An enhanced approach to signal analysis in the XENONnT dark matter experiment

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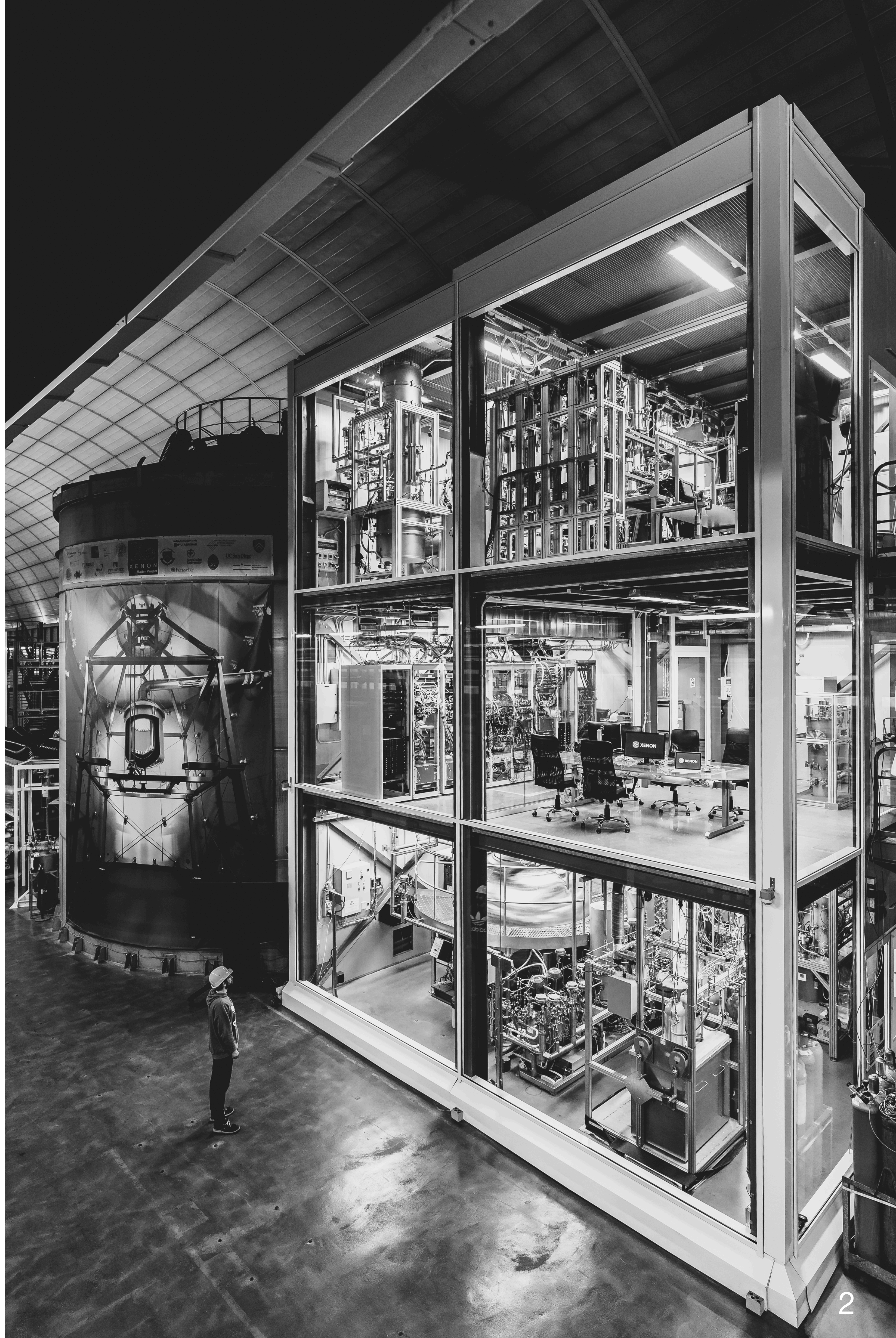
The XENONnT Experiment

An underground telescope for dark matter + beyond

- Dark matter: WIMPs, axions, dark photons, etc.
- Neutrinos: CEvNS (solar), neutrino magnetic moment, supernovae, Majorana
- Rare nuclear decays

About XENONnT:

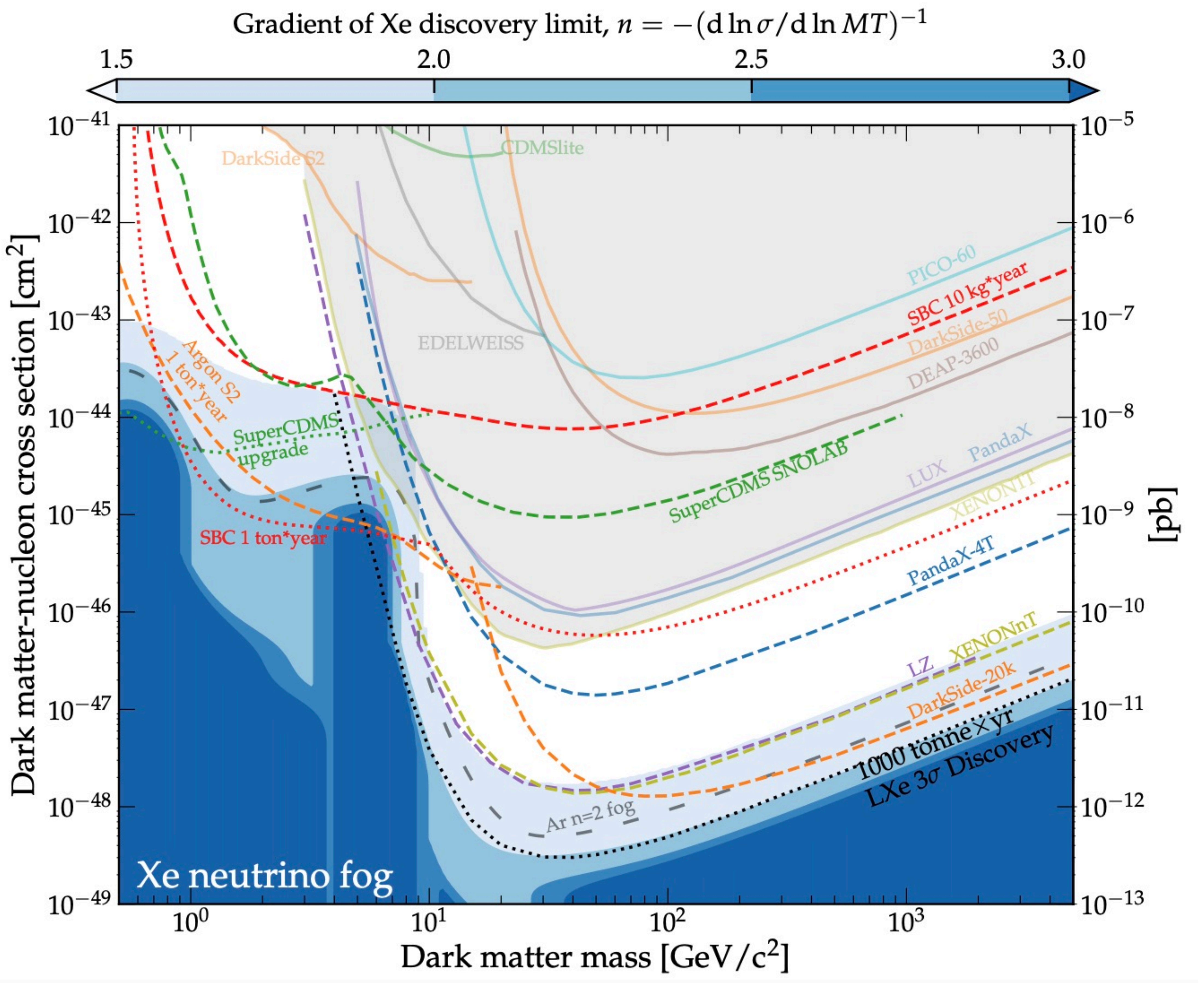
~5900 kg of active liquid xenon target @ LNGS
Commissioned in 2020, first science run (SR0) in 2021
~1 keV energy threshold
Low background: ~10 events/(t*y*keV)
Reconstruction: position, interaction type, energy
~200 scientists



Searching for dark matter

Weakly-interacting massive particles (WIMPs)

- One historically-favored theory
- Direct detectors set the most stringent limits
- Limited by background rates
    - ➡ Cosmic rays
    - ➡ Radioactivity in detector
    - ➡ Experimental artifacts (noise)
    - ➡ **Neutrinos**



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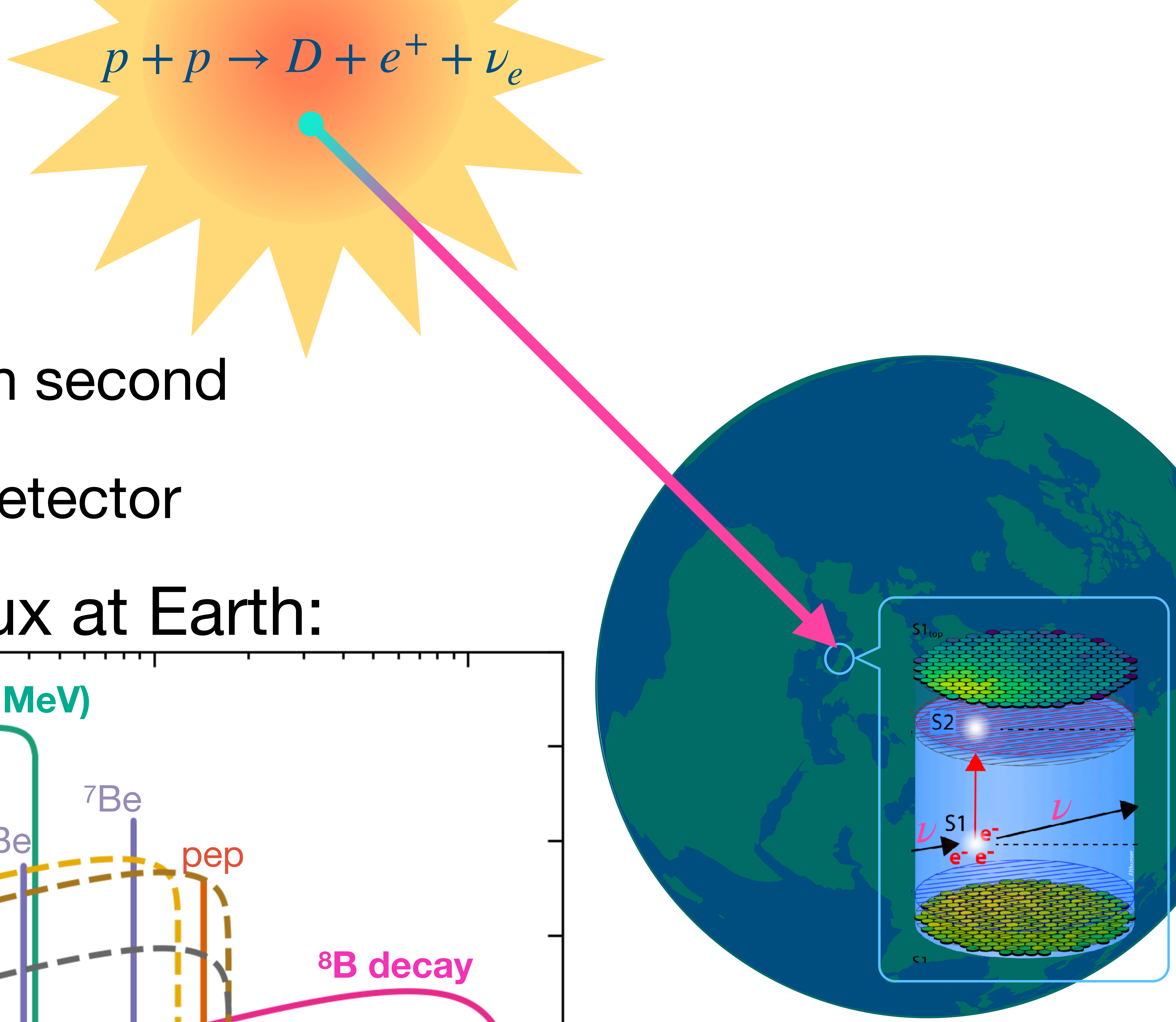
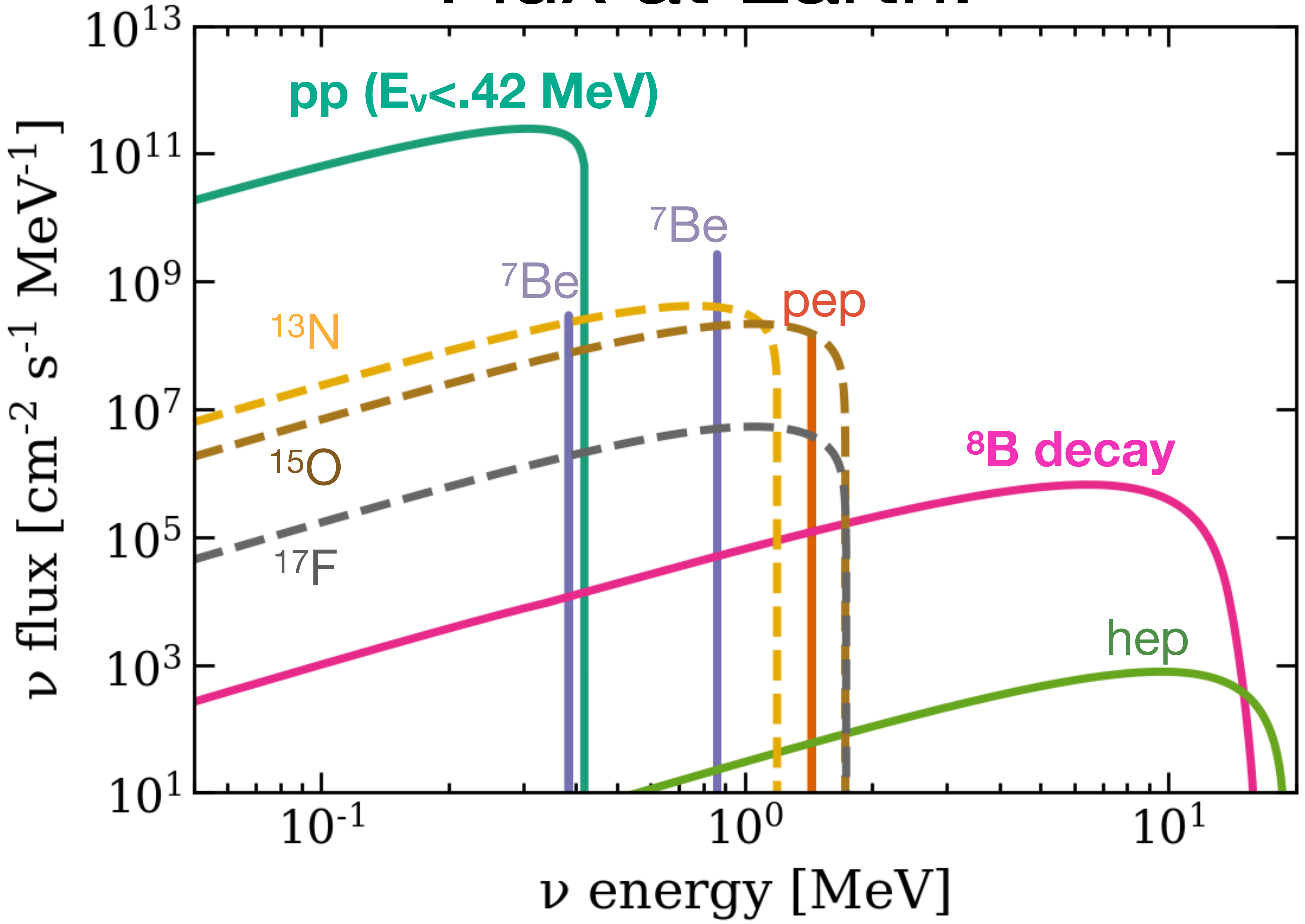


