Forecasting Metro Ridership

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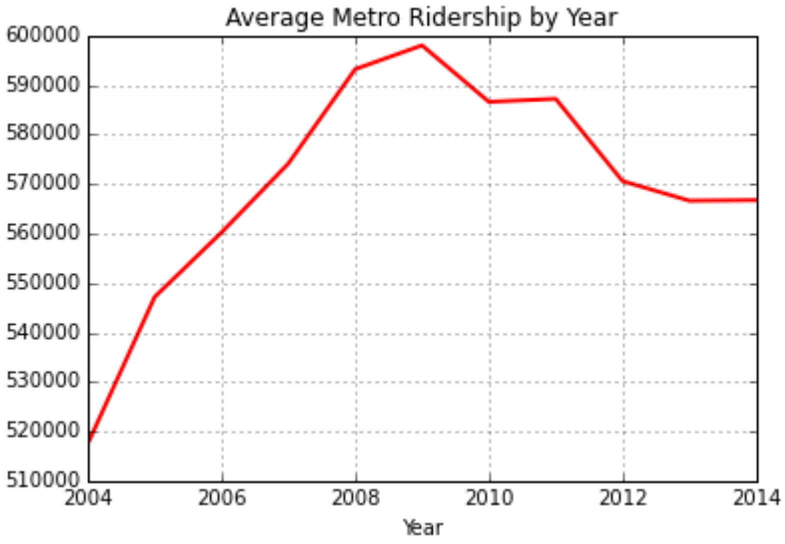
The Goal

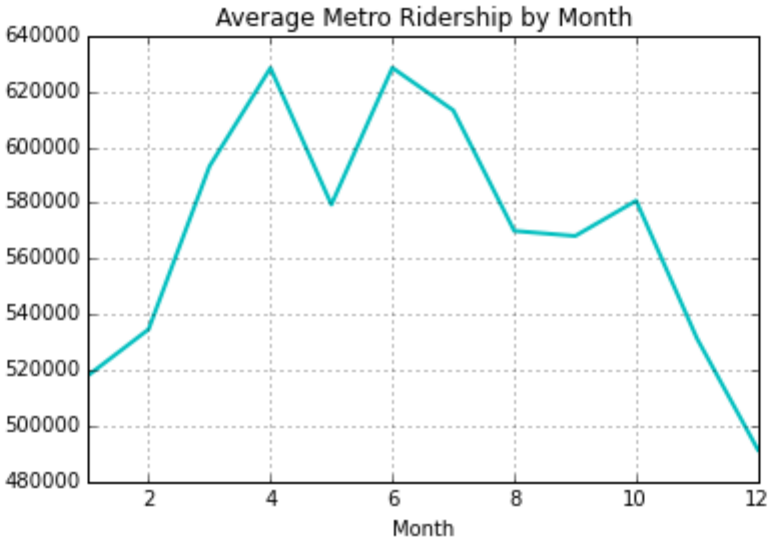
To forecast Metro ridership based on different input variables

Response:
Number of metro riders per train

- Open Data DC: total daily ridership data from 2004-2014
- Data has 4018 observations
- Used simple math and data from WMATA website about train frequency to figure out how many trains run per day
- Using riders per train somewhat deals with the effect of weekday/weekend variations and holidays.

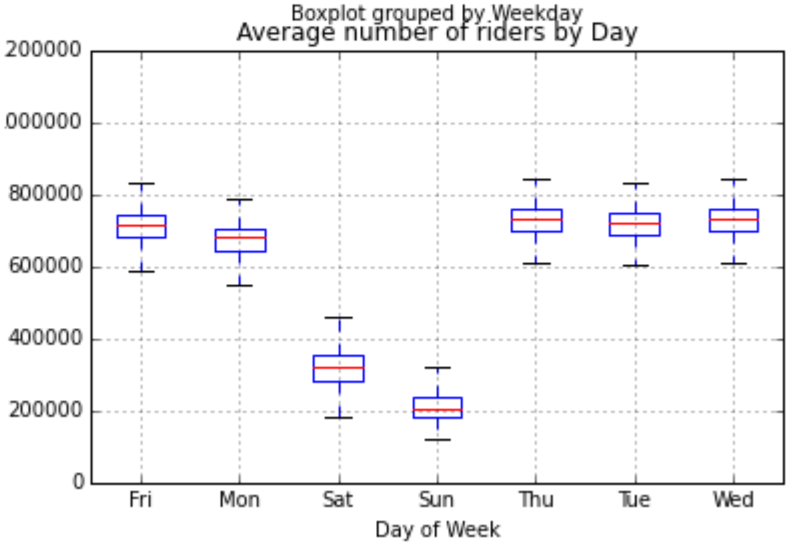
Data Visualization

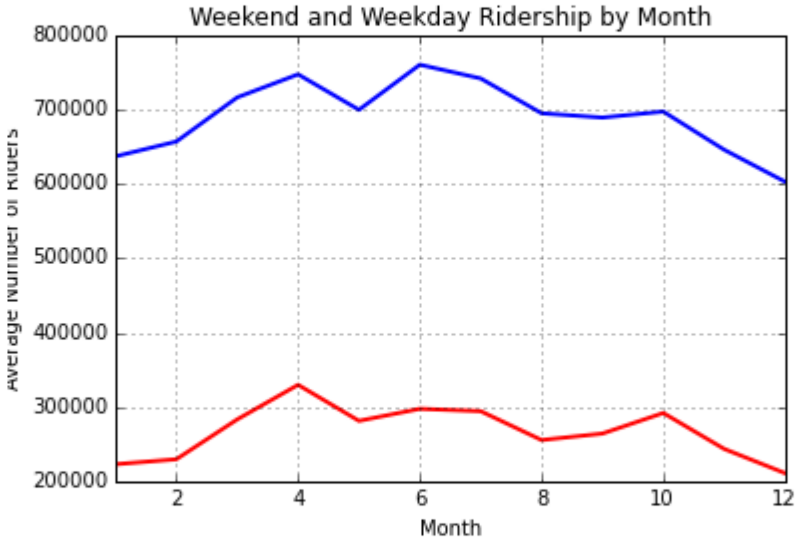




Using the metro ridership data from Open Data DC

Data Visualization





In graph above, blue line is weekday and red line is weekend

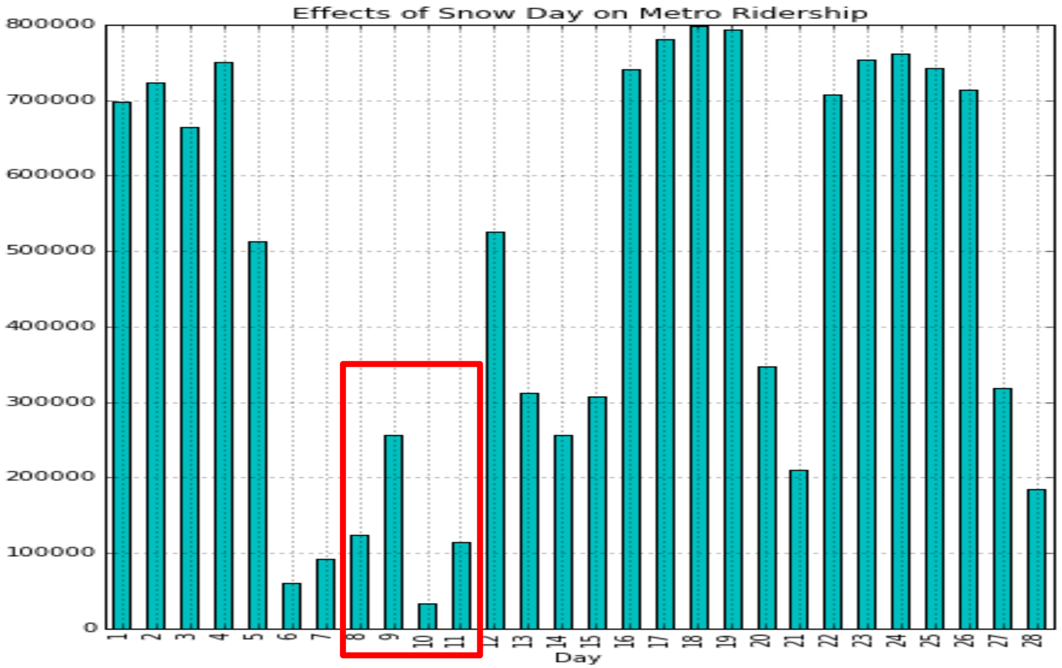
Features

- Gas prices
- Weather (ie max temp, min temp, snow amount)
- Employment (ie total number of employed people)
- Holiday (if the federal government was closed)
- Capital Bikeshare: Number of registered/casual riders
- Binary variables for every month
- Binary variables for every day of the week

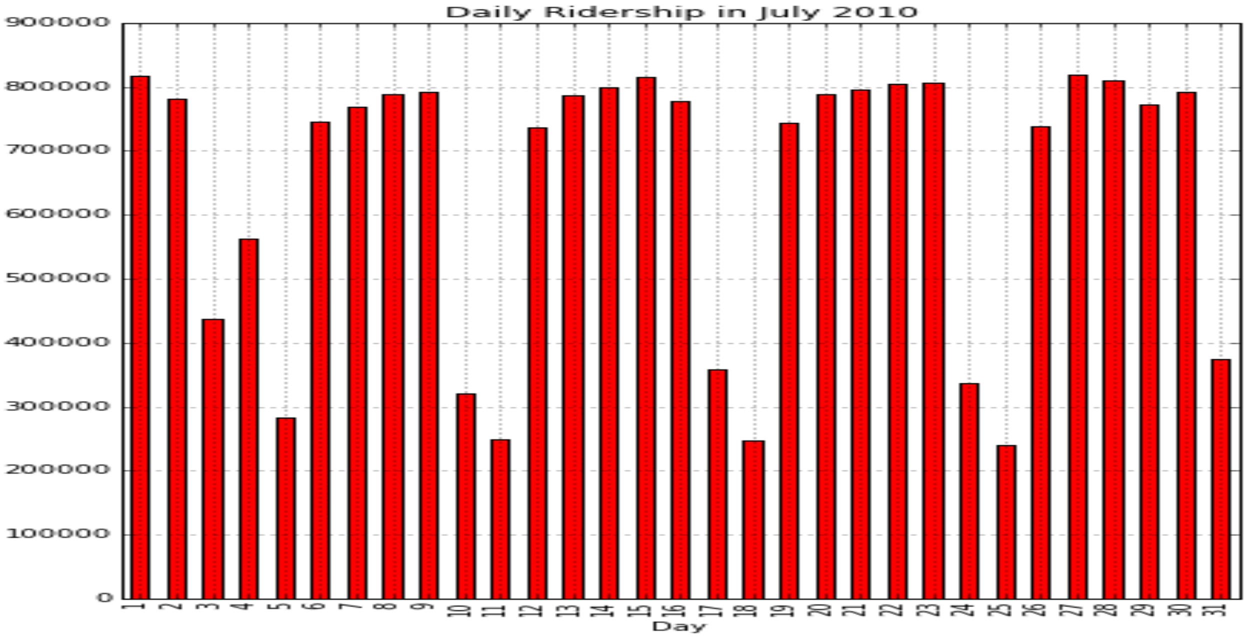
Ridership and Weather

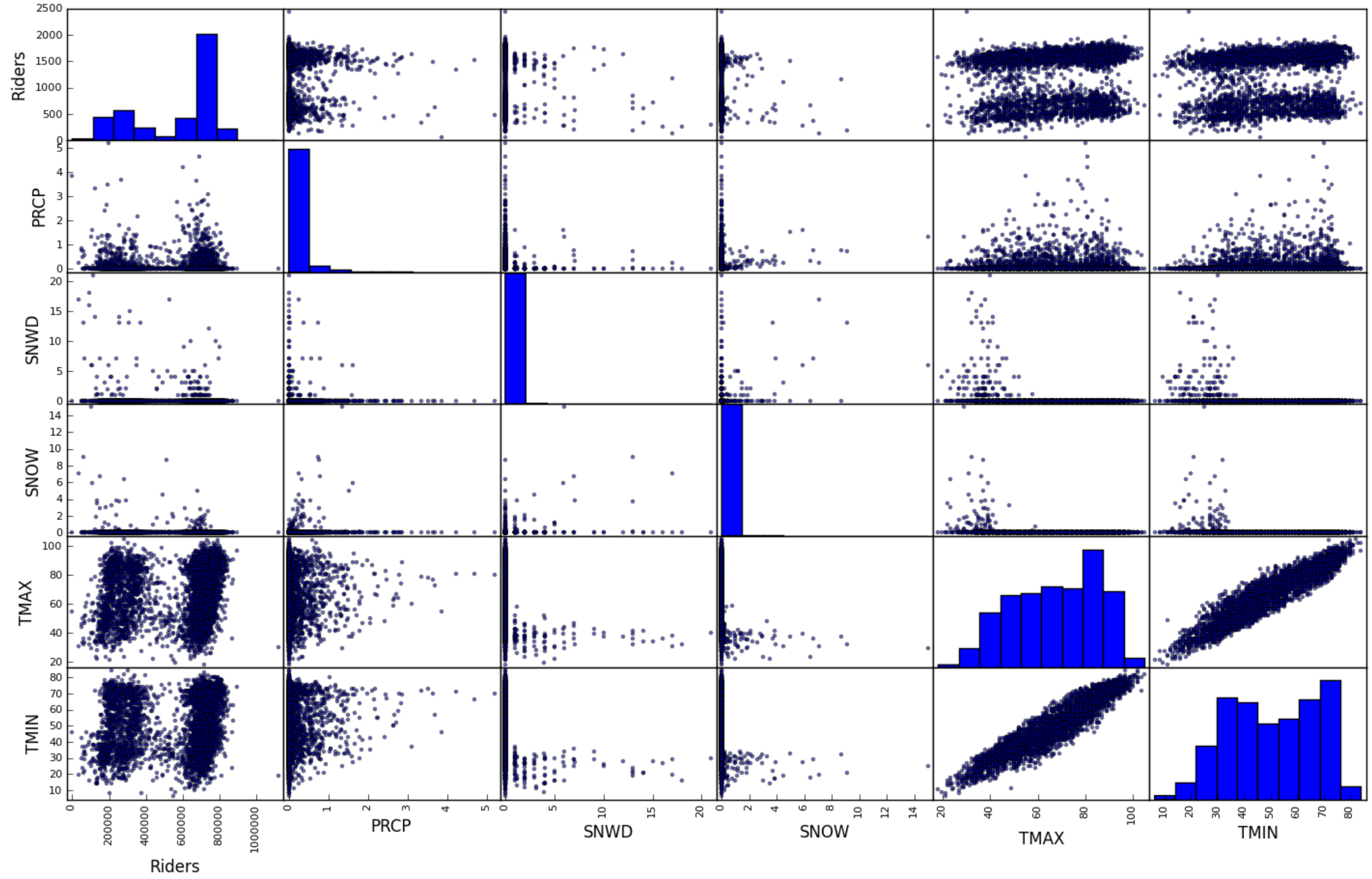
- Tourists less likely to visit during cold weather
- People are less likely to go places during bad weather
- Snow day means fewer people are going anywhere so much lower ridership

Winter Ridership (February 2010)



Summer Ridership (July 2010)

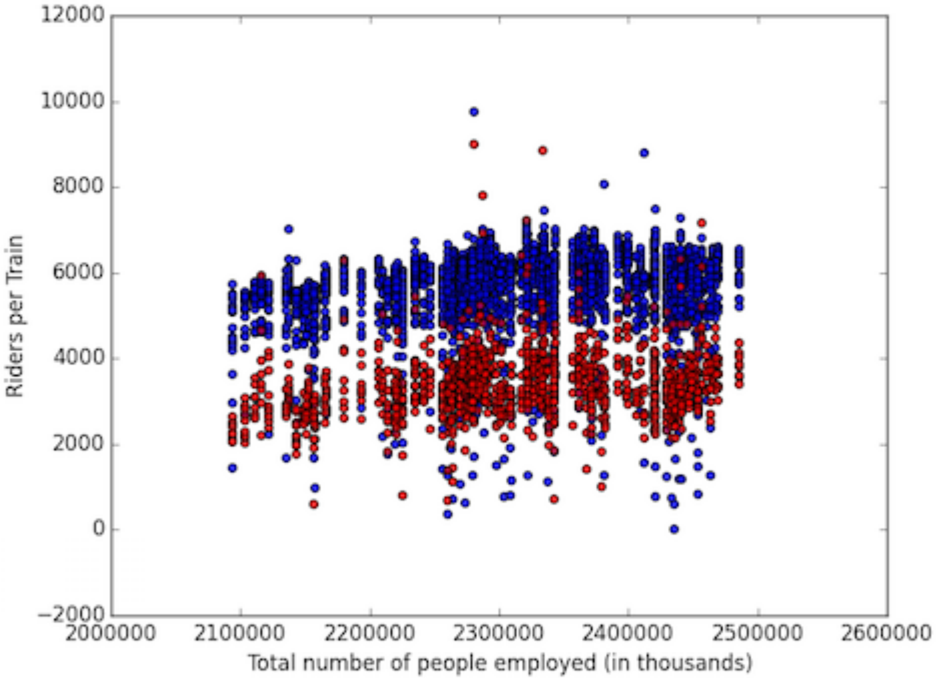




Riders
PRCP
SNWD
SNOW
TMAX
TMIN

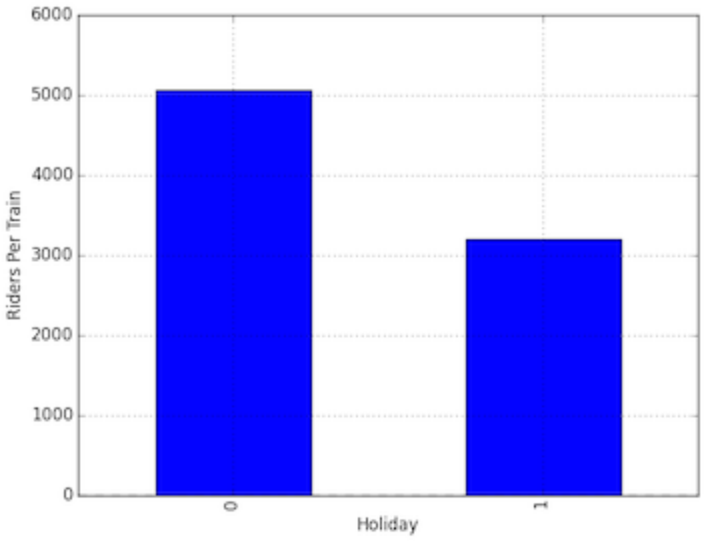
Ridership and Employment

- Weekend = Red dots; Weekday = Blue dots
- Employment does not seem to have much of an obvious relationship with number of riders



Ridership and Holidays

- It being a holiday has a very obvious relationship with metro ridership
- Number of riders per train is 40% less on holidays than on regular days



Dealing with outliers

- Linear regression models are very sensitive to outliers
- Standardized response variable with z-score
- Look at characteristics of outliers. Should they be removed?
- Ended up removing outliers greater than +/- 3.5 SDs away (Only two data points)

Feature selection

Variable	**p-values**
WT16 (Dummy rain)	0.9992
May	0.15343
August	0.56918
September	0.69783
Friday	0.36160

First set of models

- All models use trimmed dataset
- No parameter tuning
- Poor performance by all models

	CV RMSE Score	Train Set R Squared	Test Set R Squared
Linear Regression (w/o feature selection	1180.55	0.146	0.136
Linear Regression (w/ feature selection)	1256.35	0.253	0.253
Random Forest	1146.71	0.868	0.267
Gradient Boosting	1074.53	0.454	0.356

Weekday/Weekend Double Model

- Hypothesis: Features have different effect on weekend and weekday ridership.
- Split the original dataset into a weekend dataset and weekday dataset
- Train a separate model for each dataset

Weekday/Weekend Double Model

Features	**Weekday (p-values)**	**Weekend (p-values)**
WT05 (Hail)	0.00004	0.033893
WT16 (Rain)	0.69943	0.000155
WT03 (Thunder)	0.00077	0.100543
March	0.00220	0.016964
May	0.26629	0.009586
August	0.91672	0.081480
September	0.59677	0.731114

Weekday/Weekend Double Model

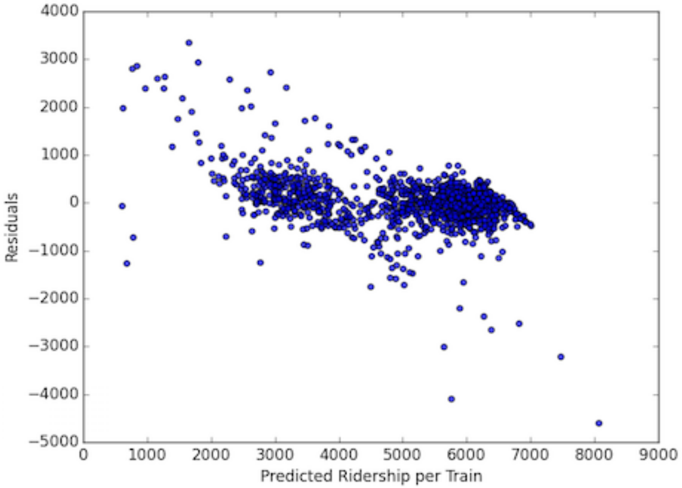
	RMSE		R squared (full dataset)	
Model	Weekday	Weekend	Weekday	Weekend
Linear Regression (w/o feat selection)	721.20	608.55	0.455	0.366
Linear Regression (w/ feat selection)	749.19	662.37	0.475	0.444
Gradient Boosting	617.17	604.65	0.546	0.412

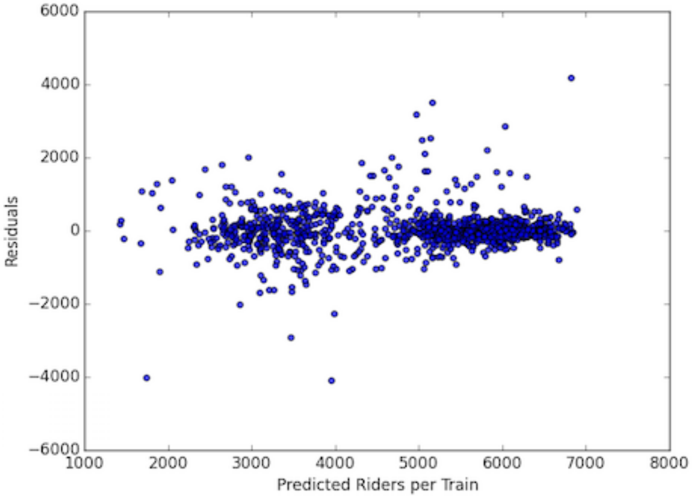
Adding more features

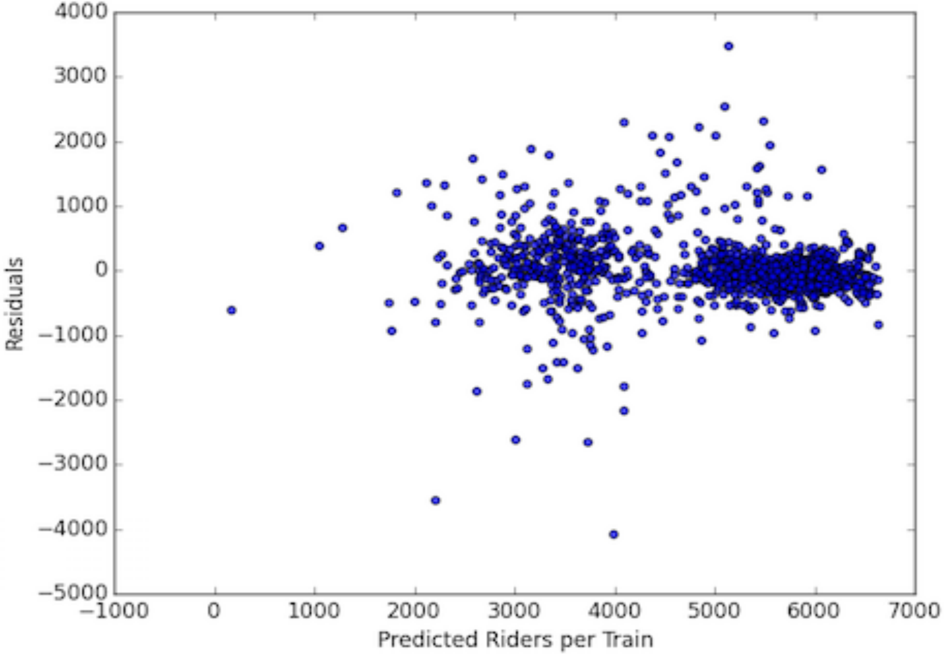
- Added days of the week as a set of binary variables
- No parameter tuning
- Significantly better performance by all models!

	CV RMSE Score	Train Set R Squared	Test Set R Squared
Linear Regression (w/o feature selection	576.64	0.817	0.818
Linear Regression (w/ feature selection)	575.56	0.820	0.821
Random Forest	529.16	0.973	0.844
Gradient Boosting	480.98	0.899	0.871

Residuals Plots
Lower left: Linear Regression
Lower right: Random Forest Regressor
Below: Gradient Boosting Regressor







Challenges and Lessons Learned

- I could not find data for all the features I wanted (ie Uber/Lyft)
- Data processing takes a long time
- People are really hard to predict
- If you do not have good features in your data, even the most finely tuned model will not save you

Future work

- Look at the larger residuals and see if they have anything in common
- Add more features, such as binary variable marking dates for sports games and cultural/political events
- Study the characteristics of long/short haul trips and see how they differ (if at all)
- Study how people are moving through the system and when certain stops/routes get more use
- Look at how the new Silver Line is affecting metrorail ridership