# Analysis of GERDA detector surface events with deep learning algorithms

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for the GERDA collaboration

26. 03. 2019

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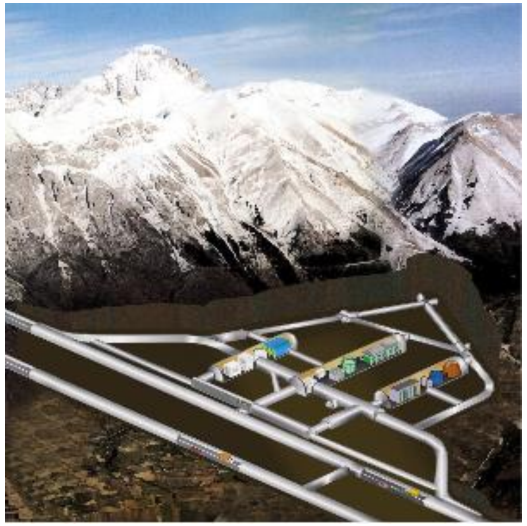
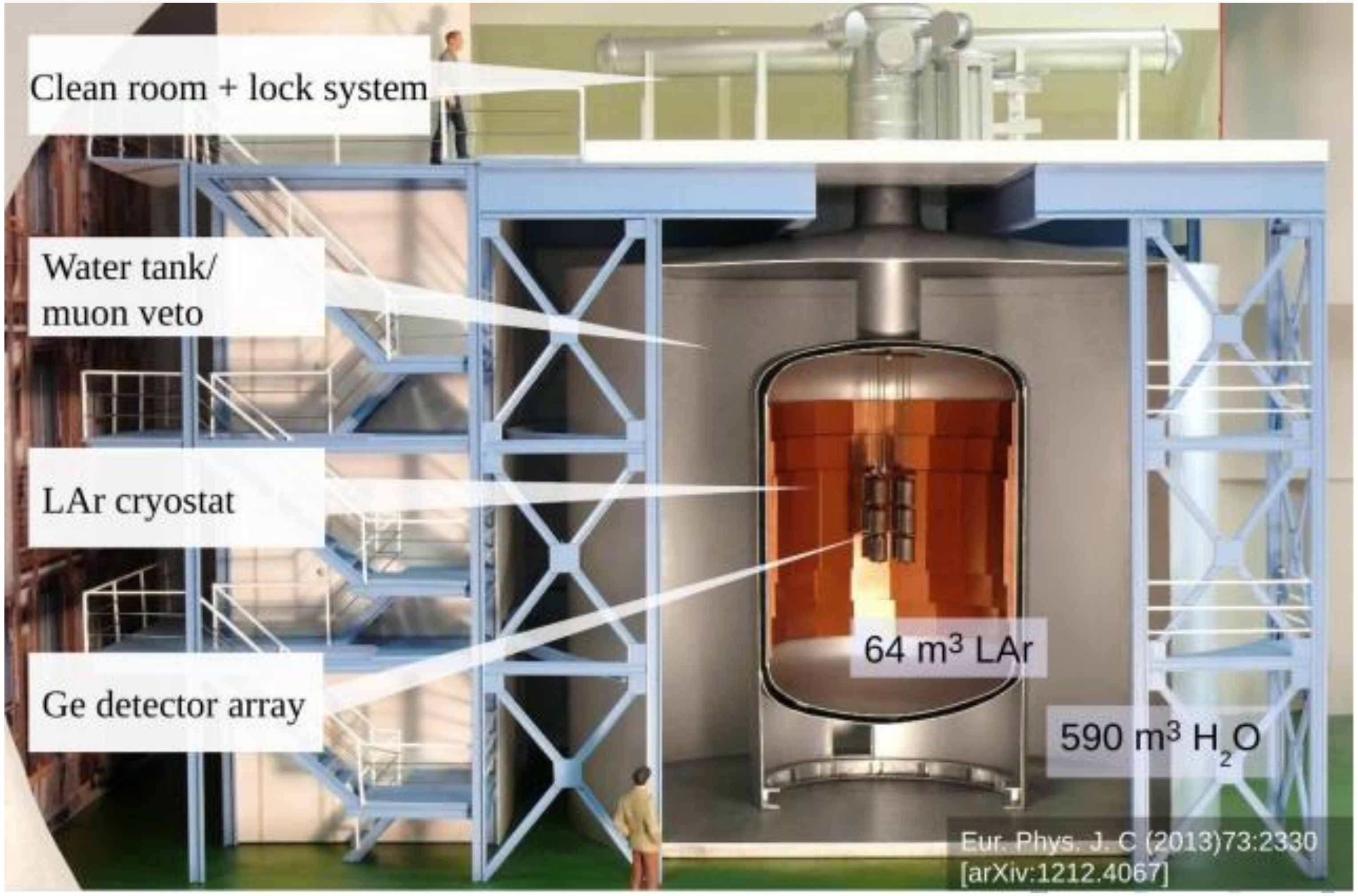
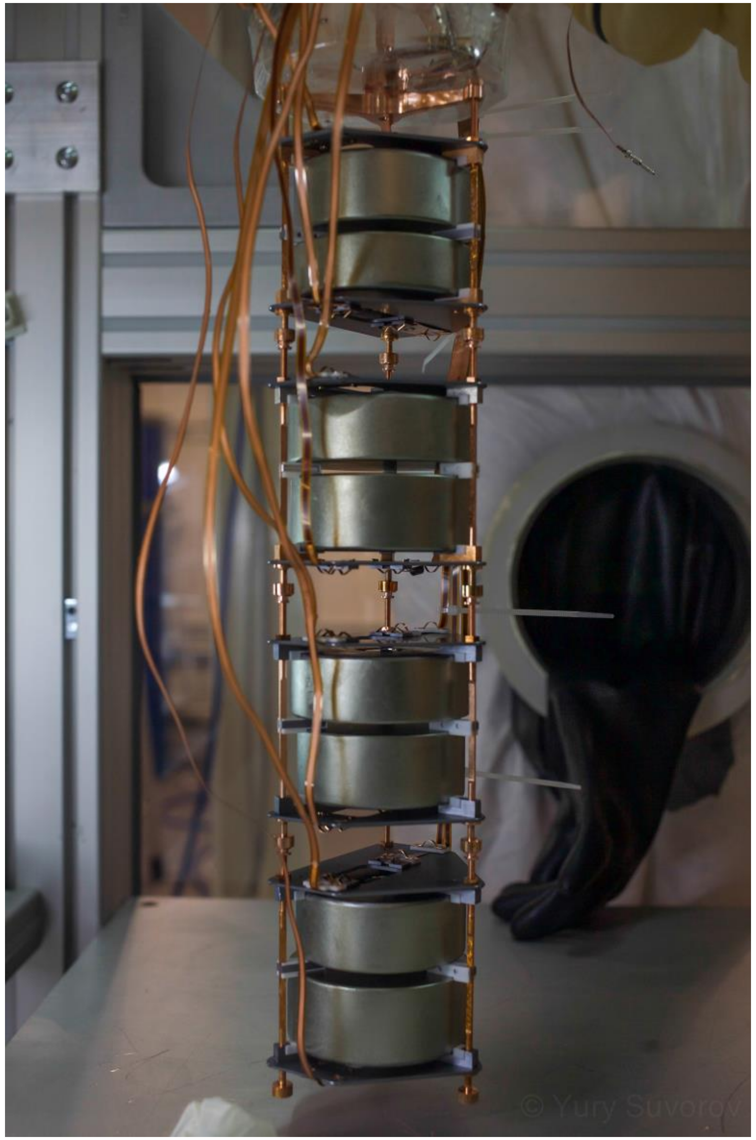
# The GERDA experiment

