Data 622 Assignment 4

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Determining water potability

Target Variable is water potability class 1 , 0

DT, RF, ADABOOST, SVM, Neural Network

Read in Data

```
file_url <- "https://raw.githubusercontent.com/division-zero/Data-622/refs/heads/main/Assignm
# Download the file to a temporary location
temp_file <- tempfile(fileext = ".csv")
download.file(file_url, destfile = temp_file, mode = "wb")
# Read the csv file
fulldata <- read.delim(file_url, sep = ",", header = TRUE, stringsAsFactors = FALSE)
# View the data
head(fulldata)
```

```
        ph Hardness   Solids Chloramines  Sulfate Conductivity Organic_carbon
1       NA 204.8905 20791.32    7.300212 368.5164     564.3087      10.379783
2 3.716080 129.4229 18630.06    6.635246       NA     592.8854      15.180013
3 8.099124 224.2363 19909.54    9.275884       NA     418.6062      16.868637
4 8.316766 214.3734 22018.42    8.059332 356.8861     363.2665      18.436524
5 9.092223 181.1015 17978.99    6.546600 310.1357     398.4108      11.558279
6 5.584087 188.3133 28748.69    7.544869 326.6784     280.4679       8.399735
  Trihalomethanes Turbidity Potability
```

```
1         86.99097  2.963135          0
2         56.32908  4.500656          0
3         66.42009  3.055934          0
4        100.34167  4.628771          0
5         31.99799  4.075075          0
6         54.91786  2.559708          0
```

```
# Clean up the temporary file
unlink(temp_file)
```

Basic data info

```
summary(fulldata)
```

```
       ph            Hardness          Solids         Chloramines
 Min.   : 0.000   Min.   : 47.43   Min.   :  320.9   Min.   : 0.352
 1st Qu.: 6.093   1st Qu.:176.85   1st Qu.:15666.7   1st Qu.: 6.127
 Median : 7.037   Median :196.97   Median :20927.8   Median : 7.130
 Mean   : 7.081   Mean   :196.37   Mean   :22014.1   Mean   : 7.122
 3rd Qu.: 8.062   3rd Qu.:216.67   3rd Qu.:27332.8   3rd Qu.: 8.115
 Max.   :14.000   Max.   :323.12   Max.   :61227.2   Max.   :13.127
 NA's   :491
    Sulfate       Conductivity   Organic_carbon  Trihalomethanes
 Min.   :129.0   Min.   :181.5   Min.   : 2.20   Min.   :  0.738
 1st Qu.:307.7   1st Qu.:365.7   1st Qu.:12.07   1st Qu.: 55.845
 Median :333.1   Median :421.9   Median :14.22   Median : 66.622
 Mean   :333.8   Mean   :426.2   Mean   :14.28   Mean   : 66.396
 3rd Qu.:360.0   3rd Qu.:481.8   3rd Qu.:16.56   3rd Qu.: 77.337
 Max.   :481.0   Max.   :753.3   Max.   :28.30   Max.   :124.000
 NA's   :781                                     NA's   :162
   Turbidity       Potability
 Min.   :1.450   Min.   :0.0000
 1st Qu.:3.440   1st Qu.:0.0000
 Median :3.955   Median :0.0000
 Mean   :3.967   Mean   :0.3901
 3rd Qu.:4.500   3rd Qu.:1.0000
 Max.   :6.739   Max.   :1.0000
```

```r
colSums(is.na(fulldata))
```

```
            ph        Hardness          Solids     Chloramines         Sulfate
           491               0               0               0             781
  Conductivity  Organic_carbon Trihalomethanes       Turbidity      Potability
             0               0             162               0               0
```

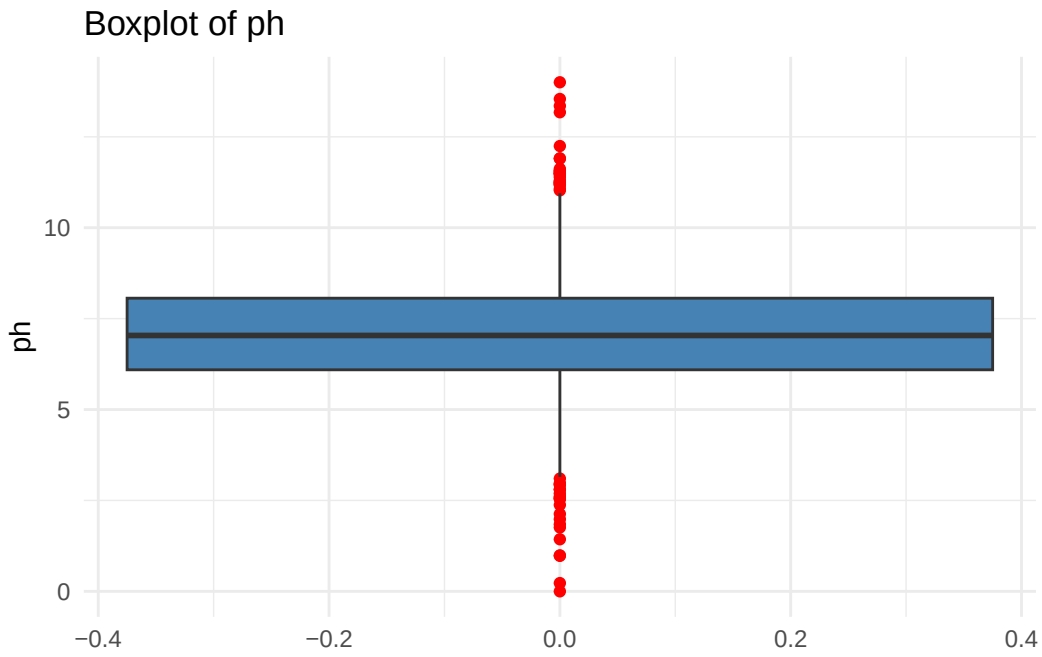
```r
cor_matrix <- cor(fulldata, use = "complete.obs")

round(cor_matrix, 3)
```

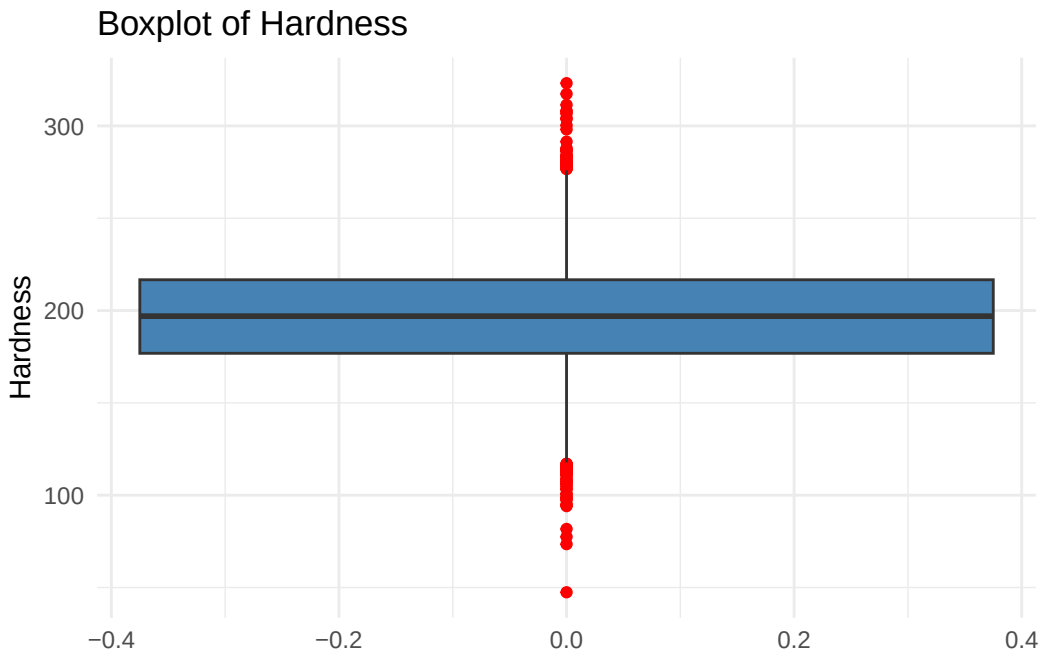
```
                   ph Hardness Solids Chloramines Sulfate Conductivity
ph              1.000    0.109 -0.088      -0.025   0.011        0.014
Hardness        0.109    1.000 -0.053      -0.023  -0.109        0.012
Solids         -0.088   -0.053  1.000      -0.052  -0.163       -0.005
Chloramines    -0.025   -0.023 -0.052       1.000   0.006       -0.028
Sulfate         0.011   -0.109 -0.163       0.006   1.000       -0.016
Conductivity    0.014    0.012 -0.005      -0.028  -0.016        1.000
Organic_carbon  0.028    0.013 -0.005      -0.024   0.027        0.016
Trihalomethanes 0.018   -0.015 -0.016       0.015  -0.023        0.005
Turbidity      -0.036   -0.035  0.019       0.013  -0.010        0.012
Potability      0.015   -0.002  0.041       0.021  -0.015       -0.015
                Organic_carbon Trihalomethanes Turbidity Potability
ph                       0.028           0.018    -0.036      0.015
Hardness                 0.013          -0.015    -0.035     -0.002
Solids                  -0.005          -0.016     0.019      0.041
Chloramines             -0.024           0.015     0.013      0.021
Sulfate                  0.027          -0.023    -0.010     -0.015
Conductivity             0.016           0.005     0.012     -0.015
Organic_carbon           1.000          -0.006    -0.015     -0.016
Trihalomethanes         -0.006           1.000    -0.020      0.009
Turbidity               -0.015          -0.020     1.000      0.023
Potability              -0.016           0.009     0.023      1.000
```

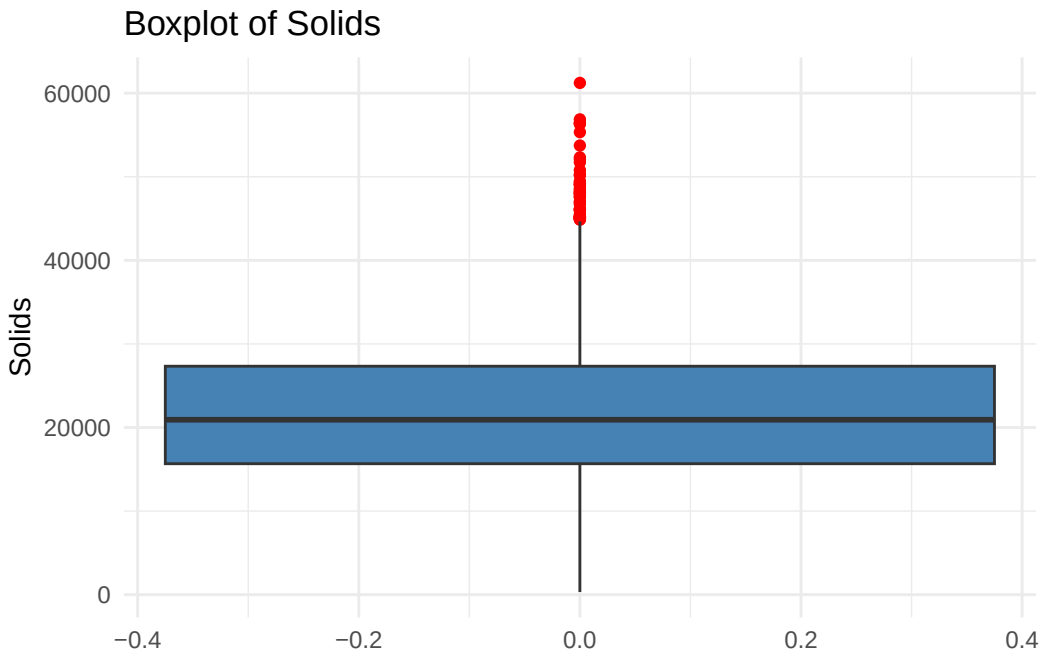
Data

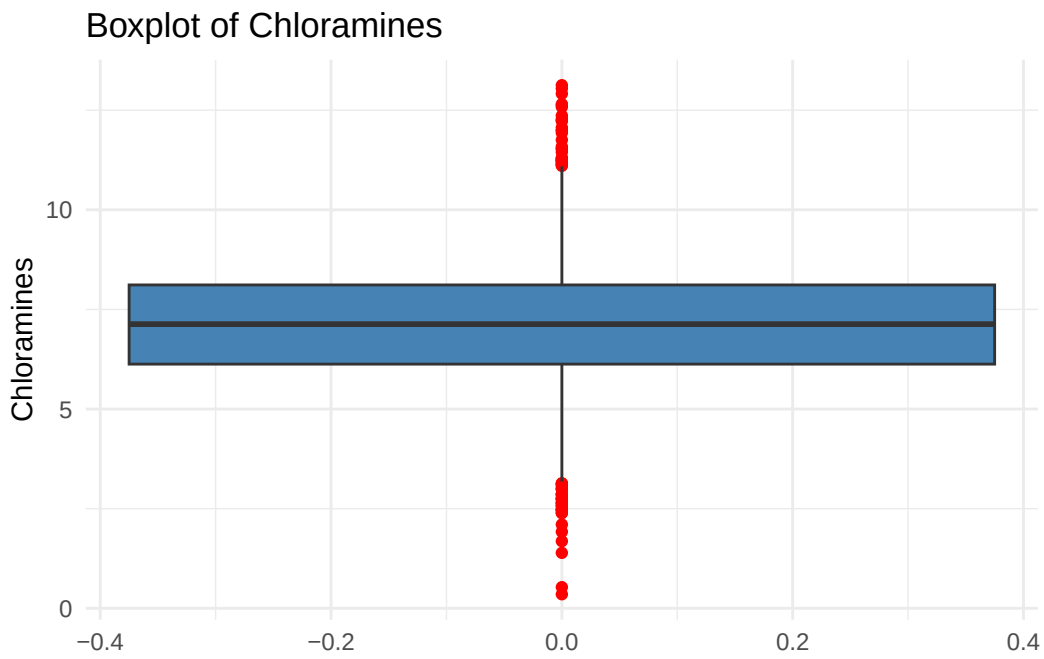
```r
for (col in names(fulldata)) {
  p <- ggplot(fulldata, aes(y = .data[[col]])) +
    geom_boxplot(fill = "steelblue", outlier.color = "red") +
    labs(title = paste("Boxplot of", col), y = col) +
    theme_minimal()

  print(p)  # prints each plot in the viewer
}
```

```
Warning: Removed 491 rows containing non-finite outside the scale range
(`stat_boxplot()`).
```

