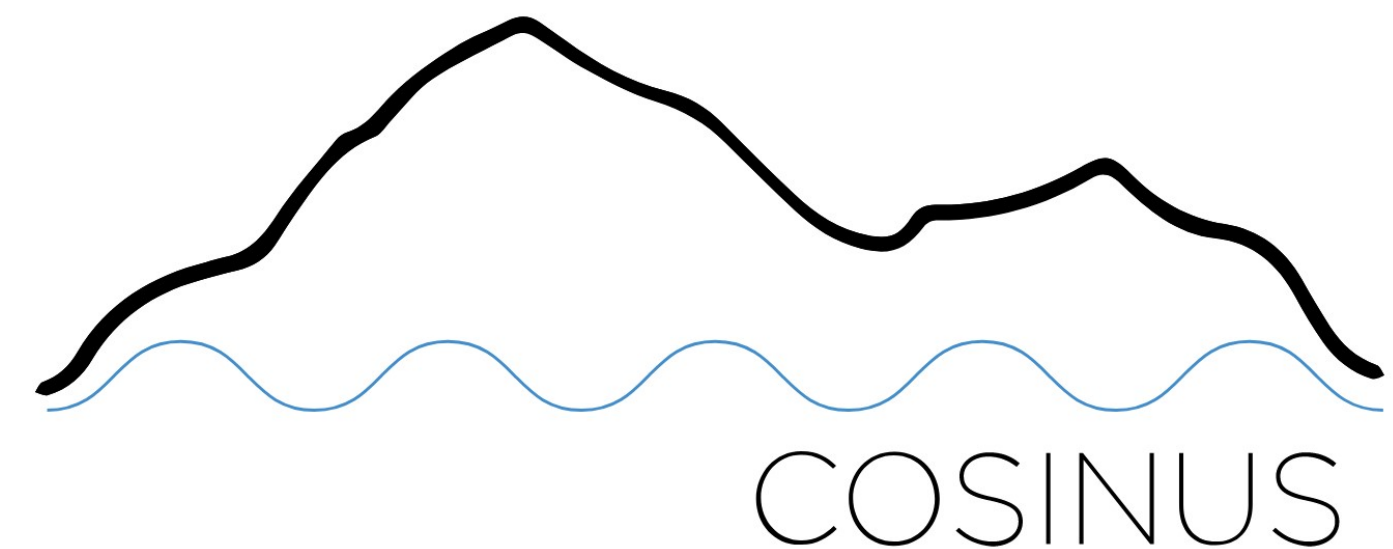


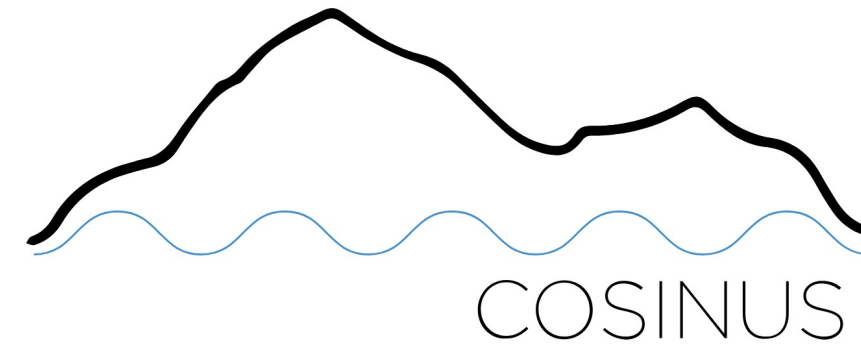
New analysis tools developed in the COSINUS collaboration



Maximilian Gapp
TeV Particle Astrophysics 2026
Tendo, 02.09.2026

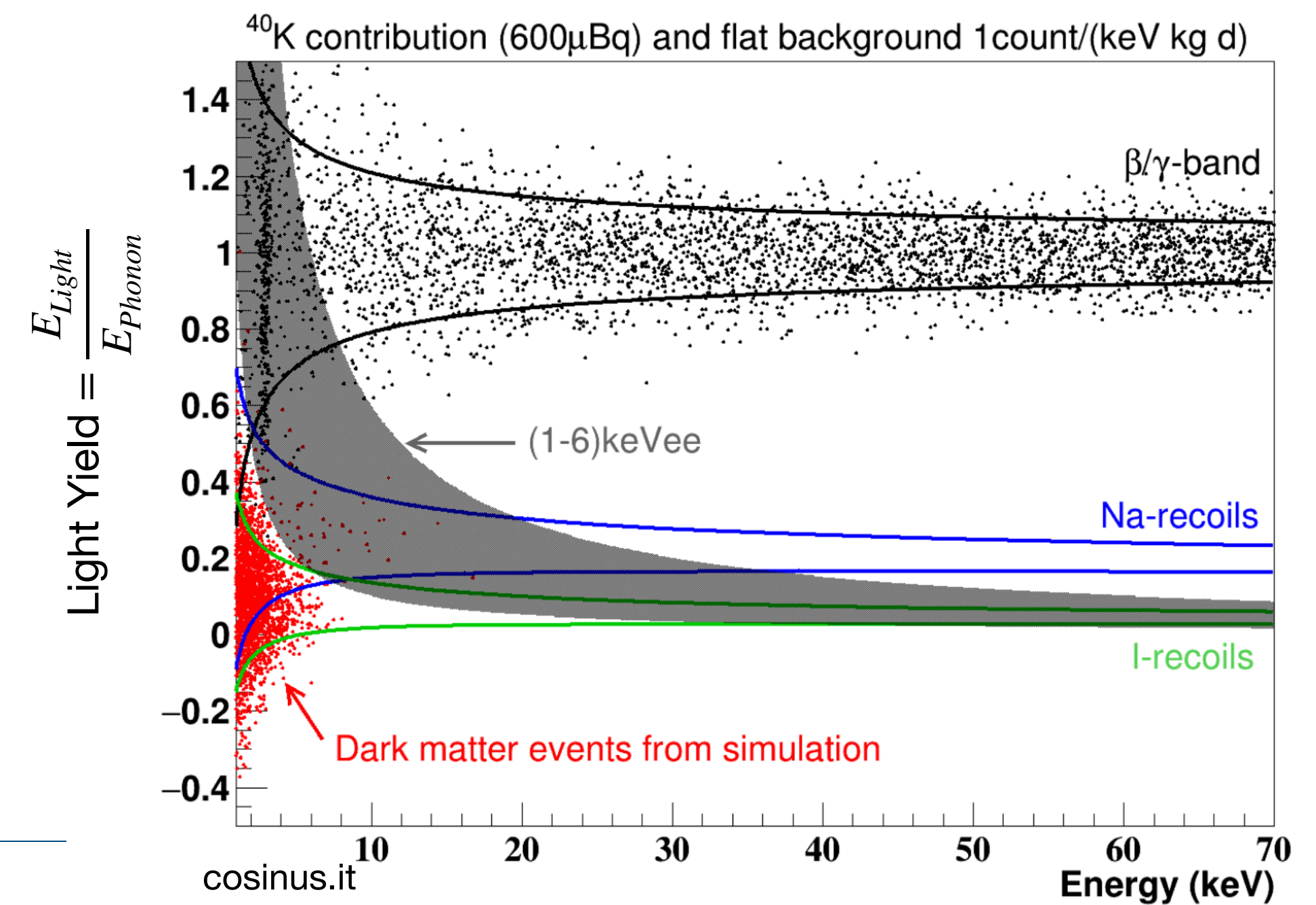
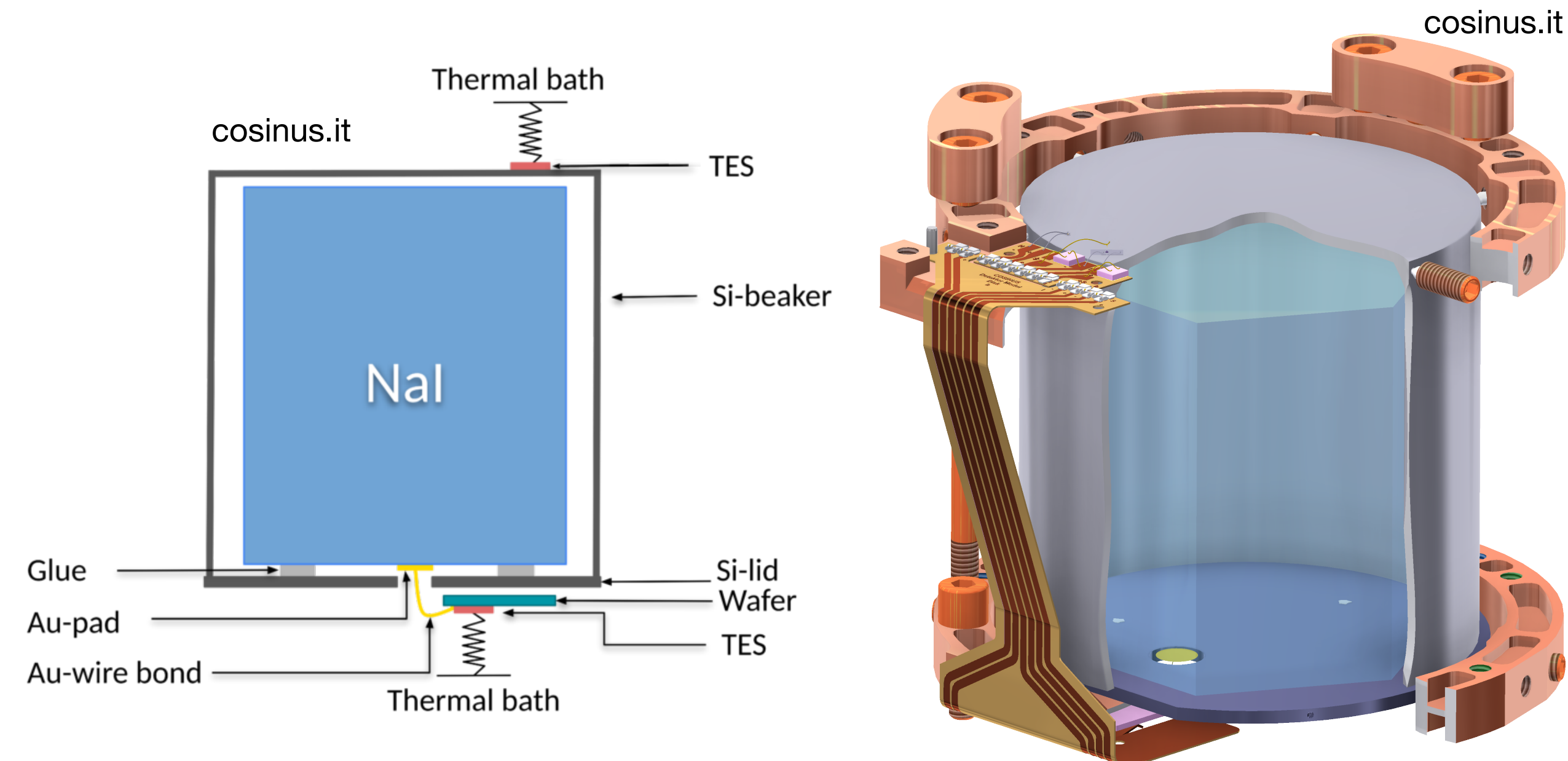


COSINUS



Features:

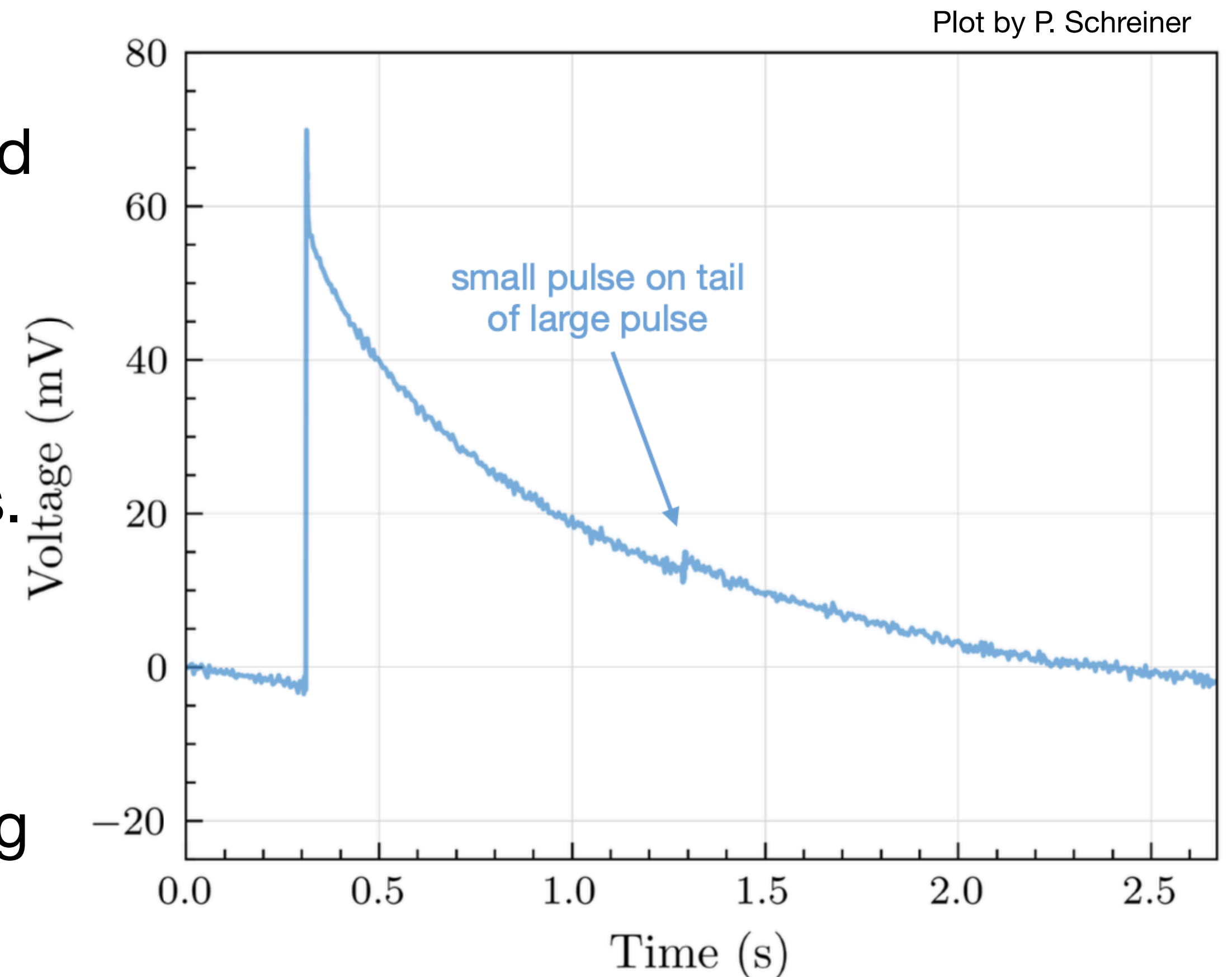
- ➡ Same target material (NaI) as DAMA/LIBRA
- ➡ Cryogenic calorimeter at 10 mK
- ➡ Two-channel readout
- ➡ Event-by-event particle discrimination
- ➡ Intrinsic quenching factor measurement



Generalized Optimum Filter

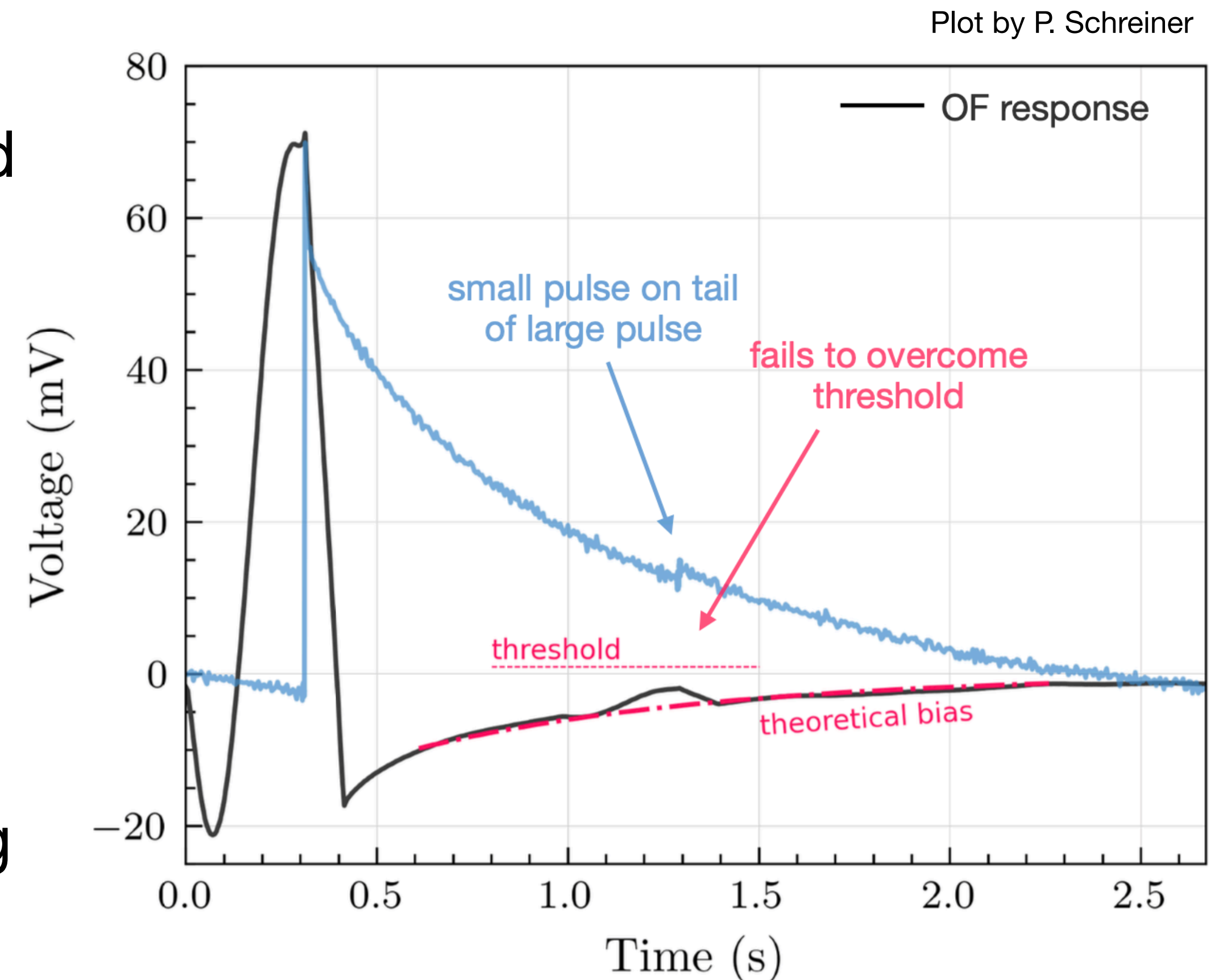
Motivation

- COSINUS NaI detector pulse-shape has decay times in the order of seconds. For above ground measurements, the event rate is in the order of Hz $\rightarrow$ pile-up
- State-of-the-art energy reconstruction, the optimum filter, struggles with non-flat baselines.
- The optimum filter does not account for non-flat baselines.
- Issues with energy reconstruction and triggering



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- COSINUS NaI detector pulse-shape has decay times in the order of seconds. For above ground measurements, the event rate is in the order of Hz $\rightarrow$ pile-up
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- The optimum filter does not account for non-flat baselines.
- Issues with energy reconstruction and triggering



Generalized Optimum Filter

Model decaying baselines. This can be well described by a polynomial.

