Machine Learning to Constrain Optical Parameters at Liquid Scintillator Detectors

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On behalf of the Eos Collaboration

National Nuclear Security Administration

BERKELEY LAB

Outline

1. Liquid Scintillator Detectors and Optical Modeling
2. The Eos Detector
3. Simulation-Based Inference
4. Neural Network Architecture
5. Results

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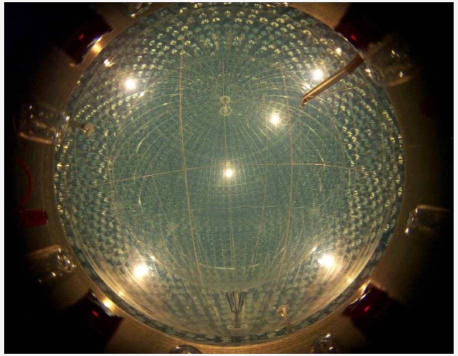
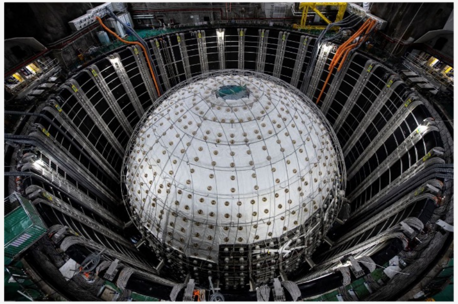
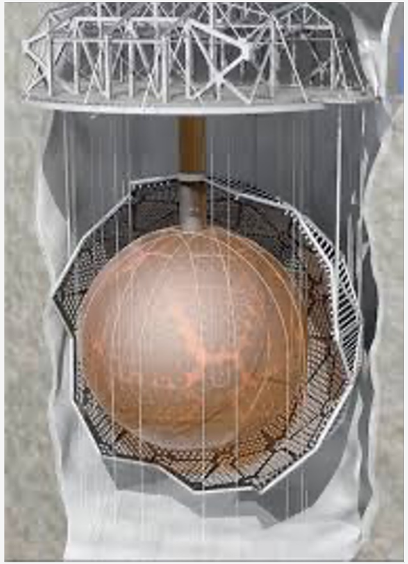
Liquid Scintillator Detectors


