Employee Absenteeism

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Contents

Chapter 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

There are 21 variables in our data in which 20 are independent variables and 1 (Absenteeism time in hours) is dependent variable. Since the type of target variable is continuous, this is a regression problem.

Variable Information:

1. Individual identification (ID)

2. Reason for absence (ICD).

- Absences attested by the International Code of Diseases (ICD) stratified into 21 categories (I to XXI) as follows:

I certain infectious and parasitic
diseases II Neoplasms

III Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism

IV Endocrine, nutritional and metabolic
diseases V Mental and behavioural
disorders

VI Diseases of the nervous
system VII Diseases of the eye
and adnexa

VIII Diseases of the ear and mastoid
process IX Diseases of the circulatory
system

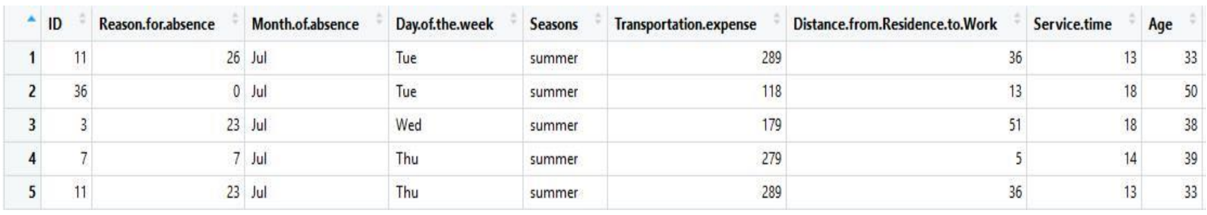
X Diseases of the respiratory
system XI Diseases of the
digestive system
XII Diseases of the skin and subcutaneous tissue

XIII Diseases of the musculoskeletal system and connective
tissue XIV Diseases of the genitourinary system
XV Pregnancy, childbirth and the puerperium
XVI Certain conditions originating in the perinatal period
XVII Congenital malformations, deformations and chromosomal abnormalities

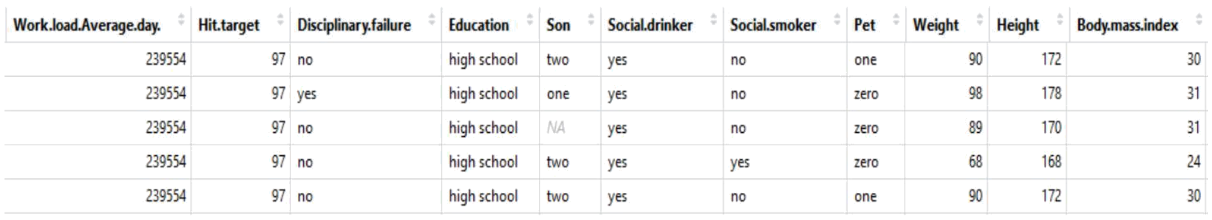
XVIII Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified XIX Injury, poisoning and certain other consequences of external causes
XX External causes of morbidity and mortality
XI Factors influencing health status and contact with health services.
And 7 categories without (CID) patient follow-up (22), medical consultation (23), blood donation
(24), laboratory examination (25), unjustified absence (26), physiotherapy (27), dental consultation
(28).

3. Month of absence
4. Day of the week (Monday (2), Tuesday (3), Wednesday (4), Thursday (5), Friday (6))
5. Seasons (summer (1), autumn (2), winter (3), spring (4))
6. Transportation expense
7. Distance from Residence to Work (KMs)
8. Service time
9. Age
10. Work load Average/day
11. Hit target
12. Disciplinary failure (yes=1; no=0)
13. Education (high school (1), graduate (2), postgraduate (3), master and doctor (4))
14. Son (number of children)
15. Social drinker (yes=1; no=0)
16. Social smoker (yes=1; no=0)
17. Pet (number of pet)
18. Weight
19. Height
20. Body mass index
21. Absenteeism time in hours (target)

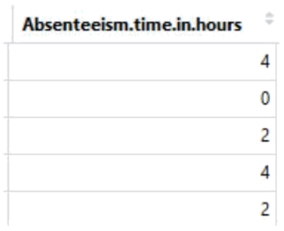
Below is the sample data from the dataset,



	ID	Reason.for.absence	Month.of.absence	Day.of.the.week	Seasons	Transportation.expense	Distance.from.Residence.to.Work	Service.time	Age
1	11	26	Jul	Tue	summer	289	36	13	33
2	36	0	Jul	Tue	summer	118	13	18	50
3	3	23	Jul	Wed	summer	179	51	18	38
4	7	7	Jul	Thu	summer	279	5	14	39
5	11	23	Jul	Thu	summer	289	36	13	33



Work.load.Average.day.	Hit.target	Disciplinary.failure	Education	Son	Social.drinker	Social.smoker	Pet	Weight	Height	Body.mass.index
239554	97	no	high school	two	yes	no	one	90	172	30
239554	97	yes	high school	one	yes	no	zero	98	178	31
239554	97	no	high school	NA	yes	no	zero	89	170	31
239554	97	no	high school	two	yes	yes	zero	68	168	24
239554	97	no	high school	two	yes	no	one	90	172	30



Absenteeism.time.in.hours
4
0
2
4
2

Fig 1.1 – First five rows of data

As you can see in the table below, we have the following 21 variables, using which we have to correctly predict the below questions.

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

Fig 1.2 – Predictor Variables

Sr. No	Variables
1	ID
2	Reason for absence
3	Month of absence
4	Day of the week
5	Seasons
6	Transportation expense
7	Distance from Residence to Work
8	Service time
9	Age
10	Work load Average/day
11	Hit target
12	Disciplinary failure
13	Education
14	Son
15	Social drinker
16	Social smoker
17	Pet
18	Weight
19	Height
20	Body mass index

Chapter 2: Methodology

2.1 Pre – Processing

Any predictive modelling requires that we look at the data before we start modelling. However, in data mining terms looking at data refers to so much more than just looking. Looking at data refers to exploring the data, cleaning the data as well as visualizing the data through graphs and plots. This is often called as Exploratory Data Analysis. To start this process, we will first try and look at all the probability distributions of the variables. Most analysis like regression, require the data to be normally distributed. We can visualize that in a glance by looking at the probability distributions or probability density functions of the variable.

2.2 Missing Value Analysis

Missing data or missing values occur when no data value is stored for the variable in an observation. Missing values are a common occurrence in data analysis. These values can have a significant impact on the results or conclusions that would be drawn from these data. If a variable has more than 30% of its values missing, then those values can be ignored, or the column itself is ignored. In our case, none of the columns have a high percentage of missing values. The maximum missing percentage is 4.18% i.e., **Body Mass Index column**. The missing values have been computed using KNN computation method.

Missing value Percentage of top 3 Variables.

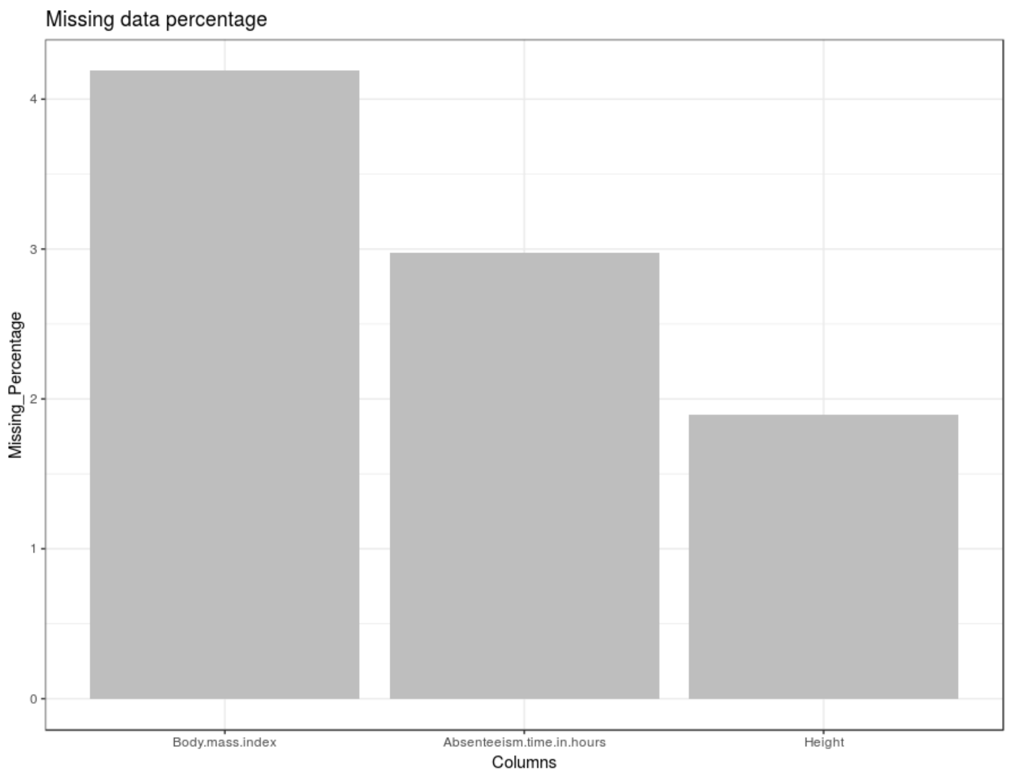
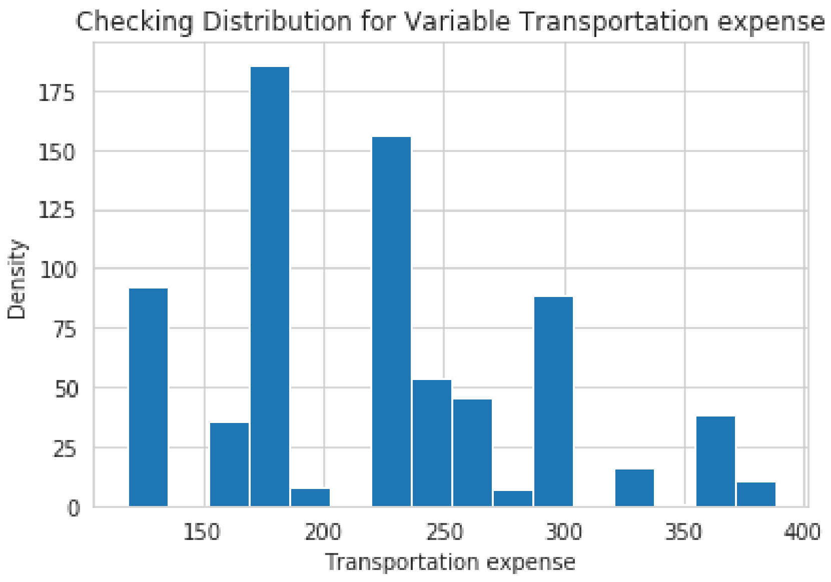
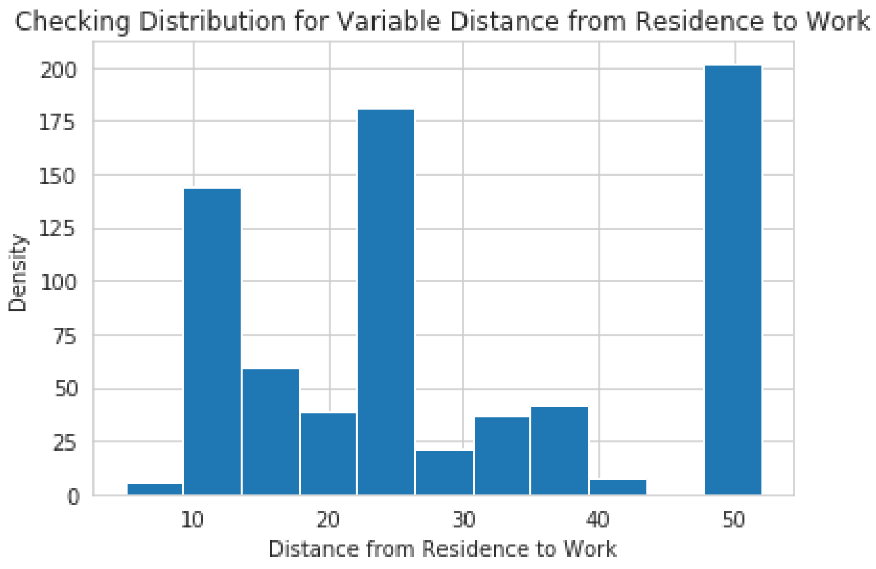
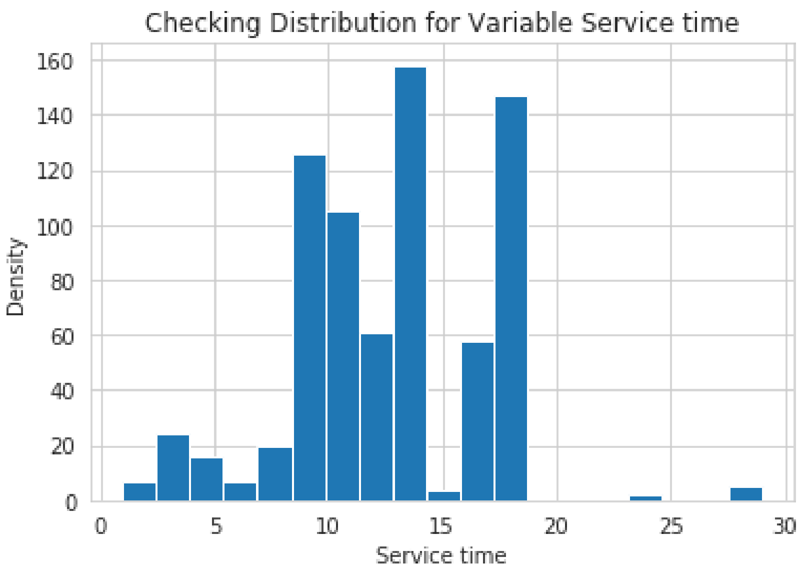


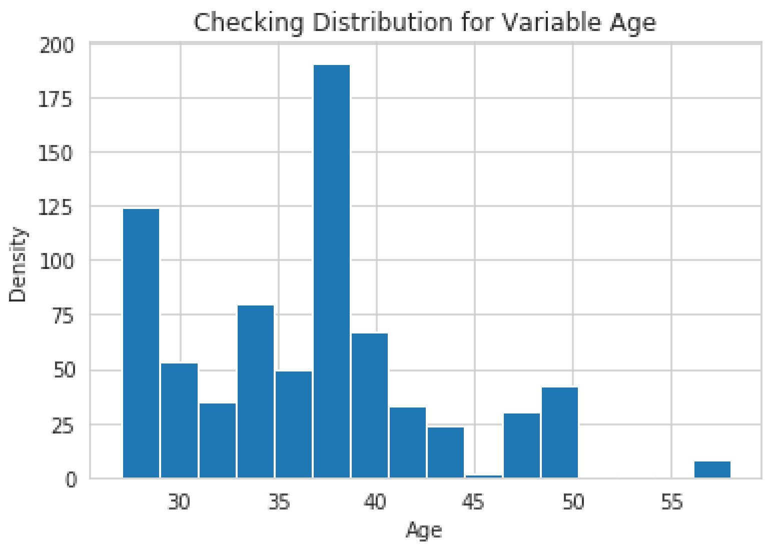
Fig 2.1 – Missing value Percentage

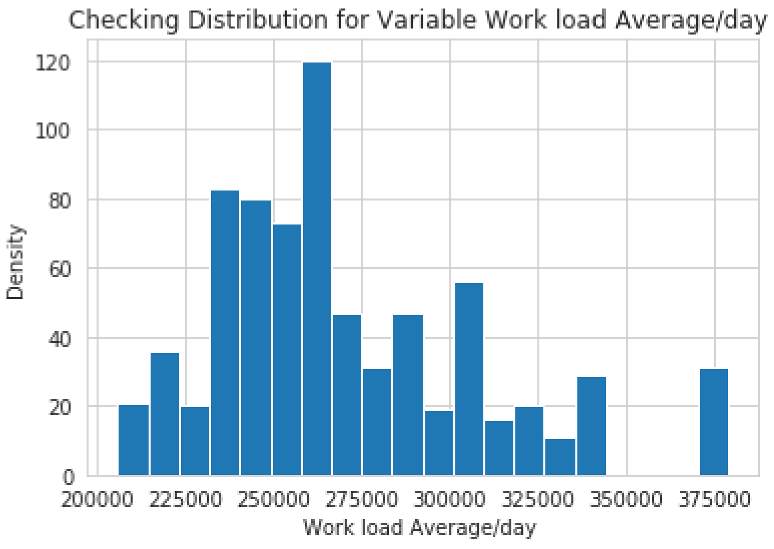
Below figure shows the Probability Distributions of Variables.






