

# Automating ATLAS Control Room Anomaly Detection with ML

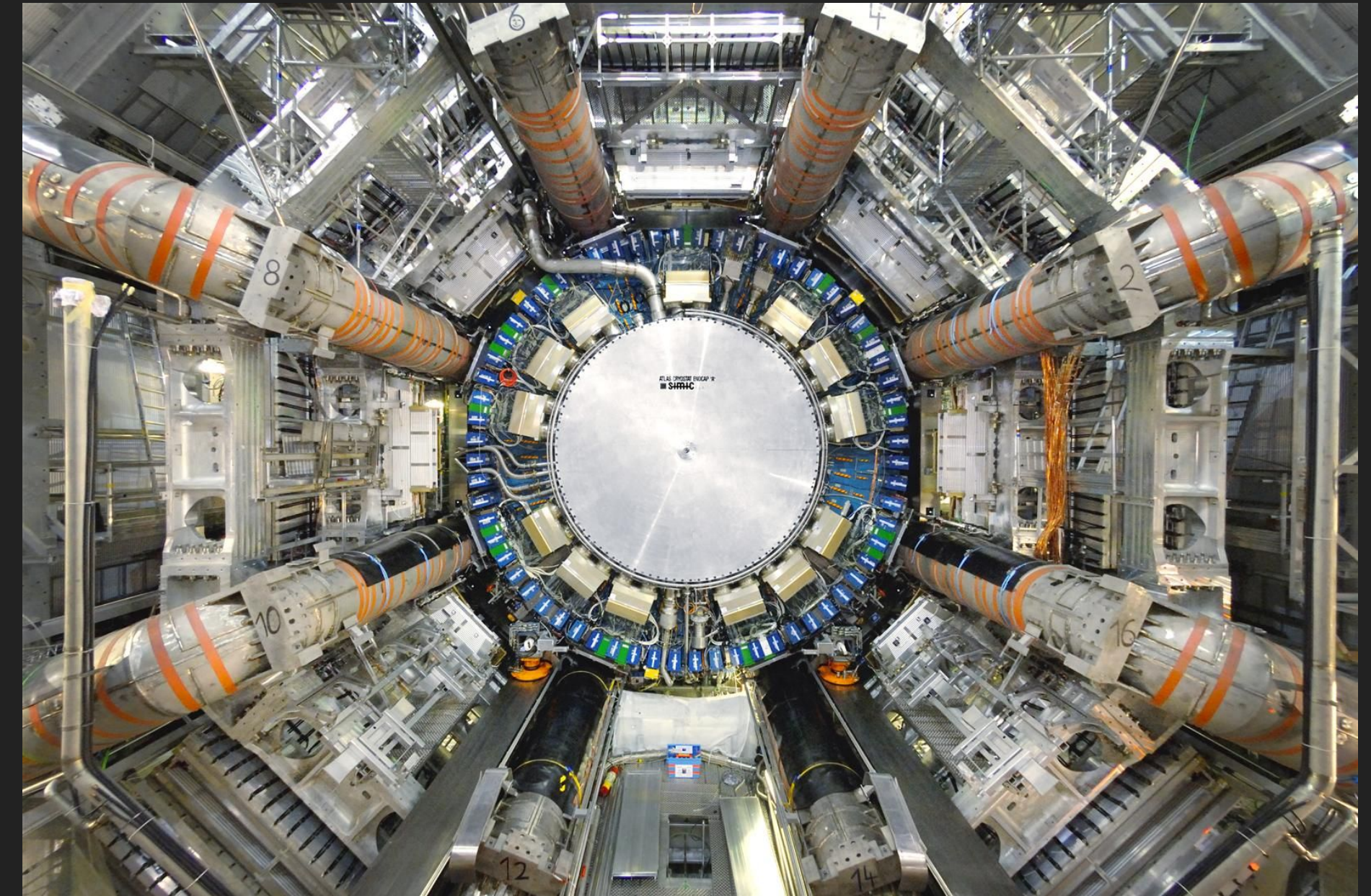
Avery Hanna, Tufts University



# My Group

---

- ATLAS Experiment
  - Detector for collisions in LHC
  - Understand fundamental particles and forces
- UCL Centre for Data Intensive Science
- Mentors: Mario Campanelli, Antoine Marzin (CERN L1 CTP Group)

