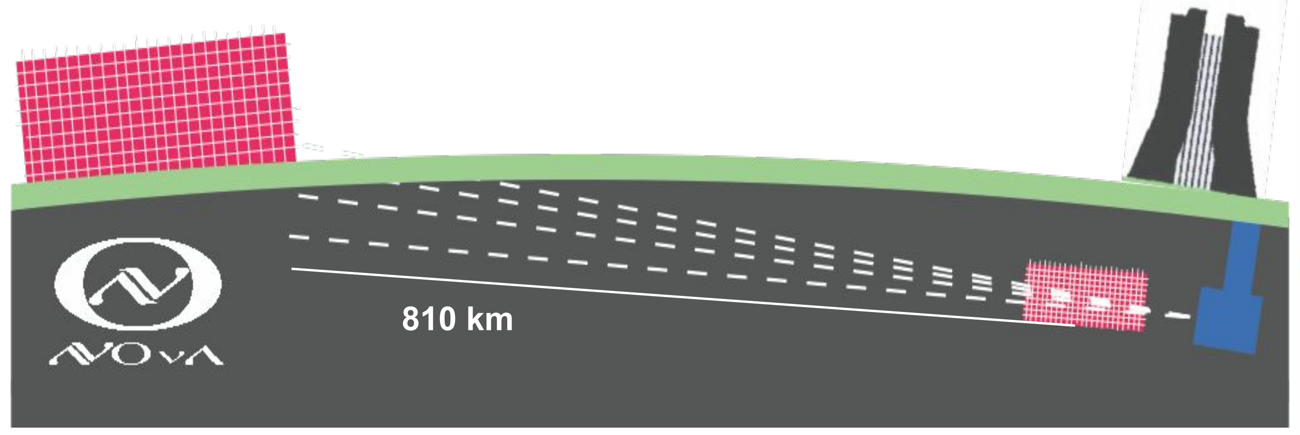
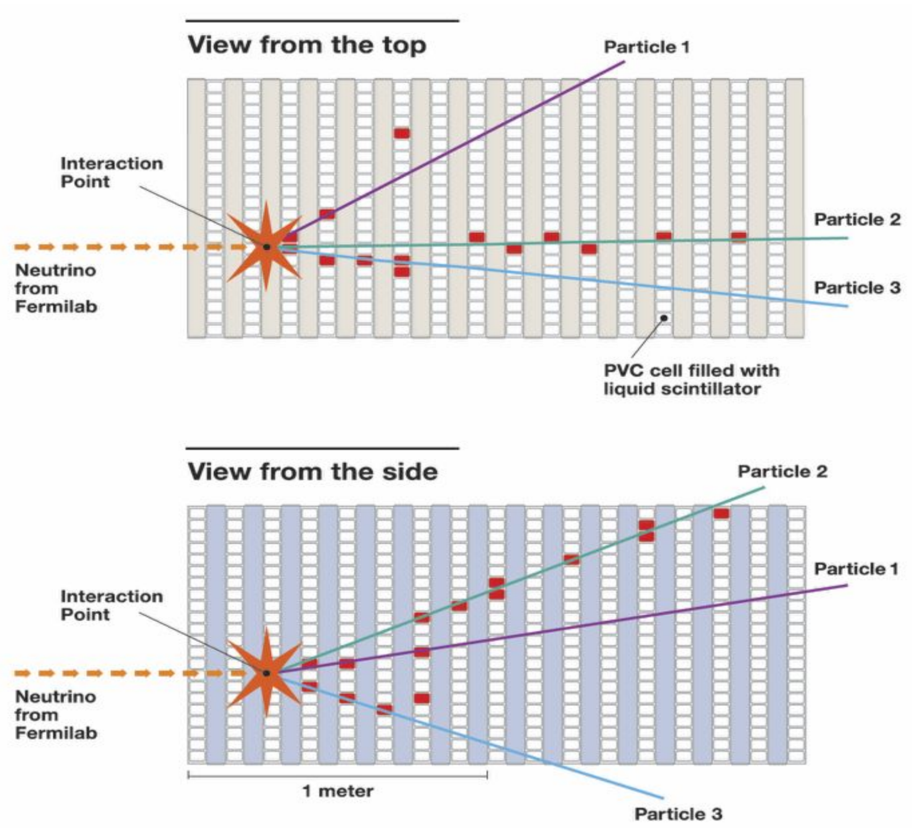
NOvA's Measurement





