PROJECT REPORT

PREDICTION OF BIKE RENTAL COUNTS BASIS SEASONAL SETTINGS

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Chapter 1

Introduction

1.1 Problem Statement

The objective of this Case is to Predication of bike rental count on daily based on the environmental and seasonal settings.

1.2 Data

Understanding of data is the very first and important step in the process of finding solution of any business problem. Here we will proceed with two years data which is 2011 and 2012 with 15 variable including one dependent variable.
Dataset Characteristics: Timeseries Multivariant
Size of Dataset Provided: - 731 rows, 15 Columns (including dependent variable)
Missing Values: Yes

Below mentioned is a list of all the variable names with their meanings:

Variables	Description
Dteday	Date of renting
Season	Season (1: springer, 2: summer, 3: fall, 4: winter)
Yr	Year (0: 2011, 1:2012)
Mnth	Month (1 to 12)
Holiday	Weekday weather day is holiday or not.
Weekday	Day of the week (starting from Sunday= 0 to Saturday= 60
Workingday	If day is neither weekend nor holiday is 1, otherwise is 0.
Weathersit	extracted from Freemeteo
Temp	Normalized temperature in Celsius.
Atemp	Normalized feeling temperature in Celsius.
Hum	Normalized humidity. The values are divided to 100 (max)
Windspeed	Normalized wind speed. The values are divided to 67 (max)
Casual	Count of casual users
Registered	Count of registered users
Cnt	Count of total rental bikes including both casual and registered

Chapter 2

Methodology

➢ Pre-Processing

When we required to build a predictive model, we require to look and manipulate the data before we start modelling which includes multiple preprocessing steps such as exploring the data, cleaning the data as well as visualizing the data through graph and plots, all these steps is combined under one shed which is **Exploratory Data Analysis**, which includes following steps:

- Looking into the data and analyzing various variables
- Missing Value Analysis
- Outlier Analysis
    - Box plot to detect outliers
    - Elimination and imputation of outliers presented
- Feature Selection
    - Correlation Analysis
    - ANOVA (Two way Annova)
- Features Scaling
    - Normalization
- Dummy variable analysis

➢ Modelling

Once all the Pre-Processing steps has been done on our data set, we will now further move to our next step which is modelling. Modelling plays an important role to find out the good inferences from the data. Choice of models depends upon the problem statement and data set. As per our problem statement and dataset, we will try some models on our preprocessed data and post comparing the output results we will select the best suitable model for our problem. As per our data set following models need to be tested:

- Linear regression
- Decision Tree
- Random forest,
- Gradient Boosting

❖ We have also used **Principal component analysis** is also used and post reducing the dimensions using PCA above models are again tested.

❖ Post applying PCA we have used hyper tuning technique with aim to improve the results.

➢ Model Selection

The final step of our methodology will be the selection of the model based on the different output and results shown by different models. We have multiple parameters which we will study further in our report to test whether the model is suitable for our problem statement or not.

Chapter 3

Pre-Processing

3.1 Looking into the data and analyzing various variables

In this report we will try to predict of bike rental count based on the environmental and seasonal settings. So here we have a data set of 15 variable of two years data which is 2011 and 2012.

Independent variables: Dteday , Season, Yr, Mnth, Holiday, Weekday, Workingday, Weathersit, Temp, Atemp, Hum, Windspeed, Casual, Registered.\

Our Dependent variable: **Cnt (count of total rental bikes including both casual and registered)**

We have also tried to find out the category of the variables:

Variable Name	**Variable Type**
instant	int64
dteday	object
season	int64
yr	int64
mnth	int64
holiday	int64
weekday	int64
workingday	int64
weathersit	int64
temp	float64
atemp	float64
hum	float64
windspeed	float64
casual	int64
registered	int64
cnt	int64

Here **int64** means categorical or non-numeric variable and **float64** means numeric variables.

3.2 Uniqueness in Variable

We need to look at the unique number in the variables which help us to decide whether the variable is categorical or numeric. So, by using python script ‘nunique’ we tried to find out the unique values in each variable. We have also added the table below:

Variable Name	Unique Counts
instant	731
Dteday	731
Season	4
yr	2
Mnth	12
Holiday	2
Weekday	7
Workingday	2
Weathersit	3
Temp	499
Atemp	690
Hum	595
Windspeed	650
Casual	606
Registered	679
cnt	696

Categorical Variables - season, year, month, holiday, weekday, working day, weathersit

3.3 Missing Value Analysis

Missing values in data is a common phenomenon in real world problems. It can have a significant effect on the conclusions that can be drawn from the data.

The most common reason for missing values in our data could be:

- Human error
- Refuse to answer
- Option to fill

As per the industry standards if a column has more than 30% of data as missing value either we ignore the entire column, or we ignore those observations.

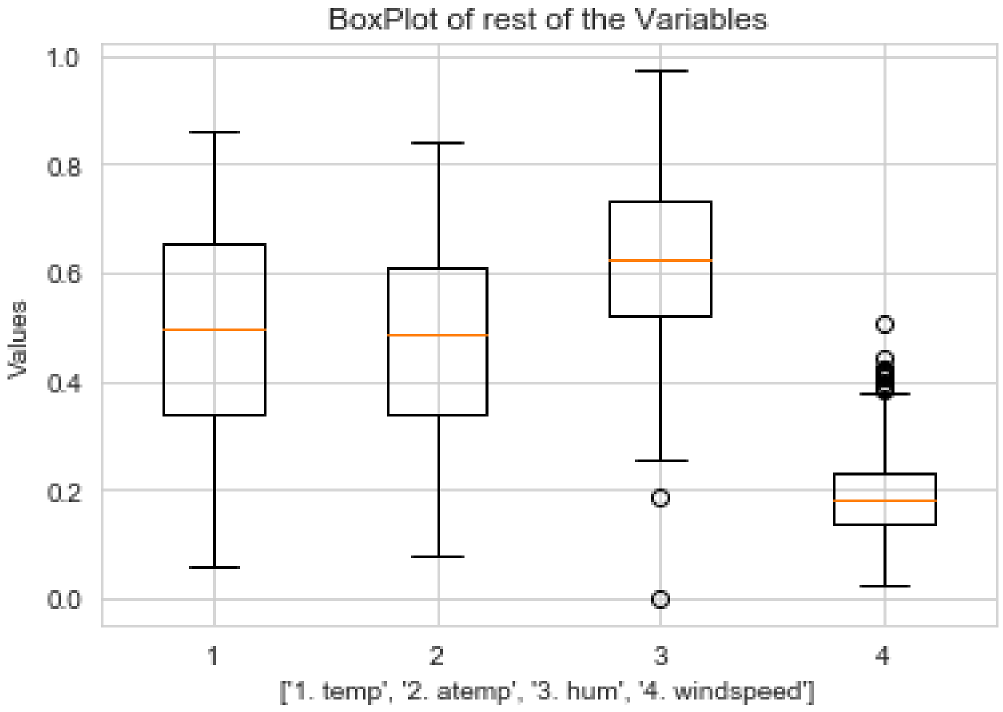
As per our data set there is no missing values present so will skip this step and move to our next step.

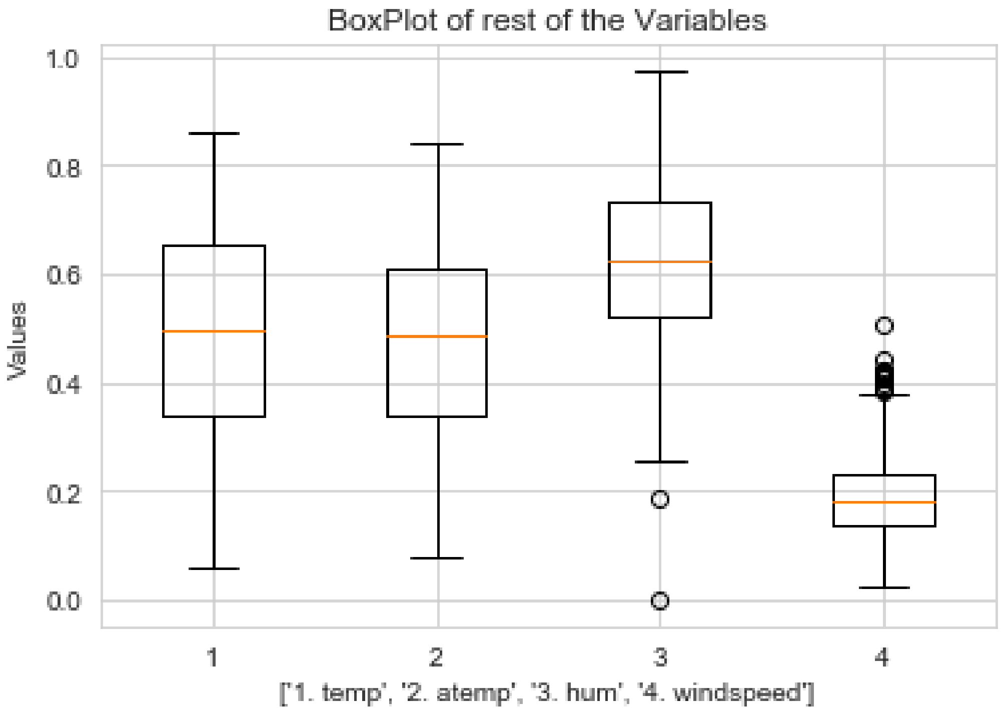
3.4 Outlier Analysis

The next step of Preprocessing Technique is **Outliers Analysis**, An Outlier is a rare chance of occurrence within a given data set. In Data Science, an Outlier is an observation point that is distant from other observations. An Outlier may be due to variability in the measurement or it may indicate experimental error.

We will use boxplot technique to see whether outliers is present in continuous variables or not.

❖ **Boxplot: - It is a method for graphically depicting groups of numerical data through their quartiles. Box plots may also have lines extending vertically from the boxes (whiskers) indicating variability outside the upper and lower quartiles**.

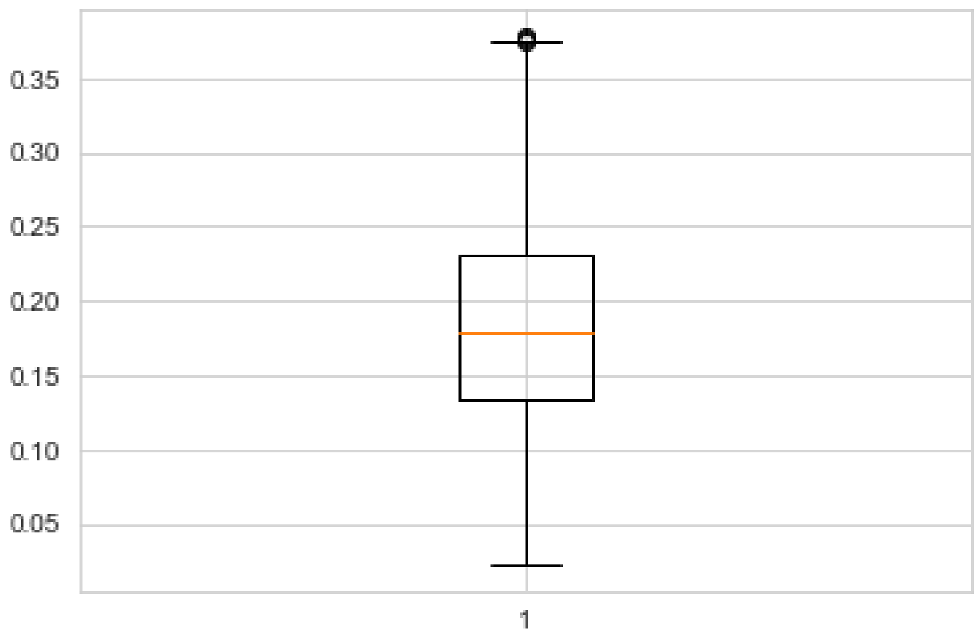




From the above boxplots we can see that variables “windspeed’ have outliers.

Treatment of outliers: remove the rows containing outlier values using the outlier formula.

