

## Statistical Modelling in R

### Semester 3 –

#### Assignment 2

# Importing necessary libraries

```
library(rpart)
```

```
library(rpart.plot)
```

```
library(tidyverse)
```

```
library(caTools)
```

```
library(caret)
```

```
library(MASS)
```

1.

Code:

```
# Creating sample to split the msc data into testing and training  
data samp = sample.split(msc$Grade, 0.7)
```

```
train = msc %>% subset(samp == T) # Creating training dataset  
test = msc %>% subset(samp == F) # Creating testing dataset
```

```
tree = rpart(Grade ~ ., data = train) # Defining the model with Grade as  
explanatory variable  
rpart.plot(tree, box.palette = "RdYlGn", main = "Decision Tree") # Plotting the  
decision tree
```

```
# Assigning predicted values to a new column in the testing dataset.  
test["Predicted.Grade"] = predict(tree, test, type = "class")
```

```
# Building confusion matrix and checking accuracy.  
confusionMatrix(test$Predicted.Grade, test$Grade)
```

## Output:

### Confusion Matrix and Statistics

Reference  
Prediction A B C D A  
6 0 0 0  
B 0 13 0 0  
C 0 0 8 0  
D 0 0 0 5

### Overall Statistics

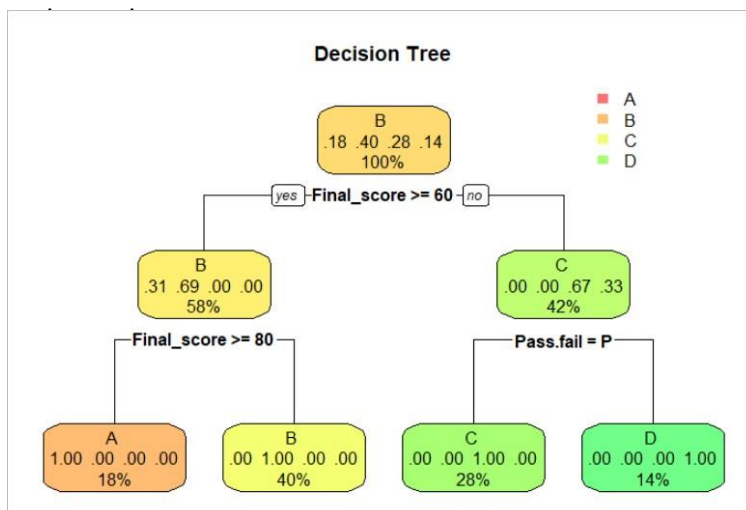
Accuracy : 1  
95% CI : (0.8911, 1)  
No Information Rate : 0.4062  
P-Value [Acc>NIR] : 3.03e-13

Kappa : 1

McNemar's Test P-Value : NA

### Statistics by Class:

|                | Class: A | Class: B | Class: C | Class: D |
|----------------|----------|----------|----------|----------|
| Sensitivity    | 1.0000   | 1.0000   | 1.00     | 1.0000   |
| Specificity    | 1.0000   | 1.0000   | 1.00     | 1.0000   |
| Pos Pred Value | 1.0000   | 1.0000   | 1.00     | 1.0000   |
| Neg Pred Value | 1.0000   | 1.0000   | 1.00     | 1.0000   |
| Prevalence     | 0.1875   | 0.4062   | 0.25     | 0.1562   |
| Detection Rate | 0.1875   | 0.4062   | 0.25     | 0.1562   |
| Detection      | 0.1875   | 0.4062   | 0.25     | 0.1562   |
| Prevalence     |          |          |          |          |



2.

```
# Defining an initial model
```

```
model = glm(Final_score ~ ., data = train)
```

```
# Running step AIC to check for best model
```

```
stepAIC(
```

```
  model,
```

```
  scope = list(
```

```
    upper = ~ Exam1 * Exam2 * Exam3 * Exam4 * Final_score * Grade * Pass.fail, lower  
    = ~ 1
```

```
  ),
```

```
  direction = "forward"
```

```
)
```

```
# Using model with lowest AIC from stepAIC.
```

```
final_model = glm(
```

```
  formula = Final_score ~ Exam1 + Exam2 + Exam3 + Exam4 + Grade +
```

```
    Pass.fail + Exam3:Grade + Exam2:Exam3 + Exam4:Pass.fail +
```

```
    Exam1:Grade + Exam2:Exam4 + Exam4:Grade + Exam2:Pass.fail +
```

```
    Exam2:Exam4:Pass.fail,
```

```
  data = train
```

```
)
```

```
summary(final_model)
```

```
# Prediction of final scores
```

```
final_pred = predict.glm(final_model, test, type = "response")
```

```
# Running t-test to test if the mean predicted values are different from actual  
values
```

```
t.test(final_pred, test$Final_score)
```

## Output:

Call:

```
glm(formula=Final_score~Exam1+Exam2+Exam3+Exam4+Grade+  
  Pass.fail + Exam3:Grade + Exam2:Exam3 + Exam4:Pass.fail +  
  Exam1:Grade + Exam2:Exam4 + Exam4:Grade + Exam2:Pass.fail +  
  Exam2:Exam4:Pass.fail, data = train)
```

Deviance Residuals:

| Min     | 1Q     | Median | 3Q    | Max    |
|---------|--------|--------|-------|--------|
| -13.175 | -2.239 | 0.000  | 2.626 | 11.089 |

Coefficients: (2 not defined because of singularities)

|                        | Estimate   | Std. Error | t value | Pr(> t )     |
|------------------------|------------|------------|---------|--------------|
| (Intercept)            | 97.583069  | 6.361748   | 15.339  | < 2e-16 ***  |
| Exam1                  | -0.003353  | 0.038274   | -0.088  | 0.930535     |
| Exam2                  | 0.392310   | 0.445833   | 0.880   | 0.383015     |
| Exam3                  | -0.530283  | 0.253665   | -2.090  | 0.041578 *   |
| Exam4                  | 2.981650   | 0.850815   | 3.504   | 0.000962 *** |
| GradeB                 | -37.715882 | 7.104749   | -5.309  | 2.43e-06 *** |
| GradeC                 | -39.383299 | 6.554371   | -6.009  | 1.99e-07 *** |
| GradeD                 | -91.943123 | 7.500678   | -12.258 | < 2e-16 ***  |
| Pass.failP             | NA         | NA         | NA      | NA           |
| Exam3:GradeB           | 0.644920   | 0.306719   | 2.103   | 0.040453 *   |
| Exam3:GradeC           | 0.059195   | 0.280526   | 0.211   | 0.833718     |
| Exam3:GradeD           | 2.354691   | 0.436383   | 5.396   | 1.78e-06 *** |
| Exam2:Exam3            | 0.027260   | 0.007117   | 3.830   | 0.000352 *** |
| Exam4:Pass.failP       | -3.663756  | 0.928866   | -3.944  | 0.000245 *** |
| Exam1:GradeB           | 0.103407   | 0.046206   | 2.238   | 0.029619 *   |
| Exam1:GradeC           | 0.009528   | 0.049871   | 0.191   | 0.849241     |
| Exam1:GradeD           | -0.412450  | 0.165083   | -2.498  | 0.015738 *   |
| Exam2:Exam4            | -0.157981  | 0.128296   | -1.231  | 0.223828     |
| Exam4:GradeB           | -0.267402  | 0.389496   | -0.687  | 0.495487     |
| Exam4:GradeC           | 0.608206   | 0.390877   | 1.556   | 0.125891     |
| Exam4:GradeD           | NA         | NA         | NA      | NA           |
| Exam2:Pass.failP       | -1.019049  | 0.430253   | -2.368  | 0.021688 *   |
| Exam2:Exam4:Pass.failP | 0.185424   | 0.128608   | 1.442   | 0.155479     |

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 25.68751)

Null deviance: 29436.3 on 71 degrees of freedom  
Residual deviance: 1310.1 on 51 degrees of freedom  
AIC: 457.21

Number of Fisher Scoring iterations: 2

### Welch Two Sample t-test

data: final\_pred and test\$Final\_score

t = 0.49697, df = 61.849, p-value = 0.621

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-8.243648 13.698429

sample estimates:

mean of x mean of y

61.81552 59.08812