Automated Monitoring Tools for the CMS Muon System Based on Machine Learning Algorithms

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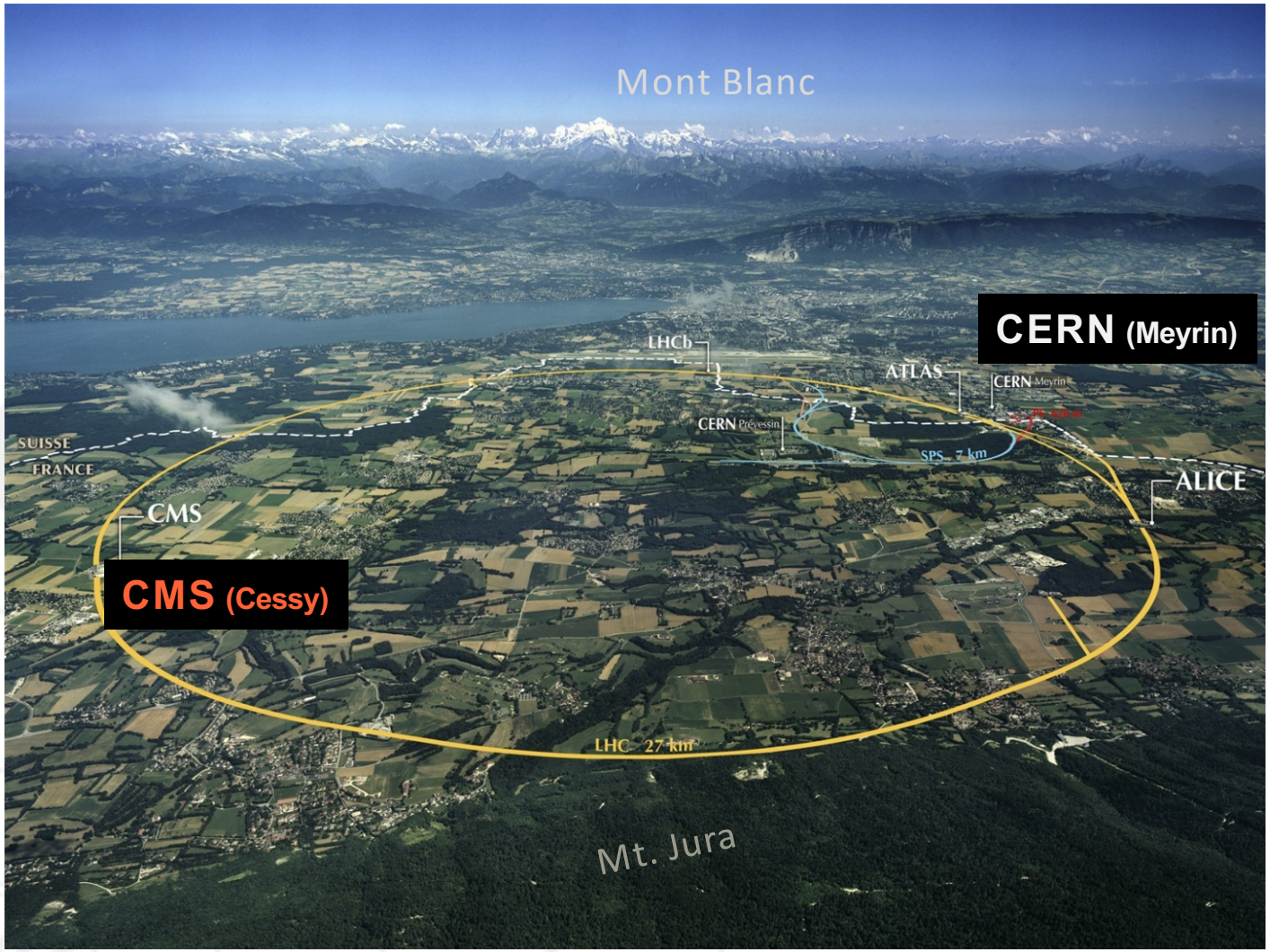
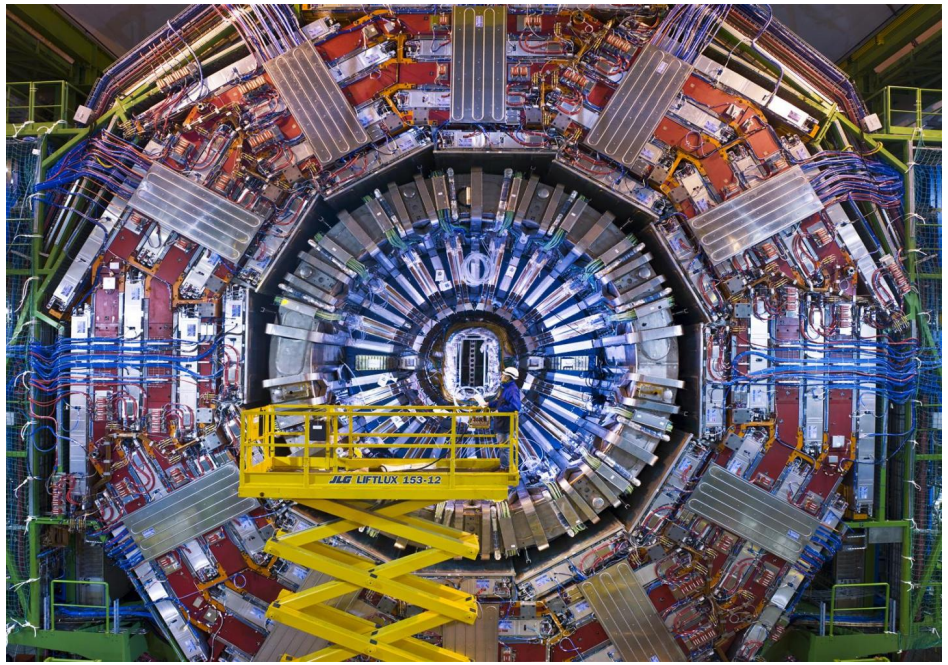
Outline

