Automating ATLAS control room anomaly detection with machine learning

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Motivations

- High-quality data acquisition via effective anomaly detection in ATLAS operation
- Currently, shifters manually monitor data in control room
    - Problems in consistency, accuracy
    - Shifters monitor many plots over 8-hour period
    - High personnel demand

Approach:

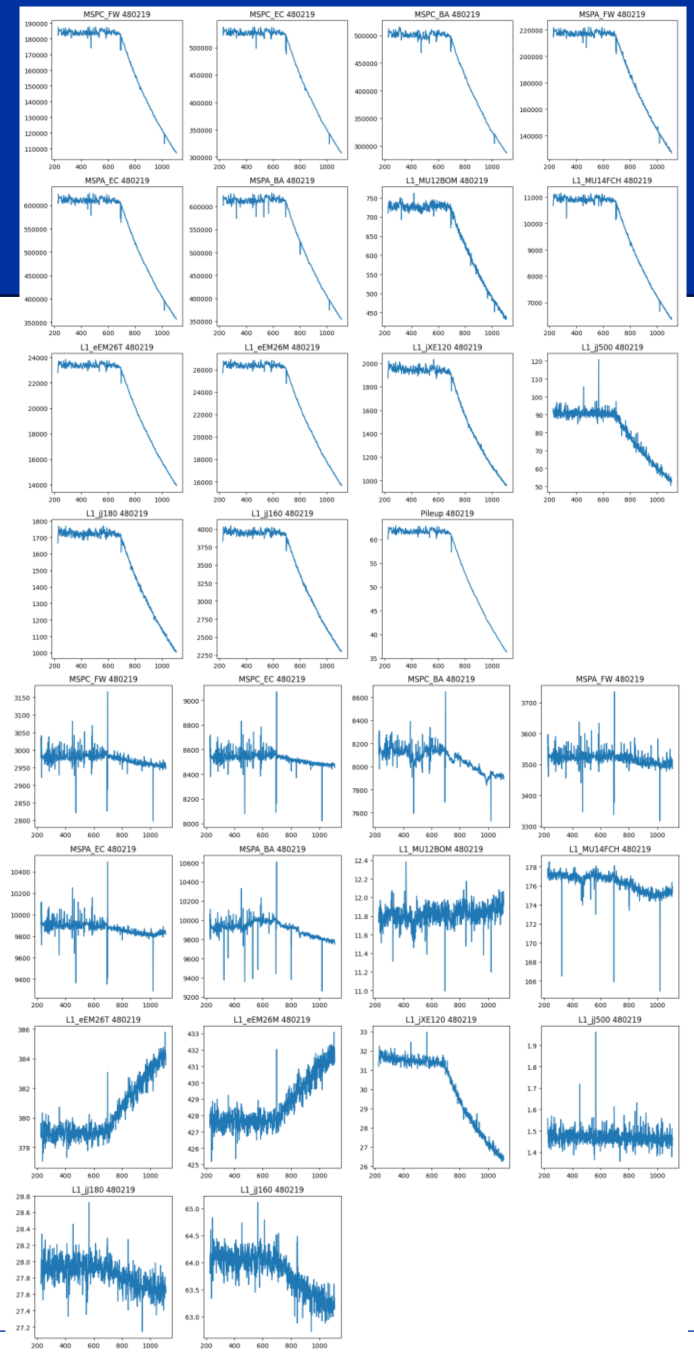
Online machine learning model to watch incoming time-series data and alert staff to anomalies

Data

Features (normalized by pileup):

- L1 trigger rates: frequency with which detect electrons, muons, missing transverse energy, jets
    - Multiple L1 rates for each corresponding to different energy levels
- L1 muon sector logic inputs: muon rate by section of detector
- Pileup: average number of interactions per bunch crossing. Constant for ~1/2 run, then decays

