Real-time AI-based dead hot map in the ePIC detector: a self-adaptive alternative to traditional big data calibration pipelines

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University of Debrecen – 13 faculties

- Agricultural and Food Sciences and Environmental Management
- Dentistry
- Economics and Business
- Education for Children and Special Educational Needs
- **Engineering**
- Health
- Humanities
- **Informatics**
- Law
- Medicine
- Music
- Pharmacy
- **Science and Technology**

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Solid background in high-energy physics and AI

- Host of the
  - CMS (CERN) group, 4 FTE
  - EPIC group, 5 FTE
- High computational capacity for AI, NVIDIA DGX (A100, H100, H200) servers
- Official industrial AI-curricula (NVIDIA DLI, MS Learn Partner, CISCO, …)
- Industrial exam centers

Background

- PHENIX detector
- direct photon analysis
- DHM@EMCal (25k towels)
- Strong energy dependence
- Patterns from HV issues

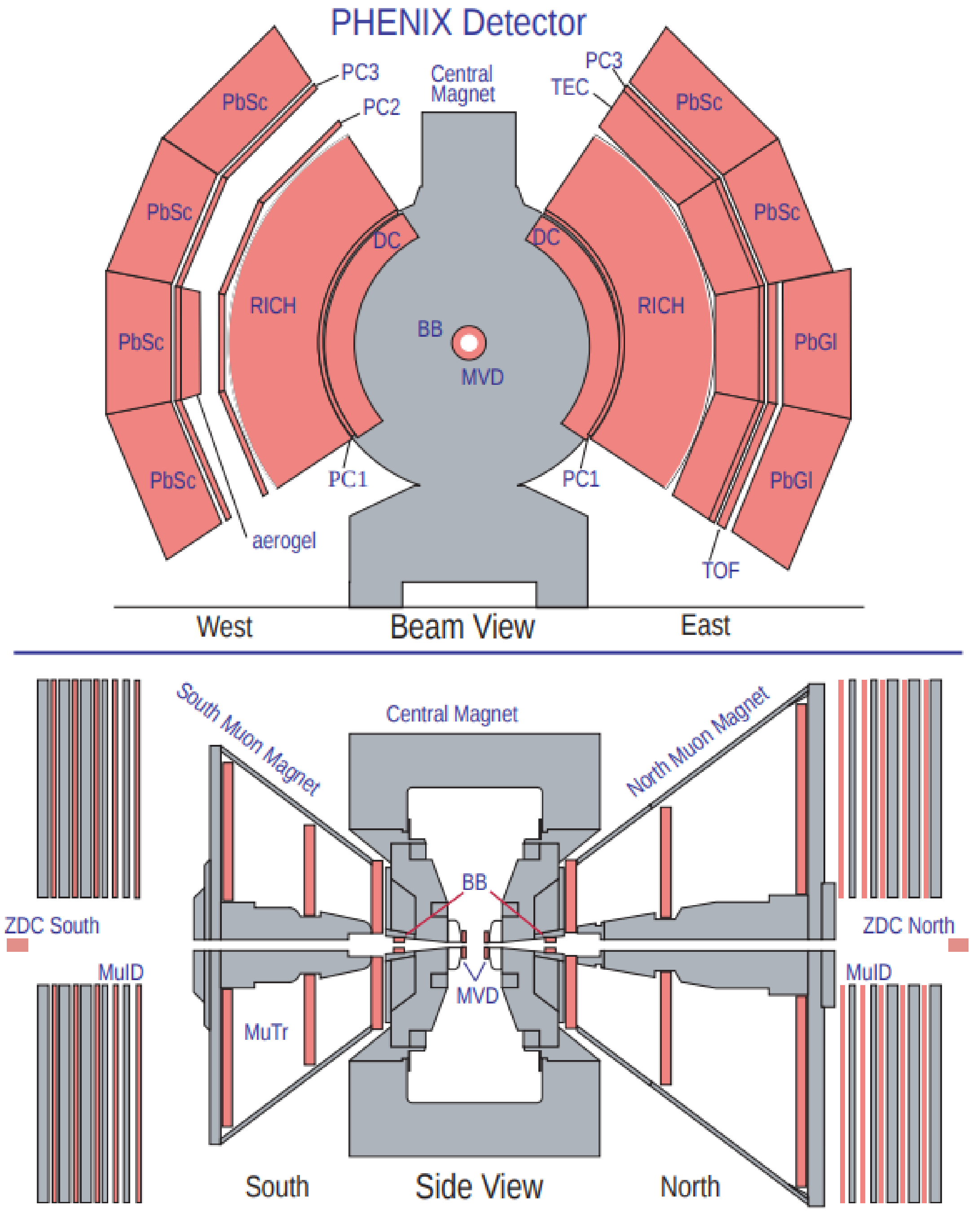

Figure 3.2: The PHENIX setup during the fourth RHIC beam period.

