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Practical 1

Aim: -Install, configure and run Hadoop and HDFS and explore HDFS on Windows

Code:

Steps to Install Hadoop:

- 1. Install Java JDK 1.8
- 2. Download Hadoop and extract and place under C drive
- 3. Set Path in Environment Variables
- 4. Config files under Hadoop directory
- 5. Create folder data node and name node under data directory
- 6. Edit HDFS and YARN files
- 7. Set Java Home environment in Hadoop environment
- 8. Setup Complete. Test by executing start-all.cmd

There are two ways to install Hadoop, i.e.

- 9. Single node
- 10. Multi node

Here, we use multi node cluster.

1. Install Java

- 11. Java JDK Link to download (https://www.oracle.com/java/technologies/javase-jdk8-downloads.html)
- 12. extract and install Java in C:\Java
- 13. open cmd and type -> javac -version

```
C:\Users>cd Beena

C:\Users\Beena>java -version
java version "1.8.0_361"

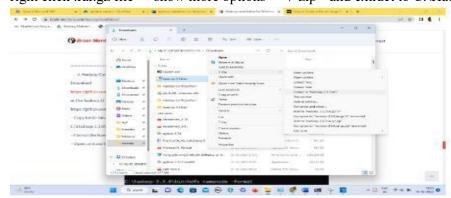
Java(TM) SE Runtime Environment (build 1.8.0_361-b09)

Java HotSpot(TM) 64-Bit Server VM (build 25.361-b09, mixed mode)
```

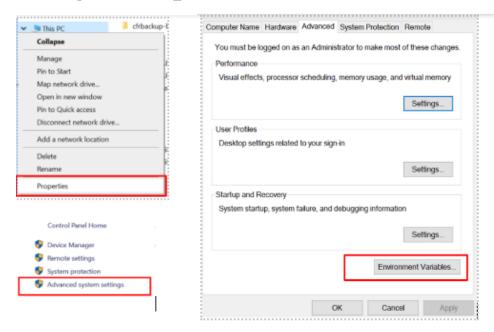
2. Download Hadoop

Link: https://www.apache.org/dyn/closer.cgi/hadoop/common/hadoop-3.3.0/hadoop-3.3.0.tar.gz

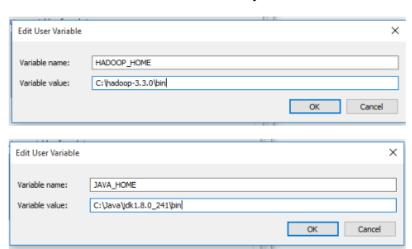
• right click .rar.gz file -> show more options -> 7-zip->and extract to C:\Hadoop-3.3.0\



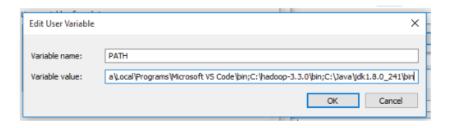
- 3. Set the path JAVA_HOME Environment variable
- 4. Set the path HADOOP_HOME Environment variable



Click on New to both user variables and system variables.



Click on user variable -> path -> edit-> add path for Hadoop and java up to 'bin'



Click Ok, Ok, Ok.

5. Configurations

Edit file -> C:/Hadoop-3.3.0/etc/hadoop/core-site.xml

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paste the xml code in folder and save
<configuration></configuration>
<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
<name>fs.defaultFS</name>
<value>hdfs://localhost:9000</value>
Rename "mapred-site.xml. Template" to "mapred-site.xml" and edit this file C:/Hadoop-3.3.0/etc/hadoop/mapred-site.xml, paste xml code and save this file.
<configuration></configuration>
<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
<name>mapreduce.framework.name</name>
<value>yarn</value>
Create folder "data" under "C:\Hadoop-3.3.0"
Create folder "datanode" under "C:\Hadoop-3.3.0\data"
Create folder "namenode" under "C:\Hadoop-3.3.0\data"
Edit file C:\Hadoop-3.3.0/etc/hadoop/hdfs-site.xml,
paste xml code and save this file.
<configuration></configuration>
<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
<name>dfs.replication</name>
<value>1</value>
<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>

<name>dfs.namenode.name.dir</name>
<value>/hadoop-3.3.0/data/namenode</value>
<pre><pre><pre><pre><pre><pre><pre><pre></pre></pre></pre></pre></pre></pre></pre></pre>
<name>dfs.datanode.data.dir</name>
<value>/hadoop-3.3.0/data/datanode</value>
Edit file C:/Hadoop-3.3.0/etc/hadoop/yarn-site.xml,
paste xml code and save this file.
<configuration></configuration>
6. Edit file C:/Hadoop-3.3.0/etc/hadoop/hadoop-env.cmd
Find "JAVA_HOME=%JAVA_HOME%" and replace it as
set JAVA_HOME="C:\Java\jdk1.8.0_361"
7. Download "redistributable" package
Download and run VC_redist.x64.exe: This is a "redistributable" package of the Visual C runtime code for 64-bit applications, from Microsoft. It contains certain shared code that every application written with Visual C expects to have available on the Windows computer it runs on.
8. Hadoop Configurations
Download bin folder from
https://github.com/s911415/apache-hadoop-3.1.0-winutils
Copy the bin folder to c:\hadoop-3.3.0. Replace the existing bin folder.
9. copy "hadoop-yarn-server-timelineservice-3.0.3.jar" from ~\hadoop-3.0.3\share\hadoop\yarn\timelineservice to ~\hadoop-3.0.3\share\hadoop\yarn folder.