- The Compact Muon Solenoid (CMS) experiment
- Muon detectors in CMS
- CMS Data Quality Monitoring (DQM)
- Automation of DQM using Machine Learning

The CMS experiment

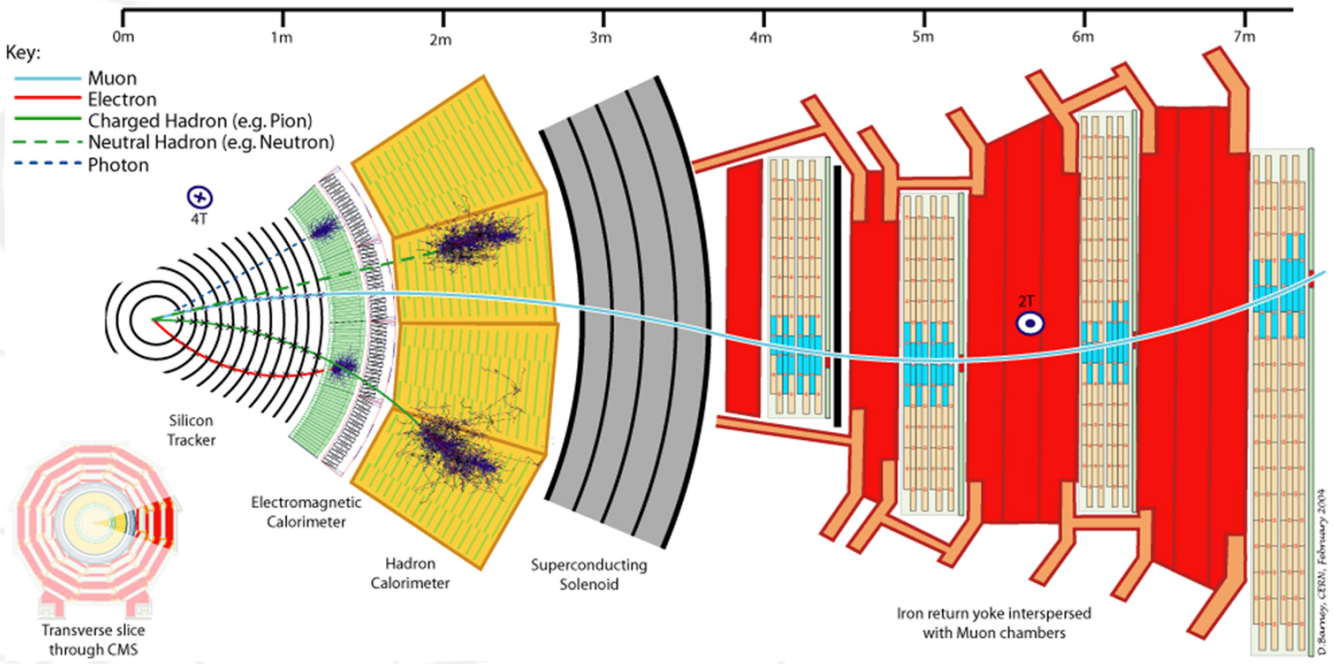


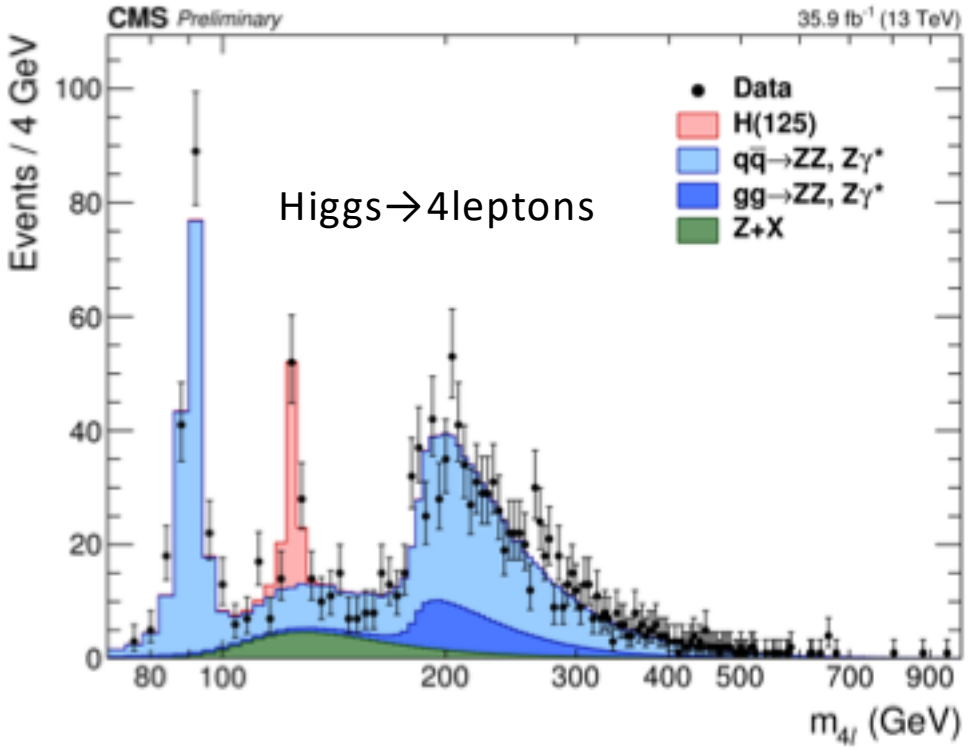
- General purpose particle detector at LHC, to study the Standard Model and search for new physics
- Efficient and precise particle reconstruction with various detector technologies with compact detector at strong B field of 3.8T



