

Topological Event Discrimination using Deep Convolutional Neural Networks for the NEXT Experiment

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The NEXT Collaboration



Ovßß Search with NEXT



Schematic of a NEXT TPC





□ <u>Neutrino Experiment with a Xenon TPC (Time</u> <u>Projection Chamber</u>)

Detector material: enriched gaseous Xe¹³⁶

 Less nuclei per volume, but better energy resolution and track reconstruction compared to liquids

□ S1: primary scintillation, detected by PMTs

S2: from electroluminescent amplification.
Used for track reconstruction and x/y position

 \Box Δt between S1 and S2 used for z position







2009-2014

Small prototypes (~1kg of Xenon)

2015-2021 **NEXT-White (NEW)** (~5 kg). Background and $2v\beta\beta$



NEXT Timeline



2024-202?

NEXT-100 (~100 kg). $0v\beta\beta$ limit setting.

20??

NEXT-HD/BOLD (~1 ton). $0v\beta\beta$ detection...?



Topological Event Discrimination



candidate event



- Bragg peak at the end of an electron track -> manifests as 'blob' that allows for topological background rejection
- Use 'double escape' events from TI²⁰⁸ decays: e+/e⁻ pair production from a single highenergy γ where the subsequent 511 keV annihilation γ-rays escape the active volume
 - **For TI²⁰⁸: at 1592 KeV**
 - -> Same topological signature as 0vββ decay
 - Continuous background of single-electron Compton scattering events



'Traditional' Approach [1]



Left: hits at their reconstructed positions in 3D; right: voxelised track





Reconstruct each sensor hit position from the sensor position and drift time between S1 and S2

- **Group hits into voxels**
- □ Use Breadth First Search (BSF) algorithm to cluster neighbouring voxels into tracks

Sum over track ends to get blob energies and cut on the second blob energy to reject background



DCNN Approach [2]



The network architecture used in this study



	<u>Deep Convolutional Neural Network</u>
	Developed for image recognition
	Convolution filters: tensors of learnable parameters that are applied linearly over an image in steps ('stride')
RELU	Here: sparse 3D convolutional network with 2 output classes: signal and background
SOFTMAX	conv(x,y,z), N: convolution using N filters of size x,y,z
	FC: fully connected layer



Data Preparation [2]



Energy spectrum of the simulated events



- ☐ MC simulation of TI²⁰⁸ double escape events using our Geant4 application Nexus
 - Run same reconstruction chain as for traditional approach, except for:
 - ☐ Total event energy normalised to one
 - □ Custom voxel size applied to re-voxelise hits after original track reconstruction



Training Procedure [2]



An example of data augmentation in 3 axes





- □ 500k training events, 30k validation
- **Cross-entropy loss**
- □ L2 weight regularisation



On-the-fly data augmentation:



☐ Track flipping, translating, zooming and SiPM charge cut variation



Data Augmentation 2





- Data and MC have some known differences in NEXT; not all are understood
- Data augmentation does <u>not</u> correct our MC but makes the model more robust to data-MC differences
- After average pooling layer: calculate <u>Energy</u> distance [3] between data/MC using the **network feature vector (512 features)**
 - -> probability that data/MC follow the same distribution can be calculated to be more that 95% with data augmentation



Results [2]



Signal acceptance vs background rejection and figure of merit ($\varepsilon_{s/b}$: fraction of signal/background events labeled as signal). Fit curves are obtained from fitting the energy spectrum with a gaussian + exponential background to estimate the number of true signal/background events. Standard curves are obtained using the non-CNN based approach described above. A significant improvement is apparent.





Next Steps: Upgrade to Graphs



A signal (top) and background event converted to graphs, and the signal efficiency - background rejection curves of three different GNN network architectures compared to the CNN curve (M. Kekic et al.) $_{\rm 12}$



Graph neural network (GNN): generalisation of CNN

Voxelised tracks are converted to nodes with a feature vector (i.e. energy, position...) and connections

-> Additional degree of freedom in graph architecture

 Removal of unnecessary information, data is inherently sparse

First tries on MC look to improve over CNNs

Suitable data-MC compatibility strategies such as data augmentation to be developed



in $0v\beta\beta$ searches

Convolutional neural networks can be used successfully for this task, even in the case of non-perfect data/Monte Carlo compatibility

Even better background rejection might be possible using graph neural networks

Summary

Gaseous TPCs provide a strong tool to reject single-electron background events





Questions?





BACKUP



















Better than 1% at 2.6 MeV! $[2]_{18}$











Bragg peak at the end of an electron track -> manifests as 'blob' and allows for topological signal detection





0.05 × 10⁻³ BF ¹³⁶Xe $\beta\beta2\nu$ BG-sub. data **Rate** χ²/dof=14.7/21 **R(¹³⁶Xe)=348.6±85.3 y⁻¹** 0.02 $T_{1/2}=1.93\pm0.47 \times 10^{21} \text{ y}$ 0.01 -0.01 -0.022.2 2.4 2.6 2.8 Energy (MeV) 1.2 1.4 1.6 1.8 2

 $T_{1/2} = (1.93 \pm 0.47) \cdot 10^{21}$ years [3] - Compatible with literature!





- **Purpose:**
 - □ Characterise background at LSC
 - **Demonstrate energy resolution**
 - □ Achieve topological event discrimination
 - \Box Measure the regular $2\nu\beta\beta$ decay mode



NEXT-100







- Will provide a competitive limit on the 0vββ decay: 4.1.10²⁵ years after 3 years of data taking
- □ 60 PMTs and 3583 SiPMs in a 1.3 m long TPC
- □ Shielded by 12 cm of pure copper, a 20 cm thick lead castle and an active muon veto

□ Already online!



NEXT-BOLD





|--|

Dense	SiPM	track	ina r	lane

- □ Optical fiber barrel
- □ Camera readout [4]
- □ Symmetric TPC -> Shorter drift lengths to mitigate diffusion
- Could probe half-lives above 10²⁷ years!

□ With Ba tagging: up to 10²⁸ years! https://journals.aps.org/prl/pdf/10.1103/PhysRevLett.120.132504

