

**DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND**

**DATA SCIENCE LAB MANUAL**

**AD23431 - STATISTICAL ANALYSIS AND COMPUTING**

# (REGULATION 2023)

**RAJALAKSHMI ENGINEERING COLLEGE**

**Thandalam, Chennai-602015**

Name: AKASH V

Register No: 231801006

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| **EXP NO:** **1** | **IMPLEMENT SIMPLE PROGRAMS IN R** |

**Aim:**

To Implement Simple Programs using R.

**Algorithm:**

**1. Basic Arithmetic Operations**

**a. Finding Area of Circle**

* Input: Read radius r.
* Process: Calculate the area using the formula:

Area=π×r2\text{Area} = \pi \times r^2Area=π×r2

* Output: Print the calculated area.

**2. Control Structures (if-else, for loop)**

1. **Check Whether the Given Year is Leap or Not** 
   * Input: Read a year ly.
   * Process: o If ly is divisible by 400, it’s a leap year.
     + Else, if divisible by 100 (but not by 400), it’s not a leap year. o Else, if divisible by 4, it’s a leap year.
     + Otherwise, it’s not a leap year.
   * Output: Print whether the year is a leap year or not.

1. **Reverse a Given Number** • Input: Read a number num.
   * Process:
     + Initialize rev = 0.
     + While num > 0:
       - Extract last digit: ld = num % 10.
       - Update rev = rev \* 10 + ld.
       - Remove last digit: num = num // 10.
   * Output: Print the reversed number.

1. **Finding Prime Numbers for the Given Range** 
   * Input: Read the number n (upper limit).
   * Process:
     + For each number i from 1 to n, check if it's prime:
       - If divisible by any number from 2 to √i, it’s not prime. ▪ If no divisors found, it is prime.
   * Output: Print all prime numbers from 1 to n.

**3. Functions and Recursive Functions**

1. **Print the Fibonacci Sequence using Functions (Iterative)** 
   * Input: Read n (number of terms in the sequence).
   * Process: o Initialize first two terms: a = 0, b = 1. o Print a and b.
     + Loop (n-2) times:
       - Calculate next term c = a + b.
       - Update a = b, b = c.
     + Print the sequence of n terms.

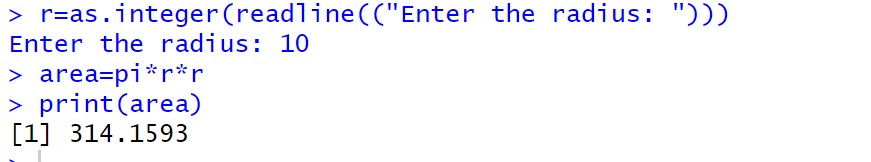
1. **Print the Fibonacci Sequence using Recursive Functions** 
   * Input: Read n (number of terms in the sequence).
   * Process:
     + Define a recursive function fibo(n):
       - If n == 0, return 0 (base case).
       - If n == 1, return 1 (base case).
       - Else, return fibo(n-1) + fibo(n-2).
     + Call fibo(i) for each i from 0 to n-1 and print the sequence.

**Programs:**

1. **Basic Arithmetic Operations**

**a. Finding Area of Circle** r=as.integer(readline(("Enter the radius: "))) area=pi\*r\*r print(area)

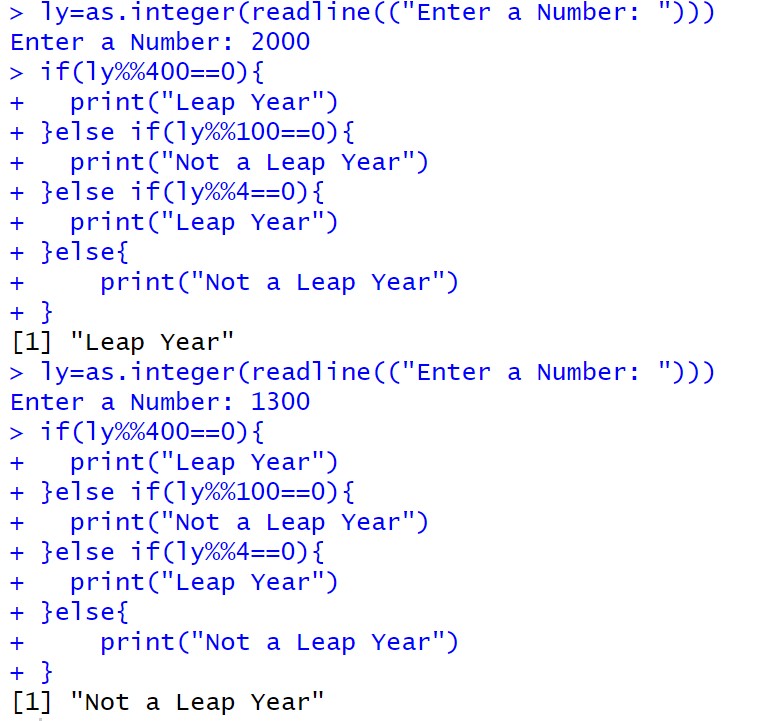
**Output:**



1. **Control Structure (if-else, for loop)** 
   1. **To Check Whether the Given Year is Leap or Not** ly=as.integer(readline(("Enter a Number: "))) if(ly%%400==0){ print("Leap Year") }else if(ly%%100==0){ print("Not a Leap Year") }else if(ly%%4==0){ print("Leap Year")

}else{ print("Not a Leap Year") }

**Output:**



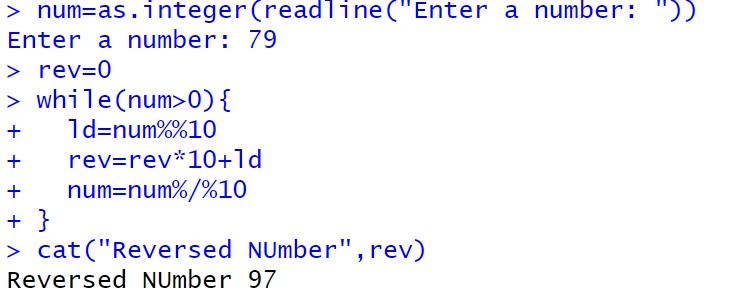
* 1. **Reverse a Given Number** num=as.integer(readline("Enter a number: ")) rev=0 while(num>0){ ld=num%%10 rev=rev\*10+ld

num=num%/%10

}

cat("Reversed NUmber",rev)

**Output:**



* 1. **Finding Prime Numbers for the Given Range** prime<-function(n){ if(n<=1){ return (FALSE)} for (i in 2:sqrt(n)){

if(n%%i==0){ return (FALSE)

}

}

return (TRUE)

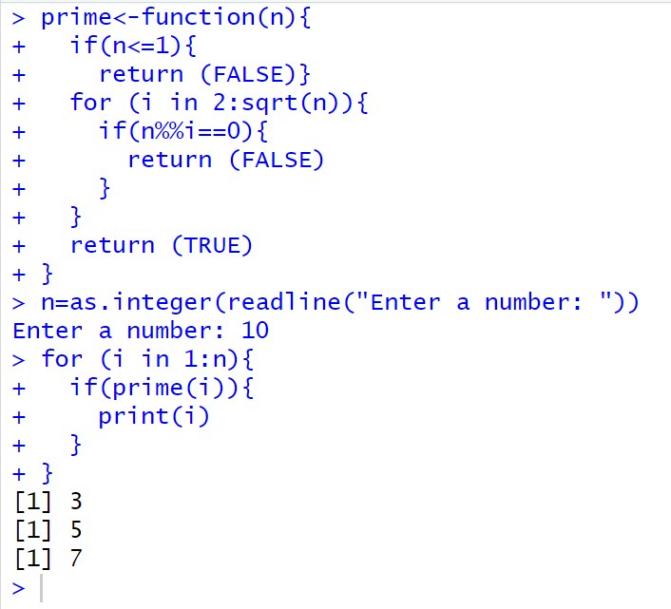
}

n=as.integer(readline("Enter a number: ")) for (i in 1:n){ if(prime(i)){ print(i)

}

}

**Output:**



1. **Functions and Recursive Functions**

**a. Print the Fibonacci Sequence using Functions** fibonacci\_iterative <- function(n) { fib\_series <- numeric(n) fib\_series[1] <- 0 if (n > 1) fib\_series[2] <- 1

for (i in 3:n) { fib\_series[i] <- fib\_series[i-1] + fib\_series[i-2]

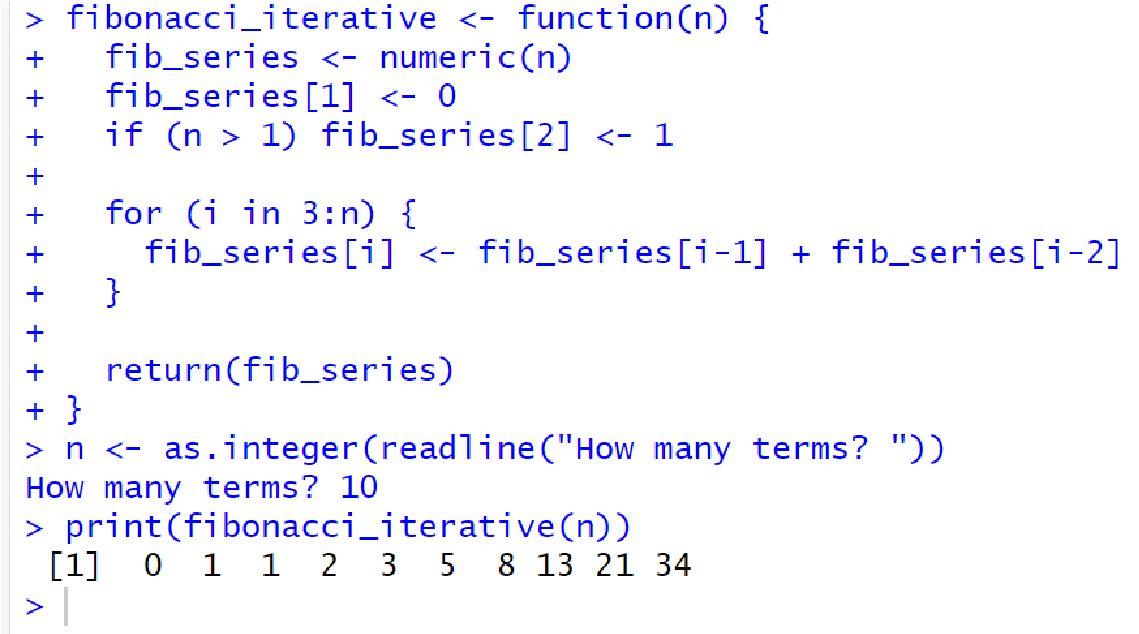
}

return(fib\_series)

}

n <- as.integer(readline("How many terms? ")) print(fibonacci\_iterative(n))

**Output:**



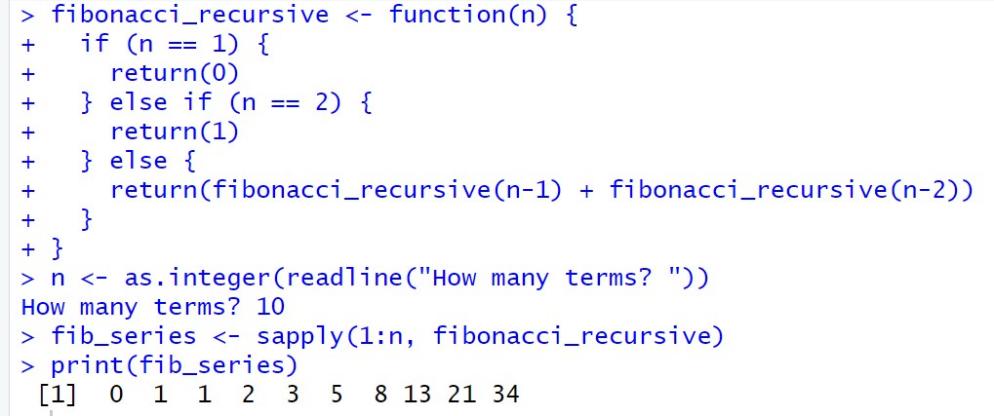
**b. Print the Fibonacci Sequence using Recursive Functions** fibonacci\_recursive <- function(n) { if (n == 1) { return(0) } else if (n == 2) { return(1) } else { return(fibonacci\_recursive(n-1) + fibonacci\_recursive(n-2))

}

}

n <- as.integer(readline("How many terms? ")) fib\_series <- sapply(1:n, fibonacci\_recursive) print(fib\_series)

**Output:**



**Result:**

The Simple Program using R is Successfully Implemented.

|  |  |
| --- | --- |
| **EXP NO:** **2** | **PERFORM DATA PREPROCESSING IN R** |

**Aim:**

To Perform Preprocessing of data using R.

**Algorithm:**

* 1. **Loading Data / Cleaning the Data:**

o Create emp\_df2 with columns: emp\_id, age, dept, salary, experience.

* 1. **Storing / Uploading Data to Excel Sheet:**

o Create a workbook wb, add a worksheet "Employee Data Preprocessing", and save emp\_df2 to emp\_df2.xlsx.

* 1. **Cleaning the Data:** 
     + Replace missing age and salary with their respective mean values.
     + Convert dept to numeric.

1. **Scaling the Data:**

o Scale the age, salary, and experience columns using z-score and update emp\_df2.

1. **Splitting the Data into Train and Test:**

o Set seed, split data into 80% train and 20% test (dataTrain, dataTest).

1. **Correlation Matrix**:

o Compute the correlation matrix for the scaled features (age, salary, experience) to examine relationships between them.

**Programs:**

library(openxlsx)

emp\_df2<-data.frame( emp\_id=1:10,

age=c(25,30,35,NA,55,65,NA,25,85,78), dept=c("AI&DS","IT","AI&ML","CSE","PHY","FT","BIOTECH","CSBS","CIVIL","MECH"), salary=c(50000,85100,52802,144510,552410,520000,445100,5552410,524160,NA), experience=c(2,5,8,14,4,6,3,2,4,5)

)

wb<-createWorkbook()

addWorksheet(wb,"Employee Data Preprocessing")

writeData(wb,"Employee Data Preprocessing",emp\_df2)

saveWorkbook(wb,"C:\\Users\\karthick.S\\OneDrive\\Documents\\231801079-

4\\SAC\\emp\_df2.xlsx",overwrite = TRUE) emp\_df2$age[is.na(emp\_df2$age)]<-floor(mean(emp\_df2$age,na.rm = TRUE))

emp\_df2$salary[is.na(emp\_df2$salary)]<-floor(mean(emp\_df2$salary,na.rm = TRUE))

emp\_df2$dept<-as.numeric(as.factor(emp\_df2$dept))

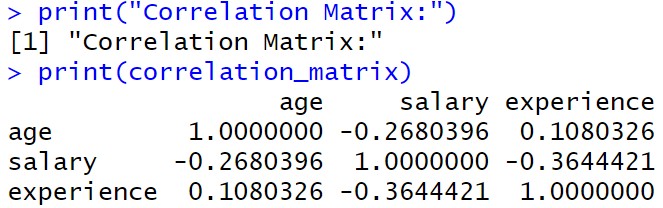
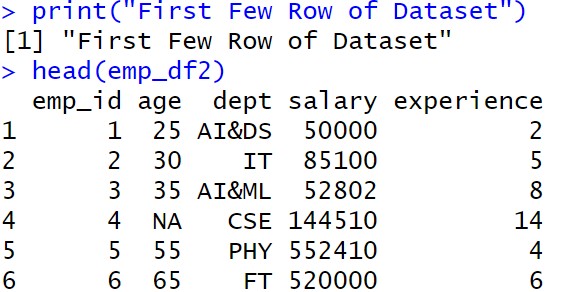
emp\_df\_scaled<-scale(emp\_df2[,c("age","salary","experience")]) emp\_df2<-data.frame(emp\_df2[,c("emp\_id","dept")],emp\_df\_scaled)

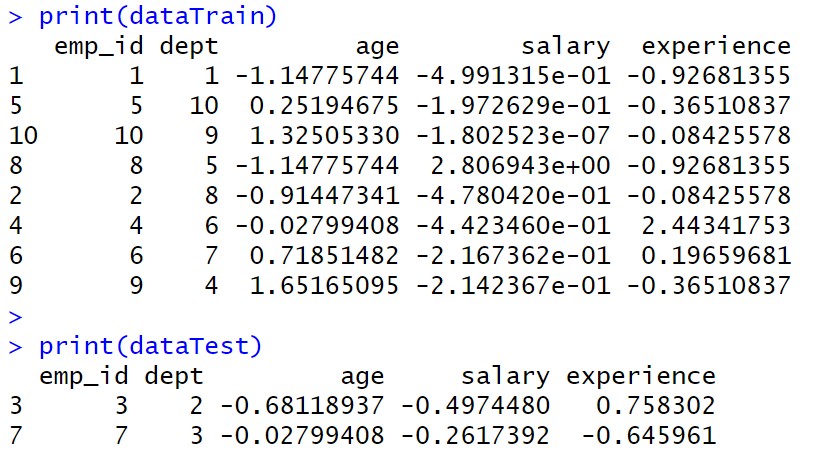
correlation\_matrix <- cor(emp\_df2[, c("age", "salary", "experience")]) print("Correlation Matrix:") print(correlation\_matrix)

set.seed(42) trainIndex<-sample(1:nrow(emp\_df2),0.8\*nrow(emp\_df2)) dataTrain<-emp\_df2[trainIndex,] dataTest<-emp\_df2[-trainIndex,]

print(dataTrain) print(dataTest)

**Output:**





**Result:**

Thus, Preprocessing data is cleaned, transformed and formatted dataset ready for analysis or modelling.

|  |  |
| --- | --- |
| **EXP NO:** **3** | **PERFORM STATISTICAL ANALYSIS FOR A GIVEN**  **DATASET** |

**Aim:**

To Perform Statistical Analysis for Given Dataset.

**Algorithm:**

1. **Loading Libraries:** 
   * Load the necessary libraries: dplyr, summarytools, psych.
2. **Loading Data:** 
   * Create a dataset data with columns Age and Salary.
3. **Statistical Analysis:** 
   * Mean: Calculate the mean of Age.
   * Median: Calculate the median of Age.
   * Mode: Calculate the mode of Age using the table function.
   * Variance: Calculate the variance of Age.
   * Standard Deviation: Calculate the standard deviation of Age.
   * Correlation: Calculate the correlation between Age and Salary.
4. **Descriptive Statistics:** 
   * Use the summary() function to generate summary statistics for the dataset.
5. **Quantile Analysis:** 
   * Calculate the quantiles for both Age and Salary.
6. **Interquartile Range (IQR):** 
   * Calculate the IQR for both Age and Salary.
7. **Hypothesis Testing (T-Test):** 
   * Perform a one-sample t-test on Salary with a hypothesized mean of 70,000.
8. **Visualization:** 
   * Boxplot: Create a boxplot for Age and Salary to visualize their distributions.
9. **Detailed Descriptive Statistics:** 
   * Use describe() from the psych package to get detailed statistics for Age and Salary.
   * Use descr() from the summarytools package for detailed descriptive statistics.

**Program:**

library(dplyr) library(summarytools) library(psych)

data <- data.frame(Age = c(25, 30, 28, 35, 40, 45, 50, 32, 38, 42),

Salary = c(50000, 60000, 55000, 75000, 80000, 85000, 90000, 65000, 78000,

82000)) cat("Dataset:\n") print(data)

mean\_age <- mean(data$Age) median\_age <- median(data$Age) mode\_age <- as.numeric(names(sort(table(data$Age), decreasing = TRUE))[1])

var\_age <- var(data$Age) sd\_age <- sd(data$Age)

corr <- cor(data$Age, data$Salary)

cat("\nStatistical Analysis Results:\n") print(mean\_age) print(median\_age) print(mode\_age) print(var\_age) print(sd\_age) print(corr)

data\_summary <- summary(data) print(data\_summary)

quantile\_age <- quantile(data$Age) quantile\_salary <- quantile(data$Salary)

IQR\_age <- IQR(data$Age)

IQR\_salary <- IQR(data$Salary)

cat("Quantile Age", quantile\_age) cat("\nQuantile Salary", quantile\_salary)

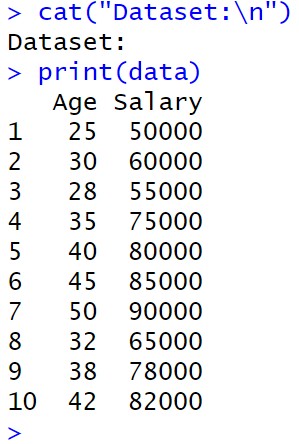
cat("\nIQR Age", IQR\_age) cat("\nIQR Salary", IQR\_salary)

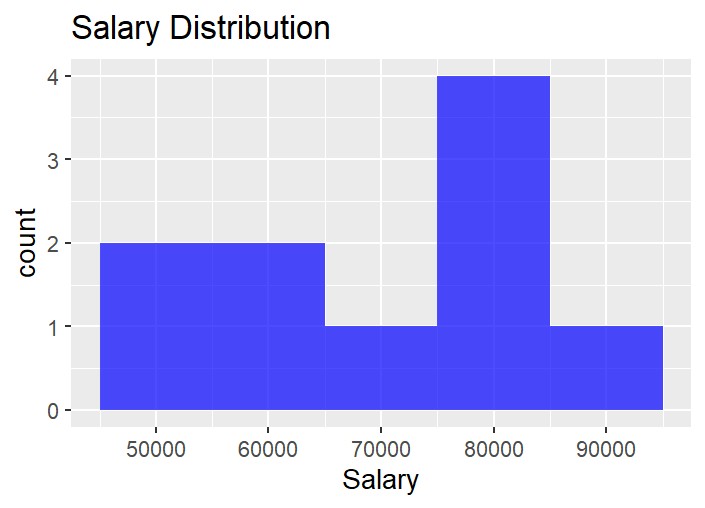
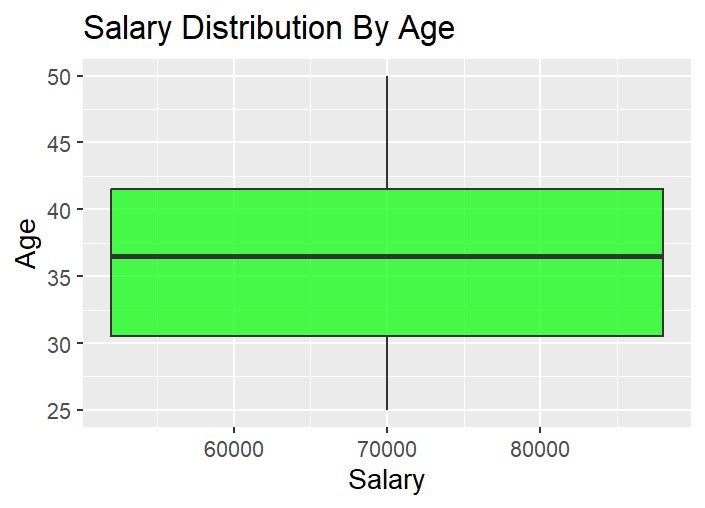
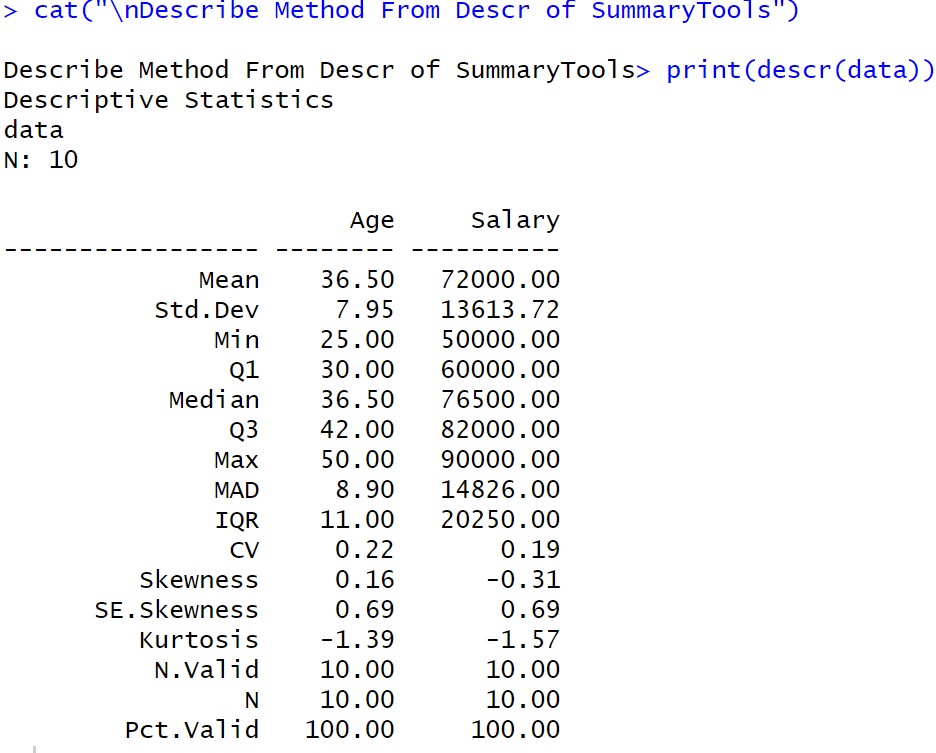
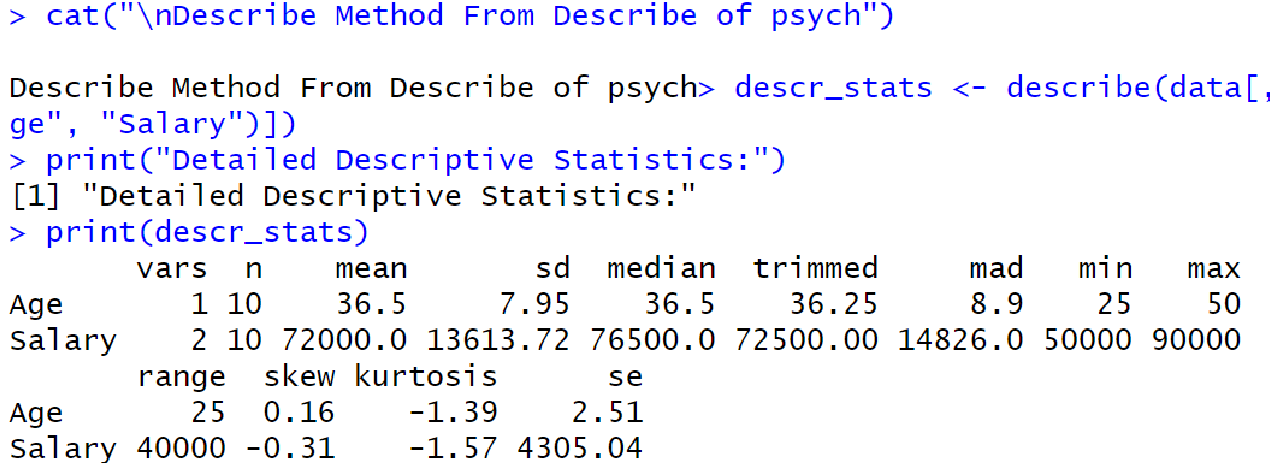
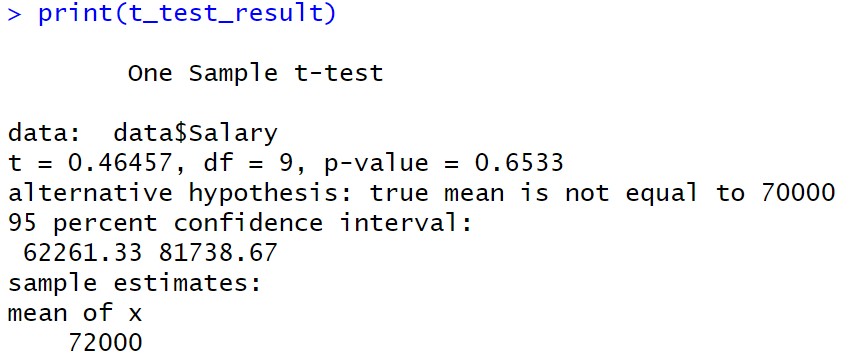
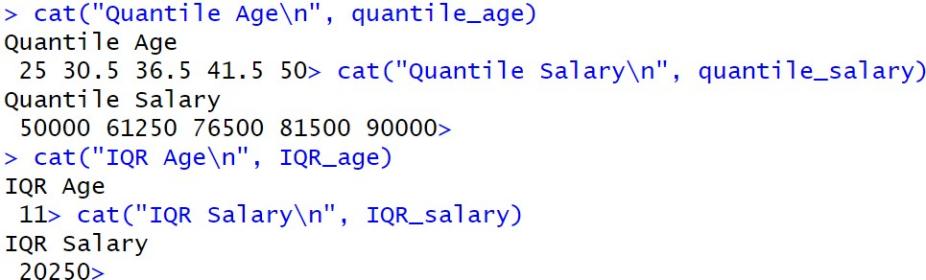
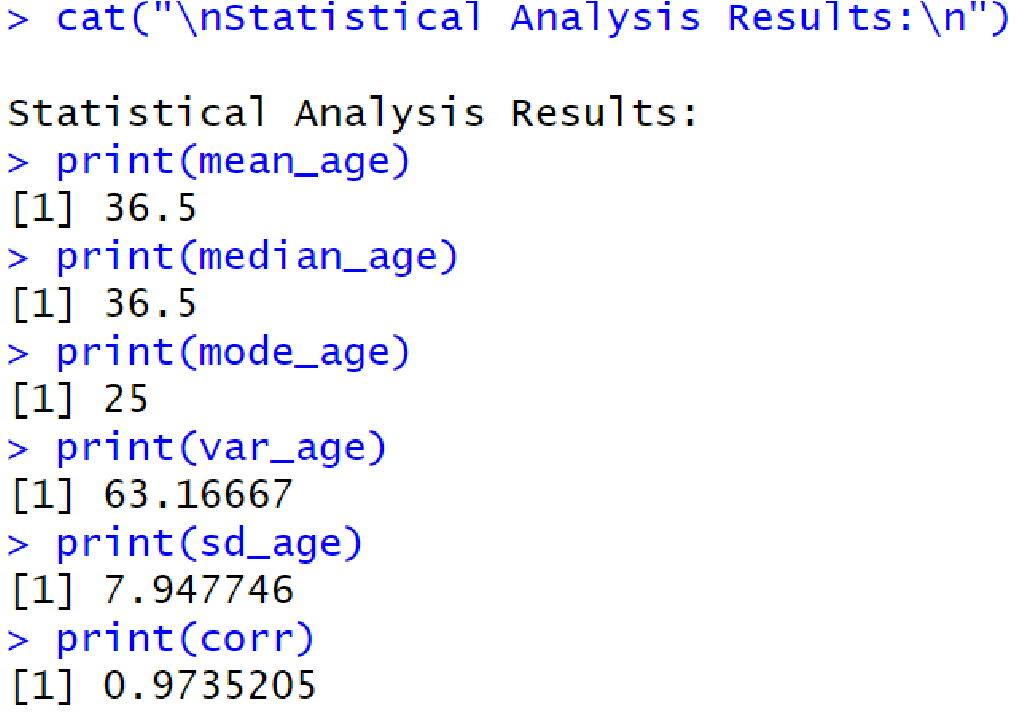
t\_test\_result <- t.test(data$Salary, mu = 70000) print(t\_test\_result)

boxplot(data$Age, main = "Boxplot of Age", ylab = "Age", col = "lightblue") boxplot(data$Salary, main = "Boxplot of Salary", ylab = "Salary", col = "lightgreen")

cat("\nDescribe Method From Describe of psych") descr\_stats <- describe(data[, c("Age", "Salary")]) print("Detailed Descriptive Statistics:") print(descr\_stats) cat("\nDescribe Method From Descr of SummaryTools") print(descr(data))

**Output:**





**Result:**

Thus, Statistical Analysis for a Given Dataset using is Analysed and Scaled.

|  |  |
| --- | --- |
| **EXP NO:** **4** | **IMPLEMENT DECISION TREE ALGORITHM IN R** |

**Aim:**

Implement a Decision Tree Classification on the Given Dataset.

**Procedure:**

1. **Load Required Libraries** 
   * Load the necessary libraries:
     + rpart for building decision tree models. o rpart.plot for visualizing decision trees.
     + caret for data splitting and model evaluation.

**Code:**

library(rpart) library(rpart.plot) library(caret)

1. **Load the Dataset** 
   * Load the Iris dataset (built-in in R).
   * Display the first few rows to understand the data structure.

**Code:**

data("iris") print("First Few Rows of Dataset") head(iris)

1. **Split the Data into Training and Testing Sets** 
   * Set a seed for reproducibility.
   * Use createDataPartition to split the data into:
     + 80% training set o 20% testing set **Code:**

set.seed(123) train\_index <- createDataPartition(iris$Species, p = 0.8, list = FALSE) train\_data <- iris[train\_index, ] test\_data <- iris[-train\_index, ]

1. **Train a Decision Tree Model** 
   * Build a decision tree classifier using rpart, predicting Species based on the features. **Code:**

tree\_model <- rpart(Species ~ ., data = train\_data, method = "class") print(tree\_model)

1. **Visualize the Decision Tree** 
   * Plot the trained decision tree using rpart.plot with enhanced formatting.

**Code:**

rpart.plot(tree\_model, main = "Decision Tree for Iris Dataset", type = 3, extra = 101, under = TRUE, tweak = 1.2, box.palette = "RdBu")

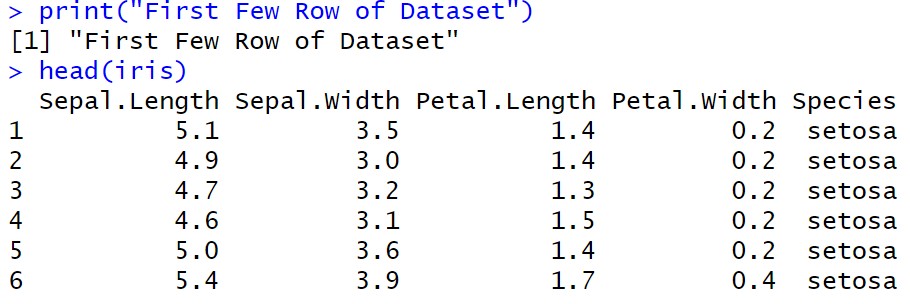
1. **Make Predictions on Test Data** 
   * Use the trained model to predict the species on the test dataset. **Code:**

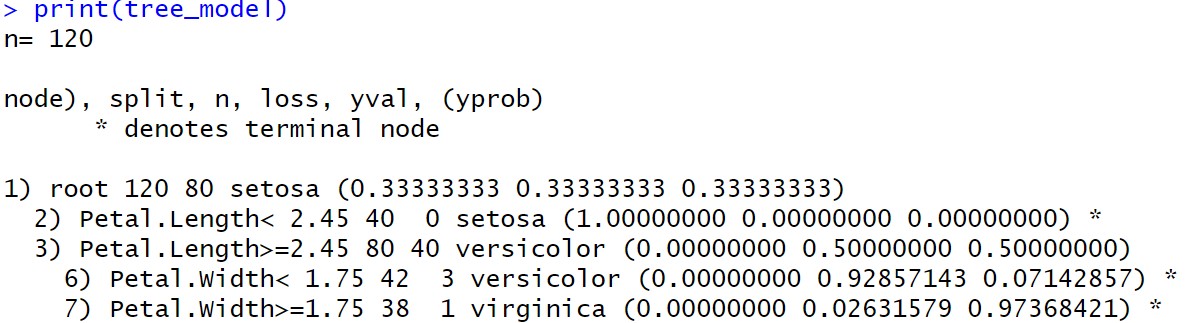
pred <- predict(tree\_model, test\_data, type = "class")

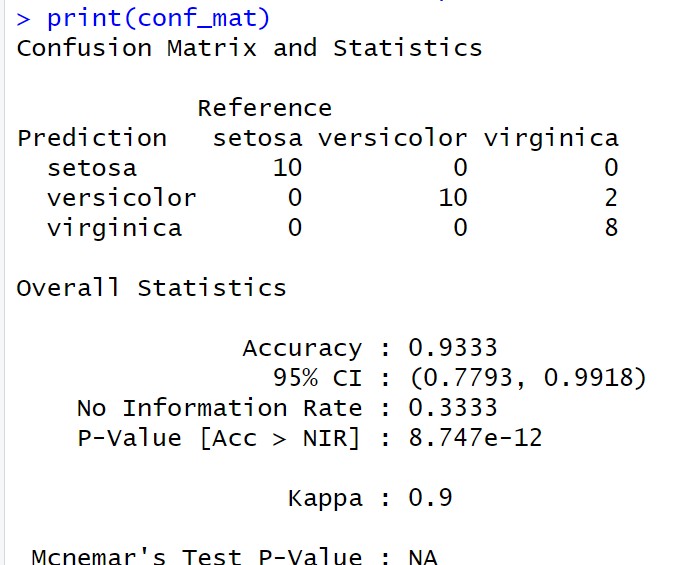
1. **Evaluate Model Performance** 
   * Create a confusion matrix to compare predicted vs actual labels.
   * Print evaluation metrics like accuracy, sensitivity, specificity, etc. **Code:**

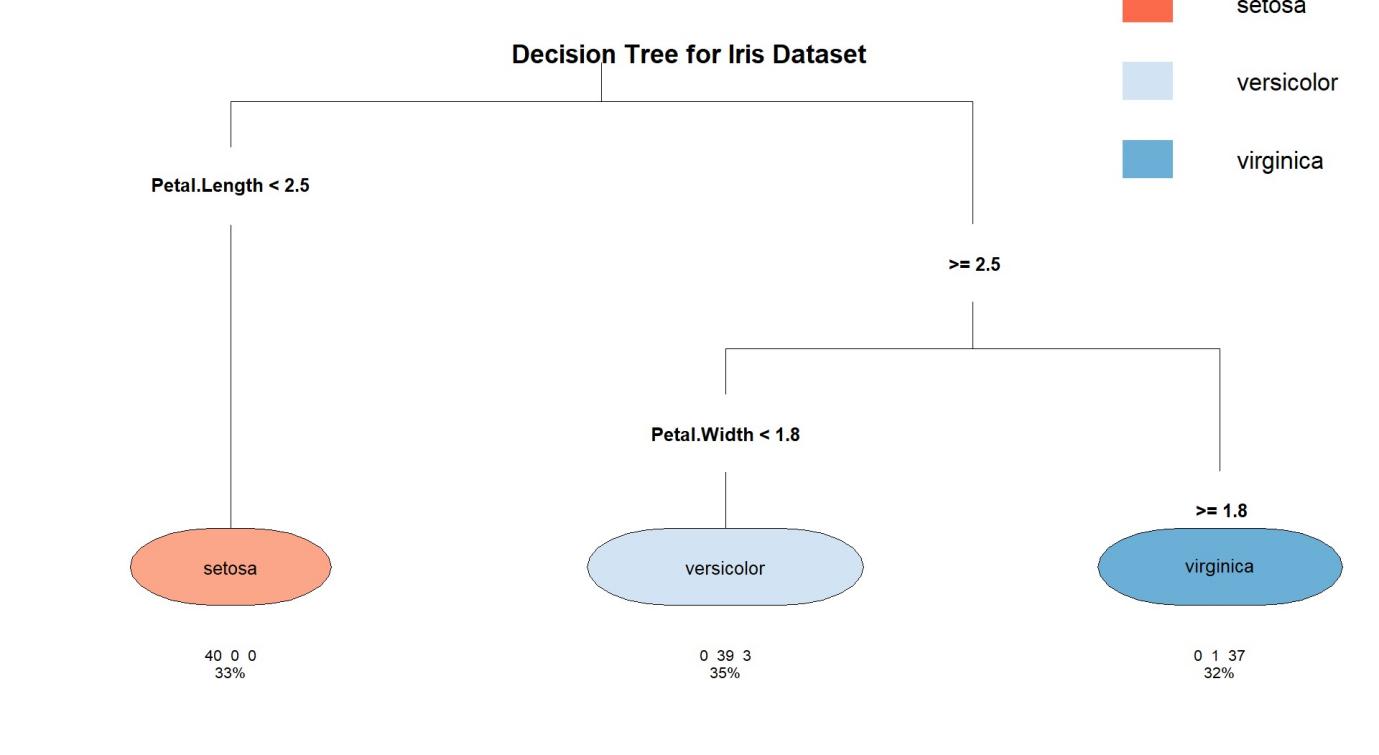
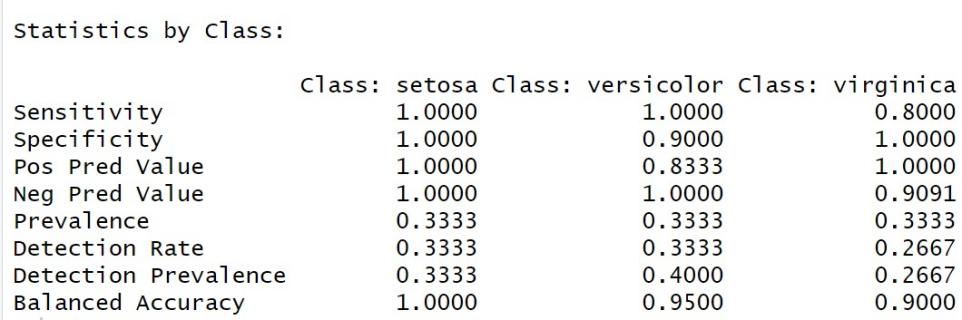
conf\_mat <- confusionMatrix(pred, test\_data$Species) print(conf\_mat)

**Output:**









**Result:**

The Decision Tree is Implemented Successfully.

|  |  |
| --- | --- |
| **EXP NO:** **5** | **IMPLEMENT K-NEAREST NEIGHBOR ALGORITHM**  **IN R** |

**Aim:**

Implement a KNN Classification on the Given Dataset.

**Procedure:**

1. **Load Required Libraries** 
   * Load the necessary libraries:
     + class for KNN model. o ggplot2 for plotting. o GGally for advanced plots (pairwise plots). o caret for data partitioning and evaluation.

**Code:**

library(class) library(ggplot2) library(GGally) library(caret)

1. **Load the Dataset** 
   * Load the Iris dataset.
   * Display the first few rows to understand the structure.

**Code:**

data("iris") print("First Few Rows of Dataset") head(iris)

1. **Define a Normalize Function** 
   * Create a custom function to normalize (scale between 0 and 1) the numerical feature columns.

**Code:**

normalize <- function(x) { return((x - min(x)) / (max(x) - min(x))) }

1. **Normalize the Feature Columns** 
   * Apply the normalization function to the first four feature columns.
   * Add back the Species column separately.

**Code:**

iris\_norm <- as.data.frame(lapply(iris[1:4], normalize)) iris\_norm$Species <- iris$Species

1. **Split the Data into Training and Testing Sets** 
   * Set a random seed for reproducibility.
   * Use createDataPartition to split:
     + 80% for training o 20% for testing

**Code:**

set.seed(123) train\_index <- createDataPartition(iris$Species, p = 0.8, list = FALSE) train\_data <- iris\_norm[train\_index, ] test\_data <- iris\_norm[-train\_index, ]

1. **Extract Training and Test Labels** 
   * Separate the labels (Species) from the feature data for both train and test sets.

**Code:**

train\_labels <- train\_data$Species test\_labels <- test\_data$Species

1. **Train the KNN Model** 
   * Train the K-Nearest Neighbors model using:
     + Normalized feature columns o k = 5 neighbors.

**Code:**

knn\_model <- knn(train = train\_data[, 1:4], test = test\_data[, 1:4], cl = train\_labels, k

= 5)

print(knn\_model)

1. **Visualize the Data** 
   * Create visualizations to understand feature distributions:
     + Scatter plot of Sepal Length vs Sepal Width. o Pairwise plots (all feature combinations).

**Code:**

ggplot(data = iris, aes(x = Sepal.Length, y = Sepal.Width, color = Species)) + geom\_point() +

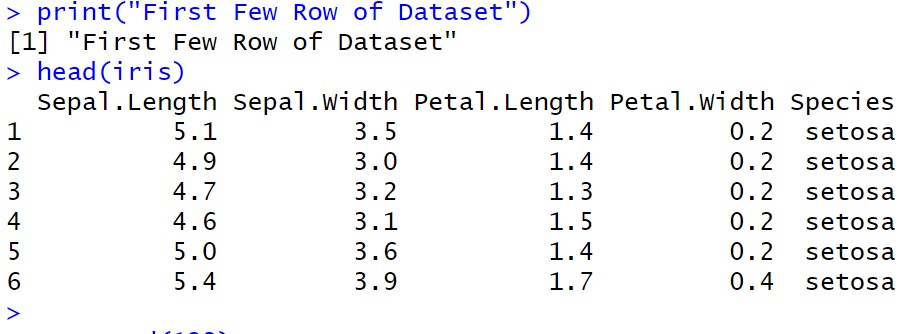
labs(title = "Scatter Plot of Sepal Dimensions", x = "Sepal Length", y = "Sepal Width") + theme\_minimal() ggpairs(iris, aes(color = Species)) + theme\_minimal()

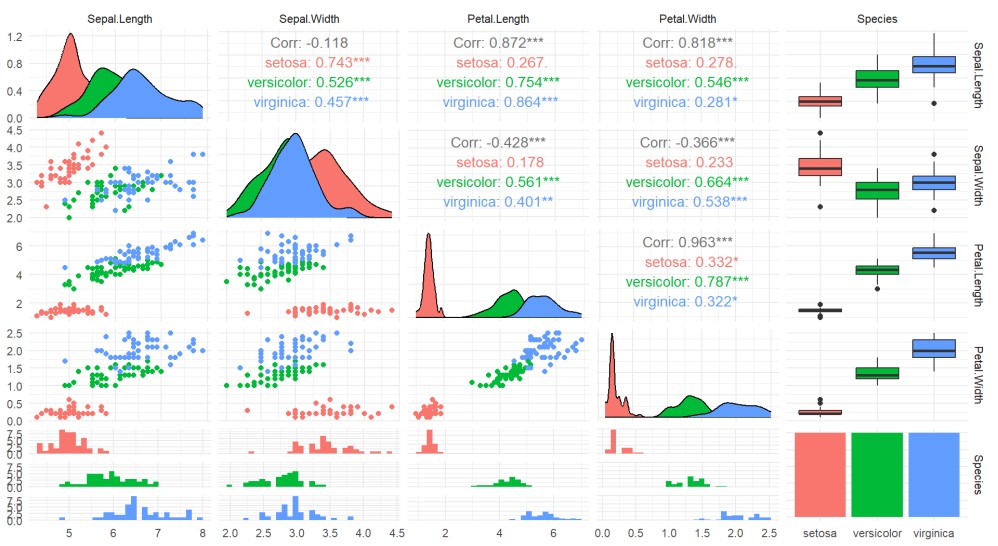
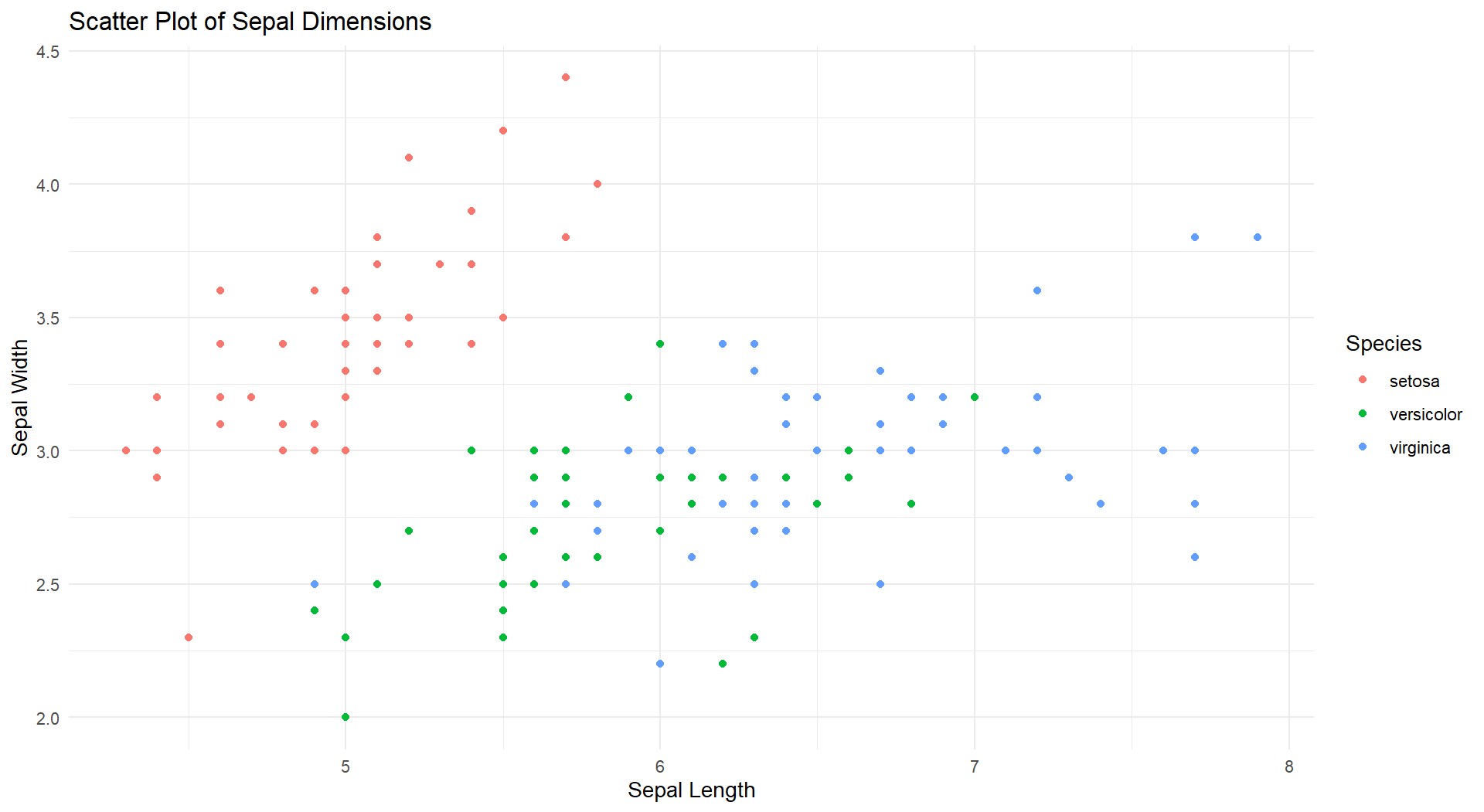
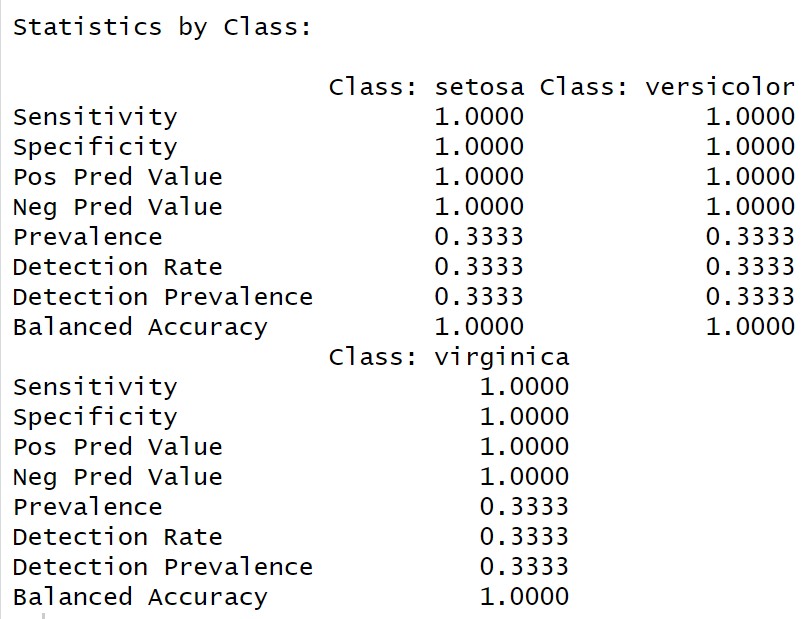
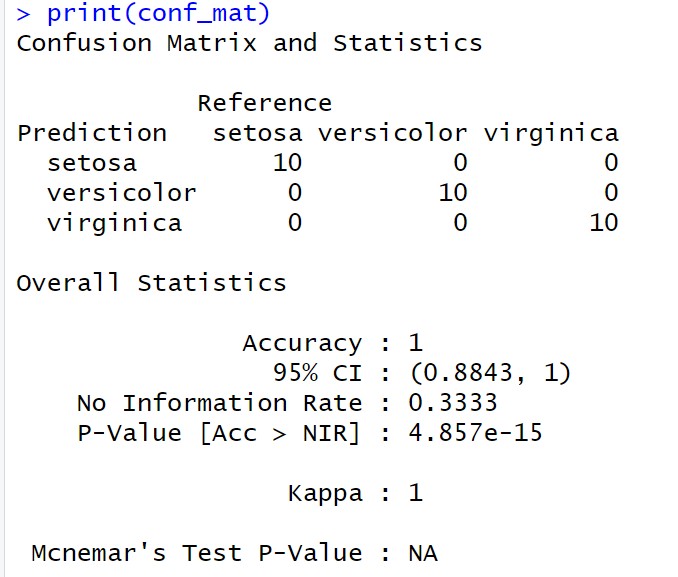
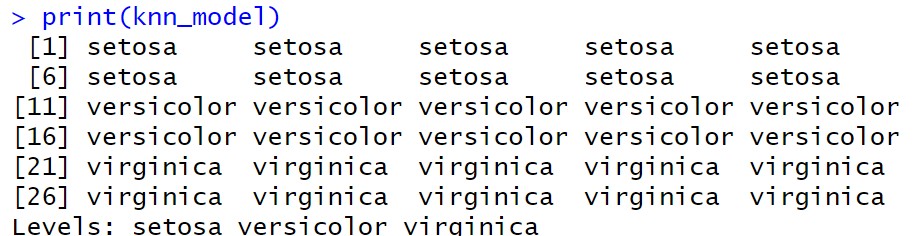
1. **Evaluate Model Performance** 
   * Generate a confusion matrix comparing predictions and true labels.
   * Print classification results including accuracy, sensitivity, and specificity.

**Code:**

conf\_mat <- confusionMatrix(knn\_model, test\_labels) print(conf\_mat)

**Output:**





**Result:**

The KNN Classification is Successfully Implemented.

|  |  |
| --- | --- |
| **EXP NO:** **6** | **IMPLEMENT NAIVE BAYESIAN CLASSIFIER IN R** |

**Aim:**

Implement a Naïve Bayes Classification on the Given Dataset.

**Procedure:**

1. **Load Required Libraries** 
   * Load the necessary libraries: o e1071 for the Naive Bayes model. o ggplot2 for visualization.

o caret for data partitioning and evaluation.

**Code:**

library(e1071) library(ggplot2) library(caret)

1. **Load the Dataset** 
   * Load the Iris dataset.
   * Display the first few rows for a quick overview.

**Code:**

data("iris") print("First Few Rows of Dataset") head(iris)

1. **Split the Data into Training and Testing Sets** • Set a random seed to ensure reproducibility.
   * Split the data into: o 80% for training o 20% for testing

**Code:**

set.seed(123) train\_index <- createDataPartition(iris$Species, p = 0.8, list = FALSE) train\_data <- iris[train\_index, ] test\_data <- iris[-train\_index, ]

1. **Extract Training and Test Labels** 
   * Assign the Species column as the labels for training and testing.

**Code:**

train\_labels <- train\_data$Species test\_labels <- test\_data$Species

1. **Train the Naive Bayes Model** 
   * Train the Naive Bayes classifier using the training data. **Code:**

nb\_model <- naiveBayes(Species ~ ., data = train\_data) print(nb\_model)

1. **Visualize the Data** 
   * Create a scatter plot of Sepal Length vs Sepal Width colored by species.

**Code:**

ggplot(data = iris, aes(x = Sepal.Length, y = Sepal.Width, color = Species)) + geom\_point() +

labs(title = "Scatter Plot of Sepal Dimensions", x = "Sepal Length", y = "Sepal Width") + theme\_minimal()

1. **Make Predictions on the Test Data** 
   * Predict the species for the test dataset using the trained model.

**Code:**

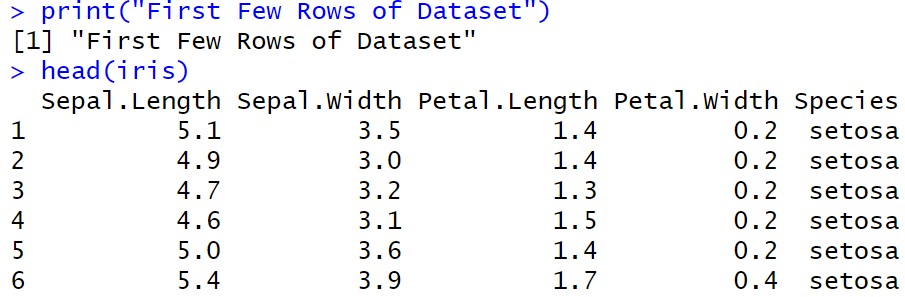
pred <- predict(nb\_model, test\_data)

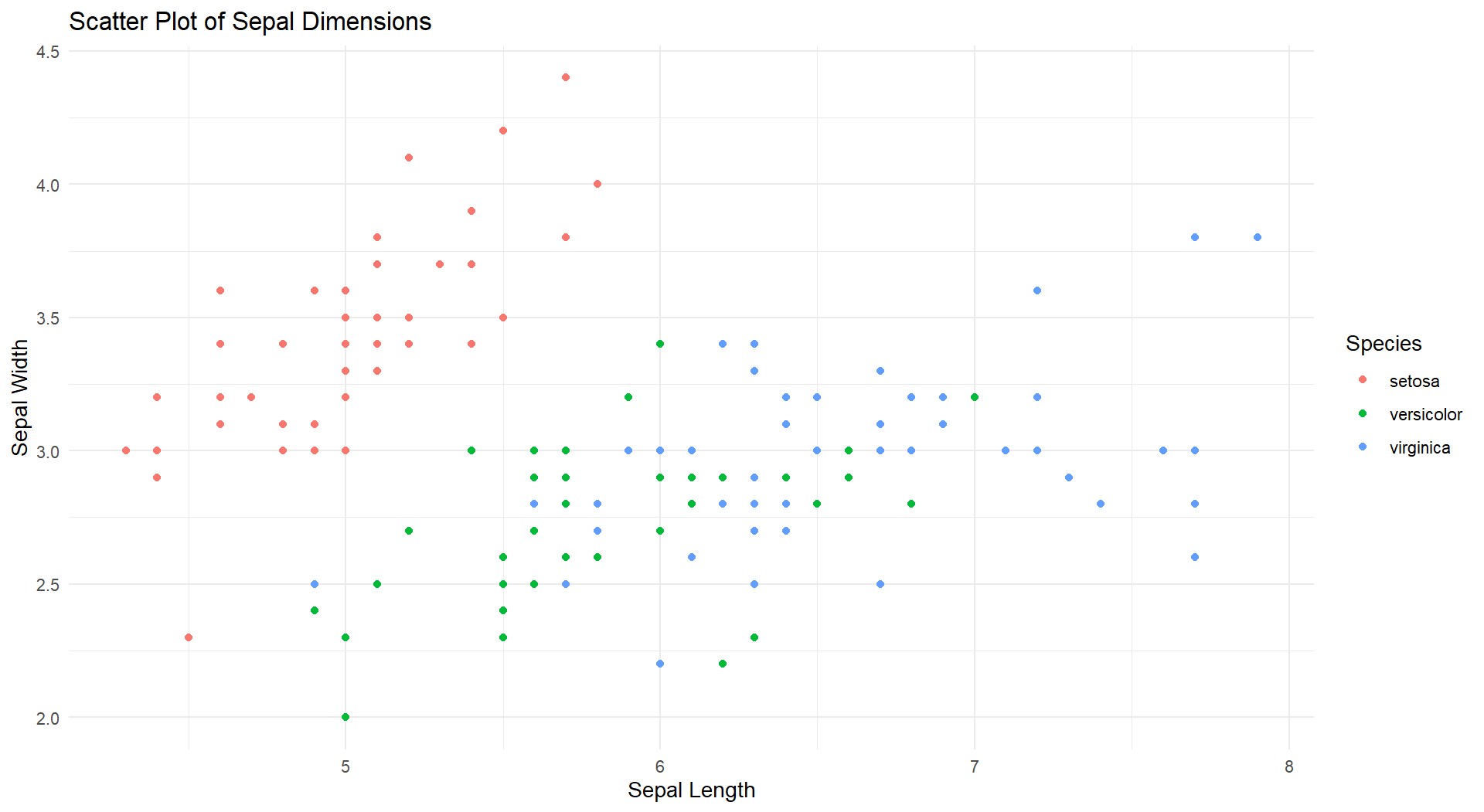
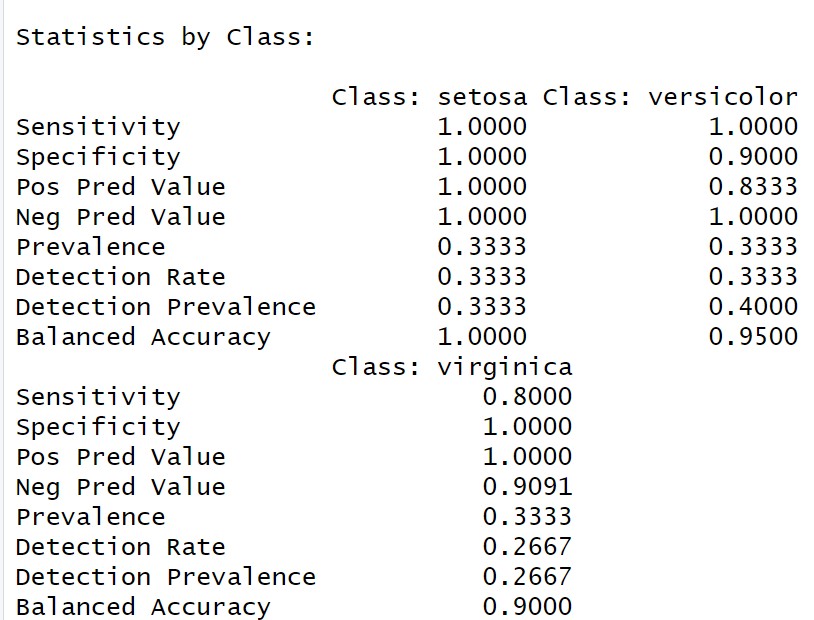
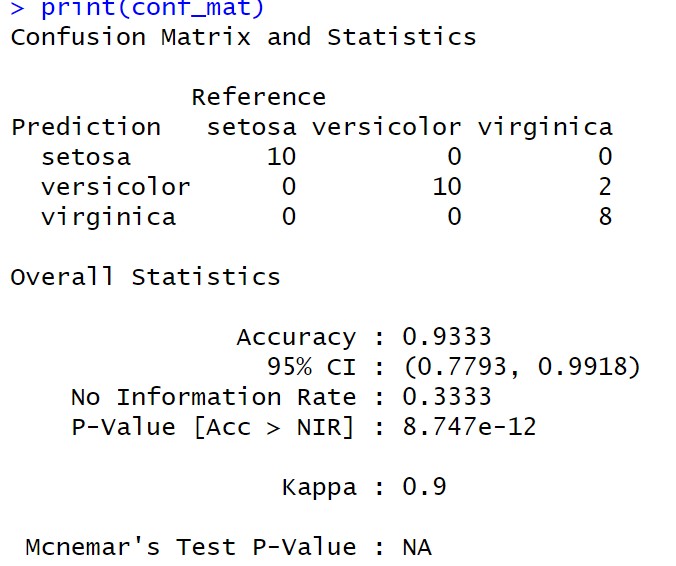
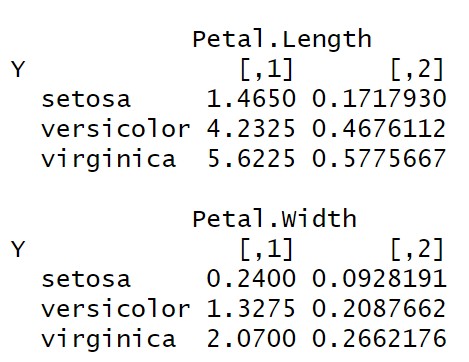
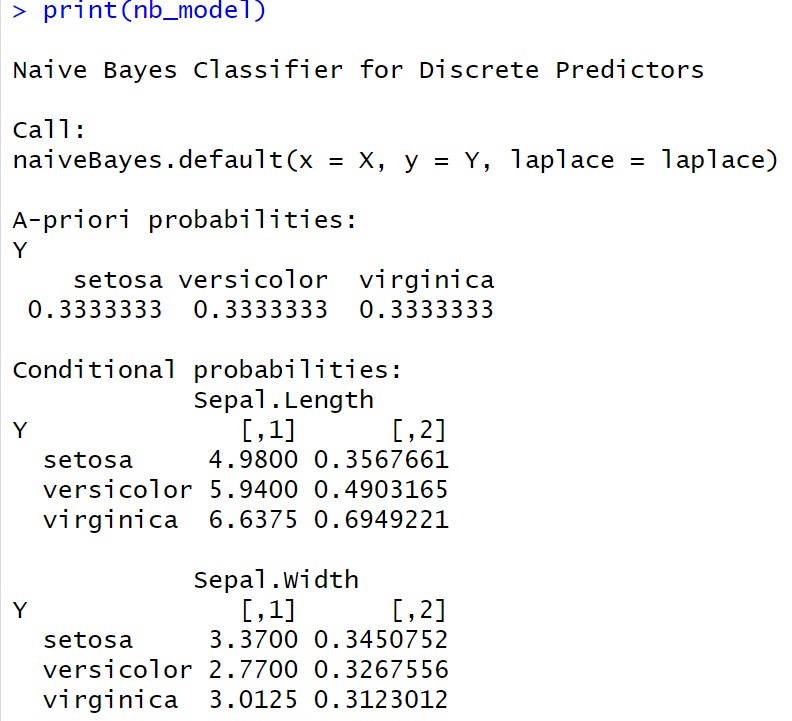
1. **Evaluate Model Performance** 
   * Generate a confusion matrix to compare the predicted labels and true labels.
   * Print evaluation metrics like accuracy, sensitivity, and specificity.

**Code:**

conf\_mat <- confusionMatrix(pred, test\_labels) print(conf\_mat)

**Output:**





**Result:**

The Naïve Bayes Classification is Successfully Implemented.

|  |  |
| --- | --- |
| **EXP NO:** **17** | **Title IMPLEMENT LINEAR REGRESSION IN R** |

**Aim:**

Implement a Linear Regression on the Given Dataset.

**Procedure:**

1. **Load Required Libraries** 
   * Load the necessary libraries:
     + ggplot2 for visualization.
     + caret for splitting the data and evaluating the model.

**Code:**

library(ggplot2) library(caret)

1. **Load the Dataset** 
   * Load the Headbrain dataset from a CSV file.
   * Display the first few rows to inspect the data. **Code:**

df <- read.csv("C:/Users/karthick.S/OneDrive/Documents/231801079-

4/SAC/headbrain.csv") print("First Few Rows of Dataset") head(df)

1. **Split the Data into Training and Testing Sets** 
   * Set a random seed for reproducibility.
   * Split the data into: o 70% for training o 30% for testing

**Code:**

set.seed(123) index <- createDataPartition(df$Brain.Weight.grams., p = 0.7, list = FALSE) train <- df[index, ] test <- df[-index, ]

1. **Train the Linear Regression Model** 
   * Train a linear regression model to predict Brain.Weight.grams. based on Head.Size.cm.3..

**Code:**

print("Linear Regression Model") model <- lm(Brain.Weight.grams. ~ Head.Size.cm.3., data = train) print(model)

1. **Make Predictions on the Test Data** 
   * Use the trained model to predict brain weight values for the test dataset.

**Code:**

pred <- predict(model, newdata = test)

1. **Evaluate Model Performance** 
   * Use postResample to calculate evaluation metrics: o RMSE (Root Mean Squared Error) o R-squared (Coefficient of Determination) o MAE (Mean Absolute Error)

**Code:**

evaluation <- postResample(pred, test$Brain.Weight.grams.) cat("RMSE:", evaluation["RMSE"], "\n") cat("R-squared:", evaluation["Rsquared"], "\n") cat("MAE:", evaluation["MAE"], "\n")

1. **Visualize the Data** 
   * Plot the scatter points of the original data.
   * Overlay the regression line based on the model’s predictions.

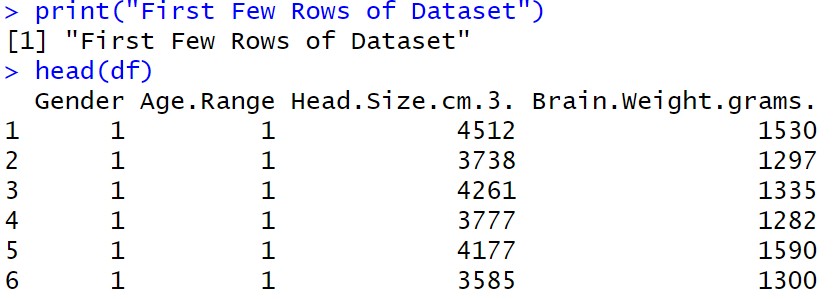
**Code:**

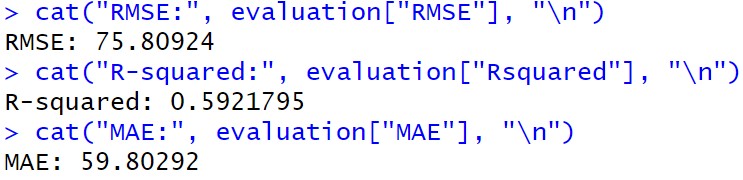
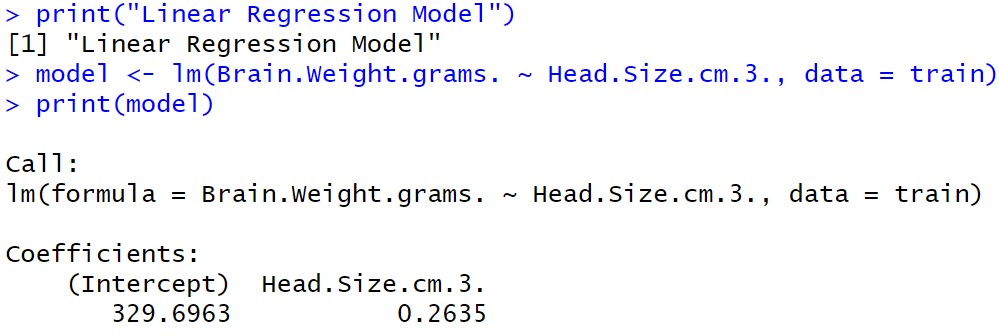
x\_vals <- seq(min(df$Head.Size.cm.3.) - 100, max(df$Head.Size.cm.3.) + 100, length.out = 1000) pred\_line <- data.frame(Head.Size.cm.3. = x\_vals) pred\_line$Brain.Weight.grams. <- predict(model, newdata = pred\_line)

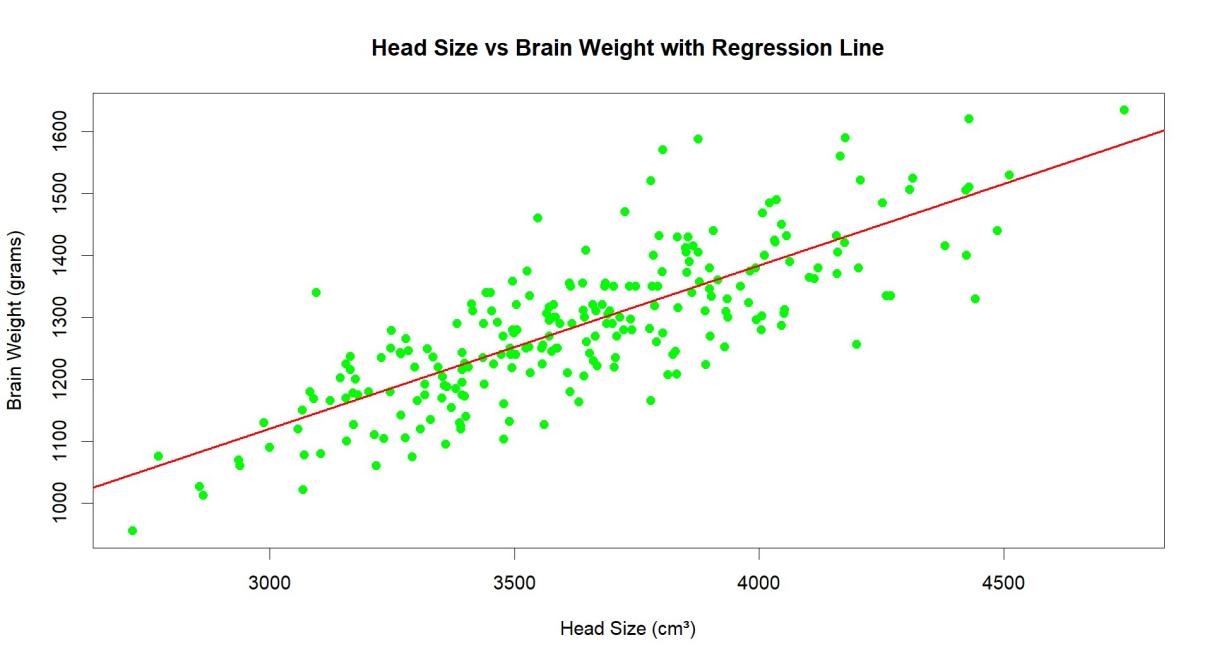
plot(df$Head.Size.cm.3., df$Brain.Weight.grams., col = "green", pch = 19, xlab = "Head Size (cm³)", ylab = "Brain Weight (grams)", main = "Head Size vs Brain Weight with Regression Line")

lines(pred\_line$Head.Size.cm.3., pred\_line$Brain.Weight.grams., col = "red", lwd = 2)

**Output:**







**Result:**

The Linear Regression is Successfully Implemented.

|  |  |
| --- | --- |
| **EXP NO:** **8** | **IMPLEMENT K-MEANS CLUSTERING ALGORITHM**  **IN R** |

**Aim:**

Implement a Kmeans Clustering on the Given Dataset.

**Procedure:**

**Procedure for Performing and Evaluating K-means Clustering in R**

1. **Load Required Libraries** 
   * Load the necessary libraries:
     + ggplot2 for plotting. o cluster for silhouette analysis.
     + factoextra for easy visualization of clustering.

**Code:**

library(ggplot2) library(cluster) library(factoextra)

1. **Load the Dataset** 
   * Load the Iris dataset.
   * Remove the Species column to focus only on the numeric features for clustering.

**Code:**

data(iris) iris\_data <- iris[, -5] head(iris\_data)

1. **Determine the Optimal Number of Clusters Using Elbow Method** 
   * Use the Within-Cluster Sum of Squares (WSS) method to decide how many clusters are appropriate.

**Code:**

fviz\_nbclust(iris\_data, kmeans, method = "wss") + ggtitle("Elbow Method for Optimal K")

1. **Apply K-means Clustering with 3 Clusters** 
   * Set a random seed for reproducibility.
   * Apply K-means clustering specifying 3 clusters (since Iris has 3 species).

**Code:**

set.seed(123)

kmeans\_model <- kmeans(iris\_data, centers = 3, nstart = 25)

1. **Print Cluster Centers and Cluster Assignments** 
   * View the center points of the clusters and how the data points were assigned.

**Code:**

print(kmeans\_model$centers) print(kmeans\_model$cluster)

1. **Visualize the Clusters** 
   * Visualize the clustering result using a scatter plot with convex hulls around clusters. **Code:**

fviz\_cluster(kmeans\_model, data = iris\_data, geom = "point", ellipse.type =

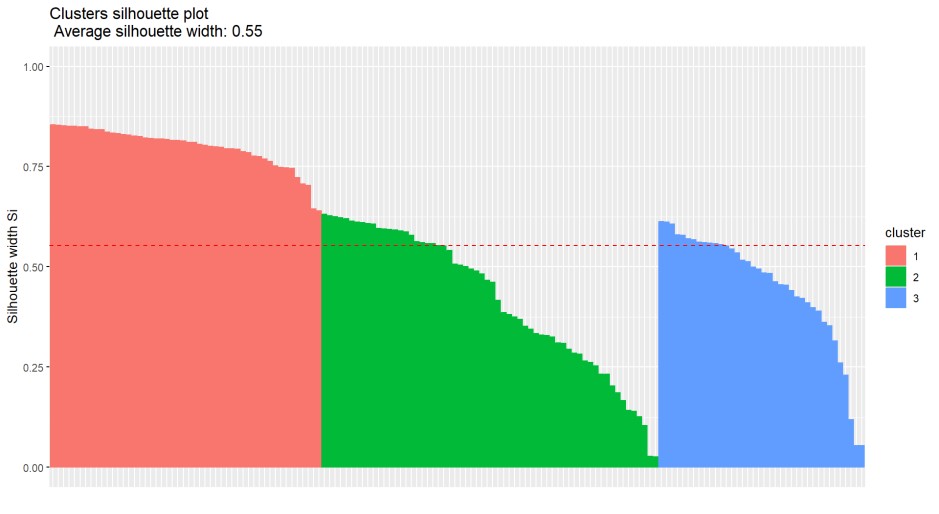
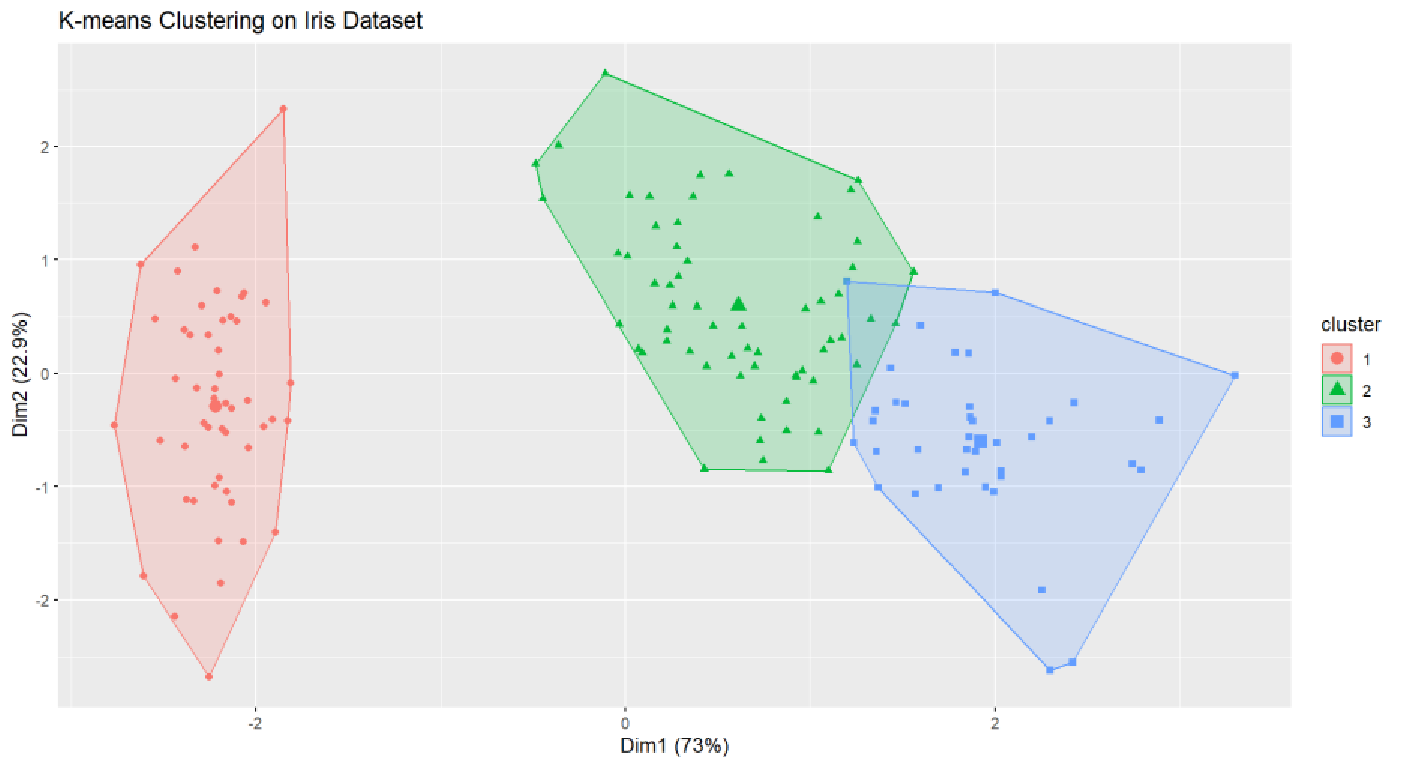
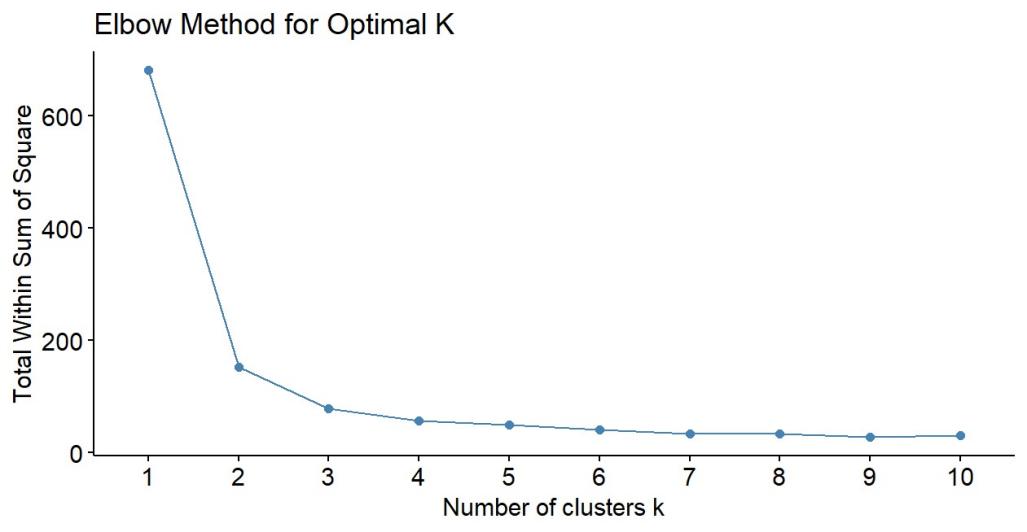
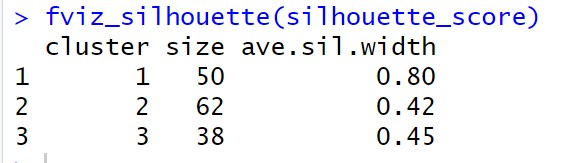
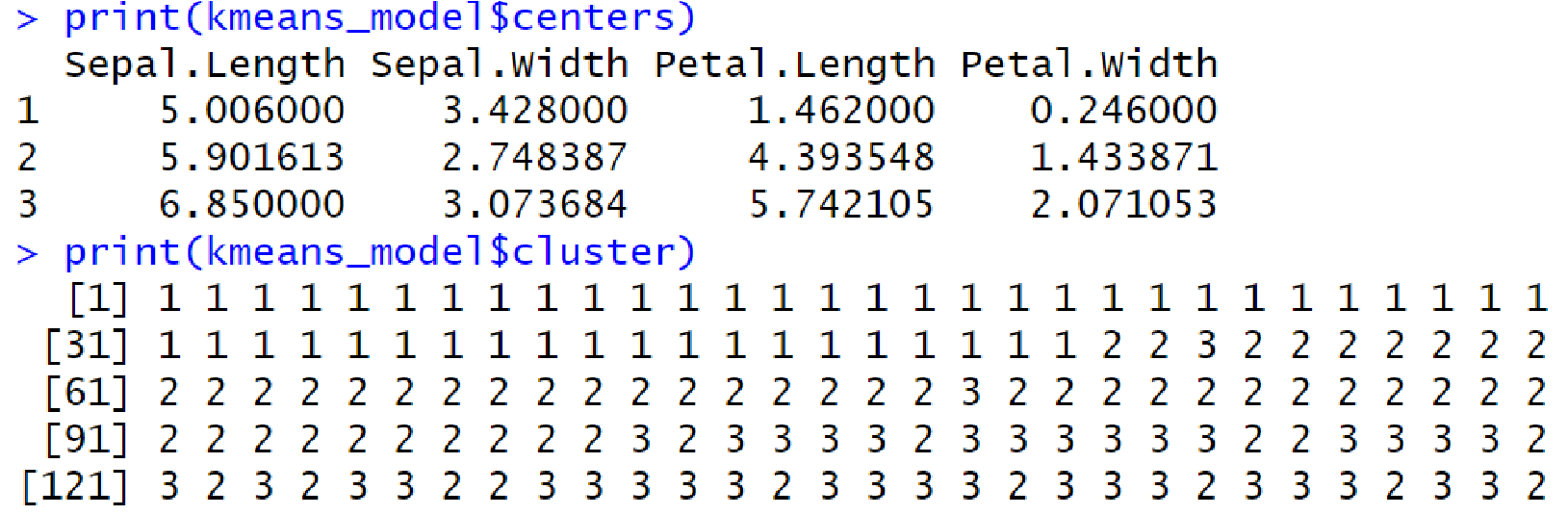
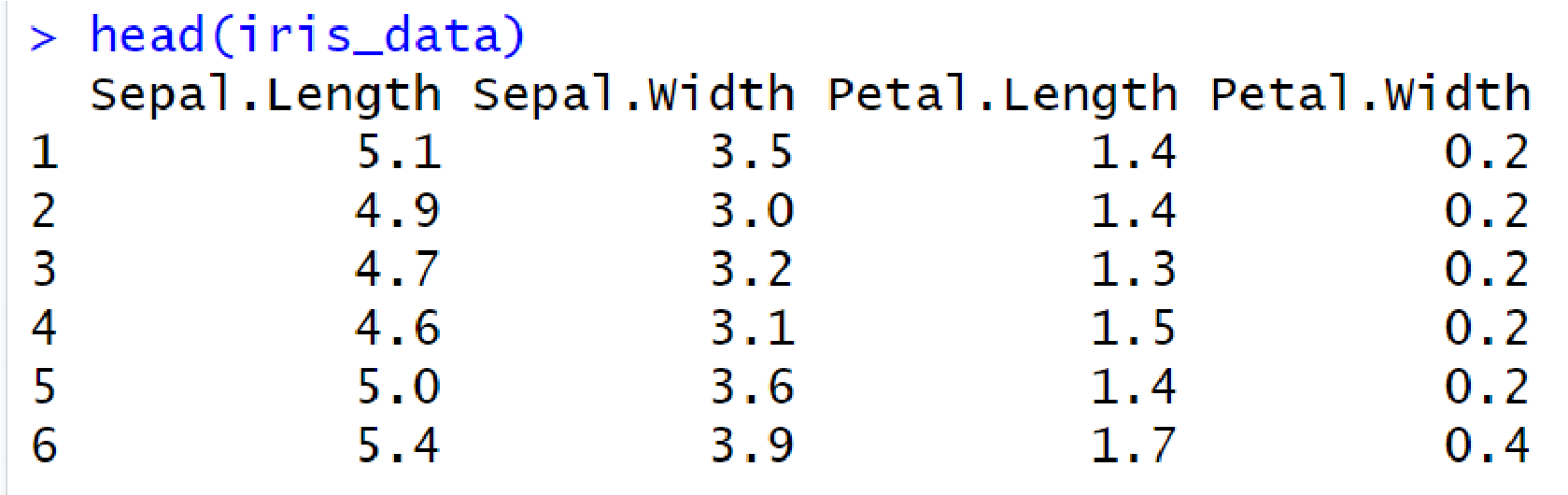
"convex") +

ggtitle("K-means Clustering on Iris Dataset")

1. **Evaluate the Clustering (Silhouette Analysis)** 
   * Perform silhouette analysis to assess the quality of the clustering. **Code:**

silhouette\_score <- silhouette(kmeans\_model$cluster, dist(iris\_data)) fviz\_silhouette(silhouette\_score)

**Output:**



**Result:**

The Kmeans is Successfully Implemented.