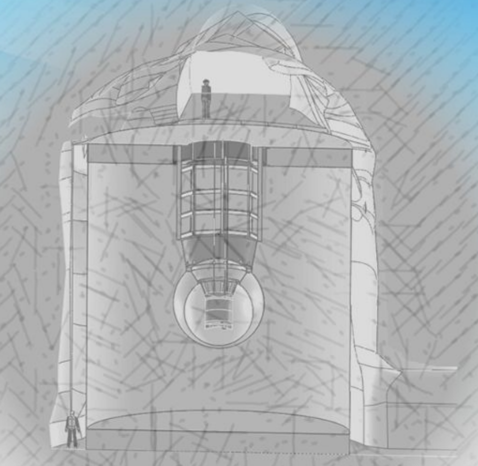
Variational Studies of nEXO's Topological Discriminator



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NPML August 2023, Tufts University
In collaboration with: Jason Brodsky, LLNL

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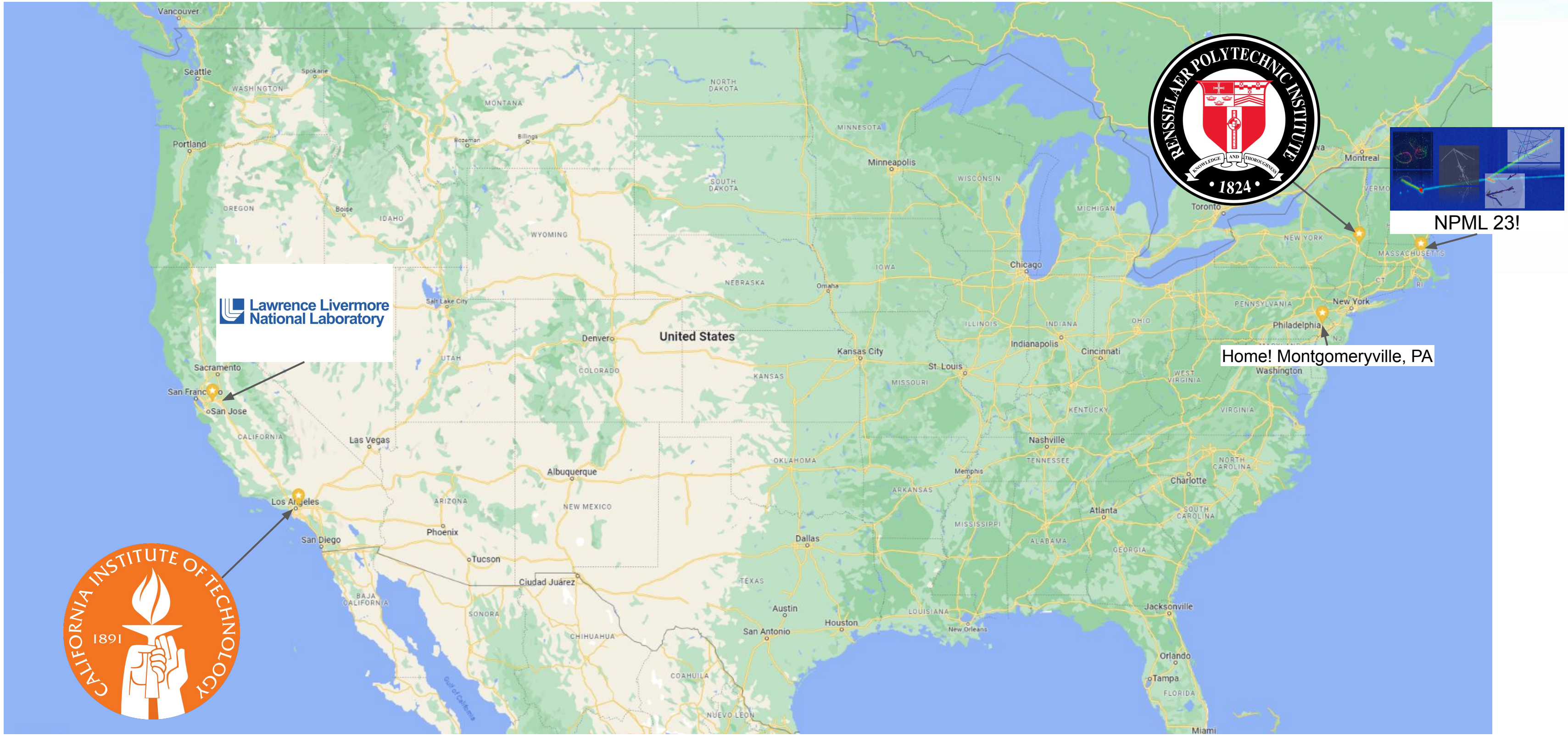
This work was supported in part by the U.S. Department of Energy, Office of Science, Office of Workforce Development for Teachers and Scientists (WDTS) under the Science Undergraduate Laboratory Internships Program (SULI).

Who is Scott Schwartz?



Who is Scott Schwartz?

Tioga!
128 AMD MI-250X GPUs
45.00 TFLOP/s/GPU Peak
Early access El Capitan

Special Thanks:
Mike Heffner
Samuele Sangiorgio
Jason Brodsky
Sam Hedges
(LLNL)

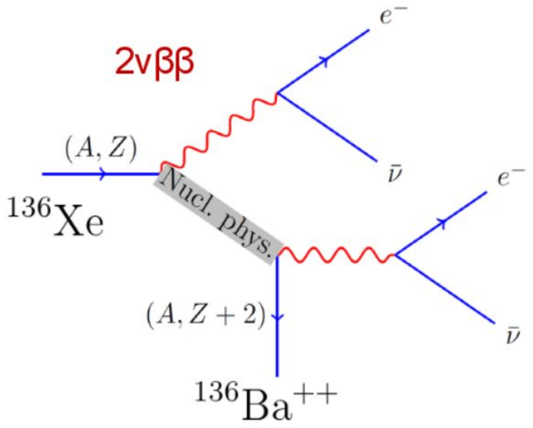
Lawrence Livermore National Laboratory

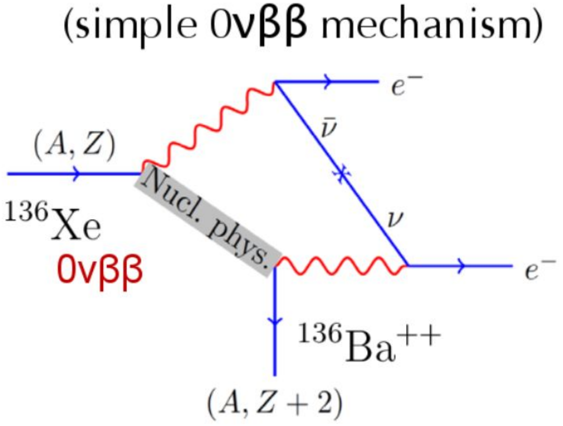
U.S. Department of Energy | Office of Science

