Machine Learning Applications to Reactor Antineutrino Detection with PROSPECT

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On behalf of the PROSPECT collaboration

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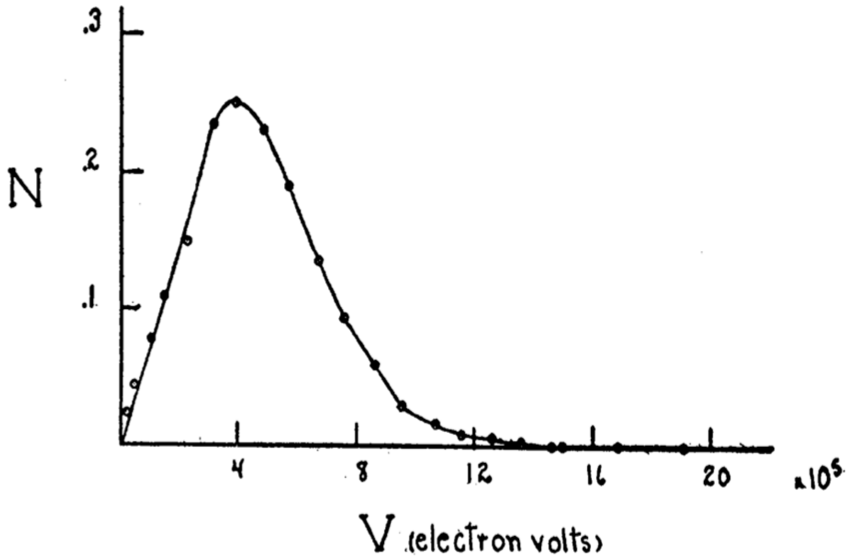
Outline

- Neutrino physics at reactors
- Overview of PROSPECT experiment
- Machine learning projects
- Ortho-Positronium tagging study
- Summary and future work

1930: Neutrino existence is proposed

Beta Decay Spectrum



Scott, F. A. Phys. Rev. 48.5 (1935): 391.

Particle properties:

- no electric charge
- spin 1/2 fermion
- massless or tiny
- Fermi's "weak" interaction

"I have done a terrible thing, I have postulated a particle that cannot be detected."

Reactor Neutrino Physics

- Nuclear reactors are the largest human-made source of neutrinos
- First neutrino detection took place at a reactor antineutrino experiment.
- First observation of a non-zero θ_{13} mixing angle

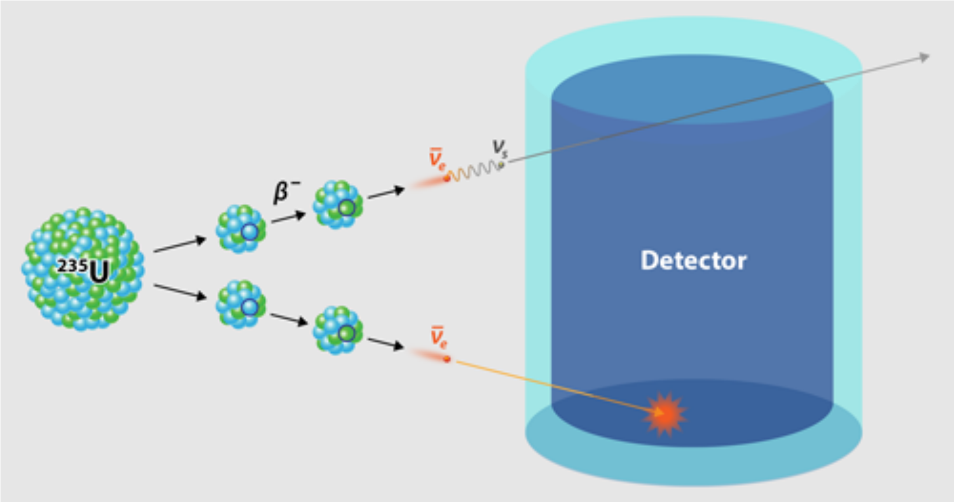
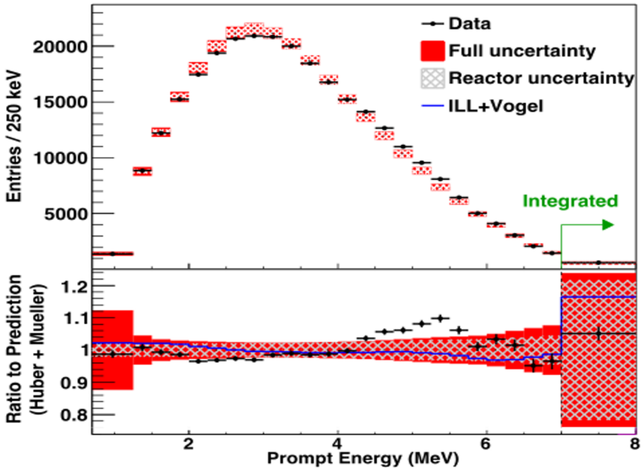


Image source: https://physics.aps.org/articles/v10/66

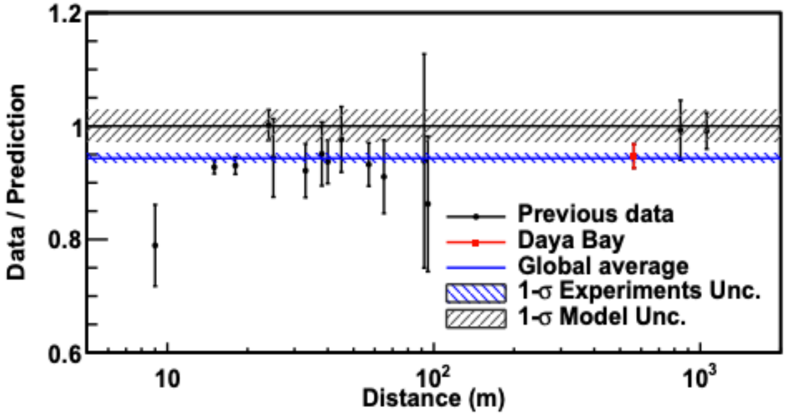
Reactor Antineutrino Anomaly, a motivation for PROSPECT

- Short-baseline reactor experiments have reported a deficit of the measured antineutrino rate when compared to theoretical predictions

