Prediction of Bike Rental Count

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Contents

Chapter 1: Introduction

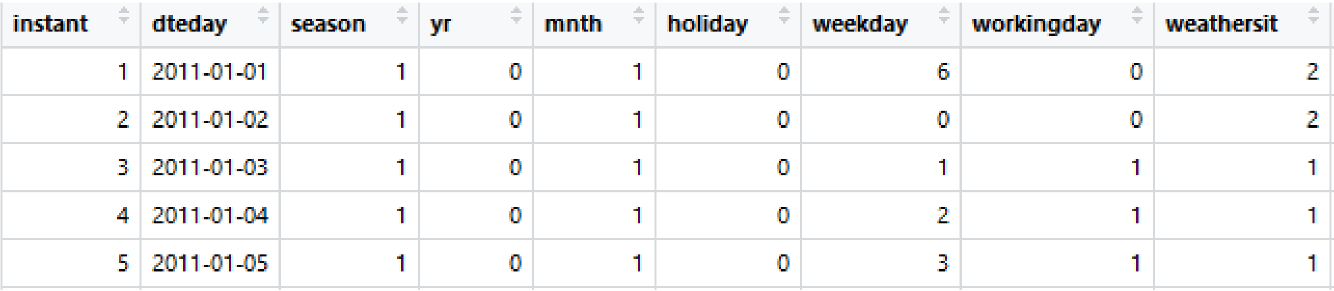
1.1 Problem Statement

The aim of this project is to predict the count of bike rentals based on the seasonal and environmental settings. By predicting the count, it would be possible to help accommodate in managing the number of bikes required on a daily basis, and being prepared for high demand of bikes during peak periods.

1.2 Data

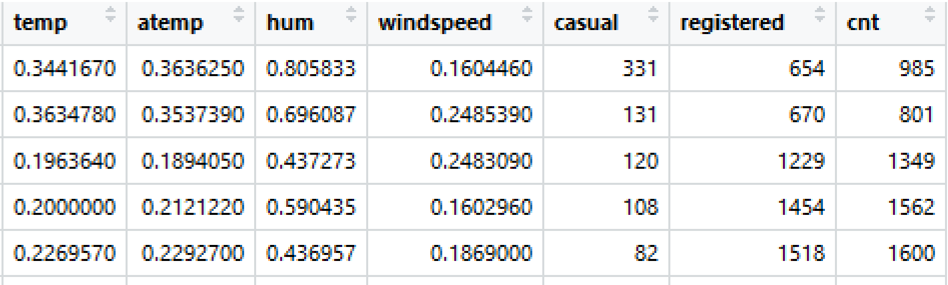
The goal is to build regression models which will predict the number of bikes used based on the environmental and season behaviour. Given below is a sample of the data set that we are using to predict the number of bikes:

Table 1.1: Bike Count Sample Data (Columns: 1-9)



instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit
1	2011-01-01	1	0	1	0	6	0	2
2	2011-01-02	1	0	1	0	0	0	2
3	2011-01-03	1	0	1	0	1	1	1
4	2011-01-04	1	0	1	0	2	1	1
5	2011-01-05	1	0	1	0	3	1	1

Table 1.2: Bike Count Sample Data (Columns: 10-16)



temp	atemp	hum	windspeed	casual	registered	cnt
0.3441670	0.3636250	0.805833	0.1604460	331	654	985
0.3634780	0.3537390	0.696087	0.2485390	131	670	801
0.1963640	0.1894050	0.437273	0.2483090	120	1229	1349
0.2000000	0.2121220	0.590435	0.1602960	108	1454	1562
0.2269570	0.2292700	0.436957	0.1869000	82	1518	1600

As you can see in the table below we have the following 13 variables, using which we have to correctly predict the count of bikes:

Sl.No	**Variables**
1	Instant
2	Dteday
3	Season
4	Yr
5	Month
6	Holiday
7	Weekday
8	Workingday
9	Weathersit
10	Temp
11	Atemp
12	Hum
13	windspeed

Table 1.3: Predictor variables

Chapter 2: Methodology

2.1 Pre-Processing

A predictive model requires that we look at the data before we start to create a model. However, in data mining, looking at data refers to exploring the data, cleaning the data as well as visualizing the data through graphs and plots. This is known as Exploratory Data Analysis.

2.2 Distribution of continuous variables

It can be observed from the below histograms is that temperature and feel temperature are normally distributed, where as the variables windspeed and humidity are slightly skewed. The skewness is likely because of the presence of outliers and extreme data in those variables.

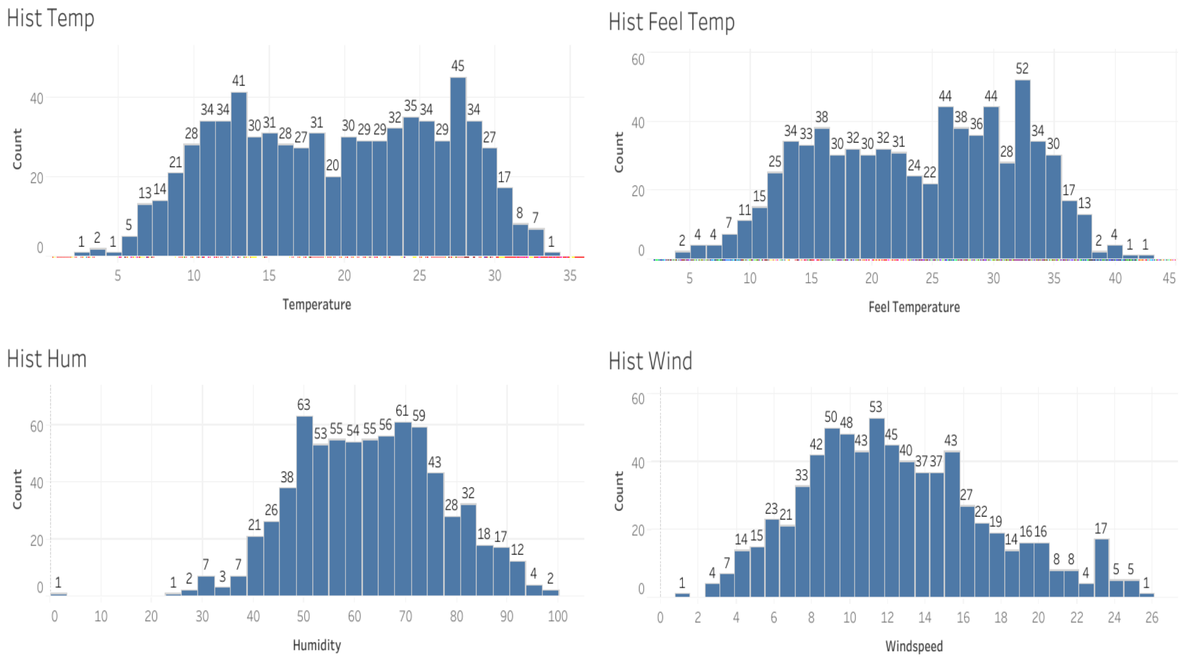


Fig 2.1: Distribution of continuous variables using Histograms

2.3 Distribution of categorical variables

The distribution of categorical variables is as shown in the below figure:

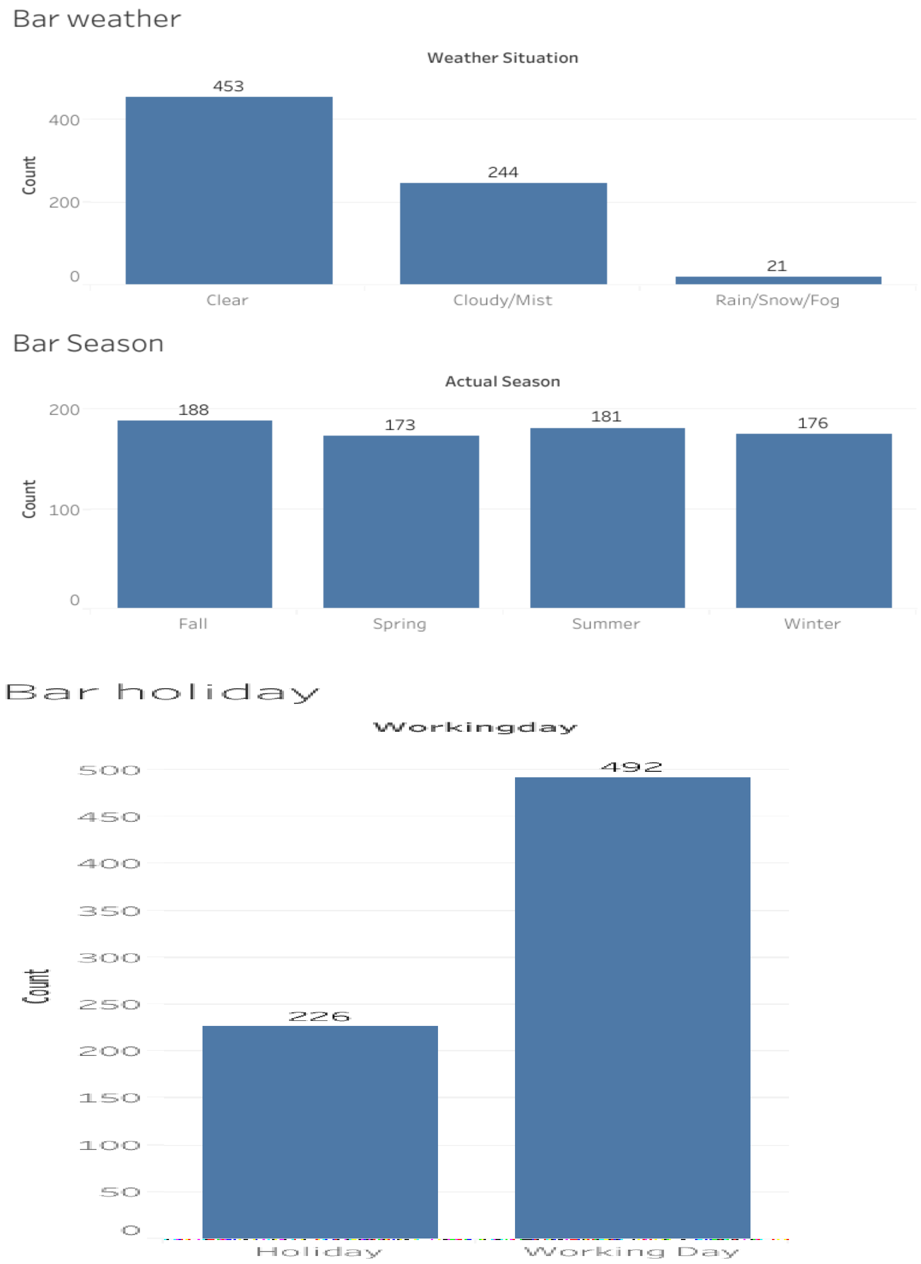


Fig 2.2: Distribution of categorical variables using bar plots

2.4 Relationship of Continuous variables against bike count

The below figure shows the relationship between continuous variables and the target variable using scatter plot. It can be observed that there exists a linear positive relationship between the variables temperature and feel temperature with the bike rental count. There also exists a negative linear relationship between the variable's humidity and windspeed with the bike rental count.

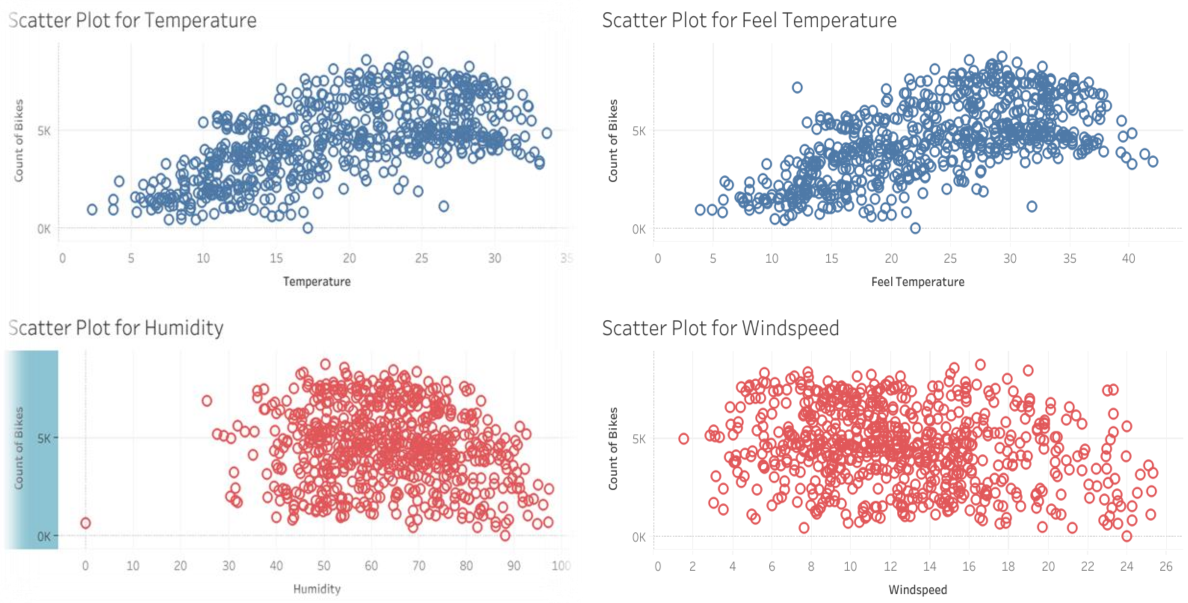


Fig 2.3: Scatter plot for continuous variables

2.5: Detection of outliers:

Outliers are detected using boxplots. Below figure illustrates the boxplots for all the continuous variables.

