Kaggle

Titanic: Machine Learning from Disaster

Introduction

This repository holds results for the Kaggle competition: Titanic: Machine Learning from Disaster.

Data

The datasets were obtained from the Kaggle Titanic Challenge: Kaggle page

- Training Dataset: training data
- Testing Dataset: test data

1. Loading Packages/ Data

```
for (package in c('knitr', 'caret', 'randomForest', 'e1071', 'gbm', 'rpart', 'rpart.plot', 'ggplot2', '

  if (!require(package, character.only = TRUE, quietly = FALSE)) {
    install.packages(package)
    library(package, character.only = TRUE)
  }

}

val_dfname <- c("train.csv", "test.csv")
val_dfpath <- paste(getwd(), "/data", sep = "/")

val_dtrawname <- c("data_training.raw", "data_testing.raw")
val_dtname <- c("data_training", "data_testing")

val_dtclass <- c("val_trainclass", "val_testclass")

val_trainclass <- c("integer",   ## PassengerId
                    "factor",    ## Survived
                    "factor",    ## Pclass
                    "character", ## Name
                    "factor",    ## Sex
                    "numeric",   ## Age
                    "integer",   ## SibSp
                    "integer",   ## Parch
                    "character", ## Ticket
                    "numeric",   ## Fare
                    "character", ## Cabin
                    "factor")    ## Embarked

val_testclass <- val_trainclass[-2]
```

```
for (i in 1:length(val_dtrawname)){

  assign(val_dtrawname[i], read.csv(paste(val_dfpath, val_dfname[i], sep = "/"),
                                    na.strings = c("NA", ""),
                                    colClasses = get(val_dtclass[i])))

  assign(val_dtname[i], get(val_dtrawname[i]))

}
```

2. Pre-process the Data

Check the original data:

```
## dim(data_training.raw)
## str(data_training.raw)
summary(data_training.raw)
```

```
##   PassengerId    Survived Pclass      Name               Sex
##  Min.   :  1.0   0:549    1:216   Length:891         female:314
##  1st Qu.:223.5   1:342    2:184   Class :character   male  :577
##  Median :446.0            3:491   Mode  :character
##  Mean   :446.0
##  3rd Qu.:668.5
##  Max.   :891.0
##
##       Age             SibSp           Parch           Ticket
##  Min.   : 0.42   Min.   :0.000   Min.   :0.0000   Length:891
##  1st Qu.:20.12   1st Qu.:0.000   1st Qu.:0.0000   Class :character
##  Median :28.00   Median :0.000   Median :0.0000   Mode  :character
##  Mean   :29.70   Mean   :0.523   Mean   :0.3816
##  3rd Qu.:38.00   3rd Qu.:1.000   3rd Qu.:0.0000
##  Max.   :80.00   Max.   :8.000   Max.   :6.0000
##  NA's   :177
##       Fare            Cabin            Embarked
##  Min.   :  0.00   Length:891         C   :168
##  1st Qu.:  7.91   Class :character   Q   : 77
##  Median : 14.45   Mode  :character   S   :644
##  Mean   : 32.20                      NA's:  2
##  3rd Qu.: 31.00
##  Max.   :512.33
##
```

Categorize passengers by ‘Title’, and create new ‘FamilySize’ Variable:

```
for (i in 1:length(val_dtname)){

  temp_data <- get(val_dtname[i])
  temp_data["Title"] <- NA
  temp_data["FamilySize"] <- NA

  for (j in 1:nrow(temp_data)){
```

```
    temp_data[j, "Title"] <- strsplit(temp_data[j, "Name"], split='[,.]')[[1]][2]
    temp_data[j, "FamilySize"] <- temp_data[j, "SibSp"] + temp_data[j, "Parch"] + 1

  }

  temp_data[temp_data == ""] <- NA

  temp_data$Title = as.character(temp_data$Title)
  temp_data$FamilySize = as.integer(temp_data$FamilySize)
  ## print(sum(is.na(temp_data$Title)))
  ## print(sum(is.na(temp_data$FamilySize)))
  assign(val_dtname[i], temp_data)

}

rm(temp_data)
```

Replace NA values within numeric class columns with mean and NA values within other class columns with most common occurrence:

```
for (i in 1:length(val_dtname)){

  temp_data <- get(val_dtname[i])

  for (j in 1:ncol(temp_data)) {

    if (class(temp_data[, j]) == "numeric") {

      temp_colmean <- mean(temp_data[, j], na.rm = TRUE)
      temp_data[, j][which(is.na(temp_data[, j]))] <- temp_colmean

    } else {

      temp_colmode <- tail(names(sort(table(temp_data[, j]))), 1)
      temp_data[, j][which(is.na(temp_data[, j]))] <- temp_colmode

    }

  }

  assign(val_dtname[i], temp_data)

}

rm(temp_data, temp_colmean, temp_colmode)
```

Check the processed data:

```
## dim(data_training)
## str(data_training)
summary(data_training)
```

```
##  PassengerId       Survived Pclass      Name                Sex
```

```
##  Length:891         0:549    1:216   Length:891         female:314
##  Class :character   1:342    2:184   Class :character   male  :577
##  Mode  :character            3:491   Mode  :character
##
##
##
##       Age           SibSp             Parch             Ticket
##  Min.   : 0.42   Length:891         Length:891         Length:891
##  1st Qu.:22.00   Class :character   Class :character   Class :character
##  Median :29.70   Mode  :character   Mode  :character   Mode  :character
##  Mean   :29.70
##  3rd Qu.:35.00
##  Max.   :80.00
##       Fare            Cabin            Embarked    Title
##  Min.   :  0.00   Length:891         C:168    Length:891
##  1st Qu.:  7.91   Class :character   Q: 77    Class :character
##  Median : 14.45   Mode  :character   S:646    Mode  :character
##  Mean   : 32.20
##  3rd Qu.: 31.00
##  Max.   :512.33
##   FamilySize
##  Length:891
##  Class :character
##  Mode  :character
##
##
##
```

Check the processed data:

```r
tblsumfunc <- function(x){

  temp_data <- data.frame(Survived = data_training$Survived, Title = data_training[[x]], stringsAsFacto
  temp_obscount <- sort(table(temp_data[, 2]), decreasing = FALSE)

  if (nrow(temp_obscount) > 10) {

    if (class(temp_data[, 2]) == "numeric") {

      temp_data[, 2] <- 10 * ceiling(temp_data[, 2] / 10)
      ## table(temp_data)

    } else {

      temp_lfobsnm <- names(temp_obscount[1:(dim(temp_obscount) - 10)])
      temp_data[, 2][which(is.element(temp_data[, 2], temp_lfobsnm))] <- "Other"
      ## table(temp_data)

    }

  }

  temp_table <- table(temp_data)
  temp_sumtable <- addmargins(temp_table, FUN = list(Total = sum), quiet = TRUE)
```

```
  temp_proptable <- prop.table(temp_sumtable[c(1, 2),], 2)
  temp_mergedtable <- rbind(temp_sumtable[1, ],
                            temp_proptable[1, ],
                            temp_sumtable[2, ],
                            temp_proptable[2, ],
                            temp_sumtable[3, ])
  rownames(temp_mergedtable) <- c("Didn't Survive", "%", "Survived", "%", "Total")

  print(x)
  temp_kabletable <- kable(temp_mergedtable, digits = 2, caption = "test", output = FALSE)
  cat(temp_kabletable, sep="\n")
  cat(sep="\n\n")

  rm(temp_data, temp_table, temp_sumtable, temp_proptable, temp_mergedtable)

}

val_sumcolname <- list("Pclass", "Title", "Sex", "Age", "FamilySize")

for(colname in val_sumcolname) { tblsumfunc(colname) }
```

