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Machine Learning for Analysis of Fast Particle Detector Data for Proton Therapy Application

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Scope

LGAD detectors

- LGAD (Low Gain Avalanche Detector) as an alternative to ionisation chamber in dosimetry
  - High spatial and temporal precision
  - Sensors developed for CMS MTD (MIP Timing Detector) and designed to operate in the LHC environment, Read-out board designed by the University of Kansas
- Sensor consists of 5x5 matrix of pixels with a dimension of 1.3x1.3mm^2 (Fig1)
- Two detectors were placed in the proton beam coming from the AIC-144 cyclotron at the Institute for Nuclear Physics in Cracow, facility was previously used for the proton therapy

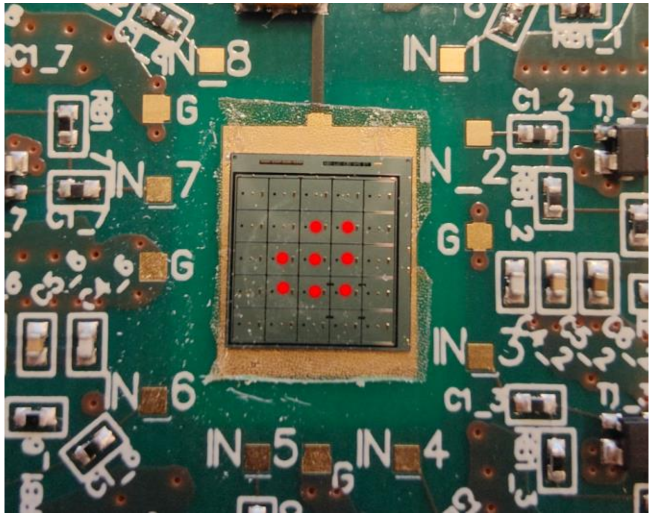

Fig1: LGAD sensor with the connected channels

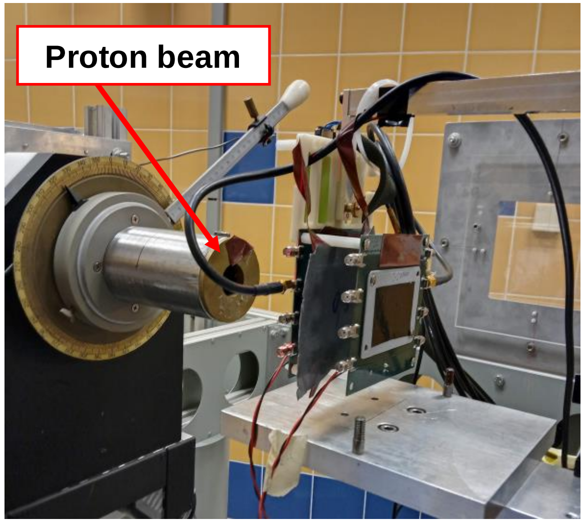

Fig2: Two mounted detector boards

Macro-pulse structure

» AIC-144 cyclotrone in Cracow accelerates protons to an energy of 58 MeV

» The Cyclotrone was producing pulses with the frequency of 50Hz (every 20ms), the length of the pulse was around 0.5ms

» Thanks to the timing precision (~50ps) of the LGAD detector it is possible to analyze the structure of the generated pulse

» A macro-pulse consists of multiple micro-pulses which occur every 38ns and last for around 1ns

