Signal Denoising with Machine Learning for LEGEND

Tianai Ye

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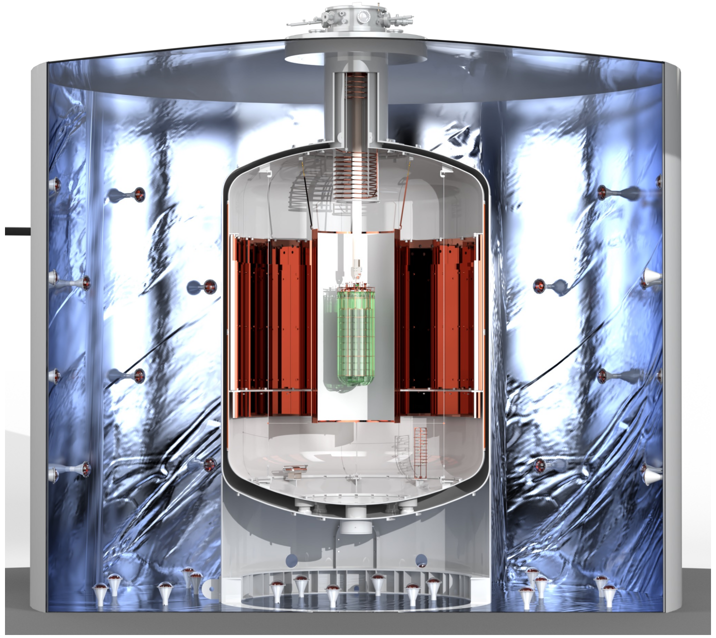
Large Enriched
Germanium Experiment
for Neutrinoless ββ Decay

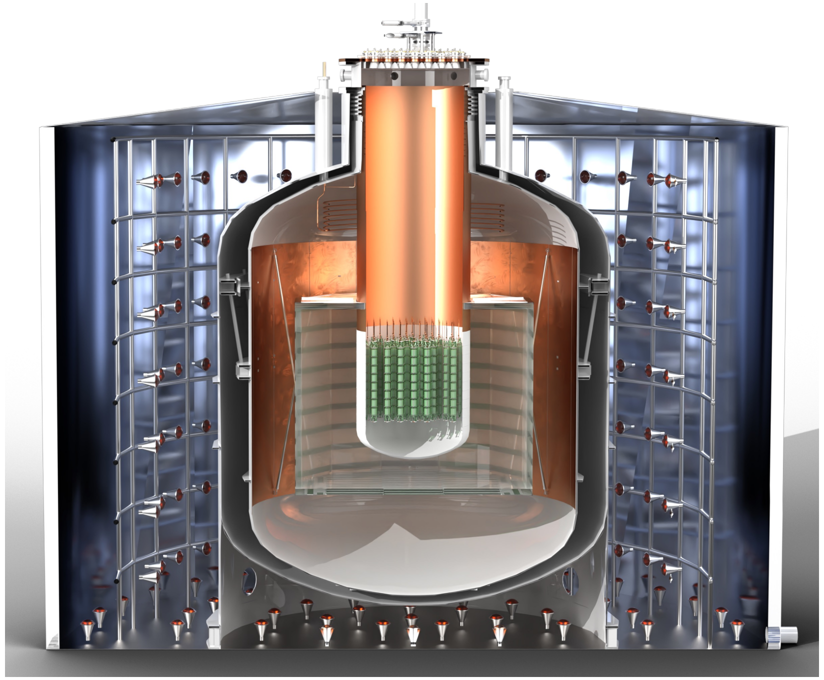
LEGEND - Large Enriched Germanium Experiment for Neutrinoless ββ Decay

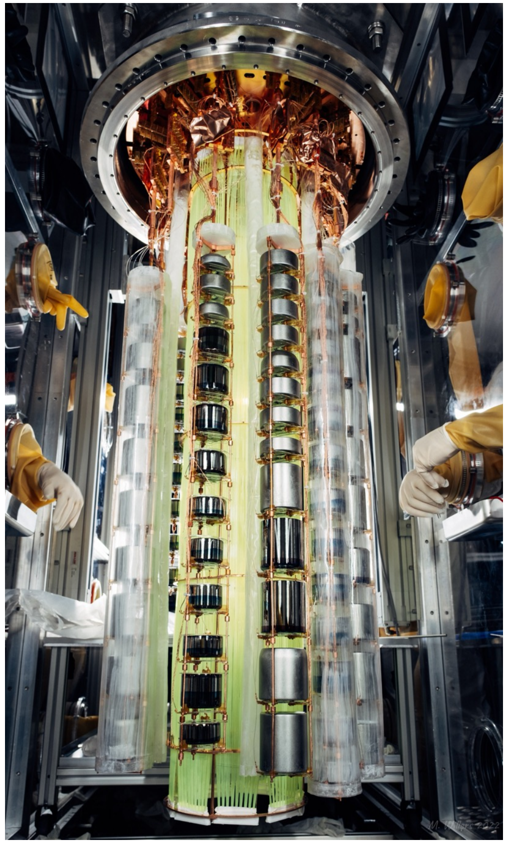
Aims to develop a phased, Ge-76 based double-beta decay experimental program with discovery potential at a half-life beyond 10^{28} years