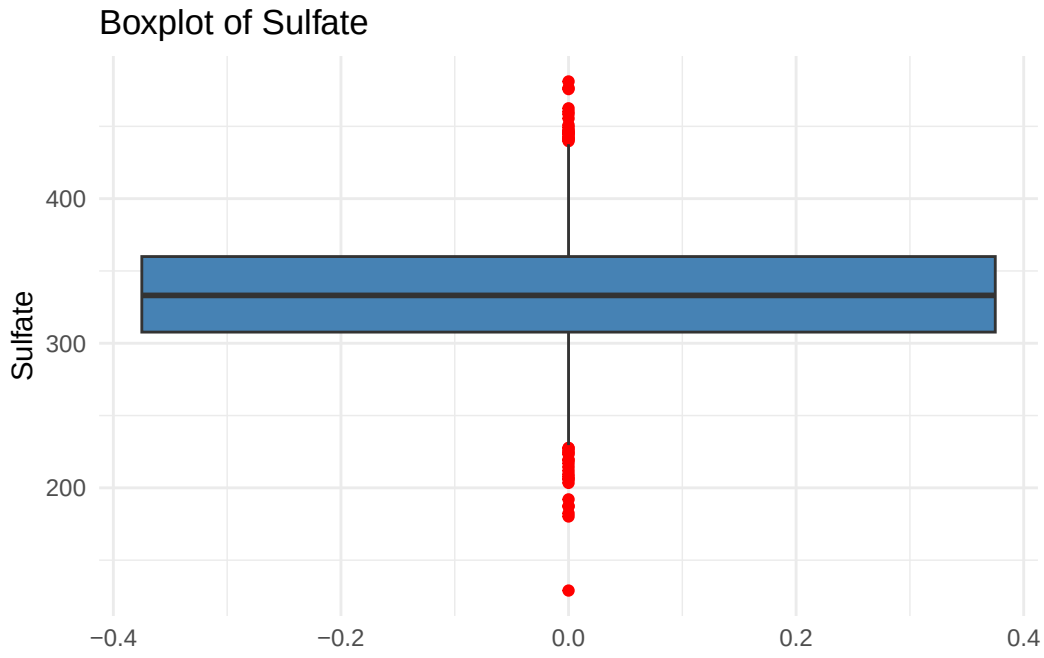


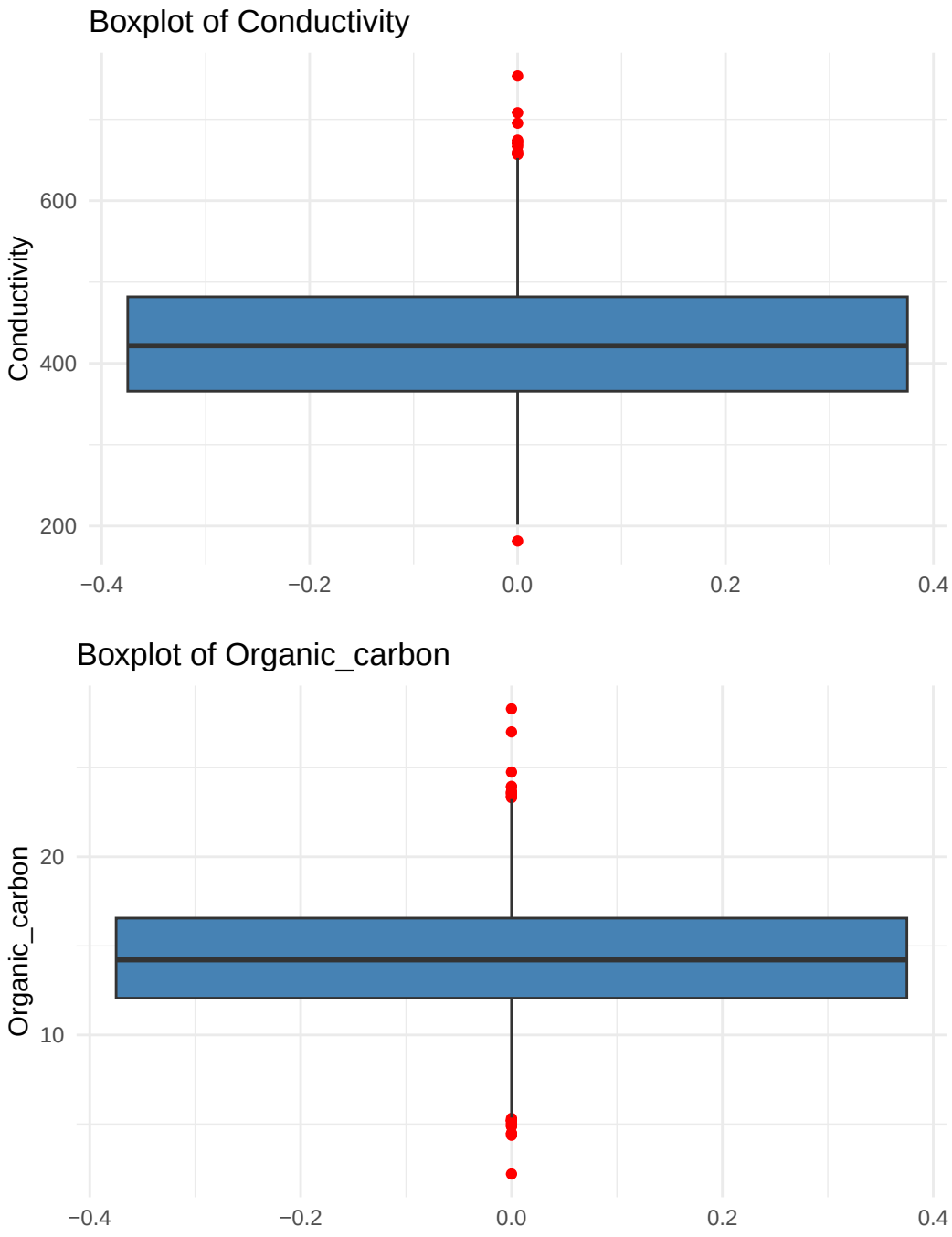

Boxplot of Hardness
Hardness
300
200
100
−0.4
−0.2
0.0
0.2
0.4


Boxplot of Solids
Solids
60000
40000
20000
0
−0.4
−0.2
0.0
0.2
0.4

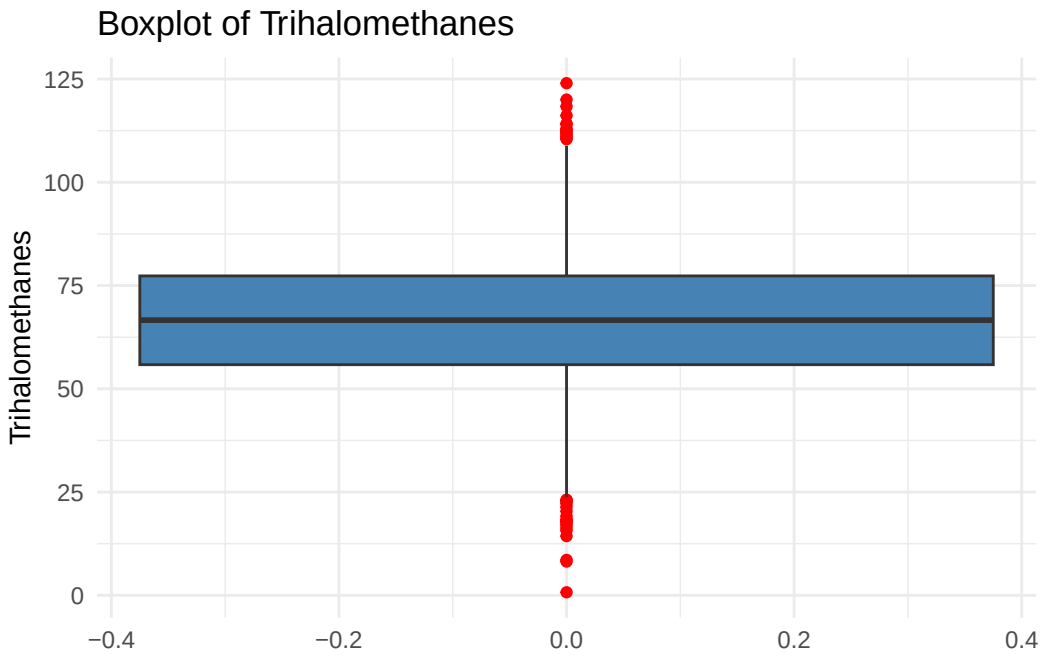


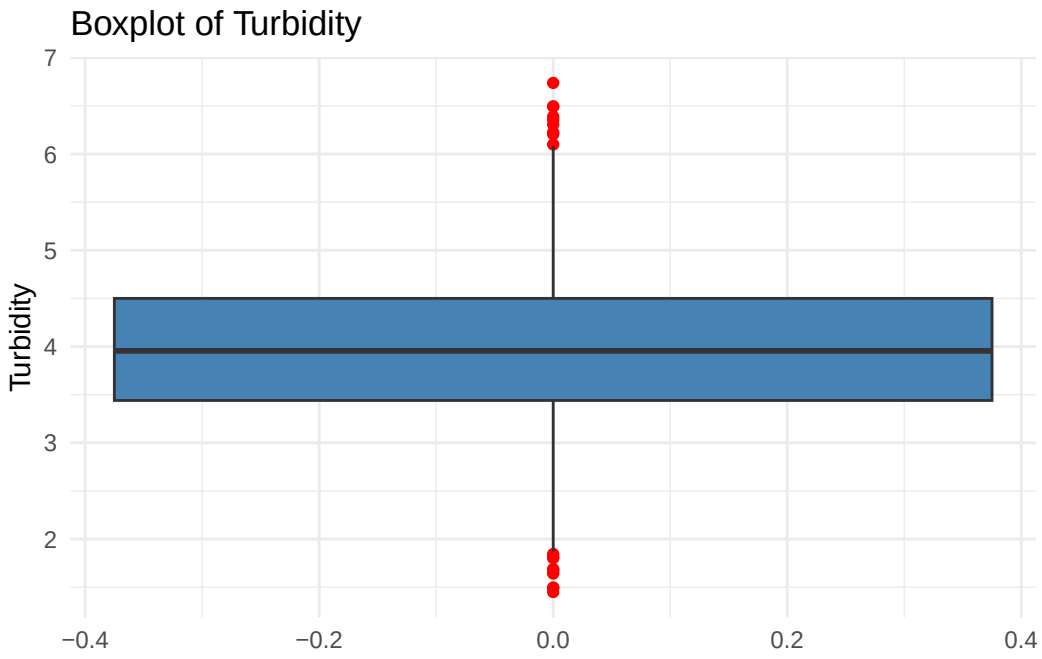

```
Warning: Removed 781 rows containing non-finite outside the scale range
(`stat_boxplot()`).
```

