Detector monitoring with artificial neural networks at the CMS experiment at the CERN Large Hadron Collider

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The CMS Data Quality Monitoring (DQM) system

- **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 assesses detector behavior and **identifies emerging problems**:
  - comparison to reference distributions;
  - comparison supported by **predefined tests**;
  - tests designed to identify **known failure modes**.
- Challenges of online w.r.t. offline, relevant to machine learning emerge:
  - the **latency** of the evaluation process;
  - absolute **normalization** of the histograms not possible;
  - higher **granularity** of the problems to spot;
  - no availability of the ground truth (**labels**).

Why machine learning for Online DQM?

Two-layer monitoring protocol was adopted by the CMS Collaboration for LHC Run I (2010-2012) and in Run II (2015-2018). The challenges include:

- **latency**: human intervention and thresholds require sufficient statistics;
- **volume budget**: amount of data a human can process in a finite time;
- **scalability of static thresholds**: 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.

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

Image-like processing of geographically organized data

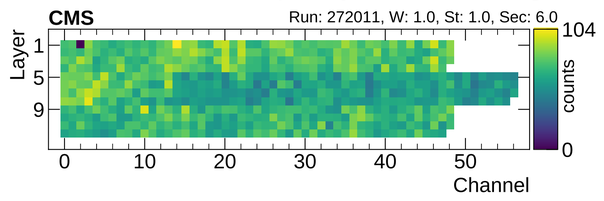
Test case: Drift Tube (DT) muon chambers hit occupancy

Data recorded by the DT chambers of the muon spectrometer during LHC Run II:

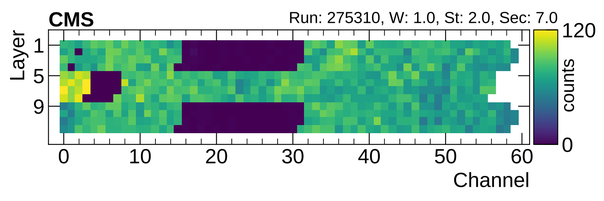
- hit occupancy C^k contains the total **number of electronic hits at each readout channel**. It is a 2-dimensional array organized along **layer** (row) and channel (column) indices

$$C^k = \{x^k_{i,j}; 1 \leq i \leq l, 0 \leq j < n_i\},$$

  $l = 12$ is the number of layers, n_i is the number of channels in layer i
- **expected**: small variance of hit occupancy between neighboring channels; example

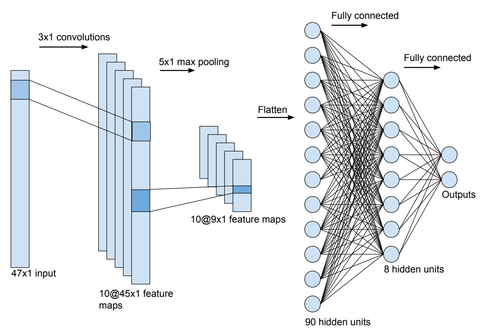


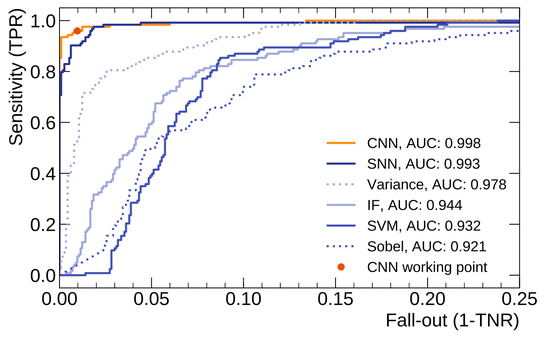
- **anomalous**: noisy or inefficient area; example, low occupancy across the 12 layers



Local strategy

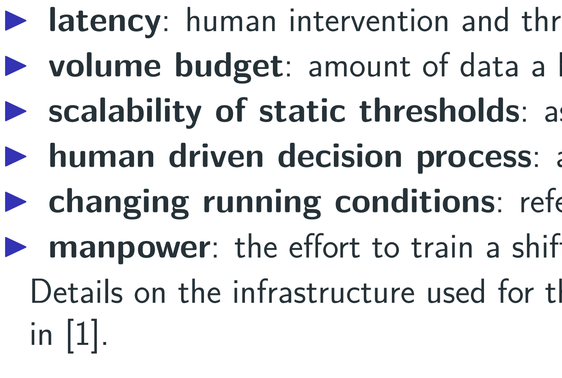
- assessing the (mis)behavior with high-granularity (**few channels**)
- data collected in each **layer** are treated **independently** from the others to detect intra-layer problems
- convolutional neural network (CNN) [2] outperforms shallow network (SNN), one-class support vector machine (μ-SVM) [3], Isolation Forest (IF) [4, 5], variance and a variation of Sobel filter [6]

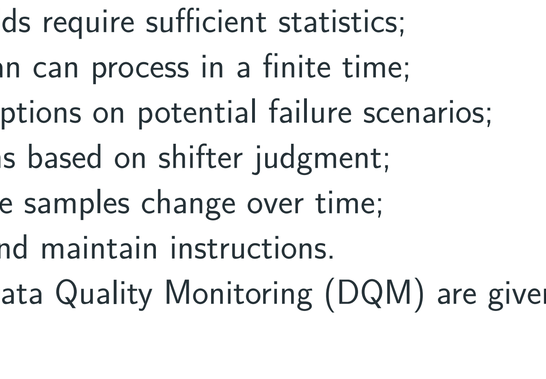




Regional strategy

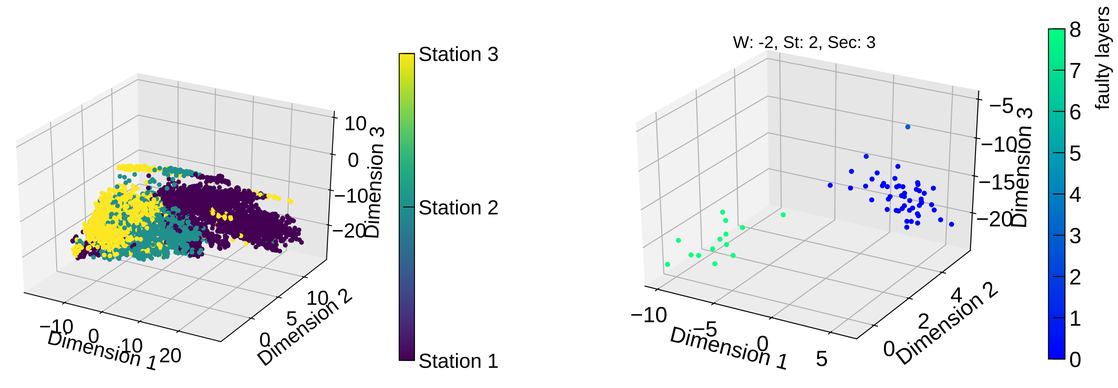
- extend local strategy to account for **intra-chamber** problems: simultaneously consider all layers in a chamber.
- semi-supervised autoencoder [7] variations trained with well-behaving chambers use **mean squared error** of input x and reconstructed $\ddot{x}$ samples: $\epsilon = \frac{1}{ij}\sum_{i,j}(x^k_{i,j} - \ddot{x}^k_{i,j})^2$
- the test is performed for intra-chamber anomalies, an example: identify layers with low efficiency (lower voltage)





Global strategy

- simultaneous use of **all the chambers** data
- the **position** impacts expected occupancy pattern
- with autoencoders, a **compressed representation** of chamber data is learned
- with **3-dimensional** bottleneck one can visually inspect those representation
- the representations **cluster** depending on their position in the detector (left: distance from the interaction point)
- the same chamber **changes** representation when problem occurs (right)



Outlook

- the **first** successfully implemented ML application in CMS DQM;
- the local approach has satisfactory performance and was successfully **implemented** in production;
- the proposed strategy is **generic** enough to be applicable to other kinds of CMS muon chambers, as well as to other sub-detectors;
- the model should be refined, e.g. integrating a mechanism of periodic retraining;
- ongoing other sub-detector efforts to apply similar strategy.

References

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