XENON

清華大學 Tsinghua University

Accidental Coincidence Background in XENONnT

for Low Energy Nuclear Recoil Searches

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Tsinghua University

On behalf of XENON collaboration

15th International Workshop on the Identification of Dark Matter

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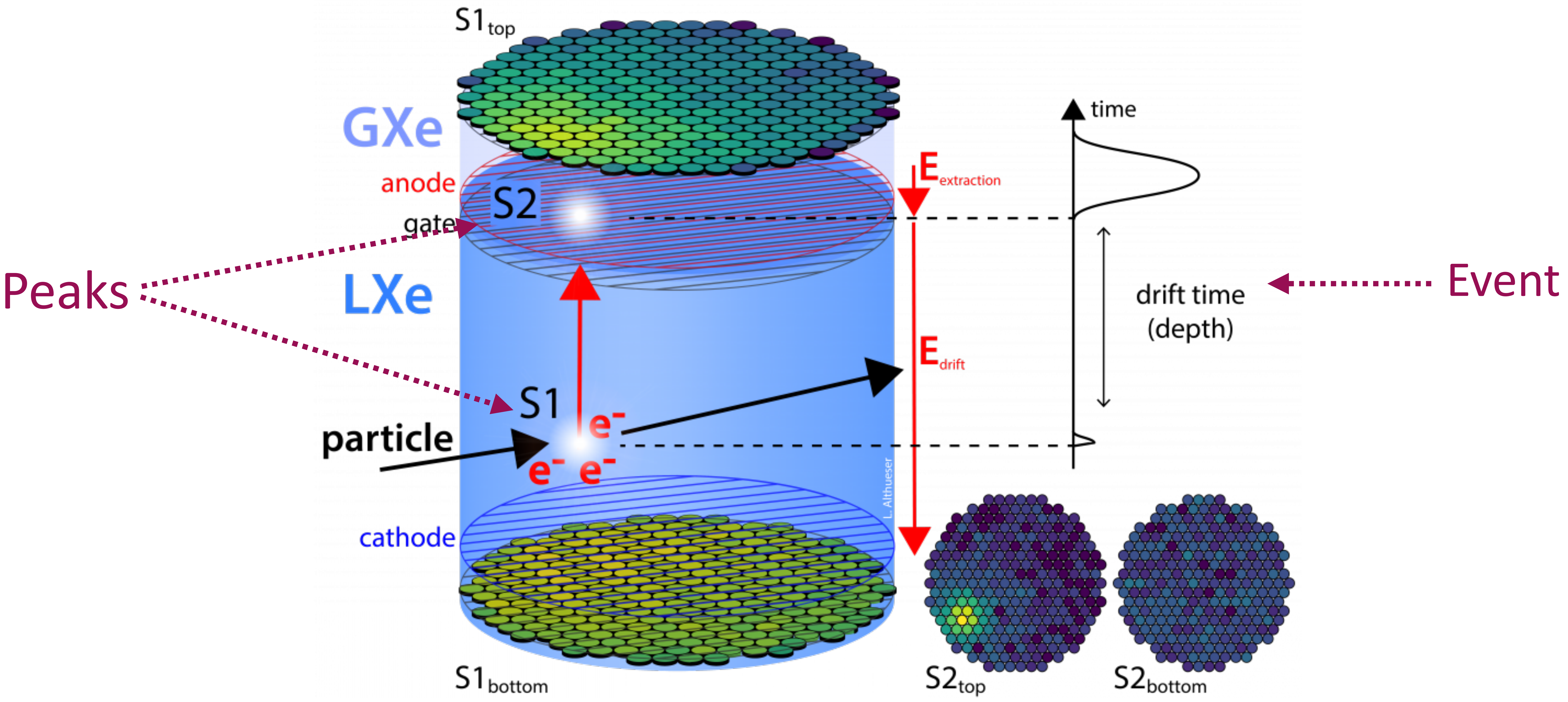
XENONnT Detector and Event Building

Two-Phase LXe TPC



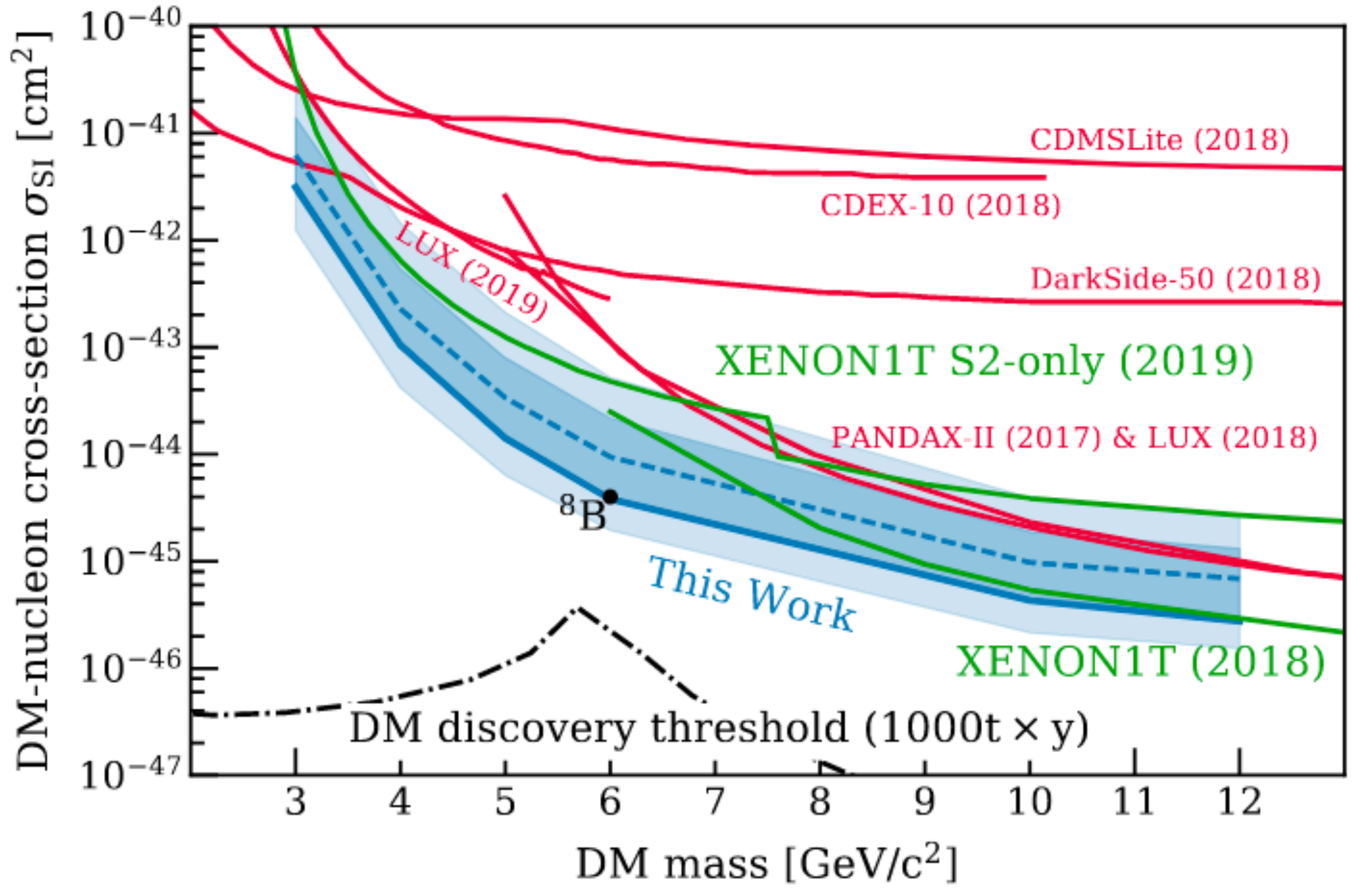
arXiv:2402.10446 accepted at Eur. Phys. J. C

Accidental Coincidence

- In XENON1T B8/light WIMP Search

Phys. Rev. Lett. 126, 091301 (2021)

Source	Expectation
CEvNS	2.11
Accidental	5.14
ER	0.21
Radiogenic	0.03
Total	7.65
Observed	6



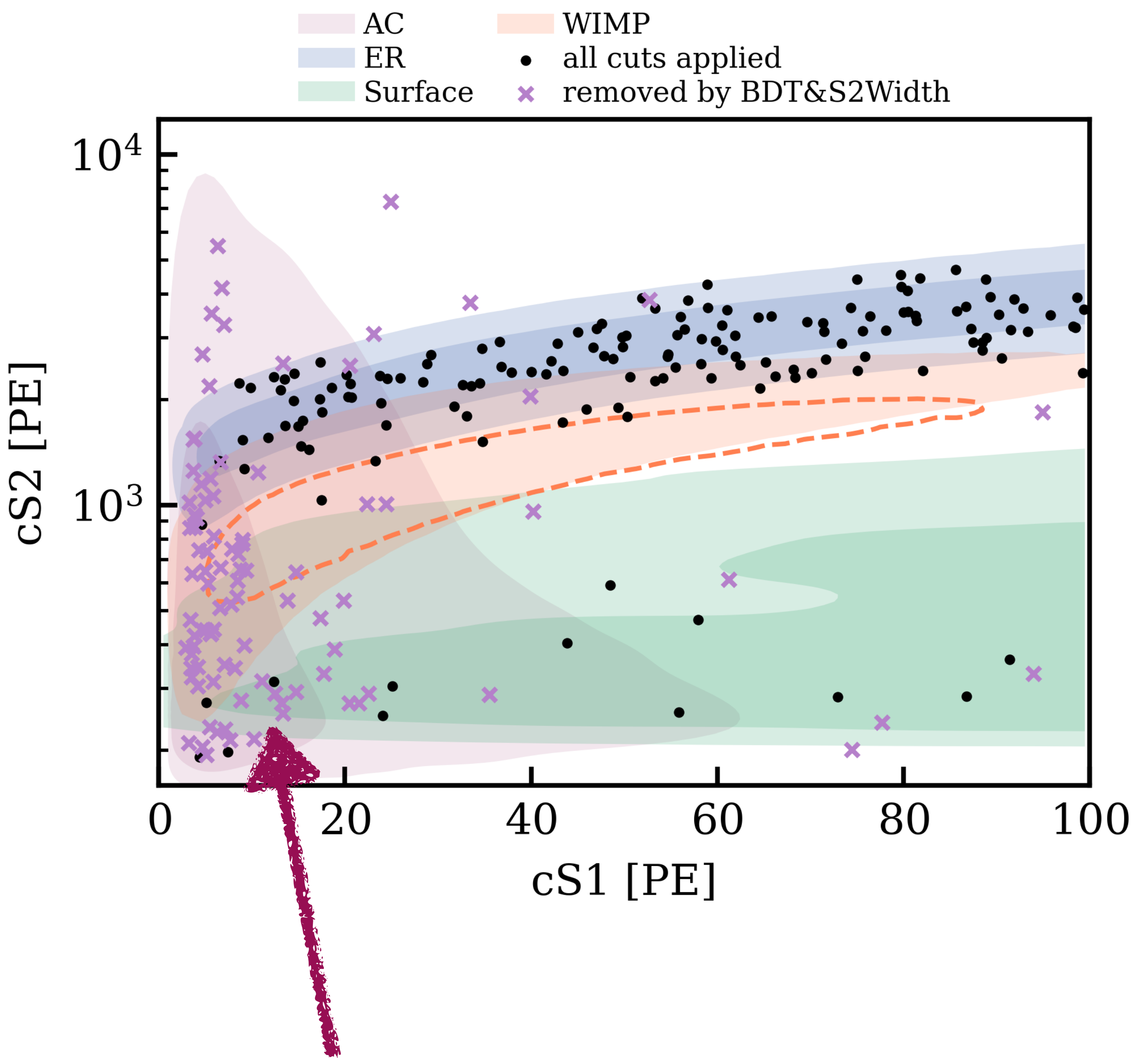
- In XENONnT WIMP Search

Phys. Rev. Lett. 131, 041003 (2023)

WIMP Dark Matter searches with the XENONnT experiment
Henning Schulze Eißing
Today-14:20

WIMP search results

	Nominal	Best Fit (200 GeV/c²)
ER	134	135(+12)(-11)
Neutrons	1.1(+0.6)(-0.5)	1.1 ± 0.4
CEvNS	0.23 ± 0.06	0.23 ± 0.06
AC	4.3 ± 0.2	4.32 ± 0.16
Surface	14 ± 3	12(+0)(-4)
Total Background	154	152 ± 12
WIMP	-	2.6
Observed	-	152

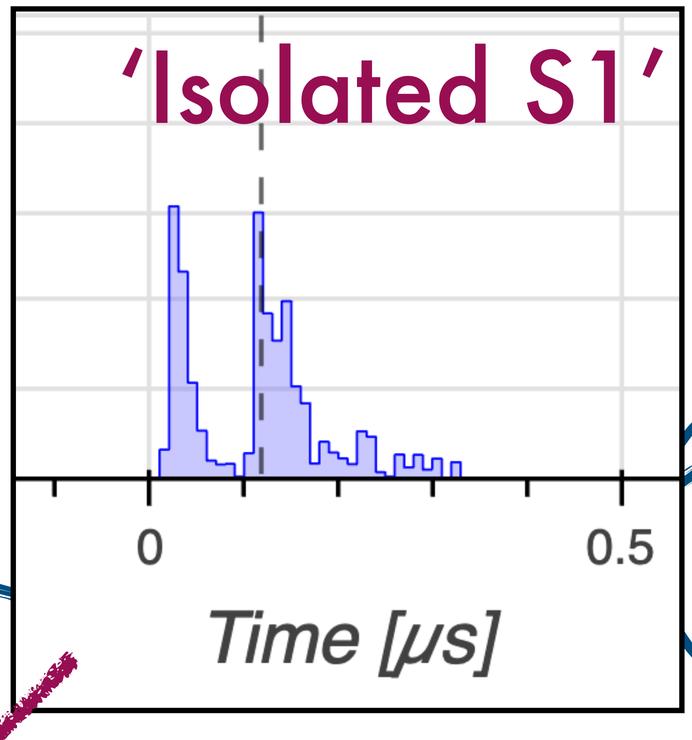


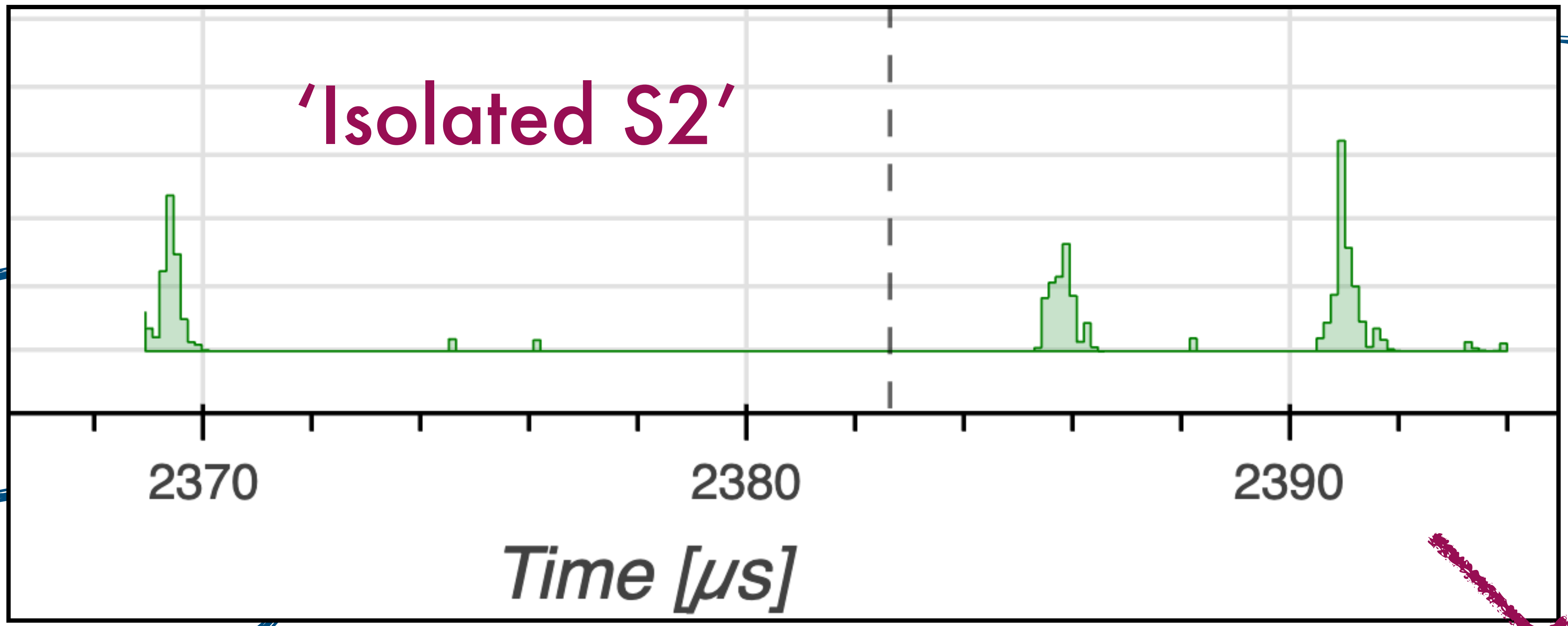
AC events removed by dedicated cuts.

