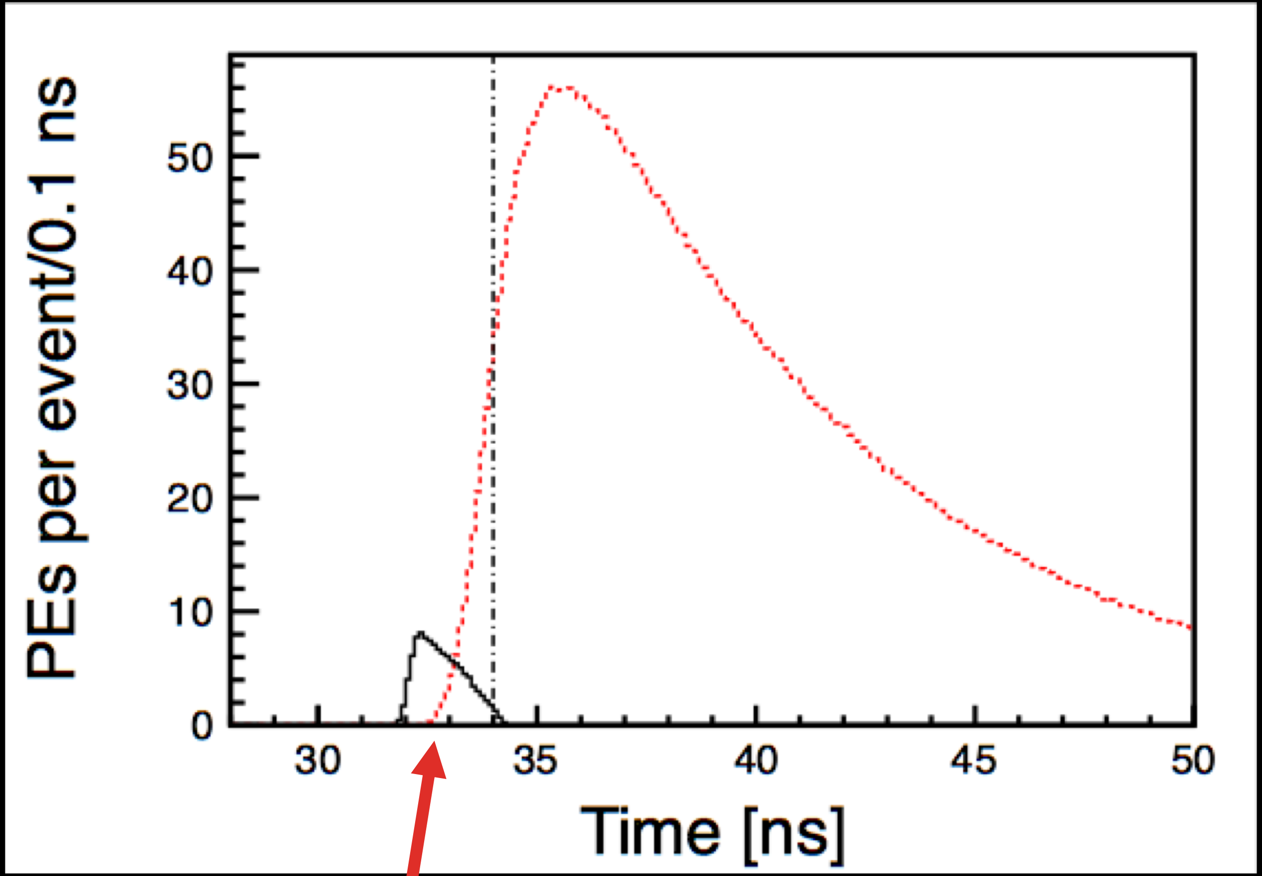
LS WORKSHOP SLIDES

Julieta Gruszko

Simulation of photon detection time

- KamLAND-style LS
- 6.5m radius detector
- Standard photocathode
- Transit time spread (TTS) of 100 ps

See JINST 9 (2014) P06012



63% separation

Perovskite Wavelength Shifters

DOI: 10.1088/1748-0221/14/11/P11024

Table 1. Results of fluorescence and absorption measurements. The quantum efficiency of a Hamamatsu model R13089 PMT at the fluorescence wavelength is provided for reference.

Sample	Absorbance (nm) Ref. [12]	Absorbance (nm) This work	Fluorescence (nm) Ref. [12]	Fluorescence (nm) This work	PMT Quantum Eff. Hamamatsu R13089
$L_2[MAPbBr_3]PbBr_4$	431	434.6	437.3	438.1	0.23
$L_2[FAPbBr_3]PbBr_4$	434	430.9	439	434.9	0.23
$L_2[CsPbI_3]PbI_4$	553	557.1	561.1	562.7	0.06
$L_2[MAPbI_3]PbI_4$	566	567.7	573.9	573.2	0.04
$L_2[FAPbI_3]PbI_4$	566	572.0	575	574.8	0.04

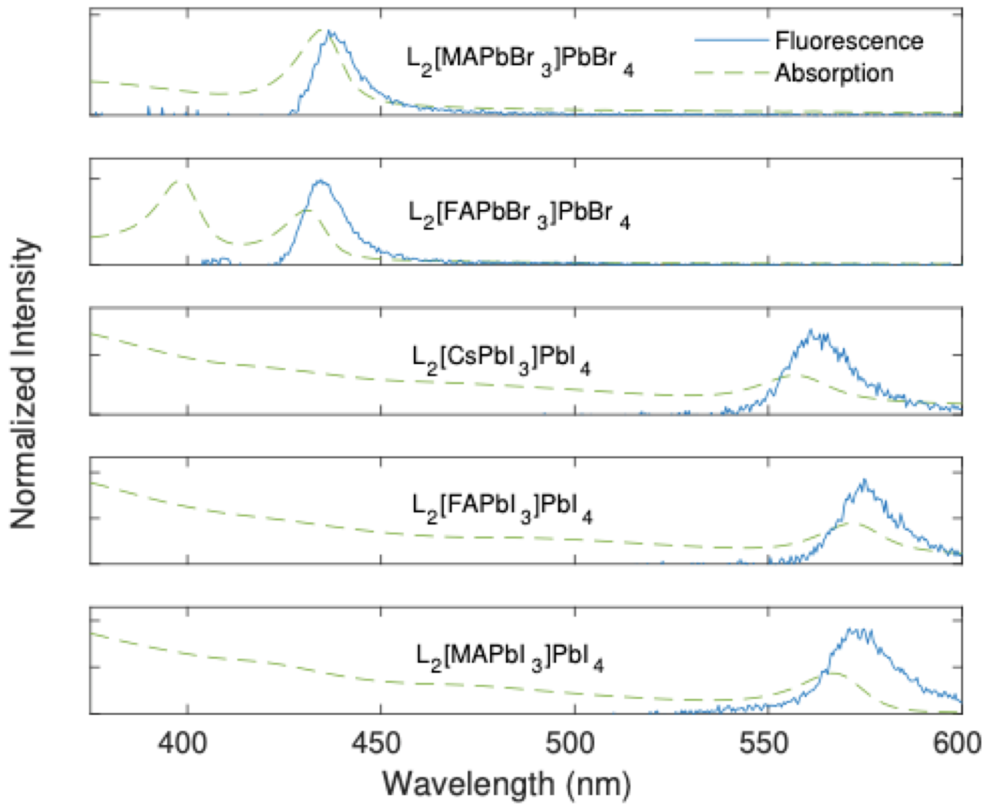
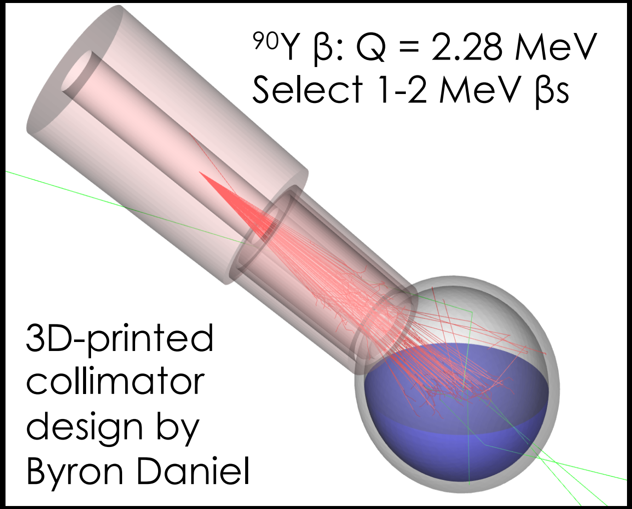
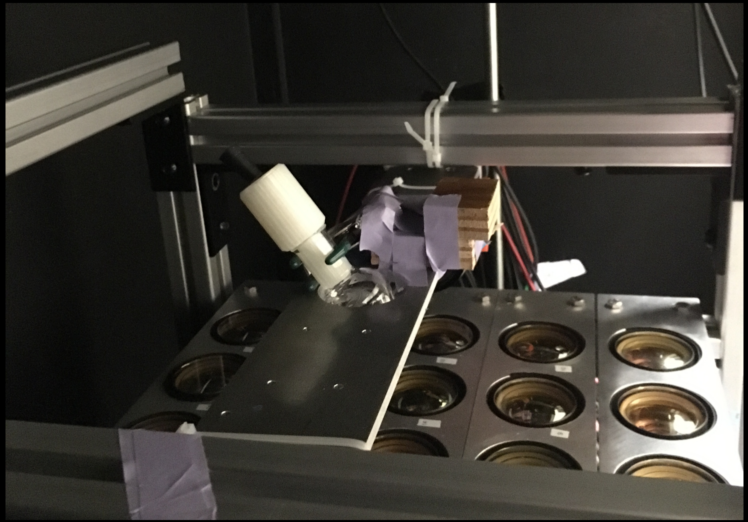