LEGEND-200

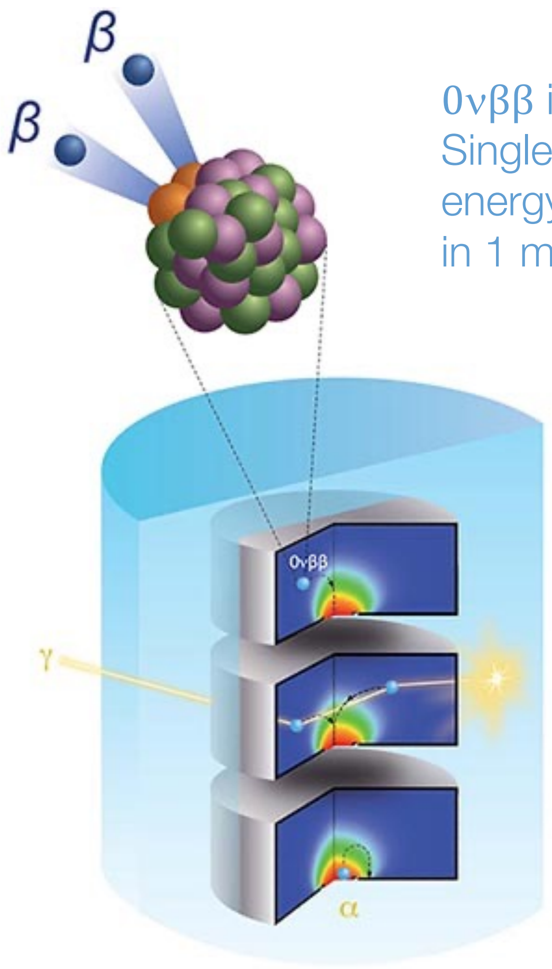


LEGEND-1000

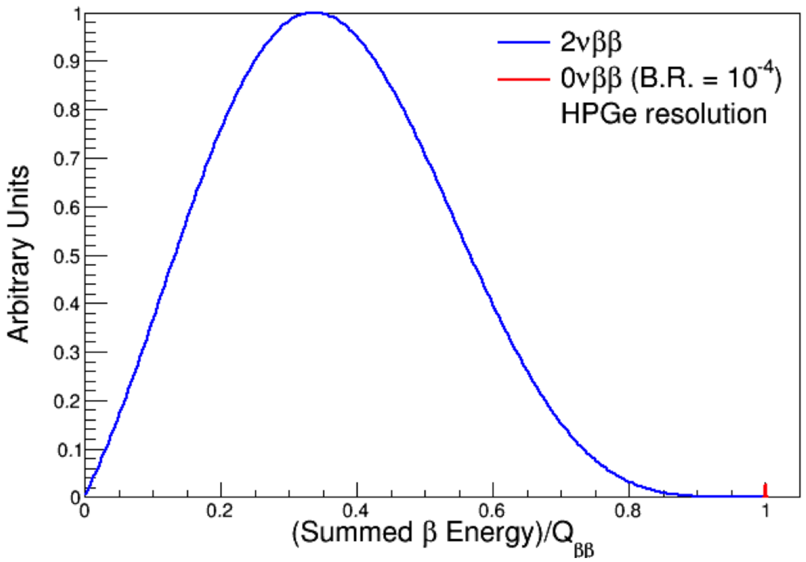




LEGEND - Large Enriched Germanium Experiment for Neutrinoless ββ Decay

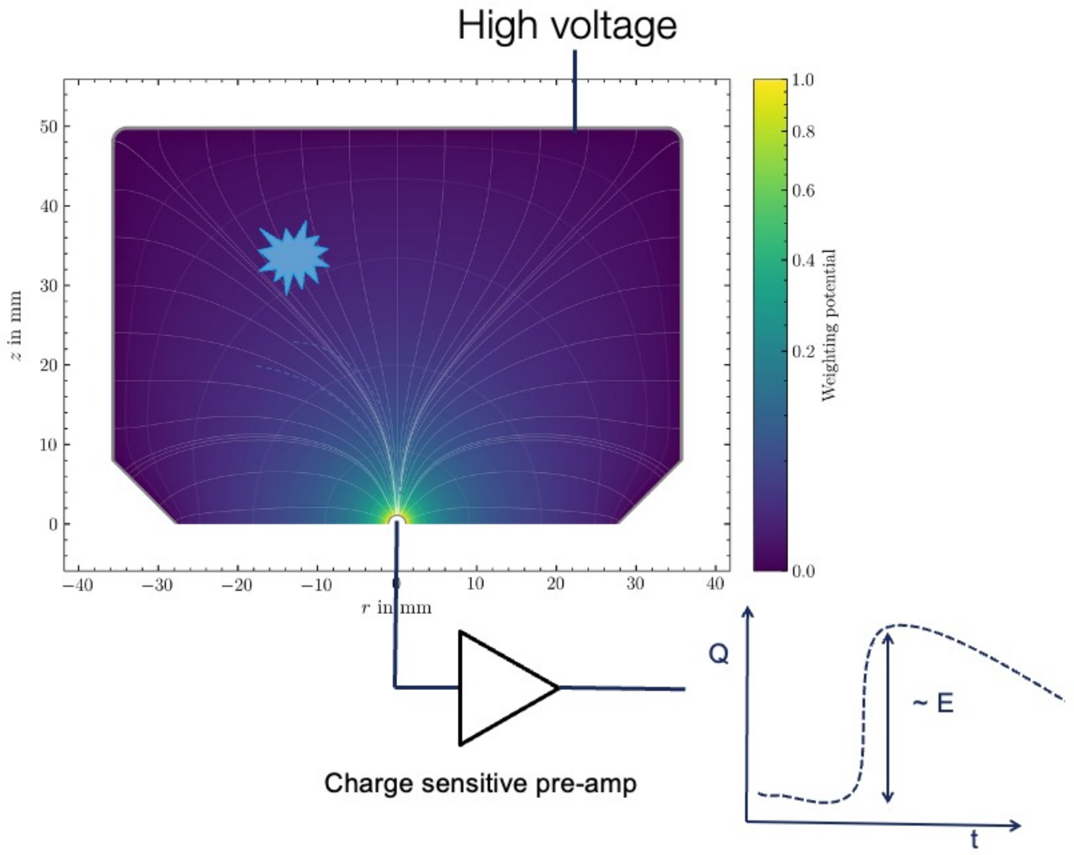


0νββ in Ge:
Single point-like energy deposition in 1 mm^3 volume



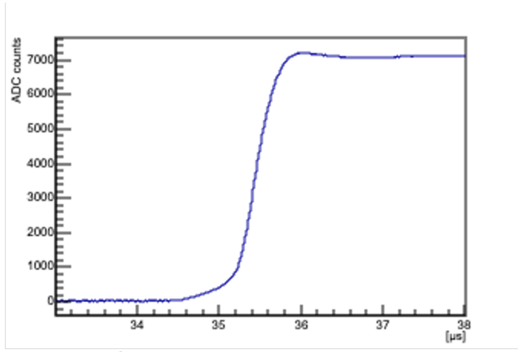
High Purity Germanium Detector

