



AMERICAN INTERNATIONAL UNIVERSITY-BANGLADESH

FINAL-TERM PROJECT

Course: INTRODUCTION TO DATA SCIENCE

Sec: A

SUBMITTED TO

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SUBMITTED BY

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DATA SCIENCE FINAL PROJECT

Student Mental Health

Dataset Description:

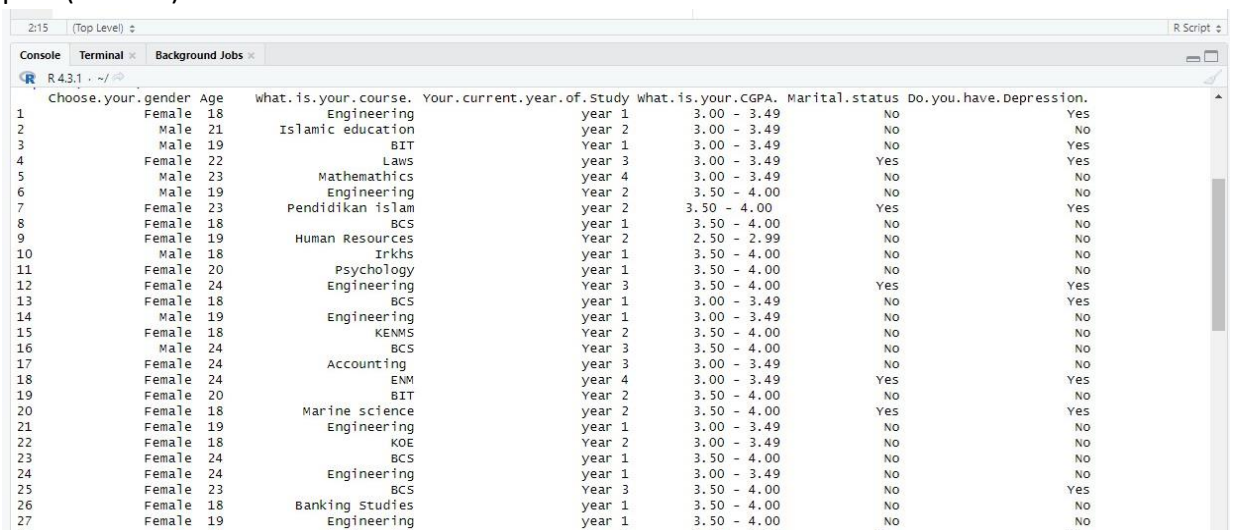
The 'Student Mental Health' dataset is a comprehensive collection aimed at exploring factors related to students' mental health. It includes key variables such as age, gender, CGPA (Cumulative Grade Point Average), course enrolment, and indicators for depression, anxiety, panic attacks, and seeking help. This dataset provides insights into demographic distributions, academic performance correlations with mental health, the prevalence of mental health conditions, and patterns of help-seeking behaviour. Potential use cases involve identifying risk factors, developing predictive models, and informing targeted interventions. Ethical considerations emphasize responsible data handling due to the sensitivity of mental health information. Overall, the dataset is a valuable resource for researchers, educators, and policymakers interested in addressing mental health challenges in the student population.

CODES – CONSOLE – DETAILS:

1. Import CSV file.

Code:

```
dataset <- read.csv("D:/FALL2023/IntroToDataScience/Student_Mental_health.csv",  
header = TRUE, sep = ",")  
print(dataset)
```