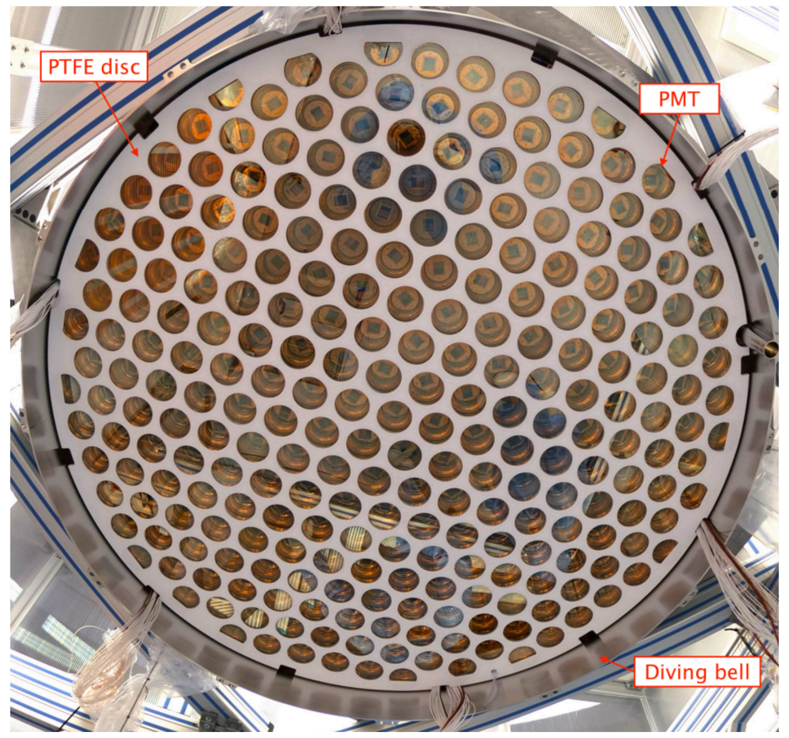
Accidental Coincidence in XENONnT

The dominant background in low energy nuclear recoil search

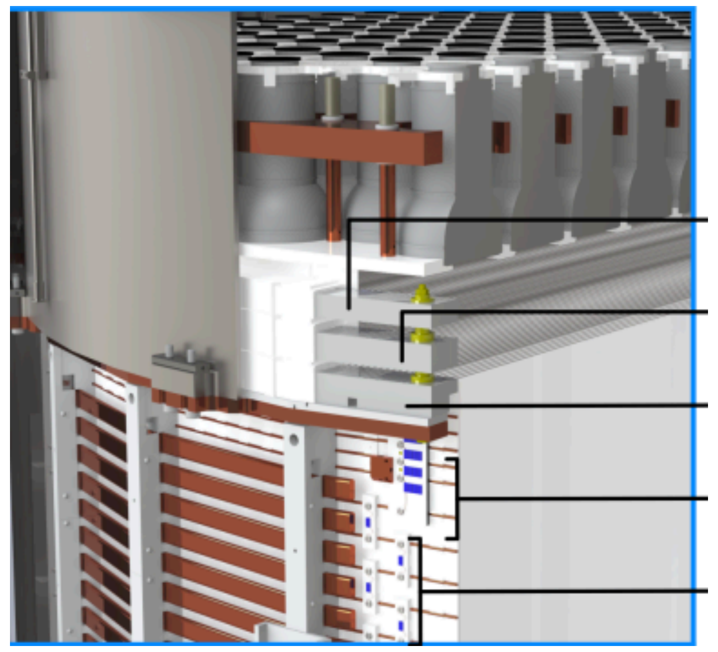
Accidentally pair S1 and S2 peaks







$$Rate_{AC} = \int_{t_0}^{t_1} R_{S1}(t) \times R_{S2}(t) \times T_{max} dt$$



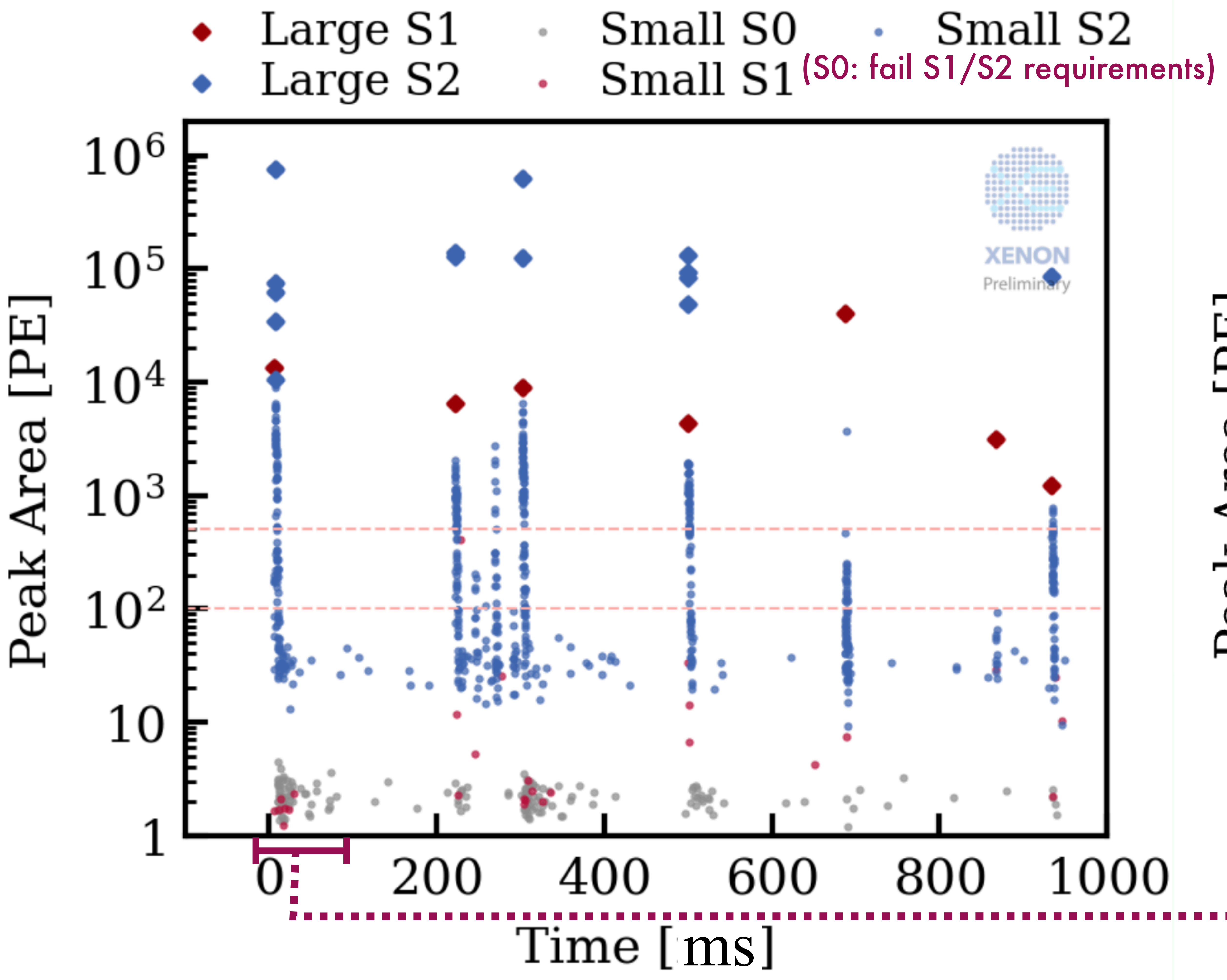
In low energy NR ROI: (S1 2/3 hits, S2 from few to dozens electrons)

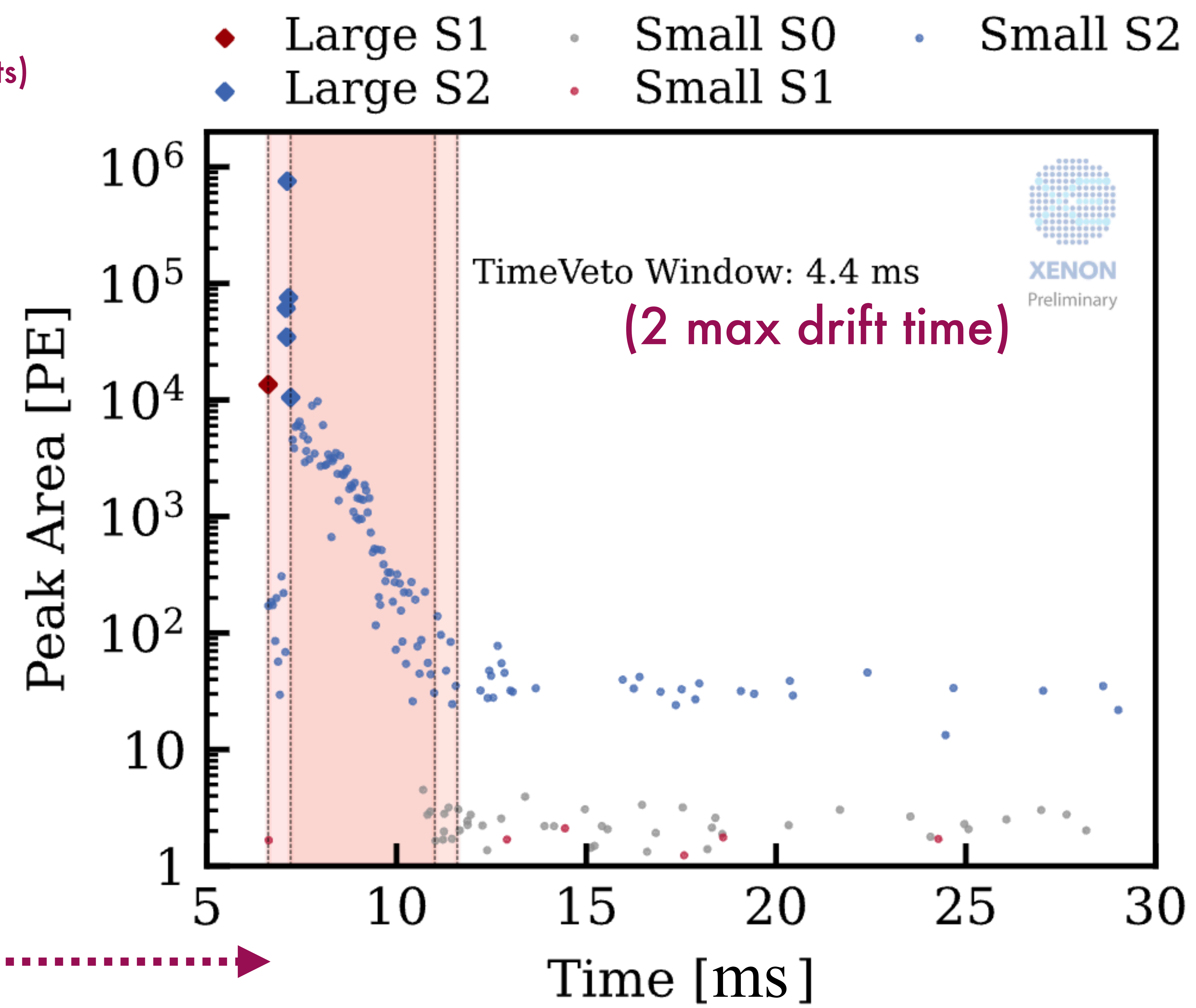
Iso-S1 Rate	Iso-S2 Rate	T max	Raw AC Rate
~ 15 Hz	~ 0.15 Hz	2.25 ms	5 mHz (~400/day)

20 V/cm drift field

1 Second in the data …

How to find clean enough exposure?

