SYMBIOSIS INSTITUTE OF TECHNOLOGY (SIT)
Constituent of Symbiosis International (Deemed University), Pune
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॥वसुधैव कुटुम्बकम्॥ Re-Accredited by NAAC with 'A' Grade

Assignment No. 03	
Name of Student	**Antriksh Sharma**
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Title of Lab Assignment	**CLUSTERING MODEL** • **Use mtcars, iris, customer churn dataset for implementation.** • **Use K-Mean clustering, Hierarchal clustering, Decision Tree, Random Forest using bagging Techniques.** • **Calculate the MAE, MSE, Entropy, Precision, Recall, Accuracy, F1-score, ROC curve.**

Code & Output:

```
#install.packages("ggplot2") library(ggplot2)
# Select the columns 'Sepal.Length' and 'Species' from the iris dataset input <-
iris[,c('Sepal.Length','Species')] input_hist <- iris$Sepal.Length
# Display the input print(input)
# Create a boxplot
boxplot(Sepal.Length~Species, data=iris, xlab="Species", ylab="Sepal Length (cm)", main =
"Iris data")
# Create a boxplot with different colors for each box
boxplot(Sepal.Length~Species, data=iris, xlab="Species", ylab="Sepal Length (cm)", main =
"Iris data", col=c("red","green","blue"))
# Create a line plot with different colors for each species
ggplot(data = iris, aes(x = Species, y = Sepal.Length, group = Species, color = Species)) +
geom_line() +
labs(x = "Species", y = "Sepal Length (cm)", title = "Iris data") # Create a histogram
hist(input_hist, main = "Histogram of Sepal Length", xlab = "Sepal Length (cm)", col = "blue")
# Create a pie chart of the species distribution species_counts <- table(iris$Species)
pie(species_counts, main = "Pie Chart of Species Distribution", col = c("red", "green", "blue"))
# Create a bar chart of the species distribution
barplot(species_counts, main = "Bar Chart of Species Distribution", xlab = "Species", ylab =
"Count", col = c("red", "green", "blue"))
# scatter plot
plot(input_hist, col = c("red", "green", "blue")) # Close the current device dev.off()
```

Round the predicted values to binary (0 or 1) predicted_binary <- ifelse(predicted_values > 0.5, 1, 0) # Calculate accuracy

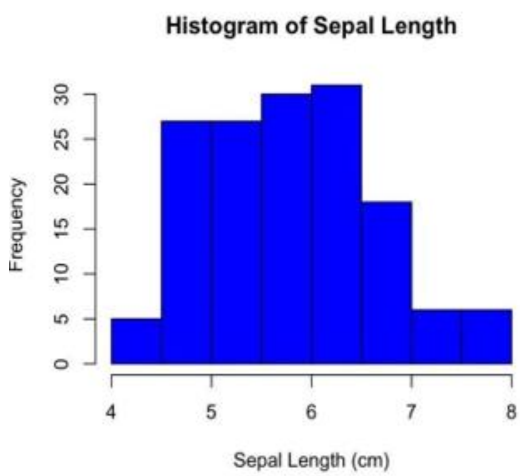
accuracy <- sum(predicted_binary == actual_values) / length(actual_values) # Calculate Mean Absolute Error (MAE)

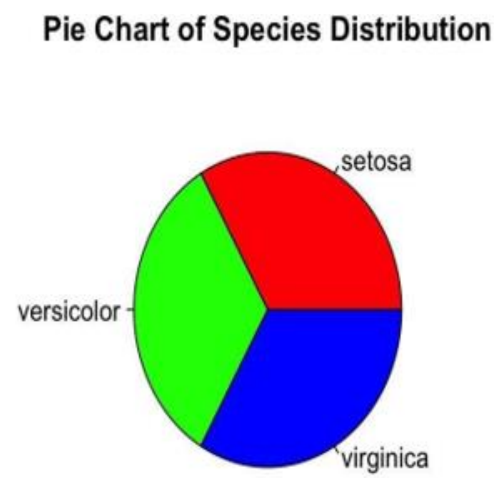
mae <- mean(abs(predicted_values - actual_values)) # Calculate Mean Squared Error (MSE)

