Pointlike events discrimination in the RED-100 experiment using ML algorithms

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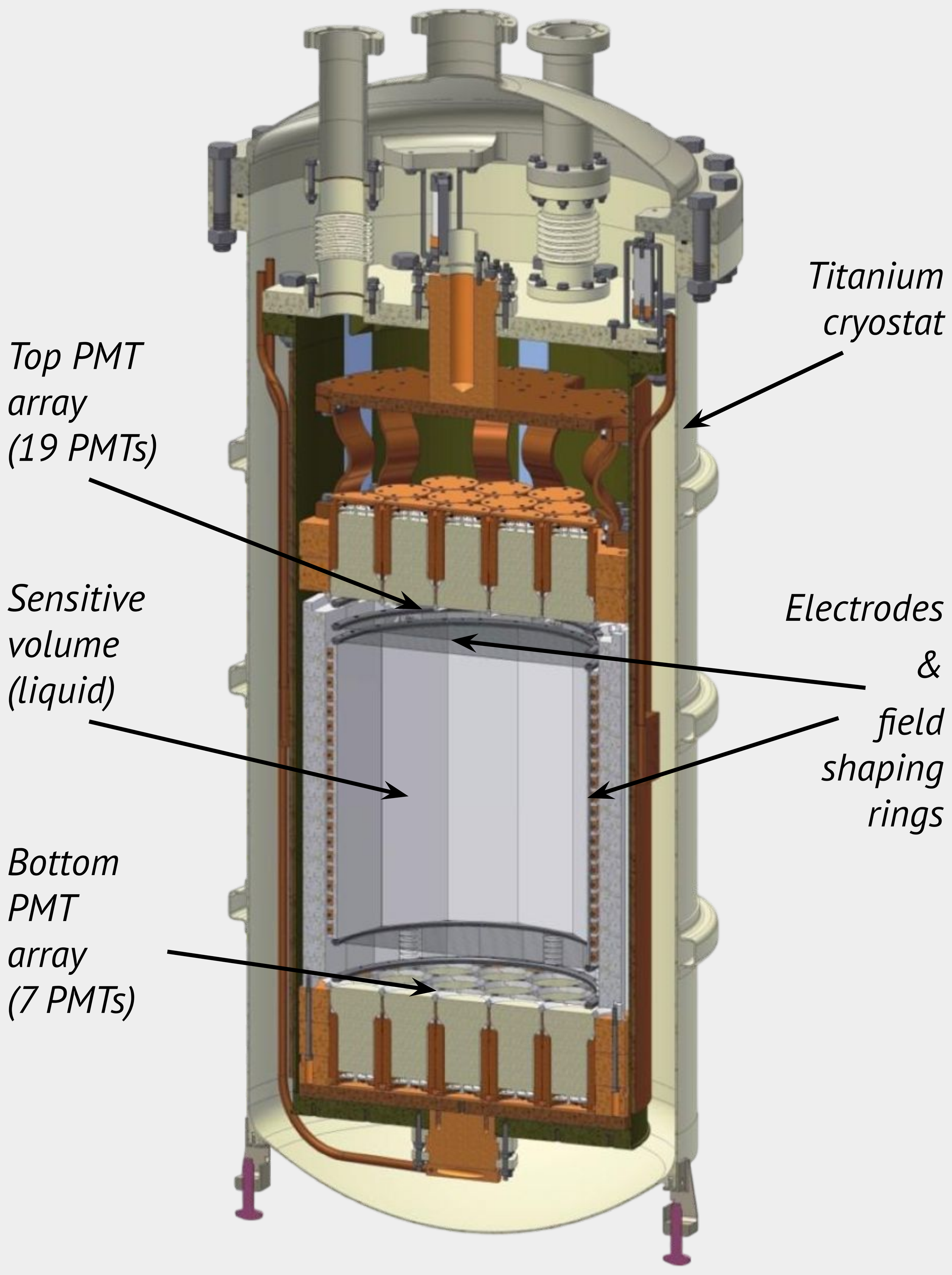
RED-100 detector

- two-phase emission detector designed to study coherent elastic scattering of reactor electron antineutrinos
- contains ~200 kg of LXe (~ 100 kg in FV) or ~100 kg of LAr (~50 kg in FV)
- 26 Hamamatsu R11410-20 PMTs
- Thermosyphon-based cooling system (LN_2)
- **Sensitive to the single ionization electron (SE) signal.**

CEvNS response is expected to be of several electrons.