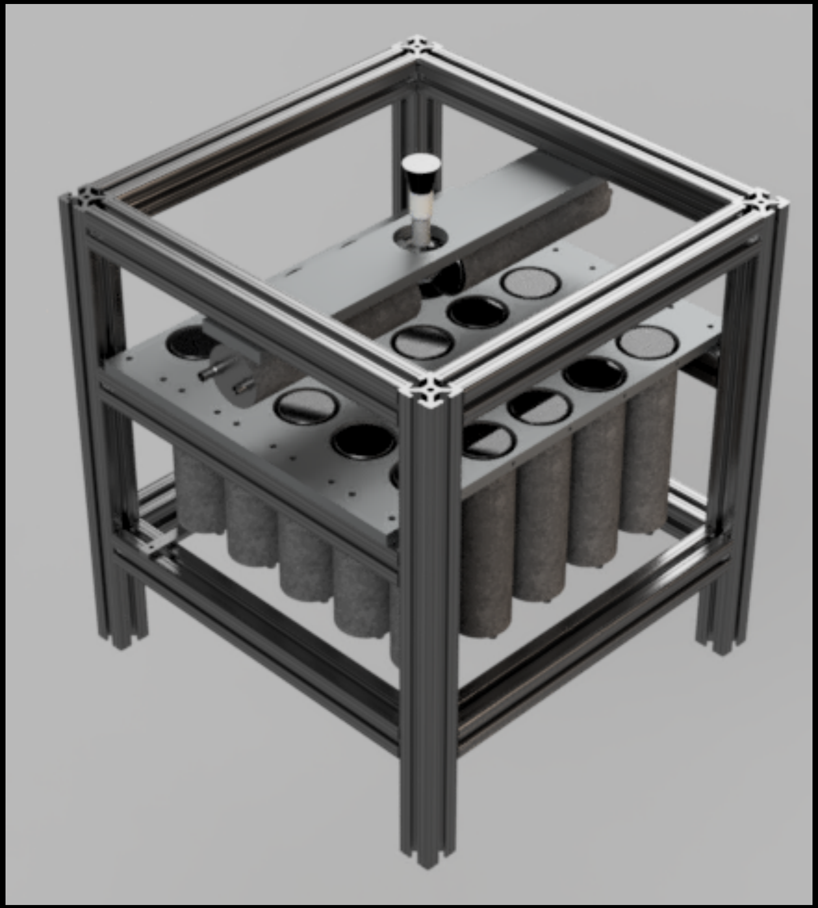
Figure 4. The absorption and fluorescence emission spectra for the prepared samples. The fluorescence measurement features a narrower binning due to the resolution of the spectrophotometer.

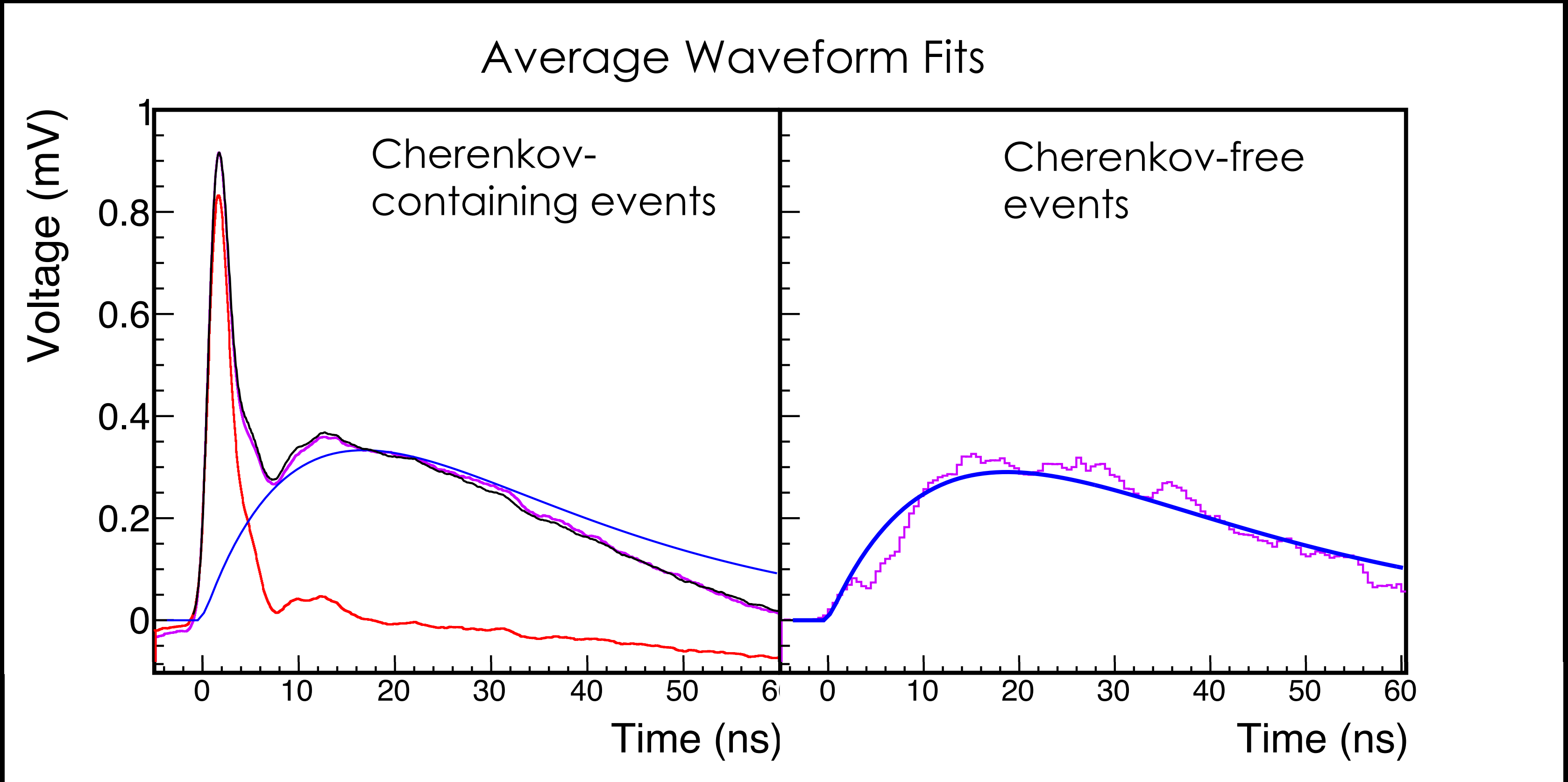
FLATDOT: PROTOTYPE OF THE PROTOTYPE

- 5x5 array of 2” PMTs w/ trigger PMTs and muon veto
- Collimated ^{90}Sr β source, plus small cuvette of LS
- Study βs directly: varying energy and increased scattering make this a harder problem than cosmic μ









LAB+^{90}Sr Data
Best Fit
Cherenkov (Data)
Scintillation (Theory)

