Appendix: Pedestrians on the Brooklyn Bridge

Brief Description of Dataset:

Our dataset is called the **Brooklyn Bridge Automated Pedestrian Counts Demonstration Project**. It is publicly available through **NYC Open Data** and can be found at this link: https://data.cityofnewyork.us/Transportation/Brooklyn-Bridge-Automated-Pedestrian-Counts-Demons/6fi9-q3ta/about_data. The New York City Department of Transportation is testing automated technology to count pedestrians, and this dataset keeps track of all records. The records are taken hourly from a counter located on the Manhattan approach of the Brooklyn Bridge. It contains **16,100 entries** with **12 variables**; however, we did not utilize all of the variables.

The columns included in the dataset are hour_beginning, location, Pedestrians (sum of towards Manhattan and towards Brooklyn), Pedestrians Toward Brooklyn, weather_summary (a categorical variable), temperature, precipitation, latitude, longitude, events, and Location1. We dropped the following columns: Towards Manhattan, Towards Brooklyn, location, latitude, longitude, and Location1. Events is a column that indicates whether there is a holiday that may affect the number of people walking on the bridge. We changed this column to has_event, a categorical column with a value of 1 for an event and 0 for no event.

Our Final Variables: Pedestrians (y), weather_summary, temperature, precipitation, has_event, hour, weekday, and month

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Our Code:

```
 #imported the file as pedestrians, include headeres, do NOT select as factor
df = pedestrians

#dropping useless cols
df$Towards.Brooklyn = NULL
df$Towards.Manhattan = NULL
df$lat = NULL
```

```
df$long = NULL
df$location = NULL
df$Location1 = NULL
#------------------------------------------------------------------------------
#this is checking the unique values for each col so we can see the NAs. I ran these lines after to see if there were still NAs
unique_values <- unique(df$weather_summary)
unique_values
unique_valuestemp <- unique(df$temperature)

#------------------------------------------------------------------------------
#changing event column to be boolean
df$has_event <- ifelse(df$events == "" | is.na(df$events), 0, 1)
df$events <- NULL

#dropping NAs for specified cols.
#this is every column except events because events
df_clean <- df[complete.cases(df$hour_beginning, df$Pedestrians, df$weather_summary, df$temperature), ]
unique_valuestemp <- unique(df_clean$temperature)
df <- df[df$weather_summary != "", ]

#setting our working dataset to df_clean now
df = df_clean

#------------------------------------------------------------------------------

#Converting Ped. Count to numeric had to remove commas because they were being treated as chars
df$Pedestrians <- as.numeric(gsub(",", "", df$Pedestrians))

#quick check
uniques <- unique(df$Pedestrians)
uniques

#weather needs to be factor
df$weather_summary <- as.factor(df$weather_summary)
#------------------------------------------------------------------------------

#checking what type of events there are
```

```
uniques <- unique(df$events)

#df$events<-as.factor(df$events)
df$hour_beginning <- as.POSIXct(df$hour_beginning,format = "%Y %b %d %I:%M:%S %p")
df$hour <- lubridate::hour(df$hour_beginning)
df$weekday <- lubridate::wday(df$hour_beginning, label = TRUE)
df$month <- lubridate::month(df$hour_beginning, label = TRUE)
df$hour_beginning <- NULL

#-----------------------------------------------------------------------------
#make base model to see what the R2 is and run variable selection.
base_model <- lm(Pedestrians ~ ., data=df)
summary(base_model)
#our F score shows our model is significant enough to use! p-val < 2.2e-16

#variable selection:
library(olsrr) #variable screening package
ols_step_both_p(base_model, penter=0.05, prem=0.1, details=TRUE)
#variable selection confirms keeping all variables. R^2 adjusted is .59 now

#-----------------------------------------------------------------------------
#PLOTTING to determine transformations on x and higher order terms
library(ggplot2)
ggplot(df, aes(x = temperature, y = Pedestrians)) +
geom_point(color = "blue") +
geom_smooth(method = "lm", se = FALSE, color = "red") +
labs(title = "Temperature vs Pedestrians", x = "Temperature", y = "Pedestrians")
#shows a linear trend

ggplot(df, aes(x = weather_summary, y = Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Weather Summary vs Pedestrians", x = "Weather Summary", y = "Pedestrians")

ggplot(df, aes(x = precipitation, y = Pedestrians)) +
  geom_point(color = "blue") +
  labs(title = "Precipitation vs Pedestrians", x = "Precipitation", y = "Pedestrians")

#applying this transformation to make it a more linear trend
#tries to linearize relationship a bit. does spread it out more. Not fully.
```

```
#In the model there should be a higher order term on precipitation.
ggplot(df, aes(x = sqrt(precipitation), y = Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Square Root of Precipitation vs Pedestrians", x = "Sqrt(Precipitation", y =
"Pedestrians")

#Conclusion here: Looks like a higher order term would help fit model better. Hour^3/ Hour^2
ggplot(df, aes(x = hour, y =Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Hour vs Pedestrians", x = "Hour", y = "Pedestrians")

ggplot(df, aes(x = month, y =Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Month vs Pedestrians", x = "Hour", y = "Pedestrians")

ggplot(df, aes(x = weekday, y =Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Weekday vs Pedestrians", x = "Hour", y = "Pedestrians")

ggplot(df, aes(x = has_event, y =Pedestrians)) +
  geom_point(color = "blue") +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  labs(title = "Has event vs pedestrians", x = "Has Event", y = "Pedestrians")


#____________________________________________________________________
#Now we have to test correlation between all our variables. Using Variable Inflation Scores
#i have to use the base model here because higher order terms were in my other models
library(car)
vif(base_model)
#No signification VIF scores. all less than 10.
#____________________________________________________________________

#lets rerun base model again
base_model <- lm(Pedestrians ~ weather_summary + temperature + precipitation + has_event
+hour + weekday + month, data=df)
```

```
summary(base_model) #R^2 adjusted is 0.5878

#apply the precipitation transformation from graph and add a higher order term for precipitation
df$precipitation = sqrt(df$precipitation)
second_model <- lm(Pedestrians ~ . + I(precipitation^2), data=df)
summary(second_model) #R^2 adjusted is 0.5901, not much of a change

#apply the higher order terms on hour
third_model <-lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3), data=df)
summary(third_model) #much better R^2 adjusted. R^2 adjusted is 0.7116

#going to try adding some interaction terms
#temperature and hour probably interact....
#does the effect of temperature depends on the time of day?
fourth_model <- lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3) +
temperature:hour, data=df)
summary(fourth_model)  #adjusted R^2 only went up a bit. Now it's 0.7191

#interaction of temperature and added event. R^2 adjusted is more or less the same.
bad_model <- lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3) + temperature:hour
+ temperature:has_event, data=df)
summary(bad_model)  #adjusted R^2 is 0.7195

#adding an interaction term for weather summary and hour.
#rain does not have the same effect at all hours. same for every other weather summary
possibility
fifth_model <- lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3) +
temperature:hour + weather_summary:hour, data=df)
summary(fifth_model) #R^2 adjusted here is 0.7437

#adding an interaction term for temperature and has event.
#temperature doesnt necessarily have the same effect on an event vs no event.
sixth_model <- lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3) +
temperature:hour + weather_summary:hour + temperature:has_event, data=df)
summary(sixth_model) #R^2 adjusted here is 0.744. Not worth adding the interaction term

#at this point we have tested all interaction terms we think may exist. These are the ones that we
kept
final_model <- lm(Pedestrians ~ . + I(precipitation^2) + I(hour^2) + I(hour^3) +
temperature:hour + weather_summary:hour, data=df)
```