Normalizing by pileup



Input

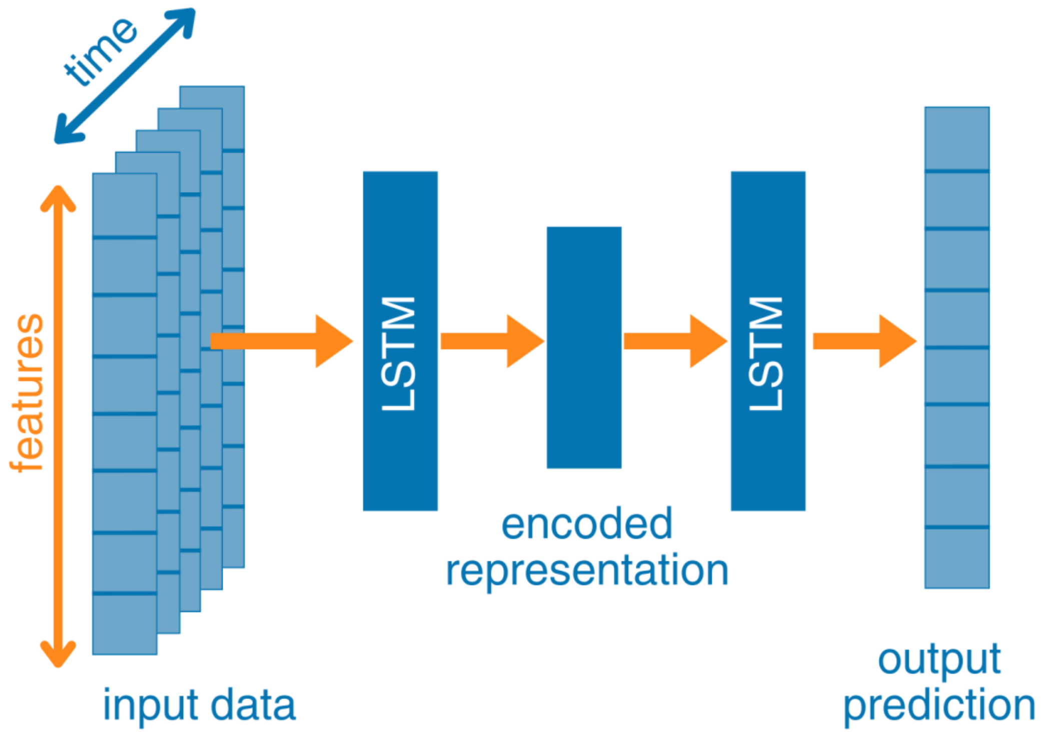
- Time series data of 5 samples
- Each sample includes values for each of 14 features
- Robust scaling

Output

- Prediction of 14 features for next sample (one luminosity block/one minute in future)

Model architecture

- Model trained on clean data so low mean squared error (MSE) with clean values, high MSE with anomalies
- Set threshold MSE between clean and anomalous classifications
- Long short-term memory (LSTM) layers incorporate time-series element of data
- Autoencoder shape forces model to learn lower dimensional representation of data
    - Will be especially important as step up number of features
- Small network with only four layers



Model performance – loss, MSE

Training data: 10 full runs (around 8000 datapoints)

Test data: single full run (around 900 datapoints)

Huber loss

- Quadratic for small errors, linear for larger
- Chosen because don't want outliers in data to influence training as occurs with MSE