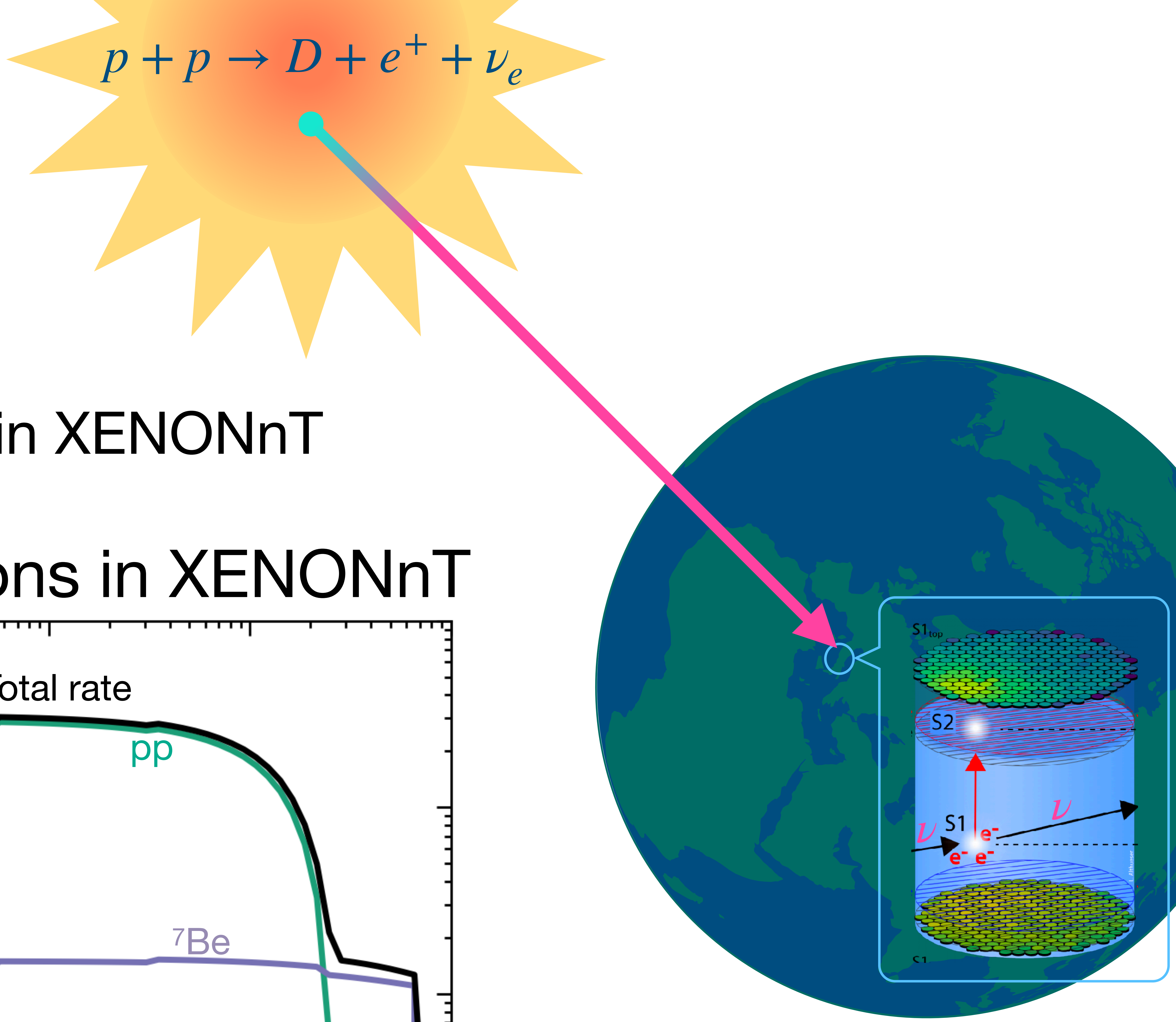
Solar neutrinos

- 70 billion pass through your finger each second
- Few interactions/day in a large-scale detector
- Irreducible background

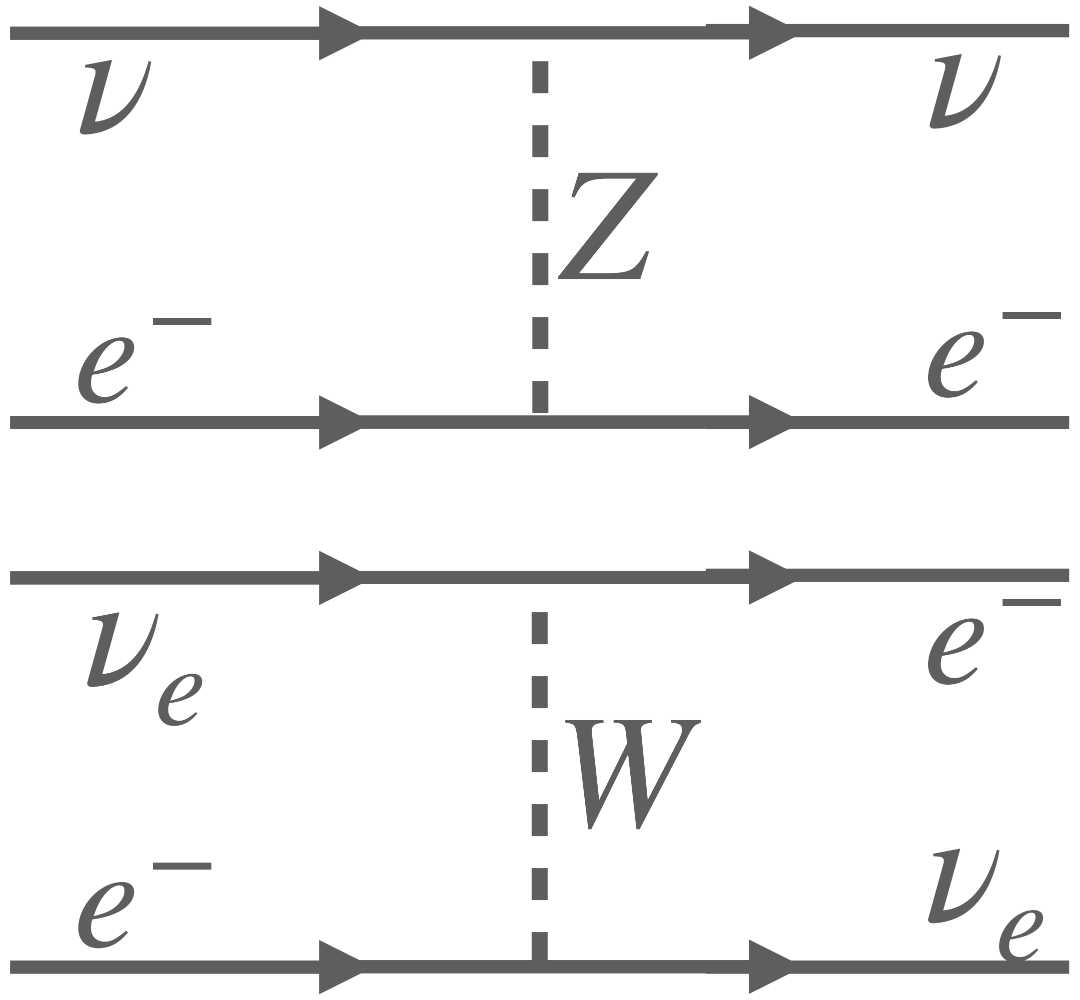
Flux at Earth:

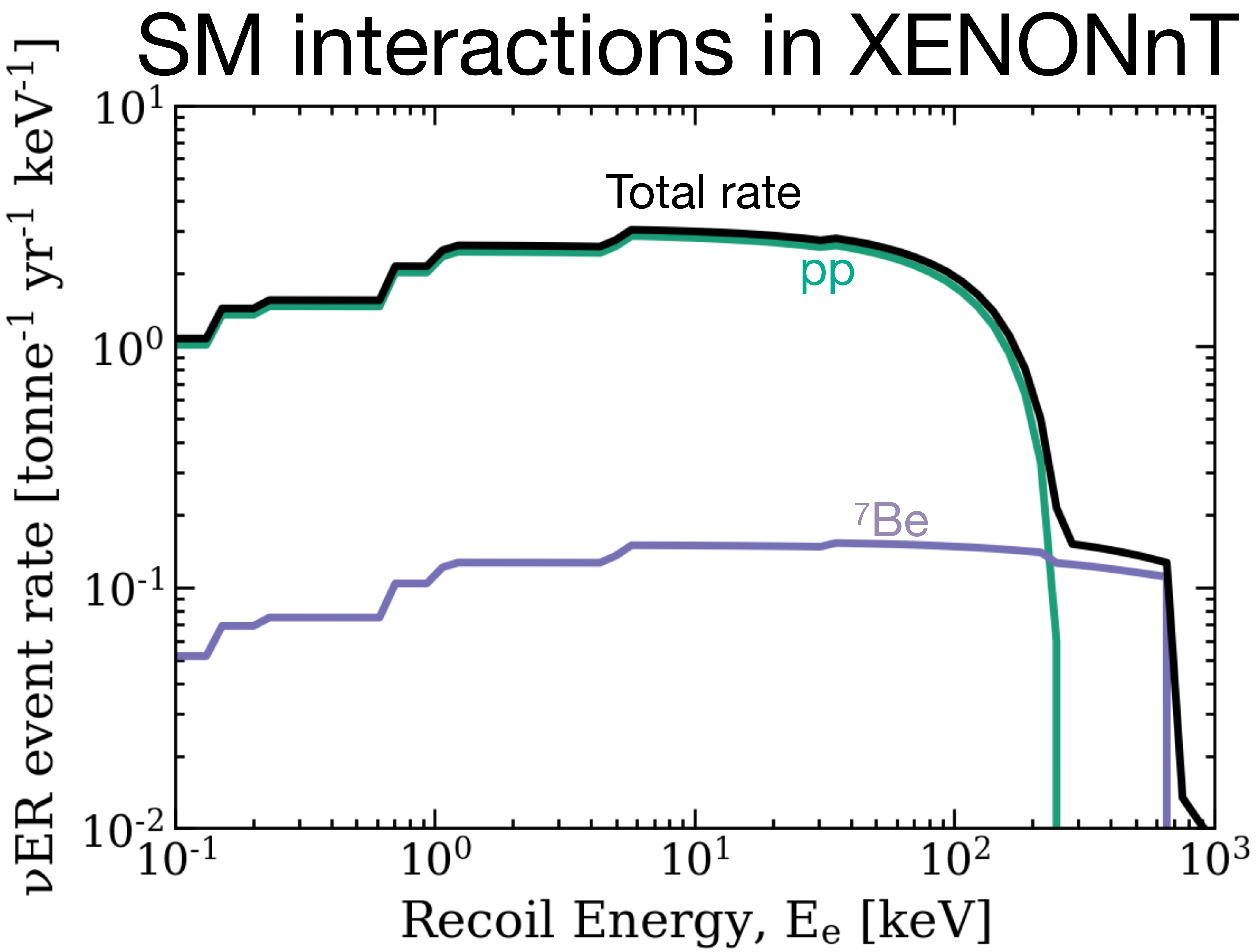


Solar neutrinos



Second-leading low energy background in XENONnT





Signatures of solar neutrinos beyond the standard model

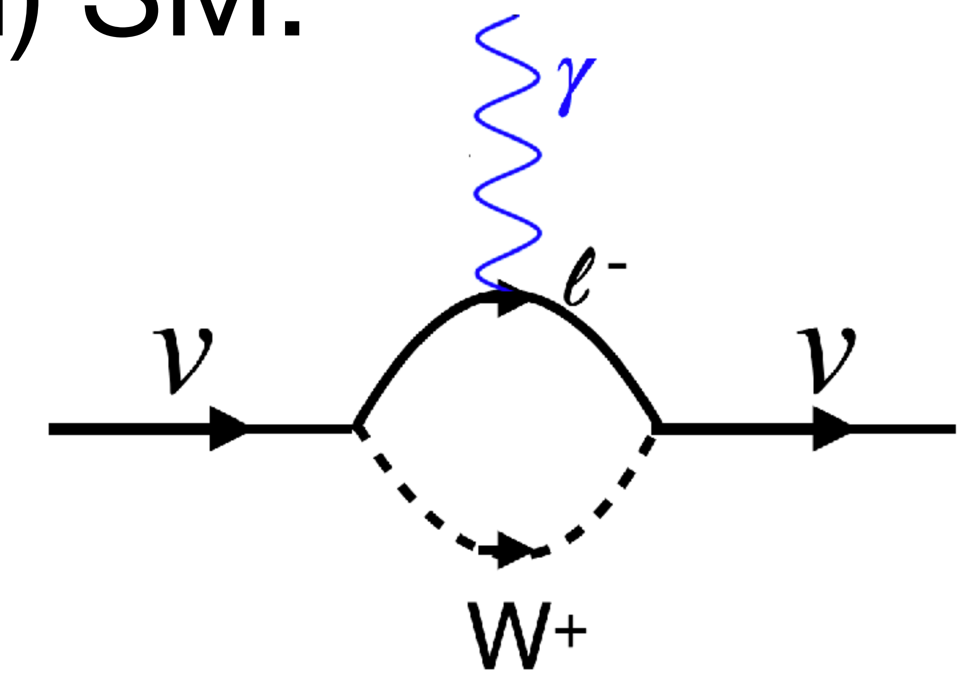
- Massive neutrinos have an effective magnetic moment

