

# Thoughts on Small Experiments

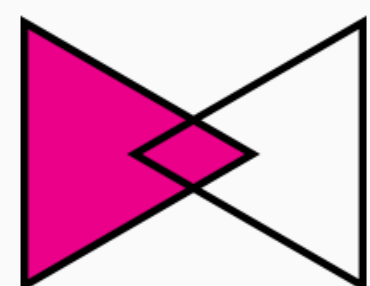
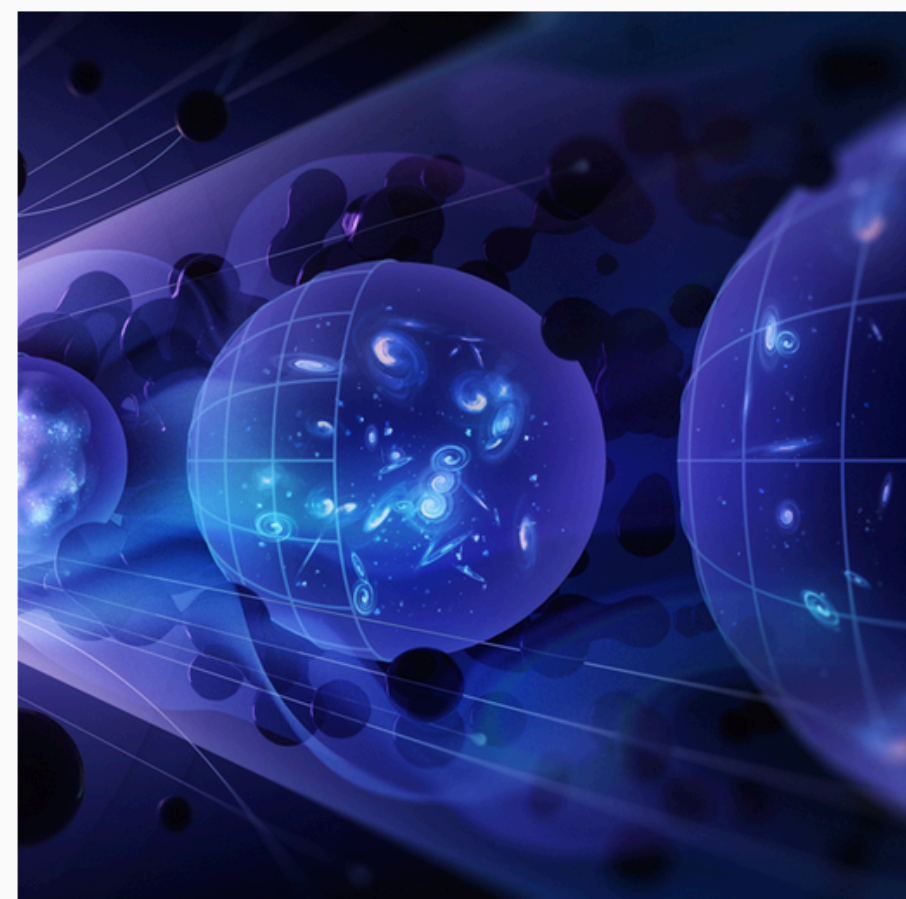