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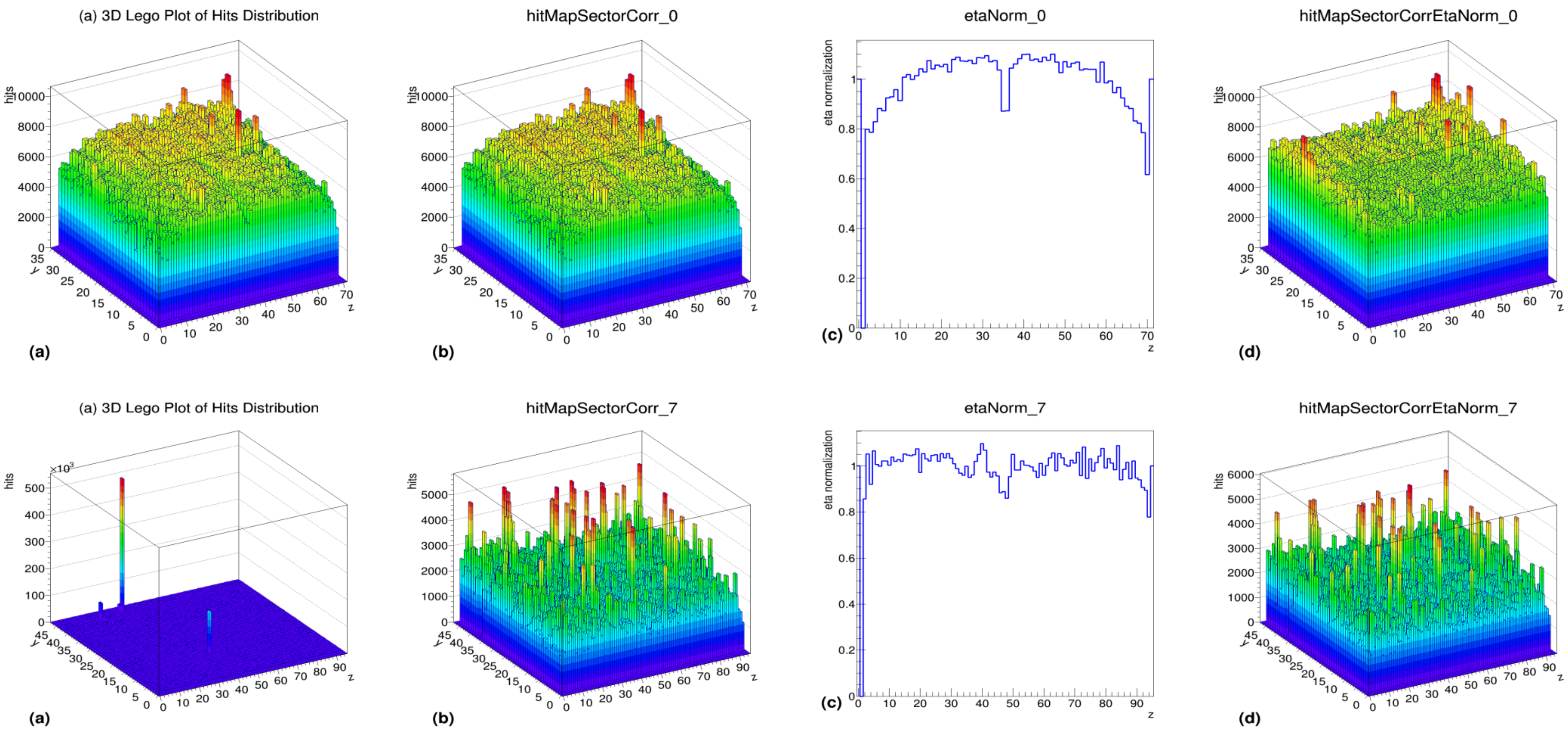
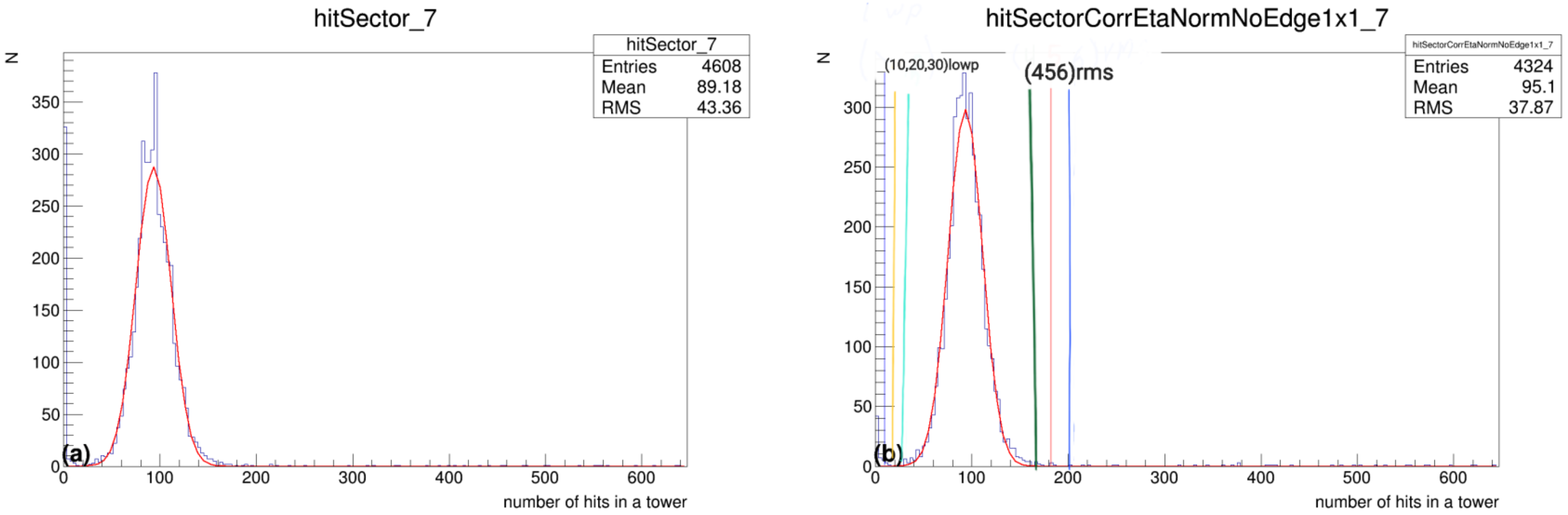
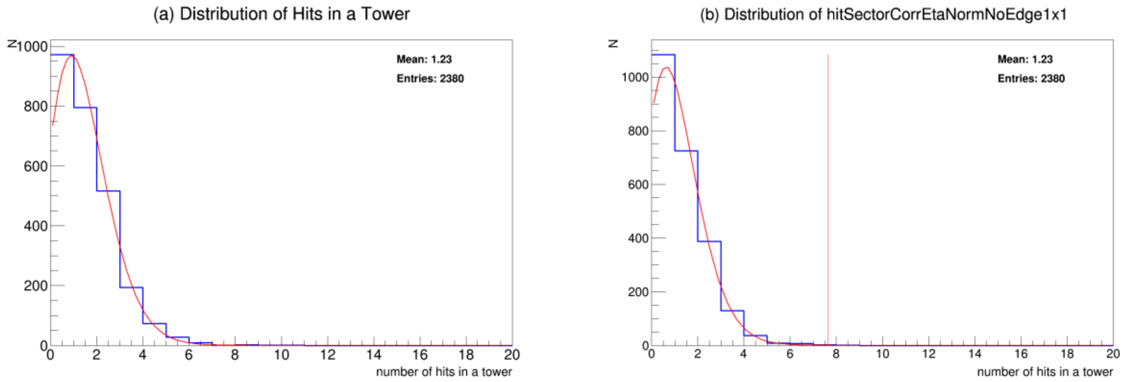
Raw maps, eta norm, 8 sectors, 40 energy bins, 1000 runs

