Seoul Bike Count Regression Project

Kasvina Tirumal

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Goal: Predict hourly bike rental count in Seoul using environmental information

Loading and Renaming Columns

Firstly, we started with loading in a dataset that contains the count of public bicycles rented per hour in the Seoul Bike Sharing System, with corresponding weather data and holiday information. This dataset was obtained from the UC Irvine Machine Learning Repository, which can be found in the following link: https://archive.ics.uci.edu/dataset/560/seoul+bike+sharing+demand.

```
bike_df <- read.csv("seoulbikedata.csv", fileEncoding = "latin1")
dim <- dim(bike_df)
head(bike_df, 3)
```

```
##         Date Rented.Bike.Count Hour Temperature..C. Humidity...
## 1 01/12/2017               254    0            -5.2          37
## 2 01/12/2017               204    1            -5.5          38
## 3 01/12/2017               173    2            -6.0          39
##   Wind.speed..m.s. Visibility..10m. Dew.point.temperature..C.
## 1              2.2             2000                      -17.6
## 2              0.8             2000                      -17.6
## 3              1.0             2000                      -17.7
##   Solar.Radiation..MJ.m2. Rainfall.mm. Snowfall..cm. Seasons    Holiday
## 1                       0            0             0  Winter No Holiday
## 2                       0            0             0  Winter No Holiday
## 3                       0            0             0  Winter No Holiday
##   Functioning.Day
## 1             Yes
## 2             Yes
## 3             Yes
```

We found that this dataset has 8760 observations and 14 columns, with one of the columns being `Rentad.Bike.Count` which is our **response variable** that we ultimately want to predict in this project.

Next, few columns were then renamed to improve readability and facilitate analysis later on.

```
colnames(bike_df)[colnames(bike_df) == 'Temperature..C.'] <- 'Temperature'
colnames(bike_df)[colnames(bike_df) == 'Humidity...'] <- 'Humidity'
colnames(bike_df)[colnames(bike_df) == 'Wind.speed..m.s.'] <- 'Wind.Speed'
colnames(bike_df)[colnames(bike_df) == 'Visibility..10m.'] <- 'Visibility'
colnames(bike_df)[colnames(bike_df) == 'Dew.point.temperature..C.'] <- 'Dew.Point.Temp'
colnames(bike_df)[colnames(bike_df) == 'Solar.Radiation..MJ.m2.'] <- 'Solar.Radiation'
colnames(bike_df)[colnames(bike_df) == 'Rainfall.mm.'] <- 'Rainfall'
colnames(bike_df)[colnames(bike_df) == 'Snowfall..cm.'] <- 'Snowfall'
head(bike_df,2)
```

```
##         Date Rented.Bike.Count Hour Temperature Humidity Wind.Speed Visibility
## 1 01/12/2017               254    0        -5.2       37        2.2       2000
## 2 01/12/2017               204    1        -5.5       38        0.8       2000
##   Dew.Point.Temp Solar.Radiation Rainfall Snowfall Seasons    Holiday
## 1          -17.6               0        0        0  Winter No Holiday
## 2          -17.6               0        0        0  Winter No Holiday
##   Functioning.Day
## 1             Yes
## 2             Yes
```

Data Cleaning

First and foremost, we want to check whether our dataset has any missing values and deal with them accordingly by either deleting them or if the columns are significant, use tools such as k-Nearest Neighbours to estimate their values.

```
sum(is.na(bike_df))
```

```
## [1] 0
```

As seen above, we found that our dataset is clean and has no missing values. Now, we can move on to insepcting the features within the dataset.

By viewing our dataset above, we see that we have a column `Functioning.Day`, which indicates whether bikes were available for rent during that day or not. Since our goal is to predict the hourly count of rented bikes, we only need the data of operational days since the count is simply 0 on non-operational days. Therefore, we will remove observations made during non-functioning days, then drop the `Functioning.Day` column since we have no more use of it anymore.

```
bike_df2 <- bike_df %>%
  filter(Functioning.Day == "Yes")

bike_df3 <- bike_df2 %>%
  select(-Functioning.Day)
```

We then looked at a summary of each feature within the dataset to further unerstand the features we are dealing with and determine the next step forward.

```r
summary(bike_df3)
```

```
##      Date           Rented.Bike.Count      Hour        Temperature
##  Length:8465        Min.   :   2.0    Min.   : 0.00   Min.   :-17.80
##  Class :character   1st Qu.: 214.0    1st Qu.: 6.00   1st Qu.:  3.00
##  Mode  :character   Median : 542.0    Median :12.00   Median : 13.50
##                     Mean   : 729.2    Mean   :11.51   Mean   : 12.77
##                     3rd Qu.:1084.0    3rd Qu.:18.00   3rd Qu.: 22.70
##                     Max.   :3556.0    Max.   :23.00   Max.   : 39.40
##     Humidity       Wind.Speed      Visibility   Dew.Point.Temp
##  Min.   : 0.00   Min.   :0.000   Min.   :  27   Min.   :-30.600
##  1st Qu.:42.00   1st Qu.:0.900   1st Qu.: 935   1st Qu.: -5.100
##  Median :57.00   Median :1.500   Median :1690   Median :  4.700
##  Mean   :58.15   Mean   :1.726   Mean   :1434   Mean   :  3.945
##  3rd Qu.:74.00   3rd Qu.:2.300   3rd Qu.:2000   3rd Qu.: 15.200
##  Max.   :98.00   Max.   :7.400   Max.   :2000   Max.   : 27.200
##  Solar.Radiation     Rainfall          Snowfall         Seasons
##  Min.   :0.0000   Min.   : 0.0000   Min.   :0.00000   Length:8465
##  1st Qu.:0.0000   1st Qu.: 0.0000   1st Qu.:0.00000   Class :character
##  Median :0.0100   Median : 0.0000   Median :0.00000   Mode  :character
##  Mean   :0.5679   Mean   : 0.1491   Mean   :0.07769
##  3rd Qu.:0.9300   3rd Qu.: 0.0000   3rd Qu.:0.00000
##  Max.   :3.5200   Max.   :35.0000   Max.   :8.80000
##    Holiday
##  Length:8465
##  Class :character
##  Mode  :character
##
##
##
```

We also check whether the numeric columns contain only numeric values to ensure that we are able to perform numerical operations on these during analysis later.

```r
indices <- c(2, 4:9)
whether_numeric <- sapply(bike_df3[, indices], is.numeric)
print(whether_numeric)
```

```
## Rented.Bike.Count       Temperature          Humidity        Wind.Speed
##              TRUE              TRUE              TRUE              TRUE
##        Visibility    Dew.Point.Temp   Solar.Radiation
##              TRUE              TRUE              TRUE
```

As seen above, the aforementioned columns contain purely numeric values. Note that I excluded the `Hour` column from the above check since it will be treated as a factor when building the prediction model.

Now that the data is clean, we move on to some feature enginnering.

Feature Engineering

Firstly, we note that the `Rainfall` and `Snowfall` columns record the actual heights of rain and snow respectively. However, since we do not know exact height measurements when making predictions of the future, we instead rely on available forecasts that indicate whether rain or snow is expected. Hence, we transformed the `Rainfall` and `Snowfall` columns into `Rained` and `Snowed` columns which take on binary indicators as their values: 1 representing the occurrence of rain or snow during that hour, while 0 indicates that there was no rain or snow respectively. Binary encoding helps to ensure best possible model performance since it is more compatible with algorithms and prevents ordinal assumptions.

```
bike_df3$Rained <- ifelse(bike_df3$Rainfall > 0, 1, 0)
bike_df3$Snowed <- ifelse(bike_df3$Snowfall > 0, 1, 0)
bike_df4 <- bike_df3[ , !(names(bike_df3) %in% c("Rainfall", "Snowfall"))]
```

Next, instead of using the date of each observation as a predictor, we simply need to know whether that day is a weekend or not. This is because we would expect bike rental patterns to differ between weekdays and weekends. To achieve this, I will create an `Is.Weekend` column.

```
bike_df4$Date <- as.Date(bike_df4$Date, format = "%d/%m/%Y")
bike_df4$Is.Weekend <- as.integer(weekdays(bike_df4$Date) %in%
                                    c("Saturday", "Sunday"))
bike_df4 <- bike_df4 %>%
  select(-Date)
```

We now have an `Is.Weekend` column that has the value 1 if that observation was recorded on a weekend and 0 otherwise. Notice that we also removed the `Date` column since we do not need it anymore.