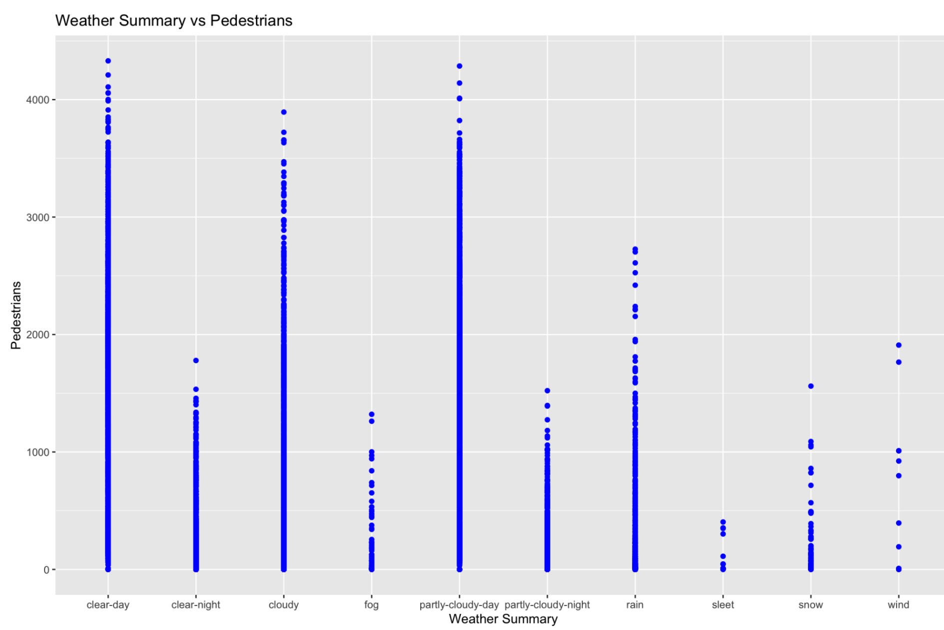
```
summary(final_model) #final R^2 adjust here is 0.7437




#---------------------------------------------
install.packages("lmtest")
library(lmtest)

#running the Durbin-Watson d-Test for correlation since this deals with time.
#d ~ 2, residuals are uncorrelated
dwtest(final_model)

#----------------------------------------------------------------------------
#RESIDUAL ANALYSIS
# plotting the residuals vs the variable "temperature":
plot(df$temperature, resid(final_model),
    xlab = "Temperature",
    ylab = "Regression Residuals",
    main = "Regression Residuals vs Temperature")
# adding a horizontal reference line at residual = 0 to the plot
abline(h = 0, col = "red")
#Residuals seem to be more or less randomly distributed. This is good.

# plotting the residuals vs the variable "hour" for the second model:
plot(df$hour, resid(final_model),
    xlab = "hour",
    ylab = "Regression Residuals",
    main = "Regression Residuals vs Hour")
# adding a horizontal reference line at residual = 0 to the plot
abline(h = 0, col = "red")
#This shows an issue with our model. Residuals are not random around hour.
#This may be because its not treating the hour as a cycle. hour 23 is only 1 hour away from hour
0
#Instead of applying a transformation, we will make the hour a factor that way they are treated
separately.
dfHour_asFactor = df
dfHour_asFactor$hour <- as.factor(df$hour)
seventh_model  <- lm(Pedestrians ~ . + I(precipitation^2) + temperature:hour,
data=dfHour_asFactor) #note: got rid of the last interaction term because it was giving NAs
```

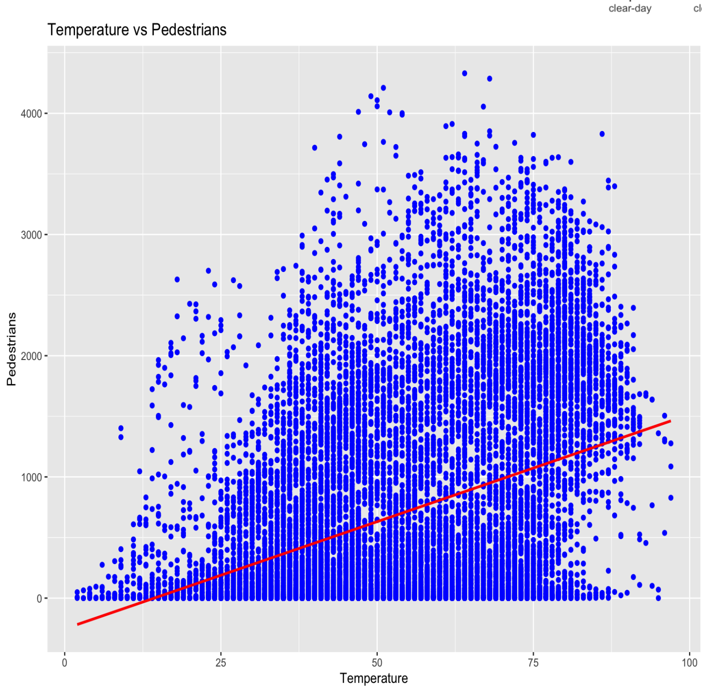
```
summary(seventh_model) #this model performs the best. It has an R^2 adjusted of 0.8181
#we got rid of the higher order terms on hour in this situation
#Now, every hour is technically allowed to have a different residual behavior

#lets keep moving with seventh_model and hour being treated as a factor
df = dfHour_asFactor
final_model <- lm(Pedestrians ~ . + I(precipitation^2) + temperature:hour,
data=dfHour_asFactor)
summary(final_model)

#not fair to judge based off of just precipitation, there are higher order terms
# plotting the residuals vs the precipitation:
plot(df$precipitation, resid(final_model),
    xlab = "1/Precipitation",
    ylab = "Regression Residuals",
    main = "Regression Residuals vs 1 over precipitation")
# adding a horizontal reference line at residual = 0 to the plot
abline(h = 0, col = "red")

#code from notes
plot(df$Pedestrians, resid(final_model),
    xlab = "Pedestrians",
    ylab = "Residuals",
    main = "Residuals vs Pedestrians")
abline(h = 0, col = "red", lwd = 2)
#very skewed increasing residuals as pedestrians increase
#multiplicative error?
#applying log transformation

plot(log(df$Pedestrians), resid(final_model),
    xlab = "Pedestrians",
    ylab = "Residuals",
    main = "Pedestrians vs Residuals")
abline(h = 0, col = "red", lwd = 2)
#log transformation definitely helped randomize our residuals.

dfcopy = df
dfcopy$Pedestrians = log(dfcopy$Pedestrians +1 ) #have to add 1 because log doesnt take in 0
final_model <- lm(Pedestrians ~ . + I(precipitation^2) + temperature:hour, data=dfcopy)
summary(final_model) #adjusted R-squared is now 0.853 because of transformation.
```

