Online Detector Monitoring Using AI

Challenges, prototypes and performance evaluation for automation of online quality monitoring of the CMS experiment exploiting machine learning algorithms

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Data Quality Monitoring (DQM)

- **guarantees high-quality data** for physics analyses:
  - *online monitoring*: **live** feedback during data acquisition;
  - *offline monitoring*: certify the data quality using offline processing;
- online DQM **identifies emerging problems**:
  - comparison to reference distributions;
  - comparison supported by **predefined tests**;
  - **tests** perform data reduction tasks (**summary plots with alarms**);
  - shifters and detector experts **inspect histograms** to spot problems;
  - tests designed to identify **known failure modes**;
- challenges of online monitoring, relevant to machine learning:
  - the **latency** of the evaluation process;
  - absolute **normalization** of the histograms is not possible;
  - **granularity** of the problems to spot;
  - no availability of the ground truth (**labels**).

Details on the infrastructure used for this Data Quality Monitoring (DQM) are given in [1].

Why machine learning?

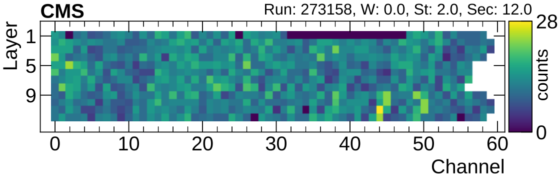
The aim of this project is to **automatize** the CMS online DQM (with machine learning), solving or reducing many of the problems below. The goal is to improve the current protocol.

- **Latency**: human intervention and thresholds require sufficient statistics.
- **Volume budget**: amount of data a human can process in a finite time.
- **Static thresholds don't scale**: assumptions on potential failure scenarios.
- **Human driven decision process**: alarms based on shifter judgment.
- **Changing running conditions**: reference samples change over time.
- **Manpower**: the effort to train a shifter and maintain instructions.

Test case: Drift Tube (DT) hit occupancy

Test case: data recorded by the DT chambers of the muon spectrometer.

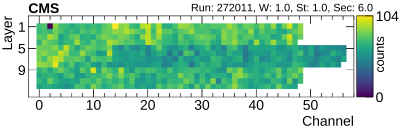
- Monitoring **pattern**: histogram-based image classification.
- Hit occupancy contains the total **number of electronic hits at each readout channel**. It is a 2-dimensional array organized along **layer** (row) and channel (column) indices:



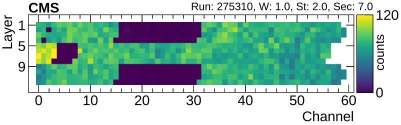
- At any time CMS DQM visualizes 250 DT occupancy histograms.
- Current test summarizes alarms in **one plot** based on the **fraction of dead cells** (zero hits).

Test case: Drift Tube (DT) hit occupancy

- **Expected**: small variance of hit occupancy between neighboring channels.



- **Anomalous**: noisy or inefficient area (example: low occupancy across all the 12 rows).

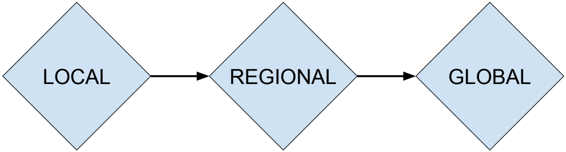


Approaches to the anomaly detection

- exploit the **geographical information** and detect different types of anomalies at **different scales** (ranging from a few channels to collective behaviors of big portion of the DT system);

Pipeline of fault detection:

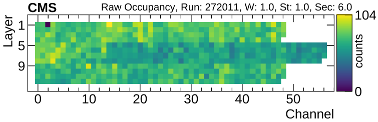
- *local*: data collected in each chamber **layer** are treated independently from the other layers;
- *regional*: extend the *local approach* to account for **intra-chamber problems**; simultaneously consider **all layers in a chamber**, but each chamber independently from the others;
- *global*: simultaneously use the information of **all the chambers** for a given acquisition run; the **position of the chamber** in the CMS detector impacts expected occupancy distribution of the channel hits.