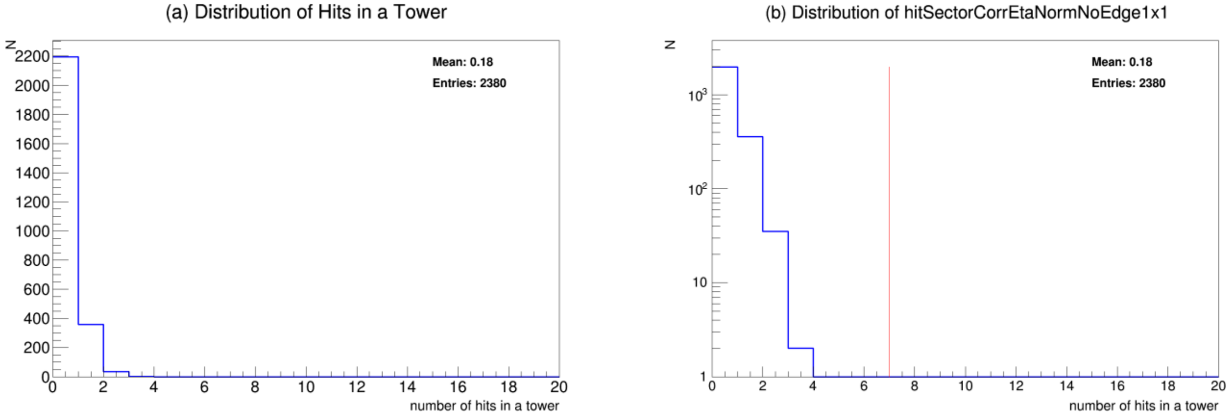


Hit distributions

- What is the normal?







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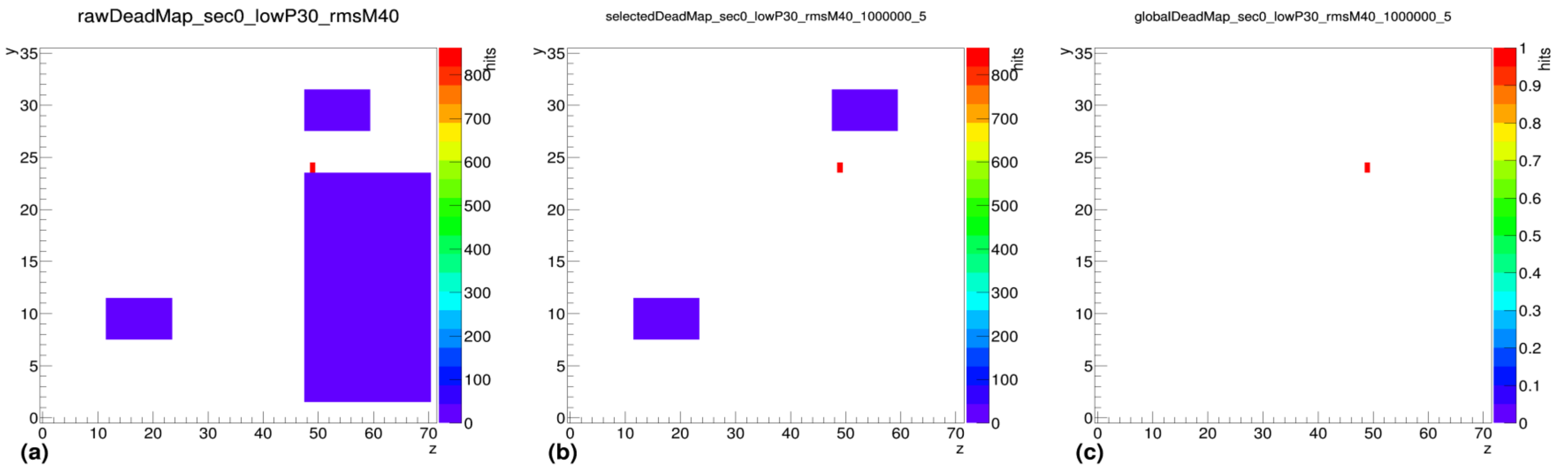
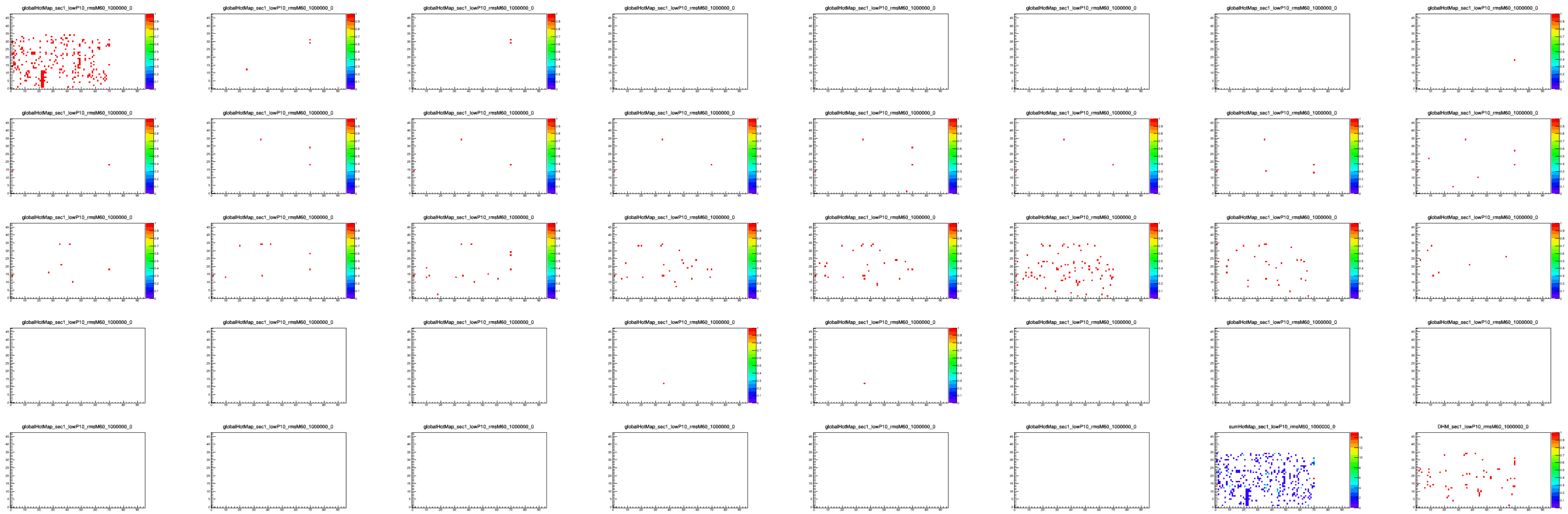
Run16 level DHM in one energy bin

- 800 good runs (low quality runs was removed from the 1000 runs)
- plot the dead towers from each run
- Keep the stable ones

