

# Ensemble Methods

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<https://www.kaggle.com/datasets/vicsuperman/prediction-of-music-genre>

```
original <- read.csv("music_genre.csv")
original$key <- factor(original$key)
original$tempo <- as.numeric(original$tempo)

## Warning: NAs introduced by coercion
original$mode <- factor(original$mode)
original$music_genre <- factor(original$music_genre)

df <- original[, -c(1,2,3,7,8,16)]

df <- df[complete.cases(df),]

df$key <- droplevels(df$key)
df$mode <- droplevels(df$mode)
df$music_genre <- droplevels(df$music_genre)

str(df)

## 'data.frame': 45020 obs. of 12 variables:
## $ popularity : num 27 31 28 34 32 46 43 39 22 30 ...
## $ acousticness : num 0.00468 0.0127 0.00306 0.0254 0.00465 0.0289 0.0297 0.00299 0.00934 0.855
## $ danceability : num 0.652 0.622 0.62 0.774 0.638 0.572 0.809 0.509 0.578 0.607 ...
## $ instrumentalness: num 7.92e-01 9.50e-01 1.18e-02 2.53e-03 9.09e-01 7.74e-06 9.03e-01 2.76e-04 1.
## $ key : Factor w/ 12 levels "A","A#","B","C",...: 2 6 12 5 10 3 11 9 1 10 ...
## $ liveness : num 0.115 0.124 0.534 0.157 0.157 0.106 0.0635 0.178 0.111 0.106 ...
## $ loudness : num -5.2 -7.04 -4.62 -4.5 -6.27 ...
## $ mode : Factor w/ 2 levels "Major","Minor": 2 2 1 1 1 1 2 2 2 2 ...
## $ speechiness : num 0.0748 0.03 0.0345 0.239 0.0413 0.351 0.0484 0.268 0.173 0.0345 ...
## $ tempo : num 101 115 128 128 145 ...
## $ valence : num 0.759 0.531 0.333 0.27 0.323 0.23 0.761 0.273 0.203 0.307 ...
## $ music_genre : Factor w/ 10 levels "Alternative",...: 6 6 6 6 6 6 6 6 6 6 ...
```

## Train Test Split

```
set.seed(1234)
i <- sample(nrow(df), .75*nrow(df), replace=FALSE)
train <- df[i,]
test <- df[-i,]
```

## Decision Tree

```
library(mltools)
library(tree)

startTime <- Sys.time()

tree <- tree(music_genre~., data = train)

endTime <- Sys.time()
print(paste("Total time: ", endTime - startTime))

## [1] "Total time: 0.16052508354187"

tree_pred <- predict(tree, newdata=test, type="class")
table(tree_pred, test$music_genre)
```

```
##
## tree_pred      Alternative Anime Blues Classical Country Electronic Hip-Hop Jazz
## Alternative      279      9    65         51      259         88      60  138
## Anime            2   497    66         19       8         39       0   17
## Blues            1   371   449         60       4        327       1  143
## Classical        3   148    59        846      17         21       0  130
## Country          249   124   223         32     572       116       7  196
## Electronic       96    46   163         68     44       417       1  386
## Hip-Hop          251     6    26          6     39       76     835   42
## Jazz             0     0     0          0     0         0       0    0
## Rap              0     0     0          0     0         0       0    0
## Rock             209     3    47         18    195         50     175   56
##
## tree_pred      Rap Rock
## Alternative    56  178
## Anime          3   2
## Blues          0   3
## Classical      0   1
## Country        2   3
## Electronic     0   2
## Hip-Hop       800  163
## Jazz           0   0
## Rap            0   0
## Rock          302  789
```

```
acc_dt <- mean(tree_pred==test$music_genre)
mcc_dt <- mcc(factor(tree_pred), test$music_genre)
print(paste("accuracy=", acc_dt))
```

```
## [1] "accuracy= 0.416170590848512"
```

```
print(paste("mcc=", mcc_dt))
```

```
## [1] "mcc= 0.359839996825828"
```

