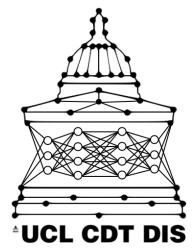


Reducing sensitivities to systematic uncertainties of the deep neural networks employed in the NOvA experiment



By Kevin Mulder, Department of physics and astronomy



The NOvA experiment



NOvA = Neutrinos at the Main Injector(N) Off-axis(O) Electron Neutrino(v) Appearance(A) Experiment.

Long baseline neutrino oscillation experiment

- Uses Fermilab's NuMI neutrino beam
- The Near Detector(ND) measures the beam at Fermilab
- The Far Detector observes the possibly oscillated beam at the 1st oscillation peak, 810 km away

$$\begin{array}{ll} \nu_{\mu} \rightarrow \nu_{e}, & \nu_{\mu} \rightarrow \nu_{\mu} \\ \bar{\nu}_{\mu} \rightarrow \bar{\nu}_{e}, & \bar{\nu}_{\mu} \rightarrow \bar{\nu}_{\mu} \\ \theta_{23}, & \delta_{CP} \end{array}$$

Physics goals

- Observe (dis-) appearance
 Measurement
 - Measurement of oscillation parameters
 - Constraints on CP violation

Additional searches:

- Sterile neutrinos
- Gravitational wave/Supernova neutrinos
- Magnetic monopoles



The NOvA Detectors



Near detector

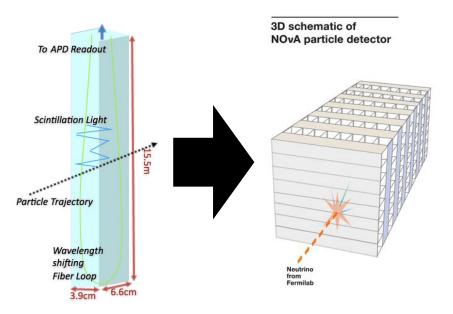
- 96 x 96 x 192 cells
- 4 x 4 x 12.7m
- 0.3 kt