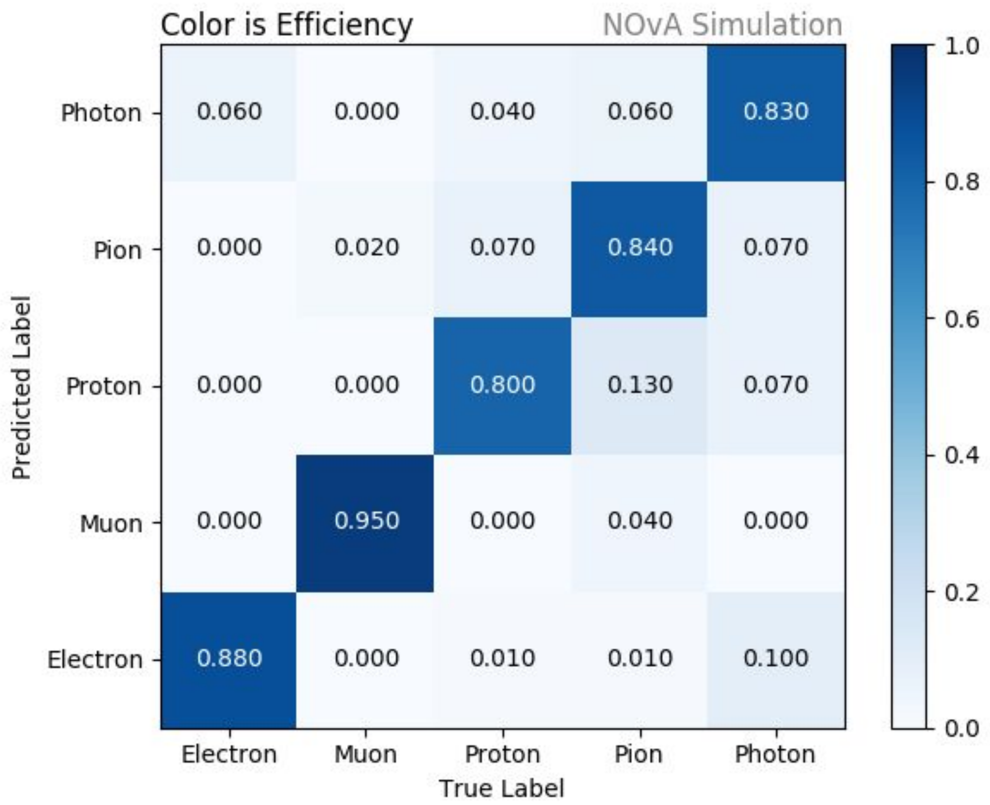
Measuring neutrino oscillations and cross sections requires neutrino flavor classification, particle identification, and energy estimation.

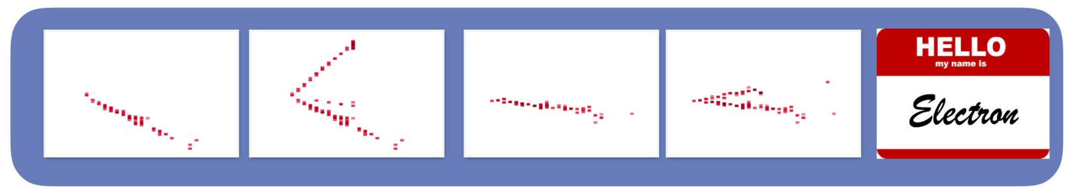
The NOvA detectors are liquid scintillator tracking calorimeter. The detection mechanism is light from charged particles.