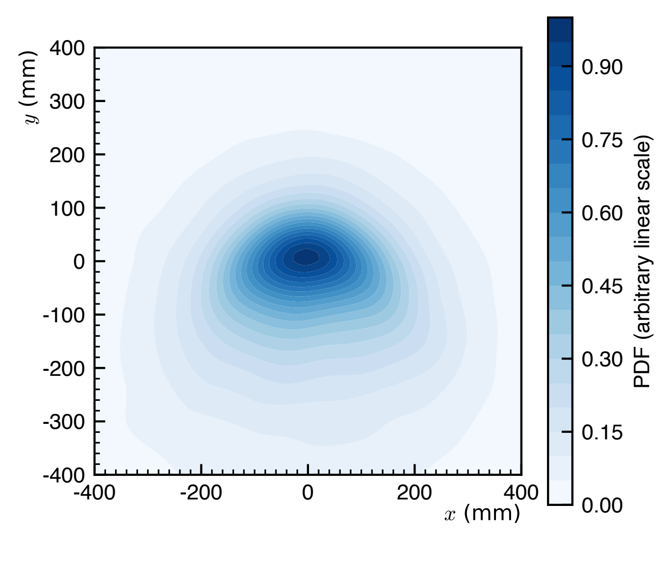
J. Gruszko et al, "Detecting Cherenkov light from 1–2 MeV electrons in linear alkylbenzene" JINST **14** (2) P02005-P02005 (2019)

- First demonstration of Cherenkov/scintillation separation for single-MeV βs
- Cherenkov signal dominates for the first 4.1ns (86% of signal in this window)

Single-PMT Avg. Waveforms: LAB + ^{90}Sr

- Cherenkov fraction depends on PMT position
- Fit each PMT separately, floating just amplitudes
- Study runs with centered and shifted source, to get a larger range of source distances

Cherenkov photon pattern



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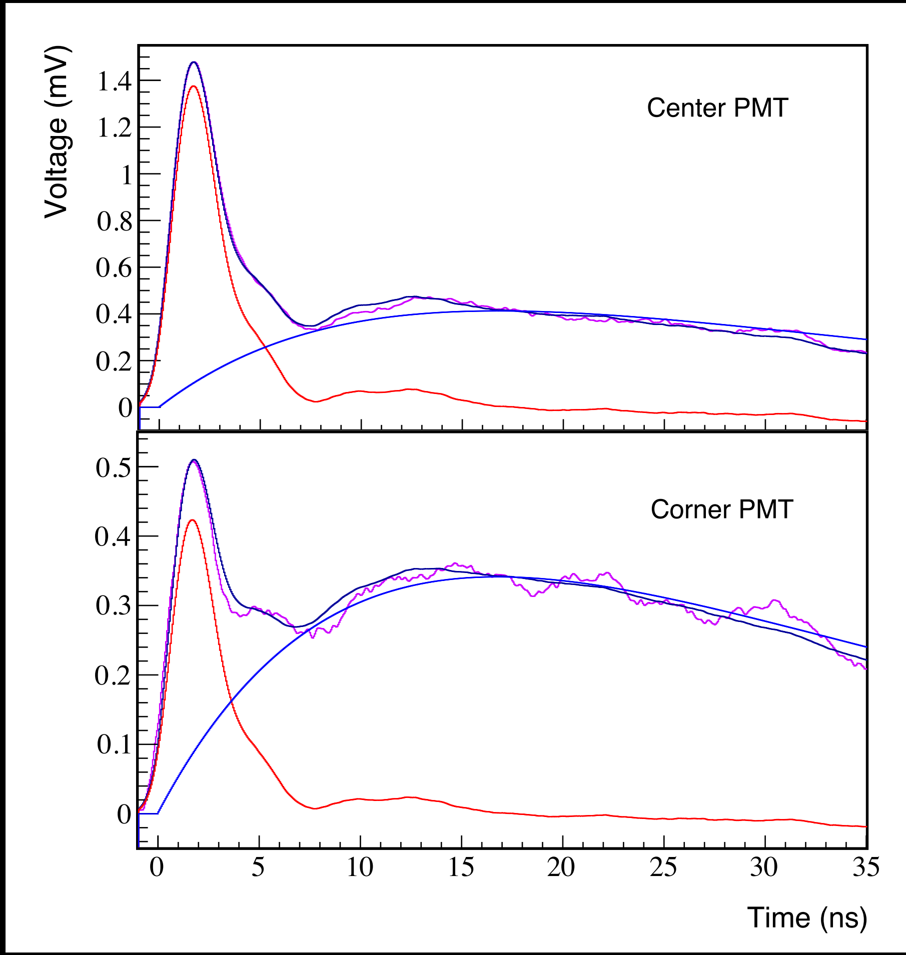
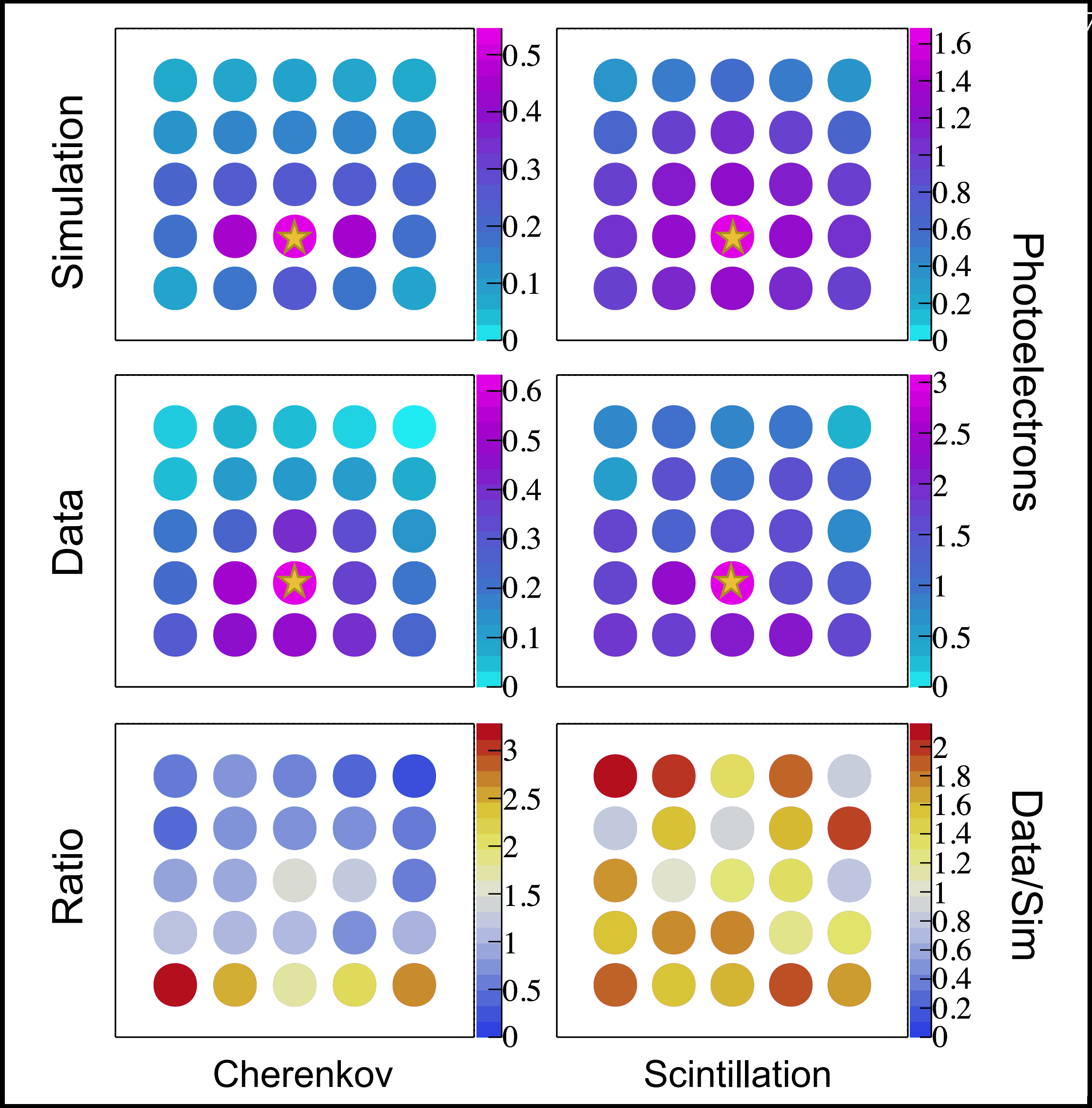
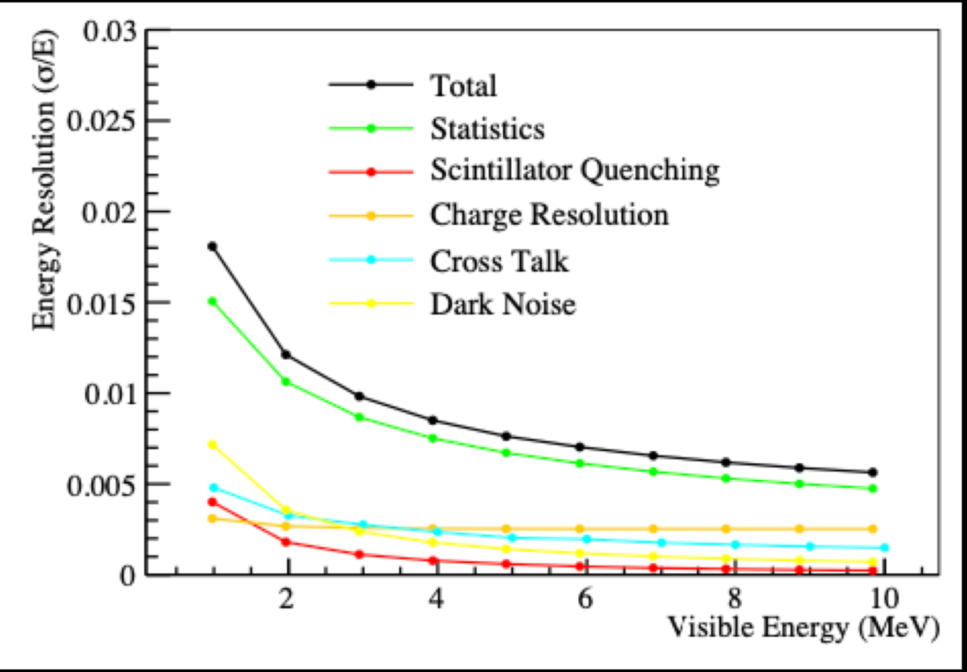