Next, based on literature within the field of meteorology, we identified three key indicators of human comfort based on environmental factors:

1. Heat Index: known as the apparent temperature, and is what the temperature feels like to the human body when relative humidity is combined with the air temperature. The formula to calculate the heat index is as follows: $HI = 0.5 * T + 61.0 + [(T - 68.0) * 1.2] + (RH * 0.094)$, where HI is the heat index, T represents temperature in Farenheit and RH the relative humidity.

2. Wind Chill: describes what the air temperature feels like to the human skin due to the combination of cold temperatures and winds blowing (wind speed) on exposed skin. The formula to calculate wind chill is as follows: $WC = 35.74 + 0.6215T - 35.75(V^{0.16}) + 0.4275T(V^{0.16})$, where WC is wind chill, T represents temperature in Farenheit whereas V represents wind speed in miles per hour.

3. Humidex: describes how hot the weather feels to the average person, by combining the effect of heat and humidity. The humidex formula is as follows: $H = T_{air} + 0.5555\{6.11 \times \exp[5417.7530\left(\frac{1}{273.15} - \frac{1}{273.15+T_{dew}}\right)] - 10\}$ where H represent the humidex, T_{air} the temperature in degrees Celcius, and T_{dew} the dew point temperature in degrees Celcius.

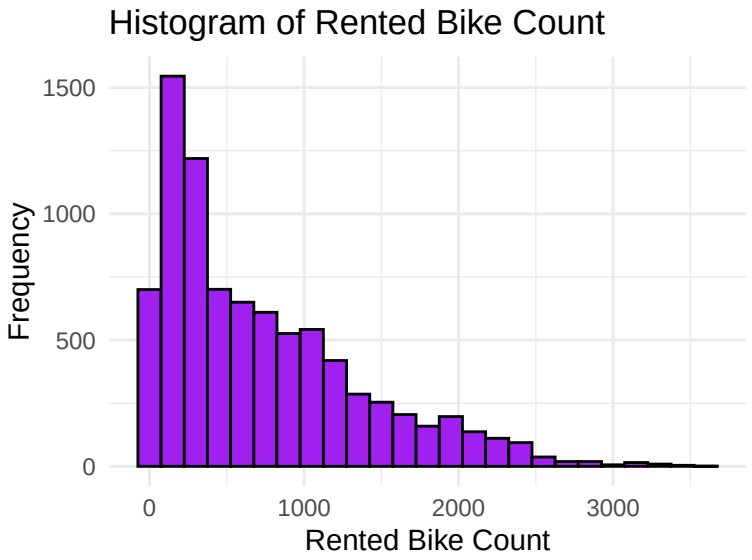
Using the above formulas, we will proceed by calculating the above 3 indexes, then add them to the dataset as new variables: `HeatIdx`, `WindChill` and `HumiDex`.

```
bike_df4$HeatIdx <- 0.5 * ((bike_df4$Temperature * (9/5) + 32) + 61 +
                    (((bike_df4$Temperature * (9/5) + 32)-68)*1.2) +
                    (bike_df4$Humidity*0.094))
bike_df4$WindChill <- 35.74 + 0.6215*(bike_df4$Temperature * (9/5) + 32) -
                      35.75*(bike_df4$Wind.Speed*2.23694)^(0.16) +
0.4275*(bike_df4$Temperature * (9/5) + 32)*(bike_df4$Wind.Speed*2.23694)^{0.16}
bike_df4$HumiDex <- bike_df4$Temperature +
                    0.5555*(6.11 * exp(5417.7530*(1/273.15 -
                    1/(273.15 + bike_df4$Dew.Point.Temp)))-10)
#summary(bike_df4)
```

Outlier Detection and Removal

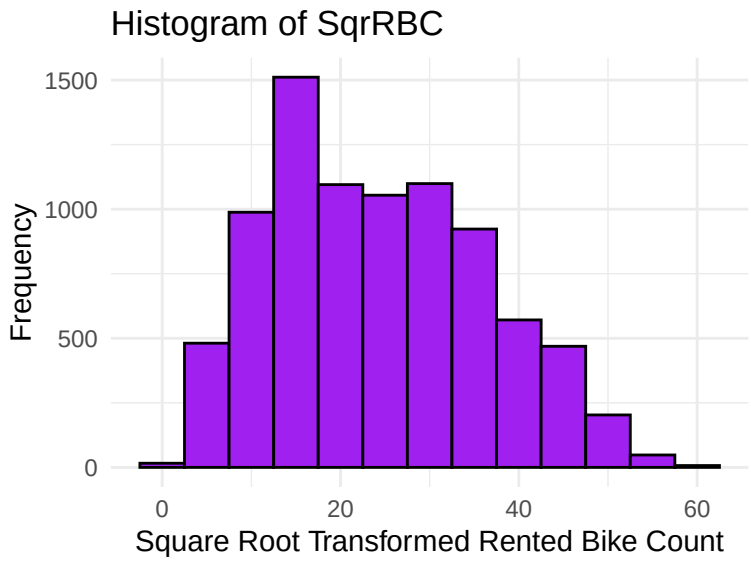
Now that we have a set of informative features, we proceed by dealing with outliers and irregularities within our dataset. Firstly, we check the distribution of our reponse variable, `Rented.Bike.Count`.

```
ggplot(bike_df4, aes(x = Rented.Bike.Count)) +
  geom_histogram(binwidth = 150, fill = "purple", color = "black") +
  labs(title = "Histogram of Rented Bike Count",
       x = "Rented Bike Count",
       y = "Frequency") +
  theme_minimal()
```



From the histogram above, we notice that the distribution of our response variable is right-skewed which is not ideal for machine learning algorithms such as linear regression that assumes normality. Therefore, we apply a square root transformation to the response variable to help make its distribution more symmetric.

```r
bike_df4$SqrRBC <- sqrt(bike_df4$Rented.Bike.Count)
ggplot(bike_df4, aes(x = SqrRBC)) +
  geom_histogram(binwidth = 5, fill = "purple", color = "black") +
  labs(title = "Histogram of SqrRBC",
       x = "Square Root Transformed Rented Bike Count",
       y = "Frequency") +
  theme_minimal()
```



Evidently, the distribution of `SqrRBC` looks a lot closer to a normal distribution compared to the distrbution of `Rented.Bike.Count`, albeit not perfect. Since we are satisfied with this distribution, we can remove `Rented.Bike.Count` from the dataset.

```r
bike_df4 <- bike_df4 %>%
  select(-Rented.Bike.Count)
```

Next, we want to examine the mean and standard deviation of the square root transformed rental bike count to identify and remove outliers. For a comprehensive approach, we will calculate means and standard deviations separately for each season and exclude observations that fall outside of three standard deviations of their respective seasonal mean.

```r
mean_rented_by_season <- bike_df4 %>%
  group_by(Seasons) %>%
  summarize(mean = mean(SqrRBC), sd = sd(SqrRBC))
kable(mean_rented_by_season)
```

Seasons	mean	sd
Autumn	28.40672	10.827240
Spring	24.64820	11.780684

Seasons	mean	sd
Summer	30.12399	11.255048
Winter	14.16039	5.003627

```
bike_df5 <- bike_df4 %>%
  left_join(mean_rented_by_season, by = "Seasons")

bike_df6 <- bike_df5 %>%
  filter(
    SqrRBC >= (mean - 3 * sd) &
    SqrRBC <= (mean + 3 * sd)
  )
dim2 <- dim(bike_df6)
bike_df6 <- bike_df6[, !(names(bike_df6) %in% c("mean", "sd"))]
```

Consequently, we removed -300 outliers from the dataset.

