Removing Electronic Noise from HPGe Detector Signals with Machine Learning

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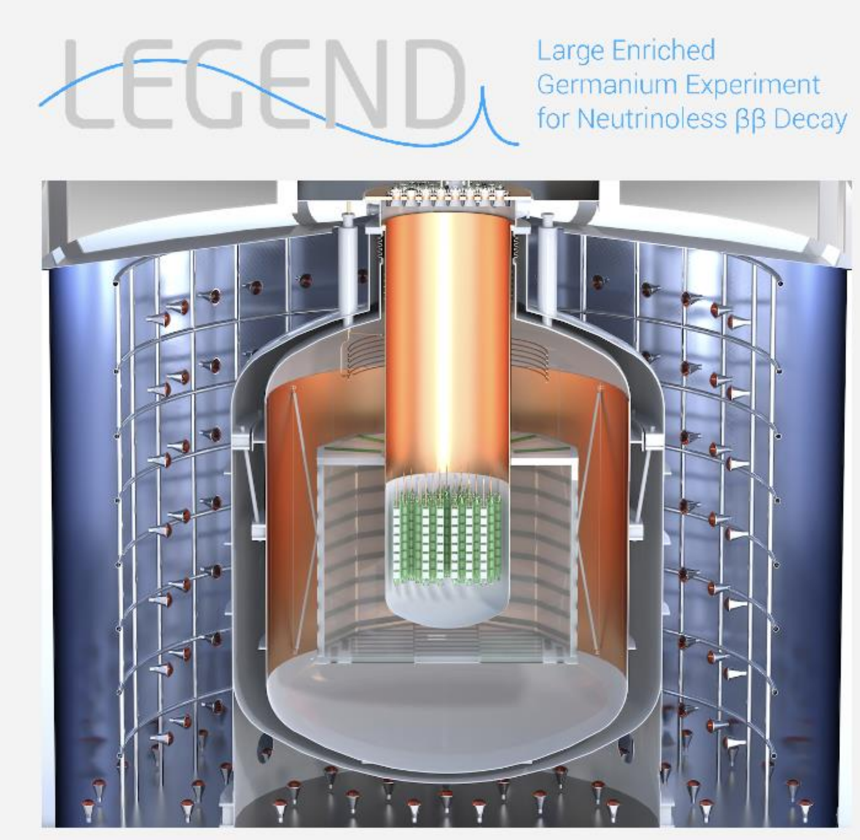
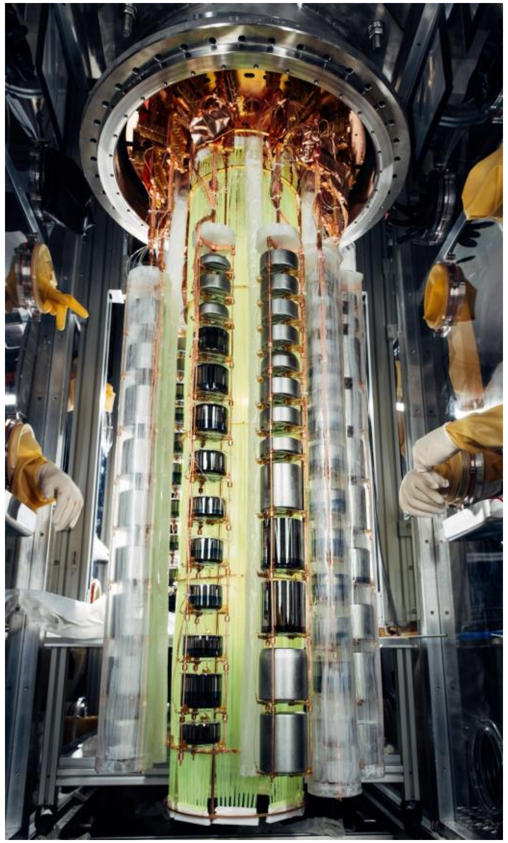
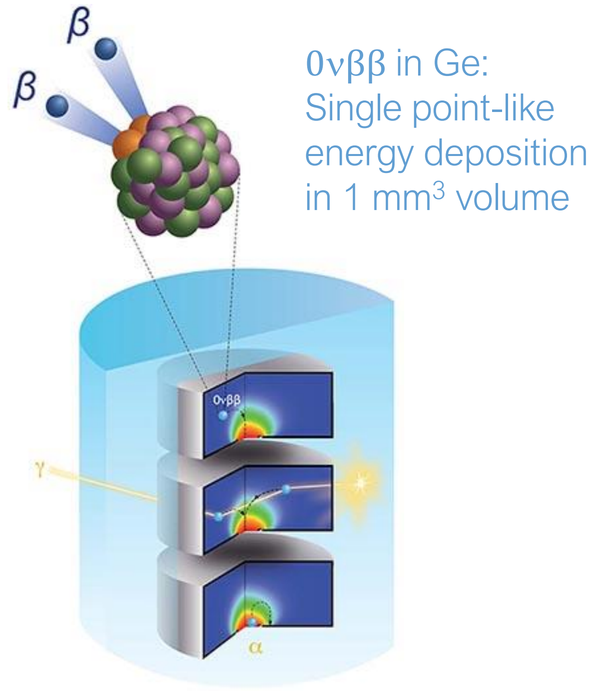
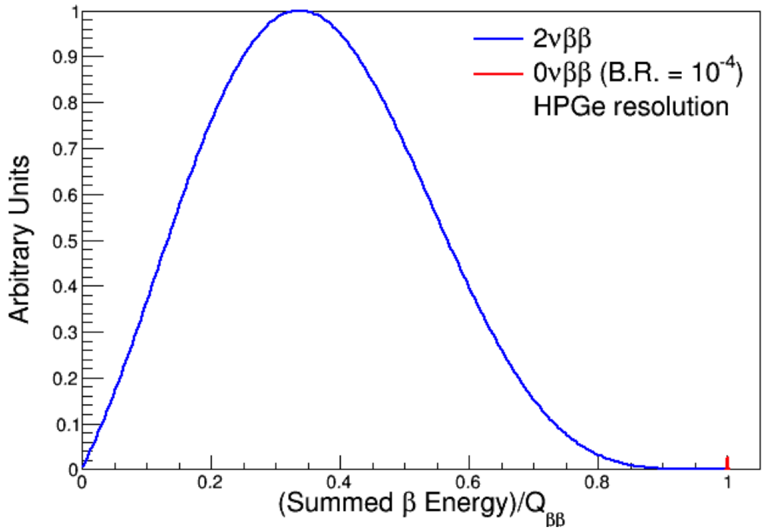
Large Enriched
Germanium Experiment
for Neutrinoless ββ Decay

