



# AUTOMATING ATLAS CONTROL ROOM ANOMALY DETECTION WITH ML

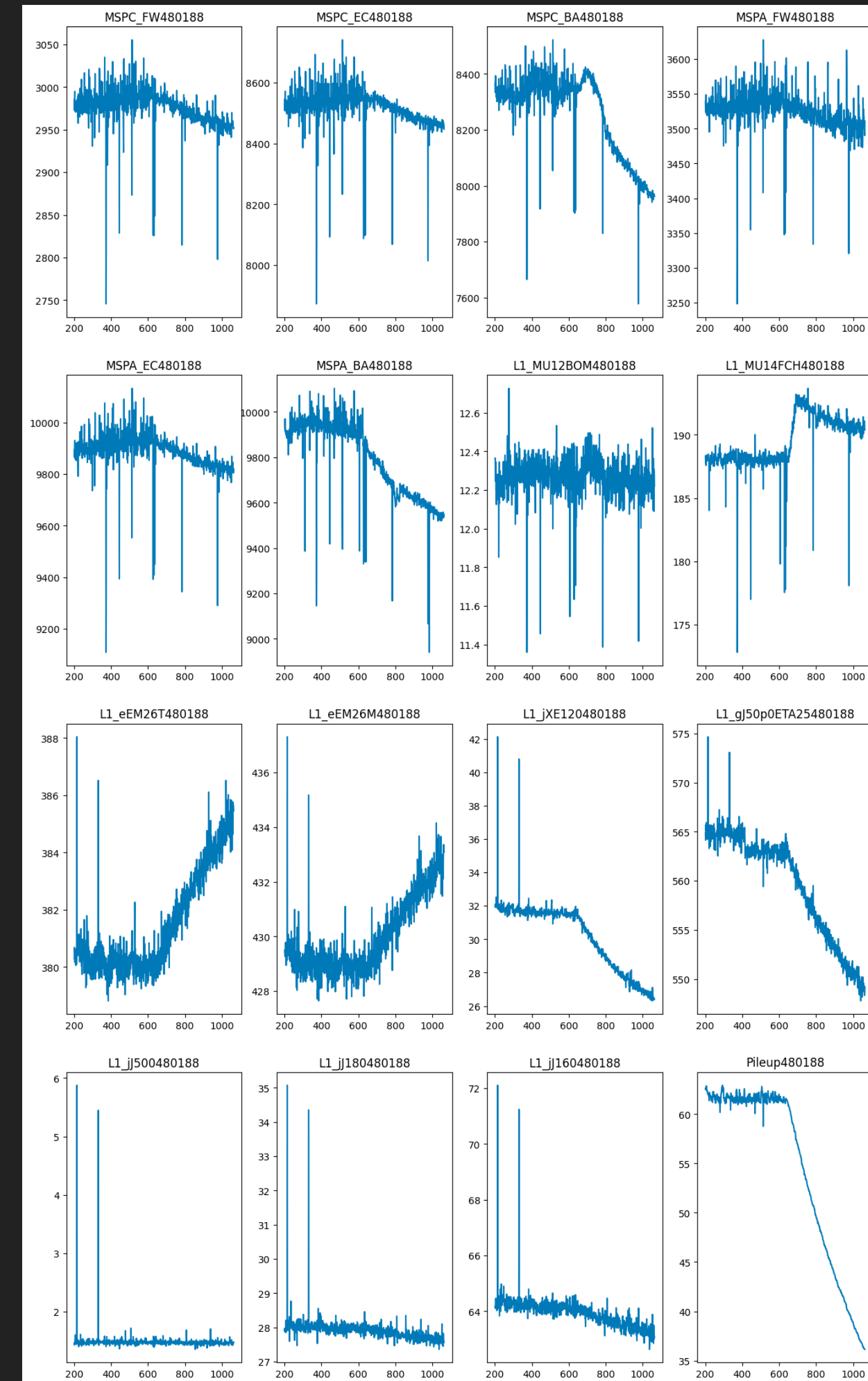
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# INTRODUCTION

- ▶ Goal: More consistently and accurately catch problems in detectors. Decrease workload of ATLAS control room staff
- ▶ Approach: Online deep learning anomaly detection algorithm
- ▶ Supervisors: Mario Campanelli and Antoine Marzin

