Identifying Anomalous Shared E-Scooter Patterns Using Unsupervised Deep Learning

Dr. Yanan Xin[1], Dr. Alan MacEachren[2]
1. ETH Zurich, Switzerland
2. The Pennsylvania State University, USA

Motivations

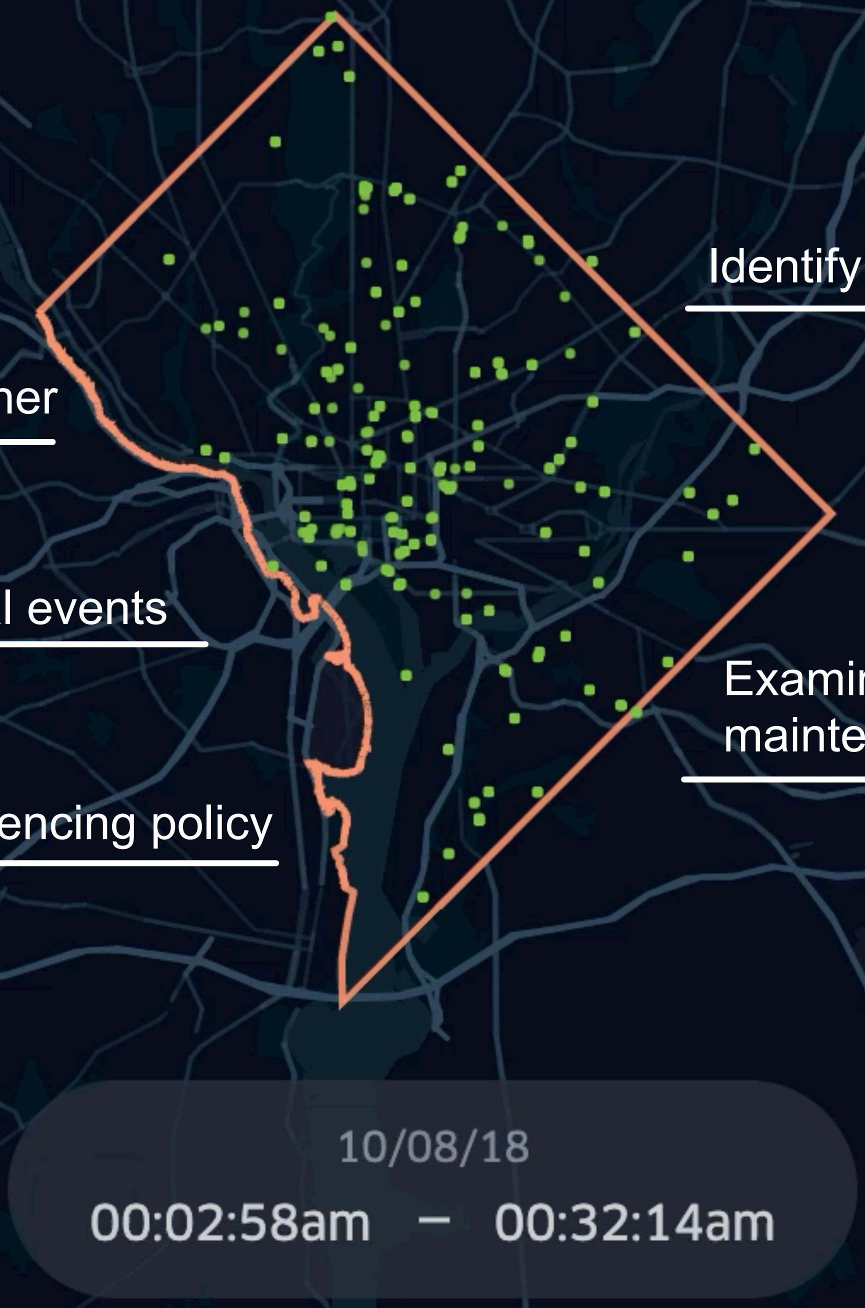
Identify illegal riding or parking

Identify impact of inclement weather

Identify impact of special events

Examine scooter companies' maintenance operation

Examine compliance with geofencing policy



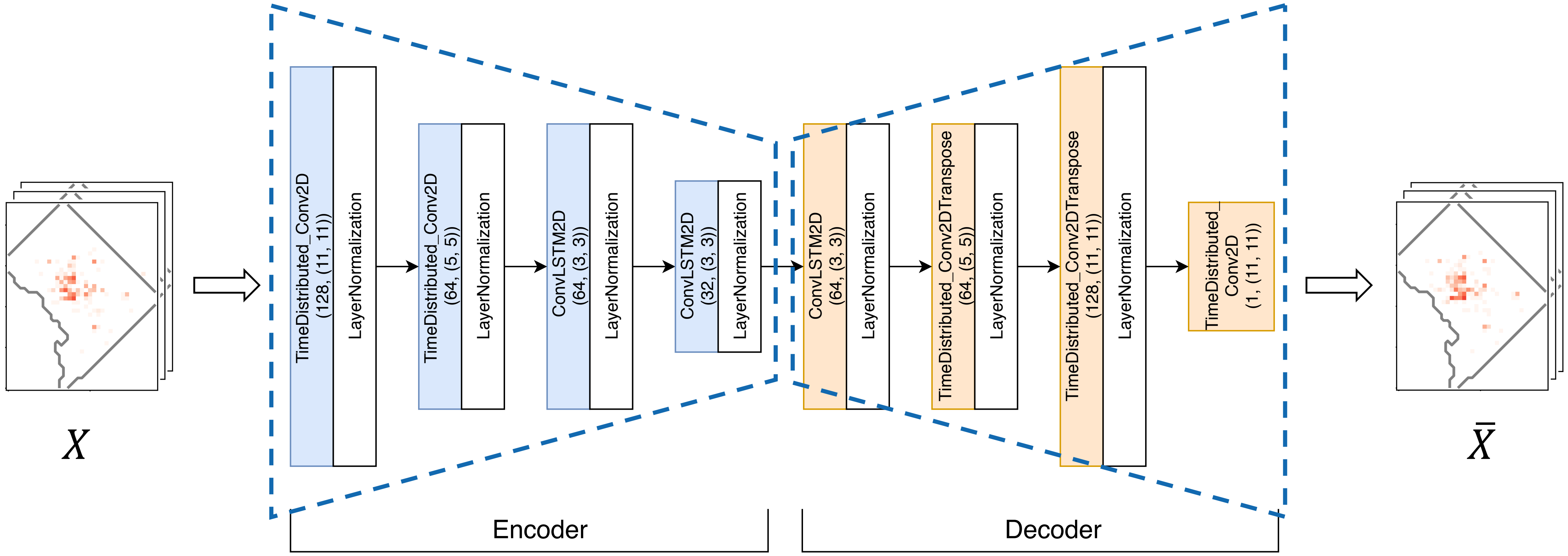
Challenges

- Difficult to define what is normal
- Challenging to label abnormal data instances
- Difficult to engineer features
- Challenging to detect both spatial and temporal anomalies

Data-Driven Unsupervised Deep Learning Approach

ConvLSTM-Autoencoder

ConvLSTM-Autoencoder



$$Loss = ||X - \bar{X}|| \quad \sim$$ unique information (Anomaly Score)

Experiments

- **Study Area**
  - Washington DC, USA

- **Data**
  - Lime scooter data (19/09/2018 – 18/07/2019, ~ 10 months)
  - Spin scooter data (27/03/2019 – 15/07/2019, ~ 4 months)
  - Lyft scooter data (27/03/2019 – 15/07/2019, ~ 4 months)

- **Experiment Design**
  - 1. Test of robustness to different data samples
  - 2. Identify anomalies across three scooter companies