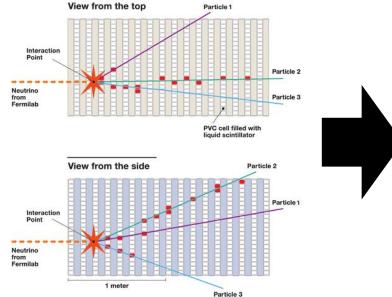


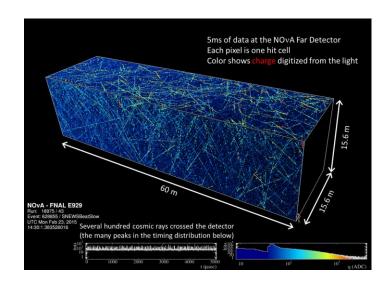
Far detector

- 384 x 384 x 896 cells
- 8 x 8 x 60m
- 14 kt



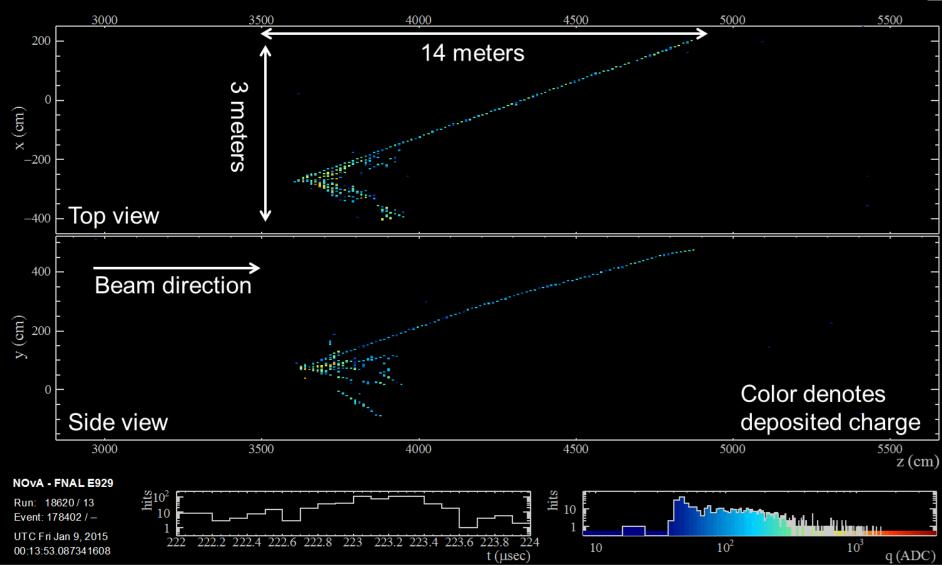




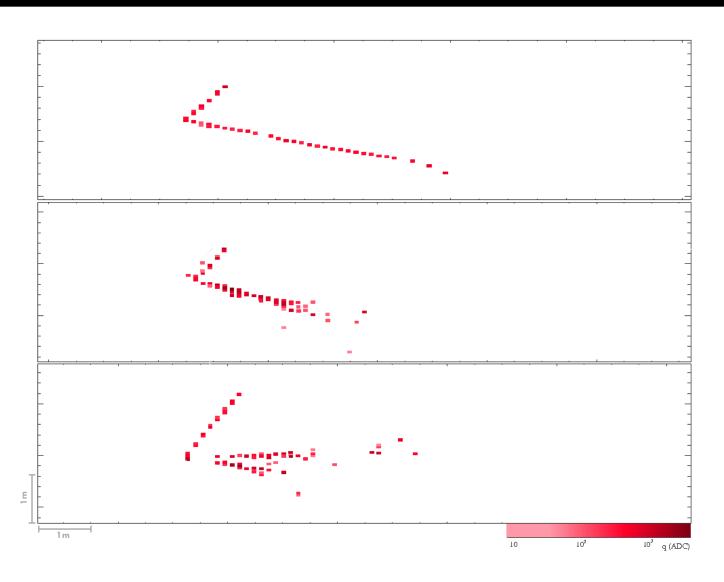


NOvA Event Display





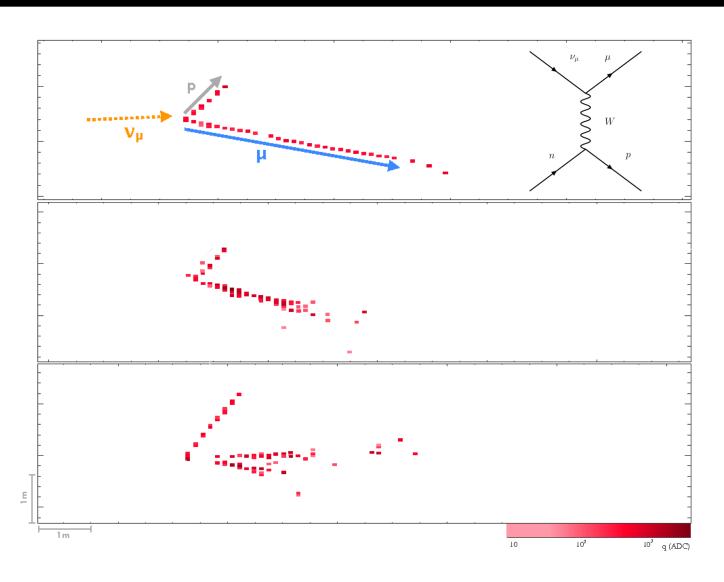




Interaction types and individual particles can be identified.

Let's try it now!