Particle Reconstruction

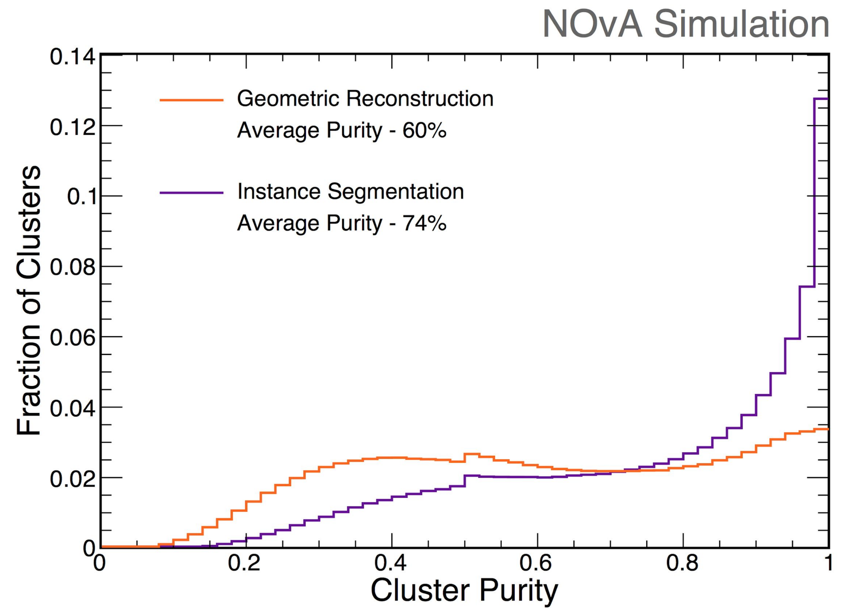
NOvA's single particle identifier classifies existing reconstructed clusters [2]. The network is trained on both the particle cluster and the entire event.

The newest version uses a balanced training sample. This improved the performance on underrepresented particles, mainly pions.



