Predicting Citi Bike Availability in NYC

DATA 698 Research Project
CUNY Fall 2022

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2022-11-22

Citi Bike Availability

Predict the count to avoid the empty racks

Problem and Objective

v3: started 11:30A on Nov 22, 2022

Introduce yourselves and describe your problem. Explain your objectives, challenges of your work, proposed methodologies, and the assumptions you made while conducting modeling and/or analysis. Provide an overview of your approach and/or conceptual model (please do not present your code directly). Describe the results you obtain and summarize the current achievements and possibility of future works.

Previous Work

- bullet 1
- bullet 2
- bullet 3
- bullet 4

Challenges and Assumptions

Large volume of data

- Over 10 million trips in 3 months under consideration
- Over 1650 docking stations in NYC

Rebalancing

- System action of moving bikes to restock docking stations
- Identification and inconsistency

User-friendly availability prediction

- Independent variables to prediction model
- End-user input values

Data Collection

Citi Bike System Data

- Download CSV file
- API call every 15 minutes for two weeks

NYC Open Data

- Borough shapes via GeoJSON files

Docking Station Elevation

- R library `elevatr`

Surplus/Shortage Timetable

- Convert trip data to dataframe of bike departure and arrival counts by docking station for a given time interval

Data Analysis

Ridership patterns

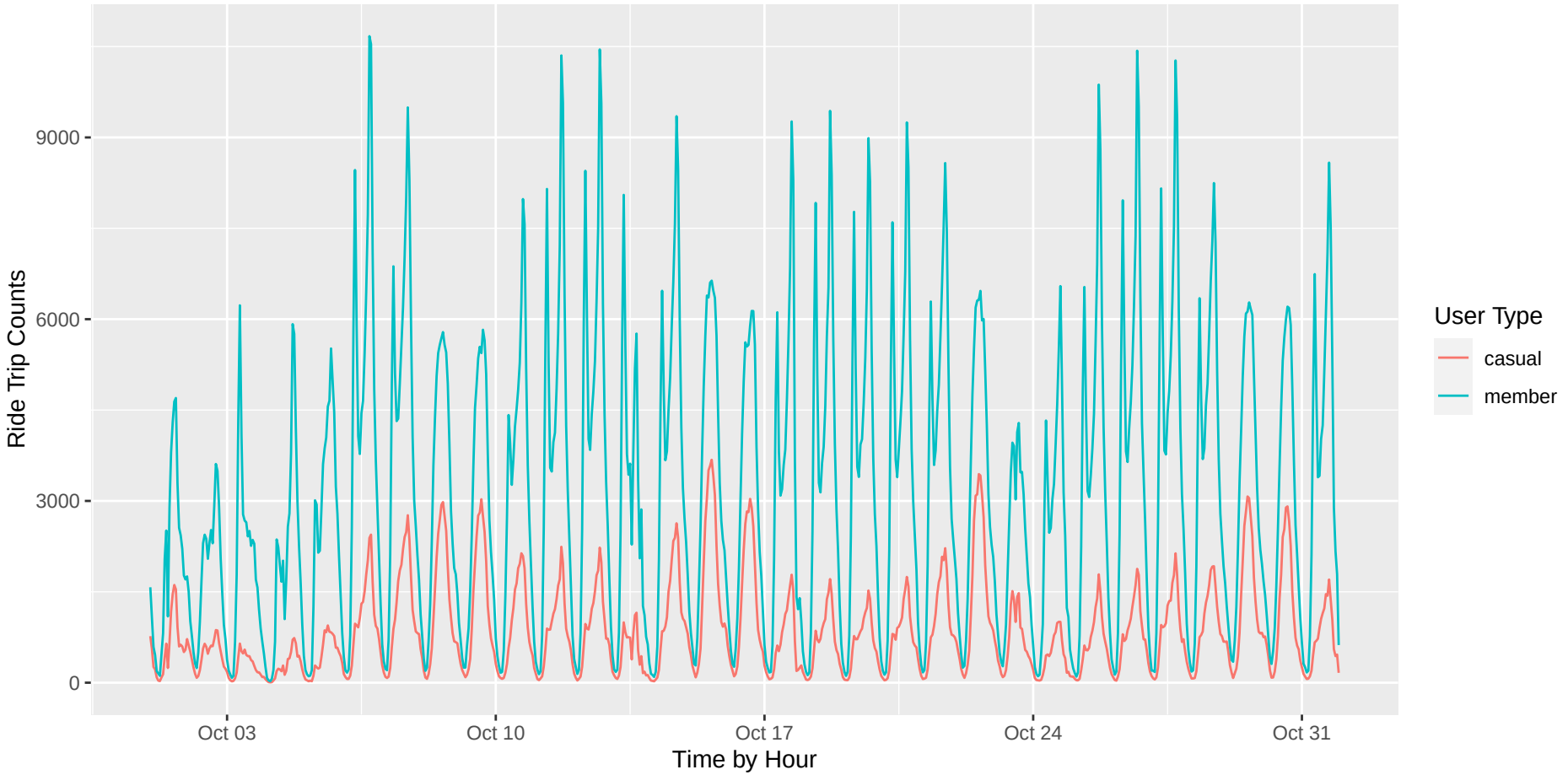
- Timeframe: August - October 2022 (92 days)
- Location: New York City departing trips
- Number of trips: 10,210,102
- Stations: 1,717
- Abandoned trips: 24,887

Bike Availability

- Timeframe: Oct. 31 - Nov. 13 (14 days)
- Location: Brooklyn

EDA: Bike Trips by Hour

Bike Trips by Hour by User Type for Aug. - Oct. 2022

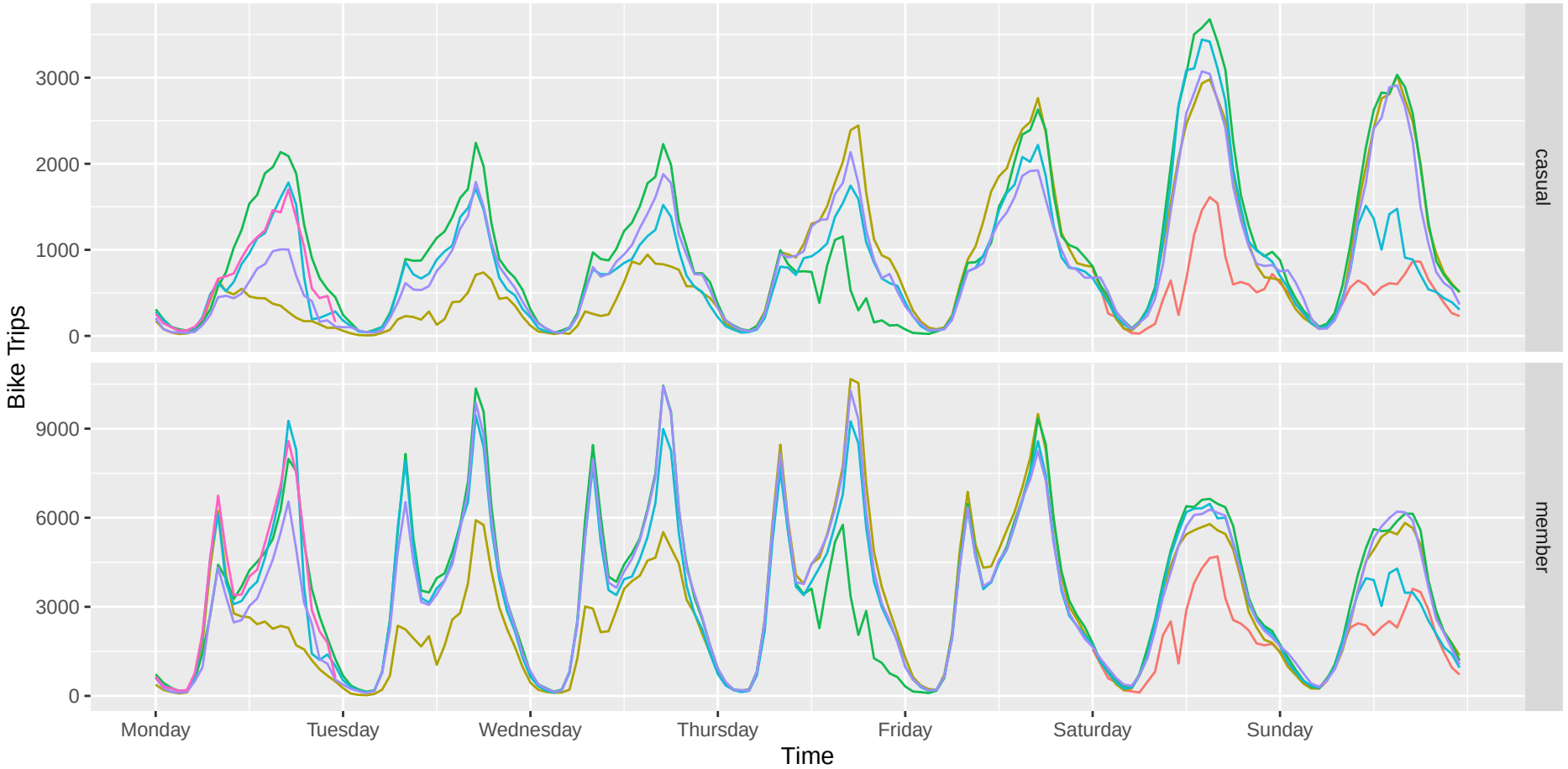


STL decomposition

cnt = trend + season_week + season_day + remainder

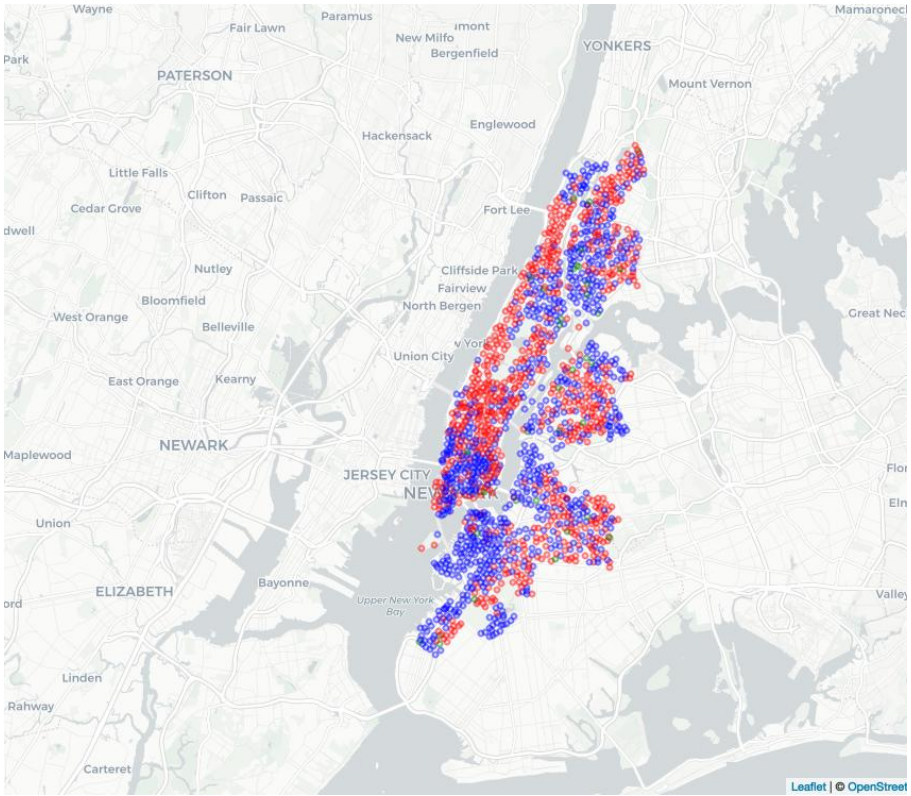
EDA: Weekly Seasonal Pattern

Weekly seasonal plot of the bike trips for Aug. - Oct. 2022



EDA: Three-Month Summary

System-wide view of surplus or shortage for every NYC docking station

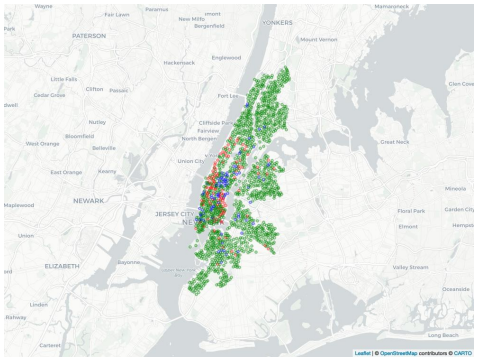


Docking Station Color

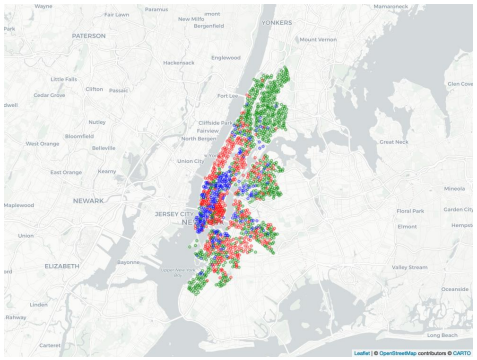
- Blue: Surplus
- Red: Shortage
- Green: Even

EDA: Daily Pattern

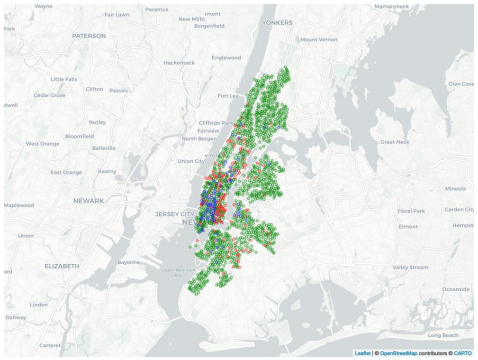
Time lapse of surplus or shortage for every NYC docking station



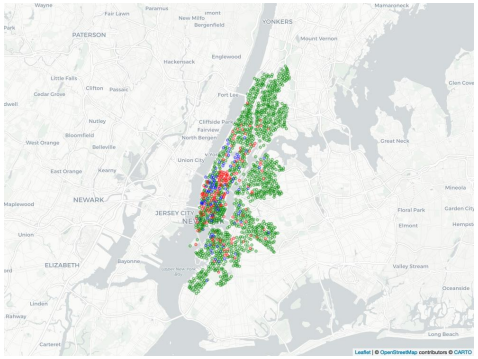
(a) 5 a.m.



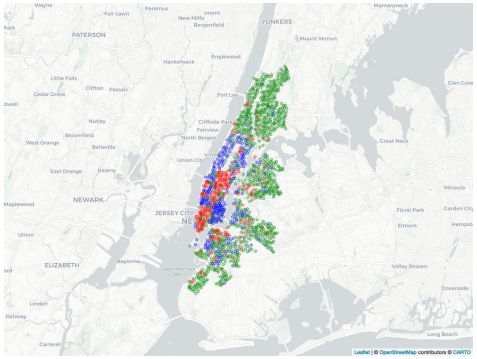
(b) 8 a.m.



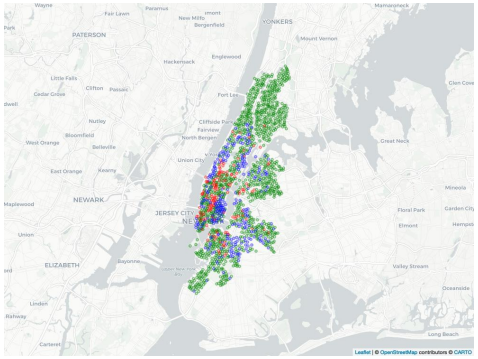
(c) 11 a.m.



(d) 2 p.m.



(e) 5 p.m.



(f) 8 p.m.

Overview of Algorithm Approach

Data Source

- Data from API call every 15 minutes for two weeks
- Citi bike availability at each station
- Two weeks is small interval to predict

Step 1: Hierarchical Clustering

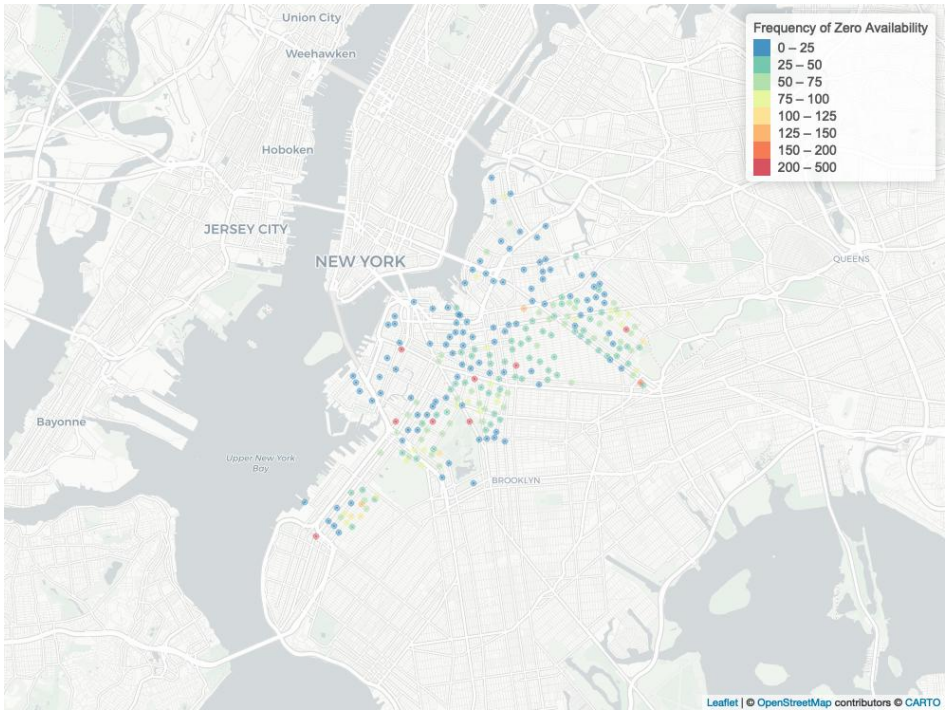
- Cluster all the Brooklyn docking stations
  - Distance: 400m (Quarter mile)

Step 2: Apply Generalized Linear Models - Predict count data -

Stations with Zero Bike Availability

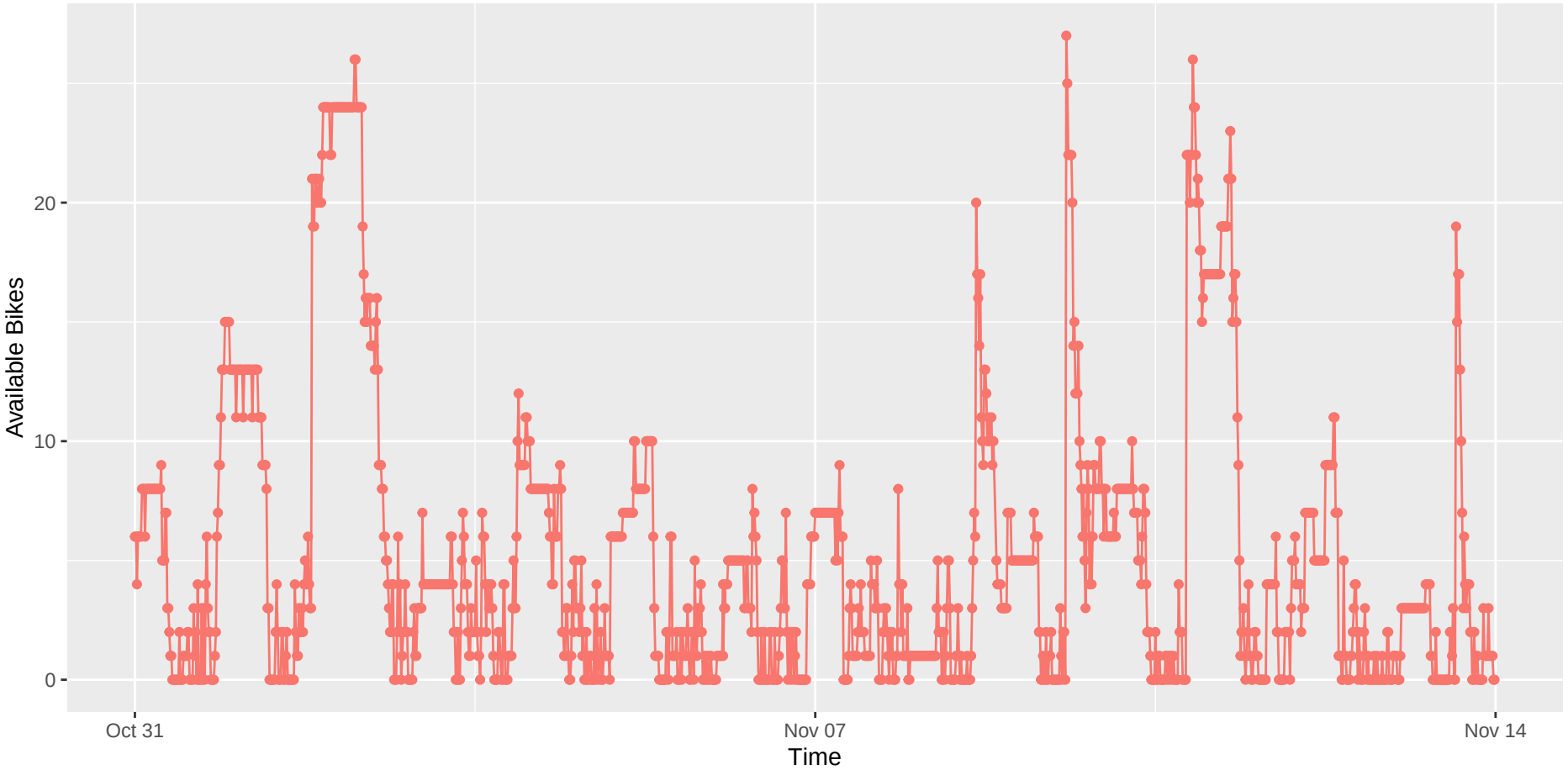
Frequency of zero bike availability per docking station in Brooklyn

- Span: Two weeks
- Instance: 15-minute interval



Rebalancing Example

Inconsistent bike availability at Docking Station 3582 in Brooklyn

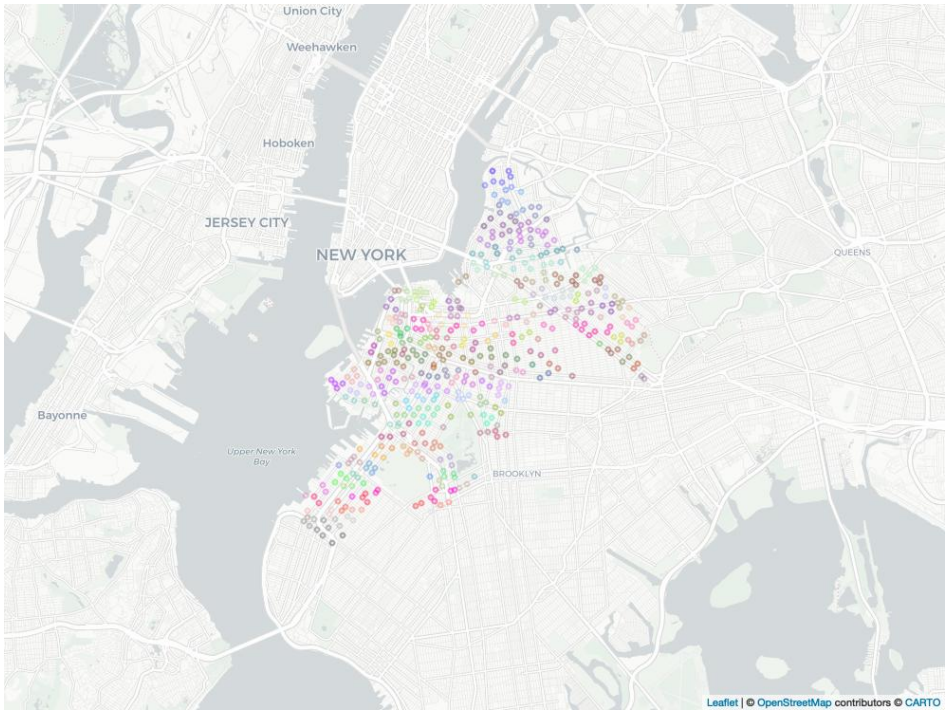


Proposed Methodologies

- Inputs
  - Latitude and longitude
    - Convert to cluster
  - Day of the Week
    - Convert to Weekday or Weekend day
  - Time of Day (15M and 1H)
- Citi Bike offers live map of availability
- Lyft provides real-time availability
- Time series model not used explanation (or really, just don't include)
- Poisson distribution and Negative Binomial given the over-dispersion

Modeling Step 1: Clustering Model

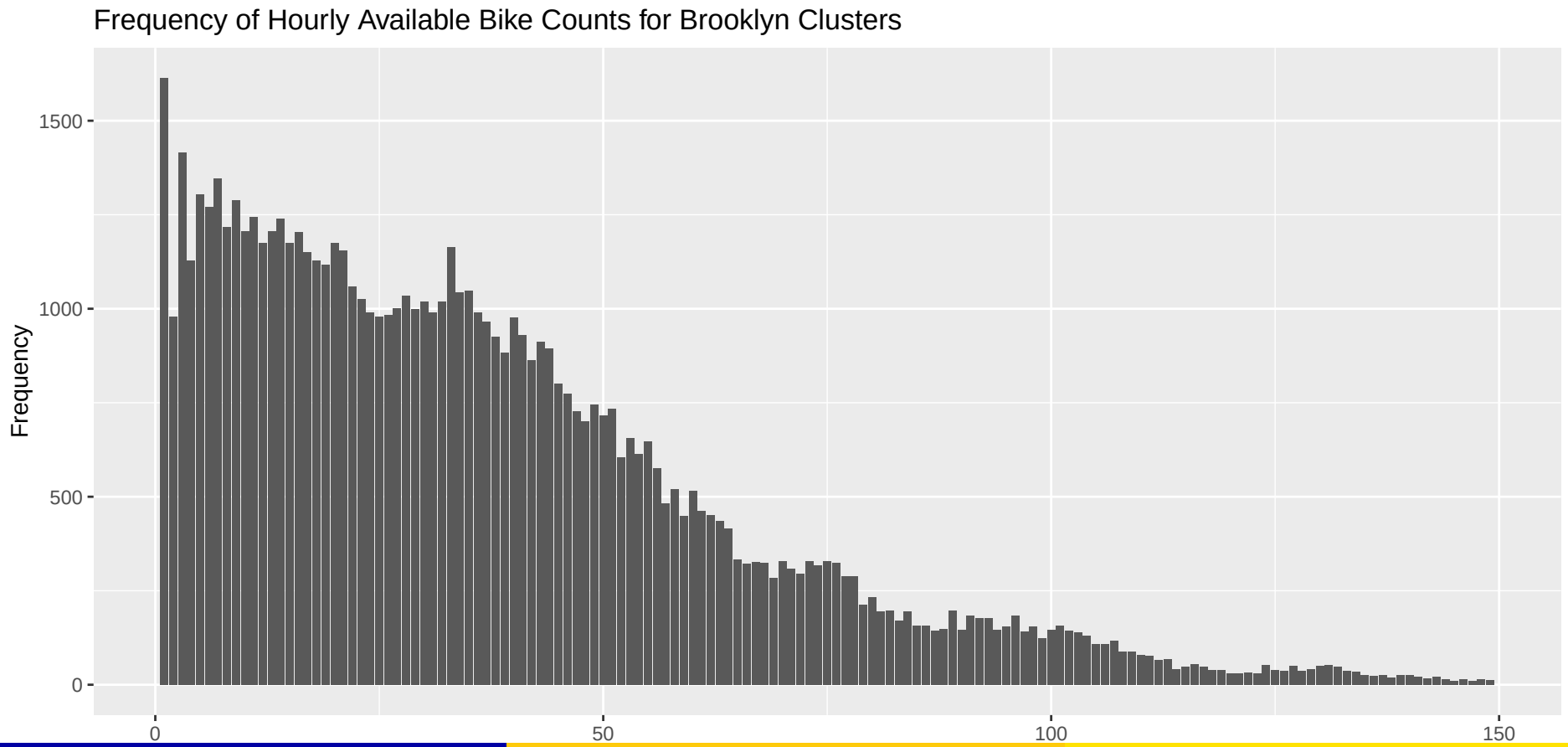
- Borough: Brooklyn
- Docking Stations: 474
- Clusters: 213



Bike Availability Count Frequency

Histogram of availability based on 1HR intervals for Brooklyn clusters

- High frequency near 0 and 2 and plateaus at docking station capacities



Modeling Step 2: Count Models

Generalized Linear Models for Count Data

- Poisson
- Quasi-Poisson
- Negative Binomial
- Hurdle
  - Poisson and Negative Binomial
- Zero-Inflated
  - Poisson and Negative Binomial

Zero-Inflated

$$Pr(Y = 0) = \pi + (1 - \pi)e^{-\lambda} \tag{1}$$

$$Pr(Y = y_i) = (1 - \pi)\frac{\lambda^{y_i} e^{-\lambda}}{y_i!}, y_i = 1, 2, 3, ... \tag{2}$$

Poisson Probability mass function

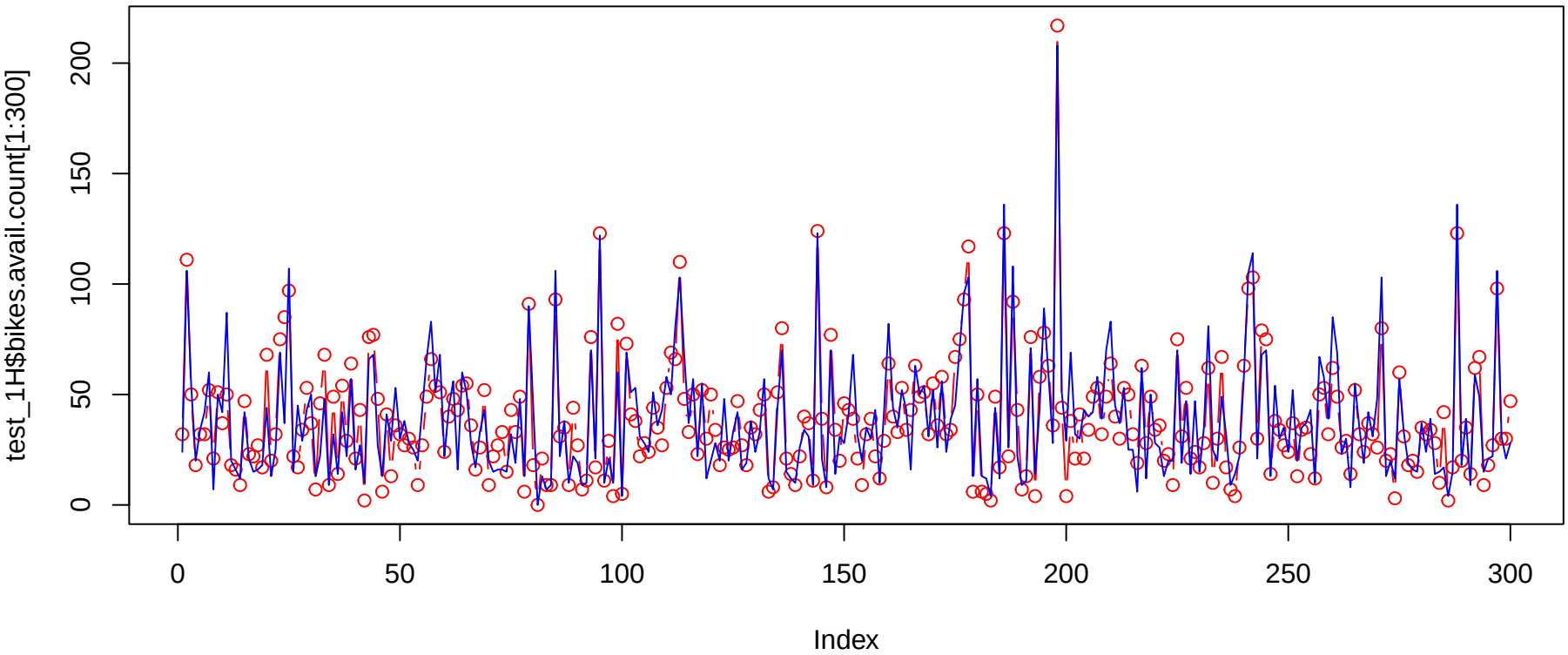
Model Results 1-Hour Interval

- Certain input to model based on 1 hour intervals below
- Results table

```
## [1] 916.2016

## [1] 785.3156

## [1] 36.50179

##
## Call:
## glm(formula = bikes.avail.count ~ cluster + time + day, fam
##     data = train_1H)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -9.7902  -1.3403  -0.0491   1.0790  12.5639
```

Model Results Visualization

- Plot of the preds and actuals for best scoring model (Zero Poisson)



Availability Prediction

- Model prediction
  - Show how it works

```
predict_num_bikes_avail(-73.960859, 40.67355, "22:00:00", "WDA
```

```
## [1] 13
```

TODO

```
predict_num_bikes_avail(-73.960859, 40.67355, "08:00:00", "WKN
```

```
## [1] 12
```

Current Achievements

- Prediction model for Brooklyn
  - Clustering
  - Zero-Inflated XXX (Pois/NB) Model
- Capture patterns of Citi Bike usage

Future Works

- Weather . . . actually, can I predict weather? would that really work?
- Subway stations: Citi Bike offers valet
- Model of all NYC
- Real-time clustering would be better
- Greater amount of availability data
- Deployed web application or smartphone app