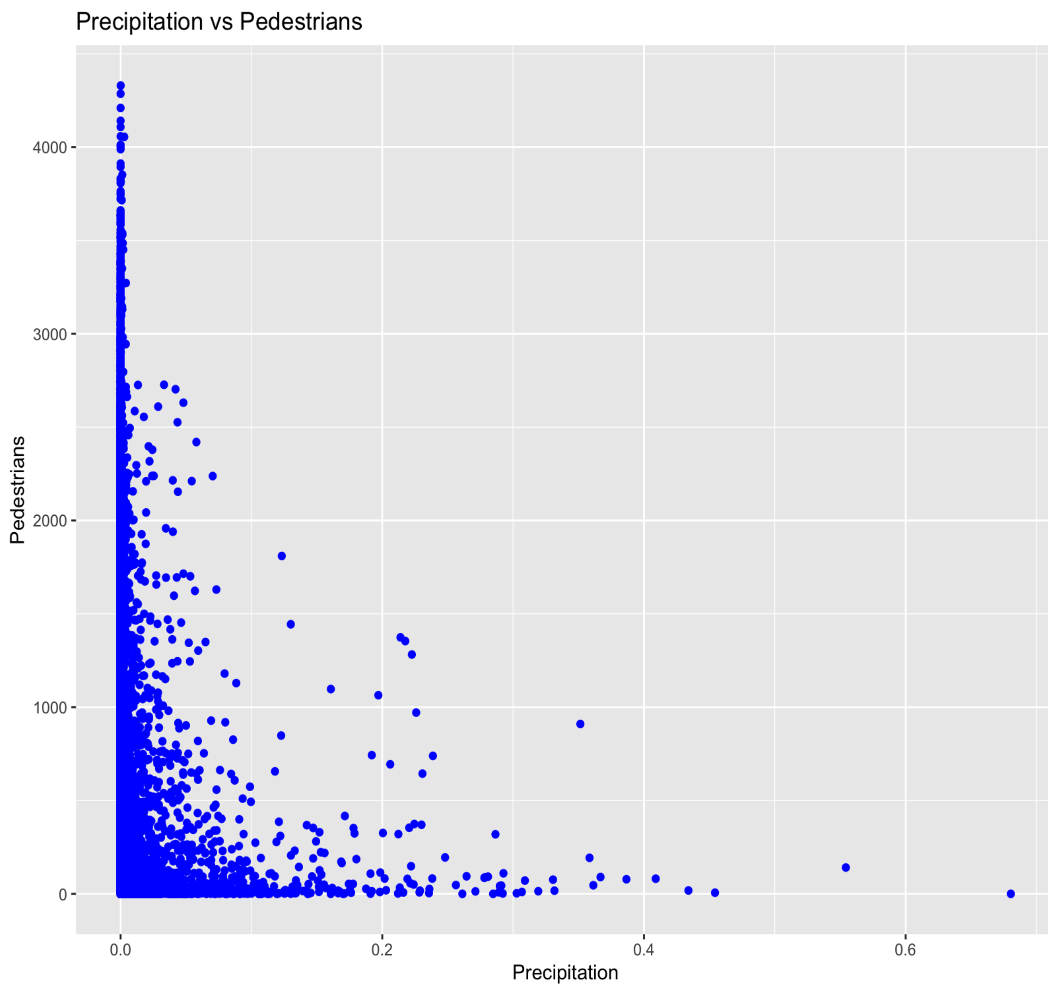
Note: The goal of our project is to make predictions, not to interpret the model. We chose to use a simpler base model in our presentation for interpretation. The code above shows models with higher order terms, interaction terms, and transformations on our x's and Pedestrian count variable (y)

Our Plots:

- Counts of Pedestrians across our variables; one blue dot represents one entry.

