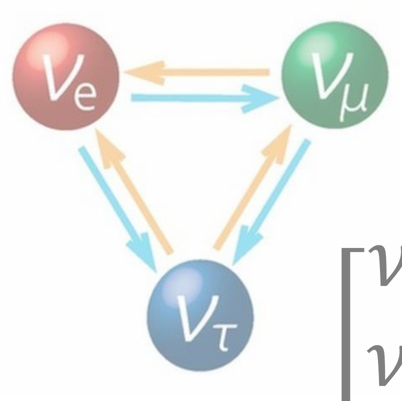
KamLAND-Zen's New ML Tricks

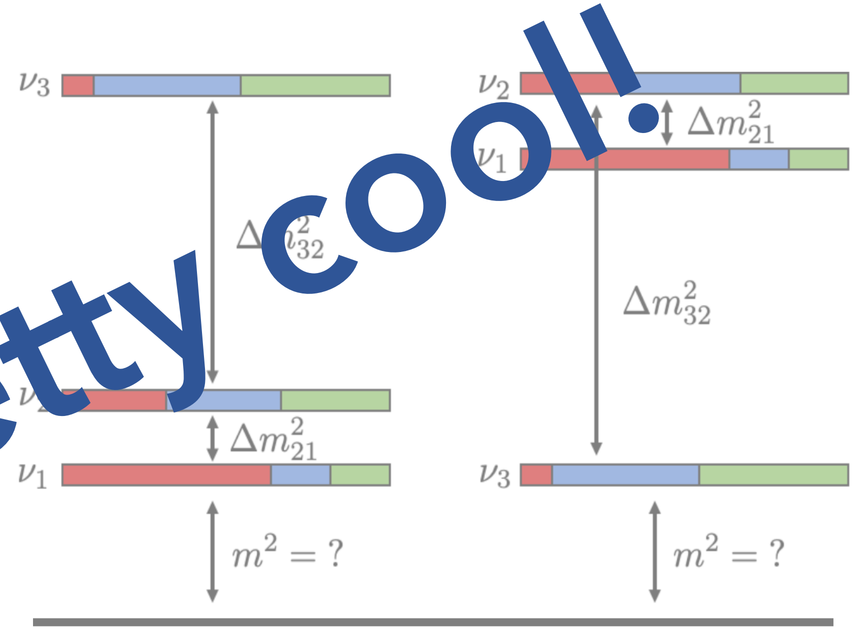
Hasung Song

Boston University

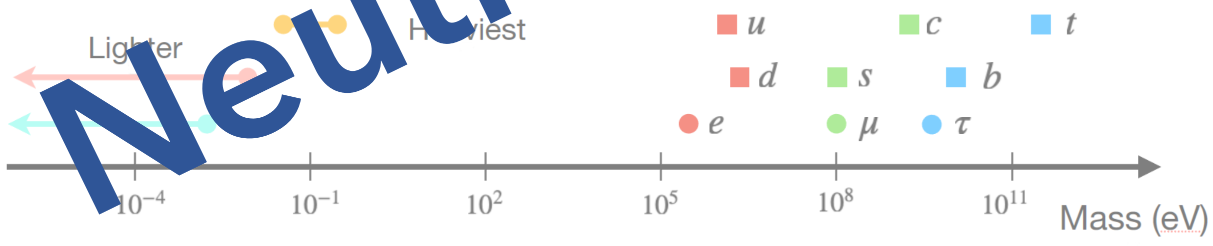
Neutrino Introduction

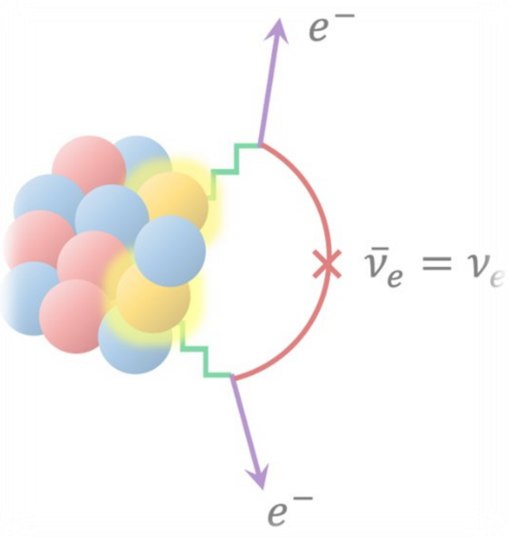


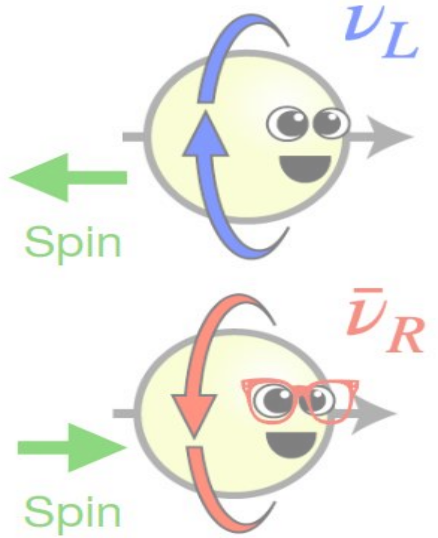
$$\begin{bmatrix}\nu_e\\ \nu_\mu\\ \nu_\tau\end{bmatrix} = \begin{bmatrix}U_{e1} & U_{e2} & U_{e3}\\ U_{\mu 1} & U_{\mu 2} & U_{\mu 3}\\ U_{\tau 1} & U_{\tau 2} & U_{\tau 3}\end{bmatrix}\begin{bmatrix}\nu_1\\ \nu_2\\ \nu_3\end{bmatrix}$$



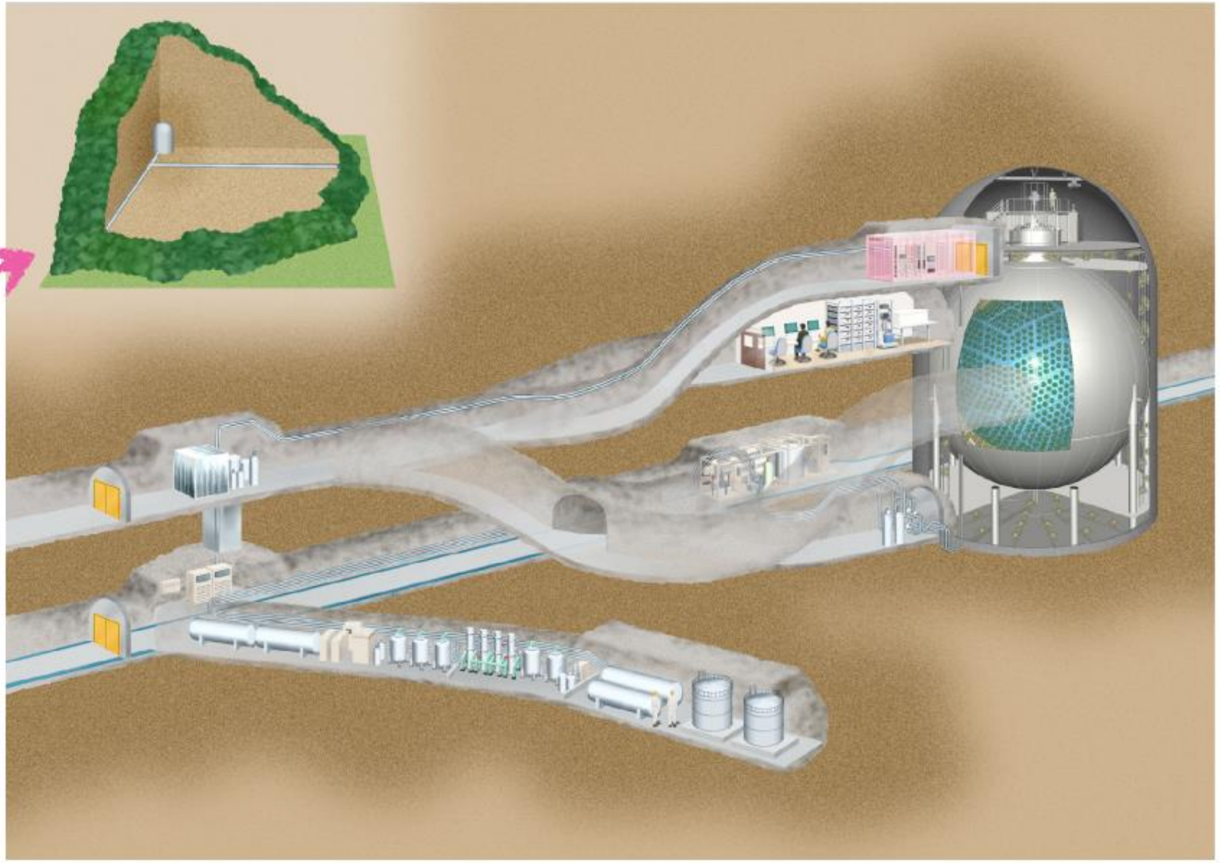
Neutrinos are pretty cool!





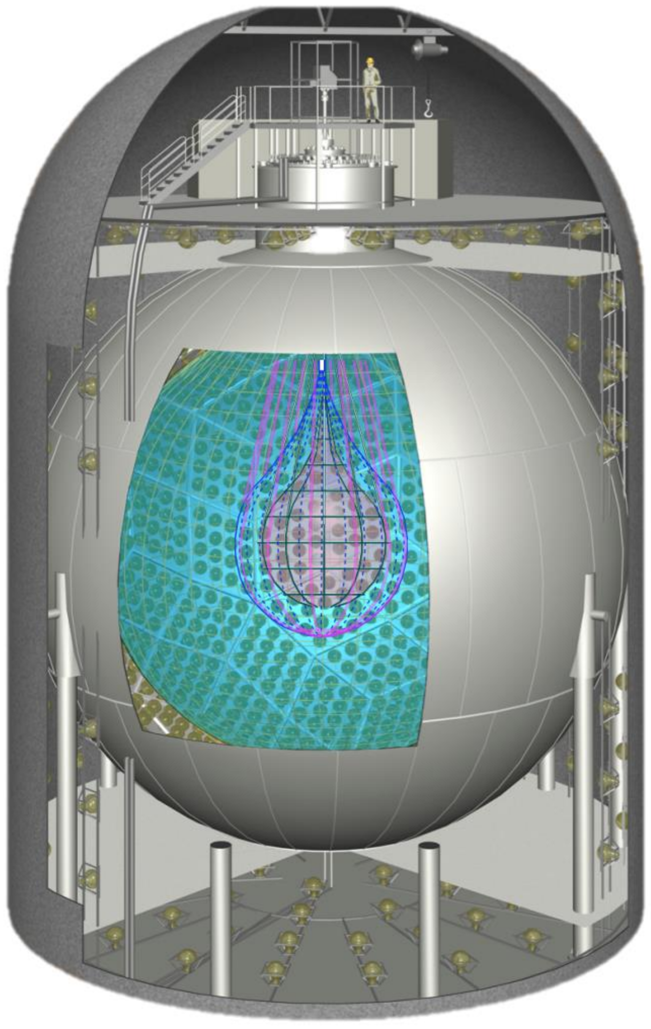


KamLAND = Kamioka Liquid scintillator Anti-Neutrino Detector



KamLAND is located inside Mt. Ikenoyama with 1,000 meter overburden (2,700 m.w.e.)


Toyama City
Mozumi Area
Mt. Ikenoyama
(Kamioka, Hida, Gifu)
XMASS
Kamland
SG
Super-Kamiokande
CLIO
3km
KAGRA
←Toyama
Takahara River
Takayama→
Tateyama→
Atotsu Entrance
Atotsu River
Image: ICRR

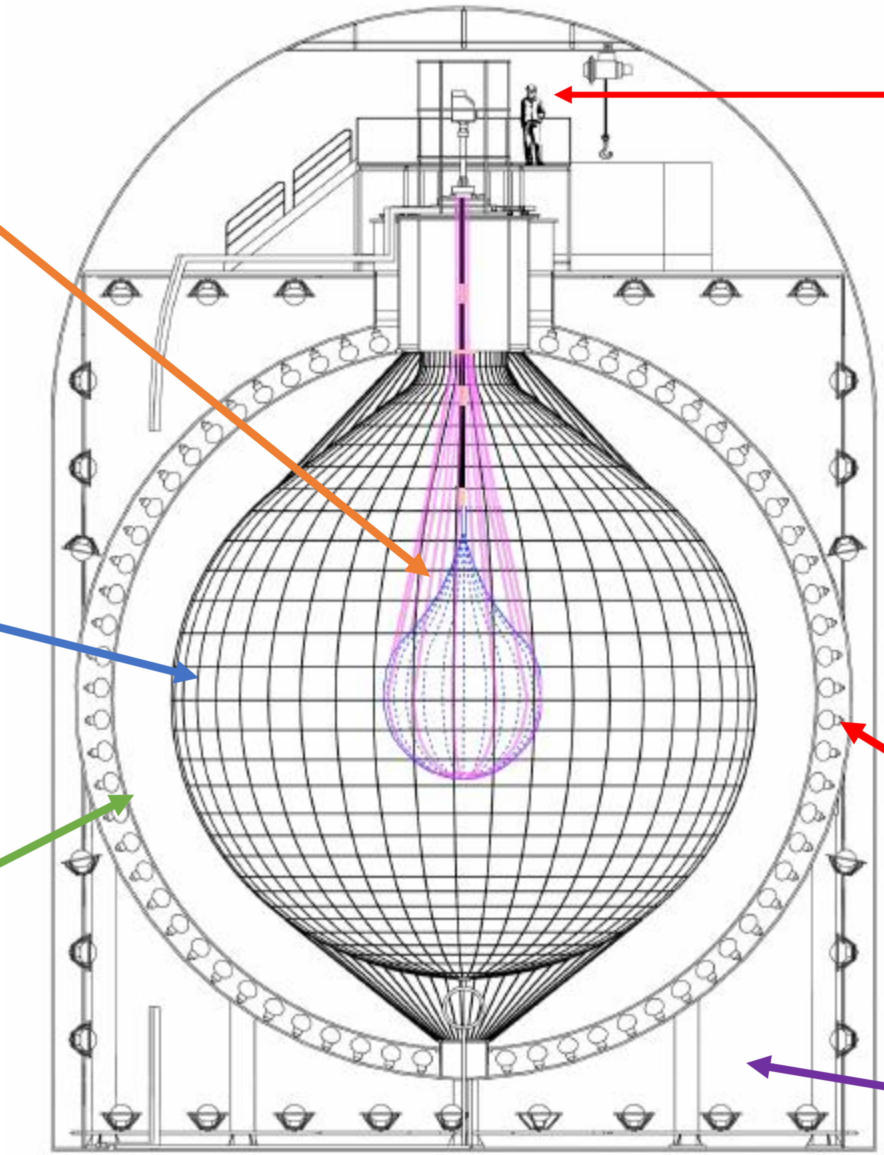


Opening the KamLAND Onion:

An inner balloon holding LS loaded with Xe-136

1 kiloton of ultra-low radioactivity liquid scintillator (LS)

Mineral oil buffer

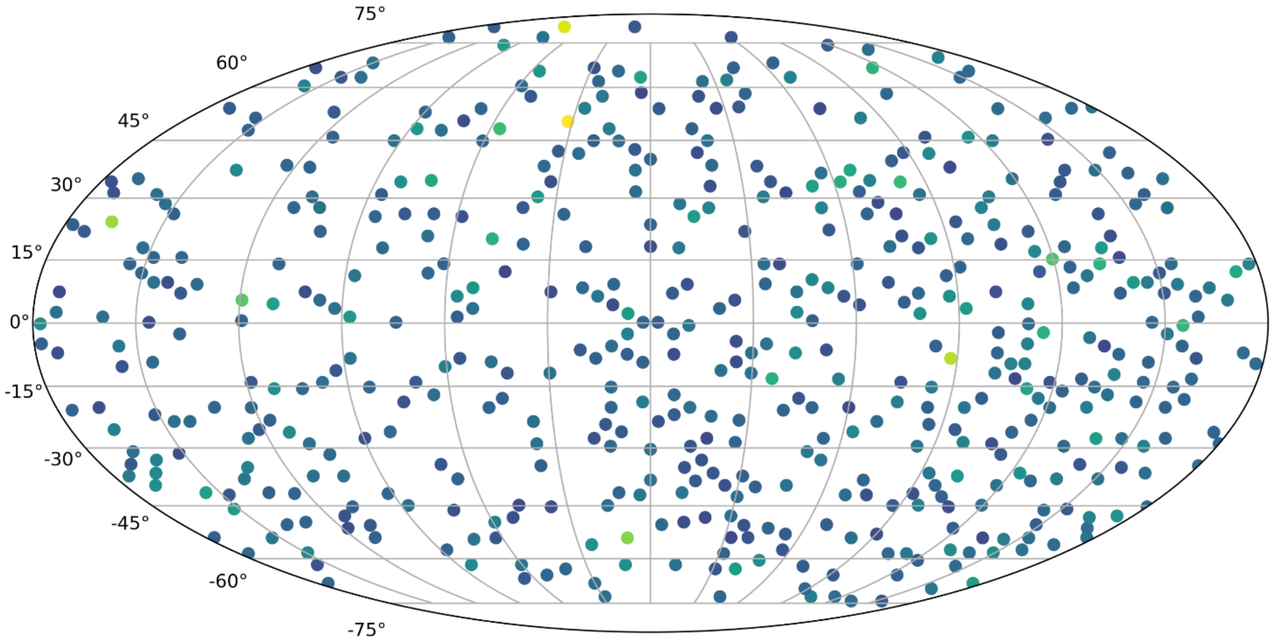


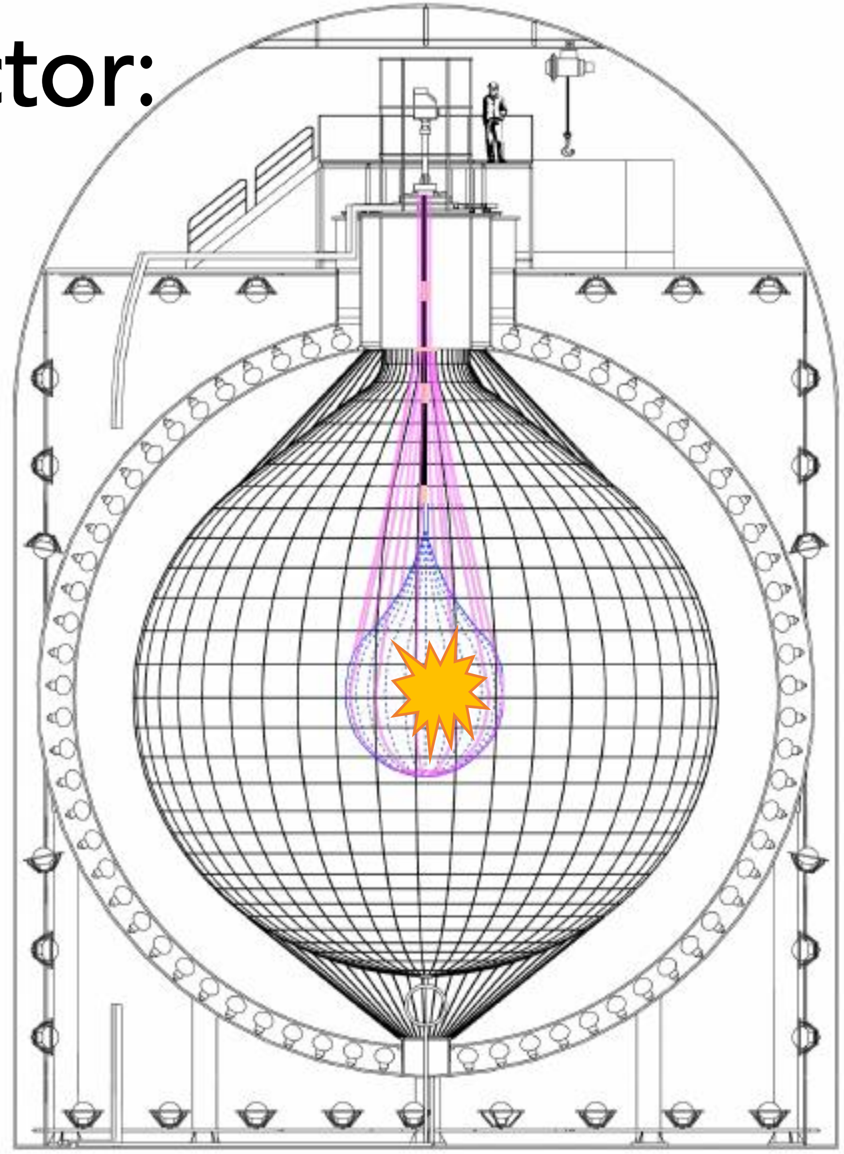
1,879 photomultiplier tubes (PMTs) face the LS providing ~34% photocoverage

