AI in Rare Event Search

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Fast & Slow: AI in Rare Event Search

Slow

- What is rare event search?

Fast

- Radiation detectors
- AI algorithms

Fast for Slow

- Fast ML for rare event

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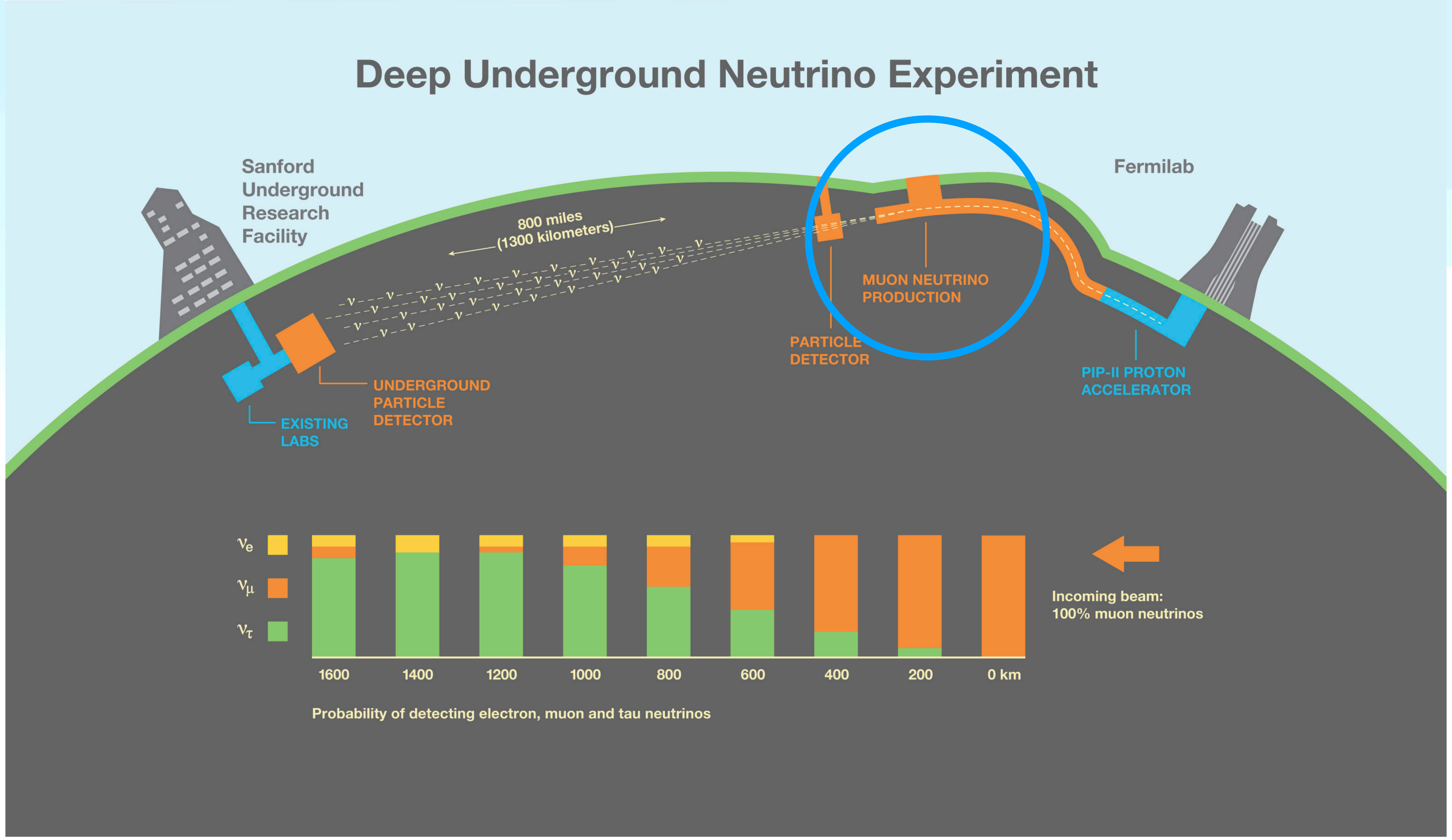
High Energy Physics Experiment

High-energy Particle Beam

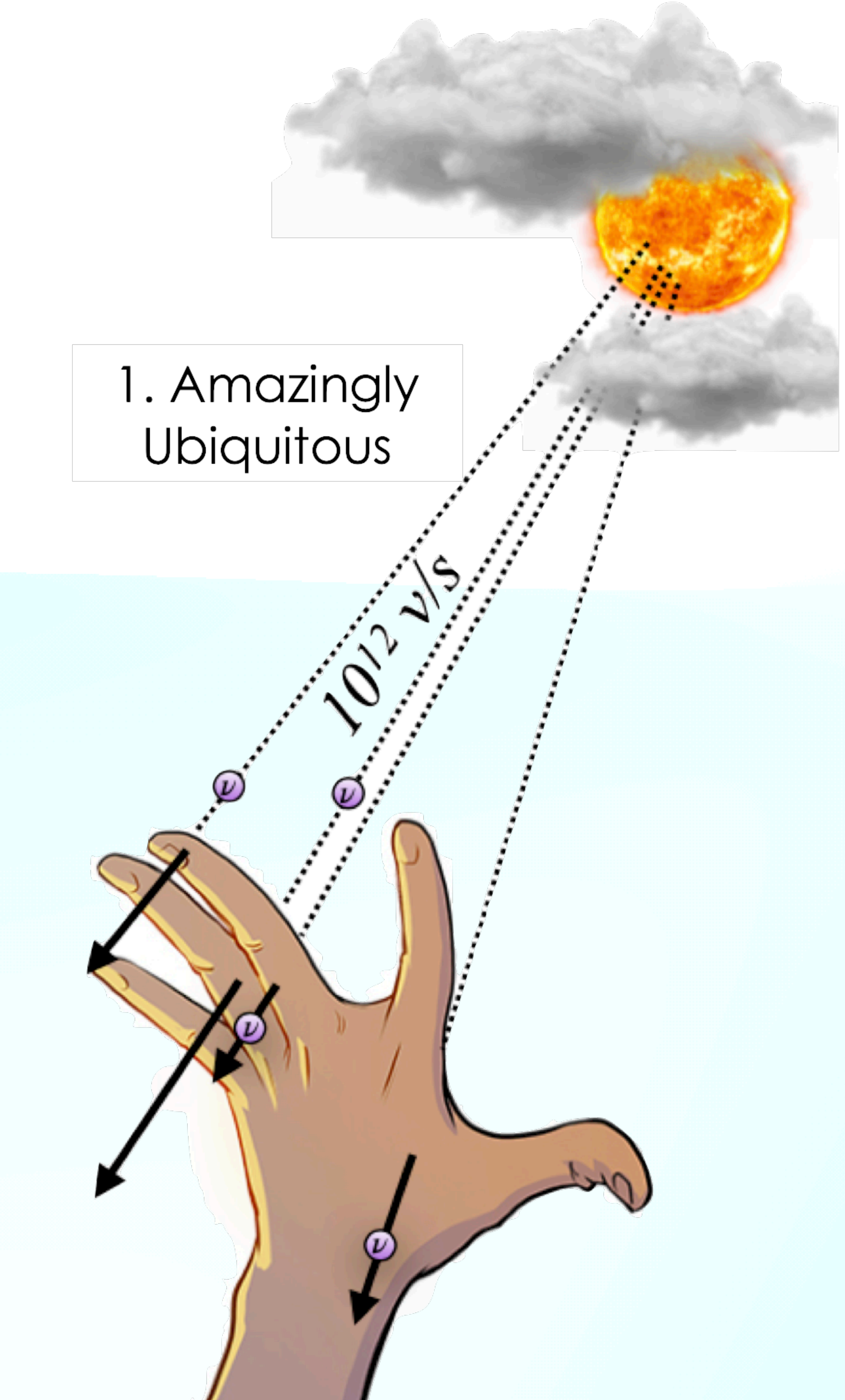
600 million collisions per second

PIP-II Neutrino Beam

Trillions of neutrinos per second



Naturally Occurring Neutrinos



1. Amazingly Ubiquitous

2. Rarely interact with the rest of the world

Rare Event Search in 1950s

The Cowan-Reine Neutrino Experiment

First detection of neutrino (via inverse beta decay):

$$\bar{\nu}_e + p \rightarrow n + e^+$$

Extremely low cross section, but unique signature:

- $e^+ + e^- \rightarrow 2\gamma$
- Neutron capture γ

Nobel Prize of 1995

Rare Event Search in 2023

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!

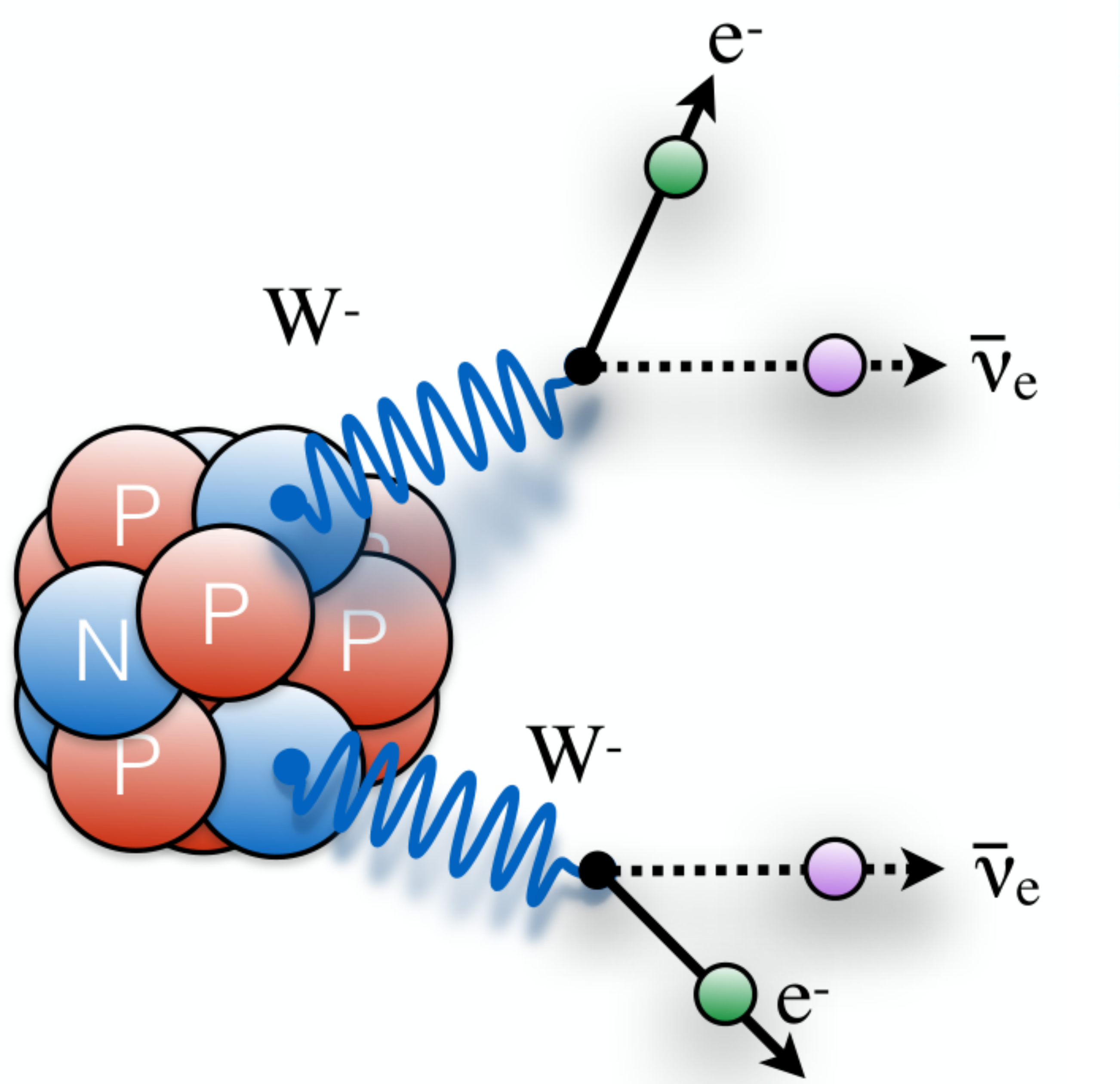
Neutrinoless Double-Beta Decay ($0\upsilon\beta\beta$)

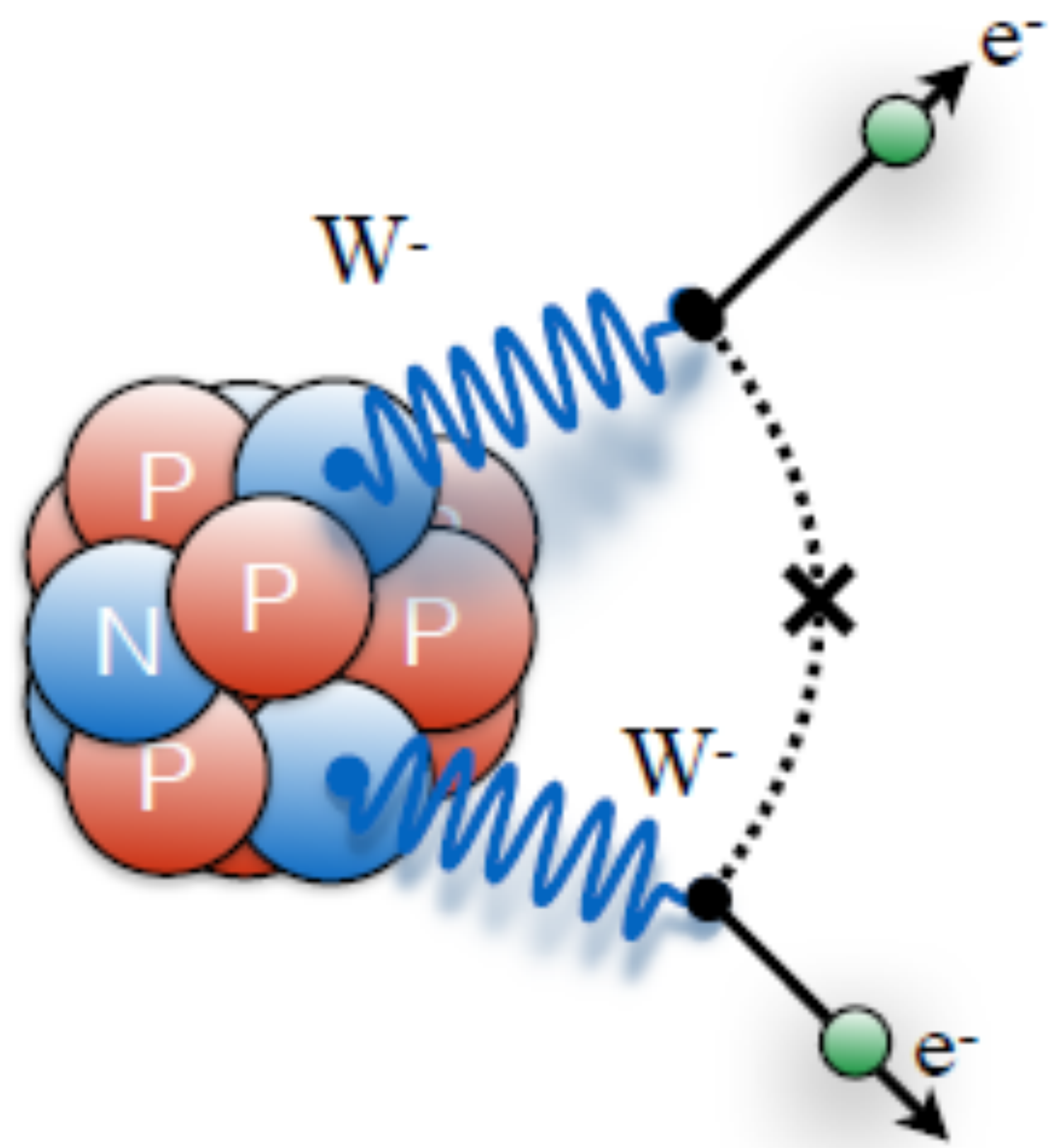
ΔL = 2 lepton number violation process

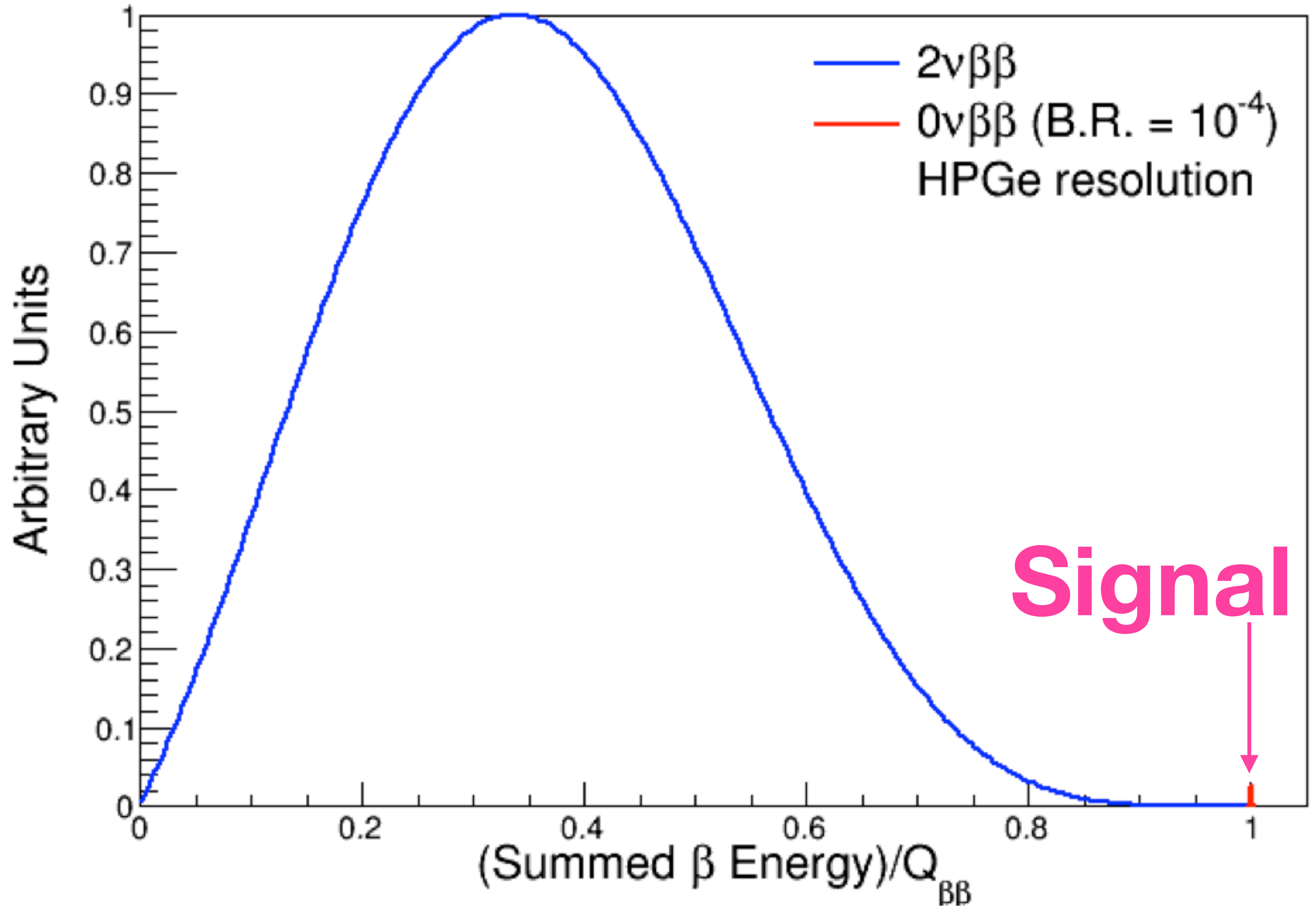
Explain the **matter-antimatter asymmetry** in our universe