LEGEND - Large Enriched Germanium Experiment for Neutrinoless ββ Decay



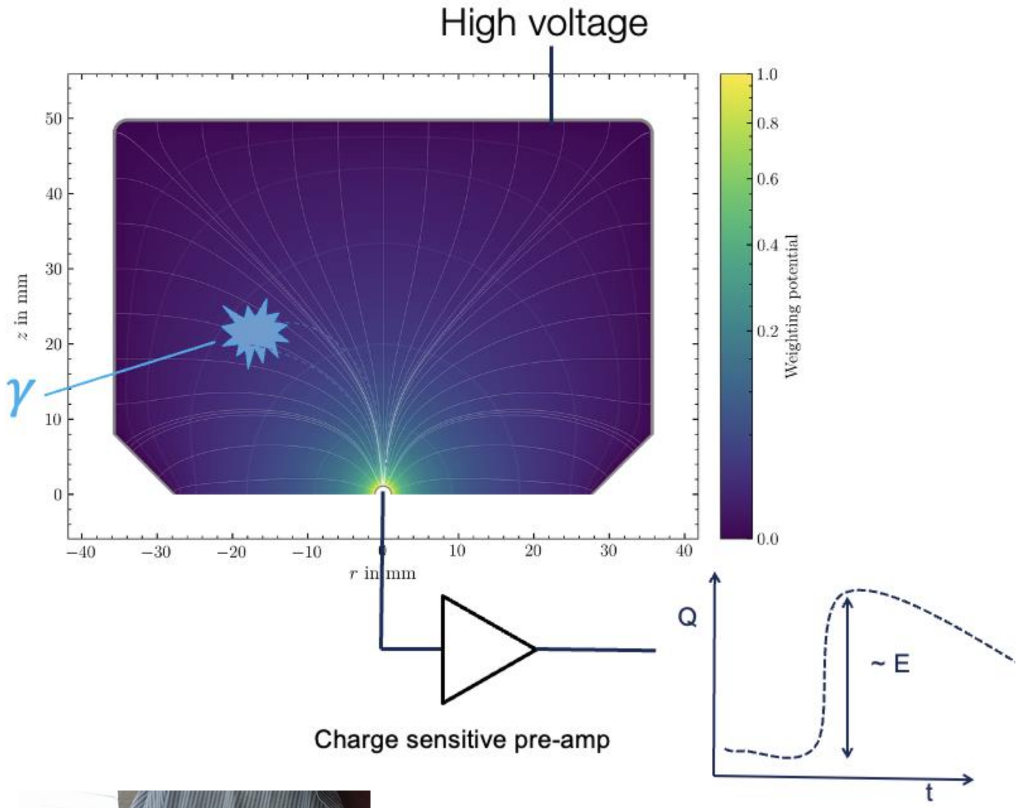






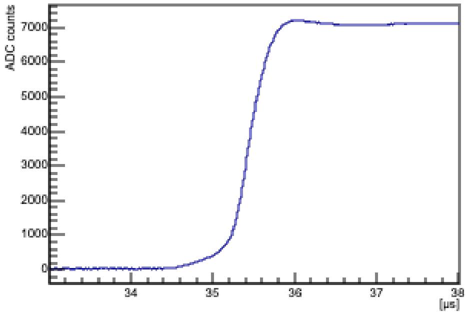
Aims to develop a phased, Ge-76 based double-beta decay experimental program with discovery potential at a half-life beyond 10^{28} years

High Purity Germanium Detector

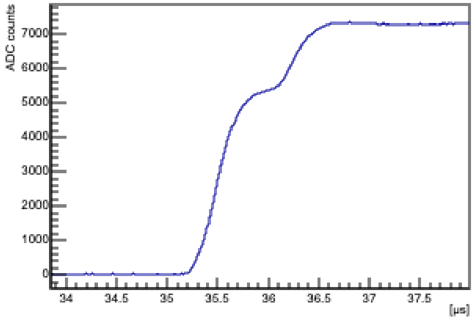


Point contact detector

Simulation:

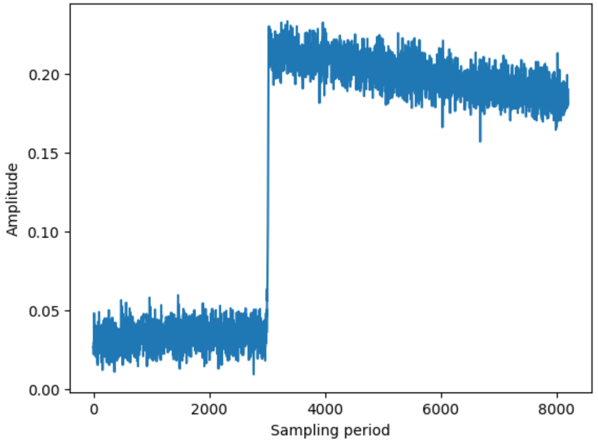


Single site event



Multi site event

Real detector pulse:



Signal Denoising with Machine Learning

- Improve measurements of pulse shape characteristics
  - ➢ Better energy resolution and background rejection efficiency
- Help 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

- Fast processing once model is trained; scalable
- Applicable to other detector technologies and one-dimensional electronic signals
- Trained models can be extended to other applications, e.g. pulse shape discrimination, drift time measurement

Data for training, validation and testing

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

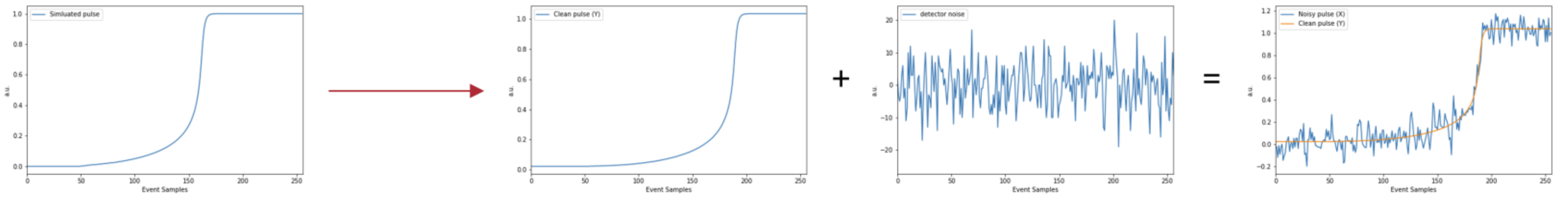
- Simulated clean pulses for the PPC detector
- Calibration data with known energy distributions: ^{241}Am (60 keV, low energy/high noise); ^{60}Co (1173 keV and 1332 keV, high energy/low noise)
- Pure detector noise (for data augmentation)

Synthetic Data Augmentation:

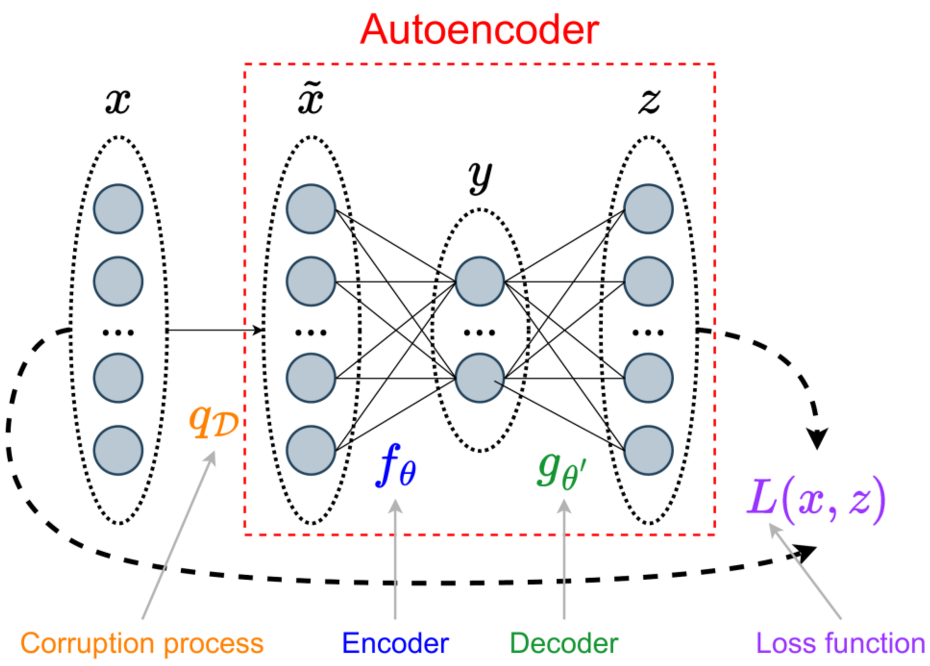
scaled and shifted horizontally and vertically

