Applications of a deep convolutional autoencoder to process pulses from a p-type point contact germanium detector

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Mark Anderson
anderson.mark@queensu.ca

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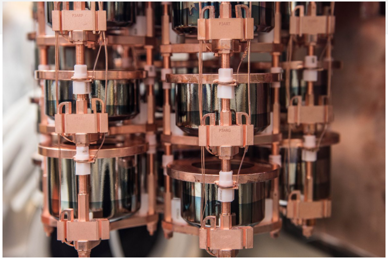
Queen's University

Canadian Association of Physicists
Association canadienne des physiciens et physiciennes

Introduction



[10]

- High-purity germanium (HPGe) detectors widely used in beyond Standard Model rare event searches ($0\nu\beta\beta$, dark matter, etc.)[2, 3, 4, 5, 6, 7, 8, 9]

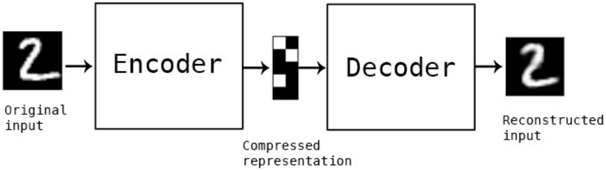
- Electronic noise makes signal identification challenging
  - Rare events in the presence of backgrounds

- Noise removal could help advance these searches
  - Identify low-energy signal events that would otherwise be dominated by electronic noise
  - Improved background rejection based on pulse shapes
  - More accurate measurements of pulse amplitudes $\rightarrow$ better energy resolution

- Deep learning has been successfully used in other fields (typically 2D images)
  - Why not 1D pulses from HPGe detectors?

Autoencoders

- An autoencoder is an algorithm used to learn a useful representation of data
  - Trained to map the inputs to the inputs (with some form of constraint)

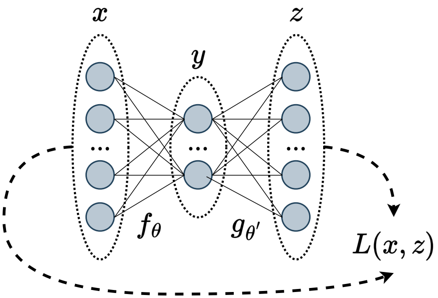


[11]

- By definition, an autoencoder is *lossy*
  - The goal is to retain as much *useful* information as possible
- Typically a (deep) neural network

Denoising autoencoders

- Denoising autoencoders impose the constraint that reconstruction must also remove noise
  - Proposed as a method to extract robust features for other classification tasks[12]
  - Input becomes a corrupted version of x, $\tilde{x}$, by some process $q_{\mathcal{D}}$



[1]

Internal/latent representation, y:

$$f_\theta(x) = y$$

Input reconstruction, z:

$$g_{\theta'}(y) = g_{\theta'}(f_\theta(x)) = z$$

Minimize some **loss function** quantifying the reconstruction of x, $L(x, z)$

$$L(x, z) = \frac{1}{N} \sum_{i}^{N} \|z_i - x_i\|_2^2$$

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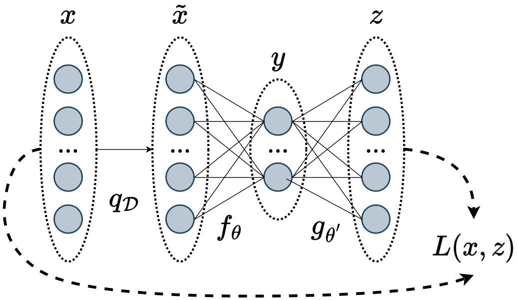

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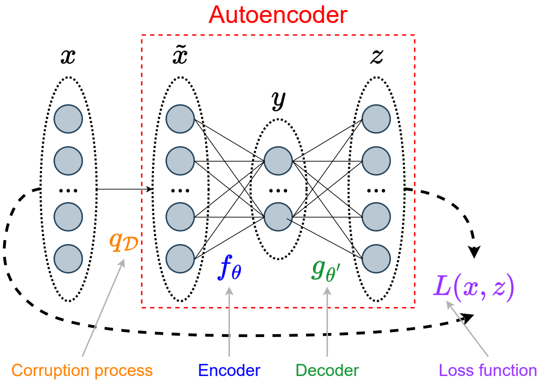

