Pushing Rare Event Search to the New Limit with Model- and Data-Centric AI

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CAS IHEP Seminar, 07/12/2024

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HALICIOĞLU DATA SCIENCE INSTITUTE

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PHYSICS

Physics in Rare Event Search

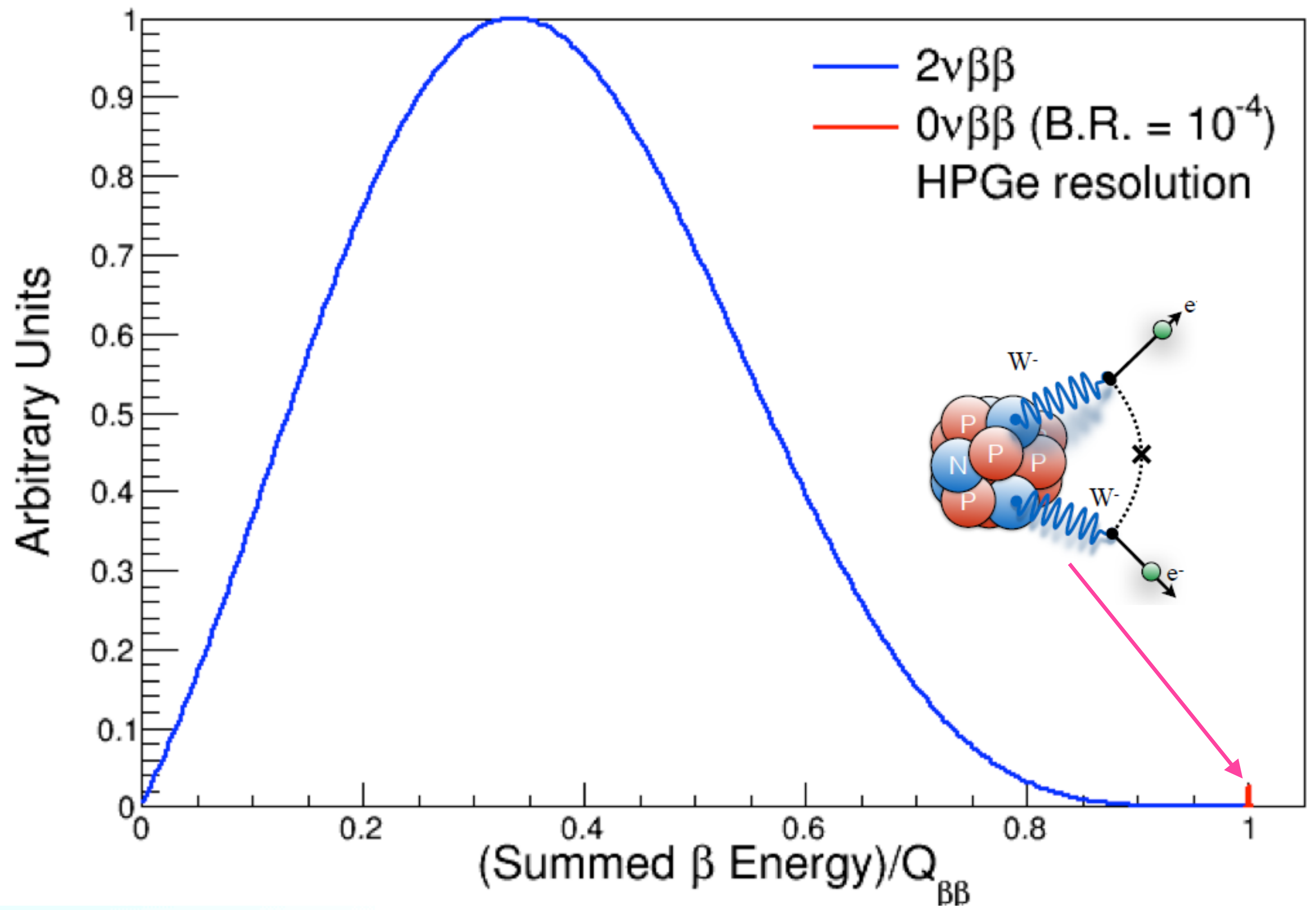
Neutrinoless Double-Beta Decay (NLDBD)

ΔL = 2 lepton number violation process

Prove that neutrinos are **Majorana particle**

Explain the **matter-antimatter asymmetry** in our universe

Has not been observed at $T_{\frac{1}{2}} > 10^{26} yrs$



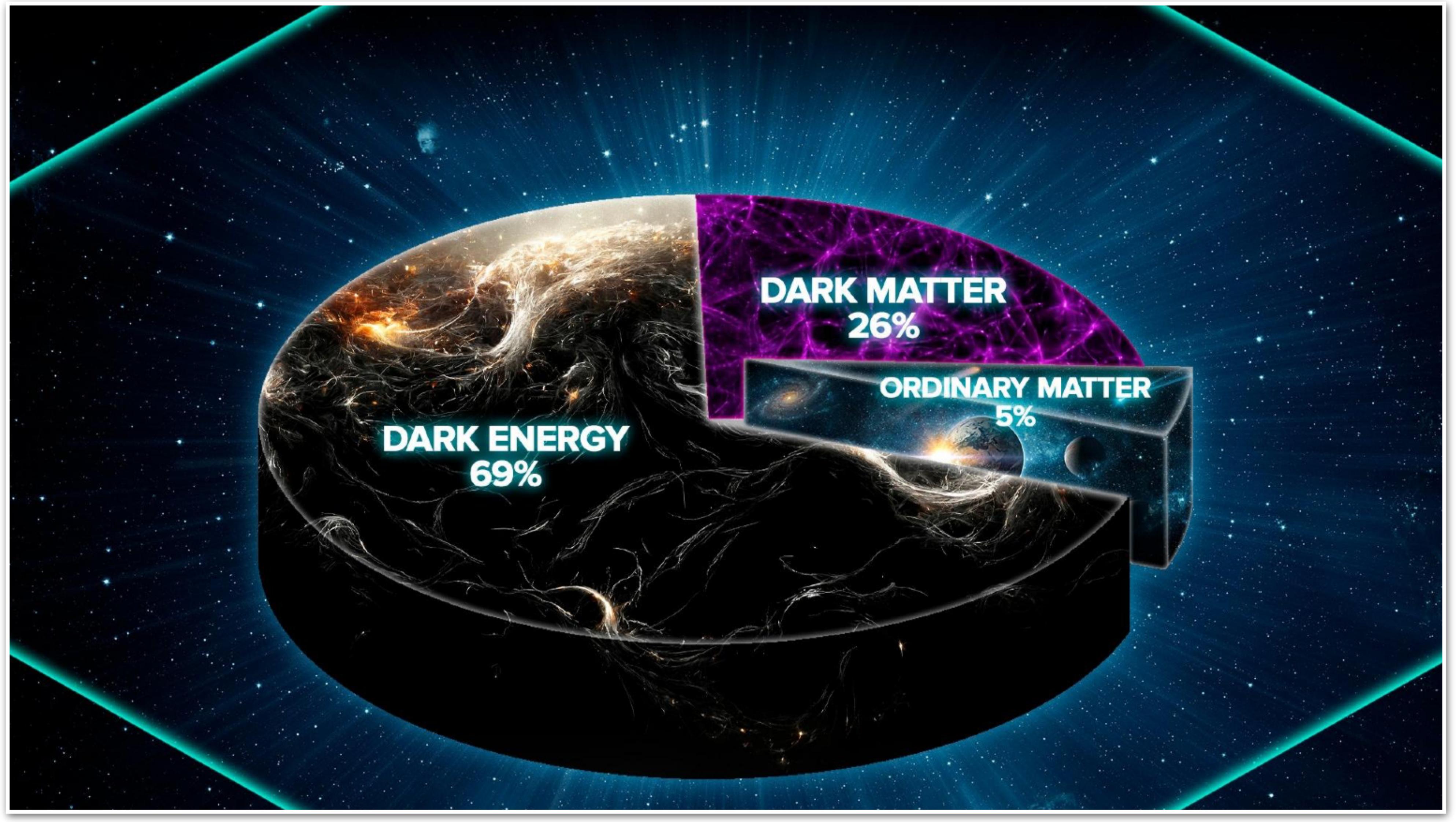
Dark Matter (DM)

Strong astrophysical evidence, no observation on earth

We don't know which particle makes up dark matter:

- Heavy, particle-like DM candidate: **WIMP**
- Light, wave-like DM candidate: **Axion**

WIMP has not been observed at $\sigma < 10^{-47} cm^2$



Rare Event Search in 2024

Double Beta Decay ($2\upsilon\beta\beta$)

First proposed by Maria Goeppert Mayer in 1935

First detection by Elliott, Hahn, Moe, in 1987

Decay half-life $T_{\frac{1}{2}} \sim 10^{14} - 10^{24} yrs$

Much longer than the age of universe!

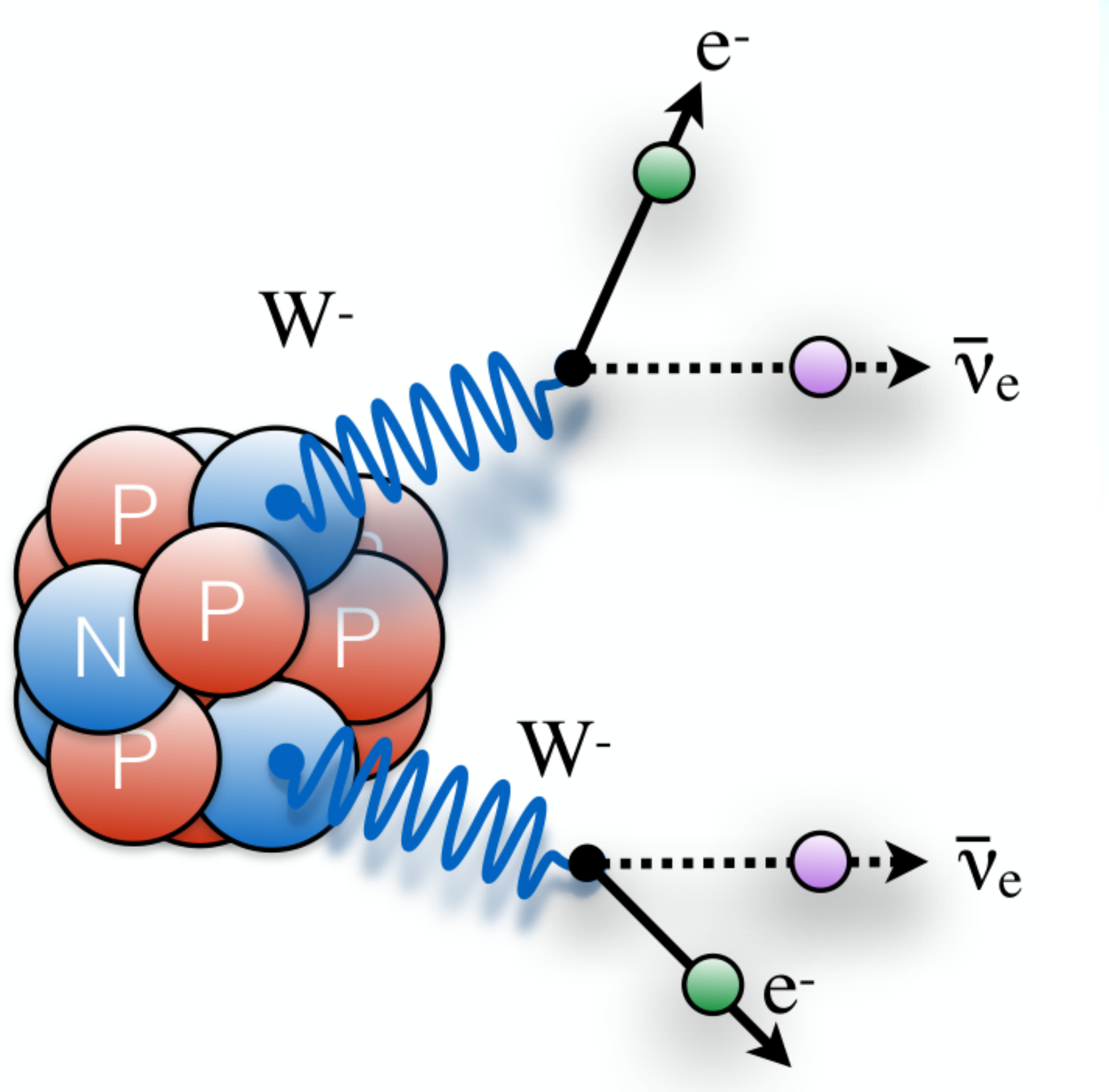
Neutrinoless Double-Beta Decay ($0\upsilon\beta\beta$)

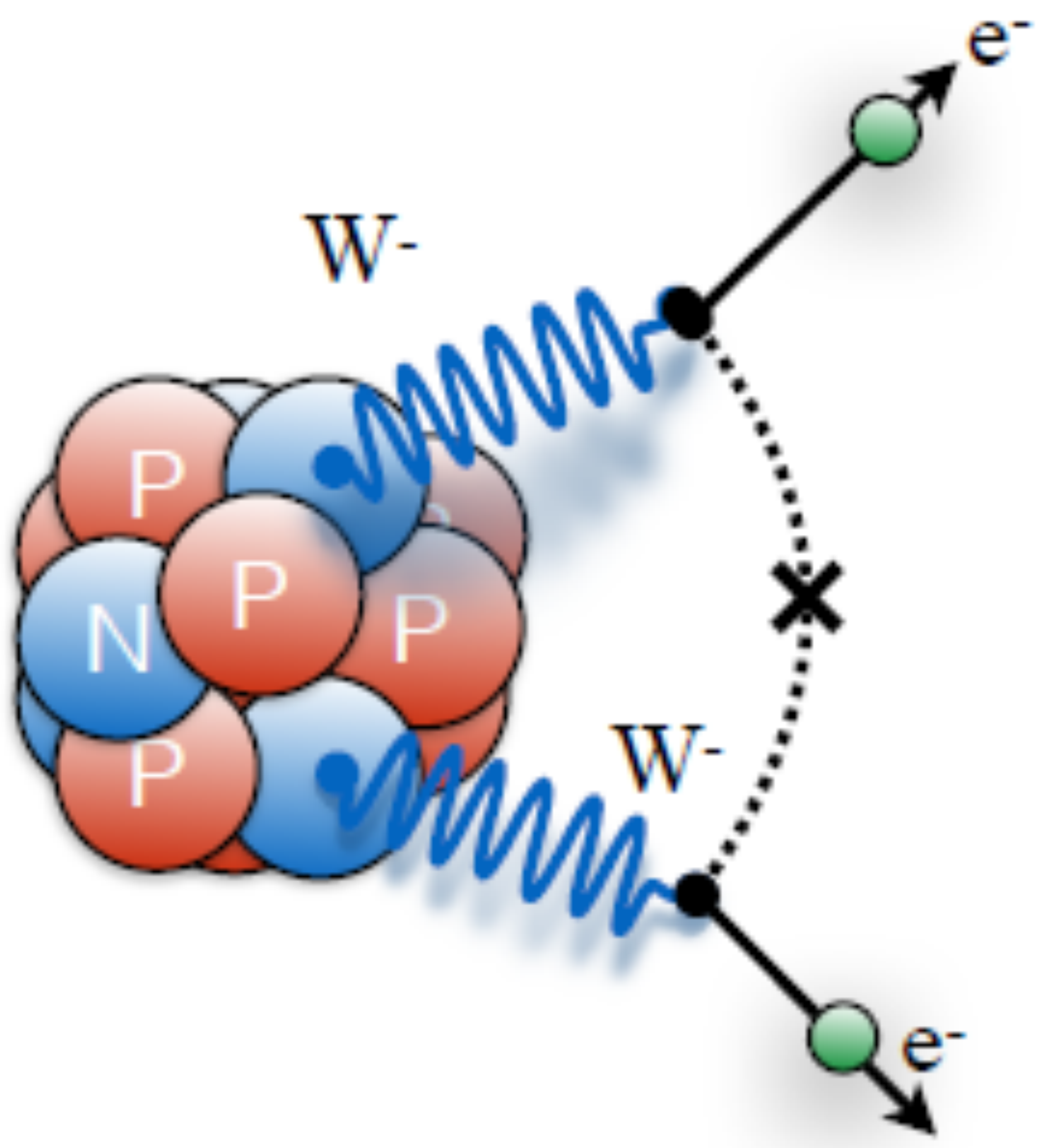
ΔL = 2 lepton number violation process

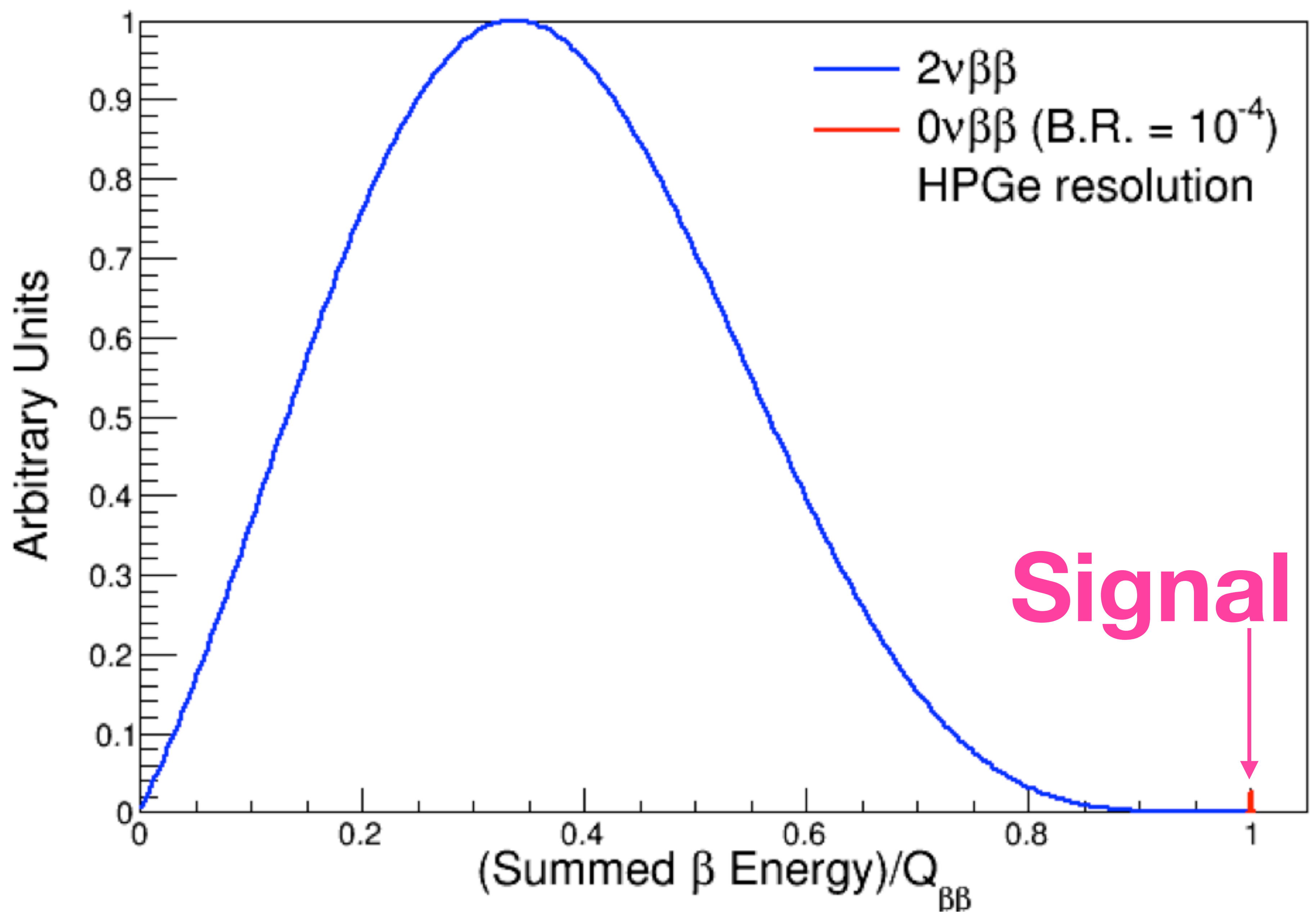
Explain the **matter-antimatter asymmetry** in our universe