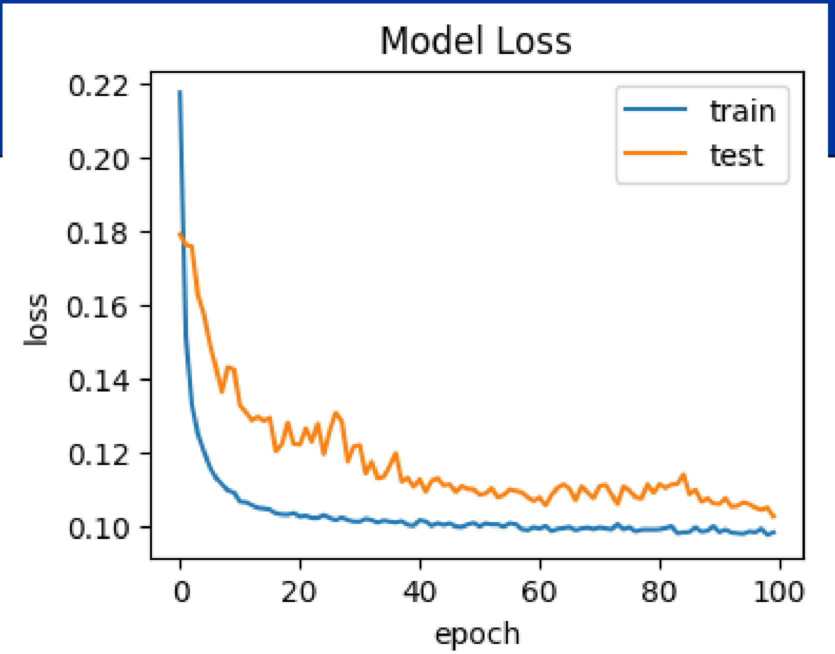
$$a = y - f(x)$$

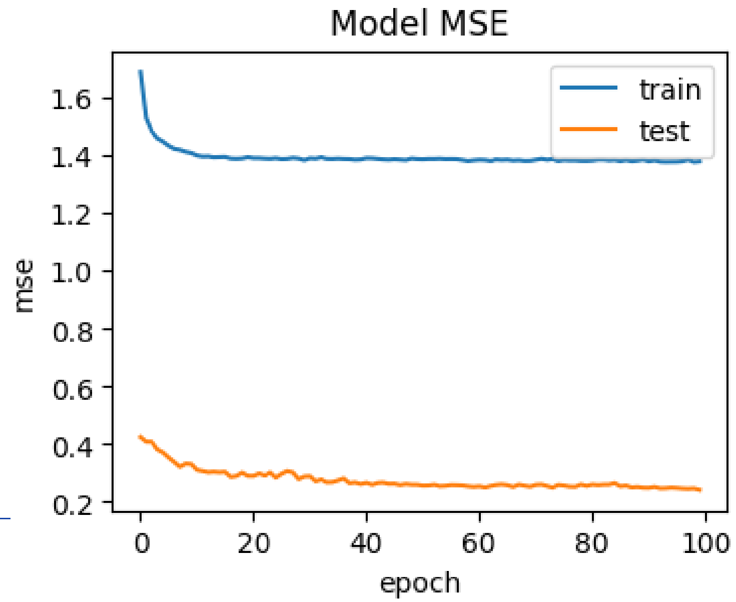
$$L_\delta(a) = \begin{cases} \frac{1}{2}a^2 & \text{for } |a| \le \delta, \\ \delta \cdot \left(|a| - \frac{1}{2}\delta\right), & \text{otherwise.} \end{cases}$$

Mean squared error

- A few outliers cause large separation in train and test

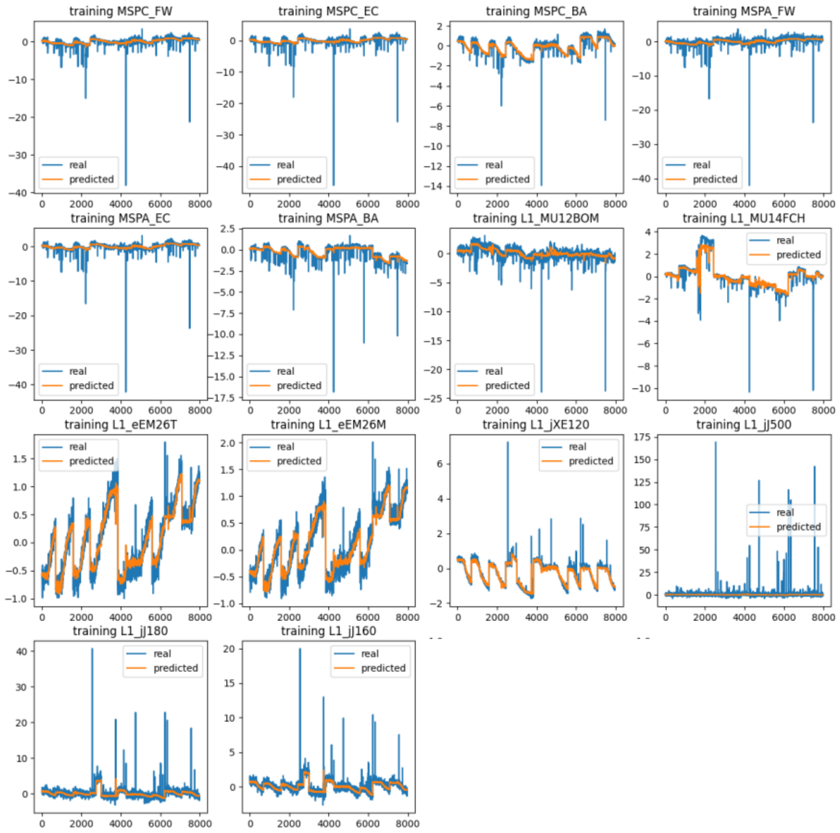
$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$



