# Part 2: Linear regression models

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## Contents

# Introduction

### Unlocking the Wheels of Urban Mobility: A Data-Driven Analysis of BIXI

In the fast-paced, ever-evolving landscape of urban transportation, the quest to create efficient and sustainable solutions for city dwellers continues to be a paramount concern. Amidst the diverse array of options that have emerged in recent years, the BIXI public cycling service stands as a beacon of sustainable urban mobility. Offering an accessible, convenient, and eco-friendly mode of transportation, BIXI has transformed the way people navigate and experience cities.

As part of our commitment to understanding and improving urban transportation systems, our consultant team has embarked on an in-depth exploration of BIXI's operational data. The objective of this report is to provide a comprehensive analysis of the data collected from the BIXI service. By leveraging statistical and data analysis techniques, we aim to uncover valuable insights into the usage patterns, financial dynamics, and various factors affecting BIXI's performance. Our study covers an extensive range of factors, including ridership trends, environmental conditions, user classifications, and more.

One of the central questions addressed in this report is whether revenue generated by the BIXI service and trip duration significantly varies during weekends compared to weekdays. we also delve into the other factors affecting the duration of trips and the revenue generated by non-members. Our methodology combines data analysis, data visualization, and statistical modeling, with a primary focus on using R, a powerful statistical tool, to extract meaningful information from the BIXI dataset.

By analyzing this data, we aim to assist BIXI in making data-informed decisions to enhance the efficiency and quality of their services, ultimately contributing to the betterment of urban living. We believe that the findings and recommendations presented in this report will not only provide valuable insights to BIXI but also serve as a valuable reference for urban planners, researchers, and policymakers who are dedicated to creating more sustainable, convenient, and enjoyable urban environments.

The following sections of the report will delve into the specifics of our data analysis, share our findings, and provide recommendations based on the insights gathered during this project.

# Business/Research questions

(keep only the ones that were answered)

Do members travel more than non-members during the rain periods? (Shows commitment of members)

Do members travel more during weekends than non-members? (Shows commitment of members)

Do stations more commonly traveled in the mornings have lower duration per trip than stations more commonly traveled in the afternoon?

Do members prefer to travel in the morning as opposed to non-members? (Members are work commuters, non-members are recreational)

Do members prefer to travel in the morning as opposed to non-members? Also including the weekend vs weekday.

Are revenues significantly higher during the weekend?

Does the average trip duration varies from member to non-member?

How does weather interact with weekday in determining the number of trips?

# Pre-processing

## Outlier detection

```r
model <- lm(n_AM_PM_delta ~ long_wknd_ind + season + rain_ind + mem, data = df_main) # Goal is to look
summary(model)
```

```
##
## Call:
## lm(formula = n_AM_PM_delta ~ long_wknd_ind + season + rain_ind +
##     mem, data = df_main)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -117.382   -2.083    1.433    4.928   24.147
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -4.1407     0.8188  -5.057 4.33e-07 ***
## long_wknd_indWeekday     1.7079     0.8182   2.087   0.0369 *
## long_wknd_indWeekend     0.4048     0.8293   0.488   0.6255
## seasonSpring            -0.1763     0.2692  -0.655   0.5126
## seasonSummer            -1.5288     0.2199  -6.951 3.86e-12 ***
## rain_indRain             1.6899     0.2006   8.424  < 2e-16 ***
## mem1                    -8.1851     0.1951 -41.950  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.726 on 9993 degrees of freedom
## Multiple R-squared:  0.1587, Adjusted R-squared:  0.1582
## F-statistic: 314.2 on 6 and 9993 DF,  p-value: < 2.2e-16
```

```r
model.diag.metrics <- augment(model)
head(model.diag.metrics)
```

```
## # A tibble: 6 x 11
```

```
##   n_AM_PM_delta long_wknd_ind season rain_ind mem   .fitted .resid     .hat
##           <int> <fct>         <chr>  <fct>    <fct>   <dbl>  <dbl>    <dbl>
## 1            -1 Weekday       Spring Rain     1       -9.10   8.10 0.000798
## 2            -7 Weekday       Spring NoRain   1      -10.8    3.79 0.000673
## 3            -5 Weekend       Spring NoRain   0       -3.91  -1.09 0.000874
## 4            -2 Weekday       Spring Rain     0       -0.919 -1.08 0.000875
## 5            -6 Weekend       Spring Rain     1      -10.4    4.41 0.000979
## 6             0 Weekday       Summer NoRain   0       -3.96   3.96 0.000441
## # i 3 more variables: .sigma <dbl>, .cooksd <dbl>, .std.resid <dbl>
```

```
# OUTLIERS  WITH COOKS DISTANCE
model.diag.metrics %>%
  top_n(3, wt = .cooksd)
```

```
## # A tibble: 3 x 11
##   n_AM_PM_delta long_wknd_ind season rain_ind mem   .fitted .resid     .hat
##           <int> <fct>         <chr>  <fct>    <fct>   <dbl>  <dbl>    <dbl>
## 1          -128 Weekday       Fall   NoRain   1      -10.6  -117.  0.000488
## 2           -54 Long Weekend  Spring NoRain   0       -4.32  -49.7 0.00734
## 3           -54 Long Weekend  Fall   NoRain   1      -12.3   -41.7 0.00709
## # i 3 more variables: .sigma <dbl>, .cooksd <dbl>, .std.resid <dbl>
```

