By Madhurima biswas

Bike Renting - R code

```
> #To clear the R environment of any predefined objects
> rm(list=ls())
> #To set working directory
> setwd("F:/DS/edWisor/Project 2")
> getwd()
[1] "F:/DS/edWisor/Project 2"
>
> #To load required libraries
> library(ggplot2)    # used for ploting
Warning message:
package ‘ggplot2’ was built under R version 3.4.4
> library(dplyr)      # used for data manipulation and joining

Attaching package: ‘dplyr’

The following objects are masked from ‘package:stats’:

    filter, lag

The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union

Warning message:
package ‘dplyr’ was built under R version 3.4.4
> library(scales)     # used for "pretty_brakes() function"
Warning message:
package ‘scales’ was built under R version 3.4.4
> library(DMwR)       # used for KNN Imputation
Loading required package: lattice
Loading required package: grid
Warning messages:
1: package ‘DMwR’ was built under R version 3.4.4
2: package ‘lattice’ was built under R version 3.4.4
> library(outliers)   # used for outlier detection & modification
Warning message:
package ‘outliers’ was built under R version 3.4.4
> library(corrgram)   # used for plotting correlation amongst variables

Attaching package: ‘corrgram’

The following object is masked from ‘package:lattice’:

    panel.fill

Warning message:
package ‘corrgram’ was built under R version 3.4.4
> library(corrplot)   # used for plotting correlation amongst variables
corrplot 0.84 loaded
Warning message:
package ‘corrplot’ was built under R version 3.4.4
> library(caret)      # used for various model training
Warning message:
package ‘caret’ was built under R version 3.4.4
> library(lubridate)  # used for handling date format data

Attaching package: ‘lubridate’
```

```
The following object is masked from ‘package:base’:

    date

Warning message:
package ‘lubridate’ was built under R version 3.4.4
> library(FNN)        # used for KNN modeling
Warning message:
package ‘FNN’ was built under R version 3.4.4
> library(randomForest) # used for Random Forest implementation
randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.

Attaching package: ‘randomForest’

The following object is masked from ‘package:outliers’:

    outlier

The following object is masked from ‘package:dplyr’:

    combine

The following object is masked from ‘package:ggplot2’:

    margin

Warning message:
package ‘randomForest’ was built under R version 3.4.4
> library(rpart)      # used for Decision Tree algorithm implementation
Warning message:
package ‘rpart’ was built under R version 3.4.4
>
> #To load the data
> data = read.csv("day.csv",header = T, na.strings = c(""," ","NA",NA))
>
> ###################Data Exploration####################
> str(data)           #"data.frame"
'data.frame':   731 obs. of  16 variables:
 $ instant   : int  1 2 3 4 5 6 7 8 9 10 ...
 $ dteday    : Factor w/ 731 levels "2011-01-01","2011-01-02",..: 1 2 3 4 5 6 7 8 9 10 ..
.
 $ season    : int  1 1 1 1 1 1 1 1 1 1 ...
 $ yr        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth      : int  1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ weekday   : int  6 0 1 2 3 4 5 6 0 1 ...
 $ workingday: int  0 0 1 1 1 1 1 0 0 1 ...
 $ weathersit: int  2 2 1 1 1 1 2 2 1 1 ...
 $ temp      : num  0.344 0.363 0.196 0.2 0.227 ...
 $ atemp     : num  0.364 0.354 0.189 0.212 0.229 ...
 $ hum       : num  0.806 0.696 0.437 0.59 0.437 ...
 $ windspeed : num  0.16 0.249 0.248 0.16 0.187 ...
 $ casual    : int  331 131 120 108 82 88 148 68 54 41 ...
 $ registered: int  654 670 1229 1454 1518 1518 1362 891 768 1280 ...
 $ cnt       : int  985 801 1349 1562 1600 1606 1510 959 822 1321 ...
> dim(data)             # 731 x 16
[1] 731  16
>
> ###Univariate Analysis###
> #col = names(data)
> #To find the unique values in each column
> #for (i in col) {
> #  print(i)
```

```
> #  print(length(unique(data[,i])))
> #}
> #Data has 7 categorical variables, 8 numeric variables & one date type variable.
> #Target variable is integer type in nature.
>
> ###Data Consolidation###
> #Convert into Proper data types
> #-->ignoring "instant" as it is just like serial number.
> data = data[,-1]
> #dim(data)       #731 x 15
>
> #_____Data type conversion_____#
> catnames = c("season","yr","mnth","holiday","weekday","workingday","weathersit")   #cat
egorical variables
> for (i in catnames) {
+   data[,i] = as.factor(data[,i])
+ }
>
> numnames = c("temp","atemp","hum","windspeed","casual","registered","cnt")         #num
erical variables
> for (i in numnames) {
+   data[,i] = as.numeric(data[,i])
+ }
>
> data$dteday = as.Date(data$dteday)     #It changed date "02-04-11" to "2011-04-02".
>
>
> str(data)
'data.frame':  731 obs. of  15 variables:
 $ dteday    : Date, format: "2011-01-01" "2011-01-02" "2011-01-03" "2011-01-04" ...
 $ season    : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 1 1 1 1 1 ...
 $ yr        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ mnth      : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ weekday   : Factor w/ 7 levels "0","1","2","3",..: 7 1 2 3 4 5 6 7 1 2 ...
 $ workingday: Factor w/ 2 levels "0","1": 1 1 2 2 2 2 2 1 1 2 ...
 $ weathersit: Factor w/ 3 levels "1","2","3": 2 2 1 1 1 1 2 2 1 1 ...
 $ temp      : num  0.344 0.363 0.196 0.2 0.227 ...
 $ atemp     : num  0.364 0.354 0.189 0.212 0.229 ...
 $ hum       : num  0.806 0.696 0.437 0.59 0.437 ...
 $ windspeed : num  0.16 0.249 0.248 0.16 0.187 ...
 $ casual    : num  331 131 120 108 82 88 148 68 54 41 ...
 $ registered: num  654 670 1229 1454 1518 ...
 $ cnt       : num  985 801 1349 1562 1600 ...



> ###_________________________Graphical analysis_______________________________###
> #And so on. The graphs are plotted and recorded in the project report.
>
>
> ###To extract days from "dteday" and make a new variable
> data$day = day(data$dteday)
> #As we already have information about the year and month, we have the whole date inform
ation & can remove the "dteday" date type variable as it may not be suitable for modeling
.
> data[,1] = data[,16]
> data[,16] = NULL            #dim = 731 x 15
>
> col = names(data)
>
> #################______________Missing Value Analysis______________#################
> sum(is.na(data))
[1] 0
```

```
>
> #There are no missing values for this data set.

> ###################___________Outlier Analysis___________#######################
> ####Box Plot distribution & outlier check####
> str(data)
'data.frame':	731 obs. of  15 variables:
 $ dteday    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ season    : Factor w/ 4 levels "1","2","3","4": 1 1 1 1 1 1 1 1 1 1 ...
 $ yr        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ mnth      : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ holiday   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ weekday   : Factor w/ 7 levels "0","1","2","3",..: 7 1 2 3 4 5 6 7 1 2 ...
 $ workingday: Factor w/ 2 levels "0","1": 1 1 2 2 2 2 2 1 1 2 ...
 $ weathersit: Factor w/ 3 levels "1","2","3": 2 2 1 1 1 1 2 2 1 1 ...
 $ temp      : num  0.344 0.363 0.196 0.2 0.227 ...
 $ atemp     : num  0.364 0.354 0.189 0.212 0.229 ...
 $ hum       : num  0.806 0.696 0.437 0.59 0.437 ...
 $ windspeed : num  0.16 0.249 0.248 0.16 0.187 ...
 $ casual    : num  331 131 120 108 82 88 148 68 54 41 ...
 $ registered: num  654 670 1229 1454 1518 ...
 $ cnt       : num  985 801 1349 1562 1600 ...
> for(i in 1:length(numnames)){
+   assign(paste0("gn",i), ggplot(aes_string(y = (numnames[i]), x = data$cnt), data = sub
set(data))+
+            stat_boxplot(geom = "errorbar", width = 0.5) +
+            geom_boxplot(outlier.colour="red", fill = "light blue",outlier.shape=18,outl
ier.size=3, notch=FALSE) +
+            theme(legend.position="bottom")+
+            labs(y=numnames[i],x="Bike Rental Count")+
+            ggtitle(paste("Box plot for",numnames[i])))
+ }
>
> #Plotting plots together
> gridExtra::grid.arrange(gn1,gn2,gn3,gn4,ncol=4)
Warning messages:
1: Continuous x aesthetic -- did you forget aes(group=...)?
2: Continuous x aesthetic -- did you forget aes(group=...)?
3: Continuous x aesthetic -- did you forget aes(group=...)?
4: Continuous x aesthetic -- did you forget aes(group=...)?
5: Continuous x aesthetic -- did you forget aes(group=...)?
6: Continuous x aesthetic -- did you forget aes(group=...)?
7: Continuous x aesthetic -- did you forget aes(group=...)?
8: Continuous x aesthetic -- did you forget aes(group=...)?
> gridExtra::grid.arrange(gn5,gn6,gn7,ncol=3)
Warning messages:
1: Continuous x aesthetic -- did you forget aes(group=...)?
2: Continuous x aesthetic -- did you forget aes(group=...)?
3: Continuous x aesthetic -- did you forget aes(group=...)?
4: Continuous x aesthetic -- did you forget aes(group=...)?
5: Continuous x aesthetic -- did you forget aes(group=...)?
6: Continuous x aesthetic -- did you forget aes(group=...)?
>
> #To check number of outliers in data (ignoring categorical variables, checked earlier)
> out = 0.0
> for(i in numnames){
+    val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+    out = out + length(val)
