Machine Learning for Event Reconstruction in the PROSPECT Detector

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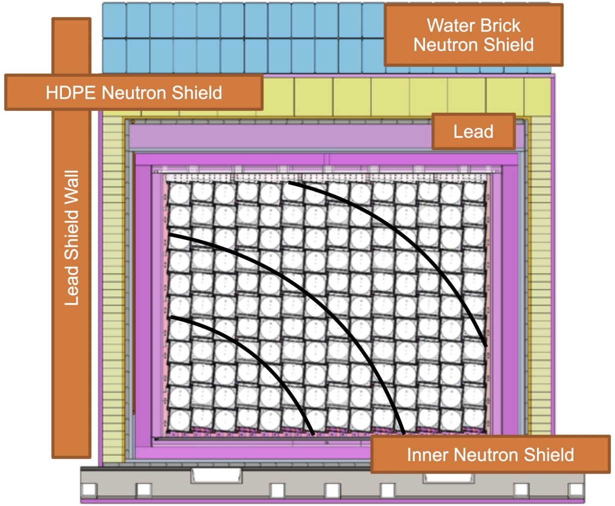
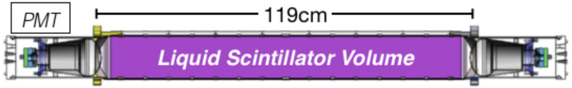
PROSPECT Overview

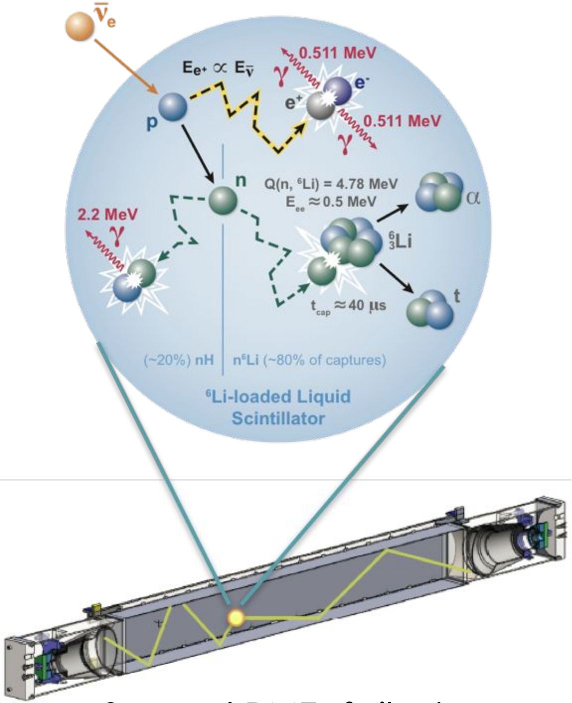
PROSPECT took data at ORNL's High Flux Isotope Reactor from 2018-2019. It is a highly enriched uranium reactor with a compact core





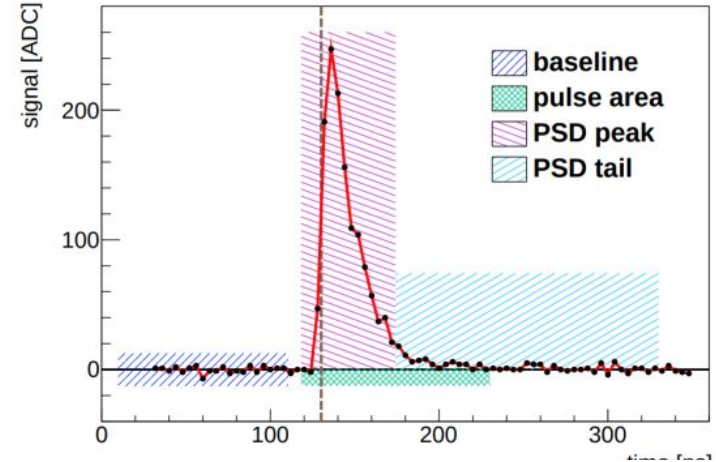
Photomultiplier tubes (PMT) on each end of a segment