Checking Distribution for Variable Service time
Density
Service time
0
20
40
60
80
100
120
140
160
0
5
10
15
20
25
30


Checking Distribution for Variable Age
Density
Age
0
25
50
75
100
125
150
175
200
30
35
40
45
50
55


Checking Distribution for Variable Work load Average/day
Density
Work load Average/day
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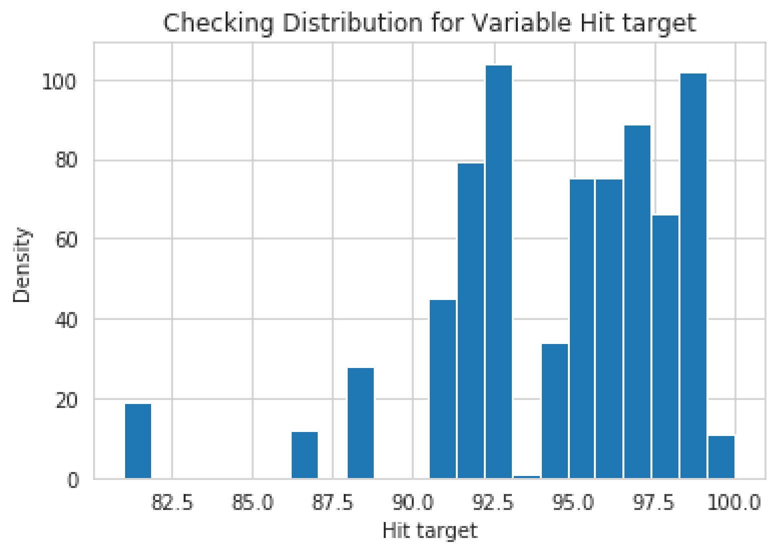
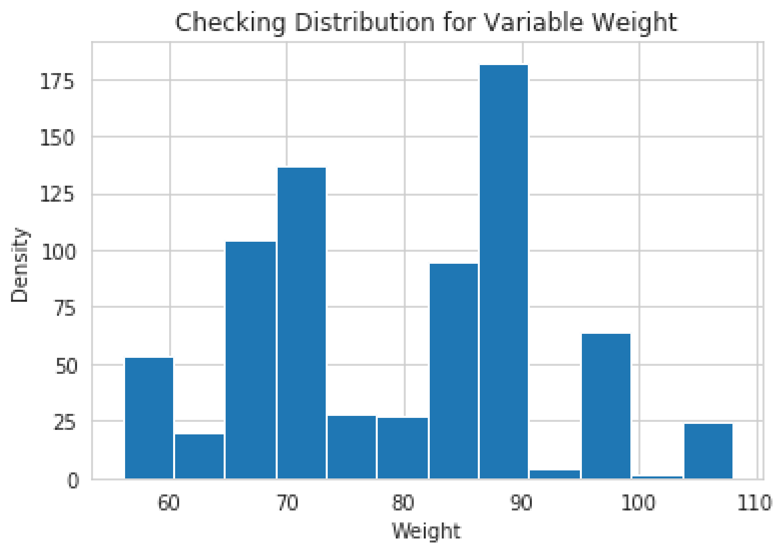
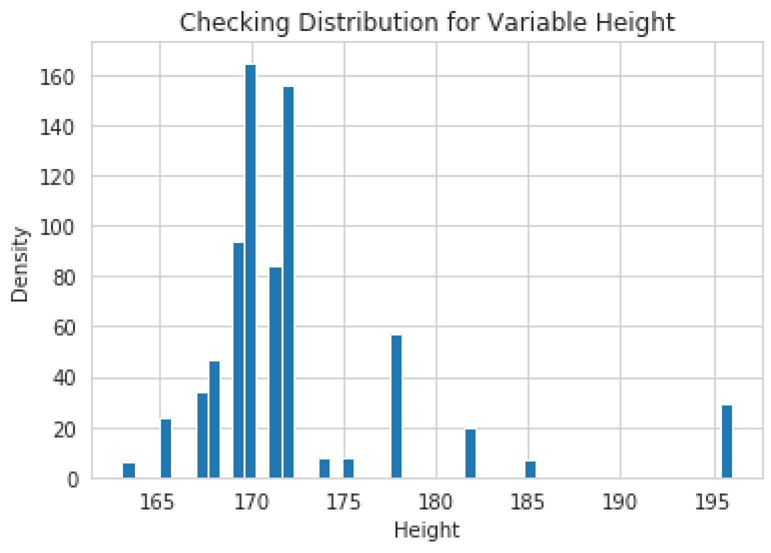
20
40
60
80
100
120
200000
225000
250000
275000
300000
325000
350000
375000


Checking Distribution for Variable Hit target
Density
Hit target
0
20
40
60
80
100
82.5
85.0
87.5
90.0
92.5
95.0
97.5
100.0


Checking Distribution for Variable Weight
Density
Weight
0
25
50
75
100
125
150
175
60
70
80
90
100
110

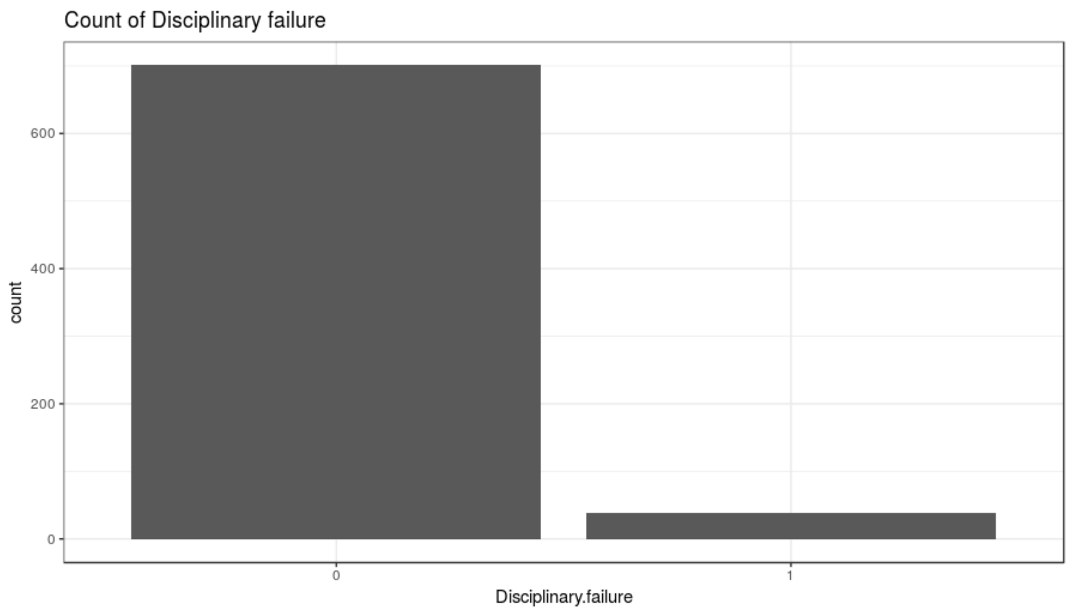

Checking Distribution for Variable Height
Density
Height
0
20
40
60
80
100
120
140
160
165
170
175
180
185
190
195

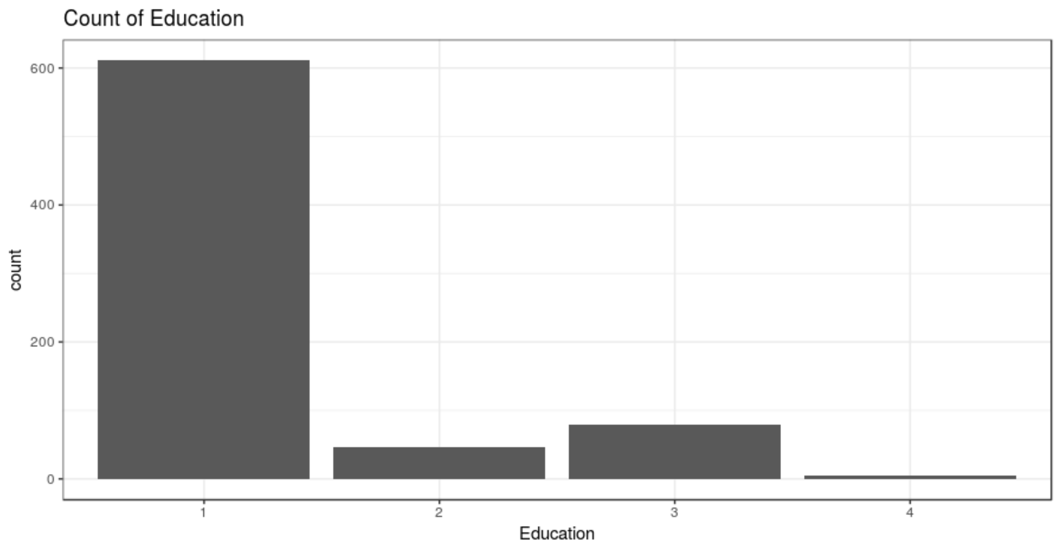
We can clearly observe from these probability distributions that most of the variables are skewed, for example, Height, Age, Transportation expense and Work load Average/day. The skew in these distributions can be most likely explained by the presence of outliers and extreme values in the data.

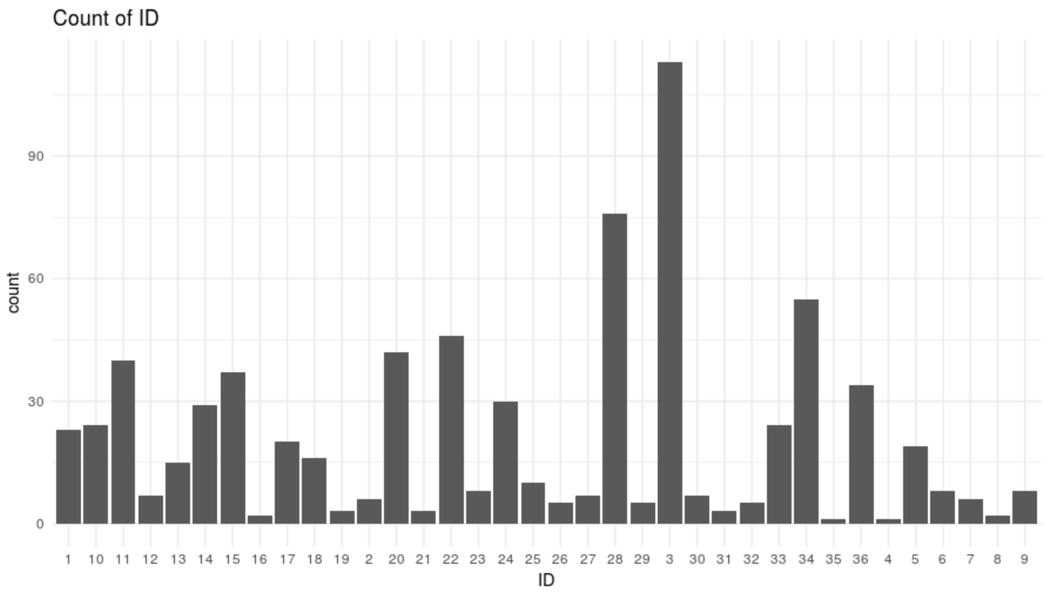
2.3 Distribution of Categorical Variables

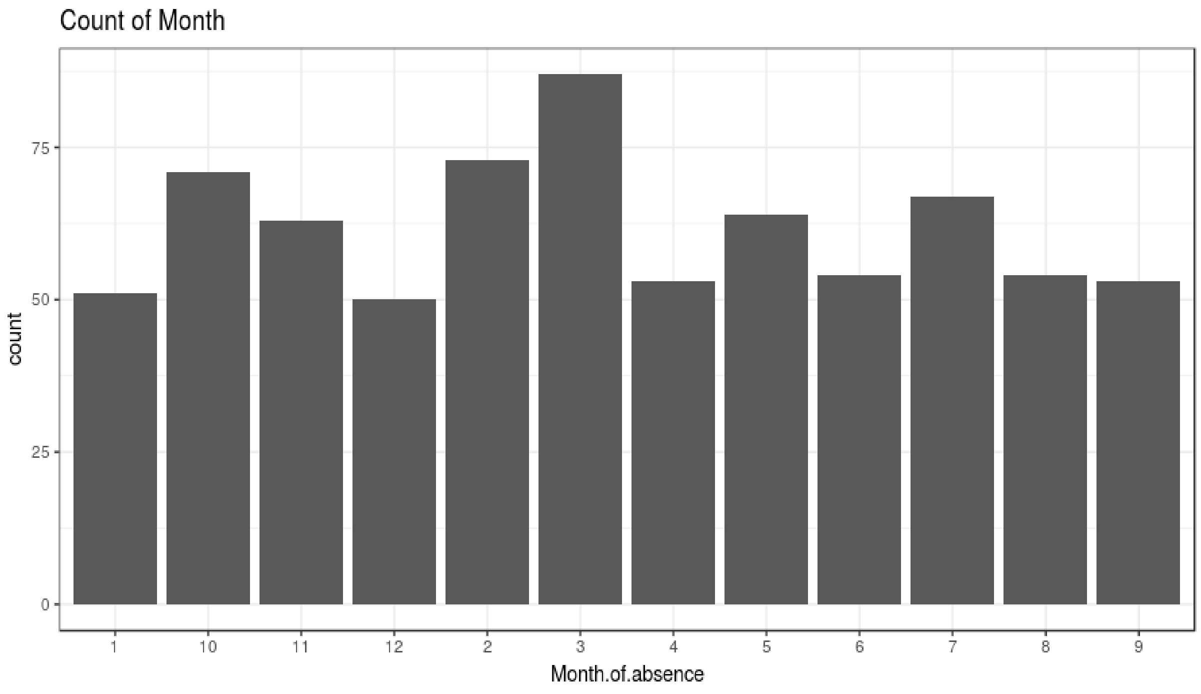
Bar graphs are used to visualize the distribution of categorical variables.

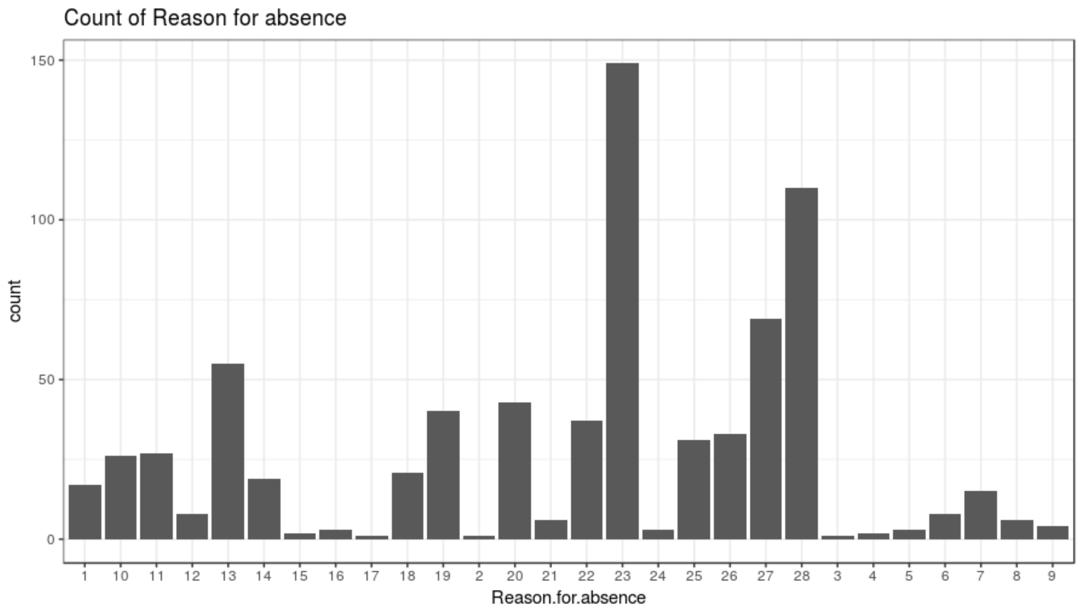
Employees who are social drinkers have more absent hours than those who do not drink.
Employees having zero, one or two children have more absent hours.
Employees with ID number 3 and 28 are absent the most.
Employees are absent the most on Mondays and the least on Thursdays.
Reason 23 and 28 are the reasons employee give the most for being absent.
Employees who have completed only high school education are absent more than others.
Employees are absent the most in the month of March.

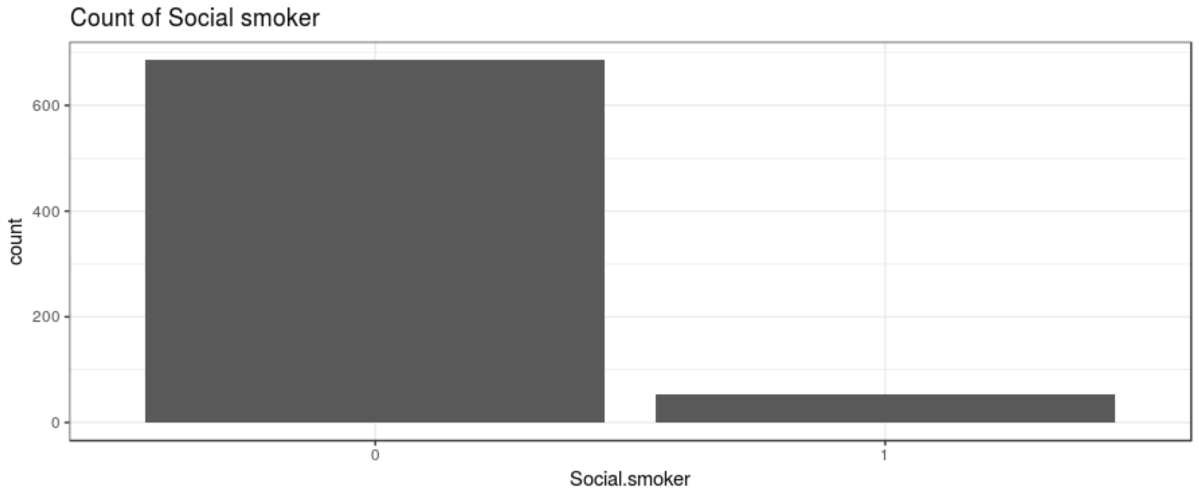





Count of ID
count
0
30
60
90
1 10 11 12 13 14 15 16 17 18 19 2 20 21 22 23 24 25 26 27 28 29 3 30 31 32 33 34 35 36 4 5 6 7 8 9
ID