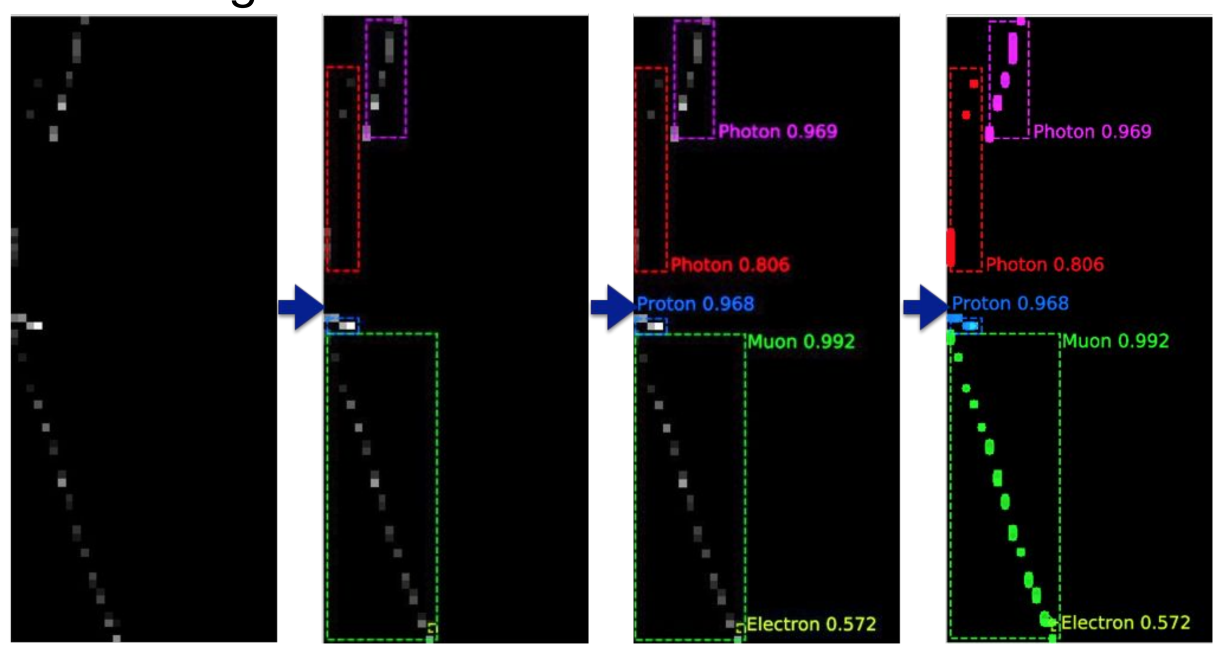


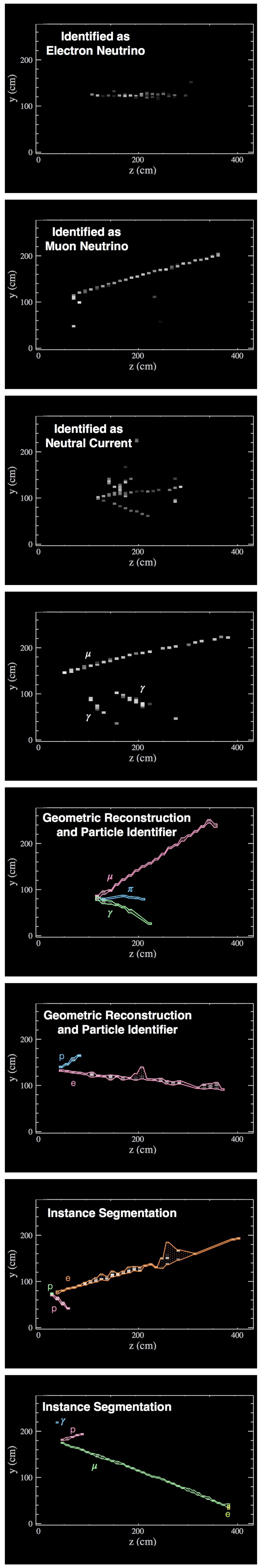
A new technique for clustering particles is to use an instance segmentation model from computer vision [3].



Initial validation of the new technique shows an improvement in the purity of particle clusters and an increase in the number of particles that make it into clusters.

An end-to-end reconstruction algorithm for particle clustering and identification.





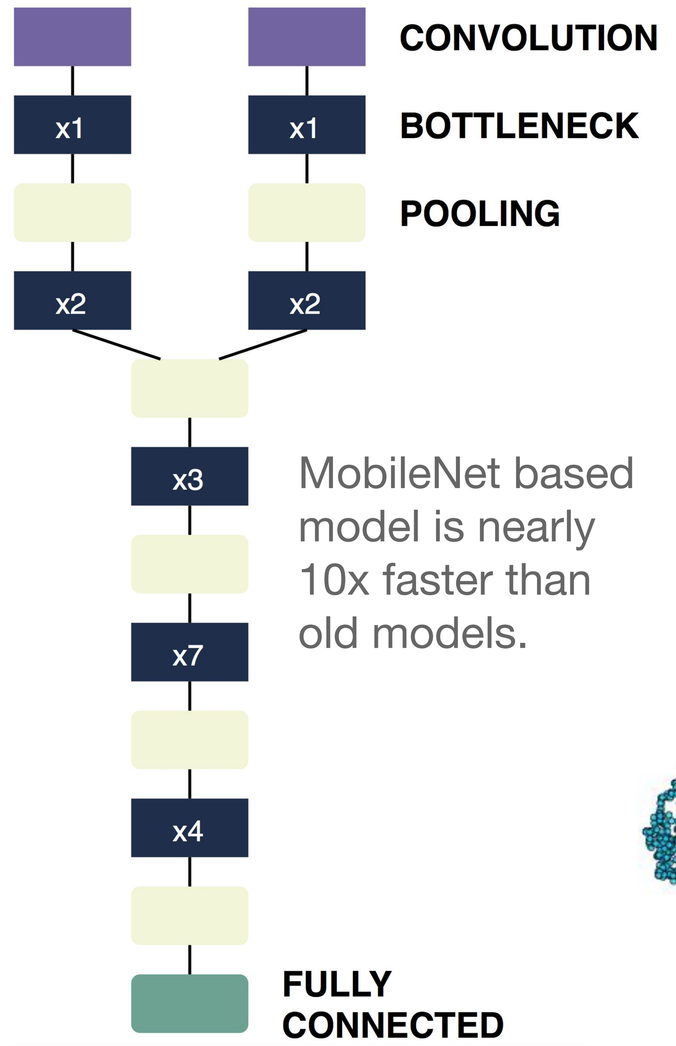
1. Long baseline neutrino oscillation results from NOvA in neutrino and anti-neutrino beam modes, Poster#83
2. F. Psihas, *et al* (2019). Context-enriched identification of particles with a convolutional network for neutrino events. Physical Review D, 100(7).
3. K. He, *et al* (2017). Mask R-CNN.
4. A. Aurisano, *et al* (2016). A Convolutional Neural Network Neutrino Event Classifier. JINST, 11(09), P09001.

Other NOvA ML Applications

1. Energy Estimation: Poster#268
2. Wrong Sign Estimation: Poster#258
3. Cross Checks: Poster#120
4. Cosmic Rejection

Can you beat CVN at neutrino classification?