Extended model

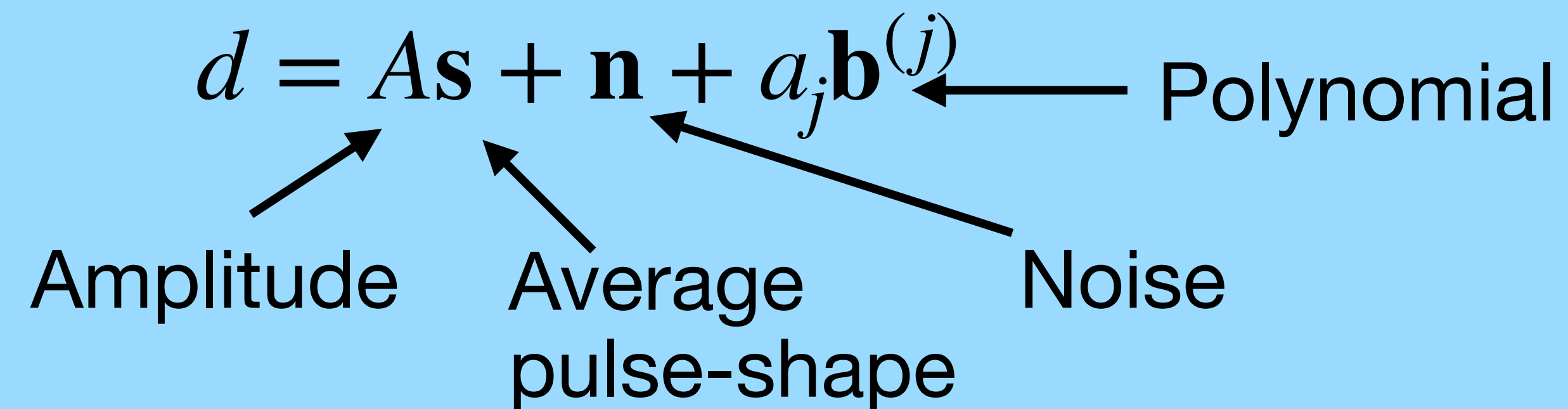
$$d = As + \mathbf{n} + a_j \mathbf{b}^{(j)}$$

Polynomial

Amplitude

Average pulse-shape

Noise



Generalized Optimum Filter

The likelihood is now given by

New log-likelihood

$$\log \Lambda(d|A) = -\frac{1}{2} \langle \tilde{d} | \tilde{d} \rangle + A \langle \tilde{d} | \tilde{s} \rangle + a^T \delta - \frac{A^2}{2} \langle \tilde{s} | \tilde{s} \rangle - A a^T \sigma - \frac{1}{2} a^T G a$$

$$G_{i,j} \equiv \langle \tilde{b}^{(j)} | \tilde{b}^{(j)} \rangle \quad \delta_j \equiv \langle \tilde{b}^{(j)} | \tilde{d} \rangle \quad \sigma_j \equiv \langle \tilde{b}^{(j)} | \tilde{s} \rangle$$

Generalized Optimum Filter

The maximum likelihood estimator for the pulse amplitude of interest $\mathbf{A}$ and for the polynomial coefficient $\mathbf{a}$ are solutions of the system

$$\begin{pmatrix} \langle \tilde{s} | \tilde{s} \rangle & \boldsymbol{\sigma}^T \\ \boldsymbol{\sigma} & \mathbf{G} \end{pmatrix} \begin{pmatrix} \hat{\mathbf{A}} \\ \hat{\mathbf{a}} \end{pmatrix} = \begin{pmatrix} \langle \tilde{d} | \tilde{s} \rangle \\ \boldsymbol{\delta} \end{pmatrix}.$$

Generalized Optimum Filter

New ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{s} | \tilde{d} \rangle - \sigma^T G^{-1} \delta}{\sigma^T G^{-1} \sigma} = \frac{\langle \tilde{s} - \tilde{s}_p | \tilde{d} \rangle}{\langle \tilde{s} - \tilde{s}_p | \tilde{s} \rangle}$$

$$s_p = \sigma^T \mathbf{G}^{-1} \mathbf{B}$$

Template with polynomial part removed

Generalized Optimum Filter

New ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{s} | \tilde{d} \rangle - \sigma^T G^{-1} \delta}{\sigma^T G^{-1} \sigma} = \frac{\langle \tilde{s} - \tilde{s}_p | \tilde{d} \rangle}{\langle \tilde{s} - \tilde{s}_p | \tilde{s} \rangle}$$

$$Var(\hat{A}_0) = \frac{1}{\langle \tilde{s} | \tilde{s} \rangle - \sigma^T G^{-1} \sigma}$$

New ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{s} | \tilde{d} \rangle - \sigma^T G^{-1} \delta}{\sigma^T G^{-1} \sigma} = \frac{\langle \tilde{s} - \tilde{s}_p | \tilde{d} \rangle}{\langle \tilde{s} - \tilde{s}_p | \tilde{s} \rangle}$$

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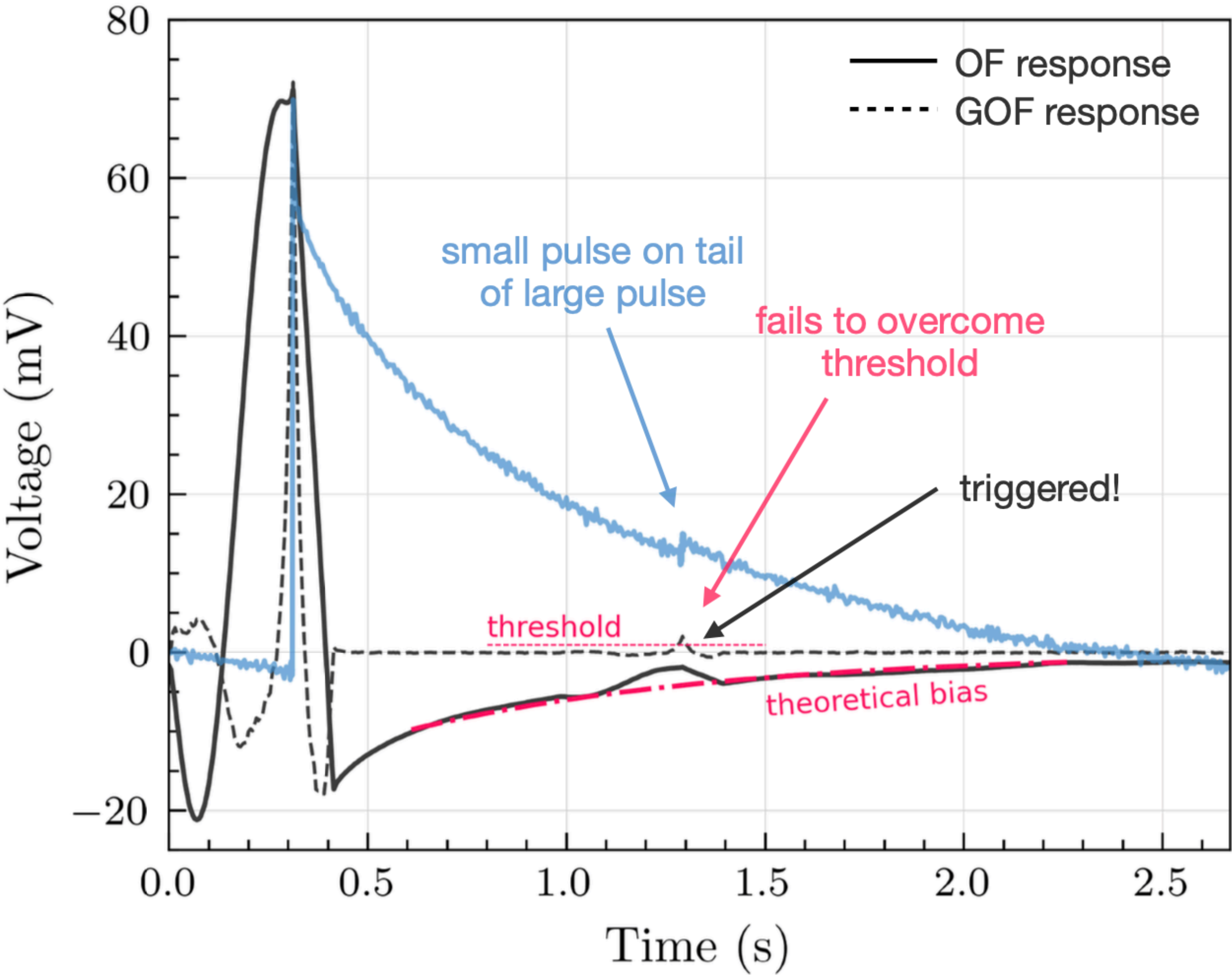
Reduced resolution

ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{d} | \tilde{s} \rangle}{\langle \tilde{s} | \tilde{s} \rangle}$$

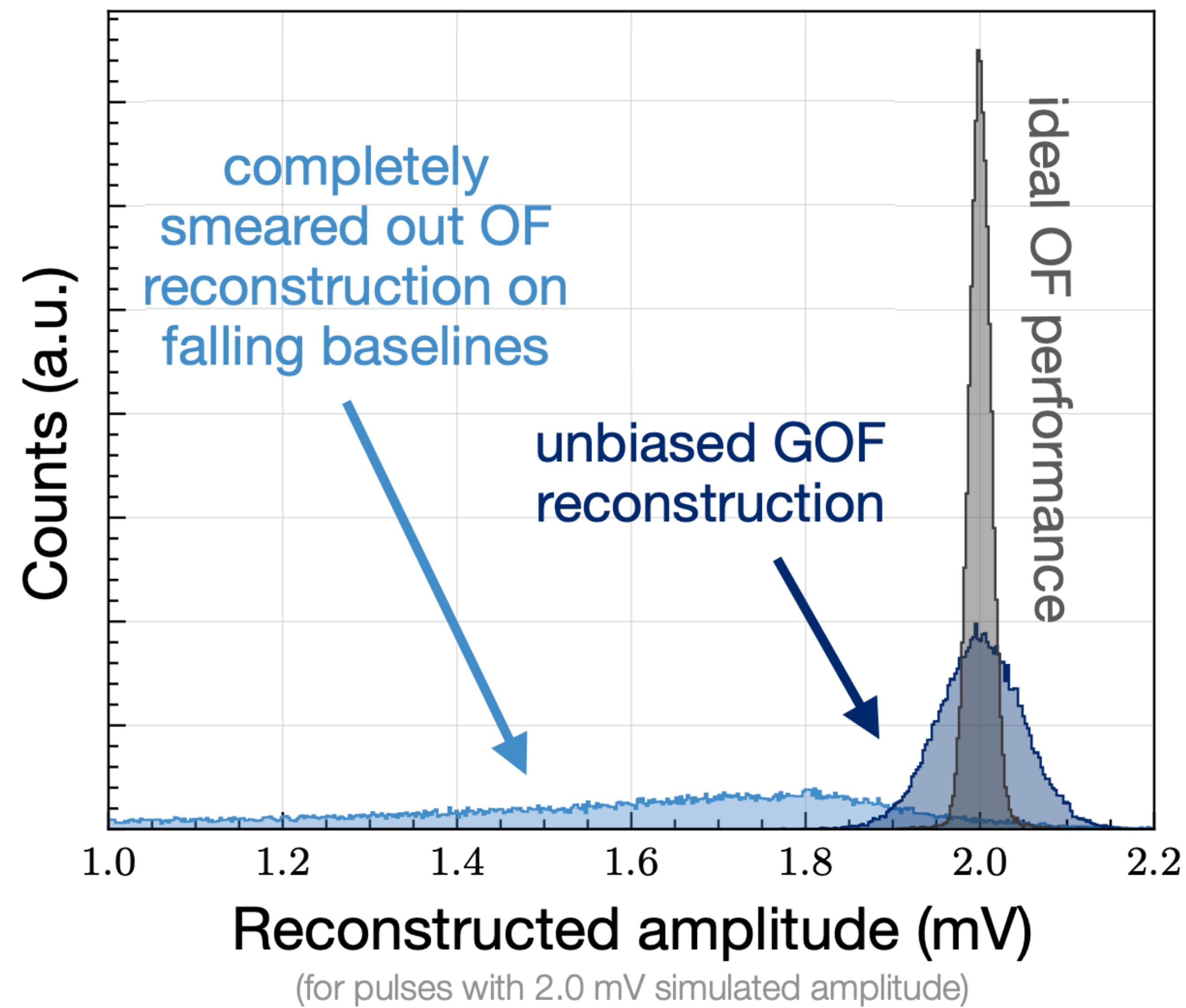
$$Var(\hat{A}_0) = \boxed{\frac{1}{\langle \tilde{s} | \tilde{s} \rangle}}$$

Best possible resolution we can get



Performance

Reduced threshold in recent measurement from 5keV to1keV



Summary

- The generalized optimum filter offers a reliable way to face the issue of non-flat baselines.
- Especially interesting in above-ground measurements
- Estimation of the underground resolution from above ground measurements

Summary

- The generalized optimum filters offers a reliable way to face the issue of flat baselines.
- Especially interesting in above-ground measurements
- Estimation of the underground resolution from above ground measurements
- Available in the latest version of Cait and CAT



Implemented by P. Schreiner (Philipp.schreiner@oeaw.ac.at)
and M. Stahlberg (martin.stahlberg@mpp.mpg.de)

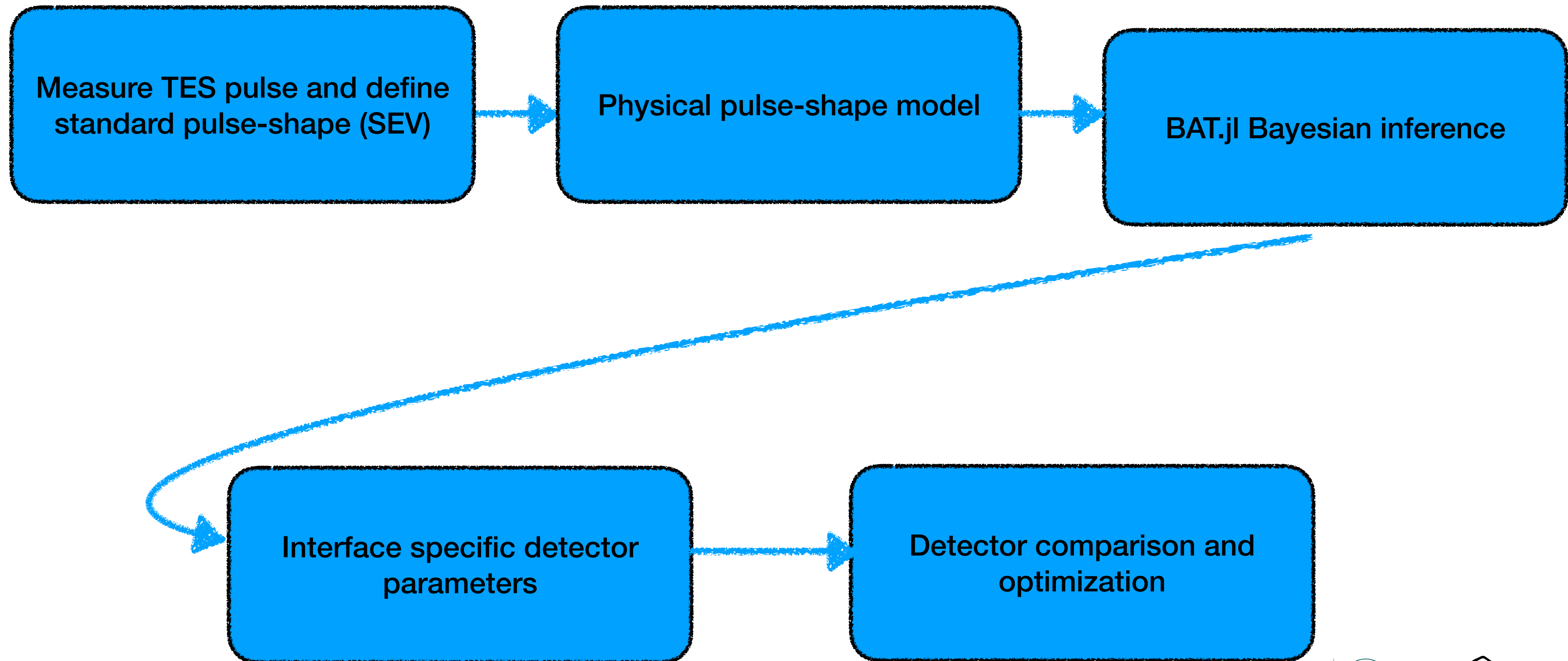
Bayesian Pulse-Shape Inference

Motivation

- Detector development requires an understanding of physical properties to make sense of differences
- Pulse-shape model selection
- Bayesian inference offers a natural way to do this
- Using the Bayesian Analysis Toolkit (BAT.jl)

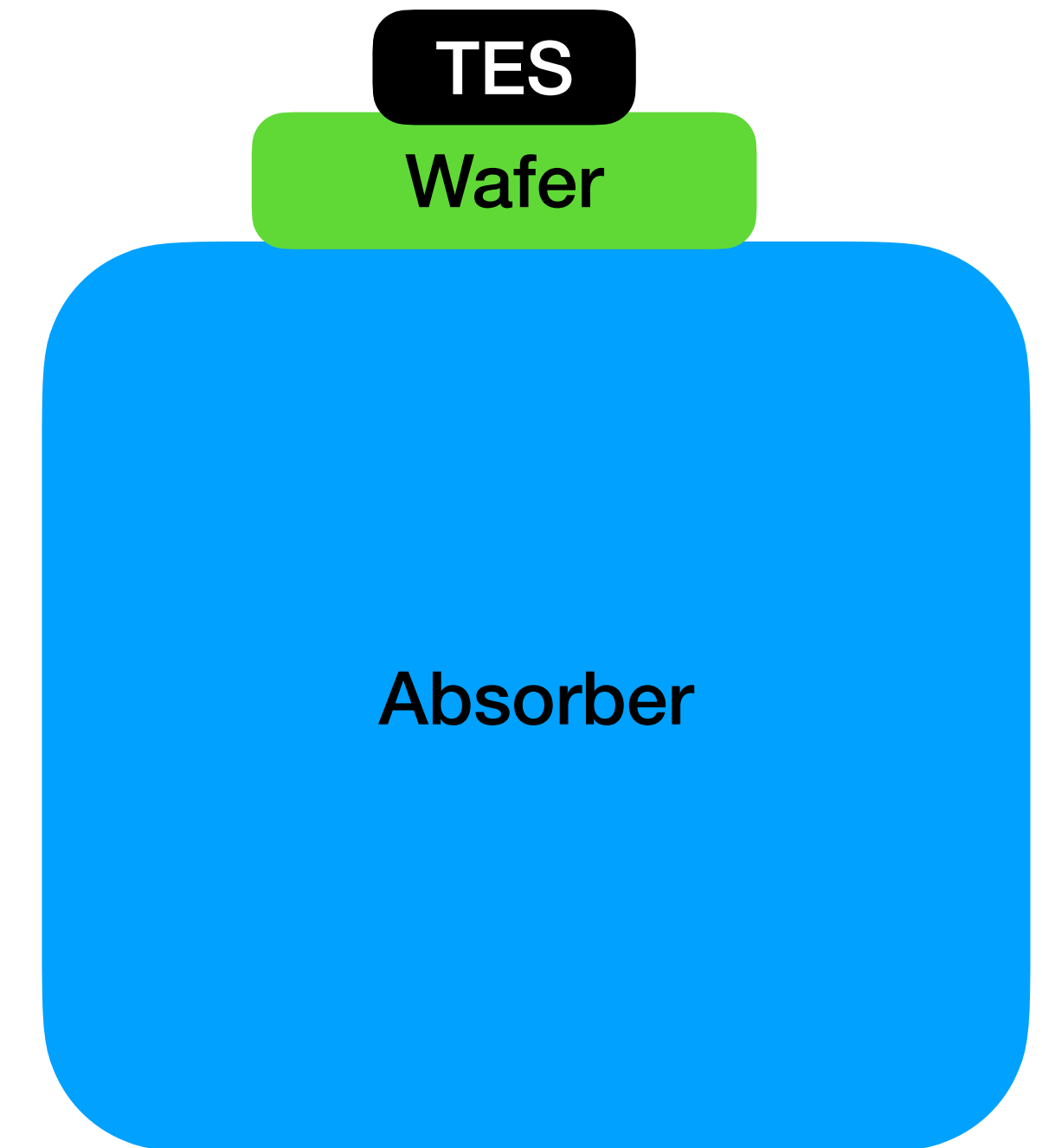


Approach



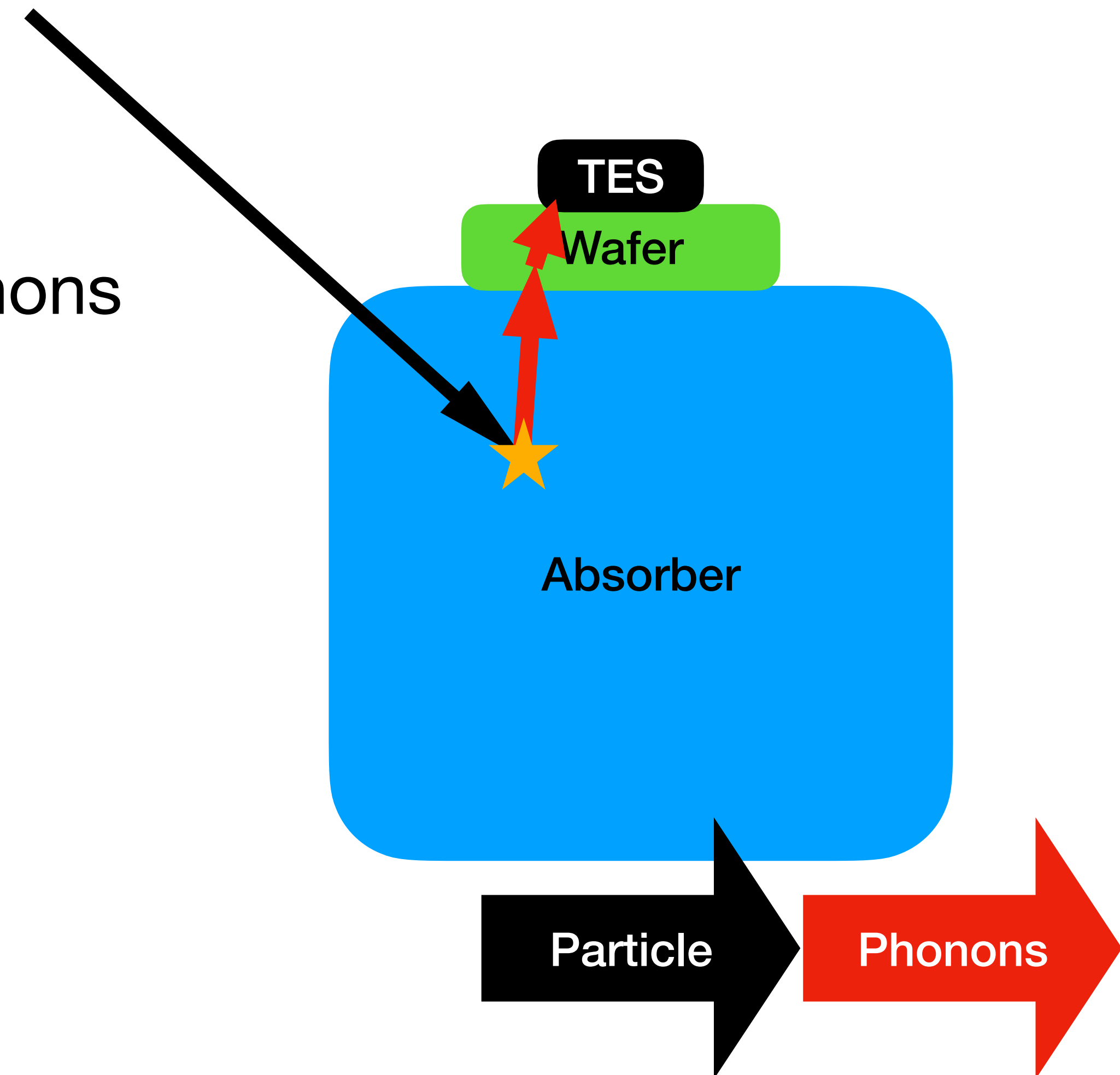
Working example

- Former composite detector design: **NaICE-detector**
- Carrier wafer directly located on the absorber