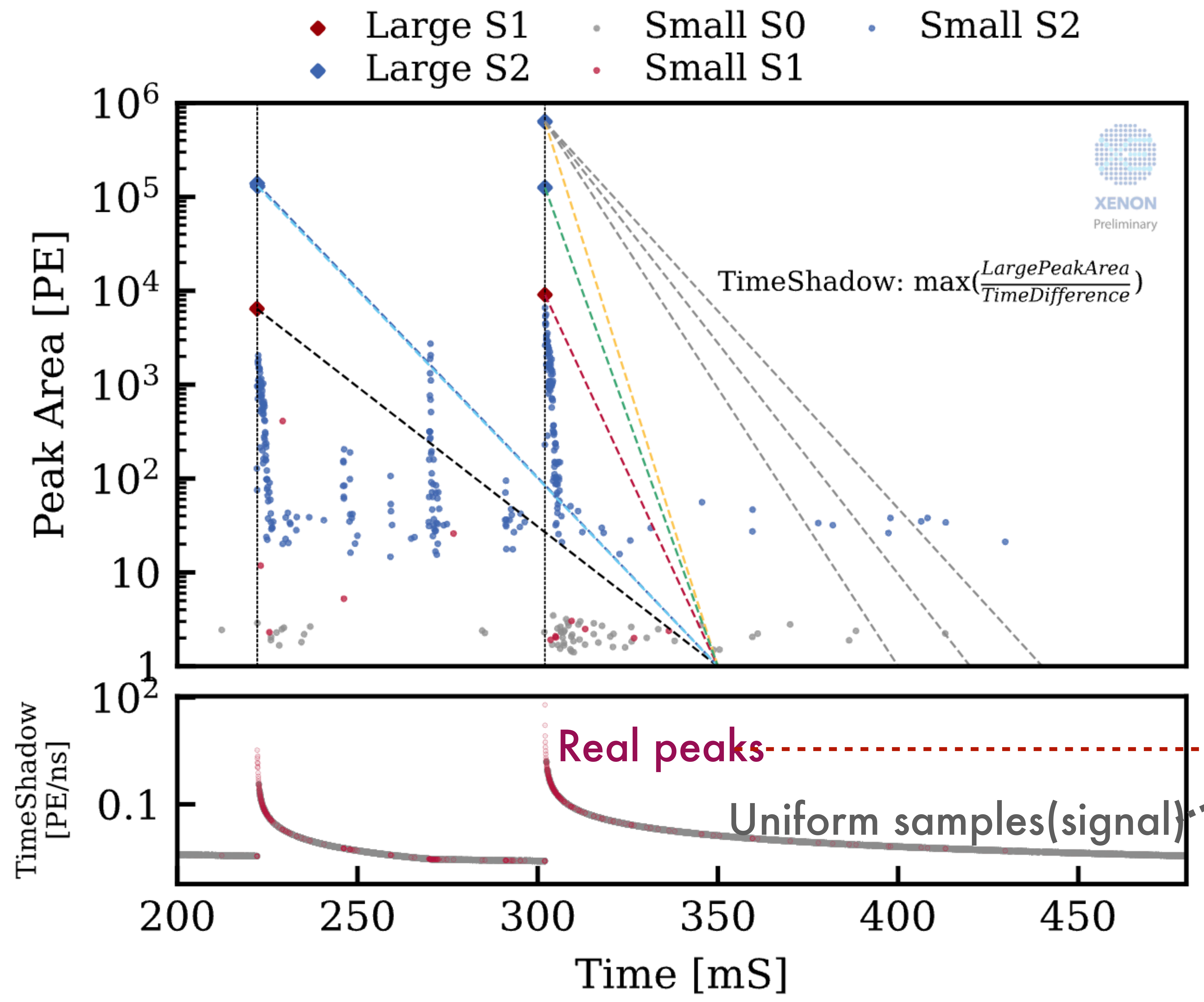


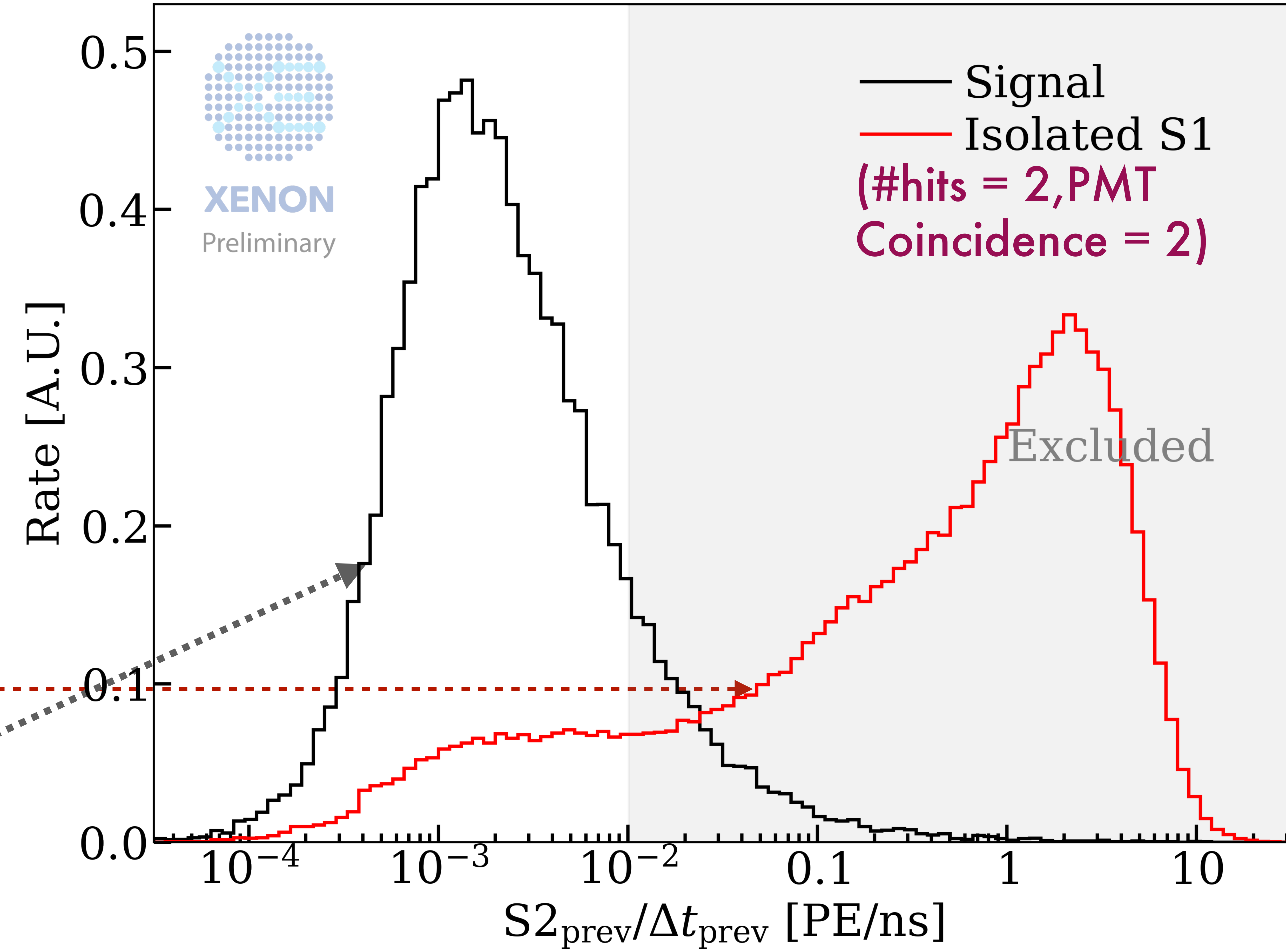


- Goal: Less iso-S1/S2 for better model

Time Shadow

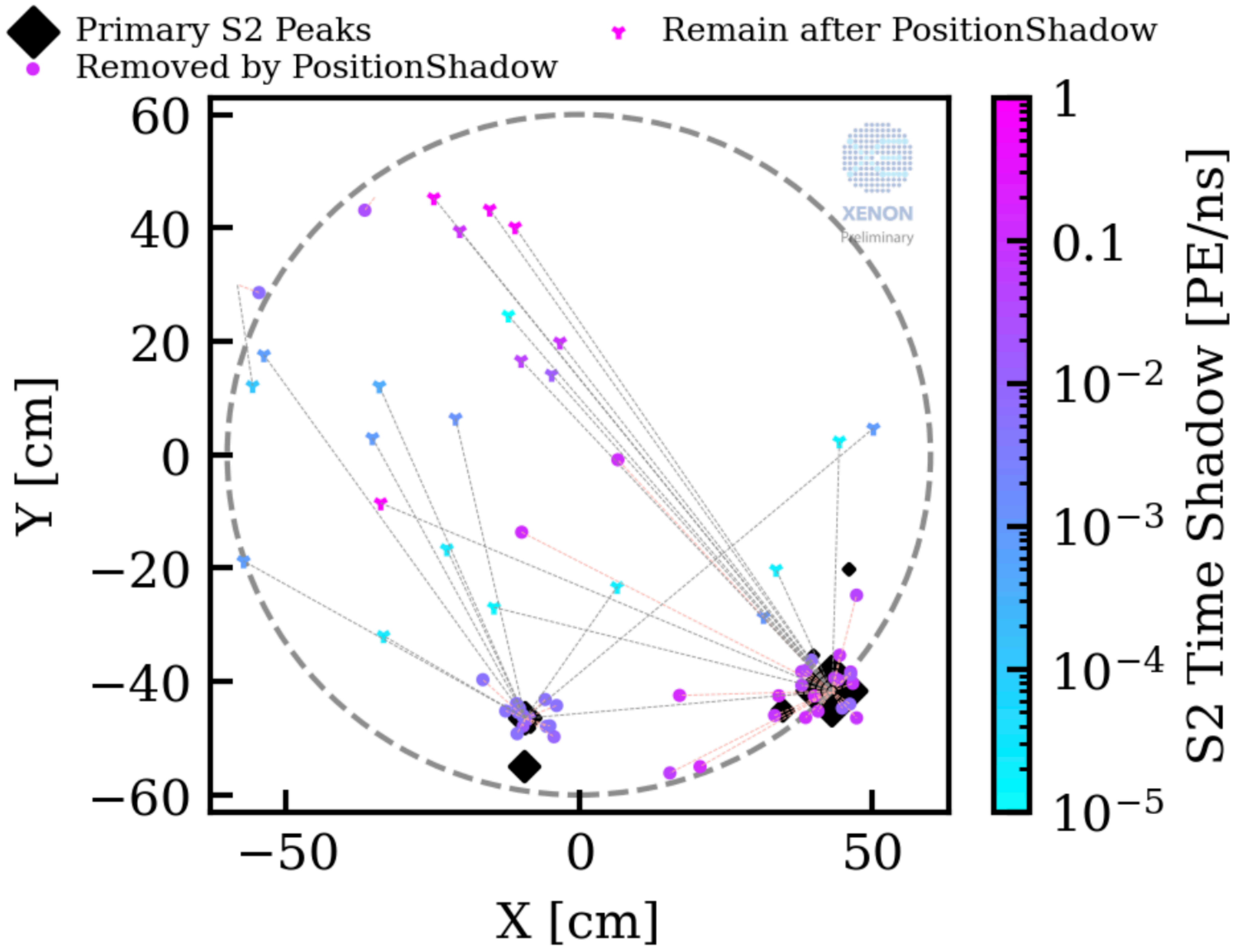
Quantify the cleanliness of the exposure

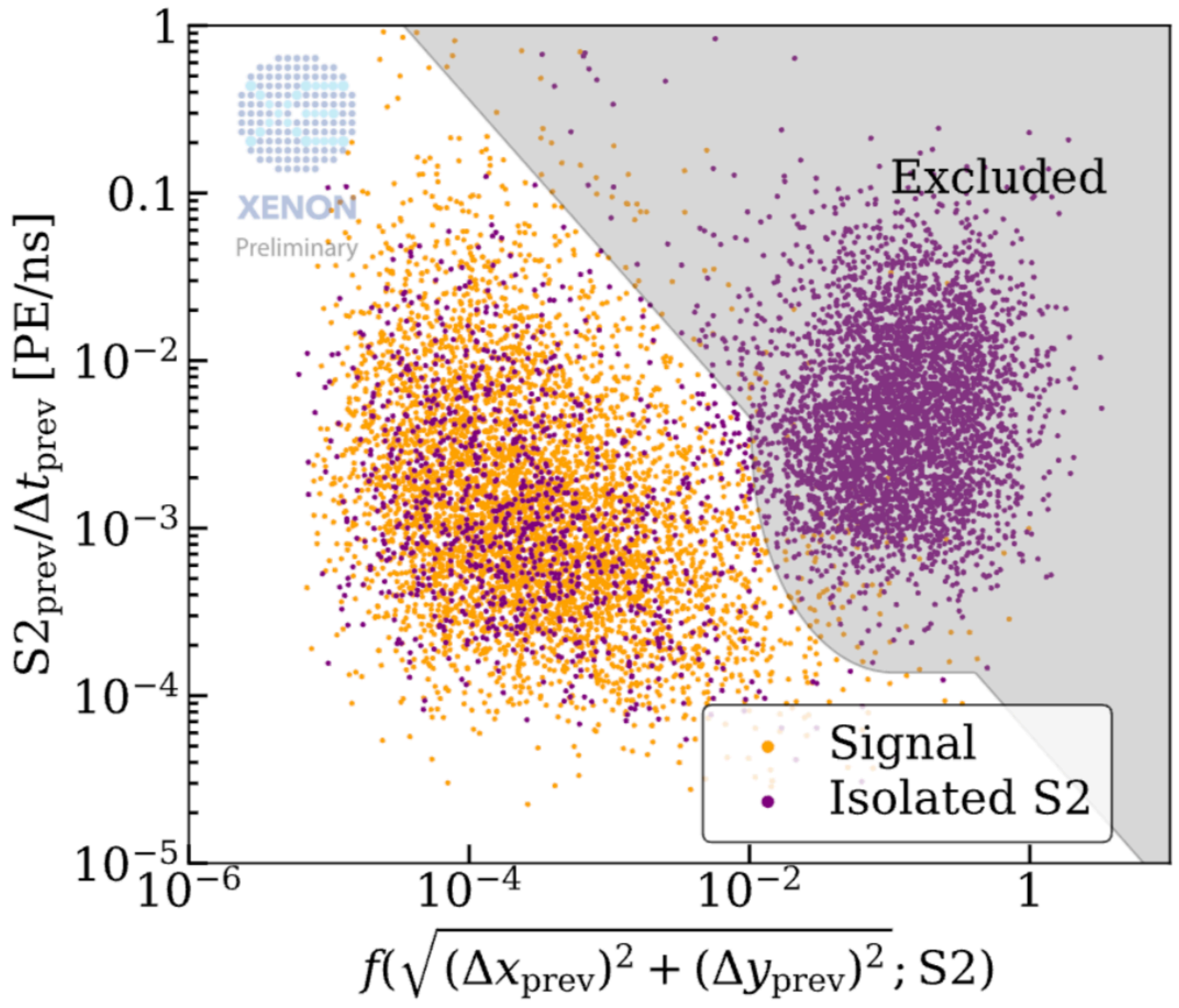




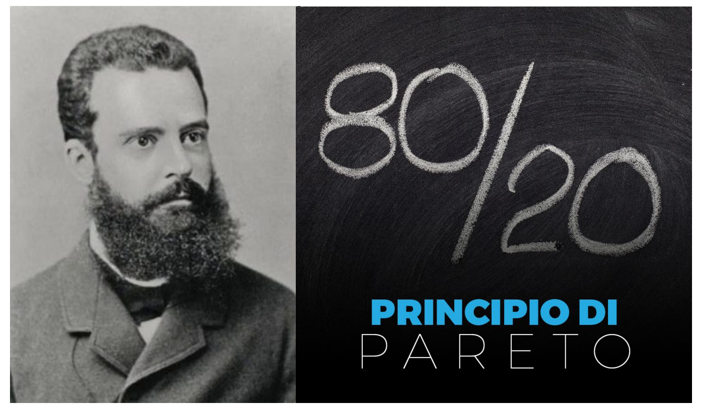
Shadow Cut (Time + Position)

Remove the time&space contains the most IsoS1/S2



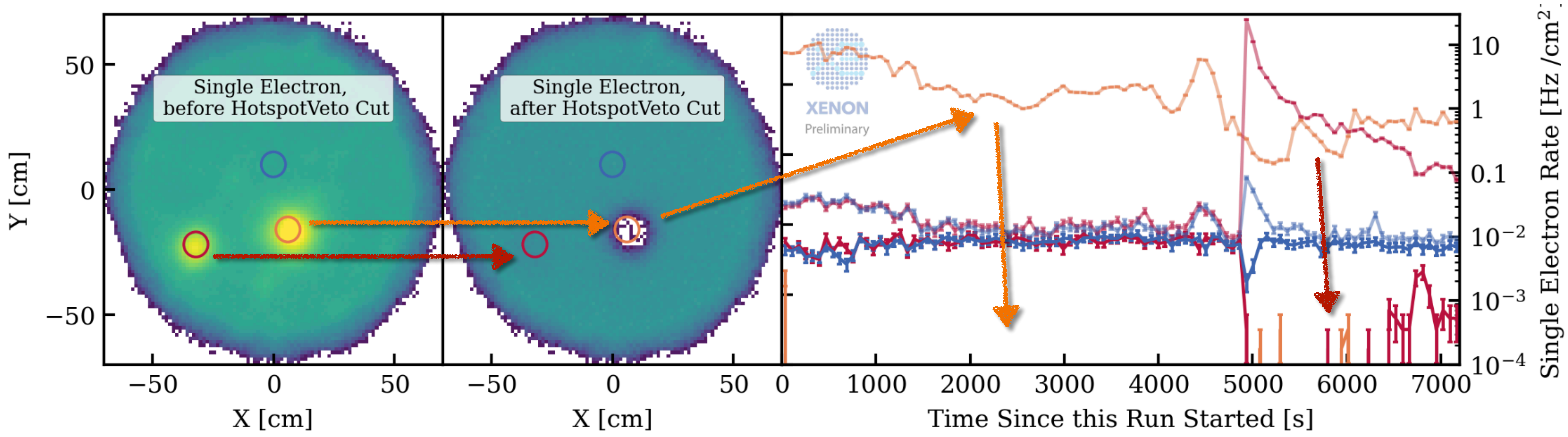


- Cut threshold set to remove the worst 20% of time & space.



Following this idea

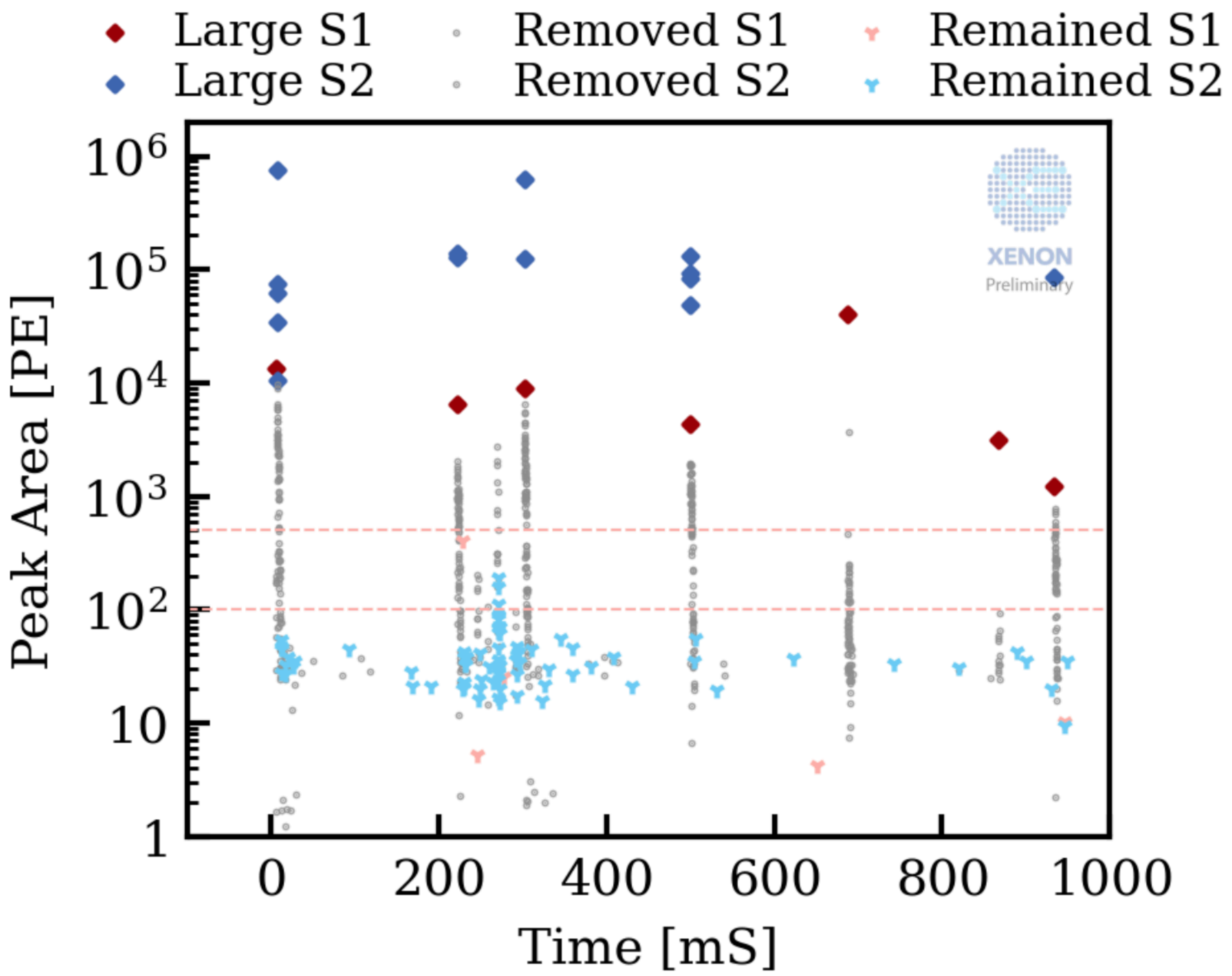
To deal with detector's imperfections— hotspot veto



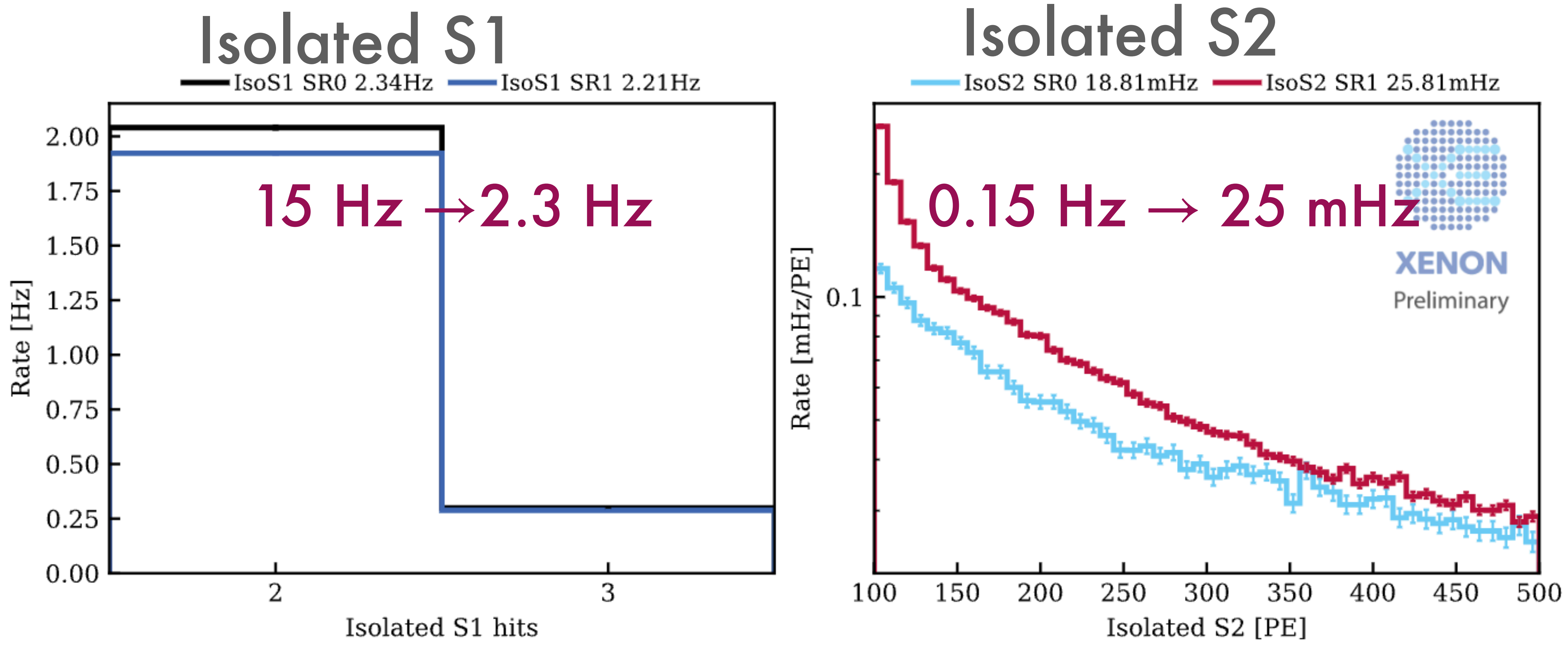
- Sit in hotspot (localized single electron burst)? —— "Hotspot Veto" selection: Remove those with more adjacent single electrons than normal; **only** remove the contaminated **time&space**.
- Sit in 'fuzzy' environment? —— "Ambience" selection: remove those peaks/events with too much S1, S2, S0, lone hits in the neighborhood

Combined efforts of suppress isolated peaks

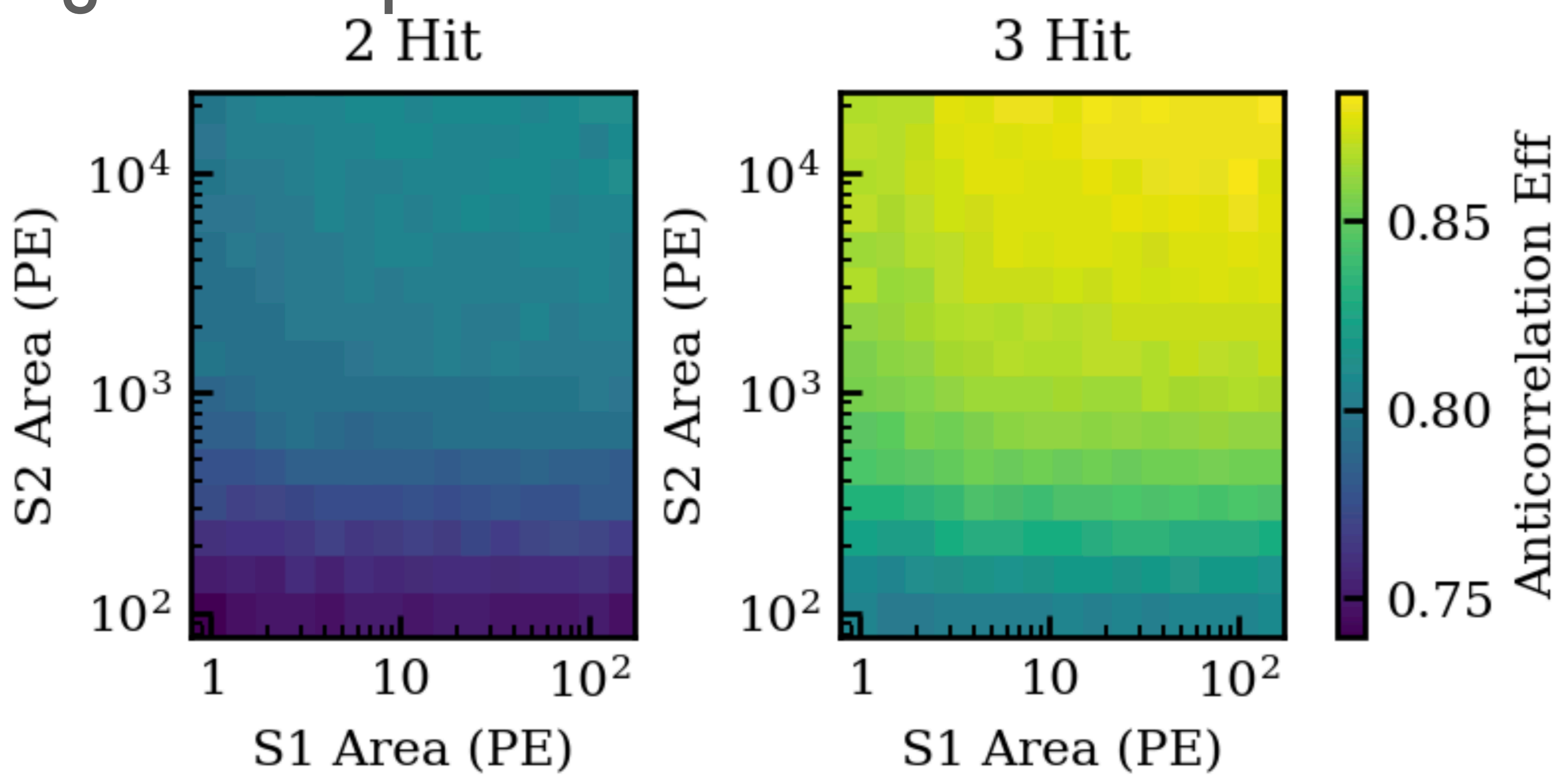
Isolated peaks suppressed vs. signal acceptance



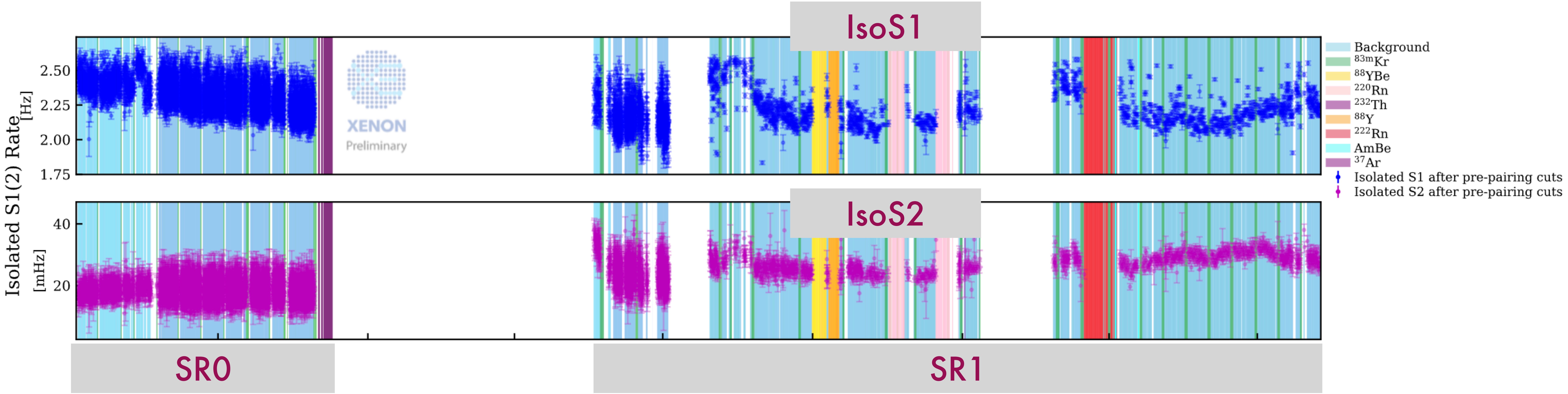
After the time&space correlation cuts, the majority of isolated peaks is removed.



Signal acceptance evaluated:



Data-driven simulation for AC Model



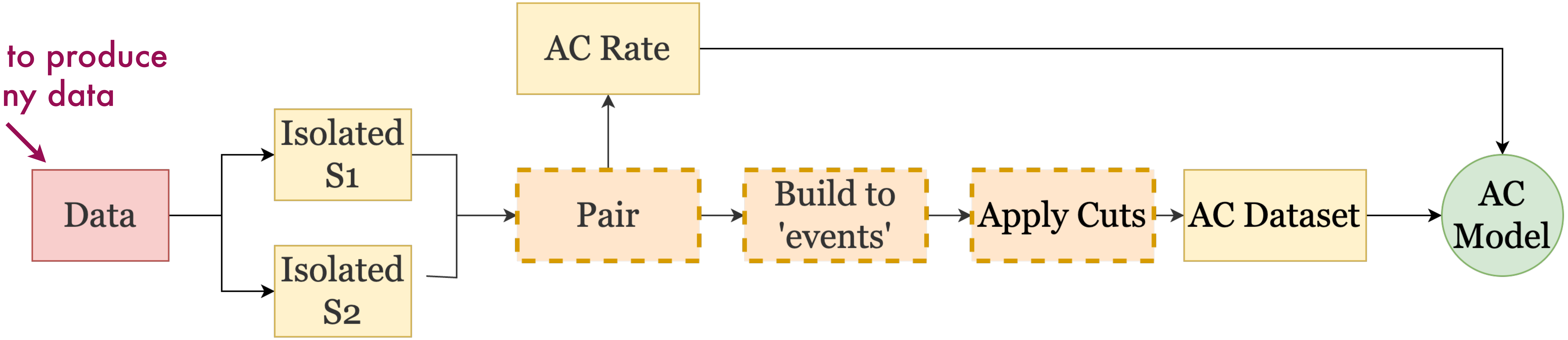
axidence 0.3.1

`pip install axidence`

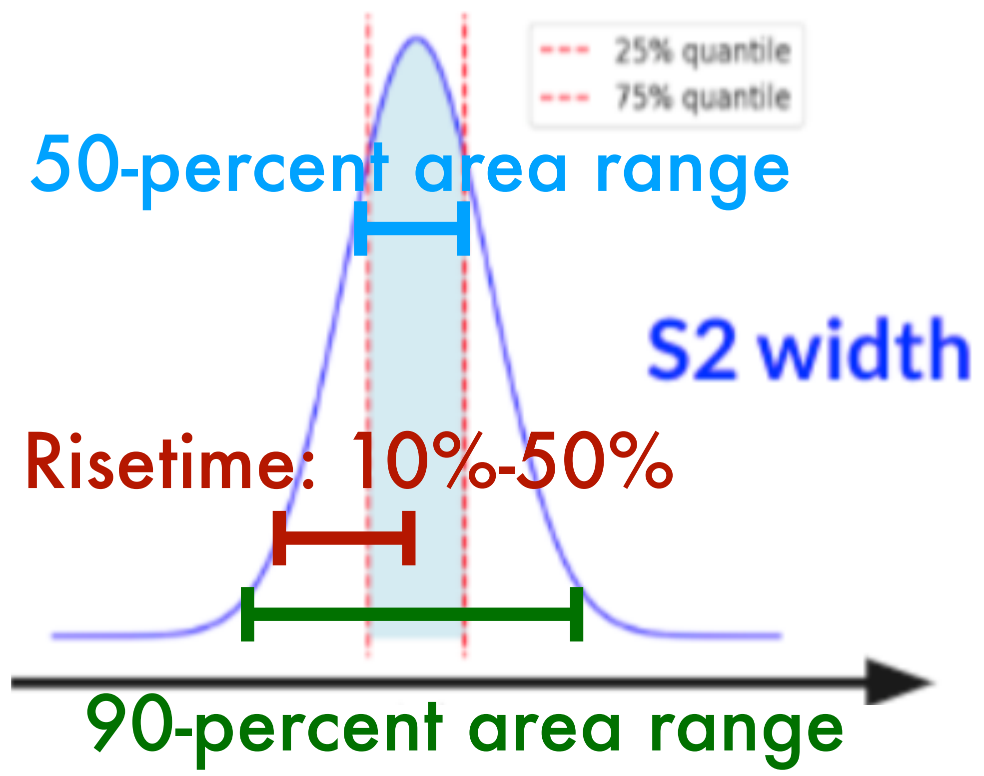
dachengx

- Stream-like structure: Bootstrap, pair(assign drift time + match time shadow), then go through event-building.