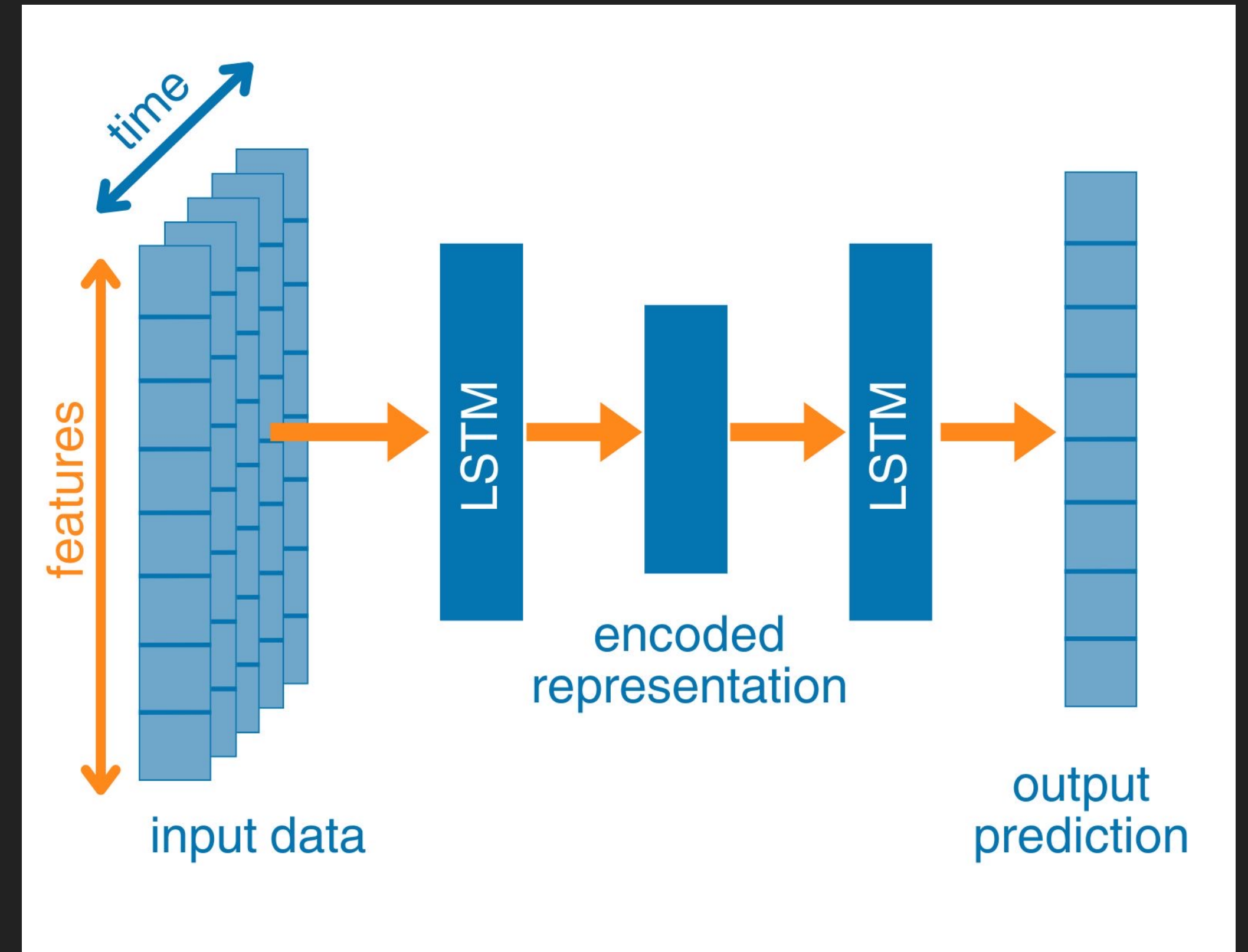
# DATA

- ▶ Input:
  - ▶ Time series data of 5 samples
  - ▶ Each sample with 16 features: L1 trigger rates, L1 muon sector logic inputs, pileup
- ▶ Output:
  - ▶ Prediction of 16 features for next sample
    - ▶ One luminosity block in future



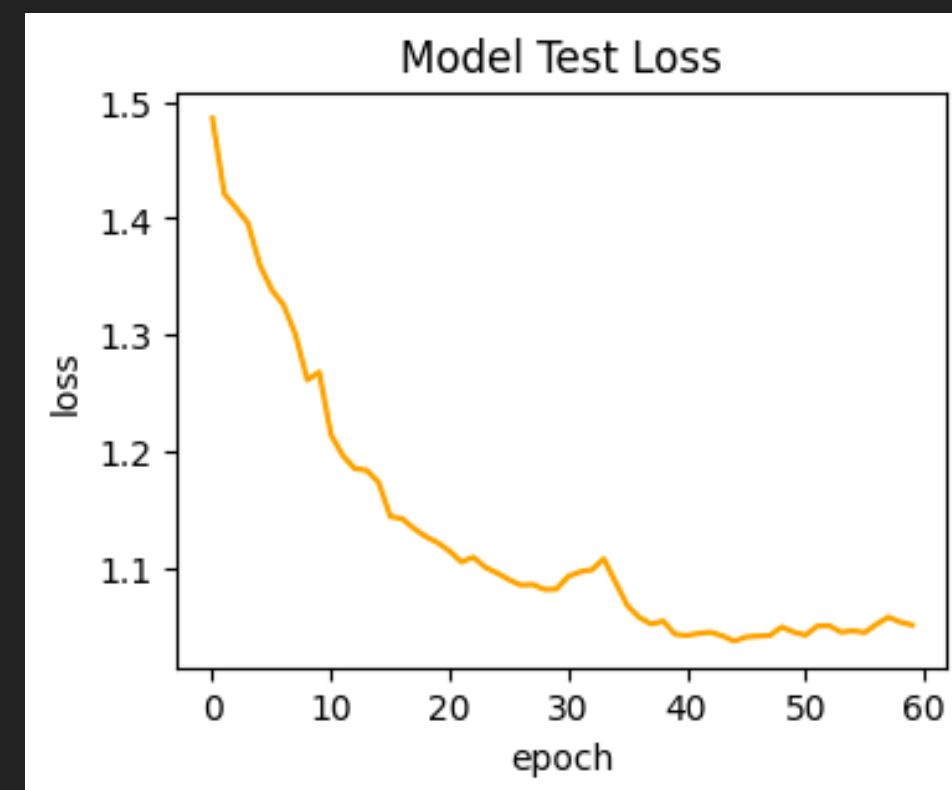
# MODEL ARCHITECTURE: PREDICTIVE LSTM AUTOENCODER

- ▶ Long short-term memory (LSTM) layers incorporate time-series element of data
- ▶ Autoencoder shape forces model to learn lower dimensional representation of data
- ▶ 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