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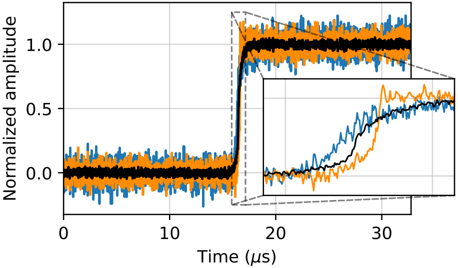
The detector

- Signals are from a $1\,$kg p-type point contact detector located at Queen's University
  - Cylindrical with a radius of $3\,$cm and height of $5\,$cm
  - Manufactured by ORTEC/AMTEK
  - Operated in a PopTop cryostat

[13]



[1]

- Each signal is a sequence of voltages sampled at a fixed interval
  - Observed noise levels after preprocessing reflect energy of pulse; signal-to-noise ratio (SNR)
  - Different rise times reflect different positions

Datasets: real detector data

Americium-241 source

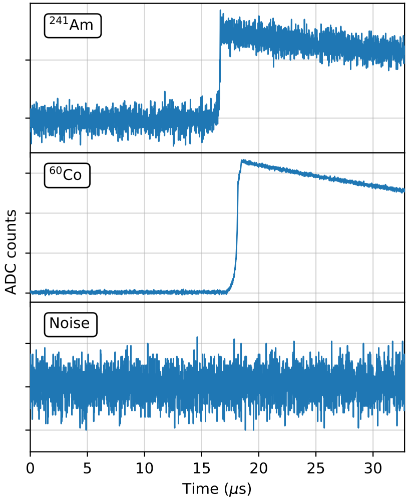
- Produces $60\,\text{keV}$ γs
- Almost entirely single-site events
- Lower energy (higher noise), good for *validation*

Cobalt-60 source

- Produces $1173\,\text{keV}$ and $1332\,\text{keV}$ γs
- Numerous multi-site events from Compton scatters
- Higher energy (lower noise), good for *training*

Detector noise

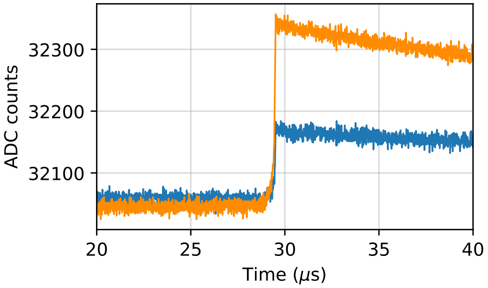
- Collected by randomly triggering the detector (and removing actual signals that occasionally occur)
- Used for *data augmentation*



Datasets: real detector data (preprocessing)

- Data pulses preprocessed to remove baseline
- Data pulses have exponential decay removed with pole zero correction
- Data pulses scaled by amplitude (calculated with a trapezoidal filter)

} **Amplitude normalization**



Before preprocessing

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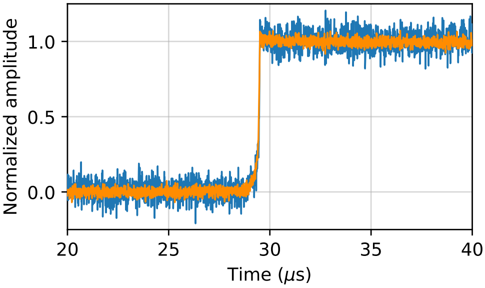
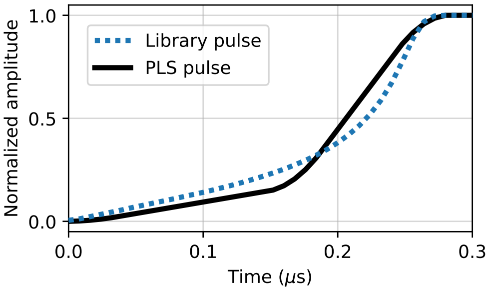


After preprocessing

Datasets: simulated data



[1]

Library pulses

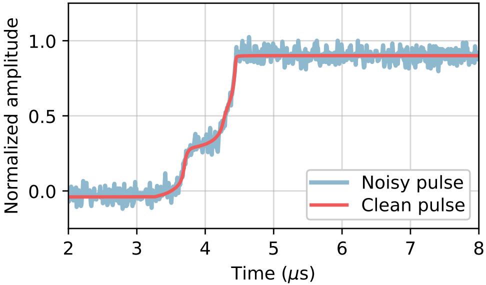
- 1724 simulated "library" pulses[14]
- Each pulse corresponds to point on 1 mm × 1 mm azimuthally symmetric grid
- Created using `siggen` simulation software[15]
- Used to infer position of real events