Change the input to produce AC datasets for any data



XENON Fuse: Framework for Unified Simulation of Events

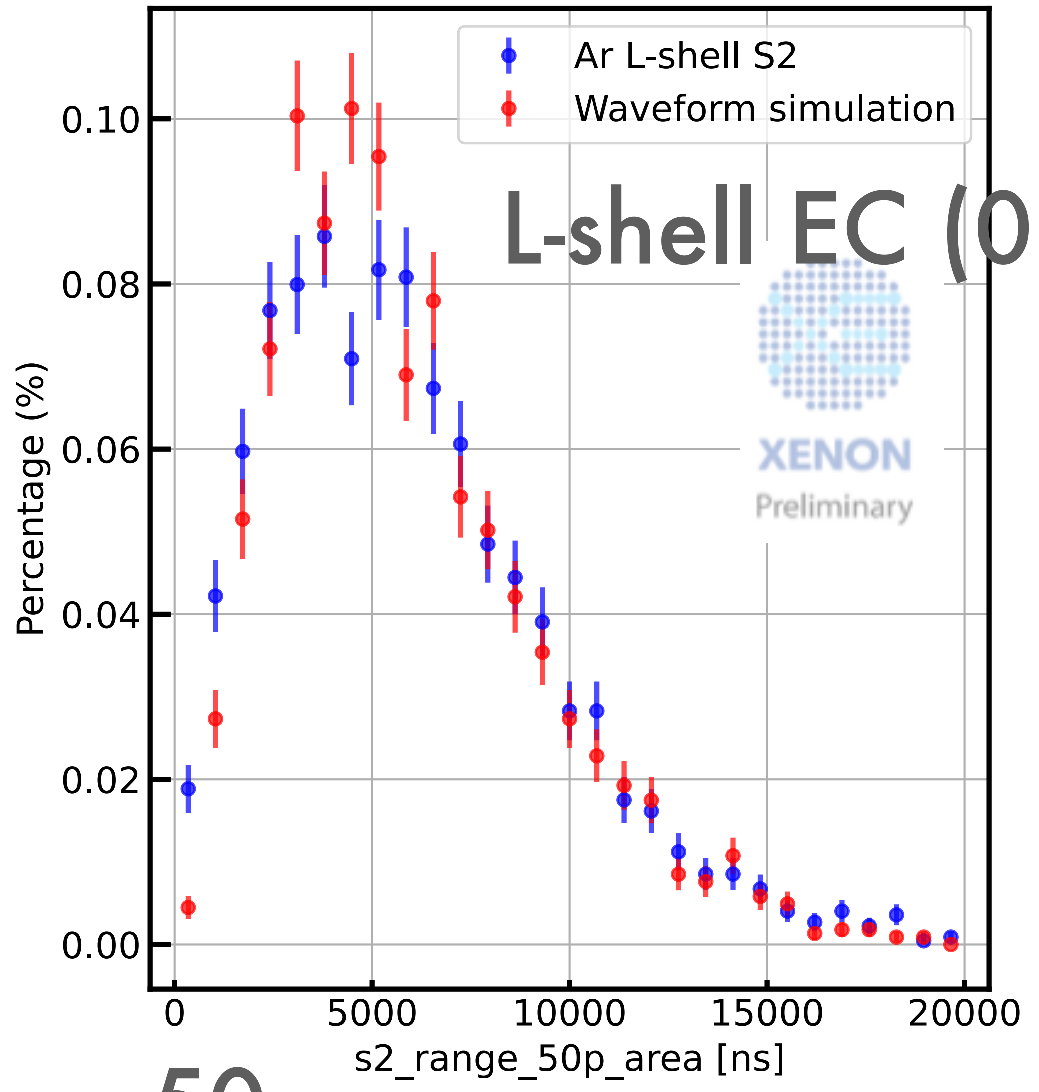


- Simulation include the microphysics, detector physics, PMT&DAQ response to get events.
- simulation & data match well

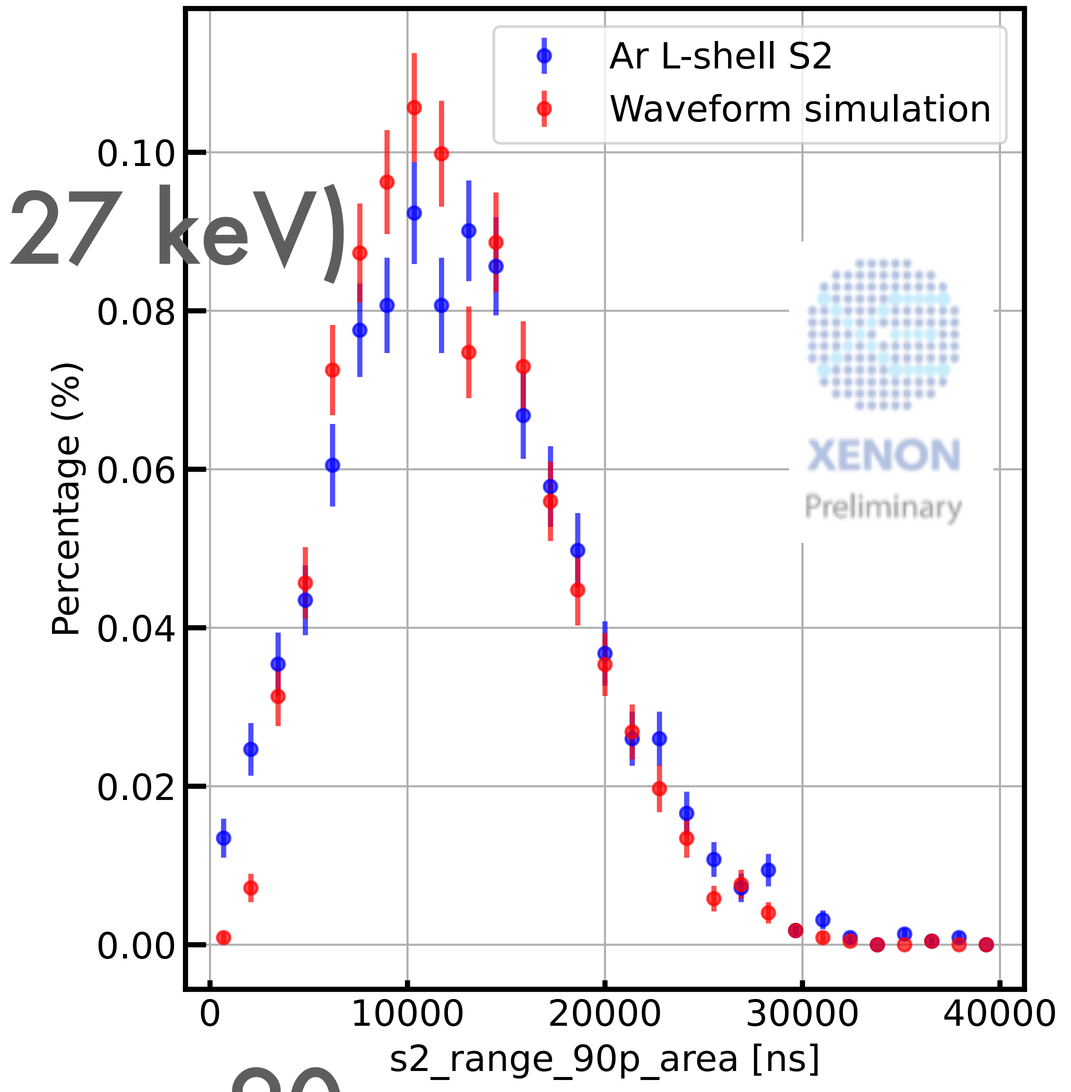
xenon-fuse 1.3.0

```
pip install xenon-fuse
```

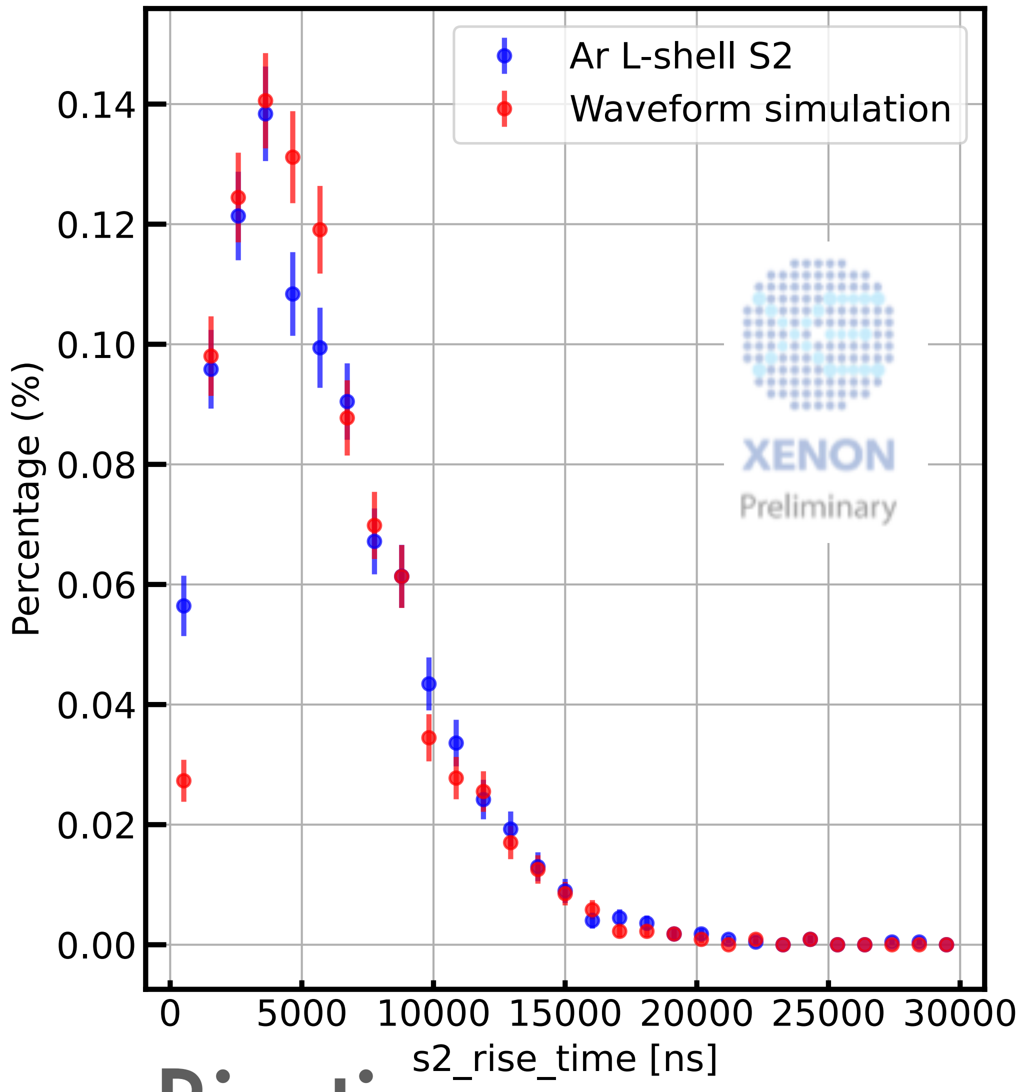
L-shell EC (0.27 keV)



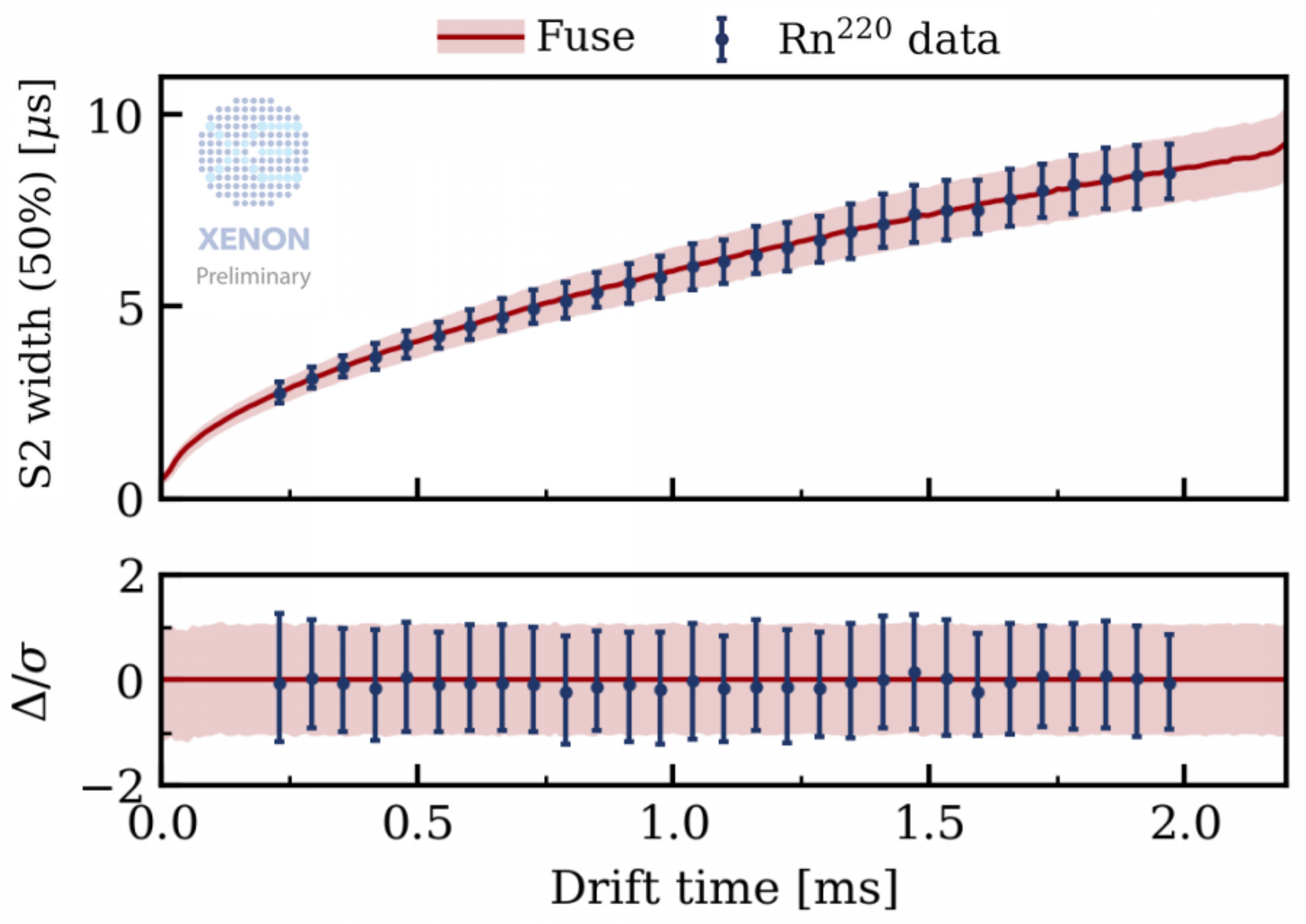
50p



90p



Risetime



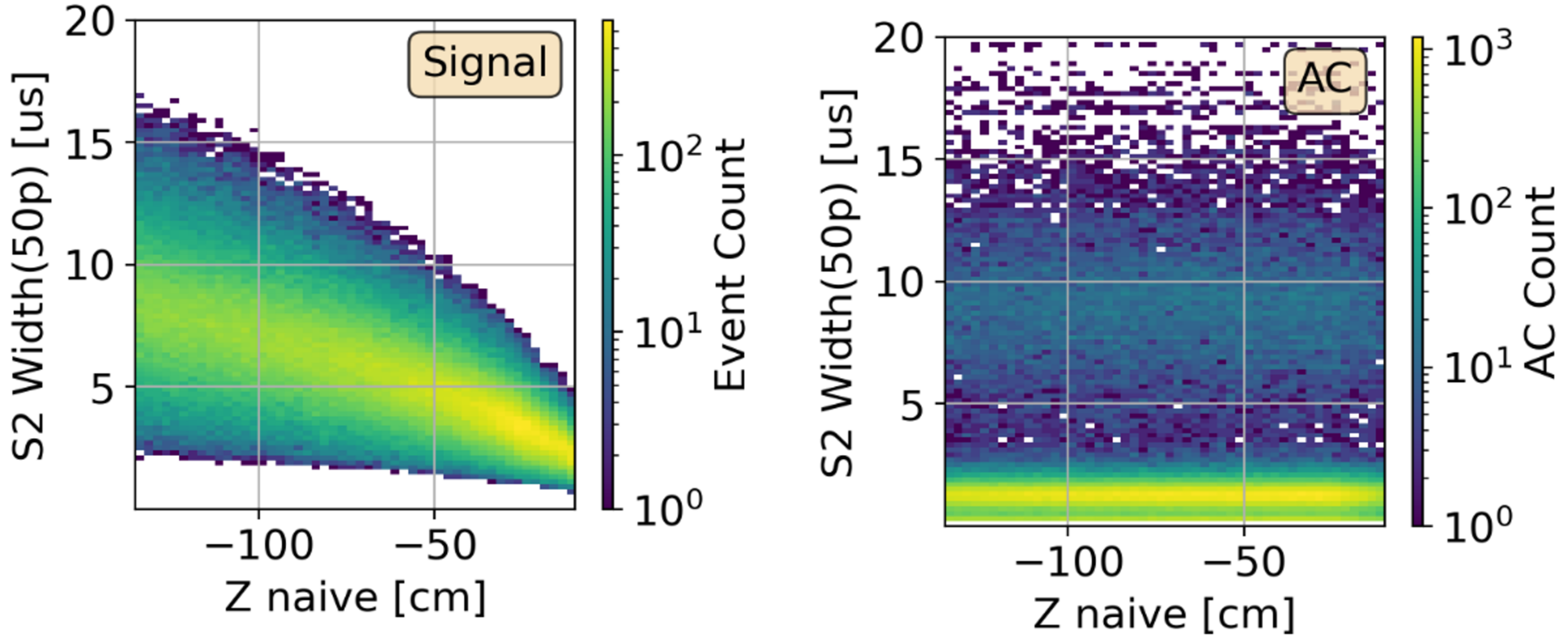
- **Enormous & reliable datasets for machine learning training!**