Changes our fundamental understanding of particle physics

Has not been observed at $T_{\frac{1}{2}} > 10^{26} yrs$



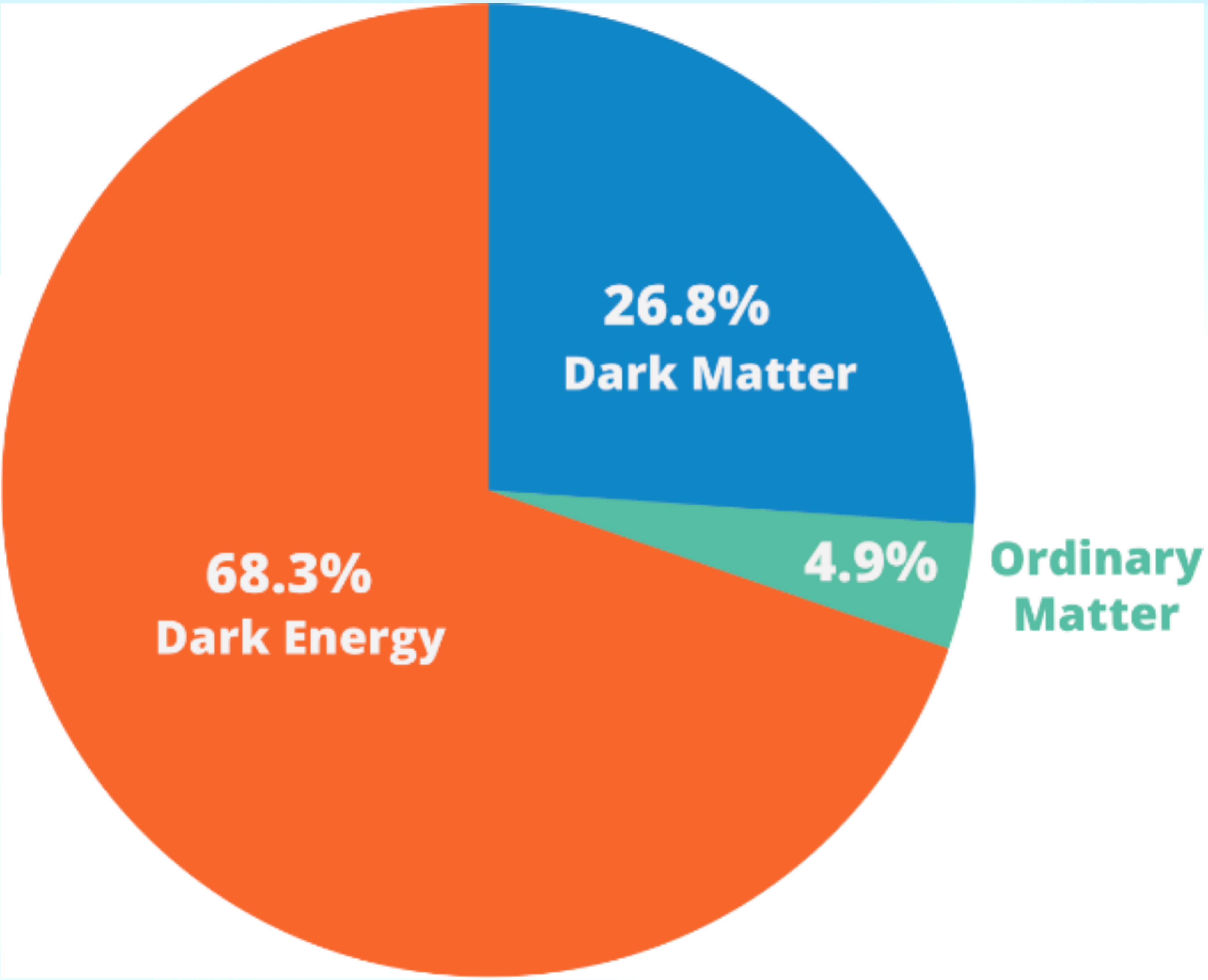


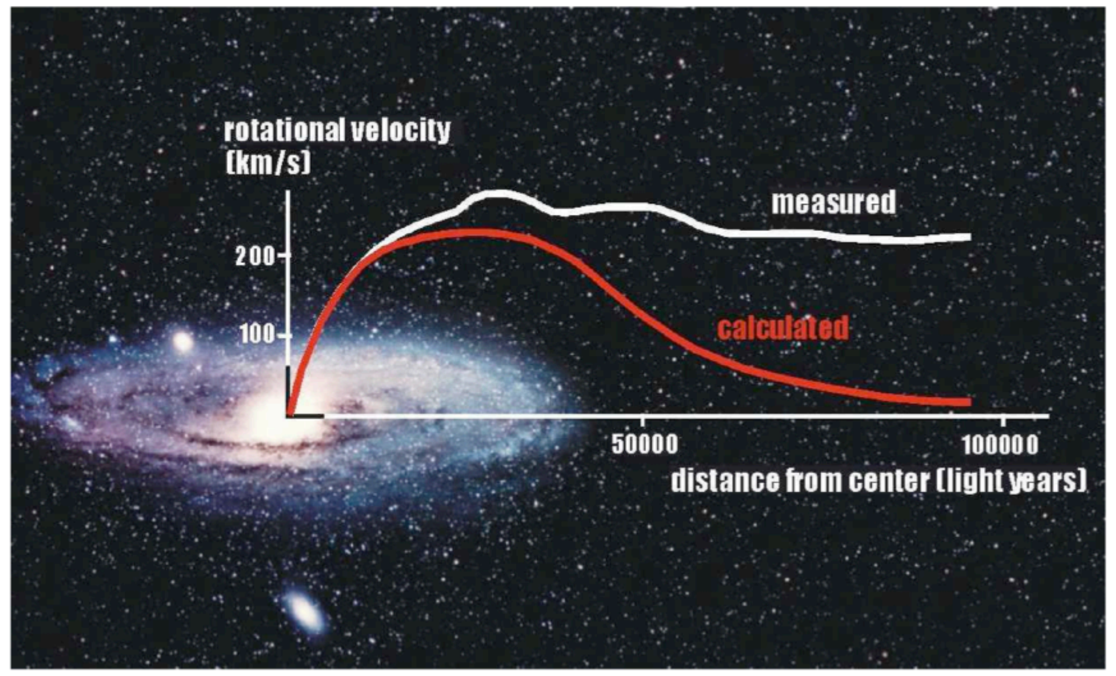


Rare Event Search in 2024

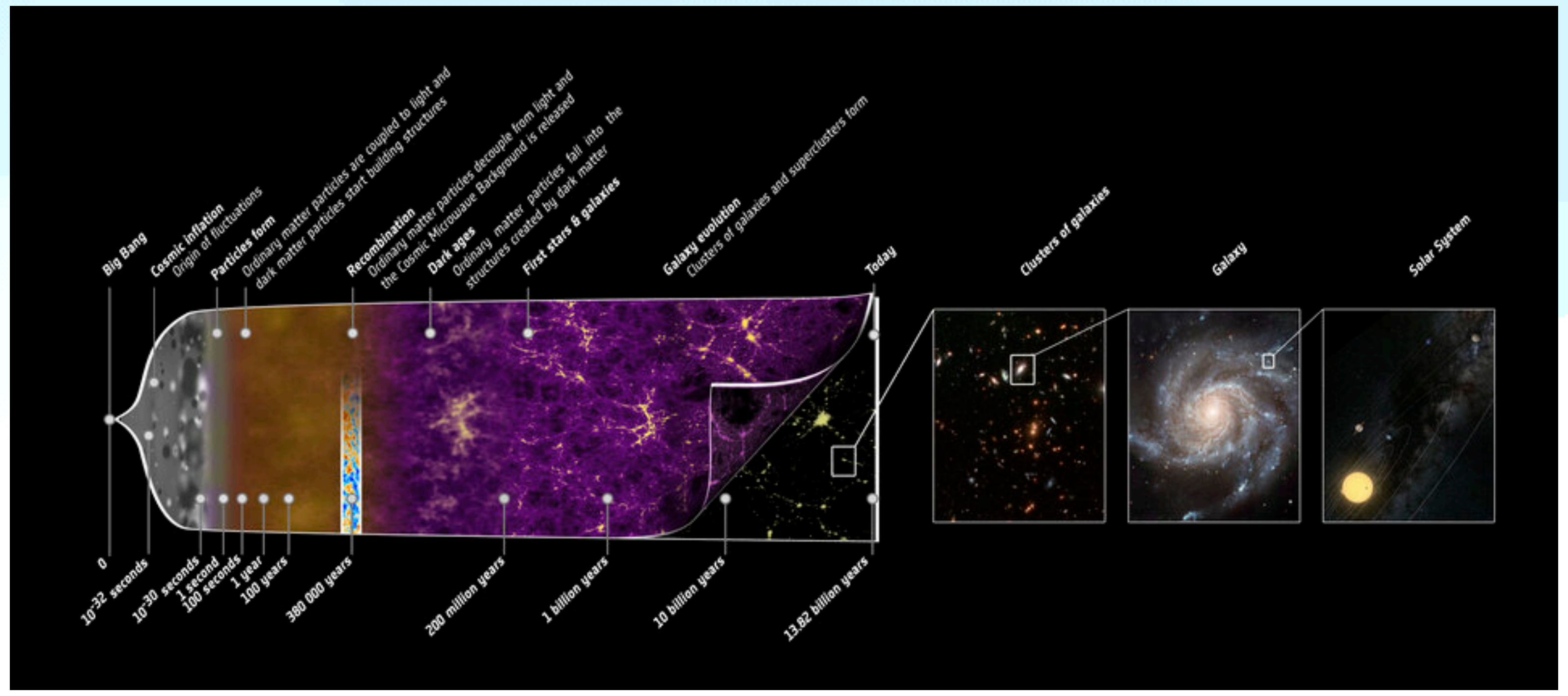
Dark Matter

The evidence for the existence of dark matter has been plenty

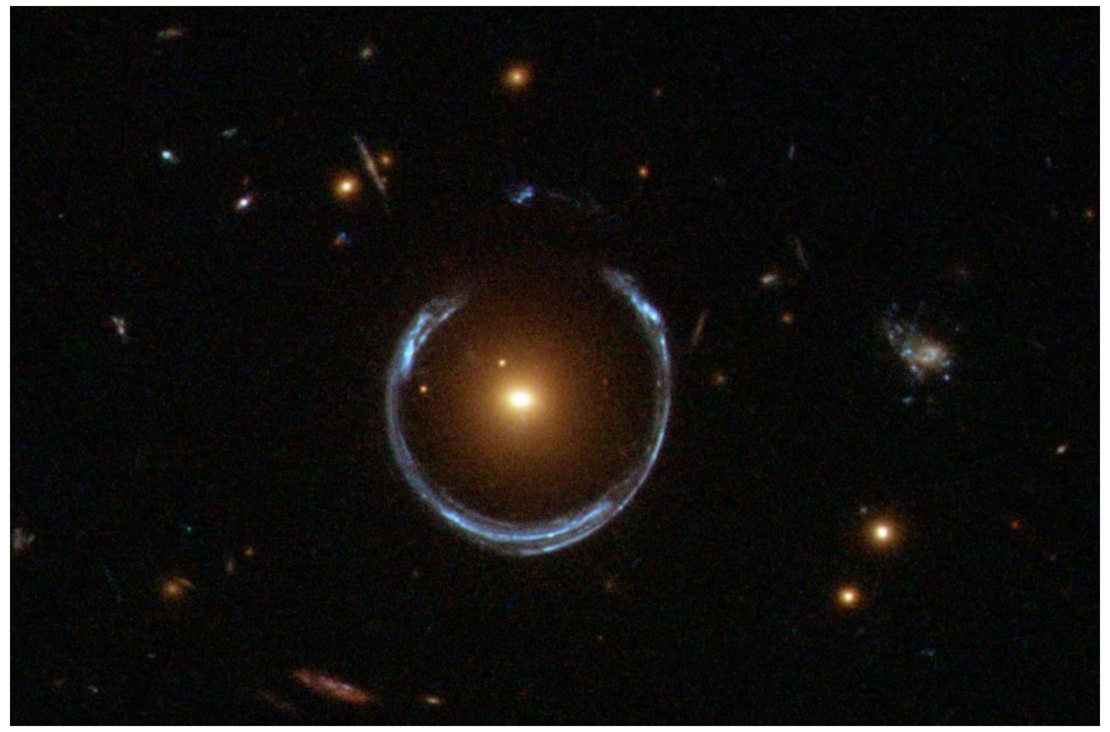




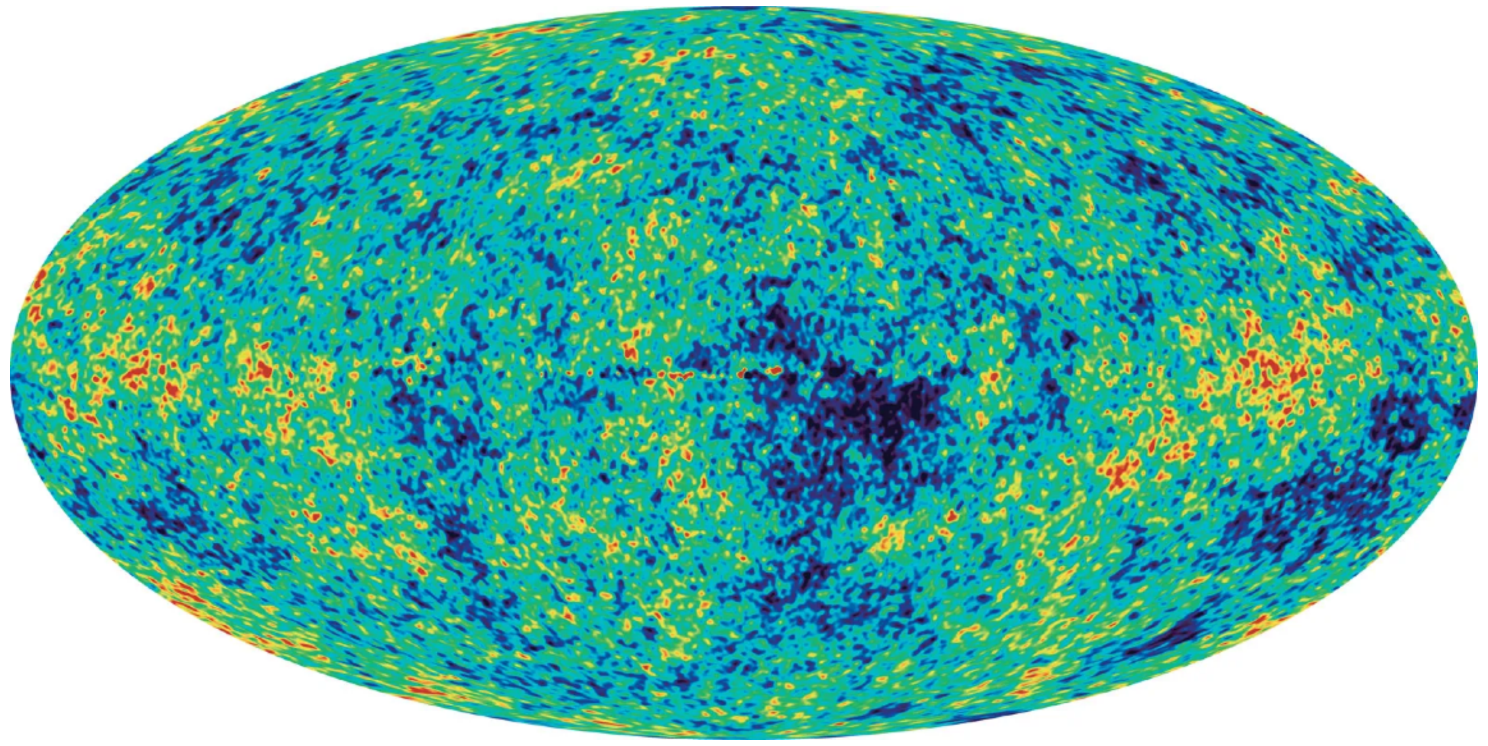
Galaxy Rotation Curve



Large Scale Structure Formation



Gravitational Lens



Cosmic Microwave Background

Rare Event Search in 2024

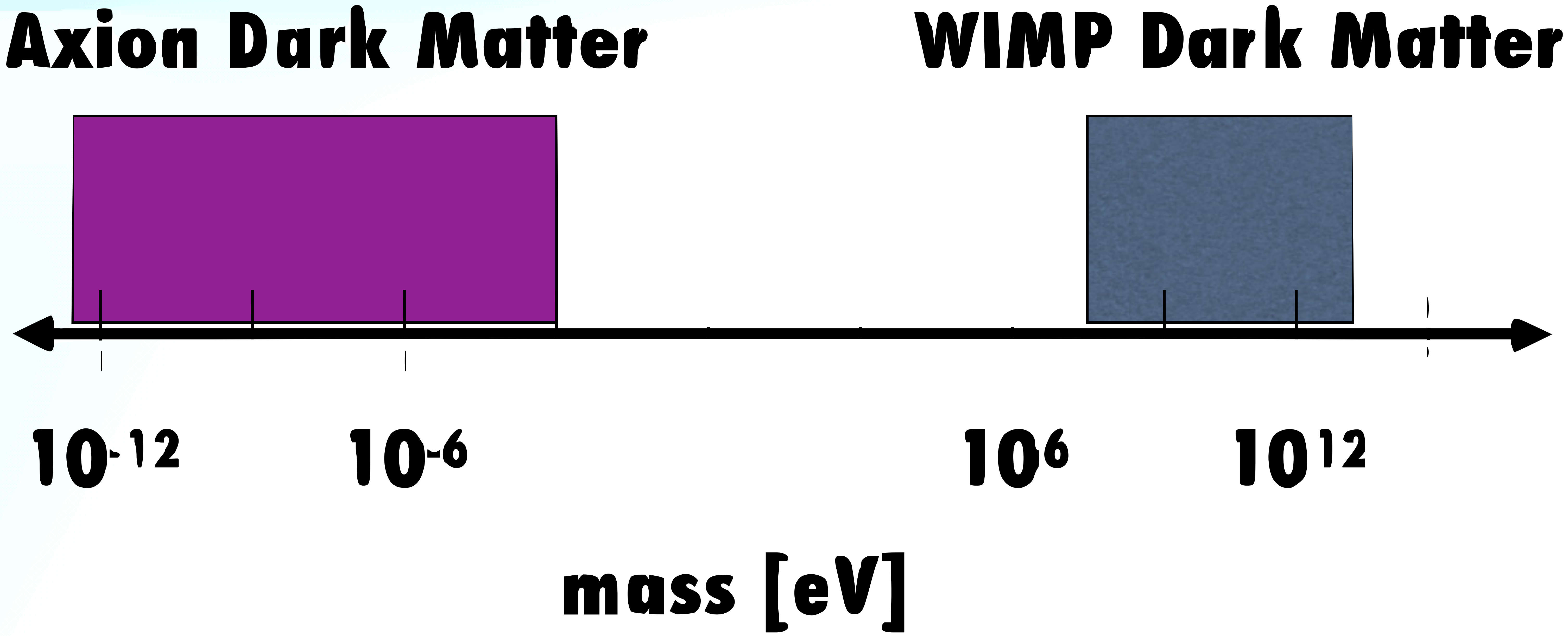
Dark Matter

The evidence for the existence of dark matter has been plenty

Many DM candidates have been proposed (WIMP, Axion, etc.)

None has been observed.

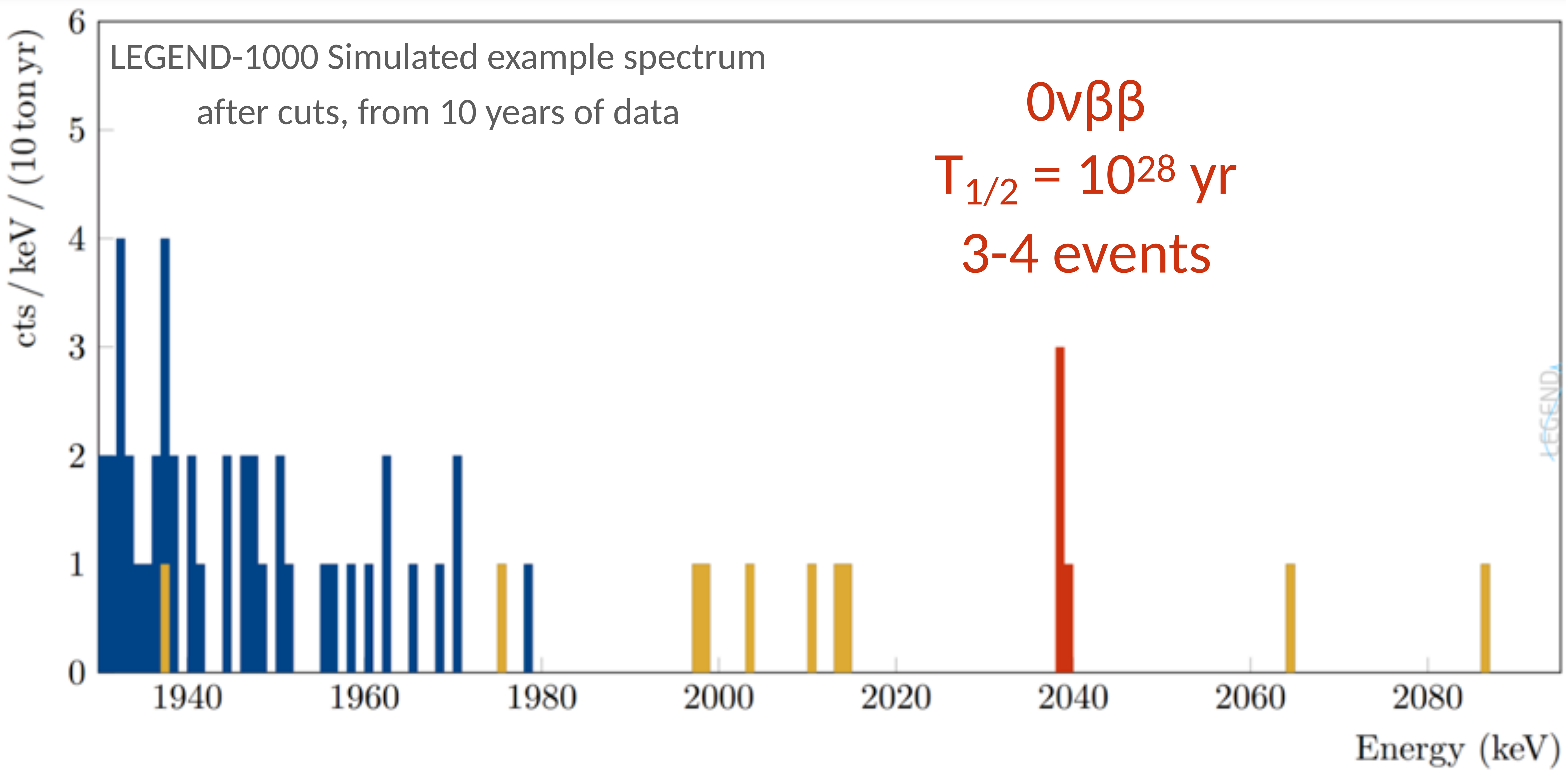
> *Dark Matter can feel like a zoo.*
>
> *—Prof. Lindley Winslow*



What Makes Rare Event Search Hard?

It is extremely rare! Using $0\upsilon\beta\beta$ as an example ...

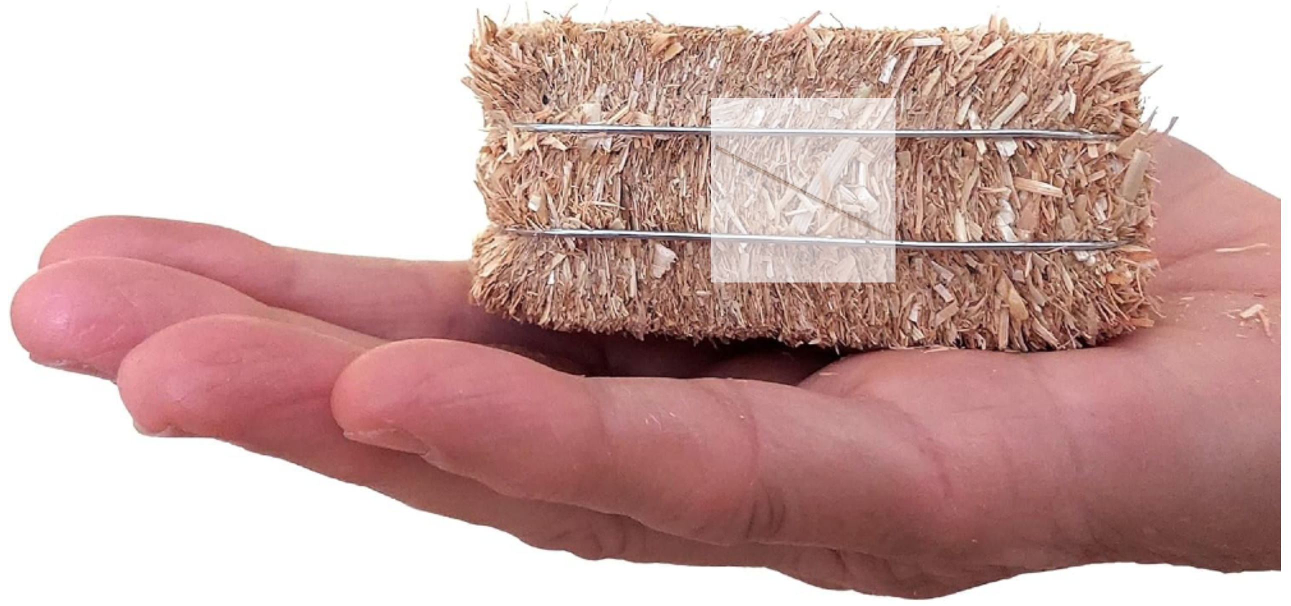
- We have not seen $0\upsilon\beta\beta$ at half life of $T_{\frac{1}{2}} > 10^{26} yrs$
- Next-generation experiments typically aims at $T_{\frac{1}{2}} > 10^{28} yrs$ ($\times$100 improvement)
- Correspond to **3-4 event** after **10 years** of data taking



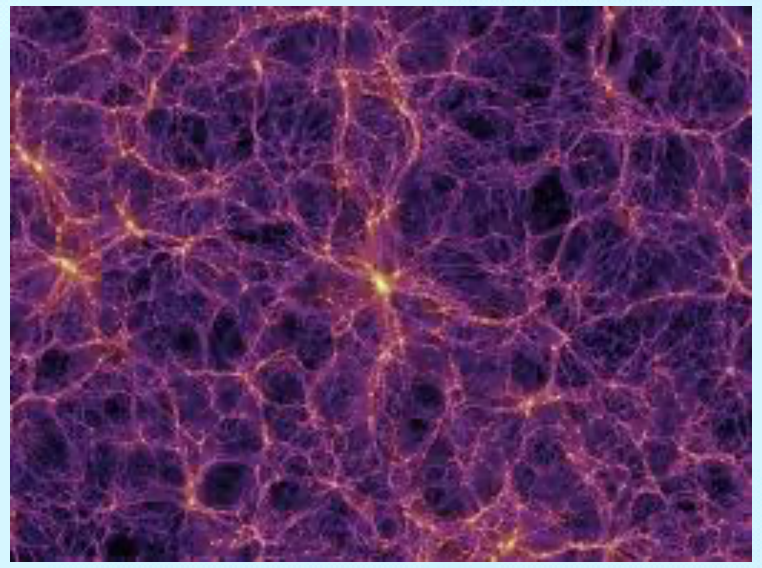
What Makes Rare Event Search Hard?

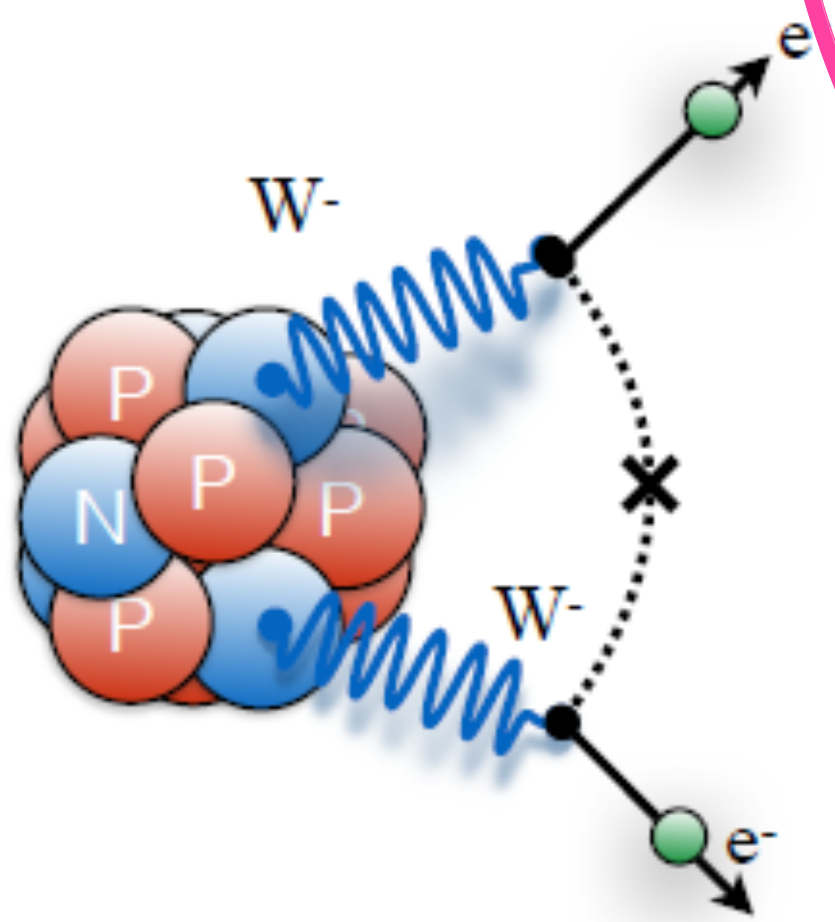
- **1 event** every **2.5-3.3 year**, we need ultra-sensitive detector to capture every event
- As our detector gets more sensitive, we also collect lots of events that are not 0νββ/WIMP DM

Search for needle in a haystack



The Rare Event Search Pipeline



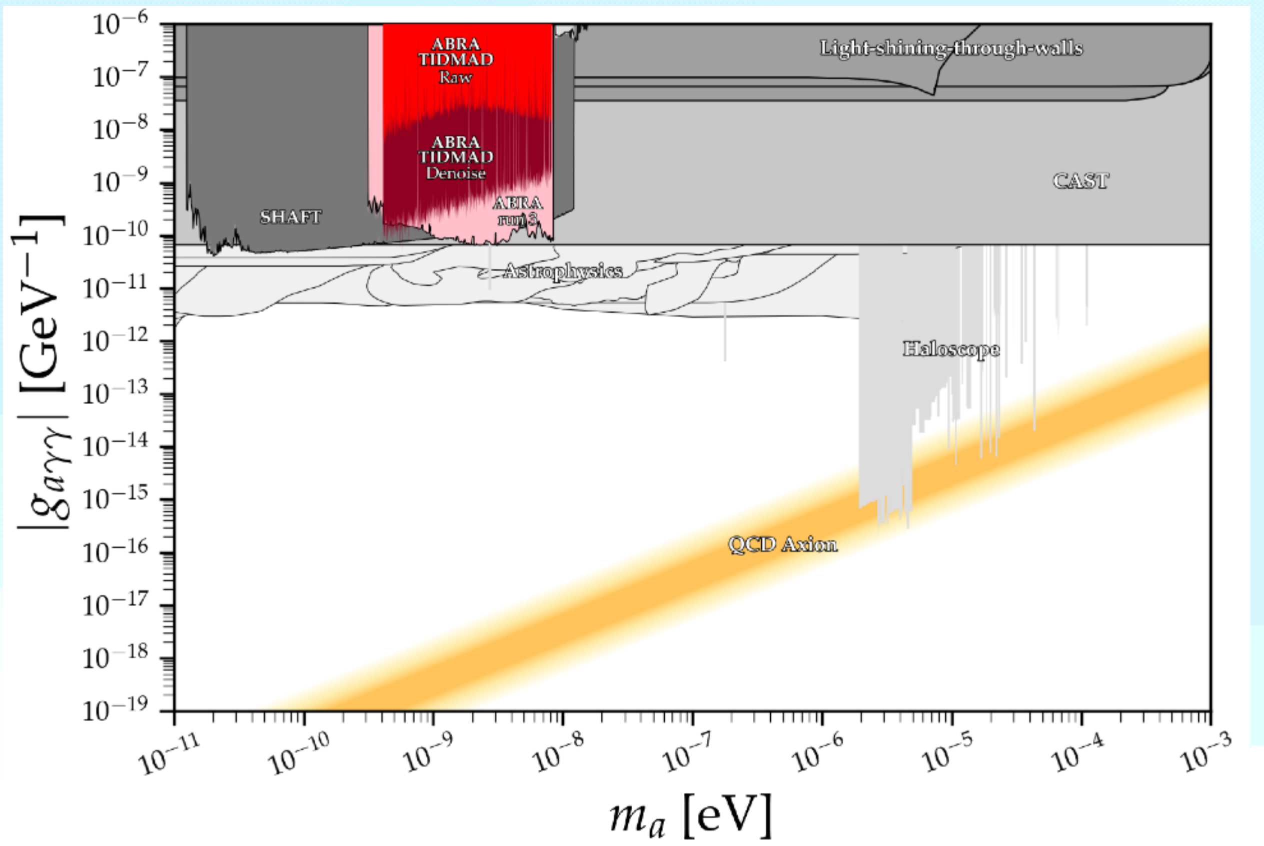


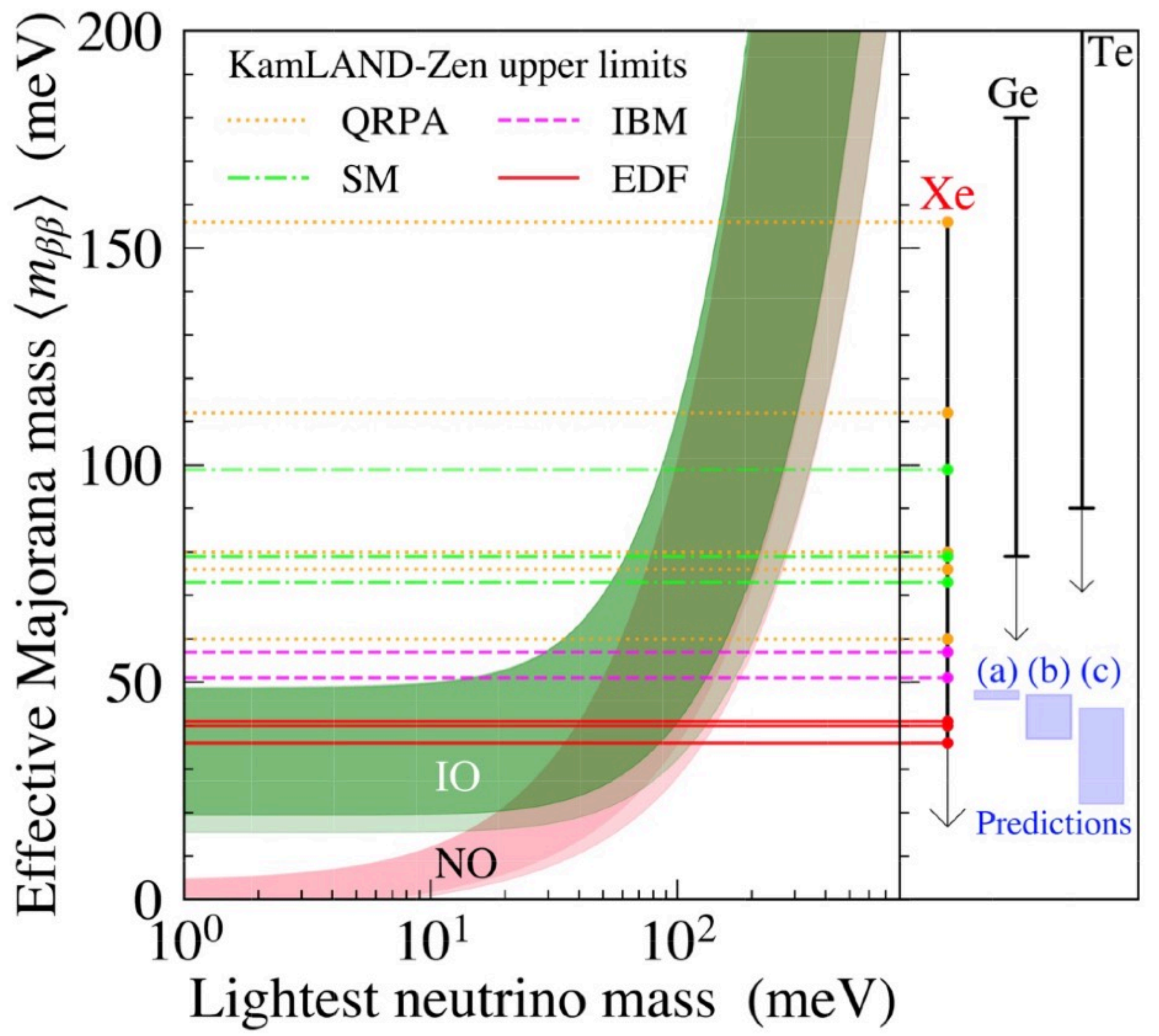
Radiation Detector

The "magnifying glass" that
help finding the needle

AI/ML

The "forklift" that help
removing the haystack

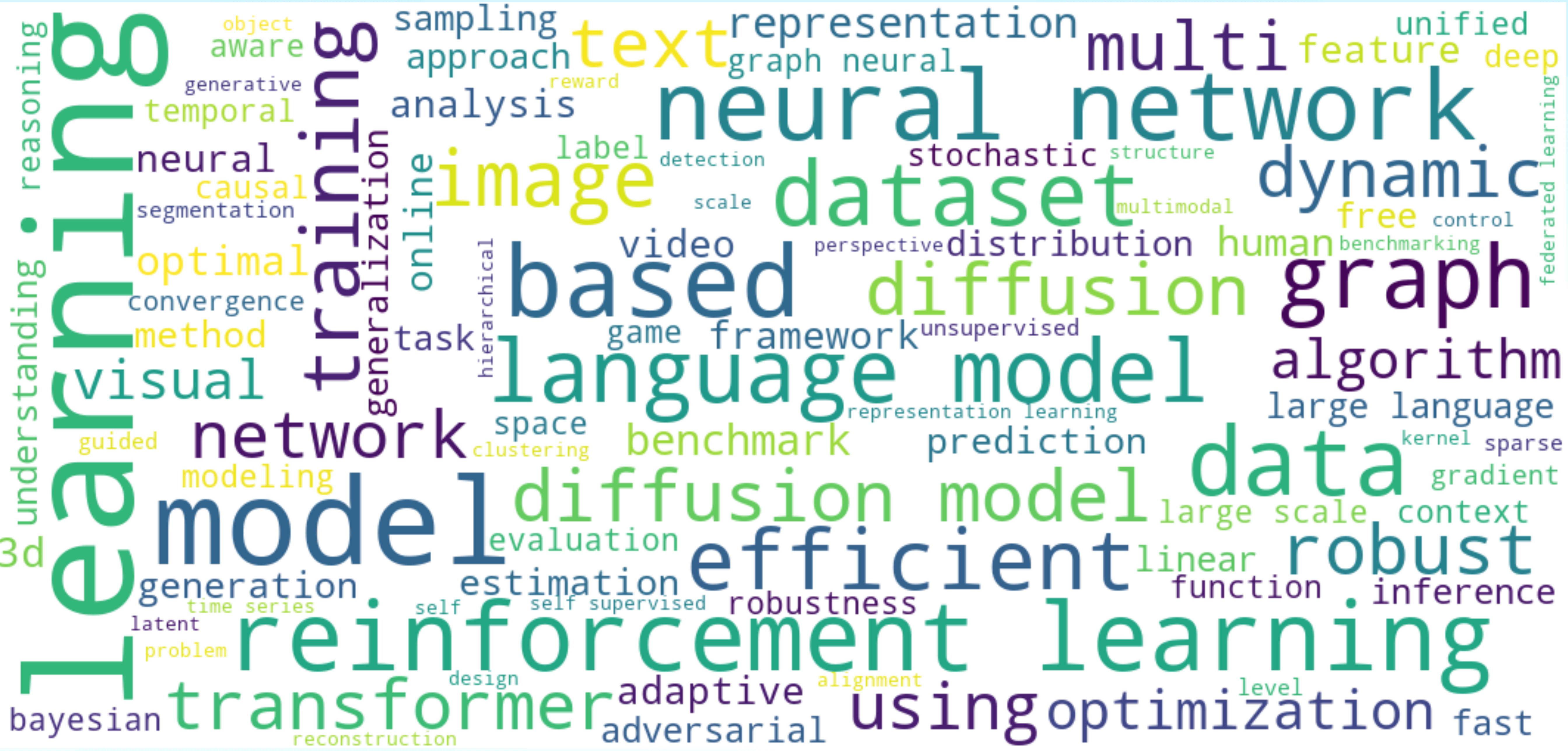




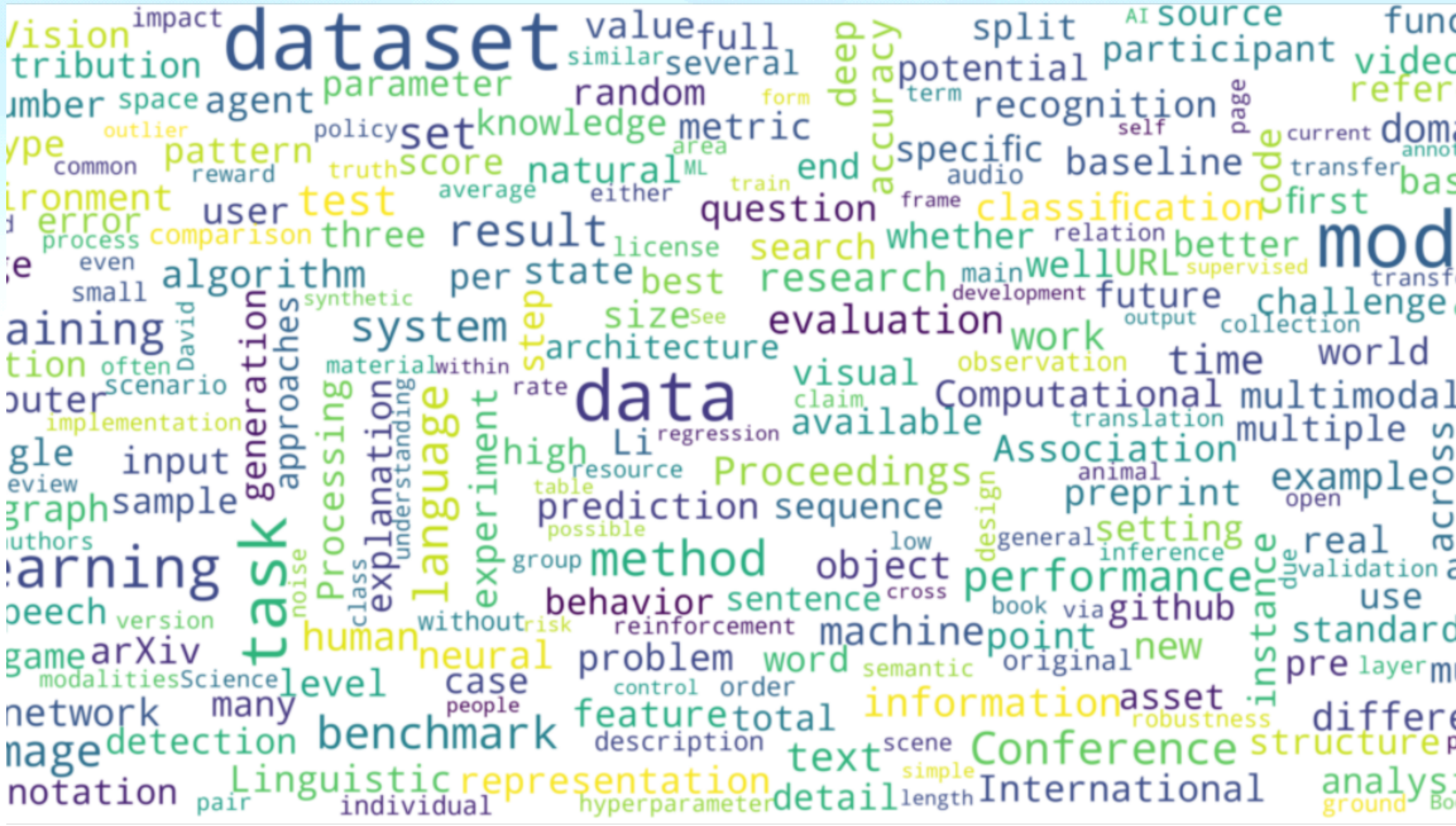
Model-Centric AI vs. Data-Centric AI

NeurIPS 2023 Word Cloud

Algorithm Track



Dataset & Benchmarking Track



Model-Centric AI for KamLAND-Zen

Monolithic Liquid Scintillator Detector for $0\nu\beta\beta$ Search

From Left to Right:

- **Dr. Christopher Grant (BU Co-PI)**
- Hasung Song (BU)
- **Dr. Lindley Winslow (MIT, Co-PI)**
- Dr. Spencer Axani (MIT/UDelaware)
- Dr. Zhenghao Fu (MIT/Jump Trading)
- Dr. Joseph Smolsky (MIT/CSU)
- Dr. Aobo Li (BU/UCSD)

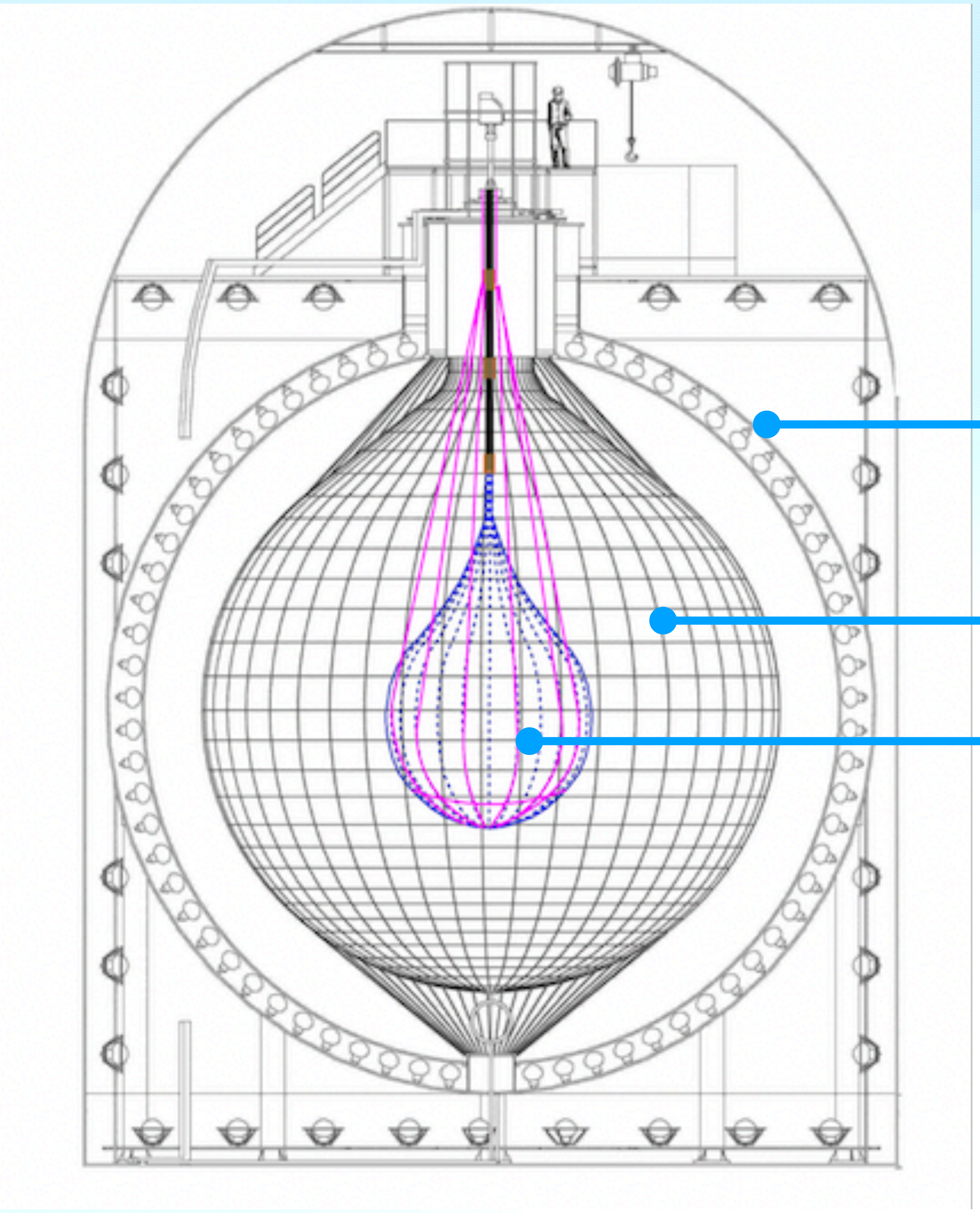
Not on this photo:

- Dr. Sumita Ghosh (MIT)
- Dr. Omer Penek (MIT)
- So Young Jeon (BU)

The MIT-BU Analysis Group

KamLAND-Zen

Monolithic Liquid Scintillator Detector for 0υββ Search



Background Source

- XeLS Background
- Film Background

Inner Detector PMTs

1325 17inch + 554 20inch

Liquid Scintillator

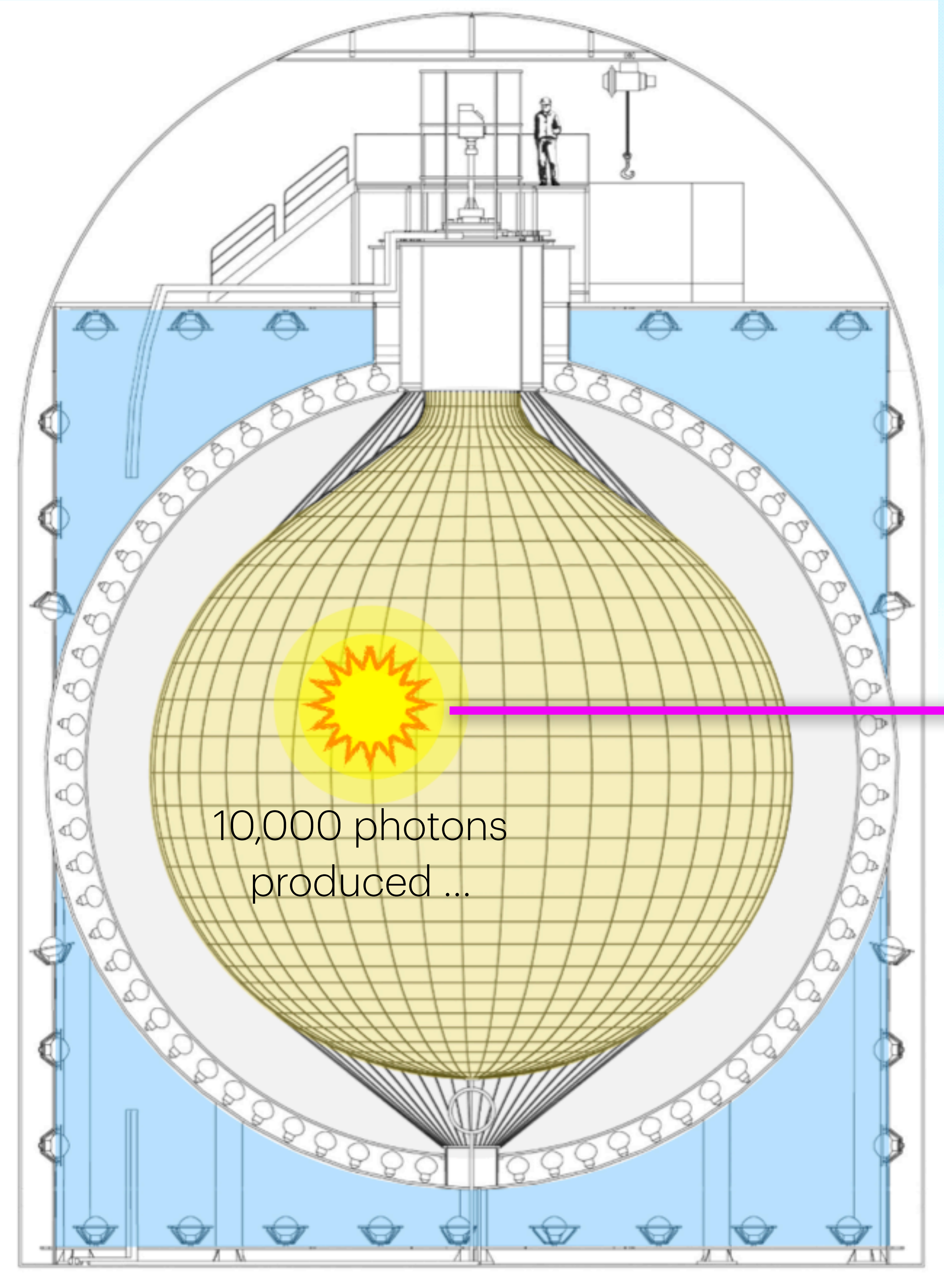
Inner Balloon

25-μm-thick transparent nylon film

Xenon Loading

Load 745 kg of double beta decay isotope ^{136}Xe (90% enriched) in LS inside inner balloon (XeLS)

KamLAND-Zen Data



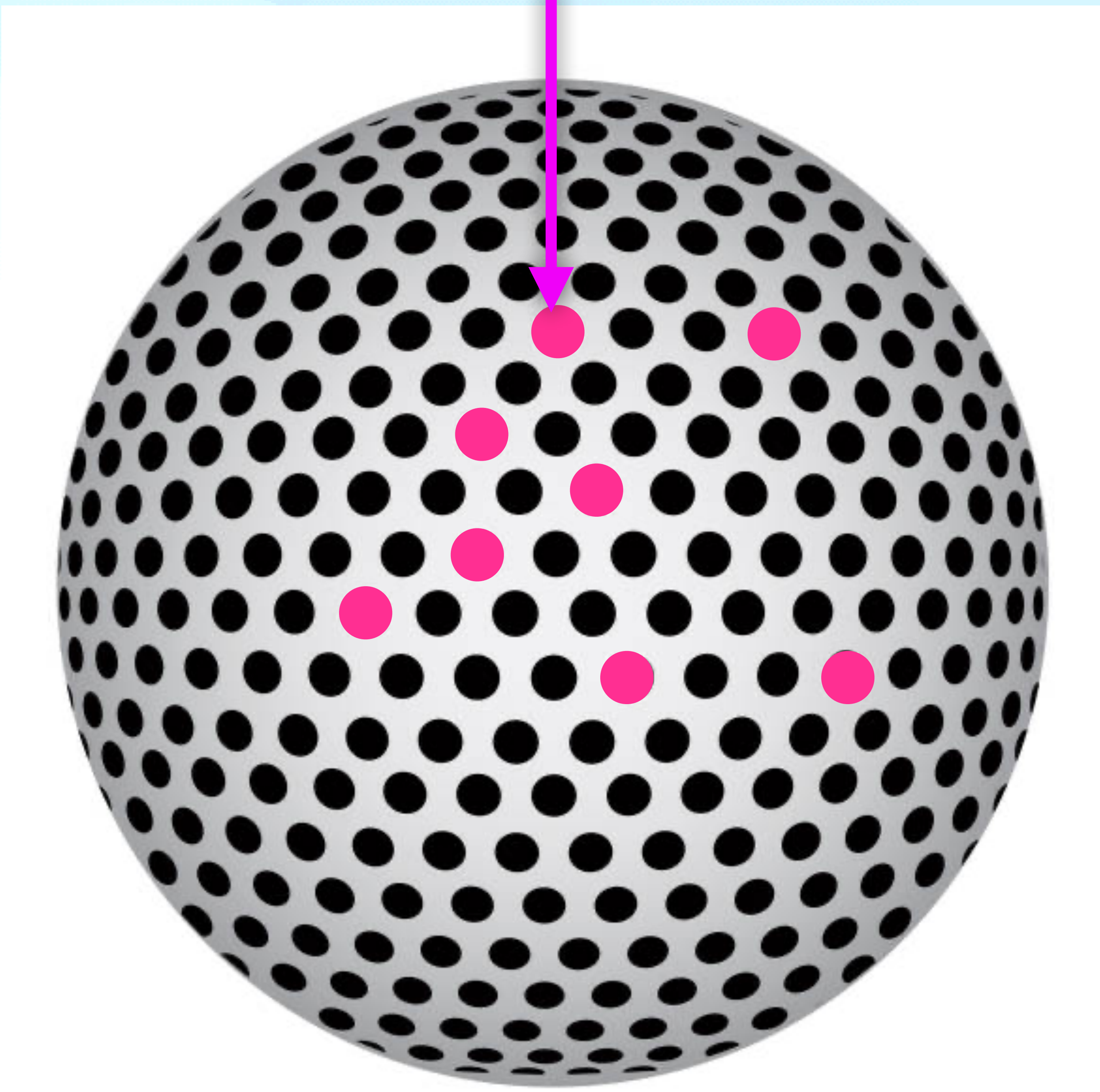
22% Photocoverage

... 2,200 photons will reach PMT ...

23% Quantum Efficiency

... 500 photons will produce a signal (photoelectron).

Triggered PMT



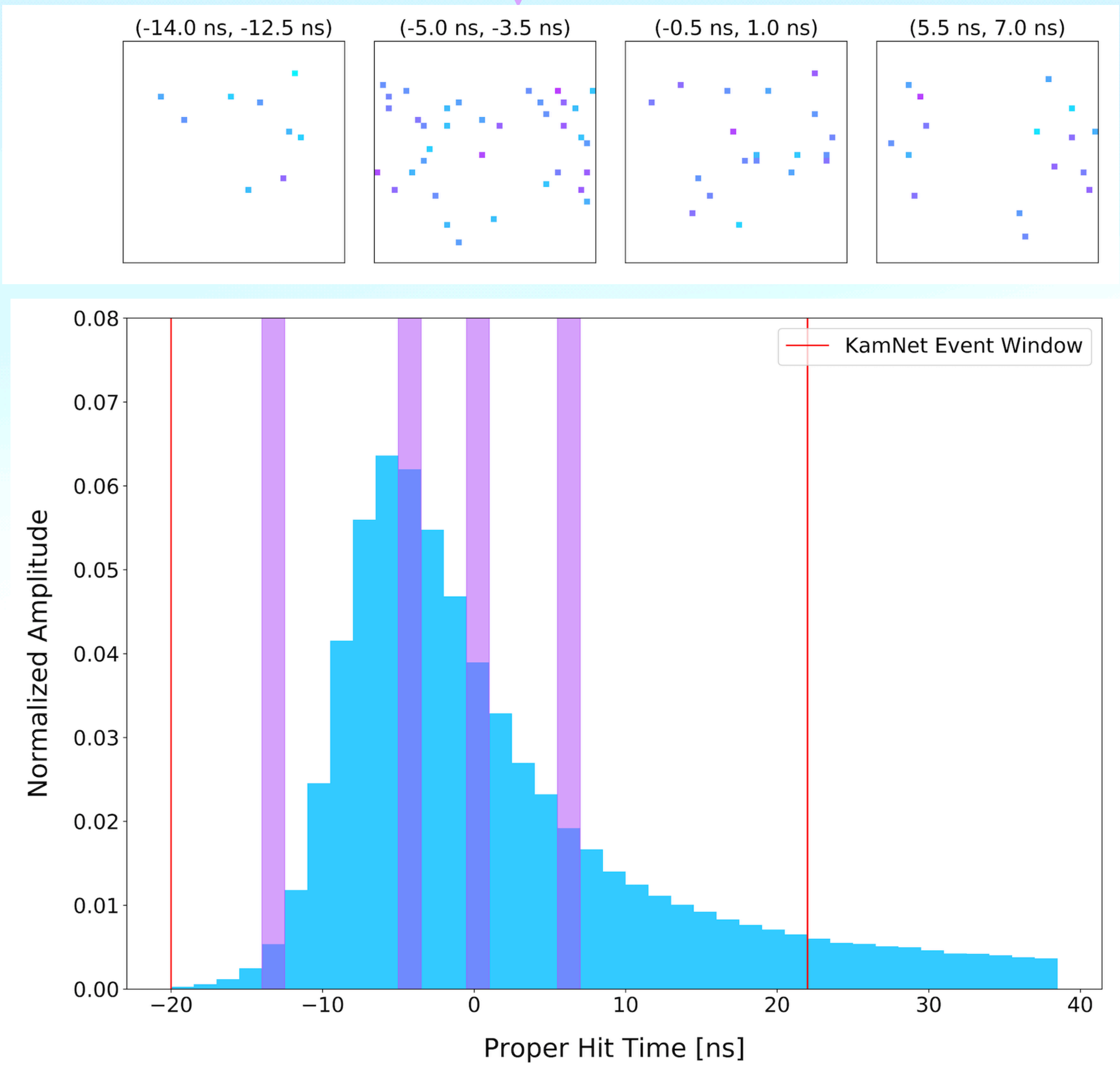
KamLAND-Zen Data

Triggered PMT

θ-ϕ Sphere Map

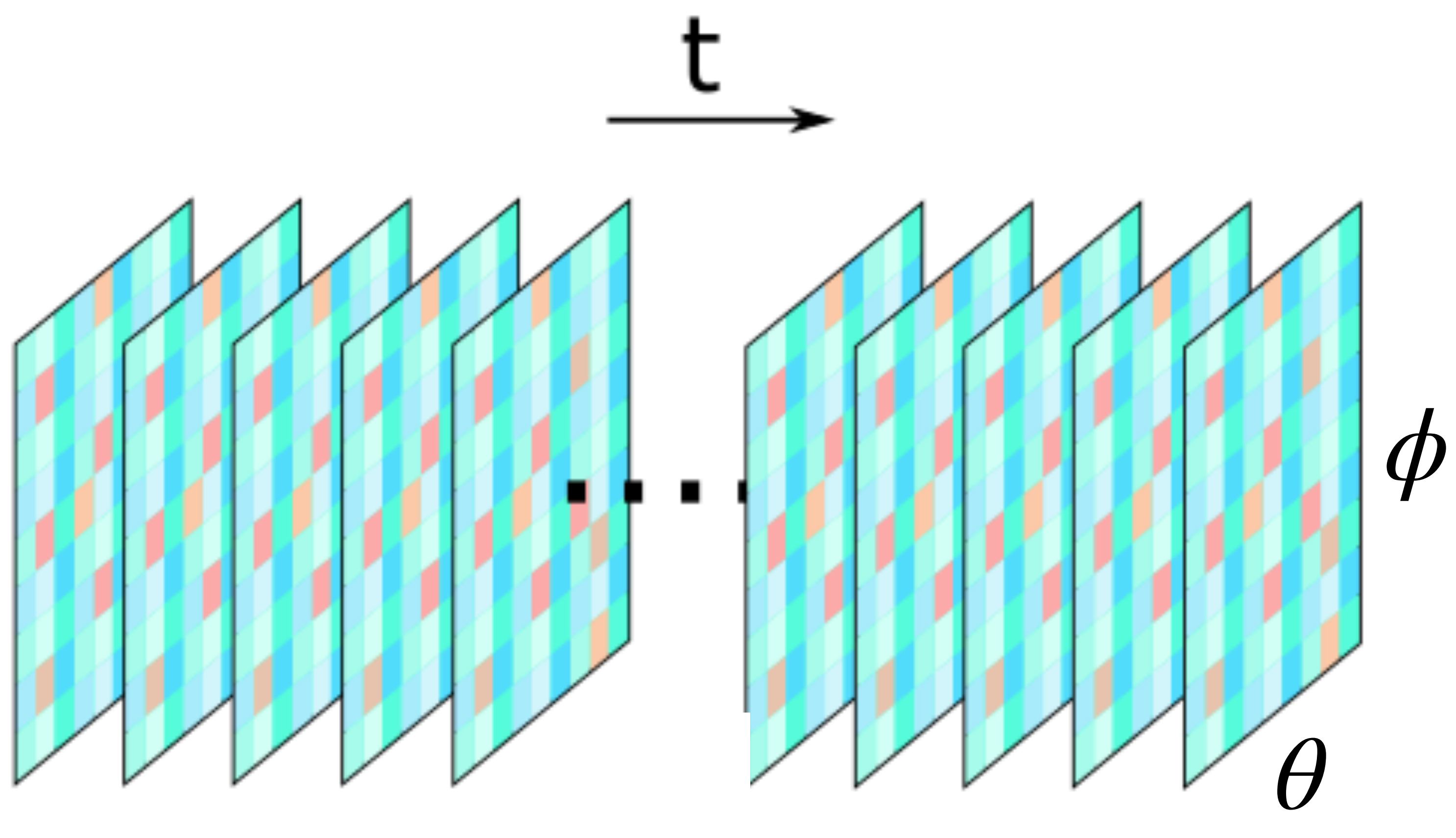
$(R, \theta, \phi, t, q) \rightarrow E = \Sigma q$

Scintillation Time Profile



Spatiotemporal Data

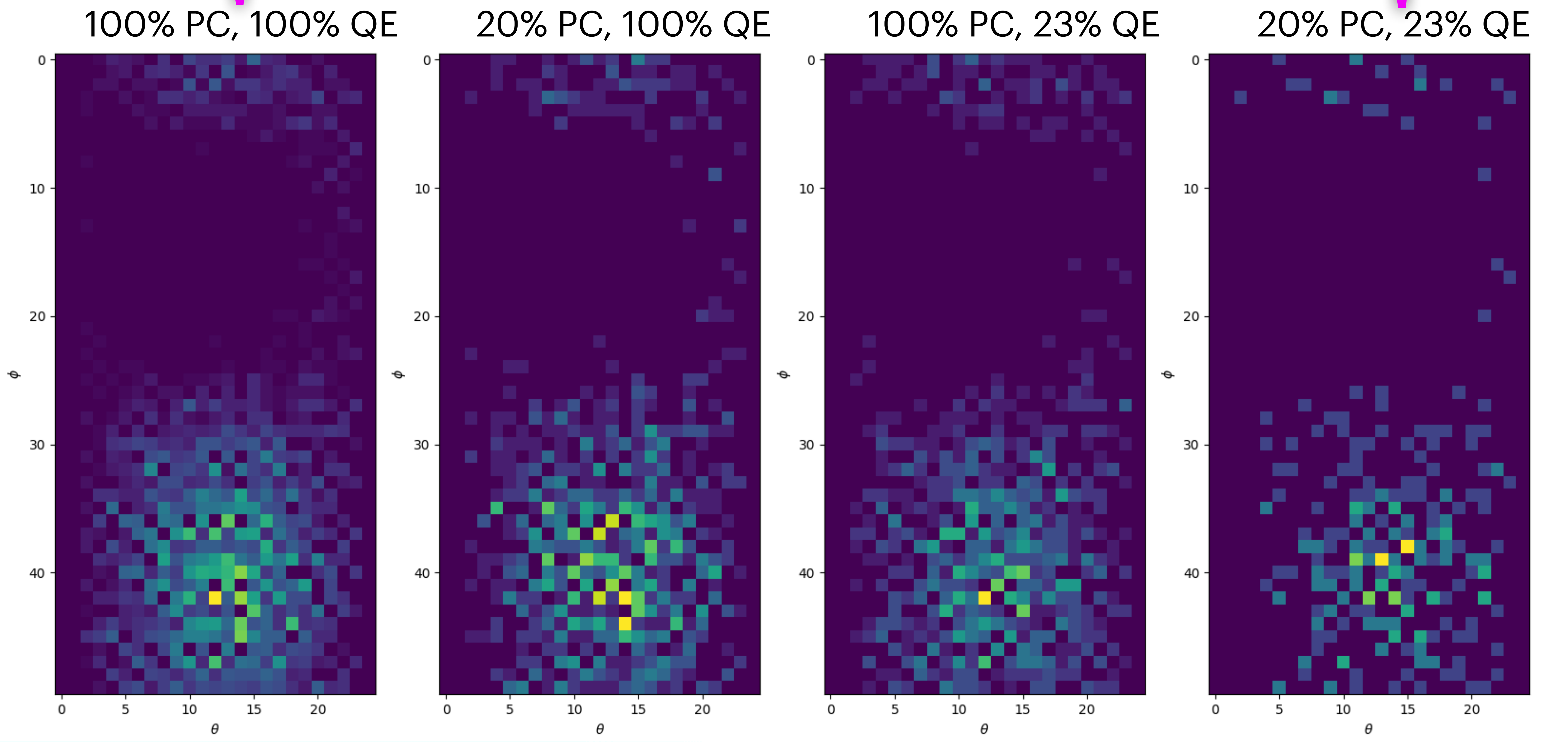
A time series of 2D images, projected onto sphere (A spherical video)

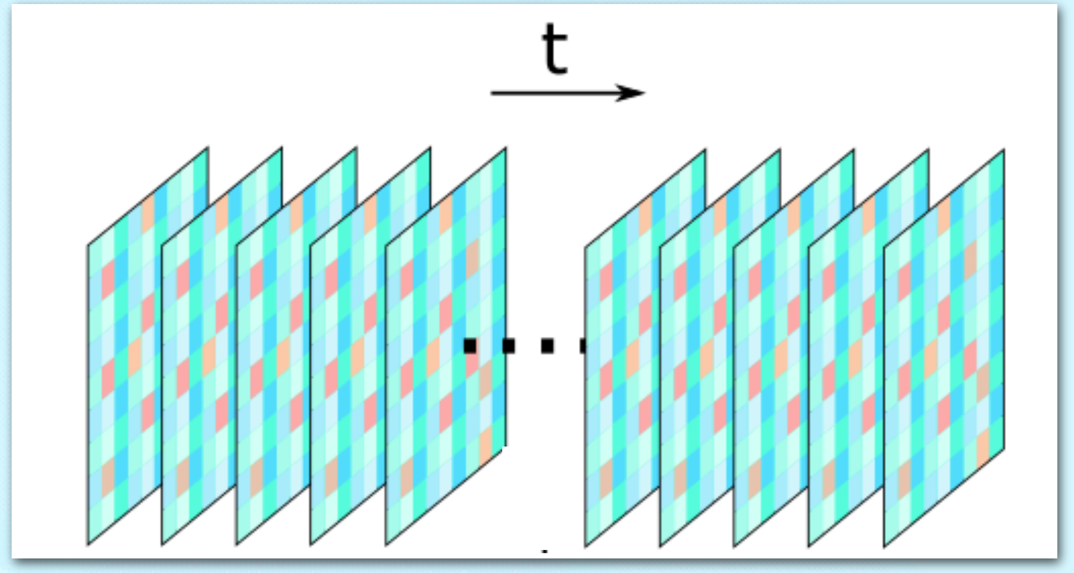


Simulating Spatiotemporal Data

Perfect Detector

Realistic KamLAND-Zen Hardware





Computer simulation for neutrinoless double beta decay signal and ^{10}C background events

Wrote PMT model that allows us to vary two **Information Parameters**:

- **Photocoverage (PC)**
- **Quantum Efficiency (QE)**

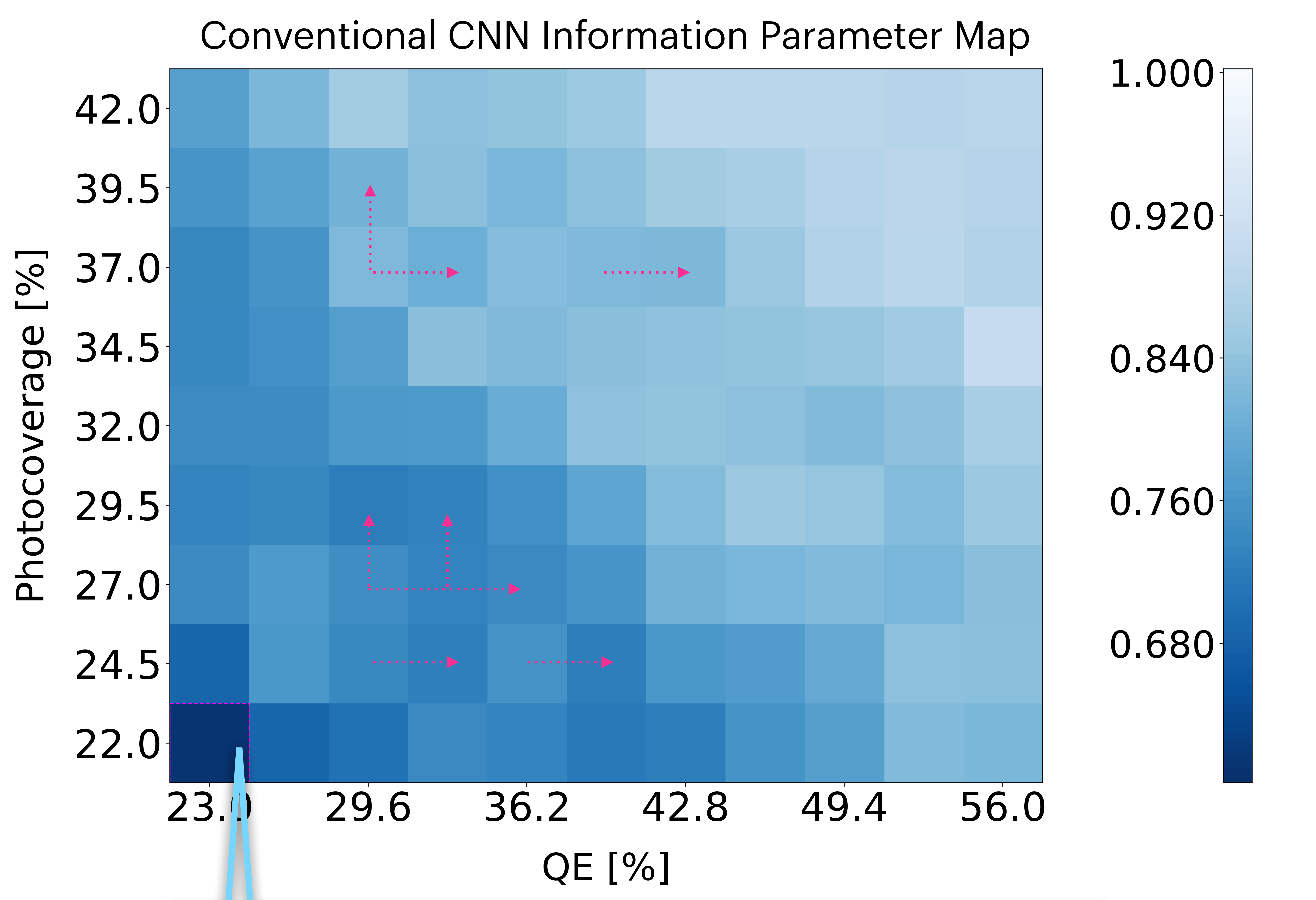
Benchmark model performance under different input conditions

better detector, more information in data

Project network performance onto future experiments with better PC and QE

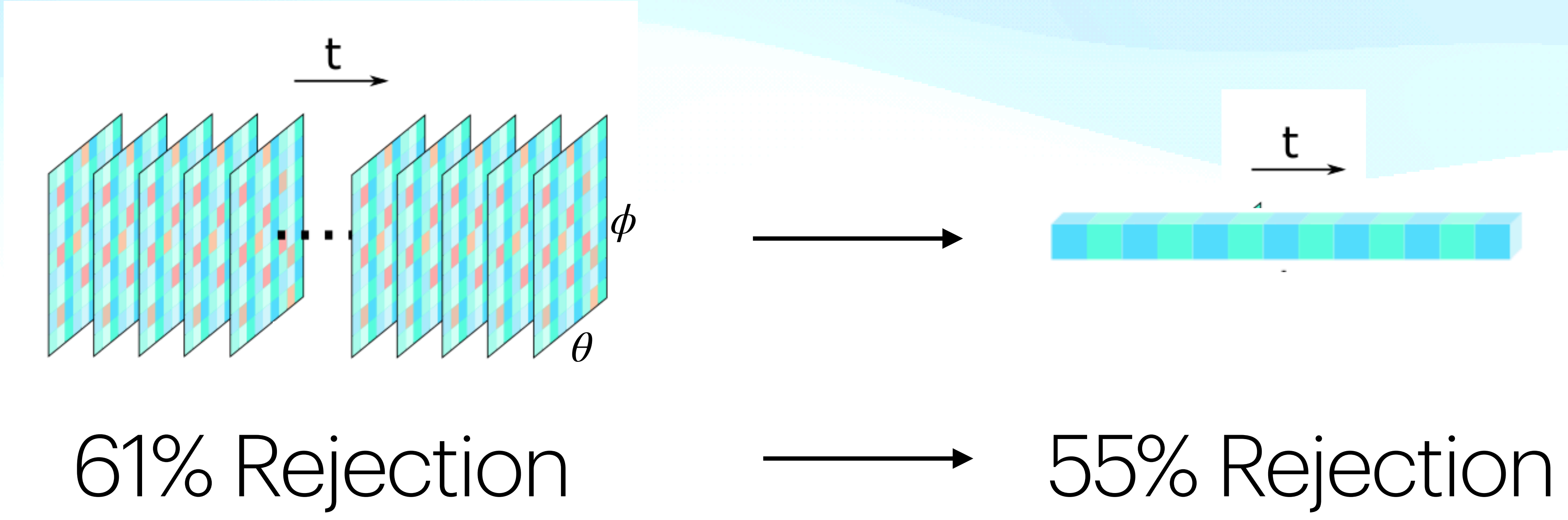
Convolutional Neural Network

A. Li et al.,
DOI: 10.1016/j.nima.2019.162604



At KamLAND-Zen hardware status, CNN rejects 61% of background while retaining 90% of the signal

Alarm 1: Background rejection performance decrease as we increase information parameter!



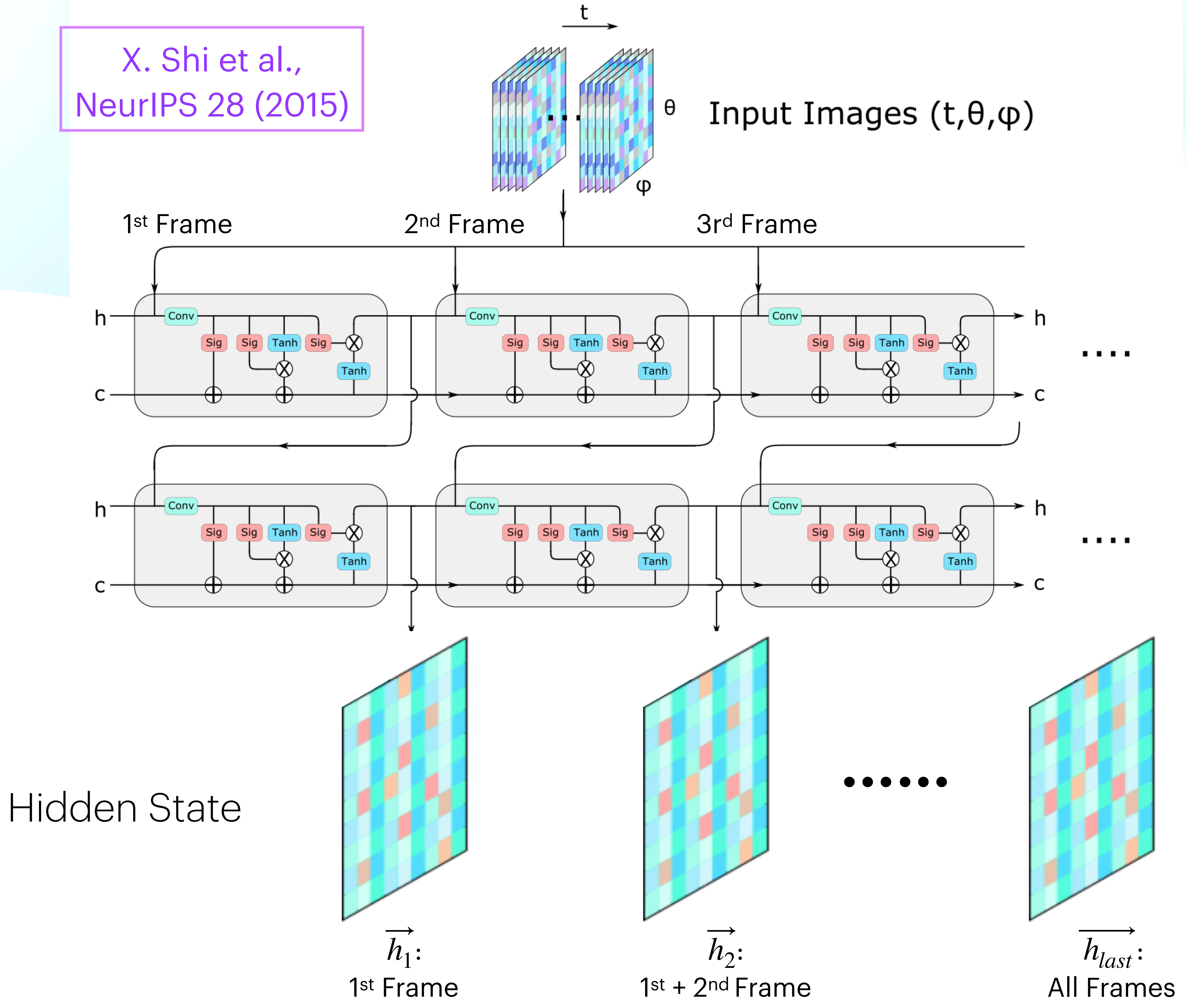
Alarm 2: Conventional CNN is not powerful enough to **harness all symmetries** in spatiotemporal data!

A Time Series of 2D Images …

ConvLSTM

Convolutional Long-Short Term Memory (LSTM) Network

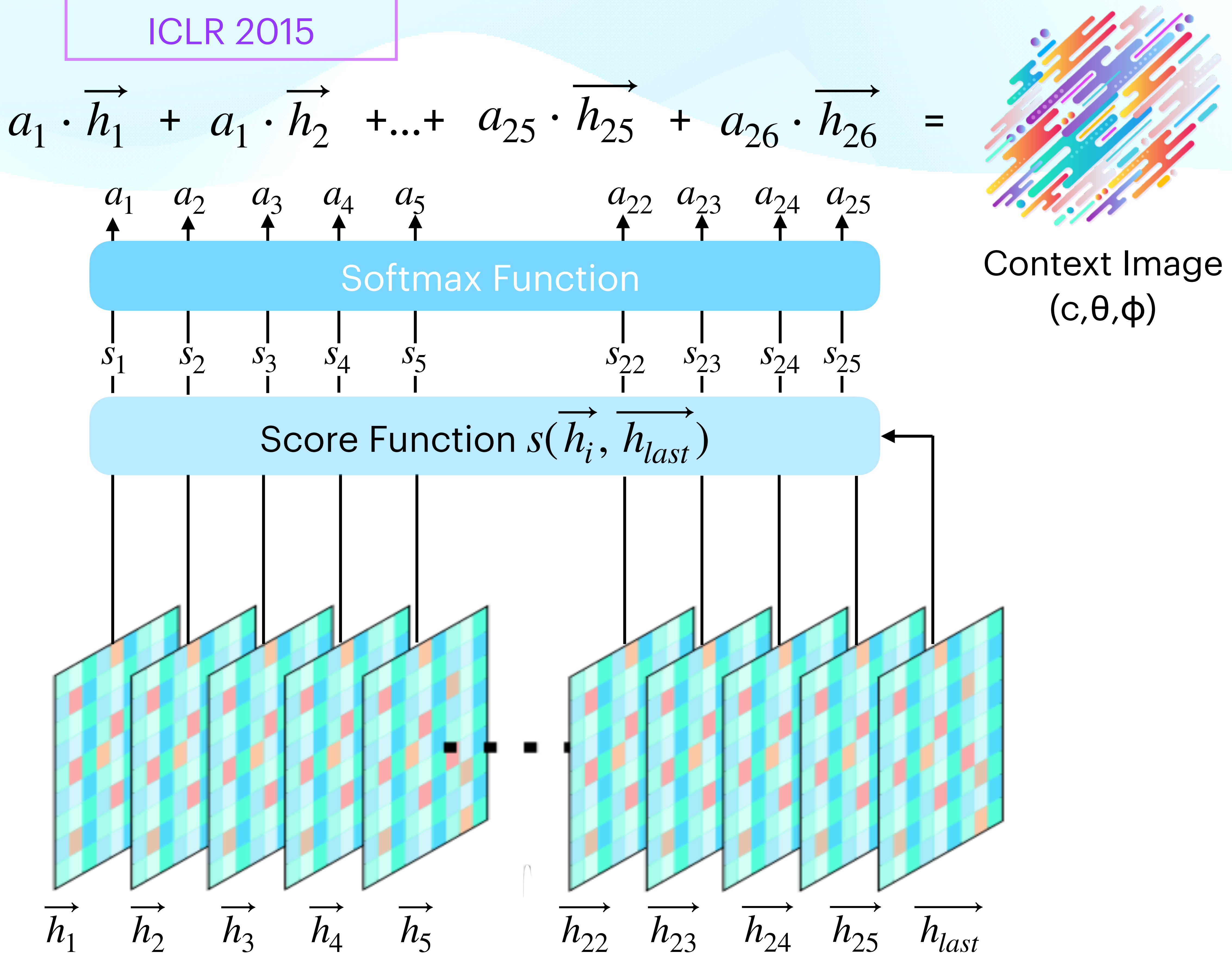
X. Shi et al., NeurIPS 28 (2015)



Attention Mechanism

Produce context images & provide interpretability

D Bahdanau et al., ICLR 2015

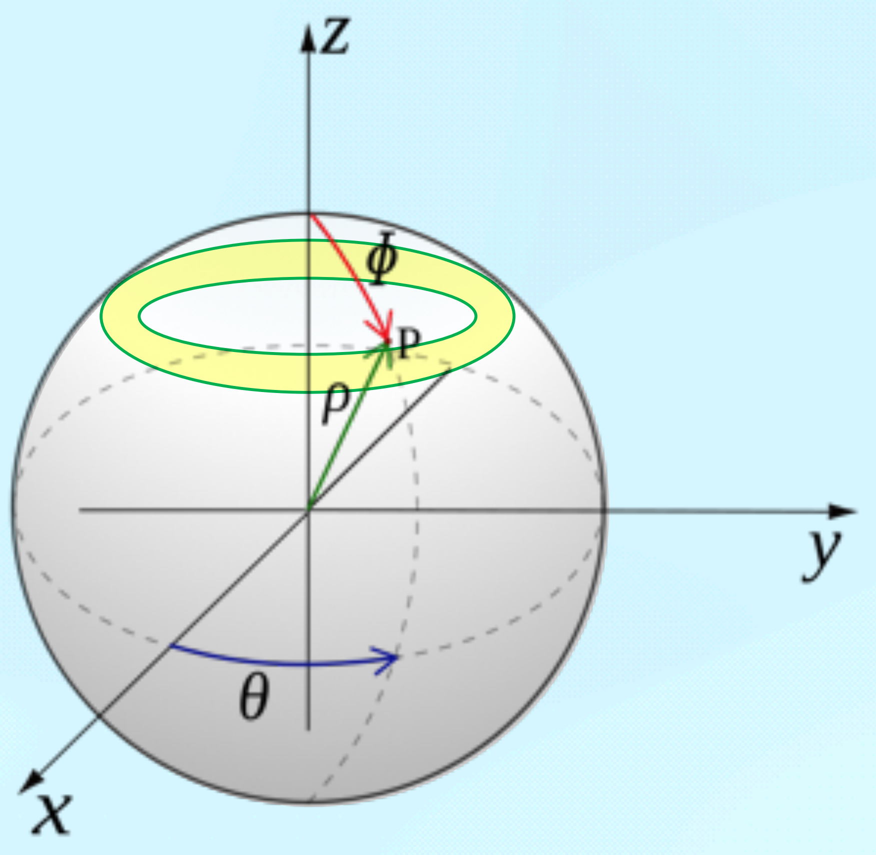


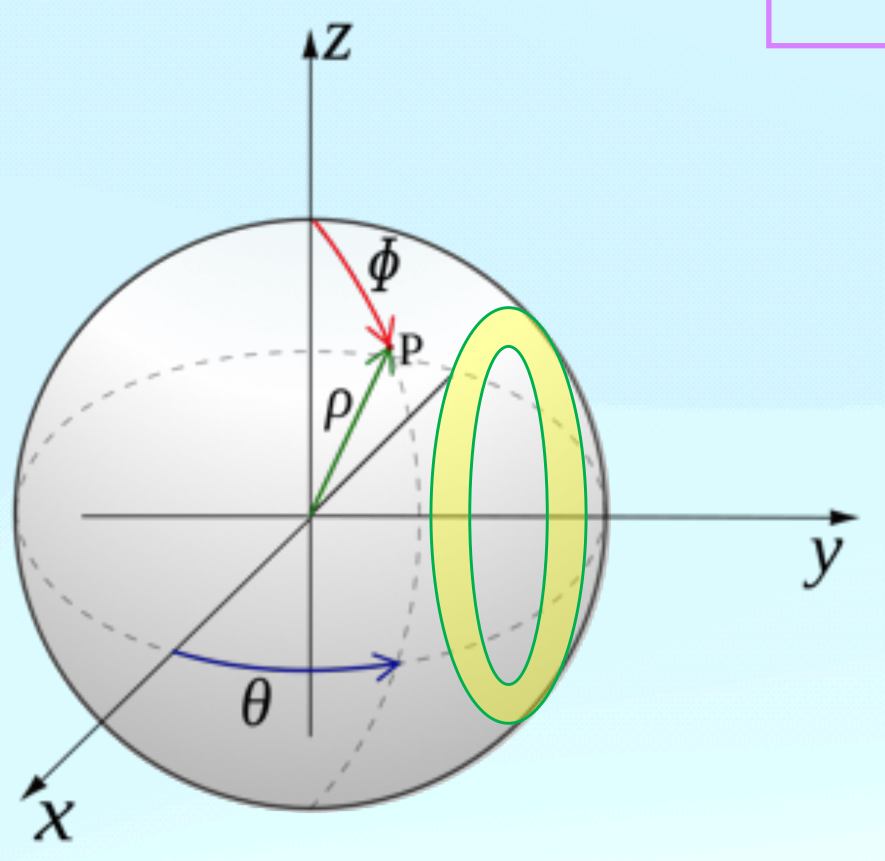
… Project onto A Sphere

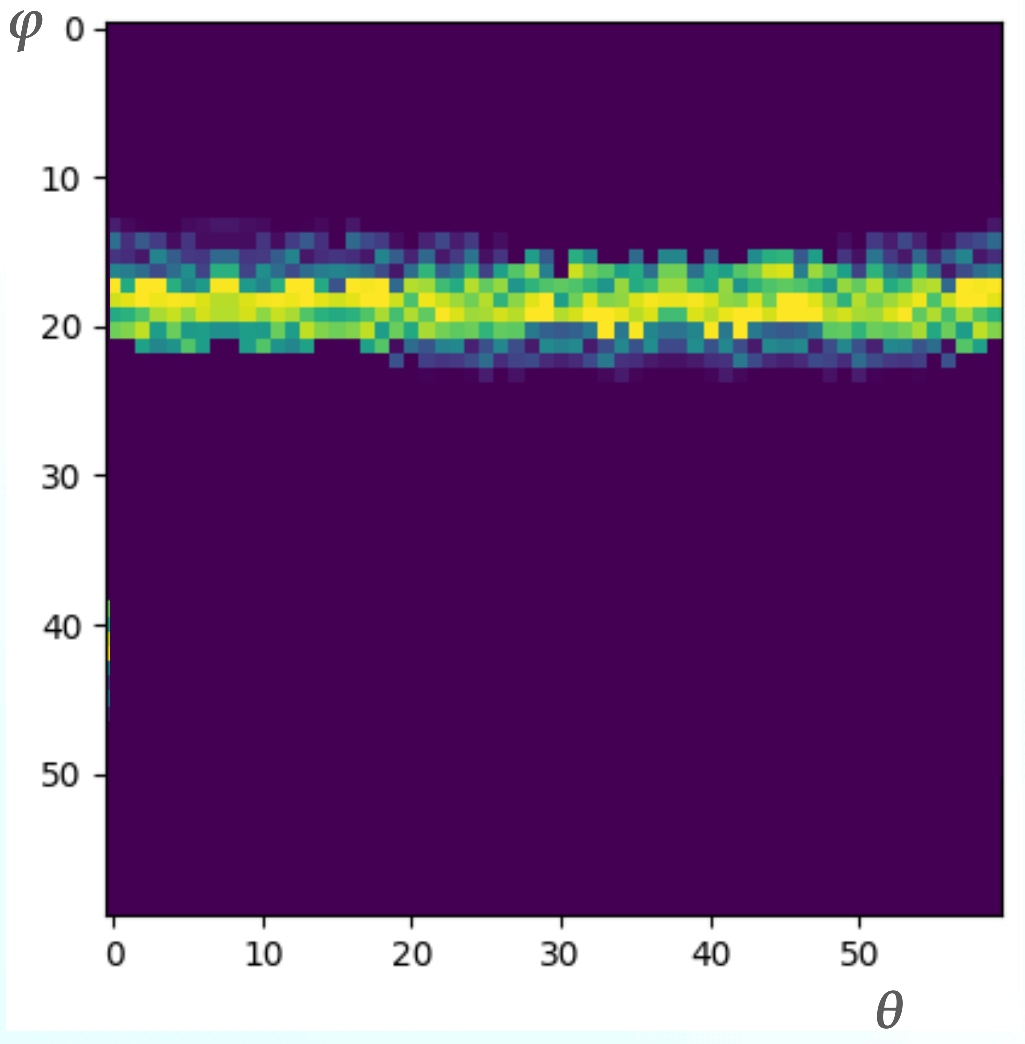
Cohen, Taco et al. "Spherical CNNs." ICLR 2018

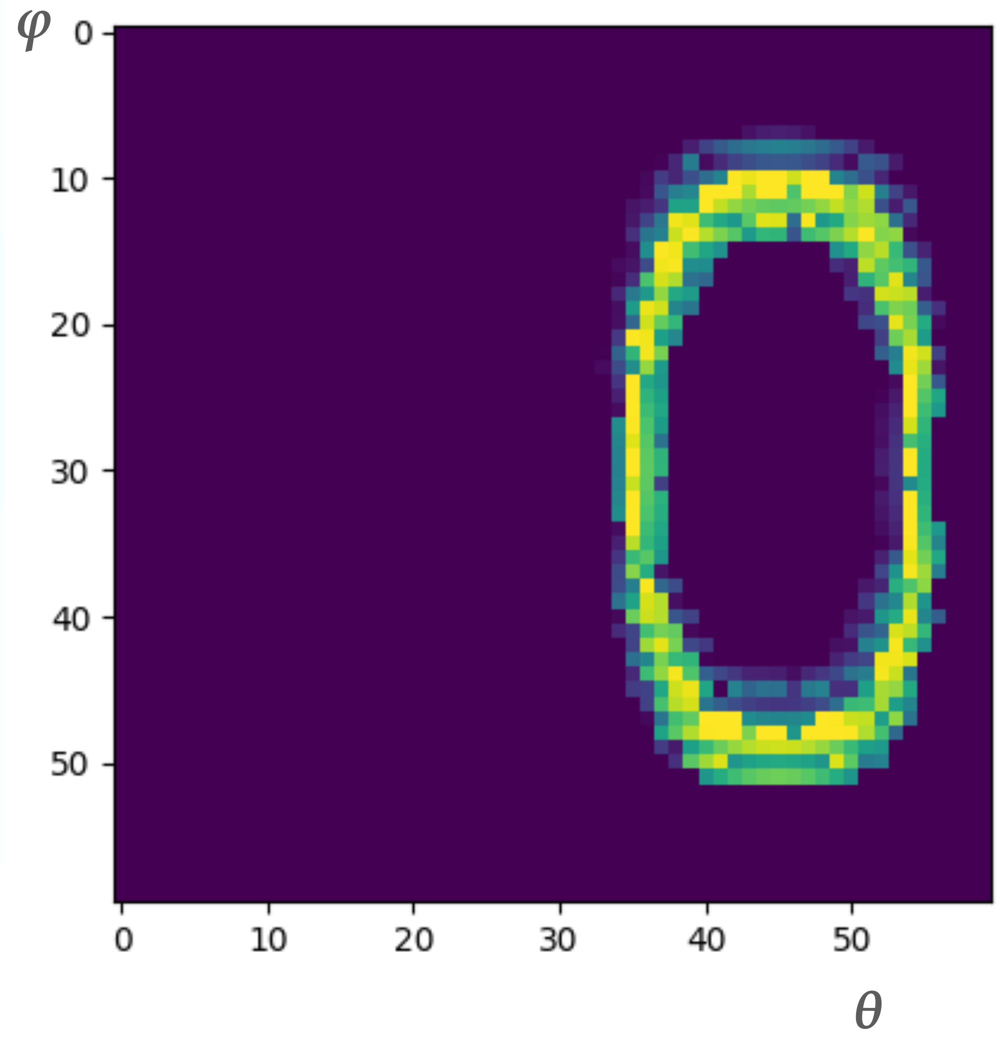
Spherical CNN

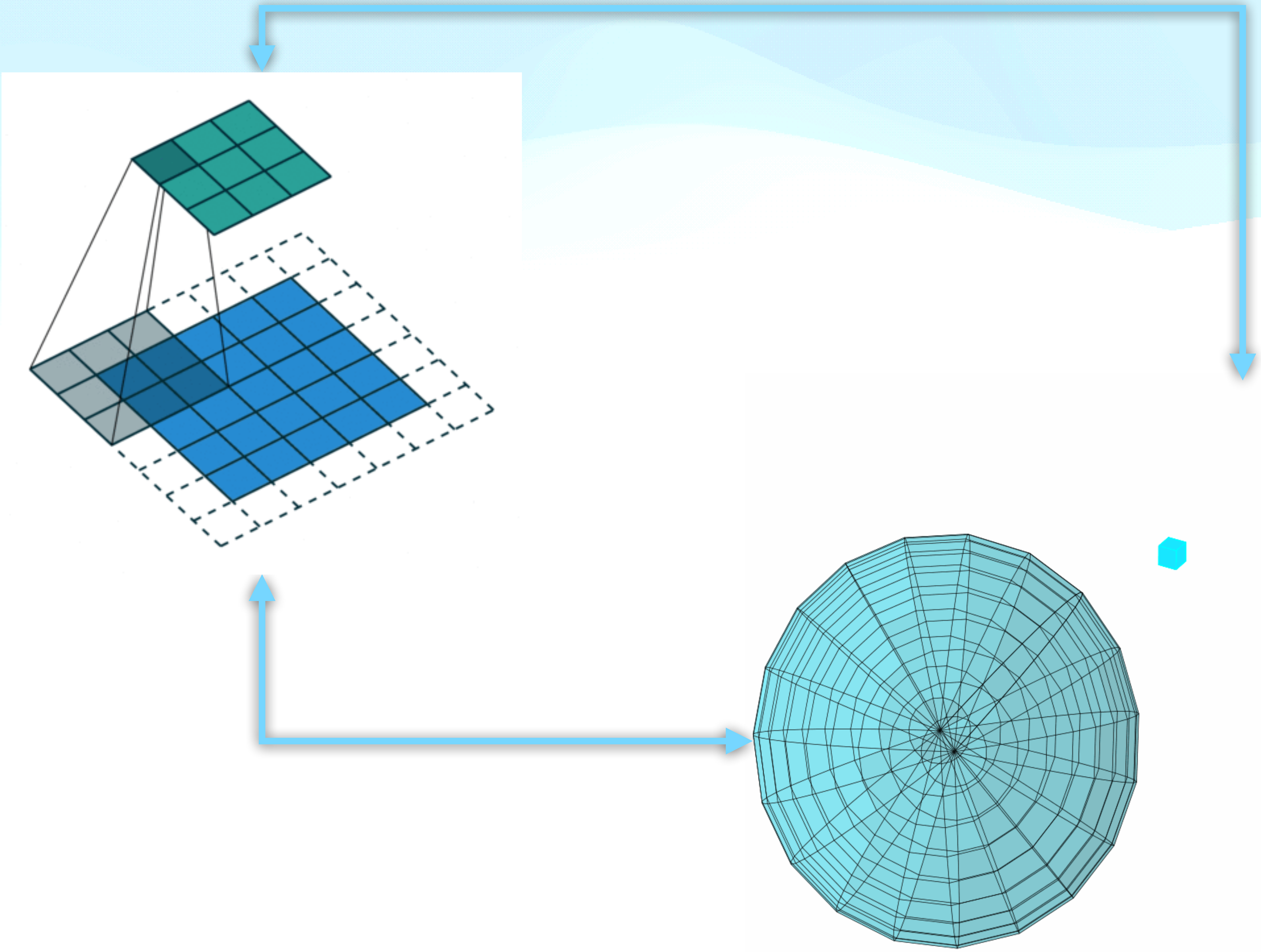
SO(3) symmetry & rotational invariance







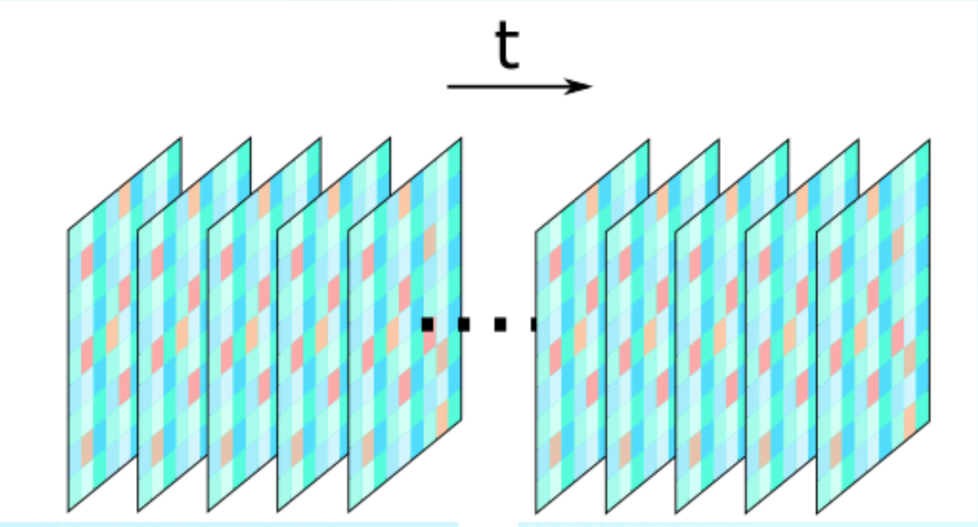




KamNet: An Integrated Spatiotemporal Neural Network

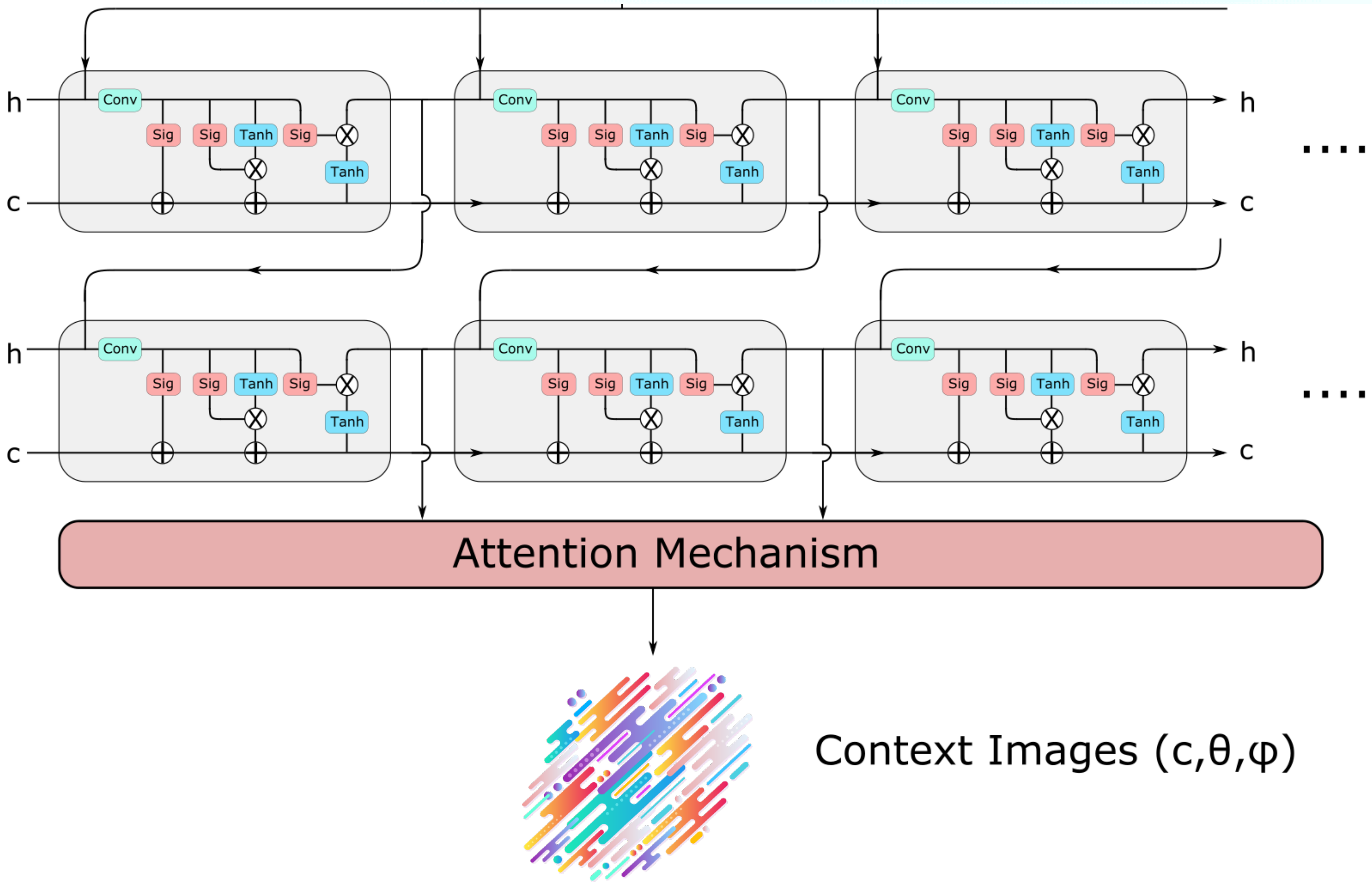
Spatiotemporal Data

A time series of images projected onto Sphere



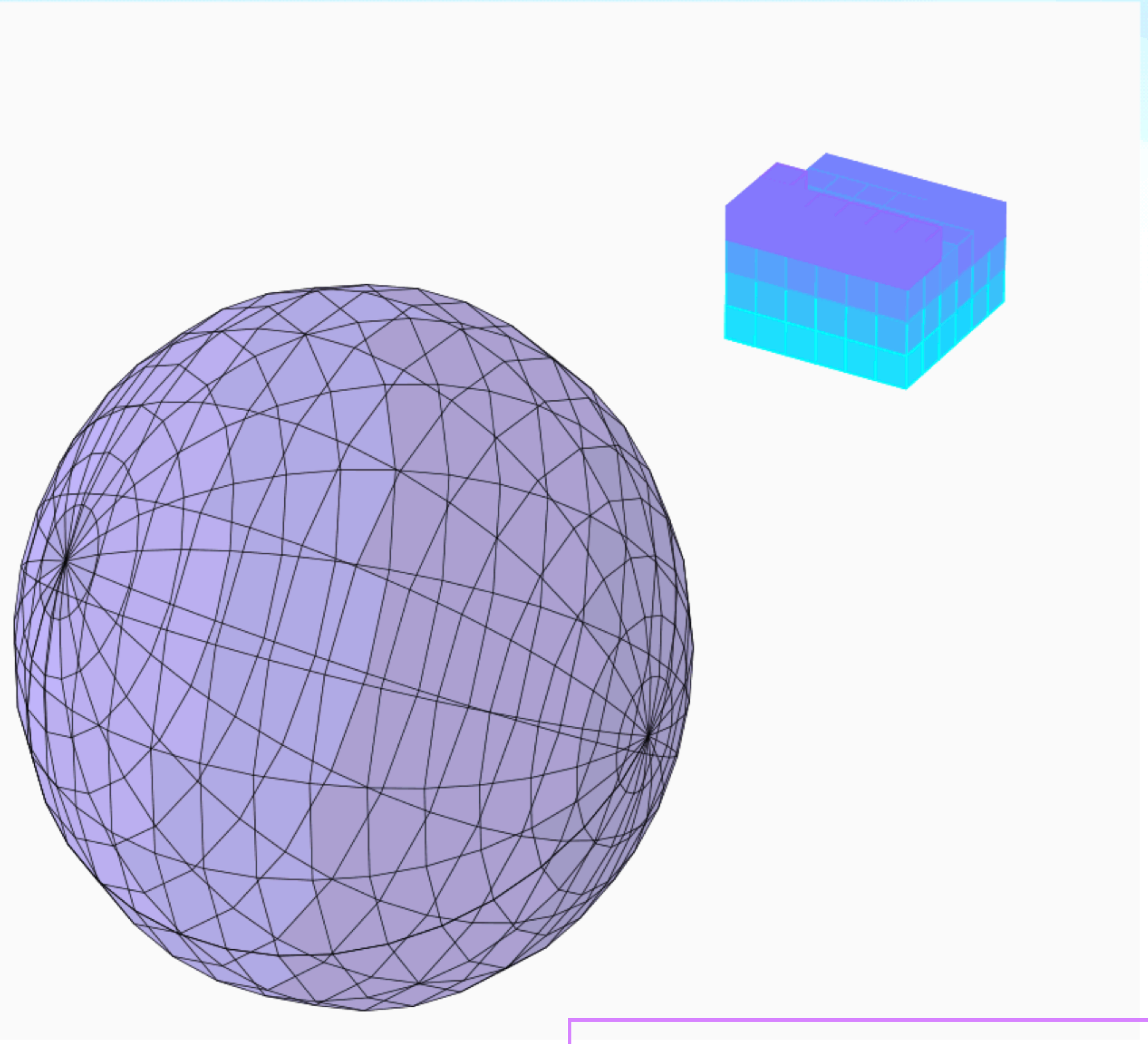
AttentionConvLSTM

for Spatiotemporal symmetry



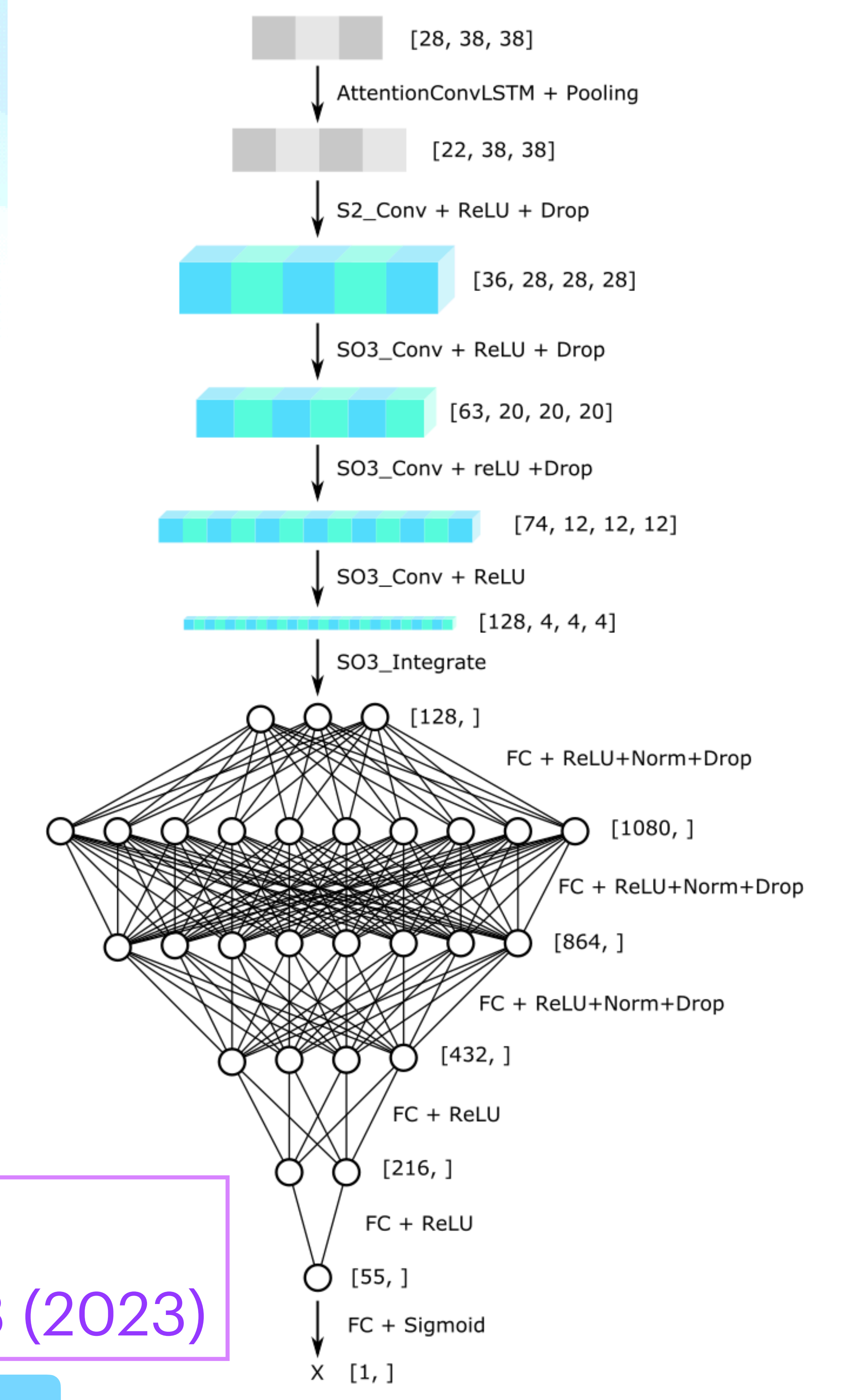
Spherical CNN

SO(3) symmetry & rotational equivariance



KamNet

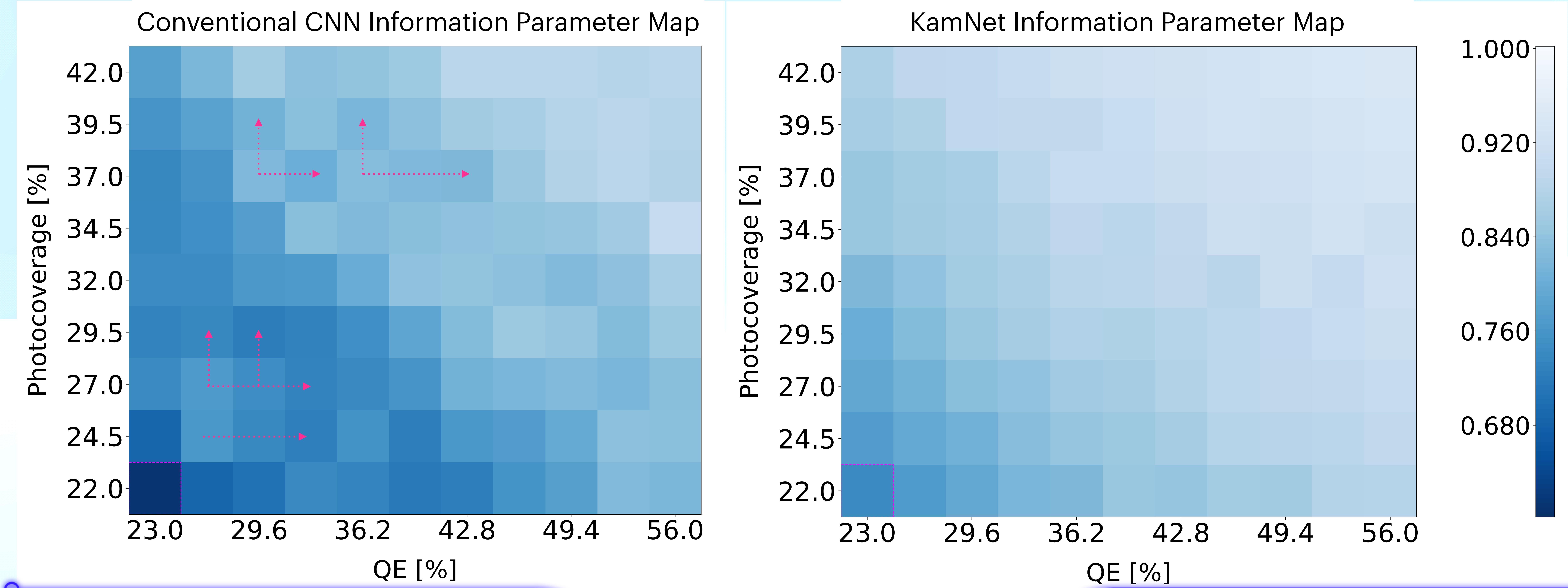
Maximal Information Extraction in KamLAND-Zen