Below are the box plot of windspeed after treating the outliers:



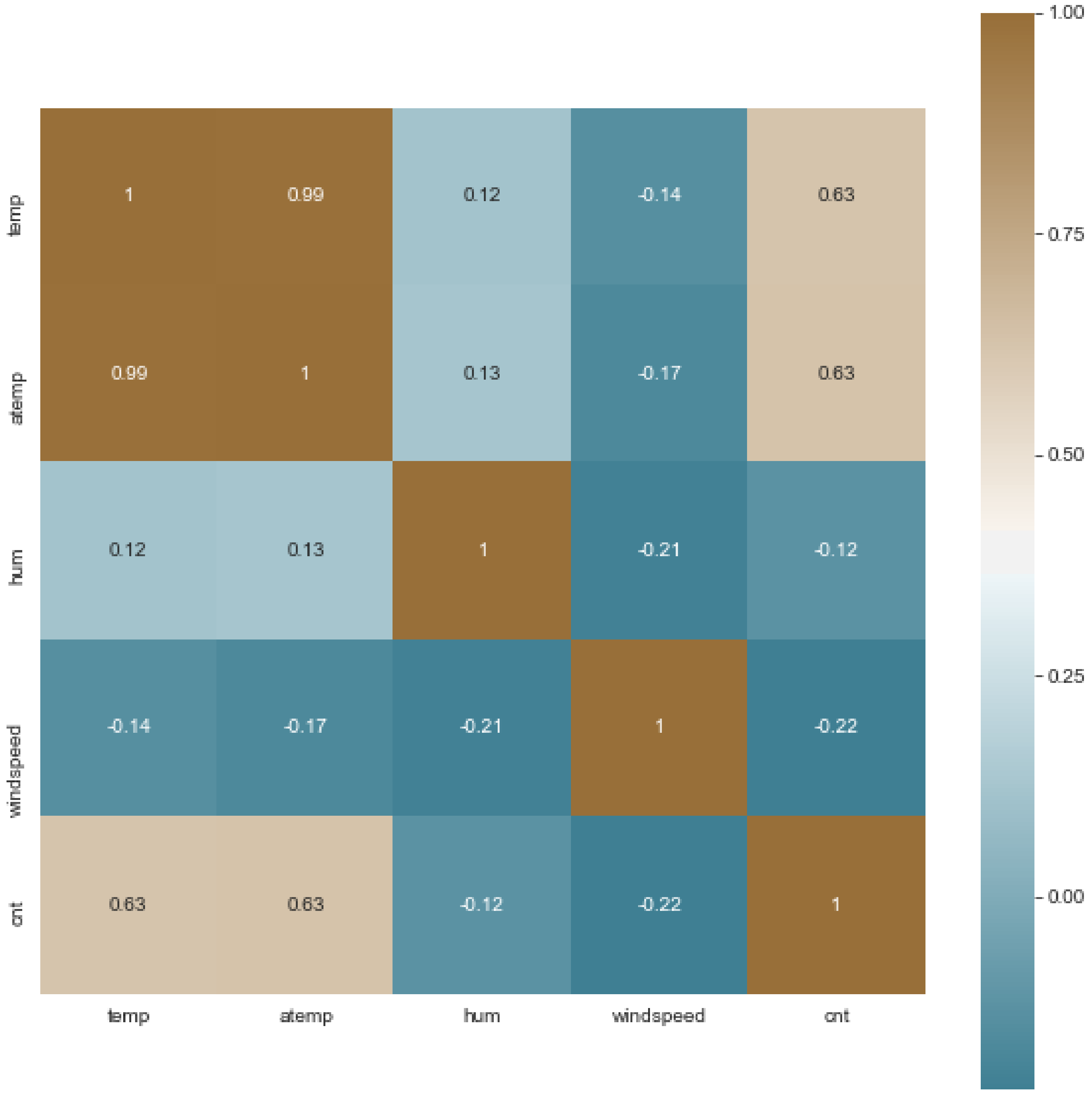
As we can see all the outlier figures has been successfully imputed.

3.5 Feature Selection

Feature selection is also called variable selection or attribute selection. Basic rule on which Machine learning works is– *if you put garbage in, you will only get garbage to come out*. By garbage here, we mean to say noise in the data.
When the number of features is very large, this rule becomes even more important. We need not use every feature at our disposal for creating an algorithm. We can assist our algorithm by feeding in only those features that are really important. We have witnessed feature subsets giving better results than complete set of features for the same algorithm or – *"Sometimes, less is better!".*
The selection of features or variables is based on following two conditions:

1. The relationship between two independent variables should be less and
2. The relationship between Independent and Target variables should be high.

A **correlogram** or **correlation** matrix allows to analyze the relationship between each pair of numerical variables of a matrix.



The variable which we are going to drop is '**temp'** as it is showing high correlation with '**atemp'** variable which means both the variables are carrying the similar information so there would be no need to continue with both the variable, we can proceed further with only one variable out of these two. So, we are proceeding with a**temp** variable.

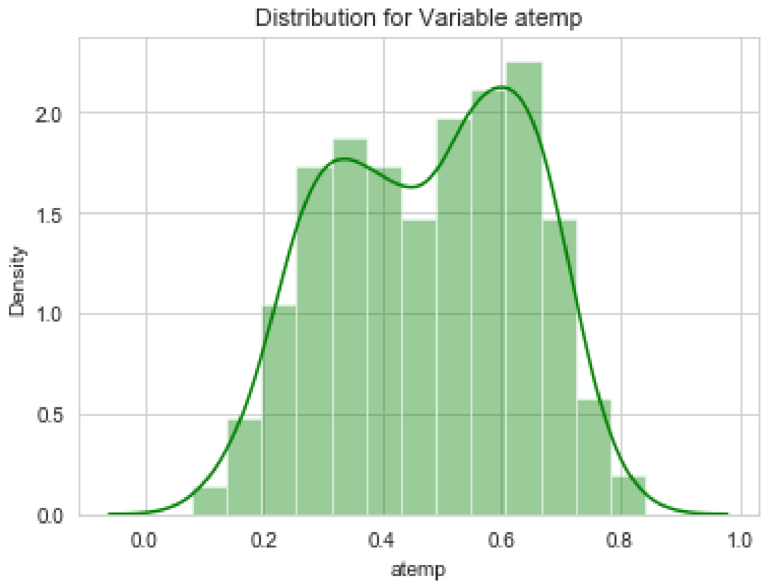
In this project we have selected Correlation Analysis for numerical variable and ANOVA testing categorical variable. So as per our hypothesis which is:
H0 – all the variables are independent of each other
H1 – all the variables are not independent of each other
We will drop categorical variables 'holiday', 'weekday','workingday', 'instant' and 'dteday' for our further modelling steps basis our ANOVA results.

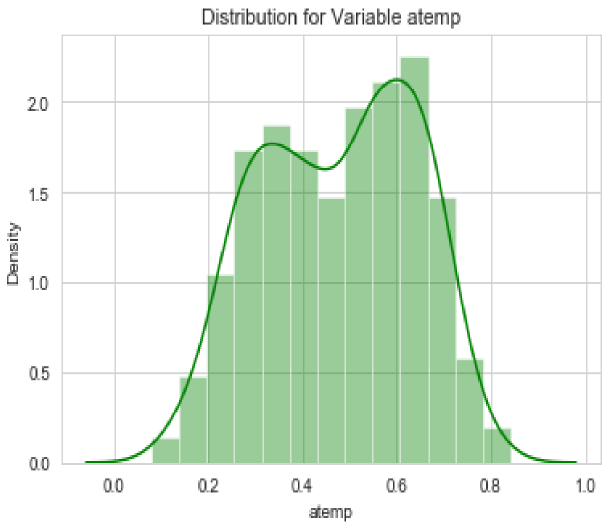
3.6 Features Scaling

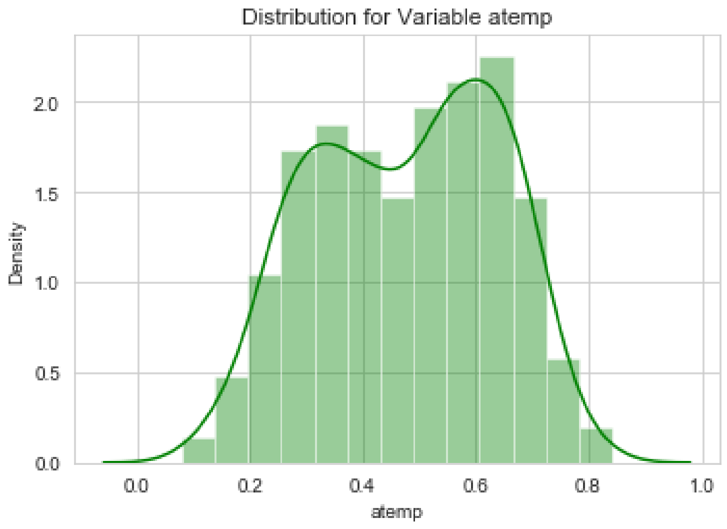
Skewness is asymmetry in a statistical distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution. Here we tried to show the skewness of our variables and we find that our target variable absenteeism in hours having is one sided skewed so by using log transform technique we tried to reduce the skewness of the same.

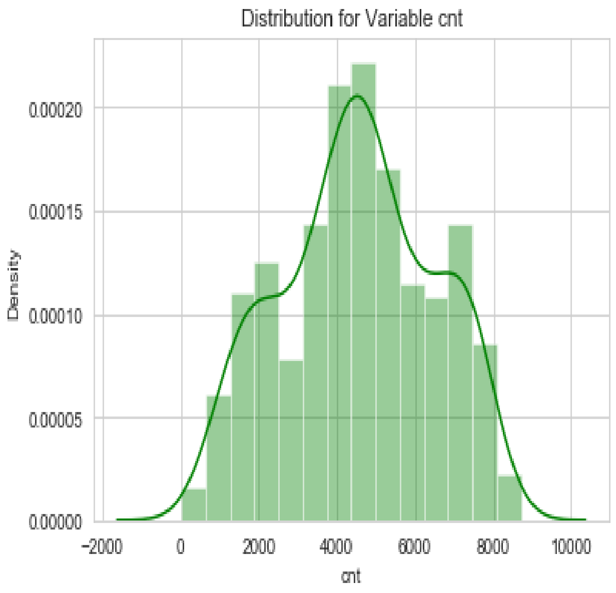
In the simplest cases, **normalization** of ratings means adjusting values measured on different scales to a notionally common scale, often prior to averaging. In more complicated cases, normalization may refer to more sophisticated adjustments where the intention is to bring the entire probability distributions of adjusted values into alignment. In the case of normalization of scores in educational assessment, there may be an intention to align distributions to a normal distribution. A different approach to normalization of probability distributions is quantile normalization, where the quantiles of the different measures are brought into alignment.

Below mentioned graphs shows the probability distribution plot to check distribution:





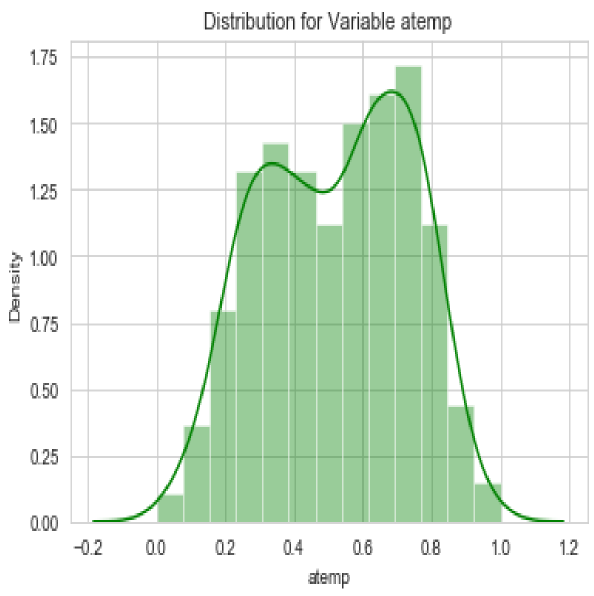


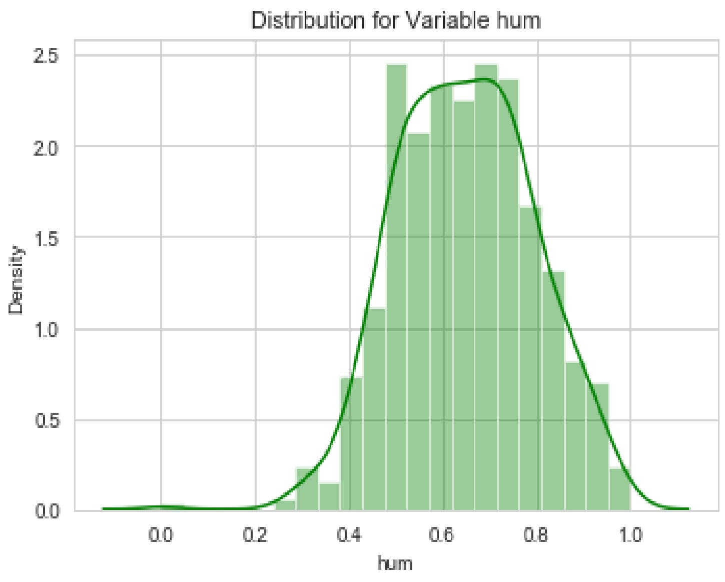


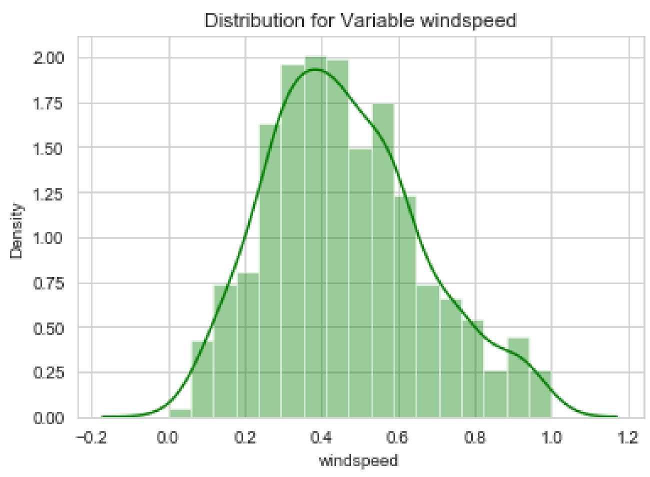
As we can see that our continuous variables are not normally distributed which means that we have to use normalization technique to normalize the values of each continuous variable to proceed for modelling stage. Rescaling data to have values between **0 and 1**. This is usually called feature scaling. One possible formula to achieve this is:

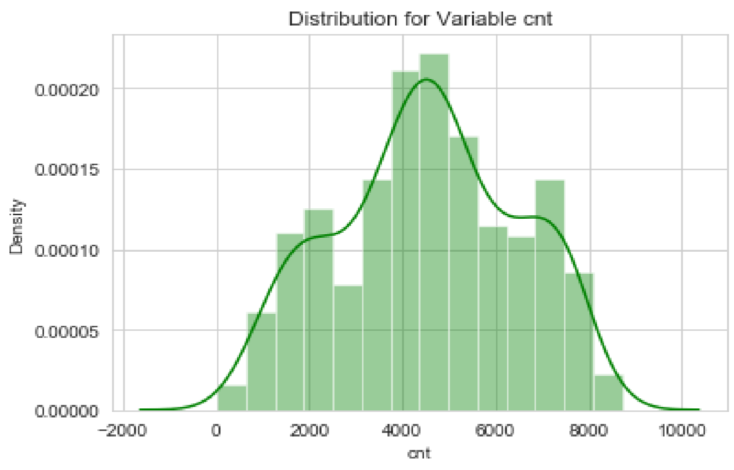
$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

After normalization plot we have created distribution below:









3.7 Dummy variable analysis

A dummy variable is a numerical variable used in regression analysis to represent the importance of categorical variables. Here we can see there are 6 categorical variables so we have created dummies for each categorical variable (there unique values). These dummy variables will interact with our model and show the significance of categorical variables in quantitative terms.

Chapter 4

Modelling

After a thorough preprocessing, we will use some regression models on our processed data to predict the target variable. Following are the models which we have built –

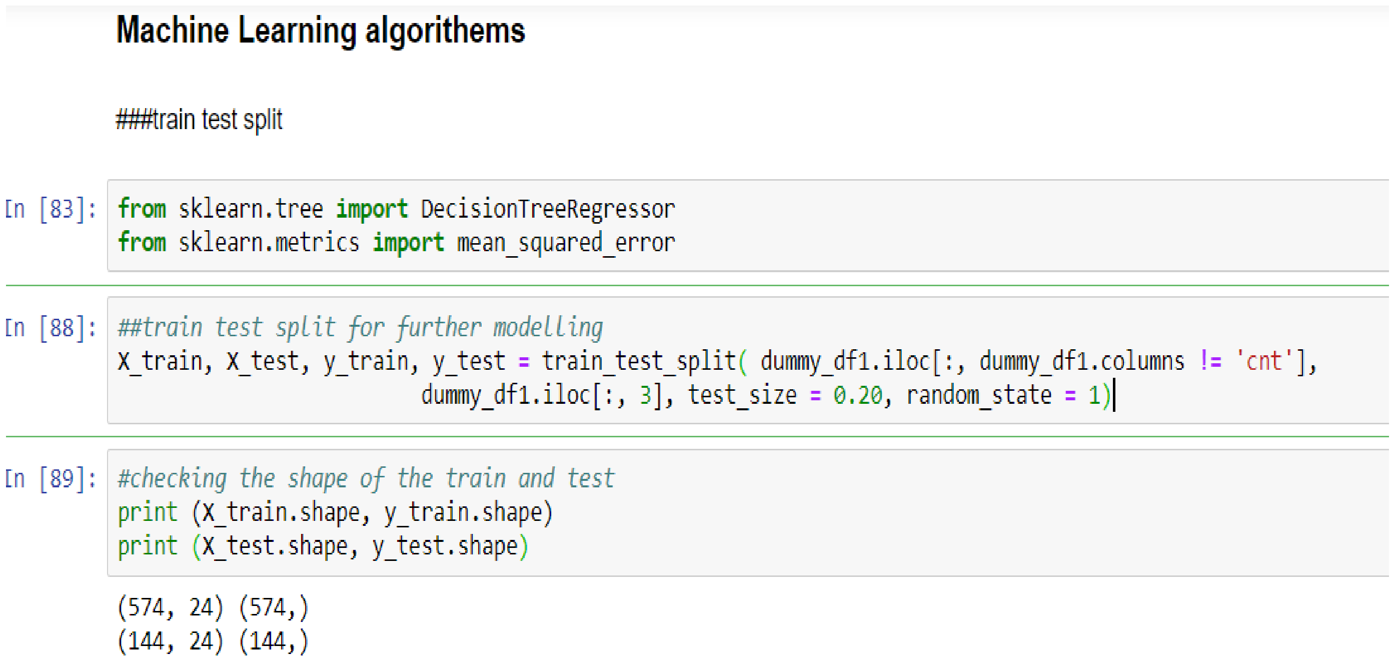
- Linear Regression
- Decision Tree
- Random Forest
- Gradient Boosting

Before we start building our models, we would like to know how our model will be evaluated.

4.1 Linear Regression

Multiple linear regression is the most common form of linear regression analysis. Multiple regression is an extension of simple linear regression. It is used as a predictive analysis, when we want to predict the value of a variable based on the value of two or more other variables. The variable we want to predict is called the dependent variable (or sometimes, the outcome, target or criterion variable).

Before running any model, we will split our data into two parts which is train and test data. Here in our case we have taken 80% of the data as our train data. Below is the snipped image of the split of train test.



Machine Learning algorithems

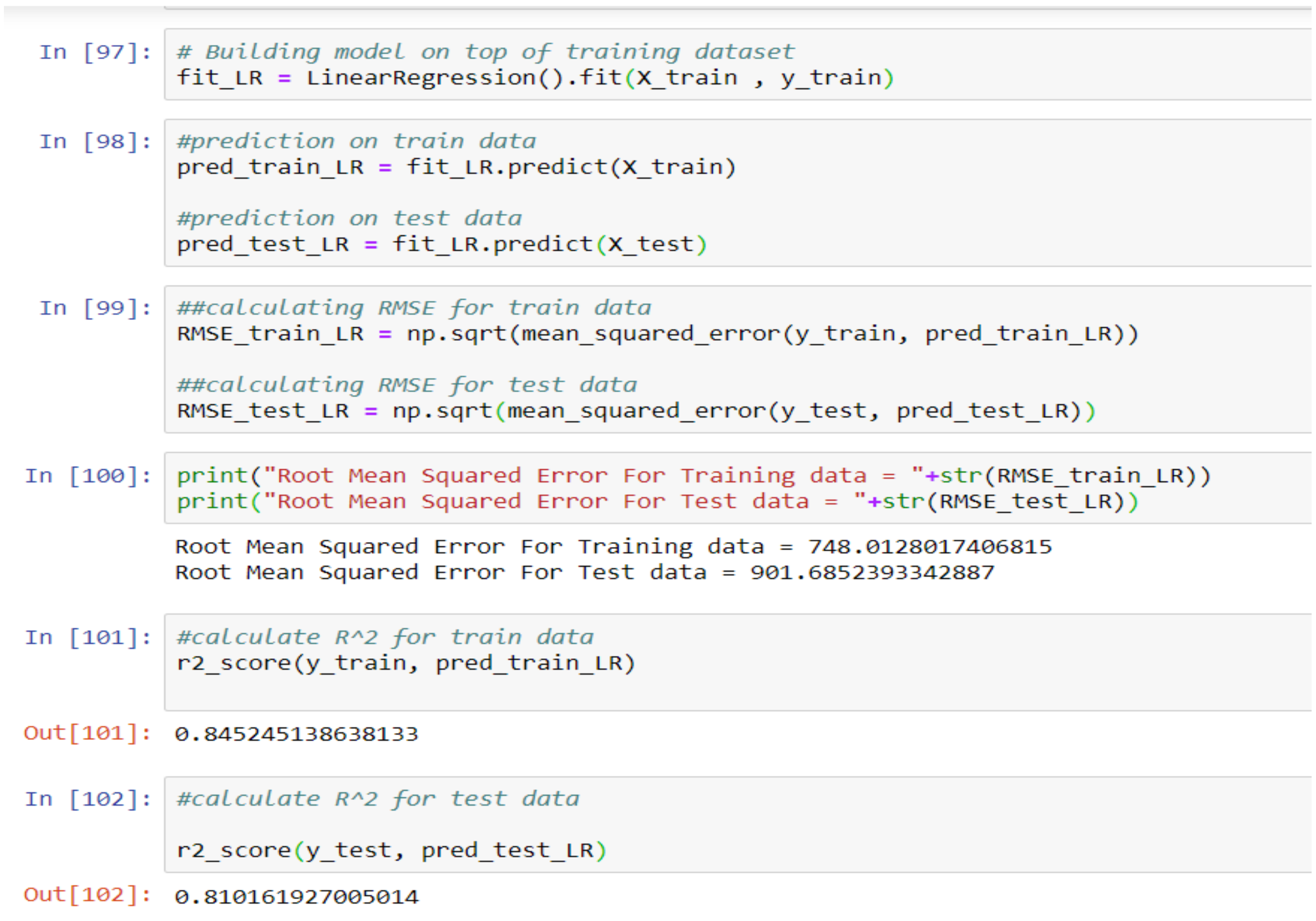
###train test split

```
In [83]: from sklearn.tree import DecisionTreeRegressor
         from sklearn.metrics import mean_squared_error
```

```
In [88]: ##train test split for further modelling
         X_train, X_test, y_train, y_test = train_test_split( dummy_df1.iloc[:, dummy_df1.columns != 'cnt'],
                                                   dummy_df1.iloc[:, 3], test_size = 0.20, random_state = 1)
```