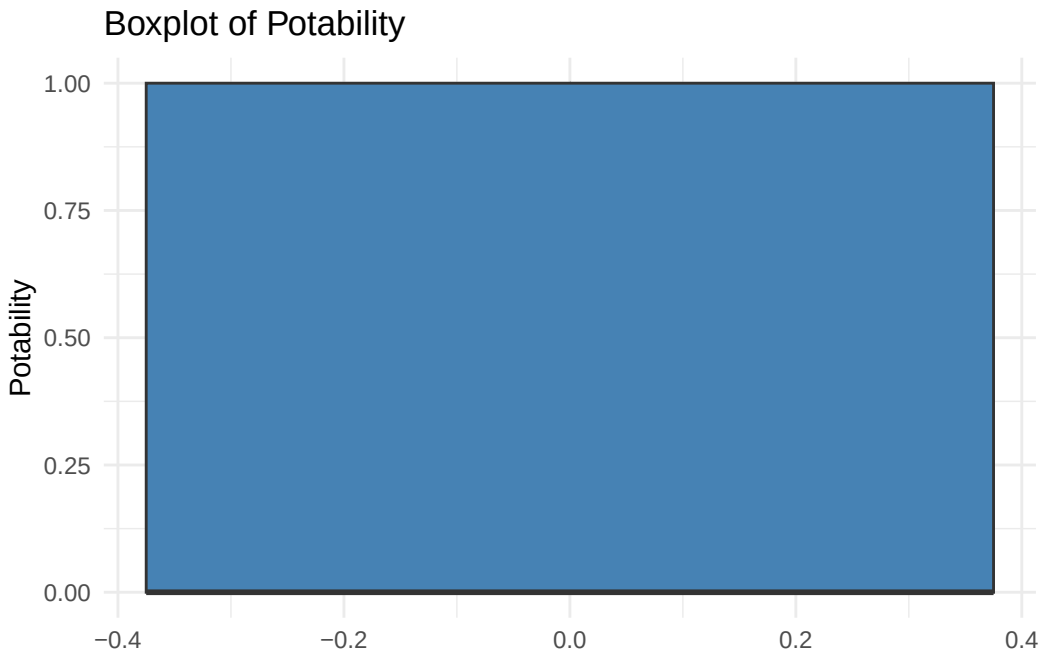




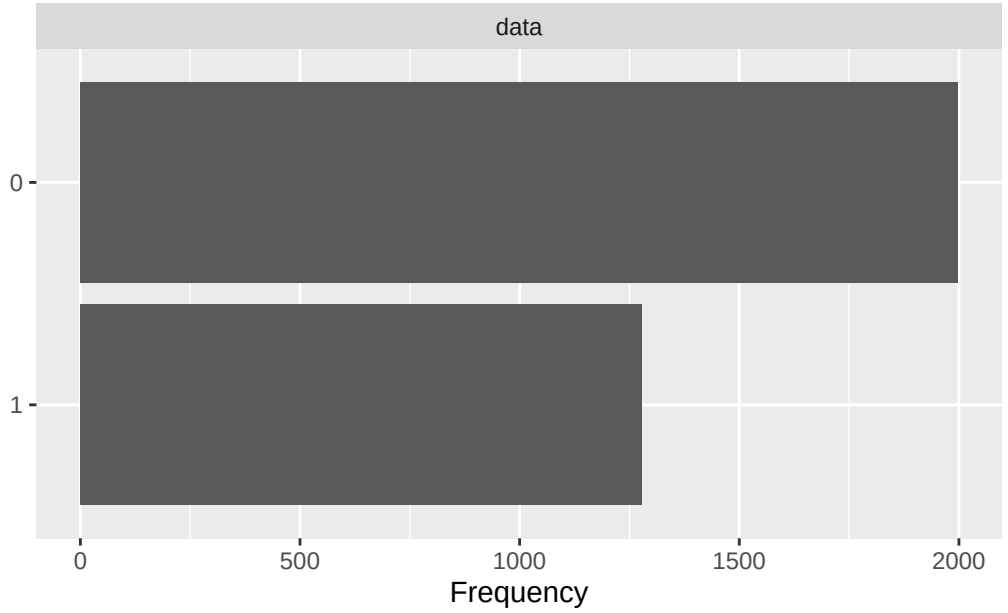

```
Warning: Removed 162 rows containing non-finite outside the scale range
(`stat_boxplot()`).
```


Boxplot of Trihalomethanes
Trihalomethanes
125
100
75
50
25
0
−0.4
−0.2
0.0
0.2
0.4


Boxplot of Turbidity
Turbidity
7
6
5
4
3
2
−0.4
−0.2
0.0
0.2
0.4




```
plot_bar(fulldata$Potability)
```



Outliers

```
set.seed(42)

#impute the original dataset with predicitve mean matching
X <- fulldata[sapply(fulldata, is.numeric)]
imputed <- mice(X, m = 1, method = "pmm", maxit = 5)
```

```
 iter imp variable
  1   1  ph  Sulfate  Trihalomethanes
  2   1  ph  Sulfate  Trihalomethanes
  3   1  ph  Sulfate  Trihalomethanes
  4   1  ph  Sulfate  Trihalomethanes
  5   1  ph  Sulfate  Trihalomethanes
```

```
X <- complete(imputed)

#data scaled
X_scaled <- scale(X)
#back to data frame
X <- data.frame(X_scaled)
X$Potability = fulldata$Potability
#remove outliers
md <-  mahalanobis(X_scaled, colMeans(X_scaled), cov(X_scaled))
outliers <- which(md > qchisq(0.975, df=ncol(X_scaled)))
outliers
```

```
  [1]   52   67   68   89  119  200  205  228  254  264  273  276  279  284  286
 [16]  288  291  314  318  331  334  343  346  347  348  352  355  358  364  366
 [31]  367  375  380  384  386  406  409  493  510  532  667  693  699  727  783
 [46]  786  787  811 1026 1032 1069 1076 1078 1097 1102 1107 1124 1156 1187 1241
 [61] 1303 1344 1362 1367 1488 1491 1503 1536 1537 1538 1543 1555 1606 1624 1643
 [76] 1650 1670 1744 1747 1766 1767 1768 1773 1774 1785 1793 1799 1816 1837 1859
 [91] 1869 1893 1909 2013 2052 2061 2076 2077 2083 2097 2099 2213 2231 2237 2250
[106] 2291 2301 2303 2319 2337 2344 2351 2371 2429 2447 2479 2555 2587 2603 2631
[121] 2632 2646 2681 2682 2695 2700 2705 2718 2743 2797 2812 2896 2929 3015 3143
[136] 3151 3163 3191 3198 3219 3222 3237 3270
```

```
length(outliers)
```

```
[1] 143
```

```
#data without outliers, and is scaled and imputed.

clean_data <- X[-outliers, ]
clean_data <- na.omit(clean_data)
clean_data$Potability <- factor(clean_data$Potability, levels = c(0, 1))
clean_data$Potability <- relevel(clean_data$Potability, ref = "1")
```

Train/Test Split

```
set.seed(42)

train_index <- sample(seq_len(nrow(fulldata)), size = 0.7 * nrow(fulldata))
train_data <- fulldata[train_index, ]
test_data  <- fulldata[-train_index, ]
clean_train_data <- clean_data[train_index, ]
clean_test_data <- clean_data[-train_index, ]

clean_train_data <- na.omit(clean_train_data)
clean_test_data <- na.omit(clean_test_data)




fulldata$Potability <- factor(fulldata$Potability, levels = c(0, 1))
train_data$Potability <- factor(train_data$Potability, levels = c(0, 1))
test_data$Potability <- factor(test_data$Potability, levels = c(0, 1))
clean_data$Potability <- factor(clean_data$Potability, levels = c(0, 1))
clean_train_data$Potability <- factor(clean_train_data$Potability, levels = c(0, 1))

clean_test_data$Potability <- factor(clean_test_data$Potability, levels = c(0, 1))


#making 1  the positive class
train_data$Potability <- relevel(train_data$Potability, ref = "1")
test_data$Potability <- relevel(test_data$Potability, ref = "1")
```

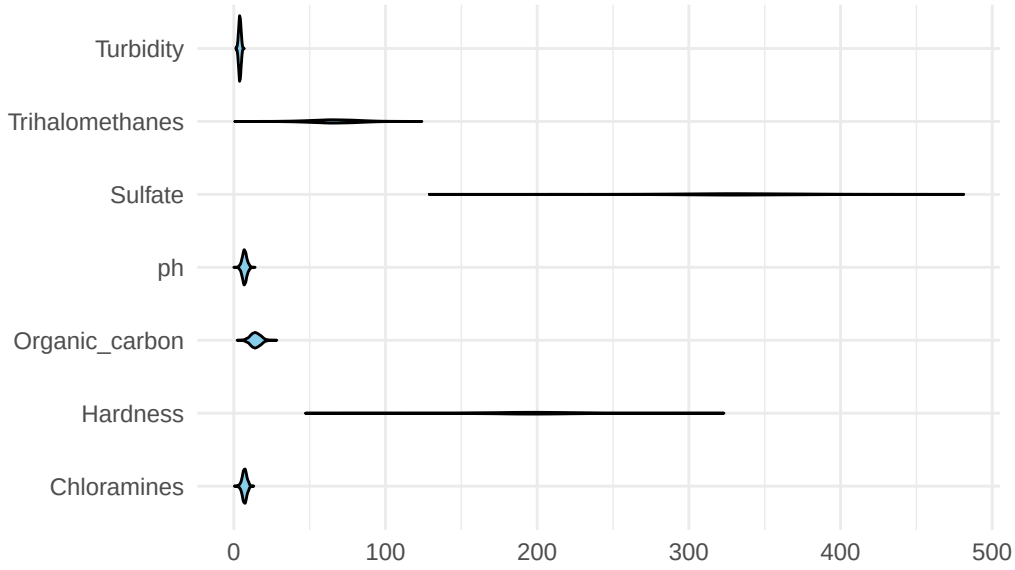
```
#making 1  the positive class
clean_data$Potability <- relevel(clean_data$Potability, ref = "1")
clean_train_data$Potability <- relevel(clean_train_data$Potability, ref = "1")
clean_test_data$Potability <- relevel(clean_test_data$Potability, ref = "1")

same_rows <- intersect(clean_train_data, test_data)
n_same <- nrow(same_rows)
n_same
```

```
[1] 0
```

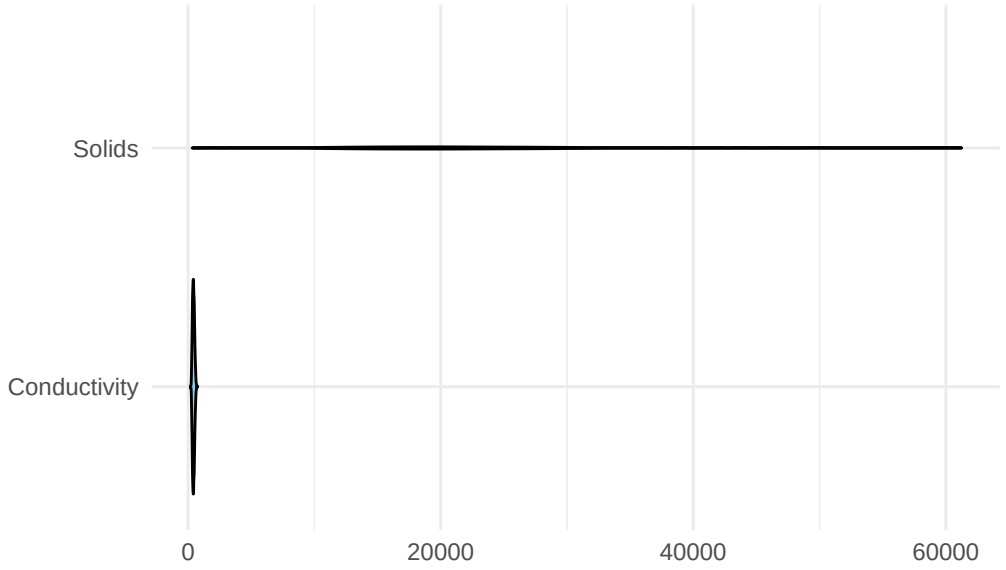
```
#removal of features
#clean_test_data <- clean_test_data |> dplyr::select(-Trihalomethanes, -Conductivity, - Turbi

#clean_train_data <- clean_train_data |> dplyr::select(-Trihalomethanes, -Conductivity, - Tur
```

```
numeric_long <- fulldata  |> dplyr::select(-Potability, -Solids, -Conductivity) |>
  pivot_longer(cols = everything(), names_to = "Variable", values_to = "Value")

ggplot(numeric_long, aes(x = Variable, y = Value)) +
geom_violin(fill = "skyblue", color = "black") +
  #scale_y_continuous(limits = c(0, 500)) +
labs(title = "",
x = "",
y = "") +
theme_minimal()+
  coord_flip()
```

```
Warning: Removed 1434 rows containing non-finite outside the scale range
(`stat_ydensity()`).
```



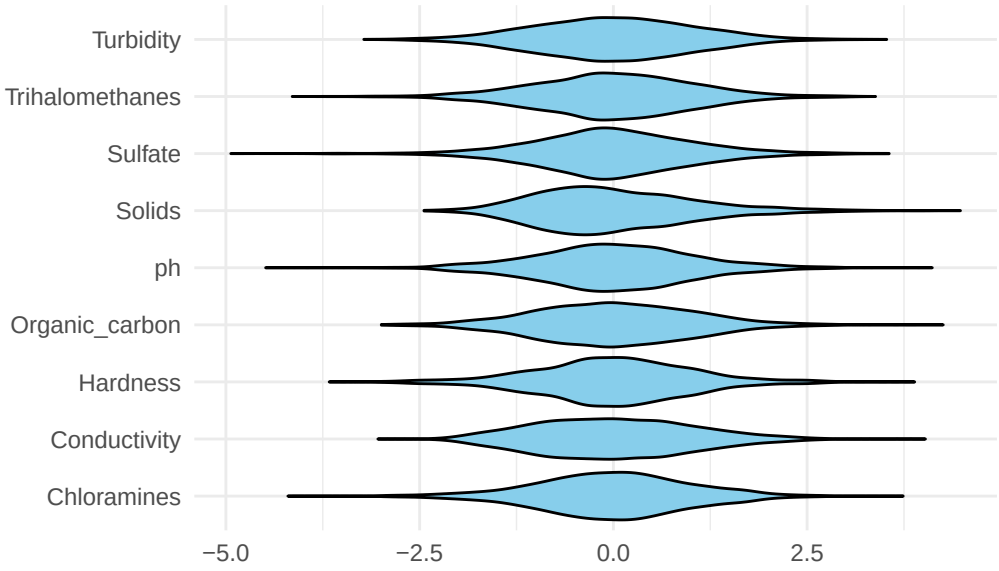

```
numeric_long <- fulldata  |> dplyr::select( Solids, Conductivity) |>
  pivot_longer(cols = everything(), names_to = "Variable", values_to = "Value")

ggplot(numeric_long, aes(x = Variable, y = Value)) +
geom_violin(fill = "skyblue", color = "black") +
  #scale_y_continuous(limits = c(0, 500)) +
labs(title = "",
x = "",
y = "") +
theme_minimal()+
  coord_flip()
```




```
#Potability should not be scaled
num_cols <- sapply(train_data, is.numeric)
num_cols["Potability"] <- FALSE

#scale all the columns except potability
train_scaled_vals <- scale(train_data[, num_cols])

#apply the scale from the training data to the test data
train_center <- attr(train_scaled_vals, "scaled:center") #pull out the center of the scaled c
train_scale <- attr(train_scaled_vals, "scaled:scale") #apply the scaling factor

#scale the test data using the scaling from the train data
test_scaled_vals <- scale(test_data[, num_cols], center = train_center, scale = train_scale)

#add the potability column back to training data and scale data
train_scaled <- data.frame(train_scaled_vals, Potability = train_data$Potability)

test_scaled <- data.frame(test_scaled_vals, Potability = test_data$Potability)

#checking the distributions to see that they are on the same scale.

numeric_scaled_long <- train_scaled  |> dplyr::select(-Potability) |>
  pivot_longer(cols = everything(), names_to = "Variable", values_to = "Value")
```

```
#distributions on the same scale
ggplot(numeric_scaled_long, aes(x = Variable, y = Value)) +
geom_violin(fill = "skyblue", color = "black") +
  #scale_y_continuous(limits = c(0, 500)) +
labs(title = "",
x = "",
y = "") +
theme_minimal()+
  coord_flip()
```

```
Warning: Removed 1016 rows containing non-finite outside the scale range
(`stat_ydensity()`).
```