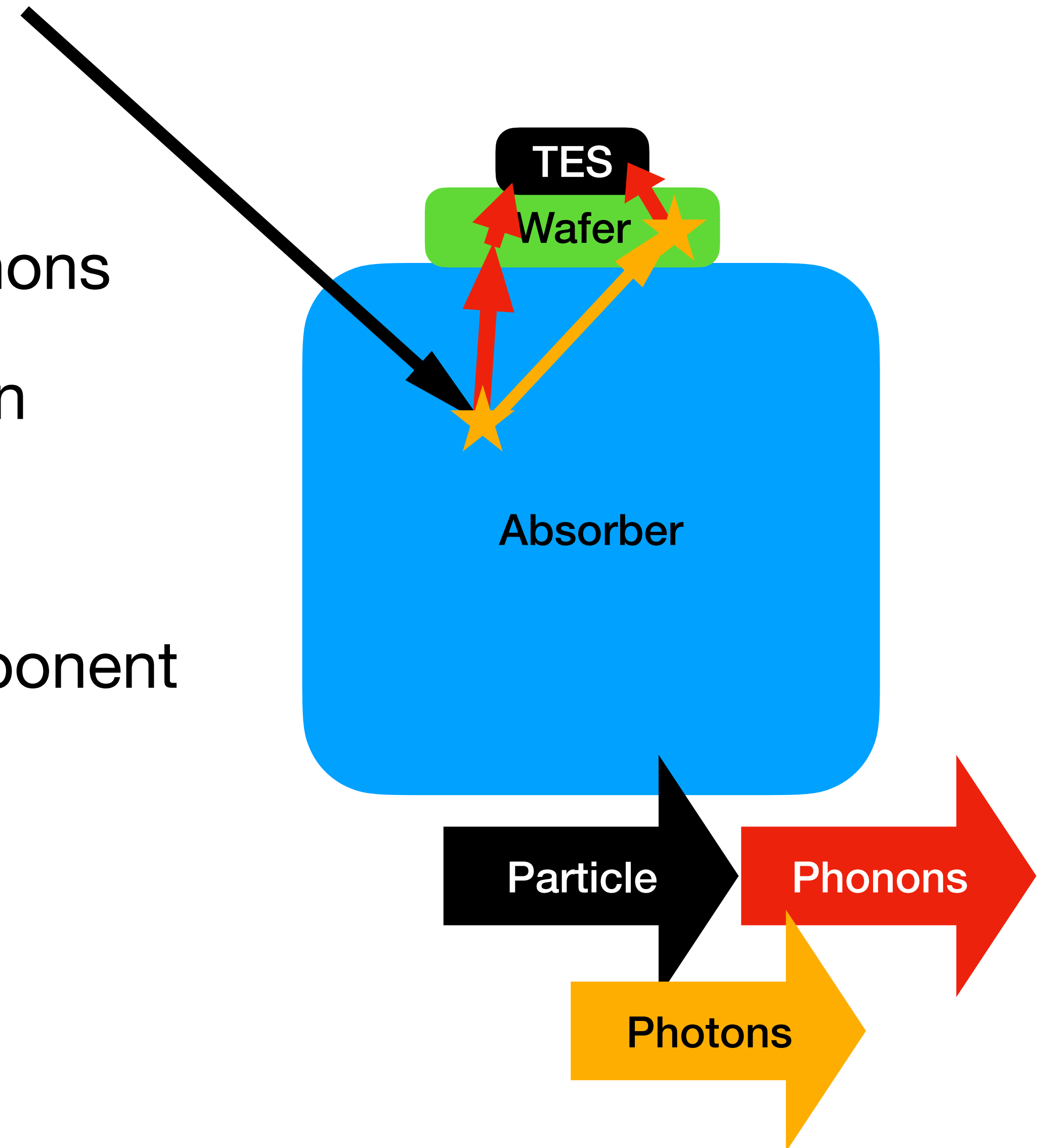
NaICE

- Particle interacts with absorber, creating phonons

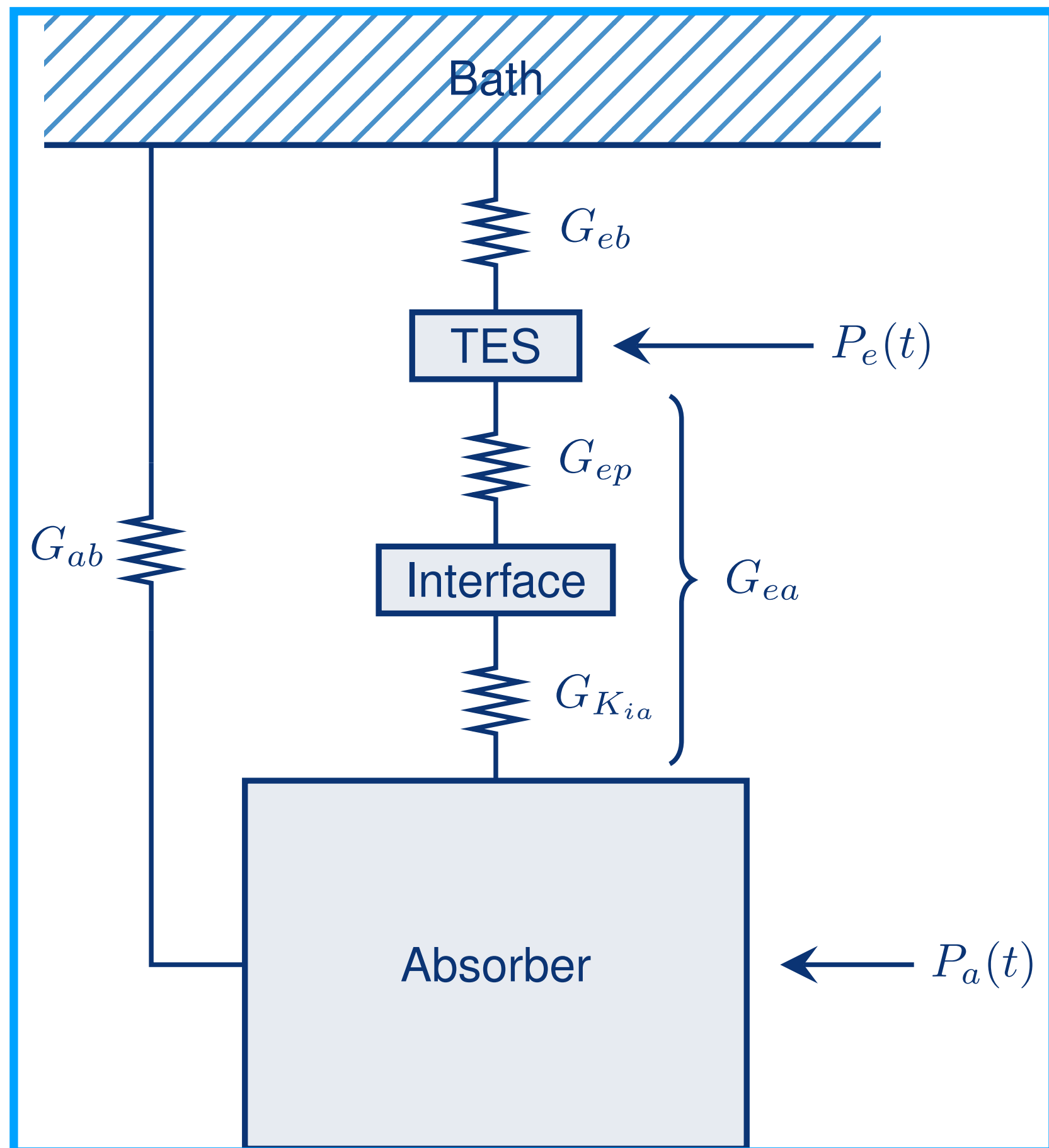


NaICE

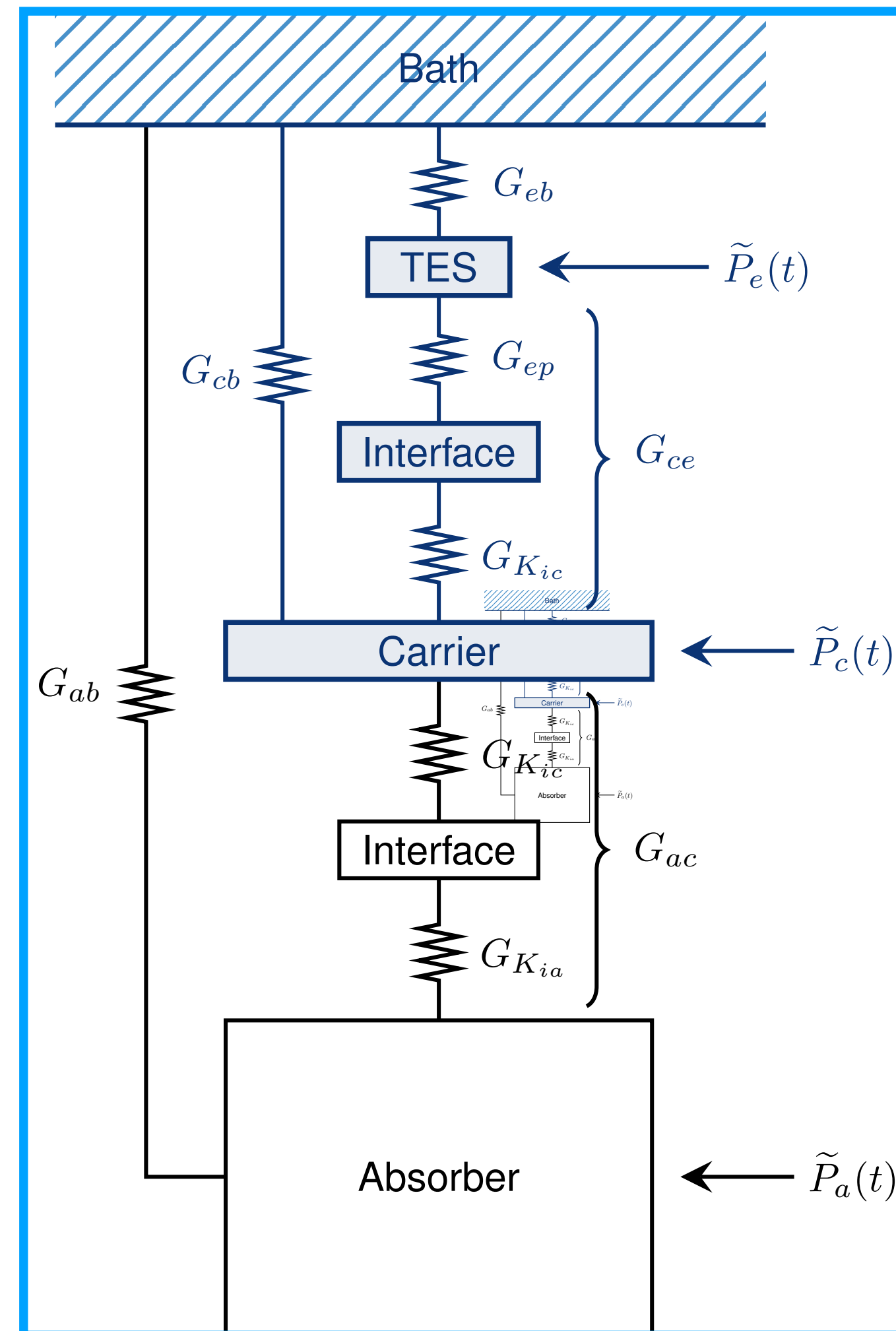
- Particle interacts with absorber, creating phonons
- Additional power input in TES from scintillation photons absorbed in the wafer
- Led to new model with additional component, compared with the commonly used two-component model
- Bayesian inference verified the new model



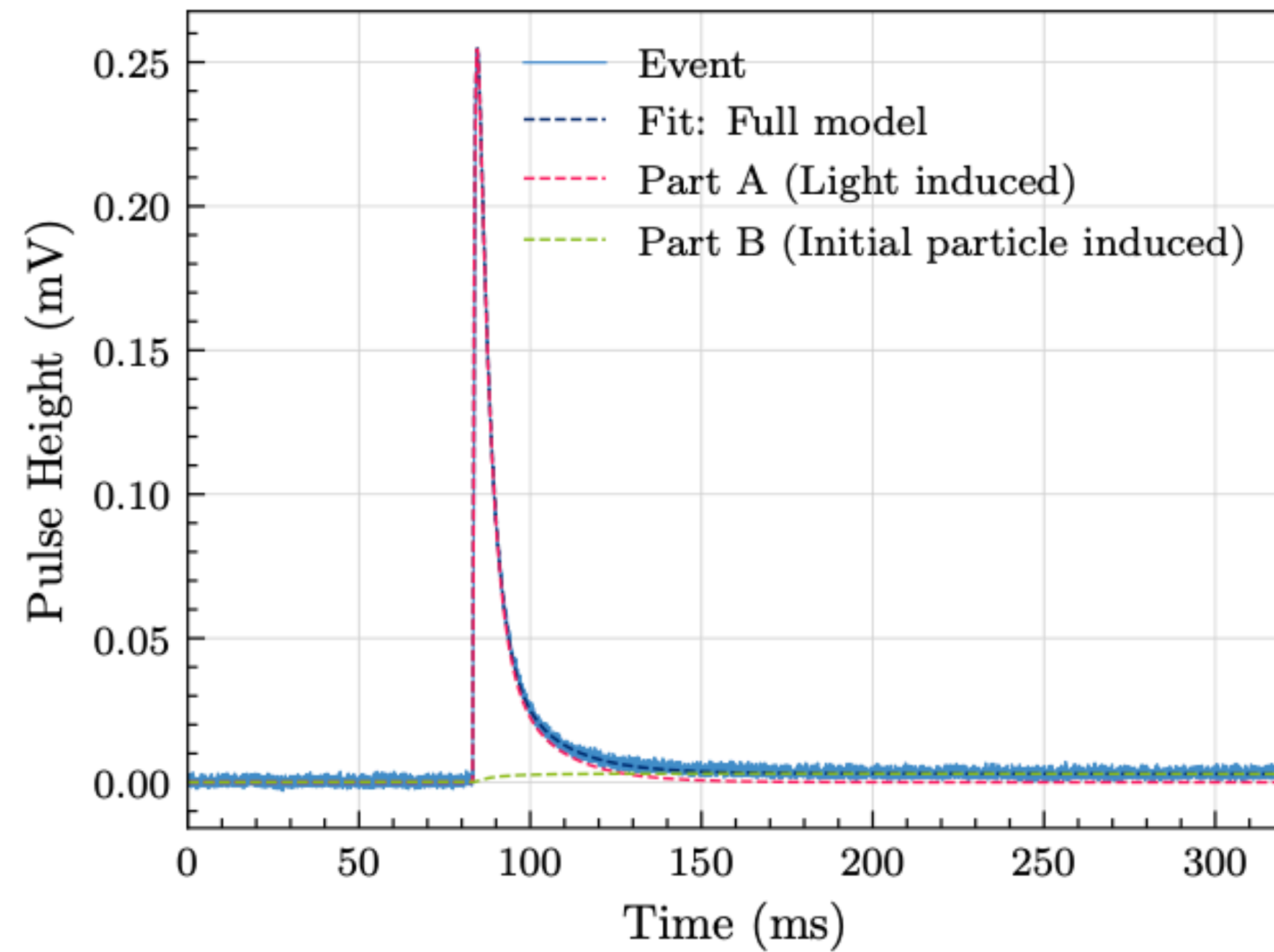
2-component model



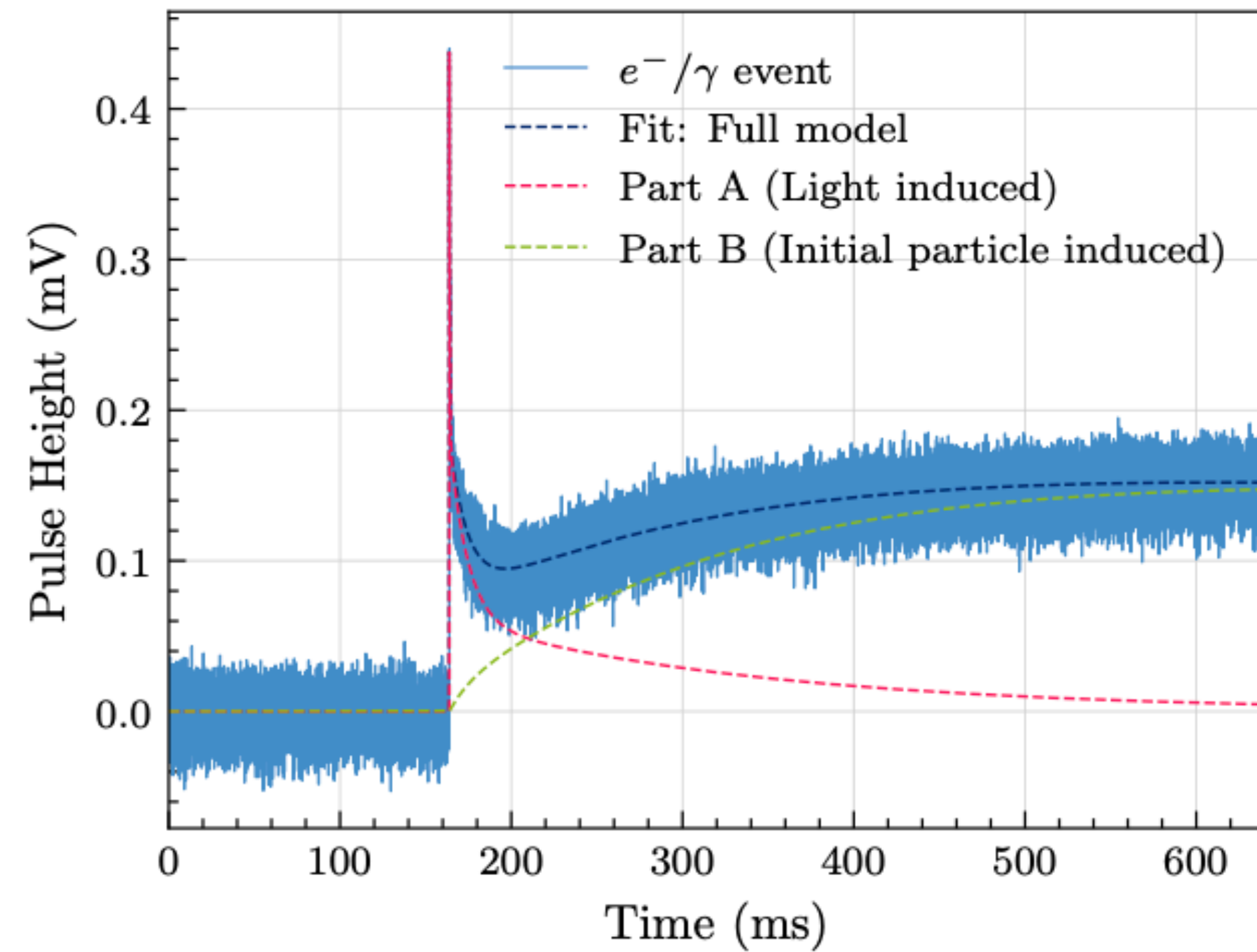
3-component model



NaICE



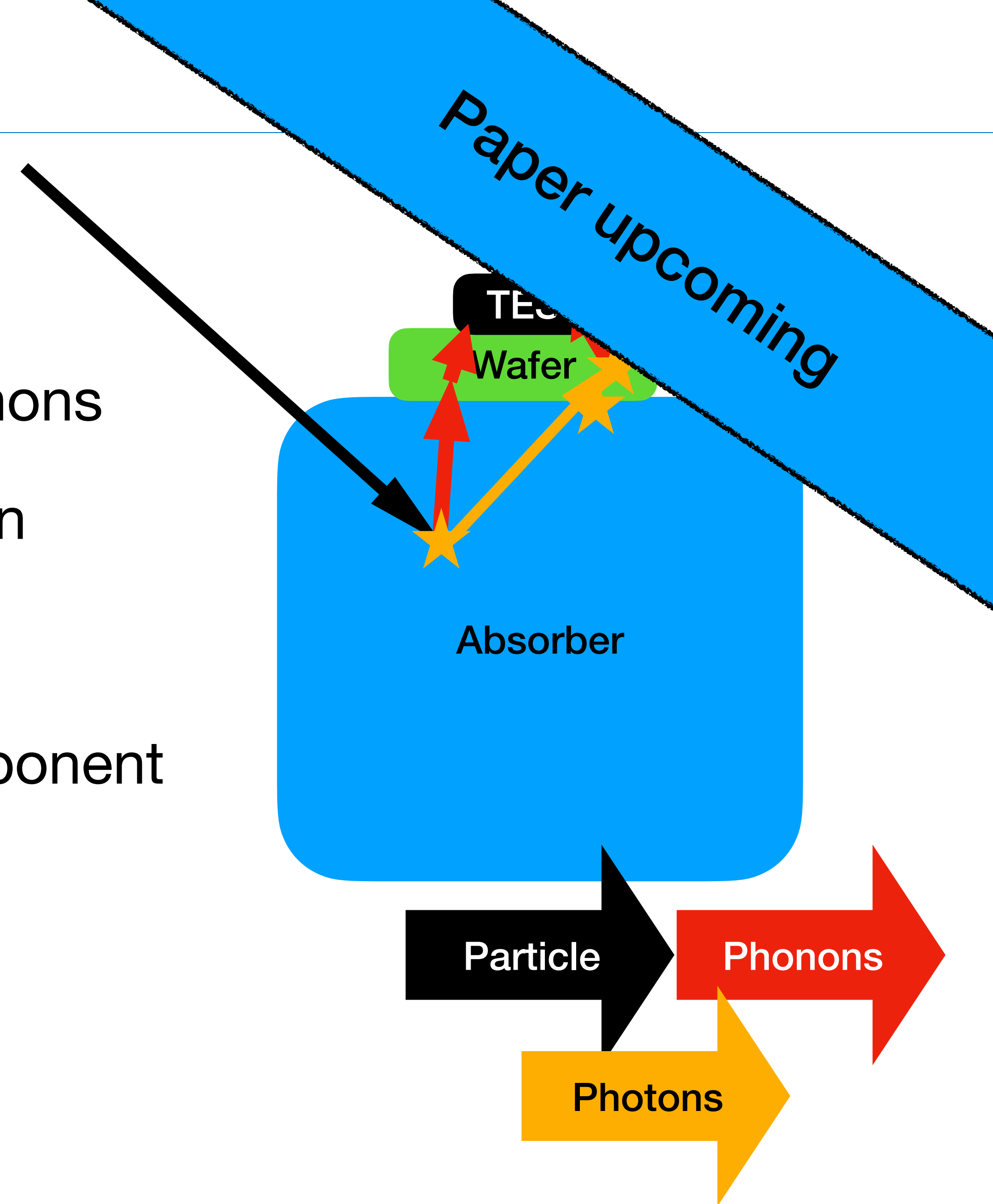
(a) NaIce2



(b) NaIce6 (e^-/γ)