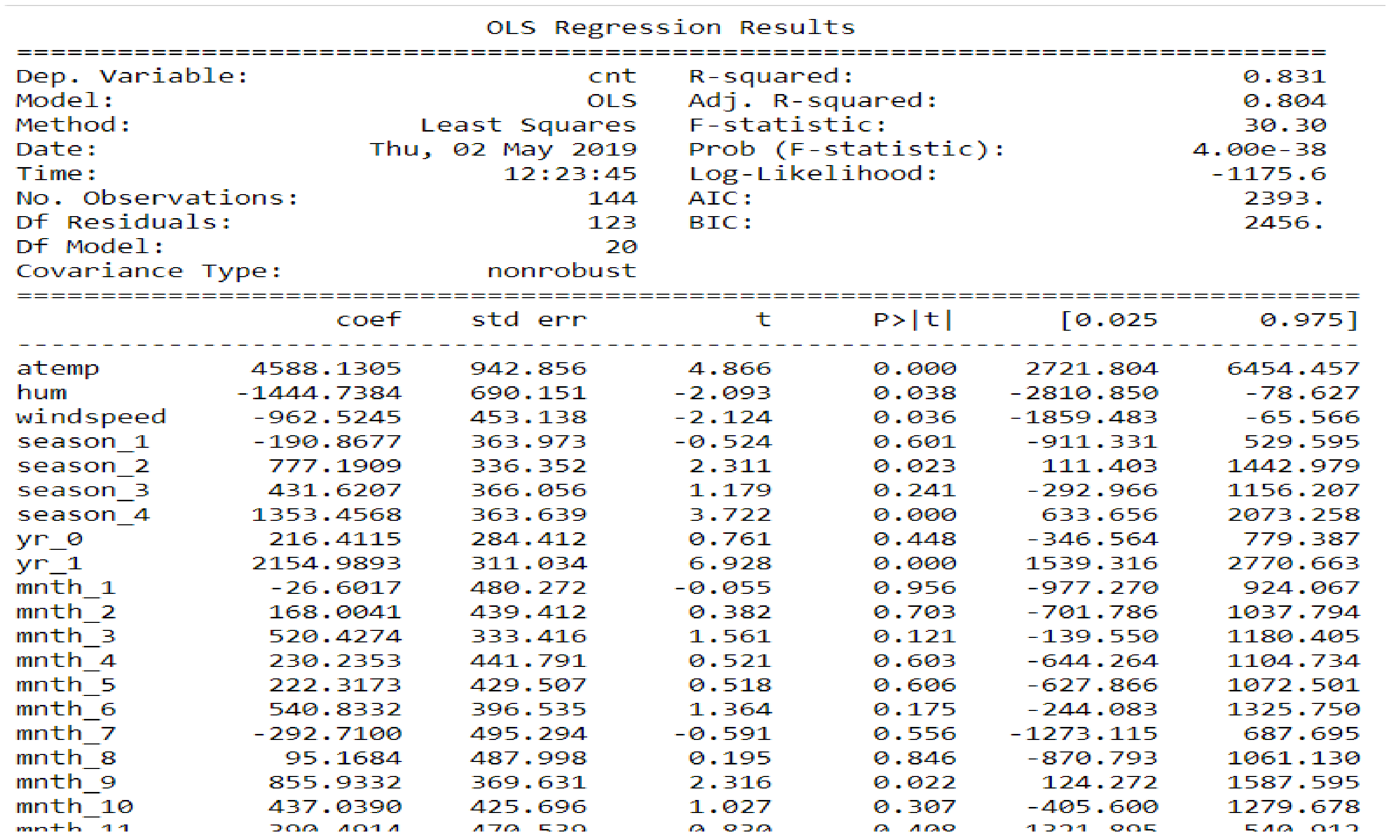
```
In [89]: #checking the shape of the train and test
         print (X_train.shape, y_train.shape)
         print (X_test.shape, y_test.shape)

         (574, 24) (574,)
         (144, 24) (144,)
```

Below is the screenshot of the query we executed and the result shown, we will compare the results of each model in a combined table later on.



```
In [97]:  # Building model on top of training dataset
          fit_LR = LinearRegression().fit(X_train , y_train)

In [98]:  #prediction on train data
          pred_train_LR = fit_LR.predict(X_train)

          #prediction on test data
          pred_test_LR = fit_LR.predict(X_test)

In [99]:  ##calculating RMSE for train data
          RMSE_train_LR = np.sqrt(mean_squared_error(y_train, pred_train_LR))

          ##calculating RMSE for test data
          RMSE_test_LR = np.sqrt(mean_squared_error(y_test, pred_test_LR))

In [100]: print("Root Mean Squared Error For Training data = "+str(RMSE_train_LR))
          print("Root Mean Squared Error For Test data = "+str(RMSE_test_LR))

          Root Mean Squared Error For Training data = 748.0128017406815
          Root Mean Squared Error For Test data = 901.6852393342887

In [101]: #calculate R^2 for train data
          r2_score(y_train, pred_train_LR)

Out[101]: 0.845245138638133

In [102]: #calculate R^2 for test data

          r2_score(y_test, pred_test_LR)

Out[102]: 0.810161927005014
```

Below is the screenshop of the Linear regression model OLS summary



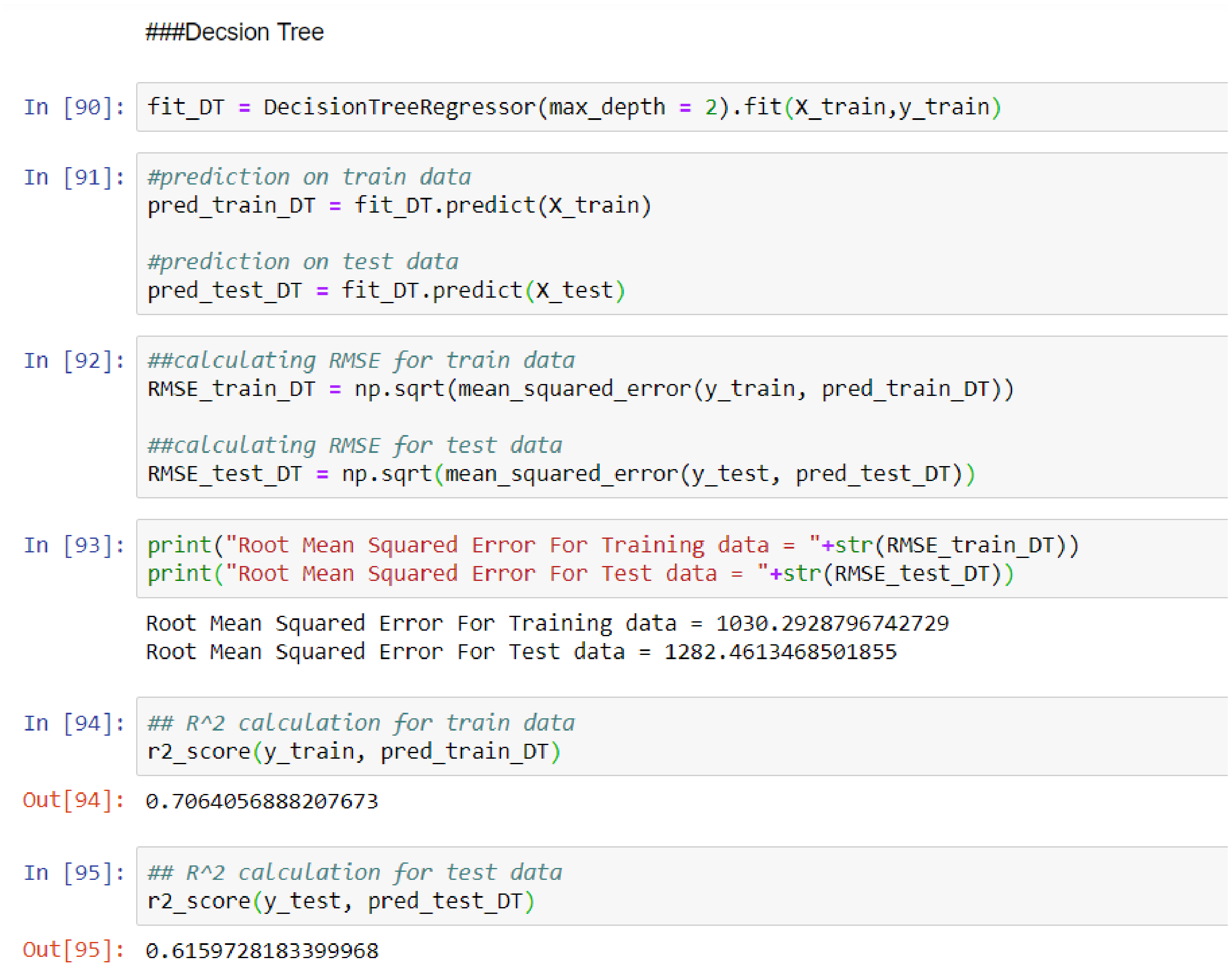
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.831
Model:                            OLS   Adj. R-squared:                  0.804
Method:                 Least Squares   F-statistic:                     30.30
Date:                Thu, 02 May 2019   Prob (F-statistic):           4.00e-38
Time:                        12:23:45   Log-Likelihood:                -1175.6
No. Observations:                 144   AIC:                             2393.
Df Residuals:                     123   BIC:                             2456.
Df Model:                          20
Covariance Type:            nonrobust
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
atemp       4588.1305    942.856      4.866      0.000    2721.804    6454.457
hum        -1444.7384    690.151     -2.093      0.038   -2810.850     -78.627
windspeed   -962.5245    453.138     -2.124      0.036   -1859.483     -65.566
season_1    -190.8677    363.973     -0.524      0.601    -911.331     529.595
season_2     777.1909    336.352      2.311      0.023     111.403    1442.979
season_3     431.6207    366.056      1.179      0.241    -292.966    1156.207
season_4    1353.4568    363.639      3.722      0.000     633.656    2073.258
yr_0         216.4115    284.412      0.761      0.448    -346.564     779.387
yr_1        2154.9893    311.034      6.928      0.000    1539.316    2770.663
mnth_1       -26.6017    480.272     -0.055      0.956    -977.270     924.067
mnth_2       168.0041    439.412      0.382      0.703    -701.786    1037.794
mnth_3       520.4274    333.416      1.561      0.121    -139.550    1180.405
mnth_4       230.2353    441.791      0.521      0.603    -644.264    1104.734
mnth_5       222.3173    429.507      0.518      0.606    -627.866    1072.501
mnth_6       540.8332    396.535      1.364      0.175    -244.083    1325.750
mnth_7      -292.7100    495.294     -0.591      0.556   -1273.115     687.695
mnth_8        95.1684    487.998      0.195      0.846    -870.793    1061.130
mnth_9       855.9332    369.631      2.316      0.022     124.272    1587.595
mnth_10      437.0390    425.696      1.027      0.307    -405.600    1279.678
mnth_11      390.4914    470.530      0.830      0.408    1321.895     540.912
```

4.2 Decision Tree

A tree has many analogies in real life, and turns out that it has influenced a wide area of machine learning, covering both classification and regression. In decision analysis, 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.

To say it in simple words: Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction.

Below is a screenshot of the model we build and its output:



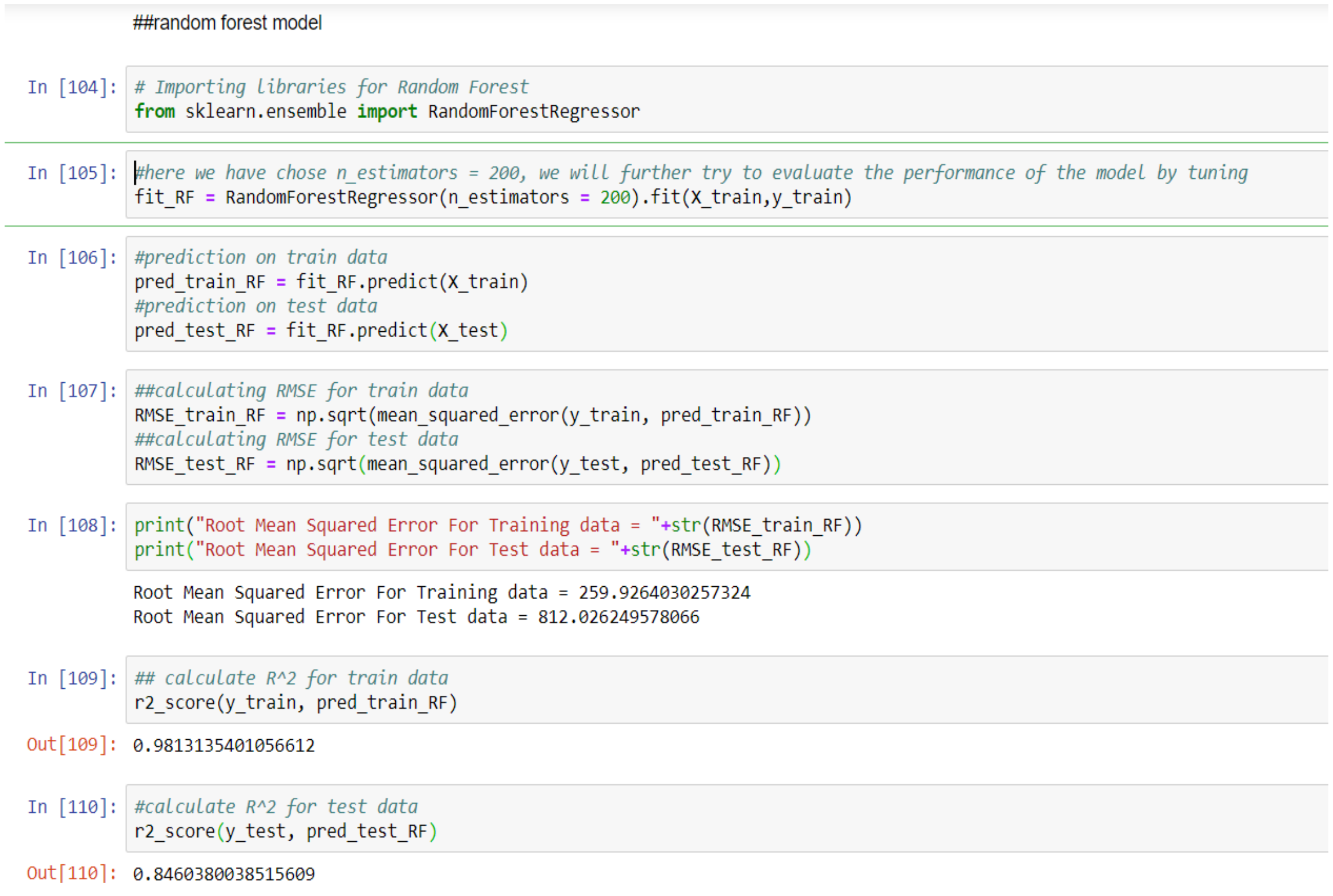
###Decsion Tree