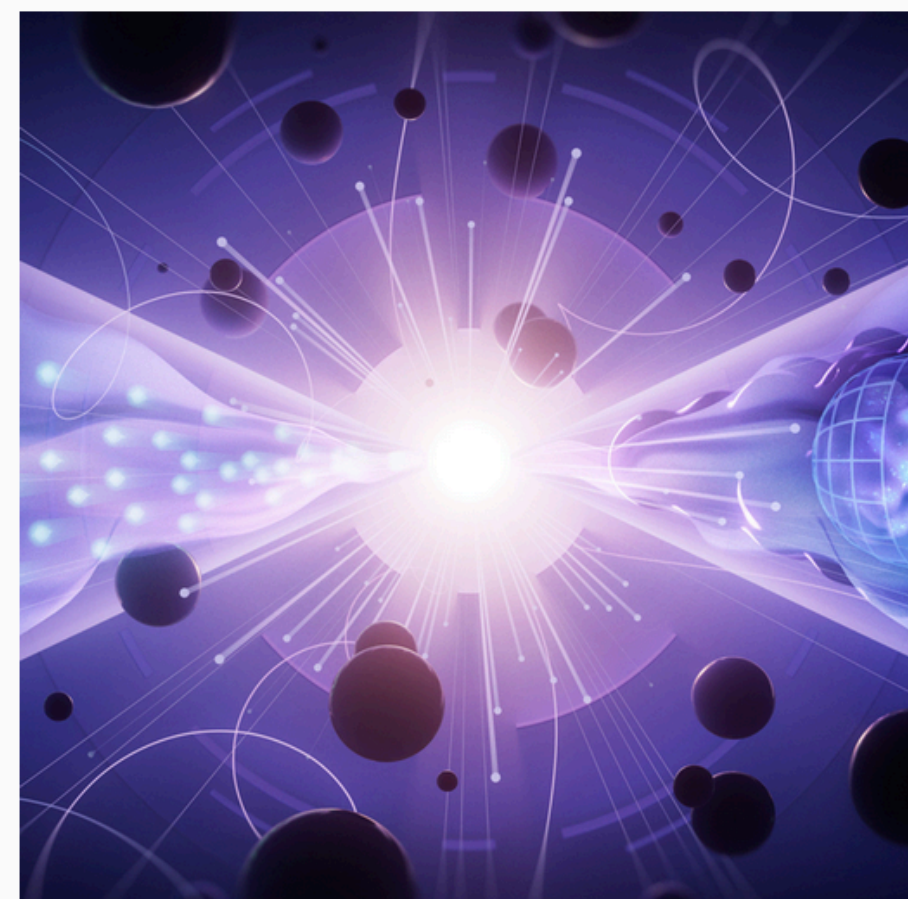
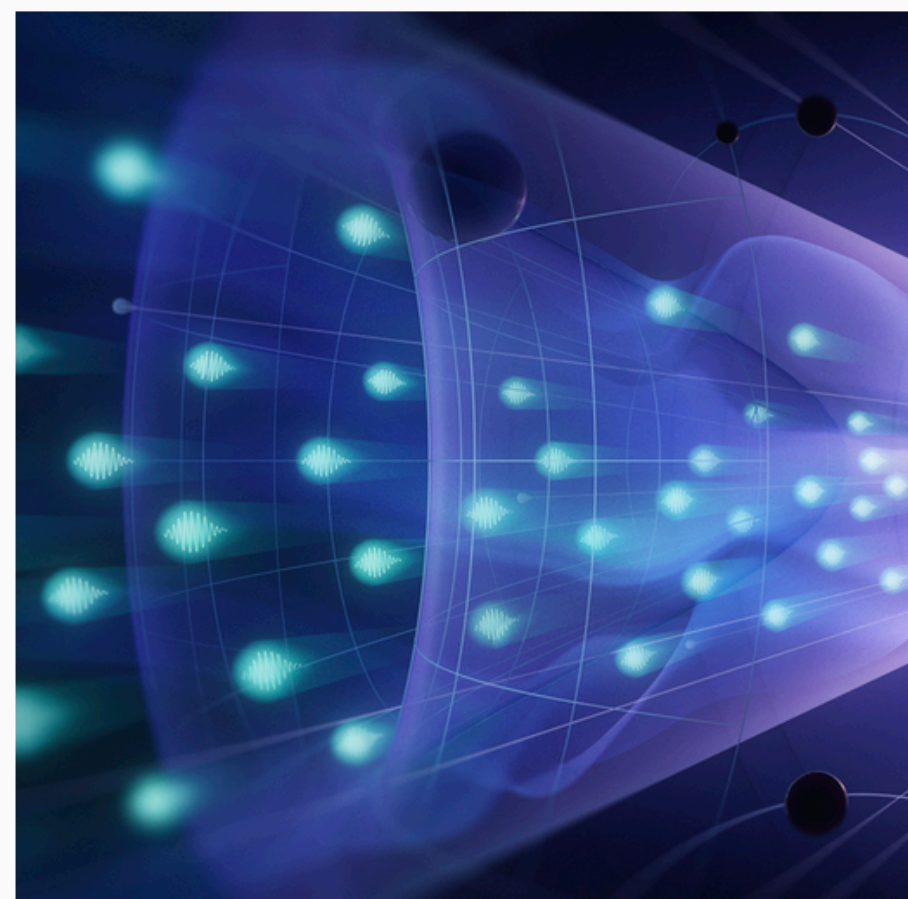
**Lindley Winslow**