SULI
Science Undergraduate Laboratory Internships

Neutrinoless Double-Beta Decay in Xenon-136

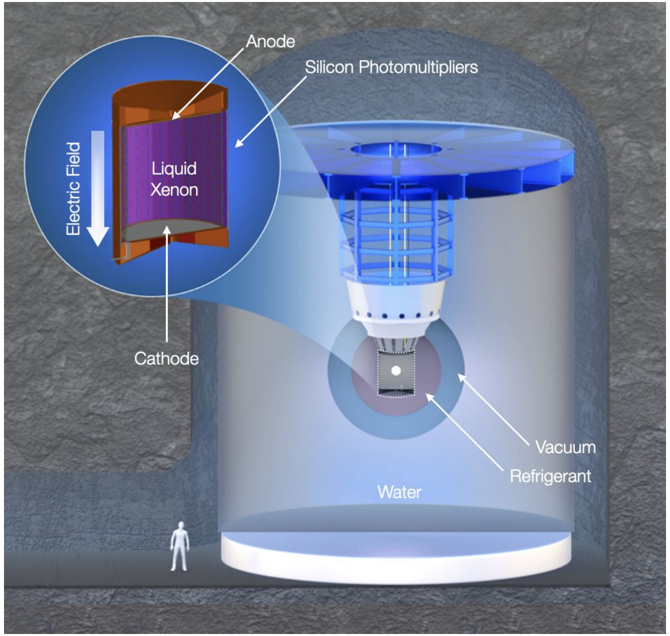
- Ordinary double-beta decay first observed in EXO-200
- Neutrinoless double-beta decay would demonstrate the Majorana nature of neutrinos and violation of lepton number conservation
- ^{136}Xe has many useful properties for this search, including ease of isotopic enrichment and high Q-value



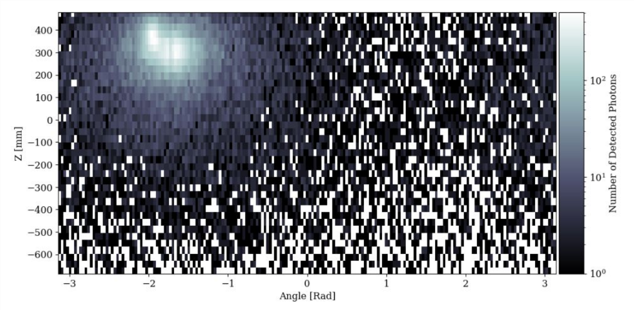


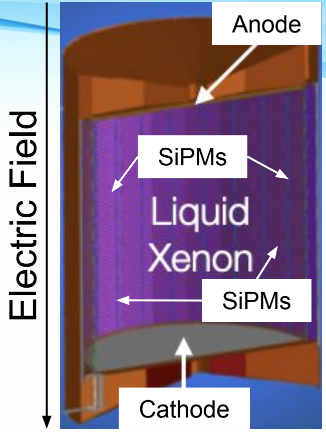
nEXO Overview

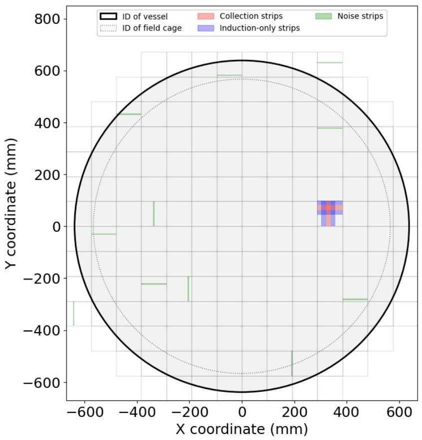
- TPC with 5000 kg of 90% enriched ^{136}Xe
- Scientific Reach - Sensitivity to 0vBB in ^{136}Xe
  - nEXO projects a 1.35×10^{28} year half-life sensitivity to 0vBB in ^{136}Xe at 90% C.L.
- nEXO's Signals
  - SiPMs to collect **scintillation** light
  - Charge Tiles to collect **ionization** signal
- nEXO has low intrinsic backgrounds
- Gamma backgrounds are dominant
  - Multiple Scatters
- Q_{BB} = ~2.5MeV