A. Li et al,
Phys. Rev. C **107**, 014323 (2023)

Editor's Suggestion

KamNet vs. CNN



More Robust

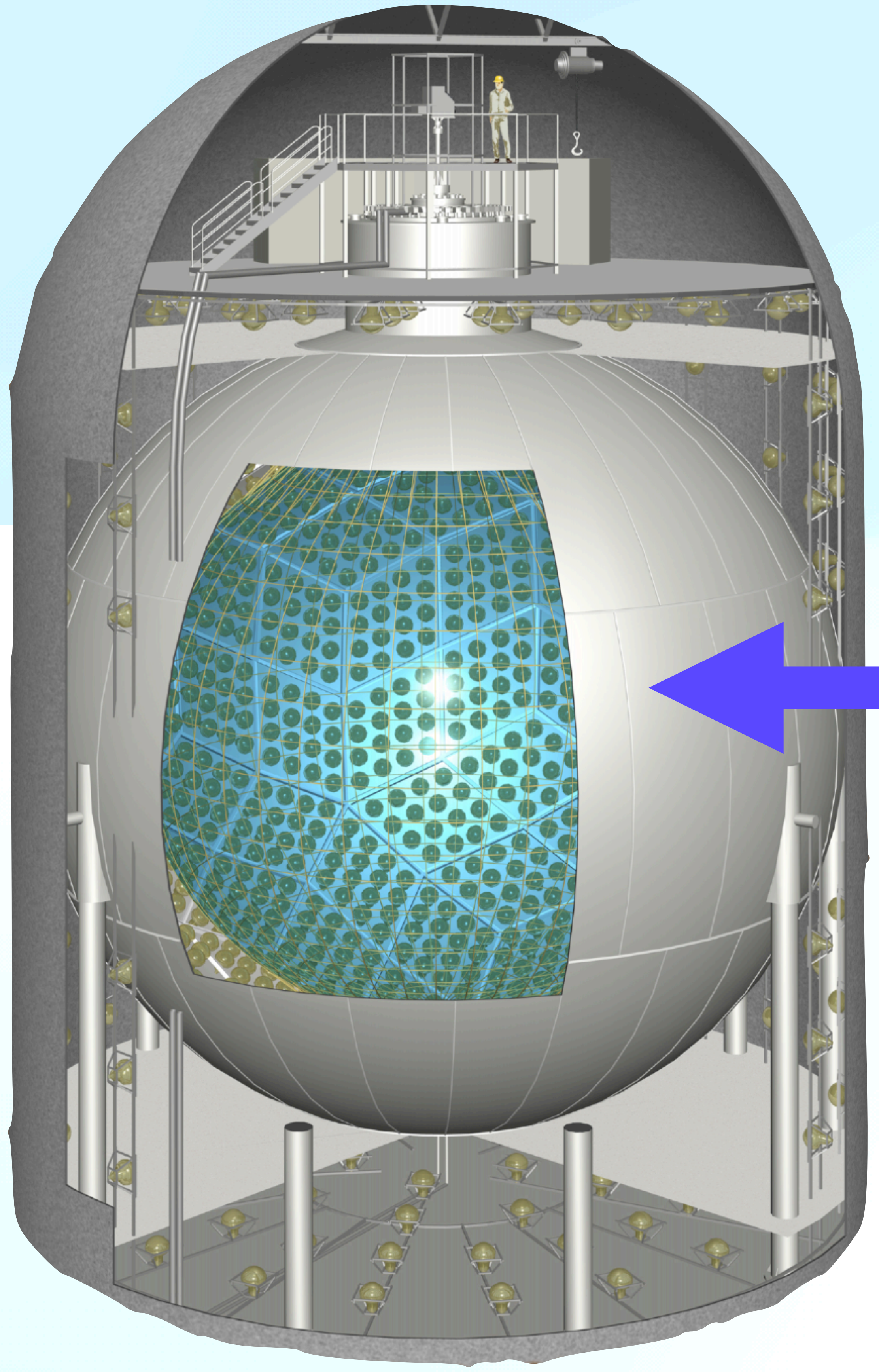
Smoother transition from low to high information parameters
Every bit of additional information is absorbed by KamNet

Better Performance

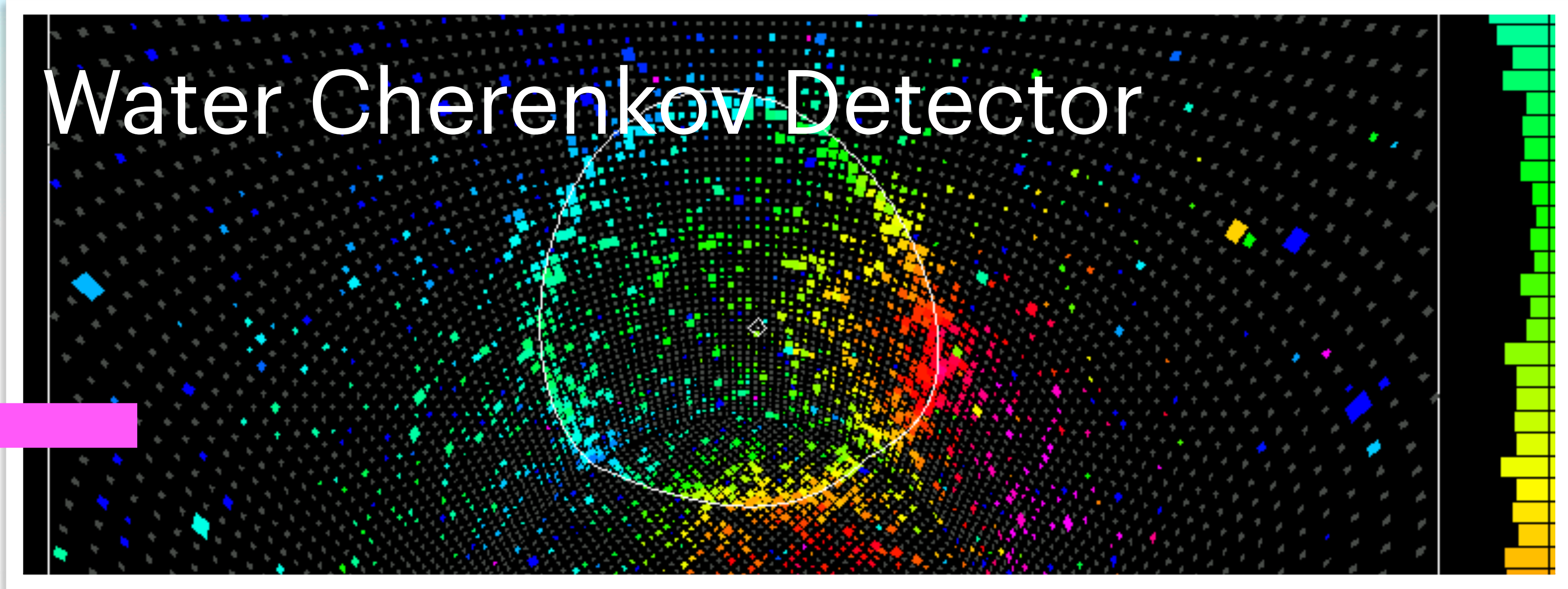
Across entire map, 61% → 74% ^{10}C rejection at KamLAND-Zen hardware configuration

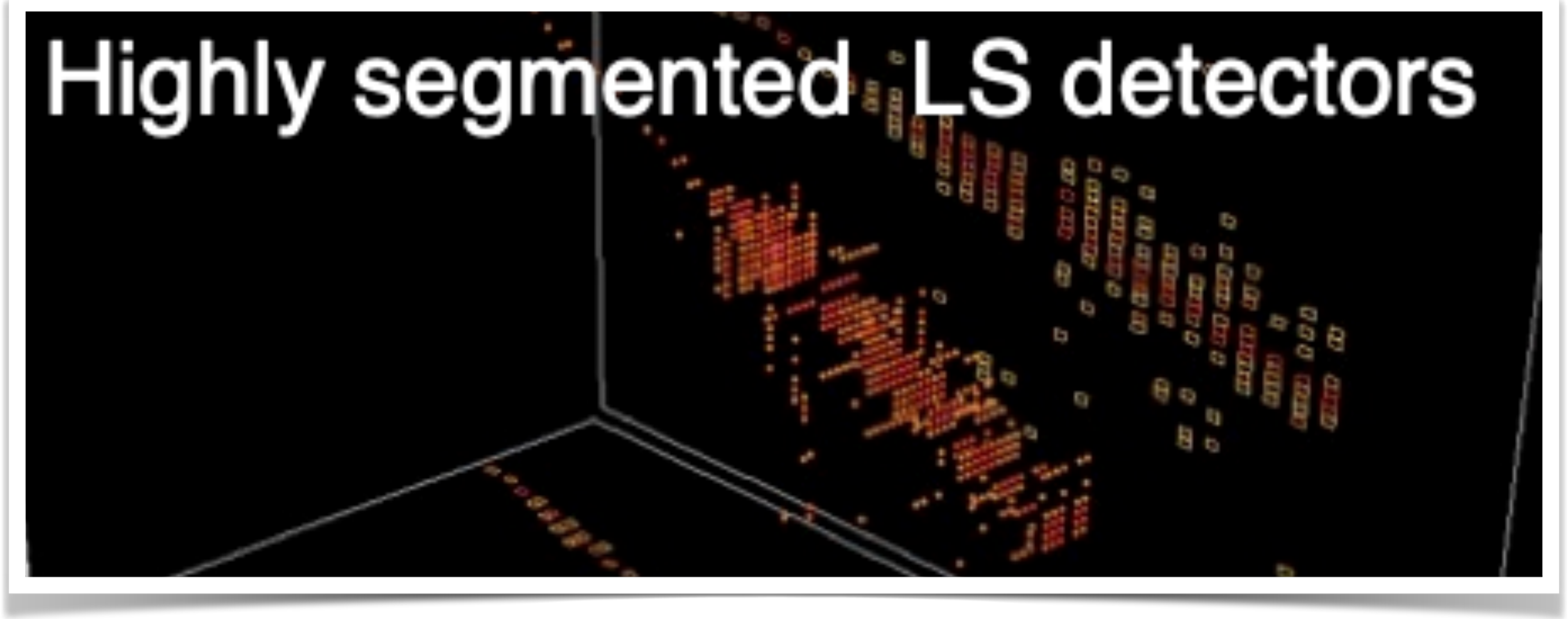
KamNet-enabled Background Rejection

Monolithic LS detector has been at the heart of many great discoveries in neutrino physics ...

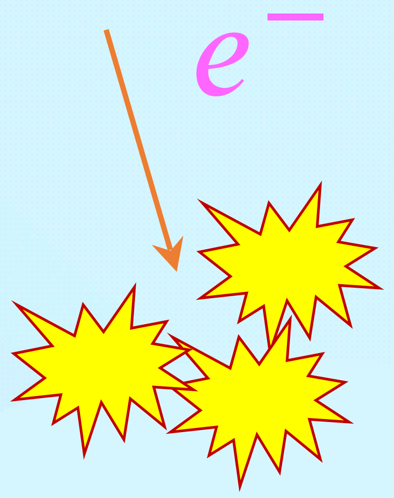


" Enhancing **monolithic LS detectors** with the capability to discriminate between different event types based on **tracking** and/or **event topology** would be a revolutionary advancement "

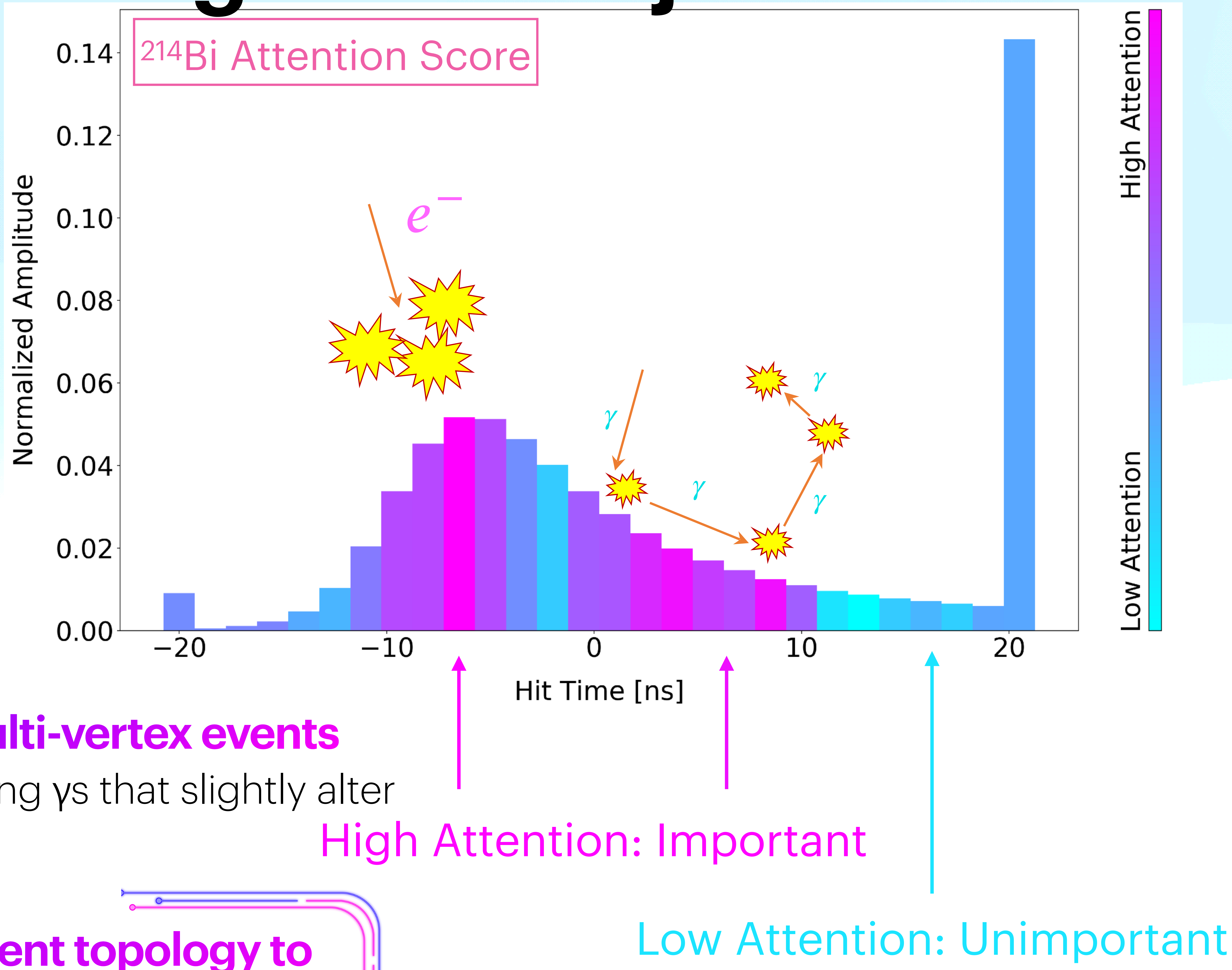




KamNet-enabled Background Rejection



- Signal are strictly **single-vertex events**
  - All energy deposited almost immediately



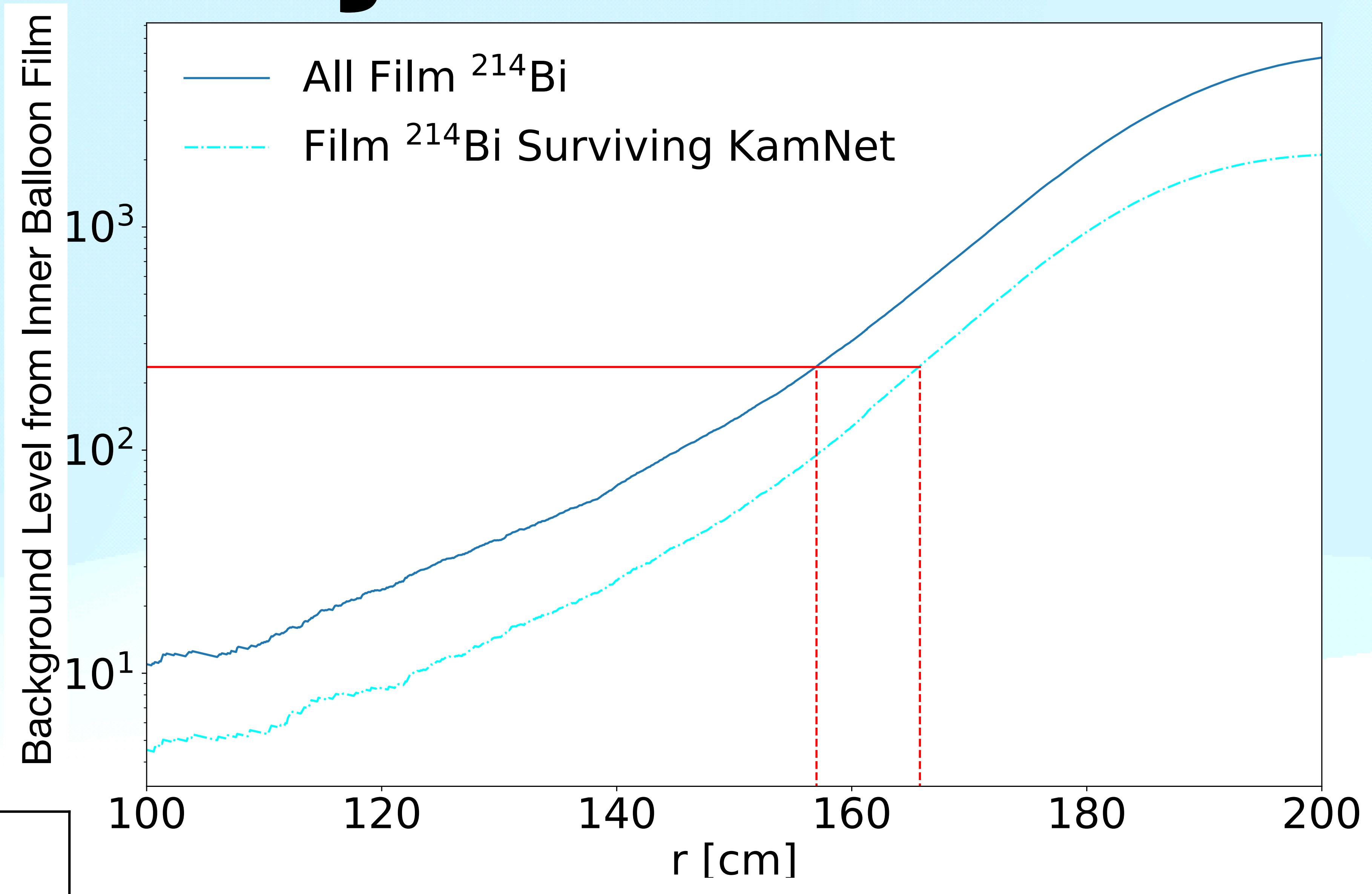
- Most backgrounds are **closely-spaced multi-vertex events**
  - part of event energy is deposited by cascading γs that slightly alter event topology

KamNet captures this tiny alteration in event topology to efficiently reject most backgrounds in KamLAND-Zen!

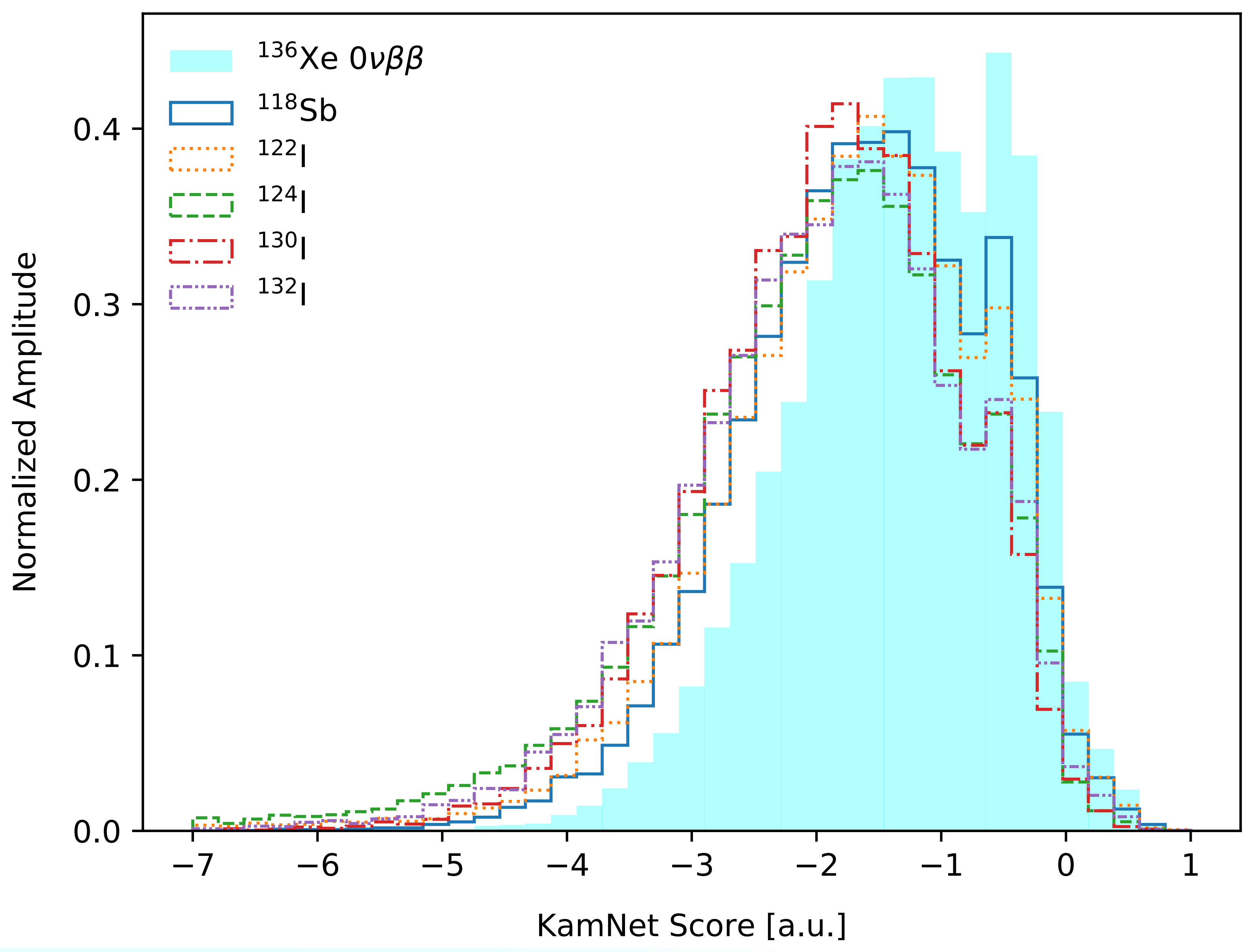
KamNet-enabled Background Rejection

While accepting **90%** of $0\nu\beta\beta$ events, KamNet rejects **~27%** of XeLS backgrounds and **~59%** of film backgrounds

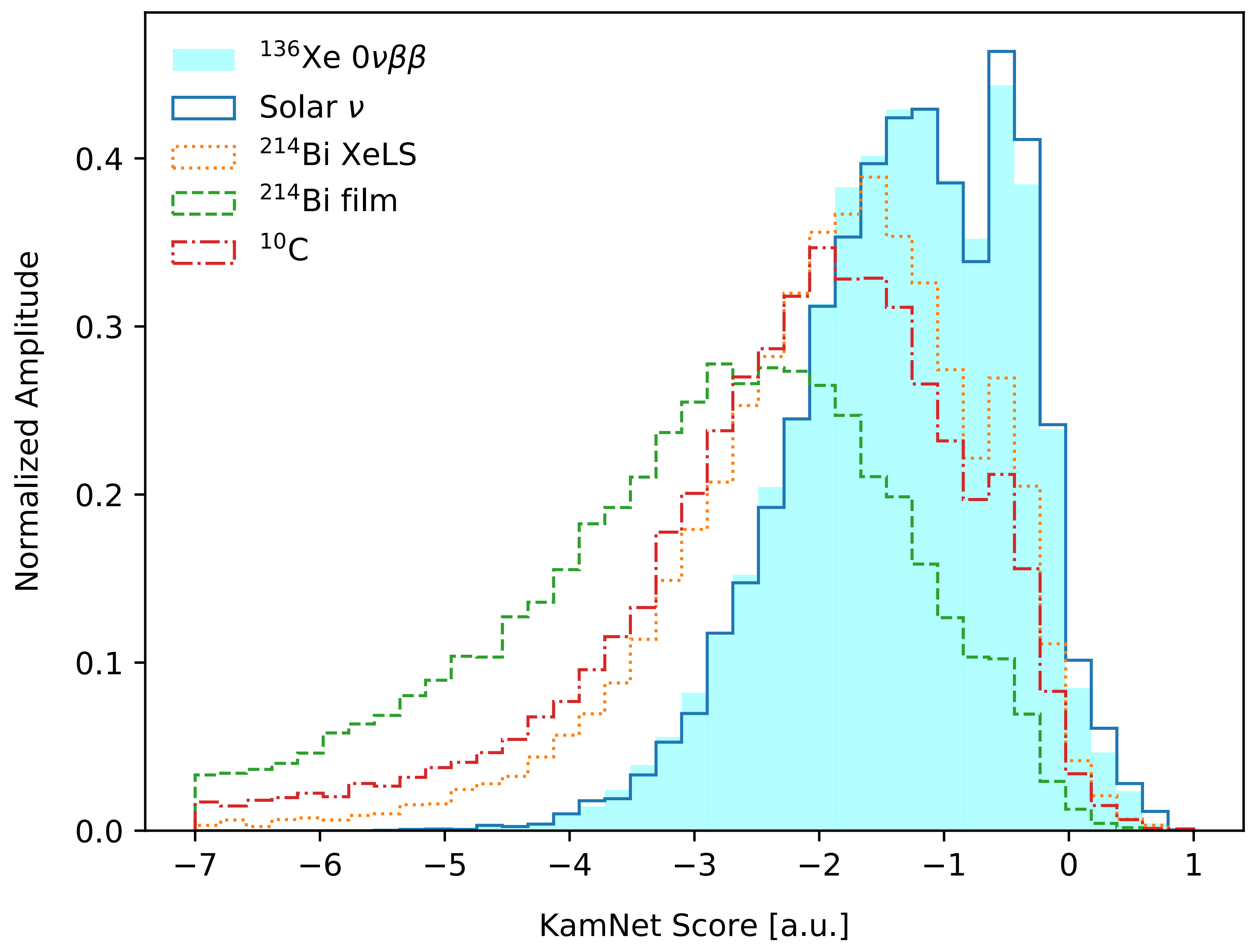
KamNet is **independent** and **multiplicative** to all existing background rejection methods in KamLAND-Zen



Long-Lived Spallation



Other Backgrounds



The increased rejection of film backgrounds allows for the expansion of the fiducial volume from 157cm to 165.8cm, resulting in **17.7% gain** on exposure

KamNet-enabled New Search

Exposure Before KamNet:

2.097 ton·yr

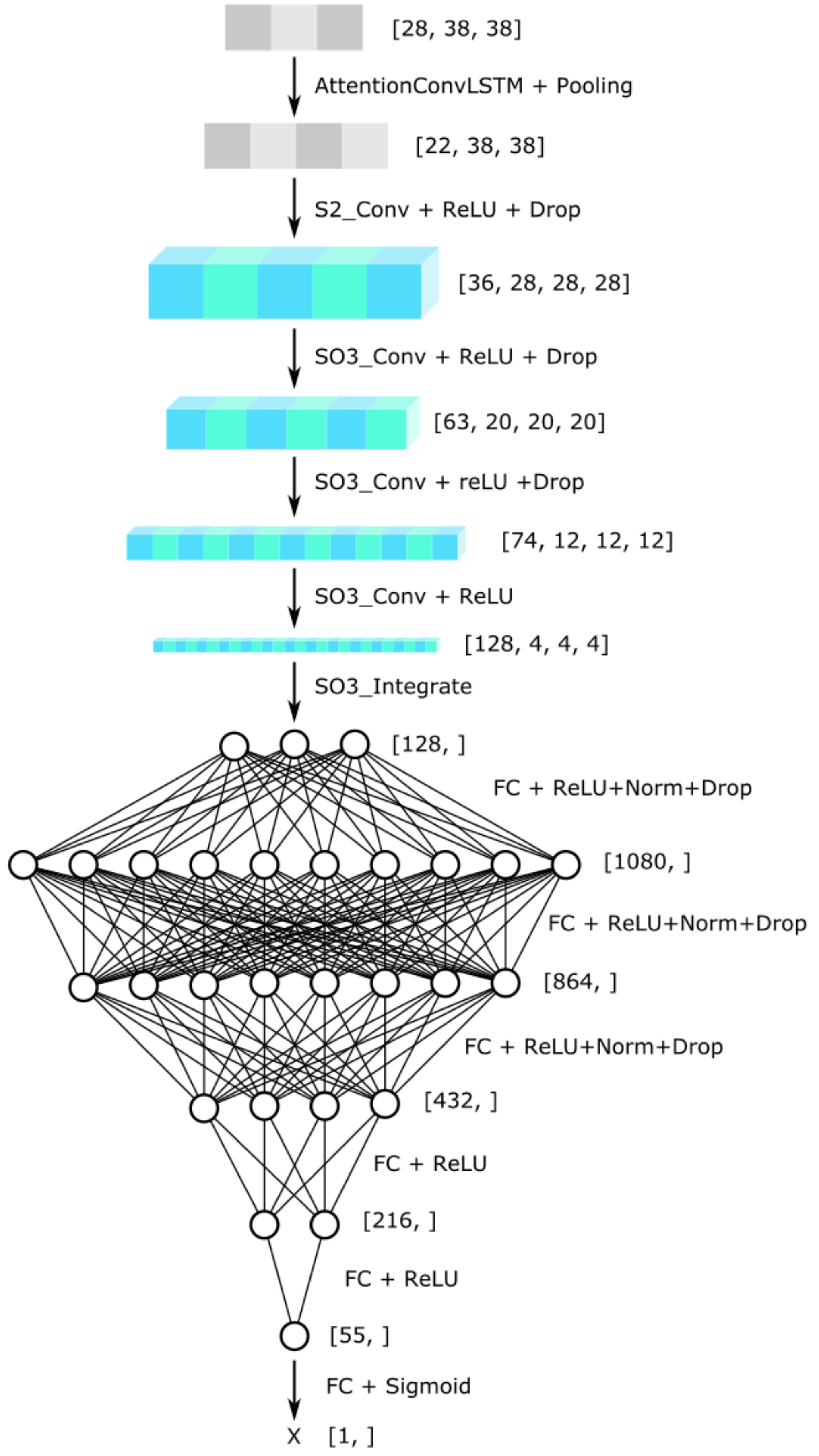
Apply KamNet to High-Background Period Only:

- Conservative use of KamNet
- Veto critical backgrounds that passes all traditional methods

Previous KamLAND-Zen 800 Limit:

$$T^{0\nu\beta\beta}_{1/2} > 2.0 \times 10^{26}\text{yr (90 \% C.L.)}$$

American Physical Society 2023 Dissertation Awards In Nuclear Physics



Exposure After KamNet:

2.453 ton·yr +17.7%

0νββ Half-life Lower Limit with Complete KamLAND-Zen Dataset:

$$T^{0\nu\beta\beta}_{1/2} > 3.8 \times 10^{26}\text{yr (90 \% C.L.)}$$

Apply KamNet to All Data:

$$T^{0\nu\beta\beta}_{1/2} > 2.7 \times 10^{26}\text{yr (90 \% C.L.)}$$ +35%

World-leading $0\upsilon\beta\beta$ Results

$$(T^{0\nu}_{1/2})^{-1} = G^{0\nu}\,|M^{0\nu}|^2\, m^2_{\beta\beta}$$

$$T^{0\nu\beta\beta}_{1/2} > 3.8 \times 10^{26}\text{yr}$$

$$\langle m_{\beta\beta}\rangle < 23\text{–}122\ \text{meV}$$

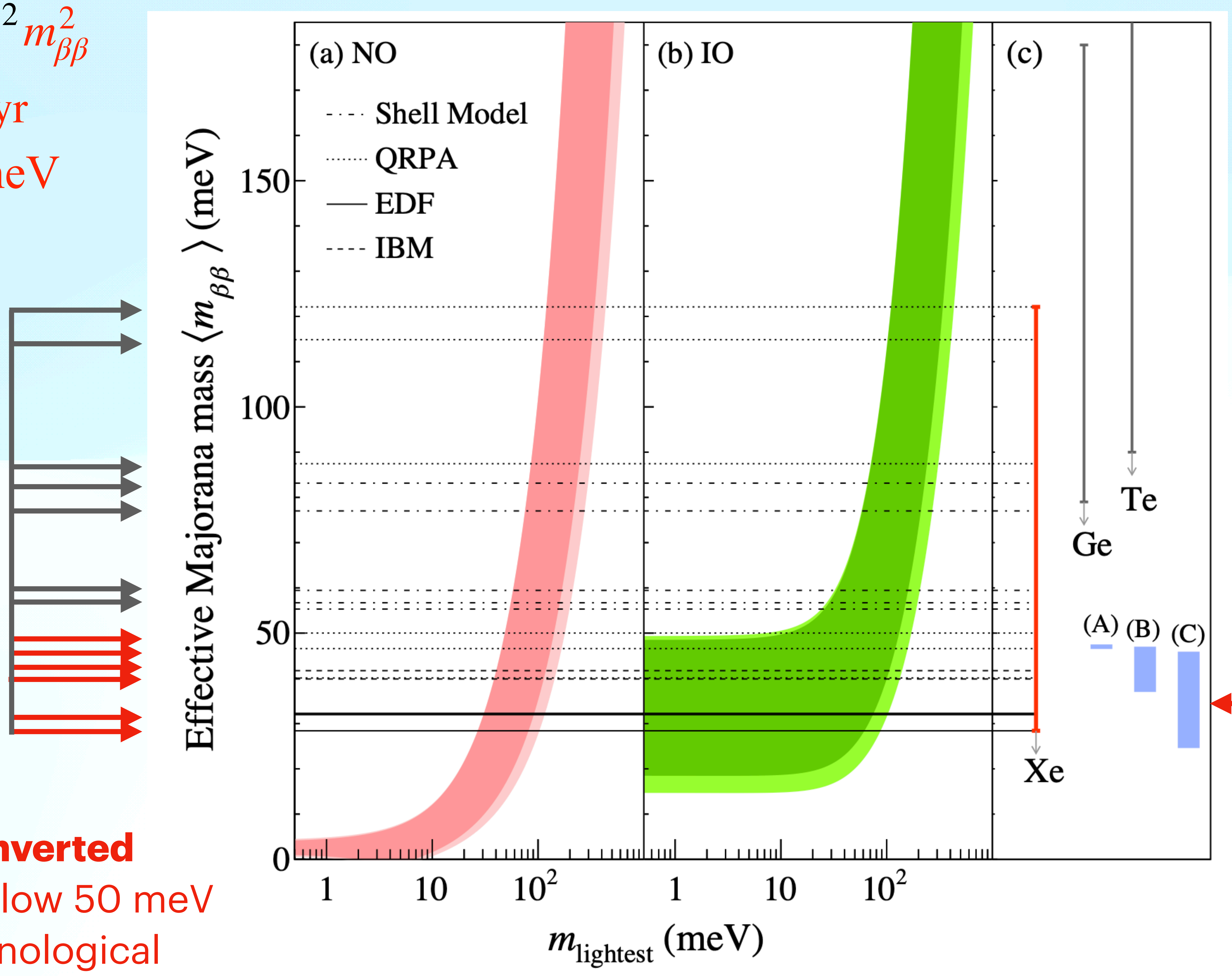
This Xe $0\nu\beta\beta$ search represents the **worlds most stringent limit** on the effective Majorana mass

KamLAND-Zen Collaboration
ArXiv: 2406.11438

KamLAND-Zen Collaboration
Phys. Rev. Lett. 130, 051801

A. Li et al,
Phys. Rev. C **107**, 014323 (2023)

Result dependent on individual NMEs



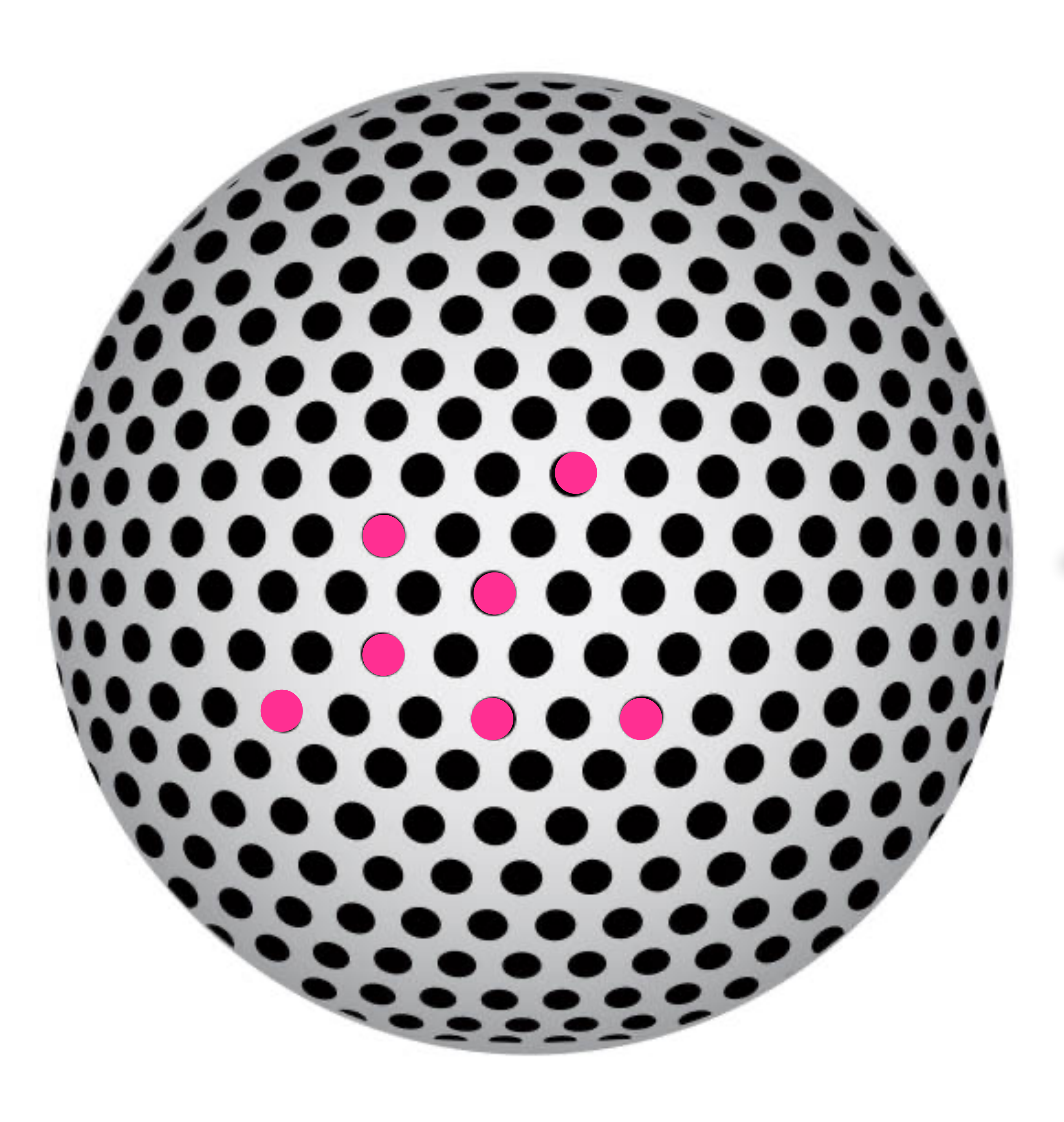
First tests of theoretical predictions.

(a) K Harigaya, Phys. Rev. D 86, 013002
(b) T Asaka, Phys. Lett.B 811 , 135956
(c) K. Asai, Euro.Phys.J.C 80, 76

This search reaches the **inverted mass ordering region** below 50 meV with half of the phenomenological NME calculations!

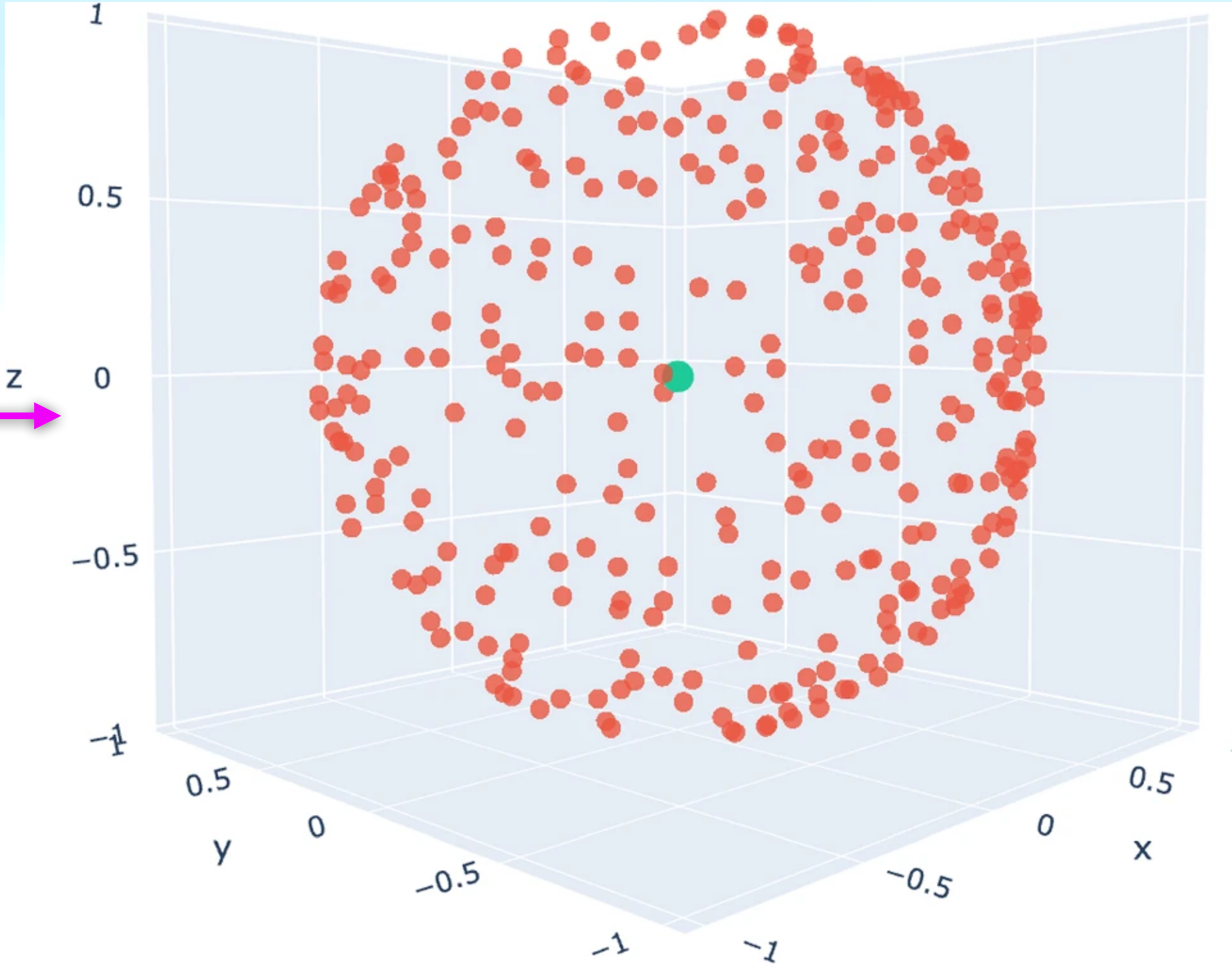
KamLAND-Zen Data as Point Cloud

Z. Fu et al.,
Eur. Phys. J. C **84**, 651 (2024)
https://doi.org/10.1140/epjc/s10052-024-12980-7



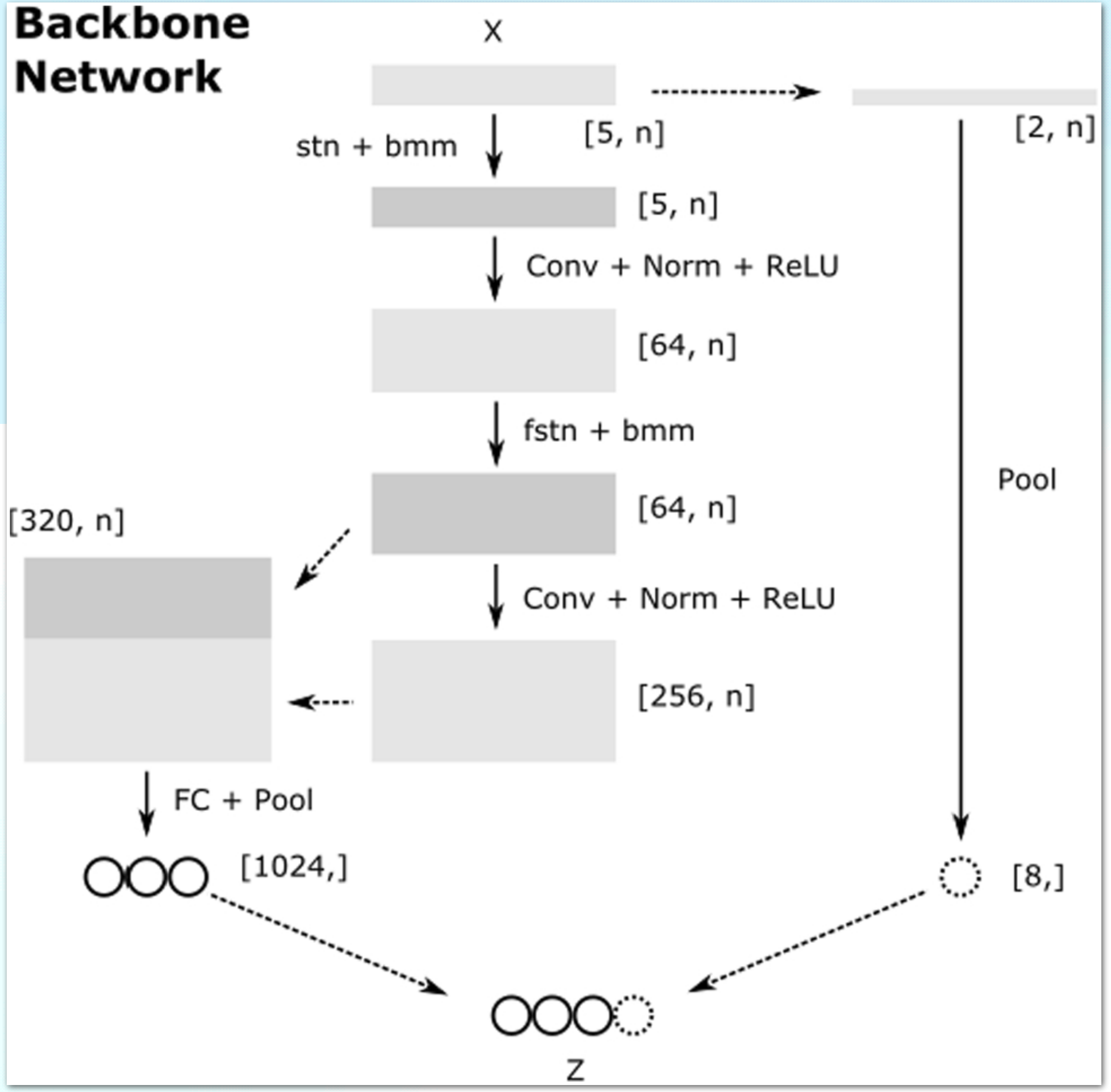
Triggered PMT

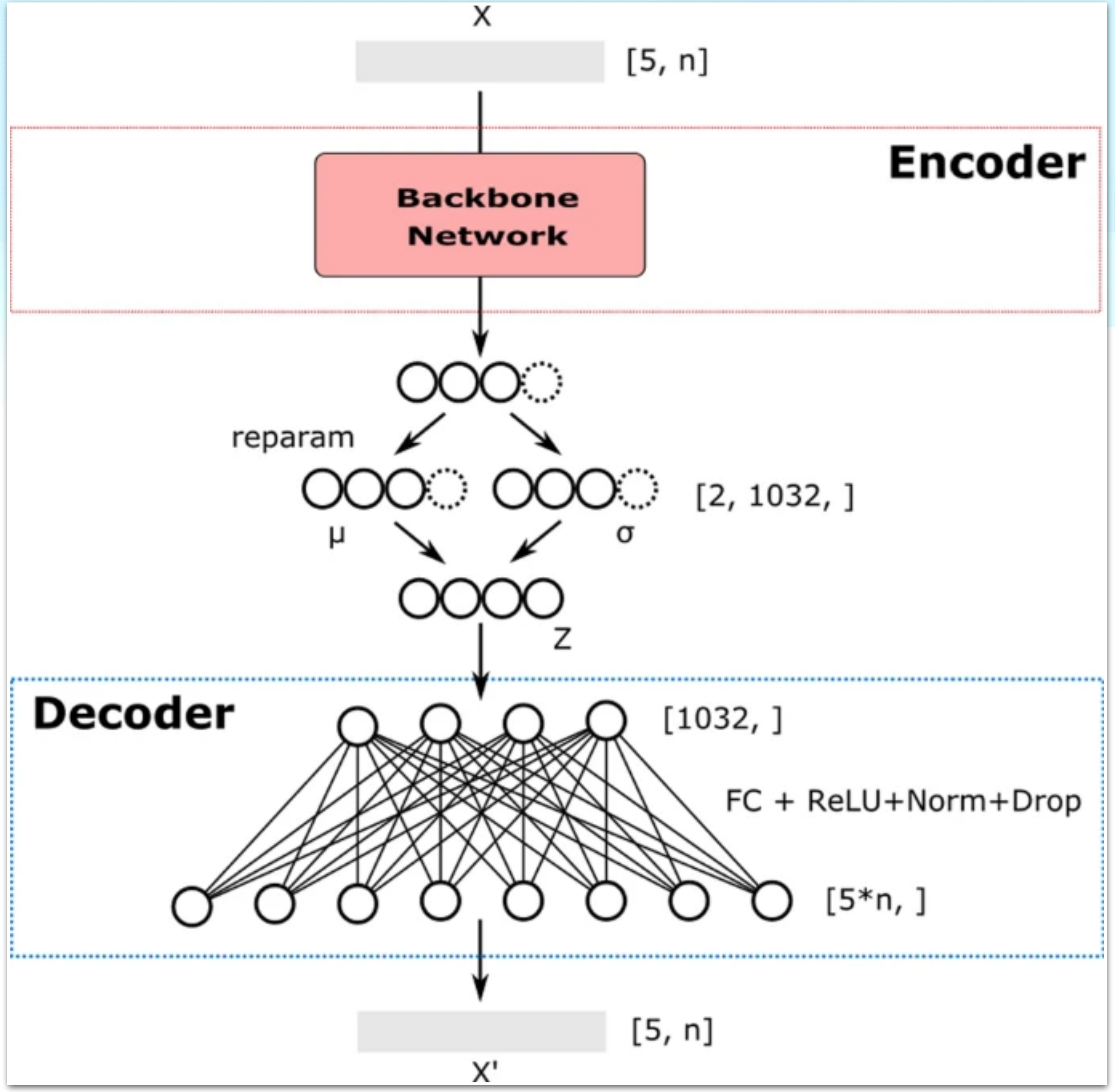
(x, y, z, t, q)



PointNet-VAE Model for Event Generation

Z. Fu et al.,
Eur. Phys. J. C **84**, 651 (2024)
https://doi.org/10.1140/epjc/s10052-024-12980-7

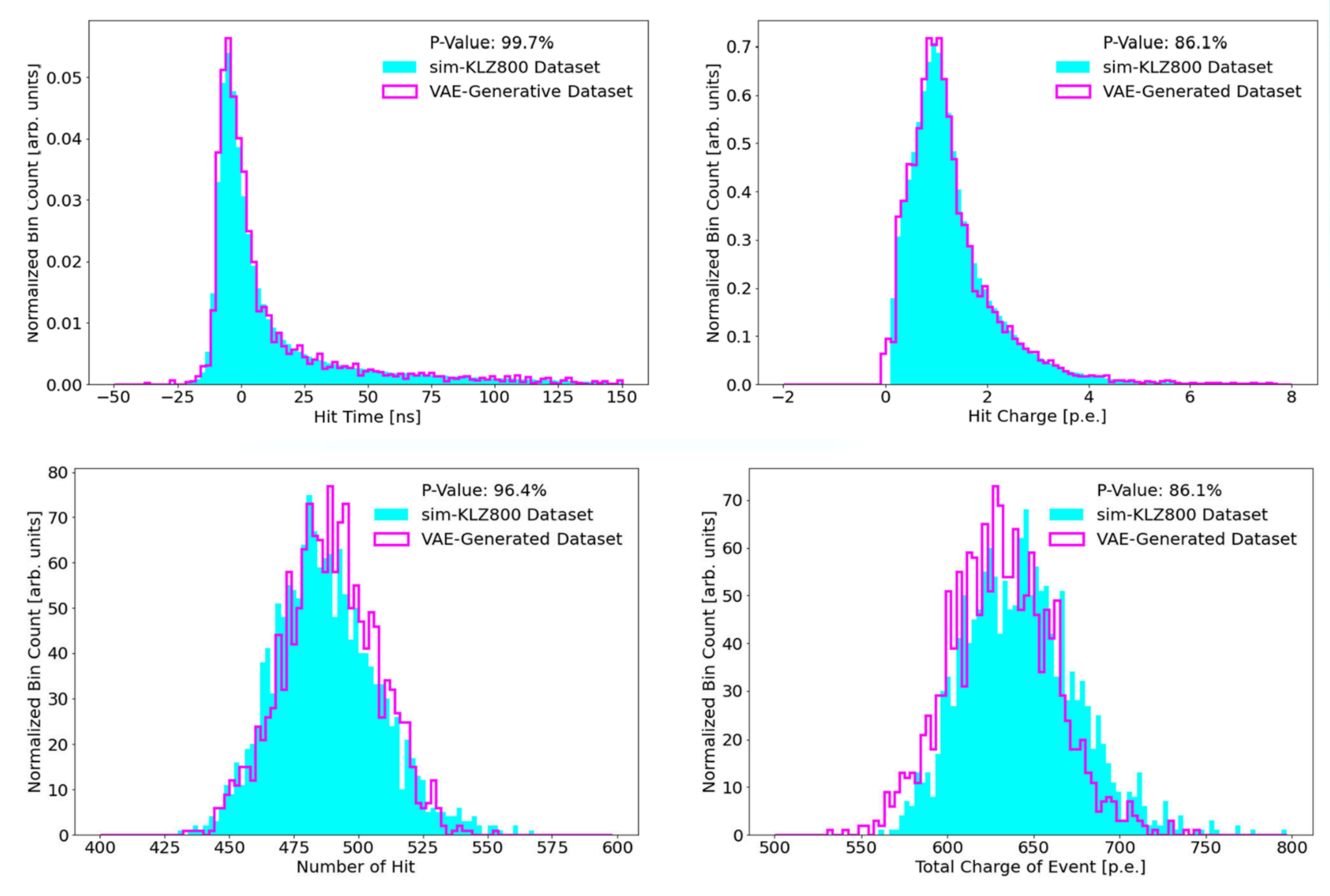




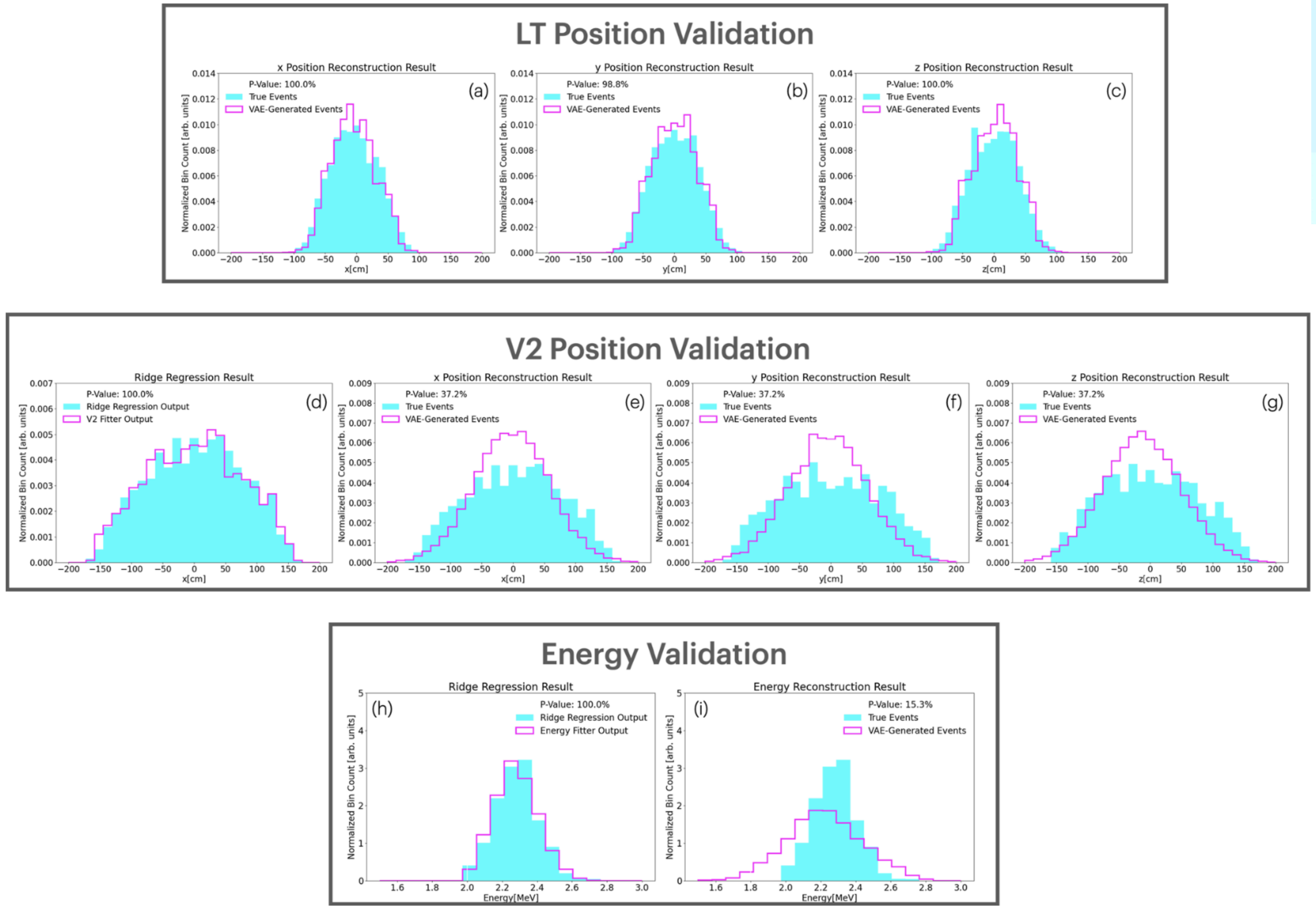
Event Generation Result

Z. Fu et al.,
Eur. Phys. J. C **84**, 651 (2024)
https://doi.org/10.1140/epjc/s10052-024-12980-7

Basic Parameters



Reconstruction Parameters

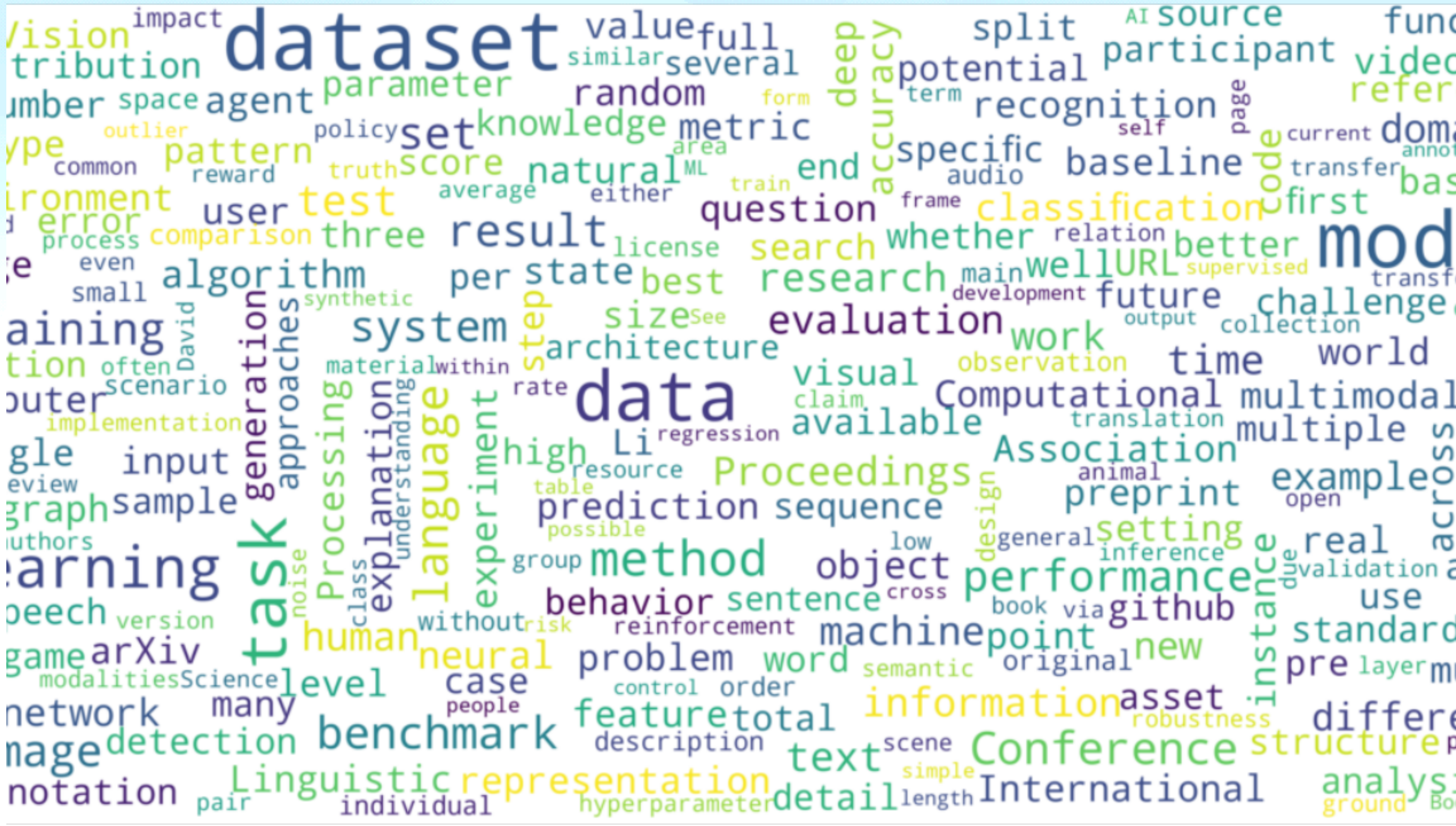


Model-Centric AI vs. Data-Centric AI

NeurIPS 2023 Word Cloud

Algorithm Track

Dataset & Benchmarking Track



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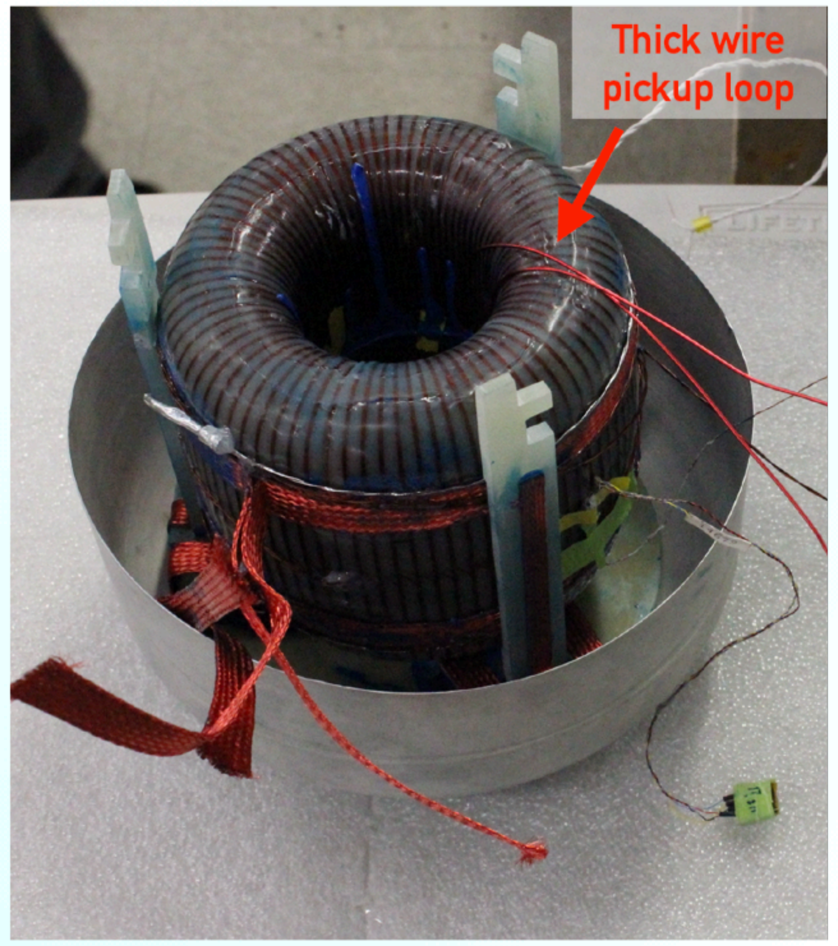
Y. Kahn, B. R. Safdi, and J. Thaler, Phys. Rev. Lett. 117, 141801