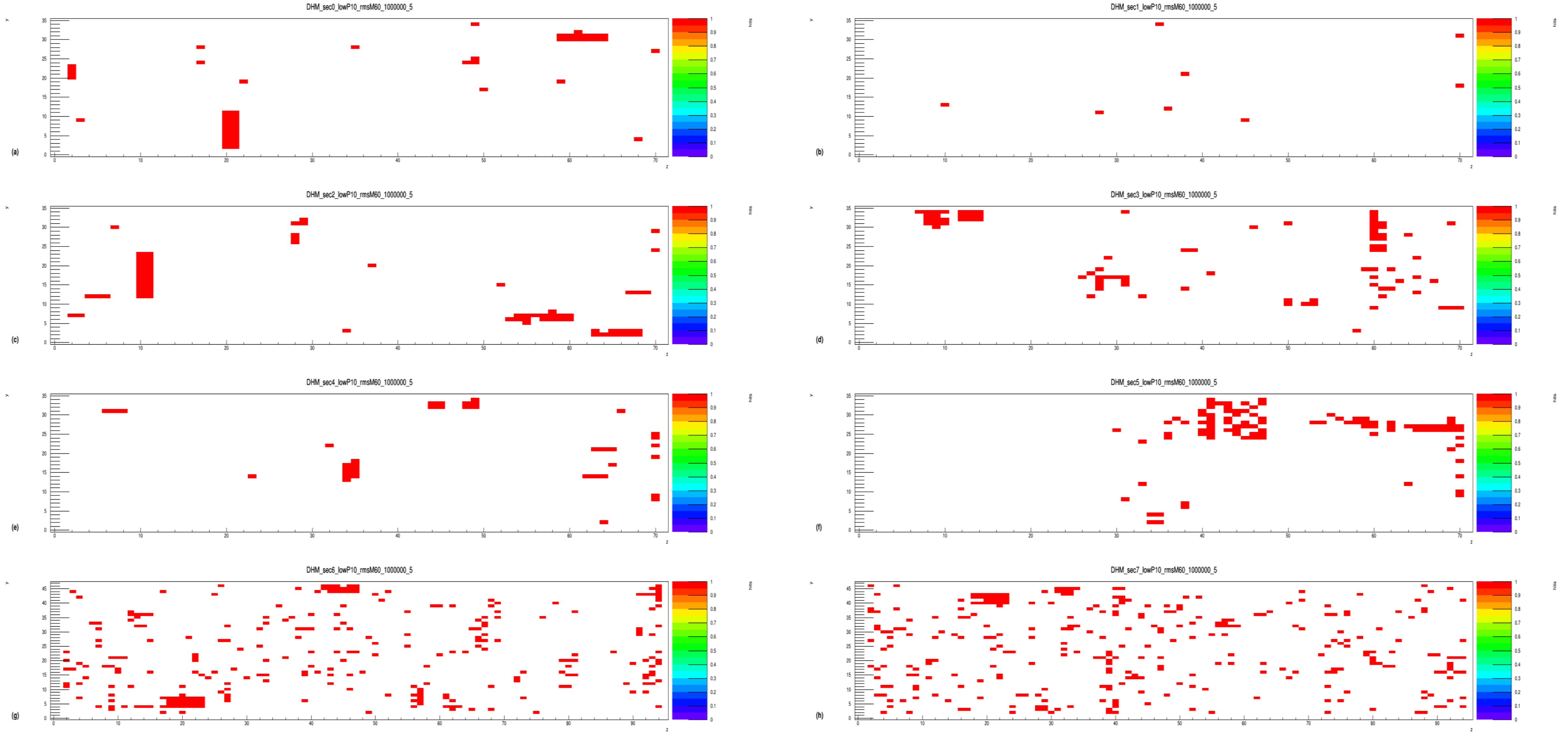


In every energy bin

- Phyisics is back, direct photon at high pT



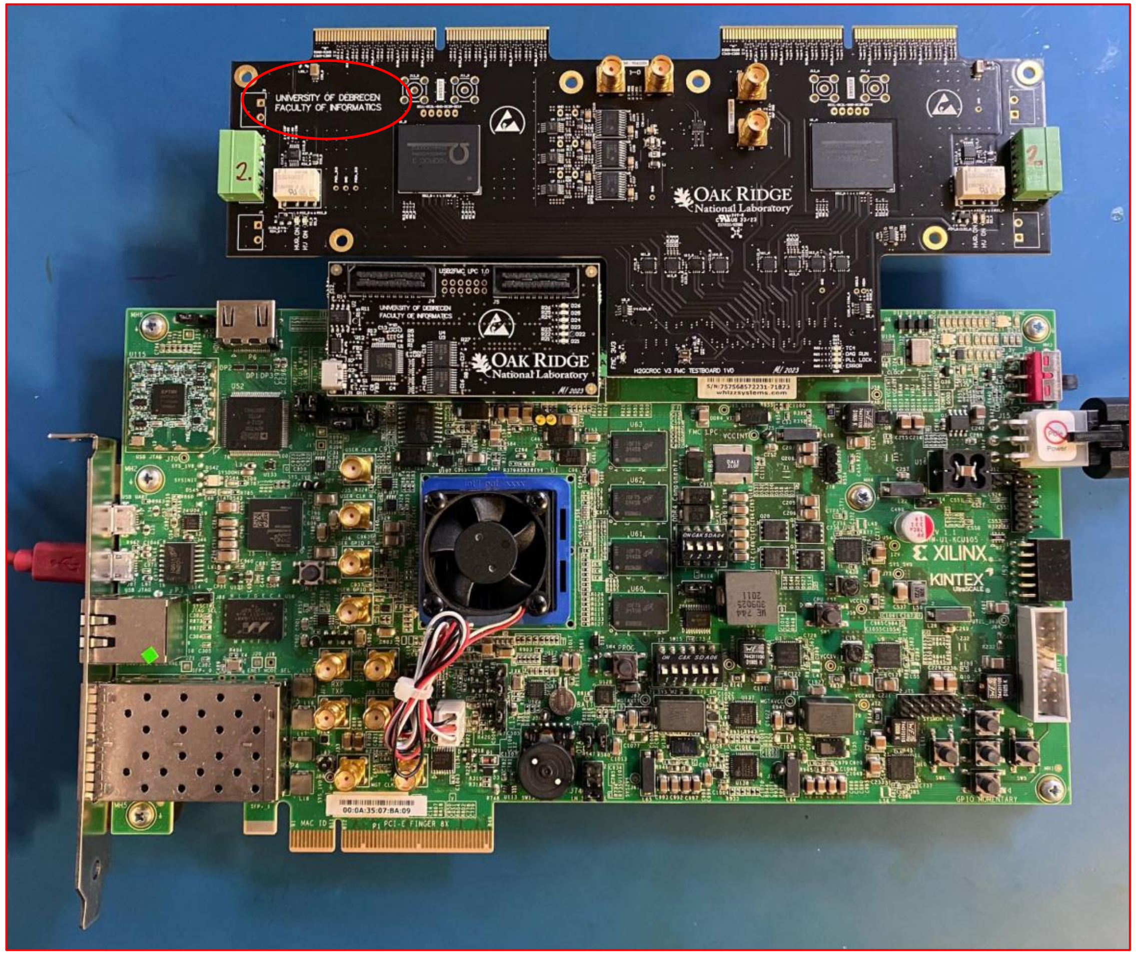
Final DHM



DHM_sec0_lowP10_rmsM60_1000000_5
DHM_sec1_lowP10_rmsM60_1000000_5
DHM_sec2_lowP10_rmsM60_1000000_5
DHM_sec3_lowP10_rmsM60_1000000_5
DHM_sec4_lowP10_rmsM60_1000000_5
DHM_sec5_lowP10_rmsM60_1000000_5
DHM_sec6_lowP10_rmsM60_1000000_5
DHM_sec7_lowP10_rmsM60_1000000_5
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)