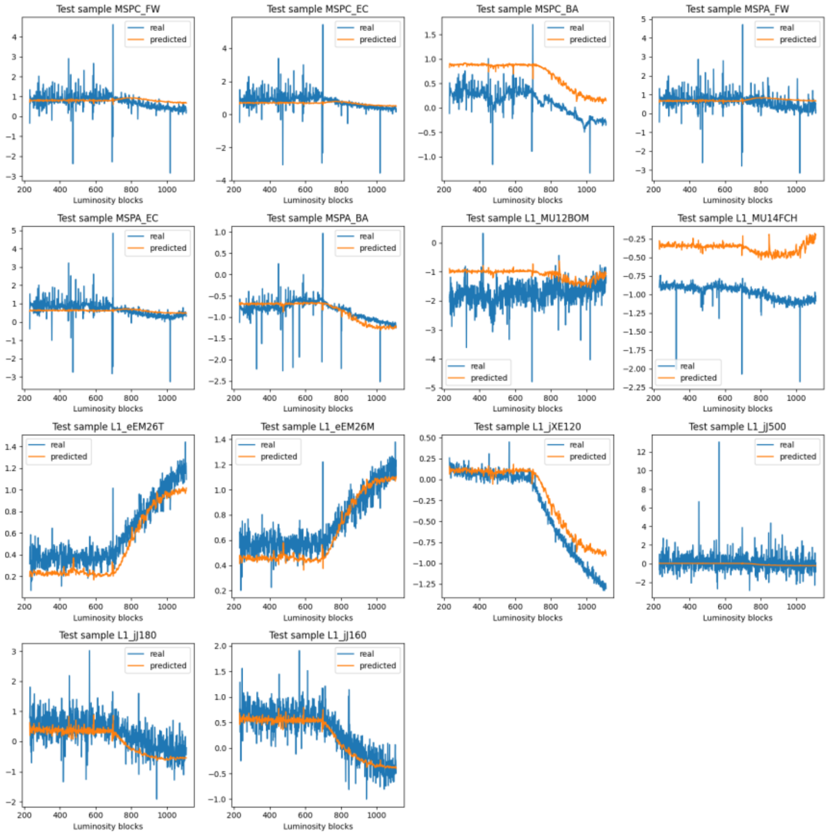


Model performance – training and test predictions

Predictions align well with training data, smooth out variations

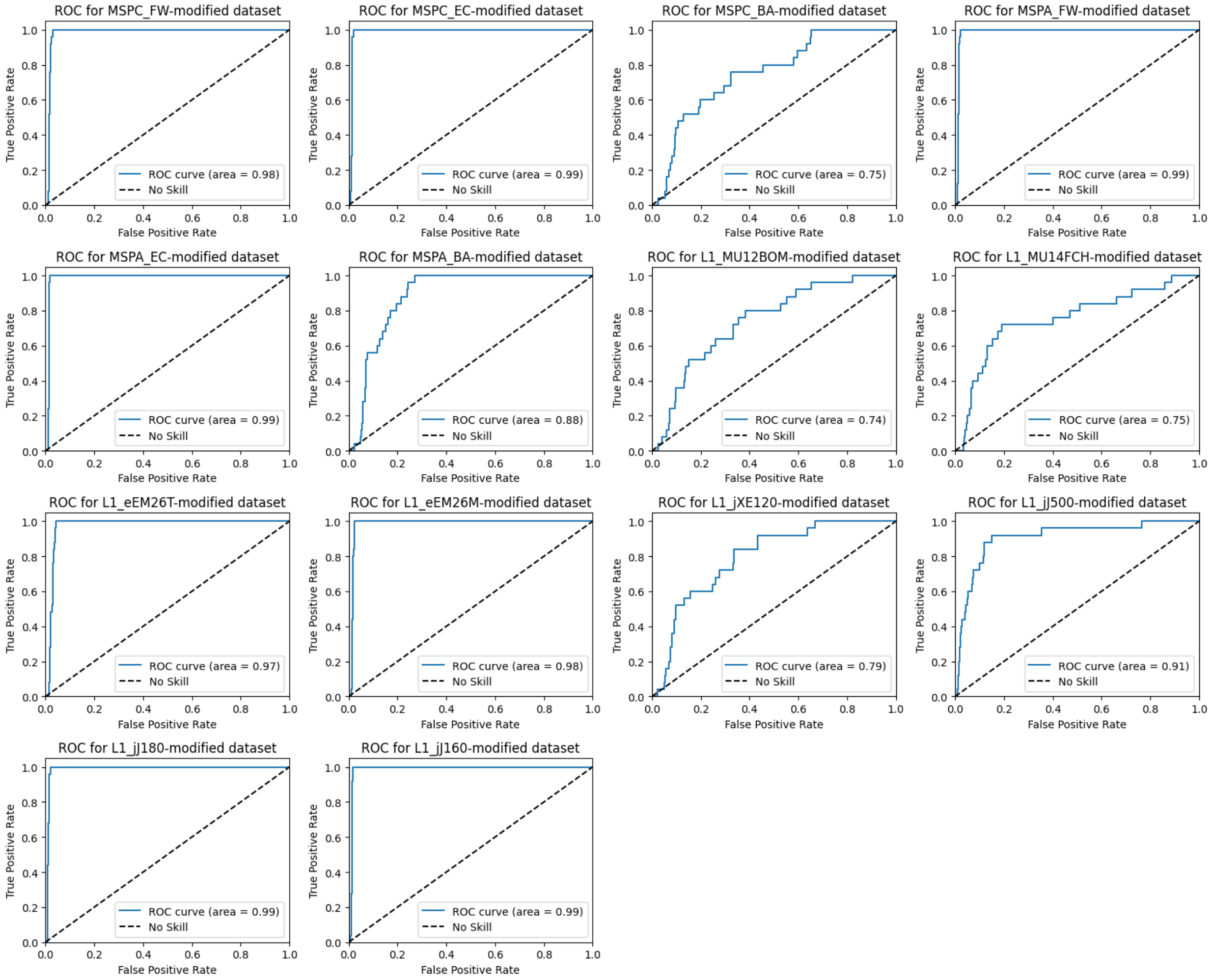


Observe offset between prediction and real in certain features, worse performance in tail of run



