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 $ZZ \rightarrow 4$ 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
• 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
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 “x1” roughly corresponds to beam intensity of the run – correlated with height of the peaks

“GOOD” runs – PCA similar to original

“BAD” runs – not described by PCA

Reconstruct using PCA

Distinguish with square-sum of errors

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

Approach to automatize 1: Detect intra-layer anomalies

- Preprocess and standardize: remove isolated dead channels, scale min-max
- 3x1 CNN using each 47-channel layers

Train various NN structures

- CNN shows best performance

OK

Faulty
(not all anomalies this obvious!)
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
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.