Data-driven identification of electoluminescence signals from low-energy nuclear recoils in a LAr TPC using self-supervised machine learning

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Hunting for low-energy nuclear recoils

- The ***Recoil Directionality (ReD)*** experiment, within the **Global Argon Dark Matter Collaboration** (**GADMC**), aims to study the low energy region (2-5 keV) for nuclear recoils using neutrons from a ^{252}Cf source and directed toward a dual-phase argon Time Projection Chamber (LAr TPC) [1] (*see talk by L. Pandola*)
- Due to the low energy deposited in the recoil, the only detectable signal is the electroluminescence light in gas (S2) from ionization electrons extracted in the gas phase after being drifted by a 200 V/cm field in liquid
- The readout system is made of Silicon Photomultipliers (SiPM) on two tiles placed on the top and bottom parts of the TPC
- The TPC is acquired in slave → S2-only signals are searched offline in candidates neutron events
- The pulse finder is tested with Monte Carlo simulation and it is full efficient for **S2 > 4** e^- (*~80 PE*)

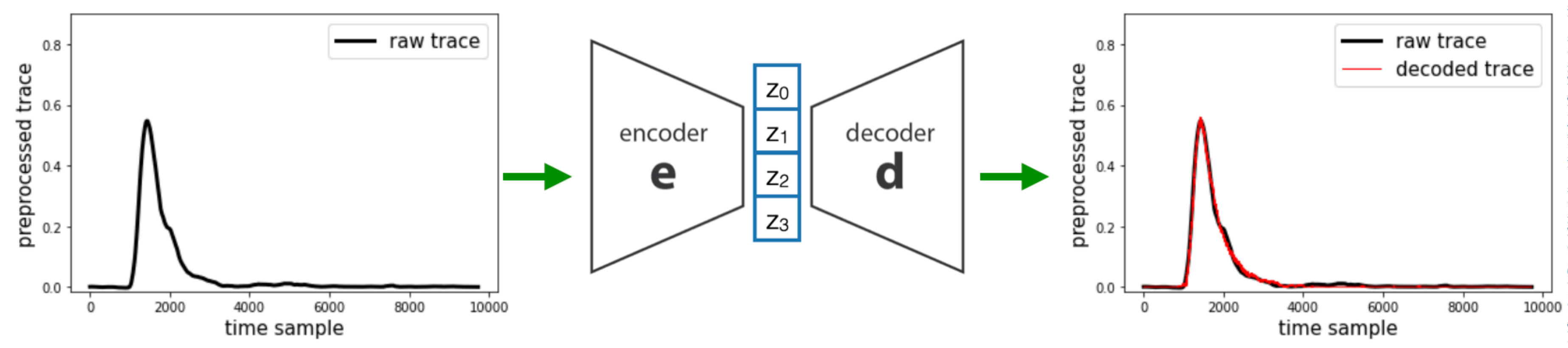
MOTIVATION
Is there a way to lower the threshold for signal detection?

Inspect the data with Convolutional AutoEncoders

- A data-driven analysis is developed training ***Convolutional AutoEncoders*** (***CAE***) to identify on S2-only events collected in the TPC
- An autoencoder is a neural network that can learn to encode the input data into a lower-dimensional representation, the **Latent Space**, and then decode it back to the original input: this neural network is composed by an **encoder** part and a **decoder** part, generally with symmetrical architecture [2]

  → autoencoders result particularly suited to finding anomalies [3] or removing noise [4] from large datasets

- The learning paradigm is ***self-supervised***, since it is not trained comparing the output with the accompanying label, but catches the features of the input encoding information in a reduced representation



