Deep Learning Techniques to Search for Rare Processes in LArTPC-based Neutrino Experiments

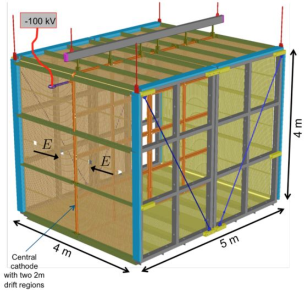
Daisy Kalra, Columbia University
On behalf of the MicroBooNE Collaboration

22nd International Workshop on Next Generation Nucleon Decay and Neutrino Detectors NNN23
October 13, 2023

The LArTPC-based Neutrino Experiments

Current Generation Liquid Argon Time Projection Chamber (LArTPC) Detectors

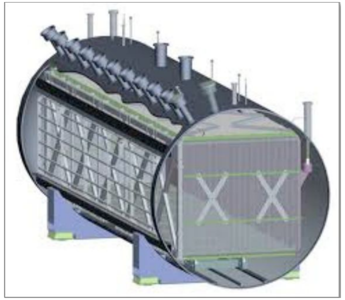
SBND - 112 tons LArTPC
Expect to begin operations in 2024



[Ann.Rev.Nucl,Part.Sci. 69, 363 (2019)]
[NNN SBN status talk]

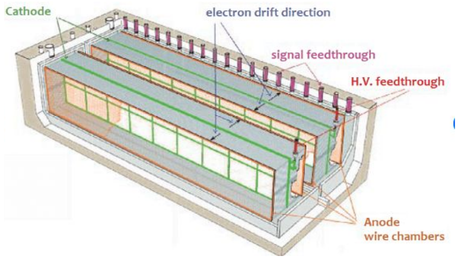
MicroBooNE - 85 tons LArTPC
Collected data 2015-2021

[JINST 12 (2017) 02, P02017]
[NNN MicroBooNE status talk]



ICARUS - 476 tons LArTPC
Taking data

[Eur.Phys.J.C 83 (2023) 6, 467]
[NNN ICARUS status talk]



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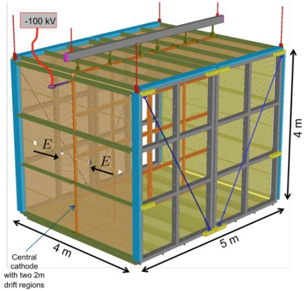

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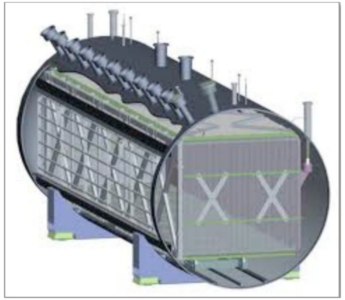

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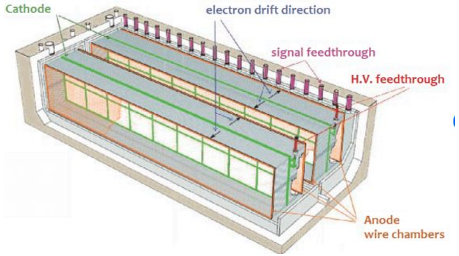
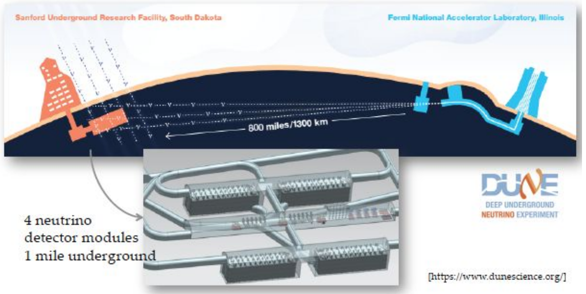
Eur.Phys.J.C 83 (2023) 6, 467
NNN ICARUS status talk



Next Generation LArTPC Detector



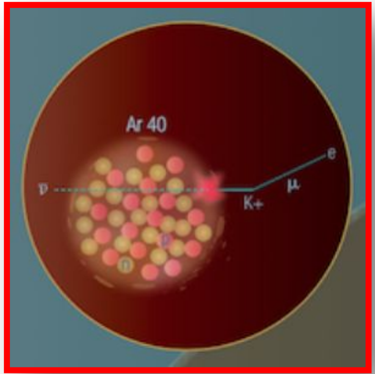
DUNE - 40 kt LArTPC
nearly x400 and x500 larger than SBND and MicroBooNE resp.
Expected to begin operations by 2026

Eur. Phys. J. C 80, 978 (2020)
NNN DUNE status talk

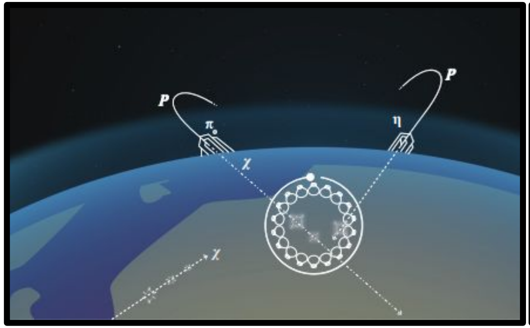
Rare Physics Processes in LArTPC-based Neutrino Experiments

➔ **Rare physics processes**

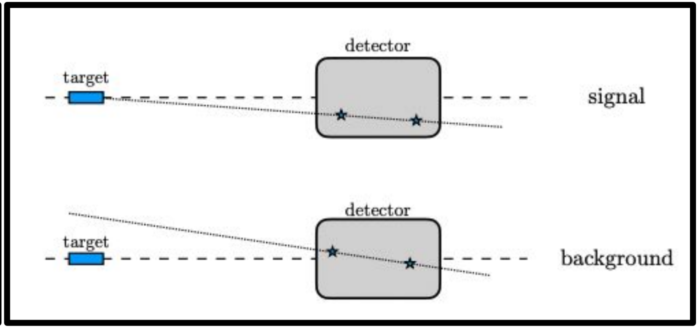
- **Neutrinos from Supernova burst** - once per century.
- **Baryon Number Violating (BNV) Processes** - proton decay (< 1 interaction per year) and neutron antineutron transitions.
- Processes involving **millicharged particles.**

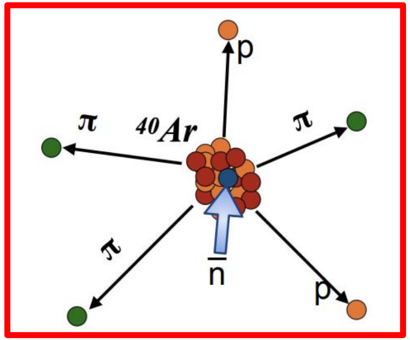


Cosmic-induced



Beam-induced





JHEP 11 (2021) 099

JHEP 07 (2019) 170

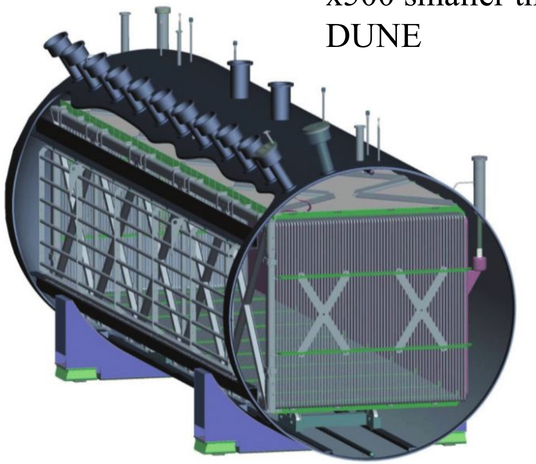
Eur.Phys.J.C 81, 322 (2021)
Eur.Phys.J.C 81, 423 (2021)

Rare Physics Processes in LArTPC-based Neutrino Experiments

- ➔ Use data from **MicroBooNE detector** to develop deep learning techniques to search for rare events
  - ◆ Focus on **neutron antineutron transition process.**

NNN MicroBooNE status talk
By Lu Ren

x500 smaller than
DUNE



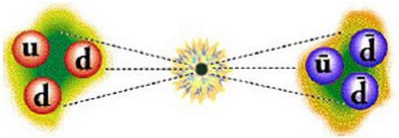
- ➔ Exposed to two beamlines-
  - ◆ On-axis to Booster Neutrino Beam (BNB).
  - ◆ Off-axis to Neutrinos at Main Injector (NuMI).
- ➔ **Recorded off-beam data (no neutrino interactions) → to develop deep learning based algorithms to search for rare events.**
- ➔ Utilize LArTPC's high resolution images of interactions.