## Research Question 1: How do seasonal factors impact trip revenue for BIXI Montréal?

### Model

```
##
## Call:
## lm(formula = rev ~ mm + temp + rain, data = df_main)
##
## Residuals:
##    Min      1Q Median      3Q     Max
## -35.02 -17.16  -7.91   6.28 780.11
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  10.6632     2.6304   4.054 5.12e-05 ***
## mm5           4.5252     2.6259   1.723   0.0849 .
## mm6           8.6248     2.9339   2.940   0.0033 **
## mm7          17.2568     2.8647   6.024 1.83e-09 ***
## mm8          15.7850     3.0995   5.093 3.67e-07 ***
## mm9          18.6931     2.6860   6.959 3.88e-12 ***
## mm10         12.1186     2.4922   4.863 1.20e-06 ***
## mm11          6.9401     2.9942   2.318   0.0205 *
## temp          0.3833     0.1456   2.632   0.0085 **
## rain         -0.4932     0.1097  -4.495 7.13e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 35.98 on 4724 degrees of freedom
```

```
##   (5266 observations deleted due to missingness)
## Multiple R-squared:  0.04008,    Adjusted R-squared:  0.03825
## F-statistic: 21.92 on 9 and 4724 DF,  p-value: < 2.2e-16
```

## Objective

**Objective of Analysis:** This regression model is examining the impact of the month (`mm`), average daily temperature (`temp`), and total amount of rainfall (`rain`) on the revenue (`rev`) generated by trips leaving from a specified station.

## Interpretation

**Seasonality (Month):** - The revenue seems to have a seasonal pattern. Compared to April (reference month), May (`mm5`) sees an increase in revenue by about 4.525. This increase is even more pronounced in the following months, with September (`mm9`) having the most substantial uplift of around 18.693$.

**Temperature (`temp`):** - For every 1°C increase in temperature, the revenue increases by approximately 0.383 $, which is statistically significant (p-value: 0.0085). - This suggests that warmer days tend to generate more revenue.

**Rainfall (`rain`):** - For every additional mm of rainfall, the revenue decreases by approximately 0.493$, which is statistically significant (p-value: 7.13e-06). - This implies that rainfall negatively impacts the revenue.

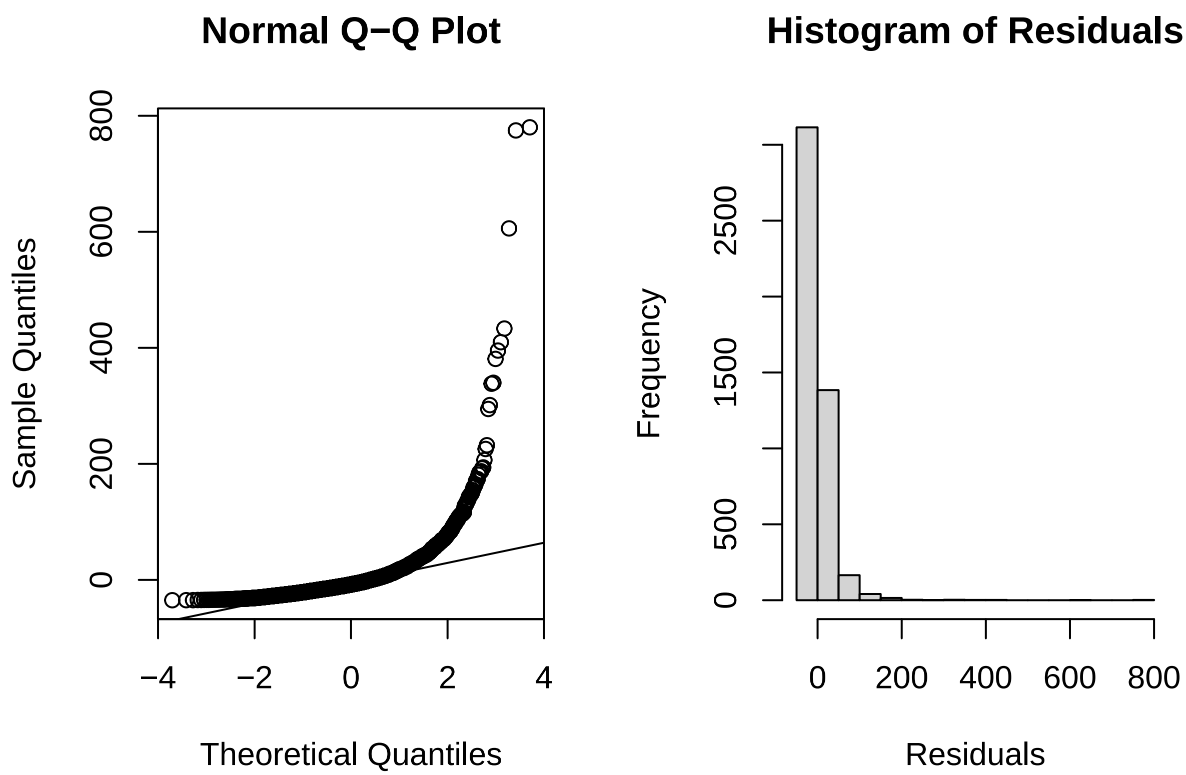
**Model Fit:** - The Multiple R-squared value (0.04008) implies that around 4% of the variation in revenue is explained by the predictors in the model. While statistically significant (F-statistic p-value: $<$ 2.2e-16), the model might benefit from considering additional predictors or non-linear effects to explain more of the variance in revenue.

## Business implications

1. **Operational Adjustments:** Given that revenue is higher in warmer months, consider optimizing operations for this period. This might involve higher staffing, more promotional activities, or ensuring optimal equipment availability.
2. **Rainy Day Strategies:** Since rainfall seems to negatively impact revenue, consider implementing strategies to mitigate this. For instance, promotional offers or special activities/events for rainy days might help attract customers.