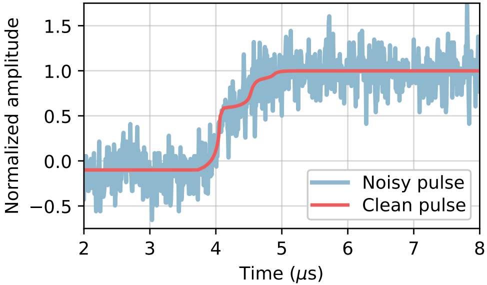
Piecewise linear smoothed (PLS) pulses

- Mimic the general shape of the library pulses without the requirement of complex physics simulations

Datasets: simulated data (data augmentation)

- From the simulated single-site event pulses, can create a diverse training set
  - Combine single-site simulated pulses to create *artificial multi-site events*
  - Apply random *horizontal shifts, vertical shifts, and amplitude scales* to each pulse
  - Add *detector noise* to each pulse with a random standard deviation





Note: no preprocessing required for simulated pulses!

Training procedures

Regular

- Trained to map the noisy pulse to the corresponding clean underlying pulse
- Must know the true pulse – *only works on simulated data*

Noise2Noise[16]

- Trained to map noisy pulse to noisy pulse (different noisy realizations of same underlying signal)
  - An impossible task in practice
  - Model will instead learn to predict the mean, given infinite different noisy realizations
- Can be used with simulations, *but this is not required*
  - For detector data, add even more noise to the already noisy pulse
  - Include a *total variation* penalty[17] to original loss function L_0 to account for the noisy true mean
  - Penalize the absolute difference between given sample (j) and subsequent sample $(j+1)$ in pulse
  - Apply scaling factor λ to control weighting

$$L = L_0 + \frac{\lambda}{N} \sum_{i}^{N} \sum_{j}^{M-1} |z_{i,j+1} - z_{i,j}|$$

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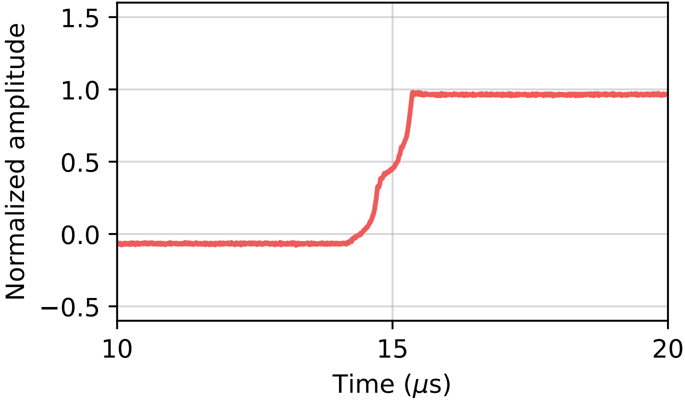
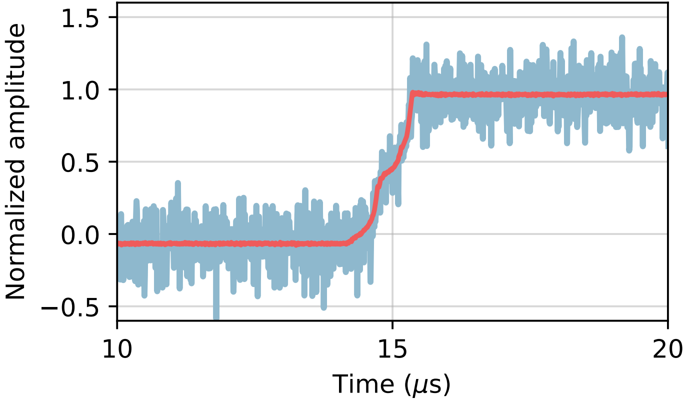
Original ^{60}Co data pulse (low noise/high energy/large SNR)



