Gamma Ray Source Localization For Time Projection Chamber Telescopes Using Convolutional Neural Networks

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Motivation and Goal

Questions

- Why should we study low MeV astrophysical gamma rays?
- How can we use machine learning to optimize the pointing capability of a gamma ray observatory to study them?

Goal

Develop a convolutional neural network to accurately reconstruct Compton scattering events within the observatory, thereby constraining the sky location of the gamma ray source.

Introduction and Background

Why study MeV Gamma rays?

Address compelling science questions related to **positrons in the Milky Way, WIMP dark matter, and binary neutron stars** [1]. Currently, astrophysical low MeV gamma rays are very poorly measured.

How will we study MeV Gamma rays?

With **GammaTPC – an instrument concept** that houses four metric tons of liquid argon and utilizes Compton scattering events to infer the sky location of the gamma ray source (Fig. II).

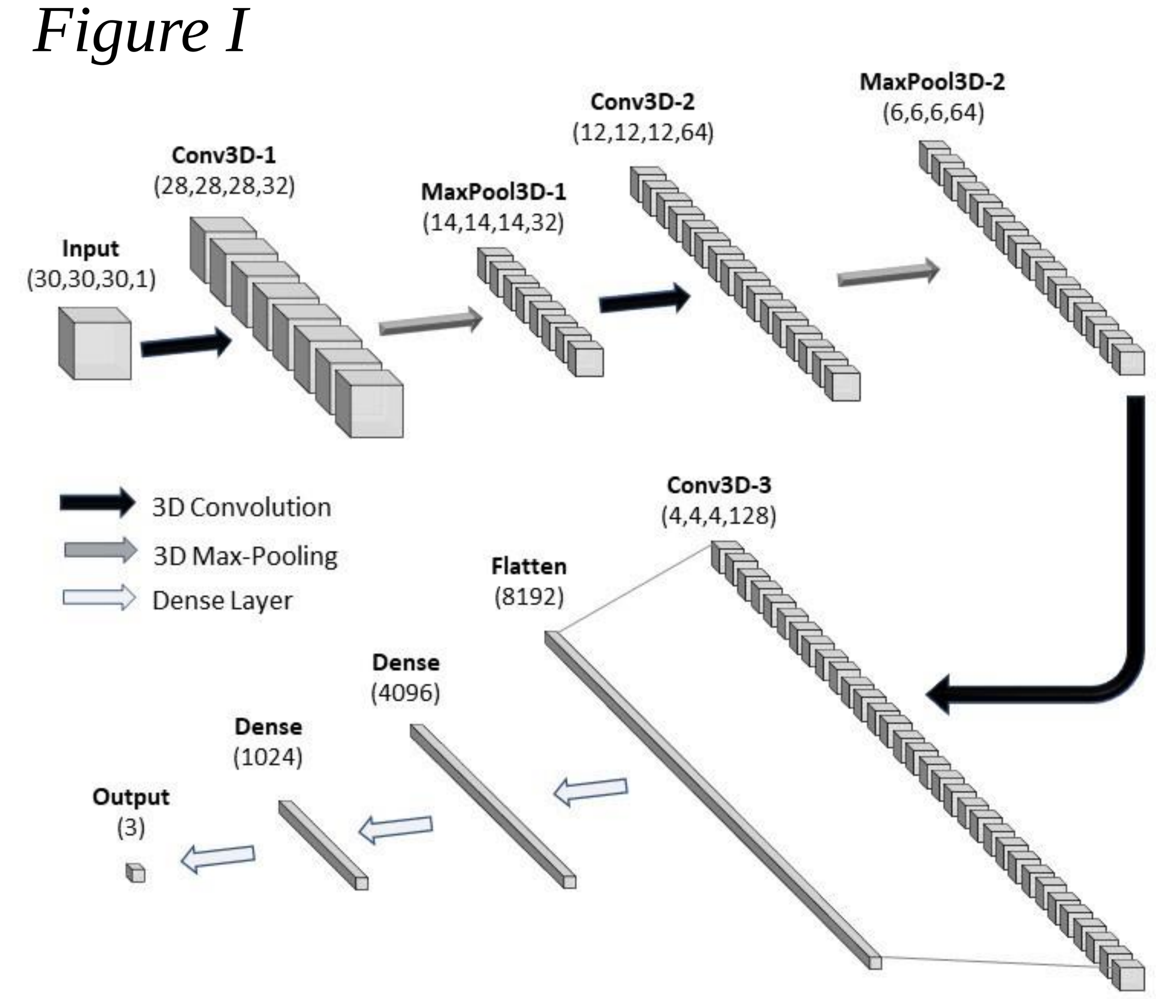
Why use machine learning?