NaICE

- Particle interacts with absorber, creating phonons
- Additional power input in TES from scintillation photons absorbed in the wafer
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Summary

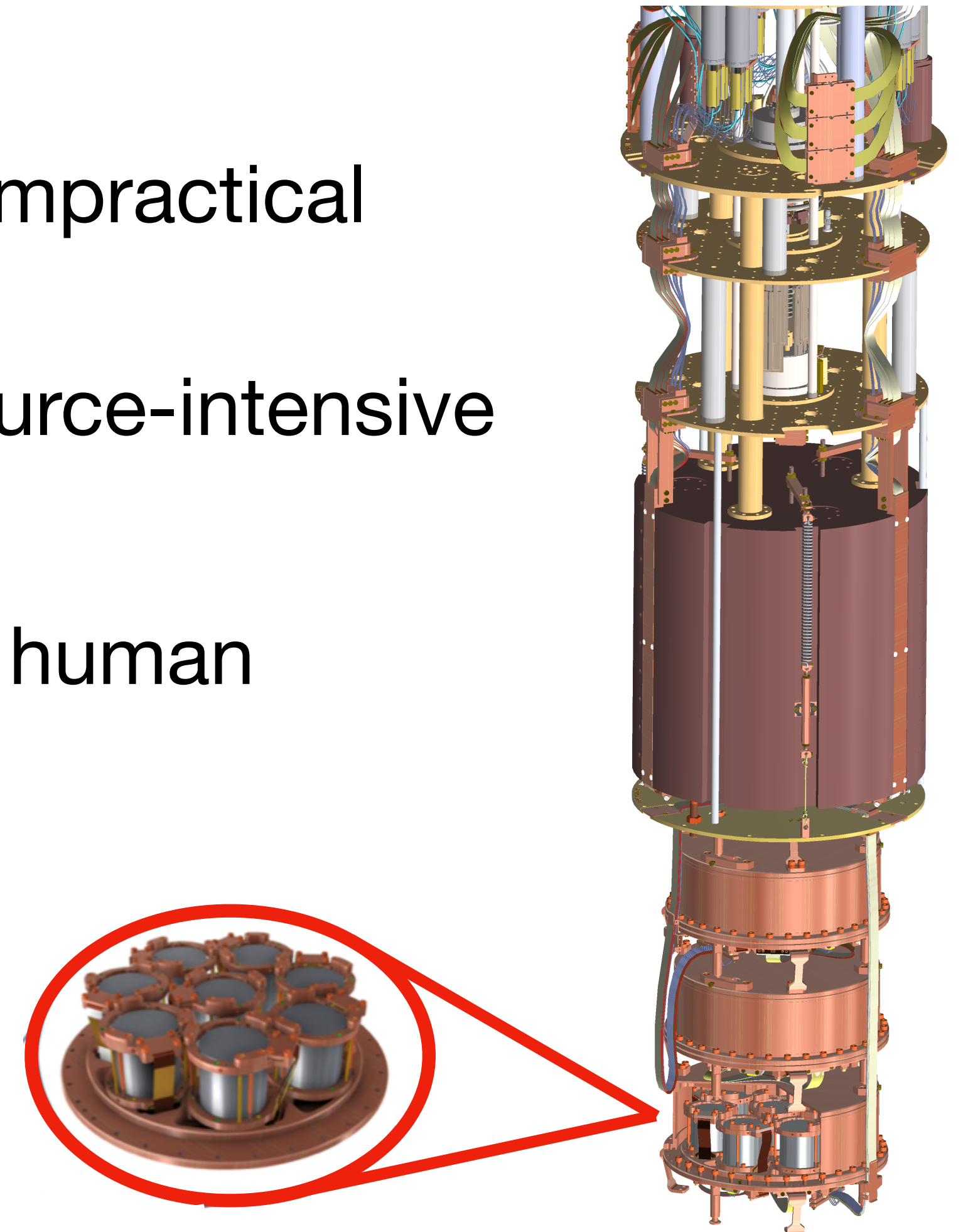
- Pulse-shape inference converts pulse-shapes into detector physical parameters
- Drastically improves quality of detector design comparison
- Enables pulse-shape model comparison

Developed by S. Braun (sarah.braun@oeaw.ac.at,) and O. Schulz (Oschulz@mpp.mpg.de)

Automated Data Analysis Chain

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



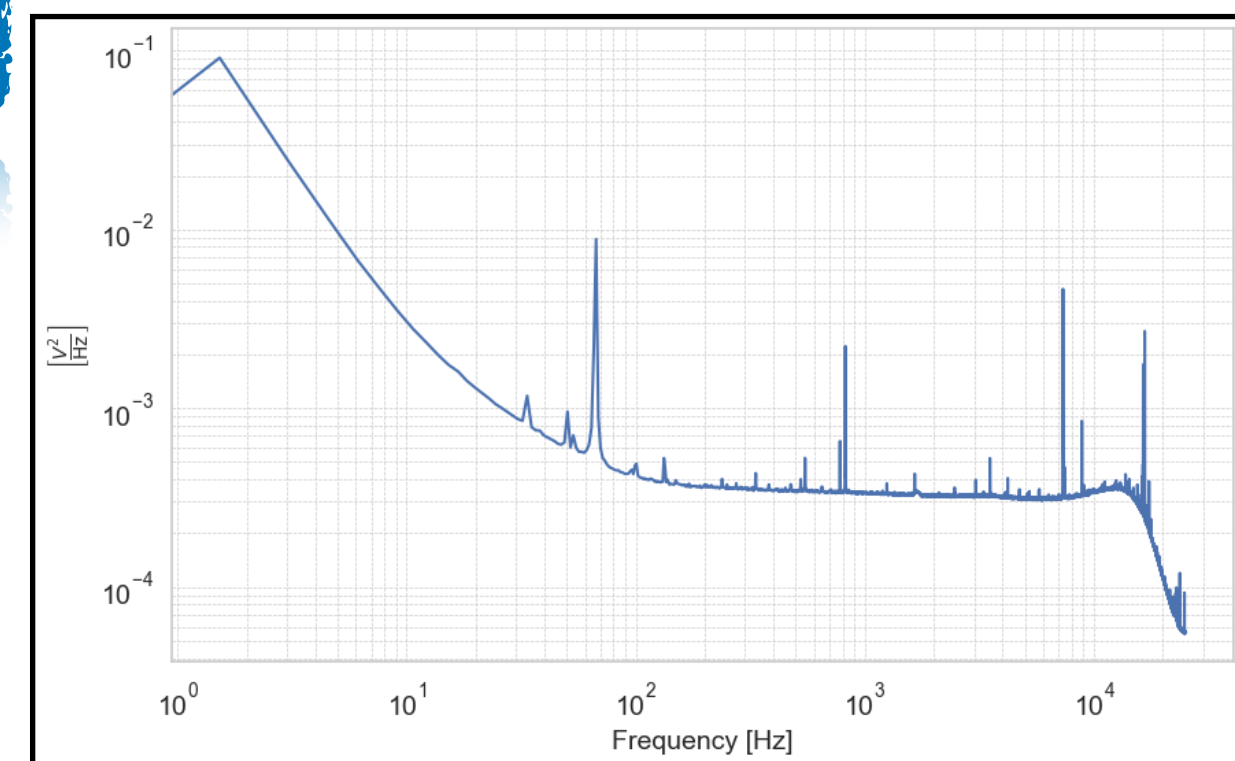
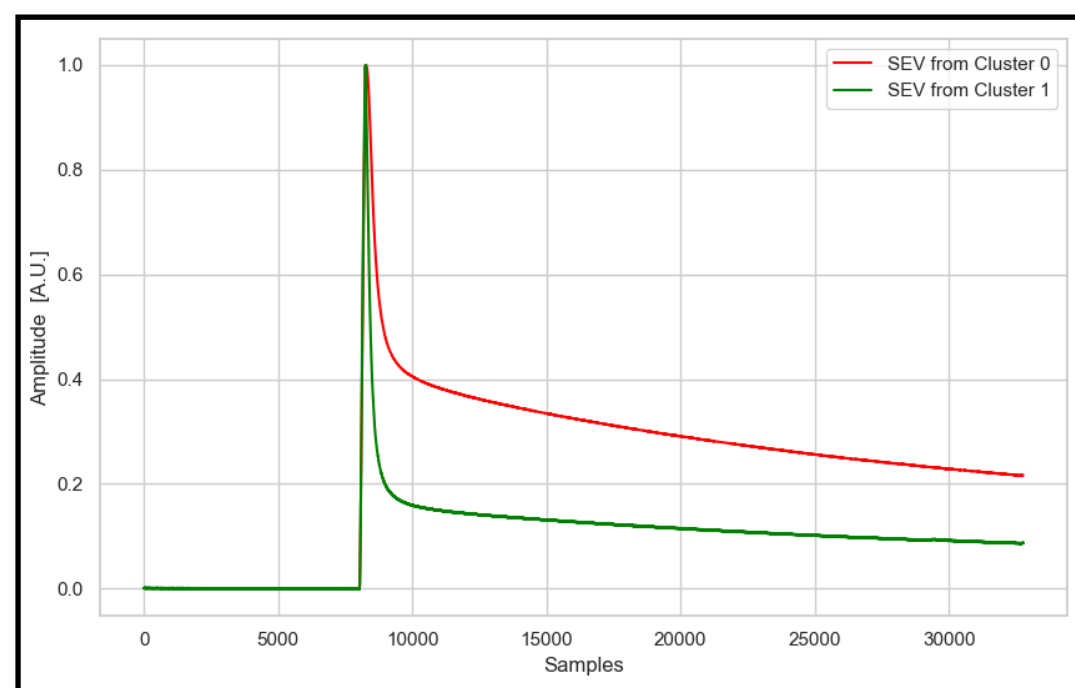
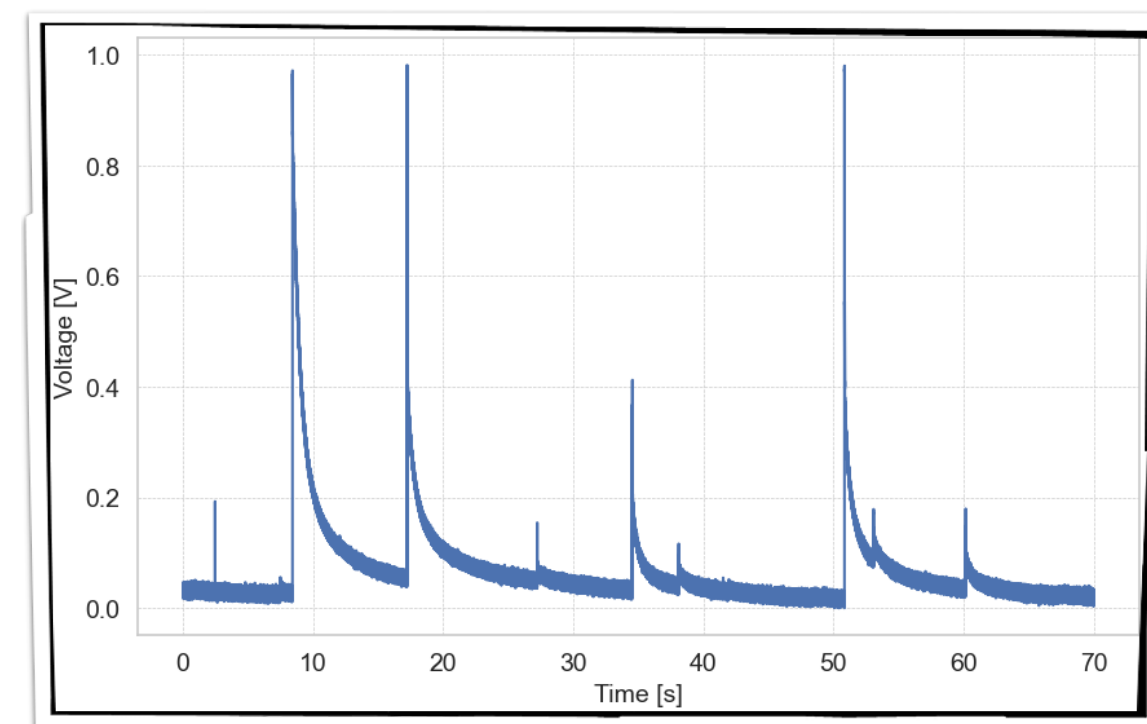
Data Stream