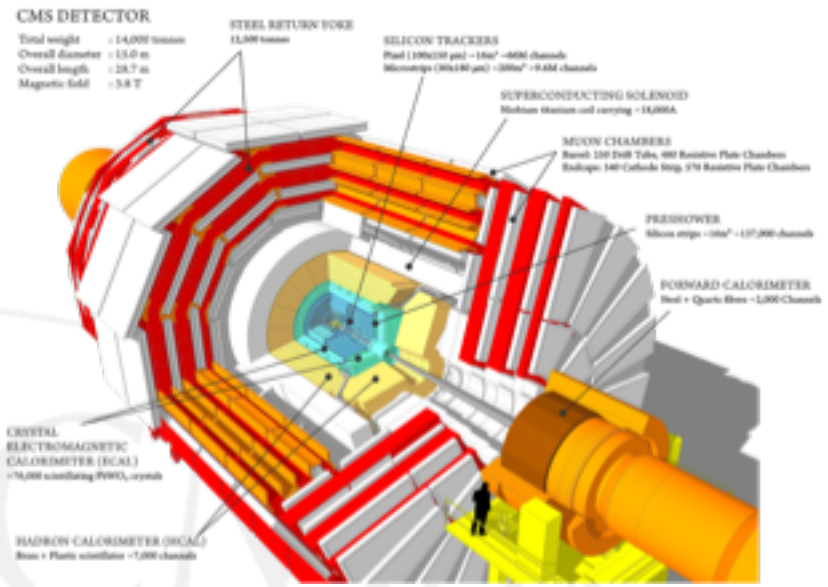
Muons at CMS

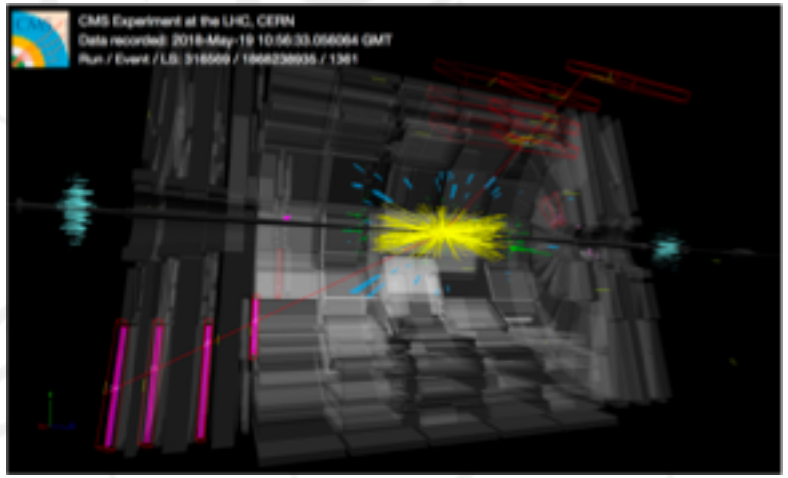
- Many Standard Model and new physics involves high energy muons in the final state
  - Discovery of Higgs boson decaying to ZZ→4 muons
  - Z' decaying to 2 muons at very high energy
- Efficient muon reconstruction and precise tracking by combining all detector information in CMS