- Enhances scattering rate at low energies

$$\frac{d\sigma_\mu}{dE_r} = \mu_\nu^2 \alpha \left(\frac{1}{E_r} - \frac{1}{E_\nu} \right)$$

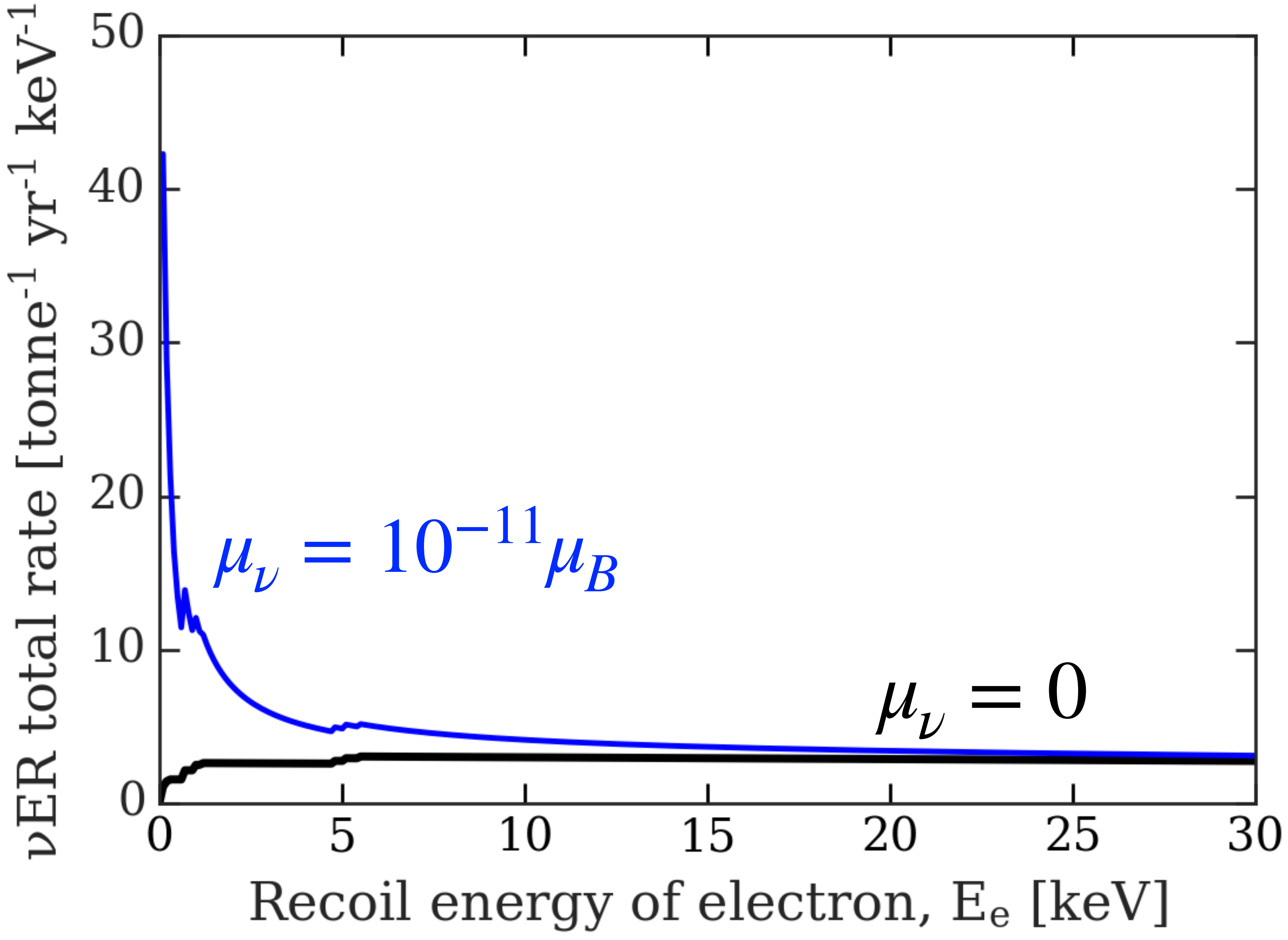
- In the (minimally-extended) SM:

$$\mu_\nu \approx 3 \times 10^{-19} \left(\frac{m_\nu}{\text{eV}} \right) \mu_B$$



- If $\mu_\nu \gtrsim 10^{-15} \mu_B$: Majorana neutrinos

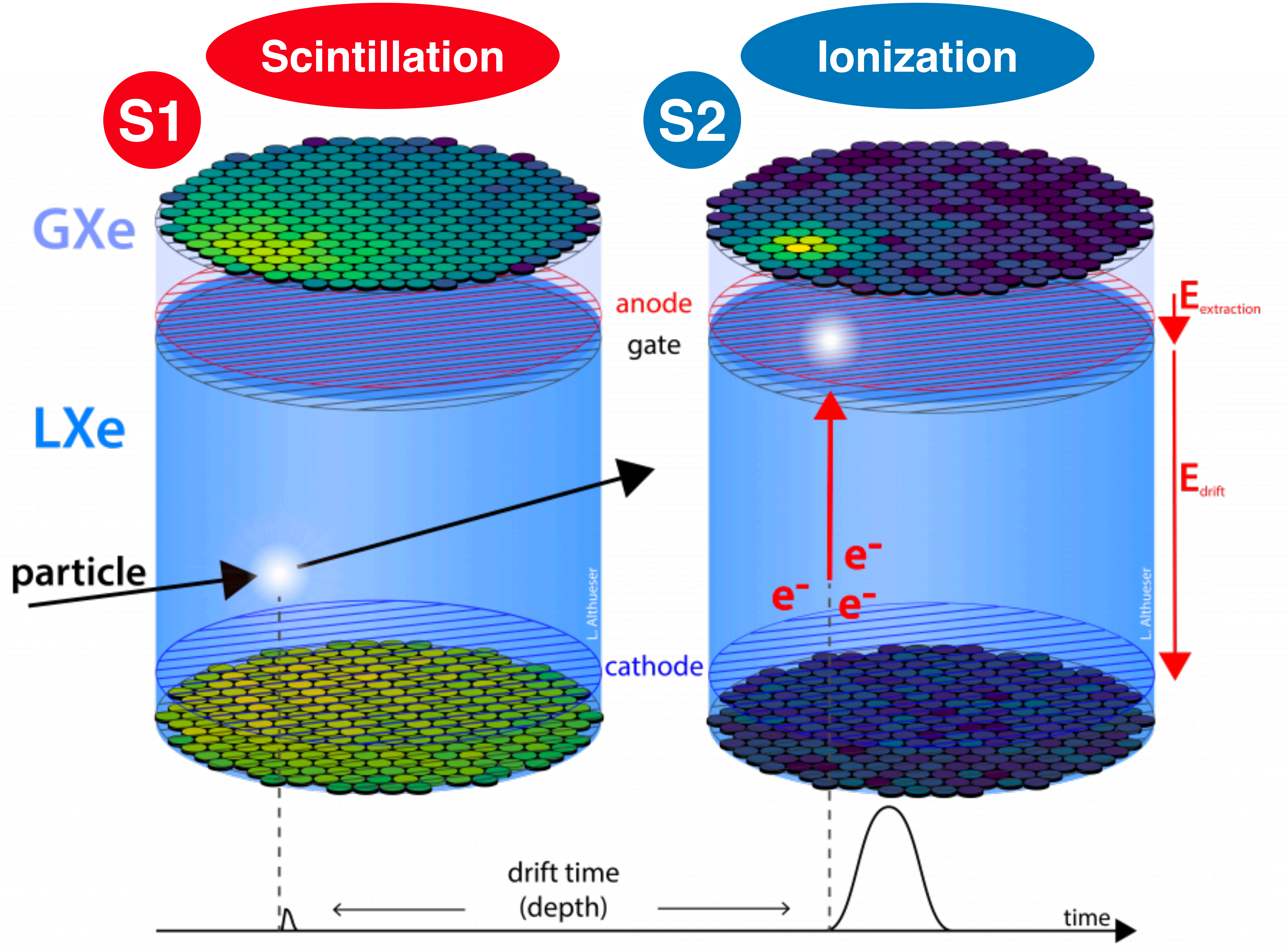
Predicted Rates in XENONnT

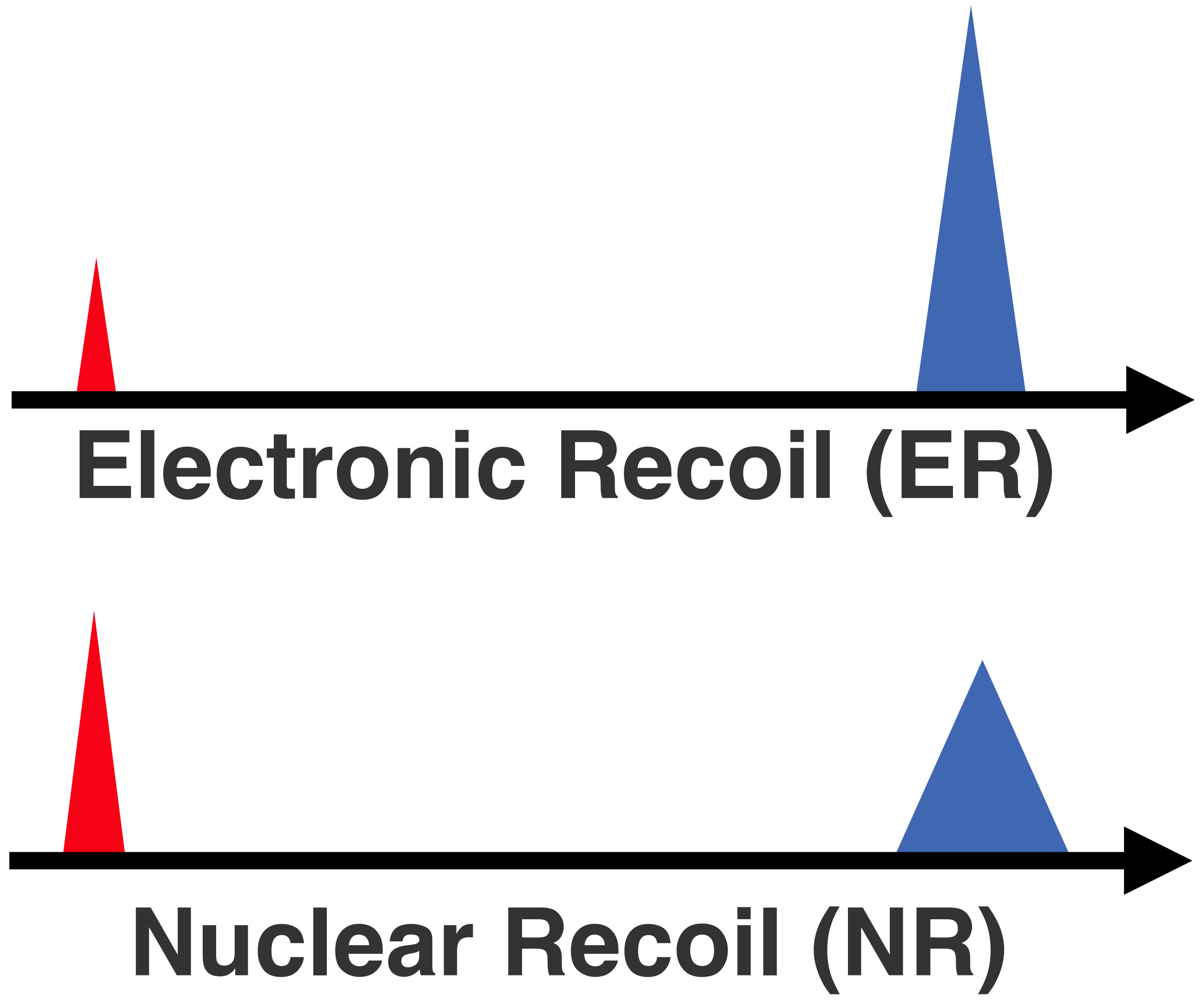


Bell et. al., 10.1063/1.2220408

Detecting interactions in XENONnT

Dual-phase xenon time projection chamber (TPC)