Imputation

Medians from training data set used to impute the training (dirty) and test data set

```
num_cols <- names(train_data)[
  sapply(train_data, is.numeric)
]

datamedians <- train_data |> select(-Potability) |> sapply( function(x) {
  if (is.numeric(x)) median(x, na.rm = TRUE)
})

for (num_cols in names(datamedians)) {
  train_data[[num_cols]][is.na(train_data[[num_cols]])] <- datamedians[num_cols]
  test_data[[num_cols]][is.na(test_data[[num_cols]])]  <- datamedians[num_cols]
}

colSums(is.na(train_data))
```

```
             ph        Hardness          Solids     Chloramines         Sulfate
              0               0               0               0               0
   Conductivity  Organic_carbon Trihalomethanes       Turbidity      Potability
              0               0               0               0               0
```

```
colSums(is.na(test_data))
```

```
             ph        Hardness          Solids     Chloramines         Sulfate
              0               0               0               0               0
   Conductivity  Organic_carbon Trihalomethanes       Turbidity      Potability
              0               0               0               0               0
```

```
fulldata$Potability <- factor(fulldata$Potability, levels = c(0, 1))
train_data$Potability <- factor(train_data$Potability, levels = c(0, 1))
test_data$Potability <- factor(test_data$Potability, levels = c(0, 1))

#making 1  the positive class
train_data$Potability <- relevel(train_data$Potability, ref = "1")
test_data$Potability <- relevel(test_data$Potability, ref = "1")
```

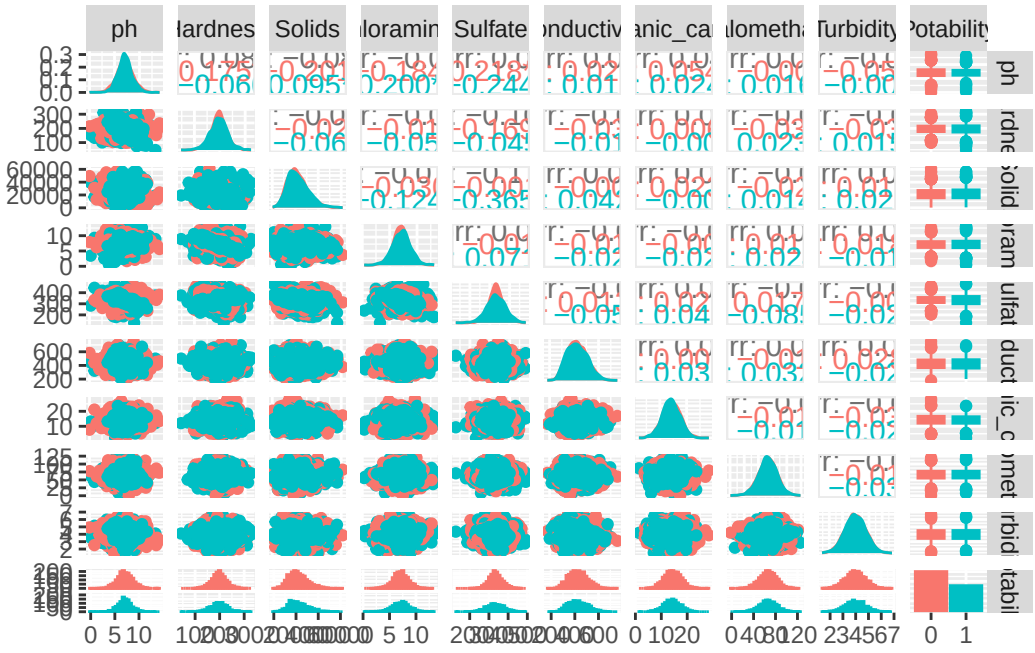
```
datapair <- fulldata |> ggpairs(
  aes(color = Potability, fill = Potability)
)

datapair
```

```
Warning: Removed 491 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 491 rows containing missing values
Removed 491 rows containing missing values
Removed 491 rows containing missing values

Warning: Removed 1160 rows containing missing values

Warning: Removed 491 rows containing missing values
Removed 491 rows containing missing values

Warning: Removed 627 rows containing missing values

Warning: Removed 491 rows containing missing values

Warning: Removed 491 rows containing non-finite outside the scale range
(`stat_boxplot()`).

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values

Warning: Removed 162 rows containing missing values

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values

Warning: Removed 162 rows containing missing values

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values
```

```
Warning: Removed 162 rows containing missing values

Warning: Removed 1160 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).
Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).
Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 781 rows containing missing values
Removed 781 rows containing missing values

Warning: Removed 903 rows containing missing values

Warning: Removed 781 rows containing missing values

Warning: Removed 781 rows containing non-finite outside the scale range
(`stat_boxplot()`).

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 162 rows containing missing values

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).
```

```
Warning: Removed 162 rows containing missing values

Warning: Removed 627 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).
Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).
Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 903 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).
Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 162 rows containing non-finite outside the scale range
(`stat_density()`).

Warning: Removed 162 rows containing missing values

Warning: Removed 162 rows containing non-finite outside the scale range
(`stat_boxplot()`).

Warning: Removed 491 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 781 rows containing missing values or values outside the scale range
(`geom_point()`).

Warning: Removed 162 rows containing missing values or values outside the scale range
(`geom_point()`).

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
Warning: Removed 491 rows containing non-finite outside the scale range
(`stat_bin()`).

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Warning: Removed 781 rows containing non-finite outside the scale range
(`stat_bin()`).

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

Warning: Removed 162 rows containing non-finite outside the scale range
(`stat_bin()`).

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



```
#describe(fulldata)
skim(fulldata)
```

Table 1: Data summary

Name	fulldata
Number of rows	3276
Number of columns	10
_____	
Column type frequency:	
factor	1
numeric	9
_____	
Group variables	None

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
Potability	0	1	FALSE	2	0: 1998, 1: 1278

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
ph	491	0.85	7.08	1.59	0.00	6.09	7.04	8.06	14.00	
Hardness	0	1.00	196.37	32.88	47.43	176.85	196.97	216.67	323.12	
Solids	0	1.00	22014.09	8768.57	320.94	15666.69	20927.83	27332.76	61227.20	
Chloramines	0	1.00	7.12	1.58	0.35	6.13	7.13	8.11	13.13	
Sulfate	781	0.76	333.78	41.42	129.00	307.70	333.07	359.95	481.03	
Conductivity	0	1.00	426.21	80.82	181.48	365.73	421.88	481.79	753.34	
Organic_carbon	0	1.00	14.28	3.31	2.20	12.07	14.22	16.56	28.30	
Trihalomethanes	162	0.95	66.40	16.18	0.74	55.84	66.62	77.34	124.00	
Turbidity	0	1.00	3.97	0.78	1.45	3.44	3.96	4.50	6.74	

all models

Train and evaluate the Models

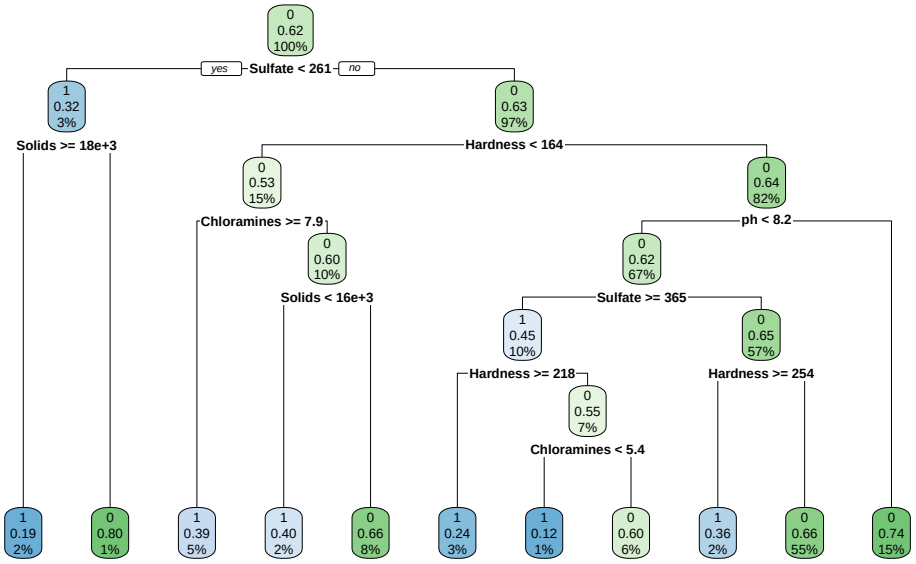
Decision Trees

```
set.seed(42)
#decision tree model

tree_model <- rpart(
  Potability ~ .,
  data = train_data, #not scaled
  method = "class",
  control = rpart.control(
    cp = 0.01,
    minsplit = 30,
    maxdepth = 20
  )
)

tree_model
```

```
n= 2293

node), split, n, loss, yval, (yprob)
      * denotes terminal node

  1) root 2293 878 0 (0.3829045 0.6170955)
    2) Sulfate< 261.2405 68  22 1 (0.6764706 0.3235294)
      4) Solids>=18346.62 53  10 1 (0.8113208 0.1886792) *
      5) Solids< 18346.62 15   3 0 (0.2000000 0.8000000) *
    3) Sulfate>=261.2405 2225 832 0 (0.3739326 0.6260674)
      6) Hardness< 164.3612 339 160 0 (0.4719764 0.5280236)
       12) Chloramines>=7.911695 117  46 1 (0.6068376 0.3931624) *
       13) Chloramines< 7.911695 222  89 0 (0.4009009 0.5990991)
         26) Solids< 16280.58 50  20 1 (0.6000000 0.4000000) *
```

```
    27) Solids>=16280.58 172  59 0 (0.3430233 0.6569767) *
  7) Hardness>=164.3612 1886 672 0 (0.3563097 0.6436903)
   14) ph< 8.206025 1538 583 0 (0.3790637 0.6209363)
     28) Sulfate>=365.4012 222 100 1 (0.5495495 0.4504505)
       56) Hardness>=217.7926 70  17 1 (0.7571429 0.2428571) *
       57) Hardness< 217.7926 152  69 0 (0.4539474 0.5460526)
         114) Chloramines< 5.44537 17   2 1 (0.8823529 0.1176471) *
         115) Chloramines>=5.44537 135  54 0 (0.4000000 0.6000000) *
     29) Sulfate< 365.4012 1316 461 0 (0.3503040 0.6496960)
       58) Hardness>=254.399 44  16 1 (0.6363636 0.3636364) *
       59) Hardness< 254.399 1272 433 0 (0.3404088 0.6595912) *
   15) ph>=8.206025 348  89 0 (0.2557471 0.7442529) *
```

```
rpart.plot(tree_model)
```




```
pred_class <- predict(tree_model, test_data, type = "class")
pred_prob <- predict(tree_model, test_data, type = "prob")



#table(Predicted = pred_class, Actual = eqtest_data$term_deposit_factor)
```

```r
#mean(pred_class == eqtest_data$term_deposit_factor)



#confusion matrix contains most metrics for classifiers
cm <- confusionMatrix(pred_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1  86  80
         0 314 503

               Accuracy : 0.5992
                 95% CI : (0.5678, 0.63)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.3612

                  Kappa : 0.0856

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.21500
            Specificity : 0.86278
         Pos Pred Value : 0.51807
         Neg Pred Value : 0.61567
             Prevalence : 0.40692
         Detection Rate : 0.08749
   Detection Prevalence : 0.16887
      Balanced Accuracy : 0.53889

       'Positive' Class : 1
```

```r
# calculate the F1 Score which is more useful than accuracy due to the focus on precision and
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]
```

```r
f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
     0.3038869
```

Deeper Decision Tree

cp = 0.001 overfit