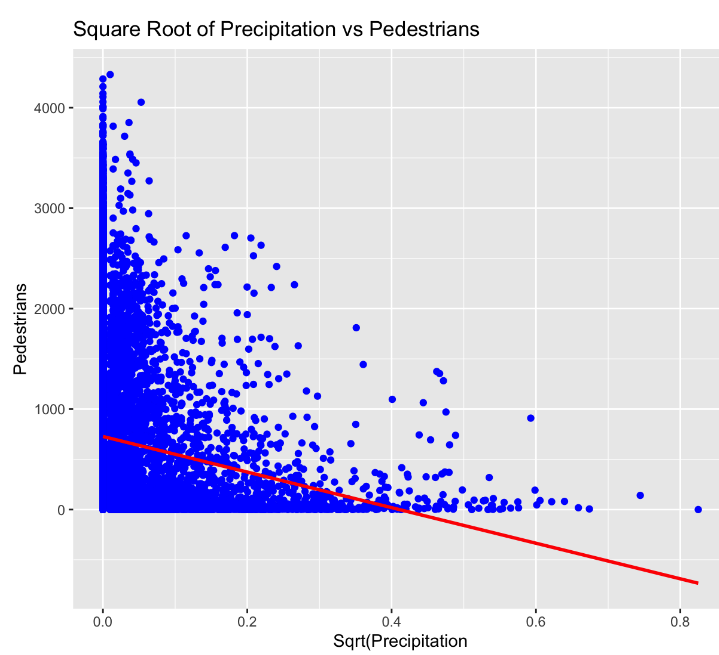


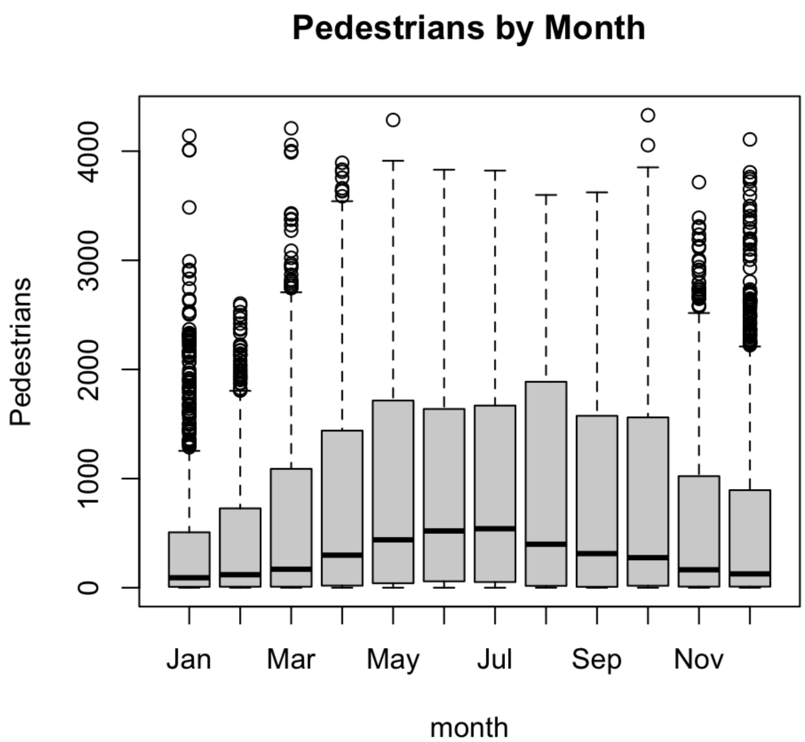


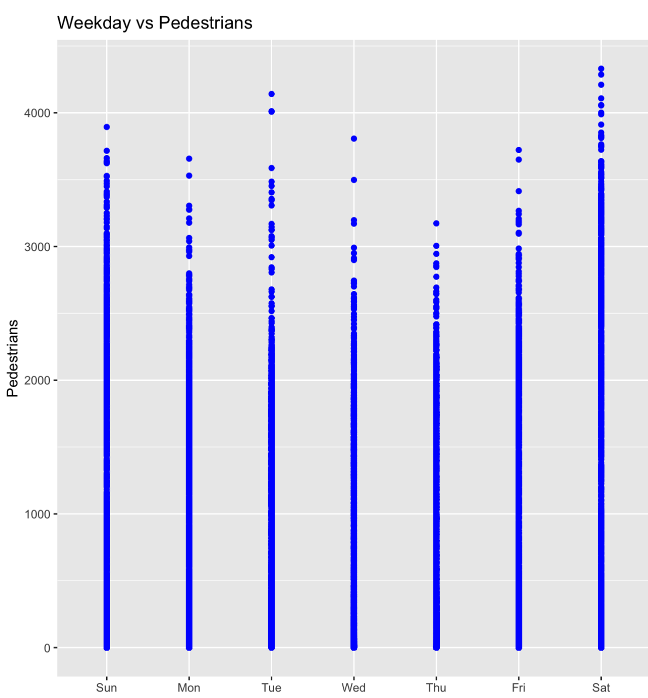


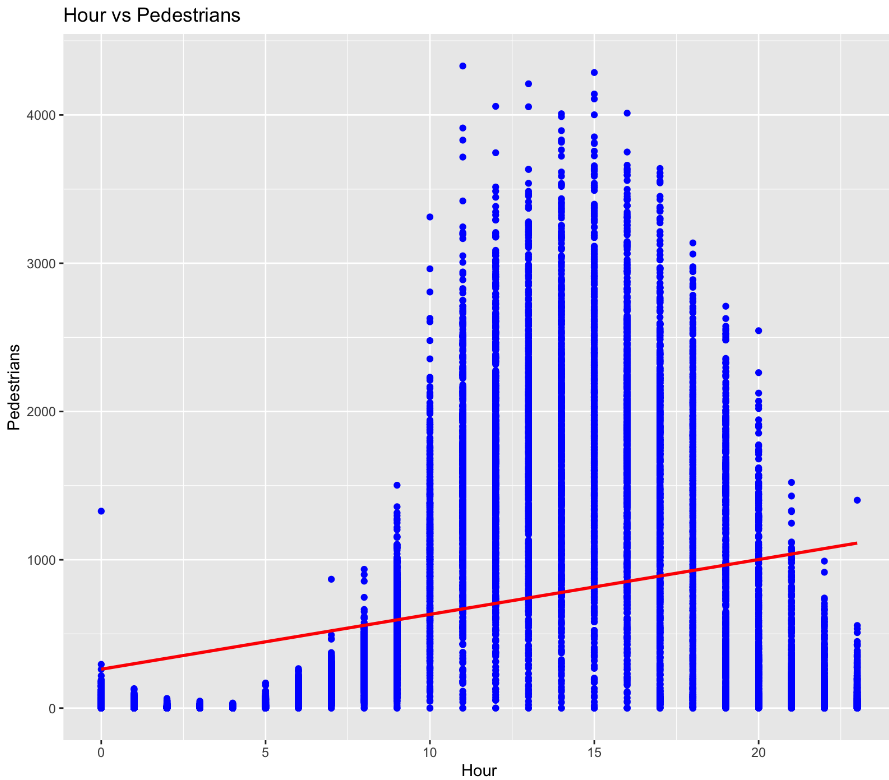
- The plot above led us to transform the Precipitation variable. We transformed it to be precipitation = square root of precipitation

- Definitely more linear in the figure to the right, but we decided we would also introduce a higher order term for precipitation.



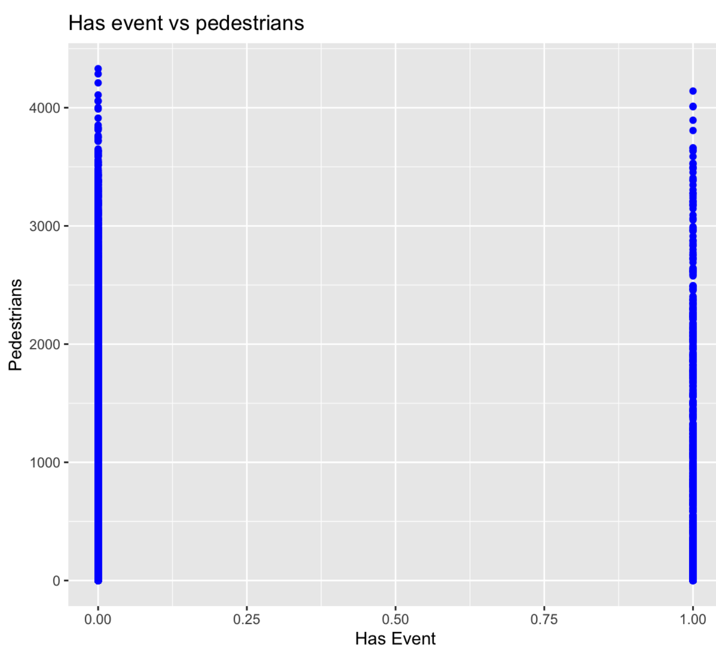

Pedestrians by Month
Pedestrians
0
1000
2000
3000
4000
Jan
Mar
May
Jul
Sep
Nov
month