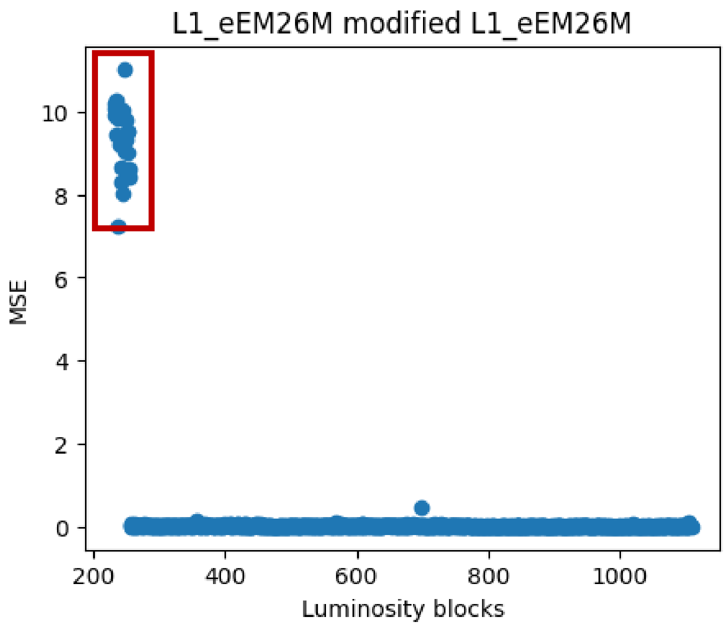
Model performance – artificial 5% anomaly

- For single feature in test data set, first 30 LBs increased by 5%
- On right, ROC curves show how performance differs based on which feature was modified
- AUC varies from 0.74 for L1_MU12BOM-modified dataset to 0.99 for five datasets

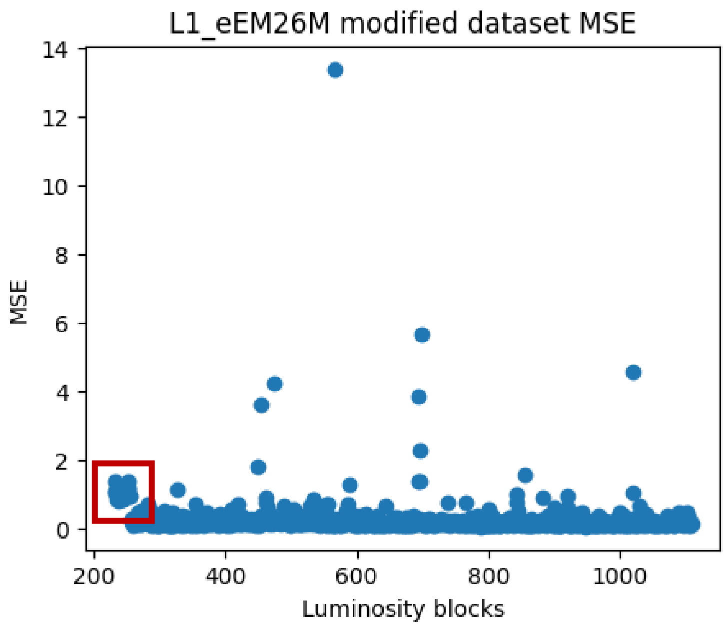


Model performance – artificial 5% anomaly

Looking at MSE for the specific feature that was modified, see clear spike



After averaging over all features still see bump, but not as clearly distinguished