Massachusetts Institute of Technology

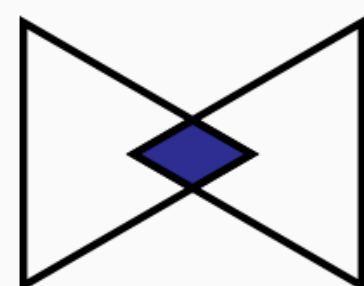


# First Thought: Physics

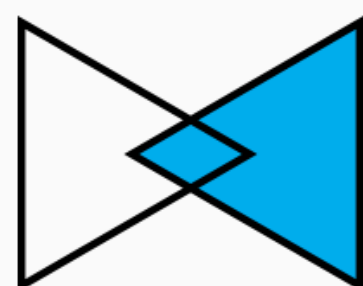
P5 Report: arXiv2407.19176



Decipher  
the  
Quantum  
Realm



Explore  
New  
Paradigms  
in Physics



Illuminate  
the  
Hidden  
Universe

Elucidate the Mysteries  
of Neutrinos

Reveal the Secrets of  
the Higgs Boson

Search for Direct Evidence  
of New Particles

Pursue Quantum Imprints  
of New Phenomena

Determine the Nature  
of Dark Matter

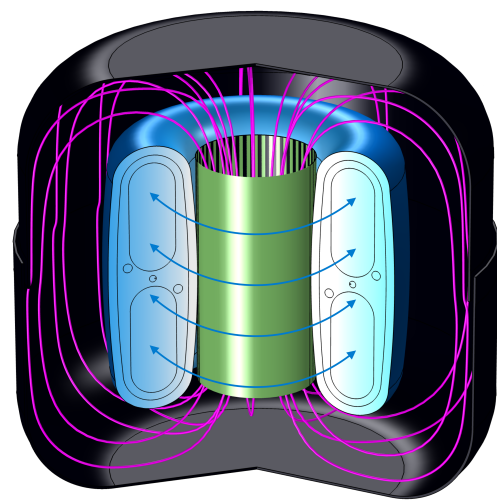
Understand What Drives  
Cosmic Evolution

*Small experiments are needed for discovery across HEP, as either auxiliary measurements or discovery machines in their own right.*



# Second Thought: A Definition

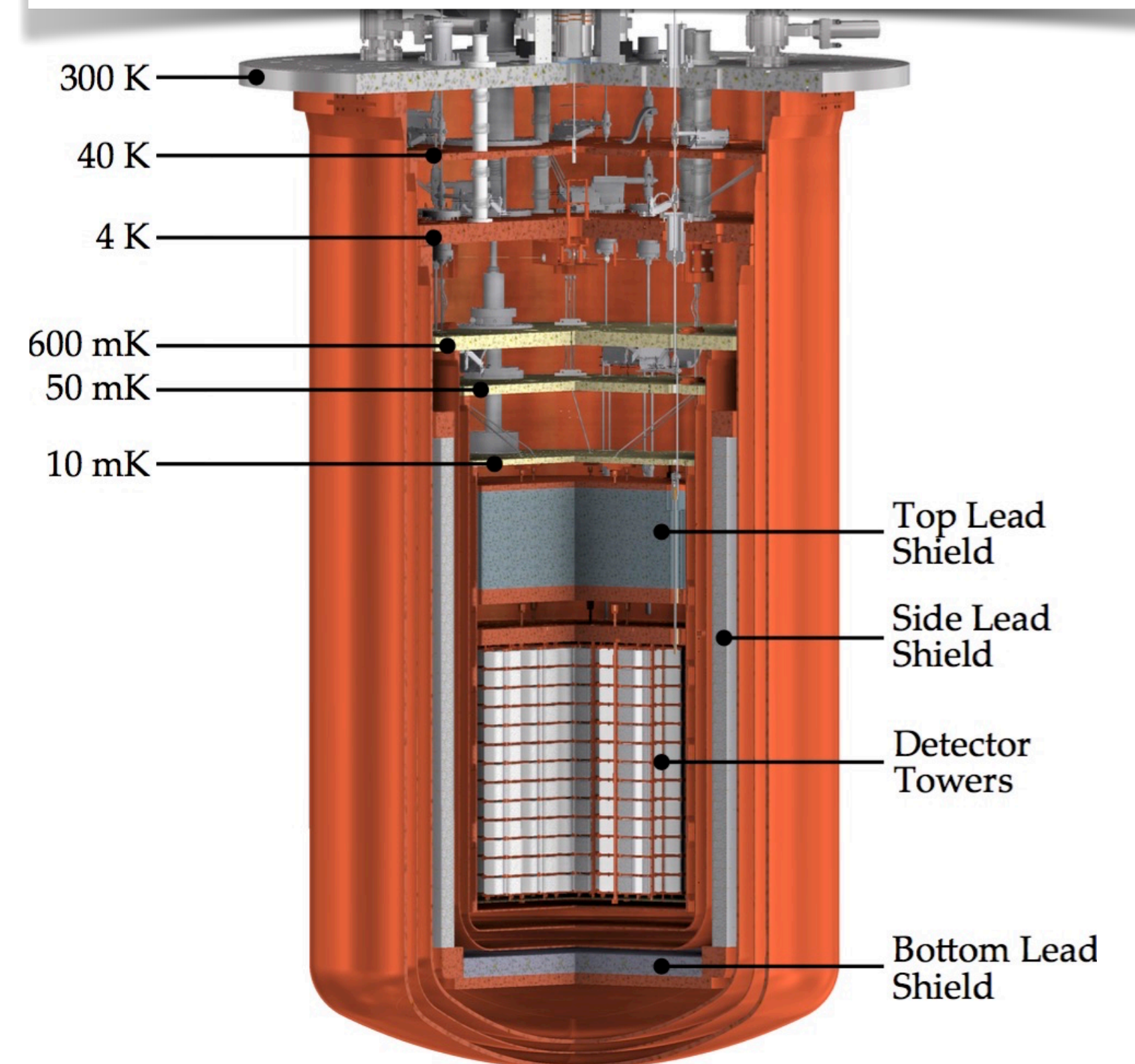
*Small experiments exist on a continuum, but they share the fact that the team doing the analysis is the same that is constructing and running the experiment.*