Categorical Variables

Next, we examine the categorical variables within the dataset:

```
table(bike_df6$Seasons)
```

```
##
## Autumn Spring Summer Winter
##   1937   2160   2208   2155
```

```
table(bike_df6$Holiday)
```

```
##
##    Holiday No Holiday
##        408       8052
```

We see that each season has an approximately similar number of observations, whereas there is significantly more observations on days which are not holidays compared to those with holiday. This imbalance is a natural outcome where there is significantly more non-holidays than holidays in a year.

We will proceed by performing **one-hot encoding** on both these columns and the columns `Rained` and `Snowed`.

```
dummy_var <- dummyVars(~ Seasons + Holiday, data = bike_df6)
encoded_df <- predict(dummy_var, newdata = bike_df6)
encoded_df2 <- as.data.frame(encoded_df)
bike_df7 <- cbind(bike_df6[ , !(names(bike_df6) %in% c("Seasons", "Holiday"))], encoded_df2)
head(bike_df7,2)
```

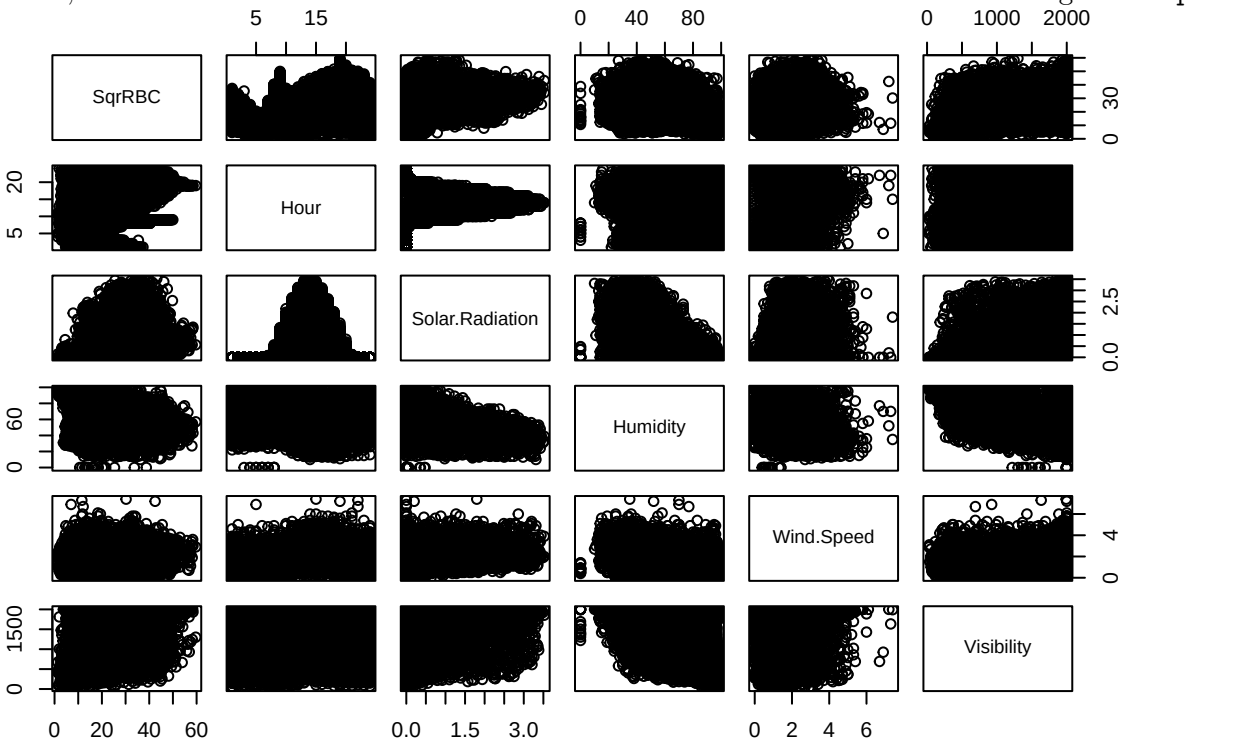
```
##   Hour Temperature Humidity Wind.Speed Visibility Dew.Point.Temp
## 1    0        -5.2       37        2.2       2000          -17.6
## 2    1        -5.5       38        0.8       2000          -17.6
##   Solar.Radiation Rained Snowed Is.Weekend HeatIdx WindChill    HumiDex
## 1               0      0      0          0  16.343  16.16761  -9.889089
## 2               0      0      0          0  15.796  20.60613 -10.189089
##     SqrRBC SeasonsAutumn SeasonsSpring SeasonsSummer SeasonsWinter
## 1 15.93738             0             0             0             1
## 2 14.28286             0             0             0             1
##   HolidayHoliday HolidayNo Holiday
## 1              0                 1
## 2              0                 1
```

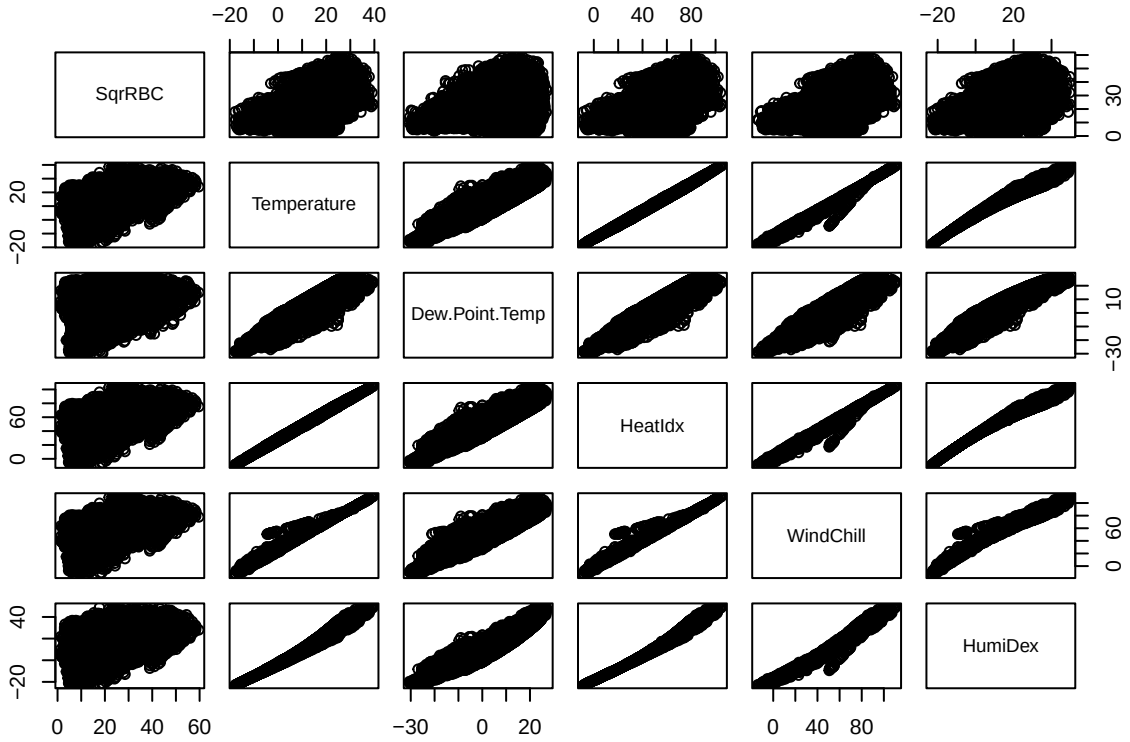
Next, we will convert the `Hour` column from an integer to a factor, and remove the `mean` and `sd` columns from the dataset.

```
bike_df7$Hour <- as.factor(bike_df7$Hour)
bike_df8 <- bike_df7[, !(names(bike_df7) %in% c("mean", "sd"))]
```

Numerical Variables

Next, we will examine our numerical variables and visualize each of them against `SqrRBC`:



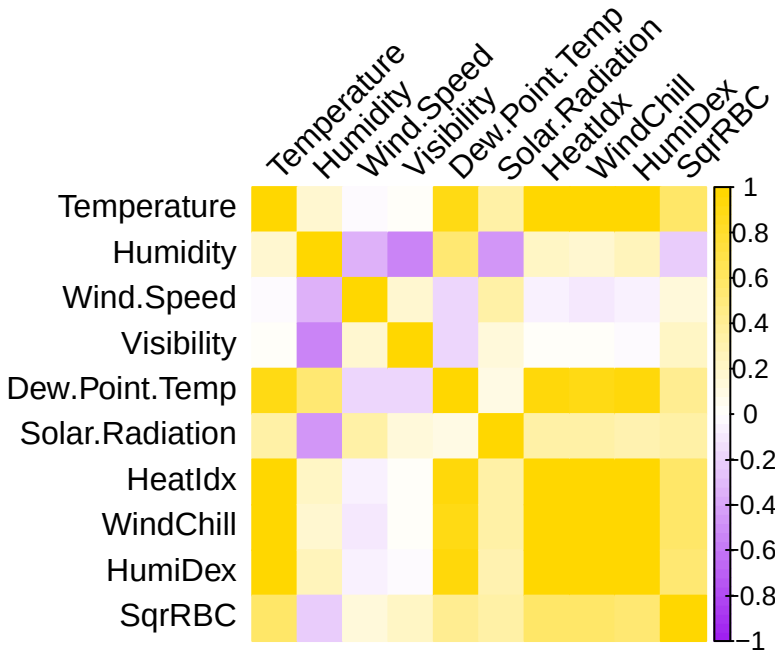


From the plots above, we see that our square root transformed rented bike count has a small peak at 8-9am and is the highest at 6-7pm which coincides with times the people go to and leave work respectively. Next, `Temperature`, `Dew.Point.Temperature`, `HeatIndex`, `WindChill` and `HumiDex` all seem to have some positive correlation with `SqrRBC`.

However, the aforementioned five features excluding `SqrRBC` also seem to have a positive correlation between each other. Therefore, we need to perform correlation analysis as we want to avoid including highly correlated features within the dataset as this may skew our model.

Final Variable Selection

Correlation Analysis:



From the heatmap, it can evidently be seen that the features `Temperature`, `Dew.Point.Temperature`, `HeatIndex`, `WindChill` and `HumiDex` are highly correlated with each other. This is to be expected since the latter 3 features were all computed using `Temperature`, with one of them also computed using `Dew.Point.Temperature`. Thus, those two variables should be removed. Although `HeatIndex`, `WindChill` and `HumiDex` are still highly correlated, they may improve model performance, which is why we did not remove these predictors. Instead, we will also remove `Wind.Speed` and `Humidity` since those features were also were to calculate `WindChill` and `HeatIdx` respectively.

Next, to remove dependancy within the dataset, we also want to remove `SeasonsWinter`, `HolidayNo Holiday`, `RainedYes` and `SnowedYes` since one one-hot encoded column for each variable must be removed.

From the heatmap, it is evident that the features `Temperature`, `Dew.Point.Temperature`, `HeatIndex`, `WindChill` and `HumiDex` are highly correlated with each other. This is to be expected since `HeatIndex`, `WindChill` and `HumiDex` are all computed using `Temperature`. In addition, `HumiDex` is also computed using `Dew.Point.Temperature`. Given this high correlation, we will remove `Temperature` and `Dew.Point.Temperature` from the dataset to reduce multicollinearity. Although `HeatIndex`, `WindChill` and `HumiDex` remain highly correlated, we will retain these features since they may still contribute valuable information.

Next, we will also remove `Wind.Speed` and `Humidity` since `WindChill` and `HeatIndex` are dependant on them respectively.

Finally, we will remove one column from each one-hot encoded categorical variable: `SeasonsWinter` and `HolidayNo Holiday` to avoid multicollinearity. Our remaining features are as follows:

```
##   Hour Visibility Solar.Radiation Rained Snowed Is.Weekend HeatIdx WindChill
## 1    0       2000               0      0      0          0  16.343  16.16761
## 2    1       2000               0      0      0          0  15.796  20.60613
##      HumiDex   SqrRBC SeasonsAutumn SeasonsSpring SeasonsSummer HolidayHoliday
## 1  -9.889089 15.93738             0             0             0              0
## 2 -10.189089 14.28286             0             0             0              0
```

Now, we are ready to train a model using the above dataset.

Model Building

Before we train our machine learning model, we first need a train set and a test set. In this project, we are using a 80-20 split where 80% of the observations from our dataset will be randomly sampled as our train set, whereas the remaining 20% will serve as the test set.

```
set.seed(435)
train_size <- floor(0.8 * nrow(bike_df9))
train <- sample(1:nrow(bike_df9), train_size)
test <- (-train)
train_data <- bike_df9[train, ]
test_data <- bike_df9[test, ]
```

Multiple Linear Regression

We chose to predict our response variable, `SqrRBC` using multiple linear regression (MLR) since it is one of the most simple and easily interpretable models which is invaluable when presenting findings to clients. To build the model, we will use all the features within the train set since we prepped the dataset to only include features that are independant and we believe are useful in predicting hourly count of rented bikes.

```
lm1 <- lm(SqrRBC ~ ., data=train_data)
summary(lm1)
```

```
##
## Call:
## lm(formula = SqrRBC ~ ., data = train_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -29.0687  -3.4202   0.1553   3.5856  24.5825
```

```
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -1.318e+01  1.140e+00 -11.570  < 2e-16 ***
## Hour1           -2.328e+00  4.846e-01  -4.804 1.59e-06 ***
## Hour2           -5.258e+00  4.887e-01 -10.758  < 2e-16 ***
## Hour3           -7.448e+00  4.921e-01 -15.134  < 2e-16 ***
## Hour4           -1.057e+01  4.916e-01 -21.498  < 2e-16 ***
## Hour5           -1.043e+01  4.879e-01 -21.379  < 2e-16 ***
## Hour6           -4.686e+00  4.922e-01  -9.520  < 2e-16 ***
## Hour7            1.300e+00  4.846e-01   2.683 0.007322 **
## Hour8            7.453e+00  4.960e-01  15.025  < 2e-16 ***
## Hour9            1.414e+00  5.022e-01   2.815 0.004891 **
## Hour10          -2.538e+00  5.238e-01  -4.845 1.29e-06 ***
## Hour11          -2.411e+00  5.440e-01  -4.432 9.49e-06 ***
## Hour12          -1.290e+00  5.581e-01  -2.311 0.020852 *
## Hour13          -1.552e+00  5.642e-01  -2.752 0.005947 **
## Hour14          -1.237e+00  5.546e-01  -2.231 0.025710 *
## Hour15          -8.138e-02  5.396e-01  -0.151 0.880132
## Hour16           1.586e+00  5.227e-01   3.035 0.002416 **
## Hour17           5.623e+00  4.978e-01  11.294  < 2e-16 ***
## Hour18           1.169e+01  4.974e-01  23.503  < 2e-16 ***
## Hour19           8.139e+00  4.925e-01  16.526  < 2e-16 ***
## Hour20           6.628e+00  4.916e-01  13.484  < 2e-16 ***
## Hour21           7.202e+00  4.906e-01  14.680  < 2e-16 ***
## Hour22           5.539e+00  4.872e-01  11.368  < 2e-16 ***
## Hour23           1.879e+00  4.876e-01   3.854 0.000117 ***
## Visibility       1.397e-03  1.256e-04  11.127  < 2e-16 ***
## Solar.Radiation  9.797e-01  1.640e-01   5.974 2.43e-09 ***
## Rained          -1.375e+01  3.174e-01 -43.329  < 2e-16 ***
## Snowed           2.880e-01  3.405e-01   0.846 0.397656
## Is.Weekend      -1.997e+00  1.547e-01 -12.911  < 2e-16 ***
## HeatIdx          7.802e-01  4.811e-02  16.218  < 2e-16 ***
## WindChill        7.981e-02  2.703e-02   2.953 0.003157 **
## HumiDex         -9.919e-01  4.893e-02 -20.273  < 2e-16 ***
## SeasonsAutumn    5.984e+00  3.043e-01  19.661  < 2e-16 ***
## SeasonsSpring    3.384e+00  2.955e-01  11.454  < 2e-16 ***
## SeasonsSummer    5.623e+00  4.302e-01  13.070  < 2e-16 ***
## HolidayHoliday  -2.761e+00  3.224e-01  -8.566  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.708 on 6732 degrees of freedom
## Multiple R-squared:  0.769,  Adjusted R-squared:  0.7678
## F-statistic: 640.1 on 35 and 6732 DF,  p-value: < 2.2e-16
```