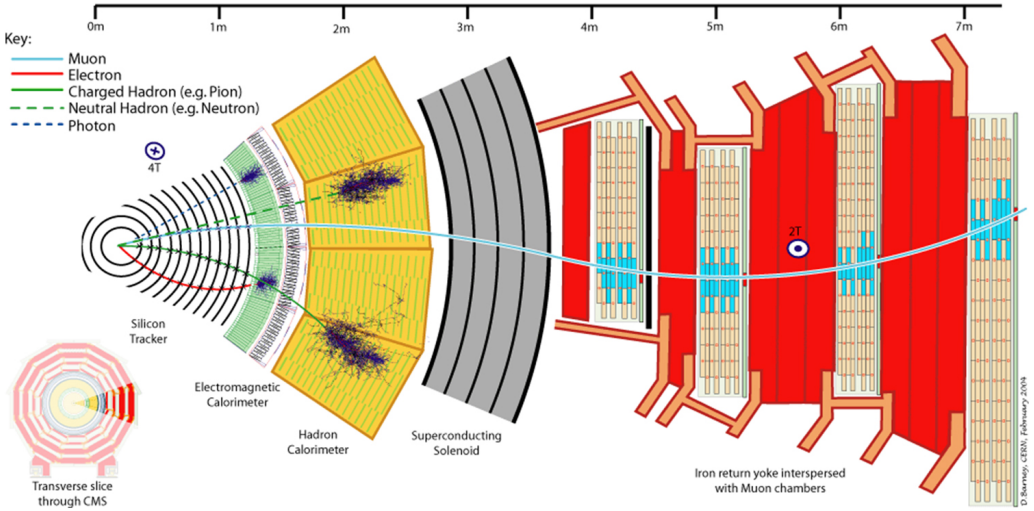


Muons at CMS



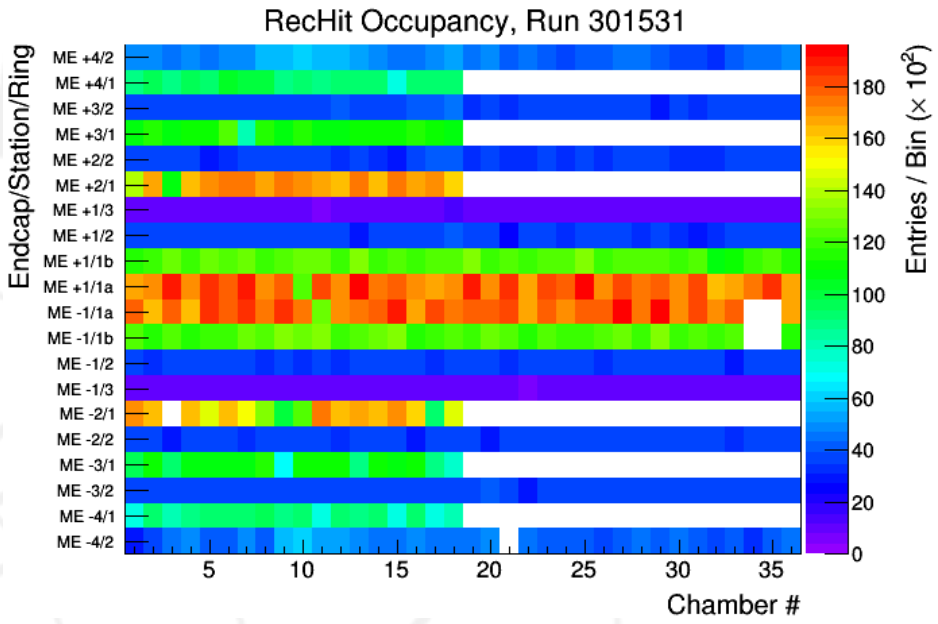


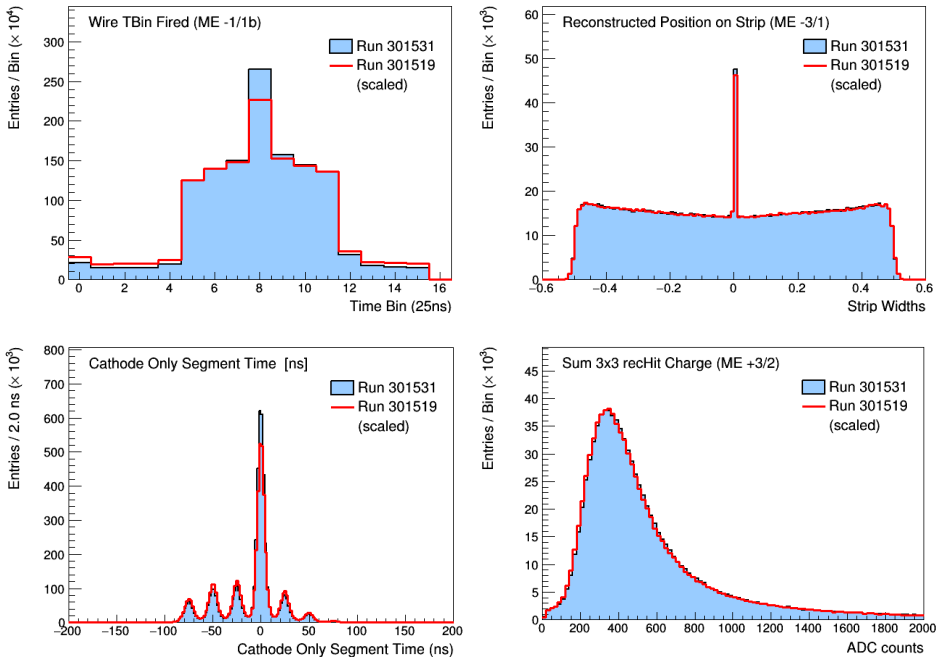
- Muon detectors are installed outermost part of CMS
- Standalone tracking with return field of the solenoid magnet
- 3 different gas-ionization detector technologies, compliment each other
  - Drift Tubes (DT): Barrel region, $|\eta| < 1.2$
  - Cathode Strip Chambers (CSC): Endcap region, $0.9 < |\eta| < 2.4$
  - Resistive Plate Chambers (RPC): Both, $|\eta| < 2.1$
- Good understanding of detector performance is important for the physics