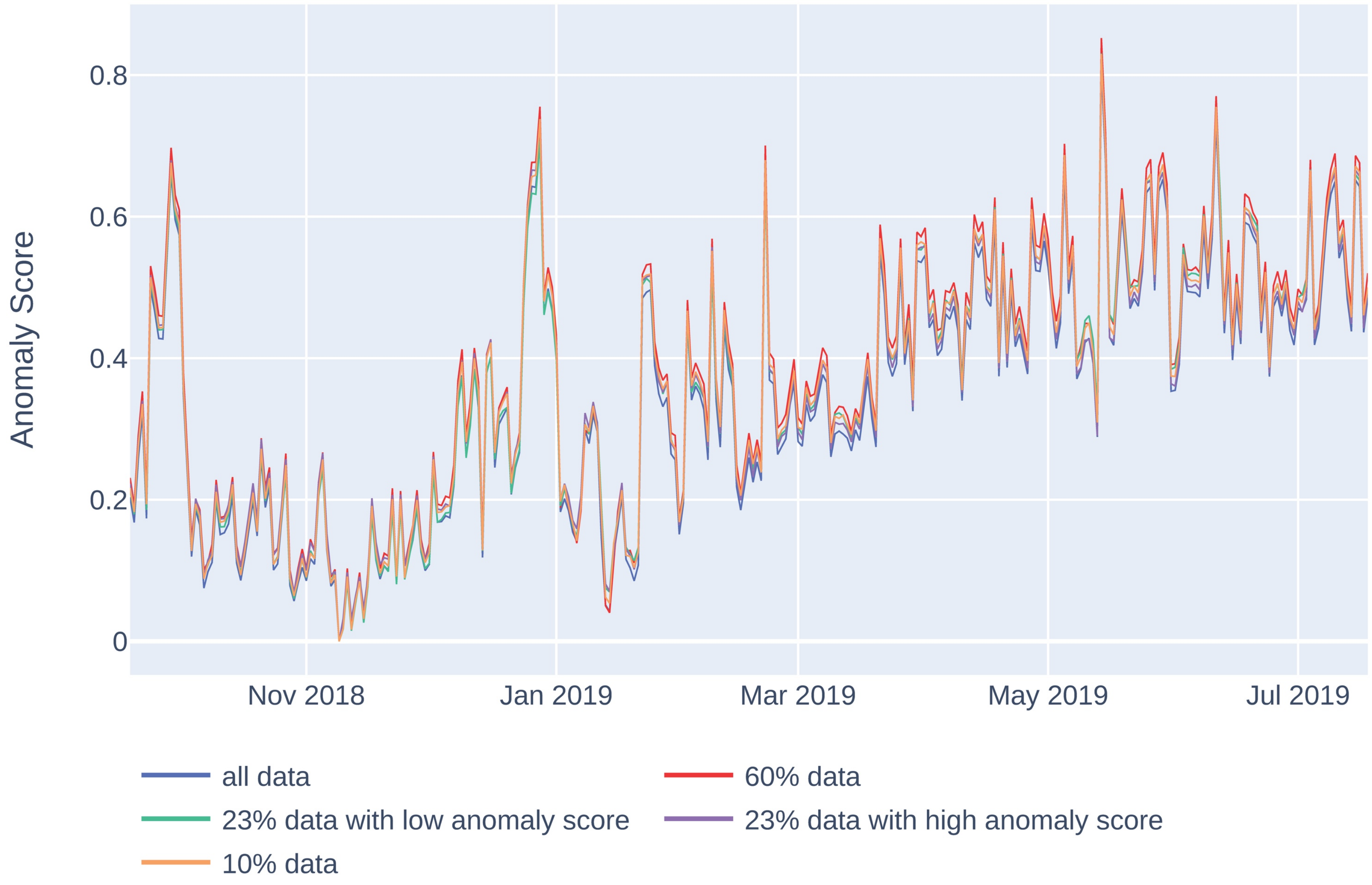
Experiment 1 – Robustness Test

- Assumptions
  - Abnormal data samples are rare compared to normal samples

- Test of Assumptions
  - Is the model robust to different compositions of normal and abnormal samples

- Data samplings (Lime data)
  - all data (303 days)
  - 60% randomly sampled data
  - 23% data with low anomaly score (<0.3)
  - 23% data with high anomaly score (> 0.4)
  - 10% randomly sampled data (30 days)