The summary of our MLR model boasts a multiple R-squared of 0.769, indicating that 76.9% of the variability in `SqrRBC` is explained by the model, which suggests a strong fit. Additionally, most

predictors are statistically significant in predicting SqrRBC, with p-values less than 0.05. However, Snowed is an exception, with a p-value of 0.397656 which is a lor larger than 0.05. This implies that the presence of snow might not significantly influence bike rental decisions of consumer. To determine whether we should remove Snowed from the model, we will perform an ANOVA test.

```
lm2 <- lm(SqrRBC ~ Hour + Visibility + Solar.Radiation + Rained + Is.Weekend +
            HeatIdx + WindChill + HumiDex + SeasonsAutumn + SeasonsSpring +
            SeasonsSummer + HolidayHoliday, data=train_data)
summary(lm2)
```

```
##
## Call:
## lm(formula = SqrRBC ~ Hour + Visibility + Solar.Radiation + Rained +
##     Is.Weekend + HeatIdx + WindChill + HumiDex + SeasonsAutumn +
##     SeasonsSpring + SeasonsSummer + HolidayHoliday, data = train_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -29.1013  -3.4264   0.1501   3.5971  24.5679
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -1.303e+01  1.125e+00 -11.583  < 2e-16 ***
## Hour1           -2.328e+00  4.846e-01  -4.804 1.59e-06 ***
## Hour2           -5.258e+00  4.887e-01 -10.759  < 2e-16 ***
## Hour3           -7.447e+00  4.921e-01 -15.132  < 2e-16 ***
## Hour4           -1.057e+01  4.915e-01 -21.498  < 2e-16 ***
## Hour5           -1.043e+01  4.879e-01 -21.386  < 2e-16 ***
## Hour6           -4.690e+00  4.922e-01  -9.529  < 2e-16 ***
## Hour7            1.300e+00  4.846e-01   2.683 0.007314 **
## Hour8            7.450e+00  4.960e-01  15.021  < 2e-16 ***
## Hour9            1.406e+00  5.021e-01   2.801 0.005115 **
## Hour10          -2.545e+00  5.237e-01  -4.860 1.20e-06 ***
## Hour11          -2.416e+00  5.440e-01  -4.442 9.06e-06 ***
## Hour12          -1.296e+00  5.581e-01  -2.322 0.020283 *
## Hour13          -1.559e+00  5.641e-01  -2.764 0.005722 **
## Hour14          -1.246e+00  5.545e-01  -2.246 0.024710 *
## Hour15          -8.576e-02  5.396e-01  -0.159 0.873729
## Hour16           1.581e+00  5.227e-01   3.024 0.002501 **
## Hour17           5.623e+00  4.978e-01  11.296  < 2e-16 ***
## Hour18           1.169e+01  4.974e-01  23.511  < 2e-16 ***
## Hour19           8.144e+00  4.924e-01  16.538  < 2e-16 ***
## Hour20           6.632e+00  4.915e-01  13.492  < 2e-16 ***
## Hour21           7.200e+00  4.906e-01  14.676  < 2e-16 ***
## Hour22           5.536e+00  4.872e-01  11.364  < 2e-16 ***
## Hour23           1.878e+00  4.876e-01   3.852 0.000118 ***
## Visibility       1.386e-03  1.249e-04  11.100  < 2e-16 ***
```

```
## Solar.Radiation  9.881e-01  1.637e-01   6.037 1.65e-09 ***
## Rained          -1.375e+01  3.174e-01 -43.337  < 2e-16 ***
## Is.Weekend      -2.001e+00  1.546e-01 -12.945  < 2e-16 ***
## HeatIdx          7.785e-01  4.806e-02  16.197  < 2e-16 ***
## WindChill        7.871e-02  2.699e-02   2.916 0.003558 **
## HumiDex         -9.889e-01  4.880e-02 -20.265  < 2e-16 ***
## SeasonsAutumn    5.972e+00  3.040e-01  19.644  < 2e-16 ***
## SeasonsSpring    3.359e+00  2.939e-01  11.428  < 2e-16 ***
## SeasonsSummer    5.614e+00  4.301e-01  13.053  < 2e-16 ***
## HolidayHoliday  -2.765e+00  3.223e-01  -8.577  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.708 on 6733 degrees of freedom
## Multiple R-squared:  0.7689, Adjusted R-squared:  0.7678
## F-statistic:   659 on 34 and 6733 DF,  p-value: < 2.2e-16
```

```
anova(lm1, lm2)
```

```
## Analysis of Variance Table
##
## Model 1: SqrRBC ~ Hour + Visibility + Solar.Radiation + Rained + Snowed +
##     Is.Weekend + HeatIdx + WindChill + HumiDex + SeasonsAutumn +
##     SeasonsSpring + SeasonsSummer + HolidayHoliday
## Model 2: SqrRBC ~ Hour + Visibility + Solar.Radiation + Rained + Is.Weekend +
##     HeatIdx + WindChill + HumiDex + SeasonsAutumn + SeasonsSpring +
##     SeasonsSummer + HolidayHoliday
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1   6732 219323
## 2   6733 219346 -1    -23.31 0.7155 0.3977
```

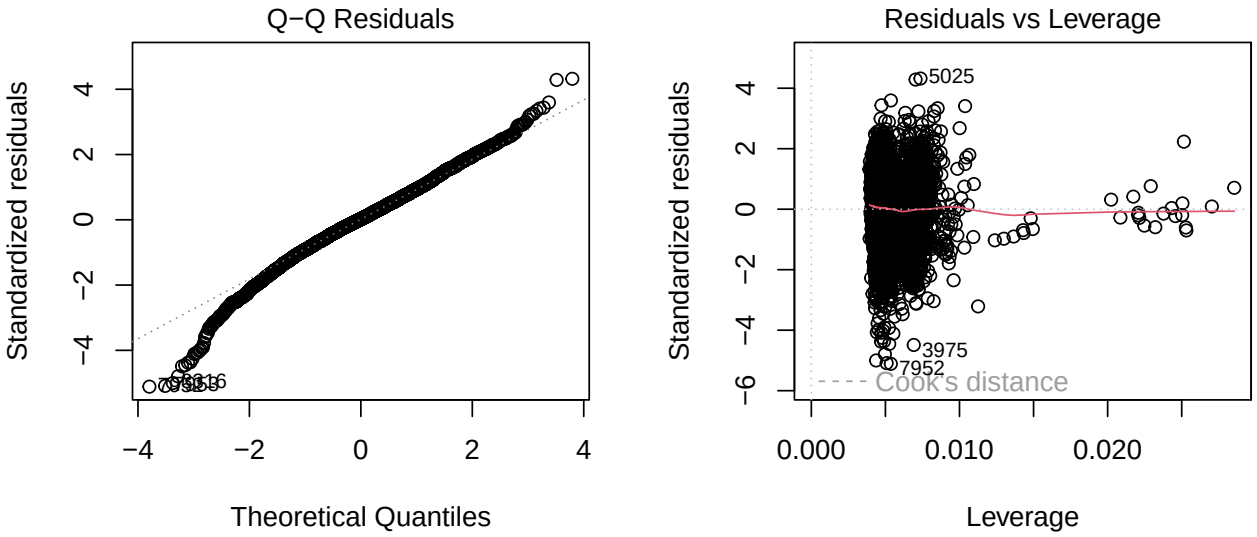
From the anova test, the p-value of 0.3977 indicates that the difference in the fit of the two models is not statistically significant. This means that the predictor `Snowed` does not provide meaningful predictive power to the model, and can be safely removed from the model without compromising the model's performance. This is further supported by identical adjusted R-squared values of 0.7678 for both the first and second model, indicating that the model performs just as well without `Snowed`.