## Random Forest

```
library(randomForest)
```

```
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
set.seed(1234)

startTime <- Sys.time()

rf <- randomForest(music_genre~., data=train, importance=TRUE)

endTime <- Sys.time()
print(paste("Total time: ", endTime - startTime))

## [1] "Total time: 4.21836849848429"

rf

##
## Call:
## randomForest(formula = music_genre ~ ., data = train, importance = TRUE)
##              Type of random forest: classification
##              Number of trees: 500
## No. of variables tried at each split: 3
##
##              OOB estimate of  error rate: 46.27%
## Confusion matrix:
##              Alternative Anime Blues Classical Country Electronic Hip-Hop Jazz
## Alternative      1187    23    82         8    441        194    308  225
## Anime            108  2341   214        253   152        152     2   50
## Blues            177   267 1806         54   287        192    13  408
## Classical         81   102   82        2871    20         72     0 159
## Country           263    43   188         4  1875         37    55 173
## Electronic        234   165   230         34    85       1977    69 408
## Hip-Hop           180     3     1          0    48         34  1336  30
## Jazz              135    49   398        237   169        428    81 1754
## Rap               151     1     3          0    44         17  1897  19
## Rock              512    11    61          9   333         16   124  71
##
##              Rap Rock class.error
## Alternative  172  765  0.6513950
## Anime         2   19  0.2890981
## Blues         2  166  0.4644128
## Classical     0   13  0.1555882
## Country       62  648  0.4399642
## Electronic    35   95  0.4066627
## Hip-Hop      1639  170  0.6117408
## Jazz         17  145  0.4860826
## Rap          893  316  0.7327148
## Rock         180 2103  0.3850877

pred <- predict(rf, newdata=test, type="response")
acc_rf <- mean(pred==test$music_genre)
mcc_rf <- mcc(factor(pred), test$music_genre)
print(paste("accuracy=", acc_rf))

## [1] "accuracy= 0.553176366059529"
```

```
print(paste("mcc=", mcc_rf))
```

```
## [1] "mcc= 0.504103151697454"
```

### boosting from adabag library

```
library(adabag)
```

```
## Loading required package: rpart
```

```
## Loading required package: caret
```

```
## Loading required package: ggplot2
```

```
##
```

```
## Attaching package: 'ggplot2'
```

```
## The following object is masked from 'package:randomForest':
```

```
##
```

```
## margin
```

```
## Loading required package: lattice
```

```
## Loading required package: foreach
```

```
## Loading required package: doParallel
```

```
## Loading required package: iterators
```

```
## Loading required package: parallel
```

```
startTime <- Sys.time()
```

```
adab1 <- boosting(music_genre~., data=train, boos=TRUE, mfinal=20, coeflearn='Breiman')
```

```
endTime <- Sys.time()
```

```
print(paste("Total time: ", endTime - startTime))
```

```
## [1] "Total time: 21.1789329051971"
```

```
summary(adab1)
```

```
##           Length Class  Mode
## formula           3 formula call
## trees             20 -none- list
## weights           20 -none- numeric
## votes            337650 -none- numeric
## prob             337650 -none- numeric
## class             33765 -none- character
## importance         11 -none- numeric
## terms              3 terms  call
## call              6 -none- call
```

```
pred <- predict(adab1, newdata=test, type="response")
```

```
acc_adabag <- mean(pred$class==test$music_genre)
```

```
mcc_adabag <- mcc(factor(pred$class), test$music_genre)
```

```
print(paste("accuracy=", acc_adabag))
```

```
## [1] "accuracy= 0.439982230119947"
```

```
print(paste("mcc=", mcc_adabag))
```

```
## [1] "mcc= 0.389561644308411"
```