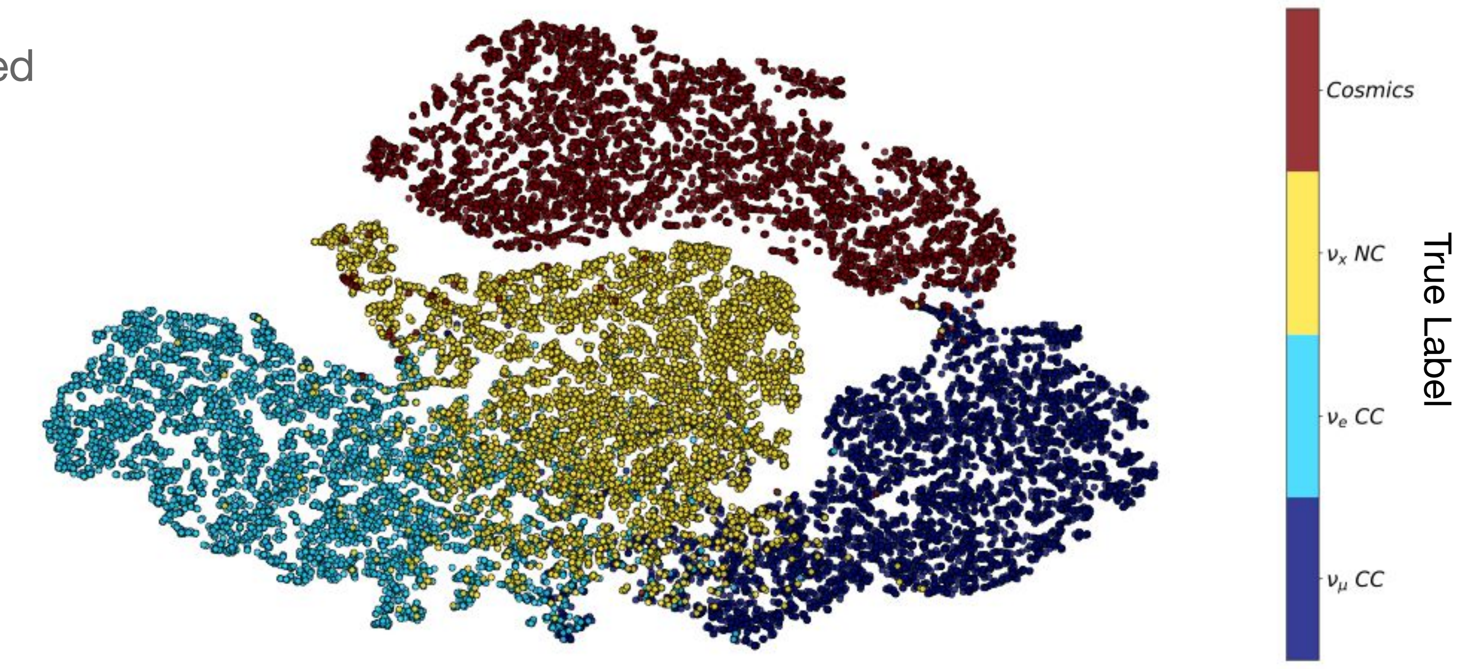
Neutrino Identification



MobileNet based model is nearly 10x faster than old models.

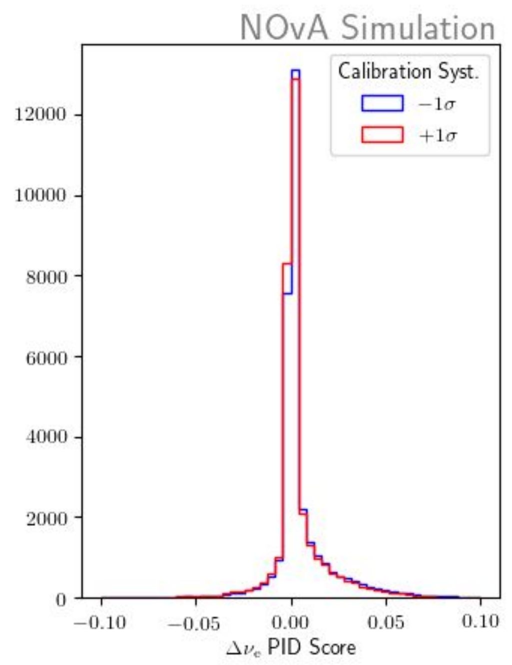
NOvA's Convolutional Visual Network (CVN) is a neutrino event classifier [4]. Event Maps are input to a convolutional network (CNN).