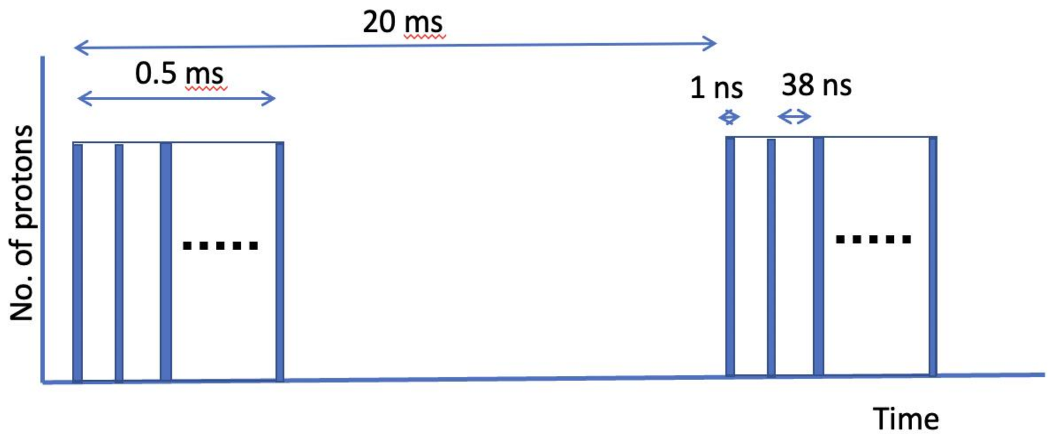

Fig3: Temporal structure of the macro-pulse

Macro-pulse structure

» We found that each micro-pulse could produce a negative (actual signals) or a positive (cross-talk) signal in the detector.

» Splitting data into individual windows allows to perform quantitive analysis and study the shape of the pulses