J. L. Ouellet et al. Phys. Rev. Lett. 122, 121802 (2019)

C. P. Salemi et al. Phys. Rev. Lett. 127, 081801 (2021)

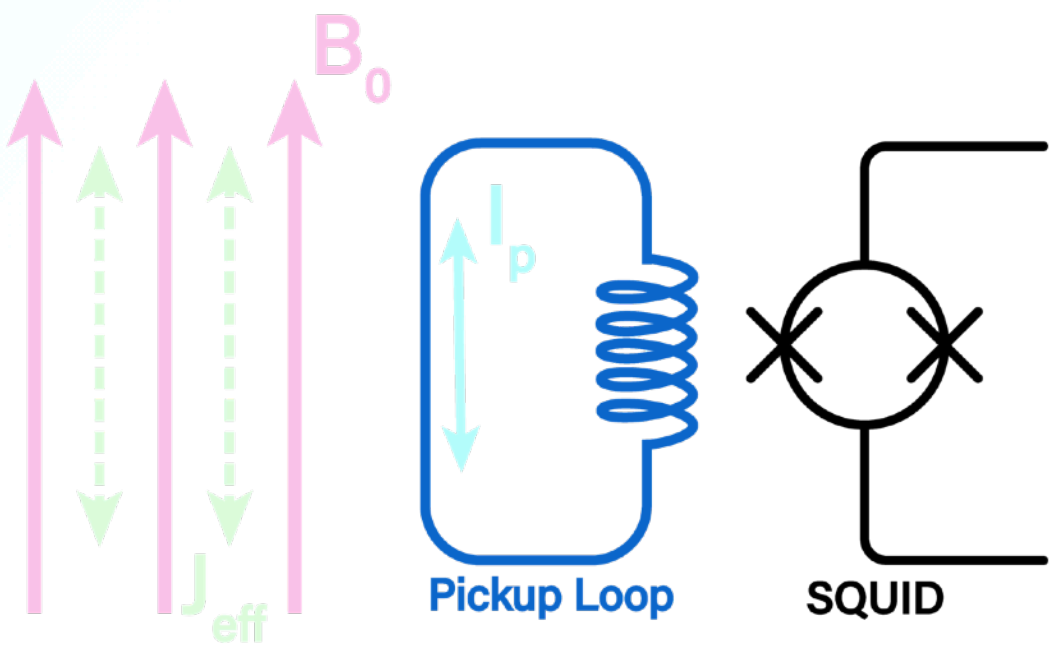
Broadband Axion Dark Matter Search with Toroidal Magnet



Axion-Modified Maxwell's Equation:

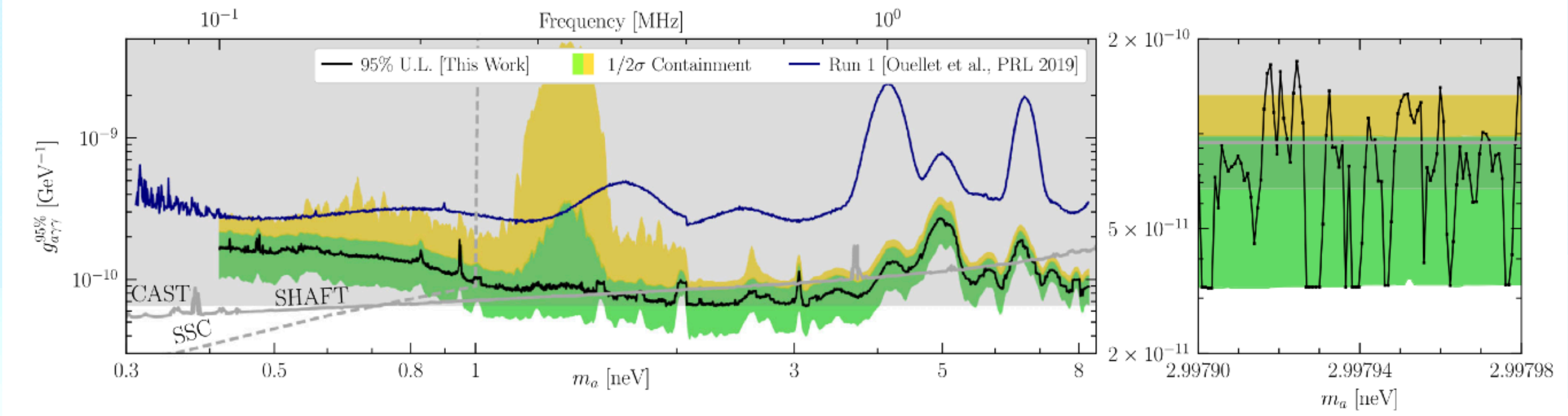
$$\nabla \times B = \frac{\partial E}{\partial t} - g_{a\gamma\gamma}(E \times \nabla a - \frac{\partial a}{\partial t} B)$$

$$J_{eff} = g_{a\gamma\gamma}\sqrt{2\rho_{DM}} cos(m_a t) B$$



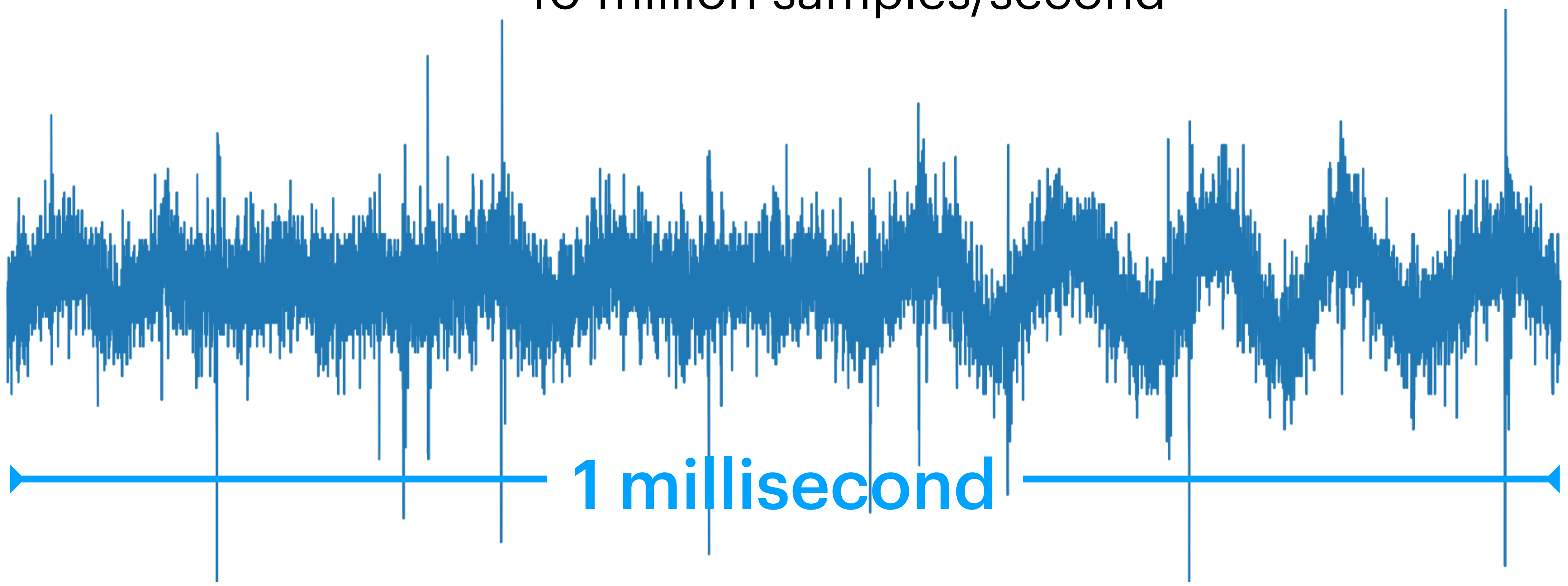
Frequency Spectrum

Broadband search for axion DM



Ultra-long Time Series

10 million samples/second



Experimental Apparatus Constructed by Winslow Lab at MIT

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J. T. Fry et al, arXiv:2406.04378
Submitted to NeurIPS Dataset & Benchmarking Track

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

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

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Open Data

Release dark matter detector data for AI/ML algorithms

Easy Benchmarking

Design a quantitative benchmarking score to quantify the performance of different algorithms

AI for Science

Enables core AI algorithms to extract the signal and produce real physics results thereby advancing fundamental science

J. T. Fry et al, arXiv:2406.04378
Submitted to NeurIPS Dataset & Benchmarking Track

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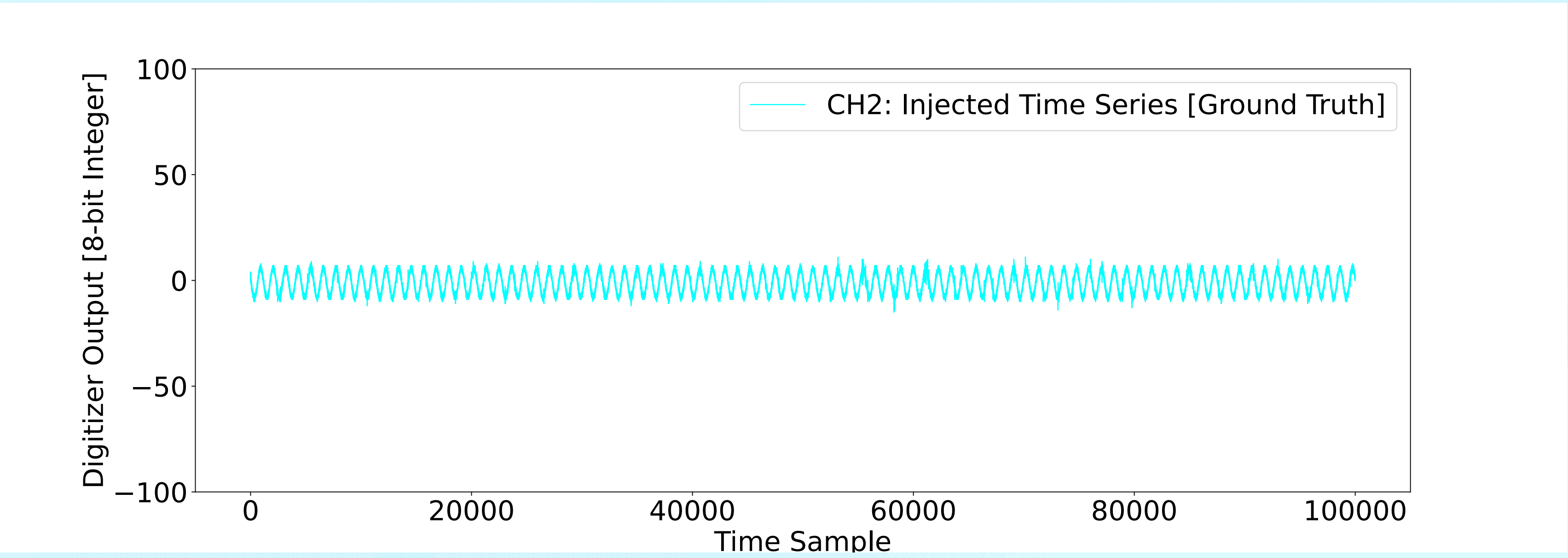
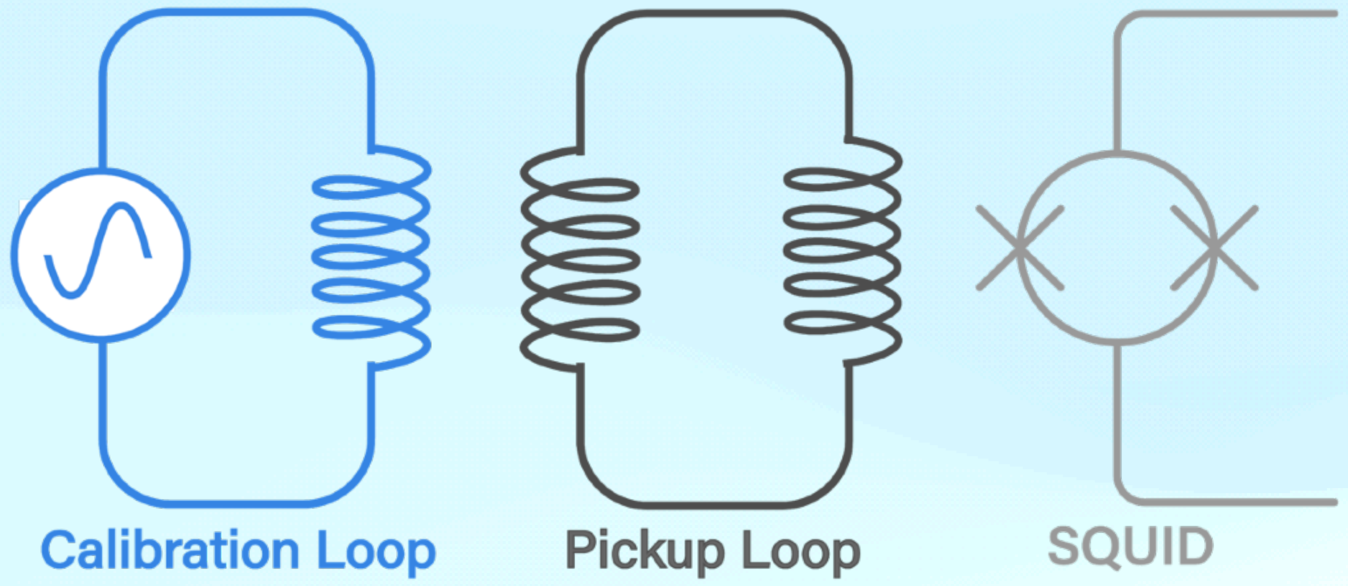
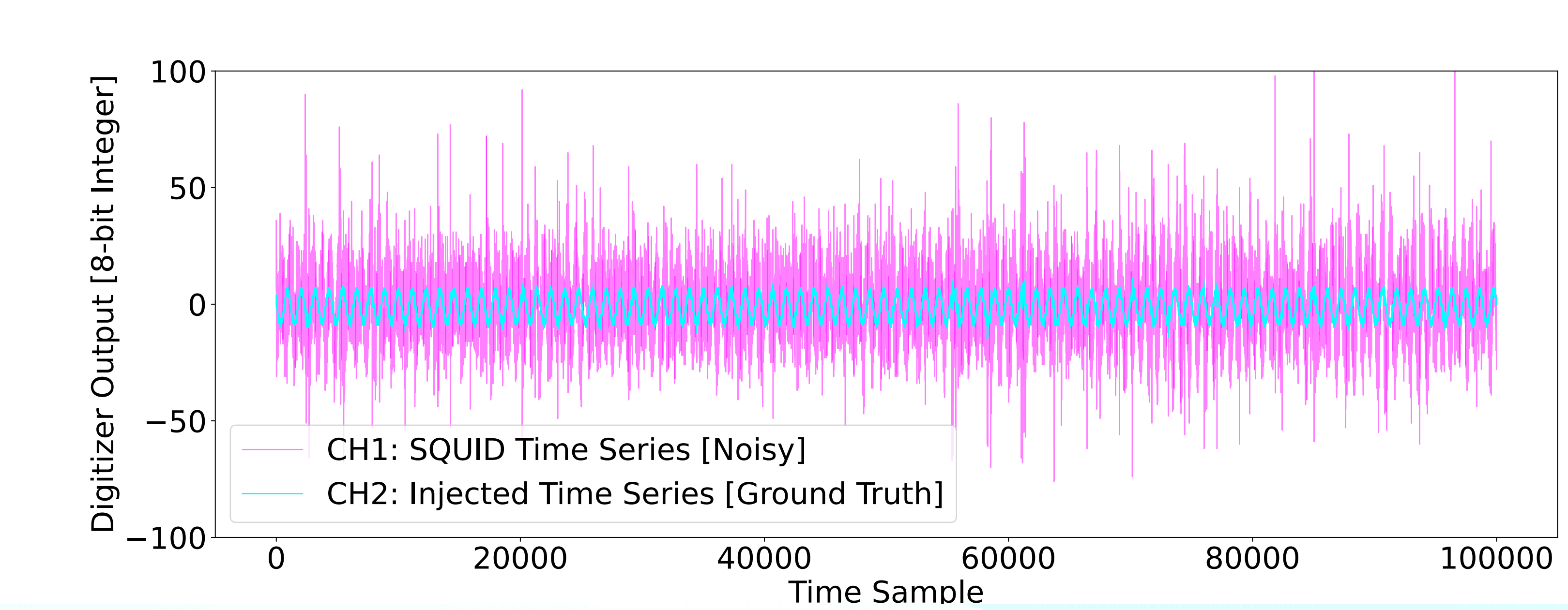
TIDMAD: Time Series Dataset for Discovering Dark Matter with AI Denoising



CH2: Injected Time Series [Ground Truth]

Injected Dark Matter Signal Excitation

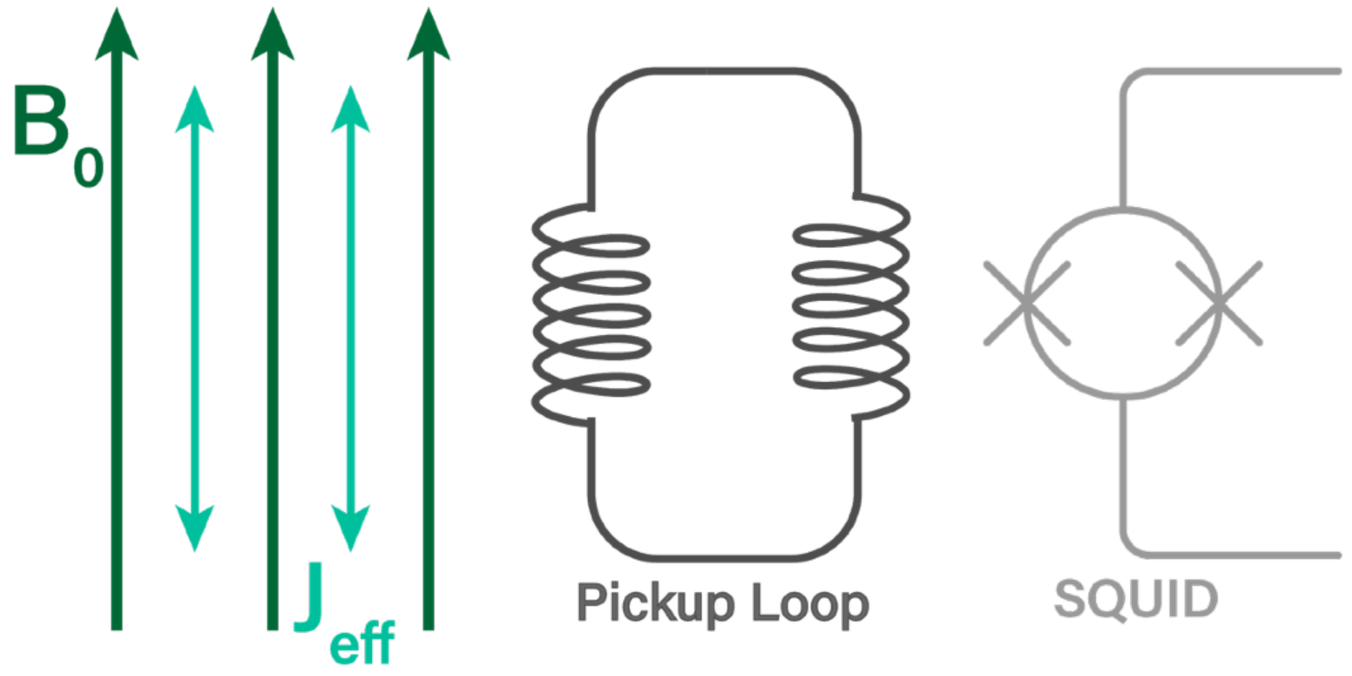




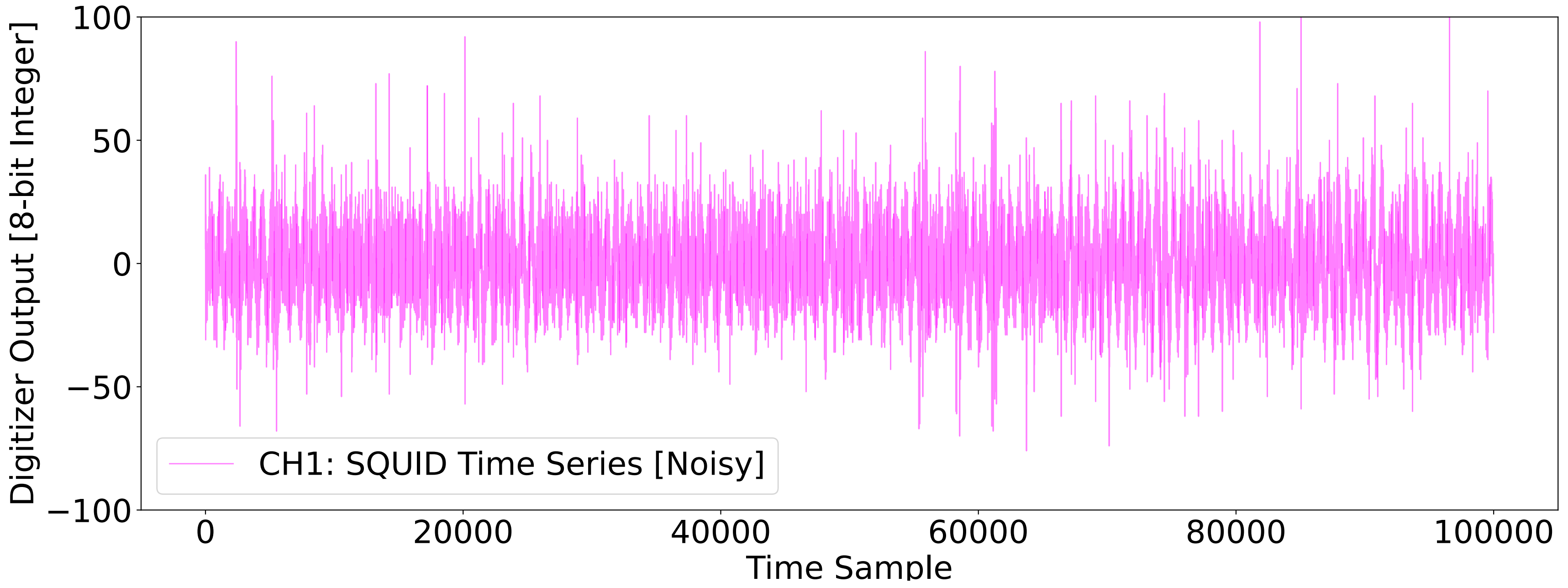
CH1: SQUID Time Series [Noisy]

Train AI denoising model to recover...

Real Dark Matter Signal Excitation



No Signal Injected



CH1: SQUID Time Series [Noisy]

Use trained AI model to denoise...

J. T. Fry et al, arXiv:2406.04378
Submitted to NeurIPS Dataset & Benchmarking Track

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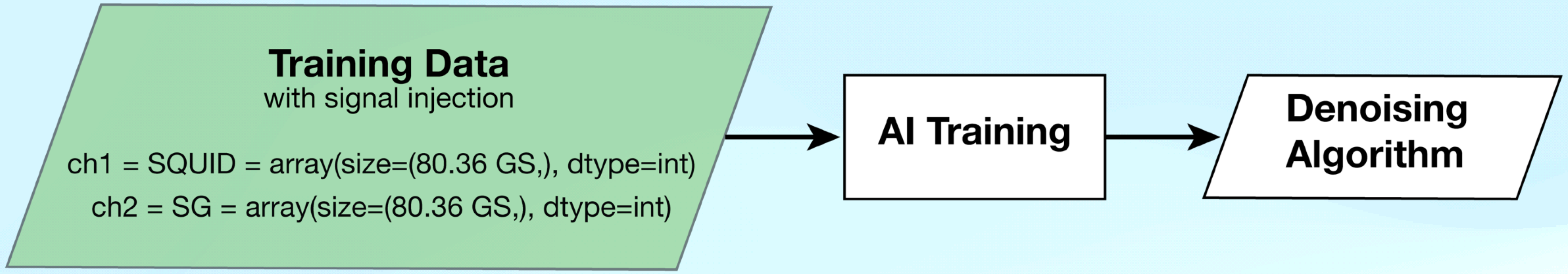
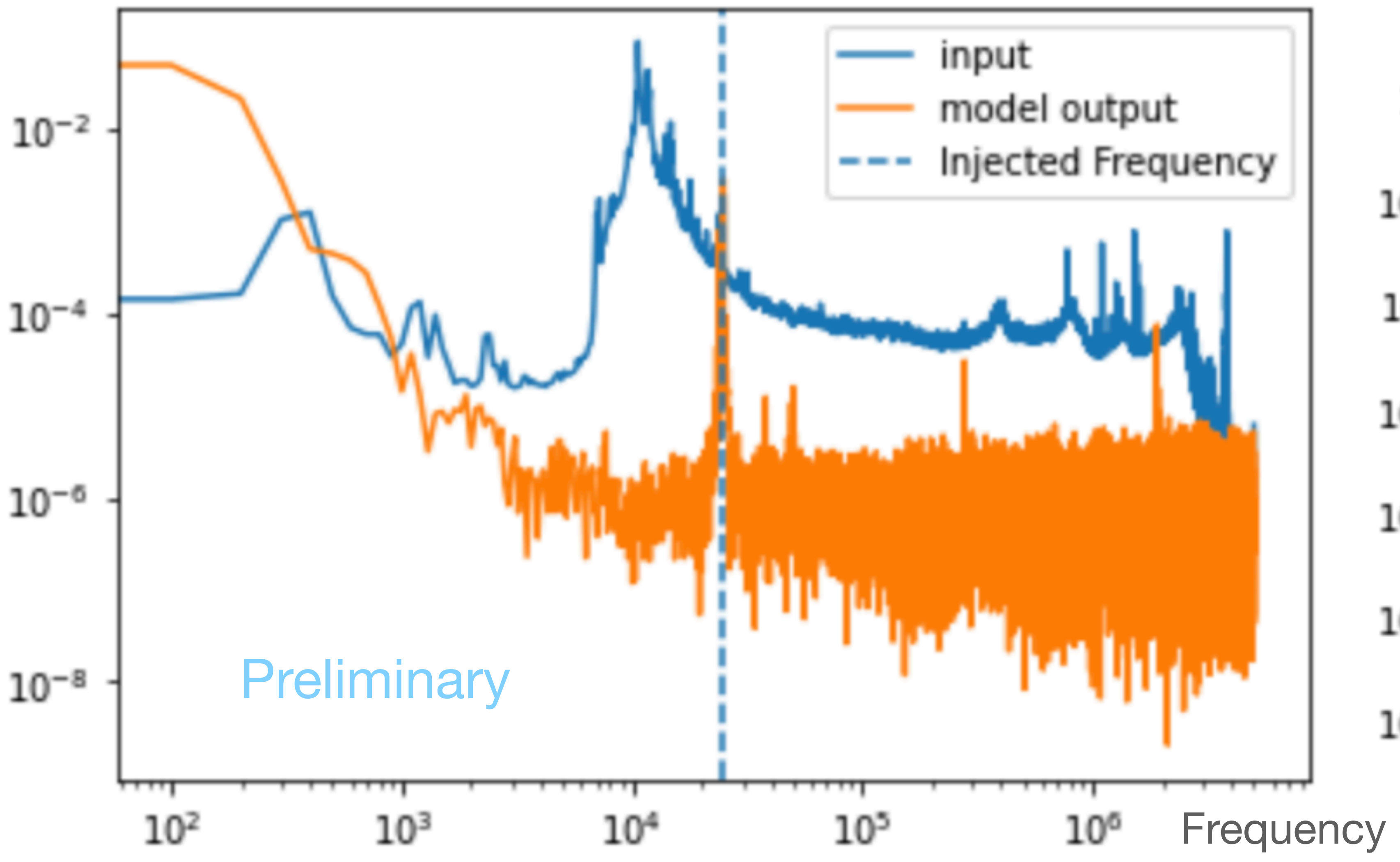
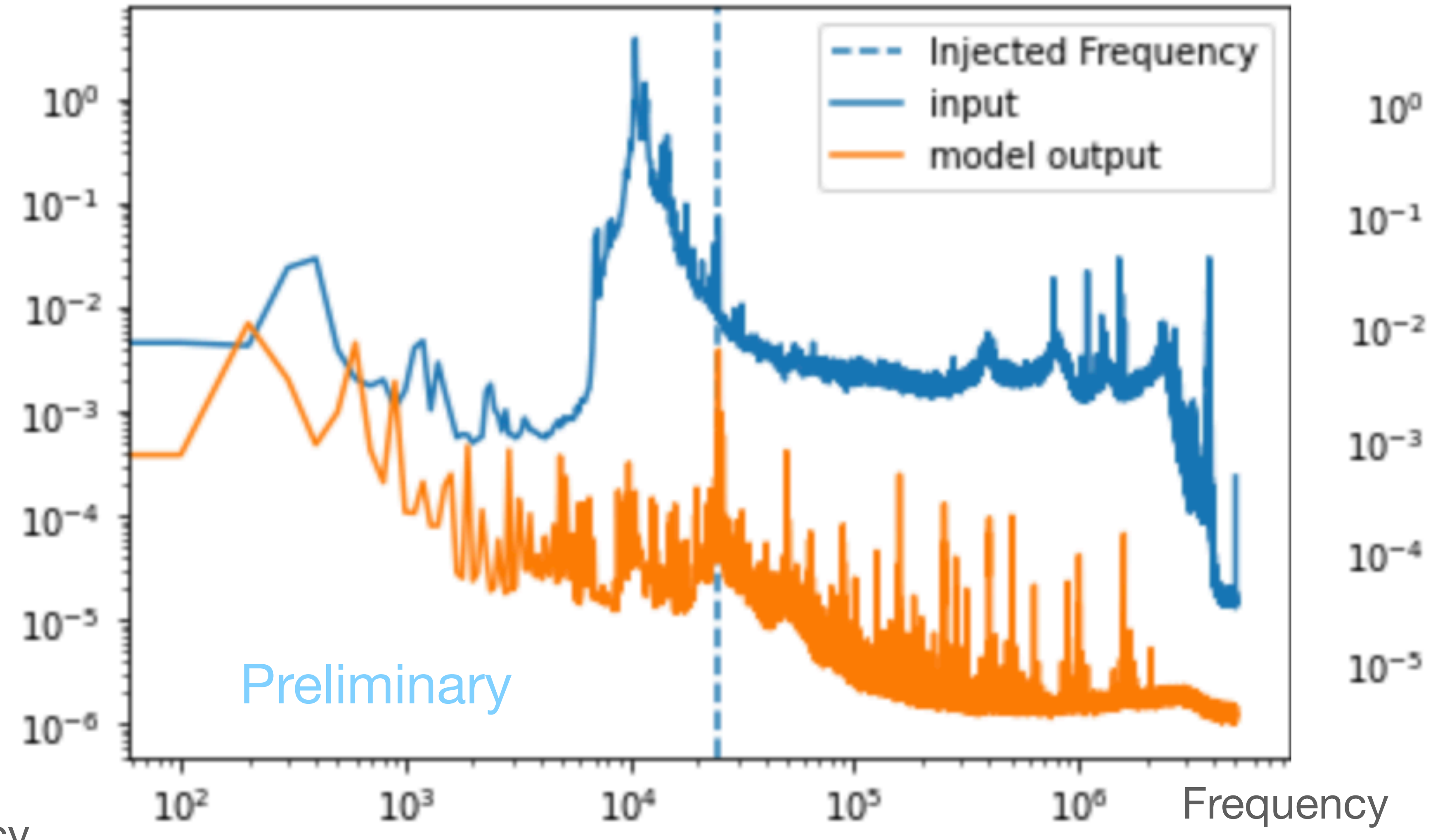
TIDMAD: Time Series Dataset for Discovering Dark Matter with AI Denoising