To **reconstruct the scattering events** within the detector. ML is used to **predict scattering locations** of the gamma photon and **initial direction** of the recoiled electron. Accurate kinematic reconstruction optimizes the pointing capability of GammaTPC. **We create two ML models** to **predict** the initial interaction vertex and initial scattered electron direction.

Methods

We **create a model architecture** (Fig. I) **to predict the location** of the scattering event and the **initial direction** of the scattered electron.

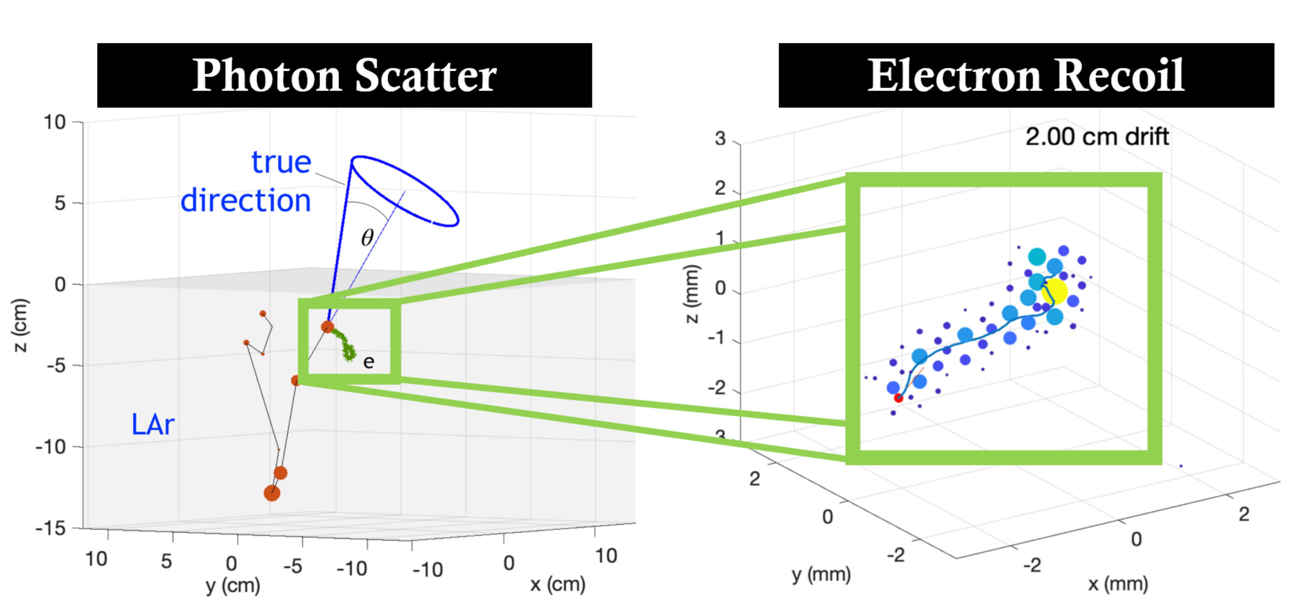
Figure I



Electron tracks are simulated in PENELOPE [2], with ~100,000 tracks made for each energy level we chose. **Custom code simulates readout** of liberated charges, including readout noise, pixel thresholding, and drift distances of charge to the pixels.

3D cubes of voxelized charge readout are fed to the ML models to train on. Models are trained both on separates energies and across all energies. We also train on a range of drift distances and pixel pitches.