Muon Data Quality Monitoring

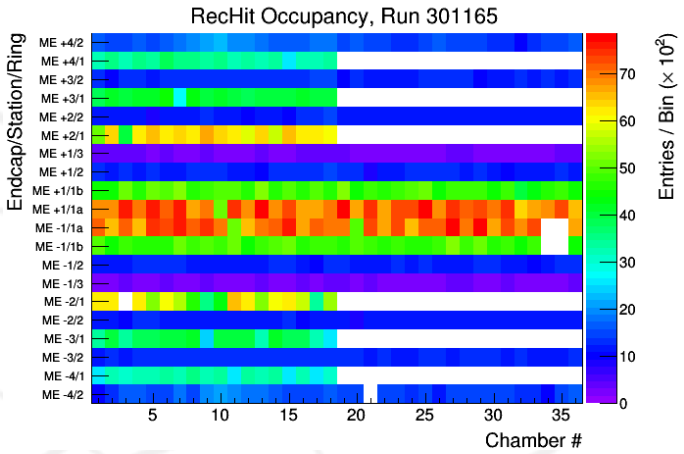
- Current Data Quality Monitoring (DQM) workflow:
  - For each “run”, a person (“shifter”) checks through hundreds of plots and compare shapes against a suitable reference run
  - Flag anything that look unusual, notify the relevant detector experts, diagnose problem
- Non-trivial to compare plots with different LHC and detector conditions
- Human factor - time consuming, error prone in some cases





Improving comparison tool: AutoDQM

- Quantify differences using statistical tests (bin-by-bin pull values, Kolmogorov-Smirnov tests, etc)
- A web-based tool is developed (AutoDQM) to assist shifters
  - User specifies reference run and the tool flags plots based on the statistical tests automatically
- User still needs to specify reference run, not always obvious
- Applying Machine Learning solutions to further automatize the task



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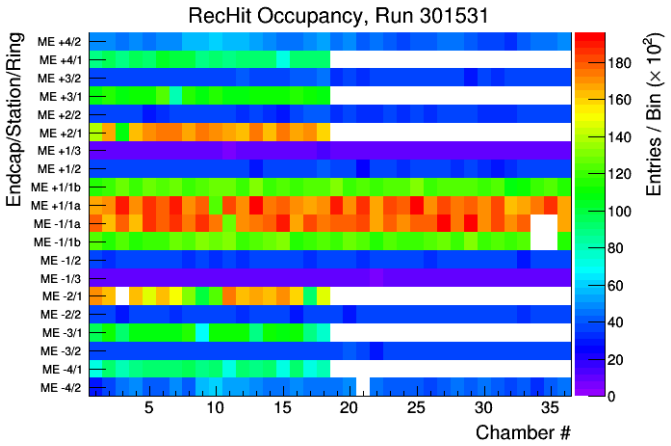

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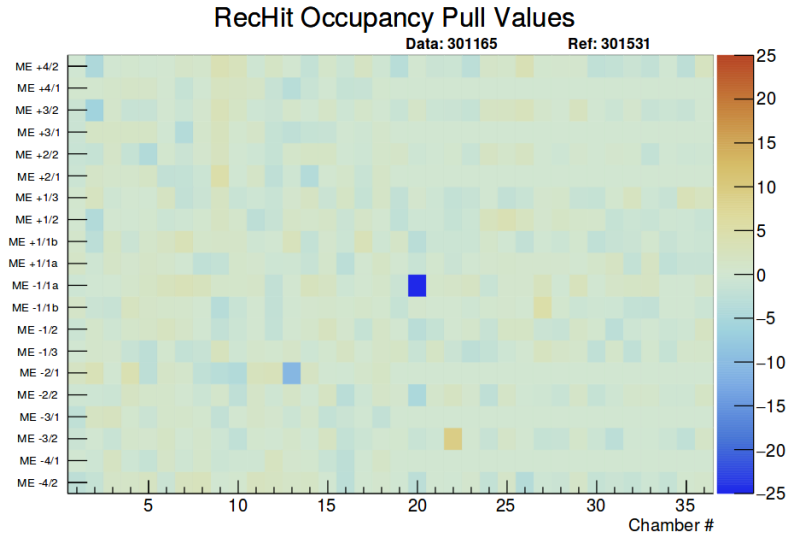
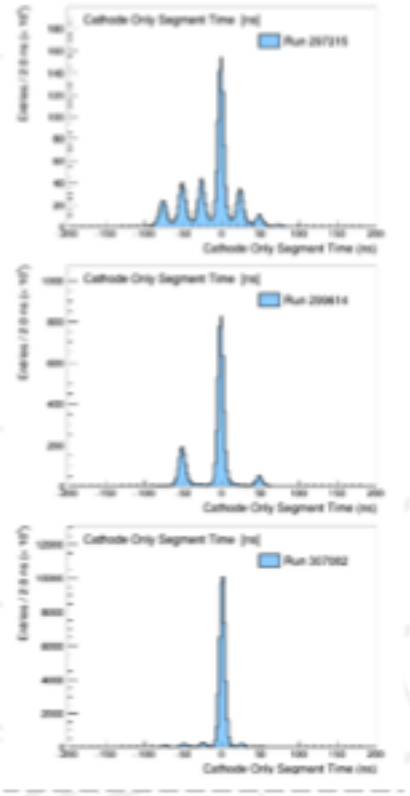
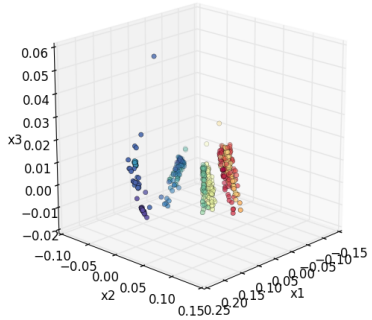


Dimensionality reduction

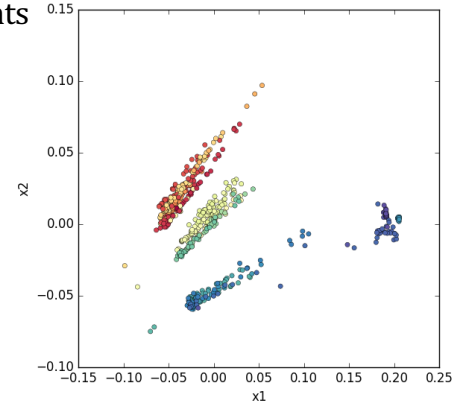
- Thousands of plots to monitor → reduce to a few principal variables to detect anomalies
- Treat input histograms as n-dimensional points and reduce to just a few dimensions using PCA.
- Find outliers which cannot be described by first 1-3 principal components



First 3 Principal Components



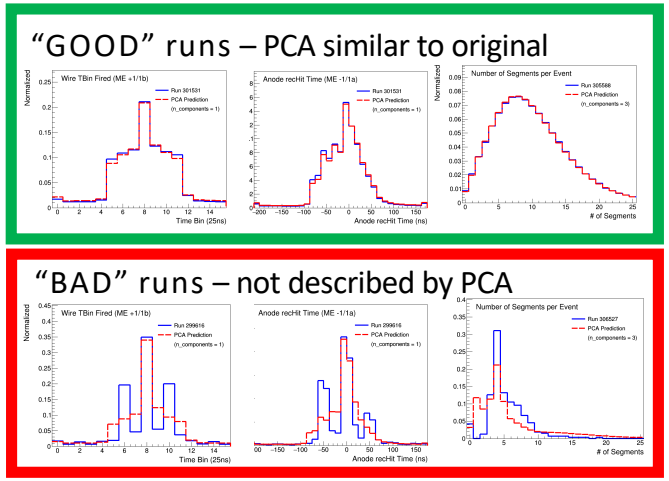
First 2 Principal Components



Different clusters correspond to different groups of runs with slight differences configuration, leading to small shifts in the histograms

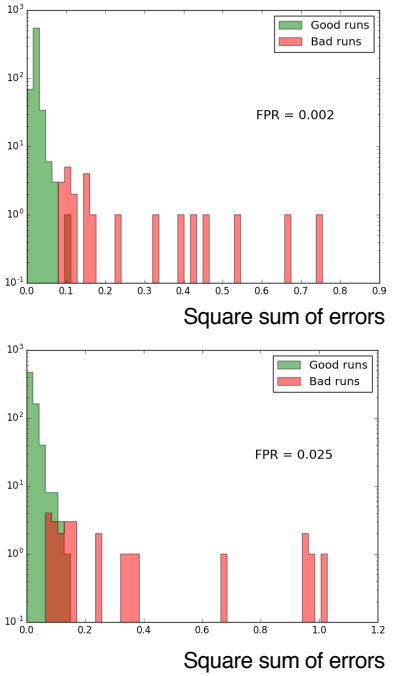
Find in this example that "x_1" roughly corresponds to beam intensity of the run – correlated with height of the peaks

Reconstruct using PCA



- Unsupervised: No manual labelling, doesn't require *bad* plot examples
- Can extrapolate to new conditions
- Easy to deploy in DQM framework

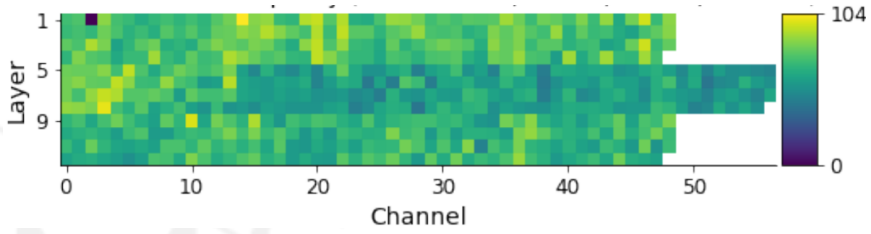
Distinguish with square-sum of errors

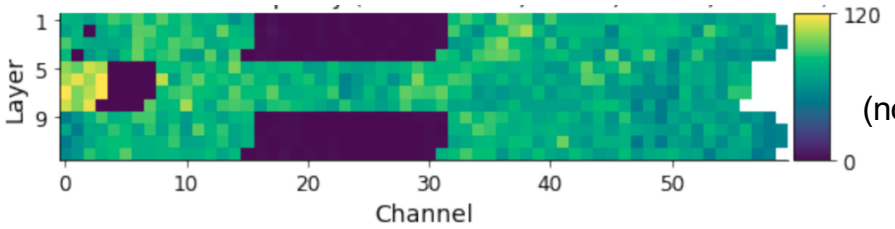


Neural Network approach for 2D occupancy plots

- Hit occupancy plots are important plots in DQM – frequency of hits in given detector channels
  - Quickly identify and diagnose problems
  - Traditional workflow: compare distribution “by eye”

OK

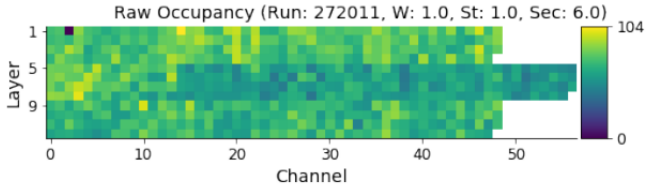




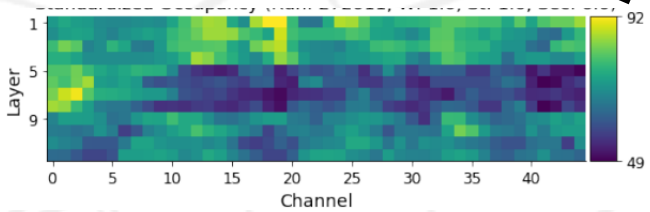
Faulty

(not all anomalies this obvious!)

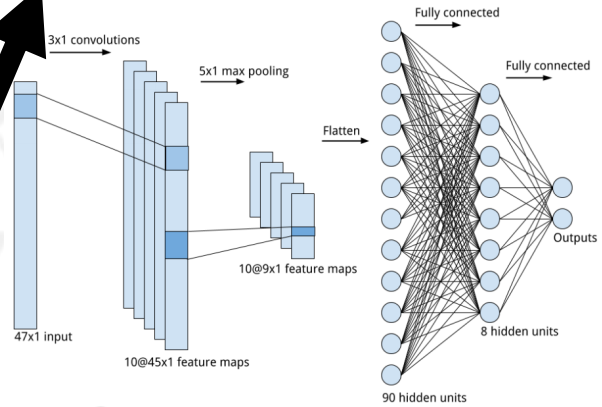
Approach to automatize 1: Detect intra-layer anomalies



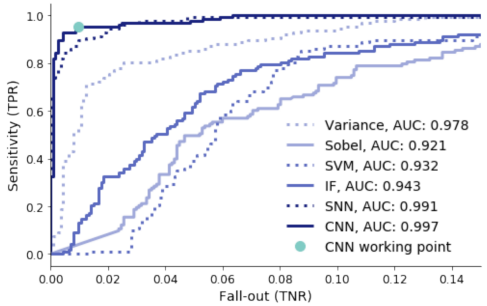
Preprocess and standardize: remove isolated dead channels, scale min-max



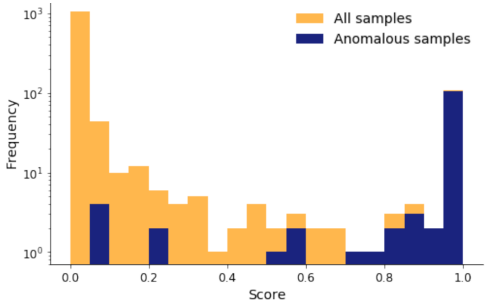
Train various NN structures



3x1 CNN using each 47-channel layers



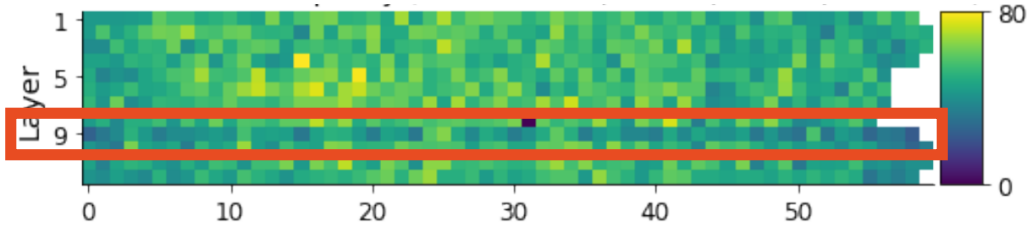
CNN shows best performance



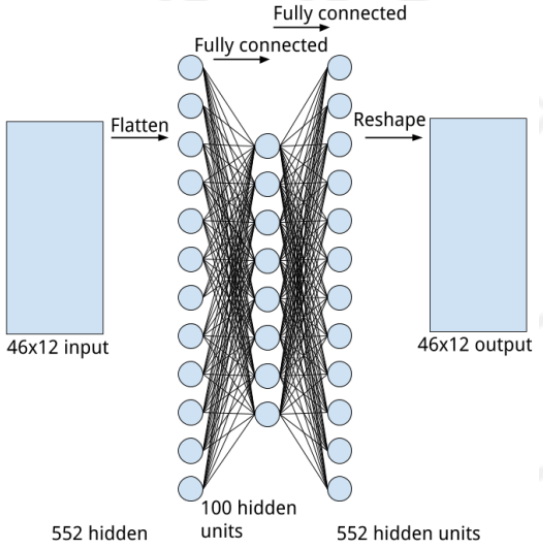
Detect anomalies

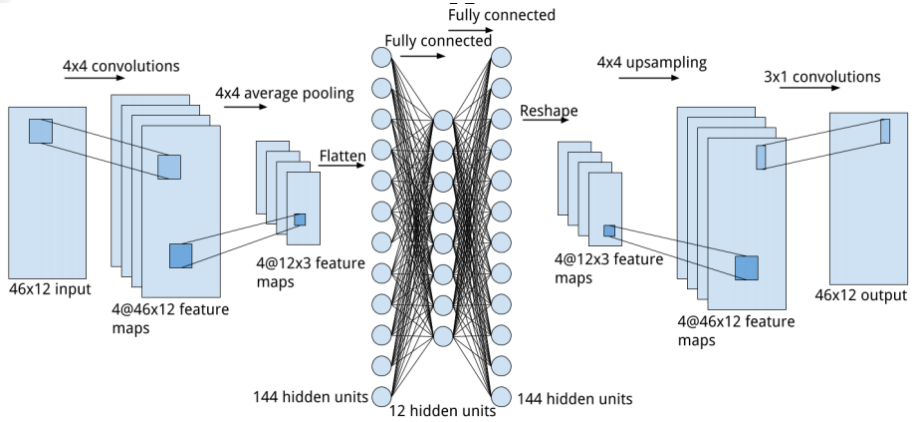
Neural Network approach for 2D occupancy plots

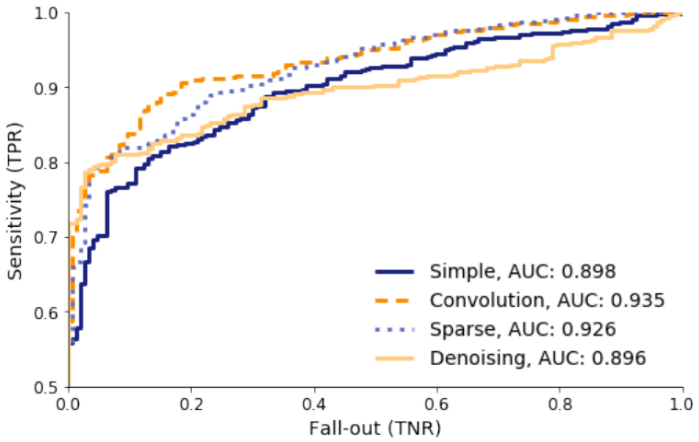
Approach 2: Detect entire-layer anomalies



- To detect anomalies across layers: low occupancy in entire layer
- Semi-supervised approach with AutoEncoders (AE)
  - Dimensionality reduction using NN: compress data from input layers, reconstruct feature by decompressing
- Remove small amount of bad plots and train AE to reconstruct normal ones
- Evaluated various AE architectures on a sample of runs with known problems

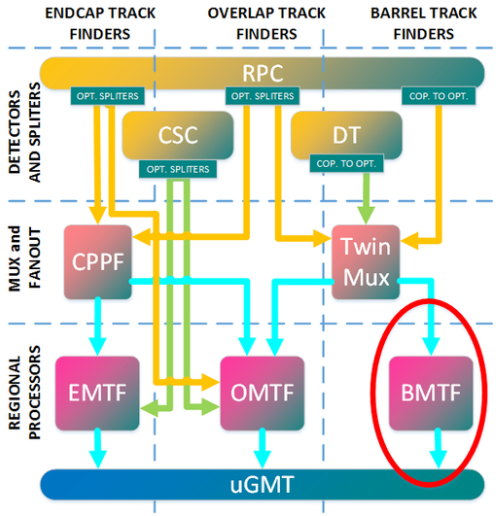






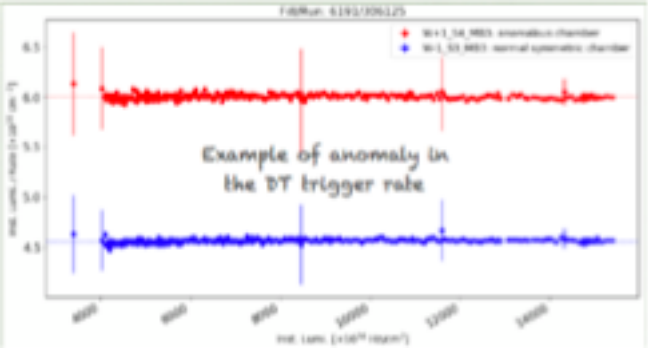
Anomaly detection for trigger rates

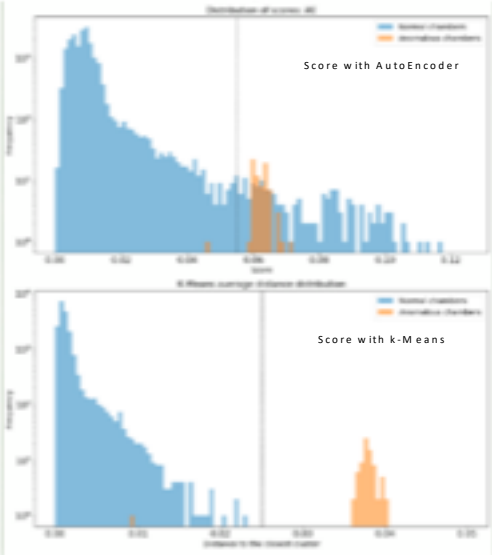
- Collision rate at LHC is too high to store every event, only “interesting” events are stored – “triggering”
- High-energy muons can be signature of interesting event
  - Identify muons at large transverse momentum using the trigger algorithms
  - Barrel muon track finder (BMTF) to select muons in the barrel region, combining DT and RPC
- Any failure of the hardware can lead to anomalies in the trigger rate



Various approaches to detect anomalies are under development

- Neural Network
  - Inputs are the rates at various stages of the trigger workflow, beam conditions including the instantaneous luminosity
  - Difficult to obtain labelled data
- Outlier detection method
  - Investigating various unsupervised outlier-detection methods
  - Local outlier factor, NN based AE approaches





Summary and conclusion

- Muons are among the most important objects in CMS experiment, monitoring the performance of muon detectors is highly important
- The current Data Quality Monitoring workflow is based heavily on the human shifters – time consuming, tedious and human error-prone
- CMS is actively pursuing a variety of ML based solutions to push the DQM process towards higher level of automation
- Works ongoing, but promising results both traditional ML and new DNN methods