Predicting Bike Share Ridership based on Weather Data in Seattle

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Introduction

Cycle share has launched in many U.S. cities since its introduction in Washington, D.C. in 2010 (1). One iteration of cycle share was Pronto! in downtown Seattle, Washington. From 2014 to 2017, 500 Pronto! bikes operated across 54 stations on the ithsmus. The City of Seattle, in partnership with Socratica, collected system data during the operating window and made it public via its open data platform. Pronto! fell short of the success realized by other bike schemes in the U.S. like Capital Bikeshare, Philly's Indego, and NYC's CitiBike. Researchers have used system data to conduct a post-mortem analysis on Pronto! as dockless bike share schemes like Lime Scooters filled the void left by Pronto (2). In this paper, we will investigate the relationship between weather in the service area and daily ridership. In particular, we want to predict daily ridership based on the weather data.

The data were downloaded from Kaggle (3). The file `trip.csv` contains data on each trip from 13 October 2014 to 31 March 2017, or 901 days. Each case in this dataset is a trip, and there were 275,091 trips over the 901 days. The relevant variables from the original 12 in this dataset are the response variables `start_time` (day and time trip started, in PST) and `trip_duration` (time of trip in seconds). In the file `weather.csv.xls`, a single case corresponds to a single day. This file contains the weather data for each day from 13 October 2014 to 31 August 2016, or 689 days. That is, the dates covered by the `weather` data set are a proper subset of the dates covered by the `trip` data set. Each day has 21 variables describing its weather. After merging these data sets and creating some of our own variables, we move on to exploratory data analysis for the response variables and predictors. This exploration informed our choice for our final model.

[INSERT PARAGRAPH SUMMARIZING CONCLUSIONS FROM THE RESEARCH]

Exploratory Data Analysis

Data Cleaning

The `trip` data frame contains 275,091 cases (or rides) and 12 variables describing each ride. The weather data frame contains 689 cases (or days) and 21 variables describing the weather that day. Ultimately, our goal is to join these two data frames. We began by aggregating trip data for each day we have data for. From the `trip` data frame, we created a new data frame called `ridership` that aggregates trips by day. At the end of this, `ridership` has 901 rows (days) and 3 columns (variables): `count`, `tripduration`, and `day_number`. Because the `trip` data covers 212 days after the last observation in the `weather` data, we want to keep only the observations in `trip` that match the observations in the smaller data frame, `weather`. We created our final data frame, `df`, by left joining weather and ridership by `day_number`. The final data frame contains 689 rows (days) and 25 columns (variables). The variable names are listed in a table below with brief descriptions.

Table 1: Variable Descriptions (689 rows, 25 columns)

Variable	Description
Max_Temperature_F	Maximum temperature (°F) recorded that day
Mean_Temperature_F	Mean temperature (°F) recorded that day
Min_TemperatureF	Minimum temperature (°F) recorded that day
Max_Dew_Point_F	Maximum dew point (°F) recorded that day
MeanDew_Point_F	Mean dew point (°F) recorded that day
Min_Dewpoint_F	Minimum dew point (°F) recorded that day
Max_Humidity	Maximum humidity (%) recorded that day
Mean_Humidity	Mean humidity (%) recorded that day
Min_Humidity	Minimum humidity (%) recorded that day
Max_Sea_Level_Pressure_In	Maximum sea-level pressure in inches recorded that day
Mean_Sea_Level_Pressure_In	Mean sea-level pressure in inches recorded that day
Min_Sea_Level_Pressure_In	Minimum sea-level pressure in inches recorded that day
Max_Visibility_Miles	Maximum visibility in miles recorded that day
Mean_Visibility_Miles	Mean visibility in miles recorded that day
Min_Visibility_Miles	Minimum visibility in miles recorded that day
Max_Wind_Speed_MPH	Maximum wind speed in miles per hour recorded that day
Mean_Wind_Speed_MPH	Mean wind speed in miles per hour recorded that day
Max_Gust_Speed_MPH	Maximum gust speed in miles per hour recorded that day
Precipitation_In	Precipitation in inches recorded that day
Events	Weather events (e.g., Rain, Snow) that occurred that day
temp_range	Temperature range (Max_Temperature_F - Min_TemperatureF)
date	Date of the observation
day_number	Days since 12 October 2014
total_trips	Total trips recorded that day
total_durations	Total duration of all trips recorded that day in seconds
average_durations	Average ride duration for that day