```r
set.seed(42)
tree_model <- rpart(
  Potability ~ .,
  data = train_data,
  method = "class",
  control = rpart.control(
    cp = 0.001,
    minsplit = 30,
    maxdepth = 20
  )
)

tree_model
```

```
n= 2293

node), split, n, loss, yval, (yprob)
      * denotes terminal node

     1) root 2293 878 0 (0.38290449 0.61709551)
       2) Sulfate< 261.2405 68  22 1 (0.67647059 0.32352941)
         4) Solids>=18346.62 53  10 1 (0.81132075 0.18867925) *
         5) Solids< 18346.62 15   3 0 (0.20000000 0.80000000) *
       3) Sulfate>=261.2405 2225 832 0 (0.37393258 0.62606742)
         6) Hardness< 164.3612 339 160 0 (0.47197640 0.52802360)
          12) Chloramines>=7.911695 117  46 1 (0.60683761 0.39316239)
            24) ph>=6.257209 77  23 1 (0.70129870 0.29870130)
              48) Sulfate< 329.3489 35   4 1 (0.88571429 0.11428571) *
              49) Sulfate>=329.3489 42  19 1 (0.54761905 0.45238095)
                98) Turbidity< 3.439771 11   2 1 (0.81818182 0.18181818) *
```

```
       99) Turbidity>=3.439771 31  14 0 (0.45161290 0.54838710)
        198) ph< 7.121211 12   4 1 (0.66666667 0.33333333) *
        199) ph>=7.121211 19   6 0 (0.31578947 0.68421053) *
    25) ph< 6.257209 40  17 0 (0.42500000 0.57500000)
      50) Sulfate>=330.6019 25   9 1 (0.64000000 0.36000000) *
      51) Sulfate< 330.6019 15   1 0 (0.06666667 0.93333333) *
  13) Chloramines< 7.911695 222  89 0 (0.40090090 0.59909910)
    26) Solids< 16280.58 50  20 1 (0.60000000 0.40000000)
      52) Solids>=13665.68 23   4 1 (0.82608696 0.17391304) *
      53) Solids< 13665.68 27  11 0 (0.40740741 0.59259259) *
    27) Solids>=16280.58 172  59 0 (0.34302326 0.65697674)
      54) Solids>=19579.79 138  55 0 (0.39855072 0.60144928)
      108) Sulfate< 376.8662 111  51 0 (0.45945946 0.54054054)
        216) Hardness>=150.5074 63  27 1 (0.57142857 0.42857143)
          432) ph>=5.50641 51  18 1 (0.64705882 0.35294118) *
          433) ph< 5.50641 12   3 0 (0.25000000 0.75000000) *
        217) Hardness< 150.5074 48  15 0 (0.31250000 0.68750000) *
      109) Sulfate>=376.8662 27   4 0 (0.14814815 0.85185185) *
      55) Solids< 19579.79 34   4 0 (0.11764706 0.88235294) *
7) Hardness>=164.3612 1886 672 0 (0.35630965 0.64369035)
  14) ph< 8.206025 1538 583 0 (0.37906372 0.62093628)
    28) Sulfate>=365.4012 222 100 1 (0.54954955 0.45045045)
      56) Hardness>=217.7926 70  17 1 (0.75714286 0.24285714)
      112) Solids< 25287.28 50   4 1 (0.92000000 0.08000000) *
      113) Solids>=25287.28 20   7 0 (0.35000000 0.65000000) *
      57) Hardness< 217.7926 152  69 0 (0.45394737 0.54605263)
      114) Chloramines< 5.44537 17   2 1 (0.88235294 0.11764706) *
      115) Chloramines>=5.44537 135  54 0 (0.40000000 0.60000000)
        230) Chloramines>=9.344868 11   2 1 (0.81818182 0.18181818) *
        231) Chloramines< 9.344868 124  45 0 (0.36290323 0.63709677)
          462) Organic_carbon>=11.24699 101  42 0 (0.41584158 0.58415842)
            924) Organic_carbon< 13.9326 36  14 1 (0.61111111 0.38888889)
            1848) Chloramines< 8.04623 23   6 1 (0.73913043 0.26086957) *
            1849) Chloramines>=8.04623 13   5 0 (0.38461538 0.61538462) *
            925) Organic_carbon>=13.9326 65  20 0 (0.30769231 0.69230769)
            1850) Trihalomethanes< 71.89747 41  17 0 (0.41463415 0.58536585)
              3700) Hardness< 188.8751 19   8 1 (0.57894737 0.42105263) *
              3701) Hardness>=188.8751 22   6 0 (0.27272727 0.72727273) *
            1851) Trihalomethanes>=71.89747 24   3 0 (0.12500000 0.87500000) *
          463) Organic_carbon< 11.24699 23   3 0 (0.13043478 0.86956522) *
    29) Sulfate< 365.4012 1316 461 0 (0.35030395 0.64969605)
      58) Hardness>=254.399 44  16 1 (0.63636364 0.36363636)
      116) Sulfate>=314.7838 33   8 1 (0.75757576 0.24242424) *
```

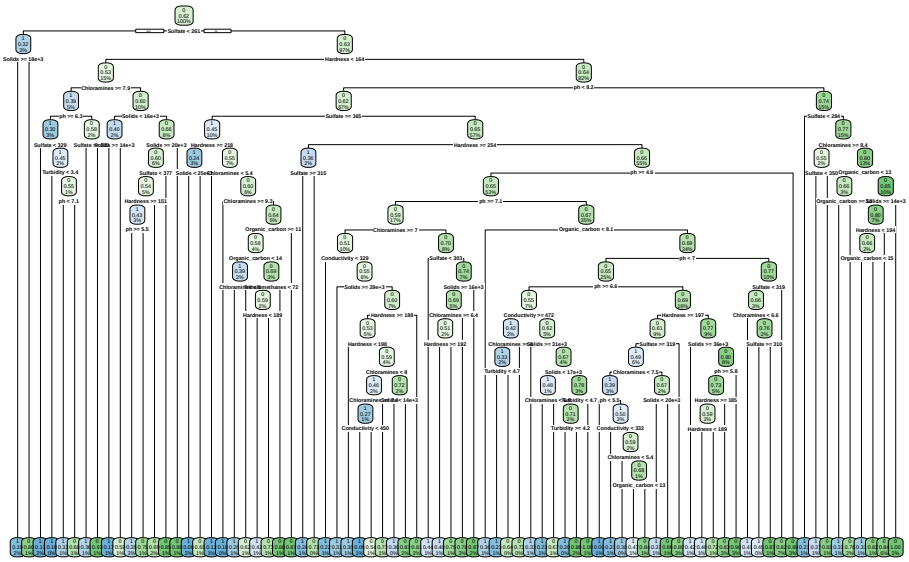
```
 117) Sulfate< 314.7838 11   3 0 (0.27272727 0.72727273) *
59) Hardness< 254.399 1272 433 0 (0.34040881 0.65959119)
 118) ph>=4.594908 1209 426 0 (0.35235732 0.64764268)
   236) ph>=7.055863 396 161 0 (0.40656566 0.59343434)
     472) Chloramines>=6.985978 218 107 0 (0.49082569 0.50917431)
       944) Conductivity< 328.9354 27   6 1 (0.77777778 0.22222222) *
       945) Conductivity>=328.9354 191  86 0 (0.45026178 0.54973822)
        1890) Solids>=29267.16 32  10 1 (0.68750000 0.31250000) *
        1891) Solids< 29267.16 159  64 0 (0.40251572 0.59748428)
          3782) Hardness>=187.906 122  57 0 (0.46721311 0.53278689)
            7564) Hardness< 198.2794 23   7 1 (0.69565217 0.30434783) *
            7565) Hardness>=198.2794 99  41 0 (0.41414141 0.58585859)
             15130) Chloramines< 8.038136 52  24 1 (0.53846154 0.46153846)
               30260) Chloramines>=7.391049 30   8 1 (0.73333333 0.26666667)
                 60520) Conductivity< 450.4485 17   1 1 (0.94117647 0.05882353)
                 60521) Conductivity>=450.4485 13   6 0 (0.46153846 0.53846154)
               30261) Chloramines< 7.391049 22   6 0 (0.27272727 0.72727273) *
             15131) Chloramines>=8.038136 47  13 0 (0.27659574 0.72340426)
               30262) Solids< 13813.33 11   4 1 (0.63636364 0.36363636) *
               30263) Solids>=13813.33 36   6 0 (0.16666667 0.83333333) *
          3783) Hardness< 187.906 37   7 0 (0.18918919 0.81081081) *
     473) Chloramines< 6.985978 178  54 0 (0.30337079 0.69662921)
       946) Sulfate< 303.4462 27  12 1 (0.55555556 0.44444444) *
       947) Sulfate>=303.4462 151  39 0 (0.25827815 0.74172185)
        1894) Solids>=16496.34 106  33 0 (0.31132075 0.68867925)
          3788) Chloramines>=6.365501 37  18 0 (0.48648649 0.51351351)
            7576) Hardness>=192.3607 25  10 1 (0.60000000 0.40000000) *
            7577) Hardness< 192.3607 12   3 0 (0.25000000 0.75000000) *
          3789) Chloramines< 6.365501 69  15 0 (0.21739130 0.78260870) *
        1895) Solids< 16496.34 45   6 0 (0.13333333 0.86666667) *
   237) ph< 7.055863 813 265 0 (0.32595326 0.67404674)
     474) Organic_carbon< 8.13401 28  10 1 (0.64285714 0.35714286) *
     475) Organic_carbon>=8.13401 785 247 0 (0.31464968 0.68535032)
       950) ph< 7.04223 563 197 0 (0.34991119 0.65008881)
        1900) ph>=6.634442 160  72 0 (0.45000000 0.55000000)
          3800) Conductivity>=472.4072 53  22 1 (0.58490566 0.41509434)
            7600) Chloramines>=6.00645 42  14 1 (0.66666667 0.33333333)
             15200) Turbidity< 4.708821 31   7 1 (0.77419355 0.22580645) *
             15201) Turbidity>=4.708821 11   4 0 (0.36363636 0.63636364) *
            7601) Chloramines< 6.00645 11   3 0 (0.27272727 0.72727273) *
          3801) Conductivity< 472.4072 107  41 0 (0.38317757 0.61682243)
            7602) Solids>=31070.29 18   6 1 (0.66666667 0.33333333) *
            7603) Solids< 31070.29 89  29 0 (0.32584270 0.67415730)
```

```
              15206) Solids< 17469.33 31  15 1 (0.51612903 0.48387097)
                30412) Chloramines< 6.847432 13   3 1 (0.76923077 0.23076923) *
                30413) Chloramines>=6.847432 18   6 0 (0.33333333 0.66666667) *
              15207) Solids>=17469.33 58  13 0 (0.22413793 0.77586207)
                30414) Turbidity< 4.733707 45  13 0 (0.28888889 0.71111111)
                  60828) Turbidity>=4.239223 10   2 1 (0.80000000 0.20000000) *
                  60829) Turbidity< 4.239223 35   5 0 (0.14285714 0.85714286) *
                30415) Turbidity>=4.733707 13   0 0 (0.00000000 1.00000000) *
            1901) ph< 6.634442 403 125 0 (0.31017370 0.68982630)
              3802) Hardness>=197.1672 204  80 0 (0.39215686 0.60784314)
                7604) Sulfate>=318.9145 128  63 1 (0.50781250 0.49218750)
                15208) Chloramines< 7.485071 80  31 1 (0.61250000 0.38750000)
                  30416) ph< 5.53909 22   2 1 (0.90909091 0.09090909) *
                  30417) ph>=5.53909 58  29 1 (0.50000000 0.50000000)
                    60834) Conductivity< 332.1286 14   3 1 (0.78571429 0.21428571)
                    60835) Conductivity>=332.1286 44  18 0 (0.40909091 0.59090909)
                     121670) Chloramines< 5.370559 10   3 1 (0.70000000 0.3000000
                     121671) Chloramines>=5.370559 34  11 0 (0.32352941 0.6764705
                       243342) Organic_carbon< 12.78914 15   7 1 (0.53333333 0.46
                       243343) Organic_carbon>=12.78914 19   3 0 (0.15789474 0.84
                15209) Chloramines>=7.485071 48  16 0 (0.33333333 0.66666667)
                  30418) Solids< 19568.21 19   7 1 (0.63157895 0.36842105) *
                  30419) Solids>=19568.21 29   4 0 (0.13793103 0.86206897) *
                7605) Sulfate< 318.9145 76  15 0 (0.19736842 0.80263158) *
              3803) Hardness< 197.1672 199  45 0 (0.22613065 0.77386935)
                7606) Solids>=35661.62 12   5 1 (0.58333333 0.41666667) *
                7607) Solids< 35661.62 187  38 0 (0.20320856 0.79679144)
                 15214) ph>=5.751502 115  31 0 (0.26956522 0.73043478)
                   30428) Hardness>=185.4236 49  20 0 (0.40816327 0.59183673)
                     60856) Hardness< 189.2005 20   8 1 (0.60000000 0.40000000) *
                     60857) Hardness>=189.2005 29   8 0 (0.27586207 0.72413793) *
                   30429) Hardness< 185.4236 66  11 0 (0.16666667 0.83333333) *
                 15215) ph< 5.751502 72   7 0 (0.09722222 0.90277778) *
           951) ph>=7.04223 222  50 0 (0.22522523 0.77477477)
            1902) Sulfate< 319.1 58  20 0 (0.34482759 0.65517241)
              3804) Chloramines< 6.590676 17   7 1 (0.58823529 0.41176471) *
              3805) Chloramines>=6.590676 41  10 0 (0.24390244 0.75609756)
                7610) Sulfate>=310.1858 11   5 1 (0.54545455 0.45454545) *
                7611) Sulfate< 310.1858 30   4 0 (0.13333333 0.86666667) *
            1903) Sulfate>=319.1 164  30 0 (0.18292683 0.81707317) *
    119) ph< 4.594908 63   7 0 (0.11111111 0.88888889) *
15) ph>=8.206025 348  89 0 (0.25574713 0.74425287)
  30) Sulfate< 284.1368 14   3 1 (0.78571429 0.21428571) *
```