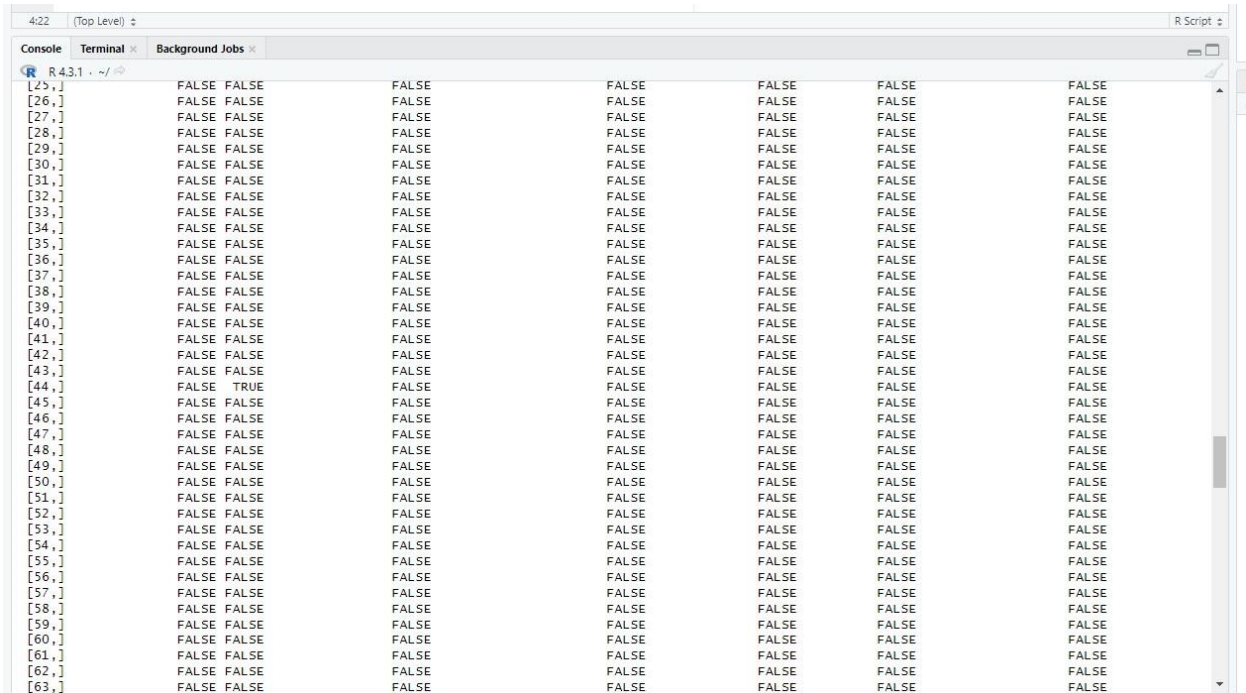
	Choose.your.gender	Age	what.is.your.course	Your.current.year.of.Study	what.is.your.CGPA	Marital.status	Do.you.have.Depression.
1	Female	18	Engineering	year 1	3.00 - 3.49	No	Yes
2	Male	21	Islamic education	year 2	3.00 - 3.49	No	No
3	Male	19	BIT	year 1	3.00 - 3.49	No	Yes
4	Female	22	Laws	year 3	3.00 - 3.49	Yes	Yes
5	Male	23	Mathematics	year 4	3.00 - 3.49	No	No
6	Male	19	Engineering	Year 2	3.50 - 4.00	No	No
7	Female	23	Pendidikan islam	year 2	3.50 - 4.00	Yes	Yes
8	Female	18	BCS	year 1	3.50 - 4.00	No	No
9	Female	19	Human Resources	Year 2	2.50 - 2.99	No	No
10	Male	18	Irkhs	year 1	3.50 - 4.00	No	No
11	Female	20	Psychology	year 1	3.50 - 4.00	No	No
12	Female	24	Engineering	Year 3	3.50 - 4.00	Yes	Yes
13	Female	18	BCS	year 1	3.00 - 3.49	No	Yes
14	Male	19	Engineering	year 1	3.00 - 3.49	No	No
15	Female	18	KENMS	Year 2	3.50 - 4.00	No	No
16	Male	24	BCS	Year 3	3.50 - 4.00	No	No
17	Female	24	Accounting	year 3	3.00 - 3.49	No	No
18	Female	24	ENM	year 4	3.00 - 3.49	Yes	Yes
19	Female	20	BIT	Year 2	3.50 - 4.00	No	No
20	Female	18	Marine science	year 2	3.50 - 4.00	Yes	Yes
21	Female	19	Engineering	year 1	3.00 - 3.49	No	No
22	Female	18	KOE	Year 2	3.00 - 3.49	No	No
23	Female	24	BCS	year 1	3.50 - 4.00	No	No
24	Female	24	Engineering	year 1	3.00 - 3.49	No	No
25	Female	23	BCS	Year 3	3.50 - 4.00	No	Yes
26	Female	18	Banking Studies	year 1	3.50 - 4.00	No	No
27	Female	19	Engineering	year 1	3.50 - 4.00	No	No

This code is used to import external Excel files (in CSV format) into R.