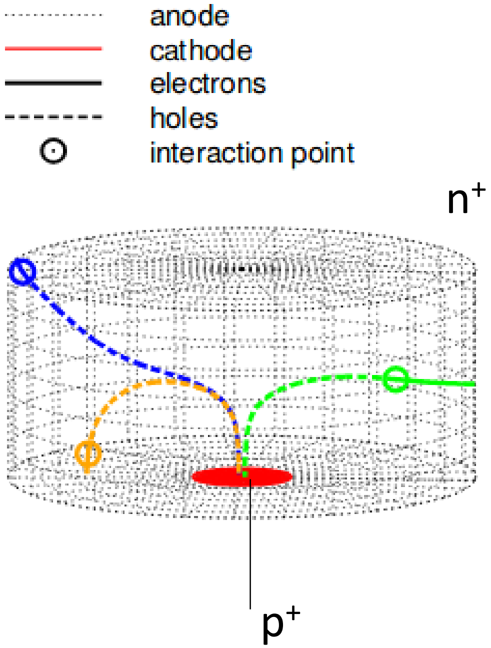
- Search for the neutrinoless double beta ($0\nu\beta\beta$) decay
- Located in Gran Sasso National Laboratory in Italy
- Water tank + LAr for background reduction

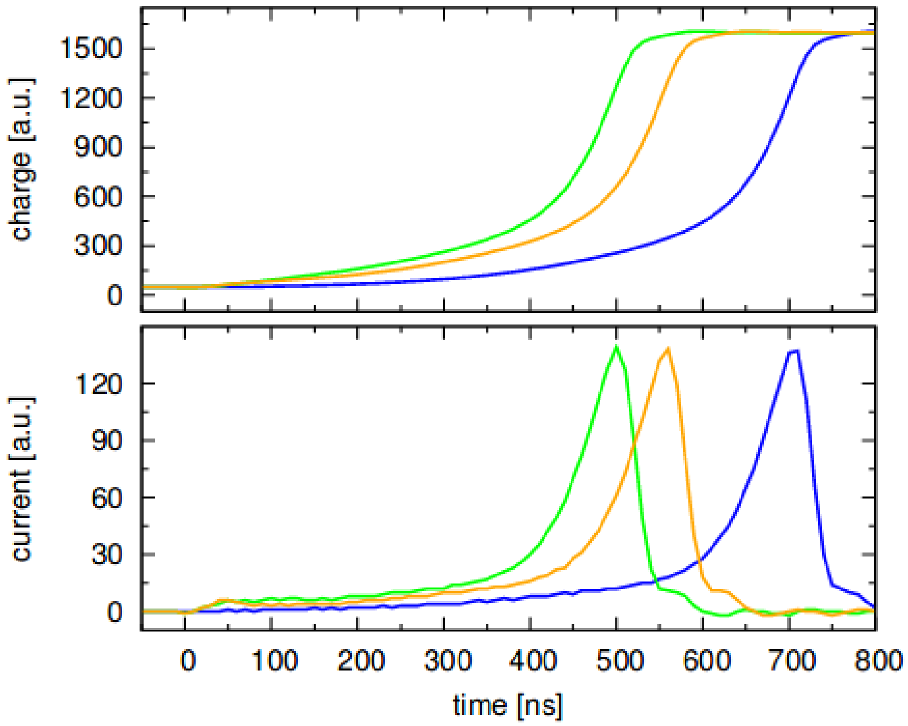




# GERDA detectors



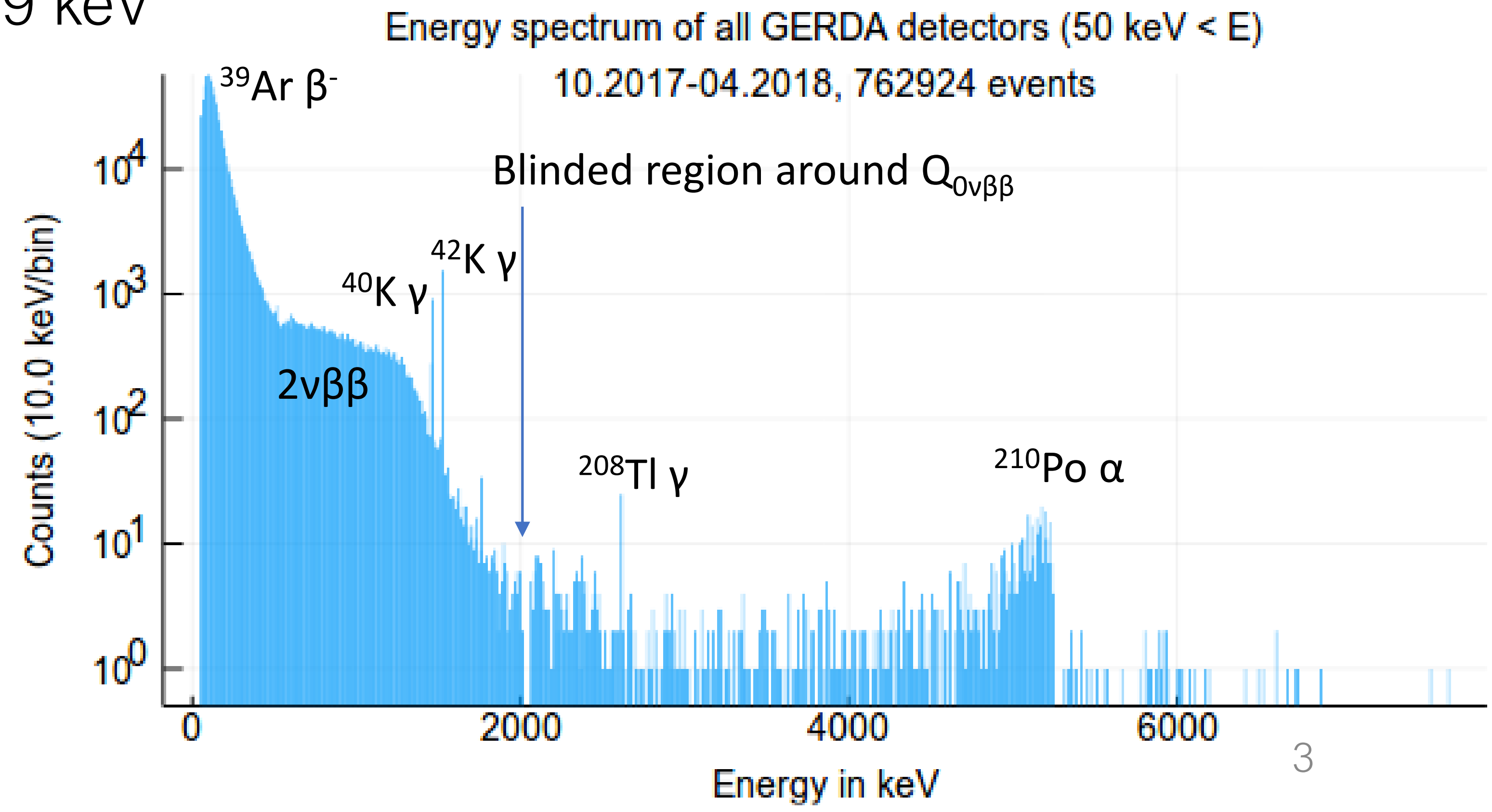




- 40 HPGe detectors enriched in $^{76}Ge$
- Readout on the p+ electrode
- Analysis for each detector