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

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



Denoising with Convolutional Autoencoder



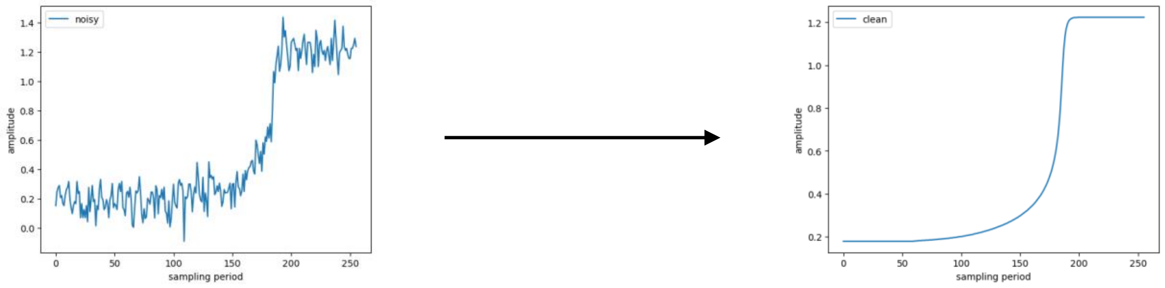
x	simulated clean pulse
$\tilde{x}$	simulated pulse with added detector noise
y	encoded/latent representation
z	reconstructed output

- A generic autoencoder maps its input back to its input
  - Compresses input data down to only the essential features (latent layer), then reconstruct the original input from this compressed representation
  - Only the most important information are stored in the latent layer

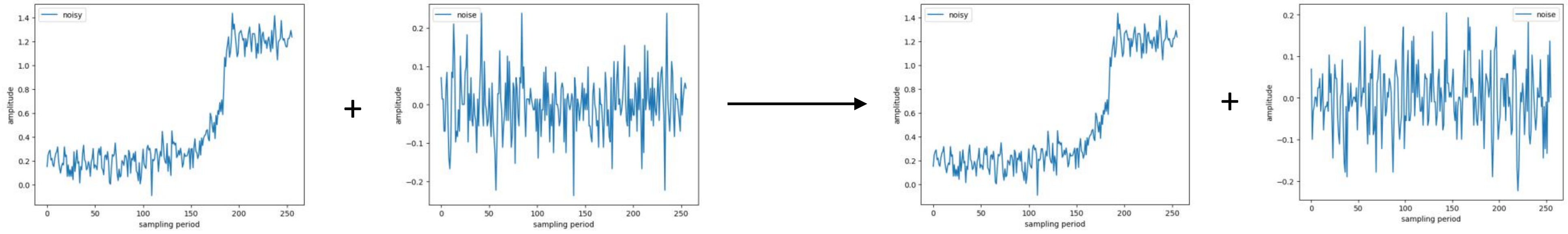
[Anderson, M. R. et al., "Performance of a convolutional autoencoder designed to remove electronic noise from p-type point contact germanium detector signals," Eur. Phys. J. C 82, 1084 (2022). arXiv:2204.06655; doi:10.1140/epjc/s10052-022-11000-w]

Denoising with Convolutional Autoencoder

<u>Regular model</u>: maps a noisy pulse to its corresponding clean pulse. Removes noise by reinforcing the model to reconstruct the clean signal from the noisy input



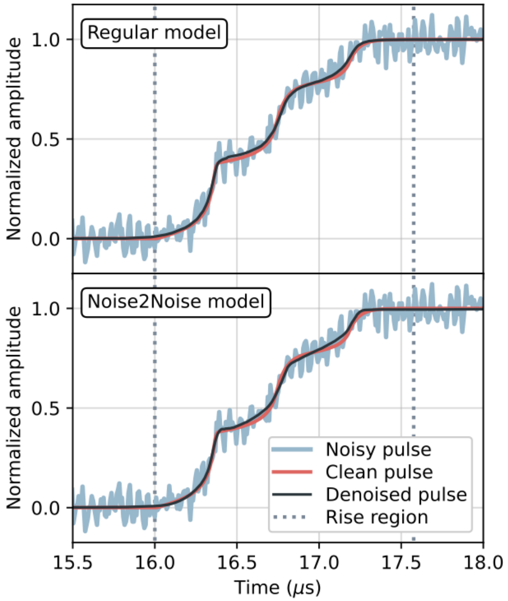
<u>Noise2Noise model [2]</u>: trained without simulation/clean pulses. Maps a noisy pulse to another noisy pulse with the same underlying trace. Model learns the mean of the distribution of the noisy pulses, which is the unobserved underlying true pulse

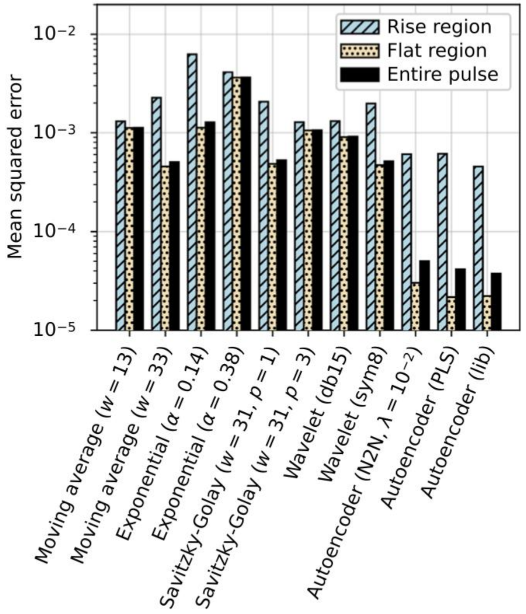


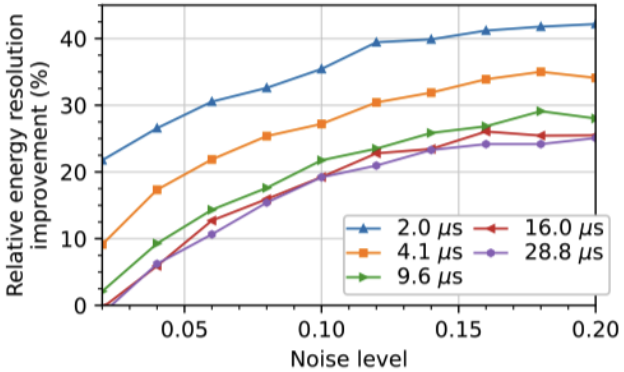
Autoencoder Results

<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



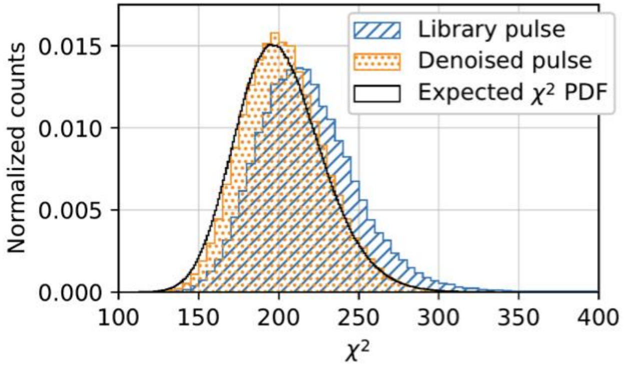


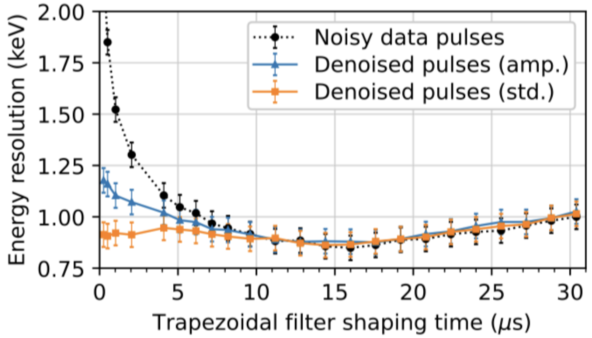


denoised vs. trapezoidal filtered

<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
- Requires lower shaping time → shorter waveform length and more efficient data storage/analysis
- 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

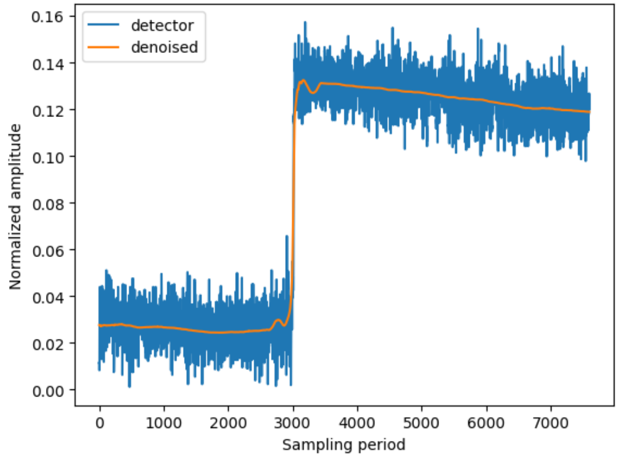


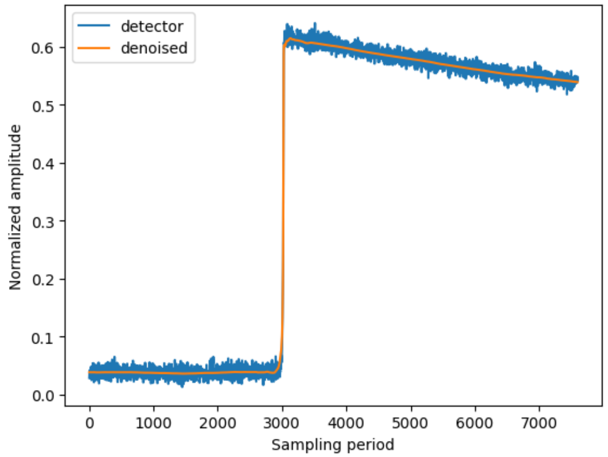


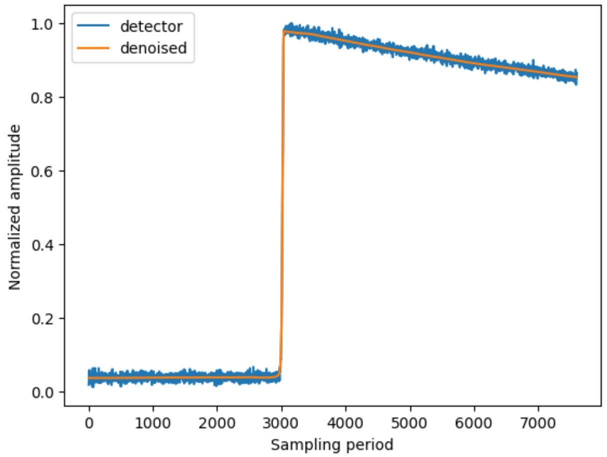
[1]

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

- Denoised by a pre-trained Noise2Noise model
- As a first look, 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







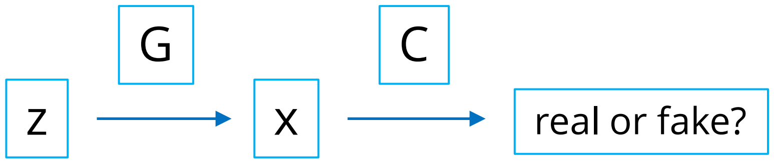
Further Investigation on Denoising without Simulation/Clean Data

- 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

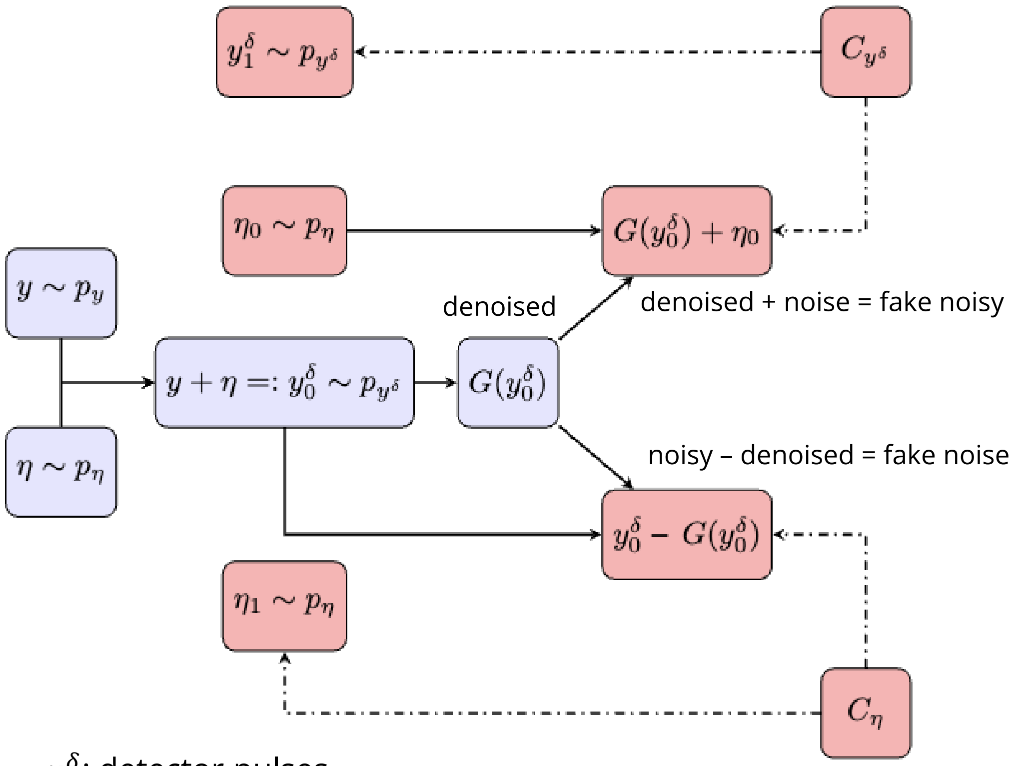
Generative Adversarial Network (GAN) [3]:

- 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

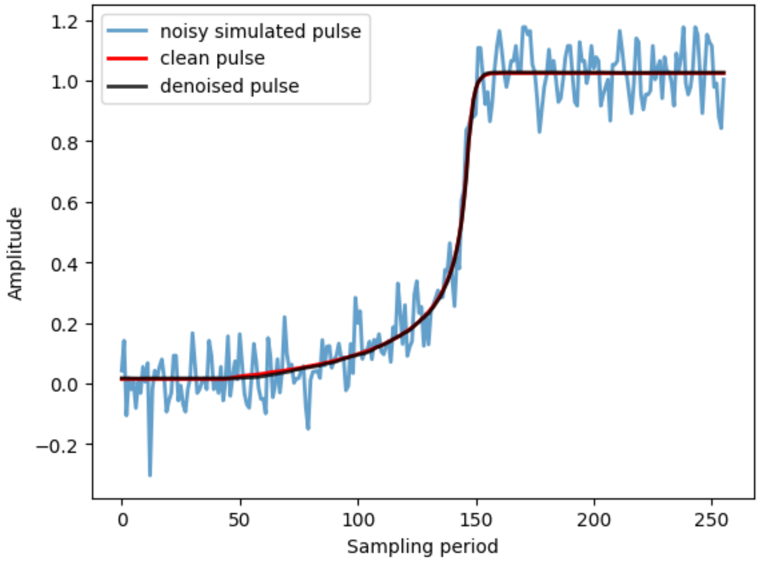


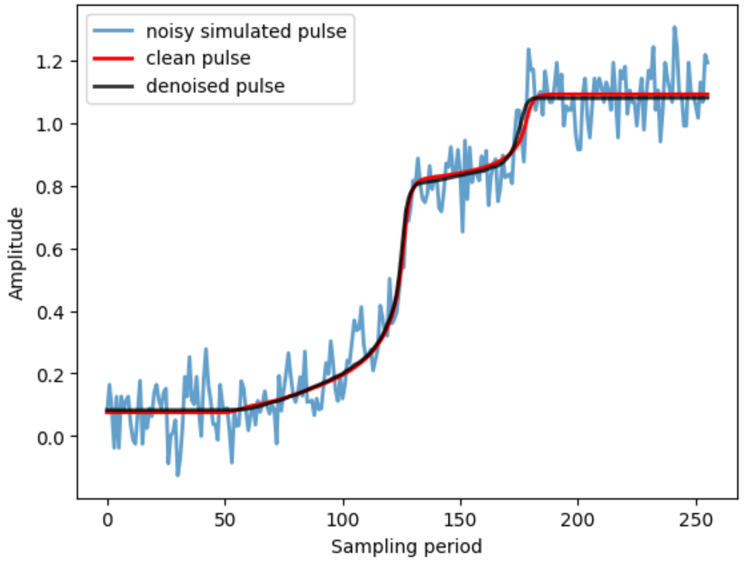
y^δ: detector pulses
η: detector noise traces

Dual Critics GAN Preliminary Results

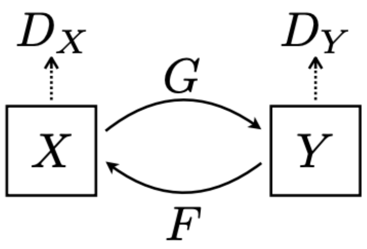
<u>On synthetic data with detector noise (Am-241, 60keV peak):</u>

- More GPU intensive to train than Noise2Noise autoencoder since this model contains multiple neural networks
- Had to train on shorter pulses due to large model size and GPU limitations
- GAN could be difficult to train and time-consuming to tune





Other Methods

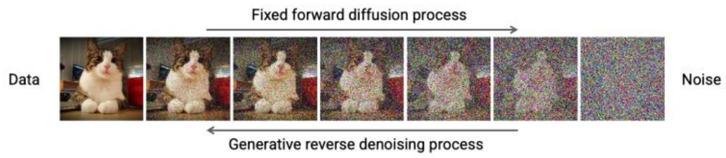


CycleGAN [5]:

- 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
- Like many GAN methods, it can often be unstable, hence difficult to train

Denoising Diffusion Probabilistic Models [6, 7]:

(Work in progress)



[8]

- 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 aid, validate or replace complex detector pulse shape simulation

Summary

- Developing a denoising method for HPGe detectors that does not need 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

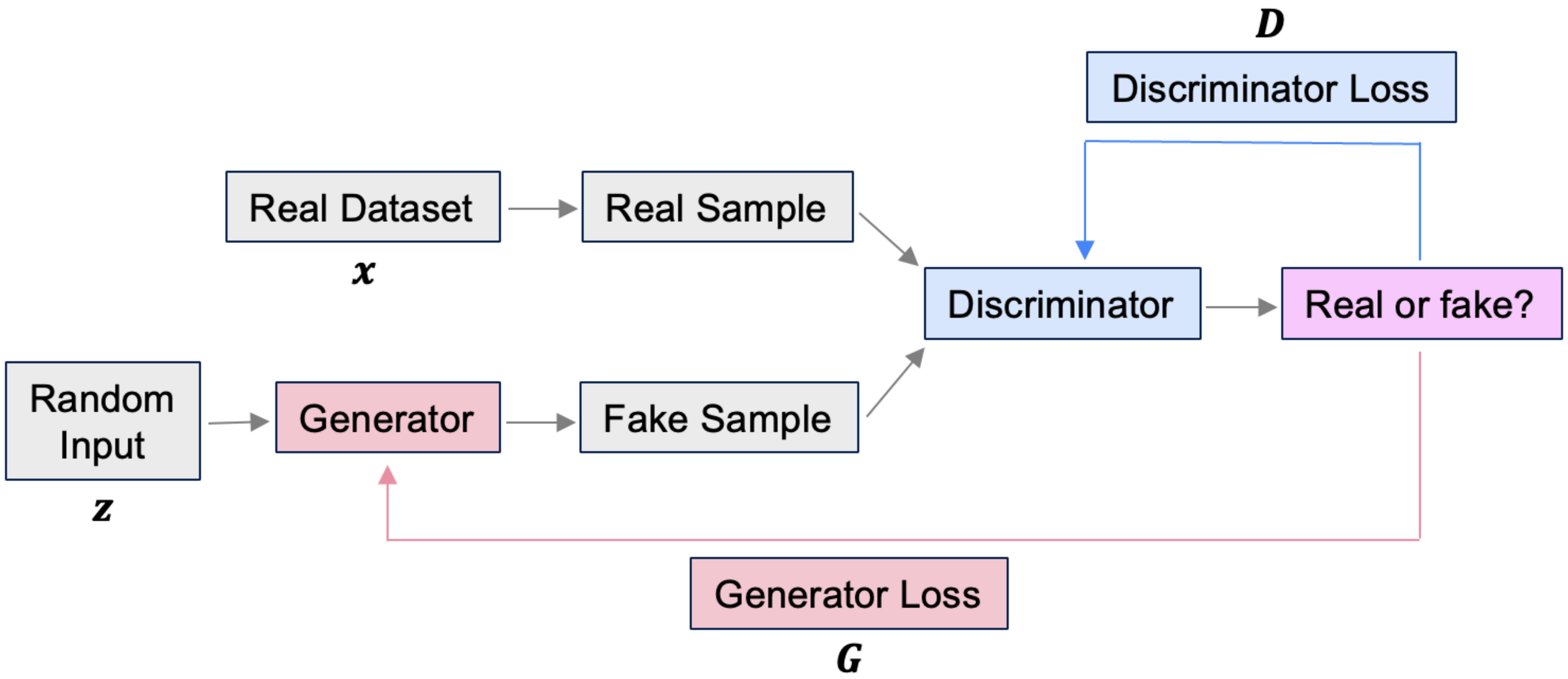
[8] CVPR 2022 Tutorial. “Denoising Diffusion-based Generative Modeling: Foundations and Applications”

Backups

High Purity Germanium Detectors

- $^{76}\mathrm{Ge}$ is a potential candidate for $0\nu\beta\beta$: Source = detector, high efficiency, low intrinsic background
- Can be enriched to >90% in Ge-76
- Excellent energy resolution: 2.5 keV FWHM @ 2039 keV ($Q_{\beta\beta}$)
- Scalable technology
- Background rejection capabilities (especially point contact detectors):
  - Multiplicity-based rejection in arrays
  - Surface event rejection
  - Multi-site event rejection ($0\nu\beta\beta$ would be a single site event)

GAN

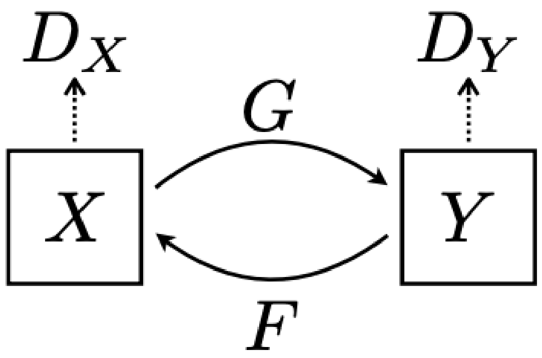


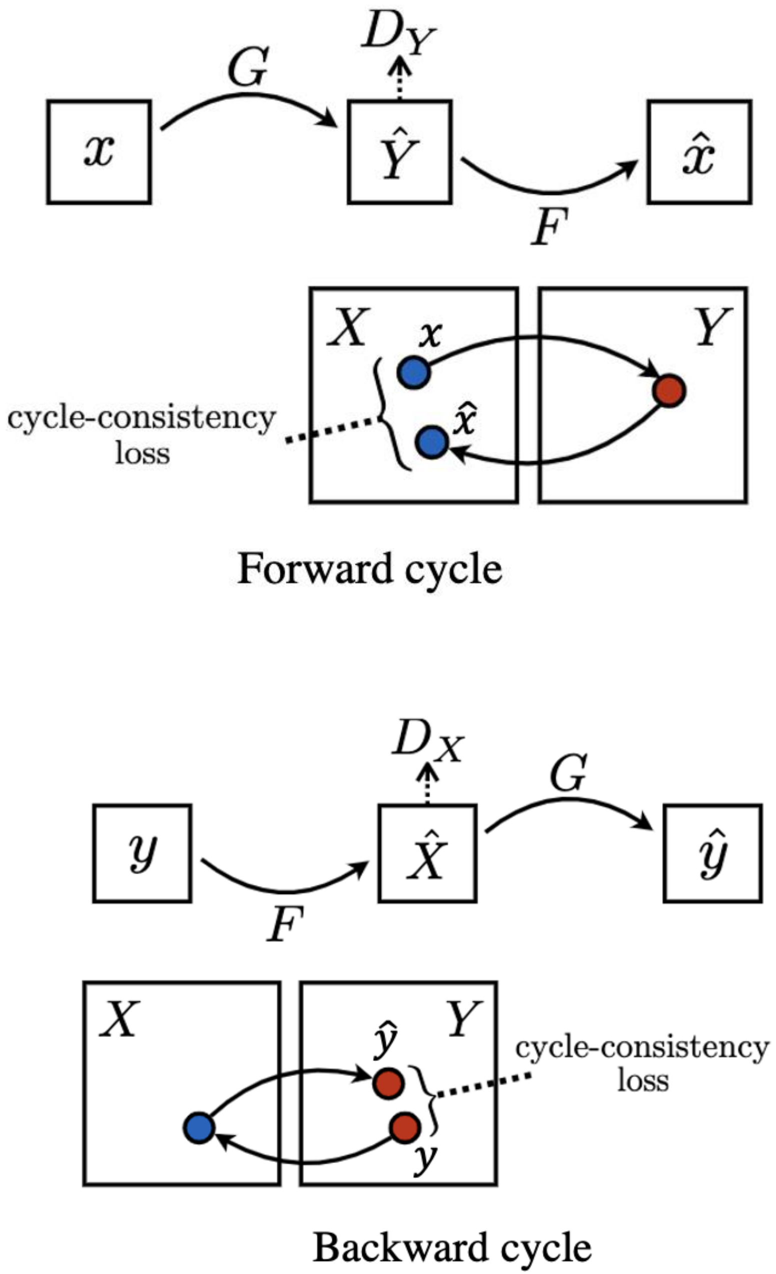
Objective: $$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log \boxed{D(\boldsymbol{x})}] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1-\boxed{D(G(\boldsymbol{z}))})]$$

discriminator's estimate of the probability that a real datum $\boldsymbol{x}$ is real

discriminator's estimate of the probability that a generated instance is real

CycleGAN


D_X
D_Y
G
X
Y
F


D_Y
G
x
$\hat{Y}$
$\hat{x}$
F
X
x
Y
$\hat{x}$
cycle-consistency
loss
Forward cycle
D_X
G
y
$\hat{X}$
$\hat{y}$
F
X
Y
$\hat{y}$
y
cycle-consistency
loss
Backward cycle

[5]