ePIC lfHCal

- lfHCal front-end development with ORNL
- lfHCal SiPM test
  - Prototype at Yale (100/day), final system
  - (~200k SiPM/years) at Yale/or and ORNL
  - We have to check at least 5%



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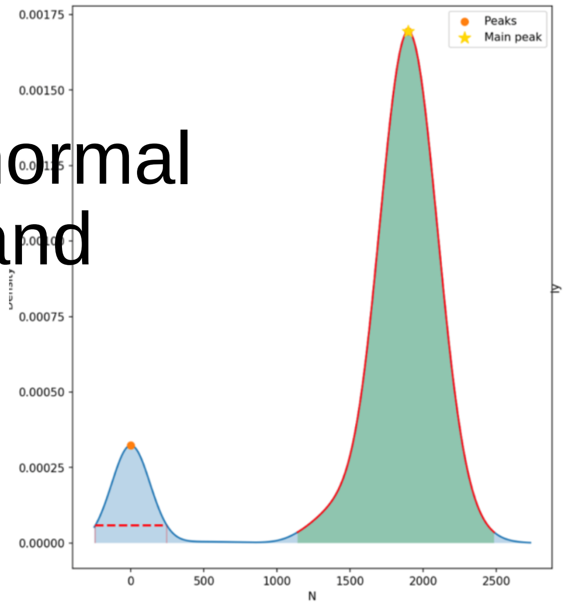
Density function

- A probability density function (PDF) is a function that shows how frequently a continuous random variable takes values in different ranges.
- The density function indicates how densely the values are distributed within an interval.
- The peak of the function corresponds to the most likely value, where observations tend to cluster.
- The method analyzes the distribution of hit rate, defines normal ranges based on the dominant peaks of the distribution, and treats any values that deviate from these as anomalies.



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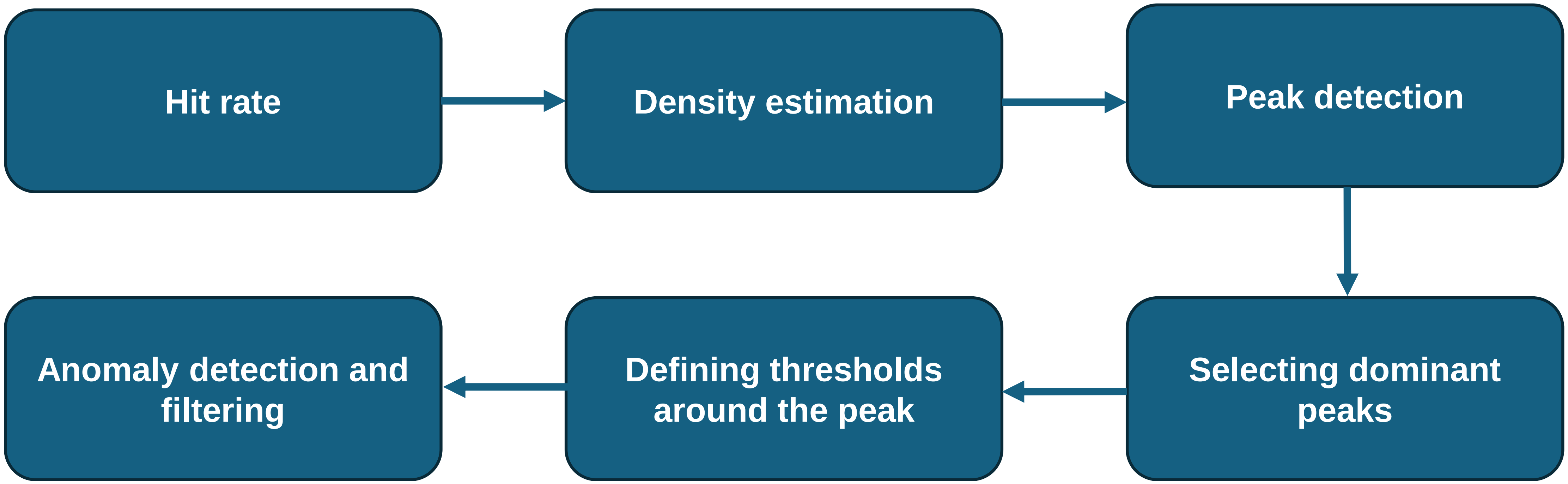
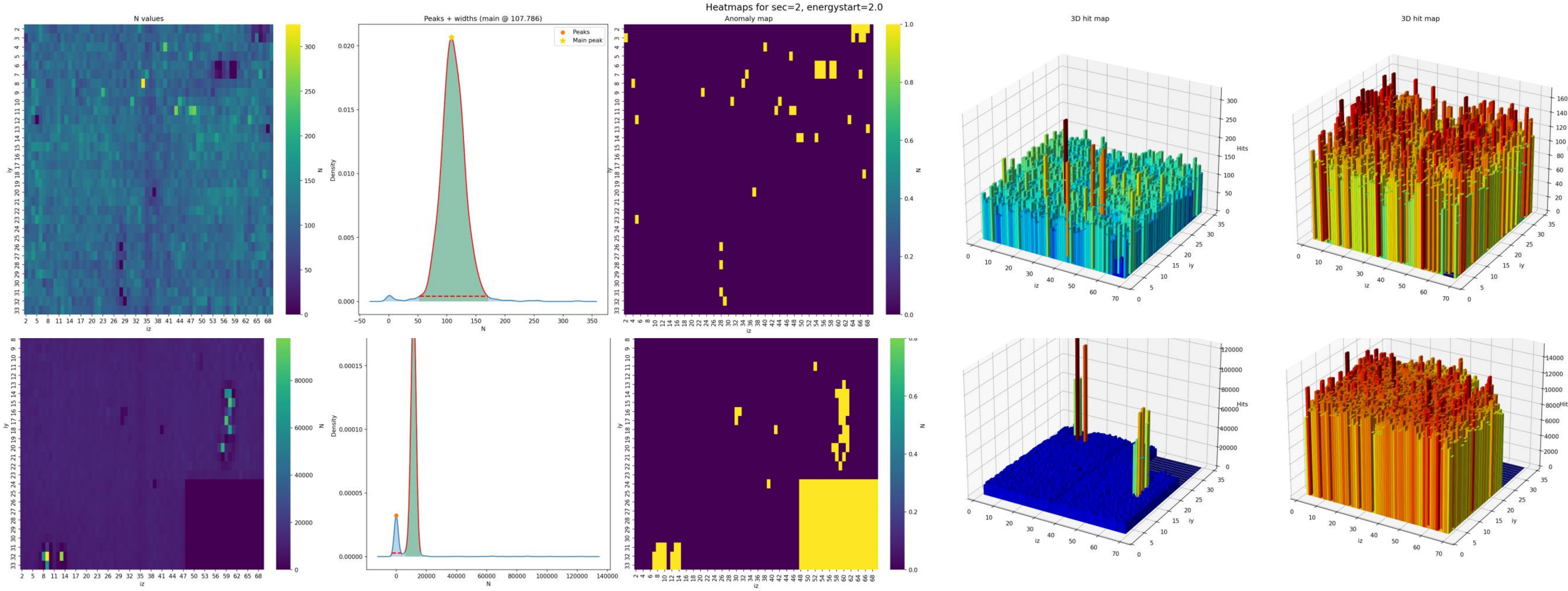
Description



Description

1. **Extracting hit rate**
2. **Density estimation:** Examining the distribution of keystroke counts using kernel density estimation (KDE), which reveals how densely values occur along the number line.
3. **Peak detection in the density function:** Identifying local maximum in the density curve, representing frequent and typical value ranges (concentration regions).
4. **Selecting dominant peaks :** Retaining only statistically significant modes. These define the system’s normal operating ranges. Currently, only the most dominant peak is used.
5. **Defining thresholds around the peak :** Determining cutoff values by analyzing the drop-off of the density curve. The tails beyond the peak boundaries represent anomaly zones.
6. **Anomaly detection and filtering**

Result

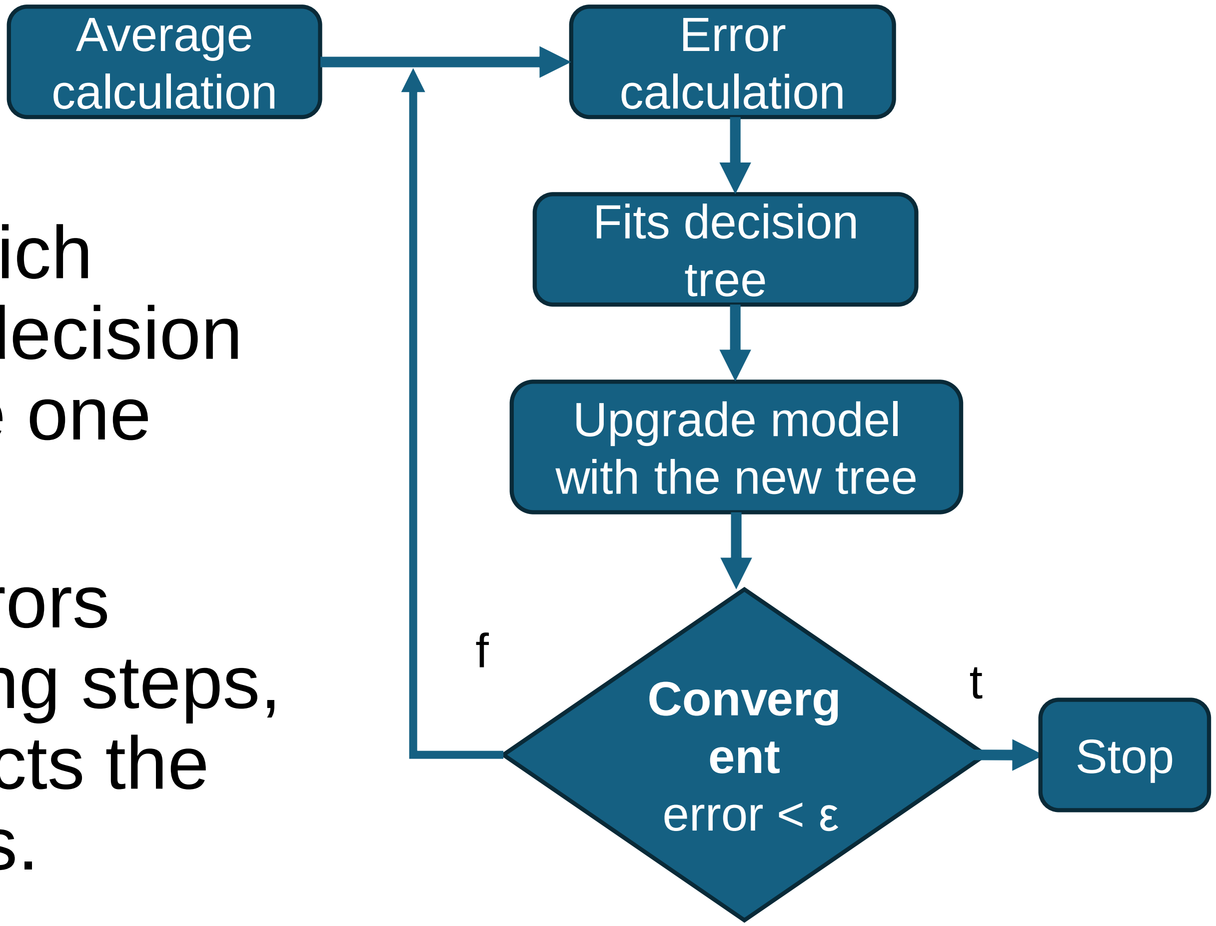


Heatmaps for sec=2, energystart=2.0
N values
Peaks + widths (main @ 107.786)
Peaks
Main peak
Anomaly map
3D hit map
3D hit map
Density
iy
iz
N
Hits

Anomaly detection by machine learning

XGBoost

- eXtreme Gradient Boosting
- Boosting is a technique in which many weak models (usually decision trees) are combined to create one strong model.
- Goal: continuously reduce errors through a sequence of learning steps, where each new model corrects the mistakes of the previous ones.



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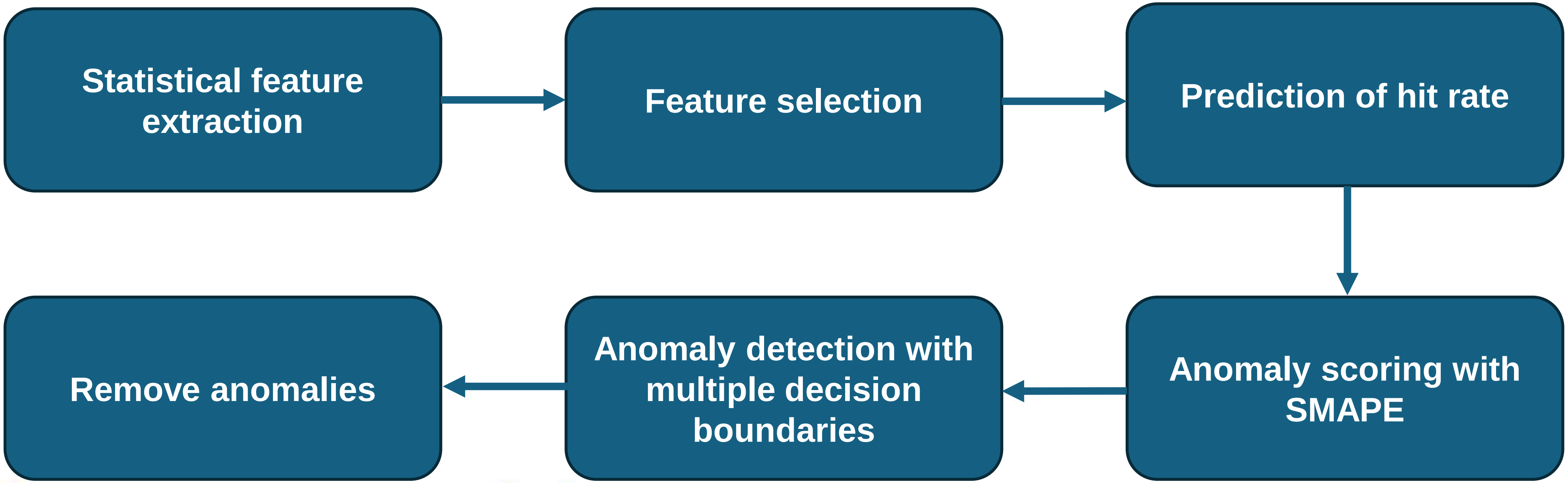
Anomaly detection by machine learning



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Anomaly detection by machine learning

1. **Statistical feature extraction:**
   Computing descriptive metrics of the data: percentiles (1%, 95%, 99%), median, mean, standard deviation, skewness, kurtosis, entropy, ratio of non-zero values.
2. **Feature selection:**
   Sector, iy coordinate, iz coordinate, initial energy level, 99th percentile, median, 1st percentile, mean, standard deviation, skewness, kurtosis, entropy, ratio of non-zero values.
3. **Anomaly scoring using SMAPE (Symmetric Mean Absolute Percentage Error) metric**
   Determining the degree of anomaly based on the difference between predicted and actual hit rate using SMAPE.
4. **Anomaly detection with multiple decision boundaries**
   Applying a mean- and standard deviation-based threshold to identify actual anomalies.
5. **Removing detected anomalies from the data**

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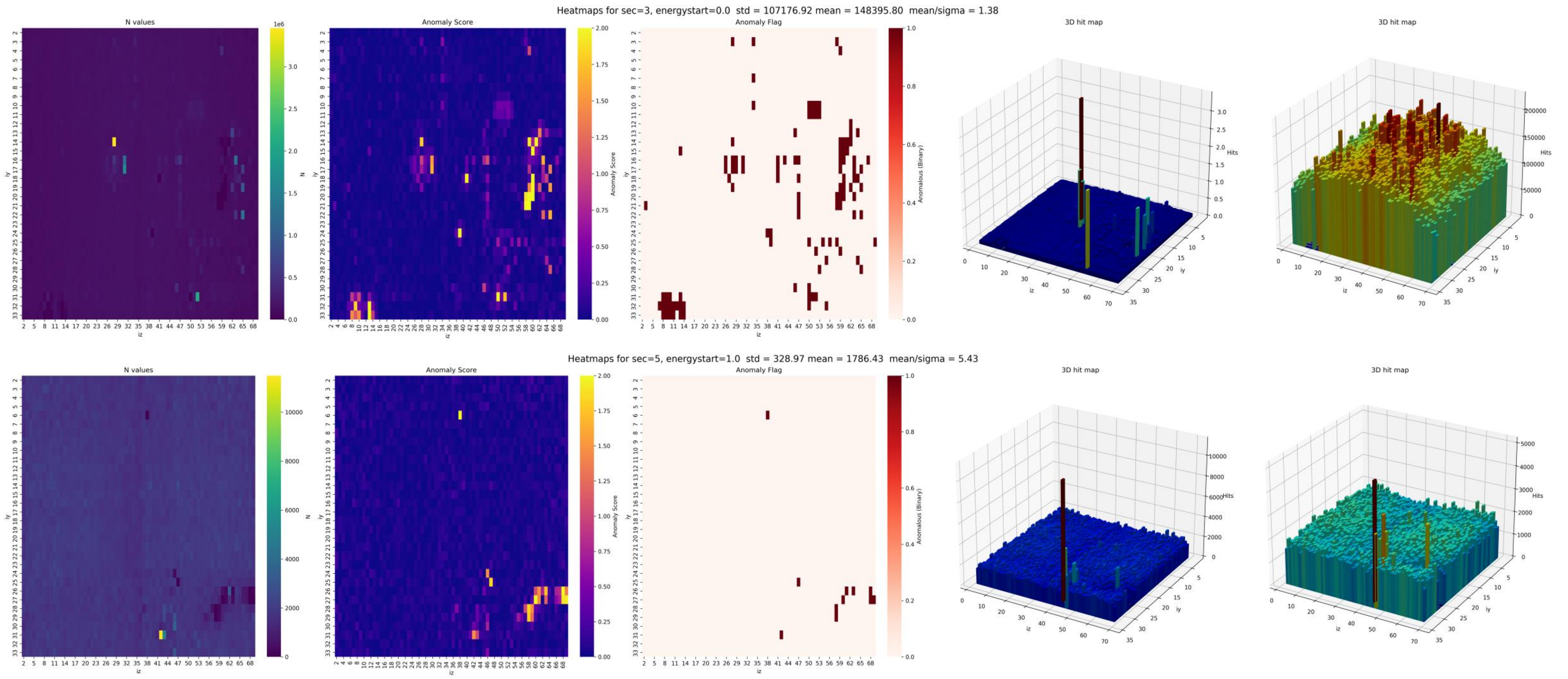
Anomaly detection by machine learning



Anomaly detection assisted by DL

Preprocessing:

- Suspicious (anomalous) pixels are marked in the grids according to statistical rules:

  - dead: values lower than a given proportion of the grid average

  - hot: values that exceed the average by several standard deviations

  - extra hot: extremely large outliers

- We replace the marked pixels with the neighborhood average (imputation).