+    print(i)
+    print(length(val))
+ }
[1] "temp"
[1] 0
[1] "atemp"
```

```
[1] 0
[1] "hum"
[1] 2
[1] "windspeed"
[1] 13
[1] "casual"
[1] 44
[1] "registered"
[1] 0
[1] "cnt"
[1] 0
> out #= 59. Total Outliers in the data set is 59.
[1] 59
> #(59/731)*100 = 8.07% of data.

> ##To test for the best method to find missing values for this dataset
> #data[12,12]   #data[12,12] = 0.304627 (actual)
> #data[12,12]= NA
> #By median method:
> #data$windspeed[is.na(data$windspeed)]=median(data$windspeed, na.rm = T)
> #data[12,12]  #data[12,12] = 0.180971 (median)
>
> #reupload data
> #data[12,12]   #data[12,12] = 0.304627 (actual)
> #data[12,12]= NA
> #by mean method:
> #data$windspeed[is.na(data$windspeed)]=mean(data$windspeed, na.rm = T)
> #data[12,12]  #data[12,12] = 0.1903299 (mean)
>
> #reupload data
> #data[12,12]   #data[12,12] = 0.304627 (actual)
> #data[12,12]= NA
> #By KNN imputation method:
> #(KNN takes only numeric inputs)
> #for (i in col) {
> #  data[,i] = as.numeric(data[,i])
> #}
> #data= knnImputation(data, k=3)      #For k=5,7,9, the difference was even more than k=
3.
> #data[12,12]  #data[12,12] = 0.2324425 (KNN)
> #We freeze NA imputation by MEDIAN method as it is closest to actual value.
>
> #reupload data
> #Converting outliers to NAs
> #Select variables with outliers
> Out_Var = c('hum','windspeed','casual')  #Variables with outliers
>
> for(i in Out_Var){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   data[,i][data[,i] %in% val] = NA
+ }
> sum(is.na(data)) #To verify
[1] 59
>
> data= knnImputation(data, k=3)
>
> sum(is.na(data)) #To verify
[1] 0

> #Confirm again if any outlier exists
> out = 0.0
> for(i in numnames){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   out= out + length(val)
```

```
+   print(i)
+   print(length(val))
+ }
[1] "temp"
[1] 0
[1] "atemp"
[1] 0
[1] "hum"
[1] 0
[1] "windspeed"
[1] 2
[1] "casual"
[1] 1
[1] "registered"
[1] 0
[1] "cnt"
[1] 0
> out #= 3. Windspeed has 2 outliers & Casual has 1 outlier.
[1] 3
> for(i in Out_Var){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   data[,i][data[,i] %in% val] = NA
+ }
> sum(is.na(data)) #To verify
[1] 3
>
> data= knnImputation(data, k=3)
>
> sum(is.na(data)) #To verify
[1] 0
> #Confirm again if any outlier exists
> out = 0.0
> for(i in numnames){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   out= out + length(val)
+   print(i)
+   print(length(val))
+ }
[1] "temp"
[1] 0
[1] "atemp"
[1] 0
[1] "hum"
[1] 0
[1] "windspeed"
[1] 1
[1] "casual"
[1] 0
[1] "registered"
[1] 0
[1] "cnt"
[1] 0
> out
[1] 1
> for(i in Out_Var){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   data[,i][data[,i] %in% val] = NA
+ }
> sum(is.na(data)) #To verify
[1] 1
>
> data= knnImputation(data, k=3)
>
> sum(is.na(data)) #To verify
```

```
[1] 0
> #Confirm again if any outlier exists
> out = 0.0
> for(i in numnames){
+   val = data[,i][data[,i] %in% boxplot.stats(data[,i])$out]
+   out= out + length(val)
+   print(i)
+   print(length(val))
+ }
[1] "temp"
[1] 0
[1] "atemp"
[1] 0
[1] "hum"
[1] 0
[1] "windspeed"
[1] 0
[1] "casual"
[1] 0
[1] "registered"
[1] 0
[1] "cnt"
[1] 0
> out
[1] 0
> write.csv(data, 'data_without Outliers.csv', row.names = F)
```

```
> #To load the data
> #data = read.csv("data_without Outliers.csv",header = T)
>
> ############################Feature Selection############################
> #Correlation Plot
> corrgram(data, order = F,
+          upper.panel=panel.pie, text.panel=panel.txt, main = "Correlation Plot", font.labels
> #cor(x), x must be numeric
> #Convert all columns to numeric type
> #for (i in col) {
> #  data[,i] = as.numeric(data[,i])
> #}    #NOTE: This changes all zero factor levels to numeric 1. so, "0" --> 1.
> #mat = cor(data)
> #corrplot(as.matrix(mat),method= 'pie',type = "lower", tl.col = "black", tl.cex = 0.7)
>
> #If |r|>0.8, those two variables are redundant variables.
> #Output: "mnth"-"season", "temp"-"atemp" & "cnt"-"registered" are highly positively correlate
>
> #redo data conversion to proper types
> catnames = c("season","yr","mnth","holiday","weekday","workingday","weathersit")   #categoric
> for (i in catnames) {
+   data[,i] = as.factor(data[,i])
+ }
>
> numnames = c("dteday","temp","atemp","hum","windspeed","casual","registered","cnt")  #numeric
> for (i in numnames) {
+   data[,i] = as.numeric(data[,i])
+ }
>
> #######Chi-square Test of Independence (within Categorical Variables)
> for(i in catnames){
+   for(j in catnames){
+     if(i!=j){
+      print(names(data[i]))
+      print(paste0(" Vs ", names(data[j])))
+      print(chisq.test(table(data[,j],data[,i])))
+     }
+   }
+ }
```

```
[1] "season"
[1] " Vs yr"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.0041569, df = 3, p-value = 0.9999

[1] "season"
[1] " Vs mnth"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1765.1, df = 33, p-value < 2.2e-16

[1] "season"
[1] " Vs holiday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1.4961, df = 3, p-value = 0.6832

[1] "season"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.39925, df = 18, p-value = 1

[1] "season"
[1] " Vs workingday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.64285, df = 3, p-value = 0.8866

[1] "season"
[1] " Vs weathersit"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 14.884, df = 6, p-value = 0.02118

[1] "yr"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.0041569, df = 3, p-value = 0.9999

[1] "yr"
[1] " Vs mnth"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.016176, df = 11, p-value = 1

[1] "yr"
[1] " Vs holiday"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 9.6166e-30, df = 1, p-value = 1
```

```
[1] "yr"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.027203, df = 6, p-value = 1

[1] "yr"
[1] " Vs workingday"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 1.6156e-30, df = 1, p-value = 1

[1] "yr"
[1] " Vs weathersit"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 4.1212, df = 2, p-value = 0.1274

[1] "mnth"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1765.1, df = 33, p-value < 2.2e-16

[1] "mnth"
[1] " Vs yr"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.016176, df = 11, p-value = 1

[1] "mnth"
[1] " Vs holiday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 9.6808, df = 11, p-value = 0.5593

[1] "mnth"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 3.372, df = 66, p-value = 1

[1] "mnth"
[1] " Vs workingday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 2.7777, df = 11, p-value = 0.9933

[1] "mnth"
[1] " Vs weathersit"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
```

```
X-squared = 38.861, df = 22, p-value = 0.01464

[1] "holiday"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1.4961, df = 3, p-value = 0.6832

[1] "holiday"
[1] " Vs yr"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 9.6166e-30, df = 1, p-value = 1

[1] "holiday"
[1] " Vs mnth"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 9.6808, df = 11, p-value = 0.5593

[1] "holiday"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 58.623, df = 6, p-value = 8.567e-11

[1] "holiday"
[1] " Vs workingday"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 43.598, df = 1, p-value = 4.033e-11

[1] "holiday"
[1] " Vs weathersit"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1.0188, df = 2, p-value = 0.6009

[1] "weekday"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.39925, df = 18, p-value = 1

[1] "weekday"
[1] " Vs yr"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.027203, df = 6, p-value = 1

[1] "weekday"
[1] " Vs mnth"

        Pearson's Chi-squared test
```

```
data:  table(data[, j], data[, i])
X-squared = 3.372, df = 66, p-value = 1

[1] "weekday"
[1] " Vs holiday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 58.623, df = 6, p-value = 8.567e-11

[1] "weekday"
[1] " Vs workingday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 644.2, df = 6, p-value < 2.2e-16

[1] "weekday"
[1] " Vs weathersit"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 14.358, df = 12, p-value = 0.2785

[1] "workingday"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 0.64285, df = 3, p-value = 0.8866

[1] "workingday"
[1] " Vs yr"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 1.6156e-30, df = 1, p-value = 1

[1] "workingday"
[1] " Vs mnth"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 2.7777, df = 11, p-value = 0.9933

[1] "workingday"
[1] " Vs holiday"

        Pearson's Chi-squared test with Yates' continuity correction

data:  table(data[, j], data[, i])
X-squared = 43.598, df = 1, p-value = 4.033e-11

[1] "workingday"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 644.2, df = 6, p-value < 2.2e-16

[1] "workingday"
[1] " Vs weathersit"

        Pearson's Chi-squared test
```

```
data:  table(data[, j], data[, i])
X-squared = 2.7427, df = 2, p-value = 0.2538

[1] "weathersit"
[1] " Vs season"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 14.884, df = 6, p-value = 0.02118

[1] "weathersit"
[1] " Vs yr"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 4.1212, df = 2, p-value = 0.1274

[1] "weathersit"