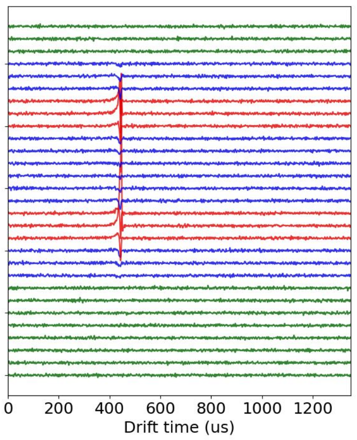


Signals in nEXO



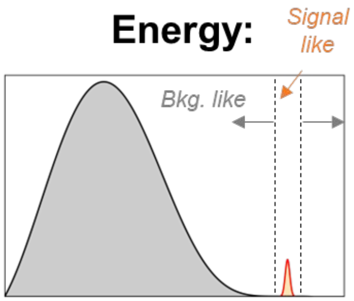


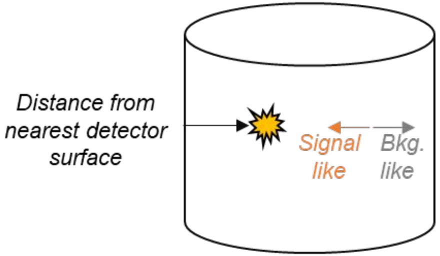


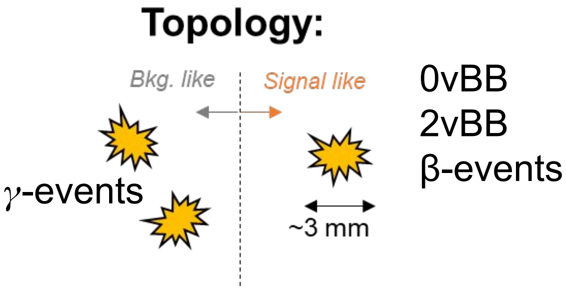


Scintillation + Drift Charge

Measures







Variational Studies of nEXO's Topological Discriminator

1. nEXO's Topological Discriminator
2. Network Performance vs Noise
3. Training a Network with Mixed Datasets

Variational Studies of nEXO's Topological Discriminator

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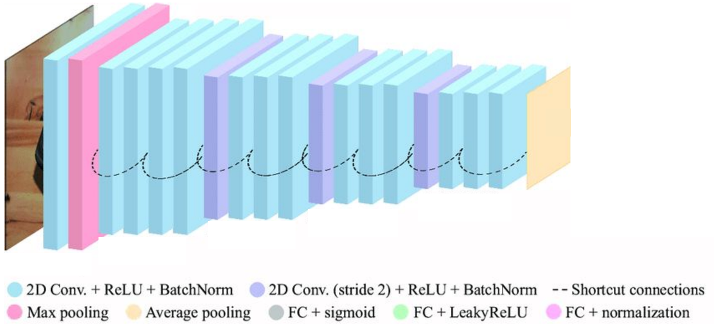
1. nEXO's Topological Discriminator - Infrastructure

Software

- PyTorch
- ResNet18 - Deep Convolutional Neural Network (D)CNN
  - 18 Layer Residual Neural Network
  - Well suited for adjacency found in time and across channels
- AdamW - Stochastic Gradient Descent Method

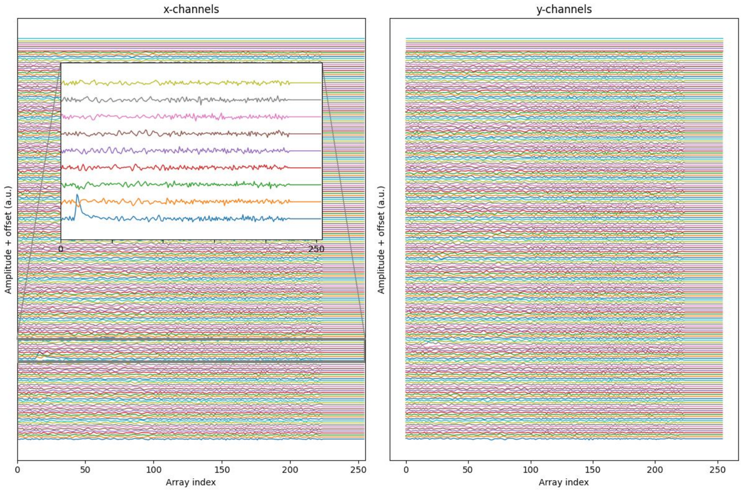


Tomašević *et al.* (2022). Reconstructing Superquadrics from Intensity and Color Images. Sensors. 22. 5332. 10.3390/s22145332.

(Not exact, just a visualization)

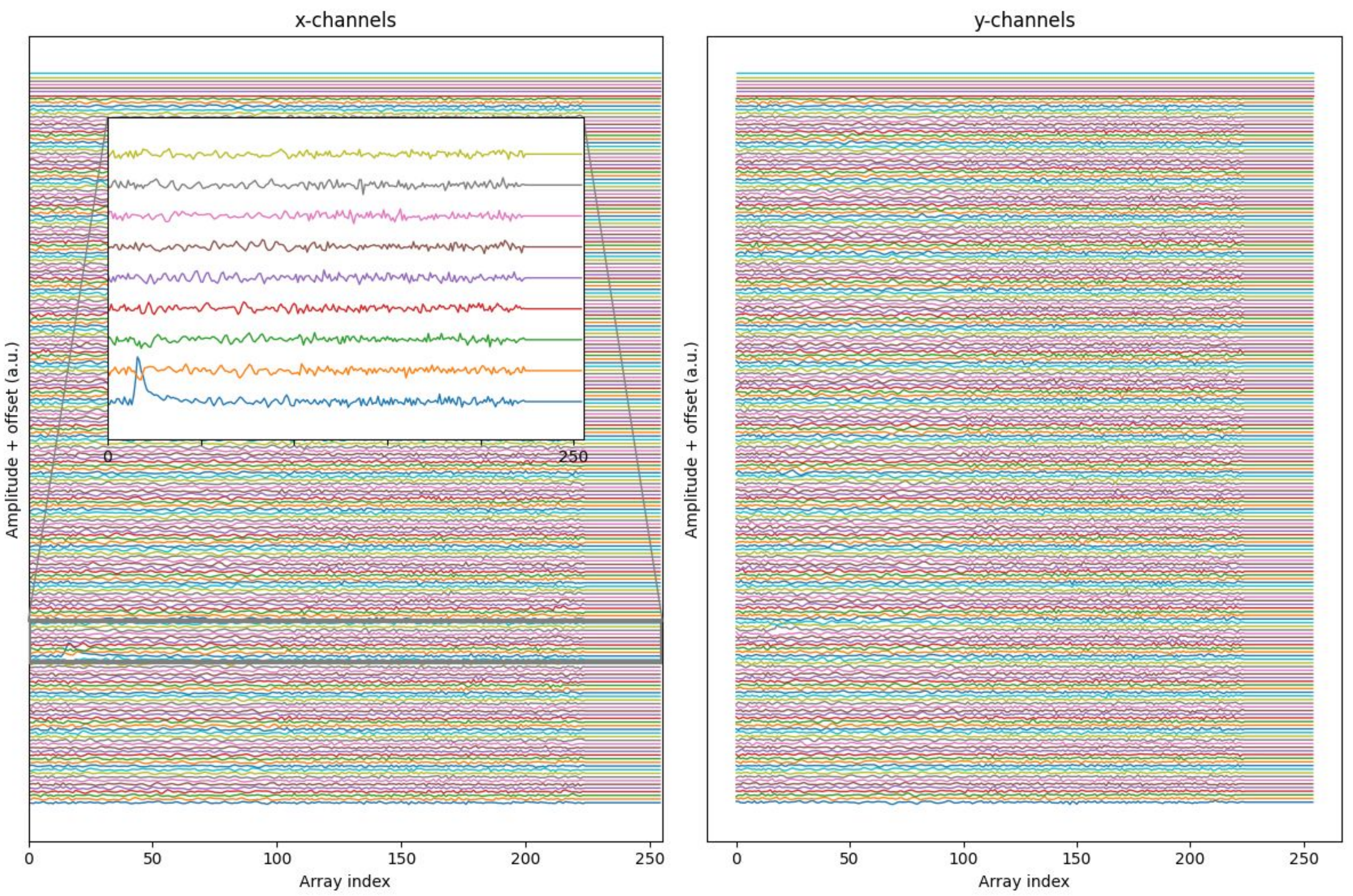
1. nEXO's Topological Discriminator - Simulations