- Integral of collected charge in each component; uses time window determined from total average waveform for Cherenkov light
- Pretty good match to RAT (Geant4-based) Monte Carlo
  - Light yield seems to have been underestimated: will be fit to spectrum in NuDot analysis
  - Source position slightly inaccurate: collimator design was adjusted



ENERGY RESOLUTION IN LARGE LS

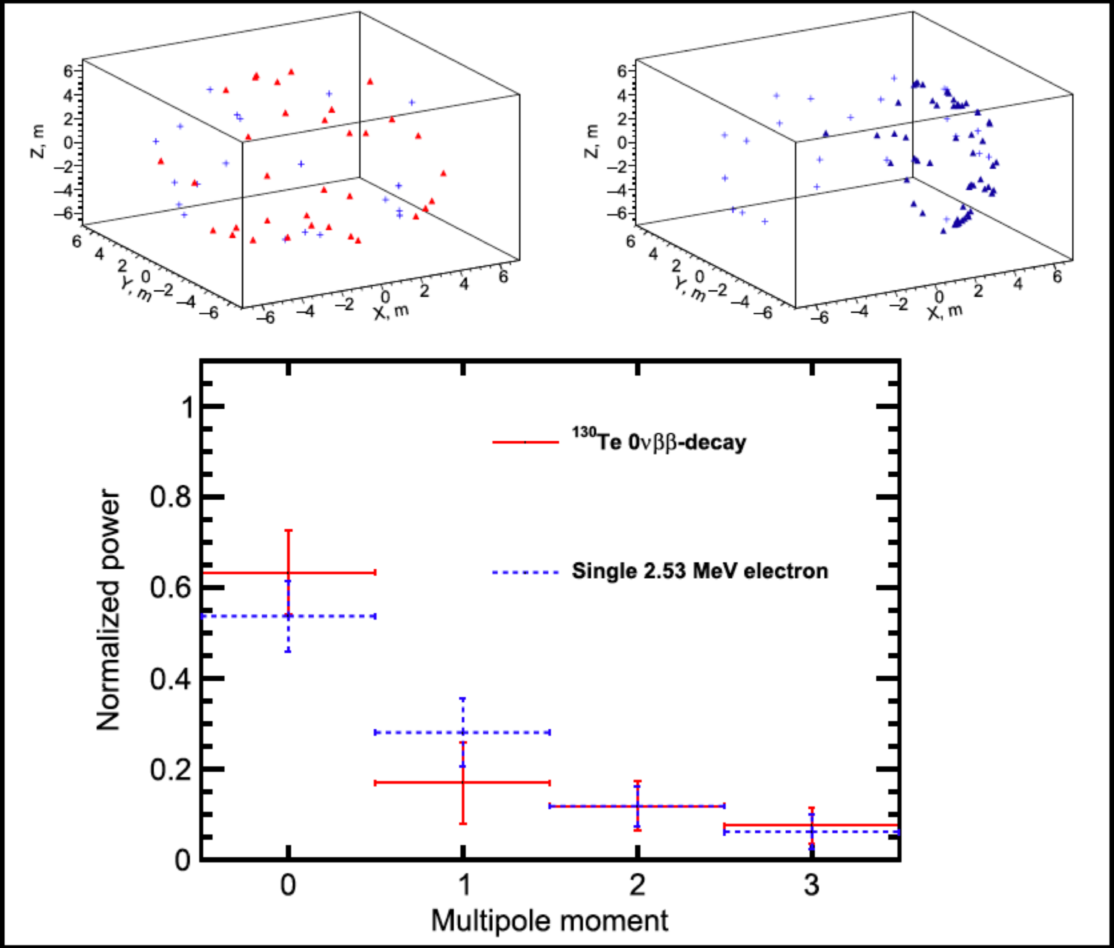
- From KamLAND-Zen to KamLAND2_Zen:
  - Addition of Winston cones: light collection x1.8
  - Larger and higher QE PMTs (from 17" and 22% to 20" and 30%): light collection x1.9
  - LAB LS with improved transparency: light collection x1.4
  - Expected σ(2.6 MeV) goes from 4% to ~2%
  - Coverage is still only 60%, further improvement is possible!
- JUNO-TAO shows possible paths for further improvement:
  - SiPM wallpaper and control of systematics leads to σ(2.6 MeV) ~1%