### Verification of Assumptions

#### Normality of residuals




1. **Histogram of Residuals**: These histograms have a clear right-skew with a peak close to zero and a long tail towards the right. This suggests that most residuals are clustered around zero, but there are a few larger positive residuals. This is an indication that the normality assumption of the residuals may be violated.
2. **Normal Q-Q Plot**: Most of the points are close to the line, which is a good sign. However, there's a clear deviation from the line on the top right corner, suggesting the presence of larger residuals that are not explained by a normal distribution. This reiterates the presence of the right skew seen in these histograms.

**Overall Interpretation**: The residuals are not perfectly normal. They show a positive skewness, indicating there might be some observations with higher residuals (perhaps outliers or instances where the model systematically underpredicts). The deviation from normality might not be a problem because the sample is large enough.

# Research Question 2: How do daily and weekly patterns impact trip durations for BIXI Montréal?

## Model

```
##
## Call:
## lm(formula = dur ~ dd + wday + holiday, data = df_main)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -330.0 -201.4 -101.5   96.4 3953.1
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   284.97626    9.71890  29.322  < 2e-16 ***
## dd              0.03792    0.35263   0.108   0.9144
## wdayMonday    -49.00428   11.63373  -4.212 2.55e-05 ***
## wdaySaturday   15.05883   11.40702   1.320   0.1868
## wdaySunday     -6.50623   11.48715  -0.566   0.5711
## wdayThursday  -16.94467   11.56156  -1.466   0.1428
## wdayTuesday   -34.48313   11.61775  -2.968   0.0030 **
## wdayWednesday -20.56897   11.53032  -1.784   0.0745 .
## holiday1       68.77802   21.23112   3.239   0.0012 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 307 on 9991 degrees of freedom
## Multiple R-squared:  0.00463,    Adjusted R-squared:  0.003833
## F-statistic: 5.809 on 8 and 9991 DF,  p-value: 2.016e-07
```

## Interpretation

**Overall Model** - The model explains approximately 87.27% of the variation in the trip duration. - The model is statistically significant (F-statistic p-value is extremely small), suggesting that the predictors in the model collectively have an effect on the trip duration.

**Intercept** - When all other variables are at their reference level (Friday not on a holiday), the predicted trip duration is about 30.77 minutes on average.

**Coefficients - dd (Day of the Month)**: For each day later in the month, the trip duration decreases by about 0.0688 minutes on average, although this effect is not statistically significant (p = 0.58548).

- **wday (Weekday)**: Compared to the Friday:
  - **Monday**: Trips are shorter by about 27.97 minutes on average.
  - **Saturday**: Trips are longer by about 29.10 minutes on average.
  - **Sunday**: Trips are longer by about 11.20 minutes on average.
  - **Thursday**: Trips are shorter by about 11.92 minutes on average.
  - **Tuesday**: Trips are shorter by about 29.25 minutes on average.
  - **Wednesday**: Trips are shorter by about 18.29 minutes on average.
  - The coefficients for all these weekdays are statistically significant.

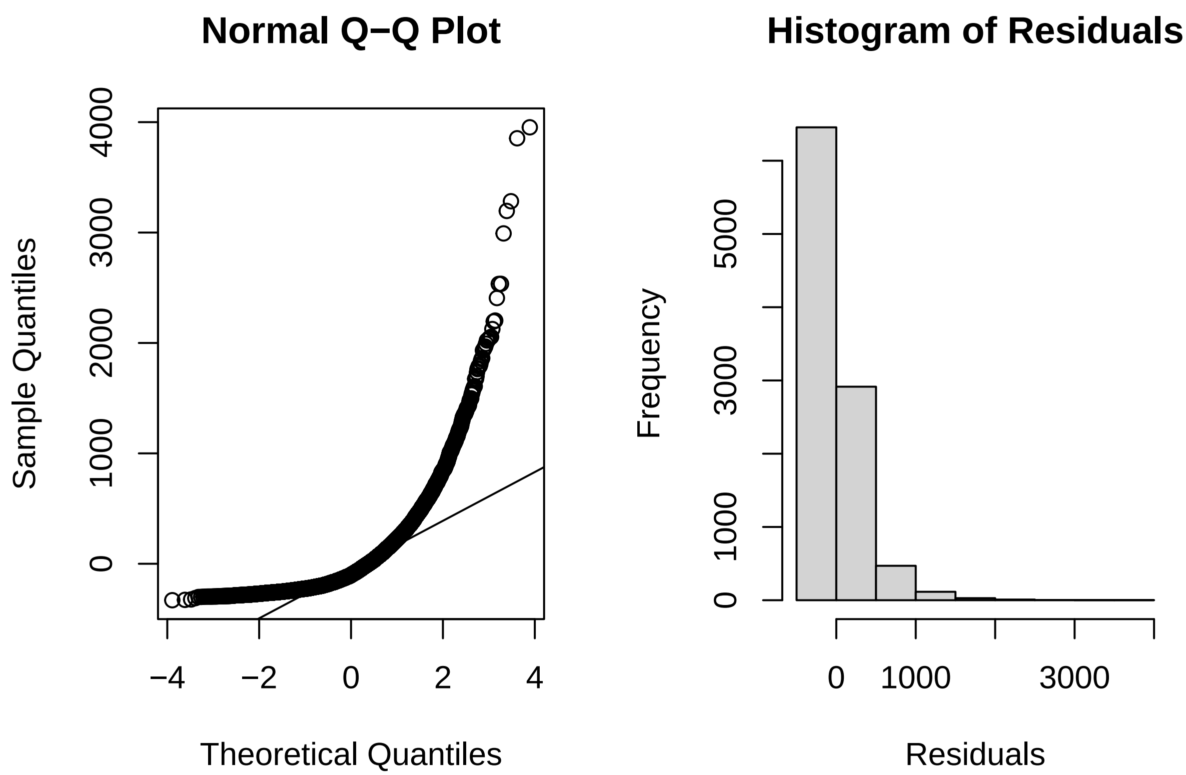
- **Holiday**: On holidays, trips are on average longer by about 56.24 minutes compared to non-holidays. This effect is statistically significant, suggesting holidays might lead to longer leisure trips or normal trips to different destinations than workdays.
- **n_AM (Number of Trips in the Morning)**: For each additional trip in the morning, the trip duration increases by about 8.51 minutes on average. This is statistically significant, implying that when there are more trips in the morning, they tend to be longer.
- **n_PM (Number of Trips in the Afternoon)**: For each additional trip in the afternoon, the trip duration increases by about 19.12 minutes on average. This is statistically significant and implies that afternoon trips tend to be longer.
- **Interaction Term (n_AM:n_PM)**: The negative coefficient (-0.0920) suggests that as the number of trips in both the morning and afternoon increases, there's a slight decrease in the overall trip duration. However, given the fact that the coefficient is really weak, the impact will be almost imperceptible.

