A Predictive Model for Capital Bikeshare Demand

Robert Kraig

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Outline

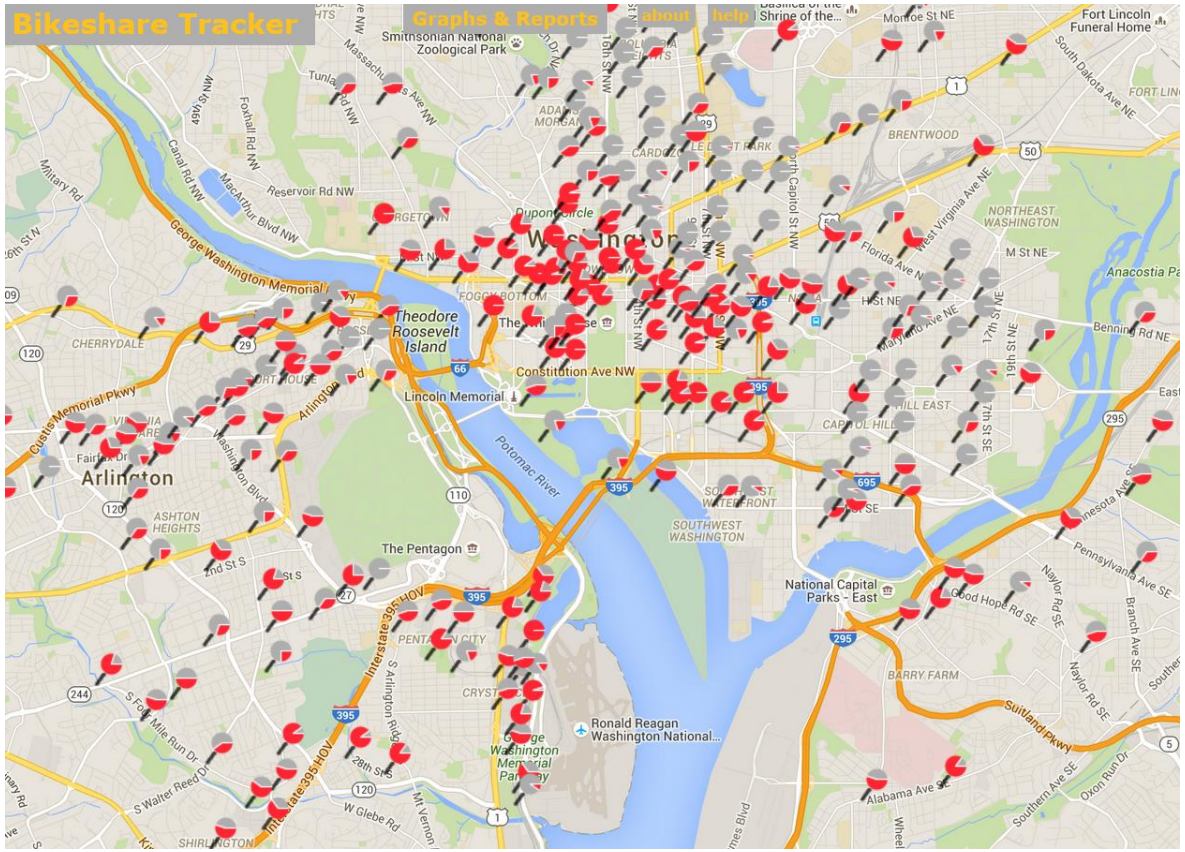
- Motivation
- Data
- Model Selection
- Investigation of Results
- Web Application

Motivation

- CaBi is capacity-limited
  - Dock-Blocking –> Outages
  - Outages -> Loss of Customers

- Mitigation Strategies
  - Examples
    - Rebalancing
    - Corrals
    - Infill Expansion
    - Alternative pricing schemes

  - All rely on understanding customer demand



Visualization by Daniel Gohlke (CaBi Tracker)

Can we use existing data to predict demand?

- Predictive Modeling
  - What data are available? Which predictors are informative?
  - How well can we predict demand?

Data and Problem Formulation

Available Data

- Trip History (CaBi)
  - List of 12M rides 2010--
  - Begin/End Location/Time, Member Type
- Weather (DCA)
- Geographic info (multiple sources)
  - Station Lat/Long/Elevation
  - Jurisdiction / Neighborhood / etc.
- Dock Status History (webscraped)

How to select predictors?

- Remove variables that are likely irrelevant (e.g. Bike id #)
- Remove highly correlated predictors (e.g. 6hPrecip, dewpoint)
- Add temporal predictors that seem relevant (e.g. Day of Week)
- Try adding observations of response in previous time bins

How to represent response (demand)?

$$P(k) = \frac{\mu^k e^{-\mu}}{k!}$$

- Poisson process
  - Single parameter: Expected # Customers Arriving in Time Window: μ
  - Drifting μ
- Binned by hour
- Regression Models predict μ for each Station and demand type

Base Predictors

```
> head(BB2[["all"]])
     DOW DOY hour isHol year tempF RH windSpeed precip01h response T_minus_003 T_minus_024 T_minus_168
2210   3   1    0     1 2014  34.0 45       0.0          0       67          99          25           6
2211   3   1    1     1 2014  30.0 60       8.1          0      106          72          14          12
2212   3   1    2     1 2014  30.9 56       3.5          0      122          61           8           1
2213   3   1    3     1 2014  33.1 49       0.0          0       65          67           1           2
2214   3   1    4     1 2014  30.9 63       0.0          0       10         106           7           0
2215   3   1    5     1 2014  32.0 63       3.5          0       12         122          18           4
```

Auto-Correlation Predictors

Model Selection: Random Forest w/o Auto-Corr

System-wide bicycle demand,
No auto-correlation predictors:

	Tuned Params	XVAL RMSE	XVAL SD	TRAIN RMSE	TEST RMSE
KNN	k=5	183	4	145	178
MARS	nprune=18,degree=2	174	5	173	171
Random Forest	not tuned: mtry=3	91	2	44	82
SVM	sigma=1,C=2	162	6	121	158

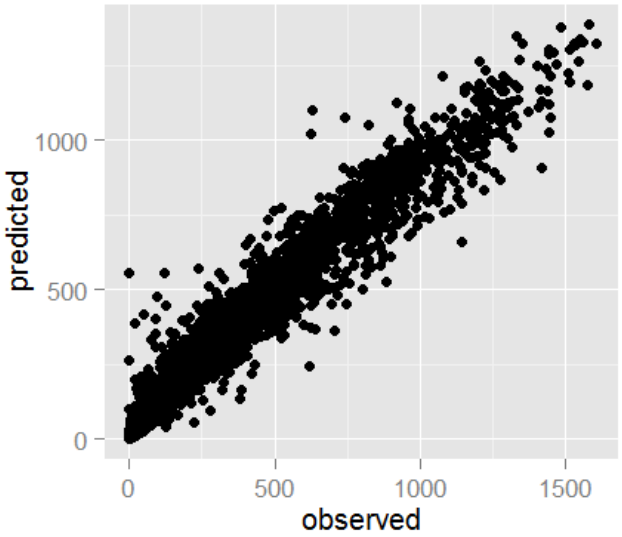
	Tuned Params	XVAL R2	XVAL SD	TRAIN R2	TEST R2
KNN	k=5	0.71	0.01	0.82	0.72
MARS	nprune=18,degree=2	0.74	0.01	0.74	0.75
Random Forest	not tuned: mtry=3	0.93	0.00	0.99	0.95
SVM	sigma=1,C=2	0.78	0.01	0.88	0.79

System-wide bicycle demand,
With auto-correlation predictors:

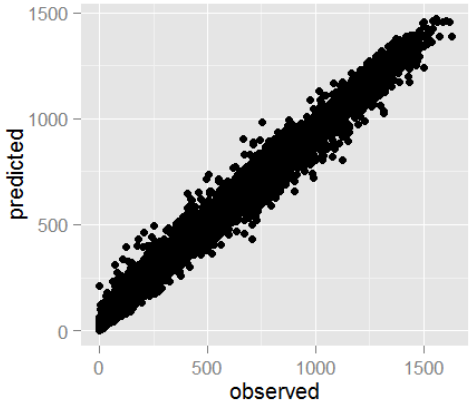
	Tuned Params	XVAL RMSE	XVAL SD	TRAIN RMSE	TEST RMSE
Random Forest	not tuned: mtry=4	89	2	37	81
SVM	sigma=0.1,C=2	92	4	82	88

		R2	SD	R2	R2
Random Forest	not tuned: mtry=4	0.93	0.00	0.99	0.94
SVM	sigma=0.1,C=2	0.93	0.01	0.94	0.93

Test Set Performance, Random Forest w/o auto-corr:



Train Set Overfit, Random Forest w/o auto-corr:

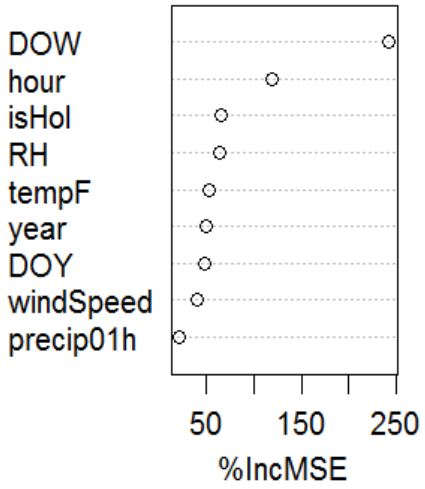


Apply Random Forest to subset Predictions

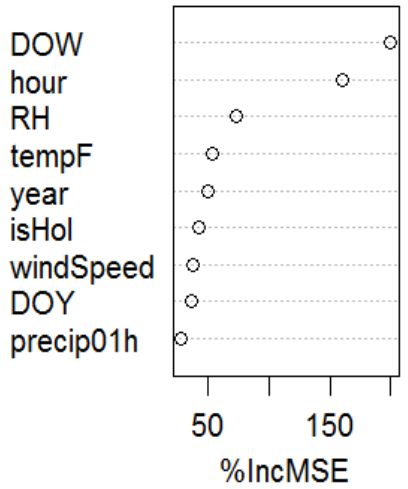
System-wide bicycle demand,
No auto-correlation predictors:

	XVAL R2	XVAL SD	TRAIN R2	TEST R2
all	0.93	0.003	0.99	0.95
casual	0.91	0.006	0.98	0.93
member	0.93	0.004	0.99	0.95
Arlington	0.89	0.004	0.98	0.91
Lincoln Memorial	0.76	0.007	0.94	0.78
Dupont Circle	0.75	0.006	0.94	0.77

Casual

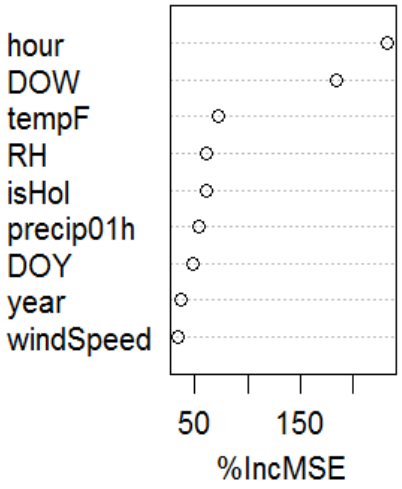


Lincoln Memorial

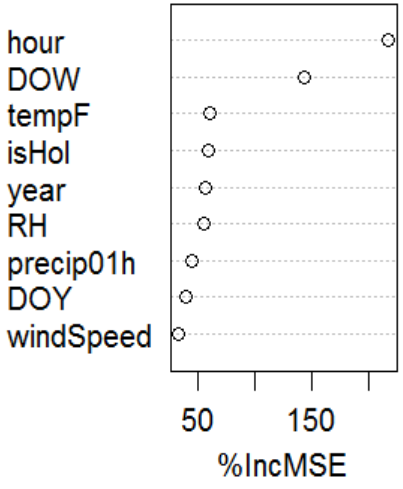


Hour is most informative predictor for member ridership; day of week is most informative for casual ridership.

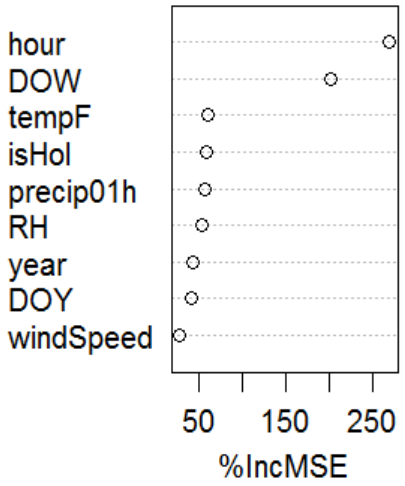
ALL



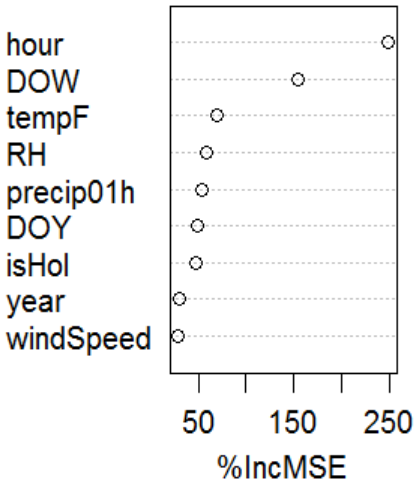
Arlington



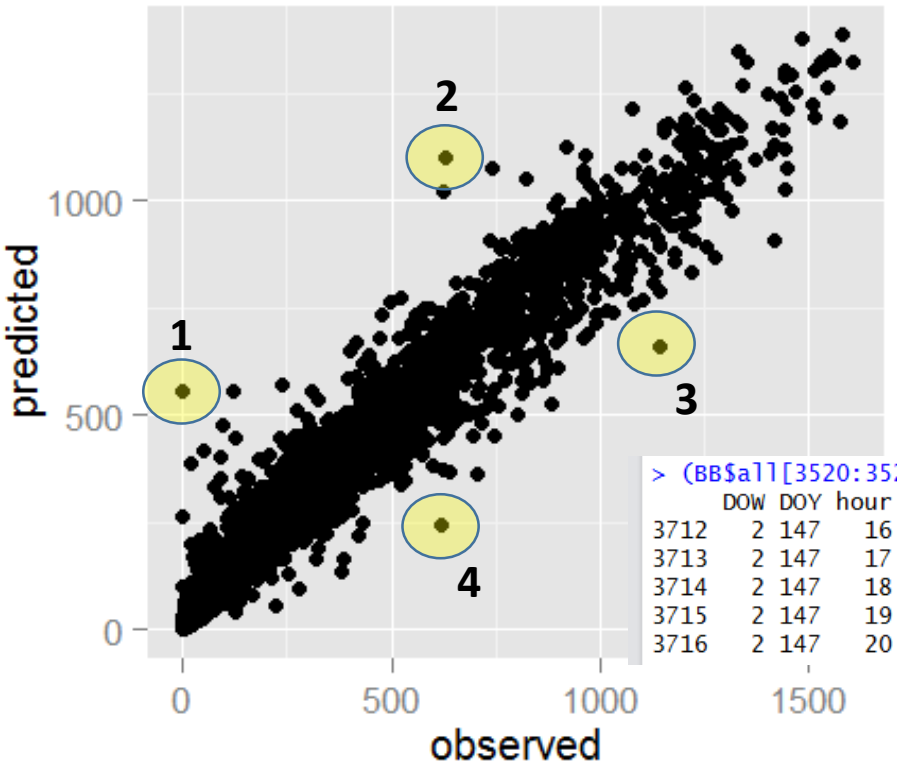
Member



Dupont Circle



Investigate Worst Misses from 2014 and 2015



1

2

```
> (BB$all[3520:3524,])
     DOW DOY hour isHol year tempF RH windSpeed precip01h response
3712   2 147   16     0 2014  90.0 37      10.4      0.00      621
3713   2 147   17     0 2014  88.0 41      12.7      0.00     1280
3714   2 147   18     0 2014  84.2 55       5.8      0.00      631
3715   2 147   19     0 2014  69.8 83      11.5      0.86       89
3716   2 147   20     0 2014  69.8 88       8.1      0.04      220
```

3

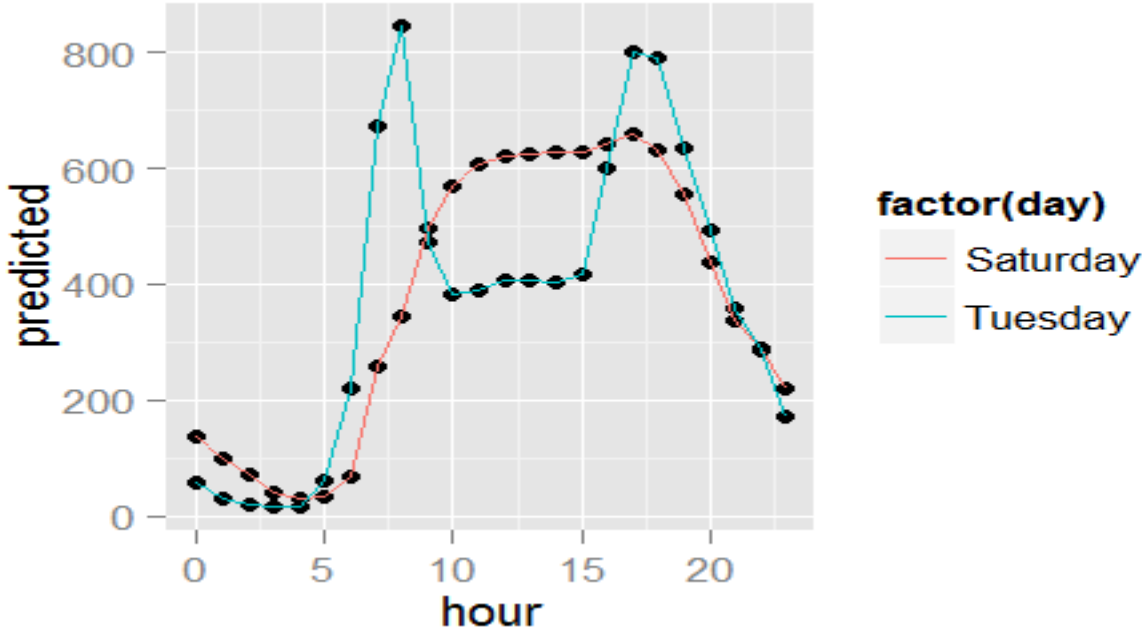
	Date	Time	Predicted	Observed	Comment
1	FRI Feb 14 2014	8 am	555	0	Day after 6" snow + ice, OPM 2-hour delay (snowDepth predictor removed!)
2	TUE May 27 2014	6 pm	1099	631	right before major thunderstorm (time bins may be too large to capture this effect)
3	TUE Dec 16 2014	8 am	660	1141	water main break at 12th and F, WMATA suspended Silver/Orange/Blue service
4	THU Oct 01 2015	5 pm	247	620	Hurricane Joaquin approaching, rain earlier much of day

Do regression tendencies make sense?

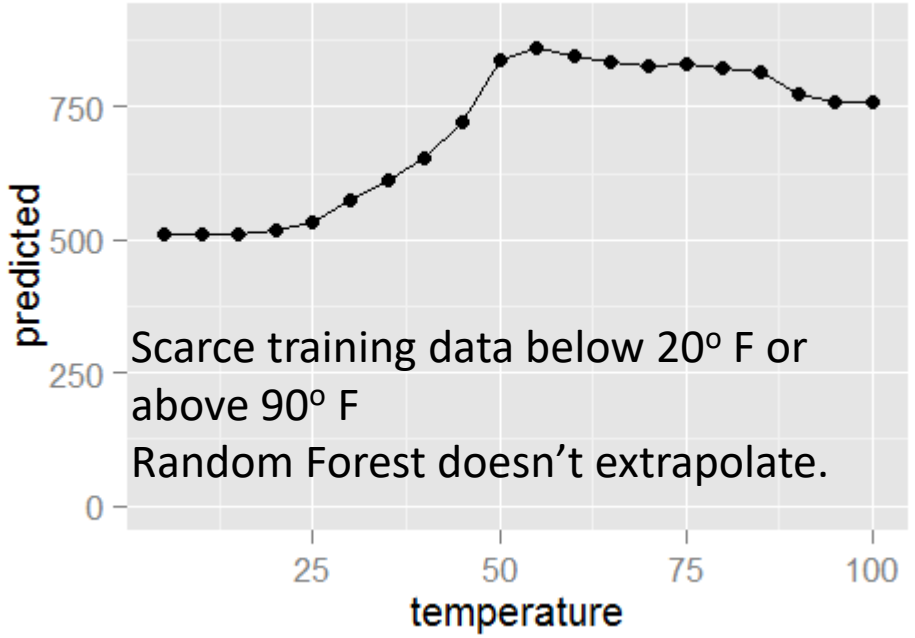
- I simulated data to isolate certain parameters one at a time
- Base:

```
> fakeDF
     DOW DOY hour isHol year tempF RH windSpeed precip01h
3714   2 120    8     0 2014    60 55         2          0
```

Now vary hour and weekday:



Vary temperature:



Web Application

By combining demand Predictions with real-time dock status data, one can predict the likelihood of outages in the near future.

Simple Model (ignoring order of arrival):

$$\boldsymbol{P}(\text{empty}) = \sum_{\boldsymbol{b=b_0}}^{\infty} \boldsymbol{P_B(b)} \sum_{\boldsymbol{d=0}}^{\boldsymbol{b-b_0}} \boldsymbol{P_D(d)}$$

$$\boldsymbol{P}(\text{full}) = \sum_{\boldsymbol{d=d_0}}^{\infty} \boldsymbol{P_D(d)} \sum_{\boldsymbol{b=0}}^{\boldsymbol{d-d_0}} \boldsymbol{P_B(b)}$$

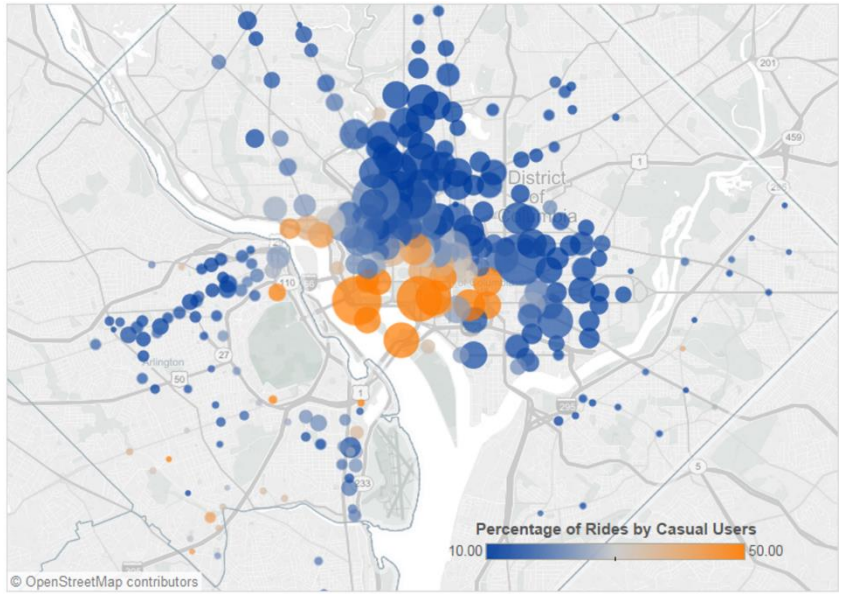
Backup Slides: Background info

Capital Bikeshare (CaBi)

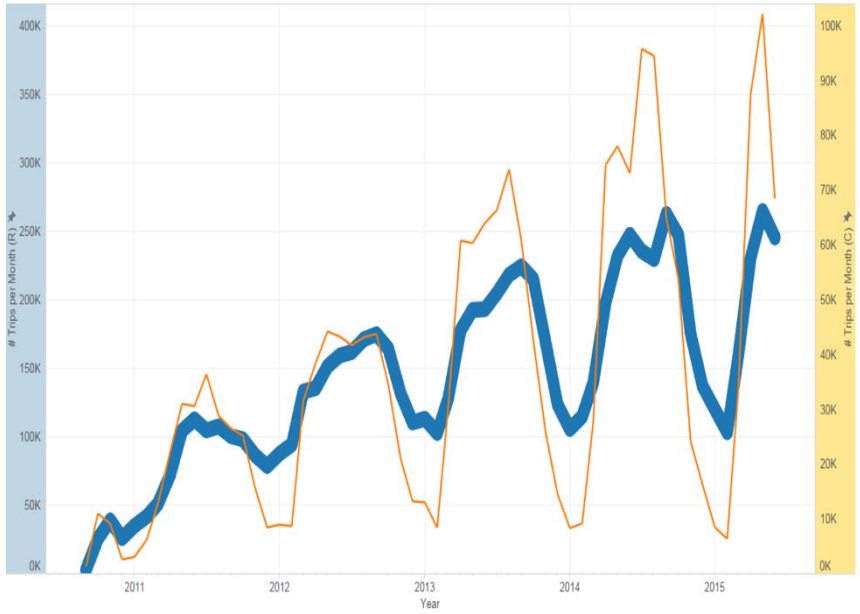
Self-guided, self-powered public transit

- DC / Arlington / Alexandria / MoCo
- First station: Crystal City, Sep 2010
- 360 Stations (10-45 docks each) used in 2014 and 2015
  - Average = 3-4 blocks between stations
- Member Types: Regular and Casual

Relative Ridership Quantity, 2014-2015



Rides per month, 2010-2015



Backup: Data Sources Used in this Project

- Capital Bikeshare Trip History
  - https://www.capitalbikeshare.com/trip-history-data
  - Click on “Download Links”
  - Unzip to extract CSVs
  - The file names and formats are inconsistent from file to file.
    - The Python code will standardize the data formats, but before running it, you must change all file names to the following naming convention: “2015-Q2-cabi-trip-history-data.csv”. The Python code is expecting that name format so that it knows which files to open.
- Weather
  - http://mesowest.utah.edu/cgi-bin/droman/download_ndb.cgi?stn=KDCA
  - I downloaded annual files, and manually converted them to CSV
  - Result: KDCA___csv_mesowest_2010-2015.csv
- Geographic Info
  - Station TerminalName/Name/Lat/Long obtained from https://www.capitalbikeshare.com/data/stations/bikeStations.xml
  - Station Elevations obtained from Google API at http://www.gpsvisualizer.com/geocoder/elevation.html
  - Jurisdiction and neighborhood added manually
  - First use and last use obtained from trip history data
  - Result: stationInfo_v8.csv
- Holiday dates
  - https://gist.github.com/shivaas/4758439
  - Added 2010 and 2011 manually
  - Result: holidays2010on.csv

Backup: Data Munging

- Python scripts convert data from original format into a SQL database
- R codes begin from SQL database
- Notes
  - Python 2.7
  - Must put all files into one directory
  - Must change CaBi trip history file names to the format indicated on slide 11
  - Line 17 of cabi_Main.py: selects which trip history files to include
    - Current selection (134,154) selects files between 2013 Q4 and 2015 Q4
    - First two digits of argument = last two digits of year
    - Last digit of argument = quarter number
- Predictive Modeling
  - Selected data set only from years 2014-2015
  - All models used preprocessing (BoxCox/center/scale) except for Random Forest
  - Discarded many weather fields immediately
  - Eventually also discarded snowDepth due to near-zero variance
  - Also Discarded precip06h and dewpointF due to high correlations with other predictors

Summary

- Random Forest model predicts system-level bikeshare demand quite well
- Tougher to predict at micro-level: SNR is much lower
- Most important predictors came out as expected (hour, day of week)
- Poor predictions satisfactorily explained by information beyond model
- Potential improvements
  - Better demand metric: account for dockblocked times
  - More predictors (e.g. snow depth)
  - Geographic considerations
    - Treat station locations as numeric lat/long rather than categorical?
    - Elevation
  - Time Series techniques?