

# AMERICAN INTERNATIONAL UNIVERSITY-BANGLADESH

## Faculty of Science and Technology



### Project Cover Page

Assignment Title:	FINAL TERM PROJECT		
Assignment No:	02	Date of Submission:	25 December 2023
Course Title:	INTRODUCTION TO DATA SCIENCE		
Course Code:	CSC 4180	Section:	A
Semester:	Fall	2023-24	Course Teacher: TOHEDUL ISLAM

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	Total Marks	

## Project Description :

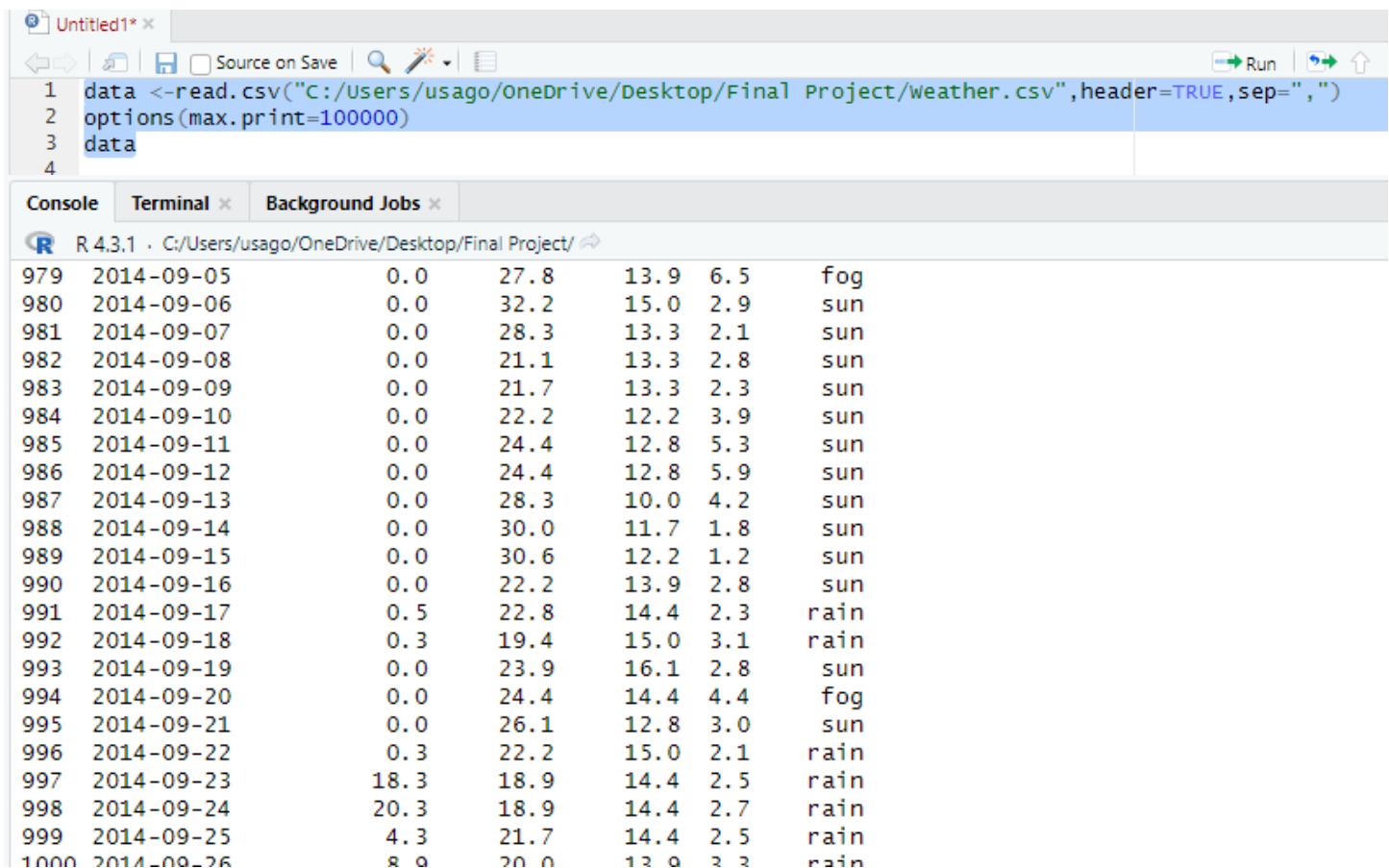
A through database of the elements that lead to predict whether it "drizzle" or "rain" or "sun" or "snow" or "fog". There are five fields for input fields and one field for an output field. date, precipitation, temp\_min (minimum temperature for each date), temp\_max (maximum temperature for each date) and wind are representing the input fields, while the output field predict the weather, which is divided into five categories ("drizzle" "rain" "sun" "snow" "fog"); We will try to recover the missing value (if there any) and prepare dataset then apply naïve bayes algorithm for the dataset and calculate about the predictive accuracy univariate analysis.

## Data Preparation

### Importing dataset from csv file:

Code :

```
data <- read.csv("C:/Users/usago/OneDrive/Desktop/Final Project/Weather.csv", header=TRUE, sep=",")
options(max.print=100000)
data
```



The screenshot shows the R Studio interface. The top pane contains the following R code:

```
1 data <- read.csv("C:/Users/usago/OneDrive/Desktop/Final Project/Weather.csv", header=TRUE, sep=",")
2 options(max.print=100000)
3 data
4
```

The bottom pane shows the console output, which is a preview of the data loaded from the CSV file. The data consists of 1000 rows (lines 979 to 1000 in the preview) with 7 columns: date, precipitation, temp\_min, temp\_max, wind, and weather. The weather column contains values like "fog", "sun", and "rain".

Line	Date	Precipitation	temp_min	temp_max	wind	Weather
979	2014-09-05	0.0	27.8	13.9	6.5	fog
980	2014-09-06	0.0	32.2	15.0	2.9	sun
981	2014-09-07	0.0	28.3	13.3	2.1	sun
982	2014-09-08	0.0	21.1	13.3	2.8	sun
983	2014-09-09	0.0	21.7	13.3	2.3	sun
984	2014-09-10	0.0	22.2	12.2	3.9	sun
985	2014-09-11	0.0	24.4	12.8	5.3	sun
986	2014-09-12	0.0	24.4	12.8	5.9	sun
987	2014-09-13	0.0	28.3	10.0	4.2	sun
988	2014-09-14	0.0	30.0	11.7	1.8	sun
989	2014-09-15	0.0	30.6	12.2	1.2	sun
990	2014-09-16	0.0	22.2	13.9	2.8	sun
991	2014-09-17	0.5	22.8	14.4	2.3	rain
992	2014-09-18	0.3	19.4	15.0	3.1	rain
993	2014-09-19	0.0	23.9	16.1	2.8	sun
994	2014-09-20	0.0	24.4	14.4	4.4	fog
995	2014-09-21	0.0	26.1	12.8	3.0	sun
996	2014-09-22	0.3	22.2	15.0	2.1	rain
997	2014-09-23	18.3	18.9	14.4	2.5	rain
998	2014-09-24	20.3	18.9	14.4	2.7	rain
999	2014-09-25	4.3	21.7	14.4	2.5	rain
1000	2014-09-26	8.0	20.0	13.0	3.3	rain

**Description:** In order to get a . csv file into R, we can use read. csv, and as the only argument, put the path to the file we want to read in within quotation marks.

## Taking 500 instance :

### Code

```
mydata <- head(data, 500)
```

```
mydata
```

5	mydata <- head(data, 500)
6	mydata

Console	Terminal ×	Background Jobs ×
R 4.3.1 ~ / ↗		
477	2013-04-21	5.5 12.2 0.7 4.1 rain
478	2013-04-22	0.0 16.1 5.0 4.3 sun
479	2013-04-23	0.0 17.8 3.9 2.8 sun
480	2013-04-24	0.0 21.1 6.1 3.0 sun
481	2013-04-25	0.0 21.7 6.7 1.1 sun
482	2013-04-26	0.0 20.6 8.3 2.2 fog
483	2013-04-27	0.0 13.9 10.6 5.9 sun
484	2013-04-28	1.0 15.0 9.4 5.2 rain
485	2013-04-29	3.8 13.9 6.7 4.2 rain
486	2013-04-30	0.0 12.8 4.4 2.4 sun
487	2013-05-01	0.0 18.3 3.3 3.1 sun
488	2013-05-02	0.0 20.6 6.7 4.0 sun
489	2013-05-03	0.0 21.7 9.4 4.9 sun
490	2013-05-04	0.0 25.0 11.1 6.5 sun
491	2013-05-05	0.0 28.9 11.7 5.3 sun
492	2013-05-06	0.0 30.6 12.2 2.0 sun
493	2013-05-07	0.0 20.6 11.1 3.3 sun
494	2013-05-08	0.0 19.4 11.1 1.9 sun
495	2013-05-09	0.0 22.8 10.0 1.3 sun
496	2013-05-10	0.0 26.1 9.4 1.0 sun
497	2013-05-11	0.0 27.2 12.2 2.6 sun
498	2013-05-12	6.6 21.7 13.9 3.9 rain
499	2013-05-13	3.3 18.9 9.4 5.0 rain
500	2013-05-14	0.0 18.3 7.8 2.4 sun

**Description:** We have taken 500 instance from our data using head(data,500) .

## Attribute name of dataset :

### Code

```
names(mydata)
```

```
4  
5 mydata <- head(data, 1000)  
6 mydata  
7 names(mydata)  
8
```

```
Console Terminal x Background Jobs x
R 4.3.1 - C:/Users/usago/OneDrive/Desktop/Final Project/
996 2014-09-22 0.3 22.2 15.0 2.1 rain
997 2014-09-23 18.3 18.9 14.4 2.5 rain
998 2014-09-24 20.3 18.9 14.4 2.7 rain
999 2014-09-25 4.3 21.7 14.4 2.5 rain
1000 2014-09-26 8.9 20.0 13.9 3.3 rain
> names(mydata)
[1] "date" "precipitation" "temp_max" "temp_min" "wind" "weather"
> |
```

**Description:** To know the names of each field in our data set we can use name() function .

Checking Missing value:

Code :

```
colsums(is.na(mydata))
```

```
7 names(mydata)
8
9 colsums(is.na(mydata))
10
```

```
Console Terminal x Background Jobs x
R 4.3.1 - C:/Users/usago/OneDrive/Desktop/Final Project/
> colsums(is.na(mydata))
      date precipitation      temp_max      temp_min      wind      weather
      0             0             0             0             0             0
> |
```

**Description:** We checked all the missing value using colsums(is.na()) . There is no missing value in our data set .

Variable types in dataset:

Code :

```
str(mydata)
```

```
10
11 str(mydata)
12
13
```

```
> str(mydata)
'data.frame': 1000 obs. of 6 variables:
 $ date      : chr  "2012-01-01" "2012-01-02" "2012-01-03" "2012-01-04" ...
 $ precipitation: num  0 10.9 0.8 20.3 1.3 2.5 0 0 4.3 1 ...
 $ temp_max   : num  12.8 10.6 11.7 12.2 8.9 4.4 7.2 10 9.4 6.1 ...
 $ temp_min   : num   5 2.8 7.2 5.6 2.8 2.2 2.8 2.8 5 0.6 ...
 $ wind       : num  4.7 4.5 2.3 4.7 6.1 2.2 2.3 2 3.4 3.4 ...
 $ weather    : chr  "drizzle" "rain" "rain" "rain" ...
> |
```

**Description:** By using str function we can get information about variable types in the dataset.

## Checking unique values in target attribute(weather):

Code :

```
unique_values <- unique(mydata$weather)
```

```
unique_values
```

```
12
13 unique_values <- unique(mydata$weather)
14 unique_values
15
```

```
Console Terminal x Background Jobs x
R 4.3.1 C:/Users/usago/OneDrive/Desktop/Final Project/
> unique_values <- unique(mydata$weather)
> unique_values
[1] "drizzle" "rain" "sun" "snow" "fog"
> |
```

**Description:** By using unique function, we can check unique values in dataset. We have five unique values in our target attribute.

## Labeling weather column values & numeric conversation:

Code :

```
mydata$weather<-factor(mydata$weather,levels = c("rain", "drizzle","sun","snow","fog"),labels = c(1,2,3,4,5))
```

```
mydata$weather <- as.numeric(mydata$weather)
```

```
15
16 mydata$weather<-factor(mydata$weather,levels = c("rain", "drizzle","sun","snow","fog"),labels = c(1,2,3,4,5))
17 mydata$weather <- as.numeric(mydata$weather)
18 mydata$weather
19
```

```

R 4.3.1 - C:/Users/usago/OneDrive/Desktop/Final Project/
[1] "drizzle" "rain"      "sun"       "snow"      "fog"
> mydata$weather<-factor(mydata$weather,levels = c("rain", "drizzle","sun","snow","fog"),labels = c(1,2,3,4,5))
> mydata$weather
 [1] 2 1 1 1 1 1 1 3 1 1 3 3 3 4 4 4 4 4 4 4 1 1 1 1 1 2 1 1 1 1 1 3 3 3 3 1 1 1 1 1 1 1 2 1 1 1 3 1 1 1 3
[55] 1 1 4 3 4 4 3 1 3 1 1 4 3 3 1 1 1 4 4 1 4 1 4 1 1 1 1 1 3 3 2 3 1 1 3 1 1 1 1 1 1 3 3 4 1 3 3 3 1 1 2 3 1 1 1 3
[109] 1 1 1 3 1 3 1 1 1 1 1 2 1 1 1 1 1 1 1 3 3 3 3 2 3 1 1 3 1 1 1 1 1 1 3 3 1 3 1 1 1 1 3 1 1 3 1 1 1 3 1 1 1 3
[163] 1 1 3 3 3 1 3 1 1 3 3 1 2 1 1 3 1 1 1 1 1 1 2 3 3 1 1 2 5 2 1 1 1 1 3 3 3 1 3 1 1 3 3 2 2 3 3 2 3 3 2 3 3
[217] 3 1 2 3 2 3 3 3 3 3 3 3 2 2 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 5 3 3 2 2 2 2 2 5 5 3 2
[271] 2 1 3 3 3 3 3 3 3 3 3 2 2 2 1 1 1 1 1 3 3 1 1 1 1 1 1 1 1 1 3 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[325] 1 1 1 1 1 2 5 3 1 1 1 1 1 1 1 1 1 1 1 3 1 1 1 1 4 4 4 4 1 1 1 1 4 1 1 1 2 2 3 3 1 1 1 1 1 1 1 4 2 3
[379] 3 3 3 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 2 1 1 1 1 3 2 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[433] 2 5 1 1 1 1 1 1 3 1 1 4 3 3 3 3 1 1 2 3 3 3 1 1 1 1 1 3 1 1 1 1 5 1 2 1 1 3 1 3 3 3 3 3 3 3 1 3
[487] 3 3 3 3 3 3 3 3 3 3 1 3 1 5 1 3 3 3 1 1 1 3 1 1 1 1 3 3 3 1 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 1 3 1 1 3 1
[541] 1 1 1 1 3 3 3 3 3 5 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 5 3 3 3 3 1 5 3 3 3 3 3 3 3 3 3 3 3 1 3 3 3 1 1 5
[595] 3 3 3 3 3 3 3 1 1 1 1 1 3 3 3 3 1 1 1 3 5 3 3 3 3 3 5 1 1 3 3 3 1 3 1 1 3 1 3 1 1 1 1 1 1 1 1 1 1 1 1 1 1

```

**Description:** We have labeled weather column 1 for rain, 2 for drizzle, 3 for sun, 4 for snow and 5 for fog. Then we have converted to numeric column for our future purpose.

### Convert date column values sequent and numeric type :

Code :

```
mydata$date <- seq_along(mydata$date)
```

```
mydata$date <- as.numeric(mydata$date)
```

```
mydata$date
```

```
19  
20 mydata$date <- seq_along(mydata$date)  
21 mydata$date <- as.numeric(mydata$date)  
22 mydata$date  
23
```

```

R 4.3.1 - C:/Users/usago/OneDrive/Desktop/Final Project/
> mydata$date <- seq_along(mydata$date)
> mydata$date <- as.numeric(mydata$date)
> mydata$date
 [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21
[22] 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42
[43] 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63
[64] 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84
[85] 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105
[106] 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126
[127] 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147
[148] 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168
[169] 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189
[190] 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210
[211] 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231
[232] 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252
[253] 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273

```

**Description:** In our dataset date column is in date format which create difficulty for applying co relation technic so for our better outcome we have replaced the date values date format to each date sequentially using seq\_along() function . Then we converted it to numeric values.

## Pearson's Correlation :

Code :

```
co_relation<-(cor(mydata[,c('date','precipitation','temp_min','temp_max','wind','weather')]))
```

```
co_relation
```

```
23  
24 co_relation<-(cor(mydata[,c('date','precipitation','temp_min','temp_max','wind','weather')]))  
25 co_relation  
26  
27
```

Console

Terminal x

Background Jobs x

R 4.3.1 . ~/

> co\_relation

	date	precipitation	temp_min	temp_max	wind	weather
date	1.0000000000	-0.01135756	0.025122367	0.0004422434	-0.06543744	-0.033175444
precipitation	-0.0113575618	1.00000000	-0.102307172	-0.2546402073	0.25768206	-0.249862903
temp_min	0.0251223673	-0.10230717	1.00000000	0.8529552351	-0.04998485	0.002183174
temp_max	0.0004422434	-0.25464021	0.852955235	1.0000000000	-0.15234978	0.270371165
wind	-0.0654374374	0.25768206	-0.049984849	-0.1523497768	1.00000000	-0.145108330
weather	-0.0331754442	-0.24986290	0.002183174	0.2703711645	-0.14510833	1.000000000

> |

**Description:** Pearson's co relation is a technic of measure the continues value of relation between two column. By using **cor()** function we can get the co relation value to check whether it is significant or not.

From our co relation value of the data set we have identified that **date** column have no relation with any of the attribute & all of the co relation value compare to **date** attribute is close to 0 . **date** attribute is non-significant attribute for the dataset , except that all the attribute is **significant attribute** for the column .

## Removing non-significant attribute:

Code :

```
mydata1<-mydata
```

```
mydata1$date<- NULL
```

```
mydata1
```

```
mydata1<-mydata  
mydata1$date<- NULL  
mydata1
```

```

R 4.3.1 . ~/
> mydata1<-mydata
Error: object 'mydata1' not found
> mydata1<-mydata
> mydata1$date<- NULL
> mydata1
  precipitation temp_max temp_min wind weather
1           0.0      12.8      5.0  4.7      2
2          10.9      10.6      2.8  4.5      1
3           0.8      11.7      7.2  2.3      1
4          20.3      12.2      5.6  4.7      1
5           1.3       8.9      2.8  6.1      1
6           2.5       4.4      2.2  2.2      1
7           0.0       7.2      2.8  2.3      1
8           0.0      10.0      2.8  2.0      3
9           4.3       9.4      5.0  3.4      1
10          1.0       6.1       0.6  3.4      1
11          0.0       6.1     -1.1  5.1      3
12          0.0       6.1     -1.7  1.9      3
13          0.0       5.0     -2.8  1.3      3
14          4.1       4.4       0.6  5.3      4
15          5.3       1.1     -3.3  3.2      4
16          2.5       1.7     -2.8  5.0      4
17          8.1       3.3       0.0  5.6      4
18         19.8       0.0     -2.8  5.0      4
19         15.2     -1.1     -2.8  1.6      4
20         13.5       7.2     -1.1  2.3      4
21          3.0       8.3       3.3  8.2      1

```

Description: Removed non-significant attribute **date**.

## Labeling target attribute to categorical :

Code:

```

mydata2<-mydata1
mydata2$weather<-factor(mydata2$weather,levels = c(1,2,3,4,5),labels = c("rain", "drizzle","sun","snow","fog"))

```

```

33
34 mydata2<-mydata1
35 mydata2$weather<-factor(mydata2$weather,levels = c(1,2,3,4,5),labels = c("rain", "drizzle","sun","snow","fog"))
36
37

```

```

R 4.3.1 . ~/
> mydata2
  precipitation temp_max temp_min wind weather
1           0.0      12.8      5.0  4.7 drizzle
2          10.9      10.6      2.8  4.5   rain
3           0.8      11.7      7.2  2.3   rain
4          20.3      12.2      5.6  4.7   rain
5           1.3       8.9      2.8  6.1   rain
6           2.5       4.4      2.2  2.2   rain
7           0.0       7.2      2.8  2.3   rain

```



**Description:**

labeled weather attribute to categorical again for understanding properly in naïve bayes

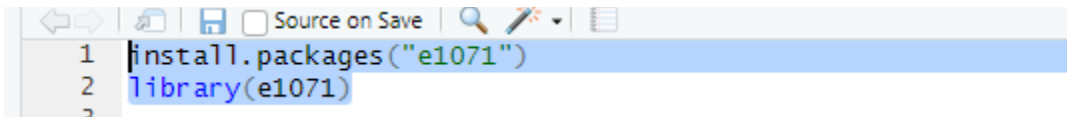
## Applying Naïve Bayes classification

### Install and load package for naivebayes:

**Code:**

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

```
library(e1071)
```

**Description:**

Installed package “e1071” for using Naïve Bayes model and loaded this package using library() function

### 1.Dividing the data into training and test set:

**Code:**

```
set.seed(123)
```

```
sample_index <- sample(1:nrow(mydata2), 0.7 * nrow(mydata2))
```

```
train_data <- mydata[sample_index, ]
```

```
test_data <- mydata[-sample_index, ]
```

```
set.seed(123)
sample_index <- sample(1:nrow(mydata2), 0.7 * nrow(mydata2))
train_data <- mydata2[sample_index, ]
test_data <- mydata2[-sample_index, ]
```

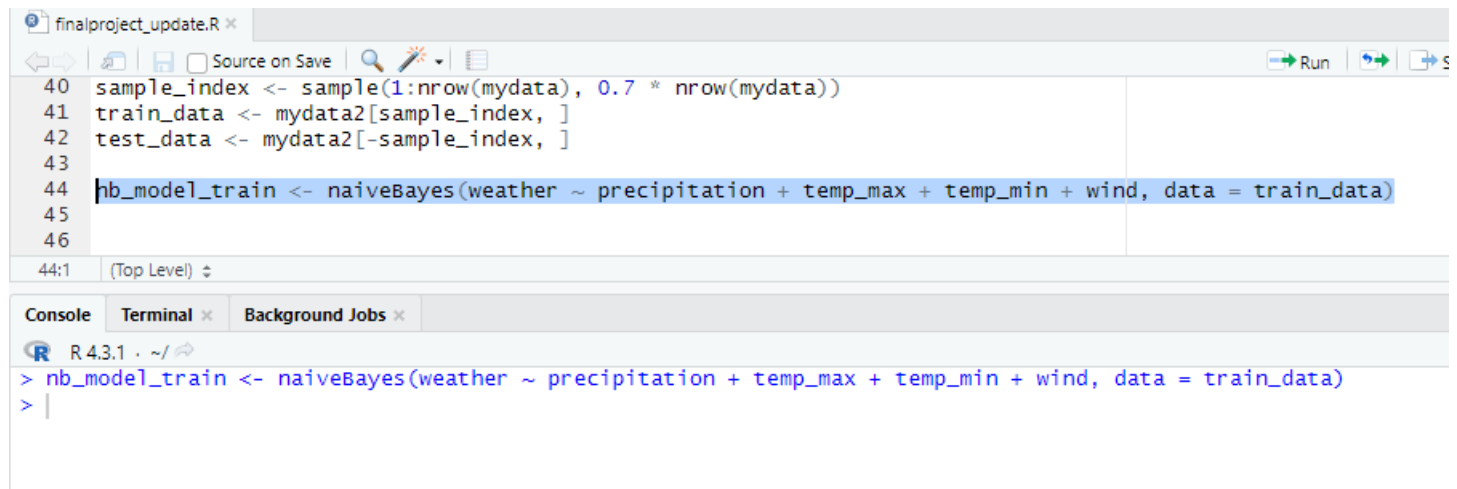
**Description :**

Dataset divided into training data and test data . set.seed(123) is used to set the seed for the random number generator . sample() used to create a random sample of indices for splitting our dataset into a training set (70%) and a test set(rest 30%) .

## Creating a Naive bayes model:

Code:

```
nb_model_train <- naiveBayes(weather ~ precipitation + temp_max + temp_min + wind, data = train_data)
```



The screenshot shows the R Studio interface. The top pane displays the script 'finalproject\_update.R' with the following code:

```
40 sample_index <- sample(1:nrow(mydata), 0.7 * nrow(mydata))
41 train_data <- mydata2[sample_index, ]
42 test_data <- mydata2[-sample_index, ]
43
44 nb_model_train <- naiveBayes(weather ~ precipitation + temp_max + temp_min + wind, data = train_data)
45
46
```

The bottom pane shows the Console with the execution of the model creation command:

```
> nb_model_train <- naiveBayes(weather ~ precipitation + temp_max + temp_min + wind, data = train_data)
> |
```

Description :

Created a Naive Bayes model using training data by using naiveBayes() function from “e1071” packages.

## Prediction Test:

Code:

```
predictions_test <- predict(nb_model_train, test_data)
```

```
predictions_test
```

```
45
46 predictions_test <- predict(nb_model_train, test_data)
47 predictions_test
48 |
49
```

```

Console Terminal × Background Jobs ×
R 4.3.1 · ~/
> nb_model_train <- naiveBayes(weather ~ precipitation + temp_max + temp_min + wind, data = train_data)
> predictions_test <- predict(nb_model_train, test_data)
> predictions_test
 [1] sun    rain   rain   drizzle rain   drizzle snow   snow   snow   rain   drizzle rain   sun
[14] rain   rain   drizzle rain   rain   sun    sun    drizzle snow   snow   rain   snow   sun
[27] rain   rain   rain   snow   rain   drizzle rain   sun    sun    sun    rain   rain   sun
[40] rain   rain   rain   sun    sun    sun    sun    sun    sun    rain   rain   sun
[53] sun    rain   rain   sun    sun    sun    rain   sun    rain   rain   sun    sun    sun
[66] sun    sun    sun    rain   sun    sun    sun    sun    sun    sun    sun    sun    sun
[79] sun    sun    sun    sun    sun    sun    sun    sun    sun    rain   rain   rain   rain
[92] sun    rain   rain   sun    rain   rain   rain   rain   rain   rain   rain   rain   snow
[105] snow   rain   rain   drizzle drizzle rain   drizzle drizzle drizzle drizzle drizzle rain   rain
[118] rain   rain   sun    sun    rain   rain   rain   rain   rain   rain   rain   sun   rain
[131] drizzle drizzle sun    rain   rain   rain   rain   sun    rain   rain   sun    sun   sun
[144] rain   sun    sun    sun    rain   rain   sun
Levels: rain drizzle sun snow fog
> |

```

### Description :

By using `predict(nb_model_train, test_data)` we get the predicted values for each observation in our test set from the dataset. So we can compare them with the actual values to evaluate the performance of our model.

## Accuracy Test:

### Code:

```
accuracy_test <- sum(predictions_test == test_data$weather) / nrow(test_data)
```

```
accuracy_test
```

```

finalproject_update.R* ×
← → | Source on Save | 🔍 | 🛠️ | 📄 | Run | ↻
44 nb_model_train <- naiveBayes(weather ~ precipitation + temp_max + temp_min + wind, data = train
45
46 predictions_test <- predict(nb_model_train, test_data)
47 predictions_test
48
49 accuracy_test <- sum(predictions_test == test_data$weather) / nrow(test_data)
50 accuracy_test
51
49:1 | (Top Level) ↕

```

```

Console Terminal × Background Jobs ×
R 4.3.1 · ~/
> accuracy_test <- sum(predictions_test == test_data$weather) / nrow(test_data)
> accuracy_test
[1] 0.7466667
> accuracy_test <- sum(predictions_test == test_data$weather) / nrow(test_data)

```

### Description:

We know,  $\text{Accuracy} = (\text{Number of Correct Prediction} / \text{Total Number of Predictions})$ . Here we calculate the sum of total correct prediction test which compare to actual data and divide by total number of test\_data. We get accuracy 0.74 which means our model accuracy is **74%**.

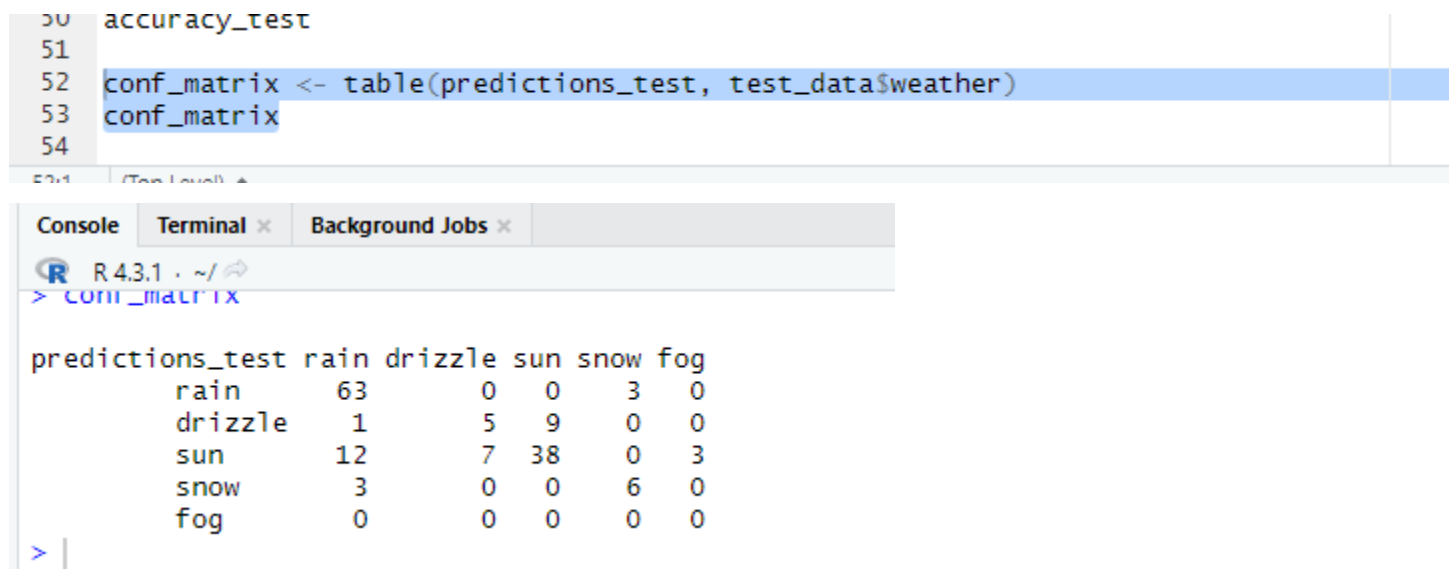
### Confusion Matrix for Naïve Bayes:

#### Code:

```
conf_matrix <- table(predictions_test, test_data$weather)
```

```
conf_matrix
```

```
50 accuracy_test
51
52 conf_matrix <- table(predictions_test, test_data$weather)
53 conf_matrix
54
```



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

```
predictions_test rain drizzle sun snow fog
      rain      63      0  0   3  0
    drizzle      1      5  9   0  0
      sun      12      7 38   0  3
    snow       3      0  0   6  0
      fog       0      0  0   0  0
```

### Description:

By using confusion matrix we can get the result of actual and prediction result quantity. Example for predicted rain: 63 instance of the data set correctly predicted as rain 1, instance incorrectly predicted as drizzle, 12 instances incorrectly predicted as sun, 0 instances incorrectly predict for fog. So same for all the target value in the test\_data\$weather attribute.

### TP, FP, FN and TN VALUES :

#### Code:

```
TP <- conf_matrix[2, 2]
```

```
FP <- conf_matrix[1, 2]
```

```
FN <- conf_matrix[2, 1]
```

```
TN <- conf_matrix[1, 1]
```

TP

FP

FN

TN

```
54
55 TP <- conf_matrix[2, 2]
56 FP <- conf_matrix[1, 2]
57 FN <- conf_matrix[2, 1]
58 TN <- conf_matrix[1, 1]
59 TP
60 FP
61 FN
62 TN
63
```

Console Terminal x Background Jobs x

R 4.3.1 · ~/

```
> TP <- conf_matrix[2, 2]
> FP <- conf_matrix[1, 2]
> FN <- conf_matrix[2, 1]
> TN <- conf_matrix[1, 1]
> TP
[1] 5
> FP
[1] 0
> FN
[1] 1
> TN
[1] 63
> |
```

### Description:

Extracting TP(True Positive),FP(False Positive),FN(False Negative ),TN(True Negative) values from confusion matrix.

### Recall, FP rate , Precision and F- measure:

#### Code:

```
recall <- TP / (TP + FN)
```

```
recall
```

```
FP_rate <- FP / (FP + TN)
```

```
FP_rate
```

```
precision <- TP / (TP + FP)
```

```
precision
```

```
f_measure <- 2 * (precision * recall) / (precision + recall)
```

```
f_measure
```

```
63  
64 recall <- TP / (TP + FN)  
65 recall  
66 FP_rate <- FP / (FP + TN)  
67 FP_rate  
68 precision <- TP / (TP + FP)  
69 precision  
70 f_measure <- 2 * (precision * recall) / (precision + recall)  
71 f_measure  
72  
73
```

Console	Terminal x	Background Jobs x
R 4.3.1 · ~/		
<pre>&gt; recall &lt;- TP / (TP + FN) &gt; recall [1] 0.8333333 &gt; FP_rate &lt;- FP / (FP + TN) &gt; FP_rate [1] 0 &gt; precision &lt;- TP / (TP + FP) &gt; precision [1] 1 &gt; f_measure &lt;- 2 * (precision * recall) / (precision + recall) &gt; f_measure [1] 0.9090909 &gt;  </pre>		

## Description:

In our naïve Bayes model we get the values from confusion matrix

- Recall: **83.33%** This means that our Naive Bayes model correctly identified approximately 83.33% of the instances that actually belonged to the positive class
- False Positive Rate (FP Rate): **0%**.
- Precision: **100%**.
- F-measure: **90.91%** It means our Naive Bayes model achieved a good balance between precision and recall.