- GEANT4 simulations using NEST generate photons/electrons in LXe
- Charge simulations - in-line channels are summed
- Downsample from ~1500 -> 255 points in time, biased towards peak
- Final product: Time reversed, noised, current waveforms
    - 2 (x/y layers) x 200 (channels/layer) x 255 (WF amplitude points)



Z. Li *et al.* (nEXO), "Simulation of charge readout with segmented tiles in nEXO," Journal of Instrumentation **14**, P09020-P09020 (2019).

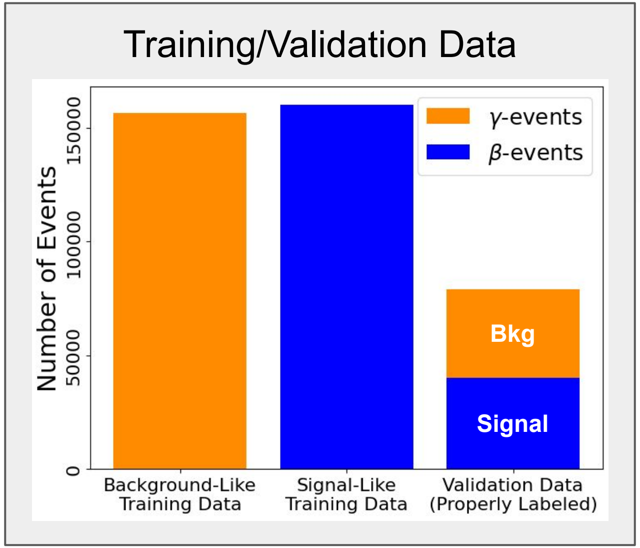
1.



x-channels
y-channels
Amplitude + offset (a.u.)
Array index
0
50
100
150
200
250

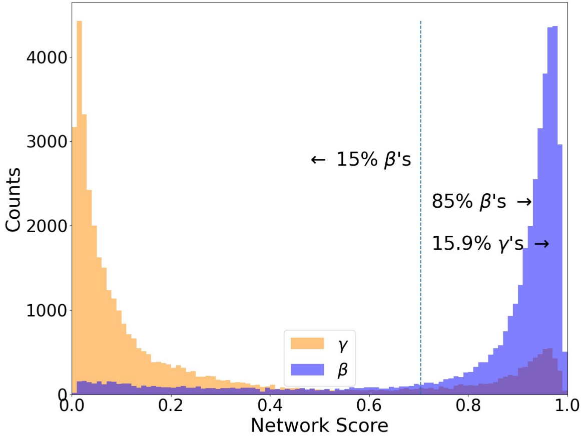
1. nEXO's Topological Discriminator - Training/Validation

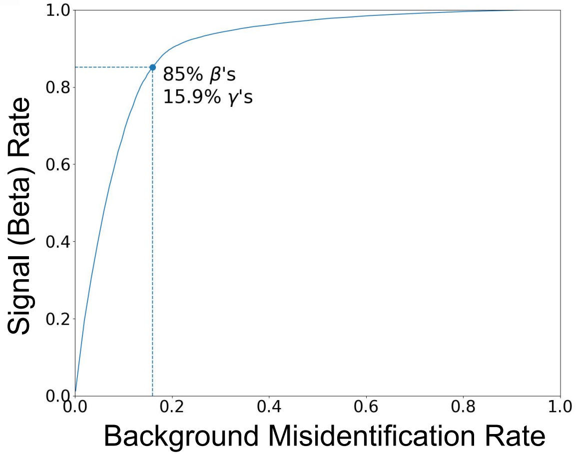
- Signal events - 200k beta events
  - Beta events have similar topology to 0vBB/2vBB
  - Easy to control energy distribution
- Background events - 200k gamma events
- Identical Event Distributions
  - Uniform energy
    - [1,2MeV] - **Lower than Q_{BB}**
  - Uniform position
    - Active LXe (bounded by field rings, cathode, anode)
- 80/20 Training/Validation Split



1. nEXO's Topological Discriminator - Analysis

- Performance Metric: Background misidentification given 85% signal efficiency
  - This differs from the statistical approach to be used in nEXO
- Assigned as such to each epoch (20 epochs per trial)
  - Overtraining - the epoch with the best performance metric is selected per trial





(Total) Bkgs ∝ Performance Metric (Background Misidentification Rate)

Sensitivity ∝ Bkgs$^{-0.35}$ ~∝ $1/\sqrt[3]{(\text{PM})}$

Variational Studies of nEXO's Topological Discriminator

1. nEXO's Topological Discriminator
2. <u>Network Performance vs Noise</u>
3. Training a Network with Mixed Datasets