Deep Learning Techniques for Rare Physics Processes

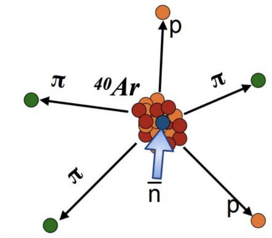
Neutron-antineutron (nnbar) transition using the MicroBooNE detector

First demonstration for a LArTPC-based search for intranuclear neutron-antineutron transitions and annihilation in 40 Ar using the MicroBooNE detector [arxiv:2308.03924](https://arxiv.org/abs/2308.03924)

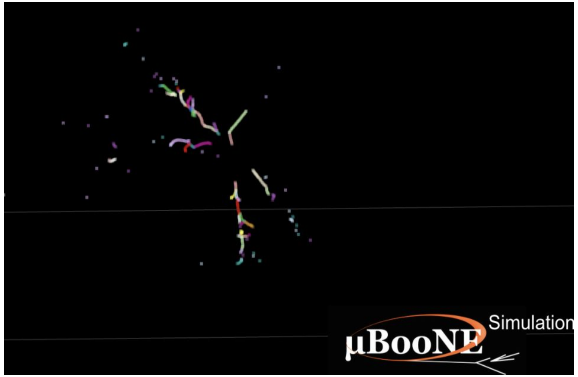
Neutron-antineutron transition



Annihilation with a nucleon

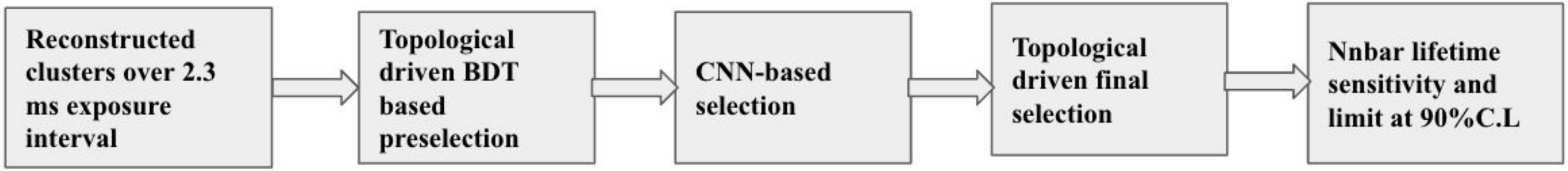


Simulated neutron-antineutron annihilation event display in MicroBooNE's LArTPC where pions are visible due to ionization energy deposits.



Deep Learning Techniques for Rare Physics Processes

The analysis flow



Deep Learning Techniques for Rare Physics Processes

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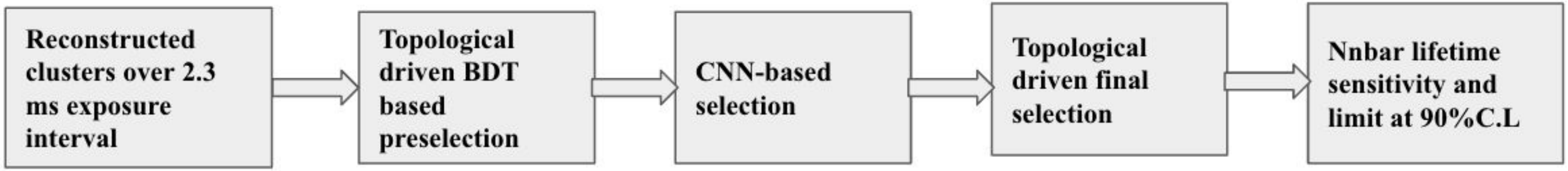
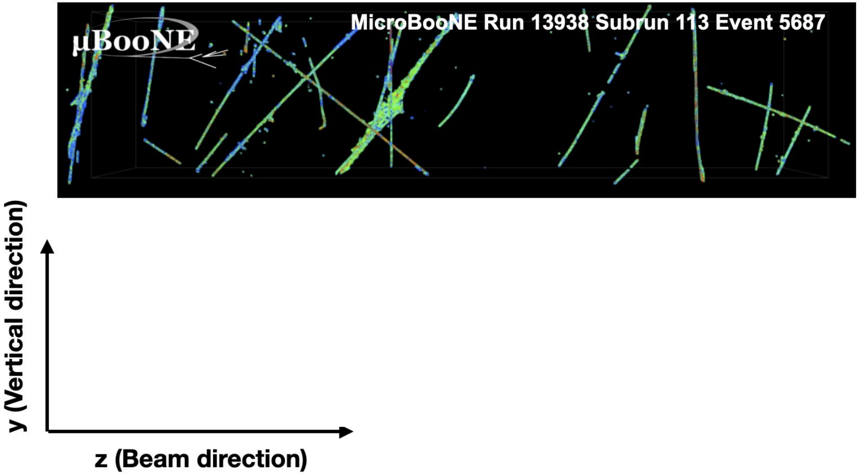


➔ The analysis begins with reconstructed “clusters” (3D objects (spacepoints) with information on position, time and charge deposition) over each exposure window of 2.3ms (~drift time) per event. [*JINST* 16 P06043]

Deep Learning Techniques for Rare Physics Processes

Neutron-antineutron (nnbar) transition - Reconstructed Clusters

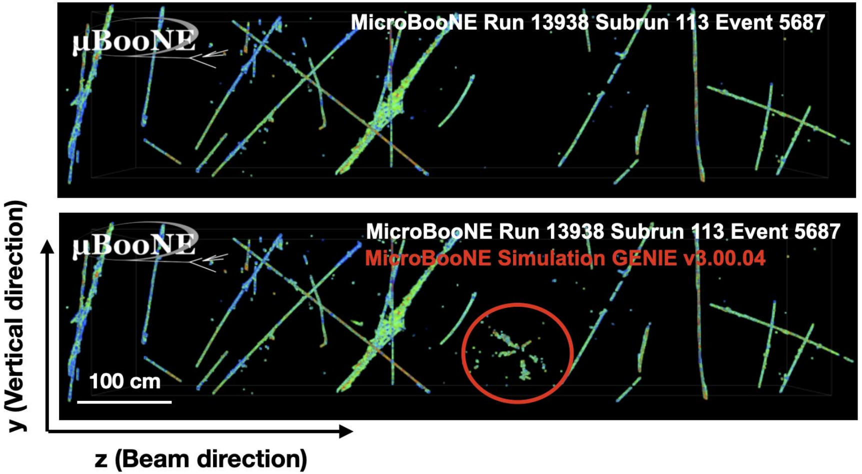
- ➔ **Background - off-beam data** (no neutrino interactions) consisting of cosmogenic interactions.
  - ◆ Cosmic ray muons and/or the induced electromagnetic and hadronic showers.
- ➔



Deep Learning Techniques for Rare Physics Processes

Neutron-antineutron (nnbar) transition - Reconstructed Clusters

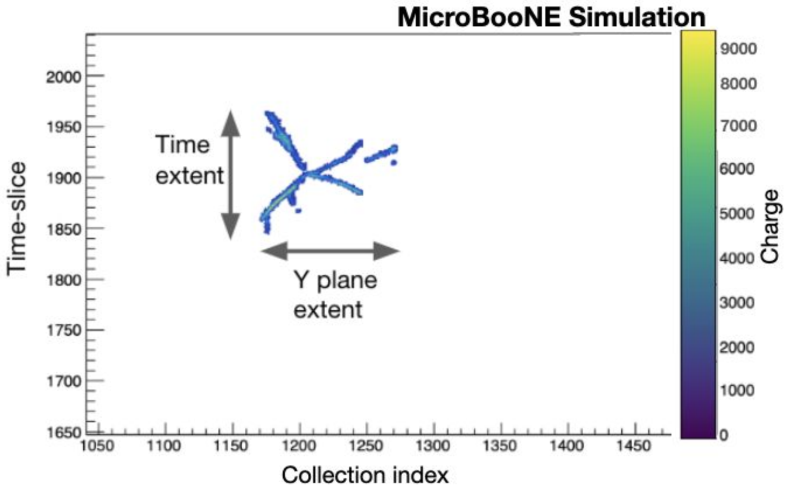
- ➔ **Background - off-beam data** (no neutrino interactions) consisting of cosmogenic interactions.
  - ◆ Cosmic ray muons and/or the induced electromagnetic and hadronic showers.
- ➔ **Signal - GENIE simulated** nnbar interactions overlaid on the top of background.
  - ◆ Utilize truth level information to separate signal and background clusters.