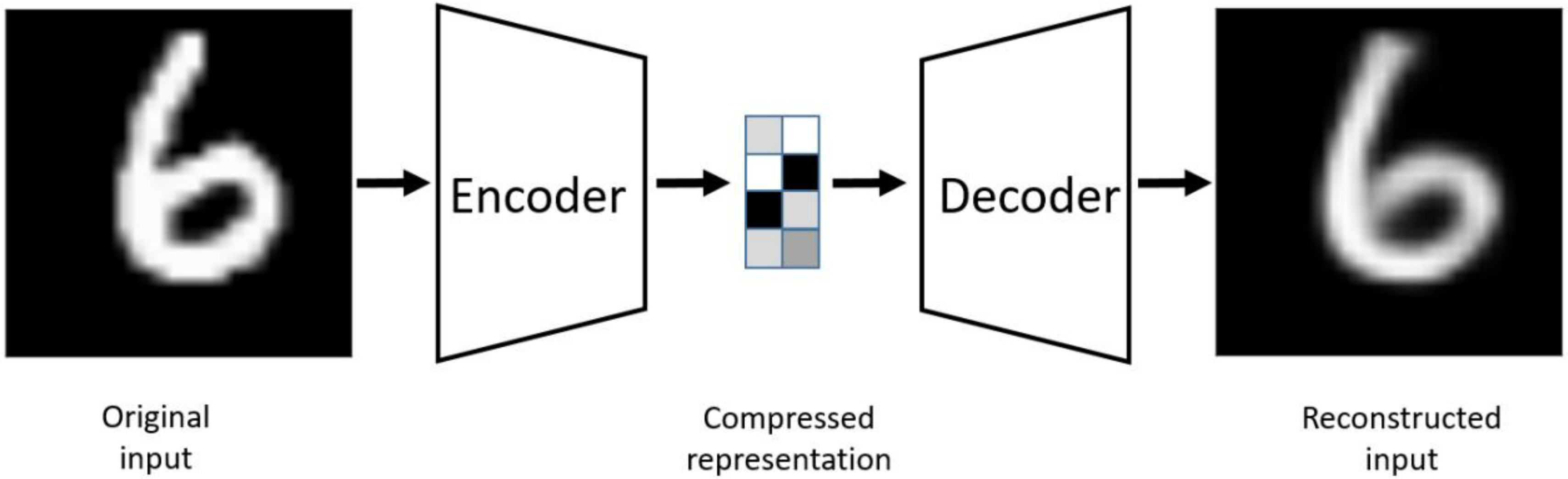
Robust scaling and normalization

- We normalize the grid reducing the impact of extreme values.
- We standardize the size of different grids (padding).

Anomaly detection assisted by DL

Convolutional Auto Encoder

- A small convolutional autoencoder:



- Goal: to learn typical, “normal” spatial patterns.

Anomaly detection assisted by DL

The training – Masked Reconstruction + Huber

- We set part of the input (mask_ratio) to zero, and the network only tries to reconstruct the omitted pixels.
- Loss function: Huber (Smooth L1) – robust to outliers.
- Early stopping: if the validation loss does not improve, we stop training.

Loss function (Huber / Smooth L1):

$$L_\delta(r) = \begin{cases} \frac{1}{2}r^2, & \text{if } |r| \le \delta \\ \delta(|r| - \frac{1}{2}\delta), & \text{otherwise} \end{cases}$$

$$r = X - \hat{X}$$

Anomaly detection assisted by DL

Inference – Residual and Thresholding

- The learned model performs reconstruction, the residual: $R = X - \hat{X}$

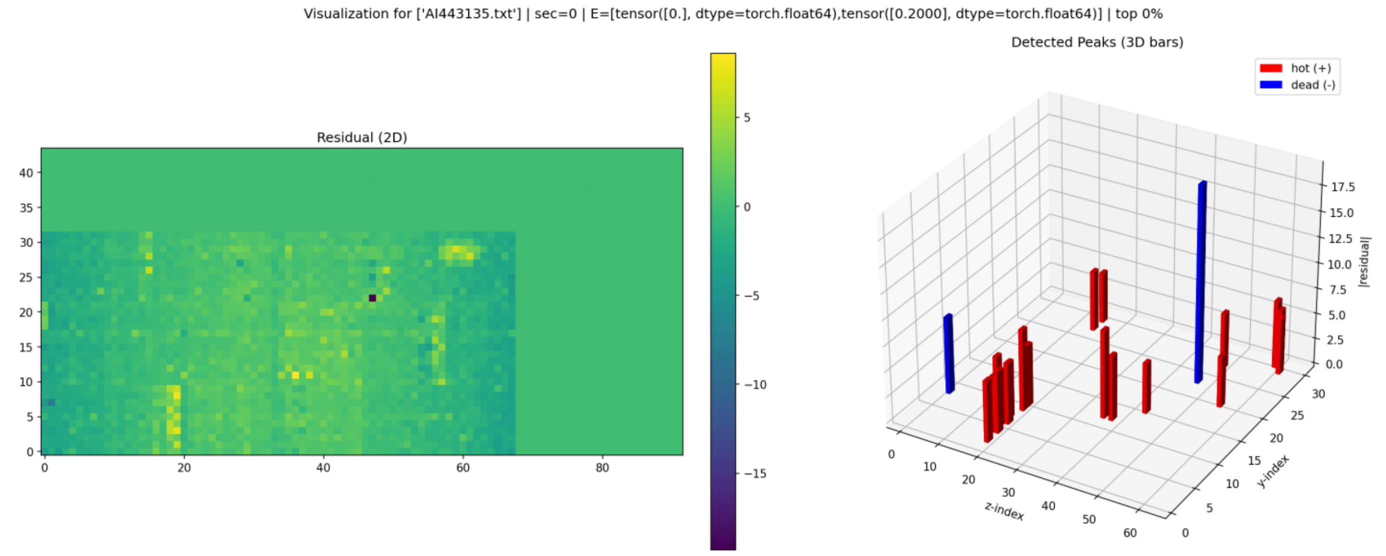
- Based on the distribution of the residual, we mark anomalies with percentile thresholds:

  - hot: above the upper percentile of the positive range

  - dead: below the upper percentile of the negative range

  - extra hot: extreme cases

- The top 1% of the largest errors is the peak.



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Thank you for your attention.

Questions?