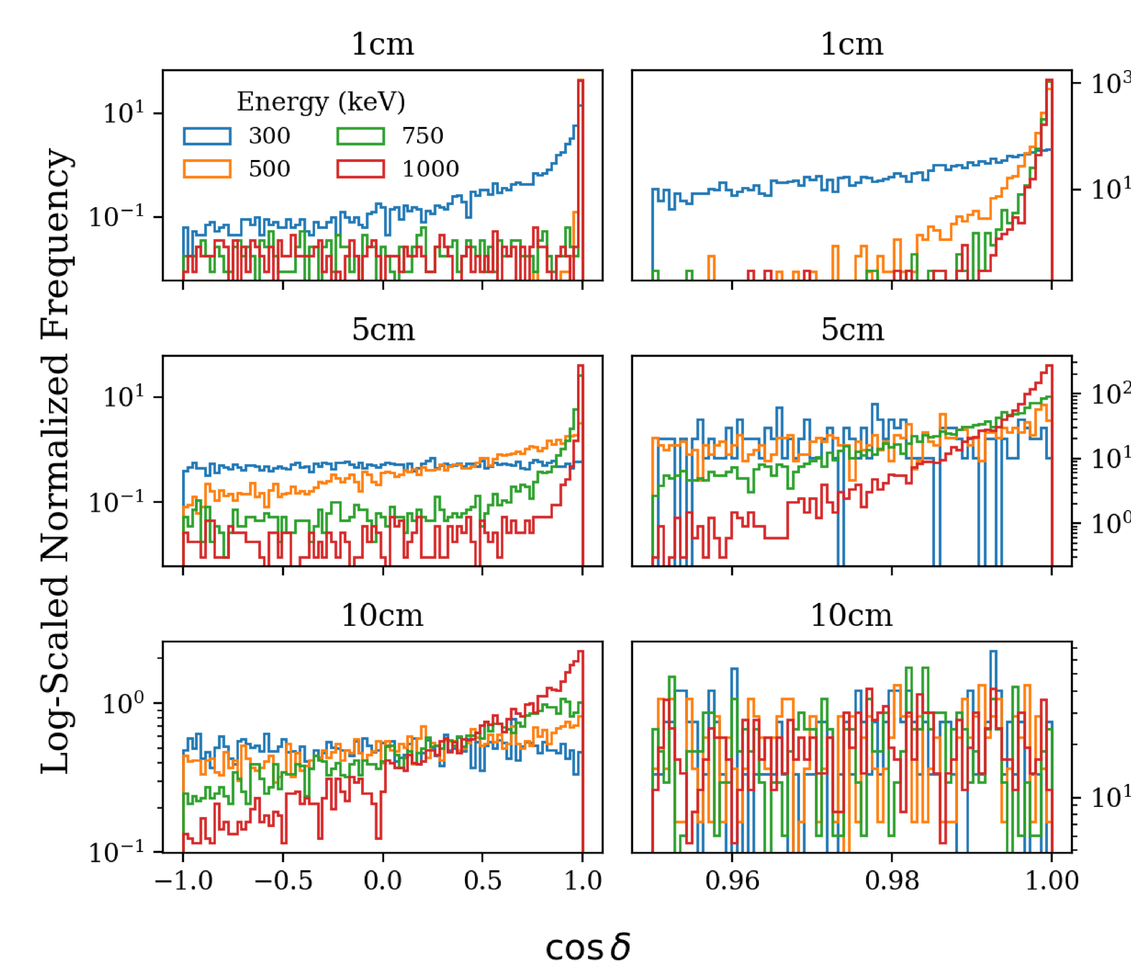
Figure II [3]



Results

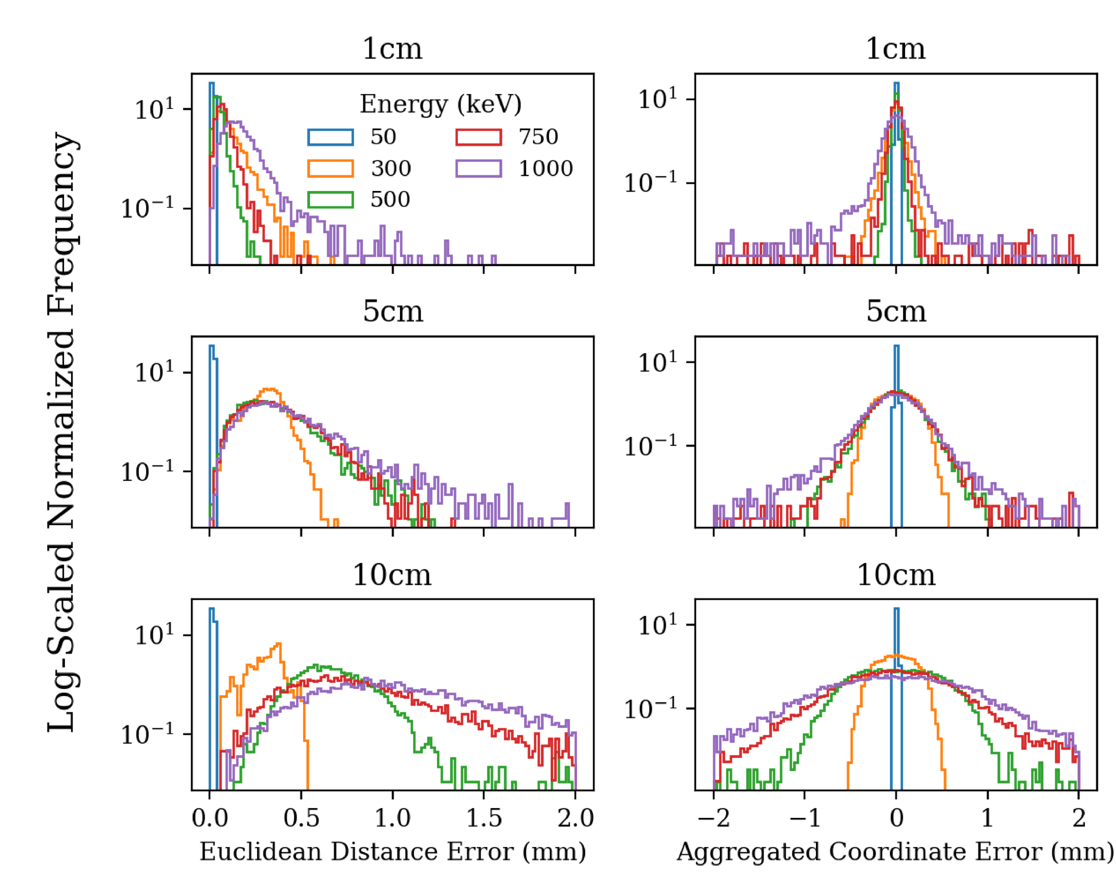
Initial Scattering Direction Prediction Error