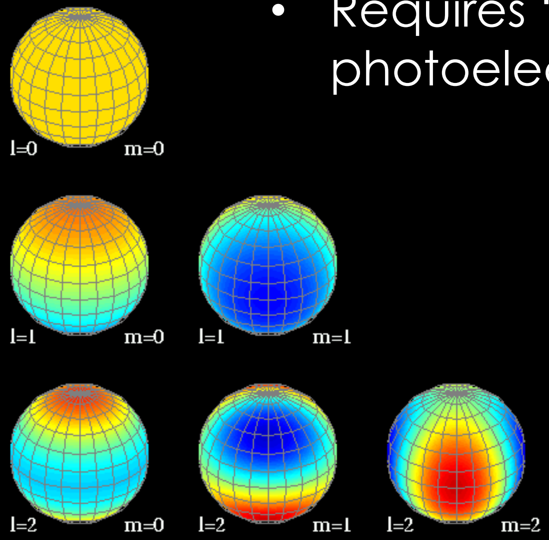


JUNO-TAO expected energy resolution, from arXiv:2005.08745

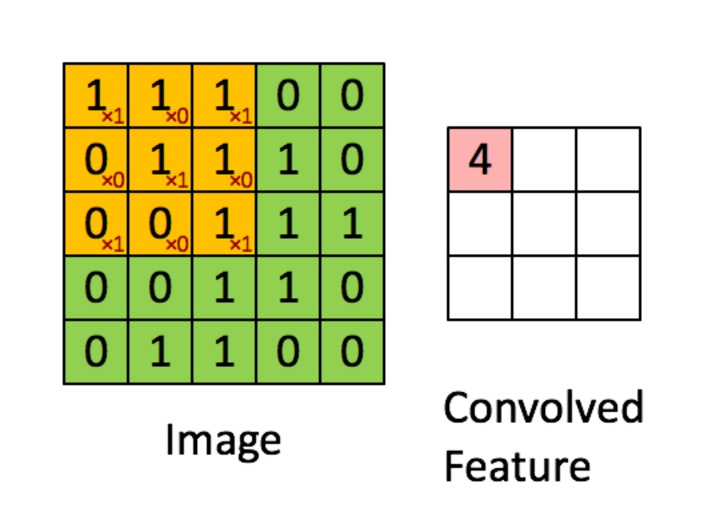
"Traditional" Analysis

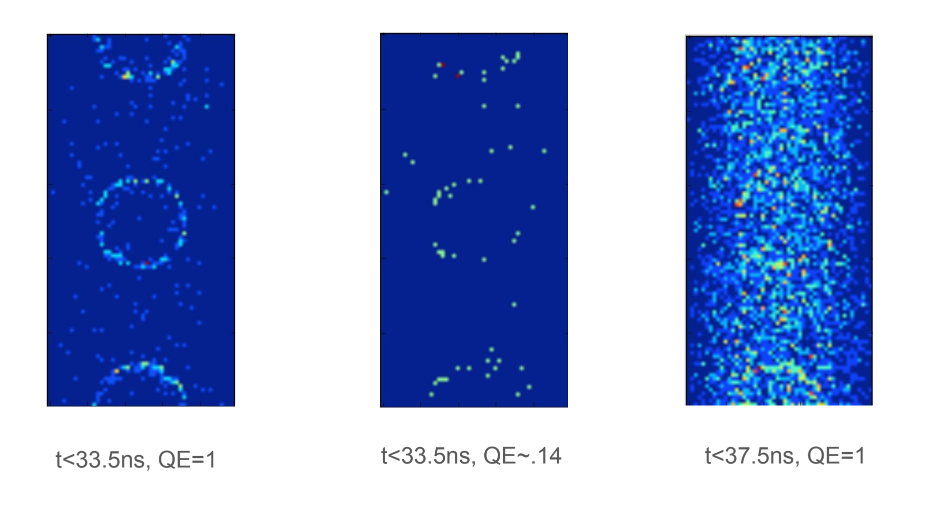
- Average pulse fitting is expected to improve timing
- Simulations of a KLZ-style detector show that single-β scatters can be distinguished from ββ events by using multipole moment decomposition
- Requires "hard cut" on photoelectron timing





From A. Elagin et al., NIM A 849 (2017) 102-111, DOI: 10.1016/j.nima.2016.12.033



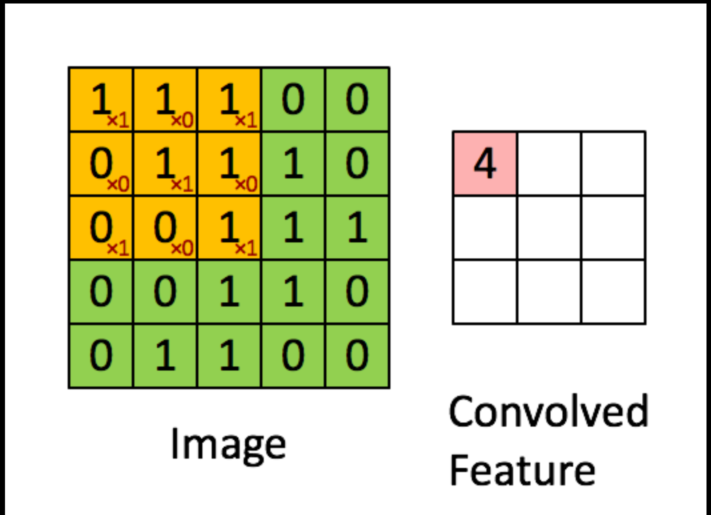


Deep Learning Analysis

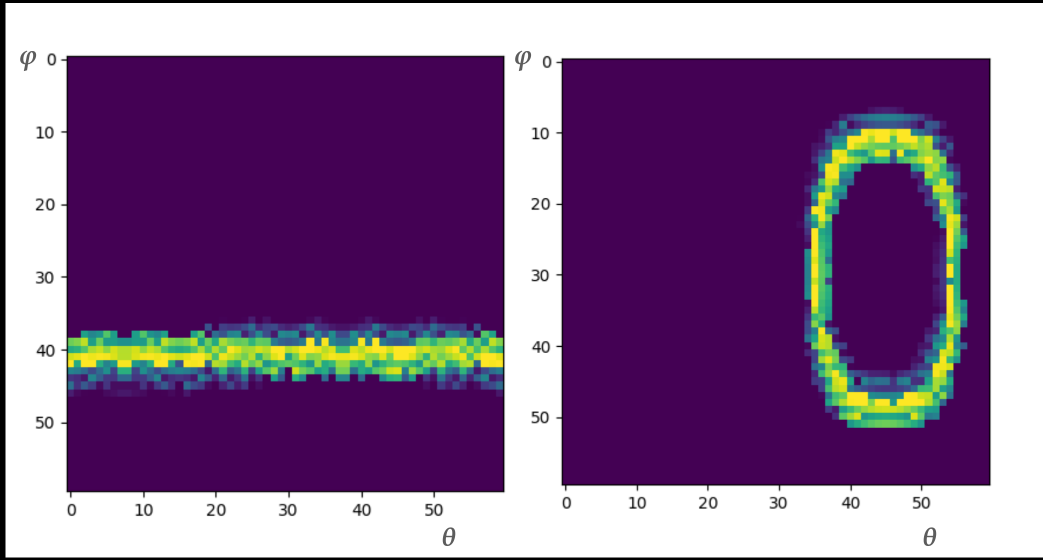
- Ring recognition is a perfect problem for machine learning!
- NuDot's rich spatial and temporal information should show the potential of these techniques
- Typically, "computer vision" problems are solved using a convolutional neural network
- In a purely convolutional approach, time is viewed as a series of snapshots, without a notion of ordering
- This approach was demonstrated in simulations of KLZ, where it can be used to reduce cosmogenic backgrounds from ^{10}C.

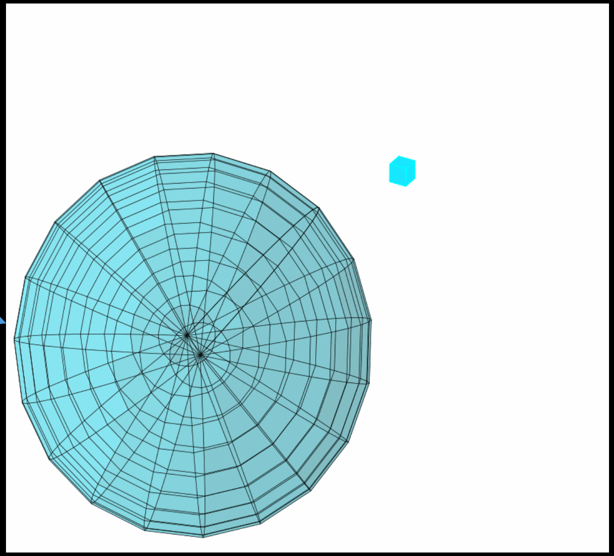
A. Li, A. Elagin, S. Fraker, C. Grant and L. Winslow, NIM A 947(2019) 162604.

- Our detector is a sphere, and CNN's aren't rotationally invariant!
- Instead use a spherical CNN:
  - Views image by rotating it into different angles
  - "Filter" covers the entire sphere and is rotationally invariant
  - Outputs 3D feature map in Euler angle space
- Add recurrent neural network layers to introduce the arrow of time

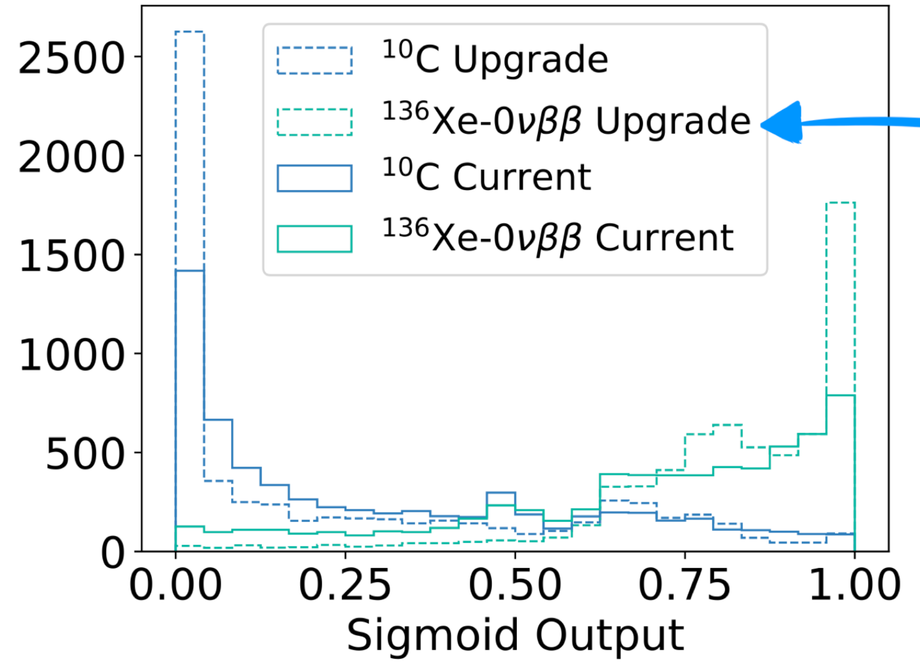


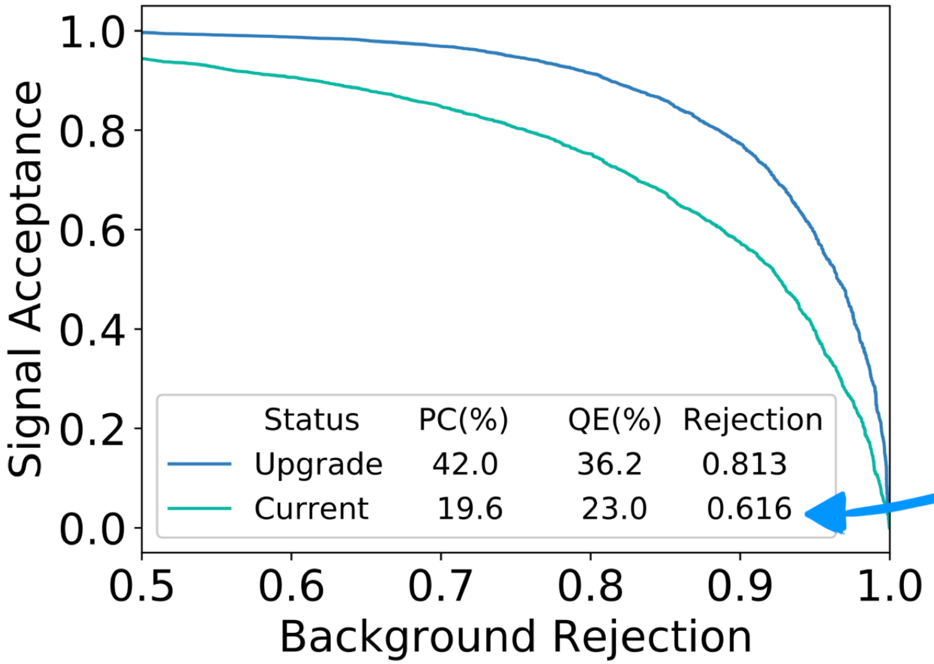
Input

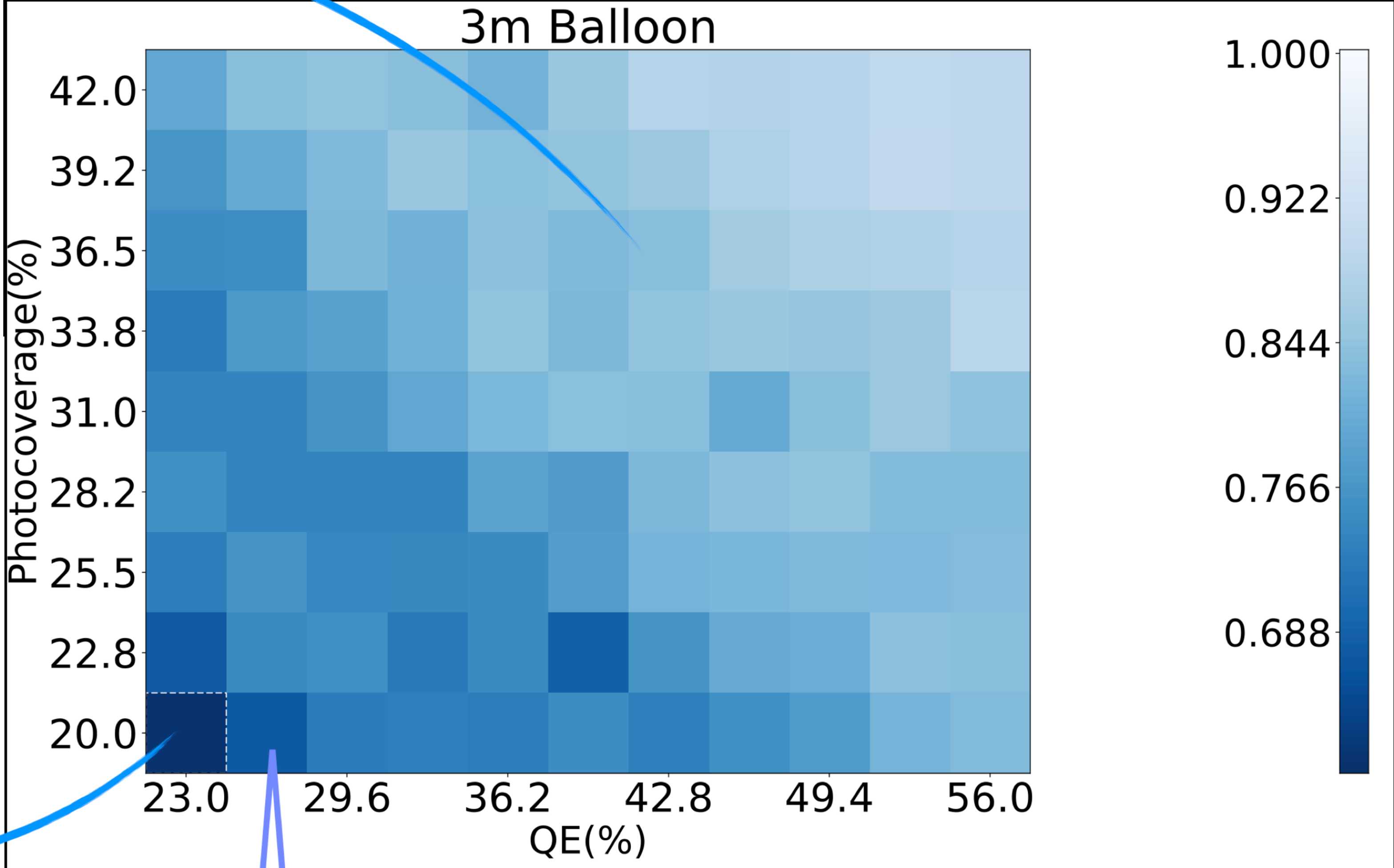




KamLAND-Zen Cosmogenic Background Identificationc

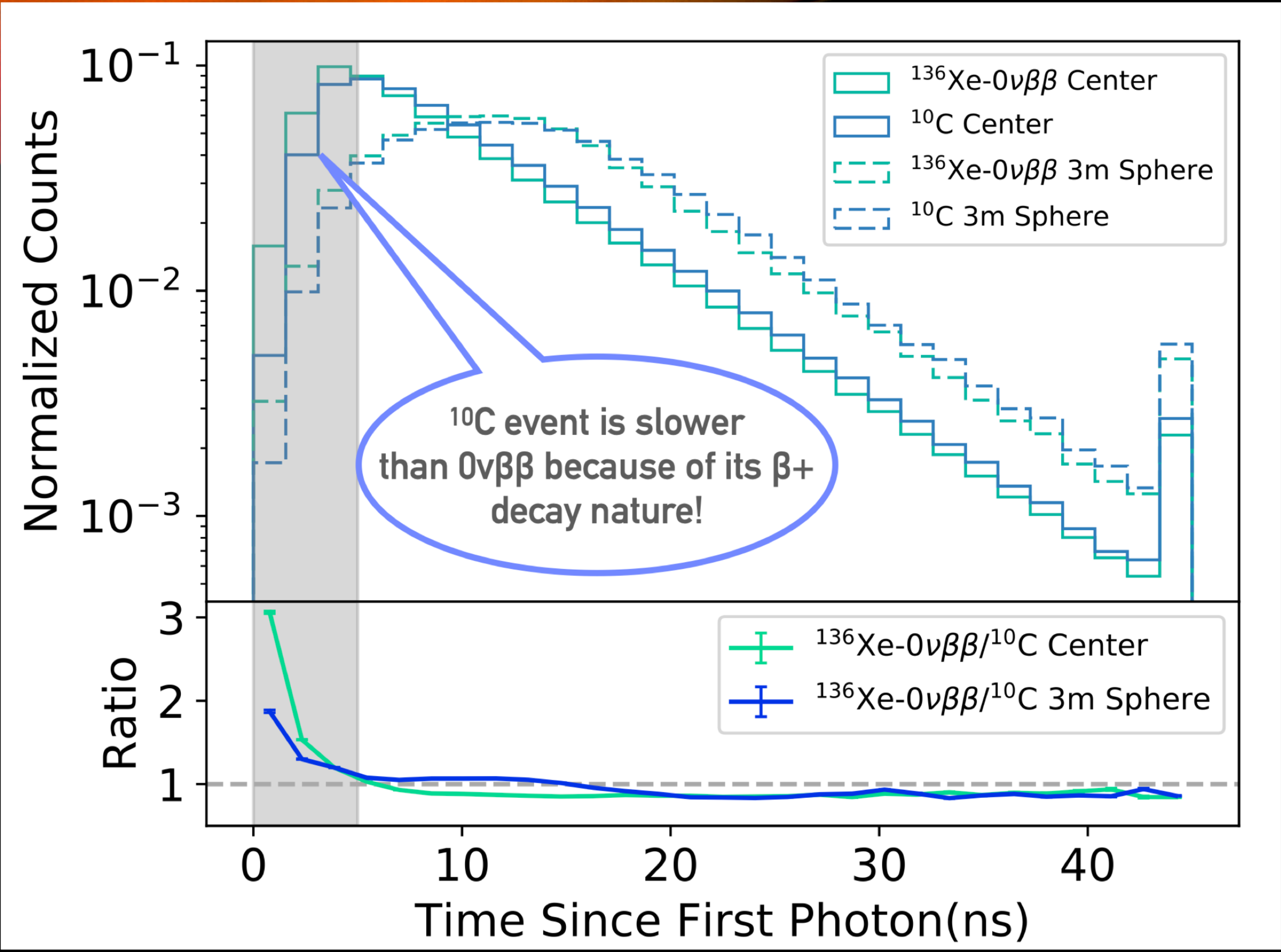






Value in each box: % of background rejected while retaining 90% of signal

Slide by Aobo Li



- Total rejection power by CNN is 61% ^{10}C rejection while retaining 90% 0vββ signal
- Timing profile of events constitute about 55% of rejection
- ^{10}C events have slower spectrum, especially in the first 5ns

Suppression of cosmic muon spallation backgrounds in liquid scintillator detectors using convolutional neural networks

DOI: 10.1016/j.nima.2019.162604

Spherical CNN

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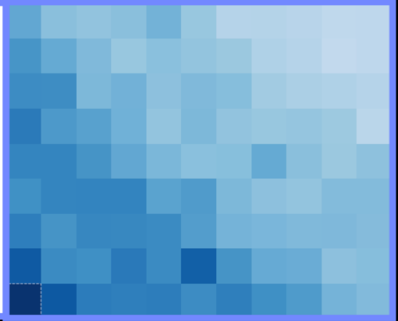
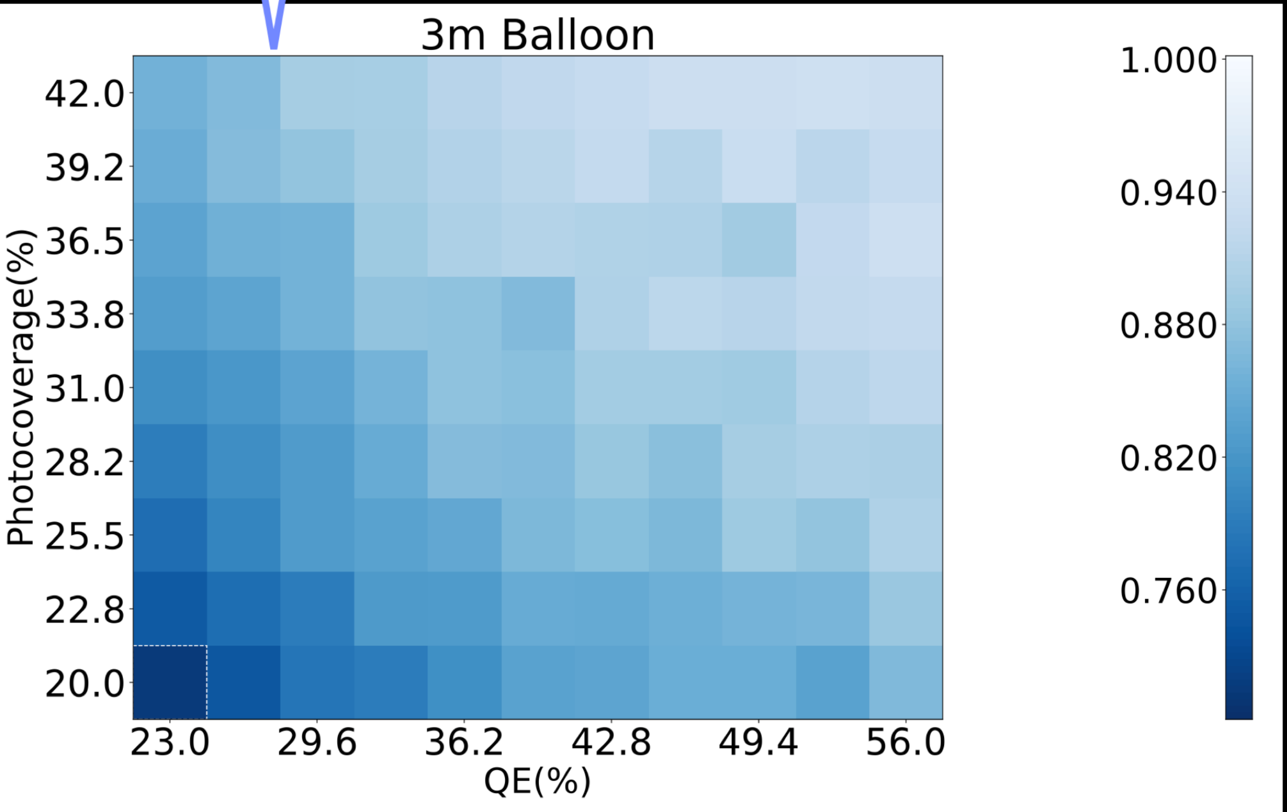
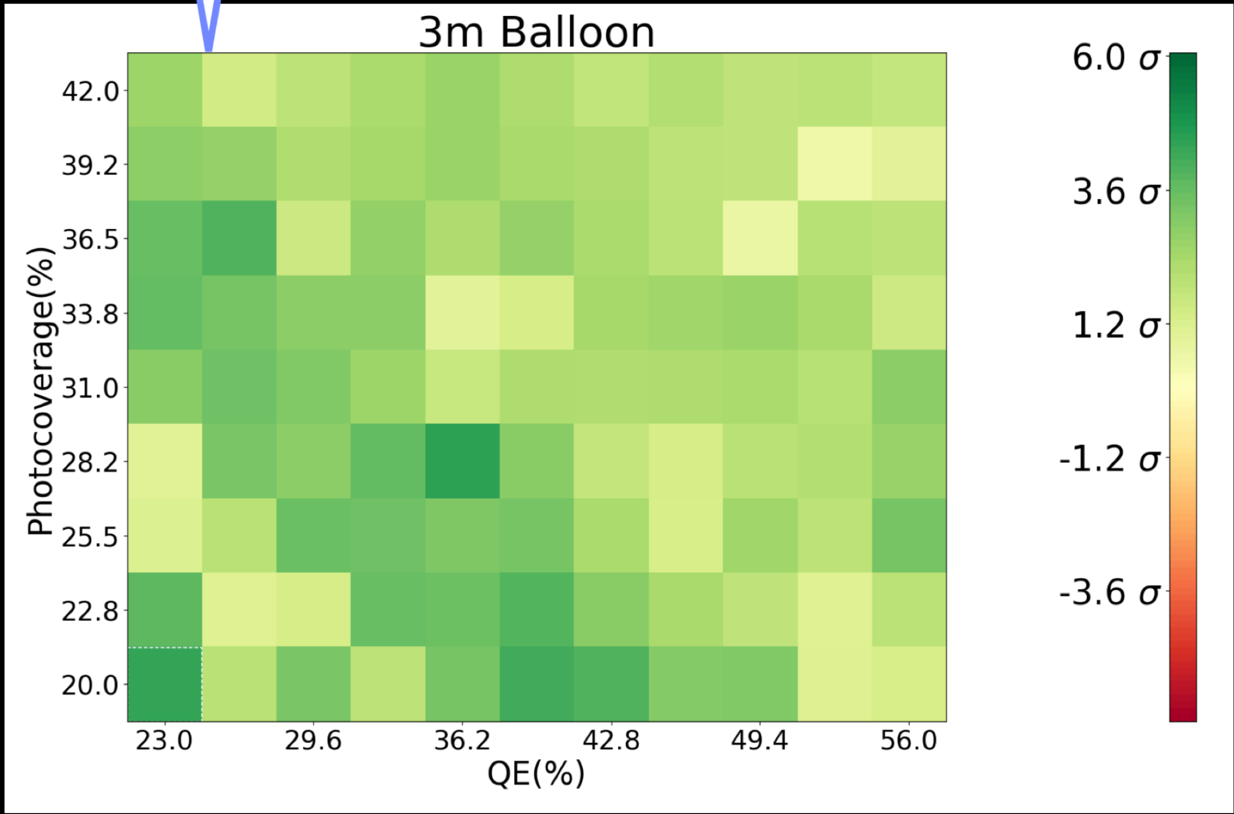
- Much smoother gradient with respect to pressure parameter change
- Proper introduction of spherical symmetry

