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Regression CNN for DUNE Prong Reconstruction

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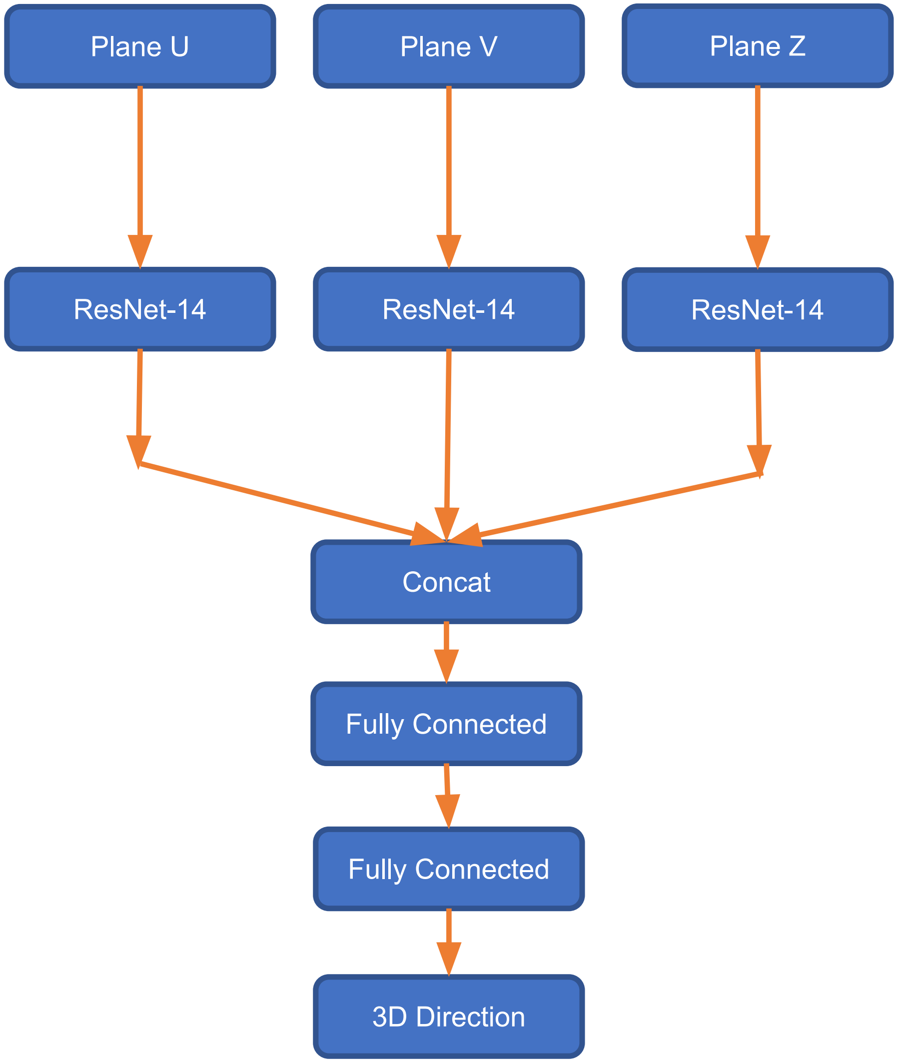
Introduction

- Motivations
  - The deep-learning based particle energy, vertices and momentum (energy+direction) reconstruction are necessary for a full AI based event reconstruction chain.
  - Combining the particle mass with its kinetic energy and direction, a final state particle's 4-momentum can be obtained
- Goals
  - Reconstructing the **neutrino energy** (first version done), **neutrino vertex** (first version done), **particle kinetic energy** (done) and **direction** (this talk) for NuE and NuMu CC
- This talk
  - Use the prong pixel map and event pixel map data with true particle tags to reconstruct:
    - Direction for NuE and NuMu CC