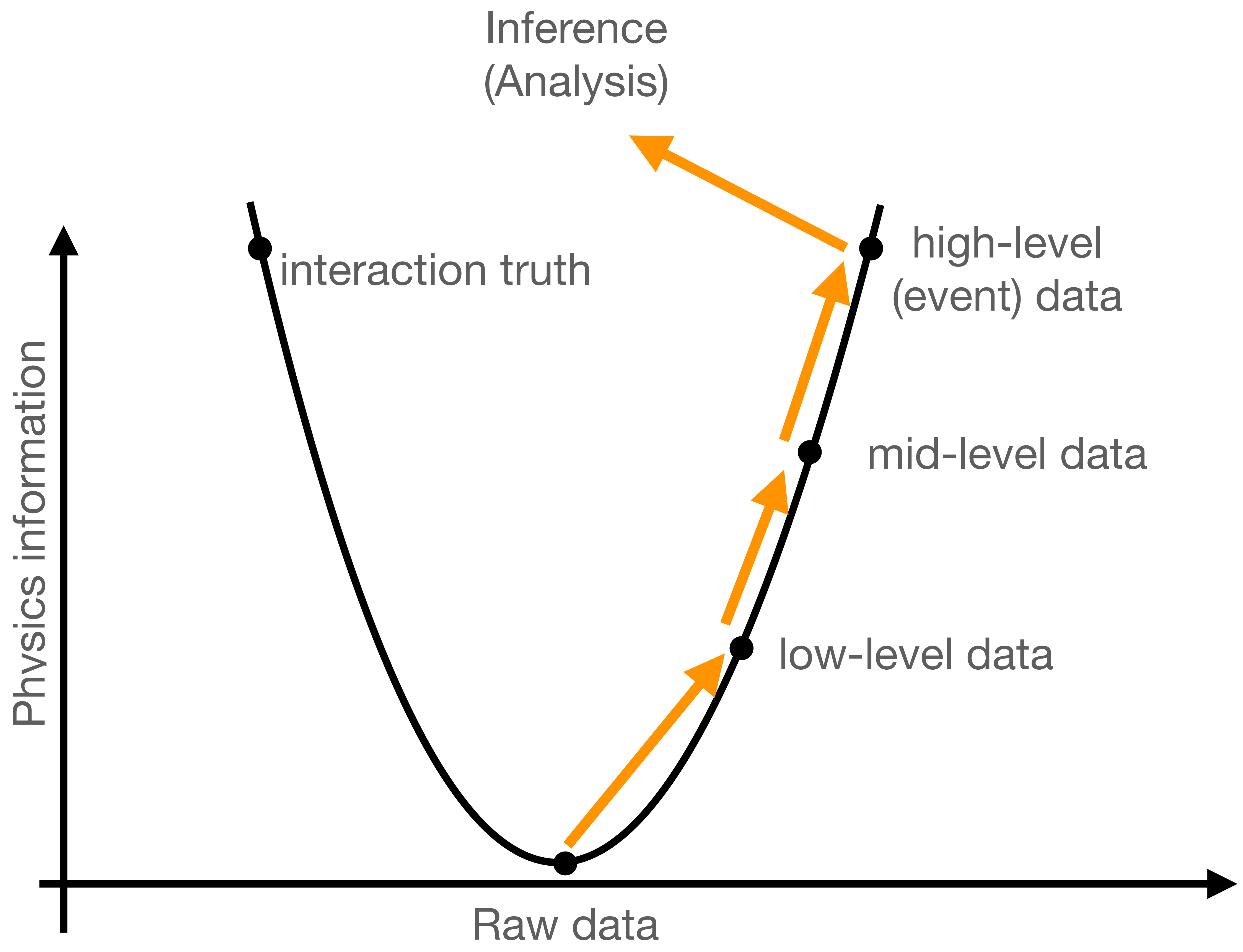




$$(S2/S1)_{ER} > (S2/S1)_{NR}$$

$$E_{ER} = W\left(\frac{cS1}{g_1} + \frac{cS2}{g_2}\right)$$

Current workflow of direct detectors



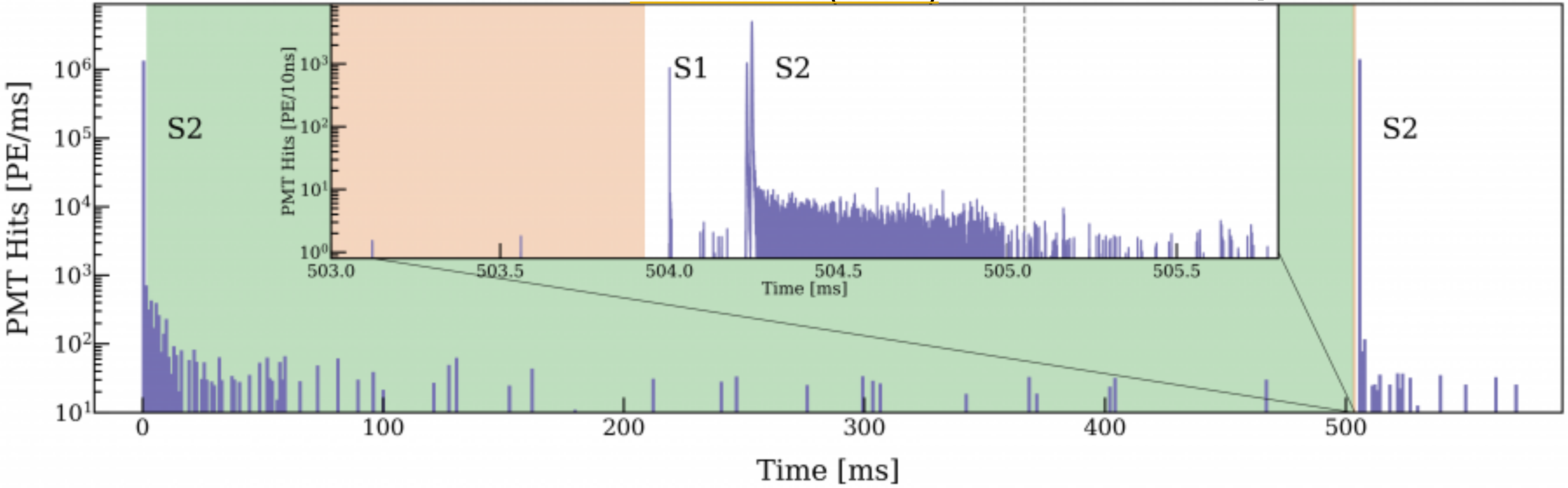
- Multi-level reconstruction framework
- Inference performed only on high-level data, inherent loss of information
- To reach inference: selection of data within ROI, based on high-level (incomplete) features
- Careful treatment of artifacts and backgrounds before analysis

Data challenges

- Many signals recorded, few are chosen
- How do we tell the physical signals from the noise?
- Reconstruction depends on accurate signal identification

XENON1T (2022)

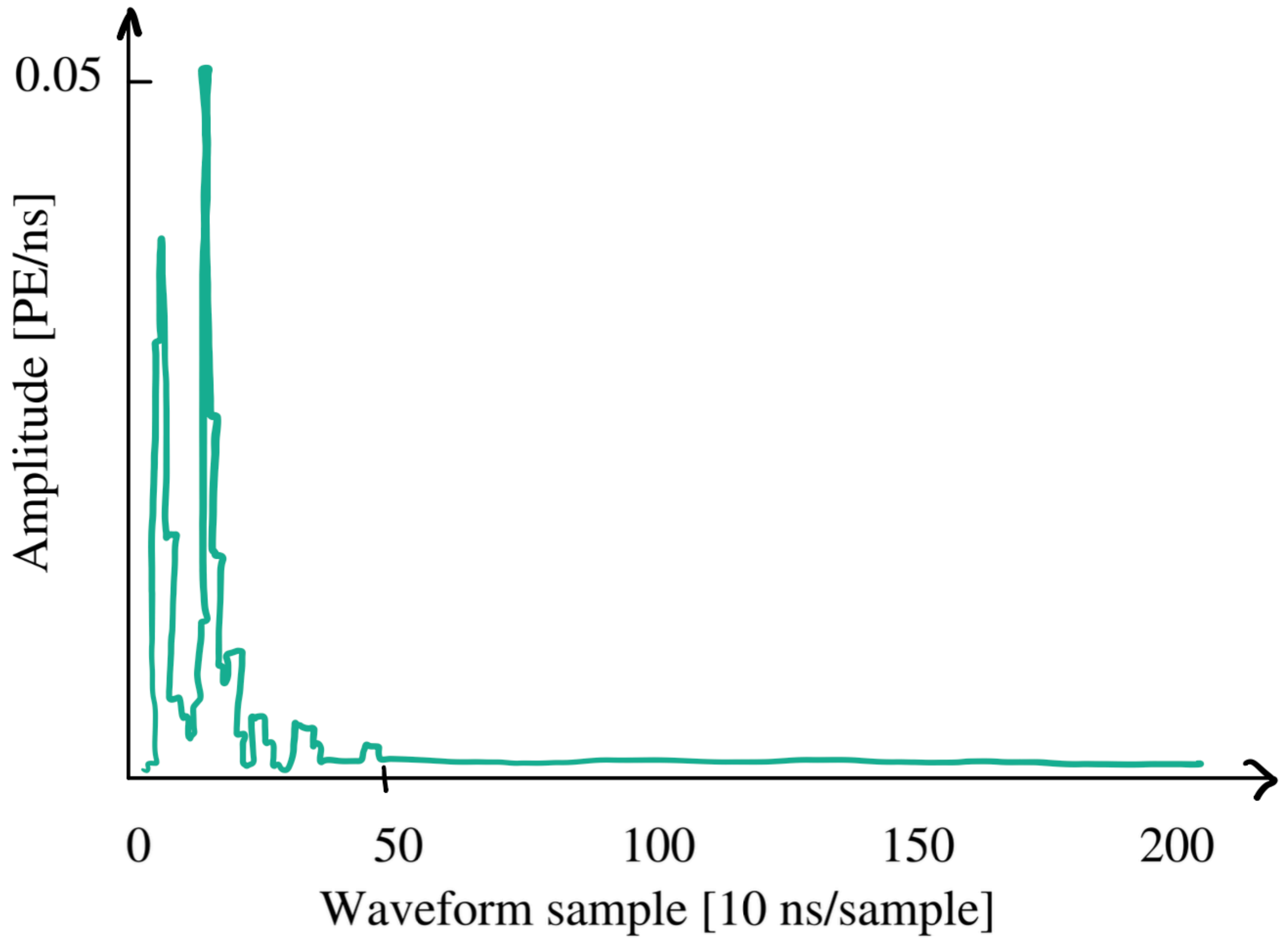
10.1103/PhysRevD.106.022001

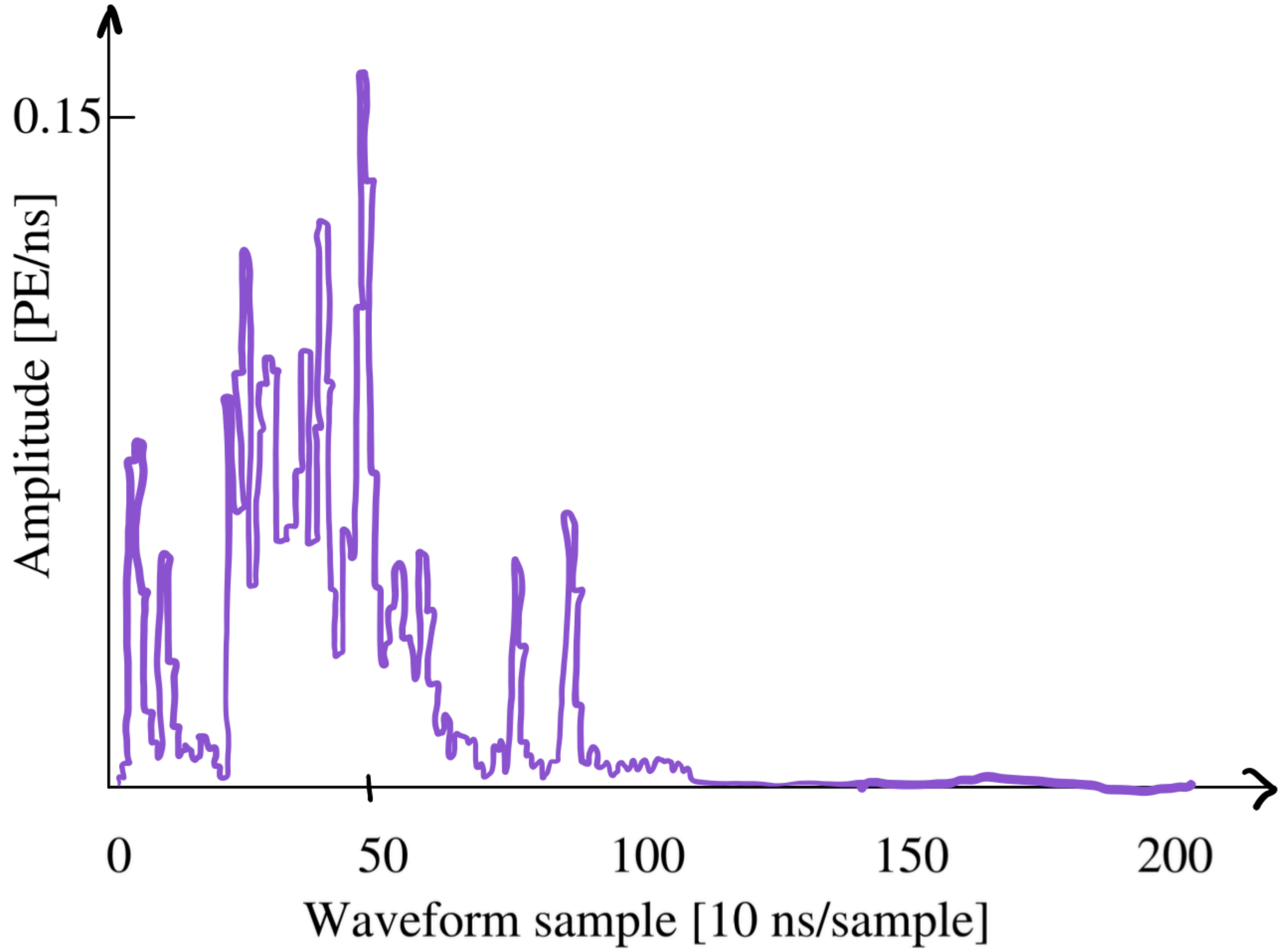


Classification in unprecedented regimes

Low-energy challenges: if 1-2 quanta produced, signal topology is stochastic

Neutrino enhancements at these energies demand a low energy threshold





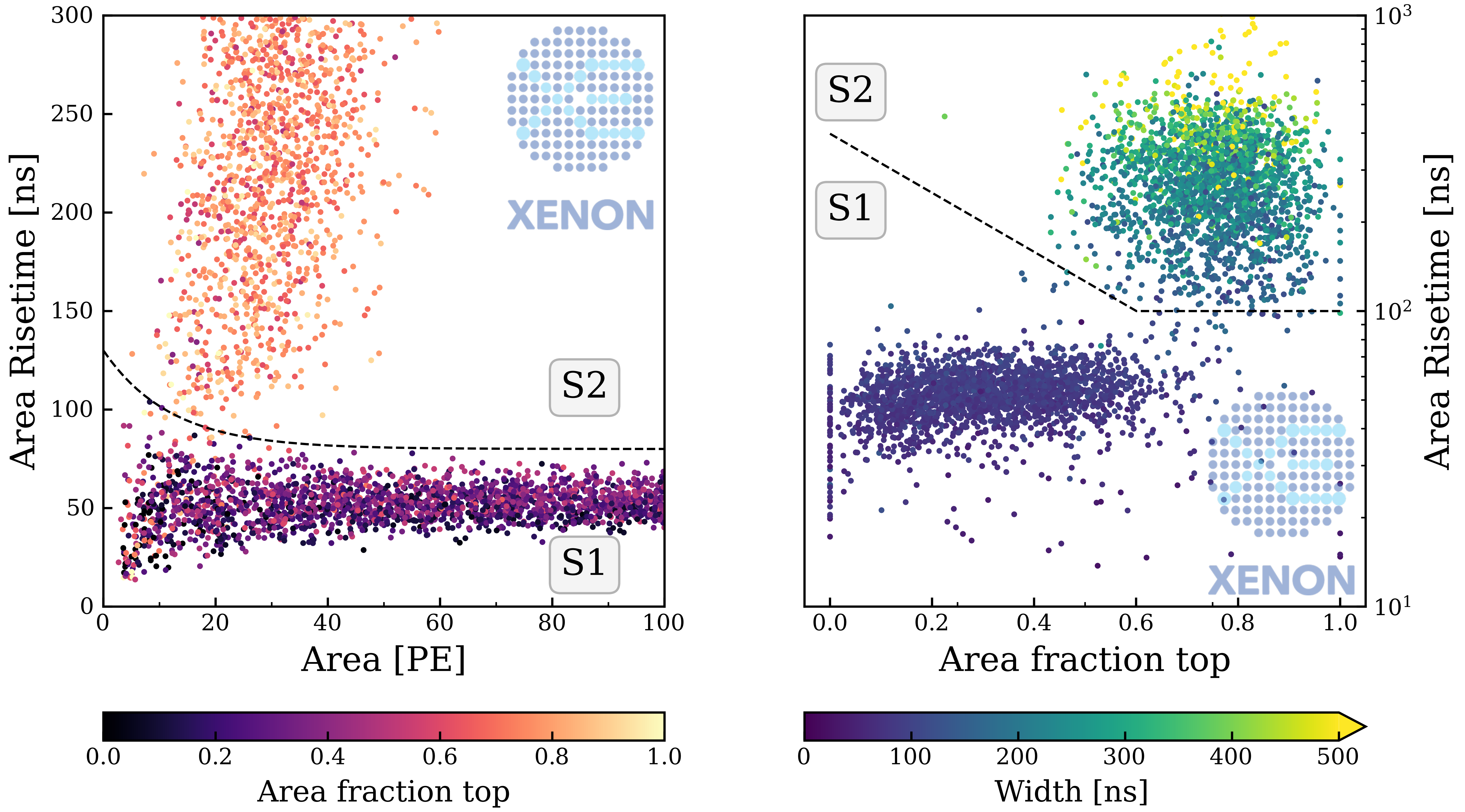
The problem of signal classification in XENONnT