2. Network Performance vs Noise - Motivation

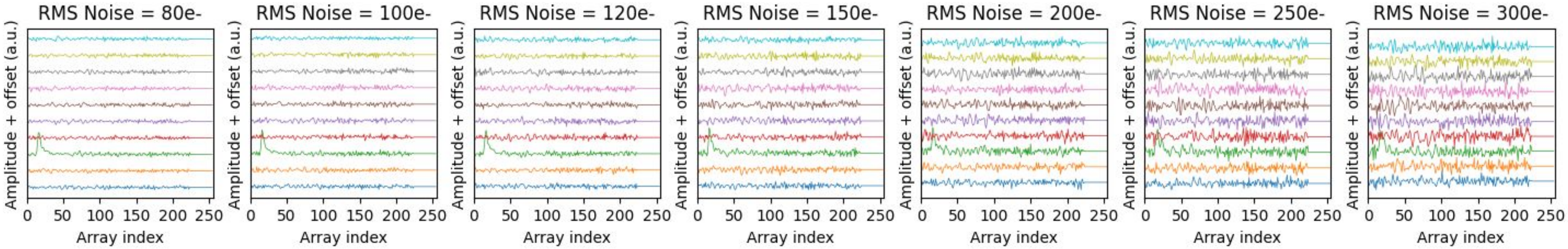
How does changing the amplitude of RMS noise on charge readout electronics impact the performance of nEXO's topological discriminator?

Performance: How well the network can identify signal events while excluding background events

2. Network Performance vs Noise - Methodology

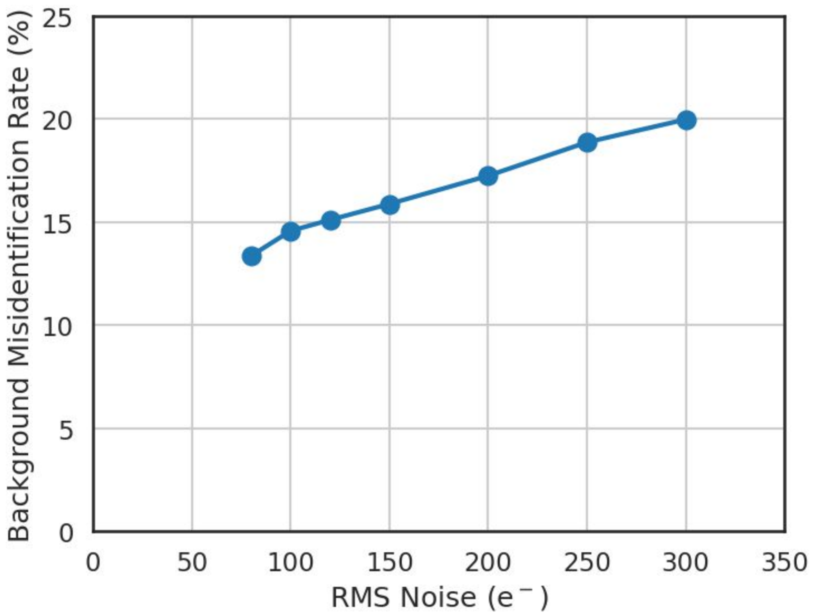
- Generate noise library with varied RMS noise amplitude
- Generate waveforms using corresponding noise library (images below)
- Train network
- Determine performance metric
    - NB: training and validation data have same noise (i.e. 120e- and 120e-)

<----------------------- nEXO ----------------------->



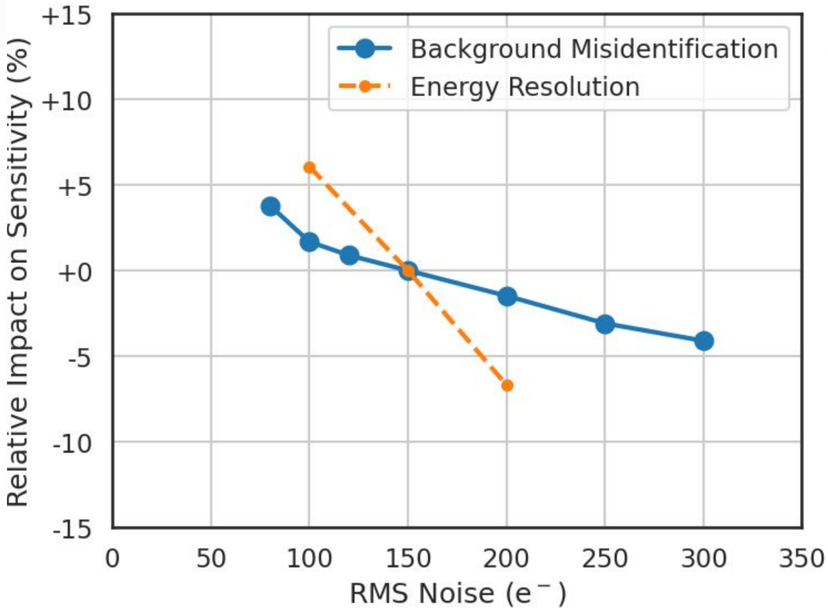
2. Network Performance vs Noise - Results

- The performance of the network **does** have a dependence on noise
- Discriminator benefits from engineering yielding low electronic noise
  - Done for the sake of improving energy resolution



2. Network Performance vs Noise - Conclusions

- Energy resolution is more sensitive to electronic noise than the topological discriminator in terms of overall impact to nEXO's scientific reach
  - nEXO's dependence on energy resolution is <u>small</u>



Variational Studies of nEXO’s Topological Discriminator

1. nEXO’s Topological Discriminator
2. Network Performance vs Noise
3. <u>Training a Network with Mixed Datasets</u>

