# Optimizing ML-Based Signal Processing for DUNE

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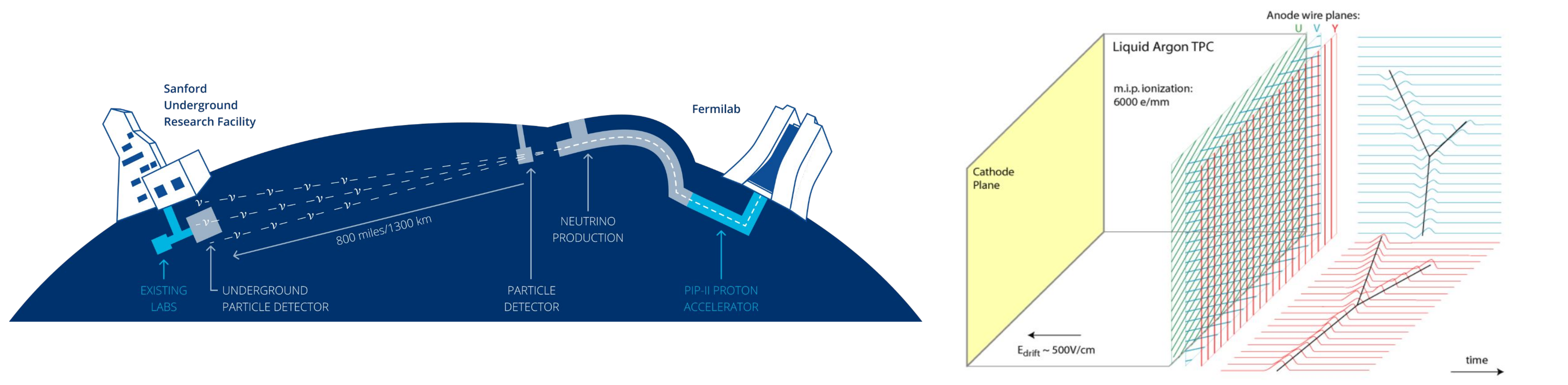
## Abstract

The Deep Underground Neutrino Experiment (DUNE) employs Liquid Argon Time Projection Chambers (LArTPCs) as its primary detection technology, taking advantage of their high spatial and calorimetric resolution. To extract ionization charge information from raw waveforms and to reconstruct events of interest, the Wire-Cell Toolkit (WCT) is under active development. However, when particle tracks are oriented nearly perpendicular to the readout electronics, signal extraction becomes challenging due to limited charge sharing and insufficient capture of the Region of Interest (ROI). In this study, we investigate advanced machine learning models to enhance signal reconstruction in these difficult event topologies within the WCT framework. This approach shows improved performance compared to conventional ROI-based methods. However, inference using deep neural networks leads to a significant increase in memory consumption. To mitigate this, we employ profiling techniques to identify memory bottlenecks, and we are currently optimizing key components through methods such as parameter pruning and restructuring of the data processing flow.

## DUNE Overview



- DUNE investigates neutrino oscillations using a 1,300 km baseline from Fermilab to the Sanford Underground Lab
- The Far Detector employs Liquid Argon Time Projection Chambers (LArTPCs) to achieve detailed 3D tracking of neutrino interactions.
- A software package called the Wire-Cell Toolkit is under development to reconstruct events of interest occurring in LArTPCs.

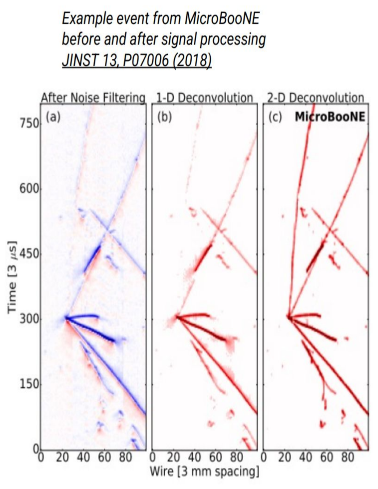
## Wire-Cell Workflow

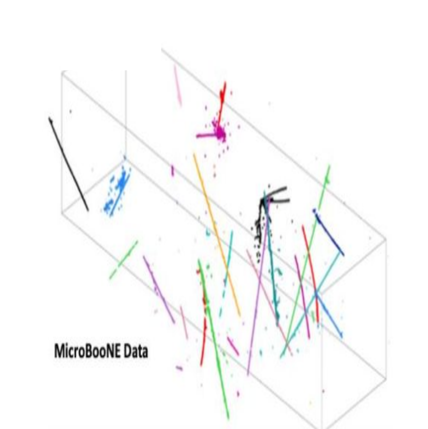
**Part 1:**
Simulation
Noise Filtering
Signal Processing