- Downsampled representation of high-dimensional, complex waveform
- Deterministic decision boundary requires additional misclassification and quality selection criteria
- Complicated by:

high background rates

operational limitations

dimensionality



Innovation 1: signal classification in XENONnT with a Bayesian network

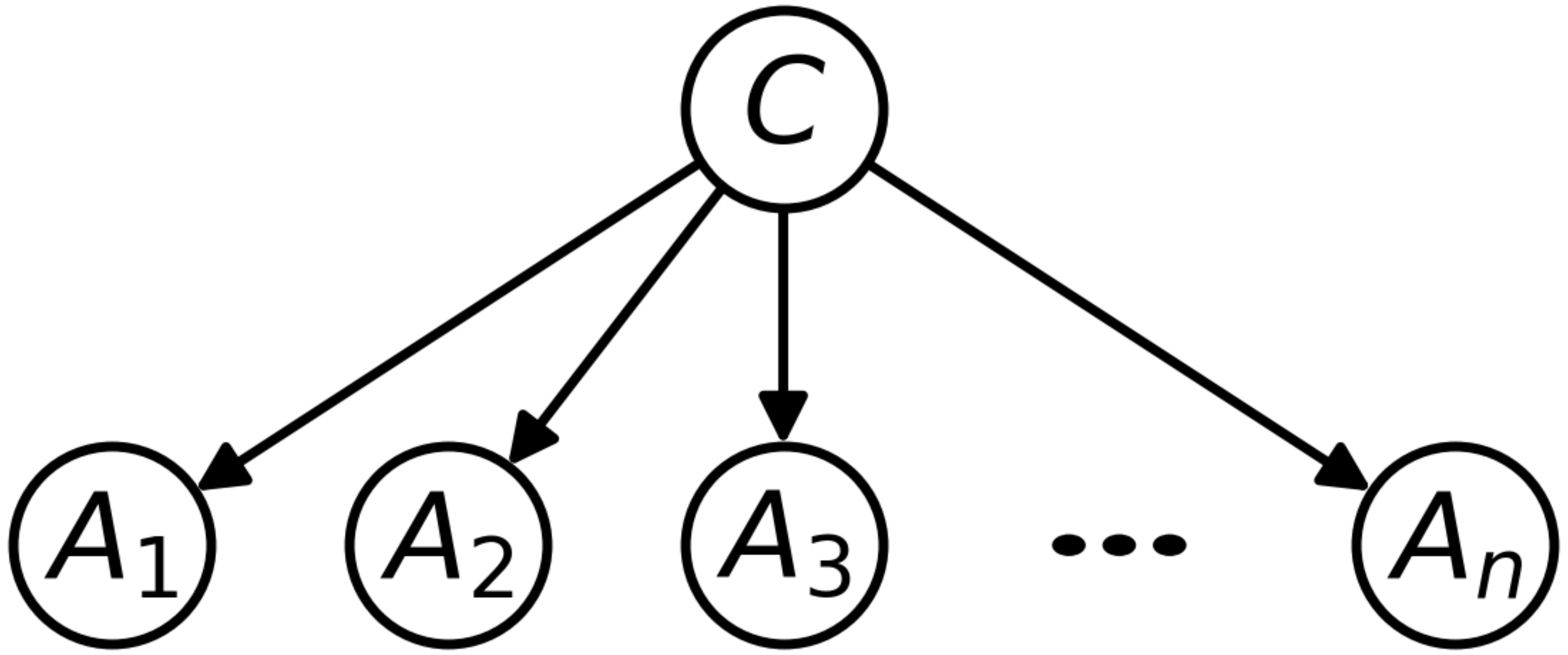
10.1103/PhysRevD.108.012016

Naive Bayes Classifier (NBC)

Classifier: observe data, $\mathbf{A}$, and infer $P(C\,|\,\mathbf{A})$

- Attributes are conditionally independent → scalable and interpretable
- Powerful even in cases where true dependencies exist

signal type (S1/S2)



detector data

Joint probability formula

$$P(C, A_1, A_2, \ldots, A_n) = P(C)\prod_{i=1}^{i=n} P(A_i\,|\,C)$$

Conditional probability formula

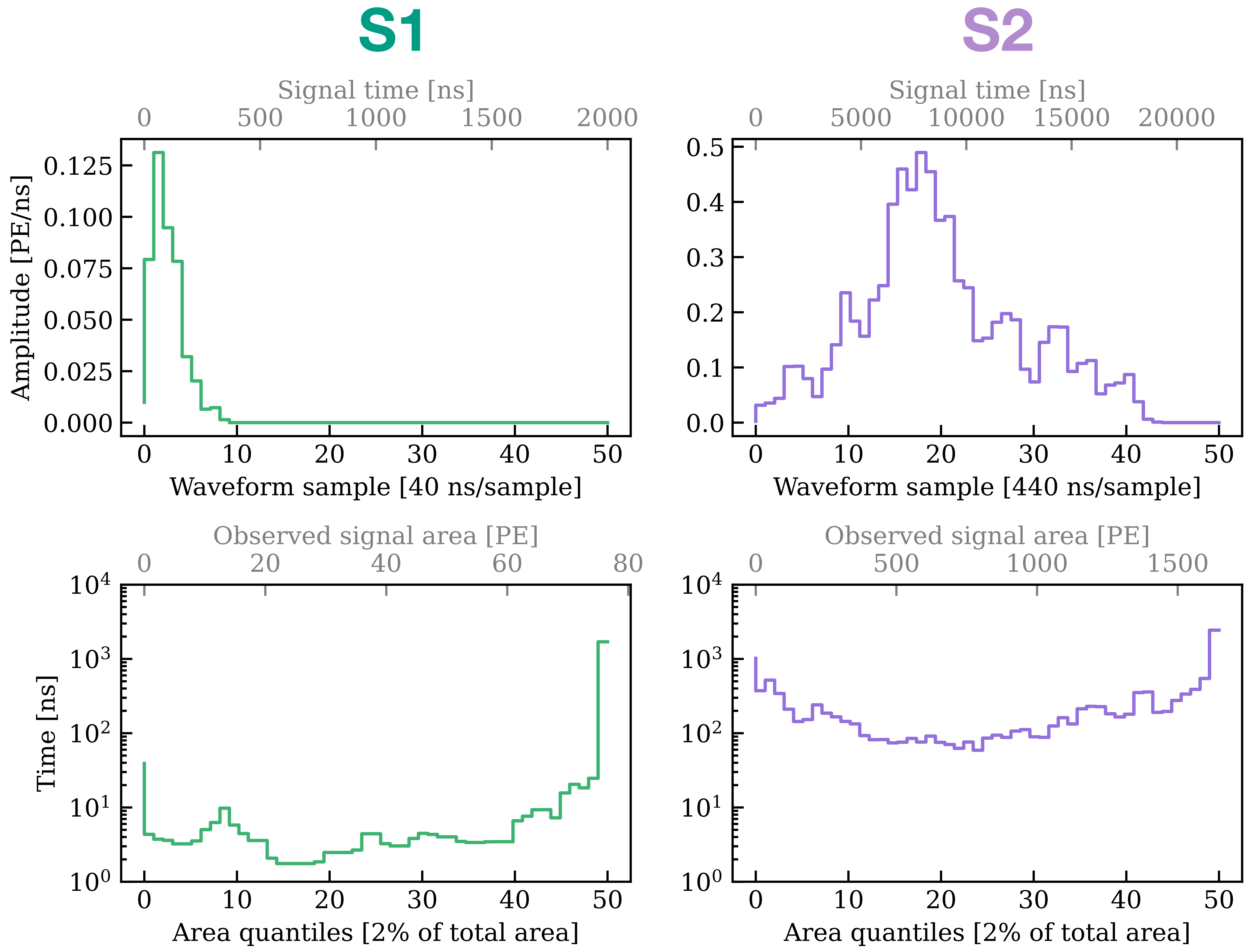
$$P(C\,|\,A_1 = a_1, \ldots, A_n = a_n) = \frac{P(C)\prod_{i=1}^{n} P(A_i = a_i\,|\,C)}{P(A_1 = a_1, \ldots, A_n = a_n)}$$

Building and tuning a Bayesian network

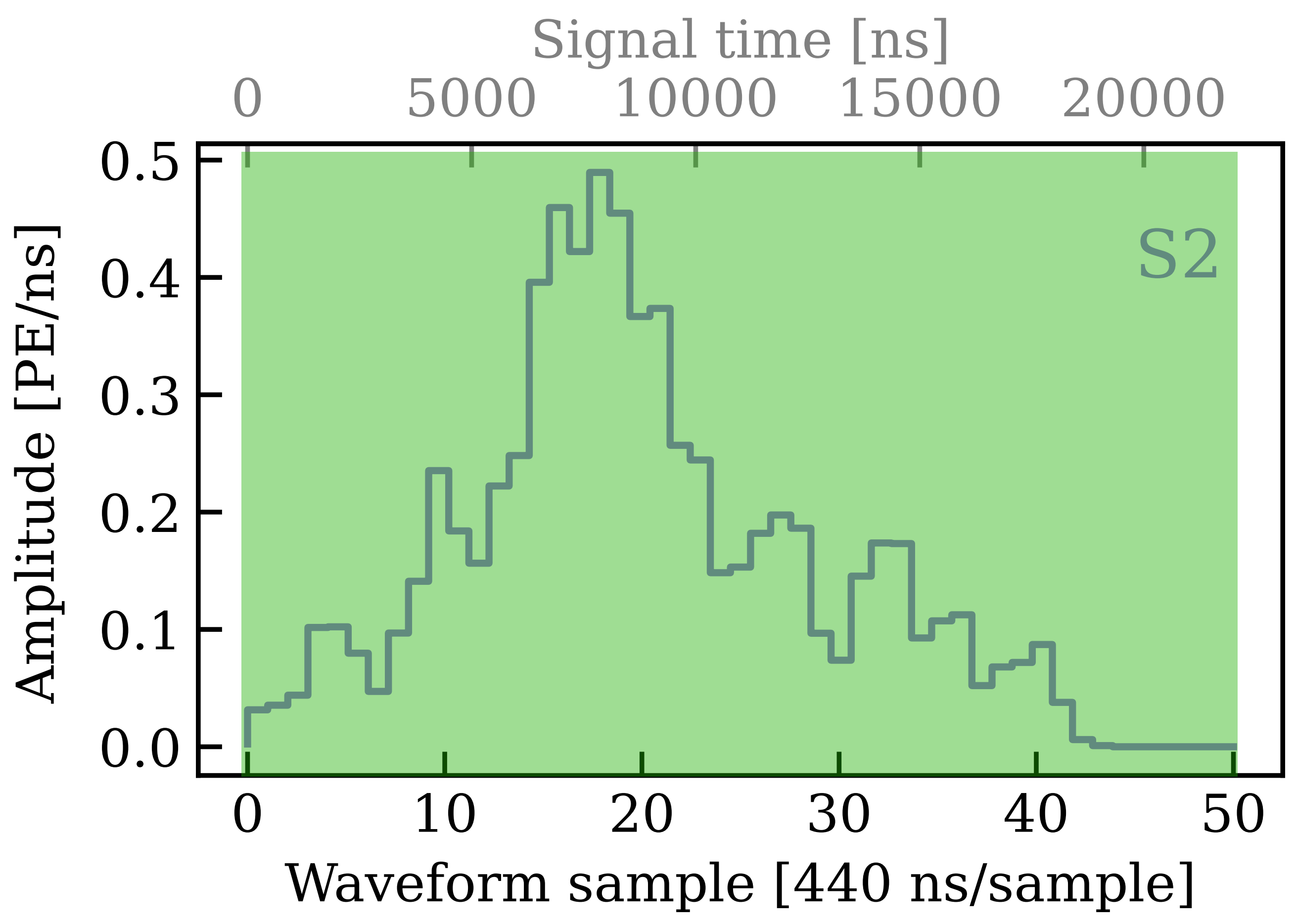
- Training dataset
- Representation of data, $\mathbf{A}$
- Parameterization (discretization) of attributes, A_i
- Choice of prior, $P(C)$
- Decision boundary $P(C \mid \mathbf{A})$ (if deterministic classification)