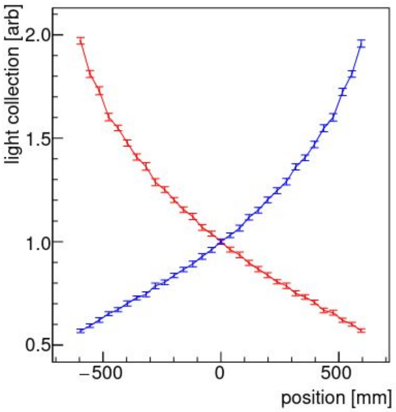
14 x 11 array of 6Li doped liquid scintillator for detecting inverse beta decay from reactor antineutrinos (6m from reactor core)

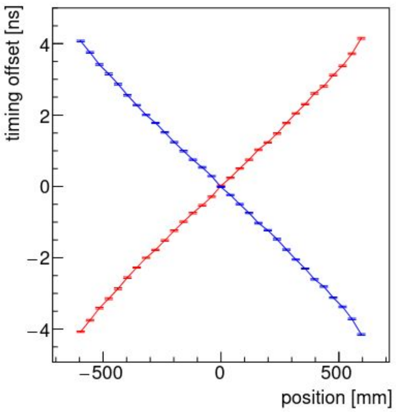


Several PMTs failed throughout the course of the data taking period. **Current efforts are underway to recover IBD statistics using single ended segments for background rejection**

PMT Pulse Analysis







PMT pulses from scintillation light collection at ends of the segment

Area and PSD (peak/peak +tail) calculated for each pulse

Pulses clustered based on 20 ns cluster width between segments

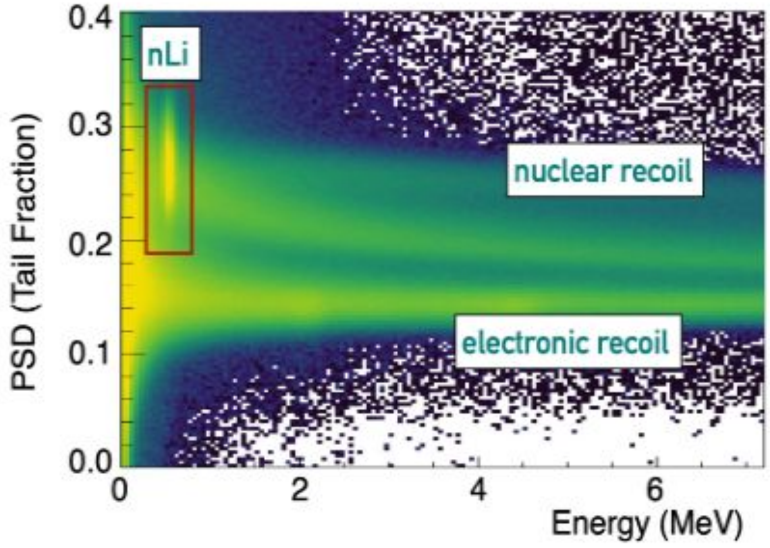
Timing differential and pulse area ratio are used for paired pulses in each segment to determine position along segment [z] along with position corrected energy, PSD

Issue: no differential timing / pulse area ratio available for single ended segments

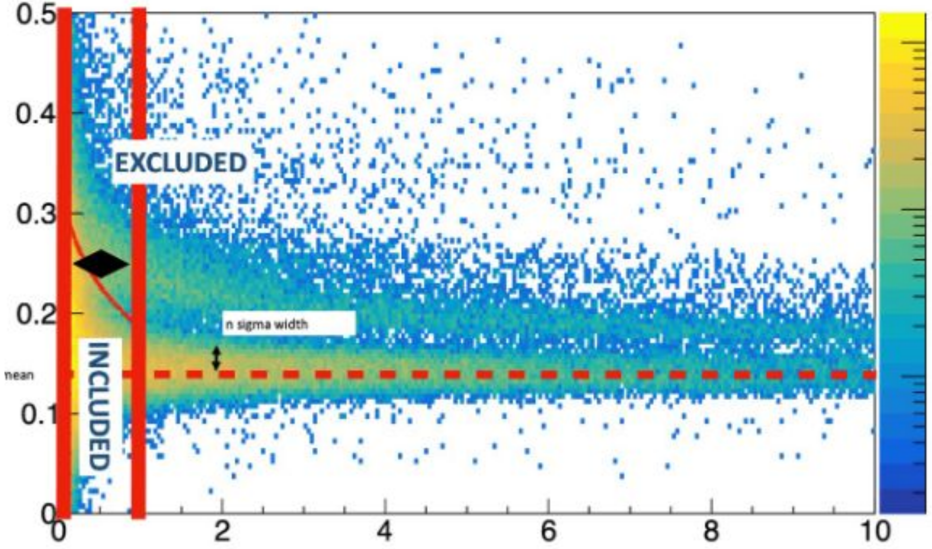
Single Ended (SE) Background Rejection Strategy