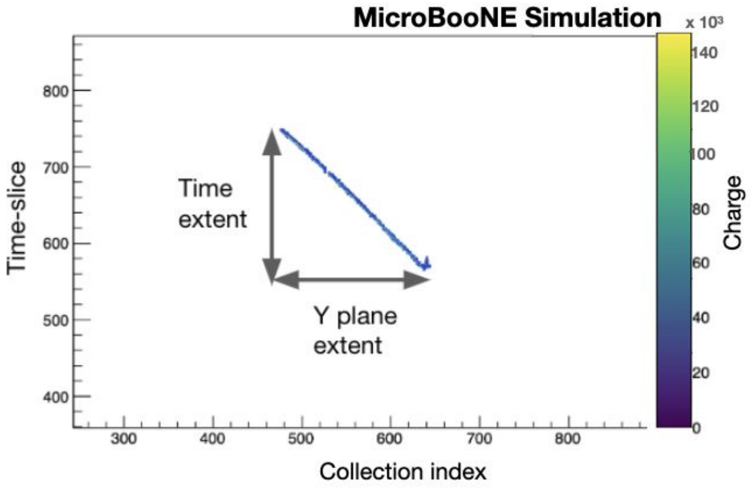


Deep Learning Techniques for Rare Physics Processes

Machine learning and deep learning based selection

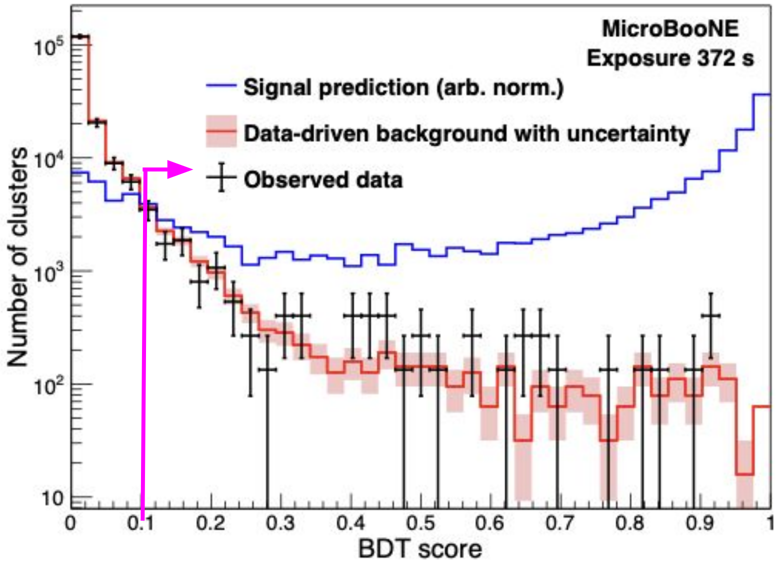
➔ Utilize topological features such as extent of a cluster (in all the planes) and number of spacepoints in a cluster to train machine-learning and deep-learning based algorithms.





Deep Learning Techniques for Rare Physics Processes

Boosted Decision Tree (BDT) performance

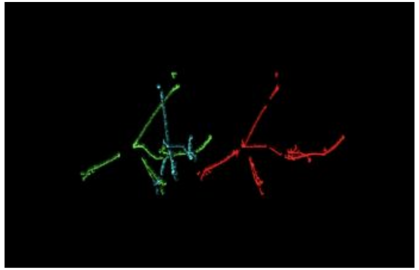


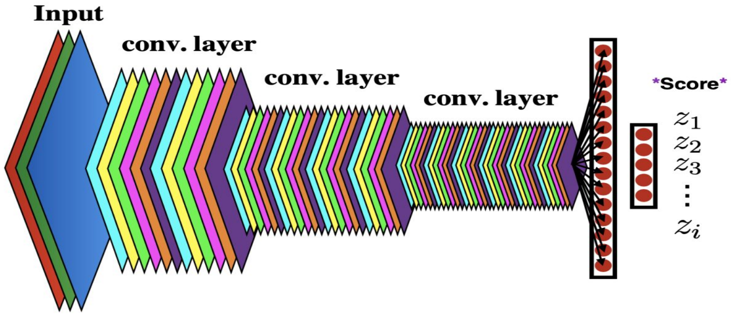
- ➔ BDT aims to effectively reject the background while maintaining signal selection efficiency.
- ➔ BDT selected clusters are used to train **deep learning (a sparse Convolution Neural Network)** network for further purify the signal and reject background.

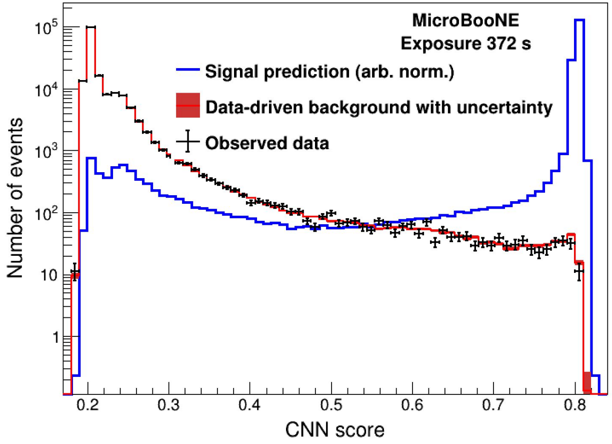
Distributions of data-driven background and **observed data** correspond to statistically independent samples where the sample used to determine data-driven background has x10 statistics than the “data” sample.

Deep Learning Techniques for Rare Physics Processes

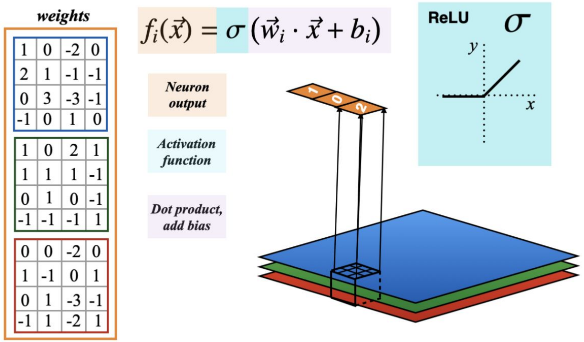
A sparse Convolution Neural Network (CNN) with *VGG16 network architecture







Sparsified (Localized) input images of interaction saving only position, time, and hit value.

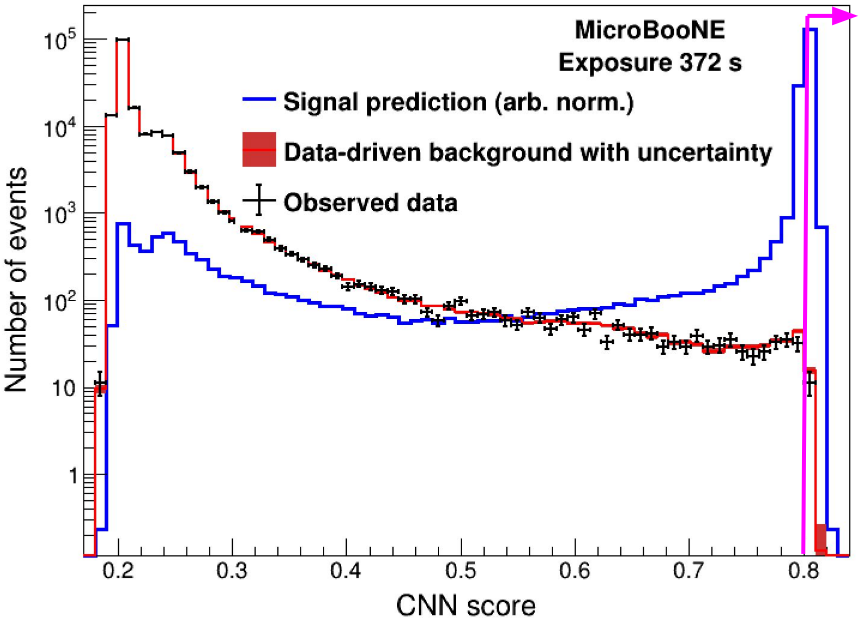


Output score represents probability, which is normalized to be summed up to 1.