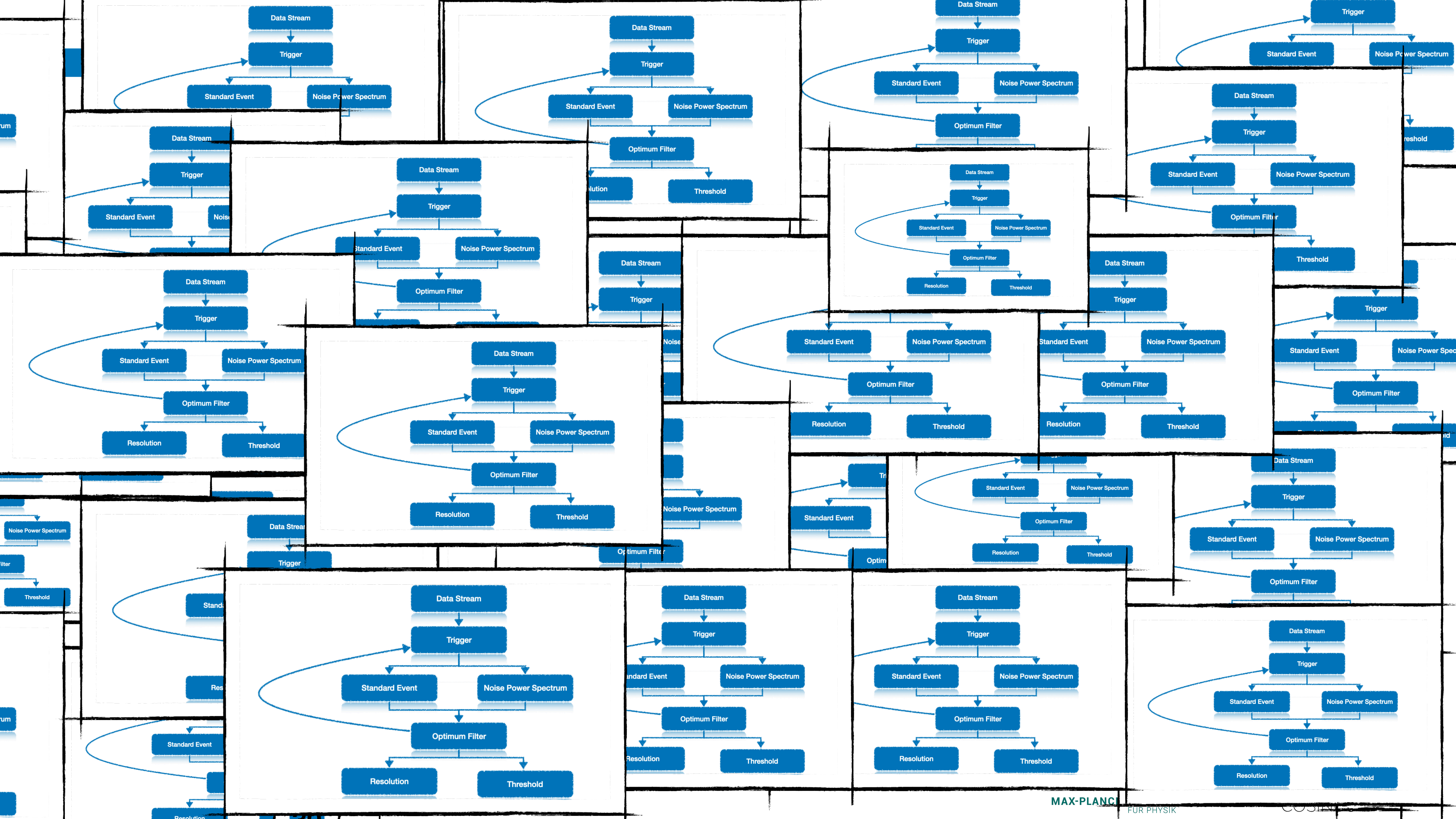
Trigger

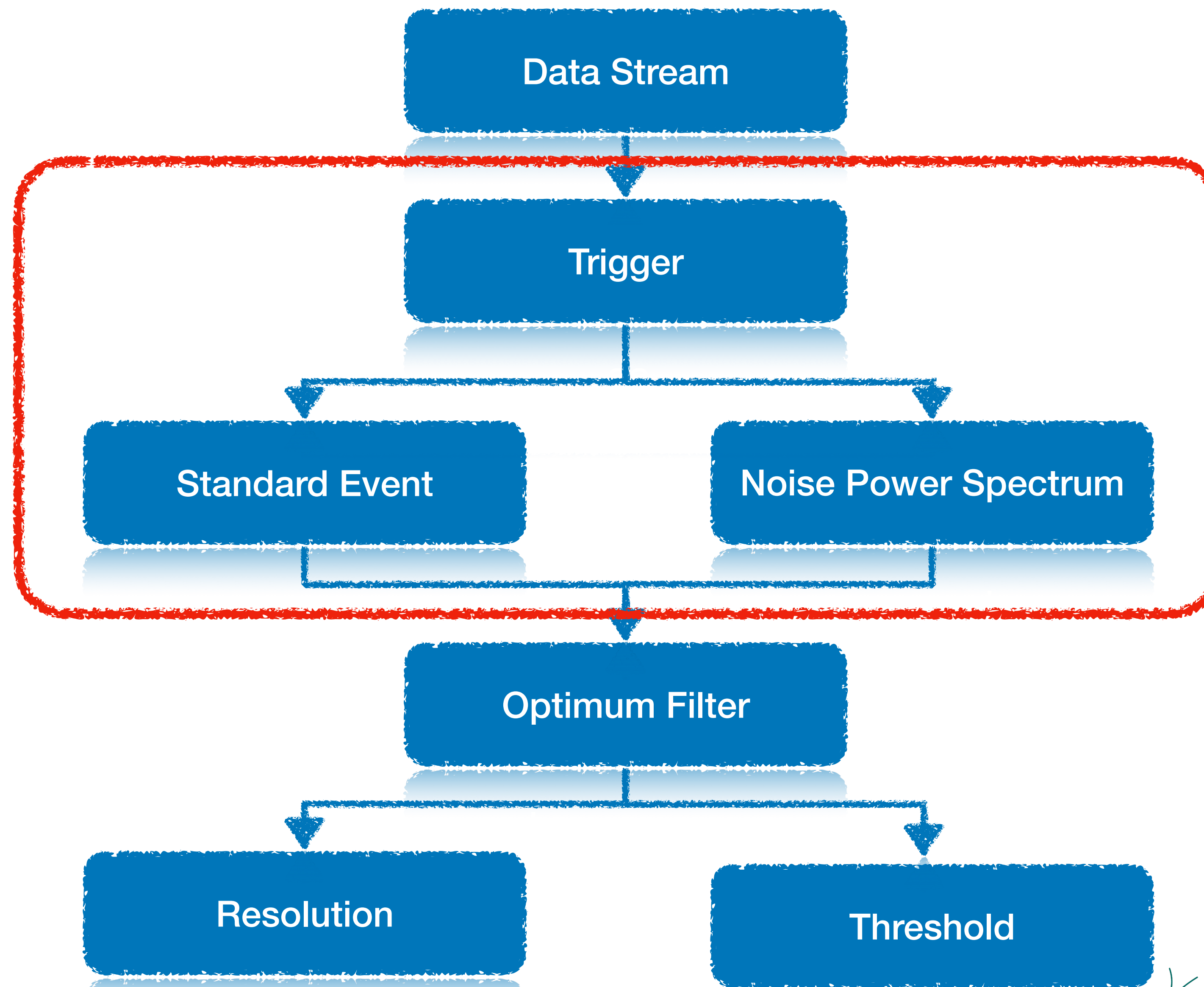
Standard Event

Noise Power Spectrum

Optimum Filter

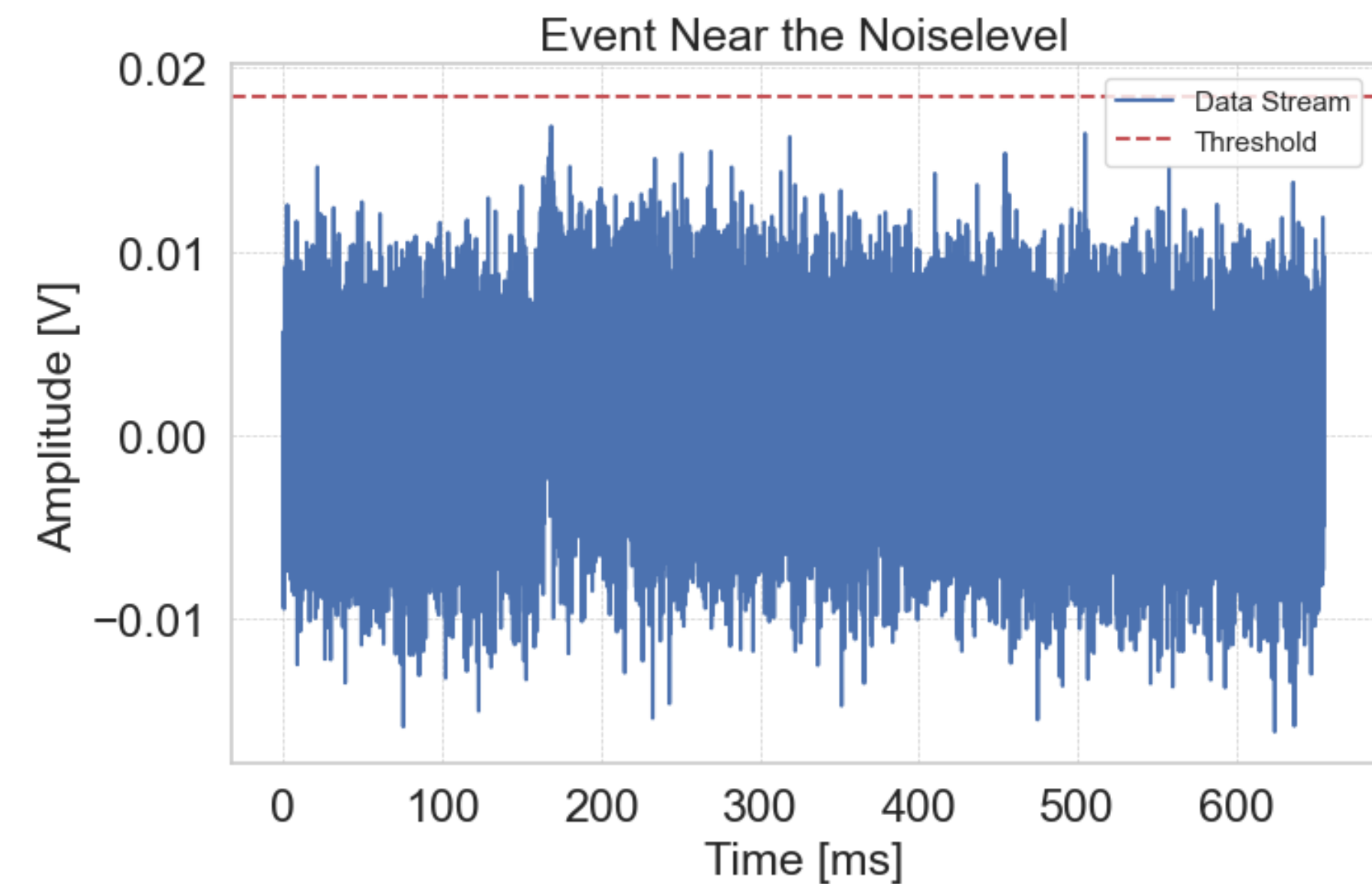
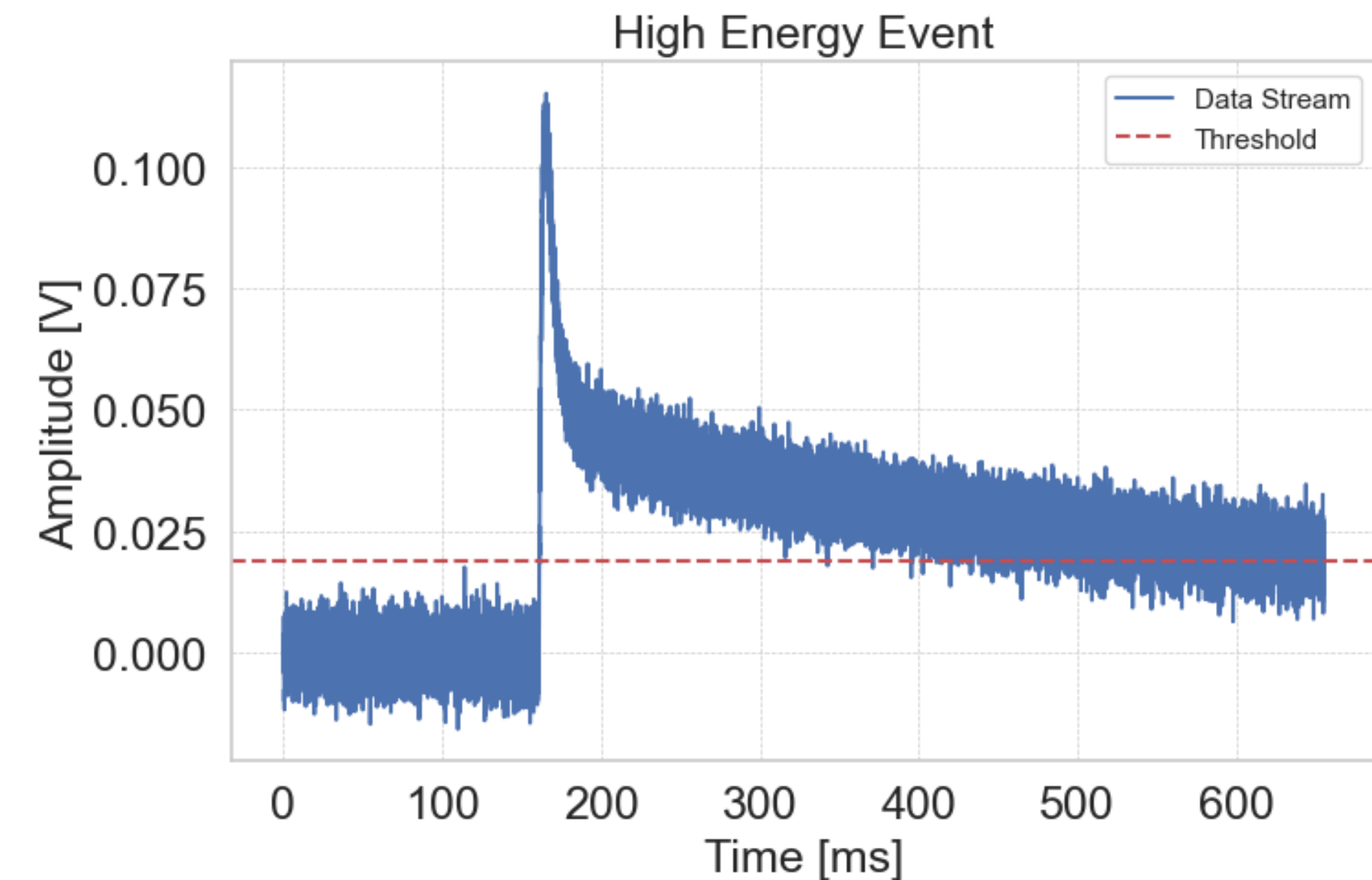






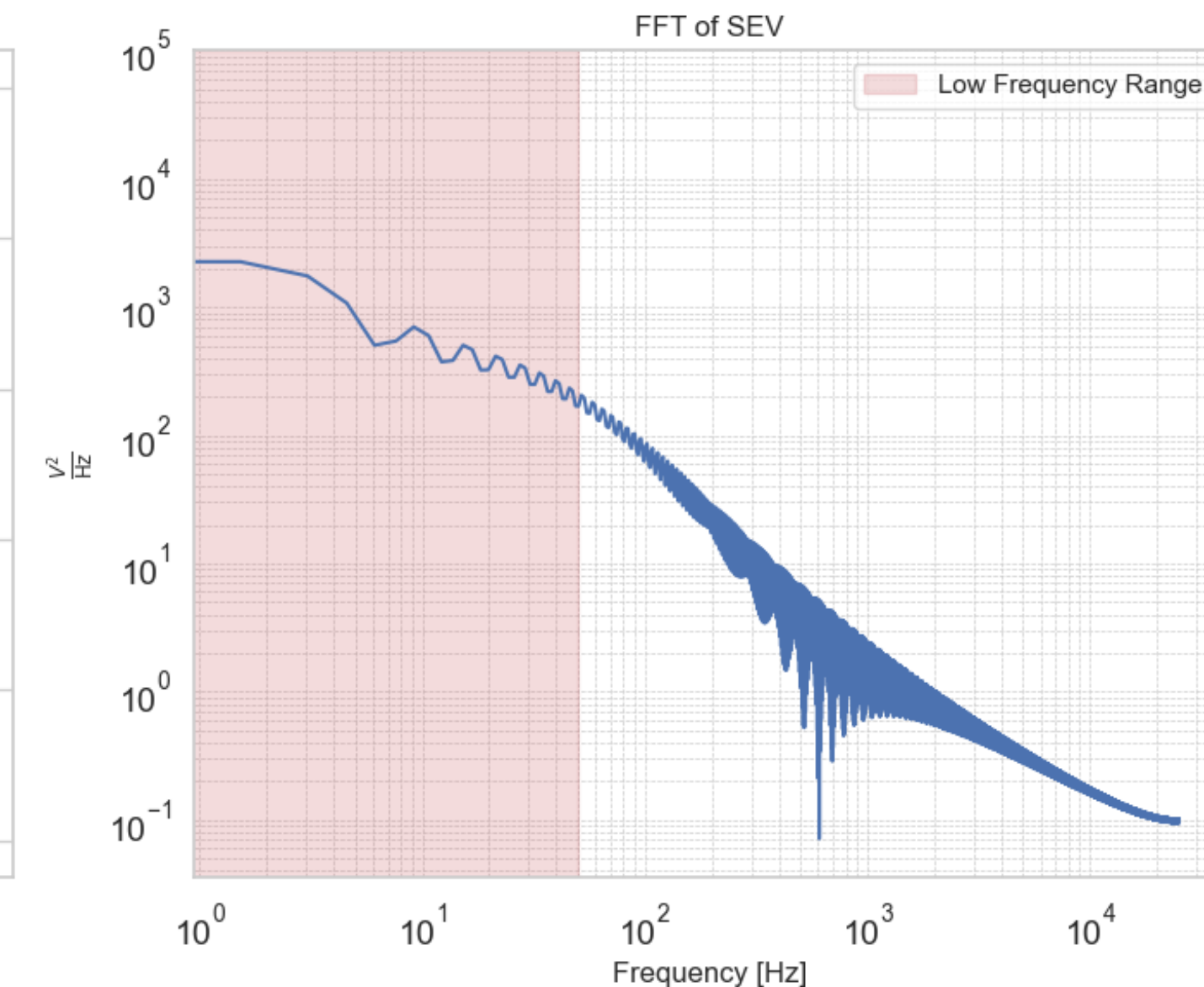
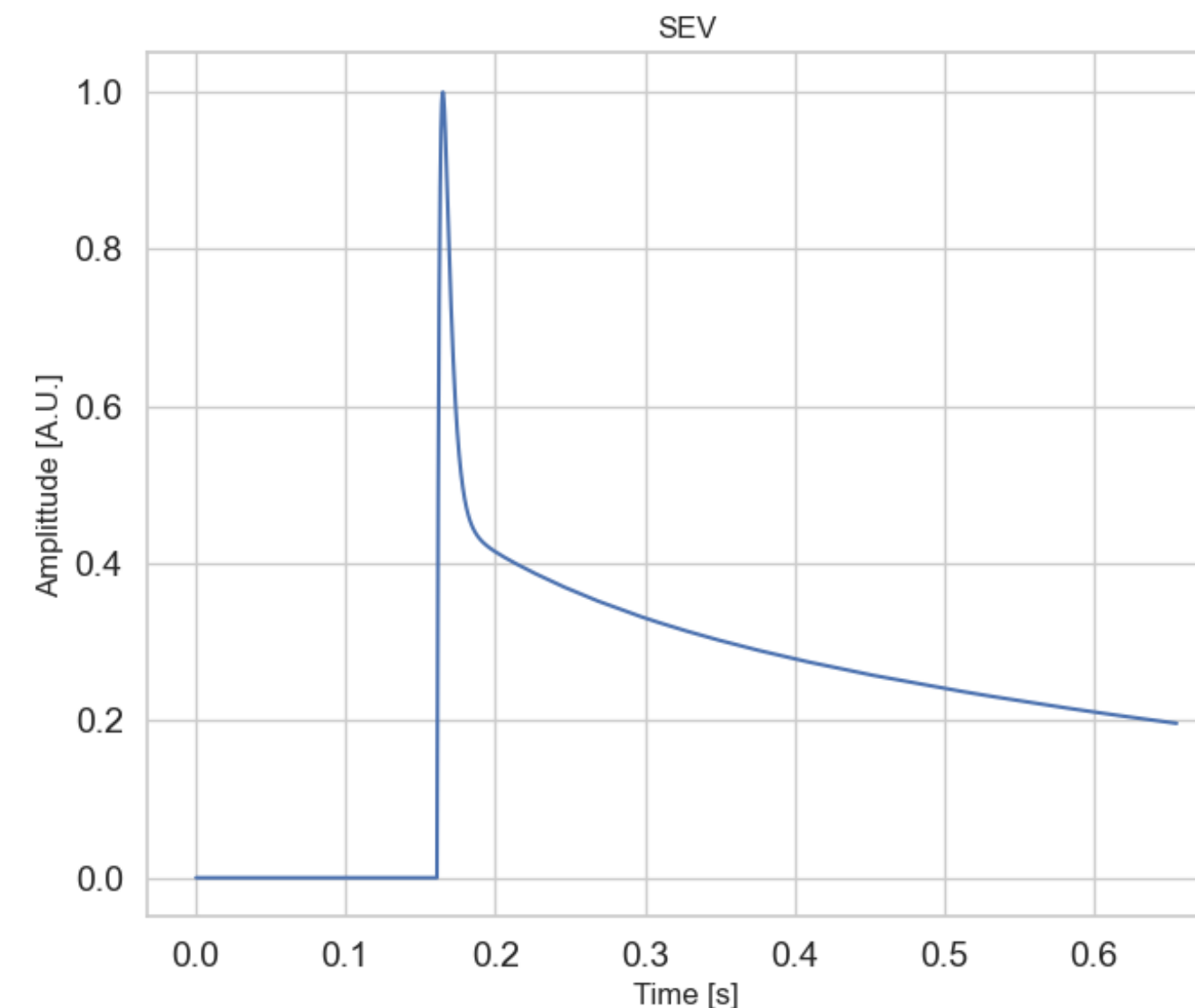
Z-score—Trigger

- Typical trigger algorithm
- Moving average trigger



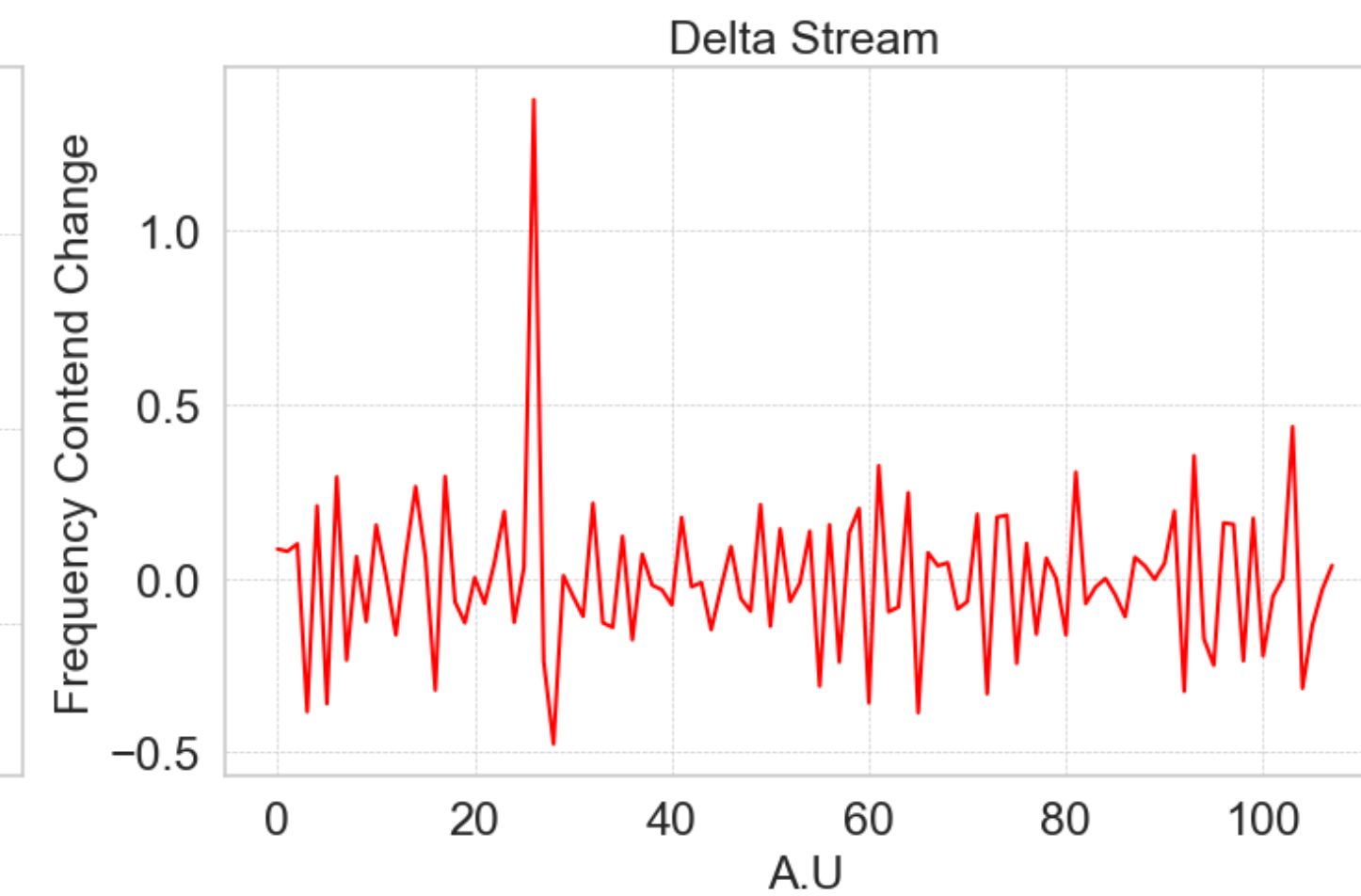
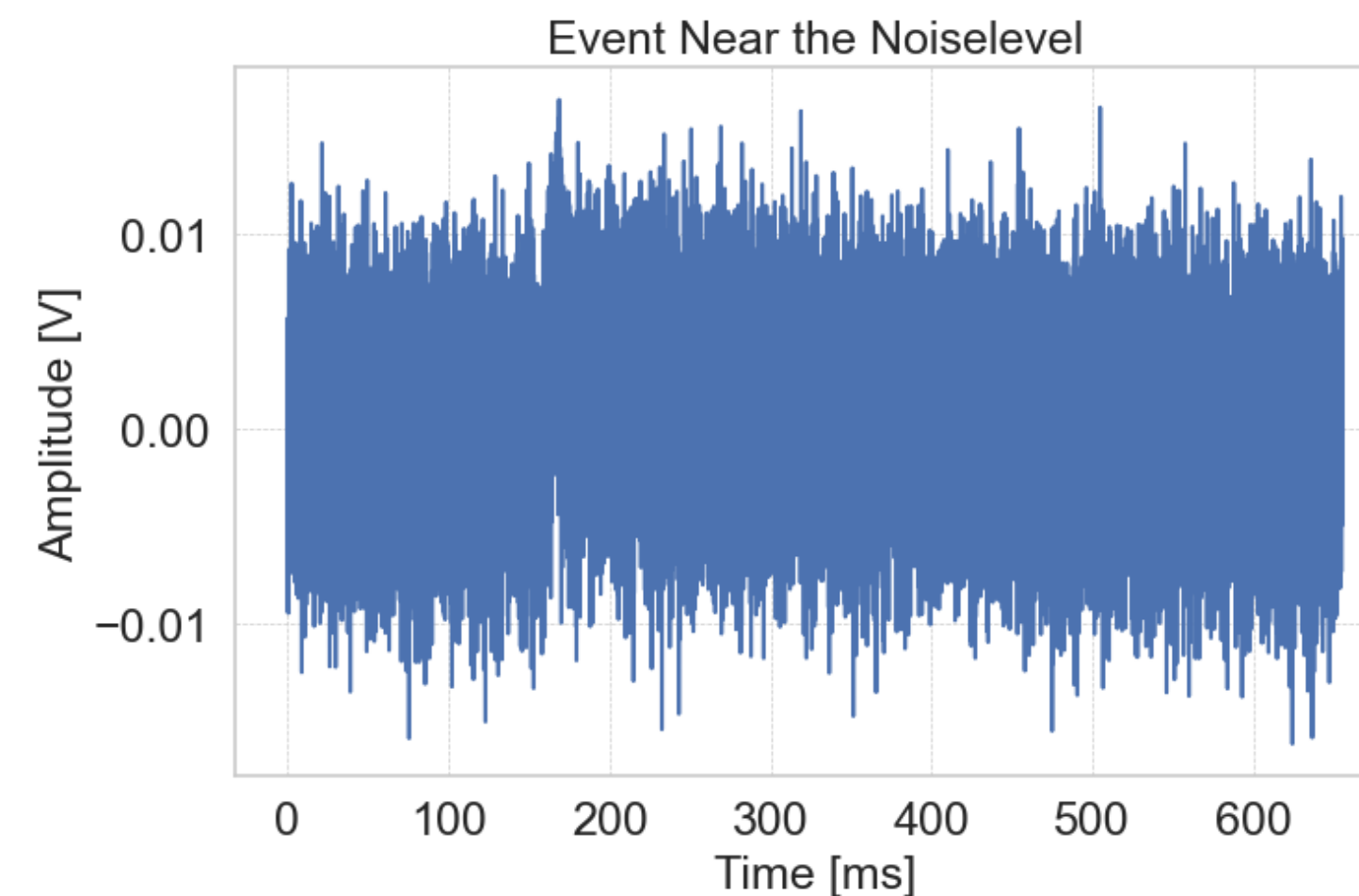
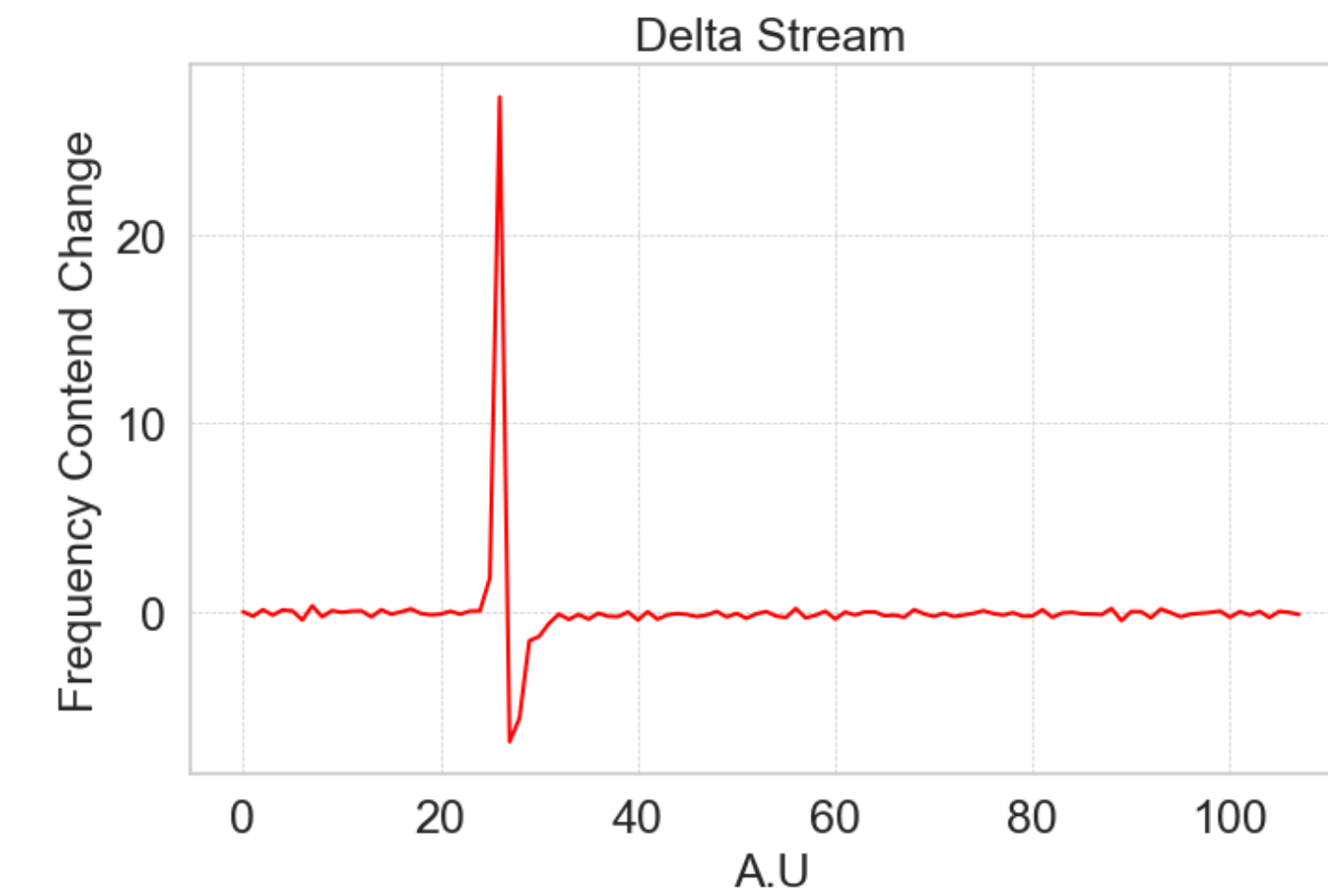
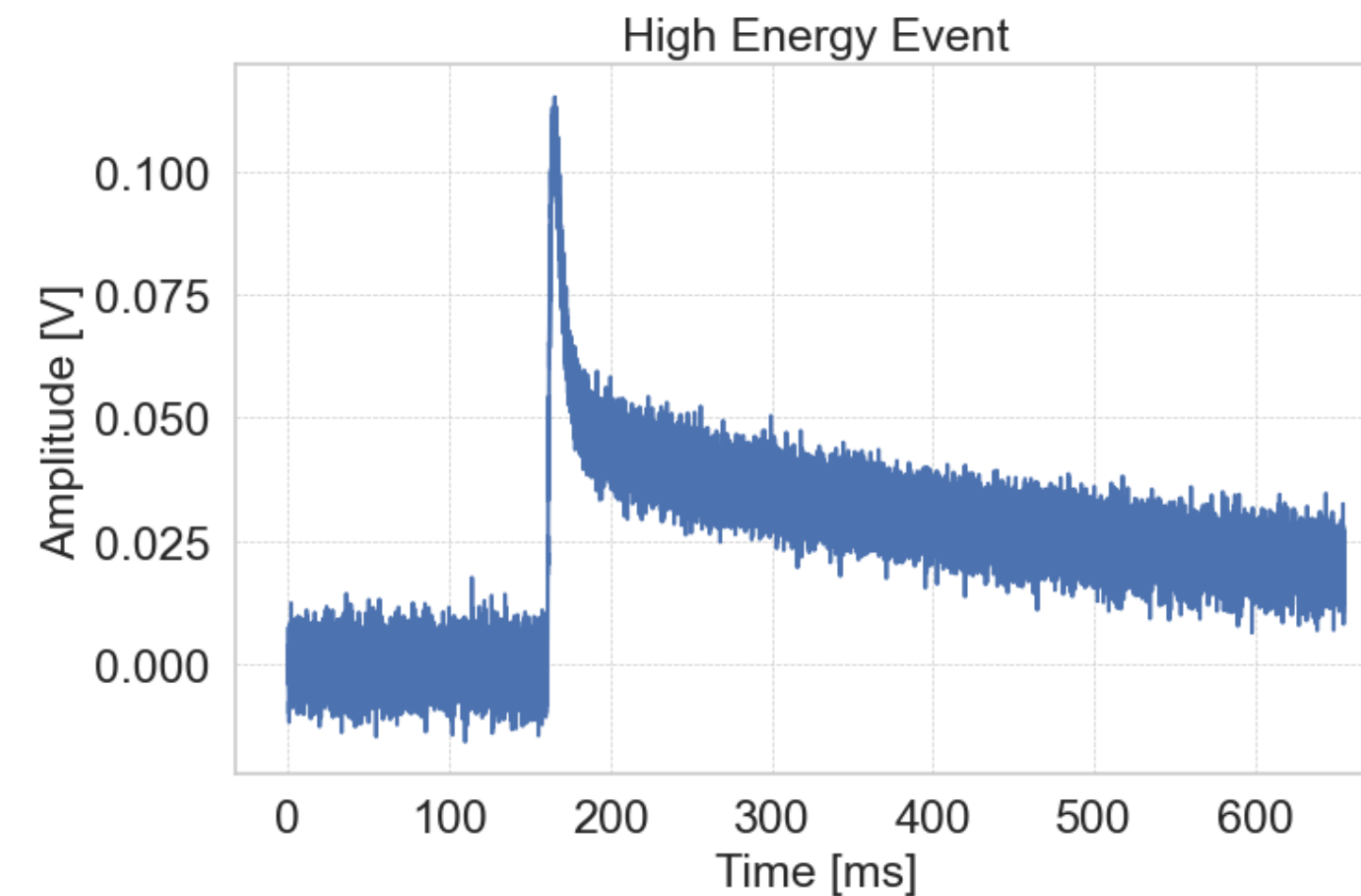
Frequency-Trigger

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



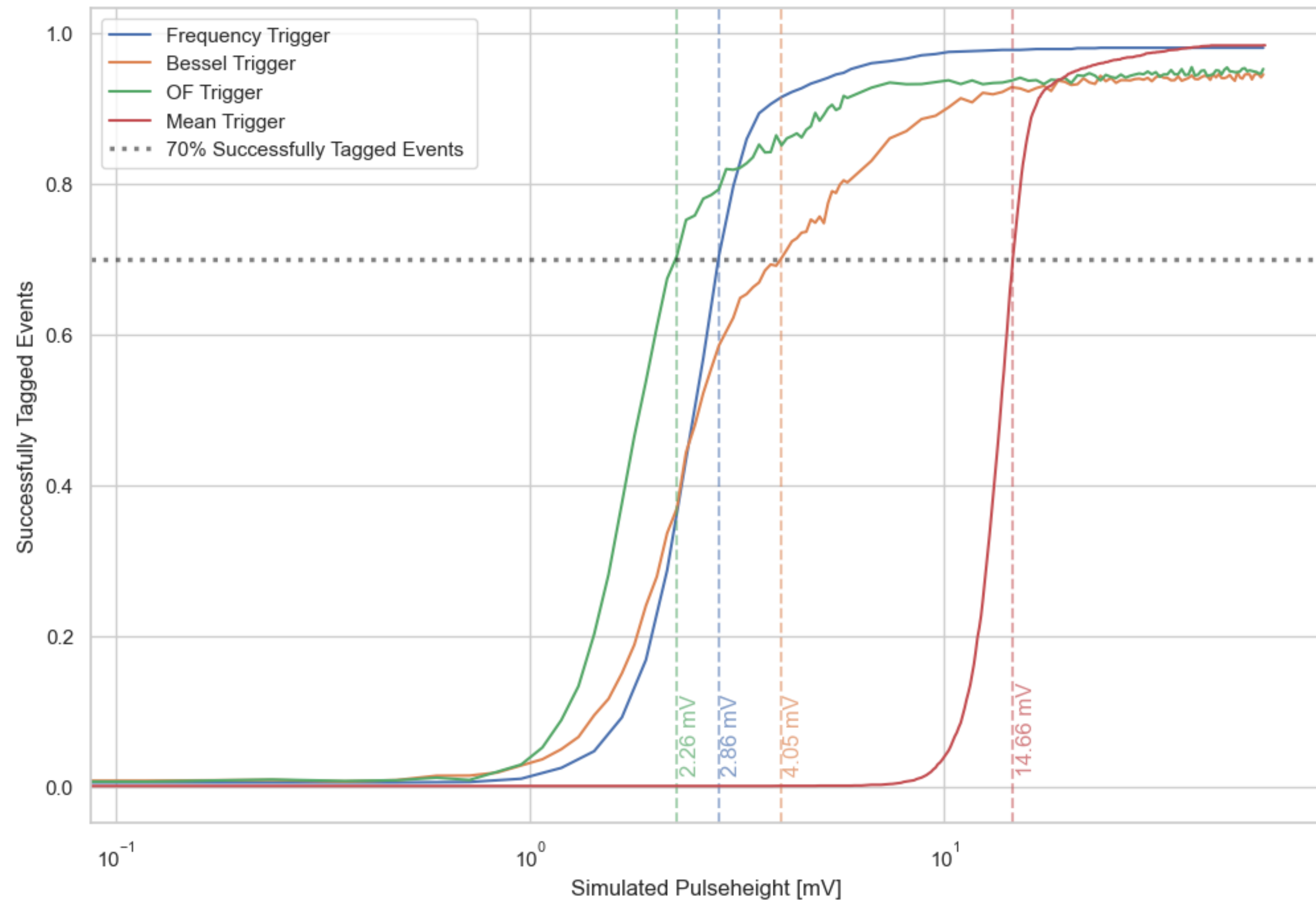
Frequency-Trigger

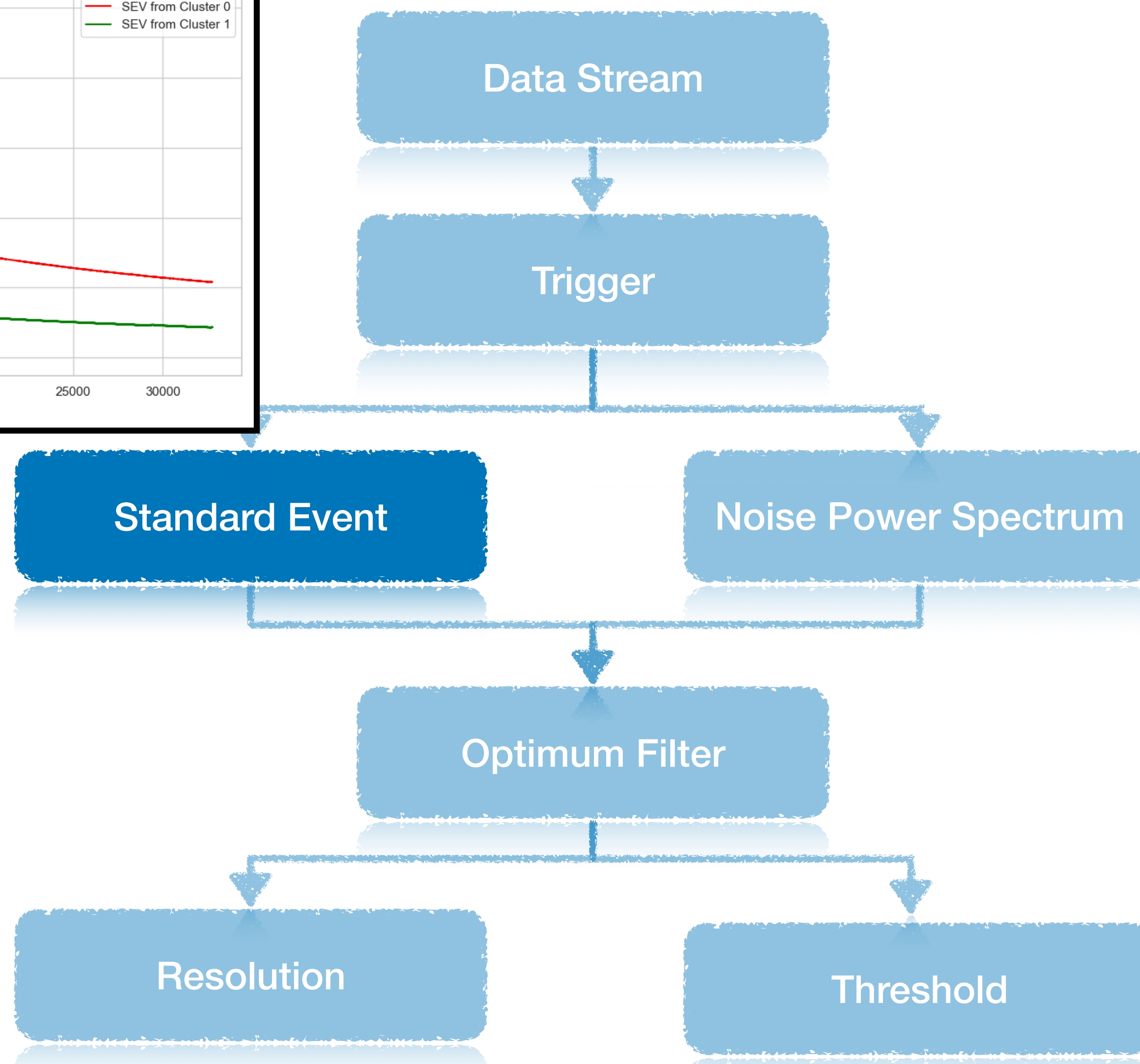
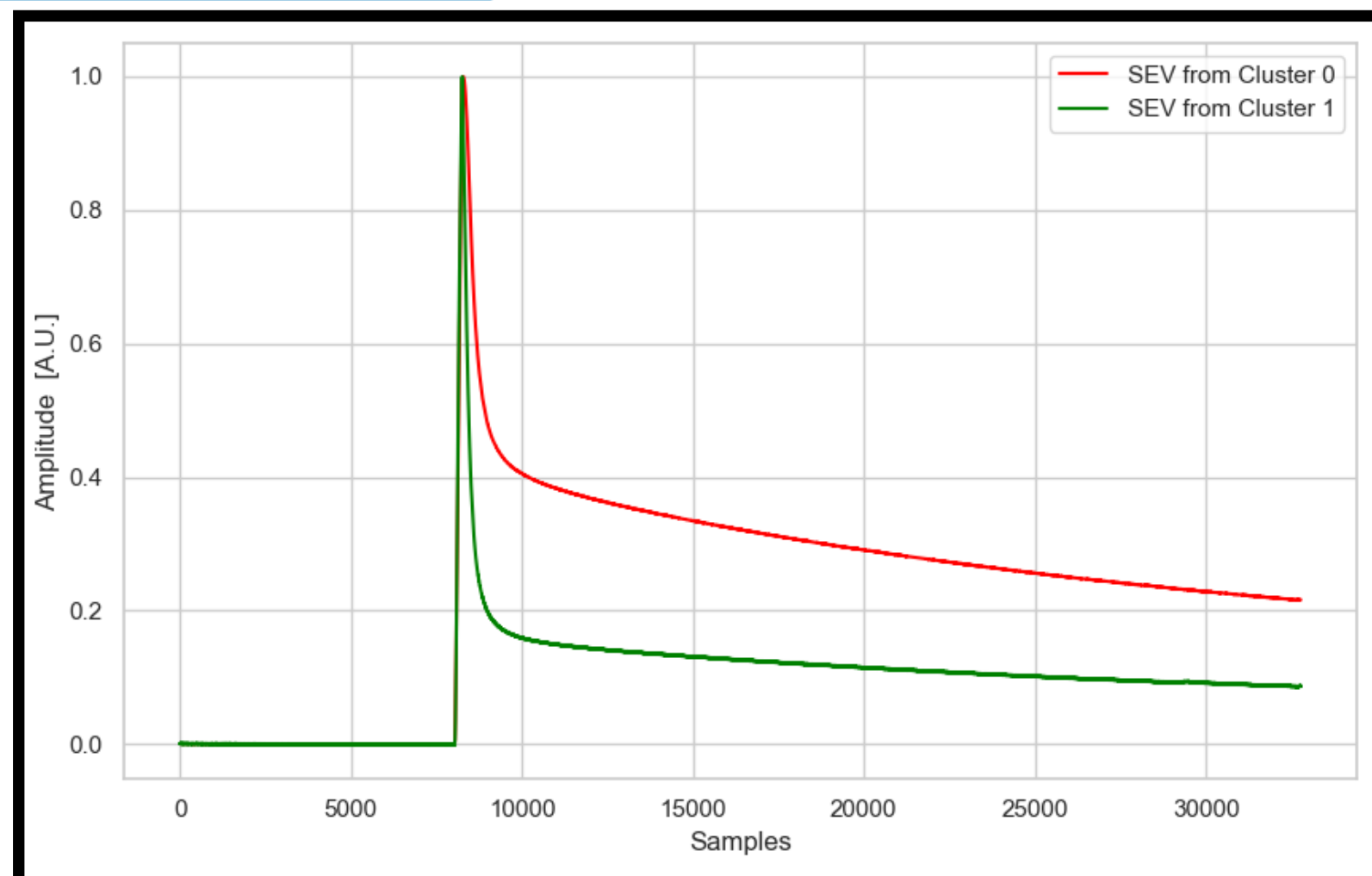
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Performance Comparison

- Superimpose randomly drawn windows with event of different amplitudes
- Frequency trigger best candidate for first trigger





Validate Events

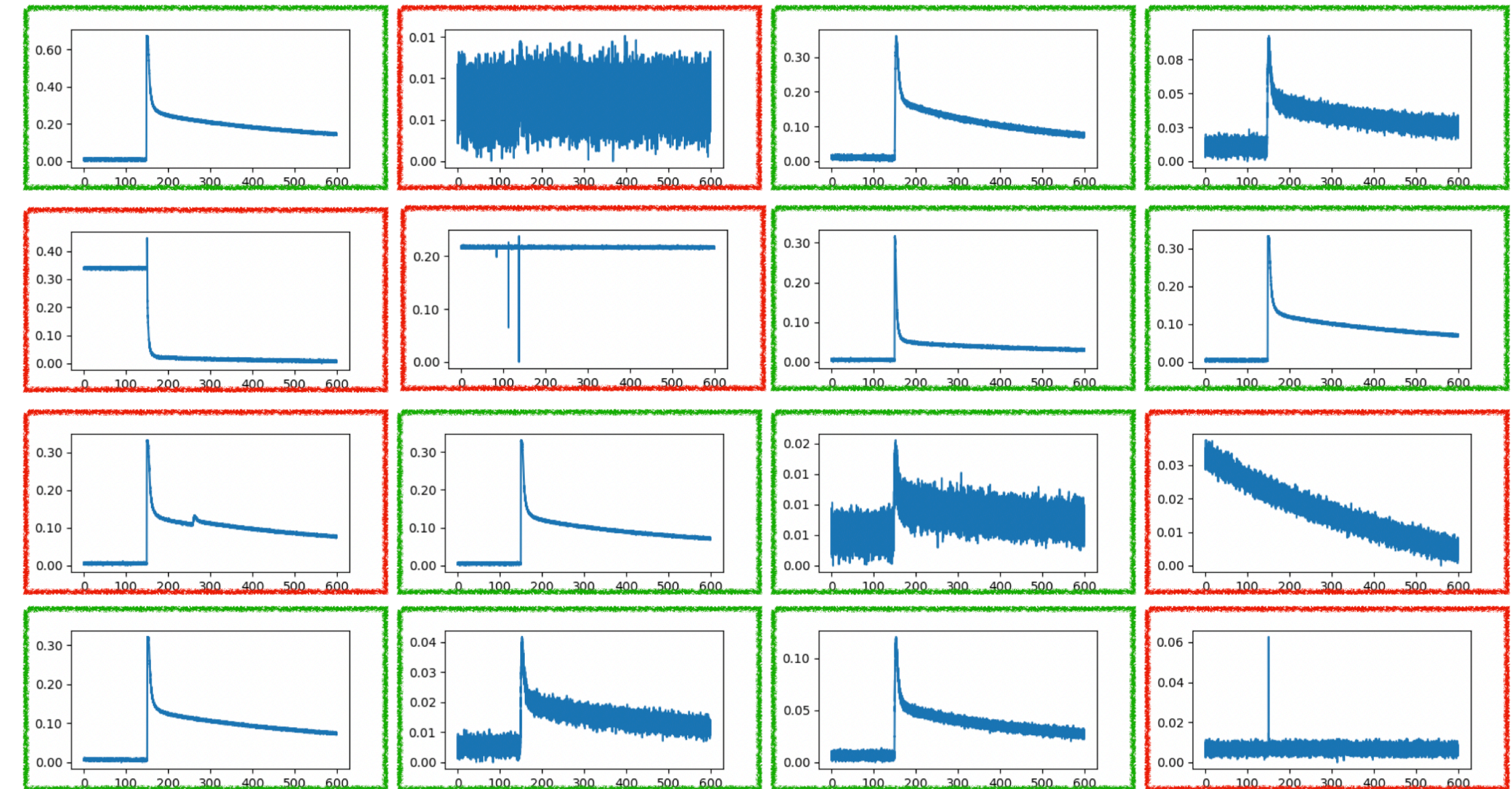
- Distinguish valid events from artifacts
- **Neural Network Approach:**
 - ➔ Train Network to identify patterns in the pulse-shapes
 - ➔ Existing Neural Network from CRESST (trained with one million real events)

(More Details:

<https://arxiv.org/pdf/2508.03078>

F. Wagner, “Towards next-generation cryogenic dark matter searches with superconducting thermometers.”)

More Details: F. Wagner, “Towards next-generation cryogenic dark matter searches with superconducting thermometers.”

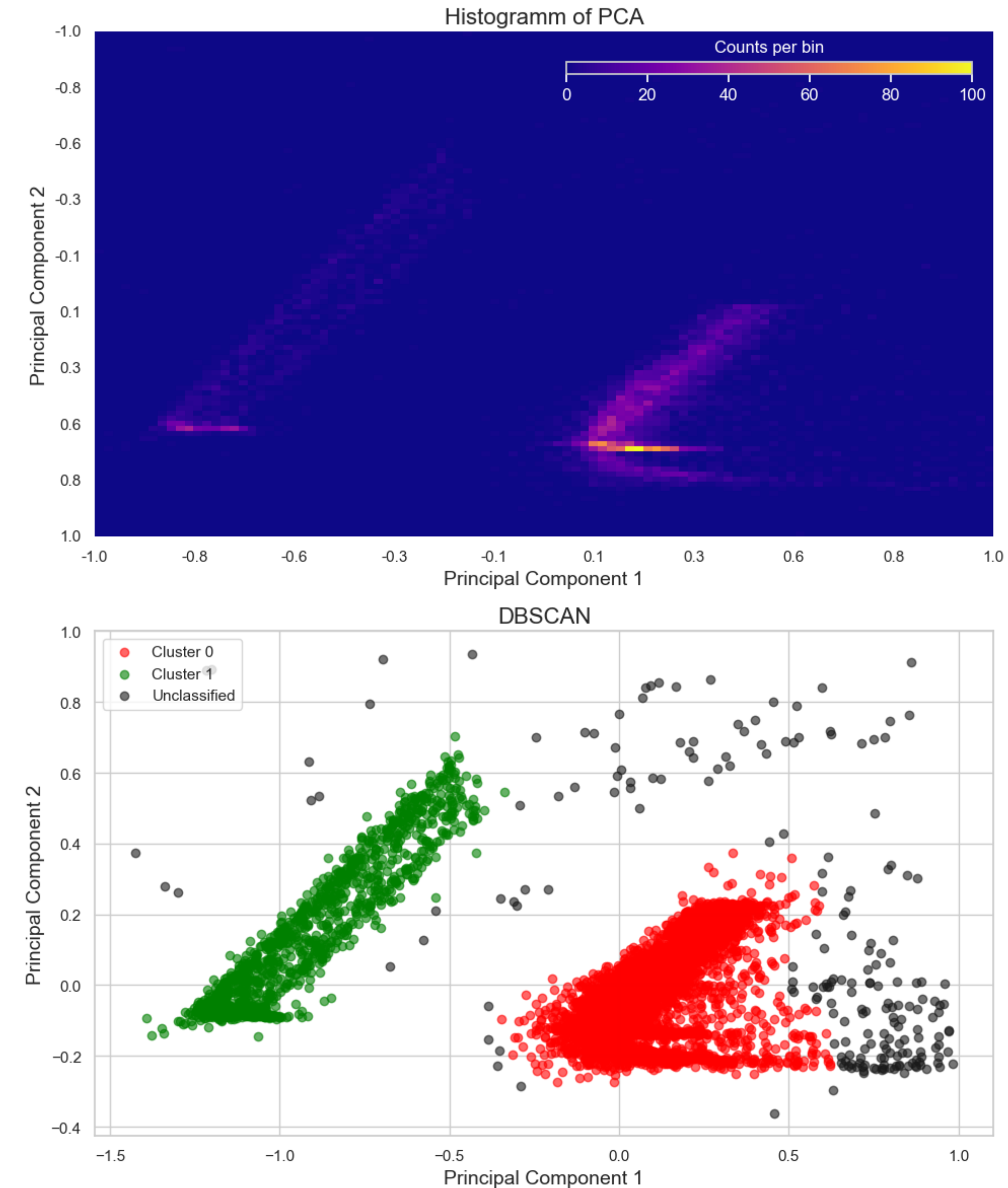


CRESST

Cryogenic Rare Event Search
with Superconducting Thermometers

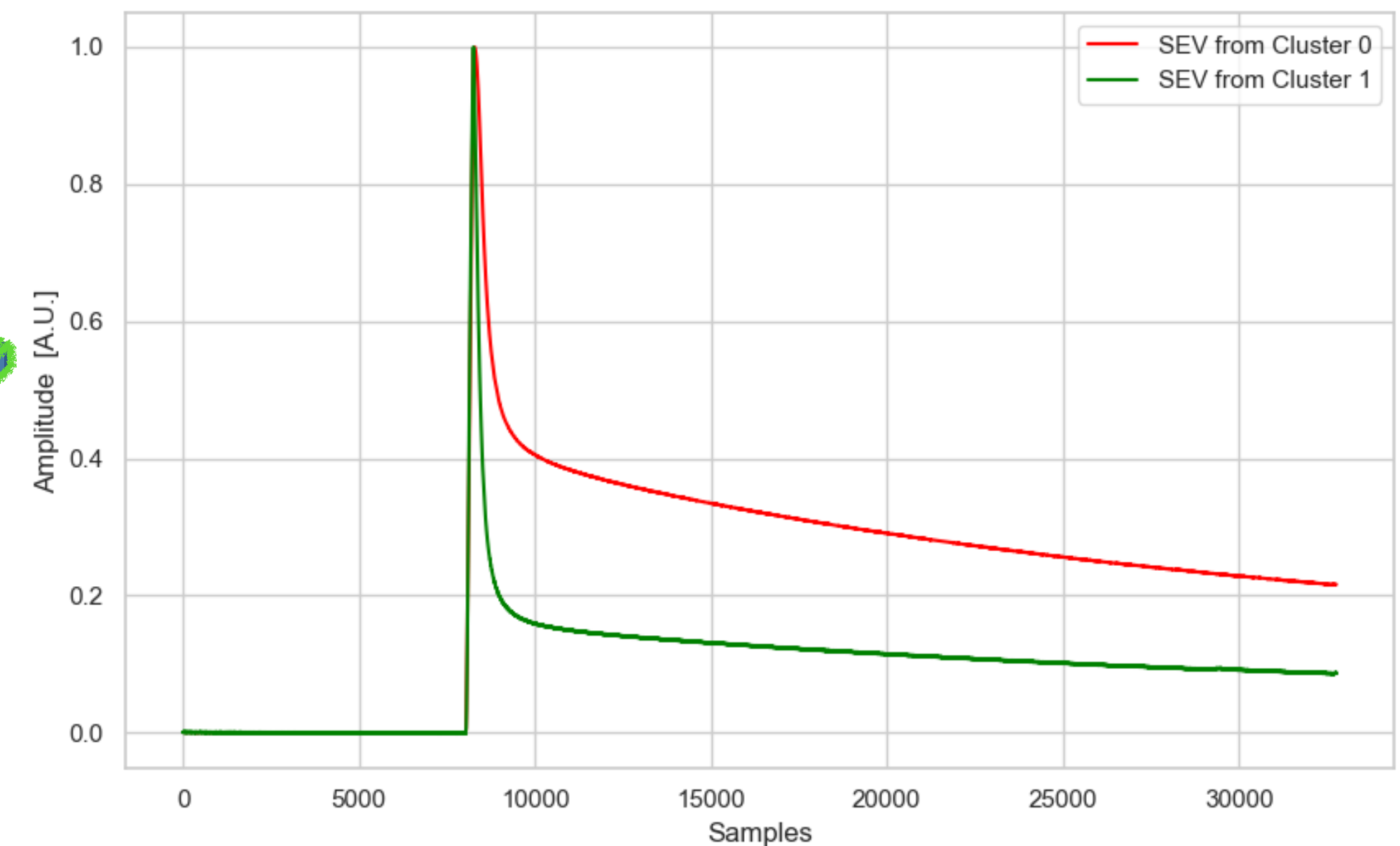
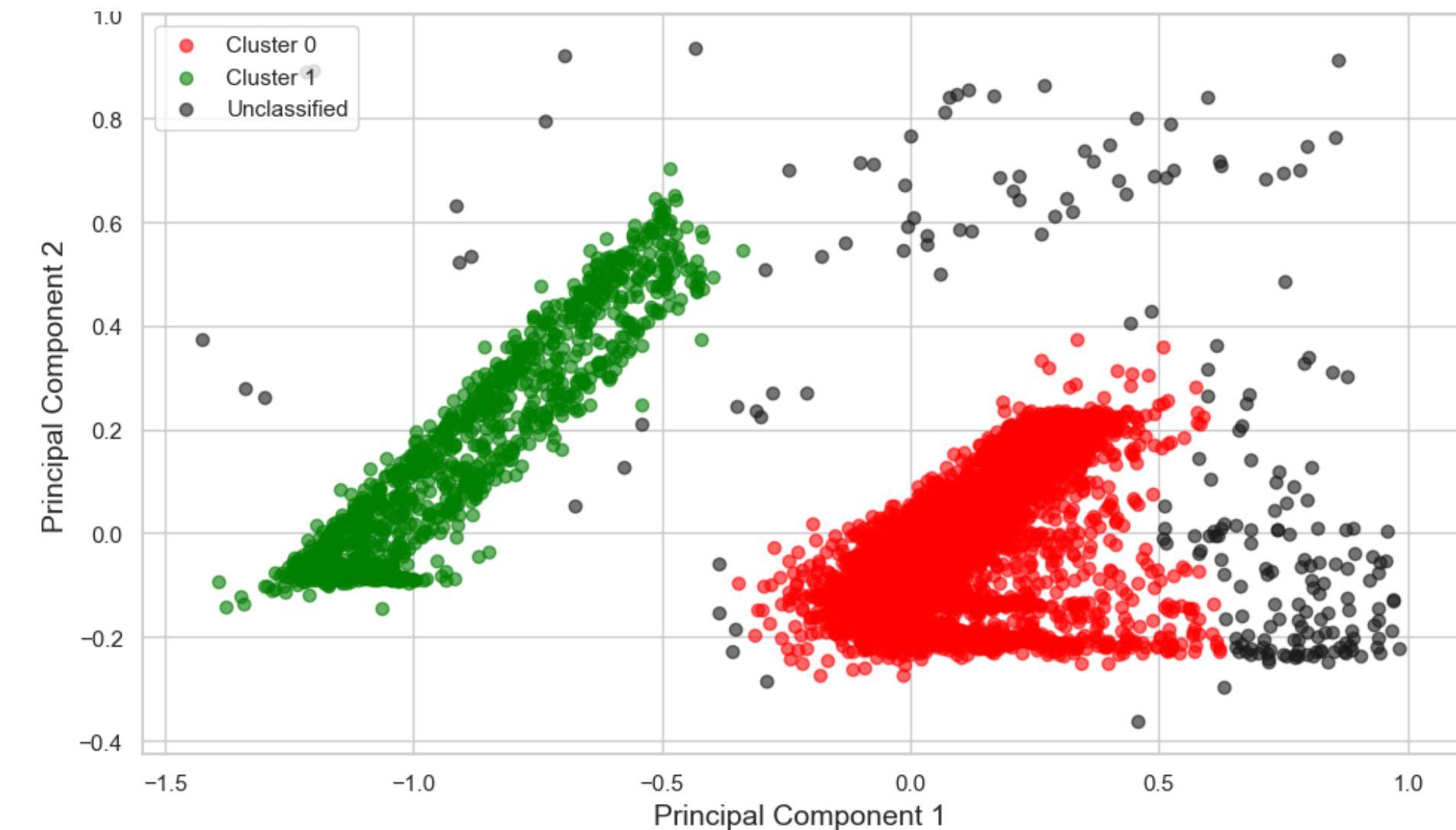
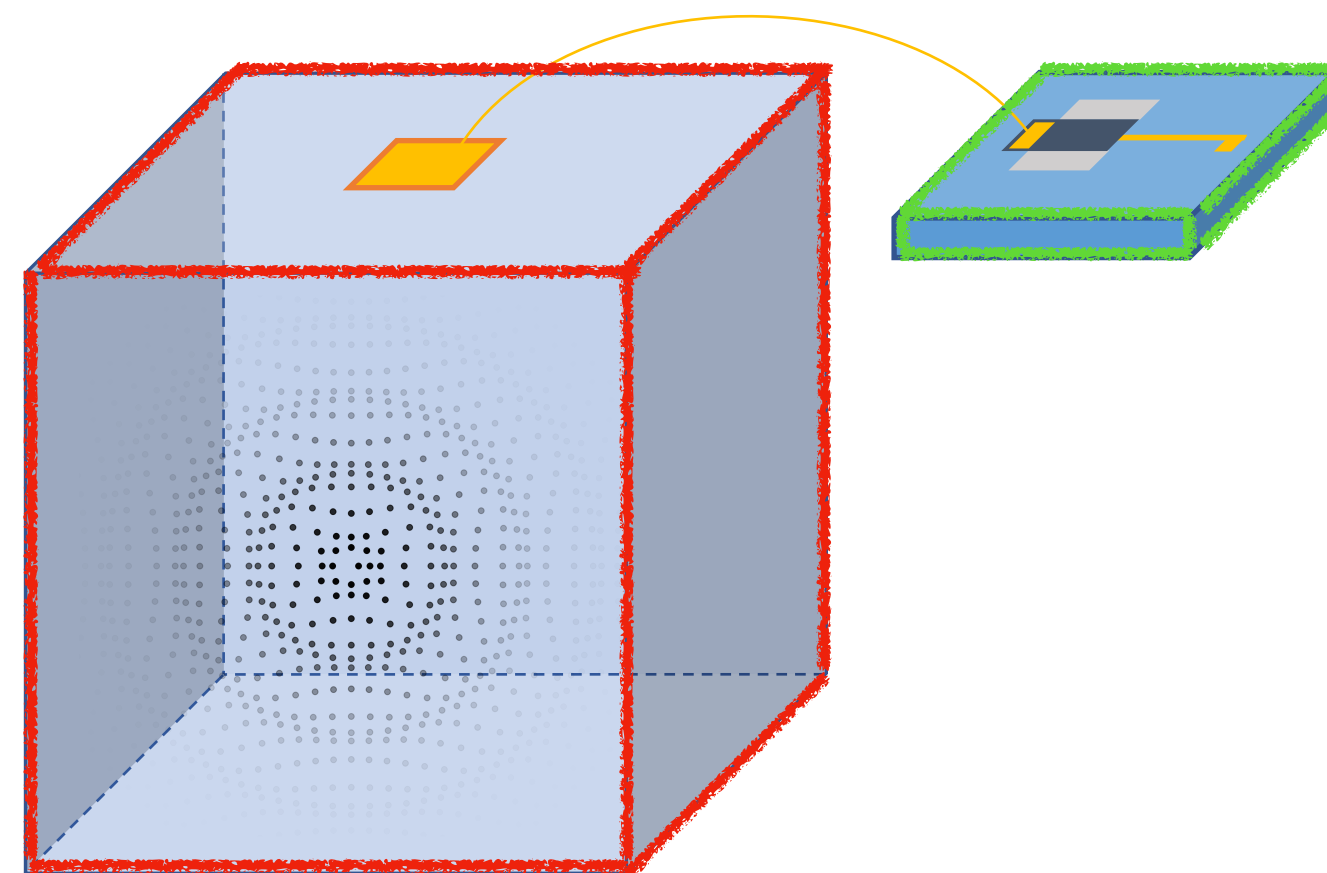
Classify Event types