Count of Month
count
0
25
50
75
1 10 11 12 2 3 4 5 6 7 8 9
Month.of.absence





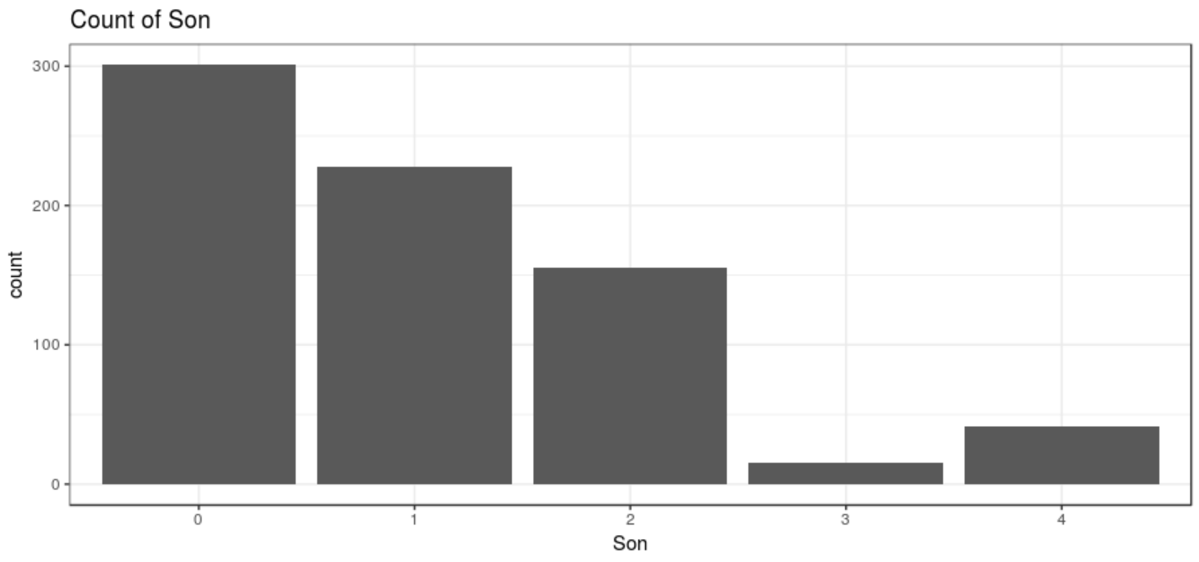
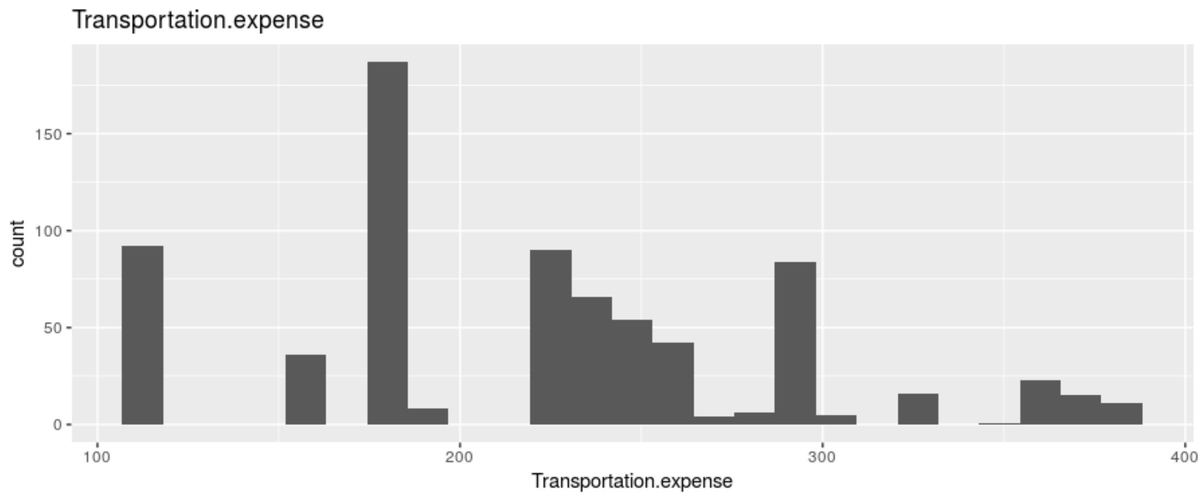
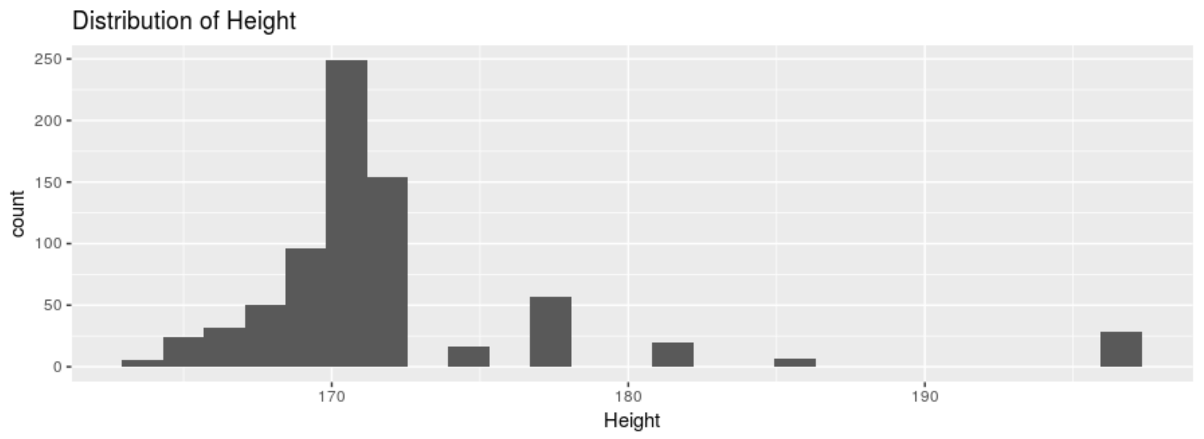
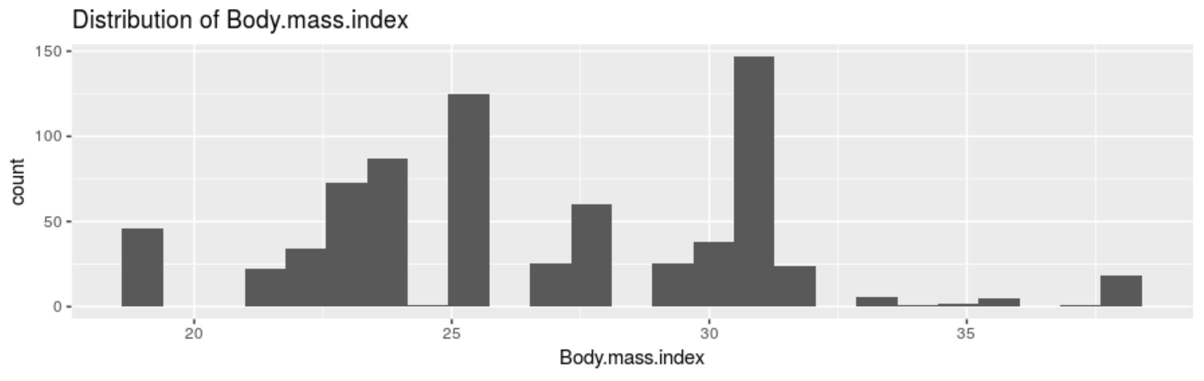


Fig 2.2 – Distribution of Categorical variables using Bar graph

2.4 Distribution of Continuous Variables







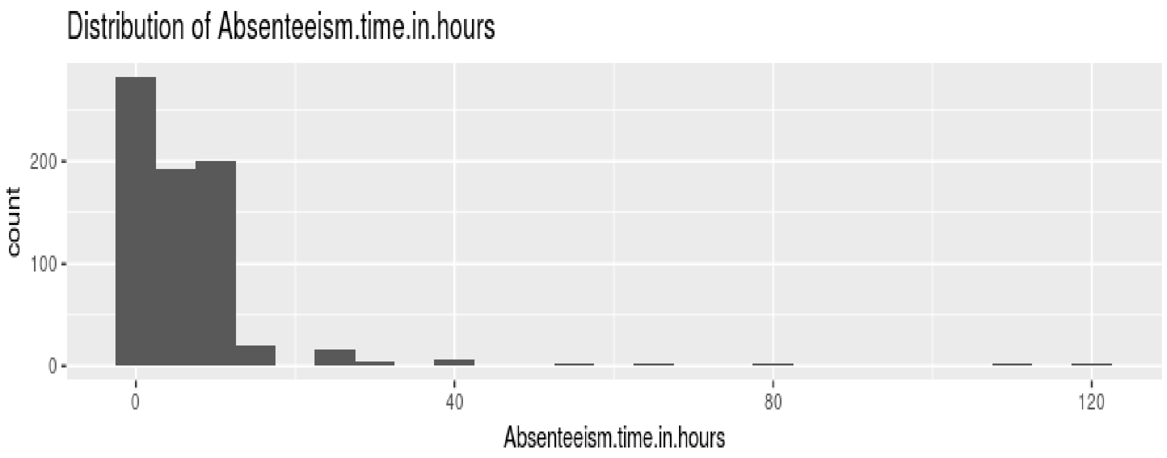
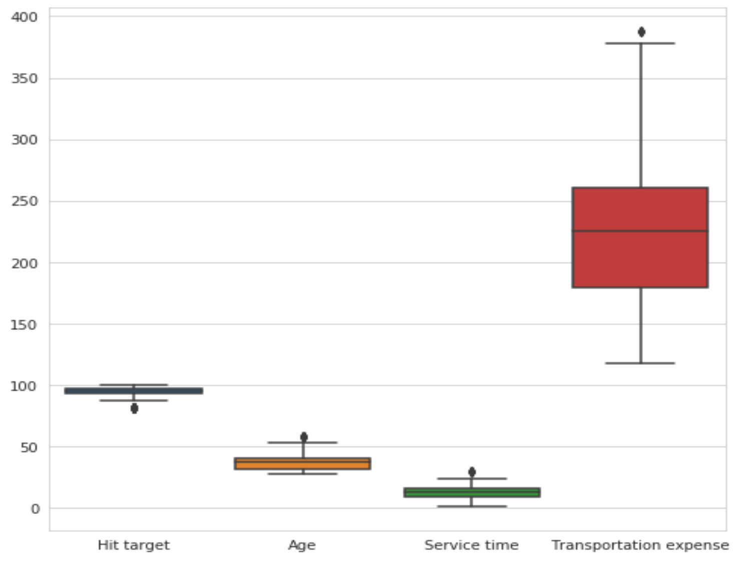


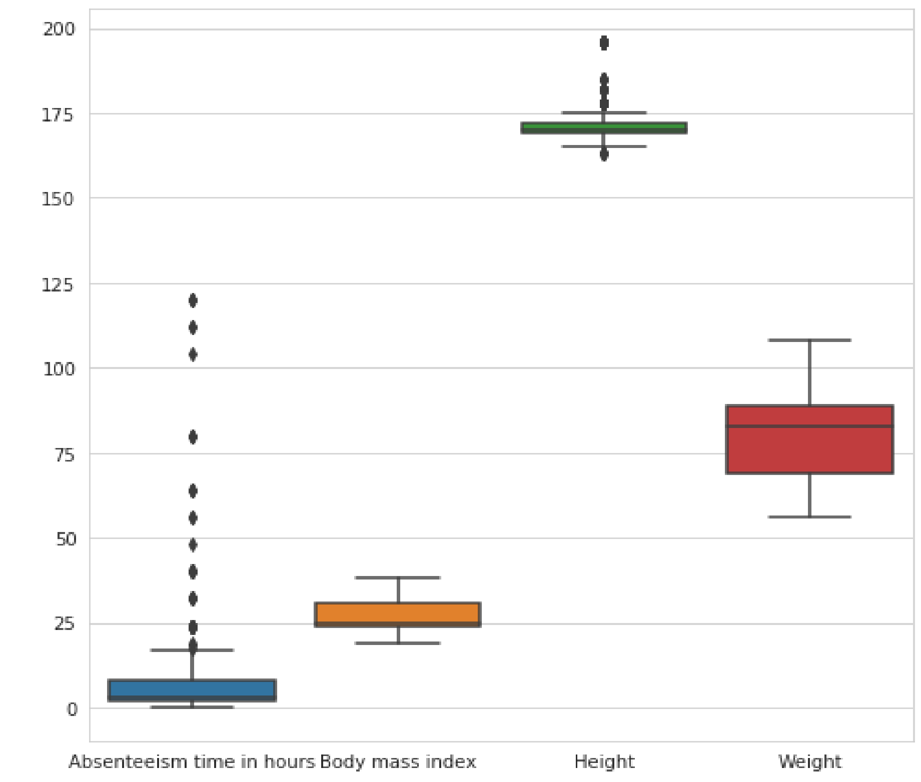
Fig 2.3 – Distribution of Continuous variables using histograms

2.5 Outlier Analysis

It can be observed from the distribution of variables that almost none of the variables are normally distributed. The skew in these distributions can be explained by the presence of outliers and extreme values in the data. One of the steps in pre-processing involves the detection and removal of such outliers. In this project, we use boxplot to visualize and remove outliers. Any value lying outside of the lower and upper whisker of the boxplot are outliers.

Variables excluding Distance from residence to work, Weight and Body mass index, contain outliers.





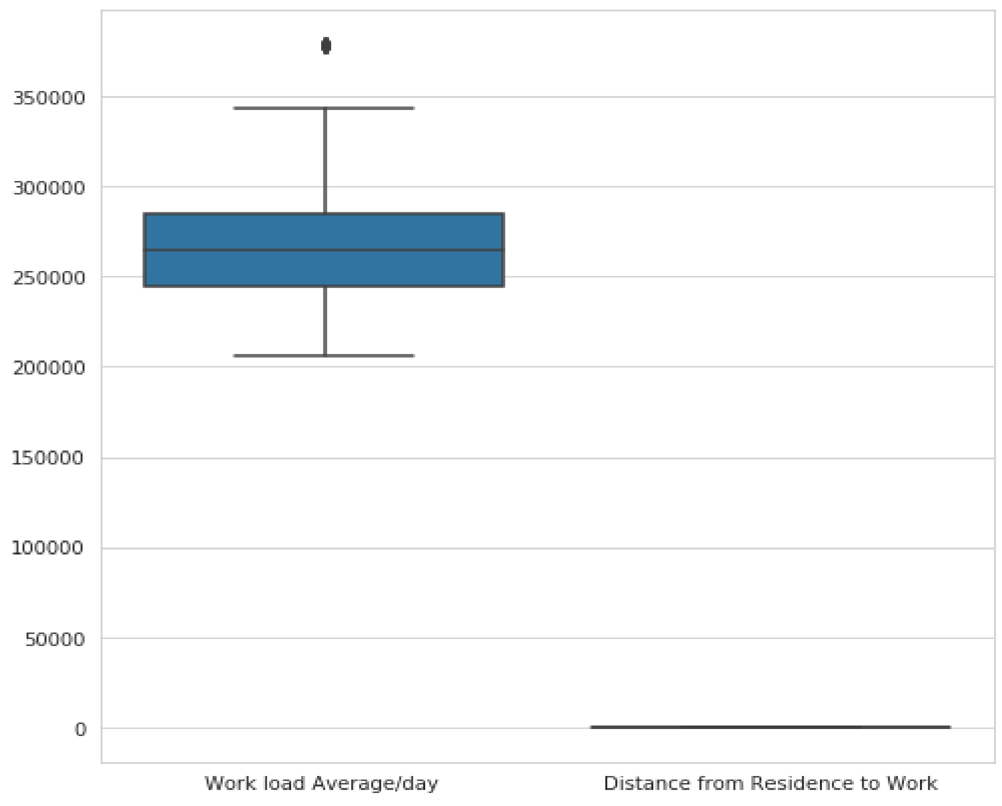
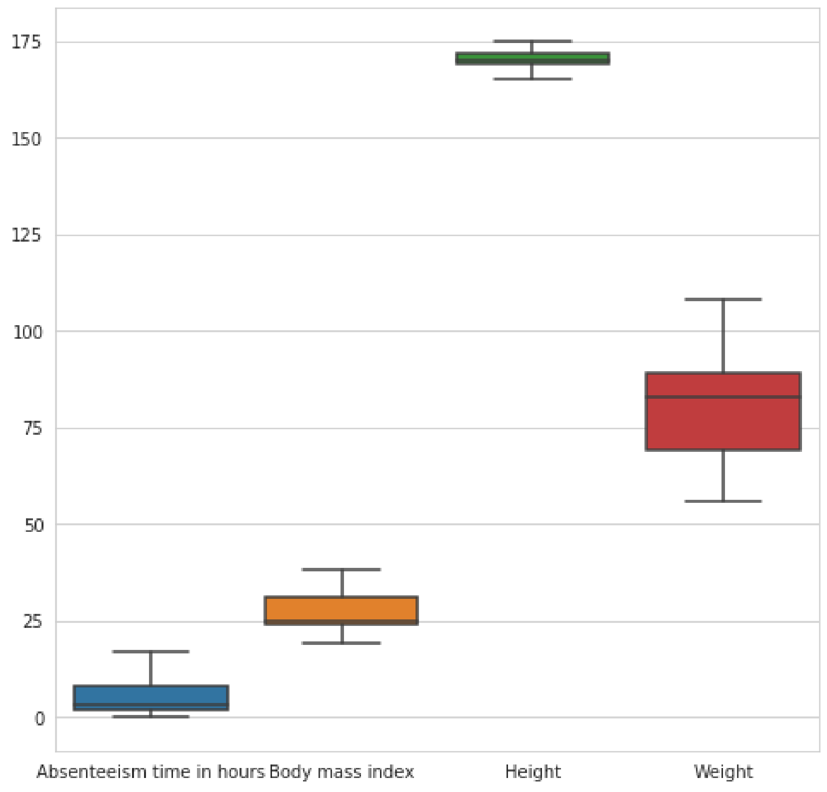


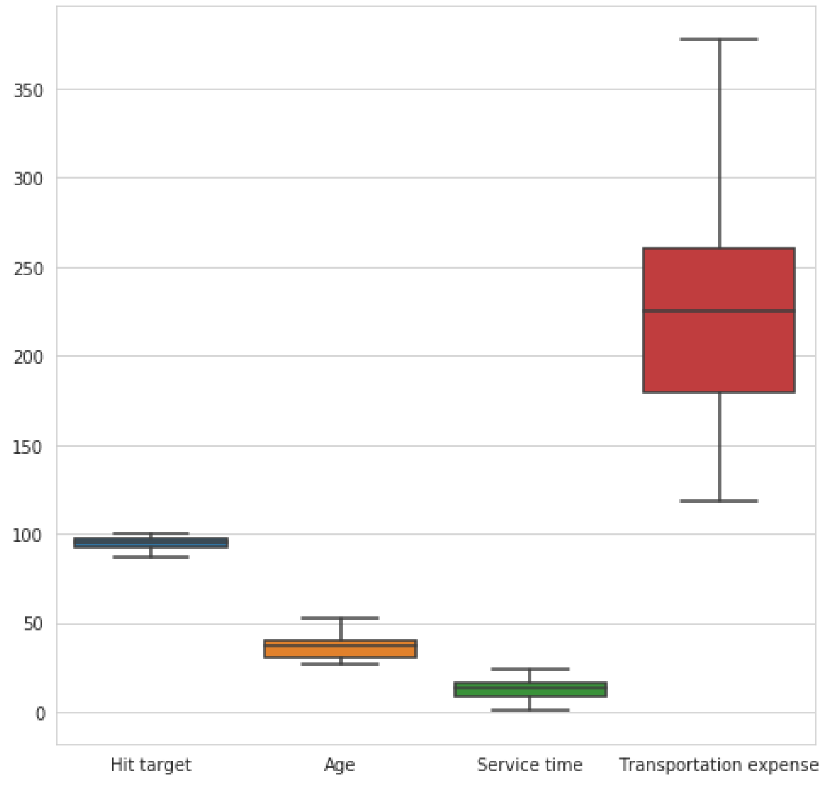
Fig 2.4 – Boxplots of continuous variables with outliers

Imputing outlier values:

Missing values obtained from boxplots are first converted to have NA values. Then these missing values are imputed using KNN imputation method.

Below figure shows the boxplots of variables after removing outliers.





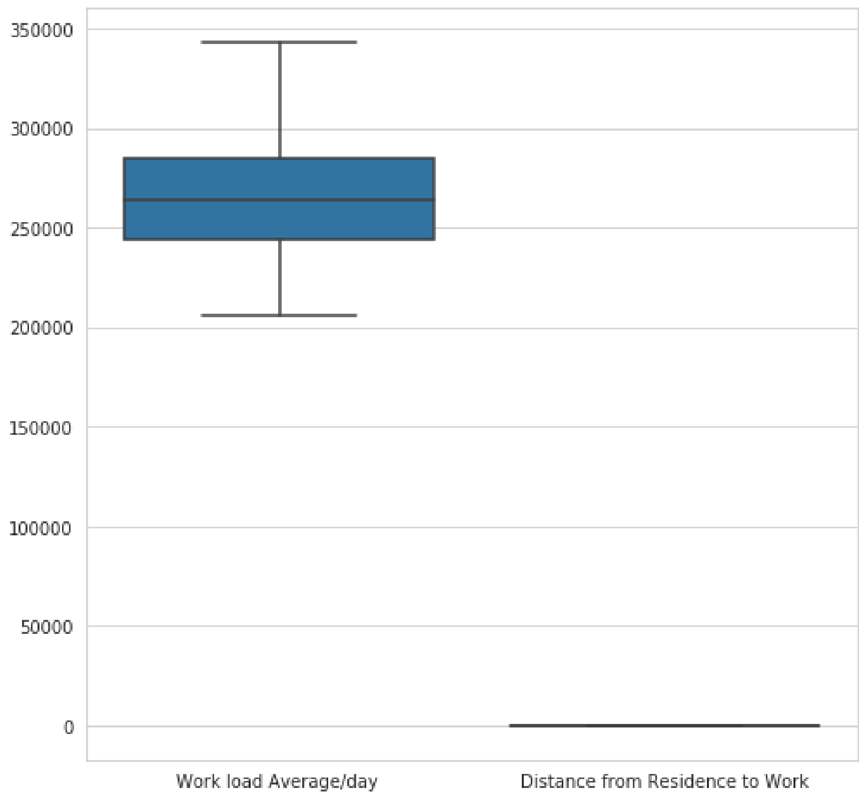


Fig 2.5 – Boxplots of continuous variables without outliers

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.