*[1]: arxiv:1711.10275
*[2]: arxiv:1706:01307
*[3]: Phys. Rev. D 103 052012

Deep Learning Techniques for Rare Physics Processes

A sparse Convolution Neural Network (CNN) based selection

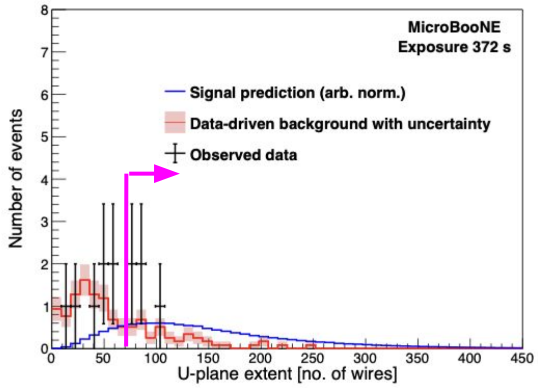


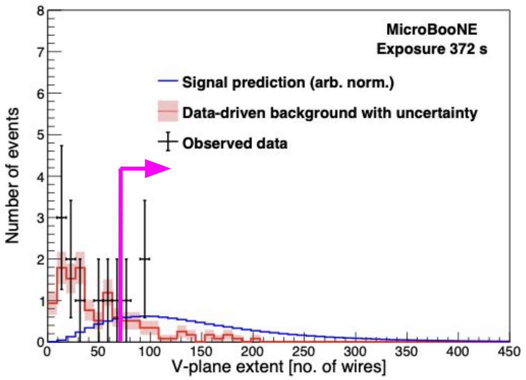
➔ Selecting signals with CNN > 0.80 (a score cut is optimized based on sensitivity (90% CL) as a figure of merit), yields 72% signal selection efficiency.

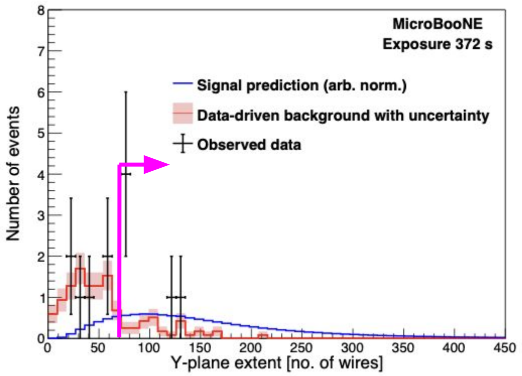
Deep Learning Techniques for Rare Physics Processes

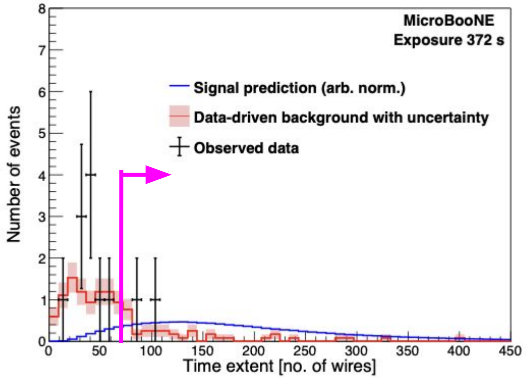
Topological based selection

➔ Further, a topological based selection is applied to further reject the background.









Deep Learning Techniques for Rare Physics Processes

Final selection

Selection Stage		Signal	Background
No selection		1,633,525	1,618,827
Stage 1	BDT > 0.1	1,411,164	139,802
Stage 2	CNN > 0.8	1,202,281	142
Stage 3	Topological	1,147,157	32
Signal selection efficiency		70.0%	-
Background rejection efficiency		-	99.99%

➔ **Deep-learning algorithms, trained utilizing topological features** only, yield an impressive **signal selection efficiency** (a **substantial improvement** over the previous results from Super-K which reported 4.1% signal selection efficiency Phys.Rev.D 103 012008).

Deep Learning Techniques for Rare Physics Processes

Uncertainties on signal selection efficiency

Systematic uncertainties	
GENIE	**4.85%**
Detector	**6.72%**
GEANT4	**2.32%**
Total systematic uncertainty on signal	**8.61% (quadrature sum of unc. From GENIE, detector and Geant4)**

Uncertainties on background

Systematic uncertainties	
Total systematic uncertainty on background	**17.68% (1/sqrt(32))**

Deep Learning Techniques for Rare Physics Processes

Limit on nnbar lifetime with 90% CL

➔ The observed events 32, corresponding to **3720 s of exposure (equivalent to 3.3 x 10^{27} neutron-years)** are used to evaluate l**ower limit on nnbar lifetime at 90% CL** using TRolke Method

Lifetime limit At 90% CL	
Bound	**5.3 x 10^{25} years**
Free	**3.3 x 10^{5} s**

arxiv:2308.03924

Suppression factor

$$\underbrace{\tau_m}_{\text{Bound neutron lifetime}} = R\,\underbrace{\tau^2_{n-\bar{n}}}_{\text{Free neutron lifetime}}.$$

➔ The obtained limits are lower than the current best limits from the Super-K experiment (Phys.Rev.D 103 012008) because of smaller-sized detector and low exposure. But, the developed methodology serves as an **important proof-of-principle for the future DUNE experiment**.

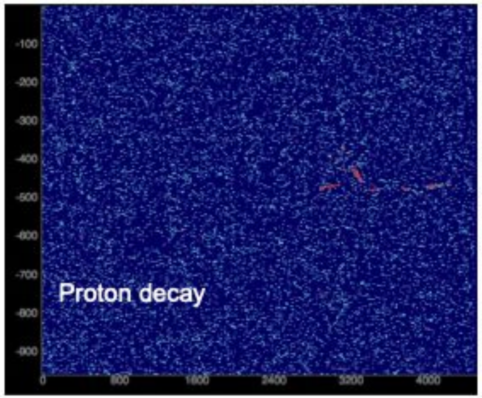
Rare Physics Searches in the Next-Generation Large-Scale LArTPC Detector (DUNE)

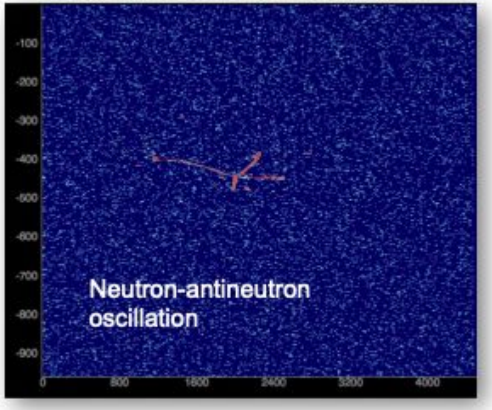
Rare Physics Searches in DUNE

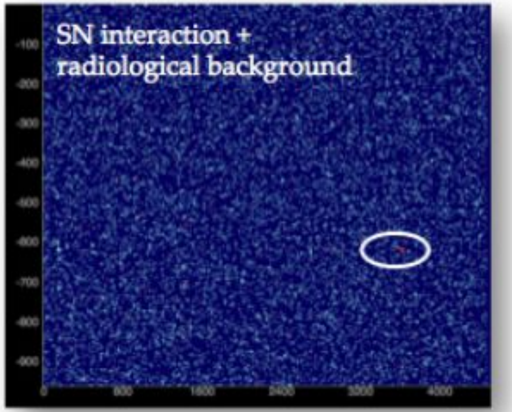
Eur.Phys.J.C 81, 322 (2021)
Eur.Phys.J.C 81, 423 (2021)

➔ One of the physics goals of the DUNE detector is to search for **non-beam rare physics events** such as neutrinos from Supernova burst and BNV processes -

- **Random in time.**
- **Require continuous readout with 100% live time.**



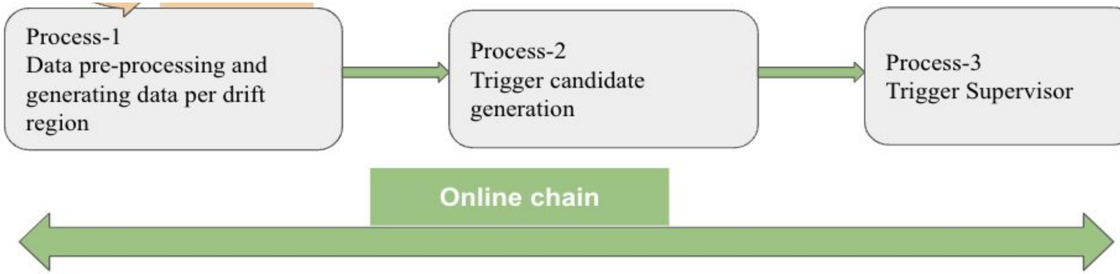




➔ DUNE, with millions of readout channels, will have uncompressed data rates > 5TB/s.