Point contact detector

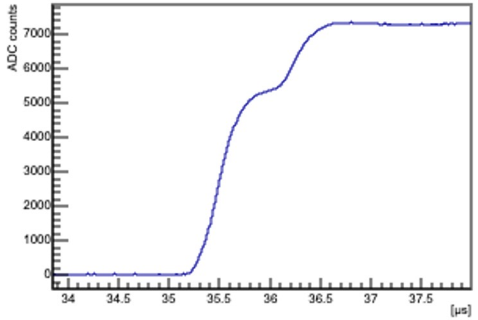


Operates at cryogenic temperature

Simulation:



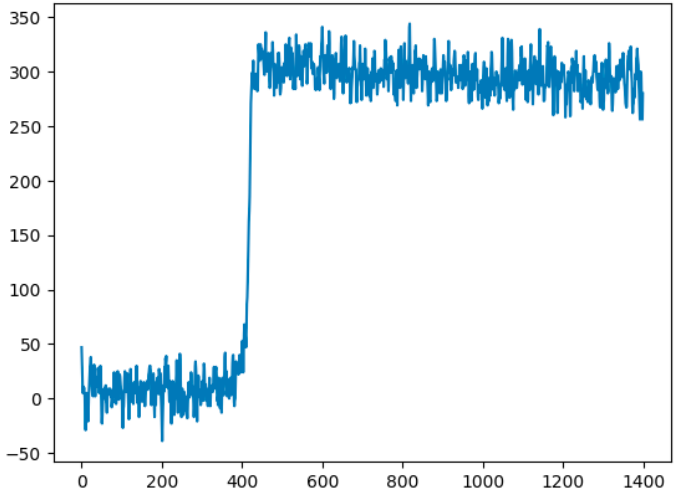
Single site event

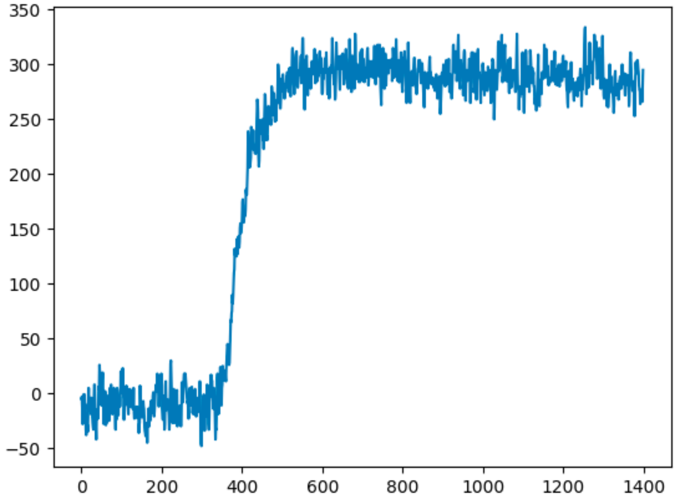


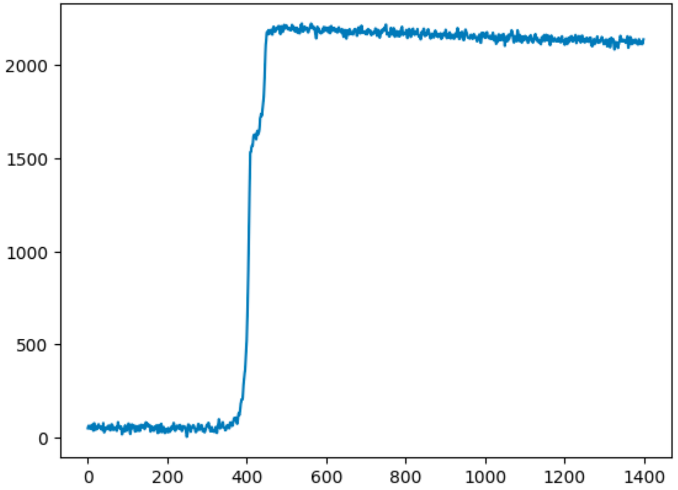
Multi site event

High Purity Germanium Detector

Real detector pulses:







Signal Denoising with Machine Learning

Signal Denoising:

- Improves measurements of pulse shape characteristics
  - ➢ Better energy resolution and background rejection efficiency
- Helps identify low-energy signal events that are masked by electronic noise
- Could push for a lower energy threshold

Especially useful for BSM studies and background identification

With Machine Learning:

- Fast processing once model is trained; scalable
- Trained models can be extended to other applications
  - ➢ e.g. pulse shape discrimination, drift time measurement
- Applicable to other detector technologies and one-dimensional electronic signals
- Outperforms many traditional denoising methods [1]

Data for training, validation and testing

Sources of data (from a PPC detector in GeRMLab at Queen's):

- Simulated clean pulses for the PPC detector
- Calibration data with known energy distributions:

  ^{241}Am (60 keV, low energy/high noise); ^{60}Co (1173 keV and 1332 keV, high energy/low noise)

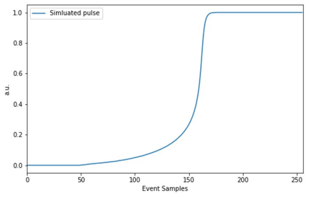
- Pure detector noise

Synthetic Data Augmentation:

scaled and shifted horizontally and vertically

scaled to the same amplitude as the noise in 60keV pulses

Simulated pulse → Clean pulse (Y) + Real detector noise = Artificial noisy pulse (X)



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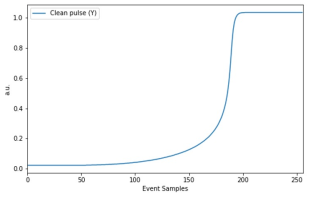

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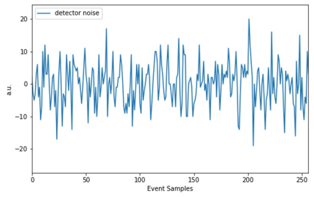

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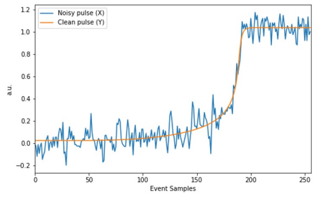
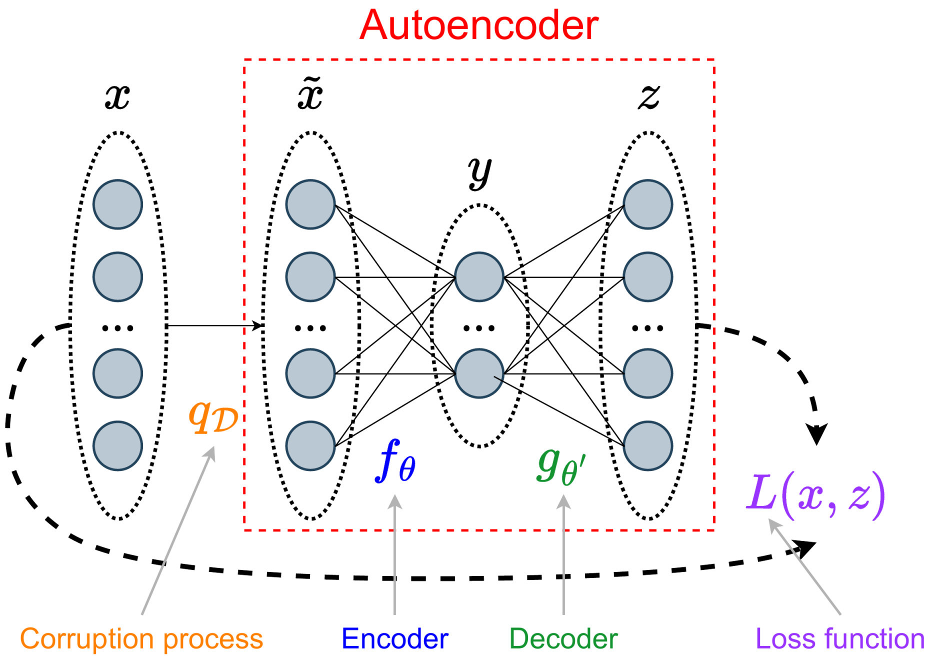