Direction Reconstruction

2D Architecture

- Loss Function
  - Cosine Distance: $\min(1 + \frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\cdot\|\mathbf{b}\|}, 1 - \frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\cdot\|\mathbf{b}\|})$
  - Angle resolution (angle difference) in radians/degrees: $\arccos(\frac{\mathbf{a}\cdot\mathbf{b}}{\|\mathbf{a}\|\cdot\|\mathbf{b}\|})$
- Models Trained
  - Event RegCNN
    - Input: 3 2D full event pixel maps
    - Output: primary electron/muon prong direction
  - Prong RegCNN
    - Input: 3 2D prong pixel maps
    - Output: electron/muon prong direction

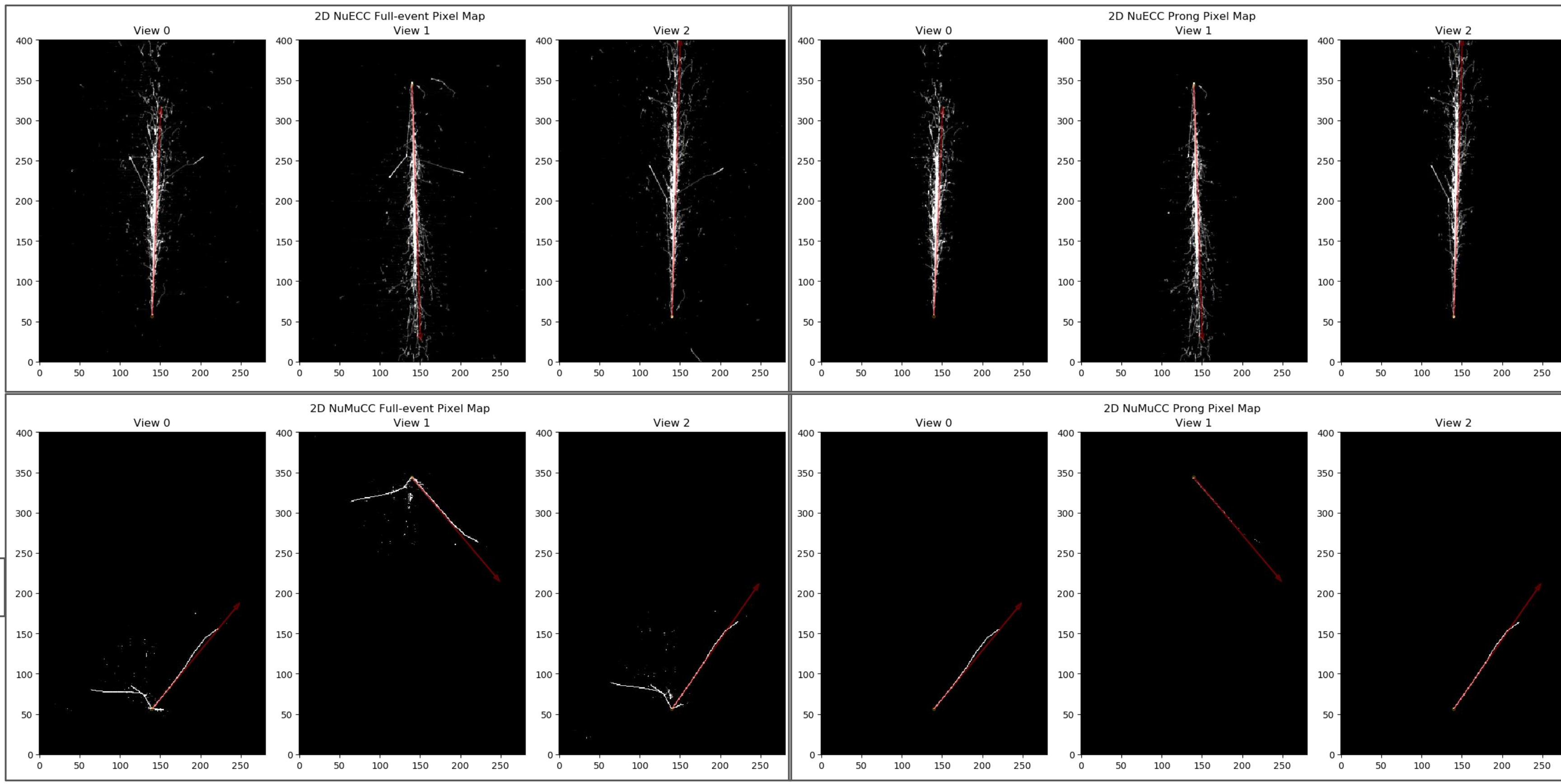


2D Pixel Maps Visualization

- Each sample contains 3 401x281 2D images (3 perspectives)

