Employee Absenteeism

Chunnu Agrawal

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1. Introduction

1.1 Problem Statement

XYZ is a courier company. As we appreciate that human capital plays an important role in collection, transportation and delivery. The company is passing through genuine issue of Absenteeism. The company has shared it dataset and requested to have an answer on the following areas:

1. What changes company should bring to reduce the number of absenteeism?
2. How much losses every month can we project in 2011 if same trend of Absenteeism continues?

1.2 Data Sets

Information is portrayed upon parameters, for example, the Reason for Absence, different things included, medical problem or outstanding burden would be the reason. The table speaks to an example of different fields accessible in the information.

Table 1.1 Absenteeism at Work

ID	Reason for absence	Month of absence	Day of the week	Seasons	Transportation expense	Distance from Residence to Work	Service time	Age	Work load Average/day	Hit target	Disciplinary failure
11	26	7	3	1	289	36	13	33	239,554	97	0
36	0	7	3	1	118	13	18	50	239,554	97	1
3	23	7	4	1	179	51	18	38	239,554	97	0
7	7	7	5	1	279	5	14	39	239,554	97	0
11	23	7	5	1	289	36	13	33	239,554	97	0

Education	Son	Social drinker	Social smoker	Pet	Weight	Height	Body mass index	Absenteeism time in hours
1	2	1	0	1	90	172	30	4
1	1	1	0	0	98	178	31	0
1	0	1	0	0	89	170	31	2
1	2	1	1	0	68	168	24	4

As should be obvious in the table underneath we have the accompanying 21 factors, utilizing which we need to accurately anticipate the Employee Absenteeism time in hour for our objective variable.

Synopsis of information is offered underneath to realize factors types and measurement of information.

Fig 1.1 Summary of data

```
'data.frame':	740 obs. of  21 variables:
 $ ID                             : num  11 36 3 7 11 3 10 20 14 1 ...
 $ Reason.for.absence             : num  26 0 23 7 23 23 22 23 19 22 ...
 $ Month.of.absence               : num  7 7 7 7 7 7 7 7 7 7 ...
 $ Day.of.the.week                : num  3 3 4 5 5 6 6 6 2 2 ...
 $ Seasons                        : num  1 1 1 1 1 1 1 1 1 1 ...
 $ Transportation.expense         : num  289 118 179 279 289 179 NaN 260 155 235 ...
 $ Distance.from.Residence.to.Work: num  36 13 51 5 36 51 52 50 12 11 ...
 $ Service.time                   : num  13 18 18 14 13 18 3 11 14 14 ...
 $ Age                            : num  33 50 38 39 33 38 28 36 34 37 ...
 $ Work.load.Average.day.         : num  239554 239554 239554 239554 239554 ...
 $ Hit.target                     : num  97 97 97 97 97 97 97 97 97 97 ...
 $ Disciplinary.failure           : num  0 1 0 0 0 0 0 0 0 0 ...
 $ Education                      : num  1 1 1 1 1 1 1 1 1 3 ...
 $ Son                            : num  2 1 0 2 2 0 1 4 2 1 ...
 $ Social.drinker                 : num  1 1 1 1 1 1 1 1 1 0 ...
 $ Social.smoker                  : num  0 0 0 1 0 0 0 0 0 0 ...
 $ Pet                            : num  1 0 0 0 1 0 4 0 0 1 ...
 $ Weight                         : num  90 98 89 68 90 89 80 65 95 88 ...
 $ Height                         : num  172 178 170 168 172 170 172 168 196 172 ...
 $ Body.mass.index                : num  30 31 31 24 30 31 27 23 25 29 ...
 $ Absenteeism.time.in.hours      : num  4 0 2 4 2 NaN 8 4 40 8 ...
```

2. Methodology

2.1 Data Preprocessing

Information in genuine world is messy it of no utilization until the point when except if we apply information pre-processing on it. At the end of the day, Pre-preparing alludes to the changes connected to your information before encouraging it to the calculation. It's an information mining procedure which that includes changing crude information into a reasonable organization or we can state that it gets ready crude information to additionally preparing. There are such huge numbers of things that we do in information preprocessing like information cleaning, information reconciliation, information change, or information decrease.

2.1.1 Missing Value Analysis

Missing Values Analysis is using to fill NULL values in data with some imputation techniques but here in our Employee Absenteeism Data, we have null Values. By the way our data contain missing value. We will impute those values using KNN.