From correlation analysis we have found that Weight and Body Mass Index has high correlation (>0.7), so we have excluded the Body Mass Index column.

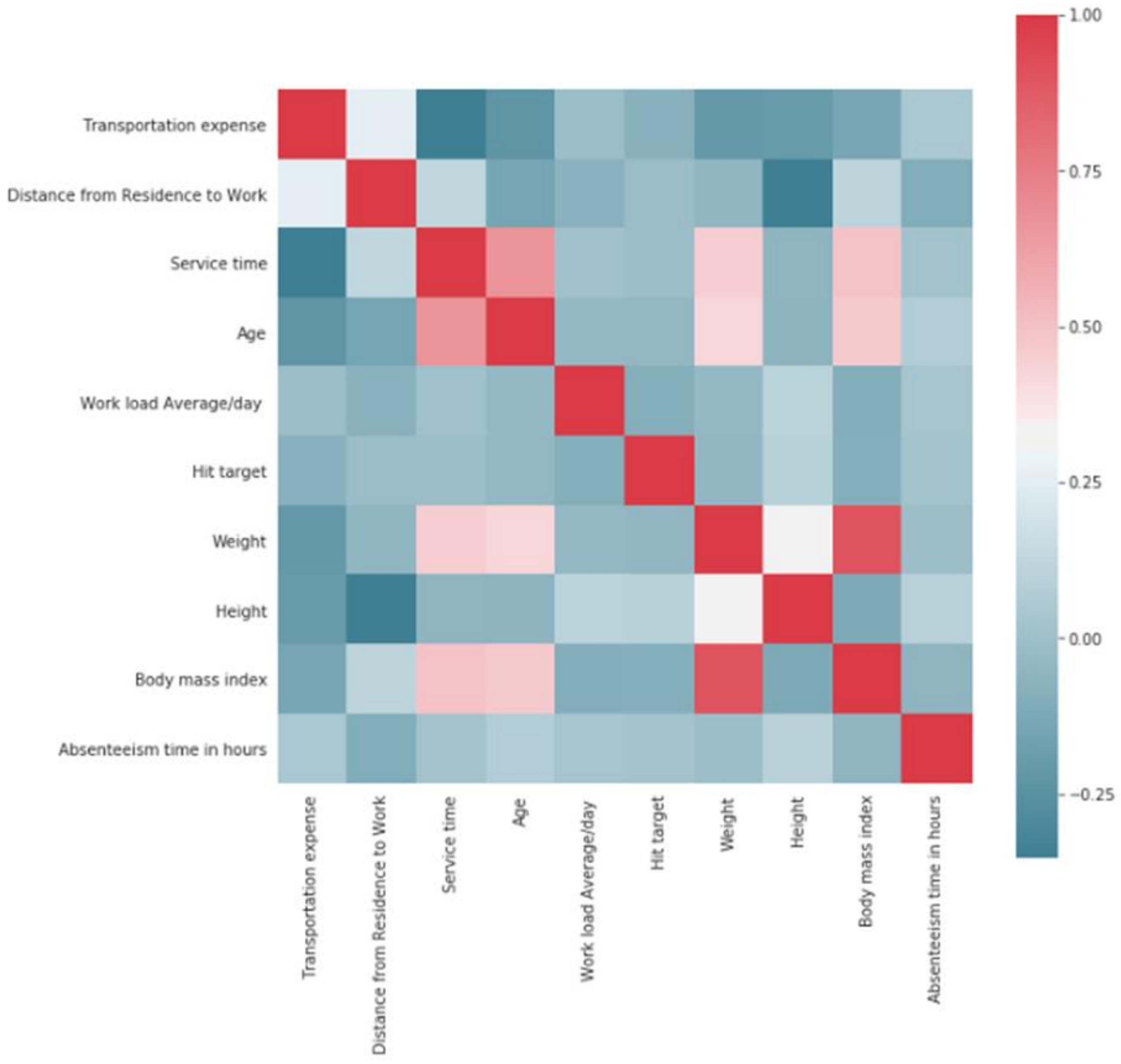


Fig 2.6 – Correlation plot of Continuous variables

2.7 Feature Scaling

Feature scaling is a method used to standardize the range of independent variables or features of data. In data processing, it is also known as data normalization and is generally performed during the data pre-processing step.

Most classifiers calculate the distance between two points by the Euclidean distance. If one of the features has a broad range of values, the distance will be governed by this feature. Therefore, the range of all features should be normalized so that each feature contributes proportionately to final distance. Since our data is not uniformly distributed, we will use Normalization as Feature Scaling Method.

2.8 Principal Component Analysis (PCA)

Principal component analysis is a method of extracting important variables (in form of components) from a large set of variables available in a data set. It extracts low dimensional set of features from a high dimensional data set with a motive to capture as much information as possible.

After creating dummy variable of categorical variables, the data would have 116 columns and 740 observations. This high number of columns leads to bad accuracy.

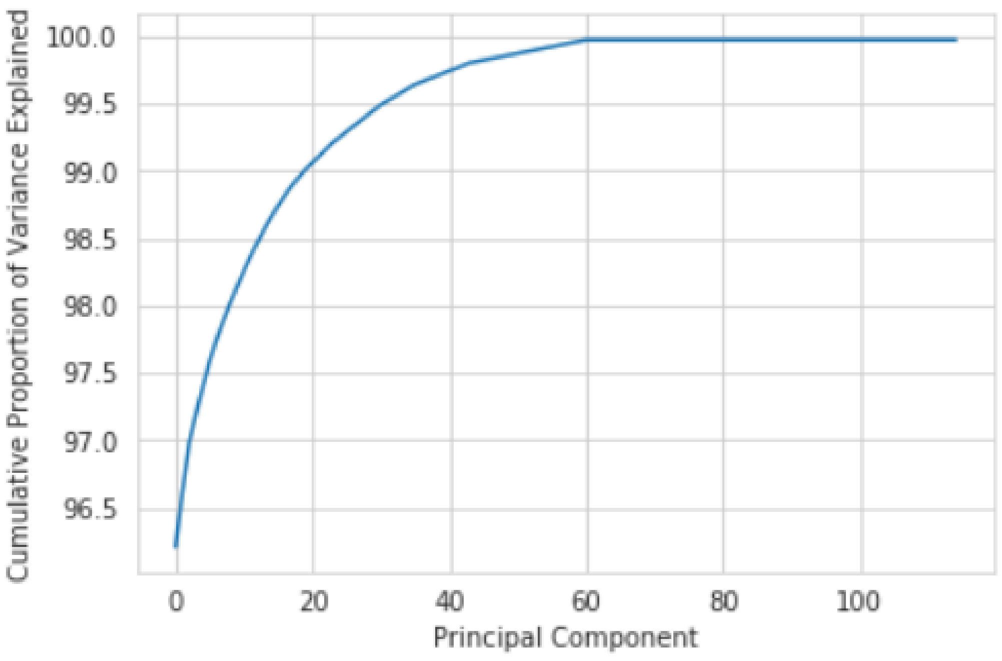


Fig 2.7 – Cumulative Graph of Principal Components

After applying PCA algorithm and observing the above Cumulative graph, it can be observed that almost 95% of the data can be explained by 45 variables out of 116. Hence, we choose only 45 variables as input to the models.

Chapter 3: Modelling

3.1 Model Selection

After a thorough pre-processing, we will be using some regression models on our processed data to predict the target variable. The target variable in our model is a continuous variable i.e., Absenteeism time in hours. Hence the models that we choose are Linear Regression, Decision Tree and Random Forest. The error metric chosen for the given problem statement is Root Mean Square Error (RMSE).

3.2 Decision Tree

Decision Tree algorithm belongs to the family of supervised learning algorithms. Decision trees are used for both classification and regression problems.

A decision tree is a tree where each node represents a feature (attribute), each link (branch) represents a decision (rule) and each leaf represents an outcome (categorical or continues value). The general motive of using Decision Tree is to create a training model which can use to predict class or value of target variables by learning decision rules inferred from prior data (training data).

The RMSE values and R^2 values for the given project in R and Python are:

DECISION TREE	RMSE	R^2
R	0.4427	0.9787
PYTHON	0.07939	0.9999

3.3 Random Forest

Random Forest is a supervised learning algorithm. Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction. It can be used for both classification and regression problems. The method of combining trees is known as an ensemble method. Assembling is nothing but a combination of weak learners (individual trees) to produce a strong learner.
The number of decision trees used for prediction in the forest is 500.

RANDOM FOREST	RMSE	R^2
R	0.4361	0.9828
PYTHON	0.0004	0.9999

3.4 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.

LINEAR REGRESSION	RMSE	R^2
R	0.0030	0.9999
PYTHON	0.0013	0.9999

Chapter 4: Conclusion

4.1 Model Evaluation

In the previous chapter we have seen the Root Mean Square Error (RMSE) and R-Squared Value of different models. Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are, RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit. Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance and has the useful property of being in the same units as the response variable. Lower values of RMSE and higher value of R-Squared Value indicate better fit.

4.2 Model Selection

From the observation of all RMSE Value and R-Squared Value we have concluded that **Linear Regression Model** has minimum value of RMSE, and its R-Squared Value is also maximum.

4.3 Solutions of Problem Statement

4.3.1 What changes company should bring to reduce the number of absenteeism?

Solution:

a. It can be observed that employees having education only till high school tend to be absent more than others. So, the company can either hire employees who have at least graduated from college or inform those employees who have completed only their high school education to reduce the number of hours they are absent.

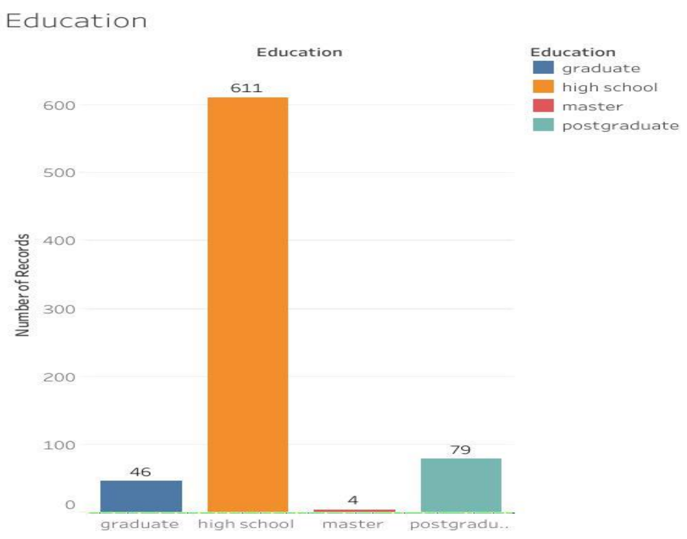


Fig 4.1 – Education vs Absent Hours

b. Employees with ID 3, 28 and 34 are some of the employees who are absent the most. The company may act warn such employees to reduce being absent a lot or if repeated further, it can against them if necessary.

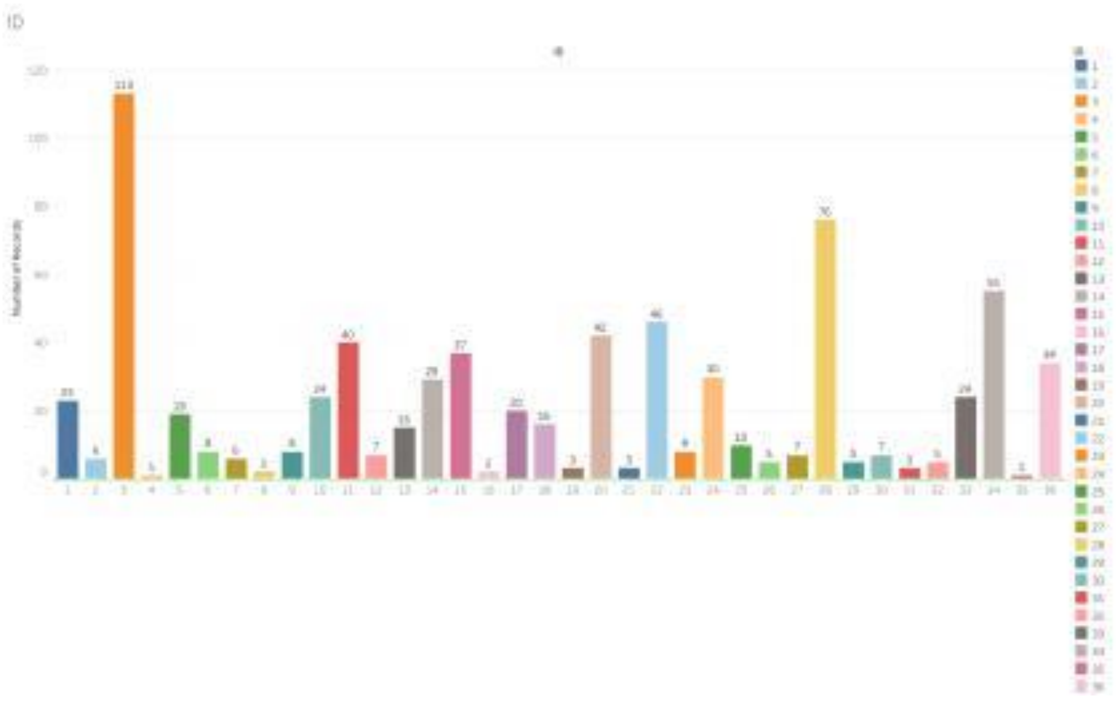


Fig 4.2 – ID vs Absent Hours

c. The reasons most used by employees to be absent are reason 13, 20, 23 and 28. These reasons include Medical consultation, Dental appointments, morbidity, mortality and diseases of musculoskeletal system and connective tissue. The company XYZ can help in informing employees on how to keep themselves healthier by having monthly campus consultations.

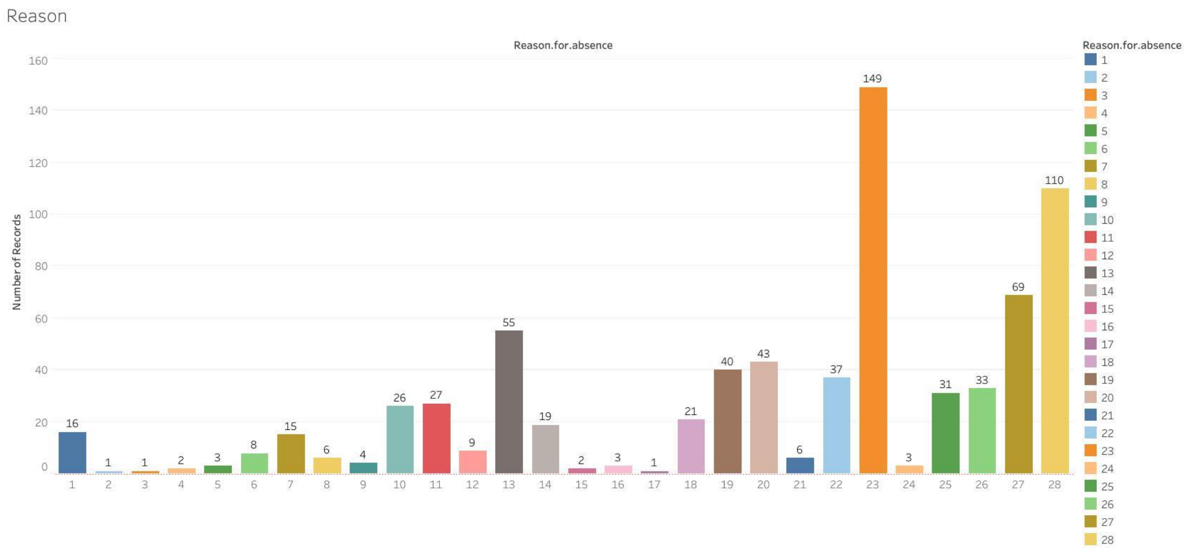


Fig 4.3 – Reason of Absence vs Absent Hours

d. People who tend to be social drinkers tend to be more absent than those who don’t drink. XYZ can keep a track of those people and inform those employees to reduce the intake of alcohol during working days.

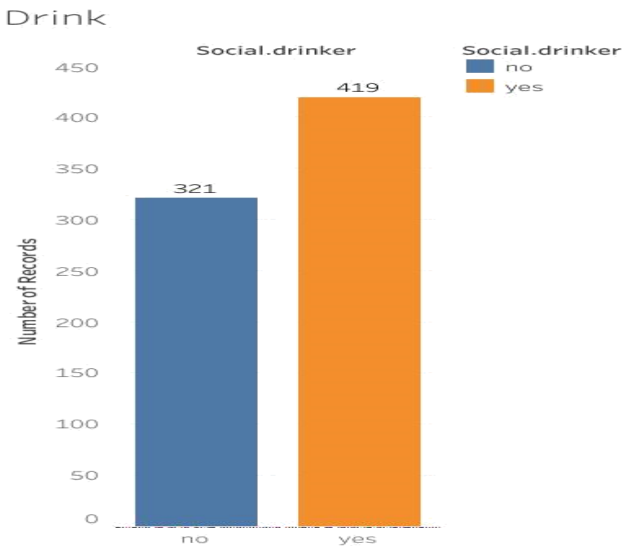


Fig 4.4 – Social Drinker vs Absent Hours

e. Employees are absent the most on Mondays with absent hours equal to 1426 and Tuesdays with absent hours equal to 1322.4. XYZ can inform employees to not take as many absent hours on such days.

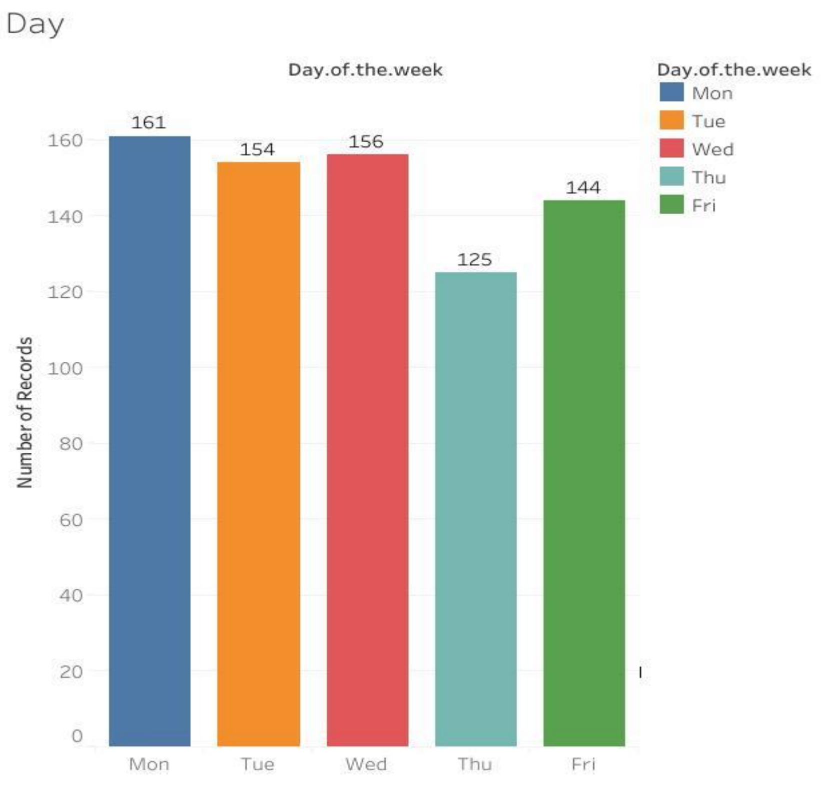


Fig 4.5 – Day of the Week vs Absent Hours

f. Employees are mostly absent during Spring Season.

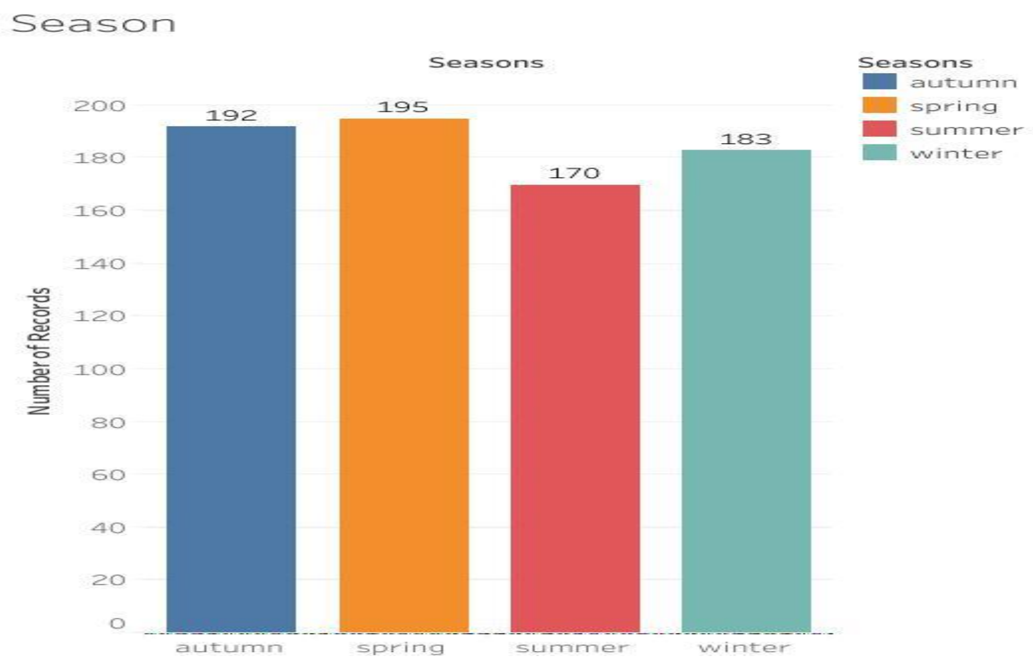


Fig 4.6 – Season vs Absent Hours

g. Employees having a maximum of two children or no child at all are absent the most.

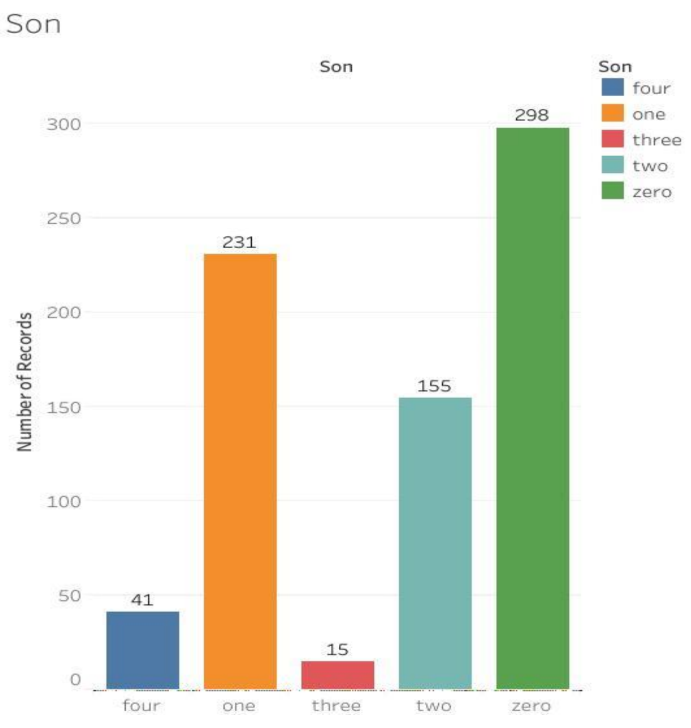


Fig: 4.7 – Sons vs Absent Hours

4.3.2 How much losses every month can we project in 2011 if same trend of absenteeism continues?

Solution:

Considering the losses to be the absenteeism time in hours, if the same trend of absenteeism continues, then the total total losses per month is as shown in the graph below.

Employees are absent the most in the month of March, with total Absenteeism hours equal to 458.2 hours. Employees are absent the least in the month of January, with total Absenteeism hours equal to 173.6.

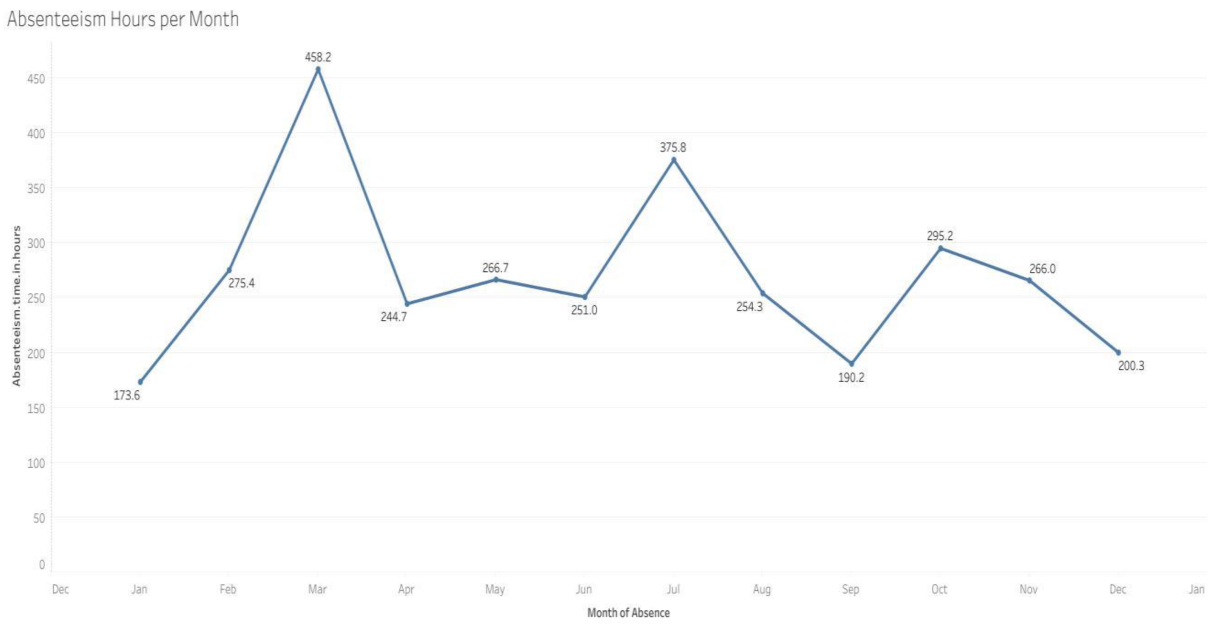


Fig 4.8 – Absenteeism Hours per Month

Below table shows the monthly losses of absenteeism hours:

Month	**Absent Hours**
January	173.6
February	275.4
March	458.2
April	244.7
May	266.7
June	251
July	375.8
August	254.3
September	190.2
October	295.2
November	266
December	200.3

Appendix A: Figures

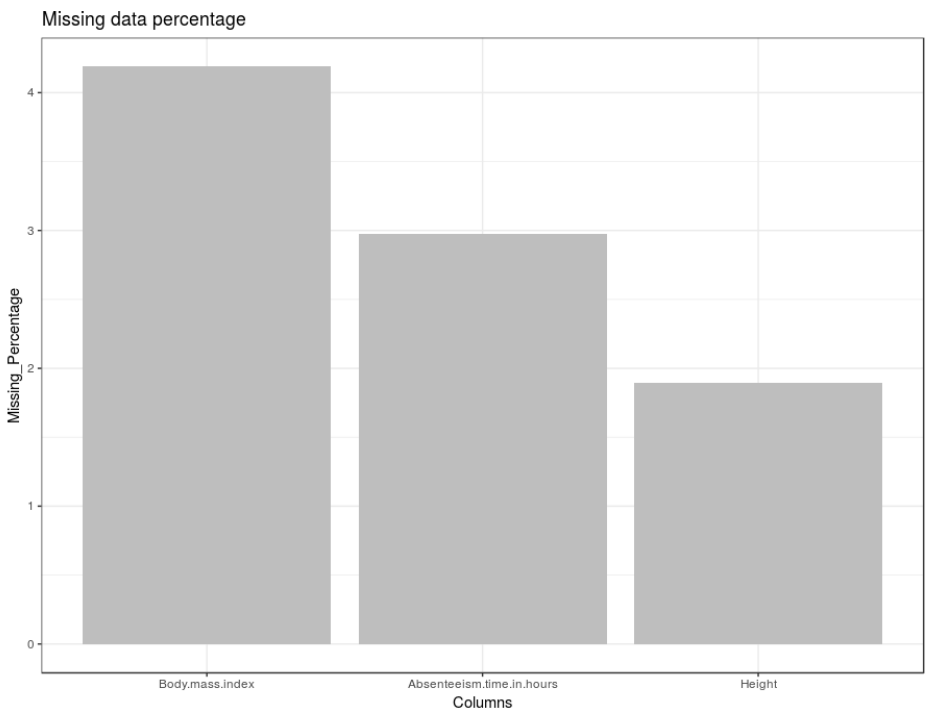
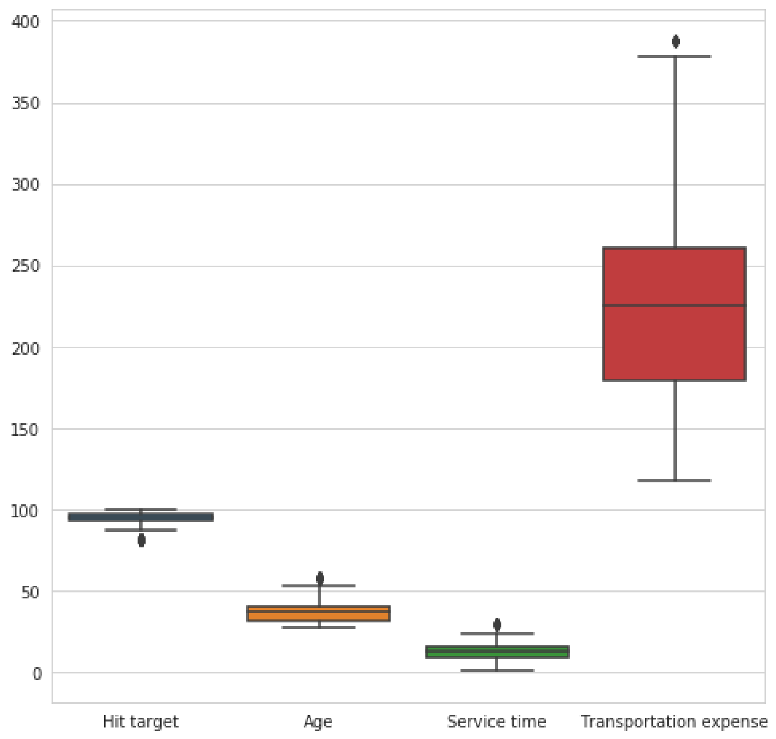
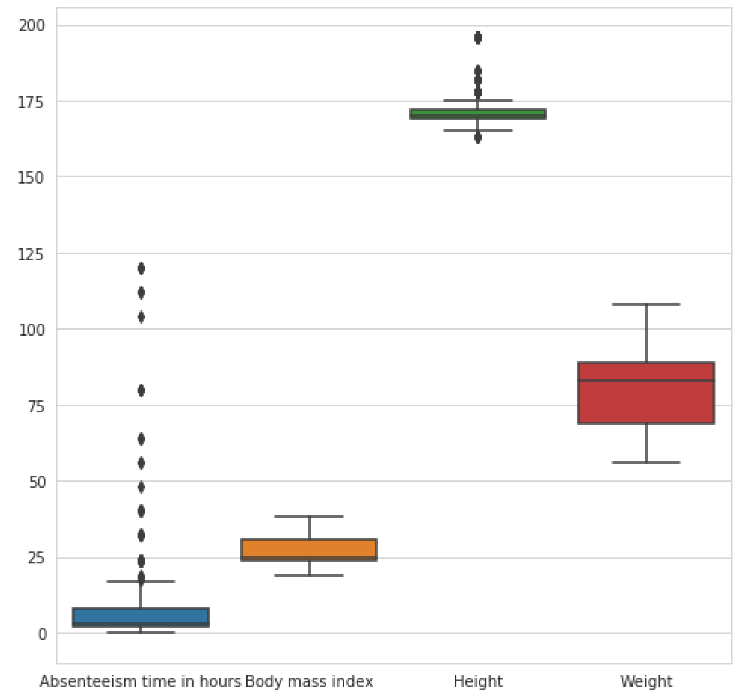


Fig 5.1 – Missing value Percentage





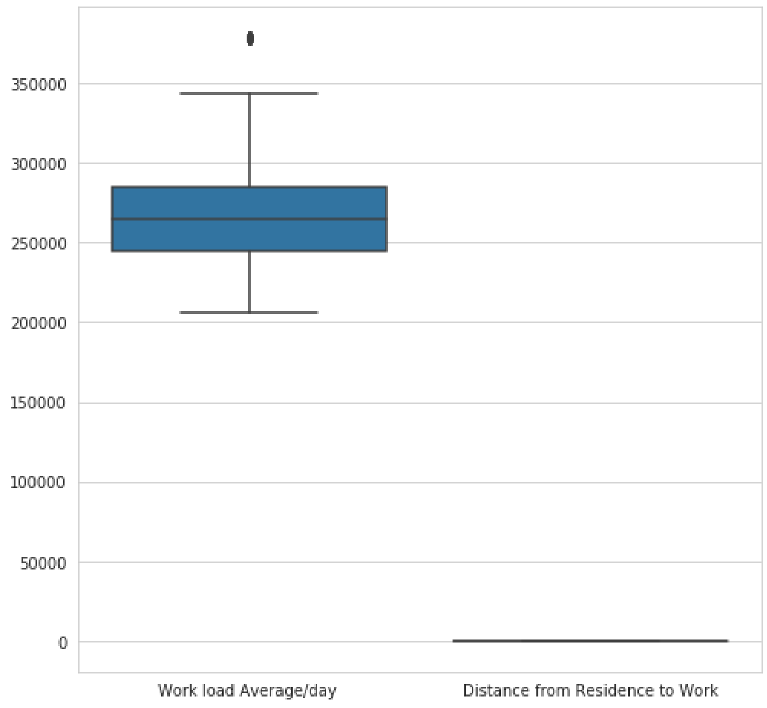
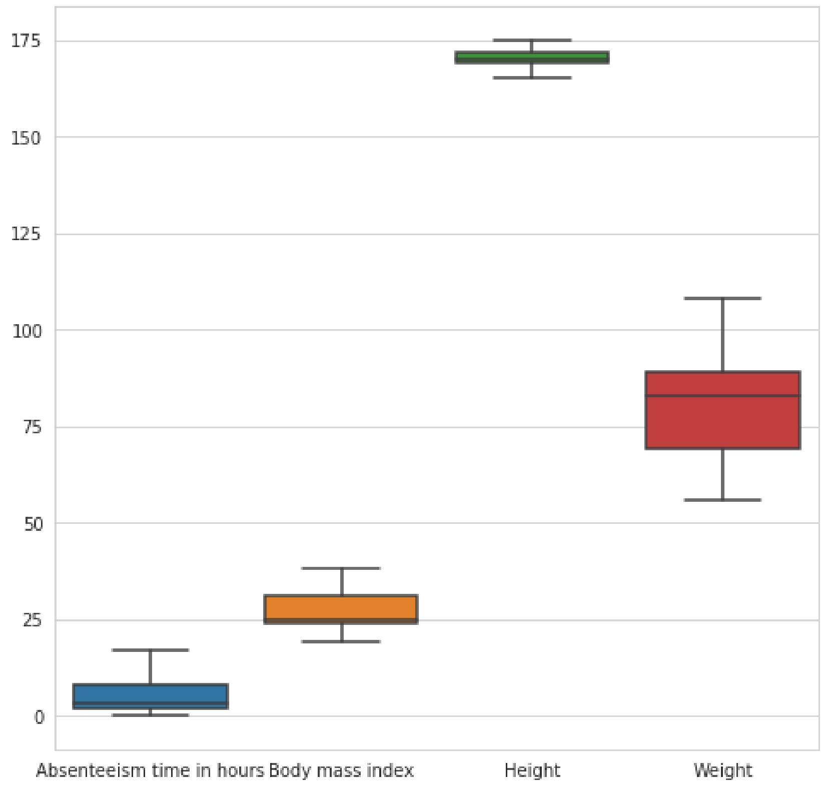
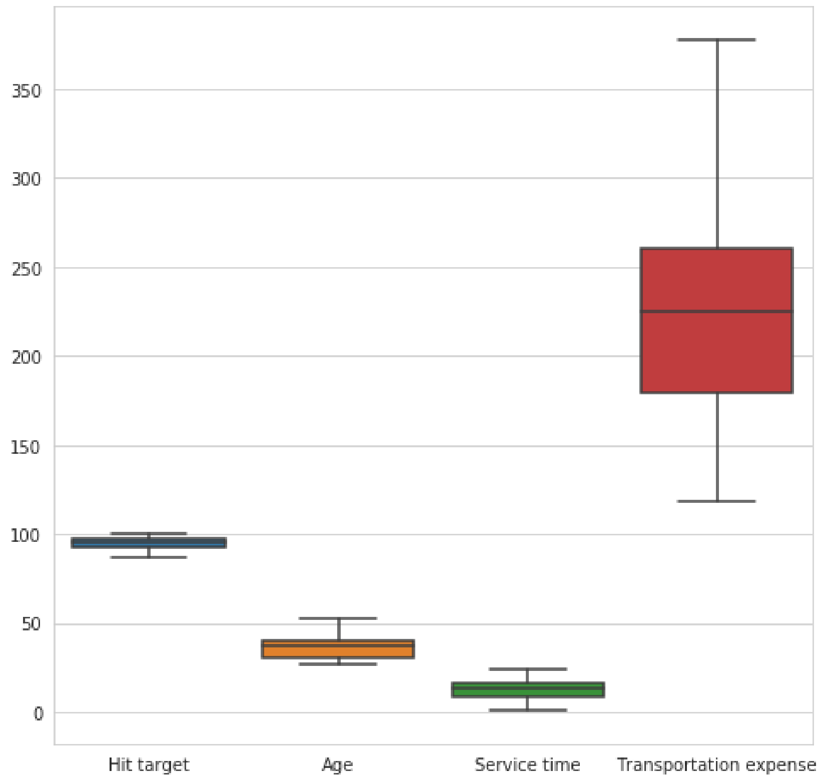


Fig 5.2 – Boxplots of continuous variables with outliers



175
150
125
100
75
50
25
0
Absenteeism time in hours
Body mass index
Height
Weight



350
300
250
200
150
100
50
0
Hit target
Age
Service time
Transportation expense

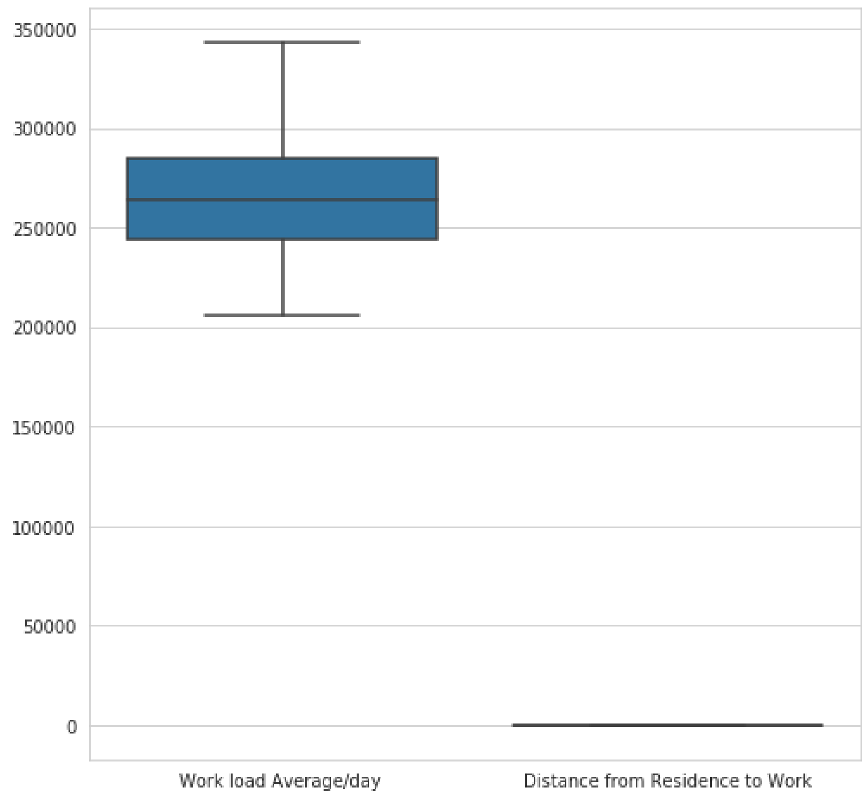
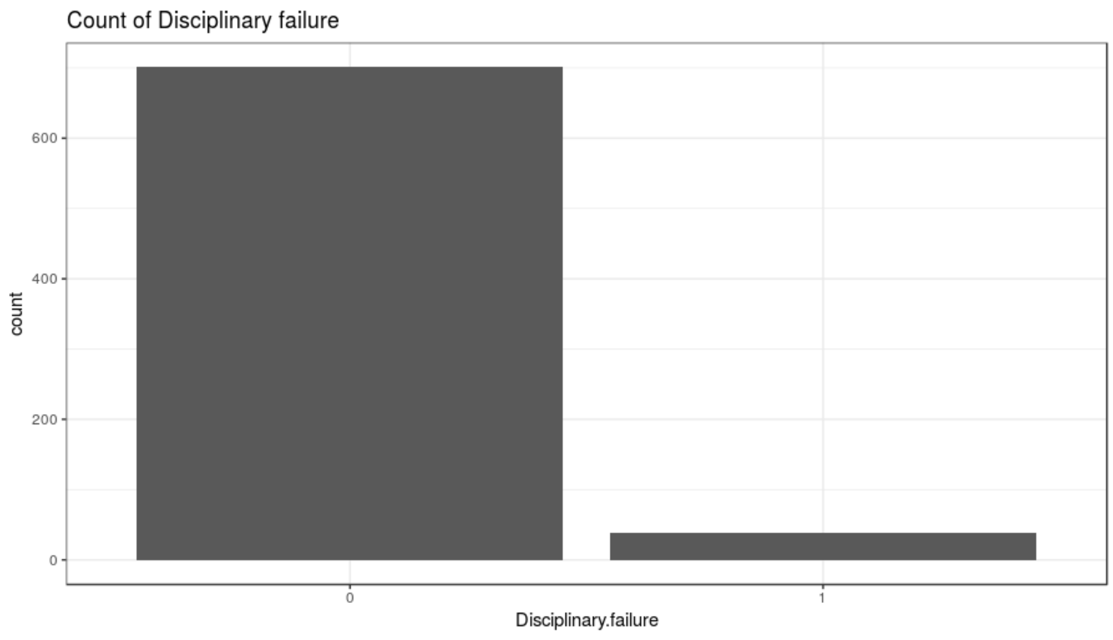
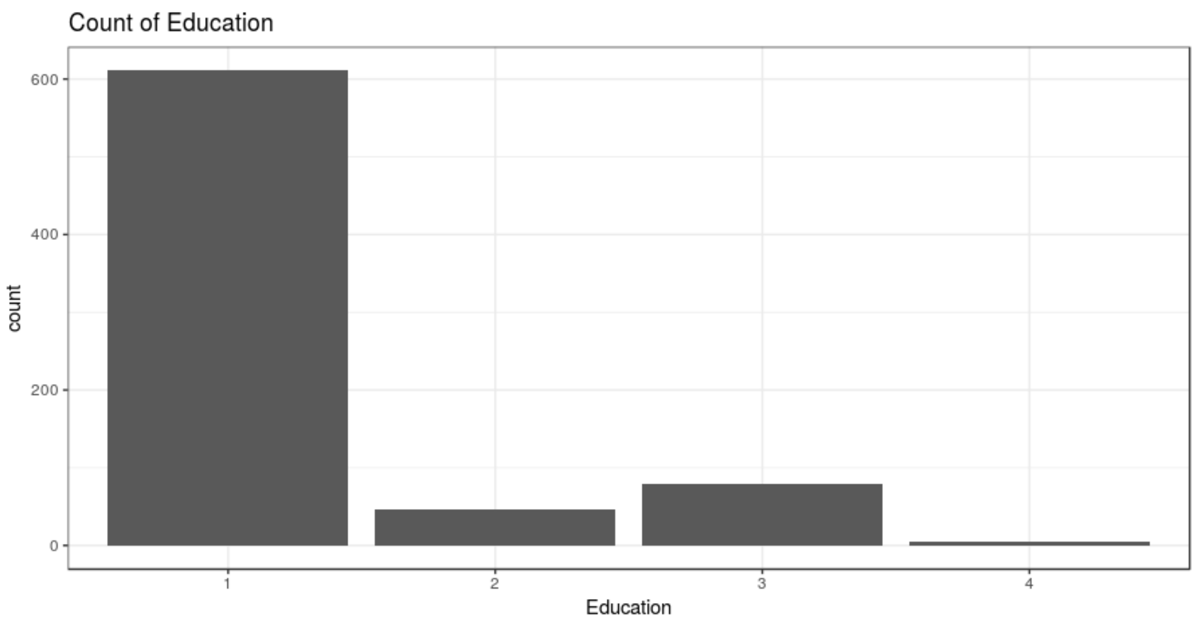
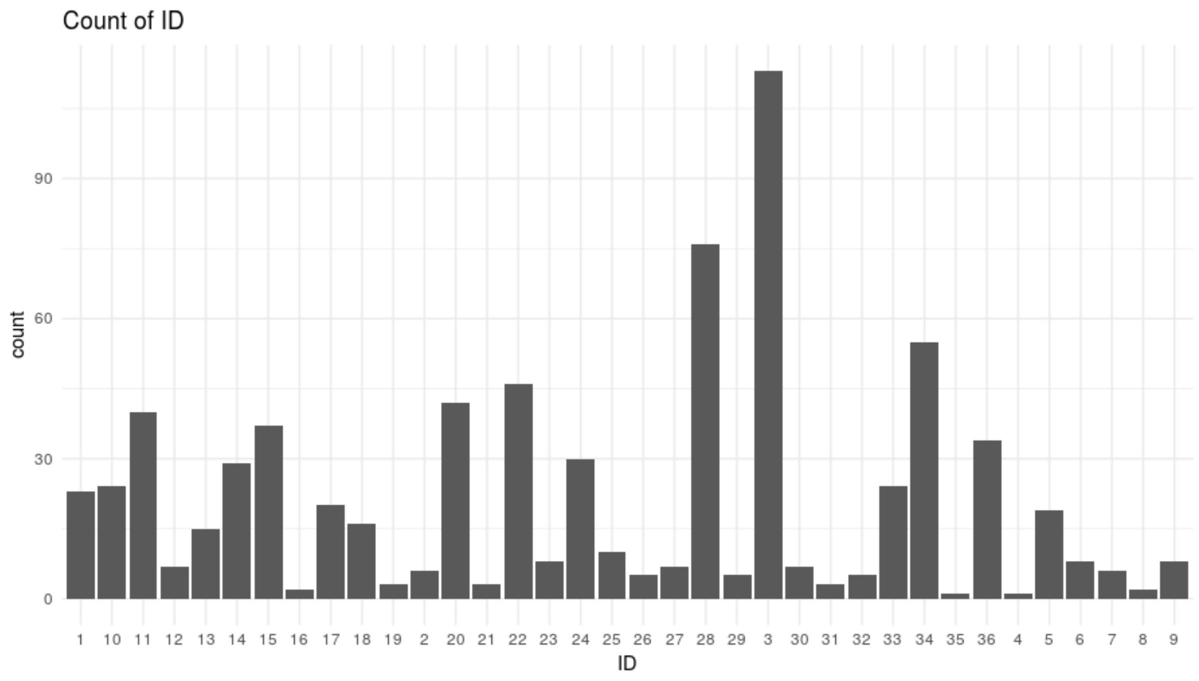
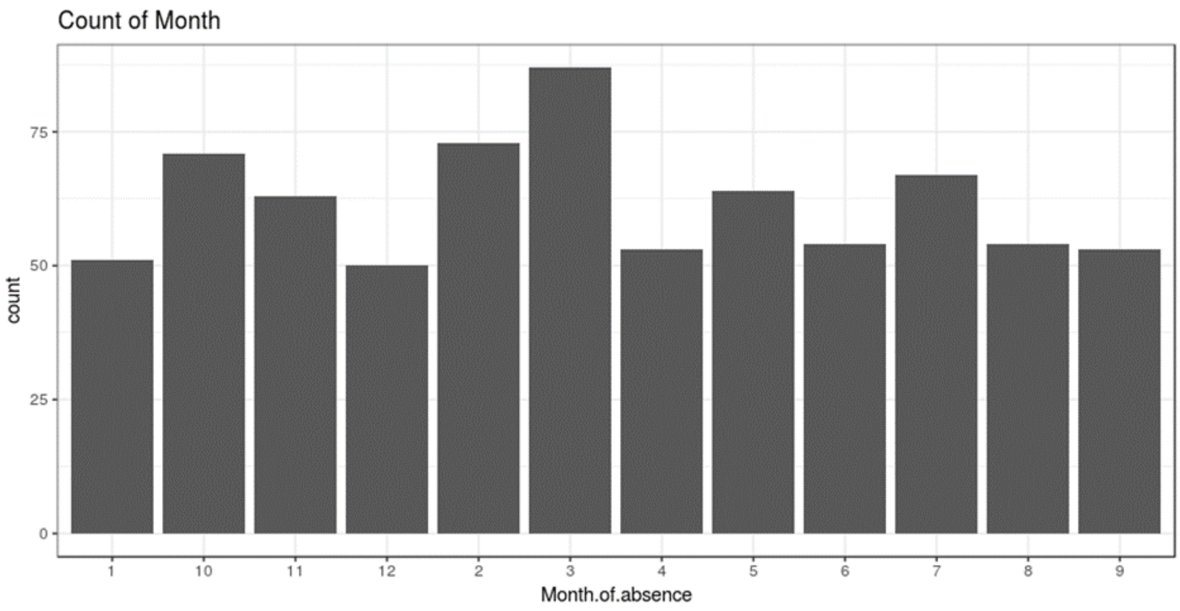


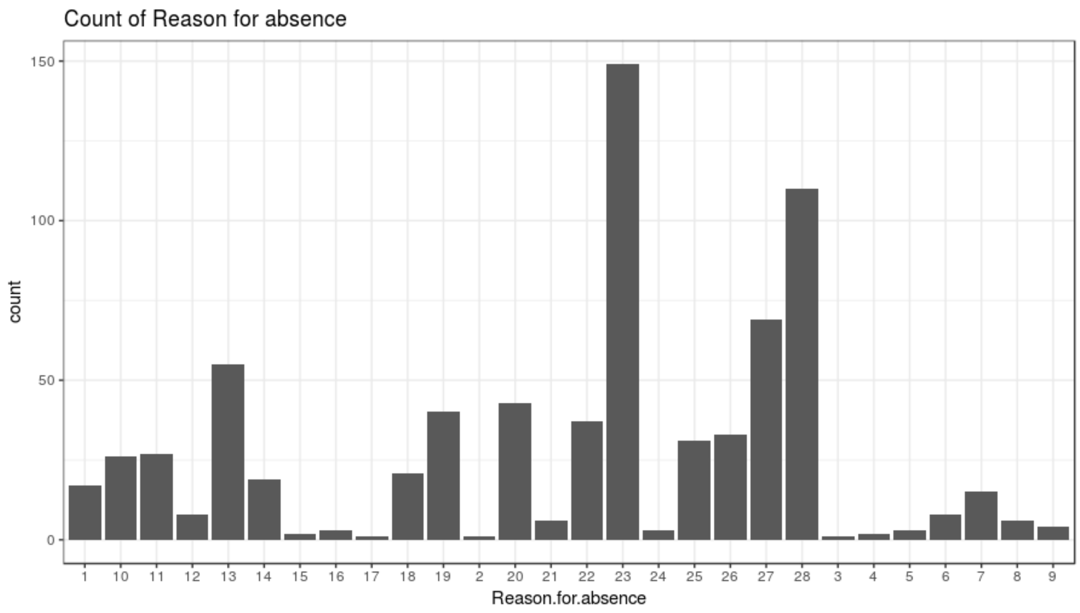
Fig 5.3 – Boxplots of continuous variables without outliers

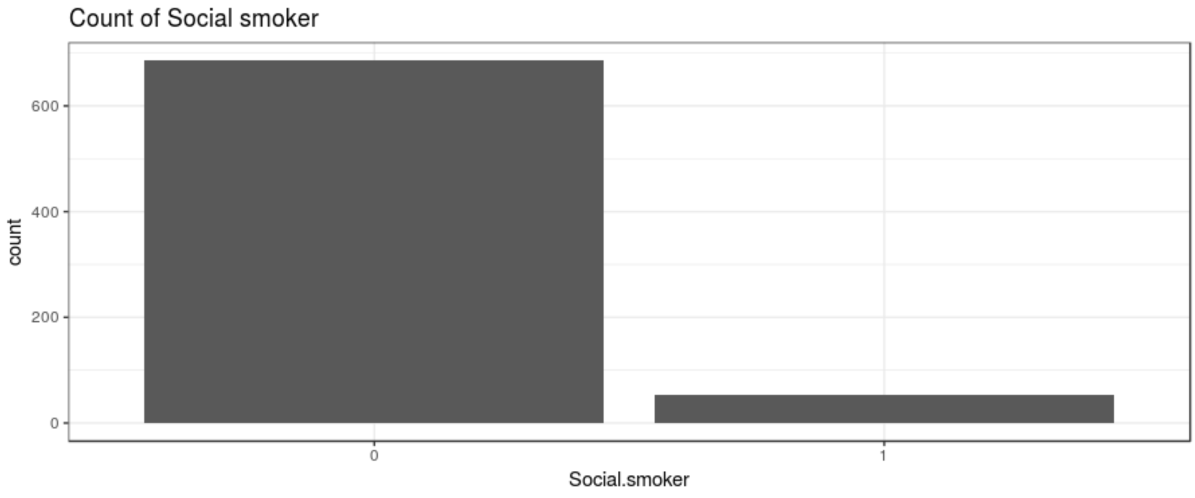



Count of Education
count
600
400
200
0
1
2
3
4
Education


Count of ID
count
90
60
30
0
1
10
11
12
13
14
15
16
17
18
19
2
20
21
22
23
24
25
26
27
28
29
3
30
31
32
33
34
35
36
4
5
6
7
8
9
ID


Count of Month
count
Month.of.absence
0
25
50
75
1
10
11
12
2
3
4
5
6
7
8
9


Count of Reason for absence
count
Reason.for.absence
0
50
100
150
1
10
11
12
13
14
15
16
17
18
19
2
20
21
22
23
24
25
26
27
28
3
4
5
6
7
8
9


Count of Social smoker
count
Social.smoker
0
200
400
600
0
1

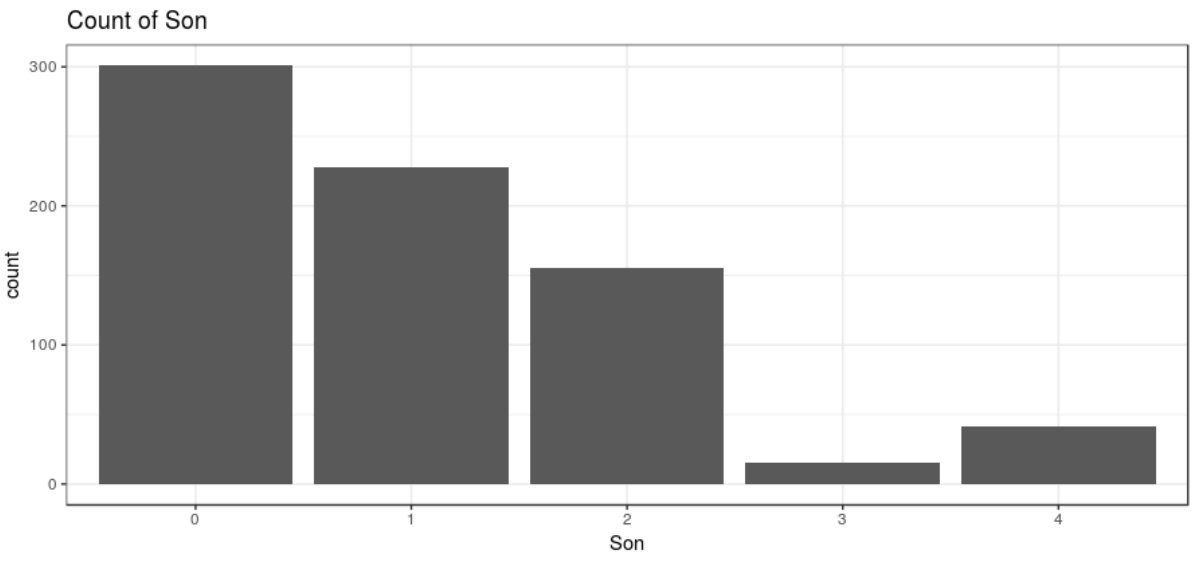
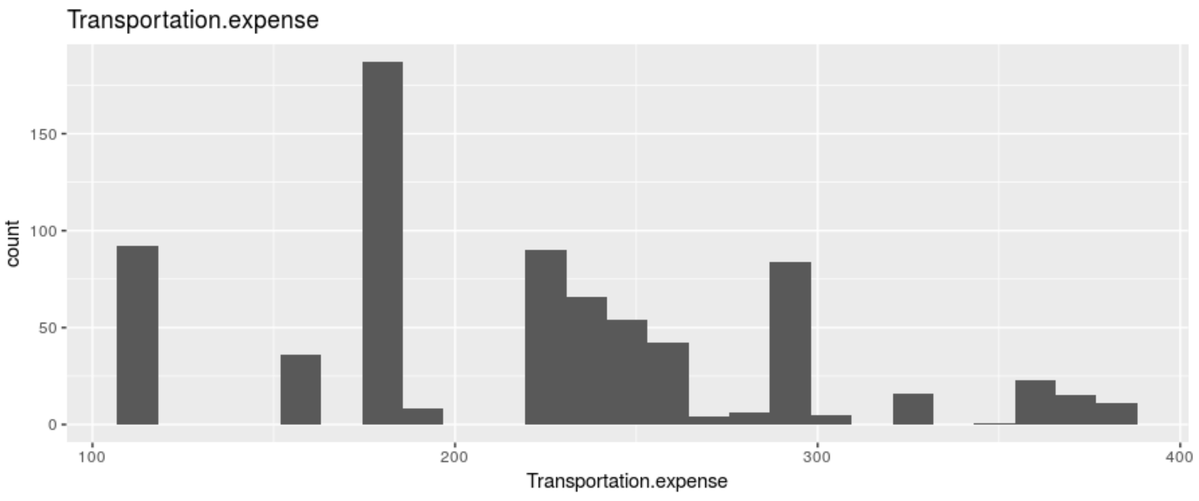
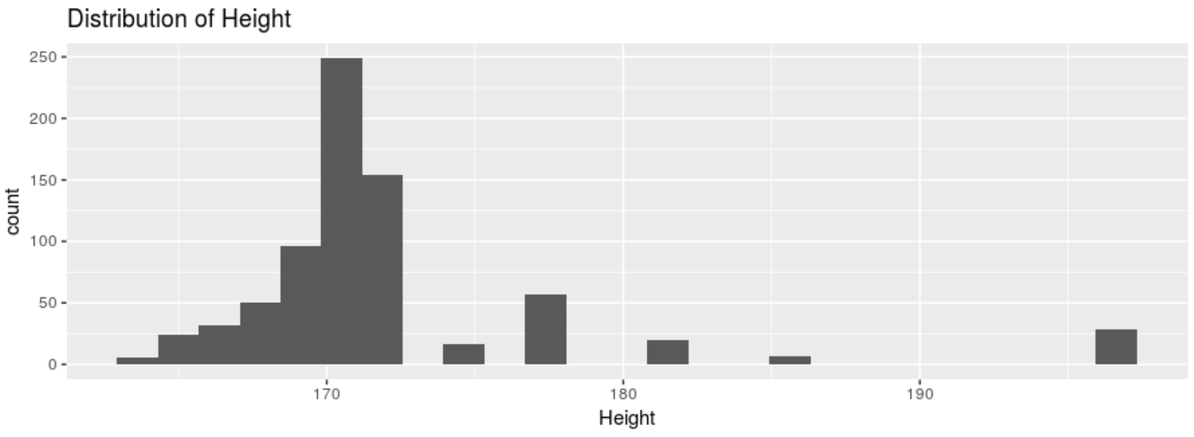
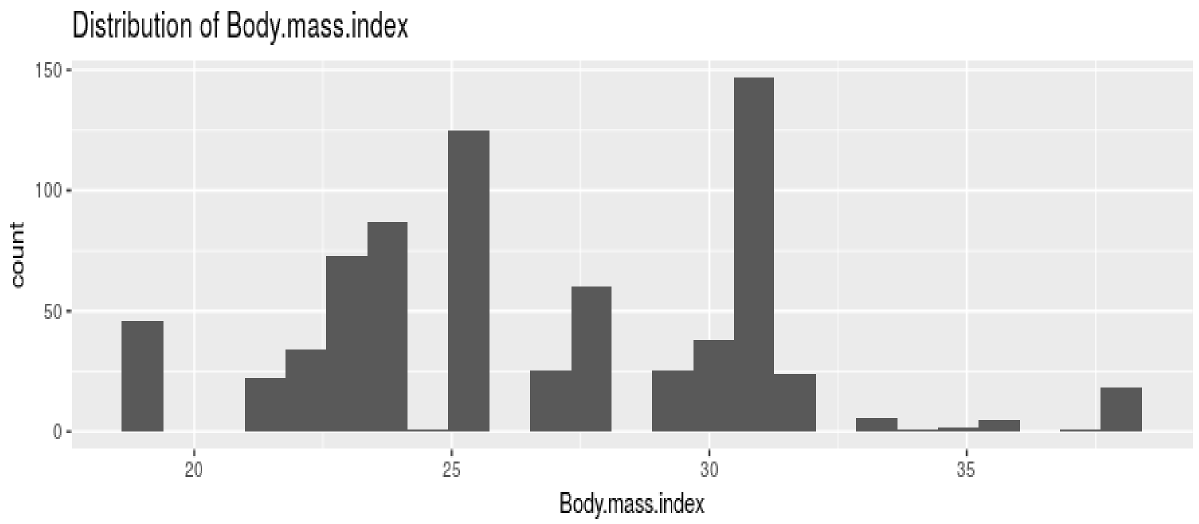


Fig 5.4 – Distribution of Categorical variables using Bar graph







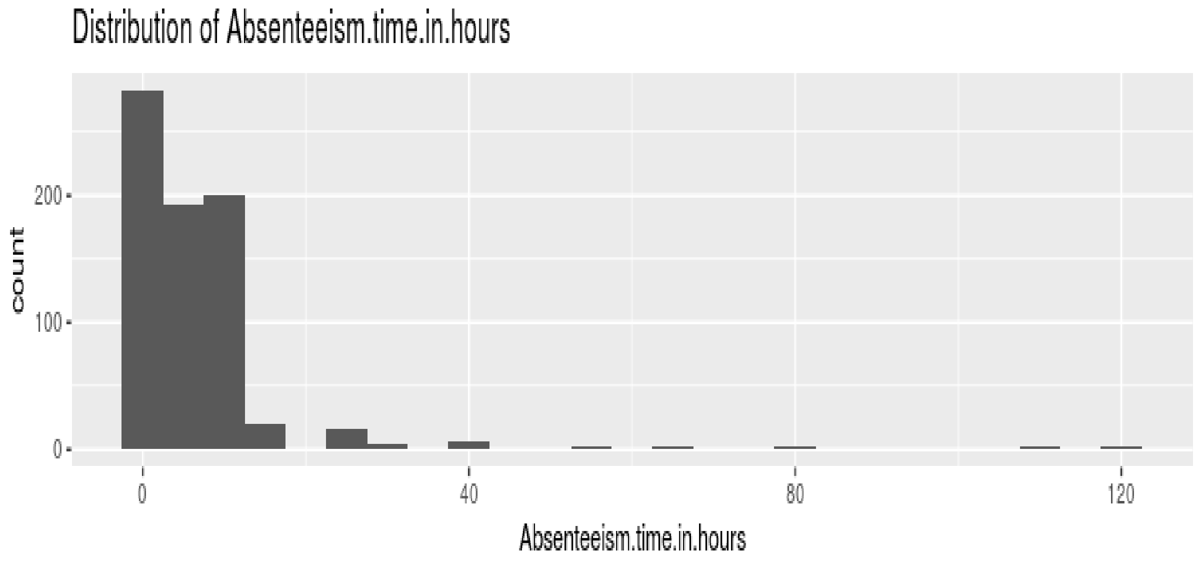


Fig 5.5 – Distribution of Continuous variables using histograms

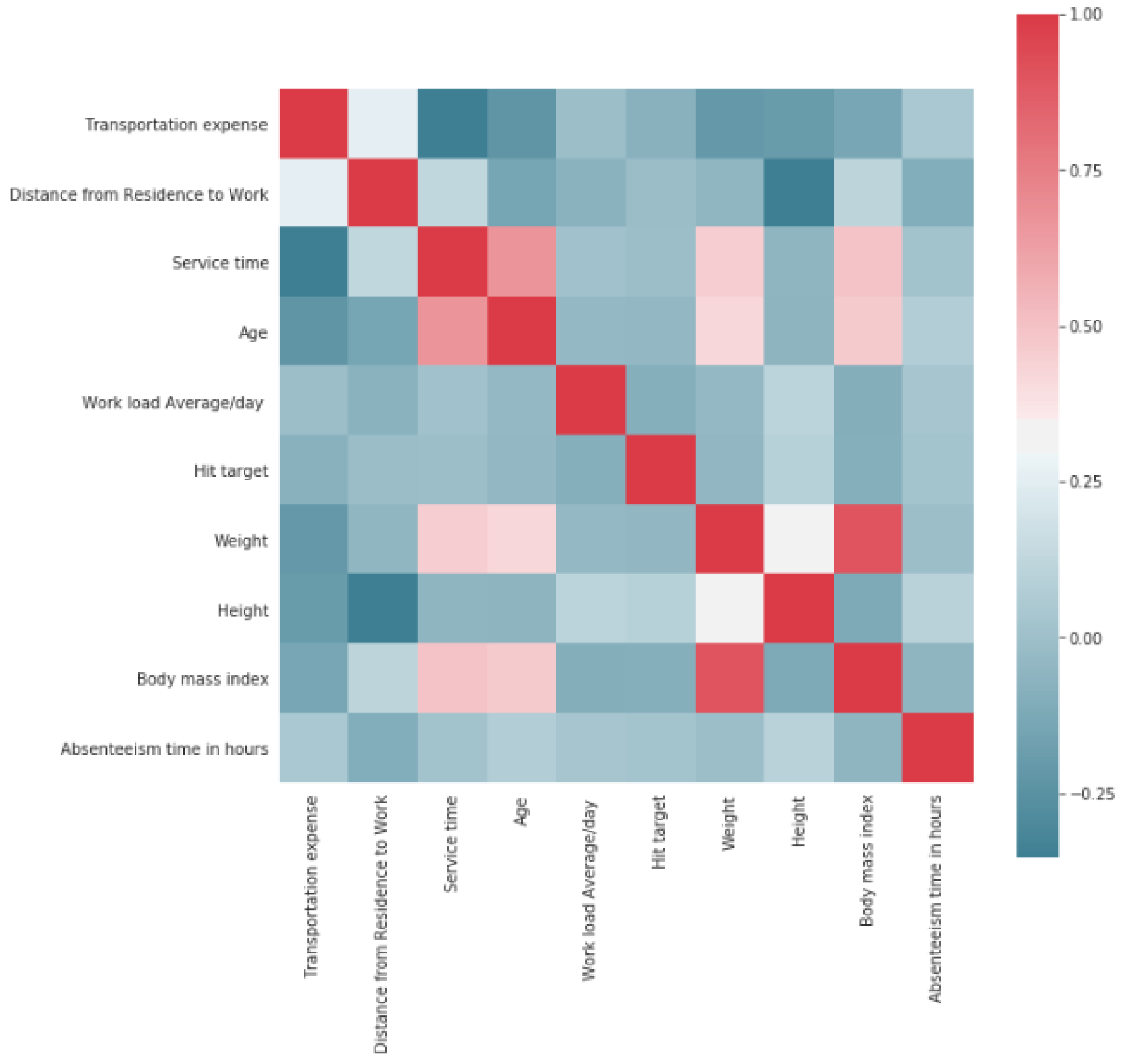


Fig 5.6 – Correlation plot of Continuous variables

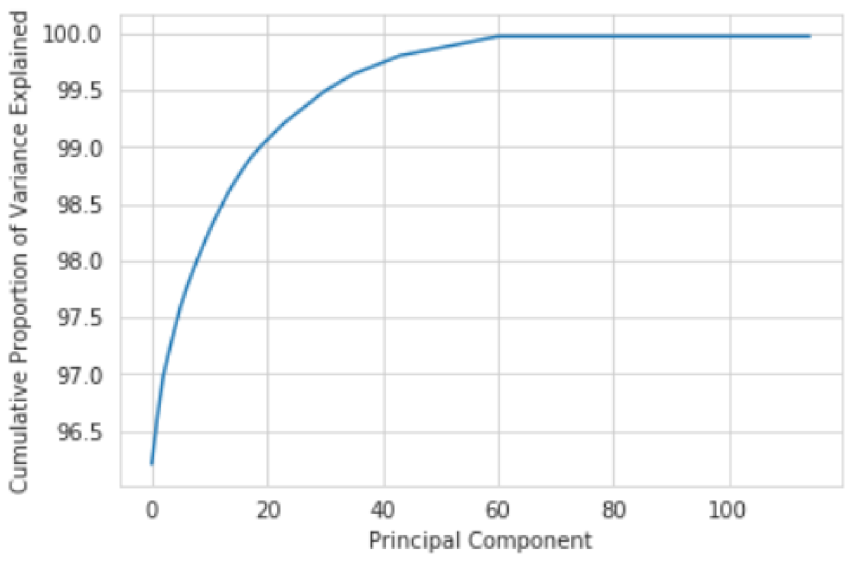


Fig 5.7 – Cumulative Plot of Principal Components

Appendix B: R code

```
#Cleaning the Environment
rm(list = ls())
#Loading the libraries
library(xlsx)
library(ggplot2)
library(DMwR)
library(gridExtra)
library(MASS)
library(corrgram)
library(rpart)
library(DataCombine)
library(inTrees)
library(caret)
library(gbm)
library(randomForest)
library(mlr)
library(dummies)
library(usdm)
library(rpart.plot)

#libraries to install
#x = c("ggplot2", "corrgram", "DMwR", "caret", "randomForest", "unbalanced", "C50",
"dummies", "e1071", "Information",
#"MASS", "rpart", "gbm", "ROSE", 'sampling', 'DataCombine', 'inTrees')

df = read.xlsx("Absenteeism_at_work_Project.xls",sheetIndex = 1)

# Univariate Analysis and Variable Consolidation
str(df)

df$ID = as.factor(as.character(df$ID))

df$Reason.for.absence[df$Reason.for.absence %in% 0] = 20
df$Reason.for.absence = as.factor(as.character(df$Reason.for.absence))

df$Month.of.absence[df$Month.of.absence %in% 0] = NA
df$Month.of.absence = as.factor(as.character(df$Month.of.absence))

df$Day.of.the.week = as.factor(as.character(df$Day.of.the.week))
df$Seasons = as.factor(as.character(df$Seasons))
df$Disciplinary.failure = as.factor(as.character(df$Disciplinary.failure))
df$Education = as.factor(as.character(df$Education))
df$Social.drinker = as.factor(as.character(df$Social.drinker))
df$Social.smoker = as.factor(as.character(df$Social.smoker))
df$Son = as.factor(as.character(df$Son))
df$Pet = as.factor(as.character(df$Pet))

str(df)

write.csv(df,"Employee.csv",row.names = FALSE)

################### Missing Values Analysis ######################
```

```
missing_val = data.frame(apply(df,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$Missing_Percentage/nrow(df))*100
missing_val = missing_val[order(-missing_val$Missing_Percentage),]
row.names(missing_val) = NULL
missing_val = missing_val[,c(2,1)]
write.csv(missing_val,"Missing_Percentage.csv",row.names = F)

# Missing value percentage representation by bar chart

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

######## Missing value imputation by KNN Method ##############

#Actual Value = 29
#mean   = 26.68
#median = 25
#knn = 29

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

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

#KNN
df = knnImputation(df,5)

#Note--- Compare to all the methods, knn method results are more near to the actual values so i
decided to go with knn method for further processing--

#Separating continuous and catagorical variables

#for numerical variables
numeric_index = sapply(df, is.numeric)
numeric_data = df[,numeric_index]
continuous_variables = colnames(numeric_data)

#continuous_variables = ["Transportation.expense", "Distance.from.Residence.to.Work",
                   "Service.time" , "Age" , "Work.load.Average.day." ,
                   "Hit.target", "Weight" , "Height", "Body.mass.index",
                   "Absenteeism.time.in.hours"
                  ]


#for catagorical variables
factor_index = sapply(df, is.factor)
factor_data = df[,factor_index]
catagorical_variables = colnames(factor_data)
```

```
#catagorical_variables = [ "ID", "Reason.for.absence", "Month.of.absence", "Day.of.the.week",
                 "Seasons", "Disciplinary.failure", "Education", "Son",
                 "Social.drinker",  "Social.smoker", "Pet"
                ]

############ Outlier Analysis ##################

#Outlier analysis for continuous variables.

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

#generating plots

gridExtra::grid.arrange(gn1,gn2,ncol=2)
gridExtra::grid.arrange(gn3,gn4,ncol=2)
gridExtra::grid.arrange(gn5,gn6,ncol=2)
gridExtra::grid.arrange(gn7,gn8,ncol=2)
gridExtra::grid.arrange(gn9,gn10,ncol=2)
##################################EDDDDDDDD#######################

#Distribution of factor data using bar plot

bar1 = ggplot(data = df, aes(x = ID)) + geom_bar() +
   ggtitle("Count of ID") + theme_minimal()

bar2 = ggplot(data = df, aes(x = Reason.for.absence)) +
   geom_bar() + ggtitle("Count of Reason for absence") + theme_bw()

bar3 = ggplot(data = df, aes(x = Month.of.absence)) + geom_bar()+
   ggtitle("Count of Month") + theme_bw()

bar4 = ggplot(data = df, aes(x = Disciplinary.failure)) +
   geom_bar() + ggtitle("Count of Disciplinary failure") + theme_bw()

bar5 = ggplot(data = df, aes(x = Education)) + geom_bar()+
   ggtitle("Count of Education")+ theme_bw()

bar6 = ggplot(data = df, aes(x = Son)) + geom_bar()+
    ggtitle("Count of Son") + theme_bw()

bar7 = ggplot(data = df, aes(x = Social.smoker)) + geom_bar() +
    ggtitle("Count of Social smoker") + theme_bw()


#Check the distribution of numerical data using histogram
```

```
hist1 = ggplot(data = numeric_data, aes(x =Transportation.expense)) +
ggtitle("Transportation.expense") + geom_histogram(bins = 25)

hist2 = ggplot(data = numeric_data, aes(x =Height)) + ggtitle("Distribution of Height") +
geom_histogram(bins = 25)

hist3 = ggplot(data = numeric_data, aes(x =Body.mass.index)) + ggtitle("Distribution of
Body.mass.index") + geom_histogram(bins = 25)

hist4 = ggplot(data = numeric_data, aes(x =Absenteeism.time.in.hours)) + ggtitle("Distribution of
Absenteeism.time.in.hours") + geom_histogram(bins = 25)


#Replace all outliers with NA and impute

for(i in continuous_variables){
  val = df[,i][df[,i] %in% boxplot.stats(df[,i])$out]
  #print(length(val))
  df[,i][df[,i] %in% val] = NA
}

#Imputing missing values with Knn method
df = knnImputation(df,k=5)

############# Feature selection ##########################################
#Checking for multicollinearity using VIF
vifcor(numeric_data)

#checking multicollinearity using correlation graph
corrgram(df[,numeric_index], order= F,
        upper.panel=panel.pie, text.panel = panel.txt, main = "Correlation Plot")


#Dimension Reduction

df_new = subset(df,select = -c(Body.mass.index))
df_new_cleaned = df_new

############### Feature Scaling ########################################

#Normality Checking
qqnorm(df_new$Absenteeism.time.in.hours)
hist(df_new$Absenteeism.time.in.hours)


#Updating the continuous variables for normalization

continuous_variables = c('Transportation.expense', 'Distance.from.Residence.to.Work',
'Service.time',
                    'Age', 'Work.load.Average.day.',
                    'Hit.target', 'Height',
                    'Weight')

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


#Normalization
for(i in continuous_variables)
{
  print(i)
  df_new[,i] = (df_new[,i] - min(df_new[,i]))/(max(df_new[,i])-min(df_new[,i]))
}

#Creating dummy variables for catagorical varibales to maintain the levels.

df_new = dummy.data.frame(df_new, catagorical_variables)


#Cleaning the Environment

rmExcept(keepers = c("df_new","df","df_new_cleaned"))

######################## Model development ###################

#dividing data into test and train using simple random sampling method (because the target
variable is continuous variable)

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

#----------------Decission tree --------------------#

#rpart for regression on training data

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

#Summary of the model
summary(model_DT)

#summary in the form of tree
rpart.plot(model_DT)

#predicting for test data
predictions_DT = predict(model_DT,test[,-115])

#creating separate dataframe for analysing actual and predicted observations.

df_new_dt_pred = data.frame("actual"=test[,115],"predicted" = predictions_DT)

#Error Metrics using PostResample method
#Calculates Performance Across Resamples

print(postResample(pred = predictions_DT, obs = test[,115]))

#Alternate method for error metrics
#regr.eval(test[,115], predictions_DT, stats = c('mae','rmse','mse'))
```

```
#Validation

#RMSE     = 2.276450
#Rsquared = 0.440758
#MAE      = 1.694686


#------------ Random Forest --------------------#

#create model using training data
model_RF = randomForest(Absenteeism.time.in.hours ~., data = train, ntree=500)

#predict for test data
predictions_RF = predict(model_RF,test[,-115])

#creating separate dataframe for actual and predicted data
df_new_rf_pred = data.frame("actual" = test[,115], "predicted" = predictions_RF)

#calculate mae, rmse, and rsquared
print(postResample(pred = predictions_RF, obs = test[,115]))

#Validation

#RMSE     = 2.1941162
#Rsquared = 0.4798489
#MAE      = 1.6107736


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

#Train the model with training data
model_LR = lm(Absenteeism.time.in.hours ~ ., data = train)

#summary of the model
summary(model_LR)

#predict for test data
predictions_LR = predict(model_LR,test[,-115])

#creating separate dataframe for actual and predicted data
df_new_lr_pred = data.frame("actual" = test[,115], "predicted" = predictions_LR)

#calculate mae, rmse, and rsquared
print(postResample(pred = predictions_LR, obs = test[,115]))

#Validation

#RMSE     = 2.5593810
#Rsquared = 0.3587518
#MAE      = 1.8604850


#Compared to all the models the performance is not optimizing due to dimension of the data,
#this can be achived using the principal component analysis
```

```
######## Dimension Reduction by PCA ############################

#principal component analysis
prin_comp = prcomp(train)

#sdev for each of the principal components

pr_stdev = prin_comp$sdev

#calculate variance
pr_var = pr_stdev^2

#Proportion of variance
pro_var = pr_var/sum(pr_var)

#Screen plot
plot(cumsum(pro_var), xlab = "Principal Component",
    ylab = "Cumulative Proportion of Variance Explained",
    type = "l")

#Add a training set with principal of components
train.data = data.frame(Absenteeism.time.in.hours = train$Absenteeism.time.in.hours,
prin_comp$x)

#From the above plot selecting 45 components since it explains almost 95+ % data variance
train.data = train.data[,1:45]

#Transform test data into PCA
test.data = predict(prin_comp, newdata = test)
test.data = as.data.frame(test.data)

#select the first 45 components
test.data = test.data[,1:45]

########### Model development after principal component analysis ##############

#----------------Decission tree --------------------#

#rpart for regression on training data

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

#Summary of the model
summary(model_DTP)

#summary in the form of tree
rpart.plot(model_DTP)

#predicting for test data
predictions_DTP = predict(model_DTP,test.data)

#creating separate dataframe for analysing actual and predicted observations.

df_new_dtp_pred = data.frame("actual"=test[,115],"predicted" = predictions_DTP
#Error Metrics using PostResample method
#Calculates Performance Across Resamples

print(postResample(pred = predictions_DTP, obs = test[,115]))

#Alternate method for error metrics
#regr.eval(test[,115], predictions_DTP, stats = c('mae','rmse','mse'))

#Validation

#RMSE     = 0.4427499
#Rsquared = 0.9787753
#MAE      = 0.3012380

#------------ Random Forest --------------------#

#create model using training data
model_RFP = randomForest(Absenteeism.time.in.hours ~., data = train.data, ntree=500)

#predict for test data
predictions_RFP = predict(model_RFP,test.data)

#creating separate dataframe for actual and predicted data
df_new_rfp_pred = data.frame("actual" = test[,115], "predicted" = predictions_RFP)

#calculate mae, rmse, and rsquared
print(postResample(pred = predictions_RFP, obs = test[,115]))

#Validation
#RMSE     = 0.4361794
#Rsquared = 0.9828053
#MAE      = 0.2505895

#------------------- Linear Regression ----------------------#
#Train the model with training data
model_LRP = lm(Absenteeism.time.in.hours ~ ., data = train.data)

#summary of the model
summary(model_LRP)

#predict for test data
predictions_LRP = predict(model_LRP,test.data)

#creating separate dataframe for actual and predicted data
df_new_lrp_pred = data.frame("actual" = test[,115], "predicted" = predictions_LRP)

#calculate mae, rmse, and rsquared
print(postResample(pred = predictions_LRP, obs = test[,115]))

#Validation
#RMSE     = 0.003016381
#Rsquared = 0.999999023
#MAE      = 0.002247516
```

Python code

```
#Importing libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from fancyimpute import KNN
from scipy.stats import chi2_contingency
from random import randrange, uniform
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import seaborn as sns
% matplotlib inline

#Reading File
df = pd.read_excel("../input/Absenteeism_at_work_Project.xls")

#checking file
df.head()

############# Exploratory Data Analysis #######################

#Rearranging datatypes of the variables

df['ID'] = df['ID'].astype('category')

df['Reason for absence'] = df['Reason for absence'].replace(0,20)
df['Reason for absence'] = df['Reason for absence'].astype('category')

df['Month of absence'] = df['Month of absence'].replace(0,np.nan)
df['Month of absence'] = df['Month of absence'].astype('category')

df['Day of the week']  = df['Day of the week'].astype('category')
df['Seasons'] = df['Seasons'].astype('category')
df['Disciplinary failure'] = df['Disciplinary failure'].astype('category')
df['Education'] = df['Education'].astype('category')
df['Son'] = df['Son'].astype('category')
df['Social drinker'] = df['Social drinker'].astype('category')
df['Social smoker'] = df['Social smoker'].astype('category')
df['Pet'] = df['Pet'].astype('category')


#separating continous and categrocal variables
continuous_variables = ["Transportation expense", "Distance from Residence to Work",
                   "Service time" , "Age" , "Work load Average/day " ,
                   "Hit target", "Weight" , "Height", "Body mass index",
                   "Absenteeism time in hours"
                  ]

categorical_variables = [ "ID", "Reason for absence", "Month of absence", "Day of the week",
                   "Seasons", "Disciplinary failure", "Education", "Son",
                   "Social drinker",  "Social smoker", "Pet"
                  ]
############ Missing Value Analysis ######################
```

```
#creating separate dataframe with misssing values

missing_val = pd.DataFrame(df.isnull().sum())
missing_val = missing_val.reset_index()
missing_val = missing_val.rename(columns = {'index' :'Variables',0:'missing_perc'})
missing_val
missing_val['missing_perc'] = (missing_val['missing_perc']/len(df))*100
missing_val = missing_val.sort_values('missing_perc', ascending=False).reset_index(drop = True)
missing_val.to_csv("missing_val.csv", index=False)

#Actual Value = 29
#Mean = 26
#Median = 25
#KNN = 27

#print(df['Body mass index'].iloc[9])
#df['Body mass index'].iloc[9] = np.nan

#Mean
#df['Body mass index'] = df['Body mass index'].fillna(df['Body mass index'].median())

#Median
#df['Body mass index'] = df['Body mass index'].fillna(df['Body mass index'].median())

#KNN
df = pd.DataFrame(KNN(k = 5).fit_transform(df), columns = df.columns)

#Checking null value count

df.isnull().sum()

#Rounding the values of categorical variables

for i in categorical_variables:
   df.loc[:,i] = df.loc[:,i].round()
   df.loc[:,i] = df.loc[:,i].astype('category')

####### Visualization of Distributed data by graphs #################

sns.set_style("whitegrid")
sns.factorplot(data=df, x='Reason for absence', kind= 'count',size=3,aspect=2)
sns.factorplot(data=df, x='Seasons', kind= 'count',size=3,aspect=2)
sns.factorplot(data=df, x='Education', kind= 'count',size=3,aspect=2)
sns.factorplot(data=df, x='Disciplinary failure', kind= 'count',size=3,aspect=2)

############# Outlier Analysis #####################

#Checking Outliers in  data using boxplot
sns.boxplot(data=df[['Hit target','Age','Service time','Transportation expense',]])
fig=plt.gcf()
fig.set_size_inches(8,8)


#Checking Outliers in  data using boxplot
```

```
sns.boxplot(data=df[['Absenteeism time in hours','Body mass index','Height','Weight',]])
fig=plt.gcf()
fig.set_size_inches(8,8)

sns.boxplot(data=df[['Work load Average/day ','Distance from Residence to Work',]])
fig=plt.gcf()
fig.set_size_inches(8,8)


#Detecting outliers using boxplot and replacing with NA
for i in continuous_variables:
   q75, q25 = np.percentile(df[i],[75,25])

   # Calculating Interquartile range
   iqr = q75 - q25

   #calculating upper and lower fences
   minimum = q25 - (iqr*1.5)
   maximum = q75 + (iqr*1.5)

   #Replace all the outliers with NA
   df.loc[df[i]<minimum,i] = np.nan
   df.loc[df[i]>maximum,i] = np.nan


#Check for missing values
df.isnull().sum()

#Impute missing values with knn
df = pd.DataFrame(KNN(k=3).fit_transform(df), columns = df.columns)

#Check for missing values after applying KNN
df.isnull().sum()

#checking once again for outliers in the data after applying KNN
sns.boxplot(data=df[['Absenteeism time in hours','Body mass index','Height','Weight',]])
fig=plt.gcf()
fig.set_size_inches(8,8)

#checking once again for outliers in the data after applying KNN
sns.boxplot(data=df[['Hit target','Age','Service time','Transportation expense',]])
fig=plt.gcf()
fig.set_size_inches(8,8)

#checking once again for outliers in the data after applying KNN
sns.boxplot(data=df[['Work load Average/day ','Distance from Residence to Work',]])
fig=plt.gcf()
fig.set_size_inches(8,8)
```

```
################ Future Selection ####################

##Correlation analysis
#Correlation plot
df_cor = df.loc[:,continuous_variables]

#Check for multicollinearity using corelation graph
#Set the width and hieght of the plot
f, ax = plt.subplots(figsize=(10,10))

#Generate correlation matrix
cor_mat = df_cor.corr()

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

#Getting copy of the data
df_old = df.copy()

#Variable reduction
df_new = df.drop(['Body mass index'], axis = 1)

#Updating columns in Continous_variable
continuous_variables.remove('Body mass index')
continuous_variables.remove('Absenteeism time in hours')

############### Future Scaling ##################

#Make a copy of cleaned data
#df_cleaned_data = df_new.copy()
df_new = df_cleaned_data.copy()
df_cleaned_data.shape

#Normality Check
for i in continuous_variables:
    plt.hist(df_new[i],bins='auto')
    plt.title("Checking Distribution for Variable "+str(i))
    plt.ylabel("Density")
    plt.xlabel(i)
    plt.show()

#Normalization of continous variables
for i in continuous_variables:

    df_new[i] = (df_new[i] - min(df_new[i]))/(max(df_new[i]) - min(df_new[i]))

#Dummy Variable creation for categorical variables
df_new = pd.get_dummies(data = df_new,columns=categorical_variables)
```

```
############ Machine Learning Models ##################

#Splitting data into train and test data
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(df_new.iloc[:,df_new.columns != 'Absenteeism
time in hours' ],df_new.iloc[:, 8],test_size = 0.20, random_state = 1)

#------------------Decision Tree------------------------#
#Importing libraries for Decision tree regressor
from sklearn.tree import DecisionTreeRegressor

#create a model decision tree using DecisionTreeRegressor
model_DT = DecisionTreeRegressor(random_state = 1).fit(X_train,Y_train)

#Predict for the test data
predictions_DT = model_DT.predict(X_test)

#Create separate dataframe for actual and predicted data
df_new_dt_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_DT})

print(df_new_dt_pred.head())

#Function to create to RMSE
def RMSE(y_actual,y_predicted):
   rmse = np.sqrt(mean_squared_error(y_actual,y_predicted))
   return rmse
#Calculate RMSE and R-Squared Value
print("RMSE: "+str(RMSE(Y_test, predictions_DT)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_DT)))

**Decision Tree
RMSE: 3.7141966443496677
R-Squared Value: -0.13882343999361768**

#--------------------Random Forest------------------------#
#Impoorting libraries for Random Forest
from sklearn.ensemble import RandomForestRegressor

#create a model Random forest using RandomForestRegressor
model_RF = RandomForestRegressor(n_estimators = 500, random_state = 1).fit(X_train,Y_train)

#predict for test data
predictions_RF = model_RF.predict(X_test)

#craete a dataframe for actual and predicted data
df_new_rf_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_RF})
print(df_new_rf_pred.head())

#calculate RMSE and RSquared values
print("RMSE: "+str(RMSE(Y_test, predictions_RF)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_RF)))

**Random Forest
RMSE: 2.725268748784219
R-Squared Value: 0.386880282274243**
```

```
#----------------------------Linear Regression---------------------------#
#Import libraries for Linear Regression
from sklearn.linear_model import LinearRegression

#Create model Linear Regression using LinearRegression
model_LR = LinearRegression().fit(X_train,Y_train)

#Predict for the test cases
predictions_LR = model_LR.predict(X_test)

#Create a separate dataframee for the actual and predicted data
df_new_lr_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_LR})

print(df_new_lr_pred.head())

#Calculate RMSE and RSquared values
print("RMSE: "+str(RMSE(Y_test, predictions_LR)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_LR)))

**Linear Regression
RMSE: 16390064550.910776
R-Squared Value: -2.2176241320666194e+19**


########### Dimension Reduction using PCA ################
#Get a target variable
target_variable = df_new['Absenteeism time in hours']
df_new.shape

#import library for PCA
from sklearn.decomposition import PCA

#Converting data into numpy array
X = df_new.values

pca = PCA(n_components = 115)
pca.fit(X)

#Proportion of variance
var = pca.explained_variance_ratio_

#Calculate Screen plot
var1 = np.cumsum(np.round(pca.explained_variance_ratio_,decimals=4)*100)

#Draw the plot
plt.plot(var1)
plt.xlabel("Principal Component")
plt.ylabel("Cumulative Proportion of Variance Explained")
plt.show()
```

```
#Selecting 45 Components since it explains almost 95+ % data variance
pca = PCA(n_components=45)

#Fitting the selected components to the data
pca.fit(X)

#Splitting data into train and test
X_train, X_test, Y_train, Y_test = train_test_split(X,target_variable, test_size=0.2, random_state =
1)

######## Model Development After PCA ############

#-----------------Decision Tree----------------------#
#Importing libraries for Decision tree regressor
from sklearn.tree import DecisionTreeRegressor

#create a model decision tree using DecisionTreeRegressor
model_DTP = DecisionTreeRegressor(random_state = 1).fit(X_train,Y_train)

#Predict for the test data
predictions_DTP = model_DTP.predict(X_test)

#Create separate dataframe for actual and predicted data
df_new_dtp_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_DTP})

print(df_new_dtp_pred.head())

#Function to create to RMSE
def RMSE(y_actual,y_predicted):
   rmse = np.sqrt(mean_squared_error(y_actual,y_predicted))
   return rmse

#Calculate RMSE and R-Squared Value
print("RMSE: "+str(RMSE(Y_test, predictions_DTP)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_DTP)))

**Decision Tree
RMSE: 0.07939996345382828
R-Squared Value: 0.9994795641369799**

#-------------------Random Forest----------------------#
#Impoorting libraries for Random Forest
from sklearn.ensemble import RandomForestRegressor

#create a model Random forest using RandomForestRegressor
model_RFP = RandomForestRegressor(n_estimators = 500, random_state = 1).fit(X_train,Y_train)

#predict for test data
predictions_RFP = model_RFP.predict(X_test)

#craete a dataframe for actual and predicted data
df_new_rfp_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_RFP})
print(df_new_rfp_pred.head())

#calculate RMSE and RSquared values
```

```
print("RMSE: "+str(RMSE(Y_test, predictions_RFP)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_RFP)))

**Random Forest
RMSE: 0.05554332987415368
R-Squared Value: 0.99974532258328**


#----------------------------Linear Regression---------------------------#
#Import libraries for Linear Regression
from sklearn.linear_model import LinearRegression

#Create model Linear Regression using LinearRegression
model_LRP = LinearRegression().fit(X_train,Y_train)

#Predict for the test cases
predictions_LRP = model_LRP.predict(X_test)

#Create a separate dataframee for the actual and predicted data
df_new_lrp_pred = pd.DataFrame({'actual':Y_test,'predicted':predictions_LRP})

print(df_new_lrp_pred.head())

#Calculate RMSE and RSquared values
print("RMSE: "+str(RMSE(Y_test, predictions_LRP)))
print("R-Squared Value: "+str(r2_score(Y_test, predictions_LRP)))


**Linear Regression
RMSE: 0.0004365935184874104
R-Squared Value: 0.9999999842644771**
```

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