## XGBoost

```
library(xgboost)
```

```
genres <- df$music_genre
```

```
label <- as.integer(df$music_genre) - 1
```

```
df$music_genre = NULL
```

```
train_label <- label[i]
```

```
test_label <- label[-i]
```

```
train_matrix <- data.matrix(df[i,])
```

```
test_matrix <- data.matrix(df[-i,])
```

```
num_class = length(levels(genres))
```

```
startTime <- Sys.time()
```

```
model <- xgboost(data=train_matrix, label=train_label, nrounds=100, num_class = num_class, objective='m
```

```
## [1] train-mlogloss:1.830949
```

```
## [2] train-mlogloss:1.617191
```

```
## [3] train-mlogloss:1.474090
```

```
## [4] train-mlogloss:1.371681
```

```
## [5] train-mlogloss:1.292881
```

```
## [6] train-mlogloss:1.228601
```

```
## [7] train-mlogloss:1.178885
```

```
## [8] train-mlogloss:1.139211
```

```
## [9] train-mlogloss:1.103771
```

```
## [10] train-mlogloss:1.073472
```

```
## [11] train-mlogloss:1.048241
```

```
## [12] train-mlogloss:1.027538
```

```
## [13] train-mlogloss:1.008616
```

```
## [14] train-mlogloss:0.992096
```

```
## [15] train-mlogloss:0.977397
```

```
## [16] train-mlogloss:0.964583
```

```
## [17] train-mlogloss:0.953058
```

```
## [18] train-mlogloss:0.940854
```

```
## [19] train-mlogloss:0.931189
```

```
## [20] train-mlogloss:0.921321
```

```
## [21] train-mlogloss:0.912080
```

```
## [22] train-mlogloss:0.903502
```

```
## [23] train-mlogloss:0.895982
```

```
## [24] train-mlogloss:0.888791
```

```
## [25] train-mlogloss:0.881858
```

```
## [26] train-mlogloss:0.875147
```

```
## [27] train-mlogloss:0.868542
```

```
## [28] train-mlogloss:0.862615
```

```
## [29] train-mlogloss:0.856649
```

```
## [30] train-mlogloss:0.851716
## [31] train-mlogloss:0.846190
## [32] train-mlogloss:0.840060
## [33] train-mlogloss:0.833777
## [34] train-mlogloss:0.827553
## [35] train-mlogloss:0.822322
## [36] train-mlogloss:0.817467
## [37] train-mlogloss:0.812629
## [38] train-mlogloss:0.807359
## [39] train-mlogloss:0.803514
## [40] train-mlogloss:0.797398
## [41] train-mlogloss:0.793021
## [42] train-mlogloss:0.789241
## [43] train-mlogloss:0.784307
## [44] train-mlogloss:0.780050
## [45] train-mlogloss:0.776037
## [46] train-mlogloss:0.772362
## [47] train-mlogloss:0.766400
## [48] train-mlogloss:0.762245
## [49] train-mlogloss:0.758490
## [50] train-mlogloss:0.754552
## [51] train-mlogloss:0.749949
## [52] train-mlogloss:0.746131
## [53] train-mlogloss:0.741529
## [54] train-mlogloss:0.738587
## [55] train-mlogloss:0.733401
## [56] train-mlogloss:0.729130
## [57] train-mlogloss:0.726558
## [58] train-mlogloss:0.722779
## [59] train-mlogloss:0.718608
## [60] train-mlogloss:0.715014
## [61] train-mlogloss:0.711193
## [62] train-mlogloss:0.707753
## [63] train-mlogloss:0.701851
## [64] train-mlogloss:0.699117
## [65] train-mlogloss:0.695538
## [66] train-mlogloss:0.691145
## [67] train-mlogloss:0.688745
## [68] train-mlogloss:0.686185
## [69] train-mlogloss:0.682394
## [70] train-mlogloss:0.677544
## [71] train-mlogloss:0.673910
## [72] train-mlogloss:0.670411
## [73] train-mlogloss:0.665571
## [74] train-mlogloss:0.663003
## [75] train-mlogloss:0.659735
## [76] train-mlogloss:0.657078
## [77] train-mlogloss:0.654303
## [78] train-mlogloss:0.651949
## [79] train-mlogloss:0.648472
## [80] train-mlogloss:0.645396
## [81] train-mlogloss:0.641935
## [82] train-mlogloss:0.639255
## [83] train-mlogloss:0.636679
```

```

## [84] train-mlogloss:0.633110
## [85] train-mlogloss:0.630806
## [86] train-mlogloss:0.627741
## [87] train-mlogloss:0.623583
## [88] train-mlogloss:0.620868
## [89] train-mlogloss:0.617608
## [90] train-mlogloss:0.614066
## [91] train-mlogloss:0.610585
## [92] train-mlogloss:0.607184
## [93] train-mlogloss:0.603206
## [94] train-mlogloss:0.598898
## [95] train-mlogloss:0.594545
## [96] train-mlogloss:0.591701
## [97] train-mlogloss:0.588164
## [98] train-mlogloss:0.584466
## [99] train-mlogloss:0.581531
## [100] train-mlogloss:0.579072

endTime <- Sys.time()
print(paste("Total time: ", endTime - startTime))

## [1] "Total time: 24.1045889854431"

summary(model)

##           Length Class          Mode
## handle           1 xgb.Booster.handle externalptr
## raw             3314421 -none-      raw
## niter            1 -none-      numeric
## evaluation_log    2 data.table      list
## call             15 -none-      call
## params            3 -none-      list
## callbacks         2 -none-      list
## feature_names     11 -none-      character
## nfeatures         1 -none-      numeric

probs <- predict(model, test_matrix, reshape=T)
probs <- as.data.frame(probs)
colnames(probs) <- levels(genres)

# Use the predicted label with the highest probability
pred <- apply(probs,1,function(x) colnames(probs)[which.max(x)])
test_label <- levels(genres)[test_label + 1]

acc_xg <- mean(pred==test_label)
mcc_xg <- mcc(pred, test_label)
print(paste("accuracy=", acc_xg))

## [1] "accuracy= 0.562594402487783"

print(paste("mcc=", mcc_xg))

## [1] "mcc= 0.514306852677017"

```

## Analysis of Results

Decision Tree: Time-.601 seconds, Acc-.416, MCC-.360

Random Forest: Time-4.575 minutes, Acc-.553, MCC-.504

Adaboost: Time-41.386 seconds, Acc-.439, MCC-.388

XGBoost: Time-14.349 seconds, Acc-.563, MCC-.514

XGBoost I would say is the overall winner here. It achieved the highest accuracy and mcc of all the models tested and within a reasonable time (2nd fastest).

Random forest produced good results on par with XGBoost, but was very computationally expensive and took the longest by far.

Adaboost was alright, but didn't produce results as good as the above models. It's just slightly better than decision tree, but takes much more time than it and XGBoost.

Decision tree ran the absolute fastest, but consequently had the worst accuracy and mcc.