KamLAND


Borexino


JUNO

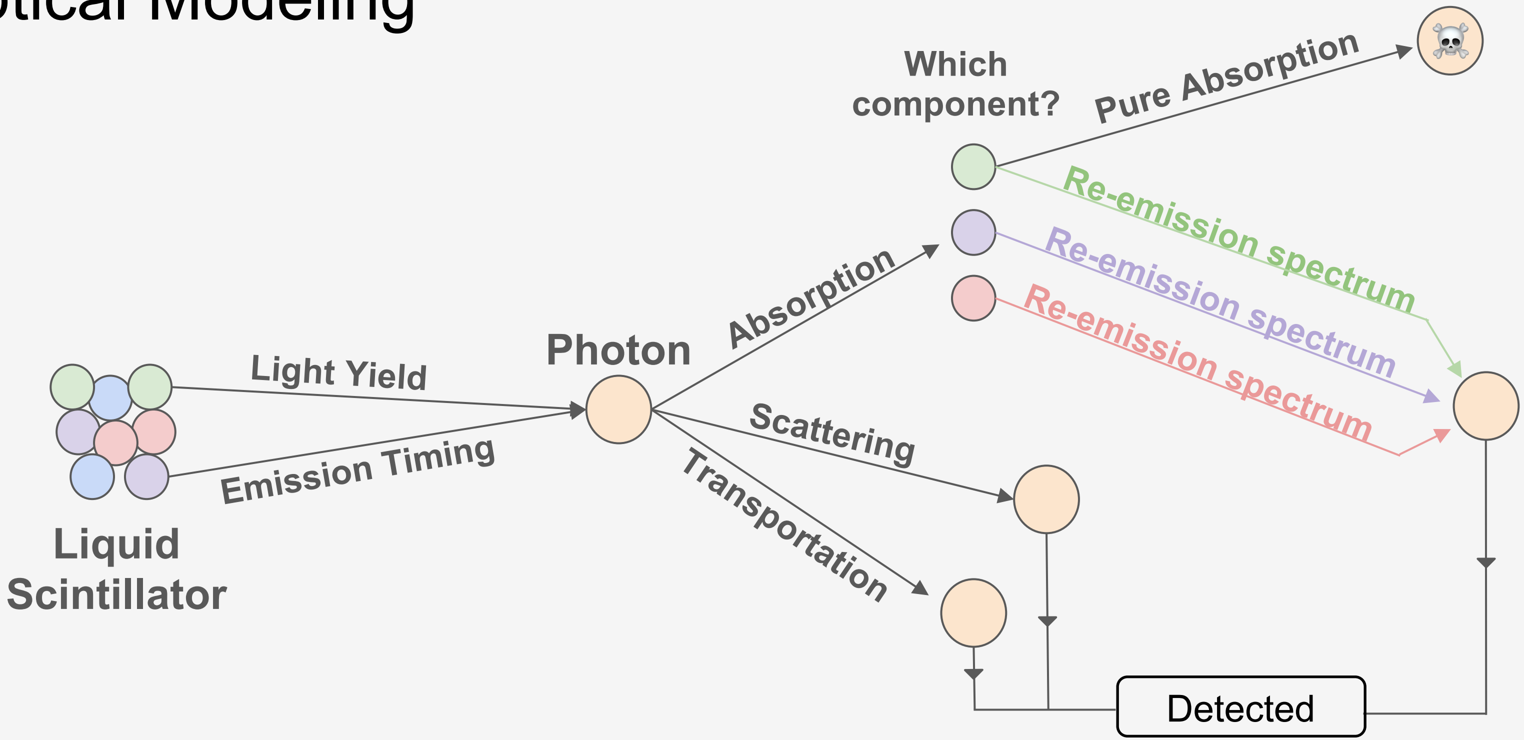

SNO+

Good energy resolution

Low event threshold

Low background

Optical Modeling



For accurate simulations, must understand all of these properties

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Eos Detector

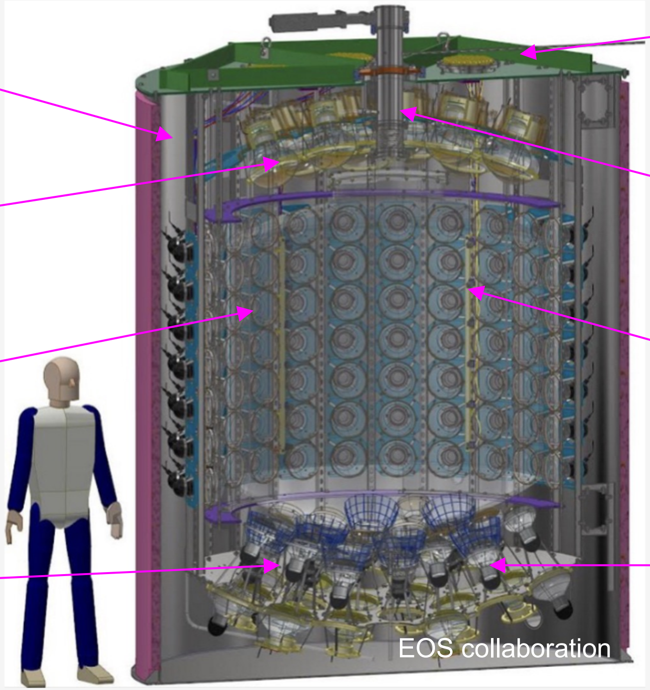
Multi-tonne scale optical detector operating at UC Berkeley

Outer Vessel: 20 tons of water

24x 12-inch PMTs for light collection

168x 8-inch fast, high QE side PMTs

12x dichroicons with 10-inch PMTs

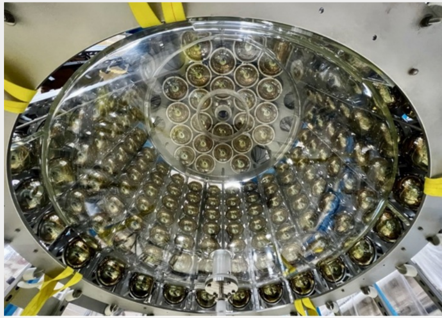


Muon veto

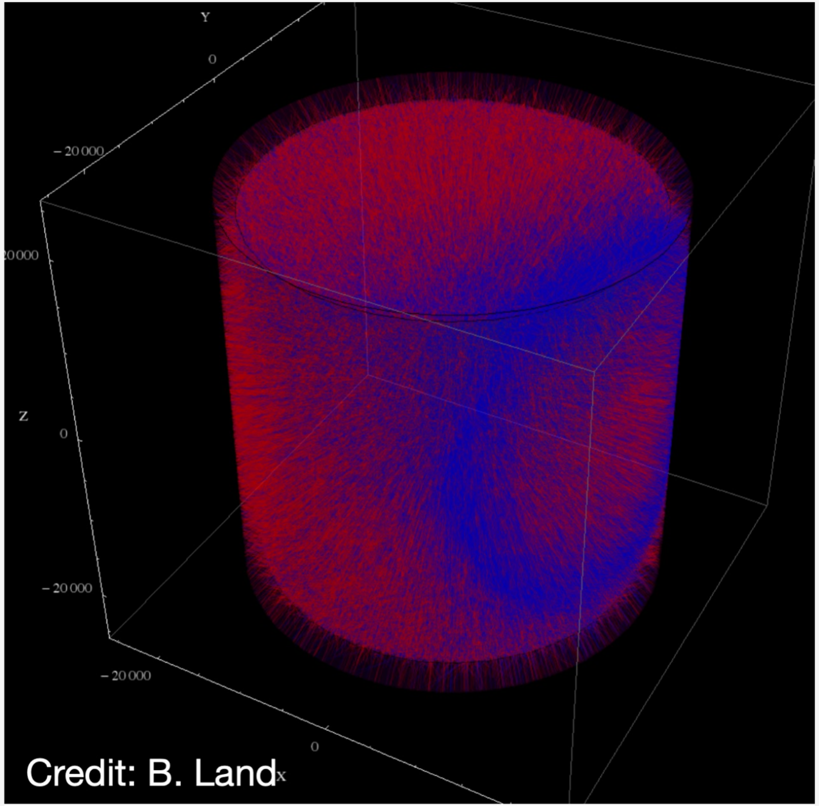
Calibration source deployment along central axis

Inner Vessel: 4 tons of target mass

32x 8-inch fast, high QE bottom PMTs

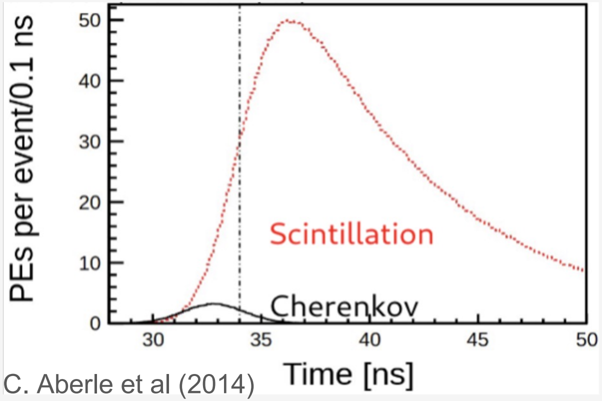


Hybrid Cherenkov/Scintillation Technology



Combining advantages from Cherenkov + Scintillation:

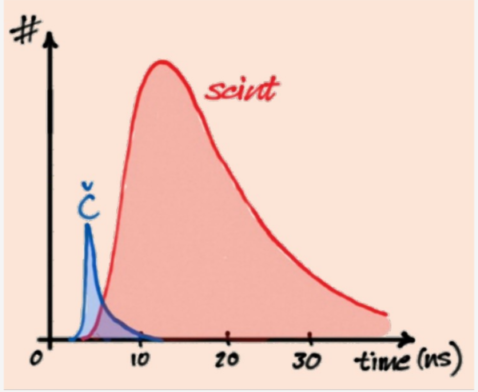
Directionality, low background, low threshold, energy resolution, particle ID