- Use healthy segments for positron energy + neutron capture ID
- Use SE segments for rejecting background events

Dual Ended PSD vs E

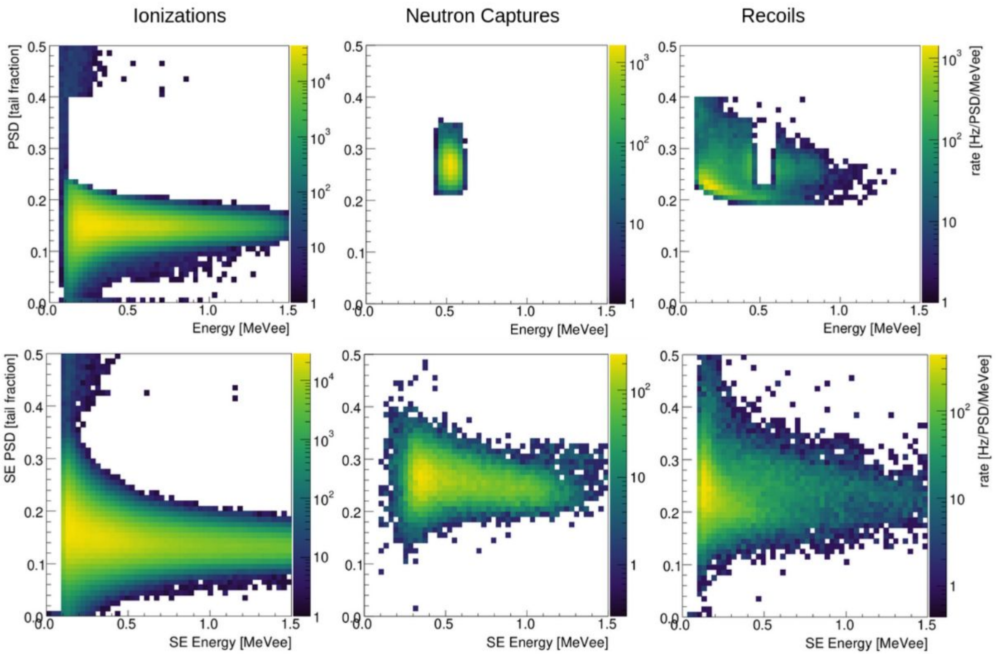


Single Ended PSD vs E



Machine Learning Based Strategy

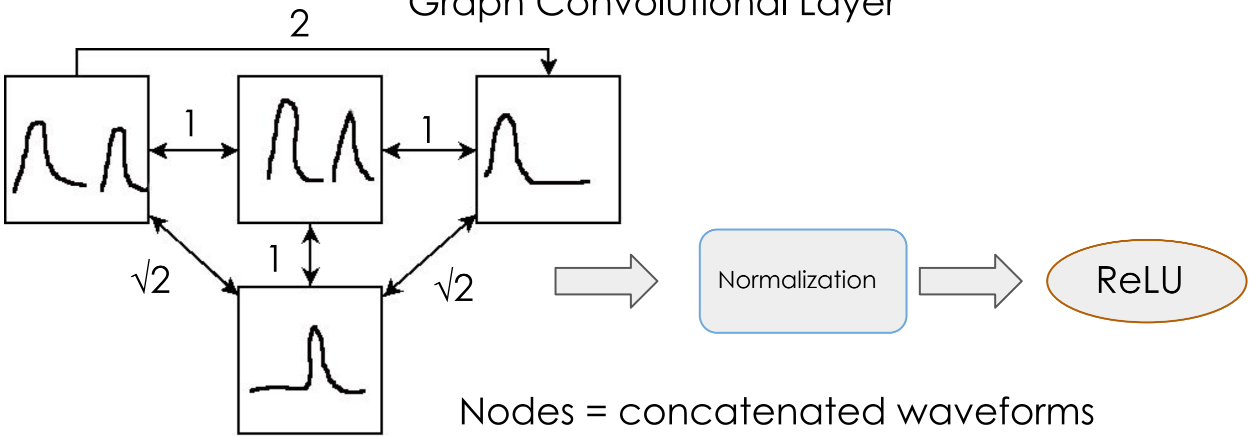
- SE PSD and E distributions are smeared out = **significant overlap** (see right plot)
- Replace recoil identification with a ML classifier trained on data when full detector was working properly (first few days of data collection)
- Replace SE energy cut with a more accurate energy reconstruction algorithm using ML to reconstruct the position along the length of the cell ("Z" position) to estimate the true energy