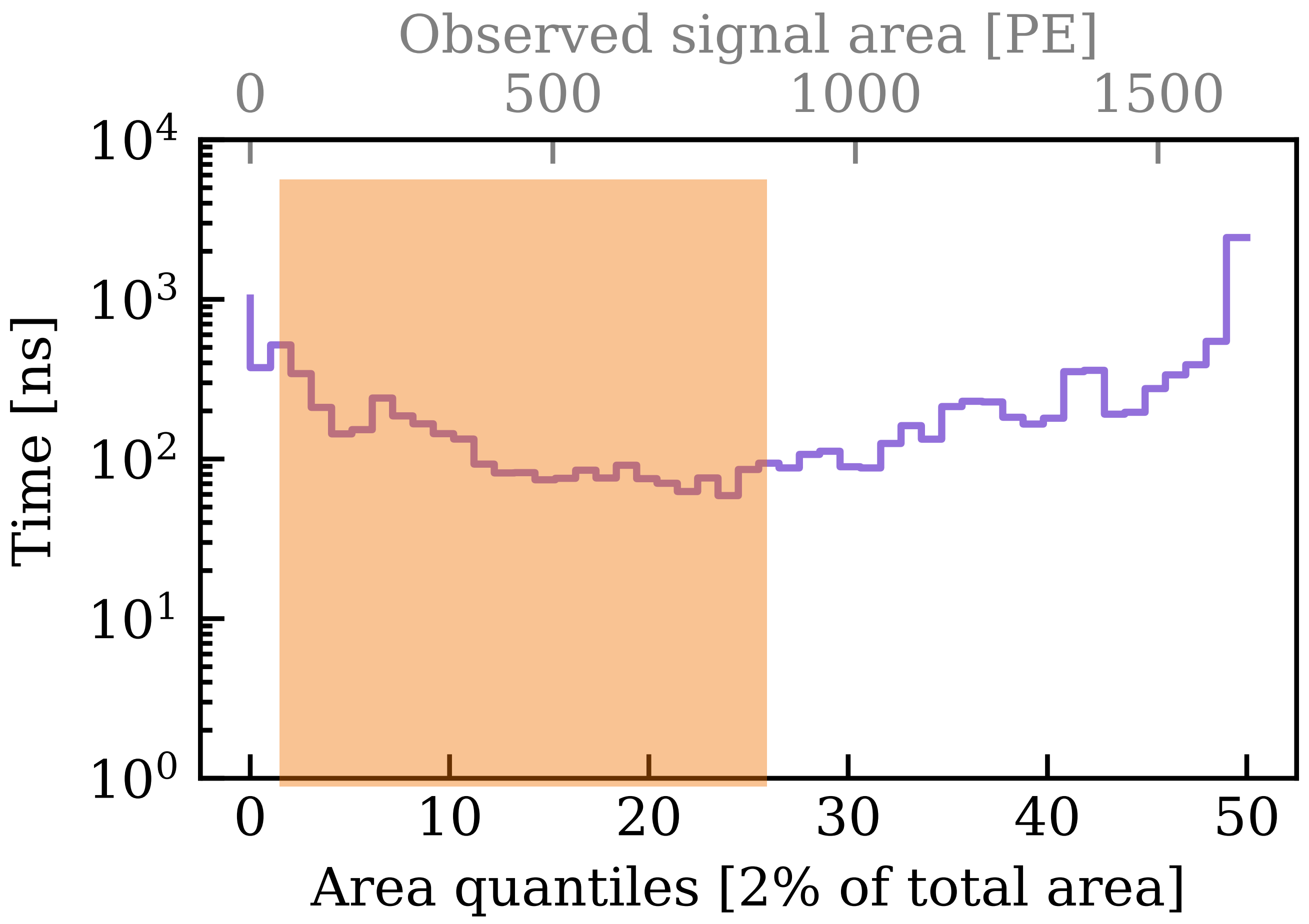
Representation of attributes, $\mathbf{A}$

- High-dimensional temporal data summed over all PMTs
- Waveform + quantiles
- 100 nodes total (optimized)
- Each node is discretized, optimized on information density



NBC evaluation: winning classifier





Mid-level data (100D)

vs.

size
shape
PMT dist.

High-level data (3D)

Naive Bayes Classifier

	True S1	True S2
Predicted S1	99.999 ± 0.001 %	0.003 ± 0.001 %
Predicted S2	0.001 ± 0.001 %	99.997 ± 0.001 %

Straxen algorithm (conventional)

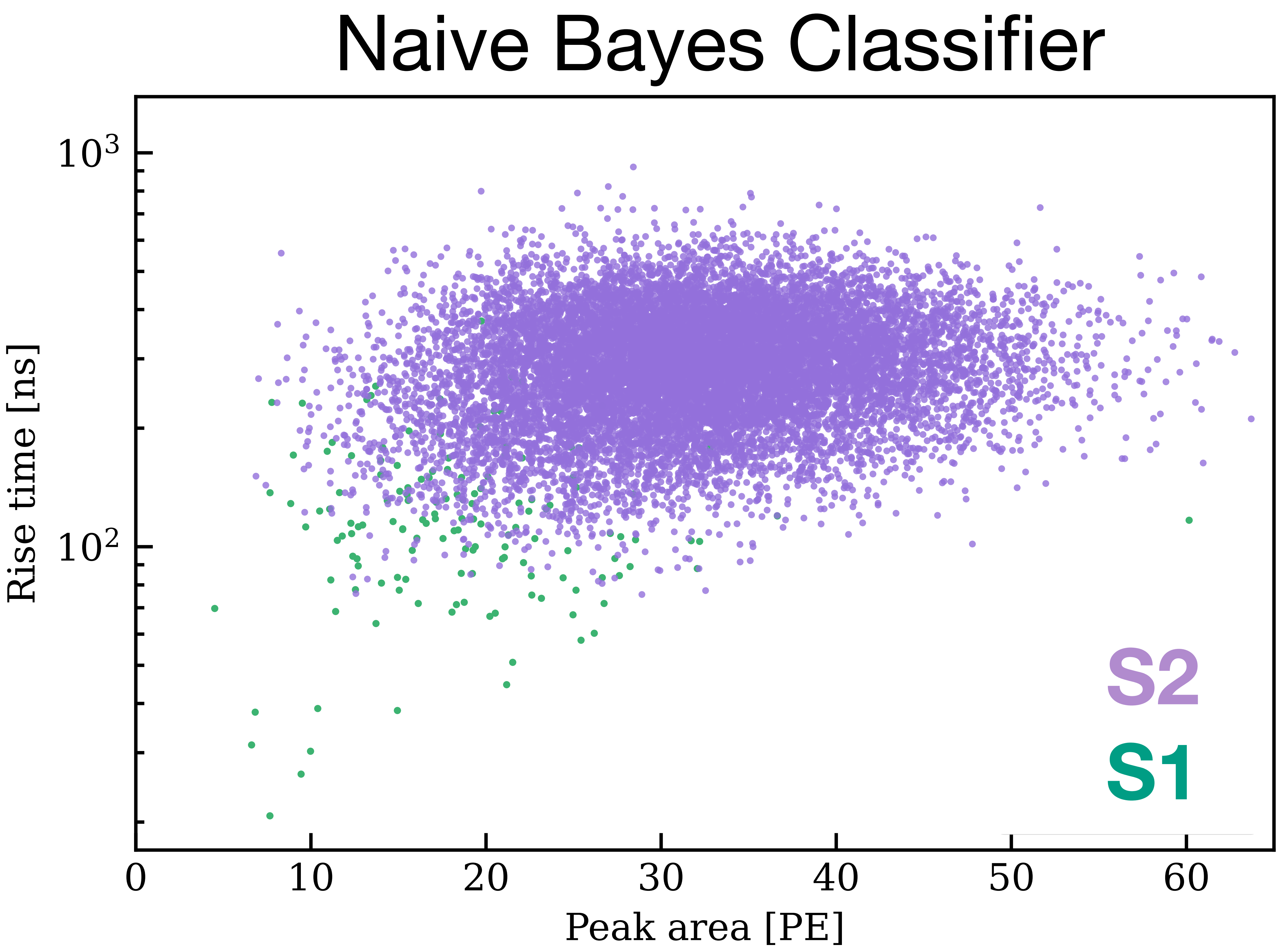
	True S1	True S2
Predicted S1	99.744 ± 0.020 %	0.017 ± 0.004 %
Predicted S2	0.057 ± 0.010 %	99.983 ± 0.004 %
Unclassified	0.199 ± 0.017 %	0.000 ± 0.001 %

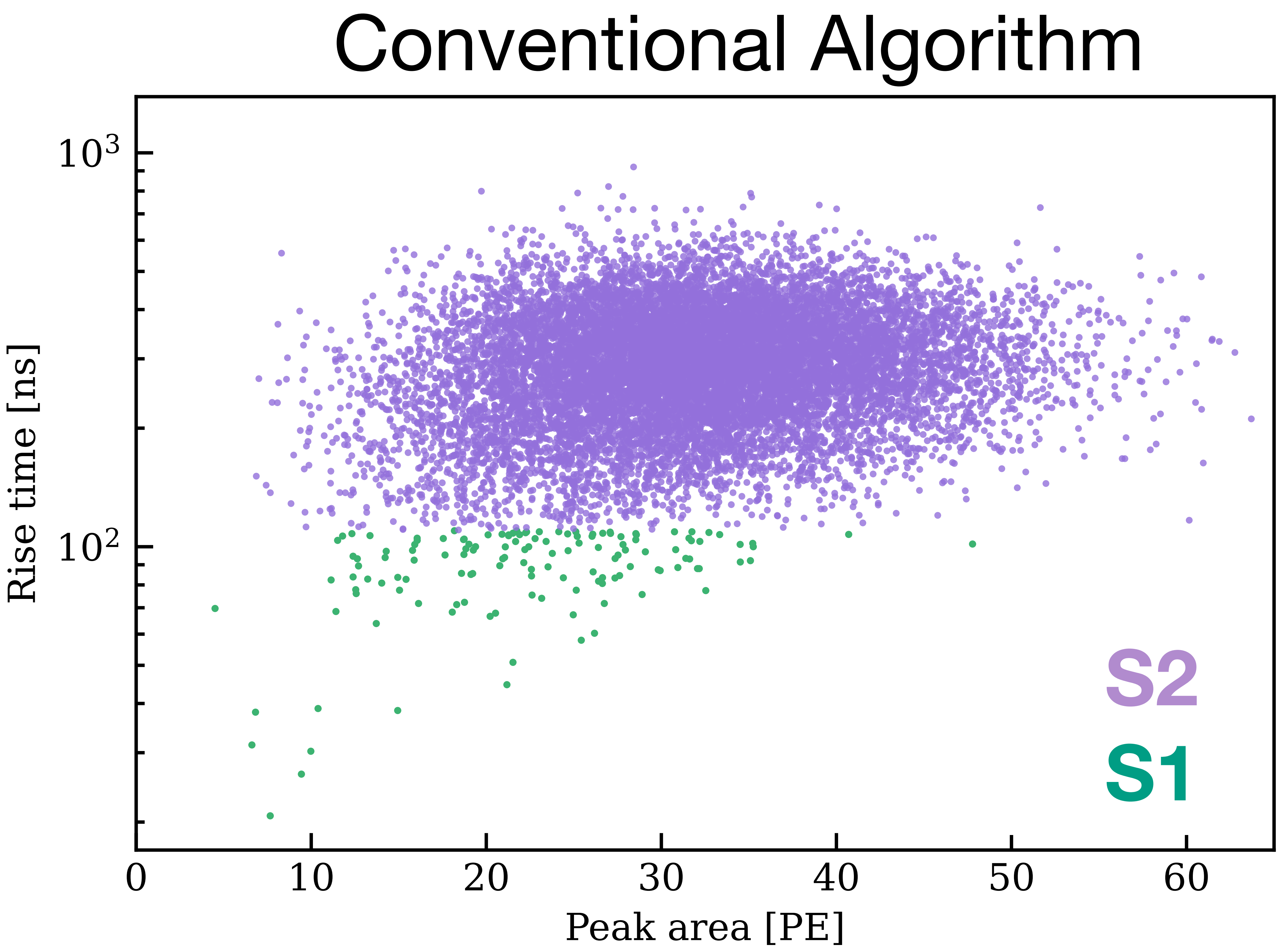
Neural network

	True S1	True S2
Predicted S1	99.975 ± 0.004 %	0.007 ± 0.002 %
Predicted S2	0.025 ± 0.004 %	99.993 ± 0.002 %

Evaluation of Naive Bayes Classifier

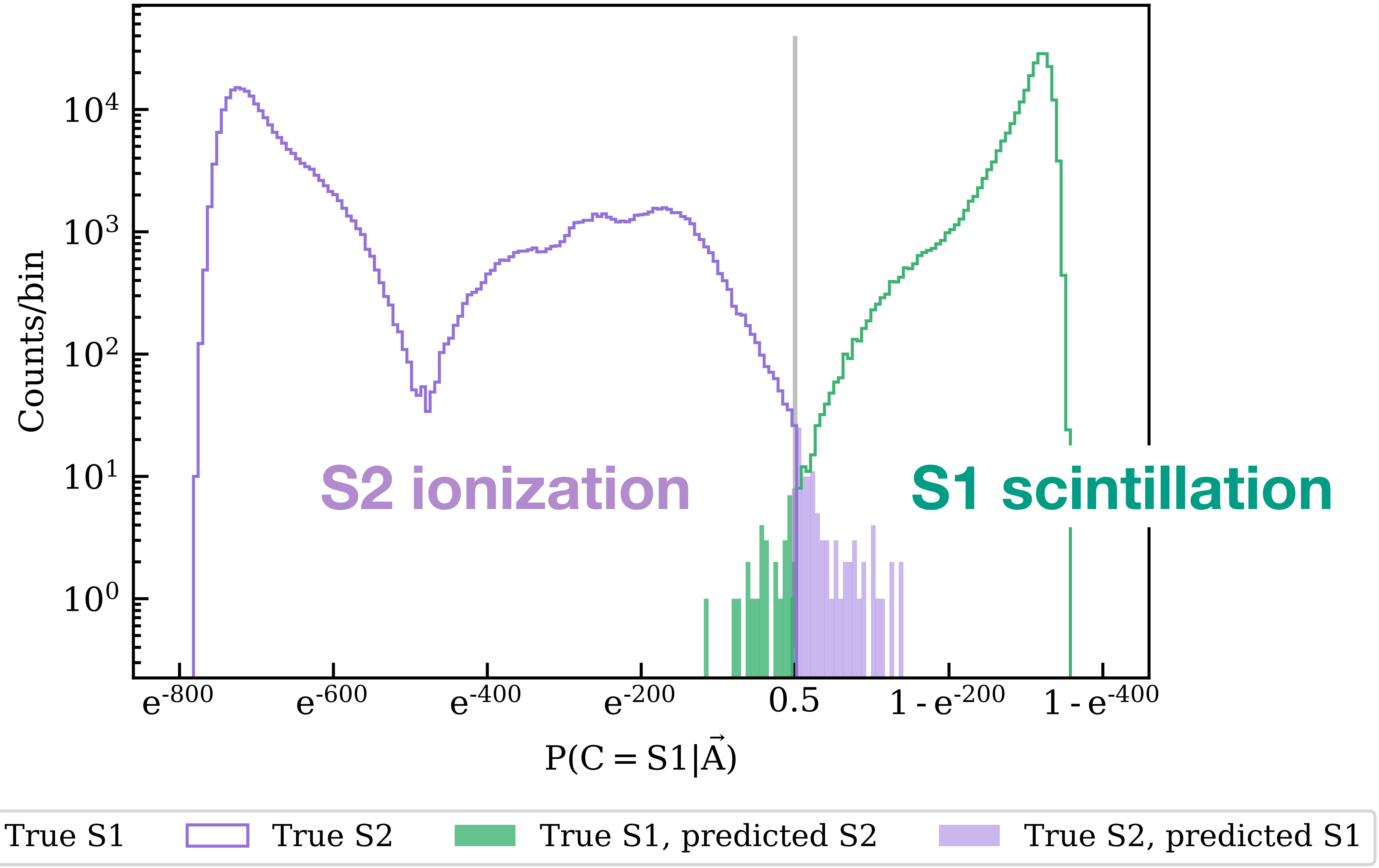
- Single electron classification (given a decision boundary of 0.5) **is less biased**