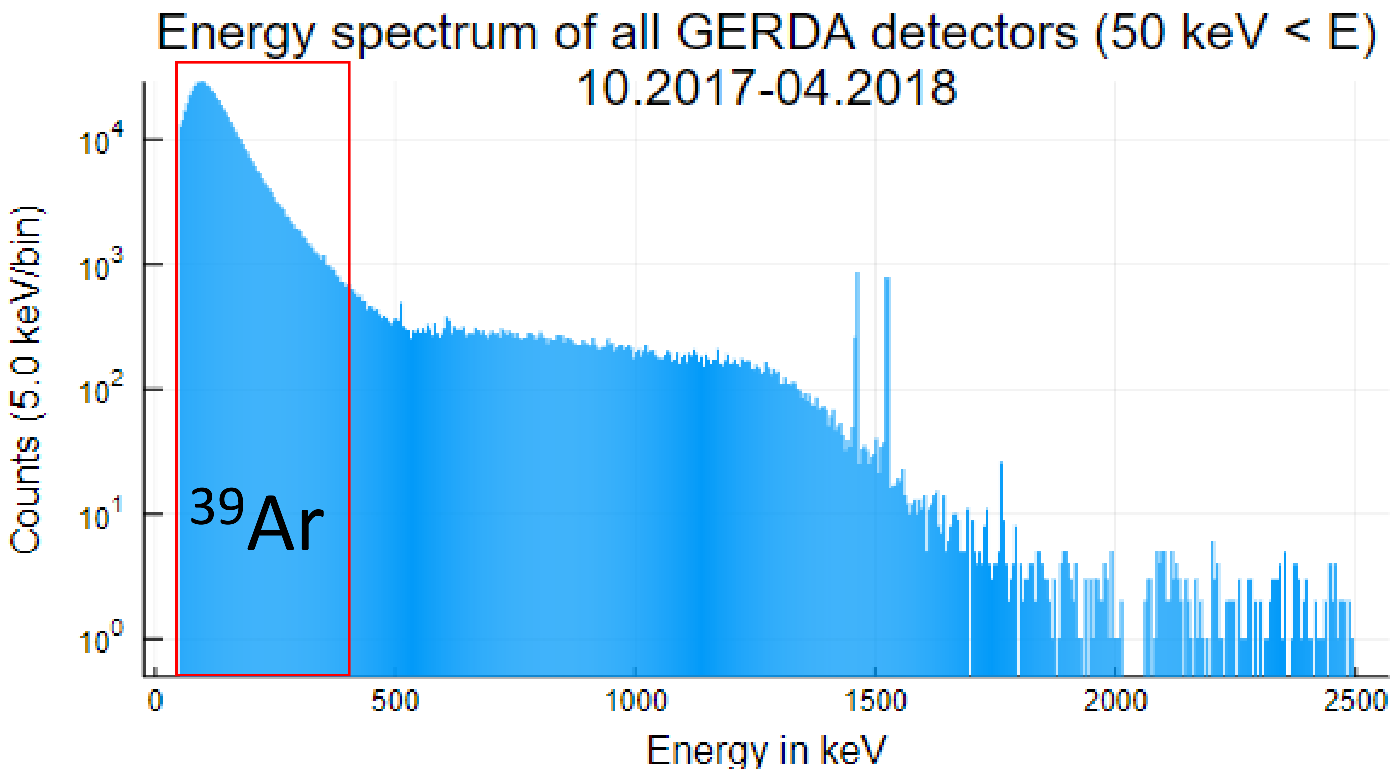
# Motivation

- Clear measurement requires background reduction
- $^{42}K$ $\beta^-$ decay ($Q_\beta$=3.5 MeV) leads to background around $Q_{0\nu\beta\beta}$=2039 keV
- β particles deposit energy near detector surface
- Separation of surface events



