REAL-TIME ANOMALY DETECTION FOR BUILDING SENSORS

Nathan Smith, Mitch Harris, Ryan Koenig

Background

The Urban Data Lab (UDL) advances data access, data management and data analytics capabilities on the University of British Columbia (UBC) campus with a goal of addressing campus-wide sustainability challenges. UDL has access to data from buildings on campus including heating, ventilation and air conditioning (HVAC) equipment and energy data. These data are stored by UDL in an InfluxDB time series database. The project goal was to develop a real-time anomaly detection system using open-source tools that could be used with InfluxDB. A subset of Campus Energy Center (CEC) boiler sensors was selected for the study.

Approach

The approach used in this study provides near real-time anomaly detection with InfluxDB. Model training is completed by querying sensor data from InfluxDB on an infrequent basis (for example monthly), training a model for each sensor, and saving the models. Anomaly detection occurs on a continuous basis by reading recent data, loading and running the previously trained models, and writing predictions to InfluxDB.

A long short-term memory recurrent neural network model with an encoder-decoder architecture (LSTM-ED) is used for anomaly detection in the study. This was selected as it provides a general model with good performance in recent studies. The generalizability of the LSTM-ED is important given the wide variety of sensor types available to UDL. The model is trained in an unsupervised approach with sequence reconstruction of input data and anomaly predictions are based on identifying data with high sequence reconstruction error. The model was found to have good initial performance on the selected subset of CEC sensors. A data pattern was identified that the model had trouble detecting but it is believed that performance can be improved using more sophisticated anomaly error/threshold identification rules.

A dashboard and notification system were also implemented with the anomaly detection model in a test InfluxDB environment. The dashboard was built directly in InfluxDB and provides a simple display of sensor data highlighted as normal or anomalous. The notification system also uses built-in InfluxDB functionality and was configured to send messages for any data predicted as anomalous.

Conclusion

This study provides an initial open-source anomaly detection approach that can be used by UDL with InfluxDB. The approach is general and should be applicable to a variety of sensors. Ideally, the detection system could ultimately be used to provide campus and building managers with real-time or near real-time notifications of potential issues in system operations reducing operational costs, downtime, and unexpected maintenance.

Additional studies that can be considered for next steps include implementing the model online and monitoring performance, improving the anomaly detection threshold method to improve performance, comparison of the LSTM-ED with additional models, testing additional sensors, and building a more complex dashboard and notification system as required.