Changes our fundamental understanding of particle physics

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



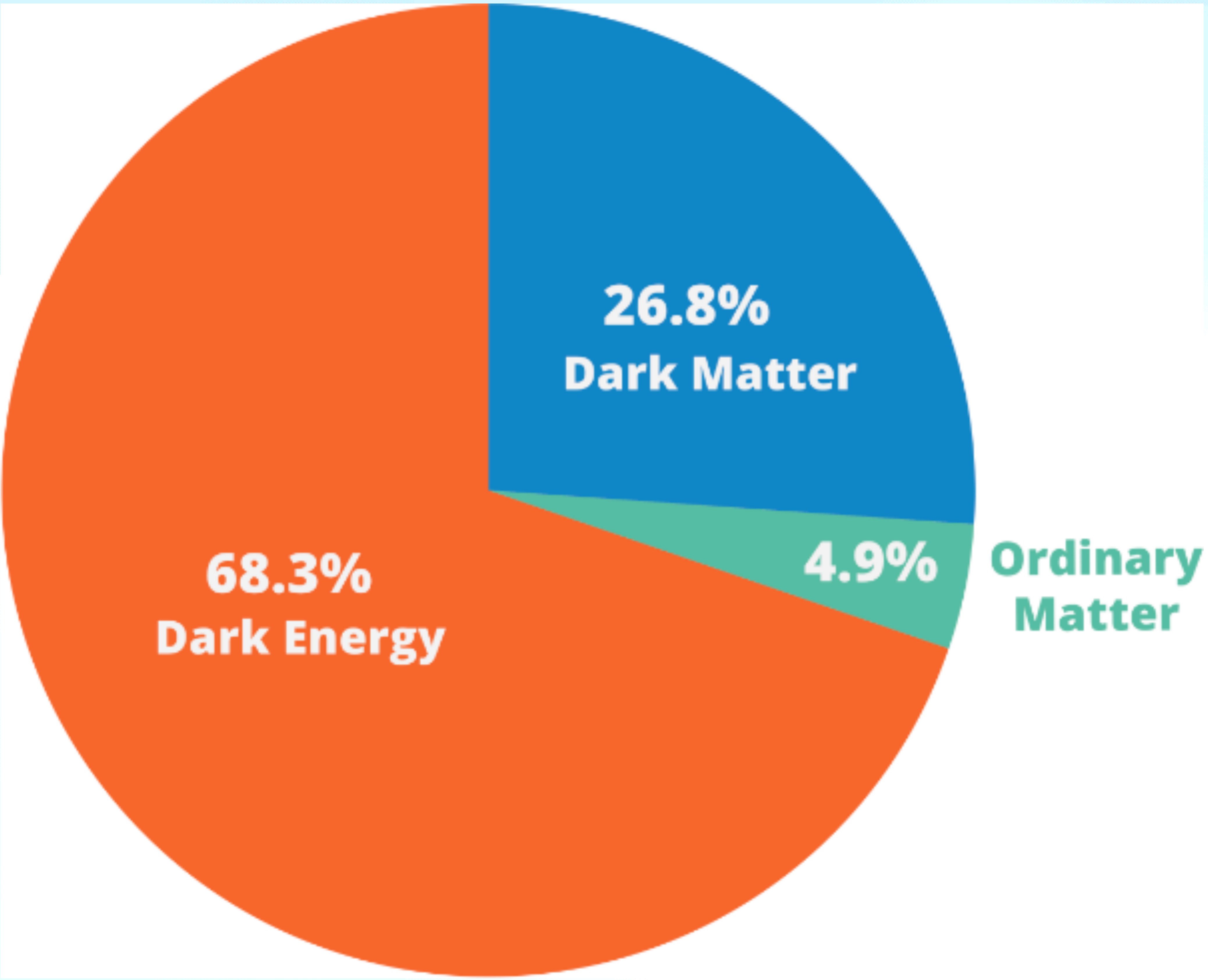


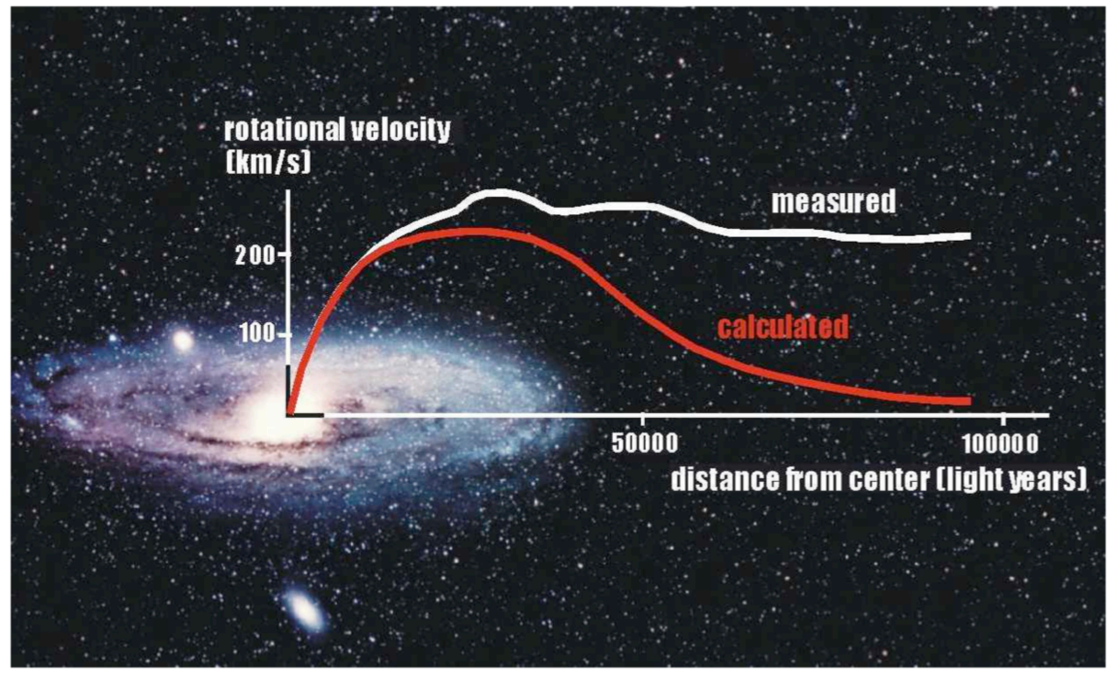


Rare Event Search in 2023

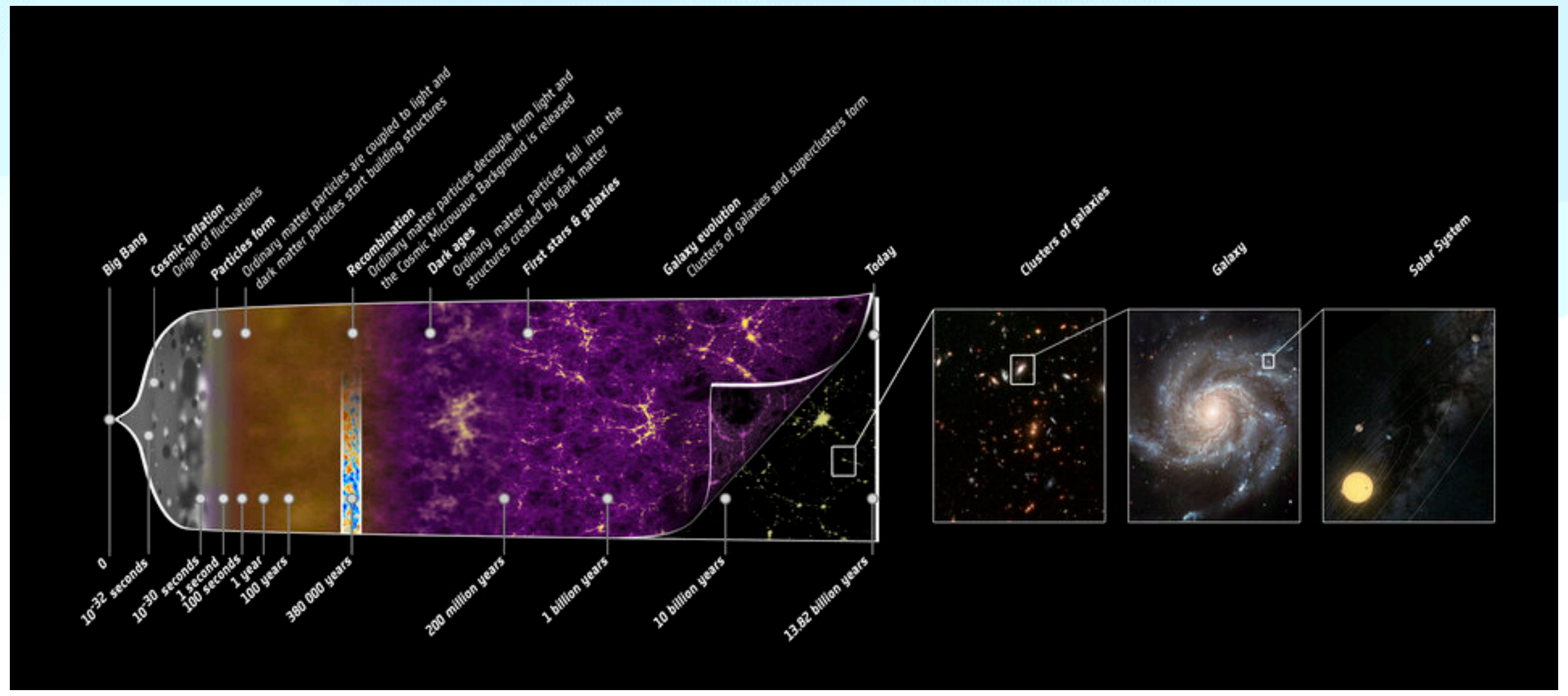
Dark Matter

The evidence for the existence of dark matter has been plenty

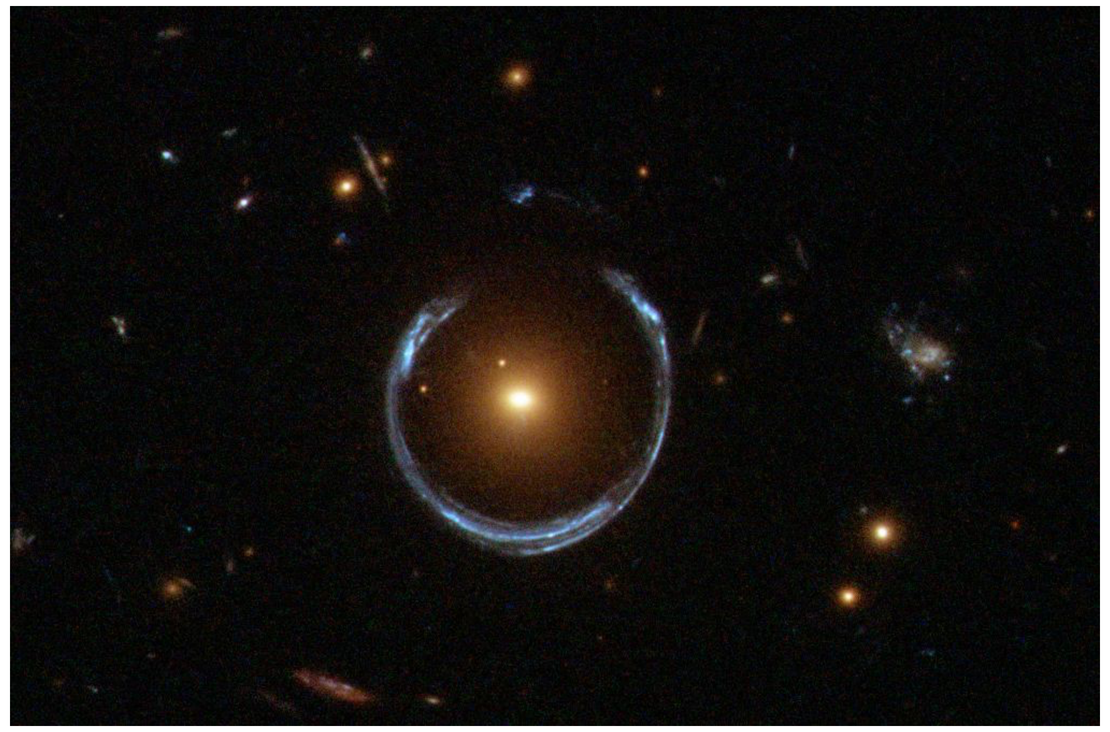




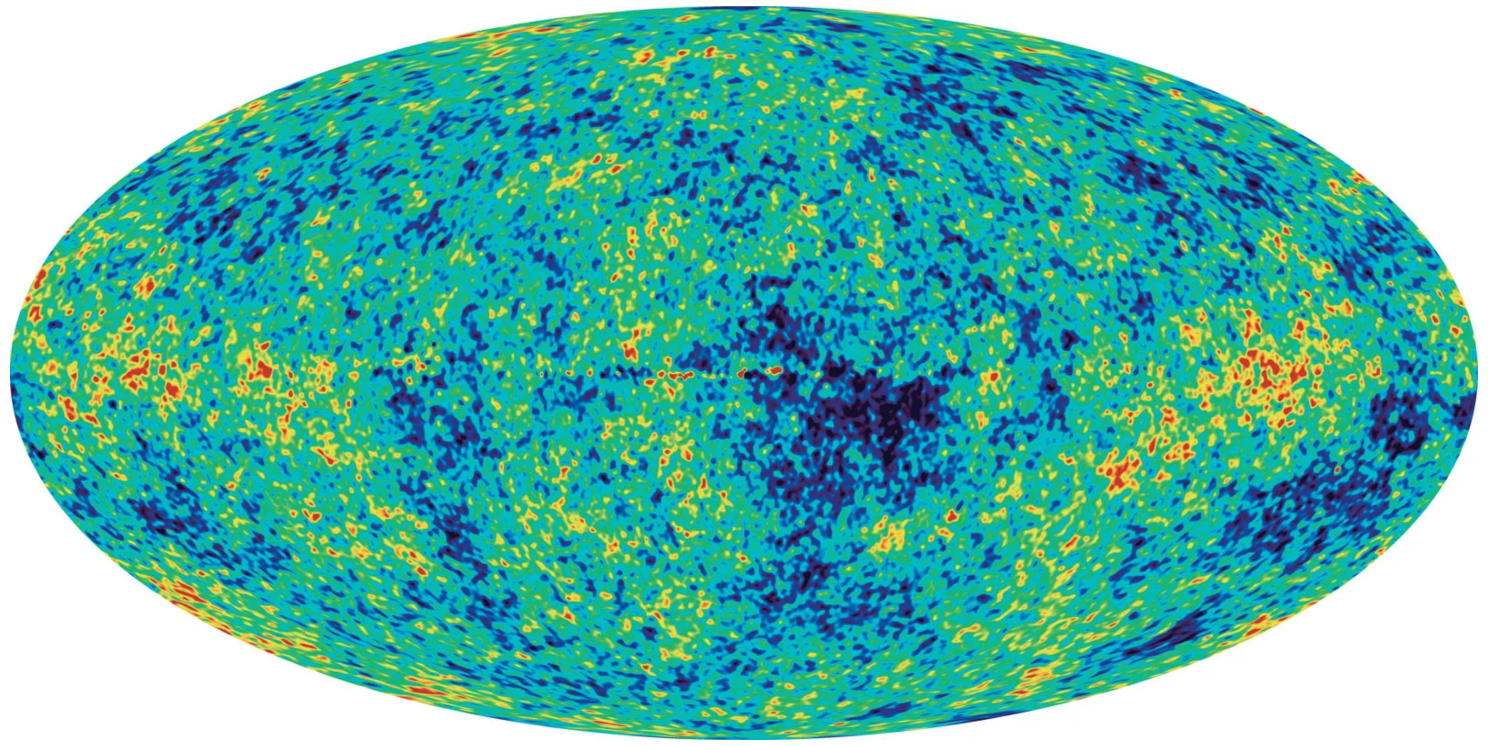
Galaxy Rotation Curve



Large Scale Structure Formation



Gravitational Lens



Cosmic Microwave Background

Rare Event Search in 2023

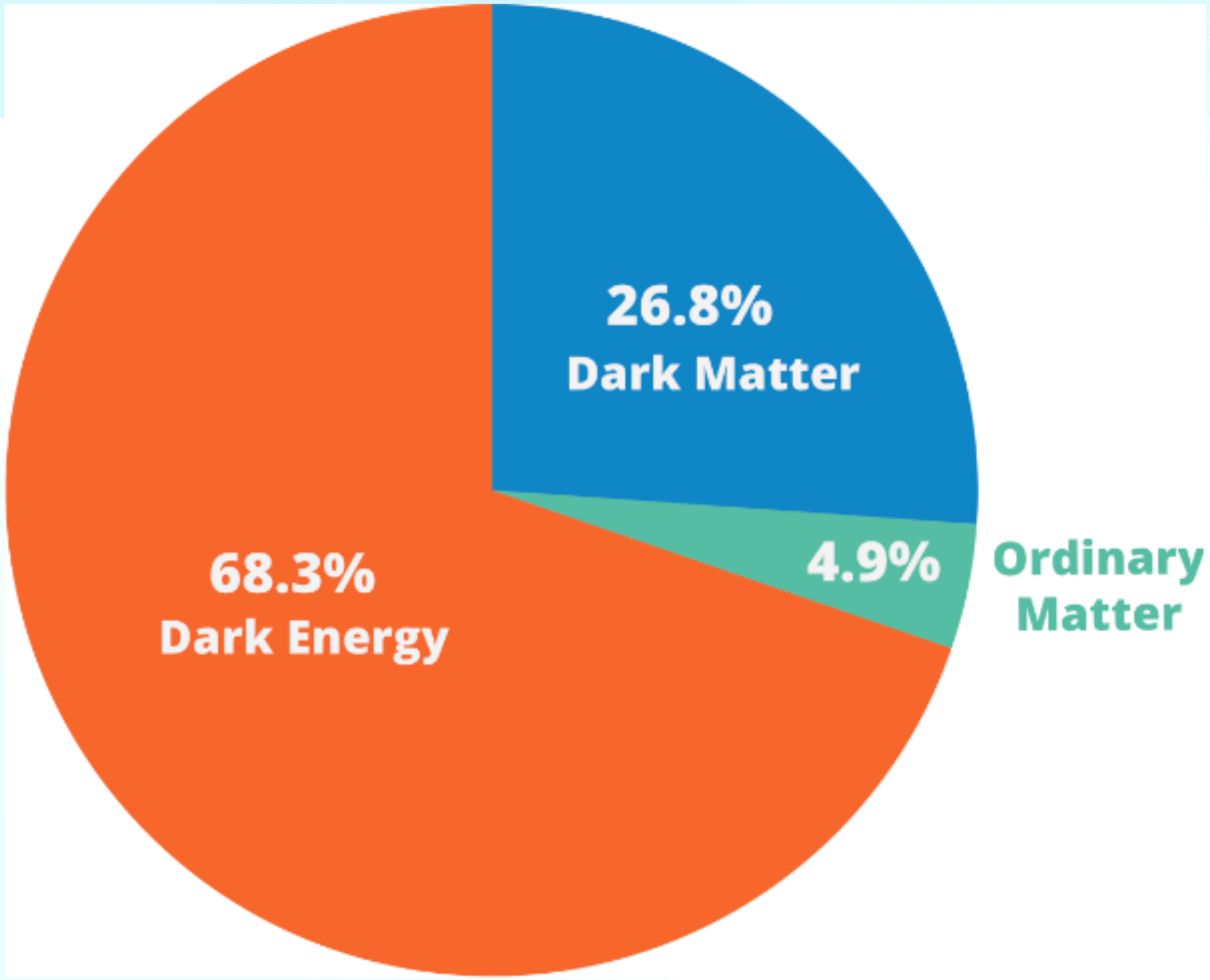
Dark Matter

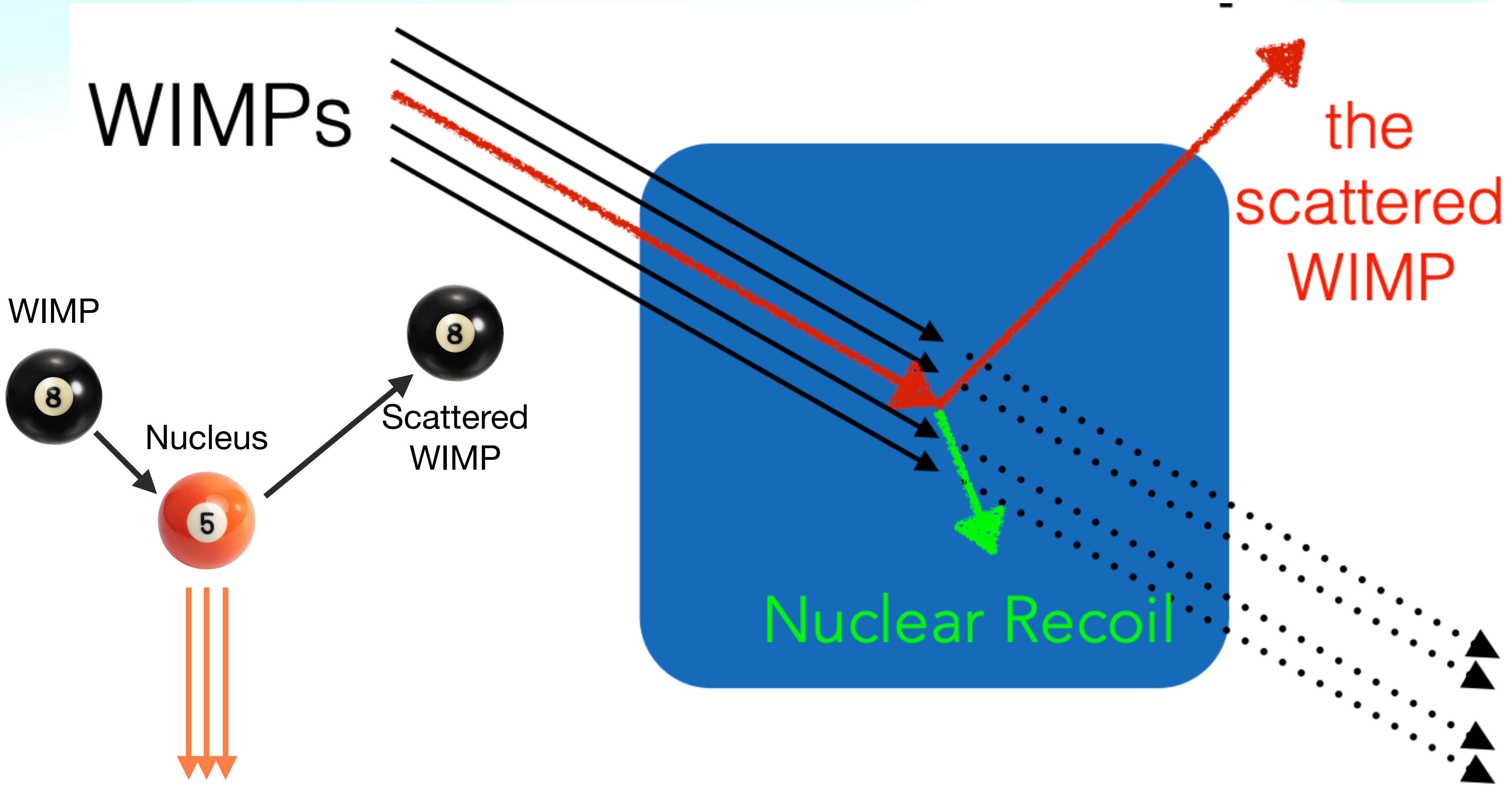
The evidence for the existence of dark matter has been plenty

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

None has been observed.

WIMP: Weakly Interacting Massive Particle

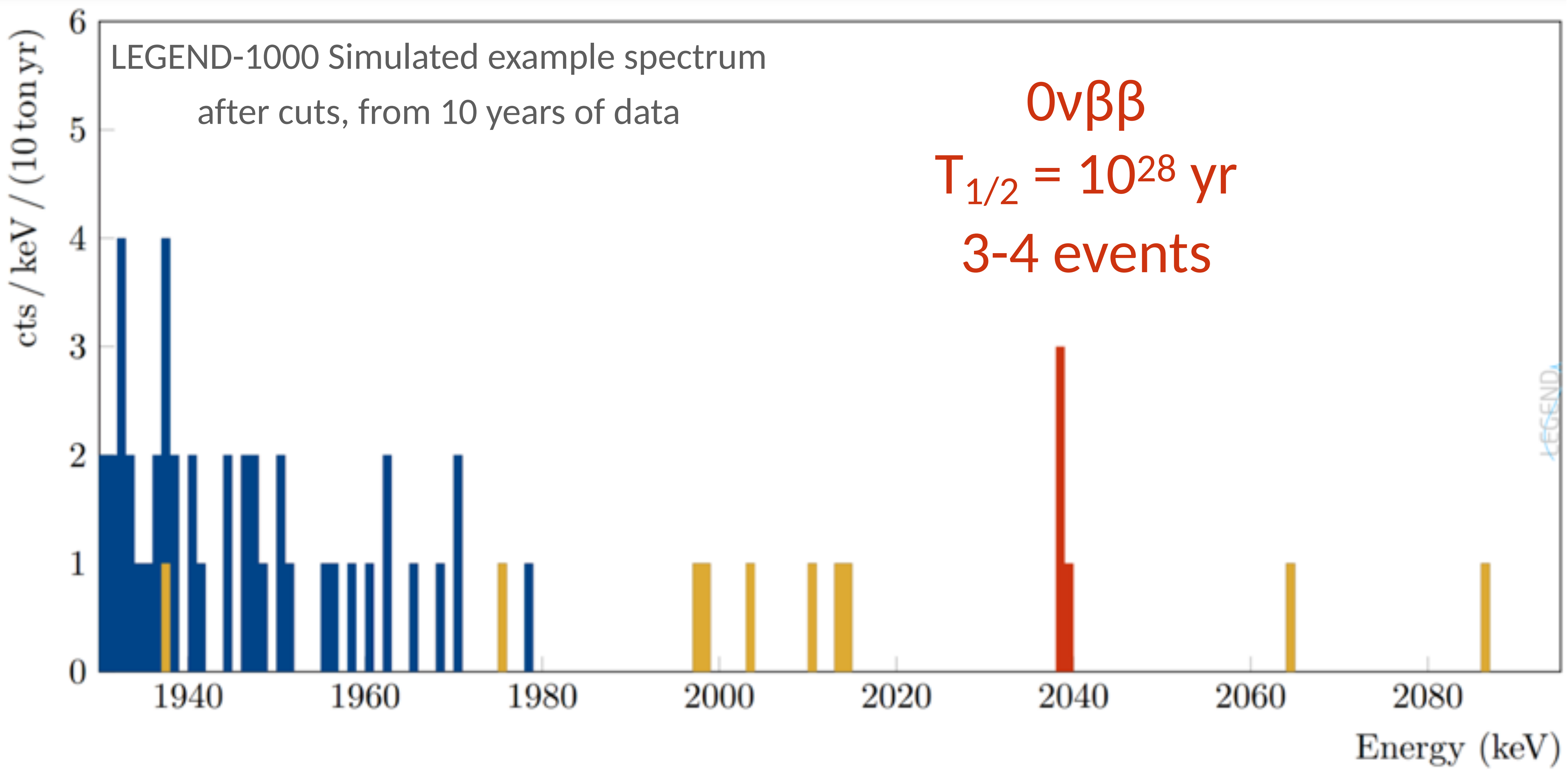




What Makes Rare Event Search Hard?

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

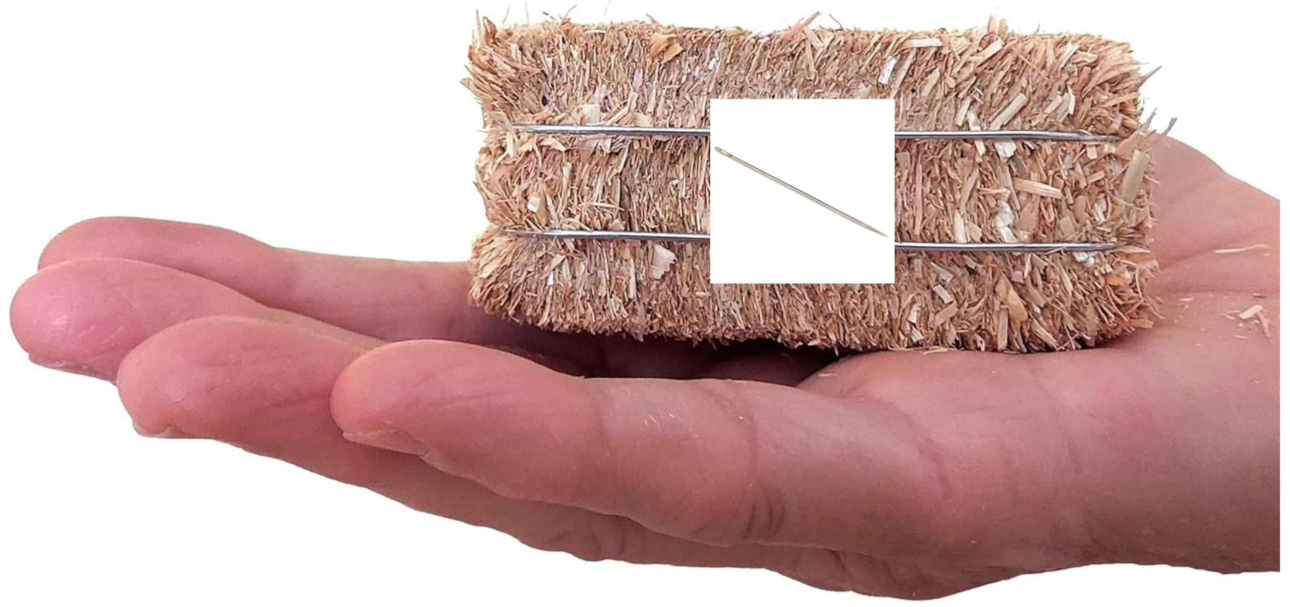
- We have not seen $0\upsilon\beta\beta$ at half life of $T_{\frac{1}{2}} > 10^{26} yrs$
- Next-generation experiments typically aims at $T_{\frac{1}{2}} > 10^{28} yrs$ (×100 improvement)
- Correspond to **3-4 event** after **10 years** of data taking



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

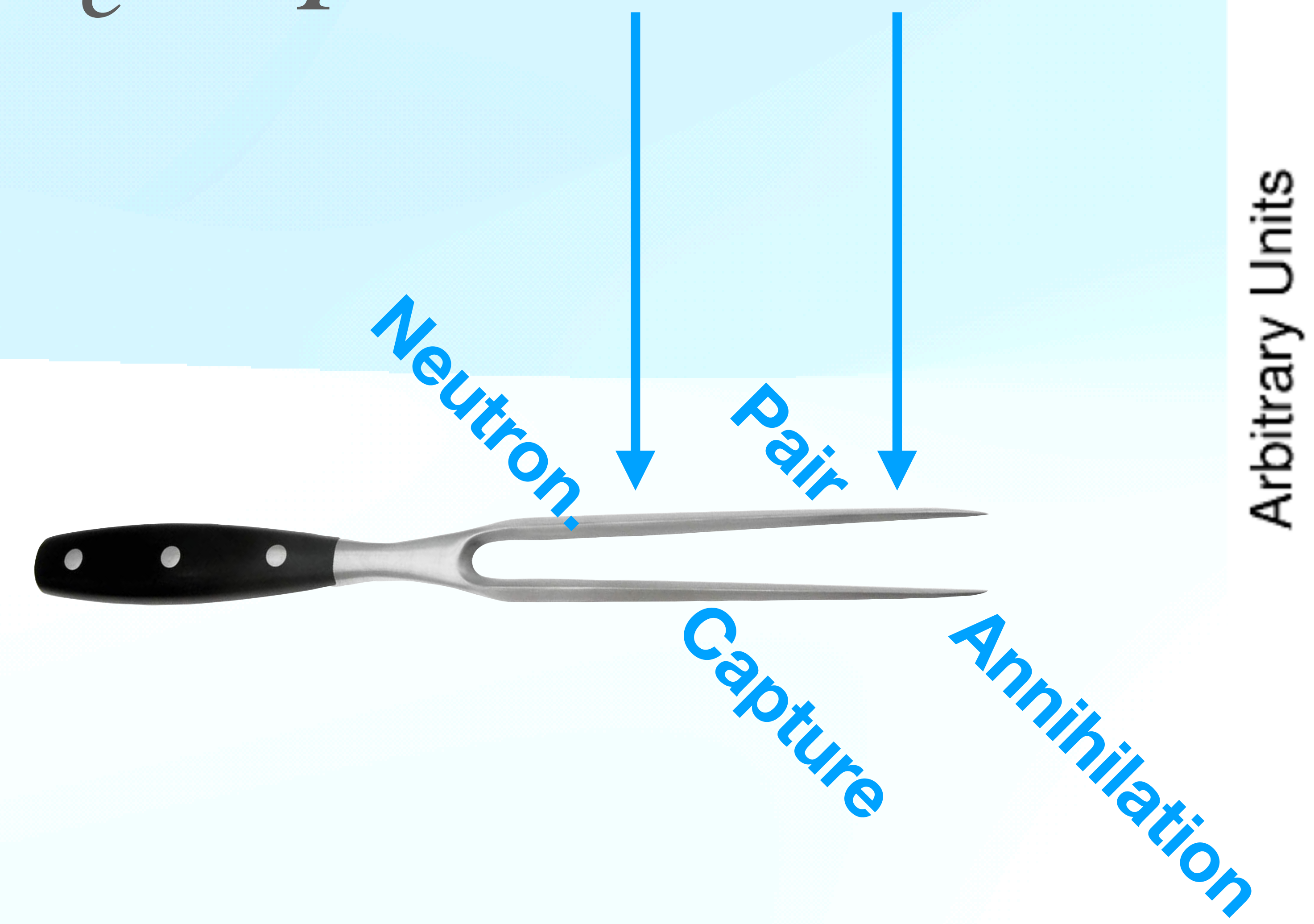
Search for needle in a haystack



What Makes Rare Event Search Hard?

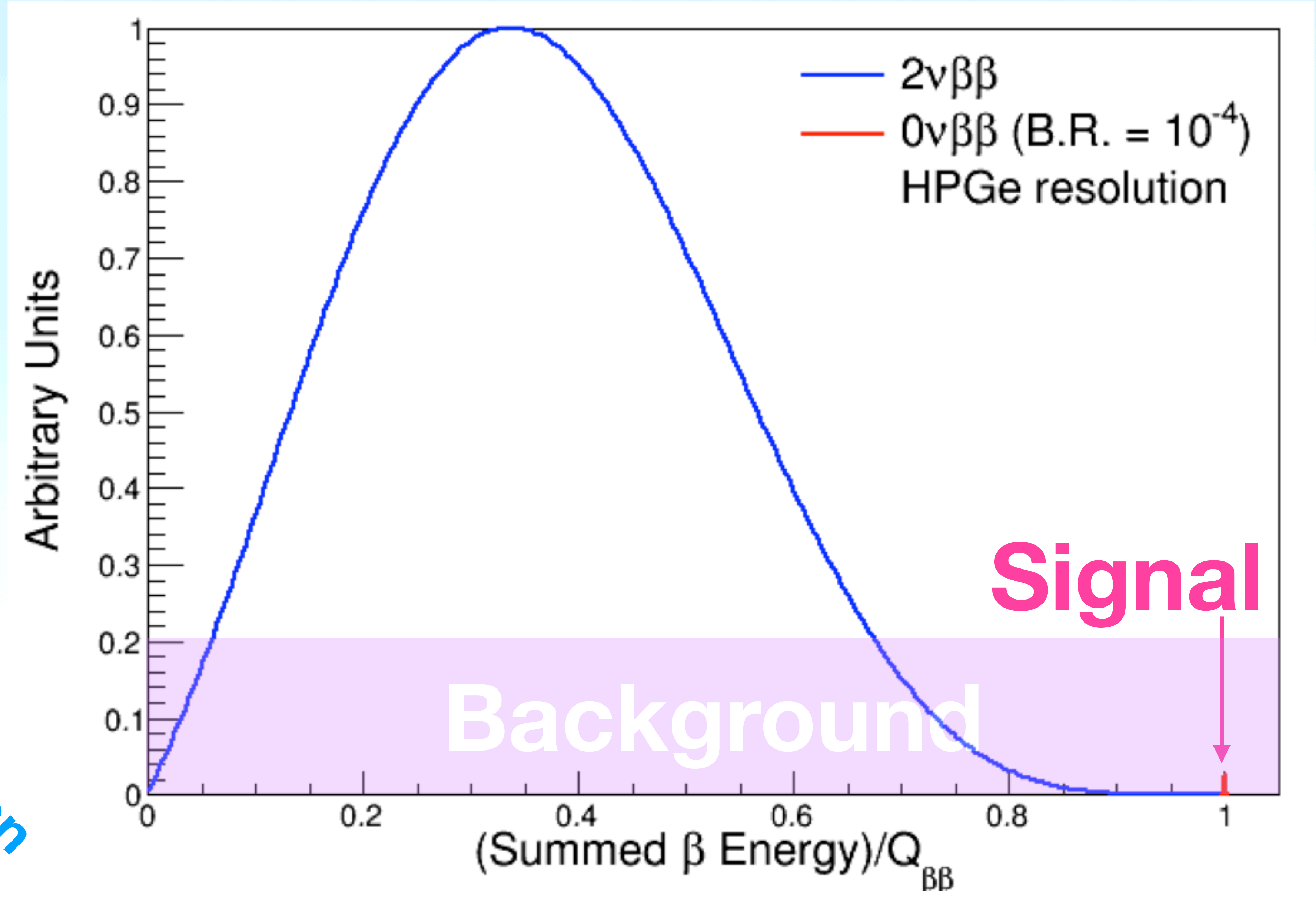
The Cowan-Reine Exp.

$$\bar{\nu}_e + p \rightarrow n + e^+$$

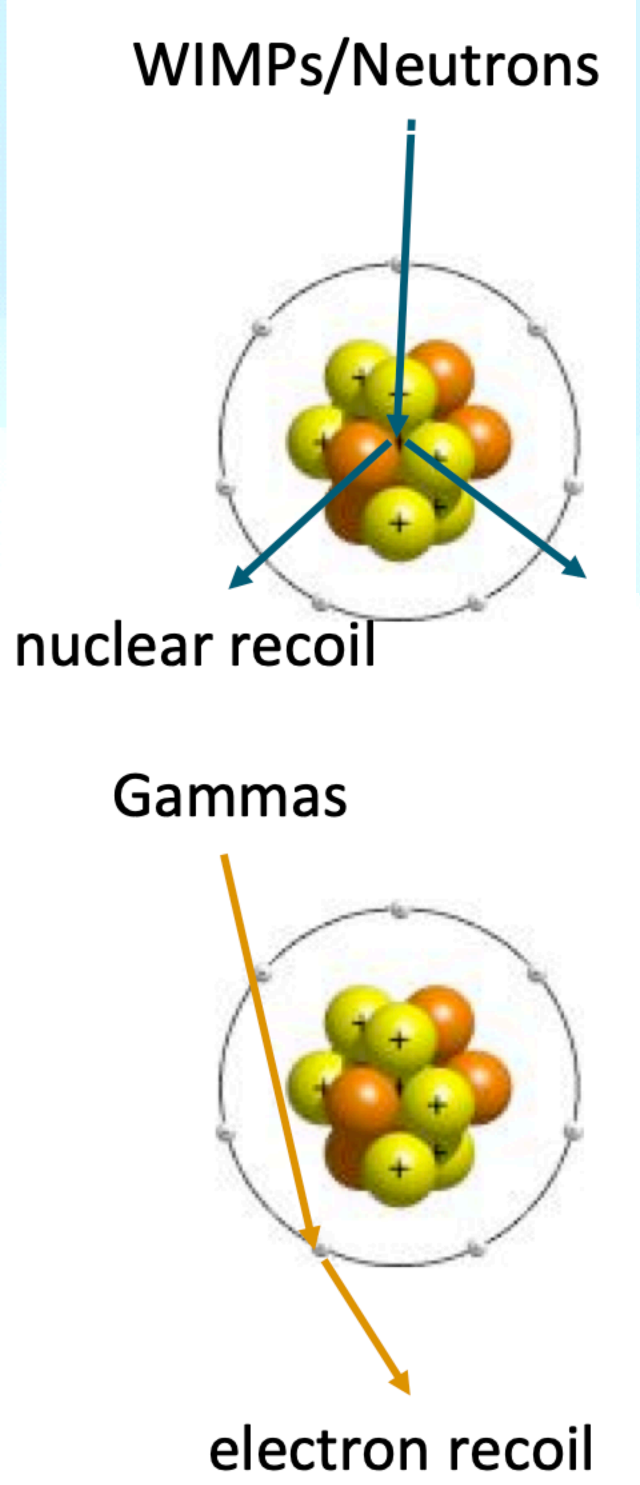


Nearly background-free

0υββ



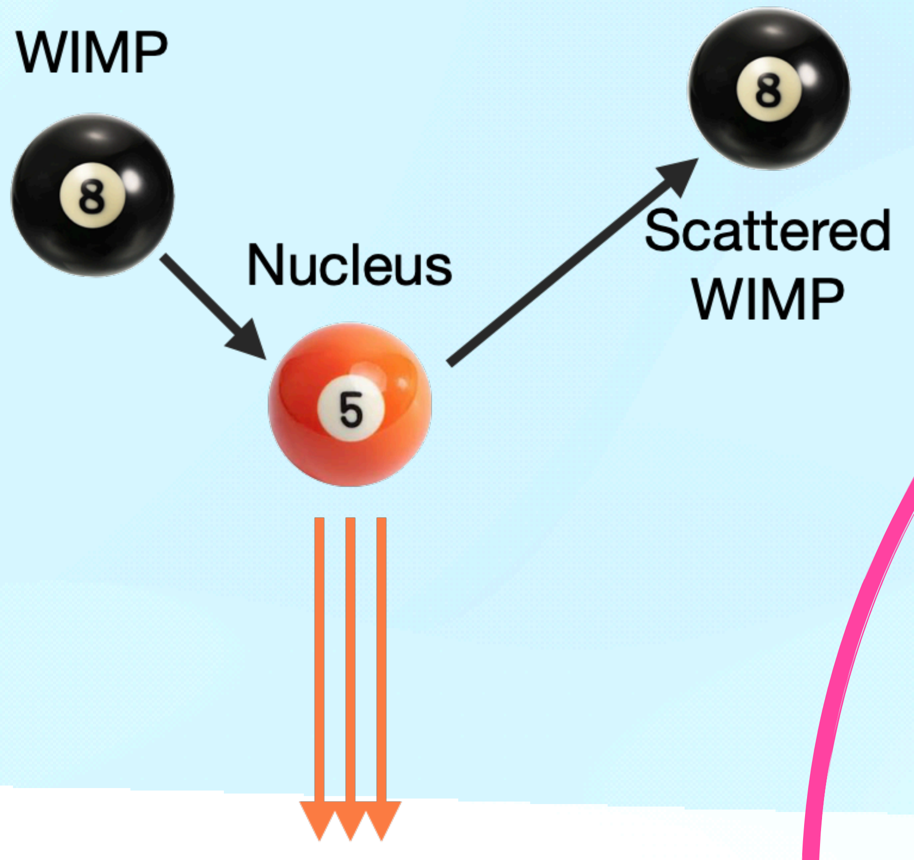
WIMP Dark Matter

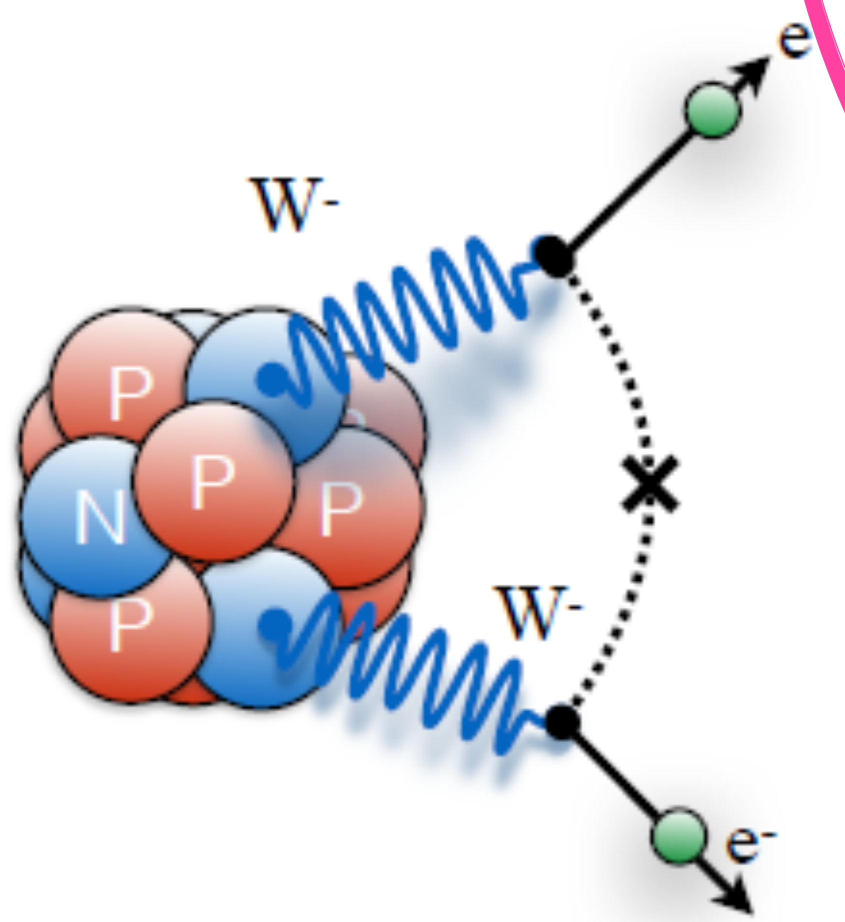


Naturally radioactive and cosmic ray background

Control background is of unparalleled importance in rare event search experiment!