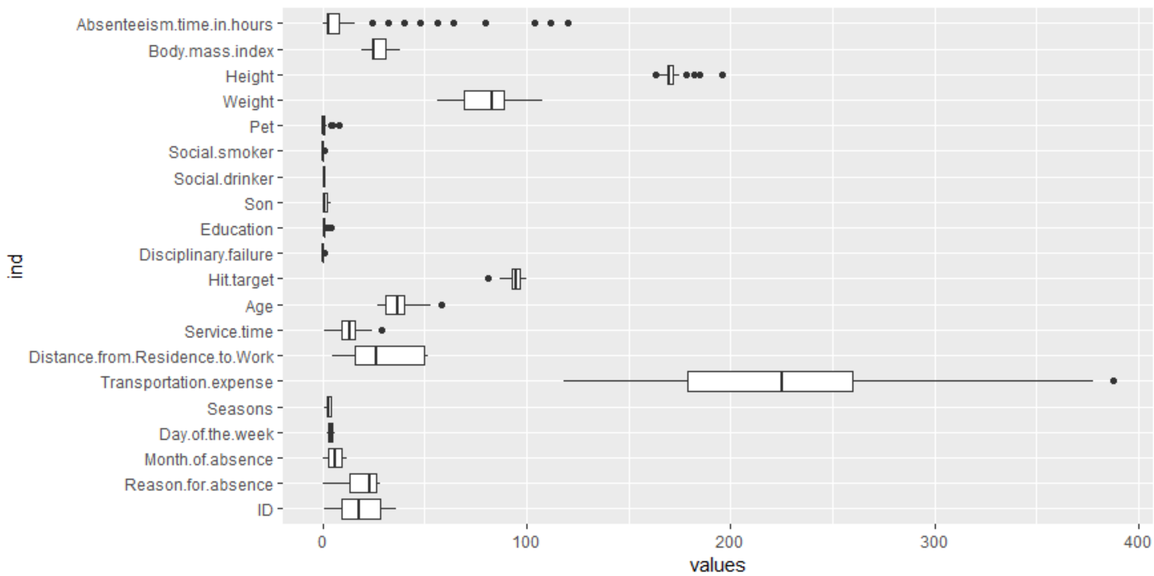
Fig 2.1 Number of missing Values

```
                       ID           Reason.for.absence             Month.of.absence
                        0                            3                            1
             Day.of.the.week                  Seasons       Transportation.expense
                        0                            0                            7
Distance.from.Residence.to.Work           Service.time                          Age
                        3                            3                            3
       Work.load.Average.day.               Hit.target          Disciplinary.failure
                       10                            6                            6
                Education                          Son                Social.drinker
                       10                            6                            3
             Social.smoker                         Pet                        Weight
                        4                            2                            1
                   Height              Body.mass.index      Absenteeism.time.in.hours
                       14                           31                           22
```

2.1.2 Outlier Analysis

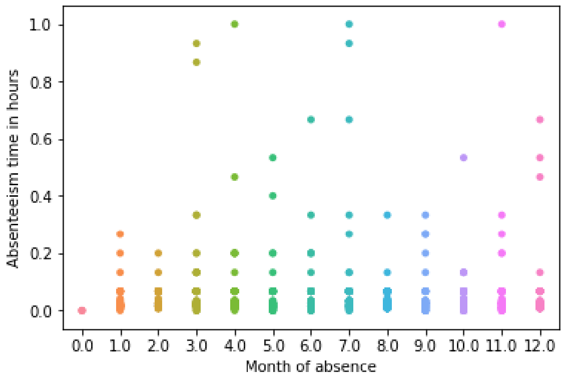
The demonstrated boxplot Fig: 2.3 alludes anomalies on the indicator’s factors, we can see different exceptions related with the highlights. Even though, the information has significant measure of exceptions, the methodology is to hold each anomaly and snatch individual conduct all things considered. As appeared, there are critical measure of anomalies present in the objective variable, which demonstrates a pattern on Employee ' conduct, there can be design, we have to treat those exceptions.