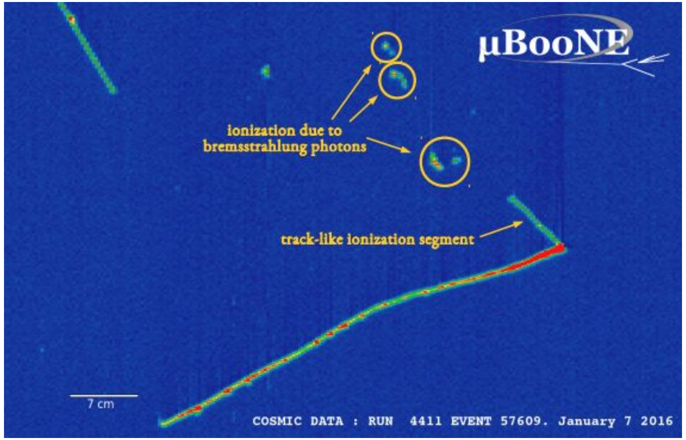
➔ This motivates to develop an **efficient data-driven triggers** to target such searches.

Data-Driven Trigger Development using MicroBooNE



Following DUNE FD selection approach

[*JINST* 16 (2021) 02, P02008]



- ➔ **Low level Trigger Primitives,** manually generated from the continuous stream **TPC data**, are used to generate a **high level trigger decision** → generate data-driven trigger.

- ➔ Currently, this framework is being demonstrated to identify michel electrons based on both the topological and calorimetric information.

[*J.Phys.Conf.Ser.* 2374 (2022) 1, 012163]

Summary

➔ **Demonstrated LArTPC's capability, using MicroBooNE's data, combined with deep-learning algorithms to select neutron-antineutron transition-like events (one of the rare physics processes) with impressive signal selection efficiency (70%) and strong background rejection.** arxiv:2308.03924

➔ **Demonstrating online data-driven self-triggering on cosmogenic activities using the MciroBooNE data**
(Stay tuned for the publication!)
- Future plans are to demonstrate self-triggering capability in real-time using SBND detector on more complex physics processes including rare events and other new signatures e.g. millicharged particles.

➔ **Both of these developments, using MicroBooNE , enhance DUNE's capability in the realms of low-energy physics and rare event searches.**

THANKS

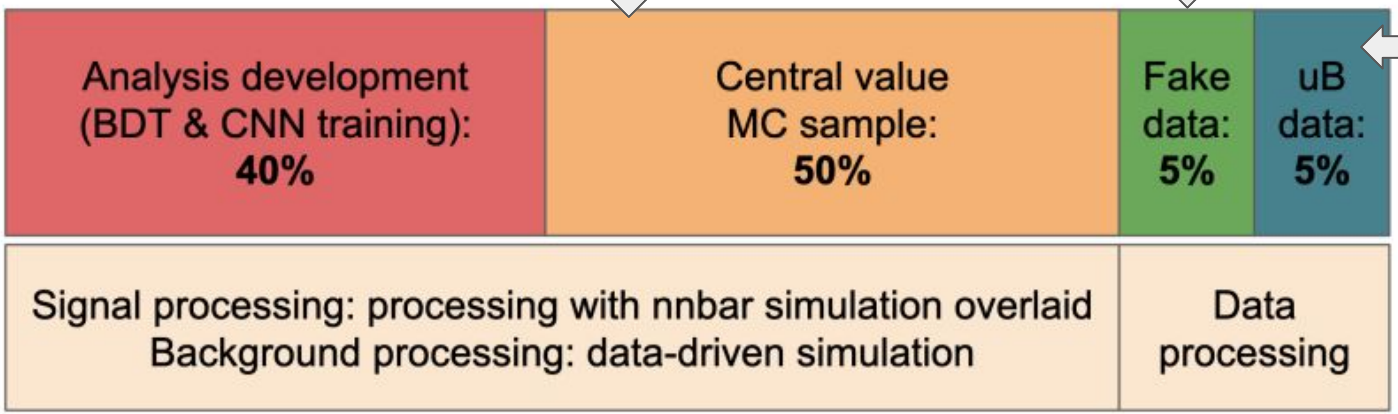
Microboone Collaboration (2021)

Sample Division

CV sample has an exposure x10 larger than the data exposure.
CV sample is used to estimate background and hence to evaluate systematic uncertainties on background (EXT-unbiased data)

And to evaluate real limit on nnbar lifetime

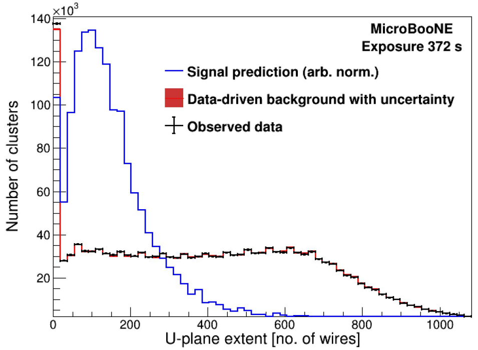
The analysis is developed as blind analysis and tested first on fake-data sample before looking into the data. Fake-data is prepared by injecting x% of nnbar signal into EXT-data.

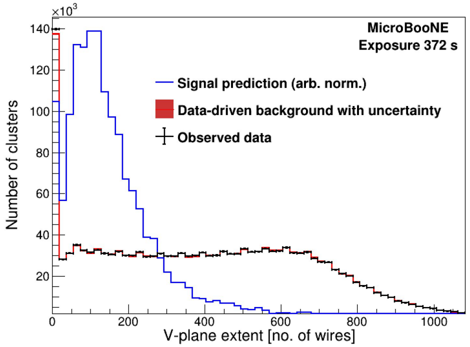


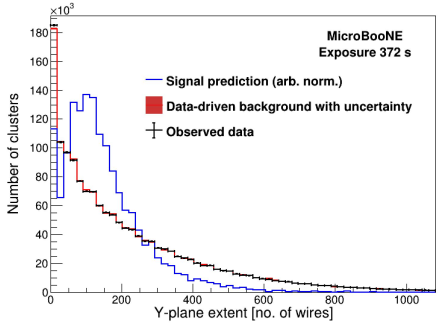
For evaluating 90% C.L sensitivity and demonstrative limits to nnbar lifetime.

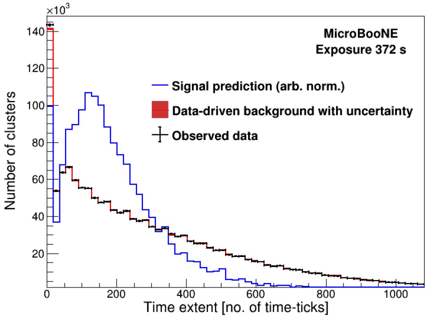
Deep Learning Techniques for Rare Physics Processes

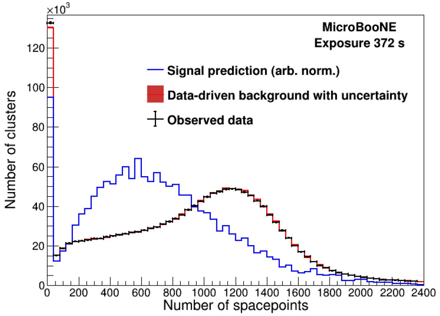
Machine learning and deep learning based selection











Current Best Limit

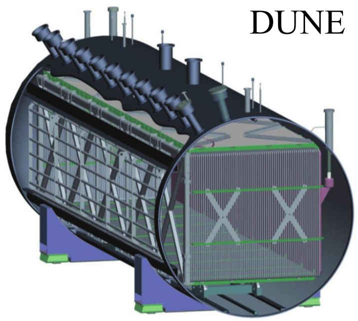
- ➔ Current best limit on nucleus (^{16}O) bound neutron-antineutron process is from Super-K experiment. (Phys. Rev. D 103 012008)
  - ◆ Using 6050 live days of data (representing 0.37 Mton-years), 11 candidate events were observed with an expected background of 9.3 ± 2.7.
  - ◆ A lower limit on the ^{16}O bound neutron-antineutron transition lifetime is placed 3.6×10^{32} years at 90% C.L.
- ➔ Stringent bound on n-nbar transition rate probes BNV theories attempting to explain the observed baryon asymmetry in the Universe Phys. Rev. D 87, 115019, Phys. Rev. D 87, 075004