The Rare Event Search Pipeline



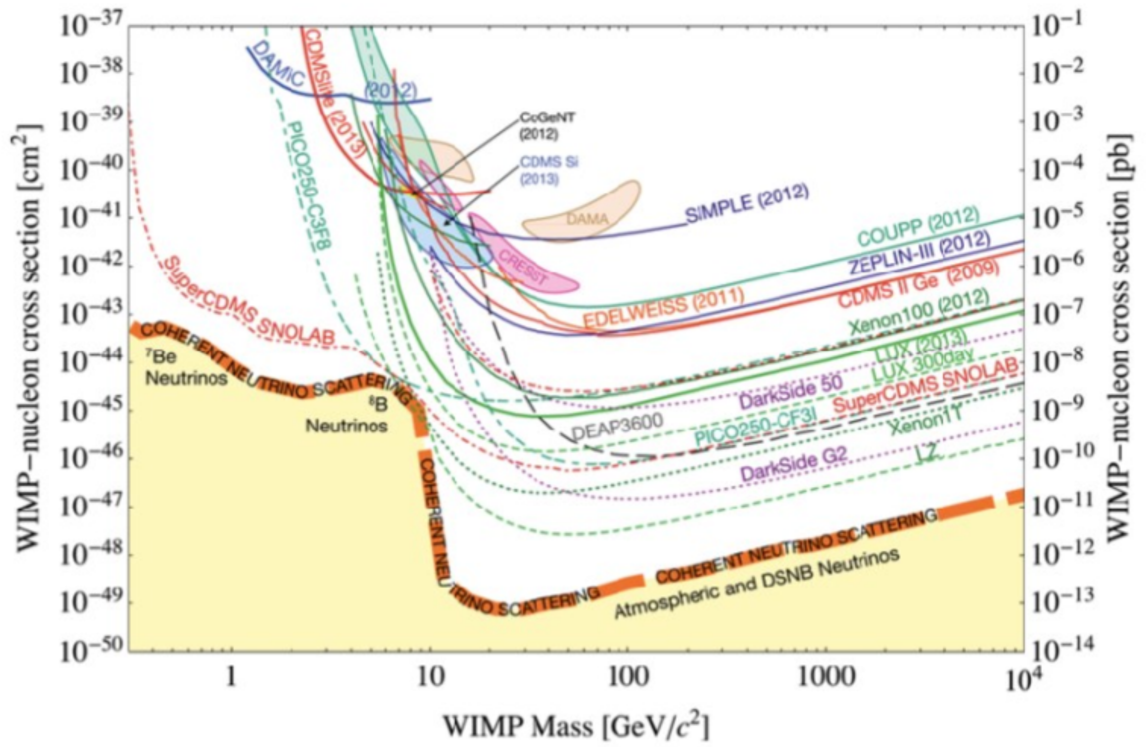


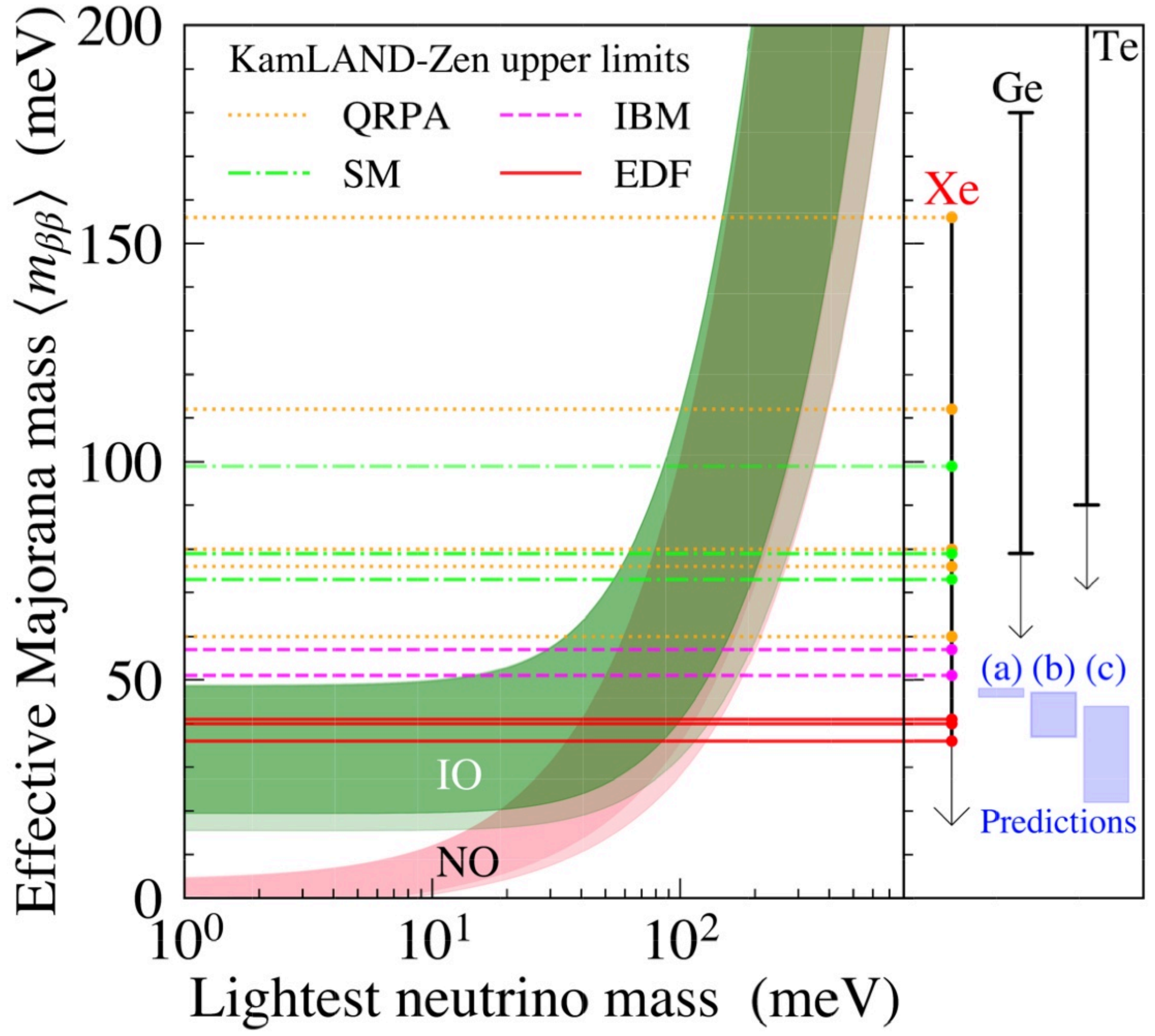
Radiation Detector

The “magnifying glass” that help finding the needle

AI/ML

The “forklift” that help removing the haystack





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Slow

- What is rare event search?

Fast

- Radiation detectors
- AI algorithms

Fast for Slow

- Fast ML for rare event

KamLAND-Zen

Monolithic Liquid Scintillator Detector for 0υββ 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/UNC/UCSD)

Not on this photo:

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

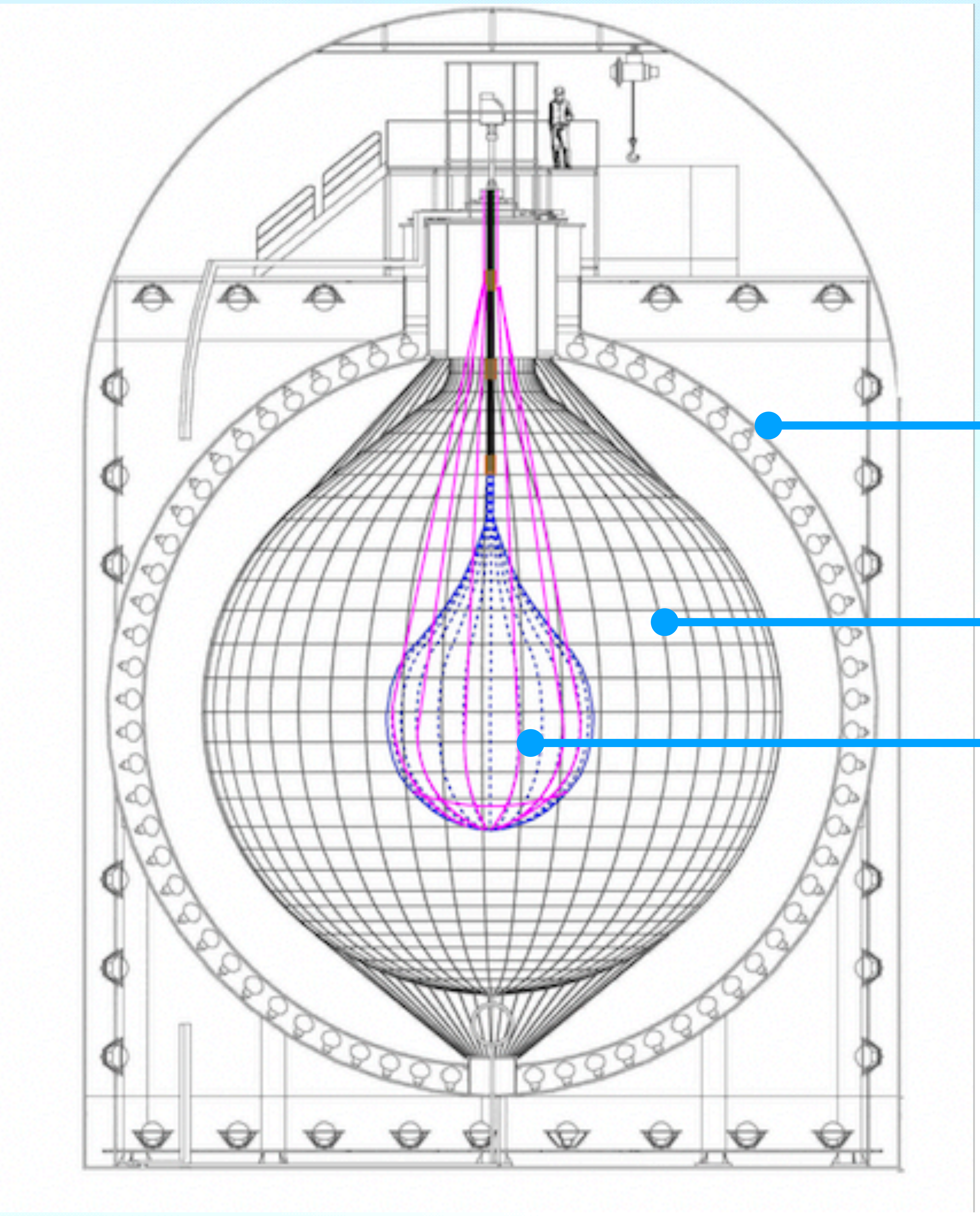
The MIT-BU Analysis Group

KamLAND-Zen

Monolithic Liquid Scintillator Detector for 0υββ Search

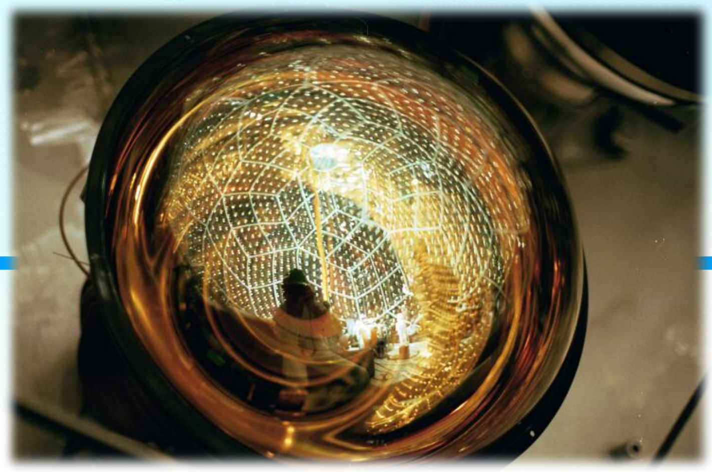
Background Source

- XeLS Background
- Film Background



Inner Detector PMTs

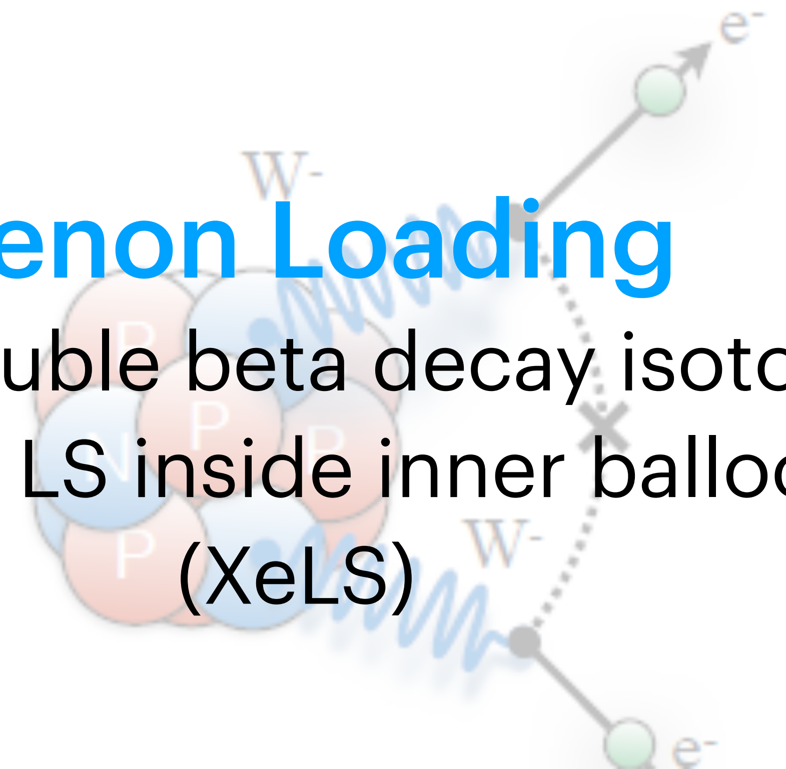
1325 17inch + 554 20inch



Liquid Scintillator

Inner Balloon

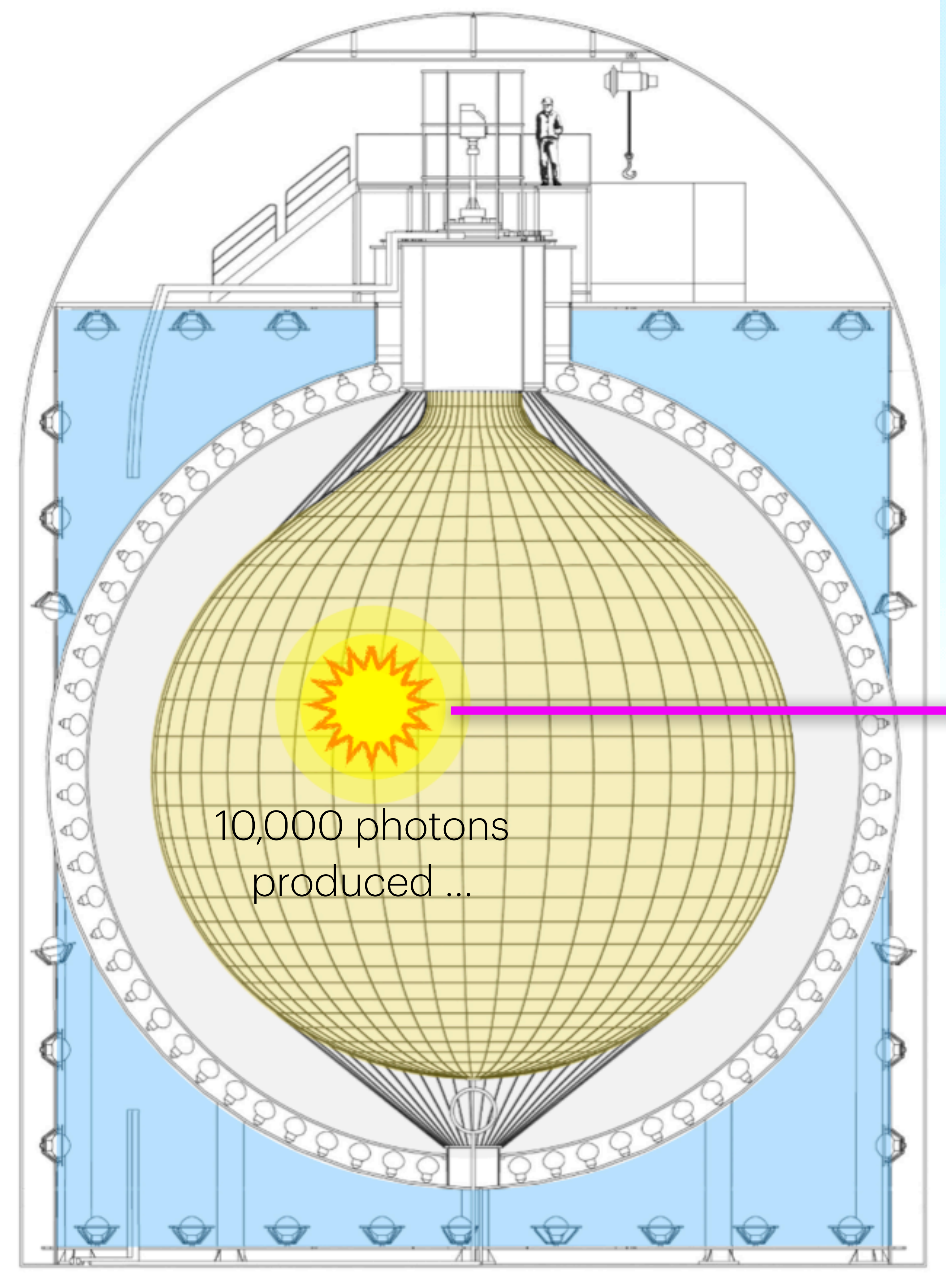
25-µm-thick transparent nylon film



Xenon Loading

Load double beta decay isotope ^{136}Xe in LS inside inner balloon (XeLS)

KamLAND-Zen Data



10,000 photons produced ...

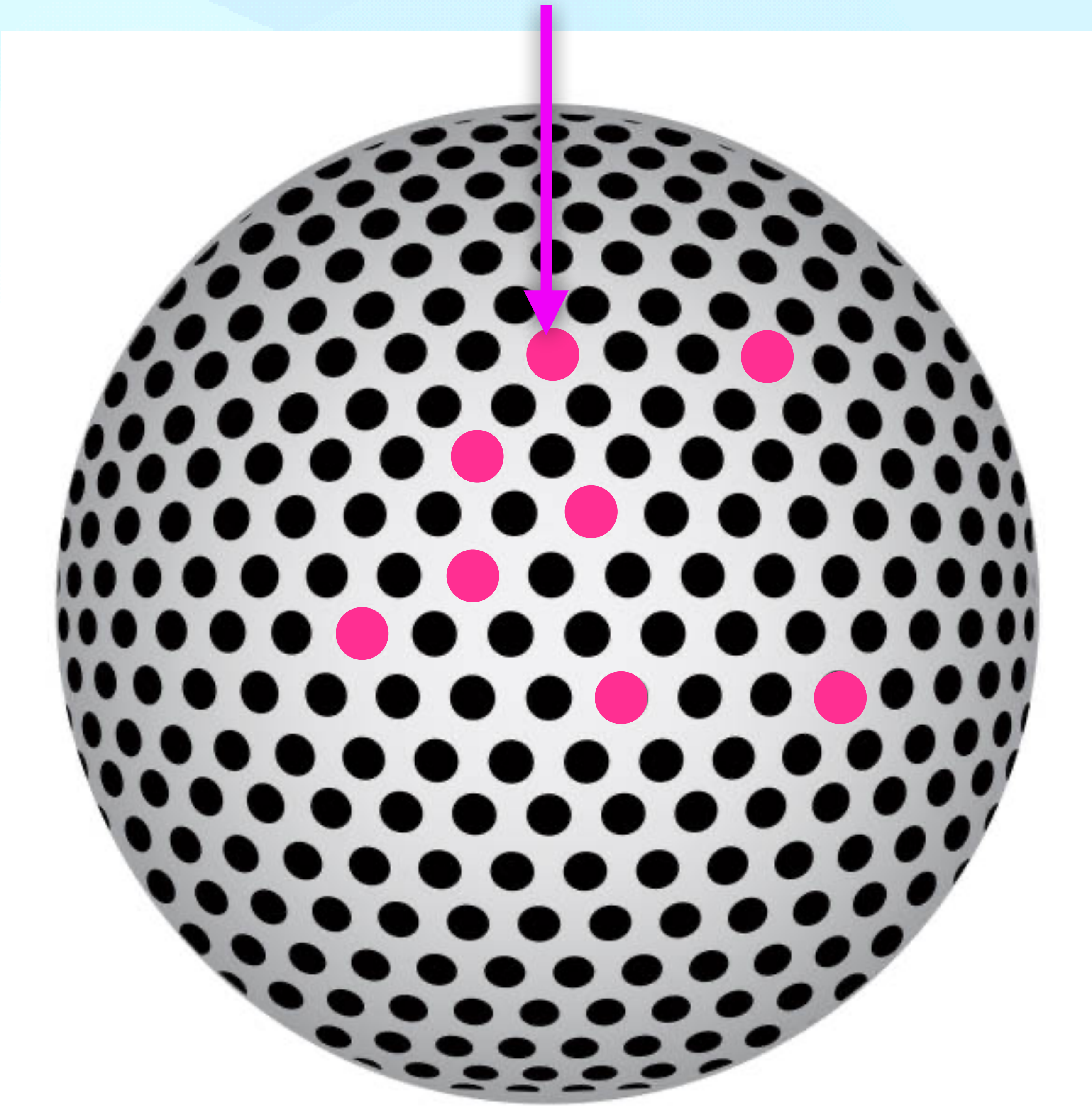
22% Photocoverage

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

23% Quantum Efficiency

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

Triggered PMT



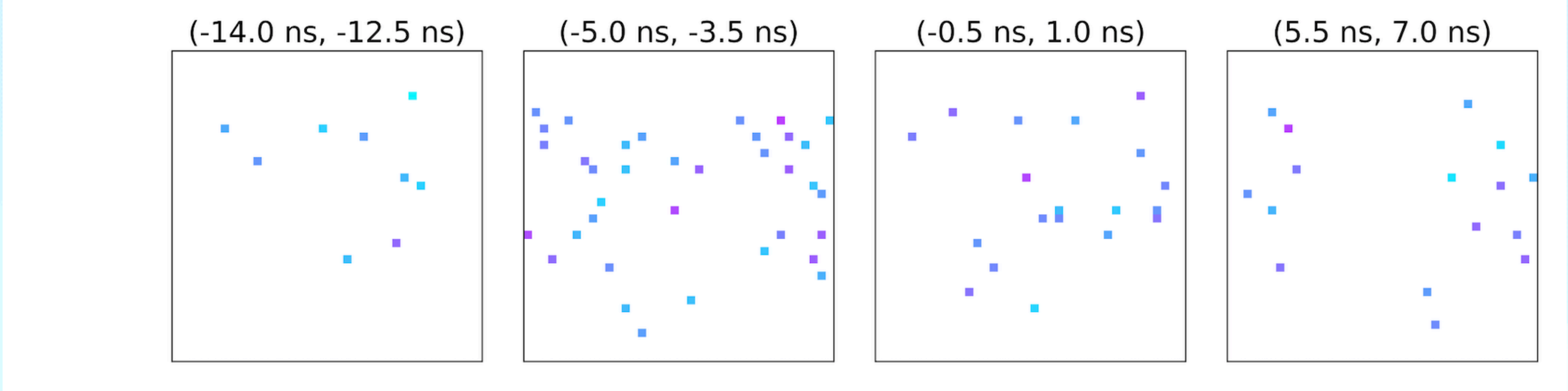
KamLAND-Zen Data

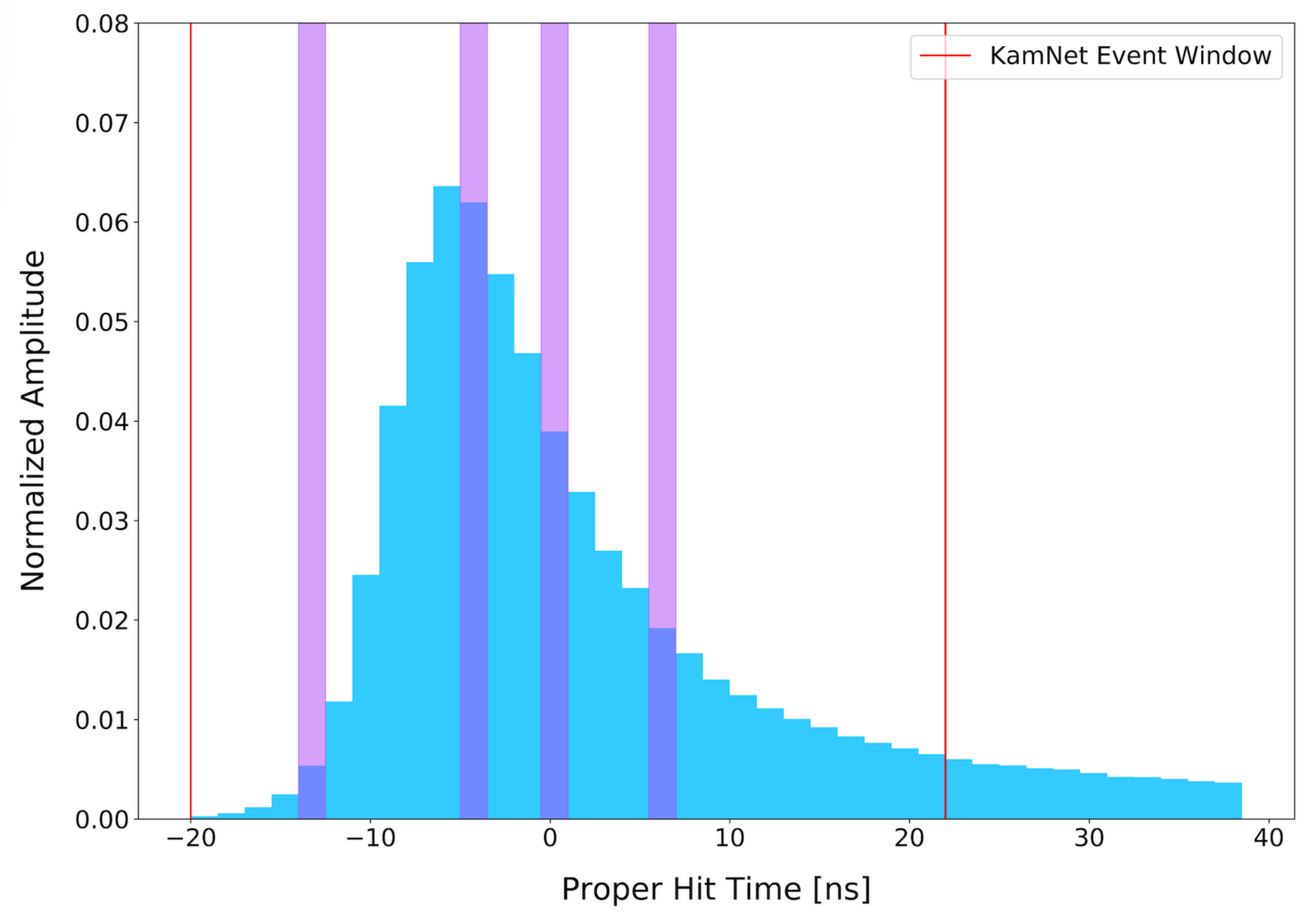
Triggered PMT

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

θ-ϕ Sphere Map

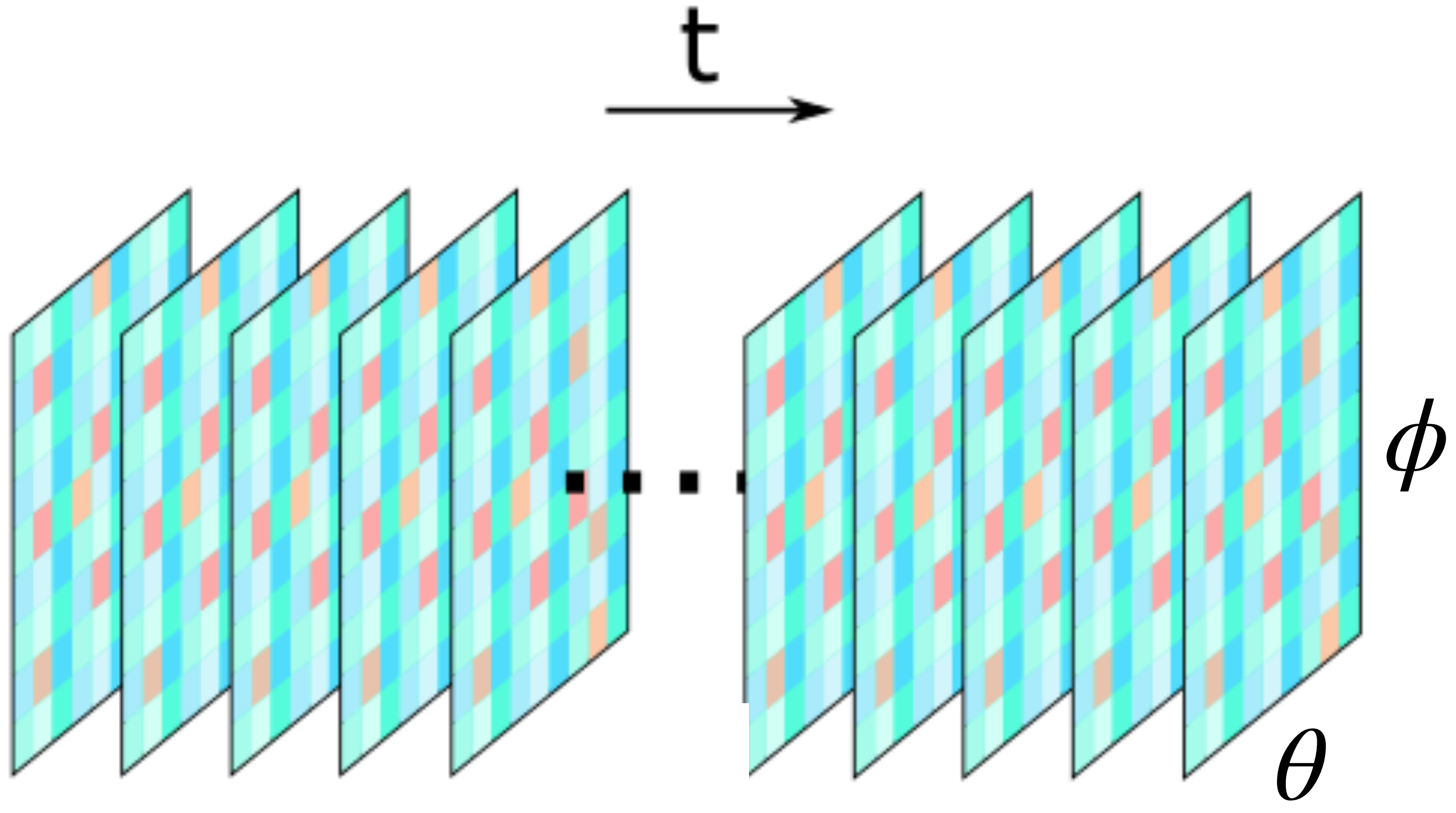
Scintillation Time Profile





Spatiotemporal Data

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

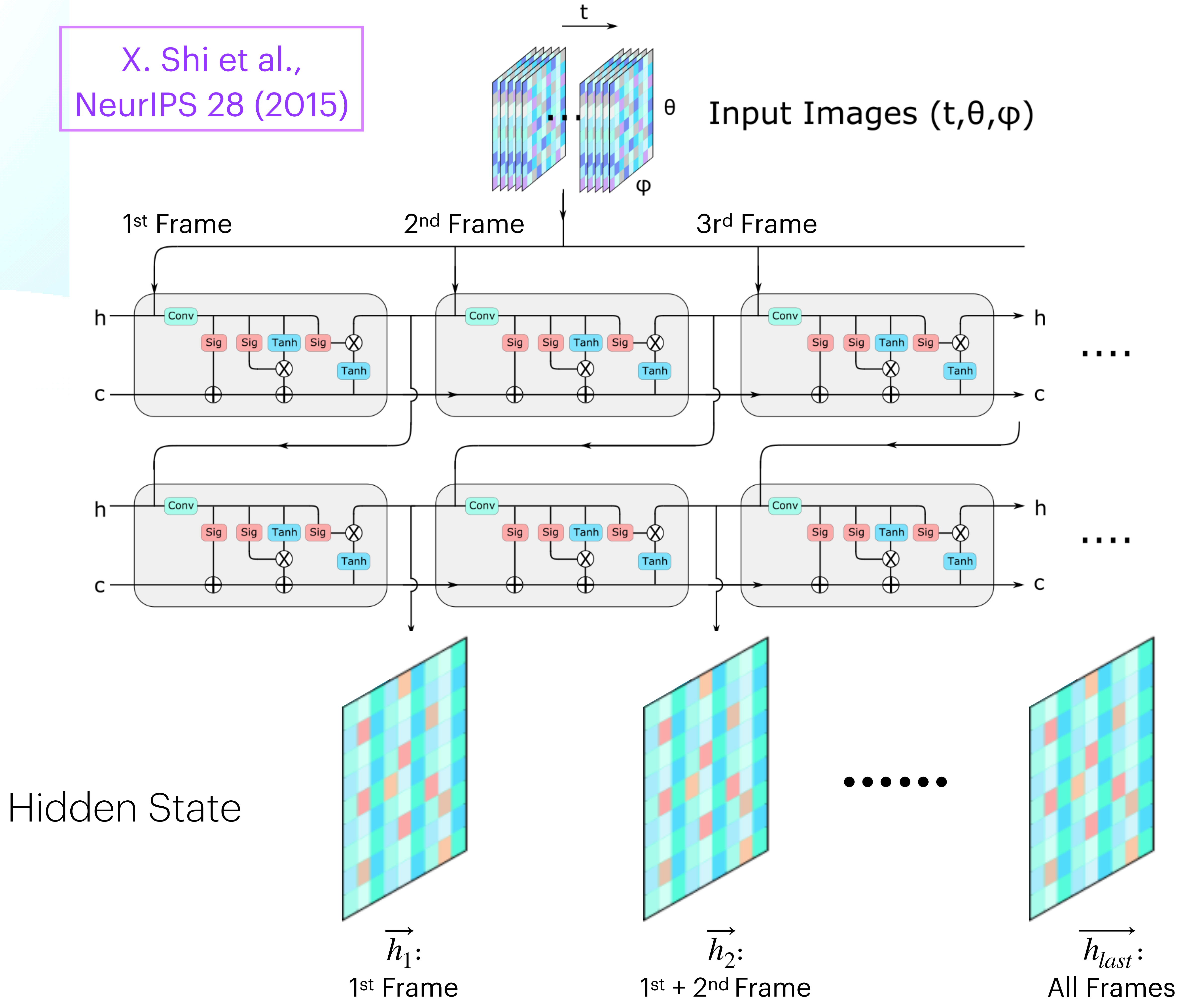


A Time Series of 2D Images …

ConvLSTM

Convolutional Long-Short Term Memory (LSTM) Network

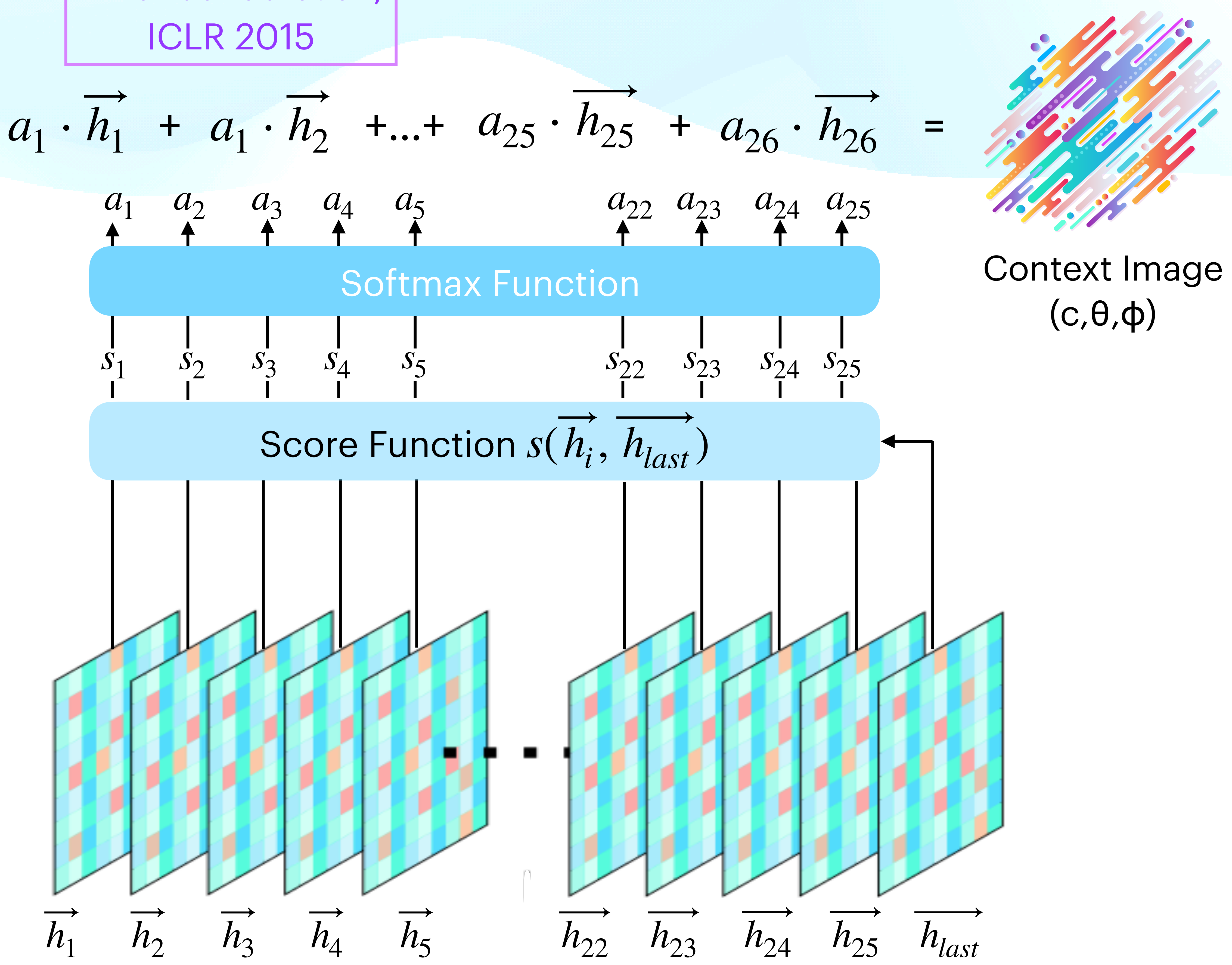
X. Shi et al.,
NeurIPS 28 (2015)