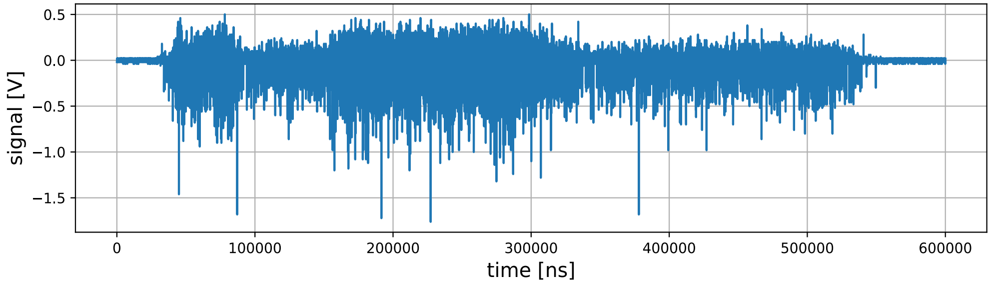

Fig4: Macro-pulse recorded by the detector for 2nA with 8 bit precision

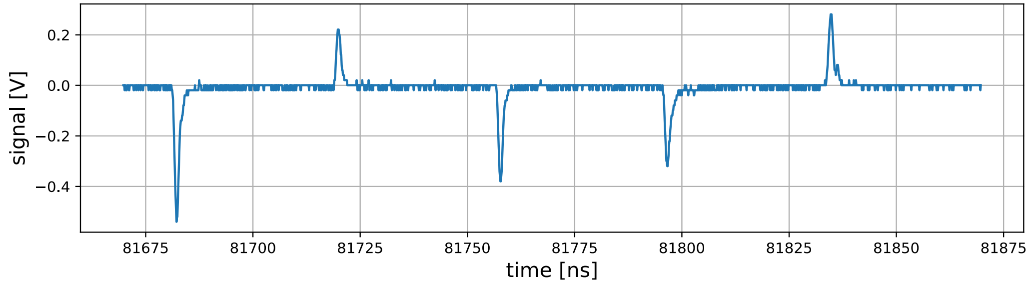

Fig5: Fragment of the macro-pulse with several micro-pulses

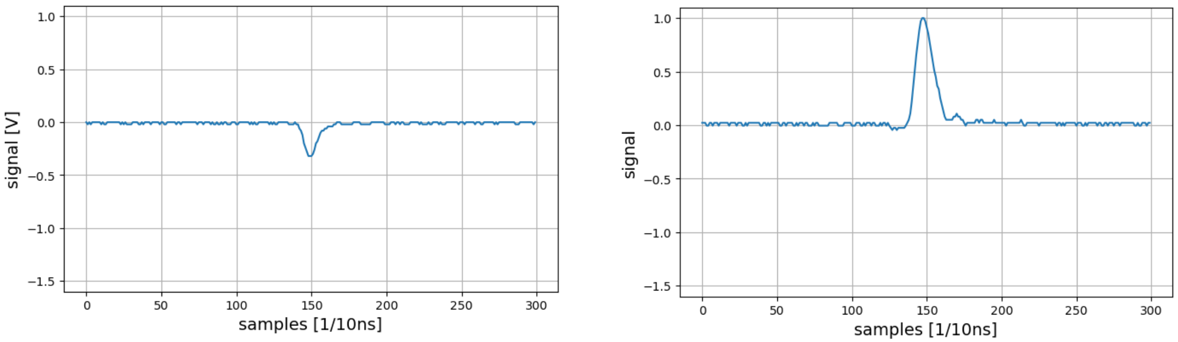

Fig6: Example of the micro-pulse window extracted from the macro-pulse, raw values on the left and normalized on the right

Problem statement

- LGAD detector can record different events depending on the number of particles passing through the sensor and the position of the deposited charge in the pixel matrix
- Analyzing those signals using conventional methods is hard given the number of possible signal shapes and interferences like noise, measurement precision and cross-talk
- Machine learning methods proved to be very powerful at tasks like pattern recognition, outlier detection, noise reduction and signal segmentation

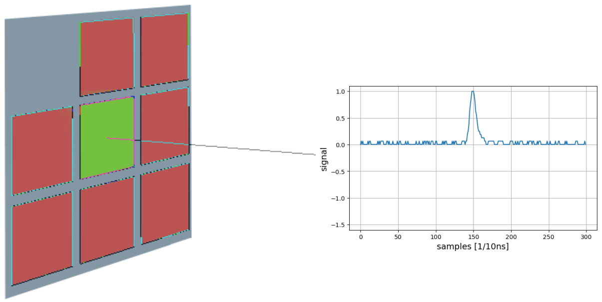

Fig7: Single particle in the middle channel

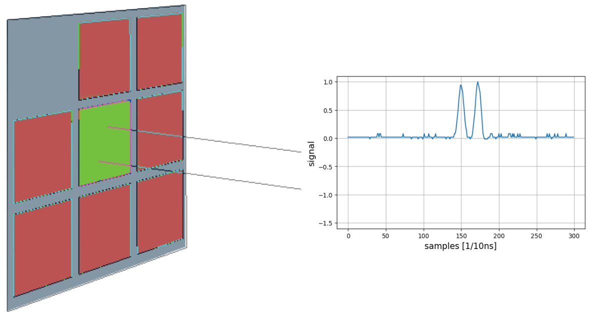

Fig8: Multiple particles in the single channel

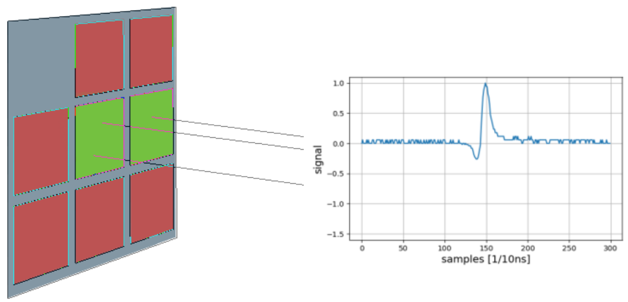

Fig9: Possible crosstalk between two activated channels

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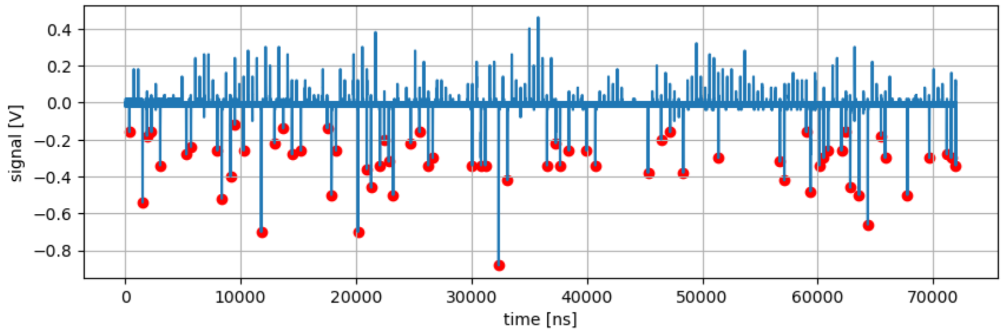
Peak detection algorithm

- Start of the macro-pulse is defined by the first micro-pulse, similarly end of the macropulse is defined by the last micro-pulse
- Baseline of the signal noise is calculated on the fly by the average of N last processed samples
- Peak is defined as the N% change from the baseline
- To compenstate for differences in amplitudes, macro-pulse is normalized:
  - Negative pulses are scaled to 1 while positive pulses remain unchanged



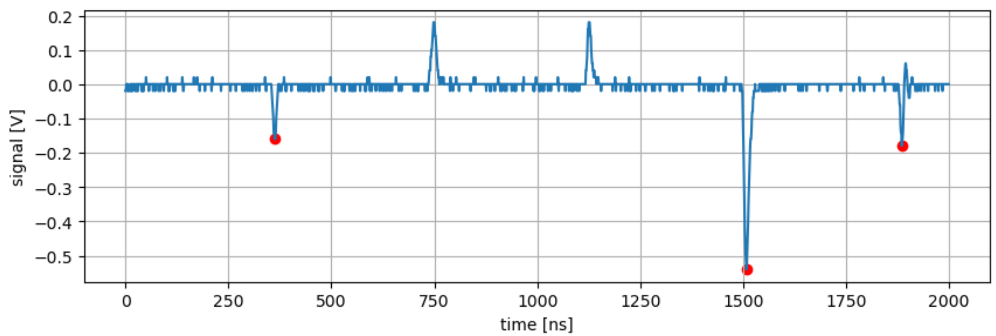


Fig10: Example of the macro-pulse fragment with micro-pulses maxima indicated by the red dot

Windows classification

» Shape of the signal pulse is unique – multiple particles passing through sensor, different levels of noise, different width, etc.