ABRACADABRA-10cm  
team O(10), runs at MIT



CUORE  
team O(100), runs at LNGS





# Third Thought: The Data

## Category #1

**Detectors  
designed for  
specific signals**

**Axions, Double-Beta Decay, eDMs...**

## Category #2

**Traditional  
multi-detector  
system  
experiments**

**Beam dumps, auxiliary experiments...**



# Third Thought: The Data

## Category #1

**Smaller data volumes**  
**Low information**

**Axions, Double-Beta Decay, eDMs...**

## Category #2

**Higher data volumes**  
**High information**

**Beam dumps, auxiliary experiments...**



# KamNET - Example Category #1

PHYSICAL REVIEW C **107**, 014323 (2023)

Editors' Suggestion

## KamNet: An integrated spatiotemporal deep neural network for rare event searches in KamLAND-Zen\*

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(Received 6 March 2022; accepted 14 September 2022; published 30 January 2023)

Rare event searches allow us to search for new physics at energy scales inaccessible with other means by leveraging specialized large-mass detectors. Machine learning provides a new tool to maximize the information provided by these detectors. The information is sparse, which forces these algorithms to start from the lowest level data and exploit all symmetries in the detector to produce results. In this work we present KamNet, which harnesses breakthroughs in geometric deep learning and spatiotemporal data analysis to maximize the physics reach of KamLAND-Zen, a kiloton scale spherical liquid scintillator detector searching for  $0\nu\beta\beta$ . Using a simplified background model for KamLAND, we show that KamNet outperforms a conventional convolutional neural network (CNN) on benchmarking Monte Carlo simulations with an increasing level of robustness. Using simulated data, we then demonstrate KamNet's ability to increase KamLAND-Zen's sensitivity to  $0\nu\beta\beta$  and  $2\nu\beta\beta$  decay to excited states. A key component of this work is the addition of an attention mechanism to elucidate the underlying physics KamNet is using for the background rejection.