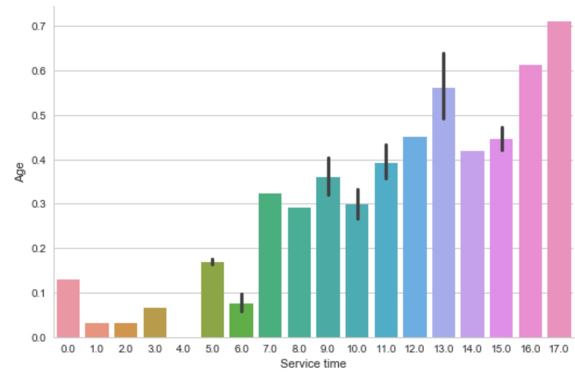
Fig 2.3 Outlier Values



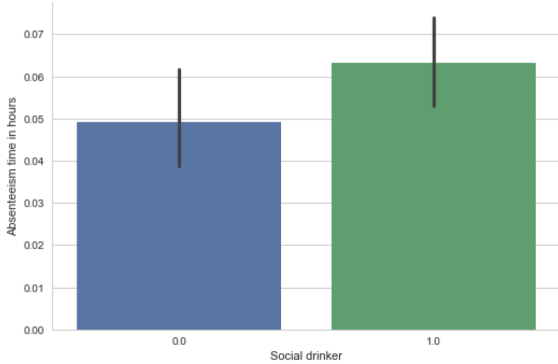
2.1.3 Data Visualization

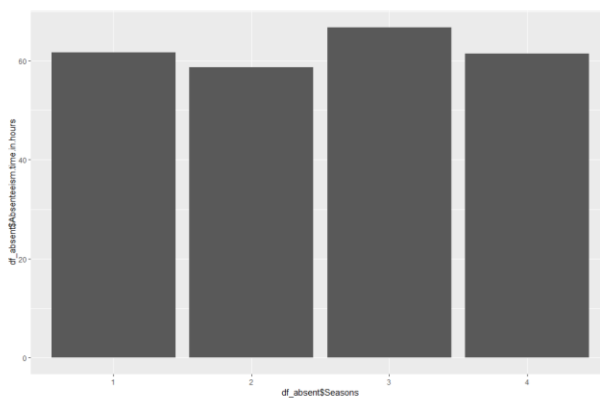
Information Visualization is essential idea it will assist us with understanding information and will disclose to us reply of different inquiries likewise it will indicate connection between factors. Information perception alludes to the graphical portrayal of data and information. By utilizing visual components like outlines, diagrams, and maps, information perception is an available method to see and comprehend patterns, anomalies, and examples in information.





From above figure we can see that *Employees* absent in several months contain pattern, Employees are of more age have relation with Service time.





From above figure we can see that Drinkers took more leaves.

3. Modelling

Absenteeism at work is a regression problem. Here according to the problem statement, we are supposed to predict the loss incurred by the company if the same pattern of absenteeism continues. Hence, we are selection the following two models,

1. Decision tree
2. Random forest model

Both training models Decision tree and random forest were implemented in R and python. After building an initial model, performance tuning was done using hyper parameter tuning for optimized parameters.

3.1 Decision Tree

Train data was divided into train dataset and validation set.

- Logistic regression models were trained on train dataset.
- Validation set, and AIC score was used to select the best models out of all trained models.
- Final test and prediction were performed on test data which was provided separately.

R implementation:

```
#decision tree analysis

#rpart for regression

fit = rpart(Absenteeism.time.in.hours ~ ., data = train, method = "anova")

#Predict for new test cases

predictions_DT = predict(fit, test[,-16])

#MAPE

#calculate MAPE

MAPE = function(y, yhat){

  mean(abs((y - yhat)/y))*100

}
```

MAPE(test[,16], predictions_DT)

Python implementation:

```
# Decision Tree
#Decision tree for regression
fit_DT = DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:9], train.iloc[:,9])
#checking for any missing valuses that has leeked in
np.where(Absenteeism_at_work.values >= np.finfo(np.float64).max)

np.isnan(Absenteeism_at_work.values.any())
test = test.fillna(train.mean())
#Decision tree for regression
fit_DT = DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:15], train.iloc[:,15])
Absenteeism_at_work.shape
#Apply model on test data
predictions_DT = fit_DT.predict(test.iloc[:,0:15])
def rmse(predictions, targets):
    return np.sqrt(((predictions - targets) ** 2).mean())
rmse(test.iloc[:,15], predictions_DT)
```

3.2 Random Forest

After decision tree, random forest was trained. It was implemented in both R and python. In both implementations random forest was first trained with default setting and the hyper parameters tuning was used to find the best parameters.

R Implementation:

```
#Random Forest

library(randomForest)

RF_model = randomForest(Absenteeism.time.in.hours ~ ., train, importance = TRUE, ntree = 1000)

#Extract rules fromn random forest

#transform rf object to an inTrees' format
```

```
library(RRF)

library(inTrees)

treeList <- RF2List(RF_model)

#Extract rules

exec = extractRules(treeList, train[,-16])  # R-executable conditions

ruleExec <- extractRules(treeList,train[,-16],digits=4)


#Make rules more readable:

readableRules = presentRules(exec, colnames(train))

readableRules[1:2,]

#Get rule metrics

ruleMetric = getRuleMetric(exec, train[,-16], train$Absenteeism.time.in.hours)  # get rule
metrics

#Predict test data using random forest model

RF_Predictions = predict(RF_model, test[,-16])
```

Python implementation:

```
#Divide data into train and test
X = Absenteeism_at_work.values[:, 0:15]
Y = Absenteeism_at_work.values[:,15]

X_train, X_test, y_train, y_test = train_test_split( X, Y, test_size = 0.2)
#Random Forest
from sklearn.ensemble import RandomForestClassifier

RF_model = RandomForestClassifier(n_estimators = 20).fit(X_train, y_train)


RF_Predictions = RF_model.predict(X_test)
```

4. Conclusion

4.1 Model Evaluation

As we can see, we have applied all the possible preprocessing analysis to our dataset to make it s uitable

For calculation.