Top: 1hr reactor on data PSD vs Energy
Bottom: same events in SE PSD vs SE Energy

Graph Neural Network based Classifier

Graph Convolutional Layer



Nodes = concatenated waveforms
Edge weights = cartesian distance between segments

Network architecture for classifier used in this work

Layer	Input Size	Output Size
GMMConv1	130	191
GMMConv2	191	252
GMMConv3	252	313
GMMConv4	313	374
GMMConv5	374	435
GMMConv6	435	364
GMMConv7	364	293
GMMConv8	293	222
GMMConv9	222	151
GMMConv10	151	80
GMMConv11	80	5

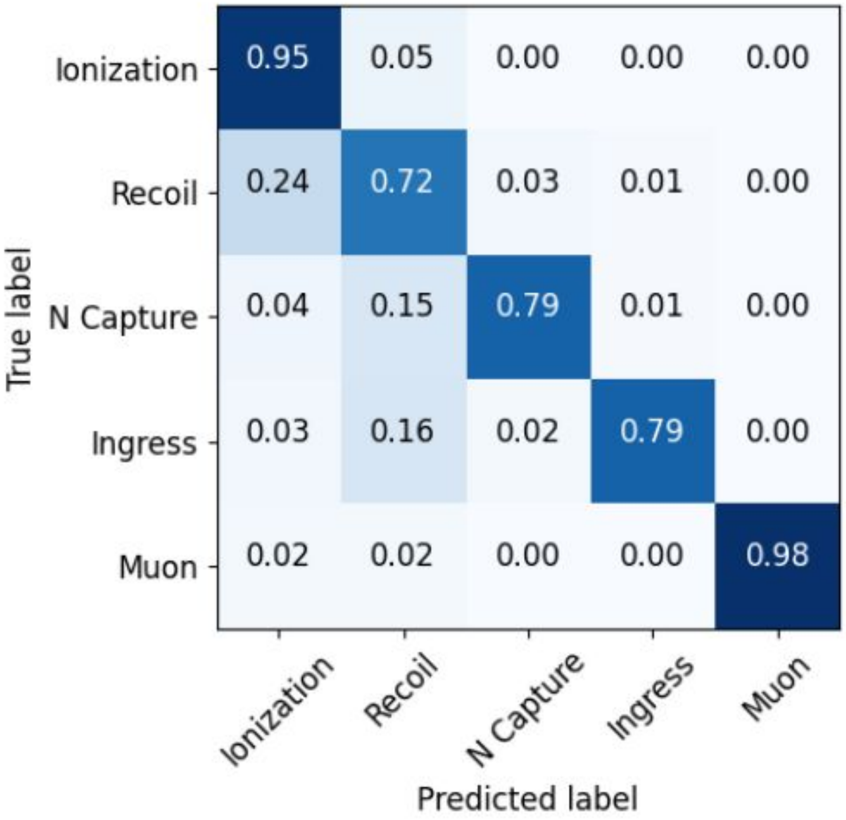
- Pytorch Geometric used, tested several graph net types
- Gaussian Mixture Model[1] network (GMMConv) performed best out of the ones tested
- Output contains 5 numbers representing the score for each class