# Idea: deep neural networks

- Clean $^{39}Ar$ $e^-$ spectrum below 400 keV
    - Surface events



# Idea: deep neural networks

- Clean $^{39}Ar$ $e^-$ spectrum below 400 keV
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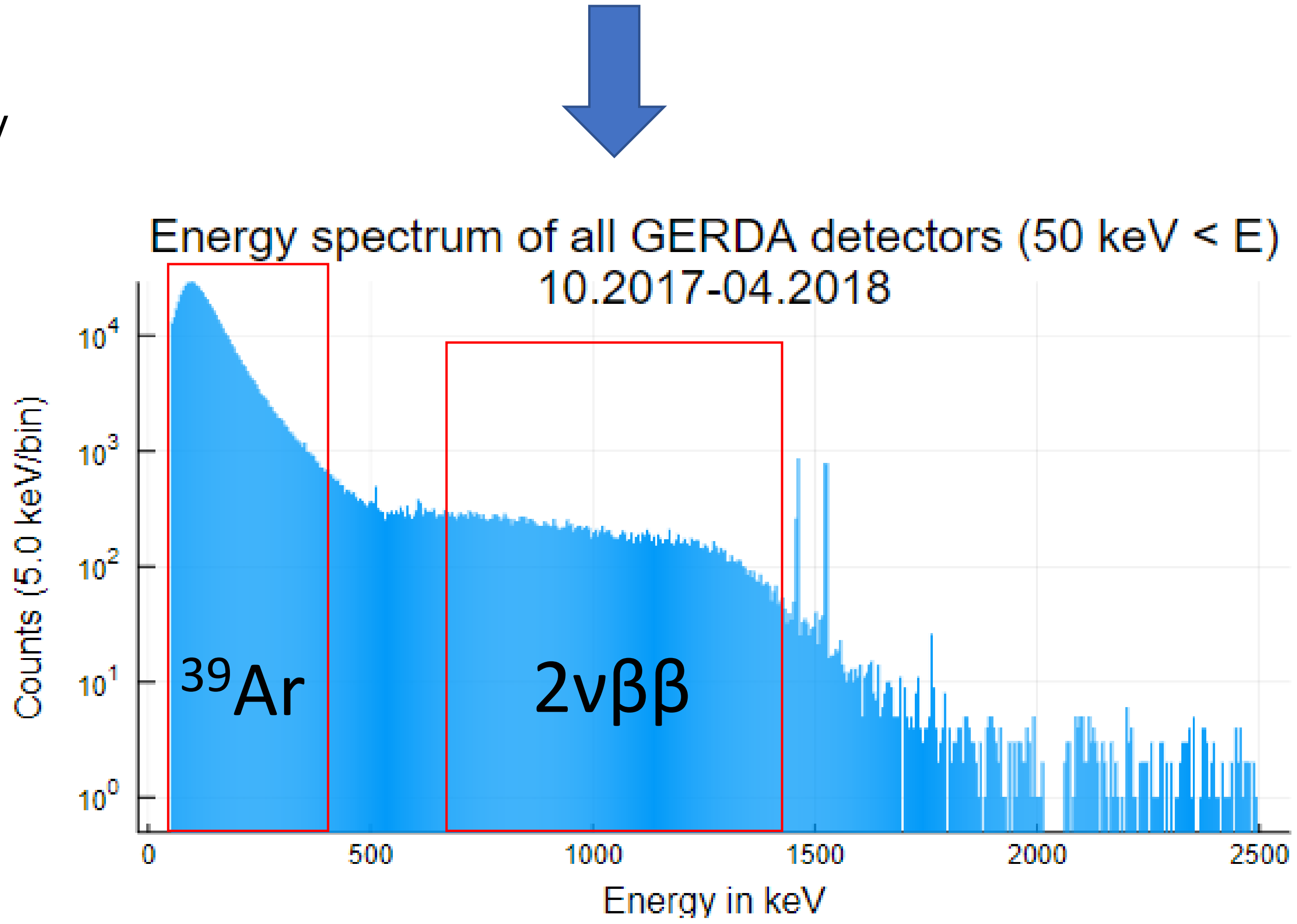
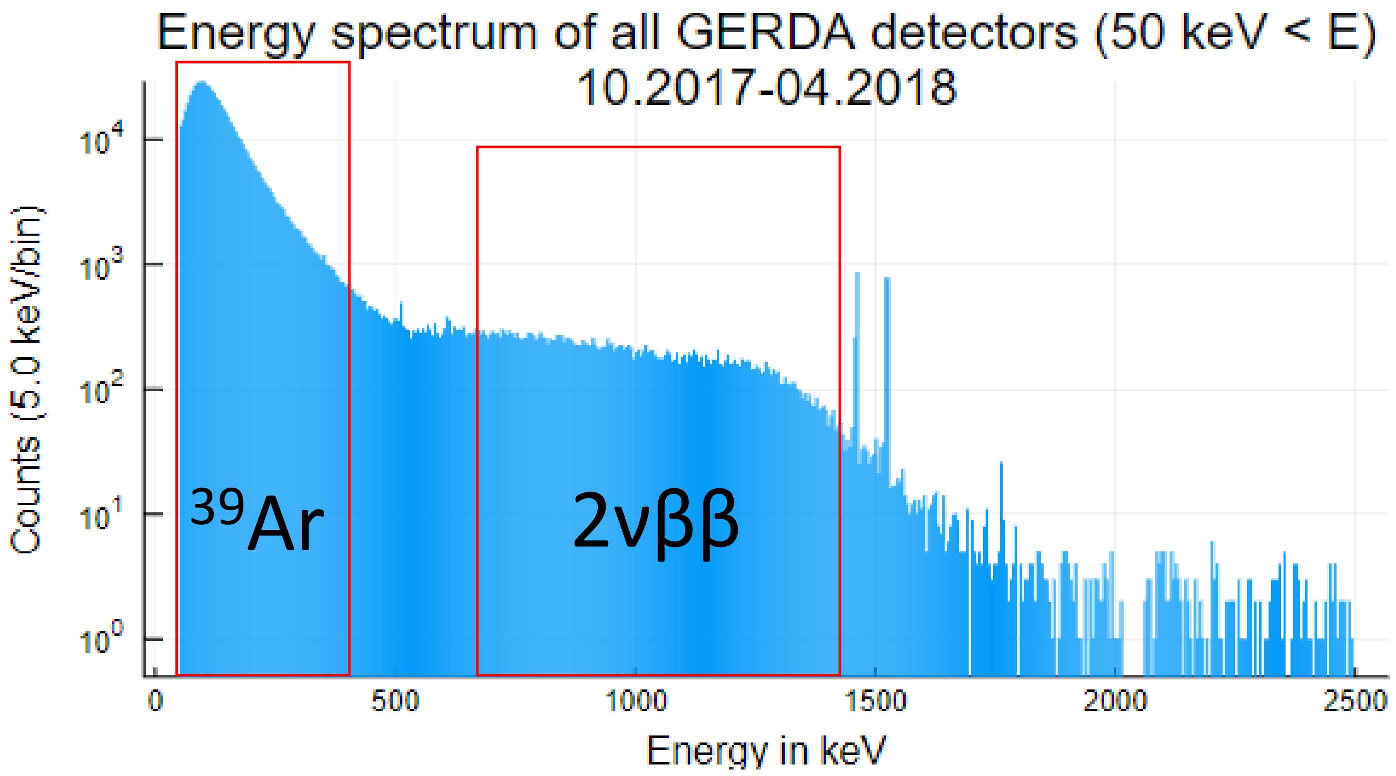
- Clean $2\nu\beta\beta$ $e^-$ spectrum after LAr veto
  - Bulk events



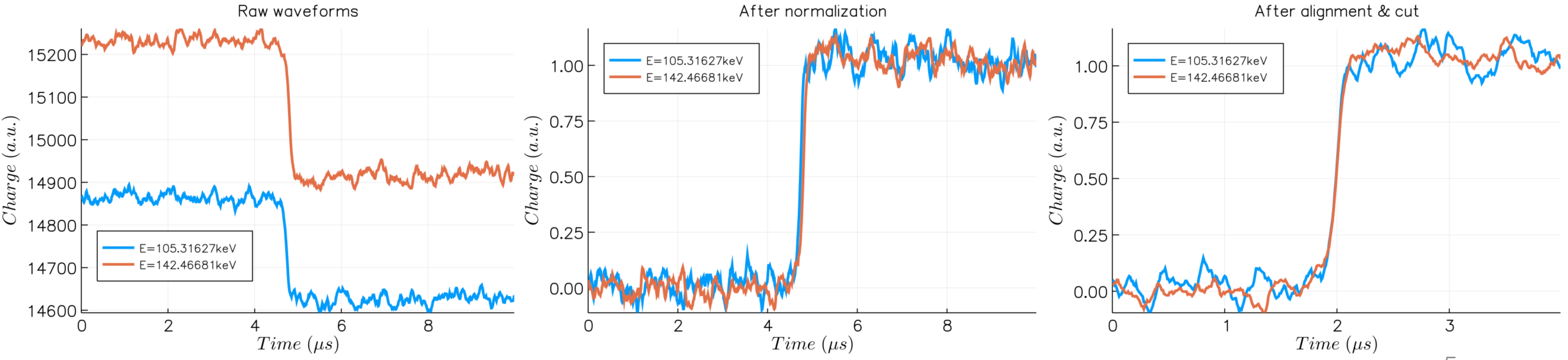
# Idea: deep neural networks

- Clean $^{39}Ar$ $e^-$ spectrum below 400 keV
  - Surface events
- Clean $2\nu\beta\beta$ $e^-$ spectrum after LAr veto
  - Bulk events
- Two steps:
  - extract features
    ➡ autoencoder
  - surface/bulk classification
    ➡ classifier network

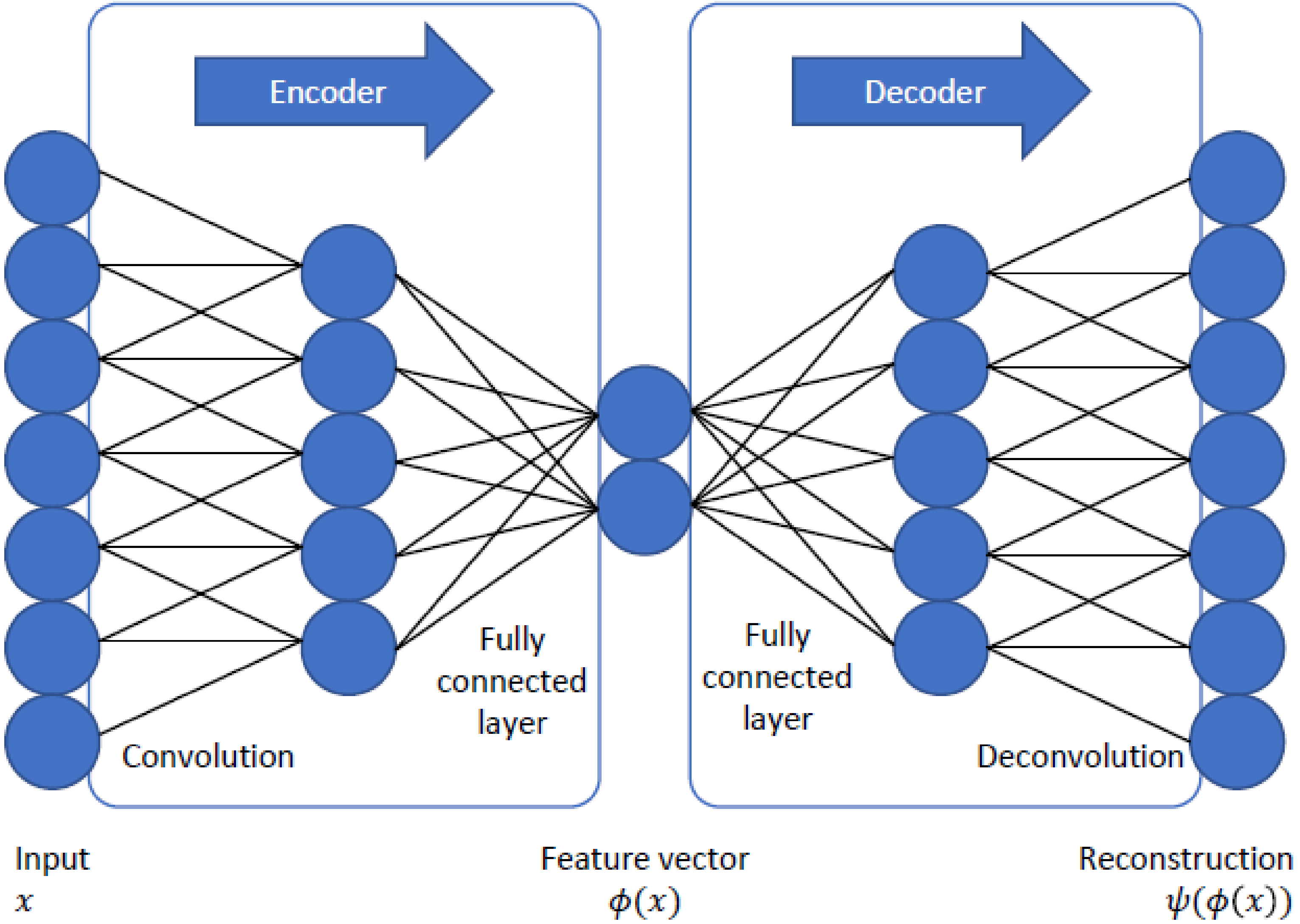


# Waveform preprocessing

- Input: preprocessed charge pulses
- Baseline substraction
- Energy normalization
- Midpoint alignment