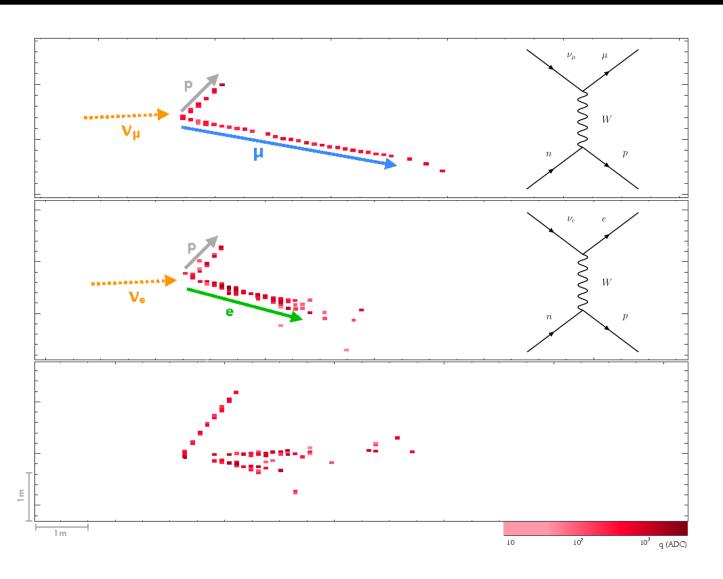


Interaction types and individual particles can be identified.

Let's try it now!

• Top: ν_{μ} Charged Current



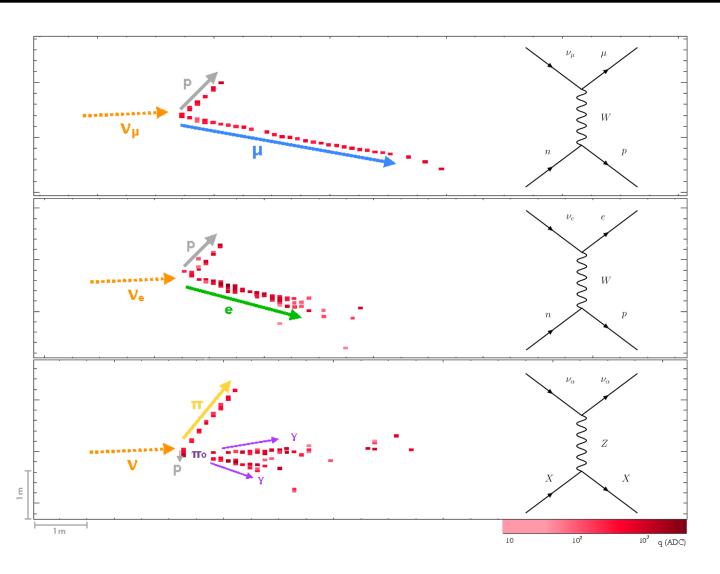


Interaction types and individual particles can be identified.

Let's try it now!

- Top: v_{μ} Charged Current
- Middle: v_e Charged Current





Interaction types and individual particles can be identified.

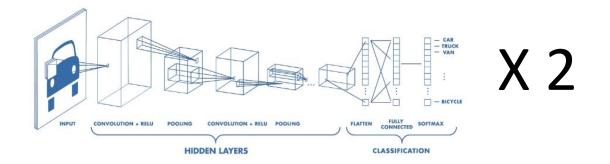
Let's try it now!

- Top: v_{μ} Charged Current
- Middle: v_e Charged Current
- Bottom: Neutral current

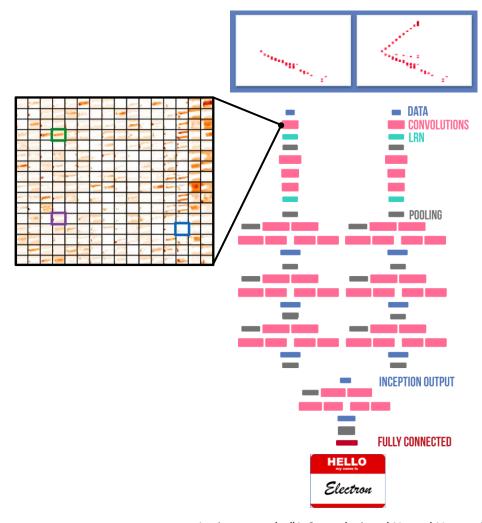
NOvA Convolutional Visual Network (CVN)