1. https://arxiv.org/abs/1611.08402

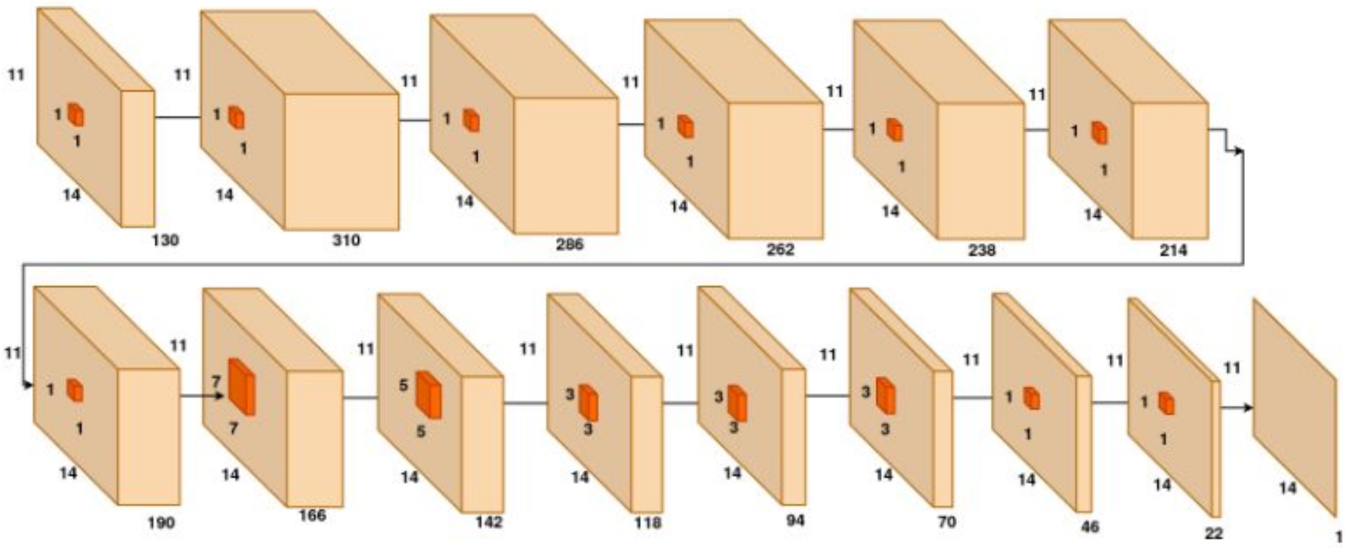
Classifier Performance

Confusion matrix showing the fraction of events labelled for each combination normalized to the true number of events for each class

Biggest difficulty are 24% of recoil events mislabelled ionization



Z Reconstruction using Sparse Submanifold CNN[1]



Brown blocks represent the spacial size of the data

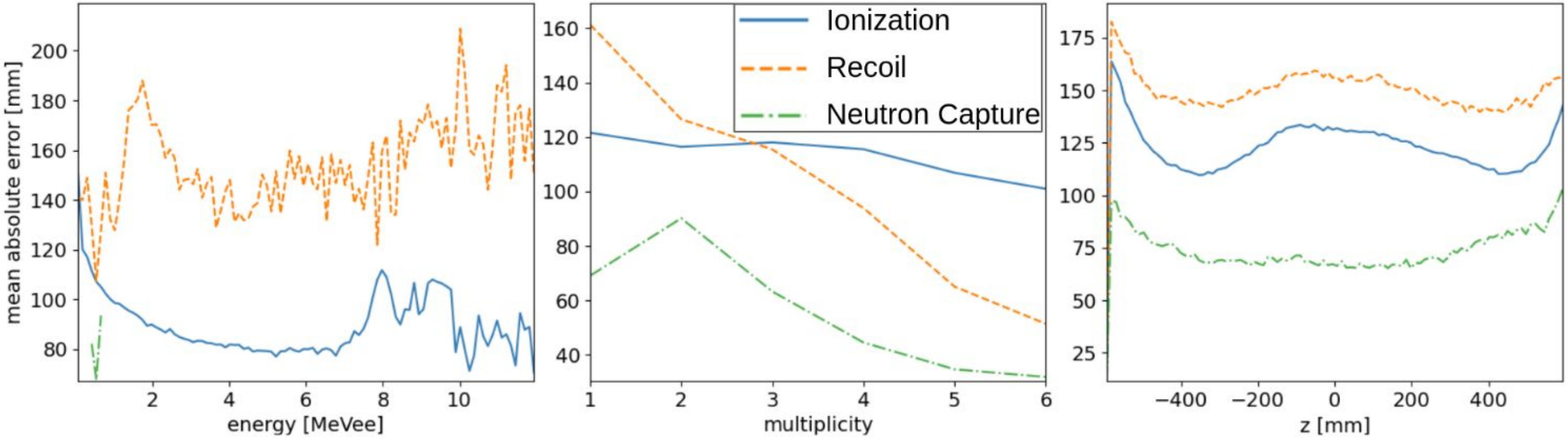
14 x 11 x 2*65 samples for each waveform