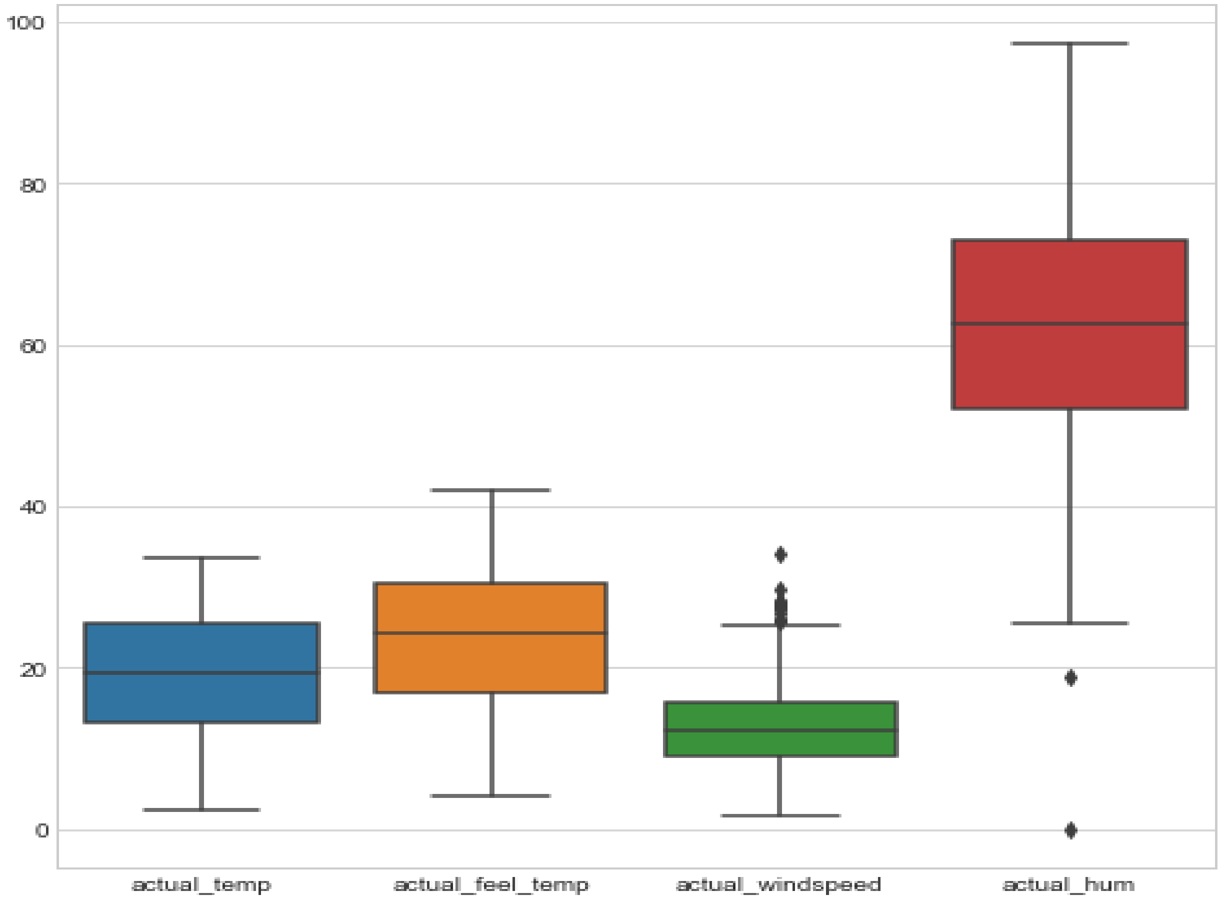


Fig 2.4: Boxplot of continuous variables

Outliers can be removed using the Boxplot stats method, wherein the Inter Quartile Range (IQR) is calculated and the minimum and maximum value are calculated for the variables. Any value ranging outside the minimum and maximum value are discarded. The boxplot of the continuous variables after removing the outliers is shown in the below figure:

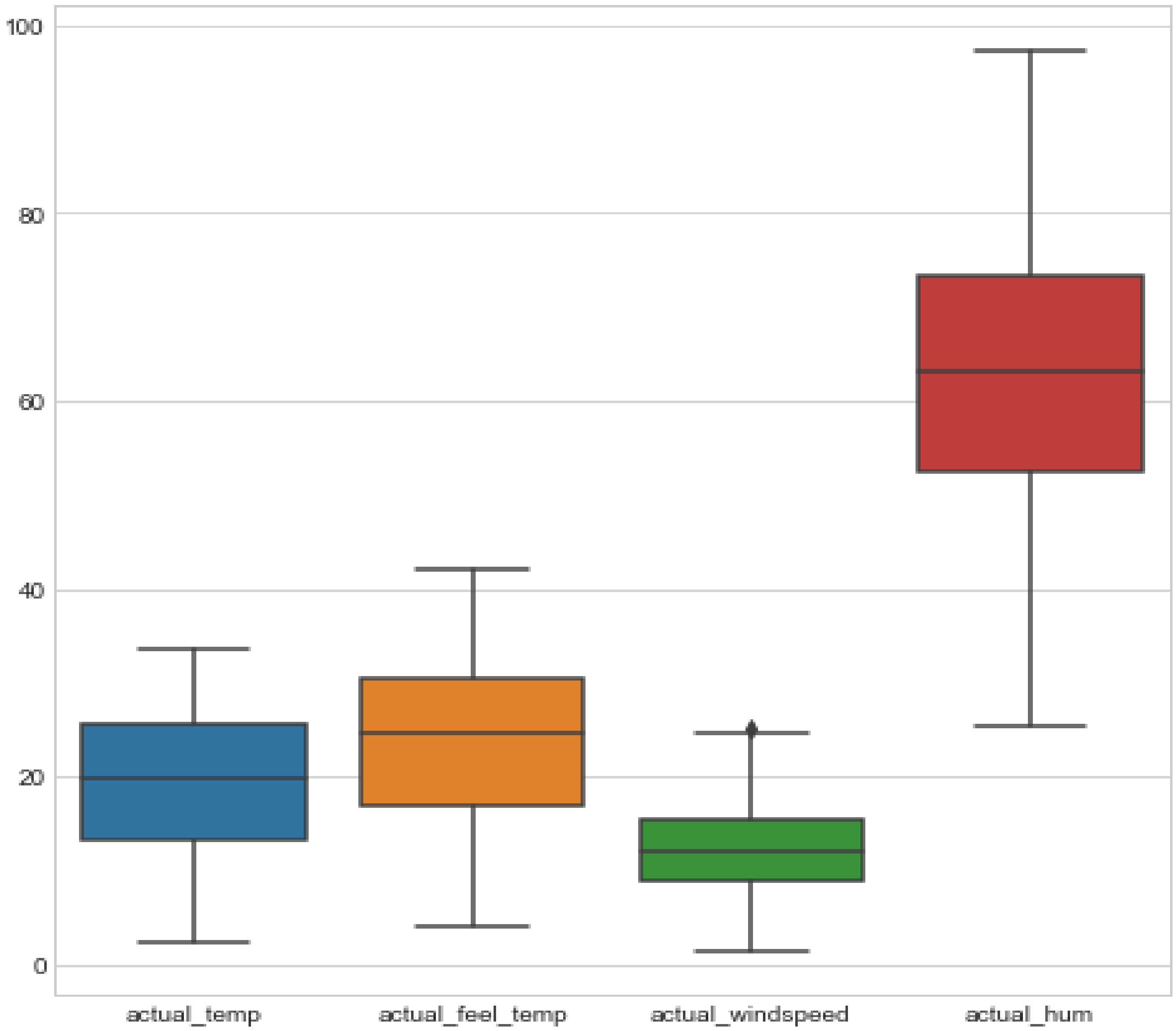


Fig 2.5: Boxplot of continuous variables after removal of outliers

It can be observed from the distribution of Windspeed and humidity after removal of outliers, is that data is not skewed as much as before the removal of outliers. The figure shown below illustrates the distribution of continuous variables using histograms.

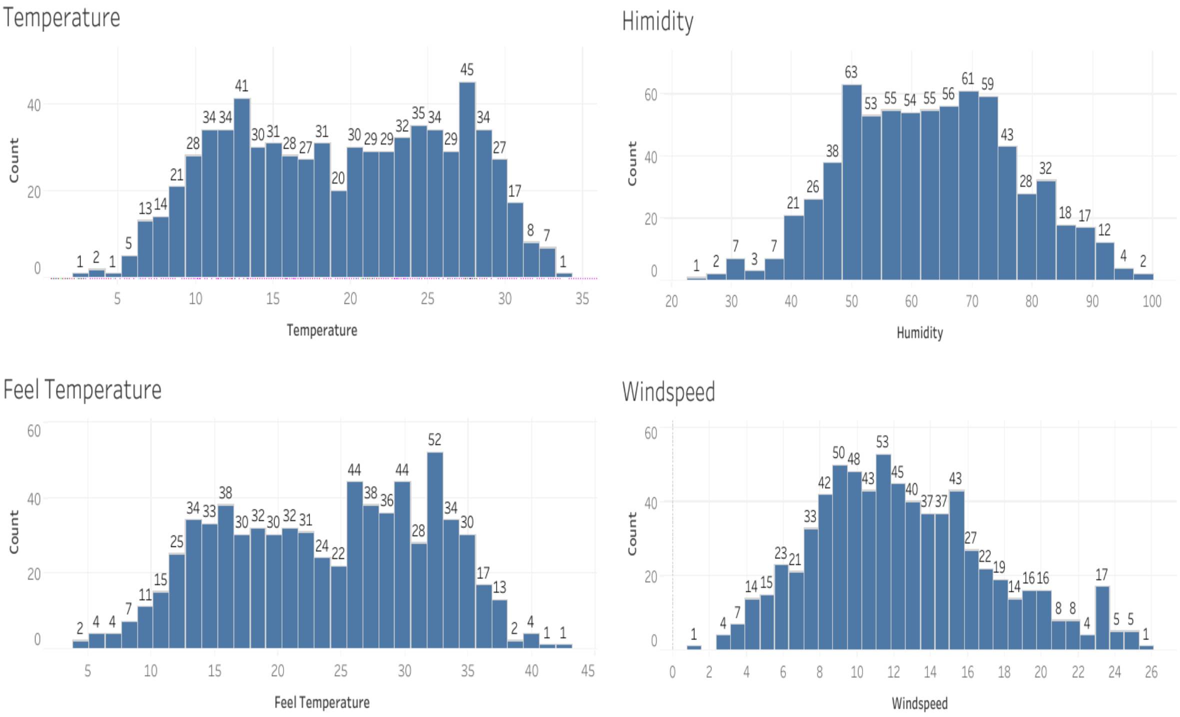


Fig 2.6: Distribution of numerical data using histograms after removal of outliers

2.6: Feature Selection

Feature Selection reduces the complexity of a model and makes it easier to interpret. It also reduces overfitting. Features are selected based on their scores in various statistical tests for their correlation with the outcome variable.
Correlation plot is used to find out if there is any multicollinearity between variables. The highly collinear variables are dropped and then the model is executed.

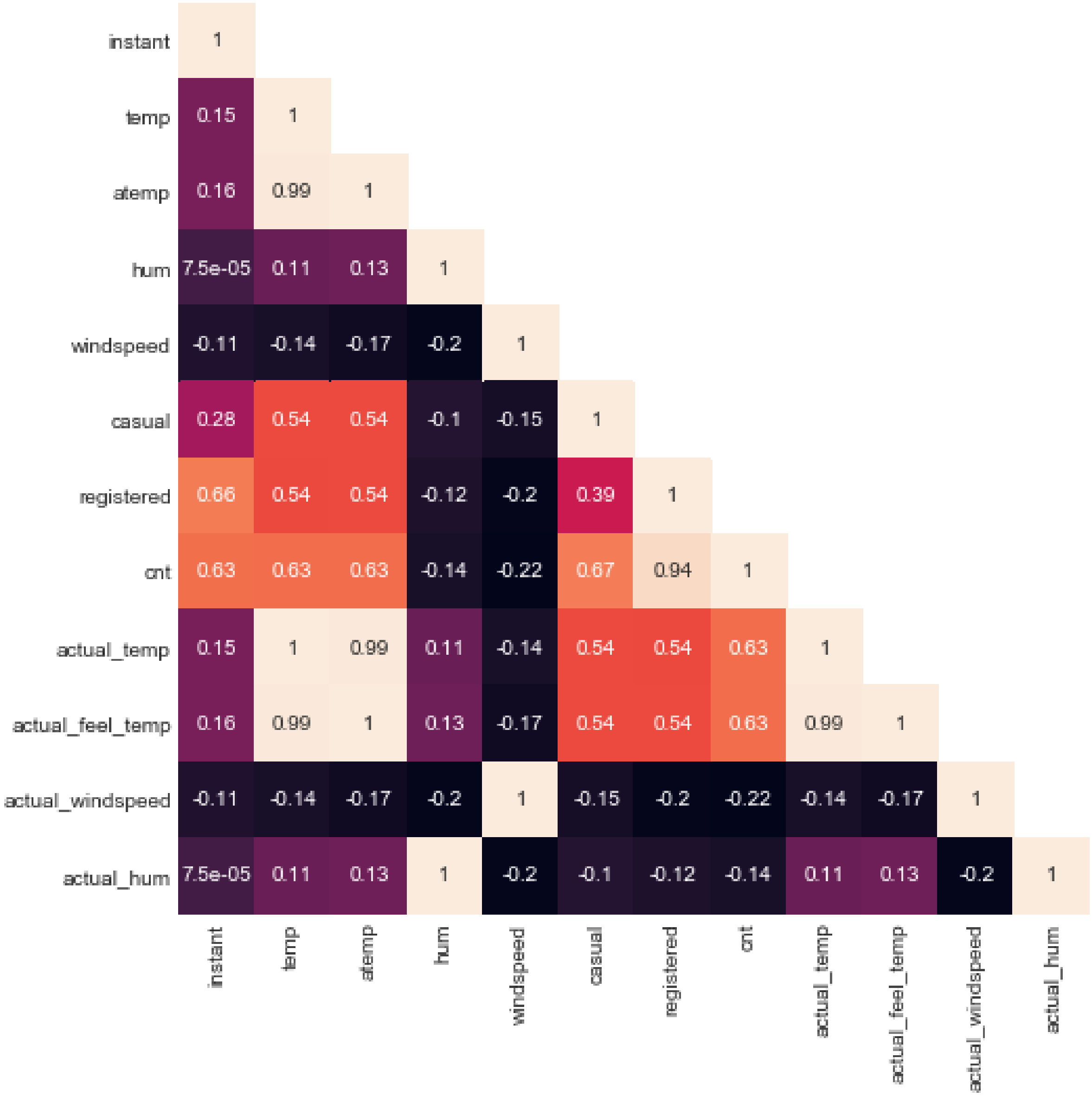


Fig 2.7: Correlation plot of all the variables

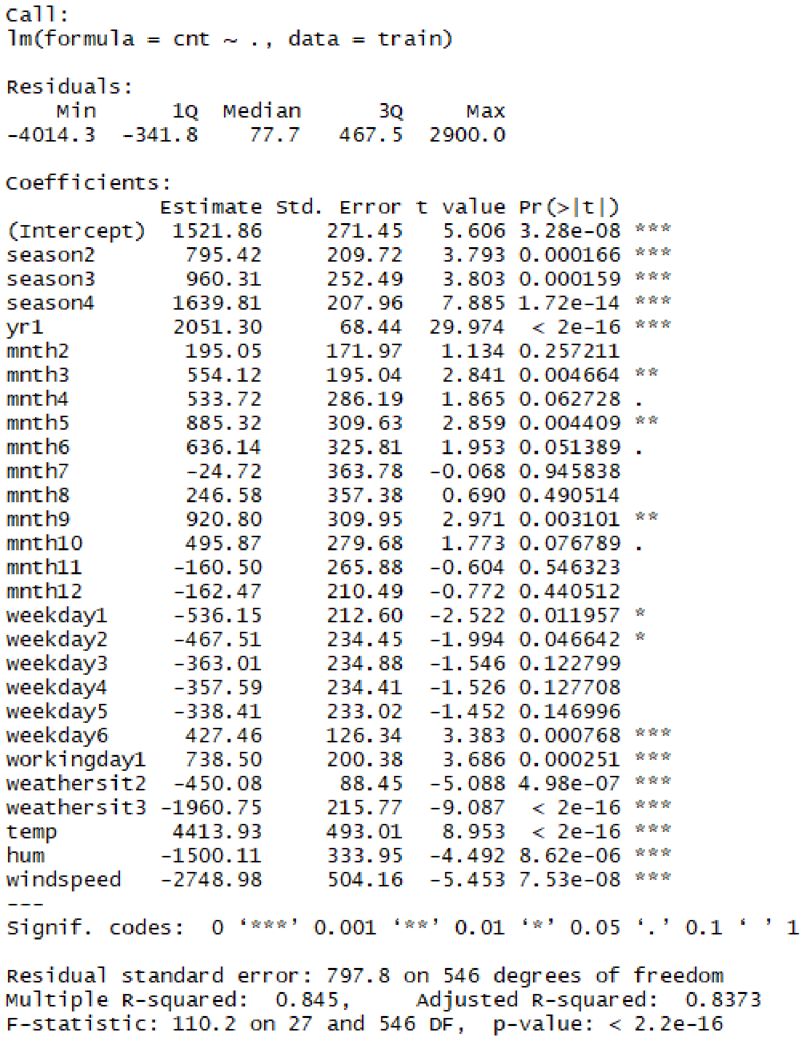
Chapter 3: Modelling

3.1 Model Selection

The dependent variable in our model is a continuous variable i.e., Count of bike rentals. Hence the models that we choose are Linear Regression, Decision Tree and Random Forest. The error metric chosen for the problem statement is Mean Absolute Error (MAE).

3.2 Multiple Linear Regression

Multiple linear regression is the most common form of linear regression analysis. Multiple linear regression is used to explain the relationship between one continuous dependent variable and two or more independent variables. The independent variables can be continuous or categorical.



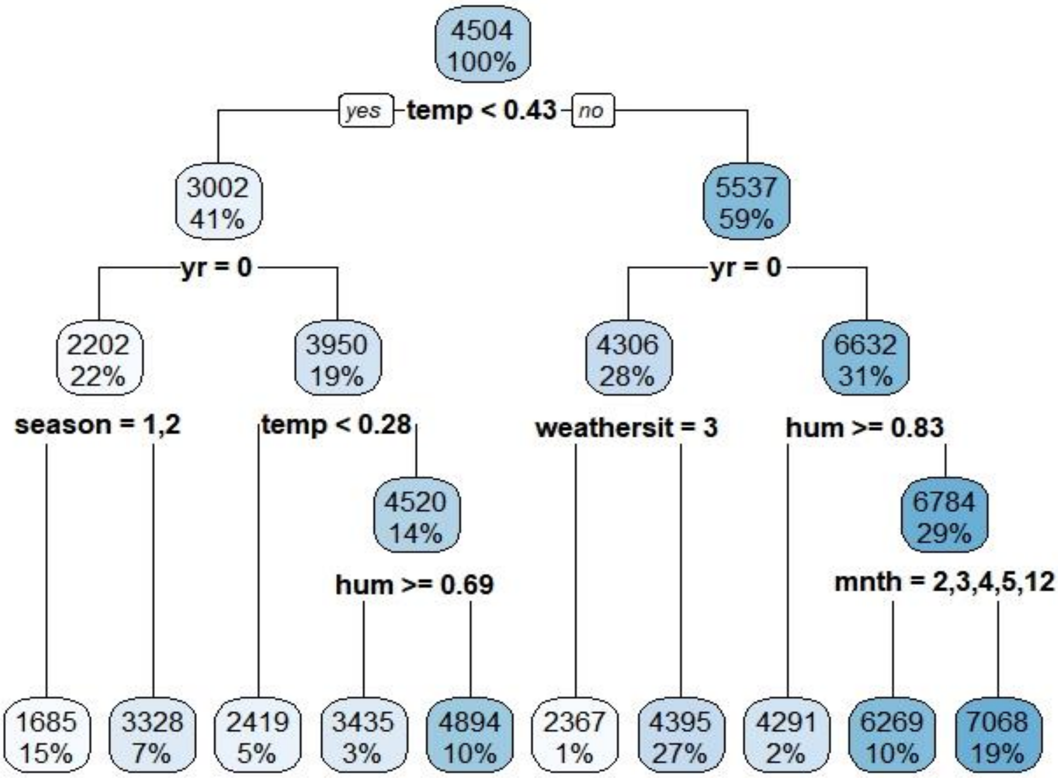
```
Call:
lm(formula = cnt ~ ., data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-4014.3  -341.8    77.7   467.5  2900.0 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1521.86     271.45   5.606 3.28e-08 ***
season2       795.42     209.72   3.793 0.000166 ***
season3       960.31     252.49   3.803 0.000159 ***
season4      1639.81     207.96   7.885 1.72e-14 ***
yr1          2051.30      68.44  29.974  < 2e-16 ***
mnth2         195.05     171.97   1.134 0.257211    
mnth3         554.12     195.04   2.841 0.004664 ** 
mnth4         533.72     286.19   1.865 0.062728 .  
mnth5         885.32     309.63   2.859 0.004409 ** 
mnth6         636.14     325.81   1.953 0.051389 .  
mnth7         -24.72     363.78  -0.068 0.945838    
mnth8         246.58     357.38   0.690 0.490514    
mnth9         920.80     309.95   2.971 0.003101 ** 
mnth10        495.87     279.68   1.773 0.076789 .  
mnth11       -160.50     265.88  -0.604 0.546323    
mnth12       -162.47     210.49  -0.772 0.440512    
weekday1     -536.15     212.60  -2.522 0.011957 *  
weekday2     -467.51     234.45  -1.994 0.046642 *  
weekday3     -363.01     234.88  -1.546 0.122799    
weekday4     -357.59     234.41  -1.526 0.127708    
weekday5     -338.41     233.02  -1.452 0.146996    
weekday6      427.46     126.34   3.383 0.000768 ***
workingday1   738.50     200.38   3.686 0.000251 ***
weathersit2  -450.08      88.45  -5.088 4.98e-07 ***
weathersit3 -1960.75     215.77  -9.087  < 2e-16 ***
temp         4413.93     493.01   8.953  < 2e-16 ***
hum         -1500.11     333.95  -4.492 8.62e-06 ***
windspeed   -2748.98     504.16  -5.453 7.53e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 797.8 on 546 degrees of freedom
Multiple R-squared:  0.845,	Adjusted R-squared:  0.8373 
F-statistic: 110.2 on 27 and 546 DF,  p-value: < 2.2e-16
```

As you can see the Adjusted R-squared value, we can explain 83.73% of the data using our multiple linear regression model. By looking at the F-statistic and combined p-value we can reject the null hypothesis that target variable does not depend on any of the predictor variables. This model explains the data very well and is considered to be good.

Even after removing the non-significant variables, the accuracy, Adjusted R-squared and F-statistic do not change by much, hence the accuracy of this model is chosen to be final.
Mean Absolute Error (MAE) is calculated and found to be 494.
MAPE of this multiple linear regression model is 12.17%. Hence the accuracy of this model is 87.83%. This model performs very well for this test data.

3.3 Decision Tree:

A decision tree can be used to visually and explicitly represent decisions and decision making. As the name goes, it uses a tree-like model of decisions.



Using decision tree, we can predict the value of bike count. MAE for this model is 684. The MAPE for this decision tree is 17.47%. Hence the accuracy for this model is 82.53%.

3.4 Random Forest:

Using Classification for prediction analysis in this case is not normal, though it can be done. The number of decision trees used for prediction in the forest is 500. MAE for this model is 392. Using random forest, the MAPE was found to be 10.68%. Hence the accuracy is 89.32%.

Chapter 4: Conclusion

Now that we have a few models for predicting the target variable, we need to decide which one to choose. There are several criteria that exist for evaluating and comparing models. We can compare the models using any of the following criteria:

1. Predictive Performance
2. Interpretability
3. Computational Efficiency

In our case of Bike count prediction Data, Interpretability and Computation Efficiency, do not hold much significance. Therefore, we will use Predictive performance as the criteria to compare and evaluate models.

Predictive performance can be measured by comparing Predictions of the models with real values of the target variables, and calculating some average error measure.

4.1 Mean Absolute Error (MAE)

MAE is one of the error measures used to calculate the predictive performance of the model. We will apply this measure to our models that we have generated in the previous section.

```
MAE <- function (actual, pred)
{
  print(mean (abs (actual - pred)))
}
```

Linear Regression Model: MAE = 494
Decision Tree: MAE = 684.
Random Forest: MAE = 392

Based on the above error metrics, Random Forest is the better model for our analysis. Hence Random Forest is chosen as the model for prediction of bike rental count.