2. Find missing values.

Code:

```
missing_values <- is.na(dataset)
print(missing_values)
```



The screenshot shows the R console output for the command `is.na(dataset)`. The output is a matrix with 39 rows (indices 25 to 63) and 8 columns. All values in the matrix are `FALSE`, indicating that there are no missing values in the dataset for these rows.

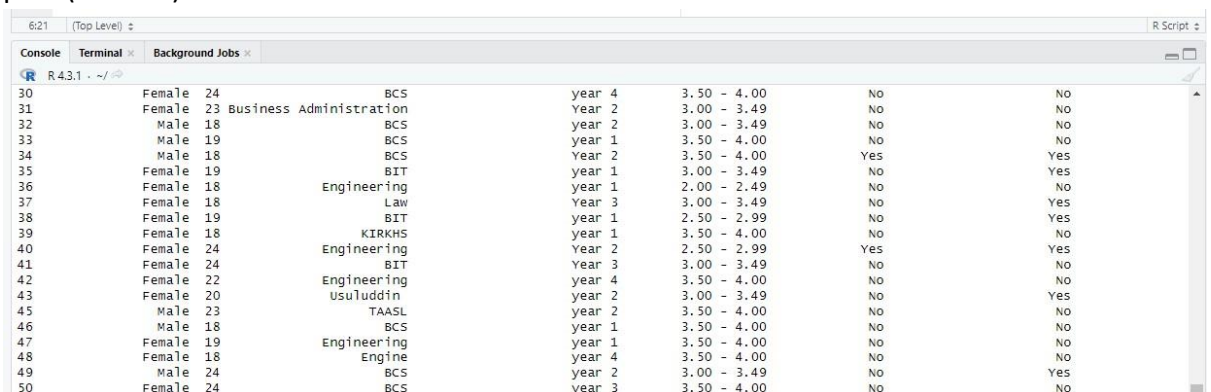
Index	Col 1	Col 2	Col 3	Col 4	Col 5	Col 6	Col 7	Col 8
[25,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[26,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[27,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[28,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[29,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[30,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[31,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[32,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[33,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[34,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[35,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[36,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[37,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[38,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[39,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[40,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[41,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[42,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[43,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[44,]	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[45,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[46,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[47,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[48,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[49,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[50,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[51,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[52,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[53,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[54,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[55,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[56,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[57,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[58,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[59,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[60,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[61,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[62,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
[63,]	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

This code is used to identify the missing values in a dataset. The one that has TRUE written in it is a missing value.

3. Discard missing values.

Code:

```
dataset <- na.omit(dataset)
print(dataset)
```



The screenshot shows the R console output for the command `na.omit(dataset)`. The output is a dataset with 21 rows (indices 30 to 50) and 8 columns. The row with a missing value (index 44) has been removed. The output is as follows:

Index	Gender	Age	Department	Year	Score	Pass	Result
30	Female	24	BCS	year 4	3.50 - 4.00	No	No
31	Female	23	Business Administration	Year 2	3.00 - 3.49	No	No
32	Male	18	BCS	year 2	3.00 - 3.49	No	No
33	Male	19	BCS	year 1	3.50 - 4.00	No	No
34	Male	18	BCS	Year 2	3.50 - 4.00	Yes	Yes
35	Female	19	BIT	year 1	3.00 - 3.49	No	Yes
36	Female	18	Engineering	year 1	2.00 - 2.49	No	No
37	Female	18	Law	Year 3	3.00 - 3.49	No	Yes
38	Female	19	BIT	year 1	2.50 - 2.99	No	Yes
39	Female	18	KIRKHS	year 1	3.50 - 4.00	No	No
40	Female	24	Engineering	Year 2	2.50 - 2.99	Yes	Yes
41	Female	24	BIT	Year 3	3.00 - 3.49	No	No
42	Female	22	Engineering	year 4	3.50 - 4.00	No	No
43	Female	20	Usuluddin	year 2	3.00 - 3.49	No	Yes
45	Male	23	TAASL	year 2	3.50 - 4.00	No	No
46	Male	18	BCS	year 1	3.50 - 4.00	No	No
47	Female	19	Engineering	year 1	3.50 - 4.00	No	No
48	Female	18	Engine	year 4	3.50 - 4.00	No	No
49	Male	24	BCS	year 2	3.00 - 3.49	No	Yes
50	Female	24	BCS	year 3	3.50 - 4.00	No	No

This code is used to remove the instance that had a missing value.