Uses 2 separate convolutional neural networks (CNN)



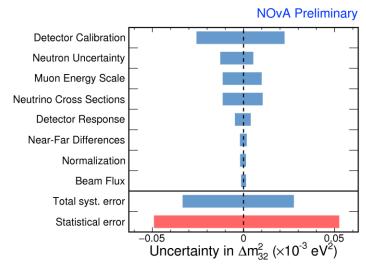
- 30% more exposure
- Included and used in published analysis (since 2016)
- Other architectures also employed.
 (4-Branch, energy estimators)

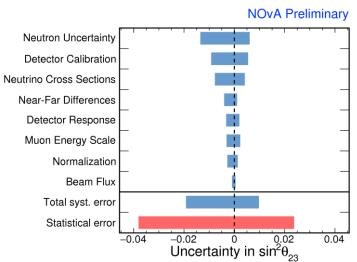


Aurisano et al., "A Convolutional Neural Network Neutrino Event Classifier", JINST 11, P09001 (2016).

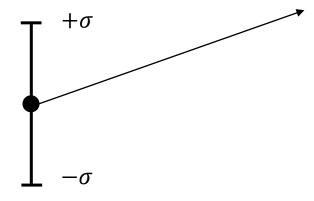
Systematic Uncertainty







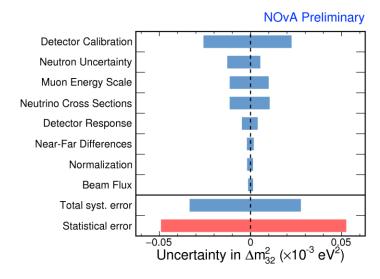
Nuisance parameter

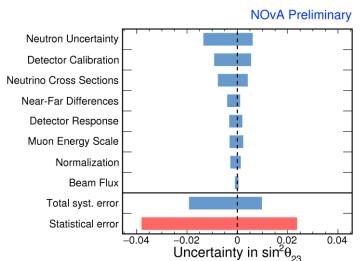


- Produce training data at nominal
- Train neural network
- Validate network
- Apply network on real data

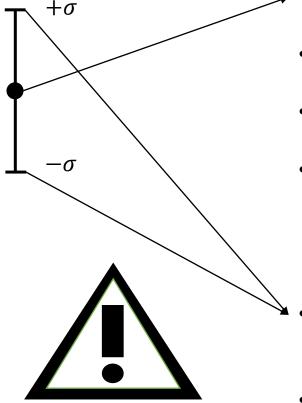
Systematic Uncertainty







Nuisance parameter

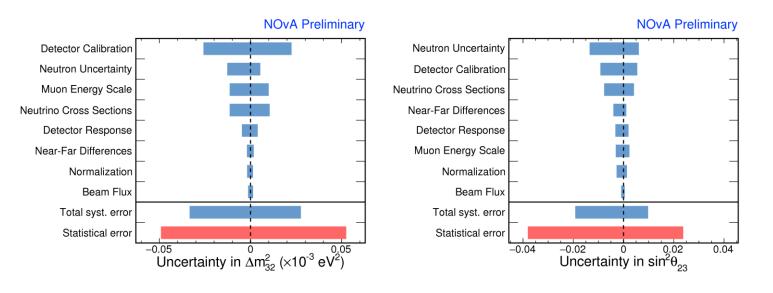


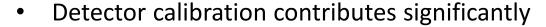
- Produce training data at nominal
- Train neural network
- Validate network
- Apply network on real data