C. Aberle et al (2014)

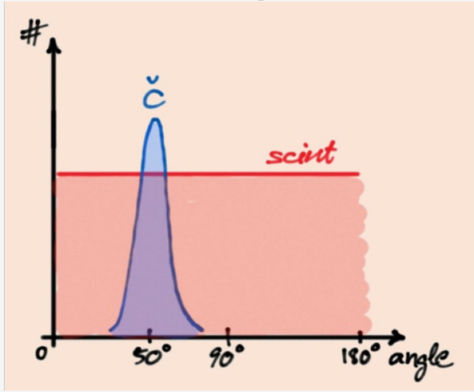
Achieving Cherenkov/Scintillation Separation

Timing



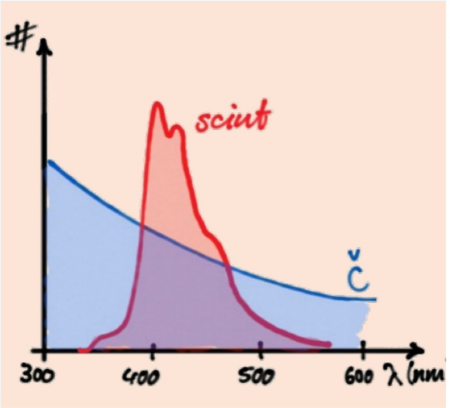
Fast PMTs capture Cherenkov peak

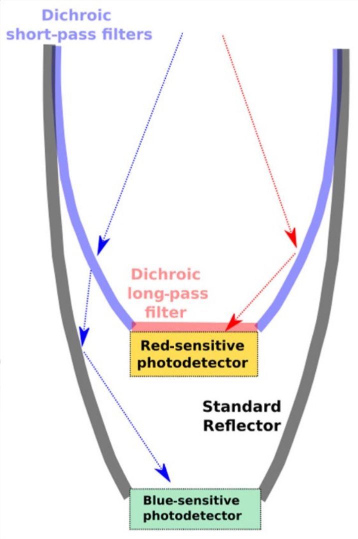
Angle



Advanced reconstruction algorithms

Spectrum

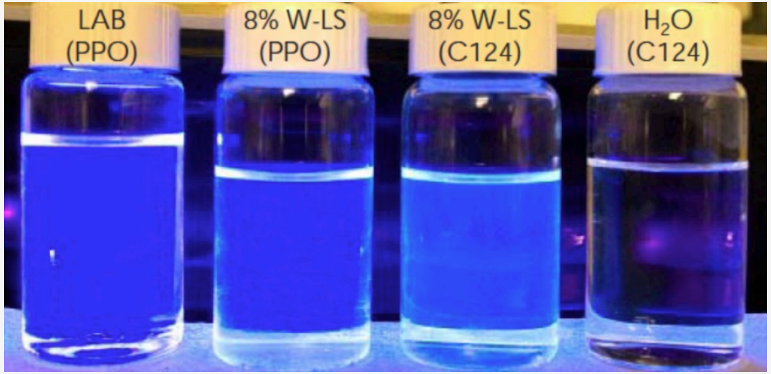




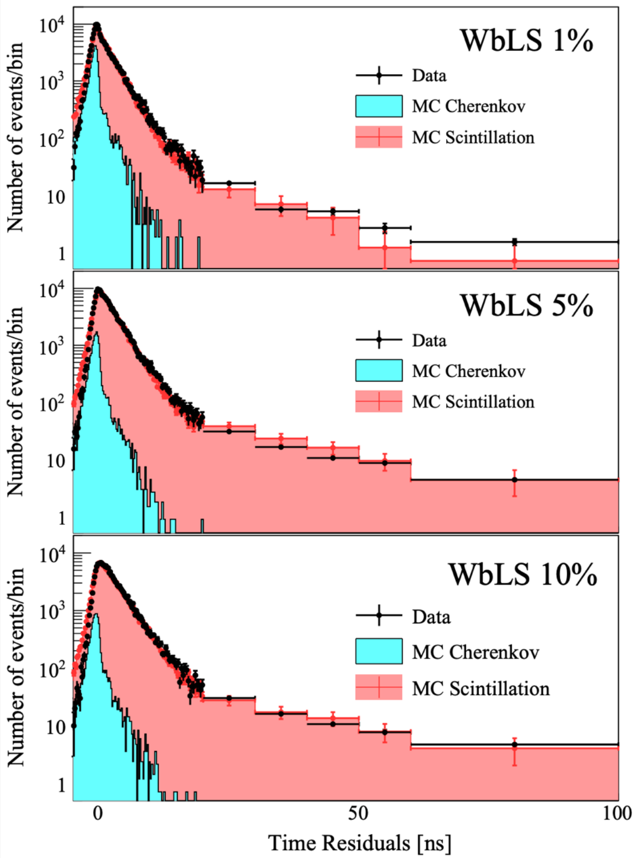
Dichroic filters

Target Materials

- Testing a variety of scintillator cocktails
- 1% Water-Based Liquid Scintillator (WbLS) used in this study



J. Caravaca, et. al., 2020



Optical Parameters and Calibration Sources

1. Absorption (Abs) length in meters
2. Scattering (RS) length in meters
3. Light yield (LY) in photons/MeV

Scattering, absorption uniformly scaled across wavelength, reported @ 500, 370 nm

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Laserball

Isotropic light using 515 nm laser

Sensitive to scattering

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Thorium

2.6 MeV gamma rays from thoriated tungsten rods

Sensitive to:
Light yield
Scattering
Absorption

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Isotropic light using 515 nm laser

Sensitive to Scattering

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2.6 MeV gamma rays from thoriated tungsten rods

Sensitive to:
Light yield
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Cherenkov