Now that we have obtained our model, let us evaluate its predictive power by calculating its mean squared error (MSE). Note that we use MSE here instead of root mean squared error (RMSE) since MSE will have the same units as `Rented.Bike.Count` which facilitates interpretation.

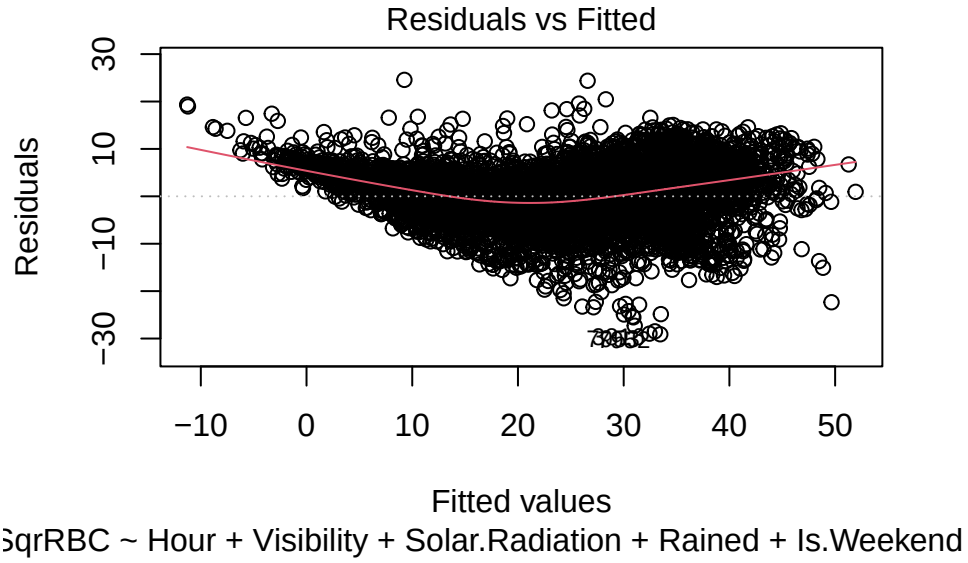
```
predictions <- predict(lm2, newdata = test_data)
mse <- mean((test_data$SqrRBC - predictions)^2)
```

We found that our model has an MSE of 32.3268, which seems reasonable given that rented bike count in our dataset ranges from 2 to 3,556, with a median of 542. However, to further improve

our model, we will examine its residual plots to check for behaviour that could indicate areas where the model may not be performing well.



Firstly, most of the points generally fall on the Q-Q line, indicating that the points are generally normally distributed. However, although there is only a slight deviation on the right tail, there is a noticeable deviation on the left tail, which suggests the presence of extreme negative residuals which may be adversely impacting the performance of the model. Similarly, although the residuals vs. leverage plot shows no high-leverage points, it does reveal several outliers with extreme negative residuals. These observations highlight the presence of outliers that could be adversely influencing the model. To further investigate these outliers, we will examine the residuals vs fitted plot to gain additional insights.



We immediately notice a distinct quadratic shape in the plot above, along with many outliers with extreme negative residuals. This quadratic pattern implies the presence of relationships between the predictors that are not being fully captured by the linear model. To address this, we decided to add natural splines to the linear model to help to capture non-linear relationships and improve model performance, which transform our linear regression into a spline regression.

Spline regression

Refering back to the pair plots of each of the numerical predictors against `SqrRBC`, we notice that `Solar.Radiation` and `Visibility` exhibit non-linear relationships with `SqrRBC`. Therefore, we will incorporate splines for these predictors. We will also add splines on `HeatIdx`, `WindChill` and `HumiDex` because, while they show some linear relationship with `SqrRBC`, it is not particularly strong.

```
spline_model <- lm(SqrRBC ~ Hour + ns(Visibility, df=2) + ns(Solar.Radiation, df = 5)
                   + ns(HeatIdx, df=7) + ns(WindChill, df=6) + ns(HumiDex, df=7) +
                   SeasonsAutumn + SeasonsSpring + SeasonsSummer + HolidayHoliday +
                   Rained, data = train_data)
#summary(spline_model)
```

Note that the degrees of freedom for each predictor was chosen through trial and error to maximize the Adjusted R-Squared value.

```
summary(spline_model)
```