Denoising with Convolutional Autoencoder

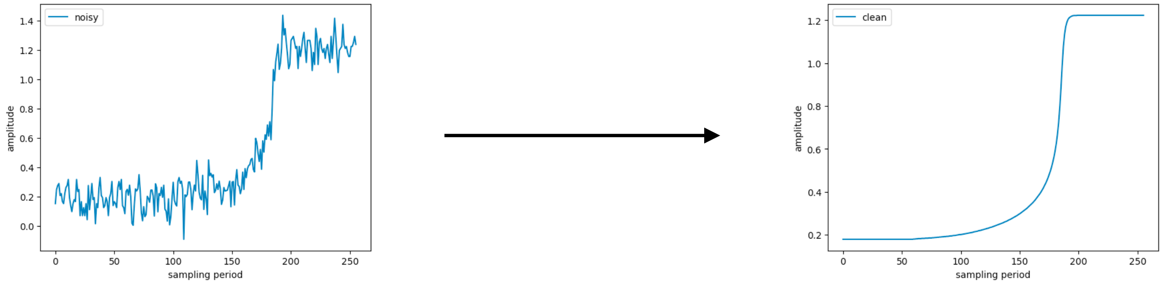


x	simulated clean pulse
$\tilde{x}$	simulated pulse with added detector noise
y	encoded/latent representation
z	reconstructed output

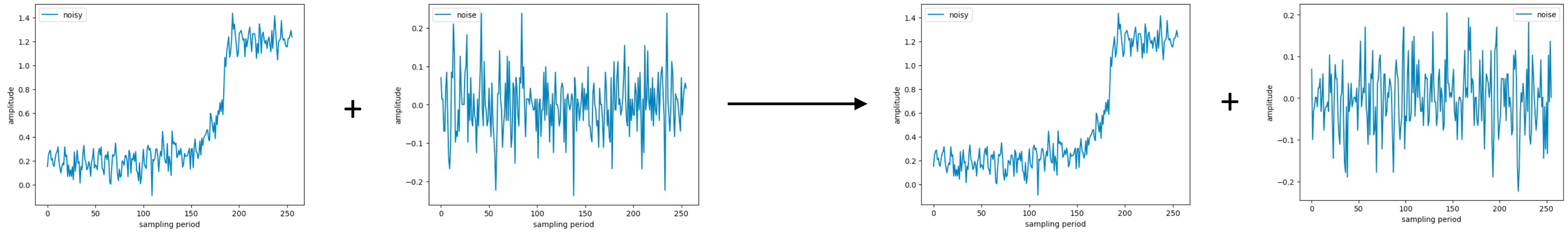
[1] : Anderson, M. R. et al., “Performance of a convolutional autoencoder designed to remove electronic noise from p-type point contact germanium detector signals,” Eur. Phys. J. C 82, 1084 (2022). arXiv:2204.06655; doi:10.1140/epjc/s10052-022-11000-w

Denoising with Convolutional Autoencoder

Regular model: maps a noisy pulse to its corresponding clean pulse. Removing noise by reinforcing the model to reconstruct the clean signal from the noisy input



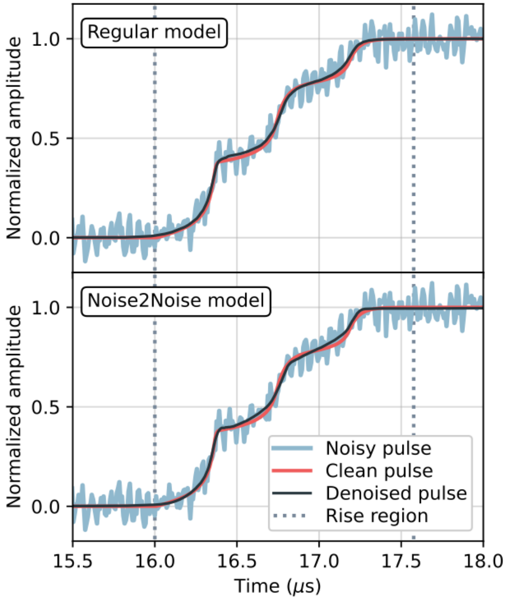
Noise2Noise model [2]: trained without simulation/clean pulses. Maps a noisy pulse to another noisy pulse with the same underlying trace. Model learns the mean of the distribution of the noisy pulses, which is the unobserved underlying true pulse

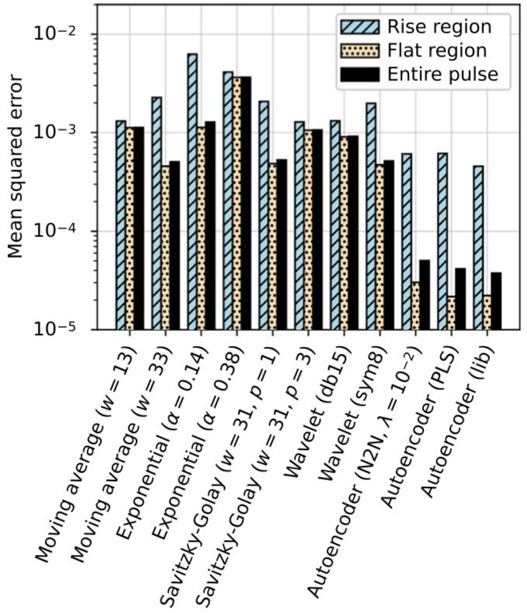


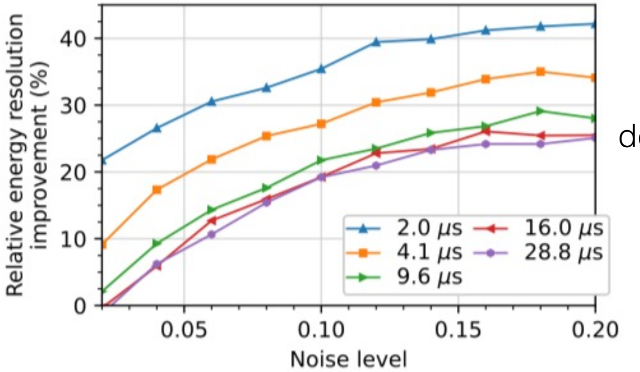
Autoencoder Results

<u>On synthetic data with detector noise (Am-241 60keV peak):</u>

- Superior over traditional denoising methods from MSE
- Improvement on energy resolution at various noise levels