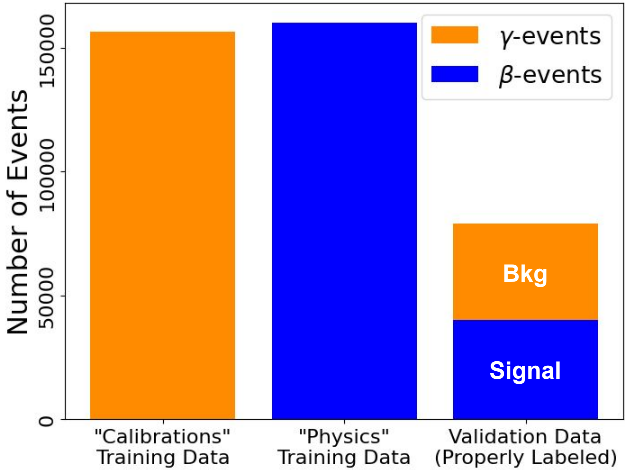
3. Training a CNN w/ Mixed Datasets - Motivation

- **How well does nEXO's topological discriminator learn from datasets that are not purely, correctly labeled, gammas/betas?**
- Why? If we want to train a network using experimental waveforms rather than simulated waveforms, we would not be able to have sets of pure beta events
  - Calibrations data: ~100% gamma events from 6 hot external sources
  - Physics data: mix of double-beta and gamma events
- Proof of concept: Simulated "calibration" and "physics" sets can train an effective discriminator for gammas and betas

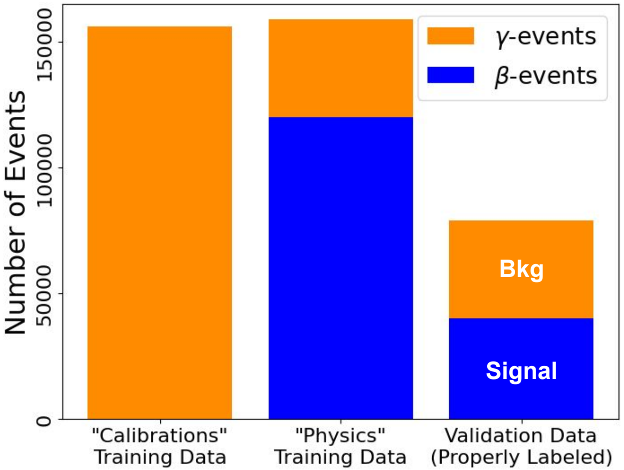
3. Training a CNN w/ Mixed Datasets - Methodology

- Training with “Calibrations” and “Physics” sets
    - Physics sets are composed of 0-20% gamma events
- Validation data is still properly labeled betas and gammas

“Pure” datasets - same as before (0% gammas)

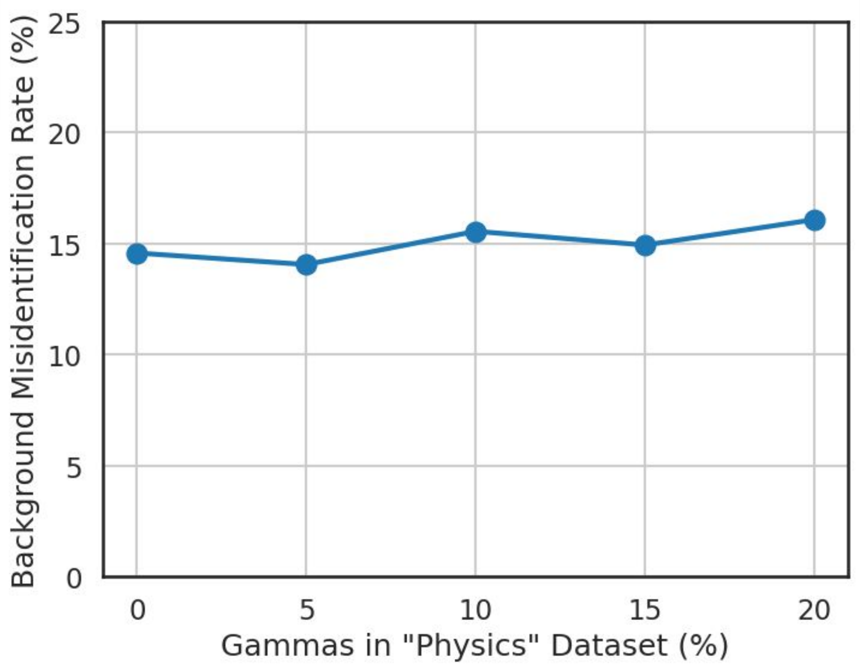


“Mixed” physics dataset (20% gammas)



3. Training a CNN w/ Mixed Datasets - Results

- Performance impacts, if any, are very small
  - Overtraining likely caused variations O(1%)

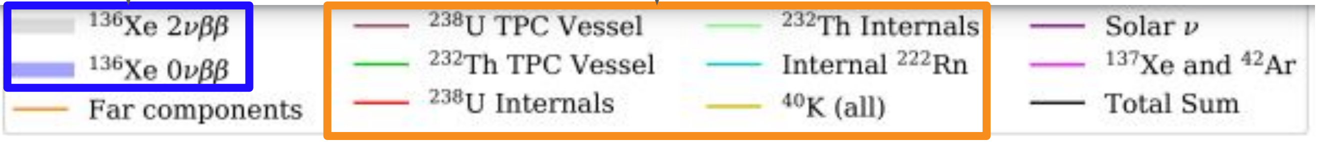


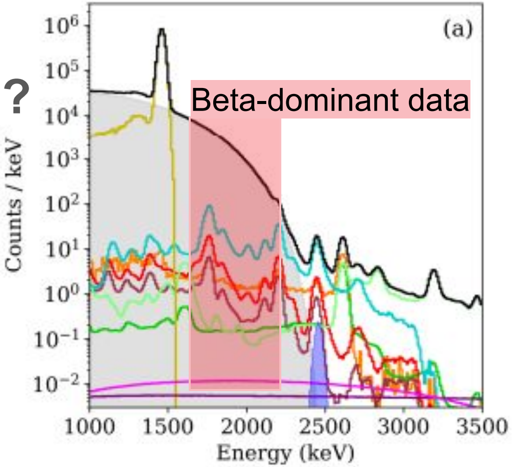
3. Training a CNN w/ Mixed Datasets - Conclusions

