Plasmas for Astrophysics Nuclear Decays Observation and Radiation for Archaeometry

SAPIENZA UNIVERSITÀ DI ROMA

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AI Tools for Plasma Diagnostics by X-ray Imaging and Spectroscopy in the PANDORA Project Frame

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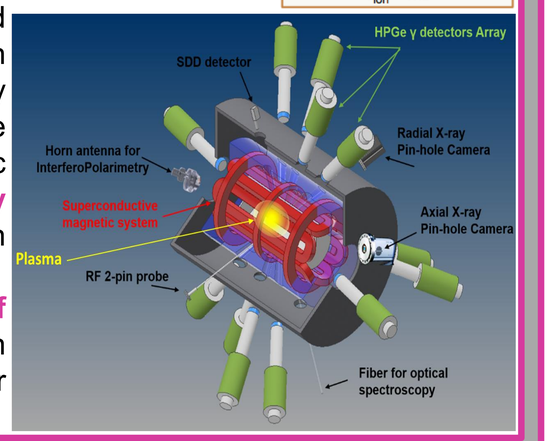
PANDORA PROJECT

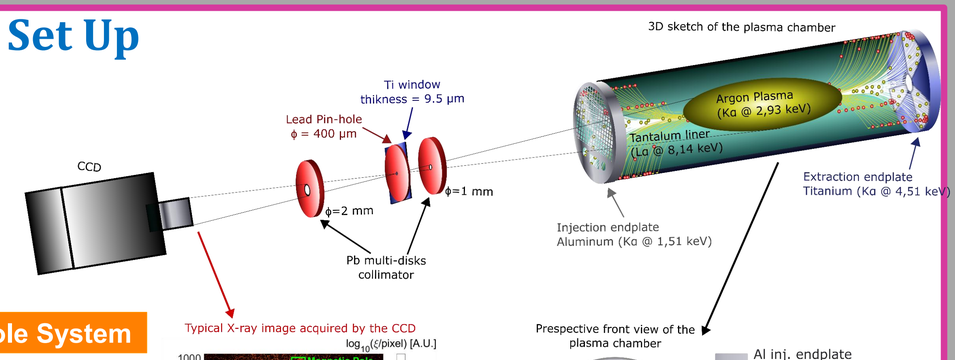
Within the **PANDORA** project (**P**lasmas for **A**strophysics, **N**uclear **D**ecays **O**bservation and **R**adiation for **A**rchaeometry), a novel approach enables the measurement of in-plasma β-decay lifetimes of astrophysical isotopes under stellar-like conditions. This is achieved using a multi-diagnostic system, with a focus on **soft X-ray spectroscopy and imaging** to characterize the warm electron population **(0.5–30 keV).**

These diagnostics allow precise **monitoring of plasma parameters**, offering direct insight into ion **source behavior** and **beam properties**, crucial for controlling nuclear decay processes.

ECR Plasma
$n_e \sim 10^{12}$ cm^{-3}
$T_e \sim$ tens keV
$T_{ion} \sim$ ms

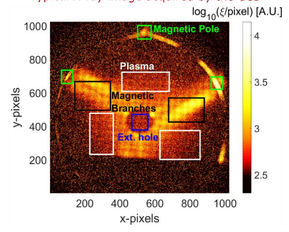


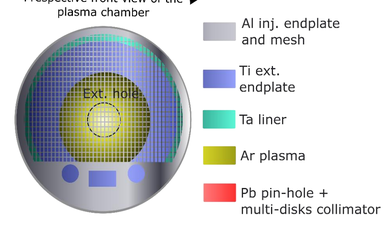
Experimental Set Up



CCD Camera & Pin-hole System

- Sensitivity range ~0,5 ÷ 30 keV (>95% QE within the range)
- Sensor Size: 2,76 cm x 2,76 cm(2048x2048 Pixels)
- Pixel size: 13.5 μm x 13.5 μm
- Lead Pin-hole (diameters 400 μm)
- Lead multi-disks collimator system to reduce the scattering noise, increasing resoltution and signal-to-noise ratio





Energy resolution: 236 eV @ 8 keV

Space resolution: 500μm

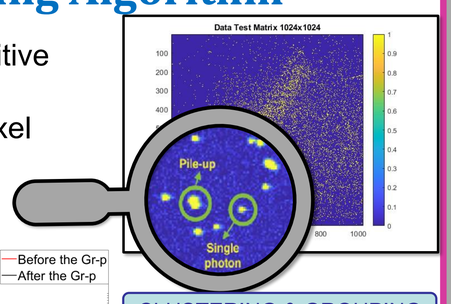
State of the Art Single Photon Counting Algorithm