## Business implications

1. **Promotion and Marketing**: If the bike sharing company wants to run promotions, they might consider targeting days when users take longer trips, like Saturdays or holidays.
2. **Resource Allocation**: Understanding that afternoon trips are longer might help in resource allocation, e.g., ensuring bikes are available and well-maintained for the afternoon surge.
3. **Pricing Strategy**: The company can consider dynamic pricing based on the day of the week or if it's a holiday, adjusting prices for longer trip durations on certain days.
4. **Operational Strategy**: The interaction term suggests that on particularly busy days (both morning and afternoon), the average trip duration decreases slightly. This could be due to increased congestion or users taking shorter trips when they notice many bikes are in use.

### Verification of assumptions

#### Normality of residuals




**Histogram of Residuals**: - At first glance, the residuals appear to be roughly normally distributed as the majority of them are centered around zero.

**Normal Q-Q Plot**: - If the residuals were perfectly normally distributed, the points would lie exactly on the diagonal line. - For the most part, the points closely follow the lines, suggesting that the residuals are approximately normally distributed. - Nevertheless, there's a deviation from the line at both the lower and upper ends. This implies that there are some residuals that are more extreme than what we'd expect under a perfect normal distribution, indicating the presence of outliers or potentially heavy tails in the residual distribution.

**Implications**:

- The residuals being approximately centered around zero and their near-normal distribution suggest that the model's assumption of linearity and constant variance (homoscedasticity) are likely met. This is good for the validity of the regression analysis.
- The presence of outliers or extreme values, as indicated by the tails in the histogram and the deviations in the Q-Q plot, might influence the regression results. These influential observations could distort the regression coefficients and reduce the precision of predictions.
- The existence of outliers suggests that it might be beneficial to investigate these specific data points further to determine if they're genuine observations or potential errors. If they're genuine, one might consider robust regression techniques or transformations to minimize their influence.

# Research Question 3: What variables impact the average bixi trip duration?

## Variables Selection

The idea is to identify the driving factors of a bixi trip length when we control for most of the variables.

Average trip duration for members is a good proxy for the revenue they would bring if they were non-members.

Variables that make business sense to include:

From our seasonality analysis we identified: - Season (season) - Temperature in degrees celcius (temp) - Rainfall in mm (rain)

From our daily and weekly pattern analysis we identified: - Part of the week i.e. weekend or weekday (wknd_ind) - If it is a holiday (holiday)

Some other variables that are interesting: - If the user is a member (mem) - Location of the bixi station compared to Parc Lafontaine (North_South) and (West_East) - Proportion of trips in the morning versus the whole day (percent_AM) - total number of trips (n_tot)

Interactions: In our EDA we observed a different week day usage of the member and non members, thus an interaction term between members and day of week would be interesting. (wday*mem).

## Model

```
##
## Call:
## lm(formula = avg ~ season + temp + rain + wknd_ind * mem + holiday +
##     North_South + West_East + n_tot + percent_AM, data = df_main)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -16.925  -3.442  -0.919   2.150  43.083
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         13.769734   0.261207  52.716  < 2e-16 ***
## seasonSpring         2.331761   0.172909  13.485  < 2e-16 ***
## seasonSummer         0.380118   0.181875   2.090  0.03664 *
## temp                 0.143744   0.013388  10.737  < 2e-16 ***
## rain                -0.125413   0.011991 -10.459  < 2e-16 ***
## wknd_indWeekend      2.638923   0.197185  13.383  < 2e-16 ***
## mem1                -0.385385   0.168773  -2.283  0.02242 *
## holiday1             1.069557   0.415570   2.574  0.01008 *
## North_SouthSouth     0.355471   0.125786   2.826  0.00472 **
## West_EastWest       -0.234144   0.131813  -1.776  0.07571 .
## n_tot               -0.055315   0.003098 -17.855  < 2e-16 ***
## percent_AM          -2.351044   0.307849  -7.637 2.43e-14 ***
## wknd_indWeekend:mem1 -1.868383   0.272843  -6.848 7.94e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.169 on 9987 degrees of freedom
## Multiple R-squared:  0.1252, Adjusted R-squared:  0.1241
## F-statistic: 119.1 on 12 and 9987 DF,  p-value: < 2.2e-16
```

## Interpretation

**Overall Model -** The model explains approximately 12.52% of the variation in the average trip duration. which means that other factors are also at play and not included in the model.