- Nuisance parameter not at nominal in real data
- Domain adaption

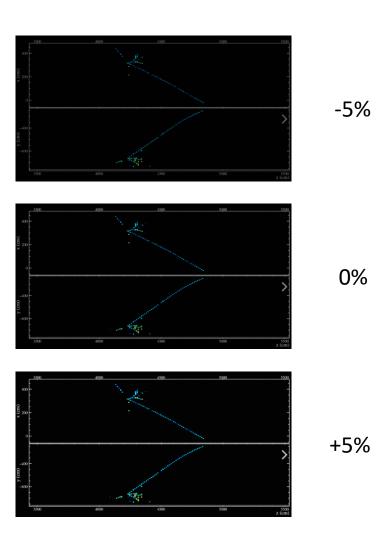
Simplified simulated systematic





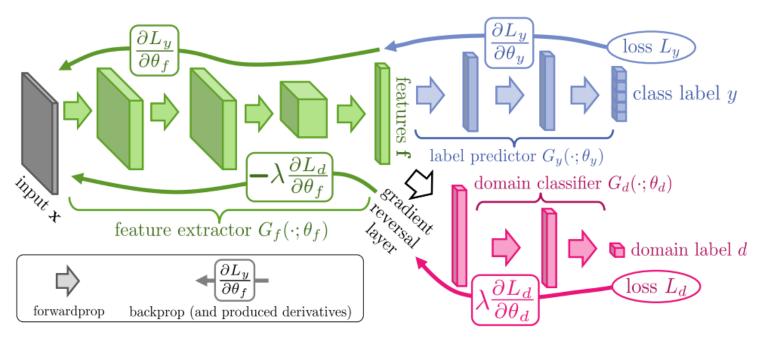


- Affects the training data
- Can be emulated by scaled brightness of pixelmaps



Domain adaption: gradient reversal





Proposed in "Domain Adversarial Training of Neural Networks" (DANN)

arxiv.org/pdf/1505.07818.pdf

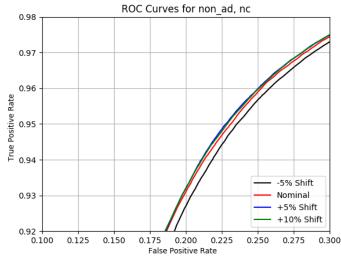
Loss = Distance(model output - truth)

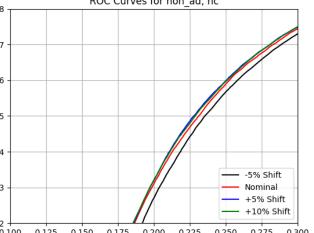
$$Loss_{AD} = Loss_{class} - \lambda * Loss_{domain}$$

 Seeks to penalize any systematic dependent features of the network through backpropagation.

Domain adaption: gradient reversal



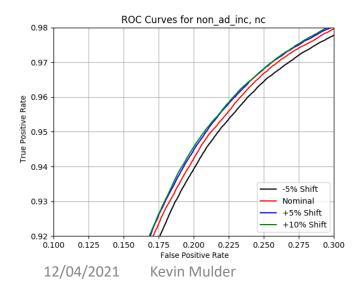


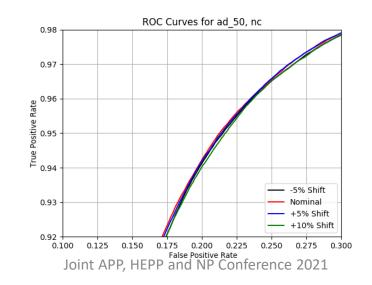


Implemented the gradient reversal layer in the NOvA CVN keras framework. (Tensorflow backend)

Initial stage look promising.

- Inclusive dataset \longrightarrow increased performance
- Adversarial strength of 50 → increased performance → lower sensitivity to the systematic





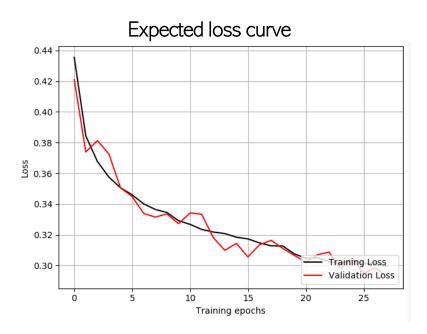
Real systematic uncertainties

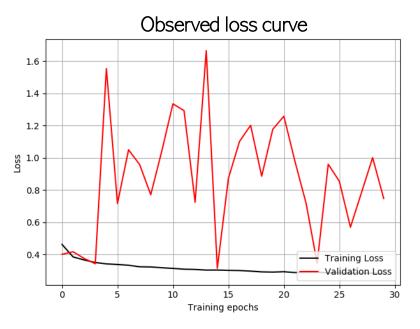


Working toward evaluation of the Calibration and Lightlevel systematics

Recent changes to the CVN architecture are problematic

- Switched from ResNet to a custom MobileNet
- Causes instability during training (confined to the inclusion of the gradient reversal layer)





Neutrino event generators



Other domains: Neutrino event generators

Uses different modeling to simulate the underlying interaction physics.