Experiment 1 - Results

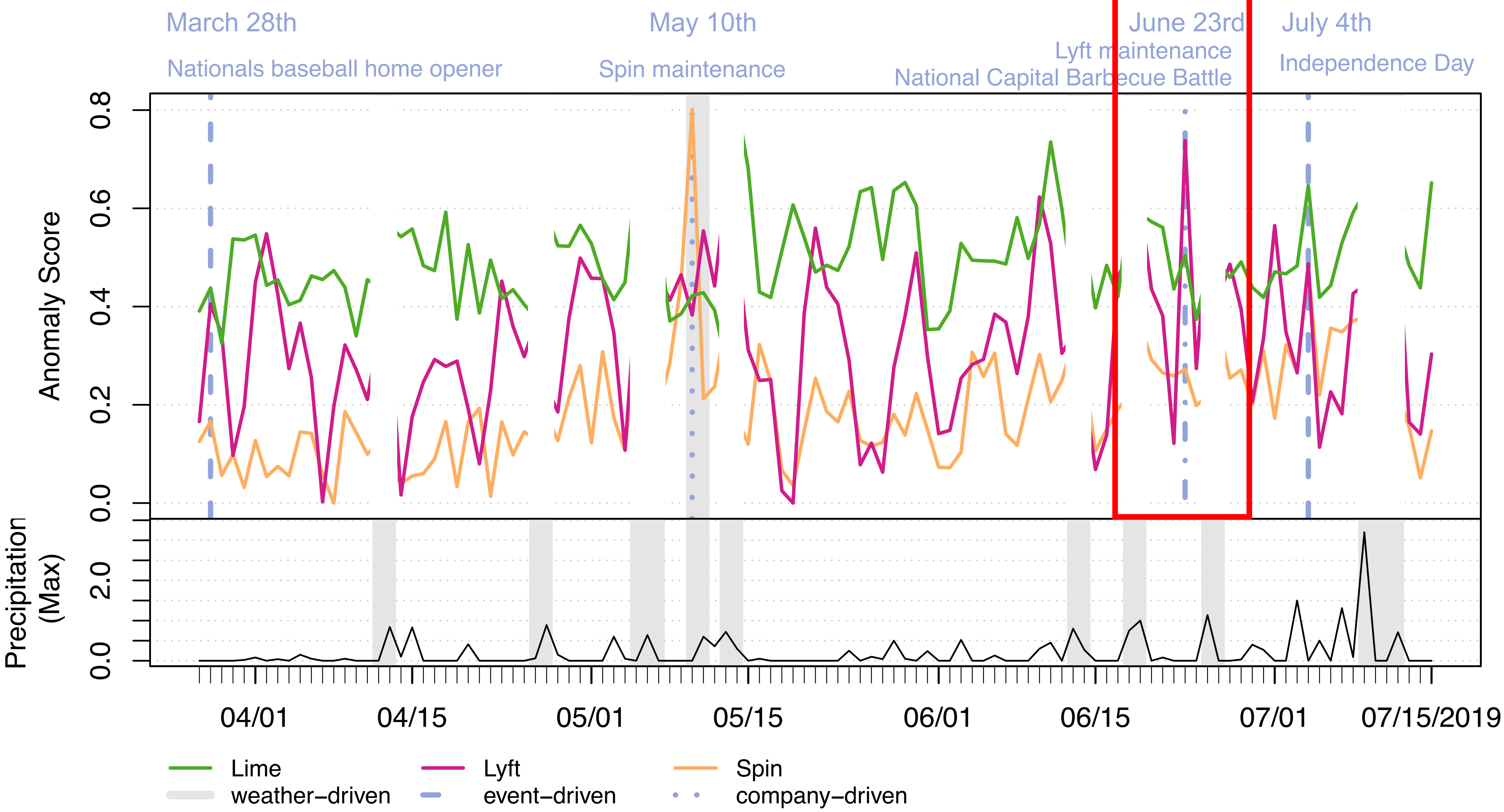


Experiment 2 – Anomaly Identification

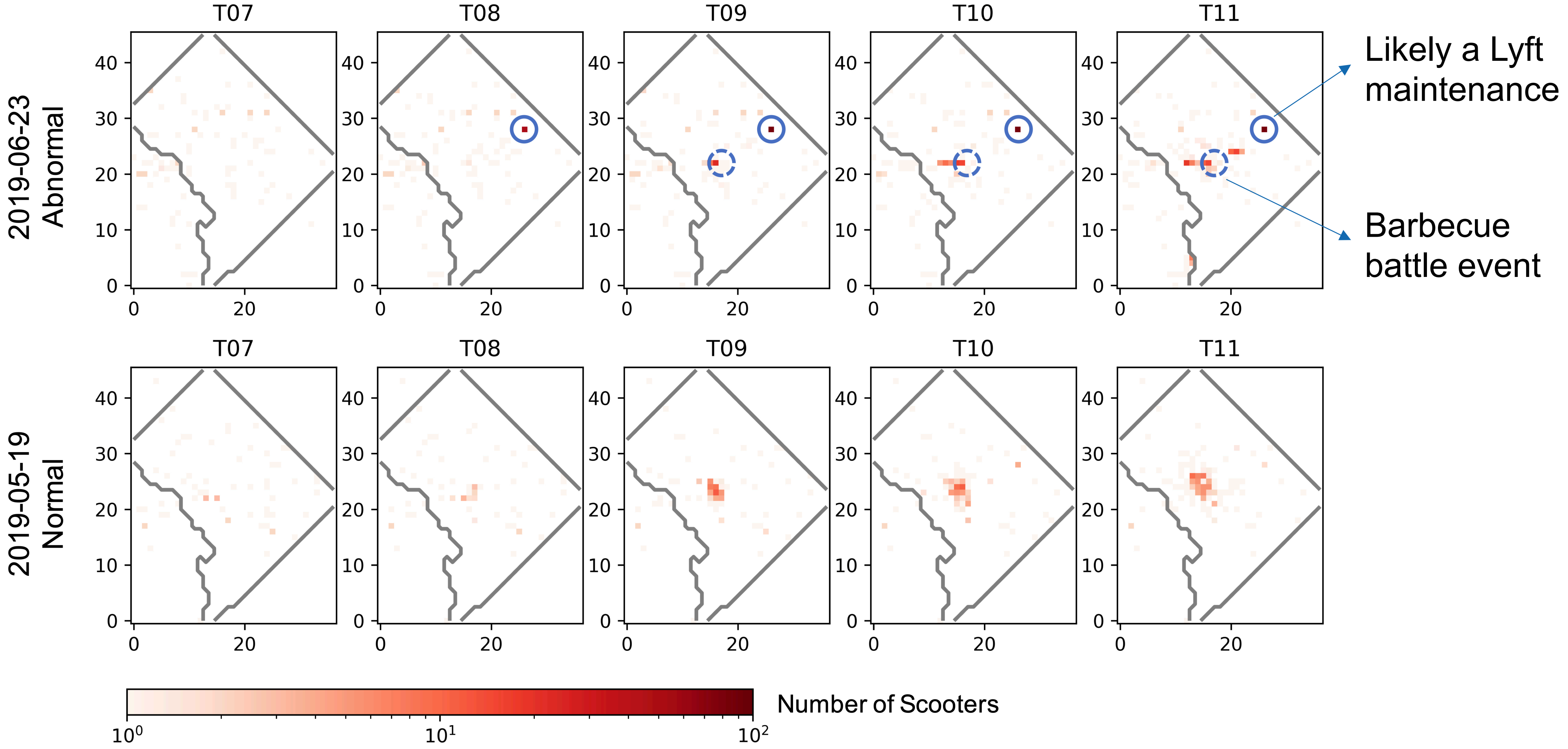
- Anomaly Definition
  - Spikes in the anomaly score
  - Common spikes across three scooter companies that indicate systematic influence

- Data Set
  - Lime, Spin, and Lyft scooter data (27/03/2019 – 15/07/2019)
  - NOAA weather data, event history, and government-issued policies

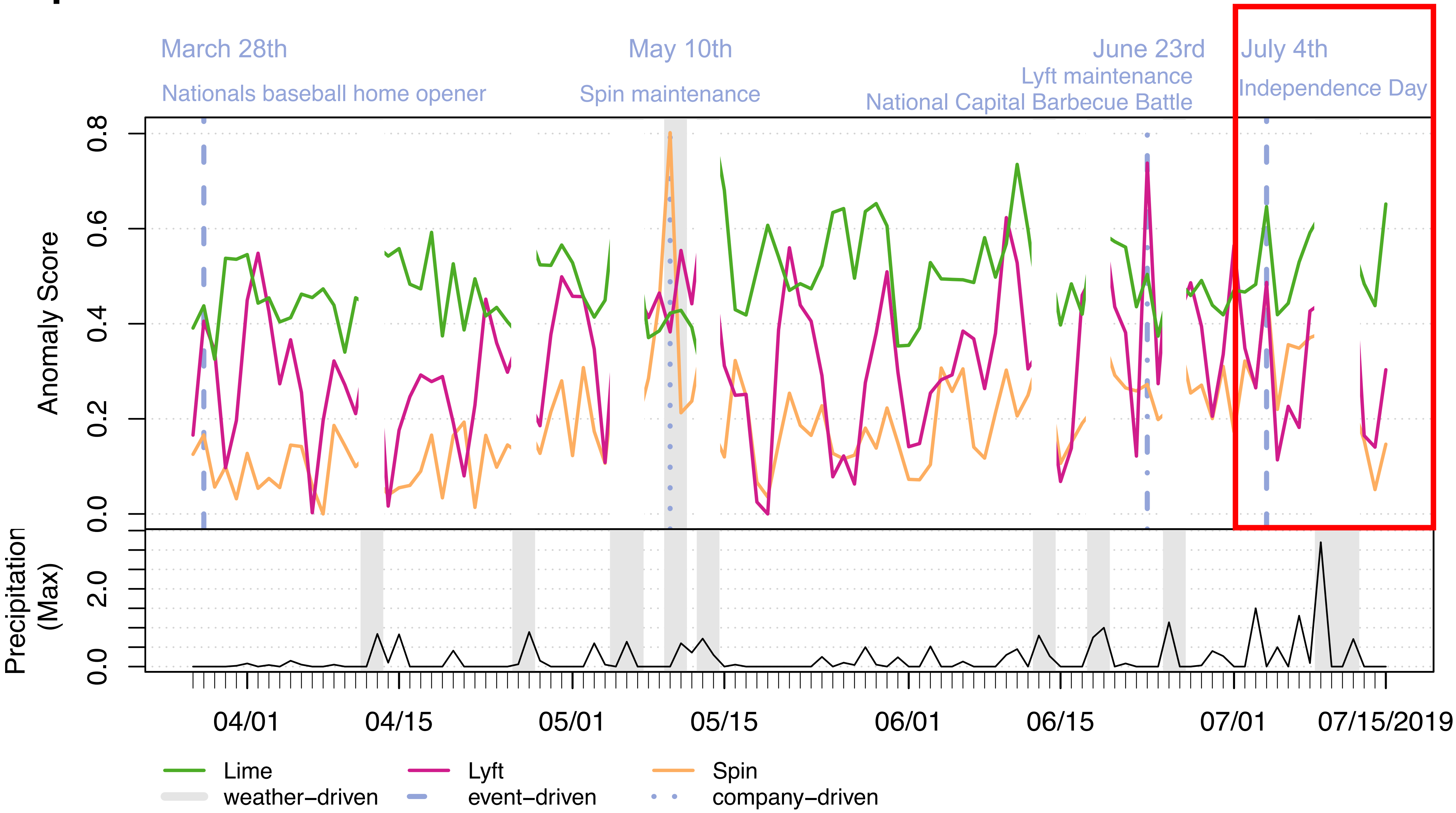
Experiment 2 - Results



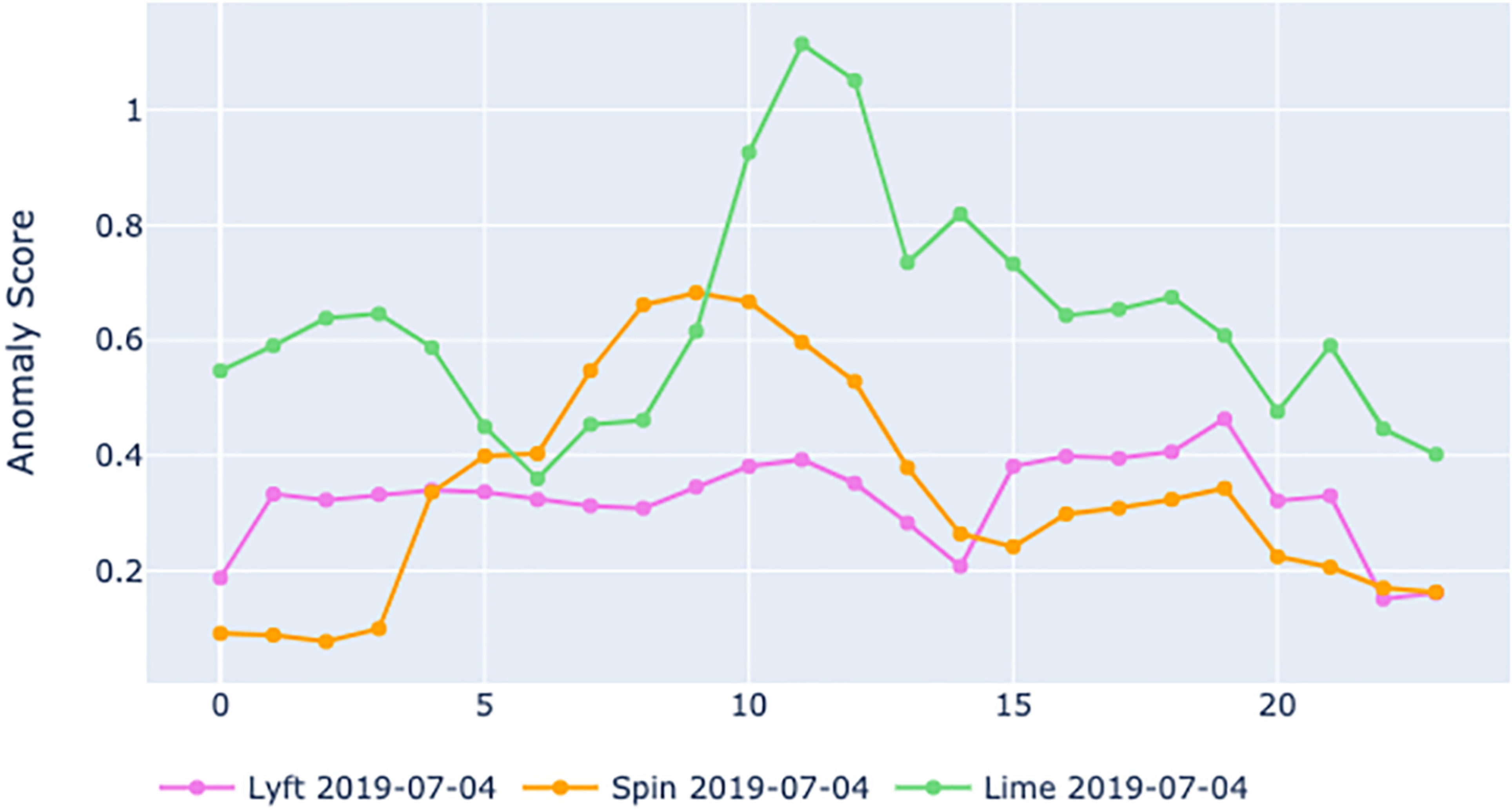
Comparing Lyft Scooter Patterns Between An Abnormal Day and A Normal Day



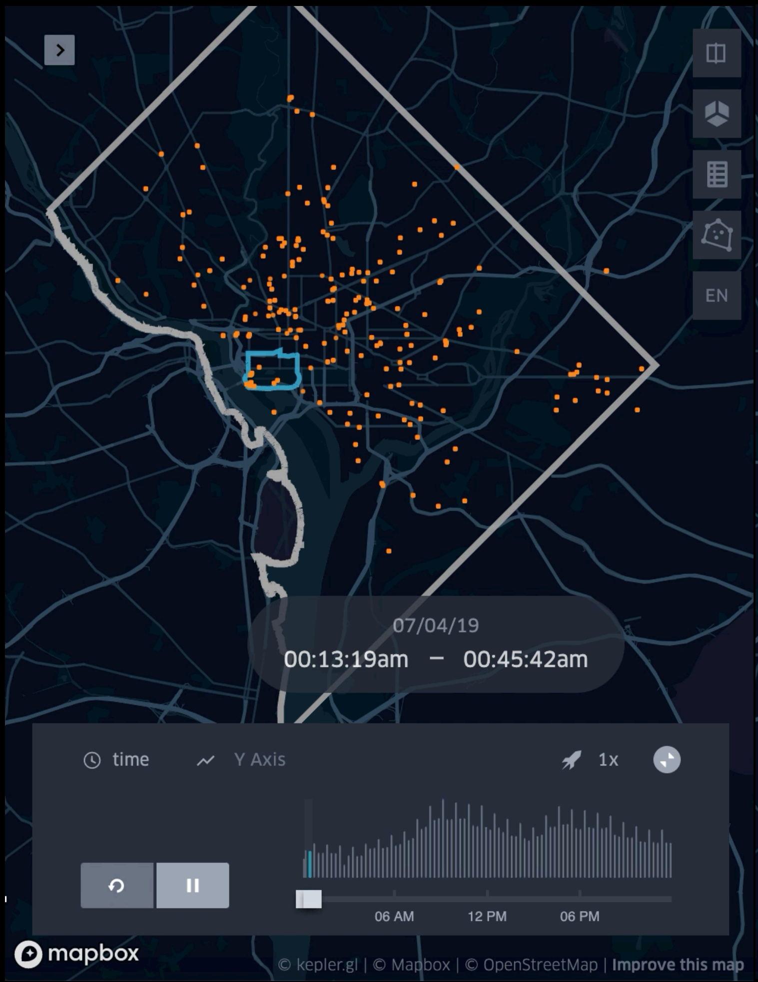
Experiment 2 - Results

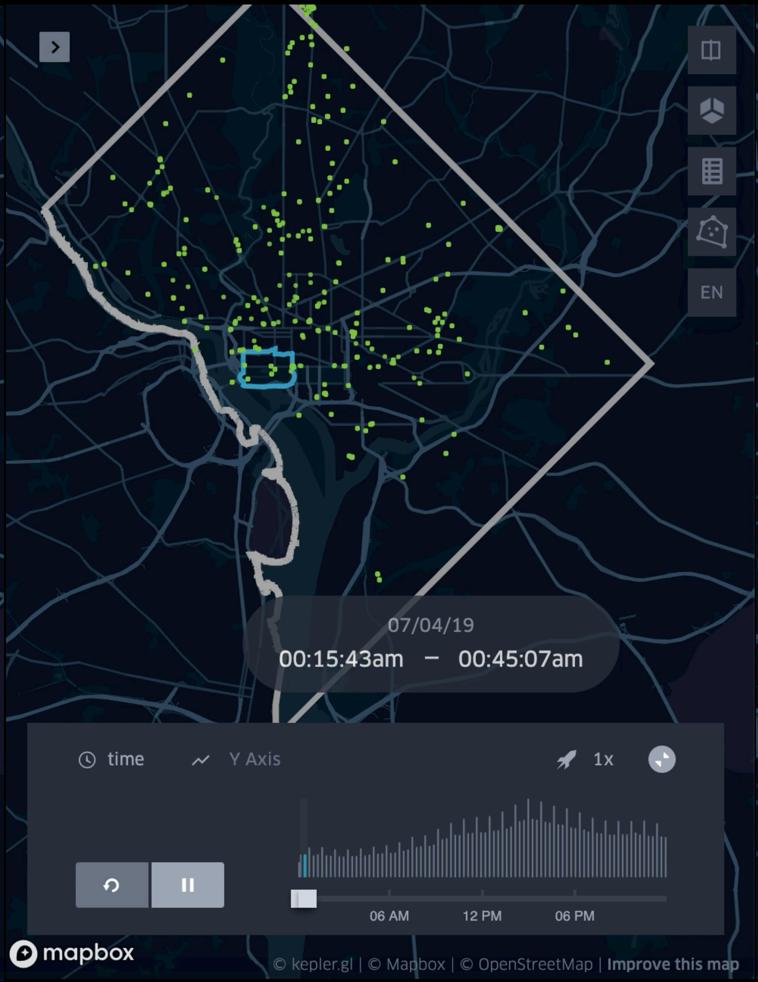


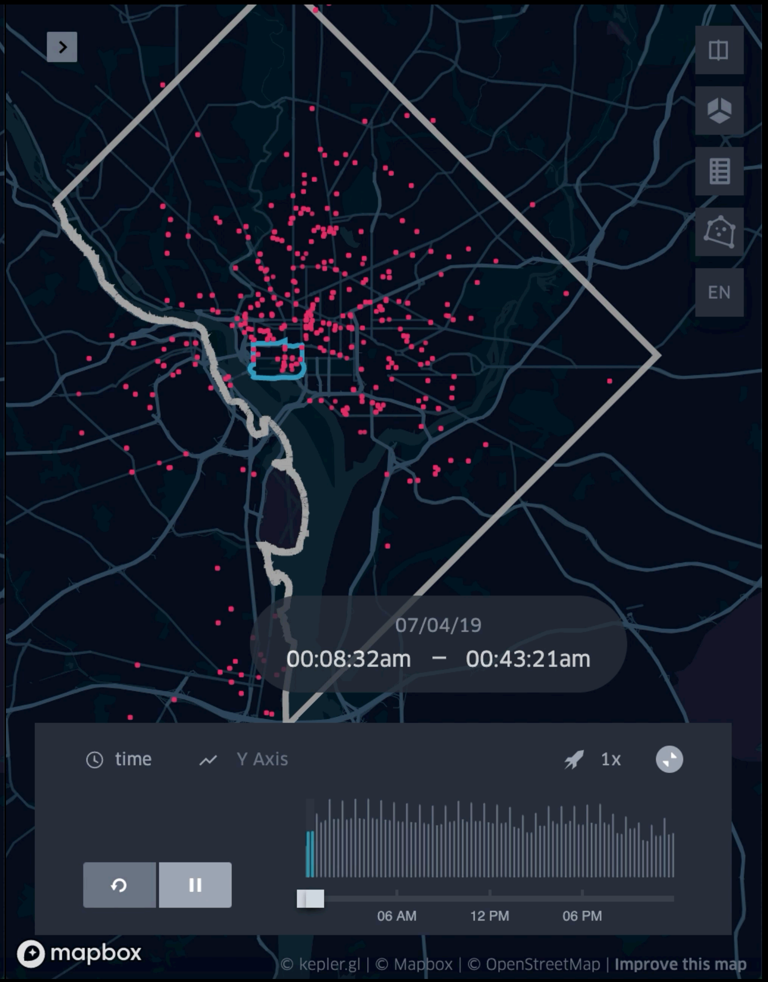
Hourly Anomaly Score Comparison



E-Scooter Patterns on July 4th, 2019







Spin Scooter

Lime Scooter

Lyft Scooter

Conclusions

1. Demonstrated the effectiveness of the ConvLSTM-Autoencoder in identifying anomalous e-scooter patterns.
2. A robustness test showed that the method is robust to low data sampling rate.
3. Identified three meaningful types of anomalies: weather-driven anomaly, event-driven anomaly, and company-driven anomaly.
4. The results could be used to monitor malicious usage of scooters, guide transportation planning, and examine the compliance of policy.

Acknowledgement

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Dr. Yanan Xin
Institute of Cartography and Geoinformation
Mobility Information Engineering (MIE) Lab
yanxin@ethz.ch

HIL D 54.2
Stefano-Franscini-Platz 5
8093 Zürich, Switzerland

http://mie-lab.ethz.ch/