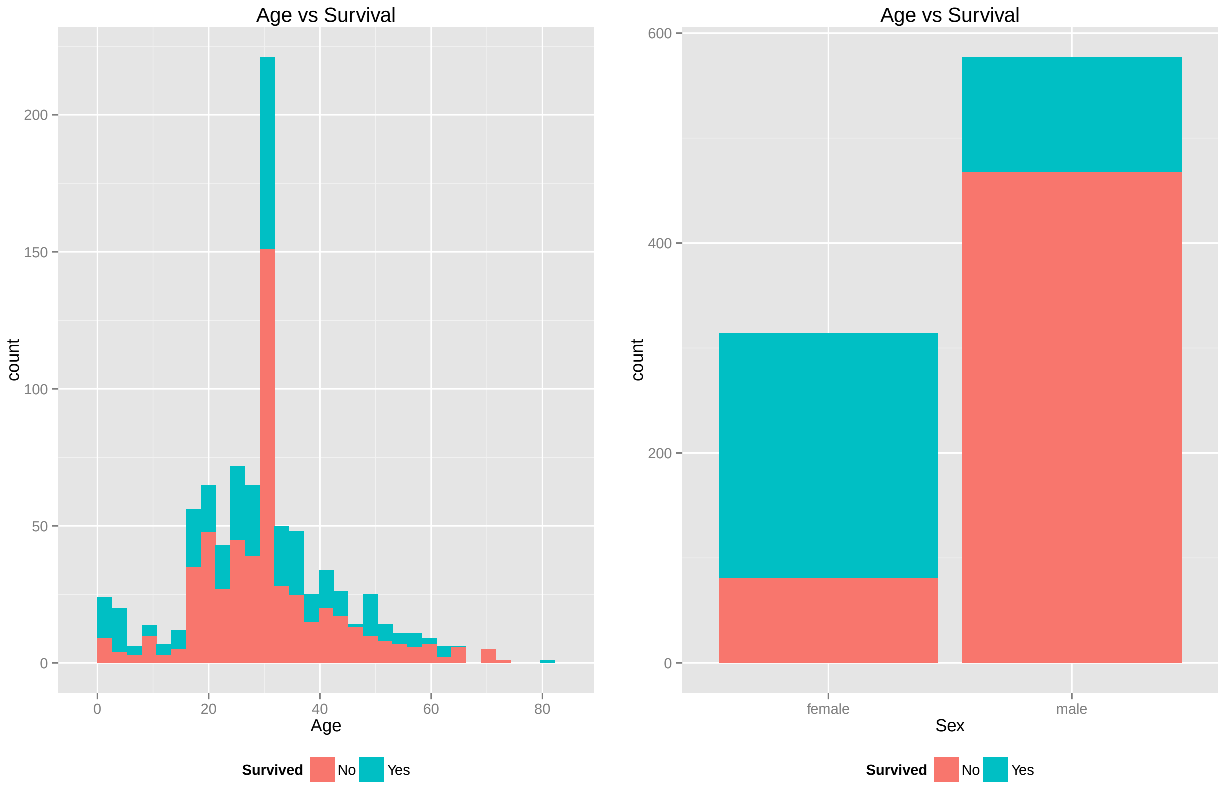
```
## [1] "Pclass"
## Table: test
##
##                       1         2         3     Total
## ---------------  -------  -------  -------  -------
## Didn't Survive     80.00     97.00   372.00   549.00
## %                   0.37      0.53     0.76     0.62
## Survived          136.00     87.00   119.00   342.00
## %                   0.63      0.47     0.24     0.38
## Total             216.00    184.00   491.00   891.00
##
## [1] "Title"
## Table: test
##
##                     Col      Dr    Major    Master     Miss     Mlle        Mr       Mrs     Rev    the Cou
## ---------------  -----  -----  -------  --------  ------  ------  -------  -------  -----  ----------
## Didn't Survive      1.0    4.00      1.0     17.00     55.0        0    436.00    26.00       6
## %                   0.5    0.57      0.5      0.42      0.3        0      0.84     0.21       1
## Survived            1.0    3.00      1.0     23.00    127.0        2     81.00    99.00       0
## %                   0.5    0.43      0.5      0.57      0.7        1      0.16     0.79       0
## Total               2.0    7.00      2.0     40.00    182.0        2    517.00   125.00       6
##
## [1] "Sex"
## Table: test
##
##                    female      male     Total
## ---------------  -------  -------  -------
## Didn't Survive      81.00    468.00    549.00
## %                    0.26      0.81      0.62
## Survived           233.00    109.00    342.00
## %                    0.74      0.19      0.38
## Total              314.00    577.00    891.00
```

```
##
## [1] "Age"
## Table: test
##
##                      10       20        30        40       50      60       70     80     Total
## ---------------  ------  -------  --------  --------  -------  ------  -------  -----  --------
## Didn't Survive    26.00    71.00    271.00     86.00    53.00    25.0    13.00    4.0    549.00
## %                  0.41     0.62      0.67      0.55     0.62     0.6     0.76    0.8      0.62
## Survived          38.00    44.00    136.00     69.00    33.00    17.0     4.00    1.0    342.00
## %                  0.59     0.38      0.33      0.45     0.38     0.4     0.24    0.2      0.38
## Total             64.00   115.00    407.00    155.00    86.00    42.0    17.00    5.0    891.00
##
## [1] "FamilySize"
## Table: test
##
##                       1   11        2         3        4       5        6        7    8     Total
## ---------------  ------  ---  -------  --------  -------  ------  -------  -------  ---  --------
## Didn't Survive    374.0    7    72.00     43.00     8.00    12.0    19.00     8.00    6    549.00
## %                   0.7    1     0.45      0.42     0.28     0.8     0.86     0.67    1      0.62
## Survived          163.0    0    89.00     59.00    21.00     3.0     3.00     4.00    0    342.00
## %                   0.3    0     0.55      0.58     0.72     0.2     0.14     0.33    0      0.38
## Total             537.0    7   161.00    102.00    29.00    15.0    22.00    12.00    6    891.00
```

