# Neutrino Event Classification with Deep Learning in NOvA

Grant Nikseresht

Department of Computer Science, Illinois Institute of Technology

June 11 - New Perspectives 2019

# Neutrino Event Classification

**Deep learning** is used to classify $\nu_\mu$, $\nu_e$, neutral current, and cosmic events based on the topology of the interactions

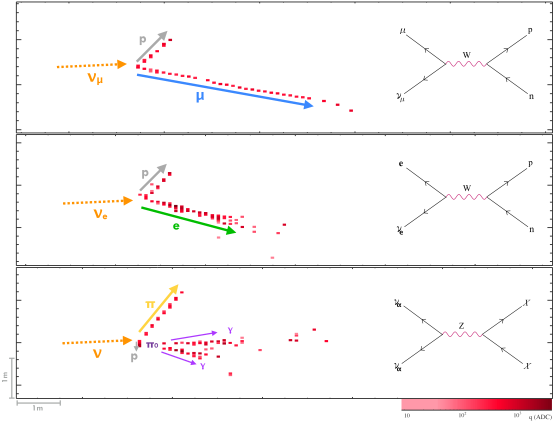
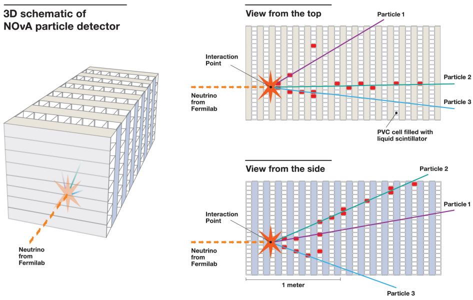
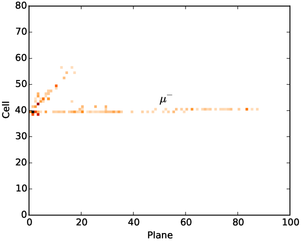



Figure 1: NOvA neutrino events.

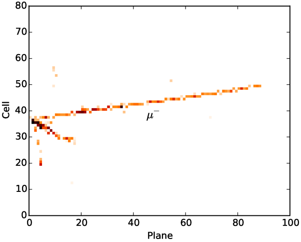
# Neutrino Event Classification




- Cell hits are captured along *XZ* and *YZ* planes and converted to pixel maps
- One charged current $\nu_\mu$ event (right) with two corresponding maps is a typical input to an event classifier

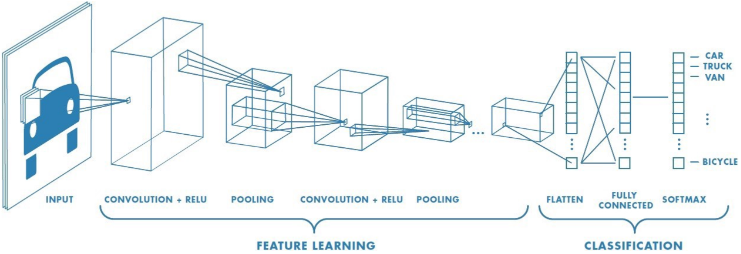



*XZ* (top) view




*YZ* (side) view

# Convolutional Neural Networks




- **Convolutional neural networks** (CNNs) learn features from images based only on pixels
- Can be applied directly to images with minimal reconstruction, forgoing the need for manual feature extraction
- CNNs have become the state-of-the-art technique for image detection problems across many fields

# Convolutional Visual Network

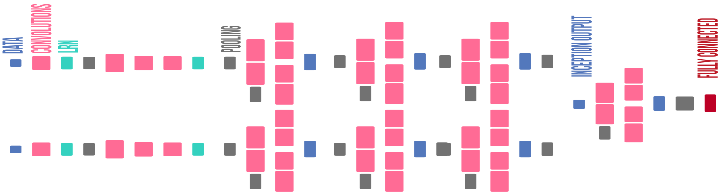



Figure 2: CVN Classic architecture. A pair of views for each event enter separate channels on the left and are mapped to an output class in the final fully connected layer.