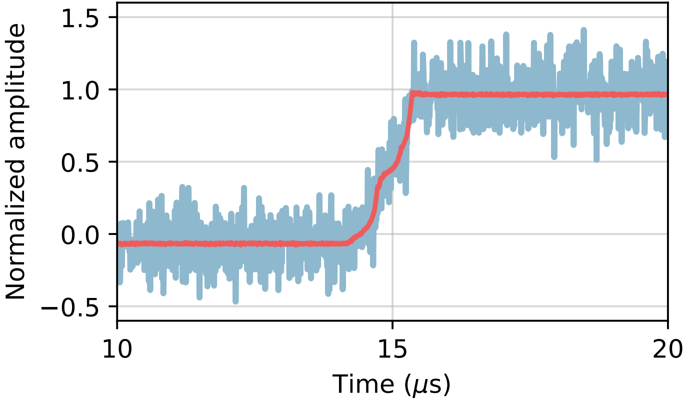
Noise2Noise

Original ^{60}Co data pulse with a random noise pulse



Noise2Noise

Original ^{60}Co data pulse with *another* random noise pulse



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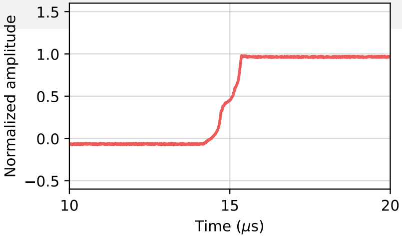
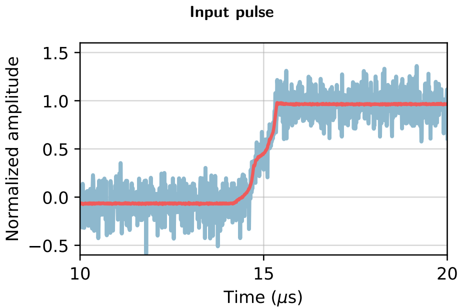
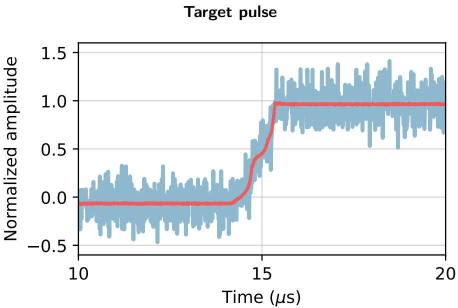
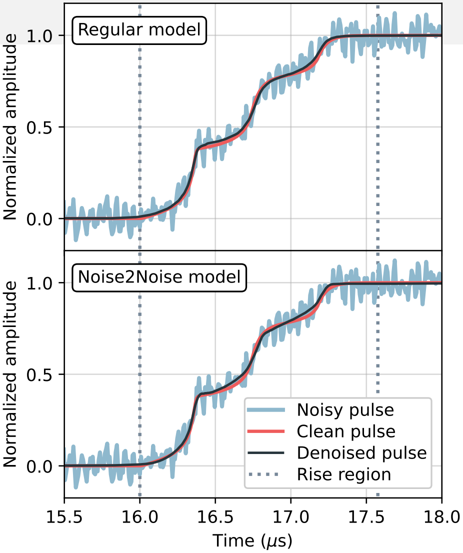






Results: simulations

- Qualitatively, denoising with deep learning performs very well on simulations
- Autoencoder is superior to all traditional denoising methods investigated
  - Compared mean squared error on test set containing simulated single-/multi-site events
  - Each method optimized on a separate validation set to select hyperparameters
- Regular training procedure (simulations) outperforms Noise2Noise (^{60}Co data)
  - Still very good performance with Noise2Noise



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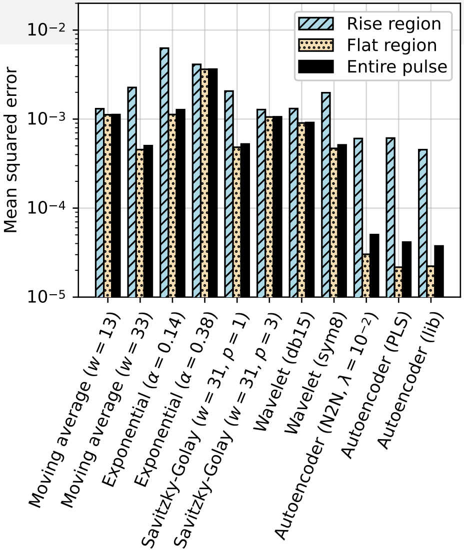

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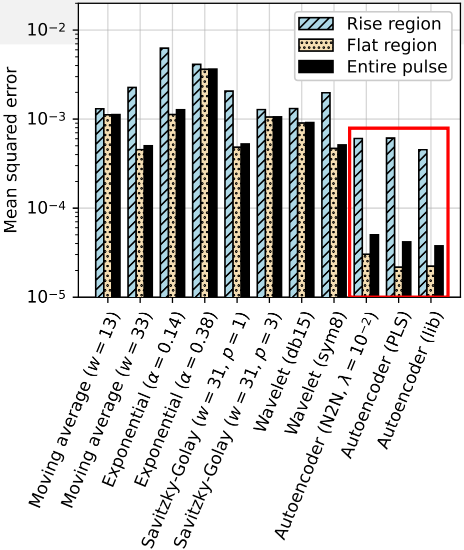
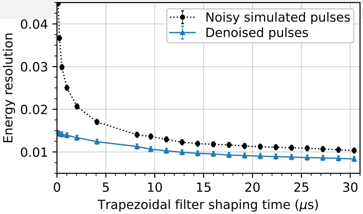