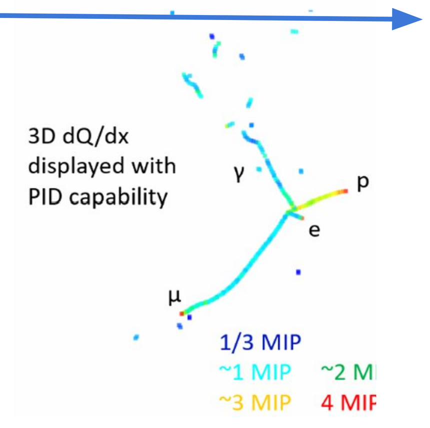
**Part 2:**
3D imaging
Clustering
Charge-Light Matching
Neutrino event selection

**Part 3:**
3D vertexing
Particle Identification
3D Pattern Recognition

**Data Analysis**




## DNN Evaluation Metric

Three Metrics for evaluation

❖ Bias: quantifies the deviation of reconstructed charge from MC truth

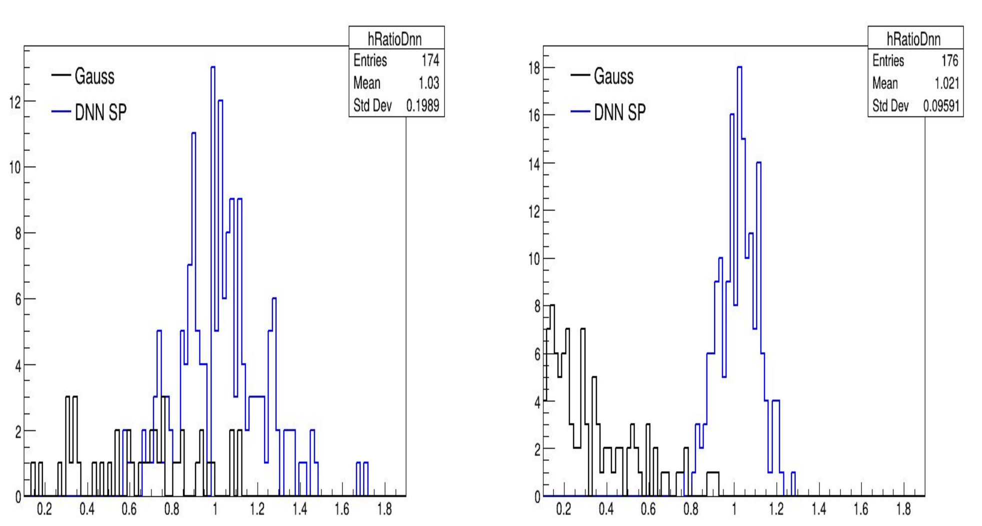
$$\text{Bias} = 100 \times \left( \left\langle \frac{Q_{\text{reco}}}{Q_{\text{truth}}} \right\rangle - 1 \right)$$

❖ Resolution: evaluates the spread in the charge ratio

$$\text{Resolution} = 100 \times \frac{\text{RMS}\left(\frac{Q_{\text{reco}}}{Q_{\text{truth}}}\right)}{\left\langle \frac{Q_{\text{reco}}}{Q_{\text{truth}}} \right\rangle}$$