4. Converting Numeric Age values to Categorical Age values.

Code:

```
catage <- "Age"
breaks <- c(0, 19, 25, Inf)
labels <- c("Teenager", "Young Adult", "Adult")
dataset$CatAge <- cut(dataset[[catage]], breaks = breaks, labels = labels,
include.lowest = TRUE)
print(dataset)
```

14:1 (Top Level)

Console Terminal Background Jobs

R 4.3.1 ~ /

86	Female	18	psychology	year 1	3.50 - 4.00	No
87	Female	19	Fiqh fatwa	Year 3	3.00 - 3.49	No
88	Female	18	psychology	year 1	3.50 - 4.00	No
89	Male	24	BIT	year 1	3.00 - 3.49	No
90	Male	24	Engineering	Year 2	2.00 - 2.49	No

	Do.you.have.Anxiety.	Do.you.have.Panic.attack.	Did.you.seek.any.specialist.for.a.treatment.	CatAge
1	No	Yes	No	Teenager
2	Yes	No	No	Young Adult
3	Yes	Yes	No	Teenager
4	No	No	No	Young Adult
5	No	No	No	Young Adult
6	No	Yes	No	Teenager
7	No	Yes	No	Young Adult
8	Yes	No	No	Teenager
9	No	No	No	Teenager
10	Yes	Yes	No	Teenager
11	No	No	No	Young Adult
12	No	No	No	Young Adult

This code is used to convert the categorize the age range to teenager, young adult, and adult. It is saved as a new column.

5. Pearson's Chi-squared Test

Code:

```
dataset <- data.frame(
  "what.is.your.cgpa" = sample(c("0-1.99", "2-2.49", "2.5-2.99", "3-3.49", "3.5-4.00"),
100, replace = TRUE),
  "Do.you.have.anxiety" = sample(c("Yes", "No"), 100, replace = TRUE)
)
contingency_table <- table(dataset$What.is.your.cgpa.,
dataset$Do.you.have.anxiety.)
chi_squared_test <- chisq.test(contingency_table)
print(chi_squared_test)
```

```
> dataset <- data.frame(
+ "what.is.your.cgpa" = sample(c("0-1.99", "2-2.49", "2.5-2.99", "3-3.49", "3.5-4.00"), 100, replace = TRUE),
+ "Do.you.have.anxiety" = sample(c("Yes", "No"), 100, replace = TRUE)
+ )
> contingency_table <- table(dataset$what.is.your.cgpa, dataset$Do.you.have.anxiety)
> chi_squared_test <- chisq.test(contingency_table)
> print(chi_squared_test)
```

Pearson's Chi-squared test

data: contingency_table
X-squared = 2.9557, df = 4, p-value = 0.5653

This code is used to find the significant attributes using Pearson's Chi-Squared Test.

6. Install Package

a) e1071

Code:

```
install.packages("e1071")  
library(e1071)
```

```
> library(e1071)  
warning message:  
package 'e1071' was built under R version 4.3.2  
> |
```

This code is used to install the necessary package for the 'Naïve Bayes' function.

b) caret

Code:

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

```
> library(caret)  
Loading required package: ggplot2  
Need help? Try Stackoverflow: https://stackoverflow.com/tags/ggplot2  
Loading required package: lattice  
warning messages:  
1: package 'caret' was built under R version 4.3.2  
2: package 'ggplot2' was built under R version 4.3.2
```

This code is used to install the necessary package for the 'Naïve Bayes' classification.

