Forecasting Metro Ridership

Lena Nguyen | May 2, 2015 | GA DAT 6

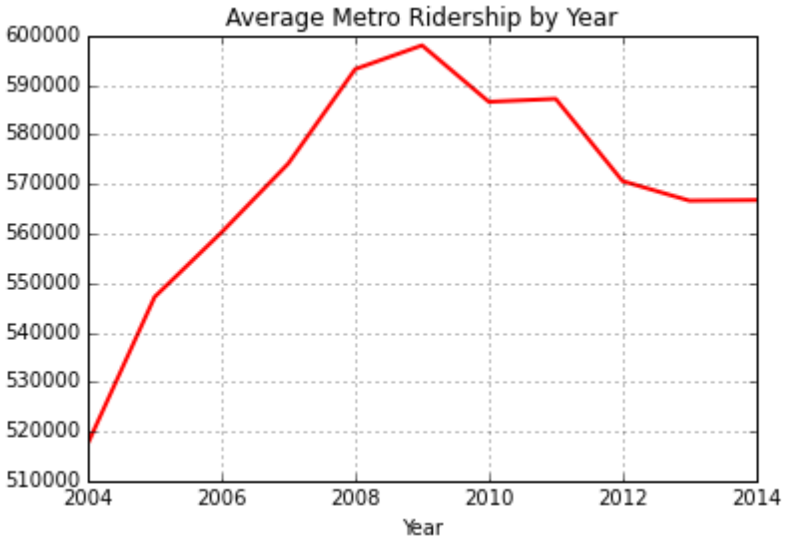
The Goal

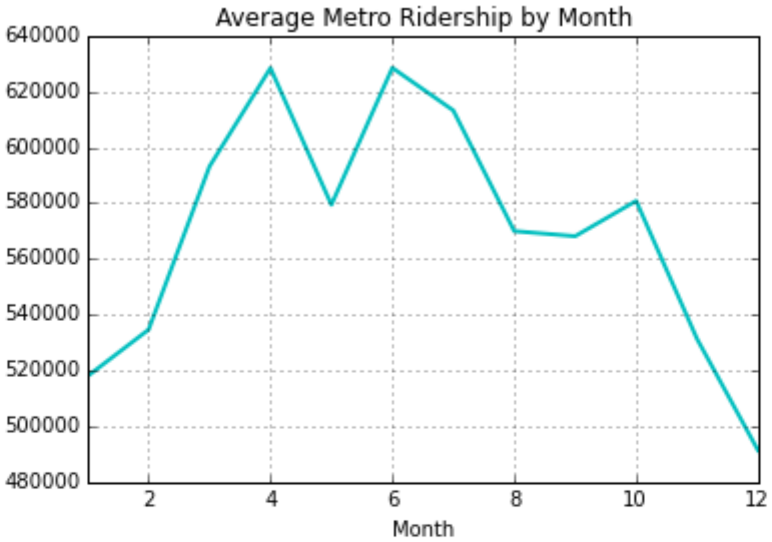
To forecast Metro ridership based on different input variables

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.

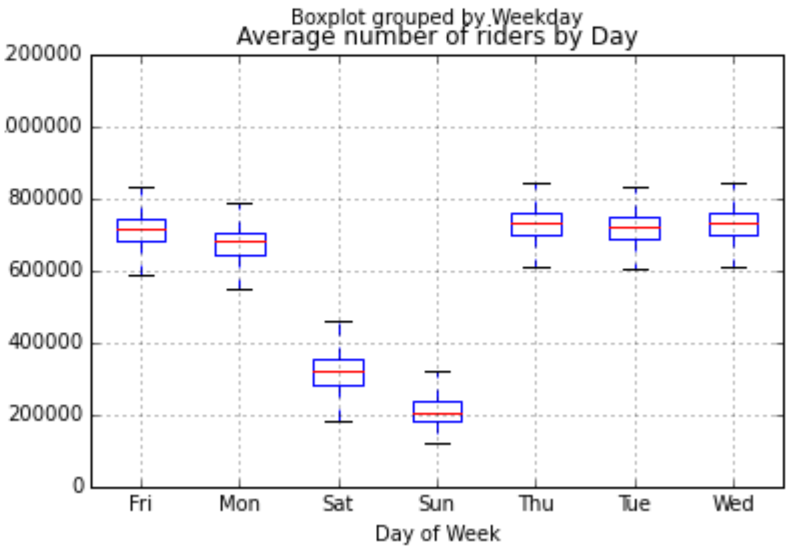
Data Visualization

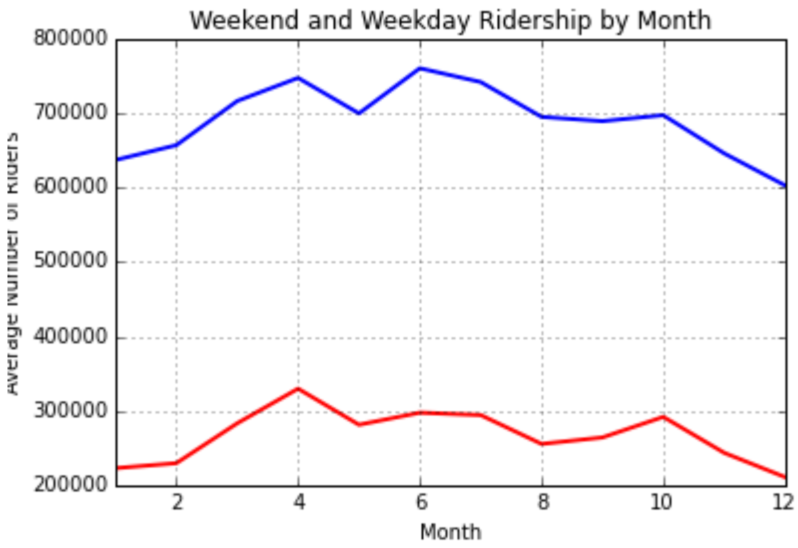




Using the metro ridership data from Open Data DC

Data Visualization





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

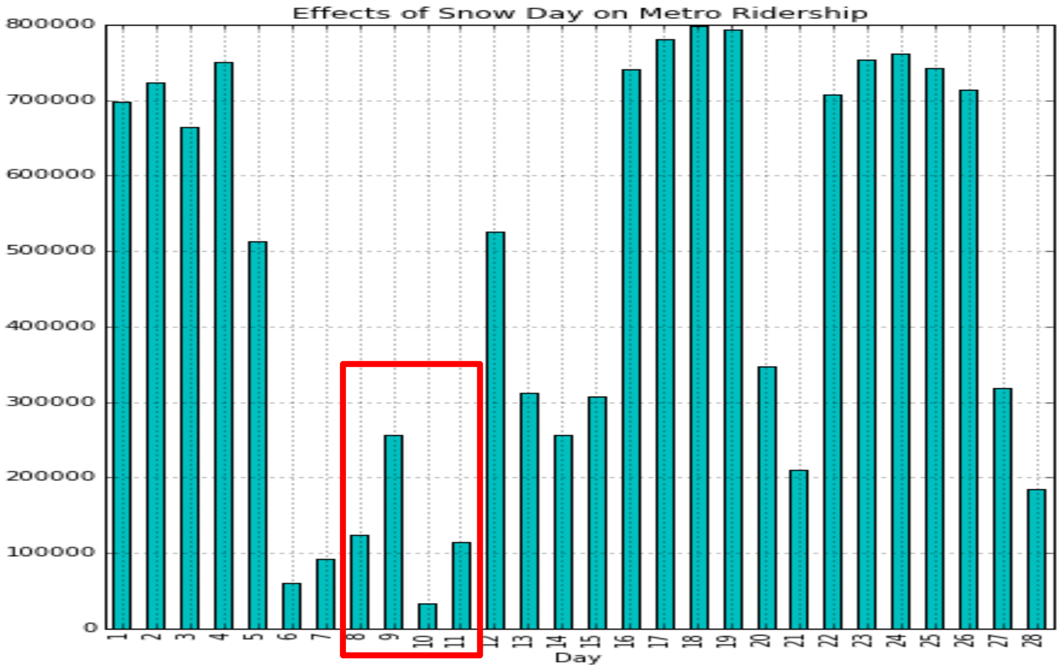
Features

- 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

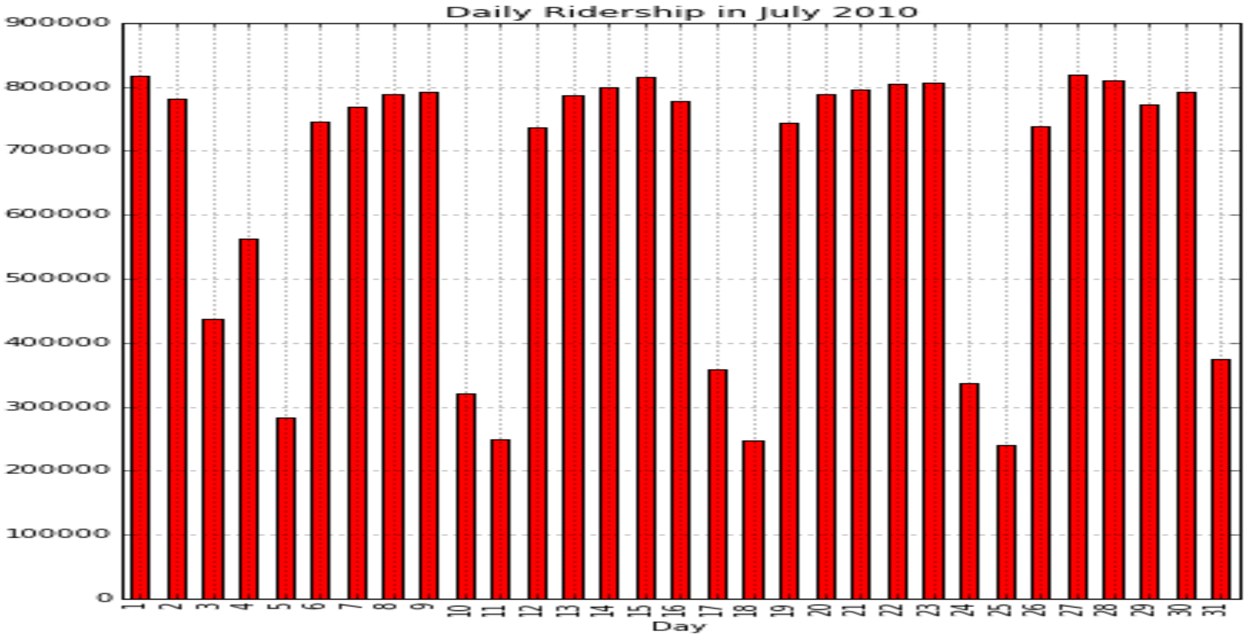
Ridership and Weather

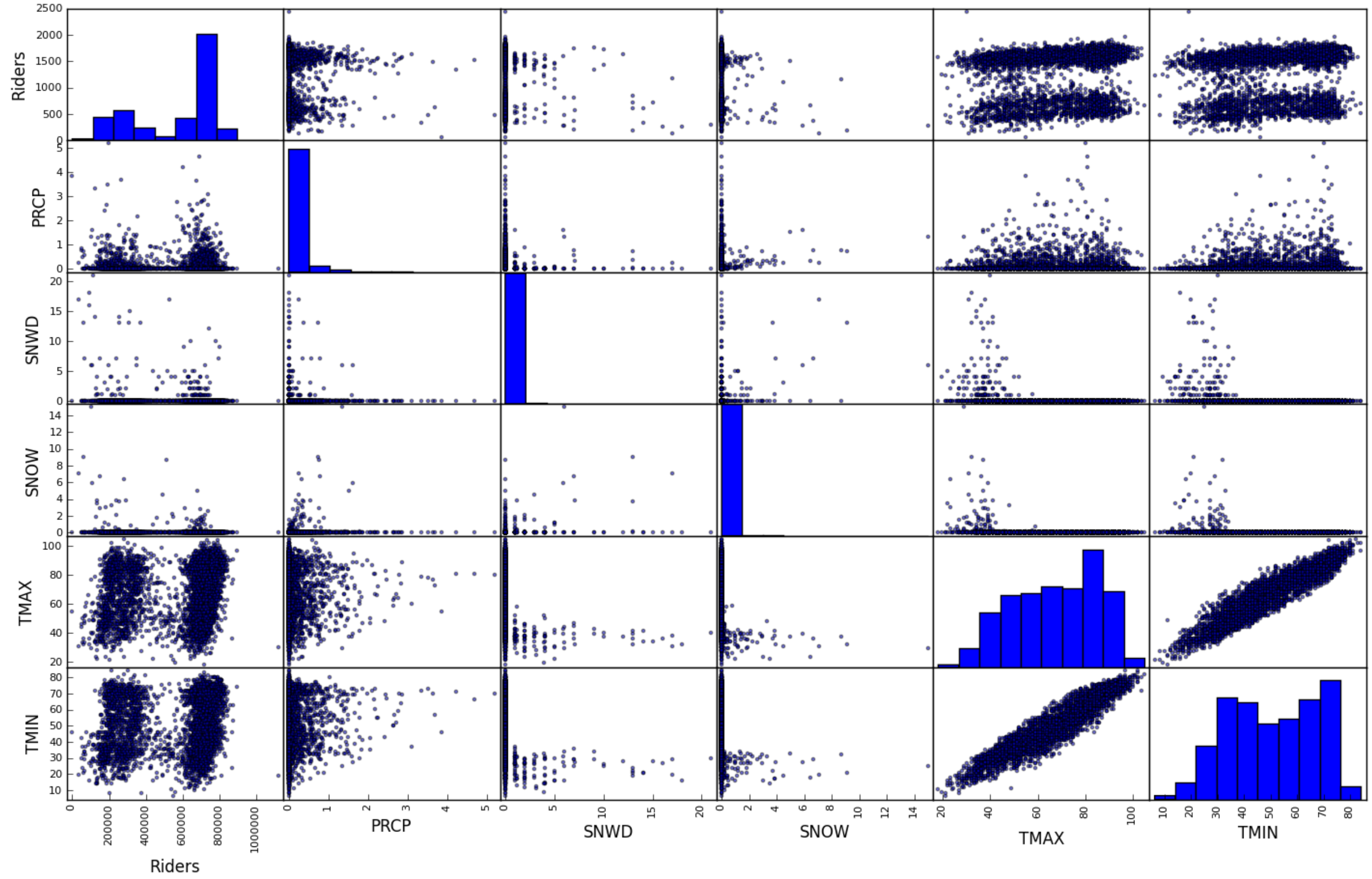
- Tourists less likely to visit during cold weather
- People are less likely to go places during bad weather
- Snow day means fewer people are going anywhere so much lower ridership

Winter Ridership (February 2010)



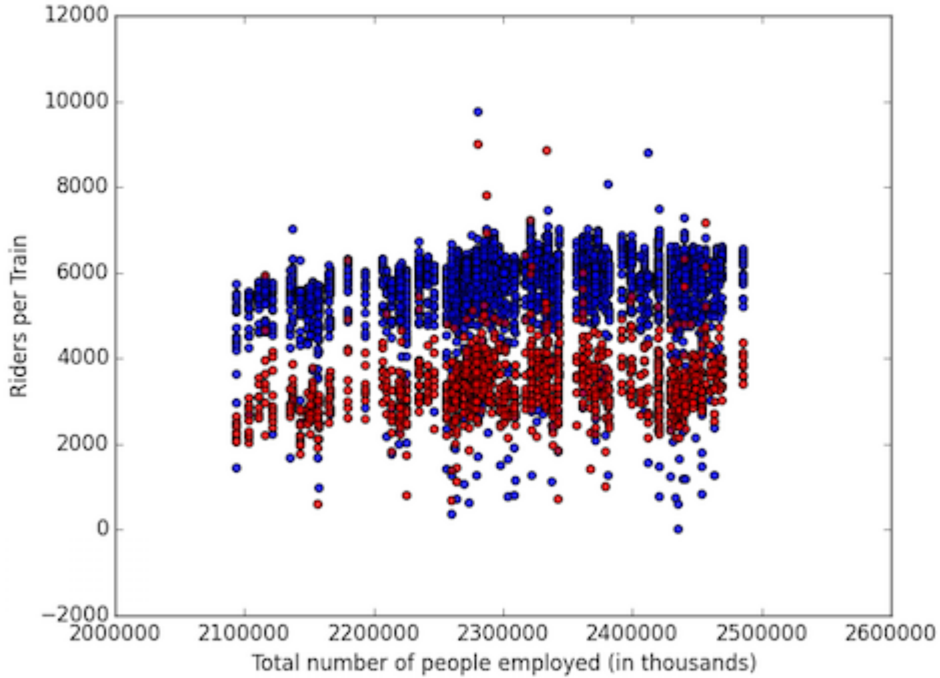
Summer Ridership (July 2010)




Riders
PRCP
SNWD
SNOW
TMAX
TMIN
Riders
PRCP
SNWD
SNOW
TMAX
TMIN

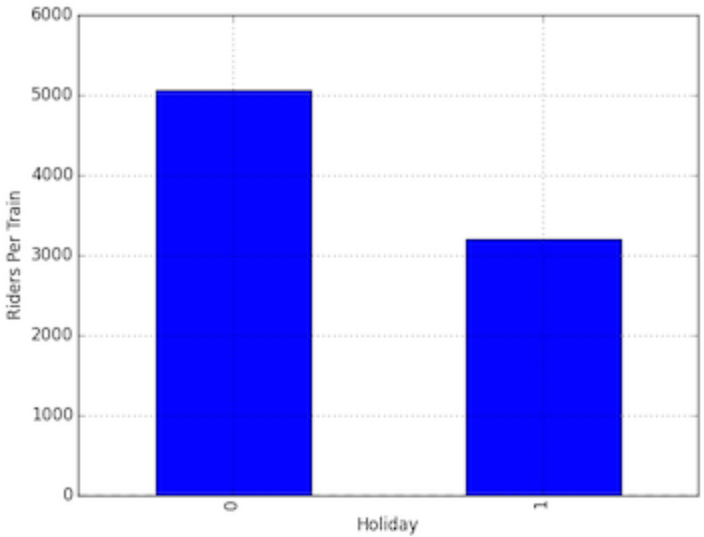
Ridership and Employment

- 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)

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

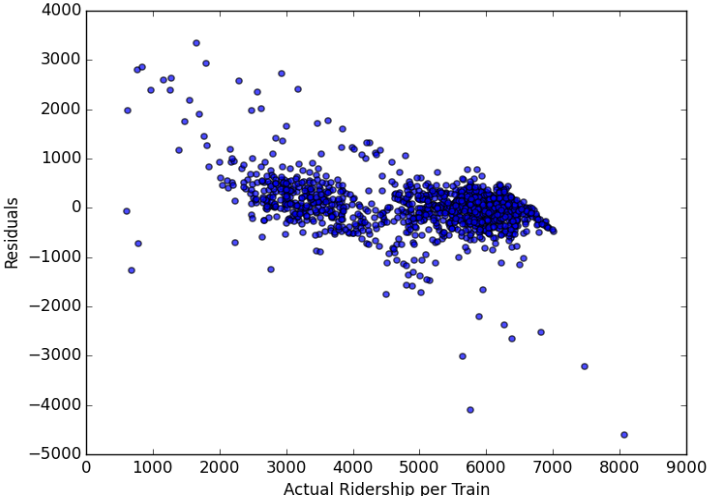
Weekday/Weekend Double Model

	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

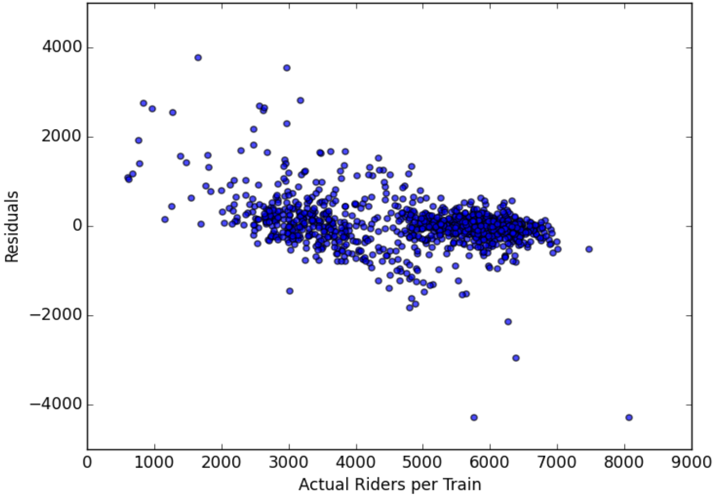
Adding more features

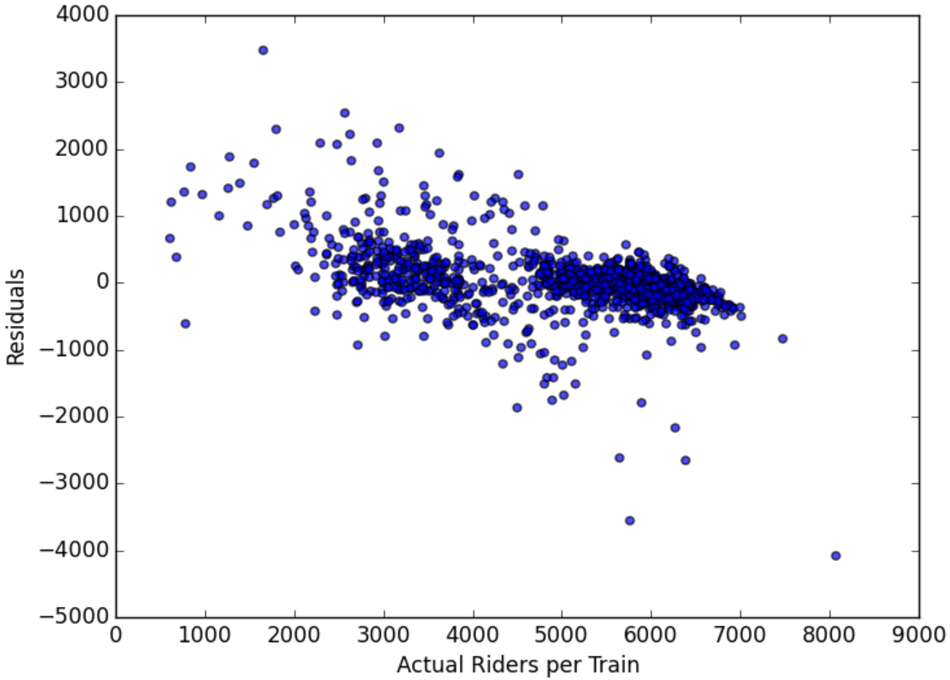
- Added days of the week as a set of binary variables
- No parameter tuning
- Significantly better performance by all models!

	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
Upper left: Linear Regression
Lower left: 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