10. Format the NameNode

- Open cmd 'Run as Administrator' and type command "hdfs namenode -format"

```
Microsoft Windows [Version 10.0.22621.1265]
(c) Microsoft Corporation. All rights reserved.

C:\Windows\System32>cd\hadoop-3.3.0\bin

C:\hadoop-3.3.0\bin>hdfs namenode -format
```

11. Testing

- Open cmd 'Run as Administrator' and change directory to C:\Hadoop-3.3.0\sbin
- type start-all.cmd

OR

- type start-dfs.cmd
- type start-yarn.cmd

```
C:\hadoop-3.3.0\sbin>start-all.cmd
This script is Deprecated. Instead use start-dfs.cmd and start-yarn.cmd
The filename, directory name, or volume label syntax is incorrect.
The filename, directory name, or volume label syntax is incorrect.
starting yarn daemons
The filename, directory name, or volume label syntax is incorrect.
```

 You will get 4 more running threads for Datanode, namenode, resource manager and node manager

```
Expande Hadoop Distribution - hadoop namehade

2023-03-07 / 20:33:00,395 INFO ipc. Server: Starting Socket Reader #1 for port 9000

2023-03-09 / 20:33:00,547 INFO namehade.FSMamesystem: Registered FSMamesystemState, ReplicatedBlocksState and FCBlockGroup state RBcans.

2023-03-07 / 20:33:00,549 INFO common.Util: Assuming 'file' scheme for path /hadoop-3.3.0/data/namehade in configuration.

2023-03-07 / 20:33:00,549 INFO blockmanagement.Datamager: Number of blocks under construction: 8

2023-03-07 / 20:33:00,566 INFO blockmanagement.BlockManager: initializing replication queues

2023-03-07 / 20:33:00,566 INFO blockmanagement.BlockManager: initializing replication queues

2023-03-07 / 20:33:00,566 INFO hdfs.StateChange: STATE* Network topology has 0 racks and 0 datamodes

2023-03-07 / 20:33:00,567 INFO hdfs.StateChange: STATE* Network topology has 0 racks and 0 datamodes

2023-03-07 / 20:33:00,569 INFO hdfs.StateChange: STATE* Number of invalid blocks - 0

2023-03-07 / 20:33:00,575 INFO blockmanagement.BlockManager: Number of invalid blocks - 0

2023-03-07 / 20:33:00,575 INFO blockmanagement.BlockManager: Number of invalid blocks - 0

2023-03-07 / 20:33:00,575 INFO blockmanagement.BlockManager: Number of blocks being written = 0

2023-03-07 / 20:33:00,575 INFO blockmanagement.BlockManager: Number of blocks being written = 0

2023-03-07 / 20:33:00,575 INFO blockmanagement.BlockManager: Number of blocks being written = 0

2023-03-07 / 20:33:00,607 INFO blockmanagement.BlockManager: Number of blocks being written = 0

2023-03-07 / 20:33:00,607 INFO blockmanagement.BlockManager: Number of blocks being written = 0

2023-03-07 / 20:33:00,607 INFO blockmanagement.BlockManager: Starting

2023-03-07 / 20:33:00,607 INFO blockmanagement.BlockManager: Starting

2023-03-07 / 20:33:00,607 INFO mamenade.FSDirectory: Proceeding services required for active state

2023-03-07 / 20:33:00,607 INFO mamenade.FSDirectory: Quota initialization completed in 7 milliseconds

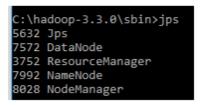
2023-03-07 / 20:33:00,607 INFO mamenade.FSDirectory: Quota initia
```

Previous Nest

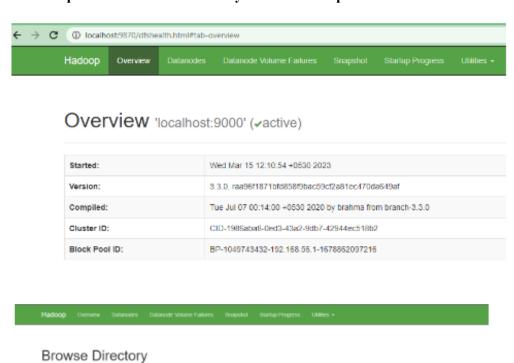
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Output:

12. Type JPS command to start-all.cmd command prompt, you will get following output.



13. Run http://localhost:9870/ from any browser or http://localhost:50070/



Owner | Group | Size | Last Modified

☐ Ili Permission

No data available in table Showing 0 to 0 of 0 entries

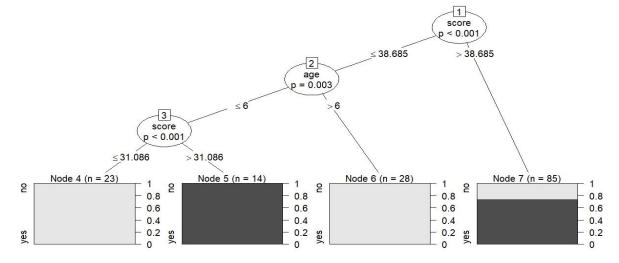
Practical 2

Aim: - Implement Decision tree classification techniques.

```
install.packages('datasets')
install.packages('caTools')
install.packages('party')
install.packages('dplyr')
install.packages('magrittr')
library(datasets)
library(caTools)
library(party)
library(dplyr)
library(magrittr)
data("readingSkills")
head(readingSkills)
sample data = sample.split(readingSkills, SplitRatio = 0.8)
train data <- subset(readingSkills, sample data == TRUE)
test data <- subset(readingSkills, sample data == FALSE)
model <- ctree(nativeSpeaker ~ ., train data)
plot(model)
```

Output:

```
Console
         Terminal \times
                   Background Jobs ×
R • R4.43 · ~/ 
> TTDrary(magrTttr)
> data("readingSkills")
  head(readingSkills)
  nativeSpeaker age shoeSize
             yes
                       24.83189 32.29385
2
                    6
                       25.95238 36.63105
3
                   11 30.42170 49.60593
              no
4
                       28.66450 40.28456
              yes
5
                   11 31.88207 55.46085
              yes
                   10 30.07843 52.83124
6
              yes
  sample_data = sample.split(readingSkills, SplitRatio = 0.8)
  train_data <- subset(readingSkills, sample_data == TRUE)
  test_data <- subset(readingSkills, sample_data == FALSE)</pre>
  model<- ctree(nativeSpeaker ~ ., train_data)</pre>
  plot(model)
```



Practical 3

Aim: - Implement SVM classification techniques.

```
#Code for installation of all necessary packages
install.packages("caret")
install.packages("ggplot2")
install.packages("GGally")
install.packages("psych")
install.packages("ggpubr")
install.packages("reshape")
# Code for importation of all necessary packages
library(caret)
library(ggplot2)
library(GGally)
library(psych)
library(ggpubr)
library(reshape)
# Code
df <- read.csv("C:/Users/DELL/Downloads/diabetes.csv")
head(df)
> # Code
 > plot(model)
 > df <- read.csv("C:/Users/DELL/Downloads/diabetes.csv")</pre>
 > head(df)
   Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome
            6
                                              29
                                                       0 26.6
                                                                                                0
                  183
                                                       0 23.3
                                                                                0.672
                                                                                       32
                                                                                                1
                                               23
                                                      94 28.1
                                                                                0.167 21
                                                                                                0
                   89
 5
                  137
                                                     168 43.1
                                 40
                                              35
                                                                                 2.288
                                                                                       33
                                                                                                1
 6
                                                       0 25.6
                                                                                0.201
                  116
# Code
sum(is.na(df))
# Code
dim(df)
  > # Code
  > sum(is.na(df))
  [1] 0
  > # Code
  > dim(df)
  [1] 768
# Code
sapply(df, class)
# Code
summary(df) # to calculate the summary of our dataset
```

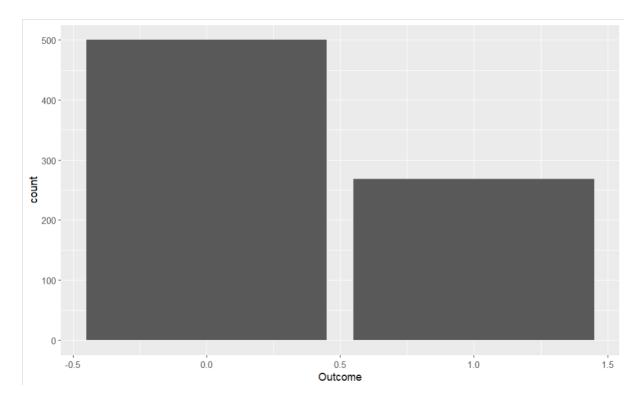
```
> summary(df) # to calculate the summary of our dataset
  Pregnancies
                     Glucose
                                 BloodPressure
                                                  SkinThickness
                                                                     Insulin
       : 0.00
                                                                                       : 0.0
                                                  Min. : 0.0
                                                                                Min.
                  Min. : 0
                                Min. : 0.0
                                                                  Min. : 0
 Min.
                  1st Qu.: 99
 1st Qu.: 1.00
                                1st Qu.: 62.0
                                                  1st Qu.: 0.0
                                                                  1st Qu.: 0
                                                                                1st Qu.:27.3
 Median: 3.00
                  Median :117
                                                                                Median:32.0
                                 Median: 72.0
                                                  Median :23.0
                                                                  Median: 30
         : 3.85
                  Mean
                        :121
                                 Mean : 69.1
                                                  Mean
                                                         :20.5
                                                                  Mean: 80
                                                                                 Mean
                                                                                        :32.0
 Mean
 3rd Qu.: 6.00
                  3rd Qu.:140
                                 3rd Qu.: 80.0
                                                  3rd Qu.:32.0
                                                                  3rd Qu.:127
                                                                                3rd Qu.:36.6
         :17.00
                         :199
                                 Max. :122.0
                                                  Max.
                                                         :99.0
                                                                  Max.
                                                                         :846
                  Max.
                                                                                Max.
 DiabetesPedigreeFunction
                                 Age
                                              Outcome
         :0.078
                           Min.
                                  :21.0
                                           Min.
                                                   :0.000
                           1st Qu.:24.0
 1st Ou.:0.244
                                           1st Ou.:0.000
 Median :0.372
                            Median :29.0
                                            Median: 0.000
                                  :33.2
 Mean
        :0.472
                            Mean
                                            Mean
                                                   :0.349
 3rd Qu.:0.626
                            3rd Qu.:41.0
                                            3rd Qu.:1.000
                                   :81.0
 Max.
         :2.420
                            Max.
                                            Max.
                                                   :1.000
# Code
a \le -ggplot(data = df, aes(x = Pregnancies)) +
 geom_histogram( color = "red", fill = "blue", alpha = 0.1) +
 geom density()
b \le -ggplot(data = df, aes(x = Glucose)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom density()
c \le ggplot(data = df, aes(x = BloodPressure)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom density()
d \le ggplot(data = df, aes(x = SkinThickness)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom_density()
e \le -ggplot(data = df, aes(x = Insulin)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom density()
f \le -ggplot(data = df, aes(x = BMI)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom density()
g \le gplot(data = df, aes(x = DiabetesPedigreeFunction)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +
 geom_density()
h \le ggplot(data = df, aes(x = Age)) +
 geom histogram(color = "red", fill = "blue", alpha = 0.1) +geom density()
ggarrange(a, b, c, d,e,f,g, h + rremove("x.text"),
     labels = c("a", "b", "c", "d", "e", "f", "g", "h"),
     ncol = 3, nrow = 3)
```

```
# Code
   a <- ggplot(data = df, aes(x = Pregnancies)) +
  geom_histogram( color = "red", fill = "blue", alpha = 0.1) +</pre>
      geom_density()
     <- ggplot(data = df, aes(x = Glucose)) +
geom_histogram( color = "red", fill = "blue", alpha = 0.1) +</pre>
      geom_density()
   c <- ggplot(data = df, aes(x = BloodPressure)) +
geom_histogram( color = "red", fill = "blue", alpha = 0.1) +</pre>
>
      geom_density()
   d <- ggplot(data = df, aes(x = SkinThickness)) +</pre>
      geom_histogram( color = "red", fill = "blue", alpha = 0.1) +
      geom_density()
   e <- ggplot(data = df, aes(x = Insulin)) +
      geom_histogram( color = "red", fill = "blue", alpha = 0.1) +
      geom_density()
   f \leftarrow ggplot(data = df, aes(x = BMI)) +
      geom_histogram( color = "red", fill = "blue", alpha = 0.1) +
      geom density()
   g <- ggplot(data = df, aes(x = DiabetesPedigreeFunction)) +
      geom_histogram( color = "red", fill = "blue", alpha = 0.1) +
      geom_density()
  ncol = 3, nrow = 3)
 'stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
                         `bins = 30`. Pick better value with
  stat_bin()` using
                                                                       `binwidth`
                         `bins = 30`. Pick better value with `bins = 30`. Pick better value with
  stat_bin()
                 using
                                                                        binwidth'
 stat_bin()
                                                                       `binwidth`
                 using
 `stat_bin()`
                         `bins = 30`. Pick better value with
                 using
 `stat_bin()` using `bins = 30`. Pick better value with `binwidth`. 

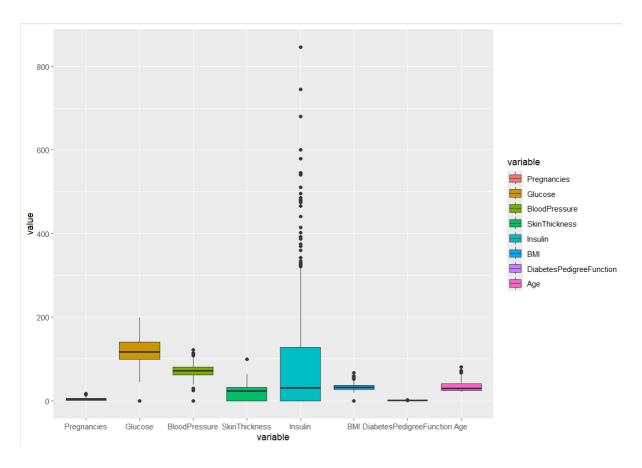
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`. 

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
                                                                               120
                                      b 80
а
                                                                            С
                                                                               90
                                        60
                                                                               60
                                                                               30 -
                                                          100
                Pregnancies
                                                       Glucose
                                                                                            BloodPressure
                                                                               100
  200
density
100
                                      density
200
                                                                               50
                                        100
   50
                                                                               25
                                                                     750
                                                                                                ВМІ
               SkinThickness
                                                         Insulin
g
  100
                                      density
                                        60
   50
           0.5 1.0 1.5 2.0 DiabetesPedigreeFunction
     0.0
```

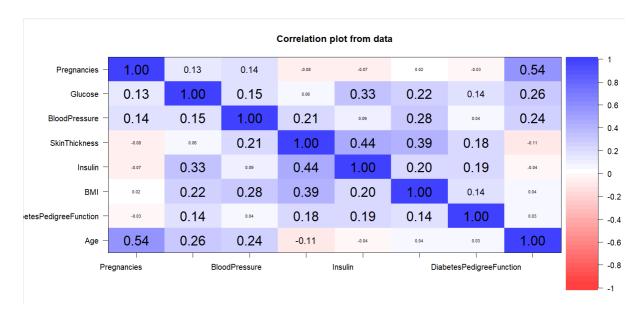
```
# Code
ggplot(data = df, aes(x =Outcome, fill = Outcome)) +
geom_bar()
```



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corPlot(df[, 1:8])



cutoff <- createDataPartition (df\$Outcome, p=0.85, list=FALSE)

select 15% of the data for validation

testdf <- df[-cutoff,]

use the remaining 85% of data to training and testing the models

traindf <- df[cutoff,]

Code to train the SVM

set.seed(1234)

```
# set the 10 fold cross validation with AU

# to pick for us what we call the best model

control <- trainControl(method="cv",number=10, classProbs = TRUE)

metric <- "Accuracy"

model <- train(Outcome ~., data = traindf, method = "svmRadial",

tuneLength = 8,preProc = c("center","scale"),

metric=metric, trControl=control)

# Code for model summary

model
```

```
Console
       Terminal ×
                  Background Jobs ×

¬ Error fetching R version · ~/ 

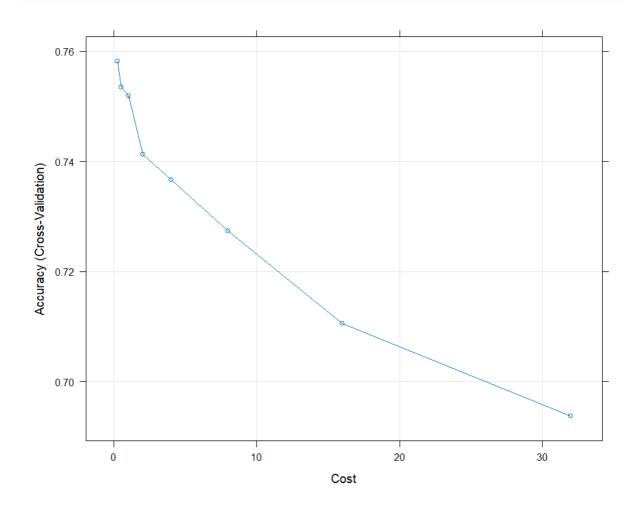
~/ 

> cutoff <- createDataPartition(df$Outcome, p=0.85, list=FALSE)</pre>
> # select 15% of the data for validation
> testdf <- df[-cutoff,]</pre>
> # use the remaining 85% of data to training and testing the models
> traindf <- df[cutoff,]</pre>
> # Code to train the SVM
> set.seed(1234)
> # set the 10 fold cross validation with AU
> # to pick for us what we call the best model
> control <- trainControl(method="cv",number=10, classProbs = TRUE)</pre>
> metric <- "Accuracy"
> model <- train(Outcome ~., data = traindf, method = "svmRadial",</pre>
                  tuneLength = 8,preProc = c("center", "scale"),
                  metric=metric, trControl=control)
> # Code for model summary
> model
Support Vector Machines with Radial Basis Function Kernel
653 samples
  8 predictor
  2 classes: 'Negative', 'Positive'
Pre-processing: centered (8), scaled (8)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 587, 588, 587, 588, 587, 589, ...
Resampling results across tuning parameters:
  C
         Accuracy
                   Kappa
   0.25
        0.758
                   0.448
                   0.432
   0.50 0.753
                   0.423
   1.00 0.752
   2.00 0.741
                   0.395
   4.00 0.737
                   0.385
   8.00 0.727
                   0.364
  16.00 0.711
                   0.311
  32.00 0.694
                   0.259
Tuning parameter 'sigma' was held constant at a value of 0.119
Accuracy was used to select the optimal model using the largest value.
```

The final values used for the model were sigma = 0.119 and C = 0.25.







Practical 4

Aim: - Implement of REGRESSION MODLE.

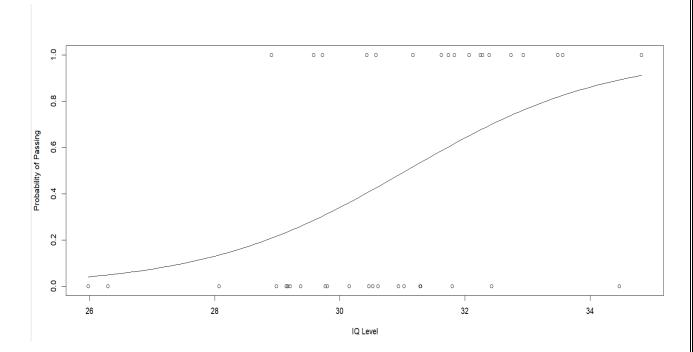
```
> # Code
> plot(model)
> # Generate random IQ values with mean = 30 and sd =2
> IQ <- rnorm(40, 30, 2)
> # Sorting IQ level in ascending order
> IQ <- sort(IQ)</pre>
> # Generate vector with pass and fail values of 40 students
 # Data Frame
> df <- as.data.frame(cbind(IQ, result))</pre>
 # Print data frame
 print(df)
    IQ result
  26.0
            0
  26.3
            0
3
  28.1
            0
  28.9
            1
5
  29.0
            0
6
  29.1
            0
  29.2
            0
  29.2
            0
  29.4
            0
10 29.6
            1
11 29.7
            1
12 29.8
            0
13 29.8
            0
            0
14 30.2
15 30.4
            1
16 30.4
            1
            0
17 30.5
            0
18 30.5
19 30.6
            1
20 30.6
            0
21 30.9
            0
22 31.0
            0
23 31.2
```

```
# Plotting IQ on x-axis and result on y-axis
plot(IQ, result, xlab = "IQ Level",
    ylab = "Probability of Passing")

# Create a logistic model
g = glm(result~IQ, family=binomial, df)

# Create a curve based on prediction using the regression model
curve(predict(g, data.frame(IQ=x), type="resp"), add=TRUE)

# Based on fit to the regression model
points(IQ, fitted(g), pch=30)
```



Summary of the regression model summary(g)

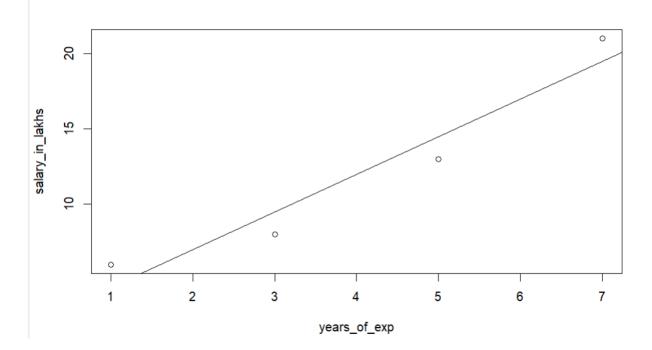
```
> summary(g)
glm(formula = result ~ IQ, family = binomial, data = df)
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -19.252
                          7.624
                                  -2.53
                                           0.012 *
                                           0.012 *
ΙQ
               0.620
                          0.246
                                   2.52
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
(Dispersion parameter for binomial family taken to be 1)
                           on 39
    Null deviance: 55.352
                                  degrees of freedom
Residual deviance: 46.336
                           on 38
                                  degrees of freedom
AIC: 50.34
Number of Fisher Scoring iterations: 4
```

Practical 5

Aim:- Implement of Simple Linear regression.

```
years of \exp = c(7,5,1,3)
salary in lakhs = c(21,13,6,8)
#employee.data = data.frame(satisfaction score, years of exp, salary in lakhs)
employee.data = data.frame(years of exp, salary in lakhs)
# Estimation of the salary of an employee, based on his year of experience and satisfaction score in
#his company.
model < -lm(salary in lakhs \sim years of exp, data = employee.data)
summary(model)
# The formula of Regression becomes
\# Y = 2 + 2.5*year of Exp
# Visualization of Regression
plot(salary in lakhs ~ years of exp, data = employee.data)
abline(model)
> years_of_exp = c(7,5,1,3)
> salary_in_lakhs = c(21,13,6,8)
> #employee.data = data.frame(satisfaction_score, years_of_exp, salary_in_lakhs)
> employee.data = data.frame(years_of_exp, salary_in_lakhs)
> employee.data
  years_of_exp salary_in_lakhs
1
2
                             13
3
              1
                              6
> # Estimation of the salary of an employee, based on his year of experience and satis
faction score in his company.
> model <- lm(salary_in_lakhs ~ years_of_exp, data = employee.data)</pre>
> summary(model)
lm(formula = salary_in_lakhs ~ years_of_exp, data = employee.data)
Residuals:
              3
 1.5 -1.5 1.5 -1.5
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
 (Intercept)
                 2.000 2.174
                                      0.92
                                              0.455
                                              0.034 *
                 2.500
                            0.474
                                      5.27
years_of_exp
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' '1
Residual standard error: 2.12 on 2 degrees of freedom
Multiple R-squared: 0.933,
                                 Adjusted R-squared:
F-statistic: 27.8 on 1 and 2 DF, p-value: 0.0342
> # The formula of Regression becomes
> # Y = 2 + 2.5*year_of_Exp
> # Visualization of Regression
> plot(salary_in_lakhs ~ years_of_exp, data = employee.data)
> abline(model)
```





Practical 6

Aim: Implement of Multiple Linear Regression.

```
# Importing the dataset
dataset = read.csv('C:/Users/DELL/Downloads/1000 Companies.csv')
# Encoding categorical data
dataset$State = factor(dataset$State,
            levels = c('New York', 'California', 'Florida'),
            labels = c(1, 2, 3)
dataset$State
# Splitting the dataset into the Training set and Test set
install.packages('caTools')
library(caTools)
set.seed(123)
split = sample.split(dataset$Profit, SplitRatio = 0.8)
training set = subset(dataset, split == TRUE)
test set = subset(dataset, split == FALSE)
# Feature Scaling
# training set = scale(training set)
\# test set = scale(test set)
# Fitting Multiple Linear Regression to the Training set
regressor = lm(formula = Profit \sim .,
        data = training set)
# Predicting the Test set results
y_pred = predict(regressor, newdata = test set)
regressor
> library(caTools)
 > set.seed(123)
> split = sample.split(dataset$Profit, SplitRatio = 0.8)
> training_set = subset(dataset, split == TRUE)
> test_set = subset(dataset, split == FALSE)
 > # Feature Scaling
 > # training_set = scale(training_set)
 > # test_set = scale(test_set)
> # Fitting Multiple Linear Regression to the Training set
> regressor = lm(formula = Profit ~ .,
                    data = training_set)
> # Predicting the Test set results
> y_pred = predict(regressor, newdata = test_set)
 > regressor
 lm(formula = Profit ~ ., data = training_set)
Coefficients:
                          R.D.Spend Administration Marketing.Spend
     (Intercept)
        -7.12e+04
                           5.95e-01
                                          1.06e+00
                                                                    5.61e-02
           State2
                              State3
       -1.66e+02
                         -9.73e+02
```

Practical 7

Aim:- Implement of Logistic regression.

```
install.packages("ISLR")
library(ISLR)
#load dataset
data <- ISLR::Default
print (head(ISLR::Default))
#view summary of dataset
summary(data)
#find total observations in dataset
nrow(data)
#Create Training and Test Samples
#split the dataset into a training set to train the model on and a testing set to test the model
set.seed(1)
#Use 70% of dataset as training set and remaining 30% as testing set
sample <- sample(c(TRUE, FALSE), nrow(data), replace=TRUE, prob=c(0.7,0.3))
print (sample)
train <- data[sample, ]
test <- data[!sample, ]
nrow(train)
nrow(test)
# Fit the Logistic Regression Model
# use the glm (general linear model) function and specify family="binomial"
#so that R fits a logistic regression model to the dataset
model <- glm(default~student+balance+income, family="binomial", data=train)
#view model summary
summary(model)
#Model Diagnostics
install.packages("InformationValue")
library(InformationValue)
predicted <- predict(model, test, type="response")</pre>
confusionMatrix(test$default, predicted)
 > predicted <- predict(model, test, type="response")</pre>
 > confusionMatrix(test$default, predicted)
 0 2912
          64
      21
```

> plotROC(test\$default, predicted)

Practical 8

Aim:- Read a datafile grades_km_input.csv and apply k-means clustering.

```
# install required packages
install.packages("plyr")
install.packages("ggplot2")
install.packages("cluster")
install.packages("lattice")
install.packages("grid")
install.packages("gridExtra")
# Load the package
library(plyr)
library(ggplot2)
library(cluster)
library(lattice)
library(grid)
library(gridExtra)
# A data frame is a two-dimensional array-like structure in which each column contains values of one
variable and each row contains one set of values from each column.
grade input=as.data.frame(read.csv("C:/Users/DELL/Downloads/grades km input.csv"))
kmdata_orig=as.matrix(grade_input[, c ("Student","English","Math","Science")])
kmdata=kmdata orig[,2:4]
kmdata[1:10,]
# the k-means algorithm is used to identify clusters for k = 1, 2, ..., 15. For each value of k, the WSS
is calculated.
wss=numeric(15)
# the option n start=25 specifies that the k-means algorithm will be repeated 25 times, each starting
with k random initial centroids
for(k in 1:15)wss[k]=sum(kmeans(kmdata,centers=k,nstart=25)$withinss)
plot(1:15,wss,type="b",xlab="Number of Clusters",ylab="Within sum of square")
#As can be seen, the WSS is greatly reduced when k increases from one to two. Another substantial
#reduction in WSS occurs at k = 3. However, the improvement in WSS is fairly linear for k > 3.
km = kmeans(kmdata,3,nstart=25)
km
c(wss[3], sum(km$withinss))
df=as.data.frame(kmdata orig[,2:4])
df\cluster=factor(km\cluster)
centers=as.data.frame(km$centers)
g1=ggplot(data=df, aes(x=English, y=Math, color=cluster)) +
 geom point() + theme(legend.position="right") +
 geom point(data=centers,aes(x=English,y=Math, color=as.factor(c(1,2,3))),size=10, alpha=.3,
       show.legend =FALSE)
g2=ggplot(data=df, aes(x=English, y=Science, color=cluster)) +
 geom point () +geom point(data=centers,aes(x=English,y=Science,
                           color=as.factor(c(1,2,3))),size=10, alpha=.3, show.legend=FALSE)
g3 = ggplot(data=df, aes(x=Math, y=Science, color=cluster)) +
 geom point() + geom point(data=centers,aes(x=Math,y=Science,
```

color=as.factor(c(1,2,3))),size=10, alpha=.3, show.legend=FALSE)

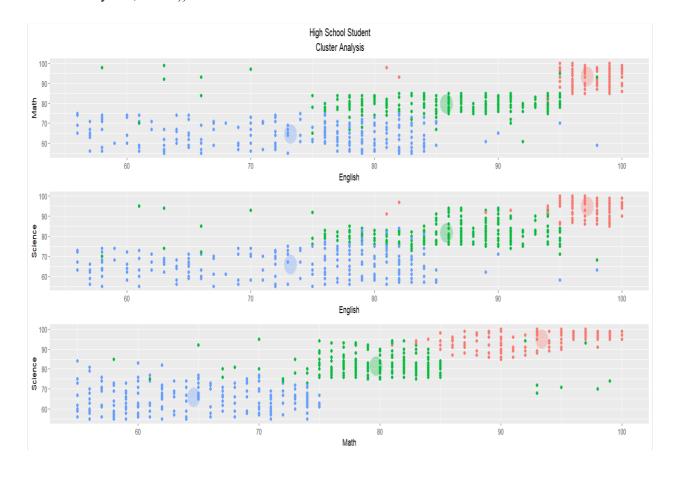
tmp=ggplot gtable(ggplot build(g1))

grid.arrange(arrangeGrob(g1 + theme(legend.position="none"),g2 +

theme(legend.position="none"),g3 + theme(legend.position="none"),top ="High

School Student

Cluster Analysis",ncol=1))



Practical 9

Aim:- Perform Apriori algorithm using Groceries dataset from the R rules package.

```
install.packages("arules")
install.packages("arulesViz")
install.packages("RColorBrewer")
# Loading Libraries
library(arules)
library(arulesViz)
library(RColorBrewer)
# import dataset
data(Groceries)
Groceries
summary(Groceries)
class(Groceries)
# using apriori() function
rules = apriori(Groceries, parameter = list(supp = 0.02, conf = 0.2))
summary (rules)
# using inspect() function
inspect(rules[1:10])
# using itemFrequencyPlot() function
arules::itemFrequencyPlot(Groceries, topN = 20,
                col = brewer.pal(8, 'Pastel2'),
                main = 'Relative Item Frequency Plot',
                type = "relative",
                ylab = "Item Frequency (Relative)")
itemsets = apriori(Groceries, parameter = list(minlen=2, maxlen=2, support=0.02, target="frequent")
itemsets"))
summary(itemsets)
# using inspect() function
inspect(itemsets[1:10])
itemsets 3 = apriori(Groceries, parameter = list(minlen=3, maxlen=3, support=0.02, target="frequent")
itemsets"))
summary(itemsets 3)
# using inspect() function
inspect(itemsets_3)
```

```
R + R 4.4.3 · ~/ ≈
> summary(itemsets_3)
set of 2 itemsets
most frequent items:
                              whole milk root vegetables
other vegetables
                                                                                yogurt
      frankfurter
                                  (Other)
element (itemset/transaction) length distribution:sizes
                                   Mean 3rd Qu.
    Min. 1st Qu. Median
                                                        Max.
summary of quality measures:
 support
Min. :0.0223
1st Qu.:0.0225
                     count
Min. :219
                       1st Qu.:221
 Median :0.0227
Mean :0.0227
3rd Qu.:0.0230
                       Median :224
Mean :224
                       3rd Qu.:226
         :0.0232
                      Max.
includes transaction ID lists: FALSE
mining info:
        data ntransactions support confidence
 Groceries
                         9835
                                    0.02
                                                                                                                                                 call
apriori(data = Groceries, parameter = list(minlen = 3, maxlen = 3, support = 0.02, target = "frequent itemsets"))
> # using inspect() function
> inspect(itemsets_3)
items support count
[1] {root vegetables, other vegetables, whole milk} 0.0232 228
[2] {other vegetables, whole milk, yogurt} 0.0223 219
```