2020: RED-100 was shipped to KNPP
2021: Deployed and tested
2022: (Jan-Feb) Physical run

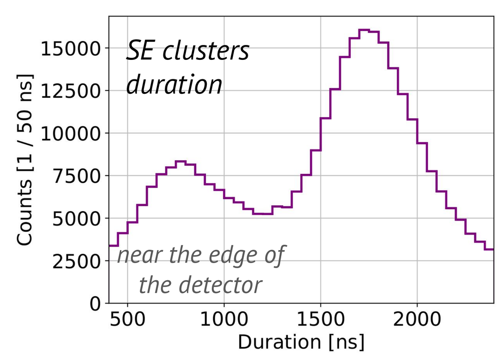
RED-100 at Kalinin NPP

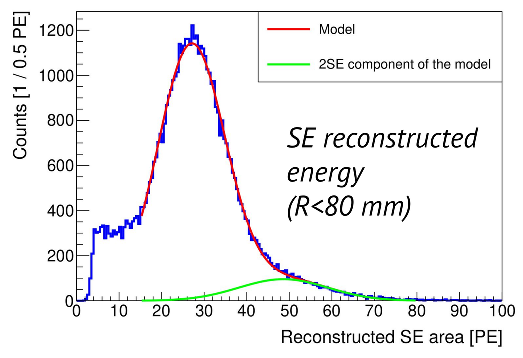
- 19 meters from the reactor core
- reactor and reactor building&infrastructure as a passive shielding from muons
- water tank as a passive shielding from neutrons
- 5 cm of copper passive shielding from gamma sources
- Antineutrino flux at place ~ 1.35*10^{13} $cm^{-2}s^{-1}$
- 65 m.w.e. in vertical direction

D.Z. Freedman, Phys. Rev. D 9 (1974) 1389
Kopeliovich V B, Frankfurt L L JETP Lett. 19 145 (1974); Pis'ma Zh. Eksp. Teor. Fiz. 19 236 (1974)
D.Akimov, J. Albert, P. An et.al., Science. – 2017.
D.Y. Akimov et al 2020 JINST **15** P02020