[1] " Vs mnth"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 38.861, df = 22, p-value = 0.01464

[1] "weathersit"
[1] " Vs holiday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 1.0188, df = 2, p-value = 0.6009

[1] "weathersit"
[1] " Vs weekday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 14.358, df = 12, p-value = 0.2785

[1] "weathersit"
[1] " Vs workingday"

        Pearson's Chi-squared test

data:  table(data[, j], data[, i])
X-squared = 2.7427, df = 2, p-value = 0.2538

Warning messages:
1: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
2: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
3: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
4: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
5: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
6: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
7: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
8: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
9: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
```

```
10: In chisq.test(table(data[, j], data[, i])) :
  Chi-squared approximation may be incorrect
> #If p-value<0.05 (Reject Null Hypothesis) => variable A depends on variable B.
> #If p-value>0.05 (Do Not Reject Null Hypothesis) => Variable A & variable B are independent o
> #Output: "workingday"-"holiday","weekday"-"workingday","weekday"-"holiday" & "mnth"-"season d
ificantly.
>
> #######Using Random Forest Algorithm:
> data.rf=randomForest(data$cnt~.,data = data, ntree=1000, keep.forest= F, importance= T)
> importance(data.rf,type = 1)
             %IncMSE
dteday      4.673530
season     21.268255
yr         40.189180
mnth       21.522989
holiday     1.985289
weekday    24.293412
workingday 22.960790
weathersit 12.793259
temp       21.295601
atemp      24.730151
hum        17.895417
windspeed   7.856791
casual     41.353669
registered 69.804438
> #"holiday" has the least importance.
> varImpPlot(data.rf,type = 1)
>
> #######ANOVA test (comparision of Target Vs categorical variables)
> anovacat = aov(cnt ~ season + yr + mnth + holiday + workingday + weekday + weathersit , data
> summary(anovacat)
             Df    Sum Sq   Mean Sq  F value  Pr(>F)
season        3 950595868 316865289  436.234 < 2e-16 ***
yr            1 884008263 884008263 1217.030 < 2e-16 ***
mnth         11 187311622  17028329   23.443 < 2e-16 ***
holiday       1   3306975   3306975    4.553 0.03321 *
workingday    1   3209216   3209216    4.418 0.03591 *
weekday       5  12629845   2525969    3.478 0.00411 **
weathersit    2 185659616  92829808  127.800 < 2e-16 ***
Residuals   706 512813988    726365
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> #If p-value<0.05 (Reject Null Hypothesis) => Population means are significantly different.
> #If p-value>0.05 (Do Not Reject Null Hypothesis) => Population means are not significantly di
```

```
> ###################___________Feature Engineering____________#####################
> #From Chi-square test, we notice that "working day", "holiday" & "weekday" depend on ea
ch other and intuitively there is a logical connection within them.
> #We make a new variable using this connection between the three varibles
> #Denote: 1-->weekend, 2--> working day, 3--> holiday
>
> data$day = NA
> for (i in 1:nrow(data)){
+   if ((data[i,7]=="0") && (data[i,5]=="0")){data[i,16] = 1}
#weekend
+   else if ((data[i,7]=="1") && (data[i,5]=="0")){data[i,16] = 2}
#working day
+   else if ((data[i,7]=="0") && (data[i,5]=="1")){data[i,16] = 3}
#holiday
+   else data[i,16] =NA
+ }
> sum(is.na(data$day)) #= 0, so no anomaly data case where it is working day & holiday bo
th.
[1] 0
>
> #################Dimensional Reduction####################
> #Won't remove "dteday" variable as the user count is tracked on each day.
```

```
> #As we added "day" new variable using "workingday" & "holiday", we can remove them both
as "day" holds the information of both.
> data$holiday = data$day
> data$day = NULL
> colnames(data)[5] = "day"
> data$day = as.factor(data$day)        # New variable "day": Factor w/ 3 levels "1","2",
"3"
> #"Season" has multicollinearity problem as well and it is related to "mnth", so we can
remove it.
> data= subset(data, select= -c(season,workingday,temp,casual,registered))
> factor_data = subset(data, select= c(yr,mnth,day,weekday,weathersit))  #5 factor variab
les
> num_data = subset(data, select= c(dteday,atemp,hum,windspeed,cnt))  #5 numerical variab
les, contains target variable
> dim(data)                     # 731 obs. x 10 variables
[1] 731  10
> str(data)
'data.frame':   731 obs. of  10 variables:
 $ dteday    : num  1 2 3 4 5 6 7 8 9 10 ...
 $ yr        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
 $ mnth      : Factor w/ 12 levels "1","2","3","4",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ day       : Factor w/ 3 levels "1","2","3": 1 1 2 2 2 2 2 1 1 2 ...
 $ weekday   : Factor w/ 7 levels "0","1","2","3",..: 7 1 2 3 4 5 6 7 1 2 ...
 $ weathersit: Factor w/ 3 levels "1","2","3": 2 2 1 1 1 1 2 2 1 1 ...
 $ atemp     : num  0.364 0.354 0.189 0.212 0.229 ...
 $ hum       : num  0.806 0.696 0.437 0.59 0.437 ...
 $ windspeed : num  0.16 0.249 0.248 0.16 0.187 ...
 $ cnt       : num  985 801 1349 1562 1600 ...
> ################################Feature Scaling################################
> #All continuous variables are already normalised in this data set.
>
>
> rm(list= ls()[!(ls() %in% c('data','factor_data','num_data'))])
>
> ##############################Sampling################################
> set.seed(777)
>
> sample.index = sample(nrow(data), 0.8*nrow(data), replace = F)   #80% data -->Train set
, 20%--> Test set
> train = data[sample.index,]
> test = data[-sample.index,]
> dim(train)    # 584 x 11
[1] 584  10
> dim(test)     # 147 x 11
[1] 147  10


> ##################################Model Development##################################
> #As the target variable is of numeric type, this is a regression problem.
> ######1.Decision Tree######
> #Decision trees can handle both categorical and numerical variables at the same time as
features.
> dt=rpart(cnt~.,data = train,method= "anova")
> summary(dt)
Call:
rpart(formula = cnt ~ ., data = train, method = "anova")
  n= 584

          CP nsplit rel error    xerror       xstd
1 0.37445616      0 1.0000000 1.0051616 0.04580505
2 0.22311915      1 0.6255438 0.6603832 0.03348656
3 0.09060873      2 0.4024247 0.4239814 0.03179904
4 0.02962425      3 0.3118160 0.3290237 0.02734505
```

```
5 0.02934392      4 0.2821917 0.3120647 0.02819117
6 0.02895436      5 0.2528478 0.3120647 0.02819117
7 0.01189898      6 0.2238934 0.2660670 0.02168208
8 0.01131214      7 0.2119945 0.2668795 0.02194647
9 0.01000000      8 0.2006823 0.2633306 0.02187781

Variable importance
     atemp       mnth         yr        hum  windspeed weathersit    weekday
        34         27         25          8          4          1          1

Node number 1: 584 observations,    complexity param=0.3744562
  mean=4565.748, MSE=3745566
  left son=2 (234 obs) right son=3 (350 obs)
  Primary splits:
      atemp      < 0.4308565  to the left,  improve=0.37445620, (0 missing)
      yr         splits as  LR, improve=0.35623910, (0 missing)
      mnth       splits as  LLLRRRRRRRLL, improve=0.30009300, (0 missing)
      weathersit splits as  RLL, improve=0.07434951, (0 missing)
      hum        < 0.824394   to the right, improve=0.06695468, (0 missing)
  Surrogate splits:
      mnth      splits as  LLLRRRRRRRLL, agree=0.894, adj=0.735, (0 split)
      hum       < 0.5464585  to the left,  agree=0.625, adj=0.064, (0 split)
      windspeed < 0.06282915 to the left,  agree=0.616, adj=0.043, (0 split)
      dteday    < 29.5       to the right, agree=0.601, adj=0.004, (0 split)

Node number 2: 234 observations,    complexity param=0.09060873
  mean=3117.359, MSE=2302852
  left son=4 (126 obs) right son=5 (108 obs)
  Primary splits:
      yr         splits as  LR, improve=0.36780560, (0 missing)
      atemp      < 0.2607295  to the left,  improve=0.23258030, (0 missing)
      mnth       splits as  LLLRL--R-RRR, improve=0.19311160, (0 missing)
      hum        < 0.678777   to the right, improve=0.06662897, (0 missing)
      weathersit splits as  RLL, improve=0.06151398, (0 missing)
  Surrogate splits:
      hum       < 0.5725     to the right, agree=0.577, adj=0.083, (0 split)
      atemp     < 0.332973   to the left,  agree=0.573, adj=0.074, (0 split)
      windspeed < 0.1871895  to the right, agree=0.568, adj=0.065, (0 split)
      mnth      splits as  LRLRL--R-LRL, agree=0.564, adj=0.056, (0 split)
      weekday   splits as  LLLLLRL, agree=0.543, adj=0.009, (0 split)

Node number 3: 350 observations,    complexity param=0.2231192
  mean=5534.1, MSE=2369868
  left son=6 (164 obs) right son=7 (186 obs)
  Primary splits:
      yr         splits as  LR, improve=0.58840310, (0 missing)
      hum        < 0.834375   to the right, improve=0.15010660, (0 missing)
      weathersit splits as  RRL, improve=0.09686697, (0 missing)
      atemp      < 0.5018855  to the left,  improve=0.06263038, (0 missing)
      mnth       splits as  -LRLRRRRRRLR, improve=0.05588727, (0 missing)
  Surrogate splits:
      hum       < 0.6947915  to the right, agree=0.580, adj=0.104, (0 split)
      mnth      splits as  -RRLRLRRRRLR, agree=0.569, adj=0.079, (0 split)
      atemp     < 0.5296815  to the left,  agree=0.549, adj=0.037, (0 split)
      weekday   splits as  RLLRRRR, agree=0.546, adj=0.030, (0 split)
      windspeed < 0.1741335  to the right, agree=0.543, adj=0.024, (0 split)

Node number 4: 126 observations,    complexity param=0.02962425
  mean=2265.302, MSE=1057926
  left son=8 (75 obs) right son=9 (51 obs)
  Primary splits:
      mnth       splits as  LLLLR----RRR, improve=0.48612910, (0 missing)
      atemp      < 0.251738   to the left,  improve=0.30669750, (0 missing)
      windspeed  < 0.112571   to the right, improve=0.24712020, (0 missing)
```

```
      hum        < 0.86       to the right, improve=0.11724950, (0 missing)
      weathersit splits as  RLL, improve=0.07345125, (0 missing)
  Surrogate splits:
      windspeed < 0.120031   to the right, agree=0.746, adj=0.373, (0 split)
      atemp     < 0.298832   to the left,  agree=0.714, adj=0.294, (0 split)
      hum       < 0.611667   to the left,  agree=0.611, adj=0.039, (0 split)
      dteday    < 22.5       to the left,  agree=0.603, adj=0.020, (0 split)
      day       splits as  LLR, agree=0.603, adj=0.020, (0 split)

Node number 5: 108 observations,    complexity param=0.02895436
  mean=4111.426, MSE=1920095
  left son=10 (31 obs) right son=11 (77 obs)
  Primary splits:
      atemp      < 0.279985   to the left,  improve=0.30542030, (0 missing)
      mnth       splits as  LLLR---R-LRL, improve=0.28345620, (0 missing)
      hum        < 0.697292   to the right, improve=0.16823620, (0 missing)
      weathersit splits as  RLL, improve=0.09756212, (0 missing)
      weekday    splits as  LLLRRRL, improve=0.07717721, (0 missing)
  Surrogate splits:
      hum        < 0.4647915  to the left,  agree=0.741, adj=0.097, (0 split)
      windspeed  < 0.349942   to the right, agree=0.731, adj=0.065, (0 split)
      mnth       splits as  RRRR---L-RRR, agree=0.722, adj=0.032, (0 split)
      weathersit splits as  RRL, agree=0.722, adj=0.032, (0 split)

Node number 6: 164 observations,    complexity param=0.01131214
  mean=4276.524, MSE=648554.7
  left son=12 (29 obs) right son=13 (135 obs)
  Primary splits:
      mnth       splits as  -LLLRRRRRRLL, improve=0.23264010, (0 missing)
      hum        < 0.849375   to the right, improve=0.23168870, (0 missing)
      weathersit splits as  RLL, improve=0.18122010, (0 missing)
      atemp      < 0.5805125  to the left,  improve=0.17080540, (0 missing)
      windspeed  < 0.1265645  to the right, improve=0.07228776, (0 missing)
  Surrogate splits:
      atemp     < 0.456723   to the left,  agree=0.872, adj=0.276, (0 split)
      windspeed < 0.299444   to the right, agree=0.854, adj=0.172, (0 split)
      hum       < 0.908125   to the right, agree=0.829, adj=0.034, (0 split)

Node number 7: 186 observations,    complexity param=0.02934392
  mean=6642.93, MSE=1263643
  left son=14 (9 obs) right son=15 (177 obs)
  Primary splits:
      hum        < 0.8322915  to the right, improve=0.27309330, (0 missing)
      weathersit splits as  RLL, improve=0.13018900, (0 missing)
      atemp      < 0.4927355  to the left,  improve=0.12328470, (0 missing)
      mnth       splits as  -LLLRRRRRR-L, improve=0.07749548, (0 missing)
      windspeed  < 0.287627   to the right, improve=0.06415826, (0 missing)
  Surrogate splits:
      weathersit splits as  RRL, agree=0.968, adj=0.333, (0 split)
      windspeed  < 0.3526145  to the right, agree=0.957, adj=0.111, (0 split)

Node number 8: 75 observations
  mean=1673.933, MSE=304991.8

Node number 9: 51 observations
  mean=3134.961, MSE=894587.3

Node number 10: 31 observations
  mean=2904.516, MSE=1394240

Node number 11: 77 observations,    complexity param=0.01189898
  mean=4597.325, MSE=1309269
  left son=22 (18 obs) right son=23 (59 obs)
  Primary splits:
```

```
      hum        < 0.700625   to the right, improve=0.25817860, (0 missing)
      mnth       splits as  LLLR-----LRL, improve=0.23626120, (0 missing)
      weathersit splits as  RL-, improve=0.15559330, (0 missing)
      atemp      < 0.3134065  to the left,  improve=0.08333220, (0 missing)
      dteday     < 19.5       to the right, improve=0.07422147, (0 missing)
  Surrogate splits:
      weathersit splits as  RL-,          agree=0.792, adj=0.111, (0 split)
      mnth       splits as  RRRR-----LRR, agree=0.779, adj=0.056, (0 split)

Node number 12: 29 observations
  mean=3438.448, MSE=473523.1

Node number 13: 135 observations
  mean=4456.556, MSE=502863

Node number 14: 9 observations
  mean=4037.778, MSE=2317994

Node number 15: 177 observations
  mean=6775.395, MSE=847392.4

Node number 22: 18 observations
  mean=3544.722, MSE=1303907

Node number 23: 59 observations
  mean=4918.458, MSE=869753.4

>
> #Predict for new test cases
> predict.dt=predict(dt,test[,-10])
>
> #Error metric:
> postResample(predict.dt,test[,10])
        RMSE     Rsquared          MAE
1036.8218286    0.7105788  768.8217306
> #Output:
> #RMSE           Rsquared     MAE
> #1036.8218286    0.7105788  768.8217306
>
> #calculate MAPE
> mape = function(y,yi)
+   {mean(abs((y-yi)/y))*100
+   }
> mape.dt = mape(test[,10],predict.dt)     #30.79%
>
> library(mltools)
Warning message:
package ‘mltools’ was built under R version 3.4.4
> rmsle(predict.dt,test[,10])    #0.3665
[1] 0.3665201
>
> #######2.Random Forest Algorithm#######
> rf = randomForest(cnt~., train, importance = TRUE, ntree = 500)
> summary(rf)
                Length Class  Mode
call              5    -none- call
type              1    -none- character
predicted       584    -none- numeric
mse             500    -none- numeric
rsq             500    -none- numeric
oob.times       584    -none- numeric
importance       18    -none- numeric
importanceSD      9    -none- numeric
localImportance   0    -none- NULL
```

```
proximity         0    -none- NULL
ntree             1    -none- numeric
mtry              1    -none- numeric
forest           11    -none- list
coefs             0    -none- NULL
y               584    -none- numeric
test              0    -none- NULL
inbag             0    -none- NULL
terms             3    terms  call
> #Predict for test case:
> predict.rf <- data.frame(predict(rf, subset(test, select = -c(cnt))))
> #Error metric:
> postResample(predict.rf,test[,10])
       RMSE    Rsquared         MAE
770.2988607   0.8533753 571.7846934
> #Output:
> #RMSE          Rsquared        MAE
> #778.4675527   0.8507608 576.6110231
>
> mape.rf = mape(test[,10],predict.rf$predict.rf..subset.test..select....c.cnt...)   # 24
.9%


> ########3.Multiple Linear Regression########
>
> #creating dummy variables for categorical data
> library(dummies)
dummies-1.5.6 provided by Decision Patterns

Warning message:
package ‘dummies’ was built under R version 3.4.4
> factor_new = dummy.data.frame(factor_data, sep = ".")   #731 x 27
>
> #sampling#
> df = cbind(factor_new, num_data)
> #for (i in 1:ncol(df)) {
> #  df[,i] = as.numeric(df[,i])
> #}
> str(df)           # 731 X 32
'data.frame':   731 obs. of  32 variables:
 $ yr.0         : int  1 1 1 1 1 1 1 1 1 1 ...
 $ yr.1         : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.1       : int  1 1 1 1 1 1 1 1 1 1 ...
 $ mnth.2       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.3       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.4       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.5       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.6       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.7       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.8       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.9       : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.10      : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.11      : int  0 0 0 0 0 0 0 0 0 0 ...
 $ mnth.12      : int  0 0 0 0 0 0 0 0 0 0 ...
 $ day.1        : int  1 1 0 0 0 0 0 1 1 0 ...
 $ day.2        : int  0 0 1 1 1 1 1 0 0 1 ...
 $ day.3        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ weekday.0    : int  0 1 0 0 0 0 0 0 1 0 ...
 $ weekday.1    : int  0 0 1 0 0 0 0 0 0 1 ...
 $ weekday.2    : int  0 0 0 1 0 0 0 0 0 0 ...
 $ weekday.3    : int  0 0 0 0 1 0 0 0 0 0 ...
 $ weekday.4    : int  0 0 0 0 0 1 0 0 0 0 ...
 $ weekday.5    : int  0 0 0 0 0 0 1 0 0 0 ...
```

```
 $ weekday.6   : int  1 0 0 0 0 0 0 1 0 0 ...
 $ weathersit.1: int  0 0 1 1 1 1 0 0 1 1 ...
 $ weathersit.2: int  1 1 0 0 0 0 1 1 0 0 ...
 $ weathersit.3: int  0 0 0 0 0 0 0 0 0 0 ...
 $ dteday      : num  1 2 3 4 5 6 7 8 9 10 ...
 $ atemp       : num  0.364 0.354 0.189 0.212 0.229 ...
 $ hum         : num  0.806 0.696 0.437 0.59 0.437 ...
 $ windspeed   : num  0.16 0.249 0.248 0.16 0.187 ...
 $ cnt         : num  985 801 1349 1562 1600 ...
>
> set.seed(123)
> train_index = sample(1:nrow(df), 0.8*nrow(df))
> train.df = df[train_index,]         #584 x 32
> test.df = df[-train_index,]         #147 x 32
>
> #Check Multicollinearity
> library(usdm)
Loading required package: sp
Loading required package: raster

Attaching package: ‘raster’

The following object is masked from ‘package:dplyr’:

    select

Warning messages:
1: package ‘usdm’ was built under R version 3.4.4
2: package ‘sp’ was built under R version 3.4.4
3: package ‘raster’ was built under R version 3.4.4
> vif(df[,-32])
      Variables      VIF
1          yr.0      Inf
2          yr.1      Inf
3        mnth.1      Inf
4        mnth.2      Inf
5        mnth.3      Inf
6        mnth.4      Inf
7        mnth.5      Inf
8        mnth.6      Inf
9        mnth.7      Inf
10       mnth.8      Inf
11       mnth.9      Inf
12      mnth.10      Inf
13      mnth.11      Inf
14      mnth.12      Inf
15        day.1      Inf
16        day.2      Inf
17        day.3      Inf
18    weekday.0      Inf
19    weekday.1      Inf
20    weekday.2      Inf
21    weekday.3      Inf
22    weekday.4      Inf
23    weekday.5      Inf
24    weekday.6      Inf
25 weathersit.1      Inf
26 weathersit.2      Inf
27 weathersit.3      Inf
28       dteday 1.010204
29        atemp 6.049203
30          hum 2.294781
31    windspeed 1.207595
> vifcor(df[,-32], th = 0.8)
```

```
3 variables from the 31 input variables have collinearity problem:

yr.1 weathersit.2 day.2

After excluding the collinear variables, the linear correlation coefficients ranges betwe
en:
min correlation ( windspeed ~ weekday.3 ):  -0.0001206042
max correlation ( weekday.0 ~ day.1 ):  0.6450846

---------- VIFs of the remained variables --------
      Variables      VIF
1          yr.0 1.049547
2        mnth.1      Inf
3        mnth.2      Inf
4        mnth.3      Inf
5        mnth.4      Inf
6        mnth.5      Inf
7        mnth.6      Inf
8        mnth.7      Inf
9        mnth.8      Inf
10       mnth.9      Inf
11      mnth.10      Inf
12      mnth.11      Inf
13      mnth.12      Inf
14        day.1      Inf
15        day.3 1.106961
16    weekday.0      Inf
17    weekday.1      Inf
18    weekday.2      Inf
19    weekday.3      Inf
20    weekday.4      Inf
21    weekday.5      Inf
22    weekday.6      Inf
23 weathersit.1 1.779943
24 weathersit.3 1.222714
25       dteday 1.010204
26        atemp 6.049203
27          hum 2.294781
28    windspeed 1.207595
> #Output:
> #3 variables from the 31 input variables have collinearity problem: yr.1, weathersit.2,
day.2
> #removing multicollinear variables and redo check:
> df = subset(df, select= -c(yr.1, weathersit.2, day.2))
> train.df = subset(train.df, select= -c(yr.1, weathersit.2, day.2))  #584 x 29
> test.df = subset(test.df, select= -c(yr.1, weathersit.2, day.2))    #147 x 29
> dim(df)  #731 x 29
[1] 731  29
> #Recheck VIFCORR: No variable from the 29 input variables has collinearity problem.
>
> #run regression model
> lr = lm(cnt~., data = train.df)
> #summary of the model
> summary(lr)

Call:
lm(formula = cnt ~ ., data = train.df)

Residuals:
    Min      1Q  Median      3Q     Max
-3876.2  -387.8    50.8   509.4  2771.2

Coefficients: (3 not defined because of singularities)
              Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)   4430.566    344.461  12.862  < 2e-16 ***
yr.0         -2113.166     71.121 -29.712  < 2e-16 ***
mnth.1        -825.824    175.718  -4.700 3.29e-06 ***
mnth.2        -716.510    179.767  -3.986 7.62e-05 ***
mnth.3         138.034    174.608   0.791 0.429552    
mnth.4         632.261    191.820   3.296 0.001043 ** 
mnth.5         957.277    209.921   4.560 6.29e-06 ***
mnth.6         673.222    240.603   2.798 0.005319 ** 
mnth.7         362.334    258.956   1.399 0.162305    
mnth.8         644.409    241.596   2.667 0.007868 ** 
mnth.9        1396.680    213.404   6.545 1.35e-10 ***
mnth.10       1391.067    187.618   7.414 4.56e-13 ***
mnth.11        785.587    172.682   4.549 6.61e-06 ***
mnth.12             NA         NA      NA       NA    
day.1            8.810    129.991   0.068 0.945990    
day.3         -813.416    212.812  -3.822 0.000147 ***
weekday.0     -424.315    129.802  -3.269 0.001146 ** 
weekday.1     -165.593    133.805  -1.238 0.216395    
weekday.2     -151.960    130.711  -1.163 0.245504    
weekday.3      -23.876    130.518  -0.183 0.854920    
weekday.4      -54.480    133.389  -0.408 0.683114    
weekday.5           NA         NA      NA       NA    
weekday.6           NA         NA      NA       NA    
weathersit.1   448.480     95.588   4.692 3.41e-06 ***
weathersit.3 -1468.420    232.217  -6.323 5.24e-10 ***
dteday         -10.119      3.989  -2.537 0.011455 *  
atemp         4592.019    519.614   8.837  < 2e-16 ***
hum          -1522.767    365.632  -4.165 3.61e-05 ***
windspeed    -2629.300    543.404  -4.839 1.69e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 837.3 on 558 degrees of freedom
Multiple R-squared:  0.8237,	Adjusted R-squared:  0.8158 
F-statistic: 104.3 on 25 and 558 DF,  p-value: < 2.2e-16

> 
> #Predict for test case:
> predict.lr= predict(lr, test.df[,-29])
Warning message:
In predict.lm(lr, test.df[, -29]) :
  prediction from a rank-deficient fit may be misleading
> #Error metric:
> postResample(predict.lr,test.df[,29])
       RMSE    Rsquared         MAE 
800.2783046   0.8303233 581.4298996 
> #Output:
> #RMSE           Rsquared         MAE
> #800.2783046   0.8303233 581.4298996
> 
> mape.lr = mape(test.df[,29],predict.lr) #17.5%


> #############4.KNN Implementation############
> #To check for best k value:
> model <- train(cnt~., data = train, method = "knn",
+                trControl = trainControl("cv", number = 10),
+                tuneLength = 15)
> model$bestTune
  k
3 9
> #k = 3 , 9
> plot(model)
```

```
>
> #K=3:
> predict.knn = knn.reg(train = train.df[,-29],test = test.df[,-29],train.df$cnt, k= 3)
> print(predict.knn)
Prediction:
  [1] 2065.6667 2536.3333 1932.3333 3527.6667 2452.6667 2715.0000 3432.6667 3249.0000 268
3.3333 2535.3333 5425.0000
 [12] 4446.0000 3188.3333 2695.3333 2765.3333 2717.6667 4299.0000 2918.6667 5065.3333 484
0.6667 5374.0000 4964.6667
 [23] 3303.3333 2663.6667 4450.0000 4485.0000 4465.6667 4904.6667 4851.6667 5427.0000 468
6.3333 4353.0000 5078.0000
 [34] 3303.6667 5599.3333 3440.0000 5282.0000 5925.6667 4382.3333 5548.3333 5256.0000 549
1.6667 5779.6667 4732.6667
 [45] 4389.6667 5922.6667 3241.6667 4966.3333 5510.0000 4561.6667 3120.3333 1752.3333 494
9.6667 4383.3333 4426.6667
 [56] 3805.6667 3521.3333 3140.6667 5116.0000 5404.3333  820.3333 3466.0000 2473.6667 314
6.6667 4362.6667 2408.6667
 [67] 3552.0000 4550.0000 4181.0000 3621.3333 3556.3333 3526.0000 2959.6667 6236.0000 462
4.3333 4371.6667 3165.6667
 [78] 2672.6667 3727.3333 4956.0000 5488.0000 5411.0000 4105.0000 3885.3333 4096.3333 457
1.0000 5457.6667 5490.6667
 [89] 5447.0000 4543.6667 4662.0000 6788.0000 6100.6667 2542.0000 6042.3333 5576.3333 329
6.0000 5726.0000 5794.0000
[100] 4209.6667 5906.3333 2978.6667 4869.3333 6659.0000 6323.6667 6317.0000 4854.0000 637
9.6667 4798.0000 5062.3333
[111] 4478.0000 4873.3333 5184.3333 6636.6667 5805.0000 6186.0000 4622.6667 5748.3333 675
1.6667 5806.3333 5742.3333
[122] 6693.0000 6282.6667 6944.3333 4264.6667 4596.6667 5916.3333 5431.0000 6396.6667 551
5.0000 6063.3333 4261.6667
[133] 3808.3333 4501.3333 6322.3333 5464.6667 2055.6667 4677.0000 4798.3333 3778.3333 608
5.3333 5459.3333 3677.6667
[144] 6222.3333 6298.6667 5863.0000 4790.0000
>
> #Error metric:
> postResample(predict.knn$pred,test.df[,29])
        RMSE     Rsquared          MAE
1392.7631351    0.4544424 1110.0045351
> #Output:
> #RMSE            Rsquared         MAE
> #1392.7631351    0.4544424 1110.0045351
>
> mape.knn = mape(test.df[,29],predict.knn$pred)  #38.98%
>
> #K=5:
> #predict.knn = knn.reg(train = train.df[,-29],test = test.df[,-29],train.df$cnt, k= 5)
> #print(predict.knn)
> #Error metric:
> #mape(test.df[,29],predict.knn$pred)
> #Output:
> #mape
> #45.26592 %
> #postResample(predict.knn$pred,test.df[,29])
> #RMSE            Rsquared         MAE
> #1450.9419952    0.4484269 1169.3782313
>
> #K=7:
> #predict.knn = knn.reg(train = train.df[,-29],test = test.df[,-29],train.df$cnt, k= 7)
> #print(predict.knn)
> #Error metric:
> #mape(test.df[,29],predict.knn$pred)
> #Output:
> #mape
> #47.63637 %
> #postResample(predict.knn$pred,test.df[,29])
```

```
> #RMSE           Rsquared        MAE
> #1456.0507716    0.4983456 1171.8736638
> ######And so on, done upto k = 11.
>
> #A new dataframe to store results
> algorithm <- c('Decision Tree','Random Forest','Linear Regression','KNN')
> MAPE_val <- c(mape.dt,mape.rf,mape.lr,mape.knn)
> results <- data.frame(algorithm, MAPE_val)
> print(results)
          algorithm MAPE_val
1     Decision Tree 30.79662
2     Random Forest 24.98612
3 Linear Regression 17.55068
4               KNN 38.98097
> barplot(results$MAPE_val, width = 1, names.arg = results$algorithm,
+         ylab="MAPE value", xlab = "Algorithm",col='pink')
>
> ##Thus, we find the "Multiple Linear Regression Algorithm" gives us the best result wit
h the least MAPE for this dataset.
```

Bike Renting – Python code

```
#Set working directory
import os
os.chdir("F:/DS/edWisor/Project 2")
os.getcwd()
```

Out[1]:

```
'F:\\DS\\edWisor\\Project 2'
```

Load libraries

In [2]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from random import randrange, uniform
from scipy.stats import chi2_contingency
from ggplot import *
```

```
C:\Users\sir\Anaconda3\lib\site-packages\ggplot\utils.py:81: FutureWarning: pandas.tslib
is deprecated and will be removed in a future version.
You can access Timestamp as pandas.Timestamp
  pd.tslib.Timestamp,
```

In [3]:

```
from fancyimpute import KNN
```

```
C:\Users\sir\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning: Conversion o
f the second argument of issubdtype from `float` to `np.floating` is deprecated. In futur
e, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

In [4]:

```
import datetime as dt
```

In [5]:

```
#Load the data
data = pd.read_csv("day.csv")
```

Data exploration

In [6]:

```
data.shape
```

Out[6]:

```
(731, 16)
```

In [7]:

In [8]:

```
type(data)
```

Out[8]:

```
pandas.core.frame.DataFrame
```

In [9]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 731 entries, 0 to 730
Data columns (total 16 columns):
instant       731 non-null int64
dteday        731 non-null object
season        731 non-null int64
yr            731 non-null int64
mnth          731 non-null int64
holiday       731 non-null int64
weekday       731 non-null int64
workingday    731 non-null int64
weathersit    731 non-null int64
temp          731 non-null float64
atemp         731 non-null float64
hum           731 non-null float64
windspeed     731 non-null float64
casual        731 non-null int64
registered    731 non-null int64
cnt           731 non-null int64
dtypes: float64(4), int64(11), object(1)
memory usage: 91.5+ KB
```

In [10]:

```
#Missing Value Analysis
#Check for missing value
data.isnull().sum()
#No missing values in the dataset
```

Out[10]:

```
instant       0
dteday        0
season        0
```

```
yr             0
mnth           0
holiday        0
weekday        0
workingday     0
weathersit     0
temp           0
atemp          0
hum            0
windspeed      0
casual         0
registered     0
cnt            0
dtype: int64
```

In [11]:

```python
#remove "instant" variable as it is just like serial number & doesn't predict
data = data.drop(['instant'], axis=1)
```

In [12]:

```python
data.shape
```

Out[12]:

```
(731, 15)
```

In [13]:

```python
#extracting day number from 'dteday' variable
data['dteday'].apply(str)
data['dteday'] = pd.to_datetime(data['dteday'])
data['dteday'] = pd.DatetimeIndex(data['dteday']).day
#removing 'dteday' variable
```

In [14]:

In [15]:

```python
#save numeric & categorical names
numnames = ["dteday","temp","atemp","hum","windspeed","casual","registered","cnt"]
catnames = ["season","yr","mnth","holiday","weekday","workingday","weathersit"]
data.shape
```

Out[15]:

```
(731, 15)
```

In [16]:

```python
for i in catnames:
    data[i] = data[i].astype('object')
for i in numnames:
    data[i] = data[i].astype('float')
```

In [17]:

```python
data.dtypes
```

Out[17]:

```
dteday        float64
season         object
yr             object
mnth           object
```

```
holiday        object
weekday        object
workingday     object
weathersit     object
temp          float64
atemp         float64
hum           float64
windspeed     float64
casual        float64
registered    float64
cnt           float64
dtype: object
```

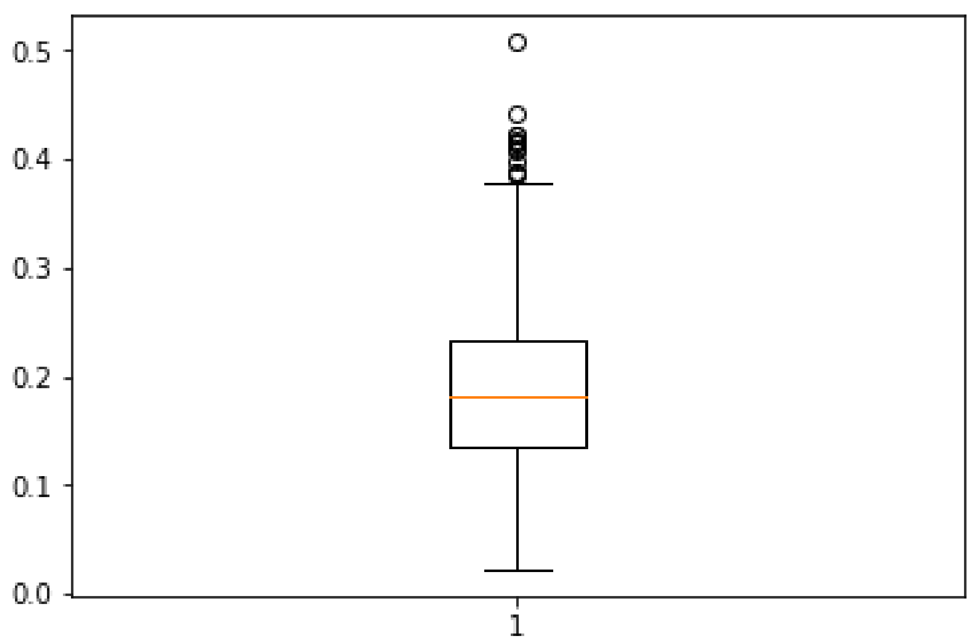
Outlier analysis

In [18]:

```
#Plot boxplot to visualize Outliers
%matplotlib inline
plt.boxplot(data['windspeed'])
```

Out[18]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x1f10645b978>,
  <matplotlib.lines.Line2D at 0x1f10645be10>],
 'caps': [<matplotlib.lines.Line2D at 0x1f106471278>,
  <matplotlib.lines.Line2D at 0x1f1064716a0>],
 'boxes': [<matplotlib.lines.Line2D at 0x1f10645b828>],
 'medians': [<matplotlib.lines.Line2D at 0x1f106471ac8>],
 'fliers': [<matplotlib.lines.Line2D at 0x1f106471ef0>],
 'means': []}
```



In [19]:

```
#Detect and delete outliers from data
for i in numnames:
     print(i)
```

```
    q75, q25 = np.percentile(data.loc[:,i], [75 ,25])
    iqr = q75 - q25

    min = q25 - (iqr*1.5)
    max = q75 + (iqr*1.5)
    print(min)
    print(max)

    #Remove the outliers
    data = data.drop(data[data.loc[:,i] < min].index)
    data = data.drop(data[data.loc[:,i] > max].index)

    #data.loc[data[i] < min,:i] = np.nan
    #data.loc[data[i] > max,:i] = np.nan

#Calculate missing value
#missing_val = pd.DataFrame(data.isnull().sum())
#Impute with KNN
#data = pd.DataFrame(KNN(21).fit_transform(data), columns = data.columns)
```

```
dteday
-14.5
45.5
temp
-0.14041600000000015
1.1329160000000003
atemp
-0.06829675000000018
1.0147412500000002
hum
0.20468725
1.0455212500000002
windspeed
-0.012431000000000025
0.380585
casual
-885.0
2323.0
registered
-840.0
8018.0
cnt
-788.125
9500.875
```

In [20]:

```
data.shape              #55 rows deleted
```

Out[20]:

```
(676, 15)
```

In [21]:

```
data.isnull().sum()
```

Out[21]:

```
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

Feature Selection

In [22]:

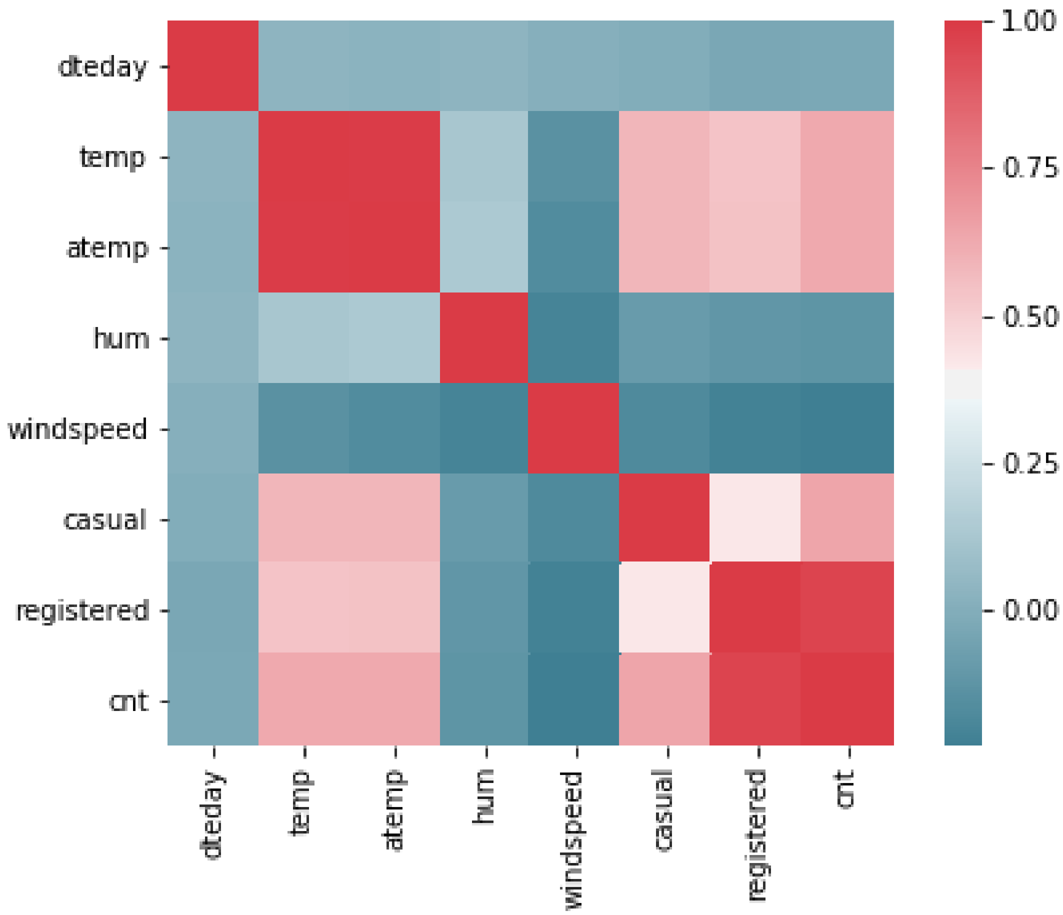
```
##Correlation analysis
#Correlation plot
df_corr = data.loc[:,numnames]
#Set the width and height of the plot
f, ax = plt.subplots(figsize=(7, 5))

#Generate correlation matrix
corr = df_corr.corr()

#Plot using seaborn library
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(220
, 10, as_cmap=True),
            square=True, ax=ax)
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f1064c17b8>
```



In [23]:

```
#Chisquare test of independence
#loop for chi square values
for i in catnames:
    print(i)
    chi2, p, dof, ex = chi2_contingency(pd.crosstab(data['cnt'], data[i]))
    print(p)
```

```
season
0.5306886312713439
yr
0.41642366315035007
mnth
0.4756091821561145
holiday
0.7870836122582522
weekday
0.43936502670720573
workingday
0.504633411642988
weathersit
0.5464467453059881
```

In [24]:

```
#New Categorical Variable containing the data of "workingday" & "holiday"
#Denote: 1-->weekend, 2--> working day, 3--> holiday
data.loc[(data['workingday'] == 0) & (data['holiday'] == 0), 'day'] = '1'
```

```
data.loc[(data['workingday'] == 1) & (data['holiday'] == 0), 'day'] = '2'
data.loc[(data['workingday'] == 0) & (data['holiday'] == 1), 'day'] = '3'
```

In [25]:

```
data = data.drop(["workingday","holiday","temp","casual","registered"], axis=1)
```

In [26]:

In [27]:

```
df = data[['dteday','mnth','yr','season','weekday','day','weathersit','atemp','hum','wind
speed','cnt']]
```

In [28]:

In [29]:

```
###############################Feature Scaling################################
#All continuous variables are already normalised in this data set.


numnames = ["dteday","atemp","hum","windspeed"]        #not including "cnt" target varia
ble
catnames = ["mnth","yr","season","weekday","day","weathersit"]
```

Model Development

In [30]:

```
#Data Sampling
nrow= len(df.index)
train, test = train_test_split(df, test_size = 0.2)
```

In [31]:

```
train.shape      #540 x 11
test.shape       #136 x 11
```

Out[31]:

```
(136, 11)
```

In [32]:

```
#####Decision Tree Algortithm
from sklearn.tree import DecisionTreeRegressor
fit_dt= DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:10],train.iloc[:,10])
```

In [33]:

```
fit_dt
```

Out[33]:

```
DecisionTreeRegressor(criterion='mse', max_depth=2, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best')
```

In [34]:

```
predict_dt= fit_dt.predict(test.iloc[:,0:10])
```

In [35]:

```
#Calculate RMSE
def RMSE(actual, pred):
    return np.sqrt(((pred - actual) ** 2).mean())
```

```
RMSE(test.iloc[:,10],predict_dt)
#output = 1162.84440171958
```

Out[35]:

```
971.553404406351
```

In [36]:

```
######Random Forest Algorithm
from sklearn.ensemble import RandomForestRegressor
fit_rf = RandomForestRegressor(n_estimators = 100, random_state = 99).fit(train.iloc[:,0:
10],train.iloc[:,10])
```

In [37]:

```
fit_rf
```

Out[37]:

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
           oob_score=False, random_state=99, verbose=0, warm_start=False)
```

In [38]:

```
predict_rf= fit_rf.predict(test.iloc[:,0:10])
```

In [39]:

```
RMSE(test.iloc[:,10],predict_rf)
#output = 765.0407919968172
```

Out[39]:

```
640.3578319299065
```

In [40]:

```
######Multiple Linear Regression
import statsmodels.api as sm
#Creat dataframe with all numerical variables
df.lr = df[['cnt','dteday','atemp','hum','windspeed']]
#create dummies for categorical variables
for i in catnames:
    temp = pd.get_dummies(df[i],prefix = i)
    df.lr = df.lr.join(temp)
```

```
C:\Users\sir\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: UserWarning: Pandas doe
sn't allow columns to be created via a new attribute name - see https://pandas.pydata.org
/pandas-docs/stable/indexing.html#attribute-access
  after removing the cwd from sys.path.
```

In [41]:

```
df.lr.shape                      #676 x 36
```

Out[41]:

```
(676, 36)
```

In [42]:

```
#split data into train-test sets
s = np.random.rand(len(df.lr))<0.8
train.lr = df.lr[s]        #80%
```

```
test.lr = df.lr[~s]          #20%
```

```
C:\Users\sir\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarning: Pandas doe
sn't allow columns to be created via a new attribute name - see https://pandas.pydata.org
/pandas-docs/stable/indexing.html#attribute-access
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\sir\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: UserWarning: Pandas doe
sn't allow columns to be created via a new attribute name - see https://pandas.pydata.org
/pandas-docs/stable/indexing.html#attribute-access
  after removing the cwd from sys.path.
```

In [43]:

```
train.lr.shape               #564 x 36
test.lr.shape                #112 x 36
```

Out[43]:

```
(140, 36)
```

In [44]:

```
#Build MLR model
fit_lr = sm.OLS(train.lr.iloc[:,0],train.lr.iloc[:,1:35]).fit()
fit_lr.summary()
```

Out[44]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.865
Model:	OLS	**Adj. R-squared:**	0.858
Method:	Least Squares	**F-statistic:**	116.5
Date:	Tue, 12 Feb 2019	**Prob (F-statistic):**	9.03e-201
Time:	11:08:15	**Log-Likelihood:**	-4251.2

No. Observations:	536	**AIC:**	8560.
Df Residuals:	507	**BIC:**	8685.
Df Model:	28		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
dteday	-4.8953	3.423	-1.430	0.153	-11.620	1.829
atemp	5004.3547	476.353	10.506	0.000	4068.486	5940.224

hum	-1495.9409	327.803	-4.564	0.000	-2139.960	-851.921
windspeed	-2653.9405	457.089	-5.806	0.000	-3551.963	-1755.918
mnth_1	-189.4452	180.020	-1.052	0.293	-543.122	164.231
mnth_2	-18.8093	169.510	-0.111	0.912	-351.837	314.218
mnth	196.	135.	1.4	0.1	-70.	463.

_3	5986	886	47	49	371	568
mnth_4	2233.8030	162.762	1.375	0.170	-95.968	543.574
mnth_5	540.8962	176.178	3.070	0.002	194.768	887.025
mnth_6	340.1530	166.083	2.048	0.041	13.857	666.449
mnth_7	-625.6951	205.824	-3.040	0.002	-1030.069	-221.321
mnt	-22	185	-0.	0.9	-38	342

h_8	.3800	.968	120	04	7.743	.984
mnth_9	605.9609	151.895	3.989	0.000	307.540	904.382
mnth_10	433.9889	165.640	2.620	0.009	108.564	759.414
mnth_11	-1333.4452	170.933	-0.781	0.435	-469.270	202.380
mnth_12	-193.9987	148.109	-1.310	0.191	-484.981	96.984

yr_0	-395.7701	159.882	-2.475	0.014	-709.882	-81.658
yr_1	1553.3972	156.655	9.916	0.000	1245.625	1861.170
season_1	-534.9101	144.198	-3.710	0.000	-818.210	-251.611
season_2	254.6098	146.252	1.741	0.082	-32.724	541.944
season	497.85	155.2	3.207	0.001	192.8	802.8

_3	68	22			99	15
season_4	940.0706	154.690	6.077	0.000	636.158	1243.983
weekday_0	70.4451	81.745	0.862	0.389	-90.156	231.047
weekday_1	3.9151	83.923	0.047	0.963	-160.965	168.795
weekday_2	165.8409	83.663	1.982	0.048	1.473	330.209
wee	155	82.	1.8	0.0	-6.	317

kday_3	.4384	438	86	60	523	.400
weekday_4	228.3534	85.785	2.662	0.008	59.816	396.891
weekday_5	248.7392	82.261	3.024	0.003	87.125	410.354
weekday_6	284.8950	79.085	3.602	0.000	129.521	440.269
day_1	355.3401	104.830	3.390	0.001	149.385	561.295

day_2	642.0964	118.837	5.403	0.000	408.623	875.569
day_3	160.1907	173.973	0.921	0.358	-181.606	501.987
weathersit_1	2139.8519	226.165	9.461	0.000	1695.516	2584.188
weathersit_2	1700.9849	207.985	8.178	0.000	1292.366	2109.603

Omnibus:	95.776	**Durbin-Watson:**	1.472
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	222.878
Skew:	-0.934	**Prob(JB):**	4.01e-49
Kurtosis:	5.548	**Cond. No.**	1.00e+16

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.72e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [45]:

```
predict_lr = fit_lr.predict(test.lr.iloc[:,1:35])
```

In [46]:

```
RMSE(test.lr.iloc[:,0],predict_lr)
#output = 713.1957640471251
```

Out[46]:

```
892.5204419745069
```

In [47]:

```
######KNN Implementation
from sklearn import neighbors
rmse_val = []            #to store rmse values for different k
for K in range(30):
    K = K+1
    fit_knn = neighbors.KNeighborsRegressor(n_neighbors = K)

    fit_knn.fit(train.iloc[:,0:10], train.iloc[:,10]) #fit the model

    predict_knn = fit_knn.predict(test.iloc[:,0:10]) #make prediction on test set
    error = RMSE(test.iloc[:,10] , predict_knn) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 1205.7335849768706
```

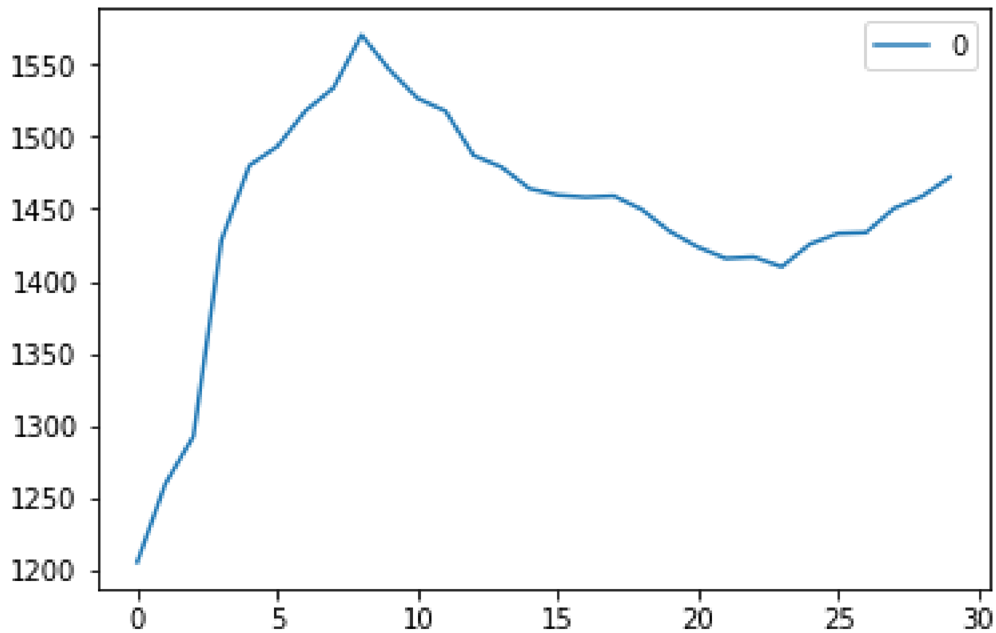
```
RMSE value for k=  2 is: 1259.7167267356765
RMSE value for k=  3 is: 1292.6514266360882
RMSE value for k=  4 is: 1428.151143569432
RMSE value for k=  5 is: 1479.955740196705
RMSE value for k=  6 is: 1493.1435739521633
RMSE value for k=  7 is: 1517.6304015518022
RMSE value for k=  8 is: 1533.6537566734078
RMSE value for k=  9 is: 1570.1710483274771
RMSE value for k=  10 is: 1546.1261414561611
RMSE value for k=  11 is: 1526.496100465862
RMSE value for k=  12 is: 1517.5136484571321
RMSE value for k=  13 is: 1486.9514980997221
RMSE value for k=  14 is: 1478.8068946139056
RMSE value for k=  15 is: 1463.907811840837
RMSE value for k=  16 is: 1459.5038055640289
RMSE value for k=  17 is: 1458.0110671935322
RMSE value for k=  18 is: 1458.9514319291206
RMSE value for k=  19 is: 1449.5929359139823
RMSE value for k=  20 is: 1434.4245678414761
RMSE value for k=  21 is: 1423.6093888400228
RMSE value for k=  22 is: 1415.6660108260676
RMSE value for k=  23 is: 1416.6971379552292
RMSE value for k=  24 is: 1409.898688944427
RMSE value for k=  25 is: 1425.570065466072
RMSE value for k=  26 is: 1432.9739021944652
RMSE value for k=  27 is: 1433.5920306962062
RMSE value for k=  28 is: 1450.2545484205818
RMSE value for k=  29 is: 1458.558312815522
RMSE value for k=  30 is: 1471.8719253246265
```

In [48]:

```
#plotting the rmse values against k values
curve = pd.DataFrame(rmse_val)
curve.plot()
#K=2 is the value of neighbors for least RMSE.
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f1069a9240>
```



In [49]:

```
#For K=12:
fit_knn = neighbors.KNeighborsRegressor(n_neighbors = 2)
fit_knn.fit(train.iloc[:,0:10], train.iloc[:,10]) #fit the model
predict_knn = fit_knn.predict(test.iloc[:,0:10]) #make prediction on test set
RMSE(test.iloc[:,10] , predict_knn)
#output = 1209.595772142617
```

Out[49]:

```
1259.7167267356765
```

In [50]:

```
#Thus, we find the "Multiple Linear Regression Algorithm" gives us the best result with t
he least RMSE for this dataset.
```