Water Cherenkov Outer Detector

KamLAND-Zen Calorimeter Detector:

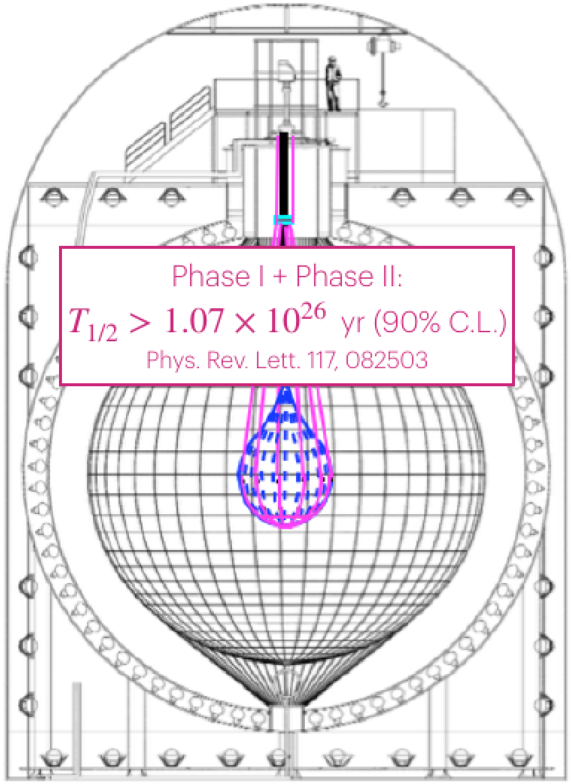
- Particles interact in the LS and deposit energy. Energy is converted to light and captured by PMTs.
- Energy Resolution: $\frac{\sigma_E}{\sqrt{E}} \sim 6.7\%$
- Vertex Resolution: $\sim 13.7cm$





KamLAND-Zen Timeline:

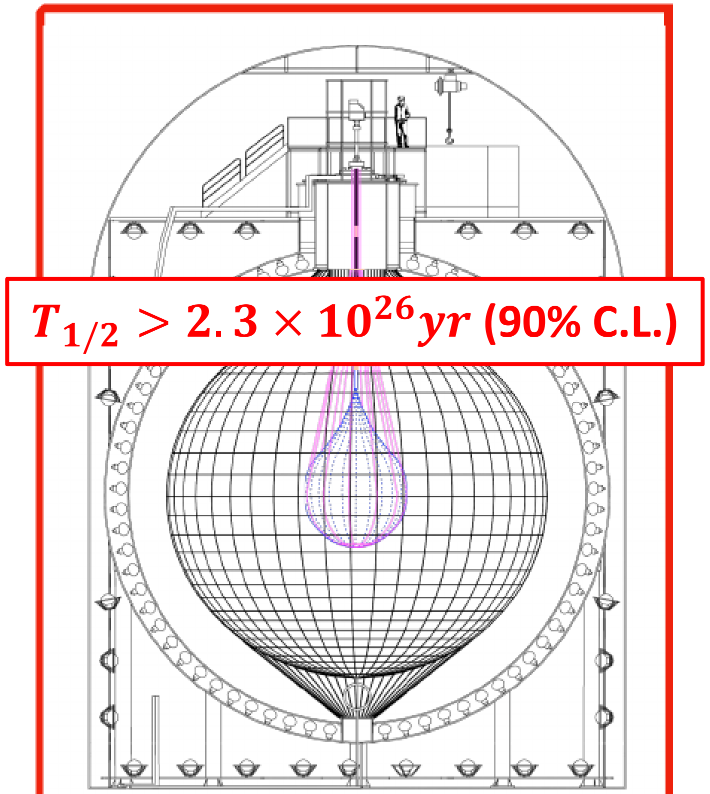
Past



KamLAND-Zen 400:

- Mini-balloon Radius = 1.54 m
- Xenon mass = 320 ~ 380 kg
- Duration: 2011 ~ 2015

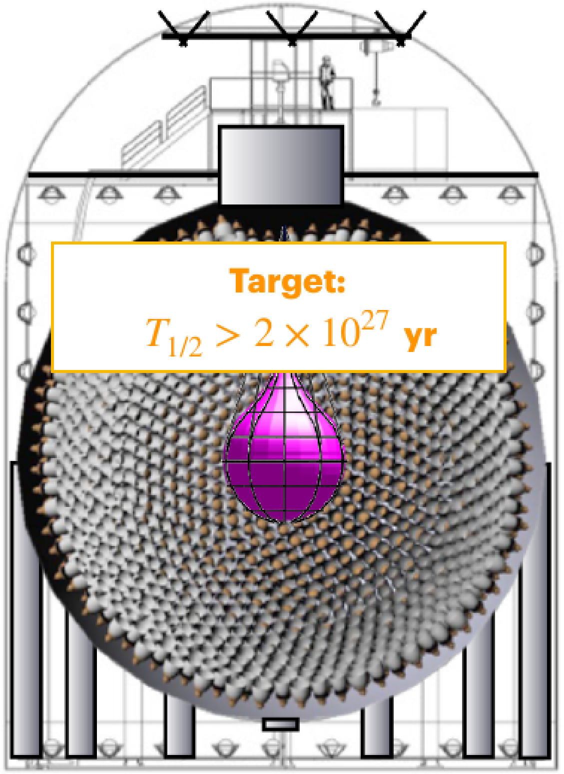
Present



KamLAND-Zen 800:

- Mini-balloon Radius = 1.90 m
- Xenon mass = 745±3 kg
- Data taking starts Jan. 2019

Future

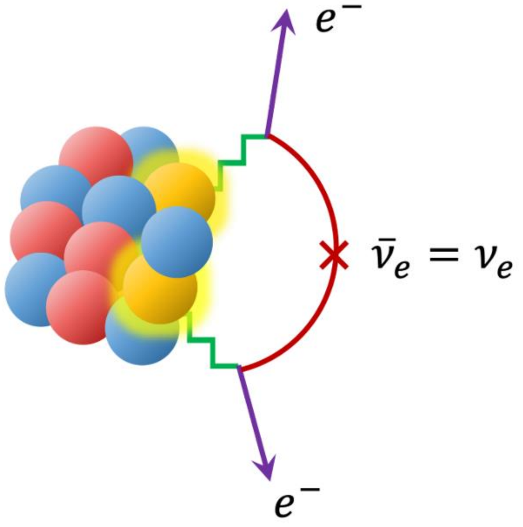


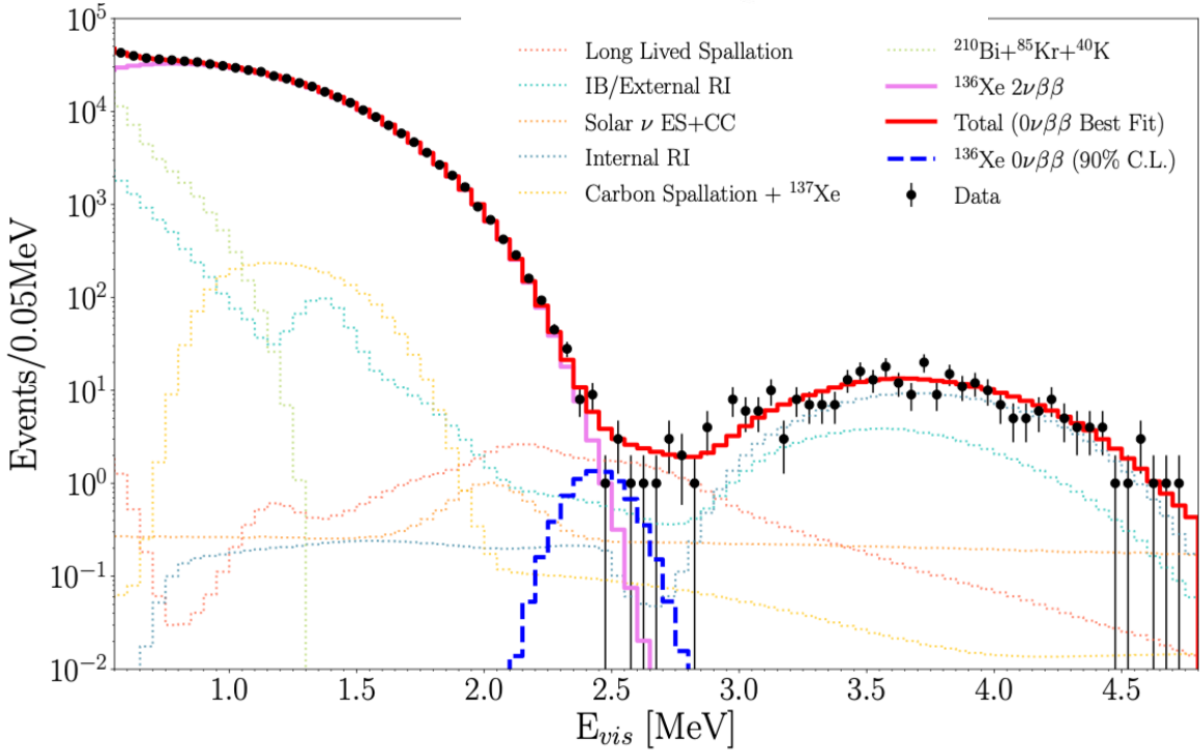
KamLAND2-Zen:

- Xenon mass ~ 1ton
- Aiming at 100% Photocoverage
- PEN scintillation balloon film

0νββ : Signal and Background

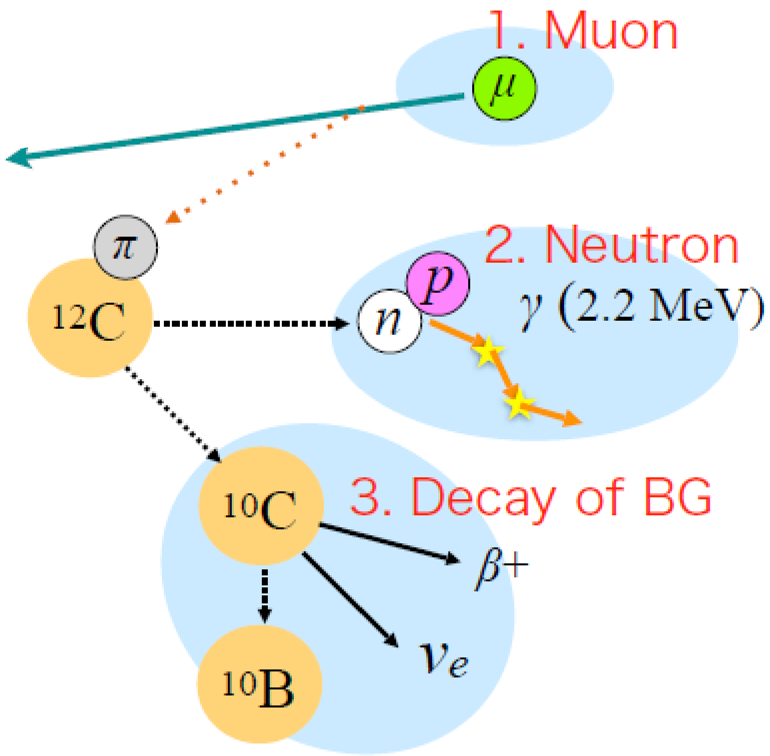
- Looking for 2.46 MeV (Xe^{136} Q-value) electron events
- Primary Backgrounds:
  - 2νββ decays
  - Cosmic muon spallation (Long-Lived)
- Minor Backgrounds
  - Radioactive contamination
  - Solar neutrinos
  - Cosmic muon spallation (Short-Lived)





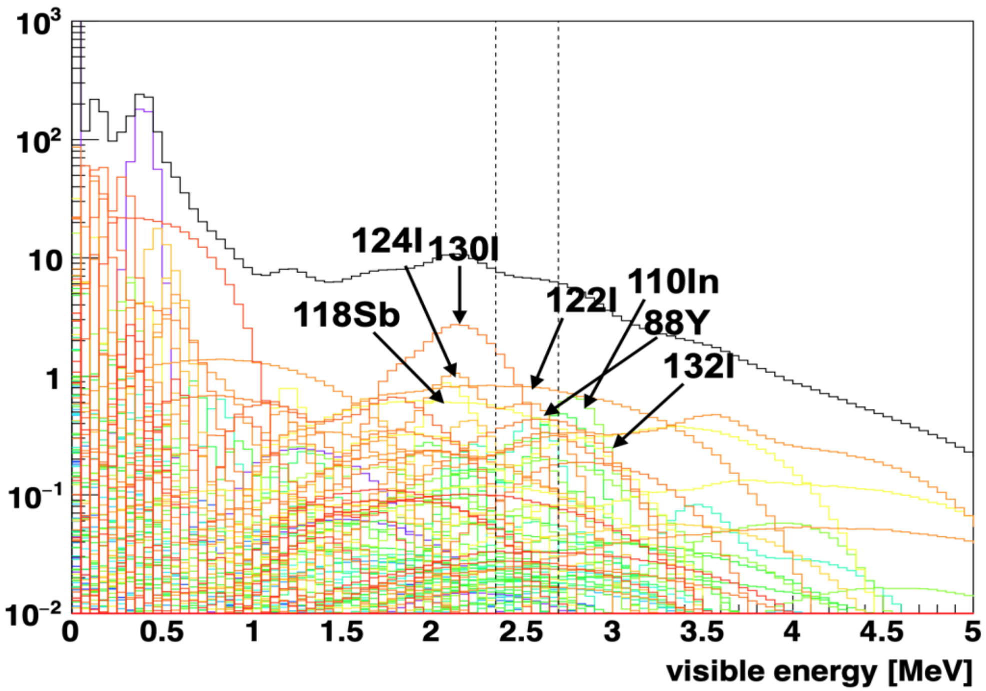
Cosmic Spallation Backgrounds

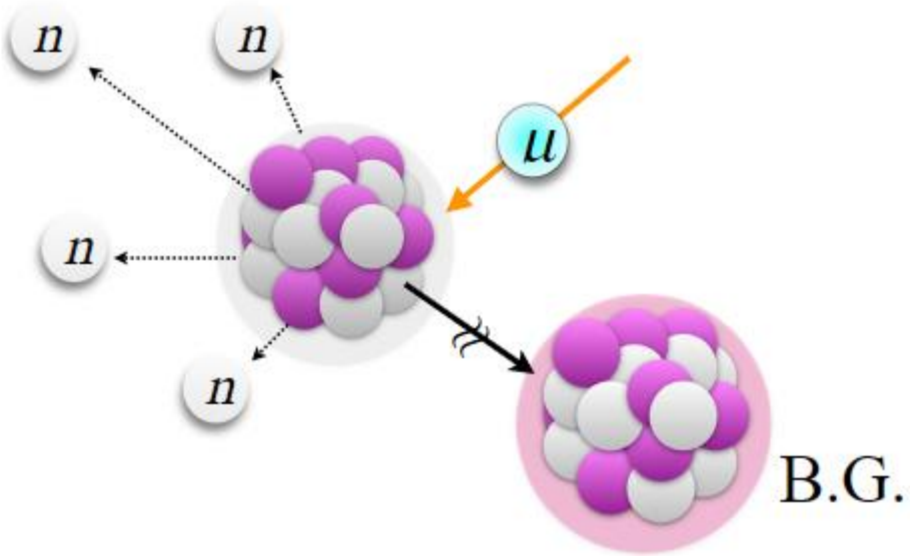
- Cosmic ray induced spallation backgrounds are the dominant background of concern for KLZ-800.
- Cosmic ray muons can break apart heavy nuclei into lighter elements.
- Some of these lighter nuclei emit **electrons** and **gamma-rays** at similar energy to our neutrinoless double-beta decay signal.
- Most of these incidents can get removed by a coincidence cut.
    - Look for events in the path of a recent cosmic muon
    - Also check for nearby detected neutron capture events



Cosmic Spallation Backgrounds

- However, some of these isotopes have half-lives of hours or days, which makes muon coincidence tagging difficult
- These events can only be rejected by their final decay products (betas/gammas)
- Machine learning has proven effective at rejecting these backgrounds





Machine Learning in KLZ-800: KamNet

Editors' Suggestion | Open Access

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

A. Li, Z. Fu, C. Grant, H. Ozaki, I. Shimizu, H. Song, A. Takeuchi, and L. A. Winslow

Phys. Rev. C **107**, 014323 – Published 30 January 2023

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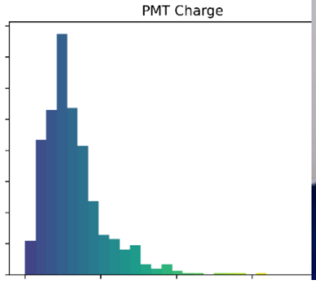
- Ka
  ma
  So
- Convolutional-LSTM (Long-Short Term Memory) Layer with attention module
  - Learns to identify and focus in on important sections of the eve
- Spherical Convolut
  - Utilizes spherical sy features

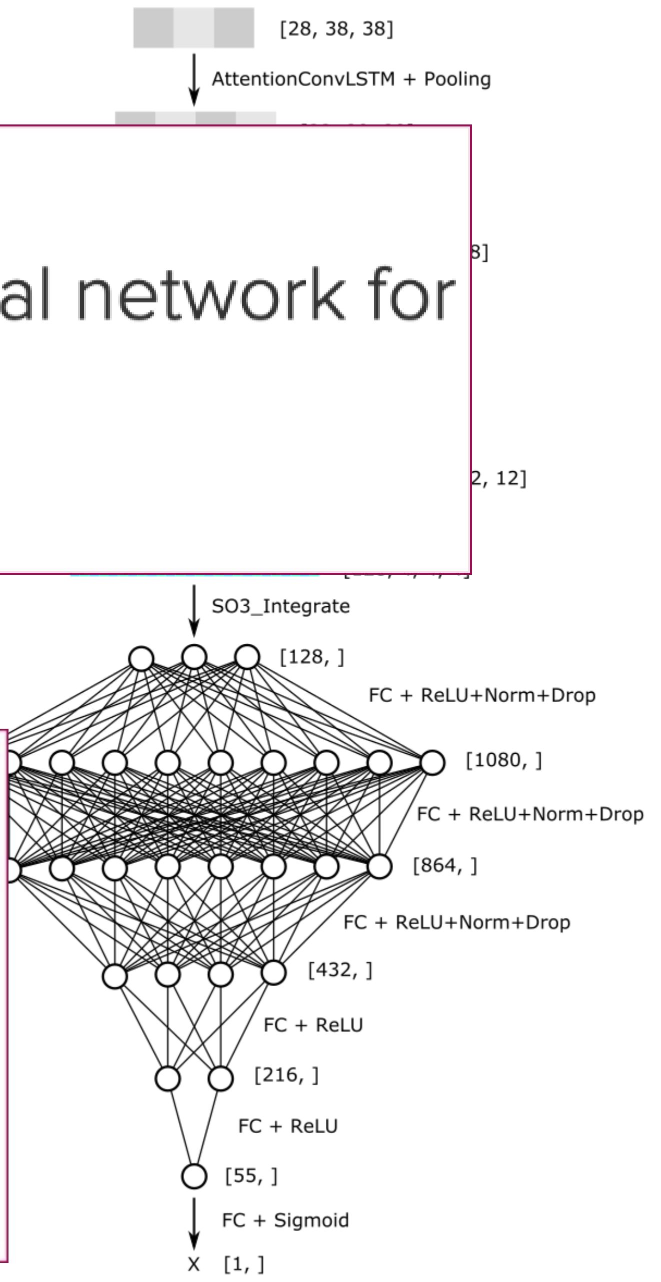


Aobo Li

PhD 2020, Boston University

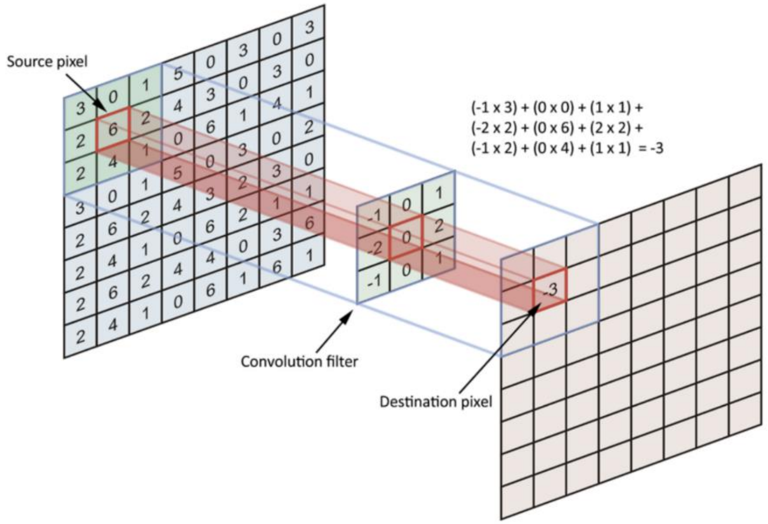
2023 Dissertation Award in Nuclear Physics