» Individual signal windows can be classified according to its features

» Clustering similar shapes allows for outlier detection and analyzing pileup

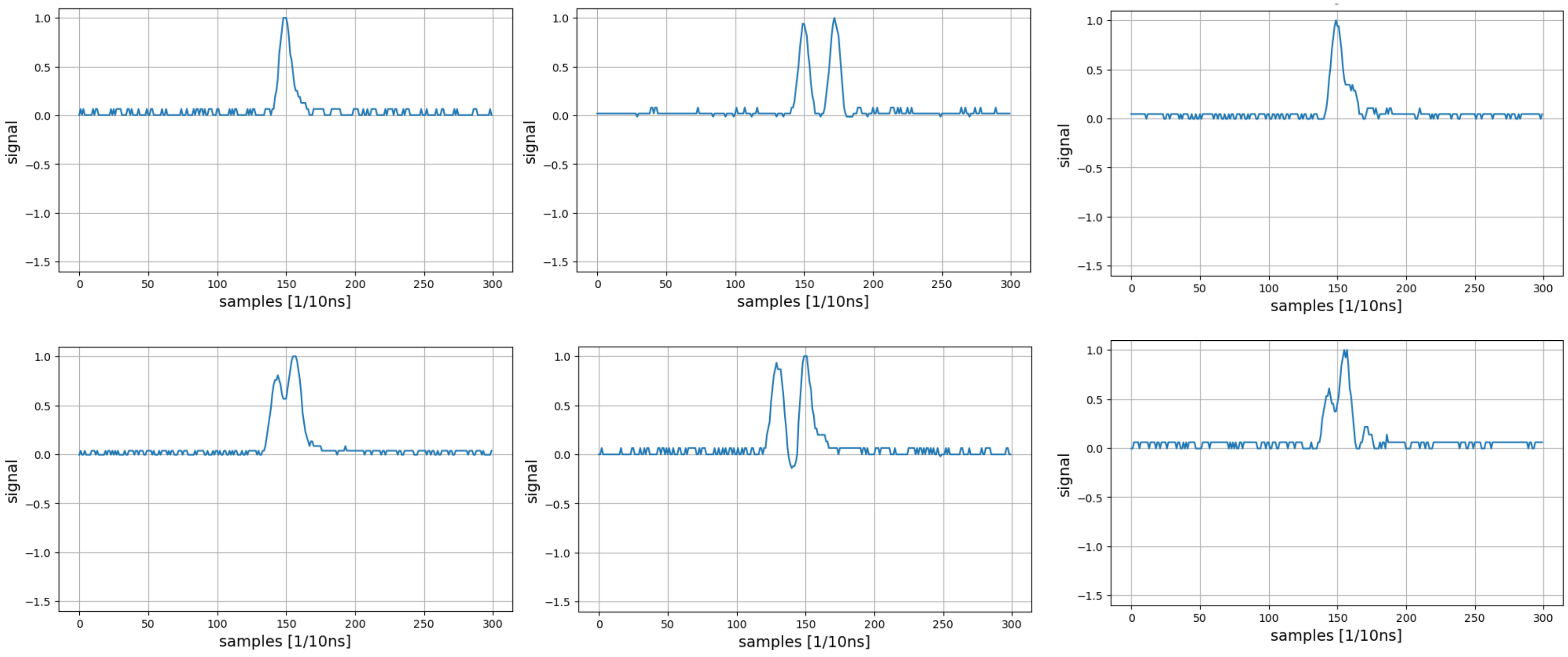


Fig11: Example of the signal shapes

Unsupervised machine learning

- Deep Neural Networks (DNNs) have gained significant attention in various fields, including physics, due to their ability to learn complex patterns and make predictions from large datasets
- Deep Neural Networks learn from training data by adjusting the weights of interconnected neurons through iterative improvement from defined error function.
- Learning can be:
  - Supervised – rely on labeled values (truth values)
  - Unsupervised – focuses on uncovering relationships within data

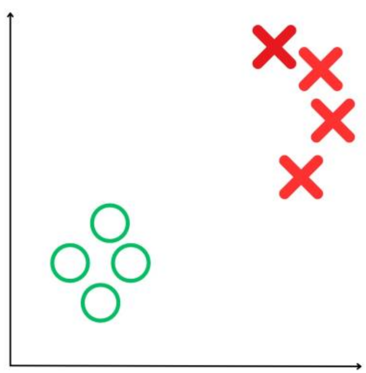


Fig11: Supervised learning (classification)

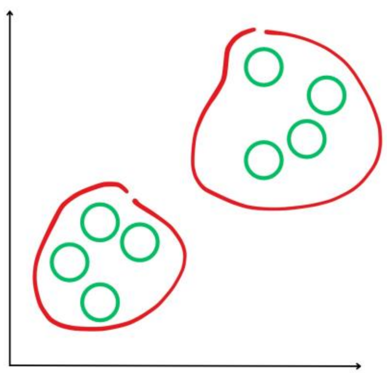


Fig11: Unsupervised learning (clusterization)

Autoencoder Neural Network

- Not every sample and feature within the micro-pulse is important for the purpose of clusterization
- Autoencoder was used to extract most important features of the micro-pulse
- Autoencoders does not require supervision and are excellent tool for extracting data features and noise reduction