^{90}Sr button source in a UVT acrylic
2.28 MeV electron

Sensitive to:
Scattering
Absorption

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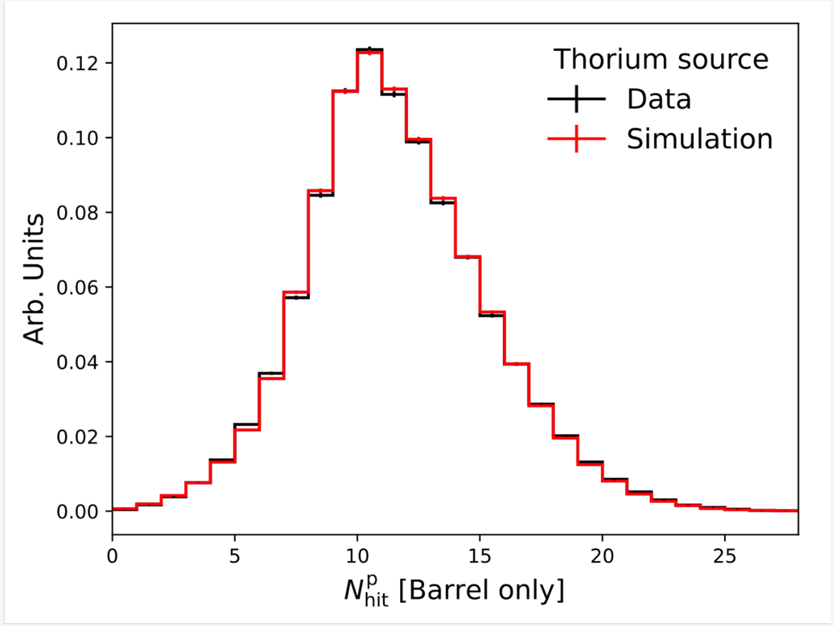
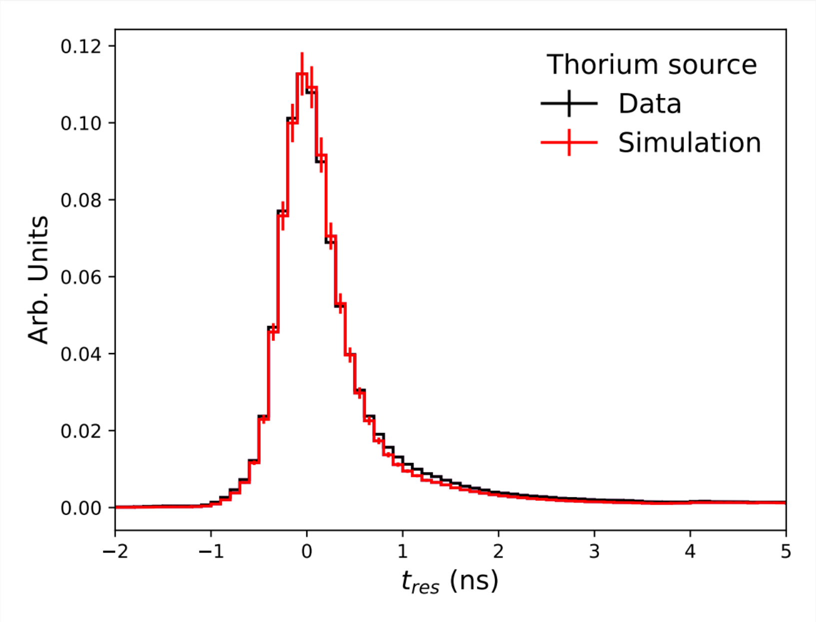
Simulation/Data Comparison in Water

Good agreement, main uncertainty in monte carlo is scintillator optical parameters