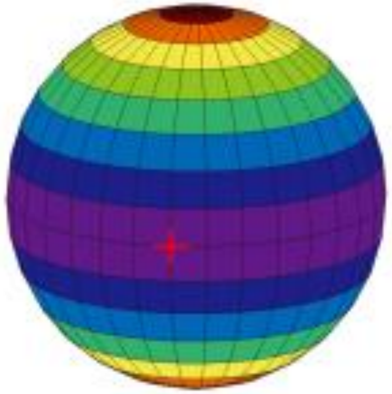
APS

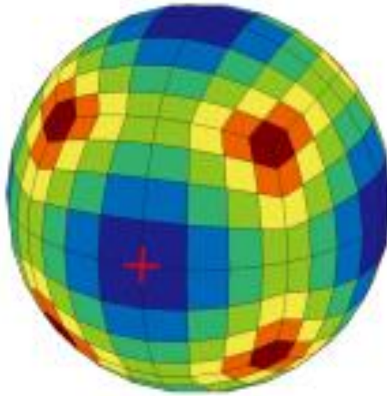


KamNet: Spherical Convolution

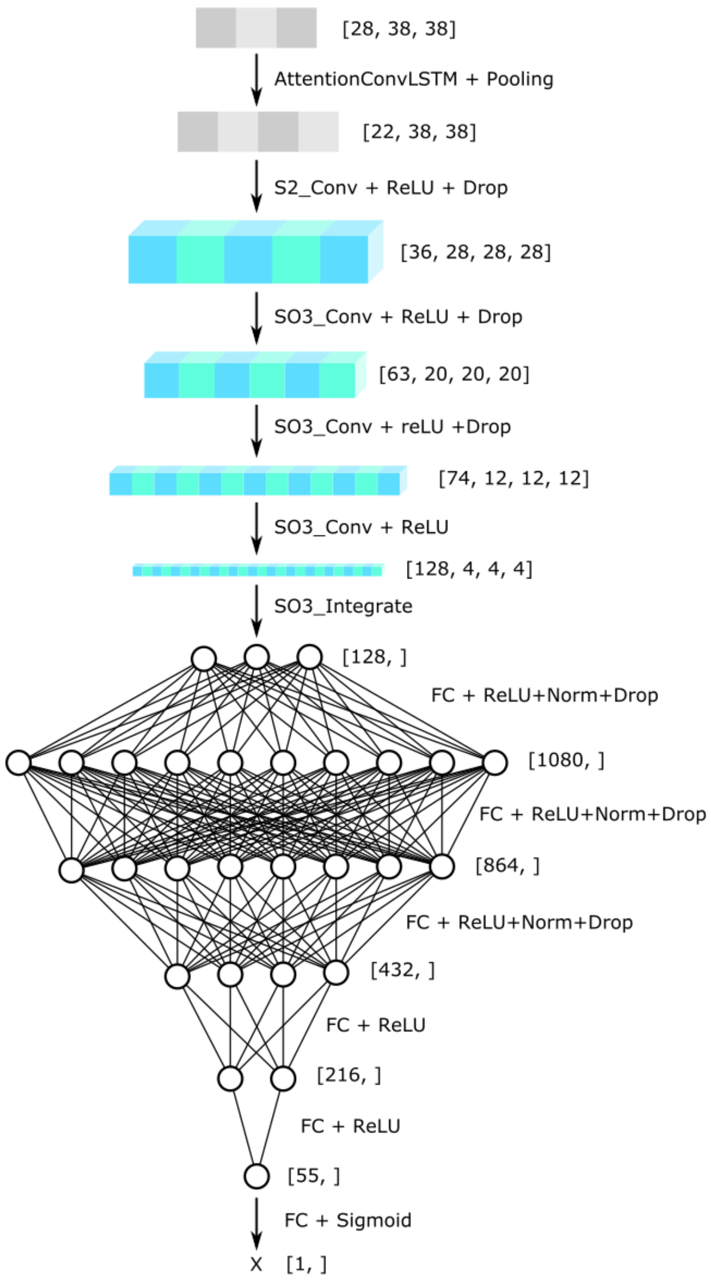
- Traditional cartesian convolution learns a small filter that is scanned over an input image
  - Produces a cartesian activation map





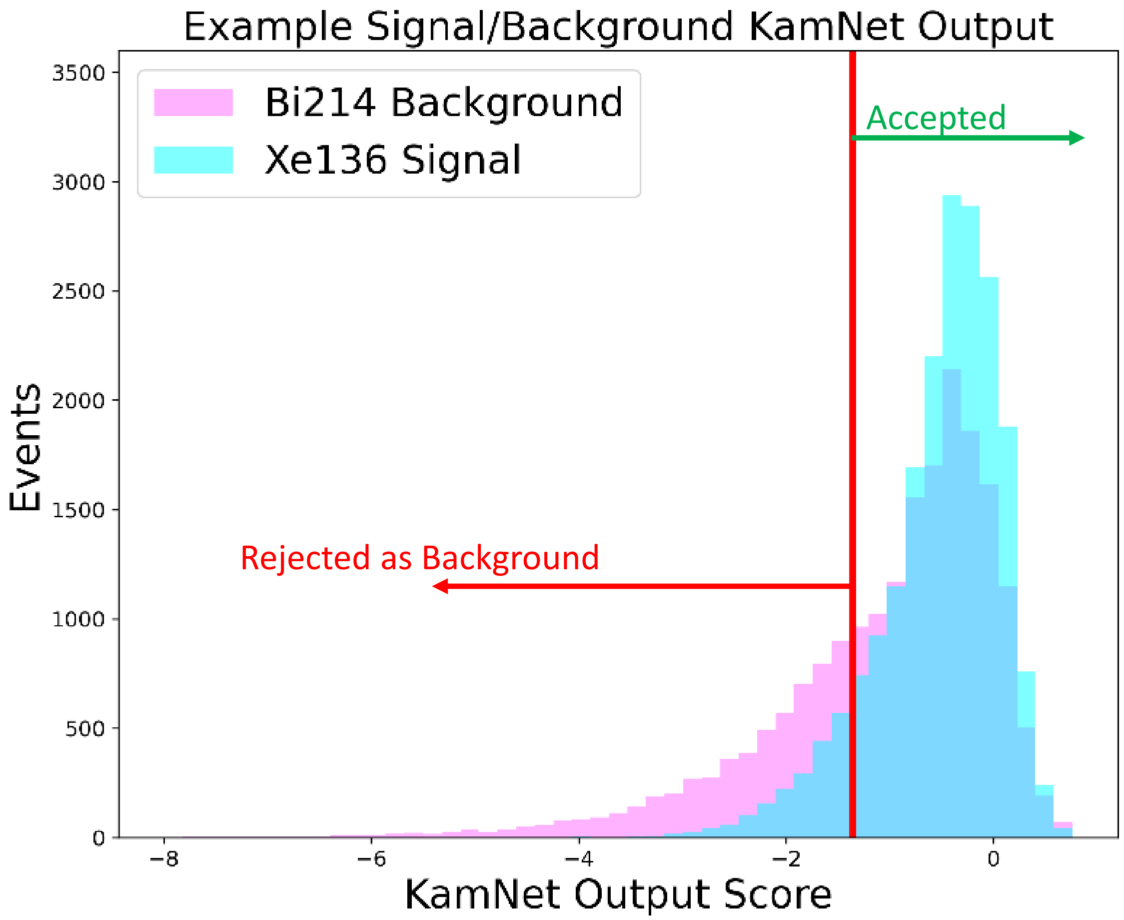


- Spherical Convolution learns a "filter" that spans the entire image, this filter is then rotated through every orientation over the Euler angle space (α,β,γ)
  - Produces an activation map in Euler angle space
- Sph. Conv. enables KamNet to learn spherical features regardless of orientation
- Subsequent convolutions learn filters over the Euler angle space



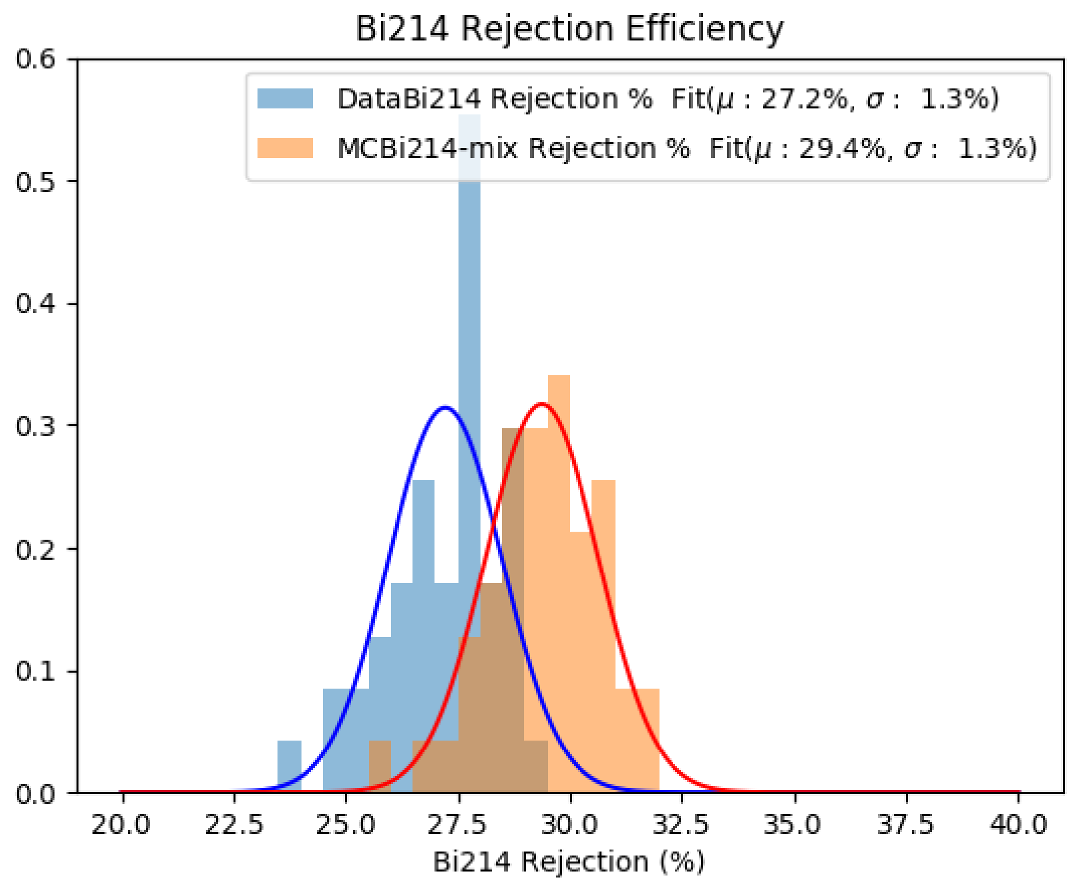
KamNet: Training

- KamNet trained on simulated MC events of each
  - Xe^{136} - 2νββ, 2 electrons
  - Bi^{214} - Decay, 1 electron and 1+ gammas
  - Bi^{214} is present in the detector as radioactive contaminant
  - Bi^{214} is chosen for background as it is easily isolated in the real experiment by coincidence with secondary alpha decay
- KamNet outputs a single value for each event, a KamNet score
  - Score describes how “signal-like” or “background-like” an event is



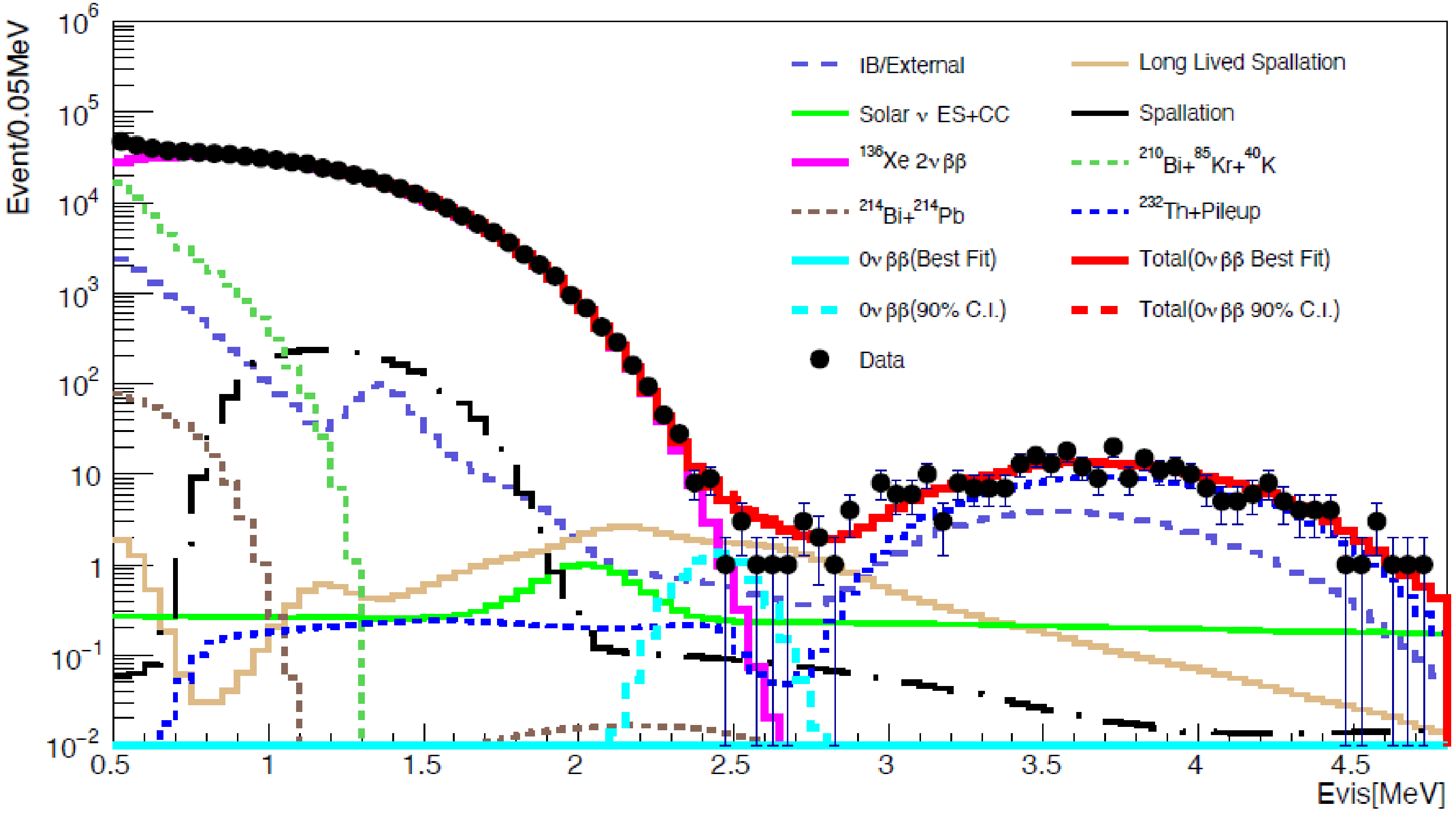
KamNet: Evaluating Performance

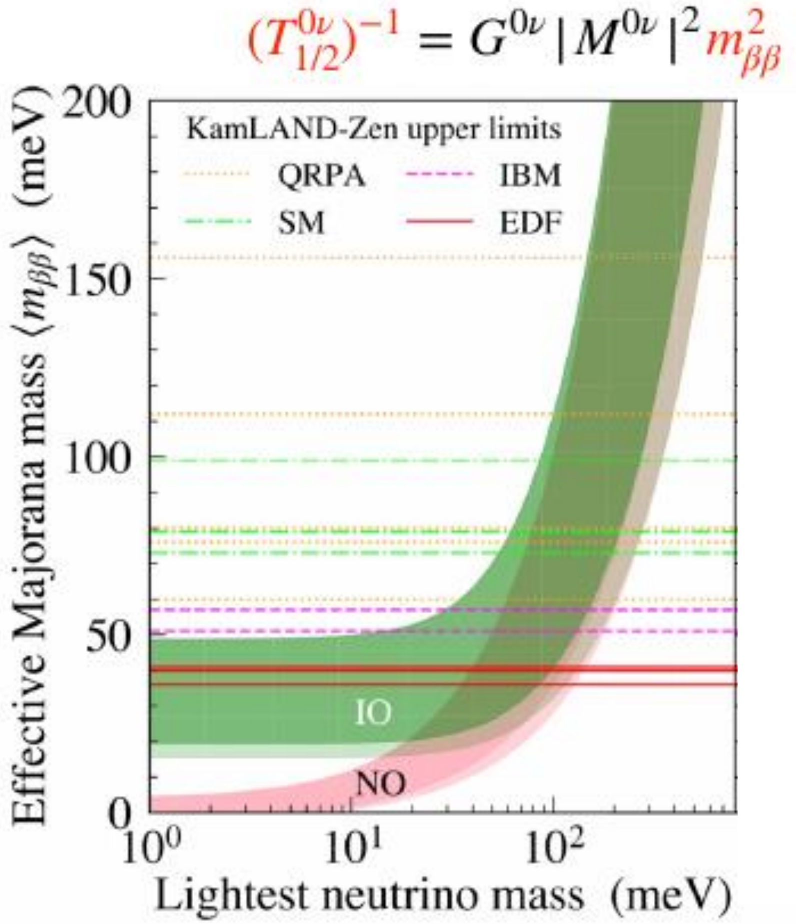
- Used bootstrapping technique to evaluate KamNet's performance and consistency
  - Train many instances of KamNet with different random samplings of training data
- Measure each of these bootstrapped models' background rejection efficiency
- Rejection Efficiency: percentage of backgrounds rejected when accepting 90% of the signal
- Also found good Data-MC agreement in KamNet performance



Latest Results: $T_{1/2} > 2.3 \times 10^{26} yrs$ (90% C.L.)