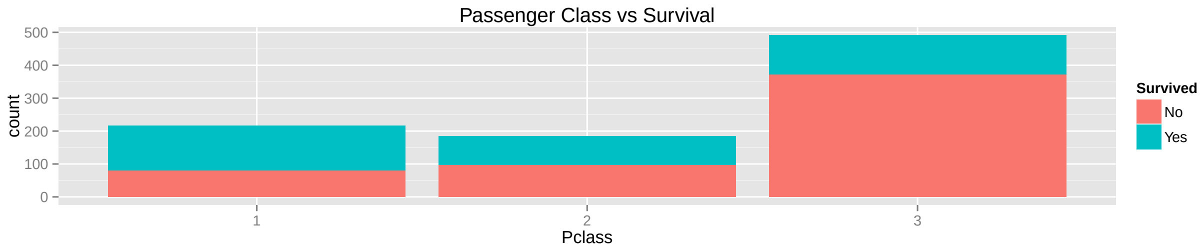
At a high level, the data suggests that passengers within the following groups had an improved survival rate: * Were Class 1 passengers * Had a title of 'Master' / aged 0-10 * Were female * Boarded with a family of size 2-4

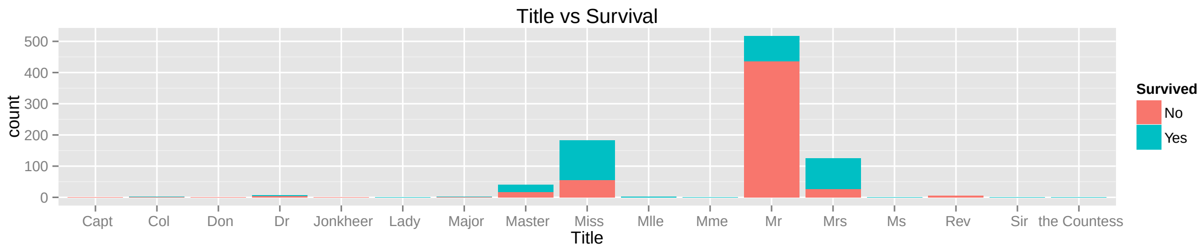
Chart the processed data:

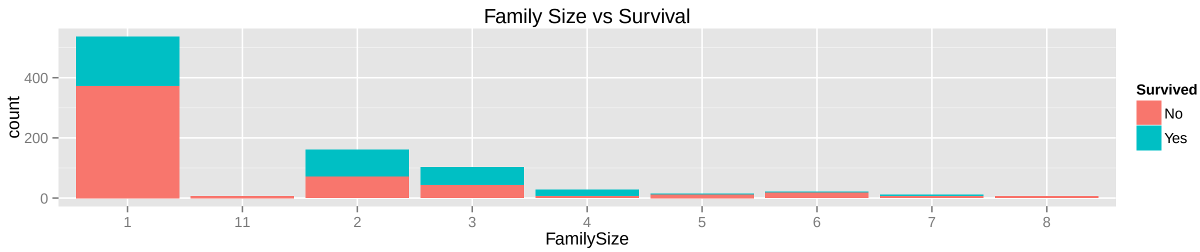
```r
val_agehist <- ggplot(data_training, aes(x = Age, fill = Survived)) +
                      geom_histogram() +
                      ggtitle("Age vs Survival") +
                      theme(legend.position = "bottom") +
                      scale_fill_discrete(labels = c("No", "Yes"))

val_sexhist <- ggplot(data_training, aes(x = Sex, fill = Survived)) +
                      geom_histogram() +
                      ggtitle("Age vs Survival") +
                      theme(legend.position = "bottom") +
                      scale_fill_discrete(labels = c("No", "Yes"))

grid.arrange(val_agehist, val_sexhist, ncol = 2)
```




```r
val_pclasshist <- ggplot(data_training, aes(x = Pclass, fill = Survived)) +
                        geom_histogram() +
                        ggtitle("Passenger Class vs Survival") +
                        theme(legend.position = "right") +
                        scale_fill_discrete(labels = c("No", "Yes"))

val_titlehist <- ggplot(data_training, aes(x = Title, fill = Survived)) +
                        geom_histogram() +
                        ggtitle("Title vs Survival") +
                        theme(legend.position = "right") +
                        scale_fill_discrete(labels = c("No", "Yes"))

val_familyhist <- ggplot(data_training, aes(x = FamilySize, fill = Survived)) +
                        geom_histogram() +
                        ggtitle("Family Size vs Survival") +
                        theme(legend.position = "right") +
                        scale_fill_discrete(labels = c("No", "Yes"))

grid.arrange(val_pclasshist, val_titlehist, val_familyhist, nrow = 3)
```