- **Convolutional Visual Network** (CVN) was inspired by GoogLeNet [1] and characterized by a two tower structure and a sequence of Inception modules
- CVN improved effective exposure by 30% for $\nu_e$ events and 10% for $\nu_\mu$ events compared to non-deep learning based reconstruction methods [2]
- In 2018, improvements in classifier efficiency were found by training RHC and FHC separately and by pruning layers from CVN Classic to create **CVN ShortSimple**

# Improving CVN

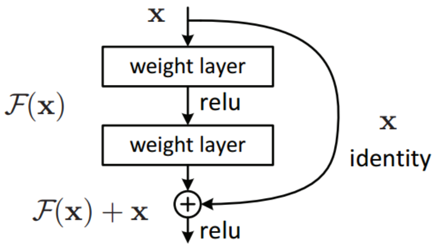
- There's a dedicated effort in NOvA to continue searching for new deep learning architectures and methods that can:
  1. Decrease the model complexity (# of trainable weights)
  2. Reduce training and inference time
  3. Maximize classifier performance in terms of efficiency and purity
- Two of these efforts are covered in the remainder of this talk:
  1. Development of CVN architectures based on residual learning
  2. Hyperparameter optimization using the DeepHyper framework at Argonne National Laboratory (ANL)
- All results here are preliminary and trainings are not final, but are shown to illustrate relative performance of different methods
- Models are compared using the harmonic mean of purity and efficiency,

$$F_1 = 2 * \frac{\text{purity} * \text{efficiency}}{\text{purity} + \text{efficiency}}$$

# Residual Learning

**Residual networks** (ResNet) are made up of chains of *residual blocks*

ResNet has been shown to outperform GoogLeNet on benchmark image classification problems [3]

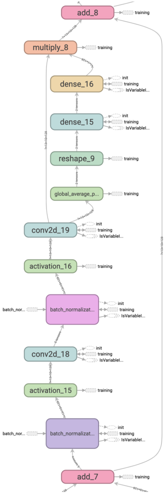



**Residual blocks** are characterized by a *skip connection* that adds the input to a block back at the end

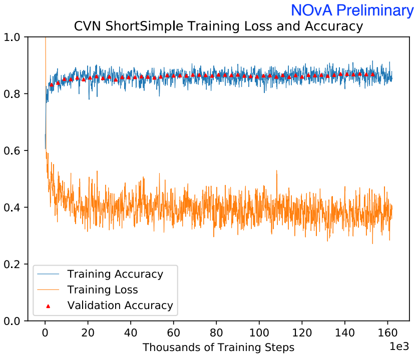
ResNets allow for training of much deeper networks

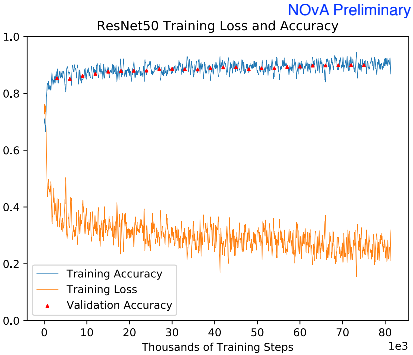
# Parallel View ResNet

- ResNet50 was modified to accept *XZ* and *YZ* views as input to follow the two tower CVN methodology
- Each view is passed through separate channels of 3 residual blocks before being combined and sent through another 13 residual blocks
- Batch normalization, convolutional, dense, and pooling layers are contained in the residual block in between the skip connection



# Model Training




- Neutrino event classifiers were trained on a sample of 6.1 million Monte Carlo events using CVN ShortSimple (left) and ResNet50 (right) architectures
- ResNet50 continues to show performance improvement after CVN ShortSimple plateaus

# Model Performance - Efficiency Matrices

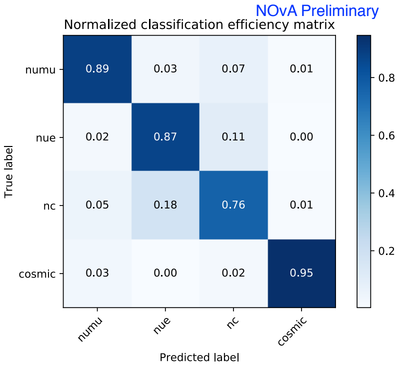



Figure 3: CVN ShortSimple, $F_1 = 0.8702$

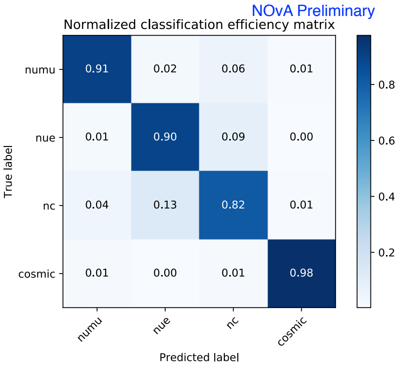



Figure 4: ResNet50, $F_1 = 0.8989$

Classification efficiency matrices for each classifier - ResNet50 achieves a higher efficiency for each class compared to CVN ShortSimple