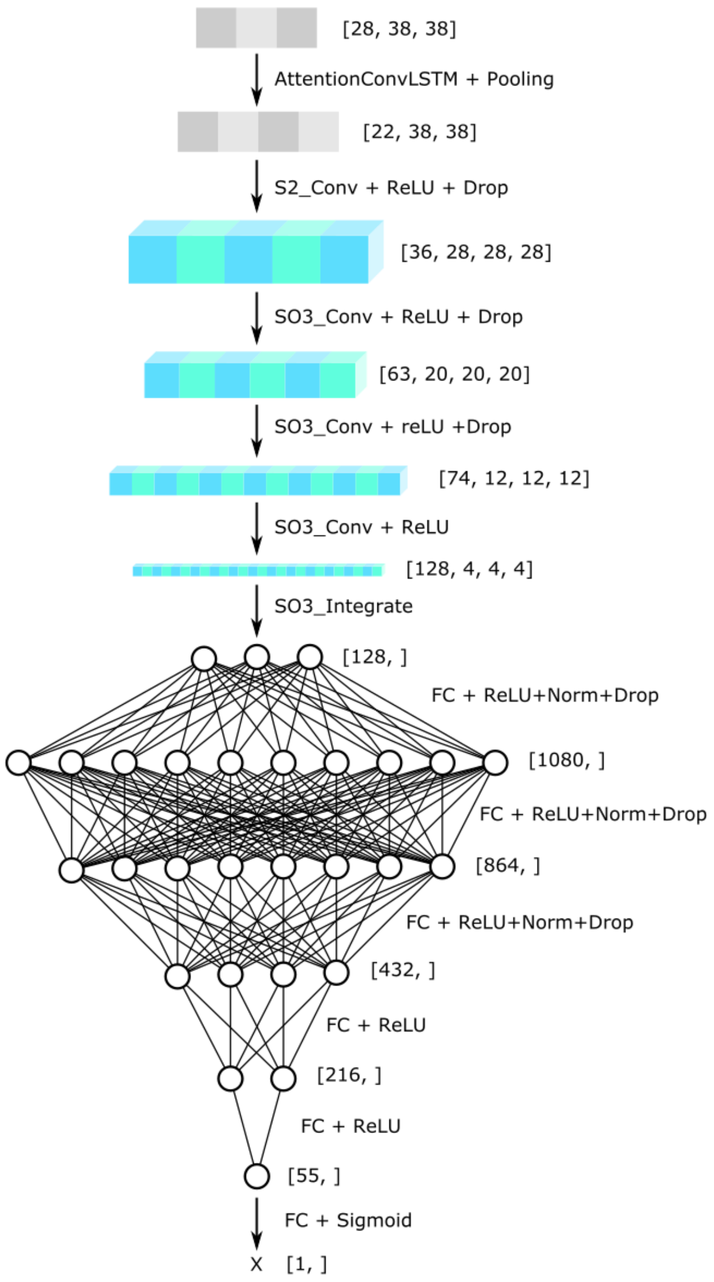
- First search for 0nubb in the Inverted Ordering region!
- Total Livetime of 523 days, 970 kg·yrs of exposure





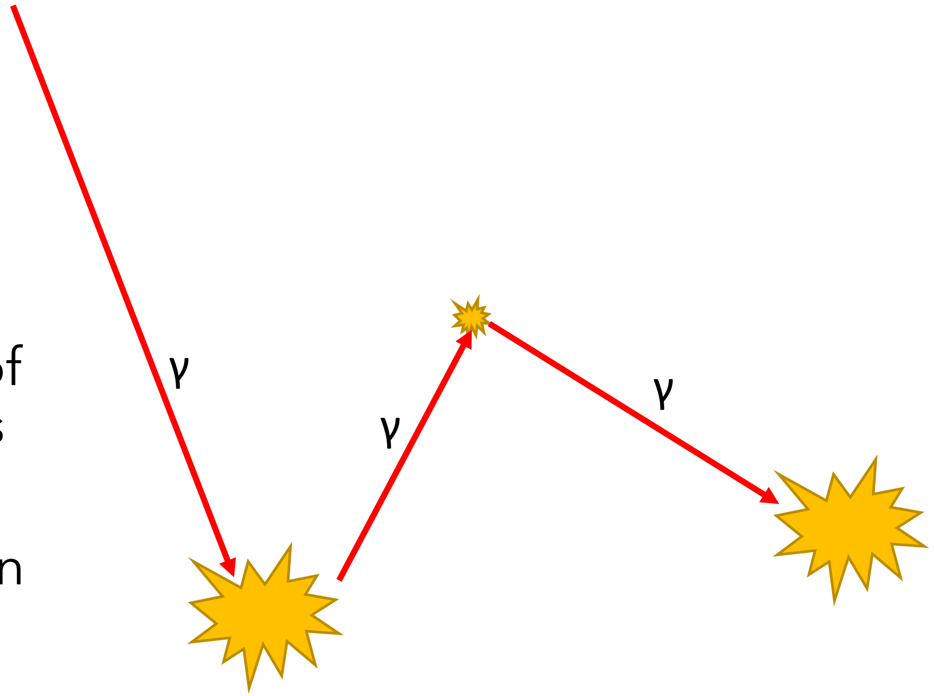
KamNet: Interpretability

- KamNet can separate electron-only signal events from a mixture of electron-gamma backgrounds
- How does KamNet do this?
  - What features are important to KamNet?
  - What kinds of events are easier/harder to classify?



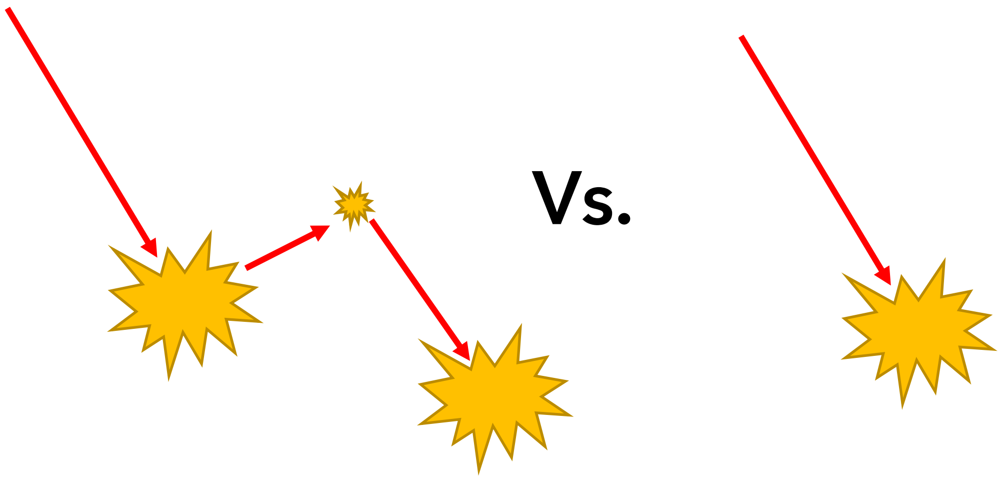
Single-Site vs Multi-Site

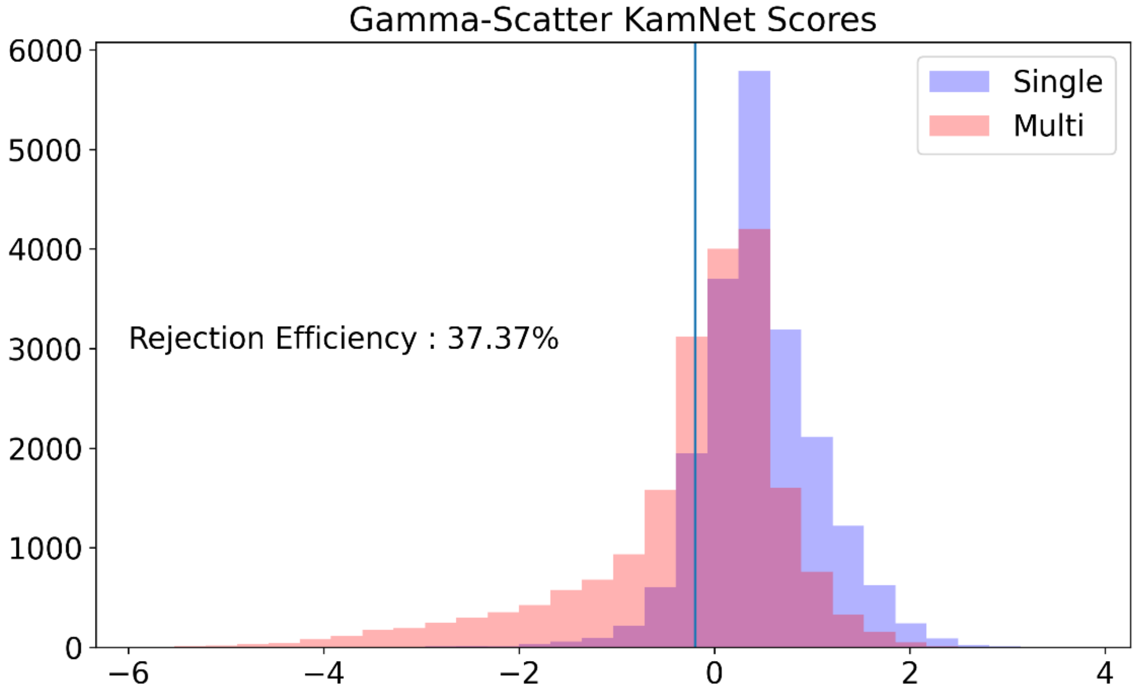
- Hypothesize that KamNet uses the multi-site nature of gammas to distinguish between electron-only events and electron-gamma mixed events
- Emitted gammas in KamLAND-Zen typically Compton scatter a few times, “kicking” electrons that then deposit energy in the scintillator



Single vs Multi-Scatter

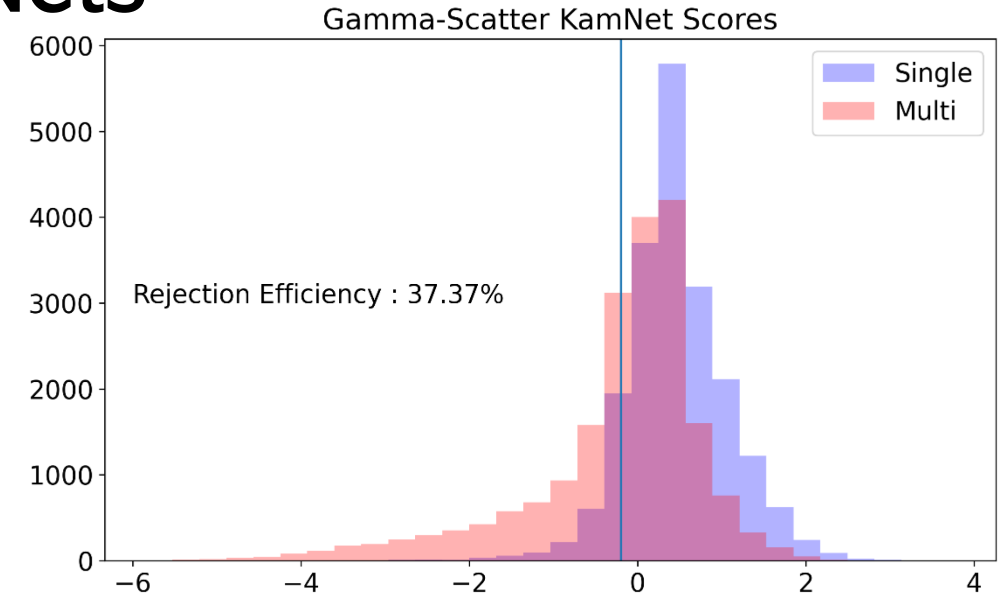
- Trained KamNet to identify events where gammas deposit energy multiple times in KLZ.
- Trained with simulated 3 MeV gammas separated by the number of sites
  - single-site events (signal)
  - multi-site events (background)
- KamNet performs well at separating single site gammas from multiple site events

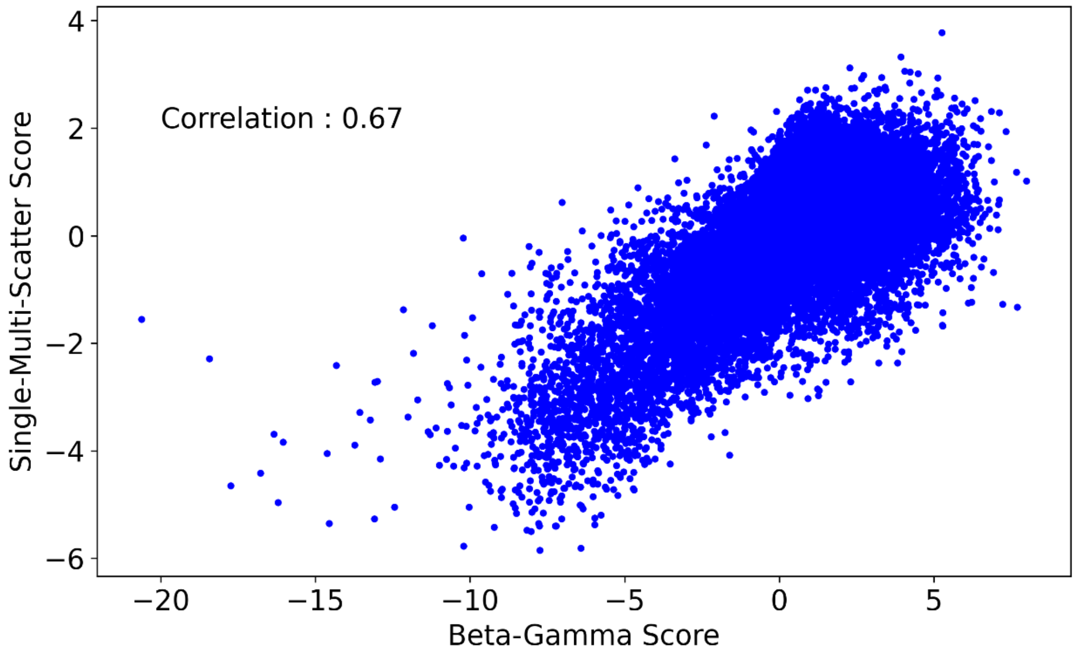


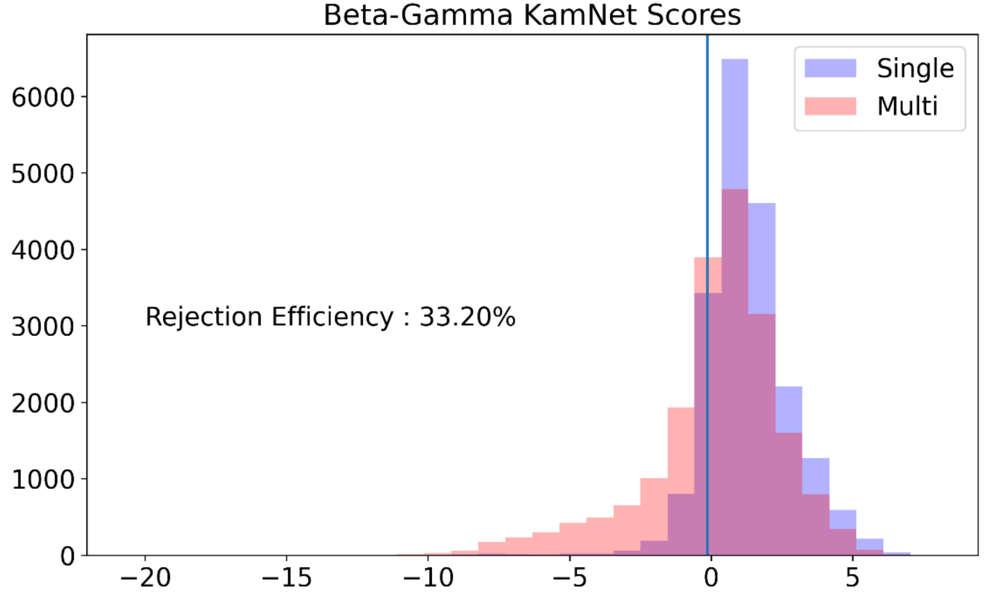


Comparing Differently Trained KamNets

- 2 KamNets trained for different tasks have well correlated outputs
  - Electron-only vs Electron-gamma-mixed Identifier
  - Single vs Multi-Site Identifier
- Ran the same 3 MeV gamma dataset through both models
- Found that their outputs are well-correlated which is a strong indicator KamNet is using the multi-site nature of gammas to separate backgrounds

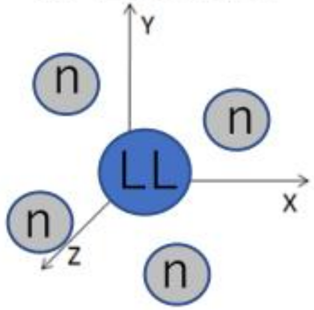


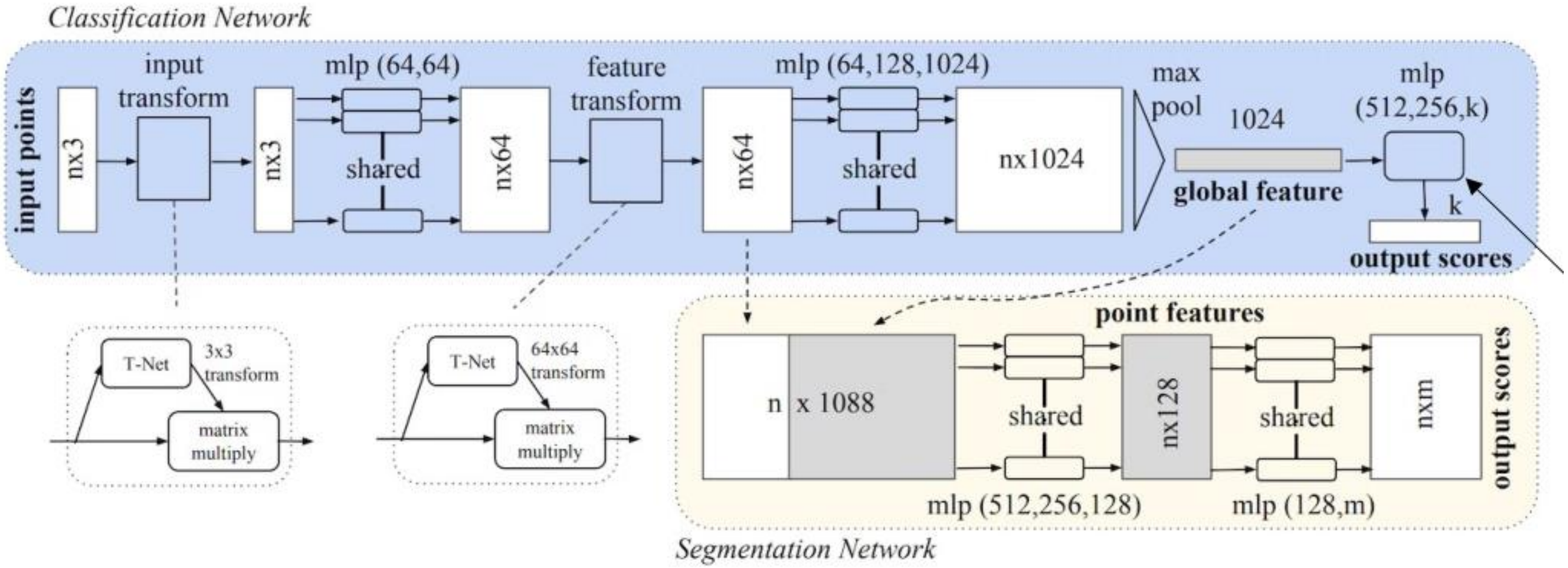




Modeling Cosmic Ray Correlation with PointNet

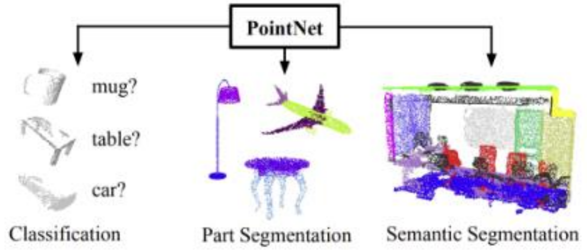
Neutron's vertices in 160cm





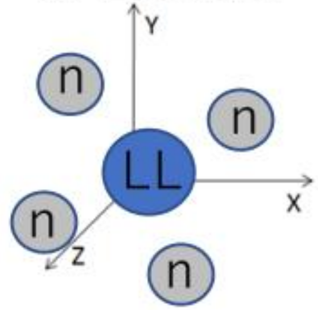
Modeling Cosmic Ray Correlation

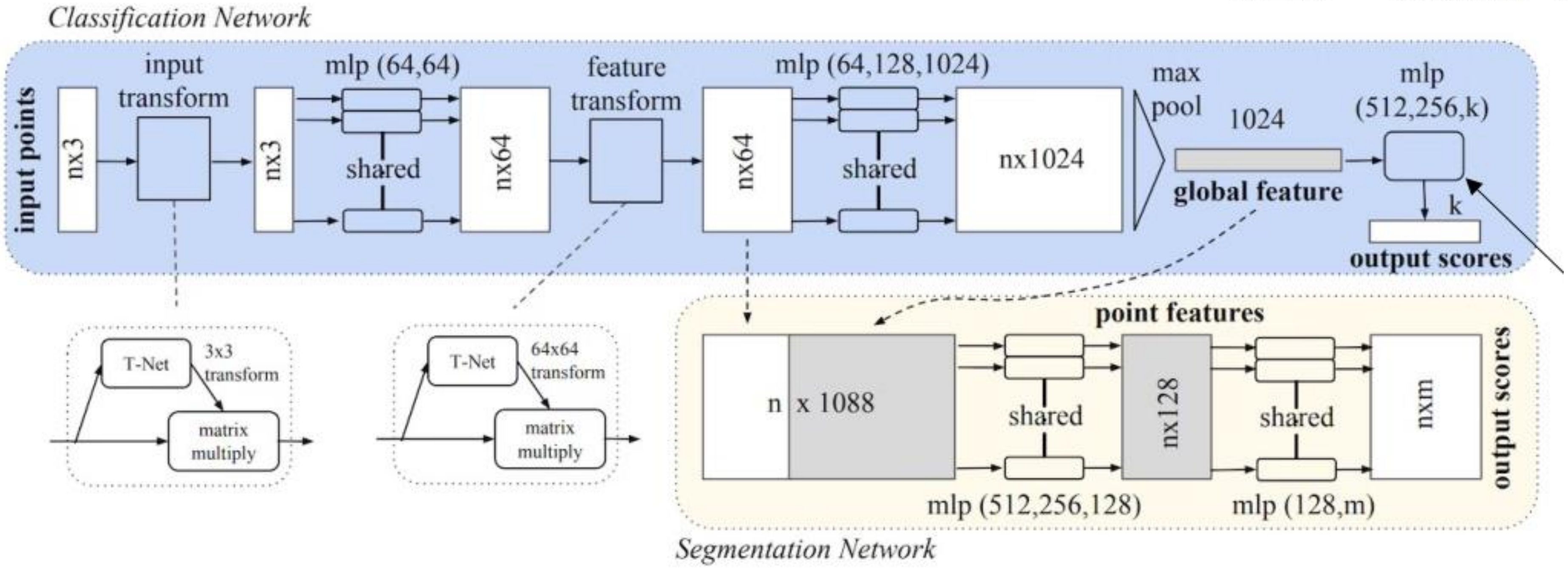
https://arxiv.org/pdf/1612.00593.pdf



- Can also model radioactive decay correlation with cosmic ray muons
- Train a PointNet to model this correlation