- We have shown mixed datasets can be used to train a discriminator
- This study used datasets with identical energy and spatial distributions, experimental data will not - how can we effectively use such datasets?
  - Calibration events, intrinsic backgrounds, and 2vBB/0vBB events all have unique energy and spatial distributions from one another
- **Can we train an effective signal/background discriminator using 2vBB events mixed with backgrounds and a pure set of calibration gammas?**

Signal events

Background events





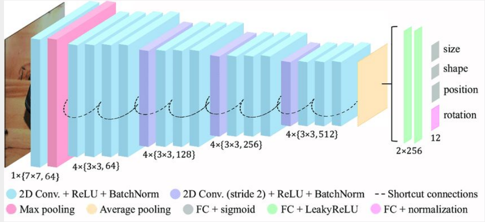
Summary Slide (End)

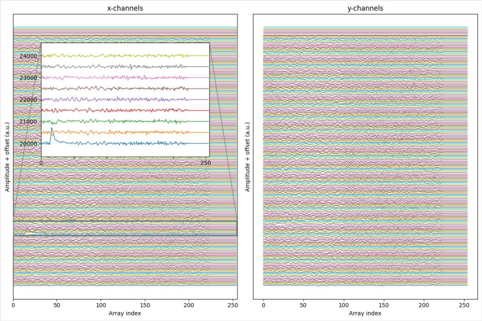
Twitter: @nEXOexperiment

https://nexo.llnl.gov/diversity-equity-and-inclusion

1. nEXO's Topological Discriminator

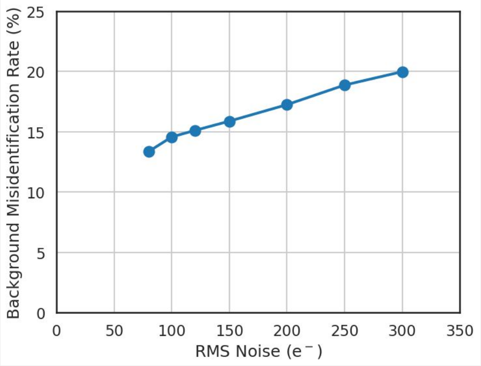
- ResNet18 - 18 layer Convolutional Neural Network

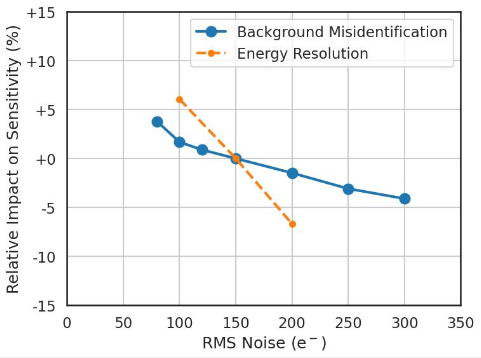




2. Performance vs Noise

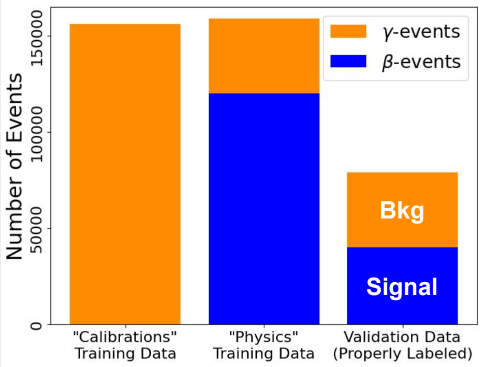
- Performance depends on noise
- Energy resolution is more sensitive to noise