Orange represents the filter size

Each layer followed by a Batch normalization layer and a ReLU activation layer

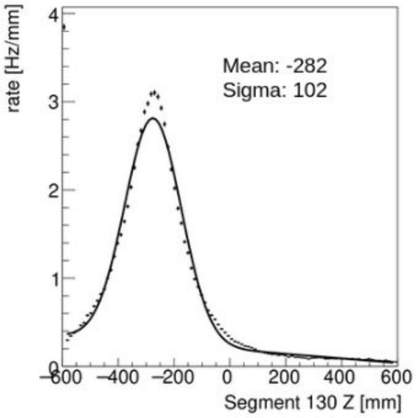
1. Spconv - https://github.com/traveller59/spconv

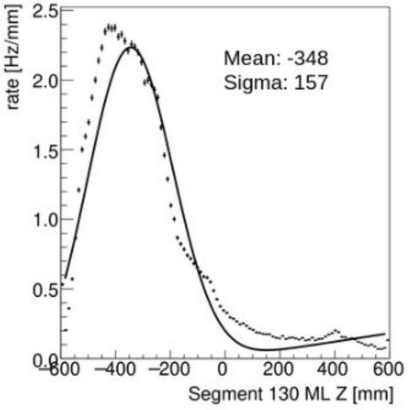
Z Reconstruction Performance



Above: error (relative to double ended prediction) as a function of energy, multiplicity, and Z position

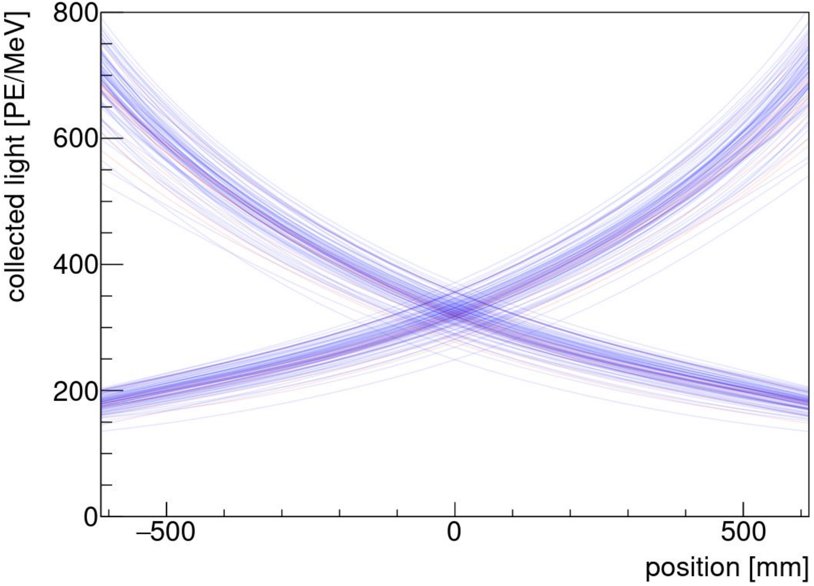
Right: histograms of events for a calibration run where a source was placed at -300 mm, left is double ended reconstruction, right is ML, solid lines are gaussian fits to data