Neutron's vertices in 160cm

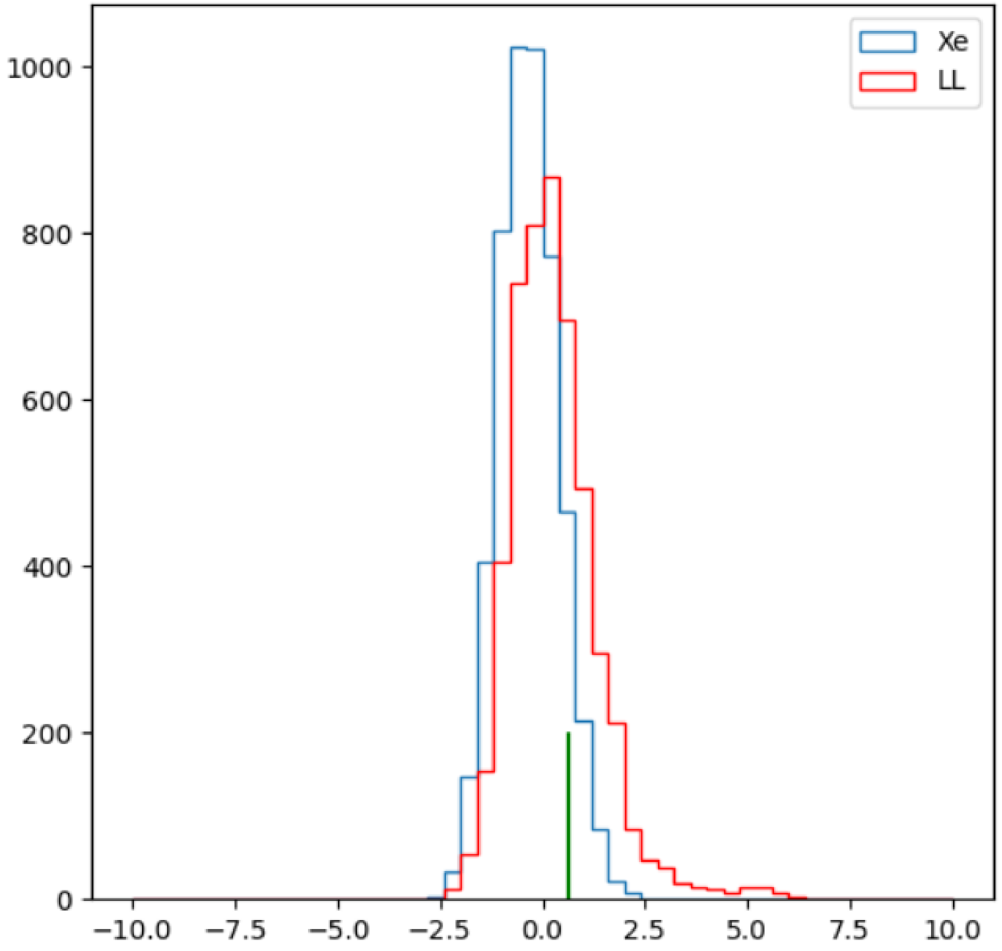




- PointNet is a neural network architecture designed for 3D point clouds
- Input: the reconstructed neutron capture vertices within 160cm of subject radioactive decay
- dT, time delay from latest muon, is piped directly to the final MLP layer

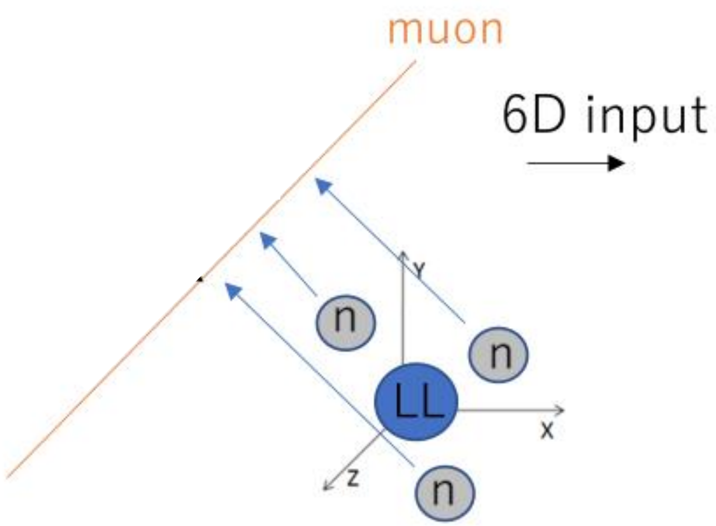
PointNet Performance

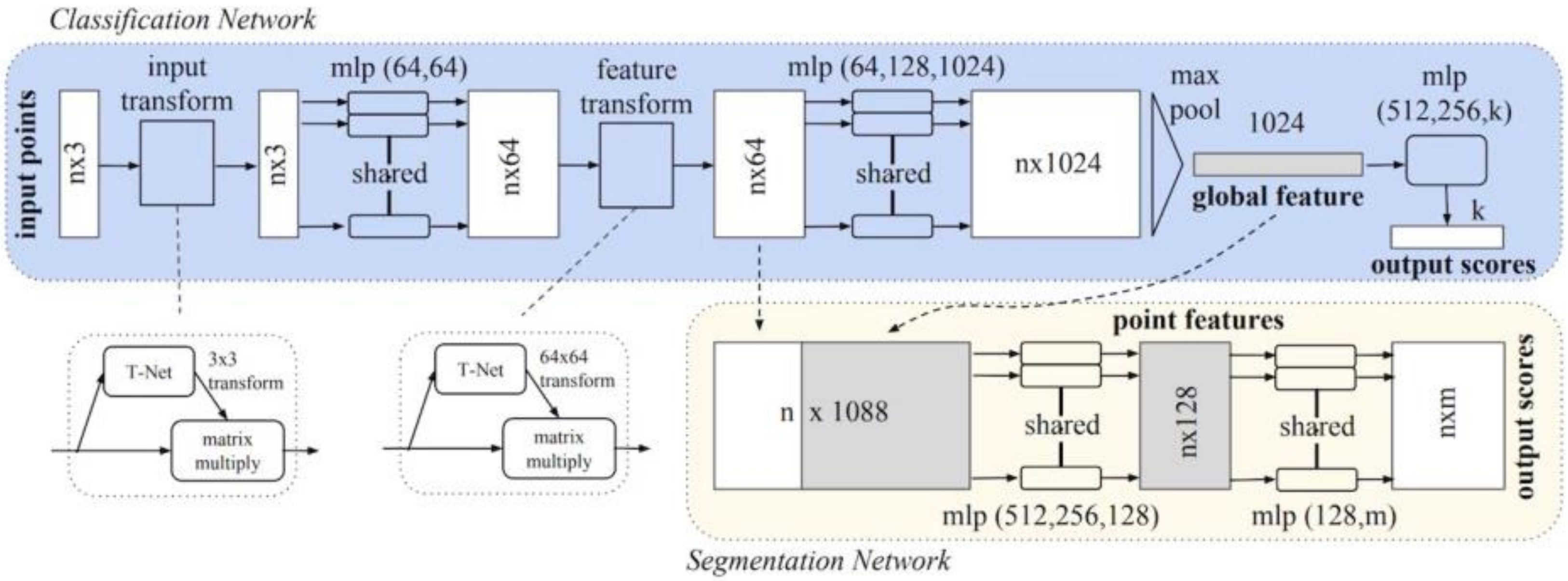
- PointNet successfully identifies events coincident with cosmic ray muons
- **49% tagging efficiency** while falsely tagging 10% of Xenon-136 decays



PointNet: Including Muon Tracks

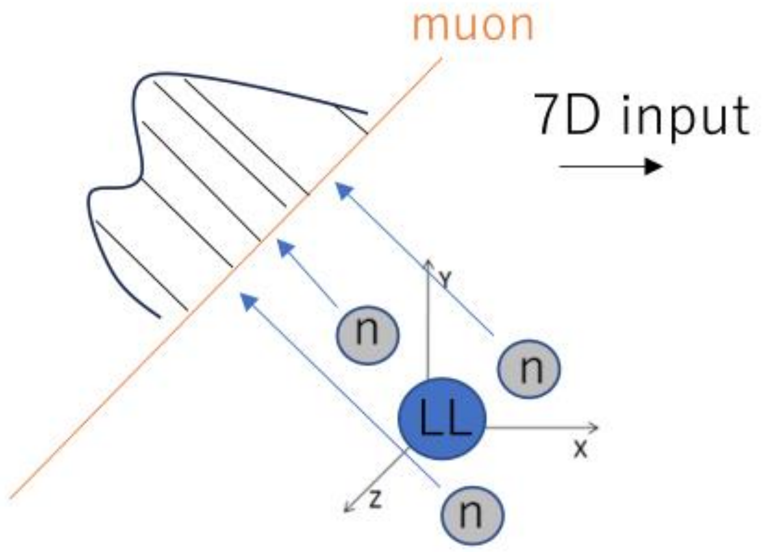
- Added displacement (x, y, z) from recent muon track for each neutron capture vertex
- Coincidence tagging improves by 3%

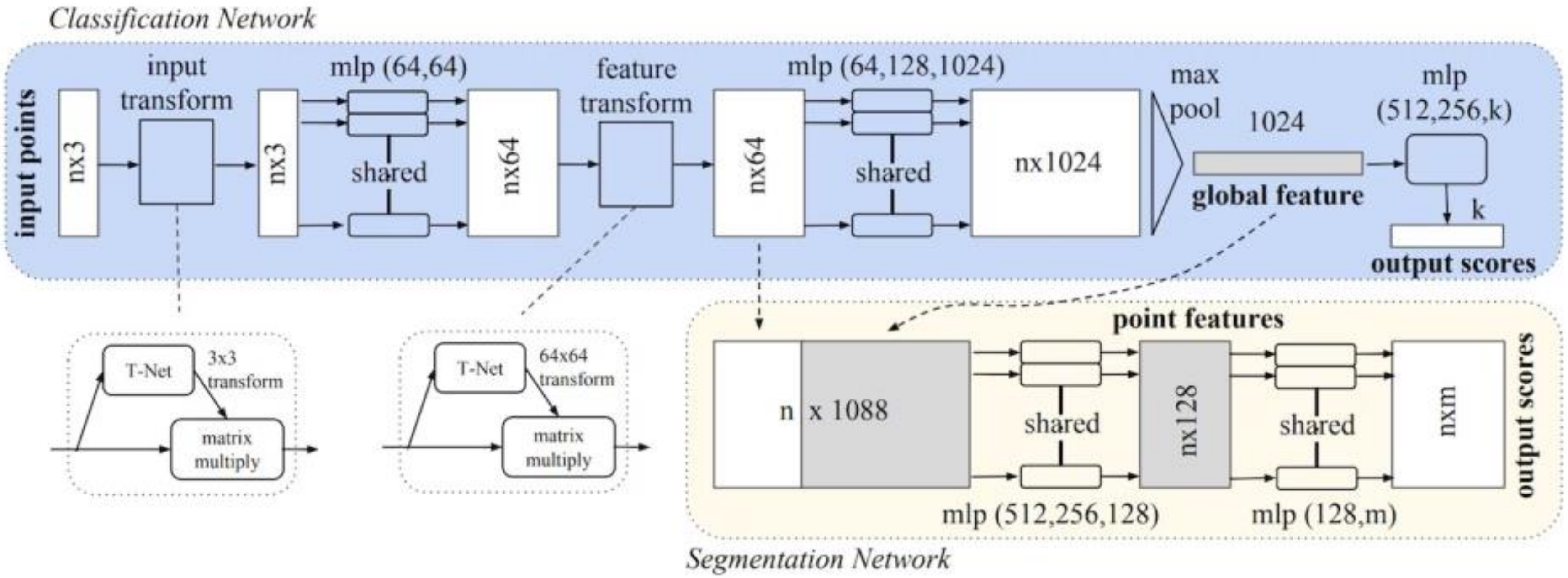




PointNet: Including Muon Tracks

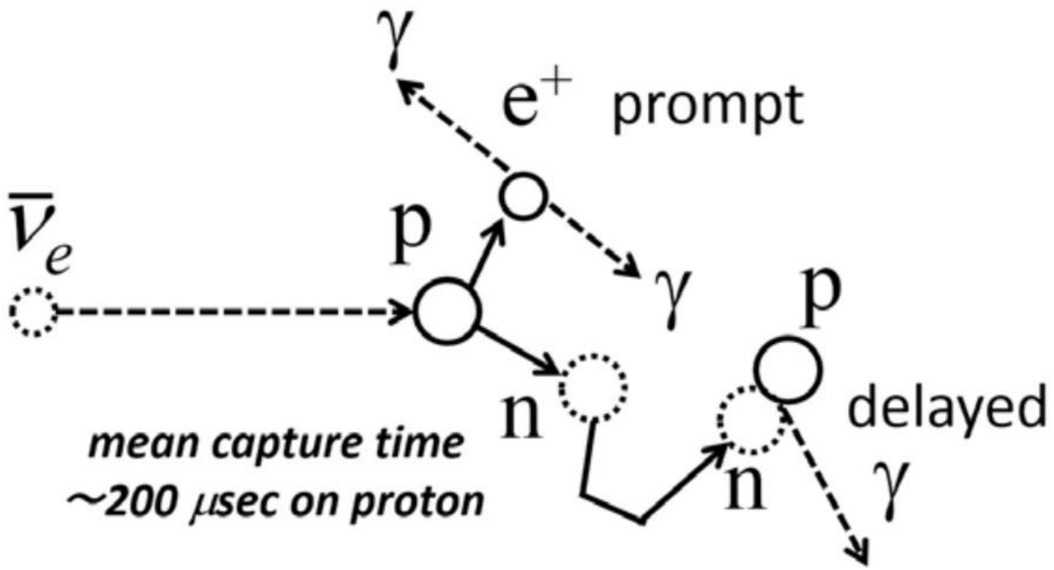
- We reconstruct energy deposition profile (dE/dx) of cosmic ray muon tracks in KamLAND
- Include the energy deposited (integrated dE/dx) within 20cm of muon track nearest to each neutron capture vertex
- Coincidence tagging efficiency improves to 53%





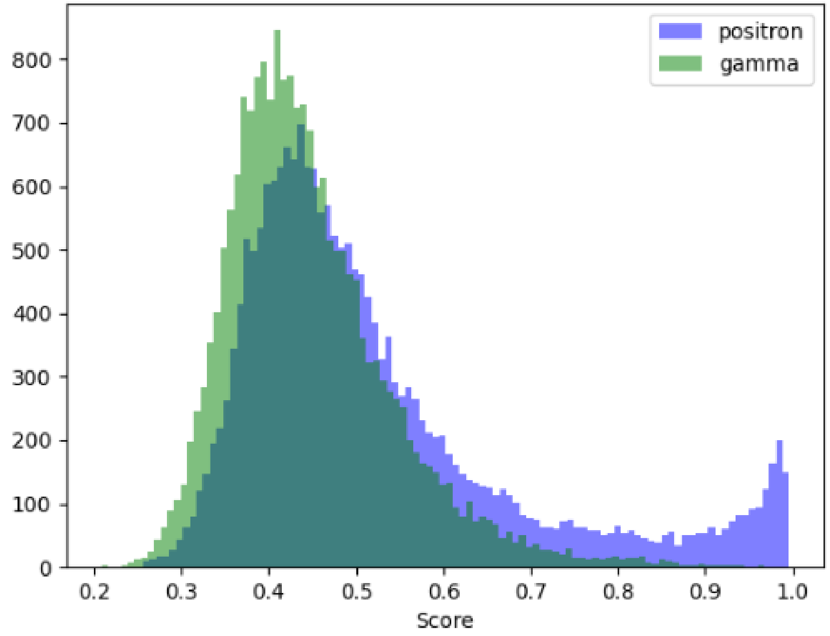
Coincidence Tagging with Decision Trees

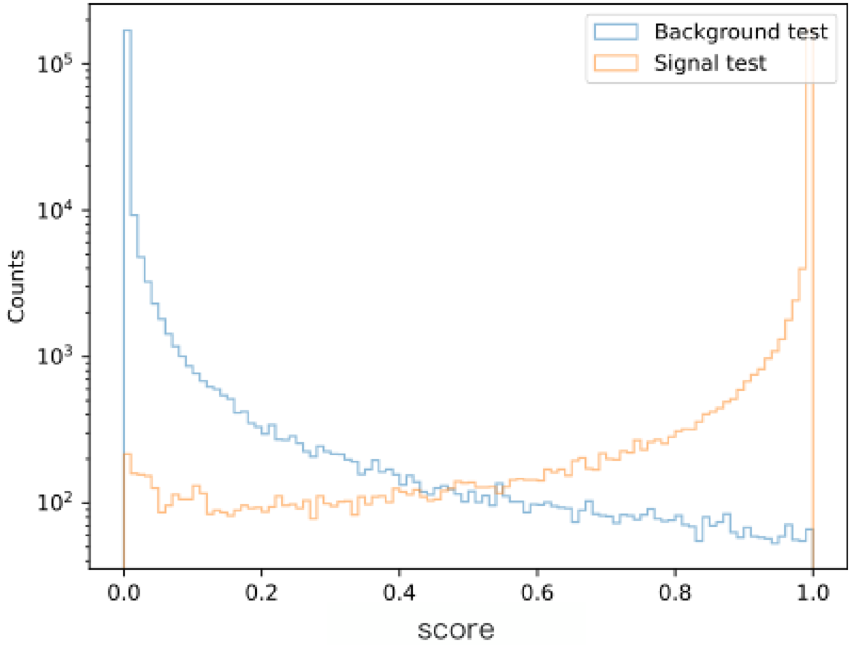
- Geological Antineutrino searches in KamLAND look for coincident positron-gamma events
- Anti-electron neutrino is captured by a proton via inverse beta decay, the free neutron is captured ~200 μsec later
- Can use machine learning to identify individual particles and model coincidence