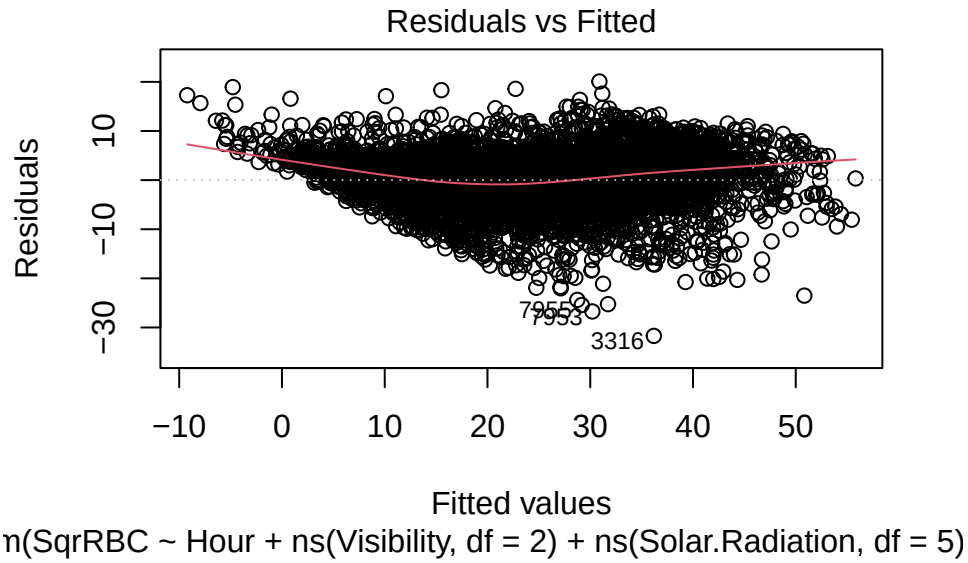
```
##
## Call:
## lm(formula = SqrRBC ~ Hour + ns(Visibility, df = 2) + ns(Solar.Radiation,
##     df = 5) + ns(HeatIdx, df = 7) + ns(WindChill, df = 6) + ns(HumiDex,
##     df = 7) + SeasonsAutumn + SeasonsSpring + SeasonsSummer +
##     HolidayHoliday + Rained, data = train_data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.718  -2.770   0.218   3.060  20.076
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      9.6020     0.9124  10.524  < 2e-16 ***
## Hour1                           -2.3981     0.4345  -5.519 3.54e-08 ***
## Hour2                           -5.3200     0.4383 -12.137  < 2e-16 ***
## Hour3                           -7.5637     0.4416 -17.129  < 2e-16 ***
## Hour4                          -10.4904     0.4415 -23.761  < 2e-16 ***
## Hour5                          -10.3272     0.4386 -23.547  < 2e-16 ***
## Hour6                           -5.3339     0.4486 -11.891  < 2e-16 ***
## Hour7                           -1.0609     0.4644  -2.284 0.022385 *
## Hour8                            2.5854     0.5184   4.987 6.27e-07 ***
## Hour9                           -5.2195     0.5690  -9.173  < 2e-16 ***
## Hour10                          -9.3773     0.5943 -15.779  < 2e-16 ***
## Hour11                          -8.8796     0.6074 -14.619  < 2e-16 ***
## Hour12                          -7.3582     0.6167 -11.932  < 2e-16 ***
## Hour13                          -7.3147     0.6192 -11.813  < 2e-16 ***
## Hour14                          -7.0958     0.6113 -11.609  < 2e-16 ***
```

```
## Hour15                          -6.0160     0.5993 -10.038  < 2e-16 ***
## Hour16                          -4.5610     0.5862  -7.781 8.29e-15 ***
## Hour17                          -0.2768     0.5596  -0.495 0.620829
## Hour18                           6.9606     0.5174  13.452  < 2e-16 ***
## Hour19                           5.2858     0.4717  11.206  < 2e-16 ***
## Hour20                           5.6011     0.4500  12.447  < 2e-16 ***
## Hour21                           6.9676     0.4403  15.824  < 2e-16 ***
## Hour22                           5.4424     0.4369  12.456  < 2e-16 ***
## Hour23                           1.7394     0.4372   3.979 7.00e-05 ***
## ns(Visibility, df = 2)1          2.3352     0.6640   3.517 0.000440 ***
## ns(Visibility, df = 2)2         -0.4117     0.1985  -2.074 0.038103 *
## ns(Solar.Radiation, df = 5)1     3.8813     0.4414   8.792  < 2e-16 ***
## ns(Solar.Radiation, df = 5)2     8.6634     0.4996  17.341  < 2e-16 ***
## ns(Solar.Radiation, df = 5)3     6.9769     0.6284  11.102  < 2e-16 ***
## ns(Solar.Radiation, df = 5)4     9.9940     0.8124  12.302  < 2e-16 ***
## ns(Solar.Radiation, df = 5)5     4.5304     0.7711   5.875 4.42e-09 ***
## ns(HeatIdx, df = 7)1            74.1549    35.5714   2.085 0.037136 *
## ns(HeatIdx, df = 7)2           101.1374    34.9880   2.891 0.003857 **
## ns(HeatIdx, df = 7)3           122.3391    35.3271   3.463 0.000537 ***
## ns(HeatIdx, df = 7)4           140.5975    35.3880   3.973 7.17e-05 ***
## ns(HeatIdx, df = 7)5           148.8599    24.4101   6.098 1.13e-09 ***
## ns(HeatIdx, df = 7)6           267.0809    64.8379   4.119 3.85e-05 ***
## ns(HeatIdx, df = 7)7           209.8050    27.8843   7.524 6.00e-14 ***
## ns(WindChill, df = 6)1          13.3751     2.5321   5.282 1.32e-07 ***
## ns(WindChill, df = 6)2          16.1764     2.7451   5.893 3.98e-09 ***
## ns(WindChill, df = 6)3          12.3438     2.9924   4.125 3.75e-05 ***
## ns(WindChill, df = 6)4          10.4672     4.5222   2.315 0.020665 *
## ns(WindChill, df = 6)5         -28.2256    11.5692  -2.440 0.014725 *
## ns(WindChill, df = 6)6         -73.4801    17.4373  -4.214 2.54e-05 ***
## ns(HumiDex, df = 7)1           -81.4263    34.7810  -2.341 0.019255 *
## ns(HumiDex, df = 7)2          -107.6122    34.4551  -3.123 0.001796 **
## ns(HumiDex, df = 7)3          -125.5769    34.6492  -3.624 0.000292 ***
## ns(HumiDex, df = 7)4          -137.0446    34.6733  -3.952 7.81e-05 ***
## ns(HumiDex, df = 7)5          -138.8575    23.7615  -5.844 5.34e-09 ***
## ns(HumiDex, df = 7)6          -225.0712    62.9611  -3.575 0.000353 ***
## ns(HumiDex, df = 7)7          -131.6092    19.1044  -6.889 6.13e-12 ***
## SeasonsAutumn                    6.5914     0.3236  20.372  < 2e-16 ***
## SeasonsSpring                    3.3294     0.3129  10.639  < 2e-16 ***
## SeasonsSummer                    5.5328     0.4139  13.367  < 2e-16 ***
## HolidayHoliday                  -2.1273     0.2949  -7.215 6.00e-13 ***
## Rained                         -12.4175     0.3004 -41.340  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.115 on 6712 degrees of freedom
## Multiple R-squared:  0.815,  Adjusted R-squared:  0.8135
## F-statistic: 537.6 on 55 and 6712 DF,  p-value: < 2.2e-16
```

From the summary of our natural spline model, we can observe that with the addition of natural splines, our multiple R-squared value increased from 0.769 to 0.815, which is a 5.98% increase.

```
predictions <- predict(spline_model, newdata = test_data)
mse2 <- mean((test_data$SqrRBC - predictions)^2)
```

We also achieved a lower MSE of 24.8046, which is a decrease of 7.5221 from our previous MSE. Despite that, the residuals vs fitted plot of the spline model shown below indicates that there are still some relationships between predictors that remain uncaptured by the natural spline model.



Given these residual patterns, we decided that it is more appropriate to train a more flexible model that is capable to capturing these non-linear relationships more reliably. This calls for Random Forests, which excel at capturing non-linear relationships and interactions between predictors without requiring explicit modeling. This is due to the fact that random forests are ensemble methods that build multiple decision trees and aggregate their predictions, allowing the model to learn various patterns across predictors.

Random Forests

Firstly, we will be re-introducing some of the predictors that were previously removed due to dependencies. Since random forests are robust to multicollinearity, they are able to perform well with dependent variables which allows them to learn a wide range of patterns.

The predictors used for the random forest model will be as follows: `Hour`, `Temperature`, `Humidity`, `Wind.Speed`, `Visibility`, `Dew.Point.Temp`, `Solar.Radiation`, `Rained`, `Snowed`, `Is.Weekend`, `HeatIdx`, `WindChill`, `HumiDex`, `SeasonsAutumn`, `SeasonsSpring`, `SeasonsSummer` and `HolidayHoliday`.

```r
set.seed(435)

bike_df10 <- bike_df8[, c(-18,-20)]

train_data2 <- bike_df10[train, ]
test_data2 <- bike_df10[test, ]


rf_model <- randomForest(SqrRBC ~ .,
                         data = train_data2,
                         ntree = 501)
```

Now that our model it trained, we will test its predictive power by calculating its MSE.

```r
predictions <- predict(rf_model, newdata = test_data2)

actuals <- test_data2$SqrRBC
mse3 <- mean((predictions - actuals)^2)
```

We found that the MSE of the random forest model is 11.9197 which is lower than the MSE of the spline regression model which was 24.8046. This shows that the MSE has decreased by 51.95 %.

However, it is important to recognize that our Random Forest model currently includes 17 predictors, which may be too many to ensure ease of use for our clients. To streamline the model while maintaining its predictive power, we aim to remove some predictors. To do so, we will evaluate the importance of each predictor in the model as follows:

```r
kable(importance(rf_model))
```

	IncNodePurity
Hour	254285.0142
Temperature	123042.9559
Humidity	95142.5309
Wind.Speed	16551.9637
Visibility	23201.5001
Dew.Point.Temp	34720.5095
Solar.Radiation	41251.1313
Rained	60740.0882
Snowed	862.2766
Is.Weekend	12199.9062
HeatIdx	90603.0163
WindChill	98875.0787
HumiDex	55873.1058
SeasonsAutumn	20471.3502
SeasonsSpring	4205.1826
SeasonsSummer	3176.3765

	IncNodePurity
HolidayHoliday	2784.4792

From the table above, we can surmise that the predictors `Snowed` and `HolidayHoliday` have low importance in the decision-making process of the random forest model. While `SeasonsSpring` and `SeasonsSummer` also show lower importance, we decided to keep them because `SeasonsAutumn` has a high importance score, and all three only require a single input from the client (type of season). Therefore, we will proceed by removing `Snowed` and `HolidayHoliday` from our dataset and retrain the random forest model.

```
set.seed(435)

bike_df11 <- bike_df10[, c(-9,-18)]

train_data2 <- bike_df11[train, ]
test_data2 <- bike_df11[test, ]

rf_model2 <- randomForest(SqrRBC ~ .,
                          data = train_data2,
                          ntree = 501)
```

```
predictions <- predict(rf_model2, newdata = test_data2)
actuals <- test_data2$SqrRBC
mse4 <- mean((predictions - actuals)^2)
```

After dropping the two predictors, we notice a slight increase in the MSE which increased from 11.9197 to 12.1059. Despite this minor loss in predictive accuracy, the trade-off is beneficial as it simplifies the model and enhances its usability and interpretability for clients.

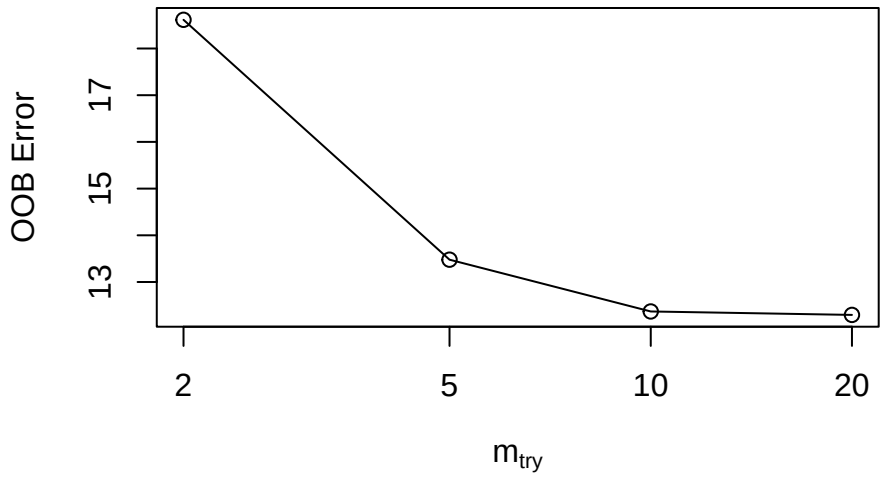
Next, we can further improve our Random Forest model by tuning the mtry value instead of using the default value by using tuneRF as shown below:

```
set.seed(435)

tuneMt <- tuneRF(train_data2[,-which(names(train_data2) == "SqrRBC")],
                         train_data2$SqrRBC,
                         stepFactor = 0.5,
                         plot = TRUE,
                         ntreeTry = 501,
                         trace = TRUE,
                         improve = 0.05)
```

```
## mtry = 5  OOB error = 13.47796
## Searching left ...
## mtry = 10    OOB error = 12.36911
## 0.08227102 0.05
```

```
## mtry = 20    OOB error = 12.29514
## 0.005980782 0.05
## Searching right ...
## mtry = 2     OOB error = 18.6146
## -0.5049259 0.05
```




```r
opt_mtry <- tuneMt[which.min(tuneMt[, "OOBError"]), "mtry"]
```

As seen from the graph above, the optimal mtry value obtained by using tuneRF is 20 as it results in the lowest Out-of-Bag (OOB) error. Next, we will retrain our Random Forest Model using this optimal mtry value and calculate the MSE of the new model.

```r
set.seed(435)
rf_model3 <- randomForest(SqrRBC ~ .,
                                  data = train_data2,
                                  ntree = 501,
                                  mtry = opt_mtry)
```

```r
predictions <- predict(rf_model3, newdata = test_data2)
actuals <- test_data2$SqrRBC
mse5 <- mean((predictions - actuals)^2)
```

We observe that our MSE has decreased again, from 12.1059 to 11.2696, which is a decrease of 6.9087%, showing that using the optimal mtry value did indeed improve the predictive power of the random forest model.

Thus, we have found that between linear regression, spline regression and random forests, the random forest model is the most accurate as it has the lowest MSE of 11.2696 compared to 32.3268 of linear regression and 24.8046 of spline regression. Finally, let us perform k-fold cross validation to ensure that our random forest model is robust.

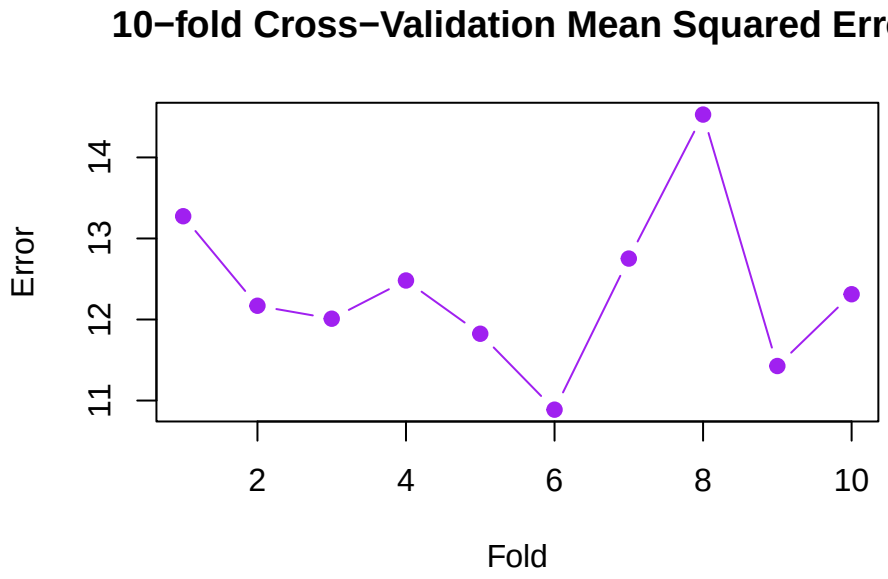
```r
set.seed(435)

k <- 10
folds <- createFolds(train_data2$SqrRBC, k = k, list = TRUE)
cv_errors <- numeric(k)

# Cross-validation loop
for (i in seq_along(folds)) {
  train_fold <- train_data2[-folds[[i]], ]
  test_fold <- train_data2[folds[[i]], ]
  rfm <- randomForest(SqrRBC ~ ., data = train_fold, ntree = 501, mtry = opt_mtry)
  predictions <- predict(rfm, newdata = test_fold)
  cv_errors[i] <- mean((predictions - test_fold$SqrRBC)^2)
}
```

```r
mean_cv_error <- mean(cv_errors)

plot(cv_errors, type = "b", pch = 19, col = "purple",
     xlab = "Fold", ylab = "Error",
     main = "10-fold Cross-Validation Mean Squared Error")
```



Since the mean of the MSE is 12.37 which is similar to the prior attained mean squared error of 11.27, we can conclude that our random forest model is robust.

With this, we have successfully trained a random forest model to predict hourly bike rental count in Seoul using environmental information. The predictors used in the model are as follows: `Hour`, `Temperature`, `Humidity`, `Wind Speed`, `Visibility`, `Dew Point Temperature`, `Solar Radiation`, `Heat Index`, `Wind Chill`, `Humidex`, `Seasons` and `Rained`.

Lastly, we write a function that allows us to predict the hourly rented bike count by providing the function all the relevant parameters. Then, we testing the function to ensure our algorithm is working.

```r
predict_rbc <- function(hr, temp, hum, ws, visibility, dpt, sr, rain, weektype,
                        season) {

  # Create a new data point for prediction
  data_point <- data.frame(
    Hour = hr,
    Temperature = temp,
    Humidity = as.integer(hum),
    Wind.Speed = ws,
    Visibility = as.integer(visibility),
    Dew.Point.Temp = dpt,
    Solar.Radiation = sr,
    Rained = rain,
    Is.Weekend = weektype,
    HeatIdx = 0.5 * ((temp * (9/5) + 32) + 61 + (((temp * (9/5) + 32)-68)*1.2) +
                     (hum*0.094)),
    WindChill = 35.74 + 0.6215*(temp * (9/5) + 32) - 35.75*(ws*2.23694)^(0.16) +
                        0.4275*(temp * (9/5) + 32)*(ws*2.23694)^{0.16},
    HumiDex = temp +
              0.5555*(6.11 * exp(5417.7530*(1/273.15 - 1/(273.15 + dpt)))-10),
    SeasonsAutumn = as.integer(season == "Autumn"),
    SeasonsSpring = as.integer(season == "Spring"),
    SeasonsSummer = as.integer(season == "Summer")
  )

  data_point$Hour <- factor(12, levels = levels(train_data2$Hour))

  prediction <- (predict(rf_model3, newdata = data_point))^2

  return(paste(round(prediction), "bikes"))
}
```

```r
predict_rbc(17, 30.1, 41, 5, 2000,12.8, 1.4, 0, 0, "Autumn")
```

```
## [1] "1007 bikes"
```

With this, we have attained our goal of predicting hourly bike rental count in Seoul using environmental information.