We have also removed the missing values and outliers.

Now since our data is a regression model, we have applied suitable models

Such as decision tree and random forest.

The error metric results of both the models are as follows,

Using R,

Rmse value applying decision tree, **0.222542**

This means that our predictions vary from the actual value by about 0.222542

Rmse value using random forest, **0.2065729**

This means that our predictions vary from the actual value by about 0.2065729

Using python,

Rmse value applying decision tree, **0.22594499**
This means that our predictions vary from the actual value by about 0.22594499
Rmse value using random forest**, 0.2076225**

This means that our predictions vary from the actual value by about 0.20762259

Hence comparing R and python, since the error rate of R is comparatively better, we consider the code of R

AND on comparing the values of decision tree and random forest, since the error rate of random forest is comparatively better, we consider the value of random forest.

Hence, finally, we are accepting the random forest model of R, which has an RMSE value of 0.2065729, which is negligible.

Appendix A

R Code

```
#remove all the objects stored
rm(list=ls())
#set current working directory
setwd("F:/Edwisor/Data Science/Project Work/Employee-Absenteeism-master")
#Check workin directory path
getwd()
library(readxl)
library(dplyr)
library(corrplot)
library(ggplot2)
library(tidyverse)
library(randomForest)
library(data.table)
library(rpart)
## Read the data
absent_data <- read_excel("Absenteeism_at_work_Project.xls", sheet = 1)
## Changing the continous variables to categorical variables
##for getting ease performance of data
absent_data$Reason.for.absence = as.factor(absent_data$Reason.for.absence)
absent_data$Month.of.absence = as.factor(absent_data$Month.of.absence)
absent_data$Day.of.the.week = as.factor(absent_data$Day.of.the.week)
absent_data$Seasons = as.factor(absent_data$Seasons)
absent_data$Service.time = as.factor(absent_data$Service.time)
absent_data$Hit.target = as.factor(absent_data$Hit.target)
absent_data$Disciplinary.failure = as.factor(absent_data$Disciplinary.failure)
absent_data$Education = as.factor(absent_data$Education)
absent_data$Son = as.factor(absent_data$Son)
absent_data$Social.drinker = as.factor(absent_data$Social.drinker)
absent_data$Social.smoker = as.factor(absent_data$Social.smoker)
absent_data$Pet = as.factor(absent_data$Pet)
absent_data$Work.load.Average.day  = as.numeric(absent_data$Work.load.Average.day)
## Outlier analysis
outlierKD <- function (dt, var) {
  var_name <- eval(substitute(var), eval(dt))
  na1 <- sum(is.na(var_name))
  m1 <- mean (var_name, na.rm = T)
  par (mfrow=c(2, 2), oma=c(0,0,3,0))
  boxplot (var_name, main="With outliers")
```

```
  hist (var_name, main="With outliers", xlab=NA, ylab=NA)
  outlier <- boxplot.stats(var_name)$out
  mo <- mean(outlier)
  var_name <- ifelse(var_name %in% outlier, NA, var_name)
  boxplot(var_name, main="Without outliers")
  hist(var_name, main="Without outliers", xlab=NA, ylab=NA)
  title("Outlier Check", outer=TRUE)
  na2 <- sum(is.na(var_name))
  cat("Outliers identified:", na2 - na1, "n")
  cat("Propotion (%) of outliers:", round((na2 - na1) / sum(!is.na(var_name))*100, 1), "n")
  cat("Mean of the outliers:", round(mo, 2), "n")
  m2 <- mean(var_name, na.rm = T)
  cat("Mean without removing outliers:", round(m1, 2), "n")
  cat("Mean if we remove outliers:", round(m2, 2), "n")
  response <- readline(prompt="Do you want to remove outliers and to replace with NA?
[yes/no]: ")
  if(response == "y" | response == "yes"){
    dt[as.character(substitute(var))] <- invisible(var_name)
    assign(as.character(as.list(match.call())$dt), dt, envir = .GlobalEnv)
    cat("Outliers successfully removed", "n")
    return(invisible(dt))
  } else{
    cat("Nothing changed", "n")
    return(invisible(var_name))
  }
}


outlierKD(absent_data,Absenteeism.time.in.hours)# outliers detected and replaced by NA
outlierKD(absent_data,Transportation.expense) #no outliers
outlierKD(absent_data,Distance.from.Residence.to.Work) #no outliers
outlierKD(absent_data,Service.time) #no outliers
outlierKD(absent_data,Age) #no outliers
outlierKD(absent_data,Work.load.Average.day.) # 1 found and replaced with NA
outlierKD(absent_data,Hit.target) # 1 found and replaced with NA
outlierKD(absent_data,Son) # no outliers
outlierKD(absent_data,Pet) # no outliers
outlierKD(absent_data,Weight) # no outliers
outlierKD(absent_data,Height) # no outliers
outlierKD(absent_data,Body.mass.index) #no outliers
```

```
################################### Missing value analysis
###################################

missing_val = data.frame(apply(absent_data,2,function(x){sum(is.na(x))}))
missing_val$Columns = row.names(missing_val)
names(missing_val)[1] =  "Missing_percentage"
missing_val$Missing_percentage = (missing_val$Missing_percentage/nrow(absent_data)) * 100
missing_val = missing_val[order(-missing_val$Missing_percentage),]
row.names(missing_val) = NULL
missing_val = missing_val[,c(2,1)]
write.csv(missing_val, "Miising_perc.csv", row.names = F)

#ggplot analysis
ggplot(data = missing_val[1:3,], aes(x=reorder(Columns, -Missing_percentage),y =
Missing_percentage))+
  geom_bar(stat = "identity",fill = "grey")+xlab("Parameter")+
  ggtitle("Missing data percentage (Train)") + theme_bw()

library(ggplot2)
#actual value =30
#absent_data[1,20]
#absent_data[1,20]= NA
# kNN Imputation=29.84314
#after various calculations, it is found that knn imputation method suits the best for the data.
