Predicting Bike Share Ridership based on Climate Data in Seattle

Joey Rodriguez and Daniel Bhatti

2024-11-22

Introduction

Bike share has launched in many U.S. cities since its introduction in Washington, D.C. in 2010 (1). One iteration of bike 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 partnered with Socratica to collect system data during the operating window and made it publicly available via its open data platform. *Pronto!* fell short of the success realized by other similar schemes in the U.S. like Capital Bikeshare, Philly's Indego, and NYC's CitiBike. Researchers have used this system data to conduct a post-mortem analysis as dockless providers like *Lime Micromobility* filled the void left by *Pronto!* (2).

In this brief paper, we investigate the relationship between weather in the service area and daily ridership. In particular, we predict daily ridership based on weather data and time of year. After cleaning the data and analyzing candidates for the response variable, we took a stepwise approach to fitting a model. At first we considered only weather-related predictors, but we strengthened our model by adding temporal predictors. We considered various aspects when comparing models such as diagnostic plots, summary statistics, multicolinearity, systematic variable selection, ANOVA and partial F-test to compare satisfactory models. For our final model, we consider interpretations, limitations, and extensions worth thorough investigation.

Exploratory Data Analysis

Data Cleaning

The data `trip.csv` and `weather.csv.xls` were downloaded from Kaggle (3). The `trip` data frame contains 275,091 cases (or rides) and 12 variables describing each ride. These data were collected over 901 days from 13 October 2014 to 31 March 2017. The relevant variables from the original 12 in this dataset are `start_time` (day and time trip started, in PST) and `trip_duration` (time of trip in seconds). The `weather` data frame contains 689 cases (or days) and 21 variables describing the weather that day. These data were collected from 13 October 2014 to 31 August 2016, or 689 days. Notice that the dates covered by the `weather` data set are a proper subset of the dates covered by the `trip` data set.

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 29 columns (variables). The variable names are listed in the table below with brief descriptions.

Table 1: Variable Descriptions (689 days, 29 variables)

Variable	Description
Max_Temperature_F	Maximum temperature (°F)
Mean_Temperature_F	Mean temperature (°F)
Min_TemperatureF	Minimum temperature (°F)
Max_Dew_Point_F	Maximum dew point (°F)
MeanDew_Point_F	Mean dew point (°F)
Min_Dewpoint_F	Minimum dew point (°F)
Max_Humidity	Maximum humidity (%)
Mean_Humidity	Mean humidity (%)
Min_Humidity	Minimum humidity (%)
Max_Sea_Level_Pressure_In	Maximum sea-level pressure (inches Hg)
Mean_Sea_Level_Pressure_In	Mean sea-level pressure (inches Hg)
Min_Sea_Level_Pressure_In	Minimum sea-level pressure (inches Hg)
Max_Visibility_Miles	Maximum visibility (miles)
Mean_Visibility_Miles	Mean visibility (miles)
Min_Visibility_Miles	Minimum visibility (miles)
Max_Wind_Speed_MPH	Maximum wind speed (MPH)
Mean_Wind_Speed_MPH	Mean wind speed (MPH)
Max_Gust_Speed_MPH	Maximum gust speed (MPH)
Precipitation_In	Precipitation (inches)
Events	Weather events (e.g., Rain, Snow)
temp_range	Temperature range (°F)
date	Date of the observation (%m/%d/%Y)
day_number	Days since 12 October 2014
total_trips	Count of total trips
total_durations	Sum of total duration for all trips (seconds)
average_durations	Average ride duration (seconds)
weekday_weekend	Encodes weekends: 1 if Saturday or Sunday, 0 otherwise
season	Encodes seasons: 0 if Spring, 1 if Summer, 2 if Fall, 3 if Winter
fall_winter	Encodes wet season: 1 if Fall or Winter, 0 if Summer or Spring

Notice that nine variables in our data dictionary were created from other variables:

- `temp_range` is computed from the difference: `Max_Temperature_F - Min_TemperatureF`
- `date` strips the day/ month/ year `"%m/%d/%Y"` from the full `starttime "%m/%d/%Y %H:%M"`
- `day_number` are the days beginning 13 October 2014, the first day of observation
- `total_trips` are the total trips recorded for each day
- `total_durations` are the total durations for all trips each day
- `avg_durations` was computed from the difference: `total_durations` / `total_trips`
- `weekday_weekend` = 1 if `date` was a Saturday or Sunday and 0 otherwise.
- `season` = 0 if `date` in Spring, 1 if Summer, 2 if Fall, 3 if Winter according the the summer and winter solstices and the spring and fall equinoxes in the Northern hemisphere.
- `fall_winter` was created based on whether the `season` was Fall or Winter, which roughly coincides with the wet season in the Puget Sound Region from October to April (SOURCE).

Understanding Outliers

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 Monday, April 20, 2015 – was also the day with the second highest sum of ride durations (359.7 hours). This is day 190, the largest outlier in the data set. It's not clear from look-up what caused bike ridership to be so high on this day; like much of the data gathered from the real world, many factors likely contributed to high ridership on this 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 occurred in Western Seattle. Knowing this, you'd expect March 15 to have been a bad day for cycling, and you'd be right: 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 totaling 4.5 hours. This also happens to be the greatest leverage point by far (0.144). The coincidence between trips and durations explains the flattening of the data – the decrease in variation from the mean – observed in `avg_durations`.

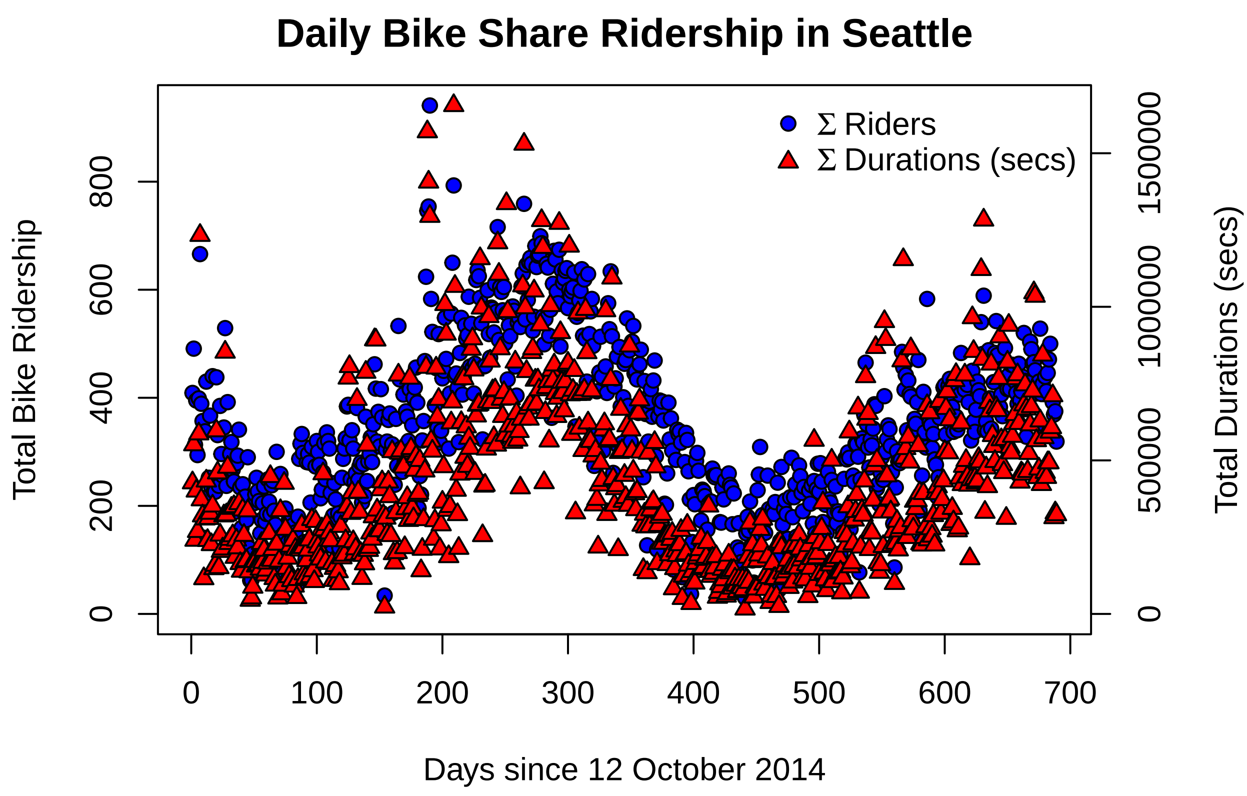

Figure 1: Daily Bike Share Ridership and Durations in Seattle.

Methods

Selecting the Response Variable

The three candidates for our 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 strengths 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 pick a bike.
- `total_durations` gives a more complete picture for the ridership on a given day. Once a rider picked 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 once they mounted.
- `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 picking up a bike *and* staying on it.

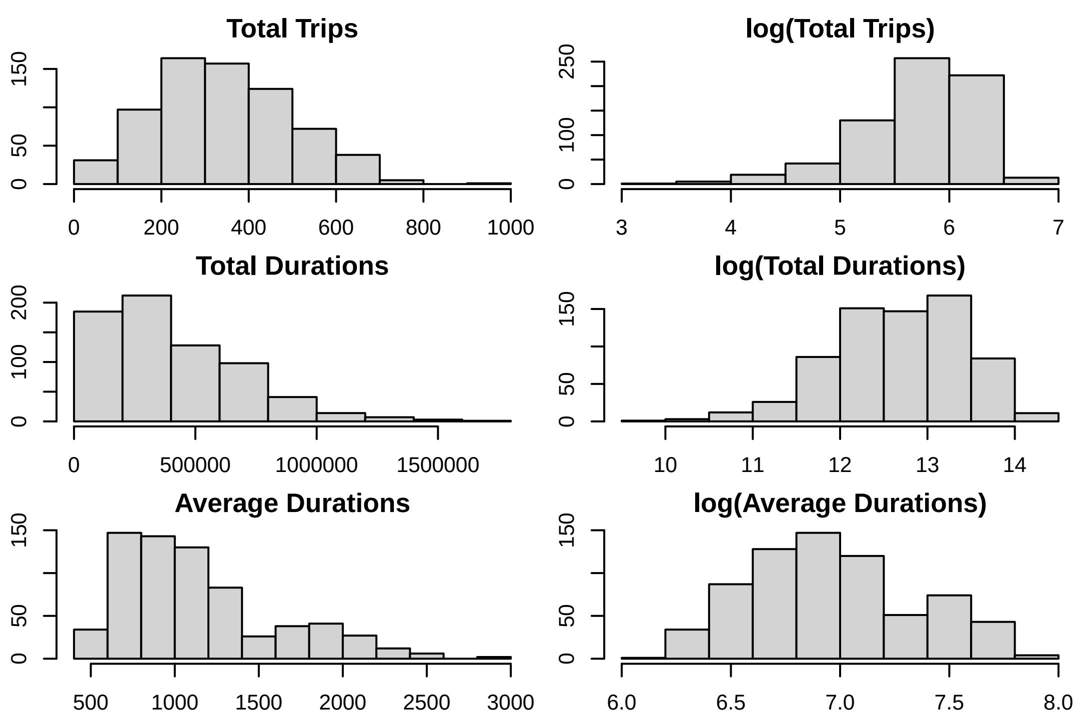

Figure 2: Variables Measuring Bike Share Ridership in Seattle

Note that `total_trips` and `total_durations` are highly correlated (>0.82). This is consistent with our discussion on outliers. Considering the shape and spread of the distributions, note that Average Durations is bimodal, Total Durations is right-skewed, and Total Trips is roughly normal. It's clear that Total Durations makes for the easiest interpretation without being transformed. Based on visual inspection, its the most normal appearing on the six distributions. We therefore use `total_trips` as our response variable going forward.

Selecting the Predictors

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

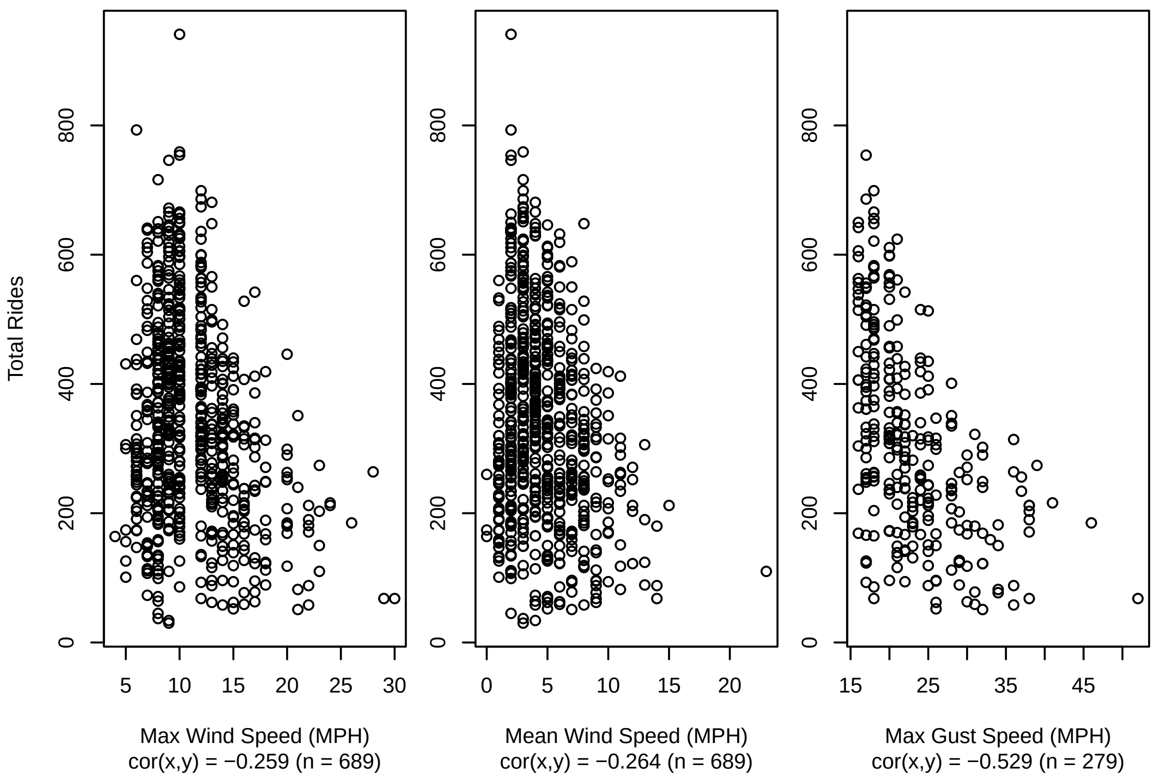

Figure 3: Effect of Wind Speed on Bike Share Ridership in Seattle.

For each of the continuous variables with recorded min, mean, and max — Visibility, Temperature, Dew Point, Humidity, and Sea Level Pressure – we calculate their correlations with the response Total Trips. By feature, it turns out that Max Temperature, Min Visibility, Mean Dew Point, Mean Humidity, and Min Sea Level Pressure have the highest correlation with Total Trips (Table 2). Total Trips' high correlation with Max Temperature may be explained by the temperature at midday, when the temperature is usually highest and when people are prone to be out biking between commutes and leisure. We added each of these highest-correlation variables with the response to our baseline model.

Wind speed is a special case with variables Max Wind Speed, Mean Wind Speed, and Max Gust Speed. Though `Max_Gust_Speed_MPH` had higher correlation with Total Trips than either `Max_Wind_Speed_MPH` or `Mean_Wind_Speed_MPH`, it also had 410 missing values. We opted to add `Mean_Wind_Speed_MPH` which had the next-highest correlation with Total Trips (Figure 3). We also added Precipitation_In (a zero-inflated continuous variable) and the descriptive variable Events.

We utilized Events in two ways. First we set it such that Event was a dummy variable representing whether there was an event that day. Events included fog, fog and rain, rain, rain and snow, rain and thunderstorm, and snow. There were 328 days where there were events and 361 without. The second way we utilized Events was by making it a dummy based on whether there was rain or snow on that day (as we might not expect a strong effect from fog).

Model Selection

Our baseline model based on initial findings from exploratory data analysis is:

$$\begin{aligned}\texttt{total\_trips}_i^{base} &= \beta_{i0} + \beta_{i1}\texttt{Mean\_Humidity}_i + \beta_{i2}\texttt{MeanDew\_Point\_F}_i \\ &+ \beta_{i3}\texttt{Mean\_Wind\_Speed\_MPH}_i + \beta_{i4}\texttt{Max\_Temperature\_F}_i + \beta_{i5}\texttt{Min\_Visibility\_Miles}_i \\ &+ \beta_{i6}\texttt{Min\_Sea\_Level\_Pressure\_In}_i + \beta_{i7}\texttt{Precipitation\_In}_i + \beta_{i8}\texttt{Events}_i\end{aligned}$$

We removed `Min_Visibility_Miles`, `Min_Sea_Level_Pressure_In` and `Events` because they were insignificant predictors for Total Trips Our full model at this point (RSE = 83.09, R^2 = 0.7141, R^2_{adj}= 0.712, *all terms significant to* 0.01) is:

$$\begin{aligned}\texttt{total\_trips}_i^{full} &= \beta_{i0} + \beta_{i1}\texttt{Max\_Temperature\_F}_i + \beta_{i2}\texttt{MeanDew\_Point\_F}_i \\ &+ \beta_{i3}\texttt{Mean\_Wind\_Speed\_MPH}_i + \beta_{i4}\texttt{Mean\_Humidity}_i + \beta_{i5}\texttt{Precipitation\_In}_i\end{aligned}$$

Cursory transformations failed to produce superior models. Application of a power transform produced coefficients that were mostly close to one. Both forwards and backwards selection failed to produce a superior model, although they selected models similar to ours. We discovered a partial model (RSE = 83.45, R^2 = 0.7112, R^2_{adj}= 0.7095, *all terms infinitesimal*) with satisfactory summary statistics and diagnostic plots. The partial model is just the full model with the `Max_Temperature_F` term dropped.

$$\begin{aligned}\texttt{total\_trips}_i^{part} &= \beta_{i0} + \beta_{i1}\texttt{MeanDew\_Point\_F}_i \\ &+ \beta_{i2}\texttt{Mean\_Wind\_Speed\_MPH}_i + \beta_{i3}\texttt{Mean\_Humidity}_i + \beta_{i4}\texttt{Precipitation\_In}_i\end{aligned}$$

Based on ANOVA / Partial F-test, the full model provides a better fit to the observed data over the partial model (F = 6.9579, p = 0.0085). However, Variance Inflation Factor (VIF) – measuring multicolinearity between the predictors and Total Trips – is abnormally high for `Mean_Humidity` (VIF = 9.05), `MeanDew_Point_F` (VIF = 10.68), and `Max_Temperature_F` (VIF = 19.09) in the full model.

It turns out that `Max_Temperature_F` has high correlation with `MeanDew_Point_F` (0.72) and `Mean_Humidity` (-0.67). The results from VIF analysis makes clear the confounding results in step-wise selection; In the forwards case, `Max_Temperature_F` makes the best 1-predictor model and it is never eliminated in successive model. The partial model has VIF values near one. Thus, the partial model is the better model.

Finally, we strengthen our model by considering temporal variation. Adding the dummy variable `weekday_weekend` accounts for weekly changes in ridership based on commute pattern changes in the downtown for leisure, work and school. Adding the variable `season` accounts for changes in ridership based on the solstices and equinoxes while adding `fall_winter` accounts for changes in ridership based only on the solstices:

$$\begin{aligned}\texttt{total\_trips}_i^{temp} = {} & \beta_{i0} + \beta_{i1}\texttt{MeanDew\_Point\_F}_i \\ & + \beta_{i2}\texttt{Mean\_Wind\_Speed\_MPH}_i + \beta_{i3}\texttt{Mean\_Humidity}_i + \beta_{i4}\texttt{Precipitation\_In}_i \\ & + \beta_{i5}\texttt{weekday\_weekend}_i + \beta_{i6}\texttt{season}_i + \beta_{i7}\texttt{fall\_winter}_i\end{aligned}$$

Considering both the high correlation between variables `season` and `fall_winter` and the insignificance of the `season` variable, we opt to drop this variable from our final model:

$$\begin{aligned}\texttt{total\_trips}_i^{fin} = {} & 485.40 + 8.10\texttt{MeanDew\_Point\_F}_i \\ & - 8.85\texttt{Mean\_Wind\_Speed\_MPH}_i - 6.20\texttt{Mean\_Humidity}_i - 103.49\texttt{Precipitation\_In}_i \\ & - 50.23\texttt{weekday\_weekend}_i - 34.11\texttt{fall\_winter}_i\end{aligned}$$

```
## [1] 63.54551
```

```
## [1] 84.79909
```

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.

Conclusion

Interpretations

For a given day with other variables held fixed, our model dictates

- For a 1% increase in Mean Relative Humidity we expect 6.2 fewer trips
- For a 1°F increase in Mean Dew Point, we expect 8.1 more trips
- For a 1 inch increase in Precipitation we expect 103.5 fewer trips
- For a 1 MPH increase in the Mean Wind Speed, we expect 8.8 fewer trips
- For a day falling in between (including) 22 September and 19 March, we expect 34.1 fewer trips than outside of those days
- For a weekend day, we expect 50.2 fewer trips than on a weekday

It makes sense for trips to drop as relative humidity rises, because higher relative humidity is uncomfortable to riders. It makes sense for trips to increase as the Mean Dew Point increases, as a higher Dew Point generally signals warmer weather. It makes sense that any precipitation would flatten ridership, as biking in rain or snow could be more risky and uncomfortable. It makes sense that an increase in the miles per hour of mean wind speed would decrease ridership, as faster winds increase wind chill which feels very uncomfortable, and biking into headwinds is tiresome. It makes sense that ridership decreases in the fall and winter, as this is when days are shorter, when Seattle's rainy season starts, and when the leaves fall, potentially making it so that biking is slippery and less scenic. Lastly, an explanation for why ridership drops on the weekend is that many people likely used Pronto to get to work, which would not happen on the weekends.

Limitations

In terms of limitations, as stated before, given that the climate of Seattle is different from many other cities, our results will have limited generalizability. Another limitation is that the weather data is for all of the Puget sound region, while the biking data is concentrated in downtown Seattle. If the weather data was specialized to the city itself, we may see the weather data have higher explanatory power. Lastly, one limitation is that two of are variables, mean humidity and mean dew point, are mathematically related, which could be cause for concern. The reason that this relationship doesn't affect the regression model is that they are not *linearly* related.

Extensions

Some possible extensions of our work here could be analyzing the relationships between weather and ridership in different cities. We might see different relationships between the weather and ridership in cities that have different climates than Seattle, for instance, Houston, Texas. Another potential extension would be to use interaction terms, and create a dummy variable for holidays, like a 2018 paper by Kyoungok Kim did.

References

Pronto Cycle Share, 2016. "Pronto Cycle Share Dataset," Kaggle. Available online at: https://www.kaggle.com/datasets/pronto/cycle-share-dataset.

Kim, Kyoungok, 2018. "Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations," Journal of Transport Geography, Elsevier, vol. 66(C), pages 309-320.

An, Ran & Zahnow, Renee & Pojani, Dorina & Corcoran, Jonathan, 2019. "Weather and cycling in New York: The case of Citibike," Journal of Transport Geography, Elsevier, vol. 77(C), pages 97-112.

University of Washington, 2019. "Bike-sharing in Seattle," UW News, October 7, 2019. Available online.

Appendix

Code Used for Data Cleaning

```r
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)
```

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

```
            total_durations = round(sum(tripduration), 1),
            .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 = round(df$total_durations / df$total_trips, 1)
```

```
df$weekday_weekend <- ifelse(weekdays(df$date) %in% c("Saturday", "Sunday"),1,0)
# Define a function to classify seasons based on actual start dates
get_season <- function(date) {
  year <- lubridate::year(date)
  spring_start <- as.Date(paste0(year, "-03-20"))
  summer_start <- as.Date(paste0(year, "-06-21"))
  fall_start   <- as.Date(paste0(year, "-09-22"))
  winter_start <- as.Date(paste0(year, "-12-21"))
  ifelse(date >= spring_start & date < summer_start, 0,  # Spring
  ifelse(date >= summer_start & date < fall_start,   1,  # Summer
  ifelse(date >= fall_start & date < winter_start,   2,  # Fall
  3)))  # Winter
}
# Apply the function to the 'date' variable
df$season <- sapply(df$date, get_season)
# Create fall/winter dummy: 1 if Fall or Winter, 0 otherwise
df$fall_winter <- ifelse(df$season %in% c(2, 3), 1, 0)
```

Summary Statistics for Final Model

```
##
## Call:
## lm(formula = total_trips ~ Mean_Humidity + MeanDew_Point_F +
##     Precipitation_In + Mean_Wind_Speed_MPH + fall_winter + weekday_weekend,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -221.24  -51.52   -3.87   45.97  442.98
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           485.3972    25.9669  18.693  < 2e-16 ***
## Mean_Humidity          -6.1999     0.3101 -19.995  < 2e-16 ***
## MeanDew_Point_F         8.1029     0.4673  17.338  < 2e-16 ***
## Precipitation_In     -103.4870    14.9002  -6.945 8.82e-12 ***
```

```
## Mean_Wind_Speed_MPH   -8.8492     1.1689  -7.570 1.21e-13 ***
## fall_winter          -34.1058     8.7685  -3.890  0.00011 ***
## weekday_weekend      -50.2268     6.7387  -7.453 2.76e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 79.64 on 682 degrees of freedom
## Multiple R-squared:  0.7378, Adjusted R-squared:  0.7354
## F-statistic: 319.8 on 6 and 682 DF,  p-value: < 2.2e-16
```

Diagnostic Plots for Final Model