The model

1. Data

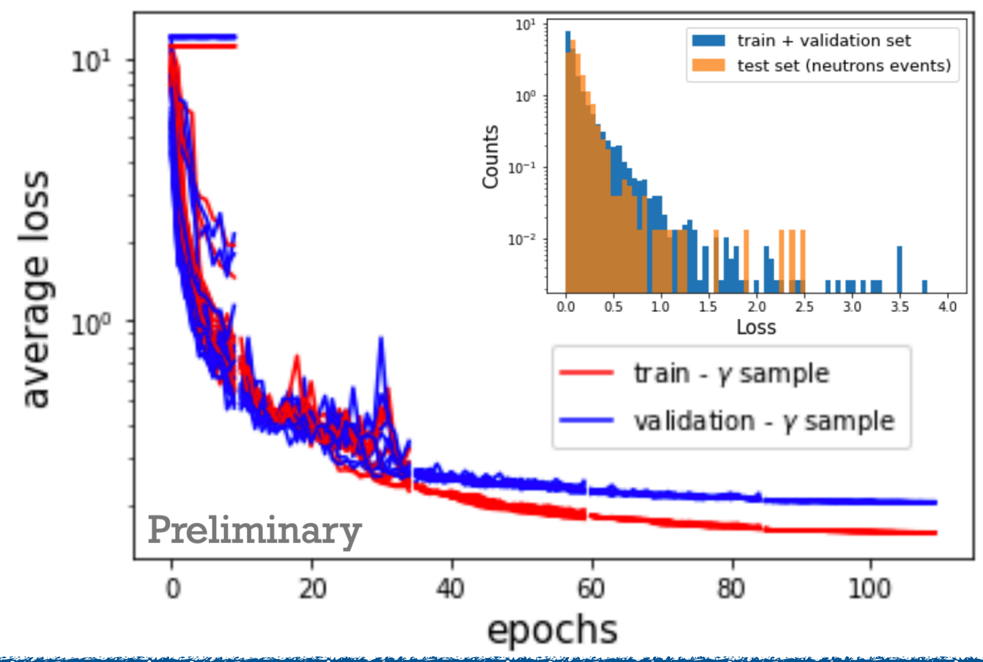
- **Averaged raw waveforms (wf)** have been used:
  - SiPMs on the top tile above the TPC anode optical window are read individually, waveforms are calibrated accordingly to single electron response
  - Calibrated wf are summed together and smoothed
- **Pre-processing**:
  - Removal of wf with unstable pedestals
  - Average in a fixed 4-sample window, to reduce length from 40,000 to **10,000 samples (8 ns per sample)**
  - Pedestal moved around 0
  - Wf inverted to have positive values between 0 and 1

2. Training procedure on INFN Cloud [5]

- **Training (+validation) set**: ~7000 wf from γ-ray accidentals with a candidate single S2 pulse, 20% of these wf are used for validation after each epoch
- Model implemented using Keras [6] with TensorFlow [7] backend: 3 Convolutional 1D + 3 Average Pooling layers, ReLu as activation function, **Mean Squared Error** (**MSE**) loss times number of time-bins
- **Competitive training procedure** between models initialized and trained with different random seeds: only the weights of the model with the lowest validation loss are saved

3. Evaluating the performance

- **Test set of candidate neutrons** : 1378 wf with a single S2 pulse

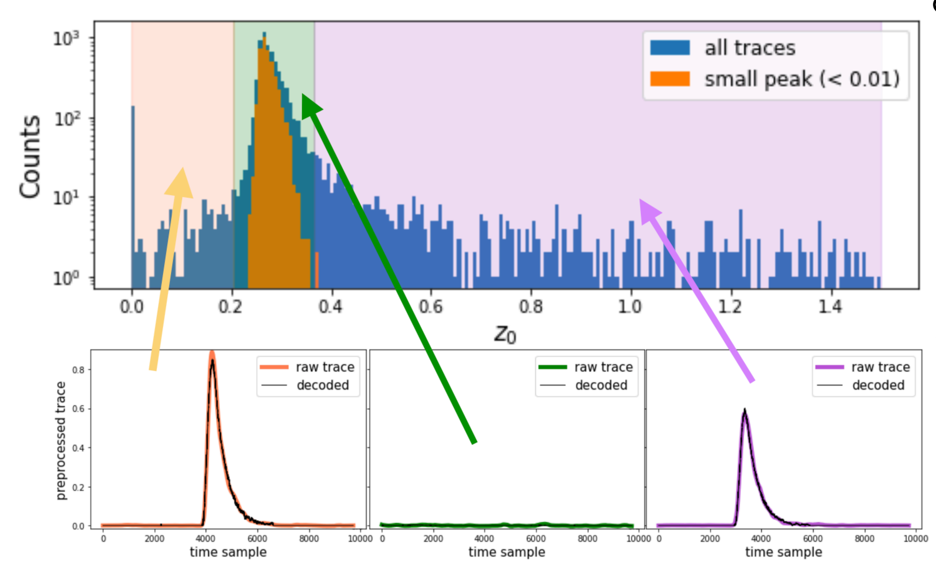


- The validation loss is decreasing. Separation w.r.t. training visible after epoch ~50 → related to the poor representativeness of the validation set
- **Inset** : comparable distributions for the loss over the test set w.r.t. the loss over the training (+ validation) dataset