[1]

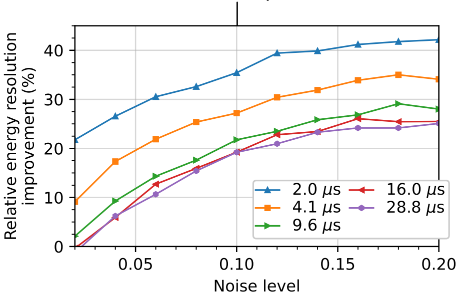
Results: simulations (energy resolution)

- In terms of physics results, allows for an improvement in the energy resolution
  - Energy calculated from the amplitude of a trapezoidal filter with given shaping time
  - FWHM of peak is the energy resolution
- Created test datasets with different noise levels and evaluated the energy resolution of each
- At every noise level and shaping time, the results after denoising with our autoencoder are superior
  - Proportionally larger improvements with increasing noise level, decreasing shaping time



[1]

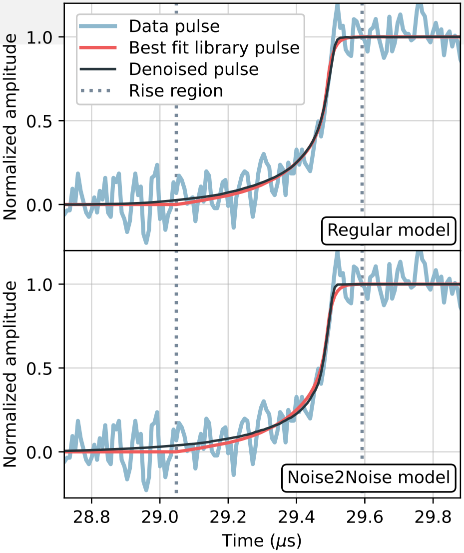
Noise level of 0.10



[1]

Results: data

- Qualitatively, denoising with deep learning performs very well on data
- More difficult to quantify denoising
  - No true underlying pulse to compare to
- However, can make a statistical comparison to evaluate the performance



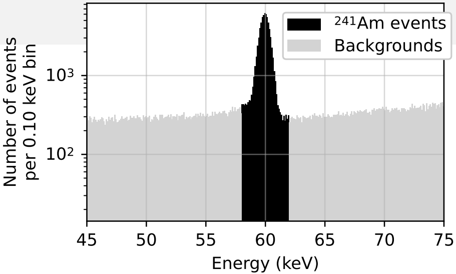
[1] (modified)

Results: data (χ^2 comparison)

- ^{241}Am dataset contains mostly single-site events from $60\,\text{keV}$ γs
- Use a χ^2 comparison between the original pulse and denoised pulse, best-fit library pulse

$$\chi^2\left(x_i, z_i\right) = \sum_{j=M_1}^{M_2} \frac{\left(z_{i,j} - x_{i,j}\right)^2}{\sigma_i^2}$$

- χ^2 distribution between noisy and denoised pulse is consistent with expected χ^2 distribution of our detector noise
  - Taken over 200 samples containing rise region (M_1, M_2 set appropriately)



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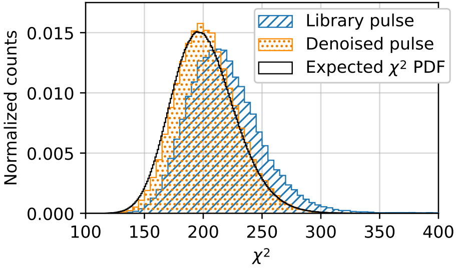


[1]

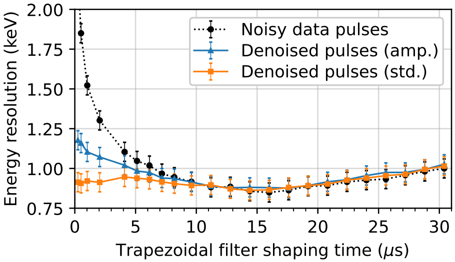
Results: data (energy resolution)

- Can also evaluate the effect of denoising on the energy resolution, compare to simulations

- Using ^{241}Am data, optimal energy resolution is comparable before and after denoising

- Much lower shaping time required to achieve good energy resolution
  - Important for data storage, analysis, etc.