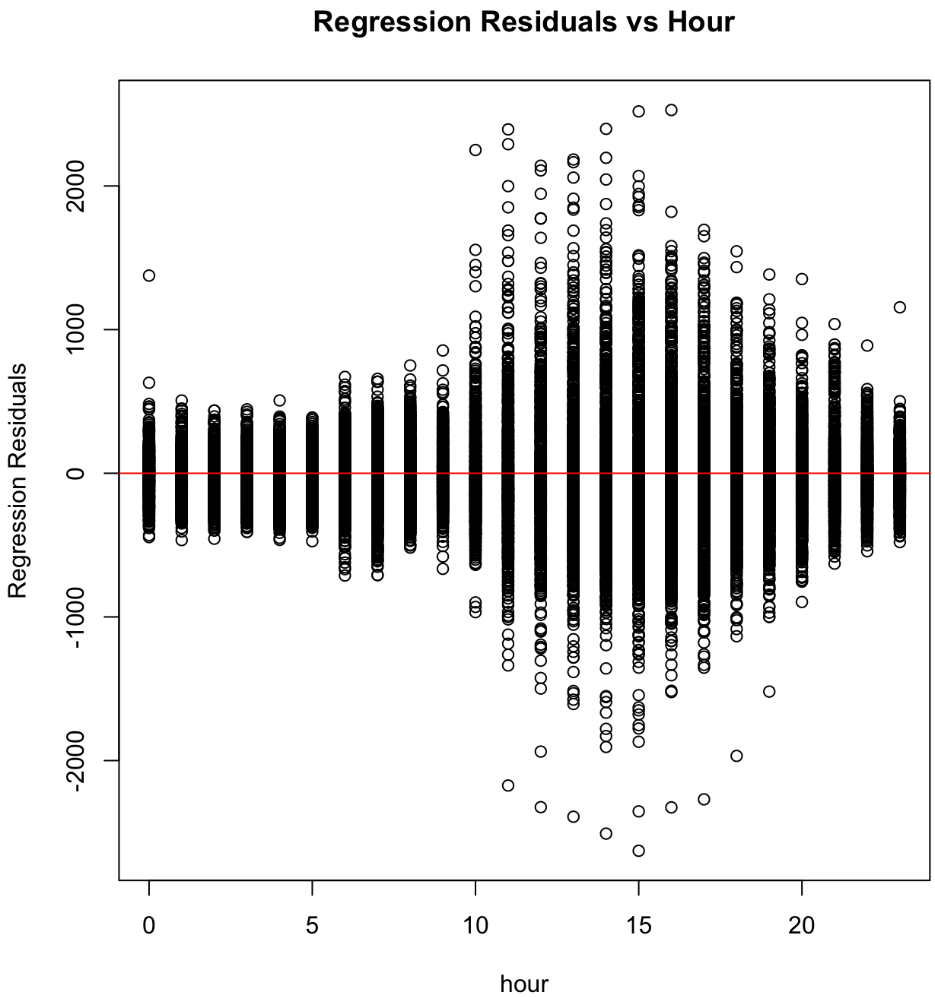

Weekday vs Pedestrians
Pedestrians
0
1000
2000
3000
4000
Sun
Mon
Tue
Wed
Thu
Fri
Sat
Hour



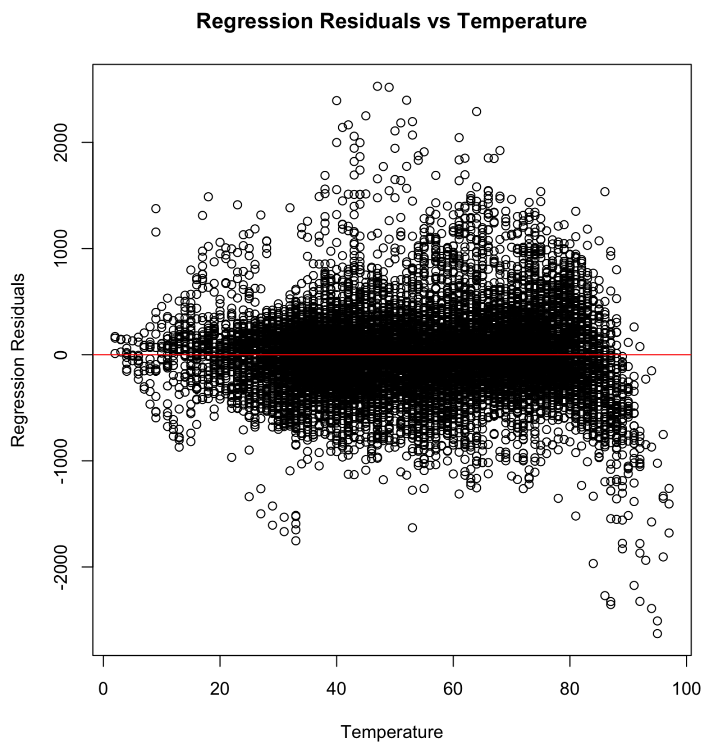
- The hour variable seemed to be cyclic. At first, we introduced higher-order terms such as x^2 and x^3 to help with this trend, while the R^2 adjusted showed an increase in performance, our residuals relative to the hour variable were not showing a random distribution.