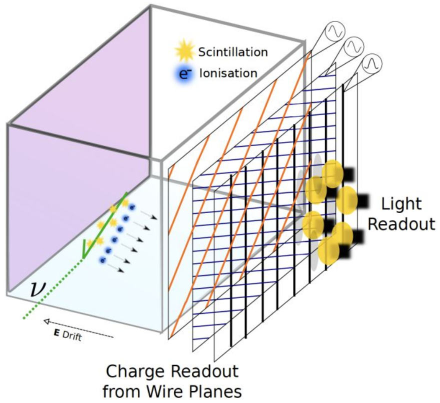
MicroBooNE

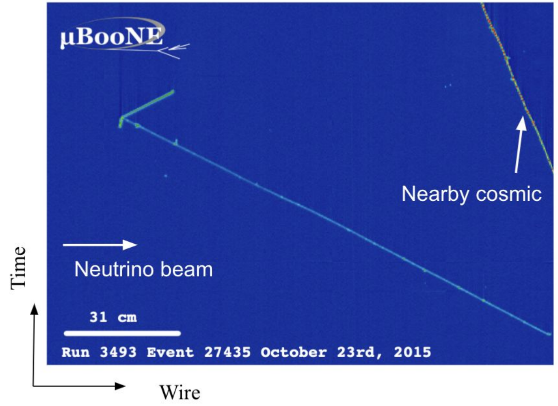
NNN MicroBooNE status talk

R&D for the next-generation LArTPC-based experiments

x500 smaller than DUNE







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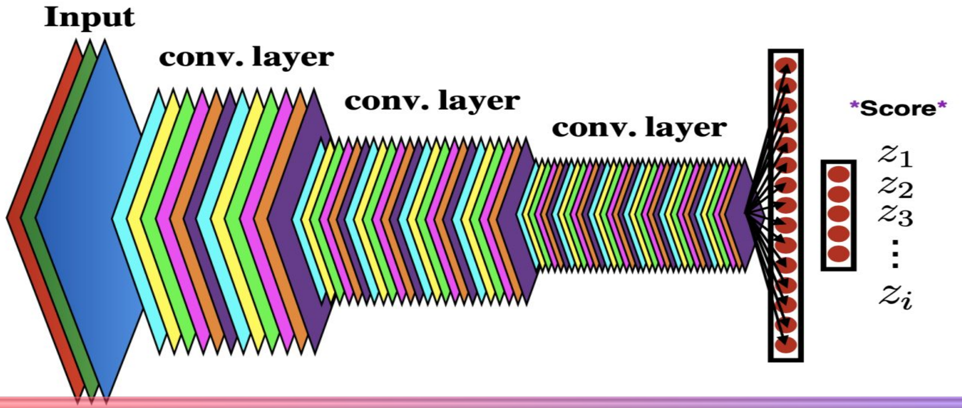
  - ◆ Off-axis to Neutrinos at Main Injector (NuMI).
- ➔ **Recorded off-beam data (no neutrino interactions) → to develop deep learning based algorithms to search for rare events.**

- ❖ 2-D images of interaction with information of deposited ionization as a function of wire and time.
- ❖ Excellent spatial resolution, particle identification and excellent calorimetry.

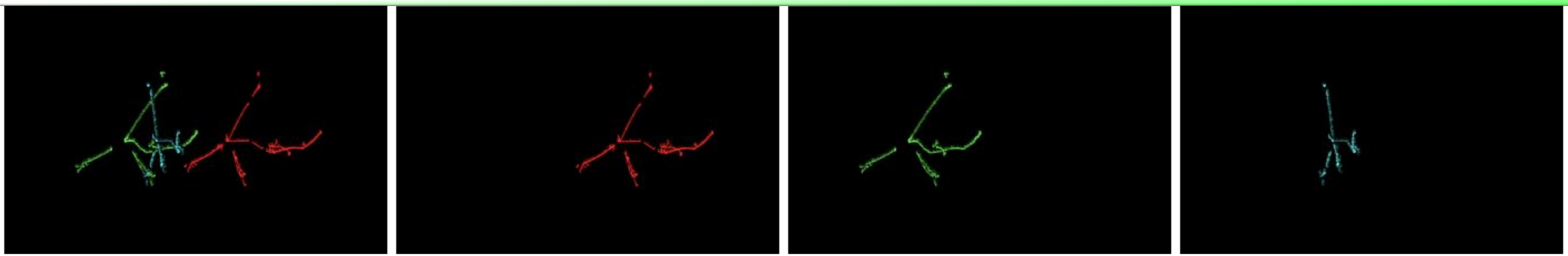
Deep Learning Techniques for Rare Physics Processes

A sparse Convolution Neural Network (CNN) with *VGG16 network architecture



*[1]: arxiv:1711.10275
*[2]: arxiv:1706:01307
*[3]: Phys. Rev. D 103 052012

The network takes sparsified 2D input images of interaction (saving only position, time and hit value) in three planes (U,V, and Y).

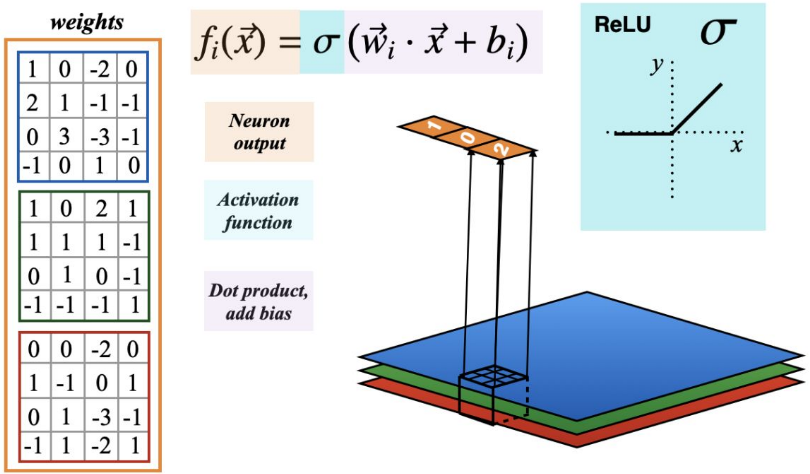


Deep Learning Techniques for Rare Physics Processes

A sparse Convolution Neural Network (CNN) with VGG16 network architecture

Input image is first convolved through linear transformation.
Rectified Linear Unit (ReLU) is used to introduce non-linearities → help CNN to learn about the input features in-depth.

Network layer	Kernel size	Filter depth
Input (Collection plane image)		
Convolution	3×3	64
Convolution	3×3	64
Max pool	2×2	
Convolution	3×3	128
Convolution	3×3	128
Max pool	2×2	
Convolution	3×3	256
Convolution	3×3	256
Max pool	2×2	
Convolution	3×3	512
Convolution	3×3	512
Convolution	3×3	512
Max pool	2×2	
Convolution	3×3	512
Convolution	3×3	512
Convolution	3×3	512
Max pool	2×2	
Fully connected		

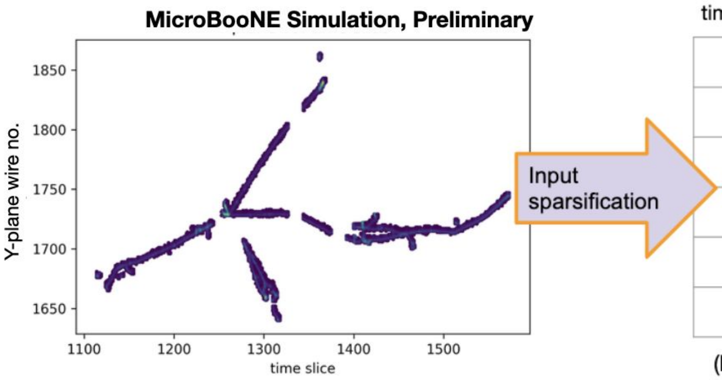


Deep Learning Techniques for Rare Physics Processes

BDT and CNN based selection

➔ A sparse-CNN uses a *VGG16 network with ~15 convolution layers, and a columnar sparse input.