3. Prediction Modelling

Split the training data:

```
set.seed(12345)
data_training.rows <- createDataPartition(data_training$Survived, p = 0.7, list = FALSE)

data_training.train <- data_training[data_training.rows, ]
data_training.test <- data_training[-data_training.rows, ]
```

Check the split data:

```
## dim(data_training.train)
str(data_training.train)
```

```
## 'data.frame':    625 obs. of  14 variables:
##  $ PassengerId: chr  "1" "3" "4" "6" ...
##  $ Survived   : Factor w/ 2 levels "0","1": 1 2 2 1 1 1 2 2 2 1 ...
##  $ Pclass     : Factor w/ 3 levels "1","2","3": 3 3 1 3 1 3 3 2 1 3 ...
##  $ Name       : chr  "Braund, Mr. Owen Harris" "Heikkinen, Miss. Laina" "Futrelle, Mrs. Jacques Heatl
##  $ Sex        : Factor w/ 2 levels "female","male": 2 1 1 2 2 2 1 1 1 2 ...
##  $ Age        : num  22 26 35 29.7 54 ...
##  $ SibSp      : chr  "1" "0" "1" "0" ...
##  $ Parch      : chr  "0" "0" "0" "0" ...
##  $ Ticket     : chr  "A/5 21171" "STON/O2. 3101282" "113803" "330877" ...
```

```
##  $ Fare       : num  7.25 7.92 53.1 8.46 51.86 ...
##  $ Cabin      : chr  "G6" "G6" "C123" "G6" ...
##  $ Embarked   : Factor w/ 3 levels "C","Q","S": 3 3 3 2 3 3 3 1 3 3 ...
##  $ Title      : chr  " Mr" " Miss" " Mrs" " Mr" ...
##  $ FamilySize : chr  "2" "1" "2" "1" ...
```

```
## summary(data_training.train)

## dim(data_training.test)
str(data_training.test)
```

```
## 'data.frame':    266 obs. of  14 variables:
##  $ PassengerId: chr  "2" "5" "11" "16" ...
##  $ Survived   : Factor w/ 2 levels "0","1": 2 1 2 2 2 1 1 2 1 2 ...
##  $ Pclass     : Factor w/ 3 levels "1","2","3": 1 3 3 2 3 2 3 3 2 3 ...
##  $ Name       : chr  "Cumings, Mrs. John Bradley (Florence Briggs Thayer)" "Allen, Mr. William Henry
##  $ Sex        : Factor w/ 2 levels "female","male": 1 2 1 1 1 2 1 1 2 2 ...
##  $ Age        : num  38 35 4 55 29.7 ...
##  $ SibSp      : chr  "1" "0" "1" "0" ...
##  $ Parch      : chr  "0" "0" "1" "0" ...
##  $ Ticket     : chr  "PC 17599" "373450" "PP 9549" "248706" ...
##  $ Fare       : num  71.28 8.05 16.7 16 7.22 ...
##  $ Cabin      : chr  "C85" "G6" "G6" "G6" ...
##  $ Embarked   : Factor w/ 3 levels "C","Q","S": 1 3 3 3 1 3 3 3 3 1 ...
##  $ Title      : chr  " Mrs" " Mr" " Miss" " Mrs" ...
##  $ FamilySize : chr  "2" "1" "3" "1" ...
```

```
## summary(data_training.test)
```

```
set.seed(12345)
val_dtmodel <- rpart(Survived ~ Pclass + Sex + Age + Fare + Embarked + FamilySize, data = data_training
val_dtmodel.predict <- predict(val_dtmodel, data_training.test, type = "class")
val_dtcm <- confusionMatrix(val_dtmodel.predict, data_training.test$Survived)
val_dtcm
```

Decision tree prediction

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 145  38
##          1  19  64
##
##                Accuracy : 0.7857
##                  95% CI : (0.7315, 0.8335)
##     No Information Rate : 0.6165
##     P-Value [Acc > NIR] : 2.603e-09
##
##                   Kappa : 0.5303
```

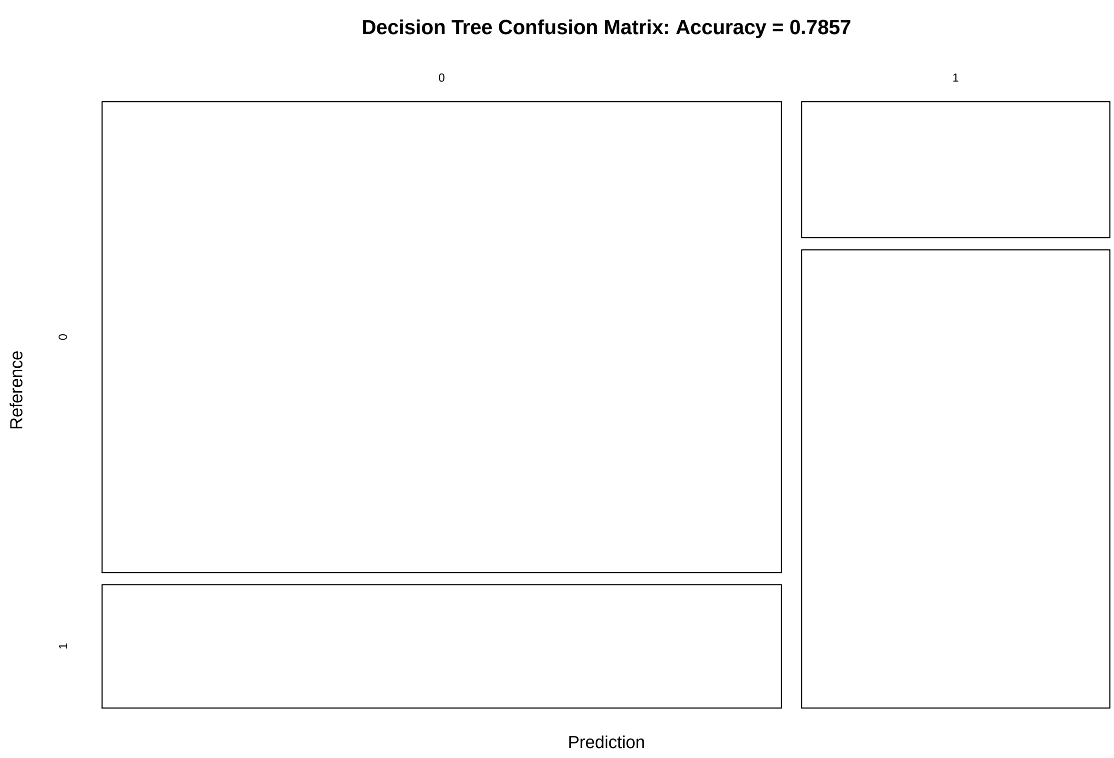
```
##  Mcnemar's Test P-Value : 0.01712
##
##             Sensitivity : 0.8841
##             Specificity : 0.6275
##          Pos Pred Value : 0.7923
##          Neg Pred Value : 0.7711
##              Prevalence : 0.6165
##          Detection Rate : 0.5451
##    Detection Prevalence : 0.6880
##       Balanced Accuracy : 0.7558
##
##        'Positive' Class : 0
##
```

Decision tree prediction has a reported accuracy against the training dataset:

```r
round(val_dtcm$overall['Accuracy'], 4)
```

```
## Accuracy
##   0.7857
```

```r
plot(val_dtcm$table,
    col = val_dtcm$byClass,
    main = paste("Decision Tree Confusion Matrix: Accuracy =",
    round(val_dtcm$overall['Accuracy'], 4)))
```



```r
set.seed(12345)
val_rfmodel <- randomForest(Survived ~ Pclass + Sex + Age + Fare + Embarked + FamilySize, data = data_t
val_rfmodel.predict <- predict(val_rfmodel, data_training.test, type = "class")
val_rfcm <- confusionMatrix(val_rfmodel.predict, data_training.test$Survived)
val_rfcm
```

Random forest prediction

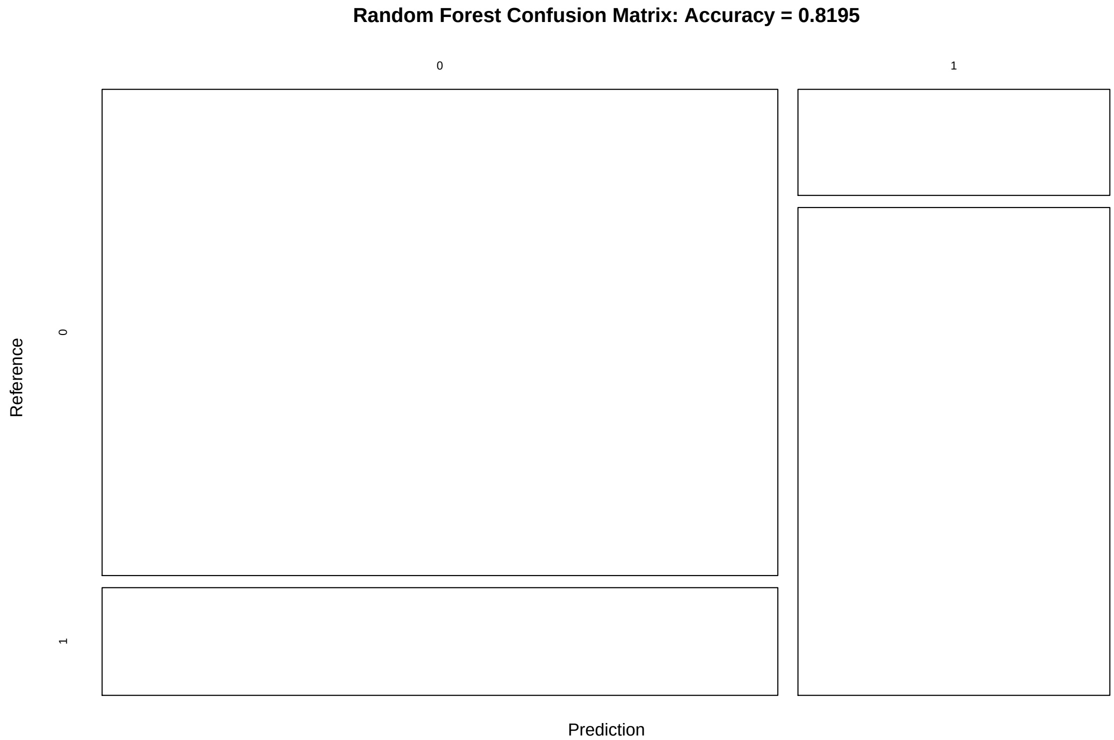
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 149  33
##          1  15  69
##
##                Accuracy : 0.8195
##                  95% CI : (0.768, 0.8638)
##     No Information Rate : 0.6165
##     P-Value [Acc > NIR] : 5.675e-13
##
##                   Kappa : 0.6052
##  Mcnemar's Test P-Value : 0.01414
##
##             Sensitivity : 0.9085
##             Specificity : 0.6765
##          Pos Pred Value : 0.8187
##          Neg Pred Value : 0.8214
##              Prevalence : 0.6165
##          Detection Rate : 0.5602
##    Detection Prevalence : 0.6842
##       Balanced Accuracy : 0.7925
##
##        'Positive' Class : 0
##
```

Random forest prediction has a reported accuracy against the training dataset:

```r
round(val_rfcm$overall['Accuracy'], 4)
```

```
## Accuracy
##   0.8195
```

```r
plot(val_rfcm$table,
    col = val_rfcm$byClass,
    main = paste("Random Forest Confusion Matrix: Accuracy =",
    round(val_rfcm$overall['Accuracy'], 4)))
```




```r
set.seed(12345)
val_fitControl <- trainControl(method = "repeatedcv", number = 5, repeats = 1)
val_gbmmodel <- train(Survived ~ Pclass + Sex + Age + Fare + Embarked + FamilySize, data = data_training
val_gbmmodel.predict <- predict(val_gbmmodel, newdata = data_training.test)
val_gbmcm <- confusionMatrix(val_gbmmodel.predict, data_training.test$Survived)
val_gbmcm
```