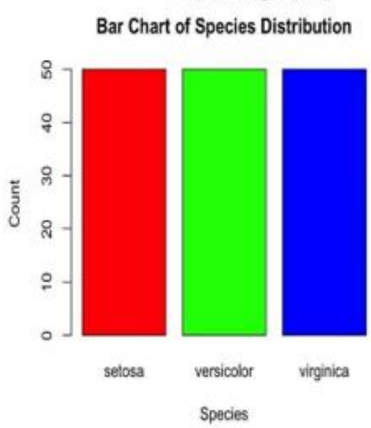
mse <- mean((predicted_values - actual_values)^2) # Print the results

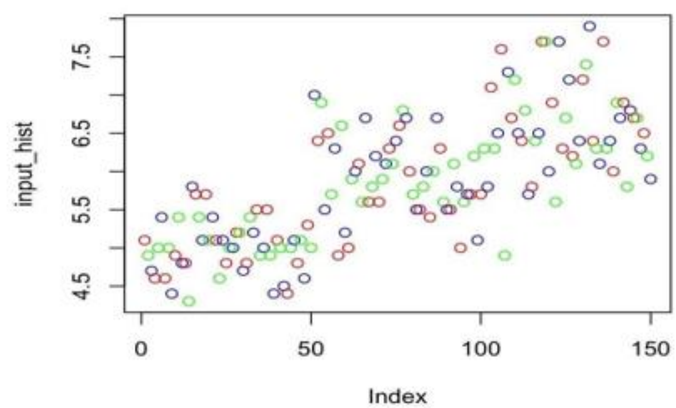
cat("Accuracy:", accuracy, "\n") cat("MAE:", mae, "\n")

cat("MSE:", mse, "\n")










```
> # Round the predicted values to binary (0 or 1)
> predicted_binary <- ifelse(predicted_values > 0.5, 1, 0)
> # Calculate accuracy
> accuracy <- sum(predicted_binary == actual_values) / length(actual_values)
> # Calculate Mean Absolute Error (MAE)
> mae <- mean(abs(predicted_values - actual_values))
> # Calculate Mean Squared Error (MSE)
> mse <- mean((predicted_values - actual_values)^2)
> # Print the results
> cat("Accuracy:", accuracy, "\n")
Accuracy: 1
> cat("MAE:", mae, "\n")
MAE: 1.09801e-11
> cat("MSE:", mse, "\n")
MSE: 5.012336e-21
>
```

MTCARS:

Install and Load Necessary Libraries install.packages("randomForest") install.packages("rpart") install.packages("caret") install.packages("e1071") install.packages("ggplot2") library(randomForest)

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

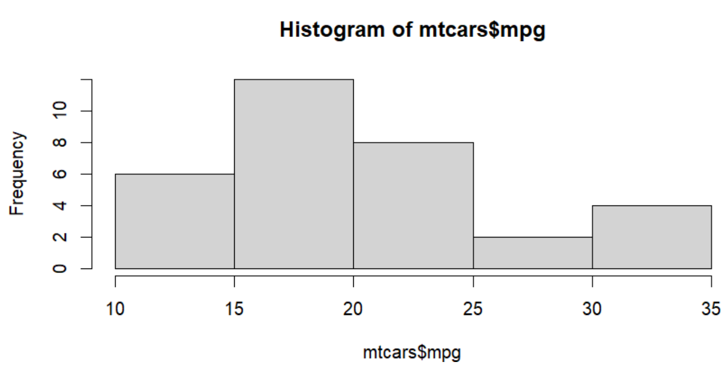
Load mtcars dataset data(mtcars)

EDA

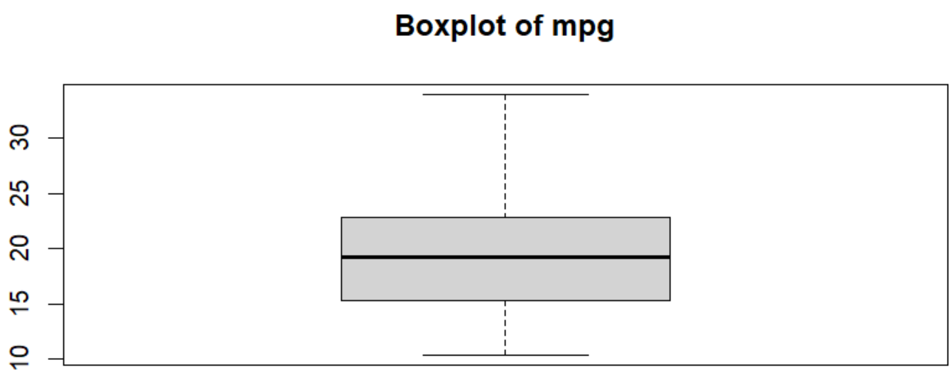
summary(mtcars)

```
> summary(mtcars)
      mpg             cyl             disp             hp             drat      
 Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0   Min.   :2.760  
 1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5   1st Qu.:3.080  
 Median :19.20   Median :6.000   Median :196.3   Median :123.0   Median :3.695  
 Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7   Mean   :3.597  
 3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0   3rd Qu.:3.920  
 Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0   Max.   :4.930  
       wt             qsec             vs               am              gear      
 Min.   :1.513   Min.   :14.50   Min.   :0.0000   Min.   :0.0000   Min.   :3.000  
 1st Qu.:2.581   1st Qu.:16.89   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:3.000  
 Median :3.325   Median :17.71   Median :0.0000   Median :0.0000   Median :4.000  
 Mean   :3.217   Mean   :17.85   Mean   :0.4375   Mean   :0.4062   Mean   :3.688  
 3rd Qu.:3.610   3rd Qu.:18.90   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:4.000  
 Max.   :5.424   Max.   :22.90   Max.   :1.0000   Max.   :1.0000   Max.   :5.000  
      carb      
 Min.   :1.000  
 1st Qu.:2.000  
 Median :2.000  
 Mean   :2.812  
 3rd Qu.:4.000  
 Max.   :8.000  
```

hist(mtcars$mpg)



```
boxplot(mtcars$mpg, main = "Boxplot of mpg")
```




```
# Convert it to factor for classification mtcars$am <- as.factor(mtcars$am)
# Splitting the dataset into training and test set set.seed(123)
index <- sample(1:nrow(mtcars), nrow(mtcars)*0.7) train <- mtcars[index,]
test <- mtcars[-index,]
# Classification using Random Forest
rf_model <- randomForest(am ~ ., data = train) rf_pred <- predict(rf_model, test)
# Classification using Decision Tree
dt_model <- rpart(am ~ ., data = train, method = "class")

dt_pred <- predict(dt_model, test, type = "class") # Metrics Calculation
metrics <- function(model_name, actual, predicted) { actual_numeric <-
as.numeric(as.character(actual)) cat("\n", model_name, "\n")
cat("    \n") # Confusion Matrix
conf_matrix <- confusionMatrix(predicted, actual) print(conf_matrix$table)
# Basic Metrics
cat("Mean:", mean(actual_numeric), "\n") cat("Median:", median(actual_numeric), "\n")
cat("Mode:", as.numeric(names(which.max(table(actual)))), "\n") # Precision and Recall
cat("Recall:", conf_matrix$byClass['Recall'], "\n") cat("Precision:",
conf_matrix$byClass['Precision'], "\n")
}
```

metrics("Random Forest", test$am, rf_pred) metrics("Decision Tree", test$am, dt_pred) # For entropy calculation

entropy <- function(data) {

prob <- table(data) / length(data)

-sum(prob * log2(prob))

}

cat("\nEntropy: ", entropy(test$am), "\n")

```
 Random Forest                      Decision Tree
------------------------------     ------------------------------
          Reference                           Reference
Prediction 0 1                     Prediction 0 1
         0 7 0                              0 7 0
         1 1 2                              1 1 2
Mean: 0.2                          Mean: 0.2
Median: 0                          Median: 0
Mode: 0                            Mode: 0
Recall: 0.875                      Recall: 0.875
Precision: 1                       Precision: 1
```

```
Entropy:  0.7219281
>
```

Load the dataset data(mtcars)

Fit a linear regression model

lm_model <- lm(mpg ~ wt + hp, data = mtcars) summary(lm_model)

```
> summary(lm_model)

Call:
lm(formula = mpg ~ wt + hp, data = mtcars)

Residuals:
   Min     1Q Median     3Q    Max 
-3.941 -1.600 -0.182  1.050  5.854 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 37.22727    1.59879  23.285  < 2e-16 ***
wt          -3.87783    0.63273  -6.129 1.12e-06 ***
hp          -0.03177    0.00903  -3.519  0.00145 ** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.593 on 29 degrees of freedom
Multiple R-squared:  0.8268,	Adjusted R-squared:  0.8148 
F-statistic: 69.21 on 2 and 29 DF,  p-value: 9.109e-12
```

```
# Fit a multiple regression model
mul_lin_reg_model <- lm(mpg ~ wt + hp + qsec + disp, data = mtcars)
summary(mul_lin_reg_model)
```

```
> summary(mul_lin_reg_model)

Call:
lm(formula = mpg ~ wt + hp + qsec + disp, data = mtcars)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.8664 -1.5819 -0.3788  1.1712  5.6468 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)   
(Intercept) 27.329638   8.639032   3.164  0.00383 **
wt          -4.609123   1.265851  -3.641  0.00113 **
hp          -0.018666   0.015613  -1.196  0.24227   
qsec         0.544160   0.466493   1.166  0.25362   
disp         0.002666   0.010738   0.248  0.80576   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.622 on 27 degrees of freedom
Multiple R-squared:  0.8351,	Adjusted R-squared:  0.8107 
F-statistic: 34.19 on 4 and 27 DF,  p-value: 3.311e-10
```

Install and load the xgboost package install.packages("xgboost") library(xgboost)

Fit an XGBoost regression model

xgb_model <- xgboost(data = as.matrix(mtcars[, -1]), label = mtcars$mpg, nrounds = 100)
summary(xgb_model)

```
> library(xgboost)
> # Fit an XGBoost regression model
> xgb_model <- xgboost(data = as.matrix(mtcars[, -1]), label = mtcars$mpg, nrounds = 100)
[1]     train-rmse:14.931315
[2]     train-rmse:10.956806
[3]     train-rmse:8.086656
[4]     train-rmse:6.014954
[5]     train-rmse:4.524509
[6]     train-rmse:3.452733
[7]     train-rmse:2.678069
[8]     train-rmse:2.092810
[9]     train-rmse:1.657410
[10]    train-rmse:1.333903
[11]    train-rmse:1.051681
[12]    train-rmse:0.853427
[13]    train-rmse:0.688968
[14]    train-rmse:0.562896
[15]    train-rmse:0.460306
[16]    train-rmse:0.382382
[17]    train-rmse:0.320703
[18]    train-rmse:0.269630
[19]    train-rmse:0.228152
[20]    train-rmse:0.194210
[21]    train-rmse:0.165316
[22]    train-rmse:0.139259
[23]    train-rmse:0.118684
[24]    train-rmse:0.102250
[25]    train-rmse:0.088770
[26]    train-rmse:0.077129
```

```
[93]    train-rmse:0.000965
[94]    train-rmse:0.000965
[95]    train-rmse:0.000965
[96]    train-rmse:0.000965
[97]    train-rmse:0.000965
[98]    train-rmse:0.000965
[99]    train-rmse:0.000965
[100]   train-rmse:0.000965
> summary(xgb_model)
               Length Class              Mode
handle              1 xgb.Booster.handle externalptr
raw            114037 -none-             raw
niter               1 -none-             numeric
evaluation_log      2 data.table         list
call               13 -none-             call
params              1 -none-             list
callbacks           2 -none-             list
feature_names      10 -none-             character
nfeatures           1 -none-             numeric
```

Fit a ridge regression model install.packages("glmnet") library(glmnet)
ridge_model <- cv.glmnet(as.matrix(mtcars[, -1]), mtcars$mpg, alpha = 0)
print(ridge_model)

```
Call:  cv.glmnet(x = as.matrix(mtcars[, -1]), y = mtcars$mpg, alpha = 0)

Measure: Mean-Squared Error

    Lambda Index Measure    SE Nonzero
min  2.747    82   6.724 1.912      10
1se 12.170    66   8.450 2.581      10
```

# Fit a lasso regression model
lasso_model <- cv.glmnet(as.matrix(mtcars[, -1]), mtcars$mpg, alpha = 1)
print(lasso_model)

```
Call:  cv.glmnet(x = as.matrix(mtcars[, -1]), y = mtcars$mpg, alpha = 1)

Measure: Mean-Squared Error

    Lambda Index Measure    SE Nonzero
min 0.6648    23   7.832 2.263       4
1se 1.5357    14   9.710 2.942       3
```

# Fit an elastic net regression model
elastic_net_model <- cv.glmnet(as.matrix(mtcars[, -1]), mtcars$mpg, alpha = 0.5)
print(elastic_net_model)

```
Call:  cv.glmnet(x = as.matrix(mtcars[, -1]), y = mtcars$mpg, alpha = 0.5)

Measure: Mean-Squared Error

    Lambda Index Measure    SE Nonzero
min  0.835    28   8.449 1.670       8
1se  2.323    17  10.043 3.029       7
```

# Fit a random forest regression model library(randomForest)
rf_model <- randomForest(mpg ~ wt + hp + qsec + disp, data = mtcars) print(rf_model)

```
Call:
 randomForest(formula = mpg ~ wt + hp + qsec + disp, data = mtcars)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 1

          Mean of squared residuals: 5.632951
                    % Var explained: 83.99
```

50_START_UPS:

startup_data<-read.csv("C:/Users/dellb/OneDrive/Desktop/SIT/SEM 7/DS/R Data Folder/50_startups.csv")

install.packages("readr") install.packages("caret") library(readr) library(caret)

Specify the proportion of data for the test set (e.g., 30%) test_size <- 0.3

Create an index vector for the test set

test_indices <- createDataPartition(startup_data$Profit, p = test_size, list = FALSE) # Split the data into training and testing sets

train_set <- startup_data[-test_indices,] test_set <- startup_data[test_indices,]

Rename columns to remove spaces or use backticks in the formula

colnames(startup_data) <- c("RnD_Spend", "Administration", "Marketing_Spend", "State", "Profit")

Fit a linear regression model

model <- lm(Profit ~ RnD_Spend + Administration + Marketing_Spend + State, data = startup_data)

Summarize the model summary(model)

```
Call:
lm(formula = Profit ~ RnD_Spend + Administration + Marketing_Spend +
    State, data = startup_data)

Residuals:
   Min     1Q Median     3Q    Max
-33504  -4736     90   6672  17338

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      5.013e+04  6.885e+03   7.281 4.44e-09 ***
RnD_Spend        8.060e-01  4.641e-02  17.369  < 2e-16 ***
Administration  -2.700e-02  5.223e-02  -0.517    0.608
Marketing_Spend  2.698e-02  1.714e-02   1.574    0.123
StateFlorida     1.988e+02  3.371e+03   0.059    0.953
StateNew York   -4.189e+01  3.256e+03  -0.013    0.990
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9439 on 44 degrees of freedom
Multiple R-squared:  0.9508,    Adjusted R-squared:  0.9452
F-statistic: 169.9 on 5 and 44 DF,  p-value: < 2.2e-16
```

# To predict Profit for a new data point:
new_data <- data.frame(RnD_Spend = 150000, Administration = 130000, Marketing_Spend = 200000, State = "New York")
predicted_profit <- predict(model, new_data) # Print the predicted Profit
cat("Predicted Profit:", predicted_profit, "\n")

```
> cat("Predicted Profit:", predicted_profit, "\n")
Predicted Profit: 172872.3
```

# Calculate Mean, Mode, and Median for Profit mean_profit <- mean(startup_data$Profit)
mode_profit <- as.numeric(names(sort(table(startup_data$Profit), decreasing = TRUE)[1]))
median_profit <- median(startup_data$Profit)
# Calculate Interquartile Range (IQR) for Profit iqr_profit <- IQR(startup_data$Profit)
# Print Mean, Mode, Median, and IQR cat("Mean:", mean_profit, "\n")

cat("Mode:", mode_profit, "\n") cat("Median:", median_profit, "\n")
cat("Interquartile Range (IQR):", iqr_profit, "\n")

```
> cat("Mean:", mean_profit, "\n")
Mean: 112012.6
> cat("Mode:", mode_profit, "\n")
Mode: 14681.4
> cat("Median:", median_profit, "\n")
Median: 107978.2
> cat("Interquartile Range (IQR):", iqr_profit, "\n")
Interquartile Range (IQR): 49627.07
```

Conclusion: *We've learnt how to read and write different types of datasets*