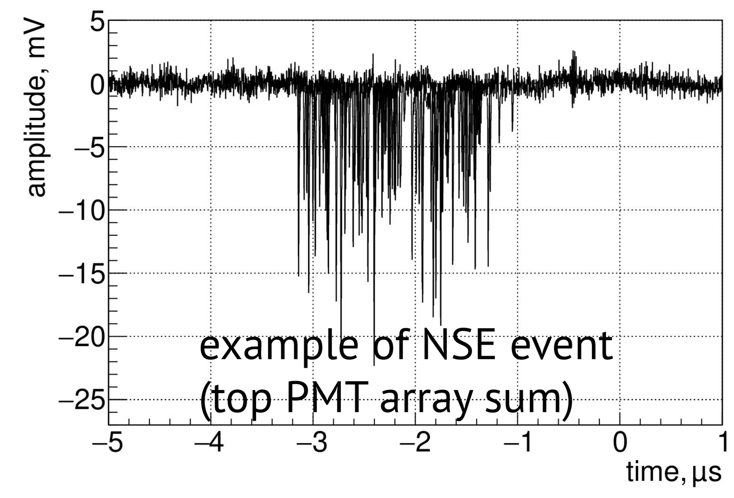
Background conditions

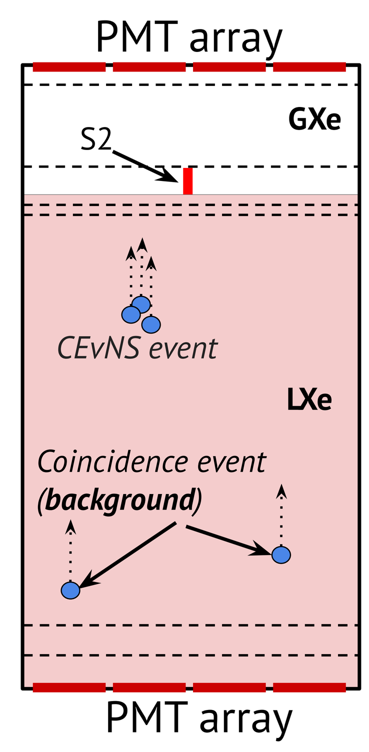
- RED-100 is working at shallow depth, unlike other similar detectors (LUX, Xenon1T).
  - → high radioactivity level
  - → significant background from spontaneous emission of SE
  - → SE rate ~25 kHz
  - → **effective is needed**





- **Background event** – coincidence of two or more spontaneous SE events (sometimes 2SE or 3SE)
- **CEvNS event** – several electrons, coming from one point





https://arxiv.org/abs/2403.12645
RED-100 at KNPP, first results and plans, ICPPA2024, A. Konovalov/O. Razuvaeva

Dataset preparation

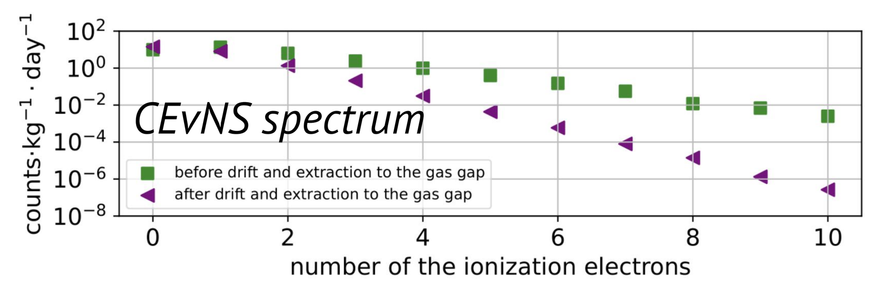
- ML solution requires training and validation data
- detailed simulation of events was performed

1. Recoil nuclei spectrum
2. Ionization in LXe (NEST)
3. Electron drift in LXe (NEST+lifetime measured experimentally)
4. Diffusion
5. Extraction (NEST+experimental ionization yield)
6. Electroluminescence (NEST+experimental light yield)
7. Optical distribution (experimental light response functions (LRFs))

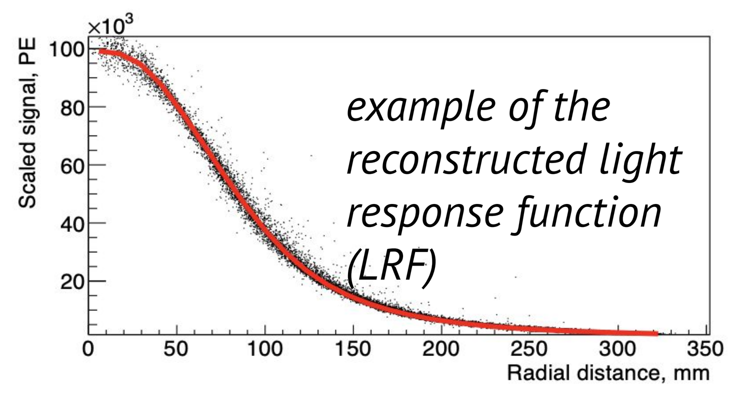
Diffusion:

$$n(\vec{x},t) = \frac{N}{4\pi D_T t \sqrt{4\pi D_L t}} \exp\left[\frac{-(x^2+y^2)}{4D_T t}\right] \times \exp\left[\frac{-(z-v_d t)^2}{4D_L t}\right]$$