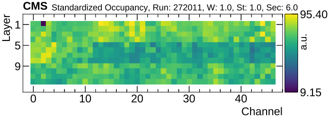


Dataset Preprocessing

The occupancy 21000 occupancy histograms were preprocessed.

- *Standardization* of the chamber data: the number of channels in a chamber layer varies. Force **fixed-input dimensionality** with a row-by-row one dimensional linear interpolation.

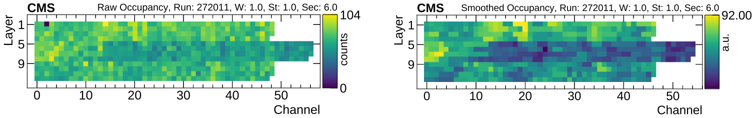




Standardization of the occupancy histogram

Dataset Preprocessing

- *Smoothing*: according to CMS DT experts **isolated** misbehaving channels are **not considered a problem**. One dimensional median filter is applied.



Smoothing of the occupancy histogram

- *Normalization*: the need for comparing data across chambers or across runs; the input data set depends on the **integration time** and on the **LHC beam configuration and intensity**.

Local strategy: Scope & Method

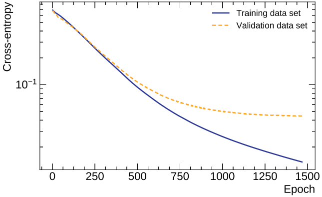
- filters out most of the anomalies;
- assessing the (mis)behavior with high-granularity (**few channels**);
- data collected in each muon chamber **layer** are treated **independently** from the others to detect intra-layer problems;
- **labels** were provided by experts: 5668 good and 612 bad (~ 0.1 positives).

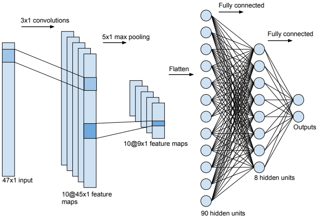
In this experiment, we compare the performances of the following:

- **unsupervised** with a simple statistical indicator (**variance** within the muon chamber layer), and an image processing technique, (maximum value of the vector obtained by applying a variant of an edge detection **Sobel filter** [2]: $S_i = \max(\begin{bmatrix} -1 & 0 & 1 \end{bmatrix} * X_i)$);
- **semi-supervised learning**, with **Isolation Forest** [3, 4], and μ-**SVM** [5] (both validated with 5 stratified folds);
- **supervised learning**, with a fully connected **shallow neural network** (SNN), and a **convolutional neural network** (CNN) [6].

Local strategy: CNN details

- *rectified linear units* and *softmax* as activations, trained with Keras/TensorFlow, *Adam optimizer* and *early stopping* (patience = 32 epochs);
- **class weight** to account for class imbalance; the weight λ for a sample in class $\psi \in \{0, 1\}$ is: $\lambda_\psi = \frac{|S|}{2 \cdot |S_\psi|}, S = S_0 \cup S_1$.

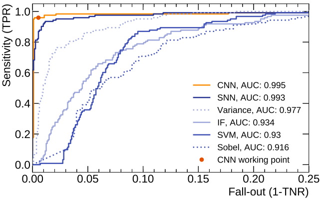


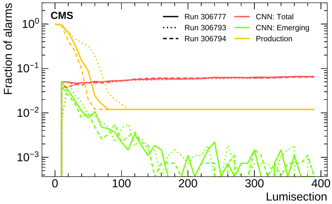


Loss function as a function of the number of epochs (left) and architecture of the CNN model (right)

Local strategy: Results

- convolutional neural network (CNN) outperforms other methods;
- performance of the CNN in low statistics region is different than the production test.

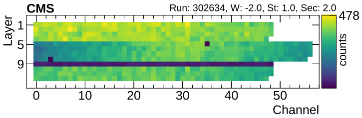


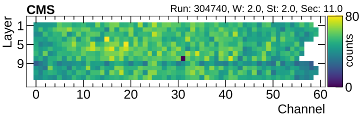


Left: ROC (Receiver Operating Characteristic) curve and AUC of the different models; Right: stability of the CNN model and the current production test as a function of time (lumisection is approx. 23 s)

Regional strategy: Scope

- extends local strategy to filter out anomalies not seen by the previous approach;
- accounts for **intra-chamber** problems: simultaneously consider all layers in a chamber;
- the occupancy pattern within a chamber depends on the layer (row) information;
- example of use: identify layers with low efficiency (lower voltage).



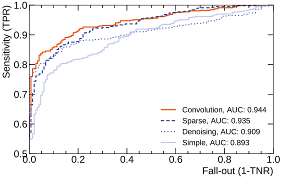


Examples of chambers having low efficiency in chamber layer 9

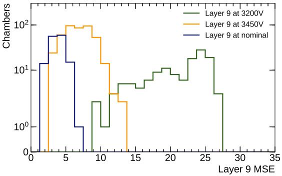
Regional strategy: Method

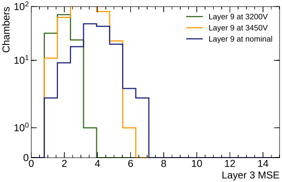
- semi-supervised **autoencoder** [7] variations:
  - bottleneck,
  - denoising,
  - sparse,
  - convolutional;
- all chambers without any chamber layers labeled as faulty by the CNN **local model** were used for training (8424 matrices);
- all models minimize the **mean squared error** ϵ of input x and reconstructed $\ddot{x}$ samples: $\epsilon = \frac{1}{ij}\sum_{i,j}(x^k_{i,j} - \ddot{x}^k_{i,j})^2$;
- a model will have a high reconstruction error ϵ on samples with voltage problem.

Regional strategy: Results



ROC and AUC of the different autoencoder models





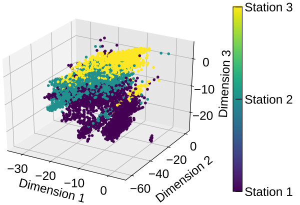
Convolutional autoencoder MSE between reconstructed and input samples for chamber layer 9 (left) and chamber layer 3 (B)

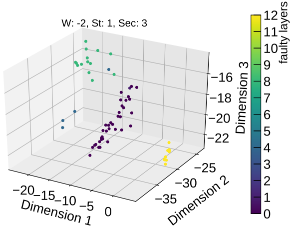
Global strategy: Scope & Method

- simultaneous use of **all the chambers** data;
- the **position** impacts expected occupancy pattern;
- with autoencoders, a **compressed representation** of chamber data is learned;
- when the bottleneck of the autoencoder is **3-dimensional** one can visually inspect those representation.

Global strategy: Results

- the representations **cluster** depending on their position in the CMS detector (left: distance from the interaction point);
- the same chamber **changes** representation when problem occurs (right).





Compressed representations of the chamber-level data

Outlook

Concluding:

- the local approach has satisfactory performance and was successfully **implemented** in production (the DT experts still test it);
- the proposed strategy is **generic** enough to be applicable to other kinds of CMS muon chambers, as well as to other sub-detectors.

Future work:

- there is other sub-detector efforts to apply similar strategy (HCAL, ECAL)*;
- addresses next monitoring pattern: failure detection in time evolution of sequential stream of DQM data.

* See: "Improving the use of data quality metadata via a partnership of technologies and resources between the CMS experiment at CERN and industry" (Track 1: Tuesday, 12:15) and "Monitoring tools for the CMS muon detector: present workflows and future automation" (Poster Session: Tuesday)

References

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Backup: Autoencoder architecture