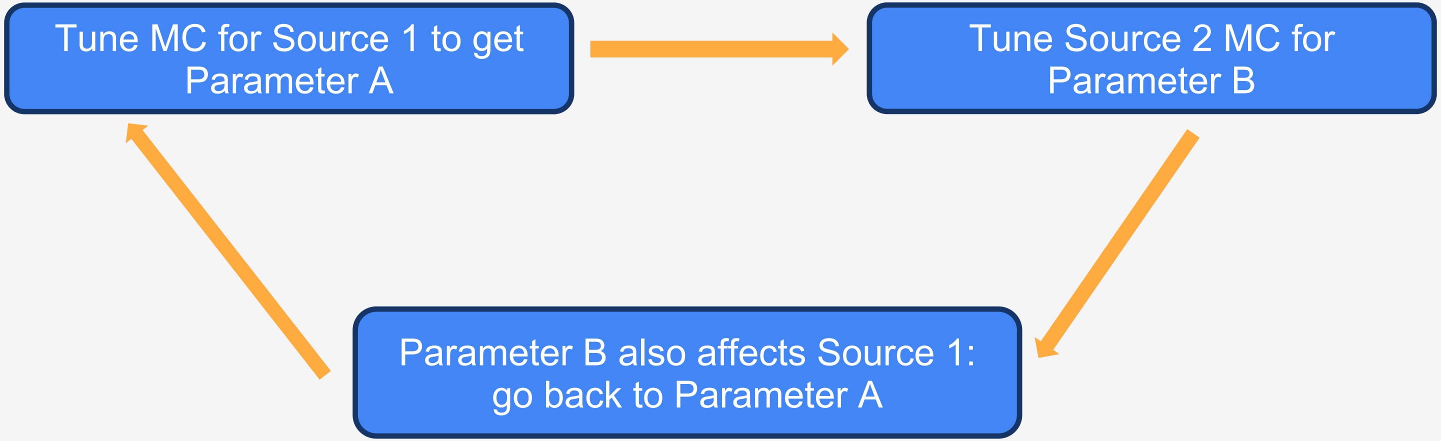


S. Arora et al (arXiv:2606.10234)

Traditional Approach

Manually tune monte carlo simulations to match the data

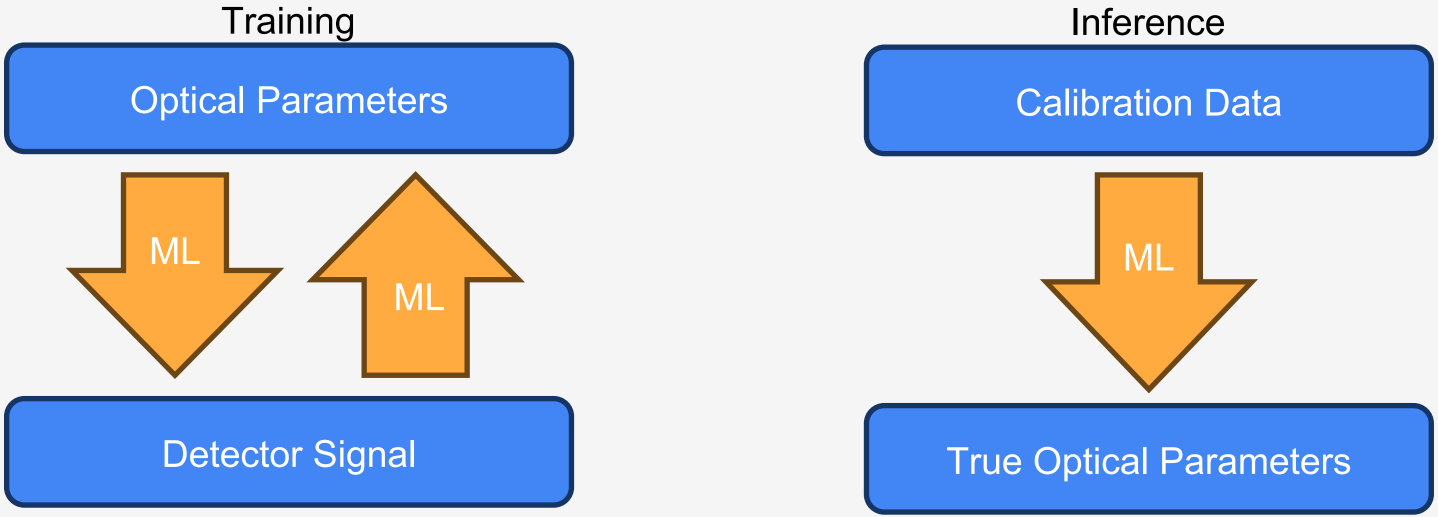
Slow, does not handle correlations well, and imprecise



Simulation-Based Inference

Train ML model on simulations to learn relationship between optical parameters and signal

Apply model to data to extract true optical parameters



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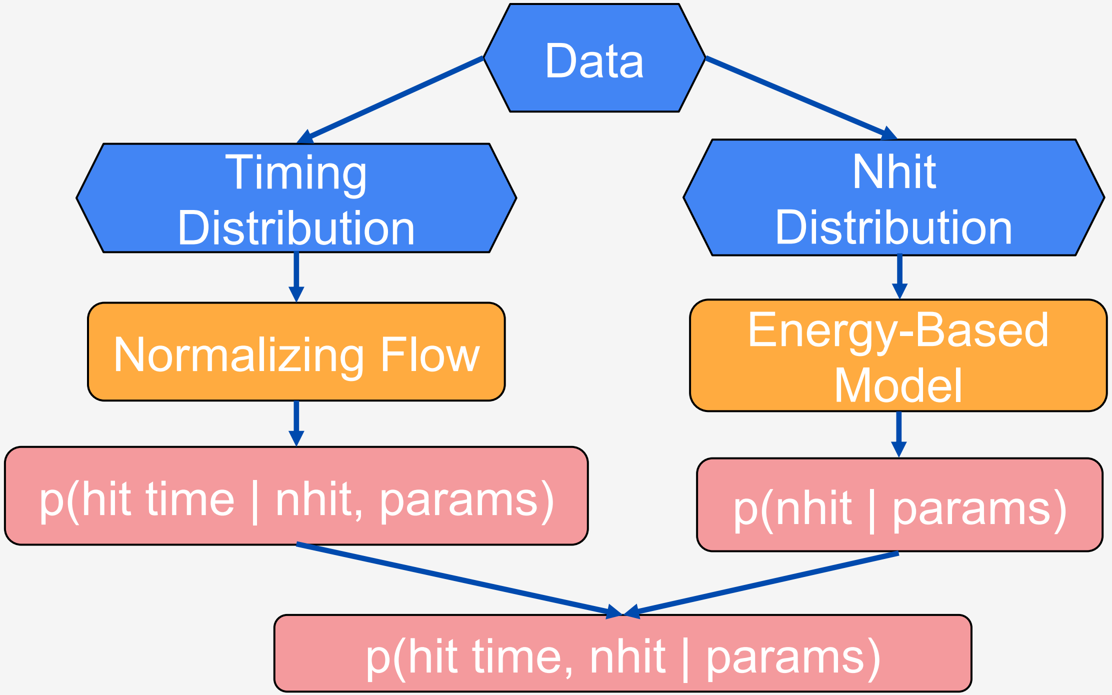
Two Signals: Nhit (discrete) and Hit Time (continuous)

Best modeled by two separate ML algorithms



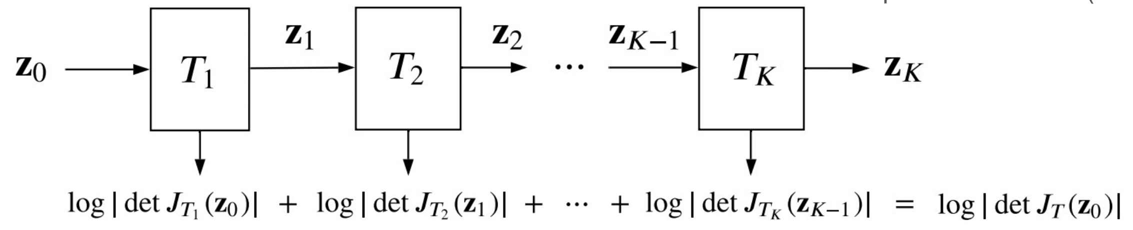
$$\ln \mathcal{L}(\text{params}) = \sum_{i=1}^{N} \left[\ln p(\, n_{\text{hit},i} \mid \text{params}\,) + \ln p(\, \{t_{\text{hit}}\}_i \mid n_{\text{hit},i}, \text{params}\,) \right]$$