NuECC

NuMuCC



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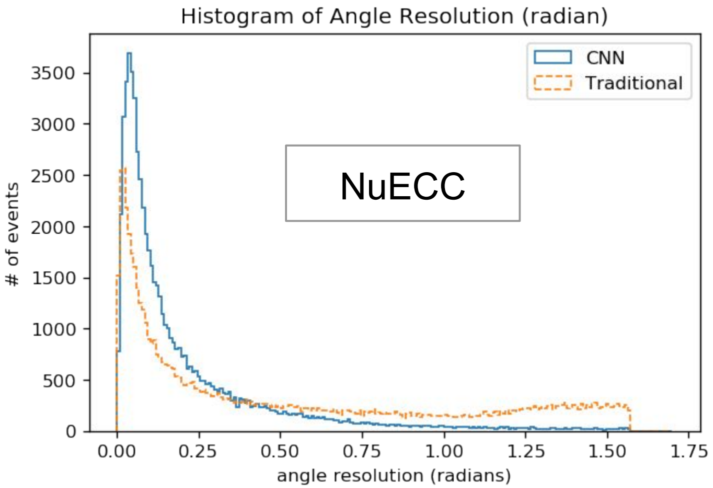
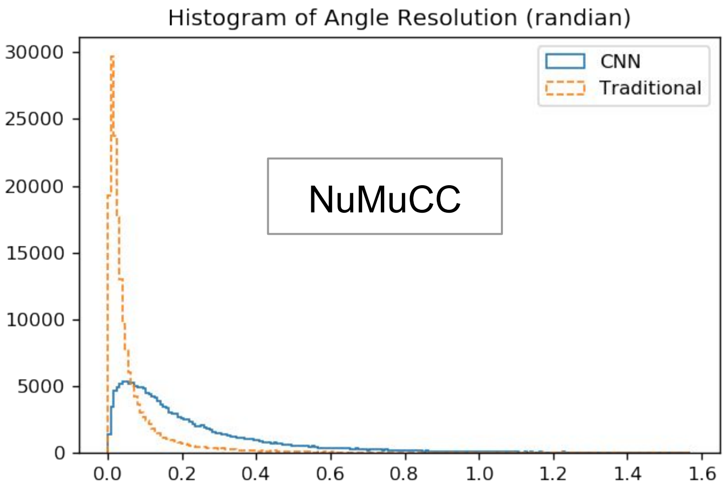
Training Results

- 2D RegCNN performs better on full-event pixel maps than prong-only pixel maps
  - Outperformed Standard method on NuECC pixel maps
  - Worse than Standard method on NuMuCC pixel maps
    - Overfitted to the training data

	Training Loss	Validation Loss	Standard Training Loss	Standard Validation Loss
NuECC	0.04831	0.05204	0.2220	0.2220
NuMuCC	0.00243	0.04184	0.0103	0.0103

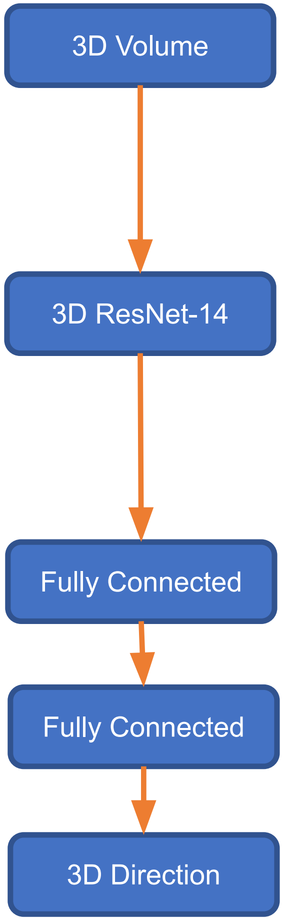
- Angle Resolution Histograms





3D Architecture

- Loss Function
  - Cosine Distance: $\min(1 + \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \cdot \|\mathbf{b}\|}, 1 - \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \cdot \|\mathbf{b}\|})$
  - Angle resolution (angle difference) in radians/degrees: $\arccos(\frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \cdot \|\mathbf{b}\|})$
- Training
  - 1000 epochs
- Models Trained
  - Event RegCNN
    - Input: 3D full event pixel map
    - Output: primary electron/muon prong direction
  - Prong RegCNN
    - Input: 3D prong pixel map
    - Output: electron/muon prong direction