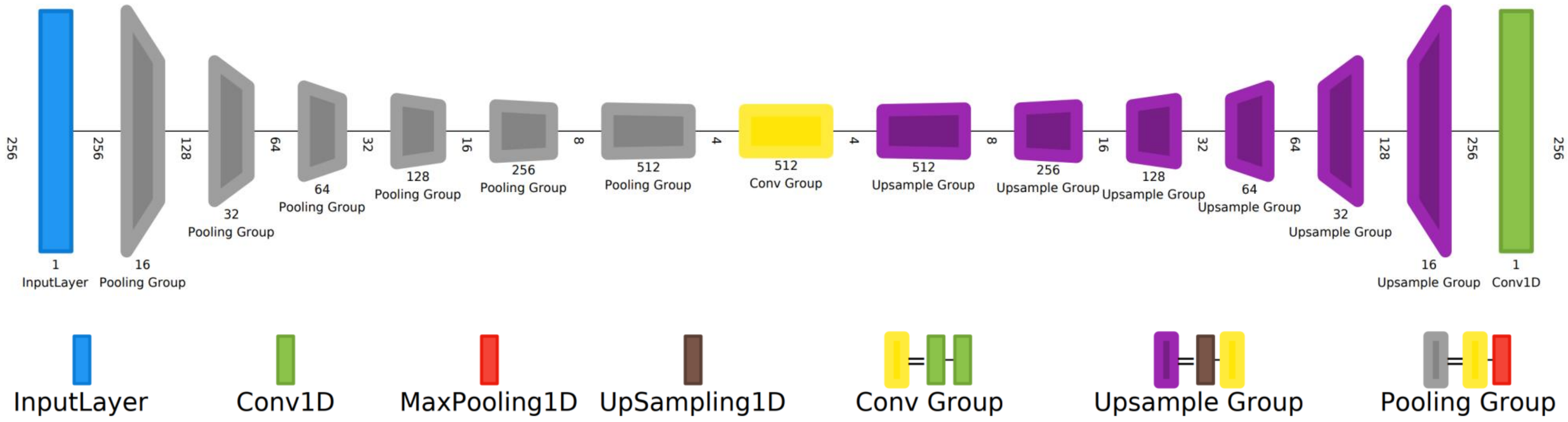


Fig12: Autoencoder architecture

Autoencoder Neural Network

» Trained autoencoder consists of two main components: encoder and decoder

» Decoder can be detached and used individually to reduce dimensionality of the pulses while preserving most important features

» Side effect of the features compression in the encoder is noise suppression

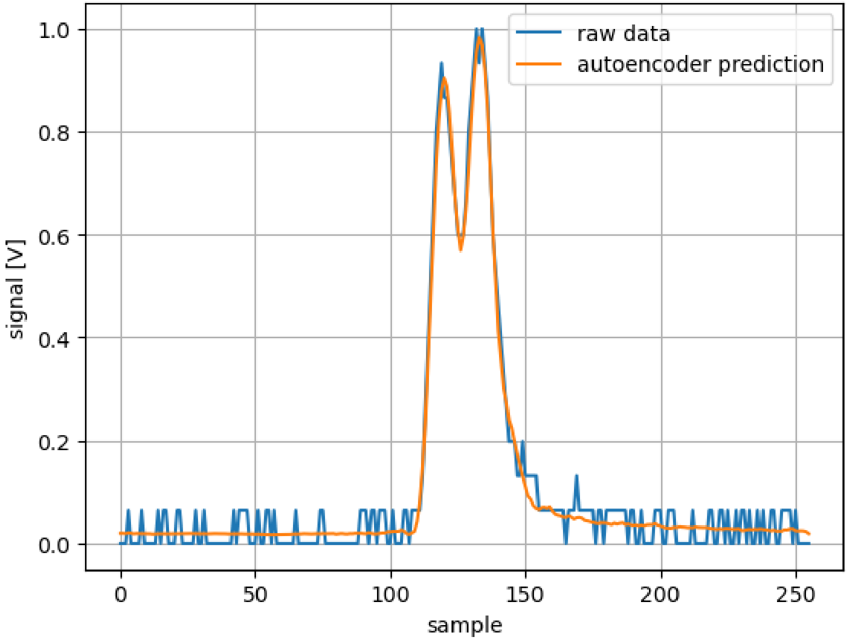


Fig13: Comparison between raw data samples and autoencoder prediction

Clusterization

» Clusterization is a form of unsupervised training that allows to group similar results according to the provided features

» Multiple methods were evaluated – KMeans, DBScan, GaussianMixture

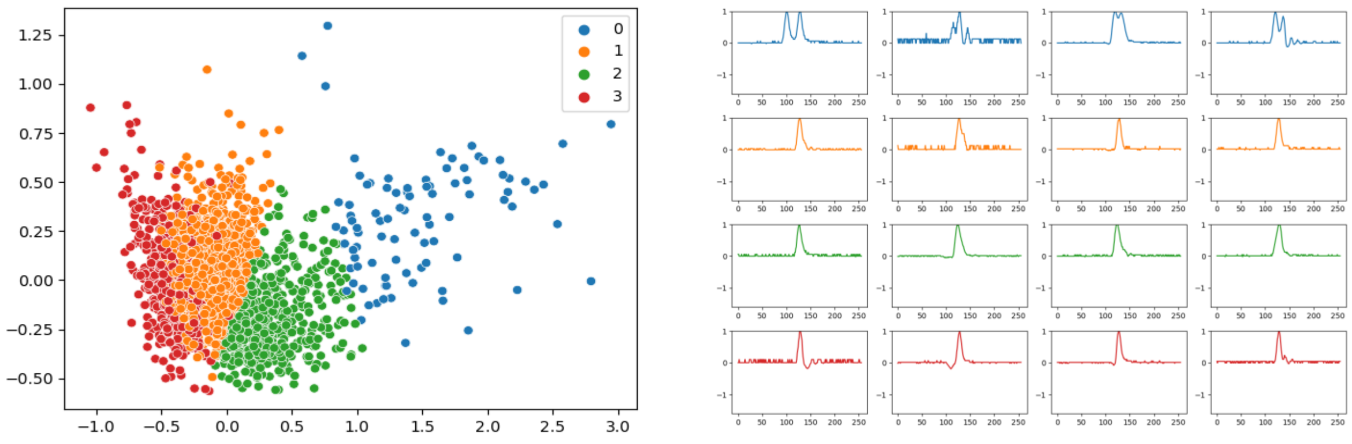


Fig14: Results of the classification on 2nA data with pileup cluster indicated by blue color and PCA projection

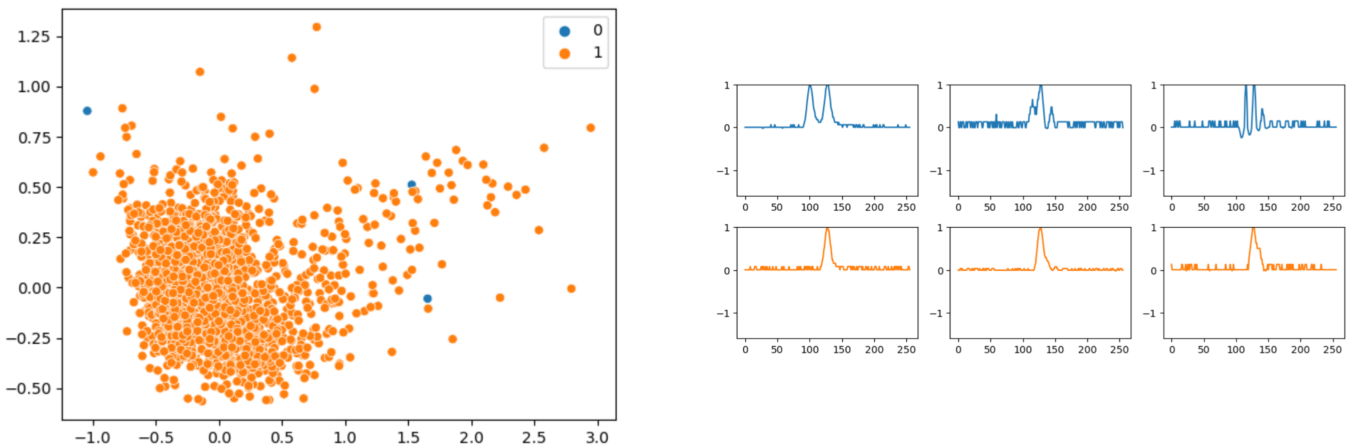


Fig15: Results of the classification on 2nA data with outliers indicated by blue color and PCA projection

Conclusions

- Machine learning techniques can be used in signal processing for analyzing signal shapes
- Separation between signals performs poorly without extracting underlying features
- Autoencoder Neural Networks allow for unsupervised extraction of the signal features, signal interpolation and noise reduction
- After feature extraction, suitable clusterization method can be used to group the data according to the need (we were concentrating on the number of peaks in the signal)
- Further studies concentrated on data with higher pileup are needed

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