Machine learning applications for NEWS-G

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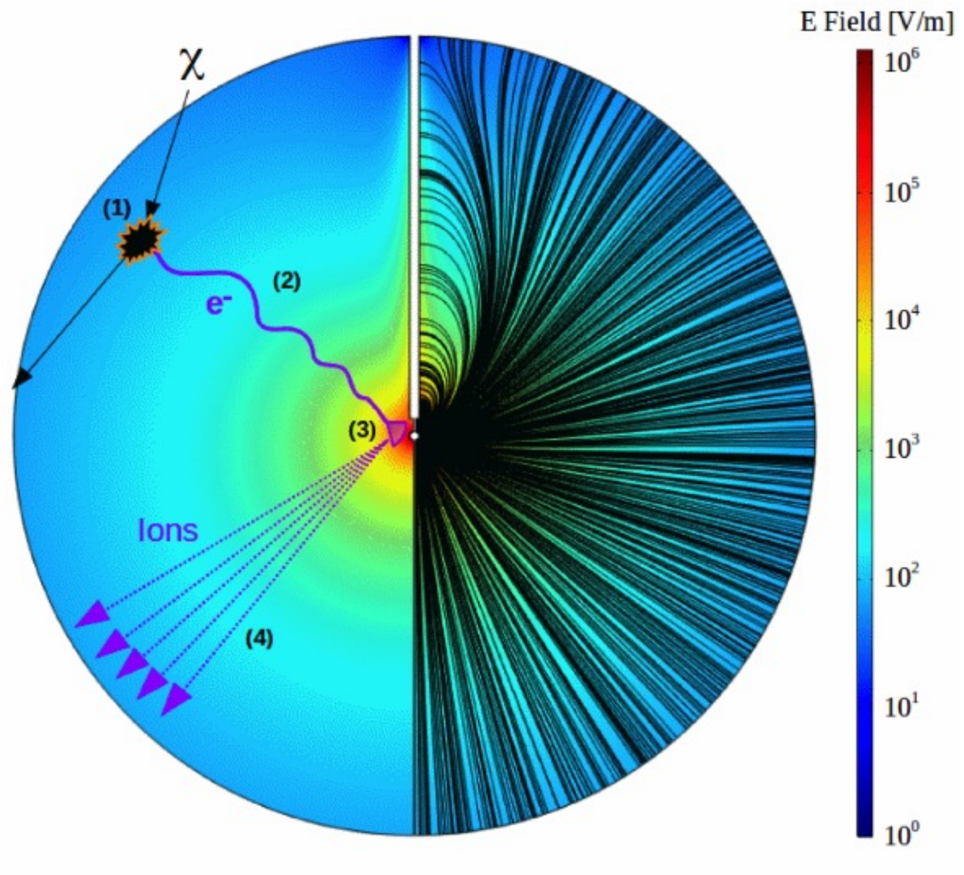
CAP 2023

NEWS-G – Spherical Proportional Counter



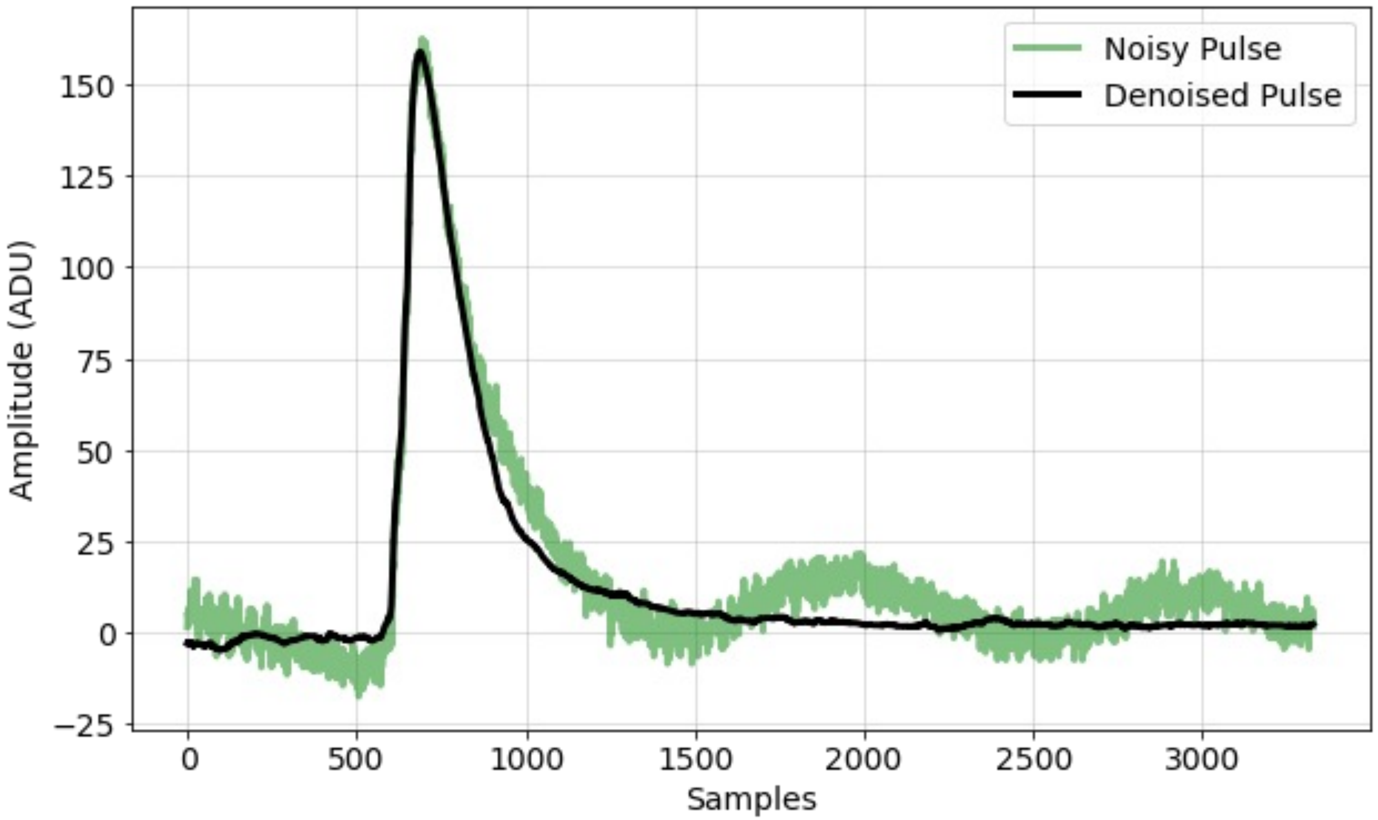
Signal Generation:

1. Primary ionization
2. Electron drift
3. Townsend avalanche
4. Positive ion drift

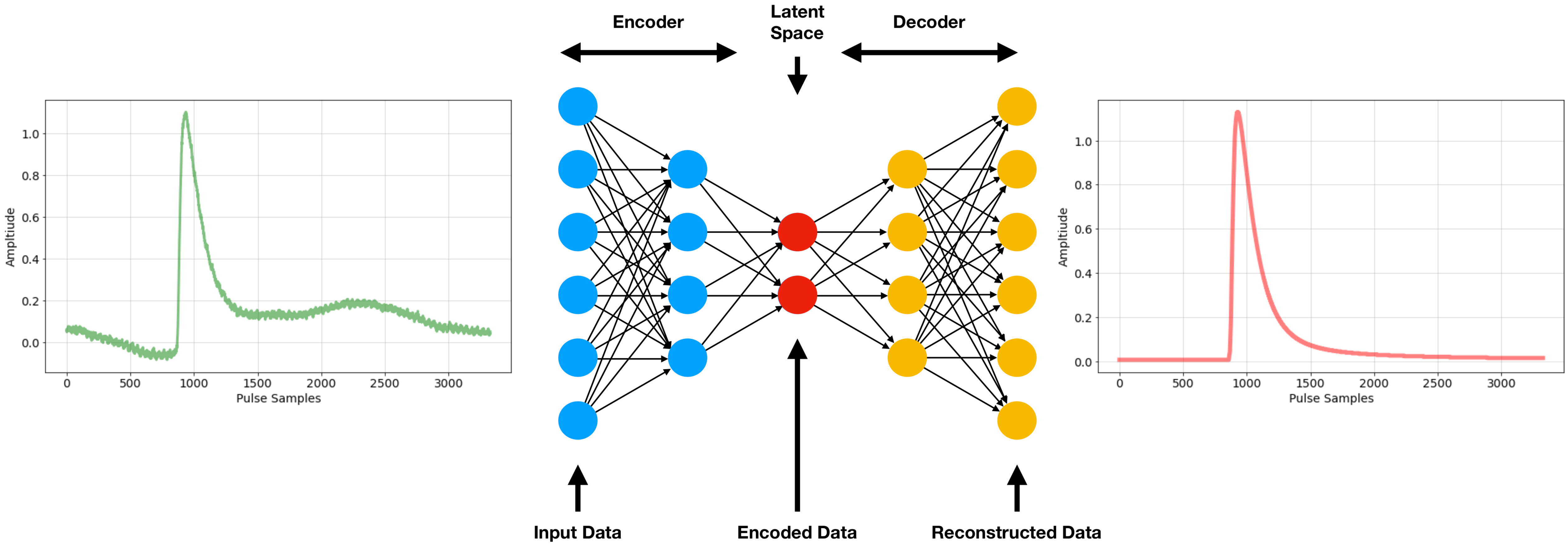
Problem Definition

Goals:

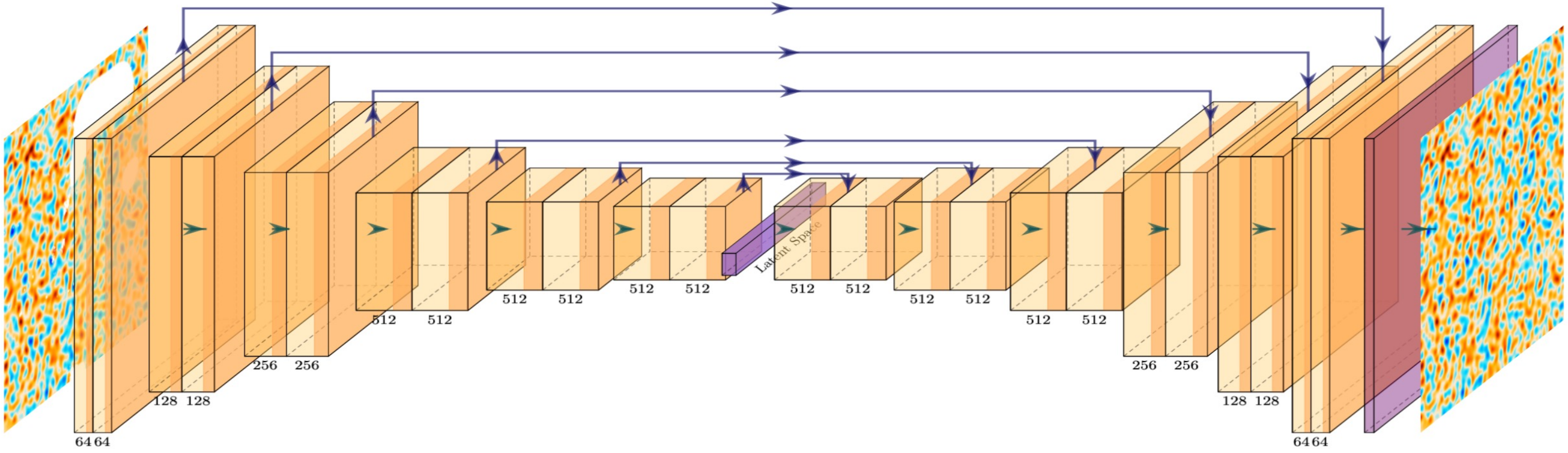
- Utilize machine learning methods to remove noise from recorded detector signals
- Model implementation should aid in measuring important signal characteristics, such as amplitude and rise-features



Methods – Model Architecture



Convolutional Autoencoder



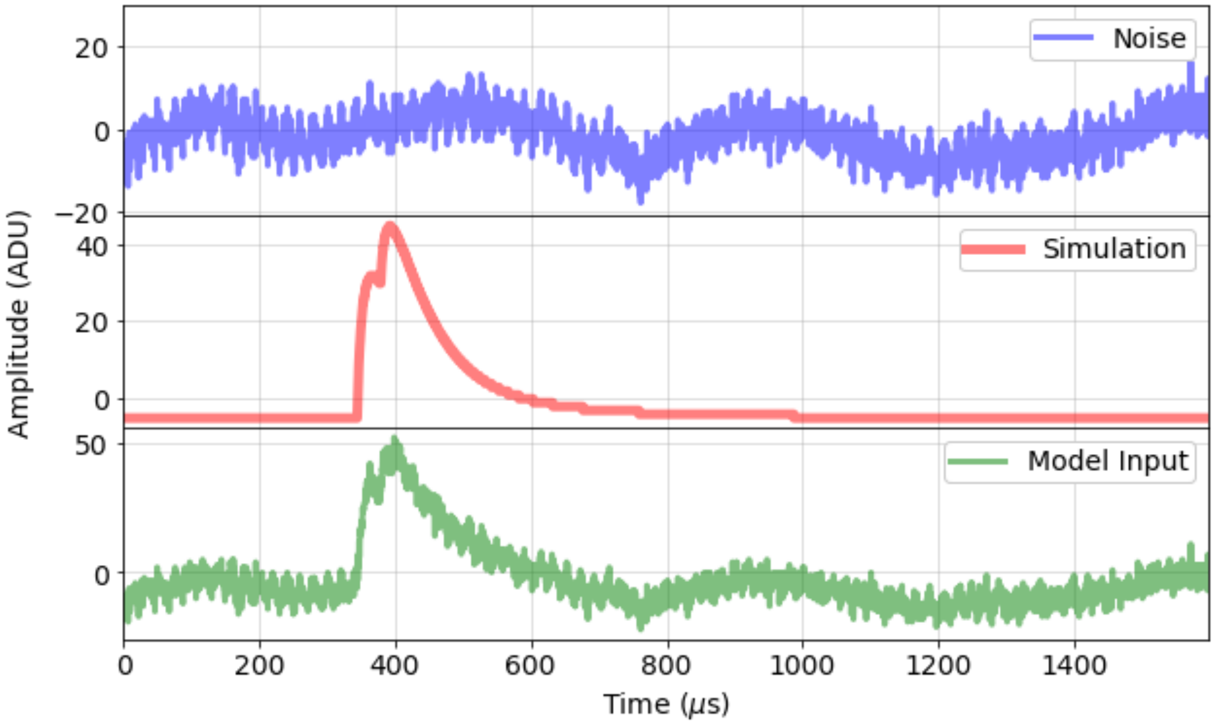
- ~300,000 parameters
- ~2-3 days of training