CNNs are designed to extract topolgical features from data. The t-SNE below shows the separation between the different training categories.



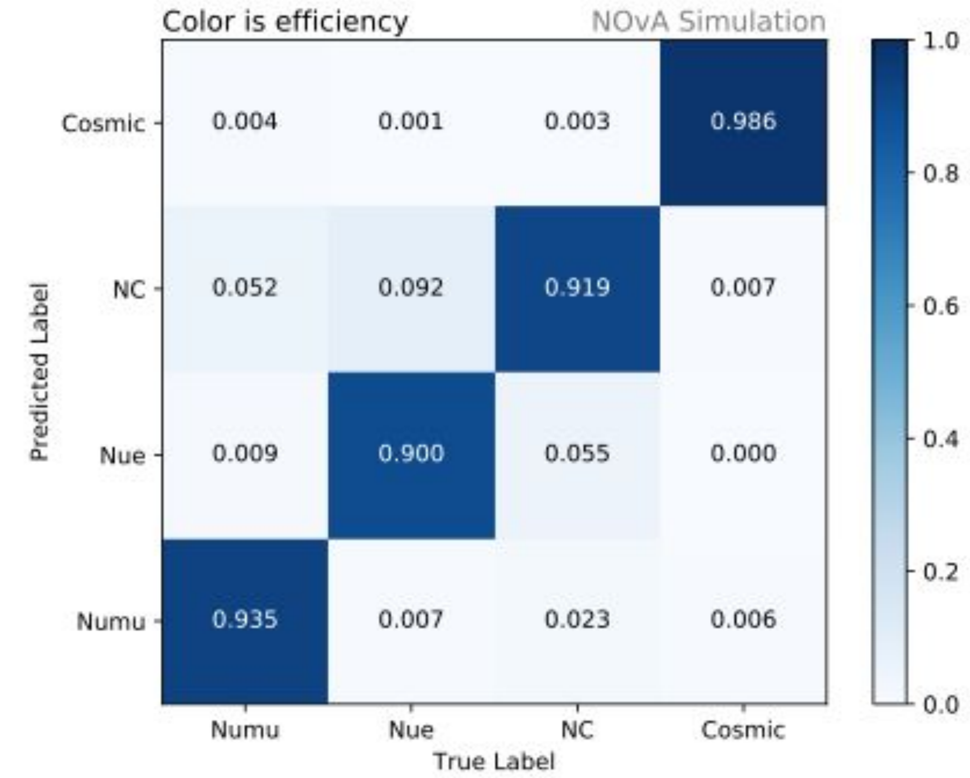
Improvements used in the 2020 analysis:

- Architecture Optimizations.
- Removal of tau neutrinos from the training.
- Systematic considerations during training.
- New software framework
- Removed trivial cosmic events from the training sample.



Left: The network was trained with less emphasis on energy scales. The change in scores for calibration shifts are less than half compared to previous versions.

Right: Efficiency of each training category and how events are misclassified.



To optimize different training samples we defined a figure of merit (FOM) that estimates the impact on our sensitivity to oscillation parameters in the 3-flavor paradigm.

$$\mathrm{FOM}^2 = \sum_i^N \left(\frac{S_i^2}{S_i + B_i + (\sigma B_i)^2} \right)$$

Network	Core FOM^2	Improvement
2018/19 CVN	28.77	-
2020 CVN	32.01	11.3 %

The FOM^2, summed over contributions from analysis bins i (from 0 to N), is proportional to our mass-hierarchy sensitivity and factors in an estimated 11 % background uncertainty (σB_i) from data-driven corrections using near detector data. Our optimization benchmark was the trained network used in our 2018/19 oscillation analyses. The new network shows just over 11 % improvement over 2018/19 CVN.

Analysis Bins

To maximize our sensitivity we split the ν_e sample into three (two core) samples:

- A tight cut on CVN defines a high purity sample ("High PID").
- A looser CVN cut defines the lower purity ("Low PID") sample.
- A tight CVN cut with looser containment and cosmic rejection requirements defines a peripheral sample.