Attention Mechanism

Produce context images & provide interpretability

D Bahdanau et al.,
ICLR 2015



$$a_1 \cdot \overrightarrow{h_1} + a_1 \cdot \overrightarrow{h_2} + \ldots + a_{25} \cdot \overrightarrow{h_{25}} + a_{26} \cdot \overrightarrow{h_{26}} =$$

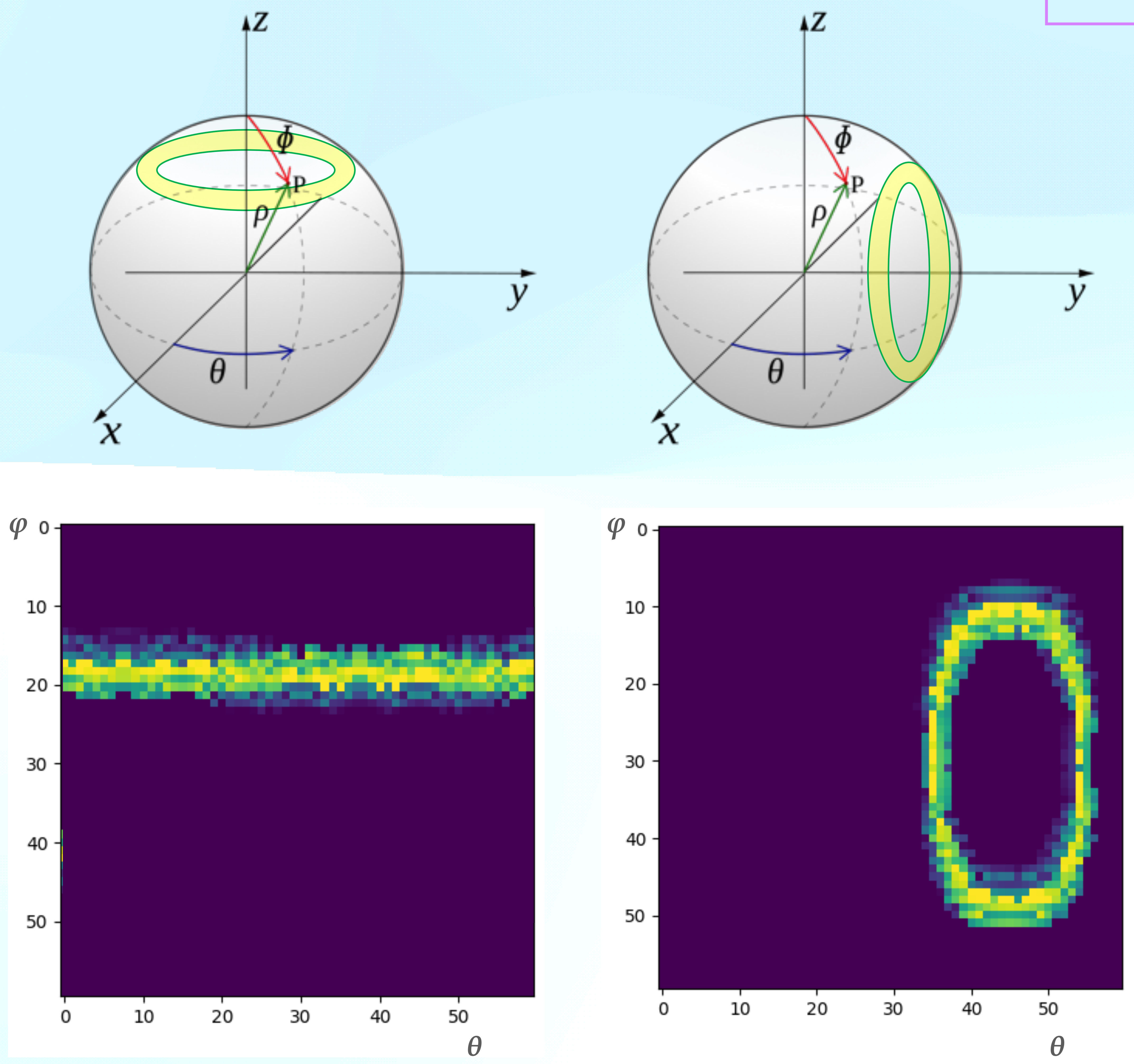
Context Image
(c,θ,ϕ)

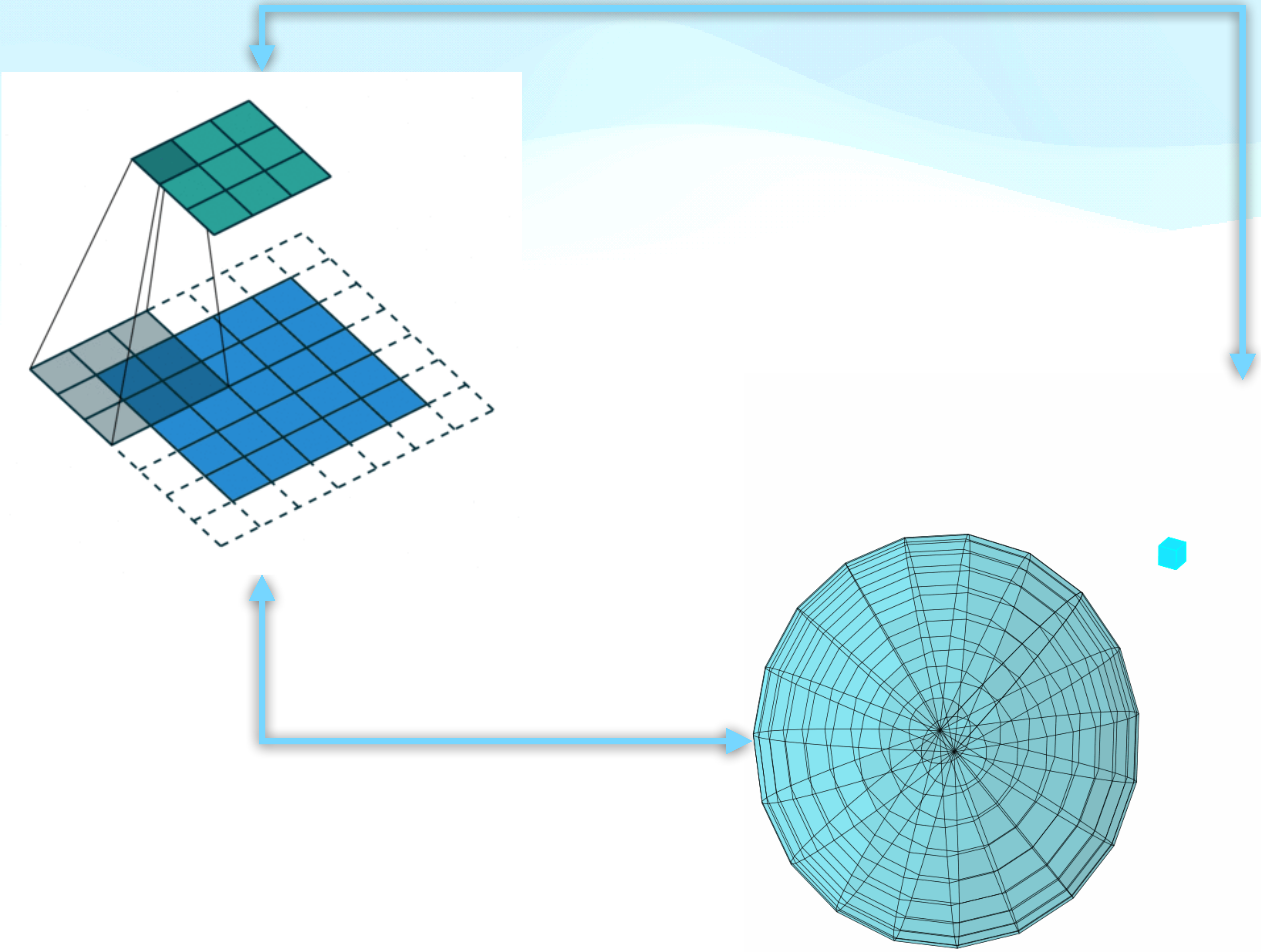
… Project onto A Sphere

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

Spherical CNN

SO(3) symmetry & rotational invariance

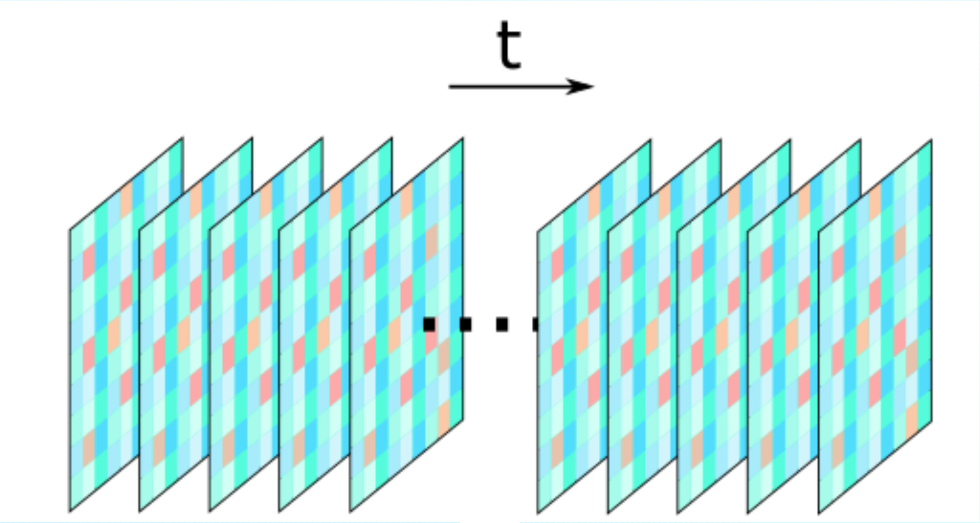




KamNet: An Integrated Spatiotemporal Neural Network

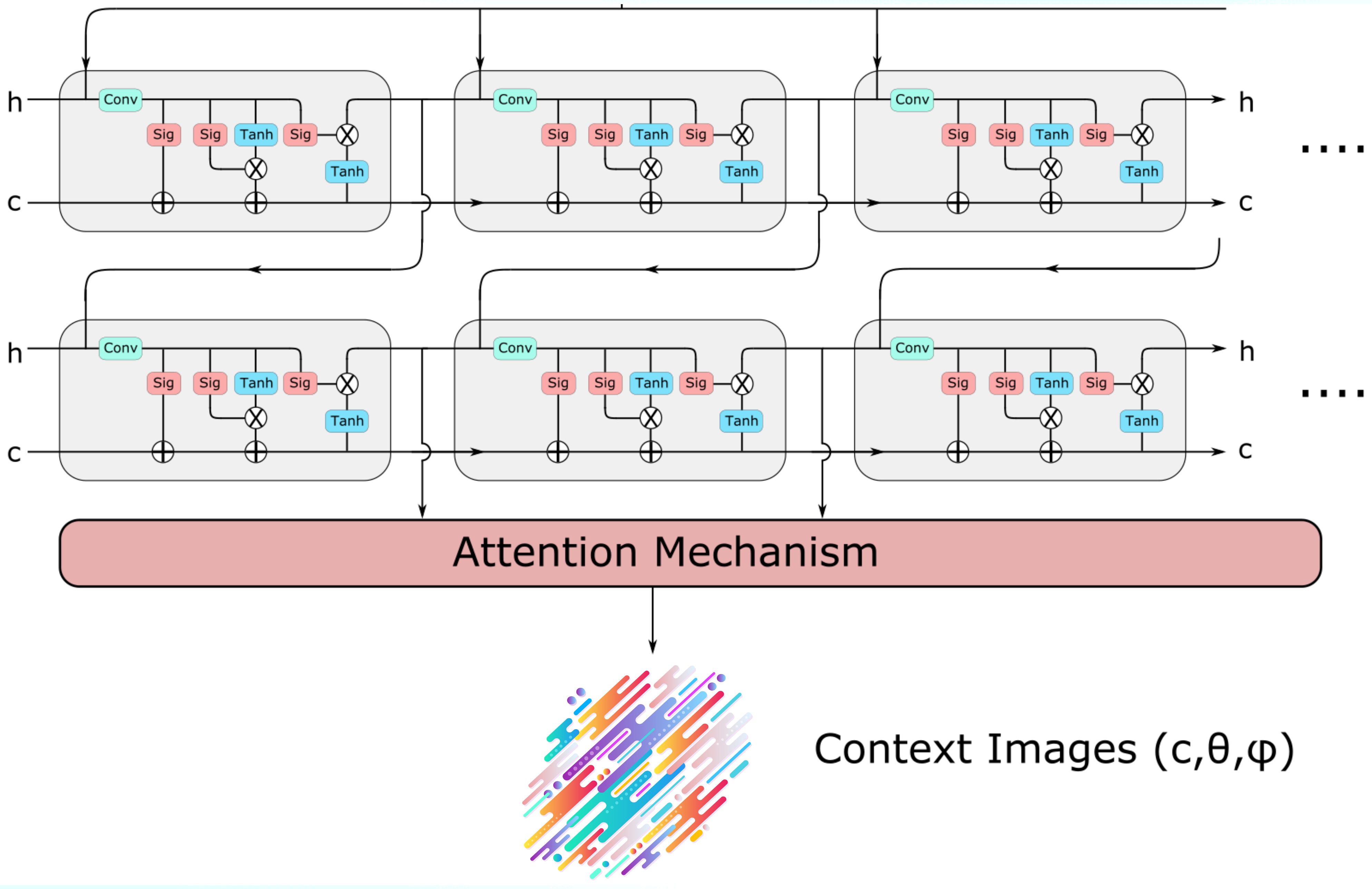
Spatiotemporal Data

A time series of images projected onto Sphere



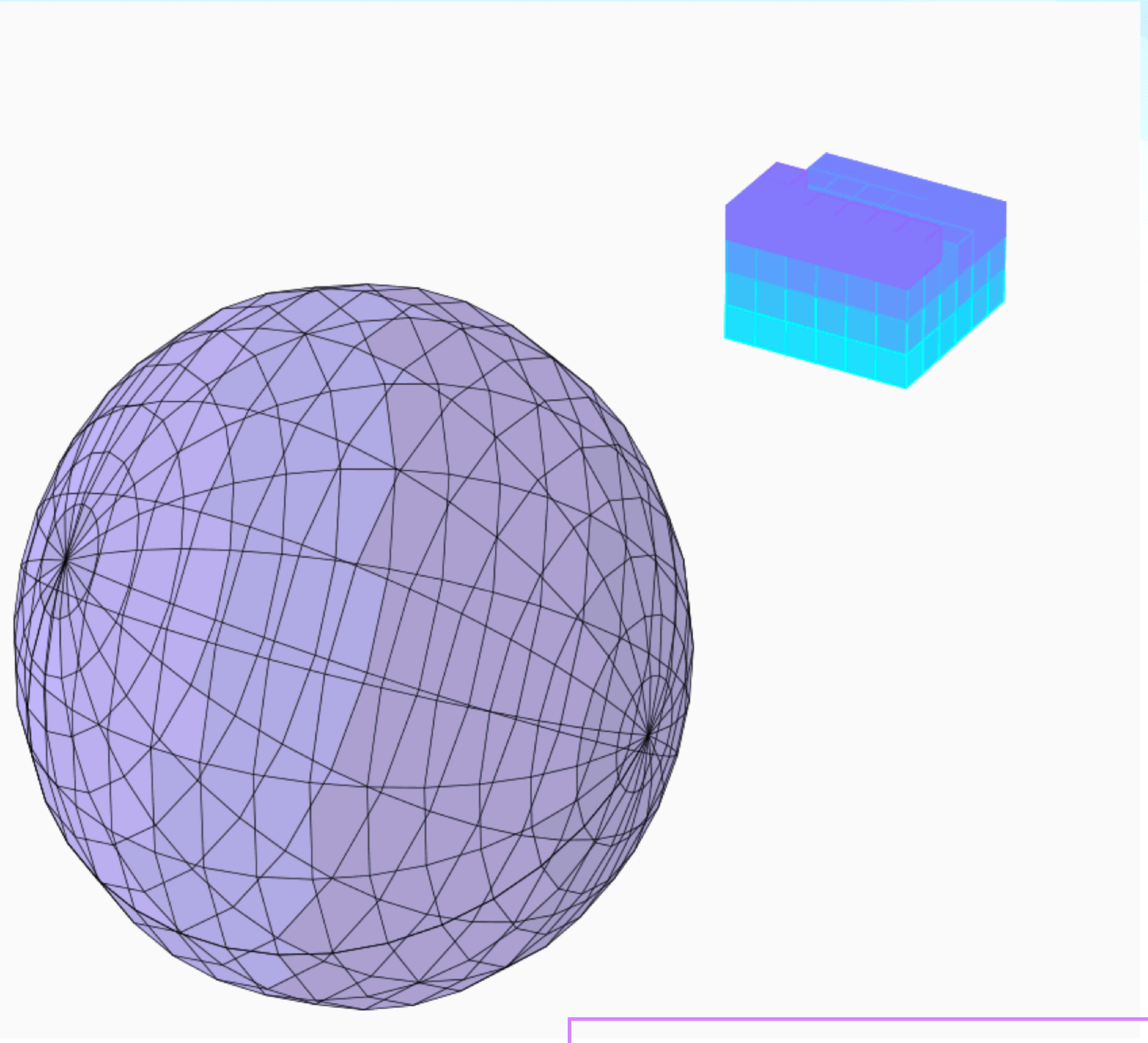
AttentionConvLSTM

for Spatiotemporal symmetry



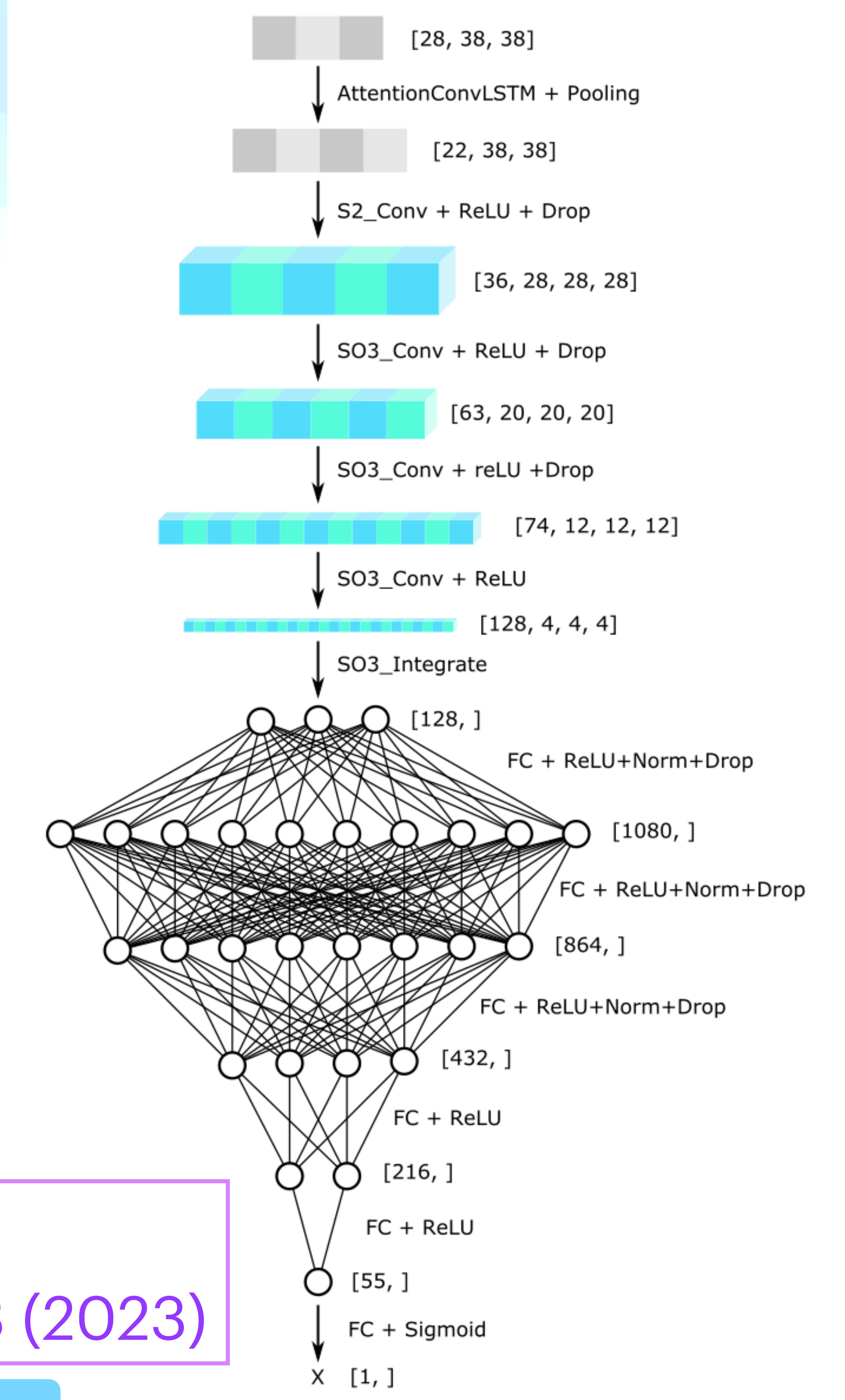
Spherical CNN

SO(3) symmetry & rotational invariance



KamNet

Maximal Information Extraction in KamLAND-Zen

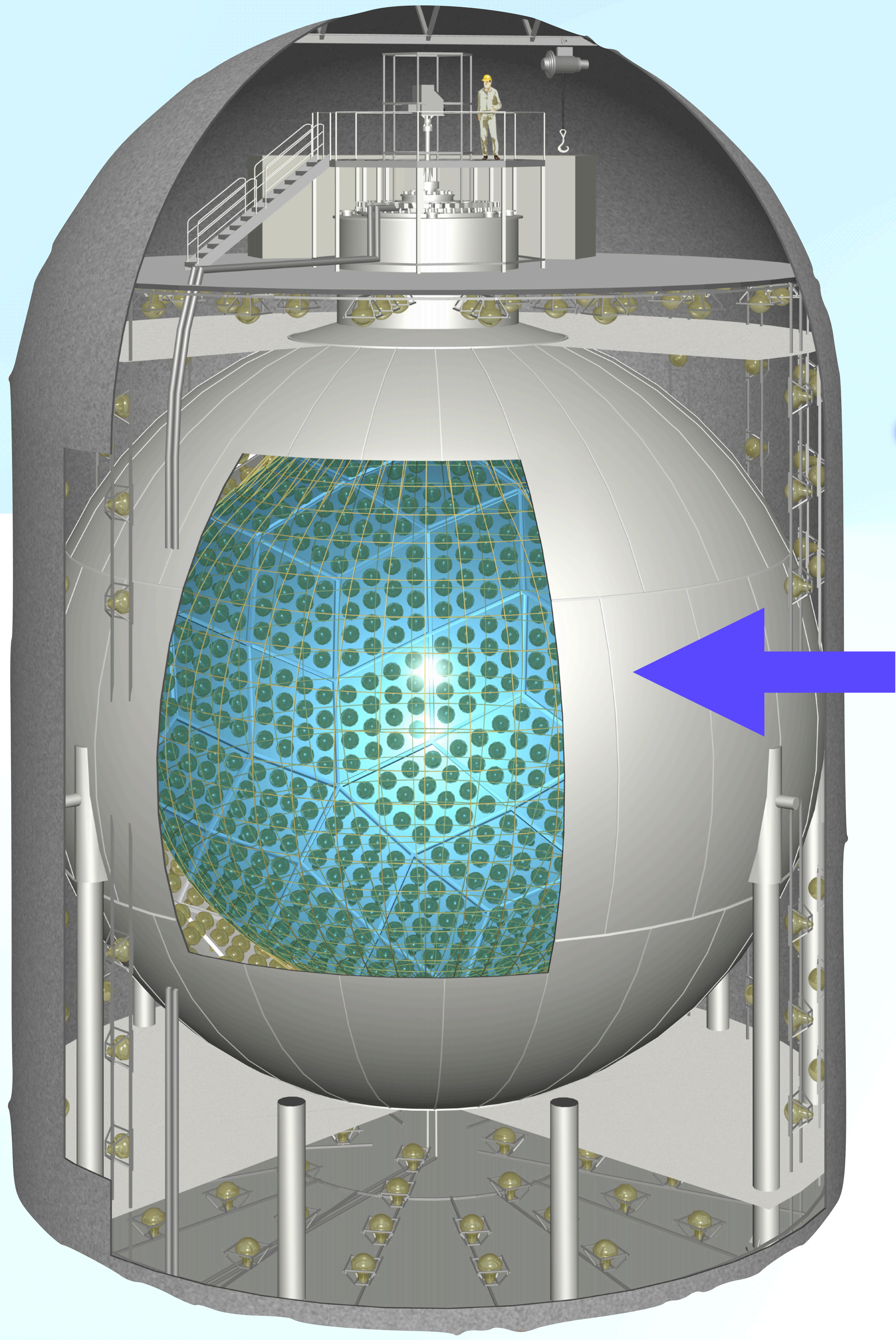


A. Li et al,
Phys. Rev. C **107**, 014323 (2023)

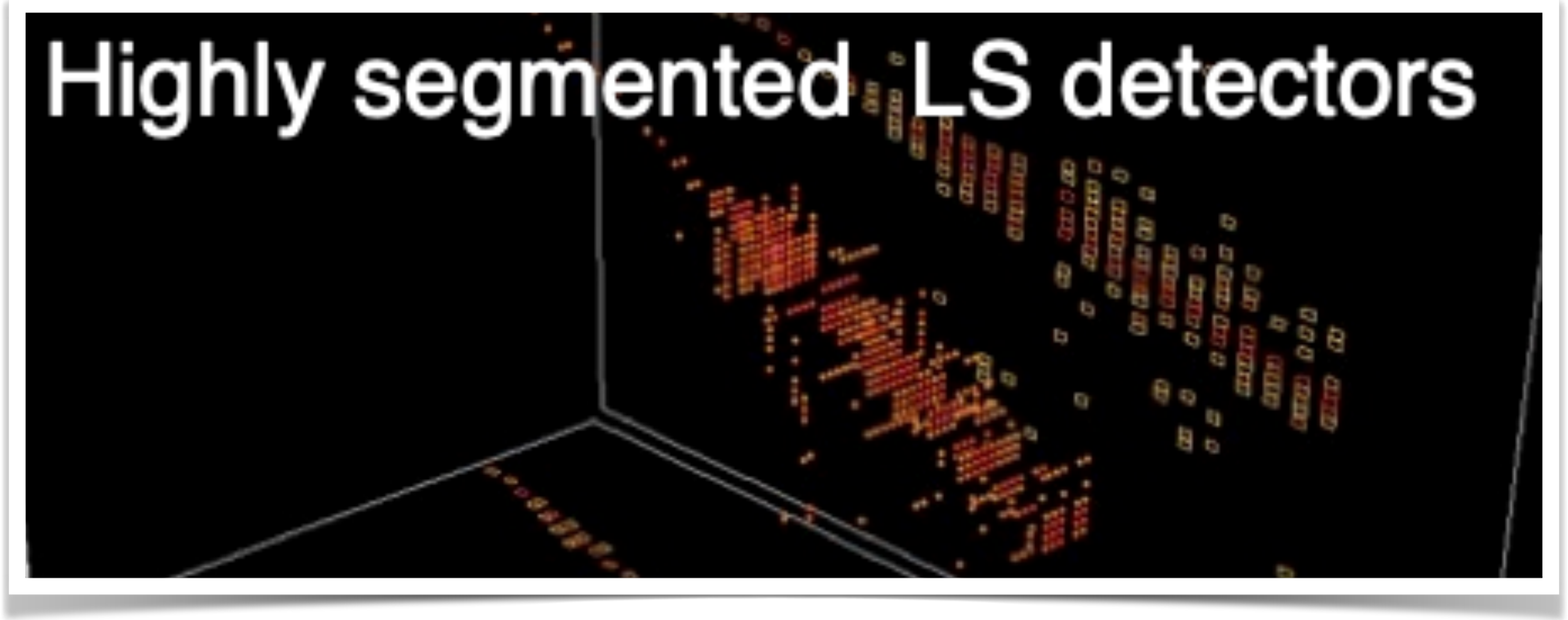
Editor's Suggestion

KamNet-enabled Background Rejection

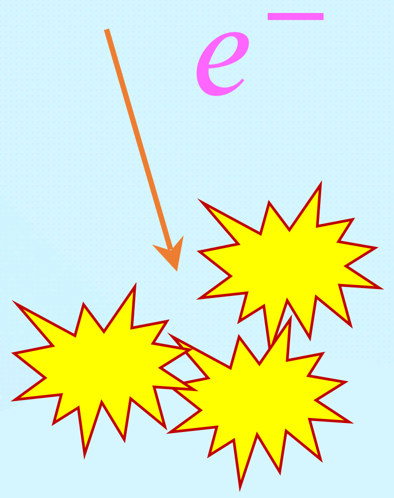
Monolithic LS detector has been at the heart of many great discoveries in neutrino physics …