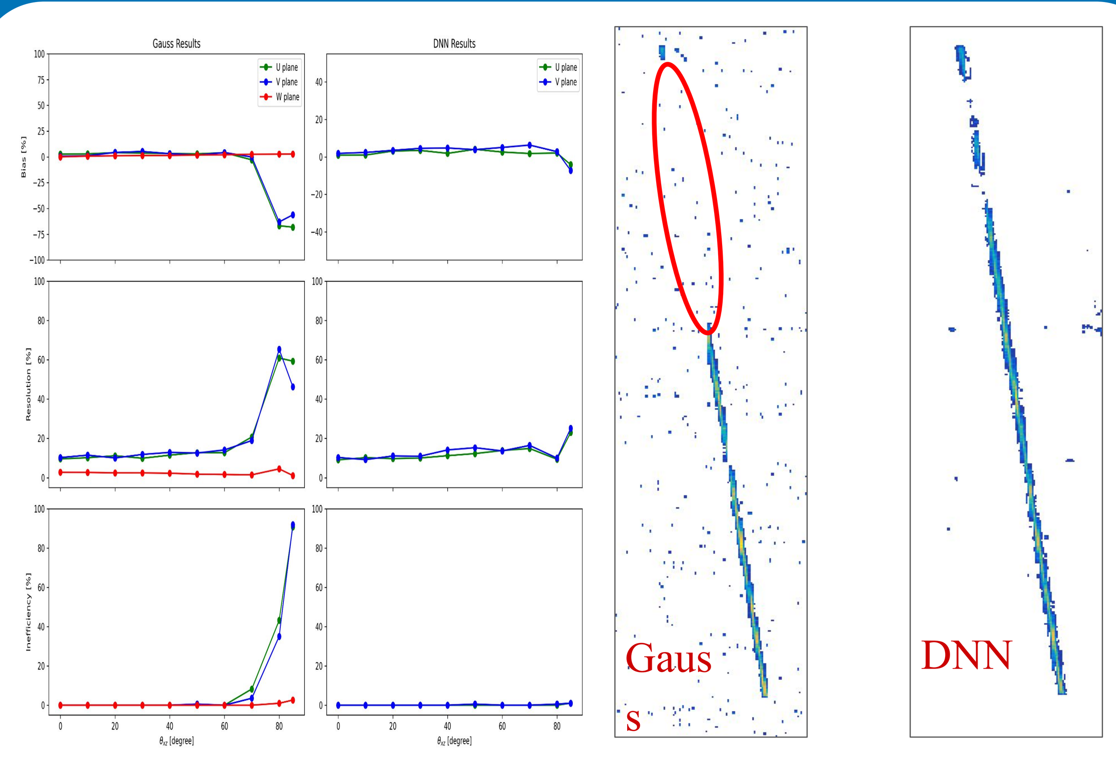
❖ Inefficiency: measures the fraction of unrecovered true signal channels

$$\text{Inefficiency} = 100 \times \frac{\text{Number of bad channels}}{\text{Number of valid truth channels}}$$



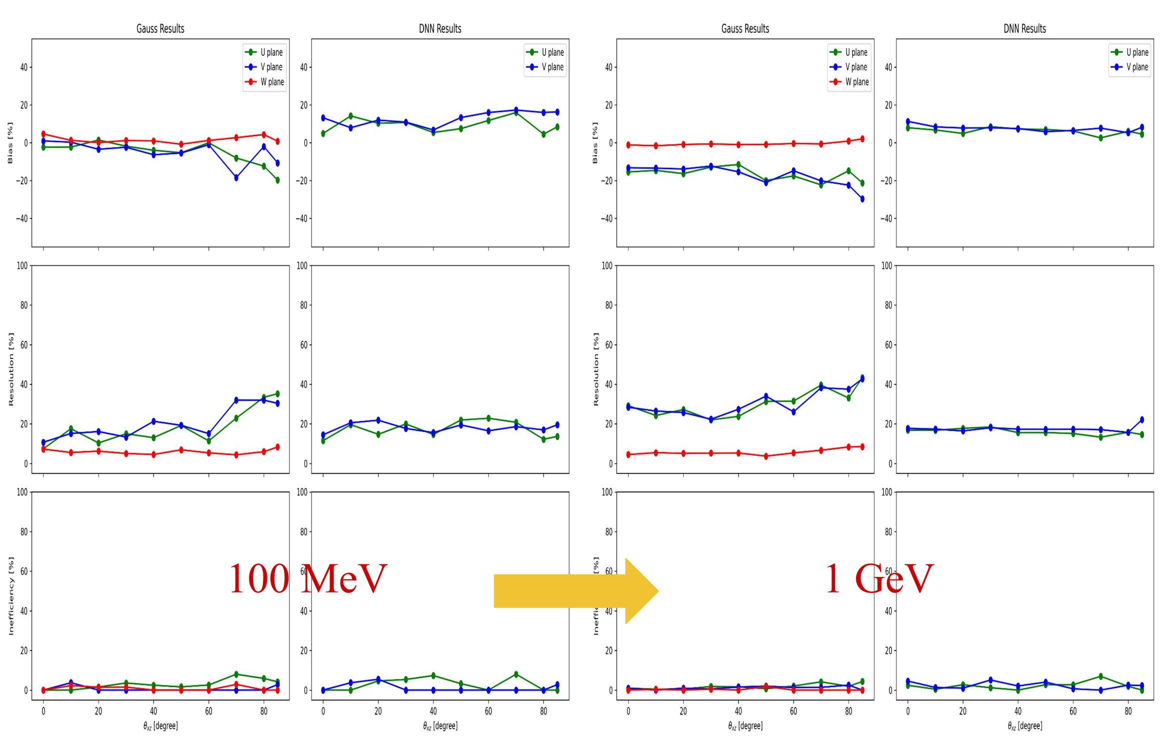

- Charge ratio distribution for Gauss (Black) and DNN (Blue)

## DNN Evaluation




- The DNN method shows stable performance across different track angles
- It reduces bias and improves resolution compared to the traditional ROI methods

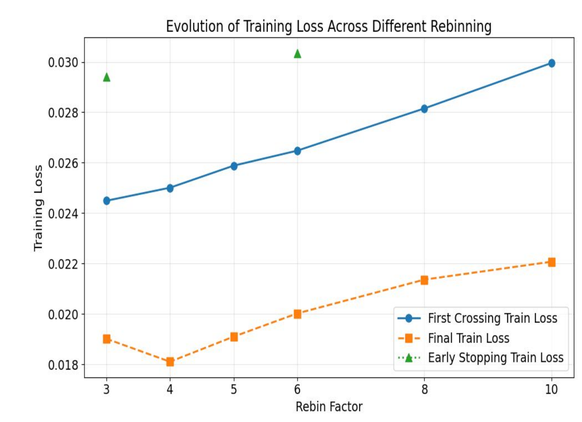
**Track**



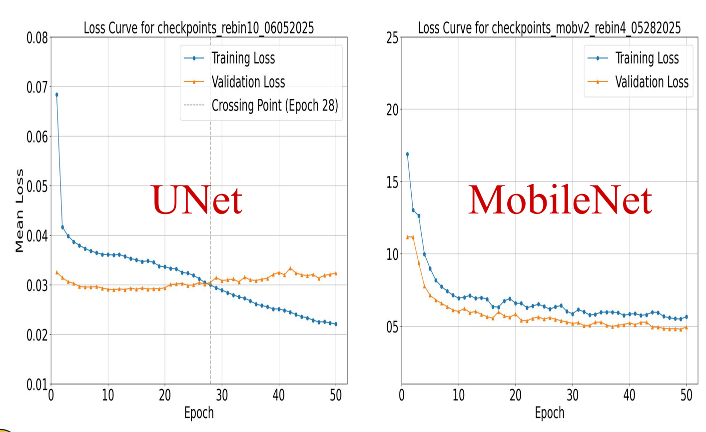

- As the energy increases, the traditional ROI methods suffer from worsening bias and resolution
- The DNN method maintains stable behavior across three representative energy levels (results for 100 MeV and 1 GeV are shown here)

**Shower**

## DNN Optimization




- Adjusting the rebinning factor enables the DNN to access finer-grained input information
- This leads to a reduction in training loss




MobileNet:
- achieves comparable performance to UNet
- resource-constrained environments

**Performance**

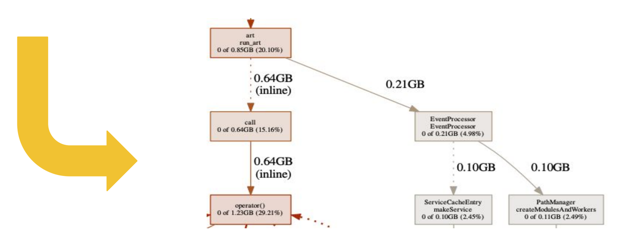
| Resource | DNN | Mem (MB) | Time (s) | Mem Ratio | Time Ratio |
|---|---|---|---|---|---|
| None | None | 1891.54 | 40.41 | 1.00 | 1.00 |
| CPU | UNet | 7419.03 | 91.45 | 3.92 | 2.26 |
| CPU | MobileNe | 4593.25 | 54.51 | 2.43 | 1.35 |

❖ DUNE VM

| Resource | DNN | Mem (MB) | Time (s) | Mem Ratio | Time Ratio |
|---|---|---|---|---|---|
| None | None | 1890.80 | 40.97 | 0.99 | 1.01 |
| CPU | UNet | 5208.58 | 53.64 | 2.75 | 1.33 |
| CPU | MobileNet | 4853.49 | 45.41 | 2.56 | 1.12 |
| GPU | UNet | 5105.16 | 46.18 | 2.70 | 1.14 |
| GPU | MobileNet | 5110.95 | 45.33 | 2.70 | 1.12 |

❖ GPU cluster

- We benchmarked inference performance on the DUNE VM and the WCWC GPU cluster
- MobileNet achieved faster inference with lower memory usage than U-Net
- GPerfTools profiles memory usage during DNN inference



**Resource**

## Conclusion

- ➢ The Wire-Cell Toolkit enables advanced signal reconstruction using tomographic imaging in LArTPCs
- ➢ Our evaluation demonstrates that DNN-based methods improve ROI selection
- ➢ Further optimization is in progress, focusing on architecture refinement
- ➢ Profiling at the Kernel level is ongoing to identify memory intensive process

## Acknowledgement

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DEEP UNDERGROUND NEUTRINO EXPERIMENT