https://doi.org/10.48550/arXiv.2001.11651

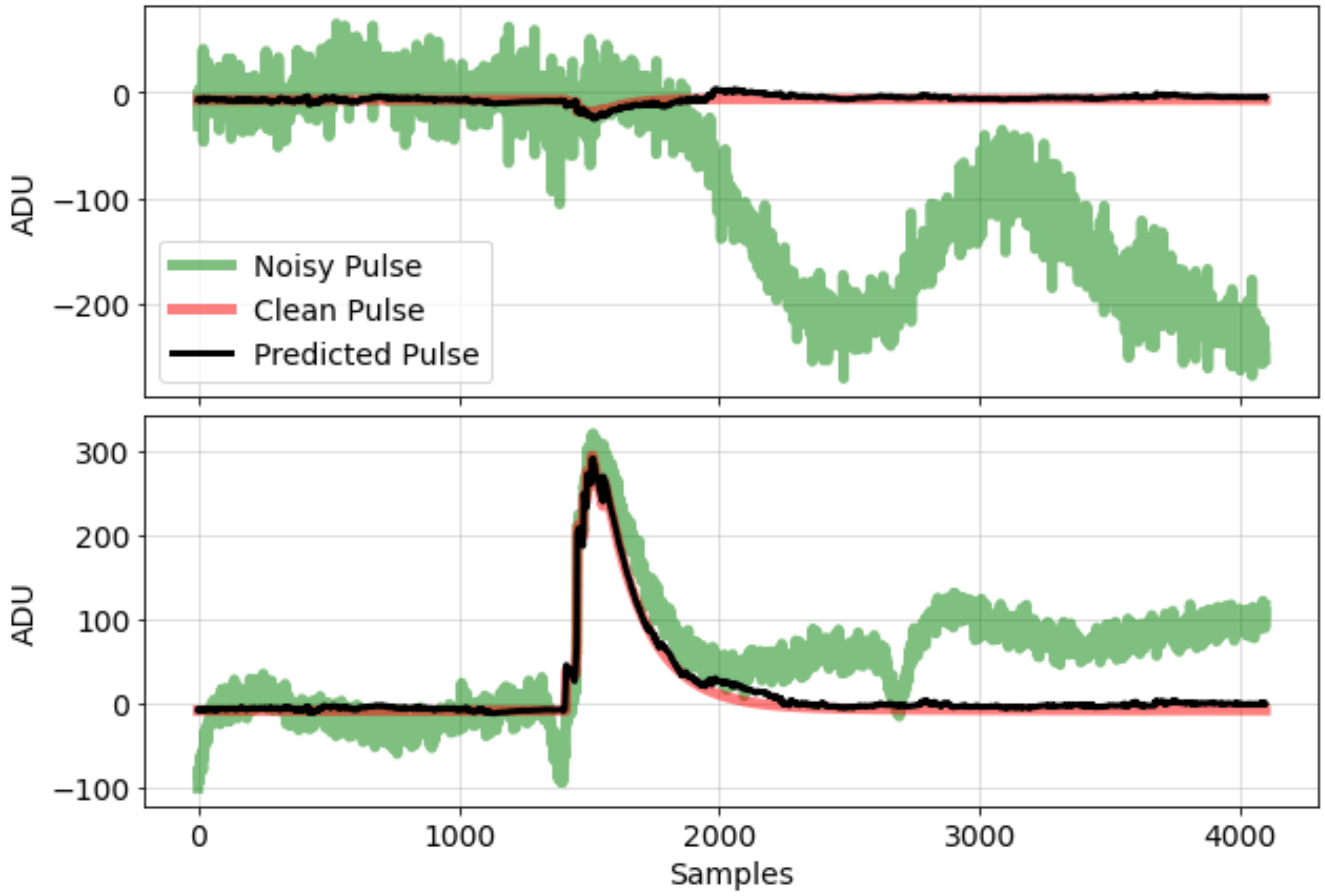
Methods – Model Training

Trained on a simulation-based dataset modeled after 2 detectors

X	Simulated pulses + real noise
Y	Simulated pulses

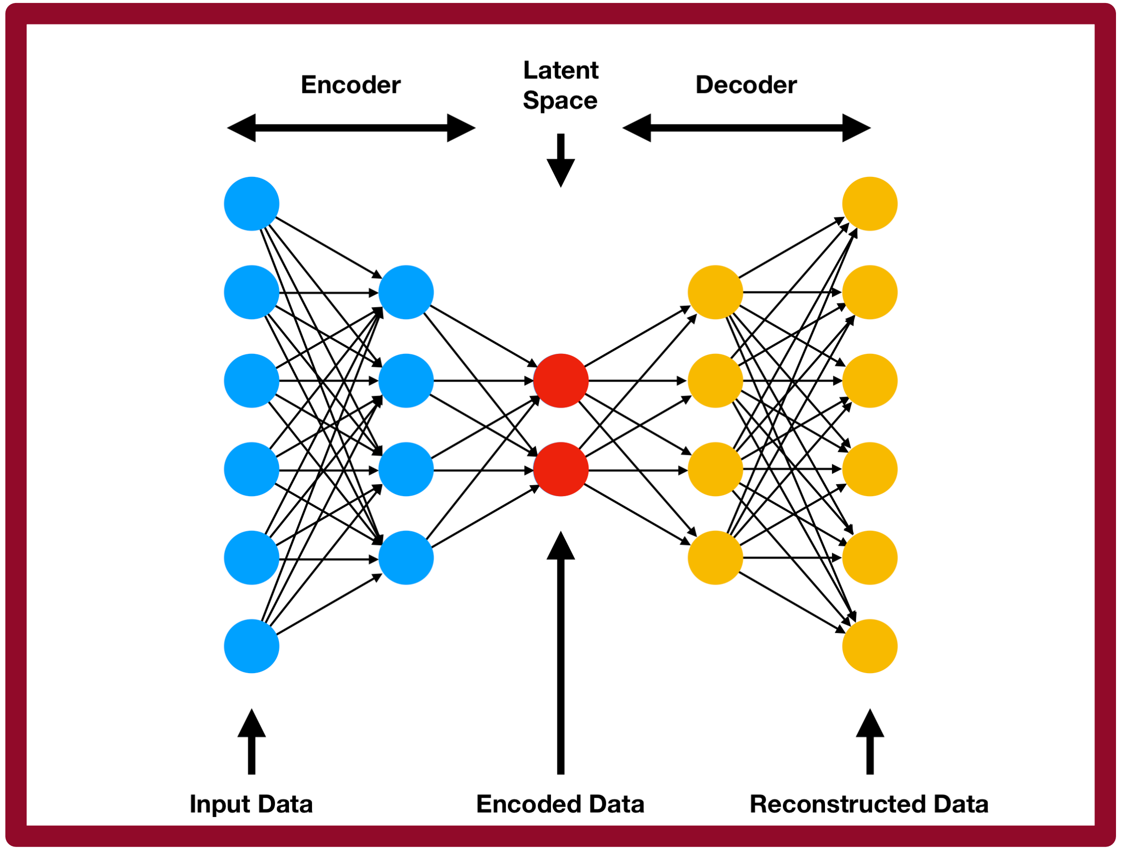


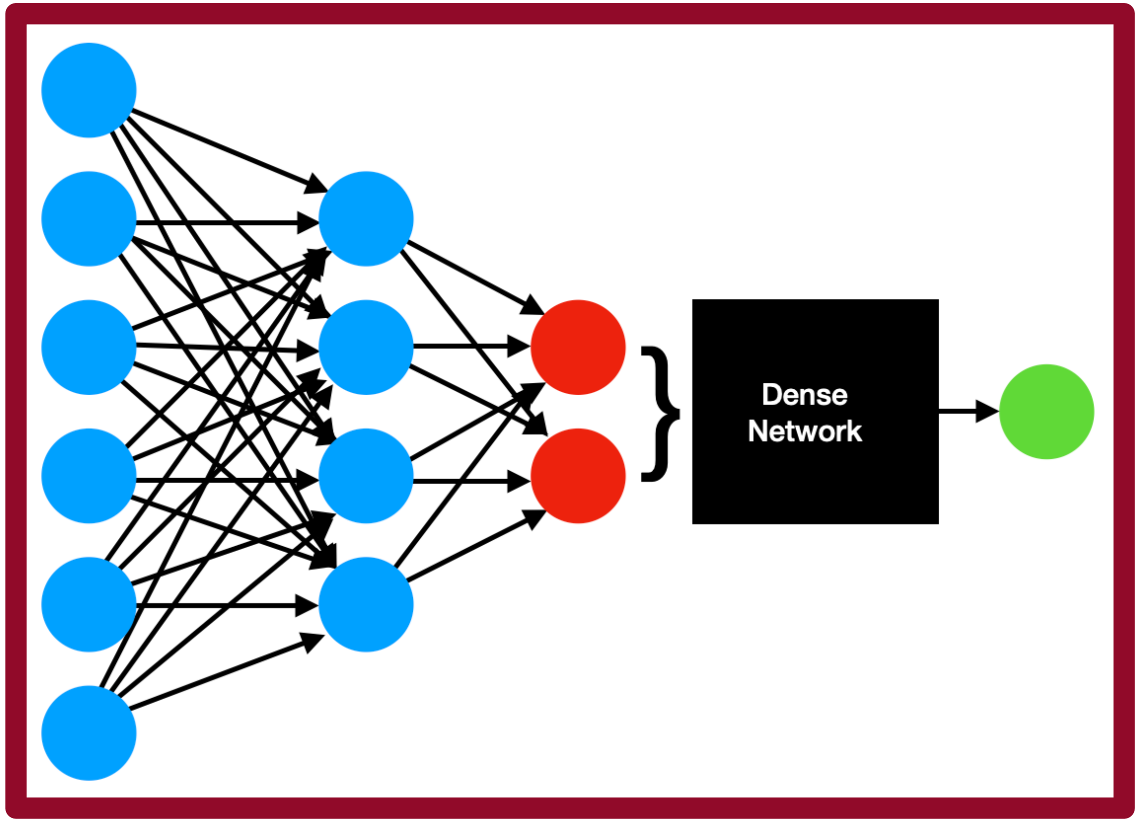
2-Channel Example Pulses



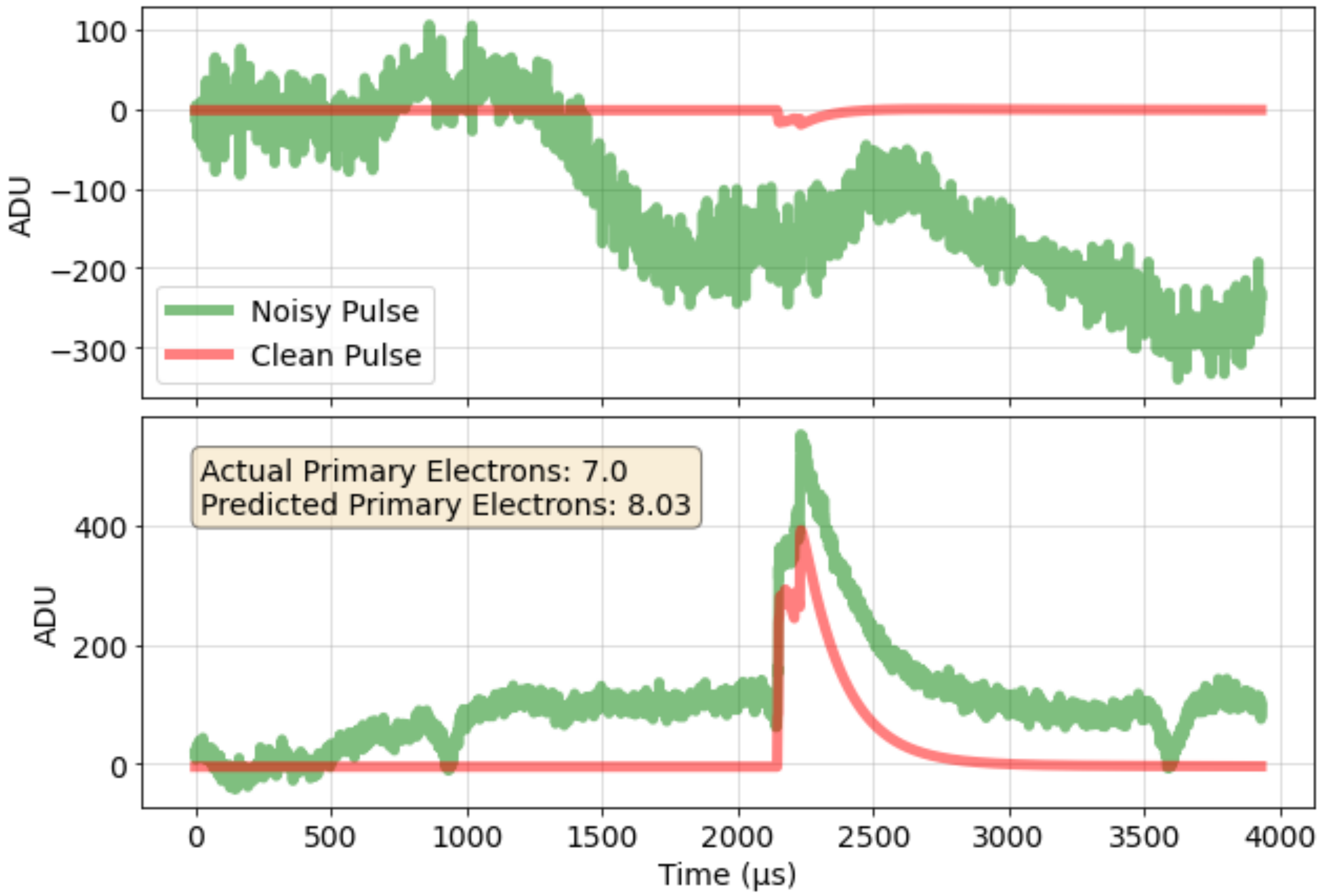
Energy: ~250eV

Single Output Model





Single Output Prediction Examples



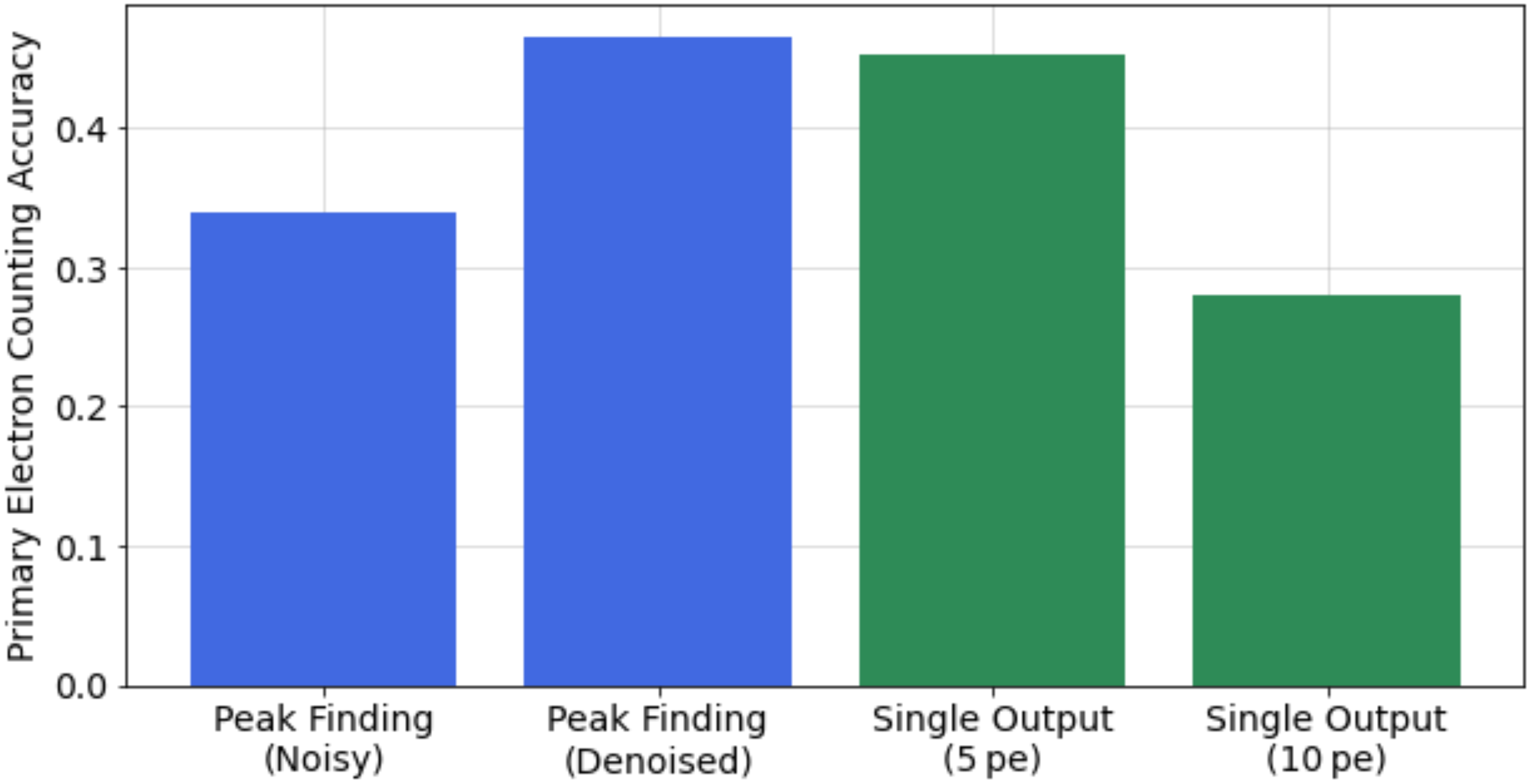
Primary Electron Counting

Tested 4 different primary electron counting strategies:

- **Peak finding**
  - Noisy data
  - Denoised data
- **Single output prediction**
  - Trained on up to 5 primary electron events
  - Trained on up to 10 primary electron events

Evaluated on a simulated two-channel dataset of up to 5 primary electrons

Primary Electron Counting



Conclusion

Developed and tested two methods to incorporate machine learning in NEWS-G

- Noise removal (denoising) model
- Single output prediction model

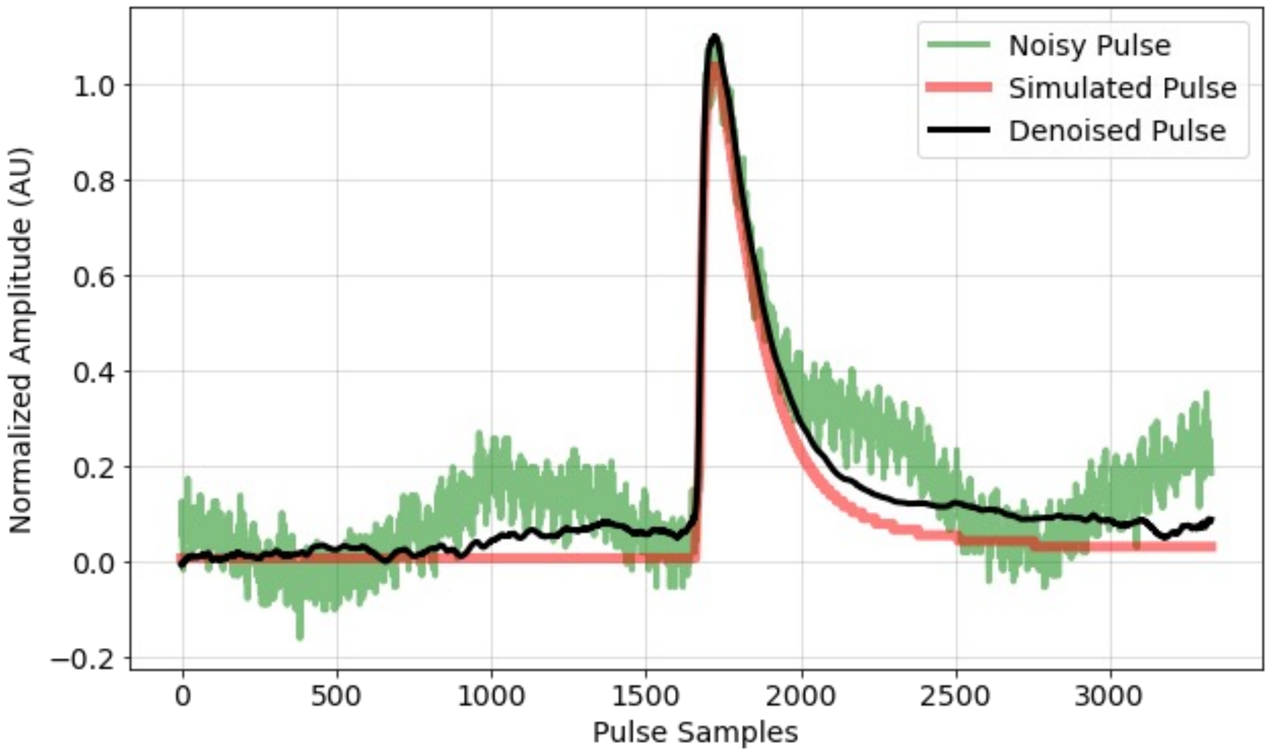
Primary electron counting results

- Single output results can offer improvements on standard approach, depending on the training dataset
- Peak finding on denoised dataset performs better than standard approach

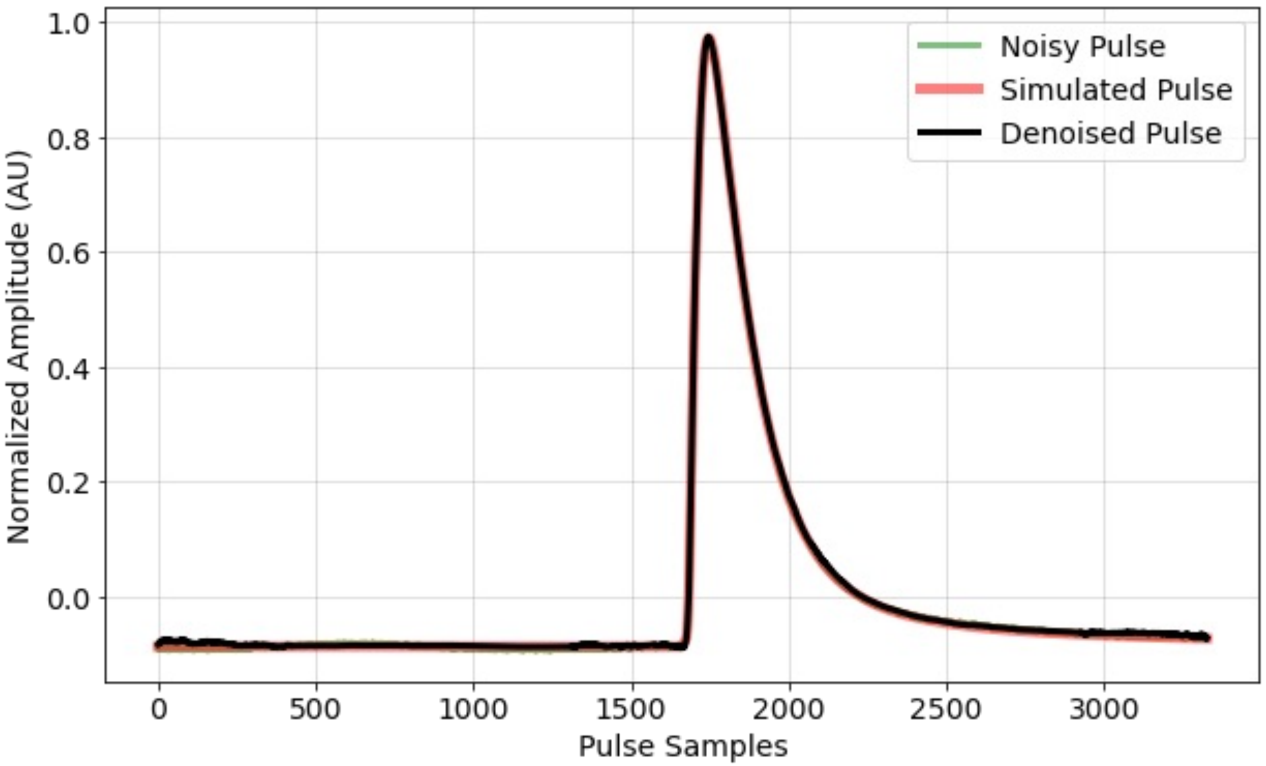
Thank you!

Additional Slides

1-Channel Example Pulses

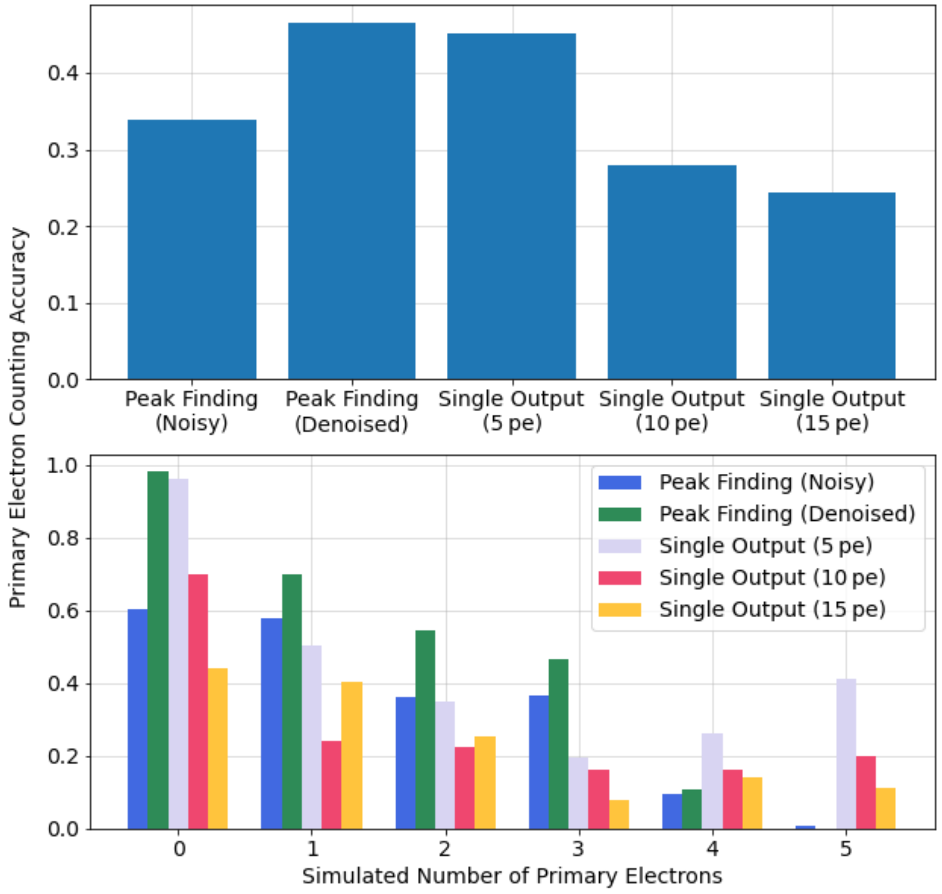


Energy: ~170eV



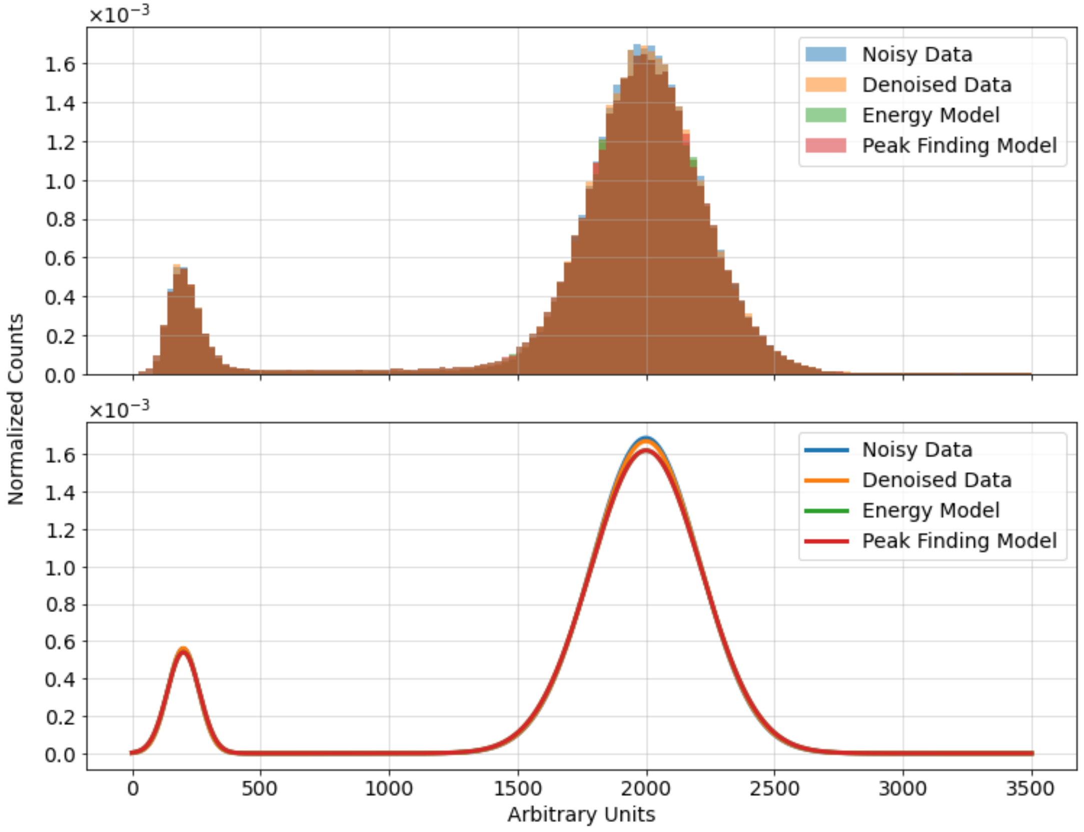
Energy: ~1370eV

Primary Electron Counting Performance



Energy Measurement – Argon Calibration

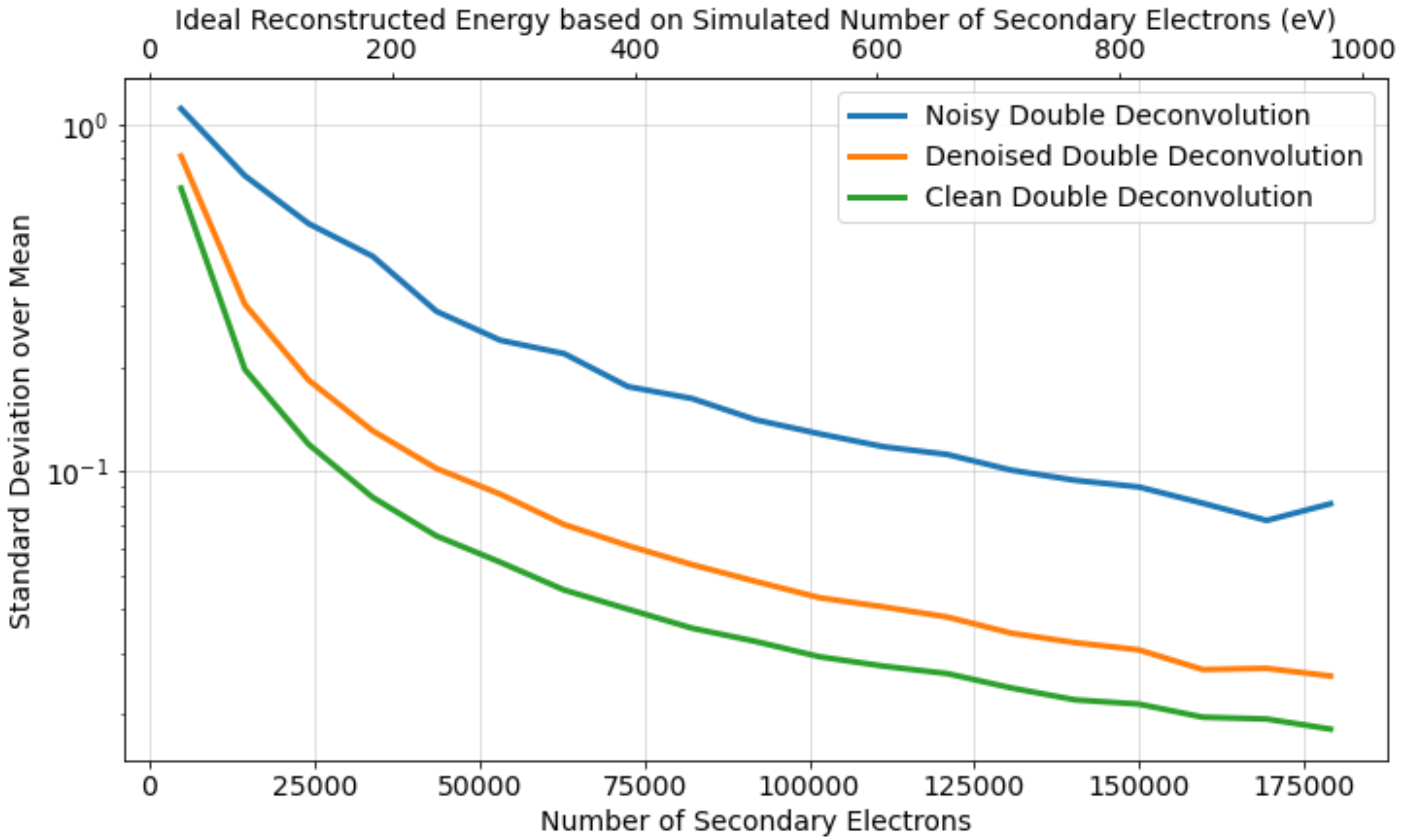
- Tested energy predictions on S30 detector Ar37 calibration data
- All energy prediction methods closely follow traditional energy predictions
  - Single output model predictions have slightly lower fitted peaks
- Above the energy range we expect improvement



Machine Learning Extensions

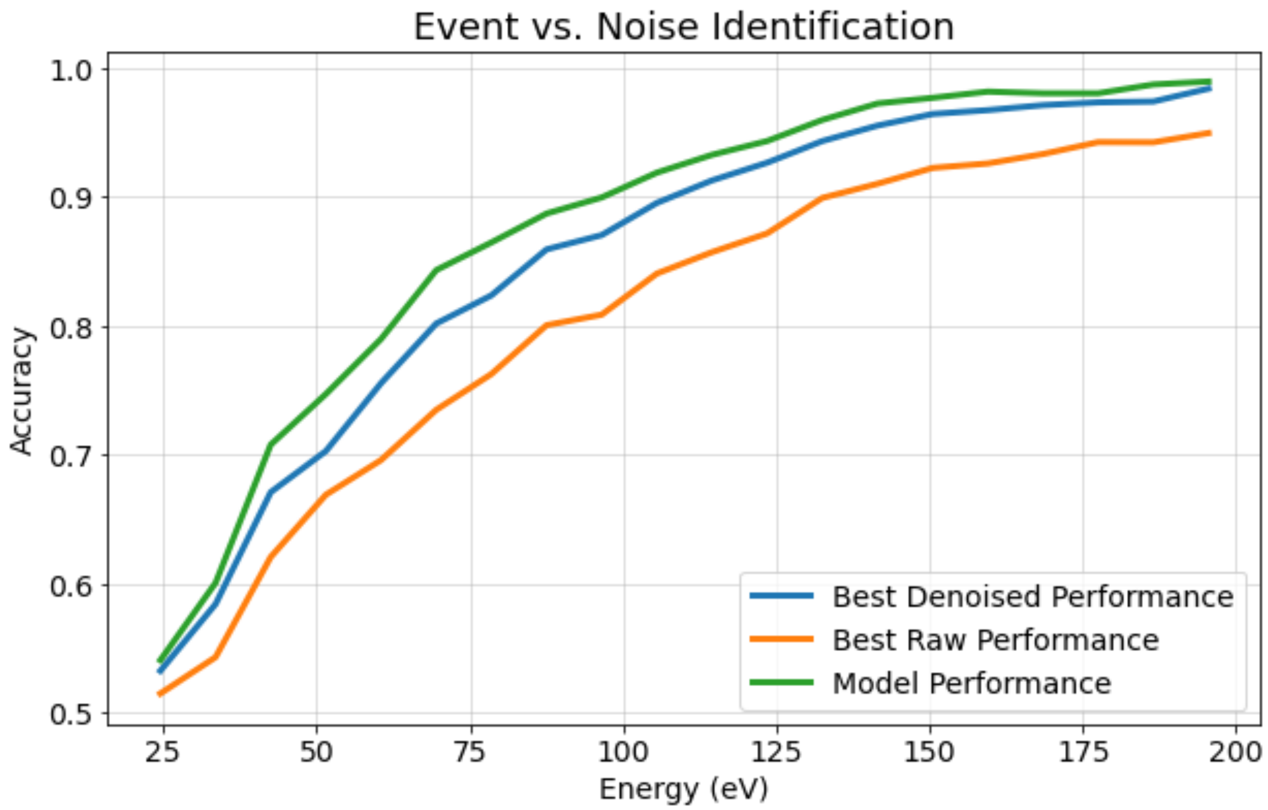
- Other single-output predictions
  - Direct energy prediction, pulse shape classification
- Double-deconvolution layer implementation
  - Explicitly add preprocessing steps to network layers
  - Learn to return primary electron arrival times
- Different model architectures for improved performance
  - Adversarial networks

Simulated Energy Resolution Results

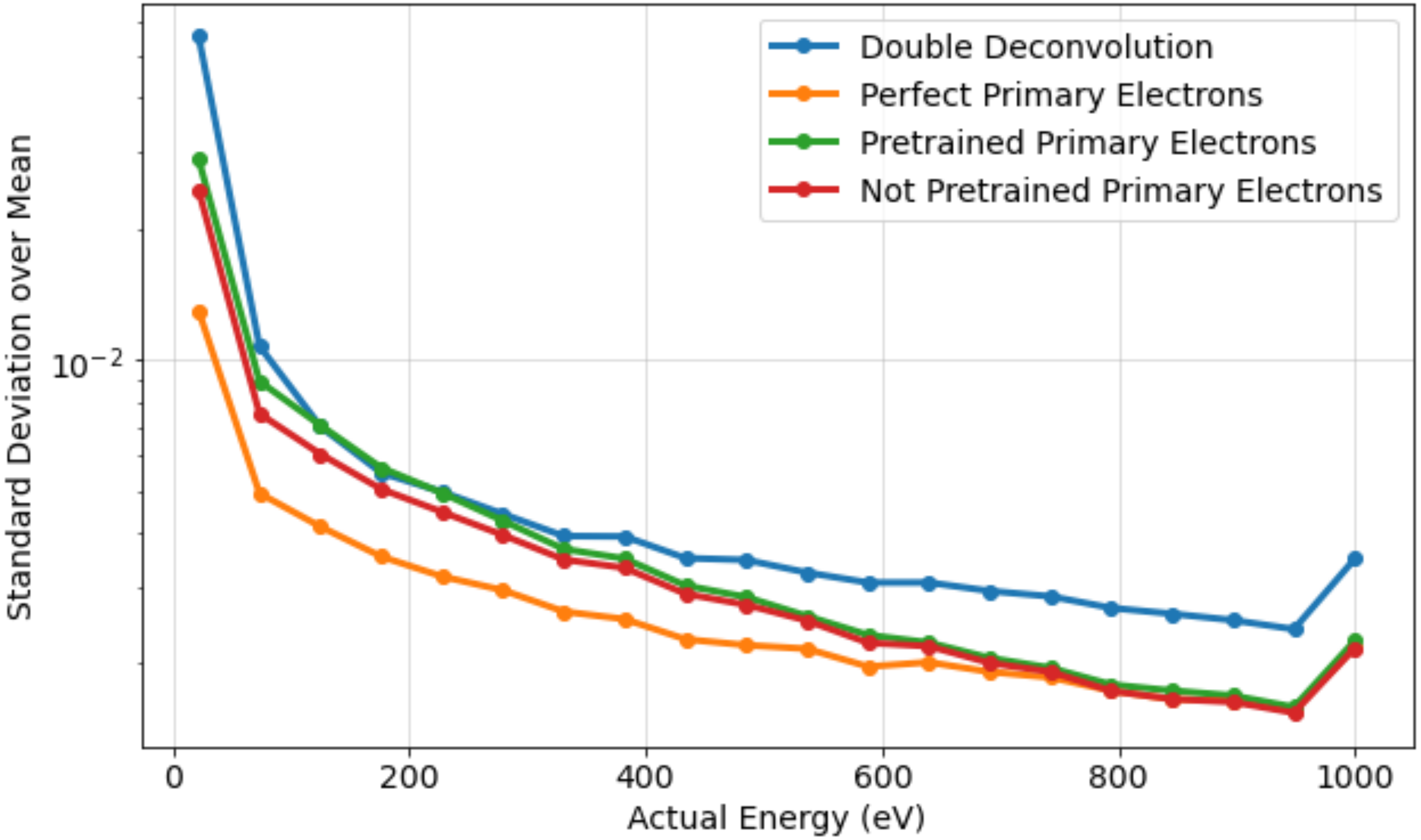


Event Triggering Results

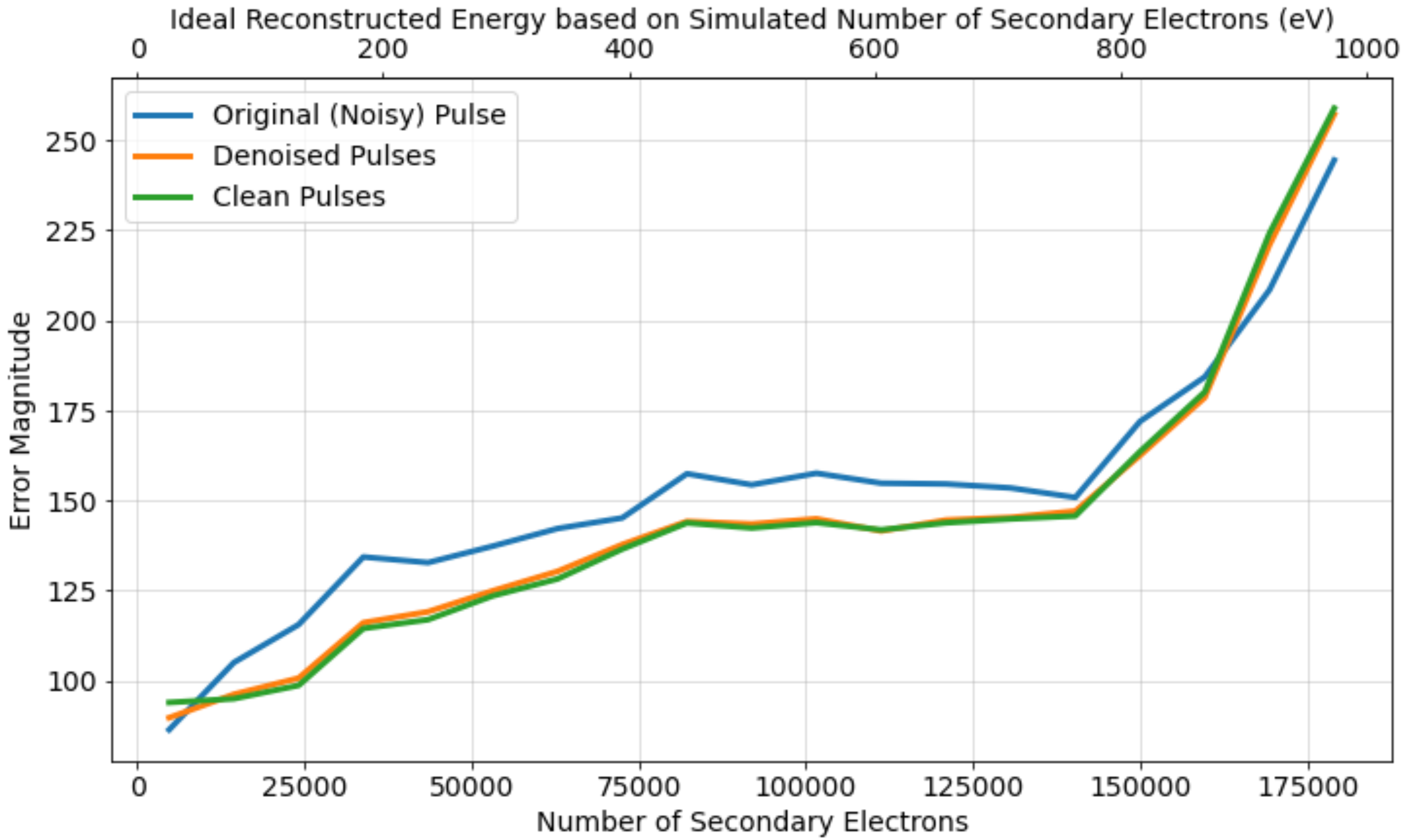
- Triggering efficiency test on simulated data
- 10000 events with a simulated pulse, 10000 noise traces



Energy Resolution Measurements



Energy Prediction Error Magnitude

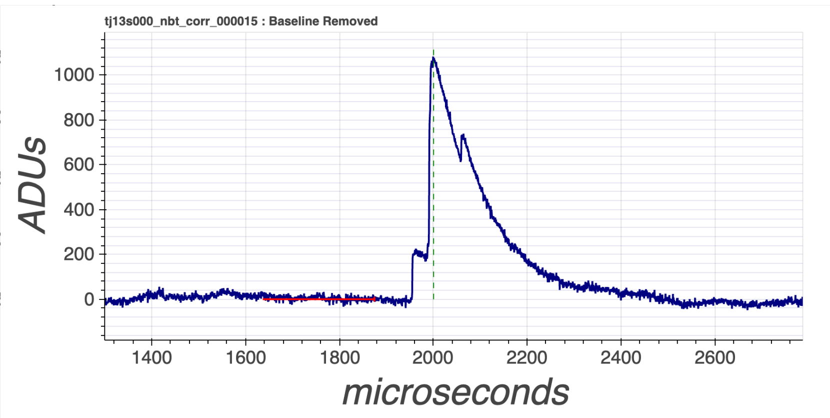


Model Architecture

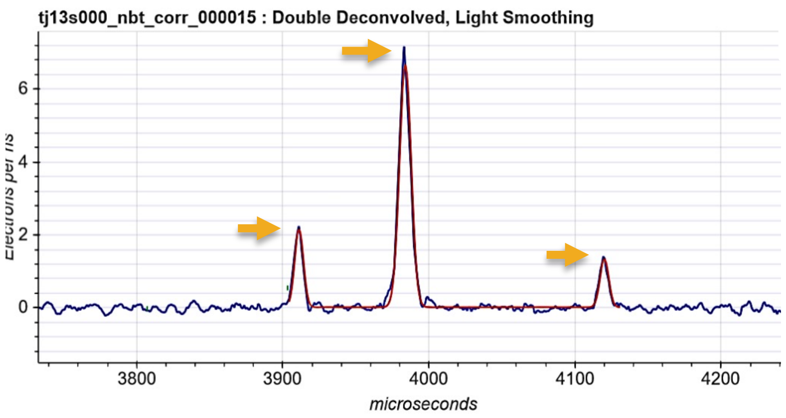
Layer	Stride	Window	Output
Input			4096, 1
Convolution	1	1	4096, 8
Convolution	1	9	4088, 16
Average Pooling	2	2	2044, 16
Convolution	1	17	2028, 32
Average Pooling	2	2	1014, 32
Convolution	1	33	982, 64
Average Pooling	2	2	491, 64
Convolution	1	33	459, 32
Transpose Convolution	1	33	491, 32
Upsampling	2	2	982, 64
Transpose Convolution	1	33	1014, 64
Upsampling	2	2	2028, 64
Transpose Convolution	1	17	2044, 32
Upsampling	2	2	4088, 32
Transpose Convolution	1	9	4096, 16
Convolution (output)	1	1	4096, 1

NEWS-G Signal Generation

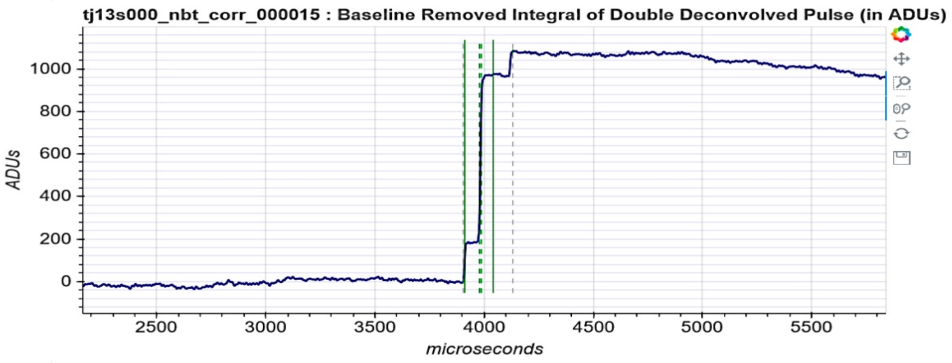
Raw Pulse



Double Deconvolved Pulse



Integrated Double Deconvolved Pulse



Double Deconvolution Algorithm →

Detector Response ←

Integration →