Detecting Rare Events Using Artificial Intelligence

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ACAT 2024, 03/14/2024

Generated Event vs. Rare Event

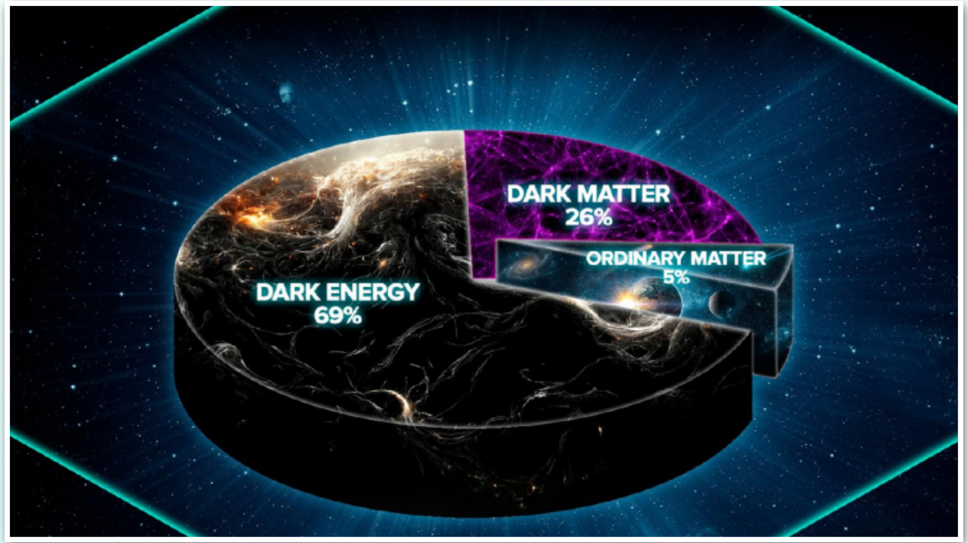
Physics Target | Experiment | Collaboration

High-Energy Particle Beam

600 million collisions per second

Neutrinoless Double-Beta Decay (NLDBD)

Half-life longer than 10^{26} years



Dark Matter (DM)

Scattering cross section smaller than 10^{-46} cm^2

Physics in Rare Event Search

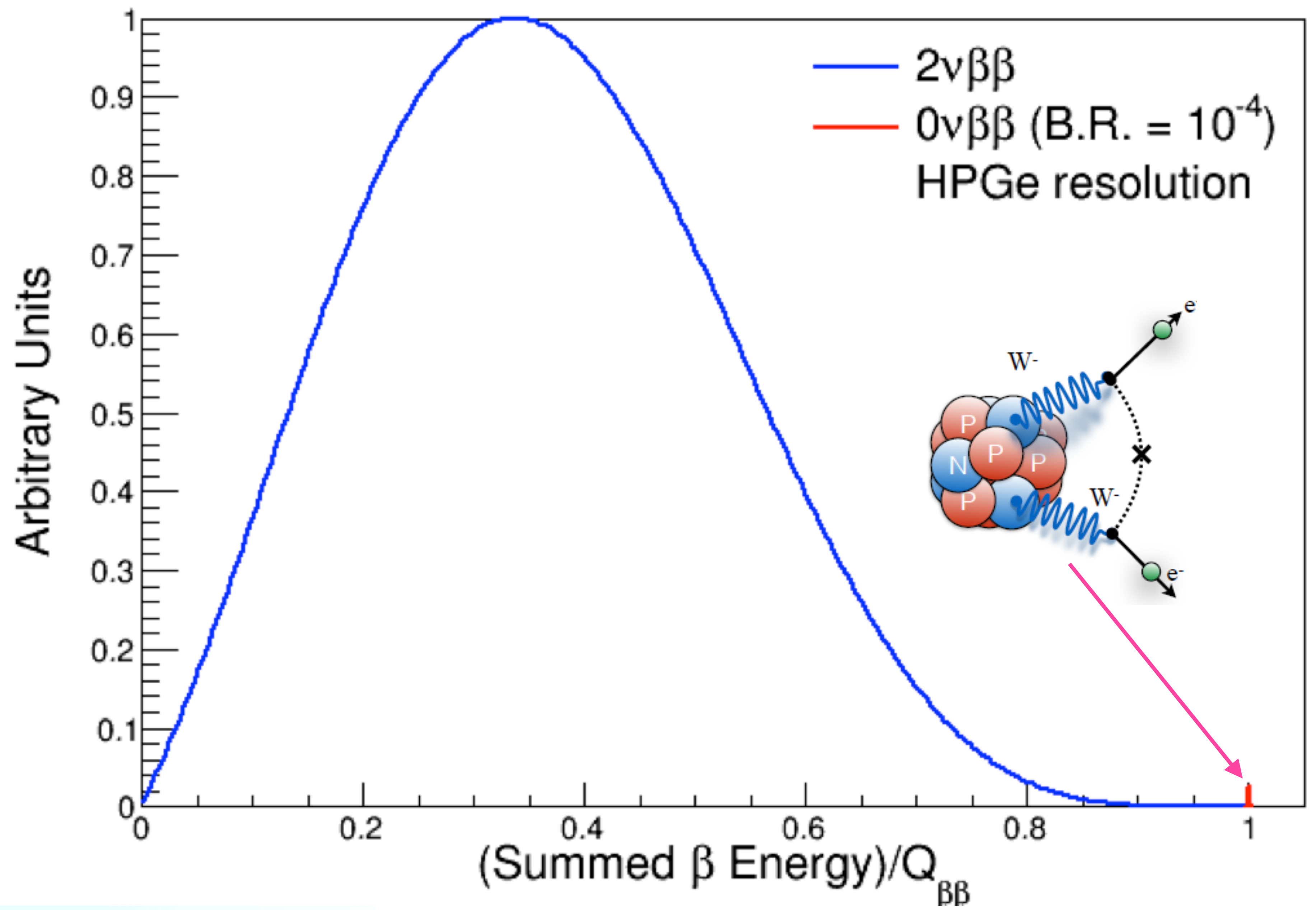
Neutrinoless Double-Beta Decay (NLDBD)

ΔL = 2 lepton number violation process

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

Explain the **tiny mass** of neutrinos

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



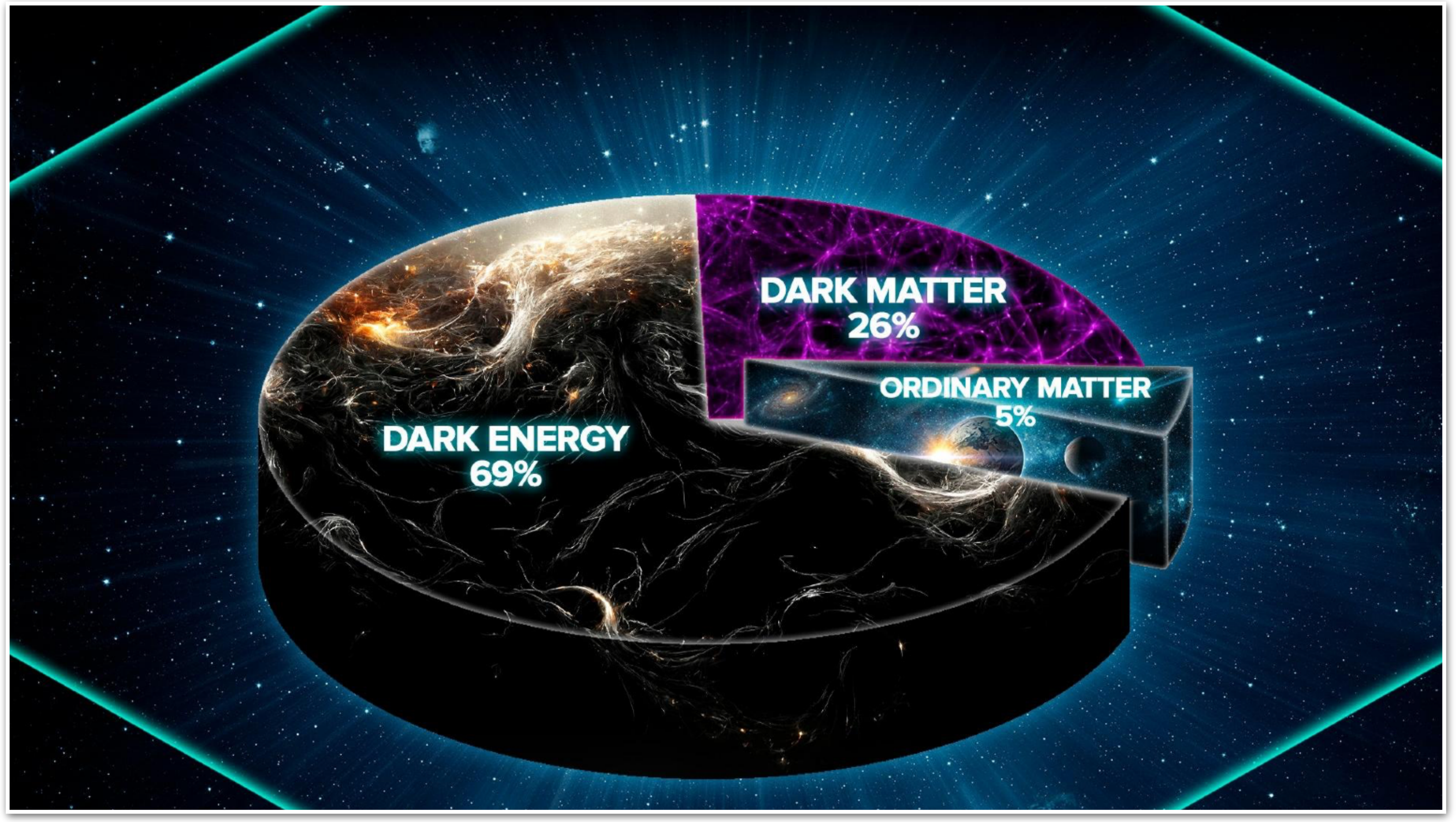
Dark Matter (DM)

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**

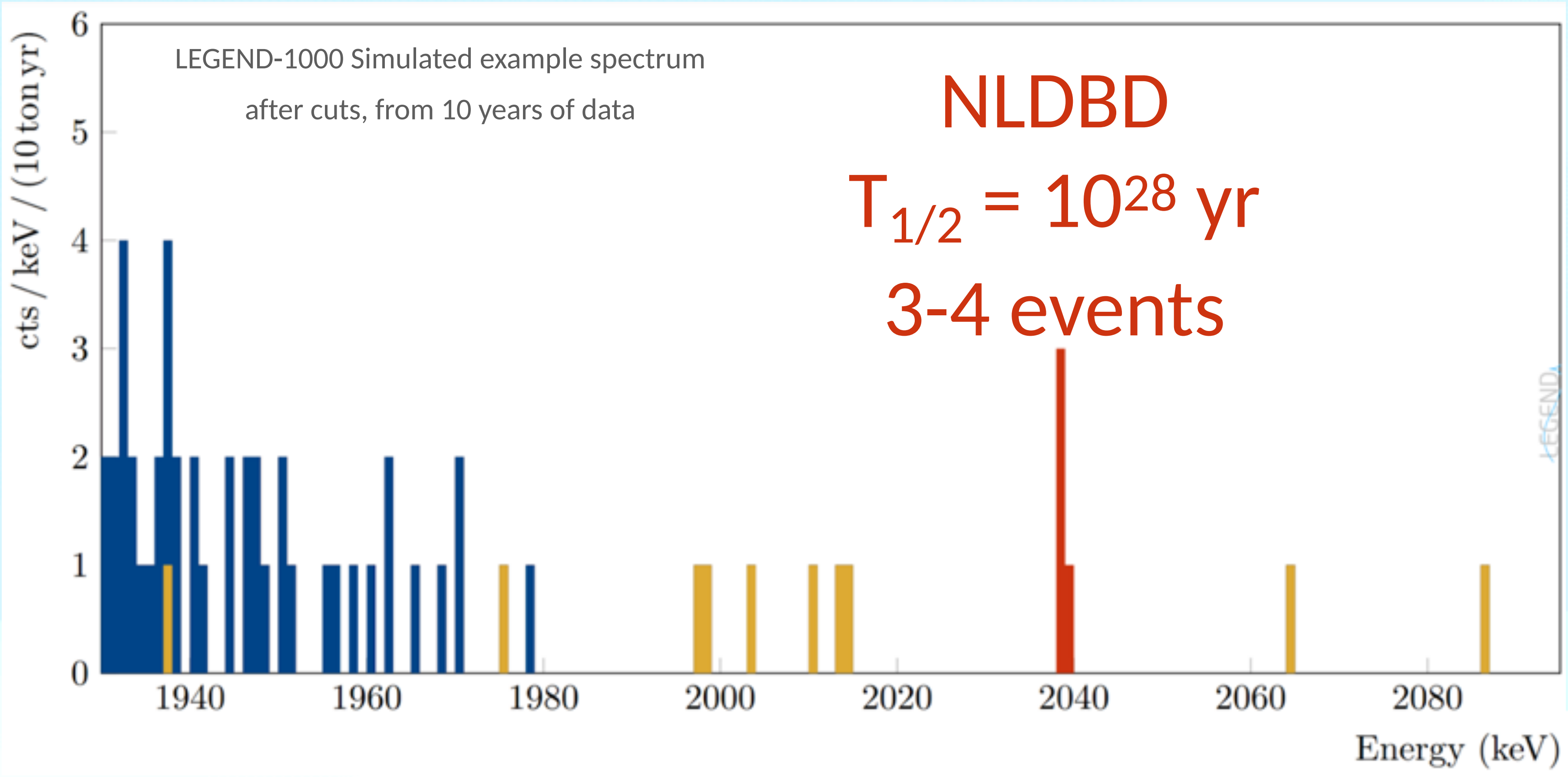
WIMP has not been observed at $\sigma < 10^{-46} cm^2$



Why hasn't we observed anything in Rare Event Search?

It is extremely rare! Using NLDBD as an example…

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



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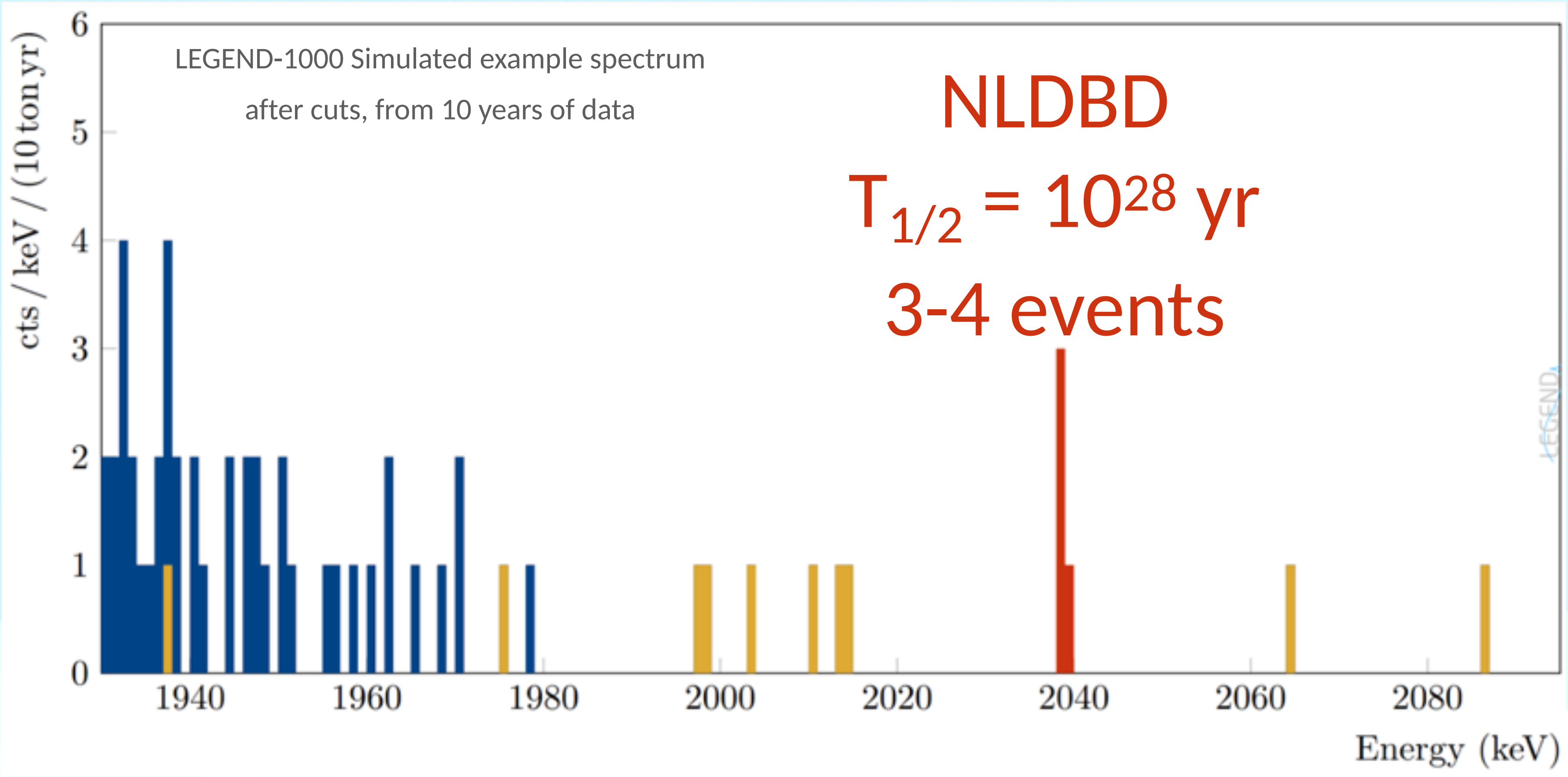

Search for needle in a haystack

- **1 event** every **2.5-3.3 year**, we need ultra-sensitive radiation detector to capture every event
- As our radiation detector gets more sensitive, we inevitably collect lots of **background events**

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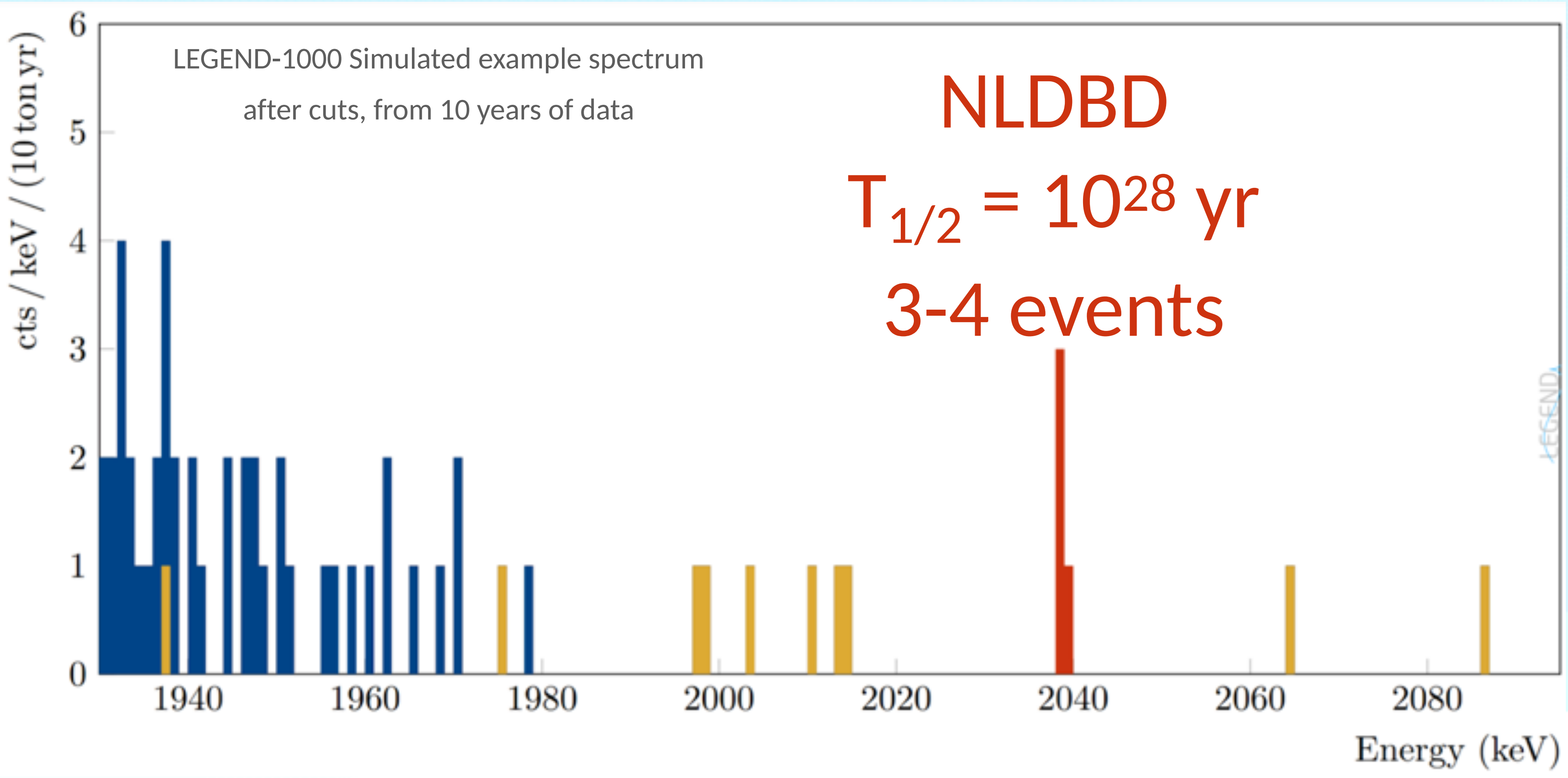
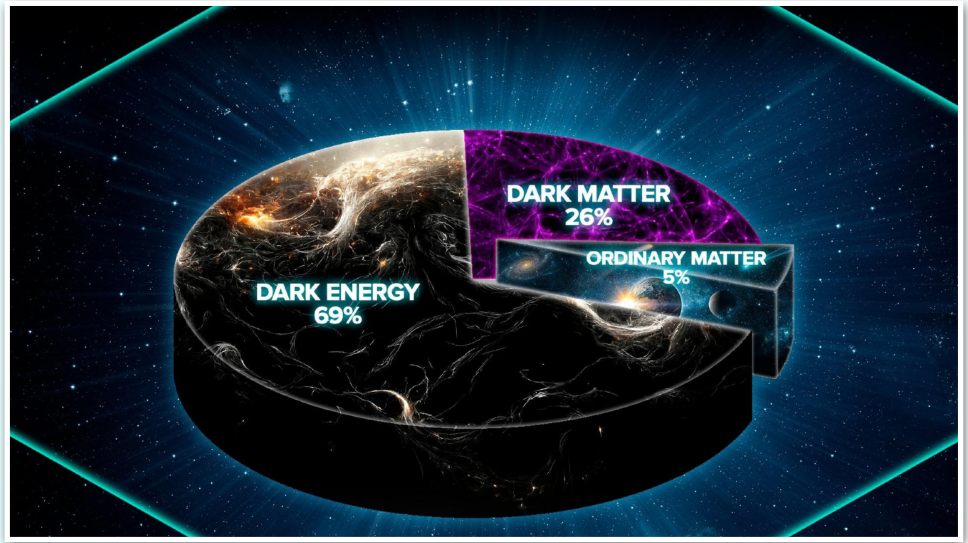


Search for needle in a haystack

- **1 event** every **2.5-3.3 year**, we need ultra-sensitive radiation detector to capture every event
- As our radiation detector gets more sensitive, we inevitably collect lots of **background events**

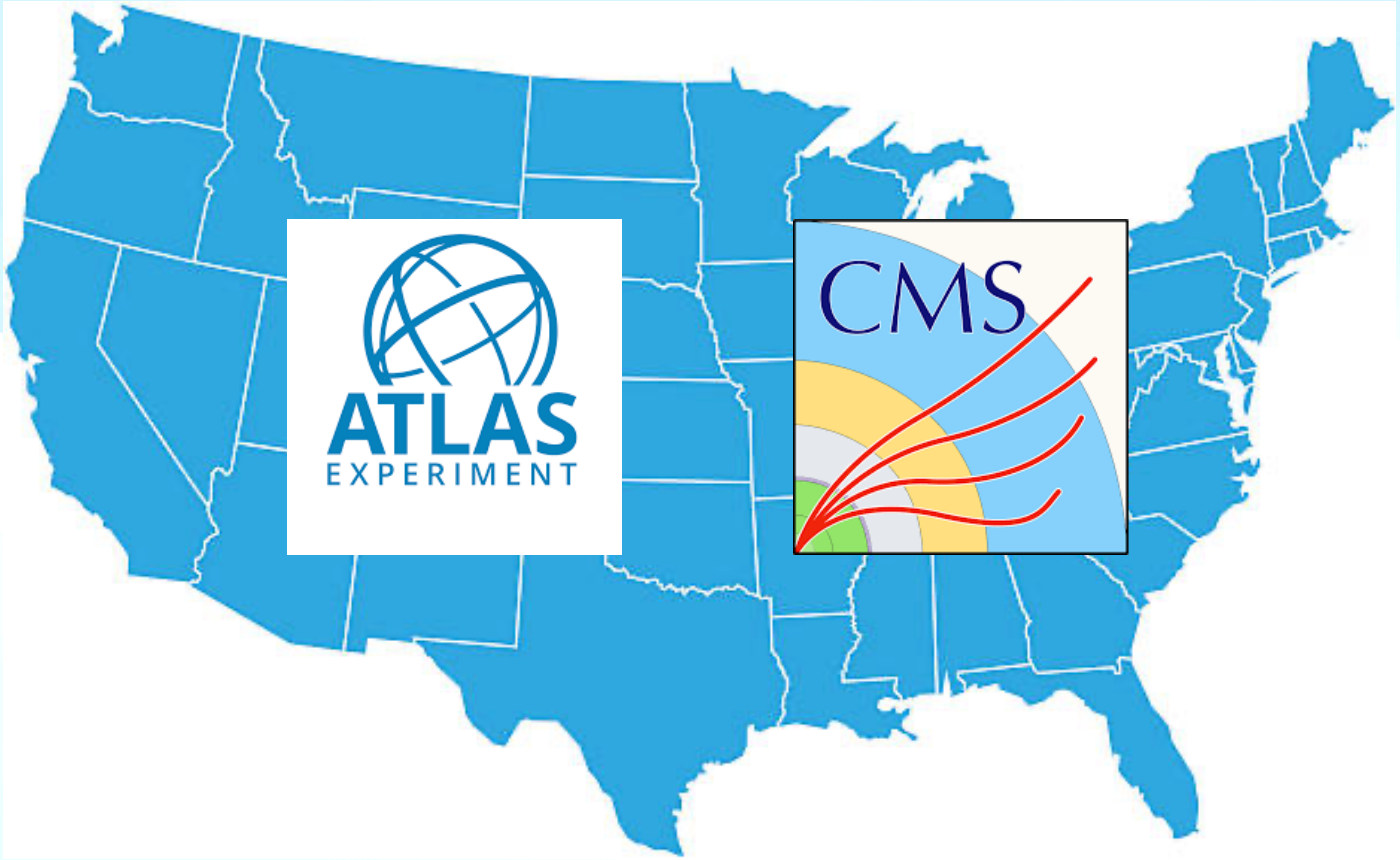
Suppressing these backgrounds is of unparalleled importance in rare event search experiment!

Generated Event vs. Rare Event

	Physics Target	Experiment	Collaboration
	High-Energy Particle Beam 600 million collisions per second	ATLAS EXPERIMENT, CMS	~3000 Collaborators Per Experiment
	Neutrinoless Double-Beta Decay (NLDBD) Half-life longer than 10^{26} years	CUPID, LEGEND, nEXO, next, KamLAND-Zen, SNO+	50-300 Collaborators Per Experiment
	Dark Matter (DM) Scattering cross section smaller than 10^{-46} cm^2	LZ, DARWIN, DARK MATTER RADIO, ABRACADABRA	

Landscape of Rare Event Search Experiment

Generated Event Search



Rare Event Search

Disclaimer: This analogy is intended purely for presentation purposes and is not intended to convey any political stance or bias.

Detecting Rare Events Using Artificial Intelligence

“A Guided Tour to Europe”

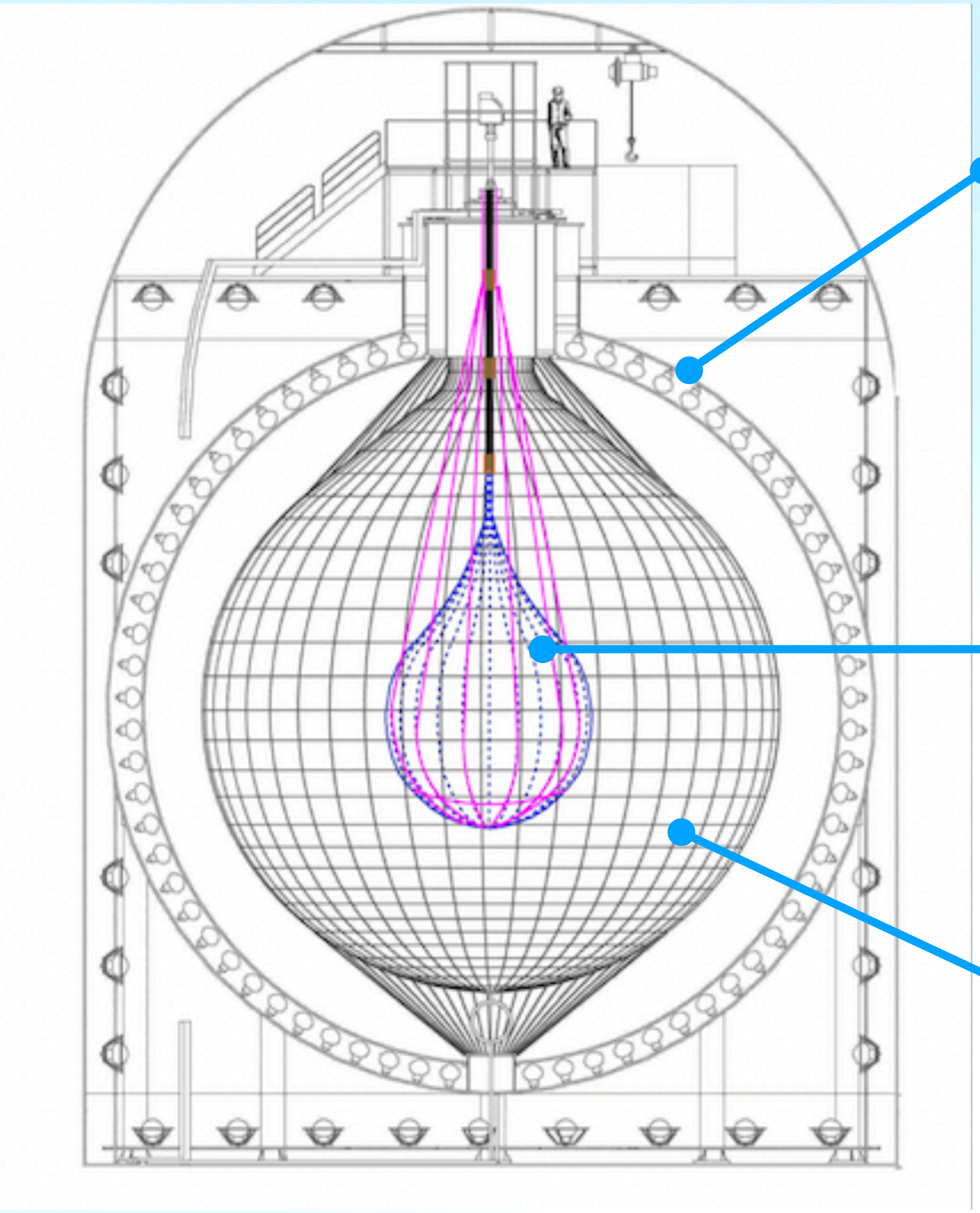
- Rare Event Search Experiments
- Radiation Detector & Data
- AI Algorithms

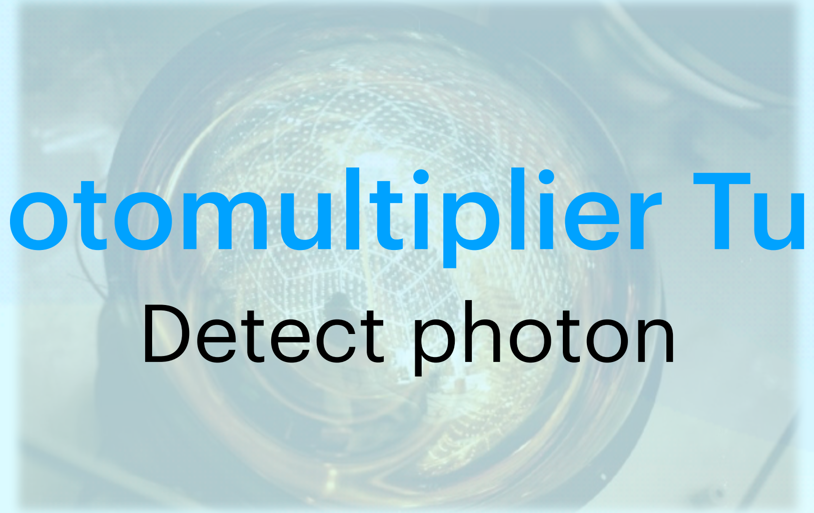
“Forging the European Union”

- Foundation Model for Rare Event Search

KamLAND-Zen

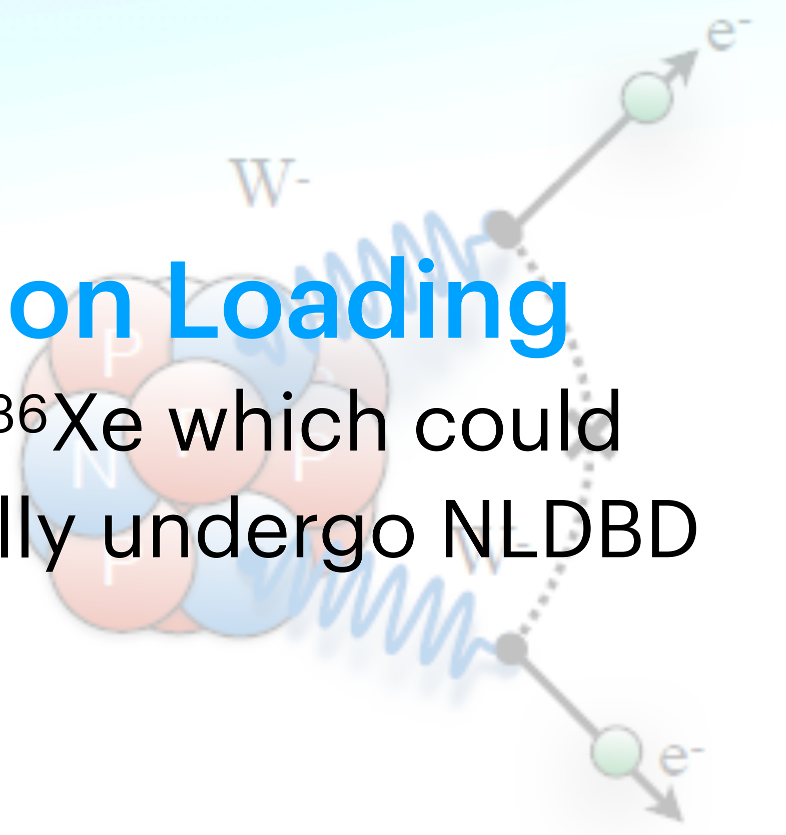
Monolithic Liquid Scintillator Detector for NLDBD Search





Photomultiplier Tube

Detect photon



Xenon Loading

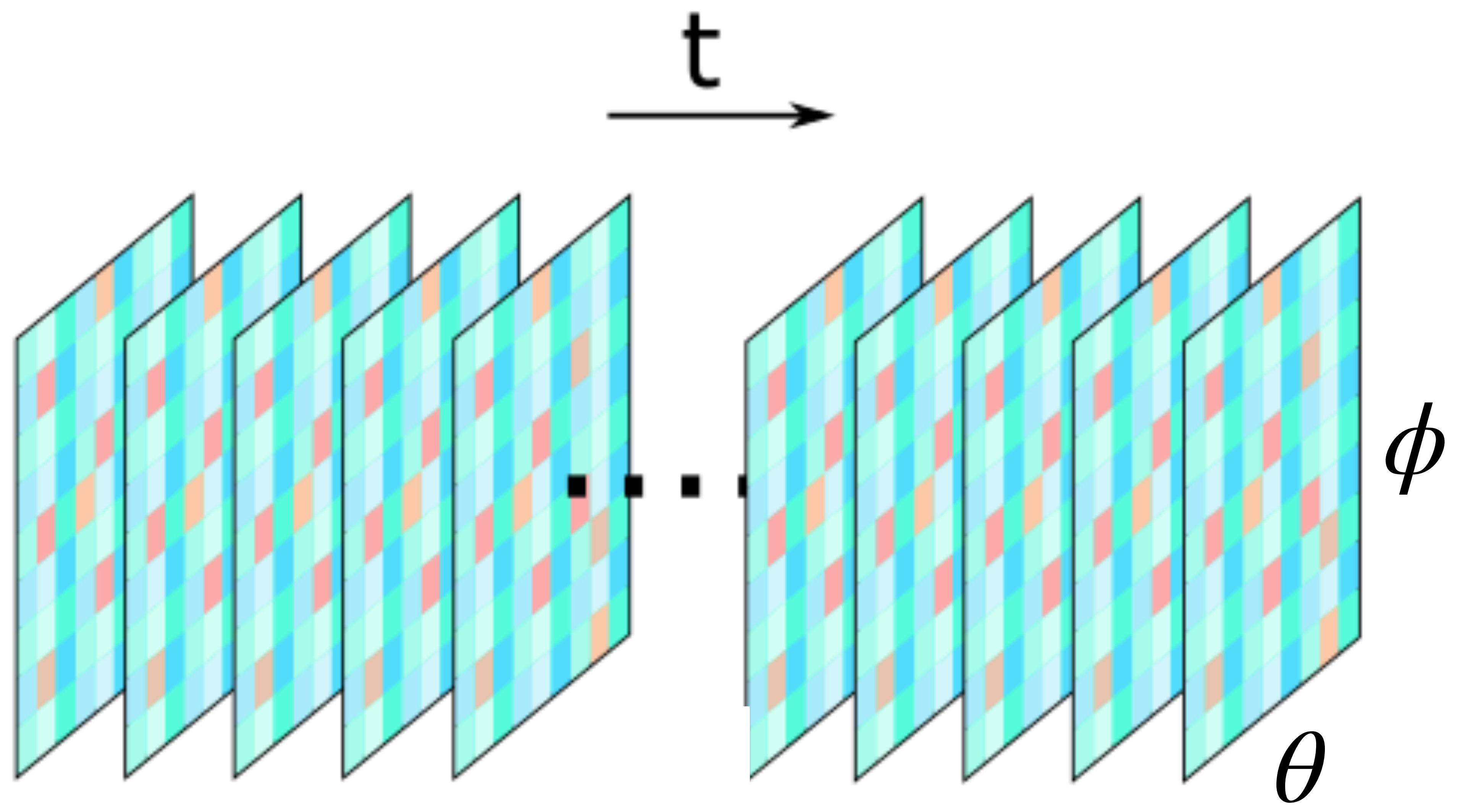
Load ^{136}Xe which could potentially undergo NLDBD

Liquid Scintillator

Generate many isotropic photon

Spatiotemporal Data

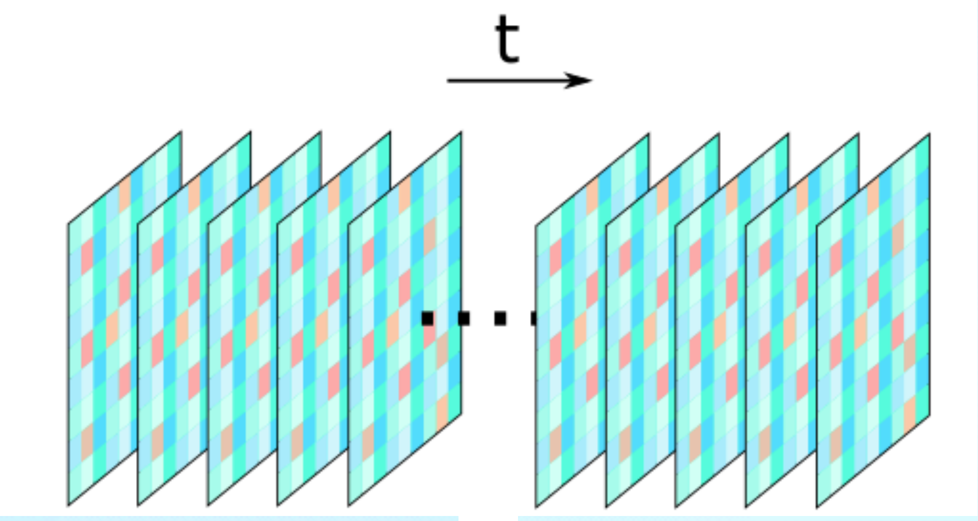
A time series of 2D images, projected onto sphere (A spherical video)



KamNet: An Integrated Spatiotemporal Neural Network

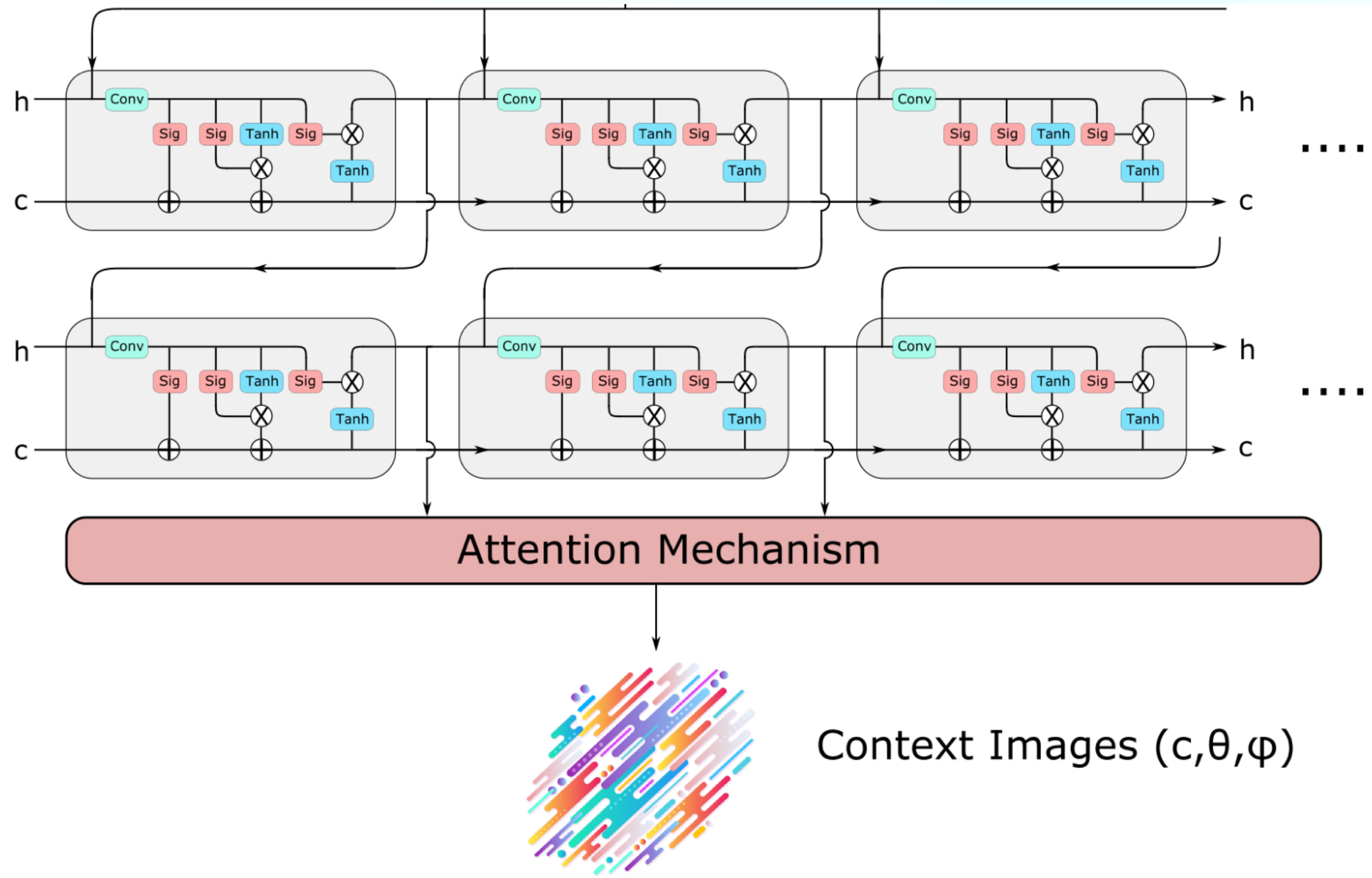
Spatiotemporal Data

A time series of images projected onto Sphere



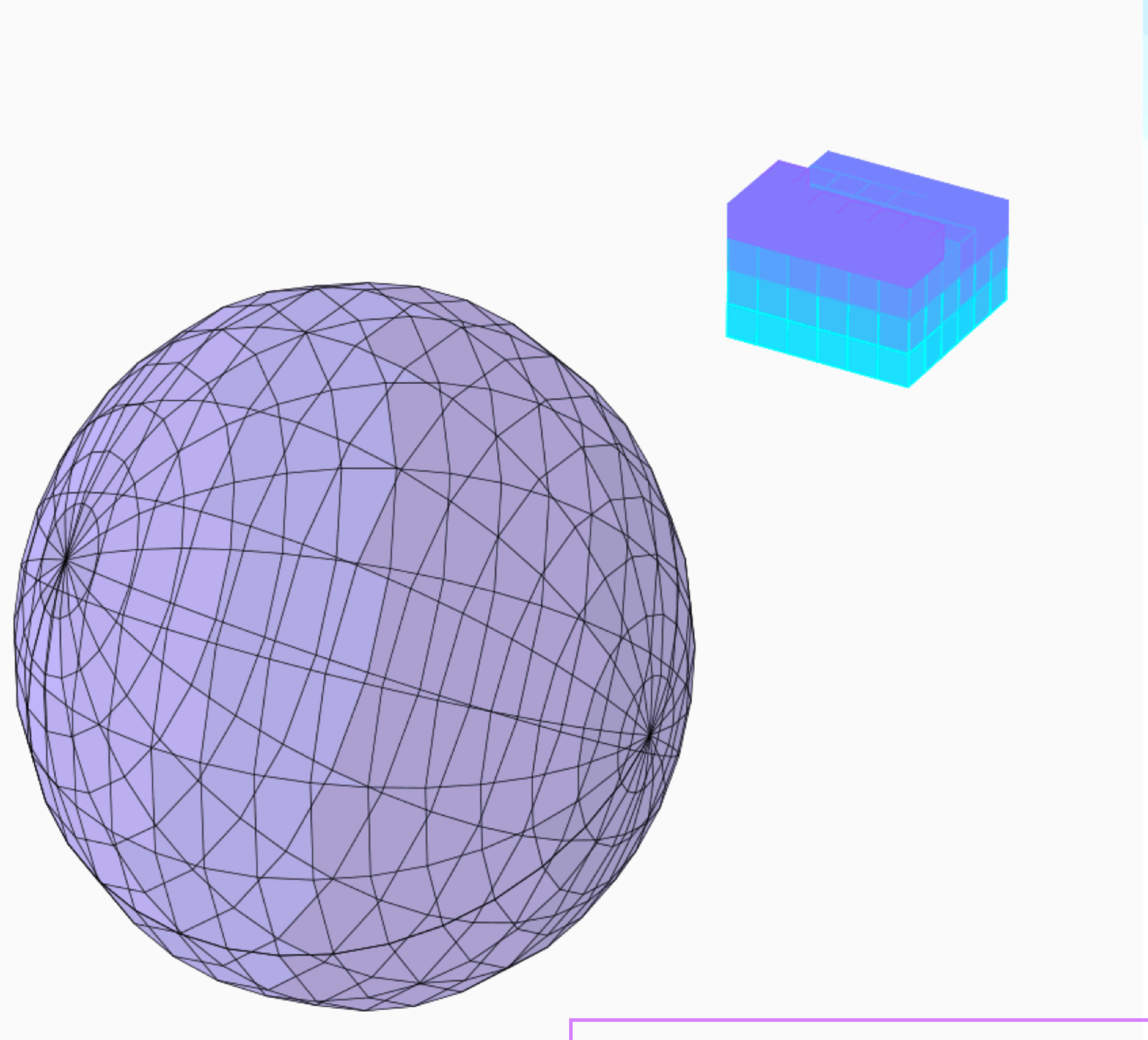
AttentionConvLSTM

for Spatiotemporal symmetry



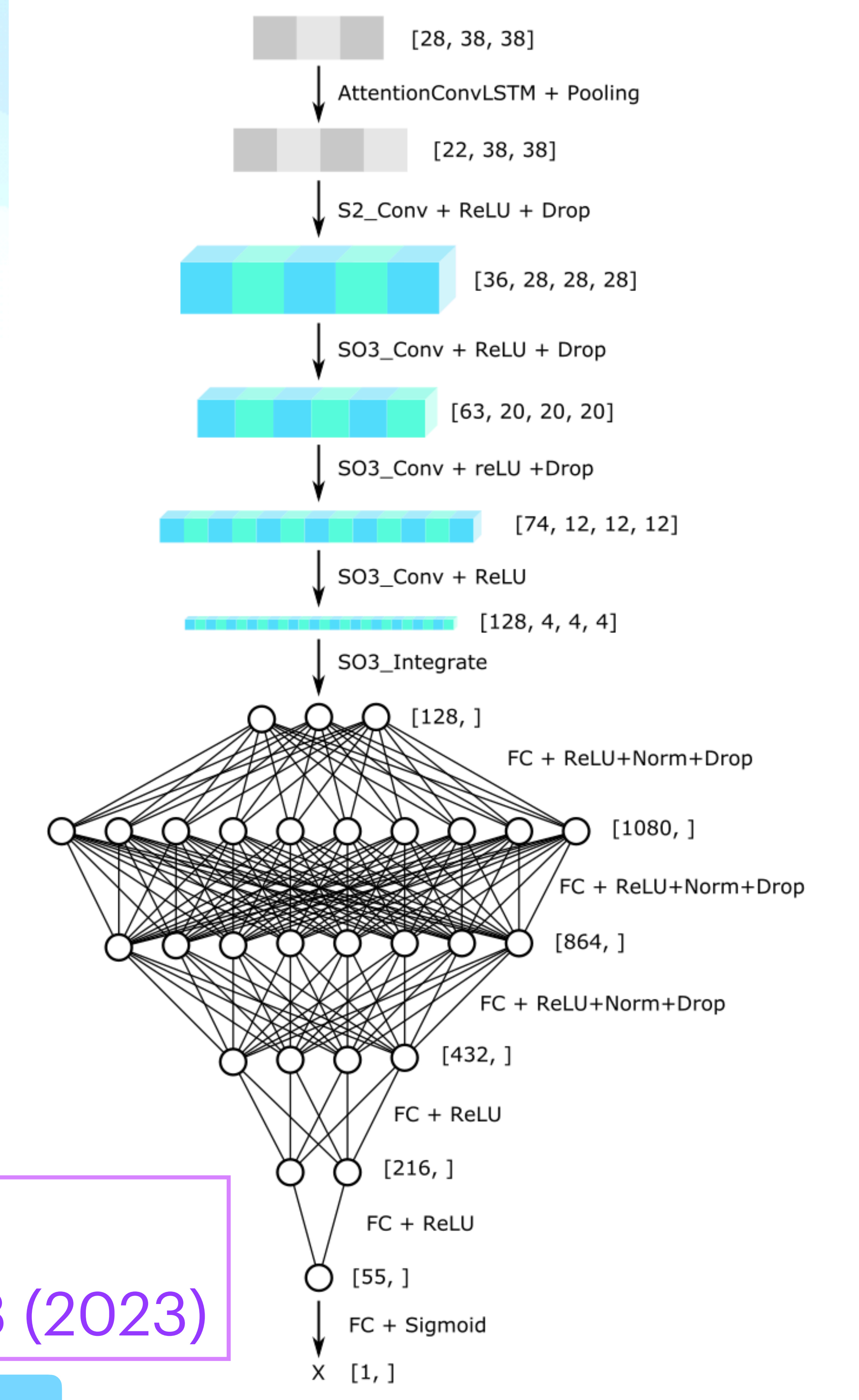
Spherical CNN

SO(3) symmetry & rotational equivariance



KamNet

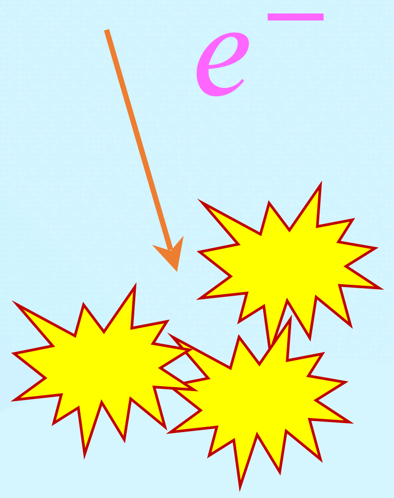
Identifying $0\nu\beta\beta$ signal in KamLAND-Zen



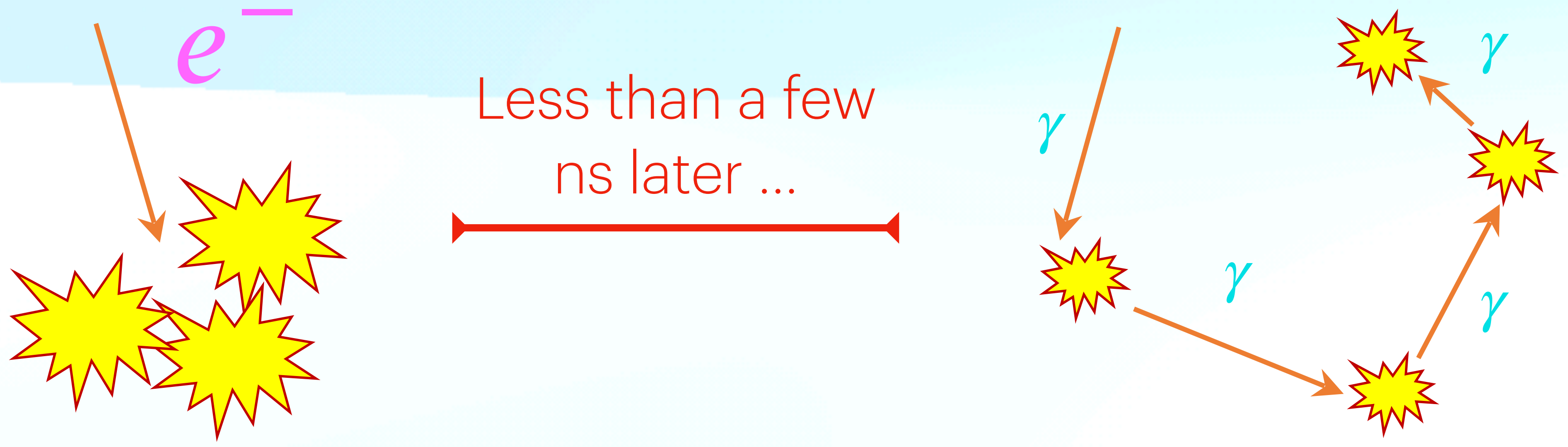
A. Li et al,
Phys. Rev. C **107**, 014323 (2023)

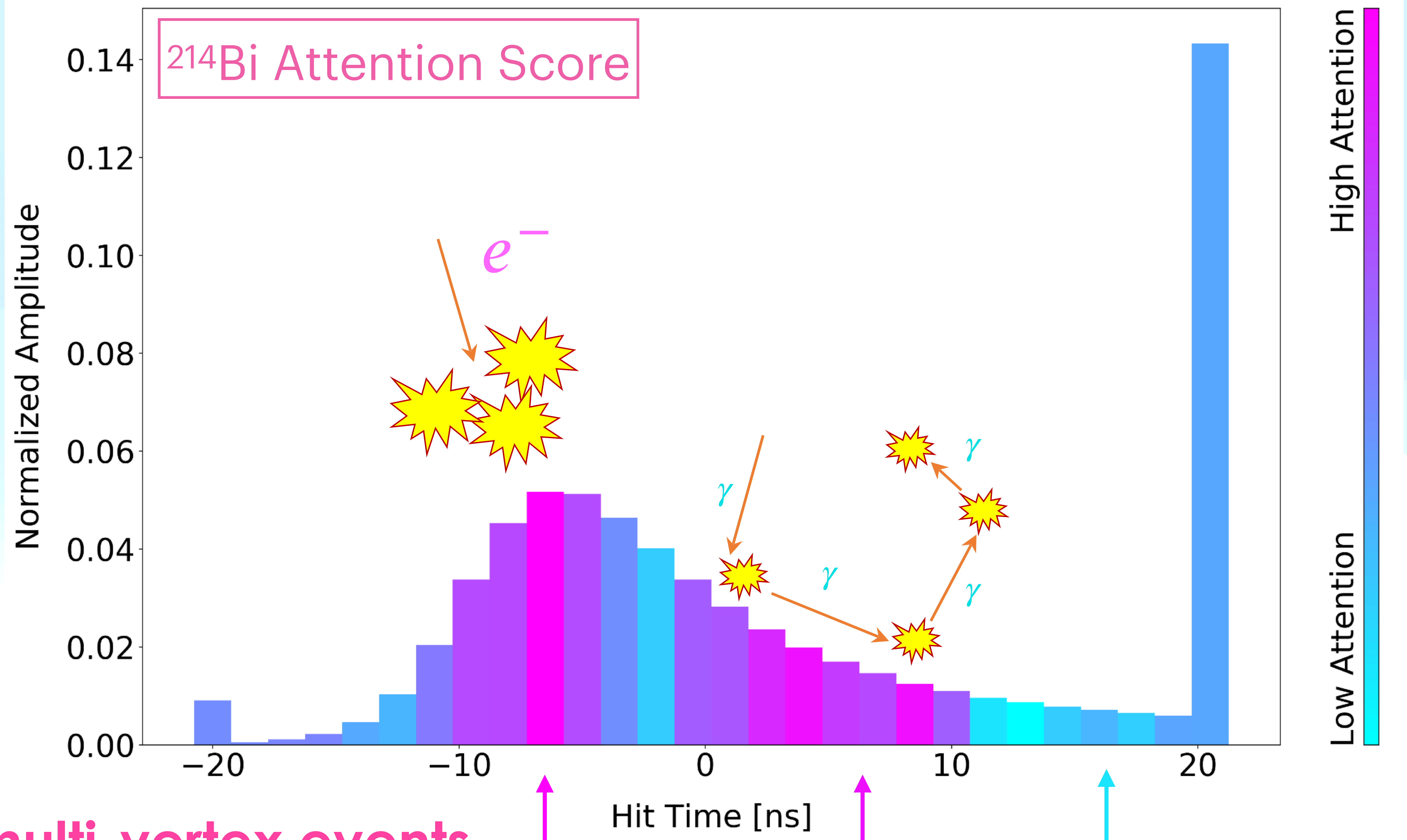
Editor's Suggestion

The Physics Behind KamNet



- 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 New Result

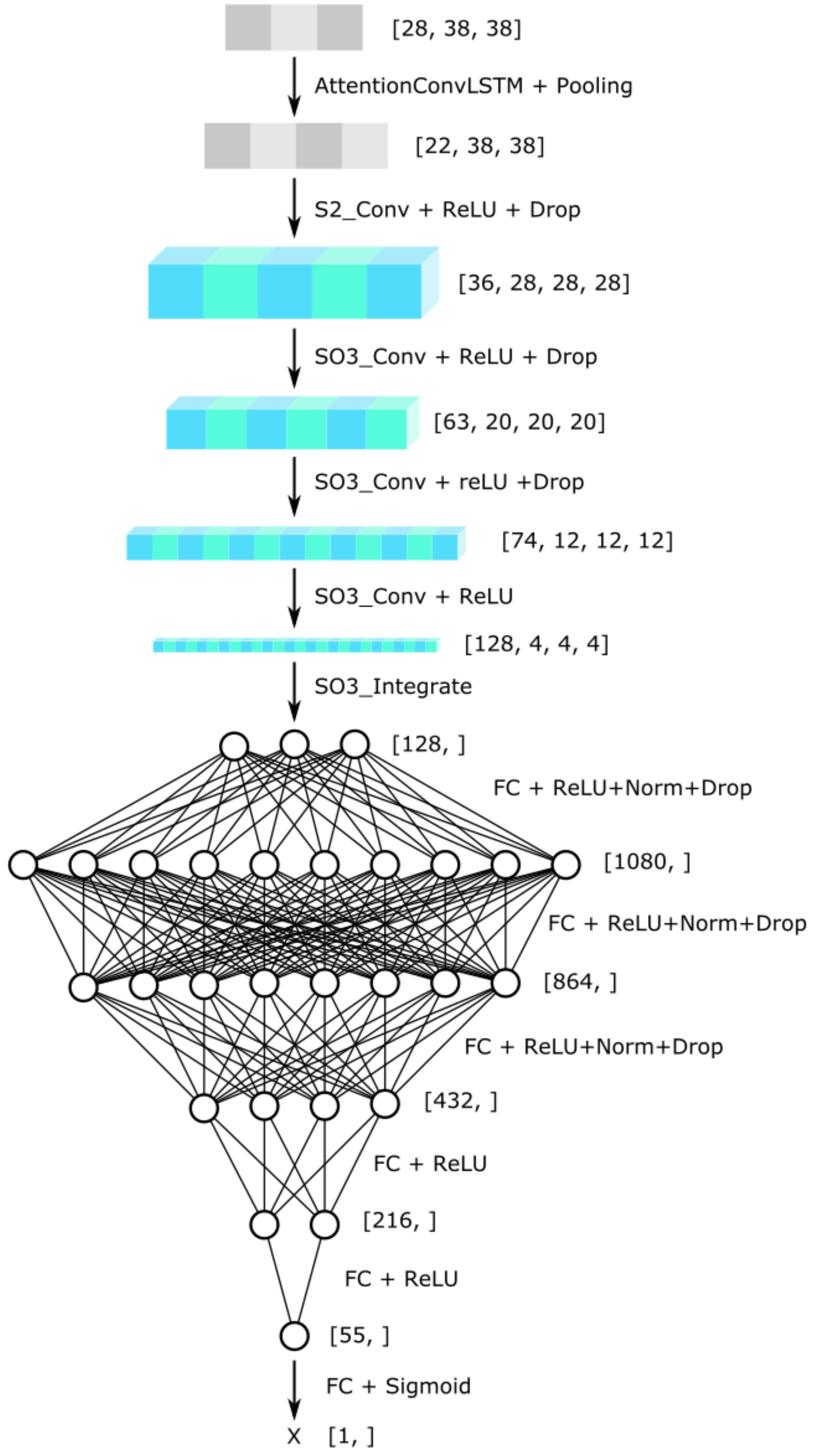
KamLAND-Zen Collaboration
Phys. Rev. Lett. 130, 051801

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

Exposure Before KamNet:

970 kg·yr

APS 2023 Dissertation Awards
In Nuclear Physics



Exposure After KamNet:

1142 kg·yr

+17.7%

Worth $2.5 million!!!
(Based on 2010 Xe price)

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<u>Exposure Before KamNet:</u>

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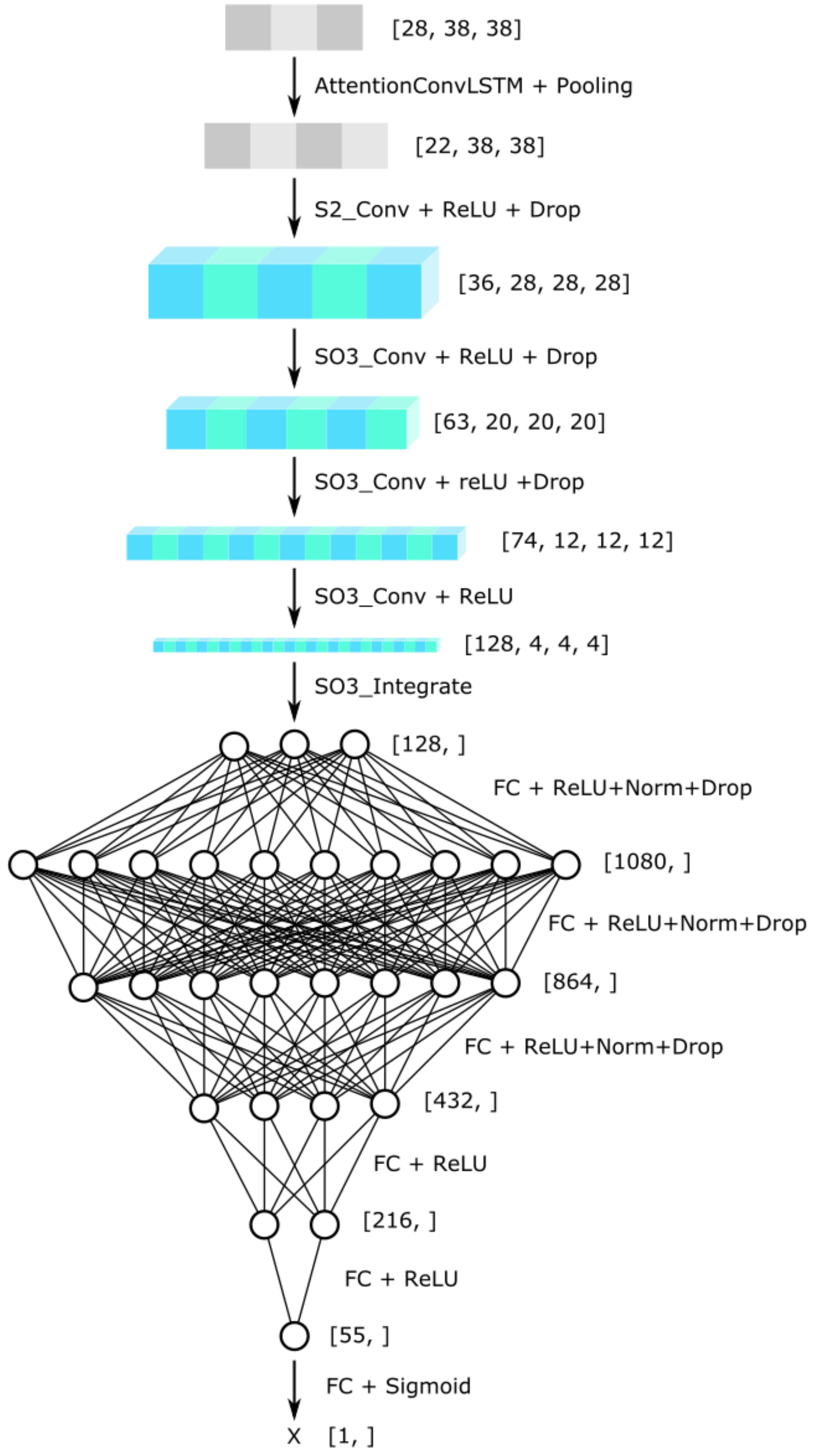
<u>Apply KamNet to High-Background Period Only:</u>

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

APS 2023 Dissertation Awards In Nuclear Physics



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<u>**Official KamLAND-Zen 800 Limit:**</u>

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

<u>**KLZ Combined Official Limit:**</u>

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This result represents the **worlds most stringent limit** on $0\nu\beta\beta$ search!

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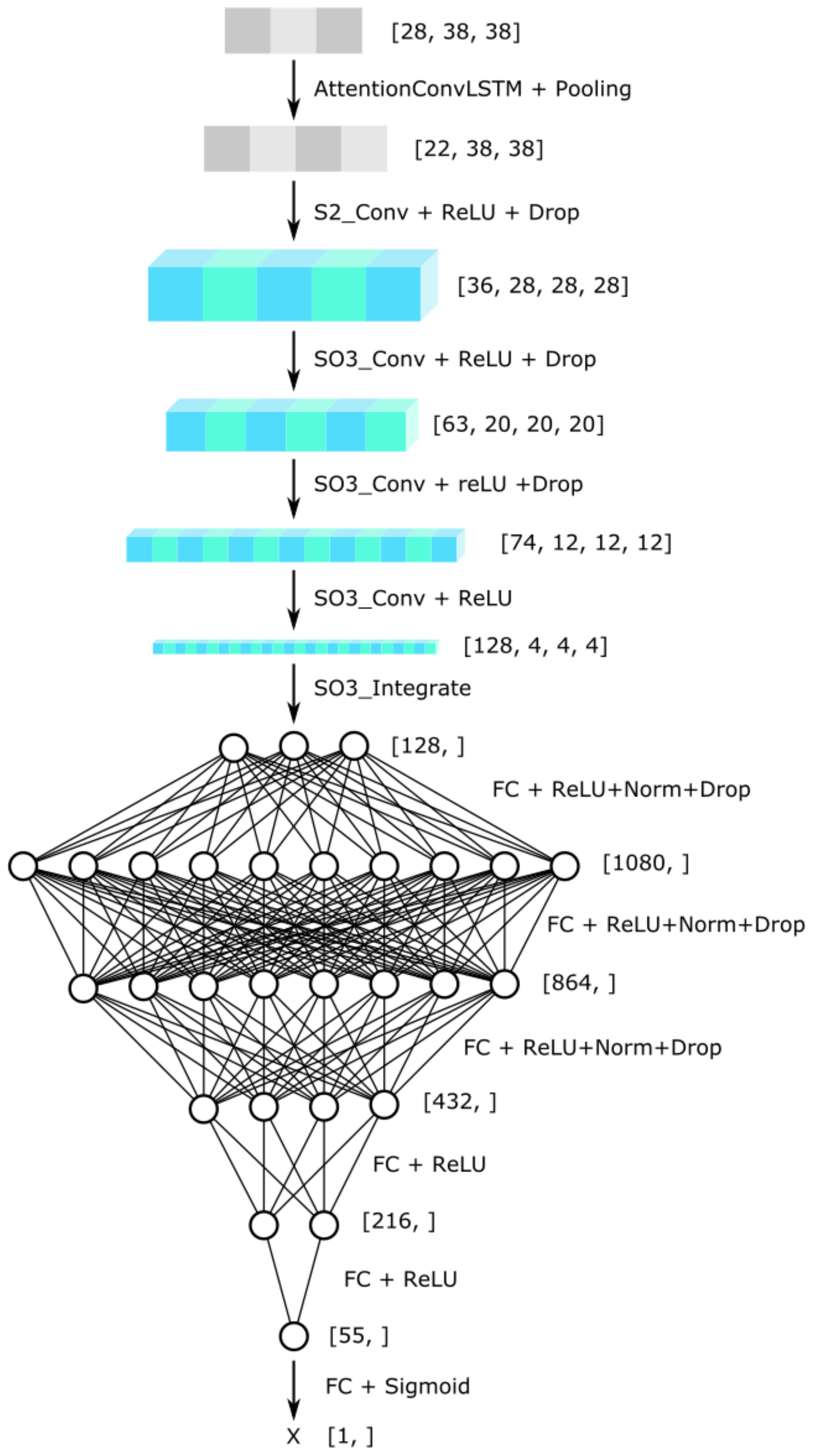

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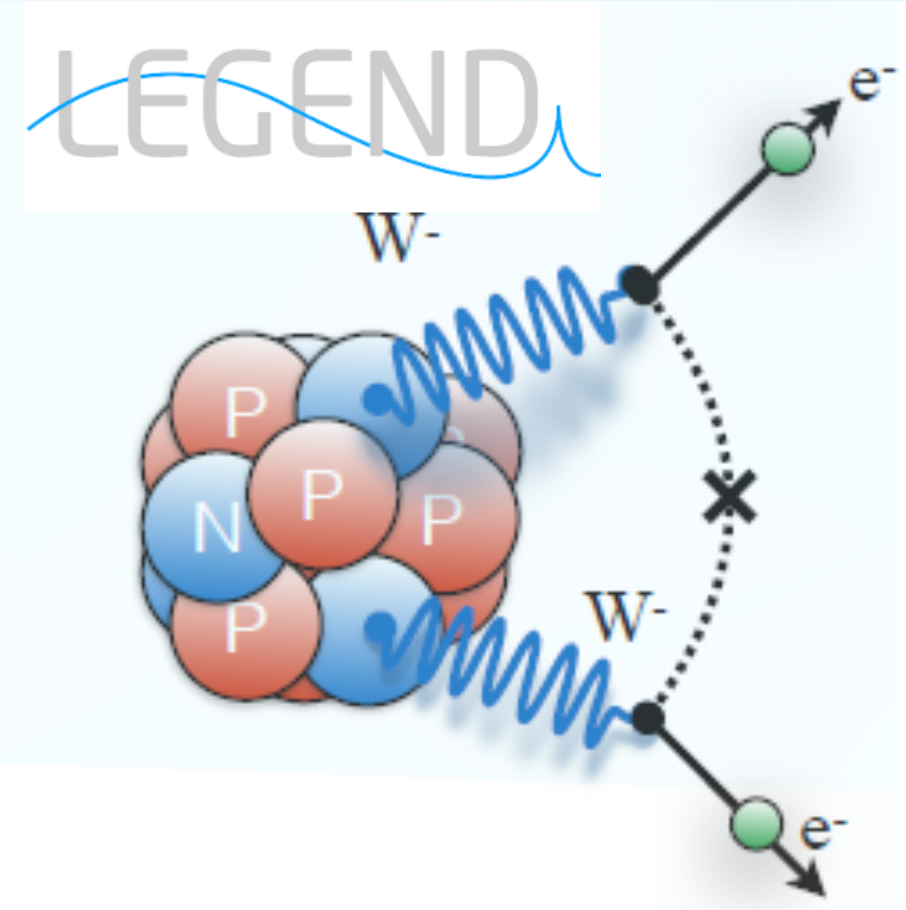
<u>Apply KamNet to All Data:</u>

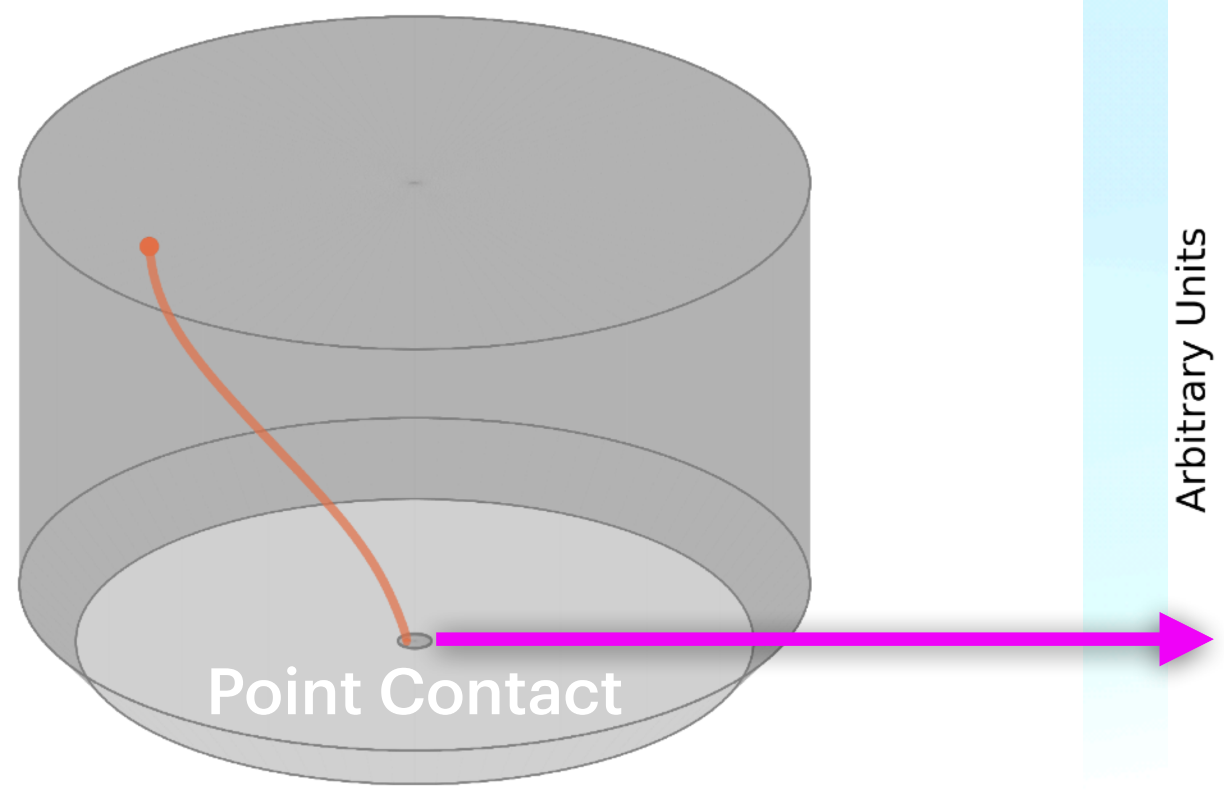
$$T_{1/2}^{0\nu\beta\beta} > 2.7 \times 10^{26}\text{yr (90 \% C.L.)}$$ **+35%**

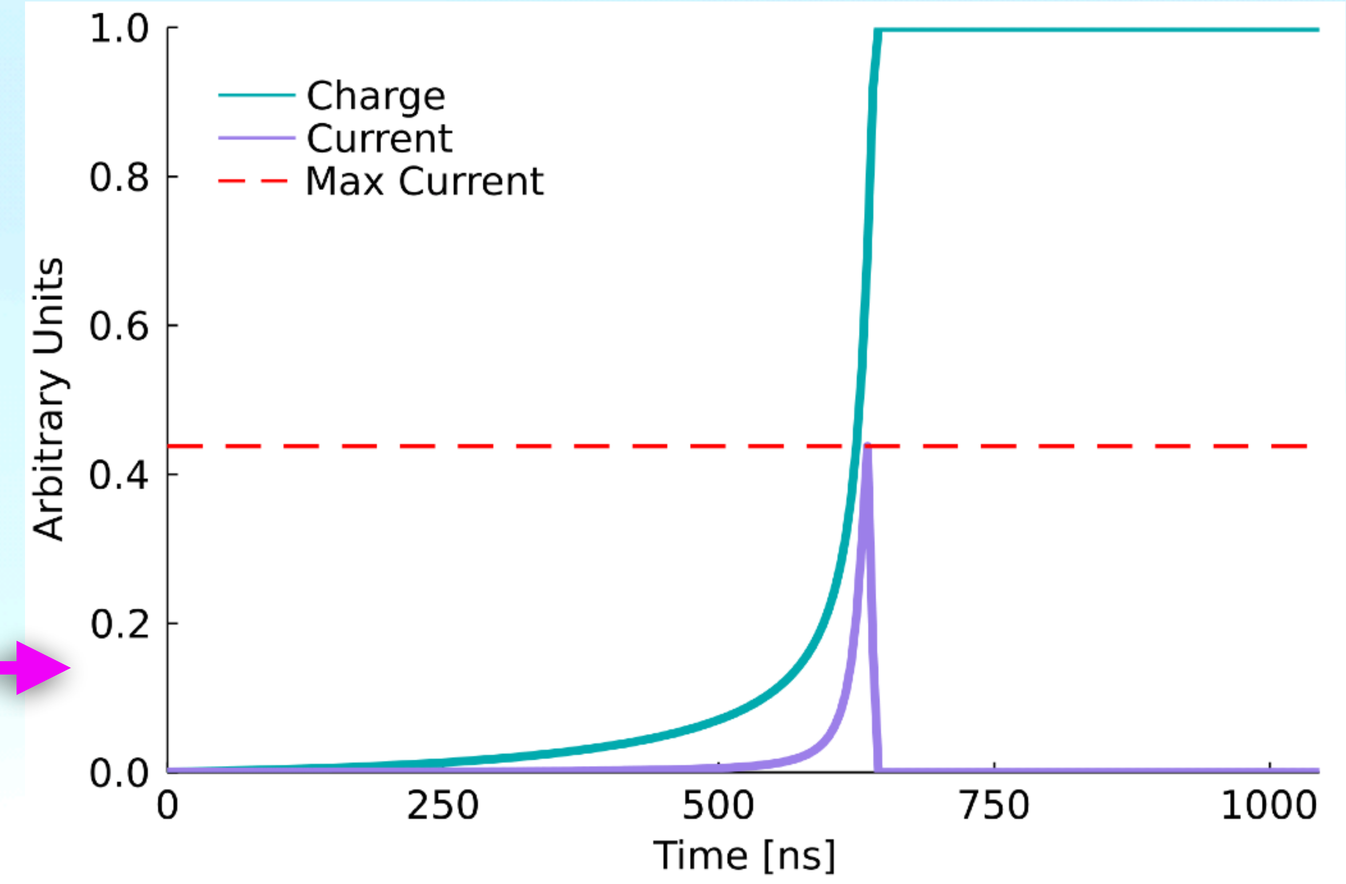
LEGEND

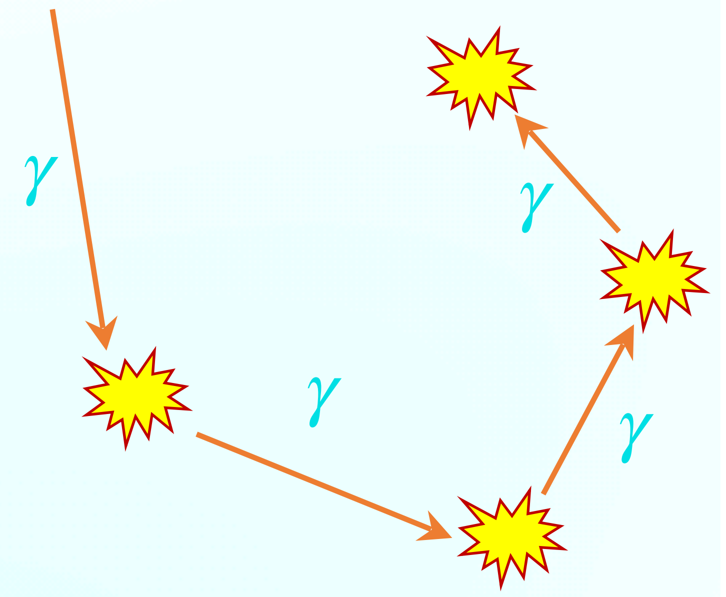
HPGe Detector Array Experiment for NLDBD Search

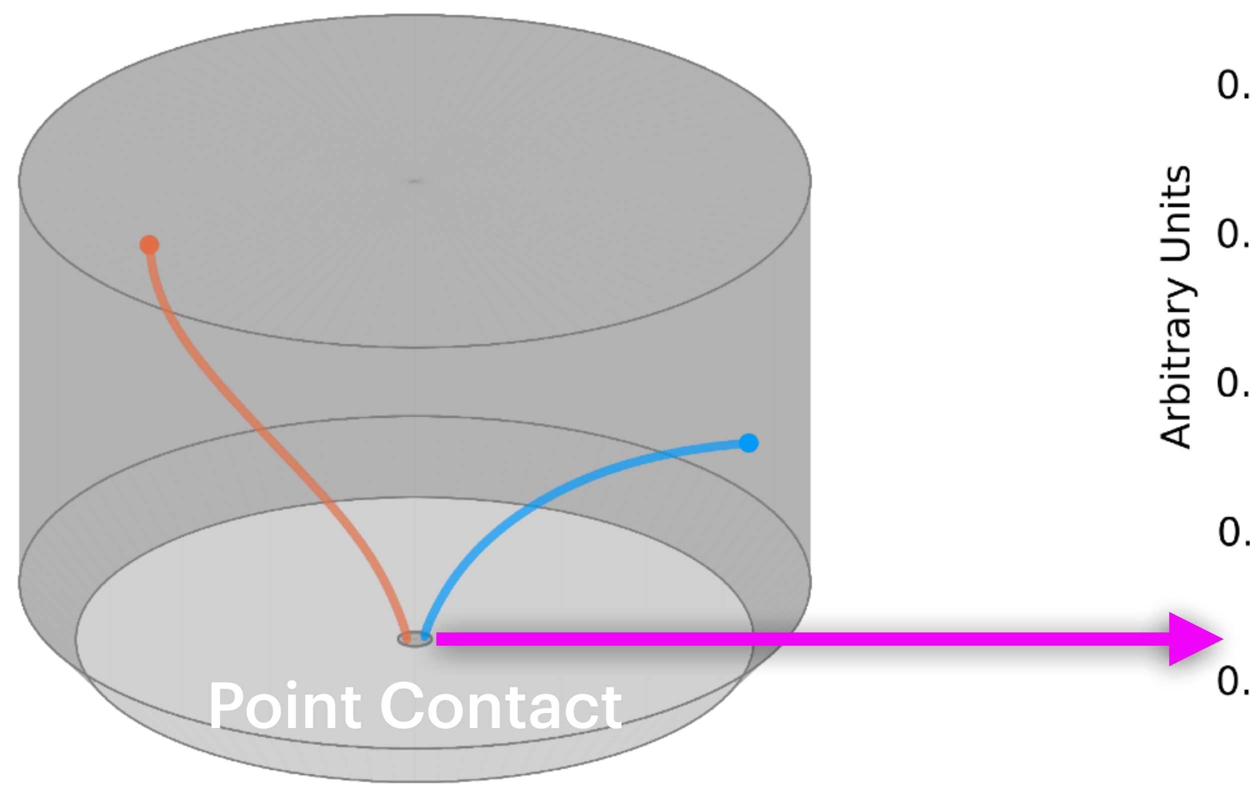
Semiconductor Detector made with ^{76}Ge | **Waveform** | **Pulse Shape Parameter**

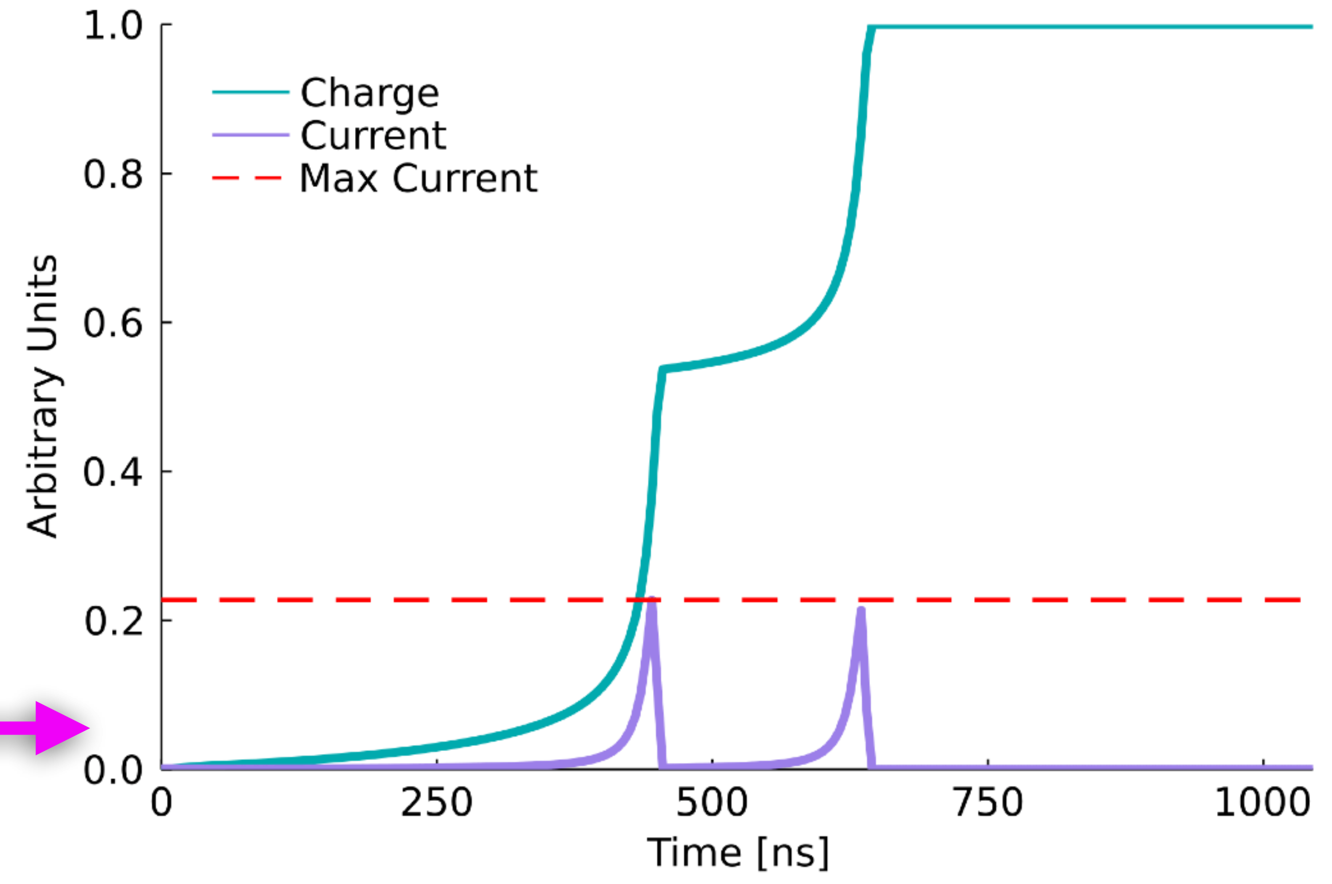












LEGEND

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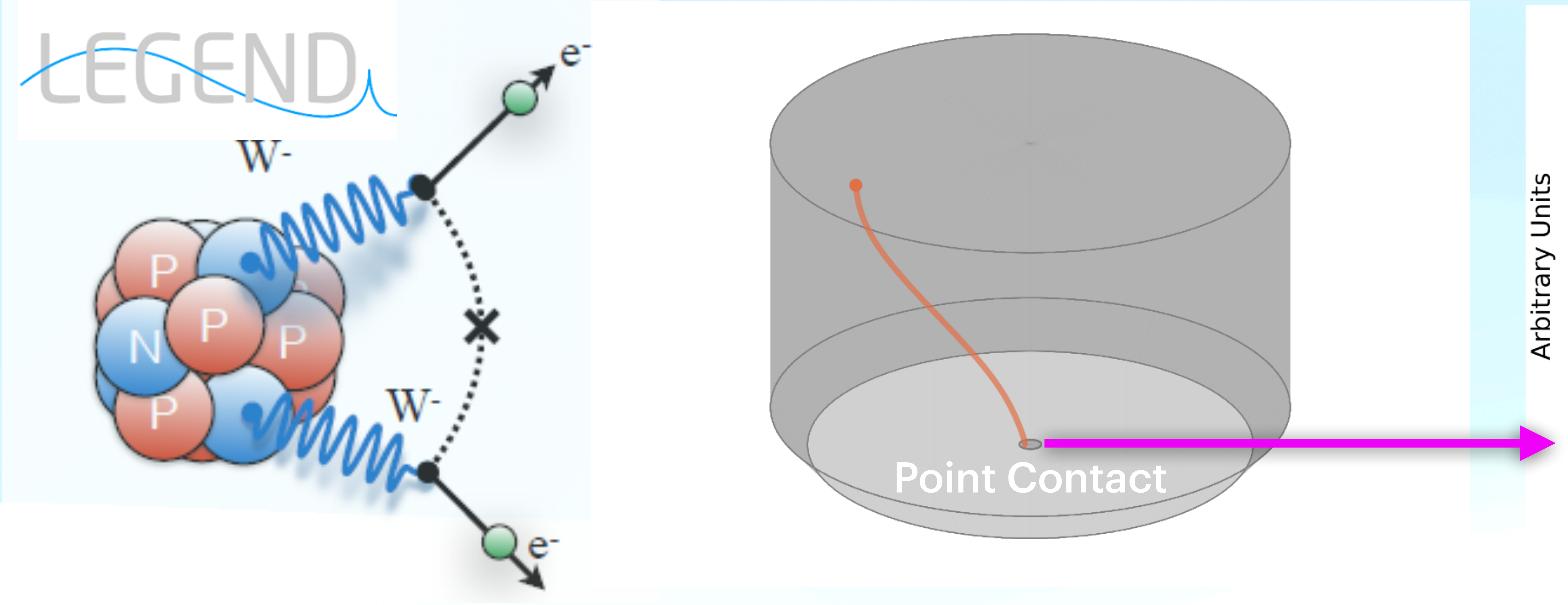
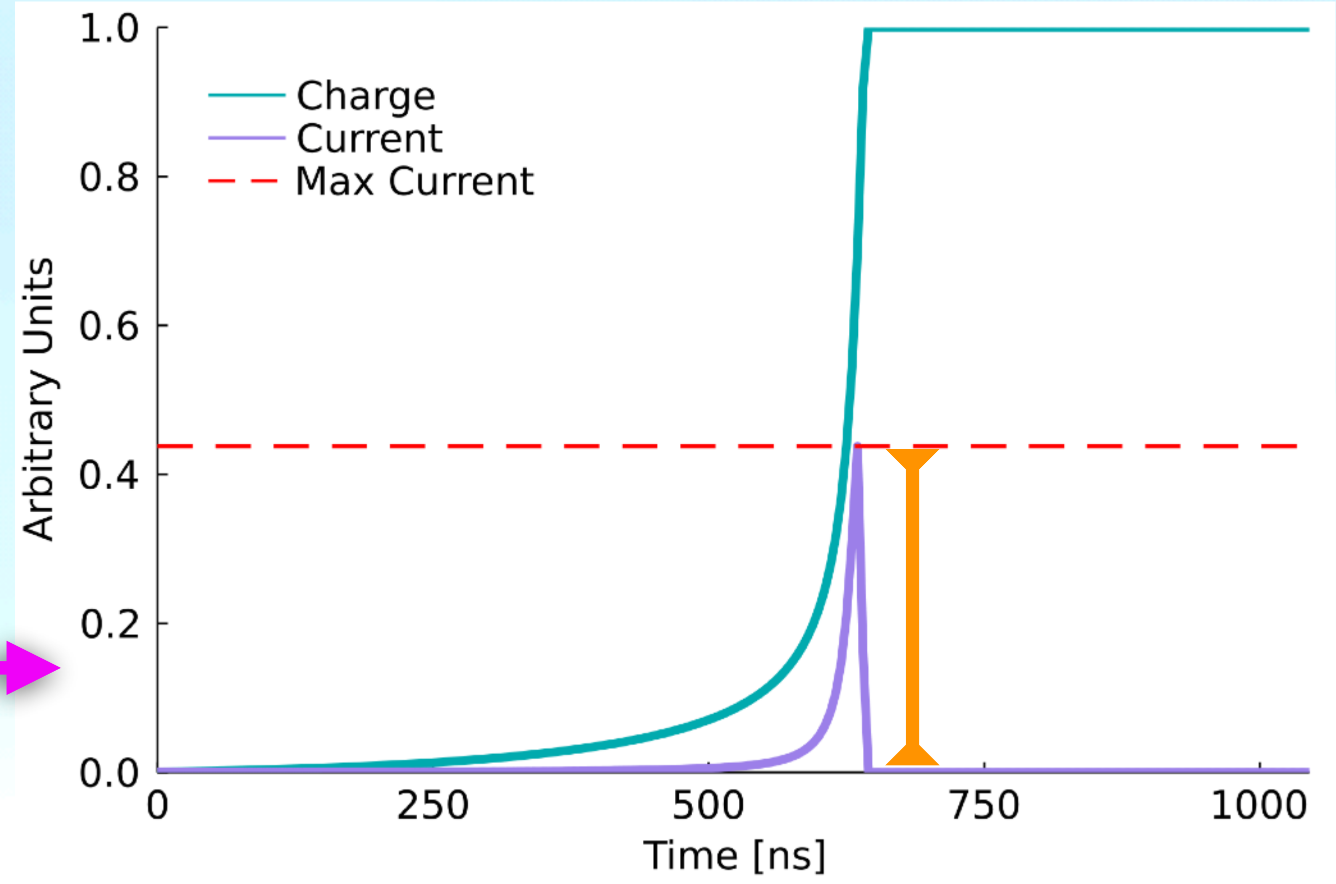
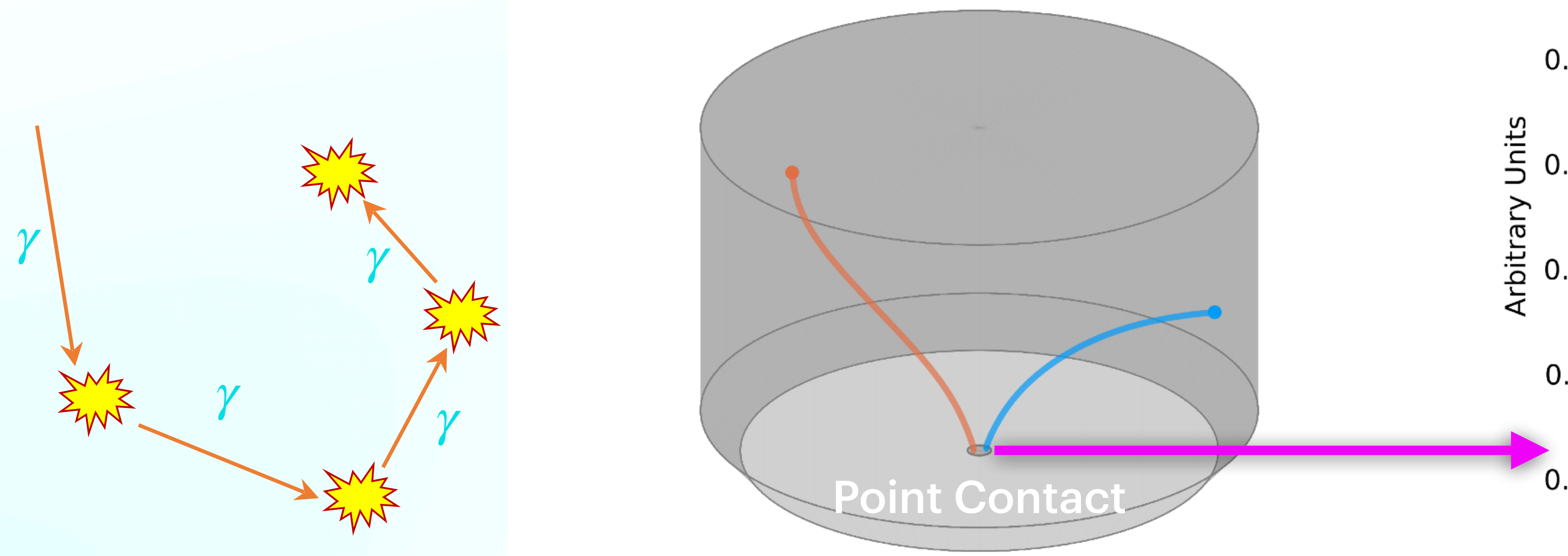
Semiconductor Detector made with ^{76}Ge

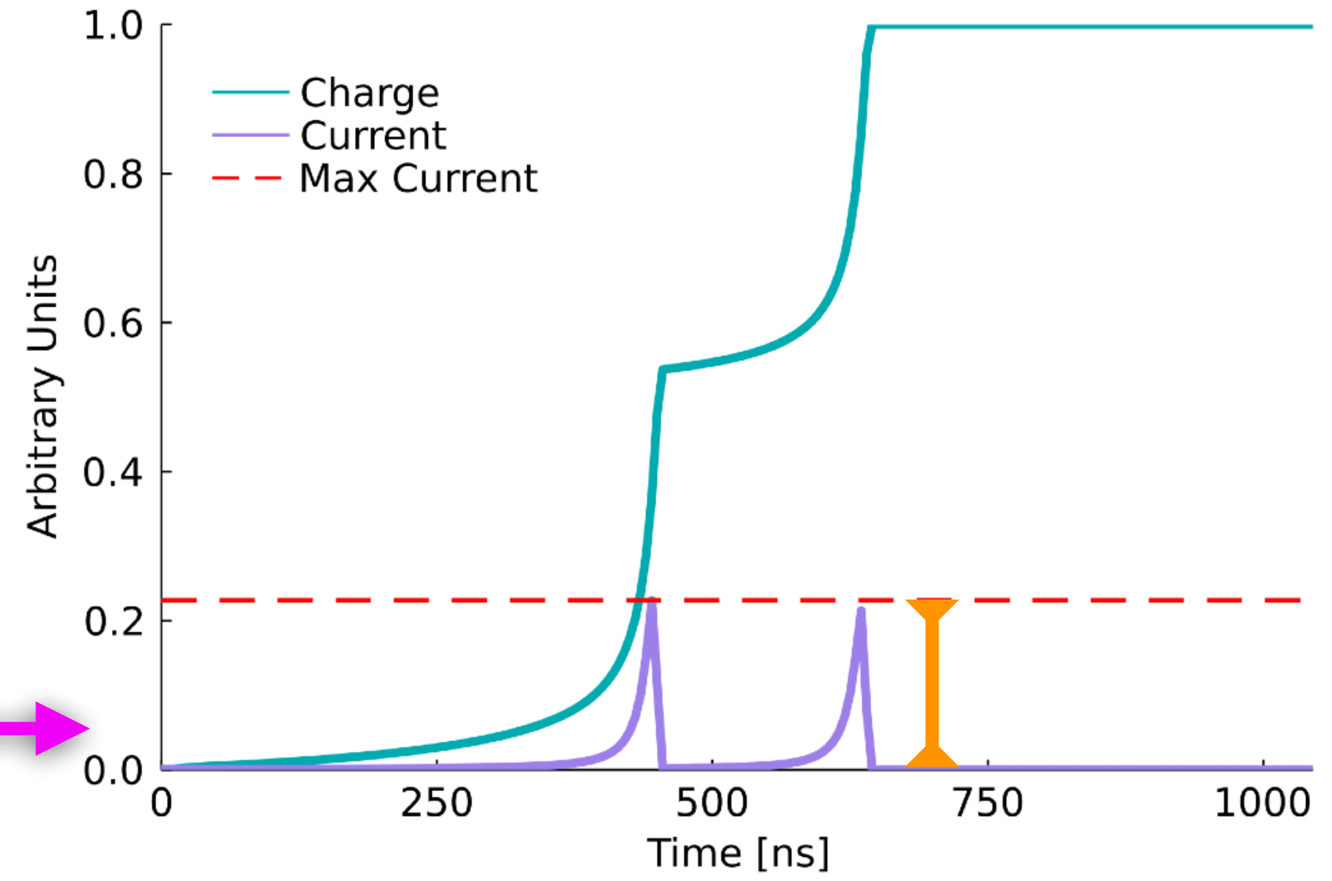
Waveform

Pulse Shape Parameter









Maximal Current Amplitude

For **multi-site background** rejection

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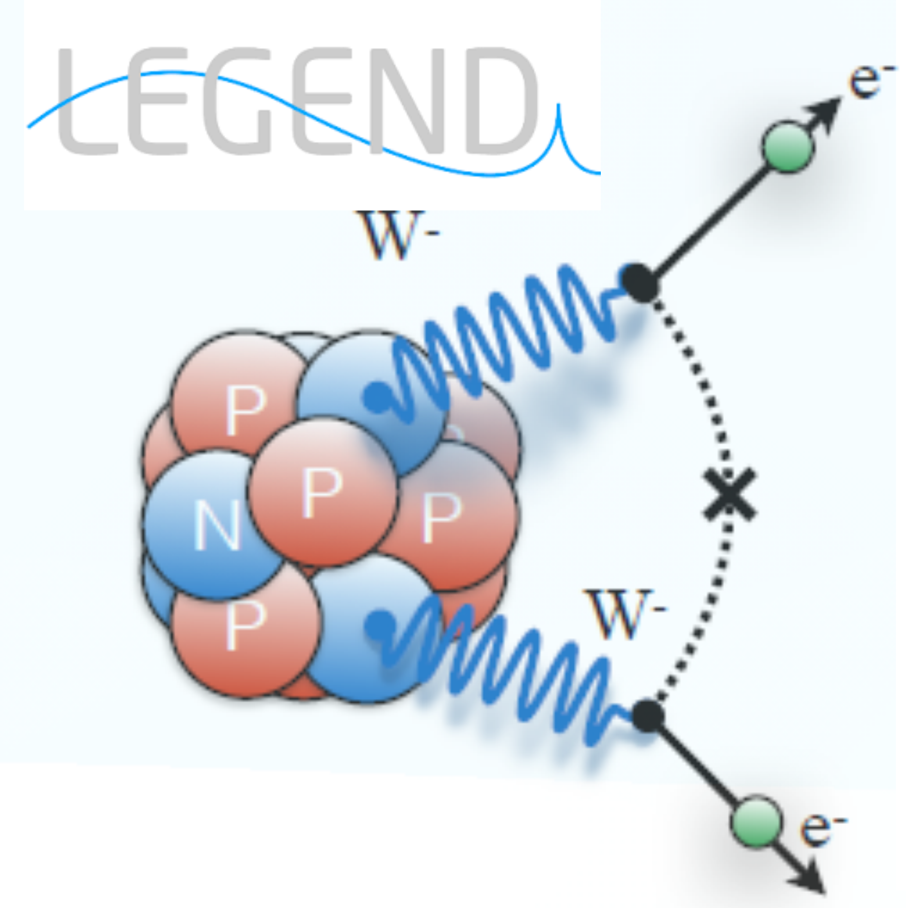
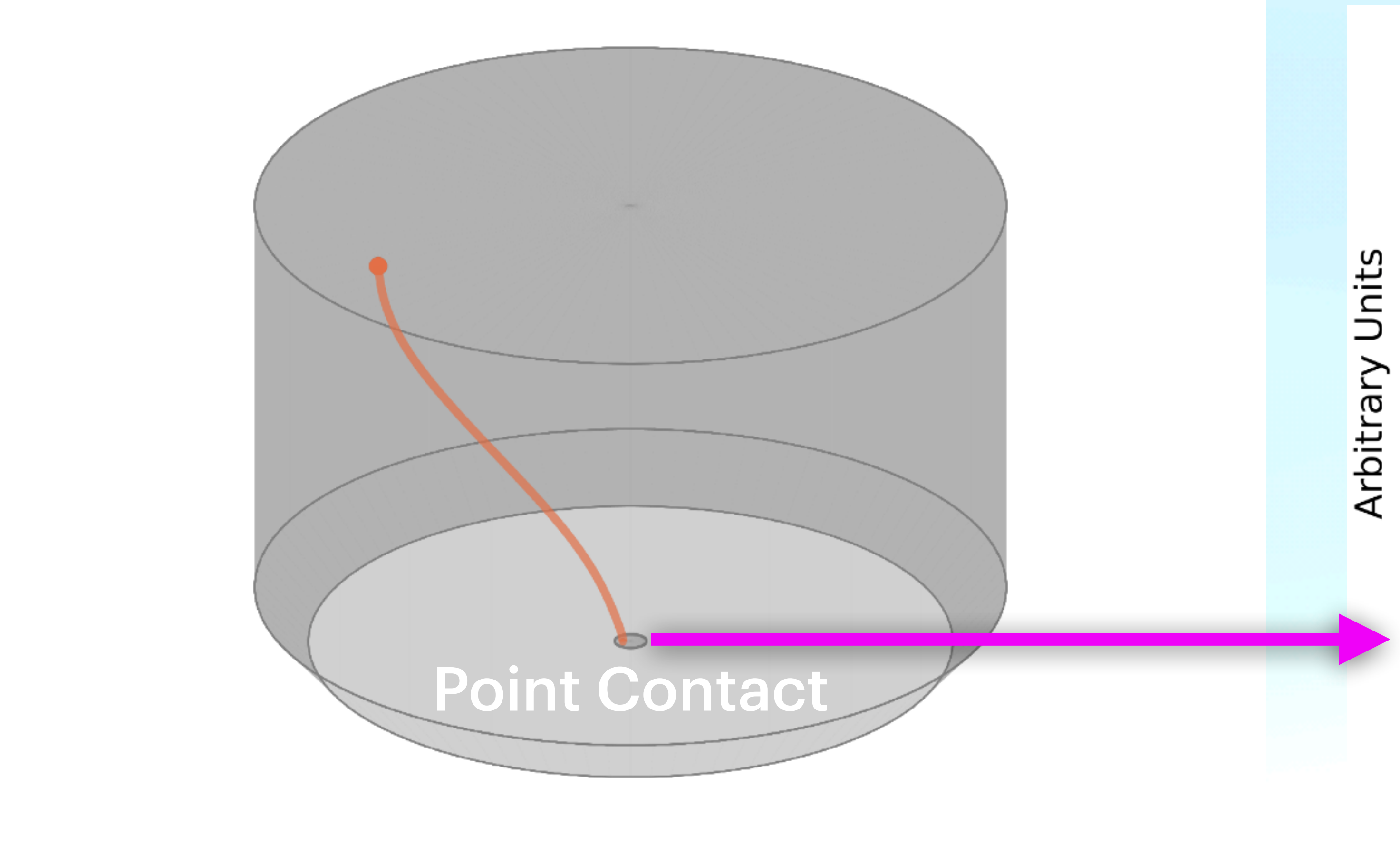
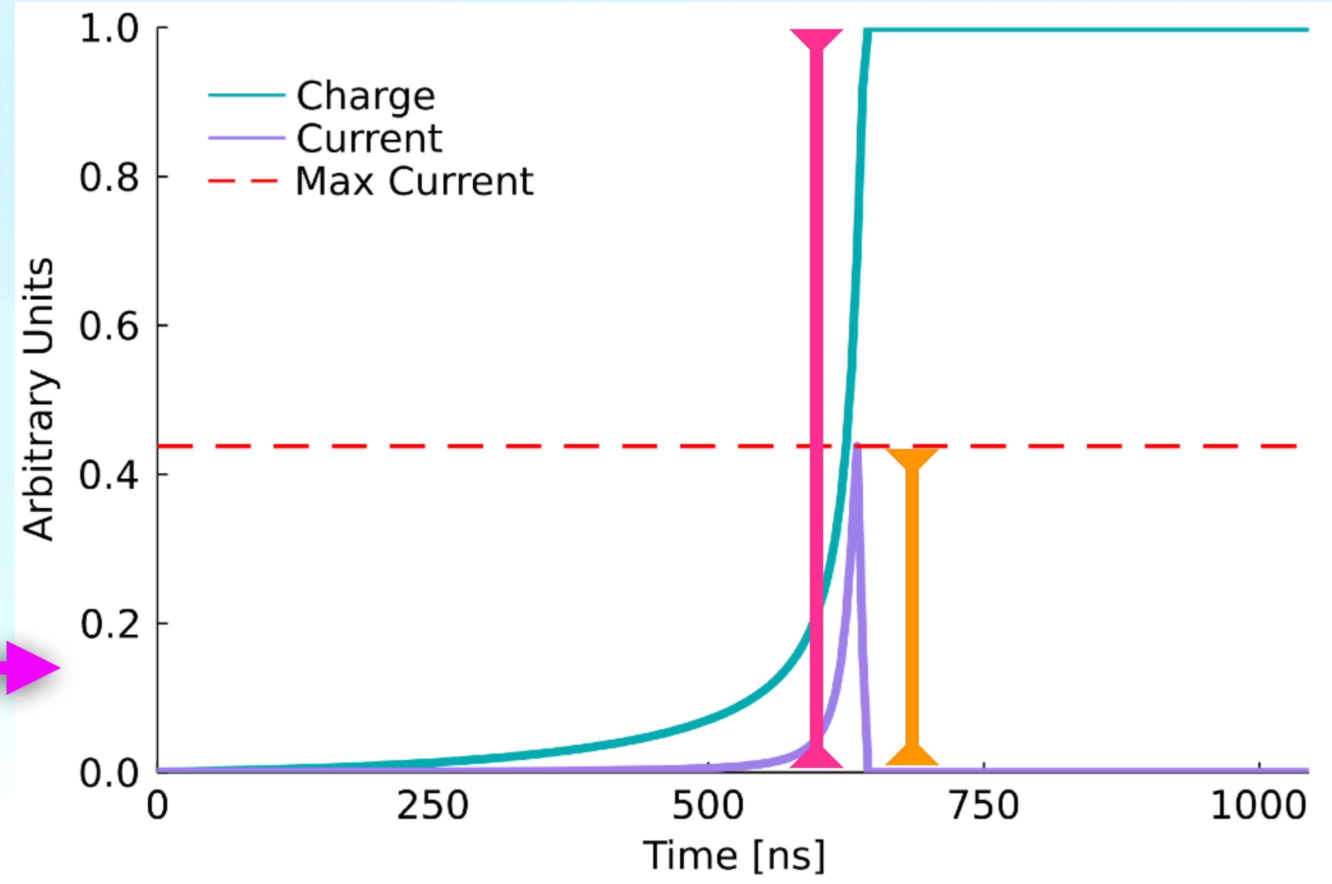
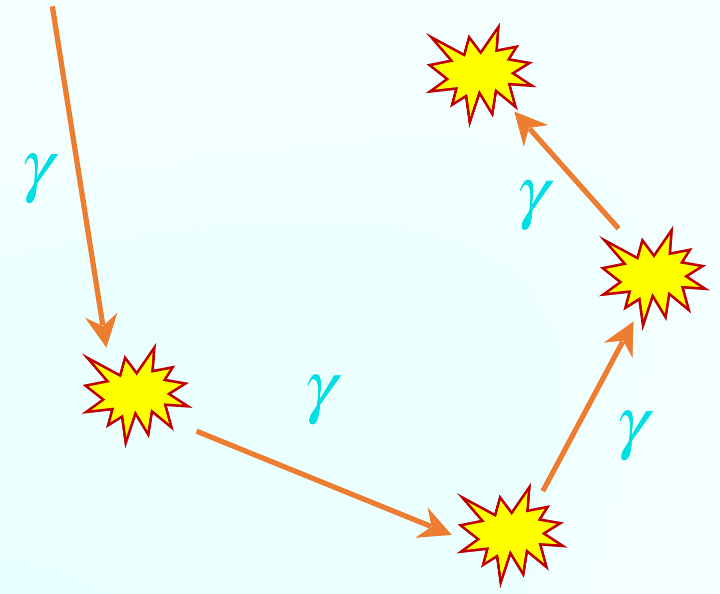
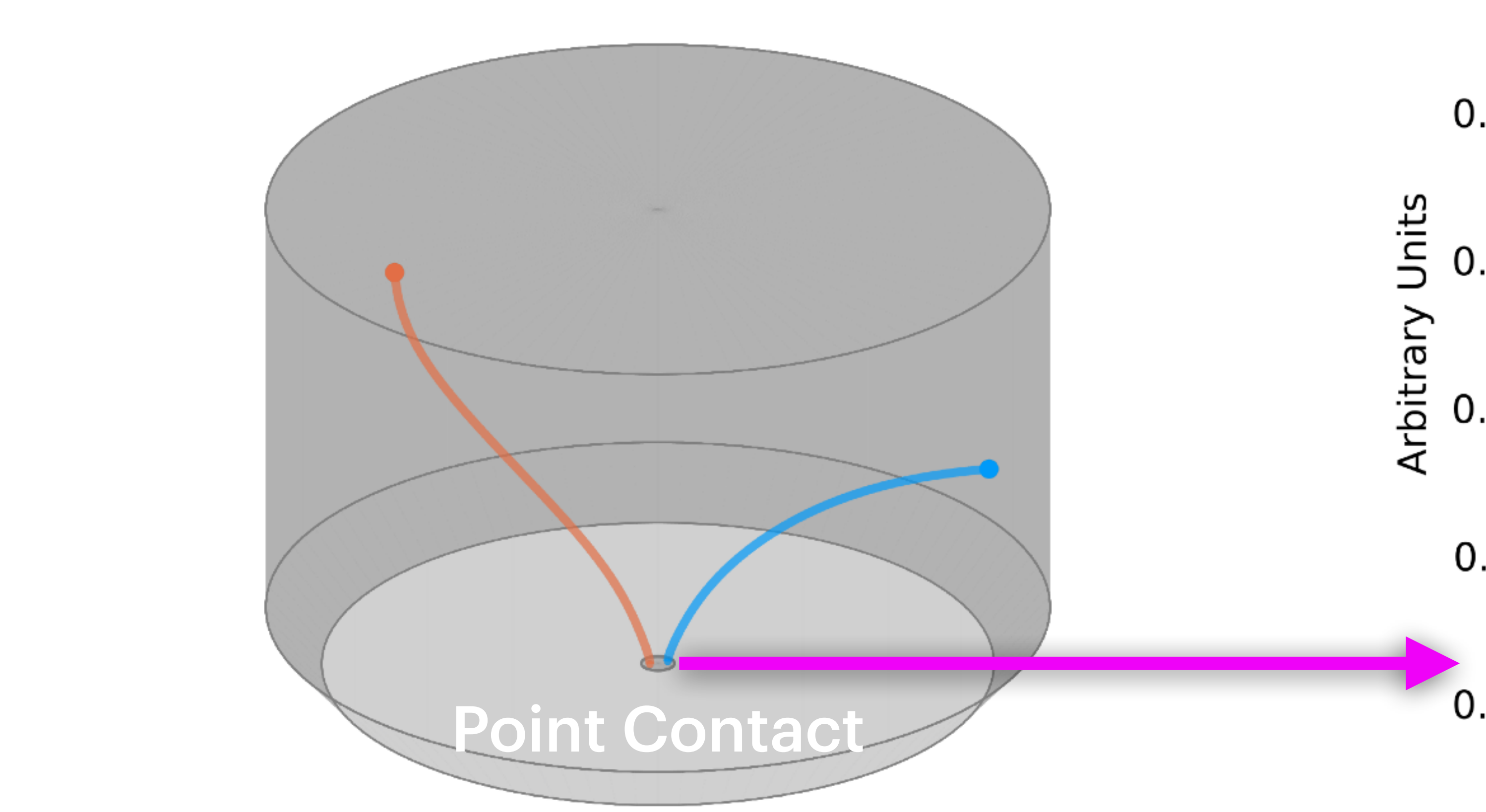


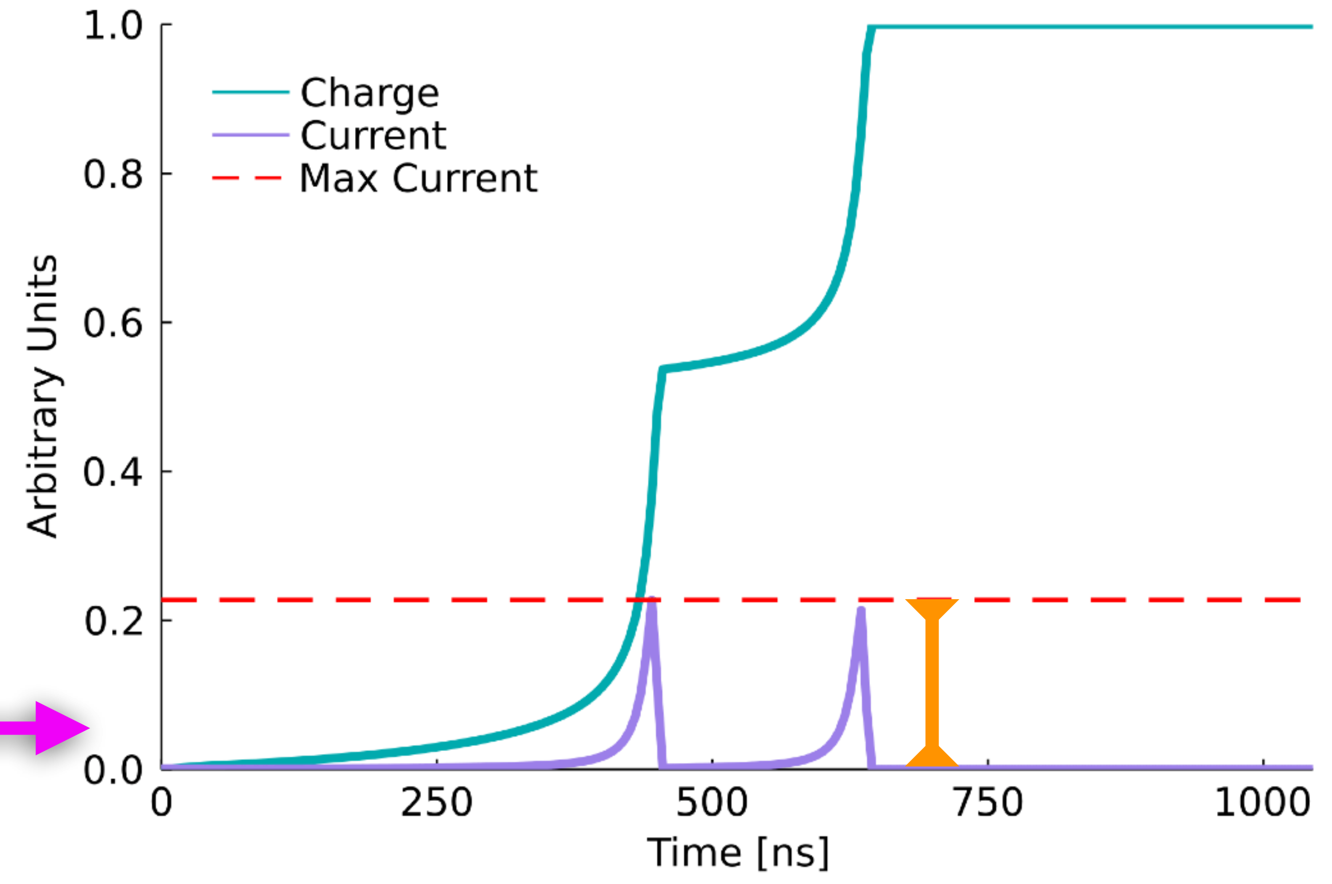




Energy







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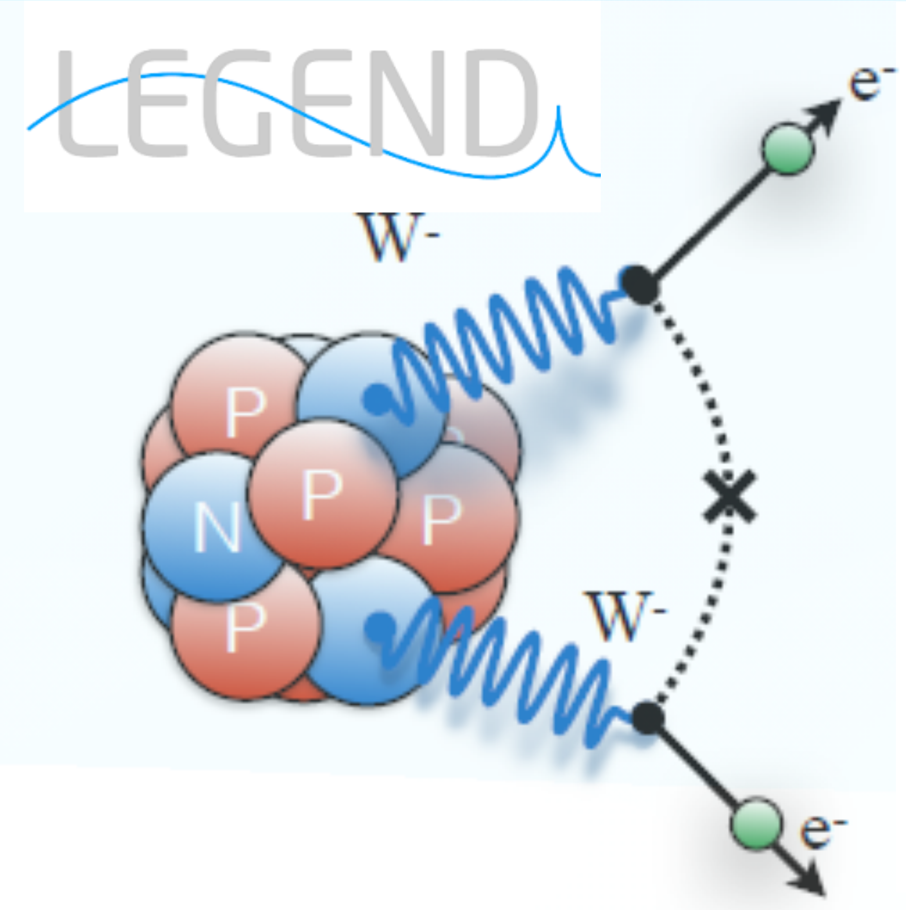
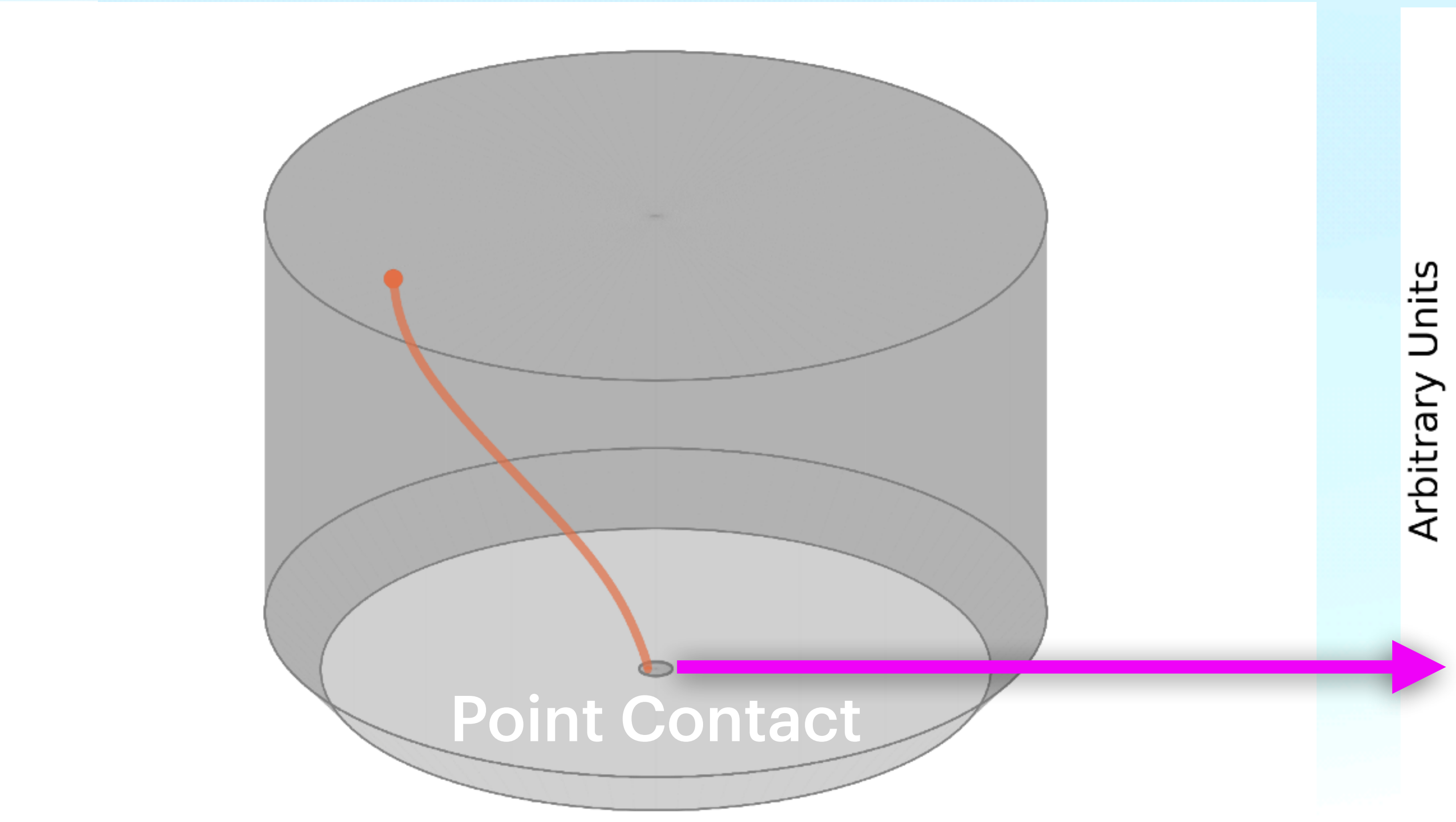
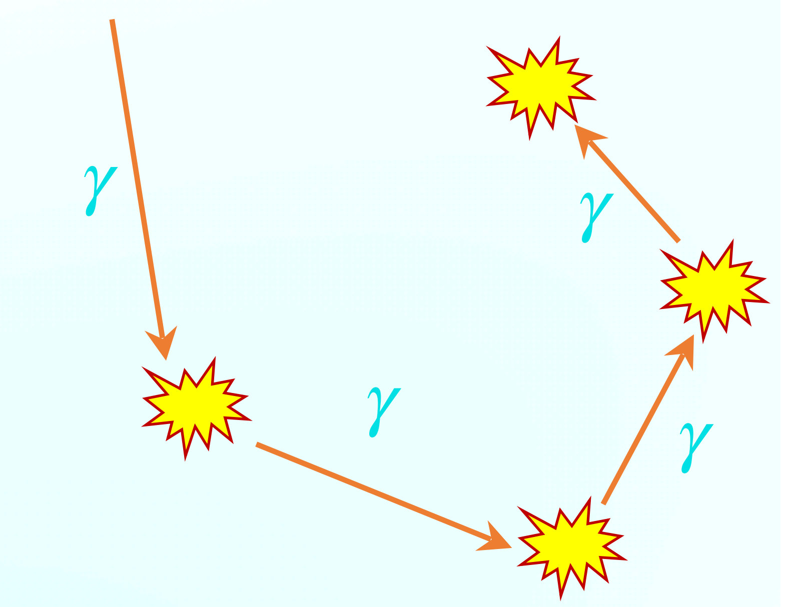
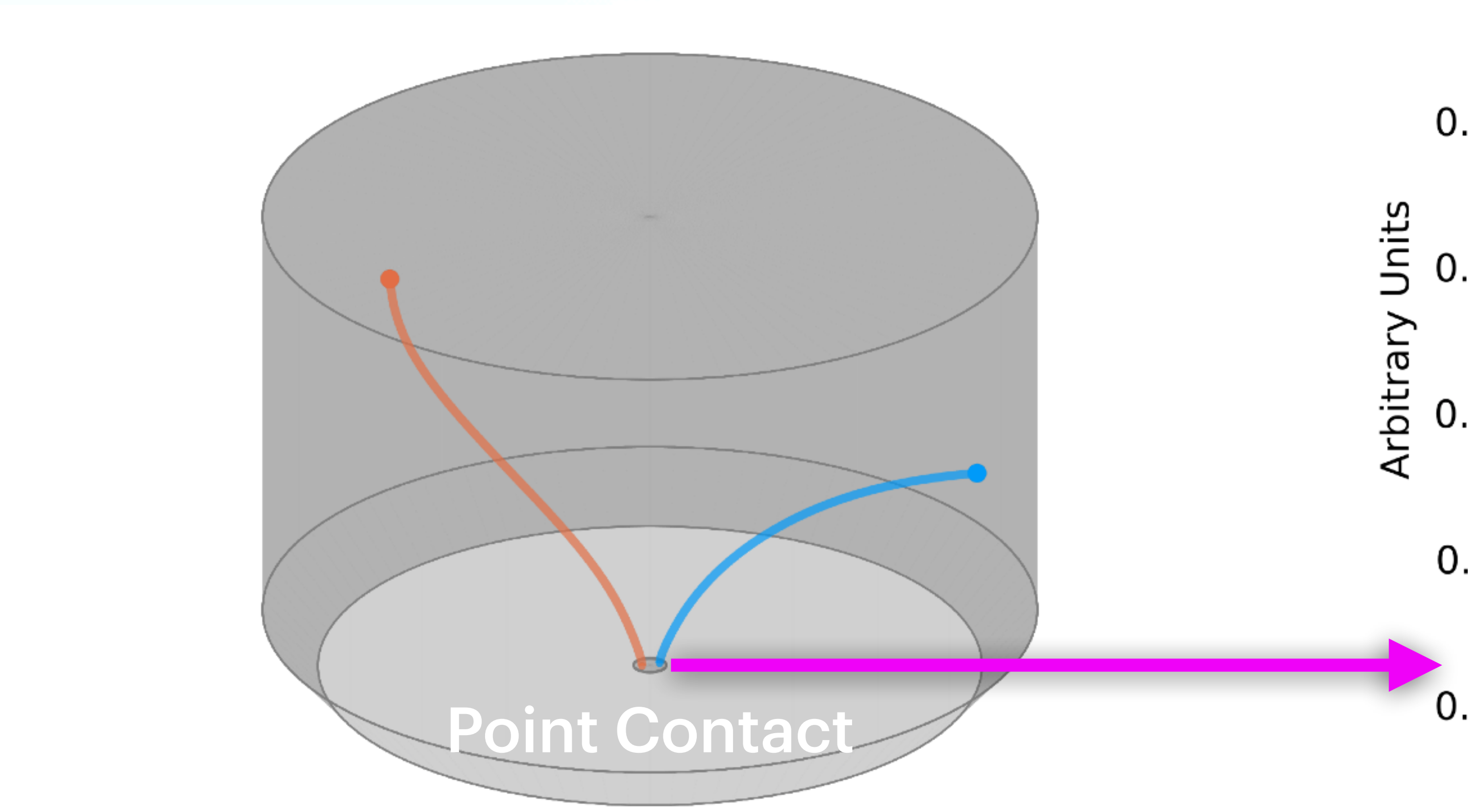
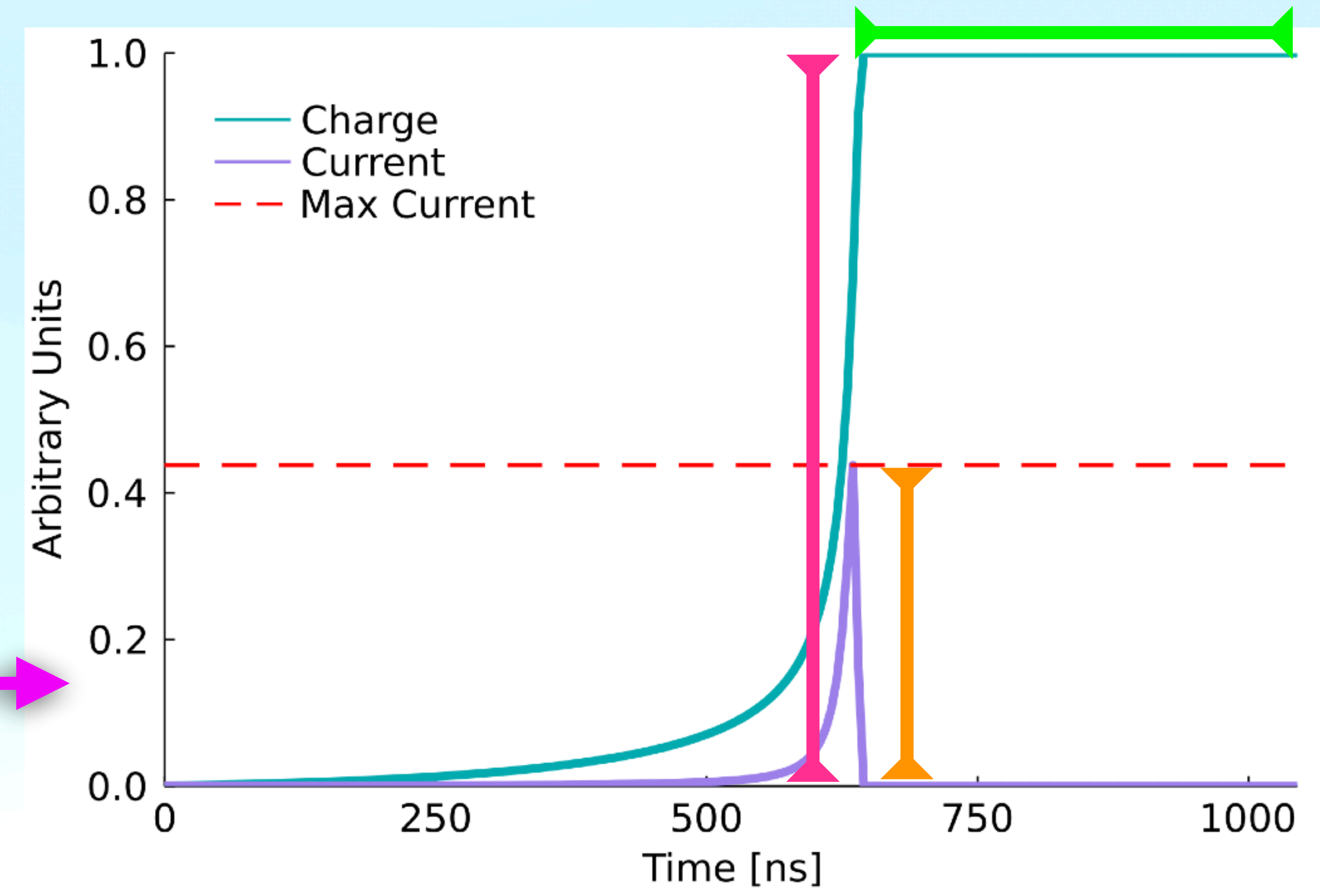


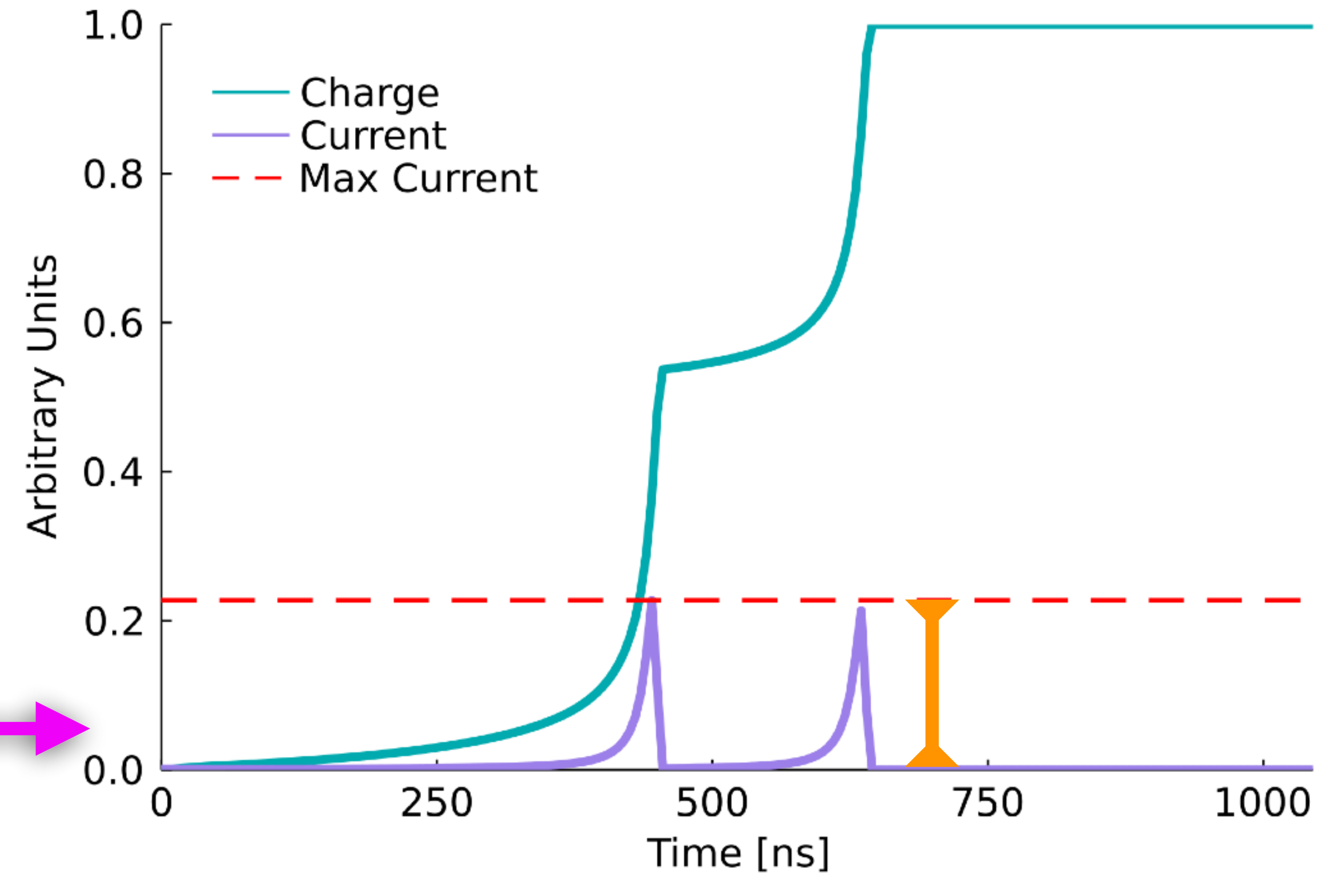






Waveform





Pulse Shape Parameter

Tail Slope

For **surface background** rejection

Energy

Maximal Current Amplitude

For **multi-site background** rejection

LEGEND

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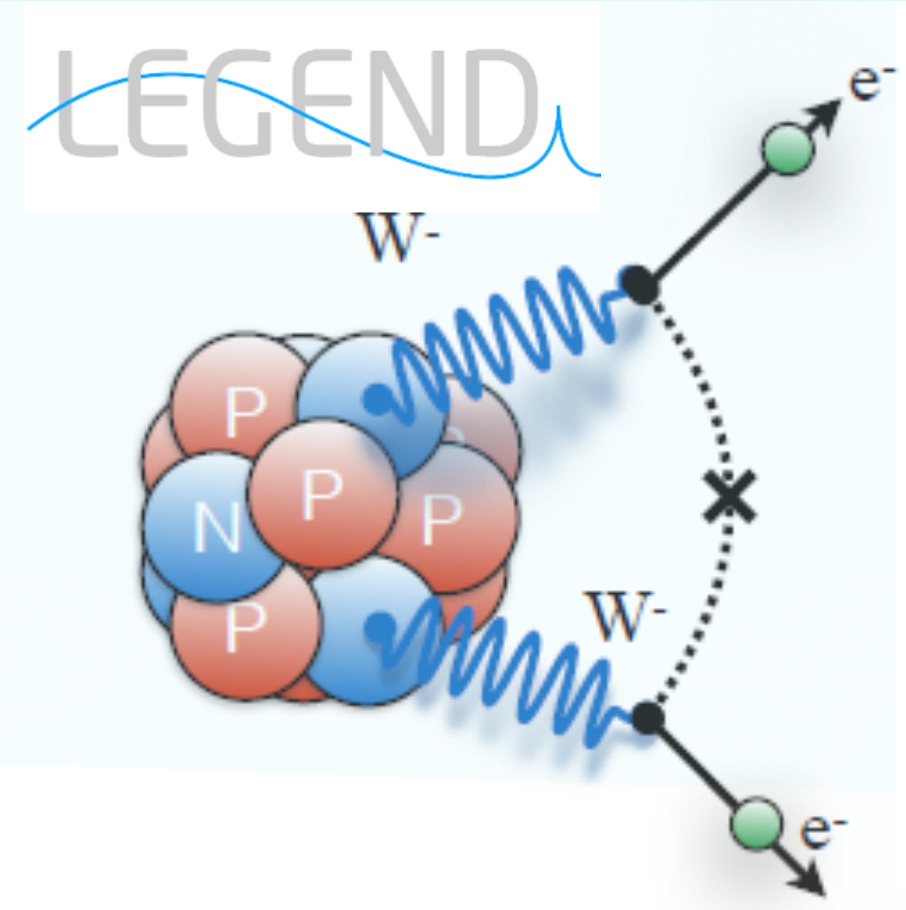
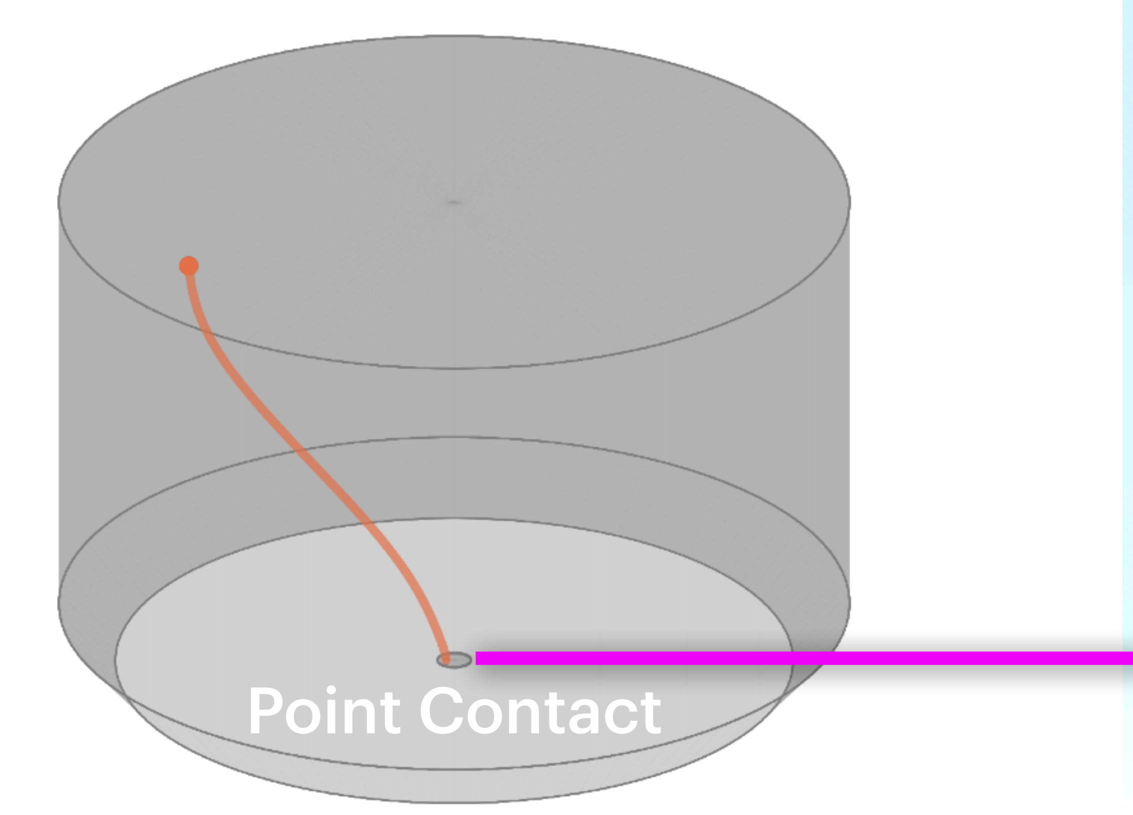
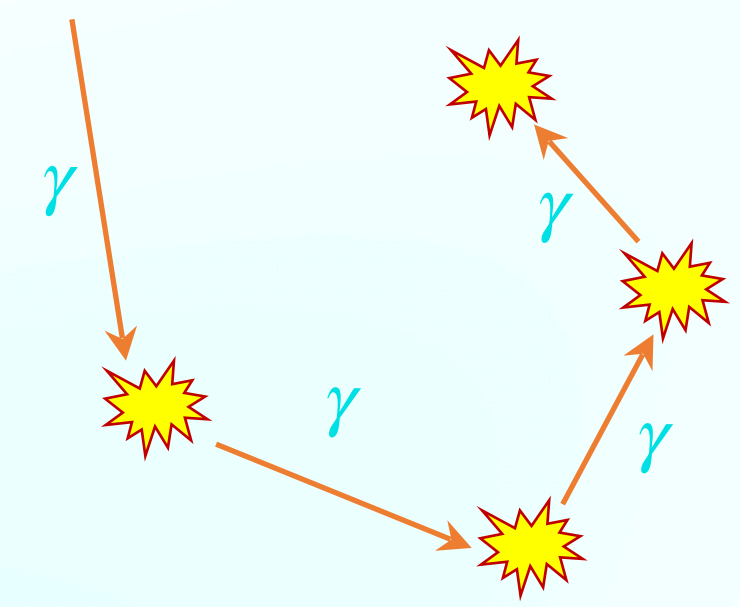
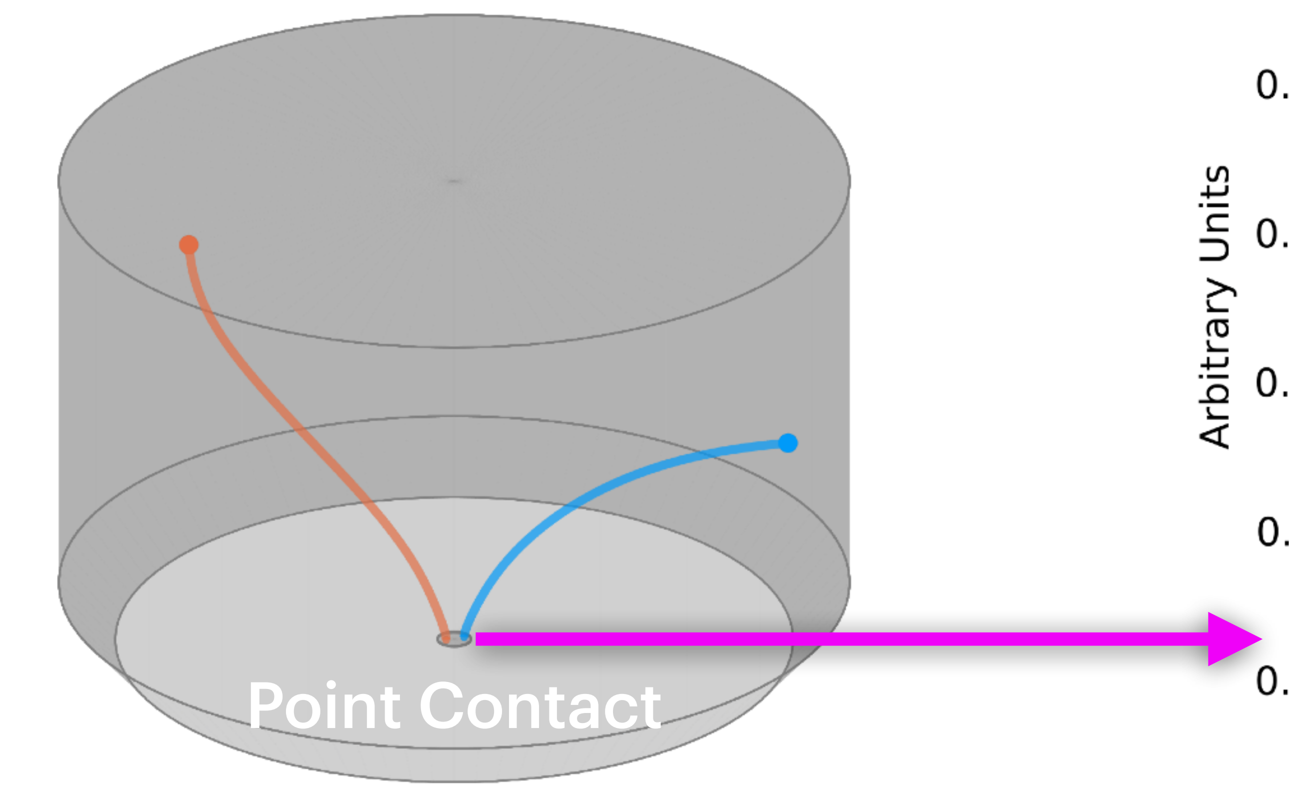
Semiconductor Detector made with ^{76}Ge