Antineutrino anomaly bump in 4-6 MeV

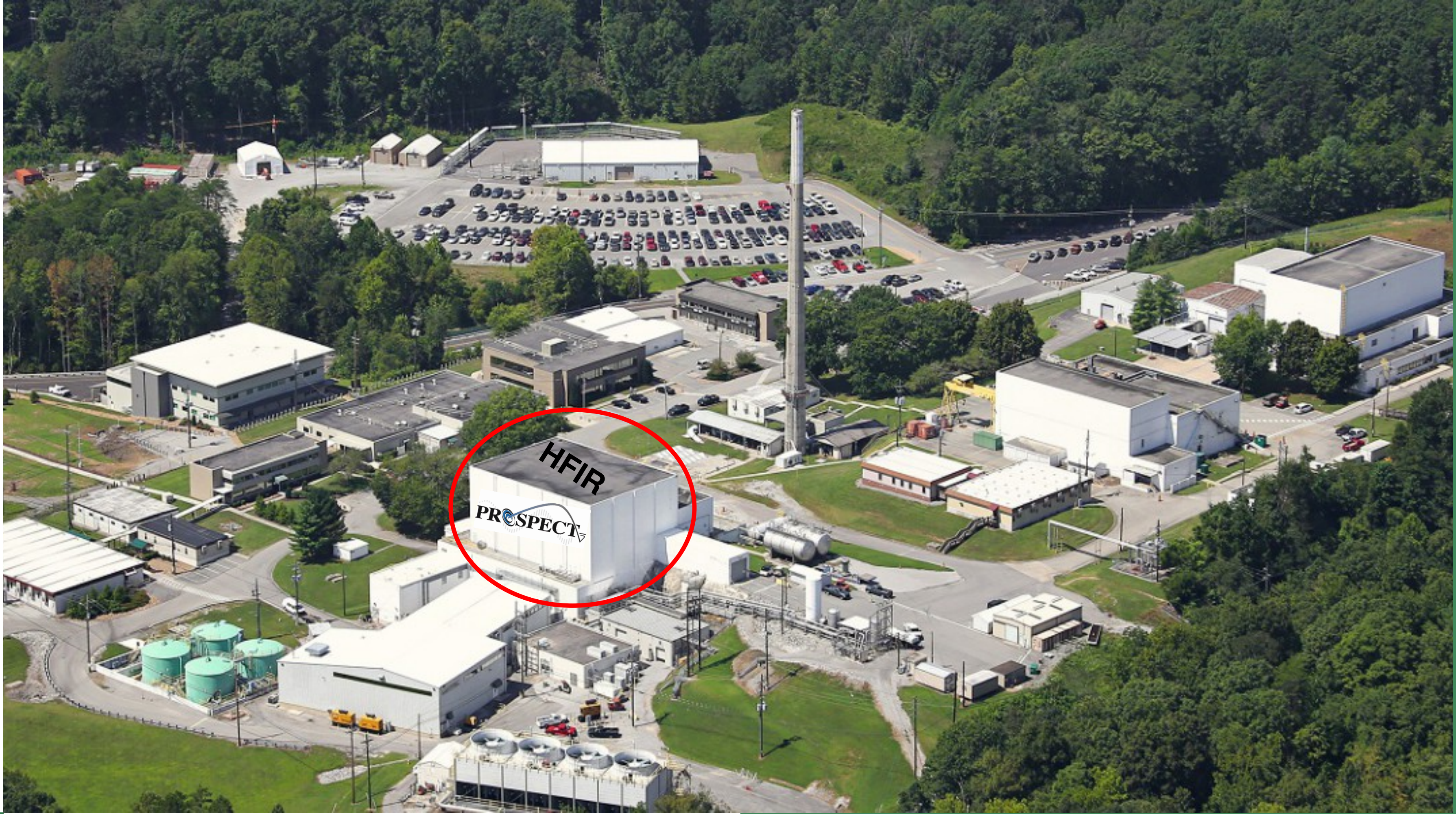


Observed flux deficit of about 6%



Feng Peng An et al. Measurement of the Reactor Antineutrino Flux and Spectrum at Daya Bay. Phys. Rev. Lett., 116(6):061801, 2016, 1508.04233.

Image source: https://neutrons.ornl.gov/hfir



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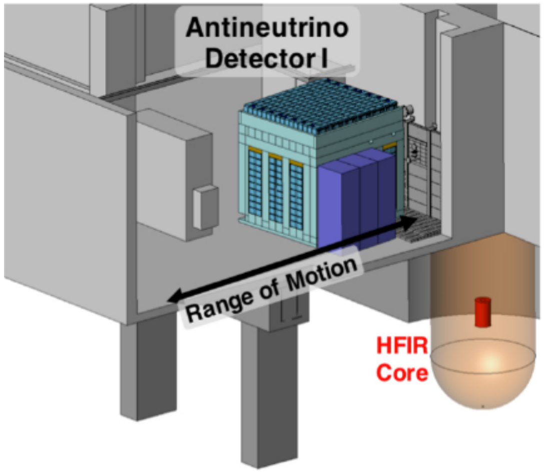
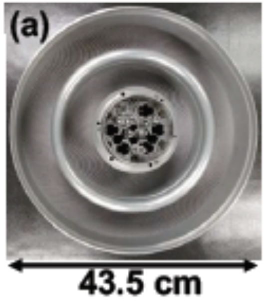
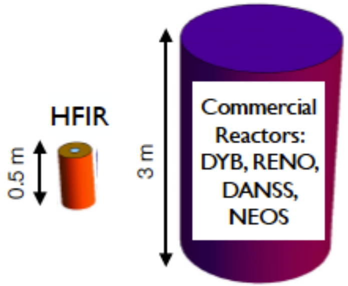
PROSPECT Detector at HFIR

Layout of the PROSPECT experiment

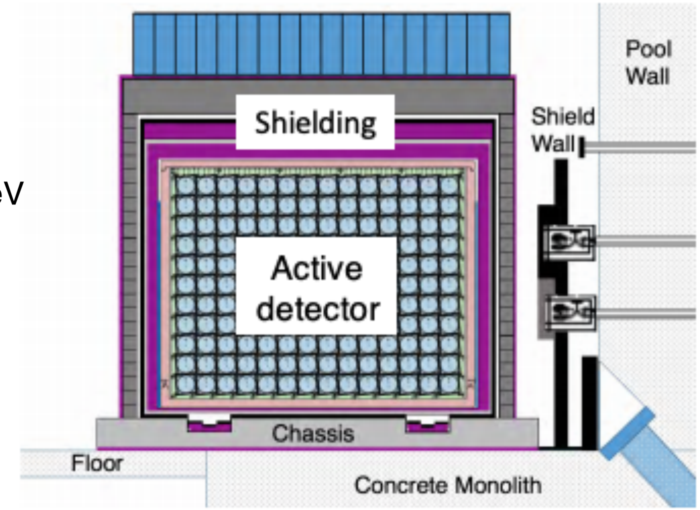


- 93% ^{235}U Fuel
- 85 MW thermal power
- Compact core
- Huge flux in the few MeV range