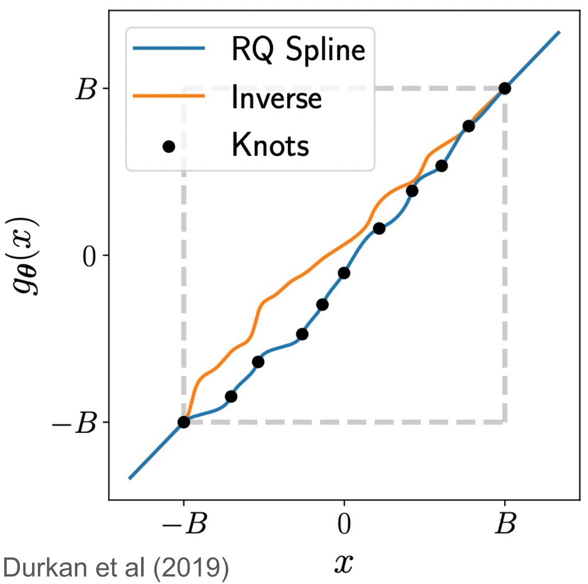
Hit Time Likelihood: Normalizing Flow

Start with a simple distribution

Apply a series of invertible conditional transformations to model the likelihood

Papamakarios et al (2021)





Durkan et al (2019)

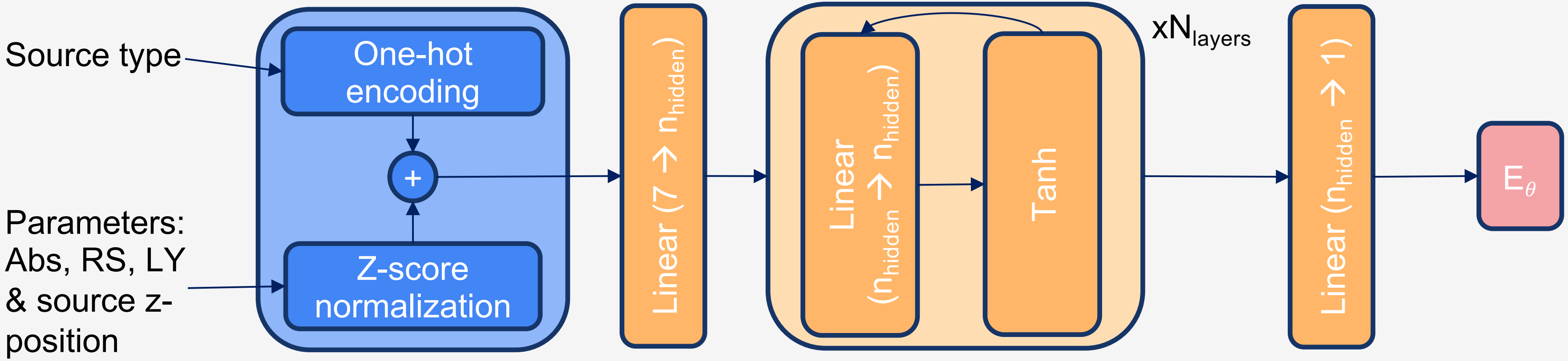
Hyperparameters (using nflows library):

16 blocks, 4 layers, 256 hidden dim

Nhit Likelihood: Energy-Based Model (EBM)

Model probability with softmax; normalization is simple sum since nhit is discrete

$$p_\theta(\,\mathrm{nhit} = k \mid \mathrm{params}\,) = \frac{\exp\big(E_\theta(k, \mathrm{params})\big)}{\sum_j^{\mathrm{max\ nhit}} \exp\big(E_\theta(j, \mathrm{params})\big)}$$



Hyperparameters: 256 hidden dim, 3 layers

Training

3 sources: Laserball, Thorium (central and at top of detector), Cherenkov
3 Optical Parameters: Abslength scaling, Rslength scaling, Light Yield

10 x 10 x 10 grid (constrained by eye to broadly encompass data):

- 200 - 400 photons/MeV in light yield
- 3 – 8m @ 370nm in absorption length
- 3 – 8.25m @ 500nm in scattering length

Training Flow and EBM separately: log likelihood loss, cosine LR scheduler, Adam optimizer

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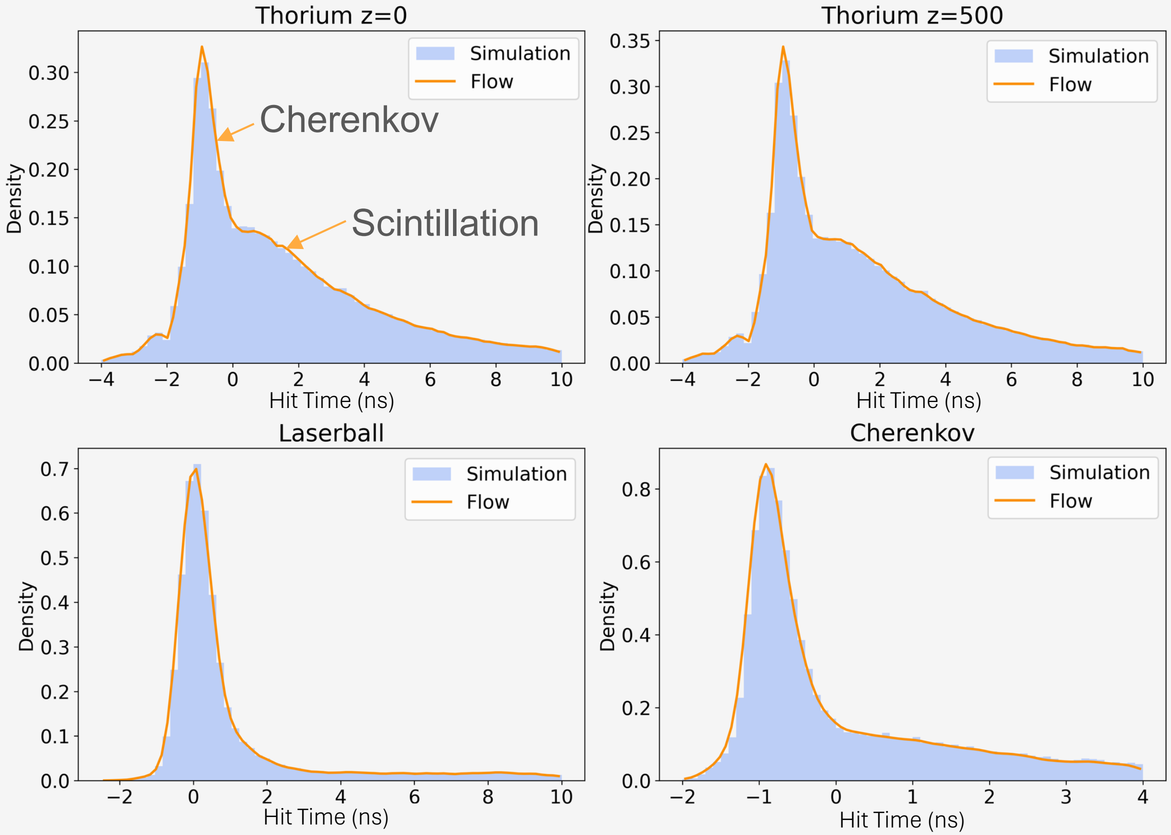
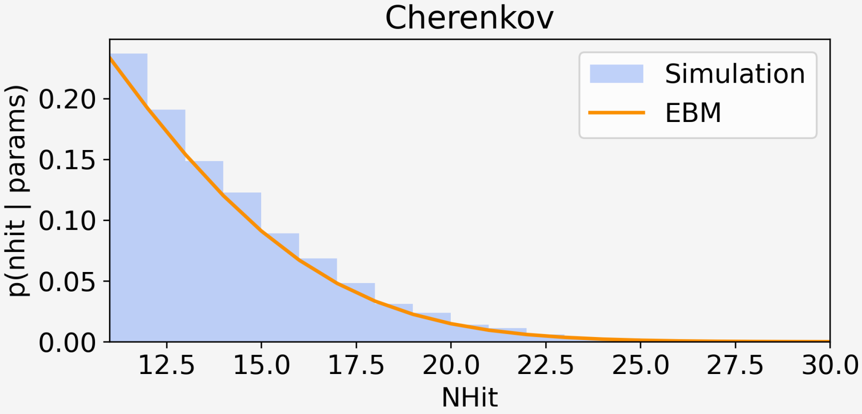
Hit Time Likelihoods Reconstructed with Normalizing Flow

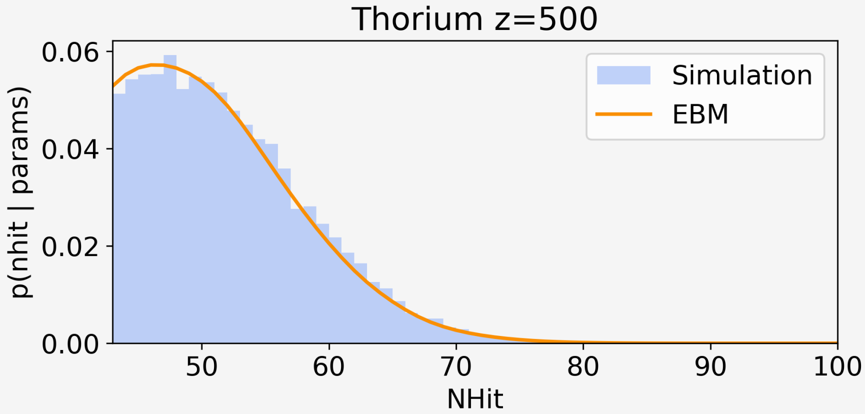
- One model can condition on source type very well
- Features are captured well in all cases

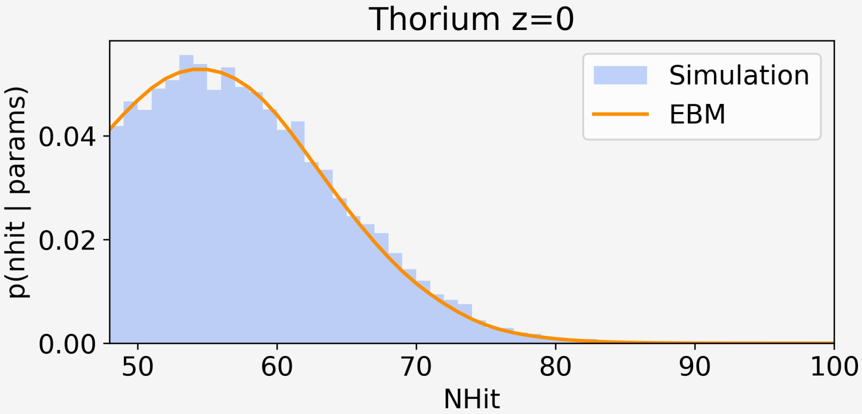


Nhit Likelihoods Reconstructed with EBM

- EBM conditions well on source type and z position
- Features are well captured by relatively simple model

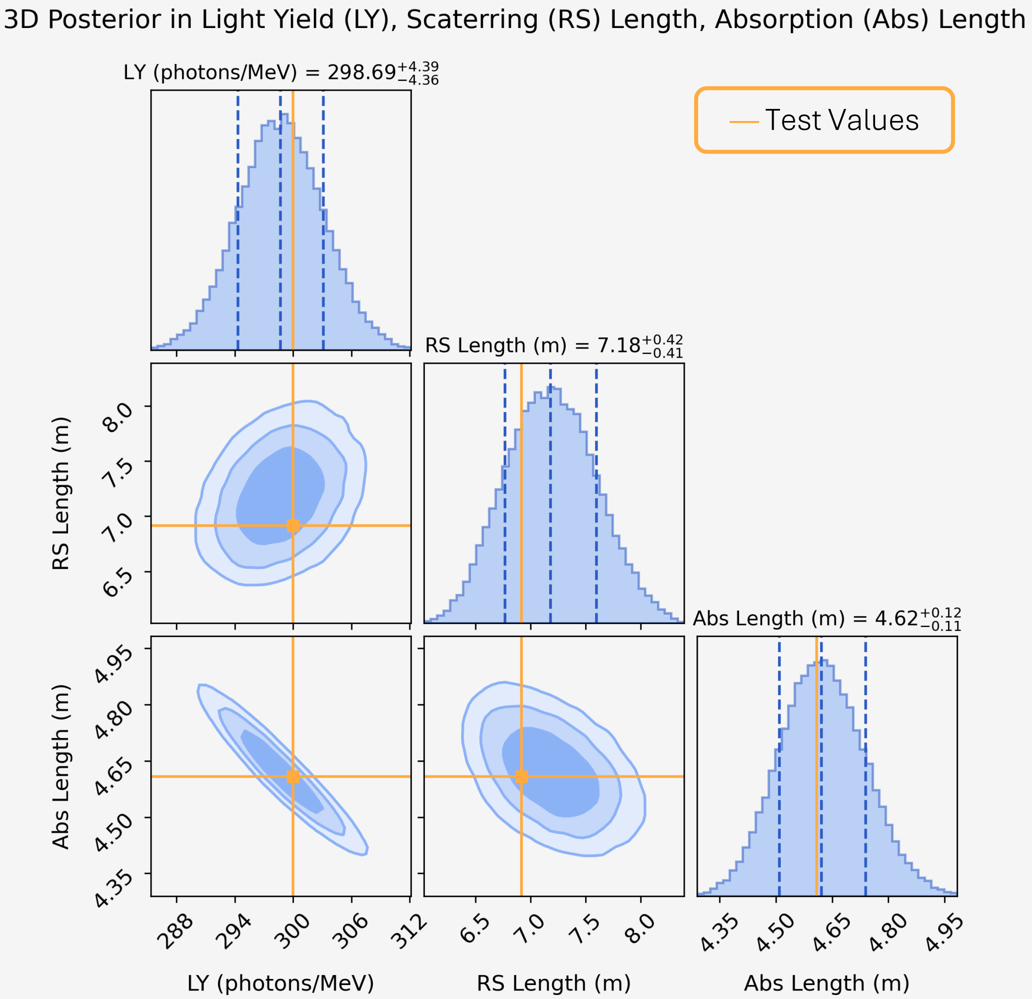






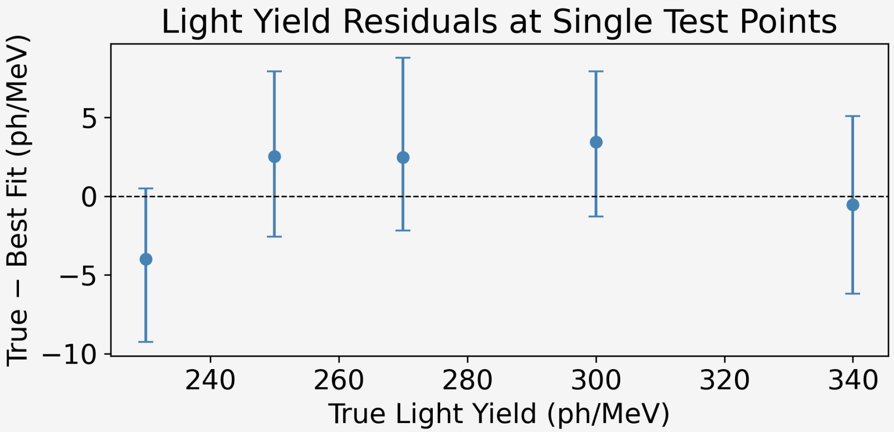
3D Posterior Results

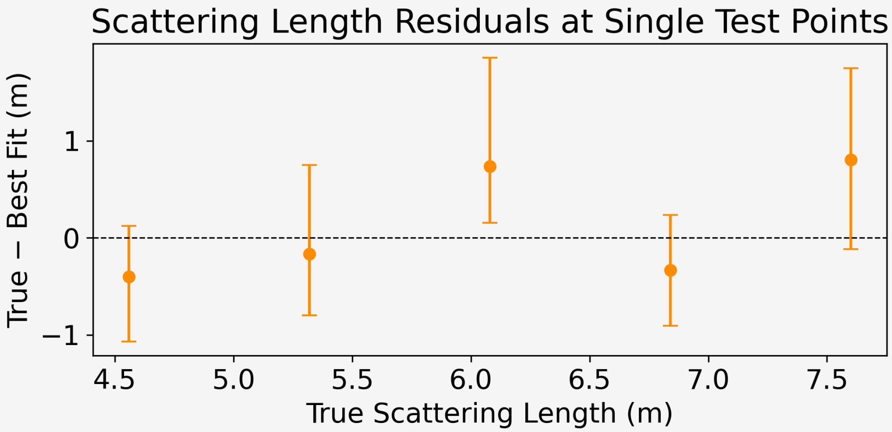
- 10,000 test events for each source
- True parameters estimated well
- Posterior captures LY-abs correlation

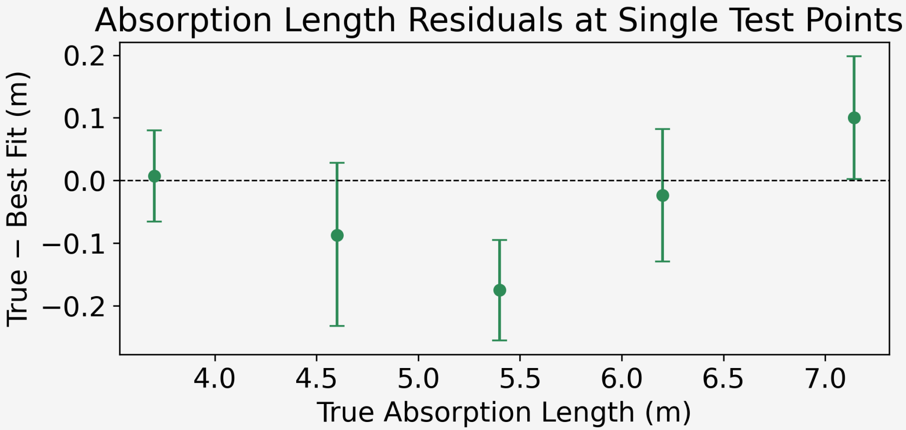


Single Test Points with Posterior Widths

- For most points, true value lies within 1σ range
- Run more trials per-point to determine systematic uncertainty from ML model







Summary

- Constraining 3 optical parameters with 3 calibration sources using 2 detector observables
- Good constraints within 1σ at nearly all test points

Future Work

- Perform full study on systematic uncertainty and bias
- Introduce more optical parameters: re-emission, Birks' coefficient
- Perform full study on data for optical model calibration

Acknowledgements

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