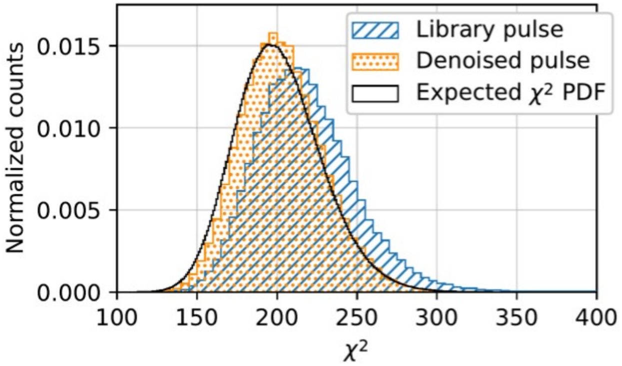


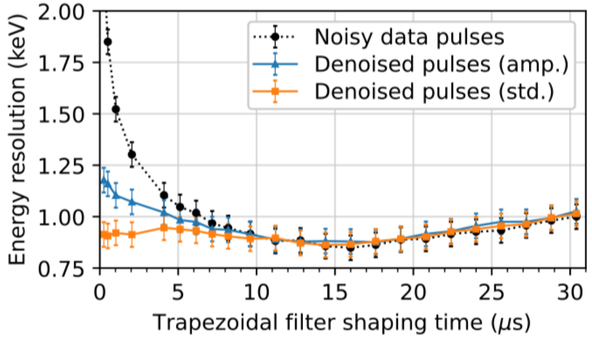


denoised vs. trapezoidal filtered

<u>On real detector data (Am-241 60keV peak):</u>

- Better statistical agreement between noisy and denoised pulses than best fit library pulse via χ^2 fit
- Less substantial improvement on energy resolution due to unmodelled effects in real data, e.g. multiple sources of exponential decay that pole-zero correction did not account for
- Requires lower shaping time → shorter pulse length and more efficient data storage/analysis

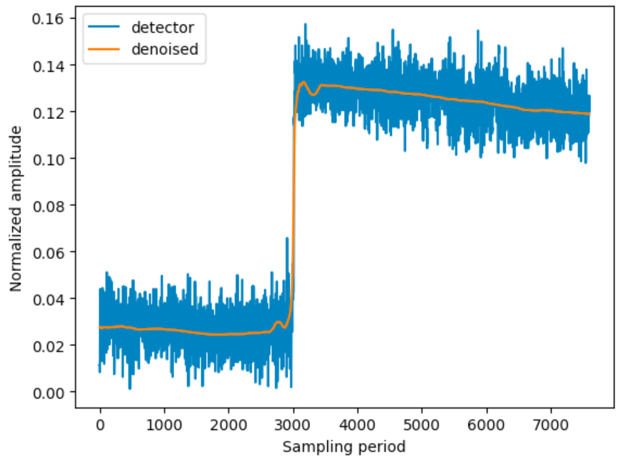


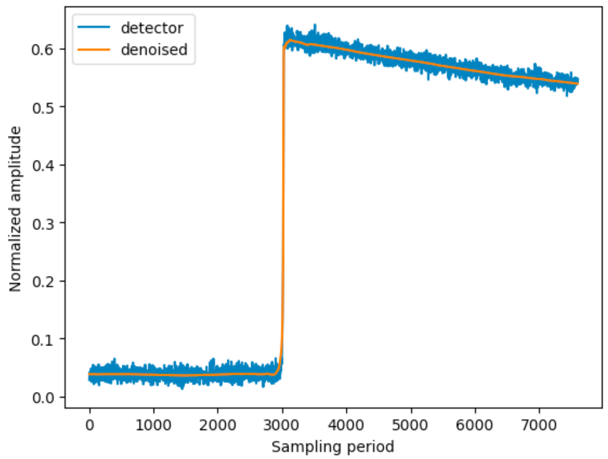


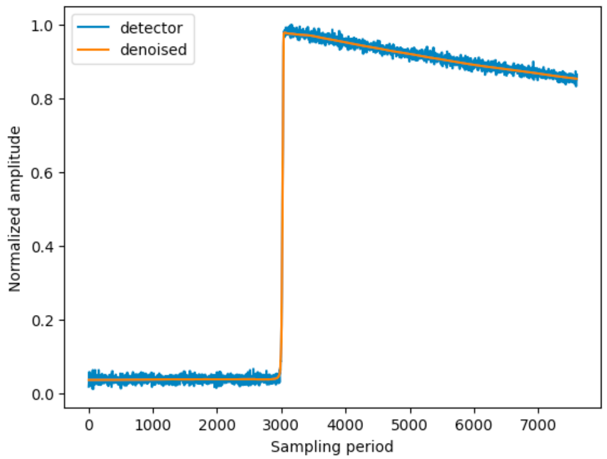
[1]: arXiv:2204.06655

A First Look at Noise2Noise Autoencoder Denoiser on LEGEND Low Energy Dataset

- Denoised by a pre-trained Noise2Noise model
- The N2N model was trained with pole-zero corrected PPC detector data and noise traces collected at Queen's lab. We expect the model to perform even better on LEGEND data once it is trained further with LEGEND data, possibly without the need of any exponential decay correction