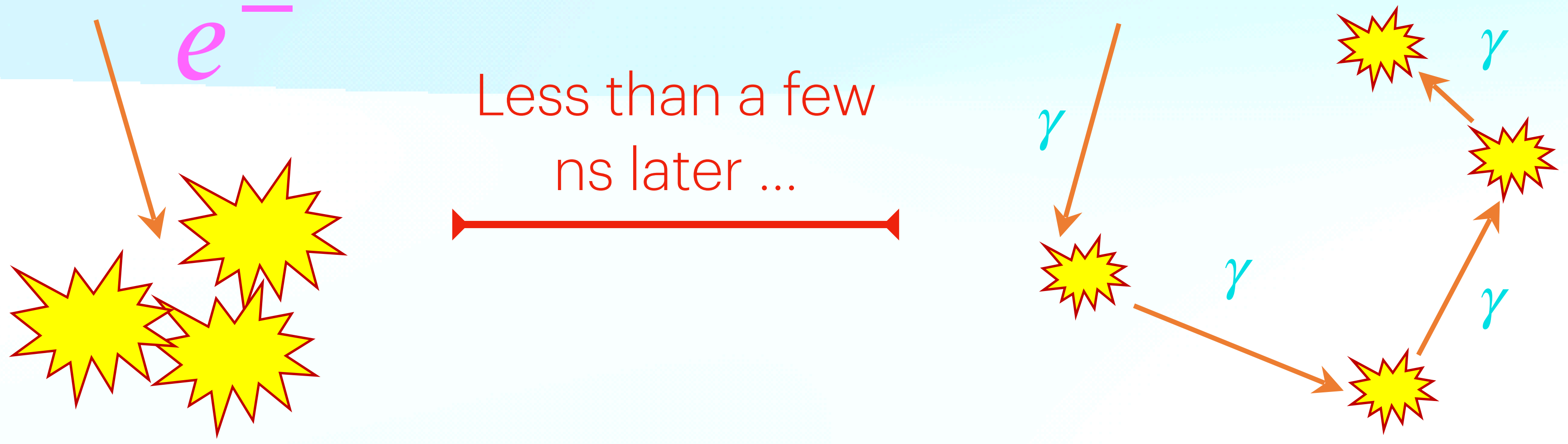
“ Enhancing **monolithic LS detectors** with the capability to discriminate between different event types based on **tracking** and/or **event topology** would be a revolutionary advancement “

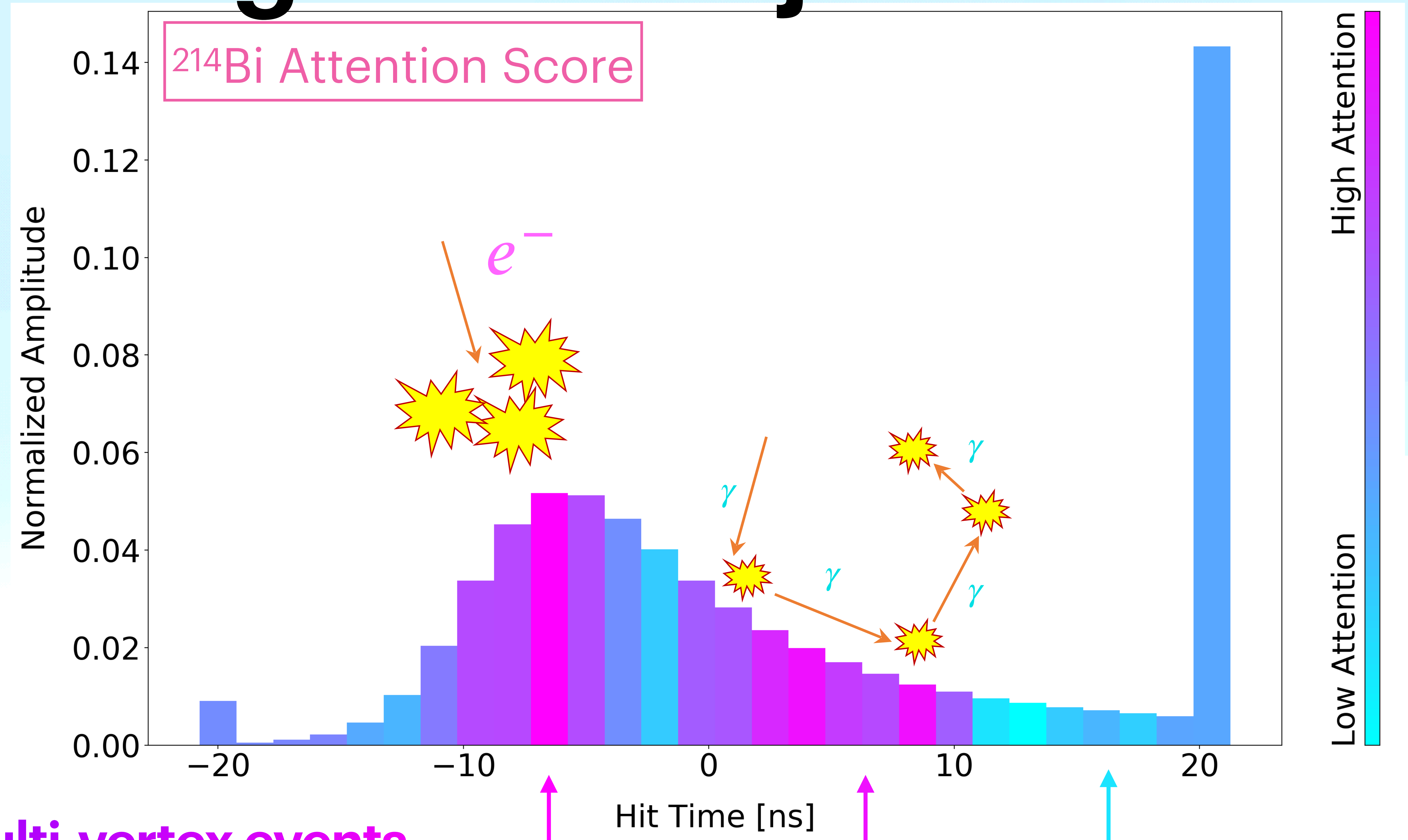


KamNet-enabled Background Rejection



- 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

High Attention: Important

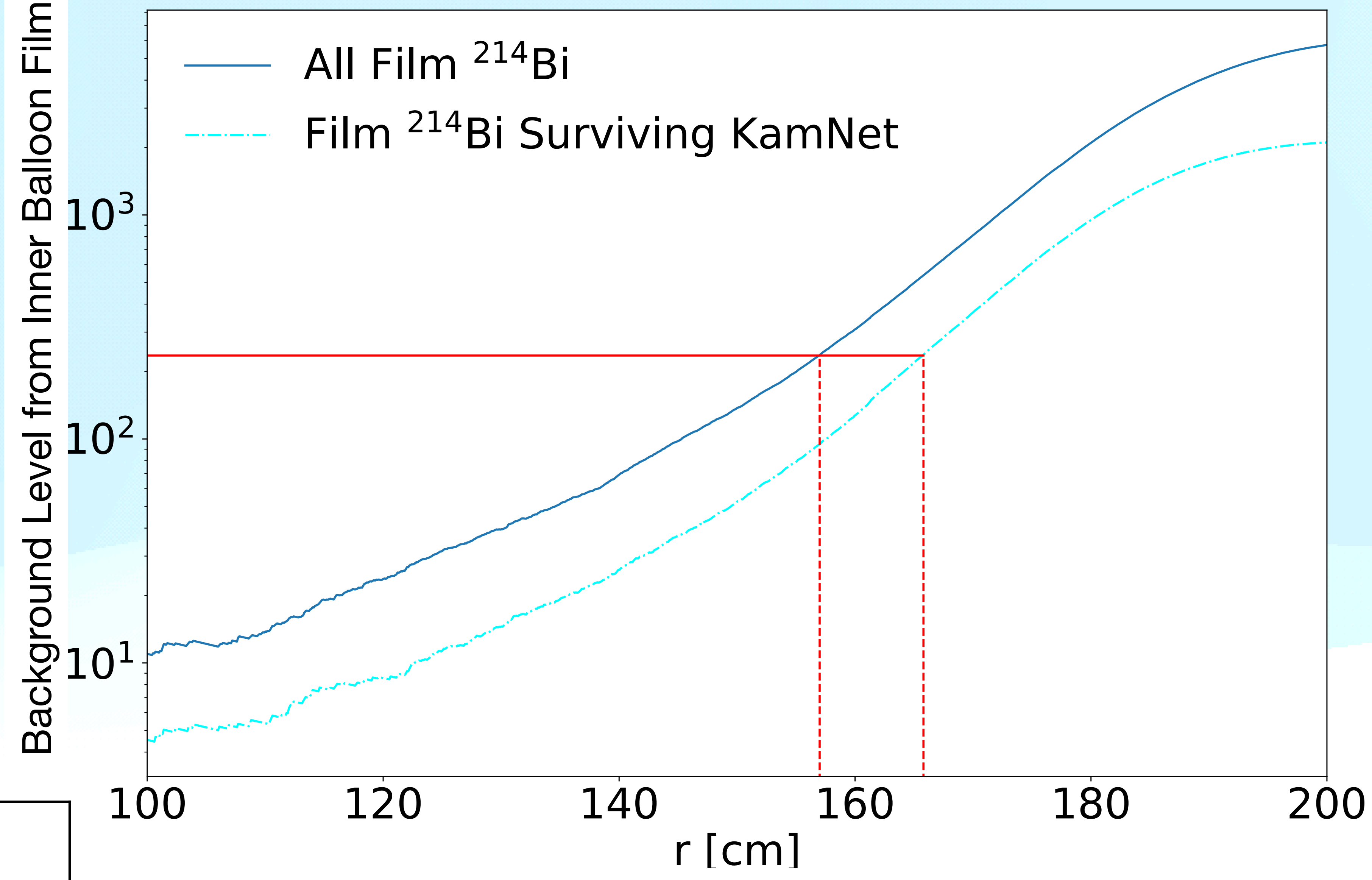
Low Attention: Unimportant

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

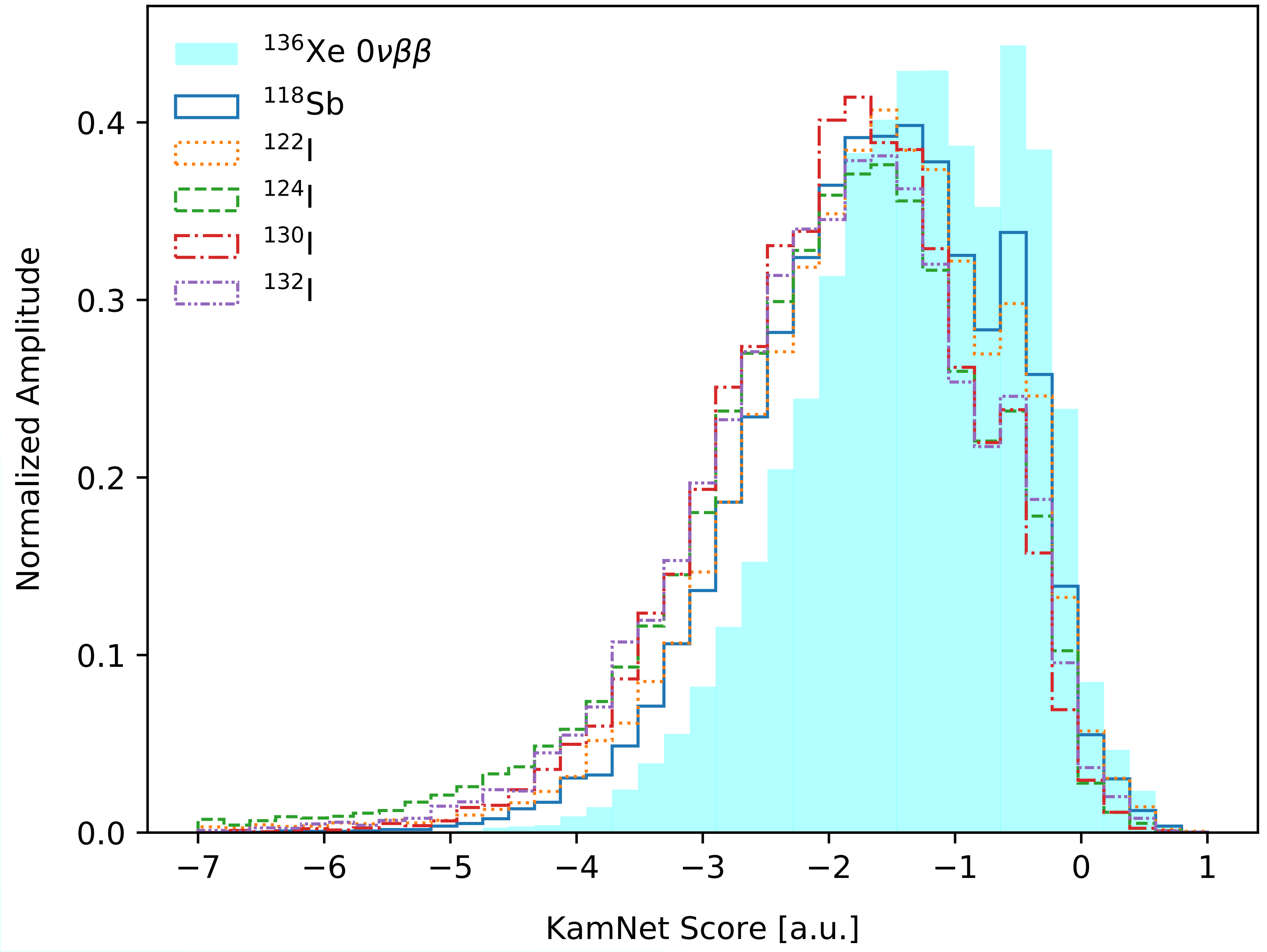
KamNet-enabled Background Rejection

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

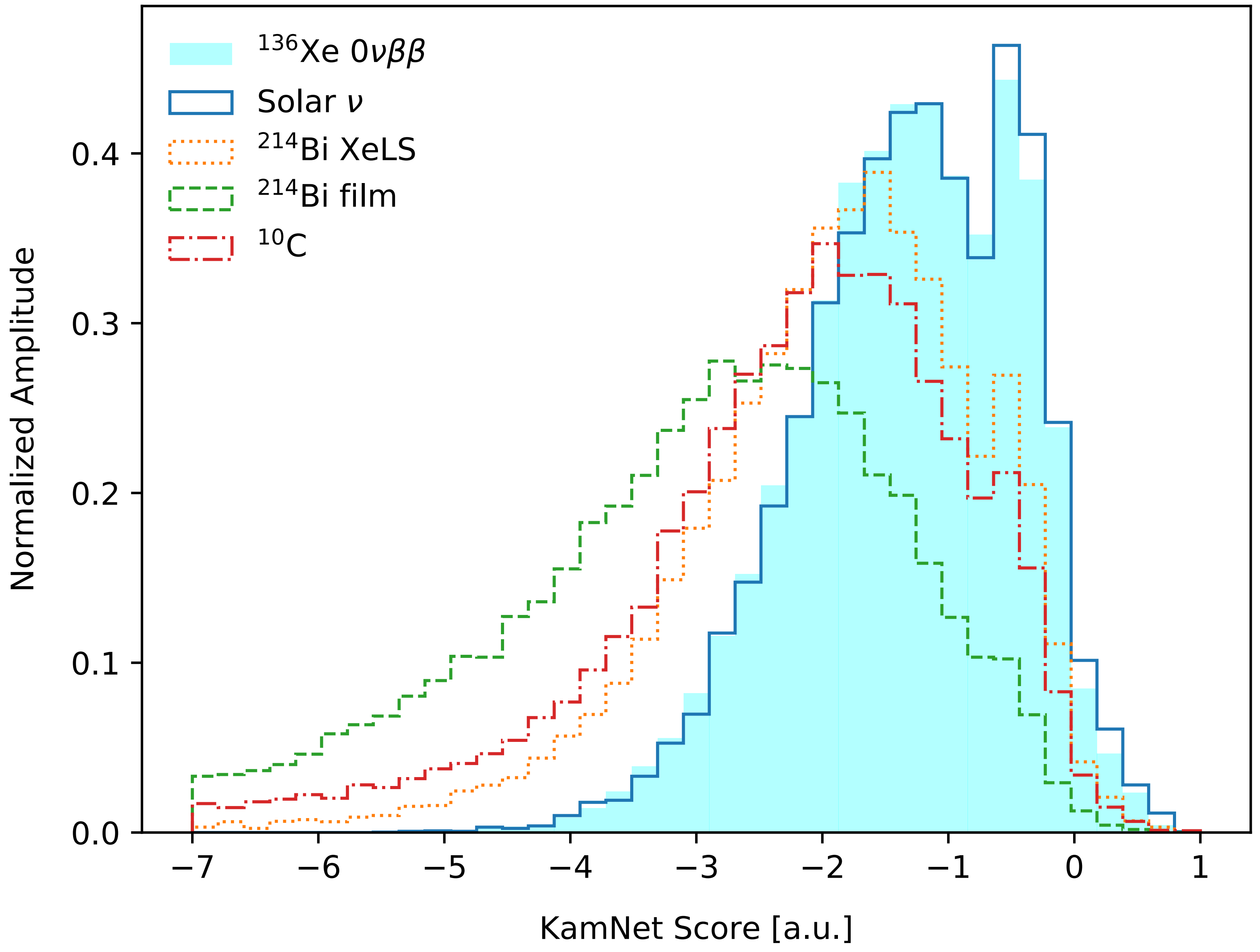
KamNet is **independent** and **multiplicative** to all existing background rejection methods in KamLAND-Zen



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:

970 kg·yr

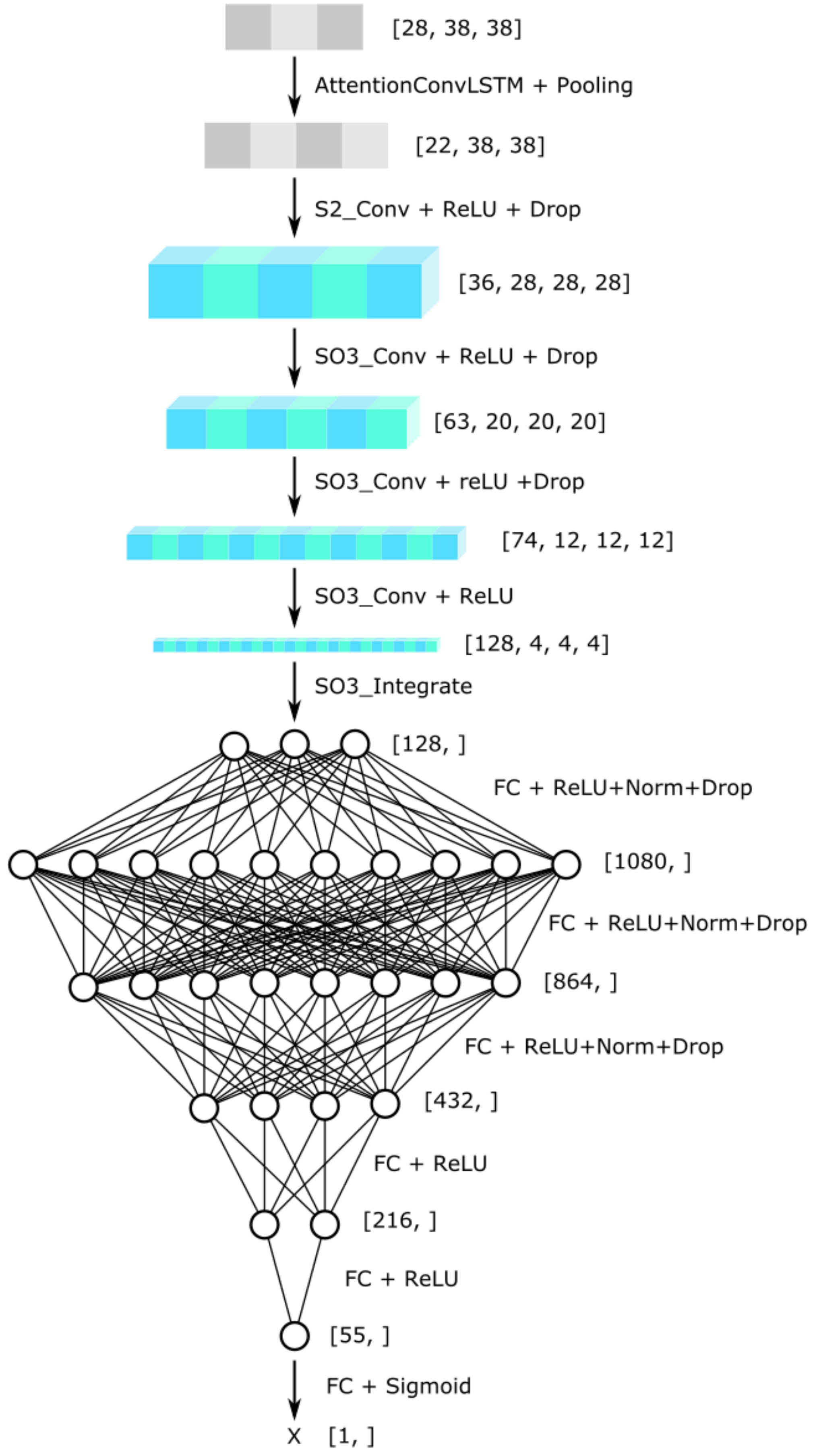
Apply KamNet to High-Background Period Only:

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

Official KamLAND-Zen 800 Limit:

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

American Physical Society
2023 Dissertation Awards
In Nuclear Physics



Exposure After KamNet:

1142 kg·yr **+17.7%**

Worth $2.5 million!!!

(Based on 2010 Xe price)

Official KamLAND-Zen 800 Limit:

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

KLZ Combined Official Limit:

$$T^{0\nu\beta\beta}_{1/2} > 2.3 \times 10^{26}\text{yr}\ (90\,\%\ \text{C.L.})$$

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

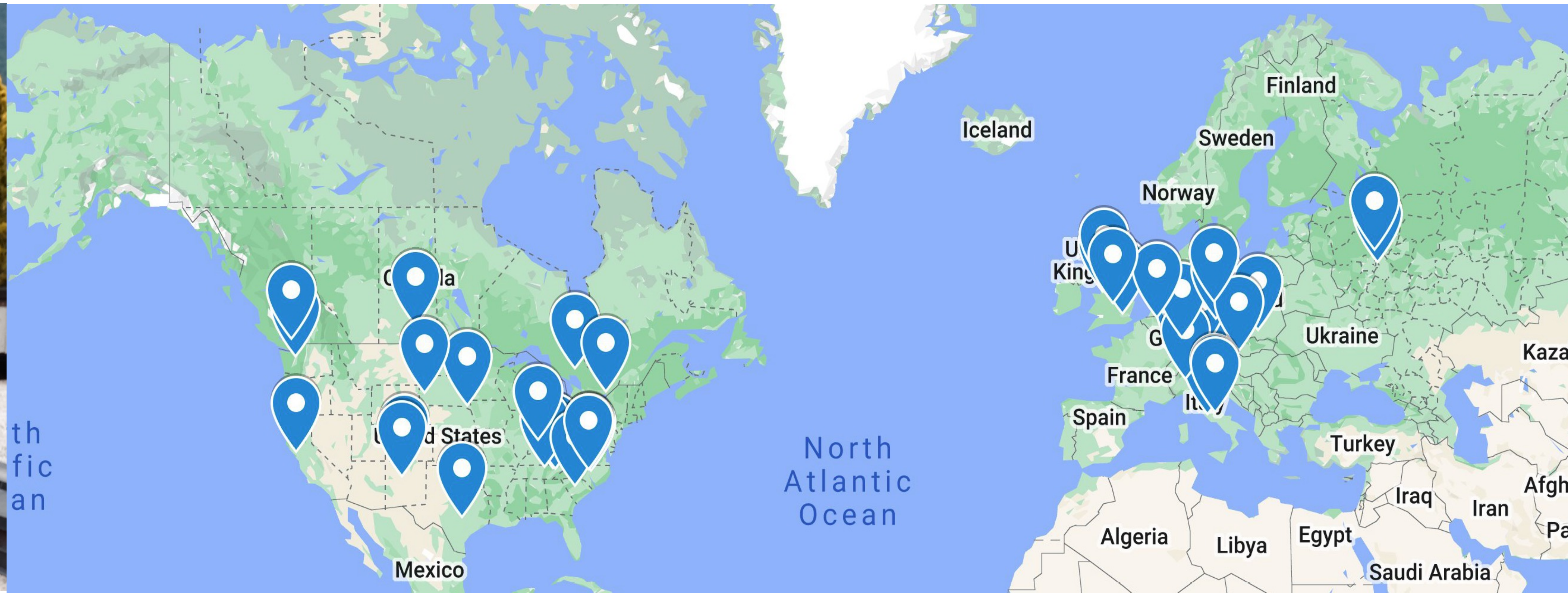
Apply KamNet to All Data:

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

Large **E**nriched **G**ermanium **E**xperiment for **N**eutrinoless ββ **D**ecay – LEGEND

56 Institutions, about 270 scientists

LEGEND collaboration meeting @ LNGS, 15-17.5.2017



> LEGEND mission: "The collaboration aims to develop a phased, ^{76}Ge based double-beta decay experimental program with **discovery potential** at a half-life beyond 10^{28} years, using existing resources as appropriate to expedite physics results."

Univ. New Mexico
L'Aquila Univ. and INFN
Univ. Texas, Austin
Lawrence Berkeley Natl. Lab.
Univ. California, Berkeley
Leibniz Inst. Crystal Growth
Univ. of Indiana
Comenius Univ.
Simon Fraser Univ.
Univ. of North Carolina
Univ. of South Carolina
Tennessee Tech.
Univ. of Warwick
Jagiellonian Univ.
Tech. Univ. – Dresden
Joint Inst. Nucl. Res. Inst.
Duke Univ.
Triangle Univ. Nuclear. Lab.
Joint Res. Centre, Geel
Max Planck Inst., Heidelberg
Queen's Univ.
Univ. Tennessee
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Lab. Naz. Gran Sasso
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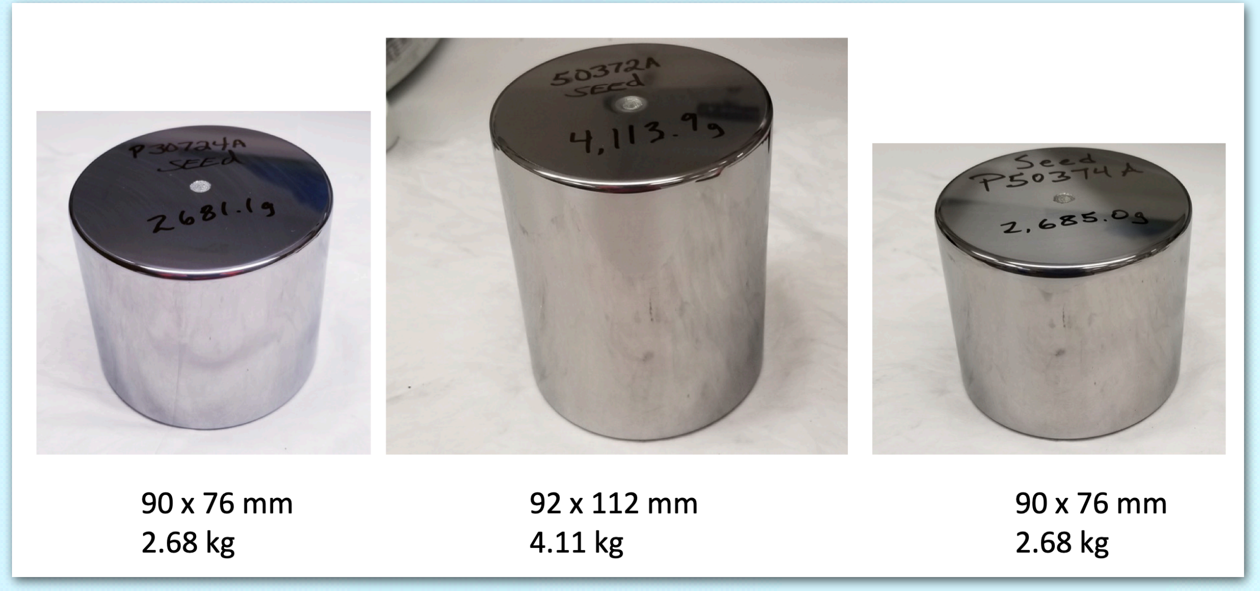
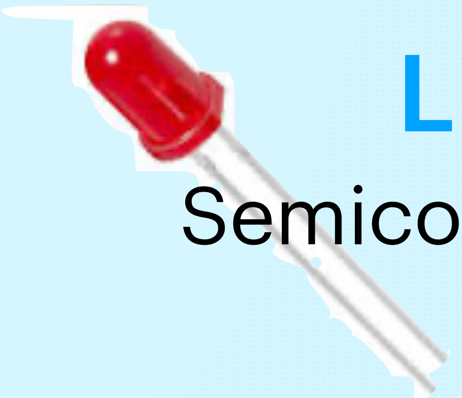
Sept.26, 2022

Speaker Aobo Li

LEGEND

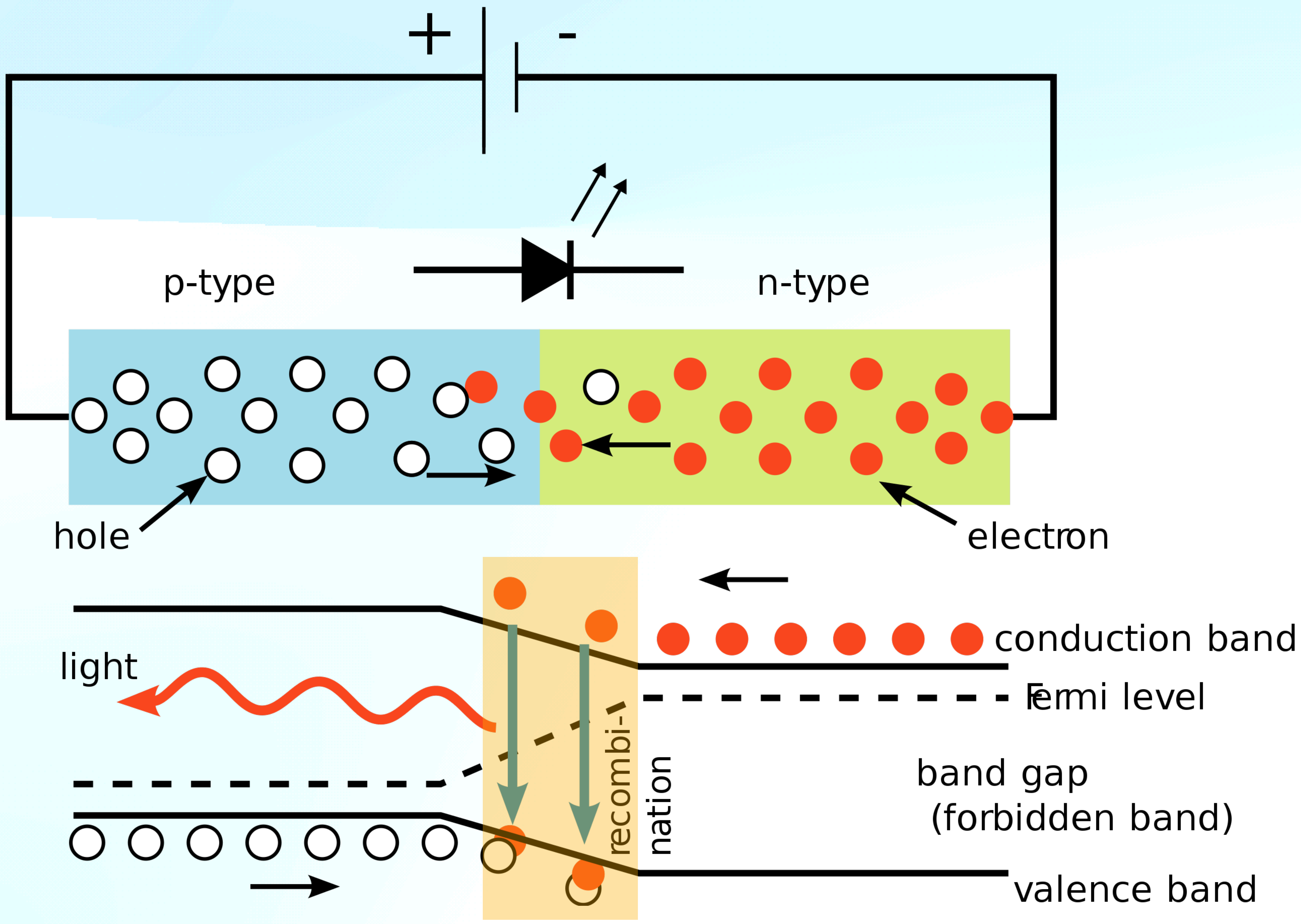
HPGe Detector Array Experiment for $0\upsilon\beta\beta$ Search