# Model Performance - ROC Curves

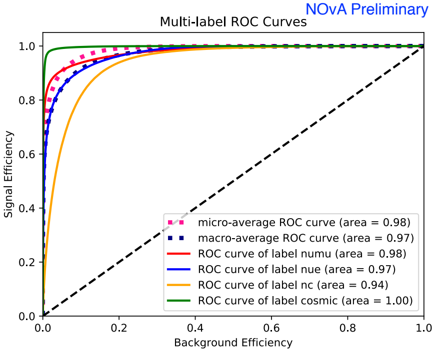



Figure 5: CVN ShortSimple

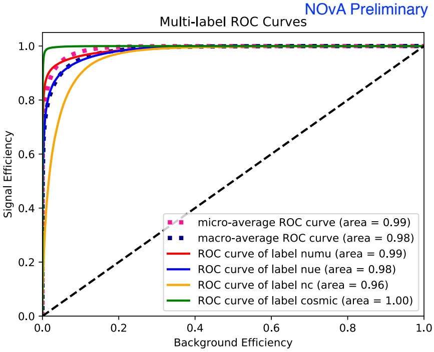
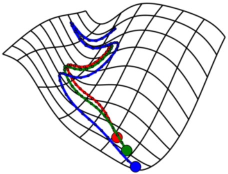



Figure 6: ResNet50

Receiver Operating Characteristic (ROC) curves for binary classifiers - ResNet50 achieves higher areas under the curve (AUC) for each class indicating better overall classifier performance

# Hyperparameter Optimization

- Training of neural networks is governed by **hyperparameters** that determine how the optimal model weights are found by gradient descent
- For neural networks, heuristics are often employed for choosing hyperparameter values when computational resources are limited
- Using ANL's Cooley GPU cluster, we utilize a framework called DeepHyper [4] which allows for **Bayesian hyperparameter optimization** at scale



# DeepHyper

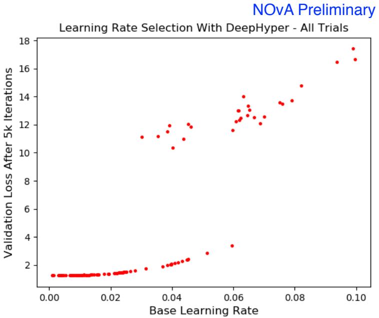



Figure 7: All trials over a 12 hour period

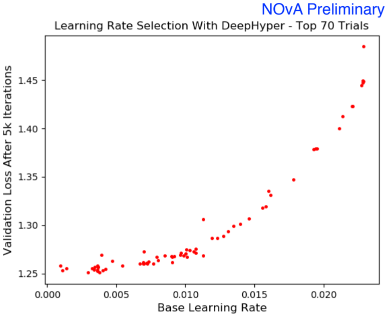



Figure 8: Subset of trials where validation loss was less than 1.5

Learning rate optimization using DeepHyper - a new learning rate is selected for each trial based on a maximum likelihood model

# Conclusion

- Improvement of CVN is one of the most critical ways to improve NOvA's event selection
- Residual networks are a natural next step in the evolution of CVN and have shown promise for increasing event classification efficiency
- Scalable hyperparameter optimization can improve the performance of existing models that could be underoptimized
- Architectural and algorithmic improvements to CVN can improve a multitude of applications in NOvA including classification of prongs, cosmic rejection, and semantic segmentation

# References I


- Christian Szegedy et al. "Going deeper with convolutions". In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* 07-12-June (2015), pp. 1–9. ISSN: 10636919. DOI: 10.1109/CVPR.2015.7298594. arXiv: 1409.4842.
- A. Aurisano et al. "A convolutional neural network neutrino event classifier". In: *Journal of Instrumentation* 11.9 (2016). ISSN: 17480221. DOI: 10.1088/1748-0221/11/09/P09001. arXiv: 1604.01444.
- K. He et al. "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. June 2016, pp. 770–778. DOI: 10.1109/CVPR.2016.90.
- P. Balaprakash et al. "DeepHyper: Asynchronous Hyperparameter Search for Deep Neural Networks". In: *2018 IEEE 25th International Conference on High Performance Computing (HiPC)*. Dec. 2018, pp. 42–51. DOI: 10.1109/HiPC.2018.00014.

# Backup Slides

# Model Performance - Purity Matrices

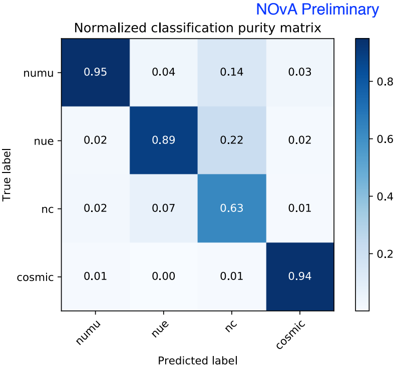



Figure 9: CVN ShortSimple, $F_1 = 0.8702$

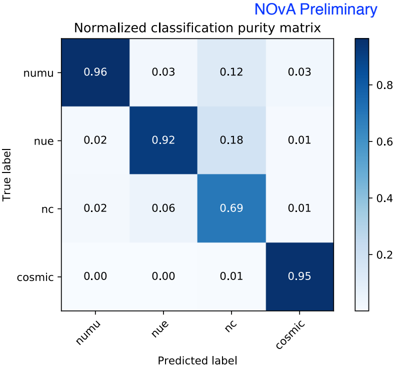



Figure 10: ResNet50, $F_1 = 0.8989$

# ResNet PIDs

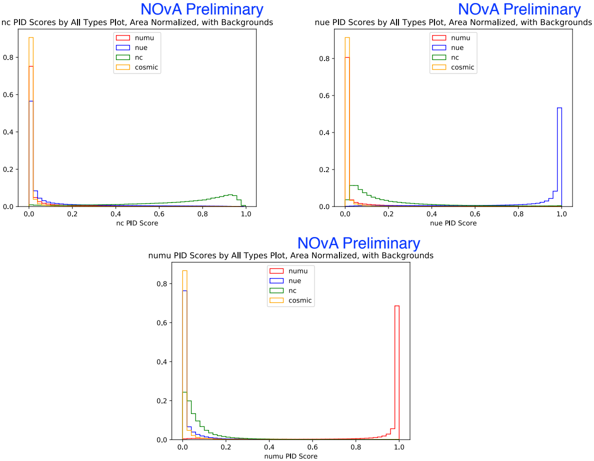
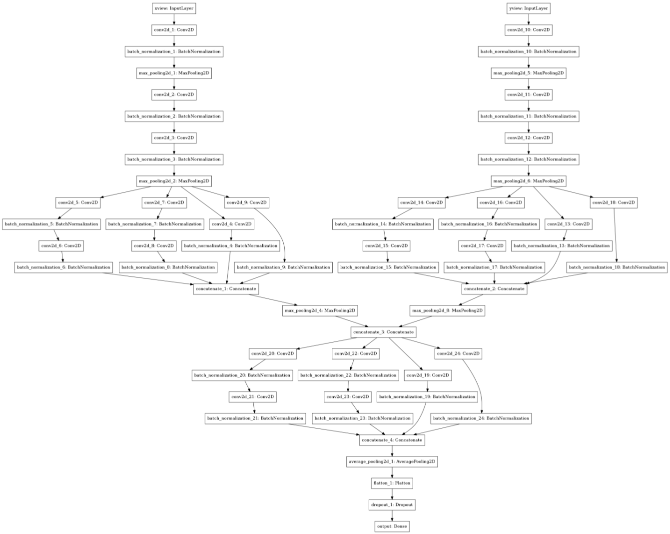



Figure 11: CVN PIDs by class output from a trained ResNet50 model

# CVN ShortSimple Architecture



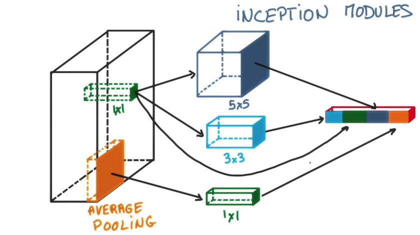

X, Y View Subnets

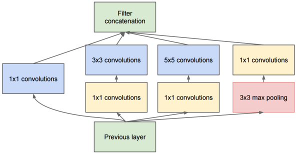
Subnet Inception Modules

Merged Inception Module

Combined Output

# Inception Modules




- **Inception modules** are a defining architectural feature of GoogLeNet
- Convolutions are taken at different scales and the results are concatenated to extract features at different spatial resolutions