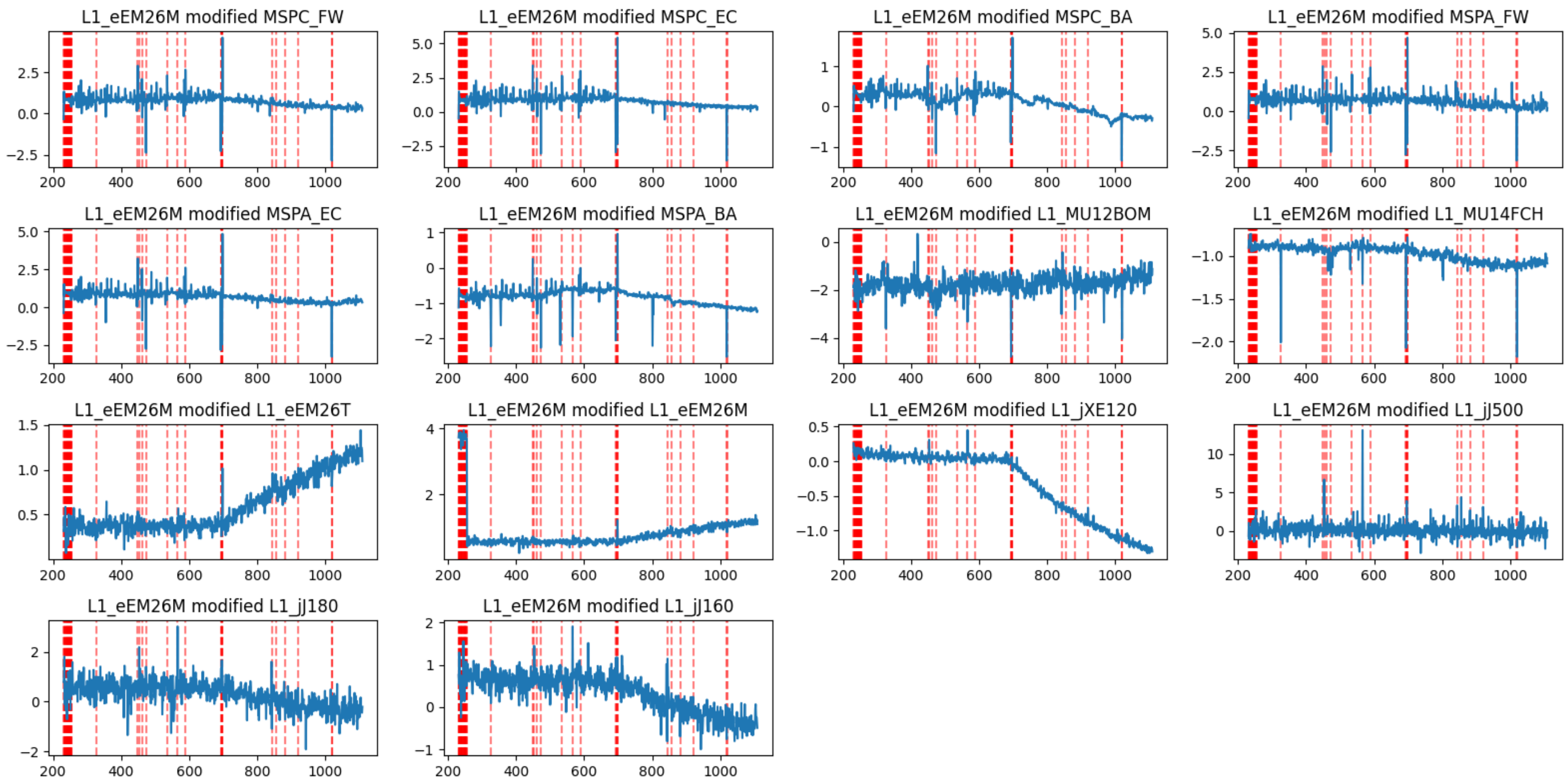


Model performance – artificial 5% anomaly

24/25 = 96% modified LBs correctly detected as anomalies

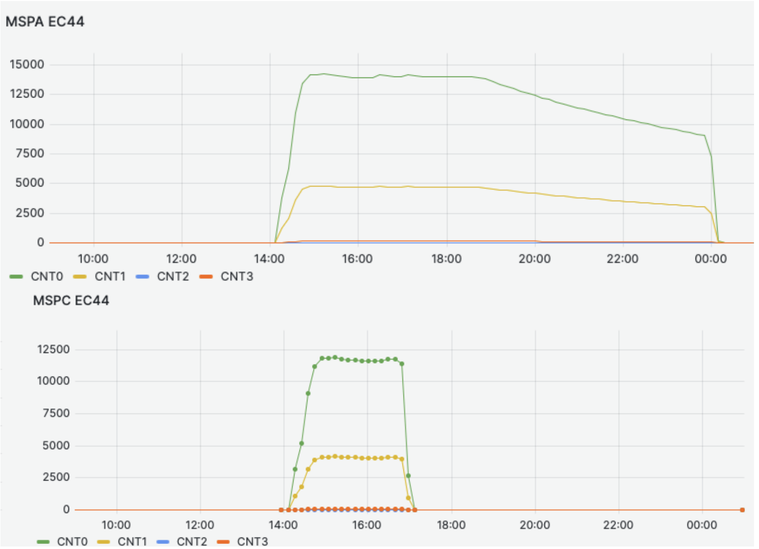
19/859 = 2.2% clean LBs falsely classified as anomalies

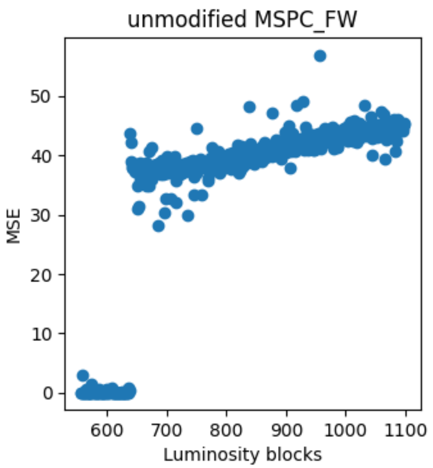
- Several of these correspond to real spikes in the dataset

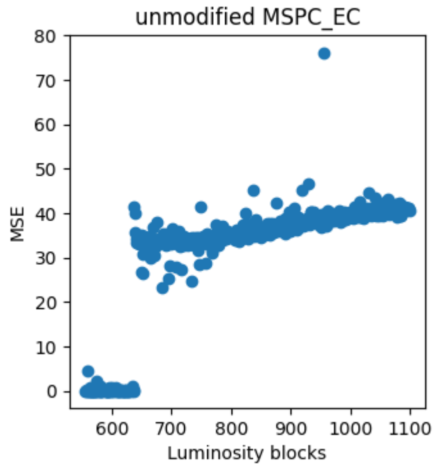


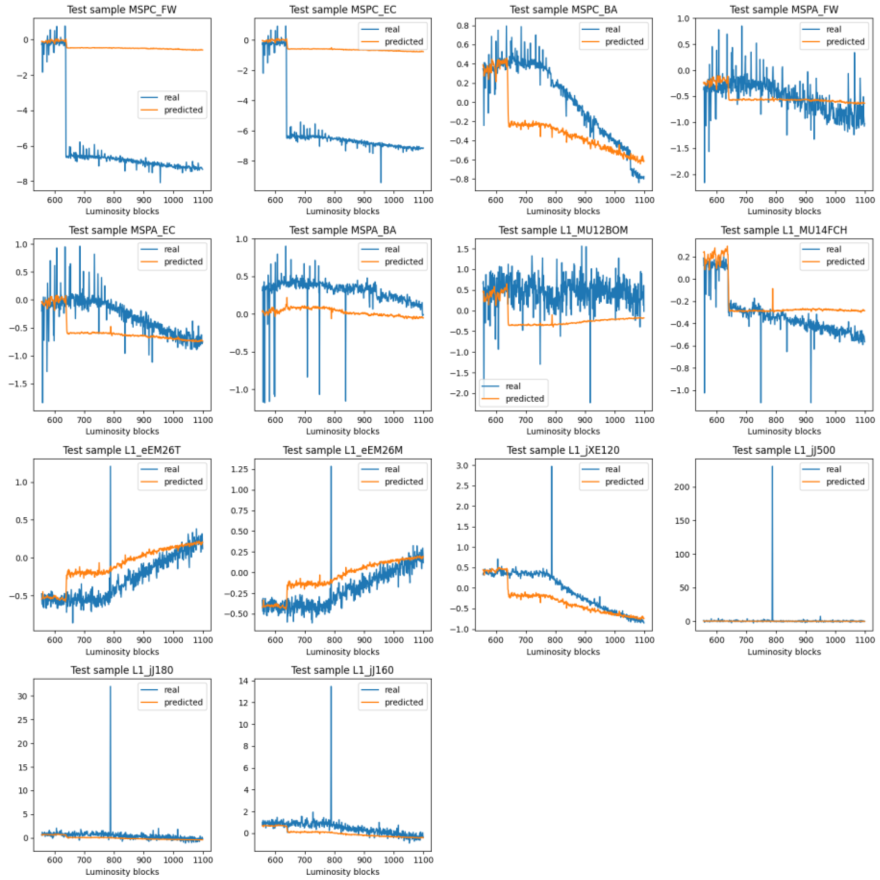
Model performance – muon end cap shutdown

In early June, a sector of the muon end cap was disabled (1/8 of one side of detector). We used this test data to see how our model responded. Clear spike in MSE when disabled corresponding to the large variation between real and predicted values.