**Intercept -** The interpretation of the intercept does not make sense in this case since the number of trips would have to be zero.

**Coefficients - Season**: The reference level is fall. We can see that on average trip duration during spring and summer are respectively 2.33 and 0.38 minutes longer than in fall holding everything else constant.

- **Temperature**: The coefficient of temperature is 0.14 which means that an increase in temperature of 1 degree celcius corresponds to an increase of average trip duration of 0.14 minutes on average holding all else constant.
- **Rainfall**: The coefficient for rain is -0.12 which means that an increase in rainfall of 1 mm corresponds to a decrease of average trip duration of 0.12 minutes on average holding all else constant.
- **Effect of Weekend Indicator and membership**: Since there exists an interaction between both variables, it is no longer possible to interpret one without the other. This implies that the relation between average trip duration and membership is different depending on the moment of the week. The opposite is also true, the relation between average trip duration and the moment of the week is different depending on the membership status.
- Weekend indicator's coefficient 2.638923 is the average difference between average trip duration during weekend and weekday for non-members. In other words, for non-members, average trip duration is higher on average than for members holding all else constant.
- Membership's coefficient -0.385385 is the average difference between average trip duration for members and non-members for weekdays. In other words, during weekdays, the average trip duration is shorter on average for members than for non-members holding all else constant.
- Interaction term's coefficient -1.868383 is ...
- **Holiday**: The coefficient for holiday is 1.069557 which means that during holidays average trip duration is 1.069 minutes higher on average than during non-holidays, holding all else constant.
- **North_South and West_East**: Their coefficients are 0.35 and -0.23 which means that on average the average trip duration for trips starting at a station South of Parc Lafontaine or West is 0.35 and -0.23 minutes different from their counter parts respectively, holding all else constant.
- **Total number of trips**: The coefficient is -0.055315 which means that on average as number of trips increase, the average trip length in minutes decreases, holding all else constant.
- **Percent AM**: The magnitude of the coefficient -2.351044 is less important than its sign for our interpretation. What it means is that as the proportion of trips in the morning increases, the average trip duration generally decreases when holding all else constant. This hints that trips in the morning might be shorter on average than trip in the afternoon, hence bring in less revenue.

## Business Implications:

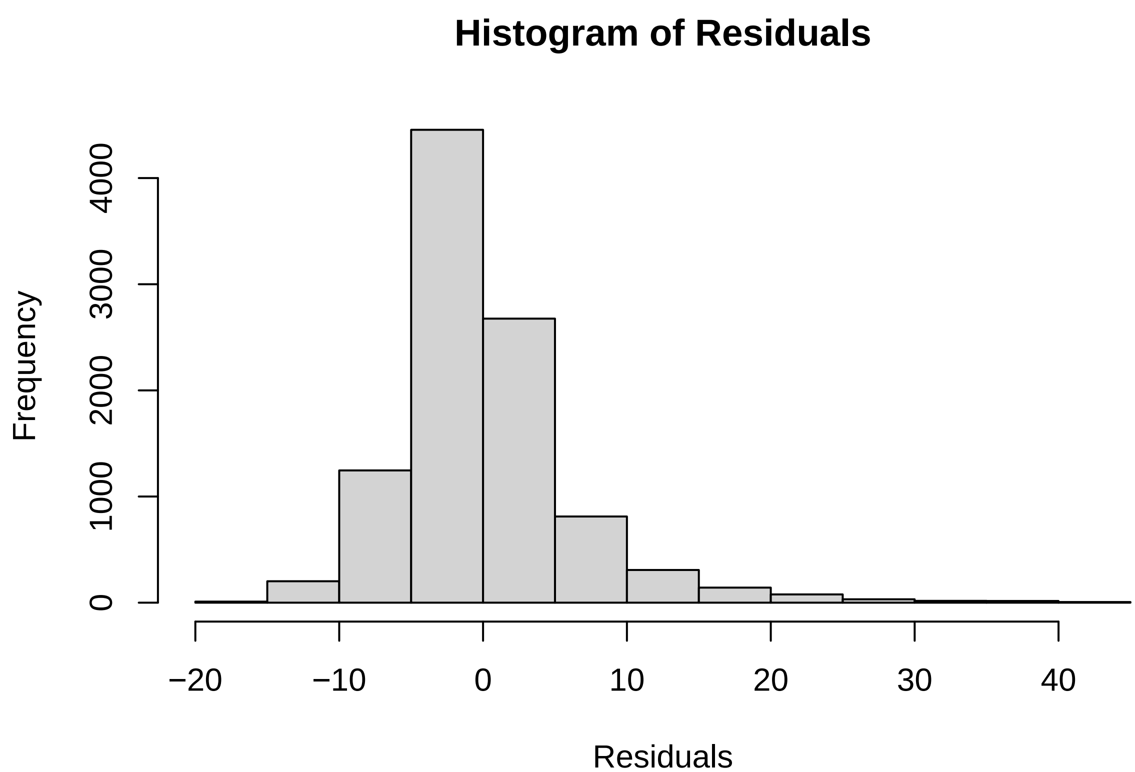
1. **Promotion and Marketing**: For the same temperature, average trip length tends to be the longest in spring. This indicates that users are eager to use bikes after winter. This insight could be used for promotion purposes.
2. **Resource Allocation**: Expect longer trips when it is hot and non-rainy outside. Even more if it is a weekend or holiday. Also, bikes tend to be borrowed longer during the afternoon than in the morning. Stations south of Parc Lafontaine have on average longer trip duration, which may suggests that stations are further from one another. There might be some space for additional stations.