Evaluation of NBC

- Model query is informative about signal shape relative to training sample



Innovation 2: Signal characterization with a Bayesian network

10.1103/PhysRevD.108.012016

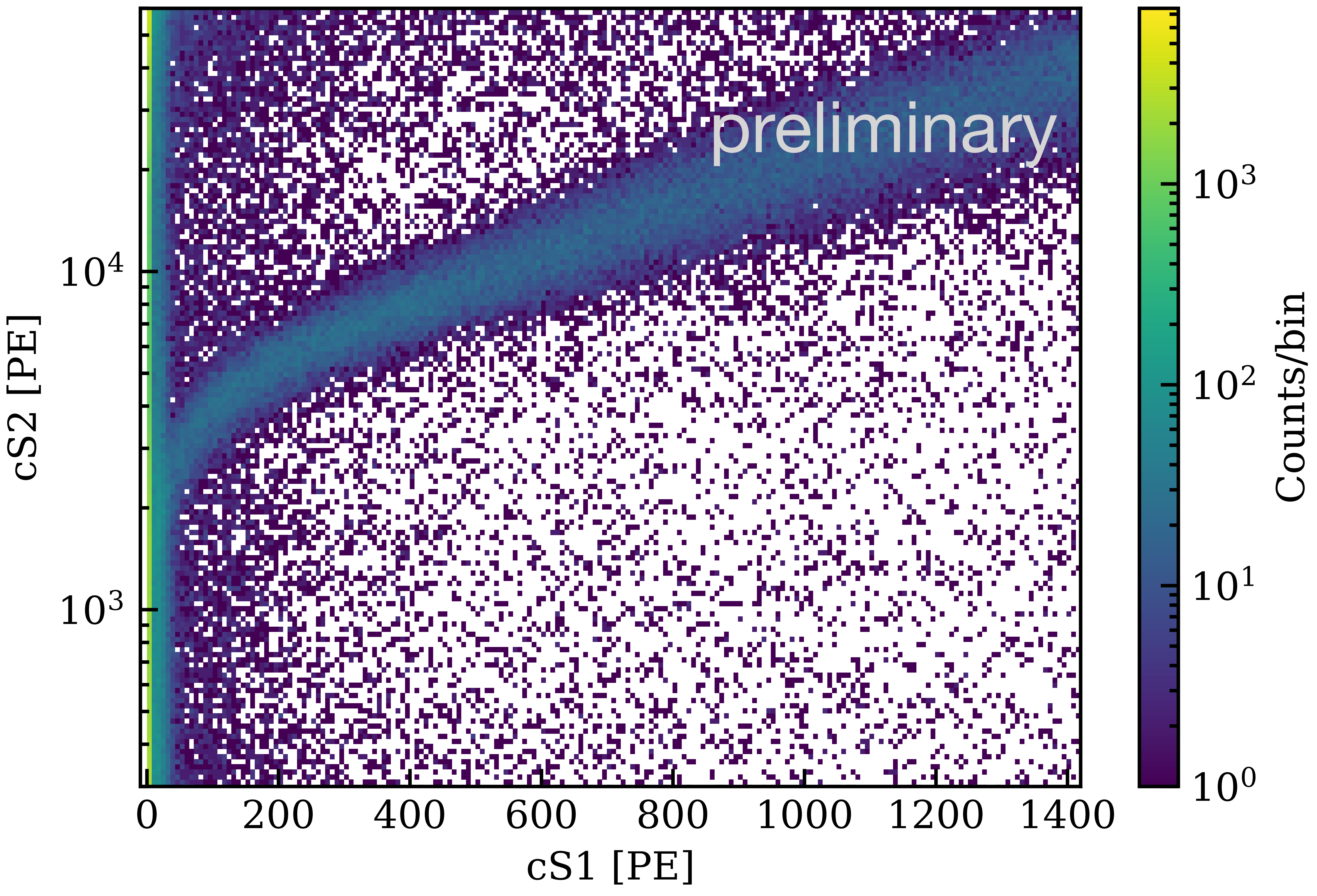
Utilizing NBC model output in analysis

- Most signals in data are unphysical and/or undesirable in analysis
- Reject these "noncanonical" backgrounds (and characterize them)

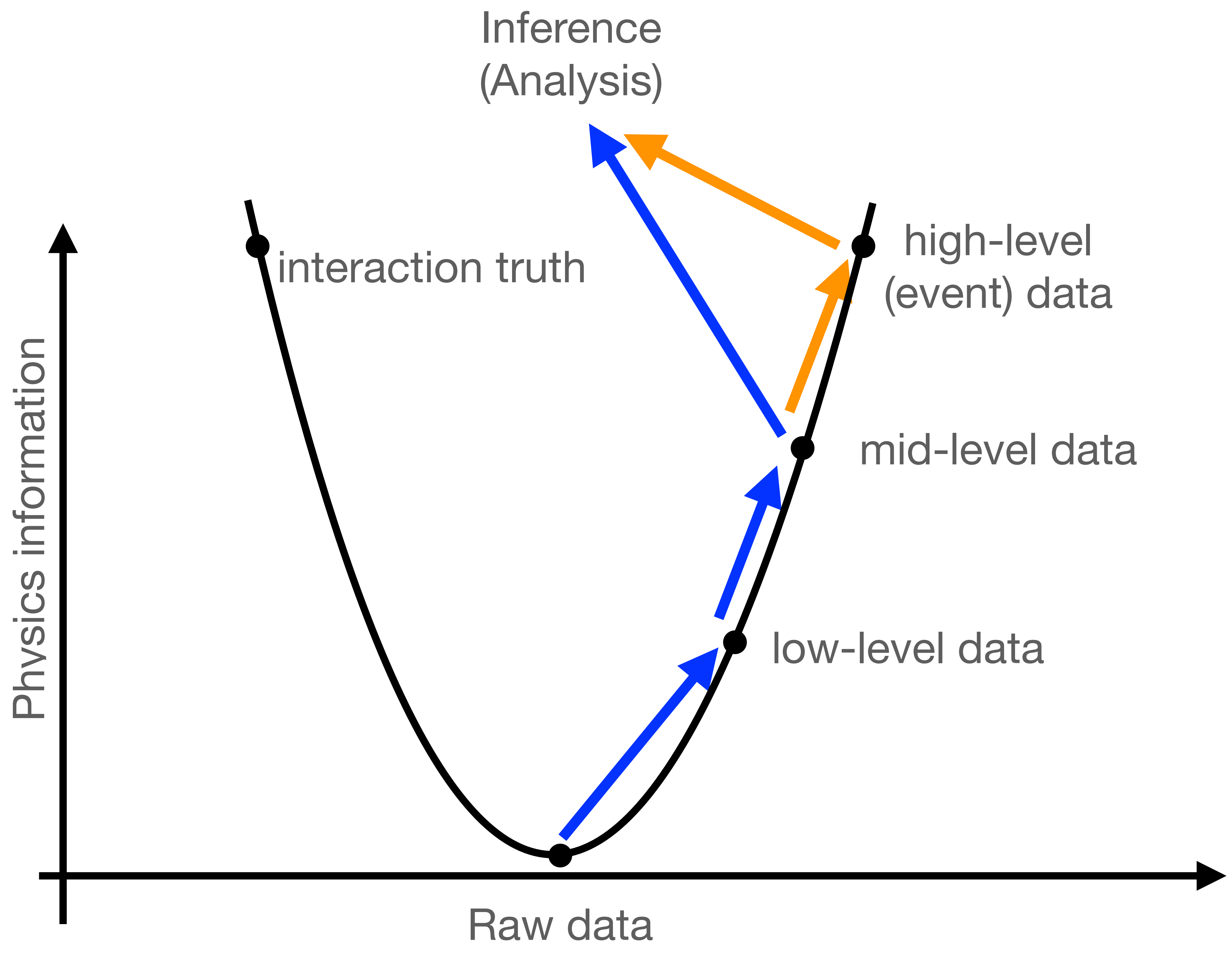
  …but accept true signals…

  depending on their NBC model output

^{220}Rn calibration data



The NBC method of signal selection

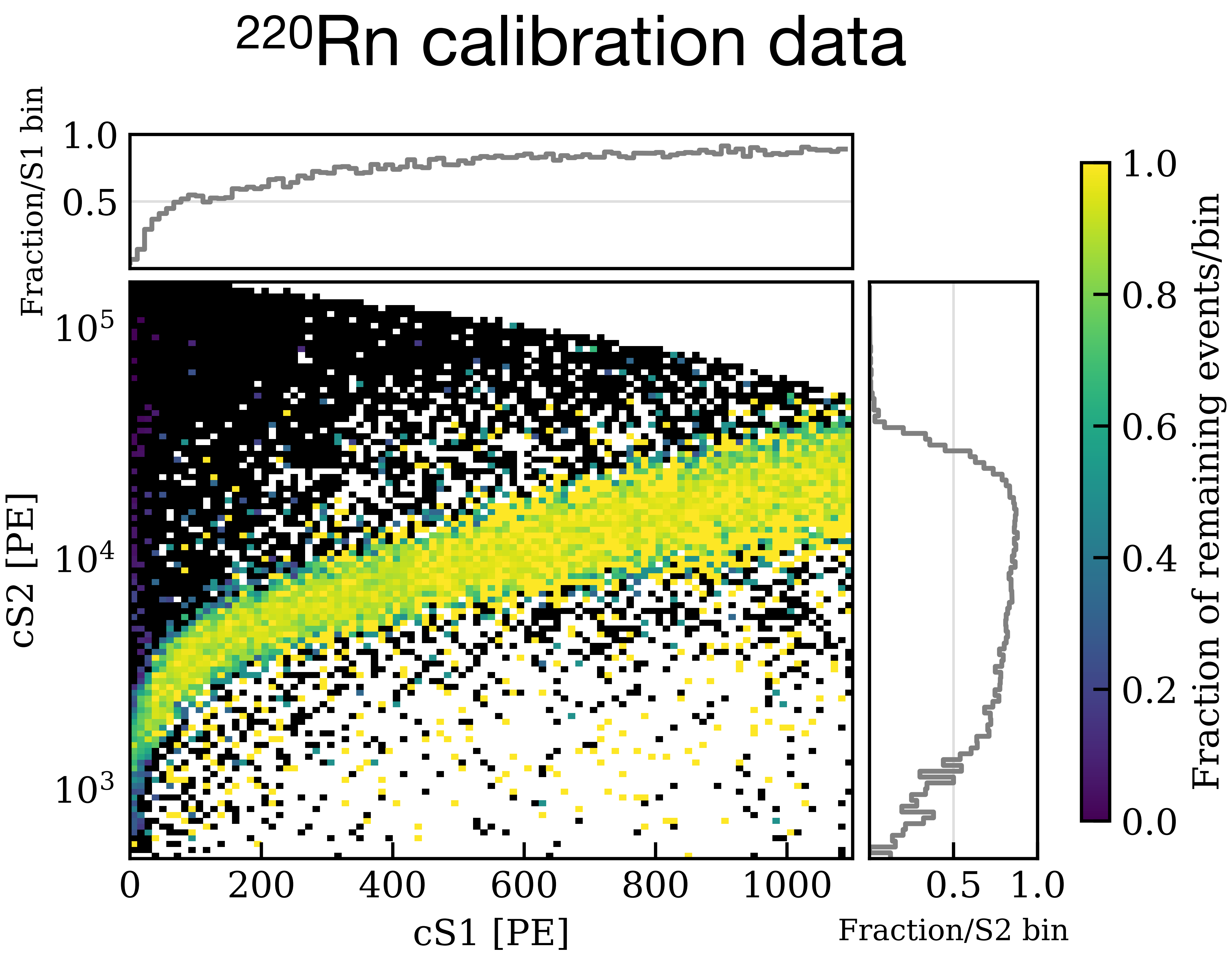


Can we improve retention of information and efficiency by relying only on waveforms to select for signal quality?

Standard: 8 cuts based on many 1-D representations of waveform

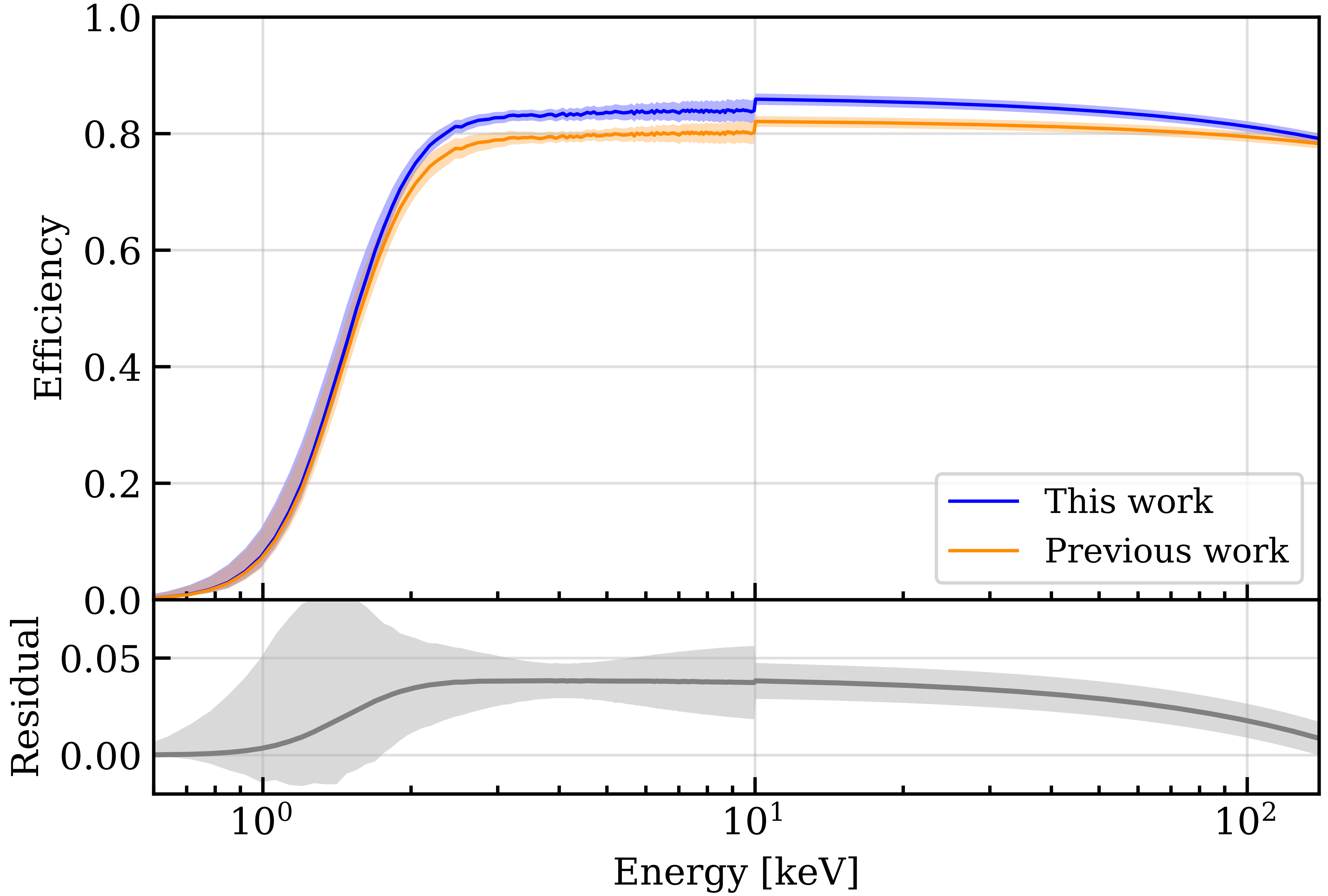
NBC: 1 unifying metric for each event signal which encodes high-D waveform

Robust background rejection power



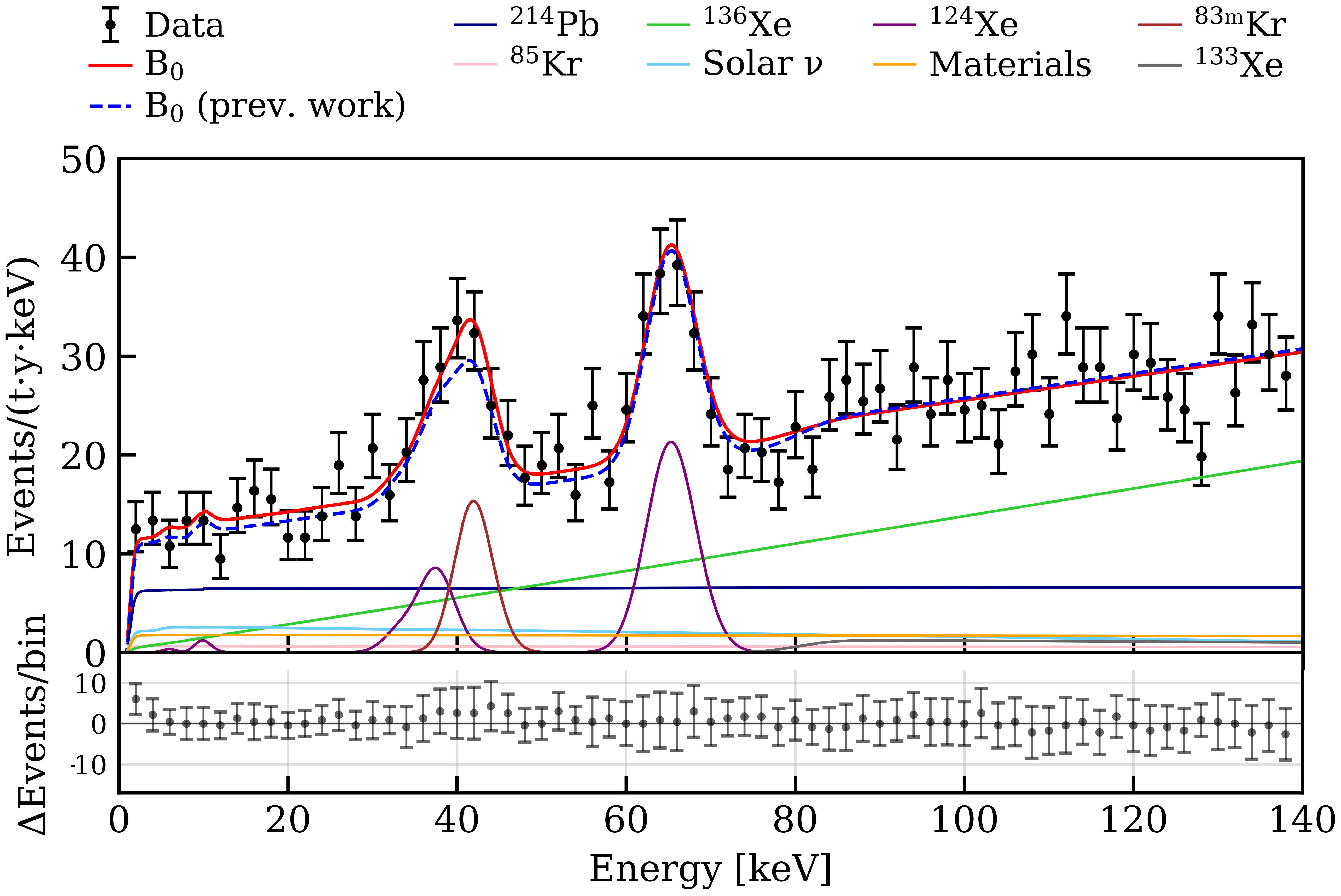
Effect of NBC selections on data

Total event acceptance



SR0 ER background components

Component	Fit (this work)	Fit (prev. work)
^{214}Pb	1050 ± 130	960 ± 120
^{85}Kr	100 ± 60	90 ± 60
Materials	280 ± 50	270 ± 50
^{136}Xe	1580 ± 60	1550 ± 50
Solar ν	310 ± 30	300 ± 30
^{124}Xe	250 ± 30	250 ± 30
AC	0.71 ± 0.03	0.71 ± 0.03
^{133}Xe	80 ± 60	150 ± 60
^{83m}Kr	101 ± 17	80 ± 16
χ^2/N_{DOF}	$128.6/128 = 1.004$	$134.0/128 = 1.047$



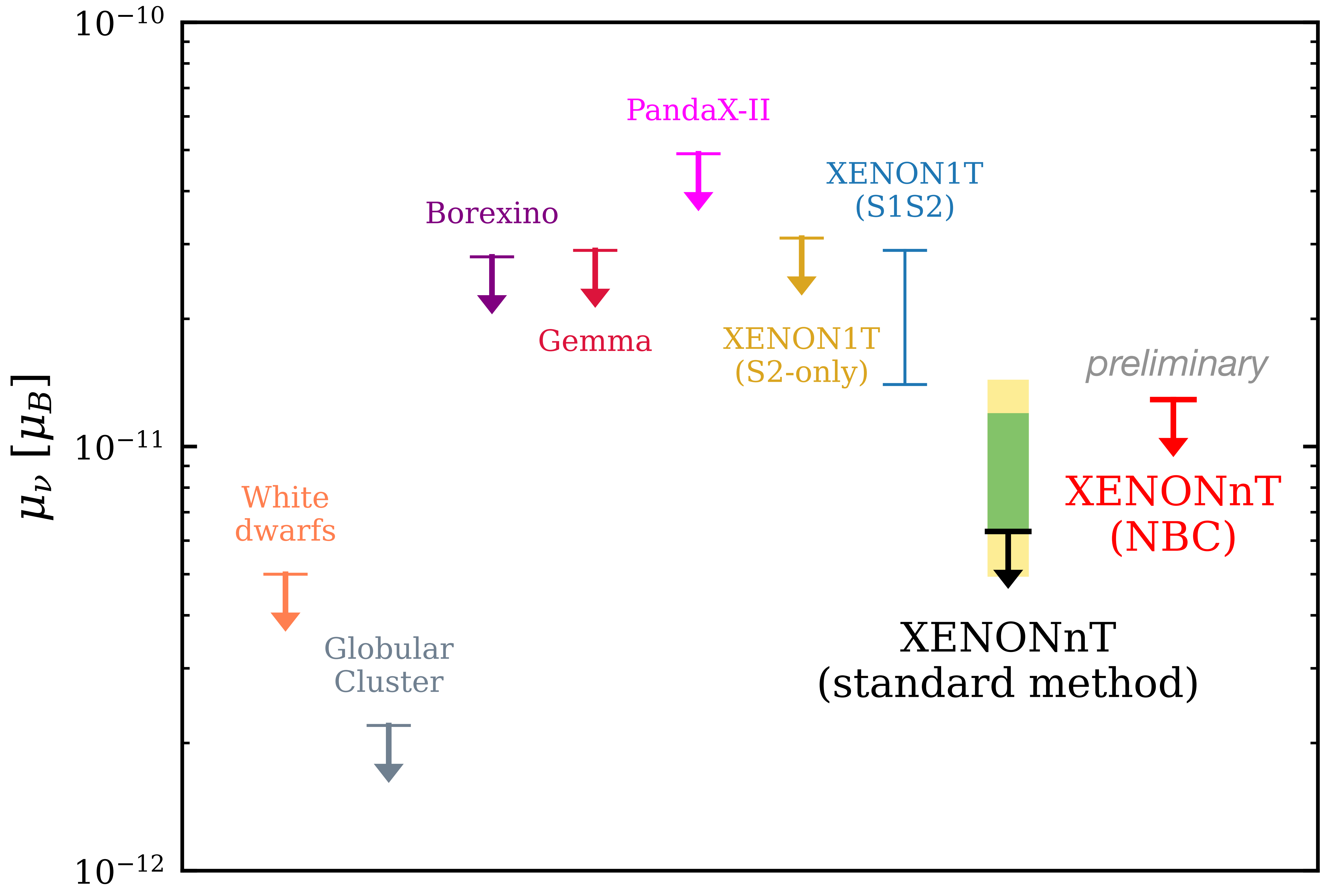
- Slightly higher rates of low-energy components due to improved efficiency

Test of signal hypothesis: μ_ν

- 90% CL upper limit:

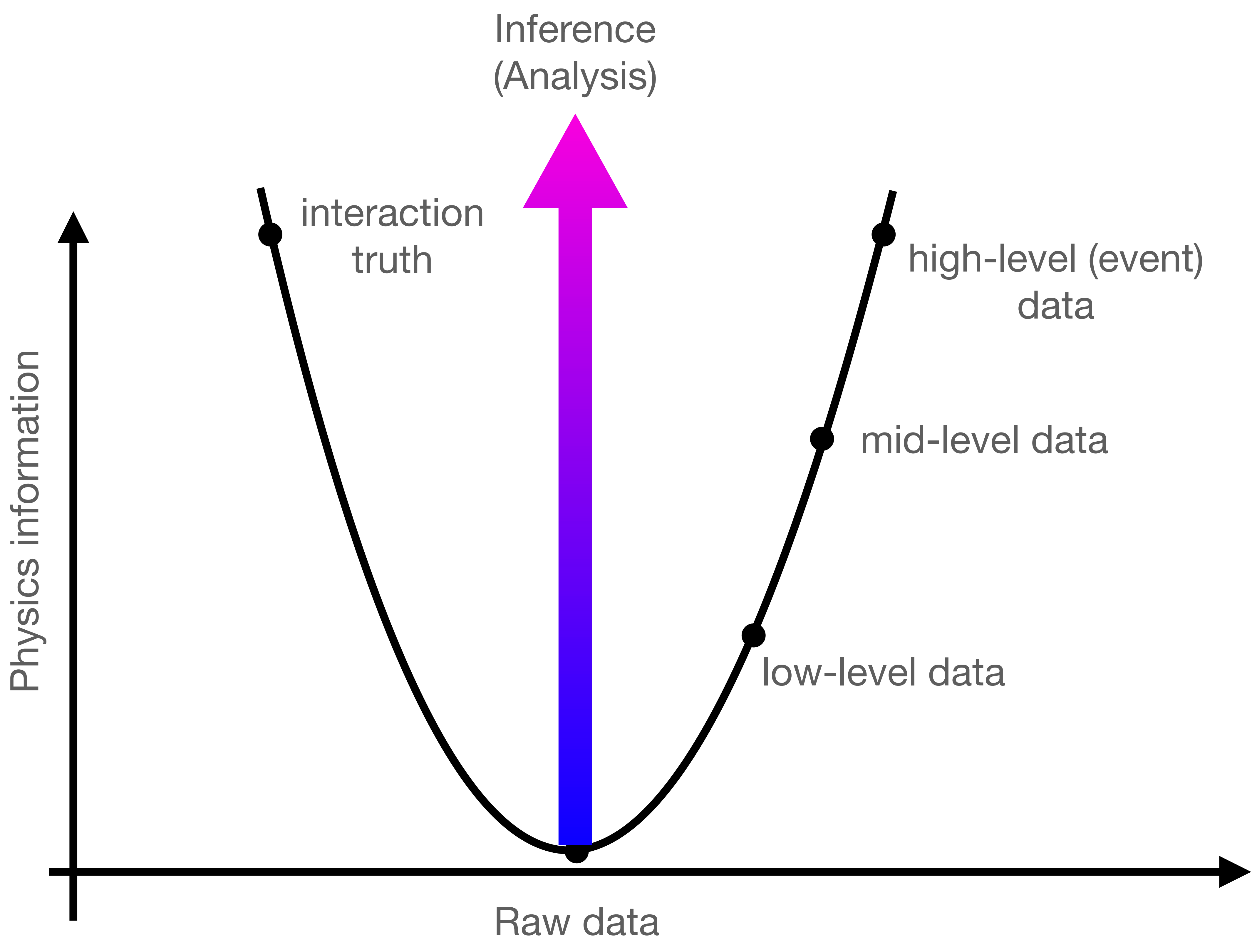
$$\mu_\nu < 1.3 \times 10^{-11} \mu_B$$

- No μ_ν favored over 3σ
- Background-only confirmation



Promising future applications

- Lowering the energy threshold to 2-quanta observation - better μ_ν, DM inference
- Ultimately: designing Bayesian networks for fully probabilistic analyses



Acknowledgements

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