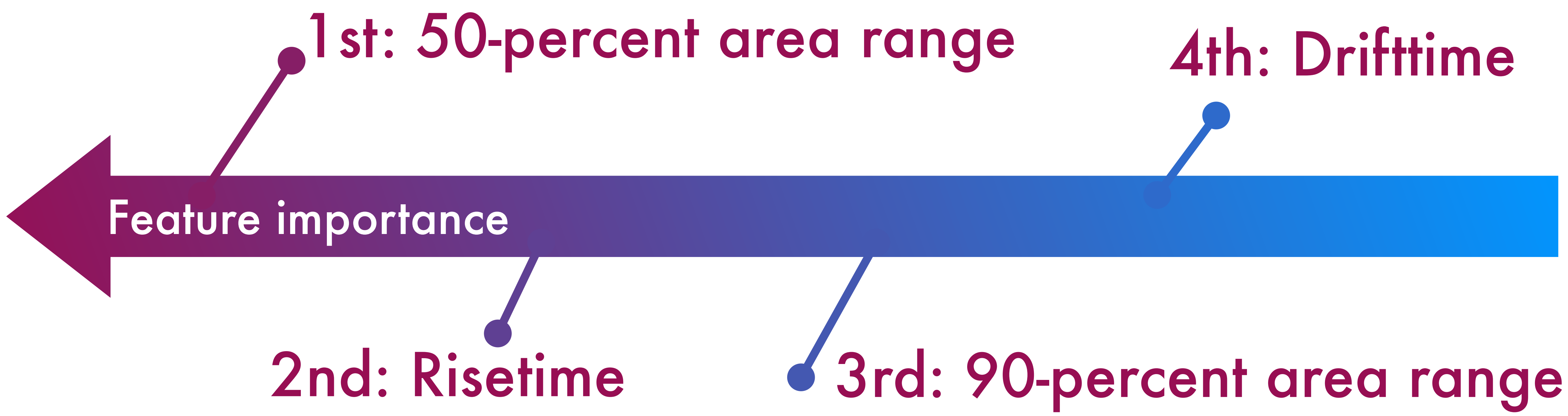
S1/S2 Pulse shape into Gradient Boosting Decision Tree

S2BDT: Diffusion model & Abnormal Width

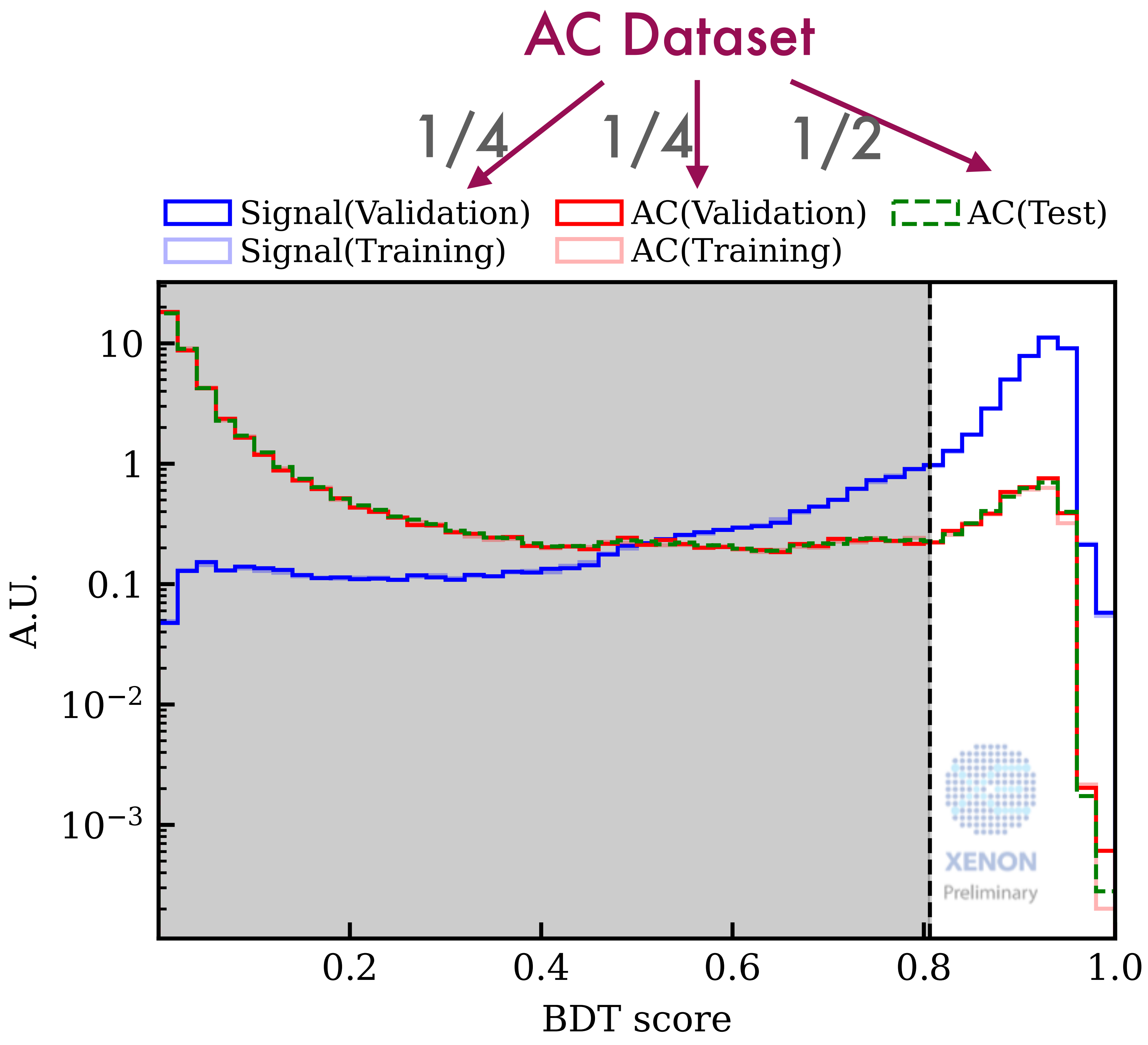
Diffusion model:

$$t_{50p} \propto \sqrt{T_{drift}}$$





- Split datasets to prevent overfitting



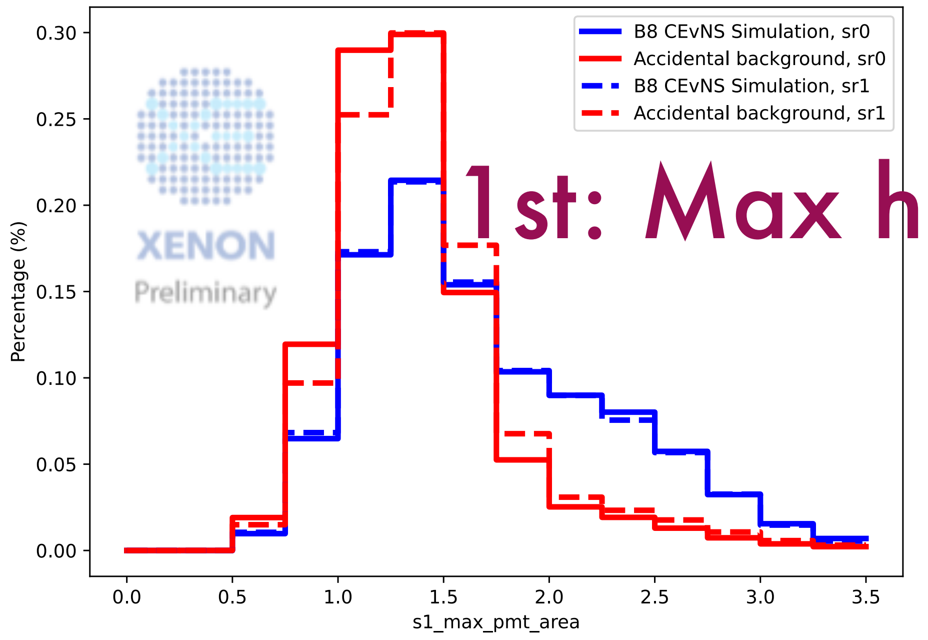
- Reject about **95%** AC with **80%** signal acceptance
- The remaining part still have discrimination power.

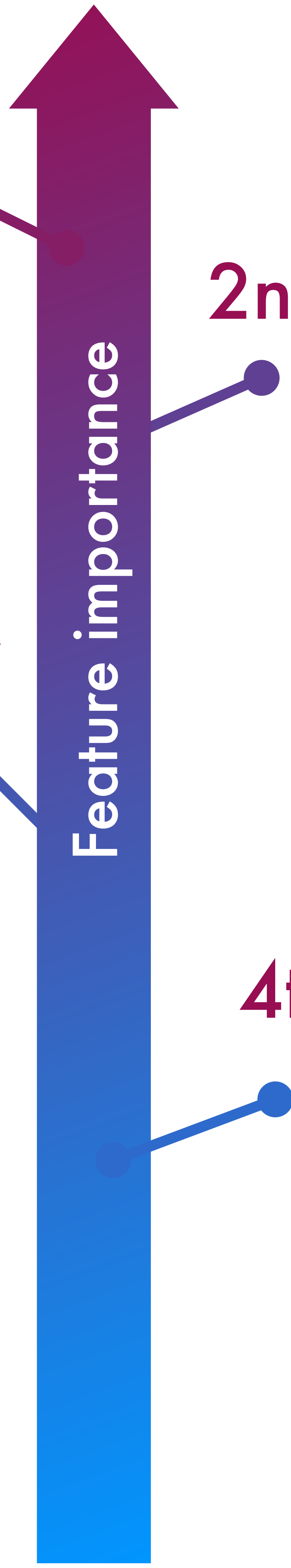
Kexin Liu

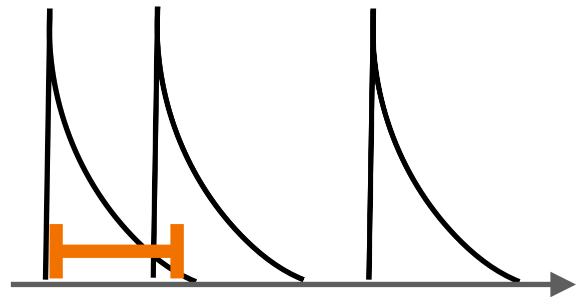
S1/S2 Pulse shape into Gradient Boosting Decision Tree