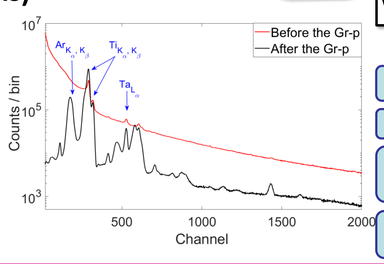
Each pixel becomes an indipendent spectrally-sensitive detector:
SPATIALLY-RESOLVED SPECTROSCOPY pixel-by-pixel

→ **Decoupling of photon number versus energy**
- **very short exposure-time (@ 50-500ms)**
- **thousands of SPhC frames**

→**Minimize** the **pile-up probability**

→**Cluster Size Filtering:**
- **Large size (> 5 pixels): multi-photons**
- **Small size (≤ 5 pixels): single-photon**





CLUSTERING & GROUPING

ENERGY CALIBRATION

HDR IMAGING & SPECTROSCOPY

READ-OUT NOISE REMOVAL

Motivation

Employing a **Machine Learning Algorithm** allows to:

- **Improve the energy resolution**
- **Improve the signal to noise ratio**
- **Minimize the spurious effect contribution, by means of the pile-up identification**

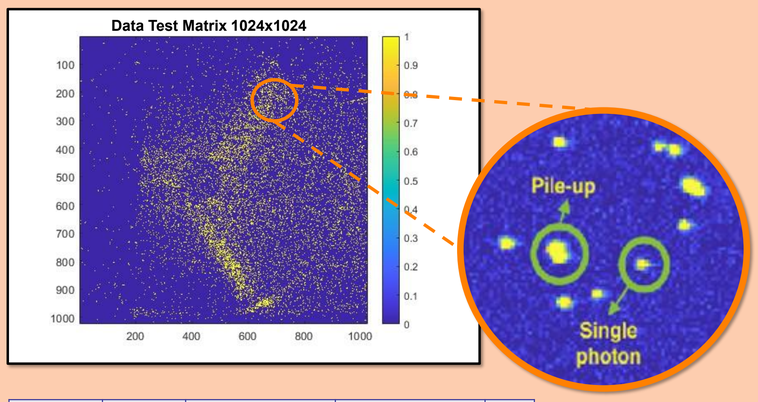
Furthermore, it will push towards different goals, such as:

- **Identification of specific patterns**
- **Online Analysis Options, in order to manage huge amount of datas while measuring**

We decided to use an **Hybrid Approach**

Imaging Tool: *bwconcomp*

State of the art **tool for image analysis**, based on **connectivity** it allows to **identify** and **characterize** each event, i.e. each photon iminging on the CCD matrix.



Events	Area	N Local Max	Eccentricity	….
1	20	1	0.3	----
2	4	3	1	----
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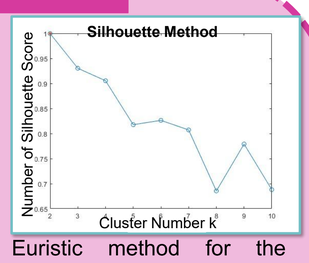
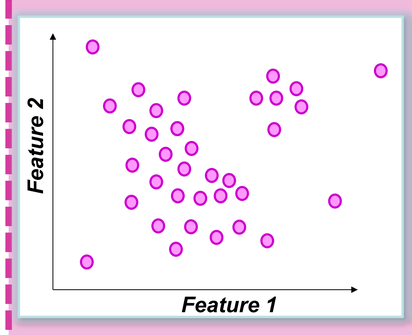
The **extracted features** play a fundamental role in **spurious event identification**.
- **Area**: the number of pixel lighted by each event
- **Number of Local Maximum:** the presence of more then one local max can highlight a multi-photon event
- **Eccentricity:** ratio between the major and minor axis of the event interest are

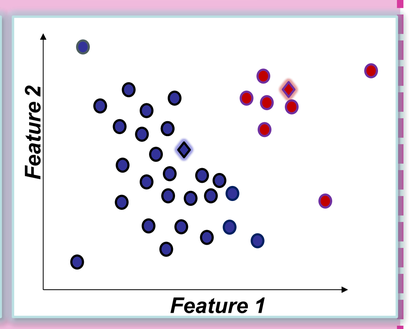
K-means Clustering

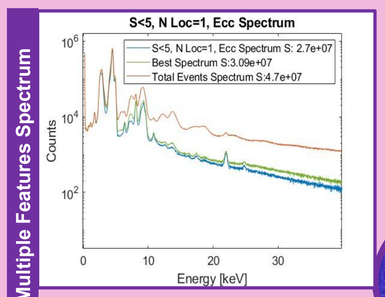
K-means is a clustering tool , belonging to an **un-supervised model** category.
It's used to **group features** based on similarities, usually used for **pattern recognition and labelling.**



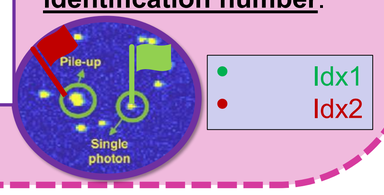
Euristic method for the evaluation of the cluster number, based on the mean **Silhouette Score.**







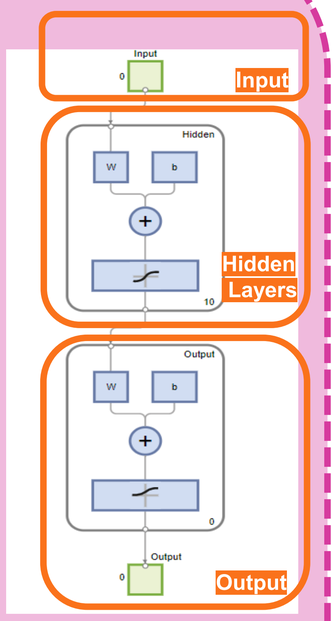
K-means is specifically used to identify two different event population with similar characteristic and then to **label** each data with an **identification number**.



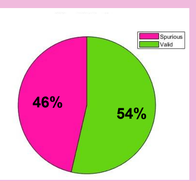
Neural Network

PATTERNET is a feed-forward net, featuring a **supervised model** that works with **a labelled data** as a **classificator,** employing the dataset for training and using the label as feedback**.**

Parameters	Value
Neurons in the Hidden Layer	10
Training Algorithm	SCG
Number of Epoch	300
Number of Events	7767611
Activation Function	Tansig
Activation Function Output	Logsig
Minimum Gradient	1 e-6
Maximum Fails	10
Loss Function	Cross Entropy

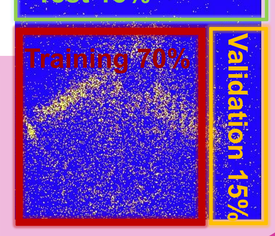


Data Pre-processing



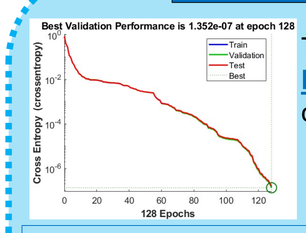
Normalization of the feature and **Balancing** the dataset

Dataset organization and randomization



Results

Net Performances

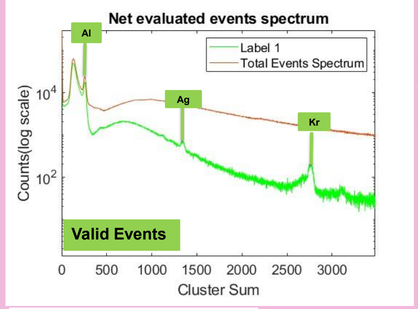


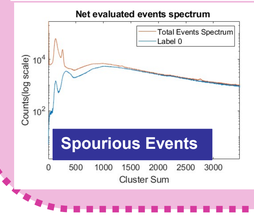
The **CrossEntropy Function** for binary classification

$$L = -\sum y log(p) + (1-y) log(1-p)$$

We manage to obtain an **Accuracy of 100 %**

Spectral Analysis

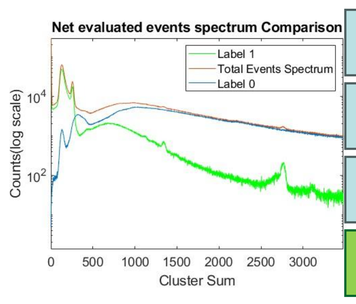




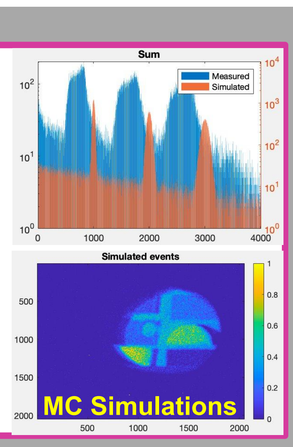
2% FWHM @ Kr peak

Spectra obtained with the employment of **machine learning approach** to dataset coming from the last experimental campain, at Debrecen ATOMKI laboratories.

Conclusions & Future Perspectives



- **Validation of the AI based unsupervised Algorithm K-means**
- **Development and Training of a Feed-Forward Neural Network**
- **First Results on the data coming from the last experimental Campaign**
- **Further Training and Test of the Net Performance on simulated data**



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