DATA SCIENCE PROGRAMMING LAB (L3+L4)

ASSESSMENT 2

Logistic Regression IN R

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1. Import Libraries and Dataset

```
#import libraries
library(dplyr)
library(tidyr)
library(readr)
library(caret)
library(ggplot2)
library(ggcorrplot)
library(tidyverse)
library(GGally)
#Load dataset
df <- read.csv("C:/Users/HP/Downloads/heart_disease_uci_3.csv", header = TRUE, check.names = FALSE)</pre>
head(df)
> #import libraries
 library(dplyr)
> library(tidyr)
> library(readr)
 library(caret)
> library(ggplot2)
> library(ggcorrplot)
  library(tidyverse)
 library(GGally)
> #Load dataset
> df <- read.csv("C:/Users/HP/Downloads/heart_disease_uci_3.csv", header = TRUE, check.names = FALSE)
> head(df)
  id age
                  dataset
                                       cp trestbps chol
                                                          fbs
                                                                      restecg thalch exang oldpeak
                                                                                                         slope
            sex
                                               145 233 TRUE lv hypertrophy
           Male Cleveland
                           typical angina
                                                                                150 FALSE
                                                                                              2.3 downsloping
  1 63
2
   2
      67
           Male Cleveland
                             asymptomatic
                                               160 286 FALSE lv hypertrophy
                                                                                 108 TRUE
                                                                                               1.5
                                                                                                          flat
3
   3
      67
           Male Cleveland
                             asymptomatic
                                               120
                                                    229 FALSE 1v hypertrophy
                                                                                 129
                                                                                     TRUE
                                                                                               2.6
                                                                                                          flat
           Male Cleveland
                                                                                 187 FALSE
                                                                                               3.5 downsloping
   4
      37
4
                              non-anginal
                                               130
                                                    250 FALSE
                                                                      normal
5
  5
     41 Female Cleveland atypical angina
                                               130 204 FALSE lv hypertrophy
                                                                                172 FALSE
                                                                                              1.4
                                                                                                   upsloping
6
  6
      56 Male Cleveland atypical angina
                                               120 236 FALSE
                                                                                178 FALSE
                                                                                               0.8
                                                                                                     upsloping
                                                                      normal
  ca
                  thal target
          fixed defect
2
   3
                            0
                normal
3
   2 reversable defect
                            1
   0
                normal
                            0
5
   0
                            0
                normal
6
   0
                normal
                            0
```

2. Cleaning the dataset

```
#Cleaning the data
colnames(df) <- names
print(names)
names (df)
which(is.na(names(df)) \mid names(df) == "")
library(janitor)
df <- janitor::clean_names(df)</pre>
library(readr)
df <- read_csv("C:/Users/HP/Downloads/heart_disease_uci_3.csv", name_repair = "unique")</pre>
colSums(is.na(df))
str(df)
  > print(names)
[1] "age"
[7] "restecg"
[13] "thal"
                     "sex"
                                   "cp"
                                                 "trestbps"
                                                               "cho1"
                                                                             "fbs"
                                  "exang"
                                                                             "ca"
                     "thalach"
                                                 "oldpeak"
                                                               "slope"
                     "heart_disease"
  > names(df)
   [1] "age"
[7] "restecg"
                    "sex"
                                   "cp"
                                                 "trestbps"
                                                               "cho1"
                                                                             "fbs"
                    "thalach"
                                  "exang"
                                                 "oldpeak"
                                                                             "ca"
                                                               "slope"
  [13] "thal"
                    "heart_disease" NA
                                                 NA
  > which(is.na(names(df)) | names(df) == "")
  [1] 15 16
  > library(janitor)
  > df <- janitor::clean_names(df)</pre>
  > library(readr)
   - df <- read_csv("C:/Users/HP/Downloads/heart_disease_uci_3.csv", name_repair = "unique")</pre>
  Rows: 920 Columns: 16
    Column specification
  chr (6): sex, dataset, cp, restecg, slope, thal
  dbl (8): id, age, trestbps, chol, thalch, oldpeak, ca, target
  lgl (2): fbs, exang
  i Use `spec()` to retrieve the full column specification for this data.
  i Specify the column types or set `show_col_types = FALSE` to quiet this message.
  > colSums(is.na(df))
       id
              age
                      sex
                           dataset
                                       cp trestbps
                                                     chol
                                                              fbs
                                                                  restecg
                                                                           thalch
                                                                                    exang oldpeak
        0
                0
                        0
                                0
                                               59
                                                       30
                                                               90
     slope
               ca
                      thal
                            target
       309
              611
                      486
```

```
> str(df)
spc_tbl_[920 \times 16] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
              : num [1:920] 1 2 3 4 5 6 7 8 9 10 ...

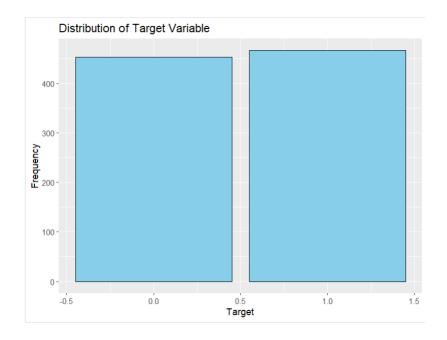
: num [1:920] 63 67 67 37 41 56 62 57 63 53 ...

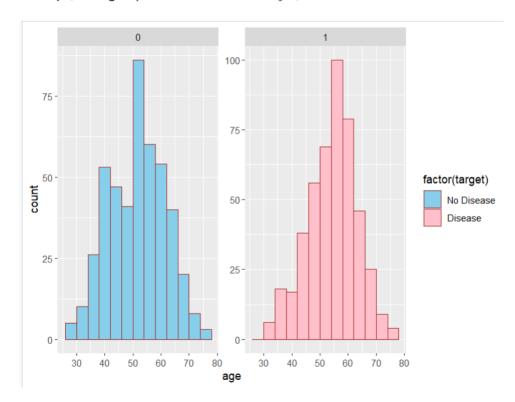
: chr [1:920] "Male" "Male" "Male" "Male" ...
 $ id
 $ age
 $ sex
 $ dataset : chr [1:920] "Cleveland" "Cleveland" "Cleveland" "Cleveland" ...
              chr [1:920] "typical angina" "asymptomatic" "asymptomatic" "non-anginal" ...
 $ cp
 $ trestbps: num [1:920] 145 160 120 130 130 120 140 120 130 140 ...
 $ chol
                num [1:920] 233 286 229 250 204 236 268 354 254 203 ...
 $ fbs : logi [1:920] TRUE FALSE FALSE FALSE FALSE FALSE ...
$ restecg : chr [1:920] "lv hypertrophy" "lv hypertrophy" "lv hypertrophy" "normal" ...
                num [1:920] 150 108 129 187 172 178 160 163 147 155 ...
$ exang : logi [1:920] FALSE TRUE TRUE FALSE FALSE FALSE ... $ oldpeak : num [1:920] 2.3 1.5 2.6 3.5 1.4 0.8 3.6 0.6 1.4 3.1 ... $ slope : chr [1:920] "downsloping" "flat" "flat" "downsloping" ...
              : num [1:920] 0 3 2 0 0 0 2 0 1 0 ...

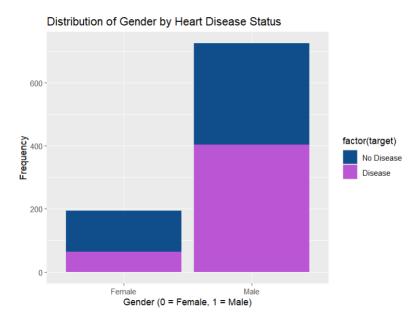
: chr [1:920] "fixed defect" "normal" "reversable defect" "normal" ...
 $ thal
 $ target : num [1
- attr(*, "spec")=
               num [1:920] 0 0 1 0 0 0 1 0 1 1 ...
  .. cols(
        id = col_double();
  ٠.
        age = col_double(),
        sex = col_character(),
  . .
        dataset = col_character(),
  . .
        cp = col_character(),
        trestbps = col_double(),
        chol = col_double(),
        fbs = col_logical(),
  . .
        restecg = col_character(),
        thalch = col_double(),
  . .
        exang = col_logical()
  . .
        oldpeak = col_double()
        slope = col_character(),
        ca = col_double(),
        thal = col_character(),
  . .
        target = col_double()
 - attr(*, "problems")=<externalptr>
```

3. Visualizations

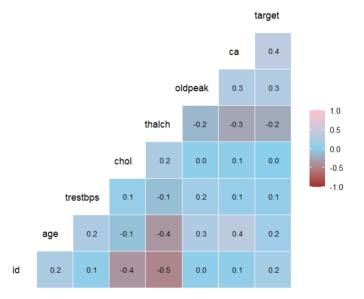
```
# Visualizing the distribution of the target variable
ggplot(df, aes(x = target)) +
   geom_bar(fill = "skyblue", color = "black", stat = "count") +
   labs(title = "Distribution of Target Variable", x = "Target", y = "Frequency")
```

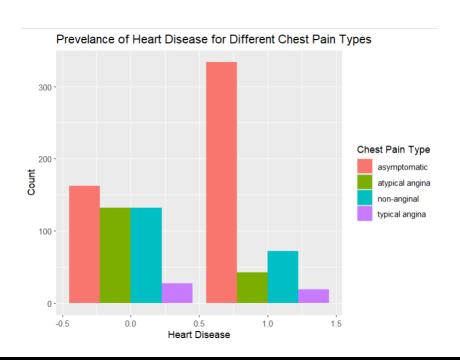






```
# Correlation matrix
numeric_df <- df %>% select(where(is.numeric))
# Plot correlation matrix with custom colors
ggcorr(numeric_df,
    label = TRUE,
    label_size = 3,
    hjust = 0.75,
    layout.exp = 1,
    low = "brown",
    mid = "skyblue",
    high = "pink")
```





4. Encoder

5. Features scaling and normalization

6. Training and testing

```
#splitting the data
set.seed(123)
split <- createDataPartition(target, p = 0.8, list = FALSE)</pre>
X_train <- features_normalized[split, ]</pre>
X_test <- features_normalized[-split, ]</pre>
Y_train <- target[split]</pre>
Y_test <- target[-split]
\label{eq:print} \begin{split} & \text{print}(\text{paste}(\text{"X\_train shape:", paste}(\text{dim}(\text{X\_train}), \, \text{collapse} \, = \, \text{"x"}))) \\ & \text{print}(\text{paste}(\text{"X\_test shape:", paste}(\text{dim}(\text{X\_test}), \, \text{collapse} \, = \, \text{"x"}))) \end{split}
#build train test
train_data <- data.frame(X_train, target = Y_train)</pre>
test_data <- data.frame(X_test, target = Y_test)</pre>
train_data <- train_data[, !duplicated(names(train_data))]</pre>
test_data <- test_data[, !duplicated(names(test_data))]</pre>
str(heart)
any(duplicated(names(train_data)))
names(train_data)[duplicated(names(train_data))]
```

```
> #splitting the data
> set.seed(123)
> split <- createDataPartition(target, p = 0.8, list = FALSE)</pre>
> X_train <- features_normalized[split, ]
> X_test <- features_normalized[-split, ]</pre>
> Y_train <- target[split]
> Y_test <- target[-split]
> print(paste("X_train shape:", paste(dim(X_train), collapse = "x")))
[1] "X_train shape: 736x12"
> print(paste("X_test shape:", paste(dim(X_test), collapse = "x")))
[1] "X_test shape: 184x12"
> #build train test
> train_data <- data.frame(X_train, target = Y_train)</pre>
> test_data <- data.frame(X_test, target = Y_test)</pre>
> train_data <- train_data[, !duplicated(names(train_data))]</pre>
> test_data <- test_data[, !duplicated(names(test_data))]</pre>
```

```
> str(heart)
      tibble [920 \times 16] (S3: tbl_df/tbl/data.frame)
                   : num [1:920] 1 2 3 4 5 6 7 8 9 10
                   : num [1:920] 63 67 67 37 41 56 62 57 63 53 ...
       $ age
                   : Factor w/ 2 levels "Female", "Male": 2 2 2 2 1 2 1 1 2 2 ...
       $ sex
       $ dataset : chr [1:920] "Cleveland" "Cleveland" "Cleveland" "Cleveland" ...
       $ cp : Factor w/ 4 levels "asymptomatic",..: 4 1 1 3 2 2 1 1 1 1 ...
$ trestbps: num [1:920] 145 160 120 130 130 120 140 120 130 140 ...
                 : num [1:920] 233 286 229 250 204 236 268 354 254 203 ...
       $ fbs : Factor w/ 2 levels "FALSE", "TRUE": 2 1 1 1 1 1 1 1 2 ...
$ restecg : Factor w/ 3 levels "lv hypertrophy",..: 1 1 2 1 2 1 2 1 1 ...
       $ thalch : num [1:920] 150 108 129 187 172 178 160 163 147 155 ...
$ exang : Factor w/ 2 levels "FALSE", "TRUE": 1 2 2 1 1 1 1 2 1 2 ...
       $ oldpeak : num [1:920] 2.3 1.5 2.6 3.5 1.4 0.8 3.6 0.6 1.4 3.1 ...
       $ slope : Factor w/ 3 levels "downsloping",..: 1 2 2 1 3 3 1 3 2 1 ... $ ca : Factor w/ 4 levels "0","1","2","3": 1 4 3 1 1 1 3 1 2 1 ...
       $ thal
                   : Factor w/ 3 levels "fixed defect",..: 1 2 3 2 2 2 2 3 3 ...
       $ target : Factor w/ 2 levels "0","1": 1 1 2 1 1 1 2 1 2 2 ...
      > any(duplicated(names(train_data)))
      [1] FALSE
      > names(train_data)[duplicated(names(train_data))]
      character(0)
# Align factor levels (important!)
for (col in names(train_data)) -
  if (is.factor(train_data[[col]])) {
     test_data[[col]] <- factor(test_data[[col]], levels = levels(train_data[[col]]))</pre>
}
# Print the shape of the training and test sets
print(paste("X_train shape:", paste(dim(X_train), collapse = "x")))
print(paste("X_test shape:", paste(dim(X_test), collapse = "x")))
 > # Align factor levels (important!)
 > for (col in names(train_data)) {
     if (is.factor(train_data[[col]])) {
         test_data[[col]] <- factor(test_data[[col]], levels = levels(train_data[[col]]))</pre>
 +
 + }
 > # Print the shape of the training and test sets
 > print(paste("X_train shape:", paste(dim(X_train), collapse = "x")))
 [1] "X_train shape: 736x12"
 > print(paste("X_test shape:", paste(dim(X_test), collapse = "x")))
 [1] "X_test shape: 184x12"
```

7. Implement the model

```
#LOGISTIC REGRESSION MODEL
# Combine features and target into a single data frame
train_data <- as.data.frame(cbind(target = Y_train, X_train))
train_data <- train_data[, !duplicated(names(train_data))]
# Fit logistic regression model
model <- glm(target ~ ., data = train_data, family = "binomial")
summary(model)</pre>
```

```
> #LOGISTIC REGRESSION MODEL
> # Combine features and target into a single data frame
> train_data <- as.data.frame(cbind(target = Y_train, X_train))</pre>
> train_data <- train_data[, !duplicated(names(train_data))]</pre>
> # Fit logistic regression model
> model <- glm(target ~ ., data = train_data, family = "binomial")</pre>
     > summary(model)
     glm(formula = target ~ ., family = "binomial", data = train_data)
     Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
                            0.067797
                                    1.233127
                                              0.055 0.956154
     (Intercept)
     age
                            0.005288
                                    0.221636 0.024 0.980964
     sexMale
                           0.746201
                                      0.516027
                                               1.446 0.148163
                                     0.553154 -1.009 0.312931
     cpatypical angina
                           -0.558182
                           -1.734670 0.501198 -3.461 0.000538 ***
     cpnon-anginal
                           cptypical angina
                           0.229049 0.212653 1.077 0.281436
     trestbps
     chol
                           0.138762
                                      0.417517
                                                0.332 0.739624
                                    0.385438 -1.453 0.146239
     restecgnormal
                           -0.560020
     restecgst-t abnormality 0.717995 1.956182
                                               0.367 0.713590
                           -0.583122 0.726874 -0.802 0.422419
     thalnormal
     thalreversable defect
                           0.778001 0.704302 1.105 0.269315
     exangTRUE
                            0.716526
                                     0.429034
                                               1.670 0.094901 .
                           0.291409 0.242088
     oldpeak
                                                1.204 0.228693
     slopeflat
                           0.348099 0.824438 0.422 0.672860
     slopeupsloping
                           -0.900451
                                      0.876639 -1.027 0.304344
                            Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
     (Dispersion parameter for binomial family taken to be 1)
         Null deviance: 335.71 on 244 degrees of freedom
     Residual deviance: 190.61 on 228 degrees of freedom
       (491 observations deleted due to missingness)
     AIC: 224.61
     Number of Fisher Scoring iterations: 5
```

8. Model evaluation

```
> #model evaluation
> # Making predictions on the test set
> predictions <- predict(model, newdata =test_data, type = "response")</pre>
> # Converting probabilities to binary predictions based on threshold 0.5
> binary_predictions <- ifelse(predictions >= 0.5, 1, 0)
> # Combining actual values and predicted values into a data frame
> result <- data.frame(actual = Y_test, predicted = binary_predictions)</pre>
> # Evaluating the model
> confusionMatrix(data = as.factor(binary_predictions), reference = as.factor(Y_test),
                  positive = "1")
Confusion Matrix and Statistics
          Reference
Prediction 0 1
         0 24 5
         1 4 21
               Accuracy : 0.8333
                 95% CI: (0.7071, 0.9208)
    No Information Rate: 0.5185
    P-Value [Acc > NIR] : 1.357e-06
                  Kappa: 0.6657
 Mcnemar's Test P-Value: 1
            Sensitivity: 0.8077
            Specificity: 0.8571
         Pos Pred Value: 0.8400
         Neg Pred Value: 0.8276
             Prevalence: 0.4815
         Detection Rate: 0.3889
   Detection Prevalence: 0.4630
      Balanced Accuracy: 0.8324
       'Positive' Class: 1
```

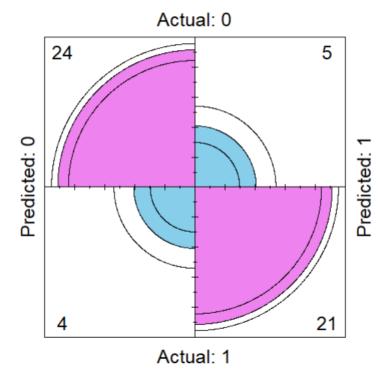
9. Confusion matrix

```
# Create a confusion matrix
conf_matrix <- table(
  factor(binary_predictions, levels = c("0", "1")),
  factor(test_data$target, levels = c("0", "1")))

# Set the dimension names of the confusion matrix
dimnames(conf_matrix) <- list(Actual = c("0", "1"), Predicted = c("0", "1"))

# Plot the fourfold plot with color and main title
fourfoldplot(conf_matrix, color = c("skyblue", "violet"), main = "Confusion Matrix")</pre>
```

Confusion Matrix



10. Predict values

```
#predict new values for the model
test_data <- as.data.frame(cbind(target = Y_test, X_test))</pre>
# Making predictions on the test set
predictions <- predict(model, newdata = as.data.frame(test_data[, -1]),type ="response")</pre>
# Converting probabilities to binary predictions based on threshold 0.5
binary_predictions <- ifelse(predictions >= 0.5, 1, 0)
# Combining actual values and predicted values into a data frame
result <- data.frame(actual = test_data$target, predicted = binary_predictions)</pre>
# Displaying the results
print(result)
> # Making predictions on the test set
> predictions <- predict(model, newdata = as.data.frame(test_data[, -1]),type ="response")</pre>
> # Converting probabilities to binary predictions based on threshold 0.5
> binary_predictions <- ifelse(predictions >= 0.5, 1, 0)
> # Combining actual values and predicted values into a data frame
> result <- data.frame(actual = test_data$target, predicted = binary_predictions)</pre>
```

	Displaying		ults	38	1	1	78	0	NA	
	int(result actual pre			39	0	0	79 80	0 0	NA NA	
1	actuar pre 0	0		40	1	1	81	0	NA NA	
2	1	1		41 42	0 1	0 1	82	1	NA	
3	1	1		42	1	0	83	1	NA	
4	1	1		44	0	1	84	1	NA	
5	0	0		45	0	0	85	0	NA	
6 7	0 0	0 1		46	1	0	86 87	1 0	NA NA	
8	0	0		47 48	1 0	1 1	88	1	NA NA	
9	0	0		49	0	0	89	1	NA	
10	1	1		50	0	0	90	1	NA	
11	0	0		51	1	0	91	1	NA	
12 13	0 0	0 0		52	1	1	92 93	1 1	NA NA	
14	0	0		53 54	1 0	1 NA	94	1	NA NA	
15	1	1		55	0	NA NA	95	1	NA	
16	1	0		56	0	NA	96	1	NA	
17 18	0	0		57	0	NA	97	1	NA	
19	0 1	0 1		58 59	0	NA NA	98 99	1 1	NA NA	
20	0	0		60	0 0	NA NA	100	1	NA NA	
21	1	1		61	Ö	NA	101	1	NA	
22	1	1		62	0	NA	102	1	NA	
23 24	0 0	0 0		63	0	NA NA	103	1	NA NA	
25	0	0		64 65	0 0	NA NA	104 105	1 1	NA NA	
26	1	1		66	0	NA NA	106	1	NA NA	
27	0	0		67	0	NA	107	1	NA	
28 29	1 1	0 1		68 69	0	NA NA	108	1	NA	
30	0	0		70	0 1	NA NA	109 110	1 0	NA NA	
31	0	0		71	0	NA	111	1	NA NA	
32	1	1		72	1	NA	112	1	NA	
33 34	1	1		73	0	NA NA	113	1	NA	
35	1 1	1 1		74 75	1 0	NA NA	114 115	0 1	NA NA	
36	0	0		76	0	NA	116	0	NA NA	
37	0	1		77	0	NA	117	n	NA	
118	1	NA								
119	1	NA								
120	0	NA								
121 122	0 1	NA NA								
123	1	NA								
124	1	NA								
125	0	NA								
126 127	1 0	NA NA								
128	0	NA								
129	0	NA								
130	1	NA								
131 132	0 0	NA NA	159	0	NA					
133	1	NA	160	1	NA					
134	0	NA	161 162	1 1	NA NA					
135	0	NA NA	163	1	NA					
136 137	1 0	NA NA	164	1	NA					
138	1	NA	165	1	NA					
139	1	NA	166	0	NA					
140	0	NA	167 168	1 1	NA NA					
141 142	0 0	NA NA	169	1	NA					
143	0	NA	170	0	NA					
144	1	NA	171	0	NA					
145	0	NA NA	172	1	NA					
146 147	1 1	NA NA	173 174	1	NA NA					
148	0	NA	174 175	1 1	NA NA					
149	0	NA	176	1	NA					
150	1	NA NA	1 77	0	NA					
151 152	1 1	NA NA	178	1	NA					
153	1	1	179 180	1	NA NA					
154	1	NA	180 181	0 0	NA NA					
155 156	1 0	NA NA	182	1	NA					
157	1	NA	183	0	NA					
			184	1	NA					
158	0	NA	104	_						