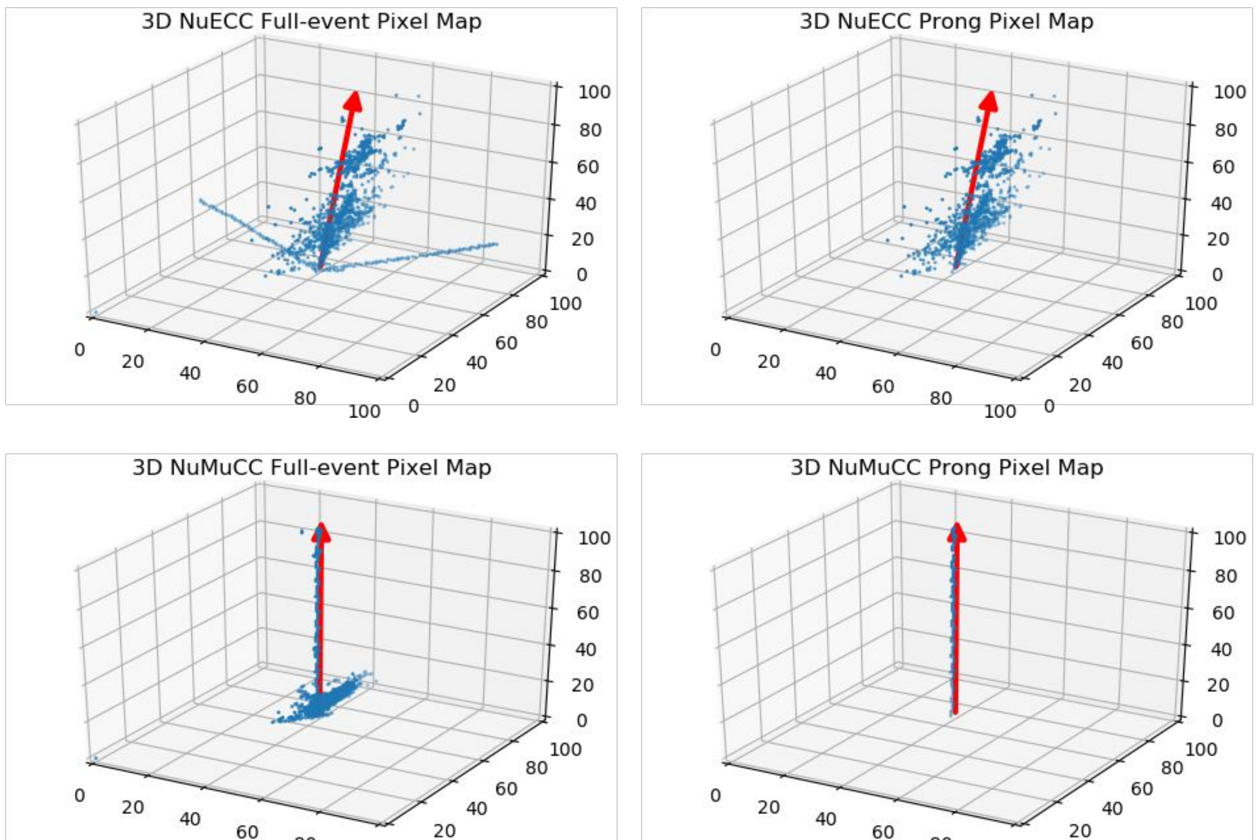


3D Pixel Maps Visualization

- Each sample is a 100x100x100 volume
  - each hit has a 3D coordinate

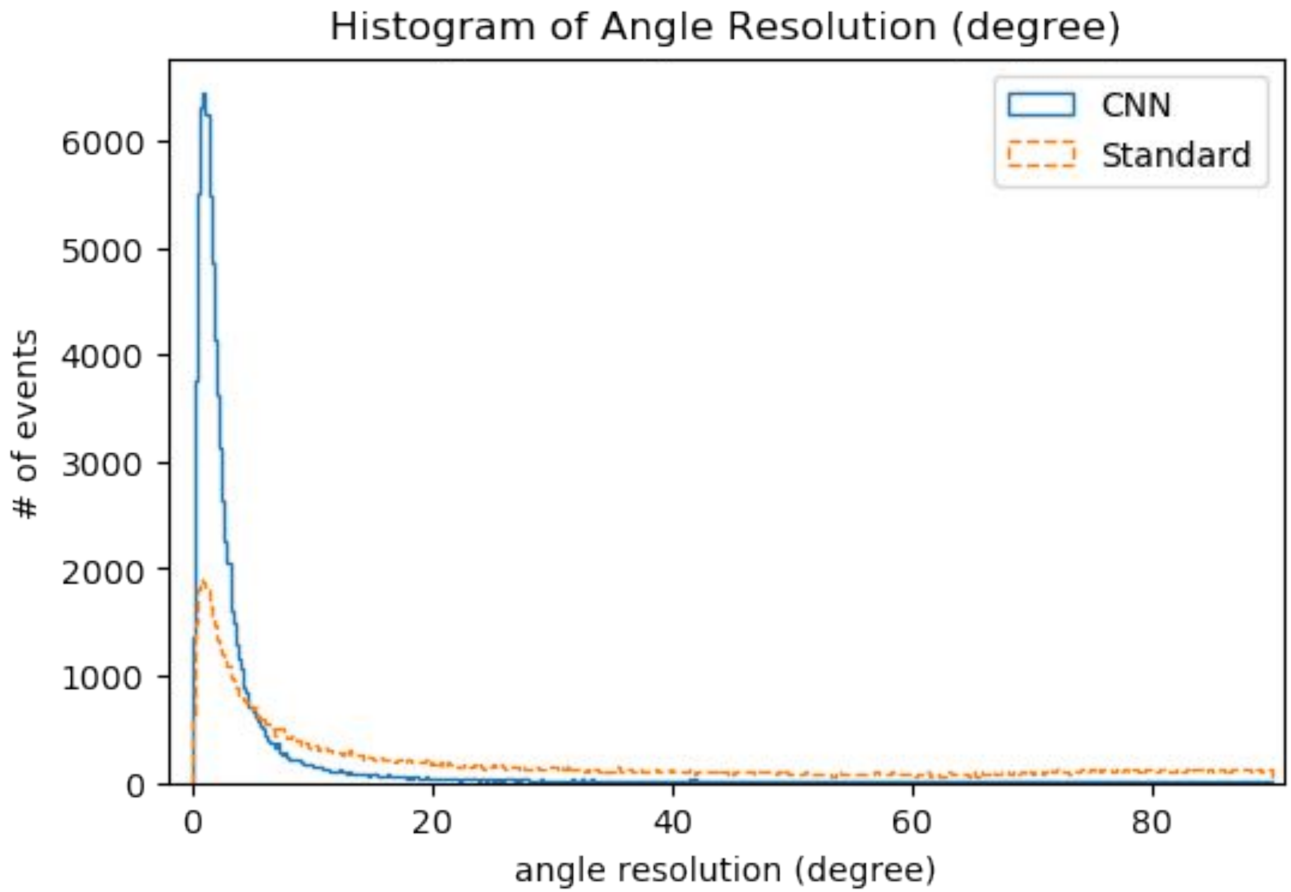
NuECC

NuMuCC

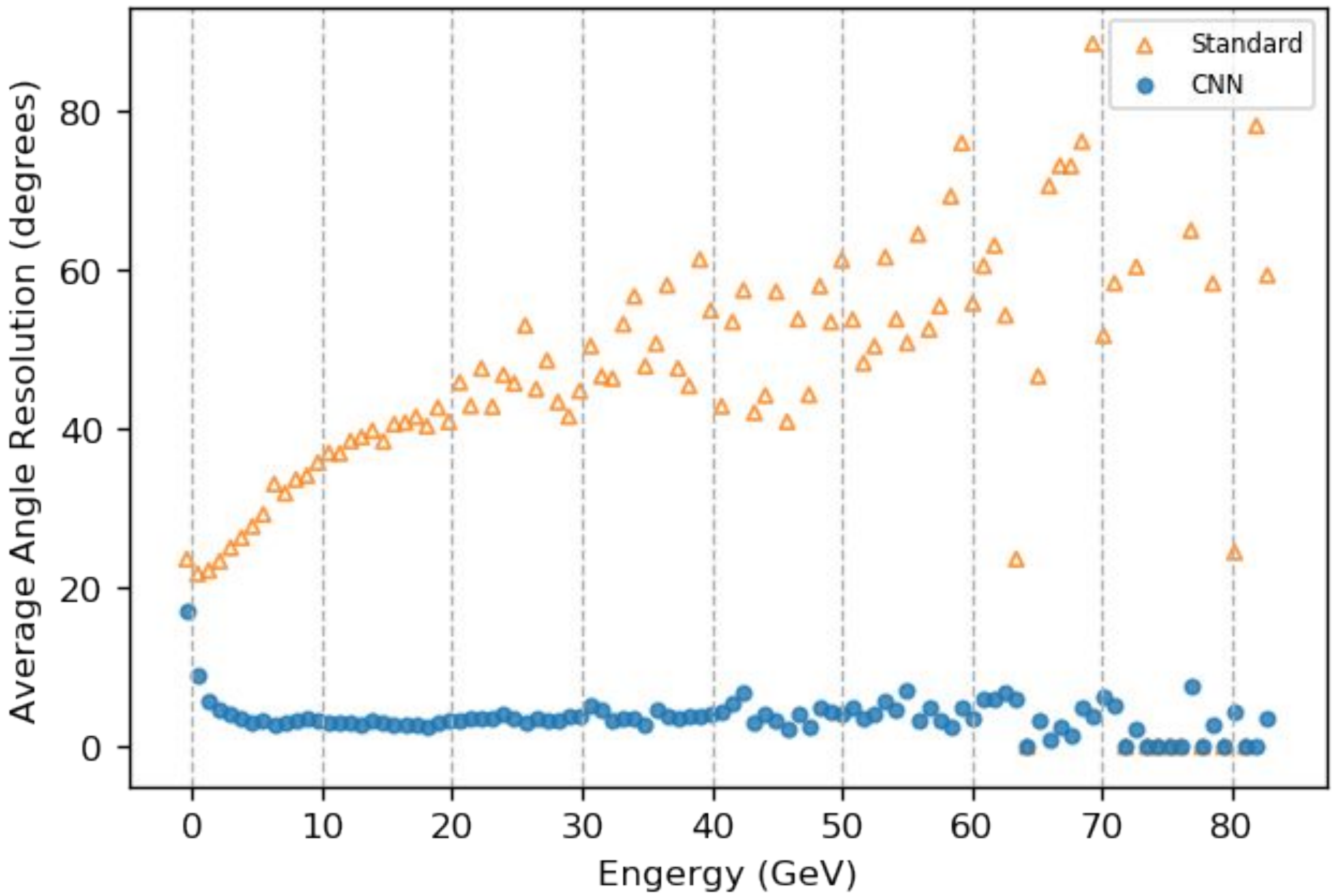


NuECC Prong Direction Regression Resolution Histogram