Schematic of the active detector volume

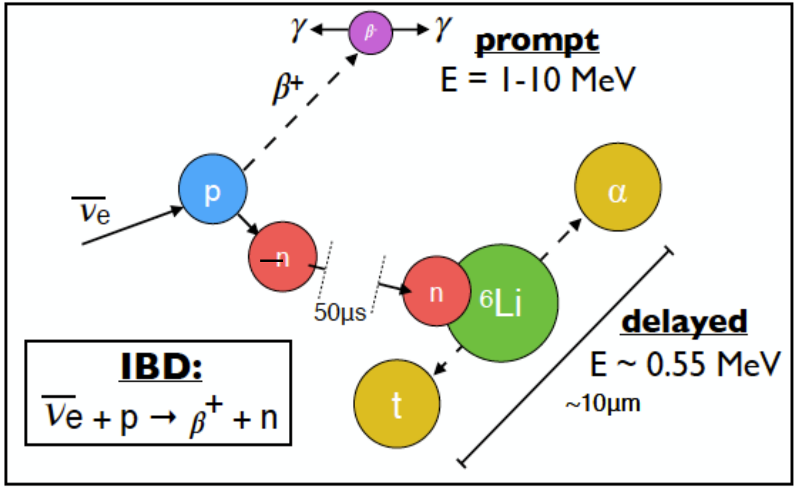


- 14 x 11 array of 6Li doped liquid scintillator for detecting reactor antineutrinos (6.7-9.2 m from compact highly enriched uranium reactor core)

J. Ashenfelter et al. (PROSPECT), Nucl. Inst. Meth. A 922, 287(2019).

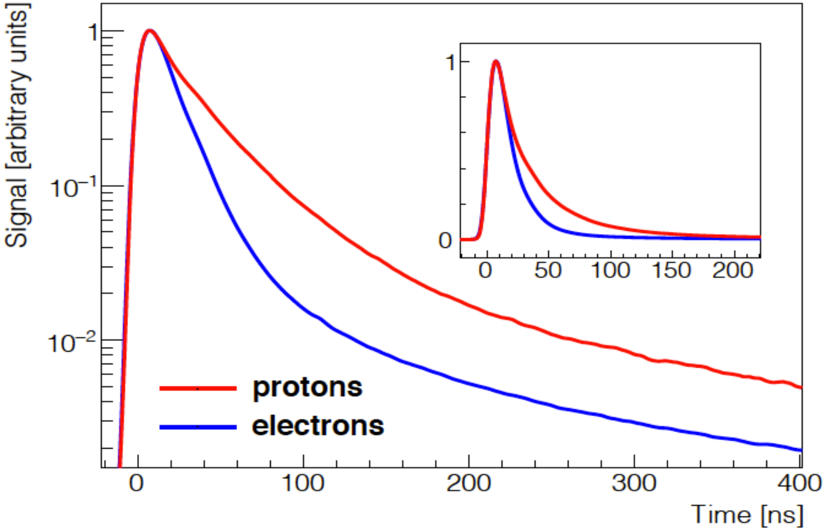
Antineutrino Detection

Schematic of IBD interaction in 6LiLS



- PROSPECT detects antineutrinos via the Inverse Beta Decay (IBD) process
- Prompt signal (e^+) provides a good energy estimate of incoming ν
- Localized delayed (n - ^6Li) signal

Average waveforms for electronic/nuclear recoil type events

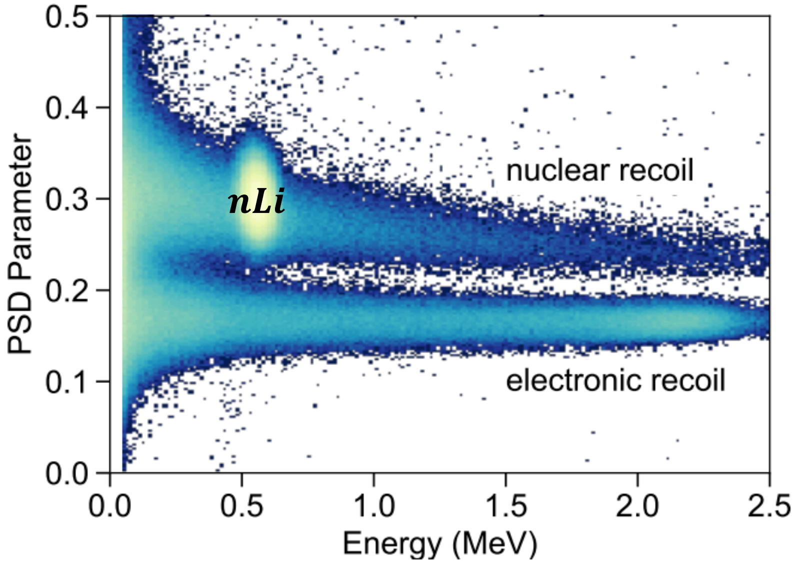


- Differences in ionization density between electronic/nuclear recoil type events result in distinct pulse shapes for each event
- Prompt and delayed signal posses unique pulse shapes (different from background events)

PROSPECT Collaboration, arXiv:2006.11210 (2020)

Antineutrino Event Reconstruction

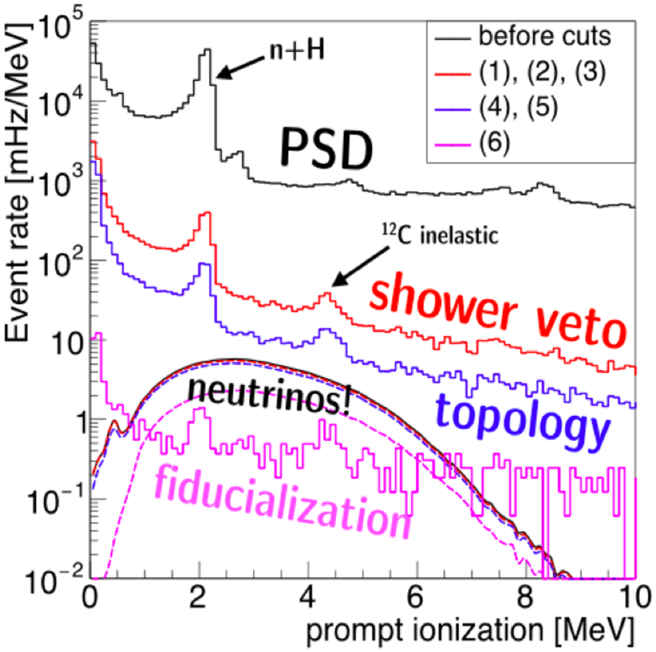
Prompt energy/PSD distribution for IBD-like events



- PSD-energy correlation is used to discriminate between prompt and delayed signal events

J. Ashenfelter et al. (PROSPECT), JINST 13, P06023 (2018).

IBD selection cuts (Simulation)

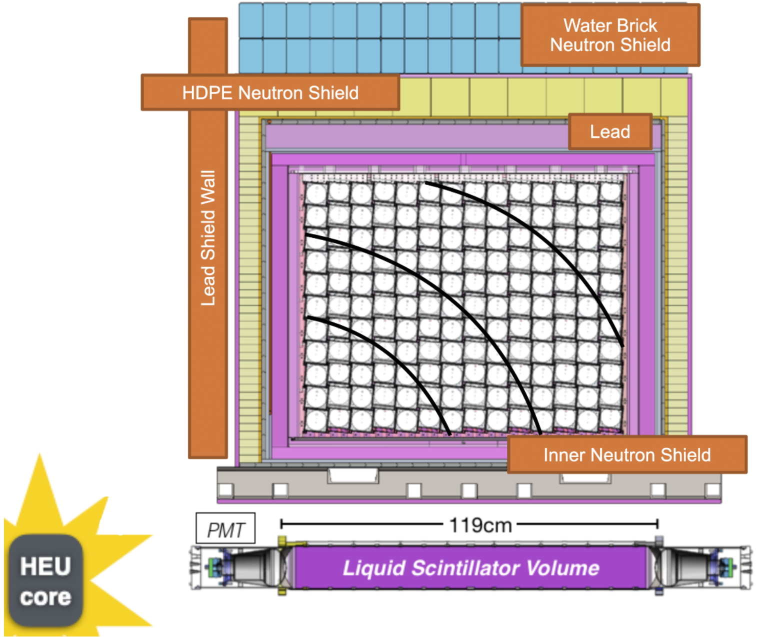


- Background reduction after sequential application of IBD selection cuts

J. Ashenfelter et al., (PROSPECT collaboration), The PROSPECT physics program, J. Phys. G 43 (2016) 113001.

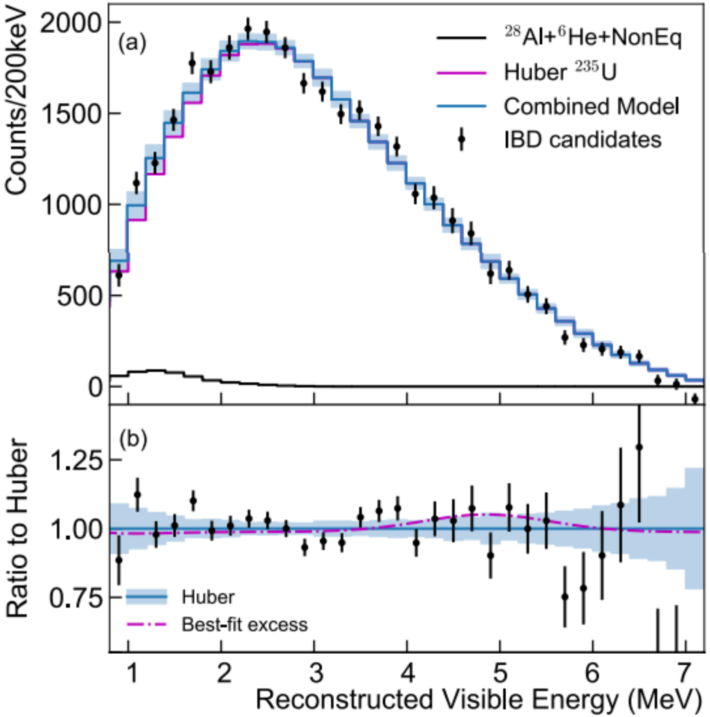
PROSPECT-FIRST Results

First search for short-baseline neutrino oscillations at HFIR with PROSPECT



J. Ashenfelter et al. (PROSPECT), Phys. Rev. Lett. 121, 251802 (2018).

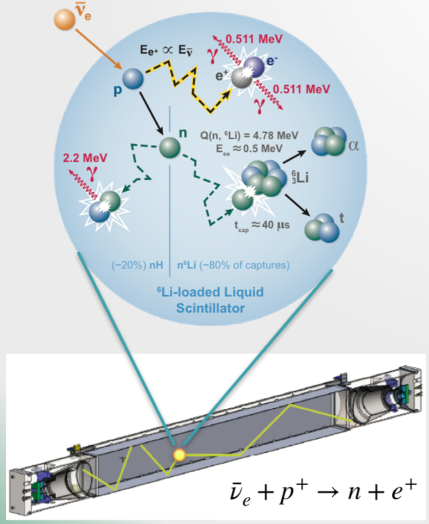
Measurement of the Antineutrino Spectrum from 235U Fission at HFIR with PROSPECT



J. Ashenfelter et al. (PROSPECT), Phys. Rev. Lett. 122, 251801 (2019).

Machine Learning Applications at PROSPECT

Goal: Improving antineutrino event reconstruction by using ML techniques.



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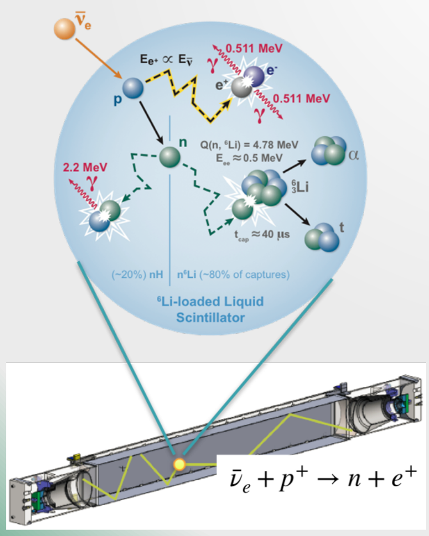
Machine Learning Applications at PROSPECT

Single PMT Event Reconstruction (ML Project 1)

- **ML techniques** to maintain/improve **particle-ID** performance regardless of evolving detector conditions (single/double ended PMT readout).
- **Supervised ML** model trained on simulation and validated on experimental data.
- Improvement on cosmogenic background reduction.



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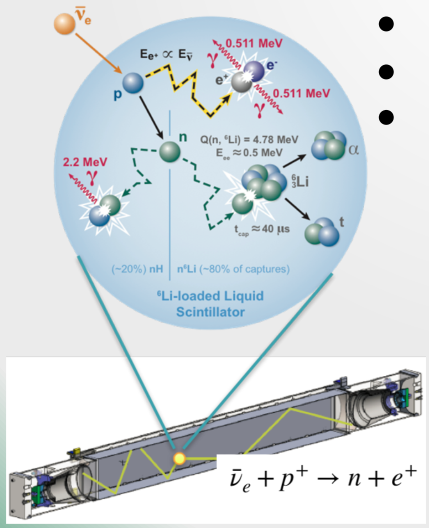
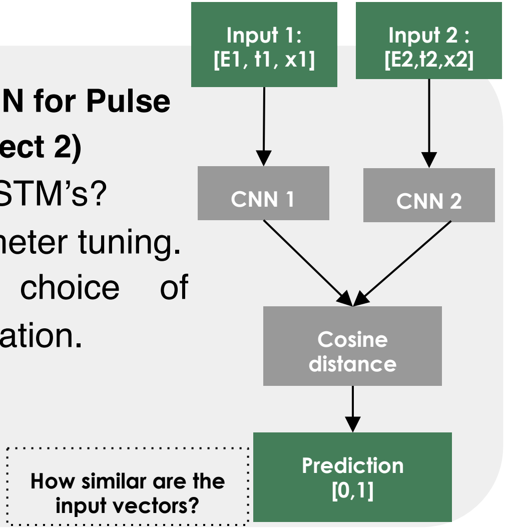


Siamese LSTM/CNN for Pulse Matching (ML Project 2)

- CNN's vs LSTM's?
- Hyperparameter tuning.
- Optimizing choice of input information.



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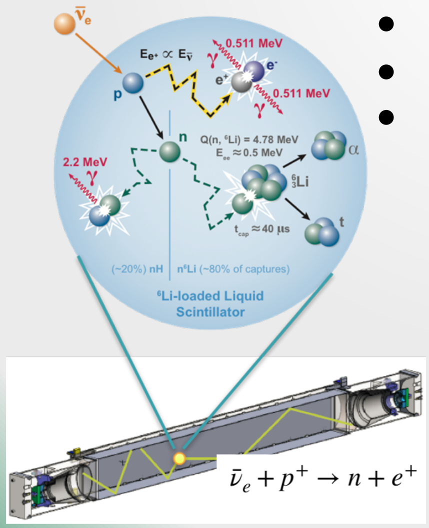

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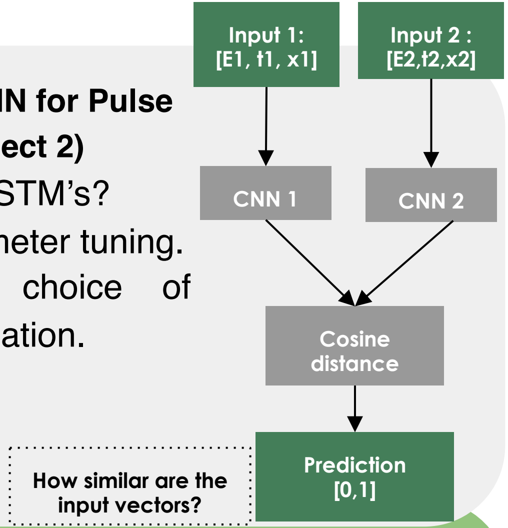

MVA Analysis for Background Suppression (ML Project 3)

- Train model in MC only.
- Study impact of using discriminant on energy spectrum.

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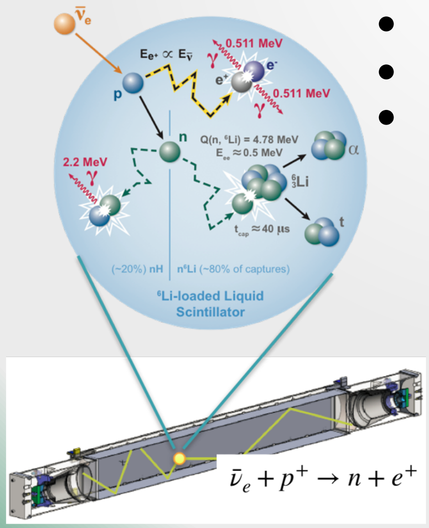

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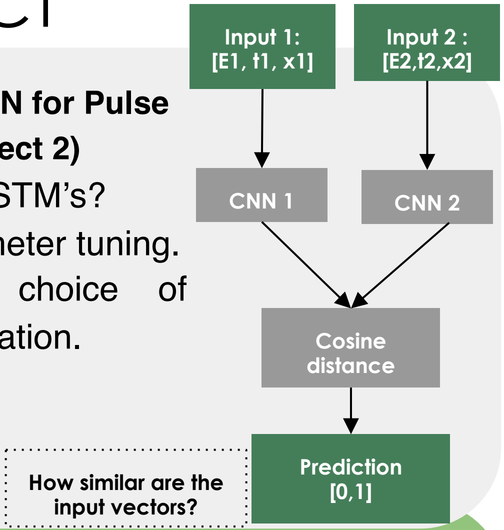

Positron ID through ortho-positronium tagging (ML Project 4)

- Attempting to perform **Particle-ID** at waveform level.
- **NN** to learn distortion in timing distribution of pulses caused by **o-Ps formation**.
- Great impact on background suppression!

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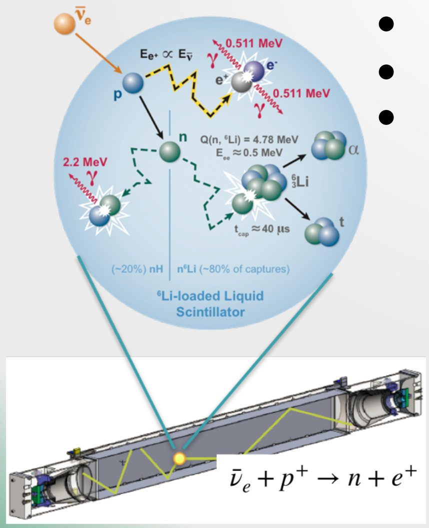

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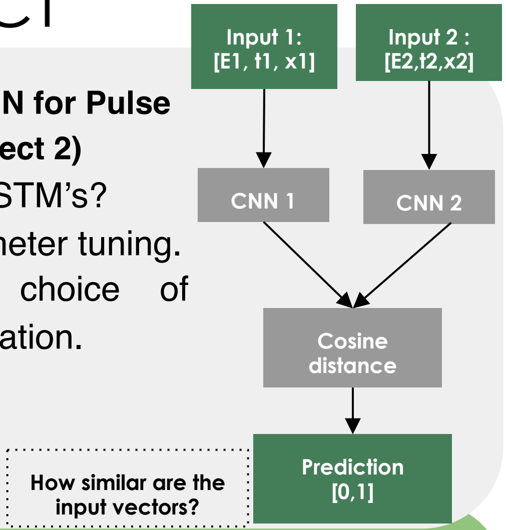

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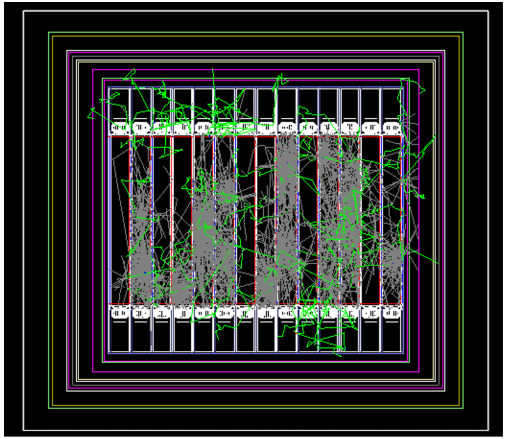
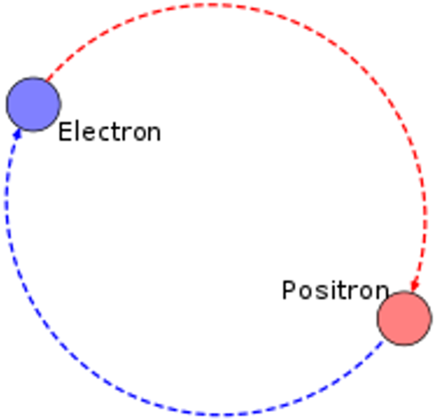
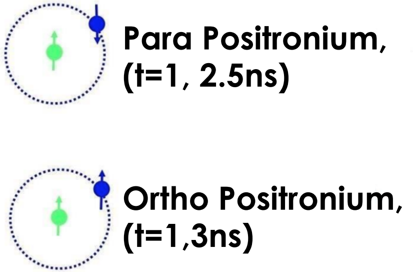
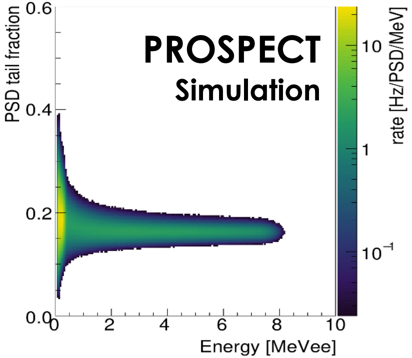
Positron ID through o-Ps tagging

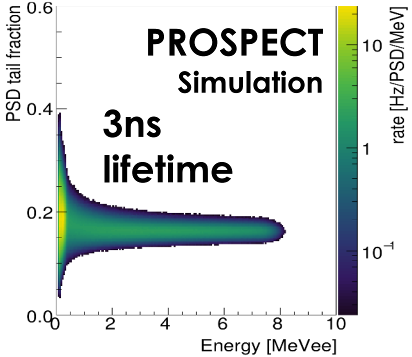
- Can we ID a subset of **positrons** though positronium formation?
- If the distortion in the **timing distribution** induced by **o-Ps** is not smeared by optical effects, we can use this feature as an extra handle for particle ID (P-ID).
- Initial simulations indicate that we are not sensitive to a 3ns OPs lifetime









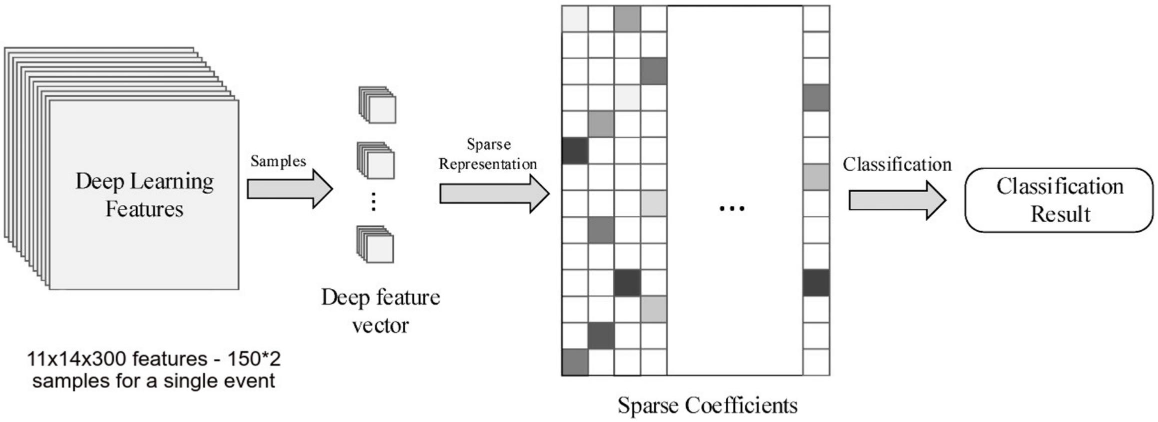


ML Techniques

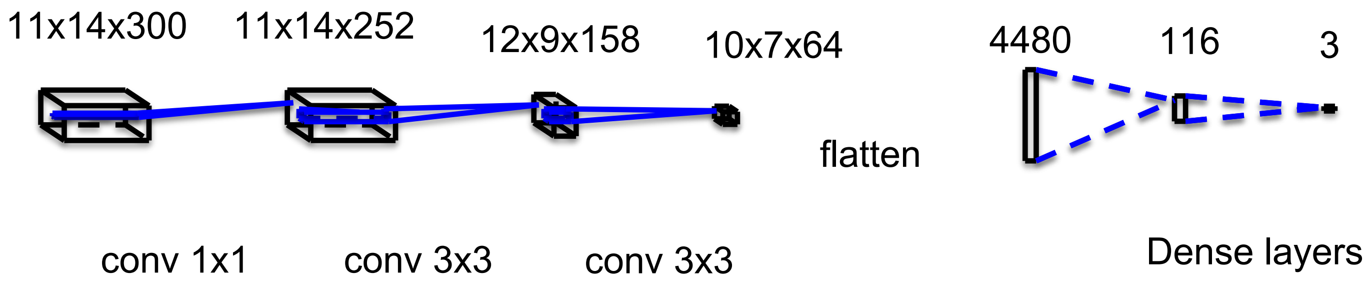
- Sparse convolutional neural networks are used to identify patterns in the energy deposition of various particles for particle discrimination
- PyTorch Lightning ML framework used for quick start to scalable multithreaded / GPU friendly code
- Spconv sparse convolutional library for pytorch
- Simulated gammas, electrons, positrons between 0-9 MeV randomly distributed within the detector

Particle Classification ML Architecture

- Sparse CNN -> linear



11x14x300 features - 150*2 samples for a single event



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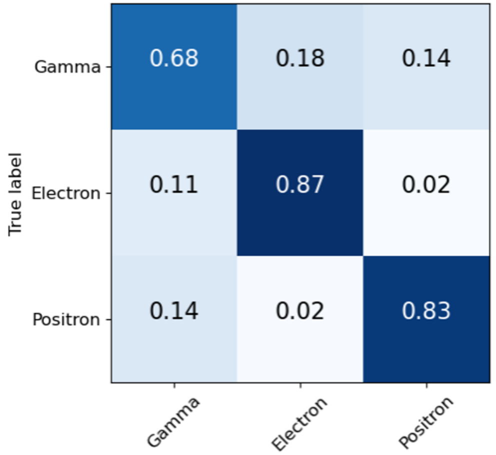
Best Trial Results

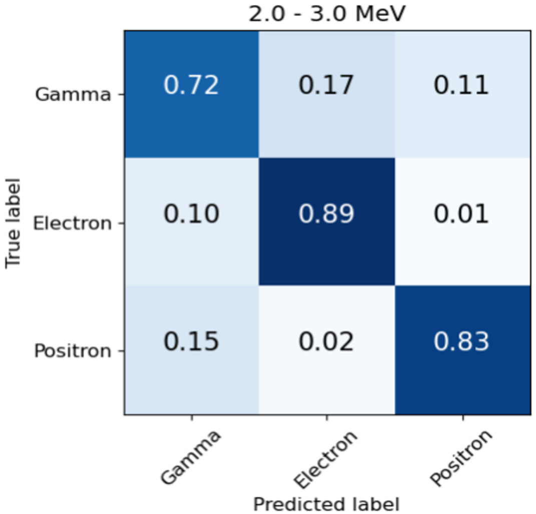
Full Energy Range

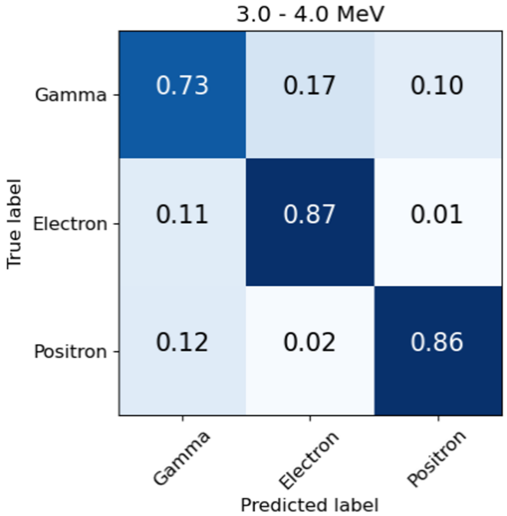


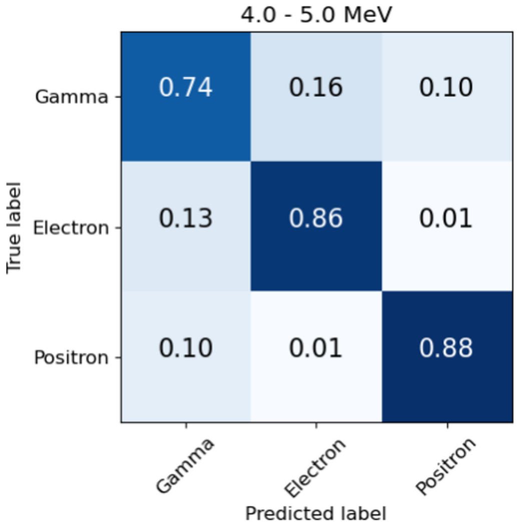
Best trial found after hyperparameter optimization (~ 100 trials)

Used Optuna optimization framework
Hyperparameters tuned:

- number of convolutional layers
- number of linear layers
- number of output feature planes
- kernel size







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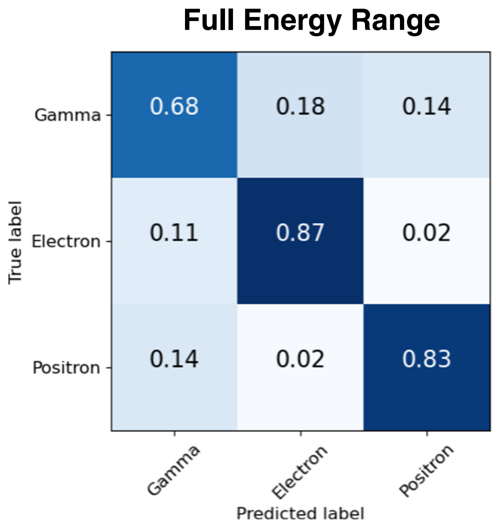

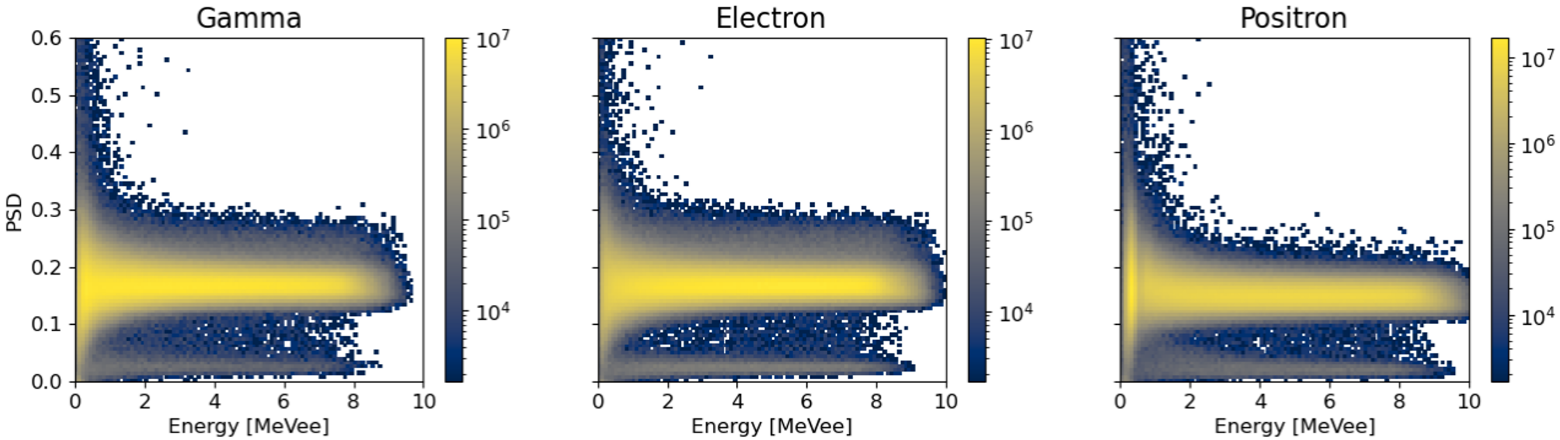

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Summary and Future work

- First application of machine learning methods to PROSPECT data
- Positrons within PROSPECT can be distinguished from gammas and electrons with up to 80% accuracy using sparse CNNs based on simulated waveform data
  - More work needs to be done to understand the physical signatures and if it is learning artifacts in the simulation
- This new method for positron ID could be incorporated into the existing analysis in order to improve background suppression
- Future work:
  - Try training on / classification of real pulse data from calibration runs
  - Incorporate sparse CNN information into classification of IBD candidates
  - Improve classification by utilizing image segmentation to identify different particles within a single event
  - Improve light simulation for more realistic simulated pulses

PROSPECT

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  (ML Project 4)
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  (ML Project 4)
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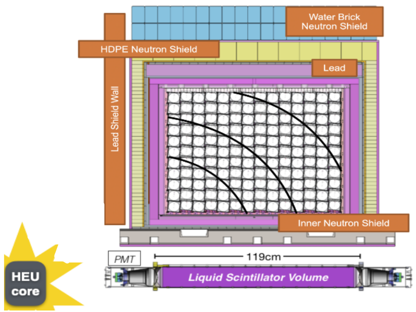
- **Adriana Ghiozzi**
  - ghiozziag@ornl.gov

Sterile Neutrino Oscillation

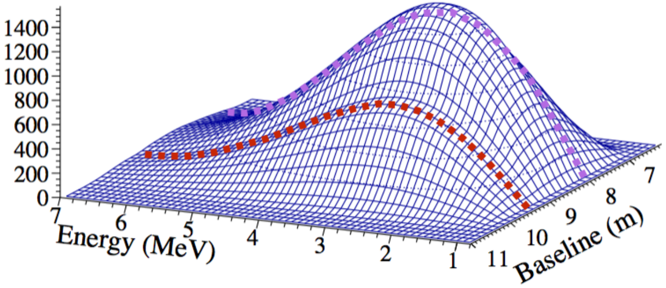
Relative Spectrum Measurement

relative measurement of L/E and spectral shape distortions

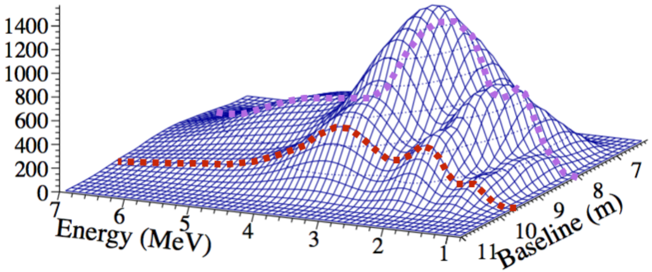
$$P_{\text{dis}} = \sin^2 2\theta \sin^2\left(1.27\Delta m^2(\text{eV}^2)\frac{L(\text{m})}{E_\nu(\text{MeV})}\right)$$



unoscillated spectrum



oscillated spectrum

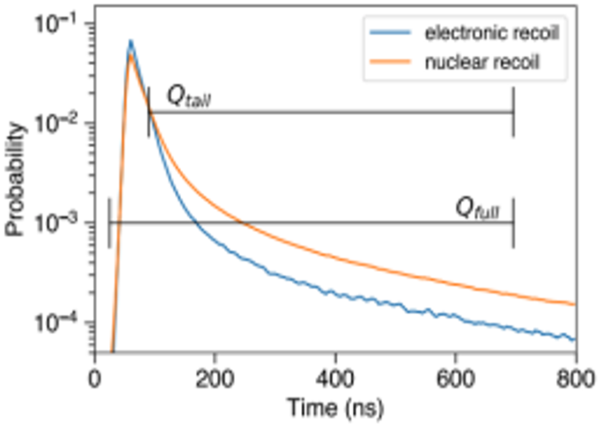


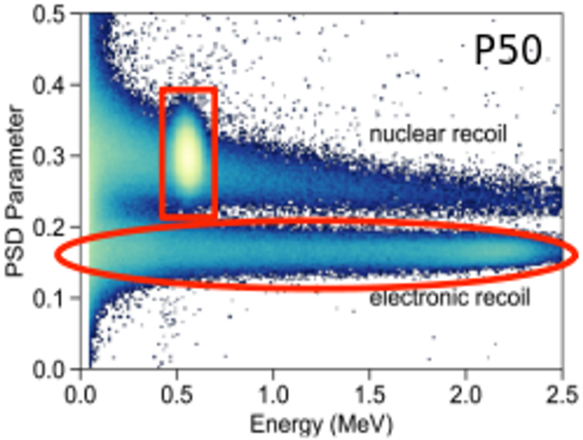
Simulations

Reactor Antineutrino Anomaly

- What is the nature of the bump?
  - Is it an incorrect modeling of the fission products?
  - Are all of them responsible or only one?
  - A. Hayes, J. Friar, G. Garvey, D. Ibeling, G. Jungman,T. Kawano, and R. Mills, Phys. Rev. D 92, 033015 (2015).
  - Y. Gebre, B. Littlejohn, and P. Surukuchi, Phys. Rev. D 97, 013003 (2018).
- Total absorption spectrometry has been used in order to investigate both the flux deficit and the bump.
  - M. Wolińska-Cichocka,K.Rykaczewski,A.Fijałkowska,M.Karny,R.Grzywacz,C.Gross,J. Johnson, B. Rasco, E. Zganjar, Nuclear Data Sheets 120 (2013) 22, ISSN 0090-3752,URL⟨http://www.sciencedirect.com/science/article/pii/S0090375214004487⟩

PSD Parameter





- Q_{Tail} = integrated charge from 40 ns to 120 ns after the leading-edge half-height
- Q_{Full} = *integrated charge 12 ns before to 120 ns after of* the leading-edge half-height
- $PSD = \frac{Q_{Tail}}{Q_{Full}}$

IBD Cut selection Description

- **Time topology cuts**:
  - (1) Delayed capture must occur within 100 μs of the prompt ionization
  - (2) Multiple hits in the prompt cluster must occur within 5 ns to reject slower-moving neutron recoil events
  - (3) Events must be isolated from other neutron recoils or captures in a ±250 μ window, to reject multi-neutron spallation showers
- **Spatial topology cuts**:
  - (4) The prompt and delayed signals must occur close to each other
  - (5) Multiple segment hits in the prompt signal must be distributed over a compact volume
  - (6) Events occurring outside the inner fiducial volume are vetoed

Simulated distributions