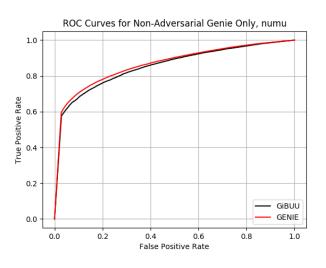
- NOvA employs GENIE
- Some other long baseline experiments employ GiBUU

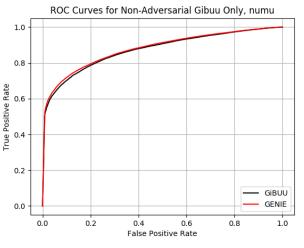
Inclusive data

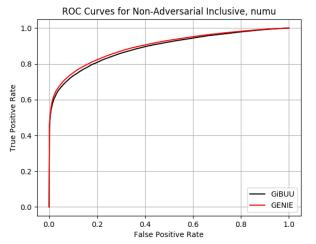
higher performance and robustness

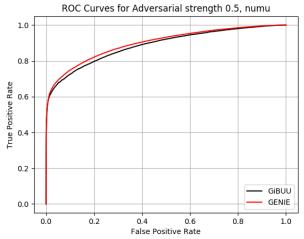
Adversarial training

no additional improvement or robustness









Summary



- NOvA's segmented detectors allow for AI reconstruction
 Systematic uncertainties could pose a problem
- Domain adaption techniques can be applied
 Adversarial training through gradient reversal
- Effective on fake systematics
- Currently working towards evaluation of real systematics:
 - Calibration & Lightlevel
- Exploring applications on alternative domains

Physics overview



NOvA supports a large variation in its physics program

- Neutrino oscillation measurements
 - Observe (dis-) appearance
 - Measurement of oscillation parameters
 - Constraints on CP violation
- Sterile Neutrino search
- Supernova/gravitational wave neutrinos
- Magnetic monopoles search

And more can be found <u>here</u>



First measurement of muon-neutrino disappearance in

Domain adaption: Learning to pivot(RW)



Add an adversarial network to a classifier.

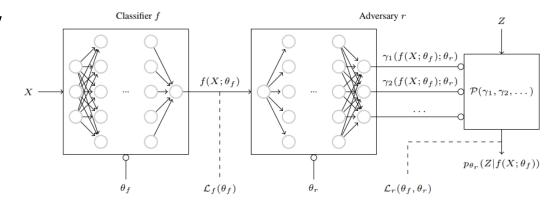
- Throughout training it seeks to identify and penalize any features which have a dependency on a nuisance parameter.
- Will reduce classifier performance, however due to the gained robustness overall significance increases.

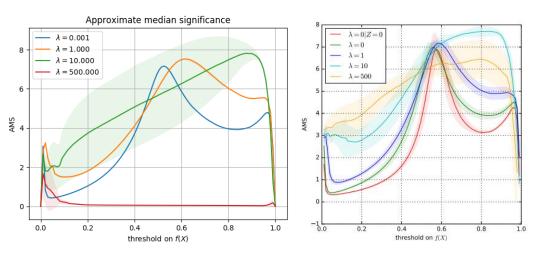
Proposed in "Learning to Pivot with Adversarial Networks"

Recreated the papers results, looked promising.

However implementing on the NOvA CVN lead to repeated mode collapse.

 Could be due to small size of the systematic, or the performance of the CVN itself.





arxiv.org/pdf/1611.01046.pdf