hence here we are applying knn imputation

################################### feature selection
###################################
library(corrgram)
## Correlation Plot - to check multicolinearity between continous variables
corrgram(absent_data[,numeric_index], order = F,
         upper.panel=panel.pie, text.panel=panel.txt, main = "Correlation Plot")
absent_data$Absenteeism.time.in.hours = as.factor(absent_data$Absenteeism.time.in.hours)

## Chi-squared Test of Independence-to check the multicolinearity between categorical variables
factor_index = sapply(absent_data,is.factor)
factor_data = absent_data[,factor_index]

for (i in 1:12)
{
  print(names(factor_data)[i])
  print(chisq.test(table(factor_data$Absenteeism.time.in.hours,factor_data[,i])))
}
```

```
absent_data$Absenteeism.time.in.hours = as.numeric(absent_data$Absenteeism.time.in.hours)

#################################### Feature reduction
###################################
## Dimension Reduction
absent_data = subset(absent_data,
                     select = -c(Weight,Hit.target,Education,Social.smoker,Pet))
#Feature Scaling
#Normality check
qqnorm(absent_data$Absenteeism.time.in.hours )
hist(absent_data$Absenteeism.time.in.hours )
str(absent_data)
#Normalisation
cnames =
c("ID","Transportation.expense","Distance.from.Residence.to.Work","Height","Age","Work.loa
d.Average.day","Body.mass.index",
           "Absenteeism.time.in.hours")

for(i in cnames){
  print(i)
  absent_data[,i] = (absent_data[,i] - min(absent_data[,i]))/
    (max(absent_data[,i] - min(absent_data[,i])))
}
########################## Univariate Distribution and Analysis
################################

# function for univariate analysis for continous variables
#       function inpus:
#       1. dataset - input dataset
#       2. variable - variable for univariate analysis
#       3. variableName - variable title in string
#       example.   univariate_analysis(absent_data,Absenteeism.time.in.hours,
#                                                    "Absenteeism.time.in.hours")
univariate_analysis <- function(dataset, variable,variableName){

  var_name = eval(substitute(variable), eval(dataset))

  if(is.numeric(var_name)){

    print(summary(var_name))
    ggplot(absent_data, aes(var_name)) +
      geom_histogram(aes(y=..density..,binwidth=.5,colour="black", fill="white"))+
```

```
      geom_density(alpha=.2, fill="#FF6666")+
      labs(x = variableName, y = "count") +
      ggtitle(paste("count of ",variableName)) +
      theme(legend.position = "null")

  }else{
    print("This is categorical variable.")

  }

}



# function for univariate analysis for categorical variables
#       function inpus:
#       1. dataset - input dataset
#       2. variable - variable for univariate analysis
#       3. variableName - variable title in string
#       example.   univariate_analysis(absent_data,ID,
#                                                  "ID")
univariate_catogrical <- function(dataset,variable, variableName){
  variable <- enquo(variable)

  percentage <- dataset %>%
    select(!!variable) %>%
    group_by(!!variable) %>%
    summarise(n = n()) %>%
    mutate(percantage = (n / sum(n)) * 100)
  print(percentage)

  dataset %>%
    count(!!variable) %>%
    ggplot(mapping = aes_(x = rlang::quo_expr(variable),
                          y = quote(n), fill = rlang::quo_expr(variable))) +
    geom_bar(stat = 'identity',
             colour = 'white') +
    labs(x = variableName, y = "count") +
    ggtitle(paste("count of ",variableName)) +
    theme(legend.position = "bottom") -> p
  plot(p)

}
## Sampling
```

```
##Systematic sampling
#Function to generate Kth index
sys.sample = function(N,n)
{
  k = ceiling(N/n)
  r = sample(1:k, 1)
  sys.samp = seq(r, r + k*(n-1), k)
}
lis = sys.sample(740, 300) #select the repective rows
# #Create index variable in the data
absent_data$index = 1:740
# #Extract subset from whole data
systematic_data = absent_data[which(absent_data$index %in% lis),]

################################### Model Development
##################################
#Clean the environment
library(DataCombine)

rmExcept("absent_data")
#Divide data into train and test using stratified sampling method
set.seed(1234)
absent_data$description = NULL
library(caret)
train.index = createDataPartition(absent_data$Absenteeism.time.in.hours, p = .80, list = FALSE)
train = absent_data[ train.index,]
test  = absent_data[-train.index,]

#load libraries
library(rpart)
#decision tree analysis
#rpart for regression
fit = rpart(Absenteeism.time.in.hours ~ ., data = train, method = "anova")
#Predict for new test cases
predictions_DT = predict(fit, test[,-16])
#MAPE
#calculate MAPE
MAPE = function(y, yhat){
  mean(abs((y - yhat)/y))*100
}

MAPE(test[,16], predictions_DT)
```

```
#Random Forest
RF_model = randomForest(Absenteeism.time.in.hours ~ ., train, importance = TRUE, ntree =
1000)
#Extract rules
exec = extractRules(treeList, train[,-16])  # R-executable conditions
ruleExec <- extractRules(treeList,train[,-16],digits=4)

#Make rules more readable:
readableRules = presentRules(exec, colnames(train))
readableRules[1:2,]
#Get rule metrics
ruleMetric = getRuleMetric(exec, train[,-16], train$Absenteeism.time.in.hours)  # get rule
metrics
#Predict test data using random forest model
RF_Predictions = predict(RF_model, test[,-16])
#rmse calculation
#install.packages("Metrics")
library(Metrics)
rmse(test$Absenteeism.time.in.hours, RF_Predictions)
#rmse value for random forest is 0.2065729
rmse(test$Absenteeism.time.in.hours, predictions_DT)
#rmse value for decision tree is 0.222542
```