Notice that some variables in our data dictionary were created from others:

- `temp_range` was created by the difference: `Max_Temperature_F - Min_TemperatureF`
- `date` is in the format `"%m/%d/%Y"`, because each trip was originally in the format `"%m/%d/%Y %H:%M"`
- `day_number` are the days since 12 October 2014, the first day of observation
- `total_trips` are the total trips recorded for that day
- `total_durations` are the total durations for all trips that day
- `avg_durations` are the average durations for a trip each day

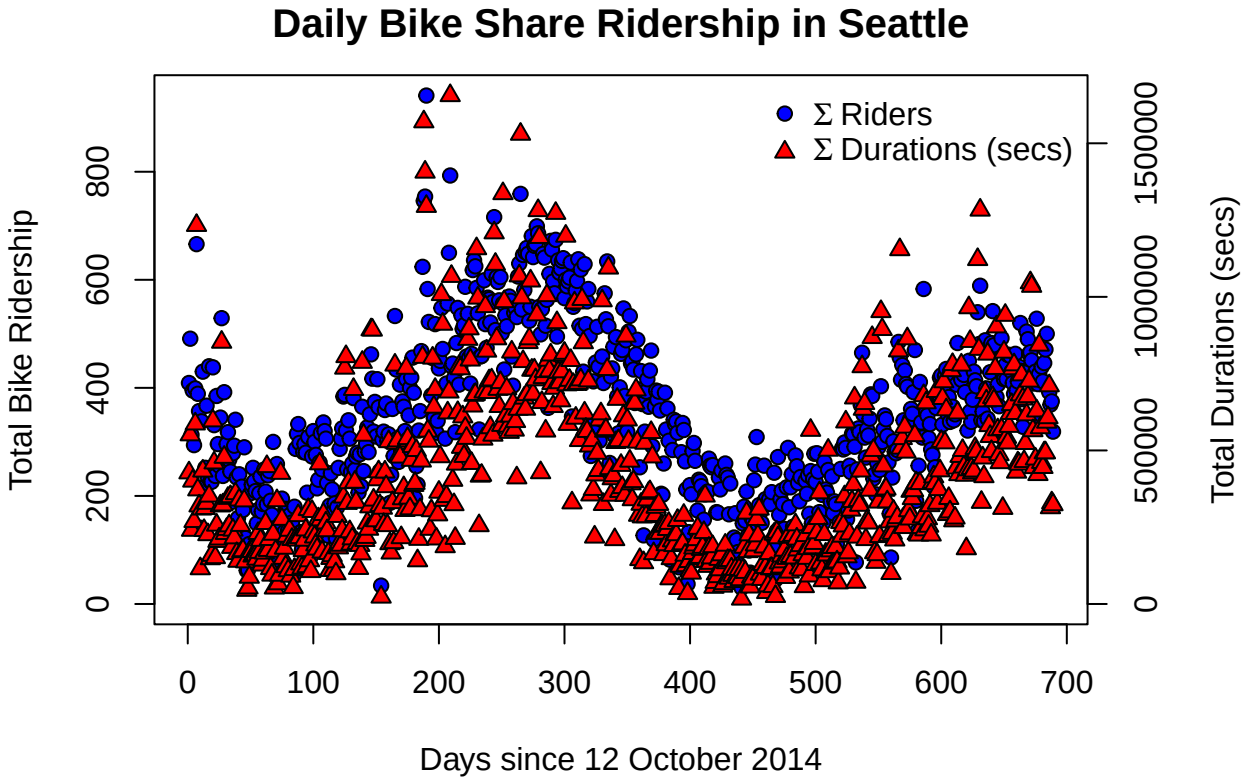
Selecting the Response Variable

The three candidates for a good response variable were created from the `trip.csv` data set, described in the `ridership` data frame, and merged into our final data frame: `total_trips`, `trip_durations`, and `avg_durations`. We briefly discuss the merits of each response variable before a quantitative judgement:

- `total_trips` is the most intuitive measure for bike ridership on a given day. It directly answers the question "How many trips were there?" for a given day. It gives us a picture of how willing people in the service area were to hop on a bike.

- `total_durations` gives a more complete picture for the ridership on a given day. Once a rider hopped on a bike, how long did they ride before docking it? This gives us a picture of how willing riders in the service area were to stay on their bikes.
- `avg_durations` controls for the interaction between bike ridership and ridership durations. By dividing total ridership over total durations, we understand the willingness of those in the service area to both picking up a bike and keep riding on that bike.

The figure below plots daily bike ridership in Seattle, with the total rides taken each day in blue circles and the sum of the durations of the rides taken each day in red triangles. This figure suggests that outliers in total riders tend to coincide with outliers in ride durations. For instance, the day with the highest bike riders – 941 on Sunday, April 20, 2015 – was also the day with the second highest sum of ride durations (359.7 hours). It's not clear from lookup what caused bike ridership to be so high on this day; like much of the data we gather from the real world, this result was influenced by many factors that day.



36 days earlier on Sunday, March 15, 2015 was the second-wettest March day on record in the Puget Sound Region (SOURCE). The rain was so severe that a mudslide occured in Western Seattle. Knowing this, you'd expect March 15 to have been a bad day for cycling. Only 34 trips took place on this day with a combined ride duration of just 6.3 hours. This was the second worst day for cycling behind Sunday, December 27, 2015 with just 30 trips and 4.5 hours. The coincidence between trips and durations explains the flattening of the data – the decline in variation from the mean – once we compute the average ride durations per day. We choose to skip a visualization of the average each day to visualizing the normality of the data.

We note (i) that `total_trips` and `total_durations` are highly correlated (>0.82), (ii) that average durations is bimodal, total durations is right-skewed, and total trips is roughly normal, and (iii) total durations makes for the easiest interpretation without being transformed. We therefore use `total_trips` as our response variable going forward.

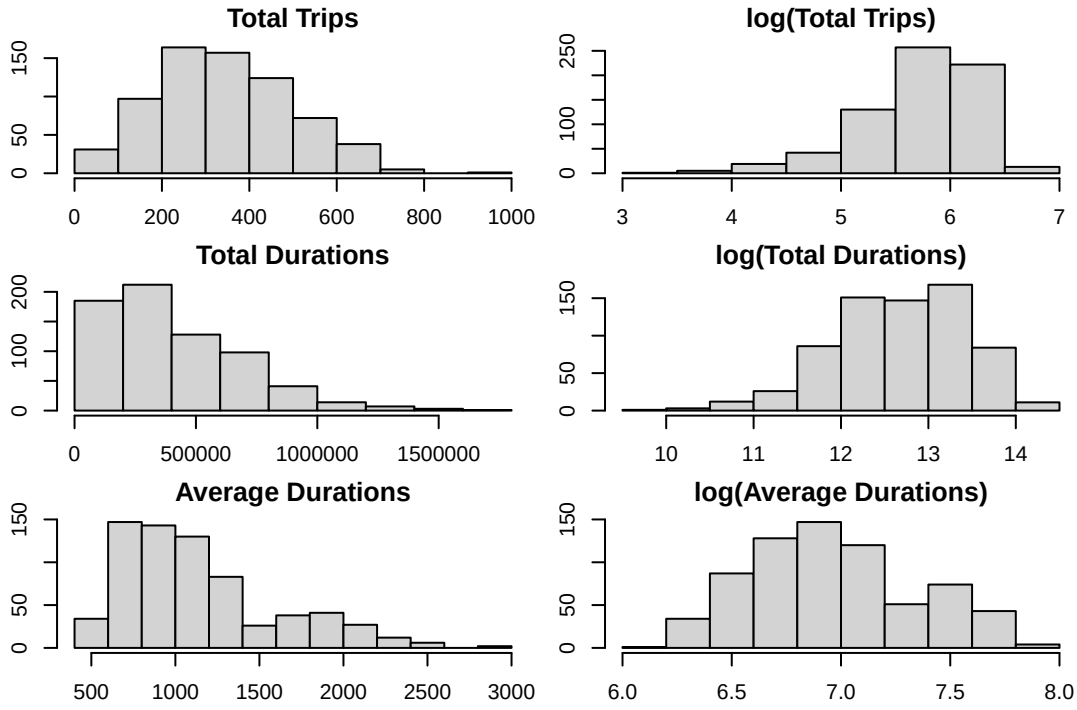
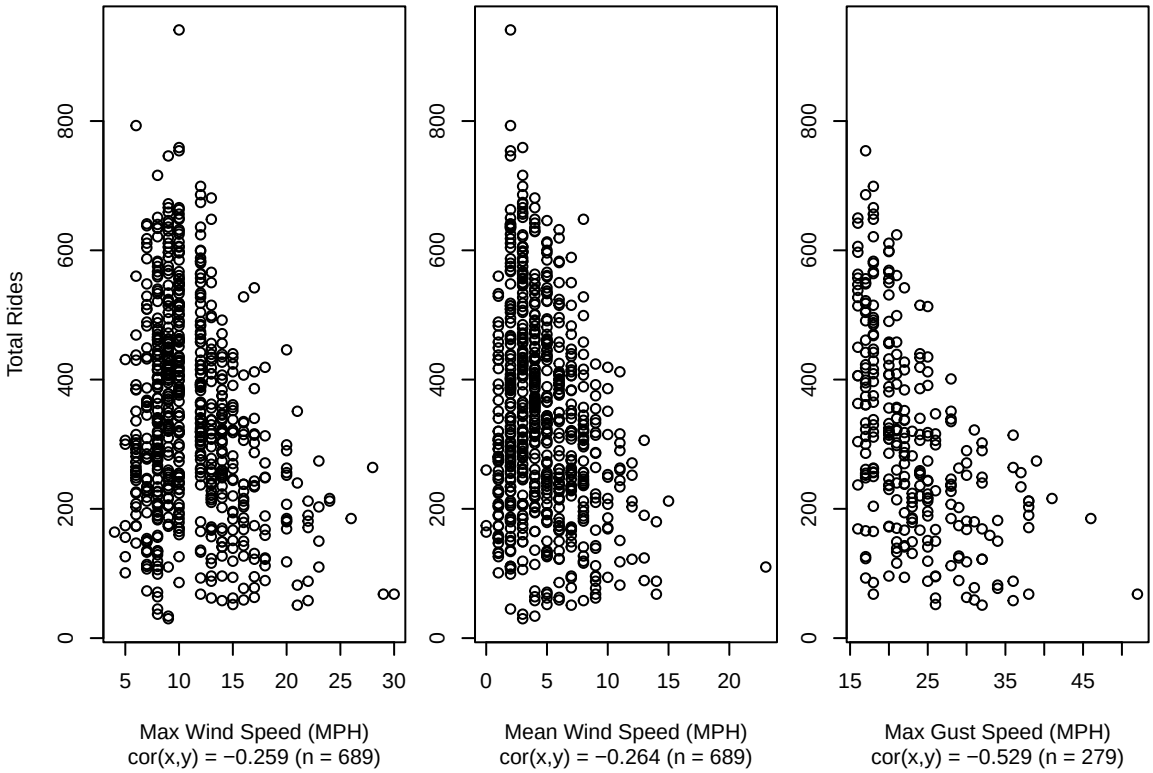


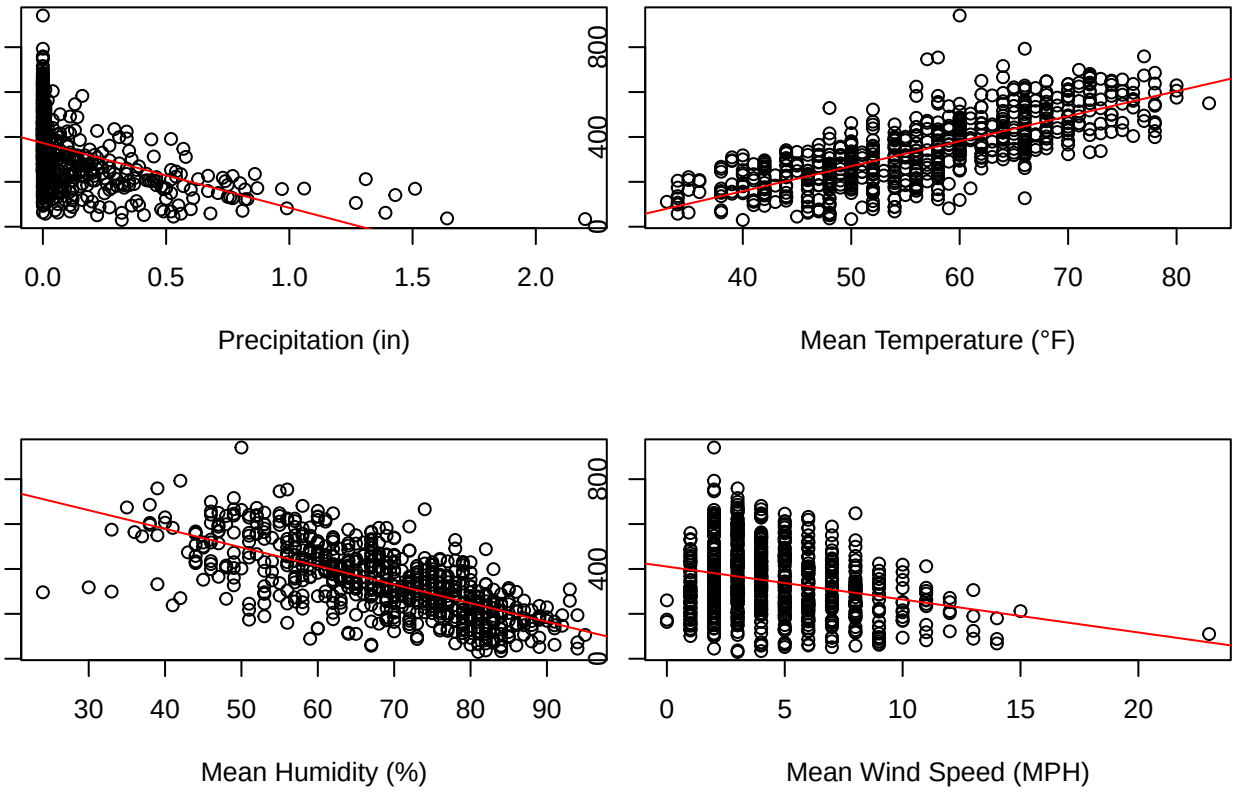
Table 2: Correlation between Weather Features and Total Trips

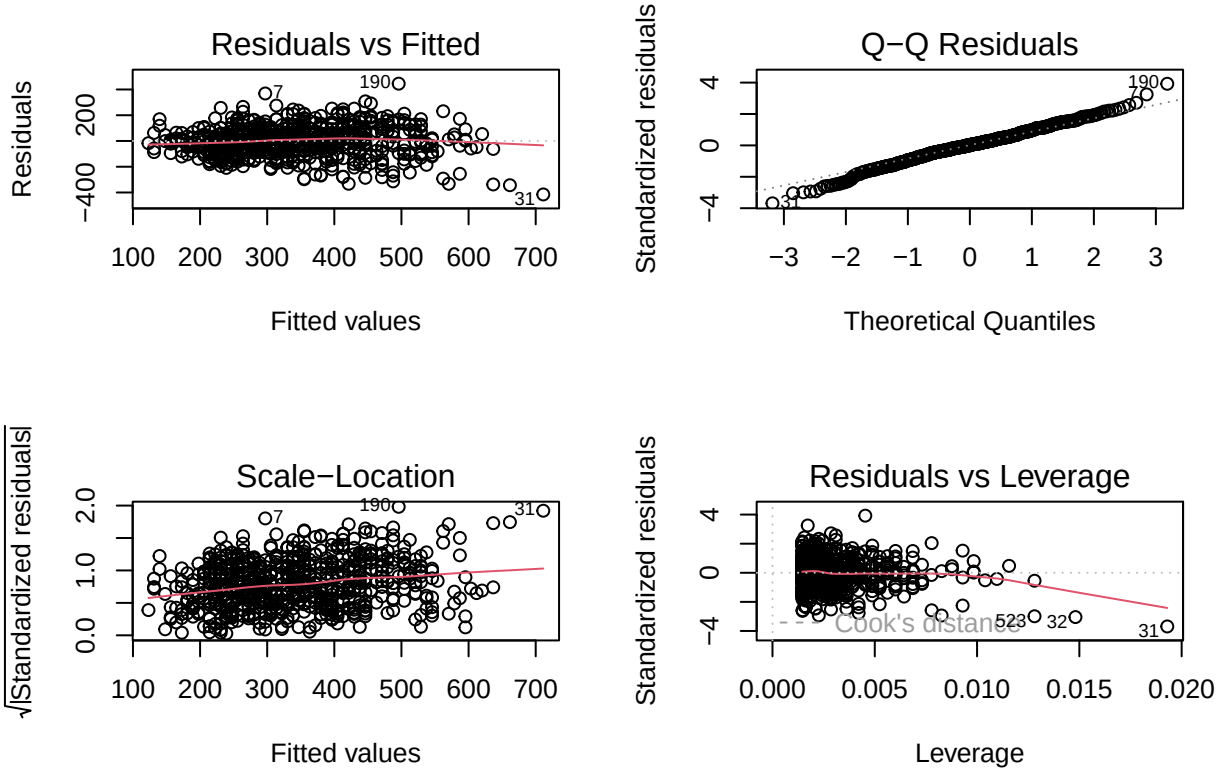
Feature	Min	Mean	Max
Temperature (°F)	0.640	0.750	0.786
Visibility (miles)	0.470	0.364	0.058
Dew Point (°F)	0.396	0.452	0.433
Humidity (%)	-0.648	-0.680	-0.579
Sea Level Pressure (in)	0.180	0.079	-0.065


Total Rides
0
200
400
600
800
5
10
15
20
25
30
Max Wind Speed (MPH)
cor(x,y) = −0.259 (n = 689)
0
5
10
15
20
Mean Wind Speed (MPH)
cor(x,y) = −0.264 (n = 689)
15
25
35
45
Max Gust Speed (MPH)
cor(x,y) = −0.529 (n = 279)

Outliers

Methods/ Analysis






```
##
## Call:
## lm(formula = total_trips ~ Mean_Humidity, data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -415.28  -63.52    1.48   67.50  445.10
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   910.0991    23.7690   38.29   <2e-16 ***
## Mean_Humidity  -8.2840     0.3412  -24.28   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 113.7 on 687 degrees of freedom
## Multiple R-squared:  0.4619, Adjusted R-squared:  0.4611
## F-statistic: 589.6 on 1 and 687 DF,  p-value: < 2.2e-16
```

Conclusion/Discussion

Model Selection

Our model and how we derived it:

The equation for our final regression model is:

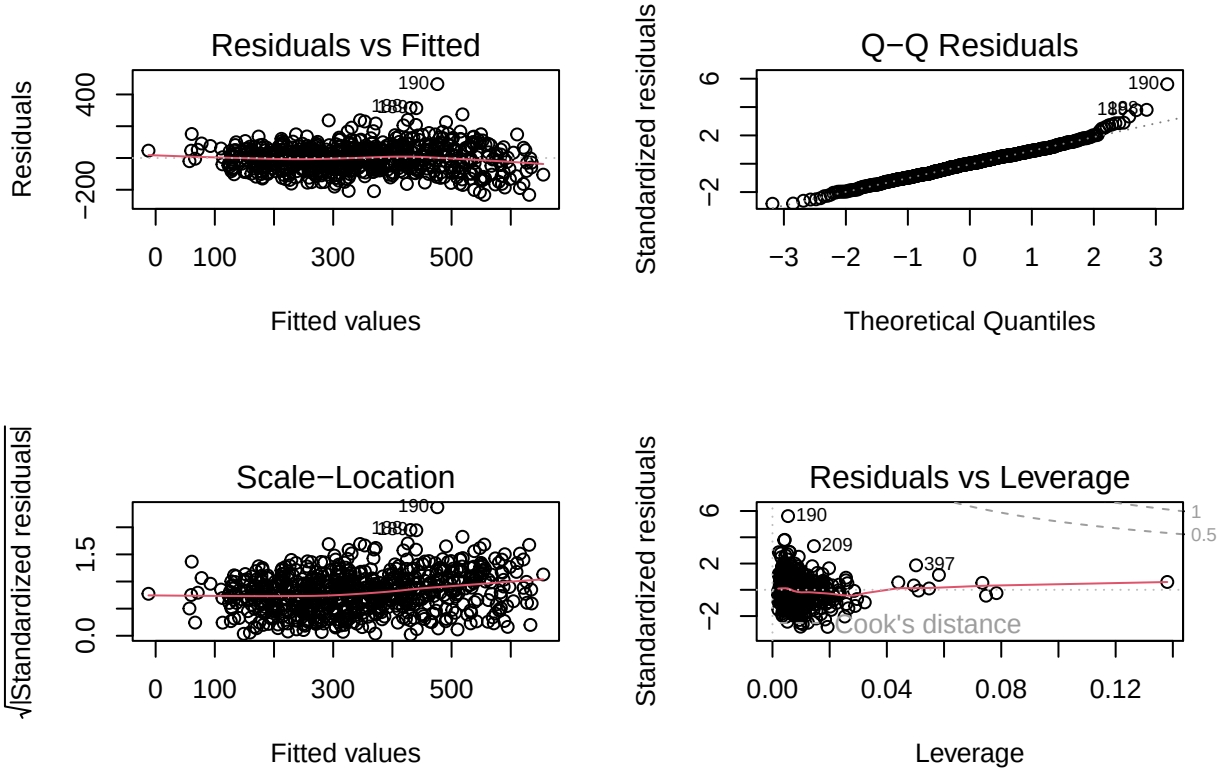
`total_trips` = 277.1643 – 4.95(`Mean_Humidity`) + 5.90(`MeanDew_Point`) – 118.151(`Precipitation_In`) – 7.91(`Mean_Wind_Speed`) + 2.94(`Max_Temperature`)

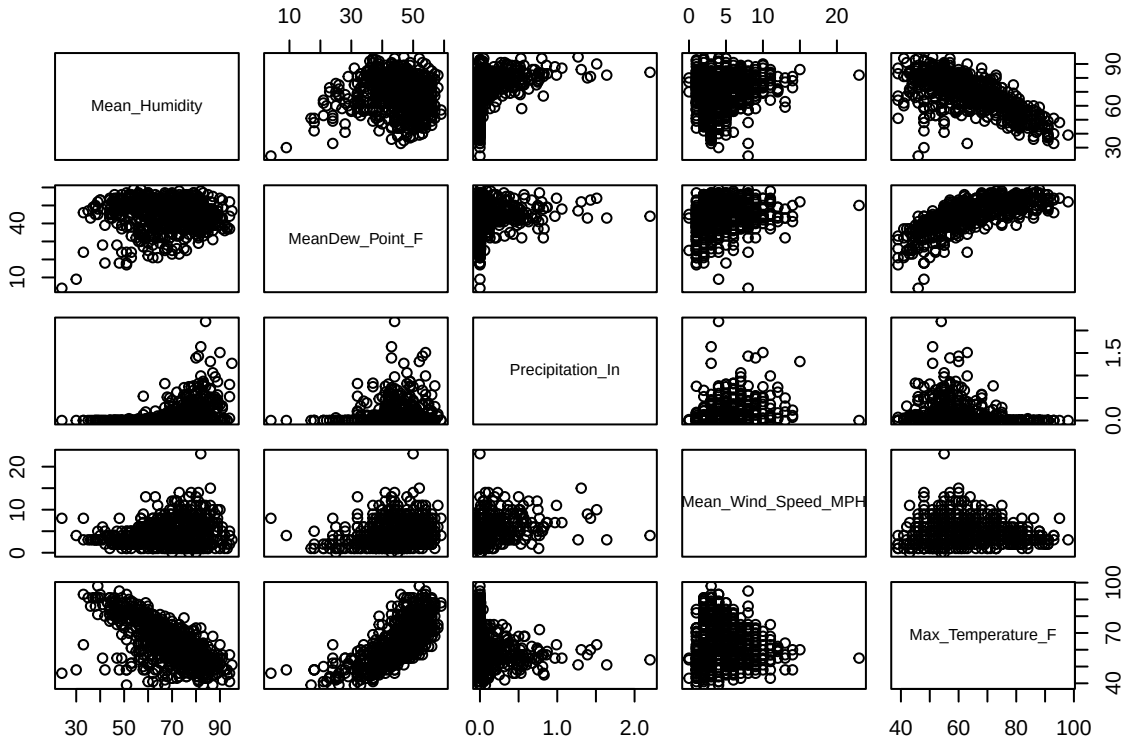
Each regressor is significant to at least the 0.01 level, and the diagnostic plots are satisfactory. The residual plot moving-average looks flat. The normal quantile plot has few departures from the line. The scale location plot is relatively flat, indicating constant variance across fitted values.

In order to obtain this model, we first did some exploratory data analysis, plotting total trips against certain variables and obtaining their correlation. We then attemped several basic (single regressor) linear models of total_trips vs some of our variables. The variables that we considered were: mean temperature, mean humidity, mean dew point, precipitation in inches, mean wind speed, mean miles of visibility, mean sea level pressure, temperature range, and max temperature. These were the original variables we considered on account of the fact that they seemed to have some relationship with total trips based on plots and correlation, and made sense to us as predictors of ridership from an intuitive perspective. After trying several single variable models, we found that few of them had very high R^2, with a notable exception that a weighted least squares model of wind speed high worked very well. We then decided to make a "full" model with all of the variables above, except only using mean temperature instead of temperature range and max temperature as 1. mean and max were extremely highly correlated (>97%) and 2. we thought two temperature variables would be redundant. The output of the full model showed that Mean temperature, mean visibility miles, and mean sea level pressure did not have coefficients that were significantly different from zero. We made a model dropping these parameters and then did an anova (partial f) between the two models to see if we could justifiably drop them and it showed that we could. At this point all of the predictors were significant and the adjusted R^2 was 0.7095. However, we got the idea to try adding temperature range or max temperature to this model. Including temperature range did not improve the R^2, and it was not significant in the model, however, including max temperature did improve the adjusted R^2 and the regressor was also significant. We decided that this would be our final model. Each regressor is significant at at least the 0.01 level, and the diagnostic plots look good. The adjusted R^2 is 0.712. We also tried to use powerTransformations, but it only worked for some of the variables as others did not have strictly positive values. For the variables that did successfully power transform, the adjusted R^2 of the subsequent model was not greatly improved and few of the regressors were significant. Our final model has some nice properties, in that the diagnostic plots show that it satisfies the assumptions for linear regression well, it is perfectly basic in terms of transformations, and partly on account of that, it is not too difficult to interpret. In terms of interpretation, our model predicts that holding all else equal, every 1% increase in average humidity will lead the total number of bike trips to decrease by 4.95. It predicts that holding all else equal, for every 1 degree increase in the average dew point (Fahrenheit for this and all future mentions of degrees) Seattle will see a drop in bike trips of 5.90. Our model predicts that all else equal, for every 1 extra inch of precipitation, total bike rides will drop by 118. It also predicts that holding all else equal, a 1 mile per hour increase in the average wind speed will decrease total bike trips by 7.91. Lastly our model predicts that holding all else equal, a 1 degree increase in the maximum temperature will increase the number of bike trips by 2.94.

```
##
## Call:
## lm(formula = total_trips ~ Mean_Humidity + MeanDew_Point_F +
##     Precipitation_In + Mean_Wind_Speed_MPH + Max_Temperature_F,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -232.29  -58.08    0.51   49.71  465.04
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          277.1643    69.9164   3.964 8.14e-05 ***
```

```
## Mean_Humidity          -4.9504     0.7503  -6.598 8.37e-11 ***
## MeanDew_Point_F         5.8968     1.3083   4.507 7.73e-06 ***
## Precipitation_In     -118.1507    15.2166  -7.765 3.00e-14 ***
## Mean_Wind_Speed_MPH    -7.9065     1.2656  -6.247 7.35e-10 ***
## Max_Temperature_F       2.9379     1.1138   2.638  0.00854 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 83.09 on 683 degrees of freedom
## Multiple R-squared:  0.7141, Adjusted R-squared:  0.712
## F-statistic: 341.1 on 5 and 683 DF,  p-value: < 2.2e-16
```





Cross Validation

Conclusion

Our work here suggests a path forward for bike share systems looking to bolster their operations and planning with weather data. However, Seattle is a city with temperate weather/climate. These results are not readily generalizable to all cities because when its too hot, people will also not ride bike!

```
trip = read_csv('pronto-cycle-share-trip-data.csv')
# map unique dates to integers starting at 1
# strips the date from its current format
trip$date <- as.Date(trip$starttime, format = "%m/%d/%Y %H:%M")
unique_dates <- sort(unique(trip$date)) # this collects unique dates
# this maps unique date to the integers, starting at 1
date_to_number <- setNames(seq_along(unique_dates), as.character(unique_dates))
# this adds the integer mapping as a column, day_number
trip$day_number = date_to_number[as.character(trip$date)]
trip$count = 1 # this adds a one to each obs; useful for add
trip = dplyr::select(trip, count, tripduration, day_number)

# construct new df, ridership, that aggregates trips by day
ridership = trip %>% group_by(day_number) %>%
  summarise(total_trips = sum(count),
```

```
            total_durations = sum(tripduration),
            .groups = 'drop'); dim(ridership)
```

```
weather = read_csv('weather.csv.xls')
# calculates temperature range for each day
weather$temp_range = weather$Max_Temperature_F - weather$Min_TemperatureF
# strips the date from its current format
weather$date <- as.Date(weather$Date, format = "%m/%d/%Y")
# maps unique date to the integers, like the chunk above
date_to_number <- setNames(seq_along(unique_dates), as.character(unique_dates))
weather$day_number = date_to_number[as.character(weather$date)]
weather = weather[,-1] # remove the old date
# this will be our data frame going forward
df = left_join(weather,ridership, by='day_number'); dim(df)
df$avg_durations = df$total_durations / df$total_trips
```