Measurements of electron transport in liquid and gas Xenon using a laser-driven photocathode, O. Njoya et. al https://arxiv.org/abs/1911.11580



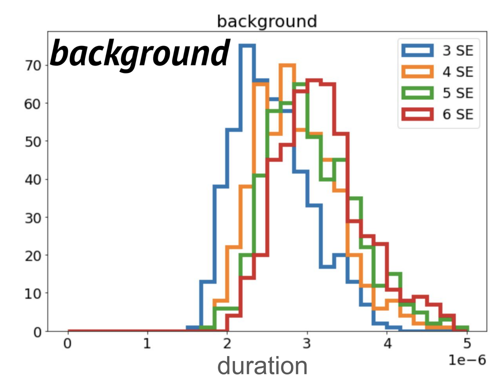
CEvNS:	background:
3 SE	[1+1+1] SE,[2+1] SE
4 SE	[1+1+1+1] SE,[2+1+1] SE,[3+1] SE, [2+2] SE
5 SE	[1+1+1+1+1] SE, [2+1+1+1] SE, [3+1+1] SE,...
6 SE	[1+1+1+1+1+1] SE, [2+1+1+1+1] SE,...

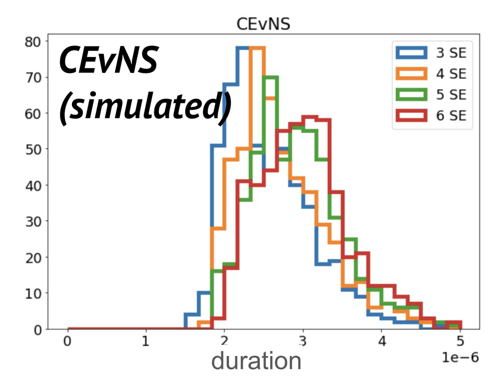


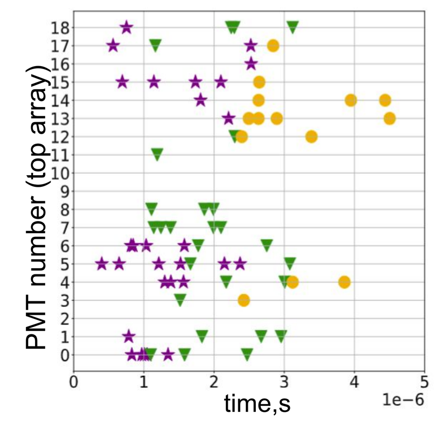
LRF reconstruction

- ANTS2 package for simulation and reconstruction
- data from ^{60}Co calibration peak were used
- both s2 energy and coordinates are reconstructed

https://arxiv.org/abs/2403.12645
A. Morozov et al 2016 JINST **11** P04022
https://nest.physics.ucdavis.edu/







Example of a simulated event
Points with different colors indicates photons from different SE

DLNN (Deep learning neural network)

Based only on the light distribution

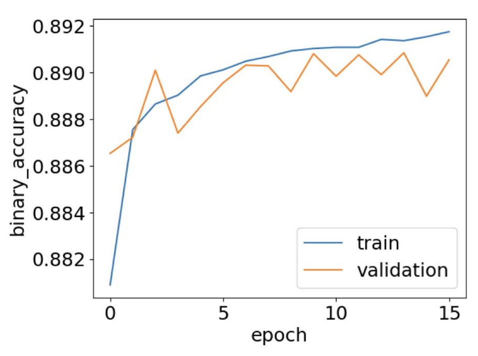
Preprocessing
- signal was normalized to make a sum of 1 across PMT matrix
- reconstructed radius<130 mm