```
      31) Sulfate>=284.1368 334  78 0 (0.23353293 0.76646707)
        62) Chloramines>=8.423856 44  20 0 (0.45454545 0.54545455)
         124) Sulfate< 349.7264 27  10 1 (0.62962963 0.37037037) *
         125) Sulfate>=349.7264 17   3 0 (0.17647059 0.82352941) *
        63) Chloramines< 8.423856 290  58 0 (0.20000000 0.80000000)
         126) Organic_carbon< 12.58131 70  24 0 (0.34285714 0.65714286)
           252) Organic_carbon>=12.02412 16   5 1 (0.68750000 0.31250000) *
           253) Organic_carbon< 12.02412 54  13 0 (0.24074074 0.75925926) *
         127) Organic_carbon>=12.58131 220  34 0 (0.15454545 0.84545455)
           254) Solids>=13653.4 169  34 0 (0.20118343 0.79881657)
             508) Hardness< 194.1059 41  14 0 (0.34146341 0.65853659)
              1016) Organic_carbon< 14.52538 13   4 1 (0.69230769 0.30769231) *
              1017) Organic_carbon>=14.52538 28   5 0 (0.17857143 0.82142857) *
             509) Hardness>=194.1059 128  20 0 (0.15625000 0.84375000) *
           255) Solids< 13653.4 51   0 0 (0.00000000 1.00000000) *
```

```r
rpart.plot(tree_model)
```

```
Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



```r
pred_class <- predict(tree_model, test_data, type = "class")
```

```r
table(Predicted = pred_class, Actual = test_data$Potability)
```

```
         Actual
Predicted   1   0
        1 185 193
        0 215 390
```

```r
mean(pred_class == test_data$Potability)
```

```
[1] 0.584944
```

```r
#confusionMatrix(pred_class$class, actual, positive = "1")
cm <- confusionMatrix(pred_class, test_data$Potability)
cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 185 193
         0 215 390

               Accuracy : 0.5849
                 95% CI : (0.5534, 0.616)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.7099

                  Kappa : 0.1326

 Mcnemar's Test P-Value : 0.2985

            Sensitivity : 0.4625
            Specificity : 0.6690
         Pos Pred Value : 0.4894
         Neg Pred Value : 0.6446
```

```
             Prevalence : 0.4069
         Detection Rate : 0.1882
   Detection Prevalence : 0.3845
      Balanced Accuracy : 0.5657

       'Positive' Class : 1
```

```
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_tree <- 2 * (precision * recall) / (precision + recall)
f1_tree
```

```
Pos Pred Value
     0.4755784
```

```
num_cols <- names(train_data)[
  sapply(train_data, is.numeric)
]

datamedians <- train_data |> select(-Potability) |> sapply( function(x) {
  if (is.numeric(x)) median(x, na.rm = TRUE)
})

for (num_cols in names(datamedians)) {
  train_data[[num_cols]][is.na(train_data[[num_cols]])] <- datamedians[num_cols]
  test_data[[num_cols]][is.na(test_data[[num_cols]])]  <- datamedians[num_cols]
}

colSums(is.na(train_data))
```

```
             ph        Hardness          Solids     Chloramines         Sulfate
              0               0               0               0               0
   Conductivity  Organic_carbon Trihalomethanes       Turbidity      Potability
              0               0               0               0               0
```

```
colSums(is.na(test_data))
```

```
             ph        Hardness          Solids     Chloramines         Sulfate
              0               0               0               0               0
   Conductivity  Organic_carbon Trihalomethanes       Turbidity      Potability
              0               0               0               0               0
```

```r
fulldata$Potability <- factor(fulldata$Potability, levels = c(0, 1))
train_data$Potability <- factor(train_data$Potability, levels = c(0, 1))
test_data$Potability <- factor(test_data$Potability, levels = c(0, 1))

#making 1  the positive class
train_data$Potability <- relevel(train_data$Potability, ref = "1")
test_data$Potability <- relevel(test_data$Potability, ref = "1")
```

Random forest

```r
set.seed(42)
#random forest model

rf_model <- randomForest(
  Potability ~ .,
  data = train_data,

  ntree = 500,
  importance = TRUE
)

forrest_pred_class <- predict(rf_model, test_data, type = "class")
forrest_pred_prob <- predict(rf_model, test_data, type = "prob")

rf_model
```

```
Call:
 randomForest(formula = Potability ~ ., data = train_data, ntree = 500,      importance = TRU
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 3

        OOB estimate of  error rate: 32.53%
Confusion matrix:
```

```
    1    0 class.error
1 291  587   0.6685649
0 159 1256   0.1123675
```

```r
table(Predicted = forrest_pred_class, Actual = test_data$Potability)
```

```
         Actual
Predicted   1   0
        1 151  70
        0 249 513
```

```r
mean(forrest_pred_class == test_data$Potability)
```

```
[1] 0.6754832
```

```r
cm <- confusionMatrix(forrest_pred_class, test_data$Potability)

cm
```

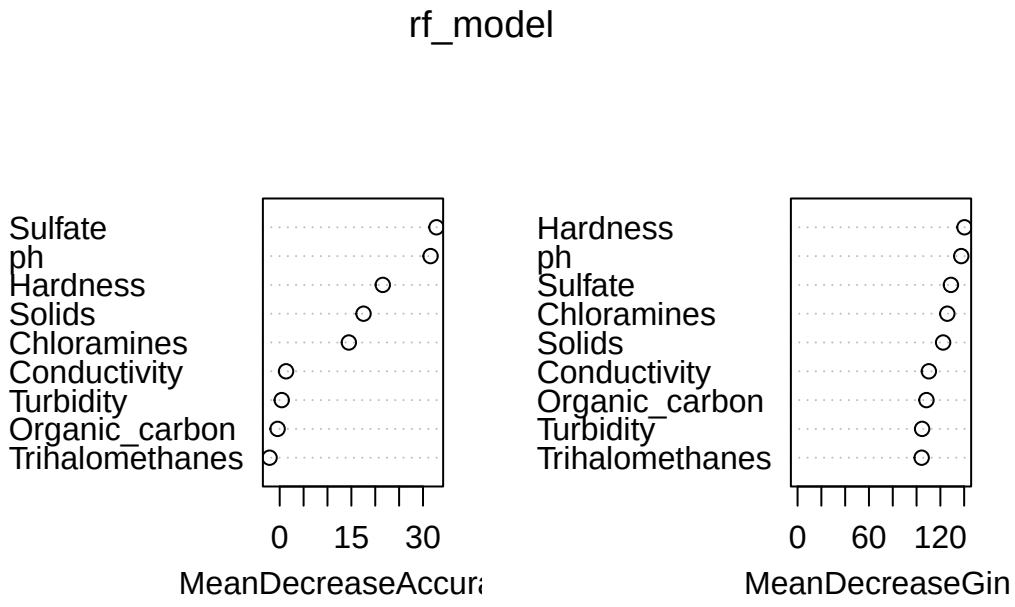
```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 151  70
         0 249 513

               Accuracy : 0.6755
                 95% CI : (0.6452, 0.7047)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 5.997e-08

                  Kappa : 0.2769

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.3775
            Specificity : 0.8799
         Pos Pred Value : 0.6833
         Neg Pred Value : 0.6732
             Prevalence : 0.4069
```

```
         Detection Rate : 0.1536
   Detection Prevalence : 0.2248
      Balanced Accuracy : 0.6287

       'Positive' Class : 1
```

```r
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_rf <- 2 * (precision * recall) / (precision + recall)
f1_rf
```

```
Pos Pred Value
     0.4863124
```

```r
varImpPlot(rf_model)
```



Random Forest with cleaner data

```
set.seed(42)
#random forest model

rf_model <- randomForest(
  Potability ~ .,
  data = clean_train_data,

  ntree = 500,
  importance = TRUE
)

forrest_pred_class <- predict(rf_model, clean_test_data, type = "class")
forrest_pred_prob <- predict(rf_model, clean_test_data, type = "prob")

rf_model
```

```
Call:
 randomForest(formula = Potability ~ ., data = clean_train_data,      ntree = 500, importance
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 3

        OOB estimate of  error rate: 35.75%
Confusion matrix:
    1    0 class.error
1 225  615   0.7321429
0 169 1184   0.1249076
```

```
#table(Predicted = forrest_pred_class, Actual = test_data$Potability)

#mean(forrest_pred_class == test_data$Potability)

cm <- confusionMatrix(forrest_pred_class, clean_test_data$Potability)

cm
```

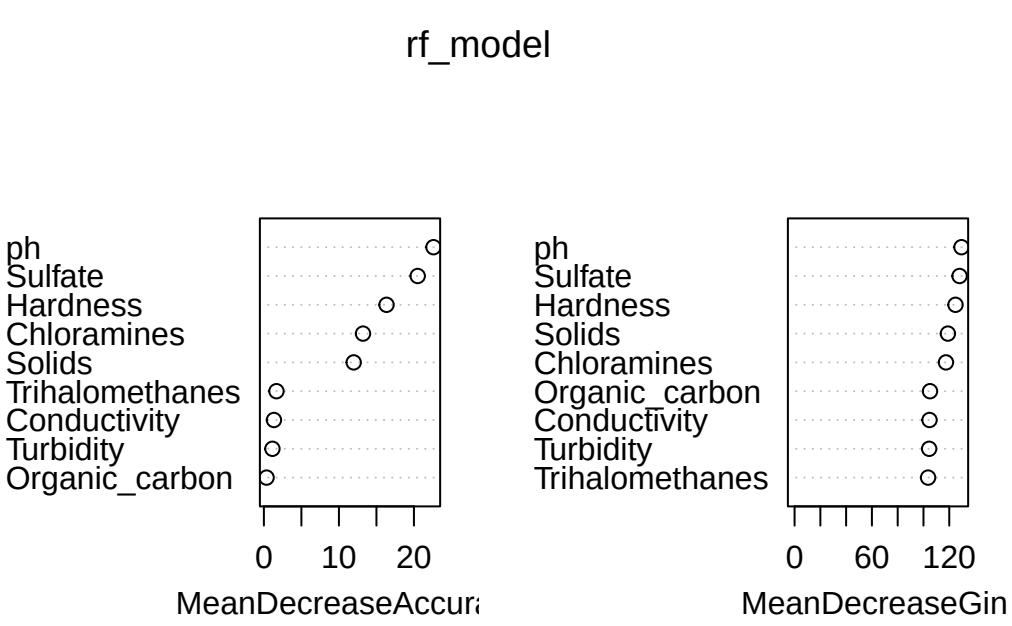
```
Confusion Matrix and Statistics
```

```
          Reference
Prediction   1   0
         1  95  67
         0 263 515

               Accuracy : 0.6489
                 95% CI : (0.6175, 0.6795)
    No Information Rate : 0.6191
    P-Value [Acc > NIR] : 0.03187

                  Kappa : 0.1679

 Mcnemar's Test P-Value : < 2e-16

            Sensitivity : 0.2654
            Specificity : 0.8849
         Pos Pred Value : 0.5864
         Neg Pred Value : 0.6620
             Prevalence : 0.3809
         Detection Rate : 0.1011
   Detection Prevalence : 0.1723
      Balanced Accuracy : 0.5751

       'Positive' Class : 1
```

```r
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_rf <- 2 * (precision * recall) / (precision + recall)
f1_rf
```

```
Pos Pred Value
     0.3653846
```

```r
varImpPlot(rf_model)
```



Adaboost

```
#adaptive boosting model


#ada_partdata <-partdata |>  dplyr::select(-y, -term_deposit, -default)
#ada_partdata[] <- lapply(ada_partdata, function(x) {
#  if (is.character(x)) factor(x) else x
#})

##ada_partdata$default <- factor(ada_partdata$default, levels = c("no", "yes", "unknown"))

set.seed(42)



ada_model <- boosting(
  Potability ~ .,
```

```
  data = train_data,
  mfinal = 100,     # number of boosting iterations
  boos = TRUE
)

#ada_model

ada_pred <- predict(ada_model, test_data)

ada_pred$class <- factor(
  ada_pred$class,
  levels = levels(test_data$Potability)
)

cm <- confusionMatrix(ada_pred$class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 169 111
         0 231 472

               Accuracy : 0.6521
                 95% CI : (0.6214, 0.6819)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 8.357e-05

                  Kappa : 0.2436

 Mcnemar's Test P-Value : 1.236e-10

            Sensitivity : 0.4225
            Specificity : 0.8096
         Pos Pred Value : 0.6036
         Neg Pred Value : 0.6714
             Prevalence : 0.4069
         Detection Rate : 0.1719
   Detection Prevalence : 0.2848
      Balanced Accuracy : 0.6161
```

```
       'Positive' Class : 1
```

```
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_ada <- 2 * (precision * recall) / (precision + recall)
f1_ada
```

```
Pos Pred Value
     0.4970588
```

```
sort(ada_model$importance, decreasing = TRUE)
```

```
             ph         Sulfate        Hardness          Solids     Chloramines
      16.769479       14.418847       13.255398       11.705347       11.301376
   Conductivity Trihalomethanes  Organic_carbon       Turbidity
       8.890219        8.409151        7.949138        7.301046
```