3. **Pricing Strategy**: The usage that is associated with the longest trip length based on our interaction term is for non-members during the weekend. Charging a heftier price for these people at that time may increase profit margins significantly.

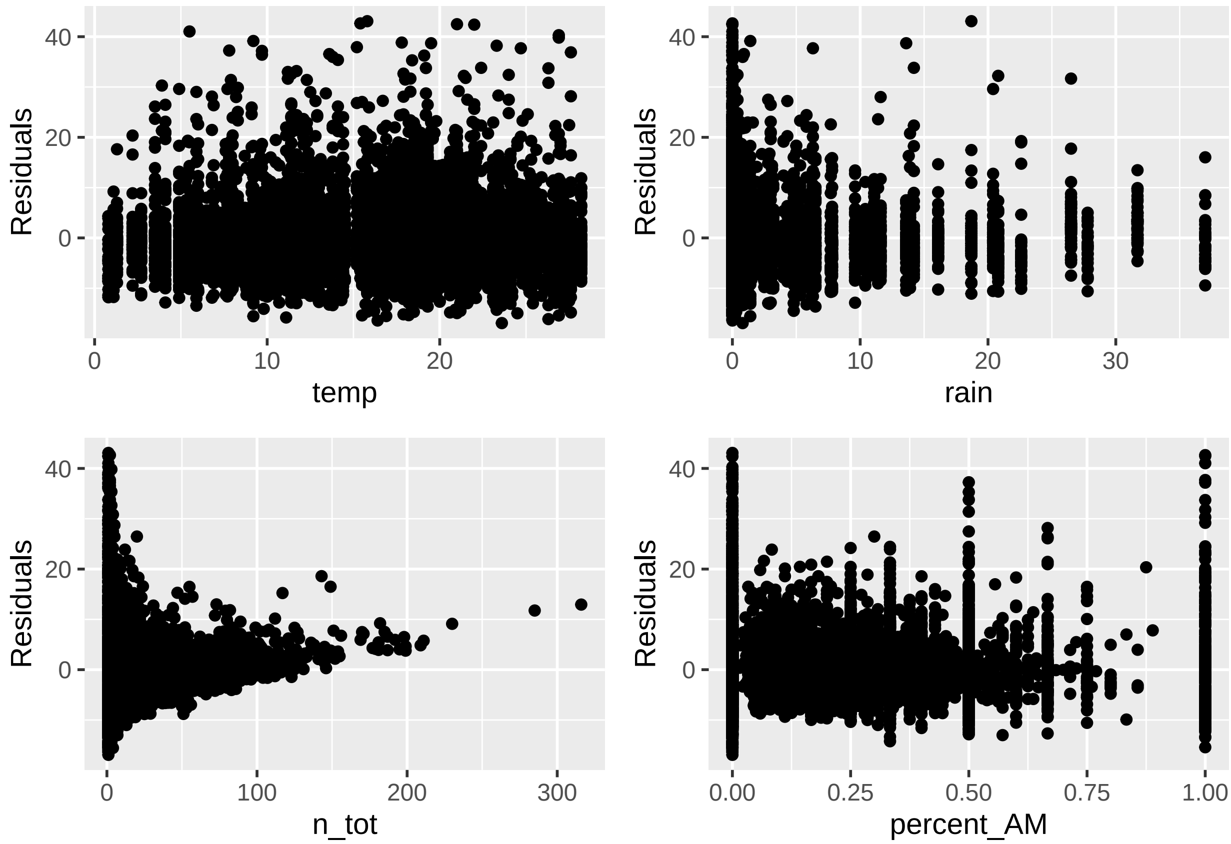
4. **Operational Strategy**: It is important to keep in mind the tradeoff between the number of trips and the average trip length. Indeed, as the number of trips increase for a given day, the average trip length decreases. This may suggest that the additional trips during those days are short haul.

## Verification of assumptions

### Verification of Normality of Residuals



**Verificaiton of Heteroscedasticity**




# Exploratory Regression

## AM/PM Delta

```
model <- lm(n_AM_PM_delta ~ long_wknd_ind + season + rain_ind + mem, data = df_main) # Goal is to look
summary(model)
```

```
##
## Call:
## lm(formula = n_AM_PM_delta ~ long_wknd_ind + season + rain_ind +
##     mem, data = df_main)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -117.382   -2.083    1.433    4.928   24.147
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -4.1407     0.8188  -5.057 4.33e-07 ***
## long_wknd_indWeekday     1.7079     0.8182   2.087   0.0369 *
```

```
## long_wknd_indWeekend   0.4048     0.8293   0.488   0.6255
## seasonSpring          -0.1763     0.2692  -0.655   0.5126
## seasonSummer          -1.5288     0.2199  -6.951 3.86e-12 ***
## rain_indRain           1.6899     0.2006   8.424  < 2e-16 ***
## mem1                  -8.1851     0.1951 -41.950  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.726 on 9993 degrees of freedom
## Multiple R-squared:  0.1587, Adjusted R-squared:  0.1582
## F-statistic: 314.2 on 6 and 9993 DF,  p-value: < 2.2e-16
```

## Trip length wkday/wknd

```r
#df_main
# SHORTER TRIPS ON WEEKDAYS THAN WEEKENDS
model <- lm(avg ~ long_wknd_ind + season + rain_ind + mem, data = df_main)
summary(model)
```

```
##
## Call:
## lm(formula = avg ~ long_wknd_ind + season + rain_ind + mem, data = df_main)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.872  -3.611  -1.152   2.113  43.681
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            16.1900     0.5321  30.429  < 2e-16 ***
## long_wknd_indWeekday  -1.0186     0.5317  -1.916   0.0554 .
## long_wknd_indWeekend   0.6199     0.5389   1.150   0.2501
## seasonSpring           2.8607     0.1749  16.353  < 2e-16 ***
## seasonSummer           1.6624     0.1429  11.631  < 2e-16 ***
## rain_indRain          -1.0075     0.1304  -7.728  1.2e-14 ***
## mem1                  -2.4147     0.1268 -19.044  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.321 on 9993 degrees of freedom
## Multiple R-squared:  0.0812, Adjusted R-squared:  0.08064
## F-statistic: 147.2 on 6 and 9993 DF,  p-value: < 2.2e-16
```

## trip length for members/non-members

```r
# MEMBERS TAKE SHORTER TRIPS
# MEMBERS TAKE LONGER TRIPS IN THE RAIN
model <- lm(avg ~ (rain_ind *mem) + long_wknd_ind, data = df_main)
summary(model)
```

```
##
## Call:
## lm(formula = avg ~ (rain_ind * mem) + long_wknd_ind, data = df_main)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.676  -3.701  -1.221   2.310  43.073
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            17.2772     0.5396  32.021  < 2e-16 ***
## rain_indRain           -1.4170     0.1938  -7.312 2.84e-13 ***
## mem1                   -2.5621     0.1633 -15.693  < 2e-16 ***
## long_wknd_indWeekday  -0.7002     0.5362  -1.306   0.1916
## long_wknd_indWeekend   0.9991     0.5438   1.837   0.0662 .
## rain_indRain:mem1      0.5474     0.2647   2.068   0.0387 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.411 on 9994 degrees of freedom
## Multiple R-squared:  0.05475,    Adjusted R-squared:  0.05428
## F-statistic: 115.8 on 5 and 9994 DF,  p-value: < 2.2e-16
```

### Revenue per trip: seasonal effect

```r
#HIGHER REVENUE PER TRIP IN SPRING AND SUMMER THAN WINTER
model <- lm(rev_per_trip ~ long_wknd_ind + season + rain_ind, data = df_main)
summary(model)
```

```
##
## Call:
## lm(formula = rev_per_trip ~ long_wknd_ind + season + rain_ind,
##     data = df_main)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.5592 -0.6838 -0.1753  0.4379  6.5634
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            3.60460    0.13423  26.854  < 2e-16 ***
## long_wknd_indWeekday -0.16215    0.13525  -1.199    0.231
## long_wknd_indWeekend  0.19319    0.13702   1.410    0.159
## seasonSpring           0.58644    0.04544  12.905  < 2e-16 ***
## seasonSummer           0.32748    0.03601   9.094  < 2e-16 ***
## rain_indRain          -0.18870    0.03346  -5.639 1.81e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.105 on 4728 degrees of freedom
##   (5266 observations deleted due to missingness)
## Multiple R-squared:  0.06704,    Adjusted R-squared:  0.06605
```

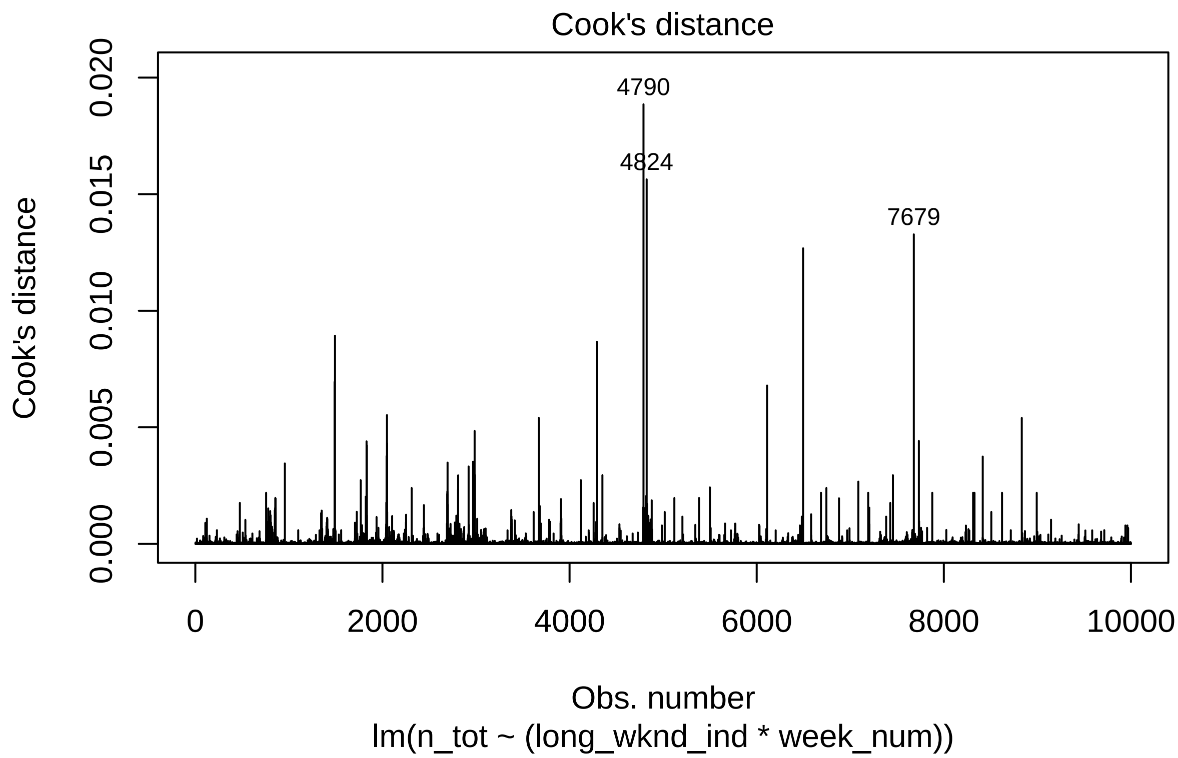
```
## F-statistic: 67.95 on 5 and 4728 DF,  p-value: < 2.2e-16
```

### Number of trips as season advances

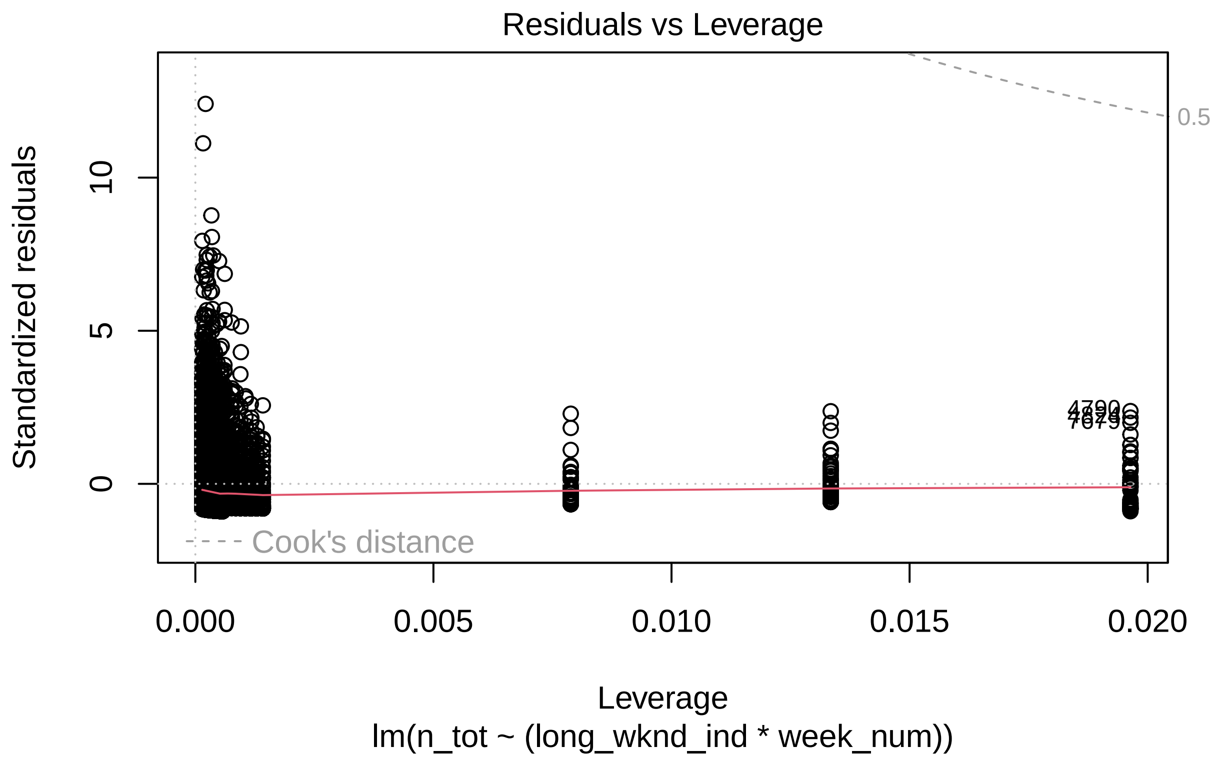
```r
#df_main
# AS BIXI SEASON GOES ON, WEEKDAY NUMBER OF TRIPS GO UP WITH A STATISTICAL SIGNIFICANCE
model <- lm(n_tot ~ (long_wknd_ind*week_num), data = df_main)
summary(model)
```

```
##
## Call:
## lm(formula = n_tot ~ (long_wknd_ind * week_num), data = df_main)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -21.290 -15.548  -8.577   6.966 294.938
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   29.4754     7.7757   3.791 0.000151 ***
## long_wknd_indWeekday         -13.4649     7.8444  -1.716 0.086103 .
## long_wknd_indWeekend          -8.7238     7.9243  -1.101 0.270971
## week_num                      -0.3531     0.2302  -1.534 0.125152
## long_wknd_indWeekday:week_num   0.4896     0.2325   2.106 0.035231 *
## long_wknd_indWeekend:week_num   0.3068     0.2353   1.304 0.192407
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.77 on 9994 degrees of freedom
## Multiple R-squared:  0.002469,   Adjusted R-squared:  0.001969
## F-statistic: 4.946 on 5 and 9994 DF,  p-value: 0.0001588
```

```r
plot(model,4)
```




```r
plot(model,5)
```




## Limitations and shortcomings

- Causation vs. Correlation: The regression model captures relationships but does not establish causation.
- Data Exclusions: The data only considers trips under 60 minutes, which might exclude a segment of users who use BIXI for longer journeys.
- Other External Factors: Events, road conditions, or public transportation disruptions can affect BIXI usage but are not captured in the dataset.
- Mention Auto-correlation (Chike)

## Conclusion

## Contribution

Charles Julien :

Gabriel Jobert :

Chike Odenigbo:

Atul Sharma: