SeoulBikeData program

```
SeoulBikeData = read.csv('C:/Users/kevin/Desktop/SeoulBikeData.csv',hea
der = TRUE)
head(SeoulBikeData)

##         Date Rented.Bike.Count Hour Temperature.degree. 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
## 4 01/12/2017               107    3                -6.2          40
## 5 01/12/2017                78    4                -6.0          36
## 6 01/12/2017               100    5                -6.4          37
##   Wind.speed..m.s. Visibility..10m. Dew.point.temperature.degree.
## 1              2.2             2000                         -17.6
## 2              0.8             2000                         -17.6
## 3              1.0             2000                         -17.7
## 4              0.9             2000                         -17.6
## 5              2.3             2000                         -18.6
## 6              1.5             2000                         -18.7
##   Solar.Radiation..MJ.m2. Rainfall.mm. Snowfall..cm. Seasons    Holi
day
## 1                       0            0             0  Winter No Holi
day
## 2                       0            0             0  Winter No Holi
day
## 3                       0            0             0  Winter No Holi
day
## 4                       0            0             0  Winter No Holi
day
## 5                       0            0             0  Winter No Holi
day
## 6                       0            0             0  Winter No Holi
day
##   Functioning.Day
## 1             Yes
## 2             Yes
## 3             Yes
## 4             Yes
## 5             Yes
## 6             Yes

#read the file and display the file

sum(is.na(SeoulBikeData))

## [1] 0
```

```r
#check missing value

library(tidyverse)

## -- Attaching packages --------------------------------------- tidyve
rse 1.3.1 --

## v ggplot2 3.3.3     v purrr   0.3.4
## v tibble  3.1.2     v dplyr   1.0.6
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   1.4.0     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_co
nflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

SeoulBikeData <- SeoulBikeData %>% rename(
    rental_count = Rented.Bike.Count,
    Temperature = Temperature.degree.,
    Humidity = Humidity...,
    Wind_speed = Wind.speed..m.s.,
    Visibility_in_10m = Visibility..10m.,
    Dew_point_temperature = Dew.point.temperature.degree.,
    Solar_Radiation = Solar.Radiation..MJ.m2.,
    Rainfall_in_mm = Rainfall.mm.,
    Snowfall_in_cm = Snowfall..cm.,
    Functioning_Day = Functioning.Day
    )
head(SeoulBikeData)

##         Date rental_count Hour Temperature Humidity Wind_speed
## 1 01/12/2017          254    0        -5.2       37        2.2
## 2 01/12/2017          204    1        -5.5       38        0.8
## 3 01/12/2017          173    2        -6.0       39        1.0
## 4 01/12/2017          107    3        -6.2       40        0.9
## 5 01/12/2017           78    4        -6.0       36        2.3
## 6 01/12/2017          100    5        -6.4       37        1.5
##   Visibility_in_10m Dew_point_temperature Solar_Radiation Rainfall_i
n_mm
## 1              2000                 -17.6               0
   0
## 2              2000                 -17.6               0
   0
## 3              2000                 -17.7               0
   0
## 4              2000                 -17.6               0
   0
## 5              2000                 -18.6               0
   0
## 6              2000                 -18.7               0
```

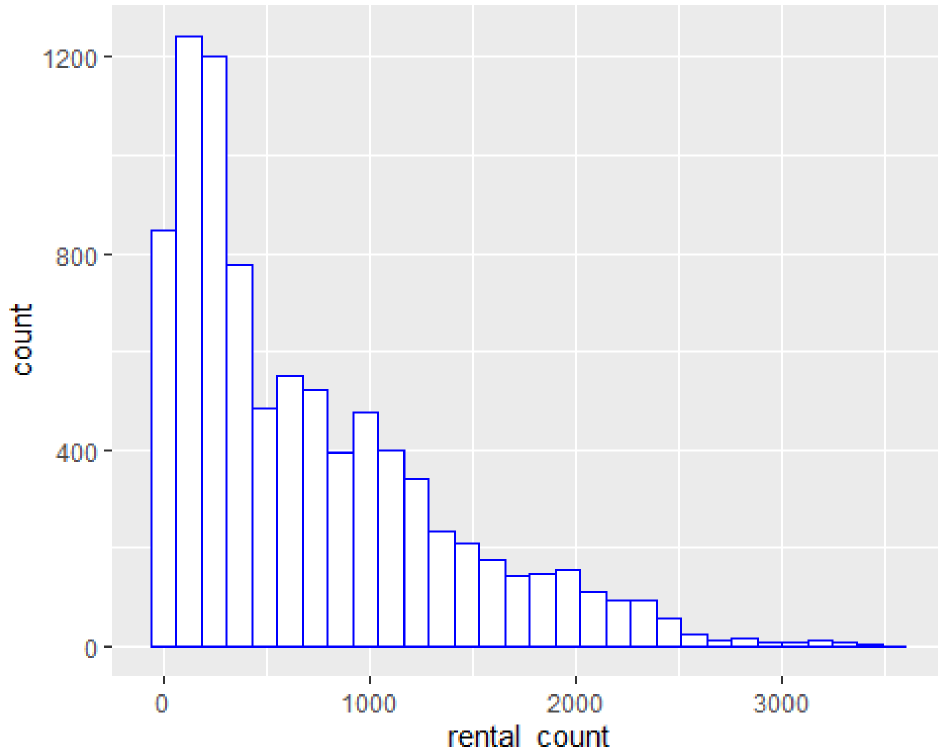
```
   0
##   Snowfall_in_cm Seasons    Holiday Functioning_Day
## 1              0  Winter No Holiday             Yes
## 2              0  Winter No Holiday             Yes
## 3              0  Winter No Holiday             Yes
## 4              0  Winter No Holiday             Yes
## 5              0  Winter No Holiday             Yes
## 6              0  Winter No Holiday             Yes
```

```r
str(SeoulBikeData)
```

```
## 'data.frame':    8760 obs. of  14 variables:
##  $ Date                 : chr  "01/12/2017" "01/12/2017" "01/12/2017
" "01/12/2017" ...
##  $ rental_count         : int  254 204 173 107 78 100 181 460 930 49
0 ...
##  $ Hour                 : int  0 1 2 3 4 5 6 7 8 9 ...
##  $ Temperature          : num  -5.2 -5.5 -6 -6.2 -6 -6.4 -6.6 -7.4 -
7.6 -6.5 ...
##  $ Humidity             : int  37 38 39 40 36 37 35 38 37 27 ...
##  $ Wind_speed           : num  2.2 0.8 1 0.9 2.3 1.5 1.3 0.9 1.1 0.5
 ...
##  $ Visibility_in_10m    : int  2000 2000 2000 2000 2000 2000 2000 20
00 2000 1928 ...
##  $ Dew_point_temperature: num  -17.6 -17.6 -17.7 -17.6 -18.6 -18.7 -
19.5 -19.3 -19.8 -22.4 ...
##  $ Solar_Radiation      : num  0 0 0 0 0 0 0 0 0.01 0.23 ...
##  $ Rainfall_in_mm       : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Snowfall_in_cm       : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ Seasons              : chr  "Winter" "Winter" "Winter" "Winter"
 ...
##  $ Holiday              : chr  "No Holiday" "No Holiday" "No Holiday
" "No Holiday" ...
##  $ Functioning_Day      : chr  "Yes" "Yes" "Yes" "Yes" ...
```

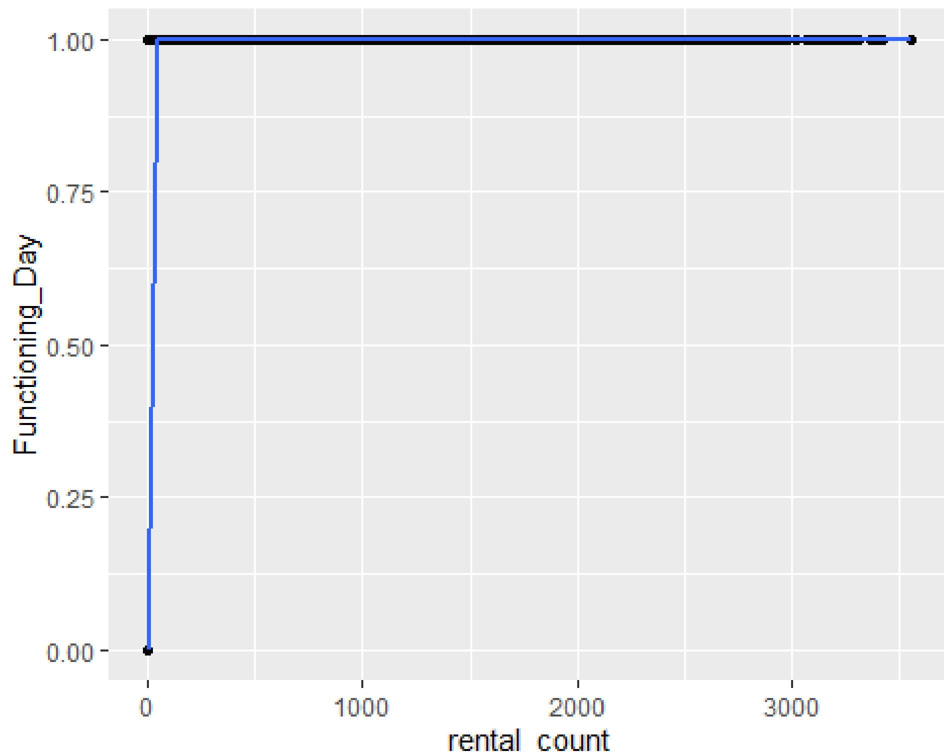
```r
#renaming the columns

ggplot(SeoulBikeData, aes(x=rental_count)) + geom_histogram(color="blue
", fill="white")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
#shape of the dependent value

nrow(subset(SeoulBikeData, rental_count==0))

## [1] 295

SeoulBikeData %>% count(Functioning_Day)

##   Functioning_Day    n
## 1              No  295
## 2             Yes 8465

SeoulBikeData$Functioning_Day[SeoulBikeData$Functioning_Day == 'No'] <-
 0
SeoulBikeData$Functioning_Day[SeoulBikeData$Functioning_Day == 'Yes'] <
- 1
SeoulBikeData$Functioning_Day <- as.numeric(SeoulBikeData$Functioning_D
ay)
ggplot(SeoulBikeData, aes(x=rental_count, y=Functioning_Day)) +
  geom_point() +
  geom_smooth(method = "glm",
    method.args = list(family = "binomial"),
    se = FALSE)

## `geom_smooth()` using formula 'y ~ x'

## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

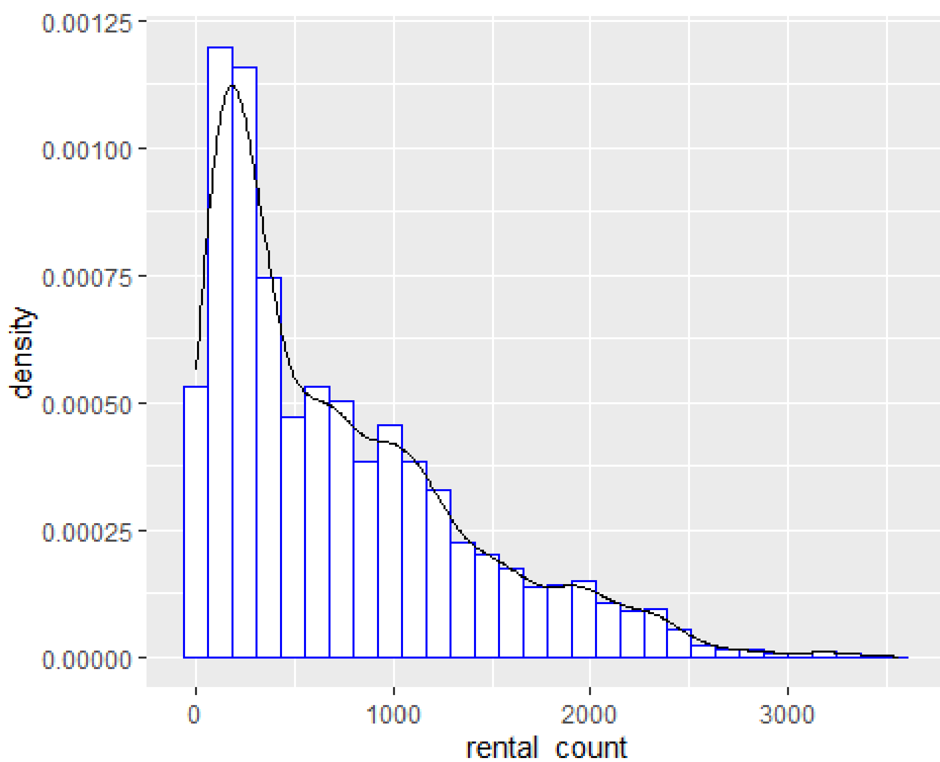



```
SeoulBikeData_nonFunction <- filter(SeoulBikeData, Functioning_Day == 0)
SeoulBikeData_nonFunction %>% count(rental_count)

##   rental_count   n
## 1            0 295

SeoulBikeData_nonFunction %>% count(Functioning_Day)

##   Functioning_Day   n
## 1               0 295

#drop the function day attribute.

SeoulBikeData_Function <- filter(SeoulBikeData, Functioning_Day == 1)
str(SeoulBikeData_Function)

## 'data.frame':    8465 obs. of  14 variables:
##  $ Date                 : chr  "01/12/2017" "01/12/2017" "01/12/2017
" "01/12/2017" ...
##  $ rental_count         : int  254 204 173 107 78 100 181 460 930 49
0 ...
##  $ Hour                 : int  0 1 2 3 4 5 6 7 8 9 ...
##  $ Temperature          : num  -5.2 -5.5 -6 -6.2 -6 -6.4 -6.6 -7.4 -
7.6 -6.5 ...
##  $ Humidity             : int  37 38 39 40 36 37 35 38 37 27 ...
##  $ Wind_speed           : num  2.2 0.8 1 0.9 2.3 1.5 1.3 0.9 1.1 0.5
```

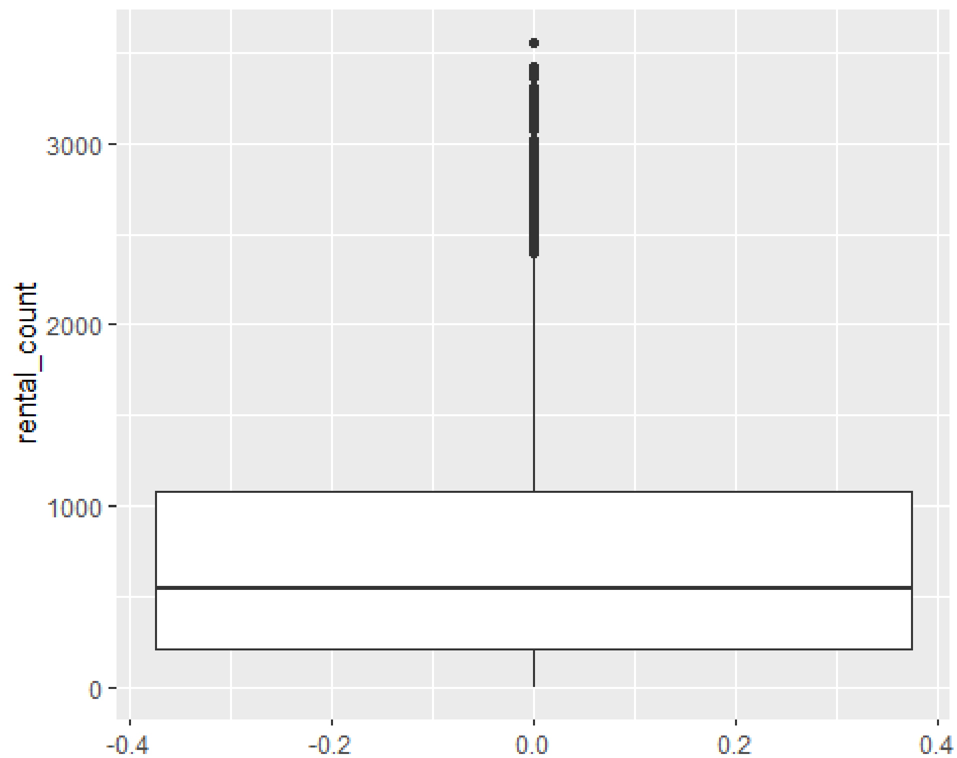
```
 ...
## $ Visibility_in_10m     : int  2000 2000 2000 2000 2000 2000 2000 20
00 2000 1928 ...
## $ Dew_point_temperature: num  -17.6 -17.6 -17.7 -17.6 -18.6 -18.7 -
19.5 -19.3 -19.8 -22.4 ...
## $ Solar_Radiation      : num  0 0 0 0 0 0 0 0 0.01 0.23 ...
## $ Rainfall_in_mm       : num  0 0 0 0 0 0 0 0 0 0 ...
## $ Snowfall_in_cm       : num  0 0 0 0 0 0 0 0 0 0 ...
## $ Seasons              : chr  "Winter" "Winter" "Winter" "Winter"
 ...
## $ Holiday              : chr  "No Holiday" "No Holiday" "No Holiday
" "No Holiday" ...
## $ Functioning_Day      : num  1 1 1 1 1 1 1 1 1 1 ...
```

```r
ggplot(SeoulBikeData_Function, aes(x=rental_count)) + geom_histogram(ae
s(y=..density..),color="blue", fill="white") + geom_density()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
#after the function day attribute, check the shape again

ggplot(SeoulBikeData_Function, aes(y=rental_count)) +
  geom_boxplot()
```




```
summary(SeoulBikeData_Function$rental_count)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     2.0   214.0   542.0   729.2  1084.0  3556.0

summary(SeoulBikeData_Function$Temperature)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -17.80    3.00   13.50   12.77   22.70   39.40

summary(SeoulBikeData_Function$Humidity)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   42.00   57.00   58.15   74.00   98.00

summary(SeoulBikeData_Function$Wind_speed)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.900   1.500   1.726   2.300   7.400

summary(SeoulBikeData_Function$Visibility_in_10m)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      27     935    1690    1434    2000    2000

summary(SeoulBikeData_Function$Dew_point_temperature)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -30.600  -5.100   4.700   3.945  15.200  27.200
```

```r
summary(SeoulBikeData_Function$Solar_Radiation)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0100  0.5679  0.9300  3.5200
```

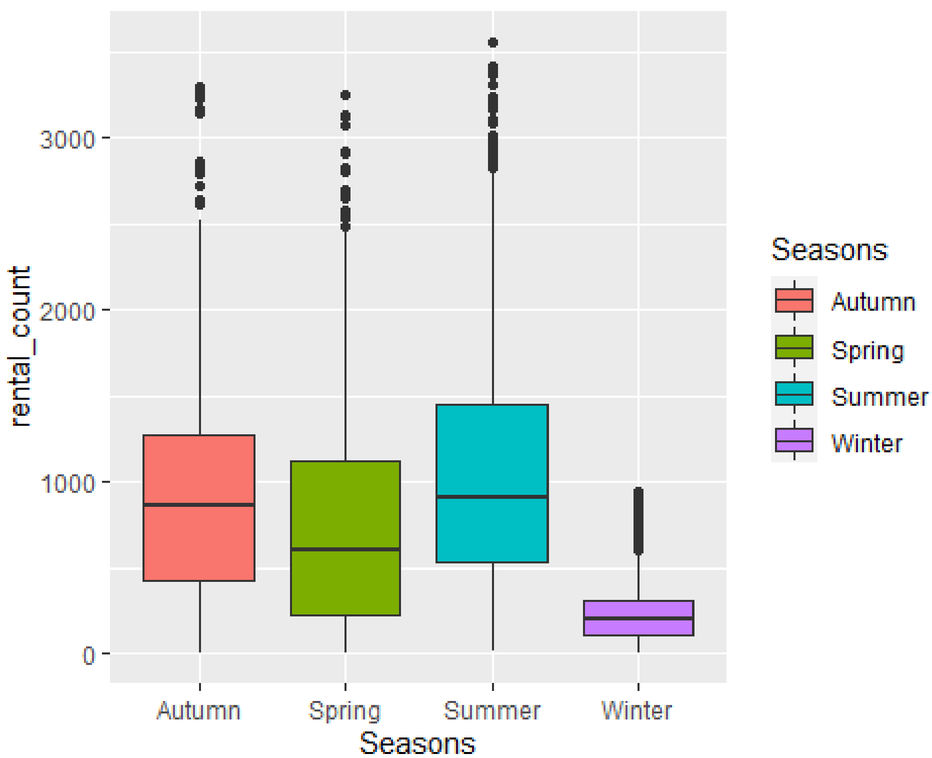
```r
summary(SeoulBikeData_Function$Rainfall_in_mm)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1491  0.0000 35.0000
```

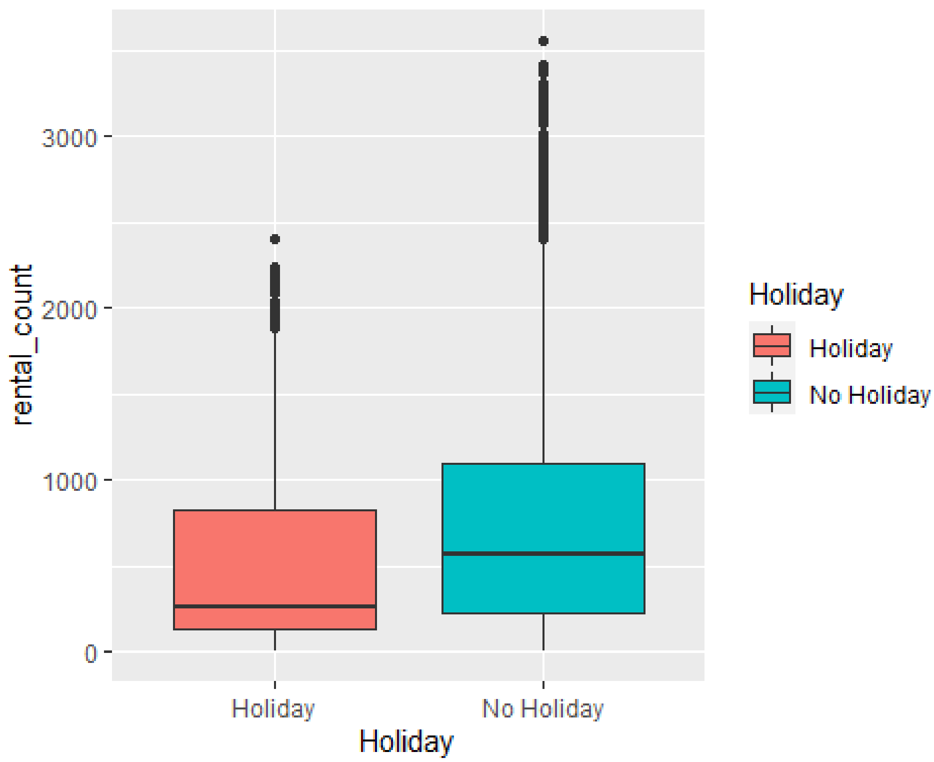
```r
summary(SeoulBikeData_Function$Snowfall_in_cm)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00000 0.00000 0.00000 0.07769 0.00000 8.80000
```

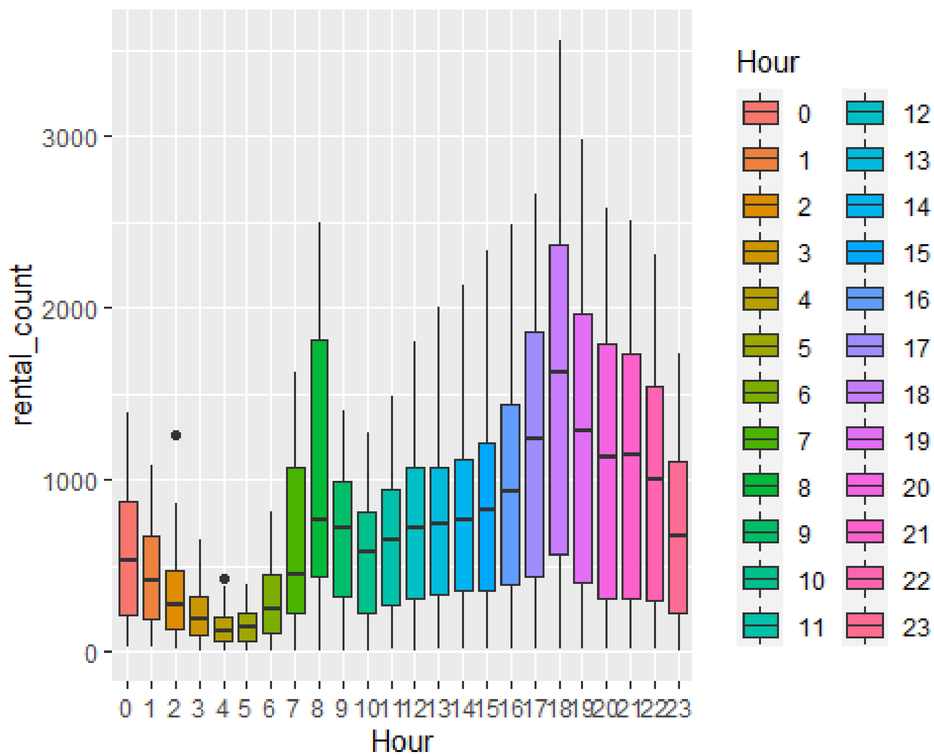
```r
ggplot(SeoulBikeData_Function, aes(x=Seasons , y=rental_count, fill=Sea
sons)) +
  geom_boxplot()
```




```r
#boxplot between counts and seasons along four seasons

ggplot(SeoulBikeData_Function, aes(x=Holiday , y=rental_count, fill=Hol
iday)) +
  geom_boxplot()
```

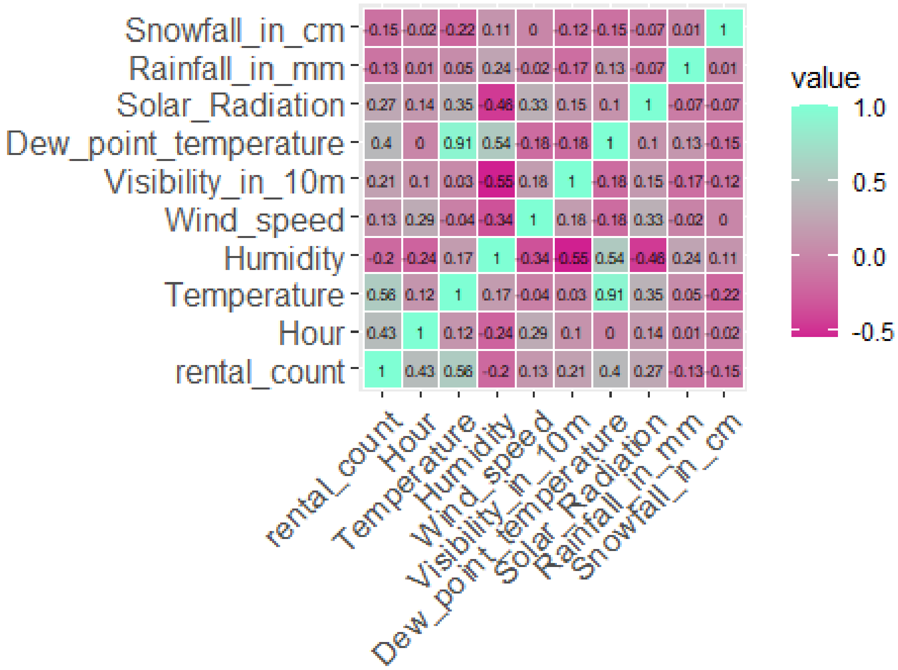



```r
#boxplot between counts and holiday

count_vs_hour <- SeoulBikeData_Function[2:3]
count_vs_hour$Hour <- as.character(count_vs_hour$Hour)
str(count_vs_hour)

## 'data.frame':    8465 obs. of  2 variables:
##  $ rental_count: int  254 204 173 107 78 100 181 460 930 490 ...
##  $ Hour        : chr  "0" "1" "2" "3" ...

count_vs_hour$Hour <- factor(count_vs_hour$Hour,levels = c("0","1", "2",
 "3", "4","5", "6", "7", "8","9", "10", "11", "12","13","14", "15", "16
", "17","18", "19", "20", "21","22", "23"))
ggplot(count_vs_hour,aes(x=Hour , y=rental_count,fill = Hour)) + geom_b
oxplot()
```

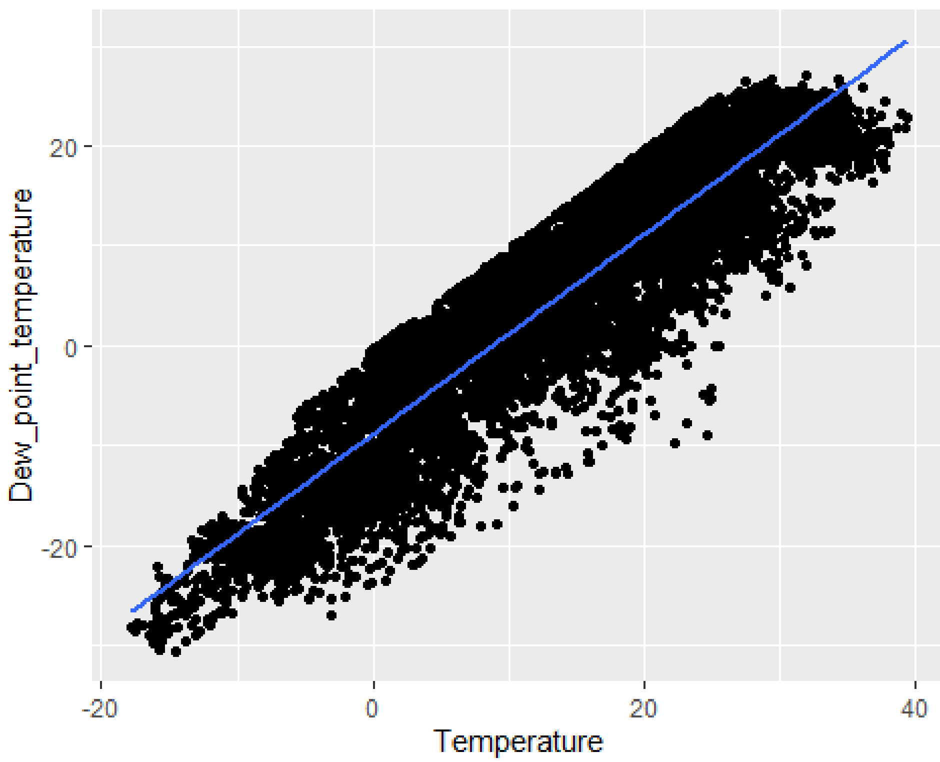



```
#boxplot between counts and hours along the different intervals

SeoulBikeData_Function$Seasons[SeoulBikeData_Function$Seasons == 'Winte
r'] <- 1
SeoulBikeData_Function$Seasons[SeoulBikeData_Function$Seasons == 'Sprin
g'] <- 2
SeoulBikeData_Function$Seasons[SeoulBikeData_Function$Seasons == 'Summe
r'] <- 3
SeoulBikeData_Function$Seasons[SeoulBikeData_Function$Seasons == 'Autum
n'] <- 4
SeoulBikeData_Function$Seasons <- as.numeric(SeoulBikeData_Function$Sea
sons)
SeoulBikeData_Function %>% count(Seasons)

##   Seasons    n
## 1       1 2160
## 2       2 2160
## 3       3 2208
## 4       4 1937

#change seasons into from 1 to 4 for the linear regression

SeoulBikeData_Function %>% count(Holiday)

##      Holiday    n
## 1    Holiday  408
## 2 No Holiday 8057
```

```
SeoulBikeData_Function$Holiday[SeoulBikeData_Function$Holiday == 'Holid
ay'] <- 1
SeoulBikeData_Function$Holiday[SeoulBikeData_Function$Holiday == 'No Ho
liday'] <- 2
SeoulBikeData_Function$Holiday <- as.numeric(SeoulBikeData_Function$Hol
iday)
SeoulBikeData_Function %>% count(Holiday)

##   Holiday    n
## 1       1  408
## 2       2 8057

#change Holiday into 1 and 2 for the linear regression

library(reshape2)

## 
## 载入程辑包：'reshape2'

## The following object is masked from 'package:tidyr':
## 
##     smiths

correlation_test <- SeoulBikeData_Function[2:11]
melted<- melt(round(cor(correlation_test),2))
library(ggplot2)
ggplot(data = melted, aes(x=Var1, y=Var2, fill=value)) + geom_tile() +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, size = 12, hj
ust = 1),axis.text.y = element_text(size = 12))+
  coord_fixed()+scale_fill_continuous(low = "violetred", high = "aquama
rine")+
  geom_tile(color = "white",lwd = 0.5,linetype = 1)+
  labs(x = "",y = "") +
  geom_text(aes(label = value), color = "black", size = 2)
```




```r
#heatmap and correlation test

ggplot(correlation_test, aes(x=Temperature, y=Dew_point_temperature)) +

  geom_point()+
  geom_smooth(method=lm, se=FALSE)

## `geom_smooth()` using formula 'y ~ x'
```




```r
test_model_1 <- lm(Temperature~Dew_point_temperature,data = correlation
_test)
summary(test_model_1)

##
## Call:
## lm(formula = Temperature ~ Dew_point_temperature, data = correlation
_test)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.2582 -3.7426 -0.6475  3.1734 22.6494
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           9.473515   0.055553   170.5   <2e-16 ***
## Dew_point_temperature 0.835880   0.004021   207.9   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.898 on 8463 degrees of freedom
## Multiple R-squared:  0.8362, Adjusted R-squared:  0.8362
## F-statistic: 4.322e+04 on 1 and 8463 DF,  p-value: < 2.2e-16

#check the correlation between dew point temperature and temperature.
```

```
SeoulBikeData_Function_mlr <- SeoulBikeData_Function[c(2:7,9:13)]
head(SeoulBikeData_Function_mlr)

##   rental_count Hour Temperature Humidity Wind_speed Visibility_in_10
m
## 1          254    0        -5.2       37        2.2                200
0
## 2          204    1        -5.5       38        0.8                200
0
## 3          173    2        -6.0       39        1.0                200
0
## 4          107    3        -6.2       40        0.9                200
0
## 5           78    4        -6.0       36        2.3                200
0
## 6          100    5        -6.4       37        1.5                200
0
##   Solar_Radiation Rainfall_in_mm Snowfall_in_cm Seasons Holiday
## 1               0              0              0       1       2
## 2               0              0              0       1       2
## 3               0              0              0       1       2
## 4               0              0              0       1       2
## 5               0              0              0       1       2
## 6               0              0              0       1       2

library(MASS)

##
## 载入程辑包：'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

library(leaps)
library(caret)

## 载入需要的程辑包：lattice

##
## 载入程辑包：'caret'

## The following object is masked from 'package:purrr':
##
##     lift

train_control <- trainControl(method = "cv", number = 10,p = 0.75)
#split dataset to 75% training data and 25% testing data.
#method = "cv" and number = 10 are 10-fold cross-validation.

set.seed(903)
model_mlr <- train(rental_count~., data=SeoulBikeData_Function_mlr,meth
```

```r
od = "lm", trControl = train_control,metric = "RMSE")
model_mlr
```

```
## Linear Regression
##
## 8465 samples
##   10 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7617, 7620, 7619, 7618, 7619, 7618, ...
## Resampling results:
##
##   RMSE      Rsquared  MAE
##   438.2147  0.535284  326.9658
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```r
summary(model_mlr)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1236.44  -278.37   -54.88   213.52  2231.49
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          57.345482  55.244293   1.038 0.299284
## Hour                 28.706993   0.746413  38.460  < 2e-16 ***
## Temperature          26.609709   0.579858  45.890  < 2e-16 ***
## Humidity             -8.431415   0.372911 -22.610  < 2e-16 ***
## Wind_speed           19.218473   5.236120   3.670 0.000244 ***
## Visibility_in_10m    -0.007595   0.009984  -0.761 0.446853
## Solar_Radiation     -79.693998   7.577910 -10.517  < 2e-16 ***
## Rainfall_in_mm      -63.431446   4.375804 -14.496  < 2e-16 ***
## Snowfall_in_cm       18.817067  11.200192   1.680 0.092981 .
## Seasons             110.785998   5.623107  19.702  < 2e-16 ***
## Holiday             128.077284  22.298547   5.744 9.58e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 437.8 on 8454 degrees of freedom
## Multiple R-squared:  0.536,	Adjusted R-squared:  0.5354
## F-statistic: 976.5 on 10 and 8454 DF,  p-value: < 2.2e-16
```

```r
#multple linear regression model
```

```r
set.seed(903)
step_model <- train(rental_count~., data = SeoulBikeData_Function_mlr,
                    method = "lmStepAIC",
                    trControl = train_control,
                    trace = FALSE)
step_model
```

```
## Linear Regression with Stepwise Selection
##
## 8465 samples
##   10 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7617, 7620, 7619, 7618, 7619, 7618, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   438.212  0.5352863  326.8619
```

```r
summary(step_model)
```

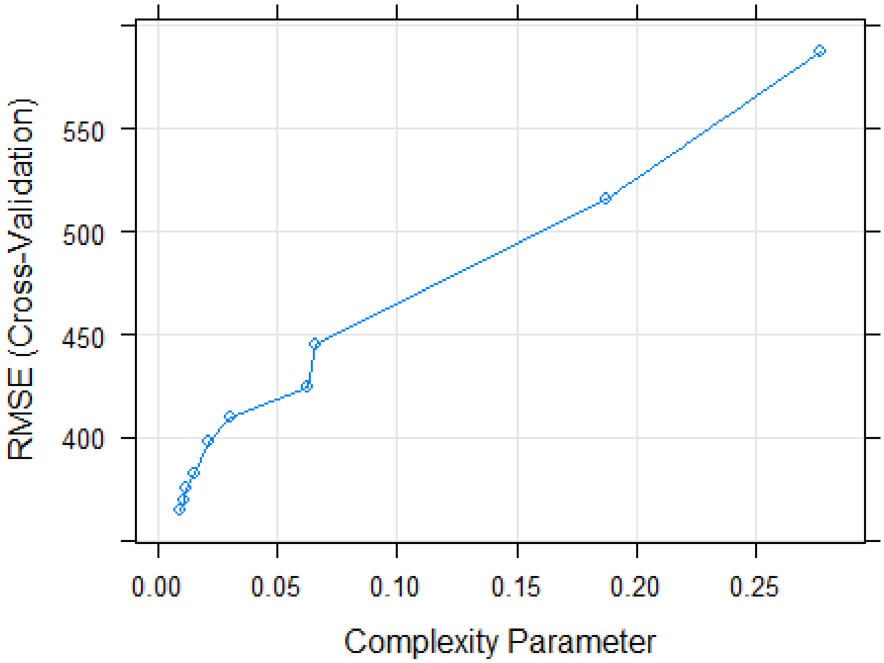
```
##
## Call:
## lm(formula = .outcome ~ Hour + Temperature + Humidity + Wind_speed +

##     Solar_Radiation + Rainfall_in_mm + Snowfall_in_cm + Seasons +
##     Holiday, data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1239.21  -278.14   -54.79   213.14  2233.86
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      39.0364    49.7244   0.785 0.432443
## Hour             28.7498     0.7443  38.628  < 2e-16 ***
## Temperature      26.5632     0.5766  46.068  < 2e-16 ***
## Humidity         -8.2726     0.3090 -26.773  < 2e-16 ***
## Wind_speed       18.8501     5.2135   3.616 0.000301 ***
## Solar_Radiation -78.3414     7.3662 -10.635  < 2e-16 ***
## Rainfall_in_mm  -63.2961     4.3721 -14.477  < 2e-16 ***
## Snowfall_in_cm   18.9046    11.1993   1.688 0.091446 .
## Seasons         109.9105     5.5039  19.969  < 2e-16 ***
## Holiday         128.2228    22.2972   5.751  9.2e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 437.8 on 8455 degrees of freedom
```

```
## Multiple R-squared:  0.536,  Adjusted R-squared:  0.5355
## F-statistic:  1085 on 9 and 8455 DF,  p-value: < 2.2e-16

#stepwise regression model.

subsets<-regsubsets(rental_count~.,
data=SeoulBikeData_Function_mlr, nbest=1)
sub.sum <- summary(subsets)
as.data.frame(sub.sum$outmat)

##          Hour Temperature Humidity Wind_speed Visibility_in_10m Sola
r_Radiation
## 1  ( 1 )                *

## 2  ( 1 )    *           *

## 3  ( 1 )    *           *        *

## 4  ( 1 )    *           *        *

## 5  ( 1 )    *           *        *

## 6  ( 1 )    *           *        *
          *
## 7  ( 1 )    *           *        *
          *
## 8  ( 1 )    *           *        *           *
          *
##          Rainfall_in_mm Snowfall_in_cm Seasons Holiday
## 1  ( 1 )
## 2  ( 1 )
## 3  ( 1 )
## 4  ( 1 )                                 *
## 5  ( 1 )          *                      *
## 6  ( 1 )          *                      *
## 7  ( 1 )          *                      *       *
## 8  ( 1 )          *                      *       *

#looking for the best attributes using regsubsets.

library(rpart)
library(rpart.plot)

set.seed(903)
dt_model <- train(rental_count ~ .,
   tuneLength = 10,metric = "RMSE", data = SeoulBikeData_Function_mlr,
method = "rpart",trControl =train_control)

## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
trainInfo, :
## There were missing values in resampled performance measures.
```

```r
print(dt_model)
```

```
## CART
##
## 8465 samples
##   10 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7617, 7620, 7619, 7618, 7619, 7618, ...
## Resampling results across tuning parameters:
##
##   cp           RMSE      Rsquared   MAE
##   0.009541003  364.5774  0.6785039  259.3501
##   0.011345923  369.3711  0.6699230  263.2851
##   0.012109507  375.2878  0.6593205  267.7438
##   0.015410349  381.8530  0.6471406  273.2710
##   0.021076976  398.3559  0.6158454  287.3467
##   0.030598818  410.0091  0.5929280  300.4972
##   0.062278865  424.3441  0.5634851  313.4617
##   0.065964898  445.3929  0.5174085  330.9601
##   0.187538412  515.4791  0.3547558  380.1379
##   0.276927210  587.5918  0.2643416  452.1301
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 0.009541003.
```

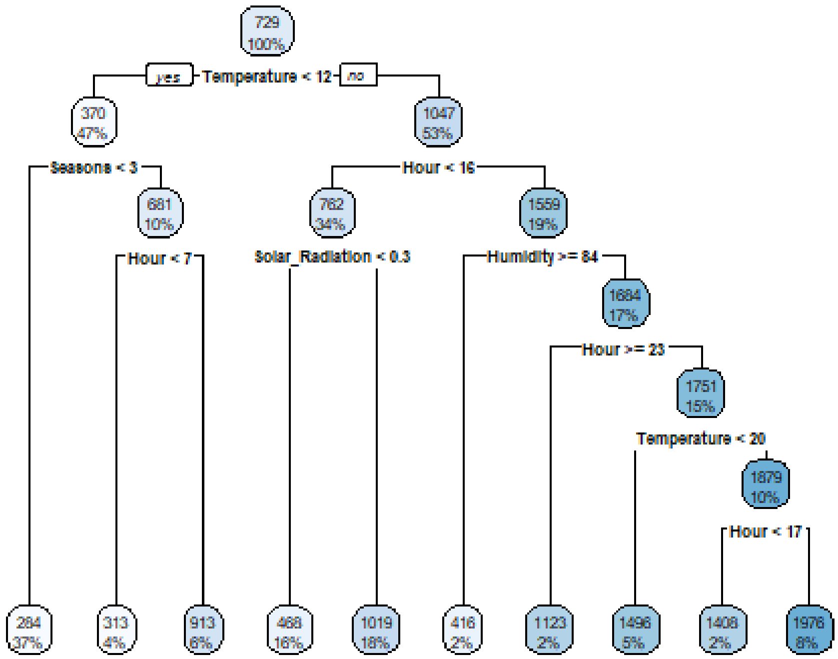
```r
#decision tree regression model.

plot(dt_model)
```



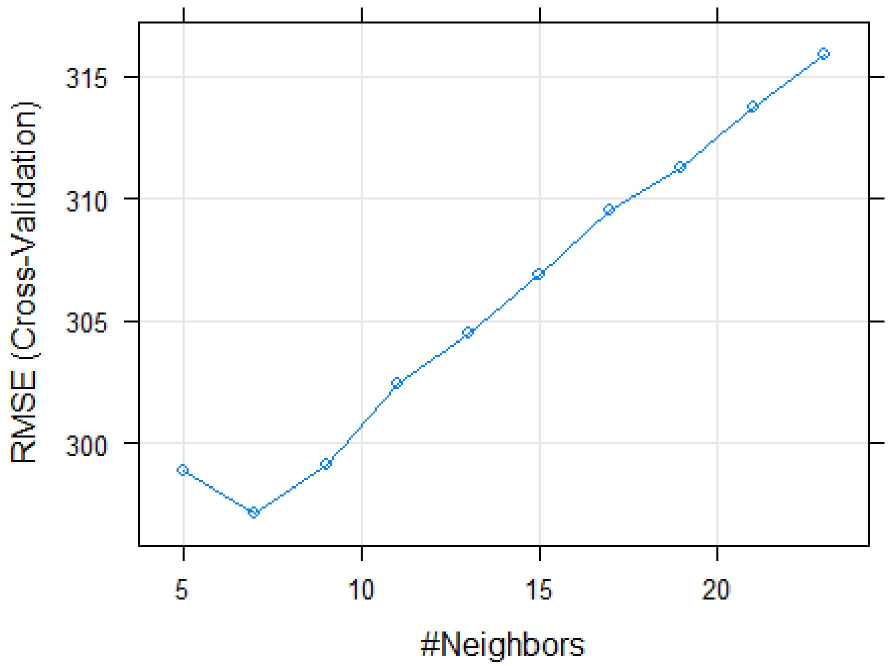

```
#plot for complexity parameter

dt_model$finalModel

## n= 8465
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##   1) root 8465 3492374000  729.1570
##     2) Temperature< 12.05 3976  484876500  370.0025
##       4) Seasons< 3 3112  194179300  283.6199 *
##       5) Seasons>=3 864  183834700  681.1400
##        10) Hour< 6.5 334   11483650  313.4581 *
##        11) Hour>=6.5 530   98742340  912.8491 *
##     3) Temperature>=12.05 4489 2040364000 1047.2680
##       6) Hour< 15.5 2882  649750900  762.0399
##        12) Solar_Radiation< 0.295 1344  163436500  468.1652 *
##        13) Solar_Radiation>=0.295 1538  268813300 1018.8460 *
##       7) Hour>=15.5 1607  735658700 1558.7960
##        14) Humidity>=83.5 159   35515400  416.1950 *
##        15) Humidity< 83.5 1448  469769300 1684.2610
##          30) Hour>=22.5 153   11268640 1123.3790 *
##          31) Hour< 22.5 1295  404681900 1750.5270
##            62) Temperature< 19.95 433   96791000 1495.5520 *
##            63) Temperature>=19.95 862  265600000 1878.6070
```

```
##             126) Hour< 16.5 148   29729470 1407.6890 *
##             127) Hour>=16.5 714  196246400 1976.2200 *
```

```r
rpart.plot(dt_model$finalModel)
```




```r
#the shape of the best tree.

set.seed(903)
model_knn <- train(
   rental_count~., data = SeoulBikeData_Function_mlr, method = "knn",
  trControl = train_control,
  preProcess = c("center","scale"),
  tuneLength = 10)
#KNN regression model.
plot(model_knn)
```




```r
#plot for number of neighbors
model_knn
```

```
## k-Nearest Neighbors
##
## 8465 samples
##   10 predictor
##
## Pre-processing: centered (10), scaled (10)
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 7617, 7620, 7619, 7618, 7619, 7618, ...
## Resampling results across tuning parameters:
##
##   k   RMSE      Rsquared   MAE
##    5  298.9053  0.7844021  192.3623
##    7  297.1353  0.7863595  194.3197
##    9  299.0939  0.7834965  197.6511
##   11  302.4515  0.7787076  200.7736
##   13  304.4817  0.7758977  203.0266
##   15  306.8399  0.7724442  204.9082
##   17  309.5172  0.7685921  207.8098
##   19  311.2797  0.7660385  209.7445
##   21  313.7222  0.7624218  211.8016
##   23  315.8738  0.7591868  213.7759
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was k = 7.
```

```r
model_knn$bestTune
```

```
##   k
## 2 7
```

```r
# the best number for neighbors.
```