Saving only the position, time and hit value rather than the full image and no loss in resolution of the image as in downsampling



time slice	Y plane index	hit value
1392	1710	9911
1393	1710	7950
...	...	...
1364	1863	1738
1362	1864	3402
1363	1864	3512

(N, 3) format
N: the number of space points in a cluster

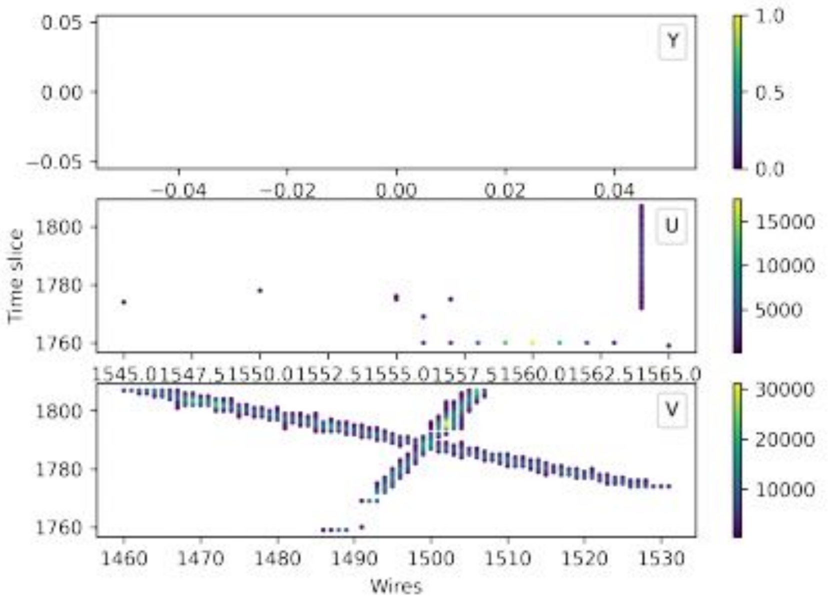
*[1]: arxiv:1711.10275
*[2]: arxiv:1706:01307
*[3]: Phys. Rev. D 103 052012

CNN score cut optimization

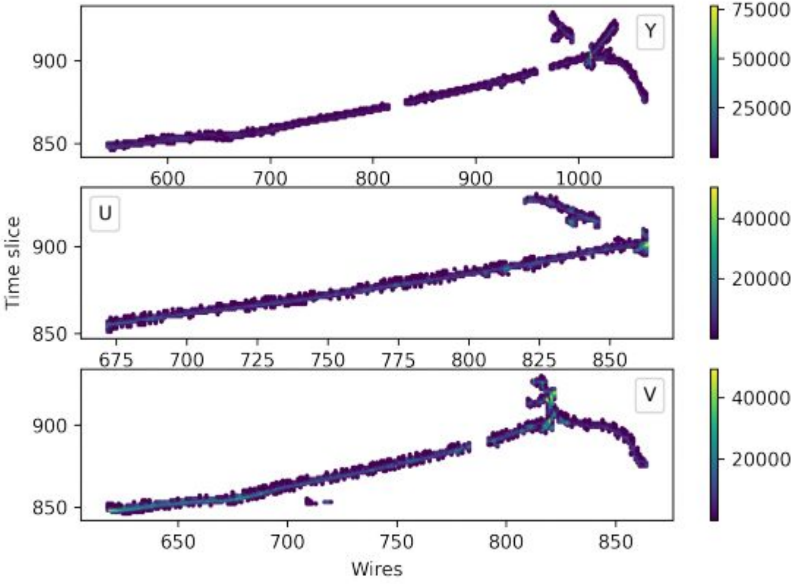
- ➔ CNN score cut is optimized based on sensitivity as a figure of merit.
- ➔ Sensitivity is evaluated with 90% CL using TRolke approach.
- ➔ A score cut at 0.8 maximizes the sensitivity.

CNN cut	Sensitivity
0.797	2.62e+25 yrs
0.798	2.83e+25 yrs
0.799	2.98e+25 yrs
0.800	2.99e+25 yrs
0.801	2.95e+25 yrs
0.802	2.65e+25 yrs
0.803	1.95e+25 yrs

CNN selected clusters

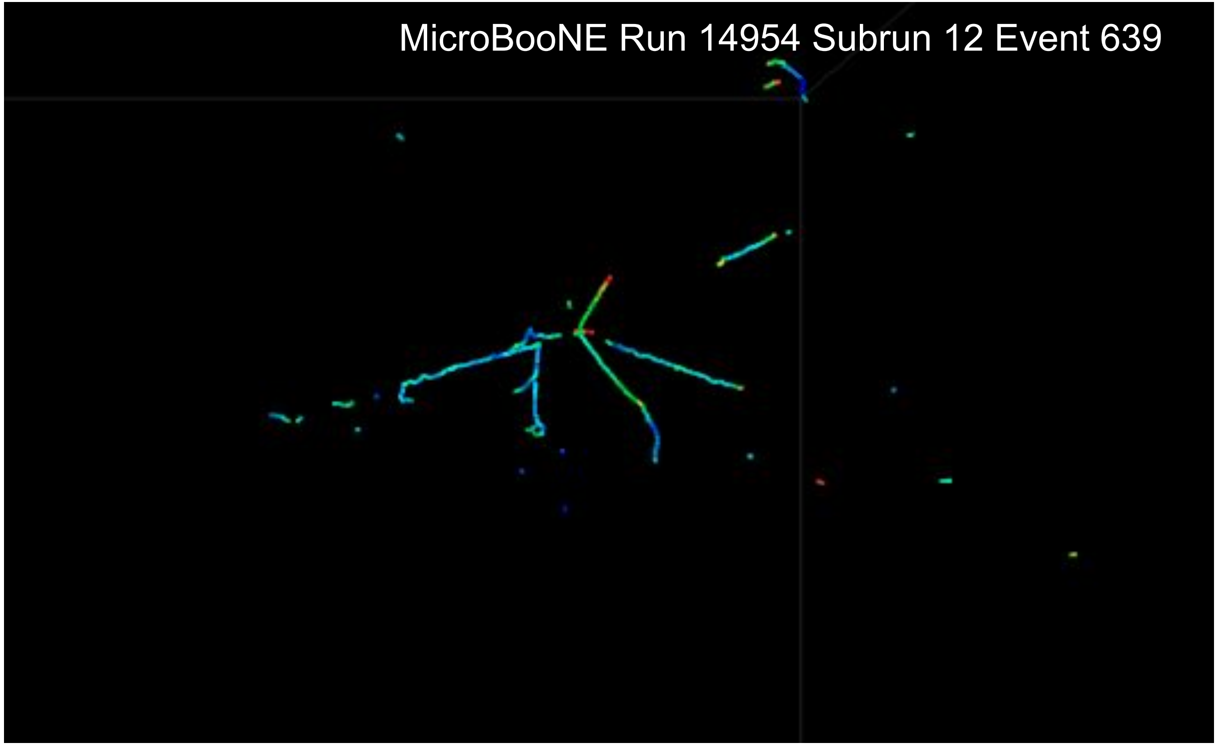


Clusters with zero extent in one of the planes.

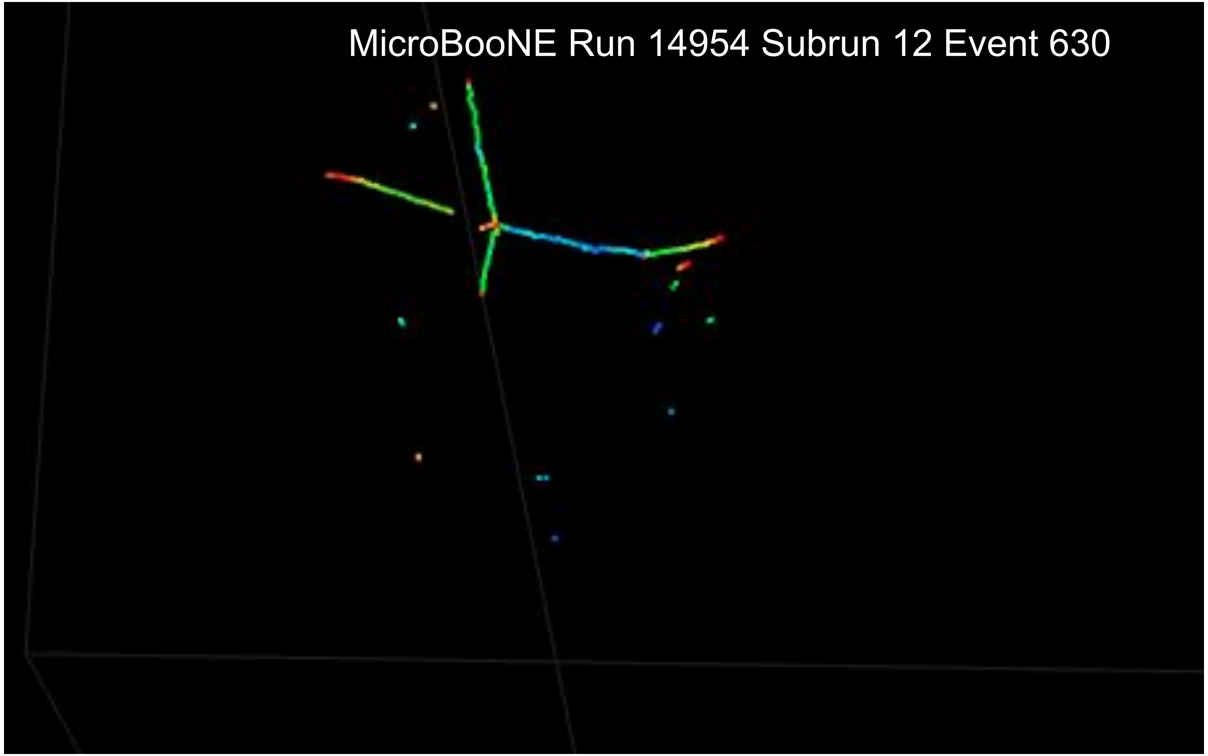


Simulated signal clusters (that passed CNN) with extent > 200 wires in all the planes

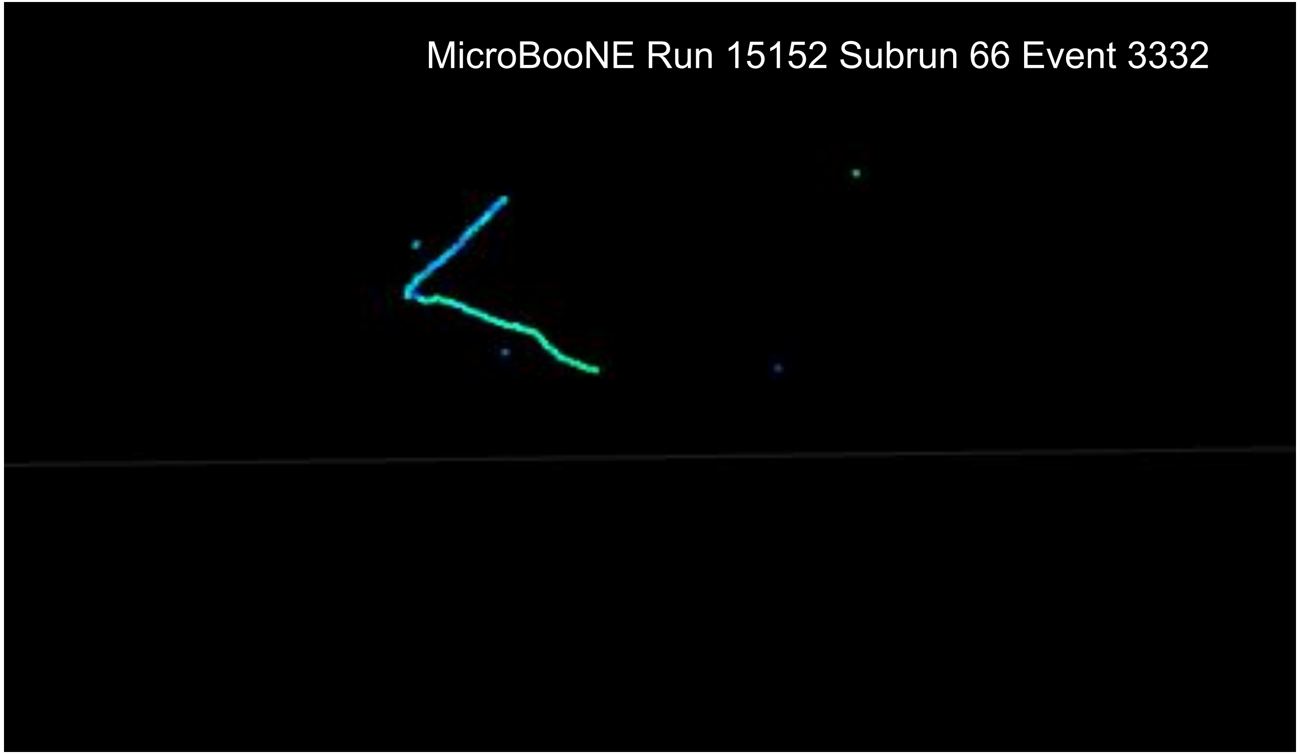
Final Selected Signal Cluster



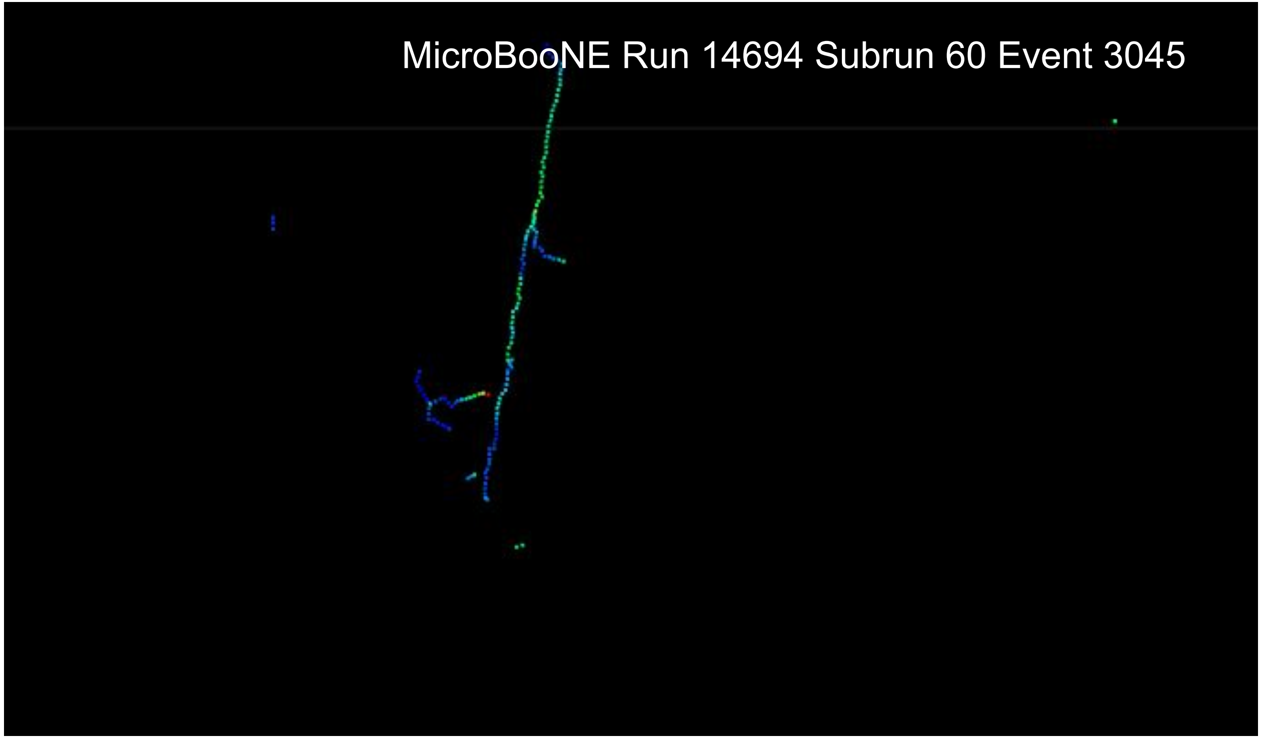
Final Selected Signal Cluster



Final Selected Background Cluster



Final Selected Background Cluster



Systematic Uncertainties on Signal

Signal selection efficiency with other models than nominal

GENIE model	η (%)
hA-BR	1.17
hN-BR	4.56
hN-LFG	1.14
Total	4.85

$$\eta = \frac{\epsilon_{\mathrm{nom}} - \epsilon}{\epsilon_{\mathrm{nom}}}$$

Nominal (hA-LFG)signal selection efficiency

$$\sigma = \frac{1}{N_{\mathrm{w}}} \sum_{i=1}^{N_{\mathrm{w}}} (W_{\mathrm{i}} - N)^2,$$

No. of weights, 1000.

Geant4 re-interactions	σ (%)
π^+	0.89
π^-	1.3
proton	1.7
Total	2.32

Systematic Uncertainties on Signal

$$\eta_{\text{err}} = \sqrt{\frac{\epsilon(1-\epsilon)}{N}},$$

$$\eta_{\text{errnom}} = \frac{\epsilon_{\text{nom}} - \epsilon}{\epsilon_{\text{nom}}},$$

Signal selection efficiency with various samples
N: number of signal events

Detector variation	η_{err} %	η_{errNom} %	η %
Recombination	0.13	0.53	0.54
Light yield	0.22	1.15	1.17
Space charge effect	0.12	0.13	0.18
TPC waveform modeling	0.24	6.59	6.59
Total			6.72