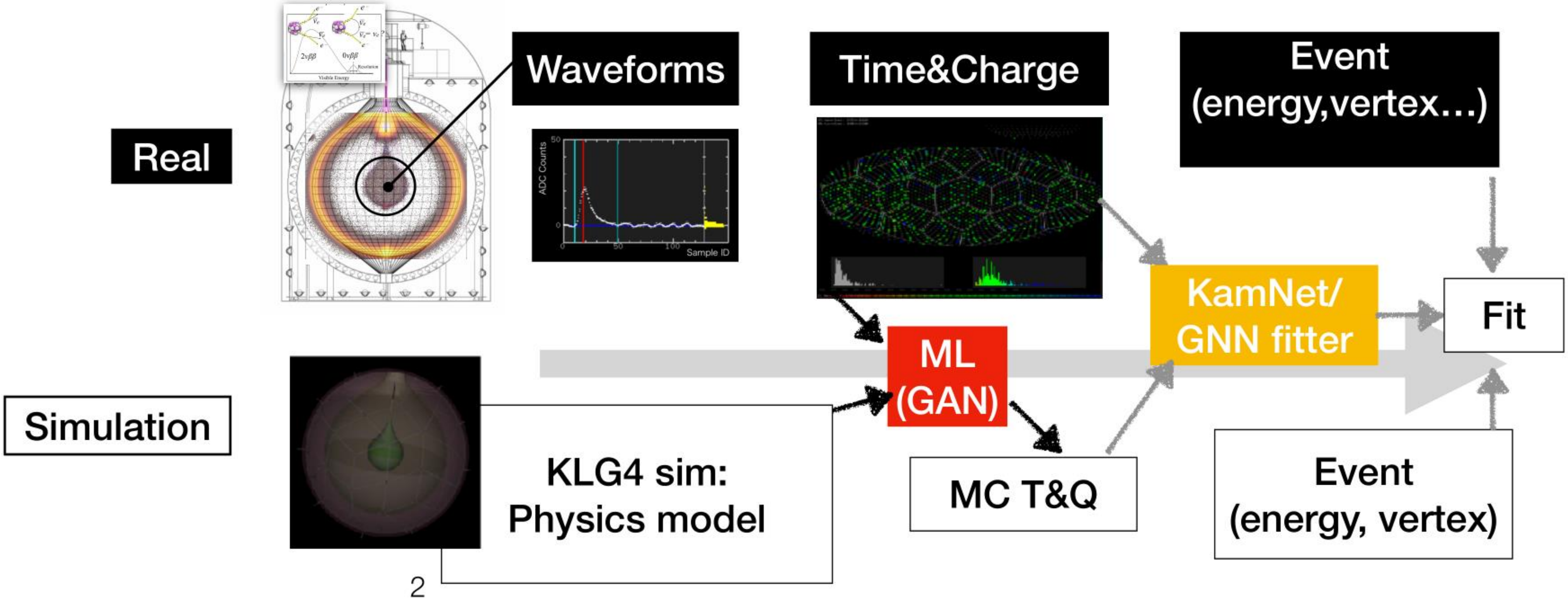
Coincidence Tagging with Decision Trees

- Trained a Graph Neural Network to perform PID between positrons and gammas
- A boosted decision tree model (XGboost) to identify true positron-gamma coincidences from accidental coincidences
- Input separation paramters (Ep, Ed, Rp, Rd, dR, dT)
- Achieved accuracy of 96%
- Plan to add more input parameters including PID score from NN



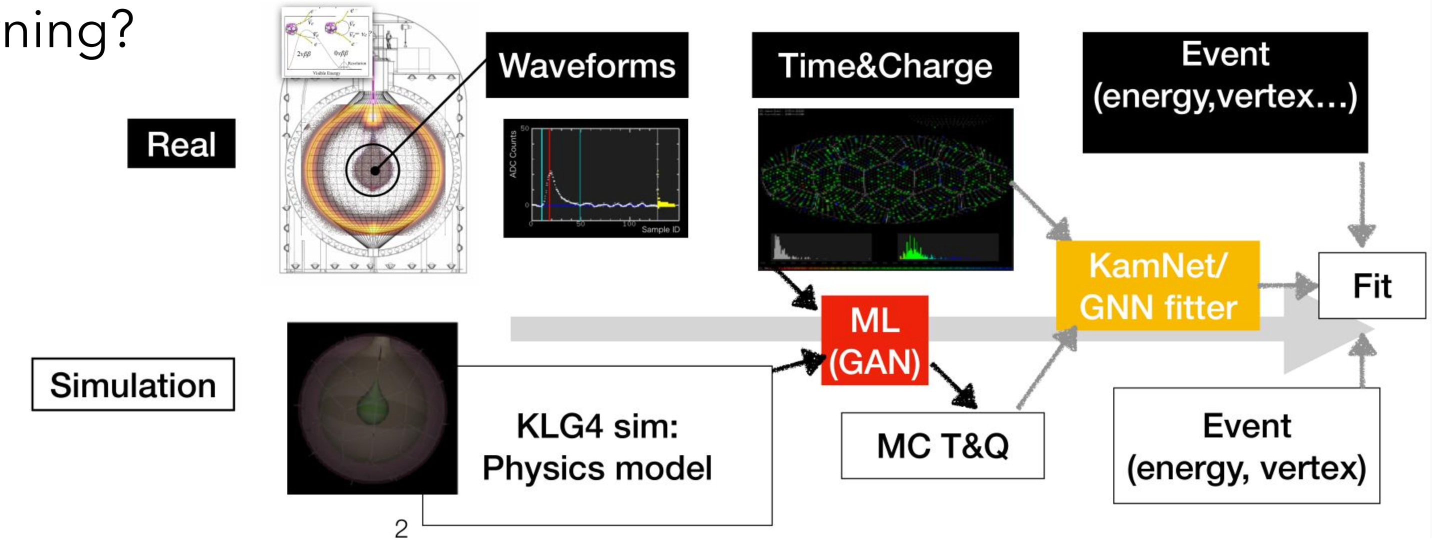


Detector Calibration with GANs



KamLAND is Evolving

- KamLAND detector conditions are changing everyday
- Detector calibration gets more difficult
- To avoid radioactive contamination, we have not deployed any calibration sources since KLZ-400
- The goal is to use high-statistics, well-understood backgrounds to perform calibration
- A task well suited for Machine Learning?



Current Simulation Scheme

Geant4 Simulation: Physics Model → GTQ Map

# of photons, time of arrival at each PMT

- **Physics and Detector Geometry**
  - Physics model & Geometry
  - Material (LS, XeLS, …) properties
    - Light emission
    - Absorption length
    - Decay time constants

Let's assume to be well tuned from initial data before purification

GTQ Map → DTQ Map

Detected Event

- **Detector Characteristics**
  - Q.E. & C.E. for each PMT
  - Time and Charge resolutions (for each PMT)
  - Electronics Effects
  - Dark hits / after pulses

Can we tune these with ML?

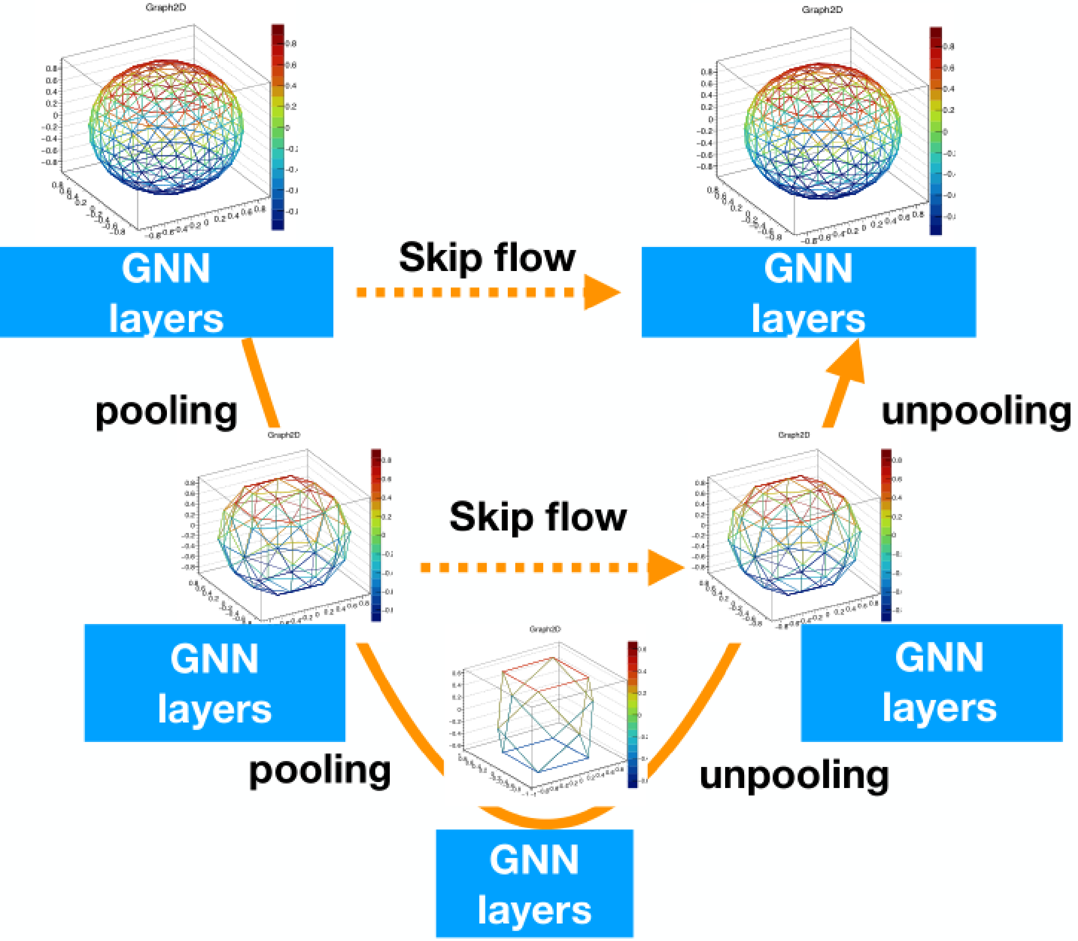
Current Status of Detector Calibration

- We observe the charge PDF for each PMT run-by-run
- We fit a single time resolution PDF for every PMT
- Dark hit rate for each PMT
- Quantum Efficiency for each PMT
- Threshold effects, electronics effects, etc.

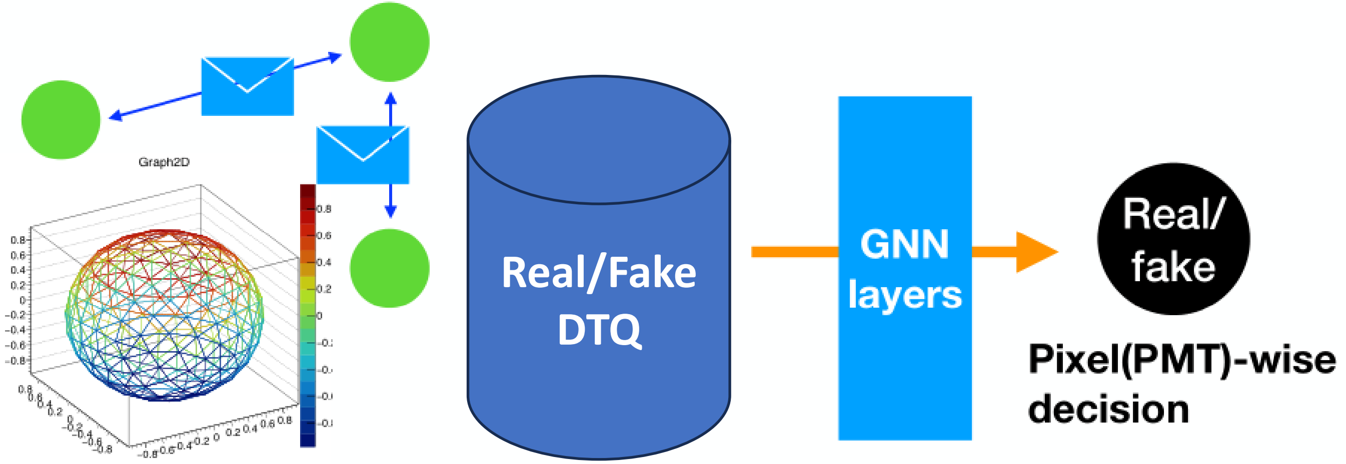
GammaTQ (GTQ, Photon hit **time and charge** for each pmt) → Detector simulation tuned by above methods → DetectorTQ (DTQ, simulated detector events for analysis)

Graph U-Net Generative Adversarial Network (GAN)

Generator (Graph NN +U-Net)



Discriminator (GNN)



Loss

For Generator $L1 = \frac{1}{2n}\Sigma_i^n(|T_i^{true} - T_i^{pred}| + |Q_i^{true} - Q_i^{pred}|)$

+ Binary cross entropy (BCE) loss (Fake to be true).

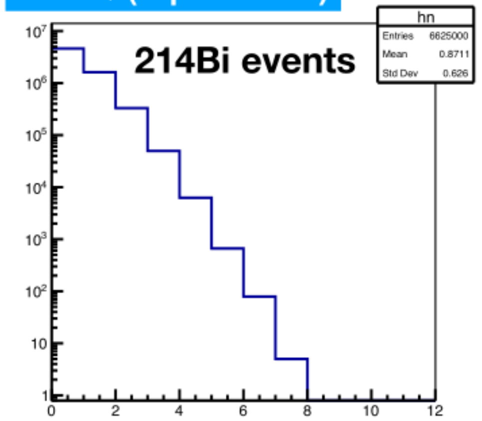
For Discriminator

2 BCE losses (Fake is false, and Real is true).

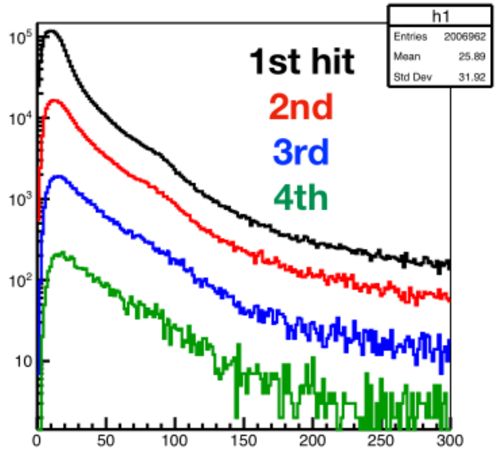
$$L_{BCE} = -(y * log\sigma(x) - (1-y) * log(1-\sigma(x)))$$

Results

MTQ (input data)

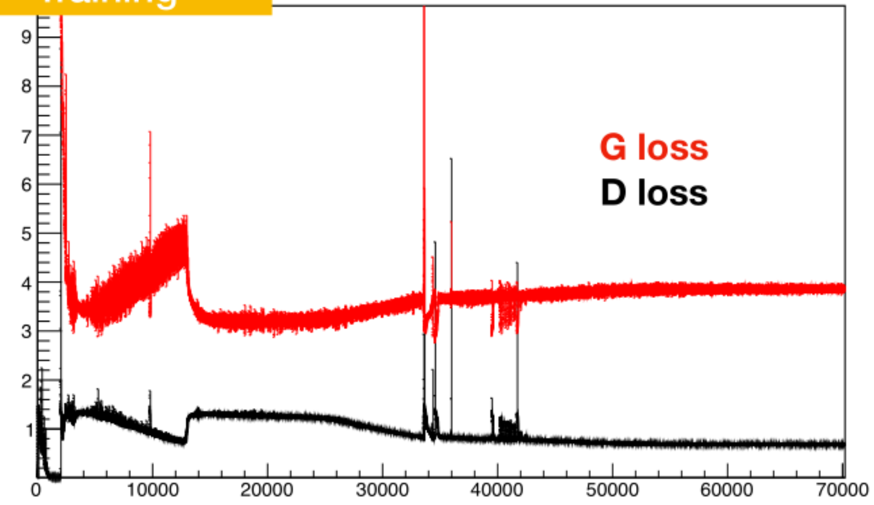


N of photons/PMT



Hit time (ADC time?)

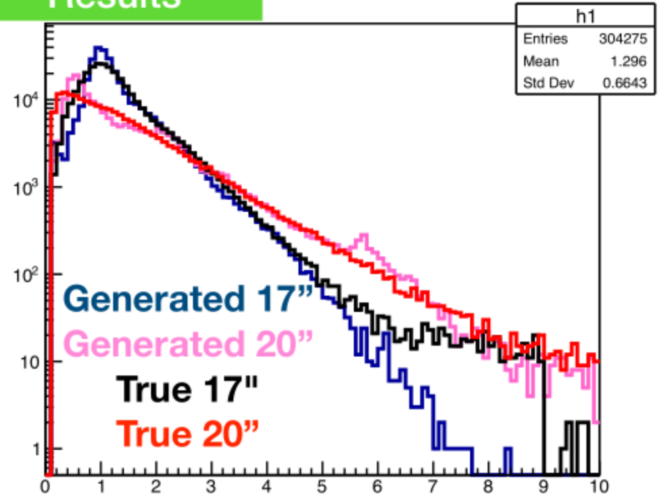
Training



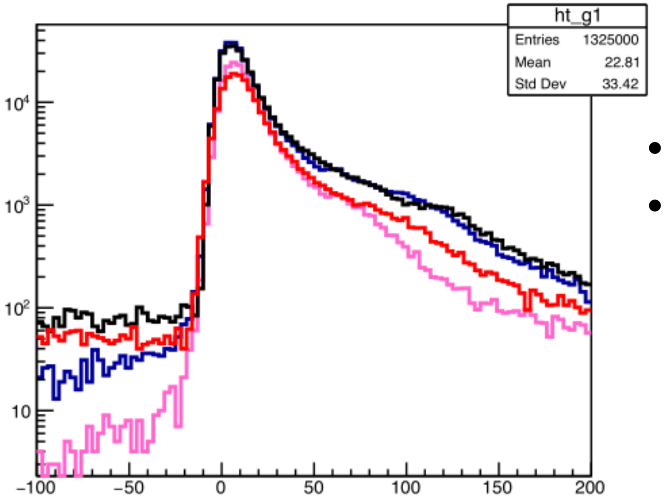
Updates

Took a few days to reach the equilibrium.

Results



Charge (p.e.)

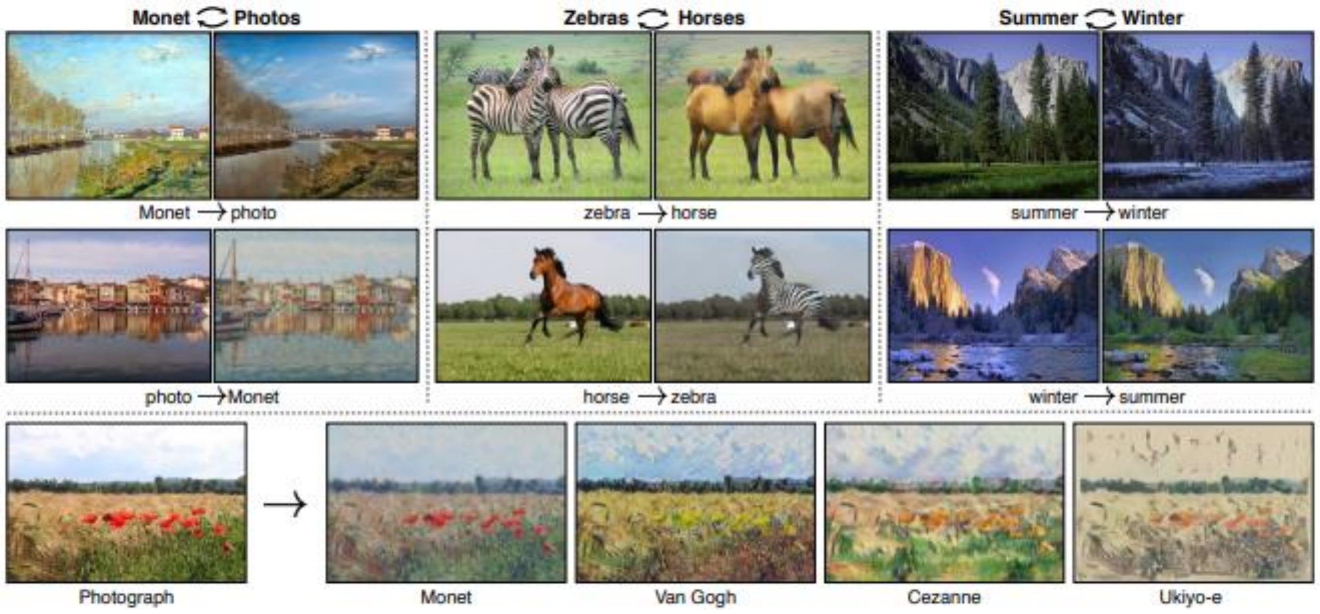


Time (ns) 8

- Training successful
- Generated events look like the training data, but
  - Not enough dark hits were generated
  - Charge and time resolution are too good
  - Some strange features in distributions

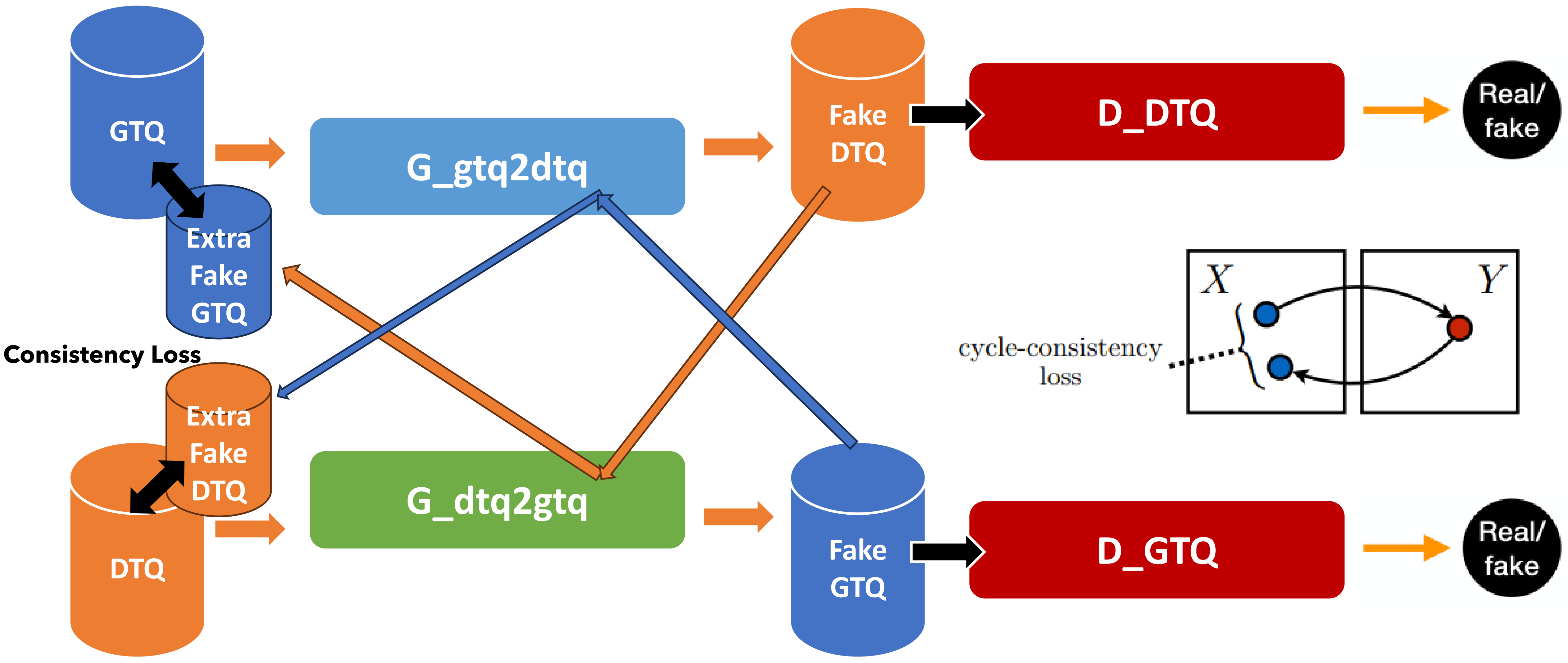
CycleGAN: Unpaired Image to Image Translation

- Implemented CycleGan to learn detector characteristics (GTQ -> DTQ)
- The task is to learn a model for translating images from one domain to another domain
- Could use a GAN if we had paired images, but we do not have access to the GTQ maps in real data
- CycleGAN is a method that learns image-to-image translation with unpaired images



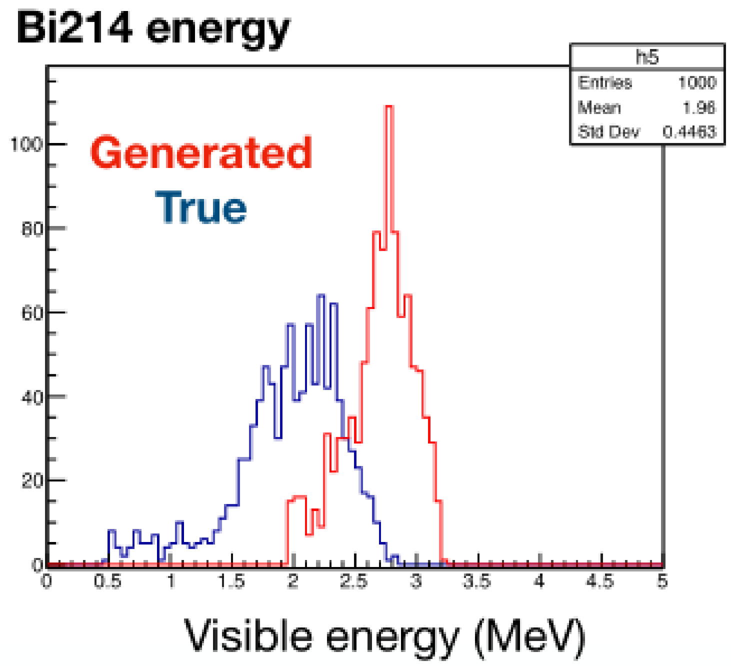
1703.10593

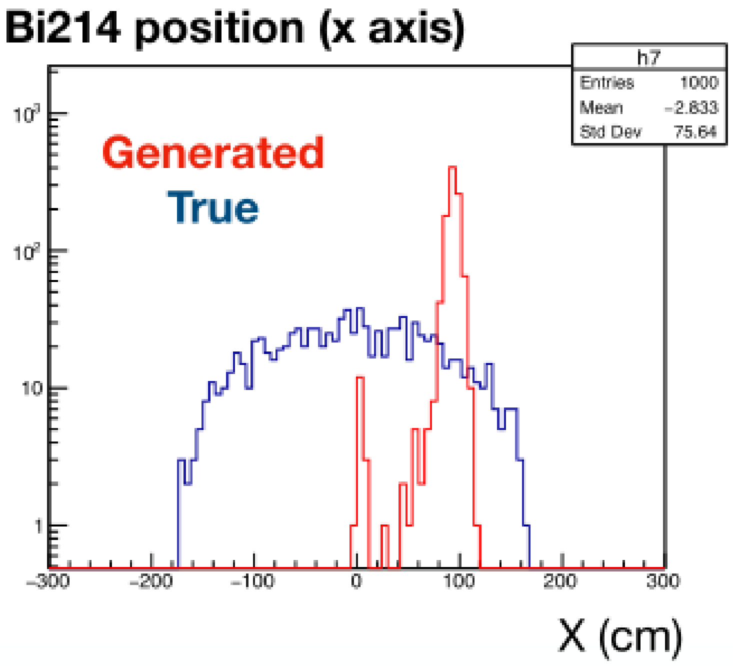
CycleGAN Training



CycleGAN Results

- NN does start learning features, but it takes a few days to reach even this level of performance
- We are considering faster models, other methods

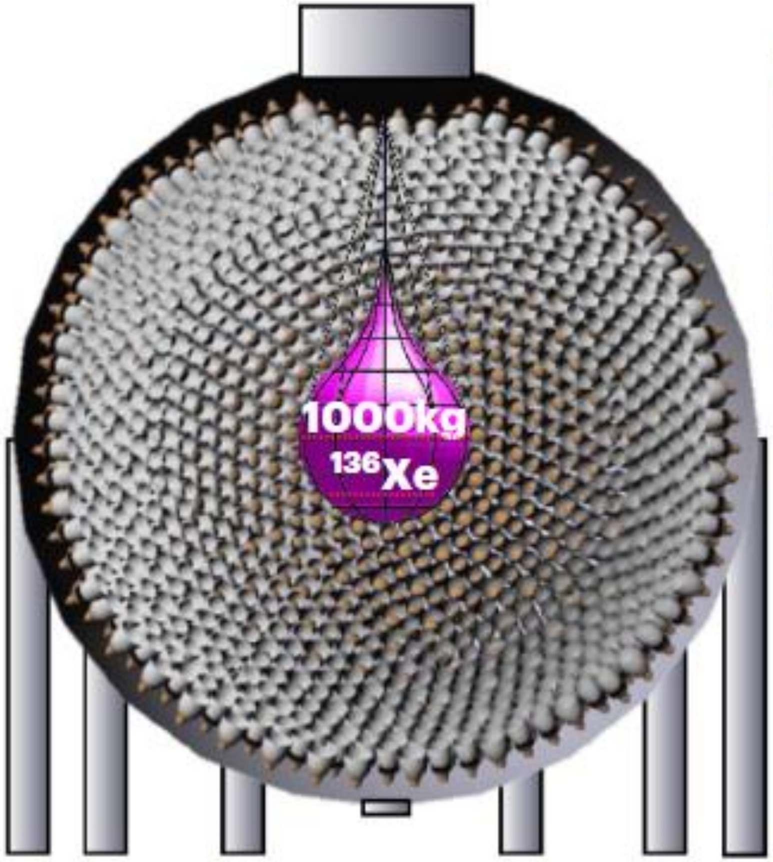


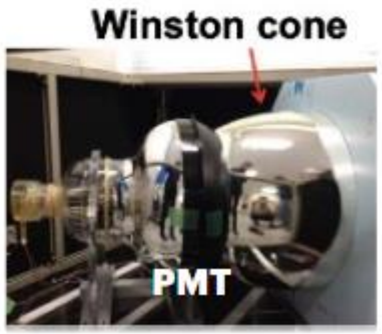


Future ML Work

- Evaluation of KamNet systematic uncertainties is ongoing
  - Further interpretability studies
- Improvements to background tagging/coincidence modeling
- Using ML to calibrate the KamLAND detector
- Combining KamNet-like event topology identification and PointNet cosmic ray muon coincidence model for comprehensive long-lived spallation rejection

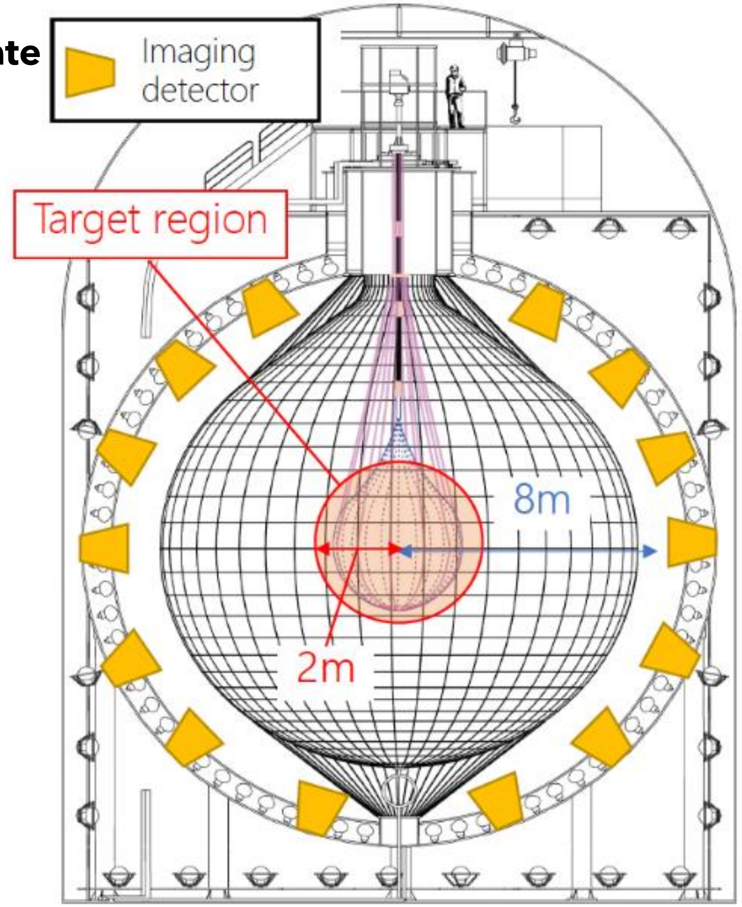
Looking to the Future: KamLAND2-Zen





Higher lightyield scintillator, high Q.E. PMTs, light collecting cones for **x100 reduction in 2nbb rate**

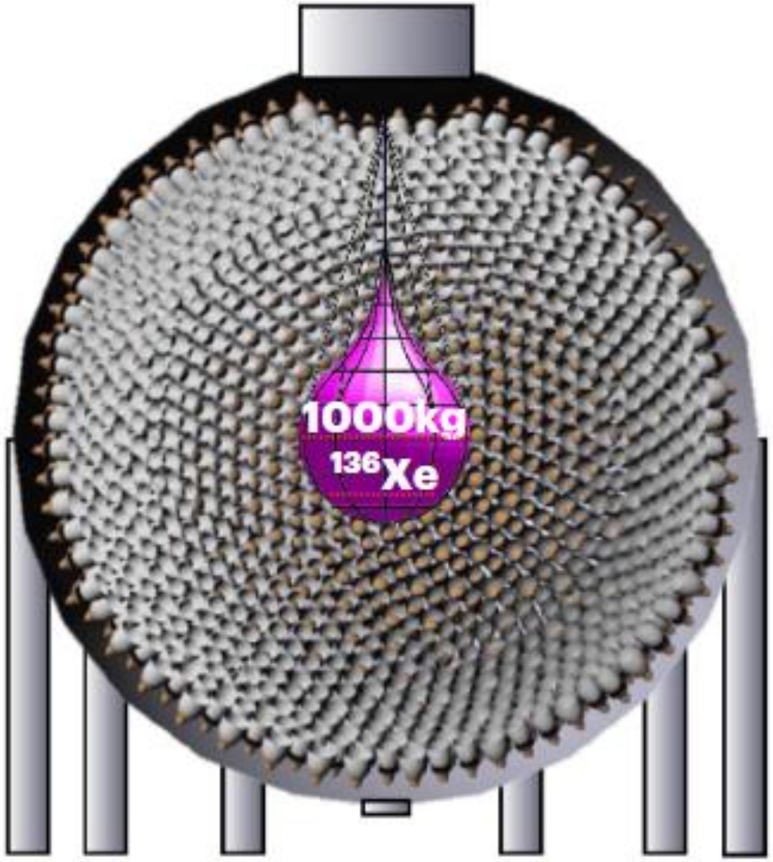
Imaging LaPPD cameras to directly observe event topology, better rejecting radioactive backgrounds. We estimate **~90% rejection**



Deadtime free electronics (RFSoC) for **better neutron capture tagging**

Scintillating Inner Balloon Film for **better tagging of film backgrounds**

Looking to the Future: KamLAND2-Zen



- Target : $\boldsymbol{T_{1/2}} > \mathbf{2.0} \times \mathbf{10^{27}} \boldsymbol{yr}$, full coverage of the Inverted Ordering Region
- Construction begins in 2025
- Comissioning and first data in 2026

Summary

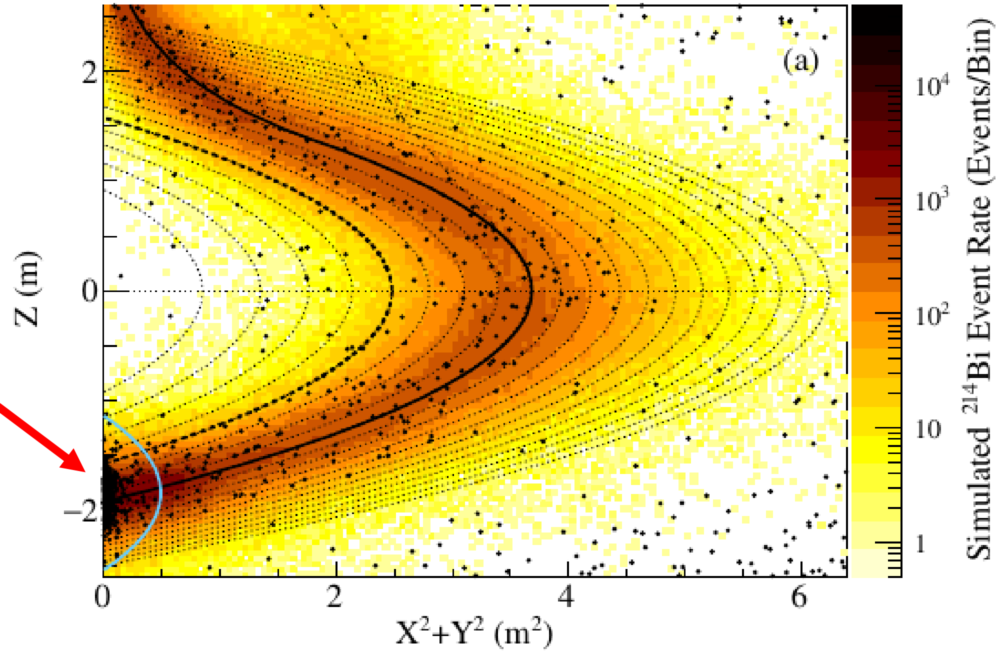
- Spherical Convolutional Neural Networks (KamNet) have opened our eyes to **event topologie**s in KamLAND-Zen
  - Graph Neural Networks have also been successful at Particle Identification
- GNNs are also used to model correlation between radioactive backgrounds and their cosmic ray muon progenitors
- Boosted Decision Trees have been used to **identify coincident signals**
- CycleGAN has been tested as a method for **detector calibration**
- KamLAND2 will offer new challenges and opportunities for applying ML techniques

Backups

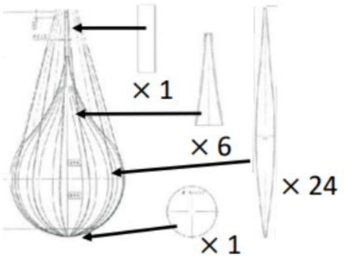
Increasing KamLAND's Fiducial Volume

- KamNet's rejection of radioactive film backgrounds allows us to increase the fiducial volume, increasing our exposure to Xe136

Hotspot at the bottom of the balloon from settling radioactive dust



All work performed inside a Class 1 clean room in Sendai



① Film Washing

② Seam Welding

③ He leak test + repairs

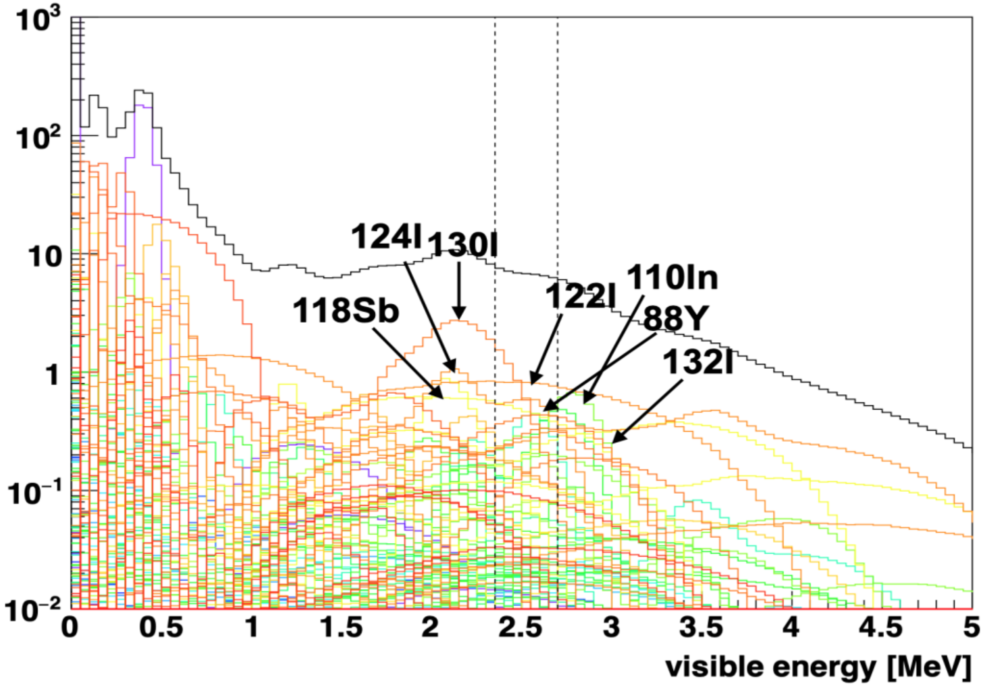
④ Folding

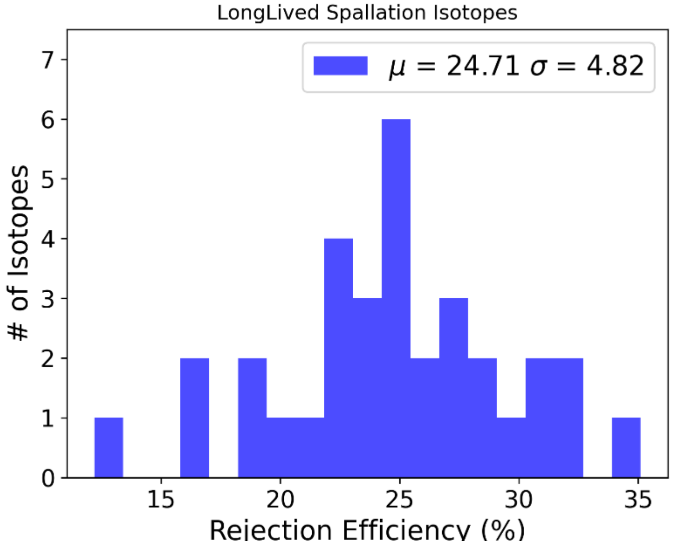
⑤ Packaging

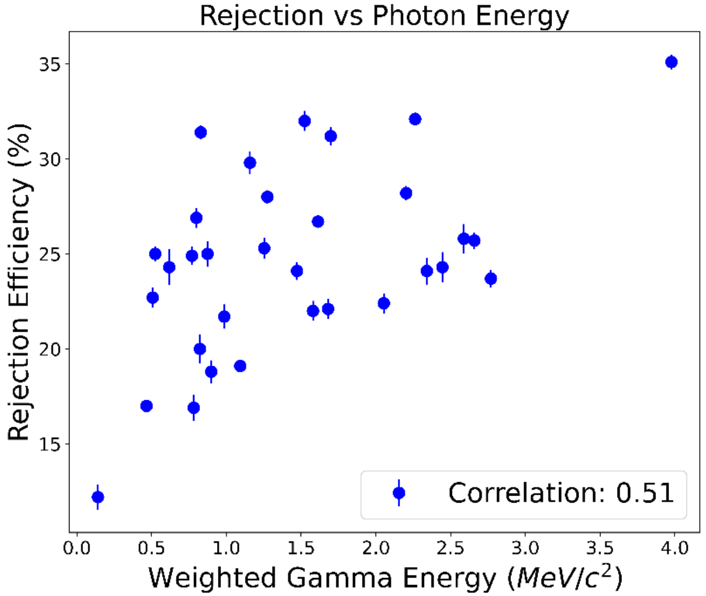
- Careful manufacture and washing of the inner balloon reduced contamination to:
  - ^{238}U ~ 3 x 10^{-12} g/g
  - ^{232}Th ~ 4 x 10^{-11}g/g
  - 10x reduction from KLZ-400

KamNet: Cosmic Spallation Isotopes

- Evaluated KamNet performance on different spallation isotope backgrounds
  - Ran isotope decay events through Bi-214 bootstrapped models
- Ask why certain isotope decays are easier to reject than others
- Found that KamNet performance correlates with ave



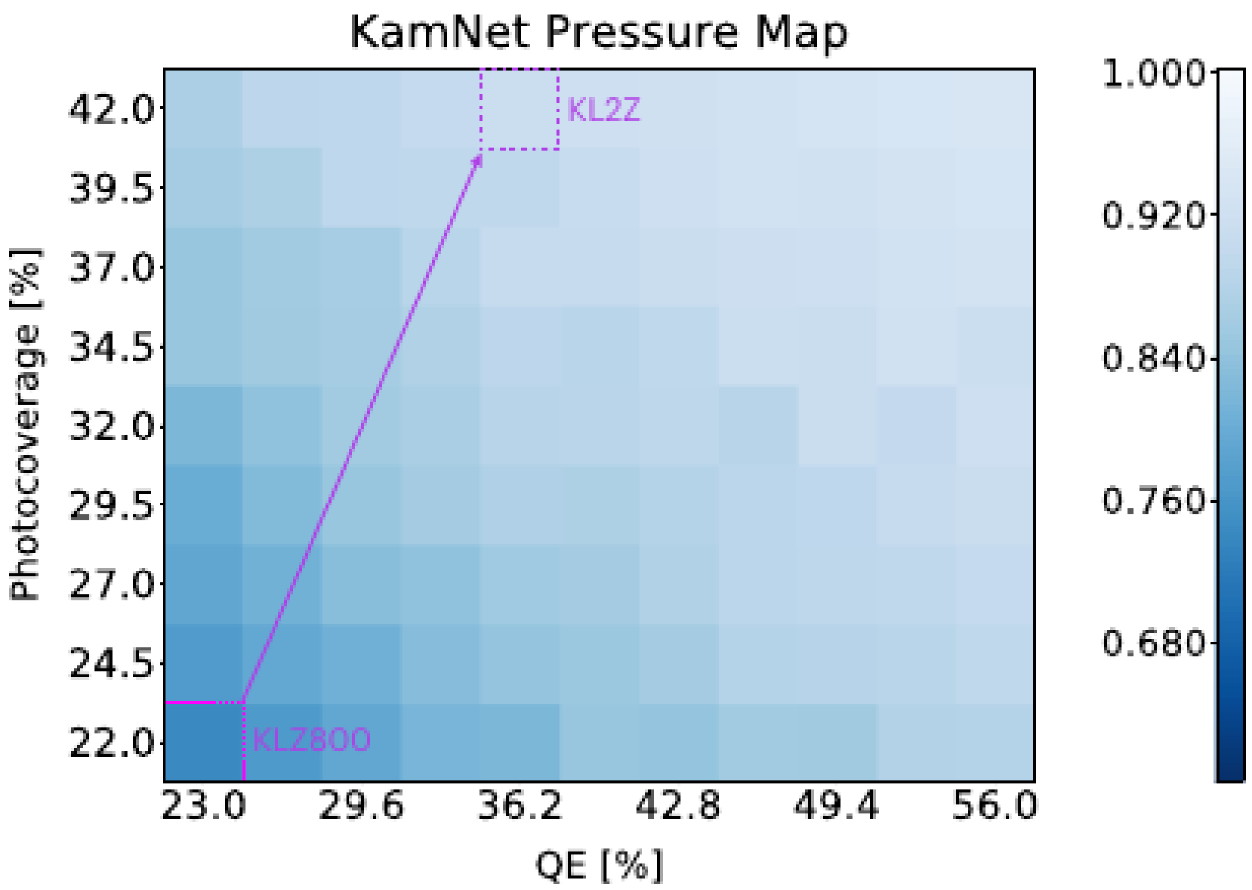


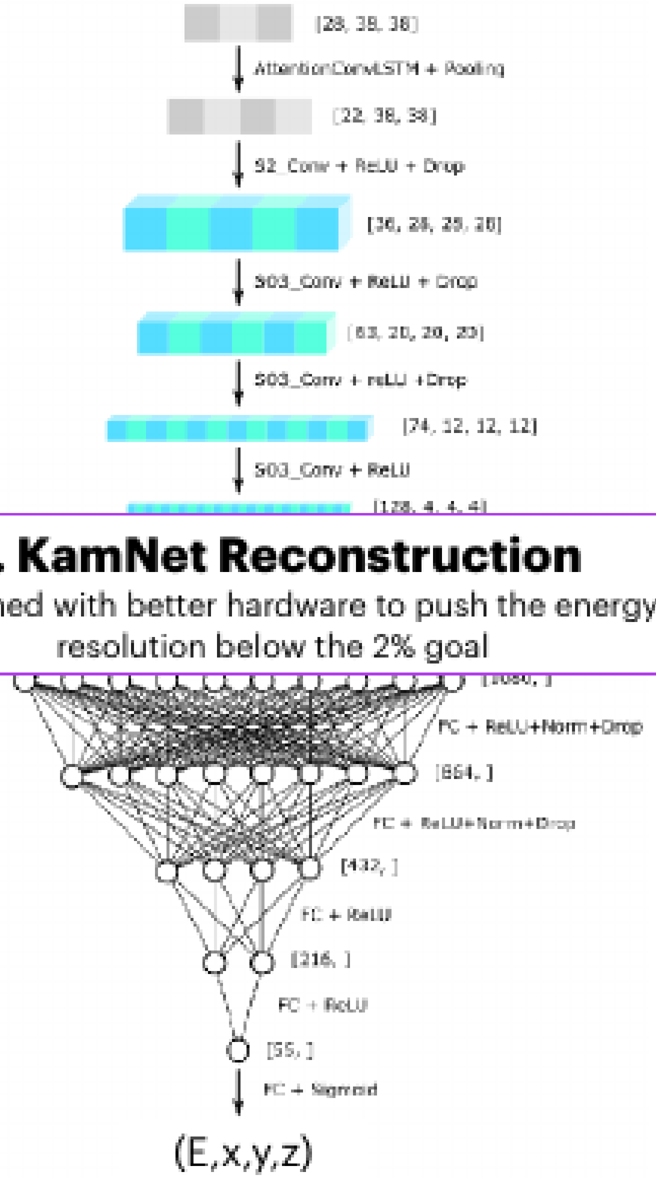


AI Powered KamLAND2-Zen

4. KamNet PID on KL2Zen

Thanks to the better hardware of KamLAND2-Zen, KamNet can reduce remaining background by at least a factor of 3 compared to KamLAND-Zen 800





5. KamNet Reconstruction

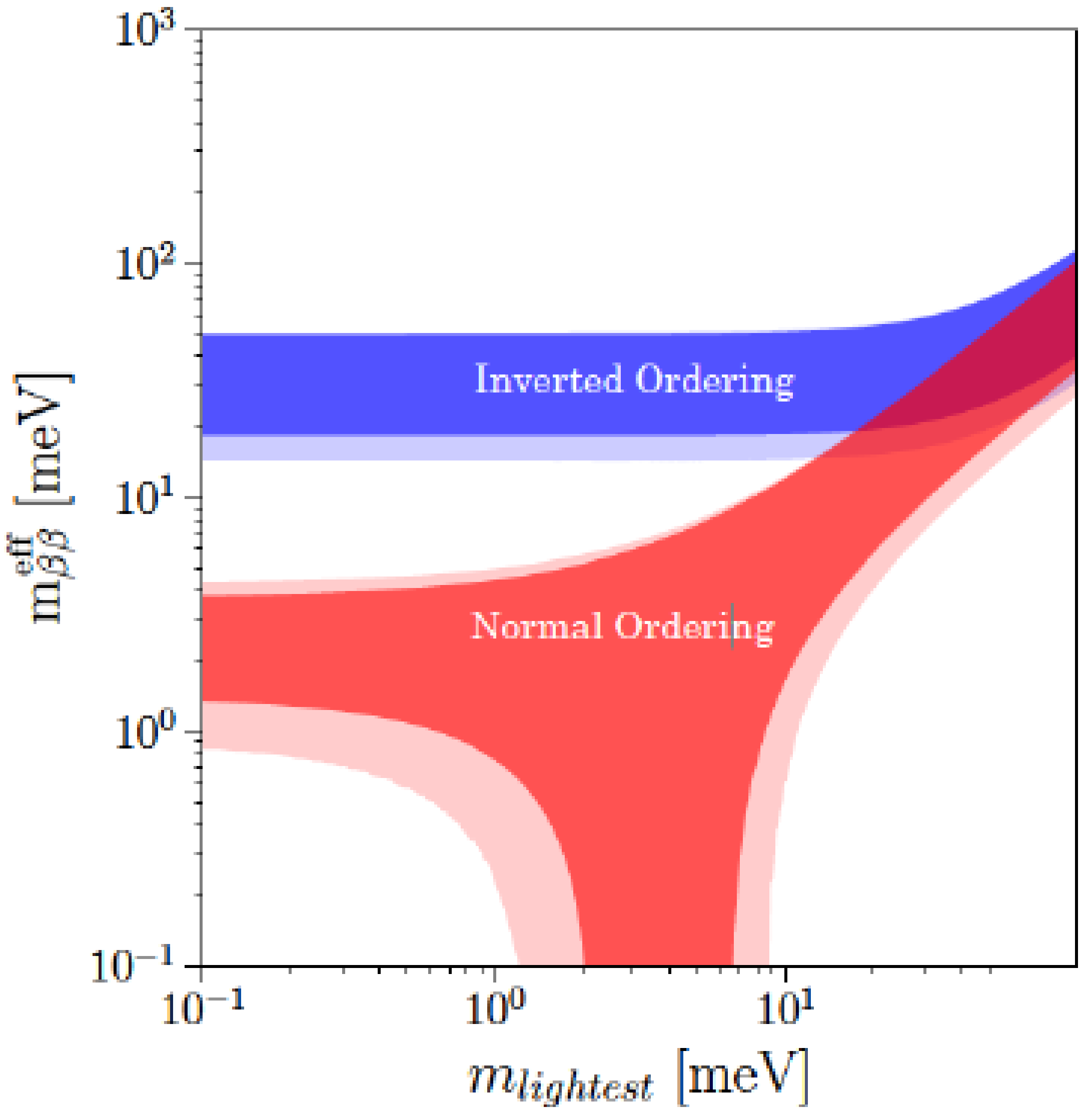
Combined with better hardware to push the energy resolution below the 2% goal

0νββ : Neutrino Masses? Ordering?

- The 0νββ half-life is directly related to the overall neutrino mass scale:

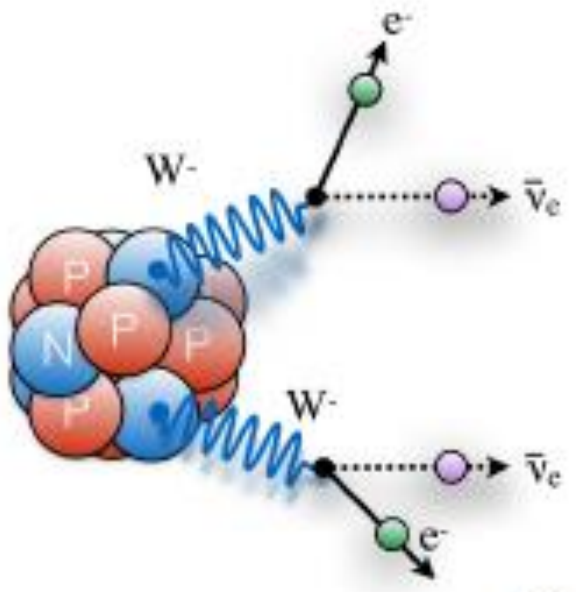
$$\left(T_{1/2}^{0\nu}\right)^{-1} = G^{0\nu}|M^{0\nu}|^2 m_{\beta\beta}^2$$

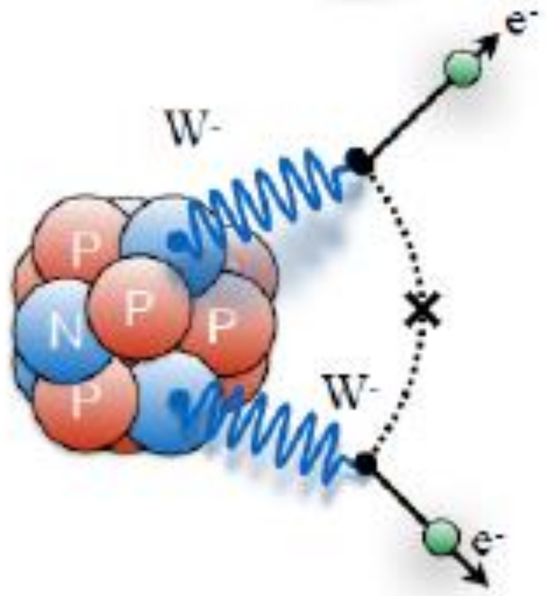
  - $G^{0\nu}$: Phase Space Factor
  - $|M^{0\nu}|^2$: Nuclear Matrix Element
  - $|m_{\beta\beta}| = \sum_i U_{ei}^2\, m_i$: effective Majorana mass
- Unknown neutrino mass ordering leaves two regions where 0νββ could be observed
- A measurement of the 0νββ half-life corresponds to a measurement of the effective Majorana mass



Neutrinoless Double Beta Decay

- KamLAND-Zen is looking for Neutrinoless Double Beta Decay, 0νββ, a single measurement that can answer multiple questions about neutrinos
- Certain isotopes can undergo Double Beta Decay
  - Exceptionally slow nuclear process $T_{1/2} \sim 10^{14-24}$ years
  - Decay energy is split between neutrinos and electrons
- If the neutrino is a Majorana particle, this process can occur without emitting a pair of anti-electron neutrinos
  - Electrons carry away all the decay energy





Onward to KamLAND2-Zen

KamLAND2-Zen will cover the Inverted Ordering region.

1. Improved energy resolution

Purpose: further separate **2νββ** from the **0νββ**.

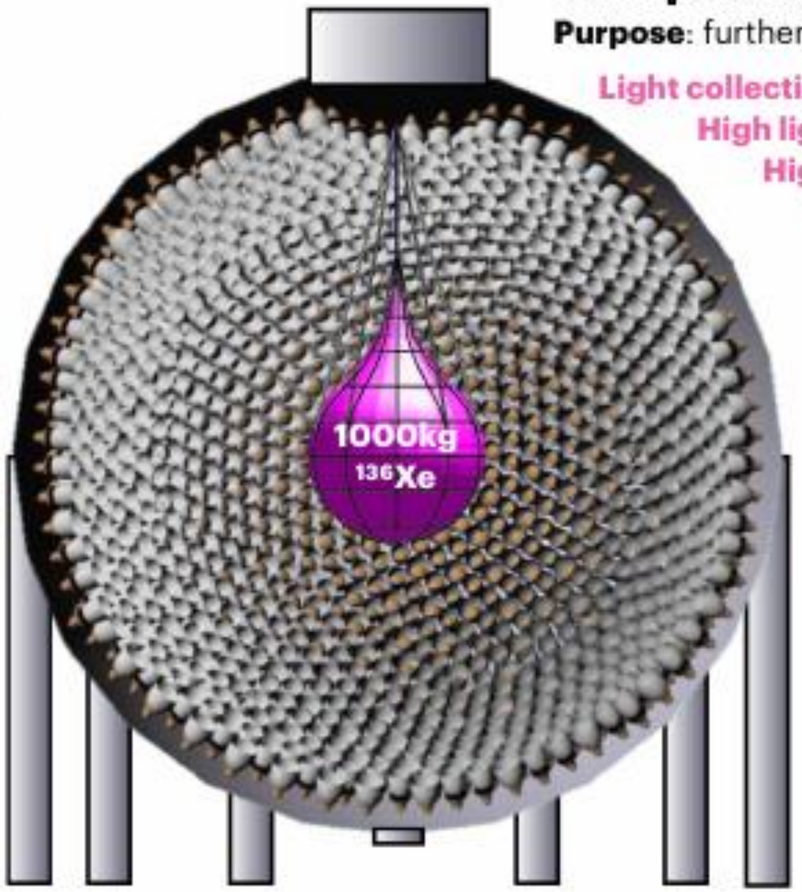
Light collection with Winston Cones (x1.8)
High light yield scintillator (x1.4)
High QE 20" PMTs (x1.9)

4% → 2% energy resolution

x100 reduction in 2νββ background rate.

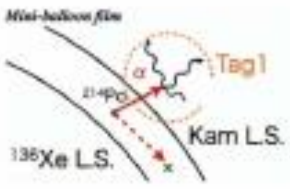
3. State-of-the-art electronics

Purpose: Tagging long lived isotope from cosmic ray spallation.

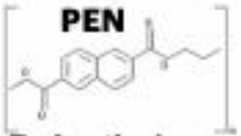


2. Improved inner balloon

Purpose: reduce backgrounds originating from balloon.



Tag ^{214}Bi decays.



Polyethylene naphthalate