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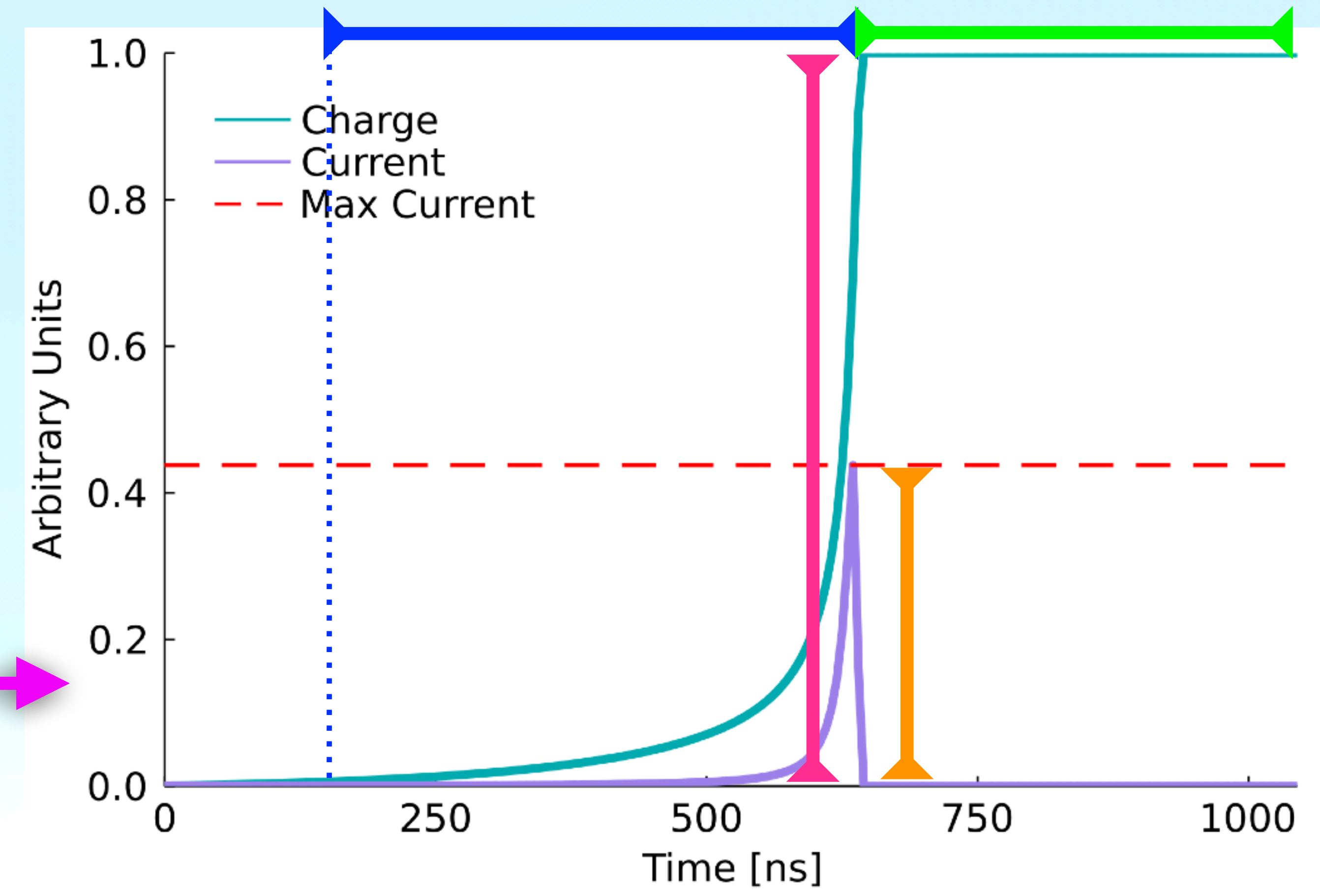
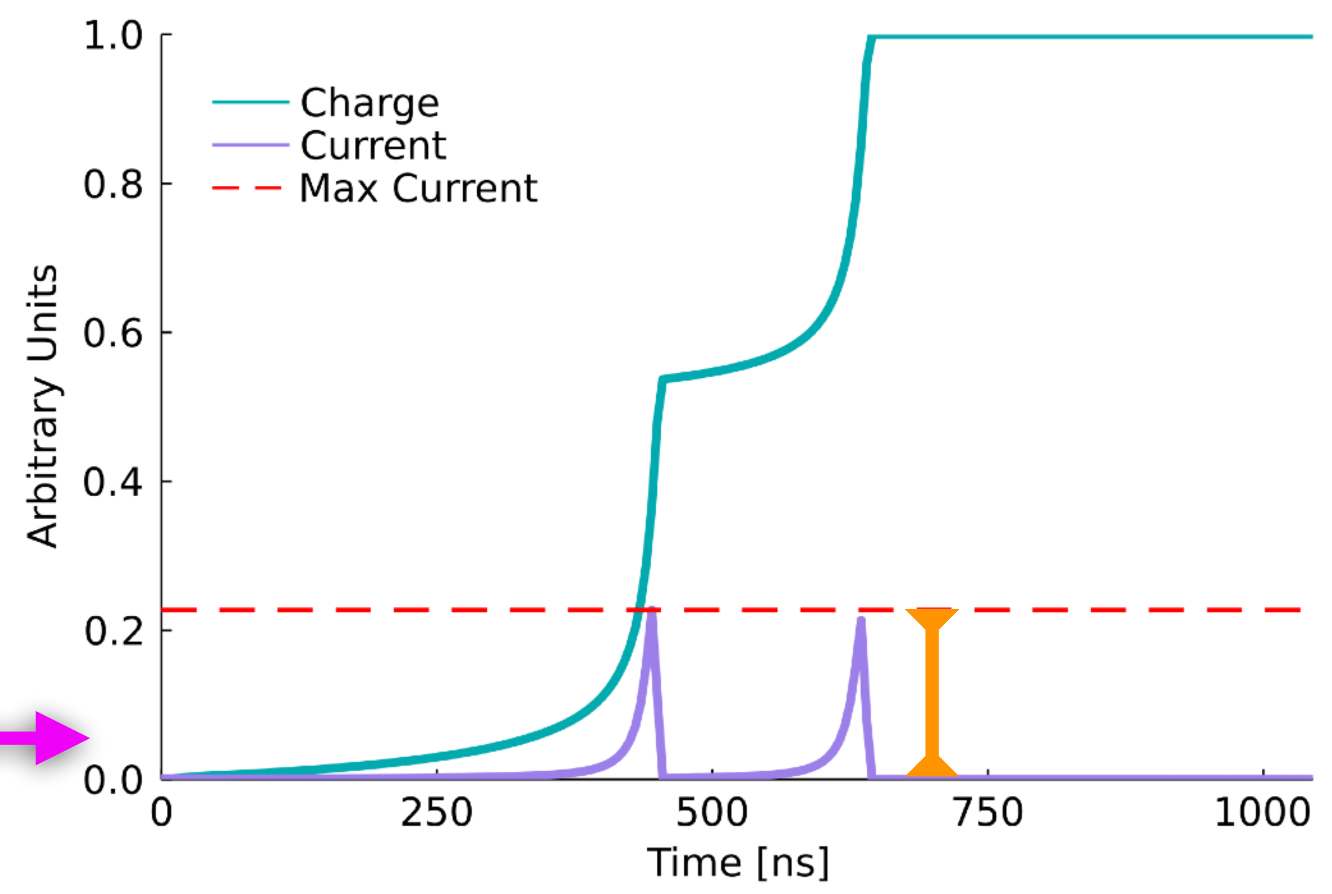




Pulse Shape Parameter

Tail Slope

For **surface background** rejection

Energy

Maximal Current Amplitude

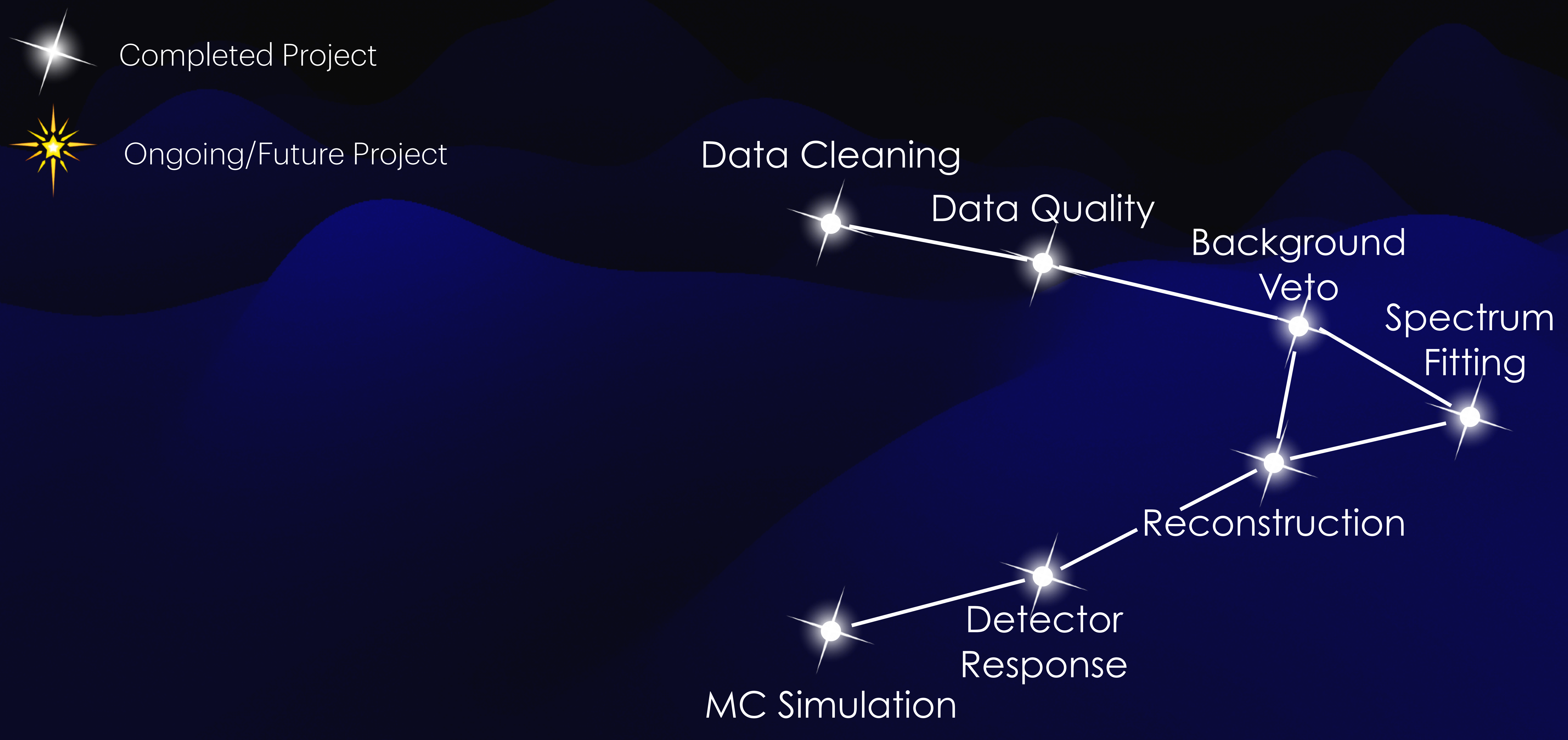
For **multi-site background** rejection

Drift Time

Reflect the location of incident particle

Germanium Machine Learning (GeM) Group

Leverage efficient and interpretable AI to aid all aspects of LEGEND analysis and simulation
Leverage resources to educate domestic and international collaborators to gain AI experience



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Completed Project

Ongoing/Future Project

E. Leon Autonomous Data Cleaning and Run Monitor

Data Cleaning

T. Ye GAN denoising

Data Quality

T. Oli LBM Network PSA

A. Li, H. Nachman Interpretable BDT

M. Babciz Transformer-based background rejection

Background Veto

Spectrum Fitting

A. Li Develop LEGEND Baseline Model (LBM)

K. Kilgus, A. Li Enhance LBM with Feature Importance Supervision

A. Alexander LBM Dead Layer Fitting

Reconstruction

L. Paudel LBM Site Energy Reconstruction

R. Pitelka LBM Position Reconstruction

Detector Response

A. Li, K. Bhimani Cyclic Positional U-Net

MC Simulation

N. Zareskii GAN Waveform Simulation

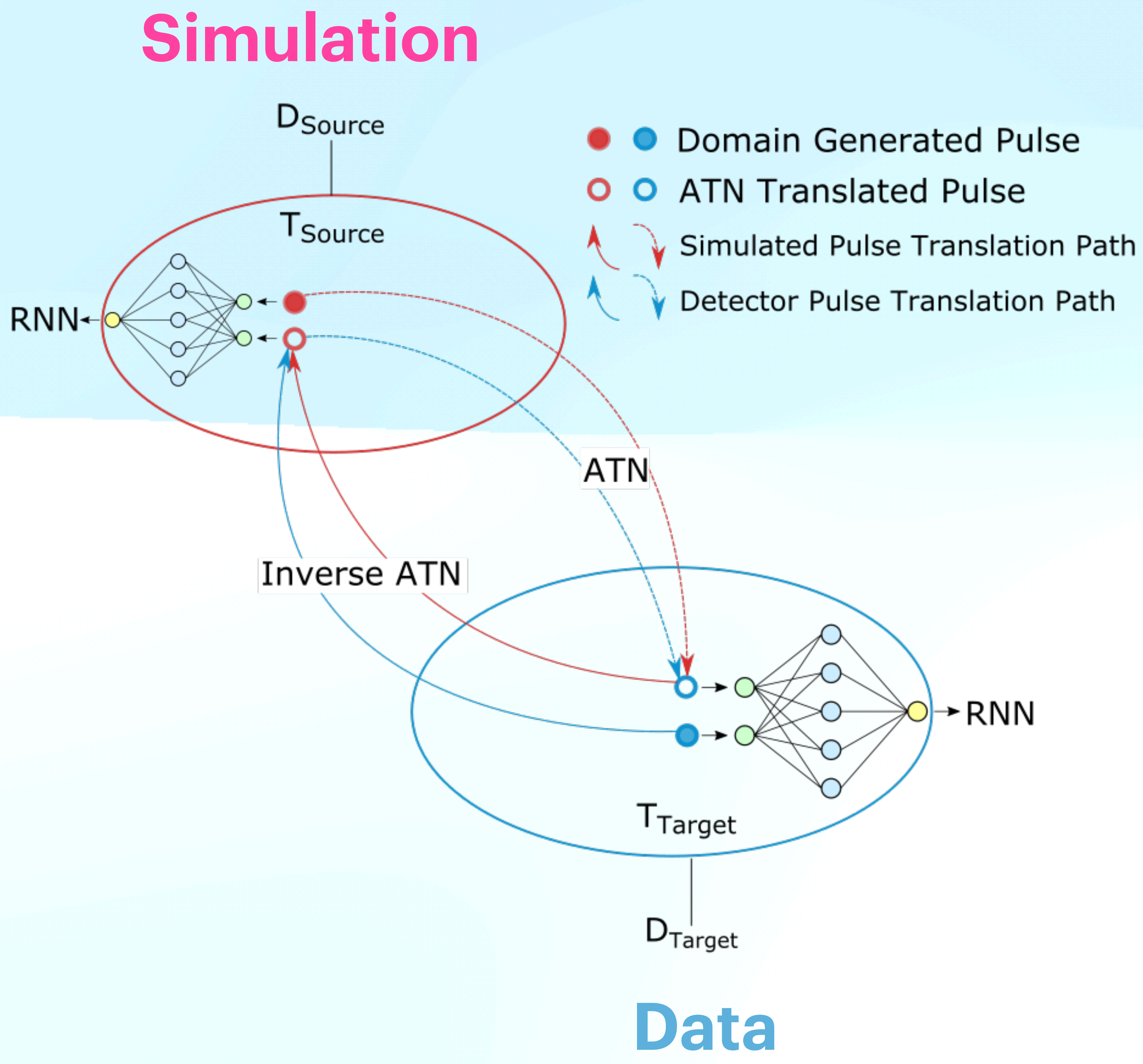
A. Shuetz Neutron Moderator Design Emulation

2 Postdocs, 9 Graduate Students, 2 Undergraduate Students

CPU-Net: Translate Simulation to Data

Unpaired Translation with CycleGAN

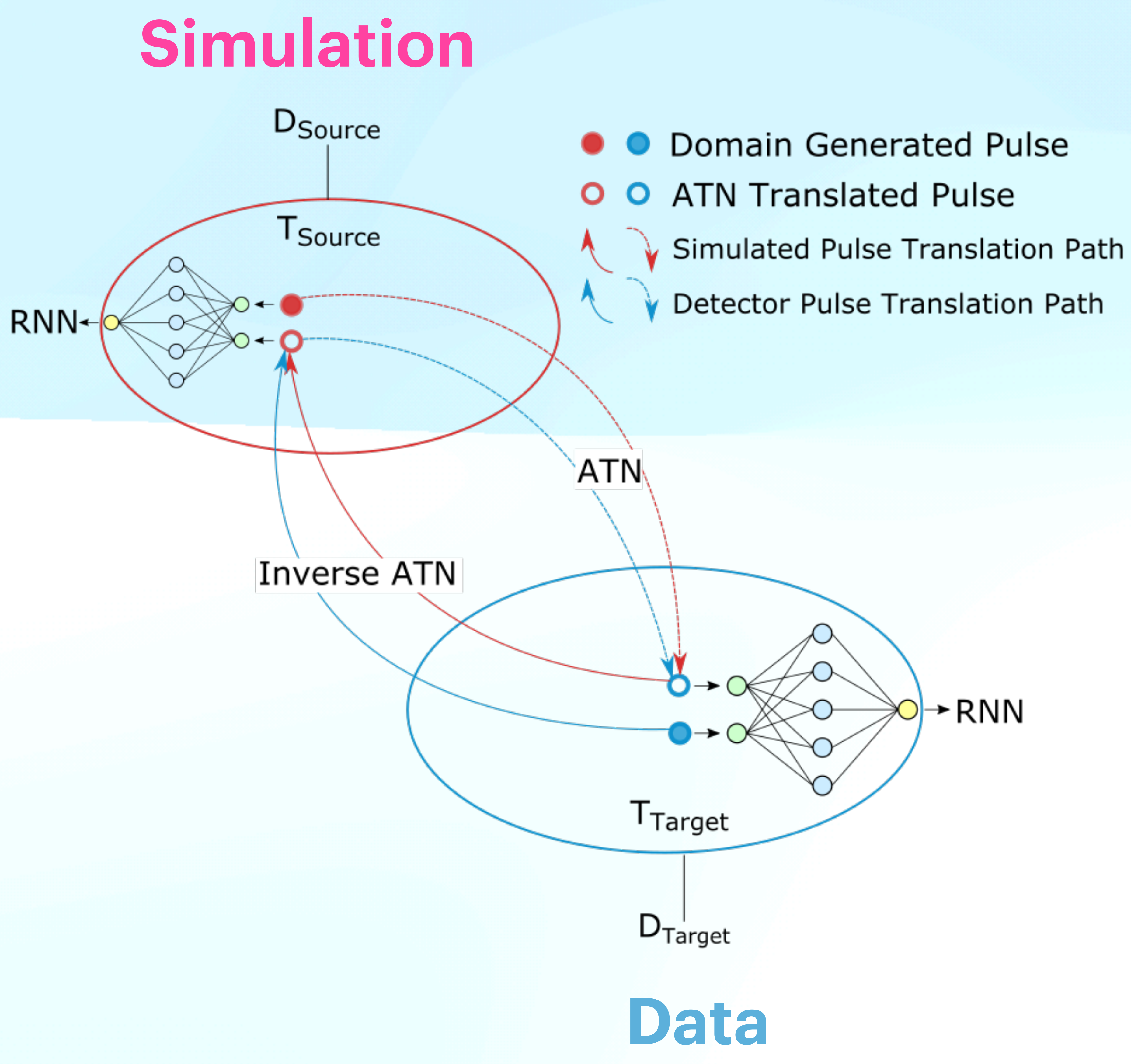
Ad-hoc Pulse Shape Simulation using Cyclic Positional U-Net
A. Li et al. NeurIPS 22 ML4PS Workshop Outstanding Paper

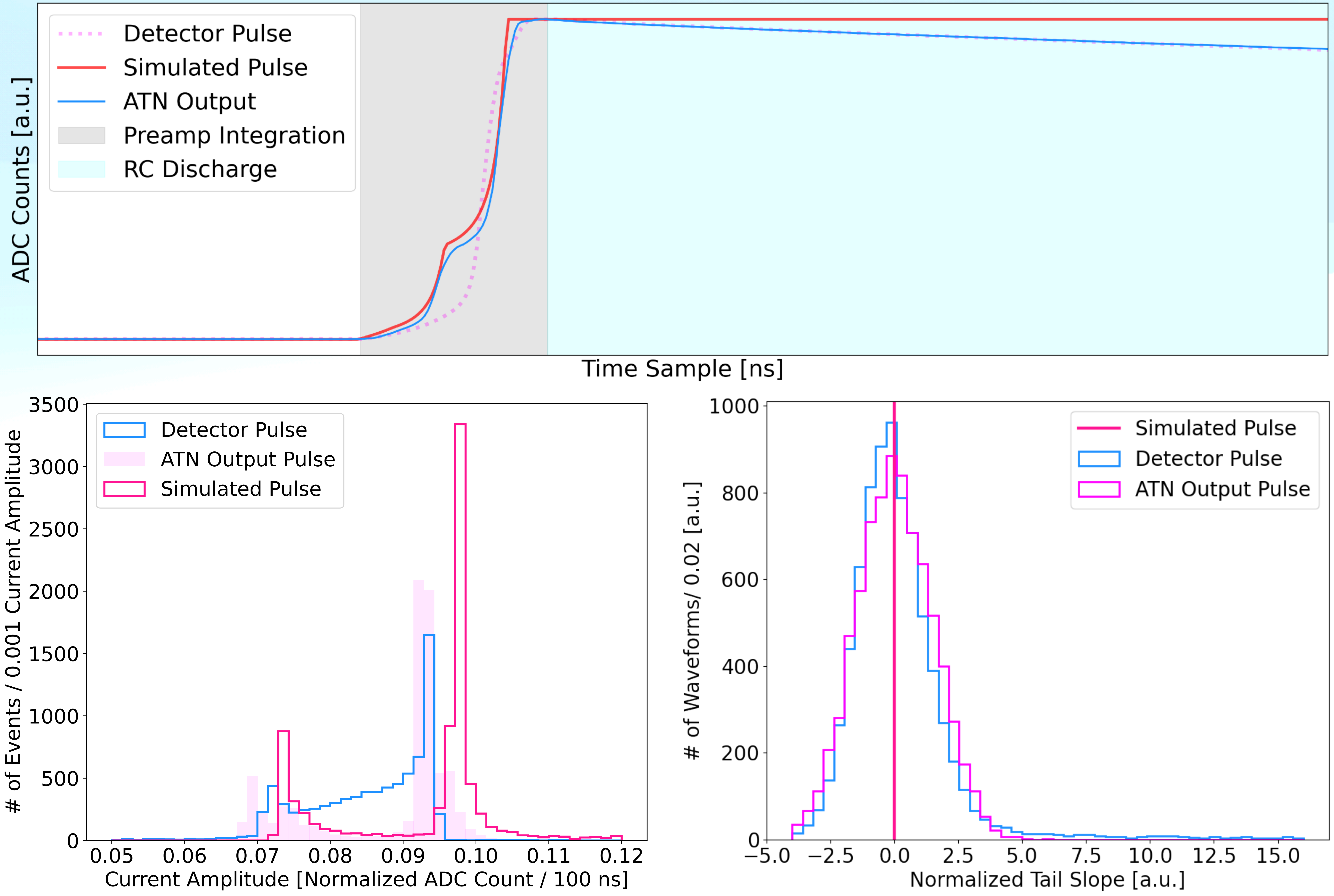


CPU-Net: Translate Simulation to Data

Unpaired Translation with CycleGAN

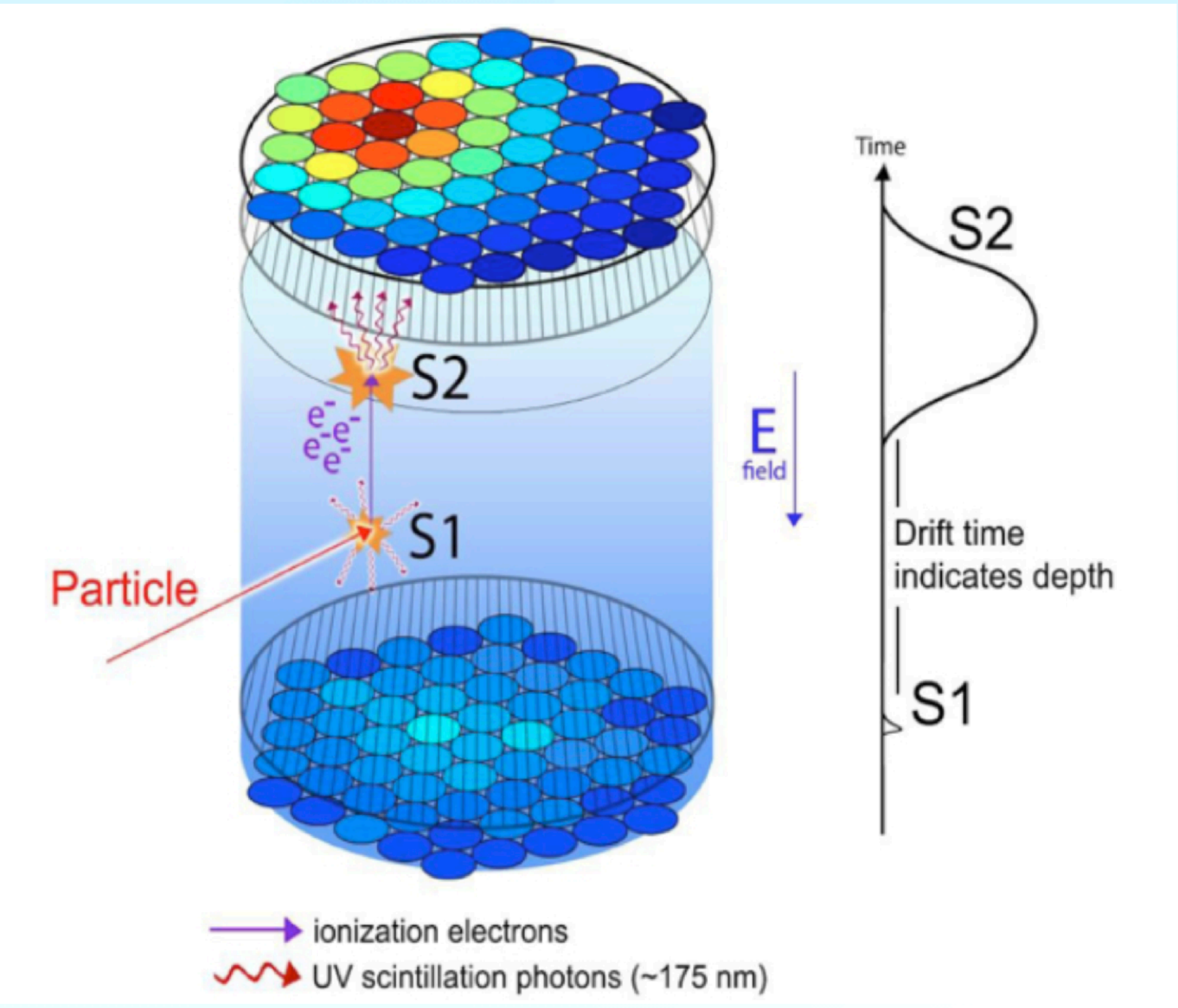
Ad-hoc Pulse Shape Simulation using Cyclic Positional U-Net
A. Li et al. NeurIPS 22 ML4PS Workshop Outstanding Paper





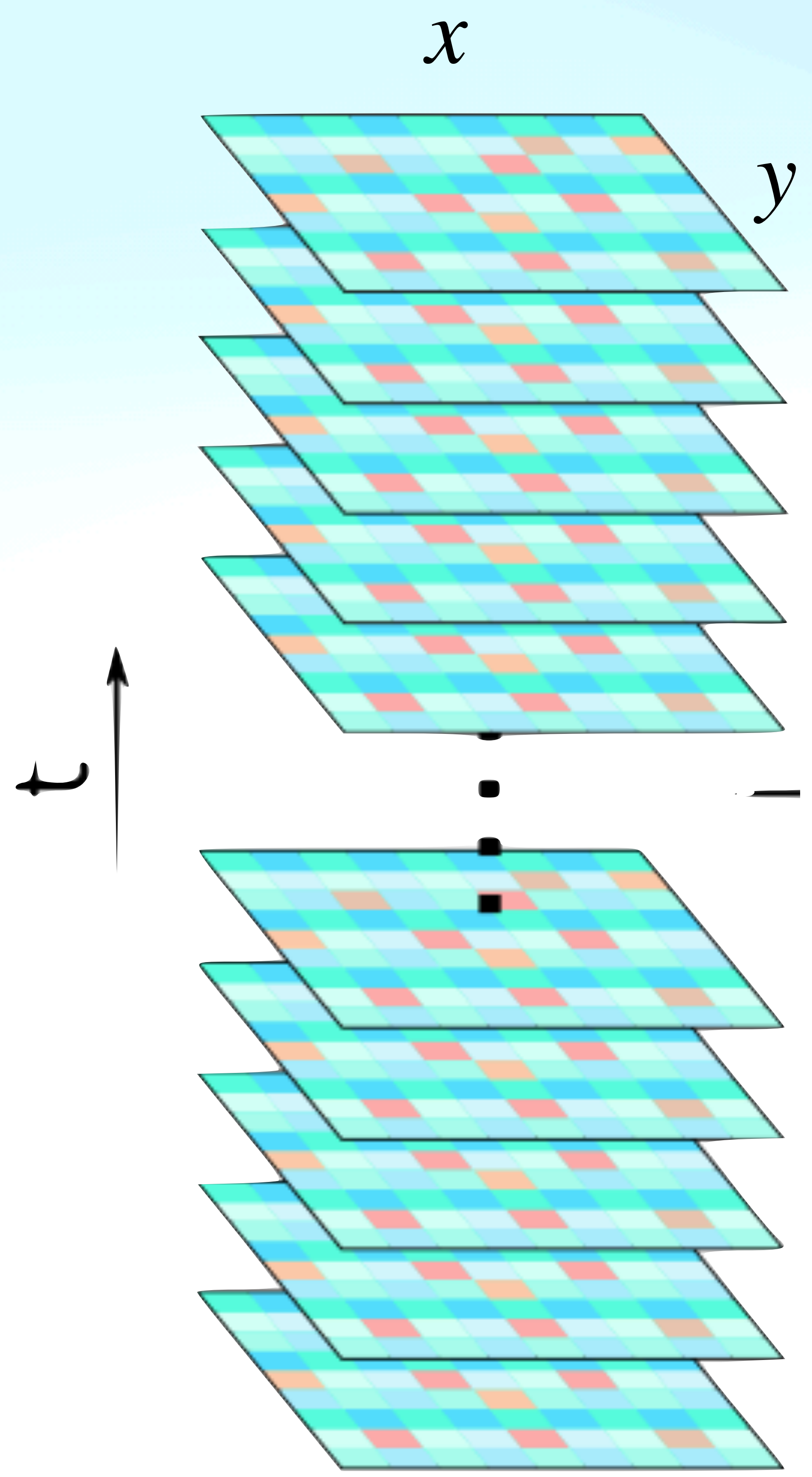
XENONnT

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



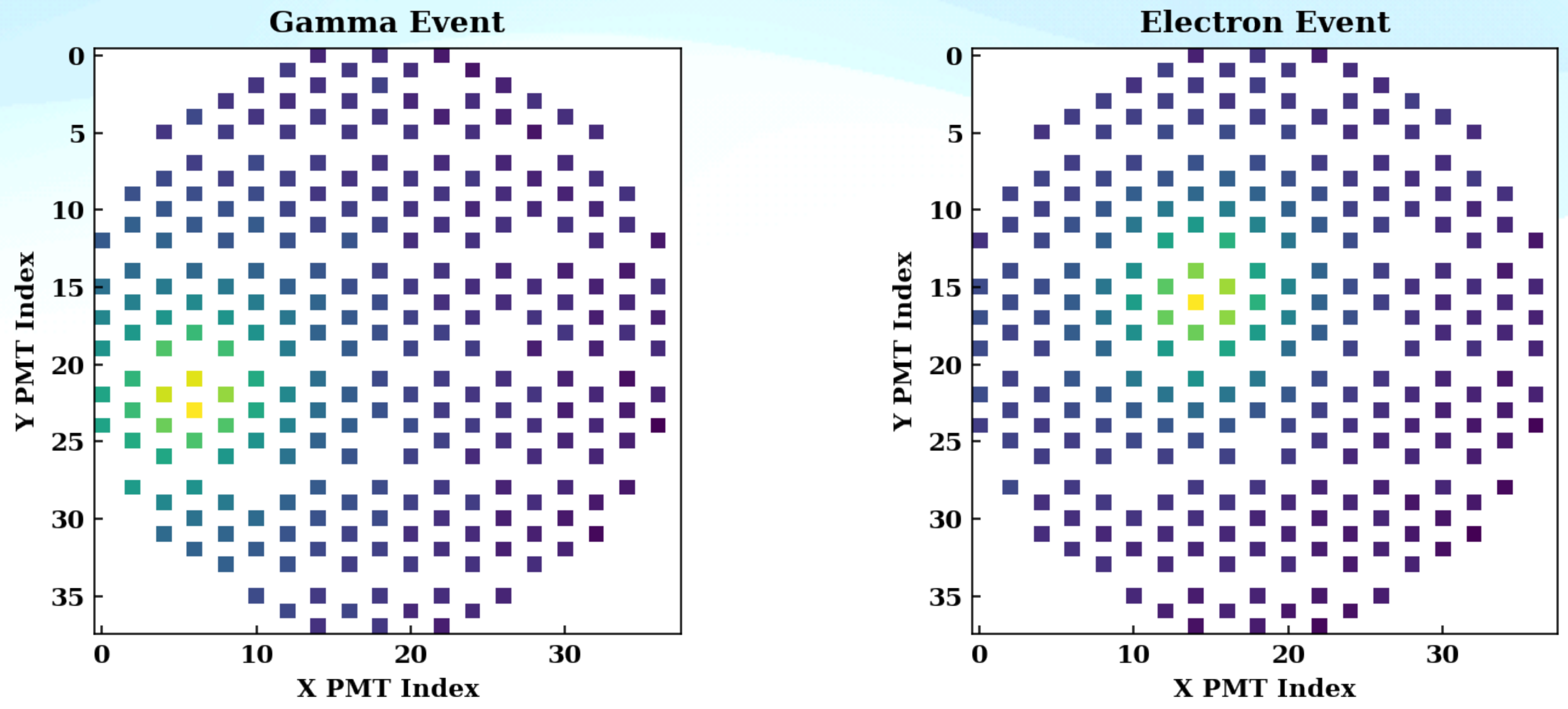
Spatiotemporal Data

A 2D flat video



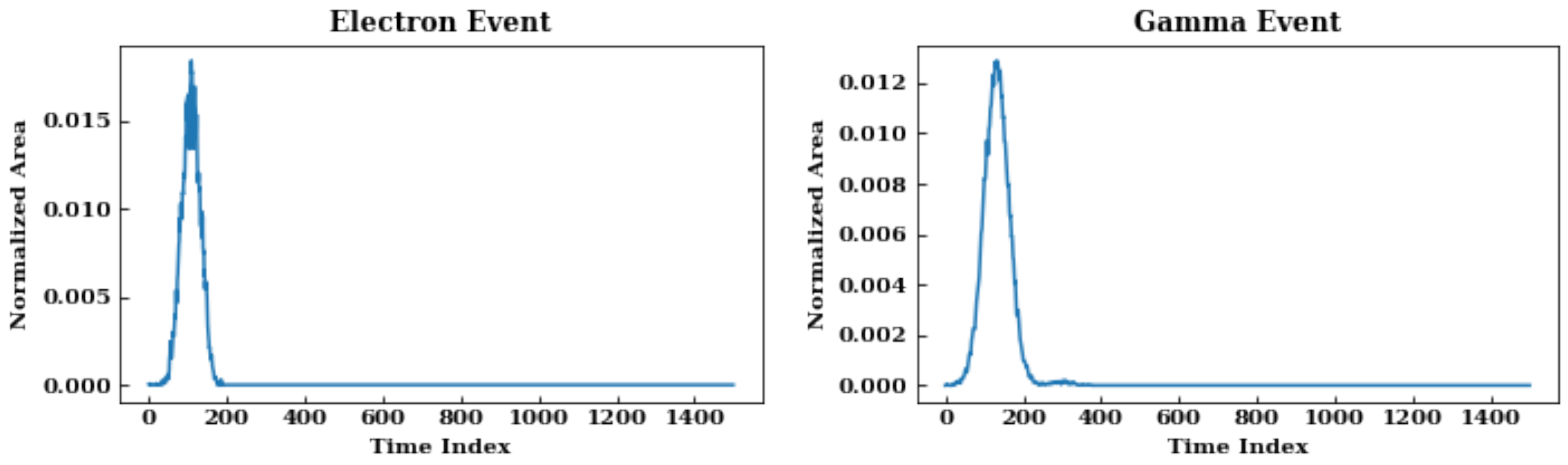
Hit Pattern

2D Image



Waveform

1D Time Series



XENONnT AI Projects

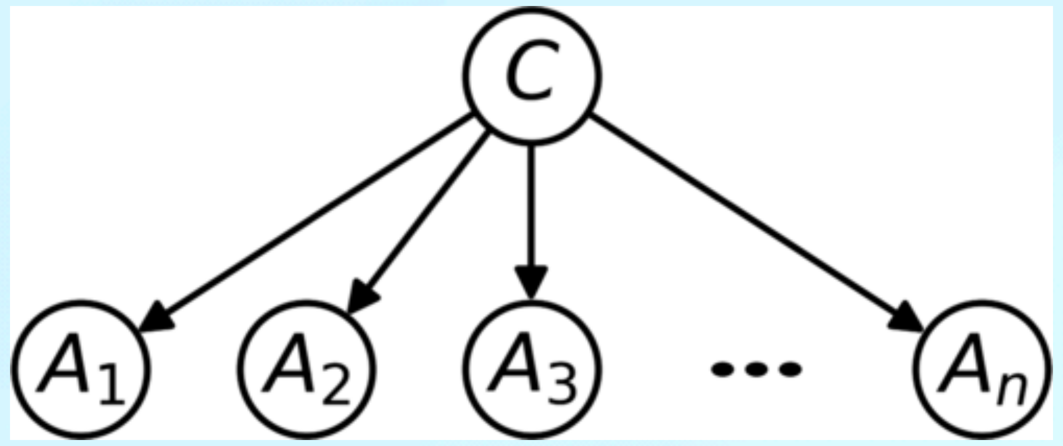
Tunnell Group @ Rice & Li group @ UCSD

Probabilistic Programming for Event Simulation

J. Qin, submitted to ICML

Please check out Dr. Qin's talk at Mar 14, 4:50 PM in Lecture Hall 2!

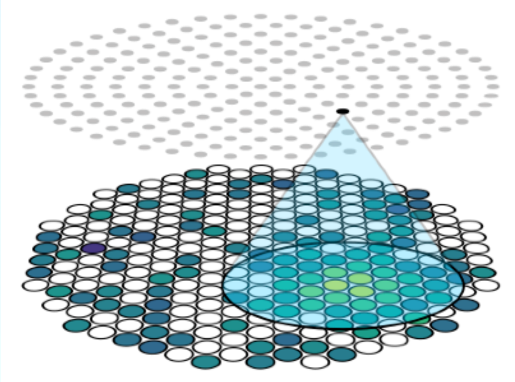
Bayesian Network for Supervised Peak Classification



S. Farrell, C. Peters, A. Higuera @ Rice

10.1103/PhysRevD.108.012016

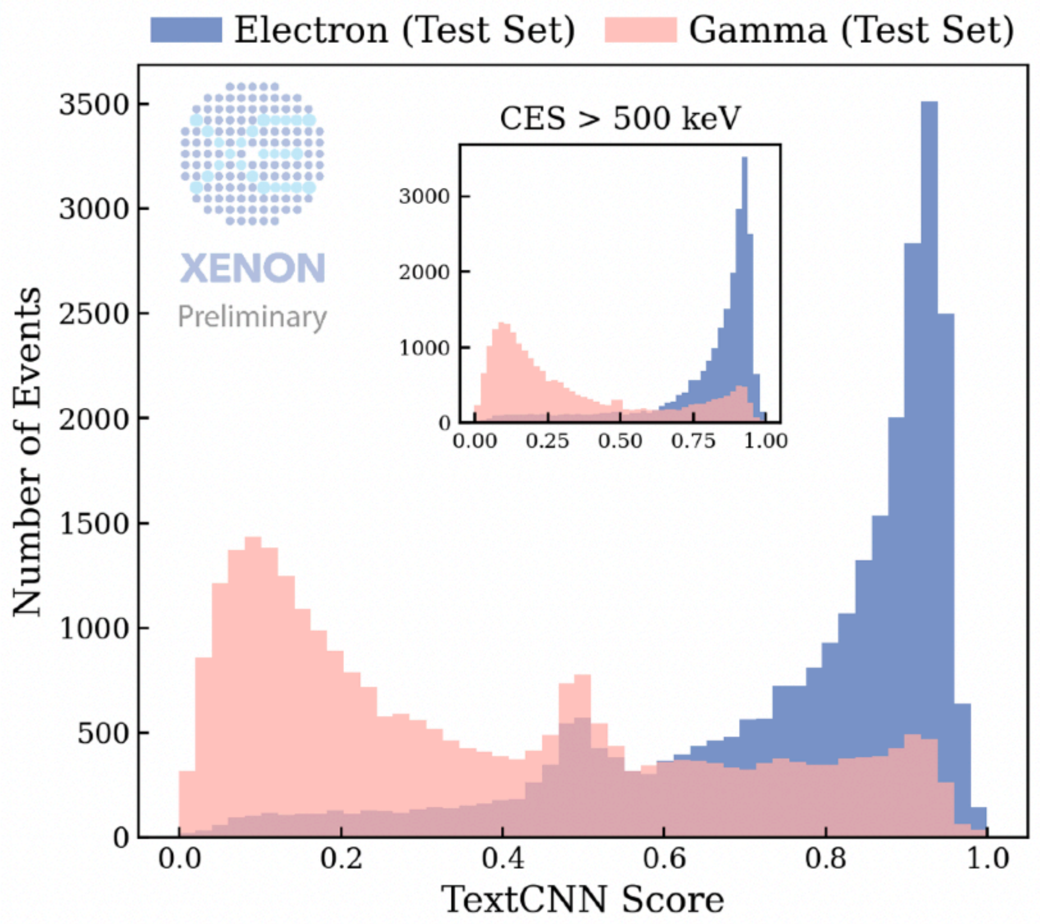
Locally-connected CNN for Position Reconstruction



S. Liang @ Rice

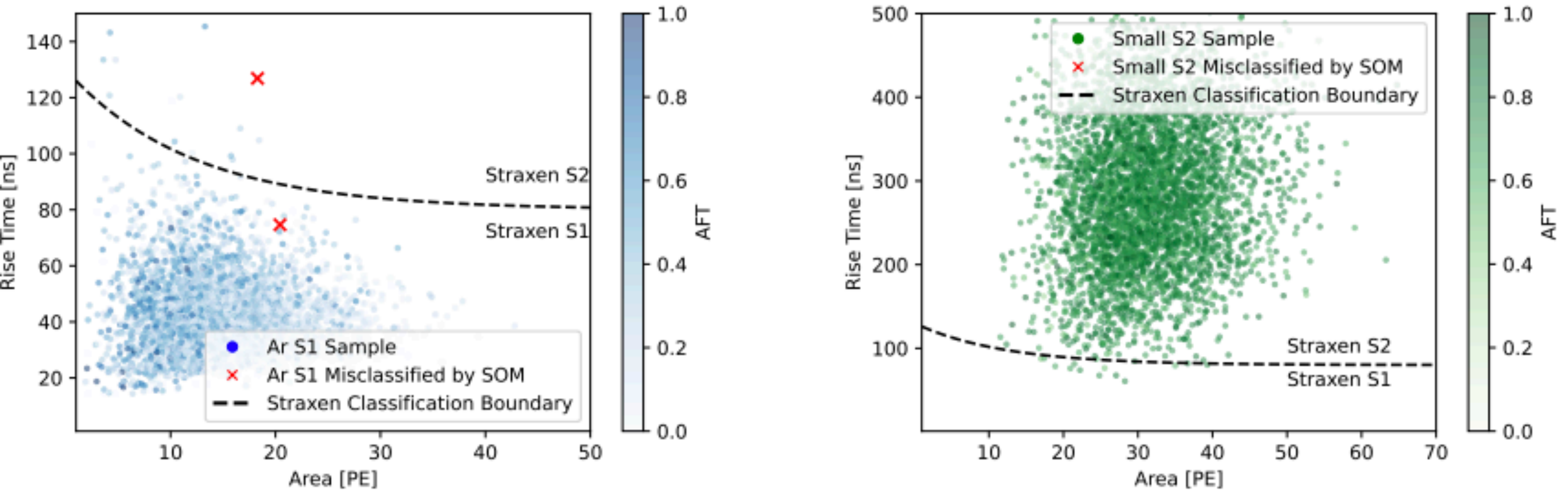
10.3389/frai.2022.832909

TextCNN for High Energy Background Rejection



M. Zhong @ UCSD

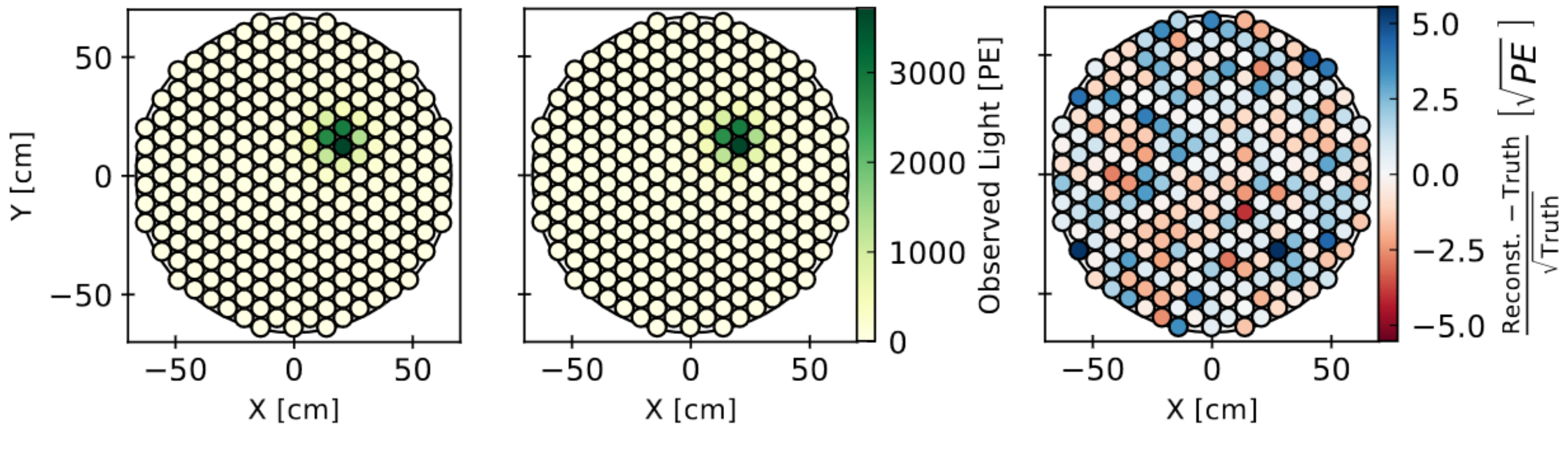
Self-Organizing Maps for Unsupervised Peak Classification



L. Sanchez @ Rice

10.14428/esann/2023.ES2023-177

Semi-supervised Autoencoder for Energy Reconstruction



(a) Reconstruction (b) Ground Truth (c) Reconst. Difference

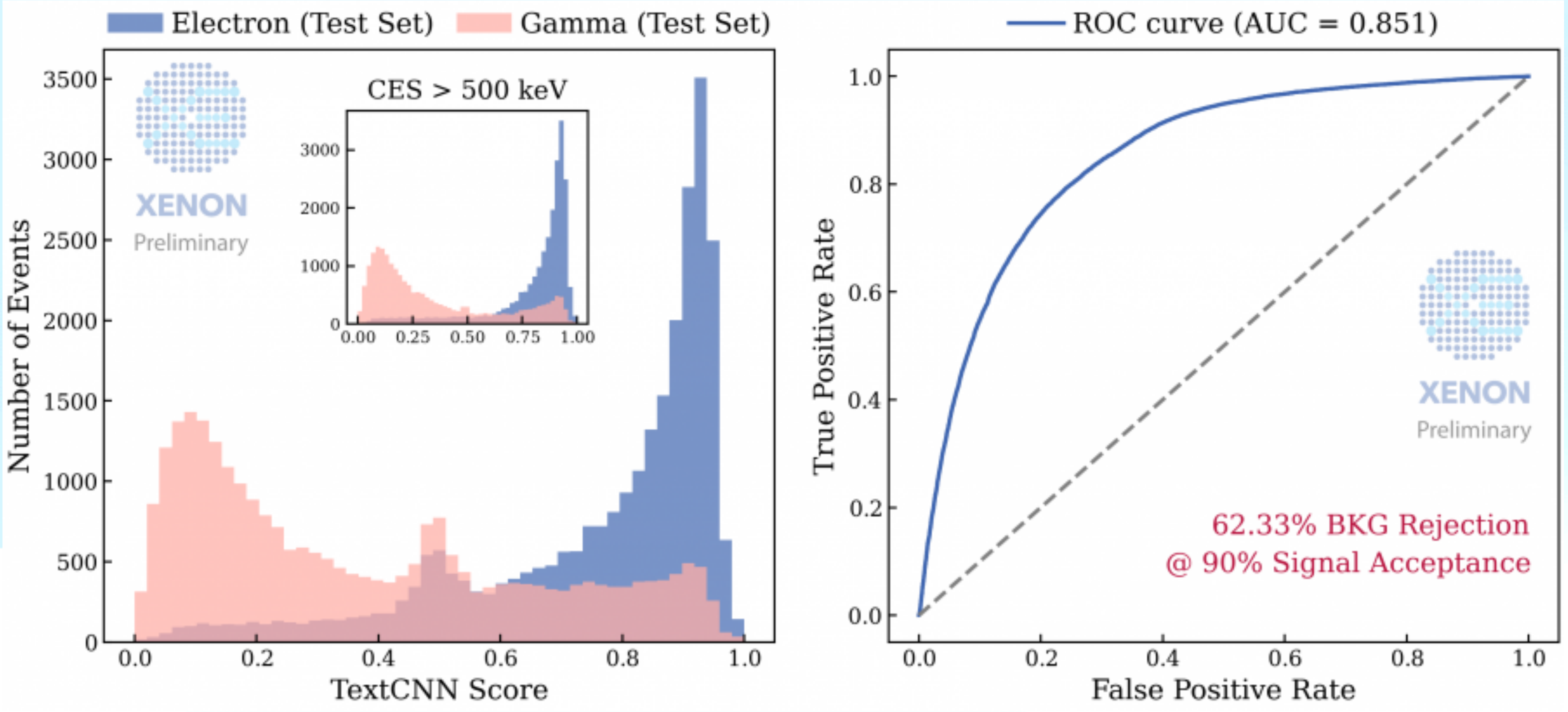
I. Li, A. Higuera, S. Liang, J. Qin, and C. Tunnell @ Rice

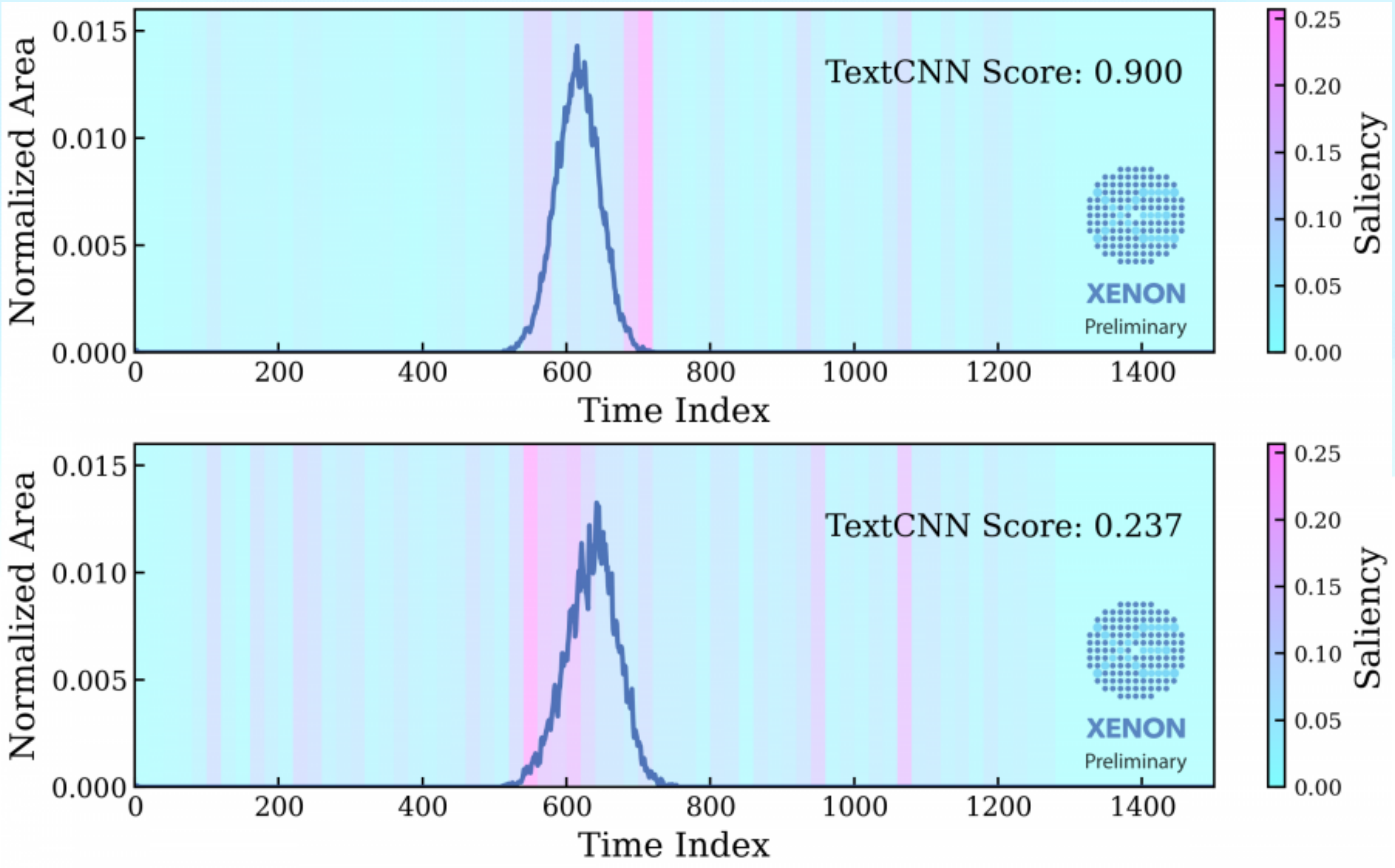
Accepted by CHEP

TextCNN for High Energy Background Rejection

Background rejection based solely on the waveforms

M. Zhong @ UCSD





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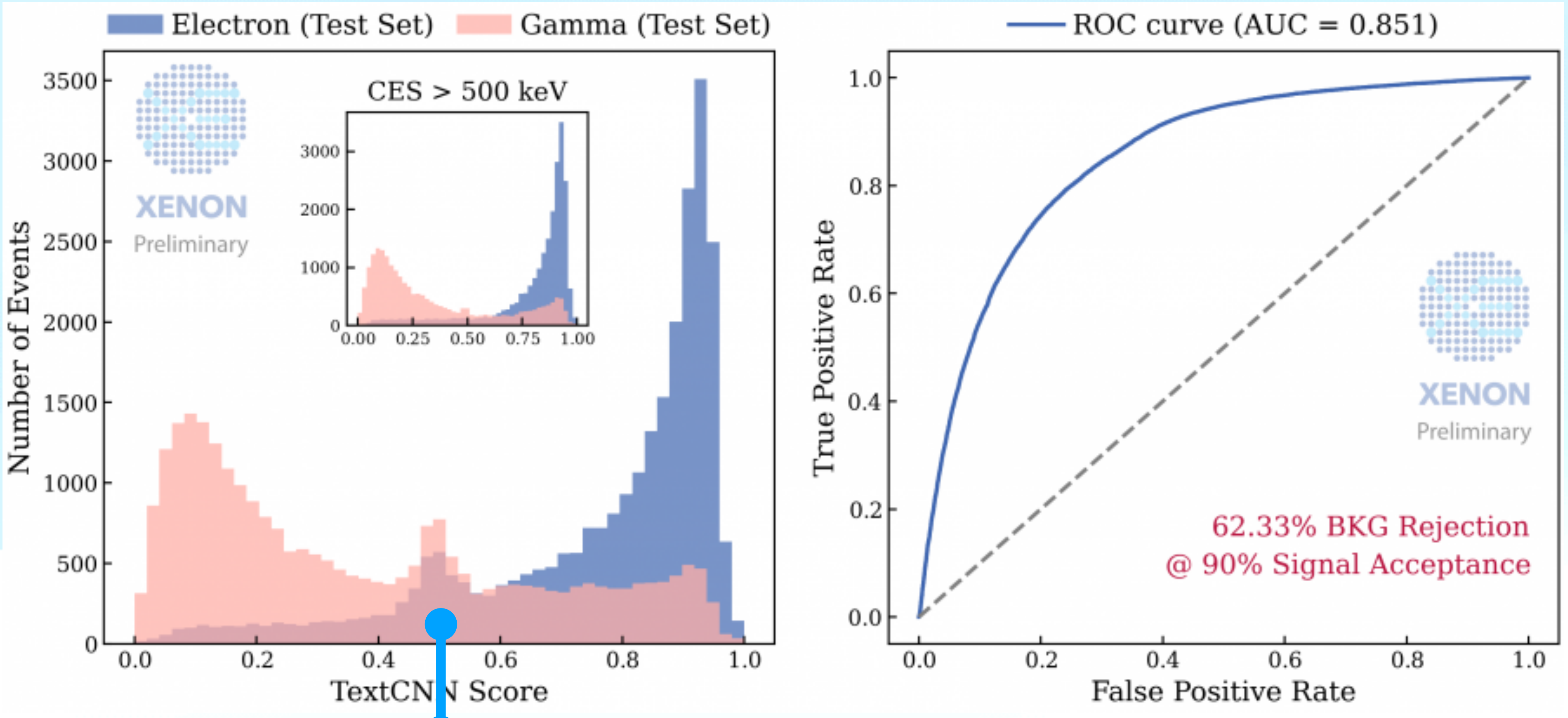
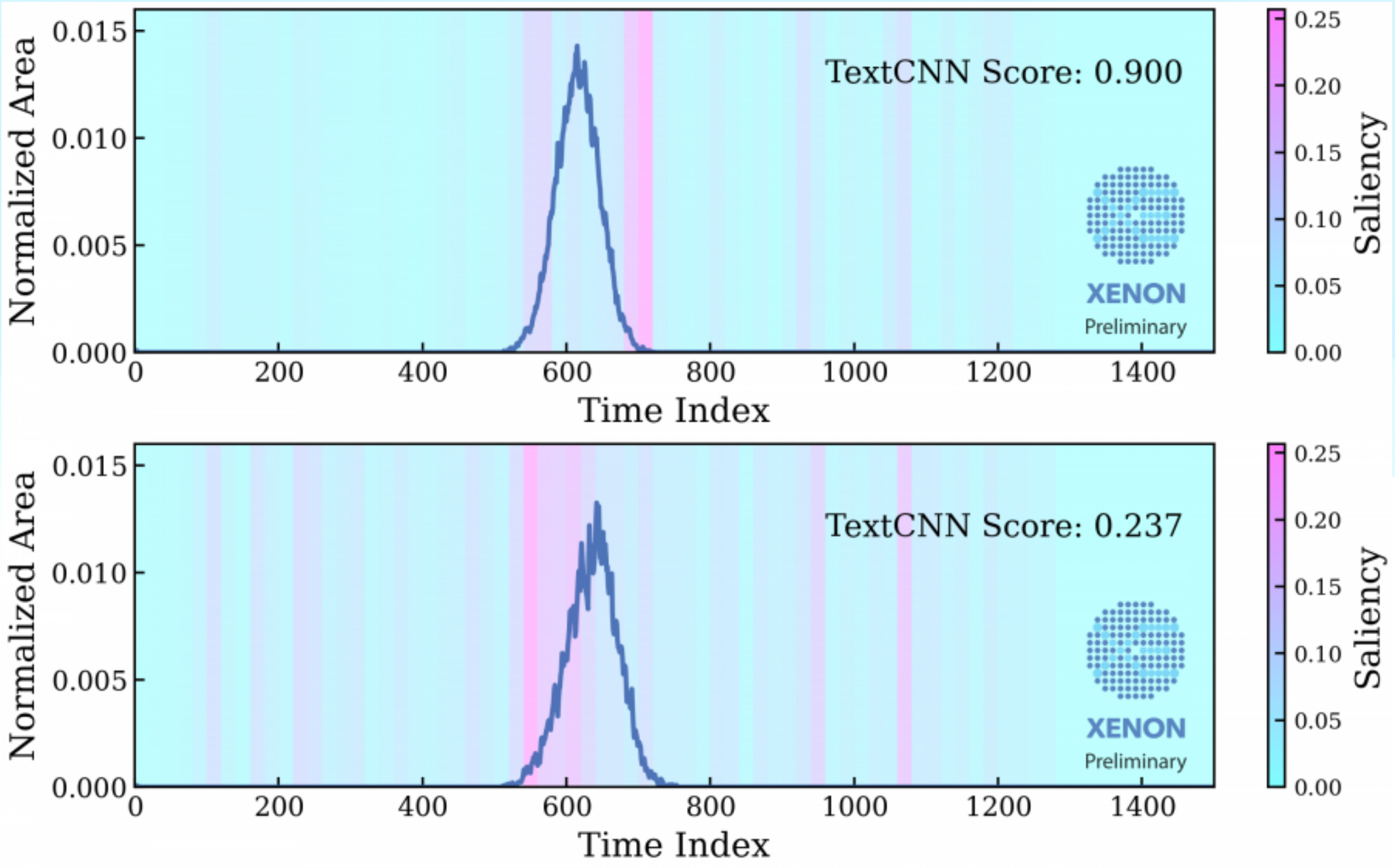


Faithful Decision

Assign score of 0.5 when encounter hard-to-classify low energy events



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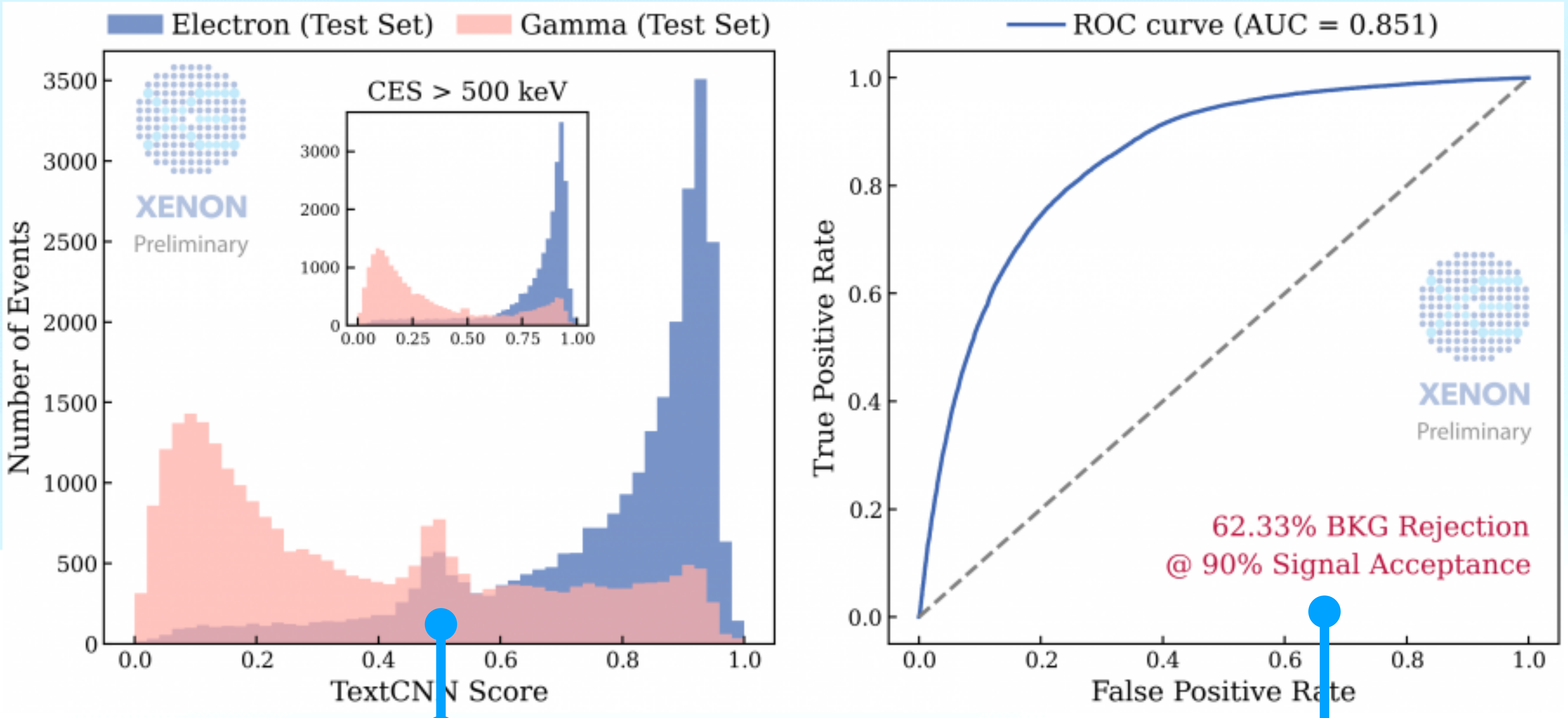
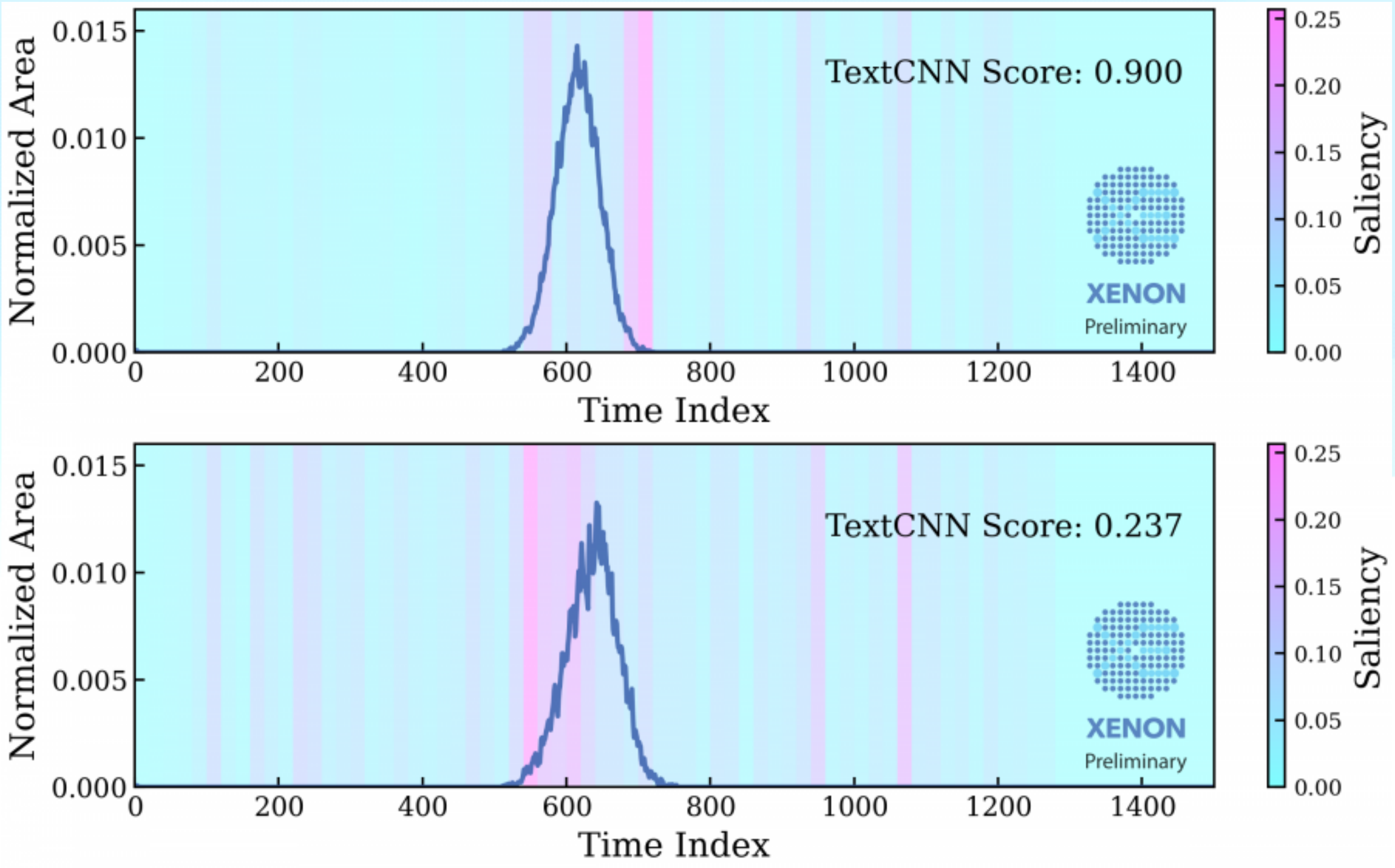
M. Zhong @ UCSD





Faithful Decision

Assign score of 0.5 when encounter hard-to-classify low energy events

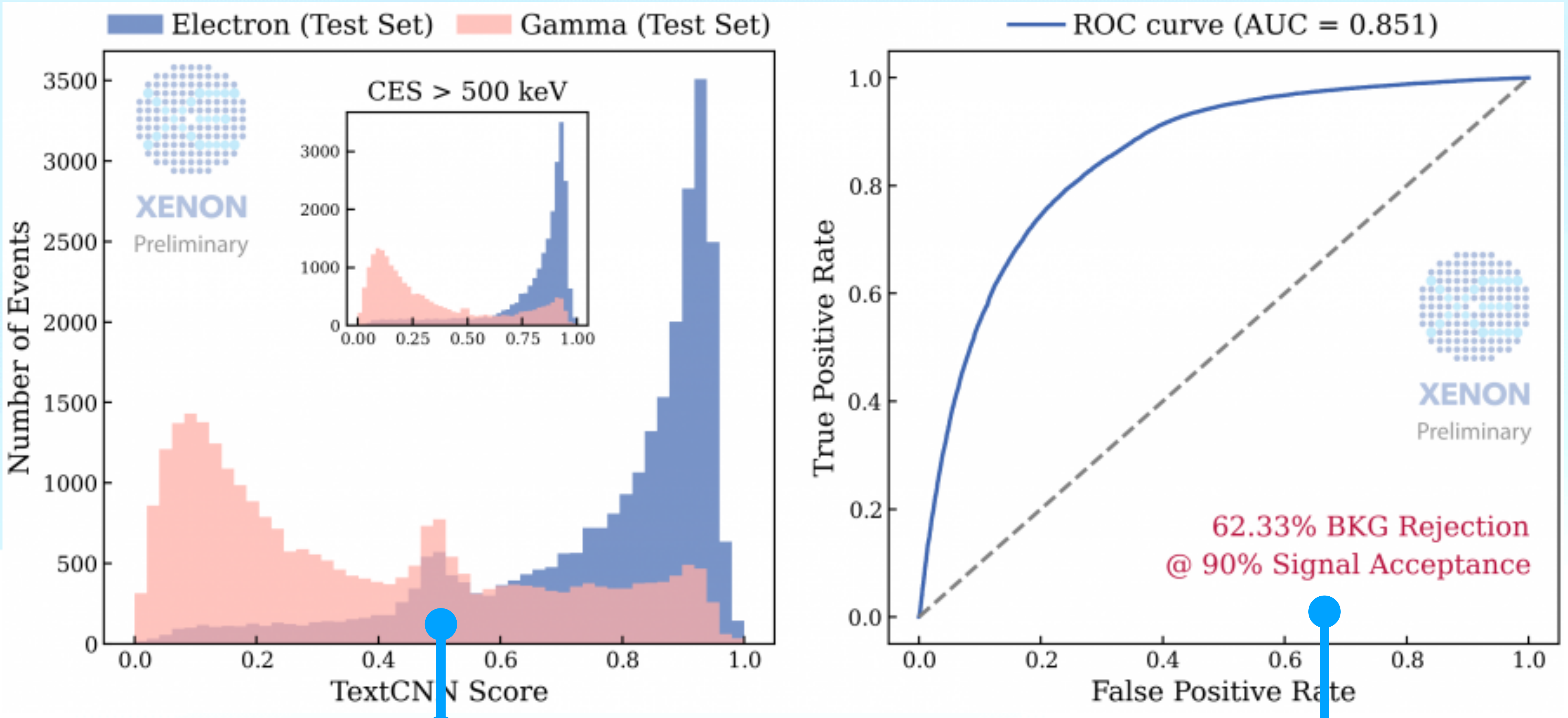
Powerful Background Suppression

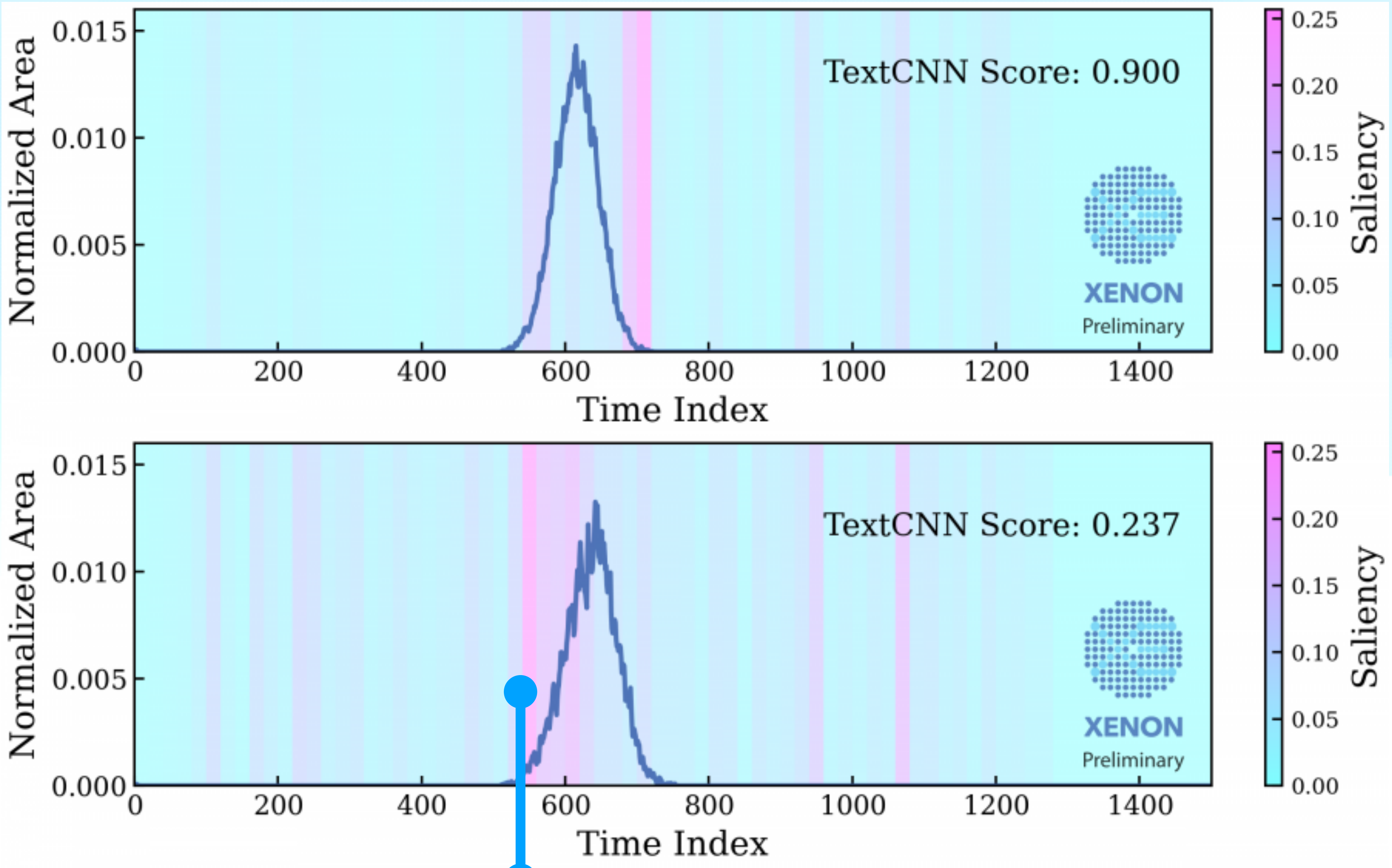
Generalizable to multiple background types based on KamLAND-Zen's experience

TextCNN for High Energy Background Rejection

Background rejection based solely on the waveforms

M. Zhong @ UCSD





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Interpretability Study

Saliency map shows that TexCNN mostly look at rising/falling edge

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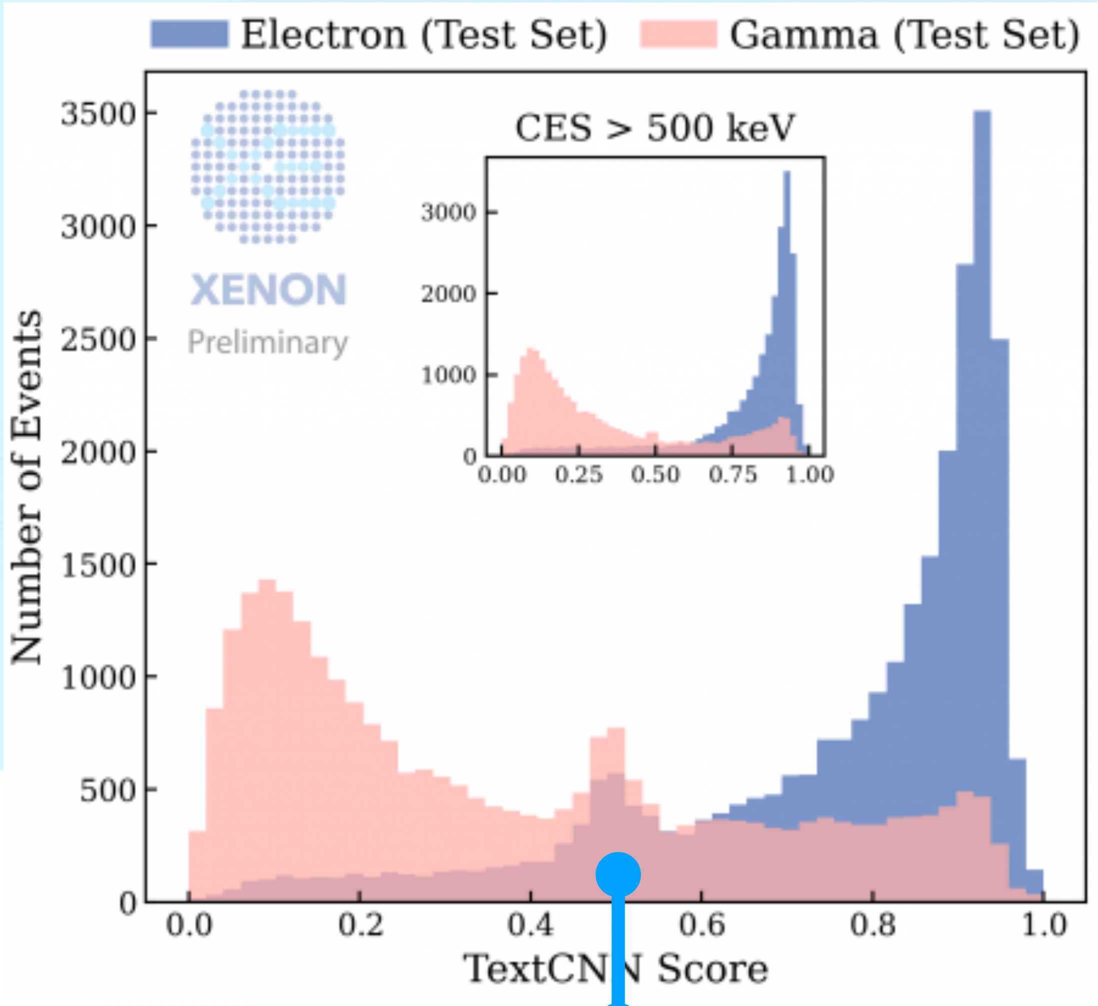

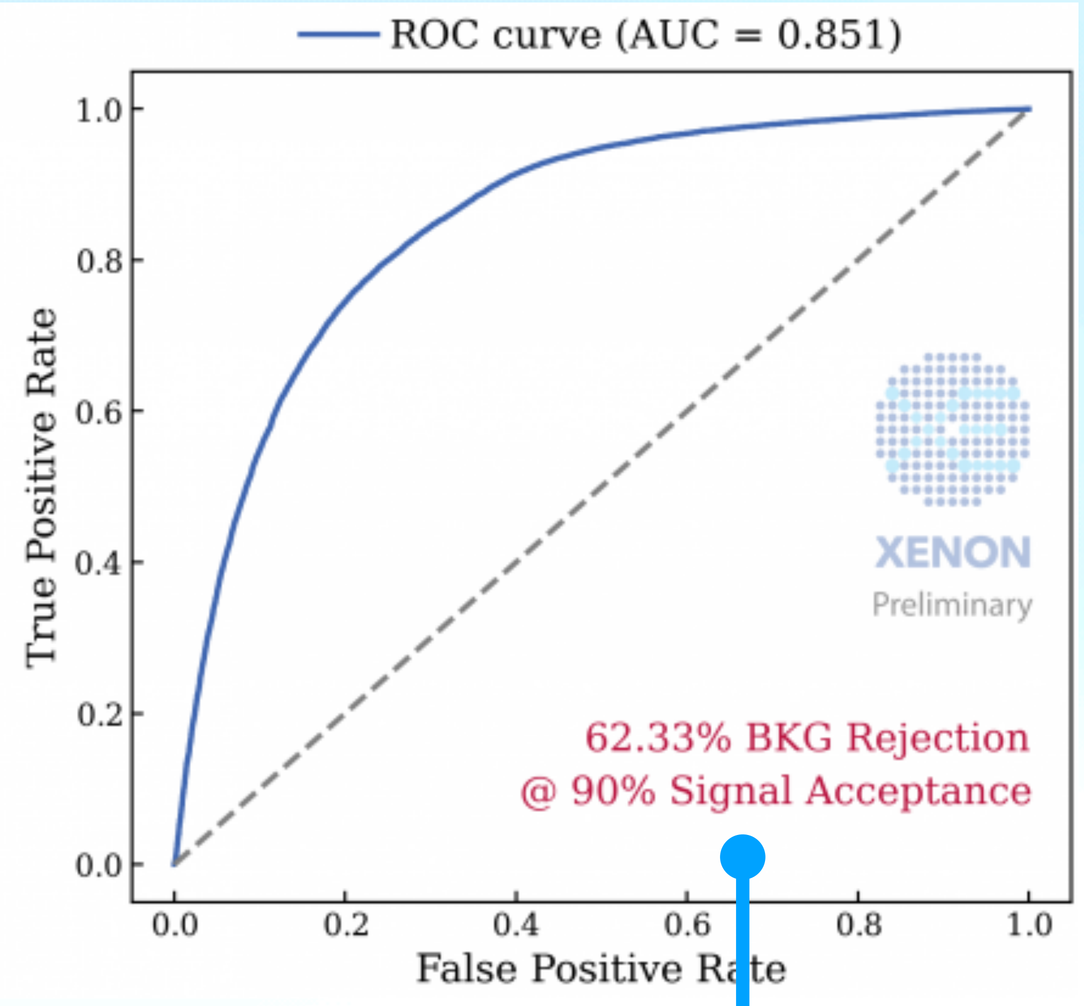

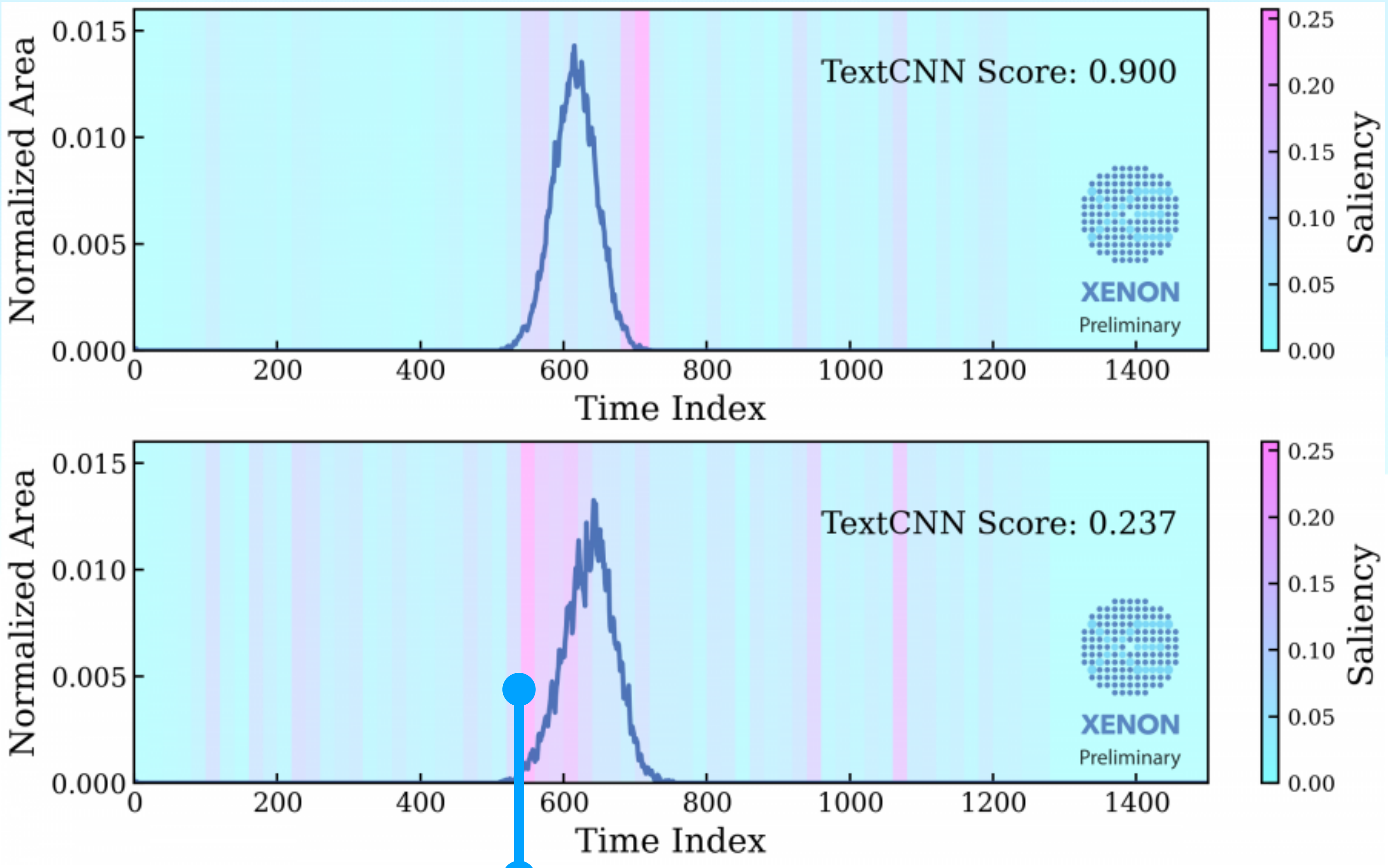

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Interpretability Study

Saliency map shows that TexCNN mostly look at rising/falling edge

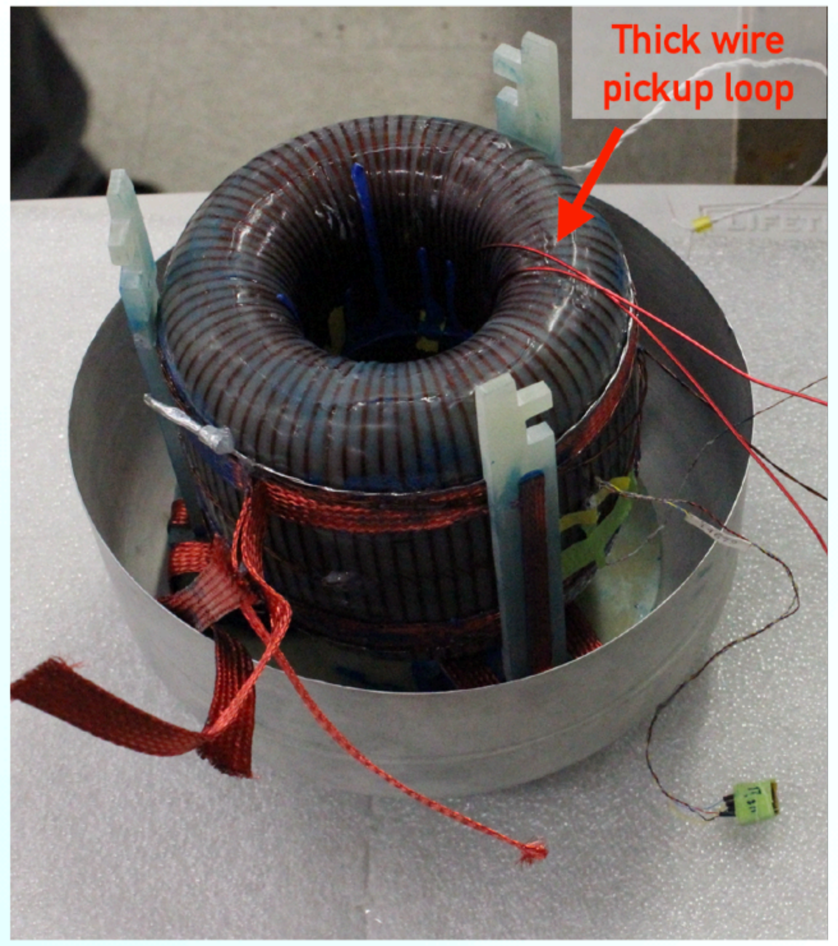
Powerful Background Suppression

Generalizable to multiple background types based on KamLAND-Zen's experience

Currently conducting validation study on real data!

ABRACADABRA

Broadband Axion Dark Matter Search with Toroidal Magnet



Axion-Modified Maxwell's Equation:

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

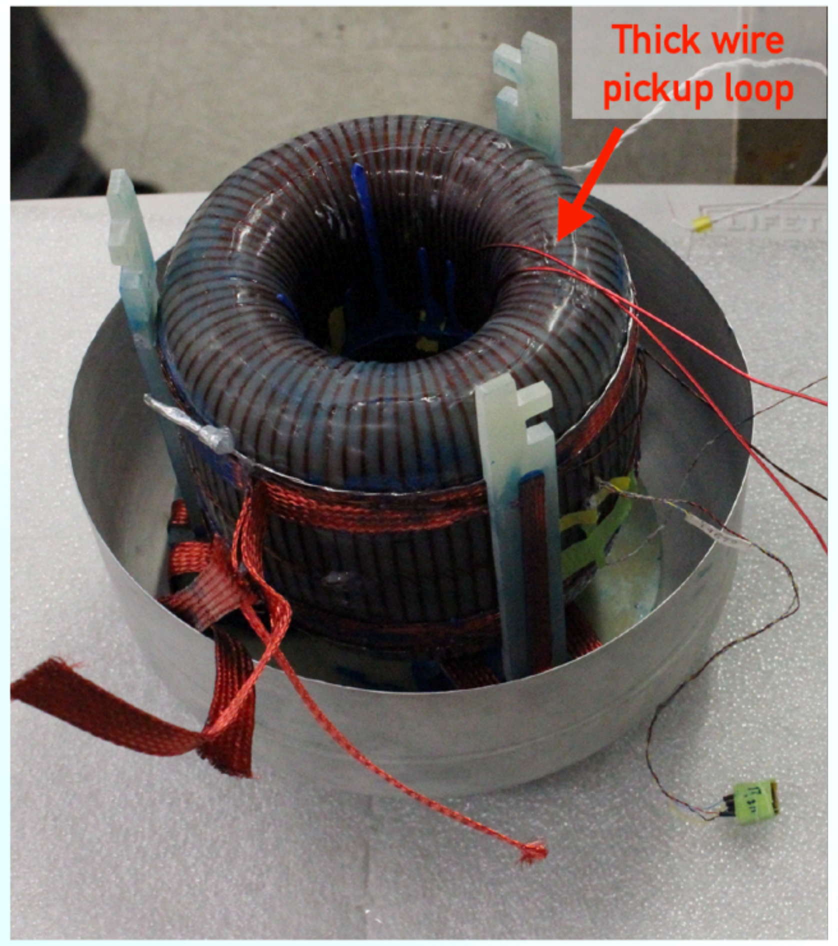
$$\nabla \times B = \frac{\partial E}{\partial t} - g_{a\gamma\gamma}(E \times \nabla a - \frac{\partial a}{\partial t}B)$$

$$\Downarrow$$

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

ABRACADABRA

Broadband Axion Dark Matter Search with Toroidal Magnet



Axion-Modified Maxwell's Equation:

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

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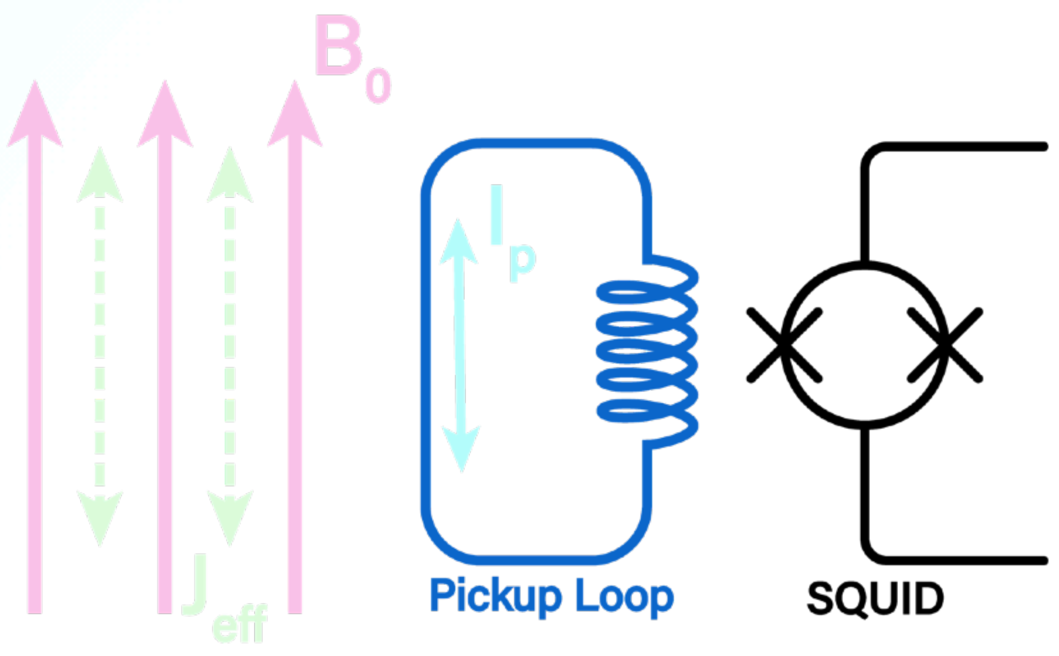


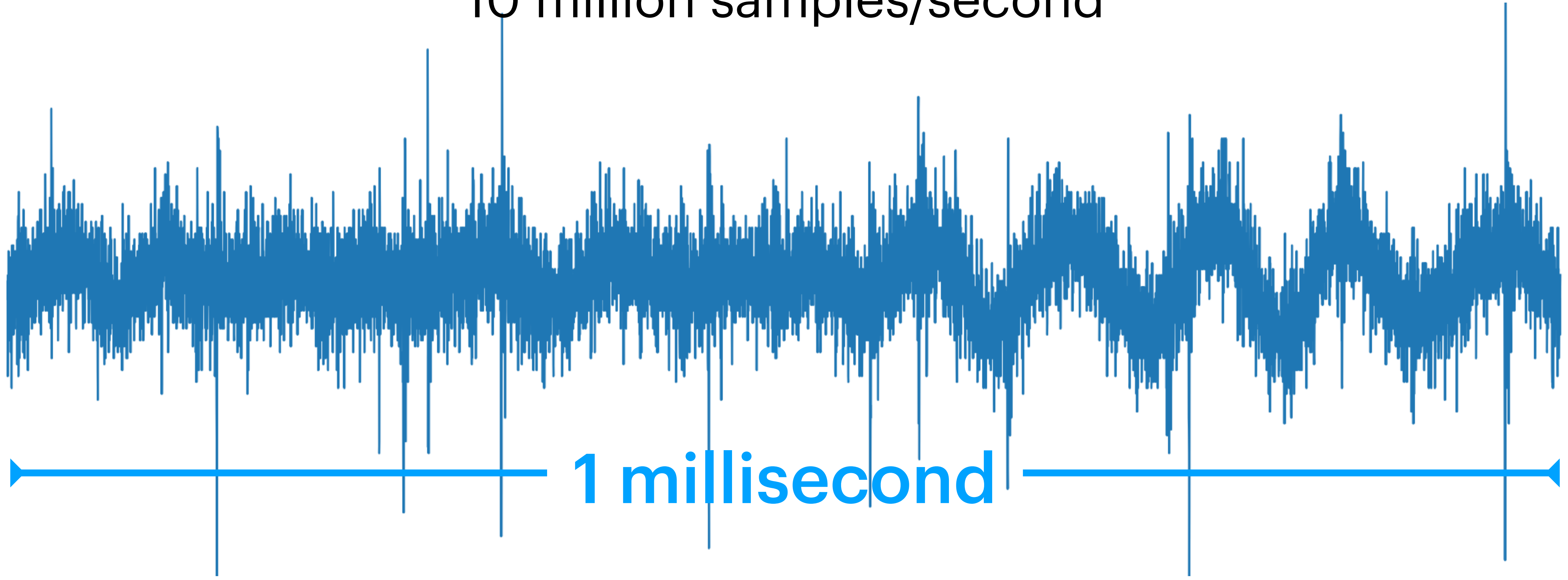
Y. Kahn, B. R. Safdi, and J. Thaler, Phys. Rev. Lett. 117, 141801

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

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

Ultra-long Time Series

10 million samples/second

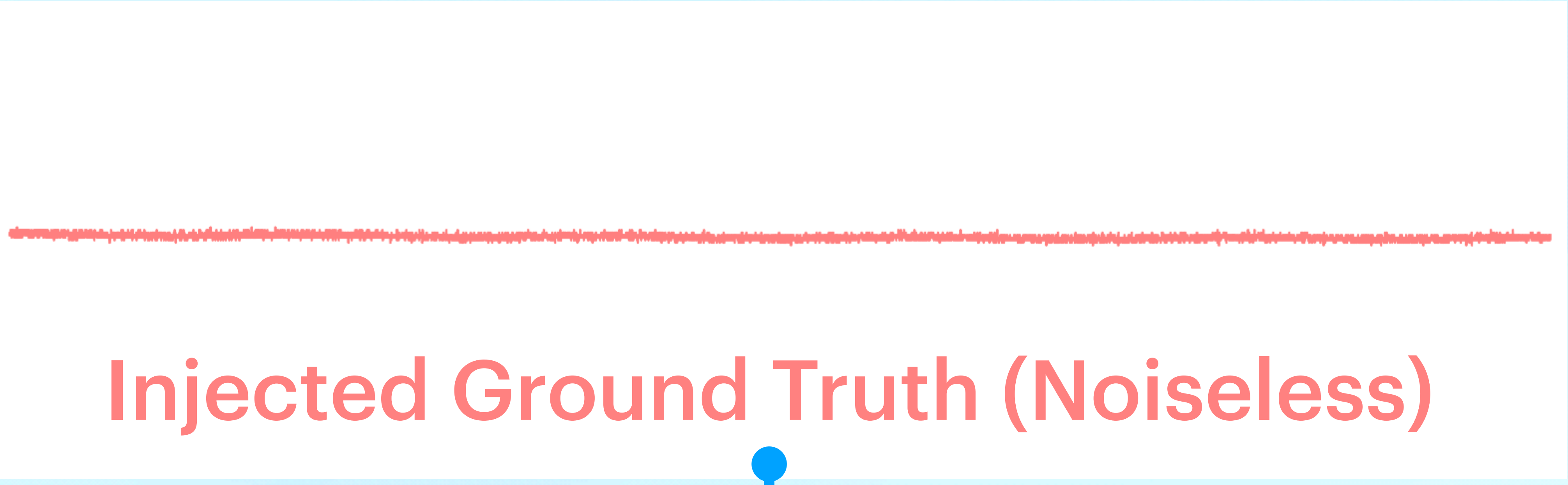


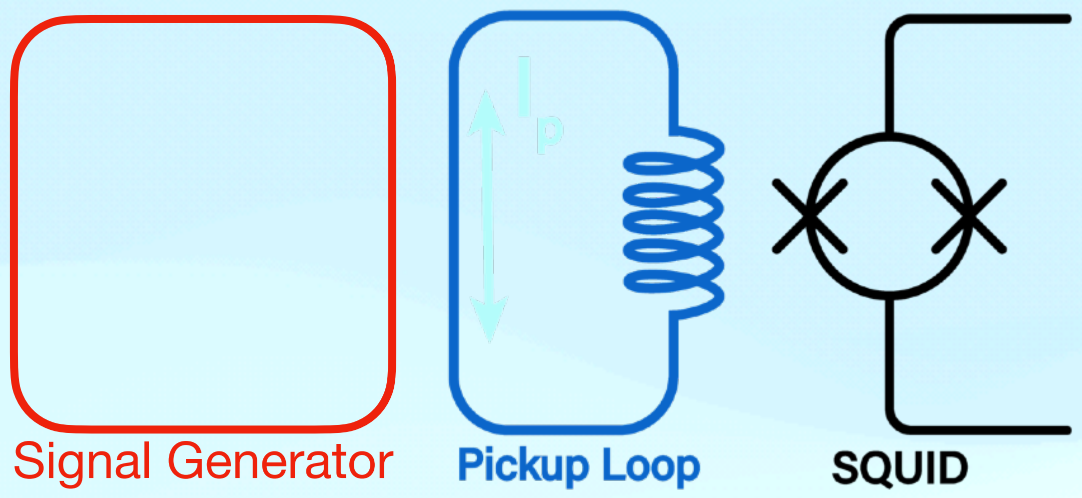
Experimental Apparatus Constructed by Winslow Lab at MIT

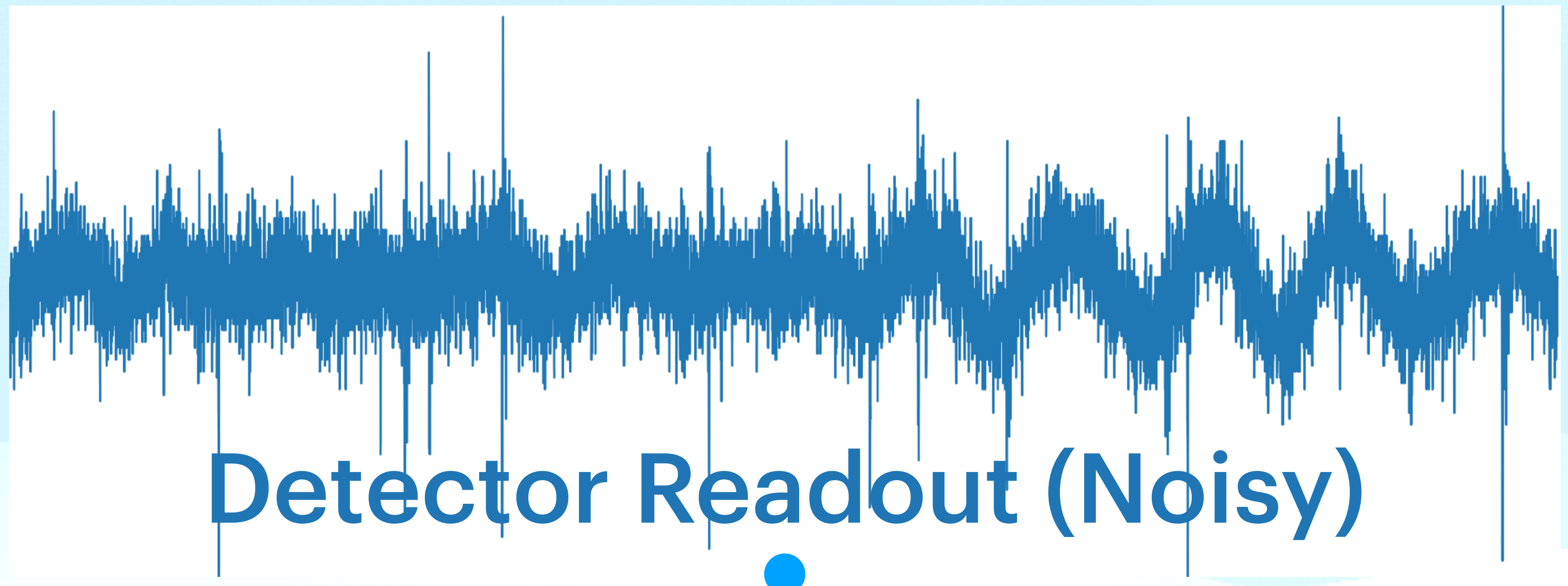
AI for ABRACADABRA

ABRACADABRA Data Release

Long Time Series Data Release from Broadband Axion Dark Matter Experiment
J. T. Fry et al, NeurIPS 2023 ML4PS





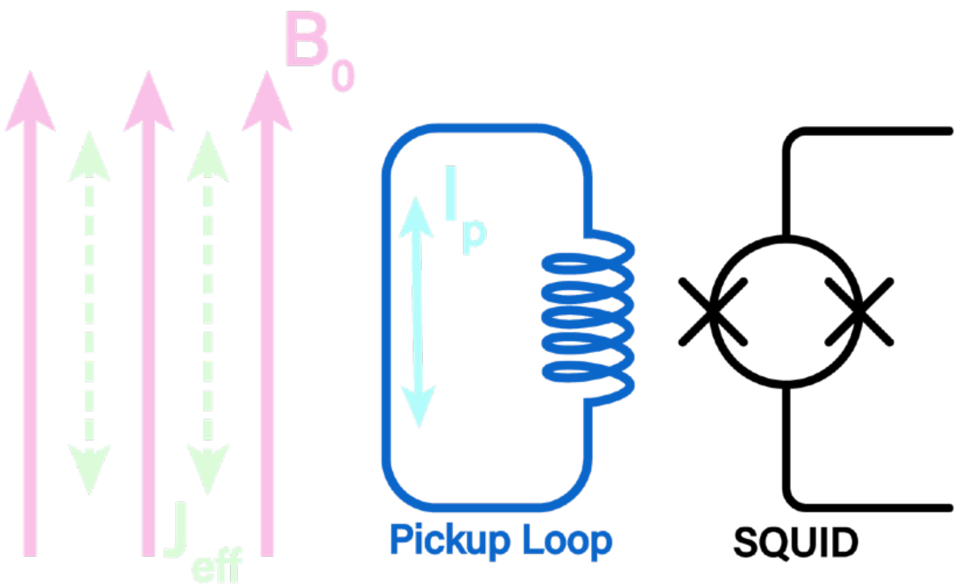


Benchmarking Dataset for Denoising Tasks

- Huge datasets with billions of samples
- Sample-to-sample correspondence between noisy and clean time series

ABRACADABRA Algorithm Design

RNN Sequense-to-Sequence Model for time series denoising



Detecting Rare Events Using Artificial Intelligence

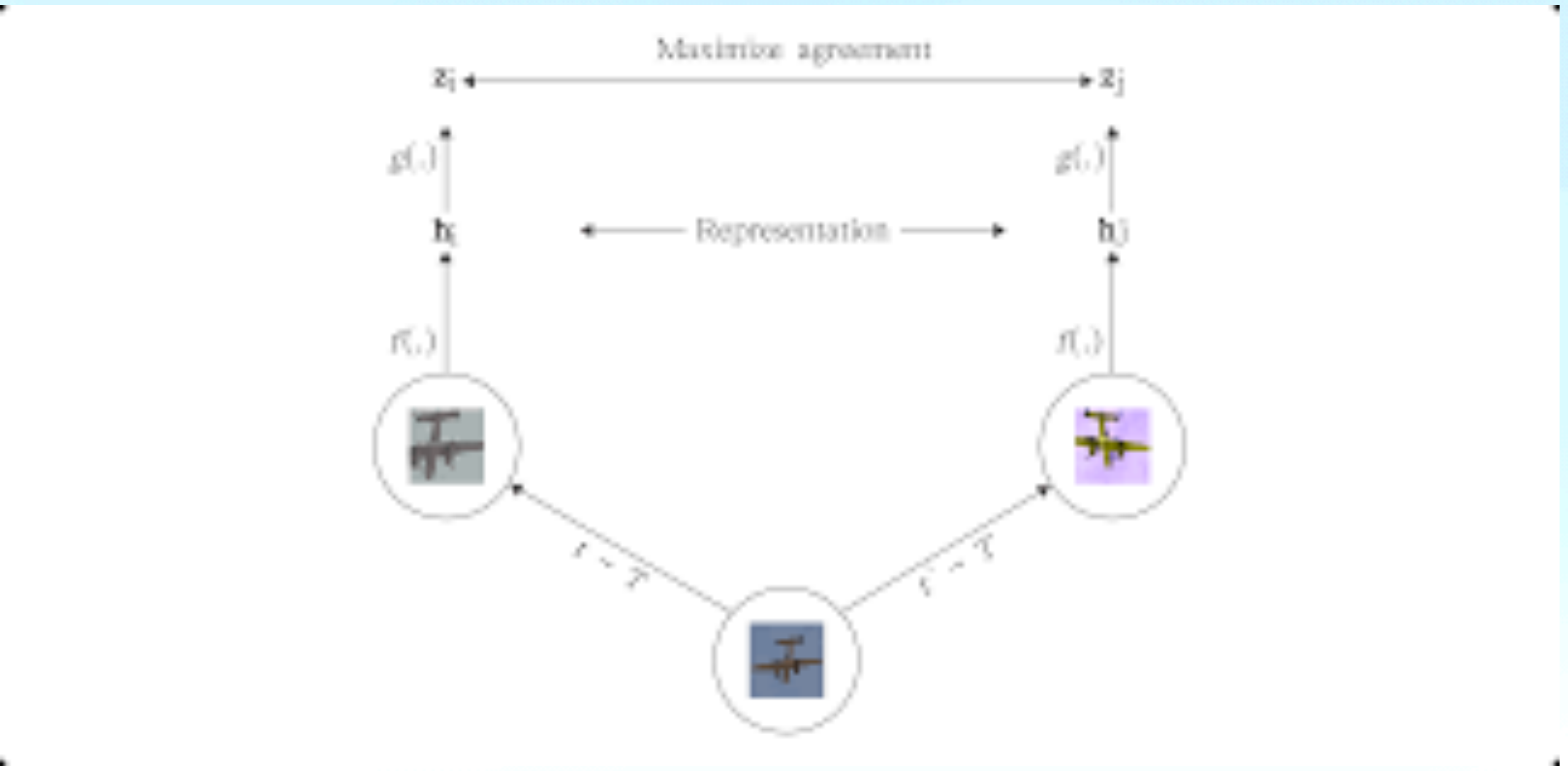
"A Guided Tour to Europe"

