Probabilistic Deep Learning with GammaTPC
Low-Energy Electron-Track Imaging for a Liquid Argon Time-Projection Chamber Compton Telescope

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Science case for GammaTPC
- 0.5-50 MeV sky is poorly measured
- Great opportunity for new instrument
- Measure galactic evolution and particle content
- Use nuclear transition lines
- Identify transient sources
- In synchrony with gravitational waves for multimeasurer astronomy
- Catalog steady sources

Technical Goals
- 1000x sensitivity improvement over COMPTEL
- Factor of $10^5$ increase in known sources
- Precisely reconstruct electron scatters from track images

Project design
- This project is purely for track analysis
- Hardware/electronics design happening in parallel
- Proof of DL technique to reconstruct electron track head and initial direction
- Proof of DL technique to estimate uncertainty
- Evaluate performance on gamma-ray sources from industry-standard MEGAlib simulator

Direction reconstruction with a convolutional neural network (CNN)
- Perfect measurement of initial electron scatter completely determines kinematics
- Points directly to gamma-ray source
- In practice, there is uncertainty in measurement
- Constrains reconstructed source circle to arc
- Use 3D CNN to reconstruct initial direction
- Does not provide uncertainty estimation: future project

Position reconstruction with Evidential Deep Learning
- Neural networks can be trained to maximize Gaussian likelihood
- Does not give prediction uncertainty
- Place normal inverse-gamma prior over Gaussian parameters
- Maximize “model evidence”
- Bayesian posterior marginalized over likelihood parameters
- Posterior mean/std. dev. for normal component give prediction/uncertainty

How to find a gamma-ray source with a TPC
- Location of two scatters + energy deposited in first scatter constrains gamma-ray origin to circle on sky
- Direction of initial electron scatter constrains circle to arc
- Electron makes O(mm) track in LAr, locate track head with a neural network

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We achieve accurate position and uncertainty predictions
- Below right: True error and predicted squared error follow parabolic relationship
- Left: Pointing error vs. uncertainty in e\(^{-}\) scatter position
  - Y-projection is ~Lorentz
  - Below left: Lorentz FWHM shrinks as threshold on position uncertainty is applied
  - Can use uncertainty estimation to improve pointing!

Measured electron scatter direction with uncertainty

Example electron track
- Small colored circles → charge collected
- Ellipse around predicted origin → prediction uncertainty

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Pixel pitch = 500 μm, drift length = 5 cm

energies
- 300 keV
- 500 keV
- 750 keV
- 1000 keV

Cosine of angle between true and reconstructed gamma-ray origin

Perfect reconstruction at $\cos(\theta) = 1$, flat distribution → no power
Distribution is peaked near $\cos(\theta) = 1 \rightarrow e^{-}$ scatter directions are generally reconstructed correctly!

Pixel width vs. total number of events

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Paper posted to arXiv soon!