# Pulse shape reconstruction with autoencoder



# Pulse shape reconstruction with autoencoder

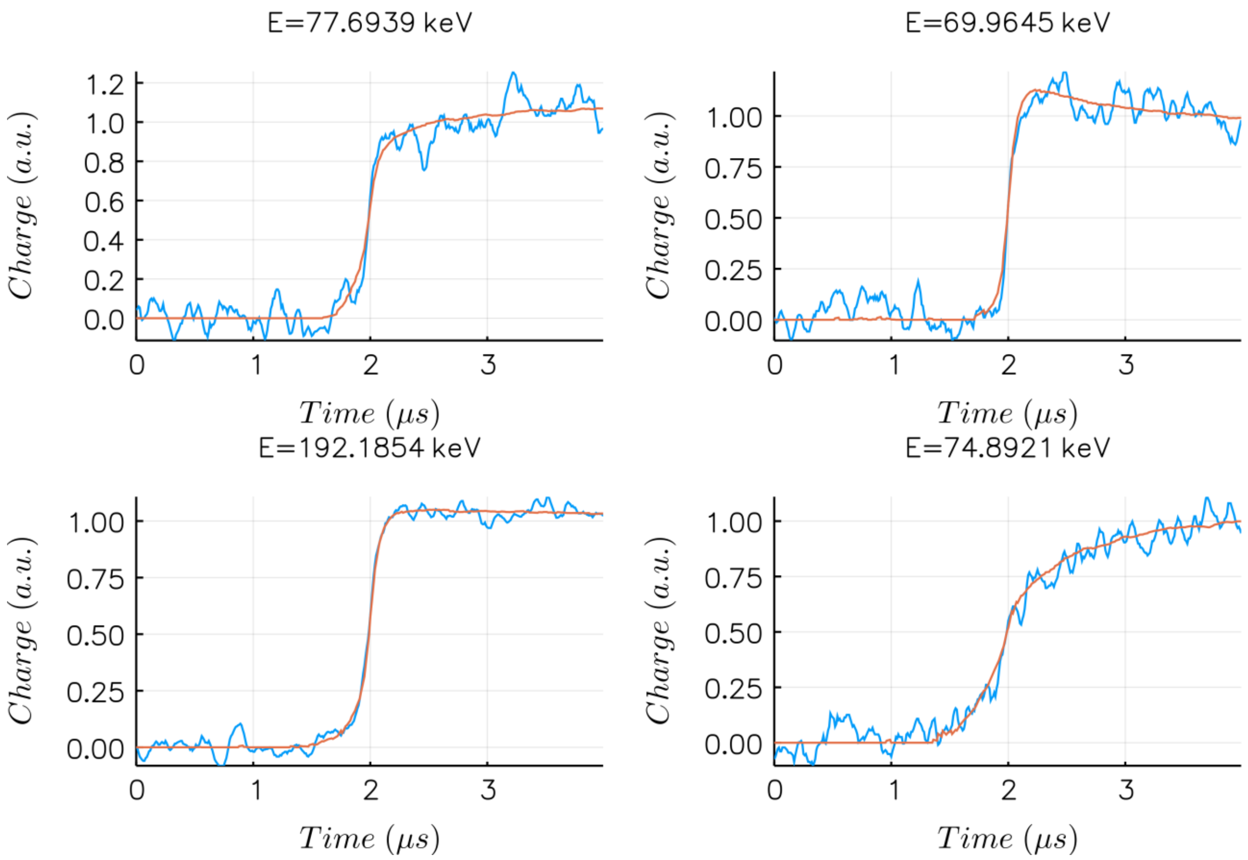
- Extend dataset with pulses from calibration runs

- ~1.000 training parameters
- ~20.000 events for training
- ~7.000 events for validation
- ~7.000 events for testing

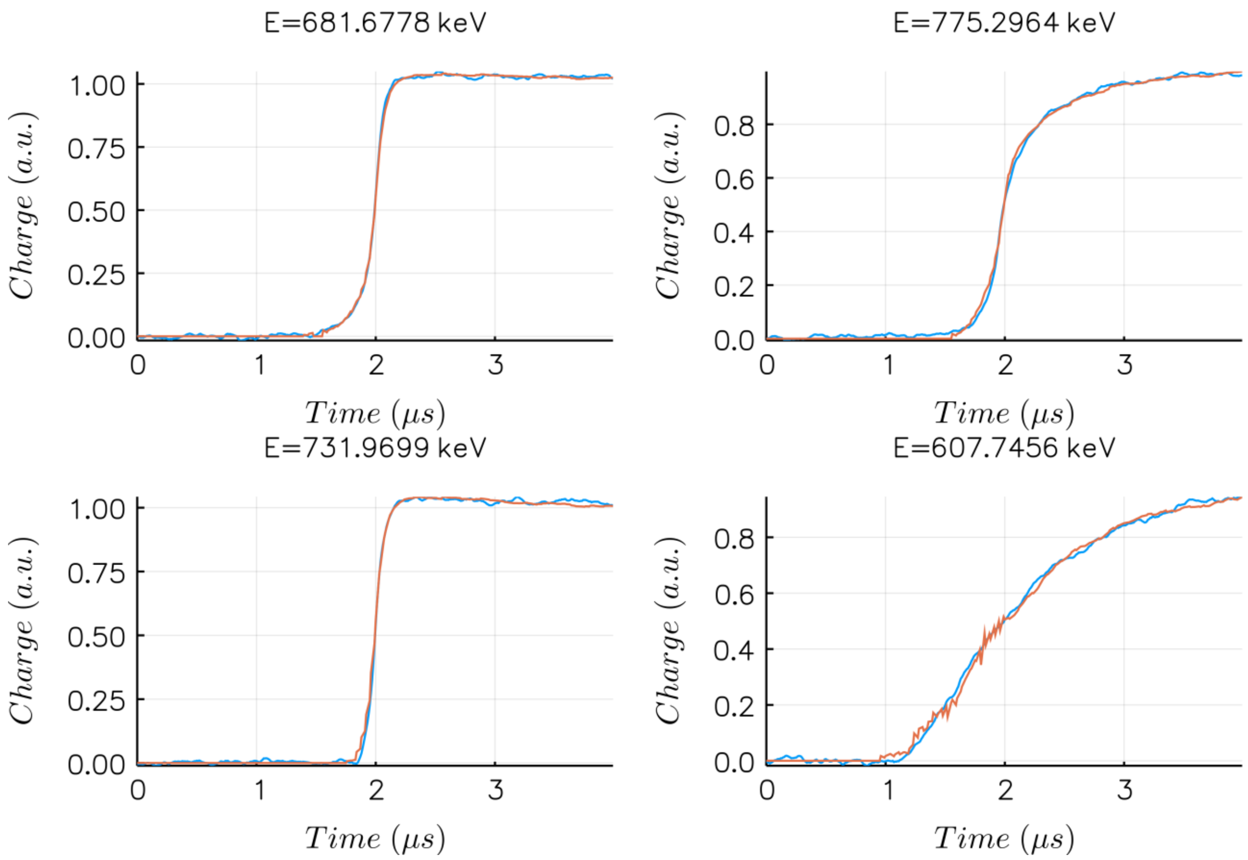
- Loss function: MSE between reconstruction and input pulse

# Pulse shape reconstruction with autoencoder

## $^{39}$Ar surface event examples




## $2\nu\beta\beta$ examples



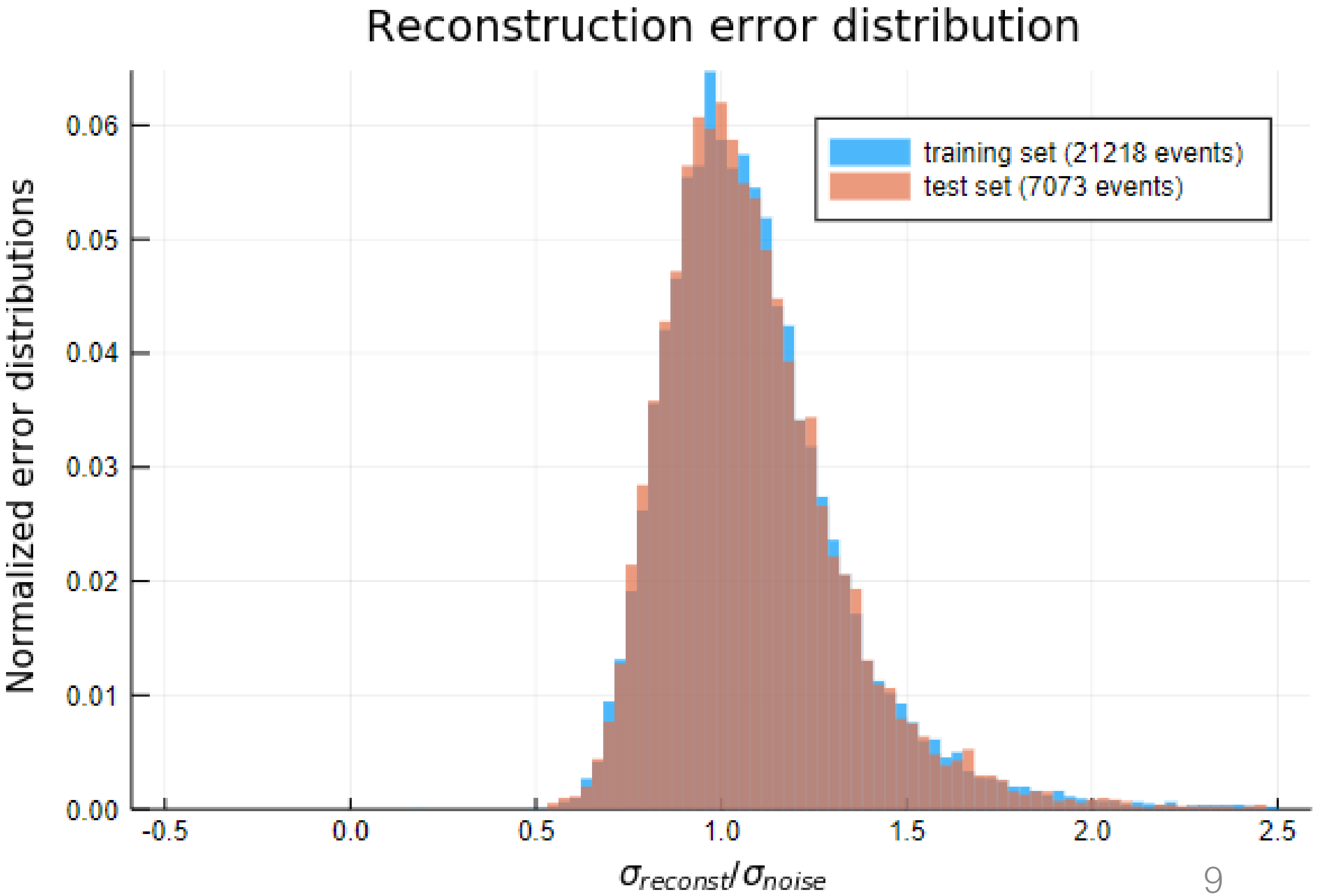
# Evaluation

- Reconstruction error scaled down by baseline noise RMS

$$\sigma_{reconst} = \sqrt{\frac{1}{256}\sum_{i=1}^{256}(x_i - y_i)^2}$$

$$\sigma_{noise} = \sqrt{\frac{1}{256}\sum_{i=1}^{256}(x_i - \hat{x})^2}$$

- Distribution of training and test set errors to check quality of reconstructions



# Next steps

- Neural network for classification
- 2 categories:
  - Surface: $^{39}Ar$ (50-400 keV)
  - Bulk: $2\nu\beta\beta$ (600-1300 keV)

- Input: encoded latent representations
  - Fewer training parameters
  - Encoding does not memorize high frequency noise
  - Classification uses extracted dominant features

# Conclusions & summary

- Low energy event reconstruction with autoencoder has promising results
- Idea of classification on latent space is advantageous
- Analysis to be performed separately on all detectors

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Thank you!