Generalized boosted regression prediction

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 148  39
##          1  16  63
##
##                Accuracy : 0.7932
##                  95% CI : (0.7395, 0.8403)
##     No Information Rate : 0.6165
##     P-Value [Acc > NIR] : 4.694e-10
##
##                   Kappa : 0.5432
##  Mcnemar's Test P-Value : 0.003012
##
```

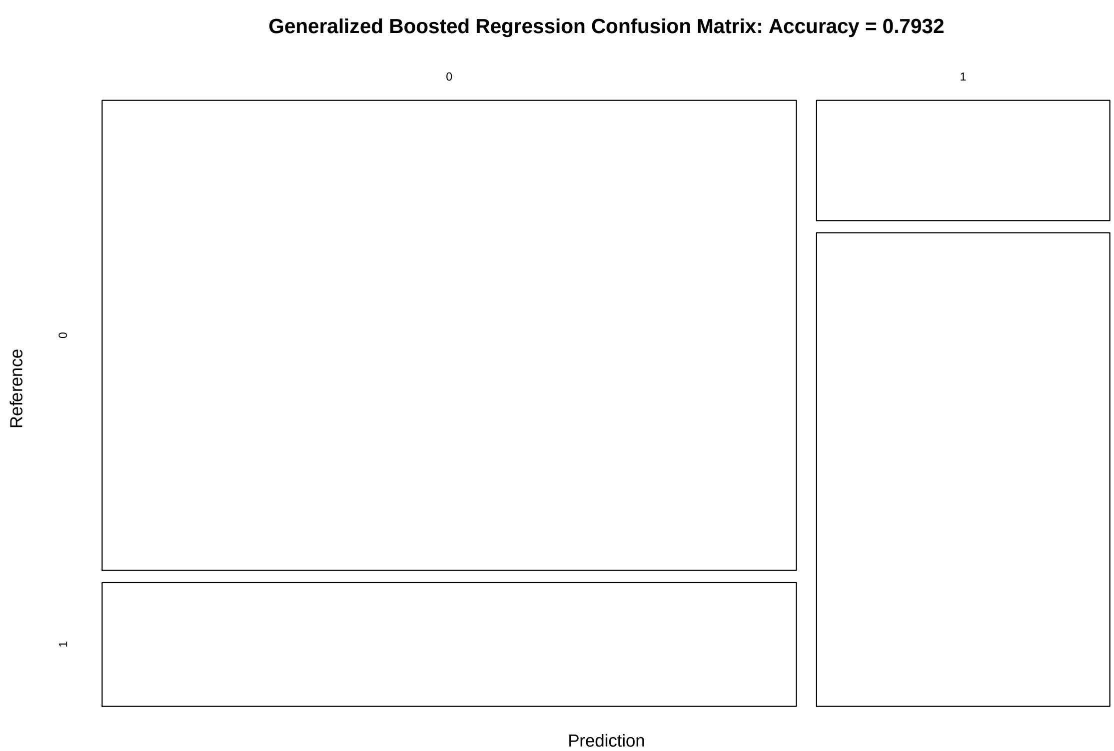
```
##              Sensitivity : 0.9024
##              Specificity : 0.6176
##           Pos Pred Value : 0.7914
##           Neg Pred Value : 0.7975
##               Prevalence : 0.6165
##           Detection Rate : 0.5564
##     Detection Prevalence : 0.7030
##        Balanced Accuracy : 0.7600
##
##         'Positive' Class : 0
##
```

Generalized boosted regression prediction has a reported accuracy against the training dataset:

```r
round(val_gbmcm$overall['Accuracy'], 4)
```

```
## Accuracy
##   0.7932
```

```r
plot(val_gbmcm$table,
     col = val_gbmcm$byClass,
     main = paste("Generalized Boosted Regression Confusion Matrix: Accuracy =",
     round(val_gbmcm$overall['Accuracy'], 4)))
```



4. Model Selection

The expected out-of-sample error is calculated as 1 - accuracy for predictions made against the cross-validation set:

```
val_ooserror <- 1 - round(val_rfcm$overall['Accuracy'], 4)
## val_ooserror <- 1 - round(val_gbmcm$overall['Accuracy'], 4)
val_ooserror
```

```
## Accuracy
##   0.1805
```

```
val_selmodel.final <- predict(val_rfmodel, data_testing)
## val_selmodel.final <- predict(val_gbmmodel, data_testing)
```

5. Kaggle Submission

```
data_prediction <- data.frame(PassengerId = data_testing$PassengerId, Survived = val_selmodel.final)
write.table(data_prediction,"data/prediction.csv", row.names = FALSE, sep=",", col.names = TRUE)
```