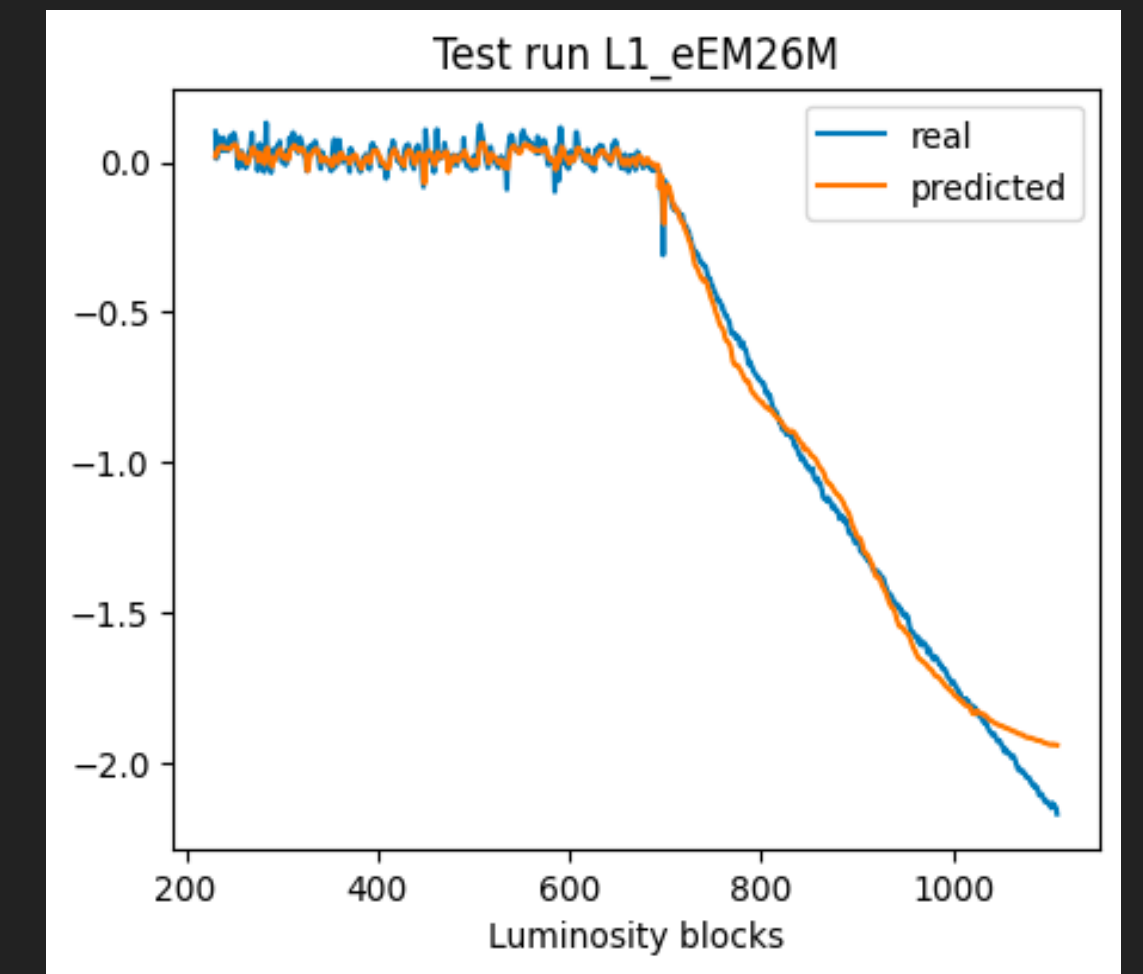
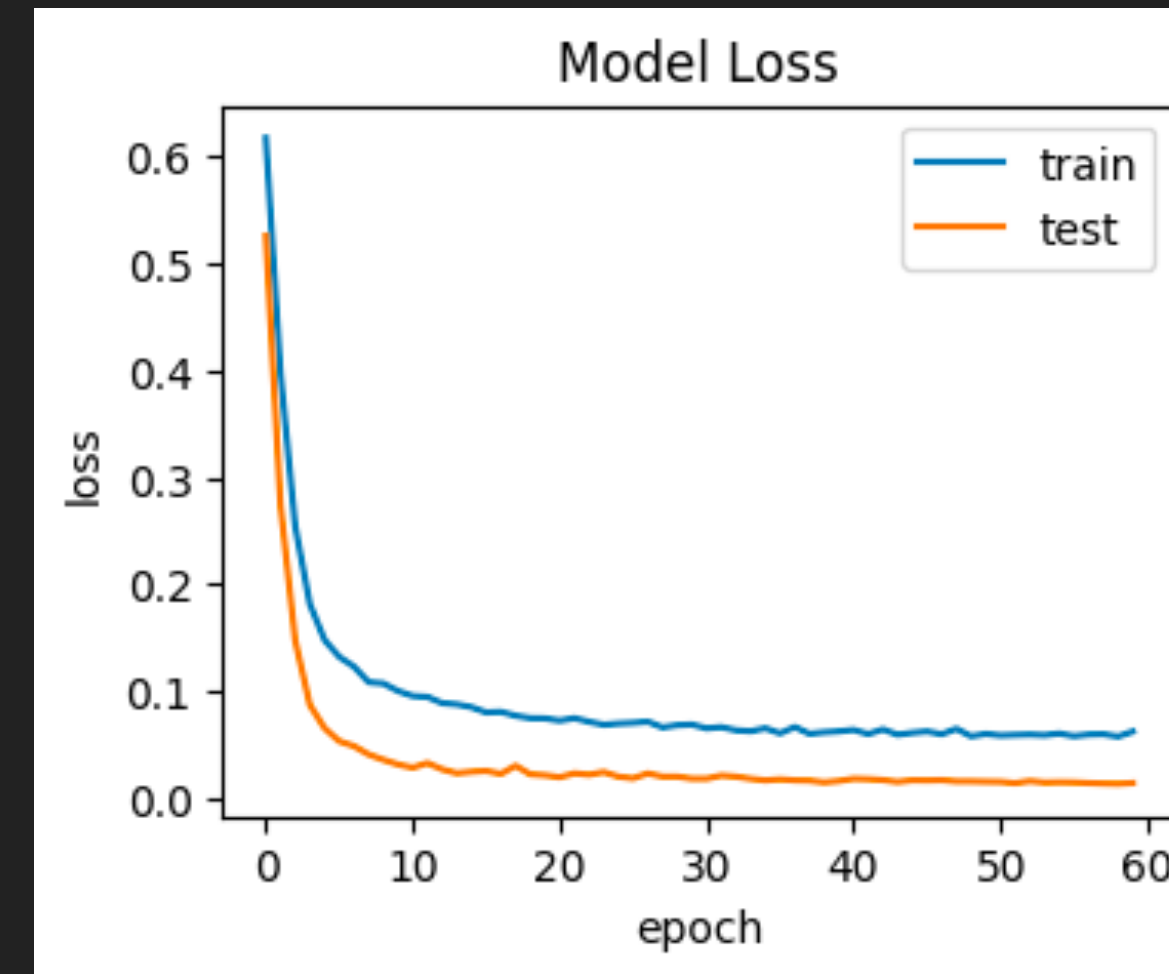


# MODEL PERFORMANCE

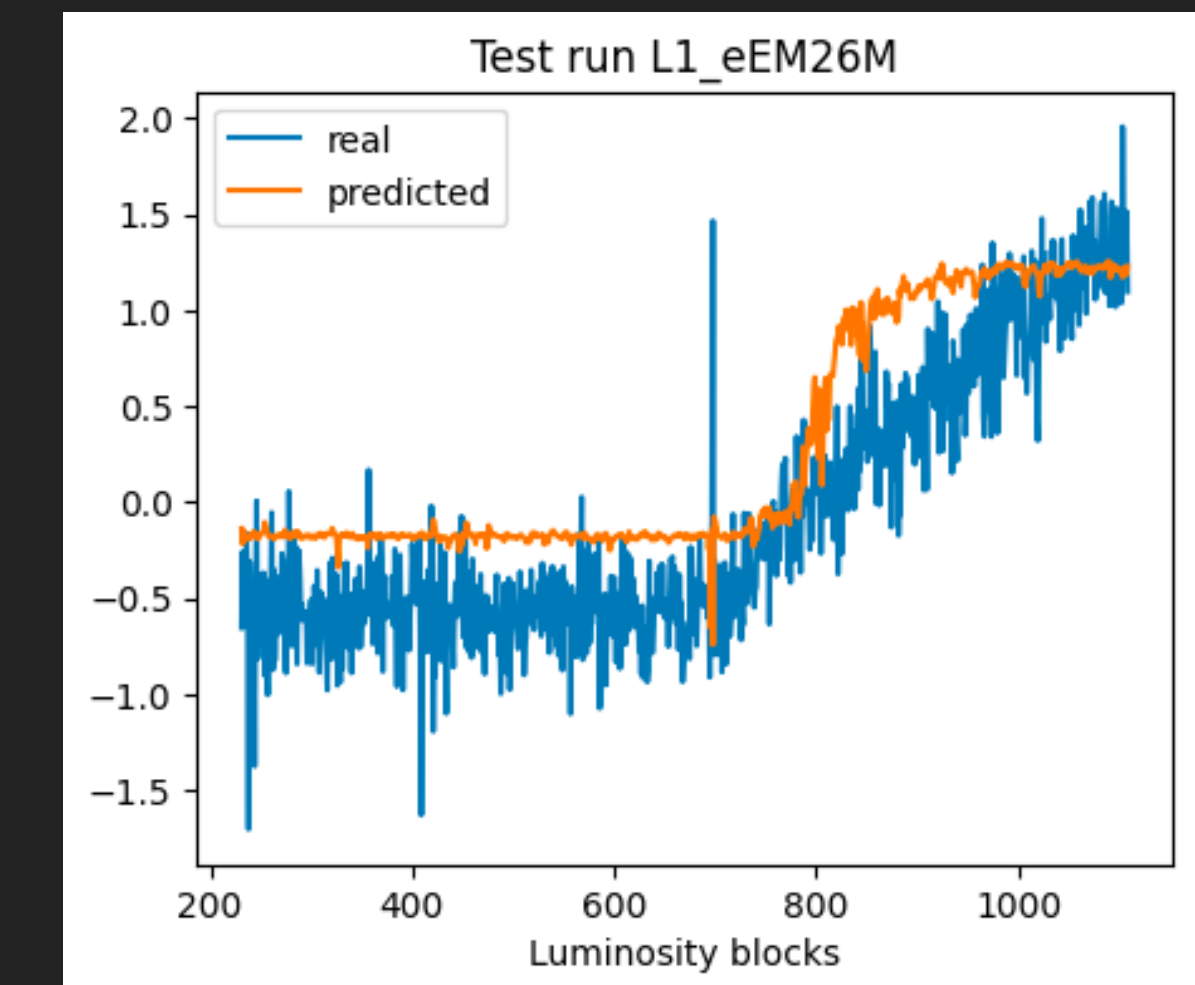
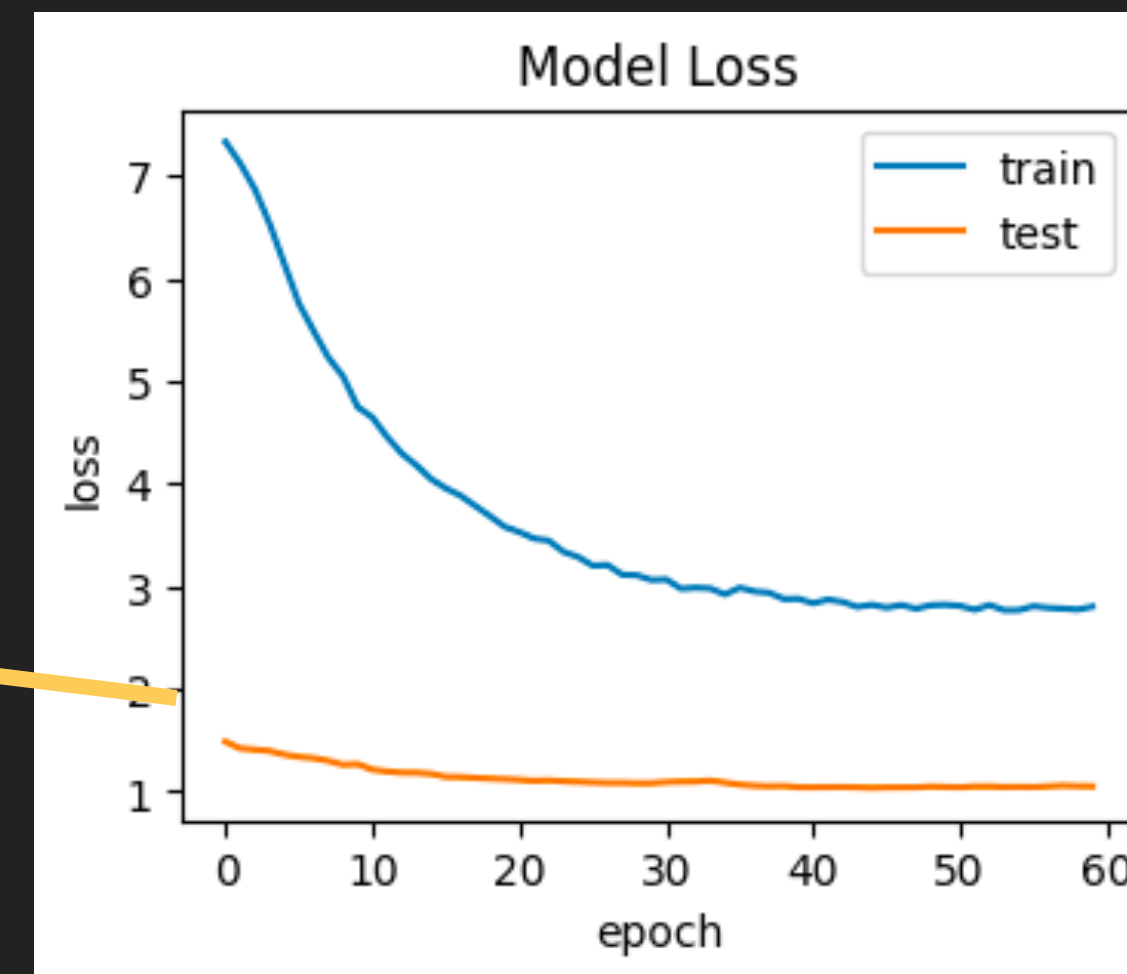
- ▶ Gap in train and test from changing run conditions
  - ▶ Train data = 3 full runs
  - ▶ Test data = 1 full run
- ▶ Robust scaling lets us lower impact of outliers
- ▶ Poor predictive power at end of run



No pre-processing



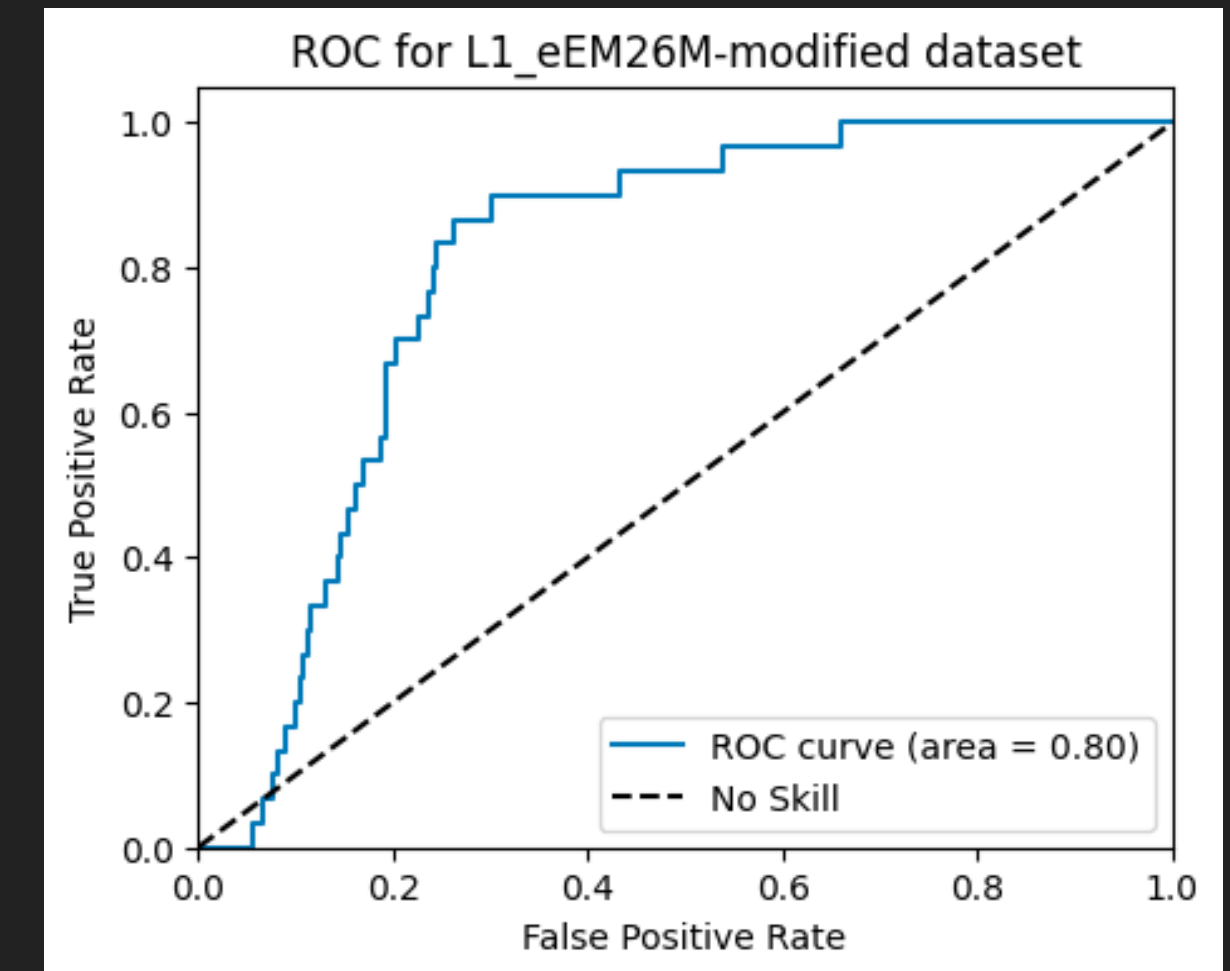
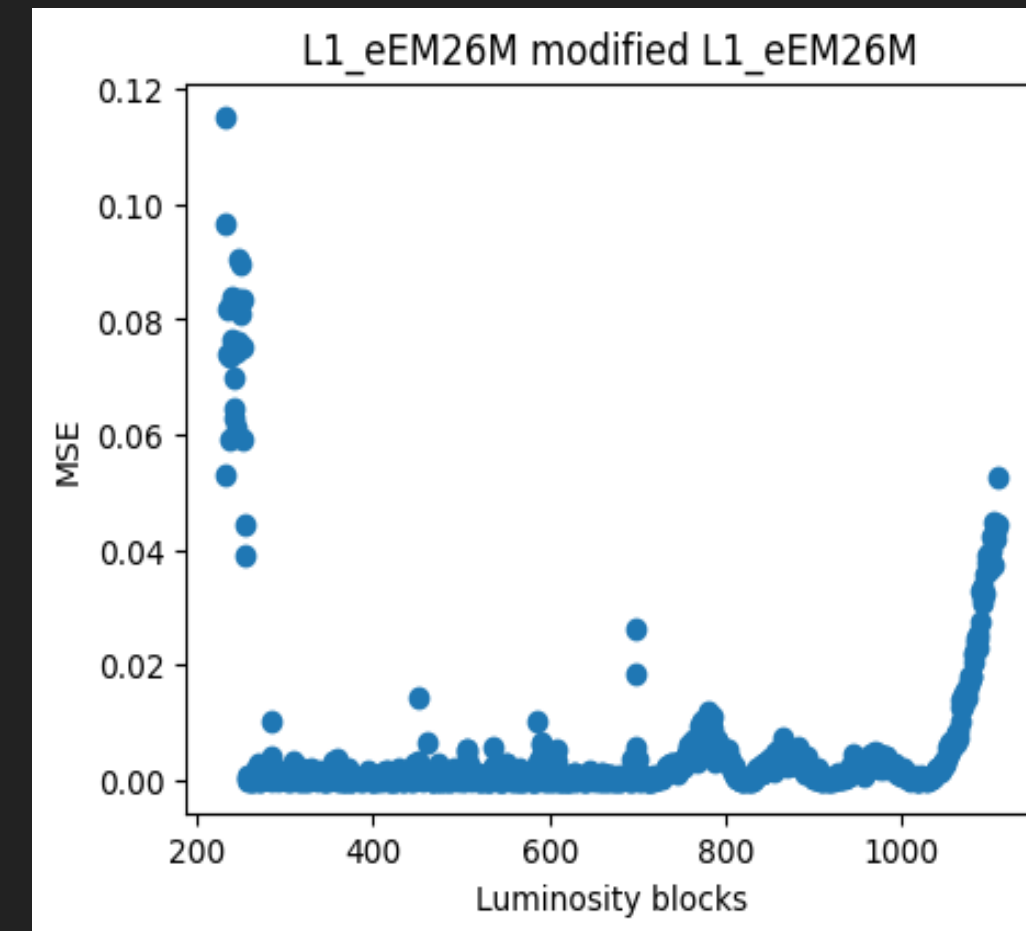
Normalizing with pileup



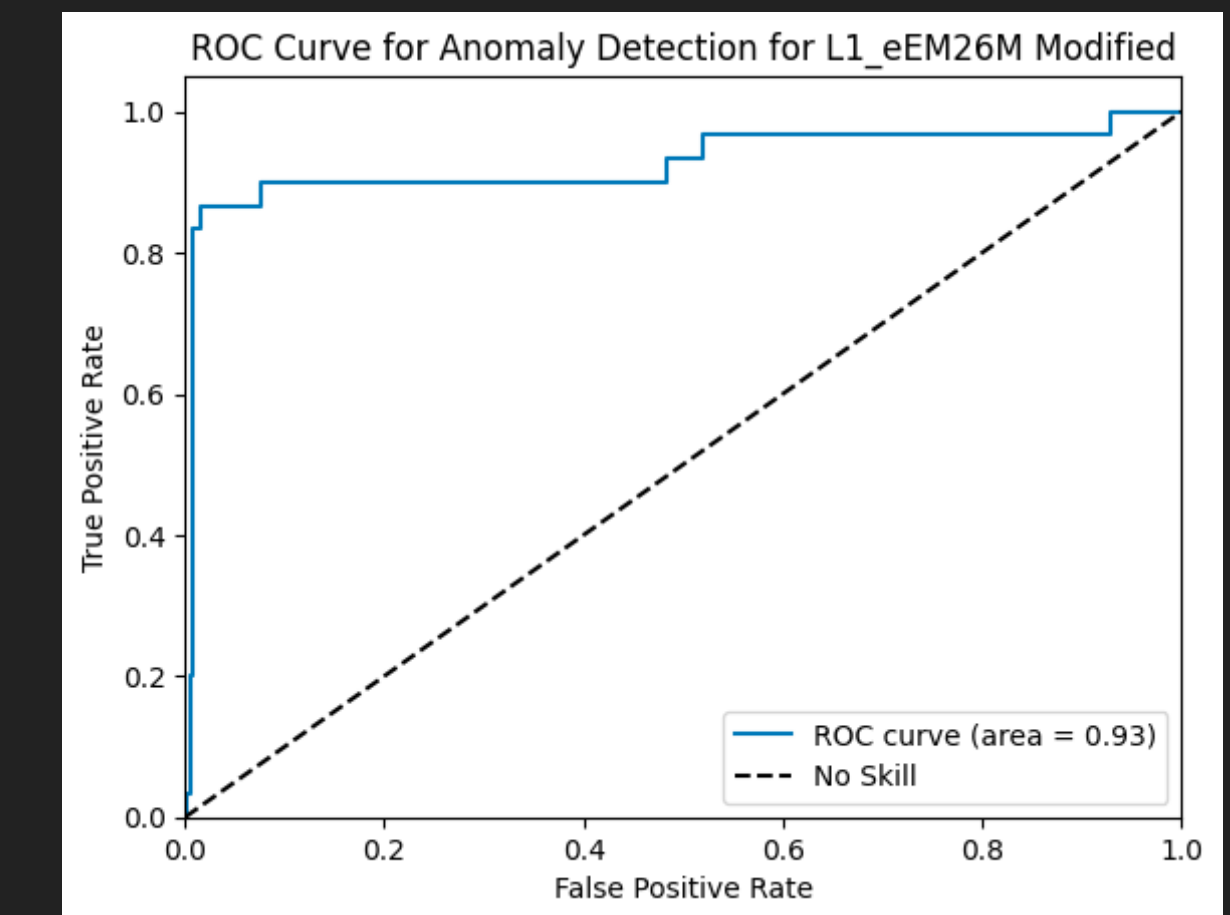
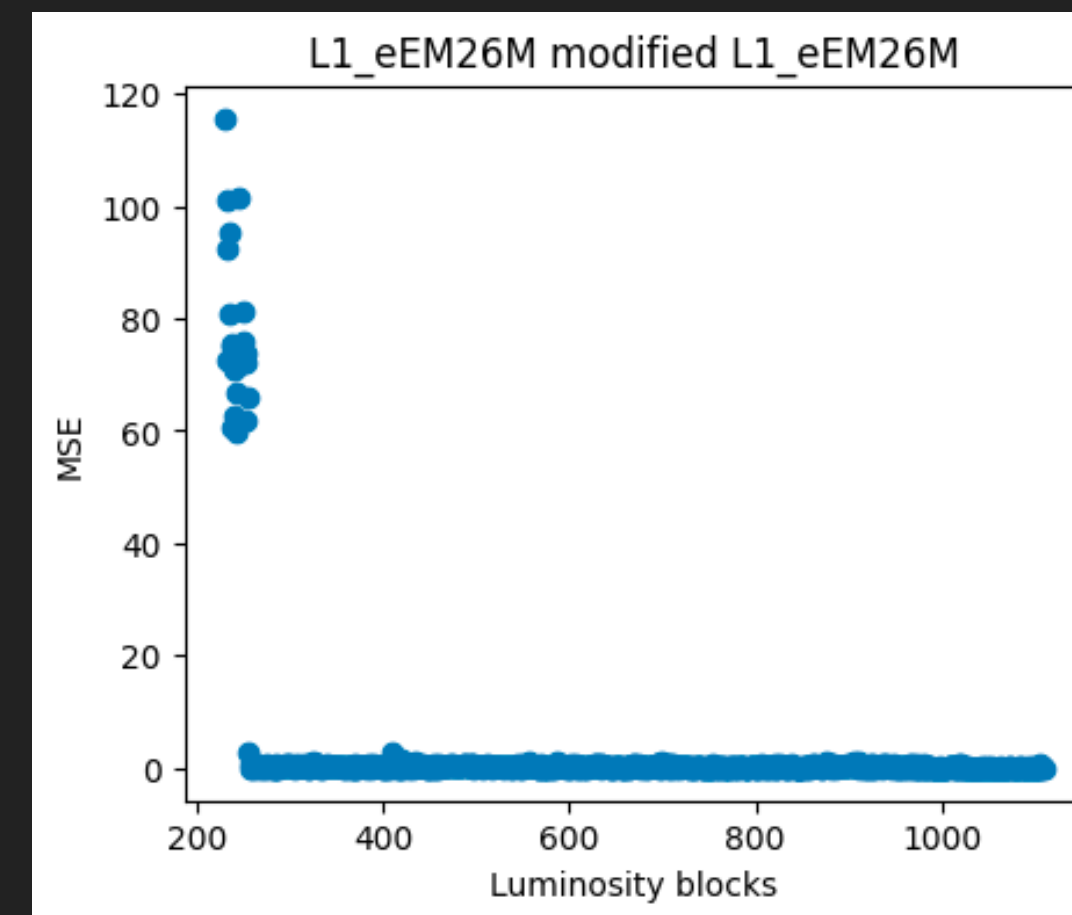
# DETECTING 5% ANOMALY

- ▶ Produce artificial anomalous data sets by taking test set and increase single feature of first 30 LBs by 5%
- ▶ Normalizing with respect to pileup gives us more consistent MSE across luminosity blocks so easier to detect anomalies

No pre-processing

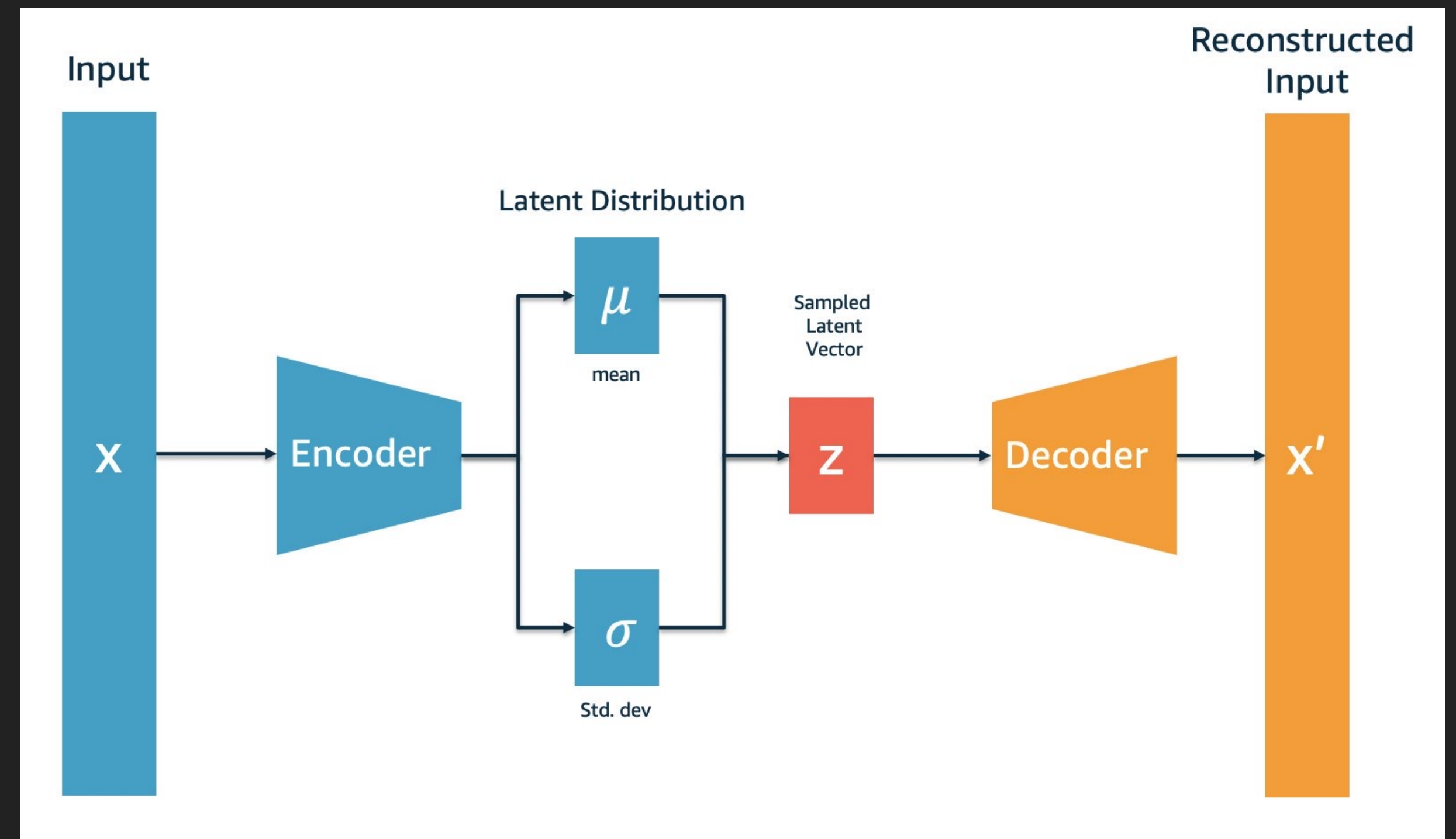


Normalizing with pileup



# NEXT STEPS

- ▶ Better cleaning of training data
- ▶ Data augmentation of low pileup region
- ▶ Extensive hyperparameter sweep
- ▶ Variational autoencoder structure



[Image source](#)



WHEN NOT CODING...