-

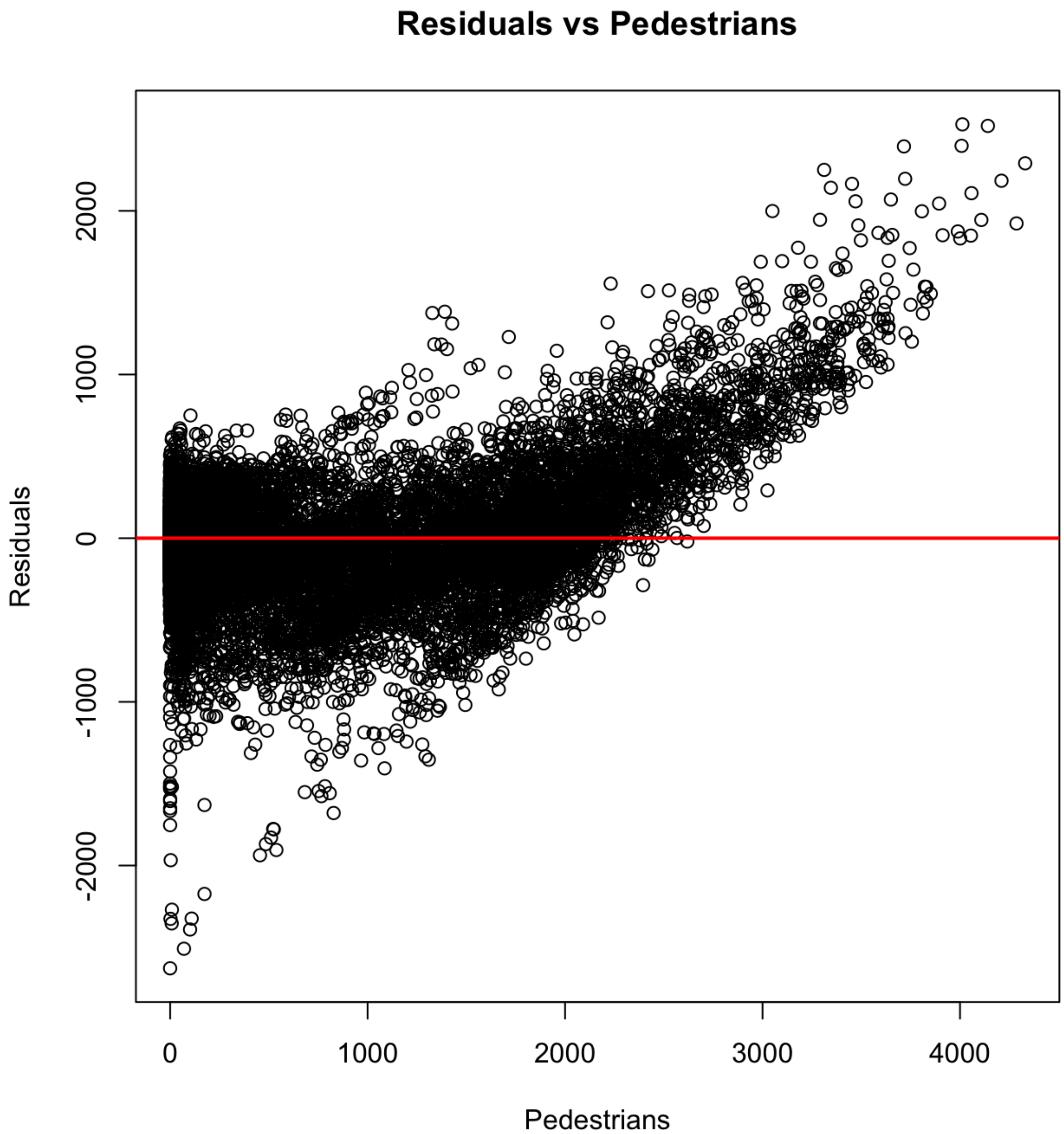




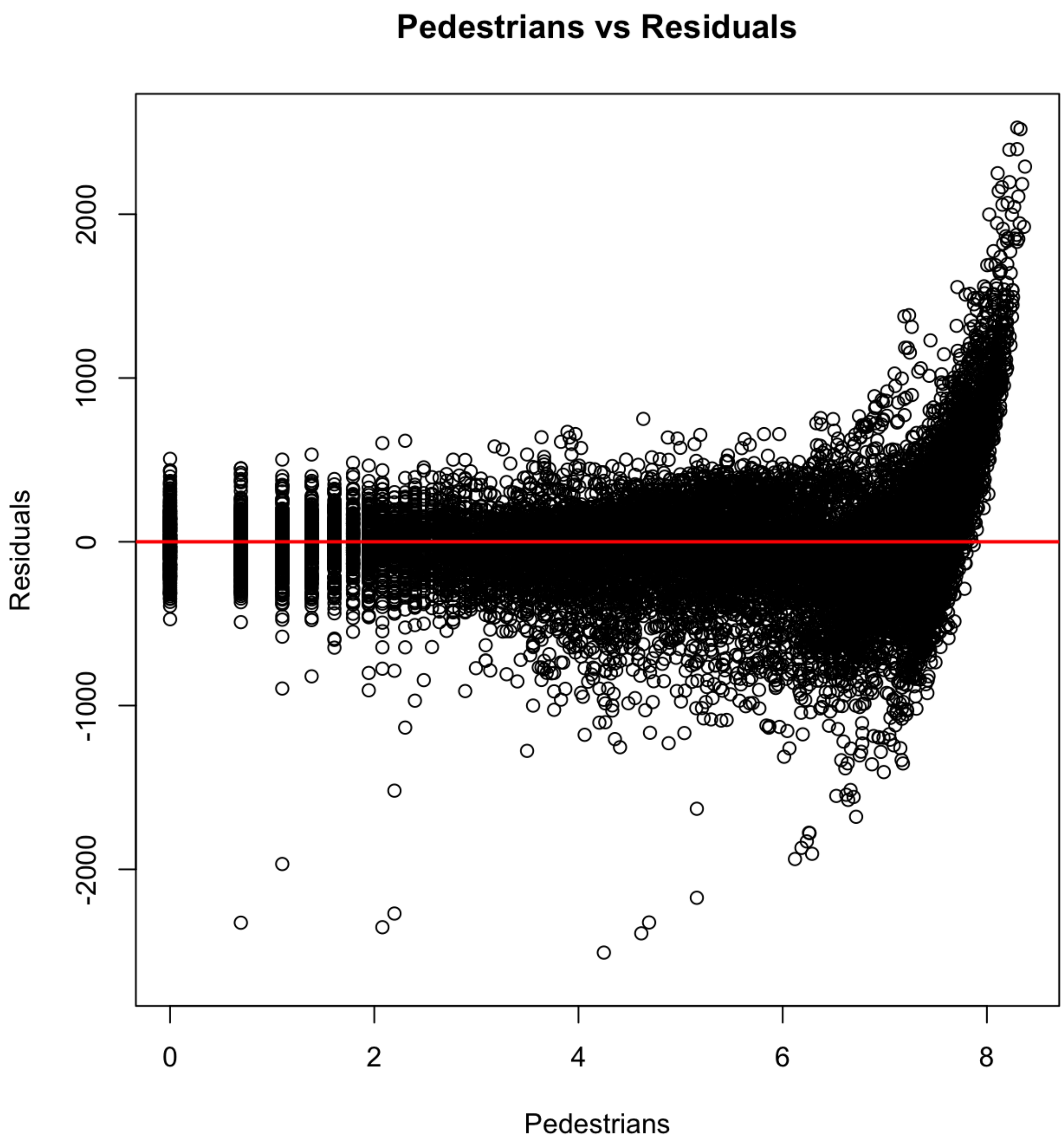
- Regression residuals are not randomly distributed. This led us to change the hour variable into a categorical variable where each hour can be treated separately. This increased our R^2 adjusted to about 0.81, but this was not our final model.



- This plot shows a more or less random distribution of residuals around the temperature variable.



- This is a plot of the Residuals relative to the number of pedestrians. The closest type of response we saw in this was the multiplicative response. So, we decided to apply the log transformation on the pedestrians variable to see if that would help.



- This plot is from after we applied the log transformation to pedestrians. Residuals are more randomly distributed.

Our final model before the transformation on Pedestrians:

```
lm(formula = Pedestrians ~ . + I(precipitation^2) + temperature:hour,
    data = dfHour_asFactor)

Residuals:
     Min       1Q   Median       3Q      Max 
-2627.89  -183.63    -5.36   157.95  2528.55 

Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                          551.6780    50.5618  10.911  < 2e-16 ***
weather_summaryclear-night          -490.5684    13.5337 -36.248  < 2e-16 ***
weather_summarycloudy               -402.9876    11.4774 -35.111  < 2e-16 ***
weather_summaryfog                  -512.5531    43.3851 -11.814  < 2e-16 ***
weather_summarypartly-cloudy-day     -94.0359     9.5340  -9.863  < 2e-16 ***
weather_summarypartly-cloudy-night  -492.4687    14.0197 -35.127  < 2e-16 ***
weather_summaryrain                 -453.8230    24.2382 -18.723  < 2e-16 ***
weather_summarysleet                -645.2121   100.8237  -6.399 1.60e-10 ***
weather_summarysnow                 -444.7883    41.9040 -10.614  < 2e-16 ***
weather_summarywind                 -510.1055   106.7736  -4.777 1.79e-06 ***
temperature                           -0.3691     0.9101  -0.406 0.685090    
precipitation                      -1957.4437   141.1402 -13.869  < 2e-16 ***
has_event                             60.4785    11.7247   5.158 2.52e-07 ***
hour1                                -16.9620    63.8237  -0.266 0.790425    
hour2                                -10.1042    63.7241  -0.159 0.874016    
hour3                                -13.0998    63.4532  -0.206 0.836444    
hour4                                -14.9907    63.3150  -0.237 0.812843    
hour5                                -41.8586    63.1792  -0.663 0.507636    
hour6                                133.1337    63.3359   2.102 0.035567 *  
hour7                                 25.7790    62.7357   0.411 0.681141    
hour8                               -338.4045    63.6766  -5.314 1.08e-07 ***
hour9                               -238.1254    64.0953  -3.715 0.000204 ***
hour10                                35.4831    64.4830   0.550 0.582141    
hour11                               305.2628    64.9508   4.700 2.62e-06 ***
hour12                               423.9641    65.3810   6.485 9.16e-11 ***
hour13                               523.3348    65.7057   7.965 1.77e-15 ***
hour14                               536.5153    66.0356   8.125 4.81e-16 ***
hour15                               597.8051    65.9941   9.058  < 2e-16 ***
hour16                               399.6273    65.7432   6.079 1.24e-09 ***
hour17                              -238.0244    64.6096  -3.684 0.000230 ***
hour18                              -531.0593    64.5494  -8.227  < 2e-16 ***
hour19                              -598.6229    64.4127  -9.294  < 2e-16 ***
hour20                              -350.5651    64.5610  -5.430 5.72e-08 ***
hour21                              -154.8276    64.5449  -2.399 0.016462 *  
hour22                               -70.9150    64.3552  -1.102 0.270508    
hour23                               -17.0655    64.1719  -0.266 0.790294    
weekday.L                            109.9624     7.8120  14.076  < 2e-16 ***
weekday.Q                            265.8775     7.7397  34.352  < 2e-16 ***
weekday.C                             30.7435     7.7085   3.988 6.69e-05 ***
weekday^4                             39.5565     7.7061   5.133 2.88e-07 ***
weekday^5                              0.3295     7.6985   0.043 0.965867    
weekday^6                              1.0018     7.7009   0.130 0.896500    
month.L                               75.9686    11.7377   6.472 9.94e-11 ***
month.Q                              -84.2274    20.9060  -4.029 5.63e-05 ***
month.C                              140.4231    11.8681  11.832  < 2e-16 ***
month^4                              -17.7675    10.5777  -1.680 0.093033 .  
month^5                              -61.3865    10.6933  -5.741 9.60e-09 ***
month^6                              121.8473    10.4807  11.626  < 2e-16 ***
month^7                               13.4279    10.4251   1.288 0.197752    
month^8                               -9.7015    10.3389  -0.938 0.348079    
month^9                               79.1956    10.8380   7.307 2.86e-13 ***
month^10                              53.1778    11.4320   4.652 3.32e-06 ***
month^11                              21.4195    10.5336   2.033 0.042025 *  
I(precipitation^2)                  2214.7203   290.1699   7.632 2.43e-14 ***
temperature:hour1                     -0.0964     1.1876  -0.081 0.935302    
temperature:hour2                     -0.3566     1.1911  -0.299 0.764660    
temperature:hour3                     -0.3675     1.1922  -0.308 0.757873    
temperature:hour4                     -0.3254     1.1953  -0.272 0.785449    
temperature:hour5                      0.5739     1.1976   0.479 0.631788    
temperature:hour6                     -3.4837     1.2107  -2.877 0.004014 ** 
temperature:hour7                     -1.8257     1.1951  -1.528 0.126620    
temperature:hour8                      5.4106     1.1779   4.593 4.40e-06 ***
temperature:hour9                      7.8634     1.1676   6.735 1.70e-11 ***
temperature:hour10                    12.0122     1.1581  10.373  < 2e-16 ***
temperature:hour11                    14.6553     1.1511  12.732  < 2e-16 ***
temperature:hour12                    15.1625     1.1456  13.235  < 2e-16 ***
temperature:hour13                    14.4153     1.1416  12.627  < 2e-16 ***
temperature:hour14                    15.0381     1.1405  13.186  < 2e-16 ***
temperature:hour15                    14.9150     1.1377  13.109  < 2e-16 ***
temperature:hour16                    16.8045     1.1350  14.806  < 2e-16 ***
temperature:hour17                    23.8409     1.1396  20.920  < 2e-16 ***
temperature:hour18                    24.2168     1.1522  21.017  < 2e-16 ***
temperature:hour19                    20.4796     1.1579  17.688  < 2e-16 ***
temperature:hour20                    11.9812     1.1660  10.276  < 2e-16 ***
temperature:hour21                     5.6998     1.1716   4.865 1.15e-06 ***
temperature:hour22                     2.8030     1.1767   2.382 0.017226 *  
temperature:hour23                     0.9686     1.1804   0.821 0.411913    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 367.8 on 15964 degrees of freedom
Multiple R-squared:  0.819,	Adjusted R-squared:  0.8181 
F-statistic: 950.2 on 76 and 15964 DF,  p-value: < 2.2e-16
```

Our final model statistics after the transformation on Pedestrians:

```
Call:
lm(formula = Pedestrians ~ . + I(precipitation^2) + temperature:hour,
    data = dfcopy)

Residuals:
    Min      1Q  Median      3Q     Max 
-8.0002 -0.4279  0.0719  0.5516  5.2584 

Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)                         2.3828294  0.1324517  17.990  < 2e-16 ***
weather_summaryclear-night         -0.2860494  0.0354530  -8.068 7.62e-16 ***
weather_summarycloudy              -0.5550387  0.0300661 -18.461  < 2e-16 ***
weather_summaryfog                 -0.5618395  0.1136517  -4.944 7.75e-07 ***
weather_summarypartly-cloudy-day   -0.0950879  0.0249754  -3.807 0.000141 ***
weather_summarypartly-cloudy-night -0.3359920  0.0367259  -9.149  < 2e-16 ***
weather_summaryrain                -1.0125199  0.0634944 -15.947  < 2e-16 ***
weather_summarysleet               -1.6610198  0.2641179  -6.289 3.28e-10 ***
weather_summarysnow                -1.0739041  0.1097718  -9.783  < 2e-16 ***
weather_summarywind                -0.7243879  0.2797043  -2.590 0.009611 ** 
temperature                         0.0118400  0.0023840   4.966 6.89e-07 ***
precipitation                      -0.7601100  0.3697312  -2.056 0.039814 *  
has_event                           0.0720773  0.0307141   2.347 0.018952 *  
hour1                              -0.9069212  0.1671928  -5.424 5.90e-08 ***
hour2                              -0.9906392  0.1669318  -5.934 3.01e-09 ***
hour3                              -1.2860298  0.1662220  -7.737 1.08e-14 ***
hour4                              -1.3751306  0.1658601  -8.291  < 2e-16 ***
hour5                              -2.0034199  0.1655044 -12.105  < 2e-16 ***
hour6                               0.6587275  0.1659149   3.970 7.21e-05 ***
hour7                               2.2969594  0.1643425  13.977  < 2e-16 ***
hour8                               2.6233530  0.1668074  15.727  < 2e-16 ***
hour9                               3.2203540  0.1679042  19.180  < 2e-16 ***
hour10                              3.9740977  0.1689198  23.527  < 2e-16 ***
hour11                              4.4455058  0.1701453  26.128  < 2e-16 ***
hour12                              4.6070374  0.1712721  26.899  < 2e-16 ***
hour13                              4.7076260  0.1721228  27.350  < 2e-16 ***
hour14                              4.7557381  0.1729870  27.492  < 2e-16 ***
hour15                              4.8184299  0.1728783  27.872  < 2e-16 ***
hour16                              4.5548738  0.1722210  26.448  < 2e-16 ***
hour17                              3.2400131  0.1692514  19.143  < 2e-16 ***
hour18                              1.9938669  0.1690938  11.791  < 2e-16 ***
hour19                              0.9866448  0.1687356   5.847 5.09e-09 ***
hour20                              0.5108117  0.1691243   3.020 0.002529 ** 
hour21                              0.5477194  0.1690819   3.239 0.001200 ** 
hour22                              0.5002742  0.1685850   2.967 0.003007 ** 
hour23                              0.4062246  0.1681048   2.416 0.015682 *  
```

```
weekday.Q                           0.2247940  0.0202750  11.087  < 2e-16 ***
weekday.C                          -0.0322853  0.0201932  -1.599 0.109880    
weekday^4                           0.0691049  0.0201870   3.423 0.000620 ***
weekday^5                          -0.0136228  0.0201671  -0.675 0.499370    
weekday^6                           0.0001959  0.0201733   0.010 0.992254    
month.L                            -0.0742967  0.0307482  -2.416 0.015691 *  
month.Q                            -0.3758522  0.0547653  -6.863 6.99e-12 ***
month.C                             0.4968623  0.0310898  15.982  < 2e-16 ***
month^4                             0.2015036  0.0277093   7.272 3.70e-13 ***
month^5                            -0.3311949  0.0280122 -11.823  < 2e-16 ***
month^6                            -0.0928273  0.0274553  -3.381 0.000724 ***
month^7                             0.1725475  0.0273095   6.318 2.72e-10 ***
month^8                             0.1831114  0.0270837   6.761 1.42e-11 ***
month^9                             0.1852161  0.0283912   6.524 7.06e-11 ***
month^10                            0.0281975  0.0299472   0.942 0.346425    
month^11                           -0.0429430  0.0275938  -1.556 0.119668    
I(precipitation^2)                 -1.6400883  0.7601297  -2.158 0.030970 *  
temperature:hour1                  -0.0002356  0.0031109  -0.076 0.939628    
temperature:hour2                  -0.0068233  0.0031203  -2.187 0.028775 *  
temperature:hour3                  -0.0075717  0.0031231  -2.424 0.015343 *  
temperature:hour4                  -0.0072165  0.0031311  -2.305 0.021192 *  
temperature:hour5                   0.0327313  0.0031373  10.433  < 2e-16 ***
temperature:hour6                   0.0172500  0.0031715   5.439 5.44e-08 ***
temperature:hour7                   0.0014242  0.0031306   0.455 0.649180    
temperature:hour8                   0.0036516  0.0030857   1.183 0.236672    
temperature:hour9                   0.0022101  0.0030587   0.723 0.469967    
temperature:hour10                 -0.0001659  0.0030337  -0.055 0.956395    
temperature:hour11                 -0.0028749  0.0030154  -0.953 0.340402    
temperature:hour12                 -0.0038162  0.0030011  -1.272 0.203532    
temperature:hour13                 -0.0050914  0.0029906  -1.702 0.088694 .  
temperature:hour14                 -0.0053969  0.0029877  -1.806 0.070876 .  
temperature:hour15                 -0.0063573  0.0029804  -2.133 0.032936 *  
temperature:hour16                 -0.0027941  0.0029733  -0.940 0.347372    
temperature:hour17                  0.0135749  0.0029854   4.547 5.48e-06 ***
temperature:hour18                  0.0280102  0.0030184   9.280  < 2e-16 ***
temperature:hour19                  0.0364447  0.0030331  12.016  < 2e-16 ***
temperature:hour20                  0.0337221  0.0030544  11.040  < 2e-16 ***
temperature:hour21                  0.0182127  0.0030690   5.934 3.01e-09 ***
temperature:hour22                  0.0114620  0.0030824   3.719 0.000201 ***
temperature:hour23                  0.0054567  0.0030921   1.765 0.077632 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9635 on 15964 degrees of freedom
Multiple R-squared:  0.8537,	Adjusted R-squared:  0.853 
F-statistic:  1225 on 76 and 15964 DF,  p-value: < 2.2e-16
```

- Our R^2 adjusted went up to 0.853 and our residuals are more random around our Pedestrians variable.
- Note: Although we have many variables, our dataset is extremely large, comprising 16,000 entries. So, we do not think our model overfits our data.

Sources:

- **Dataset:** https://data.cityofnewyork.us/Transportation/Brooklyn-Bridge-Automated-Pedestrian-Counts-Demons/6fi9-q3ta/data_preview
- **Textbook**: A Second Course in Statistics: Regression Analysis, Authors: William Mendenhall & Terry Sincich, Publisher: Pearson, Eighth Edition.
- **Class Notes** (used for code)