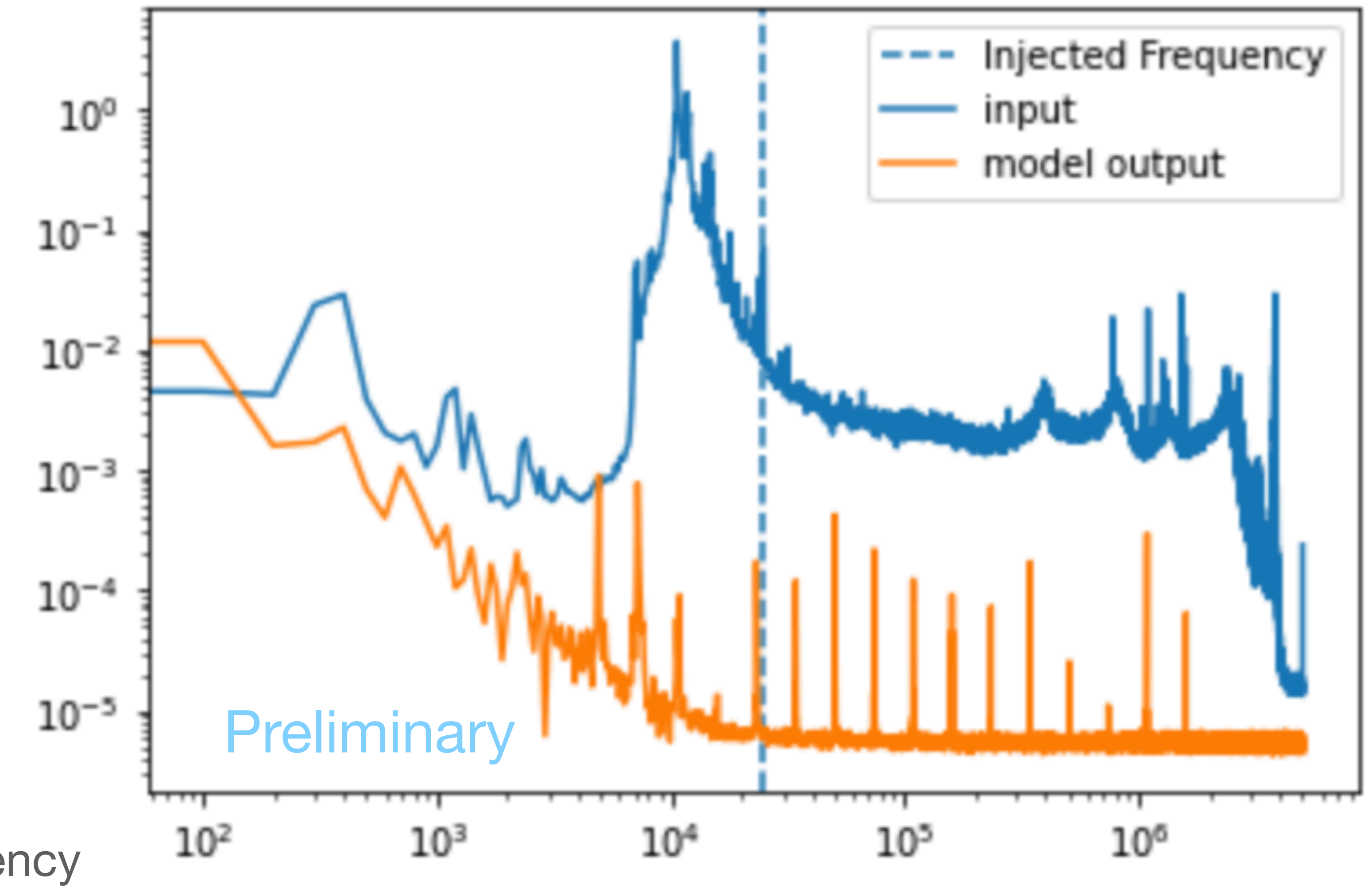




Fully Connected NN



Positional U-Net



Transformer

J. T. Fry et al, arXiv:2406.04378
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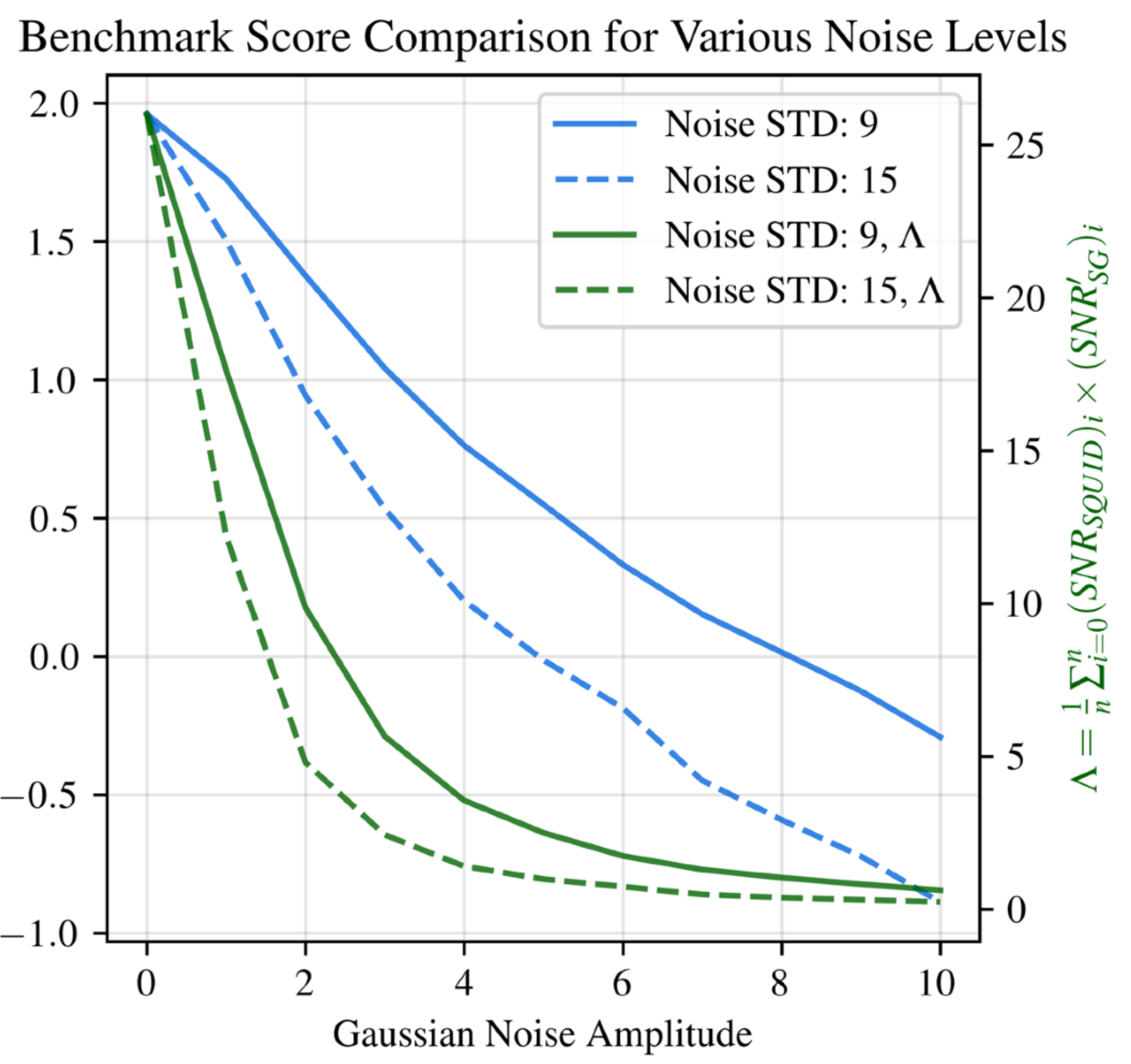
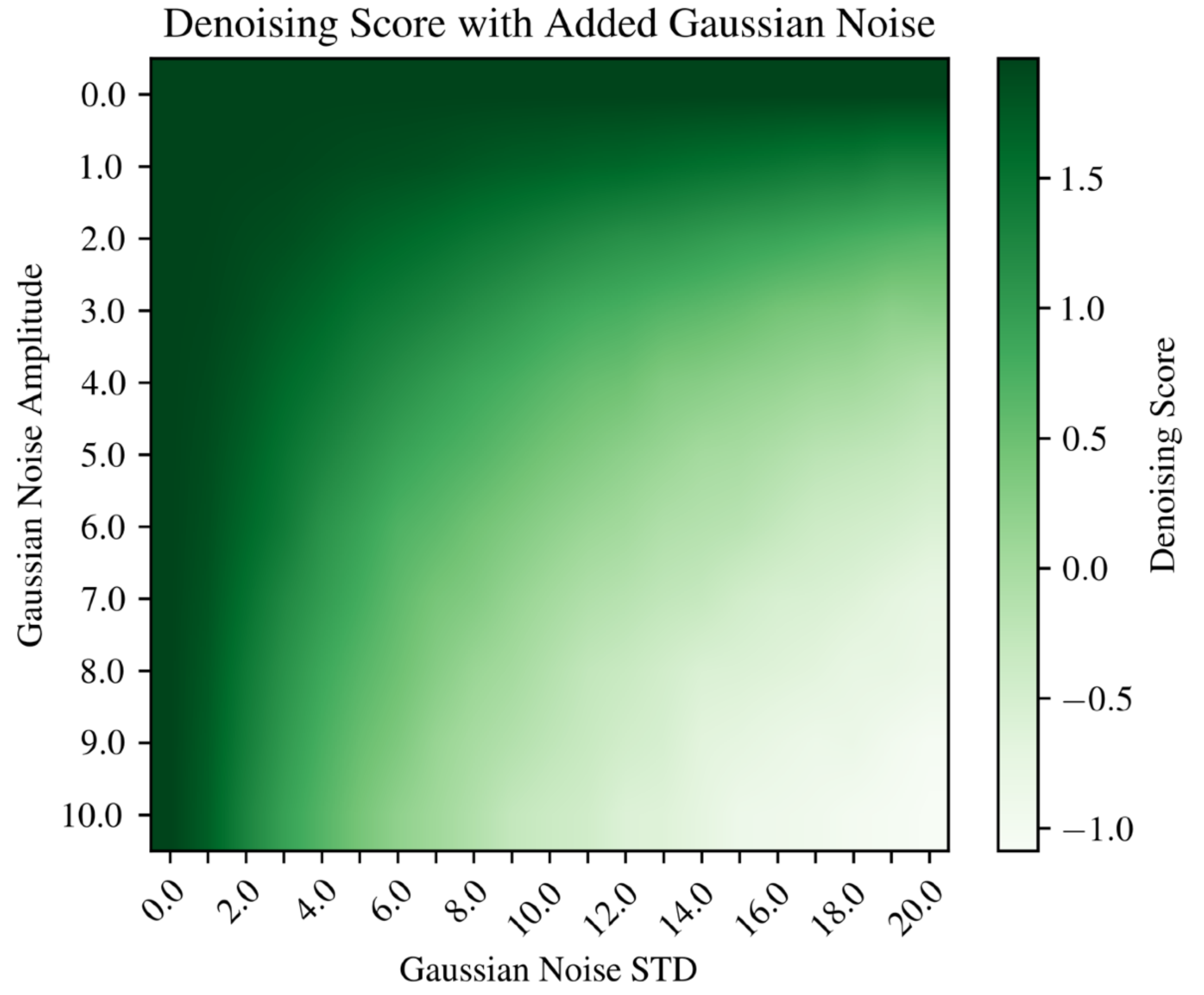
TIDMAD: Time Series Dataset for Discovering Dark Matter with AI Denoising



$$\Lambda = \left(\frac{1}{n} \sum_{i=0}^{n} (SNR_{\mathrm{SQUID}})_i \times (SNR'_{\mathrm{Injected}})_i \right)$$

$$\text{Denoising Score} = log_{5.27}\Lambda$$

Test the denoising score by doping gaussian noise into Time Series



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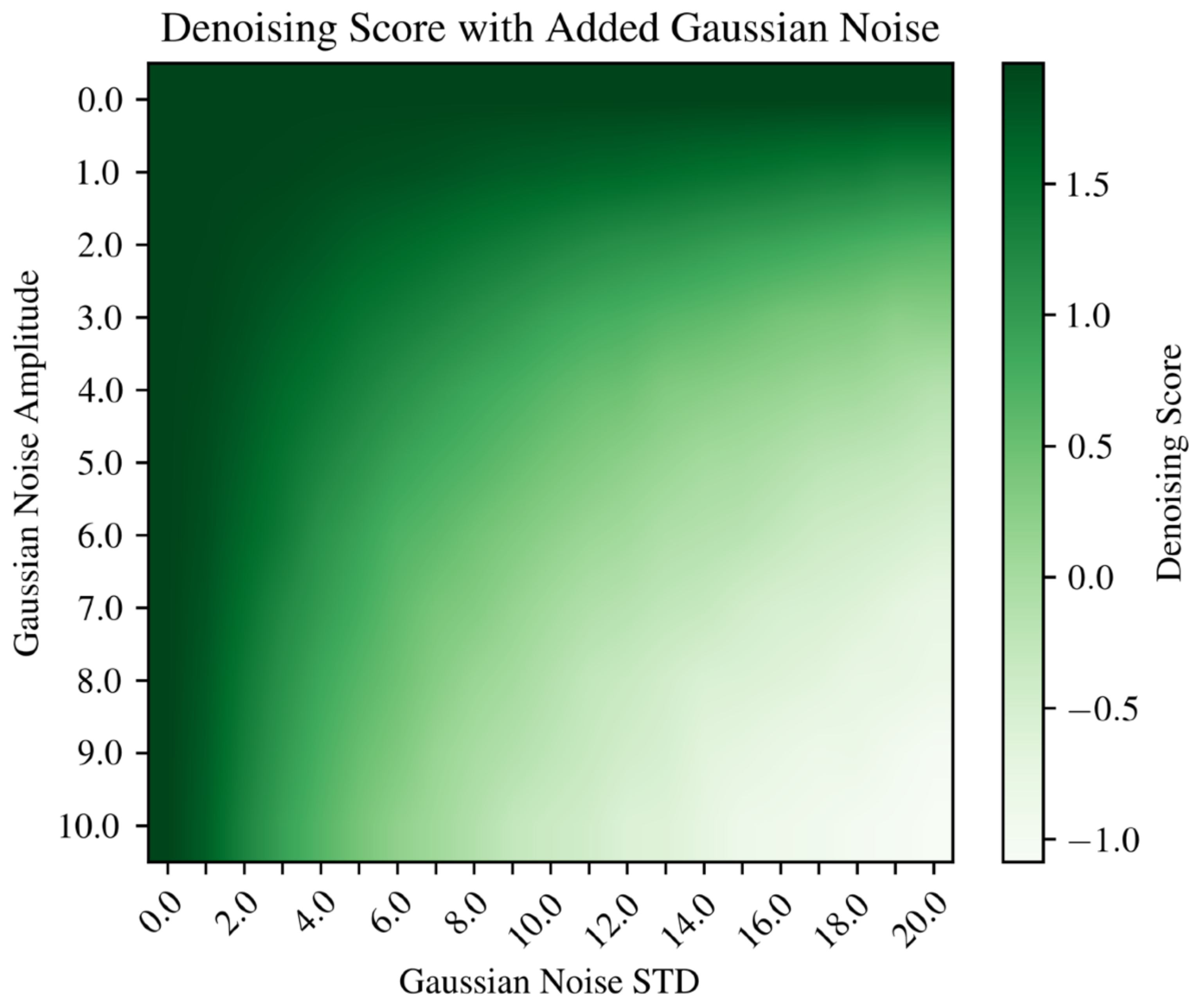
TIDMAD: Time Series Dataset for Discovering Dark Matter with AI Denoising

Table 1: Fine and coarse denoising score for raw data, traditional algorithms, and trained ML models

Algorithms	Segment Size	Parameters	Fine Score	Coarse Score
None			1.00	1.10
Moving Average	1×10^6	window = 100	0.52	0.64
SG Filter	1×10^6	window = 100, order = 11	-2.77	-2.35
FC Net	4×10^4	See Appendix A	6.43	6.55
PU Net	4×10^4	See Appendix A	3.69	3.84
Transformer	2×10^4	See Appendix A	3.95	4.18



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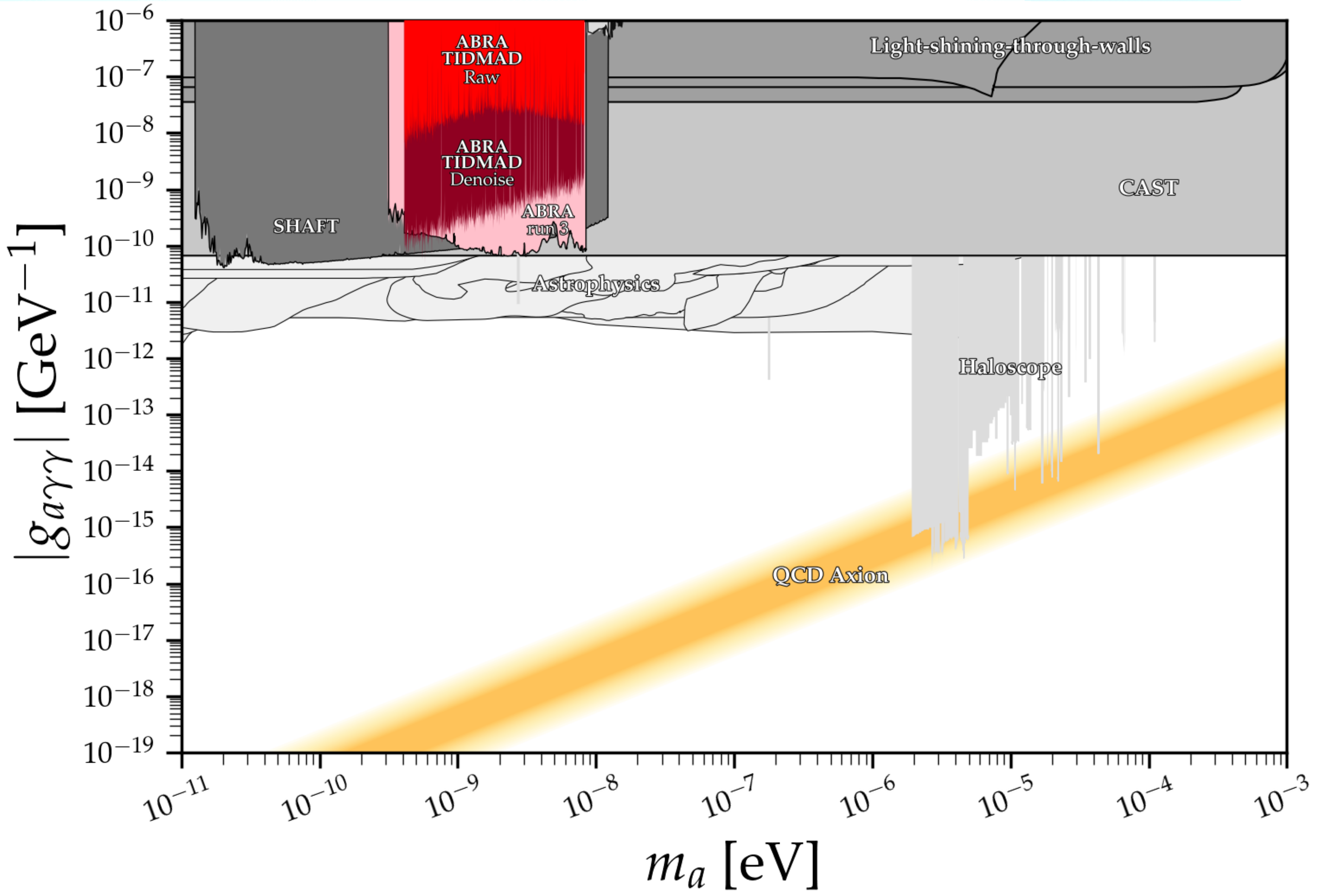
Axion Limit Boost

ABRA TIDMAD Raw: 24 hr data, no denoising

ABRA TIDMAD Denoised: 24 hr data with FCNet denoising

ABRA Run 3: 2,400 hr data, no denoising

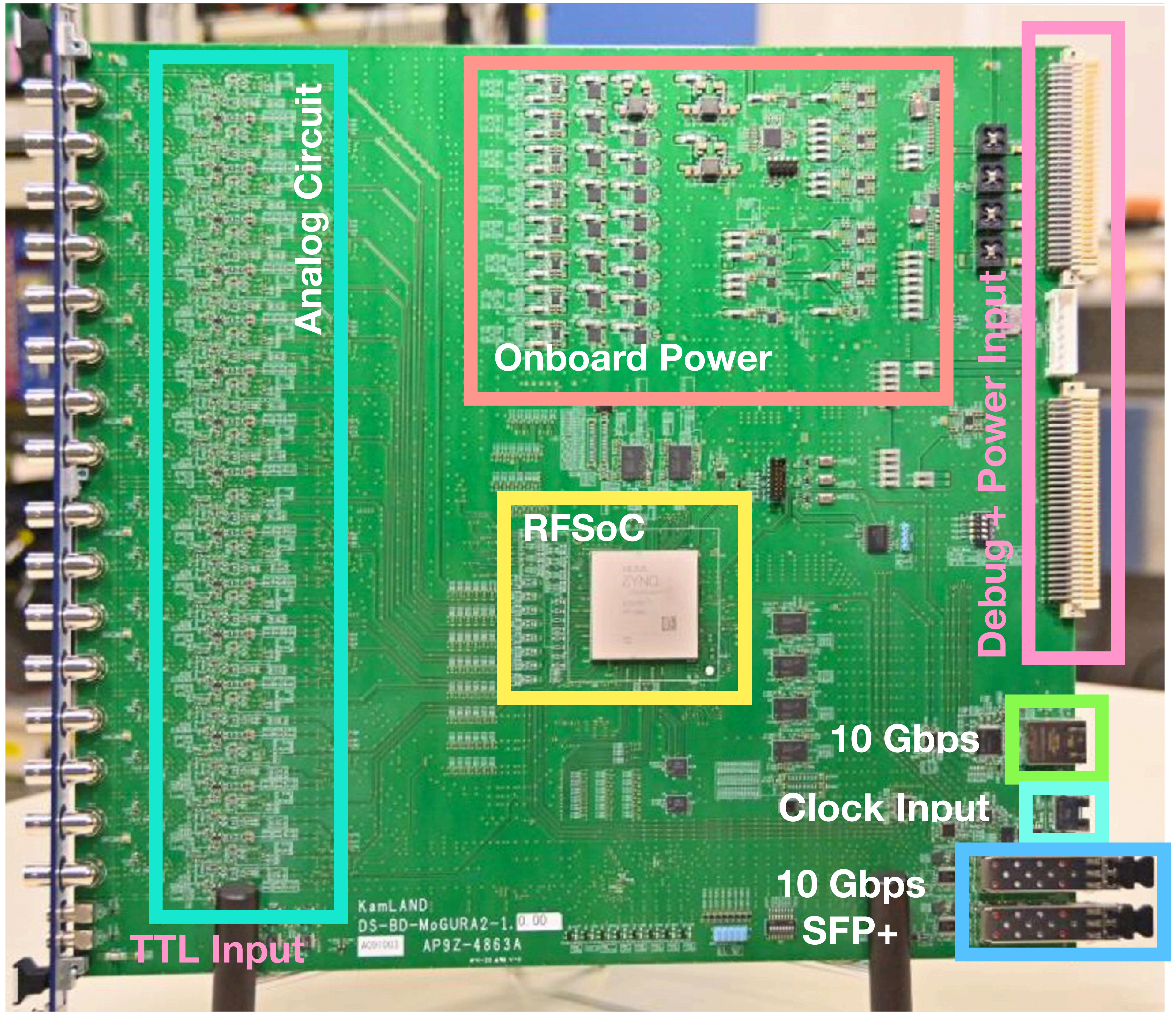
Efficient denoising algorithms increased Axion search limit by **1-2 orders of magnitude**, approaching the previous world-leading ABRA run 3 results with only **1%** of statistics




PAST
PRESENT
FUTURE

New Electronics for KamLAND-Zen

16-channel prototype for KamLAND2-Zen



Primary Goals:

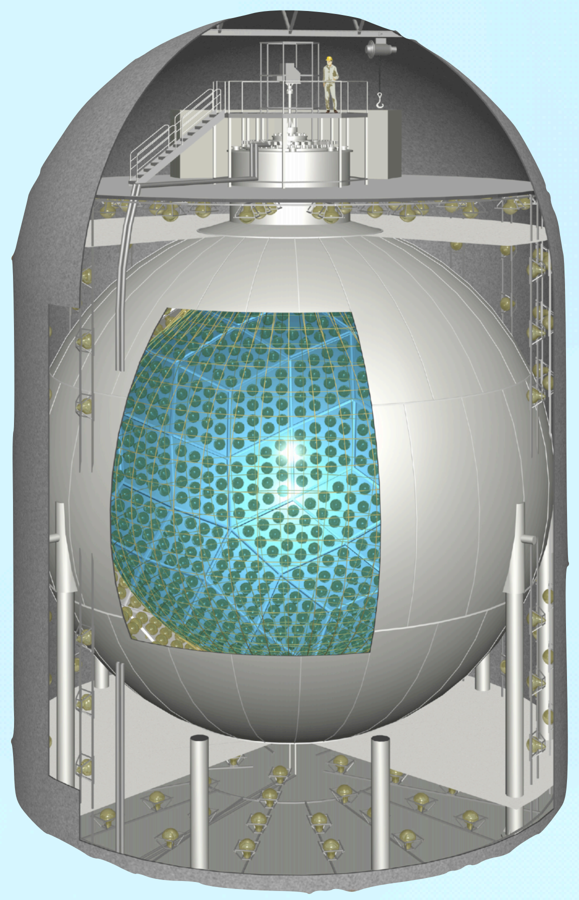
1. Digitize waveform during the chaotic period after a muon passes through the detector in order to record all neutrons, allowing us to reduce the Long-Lived spallation background.
2. Streaming data (deadtime free system), large data throughput.
3. Large memory buffers.

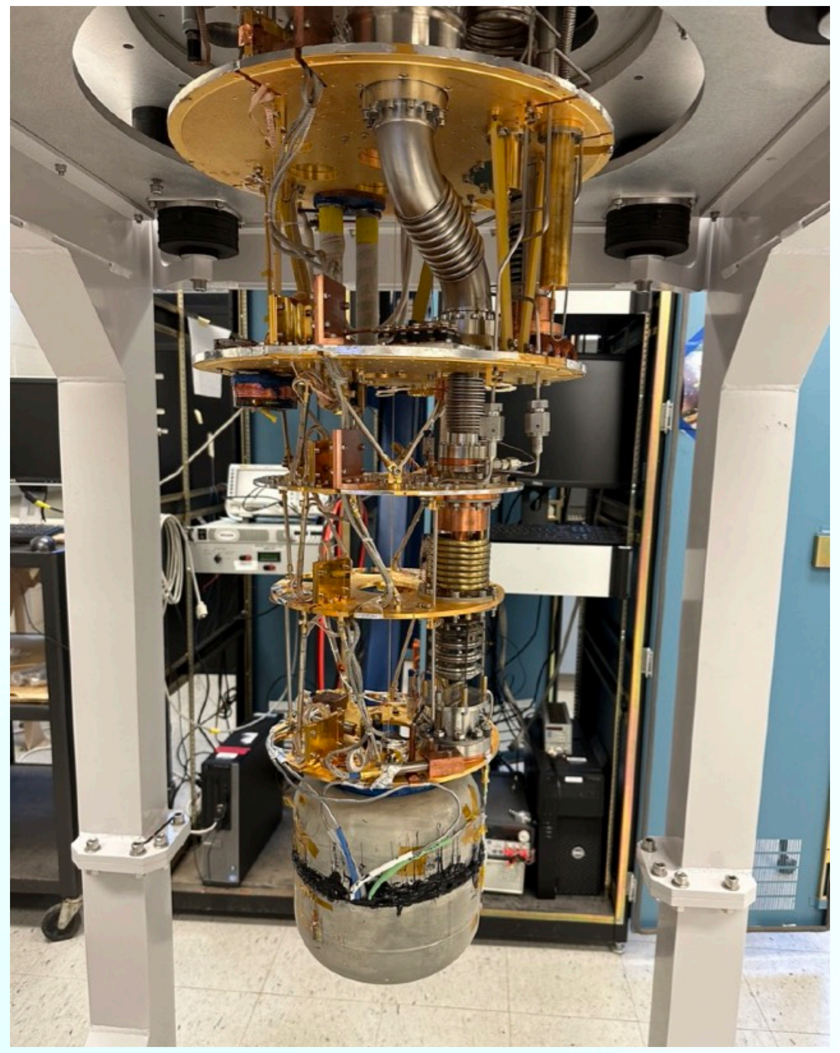
Reduction in PCB footprint	Machine learning on FPGA	*50% cost savings	*30-40% power consumption savings

* compared to standard RF signal chain

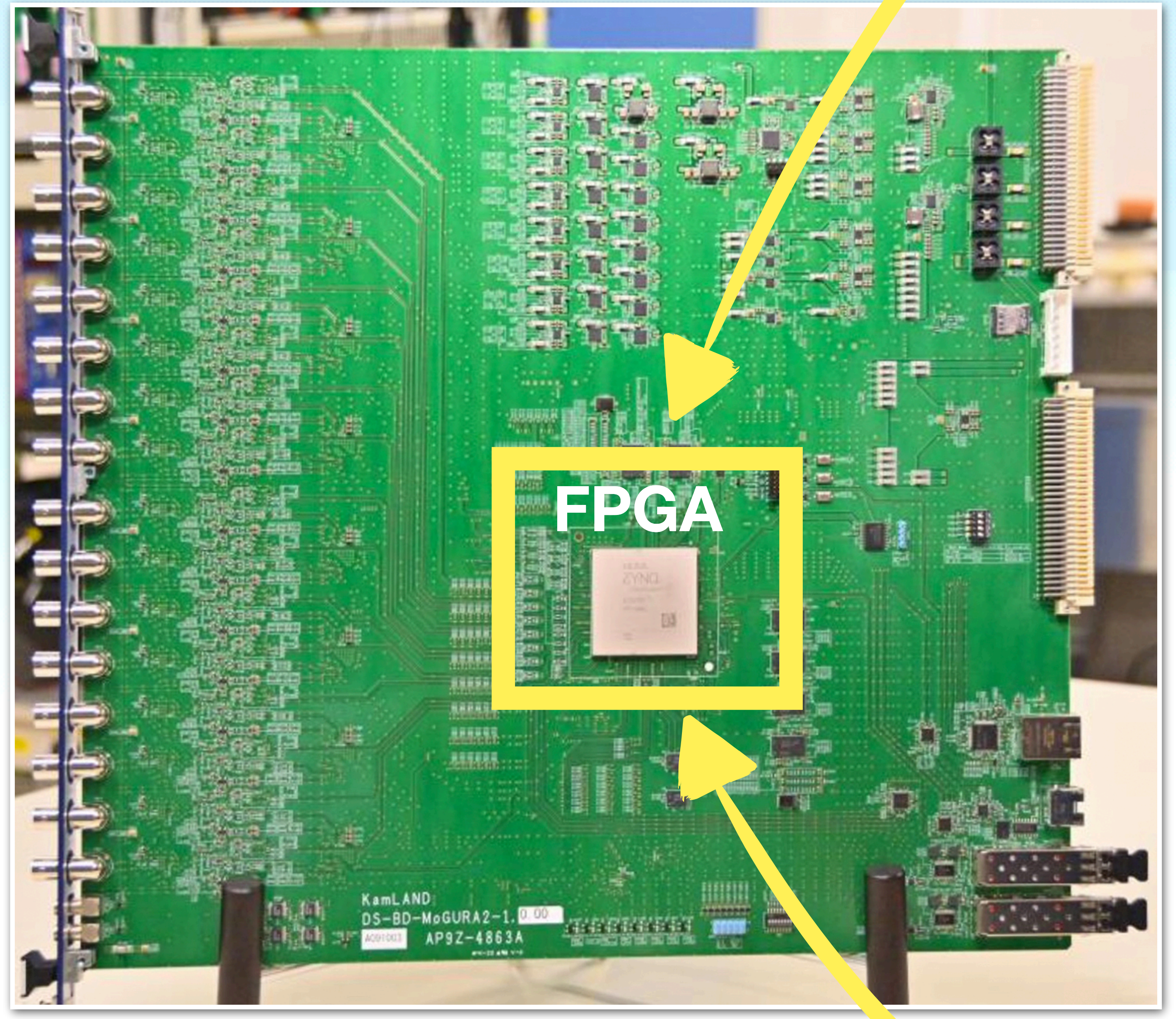
Hardware-AI Codesign

Deploy ML model onto FPGA
to produce these in real-time





Data Stream



Offline Analysis

Energy

Position

Particle Type

Detector Response

Online model update to account
for detector status change

Summary

“AI and Data Science has shaped rare event search, it’s an accelerator for new physics results”

- KamLAND-Zen: KamNet, PointNet-VAE
- ABRACADABRA: TIDMAD Data Set

“It will continue to evolve and foster discovery in next-generation experiments”

- AI for Rare Event Lab: https://aobol.github.io/AoboLi/
- Email: aol002@ucsd.edu