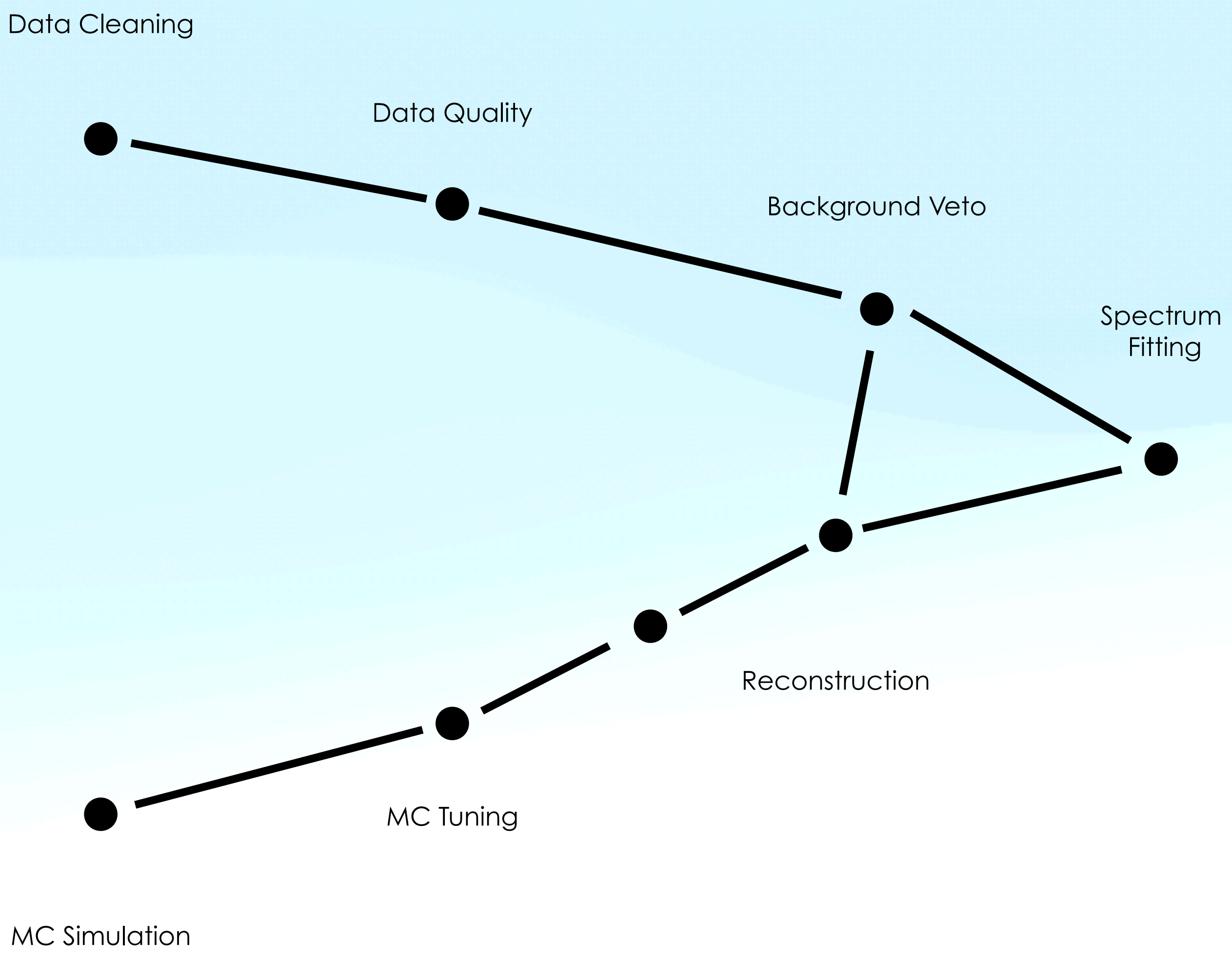
- Rare Event Search Experiments
- Radiation Detector & Data
- AI Algorithms

"Forging the European Union"

- Foundation Model for Rare Event Search

“Forging the European Union”





① Self-Supervised Learning

Basis for training foundation model

② LEGEND AI Analysis Chain

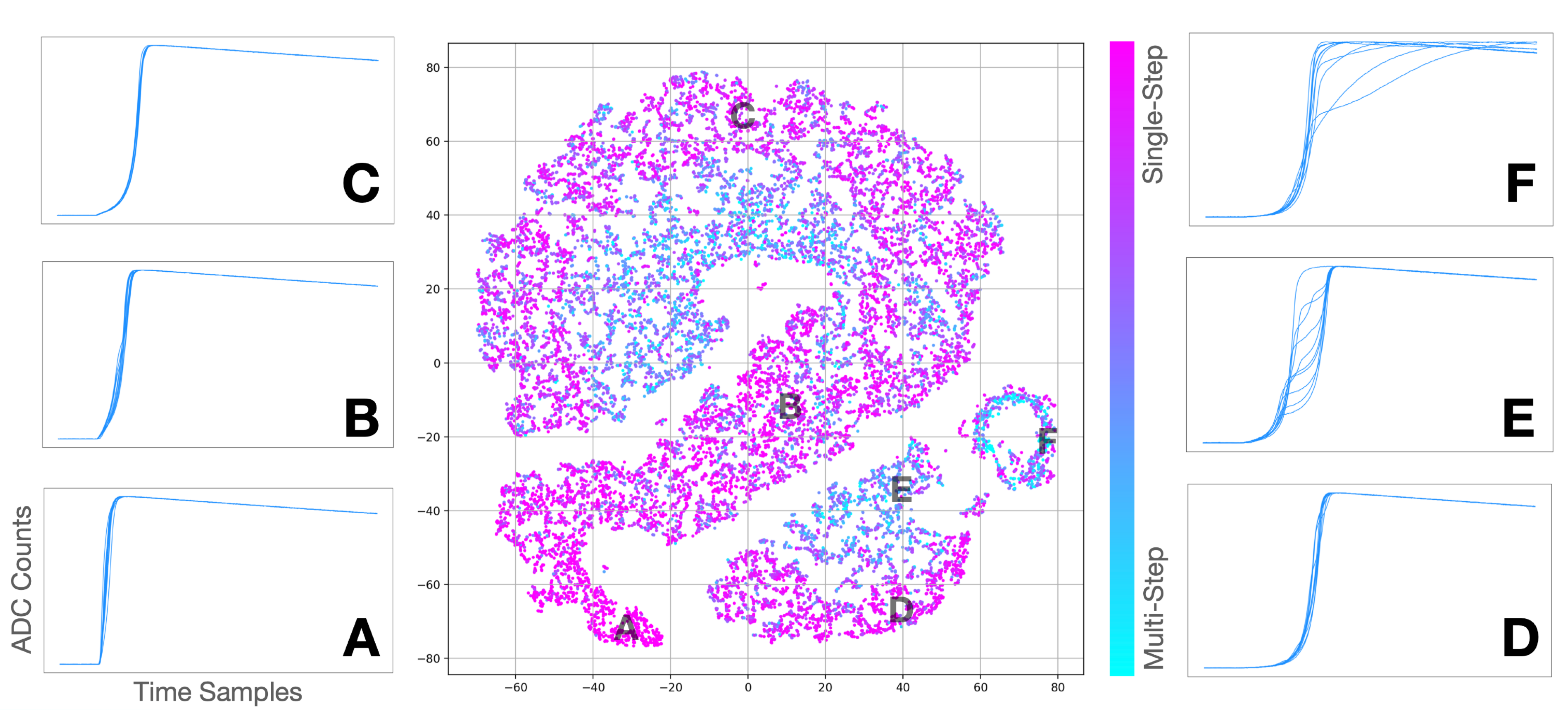
Link all AI algorithms together with foundation model and fine-tuning

③ Large Particle Model for Rare Event Search

A single, unified foundation models from all RES experiments

Self-Supervised Learning for LEGEND

Task-agnostic representation from Contrastive Learning Algorithm



Self-Supervised Learning for LEGEND

Task-agnostic representation from Contrastive Learning Algorithm

Fig. A→D: the length of the "band" is the time it takes for waveforms to reach maximum

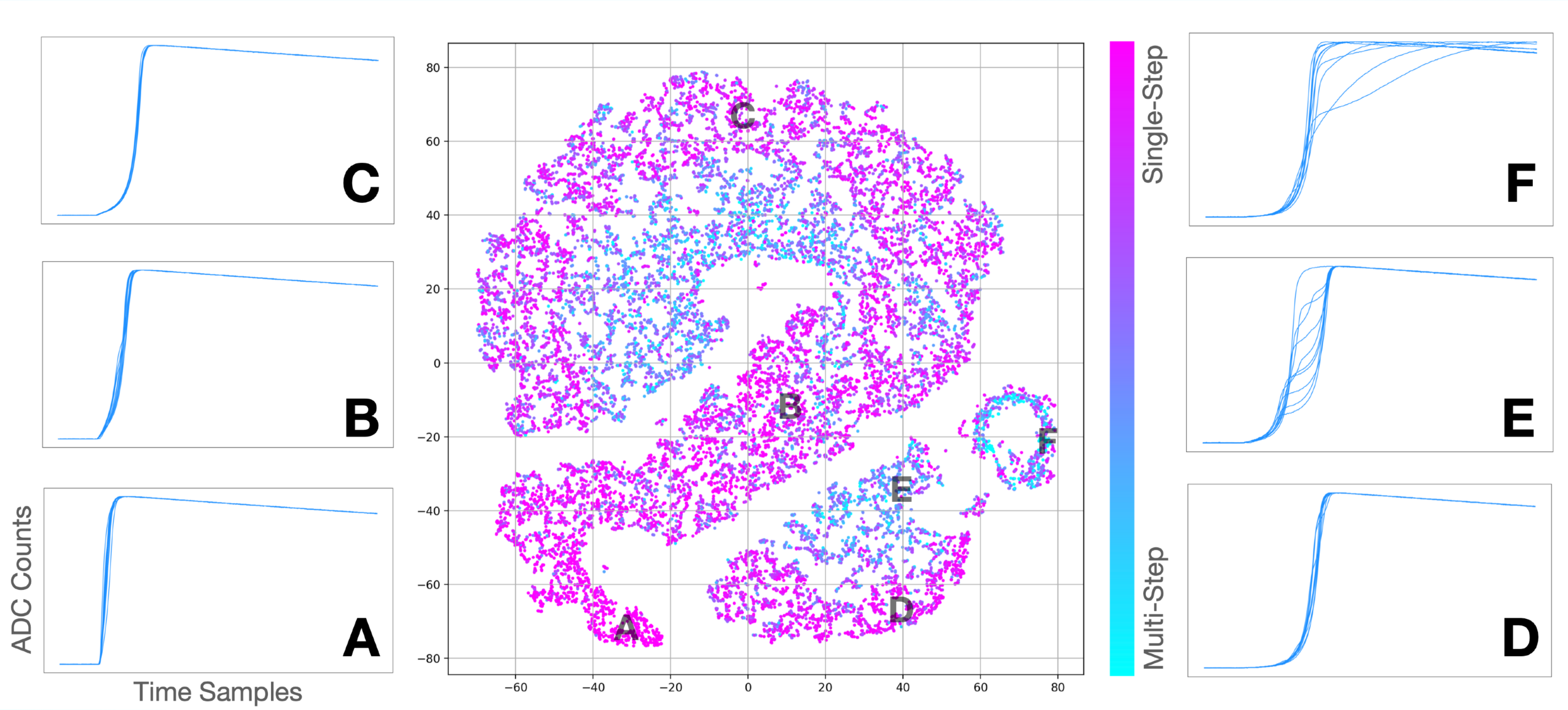


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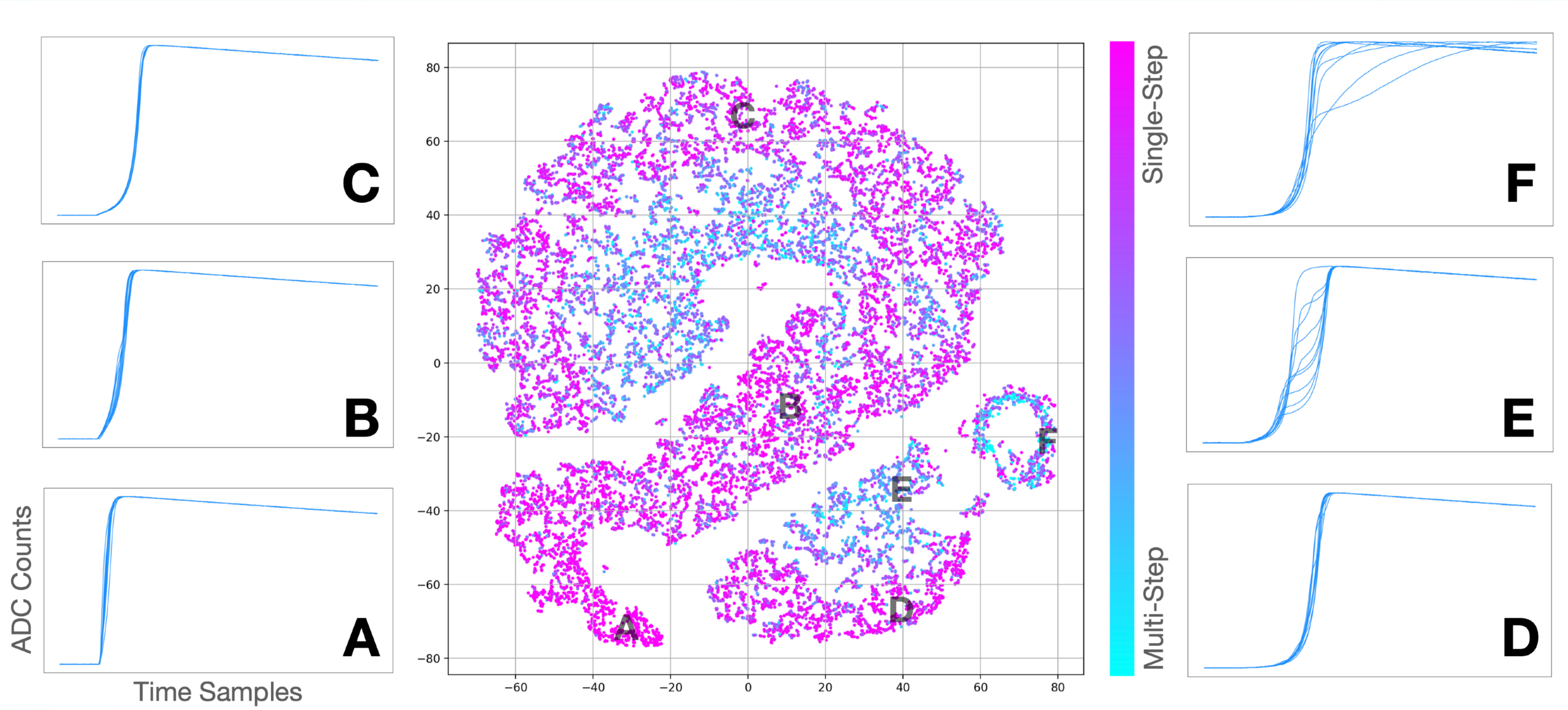
Fig. A→D: the length of the "band" is the time it takes for waveforms to reach maximum

Fig. D vs. Fig E: the width of the "band" represents the number of steps in waveforms



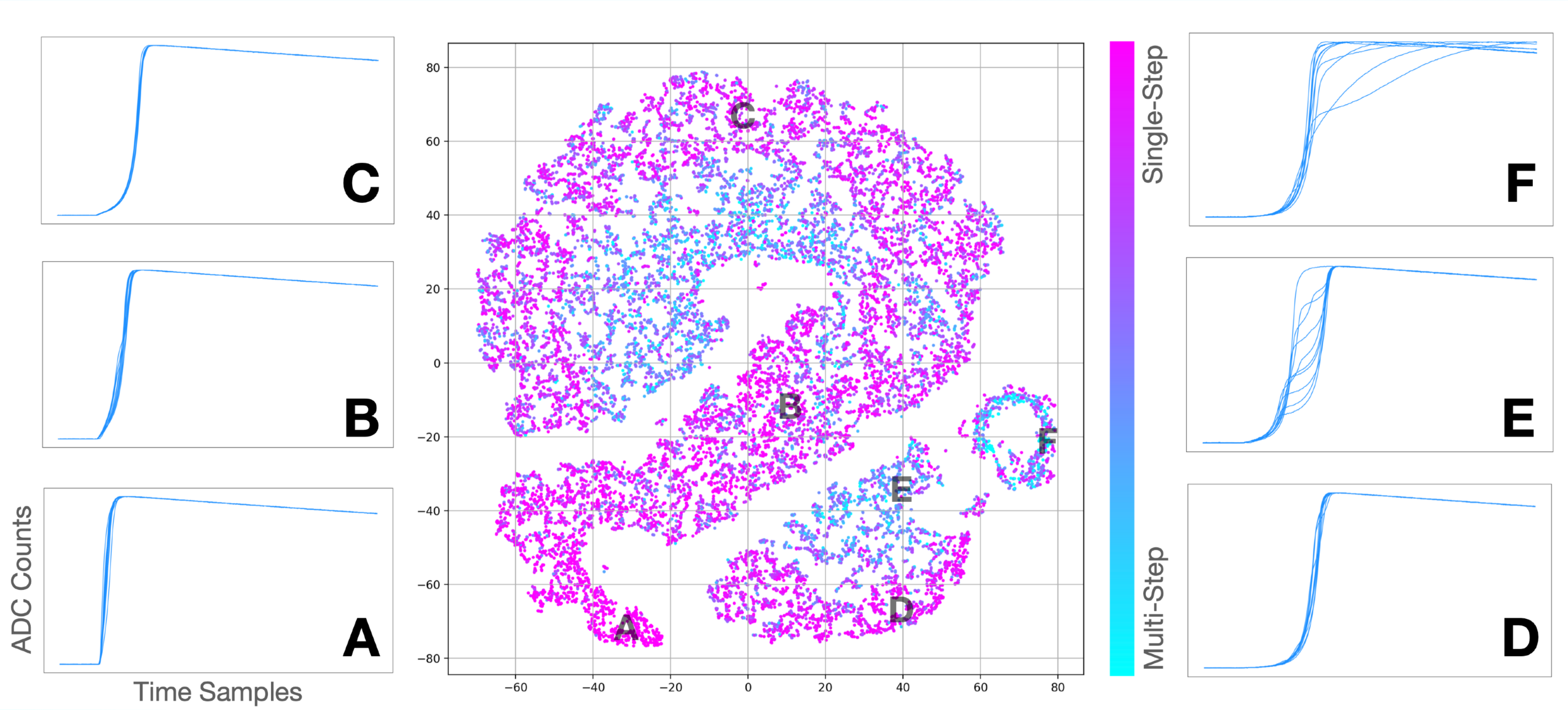
Self-Supervised Learning for LEGEND

Task-agnostic representation from Contrastive Learning Algorithm

Fig. A→D: the length of the "band" is the time it takes for waveforms to reach maximum

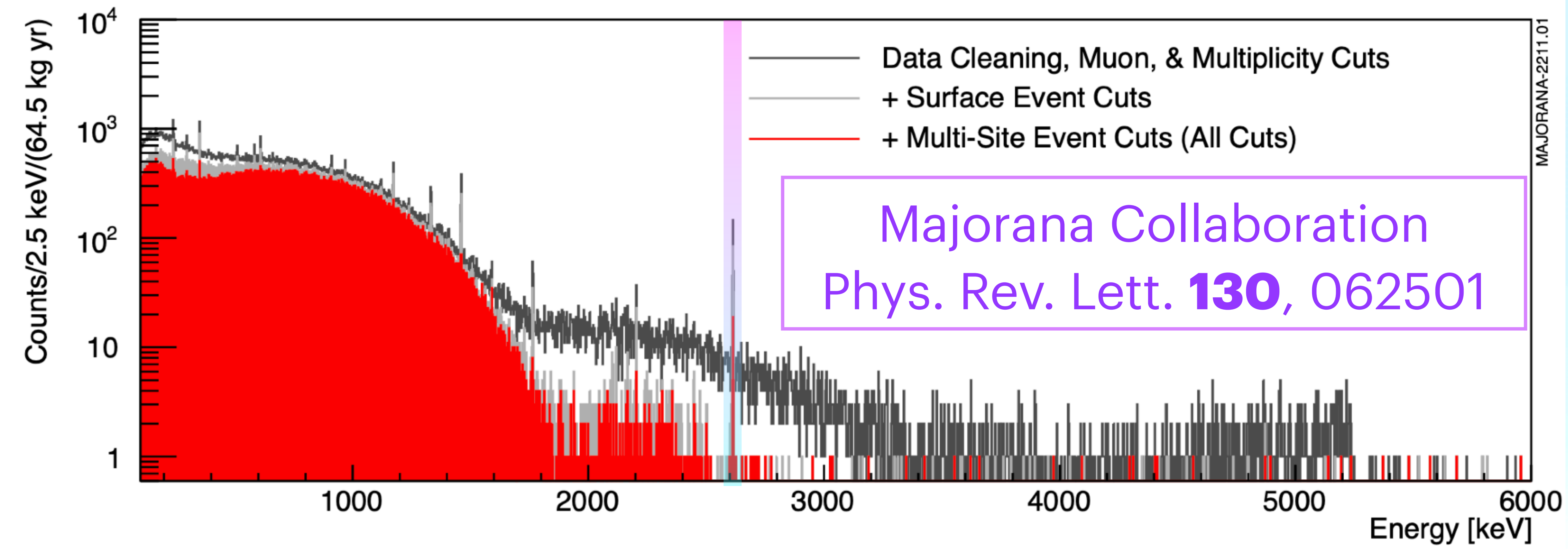
Fig. D vs. Fig E: the width of the "band" represents the number of steps in waveforms

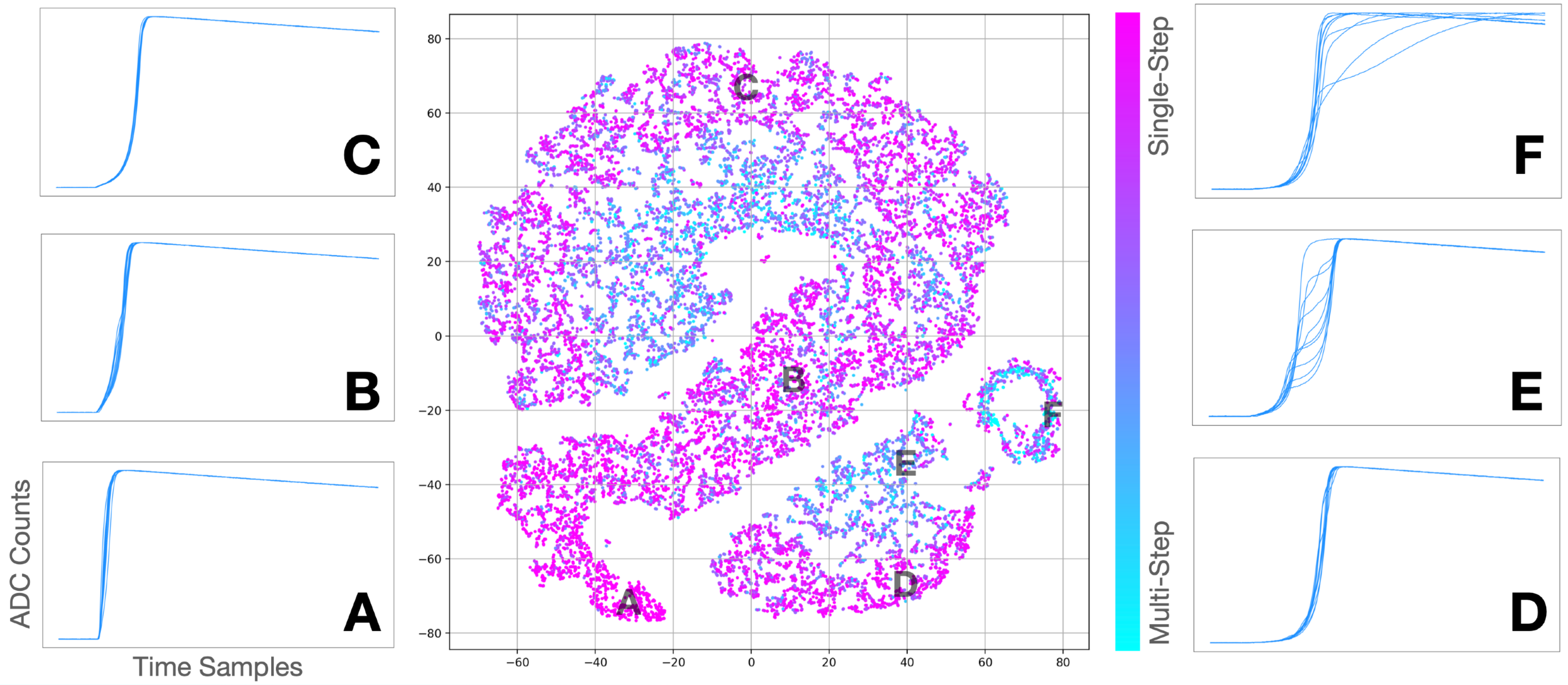
Fig. F: the "ring island" are slow-rounded-top waveforms caused by passivated surface



From SSL to LEGEND Foundation Model

SSL over specifically-curated dataset





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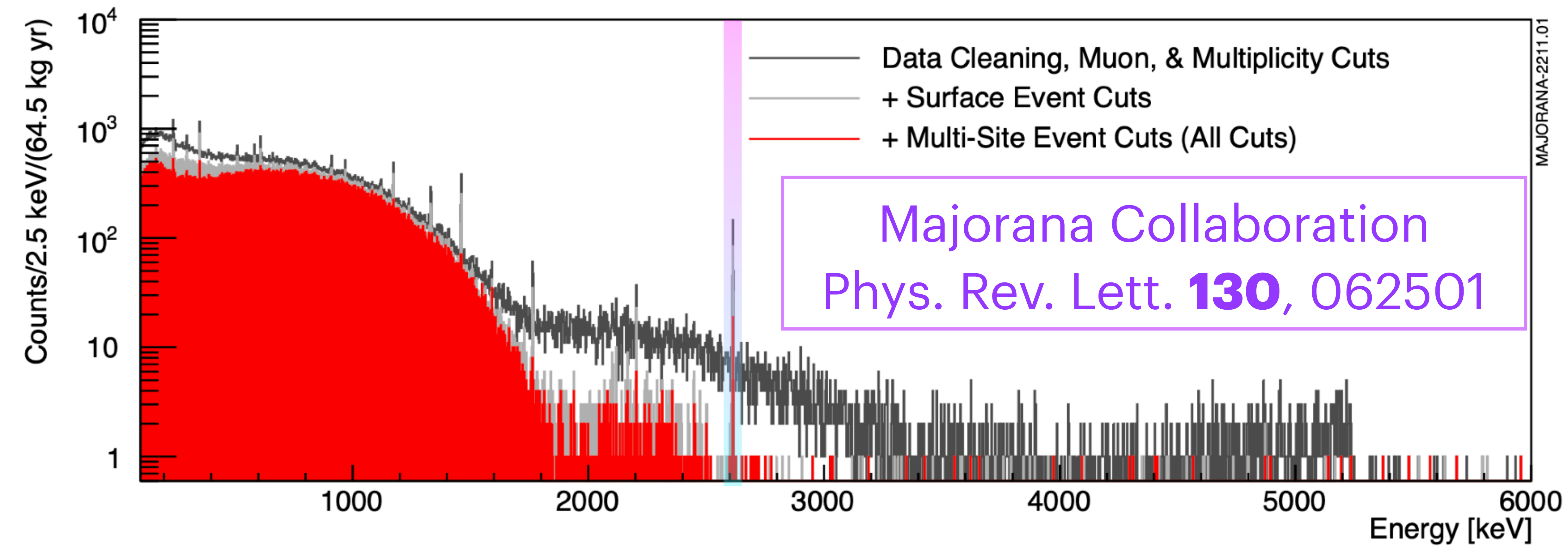
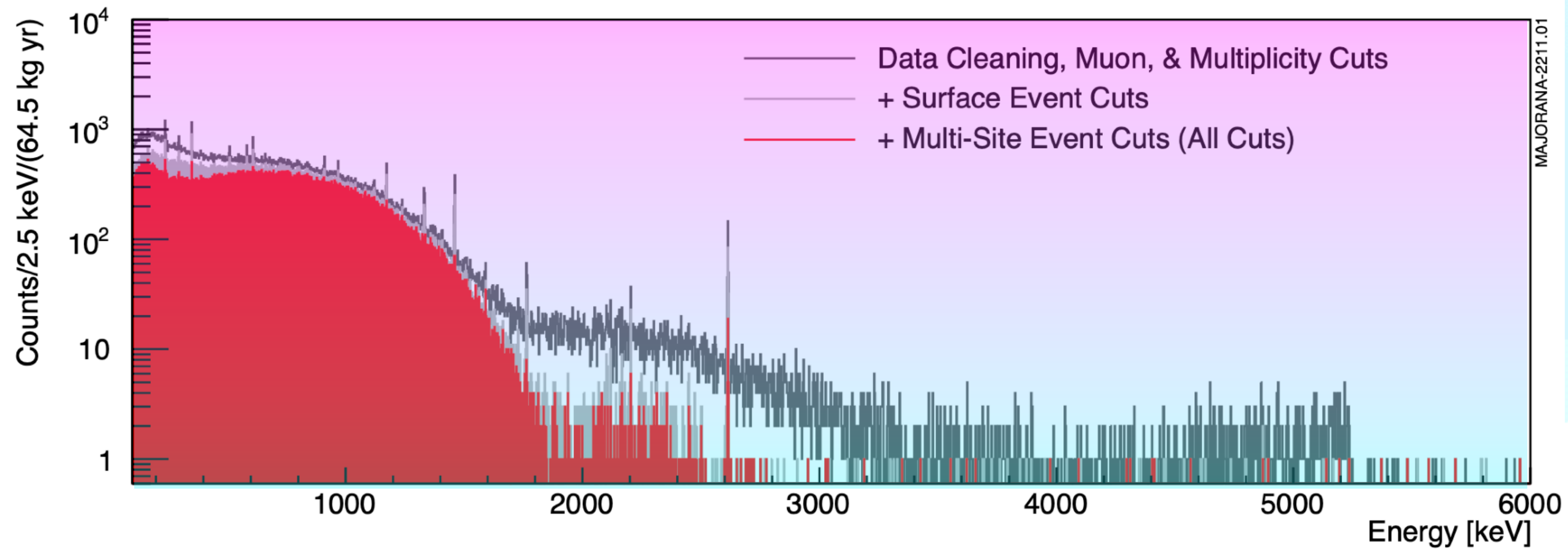
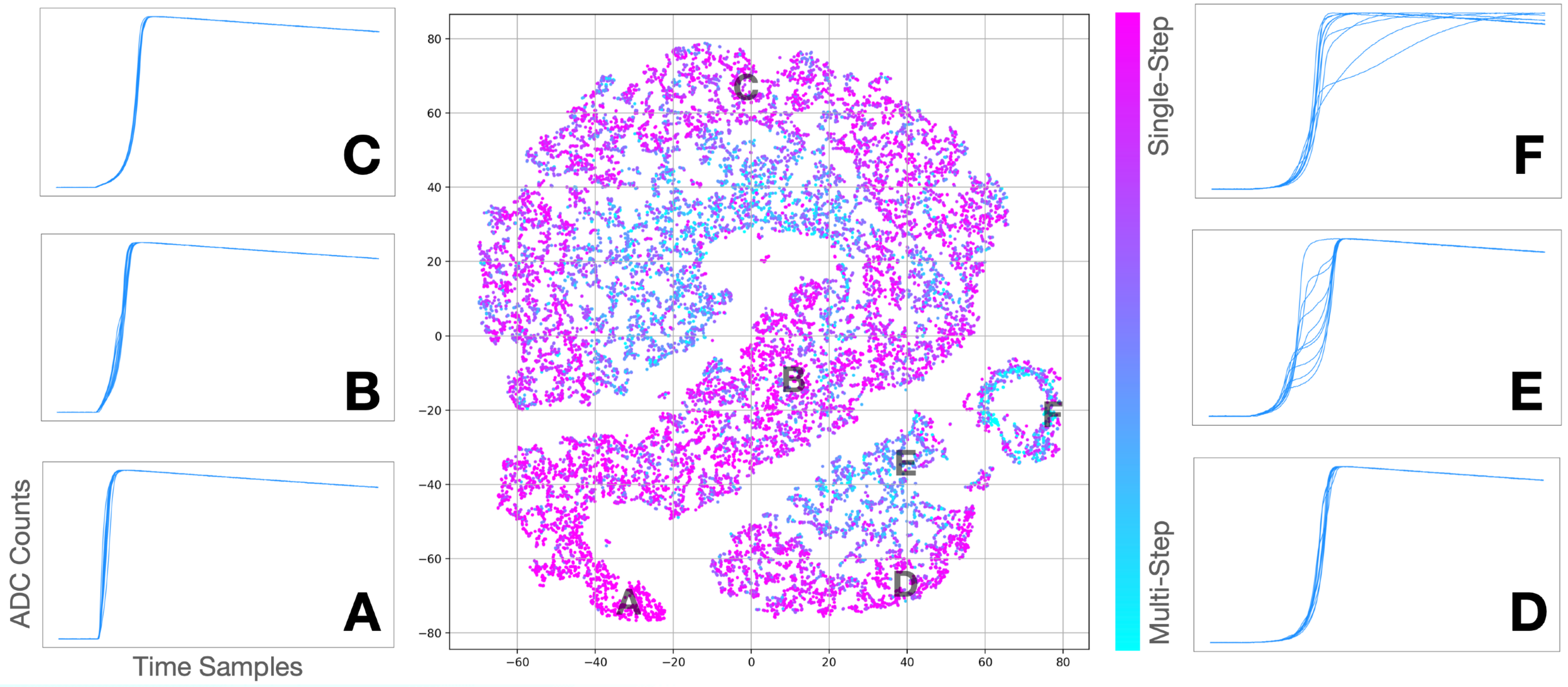


Foundation Model: SSL over general dataset





① **Highly imbalanced dataset**

② **Detector status change over time**

③ **SSL tends to learn simple features**

Germanium Machine Learning (GeM) Group

Leverage efficient and interpretable AI to aid all aspects of LEGEND analysis and simulation
Leverage resources to educate domestic and international collaborators to gain AI experience

Completed Project
Ongoing/Future Project

E. Leon Autonomous Data Cleaning and Run Monitor

T. Ye GAN denoising

T. Oli LBM Network PSA

A. Li, H. Nachman Interpretable BDT

M. Babciz Transformer-based background rejection

LEGEND Foundation Model
trained over all existing data

A. Alexander LBM Dead Layer Fitting

L. Paudel LBM Site Energy Reconstruction

R. Pitelka LBM Position Reconstruction

A. Li, K. Bhimani Cyclic Positional U-Net

N. Zareskii GAN Waveform Simulation

A. Shuetz Neutron Moderator Design Emulation

2 Postdocs, 9 Graduate Students, 2 Undergraduate Students

Large Particle Model for Particle Physics

A unified multimodal foundation model for all Rare Event Search experiment!

Simultaneous training on data from different RES experiment

Has been difficult to push rare event search experiment to release their data.

Majorana Demonstrator Data Release for AI/ML Applications
I.J. Arnquist et al, ArXiv: 2308.10856

Long Time Series Data Release from Broadband Axion Dark Matter Experiment
J. T. Fry et al, NeurIPS 2023 ML4PS

Public

Private

CUPID LEGEND nEXO LZ DARWIN

next KamLAND KamLAND-Zen SNO+ DARK MATTER RADIO ABRACADABRA

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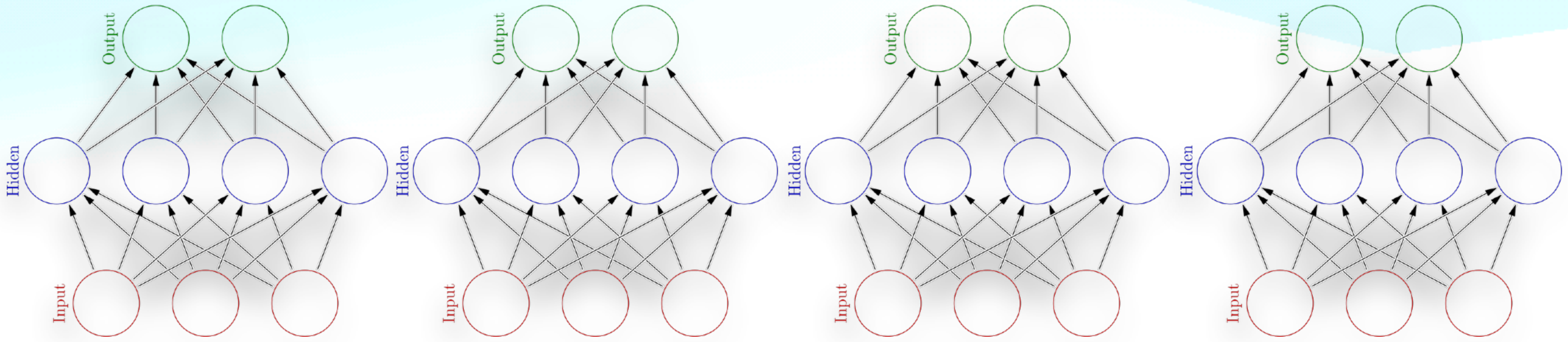
Collections of Foundation Models

- Foundation Model: black-box public key
- Detector Data: private key



Public

Private

CUPID LEGEND nEXO LZ DARWIN next KamLAND KamLAND-Zen SNO+ DARK MATTER RADIO ABRACADABRA

Detecting Rare Events Using Artificial Intelligence

“A Guided Tour to Europe”

- **KamLAND-Zen:** KamNet
- **LEGEND:** GeM AI Analysis Chain
- **XENONnT:** Low & High Level AI Projects
- **ABRACADABRA:** Data Release for AI

“Forging the European Union”

- Self-supervised Learning
- LEGEND Foundation Model
- Large Particle Model for all RES Experiments

Email: aol002@ucsd.edu