Light Emitting Diode (LED)

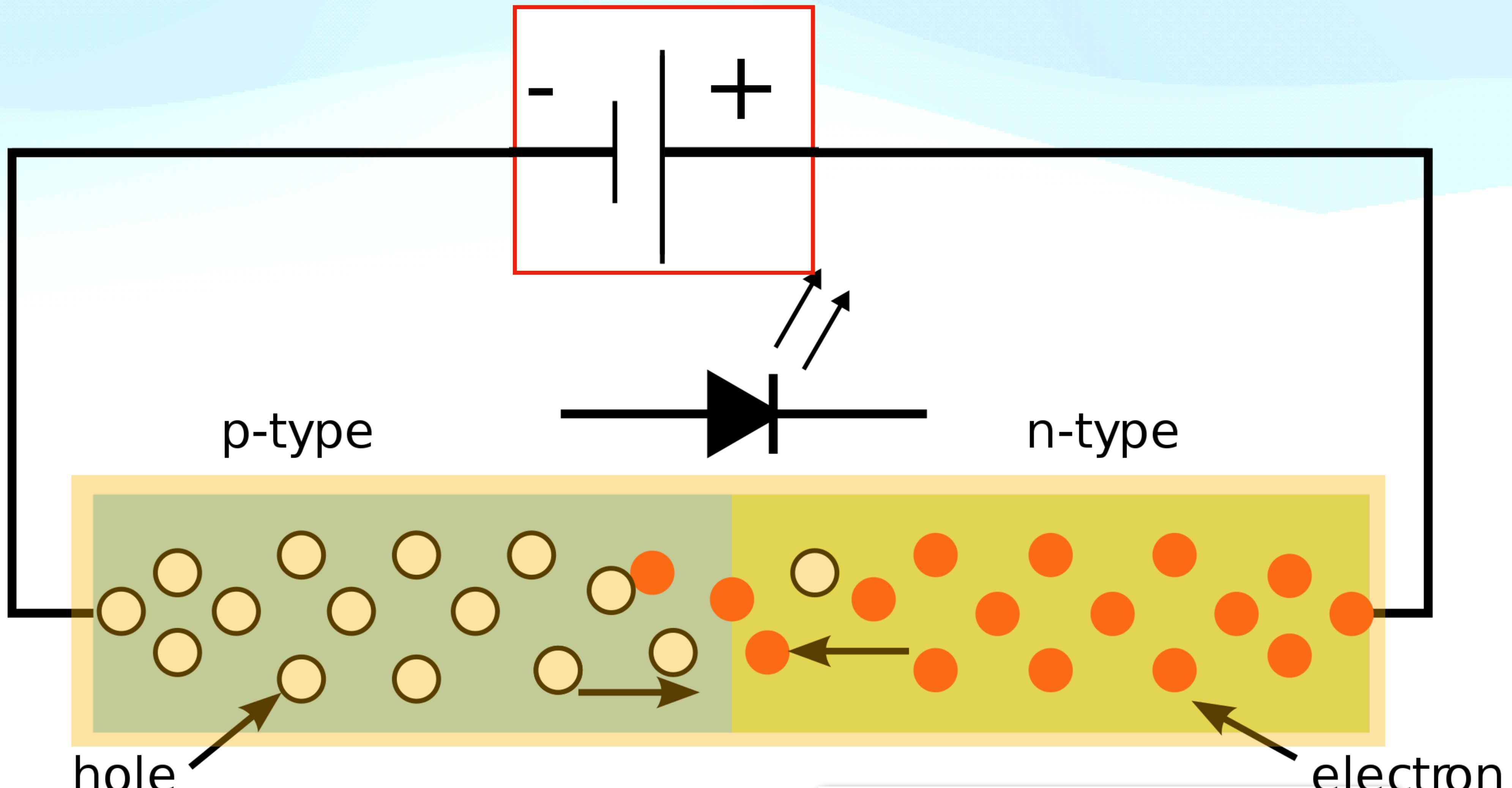
Semiconductor device with a **depletion region**



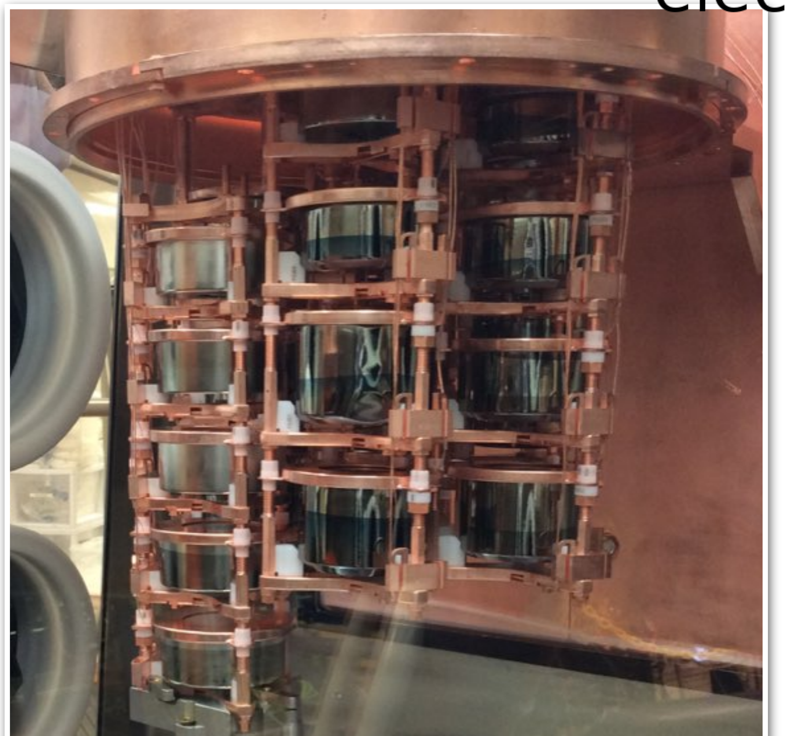
High Purity Ge Detector (HPGe)

^{76}Ge is a double-beta decay isotope

Reverse Bias: increase the size of **depletion region**



Detector Array

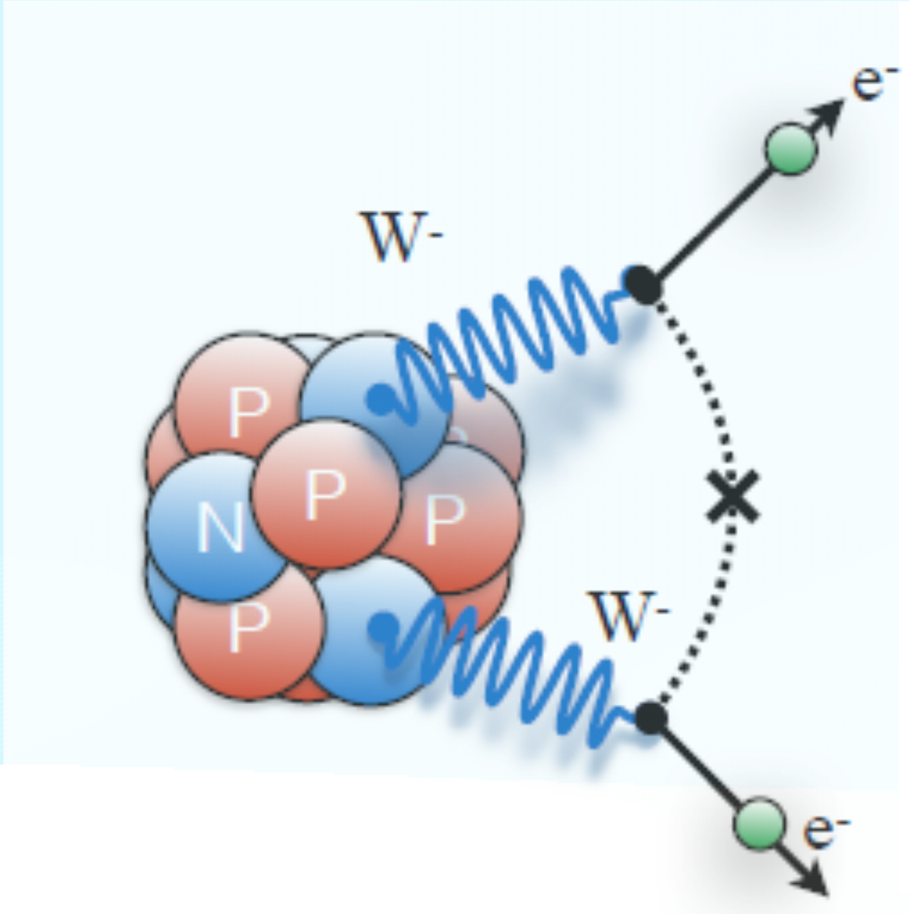


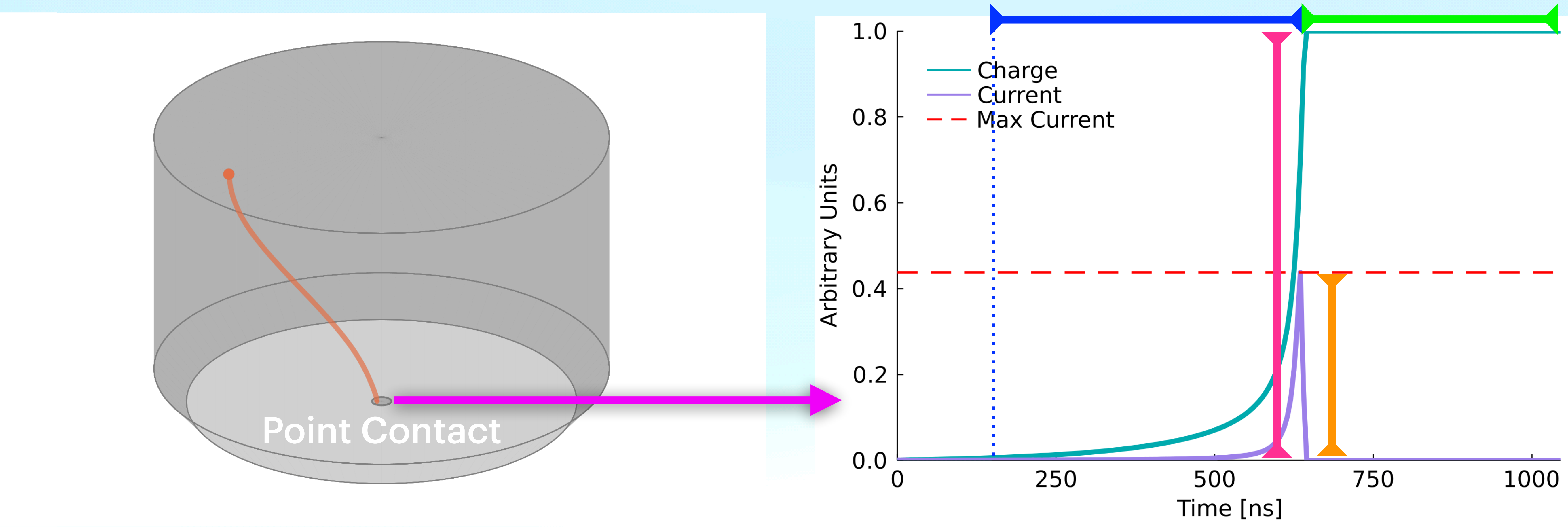
LEGEND data

Ge Detector Depletion Region

Waveform

Pulse Shape Parameter

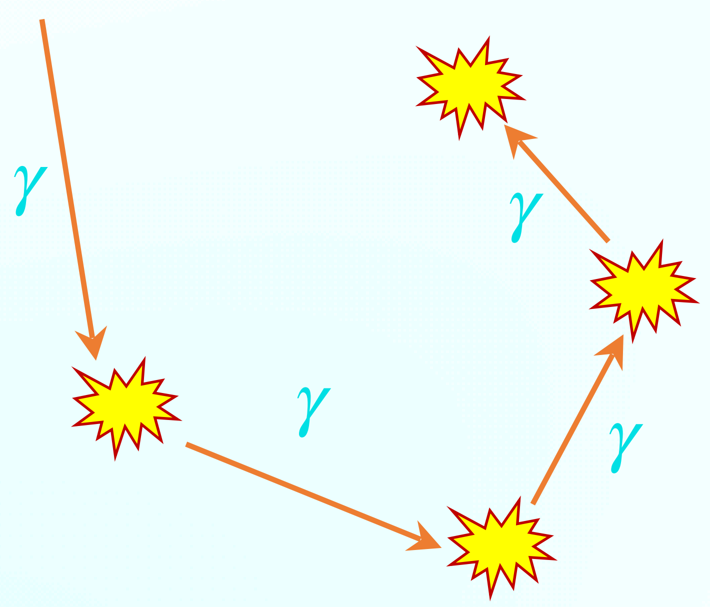


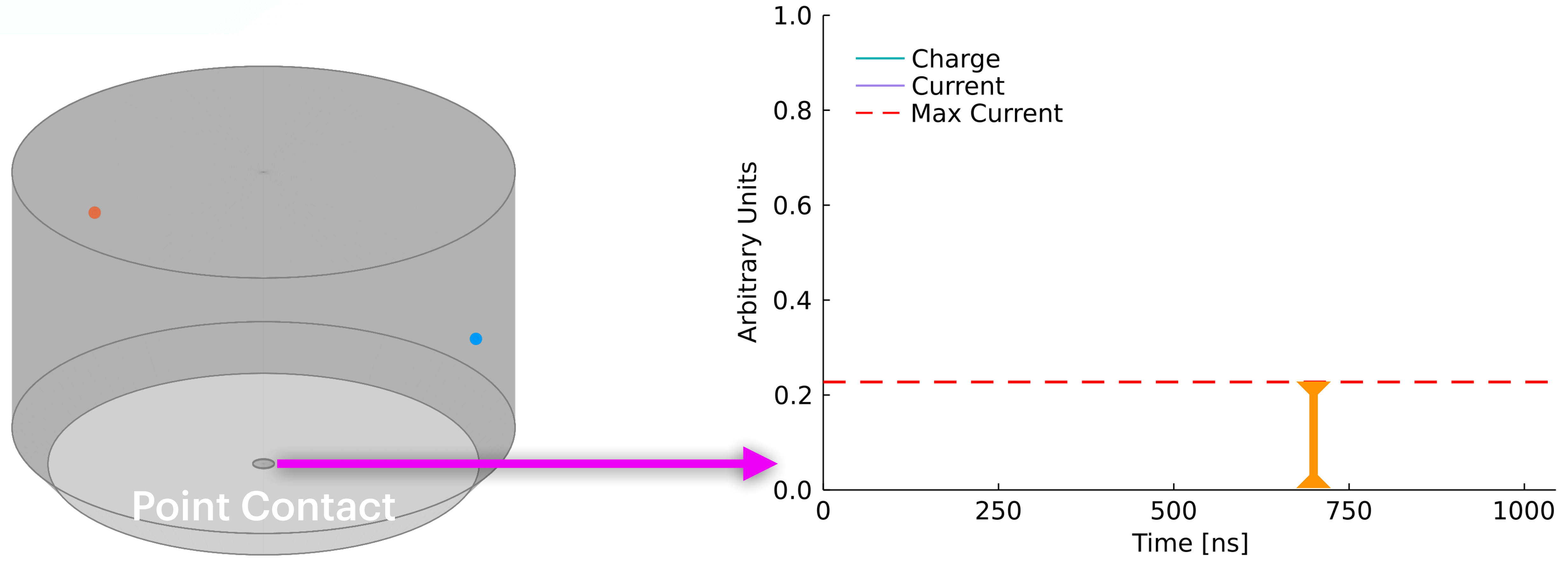


Tail Slope

For **surface background** rejection

Energy





Maximal Current Amplitude

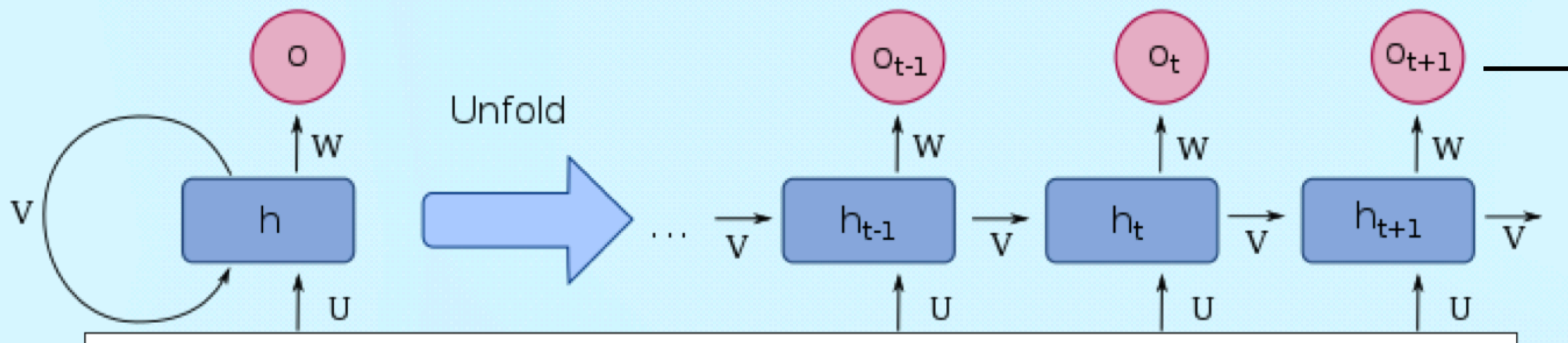
For **multi-site background** rejection

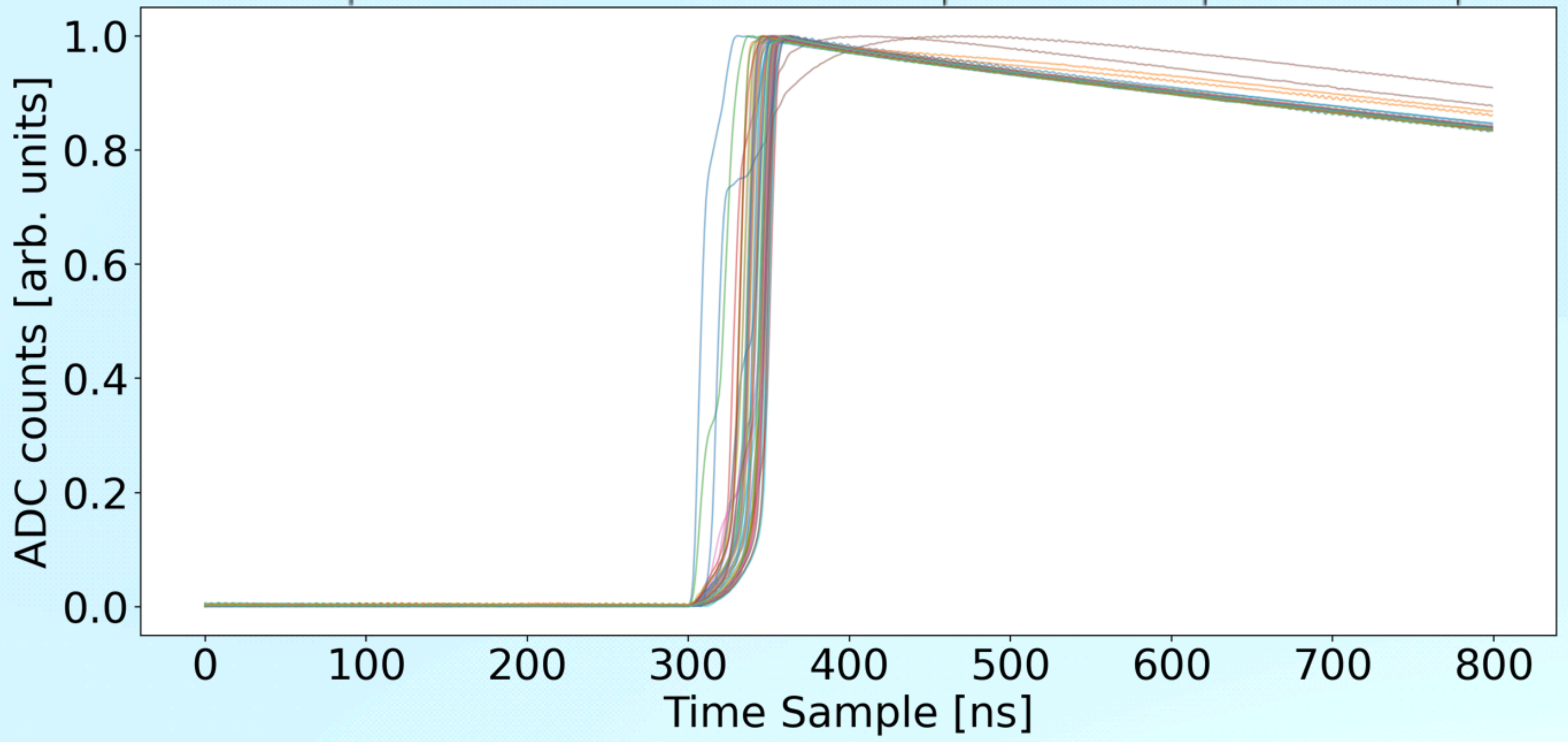
Drift Time

Reflect the location of incident particle

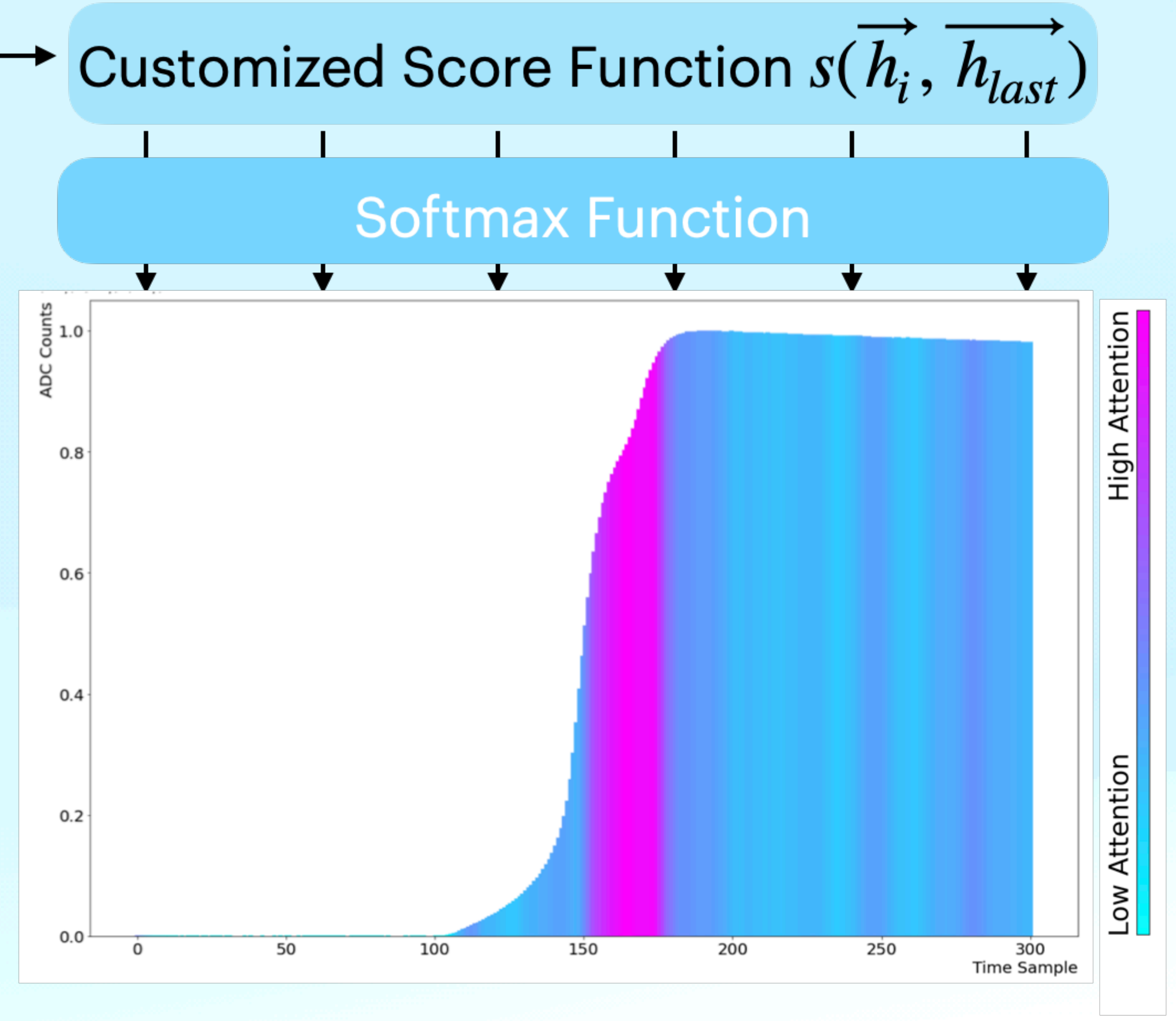
LEGEND Baseline Model

Long-Short Term Memory (LSTM) Network





Attention Mechanism



Customized Score Function $s(\overrightarrow{h_i}, \overrightarrow{h_{last}})$

Softmax Function

Background Rejection

Hooking a fully connected network( ) to the LEGEND baseline model to identify and reject background

Interpretable

Allow students to see where LBM pays attention to to make decision

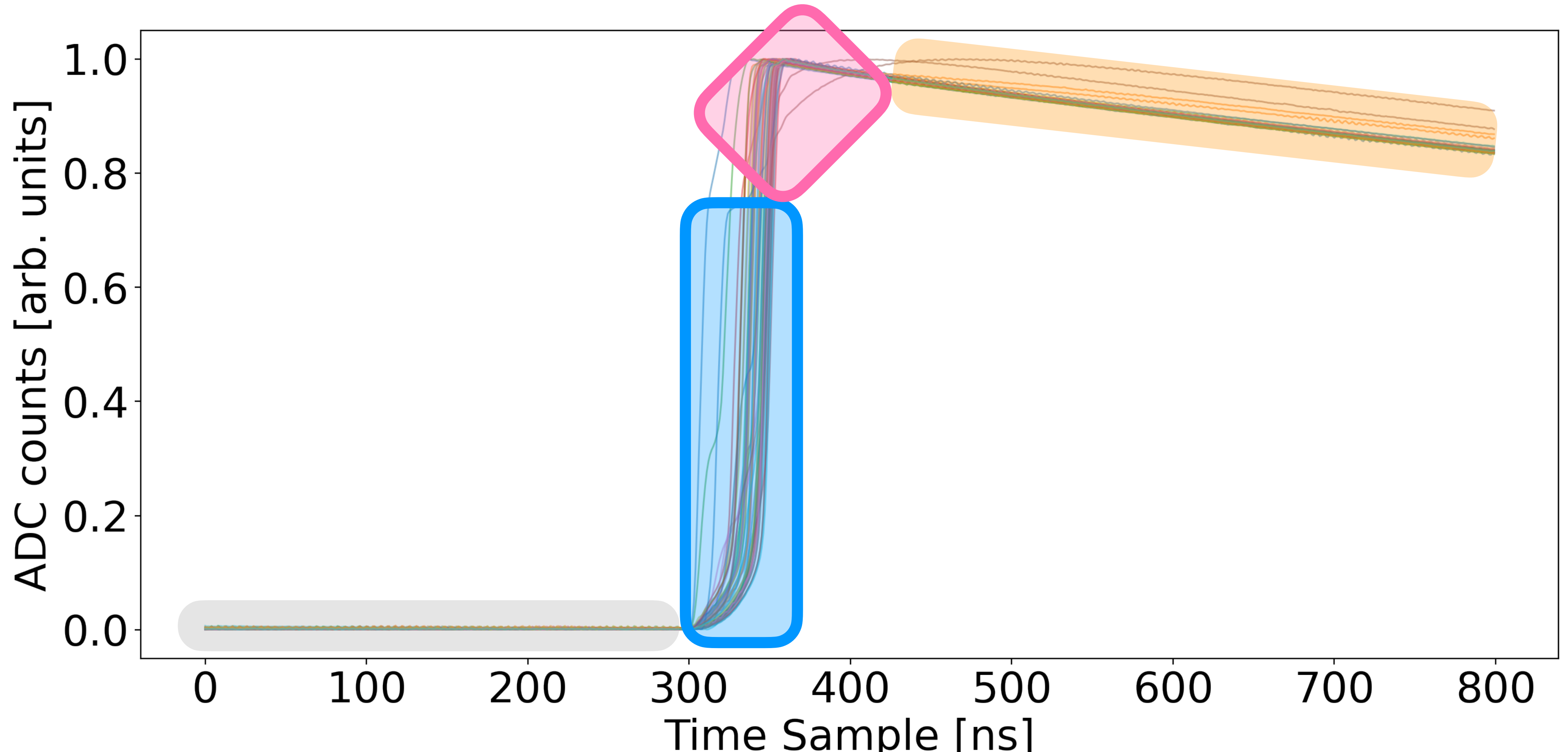
Improve LEGEND Baseline Model

Upper turning edge: Critical

Waveform tail: Irrelevant

Rising edge: Critical

baseline: Bias



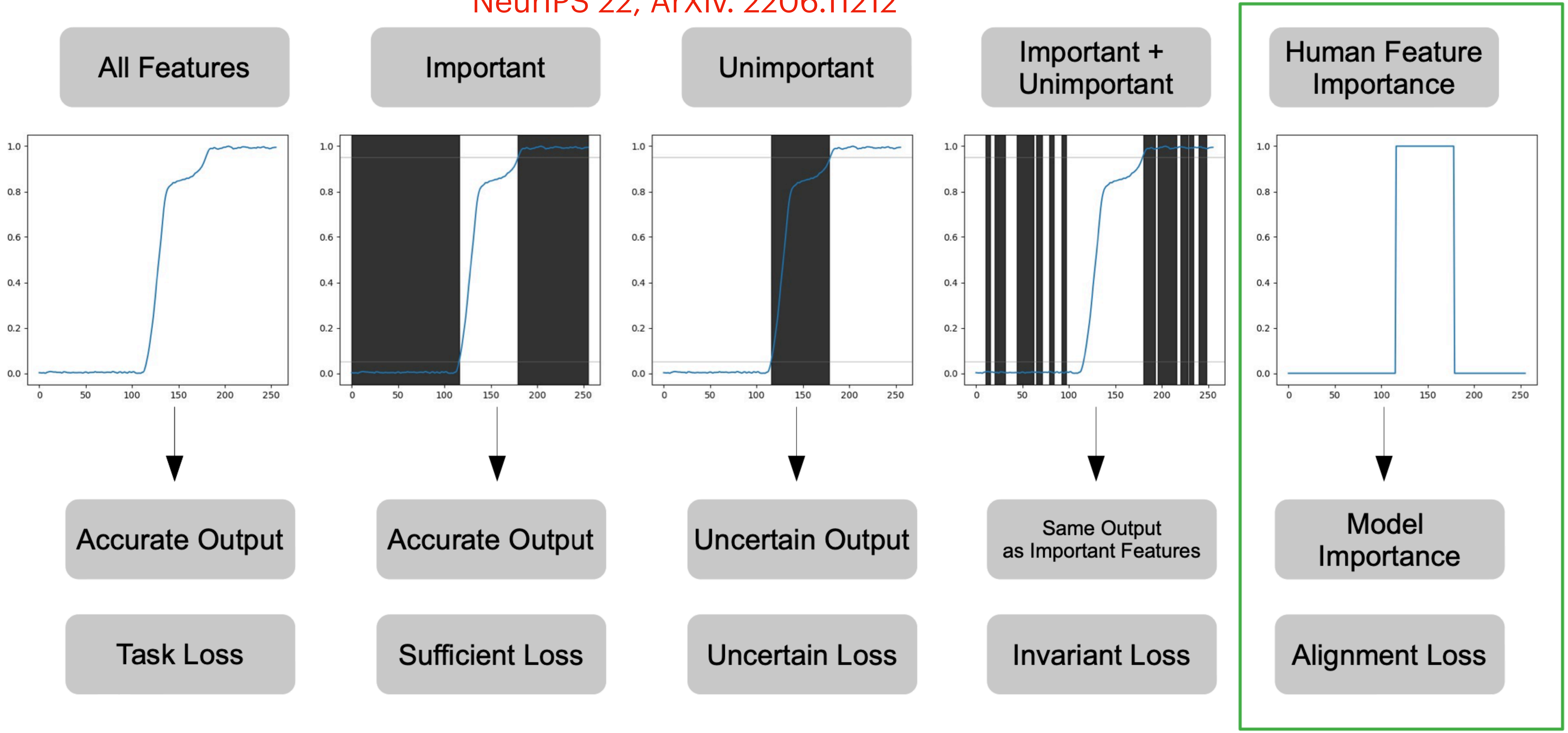
Feature Importance Supervision (FIS)

Guide ML model to be Right for the Right Reason

Z. Ying, P. Hase, M. Bansal

NeurIPS 22, ArXiv. 2206.11212

About the explanation metric



All Features → Accurate Output → Task Loss

Important → Accurate Output → Sufficient Loss

Unimportant → Uncertain Output → Uncertain Loss

Important + Unimportant → Same Output as Important Features → Invariant Loss

Human Feature Importance → Model Importance → Alignment Loss

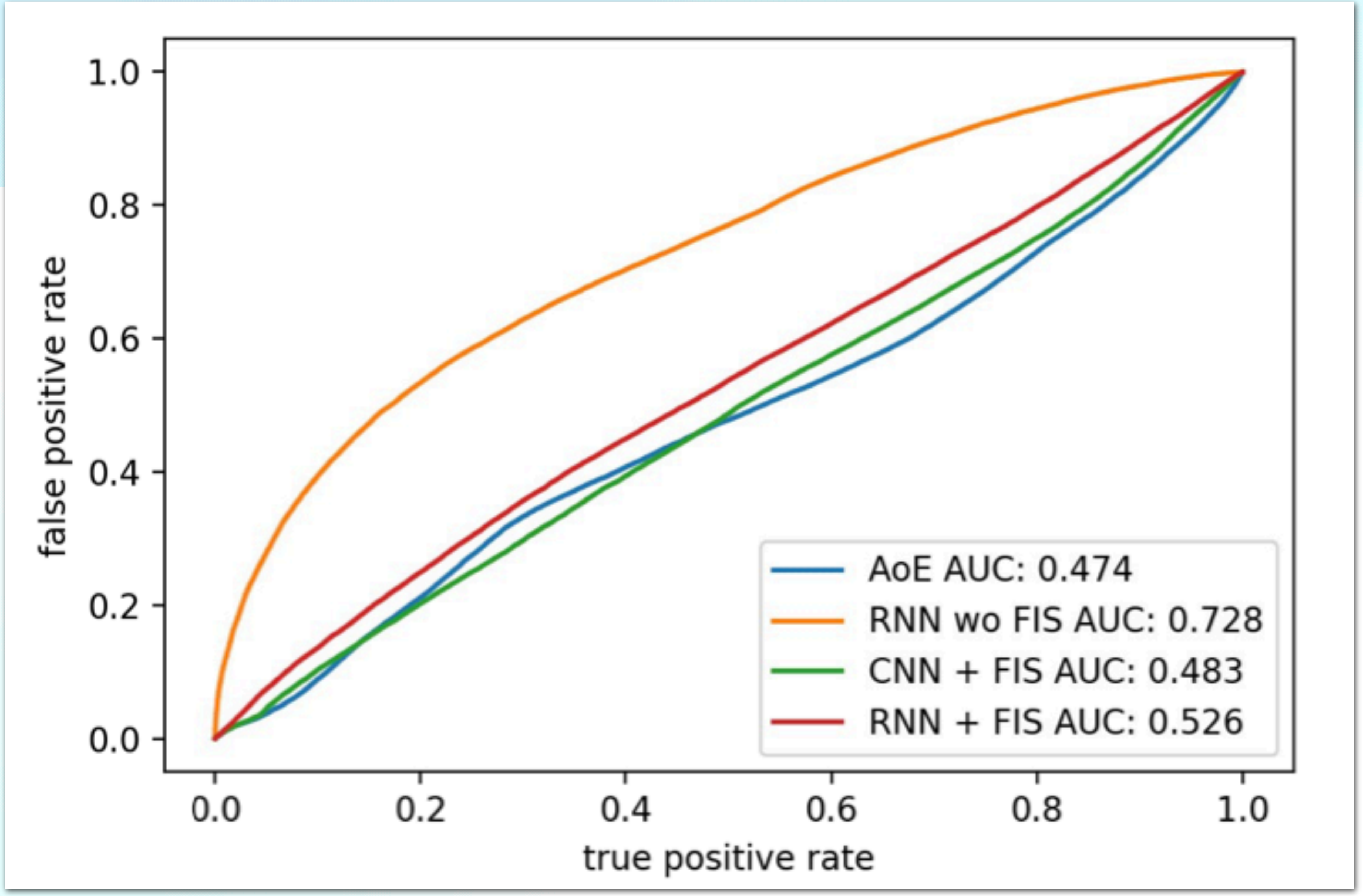
Feature Importance Supervision (FIS)

Guide ML model to be Right for the Right Reason

Quantifying Bias

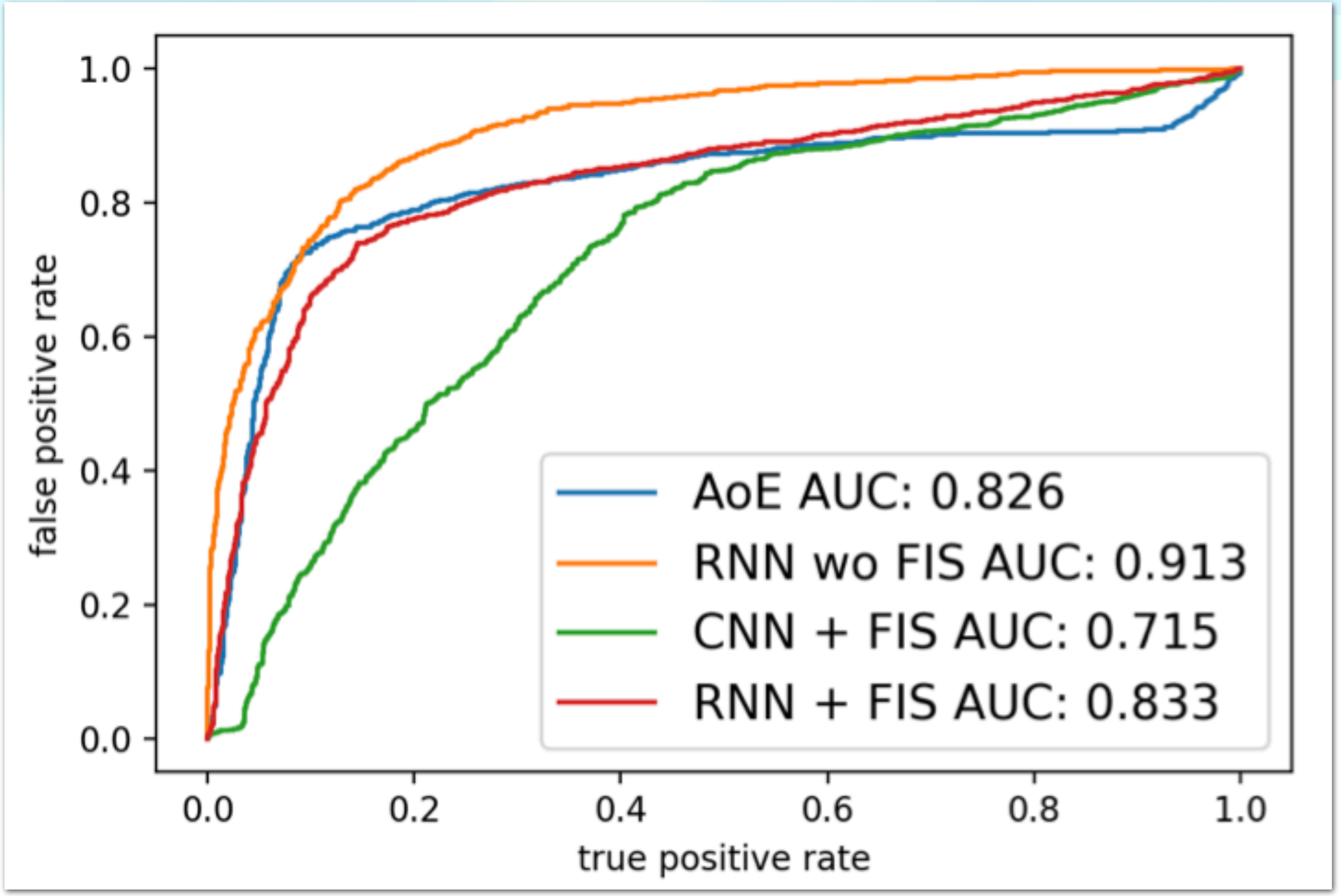
Selected dataset to test for energy dependency bias

- Biased classifier: nontrivial classification power
- Unbiased classifier: trivial classification power



Rejecting Background

Identify multi-site background in HPGe detector



XENONnT 2-Phase Liquid Xenon TPC for WIMP DM Search

Columbia
KIT
Nikhef
Muenster
Stockholm
Mainz
MPIK, Heidelberg
Freiburg
Zurich
Tsinghua