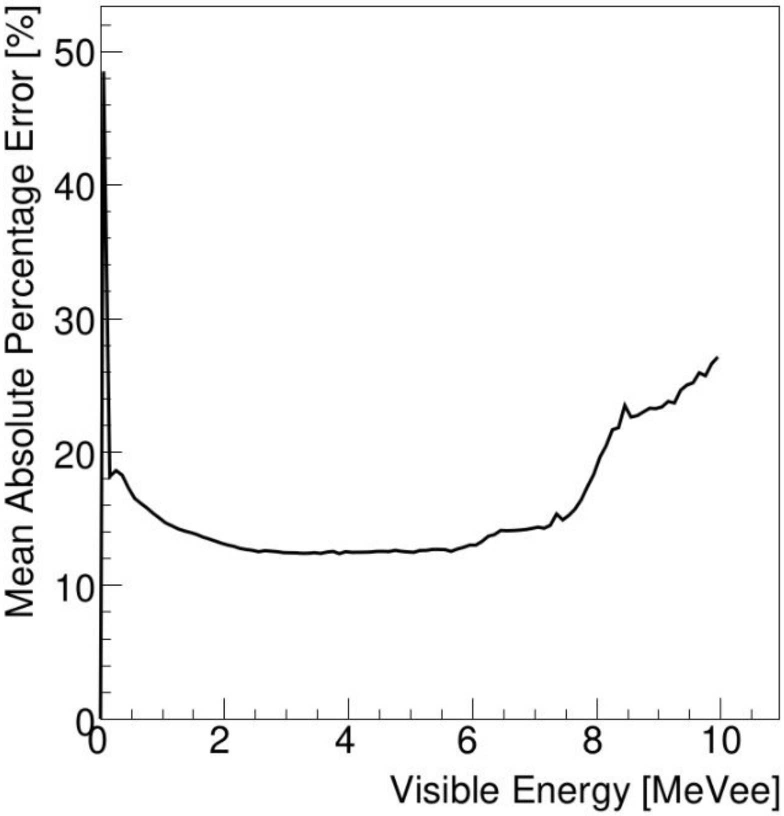




Energy Reconstruction Performance

Energy is reconstructed using the ML Z estimate and using curves representing the average light output ratio between left and right PMTs at different Z positions to estimate the total light seen by both detectors





Model Performance Comparison for SE Z Reconstruction

- Convolutional Neural nets (CNN) worked best for SE Z reconstruction
- Graph networks (GCN) performed second best with other architectures performing significantly worse
- "Single Waveform" indicates models that don't utilize neighboring segments - maximum information that can be extracted just from the waveform timing itself
- Extracted features model uses Z, PSD, timing, pulse area instead of waveform
- Extracted features+ also includes pulse width, rise time, fall time

Architecture	Mean Absolute Error [mm]
CNN with Waveform	133
GCN with Waveform	147
Single Waveform CNN	211
CNN with Extracted Features+	212
Single Waveform FCNN	218
CNN with Extracted Features	238
Nearest neighbors average	306

Neighbor average is a simple algorithm that averages neighboring double ended Z positions

Note that CNNs outperform GCN for z prediction but GCN outperform CNNs on classifier

IBD Selection Improvements

Using 20% of the dataset, we vary cut values to maximize the effective statistics of the dataset

$$\mathrm{IBD}_{\mathrm{Effective}} = \sum_{0.8MeV}^{7.2MeV} \frac{1}{(\sigma_{\mathrm{IBD}}/\mathrm{IBD})^2}$$

- Optimal ML SE energy maximum threshold for prompt event cut is 0.6 vs 0.8 for non ML (0.5% increase in effective stats)
- ML threshold for ionization is a classifier score > 0.03, (~1.5% increase in effective stats)
- Relax non-ML based cuts due to higher ionization identification precision of ML, ~1.5% increase in effective stats
- Total 23.5% increase in effective stats

	Nominal	Nominal + ML	ML Optimal
IBD Stats / Day	497.0	487.4	519.7
Signal : Correlated Background	3.33	3.50	3.27
Signal : Accidental Background	3.98	4.29	3.82
Effective Stats / Day	244.9	248.0	253.6

Conclusion

- Prediction of single ended position, energy, particle ID with graph / convolutional neural nets
- Demonstrated utilization of full waveform information required for optimal reconstruction
- Better signal discrimination leads to 4.6% more IBDs, 3.5% increase in effective statistics
- Graph nets work best for SE classification, convolutional neural nets best for Z prediction