The CAE-based method

1. Study of the Latent Space

- A 4-dimensional latent space allows direct study of the compressed representation, labeled as z

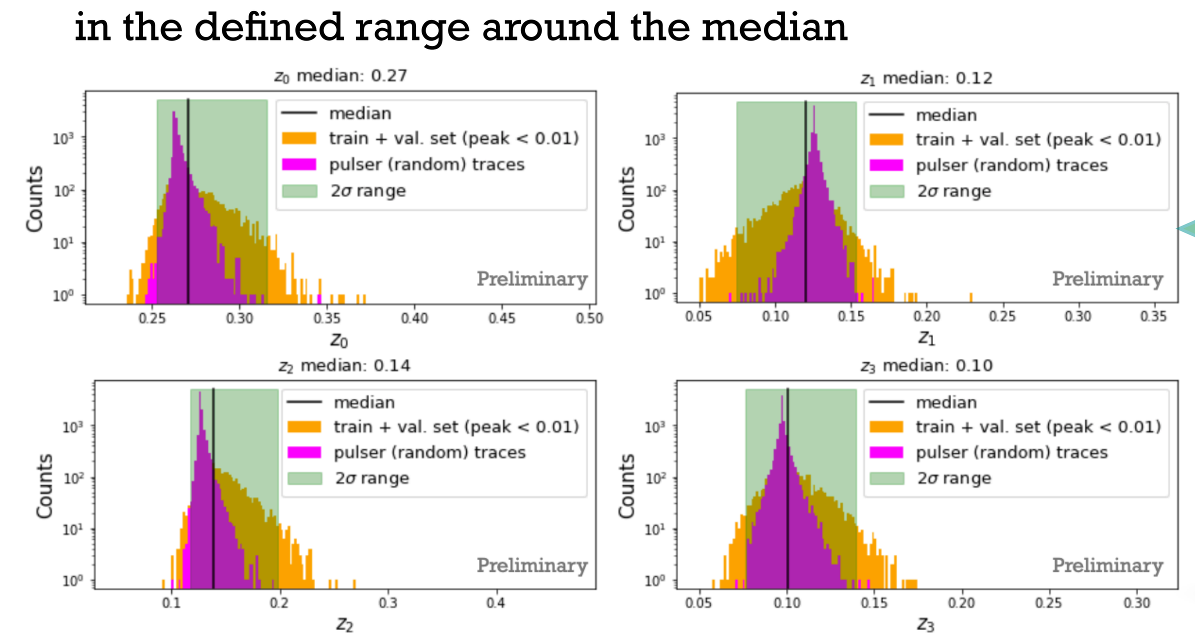


- In each z_i distribution:
  - **accumulation** around a non-zero value
  - 3 regions corresponding to the presence/absence of a visible pulse hint of a possible signal

The lower the peak (i.e. the maximum value in the waveform), the closer the z_i parameter is to the accumulation value

2. The criterion

- The accumulation point estimated as the ***median*** of the distribution for only traces with a small peak
- 2σ **range** around the median, since a small signal could be found in the ***2.5%*** of each tail of the distribution
- Discard the *"no signal"* traces within the locus in the Latent Space where all the z_i fall in the defined range around the median



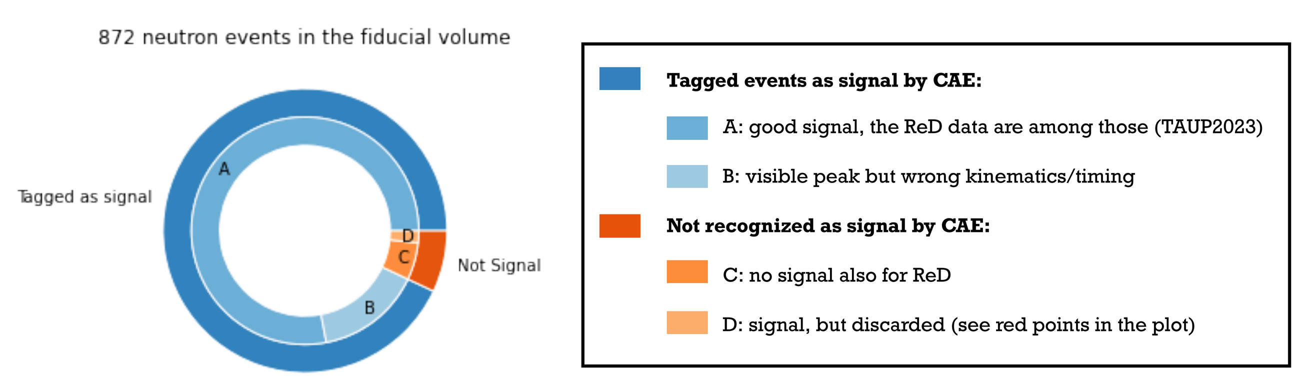
Region in the Latent Space where baseline events are most likely to be compressed