Our **model achieves high accuracy** for predicting the initial direction of the scattered electron when trained on separate energies. High energy tracks are easier to predict because they are longer and less circuitous.



Interaction Location Prediction Error

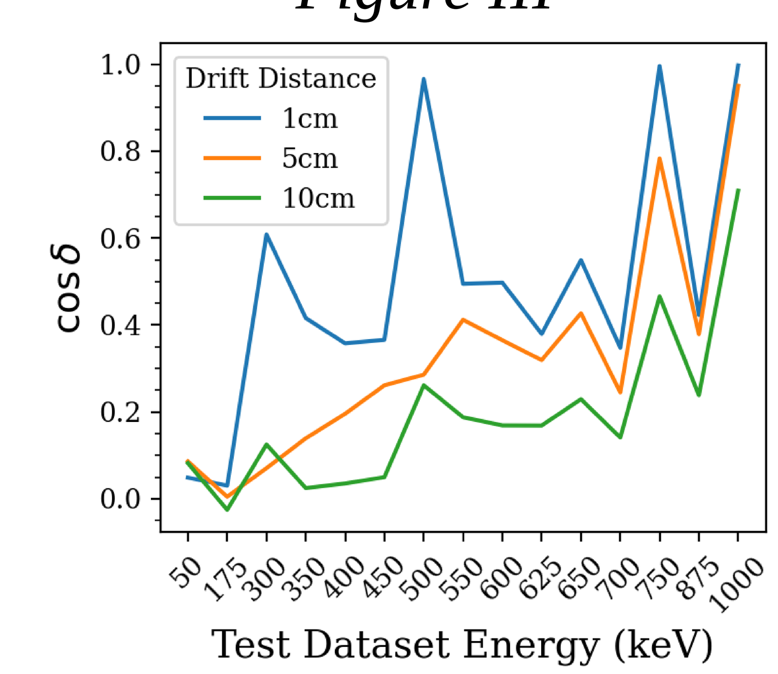
Our **model achieves the desired sub-mm accuracy** for the initial interaction location when trained on separate energies. Long tracks associated with high energies span distances on the order of a few mm, thereby allowing incorrect head predictions to produce errors larger than the incorrect predictions in tracks spanning sub-mm scales.



Model Extrapolation Ability

The predictive power of our models diminishes when trained over a range of energies. The direction model shows poor performance when tested on energies outside the dataset, with the training dataset consisting of 300, 500, 750, and 1000 keV events (Fig. III). Similar results are obtained for the head model. The hyperparameters used resulted in a failure of some head models to train.

Figure III



Conclusions

We **developed two machine learning models** to **predict the interaction vertex and initial direction** of the scattered electron. We found that models trained on specific energies are the most accurate. **Accurate reconstruction** of the scattering event allows us to **infer where the gamma ray came from.** Optimized pointing thereby allows us to explore the poorly measured MeV sky and answer science questions related to gamma emission. We are exploring quantifying the amount of uncertainty with these ML predictions, for removing uncertain predictions allows us to only consider outputs that effectively contribute to the source localization.

References

[1] Shutt, Tom, GammaTPC Science Proposal
[2] PENELOPE 2018, https://doi.org/10.1787/32da5043-en
[3] Buuck et al, astro-ph.IM/2207.07805