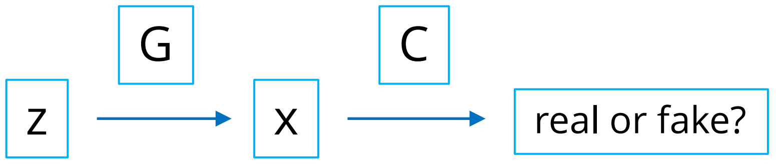
Further Investigation on Denoising without Simulation/Clean Data

- Training a denoiser without clean ground-truth pulse or simulated data is more practical, and it allows for a more realistic, flexible model, unconstrained by simulations
- Noise2Noise model works well if it is trained on a large amount of data
- There are many recent novel methods to explore that could provide further improvements

Dual Critics Generative Adversarial Network

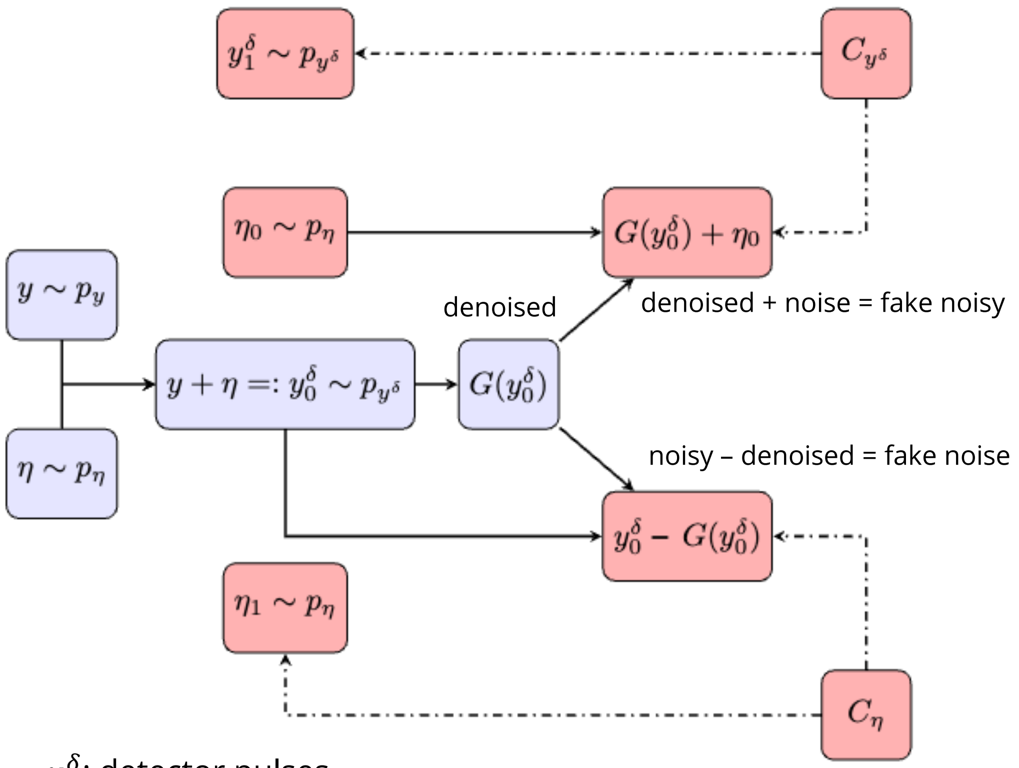
Generative Adversarial Network (GAN) [3]:

- Consists of a generator and a discriminator/critic
- Generator G generates samples x from z, and the critic C tries to determine whether the samples are from the real or generated data



Dual Critics GAN [4]:

- Consists of one generator and two critics

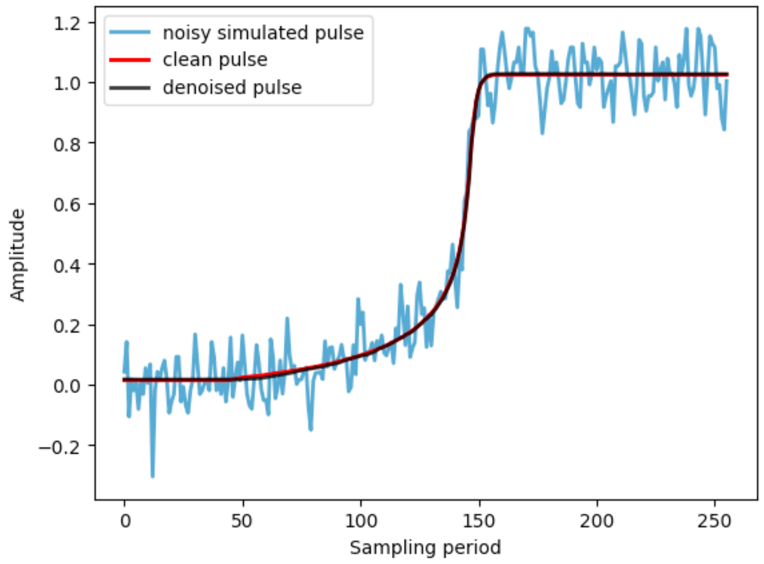


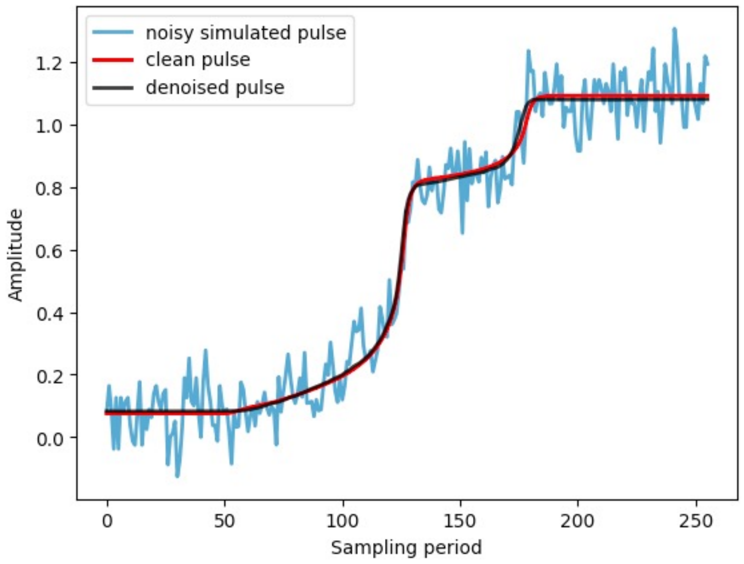
y^δ: detector pulses
η: detector noise traces

Dual Critics GAN Preliminary Results

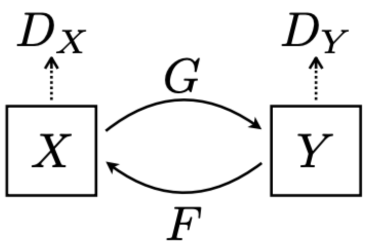
<u>On synthetic data with detector noise (Am-241, 60keV peak):</u>

- Trained on synthetic data with shorter pulse length due to GPU limitations
- Similar MSE as Noise2Noise denoising autoencoder
- GPU intensive to train since model contains multiple neural networks
- Difficult and time-consuming to train and tune
- Training on real data (Co-60 or Am-241) yields worse results





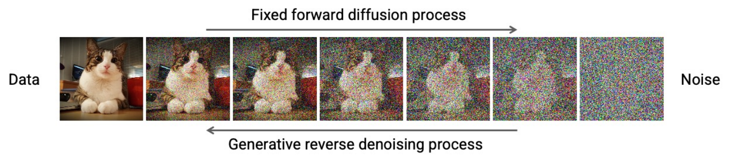
Other Methods



CycleGAN [5]:

- Good performance when trained and tested on synthetic data
- Does not require paired clean and noisy pulses for training – more realistic training condition
- However, not a good candidate for training without ground truth/clean pulses
- Unstable and time-consuming to train

Denoising Diffusion Probabilistic Models [6, 7]:



[8]

(Work in progress)

- The diffusion model is a newer generative model that has recently been shown to often outperform GAN
- More stable to train and less GPU intensive than GAN
- Shows promise in generating realistic detector pulses – could be complementary to detector pulse shape simulation

Outlook

- Developing a denoising method for HPGe detectors that does not rely on ground truth for training
- Noise2Noise is the most promising method we have tested so far
  - Could be further improved using a different neural network, e.g. U-Net, instead of autoencoder
  - Currently testing on LEGEND data; will be trained with LEGEND data as well
  - Applicable to other detector technologies – shown excellent performance on spherical proportional counters and bubble chambers
- GAN might not be the best candidate for denoising
- Exploring diffusion model for both denoising and pulse shape simulation

References

[1] Anderson et al. “Performance of a convolutional autoencoder designed to remove electronic noise from p-type point contact germanium detector signals,” Eur Phys J C Part Fields. 2022;82(12):1084. arXiv:2204.06655

[2] Lehtinen, J. et al., “Noise2Noise: Learning image restoration without clean data,” Proc. Int. Conf. Mach. Learn., vol. 80, pp. 2965–2974 (2018). arXiv:1803.04189

[3] Goodfellow et al. “Generative Adversarial Networks,” arXiv.1406.2661

[4] Dittmer et. al. “Ground truth free denoising by optimal transport,” Numerical Algebra, Control and Optimization, 2024, 14(1): 34-58. doi: 10.3934/naco.2022017

[5] Zhu, J. Y. et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks.“ Proc. IEEE Int. Conf. Comput. Vis. (2017). arXiv:1703.10593

[6] Ho et al. “Denoising Diffusion Probabilistic Models,” arXiv:2006.11239

[7] Nichol et al. “Improved Denoising Diffusion Probabilistic Models,” arXiv:2102.09672v1

[8] CVPR 2022 Tutorial. “Denoising Diffusion-based Generative Modeling: Foundations and Applications”