z_0	[0.25, 0.31]
z_1	[0.07, 0.15]
z_2	[0.12, 0.20]
z_3	[0.08, 0.14]

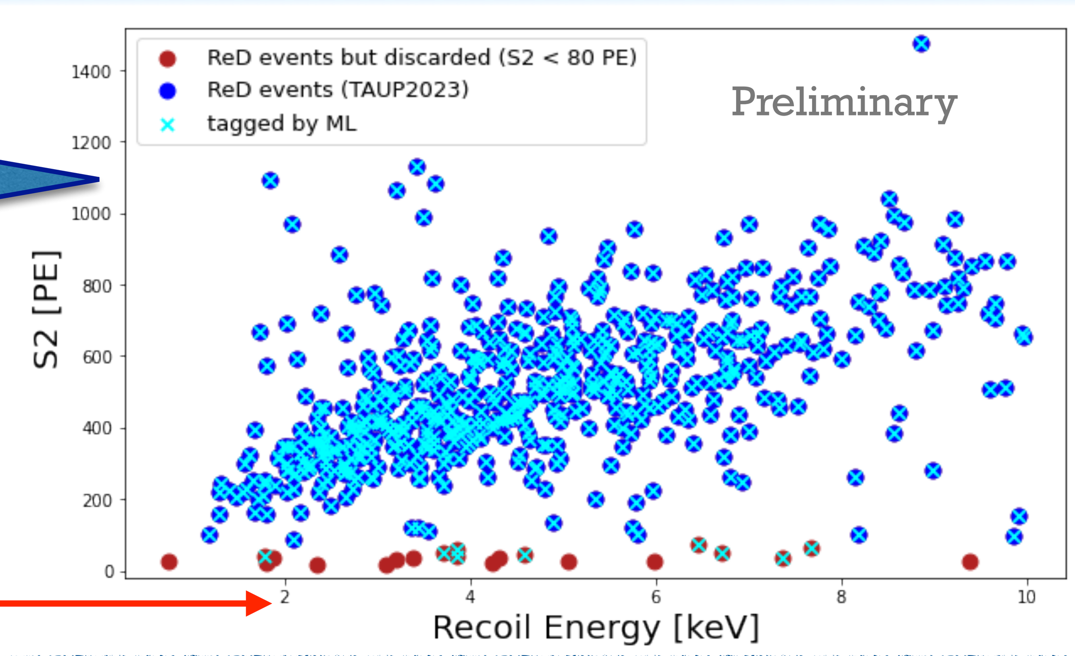
- Dataset of *noise-only events* (~10000 wf) collected with a random trigger used to validate the method and investigate the **false positives → 0.8%**
- **False negatives** investigated on a sub-set of 872 neutron wf within the inner part (4 cm x 4 cm) of the TPC (see below)

Results

- Events tagged as signals by the CAE-based method are benchmarked against the "conventional" analysis on the preliminary dataset presented by ReD at TAUP 2023 [1]



Events in the preliminary dataset presented by ReD are all tagged as signal by the CAE method



Recoil energy calculated by kinematics

References

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[5] INFN Cloud, https://www.cloud.infn.it/

[6] M. Abadi *et al*, (2015). TensorFlow: Large-scale machine learning on heterogeneous systems. https://www.tensorflow.org/

[7] F. Chollet, Keras (2017) https://github.com/fchollet/keras

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Spoke2 - WP3 - use-case **DAIDREAM** (**DA**ta-driven **ID**entification of **R**are **E**vents in **A**stroparticle physics through **M**achine learning techniques)