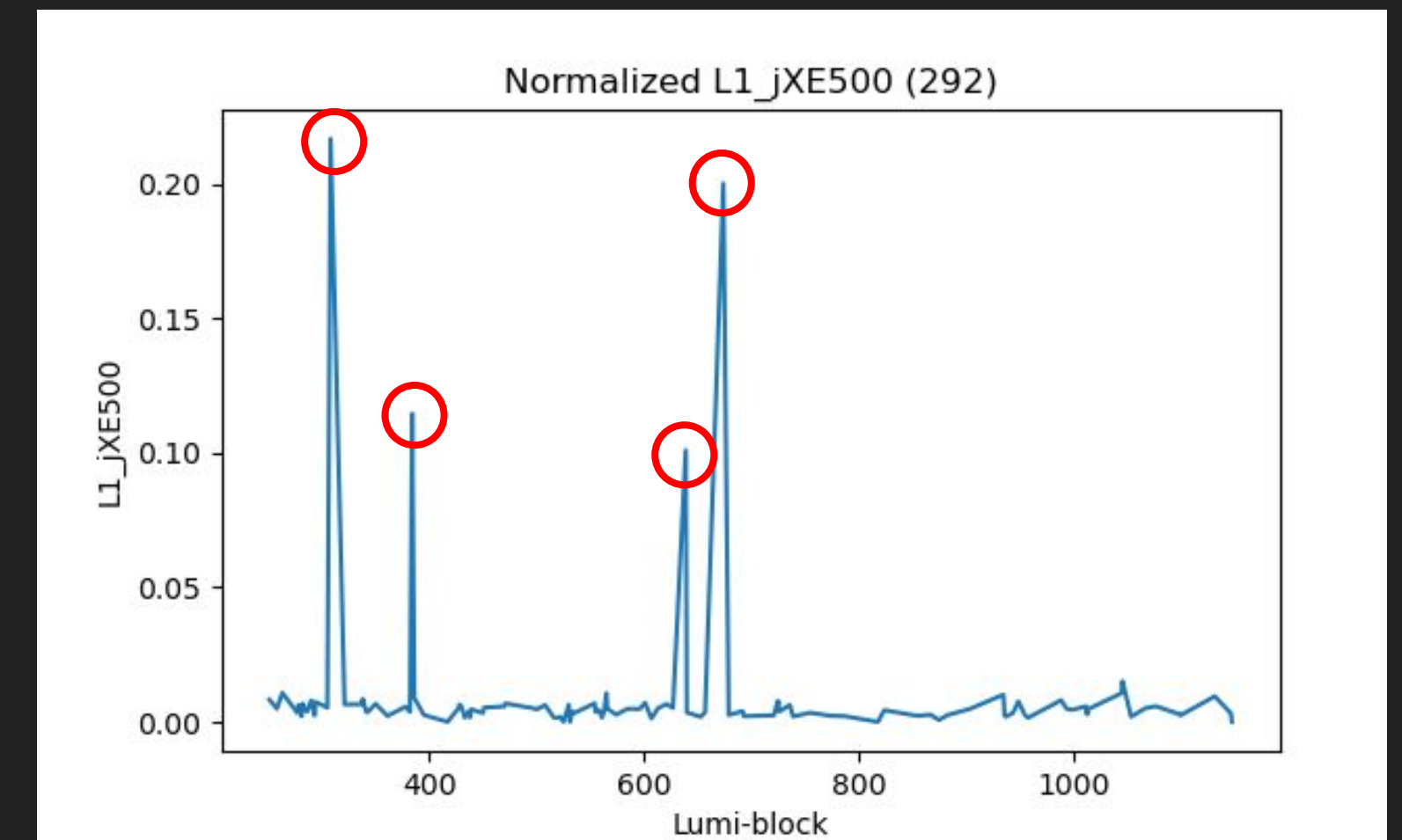


[2]

# My Project

---

- Control room shifters watch data for anomalies indicating detector malfunction
- Online model monitoring data input and flagging anomalies
- Input time-series data on status of detectors and output whether normal or anomalous
- Experimenting with models and architecture
  - Autoencoder
  - Long short term memory (LSTM)