Python Code

```python
#Load libraries
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency
import seaborn as sns
from random import randrange, uniform
from sklearn.cross_validation import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn import linear_model
from sklearn.cross_validation import train_test_split

#Set working directory
os.chdir("C:/Users/SHRAVYA/Desktop/edwisor/project 1")

#Load data
Absenteeism_at_work = pd.read_csv("Absenteeism_at_work_Project.csv")

#----------------PRE-PROCESSING-EXPLORATORY DATA ANALYSIS--------------#
```

```
#Exploratory Data Analysis
Absenteeism_at_work['Reason for absence']=Absenteeism_at_work['Reason for absence'].ast
ype(object)
Absenteeism_at_work['Month of absence']=Absenteeism_at_work['Month of absence'].astyp
e(object)
Absenteeism_at_work['Day of the week']=Absenteeism_at_work['Day of the week'].astype(o
bject)
Absenteeism_at_work['Seasons']=Absenteeism_at_work['Seasons'].astype(object)
Absenteeism_at_work['Service time']=Absenteeism_at_work['Service time'].astype(object)
Absenteeism_at_work['Hit target']=Absenteeism_at_work['Hit target'].astype(object)
Absenteeism_at_work['Disciplinary failure']=Absenteeism_at_work['Disciplinary failure'].ast
ype(object)
Absenteeism_at_work['Education']=Absenteeism_at_work['Education'].astype(object)
Absenteeism_at_work['Son']=Absenteeism_at_work['Son'].astype(object)
Absenteeism_at_work['Social drinker']=Absenteeism_at_work['Social drinker'].astype(object
)
Absenteeism_at_work['Social smoker']=Absenteeism_at_work['Social smoker'].astype(object
)
Absenteeism_at_work['Pet']=Absenteeism_at_work['Pet'].astype(object)
#------------------------MISSING VALUE ANALYSIS-------------------------#
#Create dataframe with missing percentage
missing_val = pd.DataFrame(Absenteeism_at_work.isnull().sum())

#Reset index
missing_val = missing_val.reset_index()

#Rename variable
missing_val = missing_val.rename(columns = {'index': 'Variables', 0: 'Missing_percentage'})

#Calculate percentage
missing_val['Missing_percentage'] = (missing_val['Missing_percentage']/len(Absenteeism_at
_work))*100

#descending order
missing_val = missing_val.sort_values('Missing_percentage', ascending = False).reset_index
(drop = True)

#save output results
missing_val.to_csv("Missing_perc.csv", index = False)
#KNN imputation
#Assigning levels to the categories
lis = []
for i in range(0, Absenteeism_at_work.shape[1]):
```

```
#print(i)
if(Absenteeism_at_work.iloc[:,i].dtypes == 'object'):
Absenteeism_at_work.iloc[:,i] = pd.Categorical(Absenteeism_at_work.iloc[:,i])
#print(marketing_train[[i]])
Absenteeism_at_work.iloc[:,i] = Absenteeism_at_work.iloc[:,i].cat.codes
Absenteeism_at_work.iloc[:,i] = Absenteeism_at_work.iloc[:,i].astype('object')

lis.append(Absenteeism_at_work.columns[i])
#replace -1 with NA to impute
for i in range(0, Absenteeism_at_work.shape[1]):
Absenteeism_at_work.iloc[:,i] = Absenteeism_at_work.iloc[:,i].replace(-1, np.nan)
#Impute with median
Absenteeism_at_work['Absenteeism time in hours'] = Absenteeism_at_work['Absenteeism ti
me in hours'].fillna(Absenteeism_at_work['Absenteeism time in hours'].median())
Absenteeism_at_work['Body mass index'] = Absenteeism_at_work['Body mass index'].fillna(
Absenteeism_at_work['Body mass index'].median())