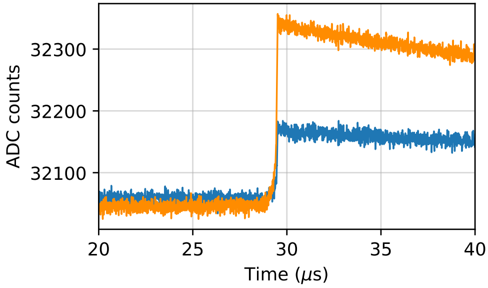
- However, results are not as good as simulations would suggest
  - What's different?



[1]

Results: data (energy resolution)

- We assume data pulses have *one* exponential decay and correct for that



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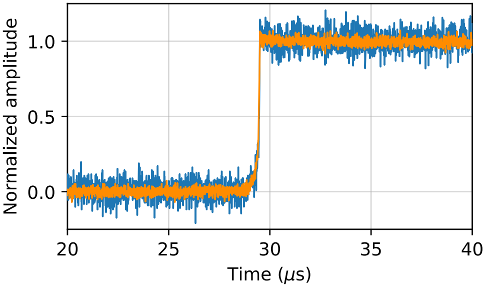
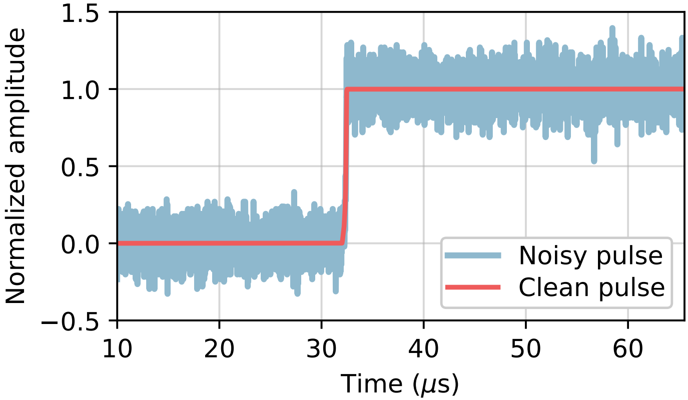


- In reality, there are *multiple* sources of exponential decay, usually small, but still contribute
- A single "effective" pole zero correction is thus imperfect and leaves residual effects from the other exponential decays

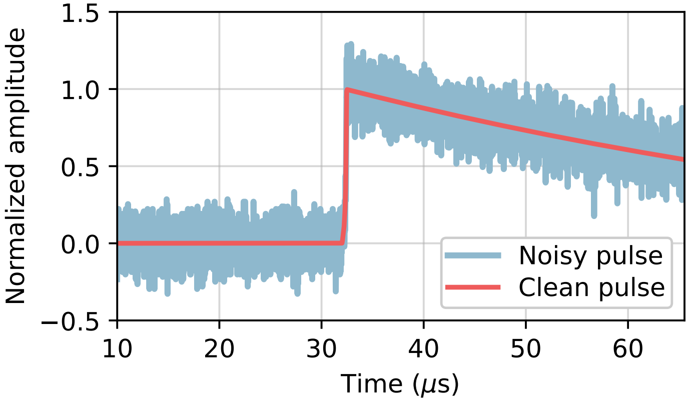
Results: data (energy resolution)

Simulated pulse with noise



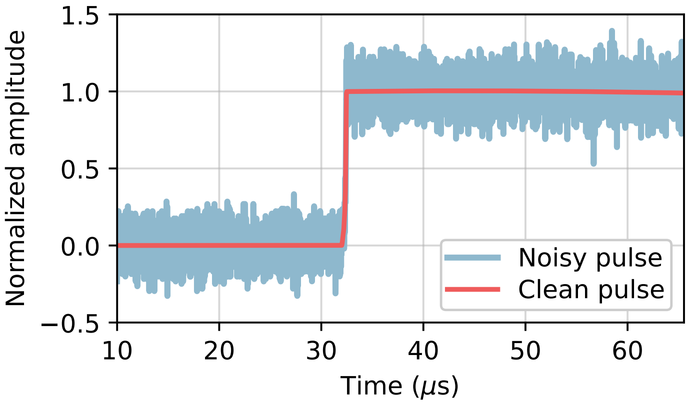
Results: data (energy resolution)

Simulated pulse with noise (convolved with multiple exponentials)