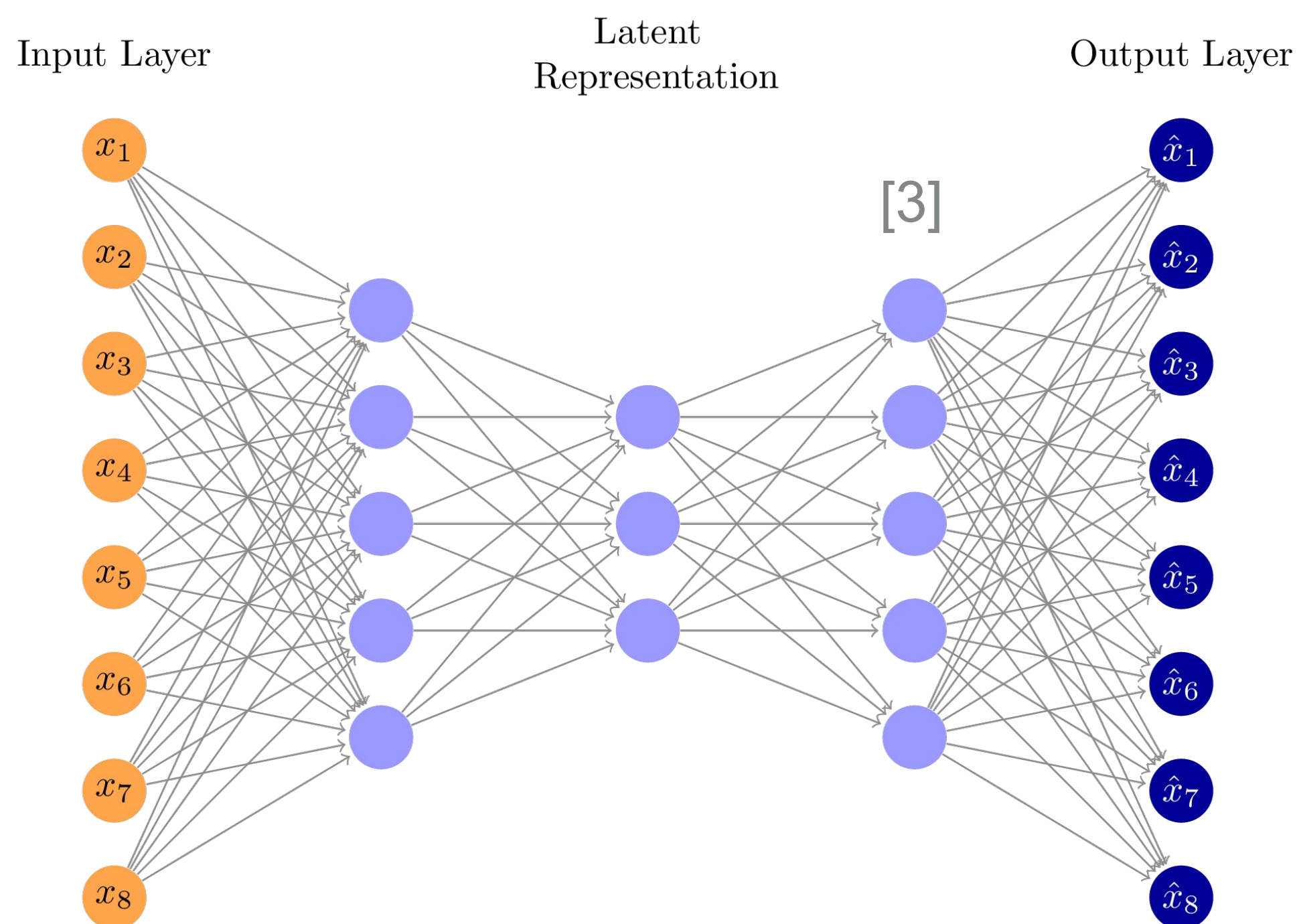
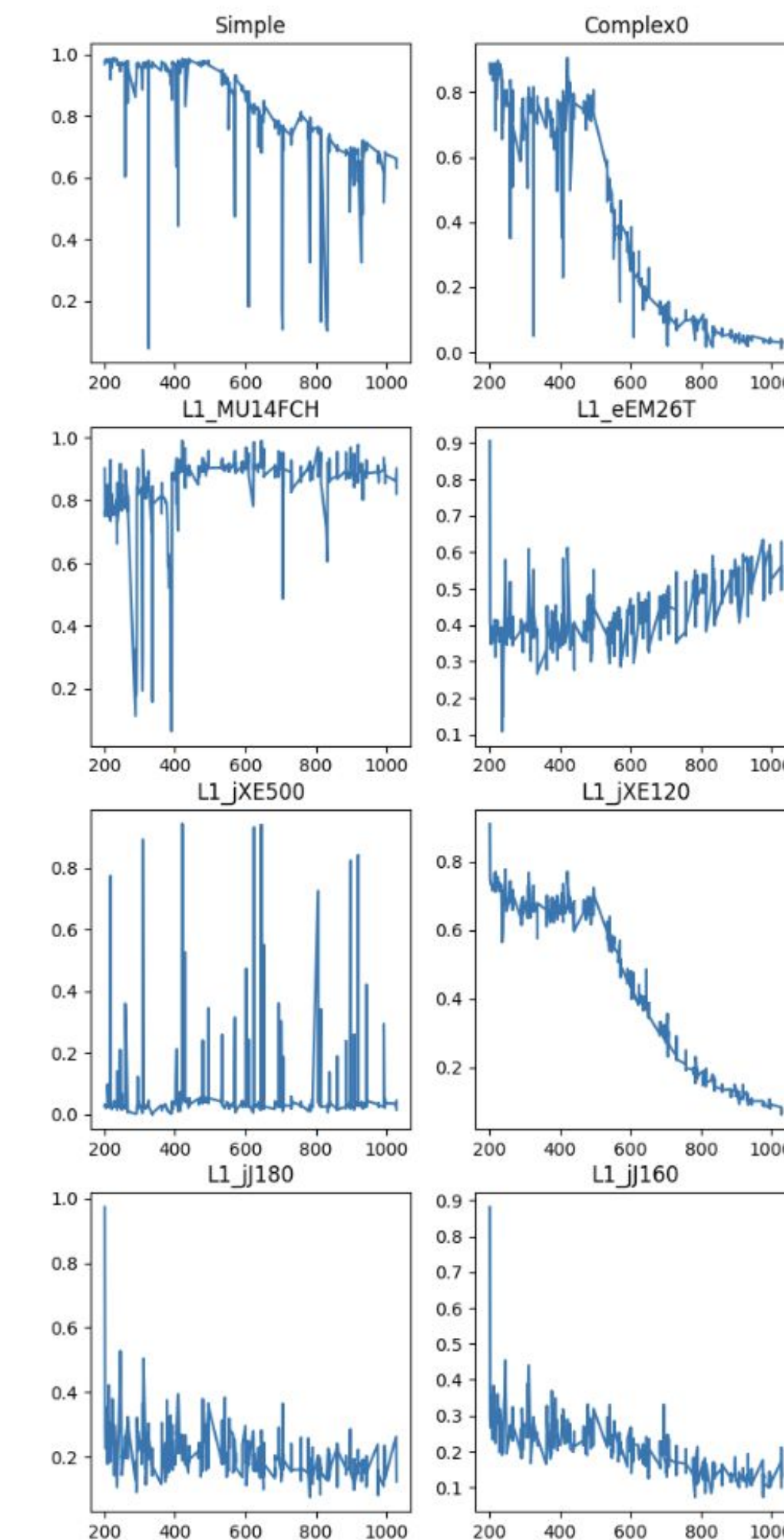
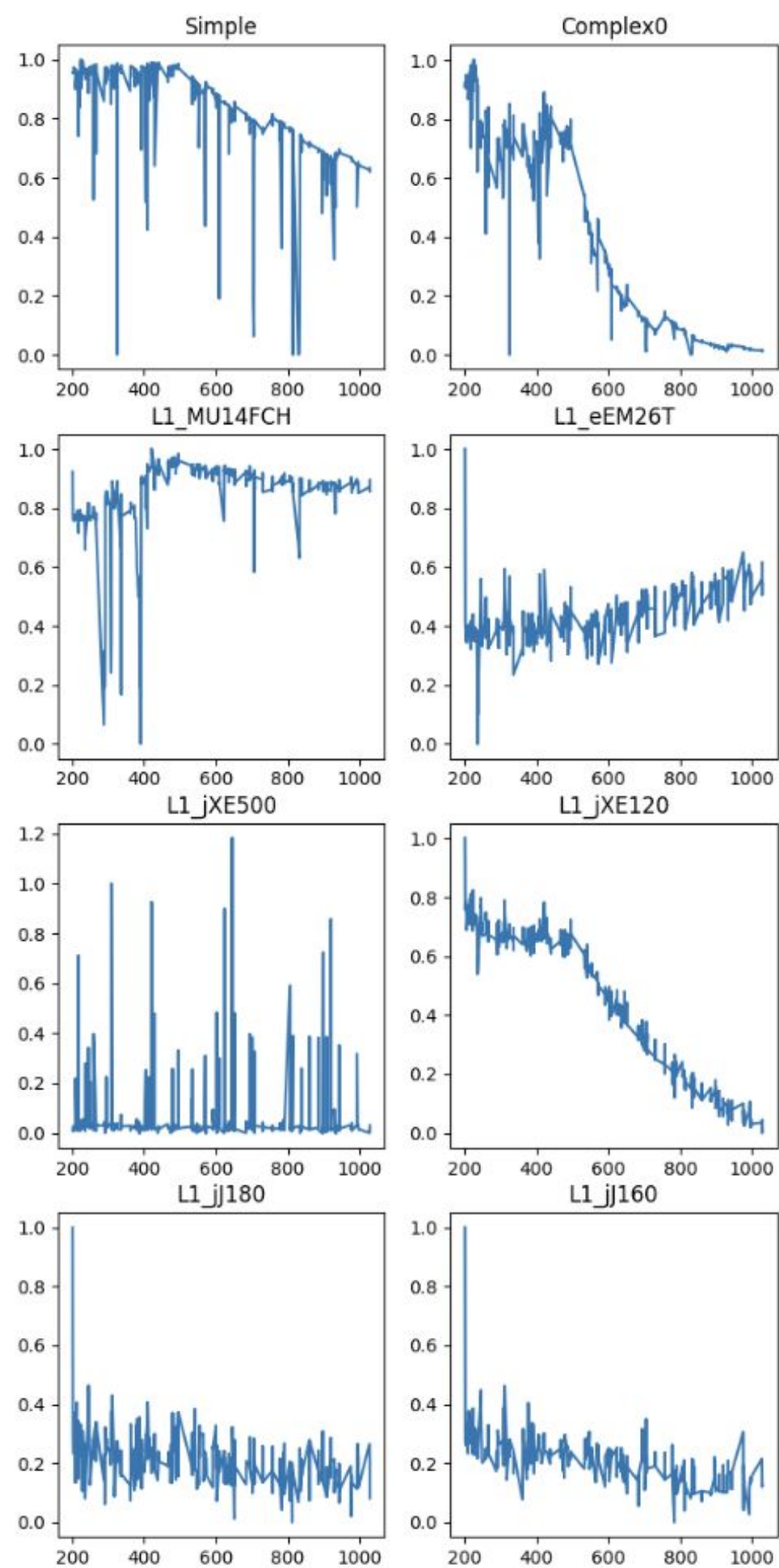
Example of input data (level 1 jet rate) with anomalies we'd like to detect circled in red

# Autoencoder

Input:  
Level 1 trigger rates (normalized by pileup), busy state, pileup

Output:  
Mirror of input

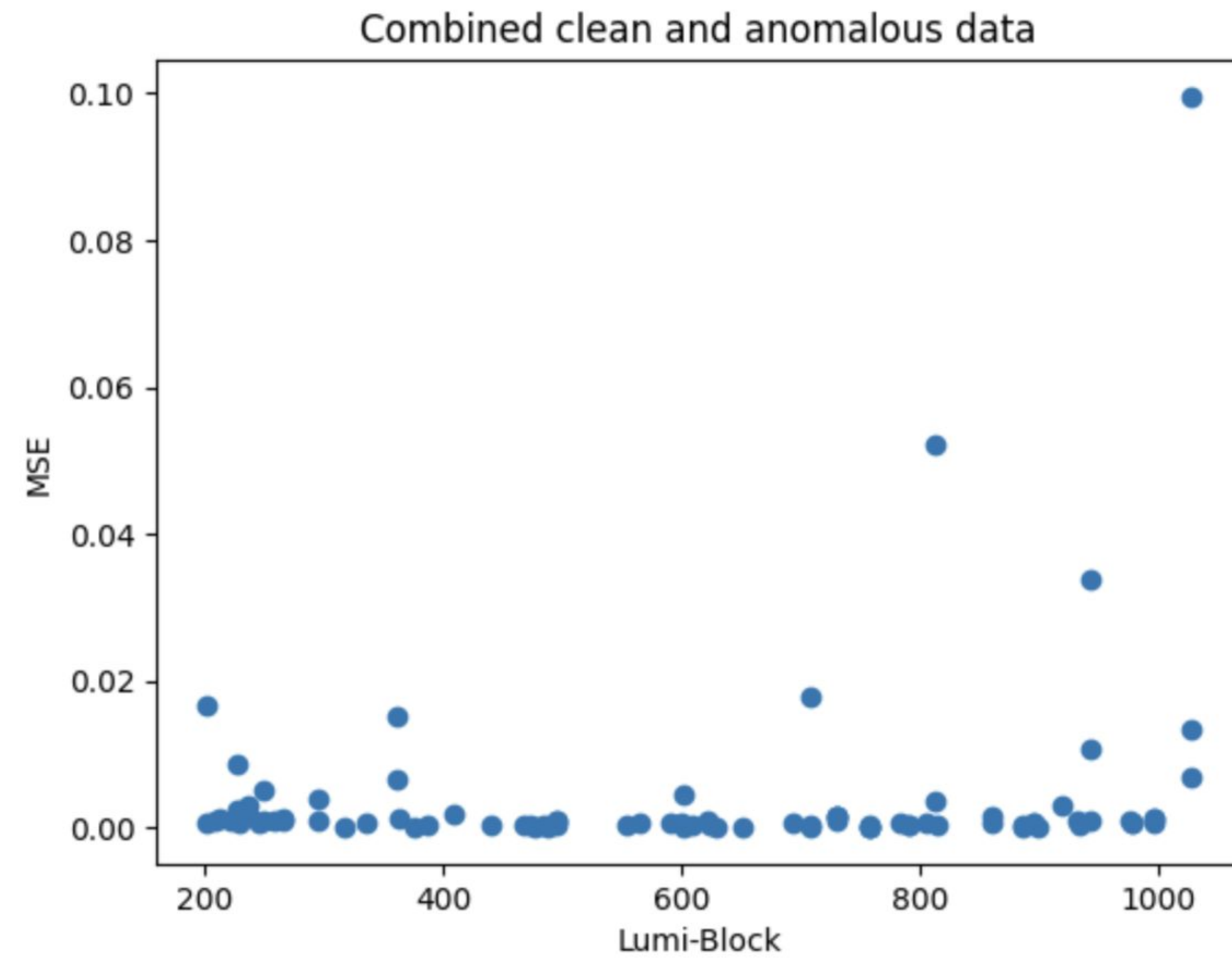
- Goal: given input, reduce dimensionality, predict the same values as output
- Train on normal data minimizing MSE
- Anomalous data produces spikes in MSE



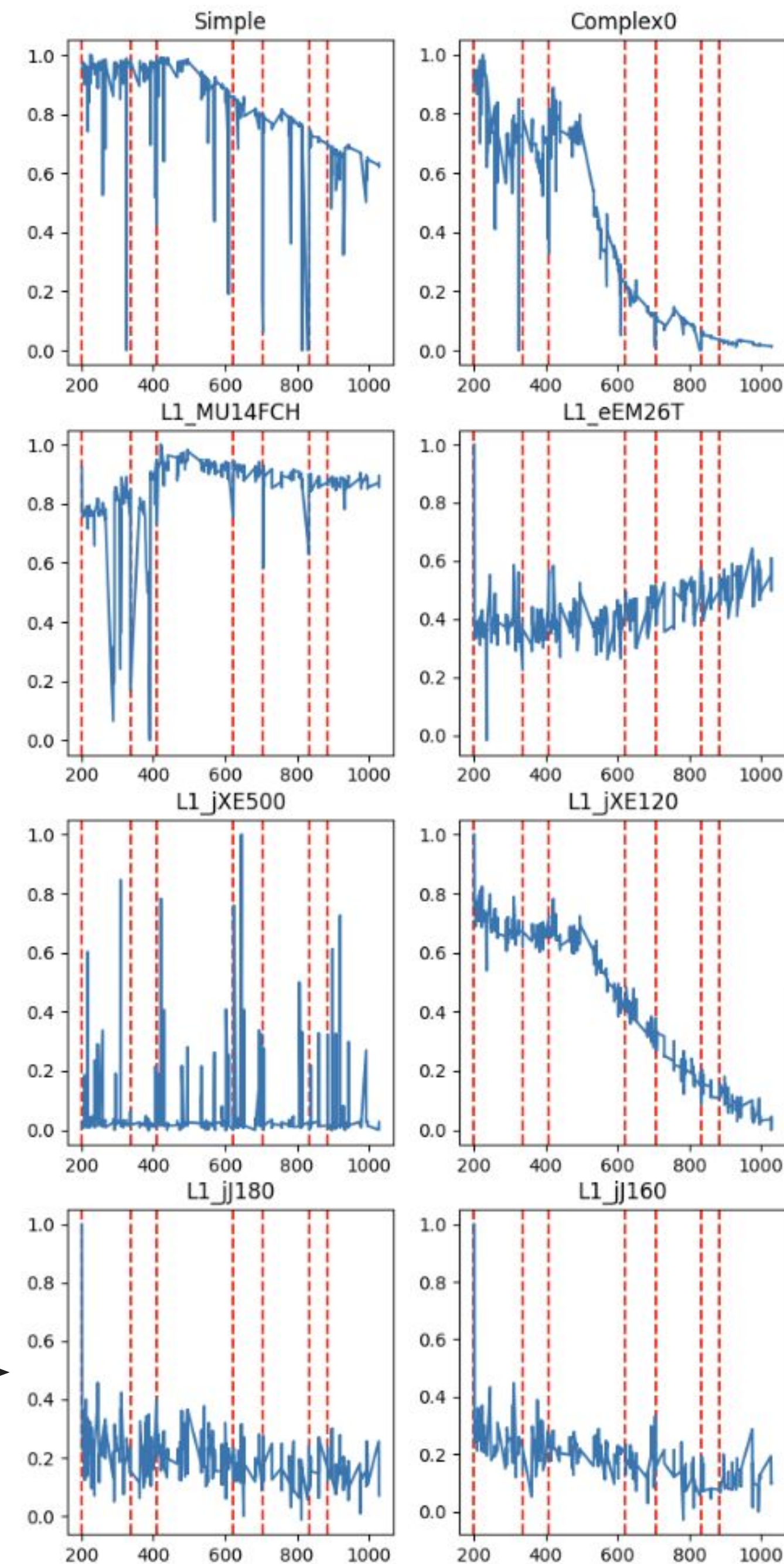
+8 additional inputs

+8 additional outputs

# Autoencoder



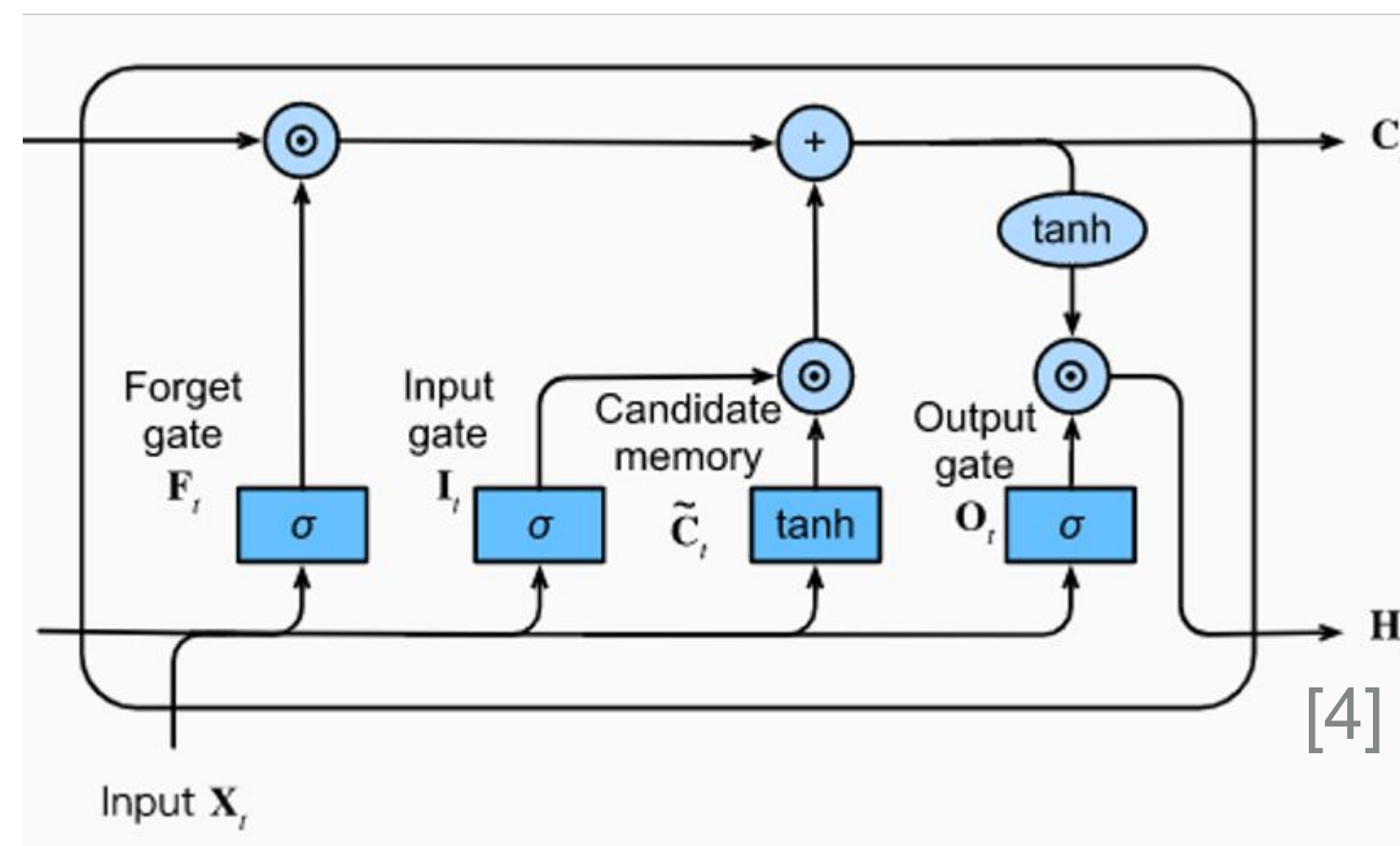
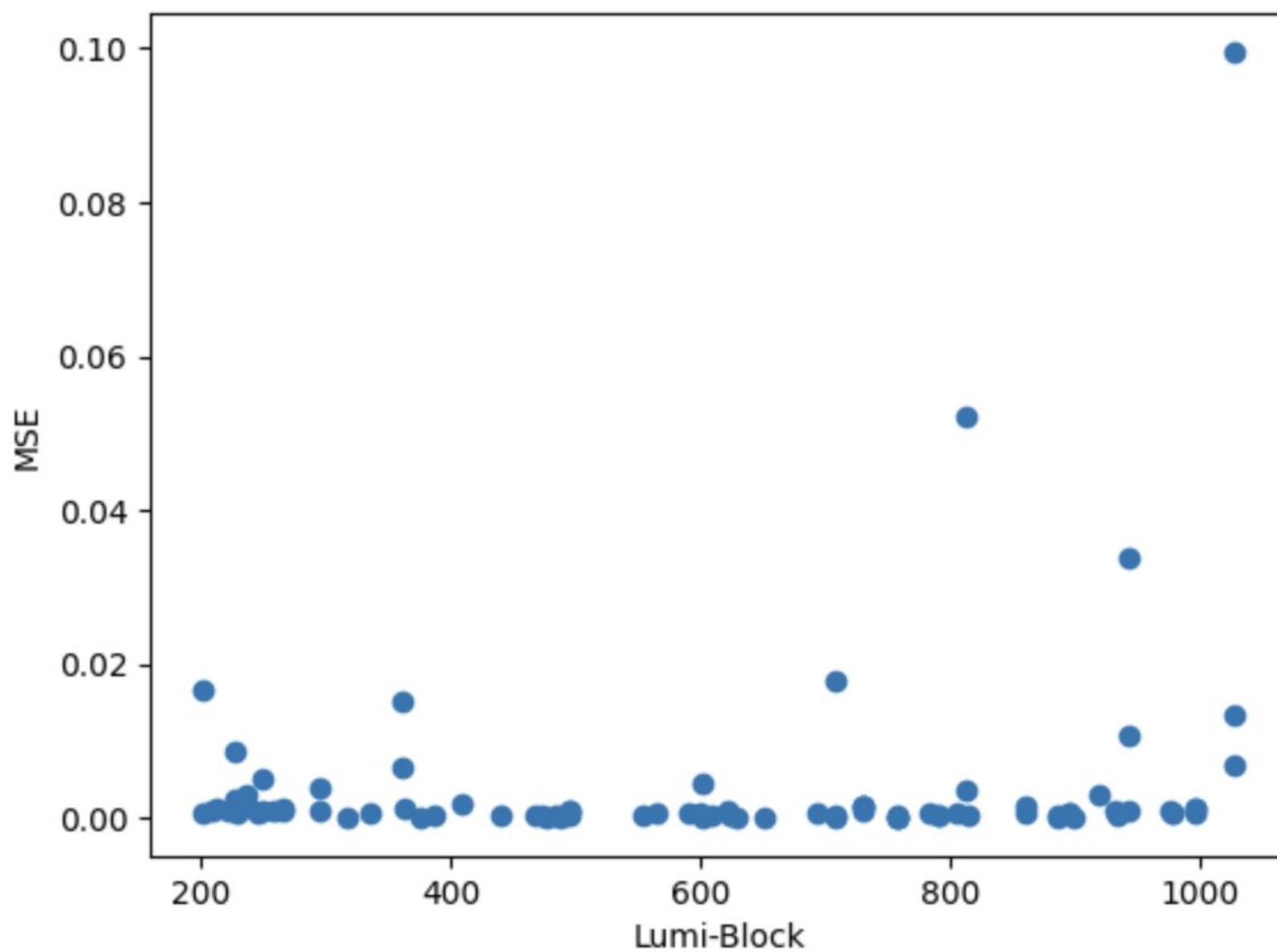
- MSE distance between input and output of autoencoder
- Inputs producing high MSE correspond to anomalies in data



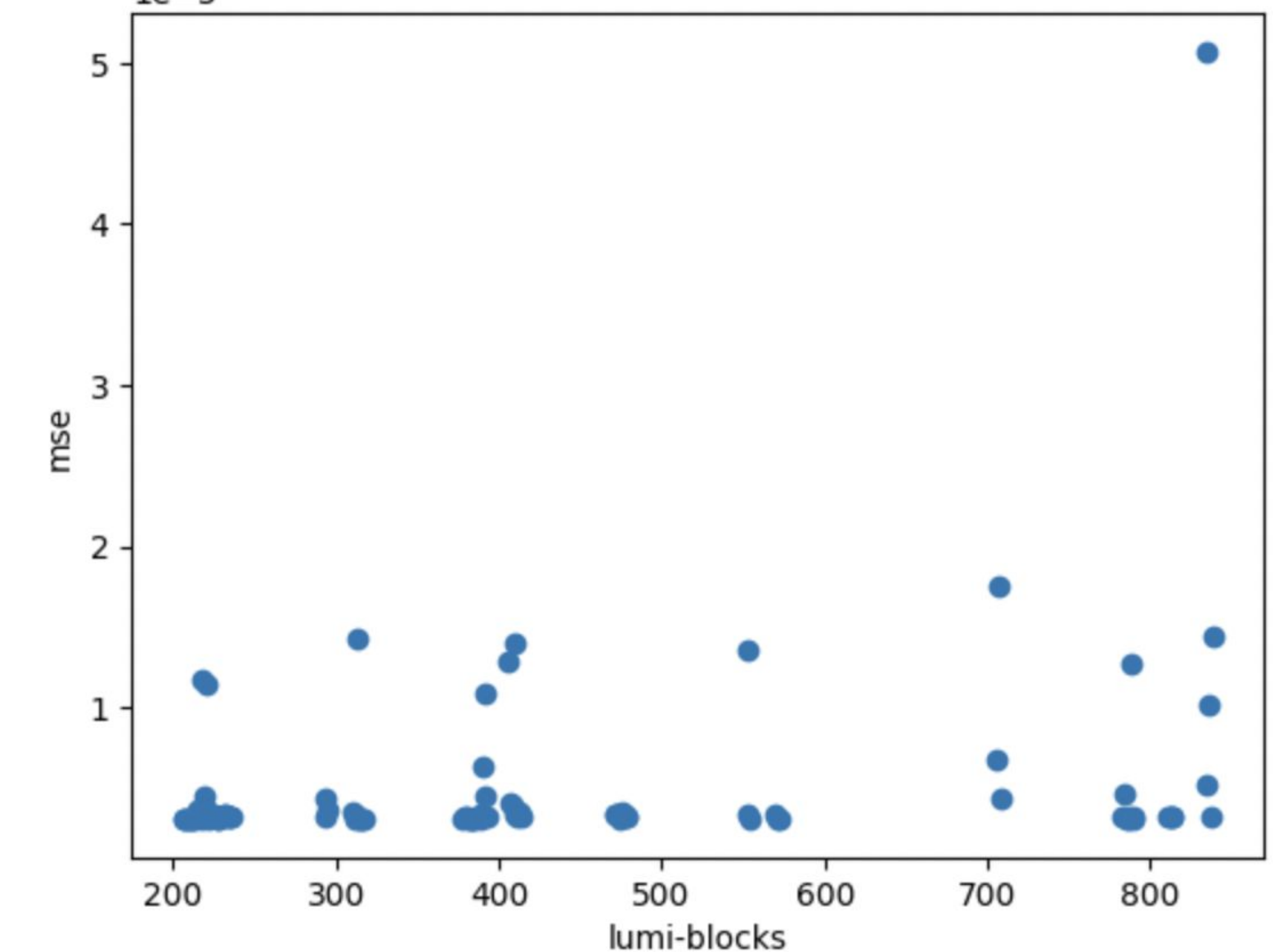
# Long Short Term Memory

- Anomalies can last longer than one time unit (about 1 minute) so LSTM allows us to build in memory
- Based on last 5 data points, predict next data point
- Compare prediction with next input and use mse to decide if normal or anomalous
- Train on normal data, so that high mse corresponds to anomalies

Combined clean and anomalous data

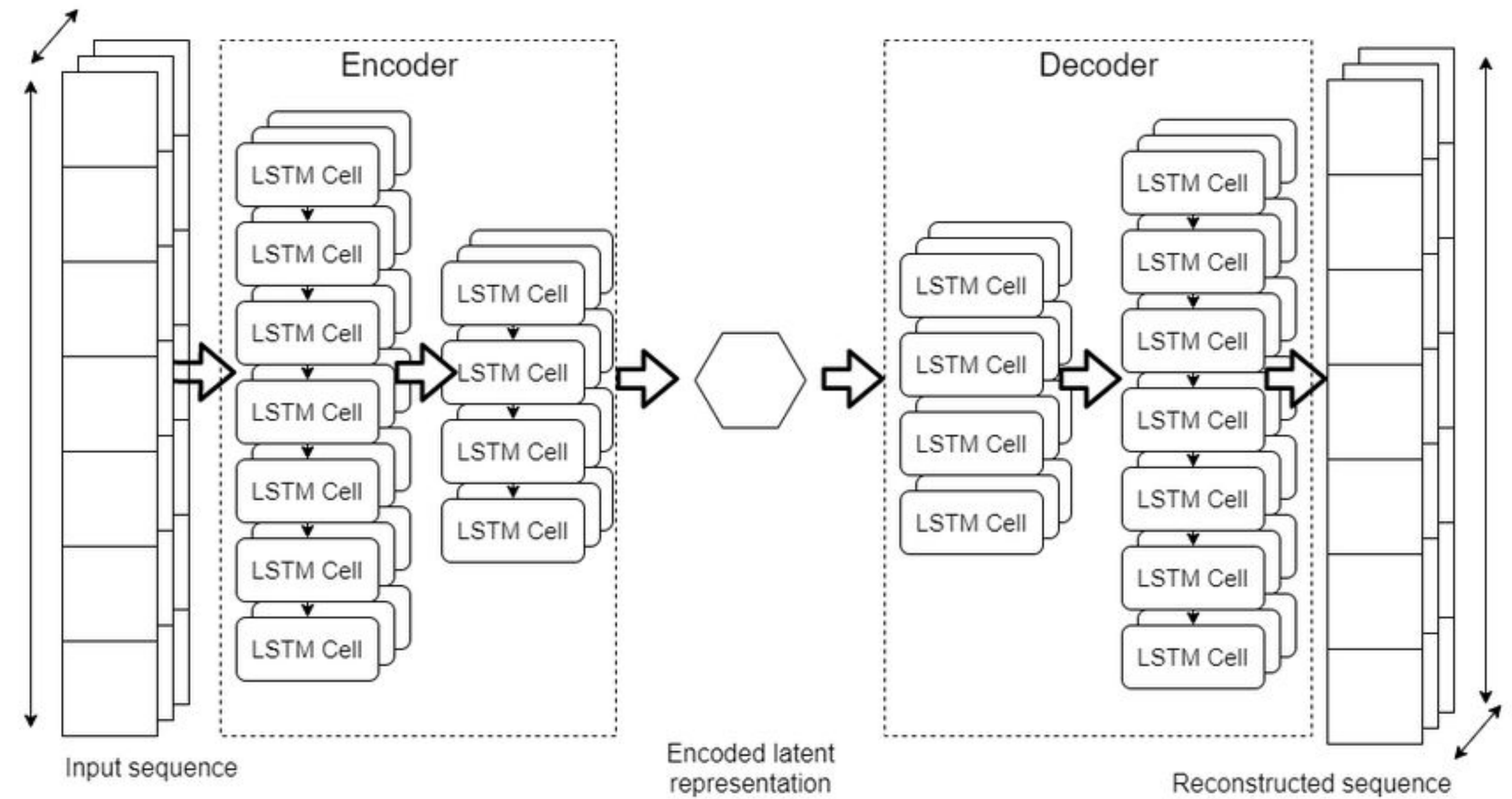


MSE v. LBs for run 476276



# Next Steps

- Expand data for training
  - Number of runs
  - Additional features
- More extensive testing
  - Assess performance on real anomalous runs
- LSTM Autoencoder
  - Build in memory around original inputs rather than autoencoder output



[5]

[4]

# EXPLORING





# Image Credits

---

[1] Romainbehar, CC0, via Wikimedia Commons

[2] CERN; <https://www.home.cern/science/experiments/atlas>

[3] Riebesell, Janosh; <https://tikz.net/autoencoder/>

[4] Dive into Deep Learning;  
[https://d2l.ai/chapter\\_recurrent-modern/lstm.html](https://d2l.ai/chapter_recurrent-modern/lstm.html)

[5] Unsupervised marine vessel trajectory prediction using LSTM network and wild bootstrapping techniques - Scientific Figure on ResearchGate.

[https://www.researchgate.net/figure/Architecture-of-LSTM-autoencoder\\_fig1\\_352898971](https://www.researchgate.net/figure/Architecture-of-LSTM-autoencoder_fig1_352898971) [accessed 24 Jun, 2024]