DOI: [10.1103/PhysRevC.107.014323](https://doi.org/10.1103/PhysRevC.107.014323)

*Improve the main analysis...*

A. LI *et al.*

PHYSICAL REVIEW C **107**, 014323 (2023)

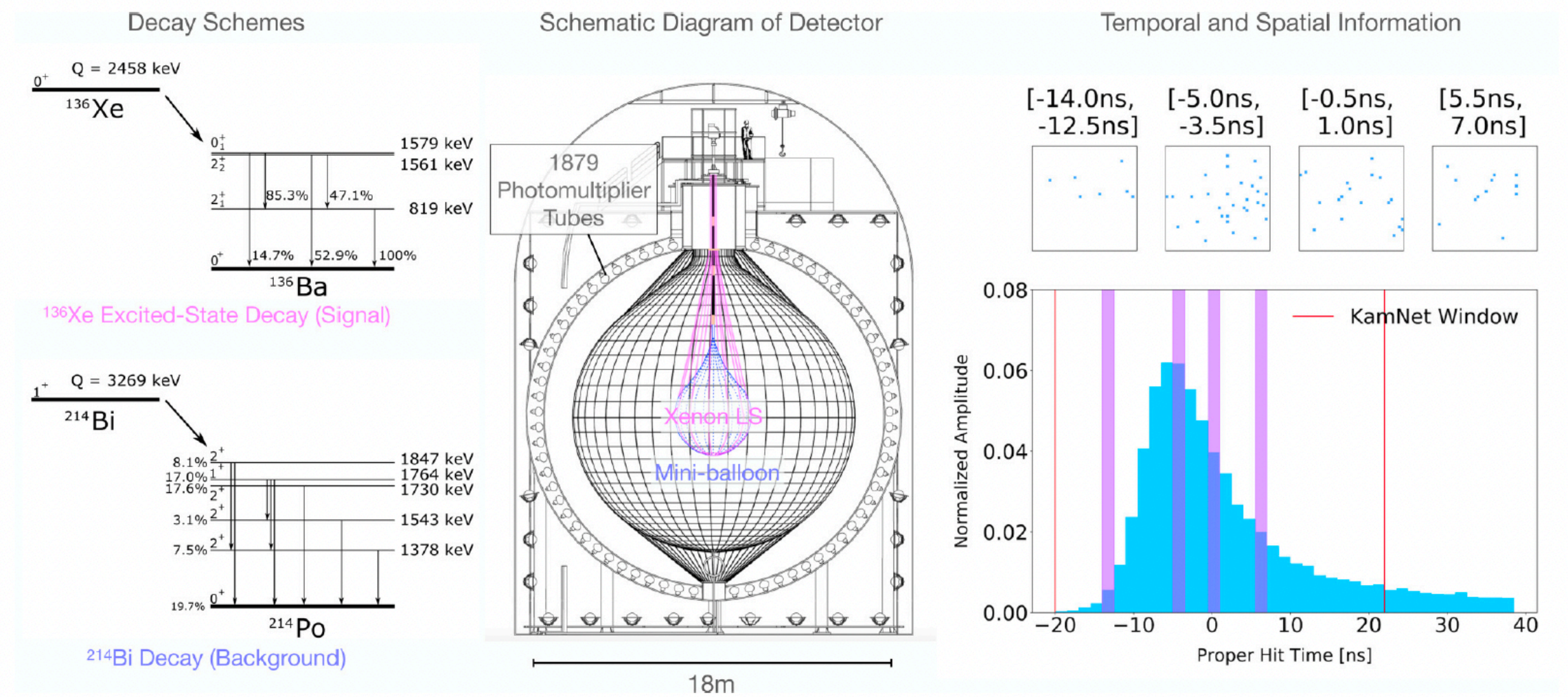


FIG. 1. Left: The decay schemes for  $^{136}\text{Xe}$  and  $^{214}\text{Bi}$  with branching ratios  $< 1\%$  are omitted for simplicity. Center: The schematic diagram of the KamLAND-Zen detector. Right: The distribution of PMT hit times for typical physics events. The spatial distribution of the PMT hit times highlighted in violet are shown above.

**With Prof. Aobo Li (UCSD) and Prof. Chris Grant (BU)**



# TIDMAD - Example Category #1

NeurIPS Spotlight led by Jessica Fry (MIT) with Prof. Aobo Li (UCSD)

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## TIDMAD: Time Series Dataset for Discovering Dark Matter with AI Denoising

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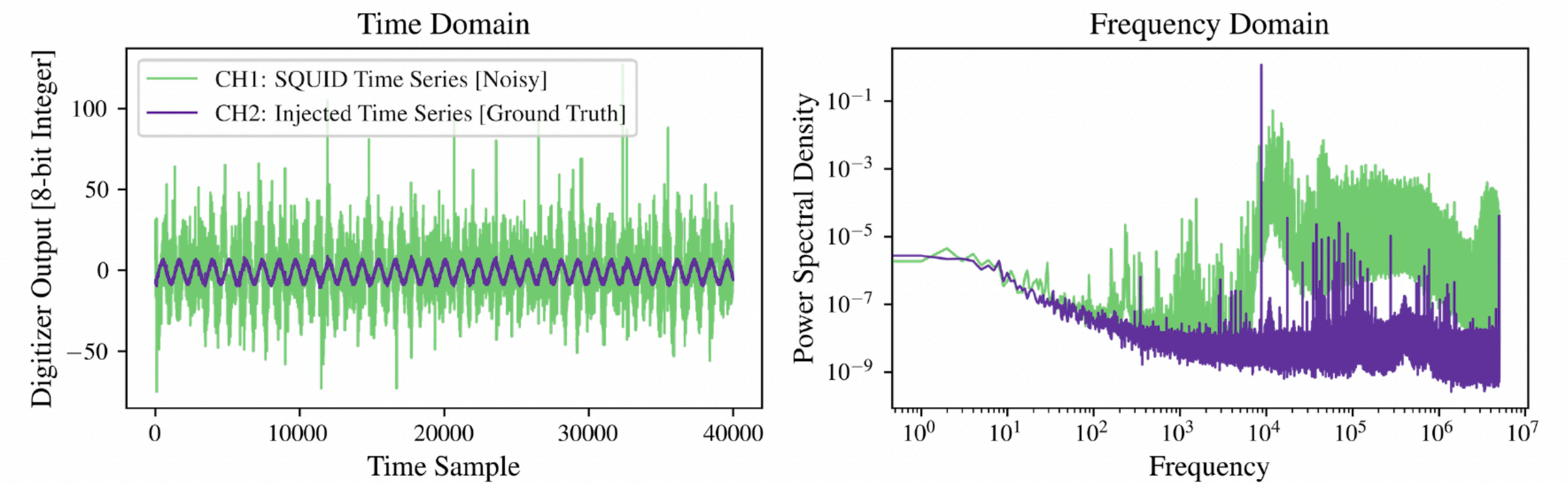


Figure 2: 10-millisecond snapshot of the time series in TIDMAD training dataset compared to the power spectral density of the same data snapshot.

*Search for non-standard signals...*

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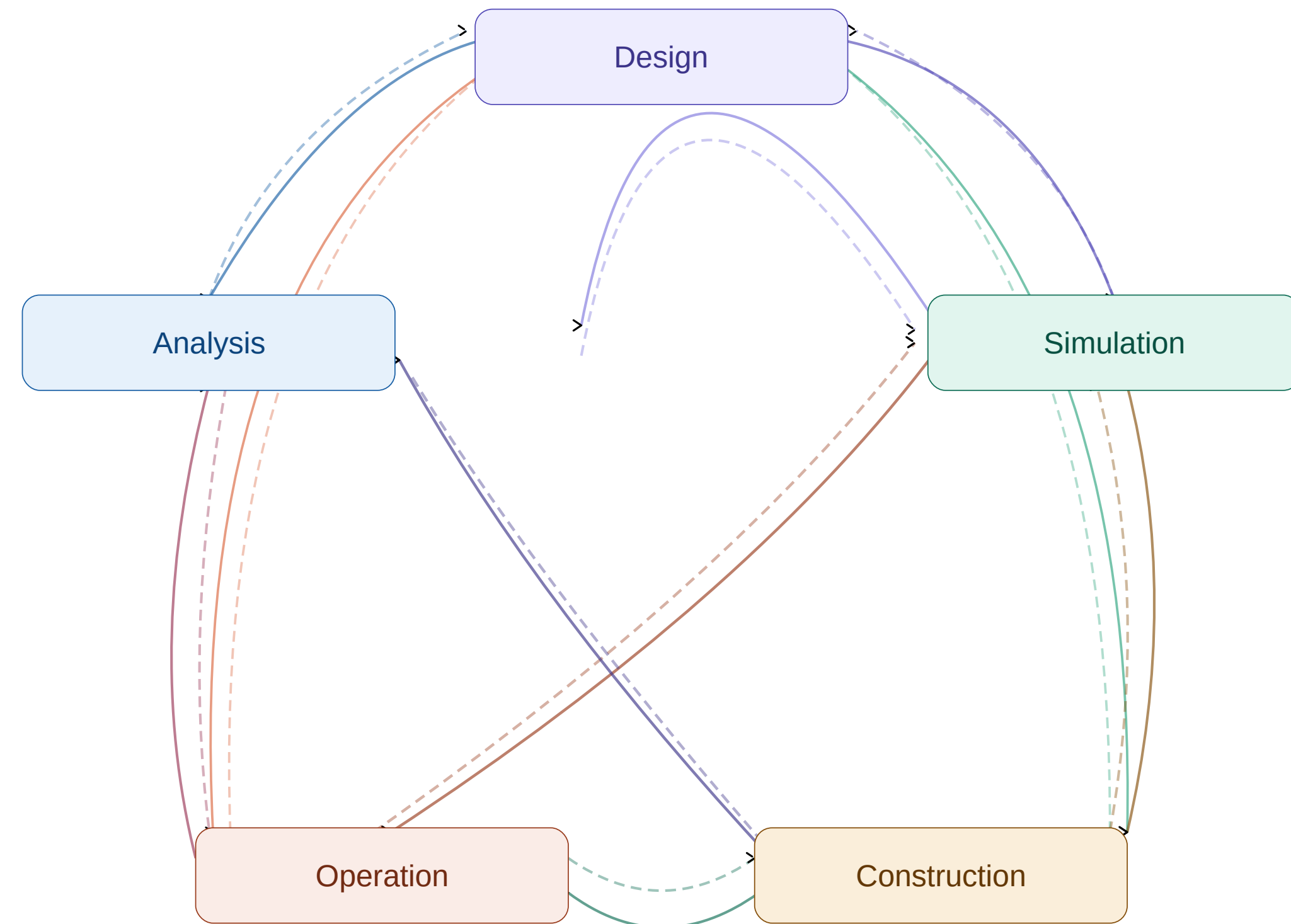
<sup>2</sup>Halicioğlu Data Science Institute, Department of Physics, UC San Diego, La Jolla, CA 92093, USA

\* Corresponding Authors



# Pulling these thoughts together

*These steps cannot be treated independently and we need better tools for each task and integration of these tasks.*



—> Forward influence  
- - -> Reverse / revisit



## **Current Ecosystem - CUORE/CUPID**

**ELOG - operations, shifts**

**Indico - meetings**

**DocDB - archive**

**Wiki - organization**

**MongoDB - slow monitoring**

**PgSQL - DAQ**

**C++ - DAQ**

**ROOT-based Analysis**

**Geant4-based Simulation**

**Materials database**

**CAD drawings**



# Current Ecosystem - ABRACADABRA

**ELOG - operations, shifts**

***Dropbox - pictures***

***DocDB - archive+meeting***

***Wiki/Confluence***

**Grafana - slow monitoring**

**C++ - DAQ**

**Python-based Analysis**

**COMSOL Simulation**

**CAD drawings**



# Setting Up An Ecosystem - DarkSNSPD

**HEP QuantISED project:  
need to track production  
and characterization of  
devices.**

**And Meetings, DAQ,  
COMSOL, Geant4 etc.**



# Summary and Final Thoughts

- **Small Experiments provide unique and complementary datasets and problems that can be explored with AI.**



## **Summary and Final Thoughts**

- **Small Experiments allow universities to have more leadership and they are well-equipped to take leadership in small projects in this space as well (in fact it is critical for them to do so).**



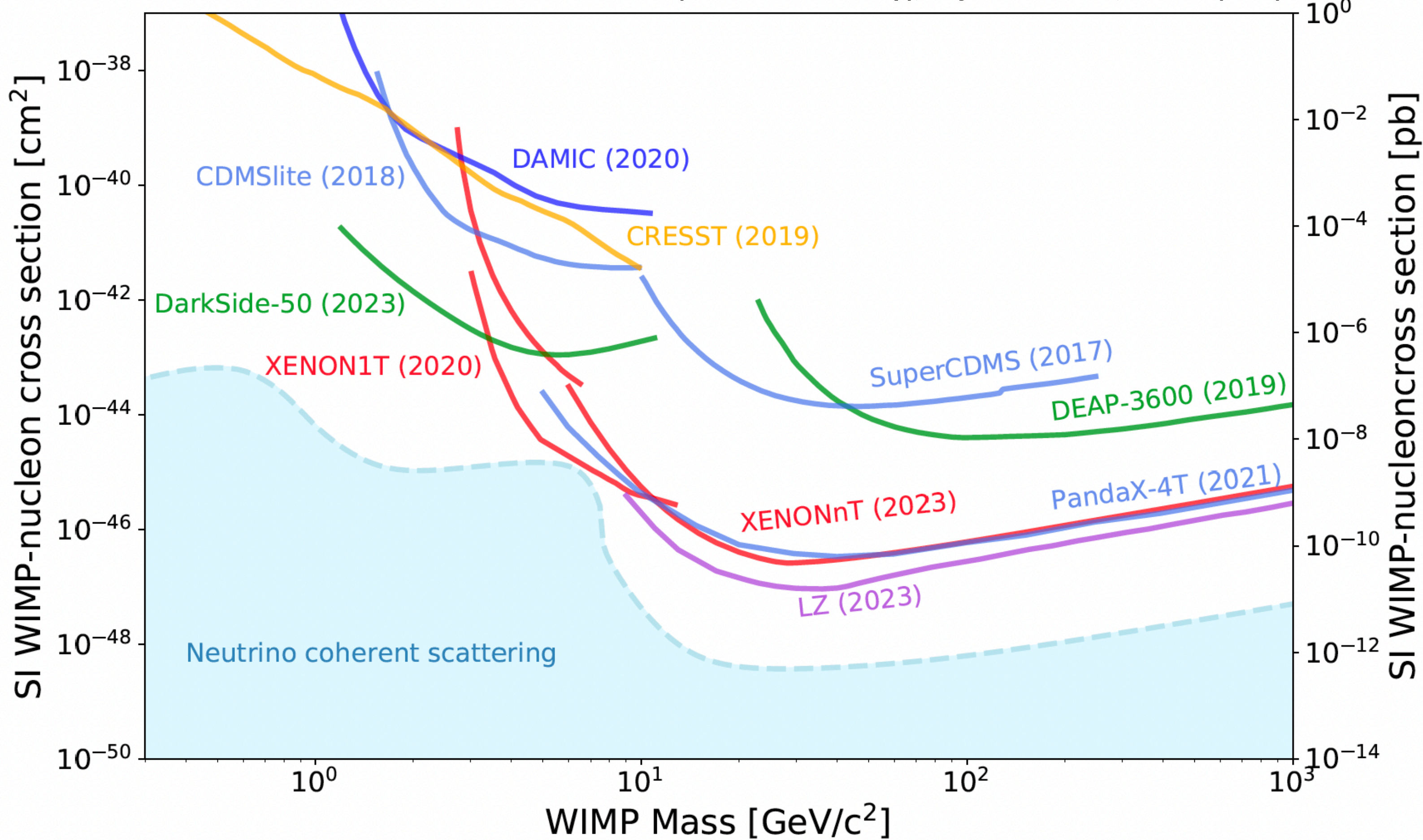
## Summary and Final Thoughts

- **Due to their size, increased efficiencies in the design, management, operation and analysis of experiments are even more critical.**
- **Workshops to spread best practices for AI workflows for software and experiment design.**
- **A modern version of ELOG and DocDB that can be interfaced to AI natively.**

# **Back-up Story of Dark Matter Across Scales**

# Current Bounds on WIMP Dark Matter

S. Navas et al. (Particle Data Group), Phys. Rev. D 110, 030001 (2024)



← Push to lower energies

# Theory

Canonical  
Athermal Models  
(QCD Axion)

Freeze-In

Freeze-Out

Canonical  
Thermal Models  
(WIMP)

1eV

1keV

1 MeV

1 GeV



Time Projection Chambers

Superfluid Helium

Molecular Scintillators

Bulk Semiconductor

**Quantum Dots**

Dirac and other exotic materials

Bulk superconductor \*

**DPHaSE (LAMPOST)**



\* SNSPD can work by itself as a superconducting detector.

# Experiment

# And lower ....

**New Horizons:  
Scalar and Vector Ultralight Dark Matter**  
arXiv:2203.14915  
*Editors: M. Safronova and S. Singh*