7. Naïve Bayes

Code:

```
nb_model <- naiveBayes(What.is.your.course. ~ ., data = dataset)
print(nb_model)
```

```

R 4.3.1 ~ /
naiveBayes(What.is.your.course. ~ ., data = dataset)
> print(nb_model)

Naive Bayes Classifier for Discrete Predictors

Call:
naiveBayes.default(x = x, y = y, laplace = laplace)

A-priori probabilities:
Y
      Accounting      ALA      Banking Studies      BCS      Benl
      0.01      0.01      0.01      0.18      0.01
      BENL      Biomedical science      Biotechnology      BIT Business Administration
      0.02      0.04      0.01      0.09      0.01
      Communication      CTS      Diploma Nursing      DIPLOMA TESL      Econs
      0.01      0.01      0.01      0.01      0.01
      engin      Engine      Engineering      ENM      Fiqh
      0.01      0.02      0.17      0.01      0.01
      Fiqh fatwa      Human Resources      Human Sciences      Irkhs      Islamic education
      0.01      0.01      0.01      0.01      0.01
      Islamic Education      IT      KENMS      Kirkhs      KIRKHS
      0.01      0.01      0.01      0.01      0.01
      koe      Koe      KOE      Kop      Law
      0.01      0.01      0.04      0.01      0.01
      Laws      Malcom      Marine science      Mathematics      MHSC
      0.02      0.01      0.01      0.01      0.01
      Nursing      Pendidikan islam      Pendidikan Islam      Pendidikan Islam      psychology
      0.01      0.01      0.01      0.01      0.02
      Psychology      Radiography      TAASL      Usuluddin
      0.01      0.01      0.01      0.01

Conditional probabilities:
Choose.your.gender
Y      Female      Male
Accounting      1.0000000 0.0000000
ALA      1.0000000 0.0000000
Banking Studies      1.0000000 0.0000000
BCS      0.6111111 0.3888889
Benl      1.0000000 0.0000000
BENL      1.0000000 0.0000000
Biomedical science      0.5000000 0.5000000
Biotechnology      1.0000000 0.0000000
BIT      0.6666667 0.3333333
Business Administration      1.0000000 0.0000000
Communication      1.0000000 0.0000000
CTS      1.0000000 0.0000000
Diploma Nursing      1.0000000 0.0000000
DIPLOMA TESL      1.0000000 0.0000000
Econs      1.0000000 0.0000000
engin      1.0000000 0.0000000
Engine      1.0000000 0.0000000
Engineering      0.7058824 0.2941176
ENM      1.0000000 0.0000000
Fiqh      1.0000000 0.0000000
Fiqh fatwa      1.0000000 0.0000000

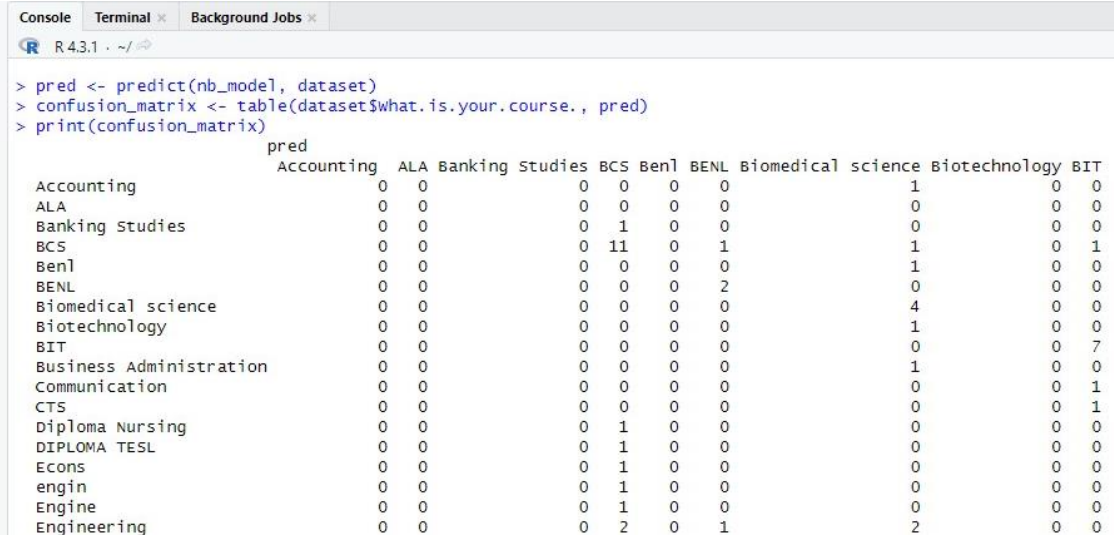
```

This code is used to find the Naïve Bayes function to predict, based on the course of the student.

8. Confusion Matrix

Code:

```
pred <- predict(nb_model, dataset)
confusion_matrix <- table(dataset$What.is.your.course., pred)
print(confusion_matrix)
```



The screenshot shows an R console window with the following output:

```
> pred <- predict(nb_model, dataset)
> confusion_matrix <- table(dataset$What.is.your.course., pred)
> print(confusion_matrix)
```

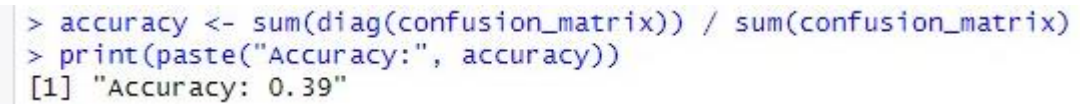
	Accounting	ALA	Banking Studies	BCS	Benl	BENL	Biomedical science	Biotechnology	BIT
Accounting	0	0	0	0	0	0	1	0	0
ALA	0	0	0	0	0	0	0	0	0
Banking Studies	0	0	0	1	0	0	0	0	0
BCS	0	0	0	11	0	1	1	0	1
Benl	0	0	0	0	0	0	1	0	0
BENL	0	0	0	0	0	2	0	0	0
Biomedical science	0	0	0	0	0	0	4	0	0
Biotechnology	0	0	0	0	0	0	1	0	0
BIT	0	0	0	0	0	0	0	0	7
Business Administration	0	0	0	0	0	0	1	0	0
Communication	0	0	0	0	0	0	0	0	1
CTS	0	0	0	0	0	0	0	0	1
Diploma Nursing	0	0	0	1	0	0	0	0	0
DIPLOMA TESL	0	0	0	1	0	0	0	0	0
Econs	0	0	0	1	0	0	0	0	0
engin	0	0	0	1	0	0	0	0	0
Engine	0	0	0	1	0	0	0	0	0
Engineering	0	0	0	2	0	1	2	0	0

This code has been used to find the confusion matrix on the student's courses.

9. Accuracy

Code:

```
accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
print(paste("Accuracy:", accuracy))
```



The screenshot shows an R console window with the following output:

```
> accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)
> print(paste("Accuracy:", accuracy))
[1] "Accuracy: 0.39"
```

This code is used to find the predictive accuracy of the Naïve Bayes classification.

10. 10-Fold Cross Validation

Code:

```
set.seed(123)
folds <- createFolds(dataset$Do.you.have.Depression., k = 10, list = TRUE, returnTrain = TRUE)

for (i in 1:10) {
  train_fold <- dataset[unlist(folds[i]), ]
  test_fold <- dataset[-unlist(folds[i]), ]

  nb_model_fold <- naiveBayes(Do.you.have.Depression. ~ ., data = train_fold)

  predictions <- predict(nb_model_fold, test_fold)

  confusion_matrix <- table(test_fold$Do.you.have.Depression., predictions)
  accuracy <- sum(diag(confusion_matrix)) / sum(confusion_matrix)

  cat("Fold", i, "Accuracy:", accuracy, "\n")
}
```

```
+
+   cat("Fold", i, "Accuracy:", accuracy, "\n")
+ }
Fold 1 Accuracy: 0.8
Fold 2 Accuracy: 0.9
Fold 3 Accuracy: 0.8181818
Fold 4 Accuracy: 0.7777778
Fold 5 Accuracy: 0.7
Fold 6 Accuracy: 0.8181818
Fold 7 Accuracy: 0.9
Fold 8 Accuracy: 0.8
Fold 9 Accuracy: 0.7777778
Fold 10 Accuracy: 0.8
> |
```

The code is used for 10 Fold Cross Validation and Accuracy.

11. Train Set and Test Set

Code:

```
train_indices <- sample(1:nrow(dataset), 0.7 * nrow(dataset))
train_data <- dataset[train_indices, ]
test_data <- dataset[-train_indices, ]

> train_indices <- sample(1:nrow(dataset), 0.7 * nrow(dataset))
> train_data <- dataset[train_indices, ]
> test_data <- dataset[-train_indices, ]
```

This code is used to generate the train set and test set according to this dataset.

12. Recall, Precision and F-measure value

Code:

```
metrics <- data.frame(Recall = numeric(10), Precision = numeric(10), F_measure =  
numeric(10))
```

```
for (i in 1:10) {  
  train_fold <- dataset[unlist(folds[i]), ]  
  test_fold <- dataset[-unlist(folds[i]), ]
```

```
  nb_model_fold <- naiveBayes(Do.you.have.Depression. ~ ., data = train_fold)
```

```
  predictions <- predict(nb_model_fold, test_fold)
```

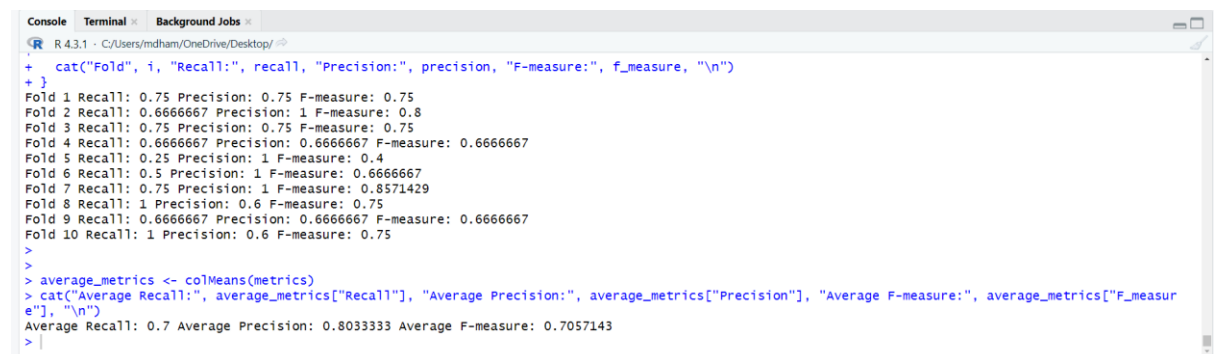
```
  confusion_matrix <- table(test_fold$Do.you.have.Depression., predictions)
```

```
  recall <- confusion_matrix[2, 2] / sum(confusion_matrix[2, ])  
  precision <- confusion_matrix[2, 2] / sum(confusion_matrix[, 2])  
  f_measure <- 2 * (precision * recall) / (precision + recall)
```

```
  metrics[i, ] <- c(Recall = recall, Precision = precision, F_measure = f_measure)
```

```
  cat("Fold", i, "Recall:", recall, "Precision:", precision, "F-measure:", f_measure, "\n")  
}
```

```
average_metrics <- colMeans(metrics)  
cat("Average Recall:", average_metrics["Recall"], "Average Precision:",  
average_metrics["Precision"], "Average F-measure:", average_metrics["F_measure"],  
"\n")
```



```
Console Terminal Background Jobs  
R 4.3.1 - C:/Users/mdham/OneDrive/Desktop/  
> cat("Fold", i, "Recall:", recall, "Precision:", precision, "F-measure:", f_measure, "\n")  
> }  
Fold 1 Recall: 0.75 Precision: 0.75 F-measure: 0.75  
Fold 2 Recall: 0.6666667 Precision: 1 F-measure: 0.8  
Fold 3 Recall: 0.75 Precision: 0.75 F-measure: 0.75  
Fold 4 Recall: 0.6666667 Precision: 0.6666667 F-measure: 0.6666667  
Fold 5 Recall: 0.25 Precision: 1 F-measure: 0.4  
Fold 6 Recall: 0.5 Precision: 1 F-measure: 0.6666667  
Fold 7 Recall: 0.75 Precision: 1 F-measure: 0.8571429  
Fold 8 Recall: 1 Precision: 0.6 F-measure: 0.75  
Fold 9 Recall: 0.6666667 Precision: 0.6666667 F-measure: 0.6666667  
Fold 10 Recall: 1 Precision: 0.6 F-measure: 0.75  
>  
>  
> average_metrics <- colMeans(metrics)  
> cat("Average Recall:", average_metrics["Recall"], "Average Precision:", average_metrics["Precision"], "Average F-measure:", average_metrics["F_measur  
e"], "\n")  
Average Recall: 0.7 Average Precision: 0.8033333 Average F-measure: 0.7057143  
>
```

The code shows 10 Fold (Recall, Precision, F-measure) value and it also shows the Average (Recall, Precision, F-measure) value.