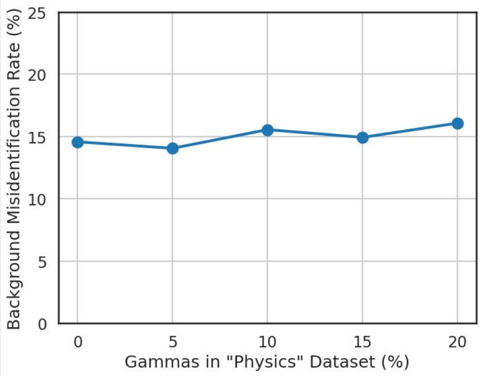




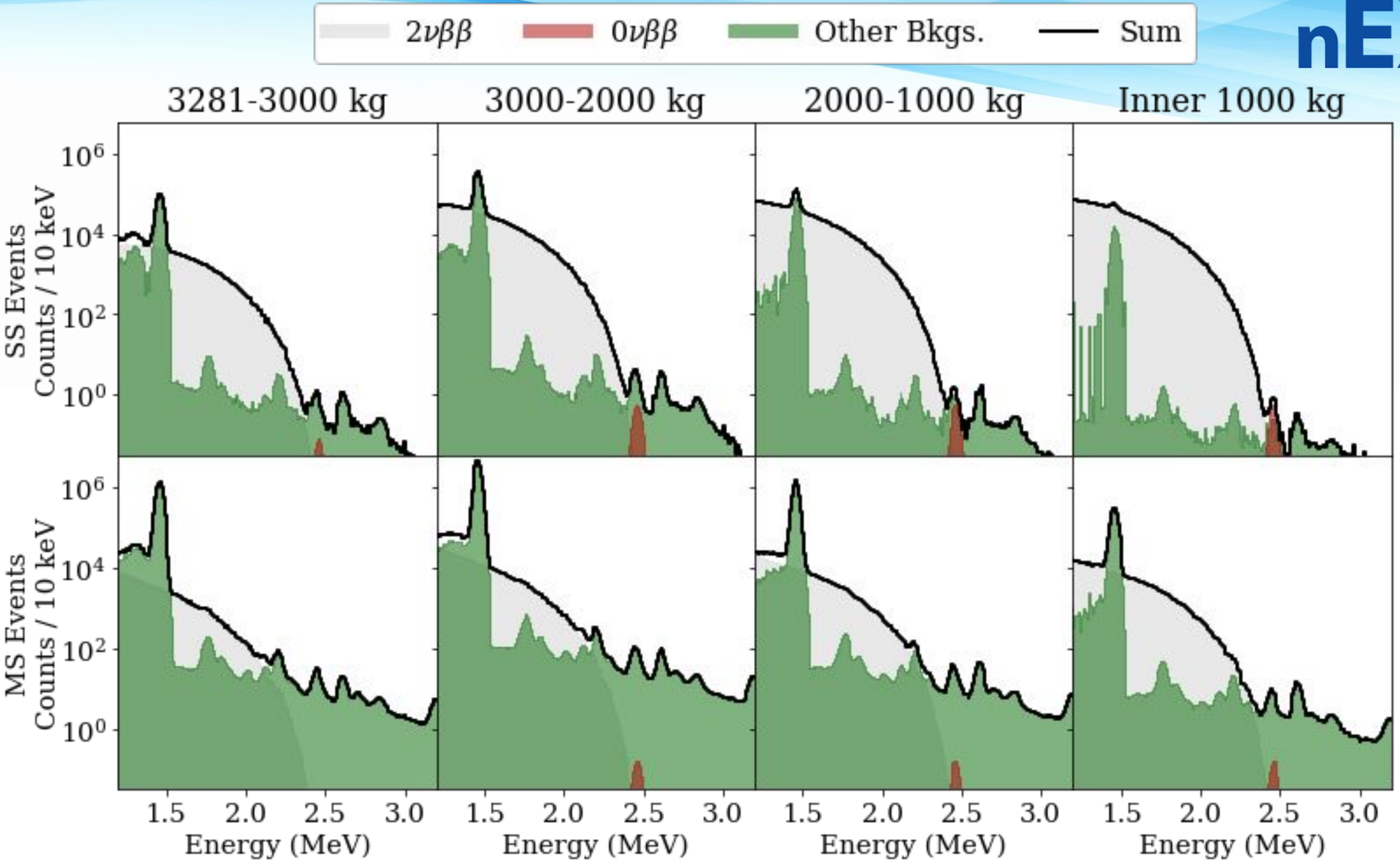
3. Mixed Dataset Study

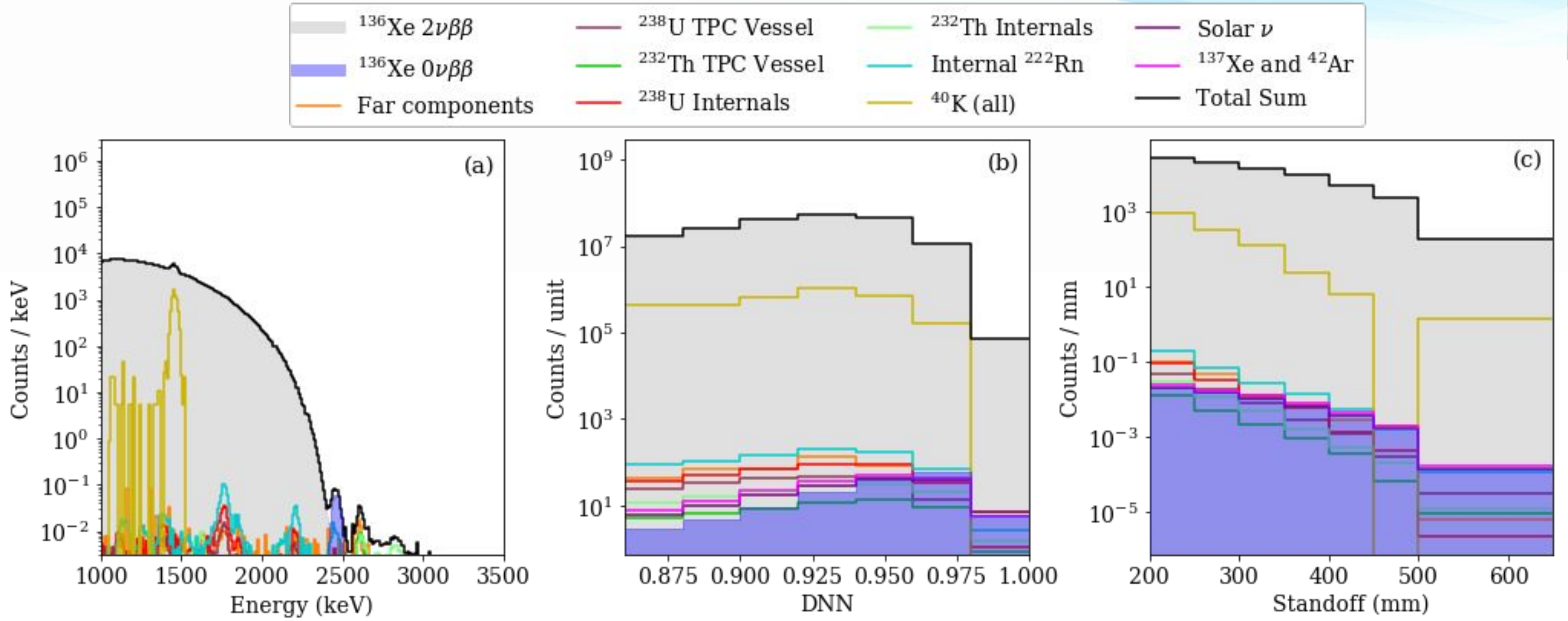
- nEXO's CNN can be trained using a pure "calibrations" dataset and mixed "physics" dataset (with identical distributions in energy and space)





Backup


2νββ
0νββ
Other Bkgs.
Sum
3281-3000 kg
3000-2000 kg
2000-1000 kg
Inner 1000 kg
SS Events
Counts / 10 keV
MS Events
Counts / 10 keV
10^6
10^4
10^2
10^0
1.5
2.0
2.5
3.0
Energy (MeV)


^{136}Xe $2\nu\beta\beta$
^{136}Xe $0\nu\beta\beta$
Far components
^{238}U TPC Vessel
^{232}Th TPC Vessel
^{238}U Internals
^{232}Th Internals
Internal ^{222}Rn
^{40}K (all)
Solar ν
^{137}Xe and ^{42}Ar
Total Sum
(a)
Counts / keV
Energy (keV)
(b)
Counts / unit
DNN
(c)
Counts / mm
Standoff (mm)