- 3D RegCNN outperforms Standard method on NuECC
  - Also better than 2D RegCNN

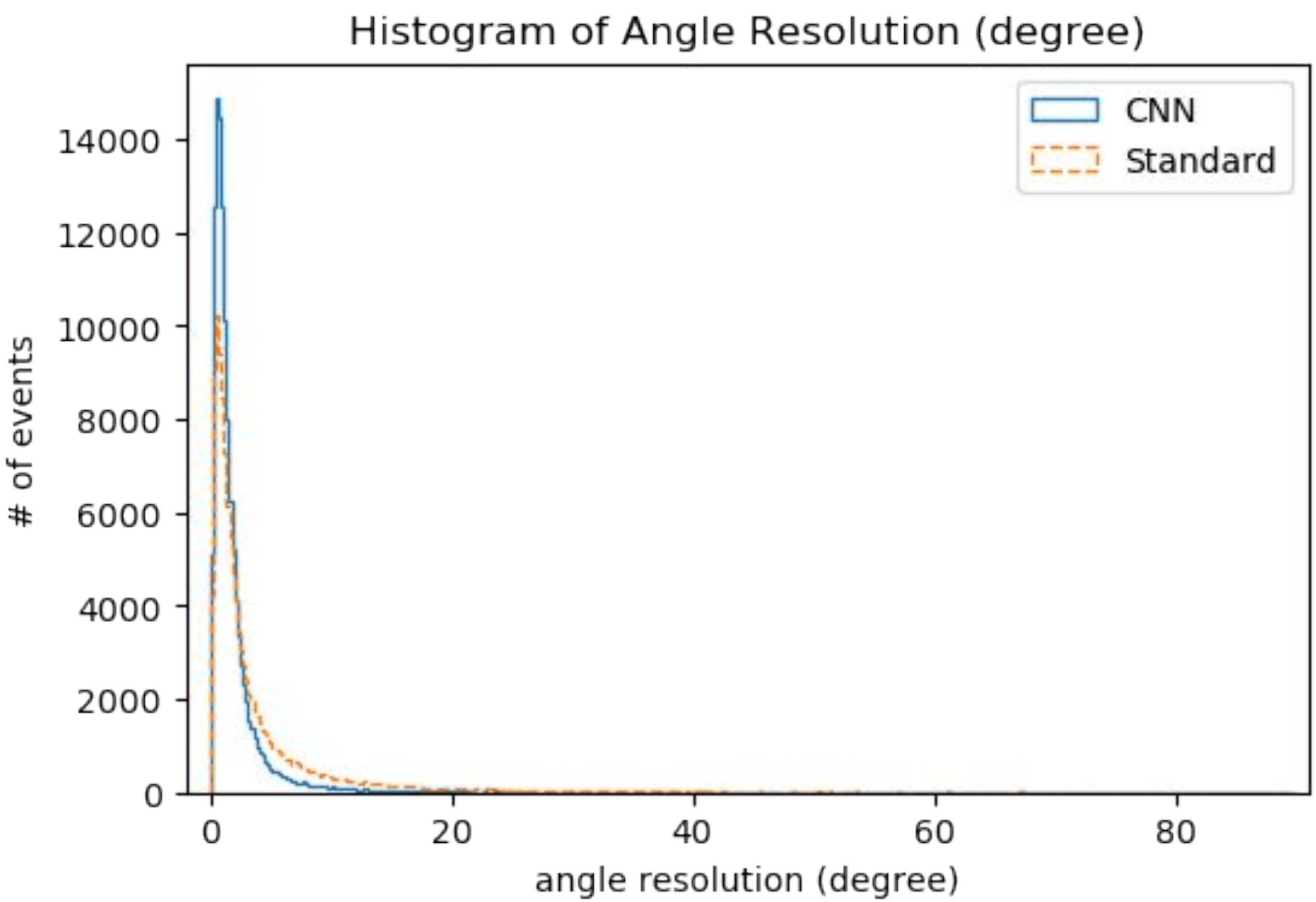


NuECC - Prong Direction Regression Error by Total Energy

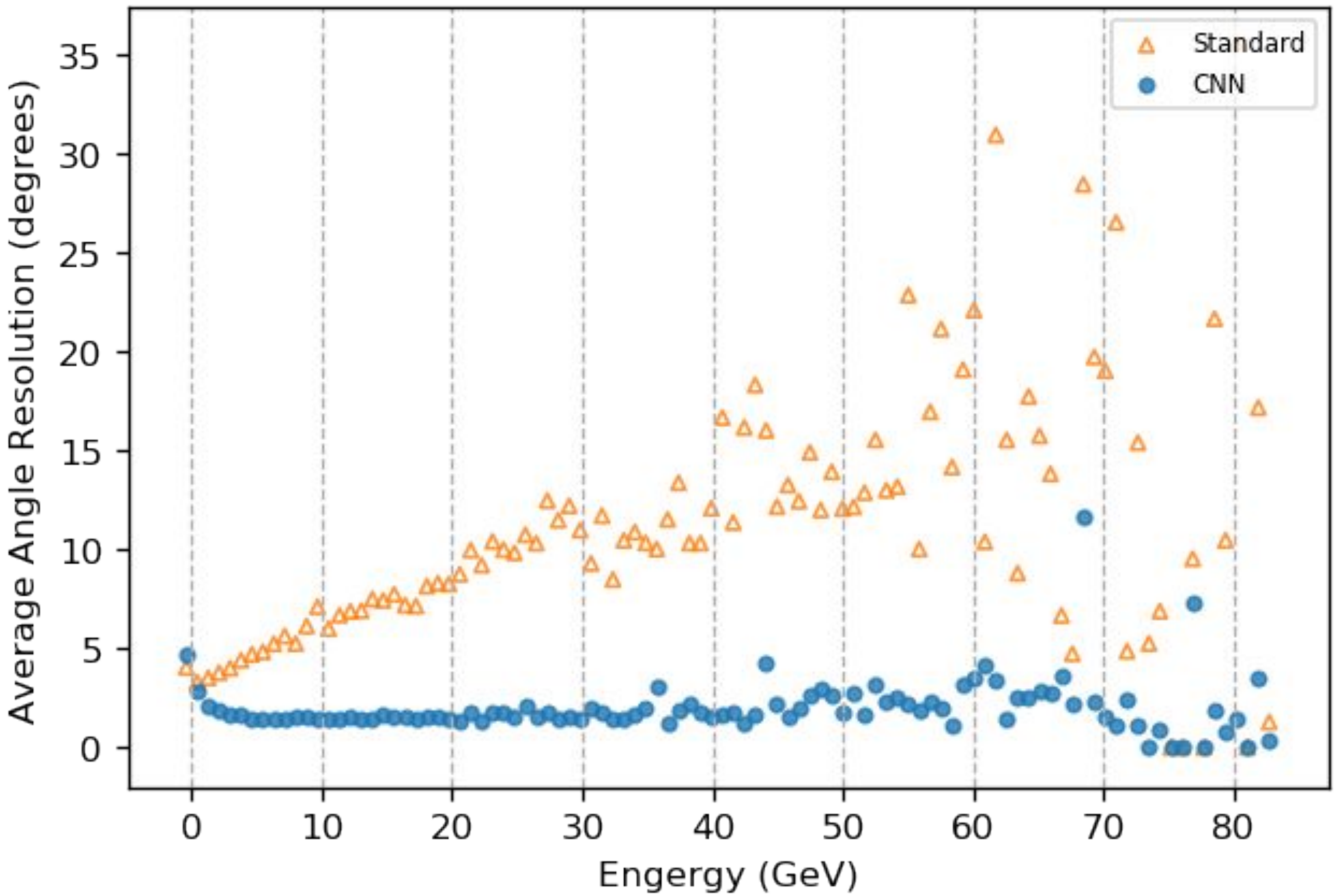


NuMuCC - Prong Direction Regression Resolution Histogram

- 3D RegCNN outperforms Standard method on NuMuCC



NuMuCC - Prong Direction Regression Error by Total Energy



Summary

- 3D RegCNN provides better performance than 2D RegCNN
  - Better understands original 3D geomeries in data
  - Consumes more GPU memory
- NuECC
  - Outperformed standard method with full-event CNN
  - Outperformed standard method further with prong-only CNN
  - Demonstrating we might not need prong clustering
- NuMuCC
  - Outperformed standard method with full-event CNN
  - Outperformed standard method further with prong-only CNN
  - Demonstrating we might not need prong clustering

Future Work

- Exploring other CNN-based architectures
  - Inception Networks
- Hyperparameter Optimization
  - Using Hyperparameter Optimization libraries, such as Sherpa, to further improve the training test and performance
- Sparse 3D CNN
  - Lighten the computation burden of 3D CNN

Thank you!