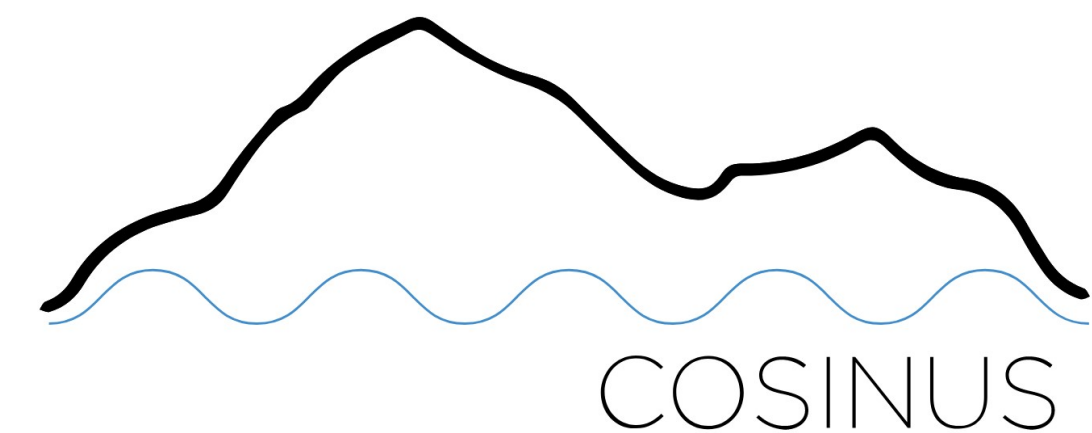


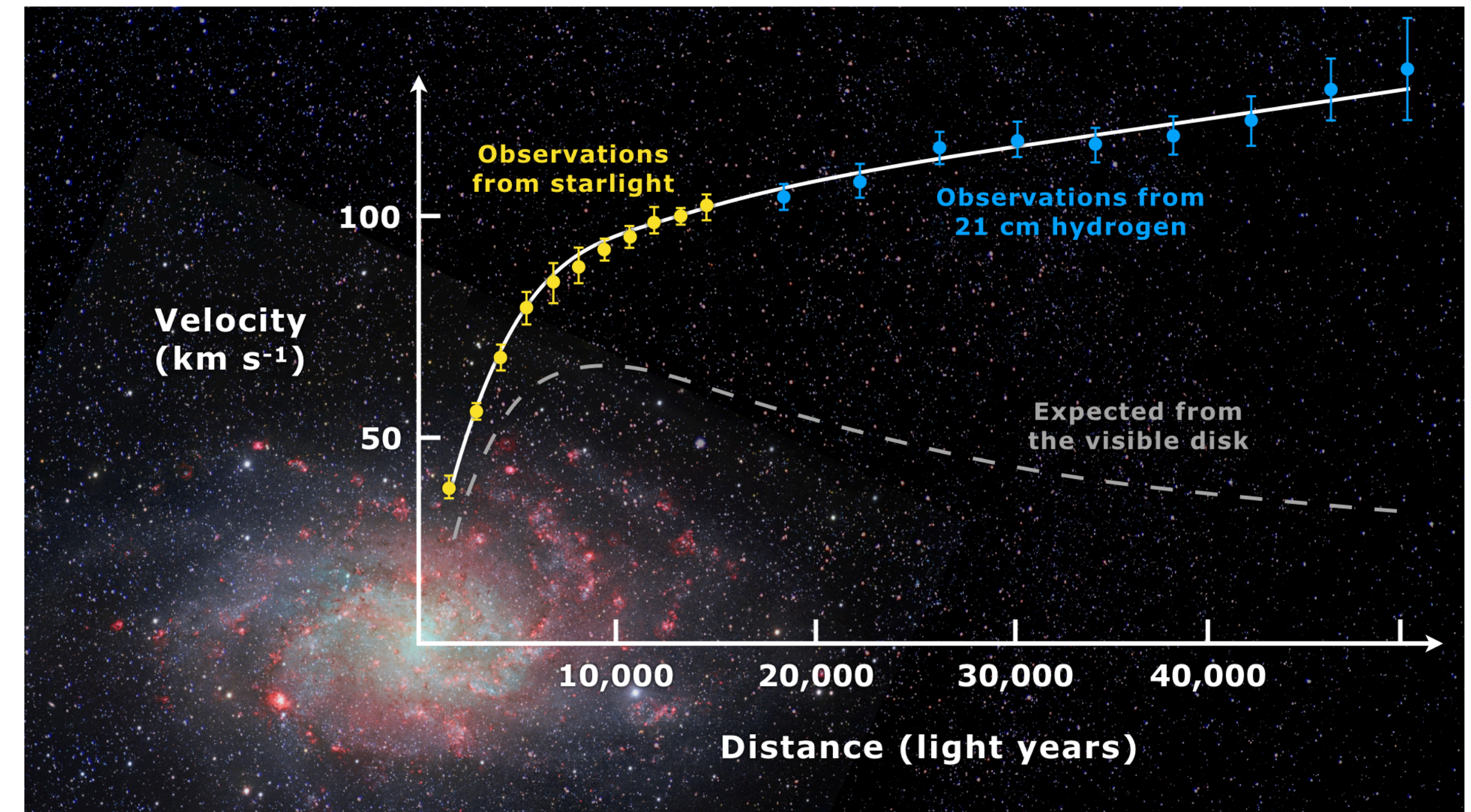
In View of Large Detector Arrays: Automated Analysis Modules for Direct Dark Matter Search

Maximilian Gapp
IMPRS recruiting workshop
Garching, 25.11.2024



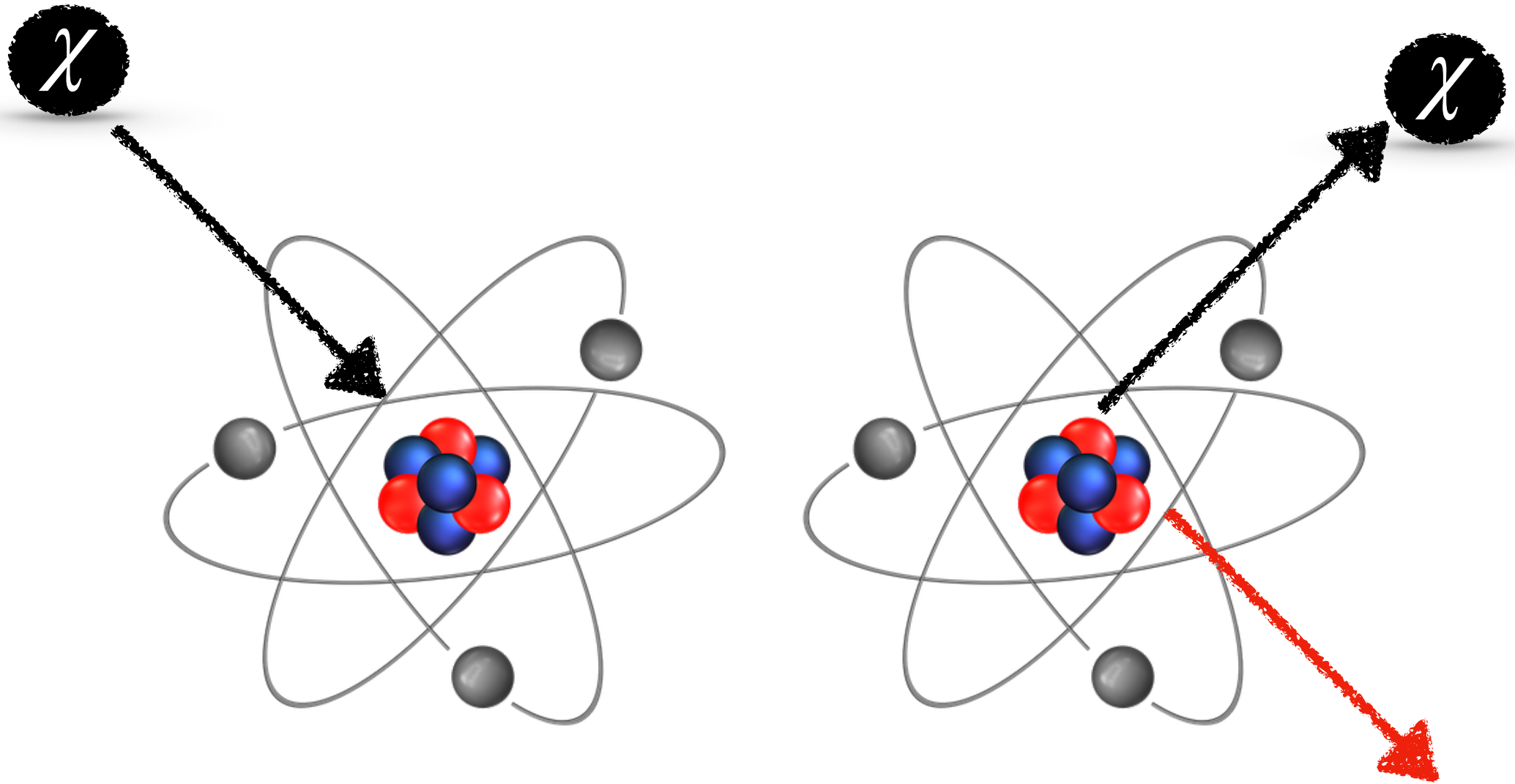
Dark Matter

- 84% of the matter in our universe is made of dark matter
- Evidence on all length scales
- Nature after ~100 years of research still unknown
 - ➔ One way to search for dark matter: Direct detection

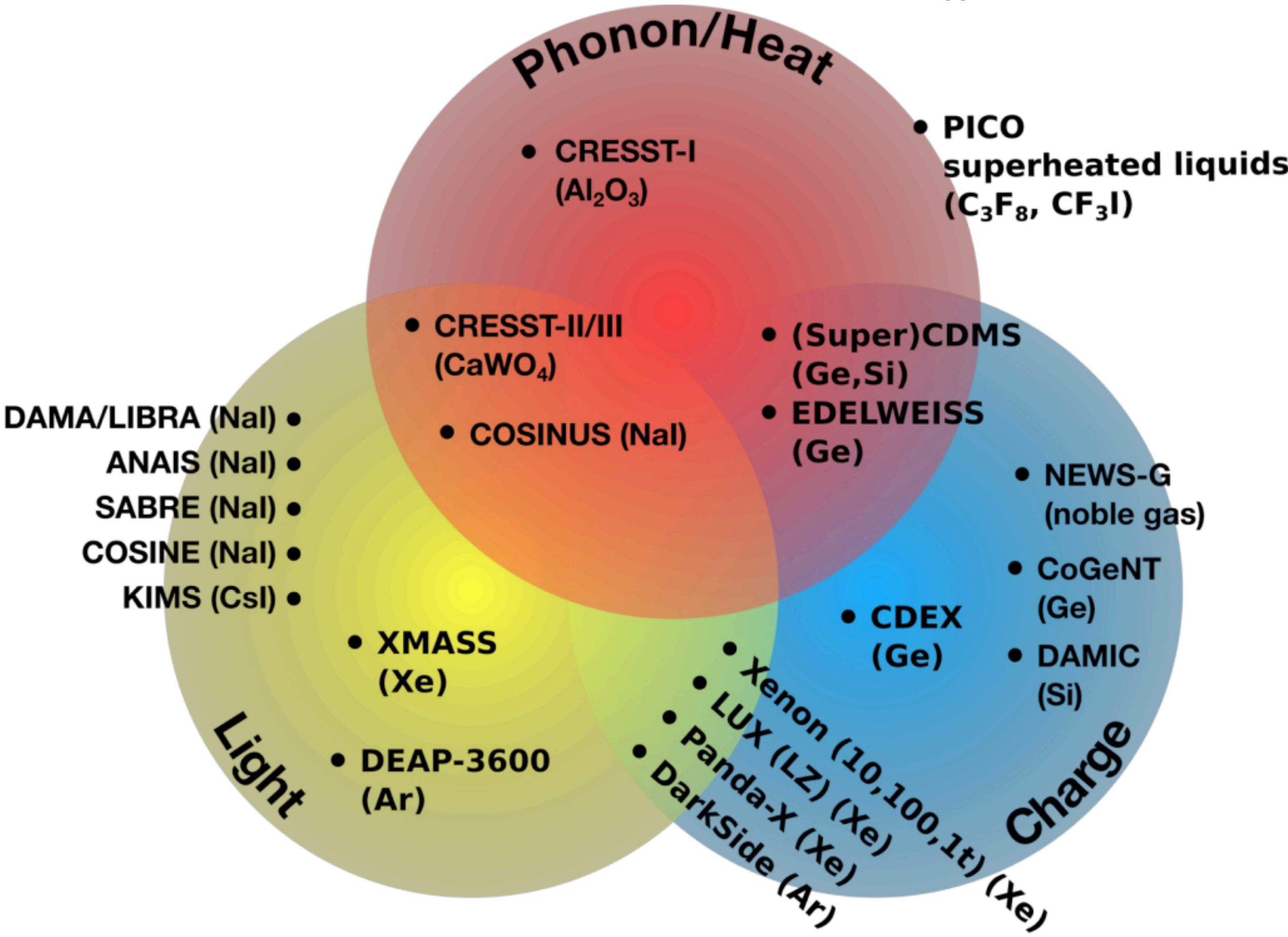


Dark Matter Direct Detection

- Scattering of DM off Standard Model particle
- Most common scenario: Detection of nuclear recoil

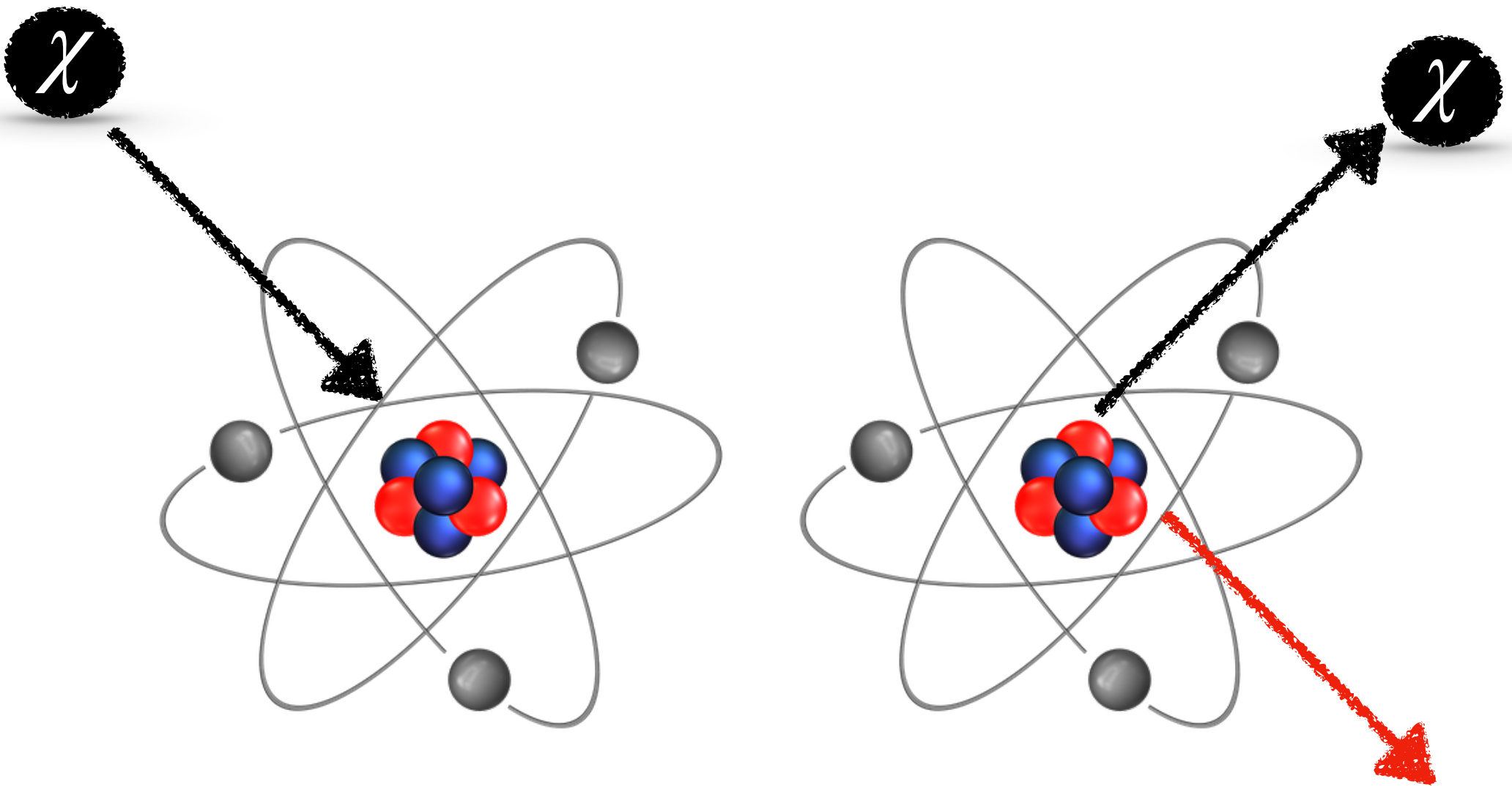


[2] Florian Reindl

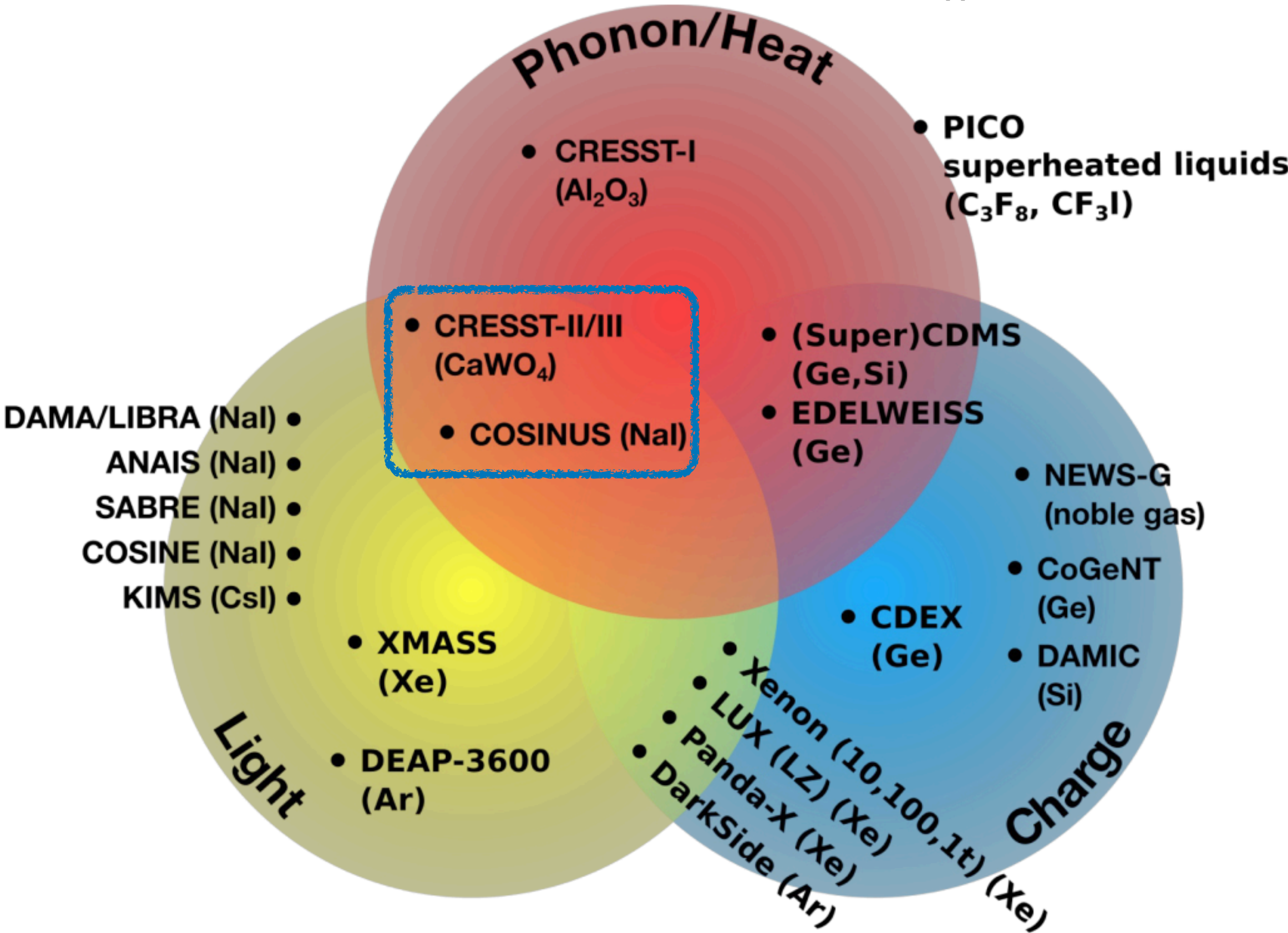


Dark Matter Direct Detection

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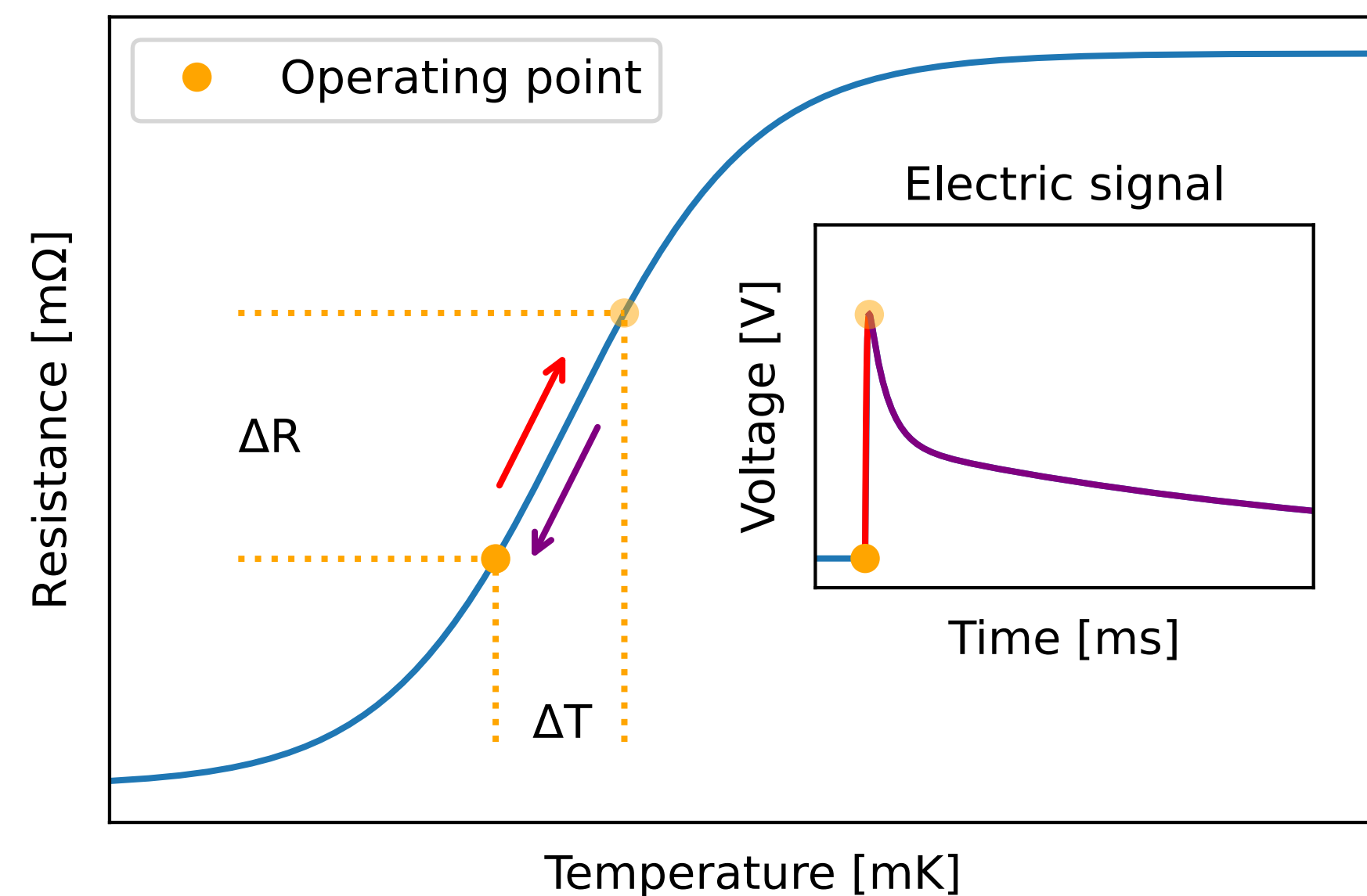
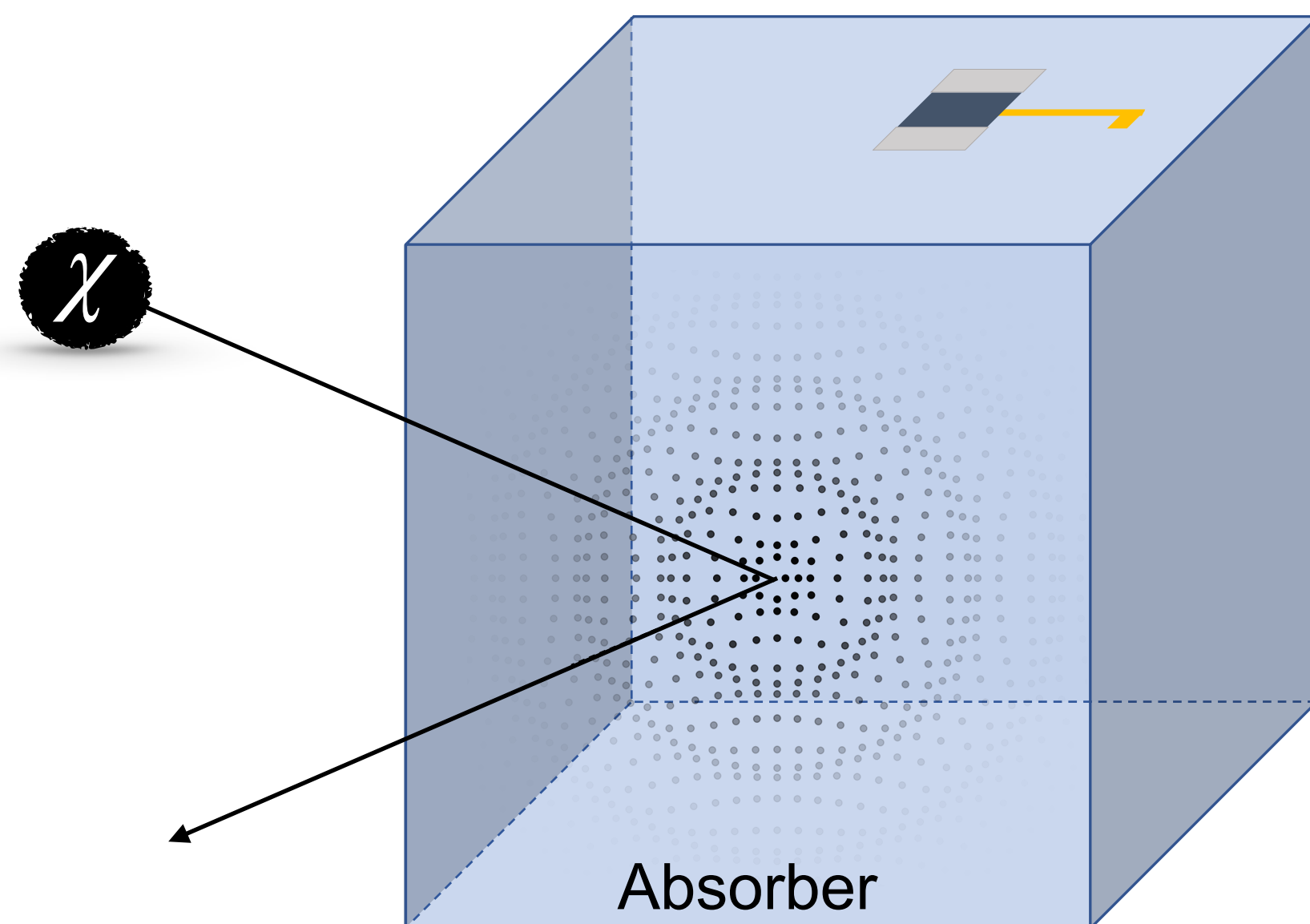


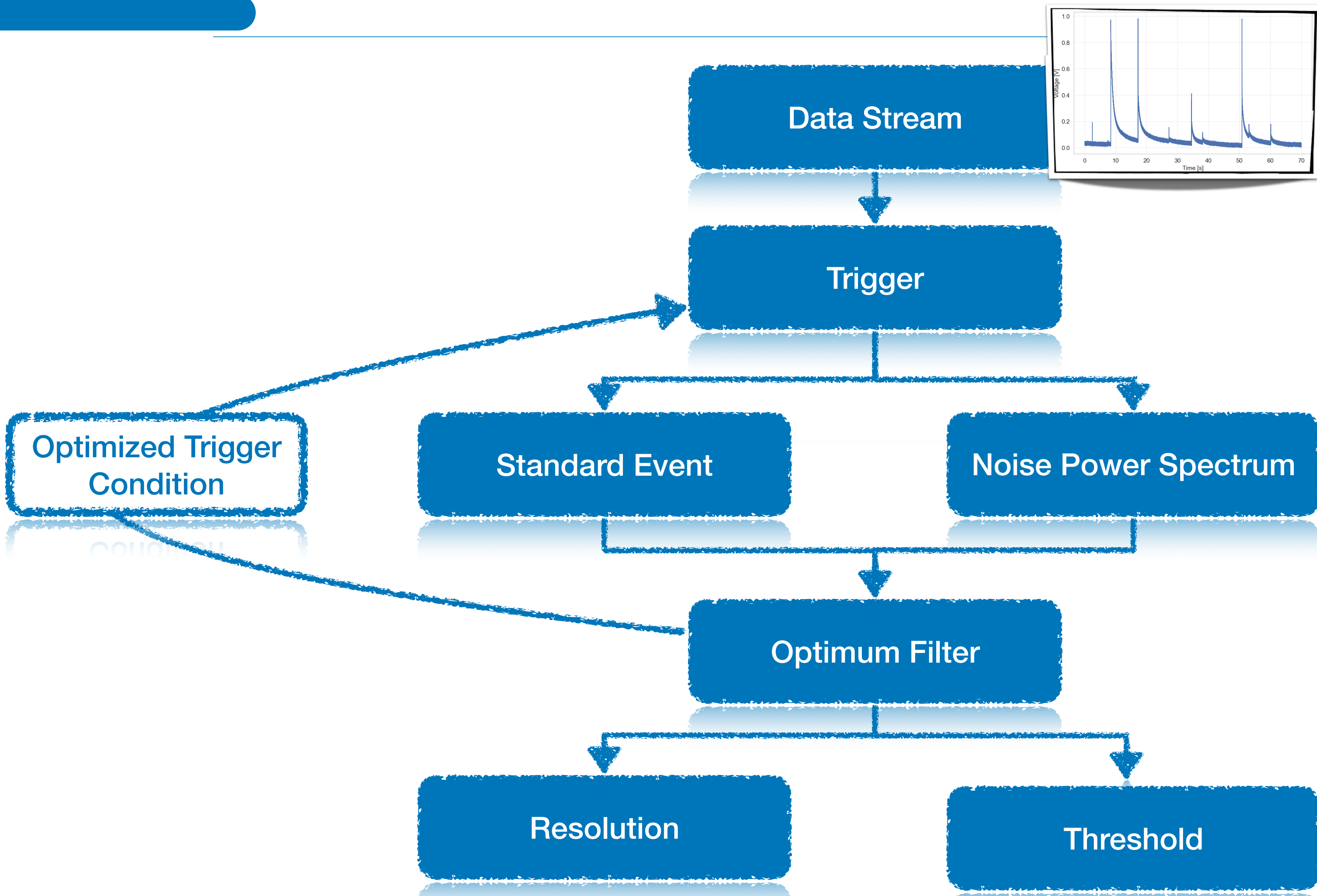
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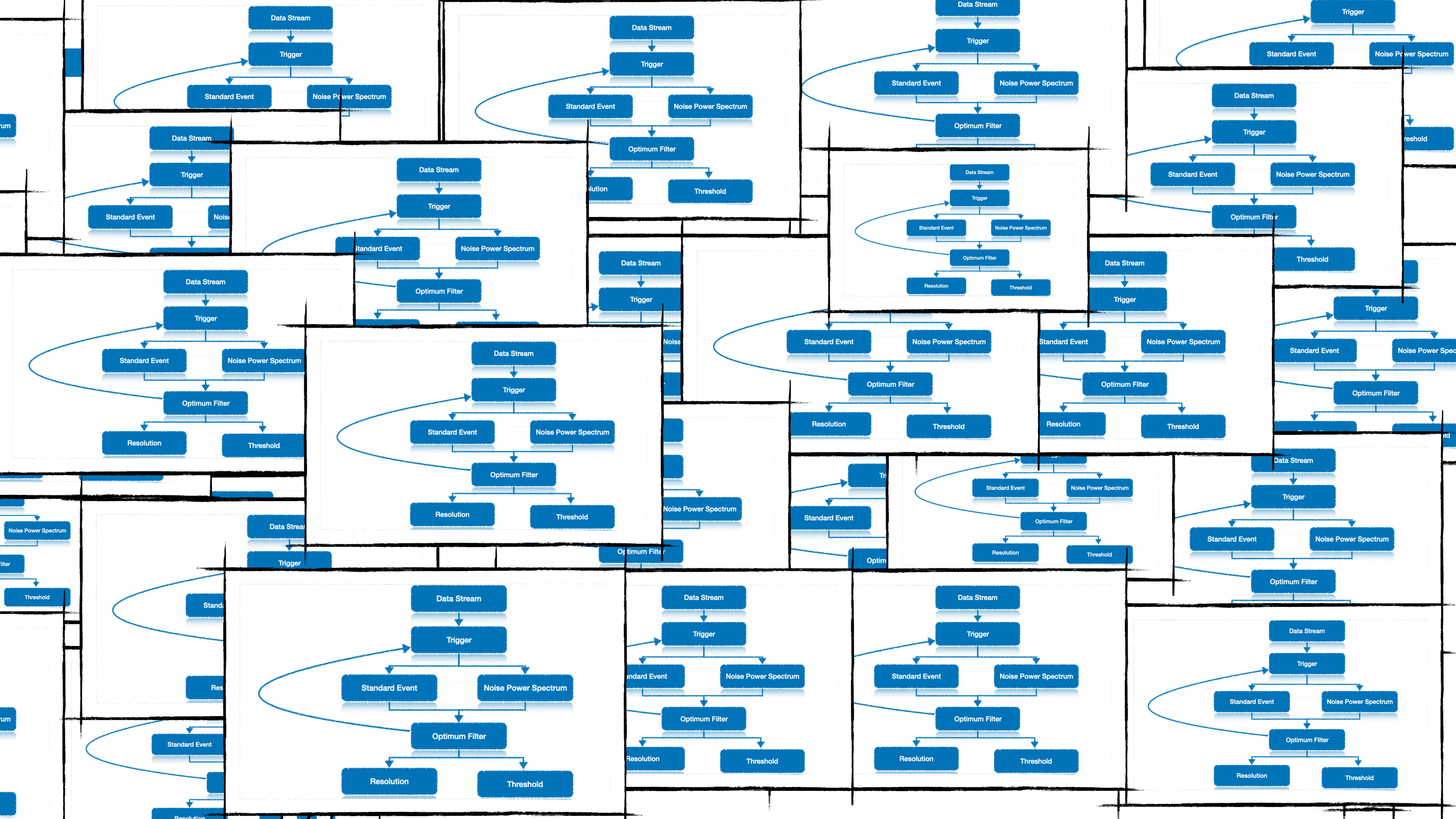


Cryogenic Detectors

- Target material cooled to <10 mK
- Particle deposits energy in the form of phonons/heat
- Temperature change $\sim\mu\text{K}$ measured with Transition Edge Sensor (TES)

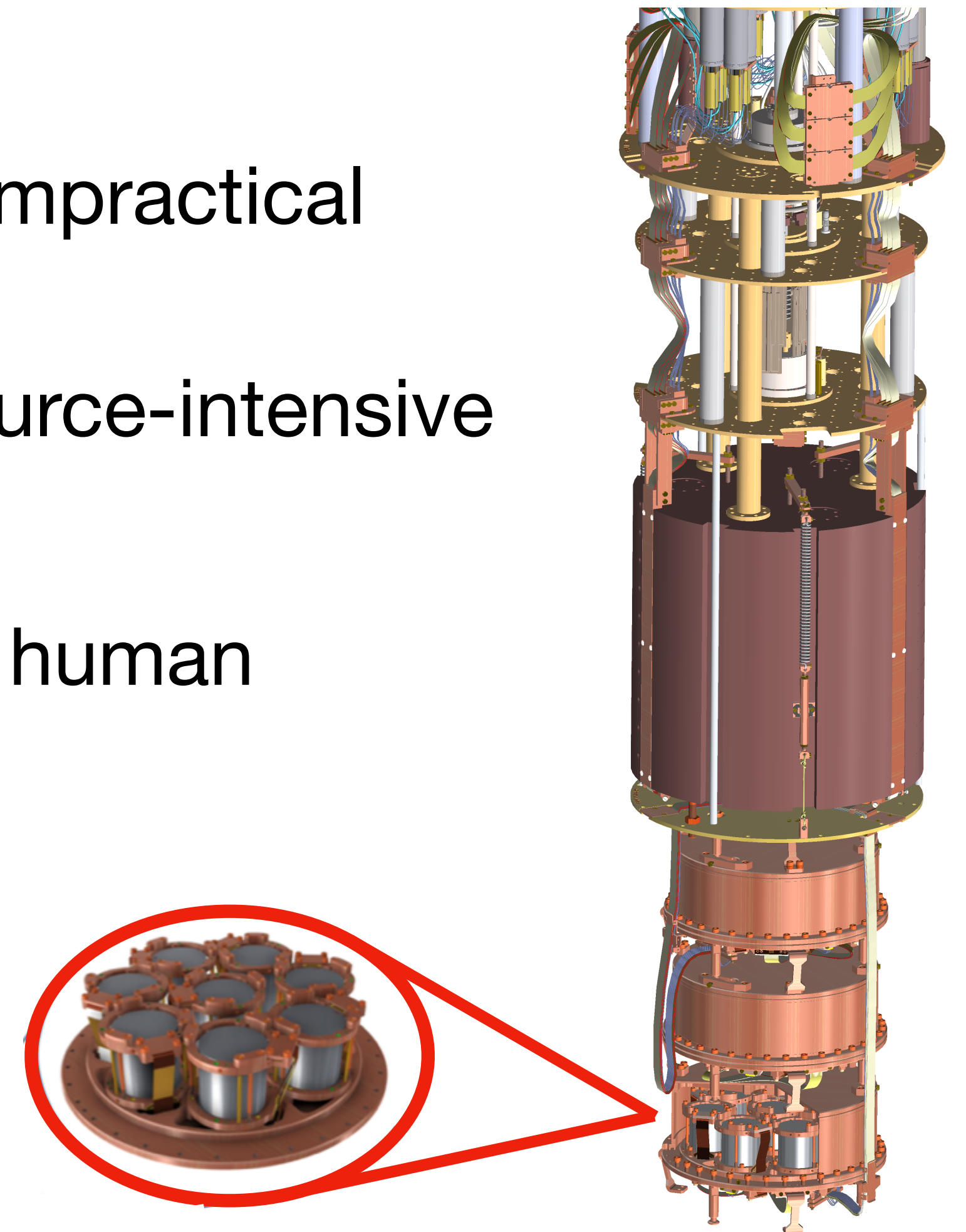






Why Automation?

- **Scaling:** Analysing larger detector arrays is currently impractical
Planned: COSINUS (48 channels) and CRESST upgrade (288 channels)
- **Time Constraints:** Manual data analysis is slow, resource-intensive and requires experience
- **Bias:** Automated tools provide an unbiased check for human analyses, boosting confidence



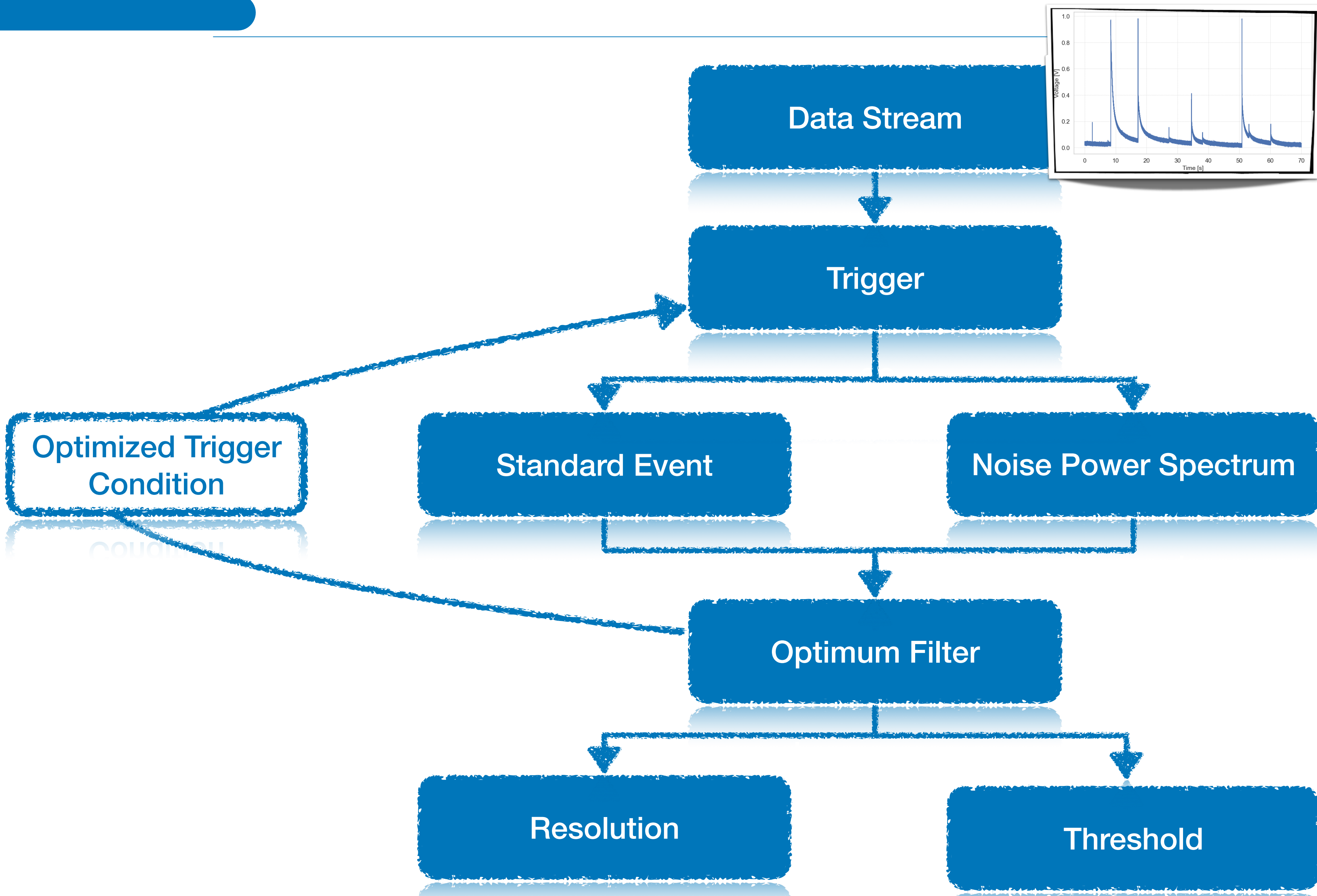
Objectives

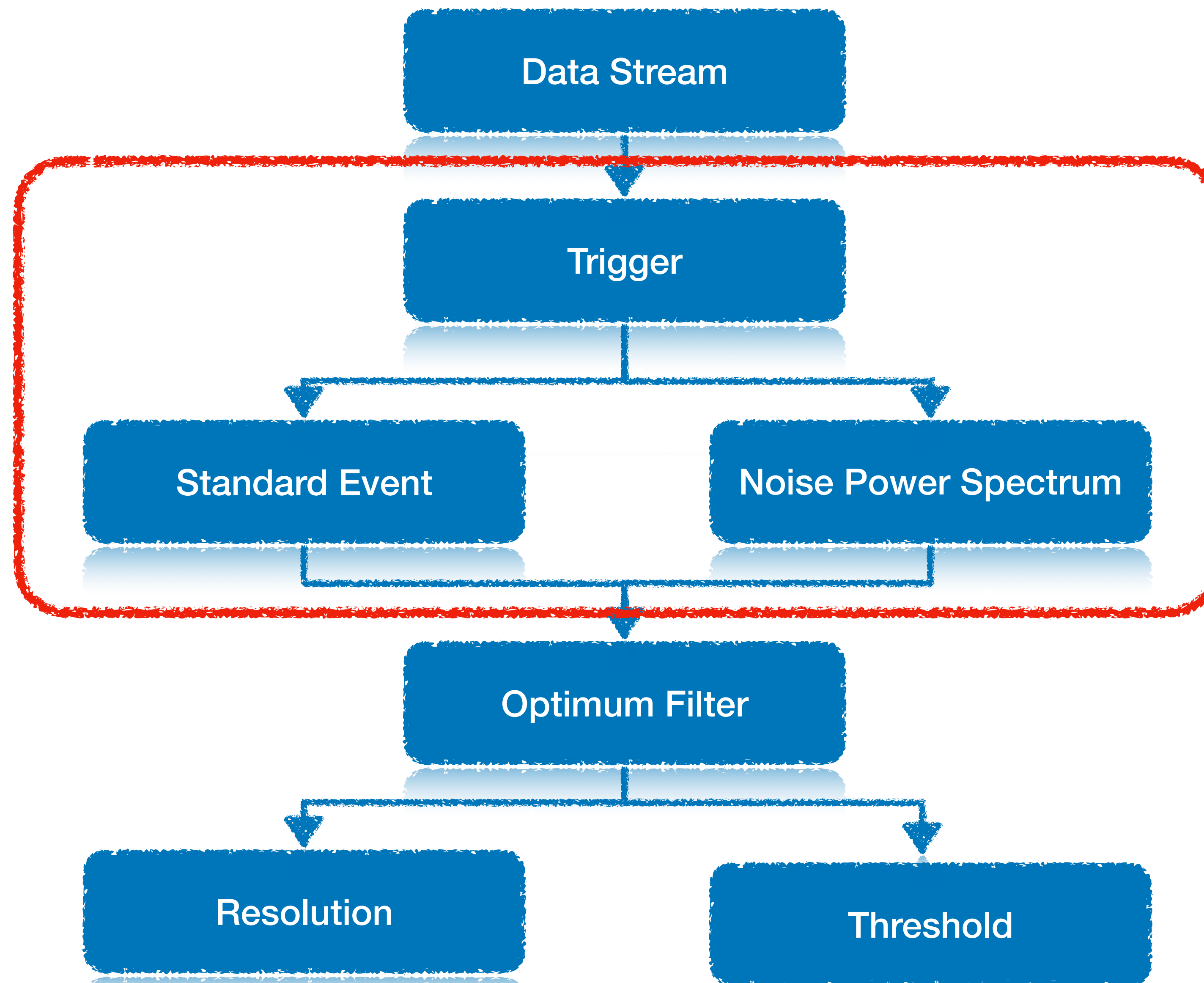
- **Automate where Possible:** Streamline the analysis process, reducing manual effort and saving time
- **Minimize Human Input:** Limit reliance on assumptions, ensuring unbiased and reproducible results
- **Be Adaptable:** Design to accommodate diverse detector modules with varying characteristics

Objectives

- **Automate where Possible:** Streamline the analysis process by reducing manual effort and saving time
- **Minimize Human Error:** Increase the reliability and reproducibility of the analysis process
- **Be Adaptable:** Design a flexible system that can handle varying input data and analysis requirements

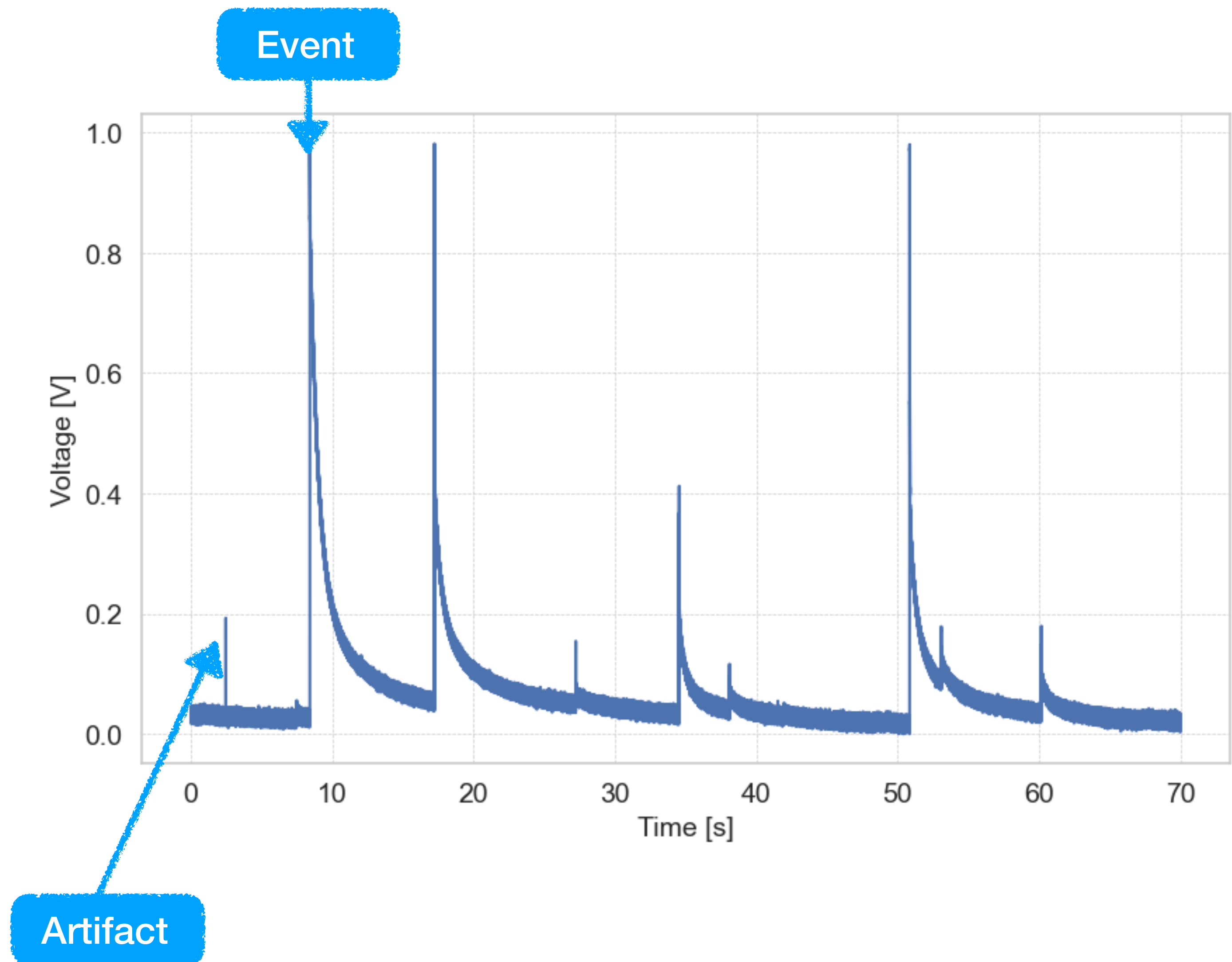
Focus of my Thesis:
Development and verification of an automated analysis workflow designed to efficiently characterize COSINUS prototype detectors





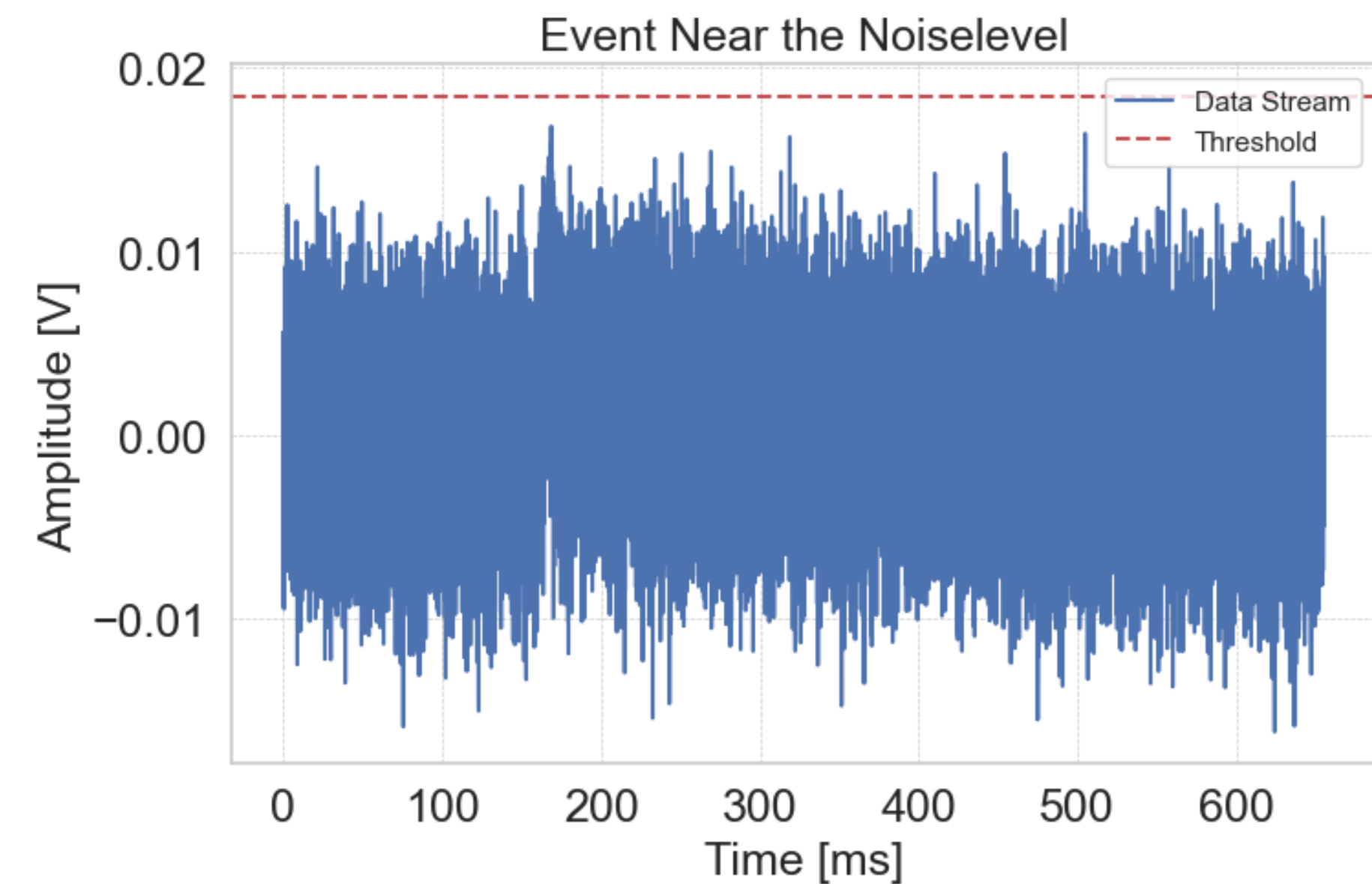
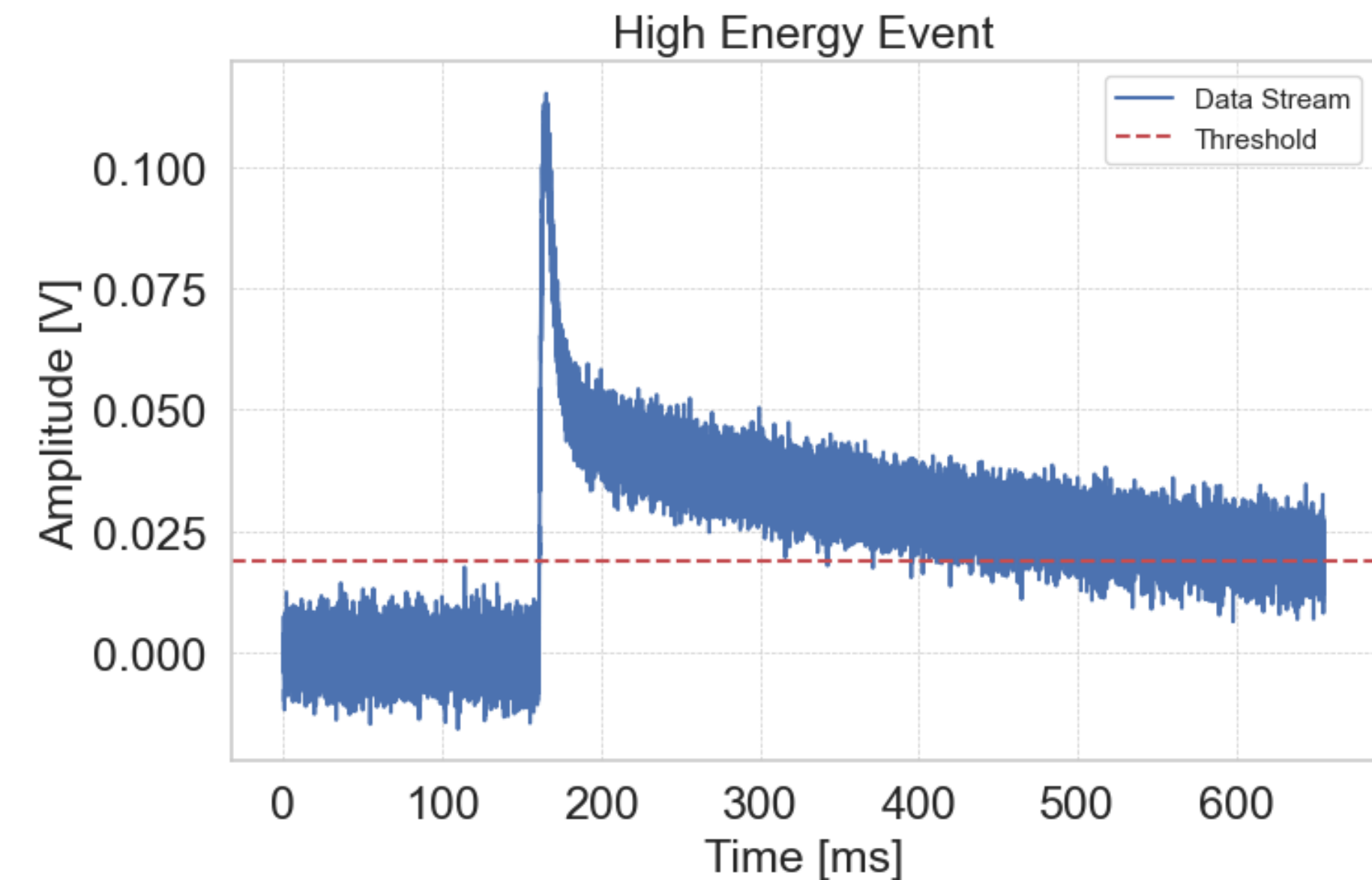
Trigger

- Raw data: voltage stream
- Apply a trigger with as few assumptions as possible
- Minimize deadtime



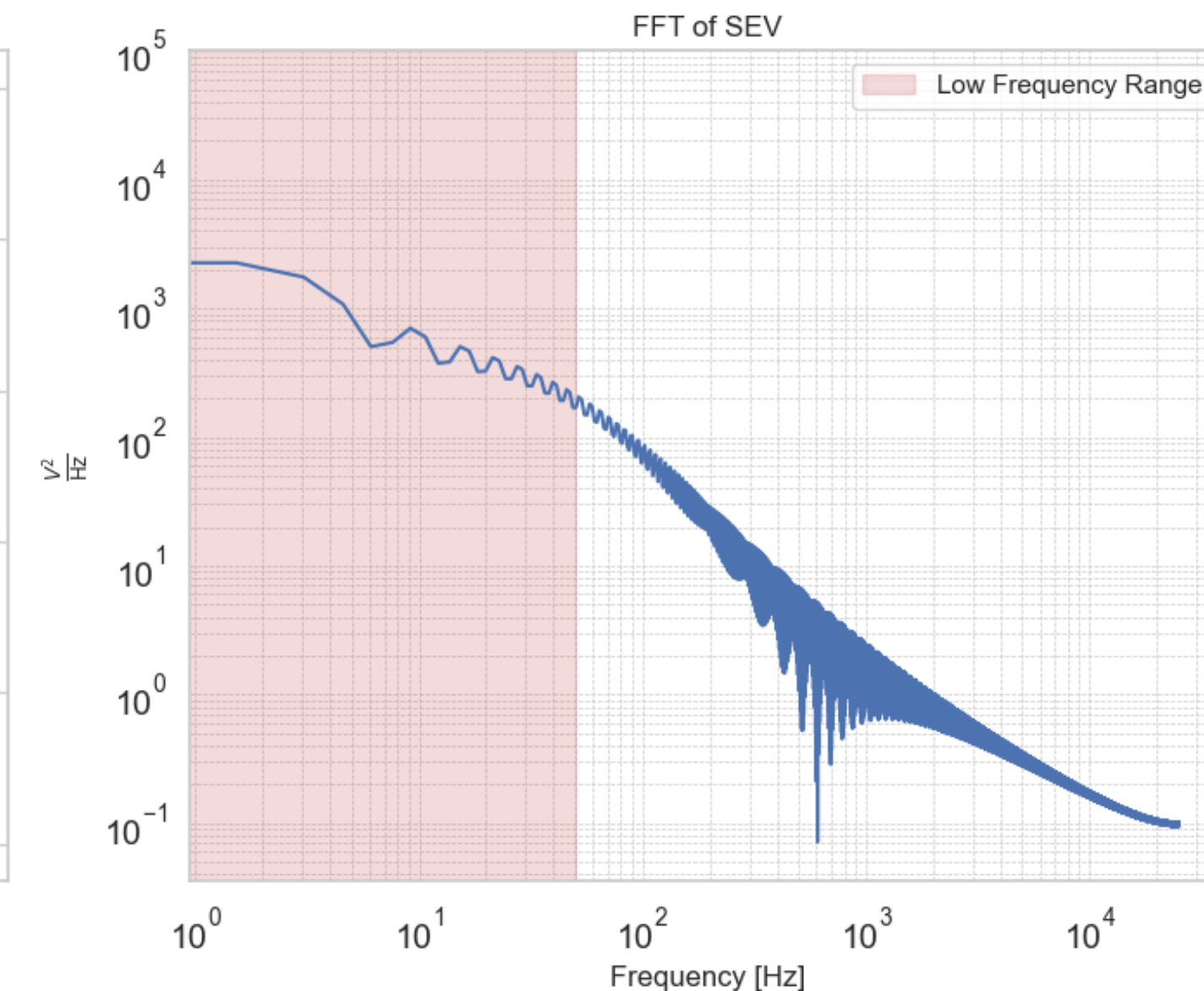
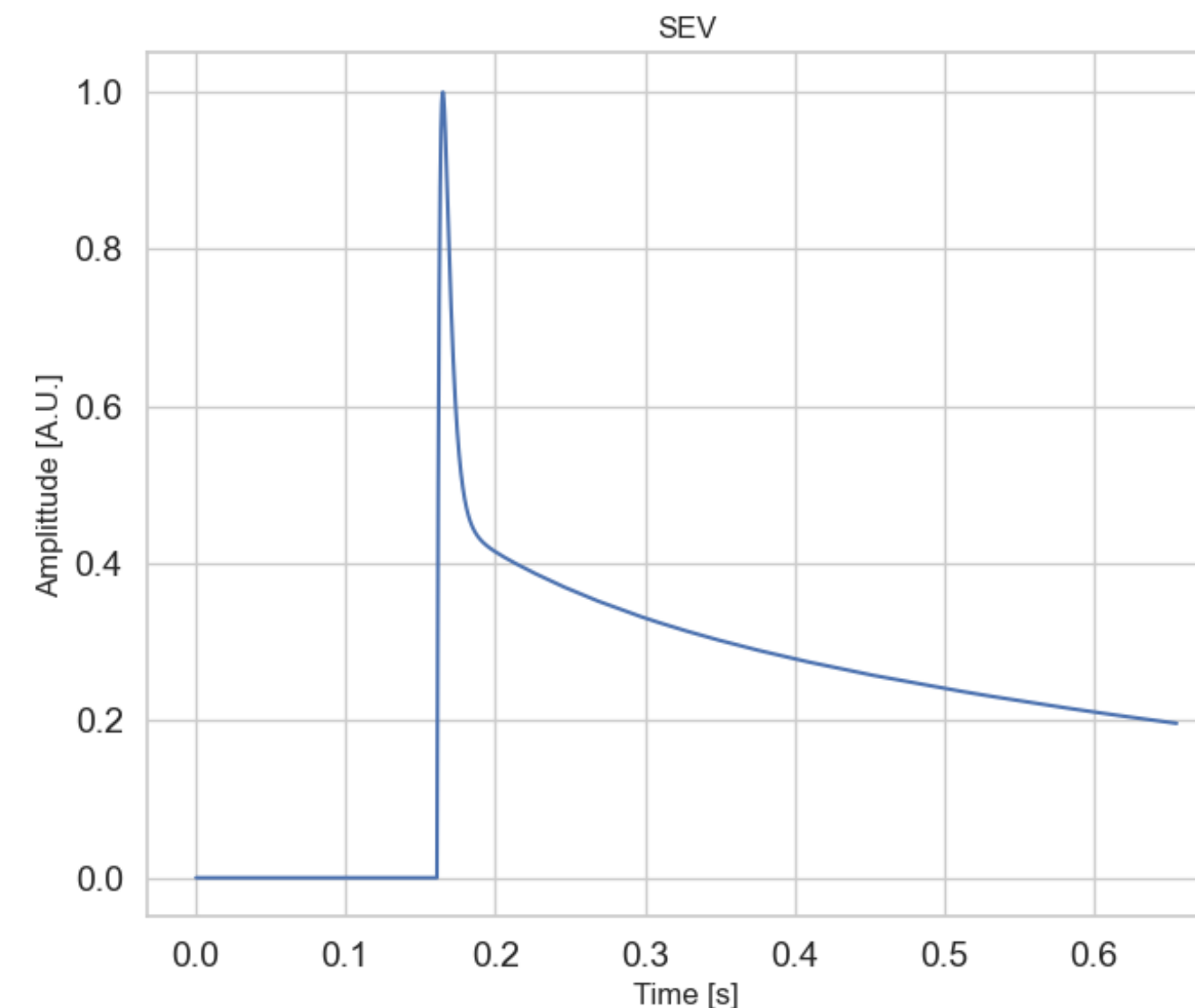
Mean-Trigger

- Typical trigger algorithm
- Moving average trigger
- No assumption on pulse-shape



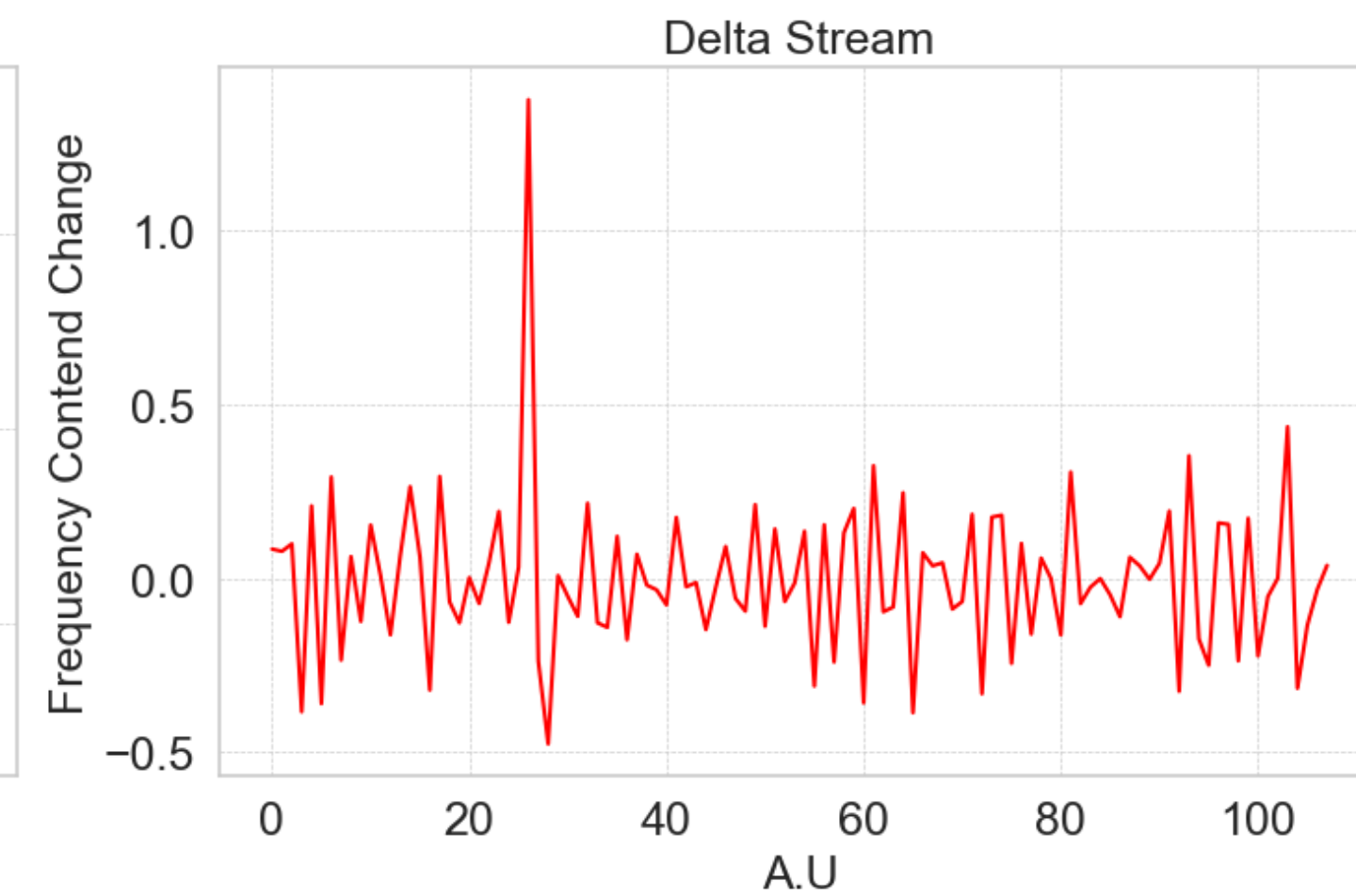
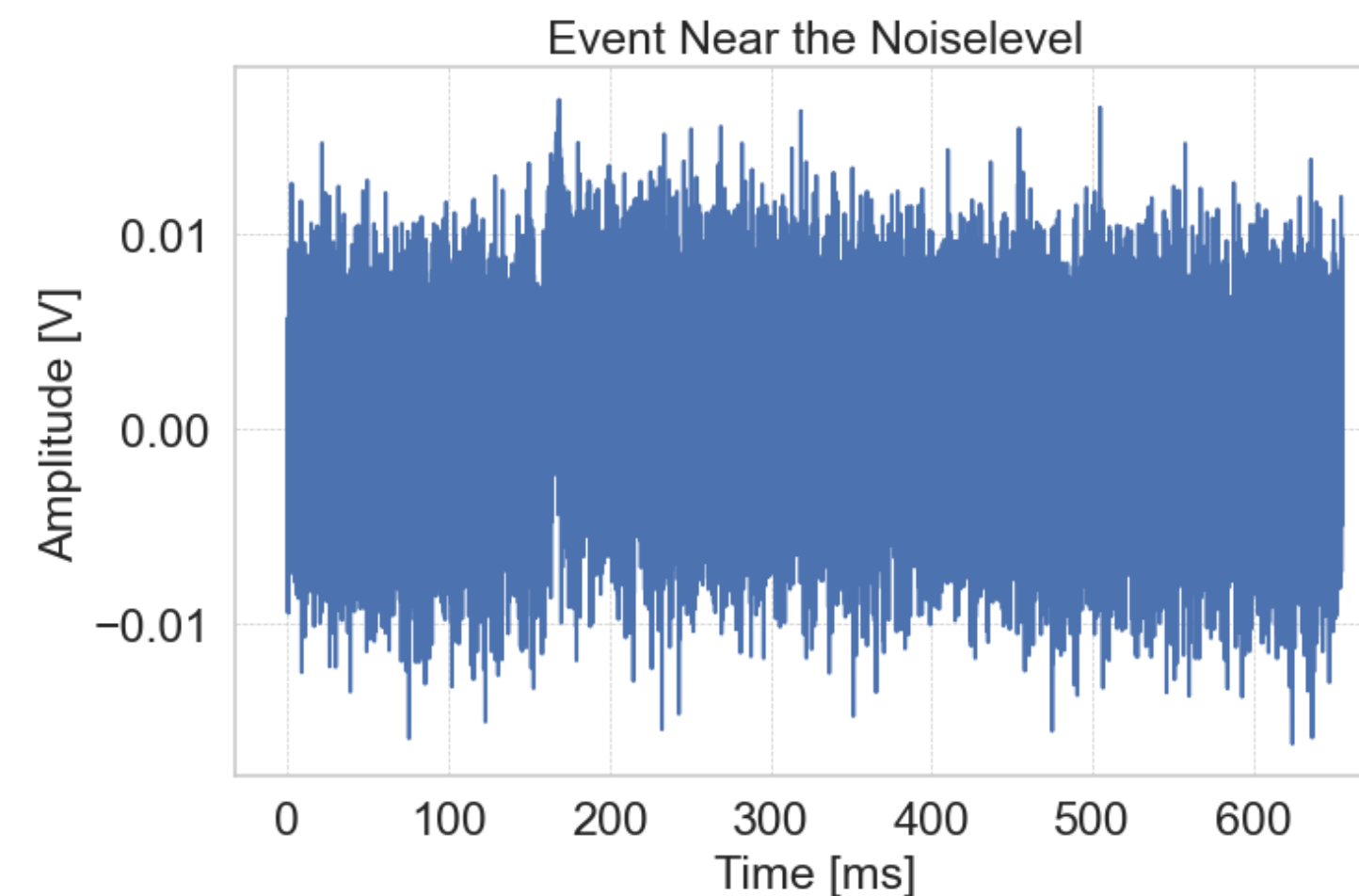
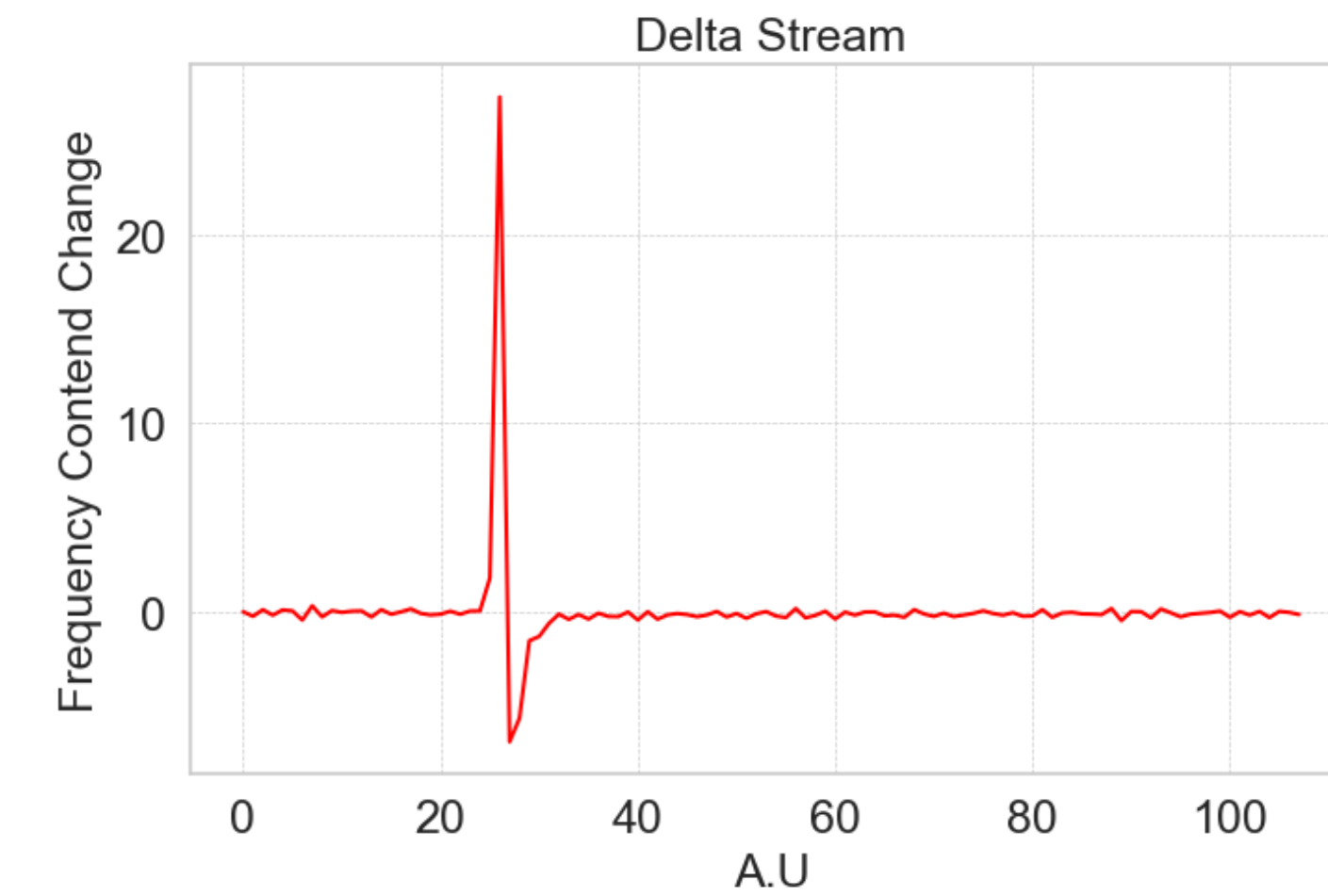
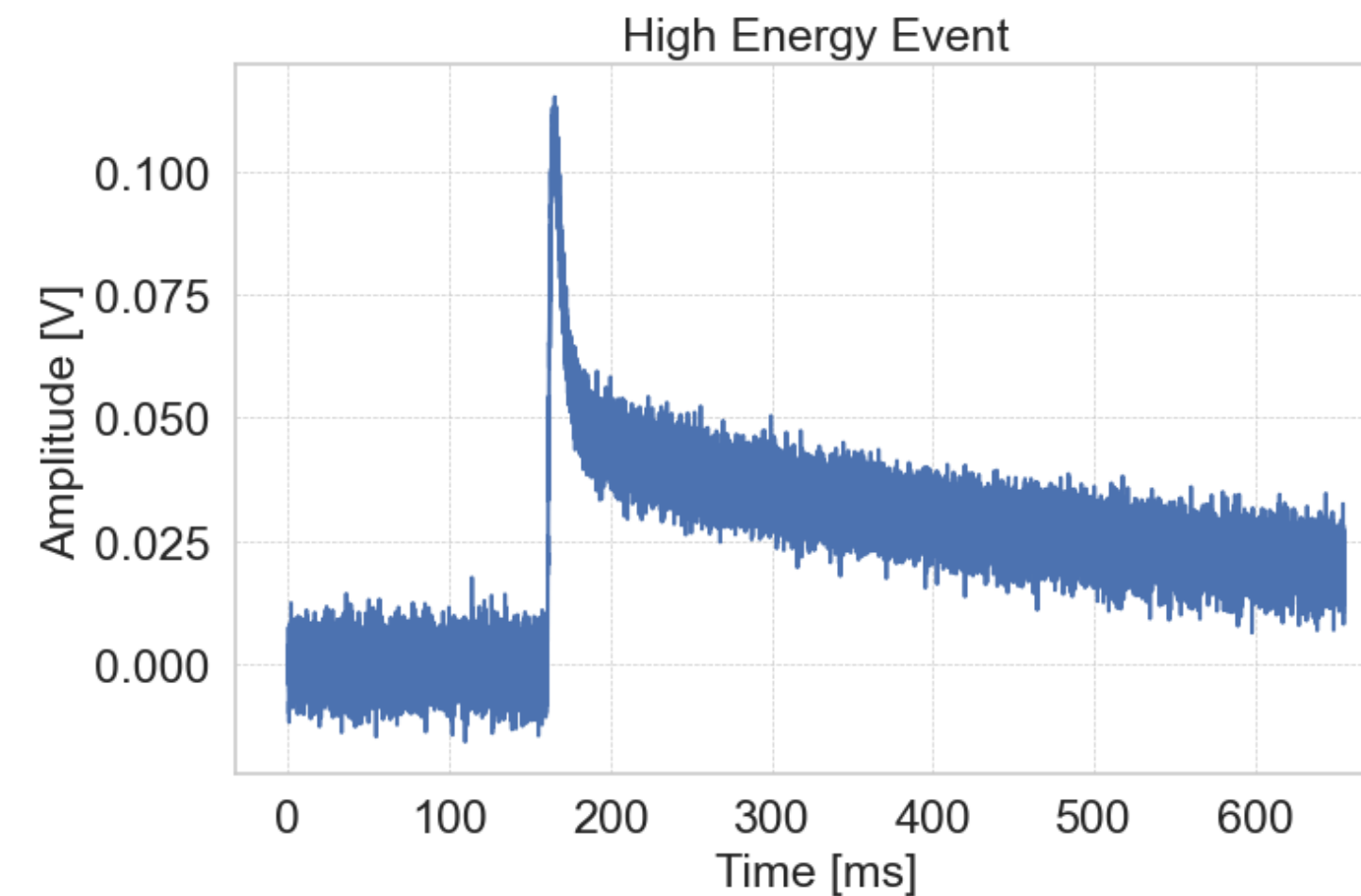
Frequency-Trigger

- **Assumption:** Frequency content of a pulse consists mainly of low frequencies
- Trigger on change of integrated low-frequency content
- Assumption: Cutoff frequency (50 Hz)



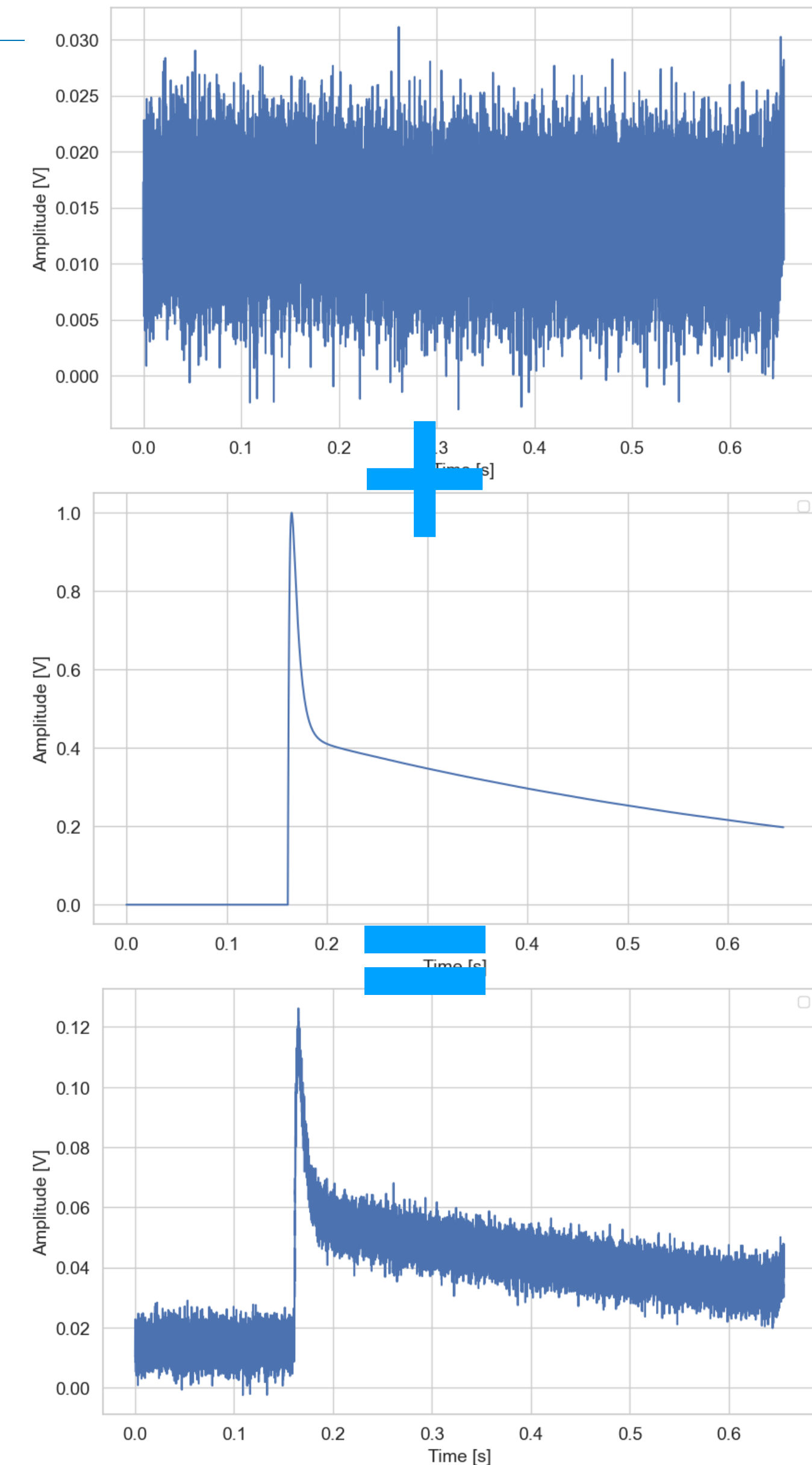
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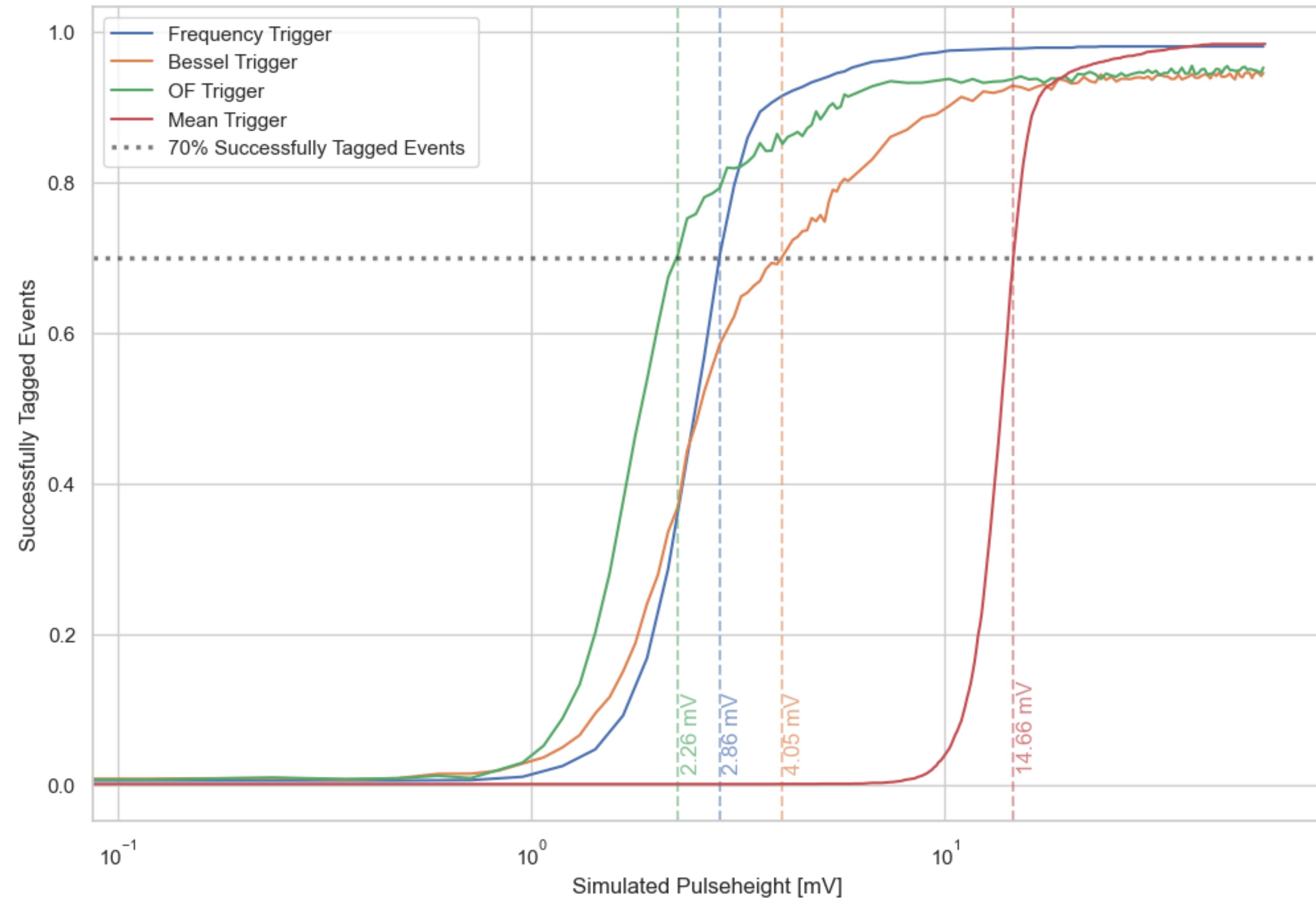
Performance Comparison

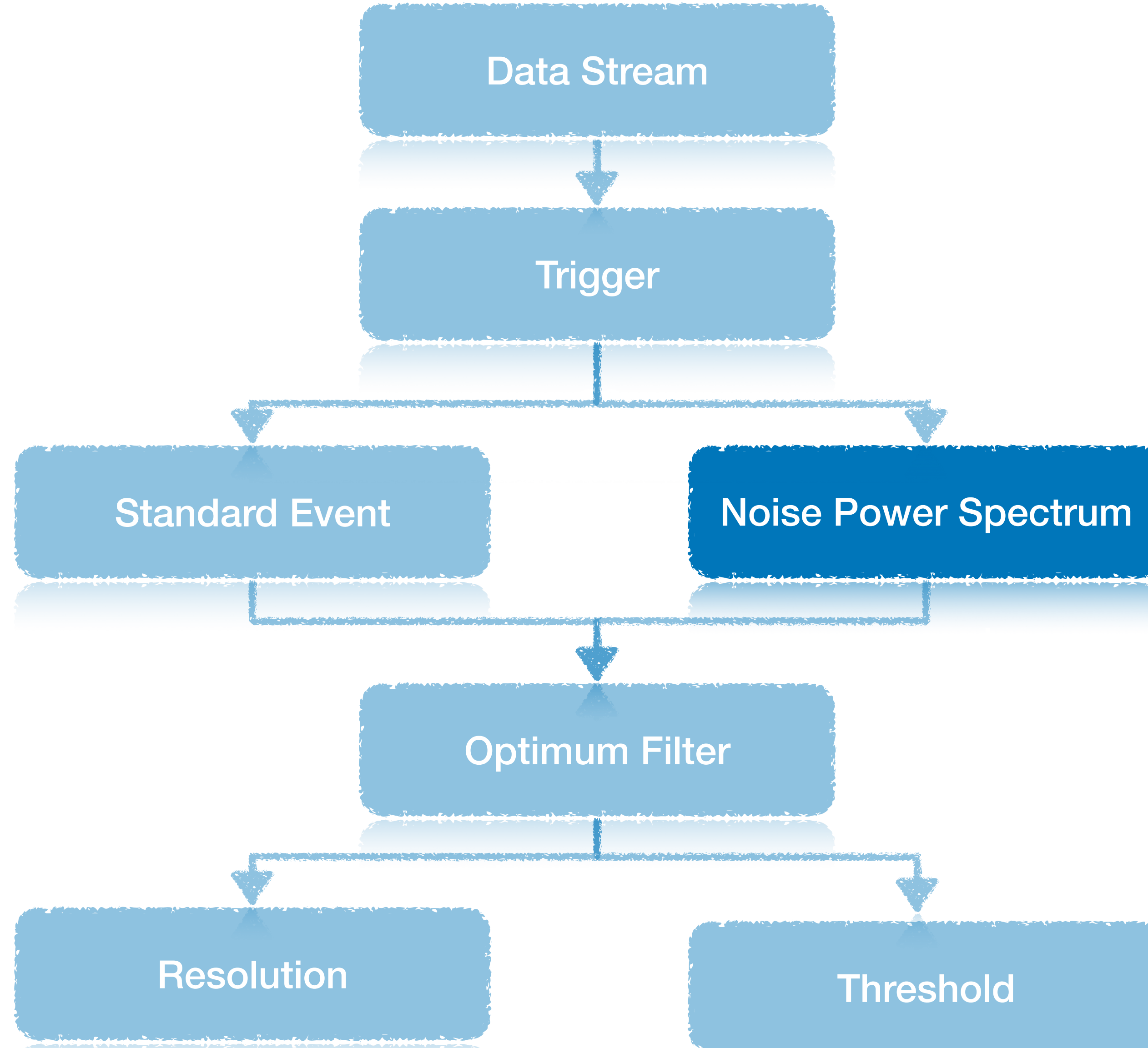
- Superimpose random drawn windows with event of different amplitudes
- If trigger and simulation point coincide, consider as valid
- Frequency trigger best candidate for first trigger



Performance Comparison

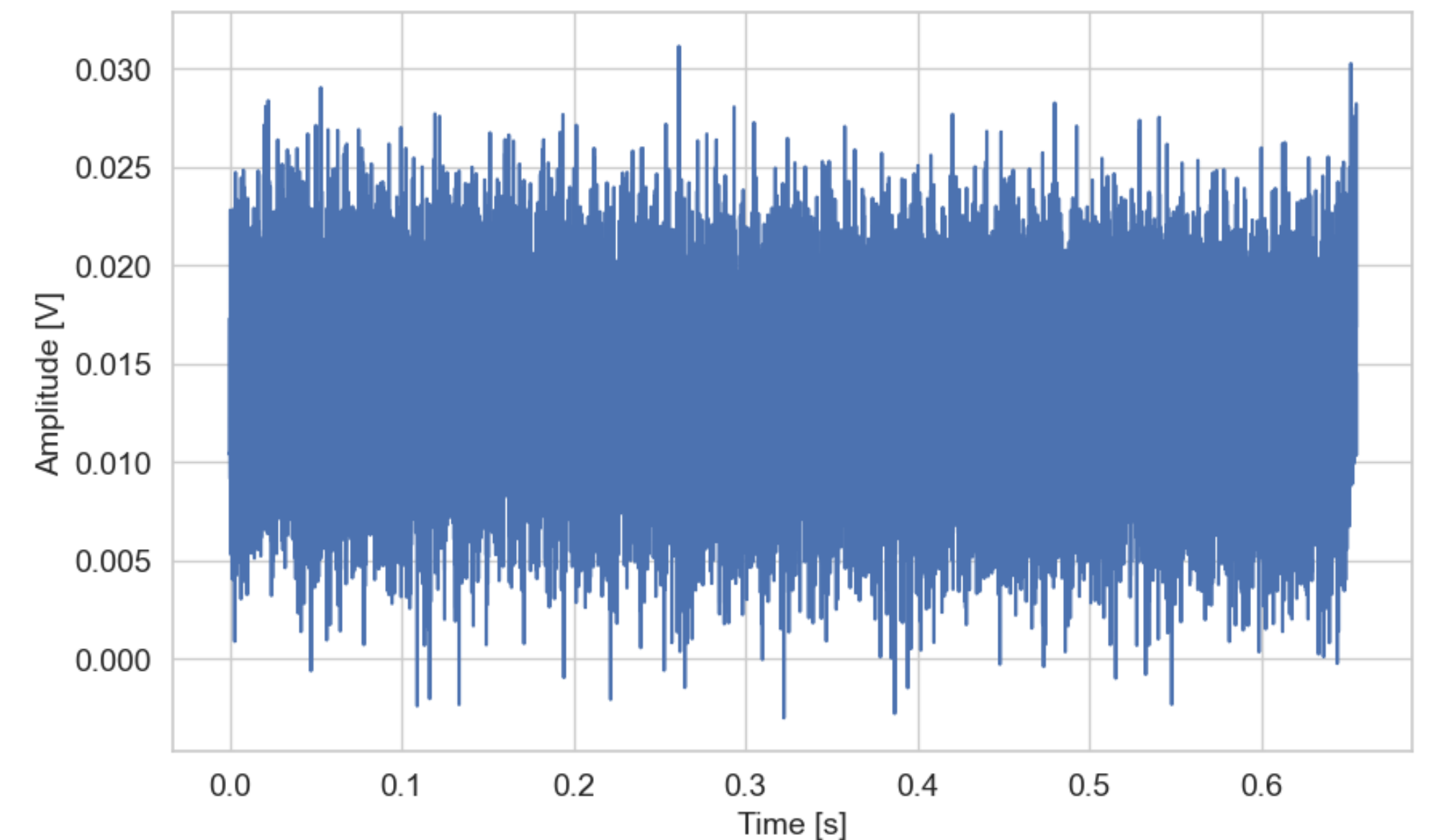
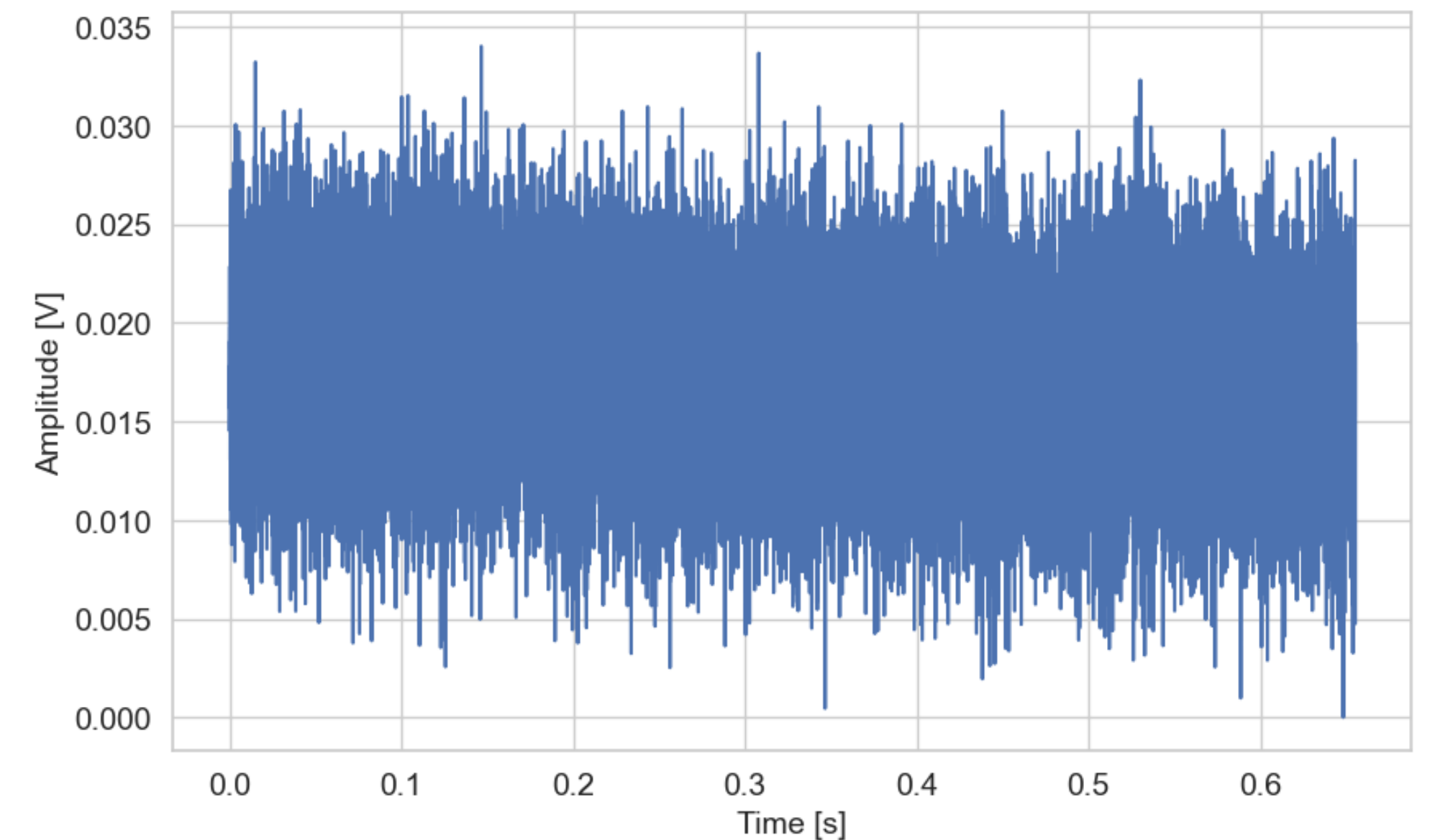
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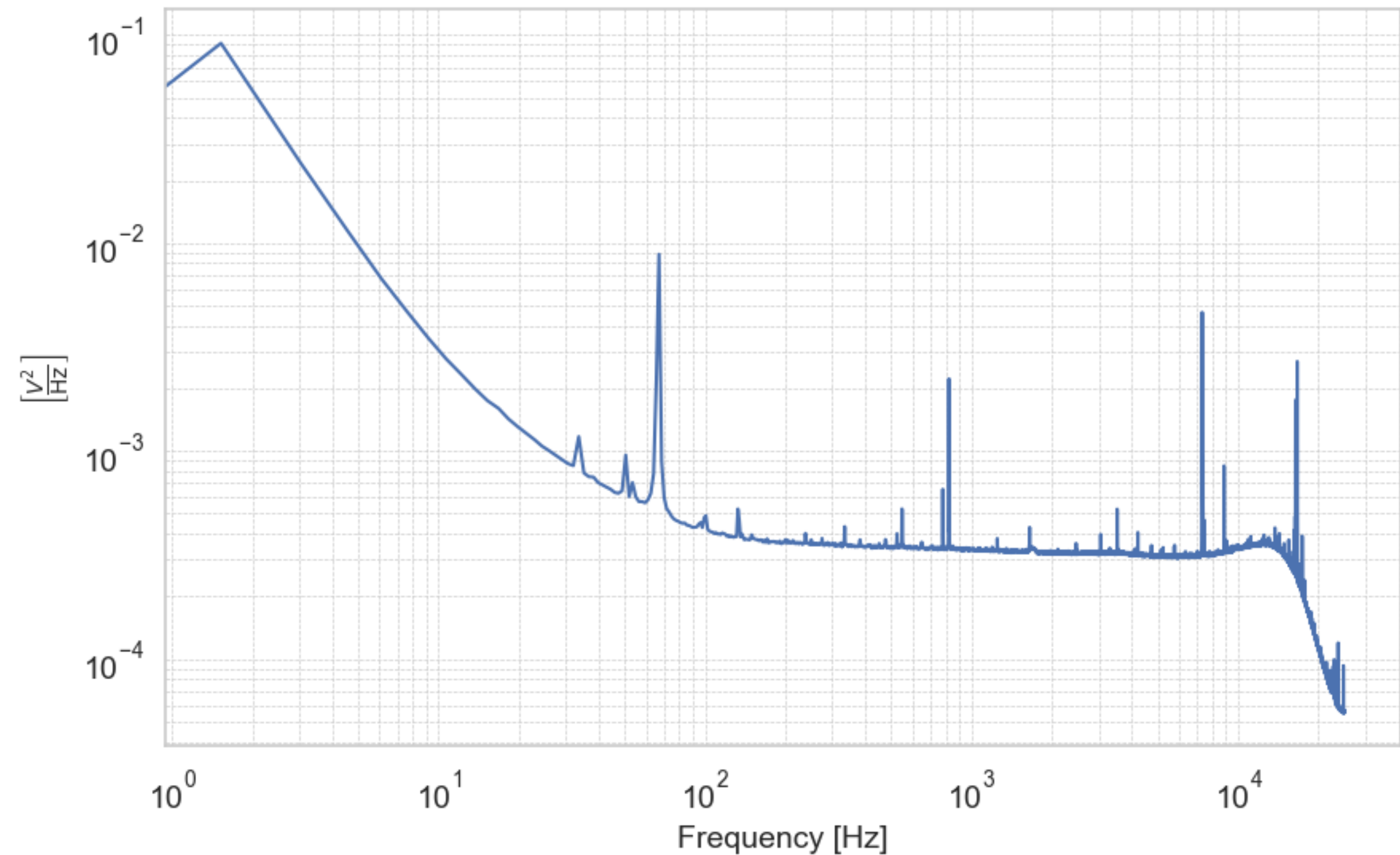
Characterize the Noise

- Draw and clean empty traces
- Create a Noise Power Spectrum (NPS)
- Characterizes the average noise conditions



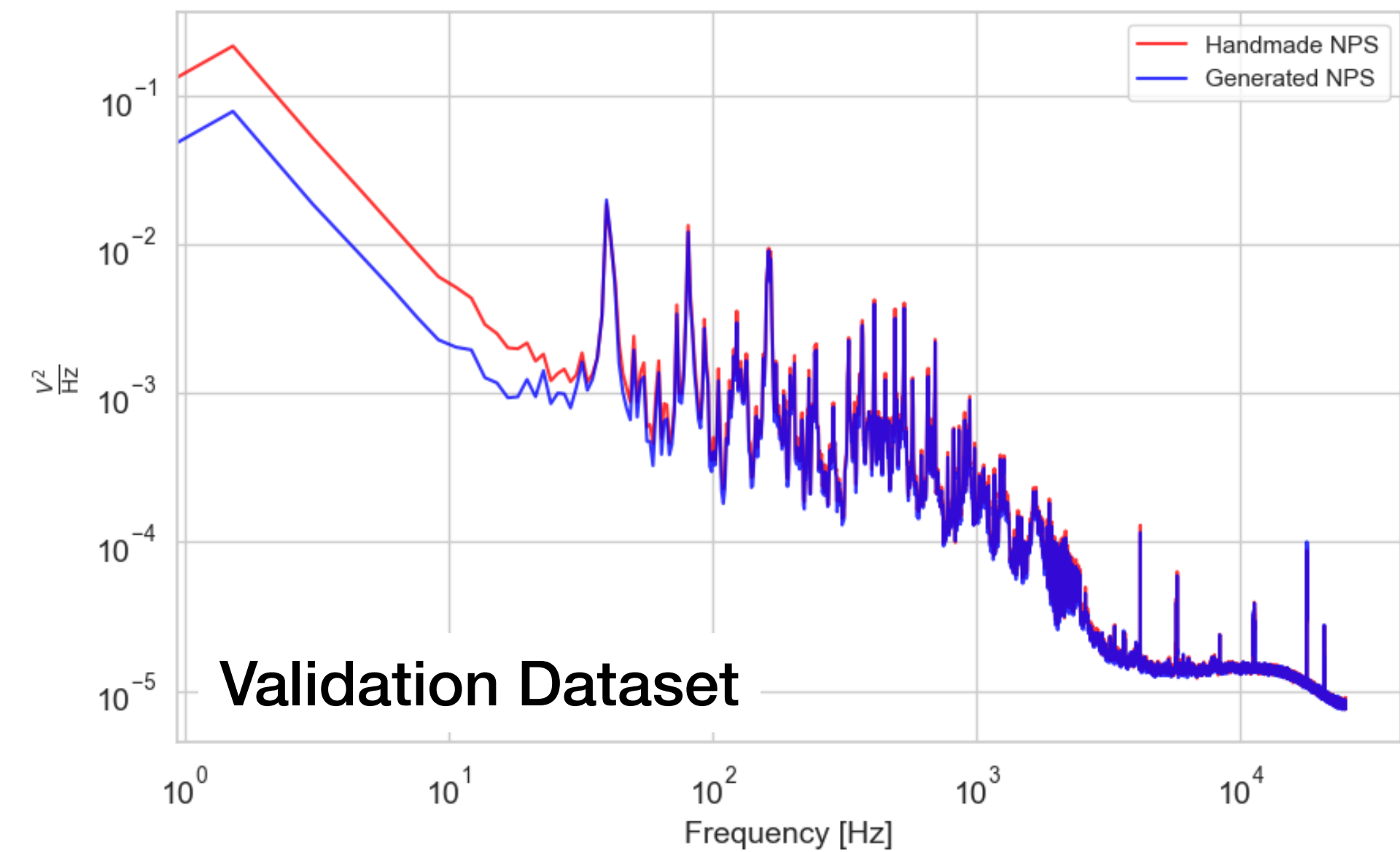
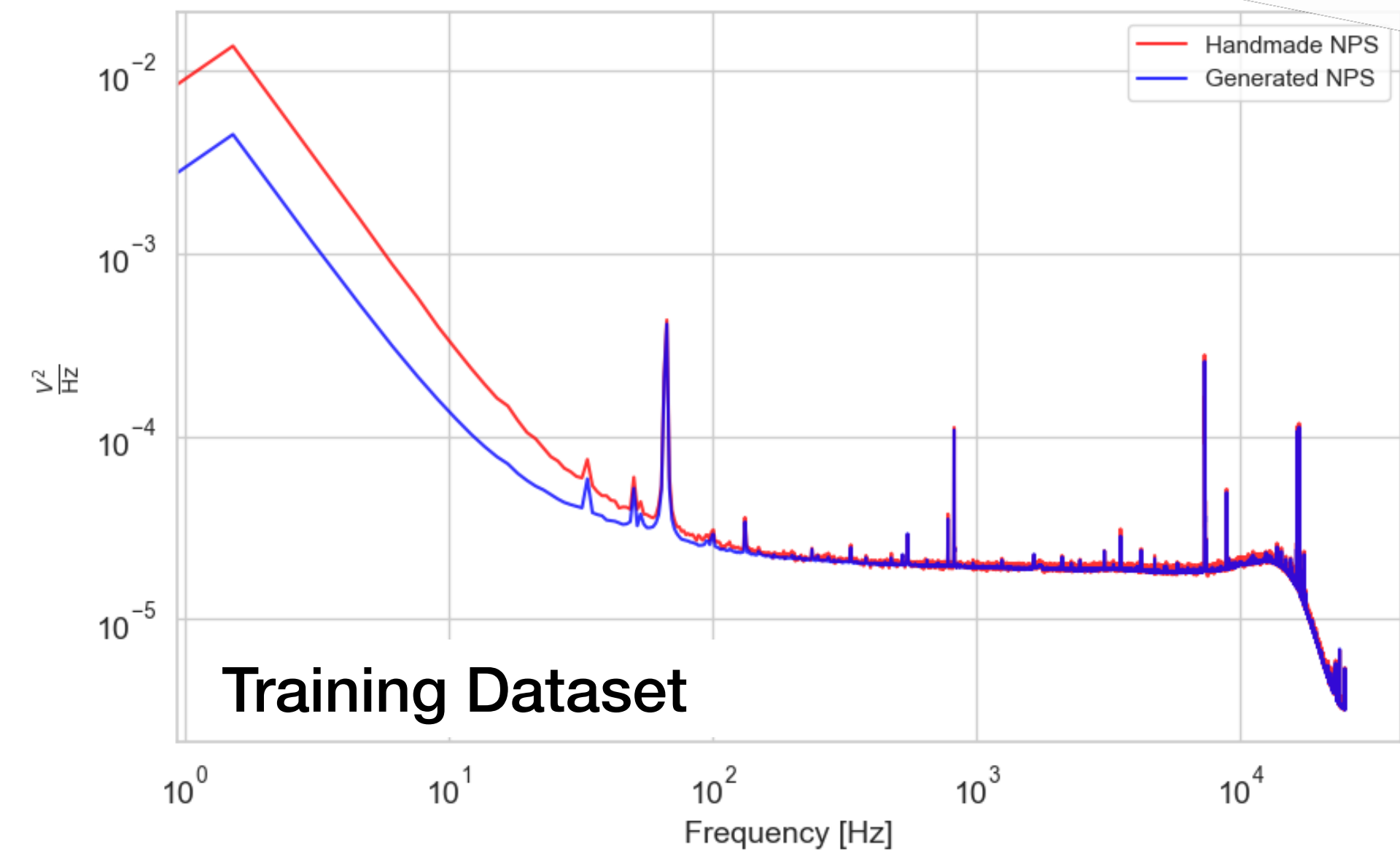
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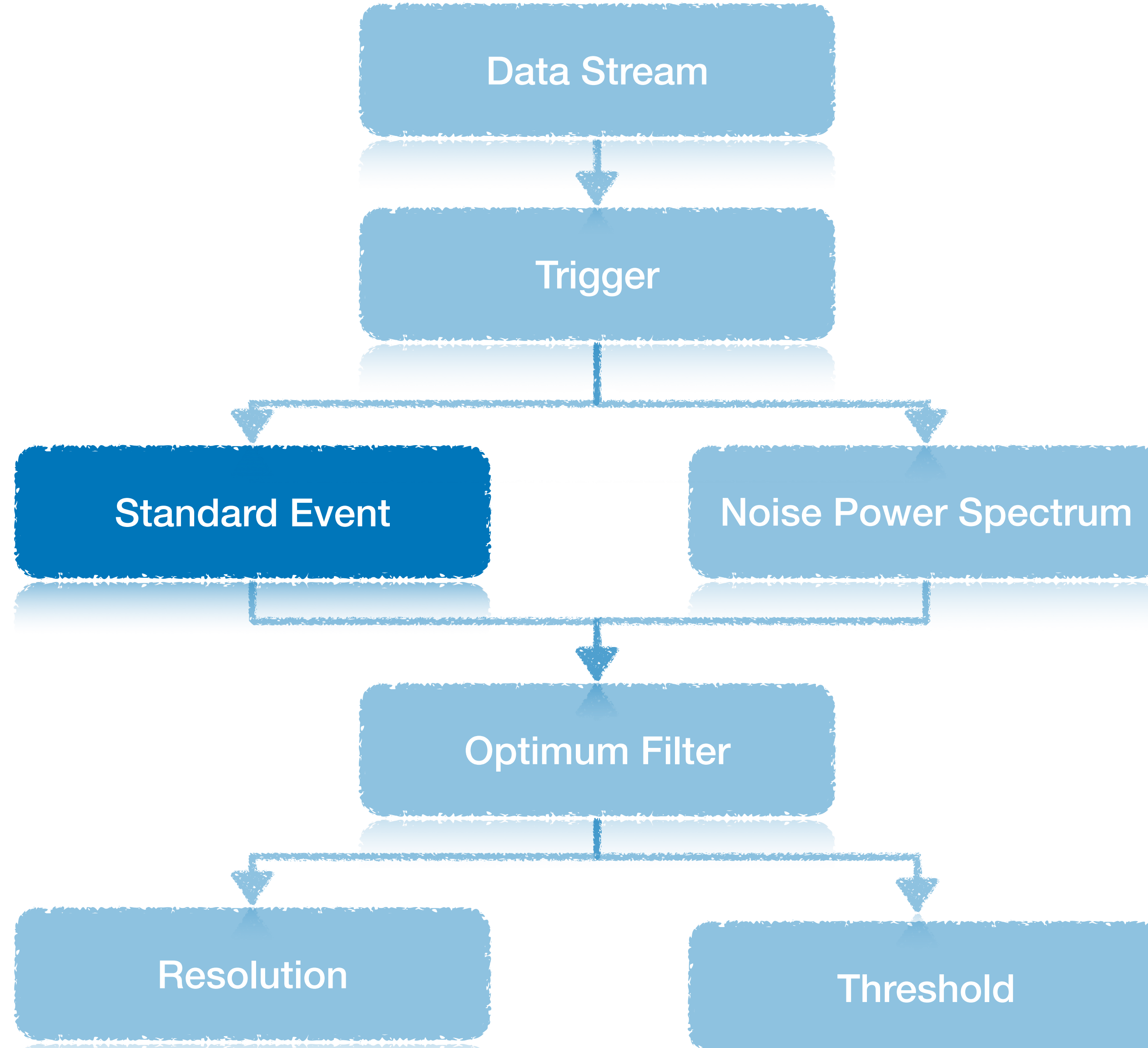
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NPS-Generator

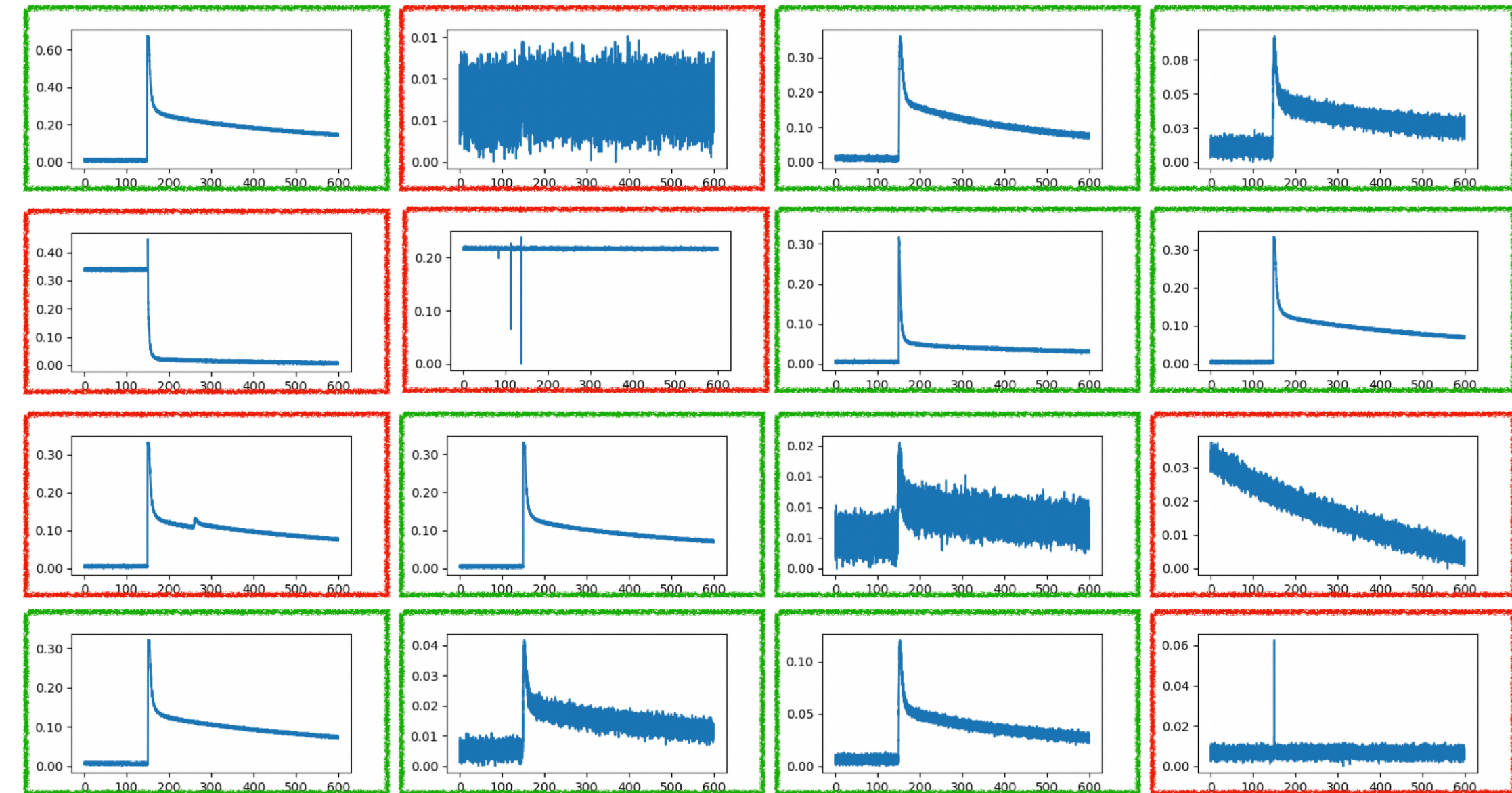
- Sequence of different trigger/cleaning modules
- Cleans data stream from events and artifacts
- **Advantages**
 - ➔ NPS creation without human input
 - ➔ Fast and reliable results





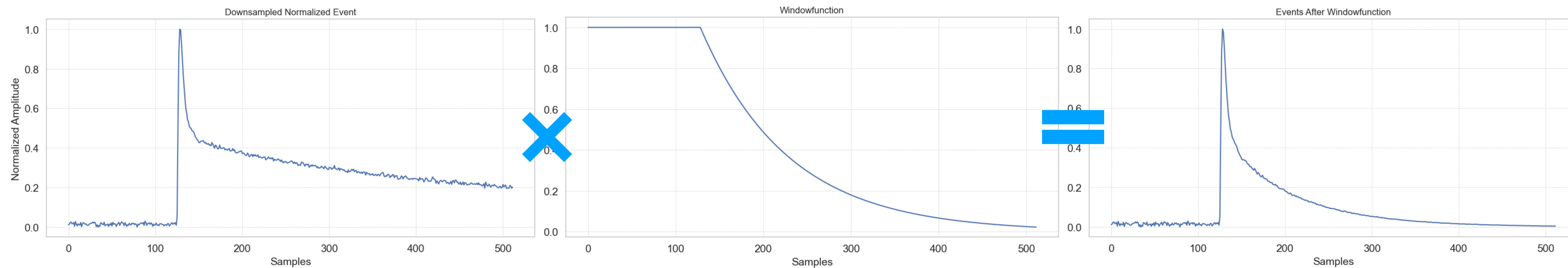
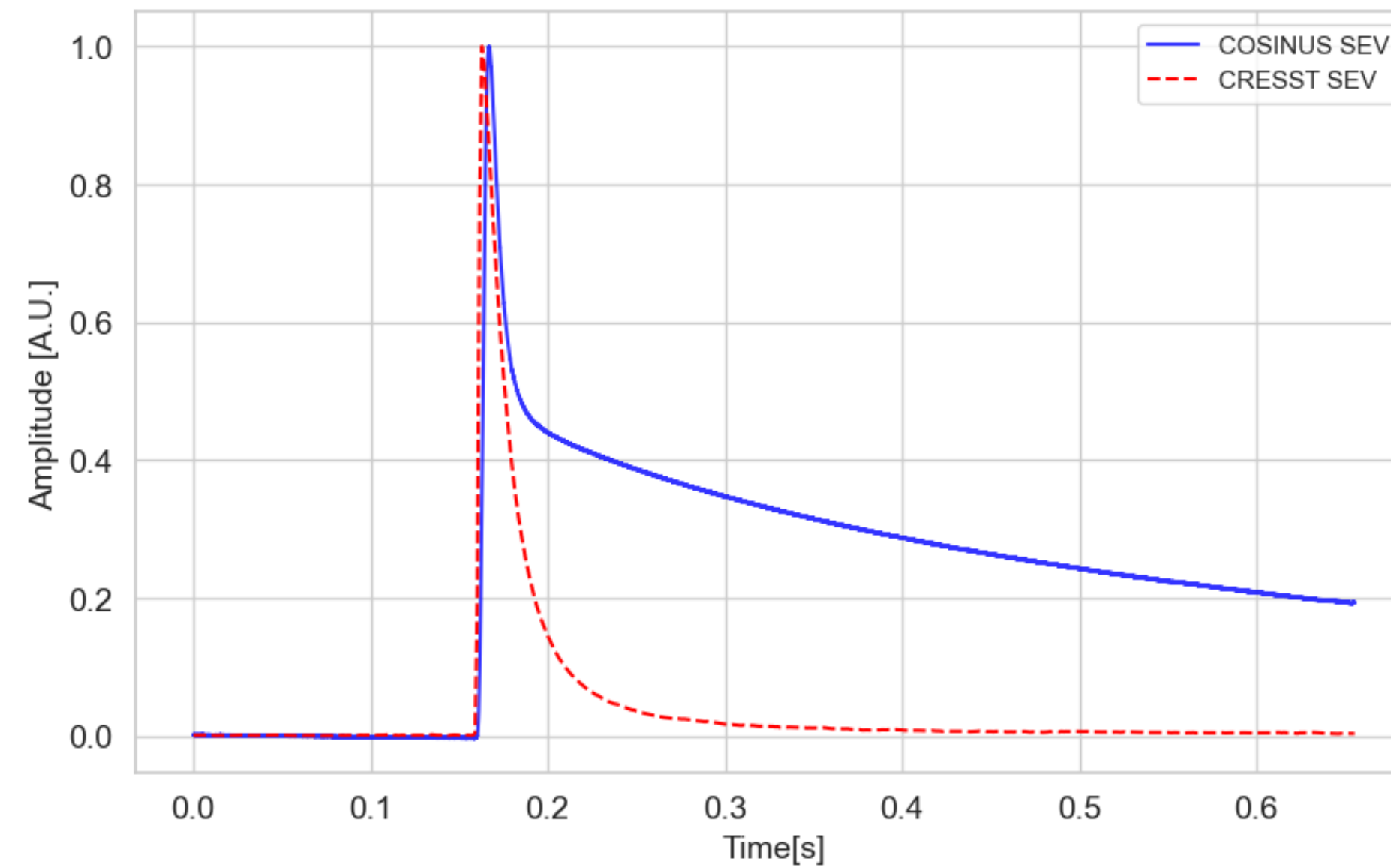
Validate Events

- Distinguish valid events from artifacts
- **Neural Network Approach:**
 - ➔ Train Neural Network with real events and artifacts
 - ➔ Network learns to identify patterns in the pulse shapes
 - ➔ Existing Neural Network from CRESST (trained with one million real events)



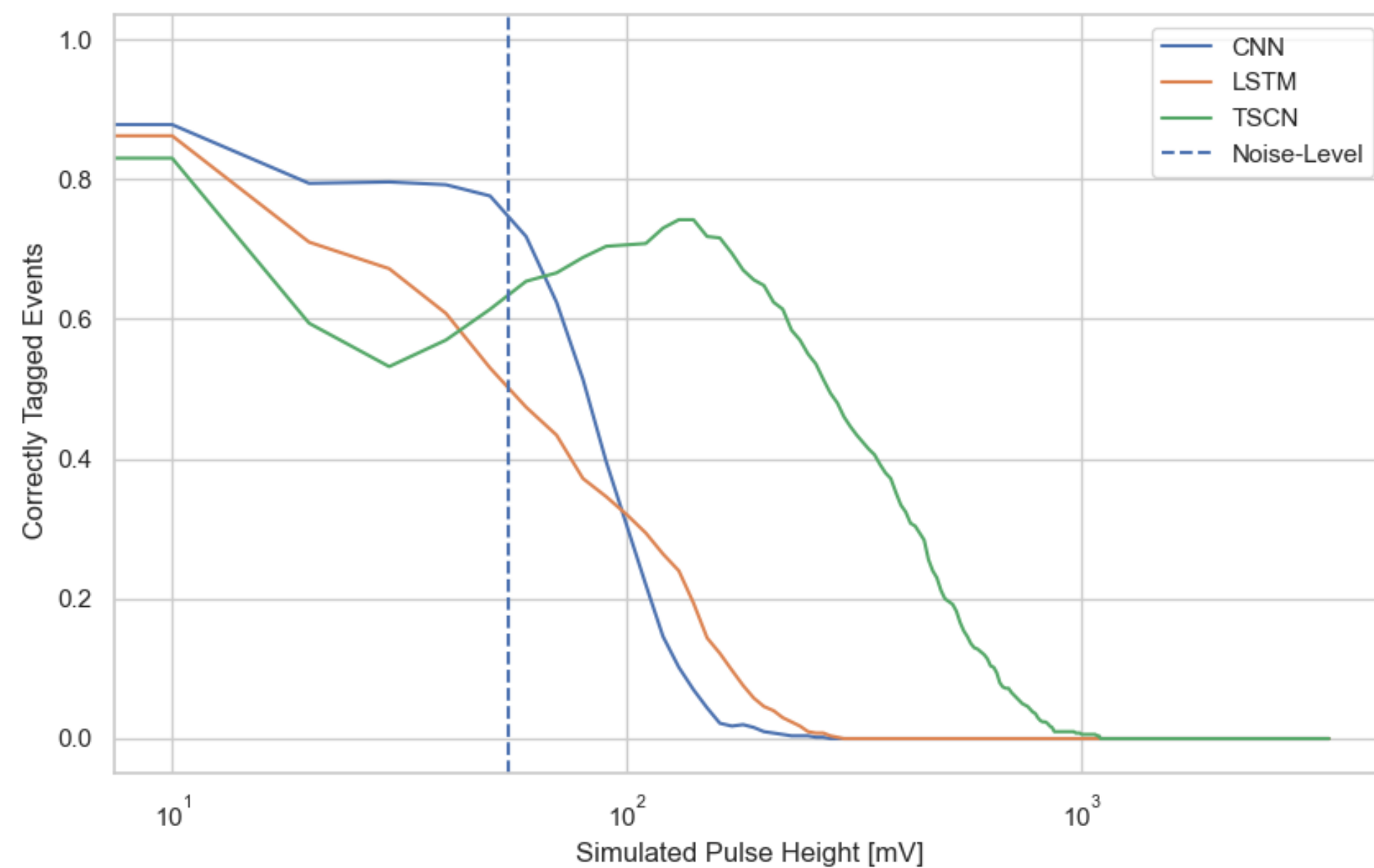
Adaptation of the Neural Network

- COSINUS-pulses are slower than CRESST-pulses
- **Solution:**
Introduce window function



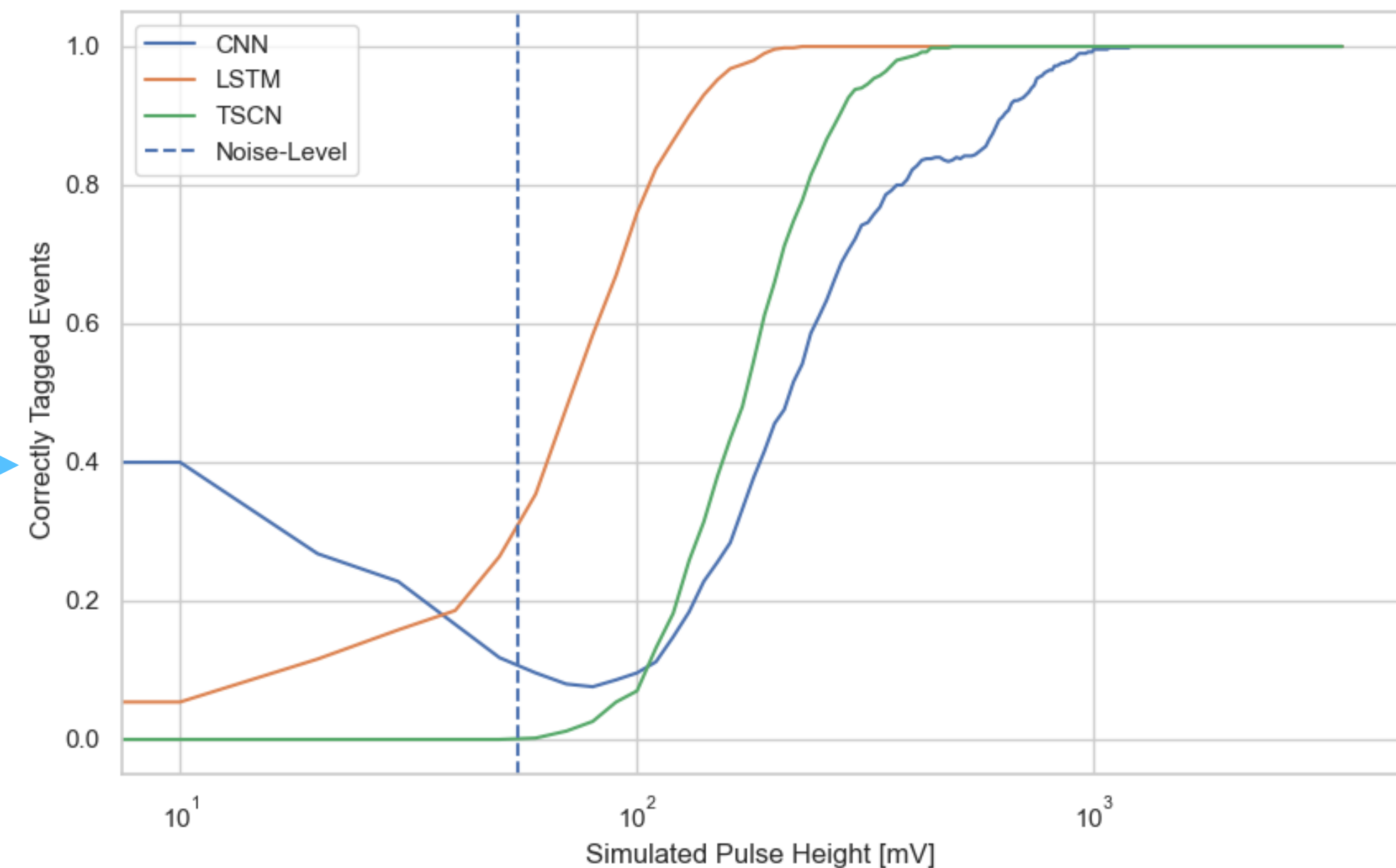
Adaptation of the Neural Network

- Poor performance on simulated COSINUS events



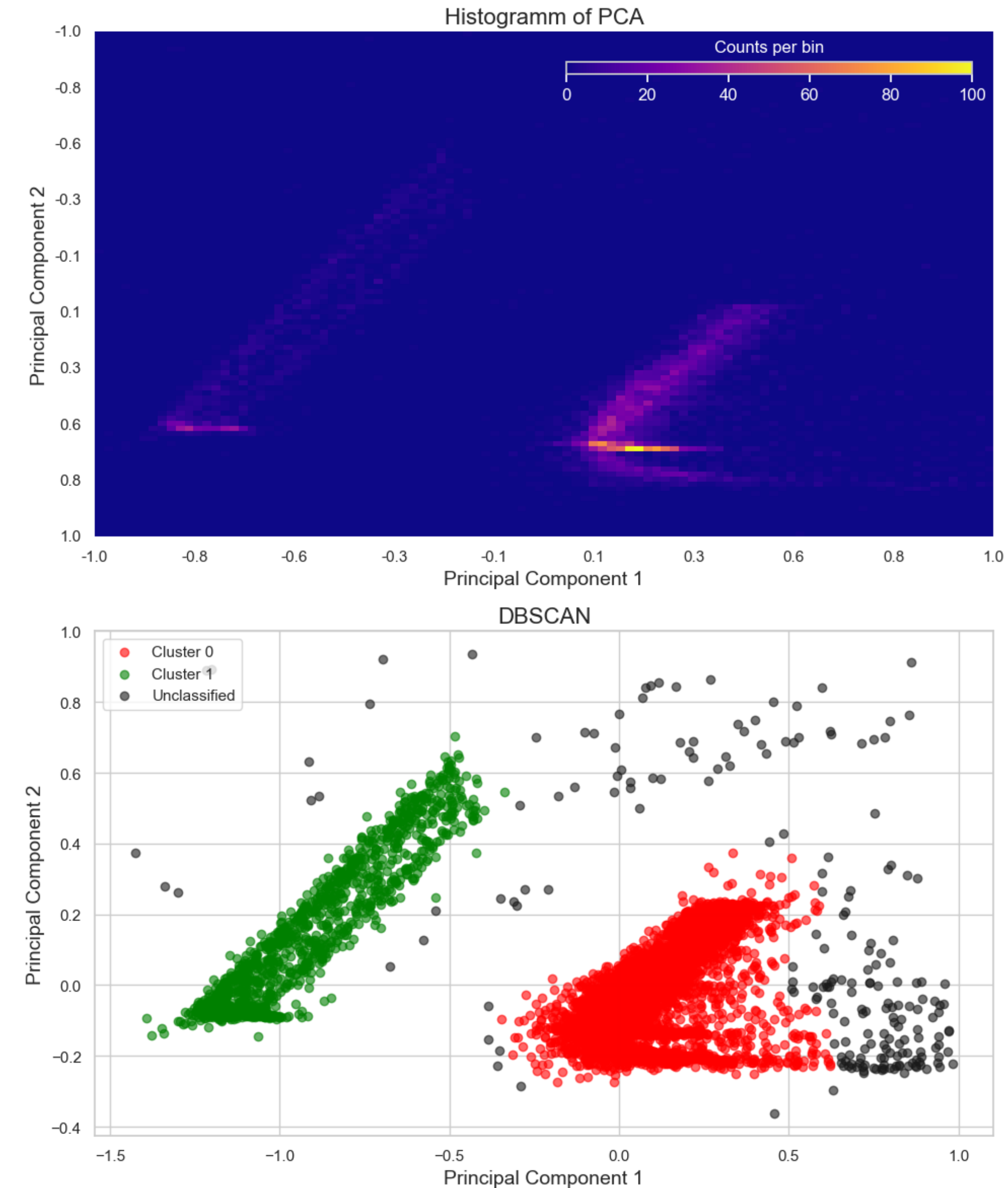
Window
function

- Good performance for events above noise level
- Some artifacts mislabeled as valid events



Classify Event types

- Possible approach
 - ➔ Apply principal component analysis
 - ➔ Cluster with DBSCAN
(Density-Based Spatial Clustering of Applications with Noise)
 - ➔ Create average pulse of clusters and select pulse shape of absorber events



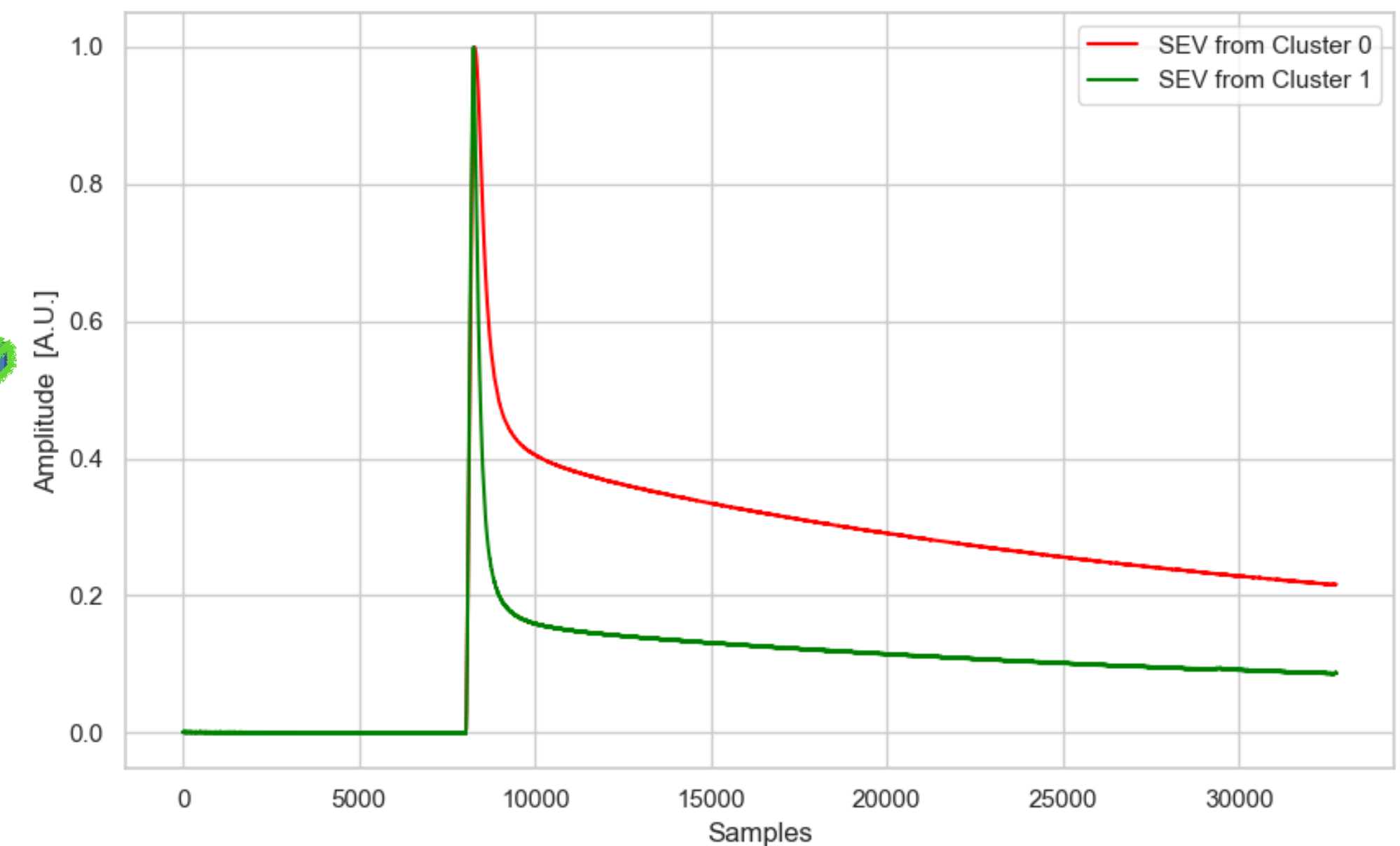
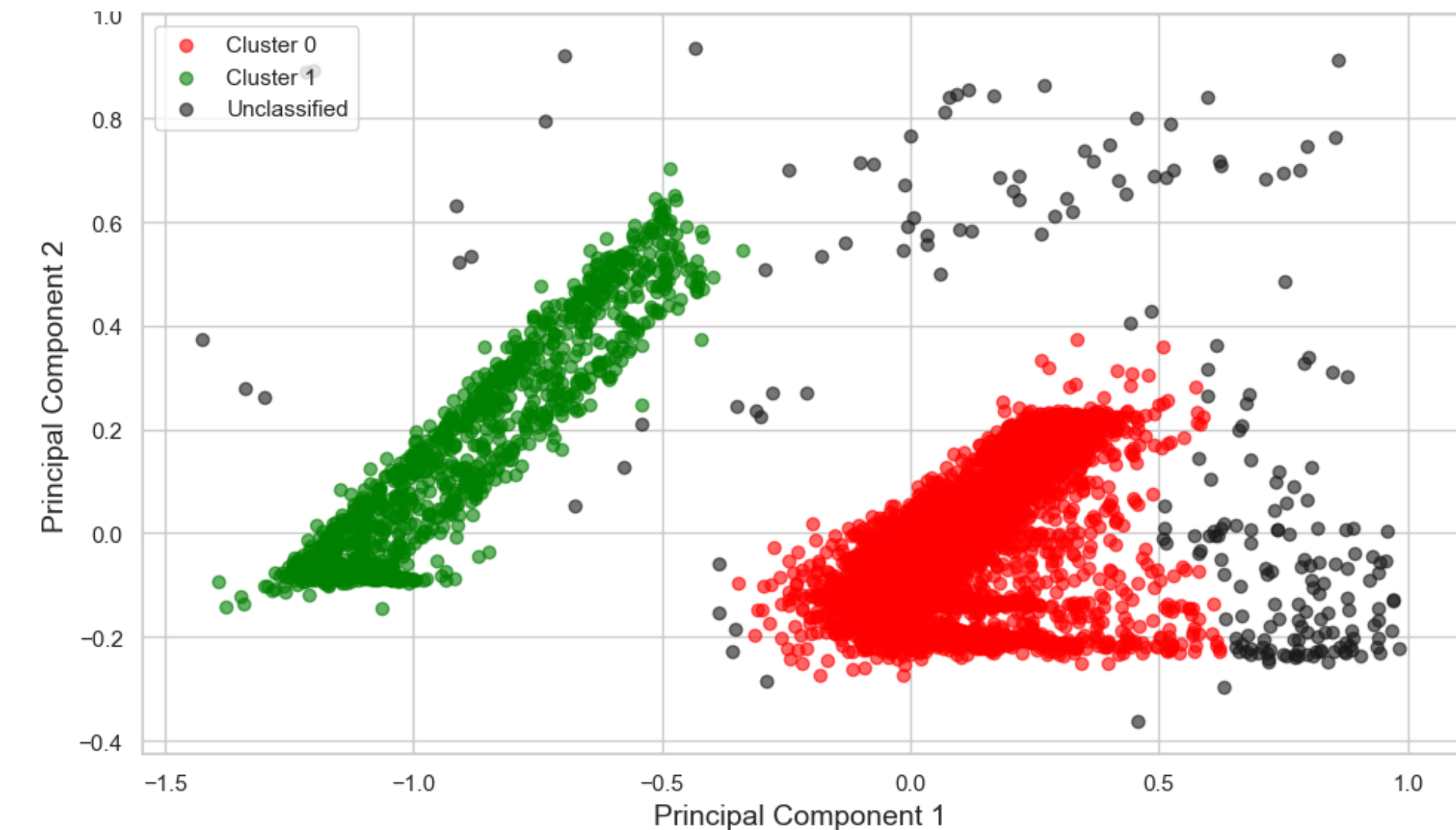
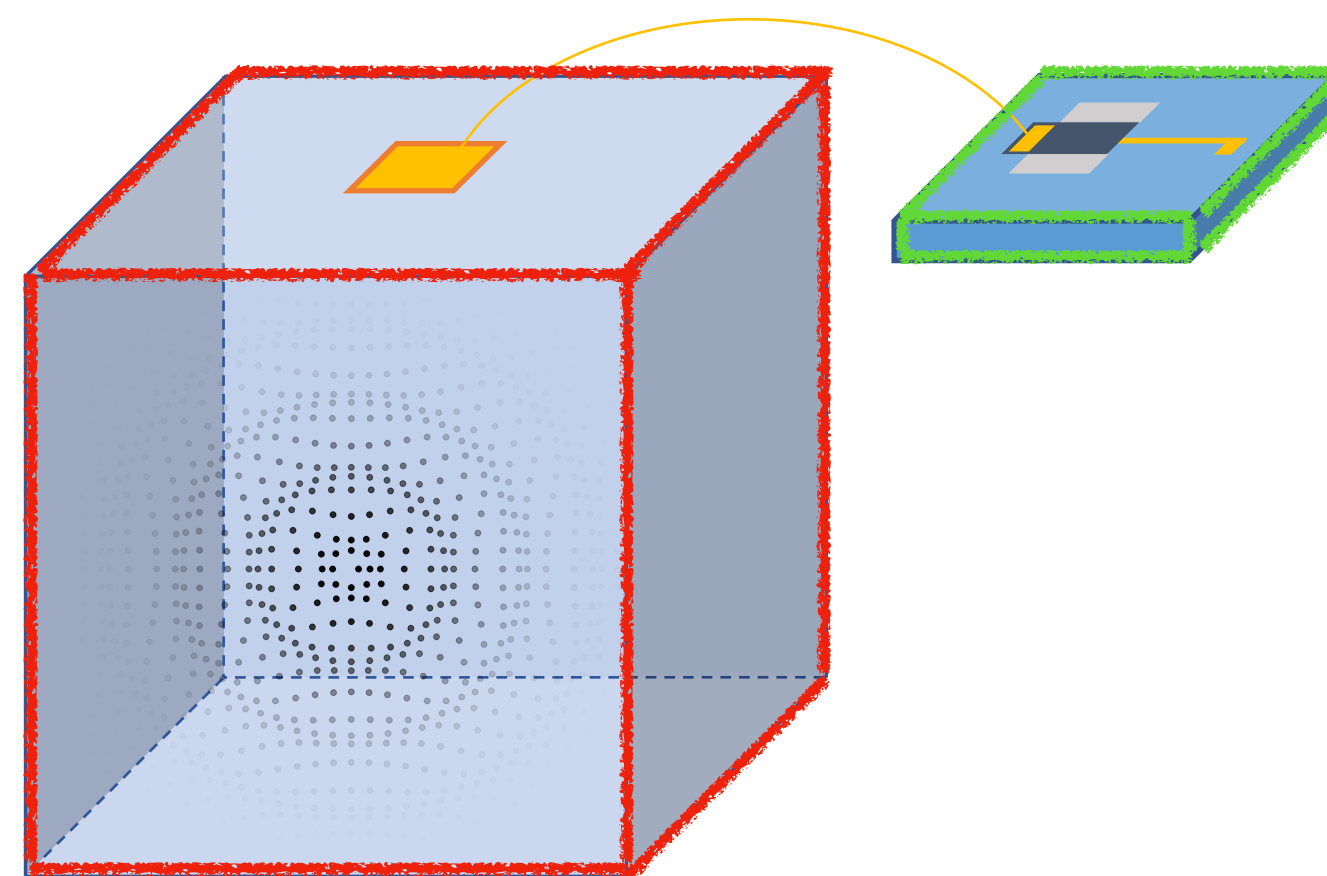
Classify Event types

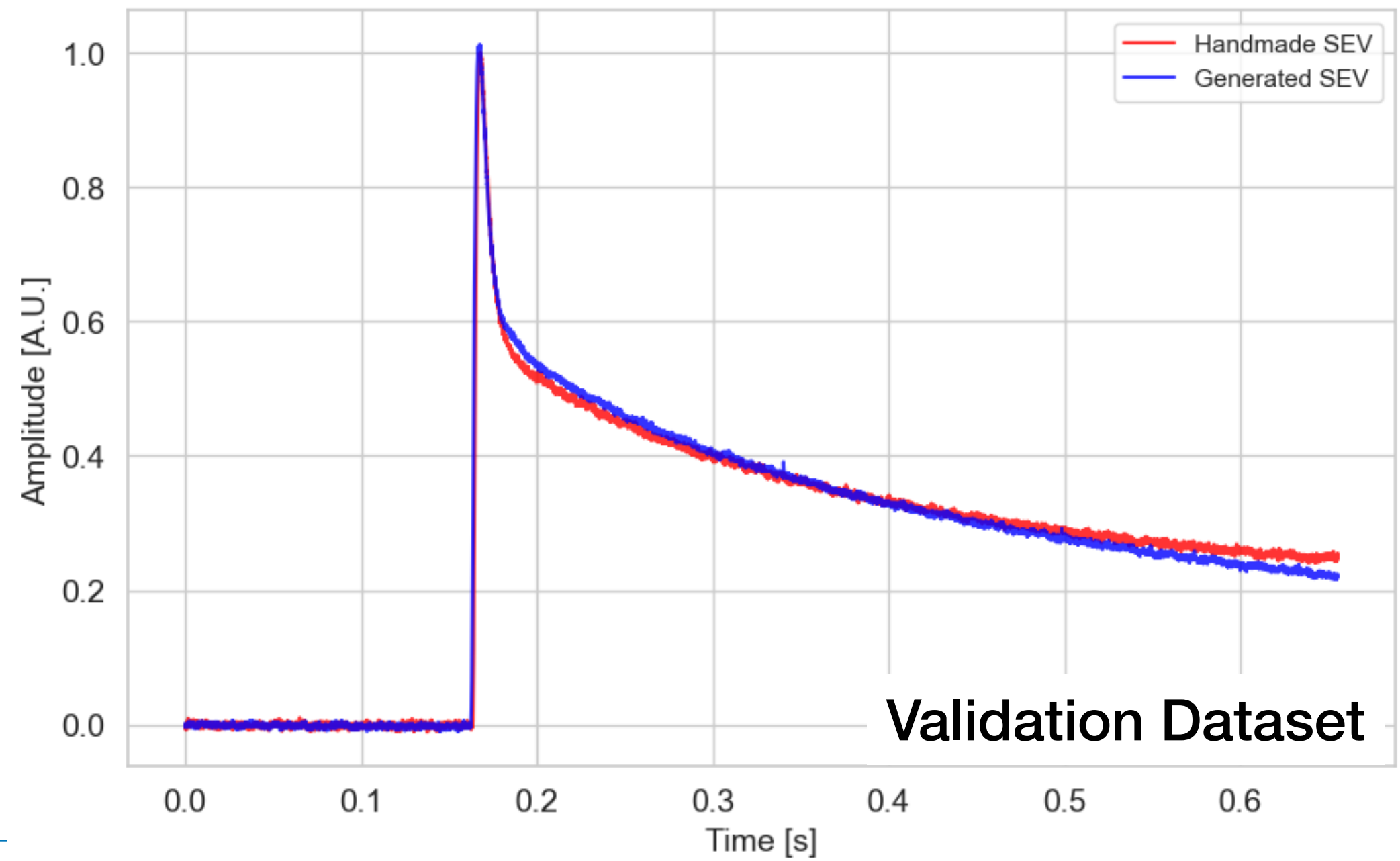
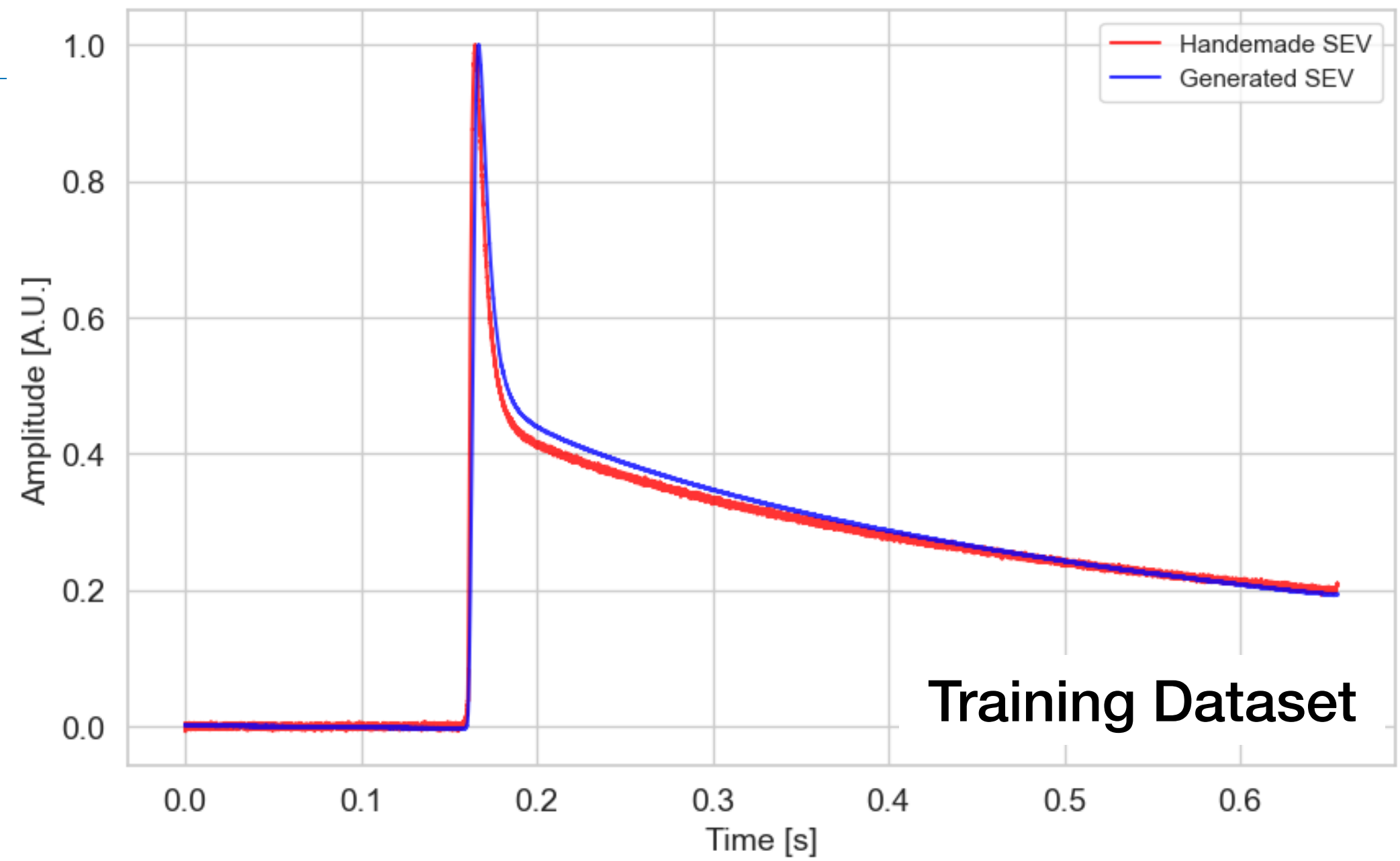
- Possible approach

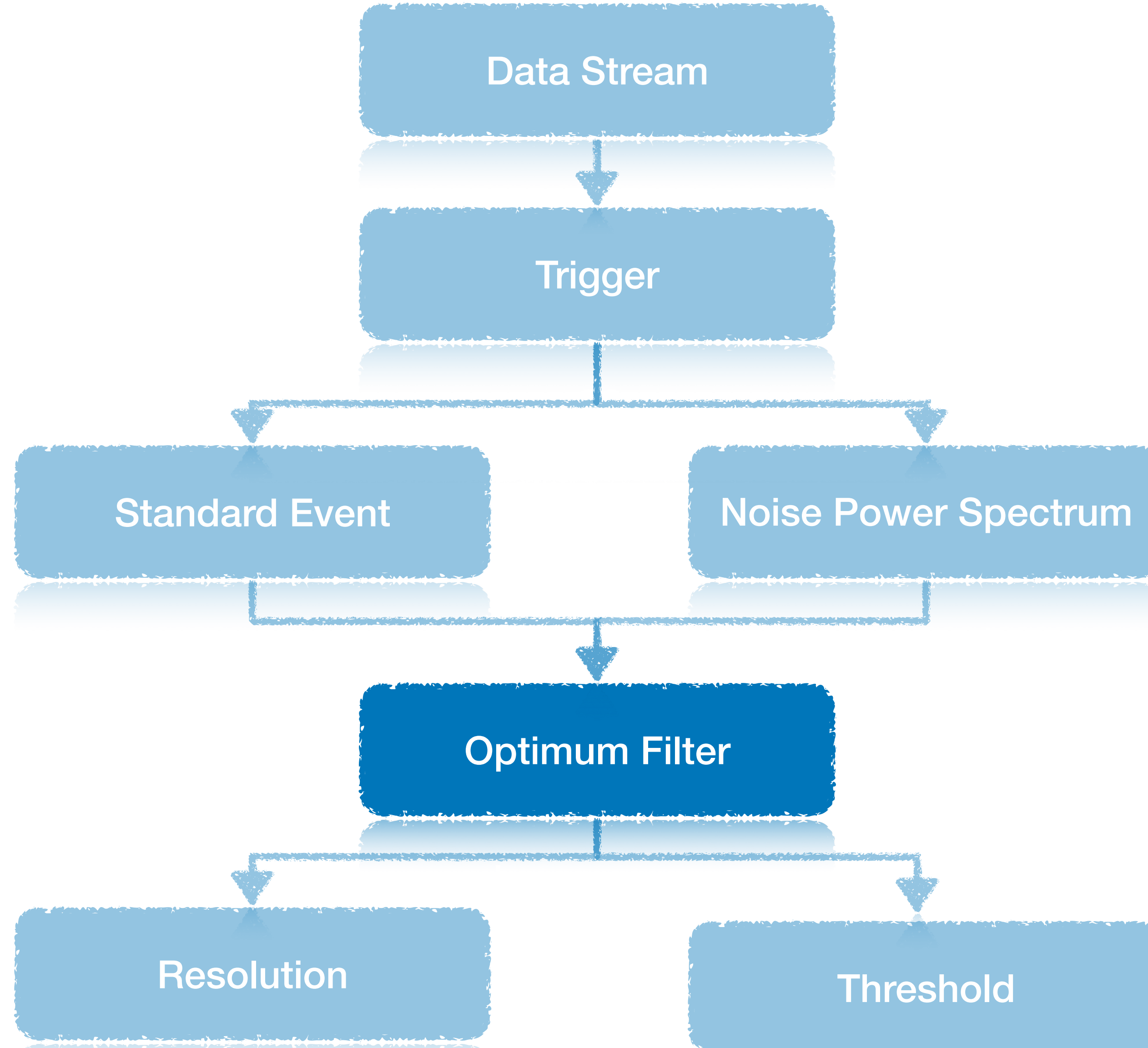
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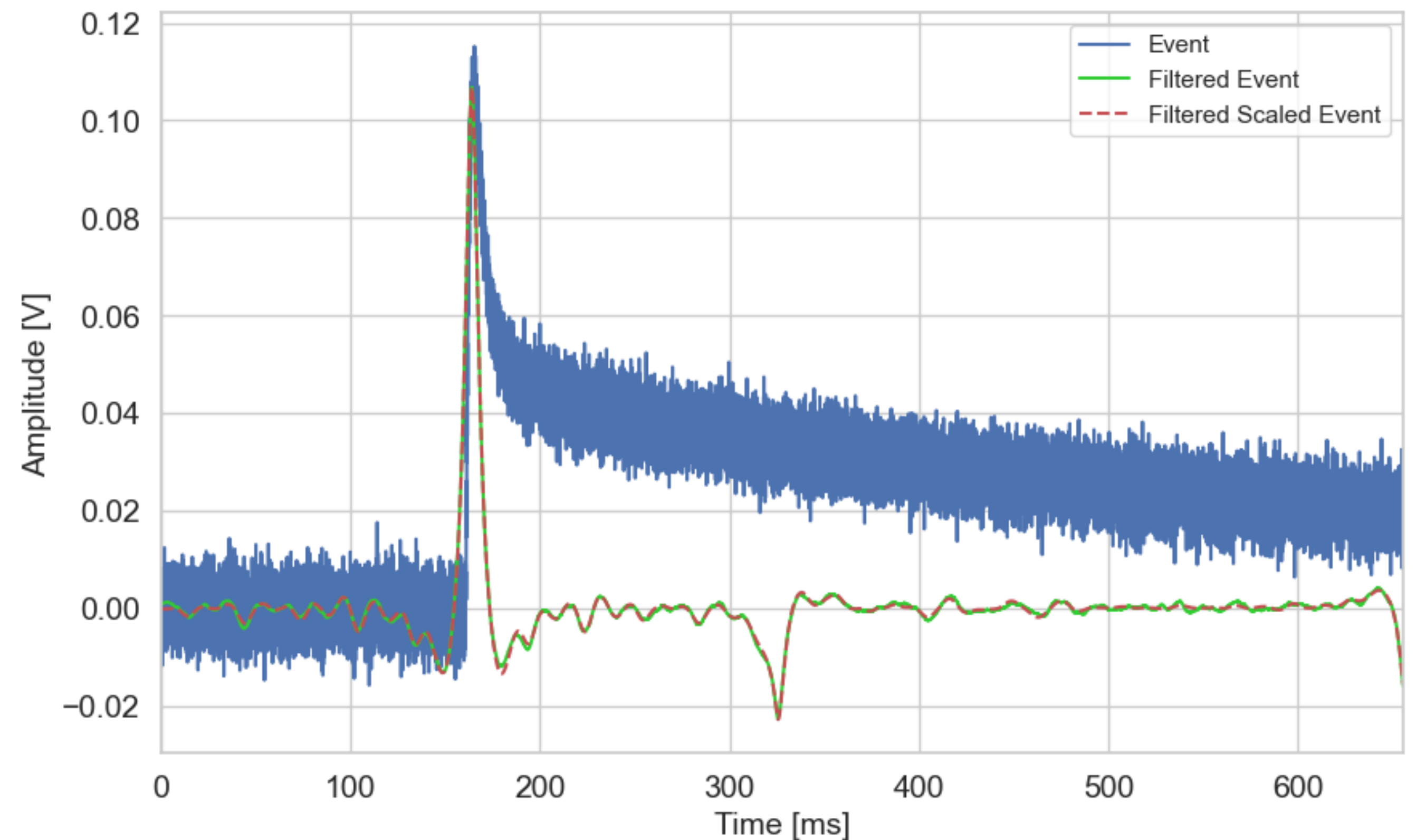


Create the Optimum Filter

- Create optimum filter from SEV and NPS

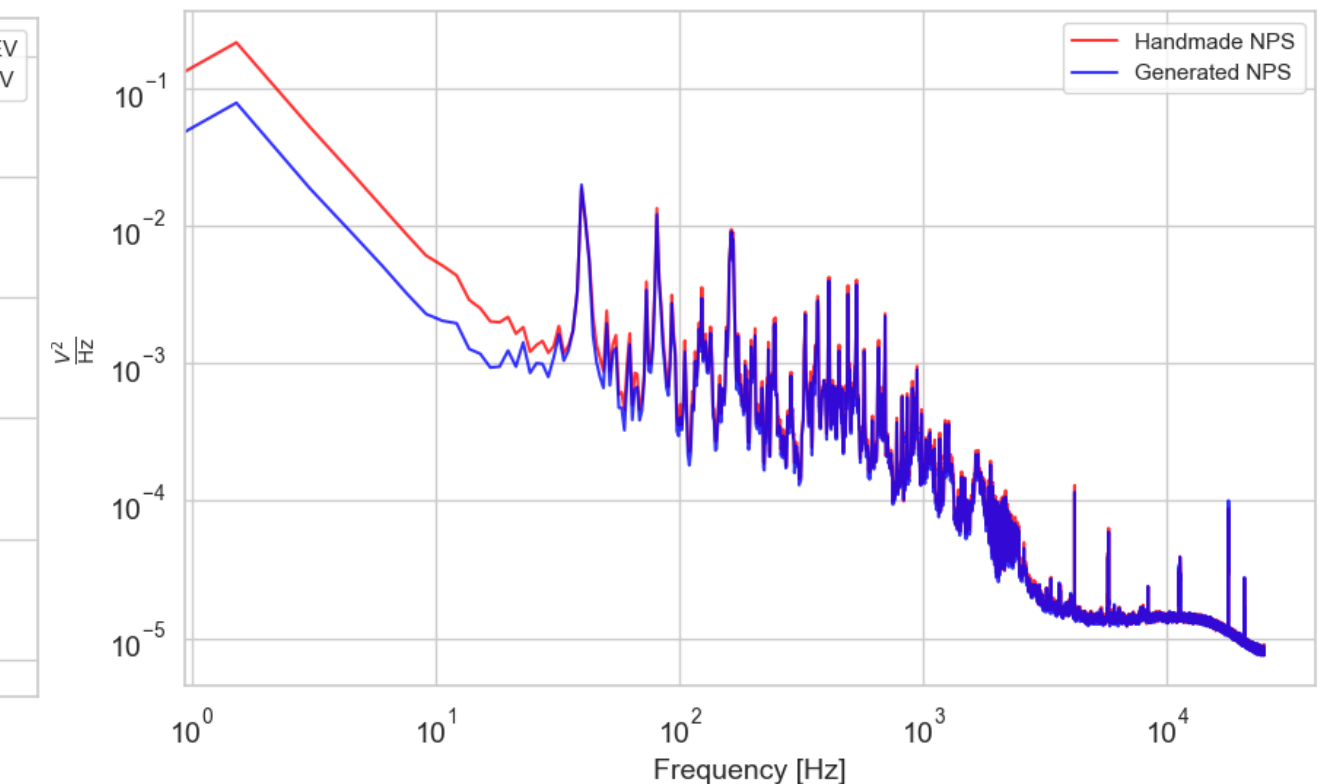
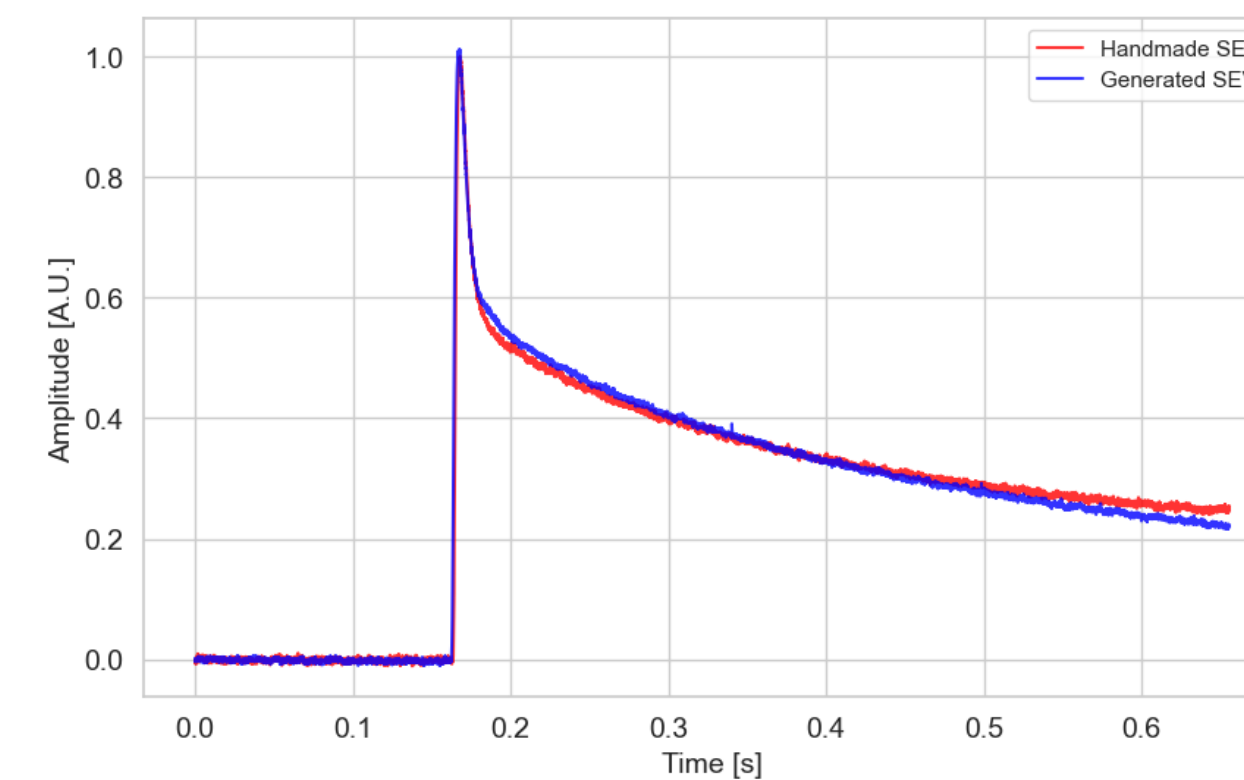
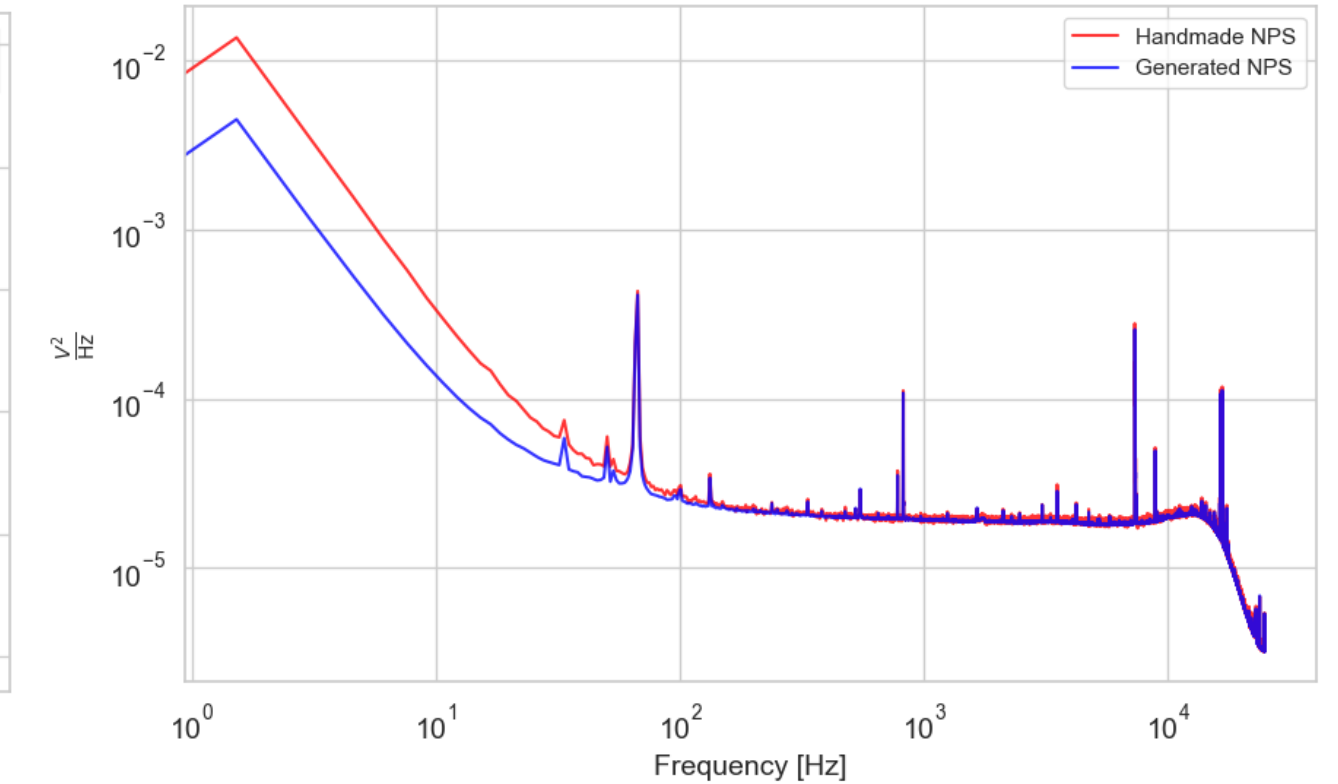
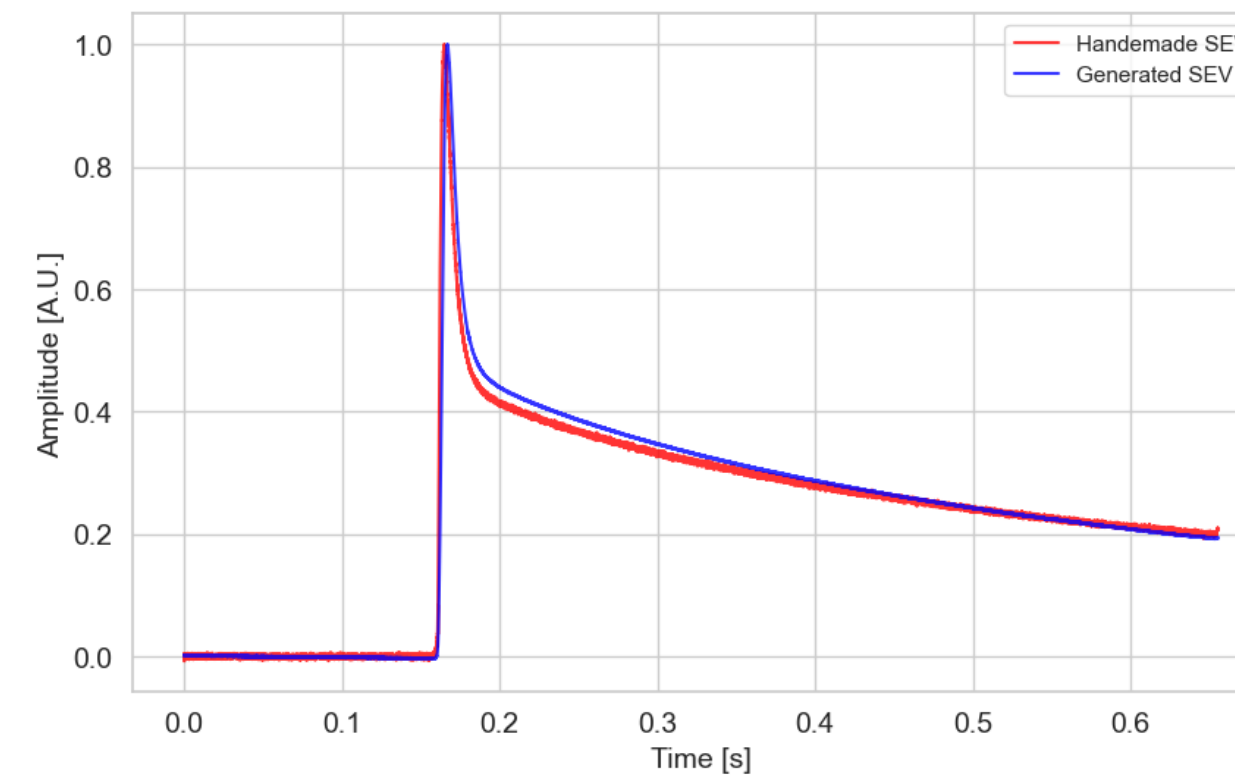
$$H(\omega) = h \frac{SEV^*(\omega)}{NPS(\omega)} e^{-2\pi i \omega \tau}$$

- Well established pulse height reconstruction method
- Best signal/noise ratio for the given signal shape and assuming constant noise conditions (NPS)



Results

	What analyse type	Resolution [mV]
Training Dataset	Handmade [Me]	0.420 ± 0.002
	Handmade [Published]	$0.379 \pm 0.009^*$
	Automation	0.377 ± 0.002
Validation Dataset	Handmade [Me]	2.90 ± 0.03
	Handmade [Published]	$1.86 \pm 0.04^{**}$
	Automation	2.35 ± 0.02



* In Energy: 0.441 ± 0.011 keV

** In Energy: 2.07 ± 0.02 keV

What's next?

- Implementation of control levels to avoid using modules as a black box
- Training of a neural network on COSINUS pulses
- Modules soon available in analysis packages Cait and CAT

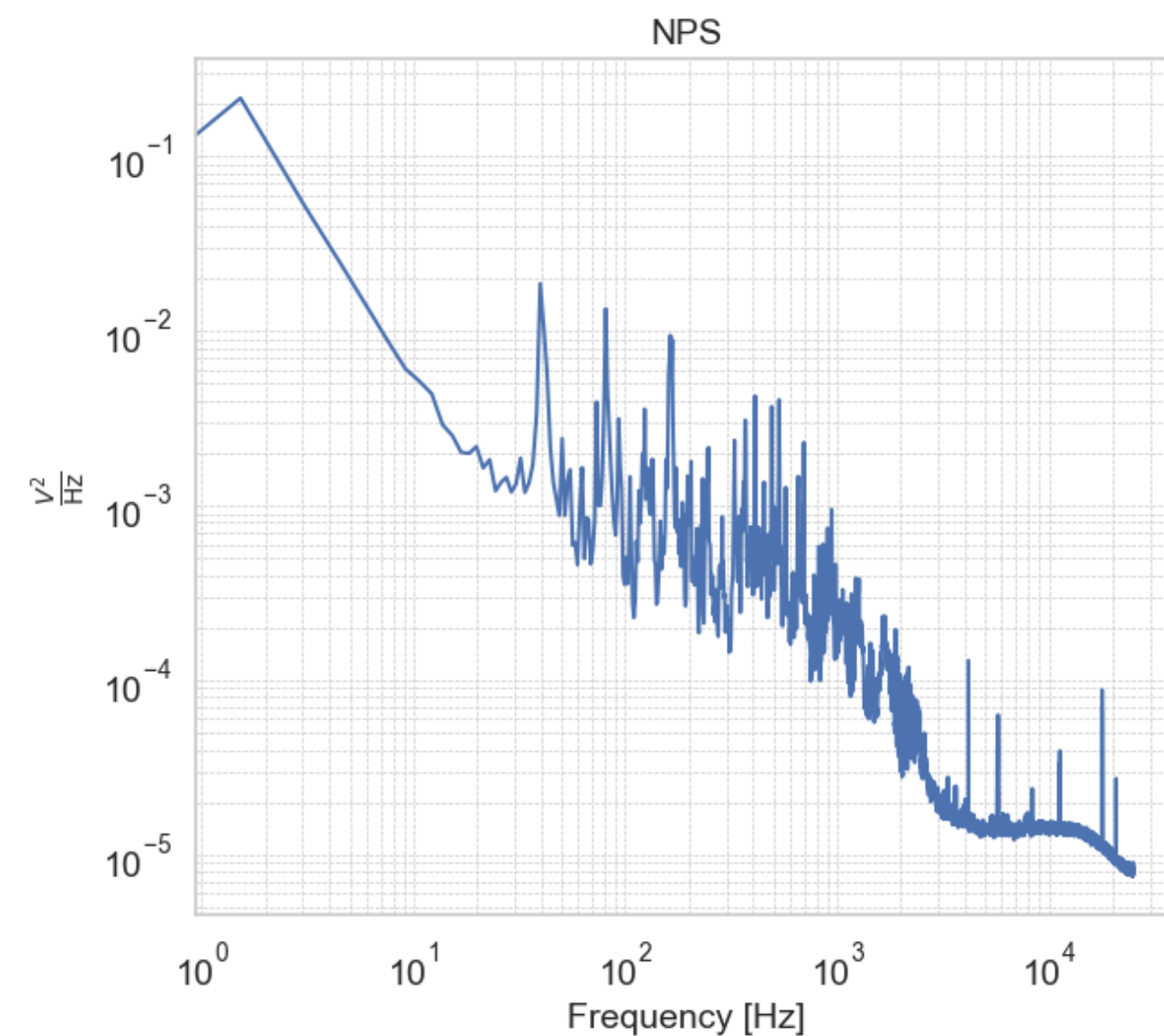
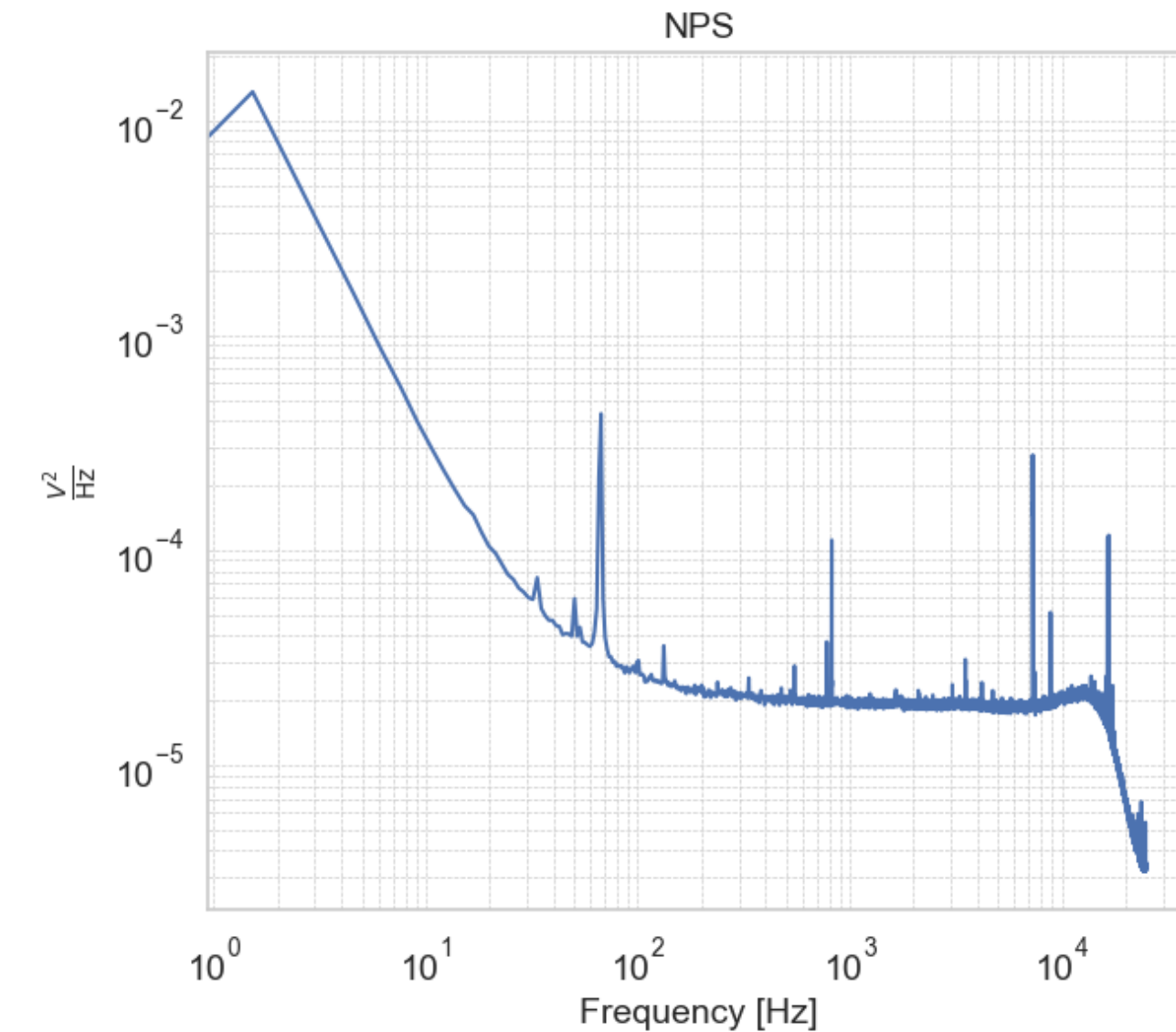




Backup

„Summer Run“

- Underground measurement carried out in a cryostat from CRESST at Laboratori Nazionali del Gran Sasso
- Low noise level
- All modules developed and optimized on this dataset
- Best module performance expected
- For more details, see <https://arxiv.org/pdf/2307.11139>

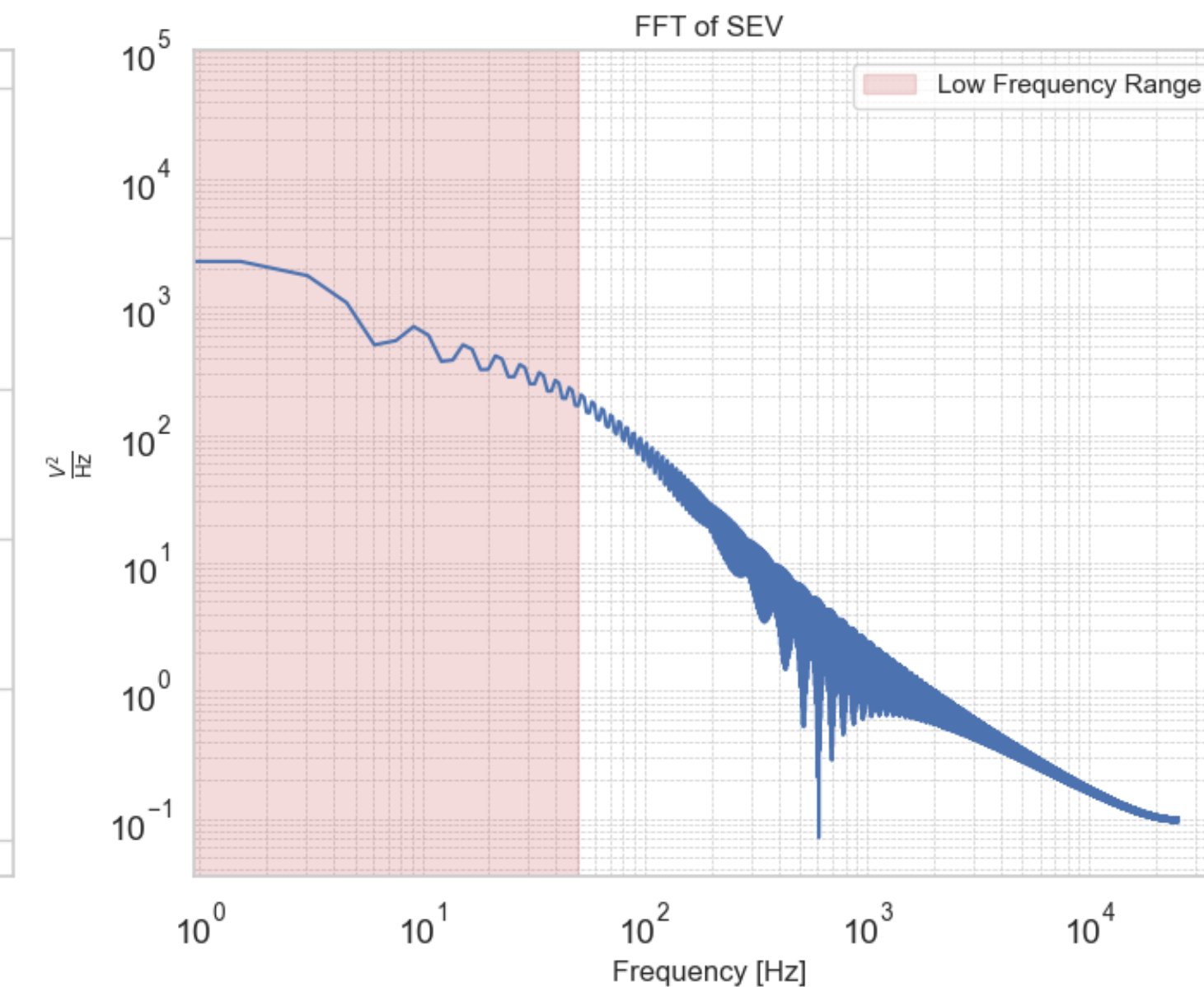
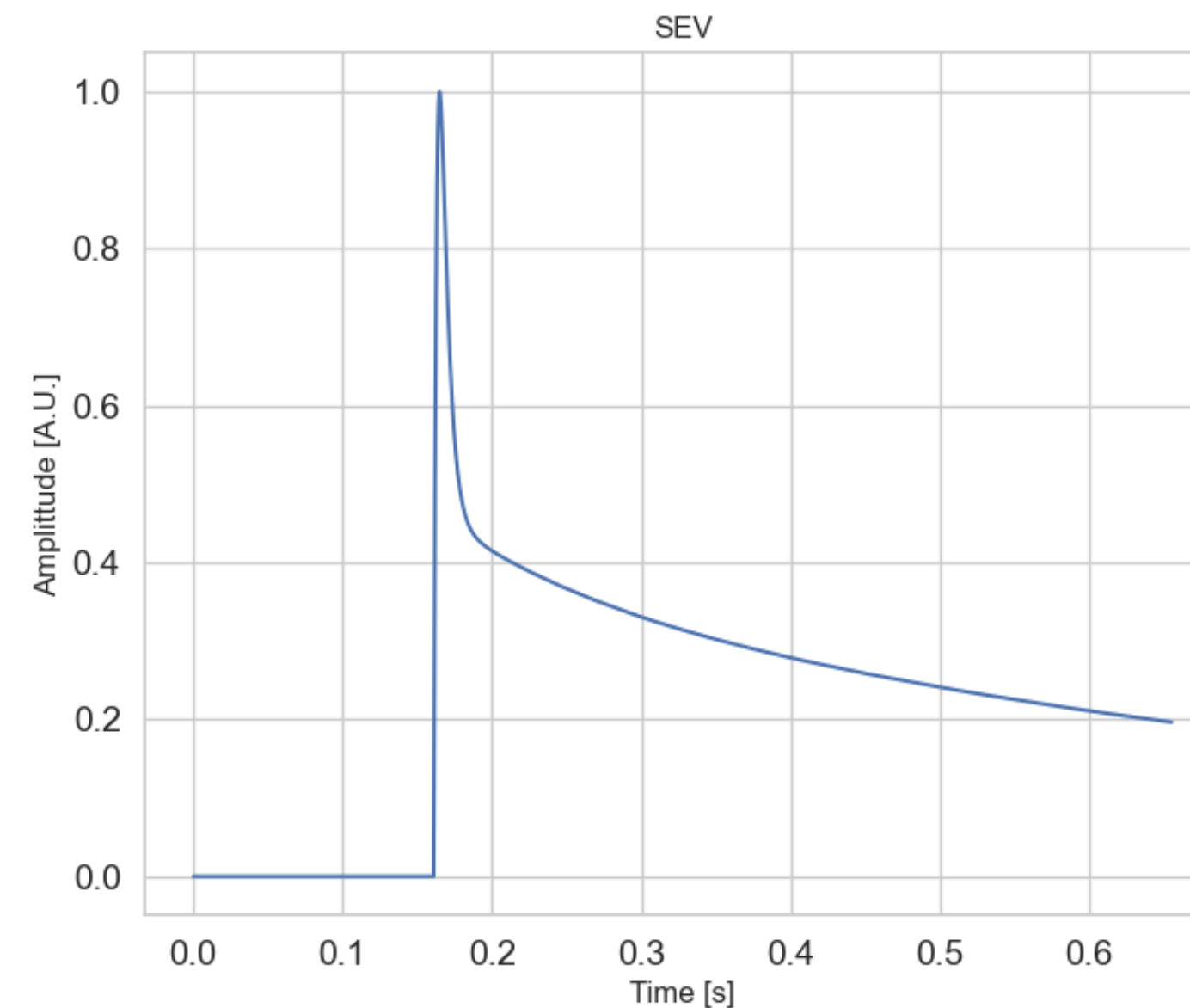


„Christmas Run“

- Above-Ground-Data carried out in a cryostat from CRESST in Munich
- Higher noise level and data rate
- „Stress test“ for the modules
- For more details, see <https://arxiv.org/pdf/2307.11066>

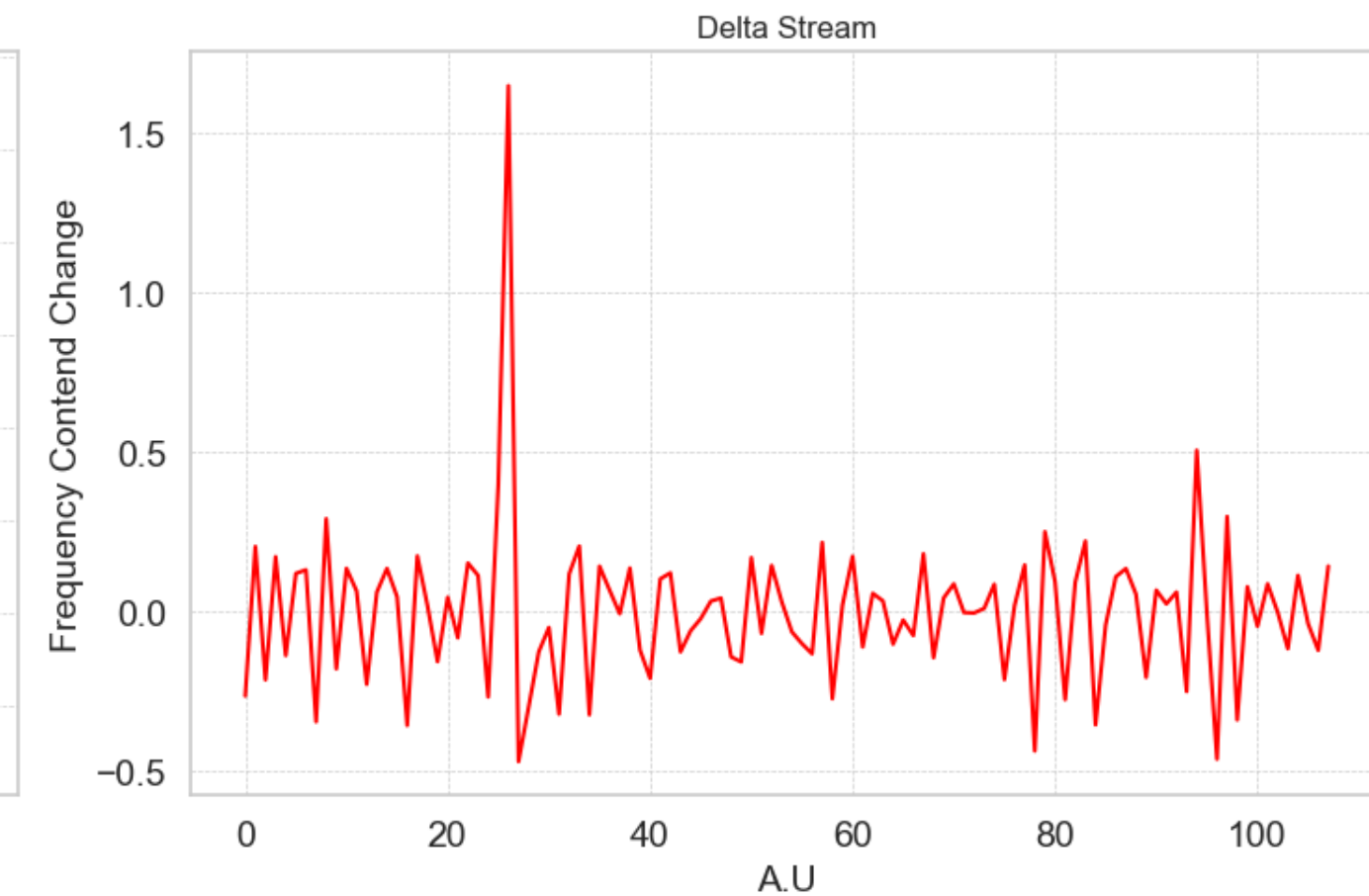
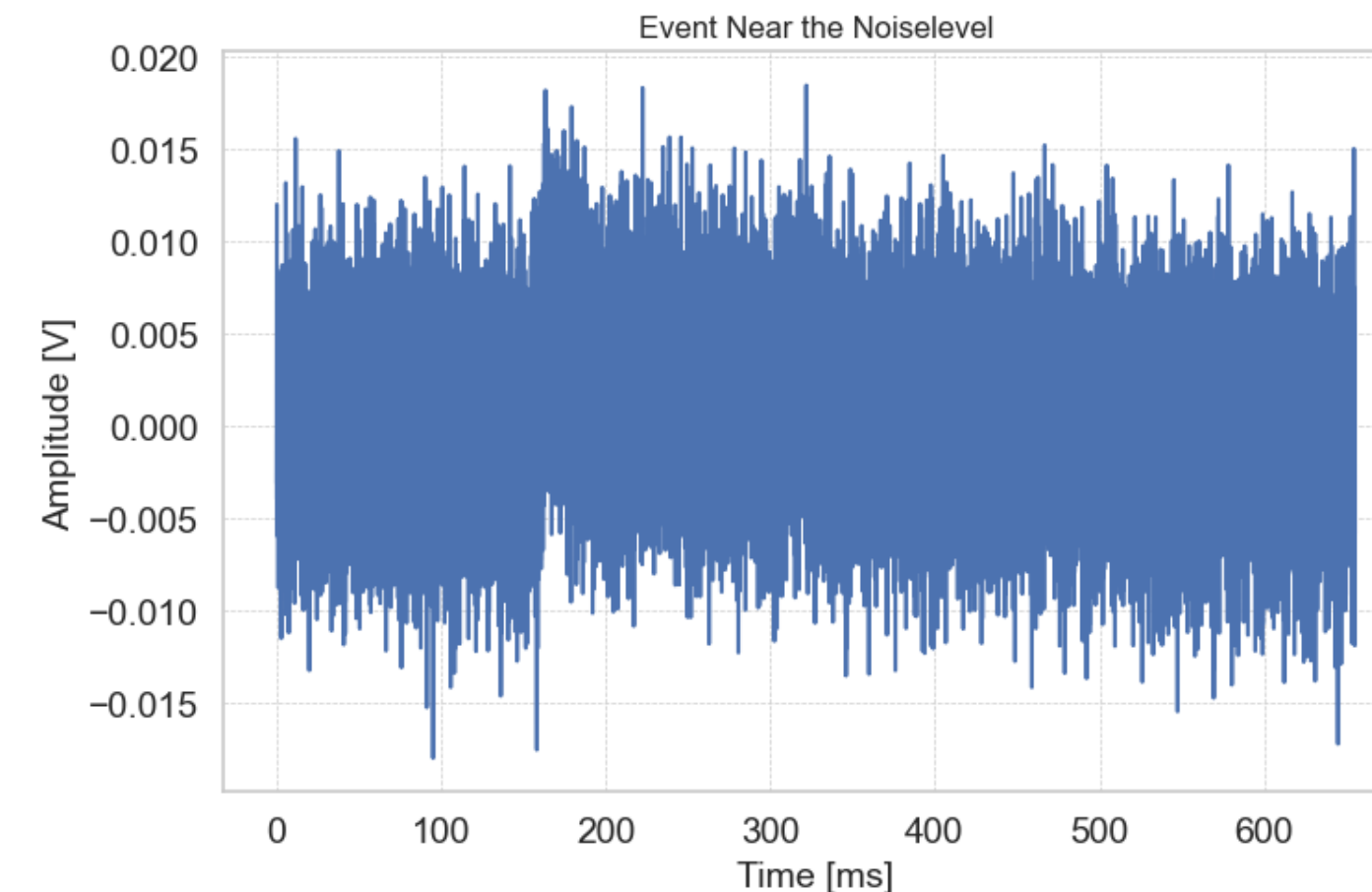
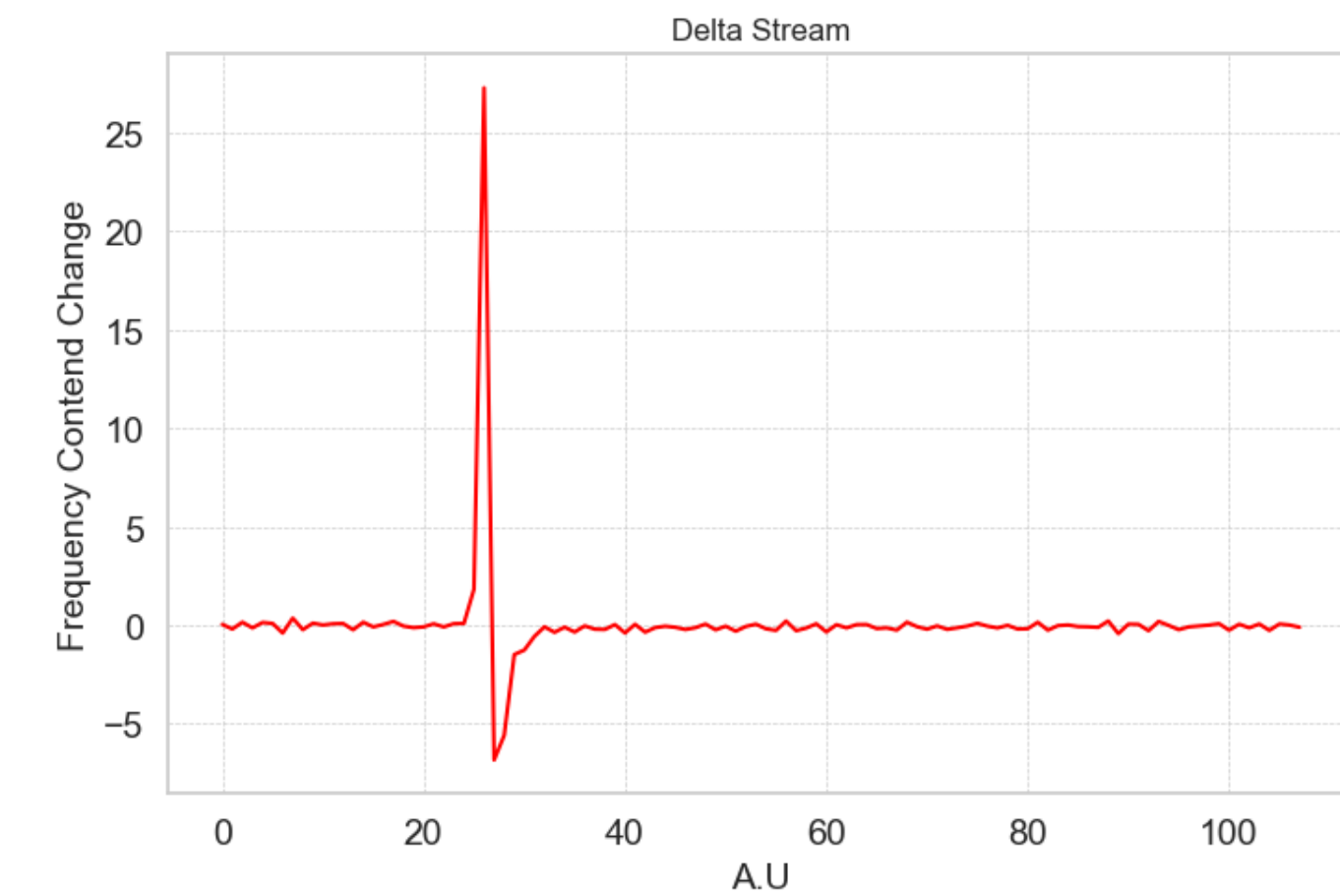
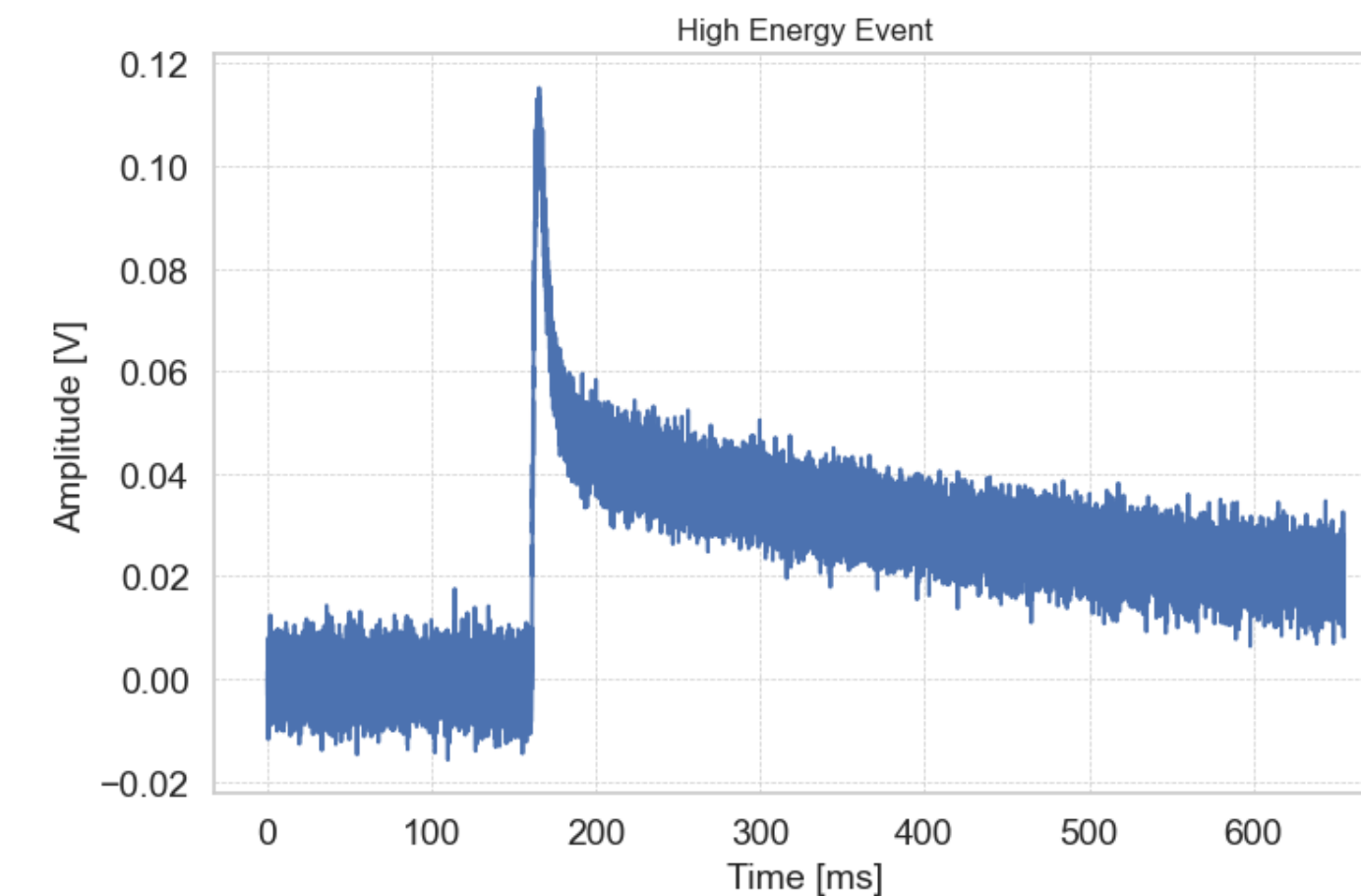
Frequency-Trigger

- **Assumption:**
Pulse-shape is defined mainly by low-frequency content
- Calculate Forurietranform for a moving window
- Integrate up to cutoff frequency (50 Hz)
- Build difference between two consecutive windows



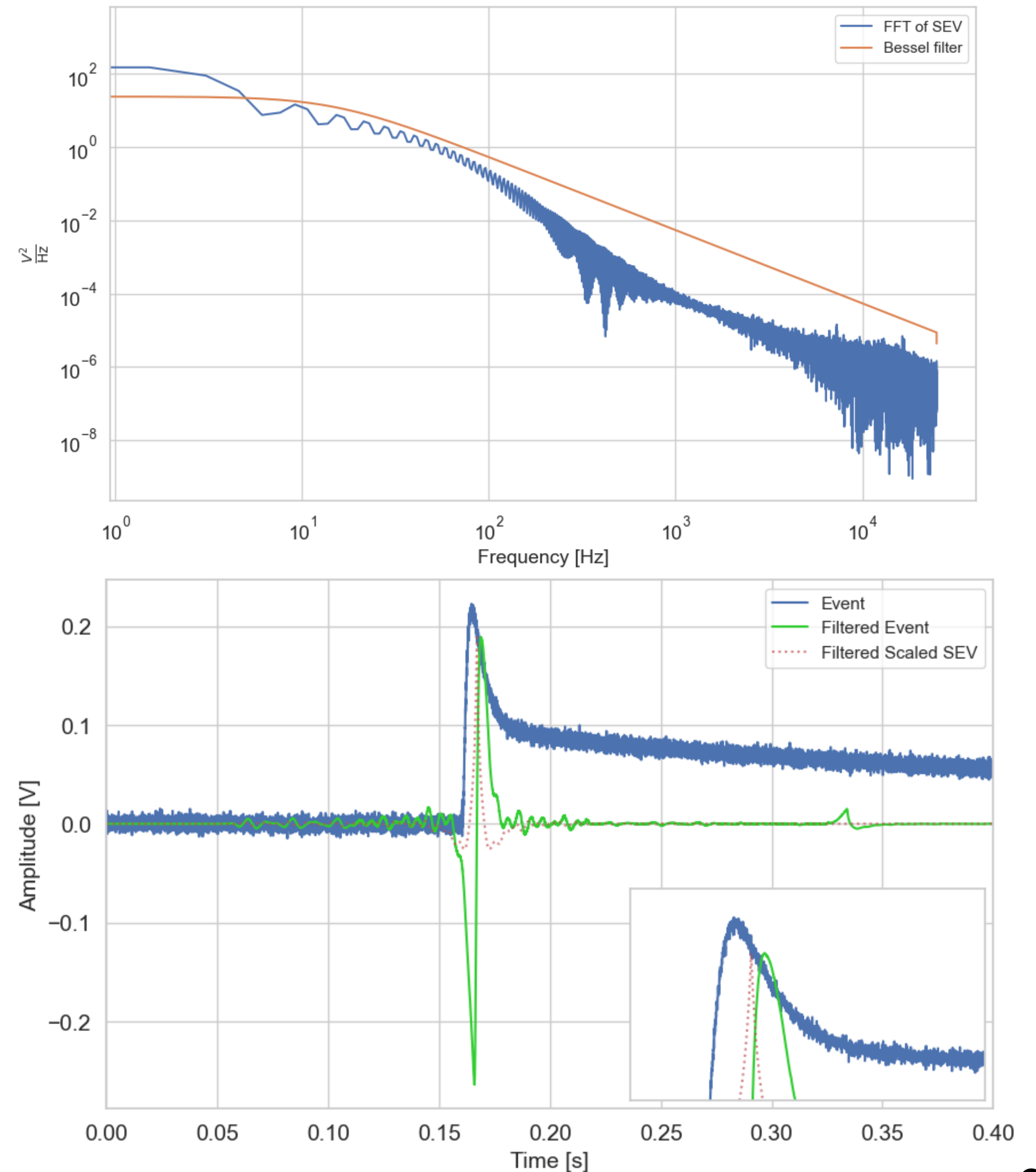
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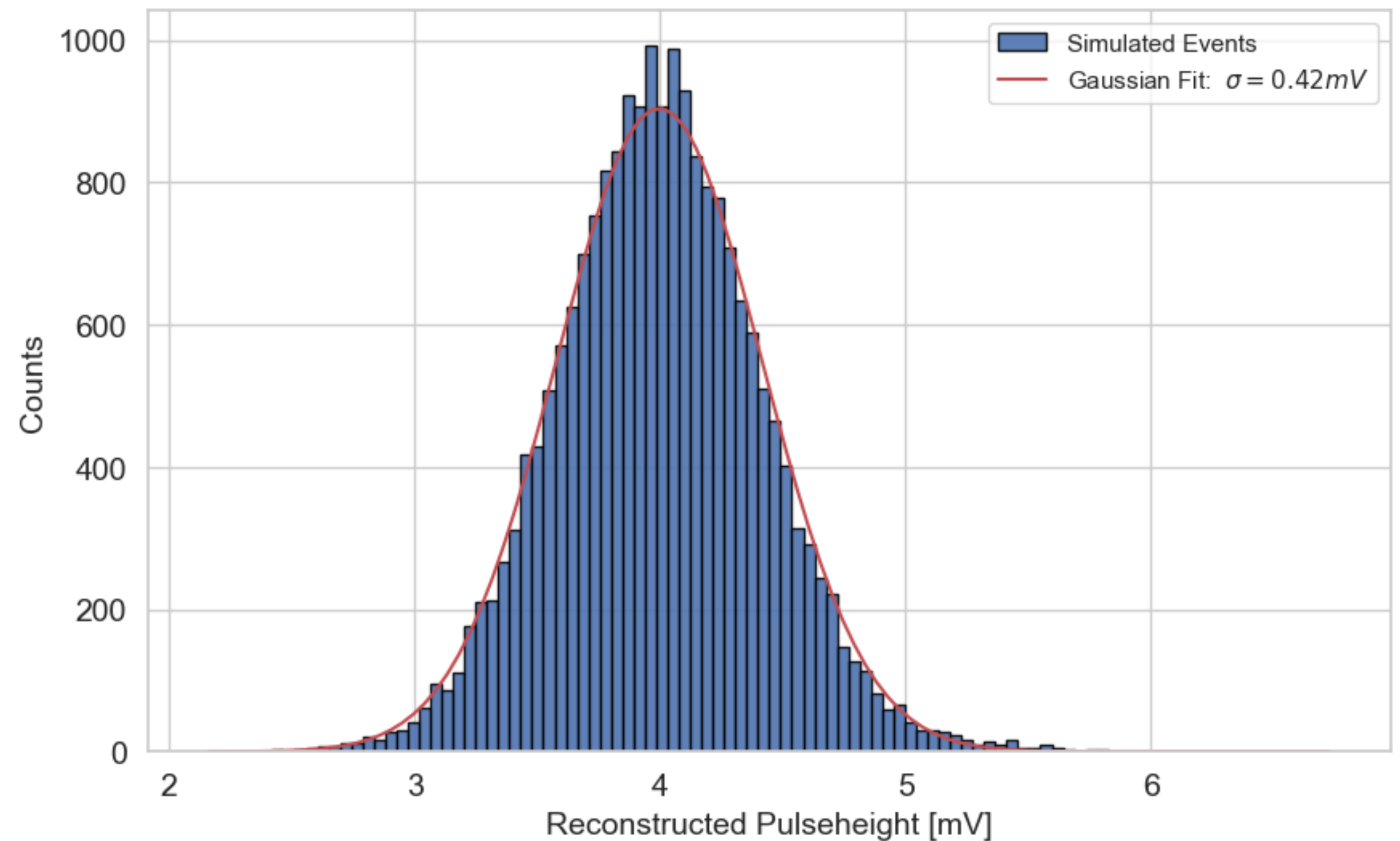
Bessel-Trigger

- Create a matched filter using Noise Power Spectrum and Bessel filter as an approximation of pulse shape
- Assumption on pulse shape: cutoff frequency
- Noise Power Spectrum needed



Baseline Resolution Determination

- Define set of clean empty baselines
- Superimpose with scaled SEV
- Reconstruct pulse height with OF
- Determine the standard deviation

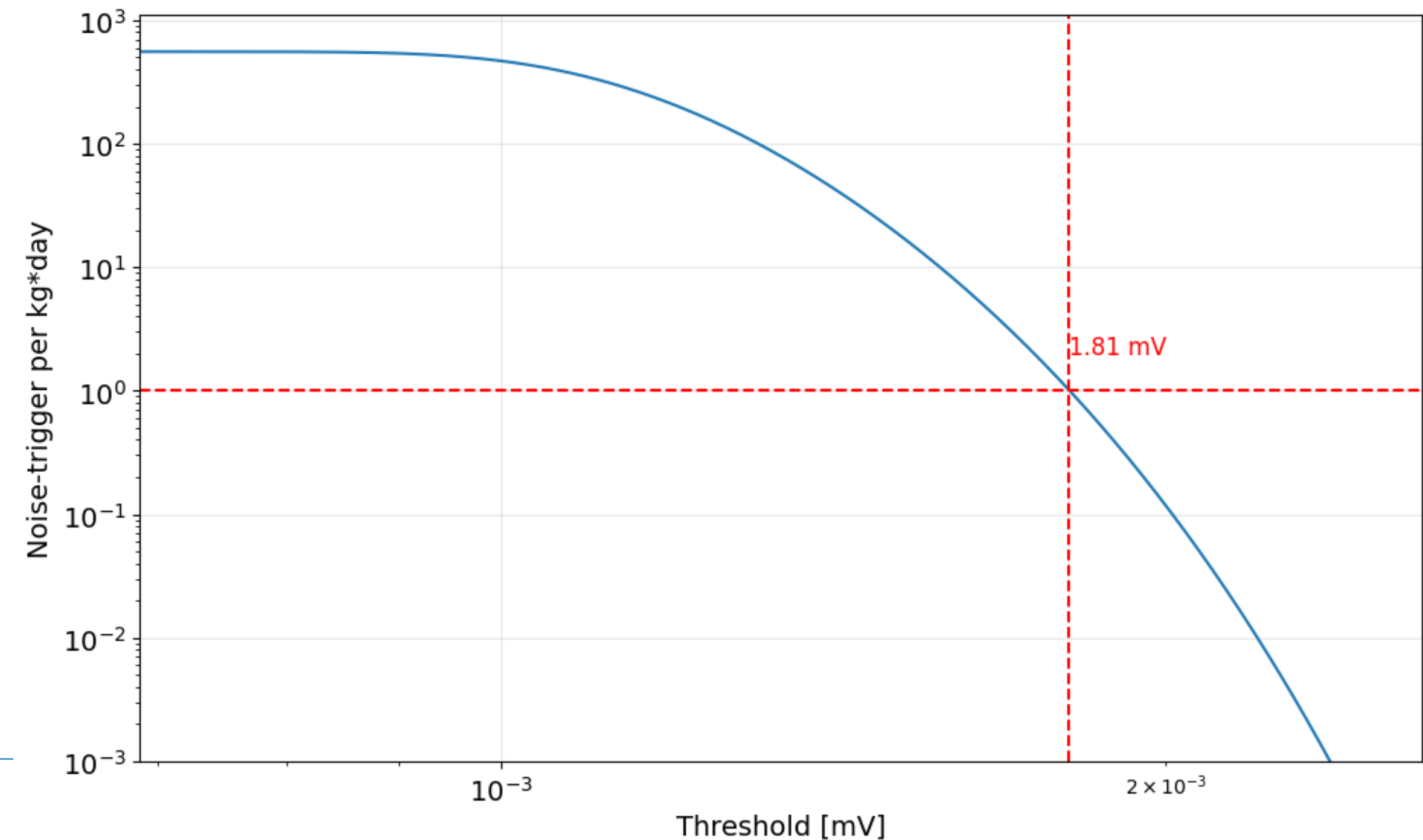
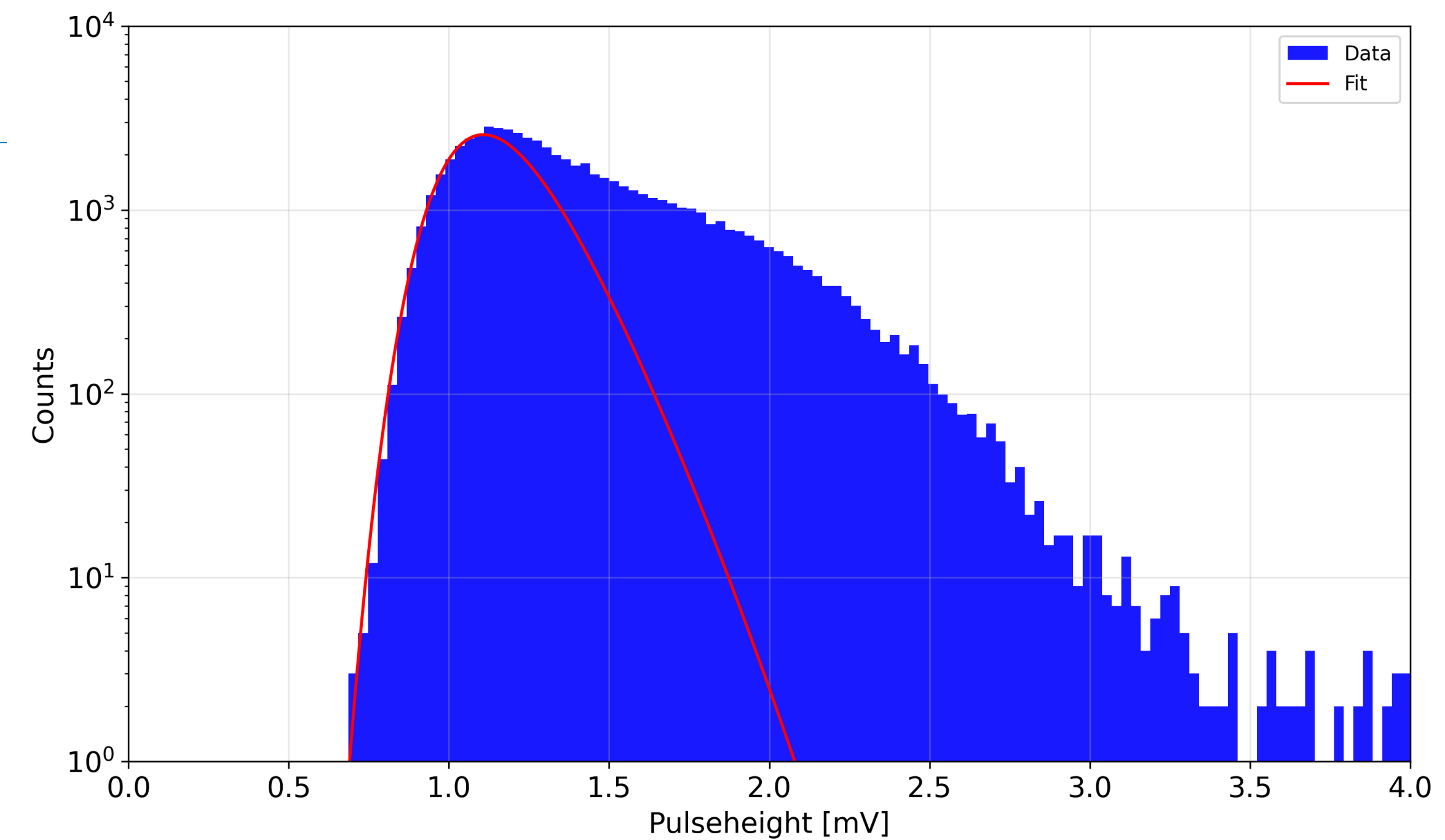


Threshold

- Apply OF on cleaned baselines
- Fit probability function to the histogram of pulse heights

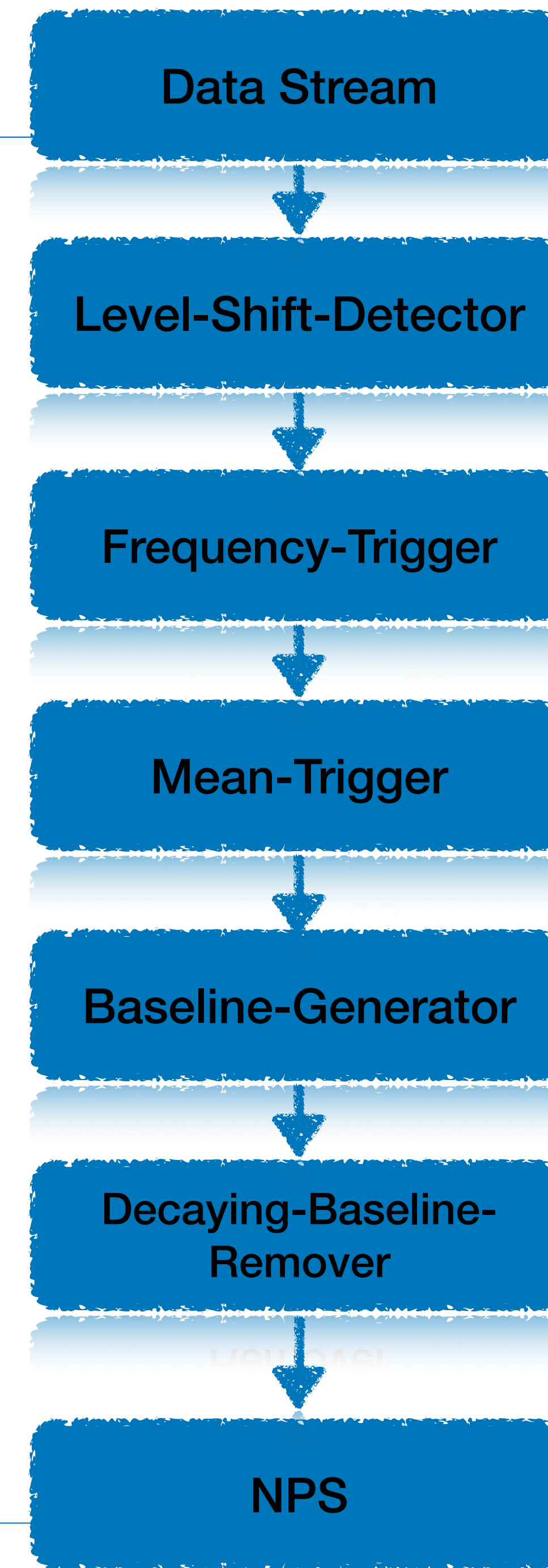
$$P_d(x) = \frac{d}{\sqrt{2\pi}\sigma} \left(e^{-\left(\frac{x}{\sqrt{2}\sigma}\right)^2} \right) \left(0.5 + \frac{\text{erf}(x/(\sqrt{2}\sigma))}{2} \right)^{d-1}$$

$$NTR(x_{th}) = \frac{1}{t \cdot m} \int_{x_{th}}^{\infty} P_d(x) dx$$



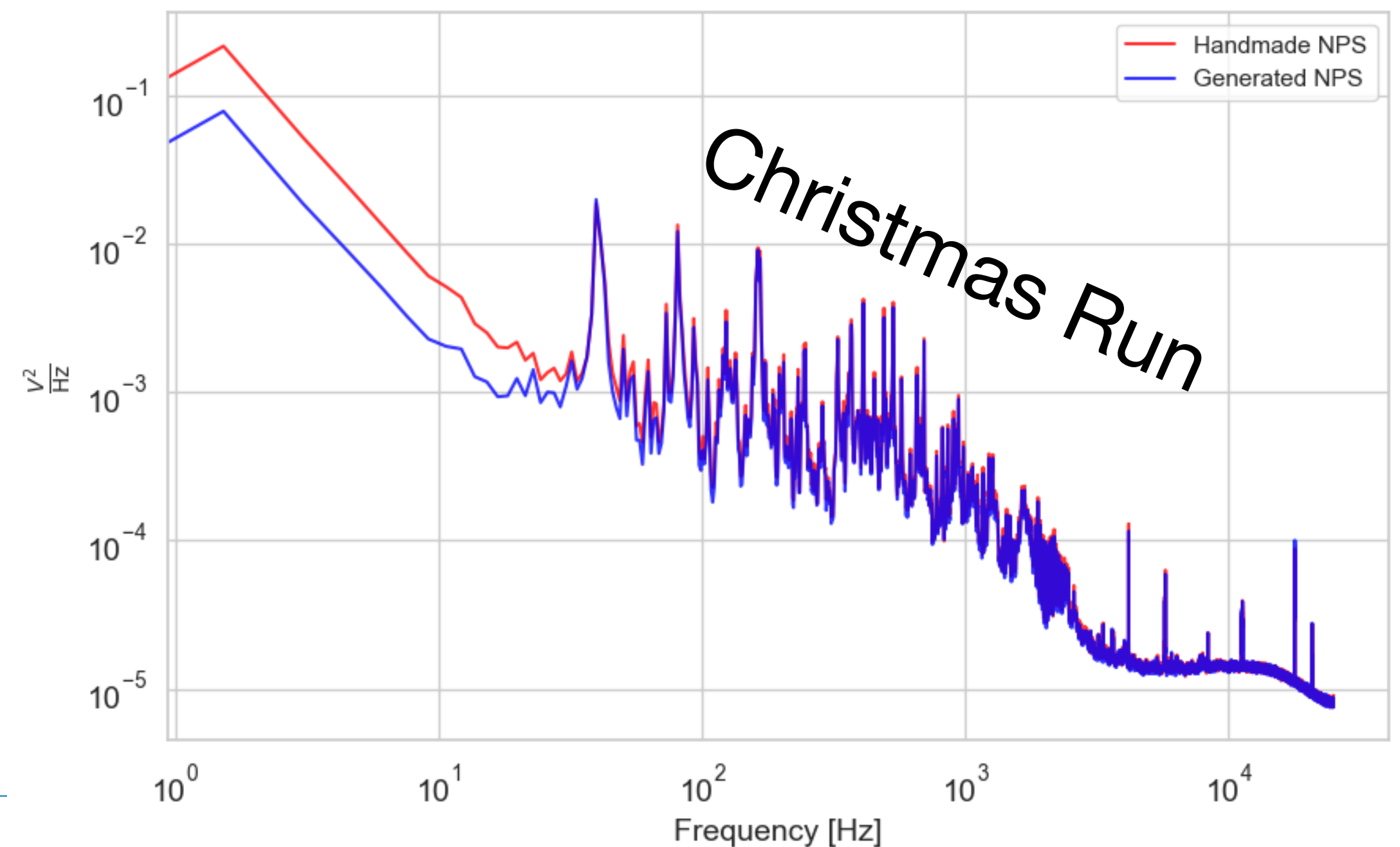
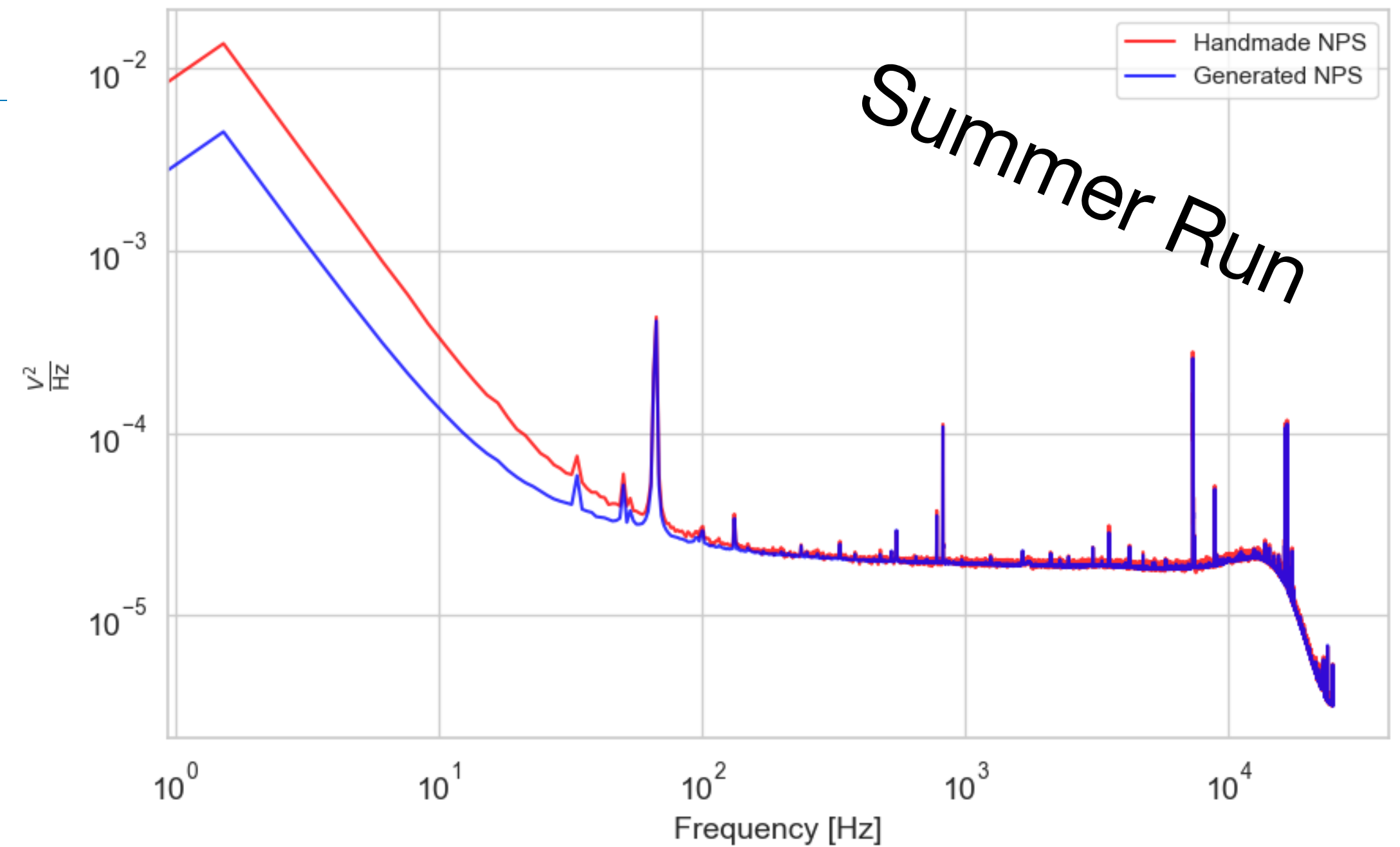
NPS-Generator

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- Cleans data stream from events and artifacts
- **Advantages**
 - ➔ NPS creation without human input
 - ➔ Fast and reliable results

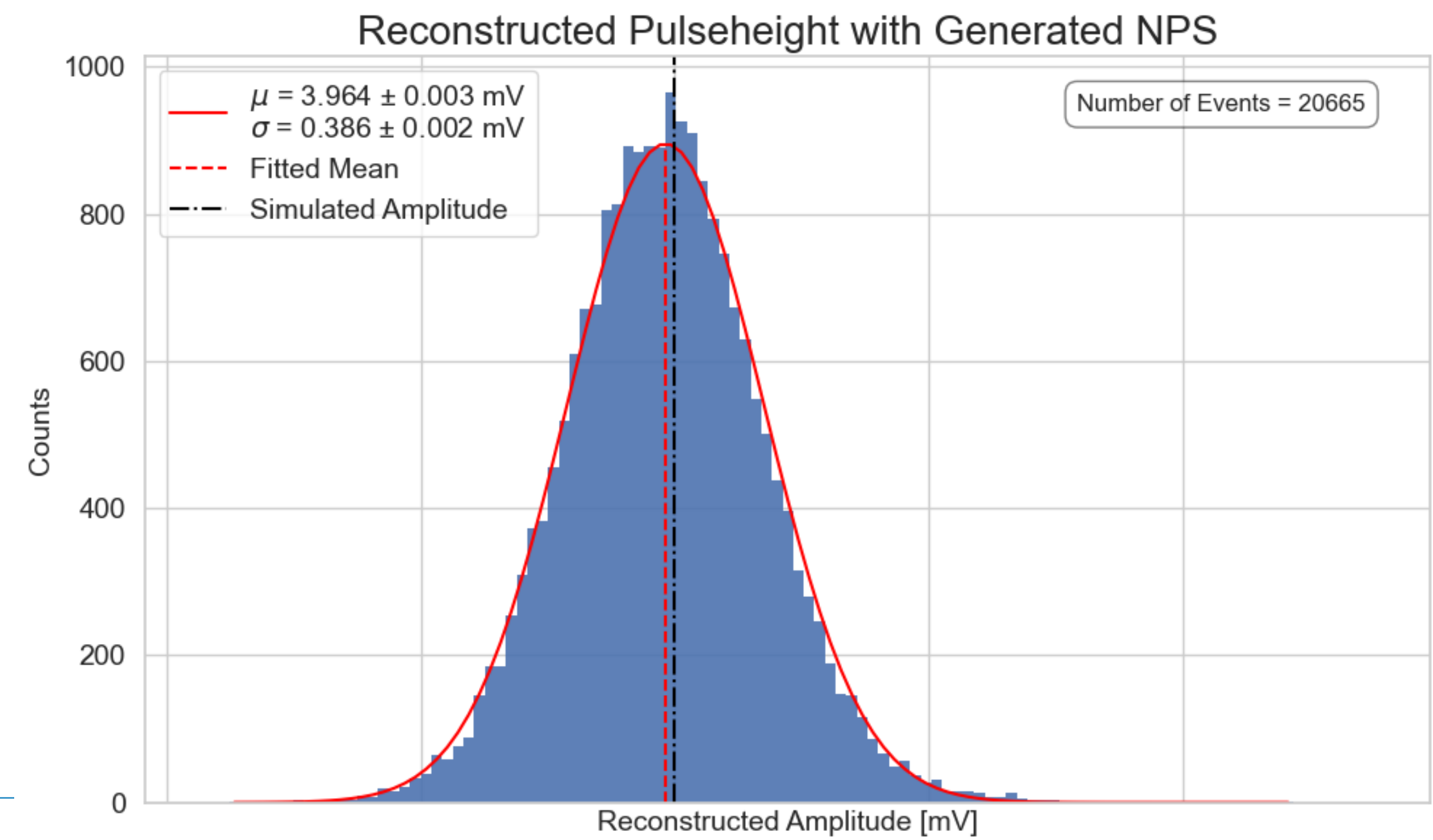
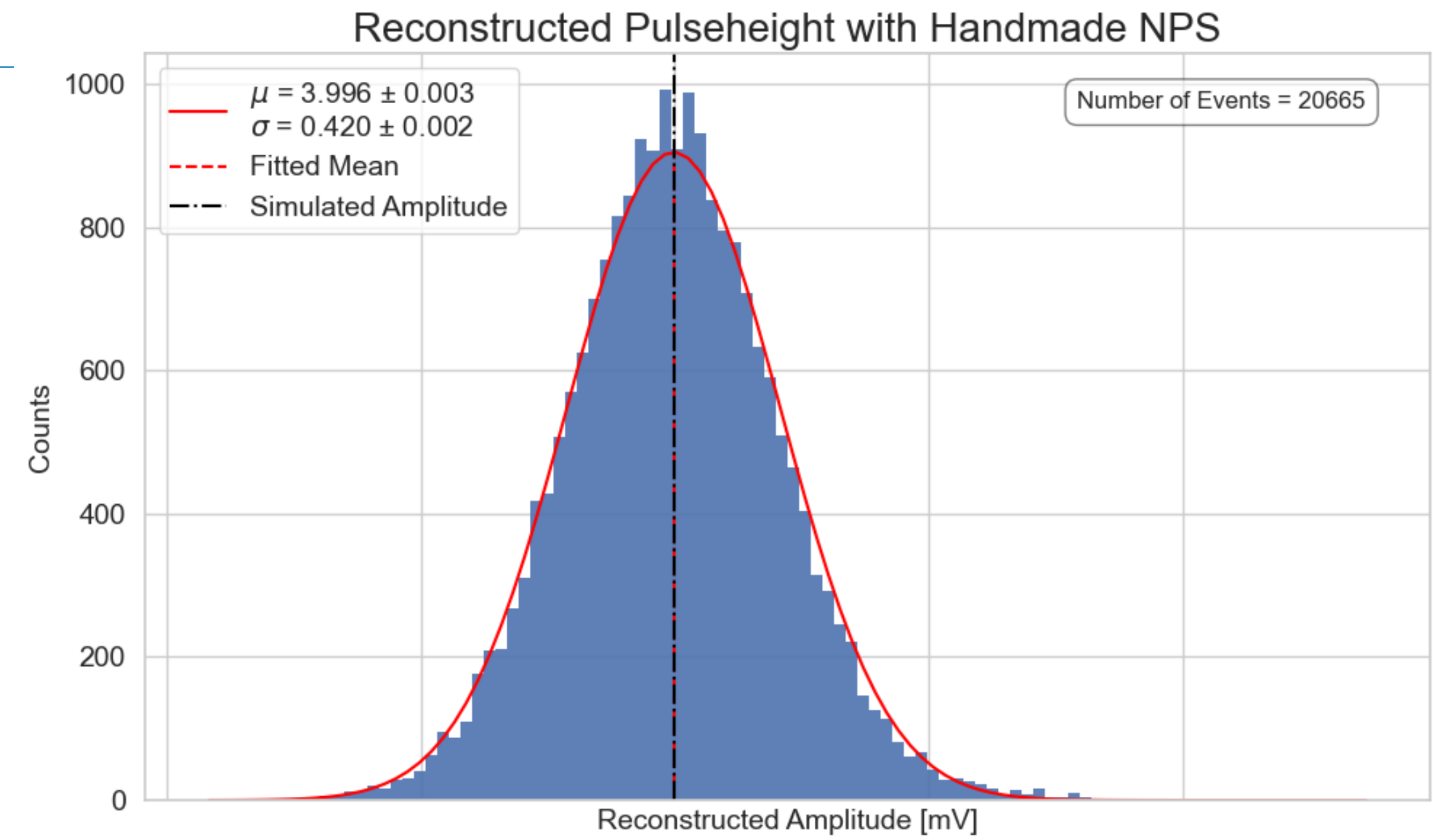


Performance Test

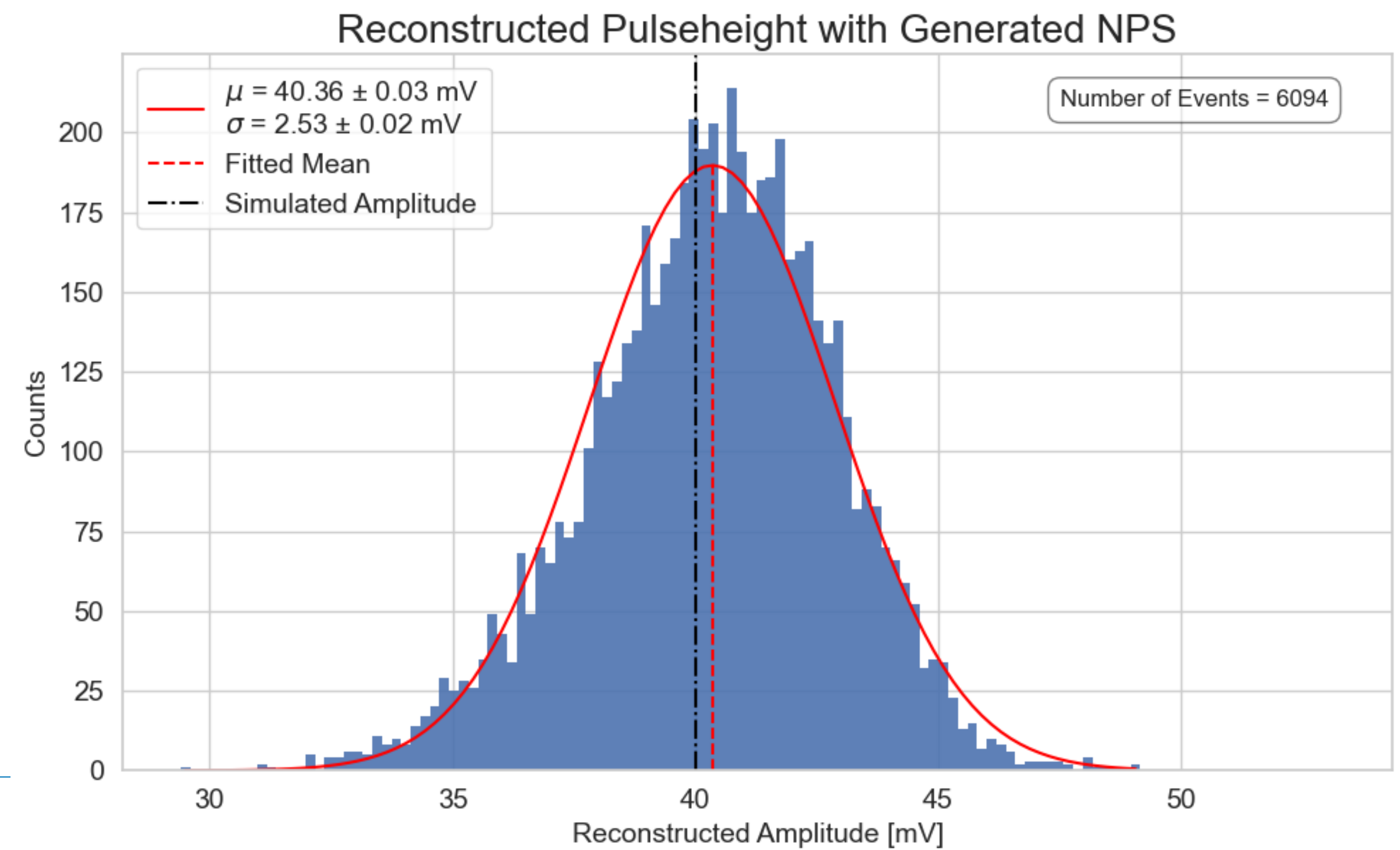
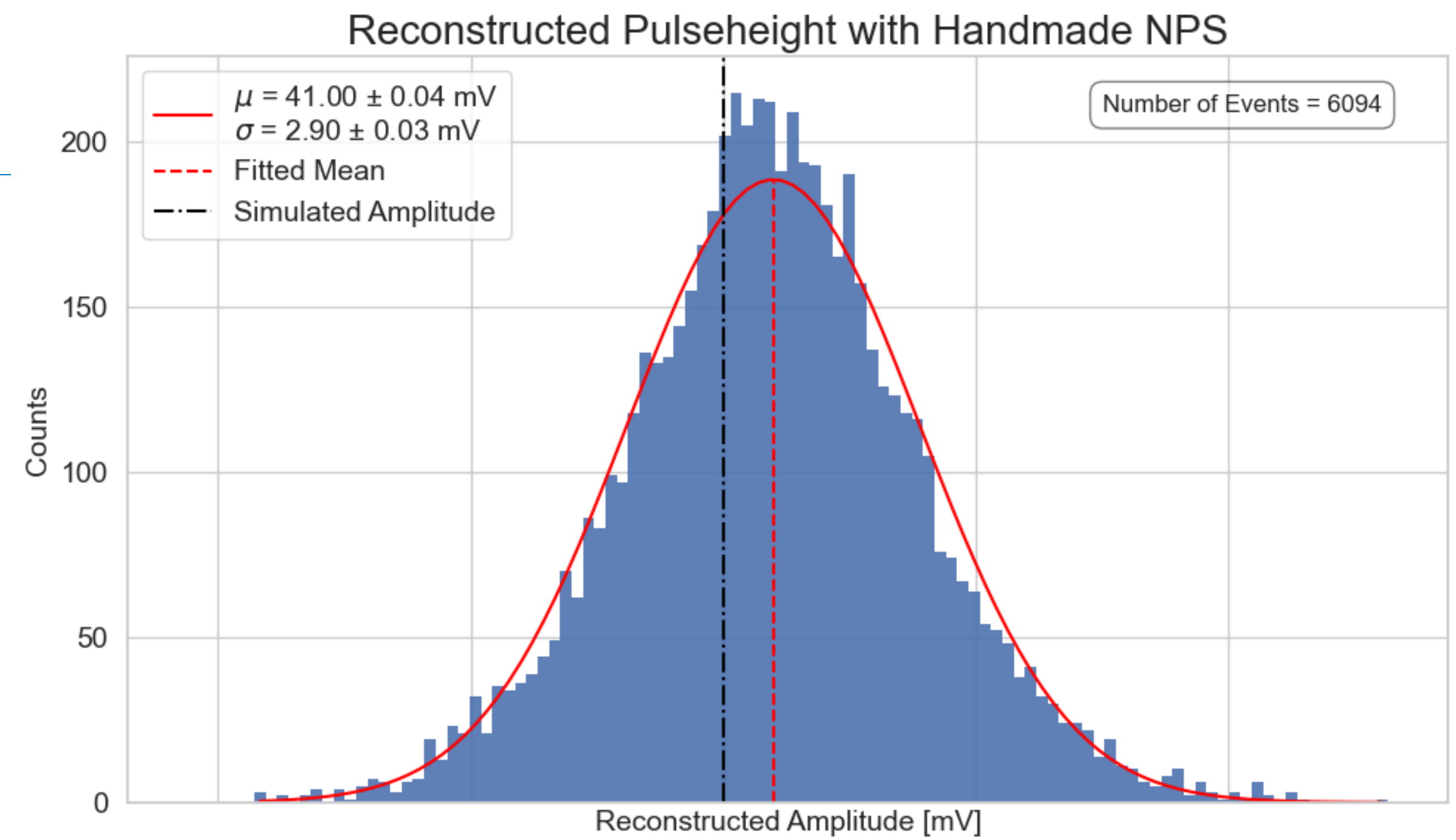
- Handmade and generated NPS very similar
- Create OF with handmade and generated NPS



Summer Run

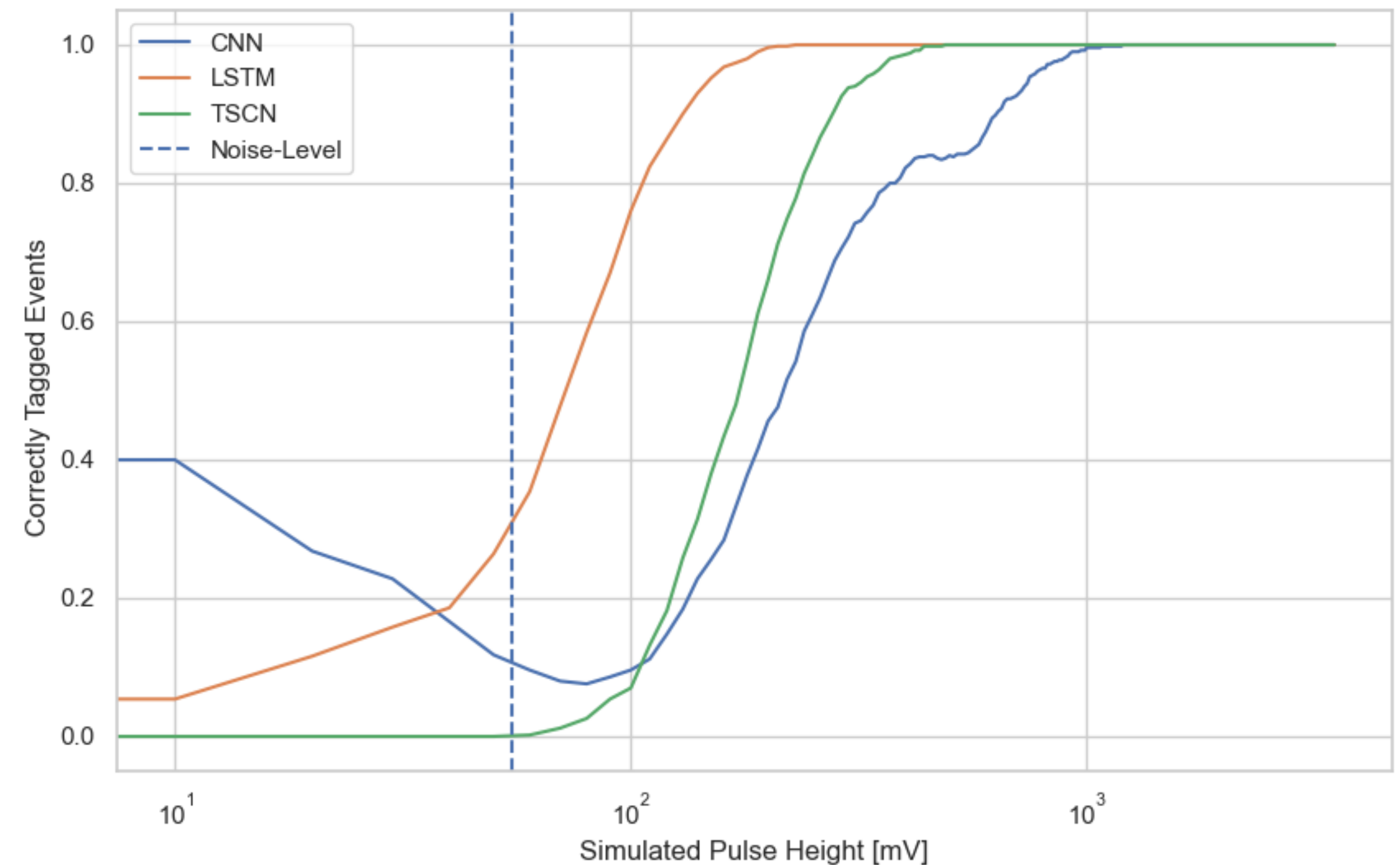


Christmas Run



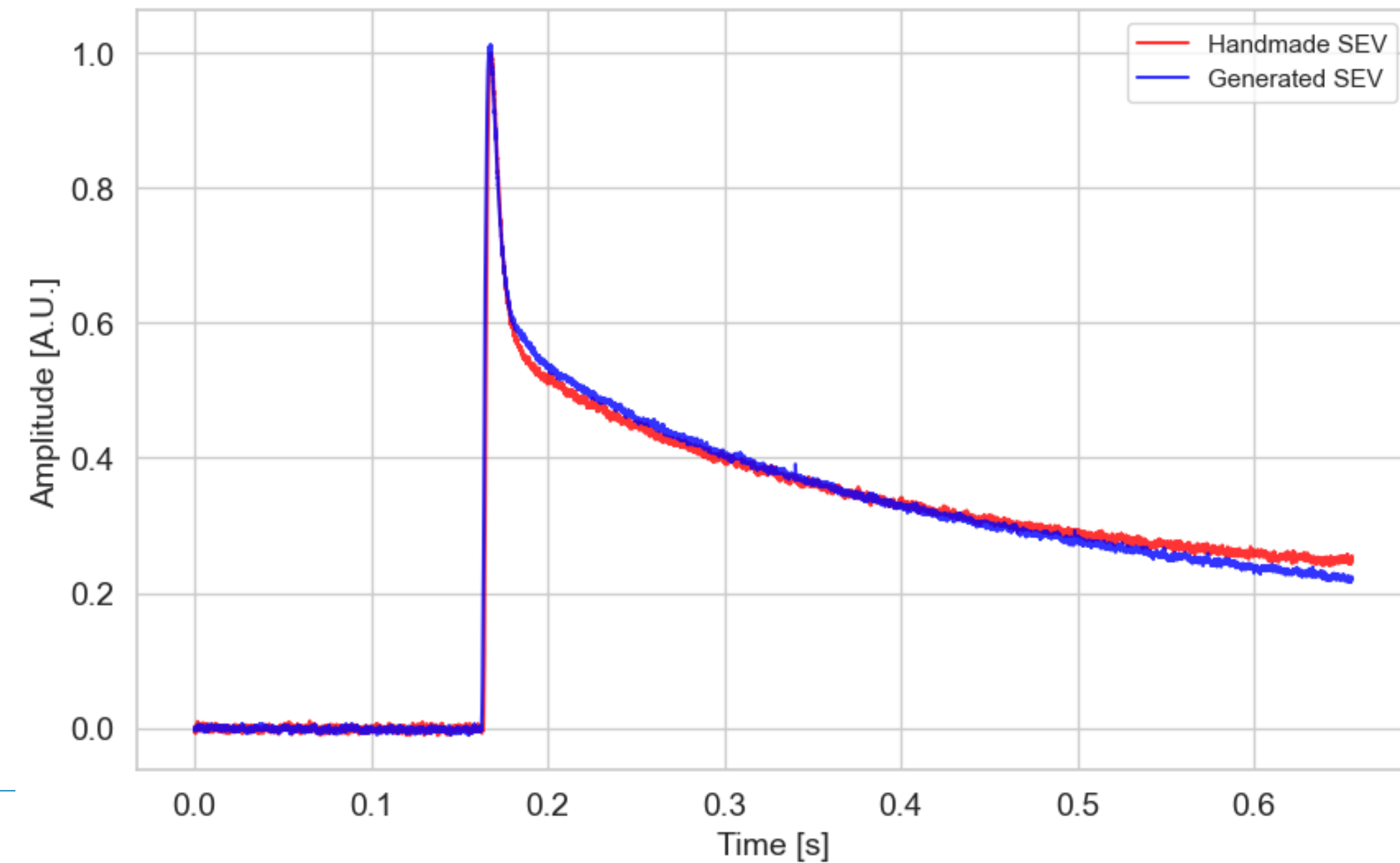
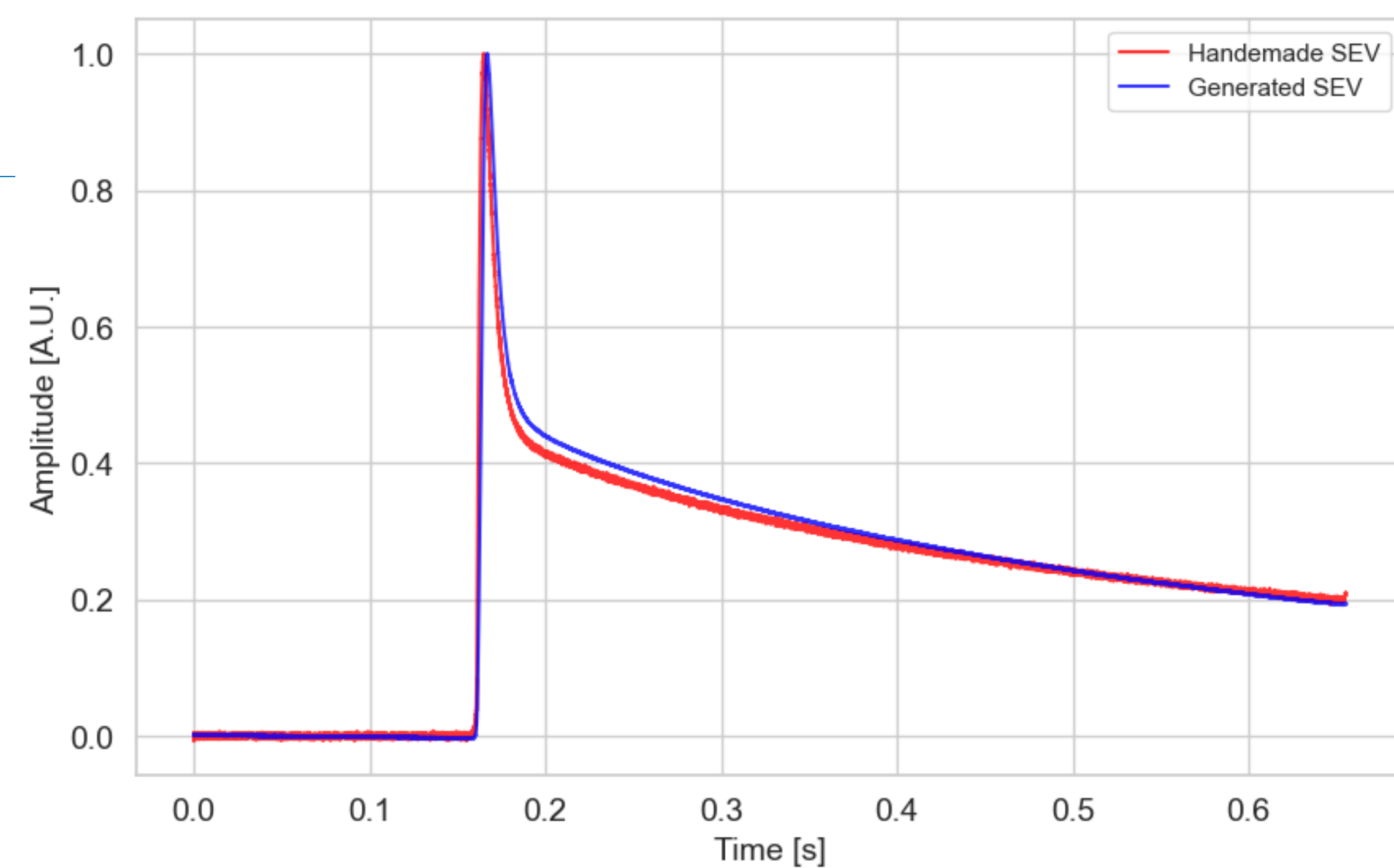
Adaptation of the Neural Network

- Good performance for events above noise level
- Some artifacts mislabeled as valid events



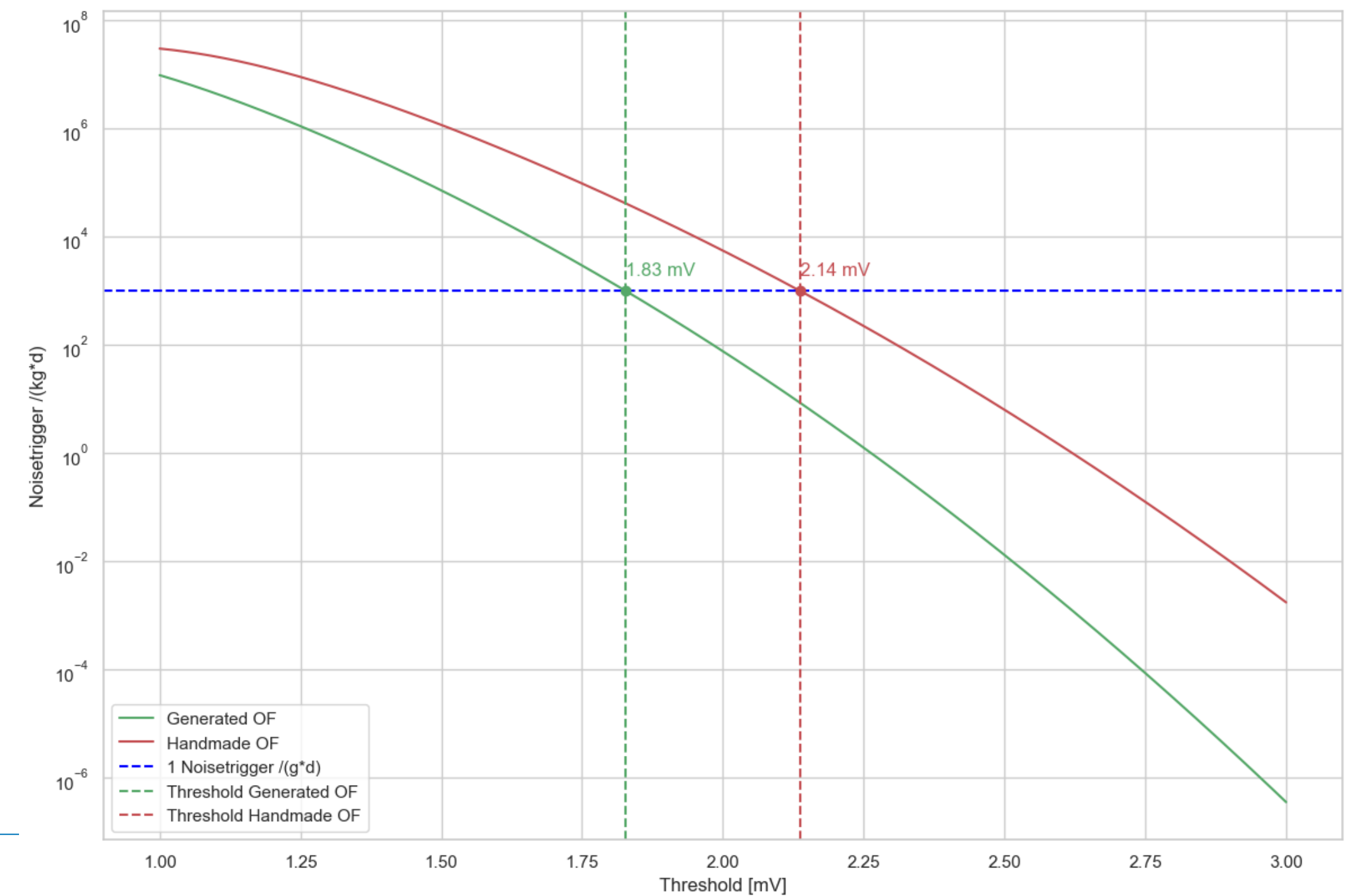
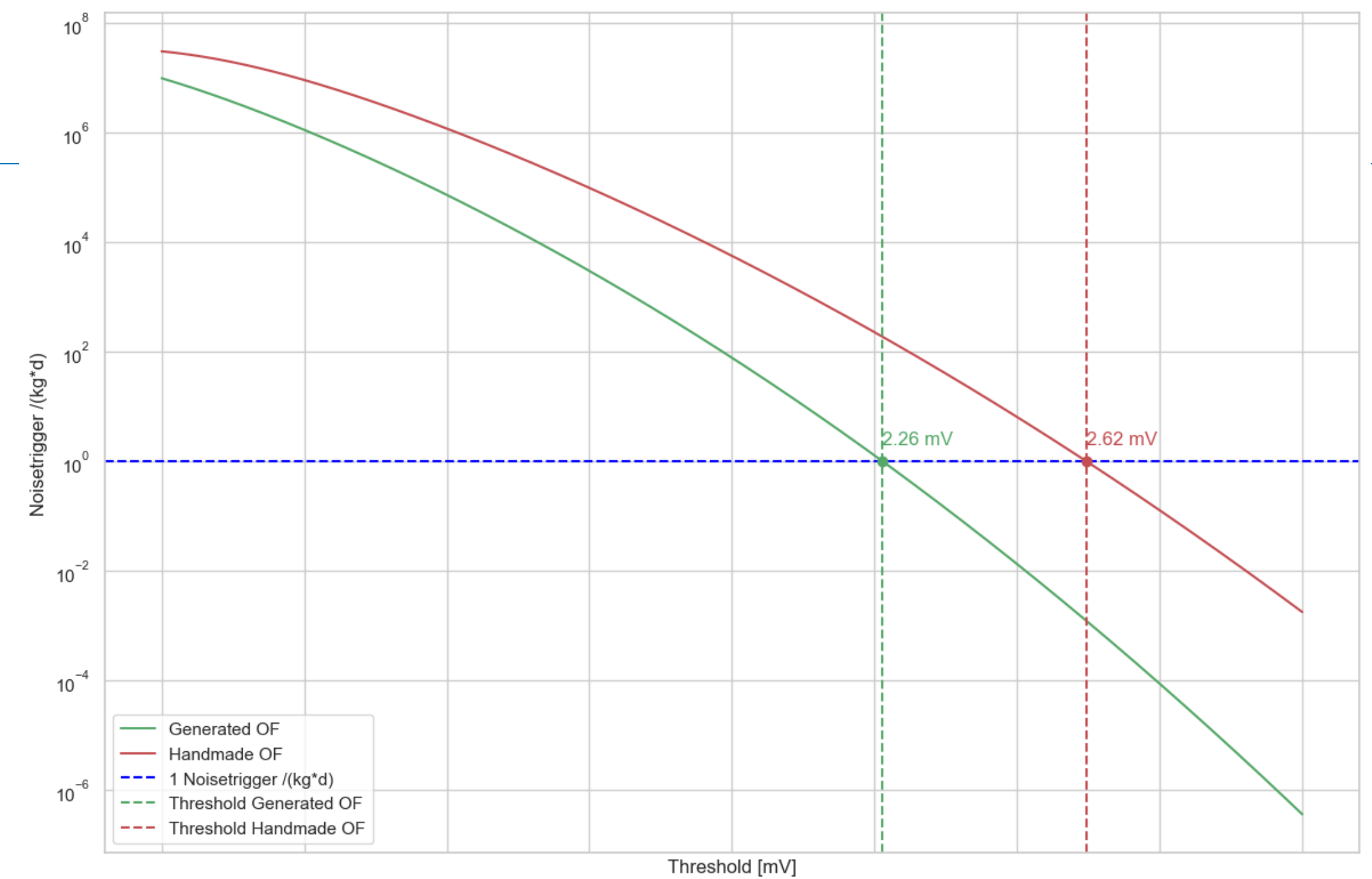
Performance Test

- Generated SEV similar to handmade SEV
- Compare the performance of fully generated OF vs. handmade OF



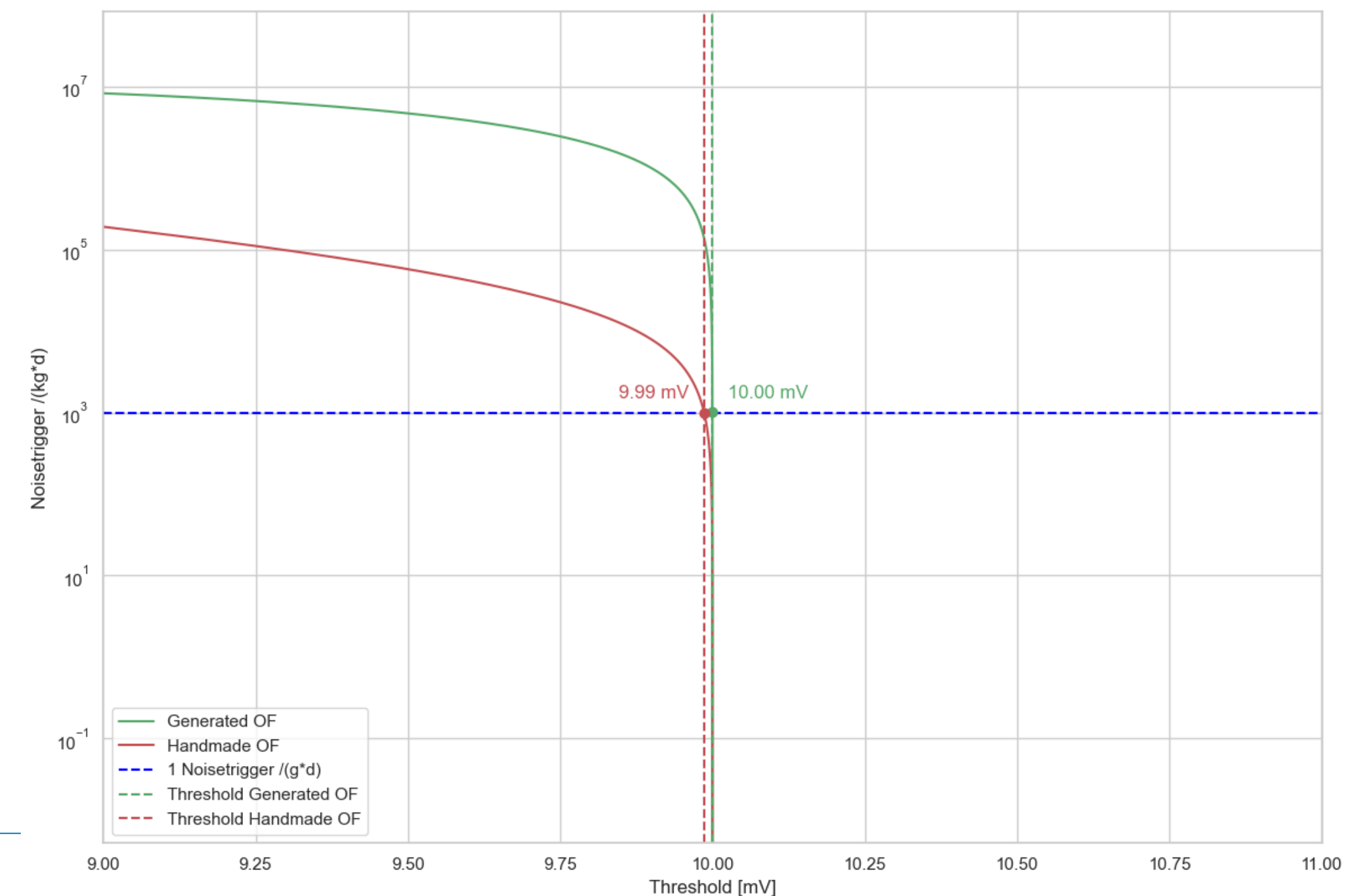
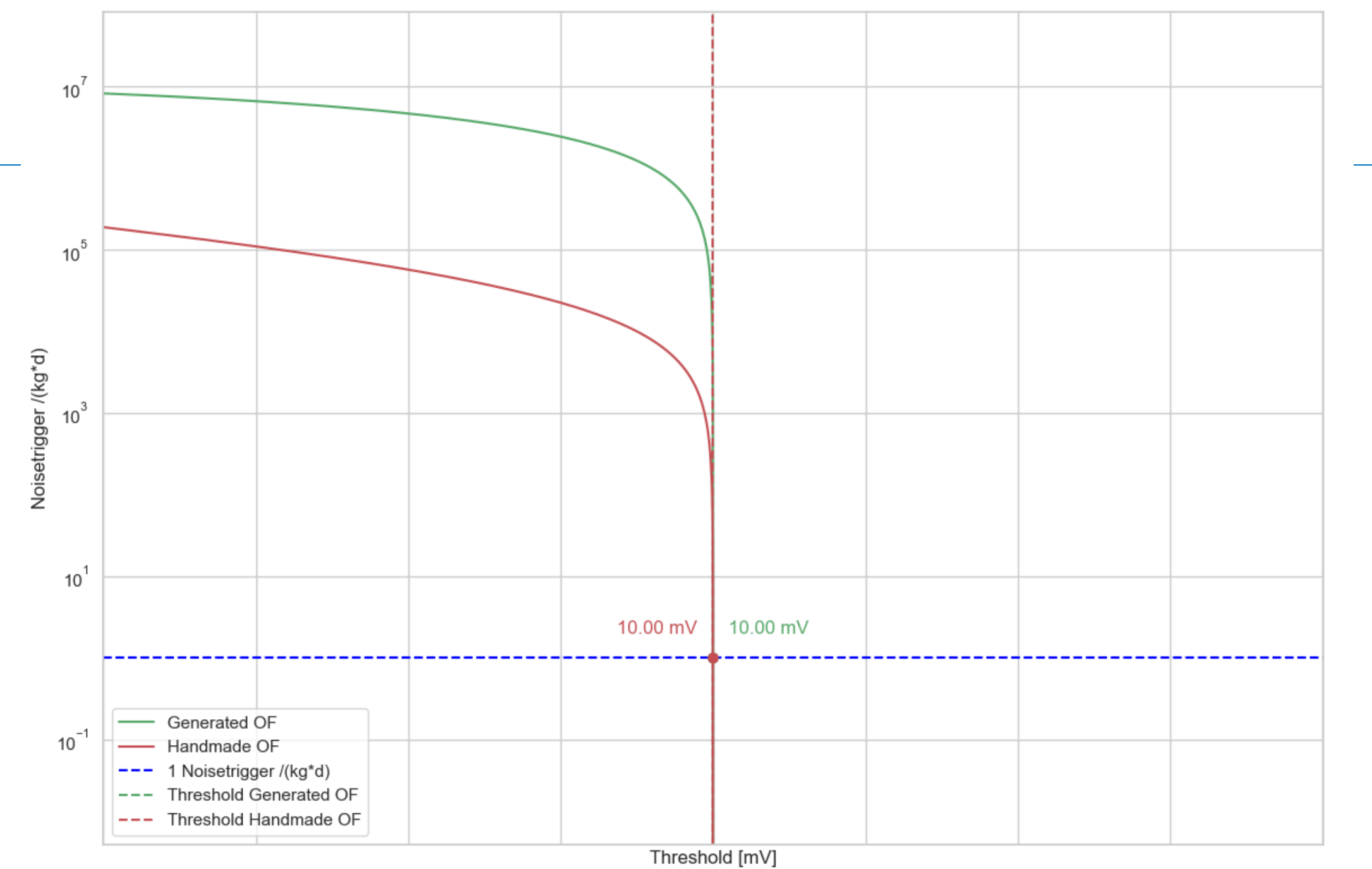
Summer Run

- Generated OF has a superior threshold compared to the handmade OF



Christmas Run

- Same threshold for both OF
- Relative high noise level forces threshold to be set to high values



Images

- [1] <https://iopscience.iop.org/book/mono/978-0-7503-3731-1/chapter/bk978-0-7503-3731-1ch6>
- [2] Florian Reindl