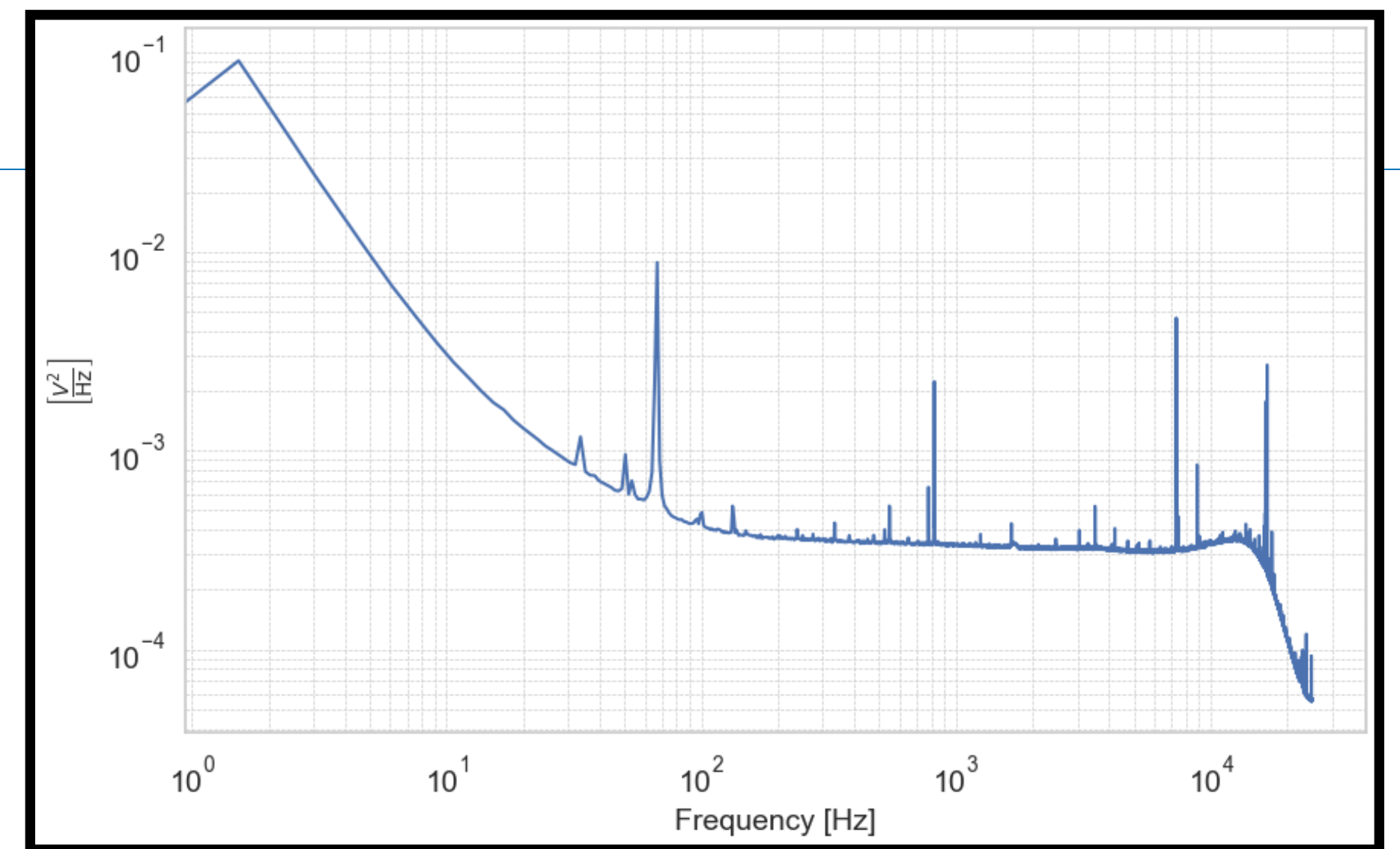
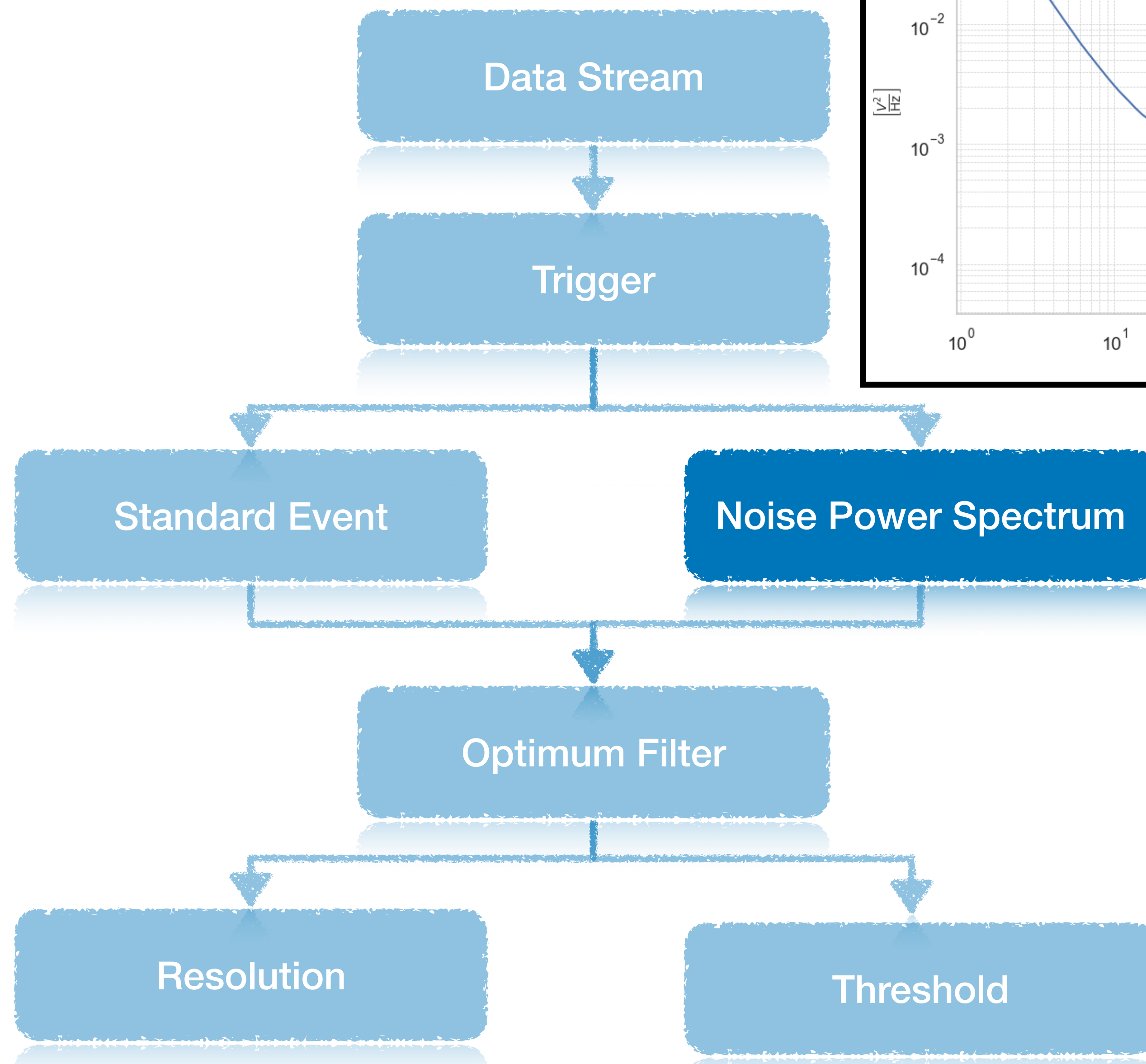
- Possible approach
 - ➡ Apply principal component analysis
 - ➡ Cluster with DBSCAN
(Density-Based Spatial Clustering of Applications with Noise)
 - ➡ Create average pulse of clusters and select pulse shape of absorber events



Classify Event types

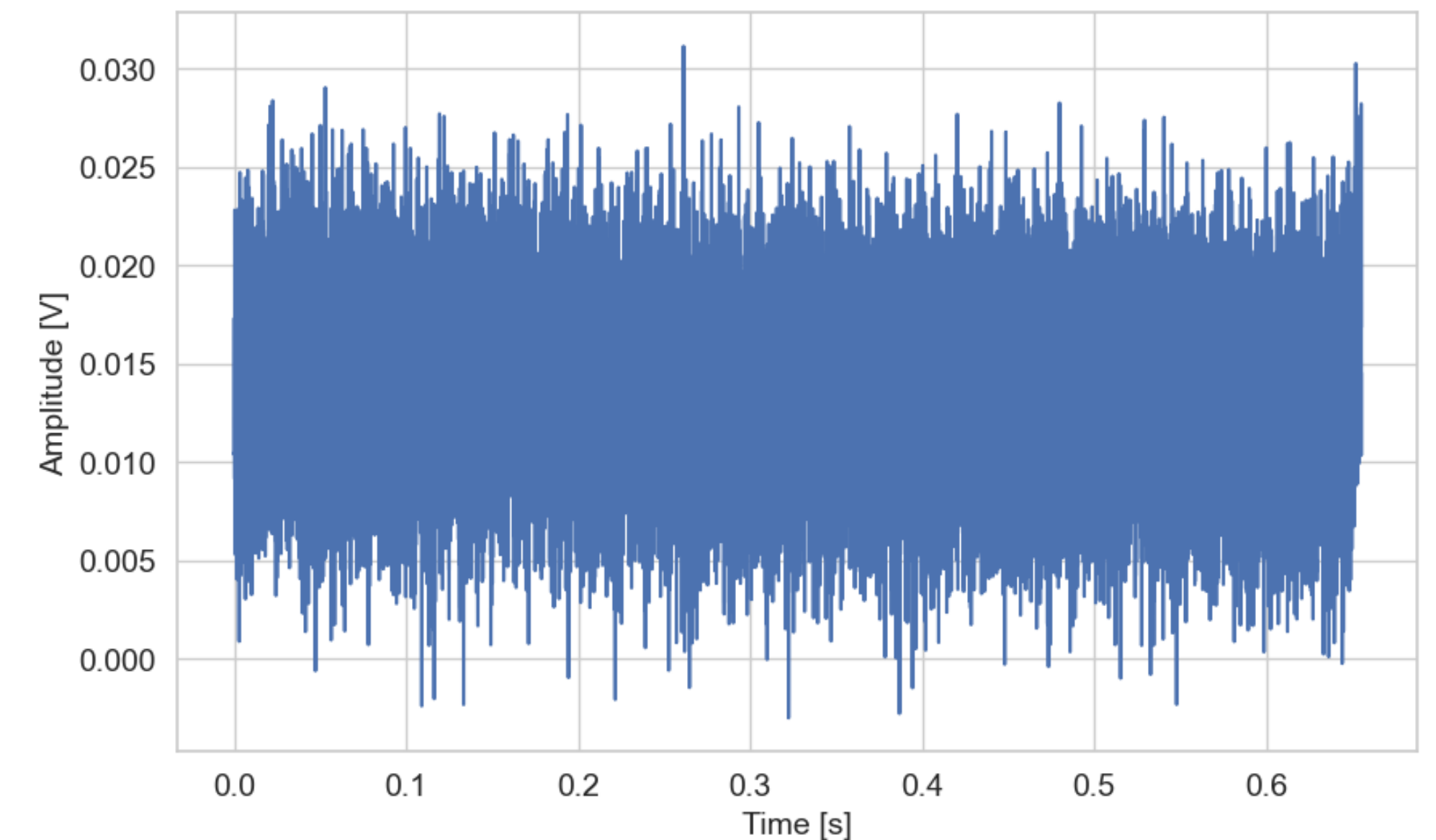
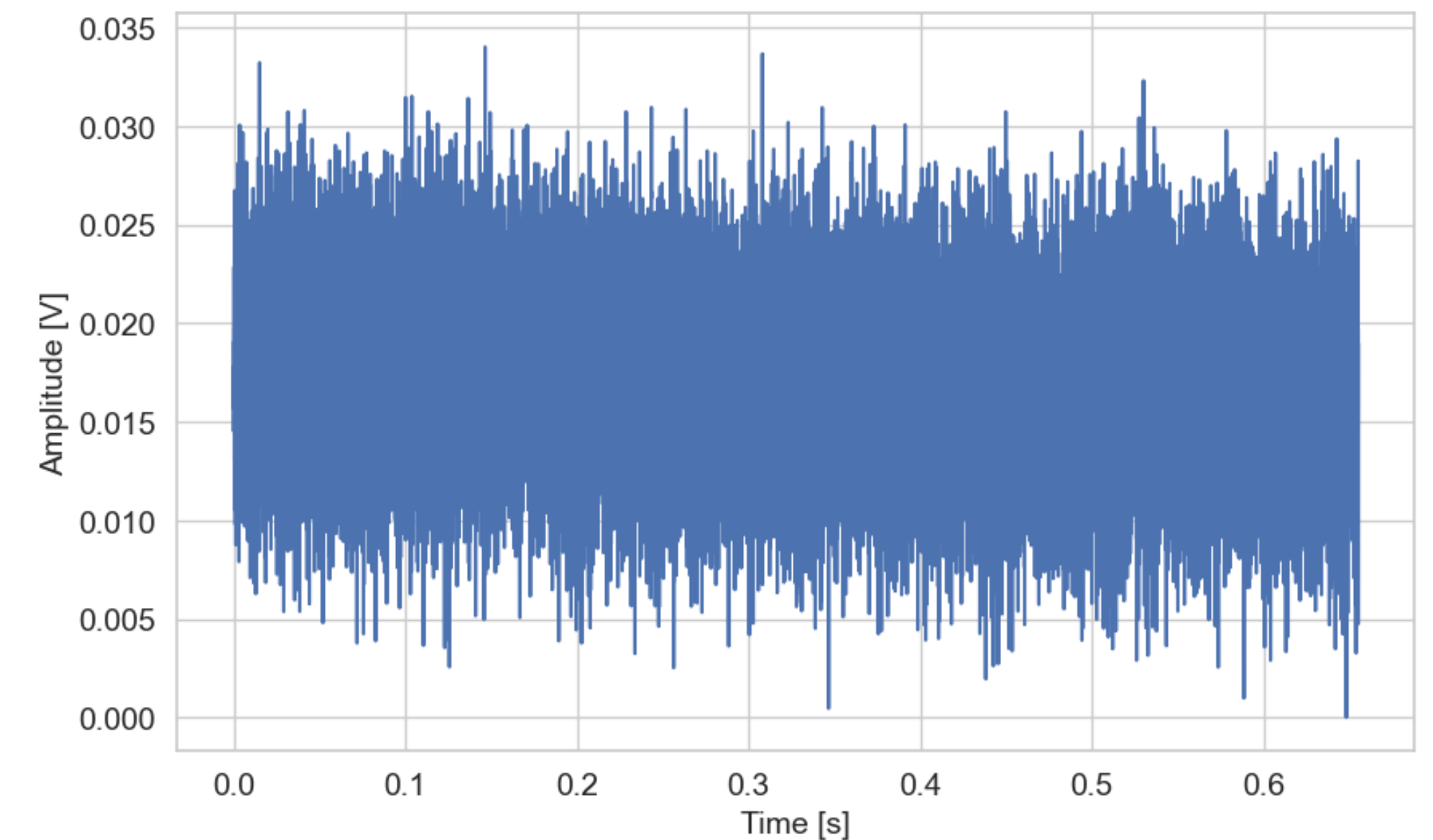
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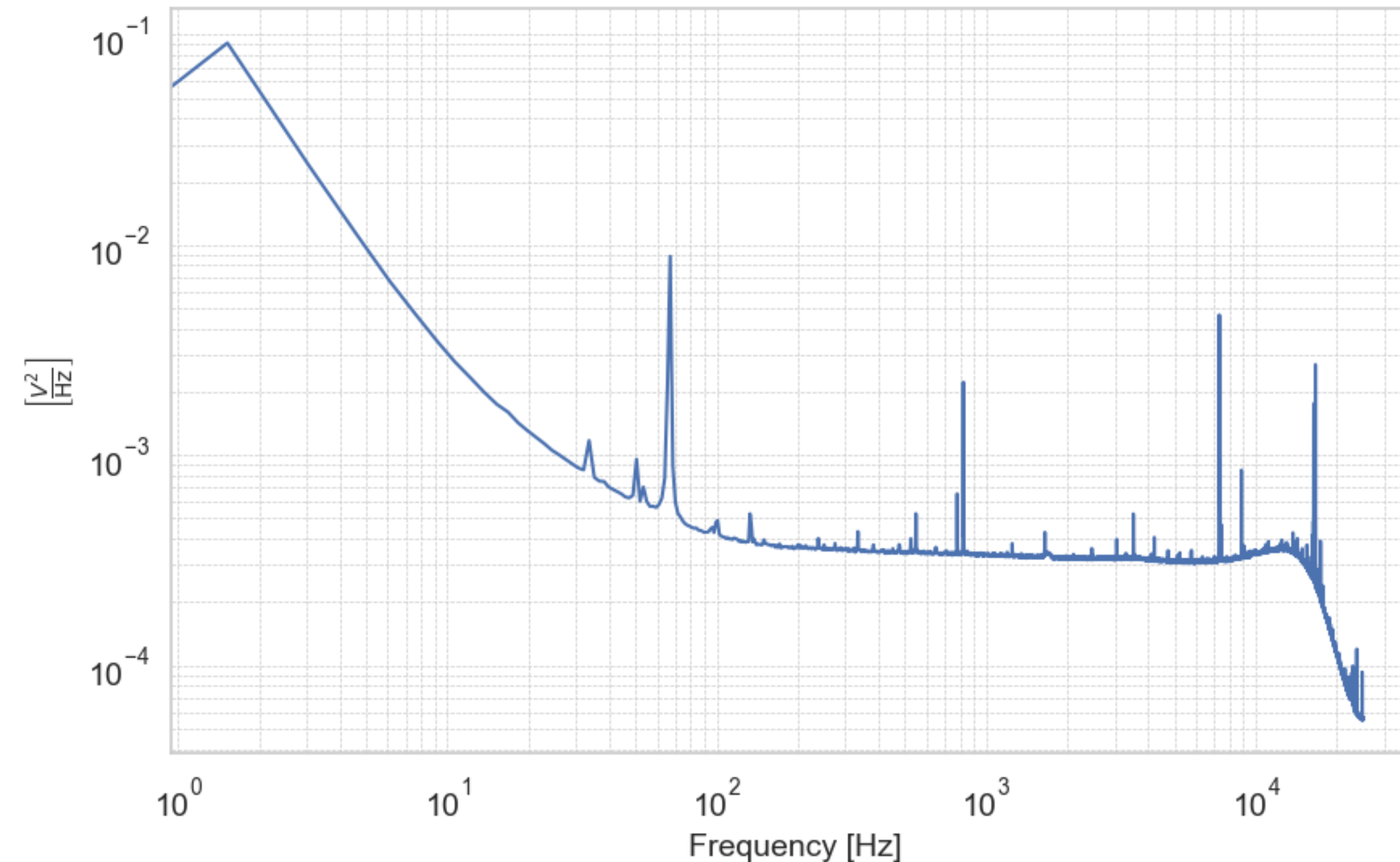
Characterize the Noise

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



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



What's next?

- Tools soon available in analysis packages Cait and CAT



Thank you for your attention

What's next?

- Tools soon available in analysis packages Cait and CAT



Backup

Summer Run

	HANDMADE OF	GENERATED OF
RESOLUTION [mV]	0.420 ± 0.002	0.377 ± 0.002
THRESHOLD [mV]	2.62	2.26
ENERGY RECONSTRUCTION	Linear $0.9886x + 0.0001$	Linear $0.99363x + 0.0001$

Christmas Run

	HANDMADE OF	GENERATED OF
RESOLUTION [mV]	2.90 ± 0.03	2.35 ± 0.02
THRESHOLD [mV]	10.0	10.0
ENERGY RECONSTRUCTION	Linear $0.984x + 0.002$	Linear $0.975x + 0.001$

Generalized filter

- To understand the generalized filter better it is instructive to revisit the regular OF
- A statistical model consists of a known template scaled with some amplitude, with some additive Gaussian noise
- An inner product In the Fourier domain can be defined and the likelihood function can be purely expressed in this.

arxiv: 1109.0442

Model

$$d = As + n$$

Amplitude
Template
Noise

log-likelihood

$$\log \Lambda(d | A) = -\frac{1}{2} \langle \tilde{d} | \tilde{d} \rangle + A \langle \tilde{d} | \tilde{s} \rangle - \frac{A^2}{2} \langle \tilde{s} | \tilde{s} \rangle$$

Fourier domain inner product

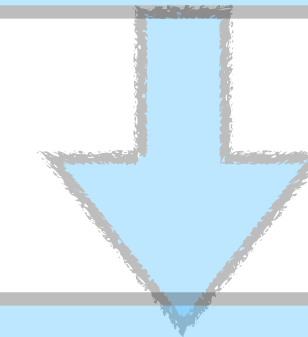
$$\langle \tilde{x} | \tilde{y} \rangle \equiv \frac{2\Delta t}{N} \sum_{k=0}^{N/2} \omega_k \frac{\tilde{x}_k^* \tilde{y}_k}{S_1(f_k)} \quad \omega_k = \begin{cases} 1, & k=0, N/2, \\ 2, & \text{else.} \end{cases}$$

Generalized filter

- By differentiating the log-likelihood the maximum likelihood (ML) estimator for the pulse amplitude is derived

log-likelihood

$$\log \Lambda(d|A) = -\frac{1}{2} \langle d|d \rangle + A \langle \tilde{d}|\tilde{s} \rangle - \frac{A^2}{2} \langle \tilde{s}|\tilde{s} \rangle$$



differentiation

ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{d}|\tilde{s} \rangle}{\langle \tilde{s}|\tilde{s} \rangle}$$

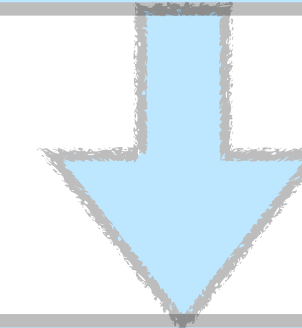
$$\text{Var}(\hat{A}_0) = \frac{1}{\langle \tilde{s}|\tilde{s} \rangle}$$

Generalized filter

- By differentiating the log-likelihood the maximum likelihood (ML) estimator for the pulse amplitude is derived

log-likelihood

$$\log \Lambda(d|A) = -\frac{1}{2} \langle \tilde{d} | \tilde{d} \rangle + A \langle \tilde{d} | \tilde{s} \rangle - \frac{A^2}{2} \langle \tilde{s} | \tilde{s} \rangle$$



differentiation

ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{d} | \tilde{s} \rangle}{\langle \tilde{s} | \tilde{s} \rangle}$$

$$\text{Var}(\hat{A}_0) = \frac{1}{\langle \tilde{s} | \tilde{s} \rangle}$$

Best possible resolution we can get

Generalized filter

- Model baseline trends with polynomial
-

Extended model

$$d = As + n + a_j b^{(j)}$$

Amplitude
Template
Noise
Polynomial

new log-likelihood

$$\log \Lambda(d|A) = -\frac{1}{2} \langle \tilde{d} | \tilde{d} \rangle + A \langle \tilde{d} | \tilde{s} \rangle + a^T \delta - \frac{A^2}{2} \langle \tilde{s} | \tilde{s} \rangle - A a^T \sigma - \frac{1}{2} a^T G a$$

$$G_{i,j} \equiv \langle \tilde{b}^{(j)} | \tilde{b}^{(j)} \rangle$$

$$\delta_j \equiv \langle \tilde{b}^{(j)} | \tilde{d} \rangle$$

$$\sigma_j \equiv \langle \tilde{b}^{(j)} | \tilde{s} \rangle$$

New ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{s} | \tilde{d} \rangle - \sigma^T G^{-1} \delta}{\sigma^T G^{-1} \sigma} = \frac{\langle \tilde{s} - \tilde{s}_p | \tilde{d} \rangle}{\langle \tilde{s} - \tilde{s}_p | \tilde{s} \rangle}$$

$$Var(\hat{A}_0) = \frac{1}{\langle \tilde{s} | \tilde{s} \rangle - \sigma^T G^{-1} \sigma}$$

s_p = Template with polynomial part removed

New ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{s} | \tilde{d} \rangle - \sigma^T G^{-1} \delta}{\sigma^T G^{-1} \sigma} = \frac{\langle \tilde{s} - \tilde{s}_p | \tilde{d} \rangle}{\langle \tilde{s} - \tilde{s}_p | \tilde{s} \rangle}$$

$$Var(\hat{A}_0) = \frac{1}{\langle \tilde{s} | \tilde{s} \rangle - \sigma^T G^{-1} \sigma}$$

Reduced resolution

ML amplitude estimator and its variance

$$\hat{A} = \frac{\langle \tilde{d} | \tilde{s} \rangle}{\langle \tilde{s} | \tilde{s} \rangle}$$

$$Var(\hat{A}_0) = \boxed{\frac{1}{\langle \tilde{s} | \tilde{s} \rangle}}$$

Best possible resolution we can get