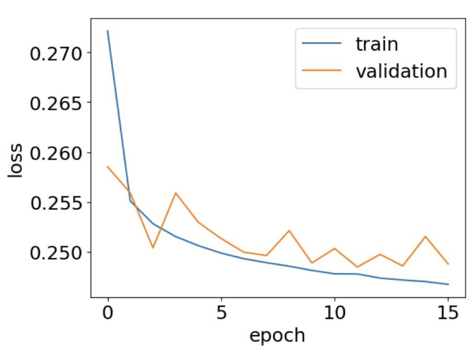
Training dataset (0.7 of all data):
~770k background events
~370k simulated CEvNS events

- Bayesian optimization from *keras_tuner* was used on validation binary accuracy metric
- A common Adam optimizer was used with a BinaryCrossentropy loss function (other optimizers were also tested without any significant improvement)

Optimized hyperparameters:
- Number of hidden layers
- Number of neurons in each layers
- Dropout/batch-normalization/no additional layers after each hidden layer
- Learning rate

Result: 4 hidden layers (70, 62, 72 and 44 neurons) with two batch-normalization layers after the first and third hidden layers





3DNN (Convolutional neural network)

Based on the light and time distribution

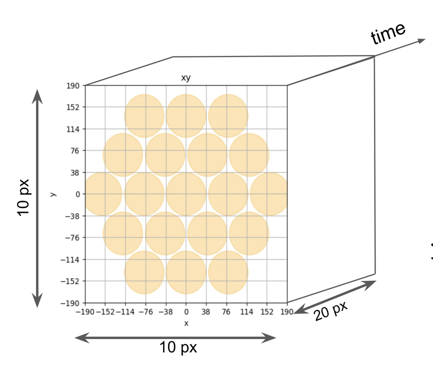
Preprocessing
- 10x10x20 pixels 3D "pseudo-images" of events were constructed
- Each pixel normalization as *(value - mean)/std,* where mean and std were calculated using all dataset

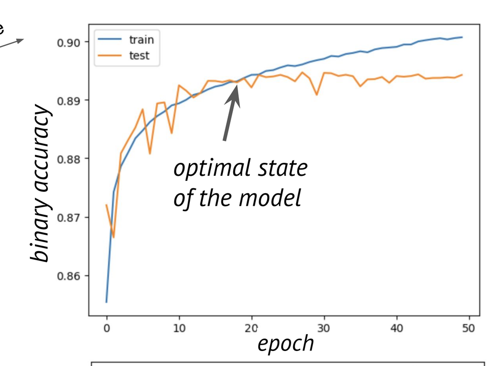
roc auc score:
0.956 (3-6 SE)
0.973 (5-6 SE)

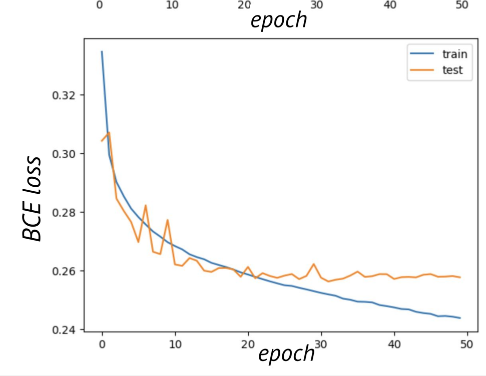
+use all available information about the event
-slow and requires a lot of information

Training dataset (0.75 of all data):
~400k background events
~400k cevns events

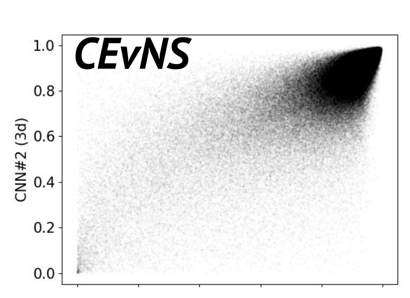
- 3 convolutional layers 3x3x5 with batch normalization after each other
- 3 fully connected layers
- Output layer with a single neuron with sigmoid activation function to show the probability of the events to be pointlike

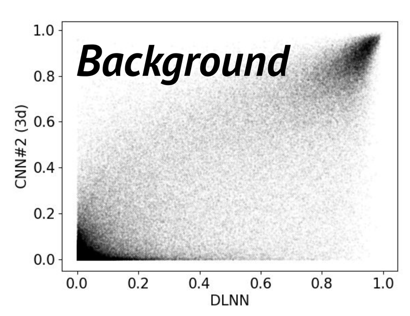






NN comparison

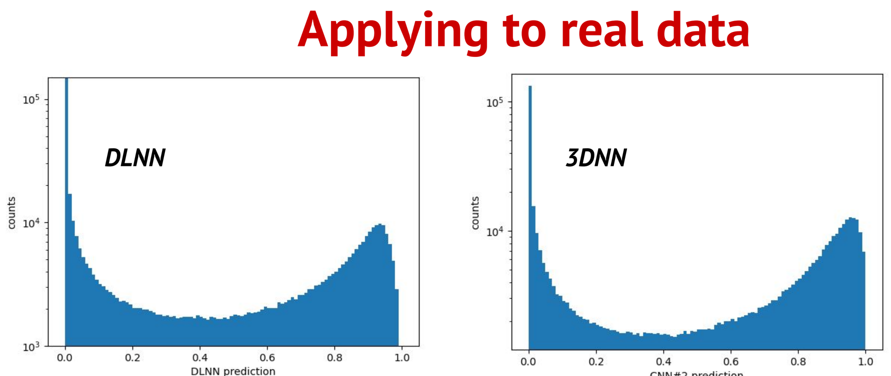




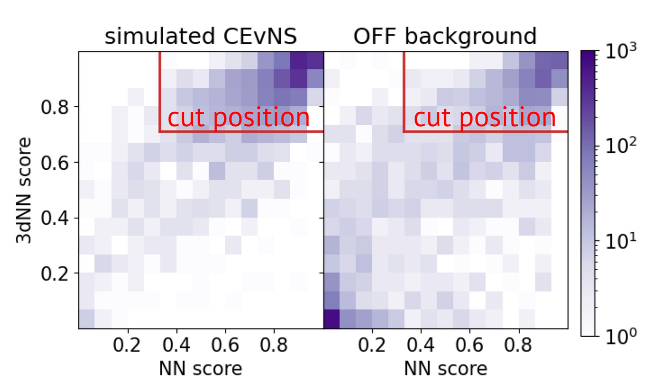
NNs predictions
(probability of pointlikeness)

- general test dataset (~600k events) was generated
- there is a correlation between NN predictions on validation dataset
- pointlike events concentrate in one place
- some background events with high probability to be pointlike

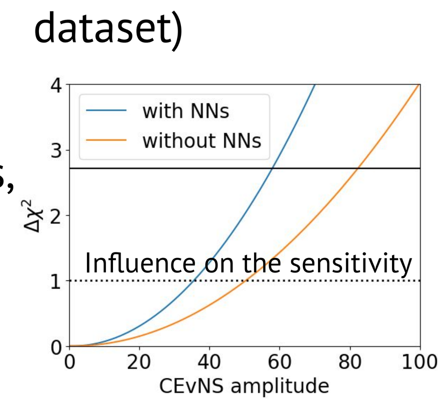
Applying to real data



A lot of pointlike events in reactor OFF background (approximately 4 times more than in a type-balanced test dataset)



After other cuts (radius, duration, signal shape)



Summary

- Two NN approaches to pointlike event selection were tested and implemented
- NNs show good results at MC events, but reality is more complicated
- DNN:

+fast learn and optimization
+less size of input data

- CNN:

+use all available information about the event
+maybe there are possibilities to improve

- 2D optimized cut is used in main branch of the RED-100 analysis