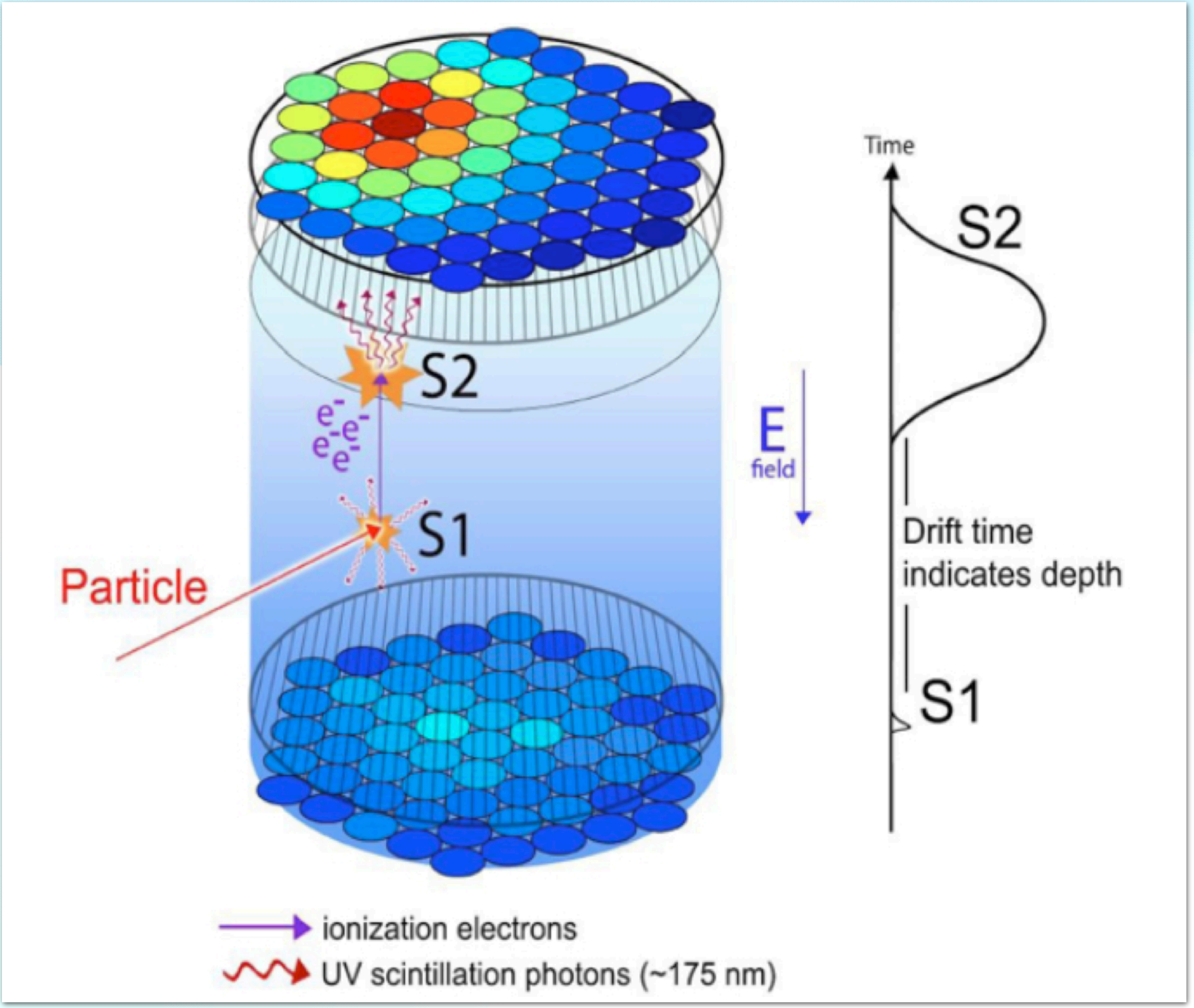
Chicago
UCSD
Rice
Purdue

Tokyo
Nagoya
Kobe
NYUAD

Subatech
Coimbra
LPNHE
IJCLab
Torino
Bologna
L'Aquila
LNGS
Napoli
Weizmann

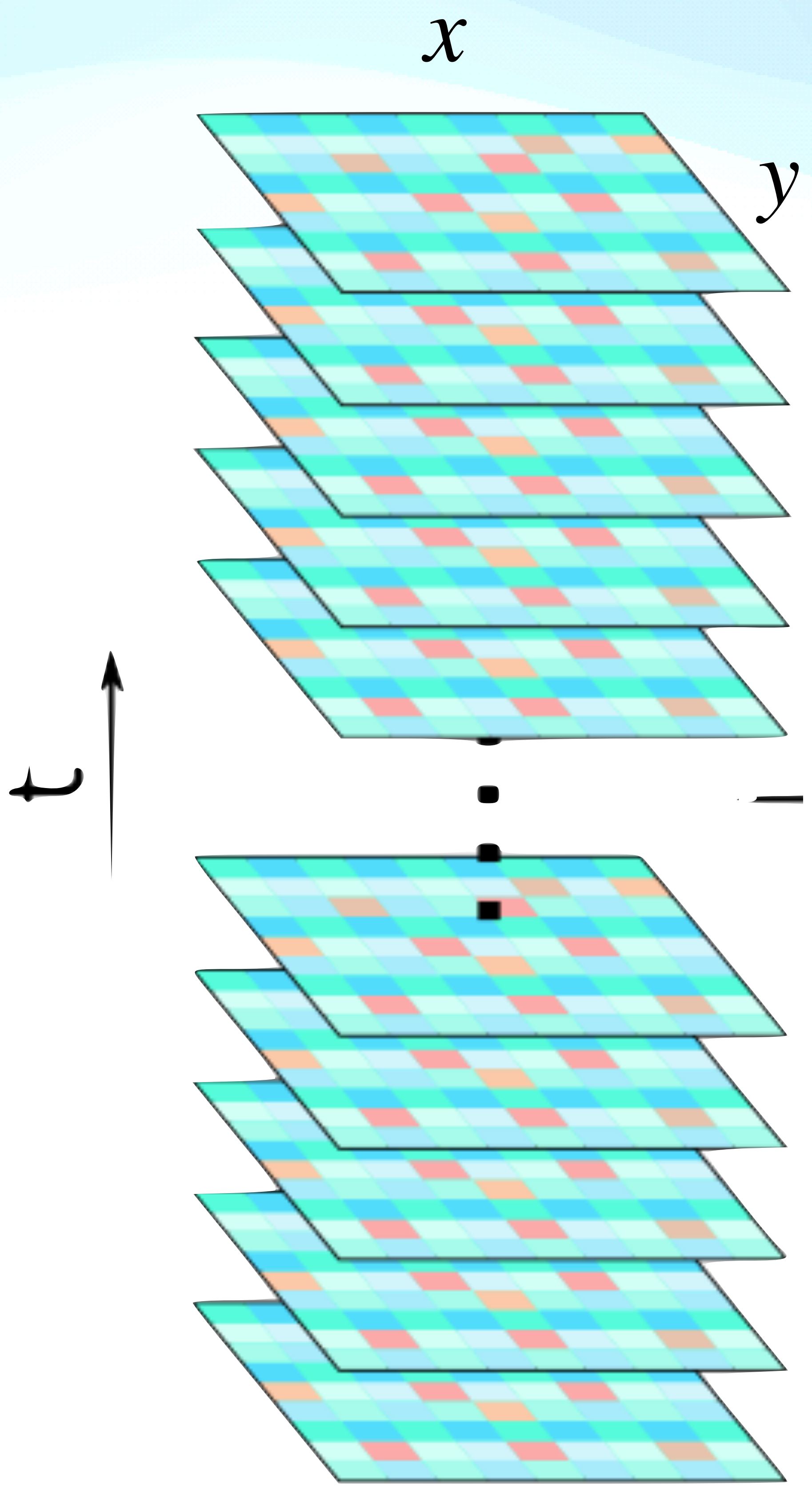
XENONnT

2-Phase Liquid Xenon Time Projection Chamber for WIMP DM Search



Spatiotemporal Data

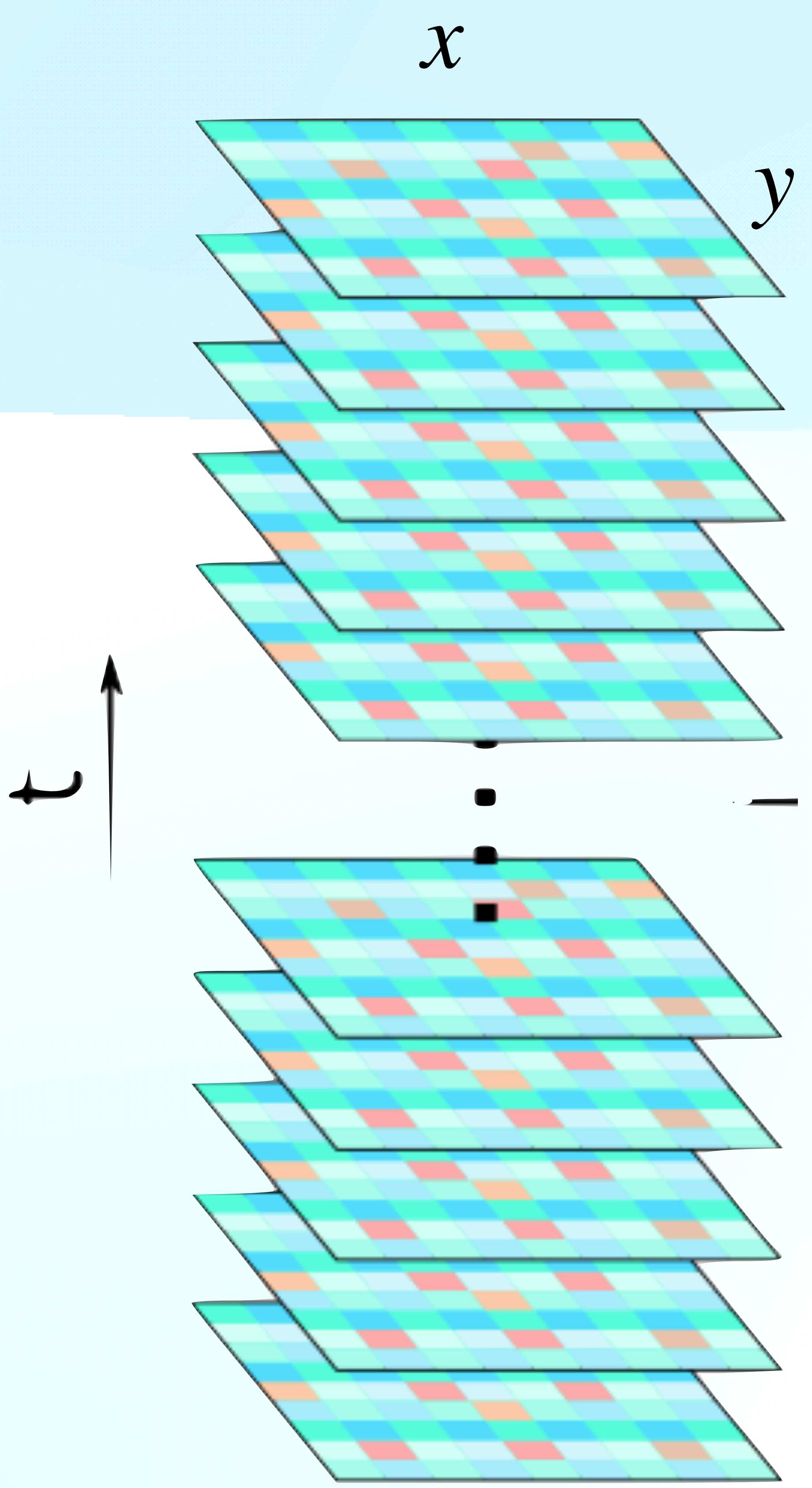
A 2D flat video



XENONnT Data

Spatiotemporal Data

A 2D flat video

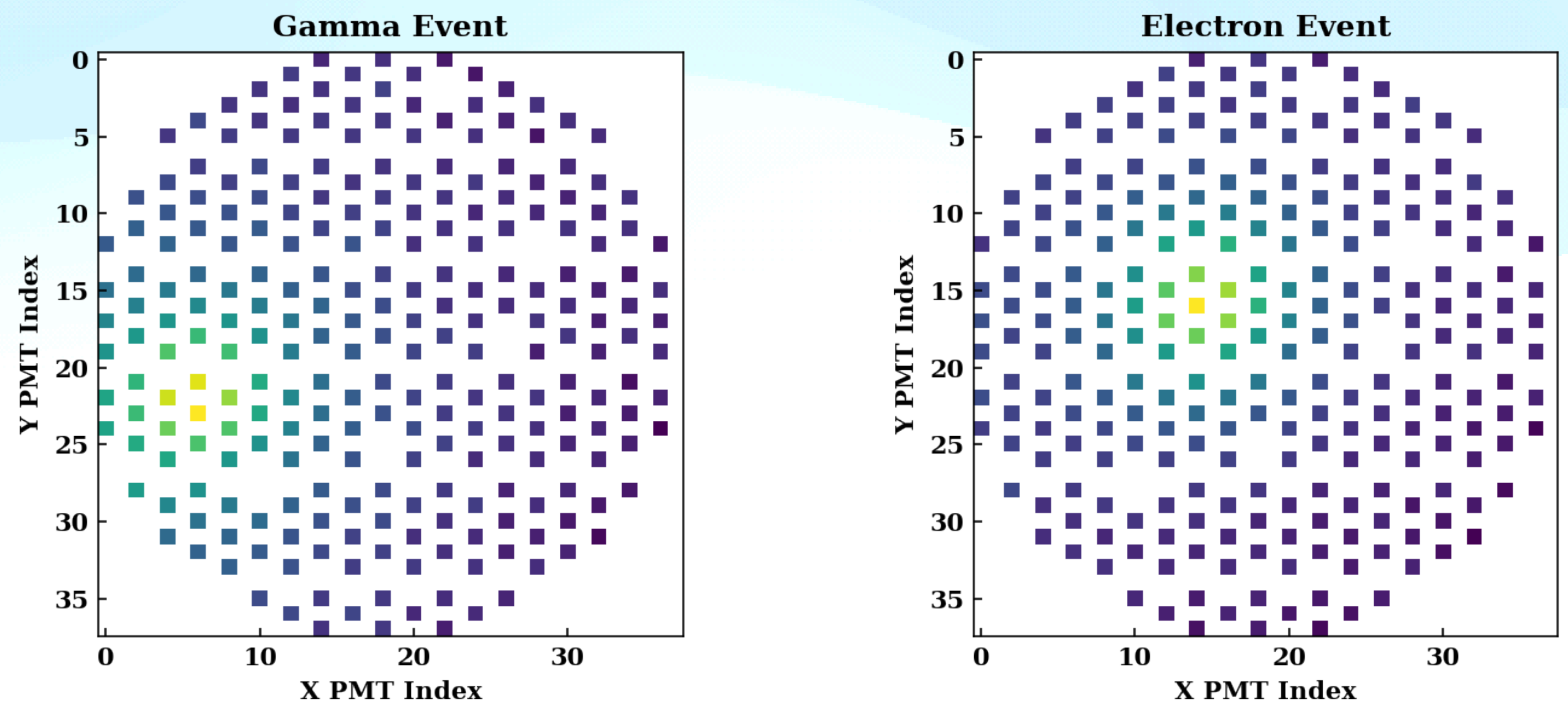


Squash along time dimension

Squash along (x,y) dimension

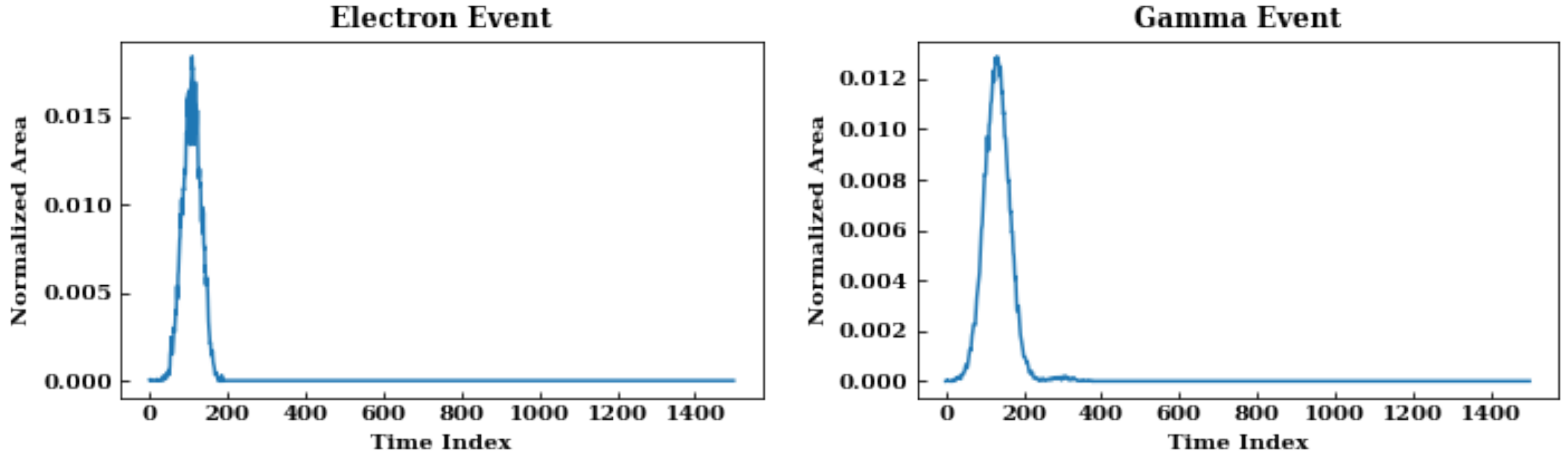
Hit Pattern

2D Image



Waveform

1D Time Series

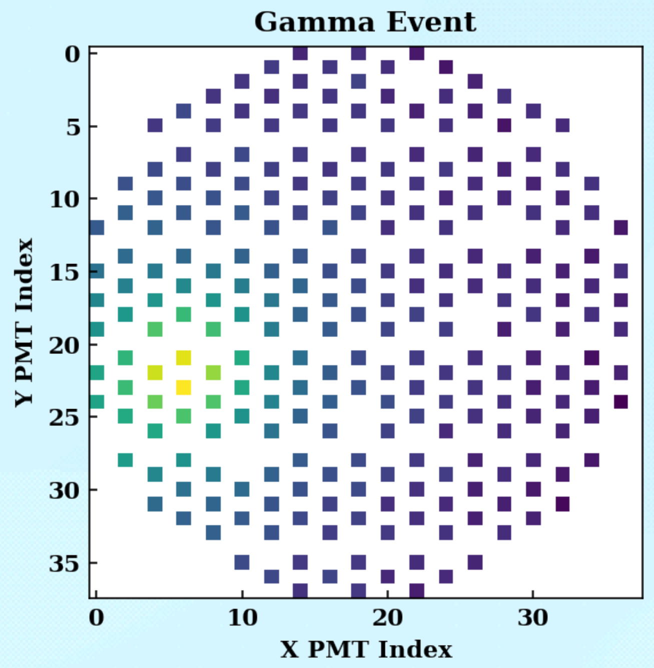


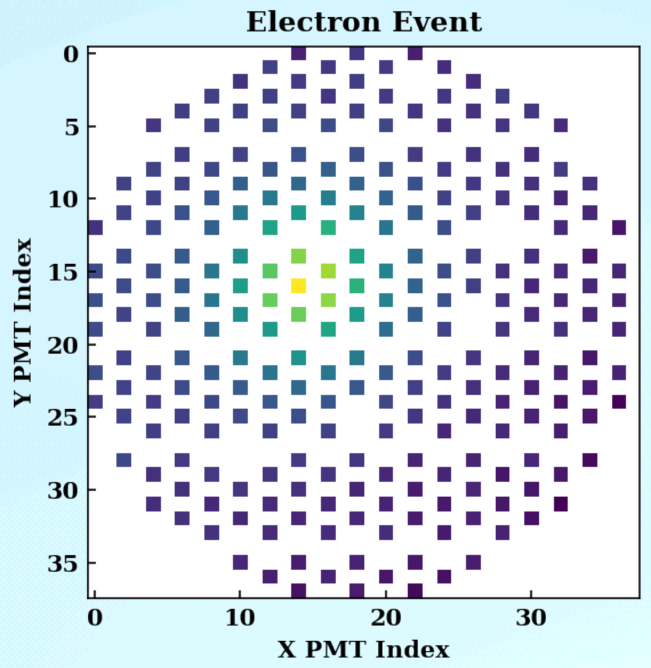
Dual Classifier

Min Zhong

Hit Pattern

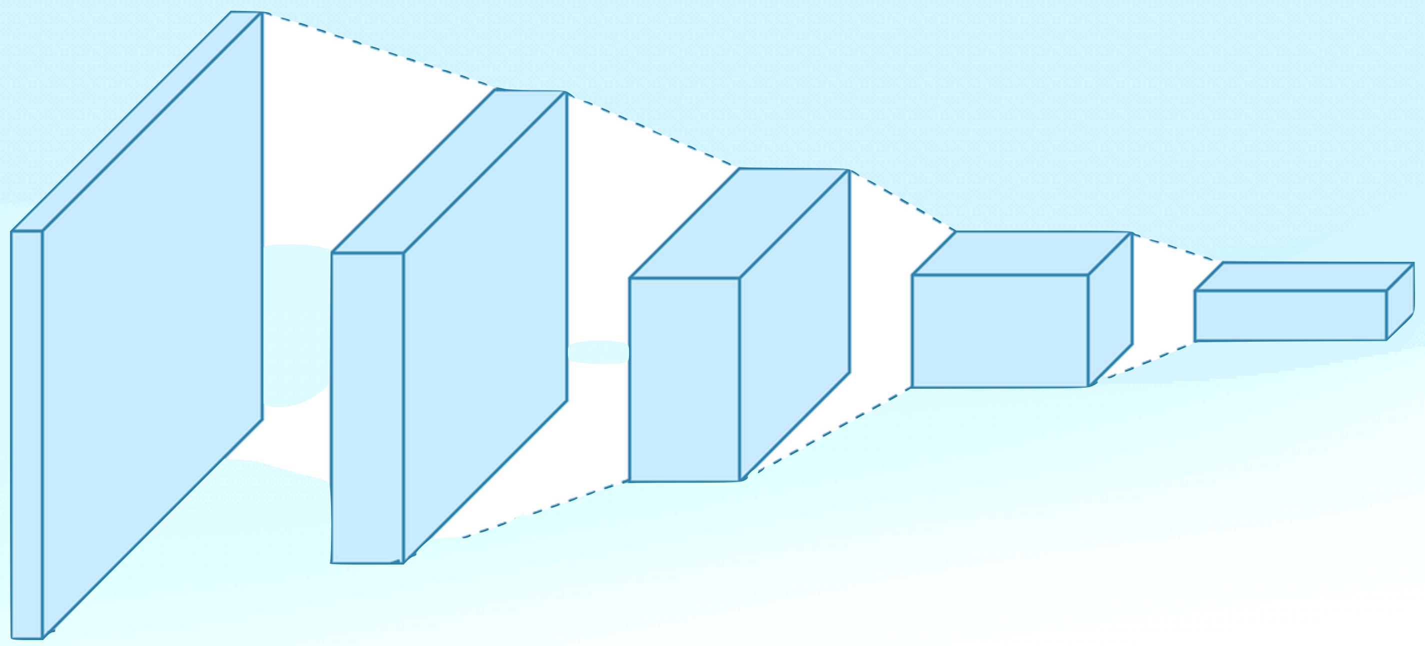
2D Image

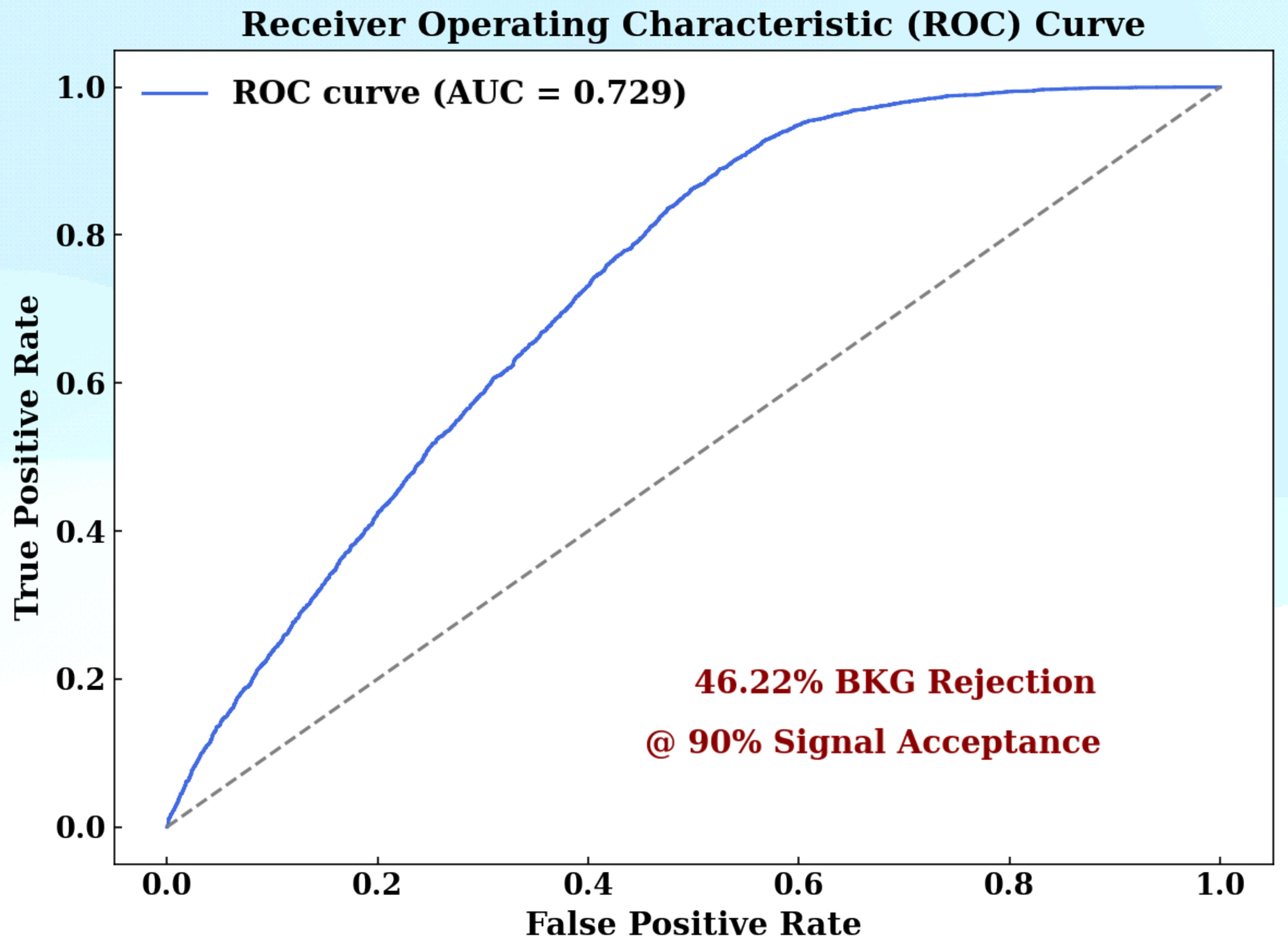




CNN

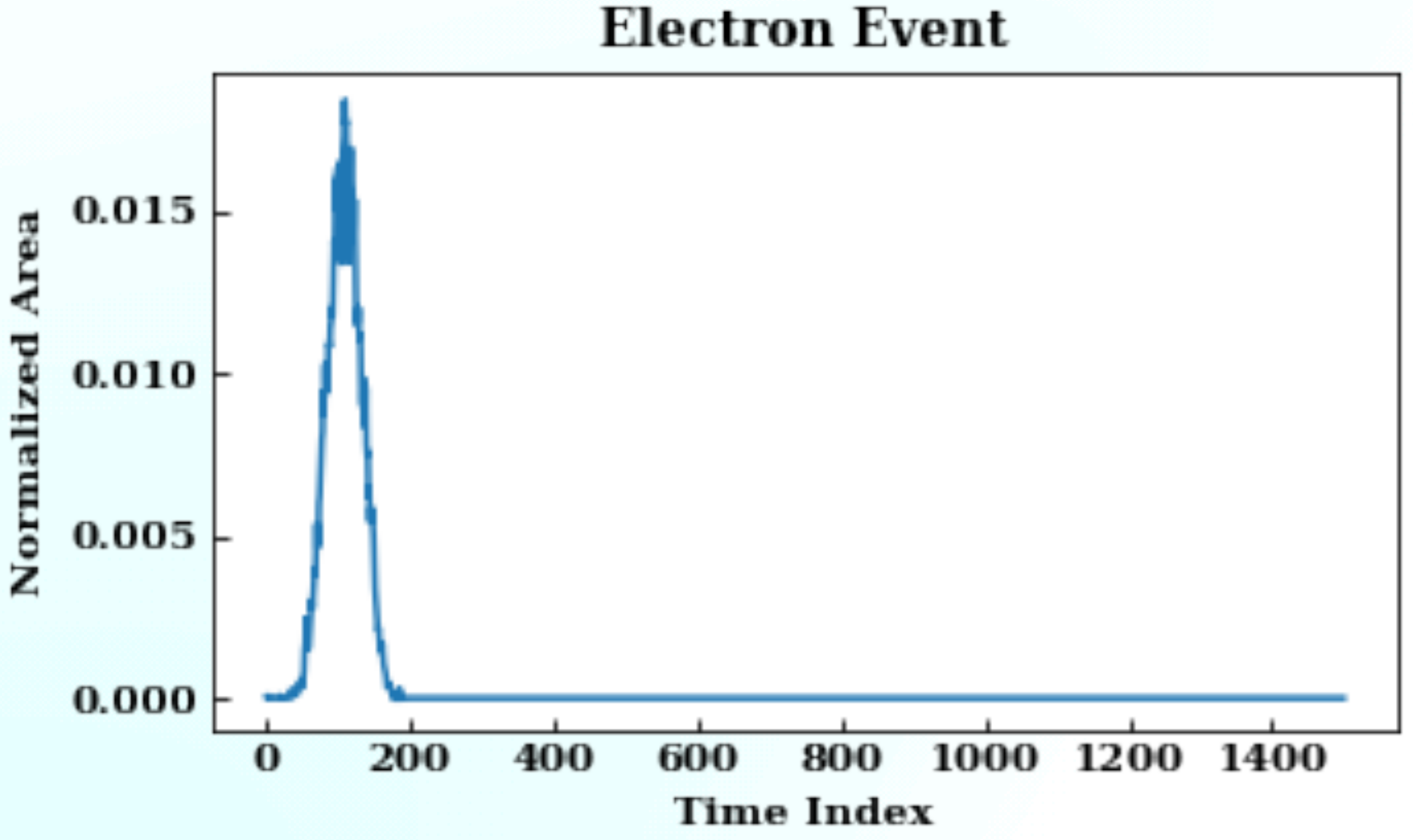
For image analysis





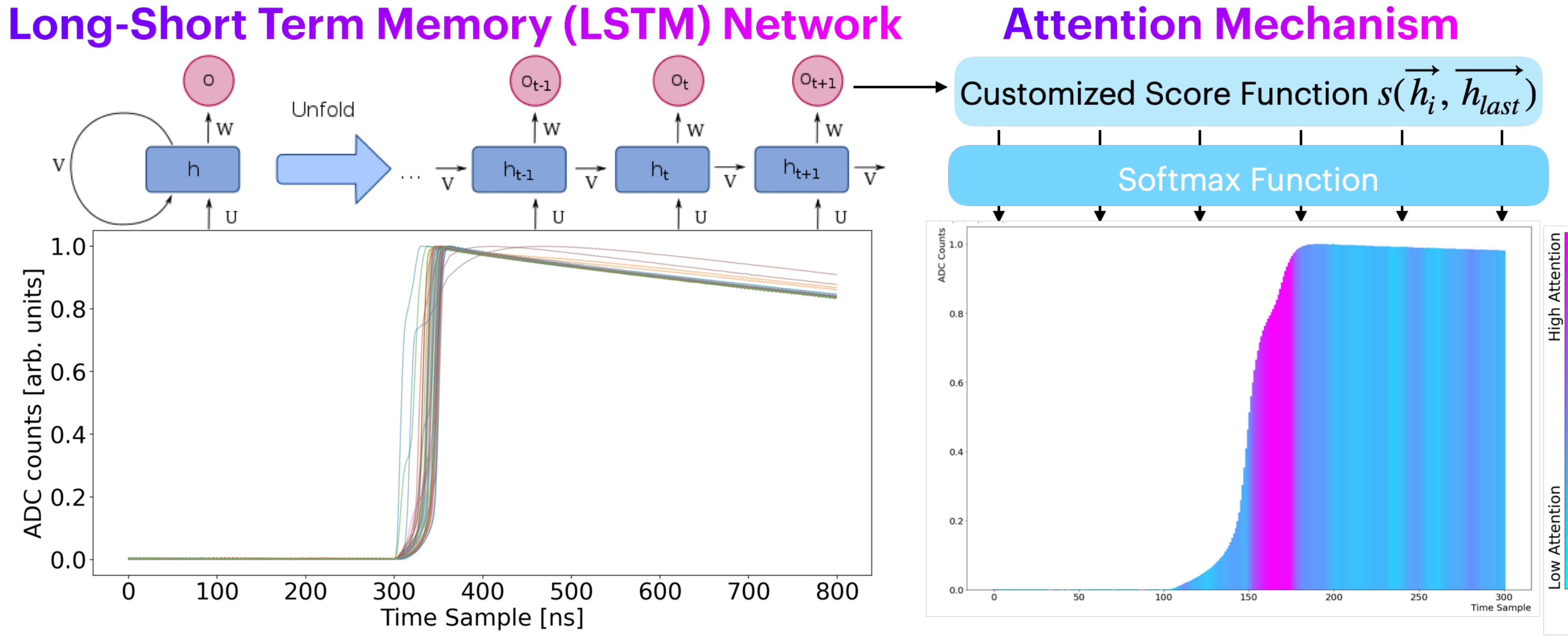
Waveform

1D Time Series



RNN + Attention

For time series analysis

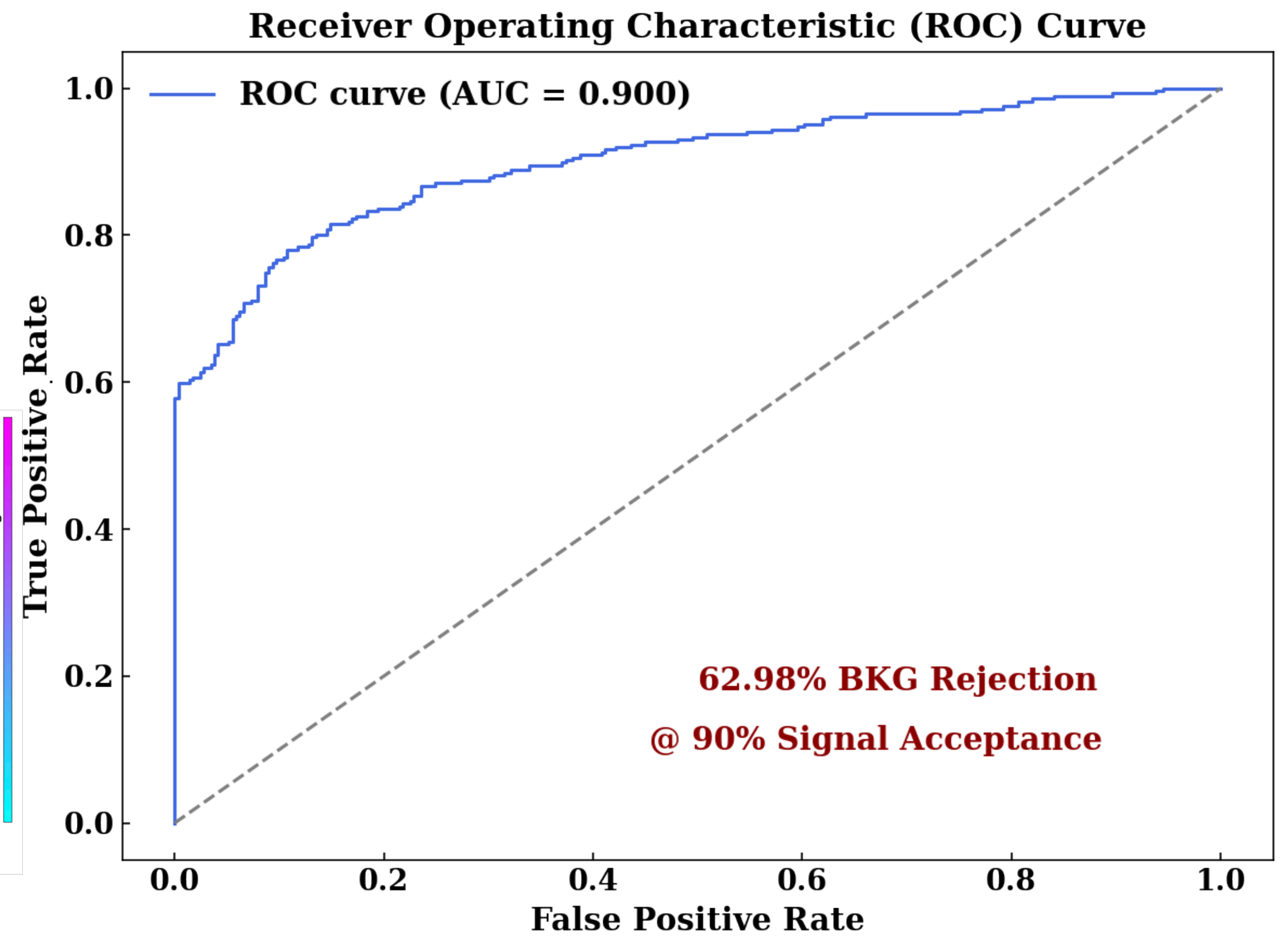


Long-Short Term Memory (LSTM) Network

Attention Mechanism

Customized Score Function $s(\overrightarrow{h_i}, \overrightarrow{h_{last}})$

Softmax Function



Combining Dual Classifier

Min Zhong

Combine CNN & RNN to classify confused events

Fast & Slow: AI in Rare Event Search

Slow

- What is rare event search?

Fast

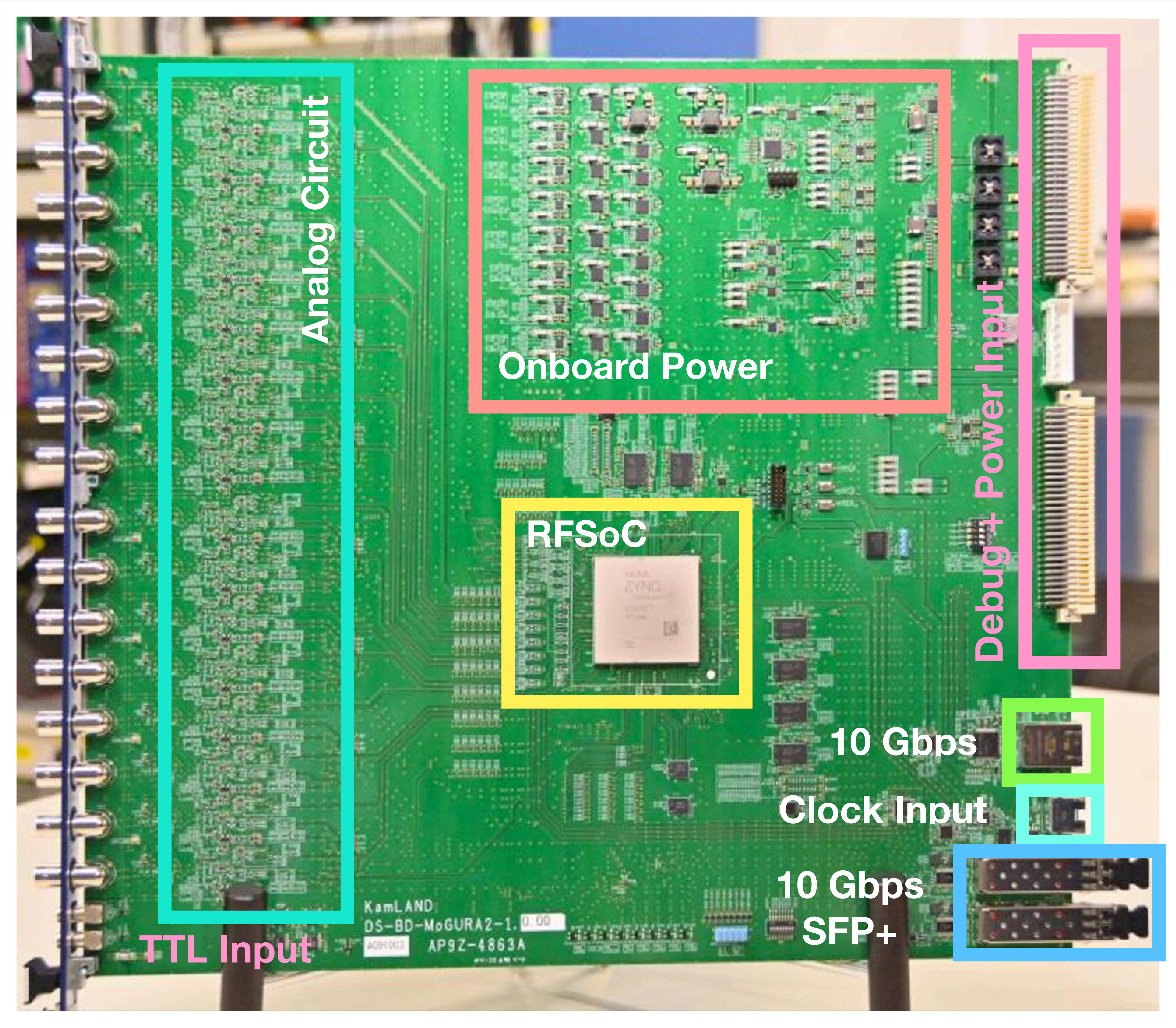
- Radiation detectors
- AI algorithms

Fast for Slow

- Fast ML for rare event

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**

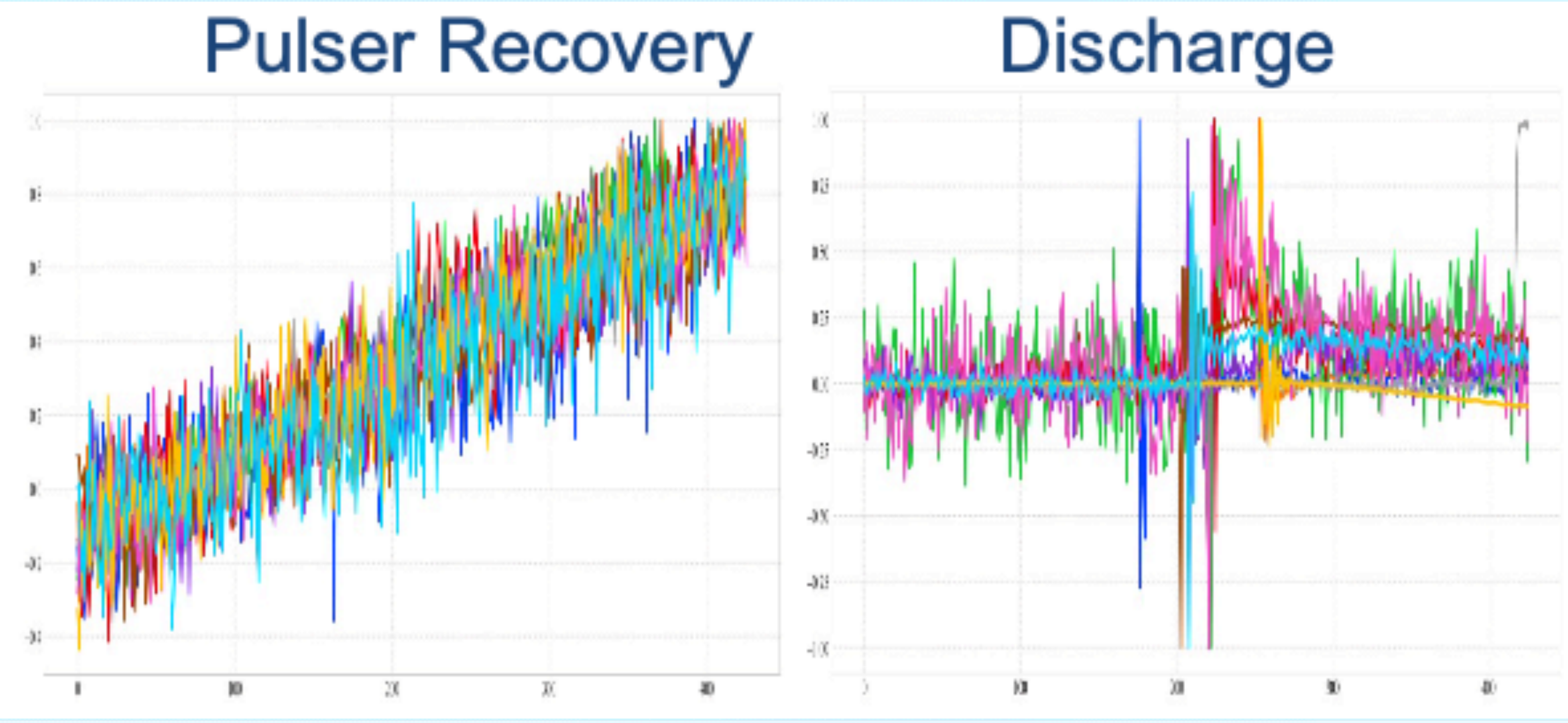
***30-40% power consumption savings**

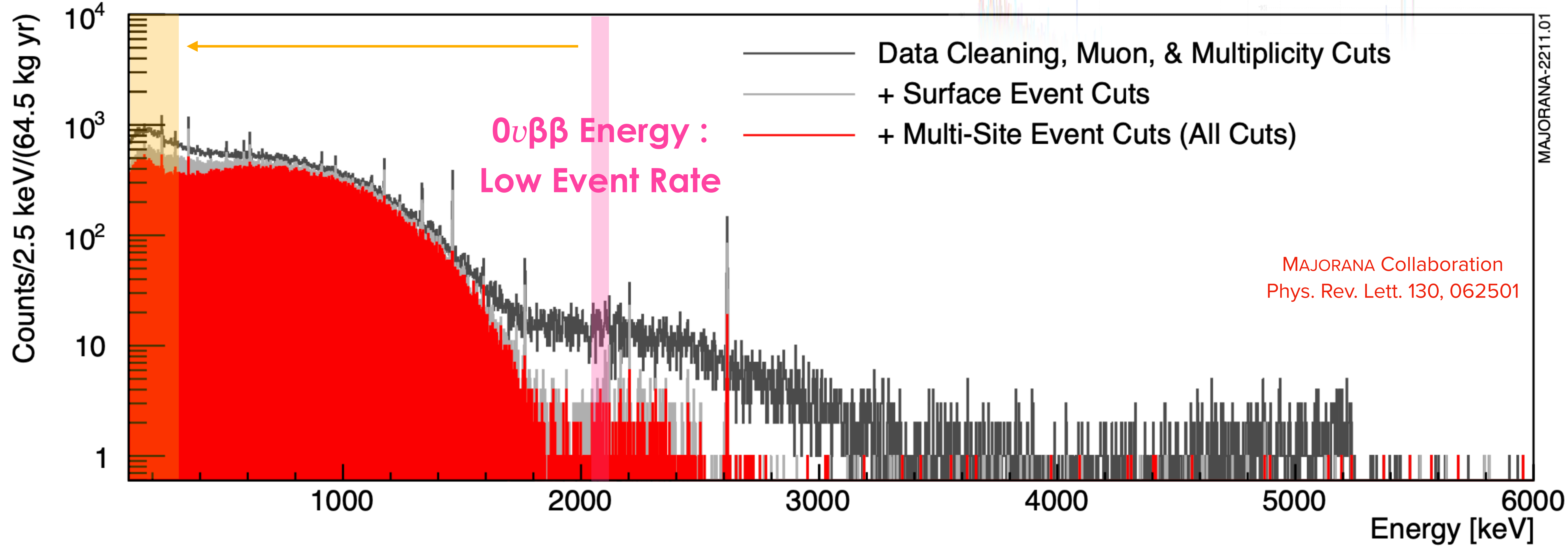
* compared to standard RF signal chain

AI Trigger for Low Energy

Exponentially Increasing Event Rate

Lots of electronic noise





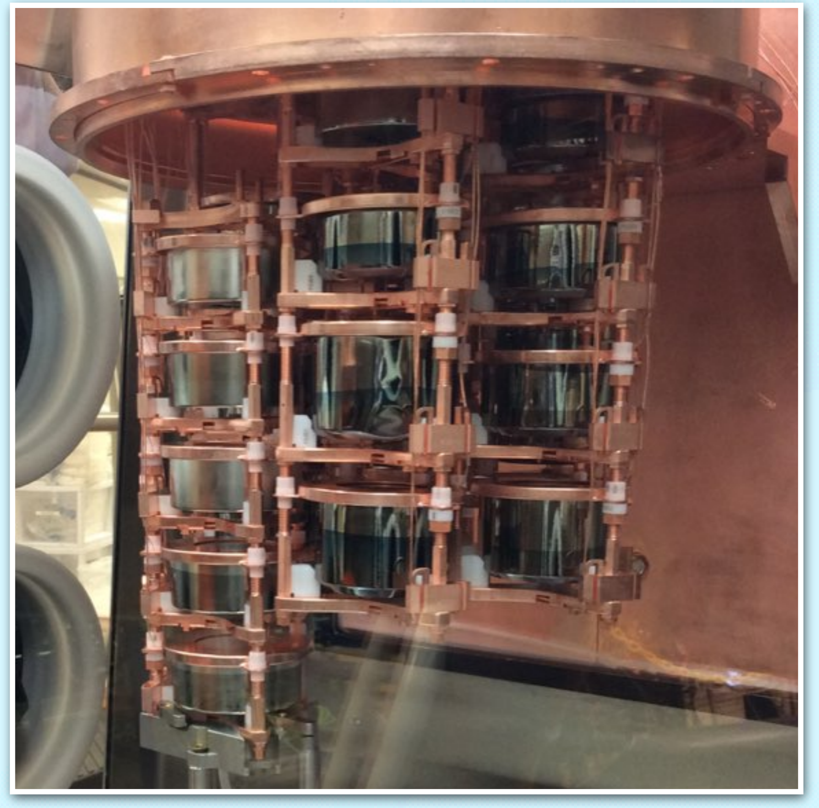
$0\upsilon\beta\beta$ Energy :

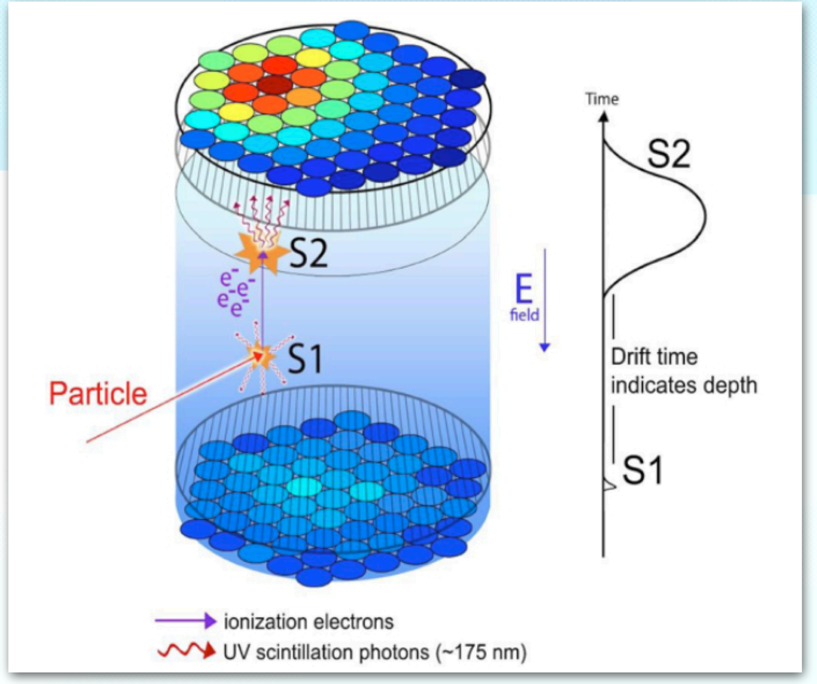
Low Event Rate

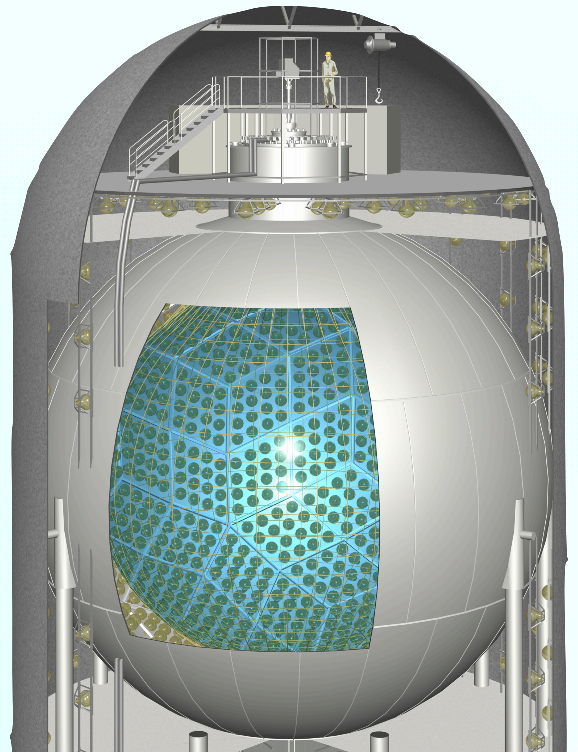
MAJORANA Collaboration

Phys. Rev. Lett. 130, 062501

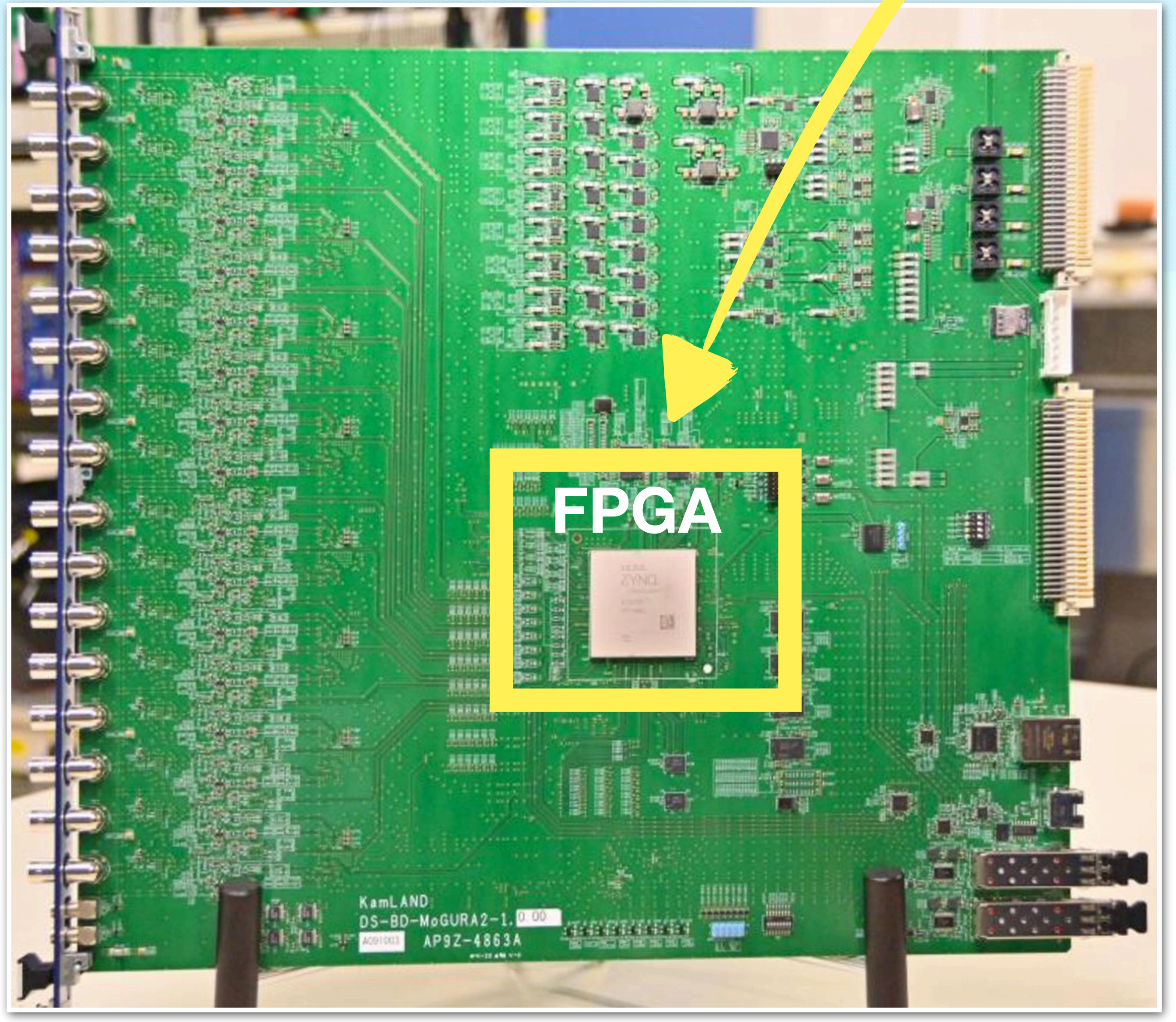
Real-Time AI Analysis







Data Stream



Online Learning

Offline Analysis

Energy

Position

Particle Type

Detector
Response

Fast & Slow: AI in Rare Event Search

Slow

- **Rare event search** provides a unique window to unravel the mystery of Neutrino & Dark Matter
- **High sensitivity** and **low background** is required

Fast

- **Radiation detectors**: KamLAND-Zen, LEGEND, XENONnT
- **AI algorithms:** KamNet, FIS, Dual Classifier

Fast for Slow

- **Hardware:** RFSoC for KamLAND-Zen and my other experiments
- **Algorithms:** AI Trigger and online AI analysis

Thank you for your attention. Please email liaobo77@ucsd.edu if you are interested in collaborating!