Motivation

- CMS data are gathered in time intervals (lumisecetions / LSs) –23.31s.
- Data certification works on Run level $\rightarrow O(1000)$ LSs.
- Experts monitor several reconstructed distributions $\rightarrow$ Monitor Elements (MEs).
- Misbehaving subsystems in one LS would cause the rejection of a whole run.
- Certifying every LS is unfeasible without an automated approach $\rightarrow$ AutoEncoder (AE) [1]

The Model

- AE: unsupervised neural network $\rightarrow$ no truth labels needed for training.
- Training:
  - on a chosen ME, performed on a GOOD run per LS data.
  - performed through the minimization of the reconstruction error (mean squared error):
    \[
    \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 ,
    \]
    where $y_i$ and $\hat{y}_i$ are respectively the input and the output of the AE and $n$ is the bin number.
- Testing:
  - on the same ME, performed on an anomalous run (BAD).
  - deviations from the learned behavior produce peaks in the reconstruction error.
- Various types of AEs, such as the LSTM AutoEncoder [2], can be employed.
- A Dense Under-complete AutoEncoder (Fig. 1) is used.

![AutoEncoder Diagram](image)

Fig. 1: The Dense AutoEncoder architecture utilized is characterized by the dimensions of two layers only.

- In the following we test two BAD runs after training the model on a GOOD run using the ME MET Significance.

![Histograms](image)

Fig. 2: The histograms of MET Significance for the three runs. The anomaly is visible in the histogram center for the blue and orange runs.

![Reconstruction Error](image)

Fig. 3: The reconstruction error of the AE as a function of the LS number for the three runs. Same peaks are visible for the two anomalous runs.

![Reconstruction Error](image)

Fig. 4: The reconstruction error of the AE as a function of the LS number for run 360950.

![Reconstruction Error](image)

Fig. 5: The reconstruction error of the AE as a function of the LS number for run 359763.

![Histograms](image)

Fig. 6: The input histogram (blue) and the output (orange) of the AE for the LS corresponding to peak of the reconstruction loss for run 360950.

![Histograms](image)

Fig. 7: The elimination of LS 469 for run 360950 completely removes the anomaly from the run.

Conclusions

- We developed an AutoEncoder-based Anomaly Detection Tool capable of detecting anomalies in DQM MEs with a per-LS granularity [3].
- We tested the tool on several runs flagged BAD by JME DQM and identified the source of the anomalous behavior in a limited set of LSs.
- In particular, in the examples presented here, we removed one LS from each anomalous run and verified that the remainder was no longer anomalous.
- The equivalent luminosity recovered from the two runs is 350 pb$^{-1}$, or around 1% of the entire 2016 CMS dataset.
- Exploiting the per-LS granularity in DQM and systematically employing the tool we presented will enable an increase in the efficiency of the DC procedure, ultimately resulting in a larger dataset available for physics analyses.

References