Chapter 5: Appendix

5.1 Figures

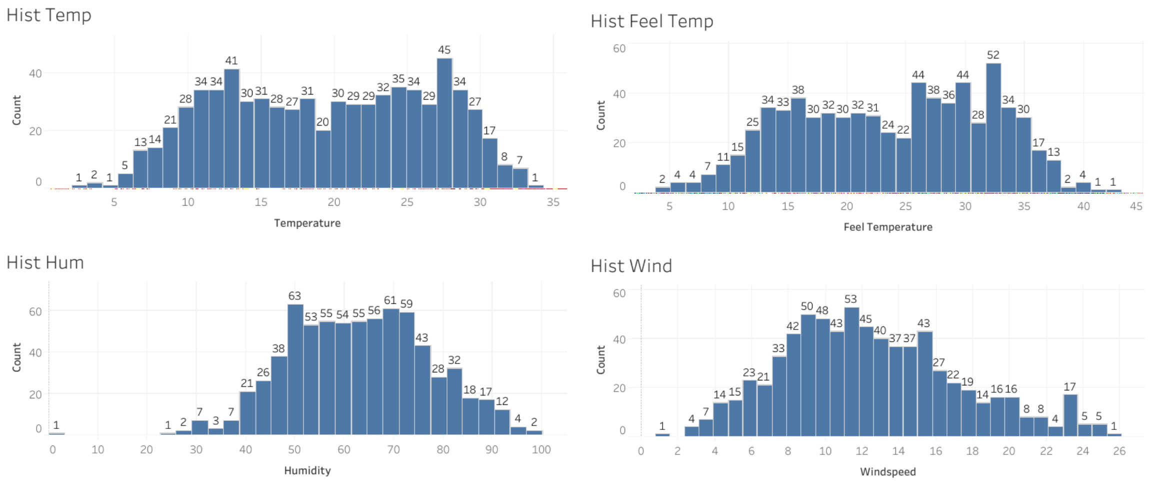


Fig 2.1: Distribution of continuous variables using Histograms

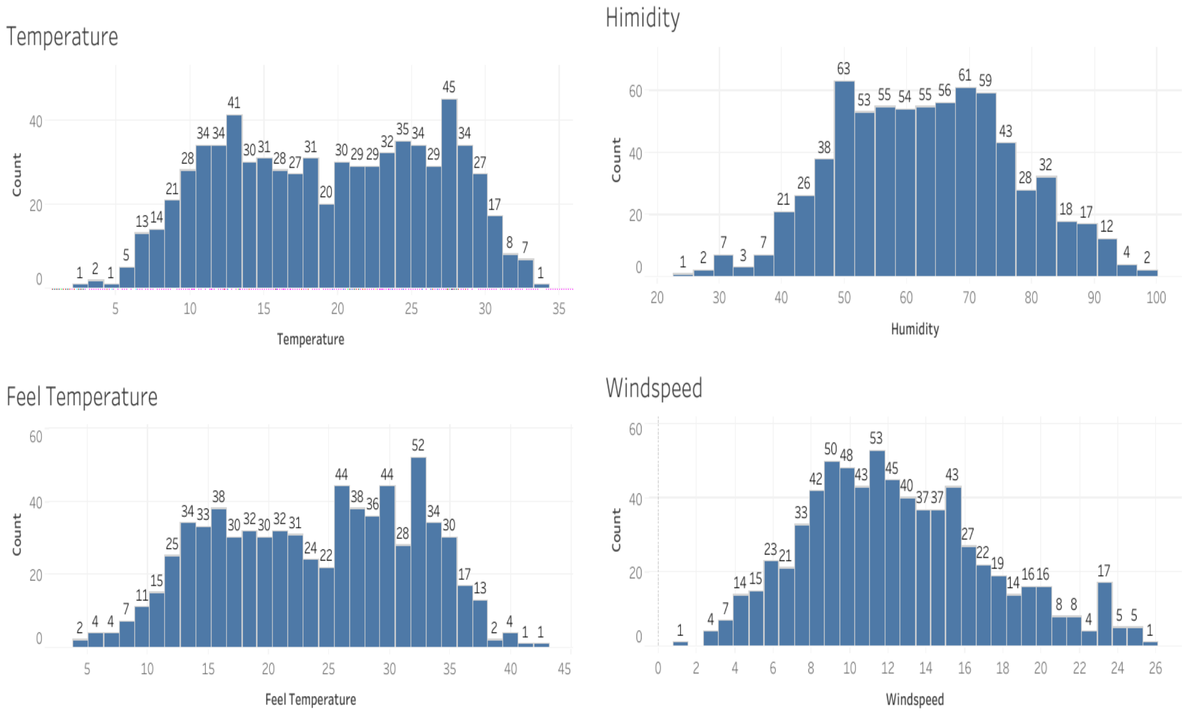


Fig 2.6: Distribution of numerical data using histograms after removal of outliers

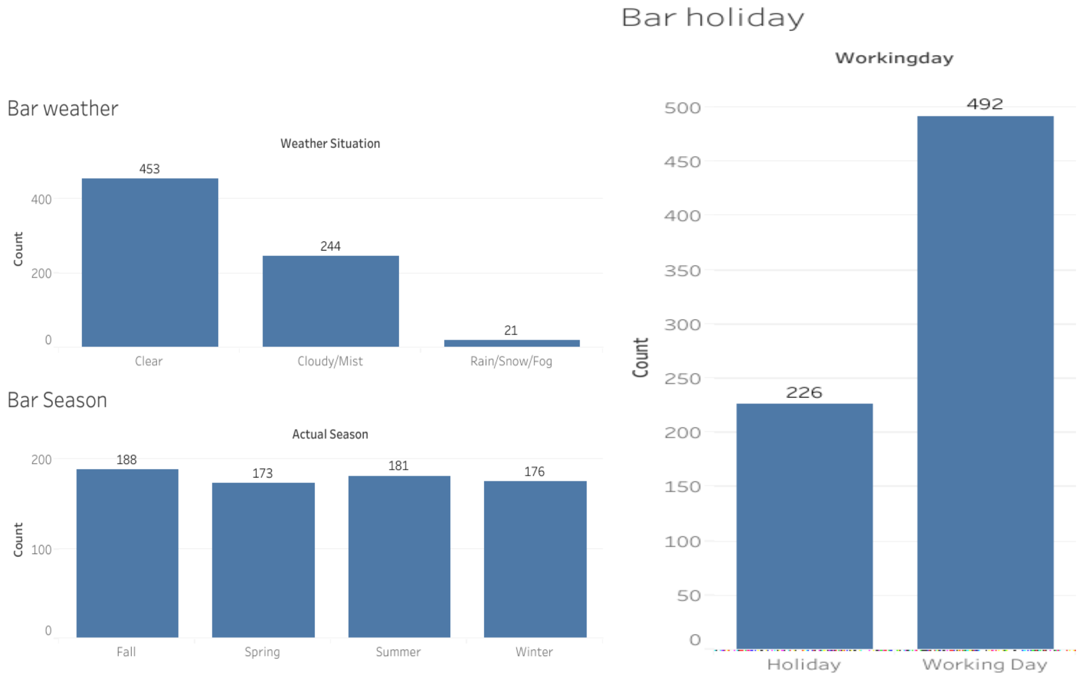


Fig 2.2: Distribution of categorical variables using bar plots

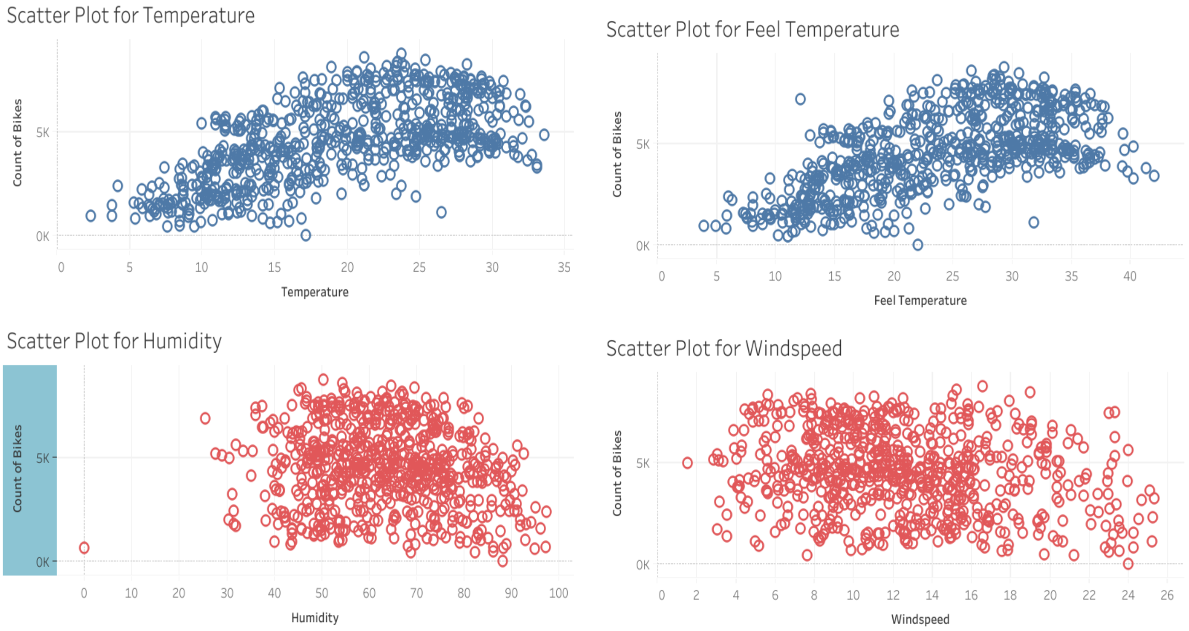


Fig 2.3: Scatter plot for continuous variables

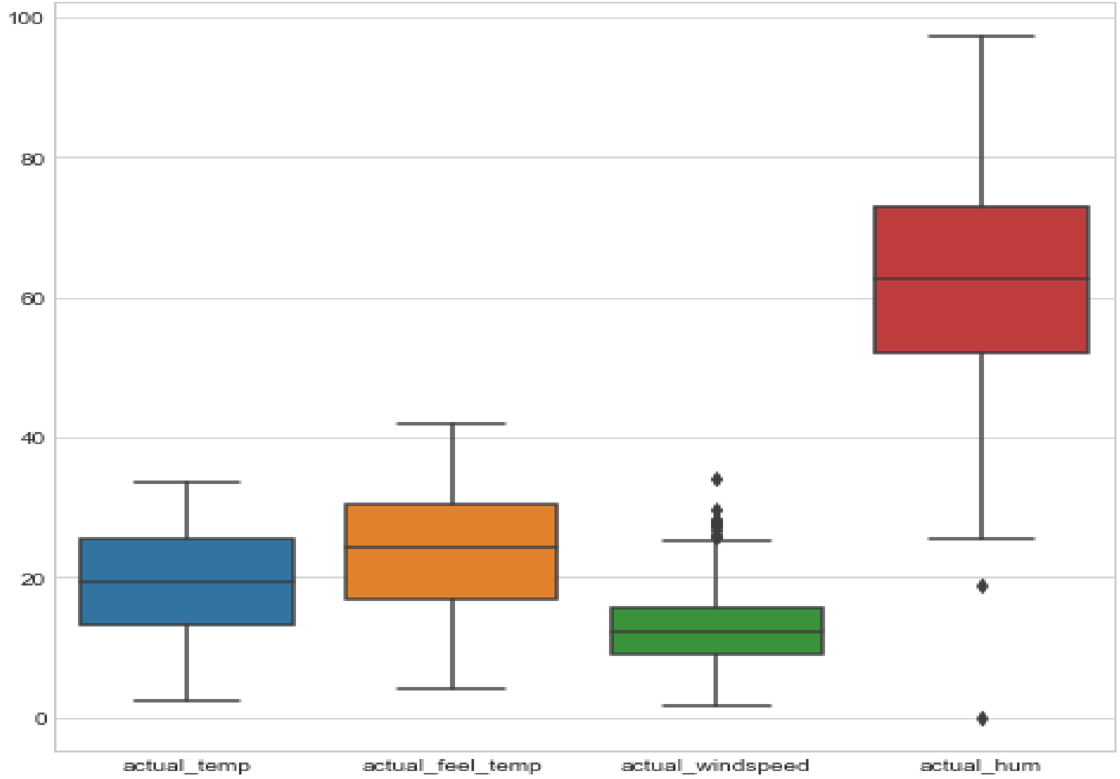


Fig 2.4: Boxplot of continuous variables

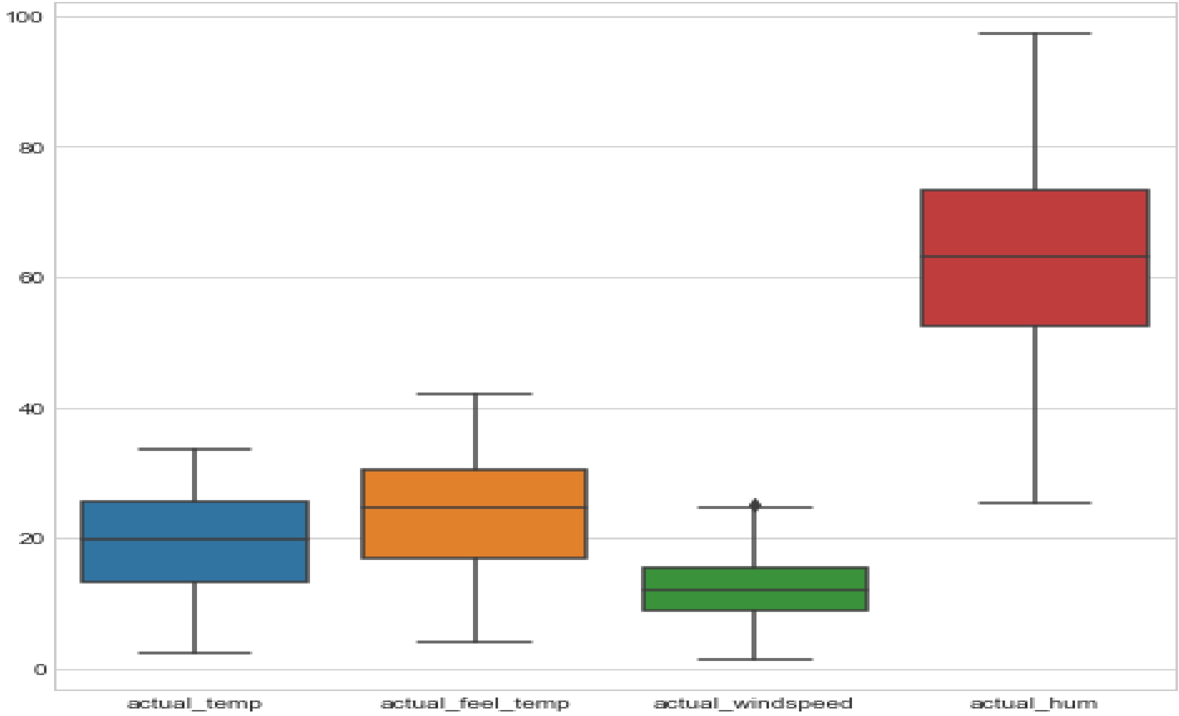


Fig 2.5: Boxplot of continuous variables after removal of outliers

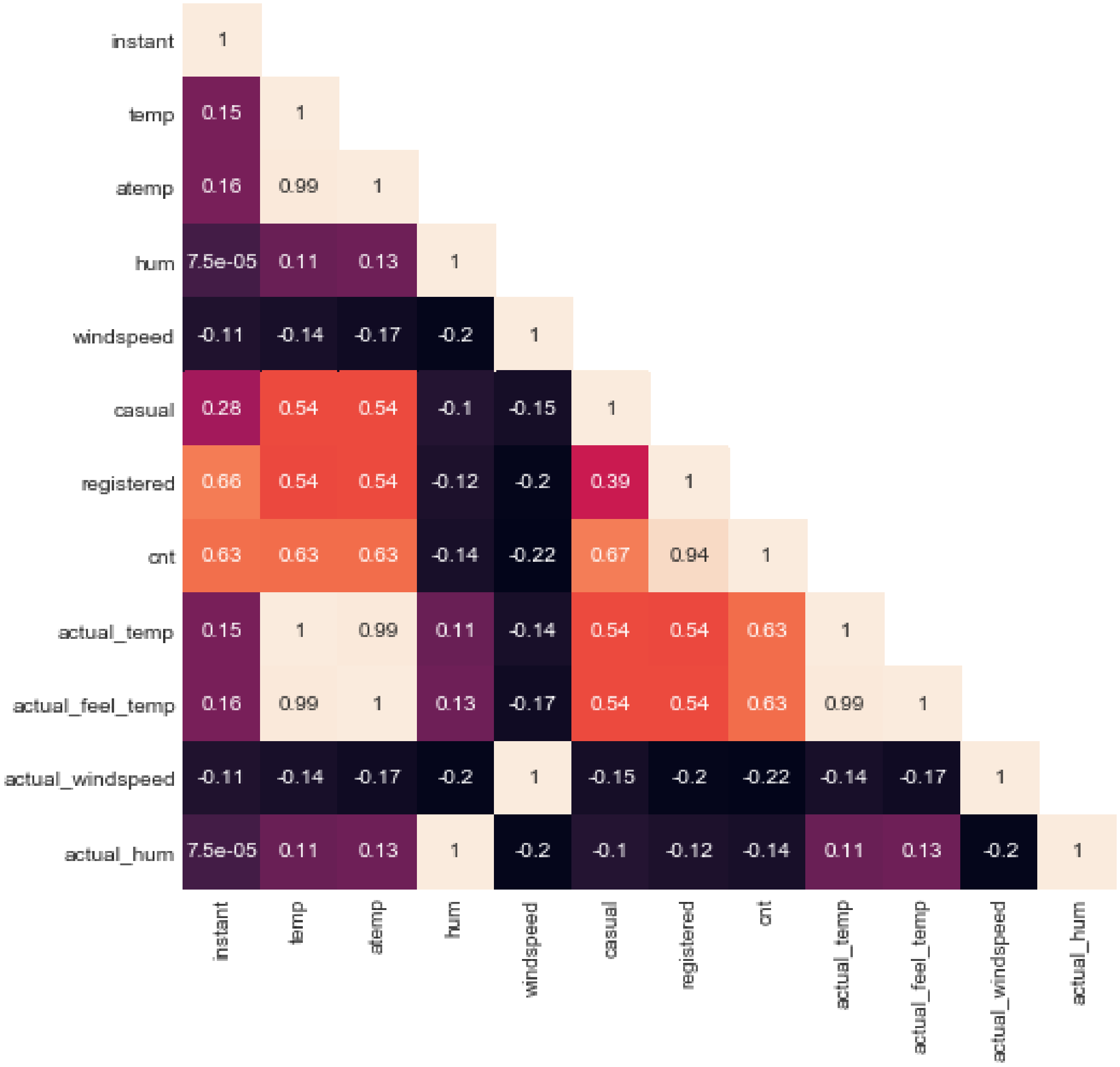


Fig 2.7: Correlation plot of all the variables

Chapter 6: R code

```
#####################EXPLORE USING GRAPHS#######################

#CHECK THE DISTRIBUTION OF CATEGORICAL DATA USING BAR GRAPH

BAR1 = GGPLOT(DATA = DAY, AES(X = ACTUAL_SEASON)) + GEOM_BAR() + GGTITLE("COUNT OF SEASON")
BAR2 = GGPLOT(DATA = DAY, AES(X = ACTUAL_WEATHERSIT)) + GEOM_BAR() + GGTITLE("COUNT OF
WEATHER")
BAR3 = GGPLOT(DATA = DAY, AES(X = ACTUAL_HOLIDAY)) + GEOM_BAR() + GGTITLE("COUNT OF HOLIDAY")
BAR4 = GGPLOT(DATA = DAY, AES(X = WORKINGDAY)) + GEOM_BAR() + GGTITLE("COUNT OF WORKING
DAY")
GRIDEXTRA::GRID.ARRANGE(BAR1,BAR2,BAR3,BAR4,NCOL=2)

#CHECK THE DISTRIBUTION OF NUMERICAL DATA USING HISTOGRAM

HIST1 = GGPLOT(DATA = DAY, AES(X =ACTUAL_TEMP)) + GGTITLE("DISTRIBUTION OF TEMPERATURE") +
GEOM_HISTOGRAM(BINS = 25)
HIST2 = GGPLOT(DATA = DAY, AES(X =ACTUAL_HUM)) + GGTITLE("DISTRIBUTION OF HUMIDITY") +
GEOM_HISTOGRAM(BINS = 25)
HIST3 = GGPLOT(DATA = DAY, AES(X =ACTUAL_FEEL_TEMP)) + GGTITLE("DISTRIBUTION OF FEEL
TEMPERATURE") + GEOM_HISTOGRAM(BINS = 25)
HIST4 = GGPLOT(DATA = DAY, AES(X =ACTUAL_WINDSPEED)) + GGTITLE("DISTRIBUTION OF WINDSPEED") +
GEOM_HISTOGRAM(BINS = 25)
GRIDEXTRA::GRID.ARRANGE(HIST1,HIST2,HIST3,HIST4,NCOL=2)

#CHECK THE DISTRIBUTION OF NUMERICAL DATA USING SCATTERPLOT

SCAT1 = GGPLOT(DATA = DAY, AES(X =ACTUAL_TEMP, Y = CNT)) + GGTITLE("DISTRIBUTION OF
TEMPERATURE") + GEOM_POINT() + XLAB("TEMPERATURE") + YLAB("BIKE COUNT")
SCAT2 = GGPLOT(DATA = DAY, AES(X =ACTUAL_HUM, Y = CNT)) + GGTITLE("DISTRIBUTION OF HUMIDITY") +
GEOM_POINT(COLOR="RED") + XLAB("HUMIDITY") + YLAB("BIKE COUNT")
SCAT3 = GGPLOT(DATA = DAY, AES(X =ACTUAL_FEEL_TEMP, Y = CNT)) + GGTITLE("DISTRIBUTION OF FEEL
TEMPERATURE") + GEOM_POINT() + XLAB("FEEL TEMPERATURE") + YLAB("BIKE COUNT")
SCAT4 = GGPLOT(DATA = DAY, AES(X =ACTUAL_WINDSPEED, Y = CNT)) + GGTITLE("DISTRIBUTION OF
WINDSPEED") + GEOM_POINT(COLOR="RED") + XLAB("WINDSPEED") + YLAB("BIKE COUNT")
GRIDEXTRA::GRID.ARRANGE(SCAT1,SCAT2,SCAT3,SCAT4,NCOL=2)

#CHECK FOR OUTLIERS IN DATA USING BOXPLOT

CNAMES =
COLNAMES(DAY[,C("ACTUAL_TEMP","ACTUAL_FEEL_TEMP","ACTUAL_WINDSPEED","ACTUAL_HUM")])
FOR (I IN 1:LENGTH(CNAMES))
{
ASSIGN(PASTE0("GN",I), GGPLOT(AES_STRING(Y = CNAMES[I]), DATA = DAY)+ STAT_BOXPLOT(GEOM =
"ERRORBAR", WIDTH = 0.5) +  GEOM_BOXPLOT(OUTLIER.COLOUR="RED", FILL = "GREY"
,outlier.shape=18, outlier.size=1, notch=FALSE) + theme(legend.position="bottom")+
labs(y=cnames[i]) + ggtitle(paste("Box plot for",cnames[i])))
}
gridExtra::grid.arrange(gn1,gn3,gn2,gn4,ncol=2)

#Remove outliers in Windspeed

val = day[,19][day[,19] %in% boxplot.stats(day[,19])$out]
day = day[which(!day[,19] %in% val),]

#Check for multicollinearity using VIF

df = day[,c("instant","temp","atemp","hum","windspeed")]
vifcor(df)

#Check for collinearity using corelation graph

corrgram(day, order = F, upper.panel=panel.pie, text.panel=panel.txt, main = "Correlation
Plot")

#Remove the unwanted variables

day <- subset(day, select = -
c(instant,dteday,atemp,casual,registered,actual_temp,actual_feel_temp,actual_windspeed,ac
tual_hum,actual_season,actual_yr,actual_holiday,actual_weathersit))

##########################DECISION TREE##########################

#Divide the data into train and test

set.seed(123)
train_index = sample(1:nrow(day), 0.8 * nrow(day))
train = day[train_index,]
test = day[-train_index,]

#rpart for regression

dt_model = rpart(cnt ~ ., data = train, method = "anova")

#Predict the test cases

dt_predictions = predict(dt_model, test[,-11])

#Create dataframe for actual and predicted values

df = data.frame("actual"=test[,11], "pred"=dt_predictions)
head(df)

#calculate MAPE

regr.eval(trues = test[,11], preds = dt_predictions, stats = c("mae","mse","rmse","mape"))
```

```
####################RANDOM FOREST################

#TRAIN THE DATA USING RANDOM FOREST

RF_MODEL = RANDOMFOREST(CNT~., DATA = TRAIN, NTREE = 500)

#PREDICT THE TEST CASES

RF_PREDICTIONS = PREDICT(RF_MODEL, TEST[,-11])

#CREATE DATAFRAME FOR ACTUAL AND PREDICTED VALUES

DF = CBIND(DF,RF_PREDICTIONS)
HEAD(DF)

#CALCULATE MAPE

REGR.EVAL(TRUES = TEST[,11], PREDS = RF_PREDICTIONS, STATS = C("MAE","MSE","RMSE","MAPE"))

####################LINEAR REGRESSION################

#TRAIN THE DATA USING LINEAR REGRESSION

LR_MODEL = LM(FORMULA = CNT~., DATA = TRAIN)

#CHECK THE SUMMARY OF THE MODEL

SUMMARY(LR_MODEL)

#PREDICT THE TEST CASES

LR_PREDICTIONS = PREDICT(LR_MODEL, TEST[,-11])

#CREATE DATAFRAME FOR ACTUAL AND PREDICTED VALUES

DF = CBIND(DF,LR_PREDICTIONS)
HEAD(DF)

#CALCULATE MAPE

REGR.EVAL(TRUES = TEST[,11], PREDS = LR_PREDICTIONS, STATS = C("MAE","MSE","RMSE","MAPE"))

#PREDICT A SAMPLE DATA

PREDICT(LR_MODEL,TEST[2,])
```