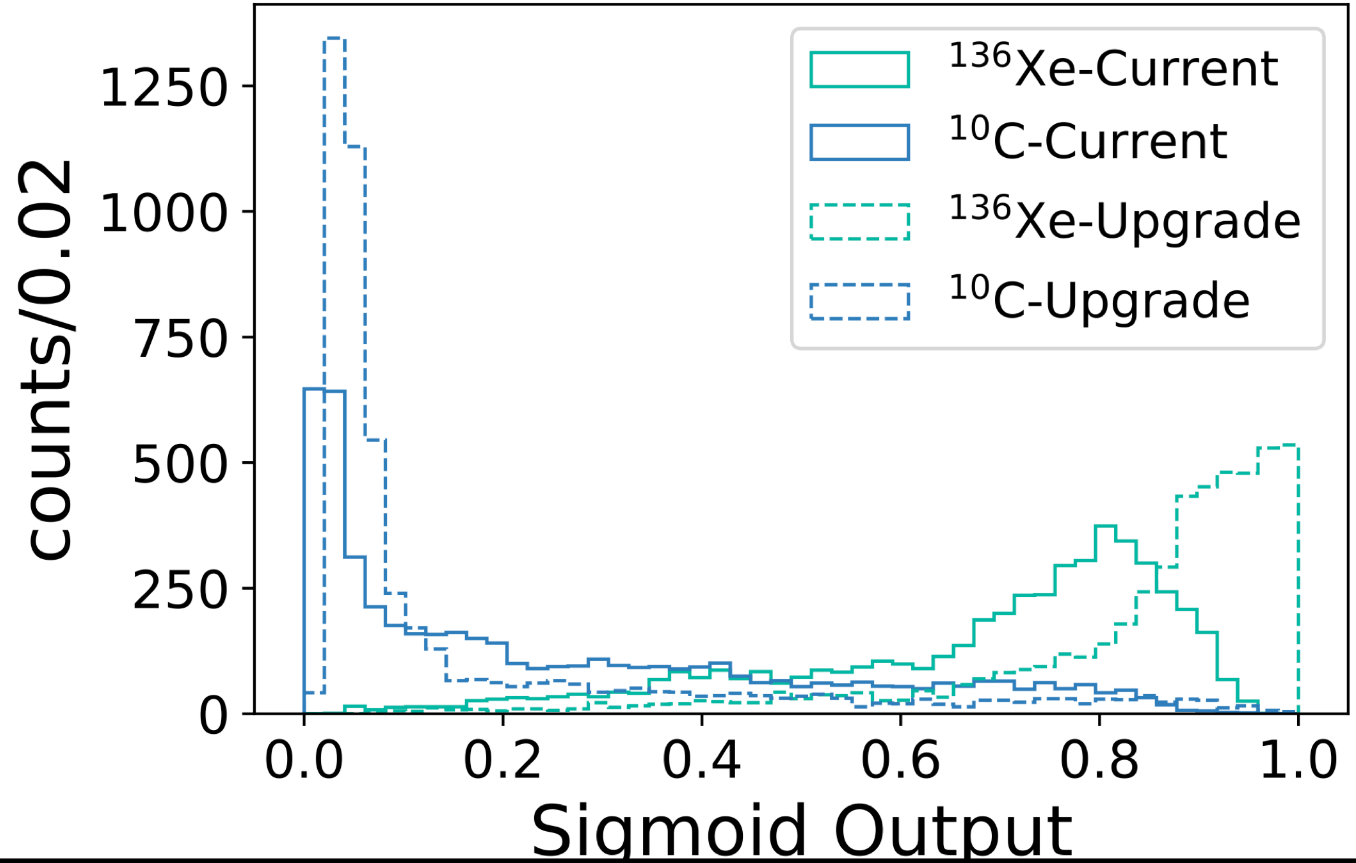


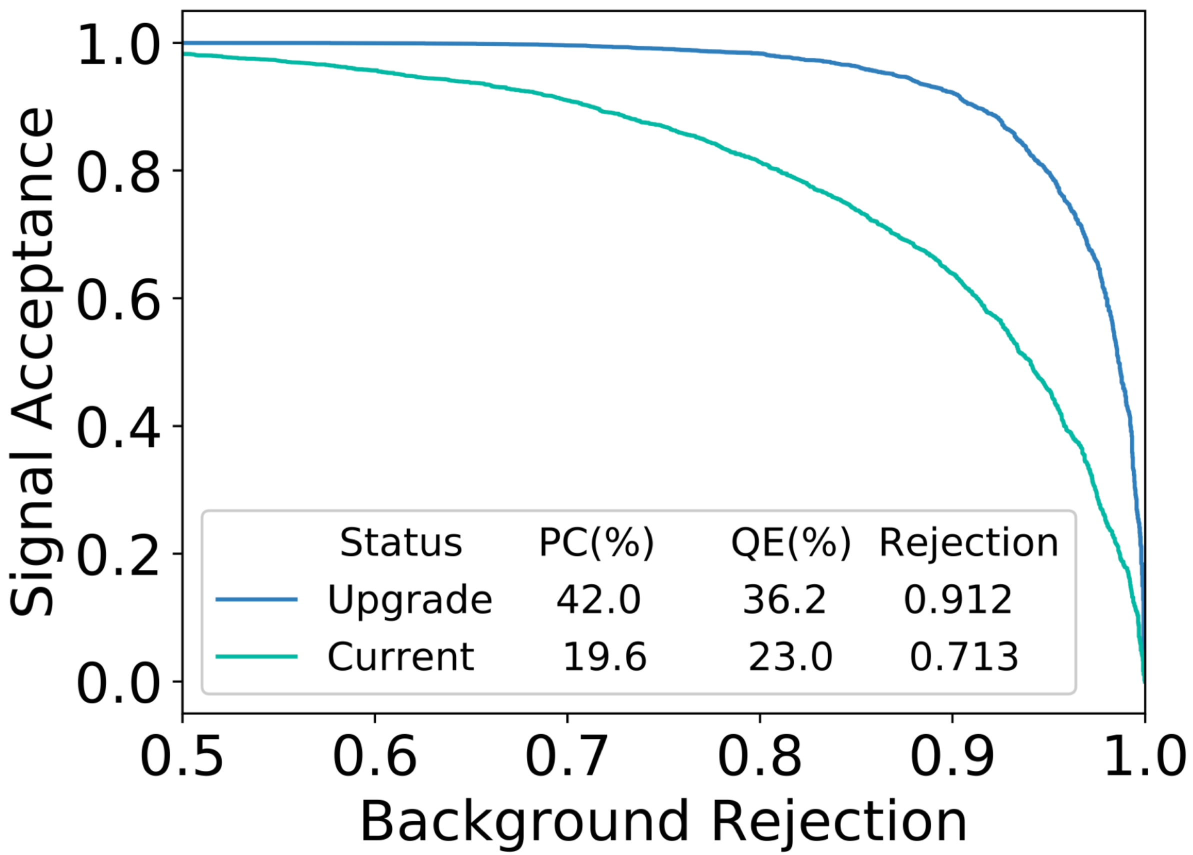
- On average 2.4σ improvement throughout the pressure map
- At KamLAND-Zen Detector Configuration: Rejection increased from 61% to 71% while accepting 90% signal
- 16.4% performance improve with respect to normal CNN





KLZ Spherical CNN Results





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