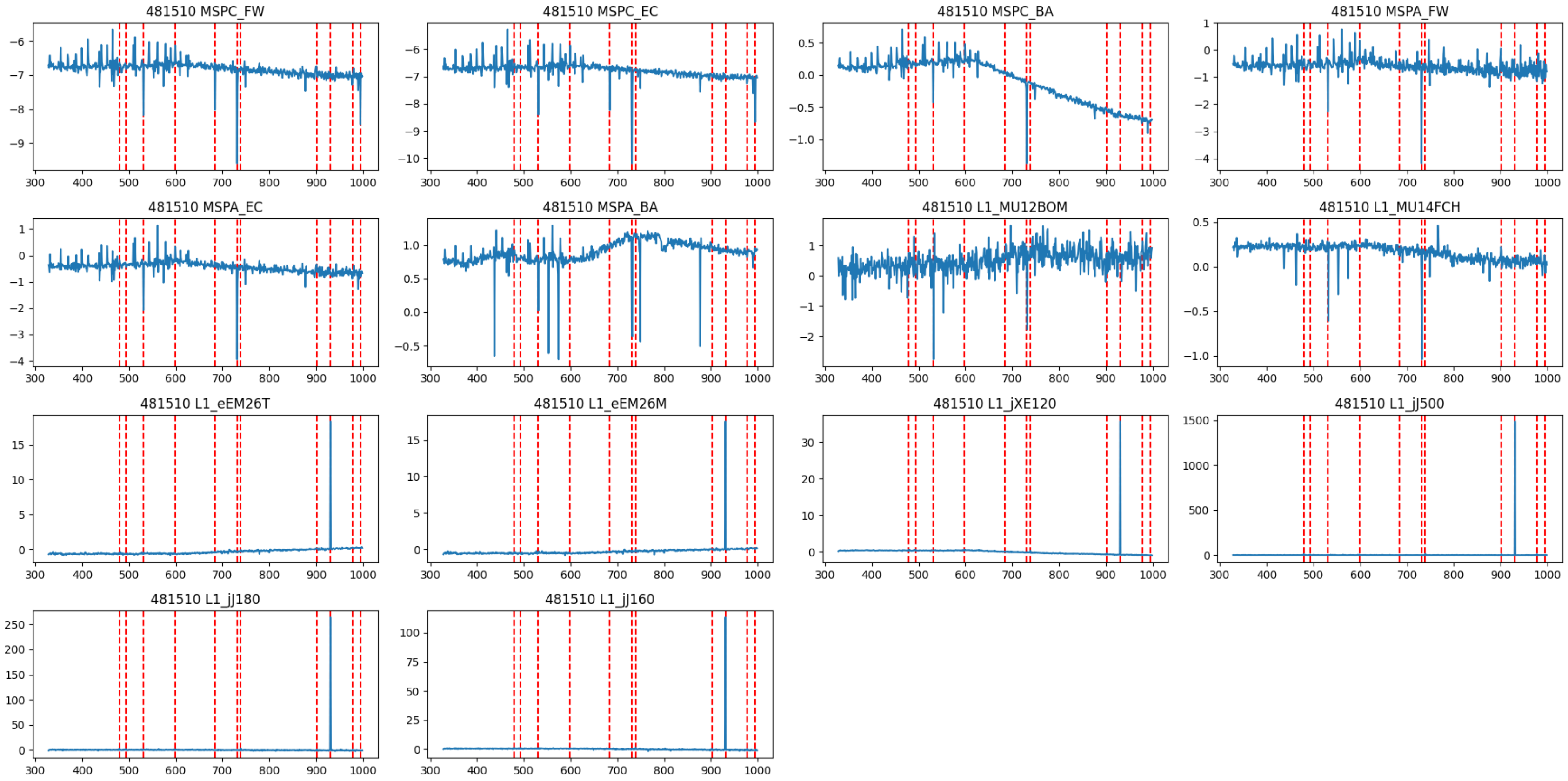






Model performance – anomalies in recent runs

- Using a recent run as test data, we check what our model identifies as anomalies
- With threshold = 8, model flags 11 anomalies in run 481510

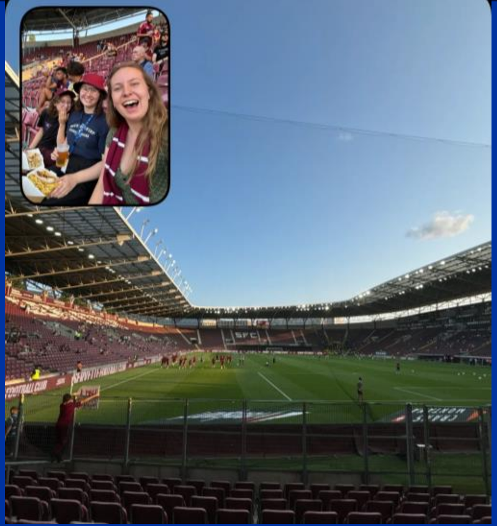


Next Steps

- Separate models for constant pileup and decaying pileup or separate models for different classes of features
- Optimizing for better performance in low pileup region
- Piecewise renormalization
- Scaling up for more extensive feature set
- Continuous learning
- Structure for online usage

Acknowledgements:

Thank you to my supervisors Mario Campanelli and Antoine Marzin for their guidance this summer. I'd also like to acknowledge the University of Michigan REU program for their support.



THANKS FOR AN AMAZING SUMMER!