S1BDT: LXe light + signal spectrum vs. lone hits pile-up

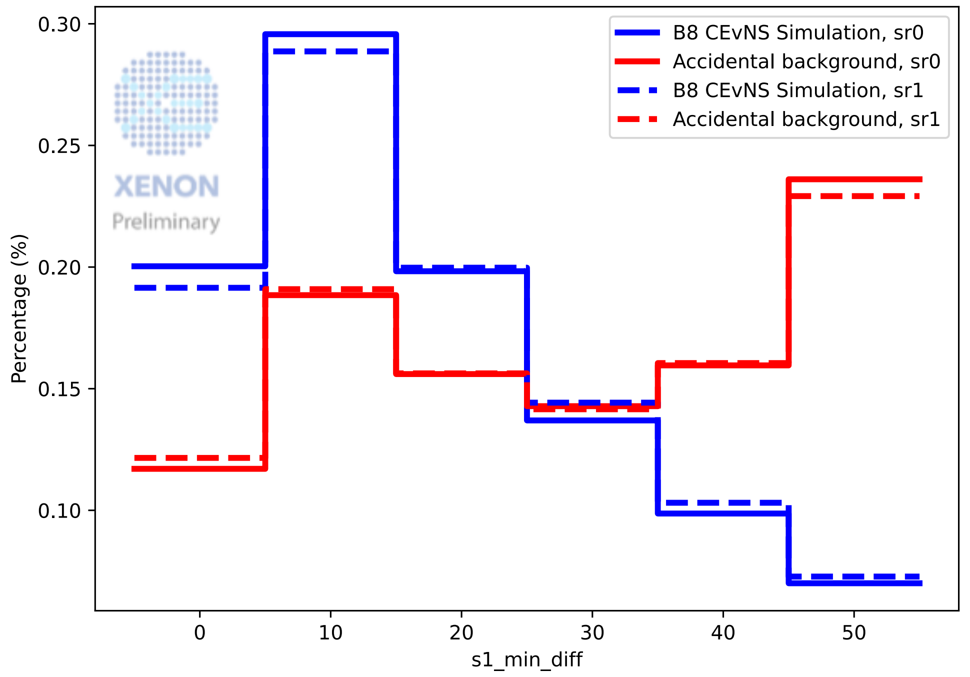
1st: Max hit Area



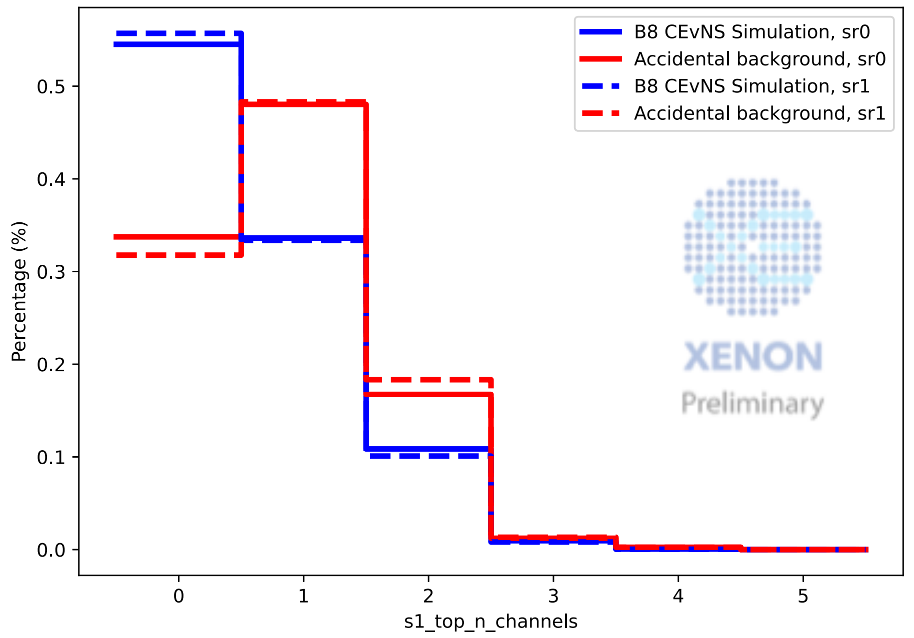




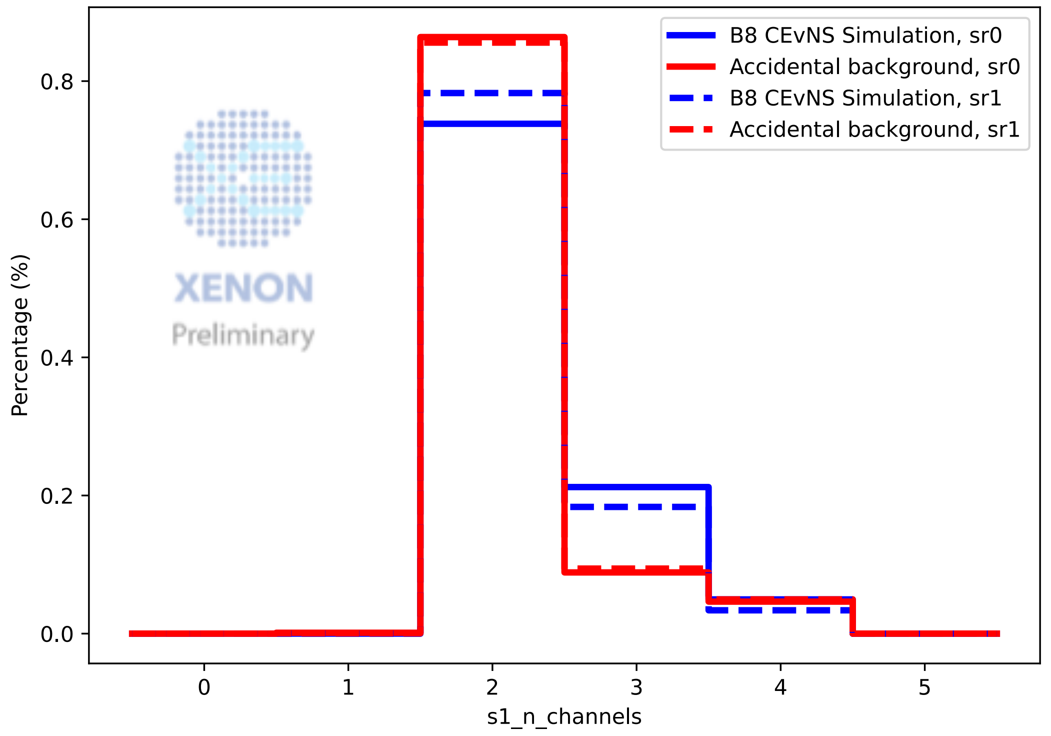
2nd: Min Time between hits

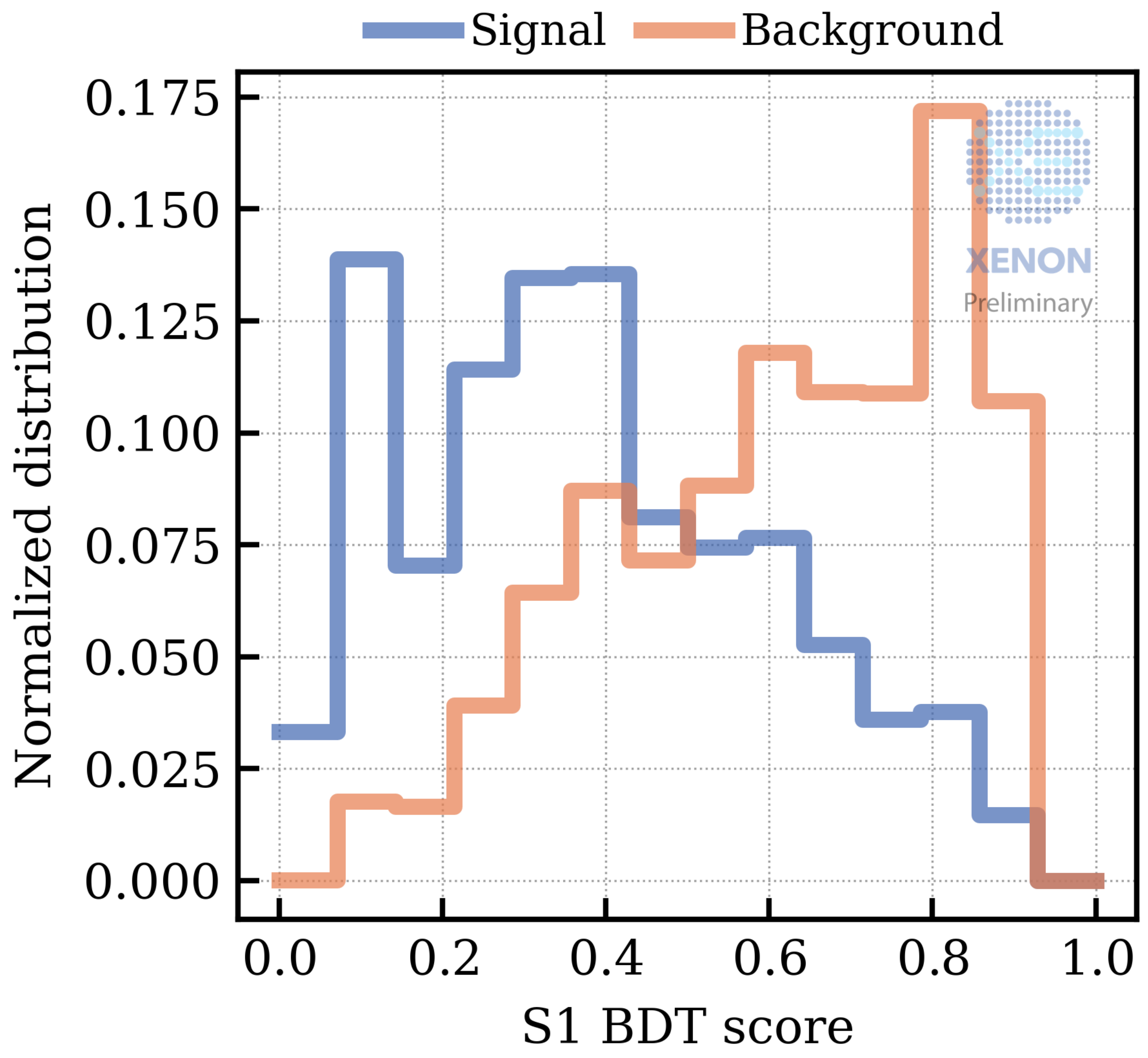


3rd: # of hits from Top Array



4th: total # of hits





- Trained with IsoS1 vs. Simulated B8 S1
- Utilize this discrimination power in the inference. So do the remaining parameter space of the TimeShadow and S2BDT cut.

Model Validation & Systematic Error

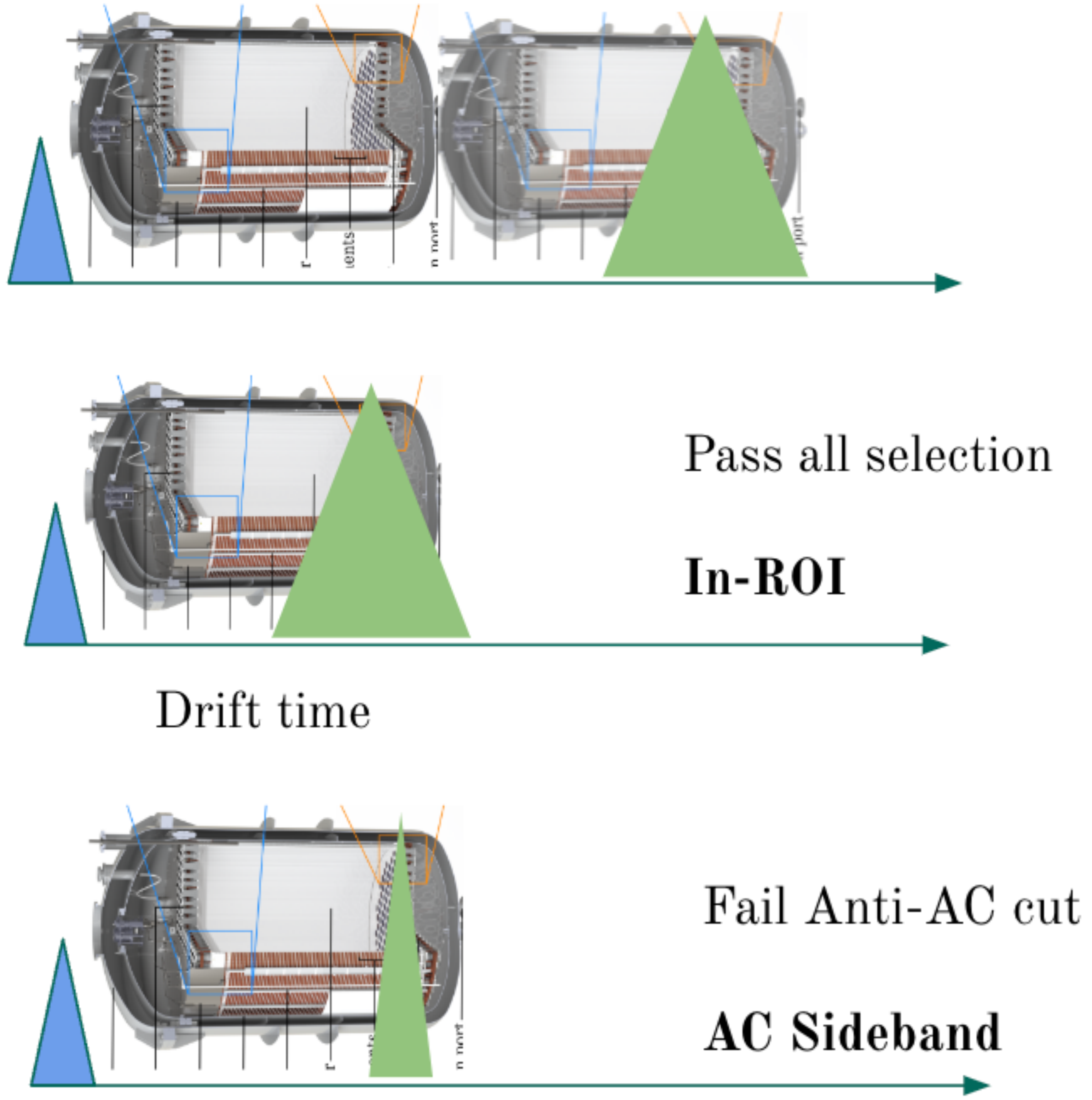
Test the mode with AC-rich datasets

- statistical error is small (less than 1%). Systematic error need to be tested by data
- How to find suitable dataset contain large and pure AC events?

A. Build events longer than the TPC, thus build pure AC events

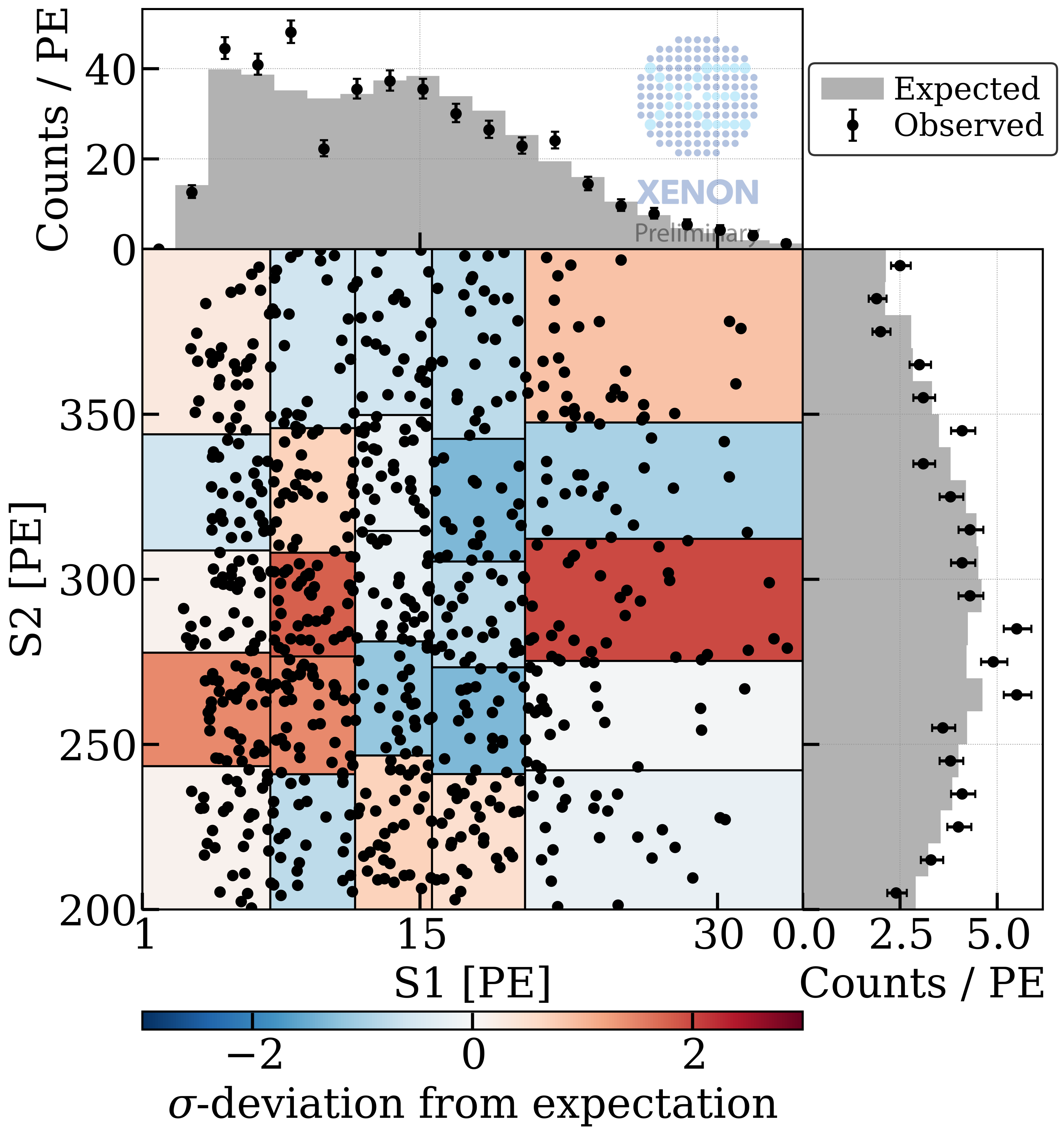
B. In high rate calibration data

C. In science search data, select events which only failed anti-AC cuts: ACSideband



Find AC in ^{37}Ar datasets

Provide High AC Counts to validate the framework

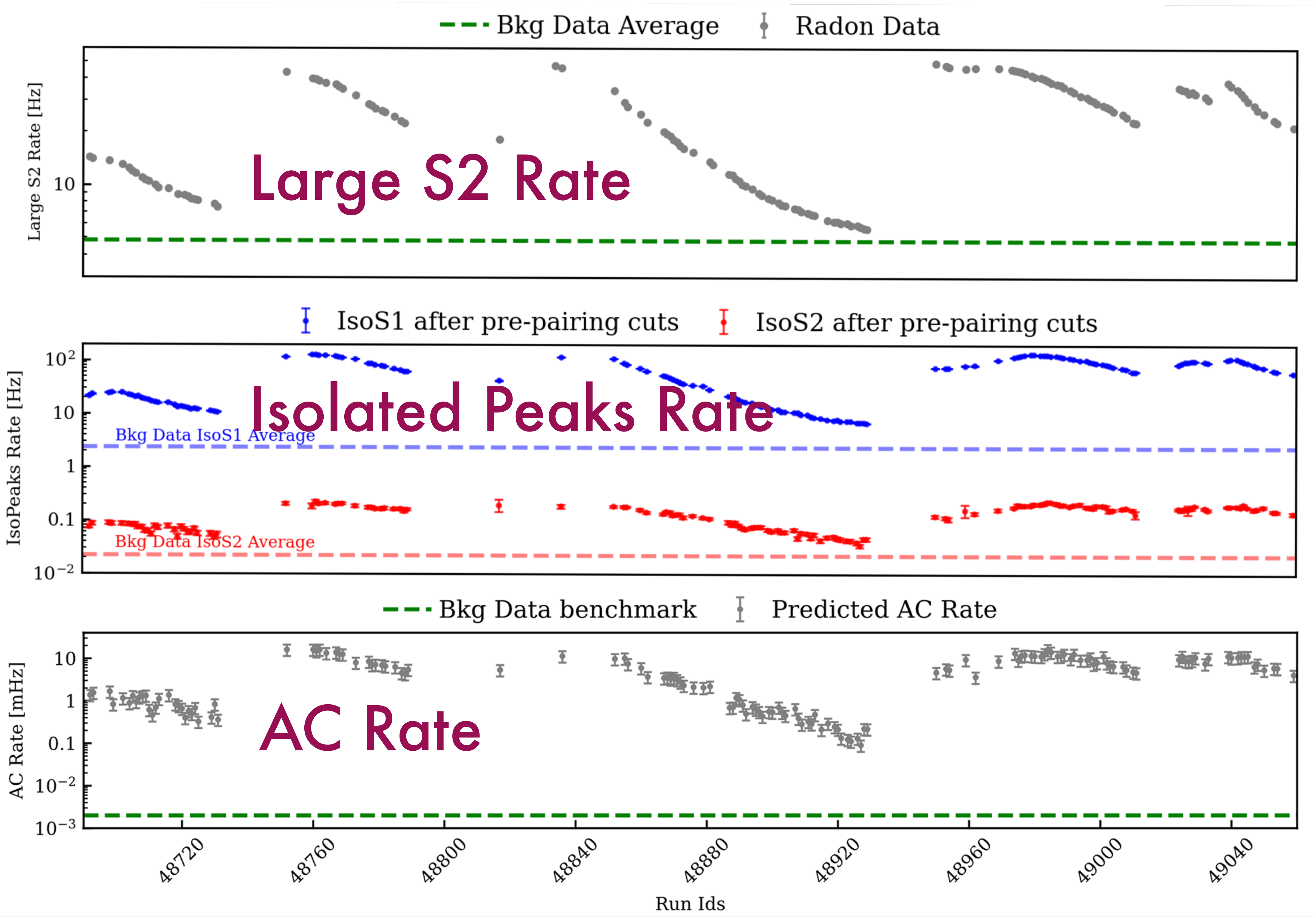


- Prediction vs. Observation, within **5%** deviation

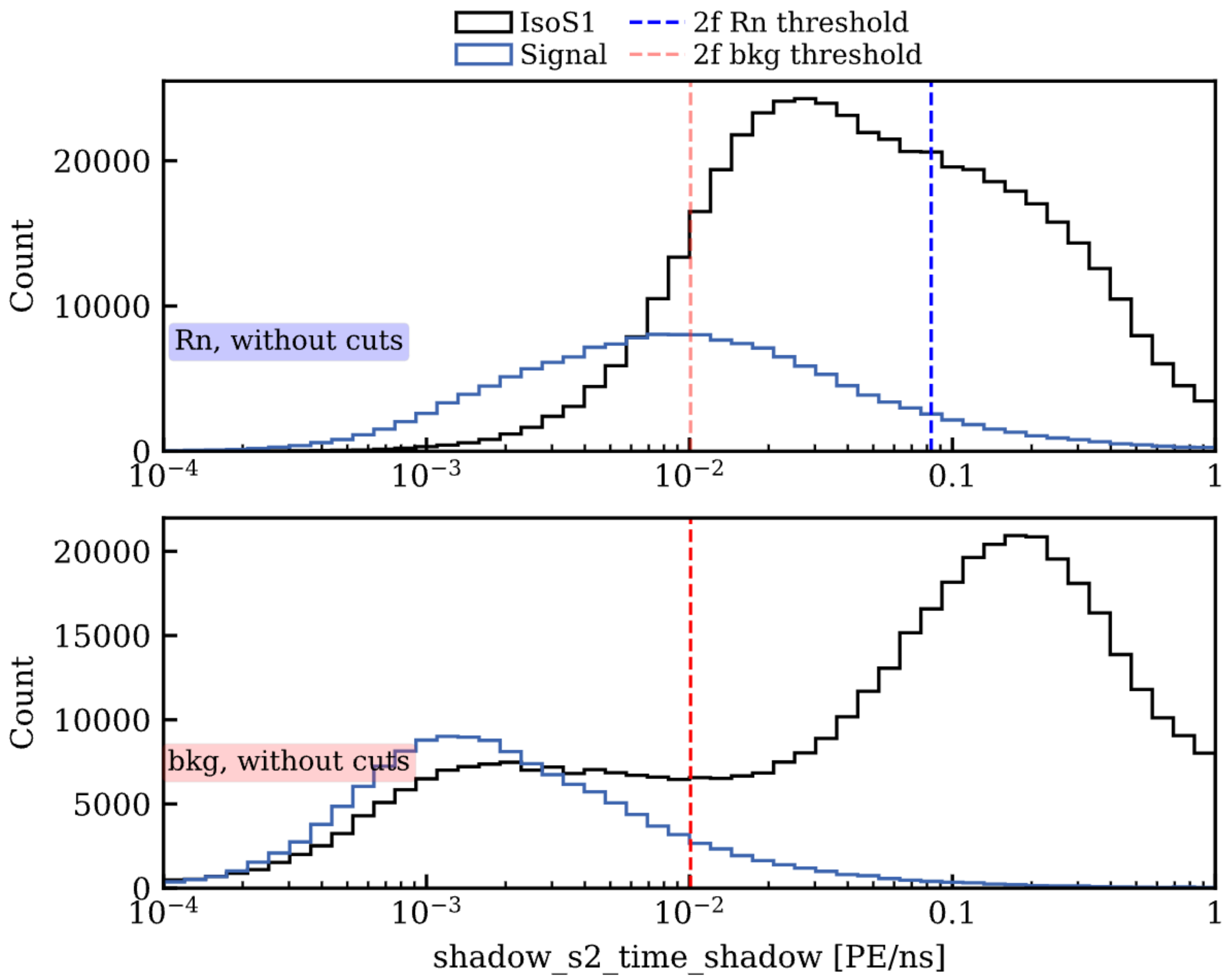
Dataset	Predicted	Observed
PureAC	1522.7	1459
ACSideband	349.7	366
In-ROI	731.6	733

Validation in ^{220}Rn dataset

Heavy ‘shadow’ challenges the AC Model



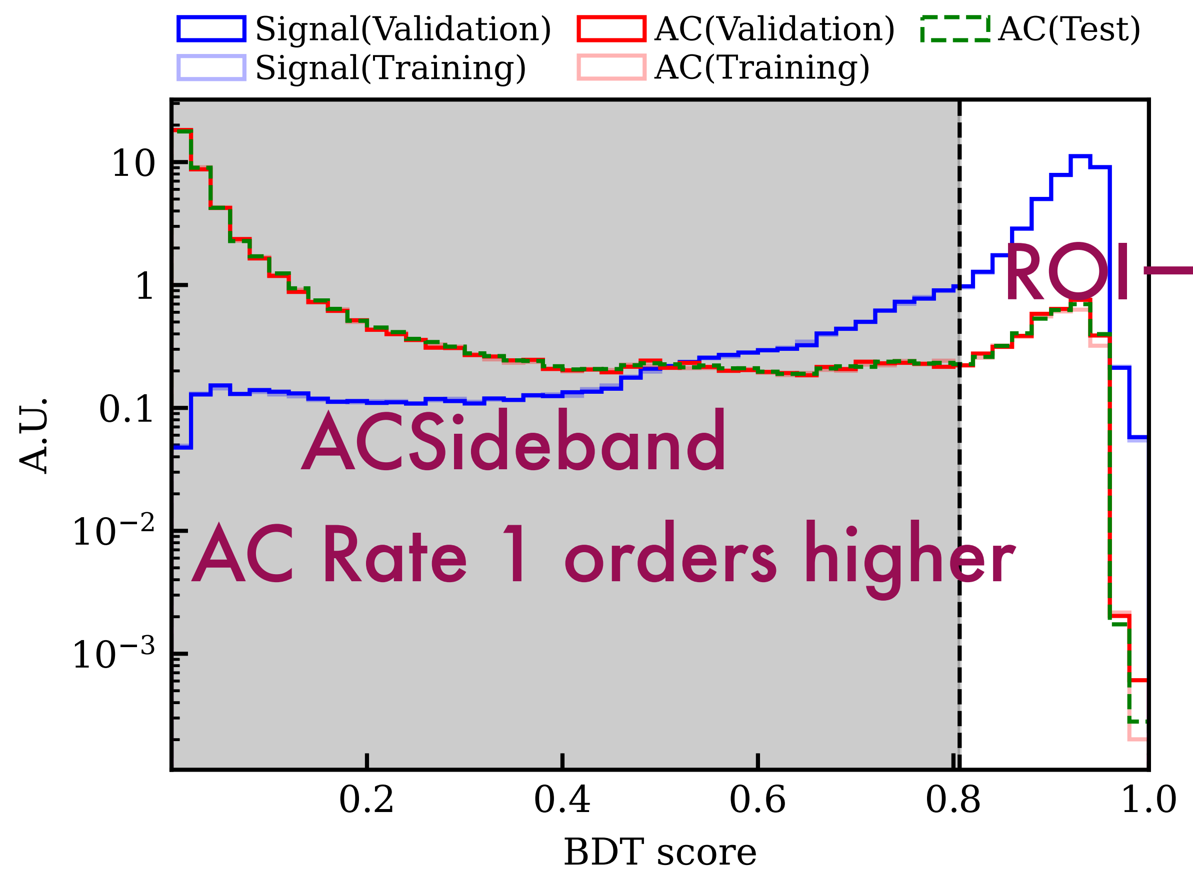
Dataset	S2 [PE]	Predicted	Observed
In-ROI	[120, 500]	54.6	57
	[100, 120]	201.0	271



- Featured with high **large peak** rate, thus larger shadow remains after applying cut
- Mis-modeling in S2 in few-electron region(100-120 PE)

Validation on Science data ACSideband

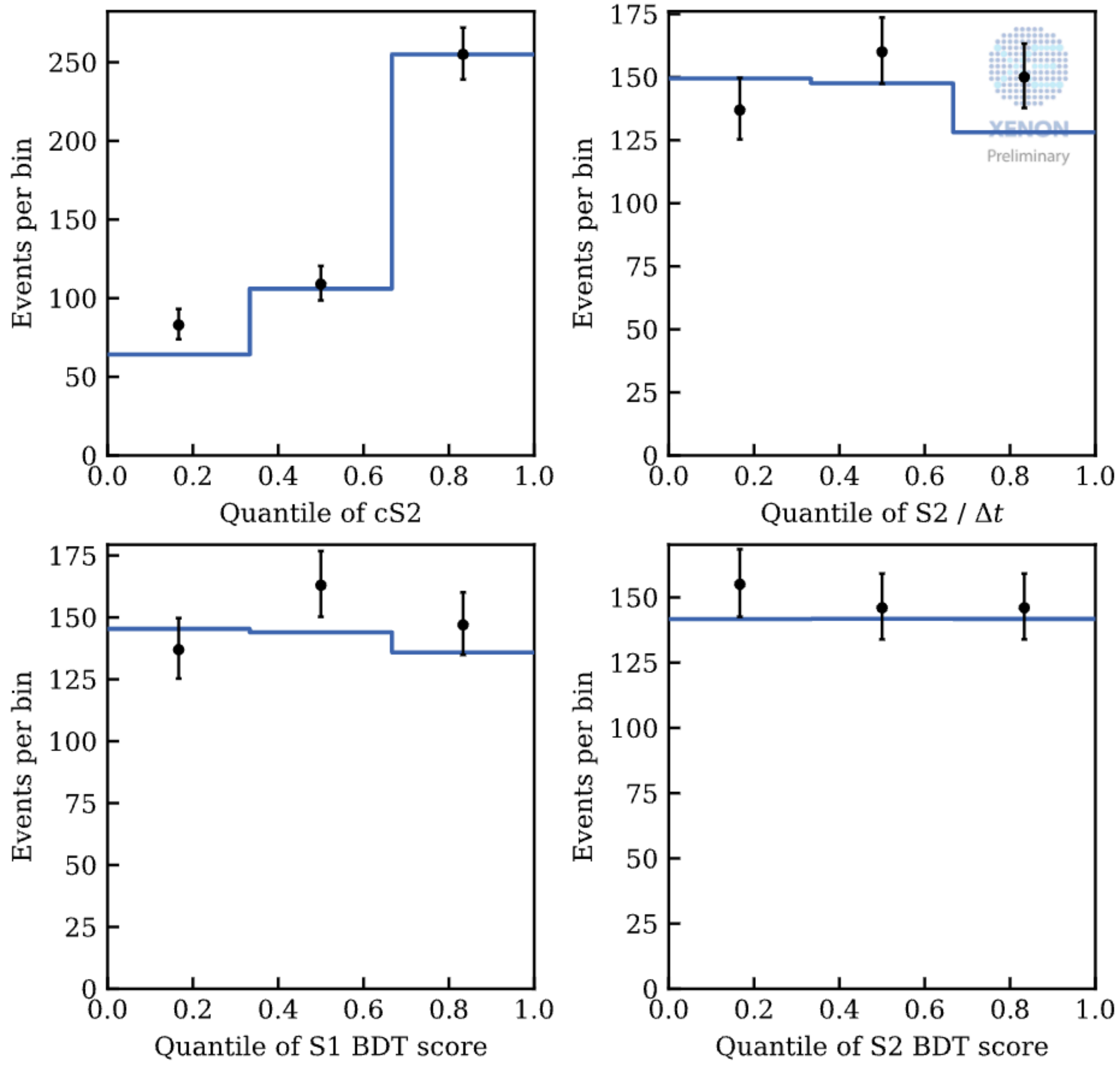
Determine Systematic Uncertainty



	AC Rate[/t/y]
SR0	6.37
SR1	7.58

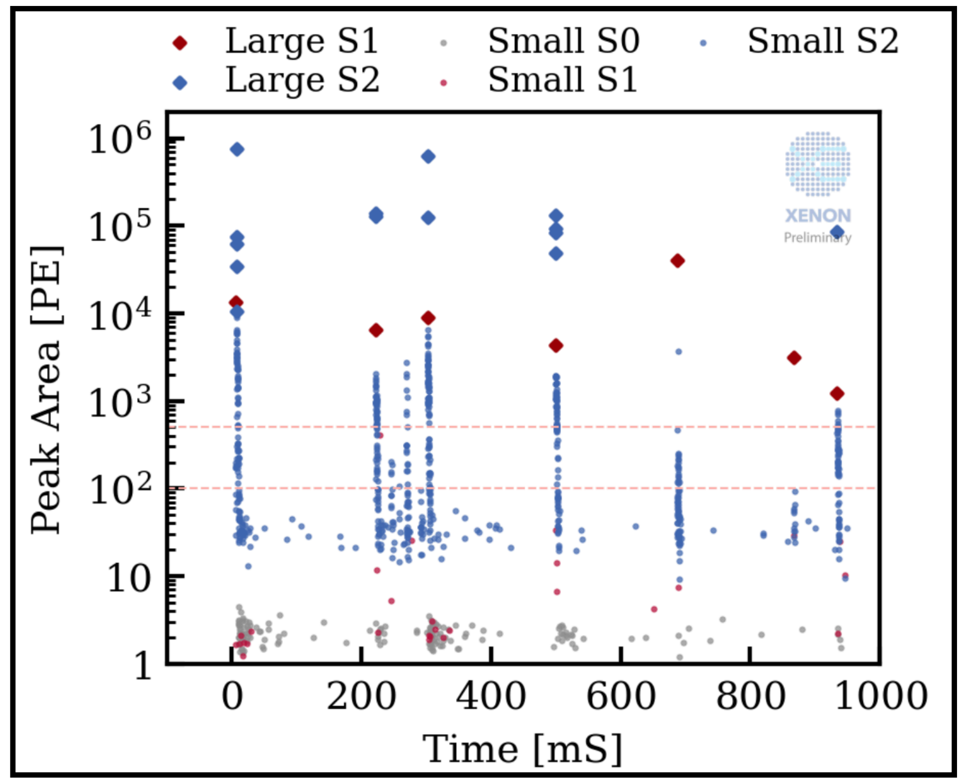
- 'Unblind' shows within 2-sigma, use the statistic uncertainty of ACSideband to be the systematics
- 4D GoF test: p-value=0.17 ✅

Dataset	Predicted	Observed	Relative Uncertainty
SR0	122.7	121	9.04%
SR1	302.5	326	5.76%
Total	425.2	447	/

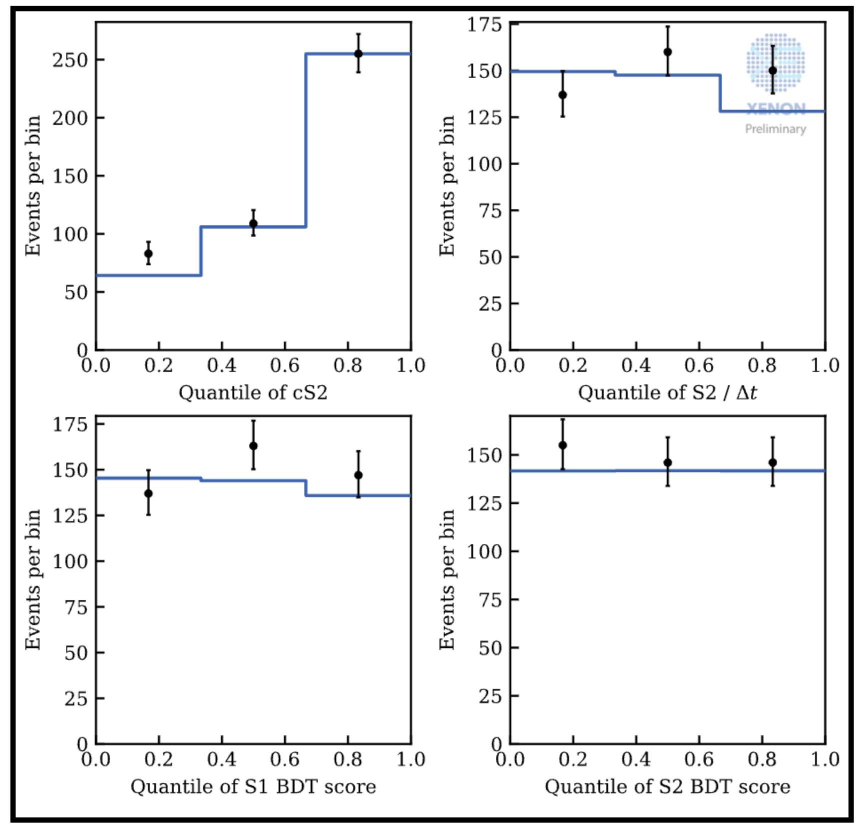


Summary

From Chaotic Isolated Peaks



To reduced & validated AC model



- Accidental Coincidence background is the dominant background in low energy NR search with a two-phase LXe TPC.
- What we can do with the AC background:
  - **Suppress** isolated peaks by time+space correlation, and suppress AC events by comprehensively use features which have discrimination power.
  - **Predict** the rate and distribution in high dimensions with data-driven simulation.
  - **Validate** the model with real data to set the systematics uncertainty

Thanks!