Absenteeism_at_work['Height'] = Absenteeism_at_work['Height'].fillna(Absenteeism_at_wo
rk['Height'].median())
Absenteeism_at_work['Weight'] = Absenteeism_at_work['Weight'].fillna(Absenteeism_at_w
ork['Weight'].median())
Absenteeism_at_work['Pet'] = Absenteeism_at_work['Pet'].fillna(Absenteeism_at_work['Pet']
.median())
Absenteeism_at_work['Social smoker'] = Absenteeism_at_work['Social smoker'].fillna(Abse
nteeism_at_work['Social smoker'].median())
Absenteeism_at_work['Social drinker'] = Absenteeism_at_work['Social drinker'].fillna(Abse
nteeism_at_work['Social drinker'].median())
Absenteeism_at_work['Son'] = Absenteeism_at_work['Son'].fillna(Absenteeism_at_work['So
n'].median())
Absenteeism_at_work['Education'] = Absenteeism_at_work['Education'].fillna(Absenteeism_
at_work['Education'].median())
Absenteeism_at_work['Disciplinary failure'] = Absenteeism_at_work['Disciplinary failure'].fi
llna(Absenteeism_at_work['Disciplinary failure'].median())
Absenteeism_at_work['Hit target'] = Absenteeism_at_work['Hit target'].fillna(Absenteeism_a
t_work['Hit target'].median())
Absenteeism_at_work['Age'] = Absenteeism_at_work['Age'].fillna(Absenteeism_at_work['A
ge'].median())
Absenteeism_at_work['Service time'] = Absenteeism_at_work['Service time'].fillna(Absentee
ism_at_work['Service time'].median())
Absenteeism_at_work['Distance from Residence to Work'] = Absenteeism_at_work['Distanc
e from Residence to Work'].fillna(Absenteeism_at_work['Distance from Residence to Work']
.median())
Absenteeism_at_work['Transportation expense'] = Absenteeism_at_work['Transportation exp
ense'].fillna(Absenteeism_at_work['Transportation expense'].median())
```

```
Absenteeism_at_work['Month of absence'] = Absenteeism_at_work['Month of absence'].fillna(Absenteeism_at_work['Month of absence'].median())
Absenteeism_at_work['Reason for absence'] = Absenteeism_at_work['Reason for absence'].fillna(Absenteeism_at_work['Reason for absence'].median())
Absenteeism_at_work['Work load Average/day '] = Absenteeism_at_work['Work load Average/day '].fillna(Absenteeism_at_work['Work load Average/day '].median())
```

```
Absenteeism_at_work.isnull().sum()
```

```
Absenteeism_at_work = Absenteeism_at_work.dropna(how='all')
```

```
Absenteeism_at_work.isnull().sum()
```

```
cnames =  ["ID", "Transportation expense", "Distance from Residence to Work", "Age", "Height", "Body mass index", "Absenteeism time in hours"]
```

```
#-------------------FEATURE SELECTION-------------------------#
```

```
##Correlation analysis
#Correlation plot
df_corr = Absenteeism_at_work.loc[:,cnames]
```

```
#Set the width and hieght 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)
plt.savefig('correlation.png')
```

```
#Chisquare test of independence
#Save categorical variables
cat_names = ["Reason for absence", "Month of absence", "Day of the week", "Seasons", "Service time", "Hit target", "Disciplinary failure", "Education", "Son", "Social drinker","Social smoker","Pet"]
```

```
#loop for chi square values
for i in cat_names:
print(i)
chi2, p, dof, ex = chi2_contingency(pd.crosstab(Absenteeism_at_work['Absenteeism time in hours'], Absenteeism_at_work[i]))
print(p)
```

```
Reason for absence
7.262525646531397e-126
Month of absence
```

2.5138924624334413e-08
Day of the week
0.003021081110471532
Seasons
1.0699164671285167e-06
Service time
0.0005117811788141375
Hit target
0.0011492200973353258
Disciplinary failure
2.811327292697691e-103
Education
0.966890372726654
Son
1.5480058926208540e-08
Social drinker
0.0023832329972678858
Social smoker
0.5104529781136267
Pet
0.12306376012607578

```
#--------------------FEATURE SCALING--------------------------#

#feature reduction
Absenteeism_at_work = Absenteeism_at_work.drop(['Weight', 'Hit target', 'Education', 'Social smoker', 'Pet'], axis=1)

#Nomalisation
for i in cnames:
print(i)
Absenteeism_at_work[i] = (Absenteeism_at_work[i] - min(Absenteeism_at_work[i]))/(max(Absenteeism_at_work[i]) - min(Absenteeism_at_work[i]))
```

ID
Transportation expense
Distance from Residence to Work
Age
Height
Body mass index
Absenteeism time in hours

```
#-------------------------DATA SAMPLING-----------------------------#

#Divide data into train and test
train, test = train_test_split(Absenteeism_at_work, test_size=0.25, random_state=42)

#-----------------------------MODELLING---------------------------------#

# Decision Tree
```

```
#Decision tree for regression
fit_DT = DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:9], train.iloc[:,9])

#checking for any missing valuses that has leeked in
np.where(Absenteeism_at_work.values >= np.finfo(np.float64).max)


np.isnan(Absenteeism_at_work.values.any())

test = test.fillna(train.mean())

#Decision tree for regression
fit_DT = DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:15], train.iloc[:,15])

Absenteeism_at_work.shape

#Apply model on test data
predictions_DT = fit_DT.predict(test.iloc[:,0:15])

def rmse(predictions, targets):
return np.sqrt(((predictions - targets) ** 2).mean())

rmse(test.iloc[:,15], predictions_DT)

#rmse value using decision tree is 0.225944999314018

#Divide data into train and test
X = Absenteeism_at_work.values[:, 0:15]
Y = Absenteeism_at_work.values[:,15]

X_train, X_test, y_train, y_test = train_test_split( X, Y, test_size = 0.2)

#Random Forest
from sklearn.ensemble import RandomForestClassifier

RF_model = RandomForestClassifier(n_estimators = 20).fit(X_train, y_train)

RF_Predictions = RF_model.predict(X_test)

#---------------------PLOTS OF VARIABLES-------------------------------#

#plots
import matplotlib as mpl
import matplotlib.pyplot as plt

import seaborn as sns
sns.set(style="whitegrid", color_codes=True)

np.random.seed(sum(map(ord, "categorical")))

Absenteeism_at_work.columns

sns.stripplot(x="Body mass index", y="Absenteeism time in hours", data=Absenteeism_at_w
ork);
plt.savefig('Body mass index.png')
```

```
sns.stripplot(x="Reason for absence", y="Absenteeism time in hours", data=Absenteeism_at
_work);
plt.savefig('Reason for absence.png')

sns.stripplot(x="Month of absence", y="Absenteeism time in hours", data=Absenteeism_at_
work);
plt.savefig('Month of absence.png')

sns.stripplot(x="Day of the week", y="Absenteeism time in hours", data=Absenteeism_at_w
ork);
plt.savefig('Day of the week.png')

sns.stripplot(x="Seasons", y="Absenteeism time in hours", data=Absenteeism_at_work);
plt.savefig('Seasons.png')

sns.stripplot(x="Transportation expense", y="Absenteeism time in hours", data=Absenteeism
_at_work);
plt.savefig('Transportation expense.png')

sns.stripplot(x="Distance from Residence to Work", y="Absenteeism time in hours", data=A
bsenteeism_at_work);
plt.savefig('Distance from Residence to Work.png')

sns.stripplot(x="Service time", y="Absenteeism time in hours", data=Absenteeism_at_work);
plt.savefig('Service time.png')

sns.stripplot(x="Age", y="Absenteeism time in hours", data=Absenteeism_at_work);
plt.savefig('Age.png')

sns.stripplot(x="Disciplinary failure", y="Absenteeism time in hours", data=Absenteeism_at
_work);
plt.savefig('Disciplinary failure.png')

sns.stripplot(x="Son", y="Absenteeism time in hours", data=Absenteeism_at_work);
plt.savefig('Son.png')

sns.stripplot(x="Social drinker", y="Absenteeism time in hours", data=Absenteeism_at_work
);
plt.savefig('Social drinker.png')

sns.stripplot(x="Height", y="Absenteeism time in hours", data=Absenteeism_at_work);
```

```
plt.savefig('Height.png')
```