```
In [90]: fit_DT = DecisionTreeRegressor(max_depth = 2).fit(X_train,y_train)

In [91]: #prediction on train data
         pred_train_DT = fit_DT.predict(X_train)

         #prediction on test data
         pred_test_DT = fit_DT.predict(X_test)

In [92]: ##calculating RMSE for train data
         RMSE_train_DT = np.sqrt(mean_squared_error(y_train, pred_train_DT))

         ##calculating RMSE for test data
         RMSE_test_DT = np.sqrt(mean_squared_error(y_test, pred_test_DT))

In [93]: print("Root Mean Squared Error For Training data = "+str(RMSE_train_DT))
         print("Root Mean Squared Error For Test data = "+str(RMSE_test_DT))

         Root Mean Squared Error For Training data = 1030.2928796742729
         Root Mean Squared Error For Test data = 1282.4613468501855

In [94]: ## R^2 calculation for train data
         r2_score(y_train, pred_train_DT)

Out[94]: 0.7064056888207673

In [95]: ## R^2 calculation for test data
         r2_score(y_test, pred_test_DT)

Out[95]: 0.6159728183399968
```

4.3 Random forests

Random forests or random decision forests are an ensemble learning method for classification, regression and other task, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set.

Below is a screenshot of the model we build and its output:



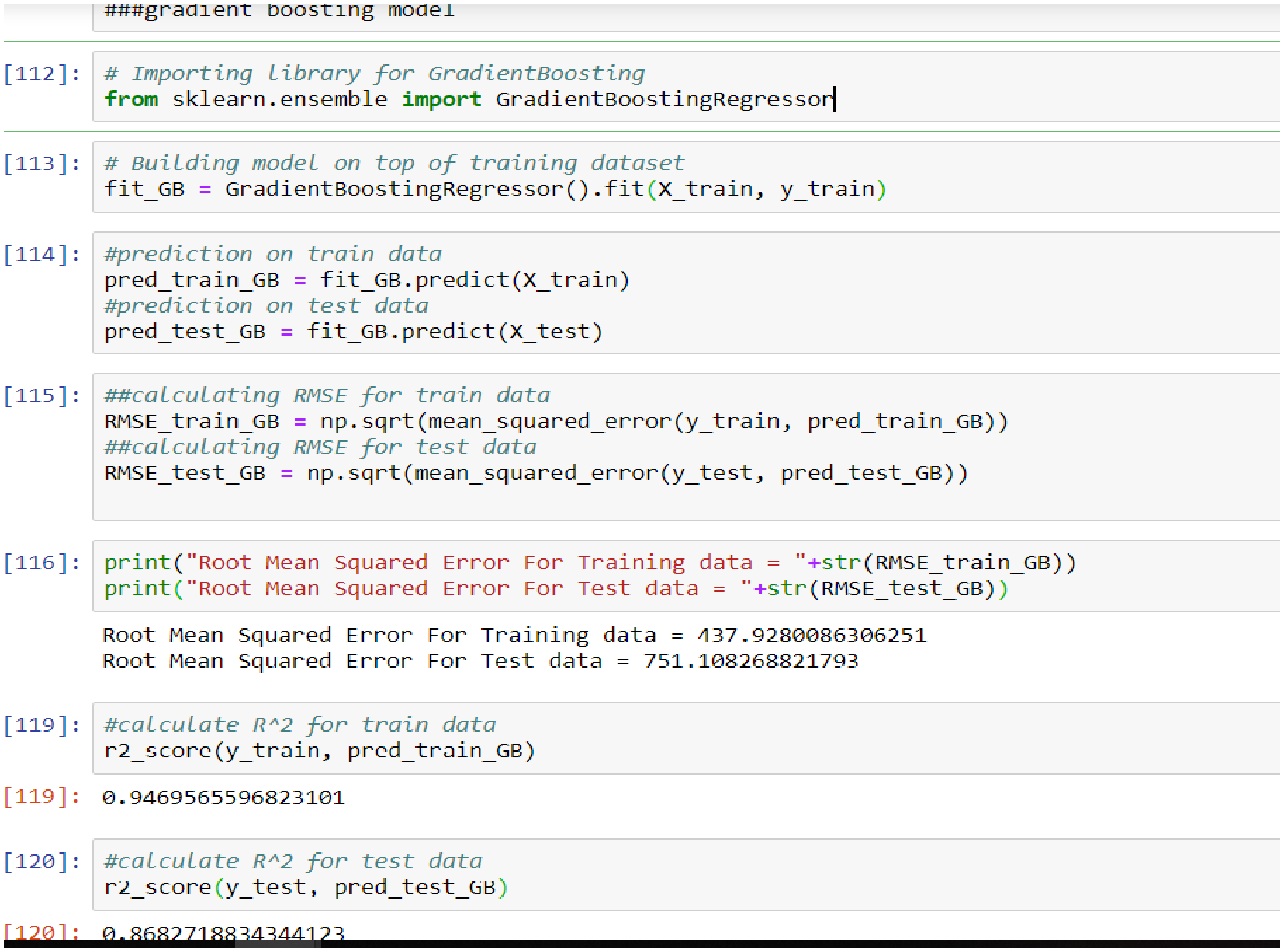
##random forest model

```
In [104]: # Importing libraries for Random Forest
          from sklearn.ensemble import RandomForestRegressor

In [105]: #here we have chose n_estimators = 200, we will further try to evaluate the performance of the model by tuning
          fit_RF = RandomForestRegressor(n_estimators = 200).fit(X_train,y_train)

In [106]: #prediction on train data
          pred_train_RF = fit_RF.predict(X_train)
          #prediction on test data
          pred_test_RF = fit_RF.predict(X_test)

In [107]: ##calculating RMSE for train data
          RMSE_train_RF = np.sqrt(mean_squared_error(y_train, pred_train_RF))
          ##calculating RMSE for test data
          RMSE_test_RF = np.sqrt(mean_squared_error(y_test, pred_test_RF))

In [108]: print("Root Mean Squared Error For Training data = "+str(RMSE_train_RF))
          print("Root Mean Squared Error For Test data = "+str(RMSE_test_RF))

          Root Mean Squared Error For Training data = 259.9264030257324
          Root Mean Squared Error For Test data = 812.026249578066

In [109]: ## calculate R^2 for train data
          r2_score(y_train, pred_train_RF)

Out[109]: 0.9813135401056612

In [110]: #calculate R^2 for test data
          r2_score(y_test, pred_test_RF)

Out[110]: 0.8460380038515609
```

4.4 Gradient Boosting

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

Below is a screenshot of the model we build and its output:



```
###gradient boosting model

[112]: # Importing library for GradientBoosting
       from sklearn.ensemble import GradientBoostingRegressor

[113]: # Building model on top of training dataset
       fit_GB = GradientBoostingRegressor().fit(X_train, y_train)

[114]: #prediction on train data
       pred_train_GB = fit_GB.predict(X_train)
       #prediction on test data
       pred_test_GB = fit_GB.predict(X_test)

[115]: ##calculating RMSE for train data
       RMSE_train_GB = np.sqrt(mean_squared_error(y_train, pred_train_GB))
       ##calculating RMSE for test data
       RMSE_test_GB = np.sqrt(mean_squared_error(y_test, pred_test_GB))

[116]: print("Root Mean Squared Error For Training data = "+str(RMSE_train_GB))
       print("Root Mean Squared Error For Test data = "+str(RMSE_test_GB))

       Root Mean Squared Error For Training data = 437.9280086306251
       Root Mean Squared Error For Test data = 751.108268821793

[119]: #calculate R^2 for train data
       r2_score(y_train, pred_train_GB)

[119]: 0.9469565596823101

[120]: #calculate R^2 for test data
       r2_score(y_test, pred_test_GB)

[120]: 0.8682718834344123
```

4.5 Principal Component Analysis

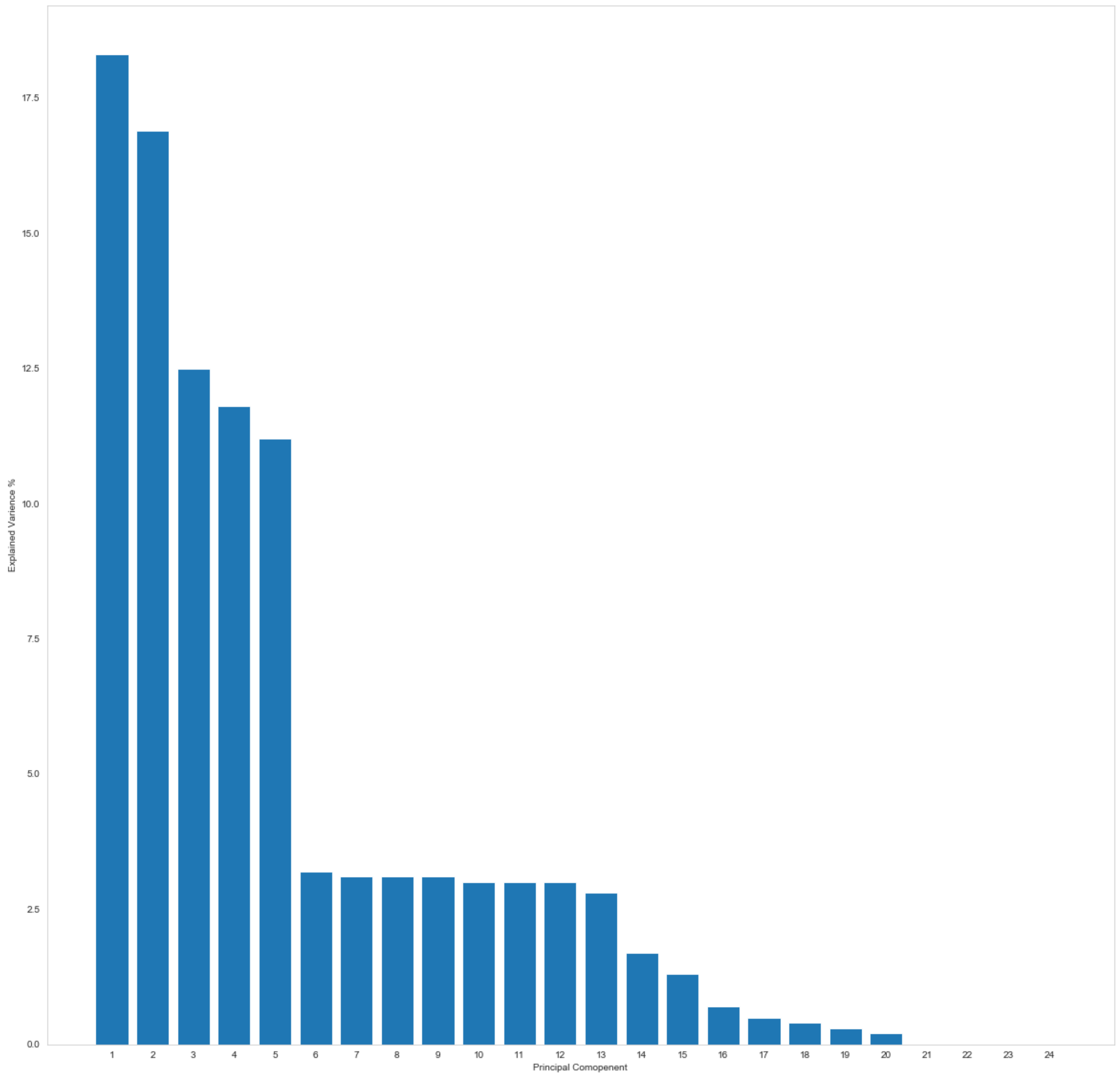
Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set.

• Principal component analysis (PCA) is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components.

• The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

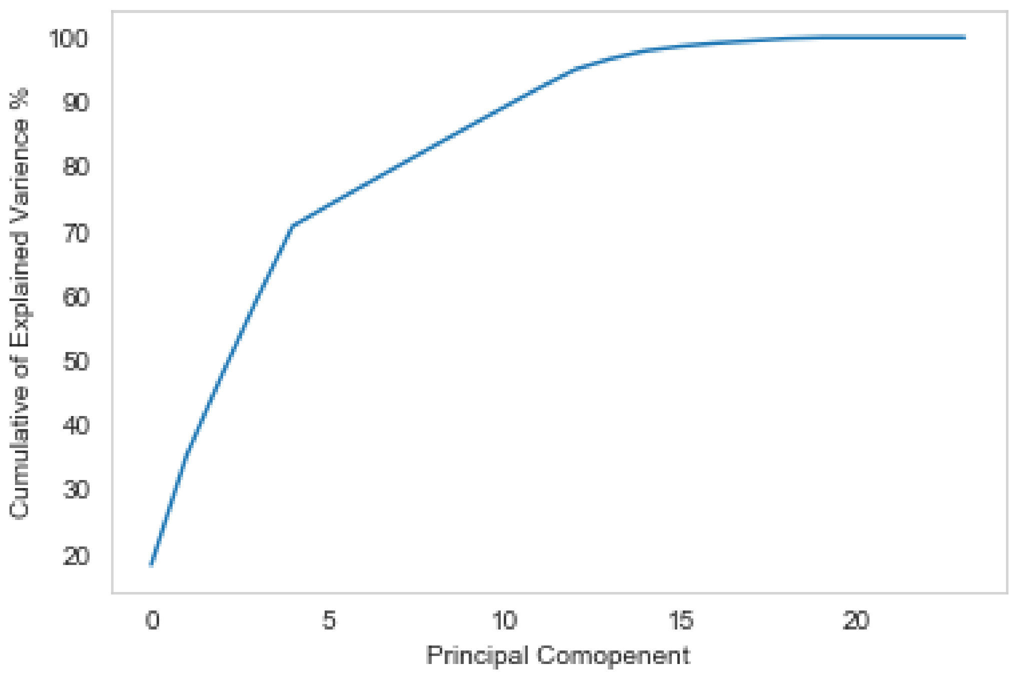
• Principal components analysis is similar to another multivariate procedure called Factor Analysis. They are often confused and many scientists do not understand the difference between the two methods or what types of analyses they are each best suited.

Below is a graph shows the number of variables explains the dependent variable:



This curve shows the % increase in the explained variance by increasing the number of factors or variables. Here we can see more than 95% of the variance is explained by 15 principal components or variables.

So here we can reduce our model dimensions from 25 variables to 15 variables with the focus of optimization of model.



We will mention the model output post using the Principal Component Analysis and check whether there is any significant change in the result is noticed in a combined table while evaluation of model.

4.6 Hyper Parameters Tunings on PCA results

Model hyperparameters are set by the data scientist ahead of training and control implementation aspects of the model. The weights learned during training of a linear regression model are parameters while the number of trees in a random forest is a model hyperparameter because this is set by the data scientist. Hyperparameters can be thought of as model settings. These settings need to be tuned for each problem because the best model hyperparameters for one particular dataset will not be the best across all datasets. The process of hyperparameter tuning (also called hyperparameter optimization) means finding the combination of hyperparameter values for a machine learning model that performs the best - as measured on a validation dataset - for a problem.

Here we have used two hyper parameters tuning techniques

- Random Search CV
- Grid Search CV

1. **Random Search CV**: This algorithm set up a grid of hyperparameter values and select random combinations to train the model and score. The number of search iterations is set based on time/resources.
2. **Grid Search CV**: This algorithm set up a grid of hyperparameter values and for each combination, train a model and score on the validation data. In this approach, every single combination of hyperparameters values is tried which can be very inefficient.

Check results post hyper parameter tuning on post PCA models in the model valuation section.

Chapter 5

Conclusion

5.1 Model Evaluation

The main concept of looking at what is called residuals or difference between our predictions f(x[I,]) and actual outcomes y[i].

In general, most data scientists use two methods to evaluate the performance of the model:

I. **RMSE** (Root Mean Square Error): is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

II. **R Squared(R^2):** is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression. In other words, we can say it explains as to how much of the variance of the target variable is explained.

III. We have shown both train and test data results, the main reason behind showing both the results is to check whether our data is overfitted or not.

Below table shows the model results before applying PCA:

Model Name	**RMSE**		**R Squared**	
	Train	**Test**	**Train**	**Test**
Linear Regression	748.0	901.6	0.84	0.81
Decision Tree	1030.29	1282.4	0.70	0.61
Random Forest model	259.92	812.02	0.98	0.84
Gradient Boosting	437.92	751.10	0.94	0.86

Below table shows the model results after applying PCA:

Model Name	**RMSE**		**R Squared**	
	Train	**Test**	**Train**	**Test**
Linear Regression (PCA)	802.6	961.03	0.82	0.78
Decision Tree (PCA)	1198.11	1336.35	0.60	0.58
Random Forest (PCA)	271.008	917.75	0.97	0.80
Gradient Boosting (PCA)	419.15	885.69	0.95	0.81

Below table shows results post using hyper parameter tuning techniques:

Model Name	**Random Search CV**		**Grid Search CV**	
	RMSE (Test)	**R Squared (Test)**	**RMSE (Test)**	**R Squared (Test)**
Random Forest (PCA)	936.51	0.80	954.82	0.79
Gradient Boosting (PCA)	1018.74	0.76	957.86	0.79

Above table shows the results after tuning the parameters of our two best suited models i.e. Random Forest and Gradient Boosting. For tuning the parameters, we have used Random Search CV and Grid Search CV under which we have given the range of n_estimators, depth and CV folds.

5. 2 Model Selection

On the basis RMSE and R Squared results a good model should have least RMSE and max R Squared value. So, from above tables we can see:

- Gradient Boosting Regressor model shows best result among all before applying the PCA.
- After applying PCA also gradient boosting model shows best results compared to rest of three.
- And also, after tuning the parameters of both random forest and gradient boost models, we get random forest shows better results compared to gradient boosting after both parameter tuning techniques.
- So finally, we can say that Gradient Boosting Regressor is the best method to solve our problem with highest explained variance of the target variables and lowest error chances.
- And if we want to optimize the parameters using Random Search CV then Random forest will be the best suitable model.

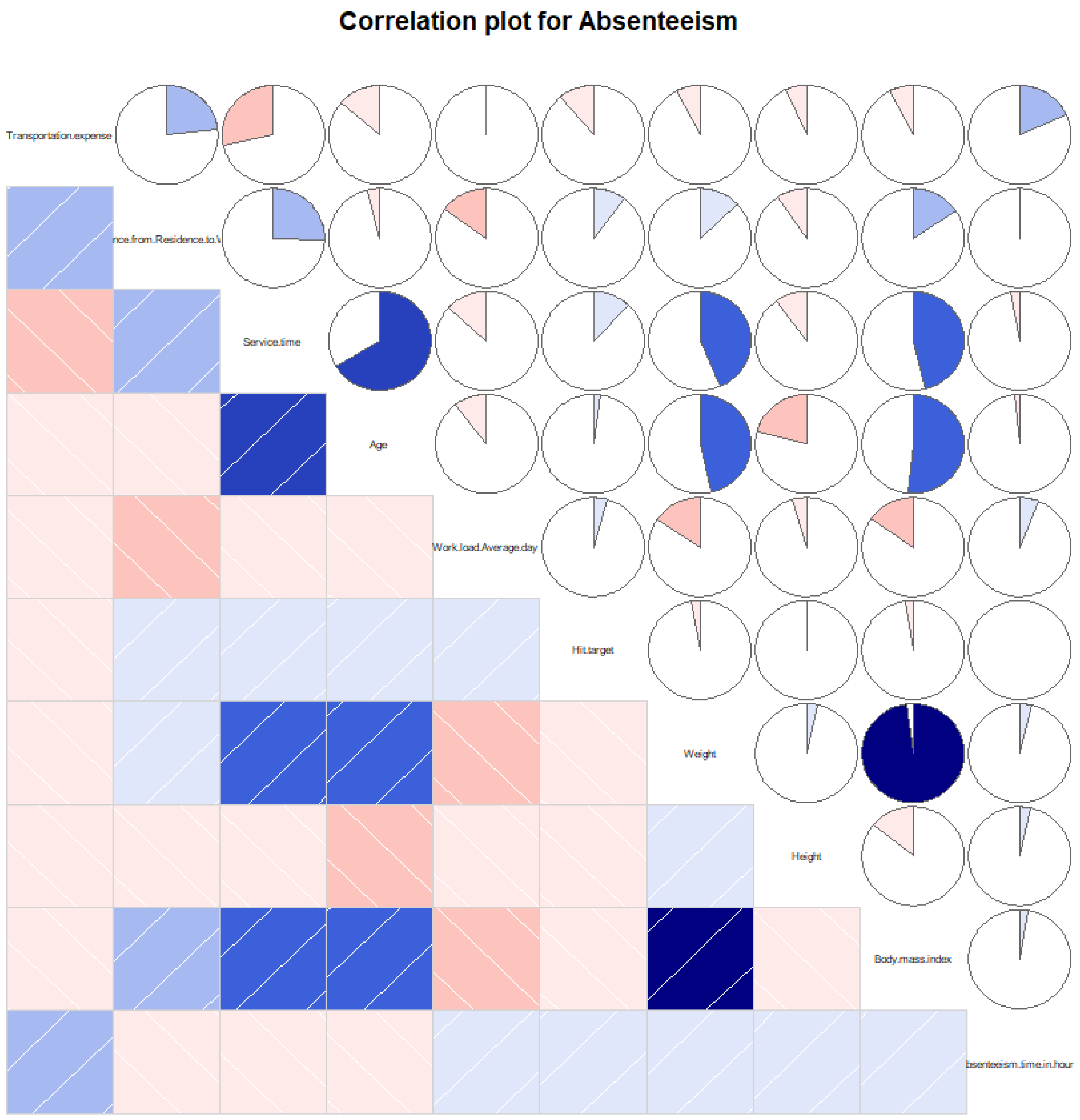
End of Report

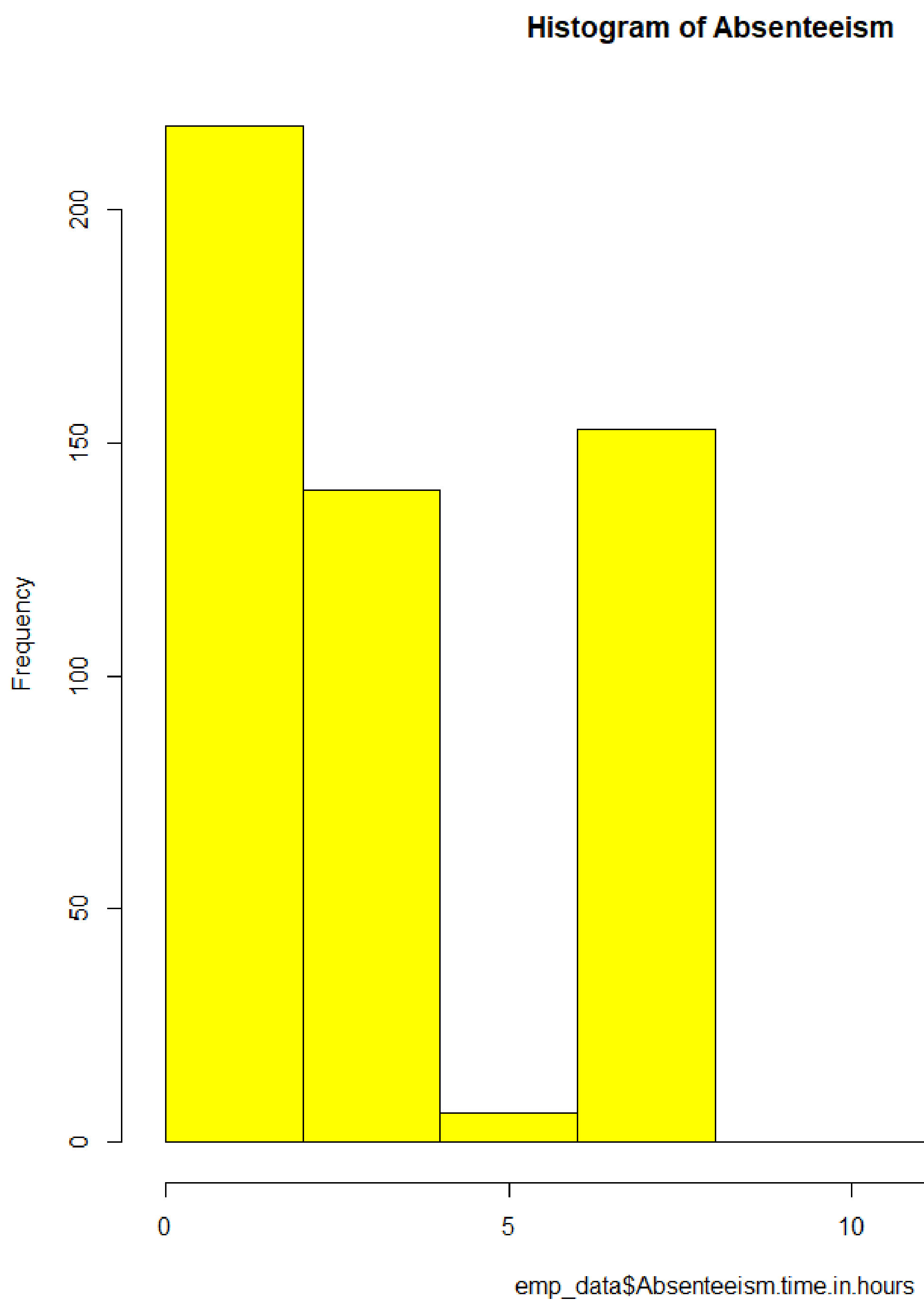
References

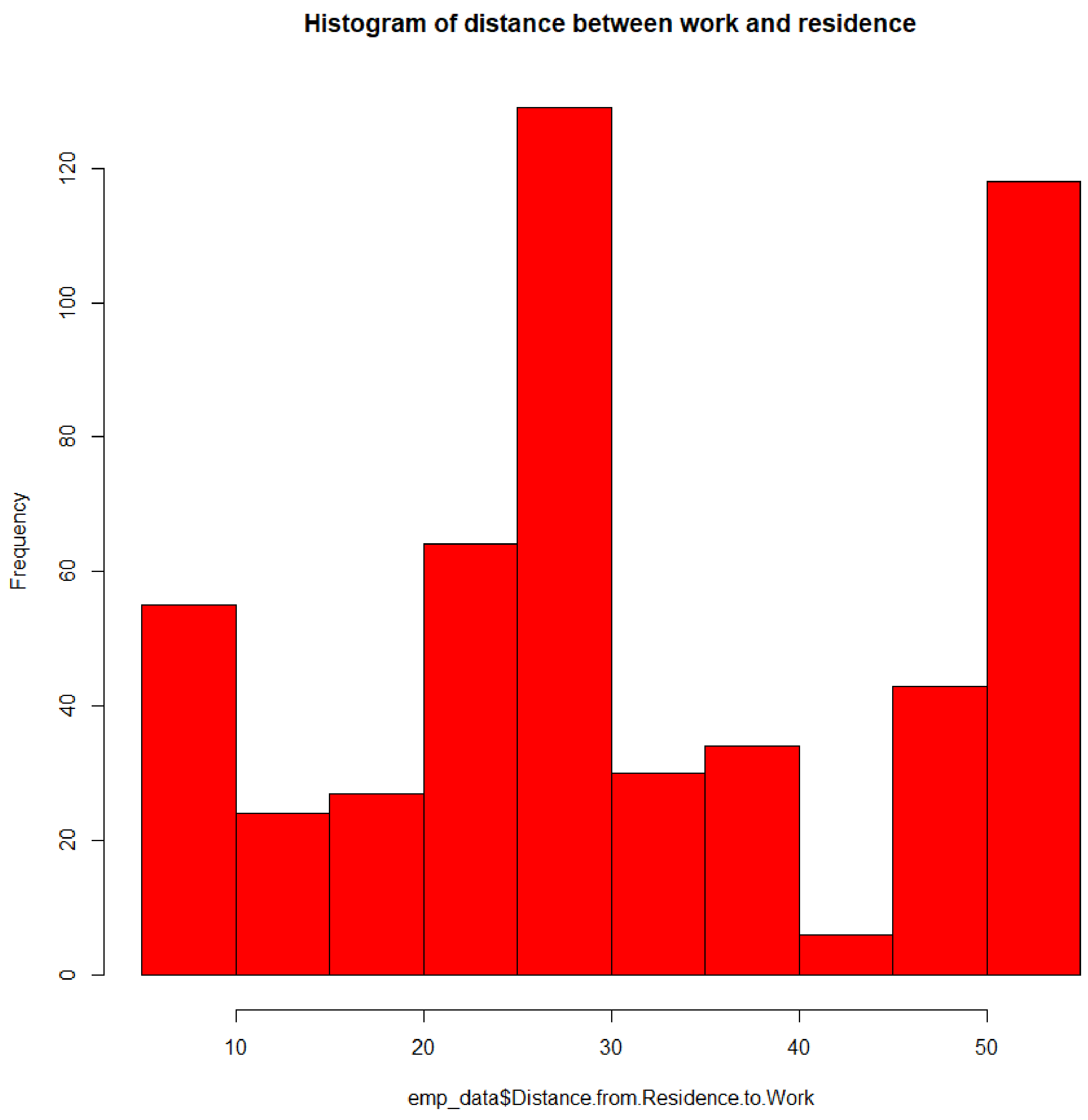
1. For Data Cleaning and Model Development - https://edwisor.com/career-data-scientist
2. For other code related queries - https://www.analyticsvidhya.com/blog/2016/03/practical-guide-principal-component-analysis-python/
3. For Visualization – https://www.udemy.com/python-for-data-science-and-machine-learning-bootcamp/
4. https://towardsdatascience.com/
5. https://stackoverflow.com/

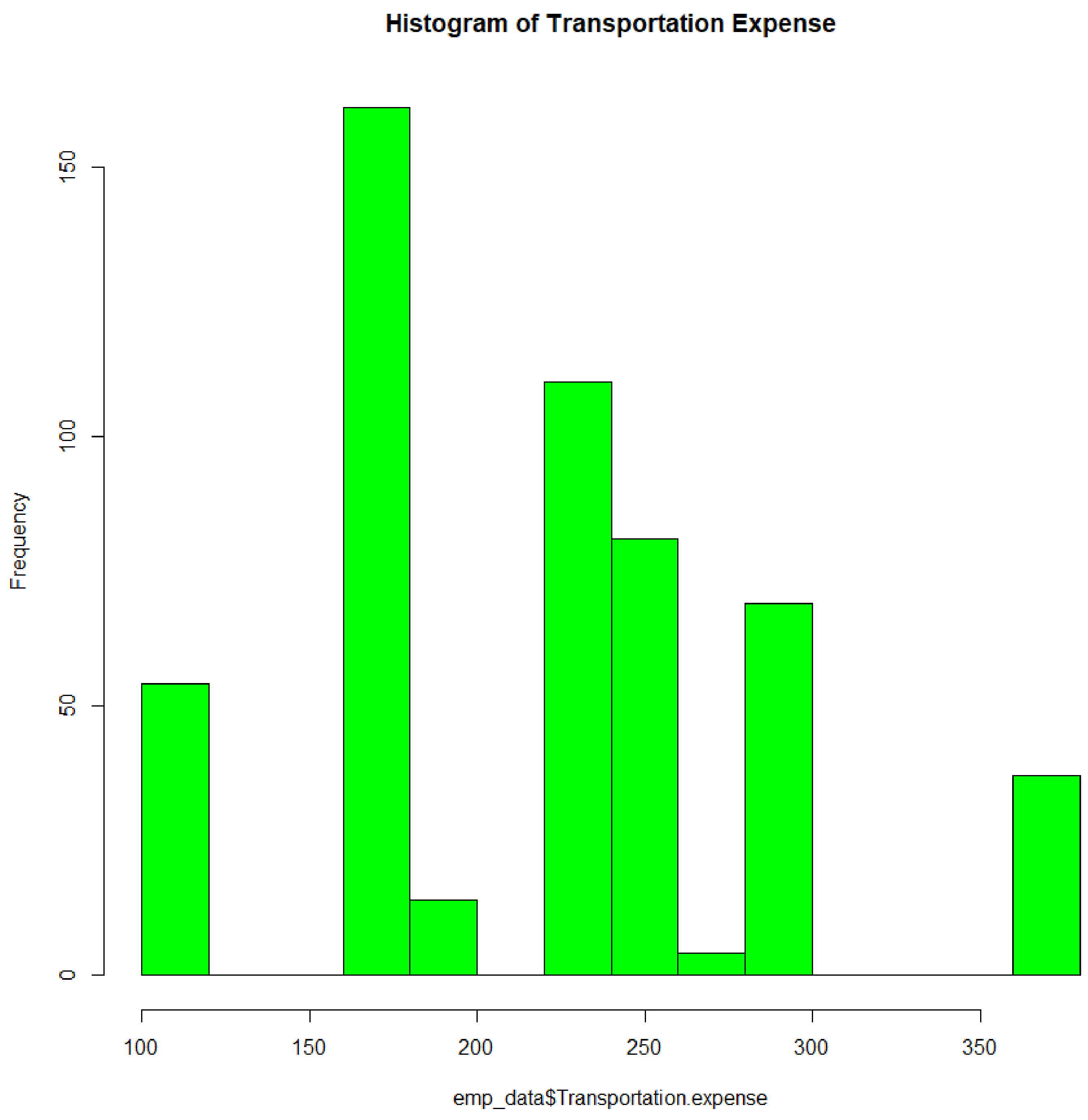
Appendix

R figures:




Histogram of Absenteeism
Frequency
0
50
100
150
200
0
5
10
15
emp_data$Absenteeism.time.in.hours


Histogram of distance between work and residence
Frequency
0
20
40
60
80
100
120
10
20
30
40
50
emp_data$Distance.from.Residence.to.Work



R code:

```
# Clearing the environment

rm(list=ls(all=T))


# Setting working directory


setwd("C:/Users/PRASHANT/Desktop/edwsior project new")
```

```
getwd()


# Loading libraries

library(ggplot2)

library(corrgram)

library(DMwR)

library(caret)

library(randomForest)

library(unbalanced)

library(dummies)

library(e1071)

library(Information)

library(MASS)

library(rpart)

library(gbm)

library(ROSE)

library(xlsx)

library(DataCombine)

library(rpart)




x = c("ggplot2", "corrgram", "DMwR", "caret", "randomForest", "unbalanced", "C50", "dummies", "e1071",
"Information",

    "MASS", "rpart", "gbm", "ROSE", 'xlsx', 'DataCombine', 'rpart')

lapply(x, require, character.only = TRUE);

rm(x)


## Reading the data

emp_data = read.csv('Absenteeism_at_work_Project_Cs.csv')
```

```
# Work.load.Average.day variable values have commas which need to be removed.

emp_data$Work.load.Average.day = gsub(',','',emp_data$Work.load.Average.day)




#---------------------------------------------------Exploratory Data Analysis-----------------------------------------------------
# Shape of the data
dim(emp_data)
# Viewing data
# View(df)
# Structure of the data
str(emp_data)
# Variable namesof the data
colnames(emp_data)

#from the data summary we can see variable ID, which is not useful variable
#in modeling further, so here removing variable ID from dataset.

emp_data= subset(emp_data,select=-c(ï..ID))

# From the above EDA and problem statement categorising data in 2 category "continuous" and "catagorical"
cont = c('Distance.from.Residence.to.Work', 'Service.time', 'Age',
              'Work.load.Average.day.', 'Transportation.expense',
              'Hit.target', 'Weight', 'Height',
              'Body.mass.index', 'Absenteeism.time.in.hours')

cat = c('Reason.for.absence','Month.of.absence','Day.of.the.week',
              'Seasons','Disciplinary.failure', 'Education', 'Social.drinker',
              'Social.smoker', 'Son', 'Pet')
```

```
#as we know that month variable can contain maximum 12 values, so here replace 0 with NA-

emp_data$Month.of.absence[emp_data$Month.of.absence %in% 0]= NA



#Dividing Work.load.Average.day by 1000 (As per discussion on the support forum)

emp_data$Work.load.Average.day= as.numeric(emp_data$Work.load.Average.day)/1000



View(emp_data)



###changing the required data type:


emp_data$Distance.from.Residence.to.Work = as.numeric(emp_data$Distance.from.Residence.to.Work)

emp_data$Service.time = as.numeric(emp_data$Service.time)

emp_data$Age = as.numeric(emp_data$Age)

emp_data$Work.load.Average.day. = as.numeric(emp_data$Work.load.Average.day.)

emp_data$Transportation.expense= as.numeric(emp_data$Transportation.expense)

emp_data$Hit.target = as.numeric(emp_data$Hit.target)

emp_data$Weight = as.numeric(emp_data$Weight)

emp_data$Height = as.numeric(emp_data$Height)

emp_data$Body.mass.index = as.numeric(emp_data$Body.mass.index)

emp_data$Absenteeism.time.in.hours = as.numeric(emp_data$Absenteeism.time.in.hours)




emp_data$Reason.for.absence = as.factor(emp_data$Reason.for.absence)

emp_data$Reason.for.absence = as.factor(emp_data$Reason.for.absence)

emp_data$Month.of.absence = as.factor(emp_data$Month.of.absence)
```

```
emp_data$Day.of.the.week = as.factor(emp_data$Day.of.the.week )

emp_data$Seasons = as.factor(emp_data$Seasons)

emp_data$Disciplinary.failure = as.factor(emp_data$Disciplinary.failure)

emp_data$Education = as.factor(emp_data$Education)

emp_data$Social.drinker = as.factor(emp_data$Social.drinker)

emp_data$Social.smoker= as.factor(emp_data$Social.smoker)
emp_data$Son = as.factor(emp_data$Son)
emp_data$Pet = as.factor(emp_data$Pet)



str(emp_data)






#===========================Data Pre-processing==============================================#

#--------------------------Missing Values Analysis----------------------------------------------#


###remove the rows which contains NA values in our target variable which is Absenteeism in hours
emp_data = emp_data[(!emp_data$Absenteeism.time.in.hours %in% NA),]
```

```
#Creating dataframe with missing values present in each variable

missing_val = data.frame(apply(emp_data,2,function(x){sum(is.na(x))}))

missing_val$Columns = row.names(missing_val)

names(missing_val)[1] =  "Missing_percentage"


#Calculating percentage missing value

missing_val$Missing_percentage = (missing_val$Missing_percentage/nrow(emp_data)) * 100


# Sorting missing_val in Descending order

missing_val = missing_val[order(-missing_val$Missing_percentage),]

row.names(missing_val) = NULL


# Reordering columns

missing_val = missing_val[,c(2,1)]


# Saving output result into csv file

write.csv(missing_val, "Missing_perc_R.csv", row.names = F)


# # Plot

ggplot(data = missing_val[1:18,], aes(x=reorder(Columns, -Missing_percentage),y = Missing_percentage))+

geom_bar(stat = "identity",fill = "grey")+xlab("Variables")+

ggtitle("Missing data percentage") + theme_bw()



#Number of missing values


as.data.frame(colSums(is.na(emp_data)))


#Reason.for.absence                    3

#Month.of.absence                      4
```

```
#Day.of.the.week                    0
#Seasons                            0
#Transportation.expense             6
#Distance.from.Residence.to.Work    3
#Service.time                       3
#Age                                2
#Work.load.Average.day              8
#Hit.target                         6
#Disciplinary.failure               5
#Education                         10
#Son                                6
#Social.drinker                     3
#Social.smoker                      4
#Pet                                2
#Weight                             1
#Height                            14
#Body.mass.index                   29
#Absenteeism.time.in.hours          0



# Actual Value = 27
# Mean = 26.68
# Median = 25
# KNN = 27

##checking actual value of body mass cell number 23
emp_data$Body.mass.index[23]


##converting the known value as na
```

```
emp_data[23,19] = NA


emp_data[23,19]



#Mean Method

emp_data$Body.mass.index[is.na(emp_data$Body.mass.index)] = mean(emp_data$Body.mass.index, na.rm = T)


#Median Method

emp_data$Body.mass.index[is.na(emp_data$Body.mass.index)] = median(emp_data$Body.mass.index, na.rm = T)


# kNN Imputation methond

##df = knnImputation(df, k = 3)

emp_data = kNN(emp_data, k=3)



#for categorical variable we will use mode imputation

mode=function(v){

  uniqv=unique(v)

  uniqv[which.max(tabulate(match(v,uniqv)))]

}


for(i in cat){

  print(i)

  emp_data[,i][is.na(emp_data[,i])] = mode(emp_data[,i])

}


##for continous variables we will use KNN imputation

# KNN Imputation
```

```
install.packages("bitops")
install.packages("DMwR")

emp_data= knnImputation(emp_data,k=3)



# Checking for missing value
sum(is.na(emp_data))







#-------------------------------------Outlier Analysis-------------------------------------#
# BoxPlots - Distribution and Outlier Check

# Boxplot for continuous variables
numeric_index = sapply(emp_data,is.numeric) #selecting only numeric

numeric_data = emp_data[,numeric_index]

cnames = colnames(numeric_data)

for (i in 1:length(cnames))
 {
  assign(paste0("gn",i), ggplot(aes_string(y = (cnames[i]), x = "Absenteeism.time.in.hours"), data = subset(emp_data))+
           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],x="Absenteeism.time.in.hours")+
           ggtitle(paste("Box plot of Absenteeism for",cnames[i])))
 }

 ## Plotting plots together
 gridExtra::grid.arrange(gn1,gn5,gn2,ncol=3)
 gridExtra::grid.arrange(gn6,gn7,ncol=2)
 gridExtra::grid.arrange(gn8,gn9,gn10,ncol=3)



 #Remove outliers from dataset-
 for(i in cnames){
  print(i)
  outlier= emp_data[,i][emp_data[,i] %in% boxplot.stats(emp_data[,i])$out]
  print(length(outlier))
  emp_data = emp_data[which(!emp_data[,i] %in% outlier),]
 }



 #Replace outliers with NA and impute using KNN method-
 for(i in cnames){
  print(i)
  outlier= emp_data[,i][emp_data[,i] %in% boxplot.stats(emp_data[,i])$out]
  print(length(outlier))
  emp_data[,i][emp_data[,i] %in% outlier]=NA
 }
```

```
  sum(is.na(emp_data))



 #KNN-
 emp_data= knnImputation(emp_data,k=3)
 sum(is.na(emp_data))




#-----------------------------------Feature Selection-----------------------------------------#

#Correlation Analysis for continuous variables-
library(corrgram)    #Library for correlation plot

corrgram(data[,cnames],order=FALSE,upper.panel = panel.pie,
        text.panel = panel.txt,font.labels =1,
        main="Correlation plot for Absenteeism")



#Correlated variable= weight

#Anova Test for categorical variable-

for(i in cat_cnames){
  print(i)
  Anova_result= summary(aov(formula = Absenteeism.time.in.hours~data[,i],data))
  print(Anova_result)
}

#redudant categorical variables- Pet,Social.smoker,Education,Seasons,Month.of.absence
```

```
#Dimensionity Reduction

data= subset(data,select=-c(Weight,Pet,Social.smoker,Education,Seasons,Month.of.absence))

dim(data)


#--------------------------------Feature Scaling--------------------------------#

#update the continuous variable dataframe after dimension reduction-

cnames1= c('Distance.from.Residence.to.Work', 'Service.time', 'Age',

           'Work.load.Average.day.', 'Transportation.expense',

           'Hit.target','Height', 'Body.mass.index')




#summary of data to check min and max values of numeric variables-

summary(emp_data)




#Normality check

hist(emp_data$Absenteeism.time.in.hours,col="Yellow",main="Histogram of Absenteeism ")

hist(emp_data$Distance.from.Residence.to.Work,col="Red",main="Histogram of distance between work and
residence")

hist(emp_data$Transportation.expense,col="Green",main="Histogram of Transportation Expense")


#From all above histogram plot we can say that data is not uniformaly distributed,

#So best method for scaling will be normalization-


#Skewness of numeric variables-

library(propagate)


for(i in cnames){

  skew = skewness(emp_data[,i])

  print(i)

  print(skew)
}


#log transform

emp_data$Absenteeism.time.in.hours = log1p(emp_data$Absenteeism.time.in.hours)


#Normalization-

for(i in cnames1){

  print(i)

  emp_data[,i]= (emp_data[,i]-min(emp_data[,i]))/(max(emp_data[,i]-min(emp_data[,i])))

  print(emp_data[,i])

}


##due to some error need to normalized without loop some of the variables


emp_data$Transportation.expense = (emp_data$Transportation.expense - min
(emp_data$Transportation.expense))/(max(emp_data$Transportation.expense -
min(emp_data$Transportation.expense)))


emp_data$Work.load.Average.day = (emp_data$Work.load.Average.day - min
(emp_data$Work.load.Average.day))/(max(emp_data$Work.load.Average.day -
min(emp_data$Work.load.Average.day)))


emp_data$Hit.target = (emp_data$Hit.target - min (emp_data$Hit.target))/(max(emp_data$Hit.target -
min(emp_data$Hit.target)))


emp_data$Height = (emp_data$Height - min (emp_data$Height))/(max(emp_data$Height - min(emp_data$Height)))


emp_data$Body.mass.index = (emp_data$Body.mass.index - min
(emp_data$Body.mass.index))/(max(emp_data$Body.mass.index - min(emp_data$Body.mass.index)))


#Summary of data after all preprocessing-

summary(emp_data)
```

```
write.csv(emp_data,"Absenteeism_Pre_processed_Data.csv",row.names=FALSE)




#------------------------------------------Model Development--------------------------------------------#

#Clean the Environment-
library(DataCombine)
rmExcept("emp_data")

#Data Copy for refrance-
df=emp_data
emp_data=df



#categorical variables-
cat_cnames = c('Reason.for.absence','Day.of.the.week','Disciplinary.failure',
        'Social.drinker','Son')

#create dummies for categorical variables-
library(dummies)
data= dummy.data.frame(emp_data,cat_cnames)
dim(emp_data)
colnames(emp_data)

#Divide the data into train and test-

set.seed(123)
```

```
train_index= sample(1:nrow(data),0.8*nrow(data))
train= data[train_index,]
test= data[-train_index,]

#--------------------------Decision Tree for Regression------------------------------------------#

#Model devlopment for train data-
library(rpart)    #Library for regression model
DT_model= rpart(Absenteeism.time.in.hours~.,train,method="anova")
DT_model

#Prediction for test data-
DT_test=predict(DT_model,test[-55])

#Error metrics to calculate the performance of model-
rmse= function(y,y1){
  sqrt(mean(abs(y-y1)^2))
}
#RMSE calculation for test data-
rmse(test[,55],DT_test)
##RMSE Result : 0.5197763



#r-square calculation-
#function for r-square-
rsquare=function(y,y1){
  cor(y,y1)^2
}

#r-square calculation for test data-
rsquare(test[,55],DT_test)
```

```
##Rsquare result : 0.4006544


#----------------------------Random Forest for Regression------------------------------------------#


library(randomForest)  #Library for randomforest machine learning algorithm

library(inTrees)       #Library for intree transformation

RF_model= randomForest(Absenteeism.time.in.hours~.,train,ntree=500,method="anova")


#transform ranfomforest model into treelist-

treelist= RF2List(RF_model)


#Extract rules-

rules= extractRules(treelist,train[-55])

rules[1:5,]

#covert rules into redable format-

readable_rules= presentRules(rules,colnames(train))

readable_rules[1:5,]

#Get Rule metrics-

rule_metrics= getRuleMetric(rules,train[-55],train$Absenteeism.time.in.hours)

rule_metrics= presentRules(rule_metrics,colnames(train))

rule_metrics[1:10,]

summary(rule_metrics)


#Check model performance on test data-

RF_test= predict(RF_model,test[-55])


#RMSE calculation for test data-

rmse(test[,55],RF_test)


#RMSE_test=  0.4949839
```

```
#r-square calculation for test data-

rsquare(test[,55],RF_test)

#r-square=0.450954


#-------------------------------Linear Regression---------------------------------------------------#



#Linear regression model-

lr_model= lm(Absenteeism.time.in.hours~.,train)

summary(lr_model)


#check model performance on test data-

lr_test= predict(lr_model,test[-55])


#RMSE calculation for test data-

rmse(test[,55],lr_test)


#RMSE_test=0.507


#r-square calculation for test data-

rsquare(test[,55],lr_test)


#r-square=0.446
```