Results: data (energy resolution)

Simulated pulse with noise (deconvolved with one "effective" exponential)



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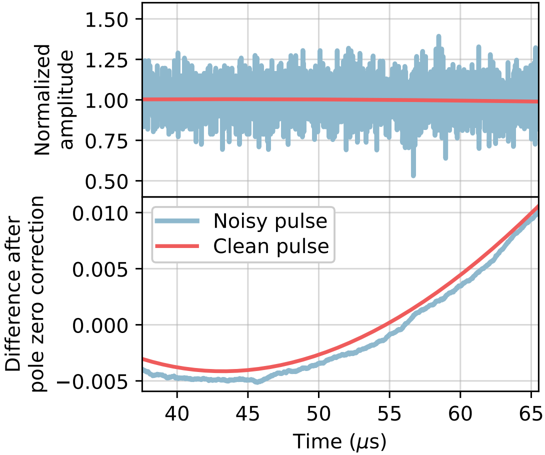
Simulated pulse with noise (deconvolved with one "effective" exponential)



Conclusions and future work

- Deep convolutional autoencoders are effective at removing electronic noise from HPGe detector pulses
  - Outperforms various traditional denoising methods
  - Denoised pulses are statistically consistent with data pulses
  - Can reach optimal energy resolution with a lower shaping time
    - Simulations suggest improvements in the overall optimal energy resolution are possible
    - Accounting for effects present in real data could improve results

- Models can be trained *without* the need for detailed detector simulations
  - PLS pulses are a very rough approximation to library pulses
  - Noise2Noise method requires *only* noisy detector data
    - Results could likely be improved with more (diverse) data

Conclusions and future work

- Results presented here are focused on HPGe detector data
  - Noise removal is beneficial in many contexts
  - Our group is applying these methods to signals from other detector technologies
    - Gaseous proportional counters (e.g., see talk from Noah Rowe), bubble chambers

- Our group is also exploring various extensions of this research
  - New network architectures such as CycleGAN[18] for improved performance
    - Potential to improve modelling of multiple exponential decays, and thus energy resolution, due to the less stringent requirement of unpaired simulated and detector pulses
  - Continuous inline denoising before triggering to reduce trigger thresholds
    - Useful to identify low SNR events otherwise dominated by electronic noise

- Work is broadly applicable to the particle astrophysics community and has great potential to be expanded on

Thank You!

More details in the published paper.
Check it out!

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arXiv:**2204.06655**

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Arthur B. McDonald
Canadian Astroparticle Physics Research Institute

INNOVATION
Canada Foundation for Innovation
Fondation canadienne pour l'innovation

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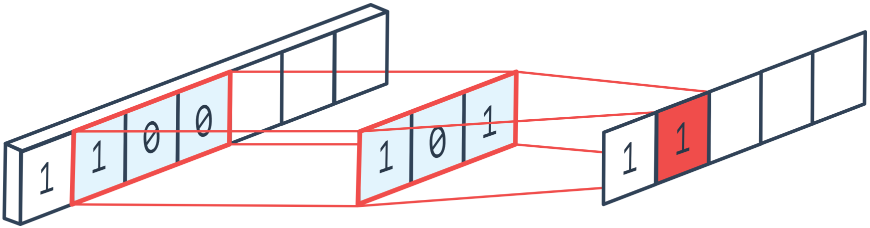
Additional Slides

Model architecture

- Fully convolutional autoencoder
  - Weight sharing provides consistent noise removal across pulse
  - Feature locality and shift equivariance
  - Allows for a variable input shape (subject to some restrictions)
  - Significant reduction in the number of trainable parameters



[19]

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

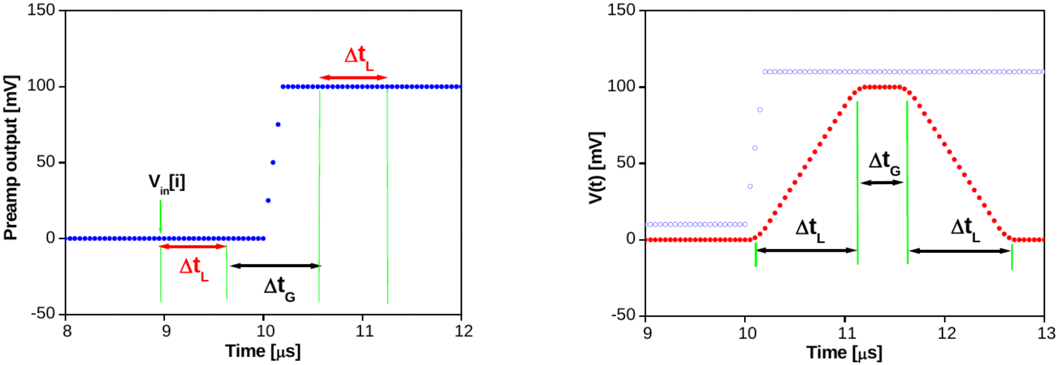
[1]

Results on simulations

Training procedure and data			Mean squared error ($\times 10^{-5}$)			
			Gaussian noise		Detector noise	
Procedure	**Data**	**Noise**	**Library**	**PLS**	**Library**	**PLS**
Regular	Library	Detector	4.12	4.72	3.76	4.21
Regular	Library	Gaussian	3.40	3.82	4.50	4.77
Regular	PLS	Detector	5.10	4.48	4.15	3.57
Regular	PLS	Gaussian	3.93	3.36	5.02	4.31
N2N ($\lambda = 0$)	Library	Detector	3.90	4.37	3.86	4.20
N2N ($\lambda = 0$)	Library	Gaussian	3.46	3.87	4.57	4.82
N2N ($\lambda = 0$)	PLS	Detector	5.11	4.48	4.14	3.55
N2N ($\lambda = 0$)	PLS	Gaussian	3.85	3.46	4.97	4.43
N2N ($\lambda = 0$)	Detector	Detector	6.54	6.30	7.78	7.40
N2N ($\lambda = 10^{-2}$)	Detector	Detector	4.17	4.54	5.04	5.26

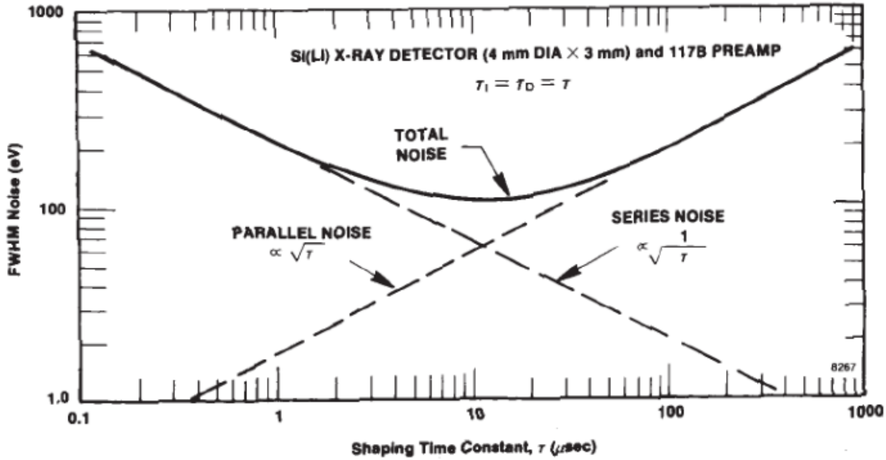
[1]

Trapezoidal filter



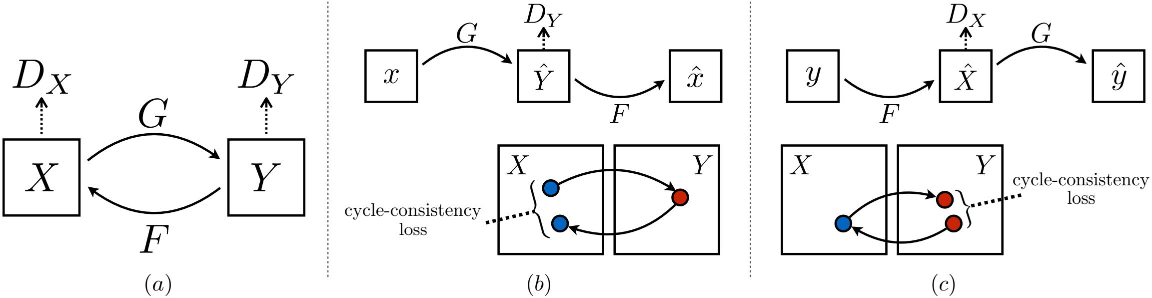
[20]

Noise curve



[20]

CycleGAN



D_X
D_Y
G
X
Y
F
(a)
D_Y
G
x
$\hat{Y}$
$\hat{x}$
F
cycle-consistency
loss
X
Y
(b)
D_X
G
y
$\hat{X}$
$\hat{y}$
F
X
Y
cycle-consistency
loss
(c)

[18]