Adaboost with "clean" data

```
set.seed(42)



ada_model <- boosting(
  Potability ~ .,
  data = clean_train_data,
  mfinal = 100,      # number of boosting iterations
  boos = TRUE
)

#ada_model

ada_pred <- predict(ada_model, clean_test_data)

ada_pred$class <- factor(
```

```
  ada_pred$class,
  levels = levels(clean_test_data$Potability)
)

cm <- confusionMatrix(ada_pred$class, clean_test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 133 130
         0 225 452

               Accuracy : 0.6223
                 95% CI : (0.5905, 0.6534)
    No Information Rate : 0.6191
    P-Value [Acc > NIR] : 0.4343

                  Kappa : 0.1561

 Mcnemar's Test P-Value : 6.069e-07

            Sensitivity : 0.3715
            Specificity : 0.7766
         Pos Pred Value : 0.5057
         Neg Pred Value : 0.6677
             Prevalence : 0.3809
         Detection Rate : 0.1415
   Detection Prevalence : 0.2798
      Balanced Accuracy : 0.5741

       'Positive' Class : 1
```

```
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_ada <- 2 * (precision * recall) / (precision + recall)
f1_ada
```

```
Pos Pred Value
     0.4283414
```

```
sort(ada_model$importance, decreasing = TRUE)
```

```
             ph        Hardness     Chloramines         Sulfate          Solids
      13.589622       13.132811       12.762566       11.902679       11.610060
Trihalomethanes  Organic_carbon    Conductivity       Turbidity
      10.752570        9.341308        8.625785        8.282599
```

SVM: Radial Basis kernel

```
set.seed(42)
#SVM model radial basis kernel



SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = train_data,
  kernel = "rbfdot"
)

SVM_rbf_model
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 1

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.0836255427875869

Number of Support Vectors : 1711

Objective Function Value : -1500.678
Training error : 0.280855
```

```r
rbf_pred_class <- predict(SVM_rbf_model, test_data, type = "response")



#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)


cm <- confusionMatrix(rbf_pred_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 121  34
         0 279 549

               Accuracy : 0.6816
                 95% CI : (0.6514, 0.7106)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 6.16e-09

                  Kappa : 0.2702

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.3025
            Specificity : 0.9417
         Pos Pred Value : 0.7806
         Neg Pred Value : 0.6630
             Prevalence : 0.4069
         Detection Rate : 0.1231
   Detection Prevalence : 0.1577
      Balanced Accuracy : 0.6221

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
      0.436036
```

radial f1

```r
num_cols <- sapply(train_data, is.numeric)
num_cols["Potability"] <- FALSE

train_scaled_vals <- scale(train_data[, num_cols])

train_center <- attr(train_scaled_vals, "scaled:center")
train_scale <- attr(train_scaled_vals, "scaled:scale")

test_scaled_vals <- scale(test_data[, num_cols], center = train_center, scale = train_scale)

train_scaled <- data.frame(train_scaled_vals, Potability = train_data$Potability)

test_scaled <- data.frame(test_scaled_vals, Potability = test_data$Potability)




set.seed(42)
#SVM model radial basis kernel




SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = train_scaled,
  kernel = "rbfdot"
)
```

```
SVM_rbf_model
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 1

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.0836255427875869

Number of Support Vectors : 1711

Objective Function Value : -1500.678
Training error : 0.280855
```

```
rbf_pred_class <- predict(SVM_rbf_model, test_scaled, type = "response")



#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)



cm <- confusionMatrix(rbf_pred_class, test_scaled$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 121  34
         0 279 549

               Accuracy : 0.6816
                 95% CI : (0.6514, 0.7106)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 6.16e-09

                  Kappa : 0.2702
```

```
 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.3025
            Specificity : 0.9417
         Pos Pred Value : 0.7806
         Neg Pred Value : 0.6630
             Prevalence : 0.4069
         Detection Rate : 0.1231
   Detection Prevalence : 0.1577
      Balanced Accuracy : 0.6221

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
      0.436036
```

```r
set.seed(42)
#SVM model radial basis kernel




SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = clean_train_data,
  kernel = "rbfdot"
)

SVM_rbf_model
```

```
Support Vector Machine object of class "ksvm"
```

```
SV type: C-svc  (classification)
 parameter : cost C = 1

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.078170040490051

Number of Support Vectors : 1699

Objective Function Value : -1517.98
Training error : 0.309166
```

```
rbf_pred_class <- predict(SVM_rbf_model, clean_test_data, type = "response")



#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)



cm <- confusionMatrix(rbf_pred_class, clean_test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1  75  34
         0 283 548

               Accuracy : 0.6628
                 95% CI : (0.6315, 0.693)
    No Information Rate : 0.6191
    P-Value [Acc > NIR] : 0.003078

                  Kappa : 0.1744

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.20950
```

```
            Specificity : 0.94158
         Pos Pred Value : 0.68807
         Neg Pred Value : 0.65945
             Prevalence : 0.38085
         Detection Rate : 0.07979
   Detection Prevalence : 0.11596
      Balanced Accuracy : 0.57554

       'Positive' Class : 1
```

```
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
     0.3211991
```

SVM: Linear kernel

```
set.seed(42)
#SVM model



SVM_lin_model <- ksvm(
  Potability ~ .,
  data = train_data,
  kernel = "vanilladot"
)
```

```
 Setting default kernel parameters
```

```
SVM_lin_model
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 1

Linear (vanilla) kernel function.

Number of Support Vectors : 1899

Objective Function Value : -1756
Training error : 0.382904
```

```r
lin_pred_class <- predict(SVM_lin_model, test_data, type = "response")



#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)



cm <- confusionMatrix(lin_pred_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1   0   0
         0 400 583

               Accuracy : 0.5931
                 95% CI : (0.5616, 0.624)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.5137

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.0000
```

```
            Specificity : 1.0000
         Pos Pred Value :    NaN
         Neg Pred Value : 0.5931
             Prevalence : 0.4069
         Detection Rate : 0.0000
   Detection Prevalence : 0.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 1
```

```
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
           NaN
```

linear f1 0.697559

SVM: hyperbolic tangent sigmoid kernel

```
set.seed(42)
#SVM model



SVM_tanh_model <- ksvm(
  Potability ~ .,
  data = train_data,
  kernel = "tanhdot"
)
```

```
 Setting default kernel parameters
```

```
SVM_tanh_model
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 1

Hyperbolic Tangent kernel function.
 Hyperparameters : scale =  1  offset =  1

Number of Support Vectors : 1315

Objective Function Value : -27507.11
Training error : 0.57174
```

```
tanh_pred_class <- predict(SVM_tanh_model, test_data, type = "response")



#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)



cm <- confusionMatrix(tanh_pred_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 105 262
         0 295 321

               Accuracy : 0.4334
                 95% CI : (0.4021, 0.465)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 1.0000

                  Kappa : -0.1894
```

```
 Mcnemar's Test P-Value : 0.1751

            Sensitivity : 0.2625
            Specificity : 0.5506
         Pos Pred Value : 0.2861
         Neg Pred Value : 0.5211
             Prevalence : 0.4069
         Detection Rate : 0.1068
   Detection Prevalence : 0.3733
      Balanced Accuracy : 0.4066

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)
f1
```

```
Pos Pred Value
      0.273794
```

tanh f1 0.5557

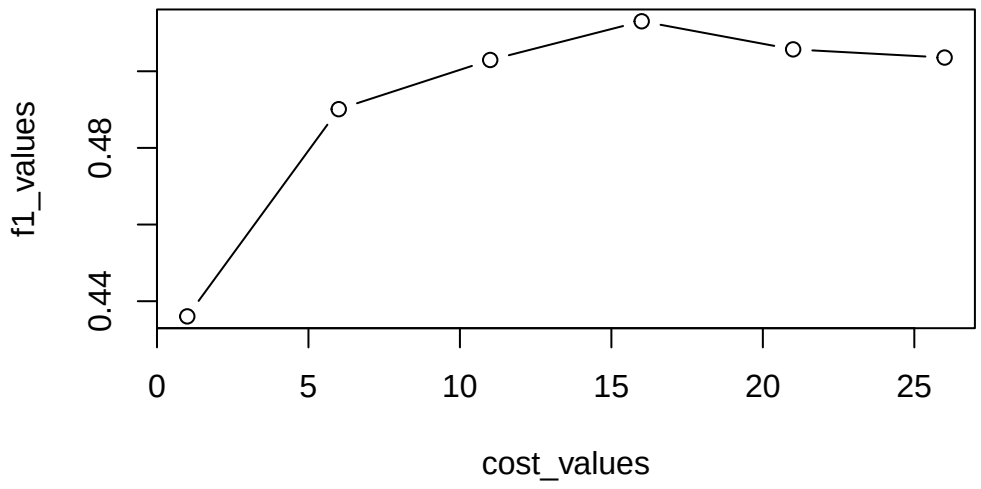
radial is the best

Cost Parameters SVM

Cost Parameter based on accuracy

```r
cost_values <- c(seq(from=1, to  = 26, by = 5))
f1_values <- sapply(cost_values, function(x){
  SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = train_data,
  kernel = "rbfdot", C = x
)
```

```
  rbf_pred <- predict(SVM_rbf_model, test_data, type = "response")
  #agree <- ifelse(rbf_pred == eqtest_data$term_deposit_factor, 1, 0)
  #accuracy <-  sum(agree) / nrow(eqtest_data)

   cm <- confusionMatrix(rbf_pred, test_data$Potability)

#cm

#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)

  return (f1)
})

plot(cost_values, f1_values, type = "b")
```



cost parameter of 16 had the highest F1 score. This was used as the best SVM model to compare to the other models.

```r
set.seed(42)
#SVM model



SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = train_data,
  kernel = "rbfdot", C = 16
)

SVM_rbf_model
```

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 16

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.0836255427875869

Number of Support Vectors : 1568

Objective Function Value : -17313.53
Training error : 0.175752
```

```r
rbf_pred_class <- predict(SVM_rbf_model, test_data, type = "response")




#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)



cm <- confusionMatrix(rbf_pred_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics
```

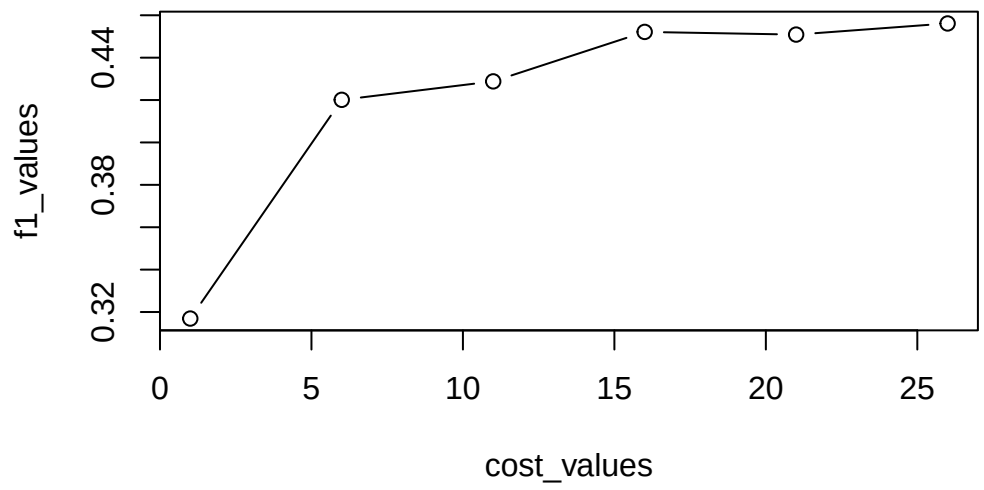
```
          Reference
Prediction   1   0
         1 177 117
         0 223 466

               Accuracy : 0.6541
                 95% CI : (0.6234, 0.6839)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 4.880e-05

                  Kappa : 0.2523

 Mcnemar's Test P-Value : 1.238e-08

            Sensitivity : 0.4425
            Specificity : 0.7993
         Pos Pred Value : 0.6020
         Neg Pred Value : 0.6763
             Prevalence : 0.4069
         Detection Rate : 0.1801
   Detection Prevalence : 0.2991
      Balanced Accuracy : 0.6209

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_svm <- 2 * (precision * recall) / (precision + recall)
f1_svm
```

```
Pos Pred Value
     0.5100865
```

```r
cost_values <- c(seq(from=1, to  = 26, by = 5))
f1_values <- sapply(cost_values, function(x){
  SVM_rbf_model <- ksvm(
  Potability ~ .,
  data = clean_train_data,
```

```
  kernel = "rbfdot", C = x
)
  rbf_pred <- predict(SVM_rbf_model, clean_test_data, type = "response")
  #agree <- ifelse(rbf_pred == eqtest_data$term_deposit_factor, 1, 0)
  #accuracy <-  sum(agree) / nrow(eqtest_data)

   cm <- confusionMatrix(rbf_pred, clean_test_data$Potability)

#cm

#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1 <- 2 * (precision * recall) / (precision + recall)

  return (f1)
})

plot(cost_values, f1_values, type = "b")
```



Logistic Regression

```r
lmodel <- glm(
  Potability ~.,
  data = train_scaled,
  family = binomial
)

summary(lmodel)
```

```
Call:
glm(formula = Potability ~ ., family = binomial, data = train_scaled)

Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)      0.47929    0.04307  11.128   <2e-16 ***
ph               0.01465    0.04365   0.336   0.7372
Hardness         0.01931    0.04351   0.444   0.6572
Solids          -0.08432    0.04383  -1.924   0.0544 .
Chloramines     -0.04804    0.04322  -1.111   0.2664
Sulfate          0.03224    0.04375   0.737   0.4612
Conductivity    -0.02672    0.04317  -0.619   0.5359
Organic_carbon   0.07072    0.04327   1.634   0.1022
Trihalomethanes  0.01253    0.04316   0.290   0.7716
Turbidity        0.02573    0.04313   0.597   0.5507
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 3051.8  on 2292  degrees of freedom
Residual deviance: 3042.1  on 2283  degrees of freedom
AIC: 3062.1

Number of Fisher Scoring iterations: 4
```

```r
log_pred_class <- predict(lmodel, test_scaled)

log_pred_class <- ifelse(pred_prob >= 0.5, 1, 0)
log_pred_class <- factor(pred_class, levels = c(0, 1))
```

```r
#table(Predicted = rbf_pred_class, Actual = eqtest_data$term_deposit_factor)
```

```r
cm <- confusionMatrix(log_pred_class, test_scaled$Potability)
```

```
Warning in confusionMatrix.default(log_pred_class, test_scaled$Potability):
Levels are not in the same order for reference and data. Refactoring data to
match.
```

```r
cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1 185 193
         0 215 390

               Accuracy : 0.5849
                 95% CI : (0.5534, 0.616)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.7099

                  Kappa : 0.1326

 Mcnemar's Test P-Value : 0.2985

            Sensitivity : 0.4625
            Specificity : 0.6690
         Pos Pred Value : 0.4894
         Neg Pred Value : 0.6446
             Prevalence : 0.4069
         Detection Rate : 0.1882
   Detection Prevalence : 0.3845
      Balanced Accuracy : 0.5657

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_svm <- 2 * (precision * recall) / (precision + recall)
f1_svm
```

```
Pos Pred Value
     0.4755784
```

```r
train_data$Potability <- factor(train_data$Potability, levels = c(0, 1))
test_data$Potability <- factor(test_data$Potability, levels = c(0, 1))
train_data$Potability <- relevel(train_data$Potability, ref = "1")
test_data$Potability <- relevel(test_data$Potability, ref = "1")


train_data$Potability <- as.numeric(as.character(train_data$Potability))
test_data$Potability  <- as.numeric(as.character(test_data$Potability))


num_cols <- sapply(train_data, is.numeric)

train_scaled <- train_data
test_scaled  <- test_data

train_scaled <- scale(train_data[,num_cols])

train_center <- attr(train_scaled, "scaled:center")
train_scale <- attr(train_scaled, "scaled:scale")

test_scaled <- scale(test_data,
  center = train_center,
  scale  = train_scale
)


set.seed(42)
#neural network
```

```r
neural_model <- neuralnet(
  Potability ~ . ,
  data = train_scaled,
  act.fct = "logistic", hidden = c(1),
  linear.output = FALSE
)

plot(neural_model)
#neural_model




neural_prob <- predict(neural_model, test_scaled) [,1]

neural_class <- ifelse(neural_prob >= 0.5, 1, 0)

neural_class <- factor(neural_class, levels = c(0,1))
neural_class <- relevel(neural_class, ref = "1")


train_data$Potability <- factor(train_data$Potability, levels = c(0, 1))
test_data$Potability <- factor(test_data$Potability, levels = c(0, 1))
train_data$Potability <- relevel(train_data$Potability, ref = "1")
test_data$Potability <- relevel(test_data$Potability, ref = "1")


cm <- confusionMatrix(neural_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1  50  23
         0 350 560

               Accuracy : 0.6205
                 95% CI : (0.5894, 0.651)
```

```
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.04228

                  Kappa : 0.0981

 Mcnemar's Test P-Value : < 2e-16

            Sensitivity : 0.12500
            Specificity : 0.96055
         Pos Pred Value : 0.68493
         Neg Pred Value : 0.61538
             Prevalence : 0.40692
         Detection Rate : 0.05086
   Detection Prevalence : 0.07426
      Balanced Accuracy : 0.54277

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]


f1_svm <- 2 * (precision * recall) / (precision + recall)
f1_svm
```

```
Pos Pred Value
     0.2114165
```

```r
clean_train_data$Potability <- factor(clean_train_data$Potability, levels = c(0, 1))
clean_test_data$Potability <- factor(clean_test_data$Potability, levels = c(0, 1))
clean_train_data$Potability <- relevel(clean_train_data$Potability, ref = "1")
clean_test_data$Potability <- relevel(clean_test_data$Potability, ref = "1")


clean_train_data$Potability <- as.numeric(as.character(clean_train_data$Potability))
clean_test_data$Potability  <- as.numeric(as.character(clean_test_data$Potability))


#num_cols <- sapply(train_data, is.numeric)
```

```r
#train_scaled <- train_data
#test_scaled  <- test_data

#train_scaled <- scale(train_data[,num_cols])

#train_center <- attr(train_scaled, "scaled:center")
#train_scale <- attr(train_scaled, "scaled:scale")

#test_scaled <- scale(test_data,
#  center = train_center,
#  scale  = train_scale
#)


set.seed(42)
#neural network



neural_model <- neuralnet(
  Potability ~ . ,
  data = clean_train_data,
  act.fct = "logistic", hidden = c(1),
  linear.output = FALSE
)

plot(neural_model)
#neural_model




neural_prob <- predict(neural_model, clean_test_data) [,1]

neural_class <- ifelse(neural_prob >= 0.5, 1, 0)

neural_class <- factor(neural_class, levels = c(0,1))
neural_class <- relevel(neural_class, ref = "1")


clean_train_data$Potability <- factor(clean_train_data$Potability, levels = c(0, 1))
```

```r
clean_test_data$Potability <- factor(clean_test_data$Potability, levels = c(0, 1))
clean_train_data$Potability <- relevel(clean_train_data$Potability, ref = "1")
clean_test_data$Potability <- relevel(clean_test_data$Potability, ref = "1")


cm <- confusionMatrix(neural_class, clean_test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1   0   0
         0 358 582

               Accuracy : 0.6191
                 95% CI : (0.5872, 0.6503)
    No Information Rate : 0.6191
    P-Value [Acc > NIR] : 0.5145

                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.0000
            Specificity : 1.0000
         Pos Pred Value :    NaN
         Neg Pred Value : 0.6191
             Prevalence : 0.3809
         Detection Rate : 0.0000
   Detection Prevalence : 0.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : 1
```

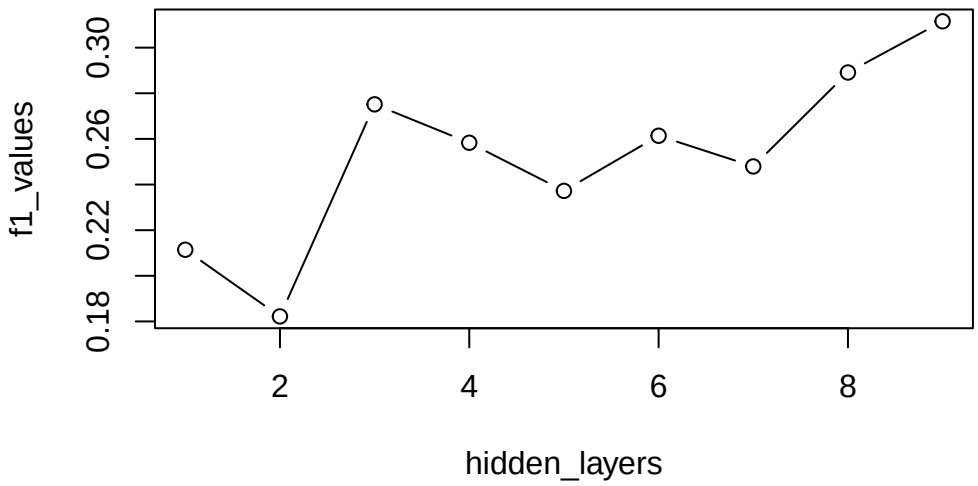
```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]
```

```
f1_svm <- 2 * (precision * recall) / (precision + recall)
f1_svm
```

```
Pos Pred Value
           NaN
```

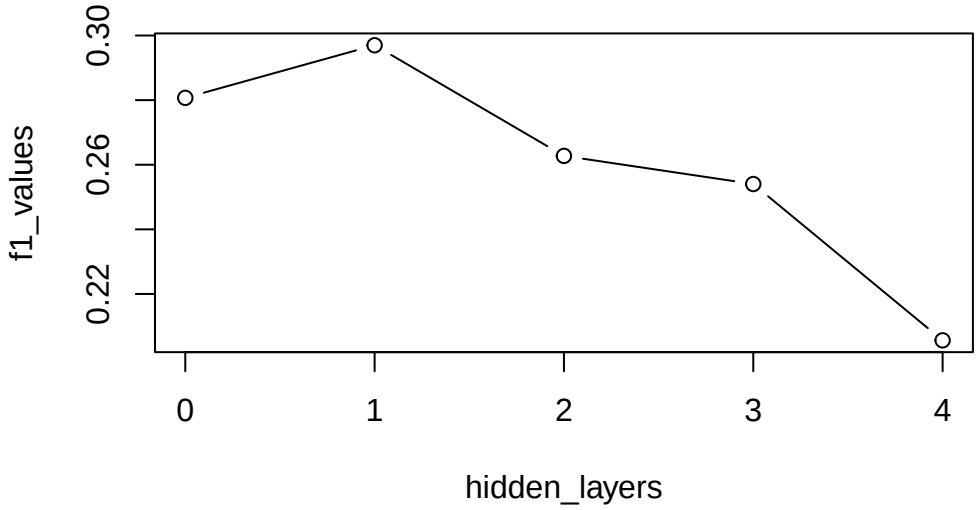
```
set.seed(42)



hidden_layers <- c(seq(from=1, to  = 9, by = 1))
f1_values <- sapply(hidden_layers, function(x){
 neural_model <- neuralnet(
  Potability ~ . ,
  data = train_scaled,
  act.fct = "logistic", hidden = x,
  linear.output = FALSE
)
  neural_prob <- predict(neural_model, test_scaled) [,1]

neural_class <- ifelse(neural_prob >= 0.5, 1, 0)

neural_class <- factor(neural_class, levels = c(0,1))
neural_class <- relevel(neural_class, ref = "1")




cm <- confusionMatrix(neural_class, test_data$Potability)

#cm

#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]



f1 <- 2 * (precision * recall) / (precision + recall)
```

```
  return (f1)
})

plot(hidden_layers, f1_values, type = "b")
```




```
set.seed(42)
#train_data$Potability <- as.numeric(as.character(train_data$Potability))
#test_data$Potability  <- as.numeric(as.character(test_data$Potability))

hidden_layers <- c(seq(from=0, to  = 4, by = 1))
f1_values <- sapply(hidden_layers, function(x){
 neural_model <- neuralnet(
  Potability ~ . ,
  data = train_scaled,
  act.fct = "logistic",
  linear.output = FALSE,
  if (x == 0) {
     hidden = 9

  }
  else{
    hidden = c(9,x)
```

```
  }


)
  neural_prob <- predict(neural_model, test_scaled) [,1]

neural_class <- ifelse(neural_prob >= 0.5, 1, 0)

neural_class <- factor(neural_class, levels = c(0,1))
neural_class <- relevel(neural_class, ref = "1")


cm <- confusionMatrix(neural_class, test_data$Potability)

#cm

#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]




f1 <- 2 * (precision * recall) / (precision + recall)

  return (f1)
})

plot(hidden_layers, f1_values, type = "b")
```




```
set.seed(42)
#neural network



neural_model <- neuralnet(
  Potability ~ . ,
  data = train_scaled,
  act.fct = "logistic", hidden = c(9,1),
  linear.output = FALSE,
  threshold = 0.05
)

plot(neural_model)
#neural_model




neural_prob <- predict(neural_model, test_scaled) [,1]

neural_class <- ifelse(neural_prob >= 0.5, 1, 0)
```

```r
neural_class <- factor(neural_class, levels = c(0,1))
neural_class <- relevel(neural_class, ref = "1")




cm <- confusionMatrix(neural_class, test_data$Potability)

cm
```

```
Confusion Matrix and Statistics

          Reference
Prediction   1   0
         1  81  35
         0 319 548

               Accuracy : 0.6399
                 95% CI : (0.609, 0.6699)
    No Information Rate : 0.5931
    P-Value [Acc > NIR] : 0.00148

                  Kappa : 0.1603

 Mcnemar's Test P-Value : < 2e-16

            Sensitivity : 0.2025
            Specificity : 0.9400
         Pos Pred Value : 0.6983
         Neg Pred Value : 0.6321
             Prevalence : 0.4069
         Detection Rate : 0.0824
   Detection Prevalence : 0.1180
      Balanced Accuracy : 0.5712

       'Positive' Class : 1
```

```r
#calculate f1 from precision and recall
precision <- cm$byClass["Pos Pred Value"]
recall    <- cm$byClass["Sensitivity"]
```

```r
f1_svm <- 2 * (precision * recall) / (precision + recall)
f1_svm
```

```
Pos Pred Value
     0.3139535
```

reference: