Self-Supervised Mapping of Space-Charge Distortions in Liquid Argon TPCs

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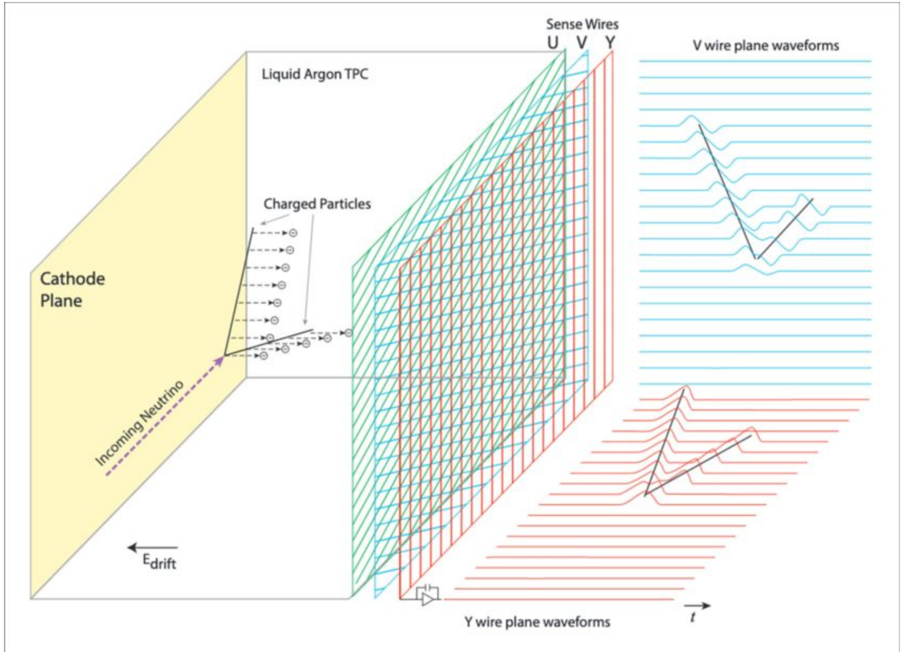
Liquid Argon Time Projection Chambers

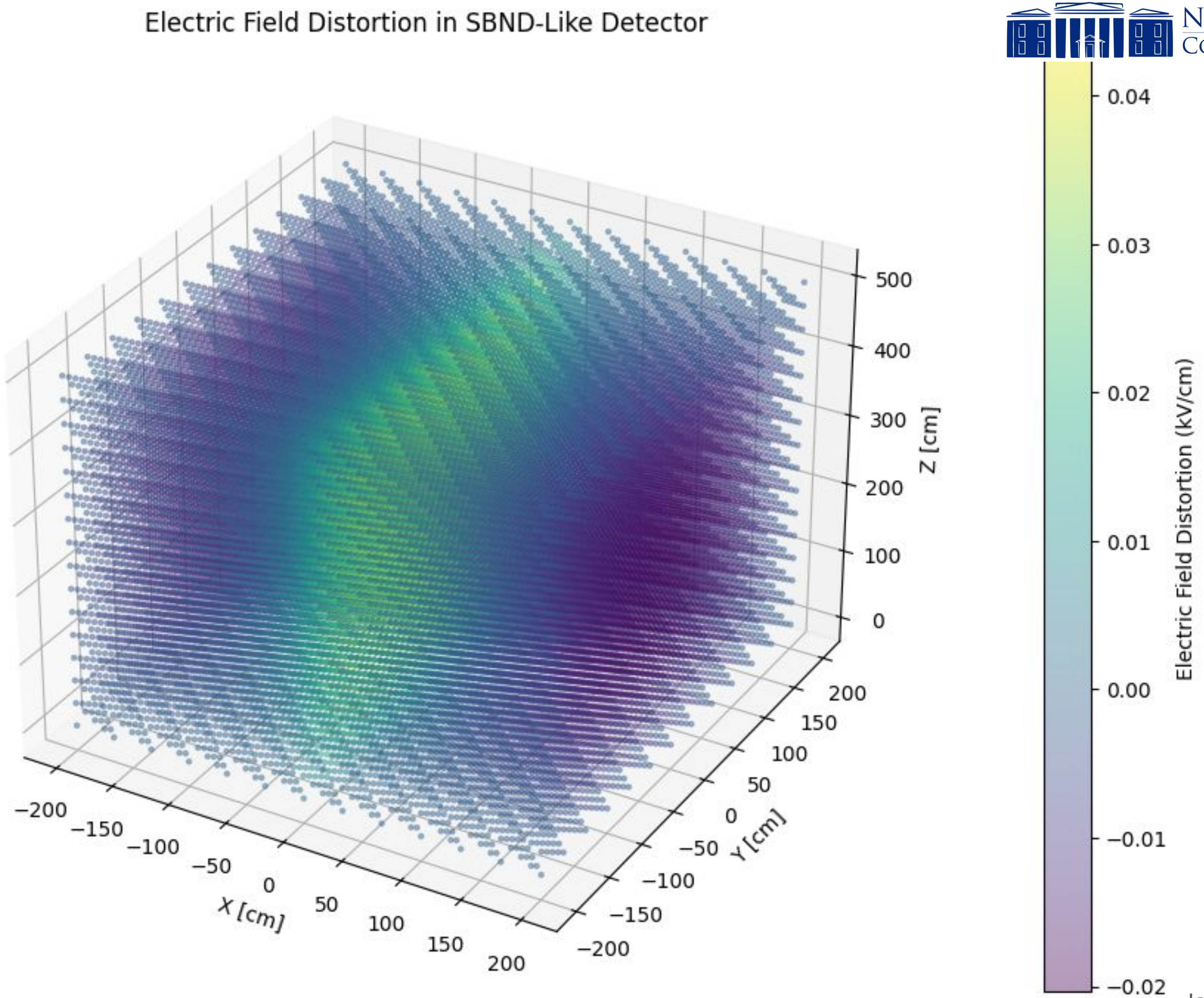
Neutrinos stream through the detector and interact with Ar nuclei, creating charged particles.

Charged particles create ionization electrons along their trails.

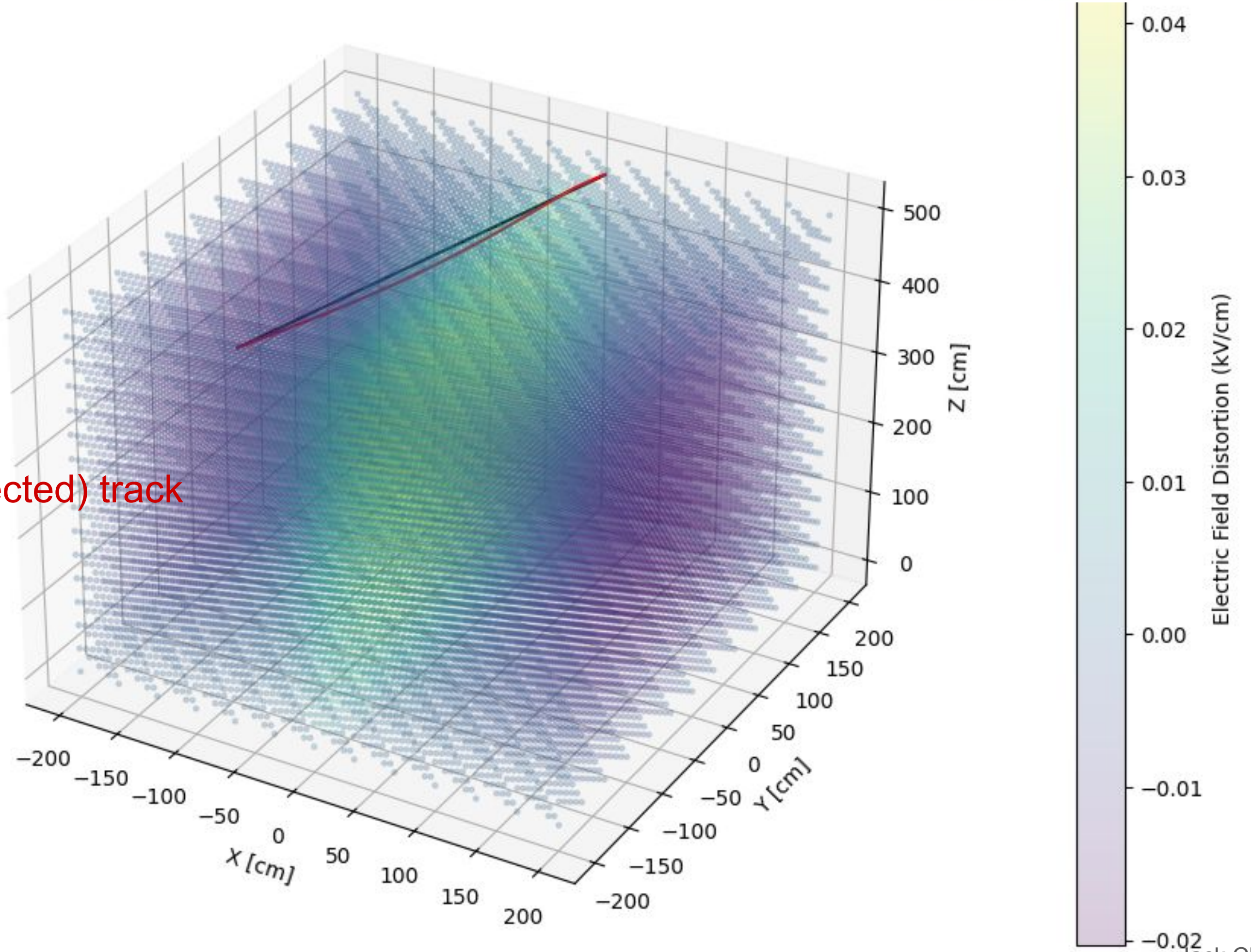
Ionization electrons drift in a large, ***uniform*** electric field and are sensed by wire sensor arrays.

Extensively used technology in Neutrino Experiments (DUNE, SBND, MicroBooNE, ICARUS) as well as astro-particle physics experiments (GRAMS)




Electric Field Distortion in SBND-Like Detector
X [cm]
Y [cm]
Z [cm]
−200
−150
−100
−50
0
50
100
150
200
300
400
500
Electric Field Distortion (kV/cm)
0.04
0.03
0.02
0.01
0.00
−0.01
−0.02

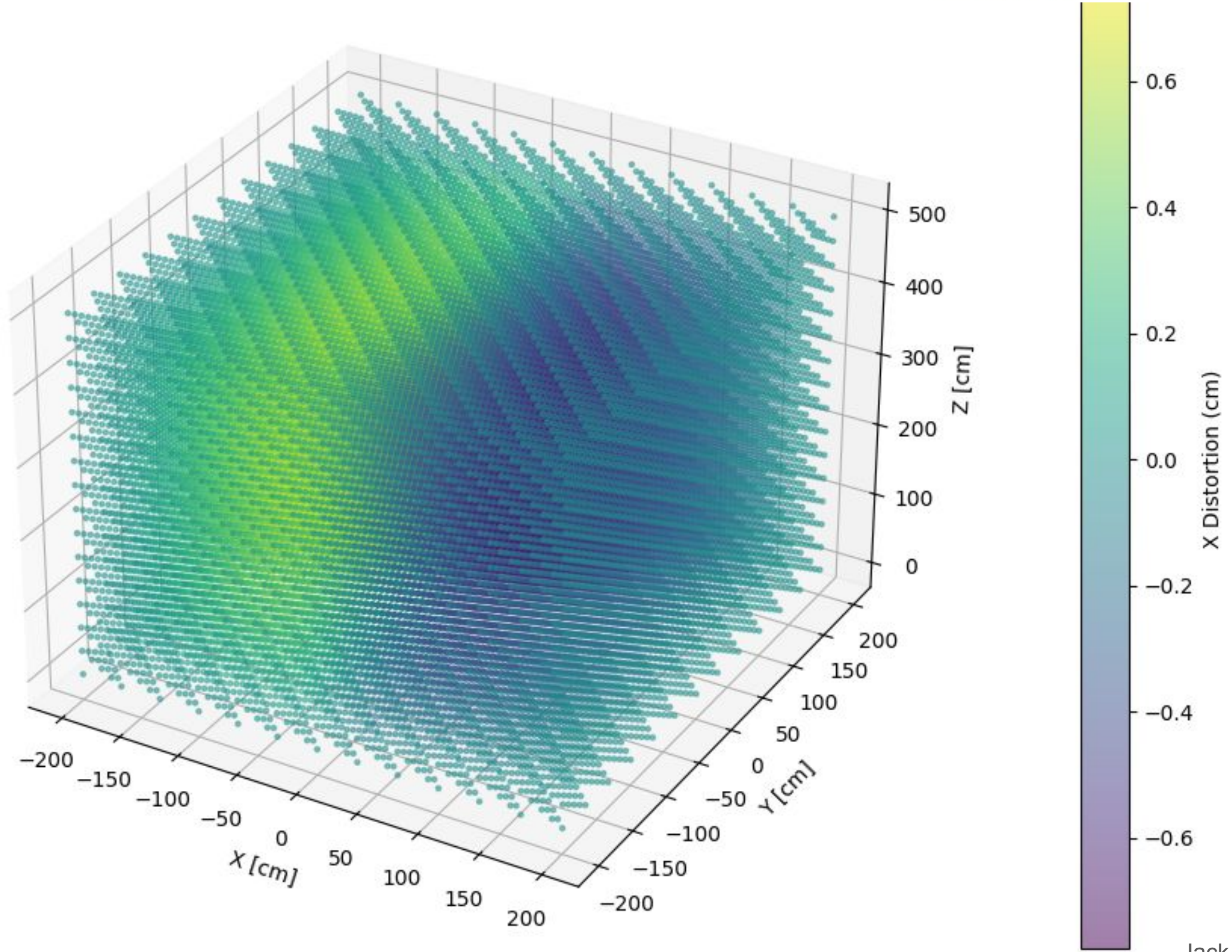
Ground Truth Electric Field Distortion with Sample Path



True track

Distorted (detected) track

Ground Truth 3D Distortion Values



Distortion Removal in LArTPCs

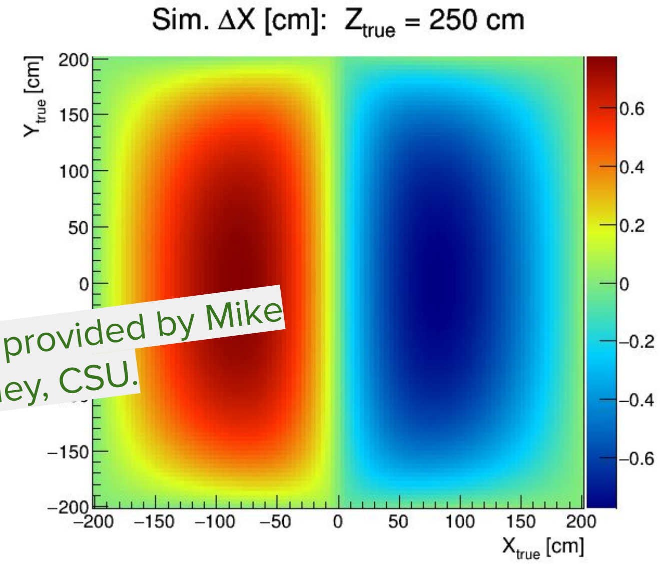
- Future LArTPC detectors will be operated in different environments, exposing them to more cosmic rays and potential significant “space charge” effects in their detectors, leading to distortions in the electric field and modified reconstructed neutrino paths.

- **Our goal is to create an unsupervised machine learning model that learns from the distorted charged particle track data to infer the electric field.**

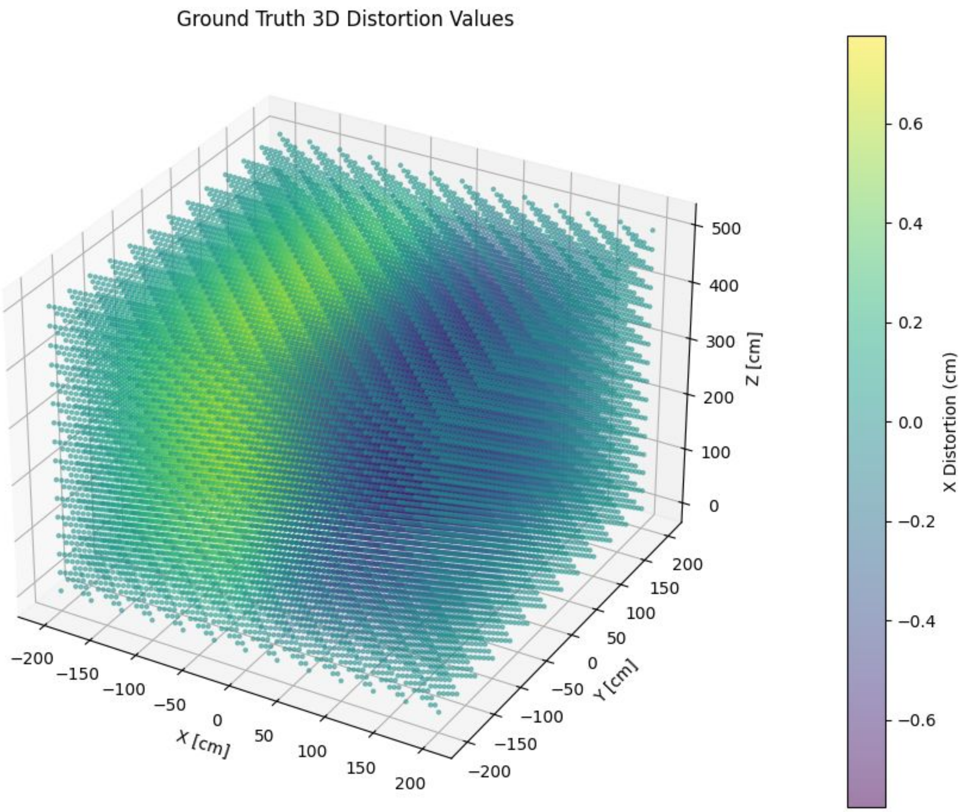
SBND-Like Distortion Simulation

E-field simulation inputs:

- Ionization creation rate: 2E-10 C/m^3/s
- TPC dimensions: 4m x 4m x 5m in x, y, z,
- E field direction: along x, toward the center plane of the detector (x=2m plane)
- E field magnitude: 500 V/cm



Maps provided by Mike Mooney, CSU.



Simulated Path Creation

True Paths: Assume through-going, straight line.

Distorted Paths: simulated x-distortion is added to the coordinates of the path for each point in the undistorted path.

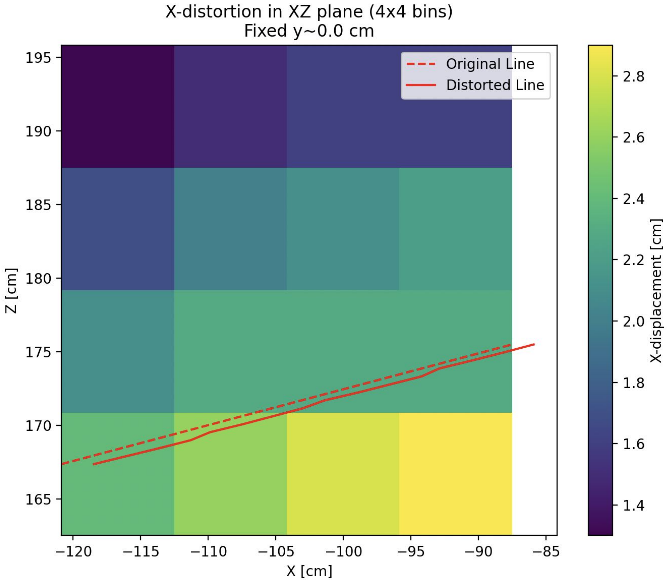
Note that we simulate Distortion with 8 cm resolution, whereas the detector itself has wire spacing of 3 mm. Need to introduce interpolation to smooth the mismatch.

Simulation Data:

49 x-bins: [-204.167, 204.167], each bin 8.33cm

49 y-bins: [-204.167, 204.167], each bin 8.33cm

61 z-bins: [-4.167, 504.167], each bin 8.33cm



Sample Paths

200,000 sample paths were generated, a handful of which are pictured on the right.

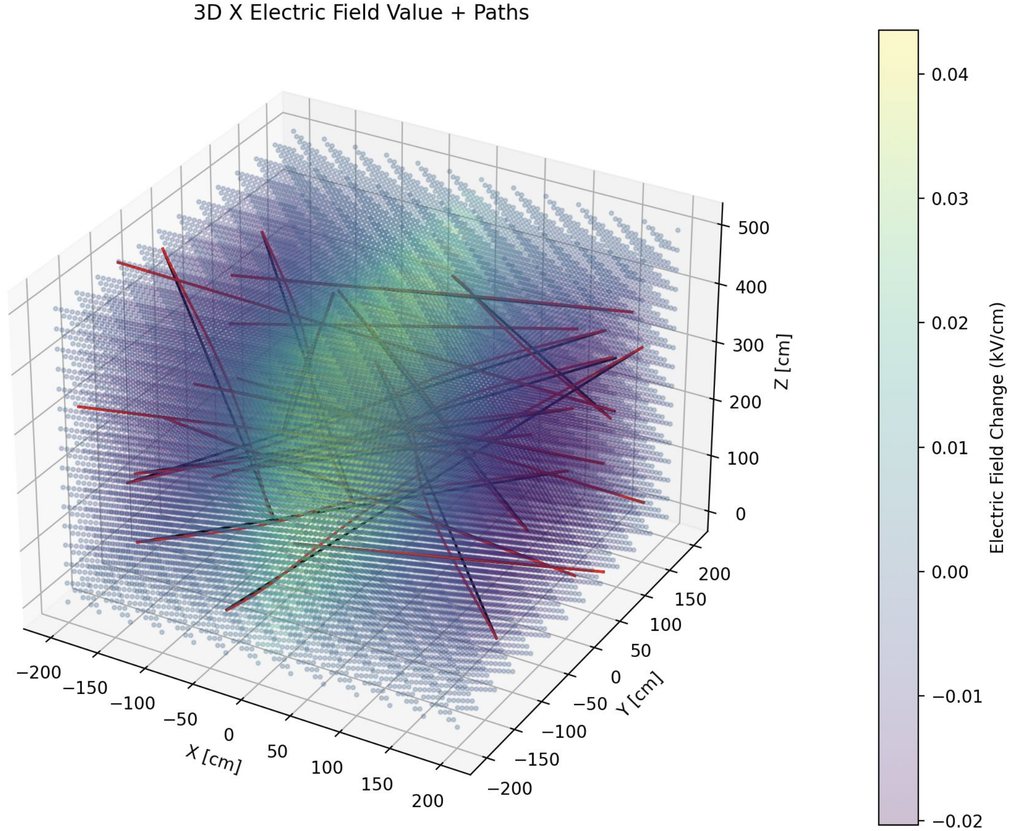
146461/146461 bins were hit, the median number of hits in a bin was 4000.

Format: each pair of paths is represented as two lists, one of distorted coordinates, one of true coordinates for each hit on the wire cell

dists : [(x_0', y_0', z_0') , (x_1', y_1', z_1') ...]

true: [(x_0, y_0, z_0) , (x_1, y_1, z_1) ...]

Note the model will only have access to the distorted paths.



**Assuming 3D reconstructed Paths

Physical Constraints

Straightness:

Assumption: In a uniform electric field, cosmic muon tracks are straight.

Reasoning: Liquid-argon TPC drift fields are designed to be uniform so that a minimum-ionising muon travels essentially in a straight line. Any residual curvature in the corrected 3-D path must come from distortion.

Endpoint:

Assumption: The electric-field distortion vanishes at the cathode and anode and is near negligible at the other TPC faces.

Reasoning: Since Δx is the time integral of E_x along the drift, it must be exactly zero on the readout and cathode planes and only a few mm on the other faces, typically ~20x smaller than inside the volume.

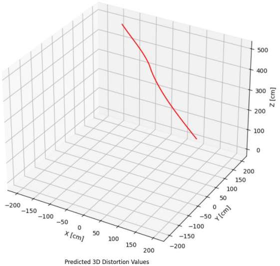
Potential Smoothness:

Assumption: The underlying electric-field distortion varies smoothly over the detector volume.

Reasoning: Space-charge distortions arise from diffuse charge distributions, not sharp spikes. Penalising the Laplacian of the learned scalar potential ensures the predicted field is physically plausible, so there won't be unphysical "jumps" between neighboring voxels.

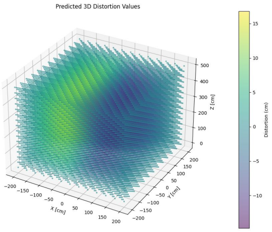
Self-Supervised Methods for Distortion Estimation

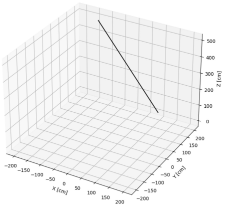
- Input Distorted Path



$$\mathbf{J}(\mathbf{x}) = \mathbf{I}(\mathbf{x} + \tilde{\mathbf{W}}(\mathbf{x}))$$

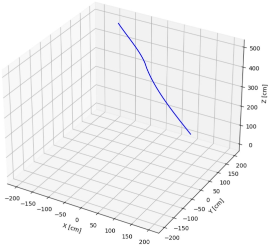
- Model learns Distortion Map and *Assumed True Path* (derived from straightness and endpoint constraints) simultaneously.



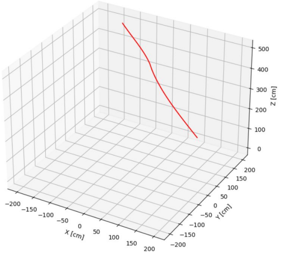


$$\mathbf{G}_{\theta} \cdot (\mathbf{J}(\mathbf{x}), \mathbf{x}) = \mathbf{J}(\mathbf{x} + \mathbf{W}_{\theta}(\mathbf{J}(\mathbf{x})))$$

- Primary Loss between Input Distorted Path and learned Distortion Map applied to learned True Path



VS



$$L_{con} = \sum_{\mathbf{x}} |\mathbf{I}(\mathbf{x}) - \mathbf{G}_{\theta\phi}(\mathbf{J}(\mathbf{x}), \mathbf{x})|$$

Self-Supervised Model Details

Model Architecture:

Inputs: Normalized hit coordinates $(x,y,z)\in[-1,1]^3$

MLP "phi-net": 4 hidden layers (128 units, SiLU activations), input size 3+36 output a scalar $\phi(x,y,z)$.

Curl-free constraint: The predicted x-shift is $\Delta x=\partial\phi/\partial x$ (via autograd), guaranteeing $\nabla\times E=0$

Baseline + Residual: We precompute a straight-line self-supervised baseline Δx_{base} by bin-averaging end-point tracks. The network learns only a small residual $r=\Delta x-\Delta x_{base}$

Training:

Data loader: Reads distorted tracks, normalizes coordinates, and for each hit looks up the fixed Δx_{base} from the pre-binned grid.

Loss terms (per track):

- **Line-consistency:** 2nd finite-difference along the corrected track ➔straightness penalty.
- **Endpoint clamp:** $\Delta x(0)^2+\Delta x(1)^2$ at the two faces.
- **Smoothness:** Laplacian of ϕ on the full 3-D grid ➔ penalize $\nabla^2\phi$

Self-Supervised Model Performance Metrics

Goal: Determine how well the Self-Supervised Model learns the Distortion Map

Want to minimize (note x here is the predicted distortion in x):

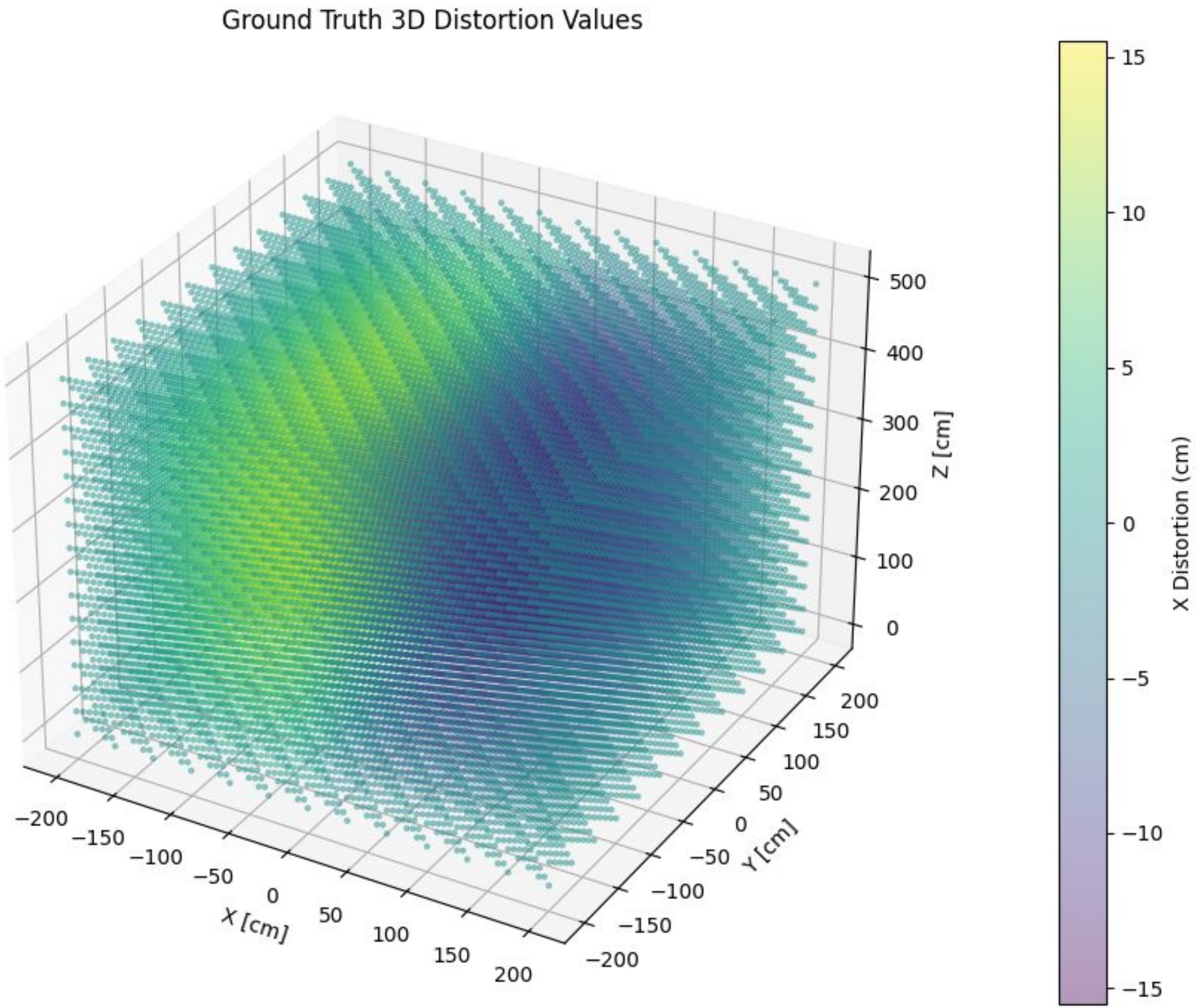
$$\Delta x = x_{true} - x_{pred}$$

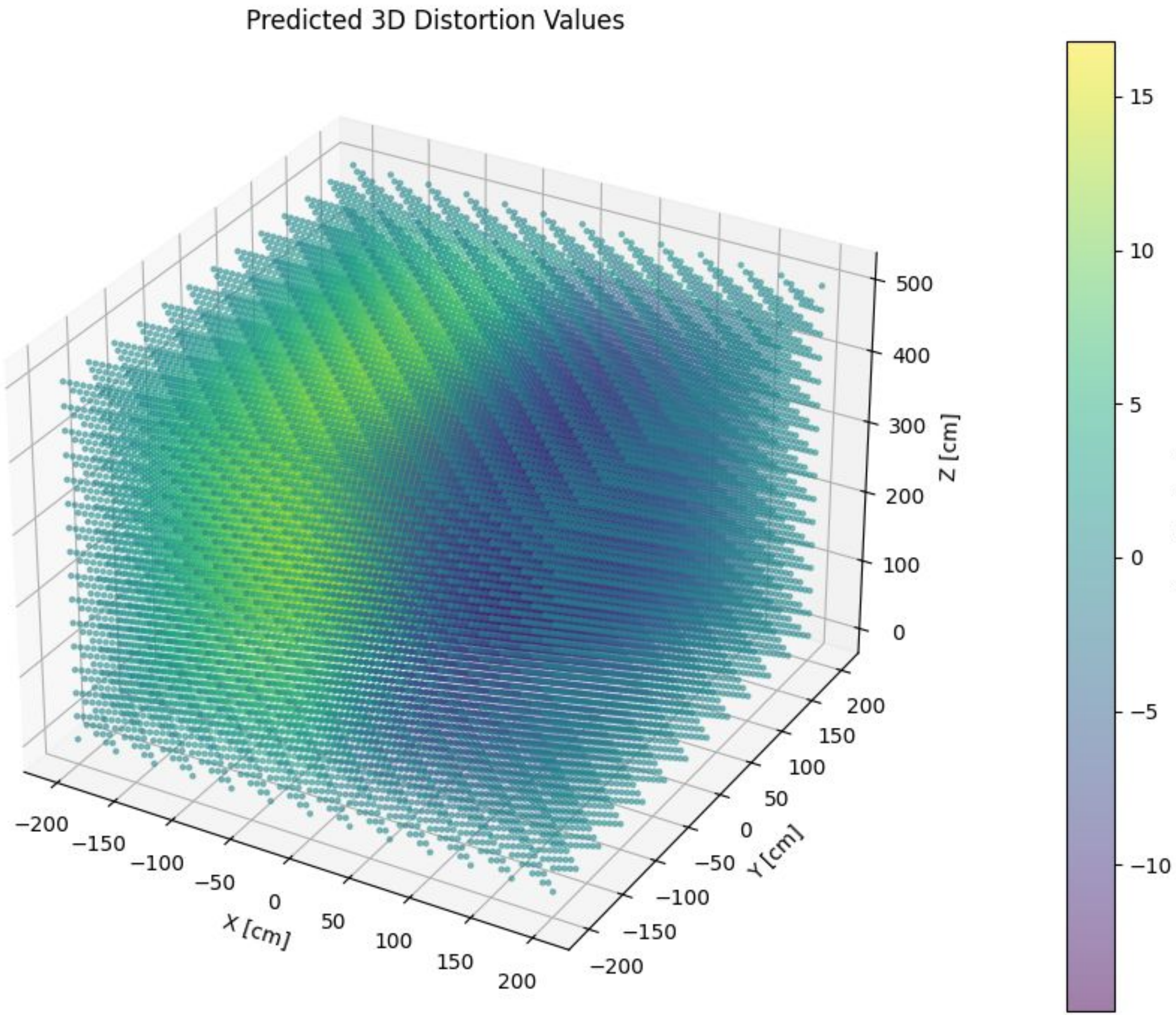
Note the metric Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(x_{pred} - x_{true})^2}{n}}$$

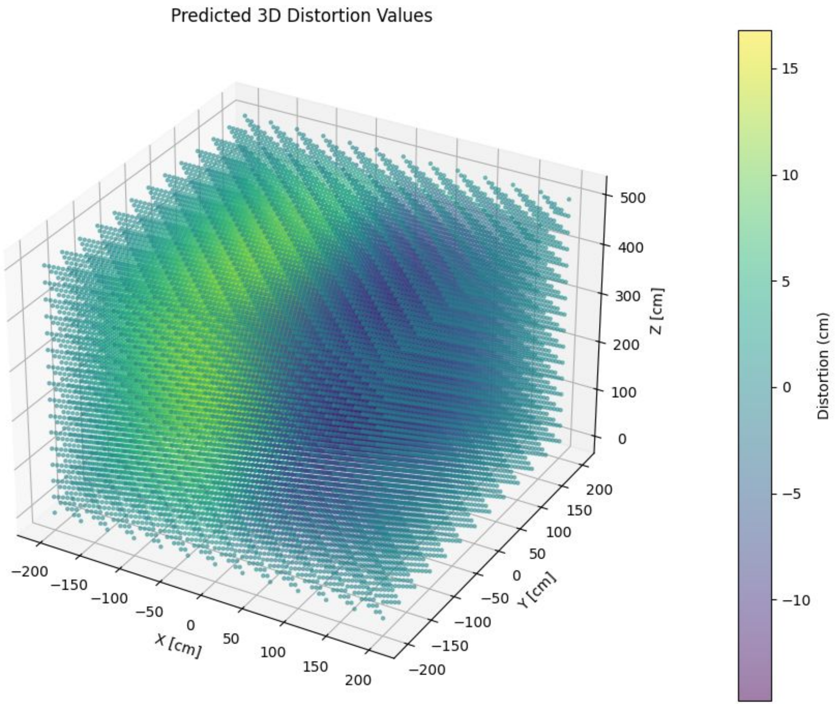
We'll also look at the median of the percent error:

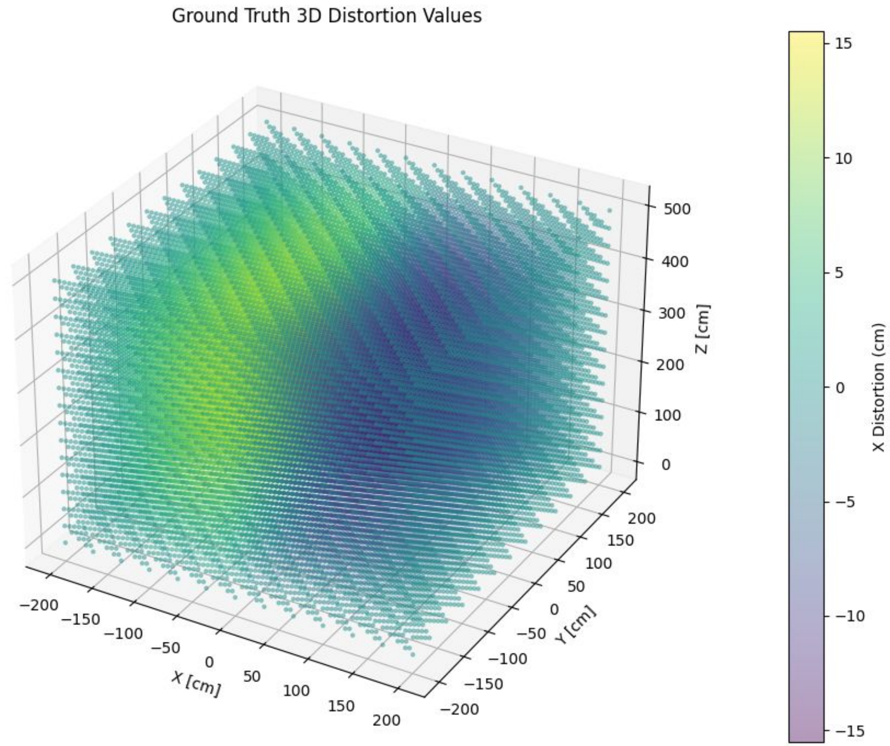
$$\text{Percent Error} = \frac{\Delta x}{x_{true}}$$


Ground Truth 3D Distortion Values
X [cm]
Y [cm]
Z [cm]
−200
−150
−100
−50
0
50
100
150
200
500
400
300
200
100
0
X Distortion (cm)
15
10
5
0
−5
−10
−15


Predicted 3D Distortion Values
X [cm]
−200
−150
−100
−50
0
50
100
150
200
Y [cm]
−200
−150
−100
−50
0
50
100
150
200
Z [cm]
0
100
200
300
400
500
Distortion (cm)
15
10
5
0
−5
−10

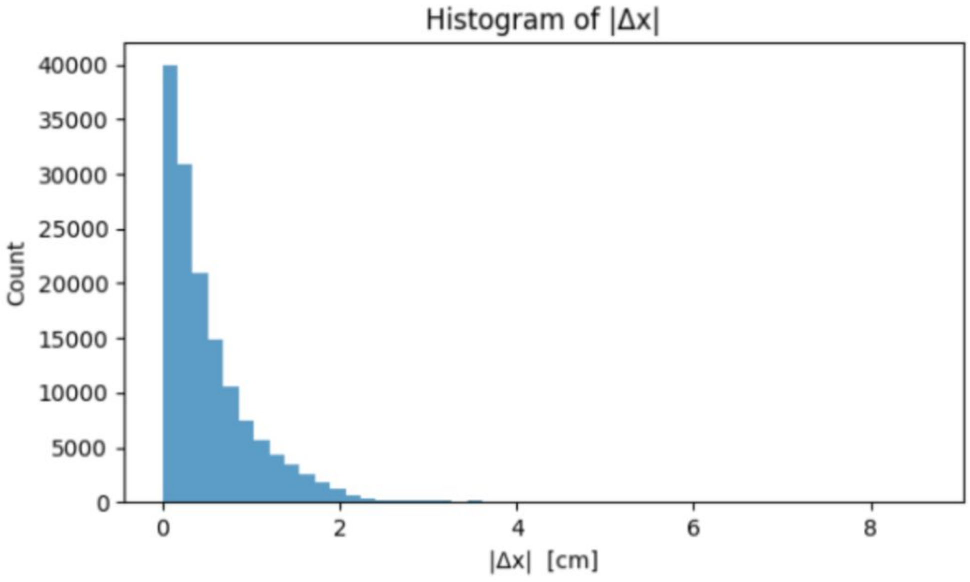
Self-Supervised Model Performance 3D Graphs

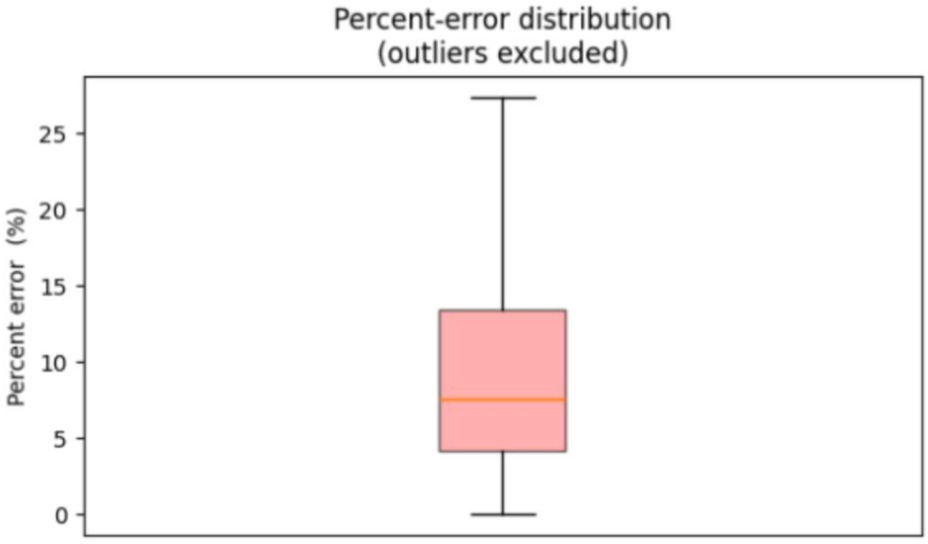




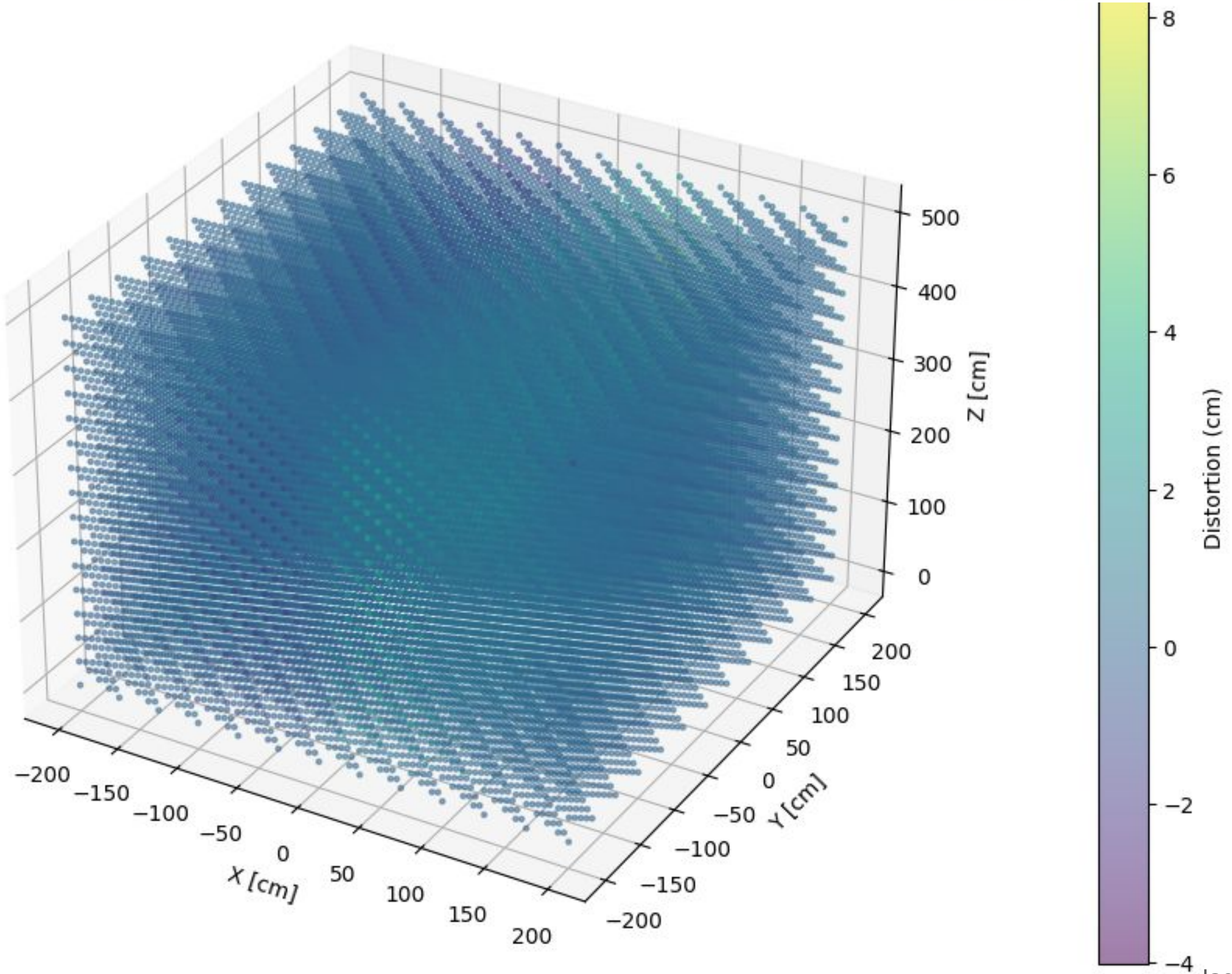
Self-Supervised Model Performance

RMSE: 0.8060 cm
Median Percent Error: 7.63%
95th percentile error: 1.59cm





Difference between Ground Truth and Predicted Distortion



Overview and Next Steps

Using a self-supervised multi-layer perceptron neural network with 3 key physical assumptions we were able to reproduce simulated space charge distortion effects with a median percent error of 7.63% and an RMSE of 0.8cm on a scale of 10-15 cm distortions.

Classical methods in [P. Abratenko *et al* 2020 *JINST* 15 P12037] produced 0.1 cm average error on a similar scale of about 10-15 cm for the MicroBooNE detector.

So at the moment the model produces similar levels of accuracy to classical methods with extensive UV laser system, though does not perform quite as well.

Next Steps

1: Continue to improve model performance

2: Different Scale of Distortions: 1x, 10x, 20x (shouldn't affect model)

3: Determine precise timing for model inference