Final Group Project: Spotify Analysis

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1. Introduction

Exploring the Dynamics of Music Popularity and Genre Classification Through Spotify's Audio Features

This document includes all the code and visualizations used in our analysis.

2. Research question

Research Question: In our daily lives, we are constantly immersed in a diverse array of music. We are wondering - Can the popularity and genre of a song be accurately predicted based on its audio features using data from the Spotify API? We believe the analysis can offer insights into musical trends, enabling the industry to adapt and innovate proactively.

- Objective 1: Predict song popularity by audio features from Spotify data
- Objective 2: Predict song genres by audio features from Spotify data

Assumption: Quantifiable Audio Features: For music related data analysis, one of the biggest problems historically has simply been a way to quantify music, but Spotify has been leading the way detailing the audio features.

3. Spotify Dataset

The Spotify Database API provides a comprehensive dataset, encompassing a wide array of audio features for songs. This dataset is ideal for our objectives due to several reasons:

1. **Free API:** The Spotify API is freely accessible to developers.
2. **Diverse Data Points:** Spotify has data of thousands of tracks spanning various genres, offers a rich foundation for our analysis
3. **Reliable Popularity Metric:** Spotify's popularity score is derived from actual user engagement, offering a tangible metric for song success.

For data downloading part, we are using Python API to access Spotify data, please refer to Spotify_Download_API.ipynb for more details.

At the heart of our investigation are two primary dimensions: the popularity of tracks and their genres.

- **Popularity:** The value will be between 0 and 100, with 100 being the most popular. The popularity is calculated by Spotify algorithm and is based, in the most part, on the total number of plays the track has had and how recent those plays are. Given the left-skewed distribution, with a vast majority of tracks clustering at the lower end, we define tracks with a popularity score greater than 16 as "popular".
- **Genre:** Our dataset encompasses approximately 1000 tracks each from six distinct genres (total ~6k track data): Electronic, Hip-hop, Jazz, Pop, Country, and Rock.
- **Other Audio features:**

1. Acousticness: A measure on a scale from 0 to 1 indicating the acoustic nature of a track.
2. Danceability: A metric assessing how suitable a track is for dancing.
3. Energy: Reflects the intensity and activity of a track.
4. Instrumentalness: Indicates the presence of instrumental sounds in a track.
5. Liveness: Differentiates live recordings from studio productions.
6. Loudness: Measures the overall decibel level of a track.
7. Speechiness: Quantifies the spoken word content in a track.
8. Tempo: The speed at which a piece of music is played, measured in beats per minute (BPM).
9. Time Signature: Describes how beats in a song are grouped, contributing to the song's rhythm.
10. Key: Identifies the tonal center and harmonic foundation of a track.
11. Valence: Measures the musical positiveness conveyed by a track.

4. Data Loading

Load Packages

```
library(readr)
library(tidyverse)
library(ggplot2)
library(gridExtra)
library(corrplot)

library(dplyr)
library(tidyr)
library(caret)
library(rpart)

library(randomForest)
library(e1071)
library(nnet)
library(kernlab)
```

Load Dataset

```r
data <- read.csv("total.csv", stringsAsFactors = FALSE)
```

5. Data Pre-processing

Check if there are duplicate Track in our dataset

```r
duplicates <- duplicated(data$track_id)
num_duplicates <- sum(duplicates)
cat("Number of duplicates in 'track_id' column:", num_duplicates, "\n")
```

```
## Number of duplicates in 'track_id' column: 0
```

```r
if(num_duplicates > 0) {
  duplicate_rows <- data[duplicates, ]
  cat("Duplicate rows based on track_id:\n")
  print(duplicate_rows)
} else {
  cat("No duplicate rows based on track_id found.\n")
}
```

```
## No duplicate rows based on track_id found.
```

Check Missing Values

```r
n_df <- nrow(data)

for(col in colnames(data)) {
  missing <- sum(is.na(data[[col]]))
  mis_perc <- (missing / n_df) * 100

  cat(sprintf("The missing percentage of %s is %.2f%%\n", col, mis_perc))
}
```

```
## The missing percentage of Name is 0.00%
## The missing percentage of track_id is 0.01%
## The missing percentage of Album is 0.00%
## The missing percentage of album_id is 0.00%
## The missing percentage of Artist is 0.00%
## The missing percentage of Release_date is 0.00%
## The missing percentage of Length is 0.00%
## The missing percentage of Popularity is 0.00%
## The missing percentage of Acousticness is 0.00%
## The missing percentage of Danceability is 0.00%
## The missing percentage of Energy is 0.00%
## The missing percentage of Instrumentalness is 0.00%
## The missing percentage of Liveness is 0.00%
```

```
## The missing percentage of Loudness is 0.00%
## The missing percentage of Speechiness is 0.00%
## The missing percentage of Tempo is 0.00%
## The missing percentage of Time_signature is 0.00%
## The missing percentage of key is 0.00%
## The missing percentage of valence is 0.00%
## The missing percentage of genre is 0.00%
```

Feature Distribution

```
df_features = subset(data, select = -c(Album,Release_date,Artist,album_id,Name,track_id,Popularity) )
df_features <- na.omit(df_features)

n_rows <- nrow(df_features)
n_cols <- ncol(df_features)
cat("There are", n_rows, "rows and", n_cols, "columns\n")
```

```
## There are 7262 rows and 13 columns
```

```
summary_df <- t(summary(df_features))
cols <- colnames(df_features)
print(summary_df)
```

```
##
##     Length       Min.   :  13855     1st Qu.: 172080     Median : 214449
##  Acousticness    Min.   :0.0000018   1st Qu.:0.0274000   Median :0.1970000
##  Danceability    Min.   :0.0000      1st Qu.:0.5010      Median :0.6170
##     Energy       Min.   :0.00177     1st Qu.:0.42800     Median :0.62600
## Instrumentalness Min.   :0.000000    1st Qu.:0.000000    Median :0.000233
##    Liveness      Min.   :0.0131      1st Qu.:0.0970      Median :0.1260
##    Loudness      Min.   :-34.149     1st Qu.:-11.552     Median : -8.242
##  Speechiness     Min.   :0.00000     1st Qu.:0.03570     Median :0.04980
##     Tempo        Min.   :  0.00      1st Qu.: 97.78      Median :120.00
## Time_signature   Min.   :0.000       1st Qu.:4.000       Median :4.000
##      key         Min.   : 0.000      1st Qu.: 2.000      Median : 5.000
##    valence       Min.   :0.0000      1st Qu.:0.3190      Median :0.5170
##    genre         Length:7262         Class :character    Mode  :character
##
##     Length       Mean   : 235801     3rd Qu.: 271237     Max.   :1606920
##  Acousticness    Mean   :0.3310017   3rd Qu.:0.6037500   Max.   :0.9960000
##  Danceability    Mean   :0.6063      3rd Qu.:0.7240      Max.   :0.9700
##     Energy       Mean   :0.59667     3rd Qu.:0.80000     Max.   :0.99900
## Instrumentalness Mean   :0.215055    3rd Qu.:0.378750    Max.   :0.984000
##    Liveness      Mean   :0.1954      3rd Qu.:0.2410      Max.   :0.9920
##    Loudness      Mean   : -9.317     3rd Qu.: -5.976     Max.   :  1.103
##  Speechiness     Mean   :0.09493     3rd Qu.:0.09730     Max.   :0.95800
##     Tempo        Mean   :120.01      3rd Qu.:137.02      Max.   :249.85
## Time_signature   Mean   :3.908       3rd Qu.:4.000       Max.   :5.000
##      key         Mean   : 5.356      3rd Qu.: 9.000      Max.   :11.000
##    valence       Mean   :0.5131      3rd Qu.:0.7147      Max.   :0.9860
##    genre
```

*To address our two primary research objectives, we have systematically structured our approach into EDA (visualization), feature selection and modeling. Each phase is conducted separately for both objectives.

6. Objective 1: Predict song popularity by audio features from Spotify data

6.1. EDA

6.1.1. Predict Varibales Distribution

```
df_y=data$Popularity
summary_dfy <- t(summary(df_y))
cols <- colnames(df_y)
print(summary_dfy)
```

```
##       Min. 1st Qu. Median  Mean 3rd Qu.  Max.
## [1,]  0.00    0.00   3.00 16.59   24.00 96.00
```

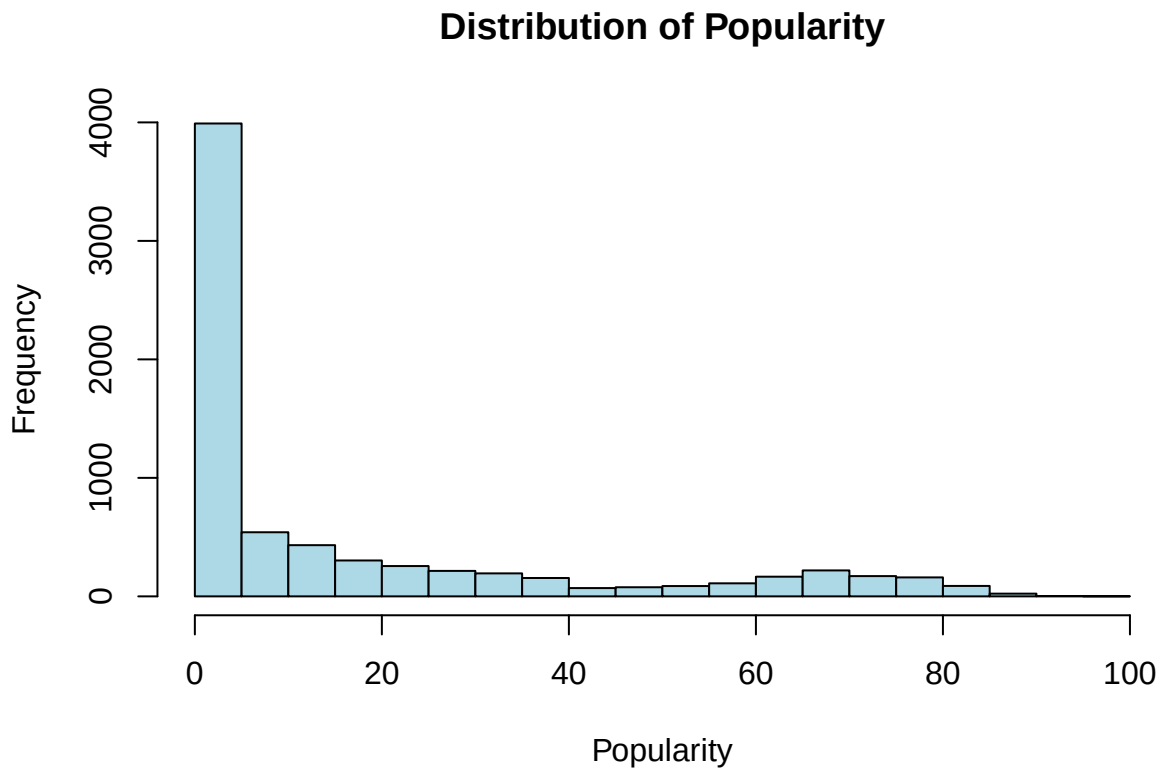
```
# Calculate the mean of popularity by different genres
mean_by_category <- data %>%
                    group_by(genre) %>%
                    summarise(mean_value = mean(Popularity, na.rm = TRUE))

# number of rows in each genre
rows <- data %>%  count(genre)

print(mean_by_category)
```

```
## # A tibble: 6 x 2
##   genre      mean_value
##   <chr>           <dbl>
## 1 country         11.9
## 2 electronic      12.5
## 3 hiphop          23.5
## 4 jazz             7.52
## 5 pop             21.1
## 6 rock            22.5
```

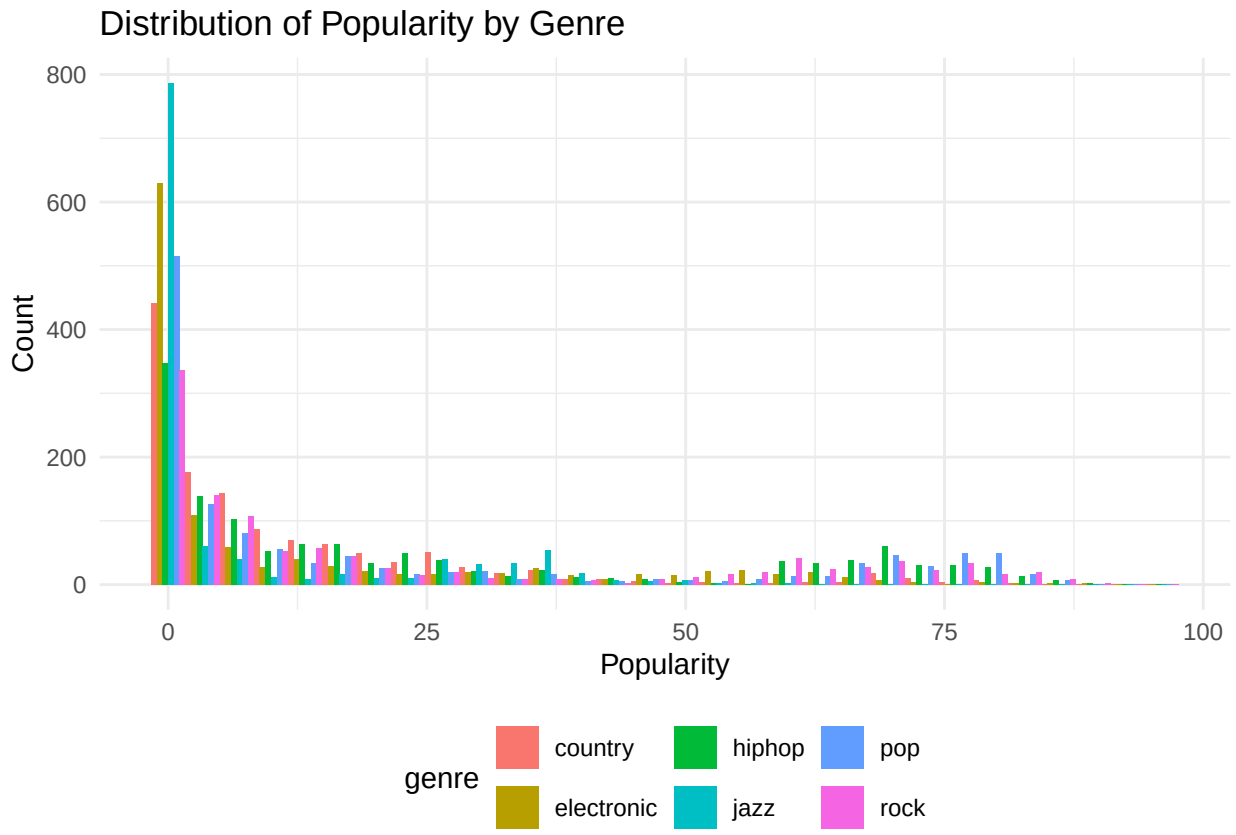
```
print(rows)
```

```
##        genre    n
## 1    country 1274
## 2 electronic 1178
## 3     hiphop 1268
## 4       jazz 1150
## 5        pop 1268
## 6       rock 1124
```

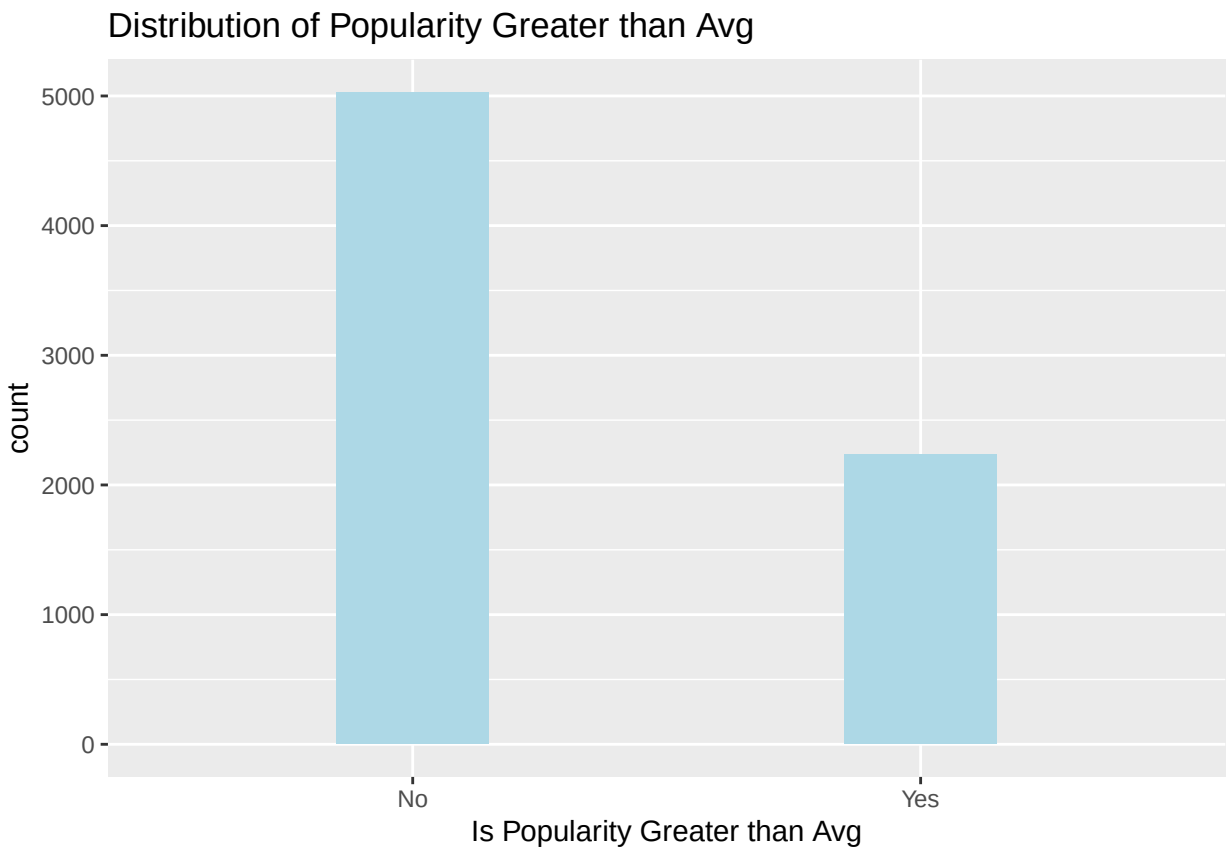
```r
# Plot distributions of numerical features
hist(df_y, col = "#ADD8E6",main="Distribution of Popularity", xlab="Popularity")
```




```r
# Separate histograms for each genre
# make genre as factor
data$genre <- as.factor(data$genre)

ggplot(data, aes(x = Popularity, fill = genre)) +
  geom_histogram(position = "dodge", bins = 30) +
  theme_minimal() +
  labs(x = "Popularity", y = "Count", title = "Distribution of Popularity by Genre") +
  theme(legend.position = "bottom")
```

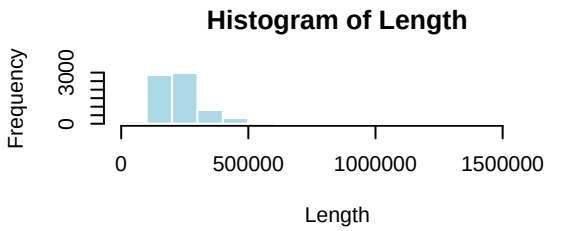


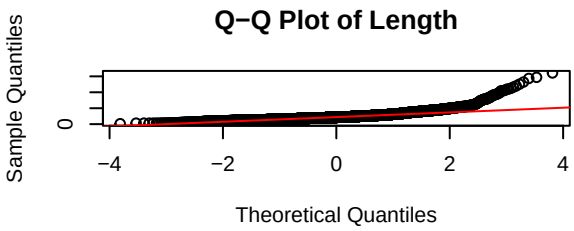

```
ggplot(data = data) +stat_count ( aes(x= ifelse(data$Popularity > 16, "Yes", "No")) ,  fill = "lightblu
labs(title = "Distribution of Popularity Greater than Avg",x = "Is Popularity Greater than Avg")
```

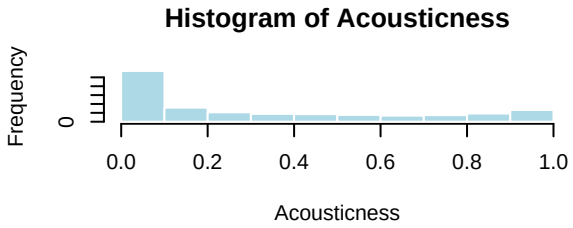


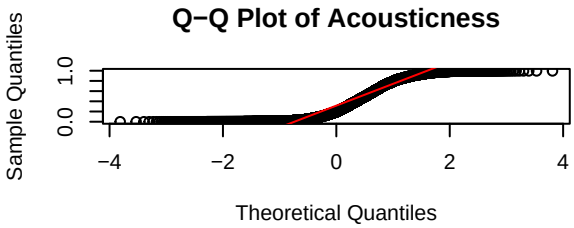
6.1.2. Feature Distribution Visualization

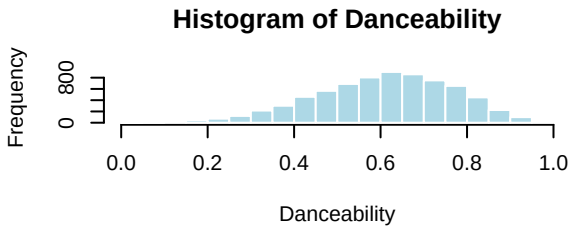
```
# Filter cols to include only numeric columns to avoid errors in plotting
numeric_cols <- sapply(df_features, is.numeric)
cols <- names(df_features)[numeric_cols]


par(mfrow = c(3, 2))

# Loop through the numeric columns and create plots
for (col in cols) {
  # Histogram plot
  hist(df_features[[col]], main = paste("Histogram of", col), xlab = col, col = "lightblue", border = "
  # Q-Q plot
  qqnorm(df_features[[col]], main = paste("Q-Q Plot of", col))
  qqline(df_features[[col]], col = "red")
}
```

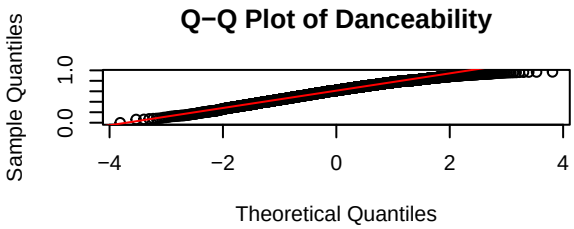

Histogram of Length
Frequency
0
3000
0
500000
1000000
1500000
Length

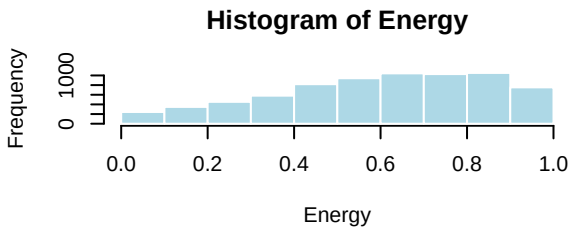

Q−Q Plot of Length
Sample Quantiles
0
−4
−2
0
2
4
Theoretical Quantiles

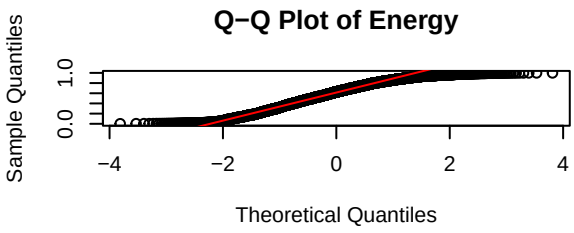

Histogram of Acousticness
Frequency
0
0.0
0.2
0.4
0.6
0.8
1.0
Acousticness

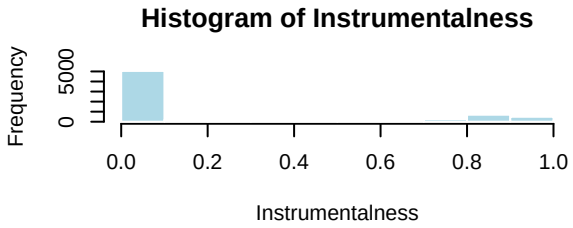

Q−Q Plot of Acousticness
Sample Quantiles
0.0
1.0
−4
−2
0
2
4
Theoretical Quantiles

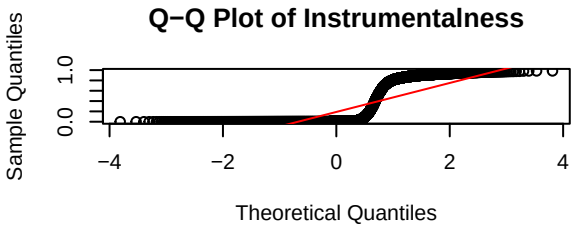

Histogram of Danceability
Frequency
0
800
0.0
0.2
0.4
0.6
0.8
1.0
Danceability

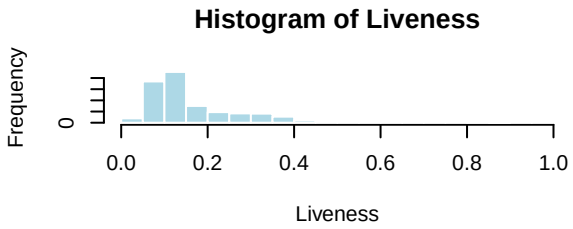

Q−Q Plot of Danceability
Sample Quantiles
0.0
1.0
−4
−2
0
2
4
Theoretical Quantiles

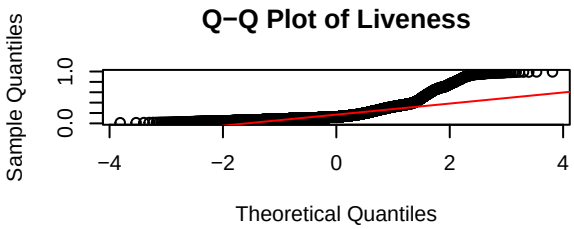

Histogram of Energy
Frequency
0
1000
0.0
0.2
0.4
0.6
0.8
1.0
Energy

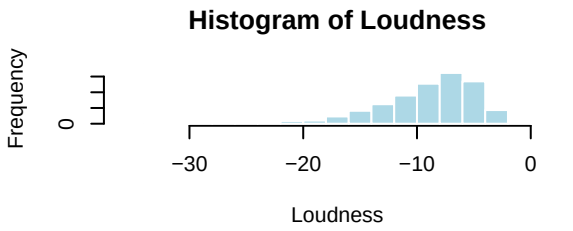

Q−Q Plot of Energy
Sample Quantiles
0.0
1.0
−4
−2
0
2
4
Theoretical Quantiles

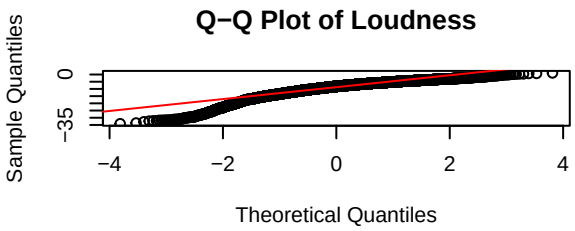

Histogram of Instrumentalness
Frequency
0
5000
0.0
0.2
0.4
0.6
0.8
1.0
Instrumentalness

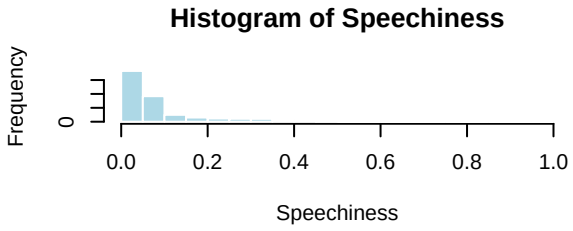

Q−Q Plot of Instrumentalness
Sample Quantiles
0.0
1.0
−4
−2
0
2
4
Theoretical Quantiles

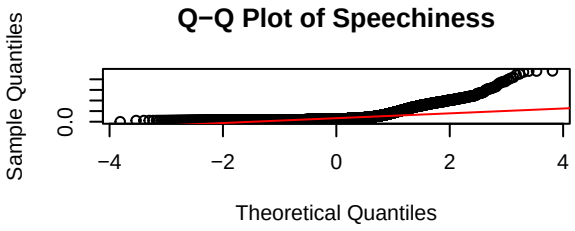

Histogram of Liveness
Frequency
0
0.0
0.2
0.4
0.6
0.8
1.0
Liveness

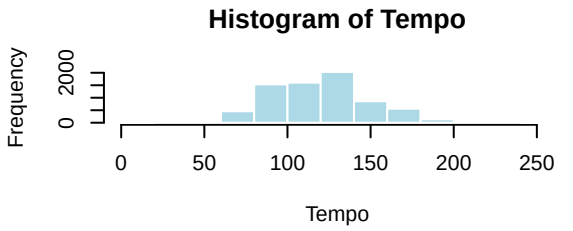

Q−Q Plot of Liveness
Sample Quantiles
0.0
1.0
−4
−2
0
2
4
Theoretical Quantiles

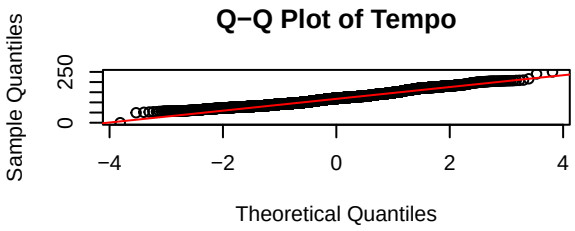

Histogram of Loudness
Frequency
0
−30
−20
−10
0
Loudness

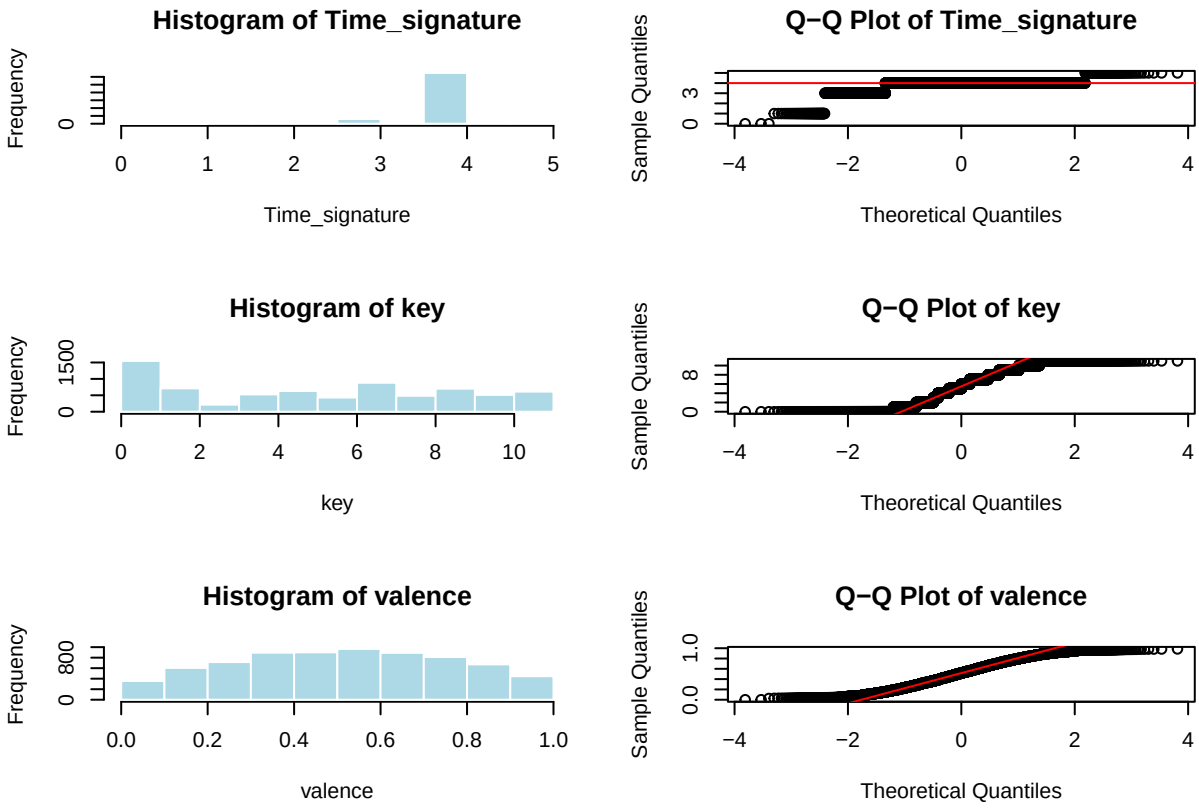

Q−Q Plot of Loudness
Sample Quantiles
0
−35
−4
−2
0
2
4
Theoretical Quantiles


Histogram of Speechiness
Frequency
0
0.0
0.2
0.4
0.6
0.8
1.0
Speechiness


Q−Q Plot of Speechiness
Sample Quantiles
0.0
−4
−2
0
2
4
Theoretical Quantiles

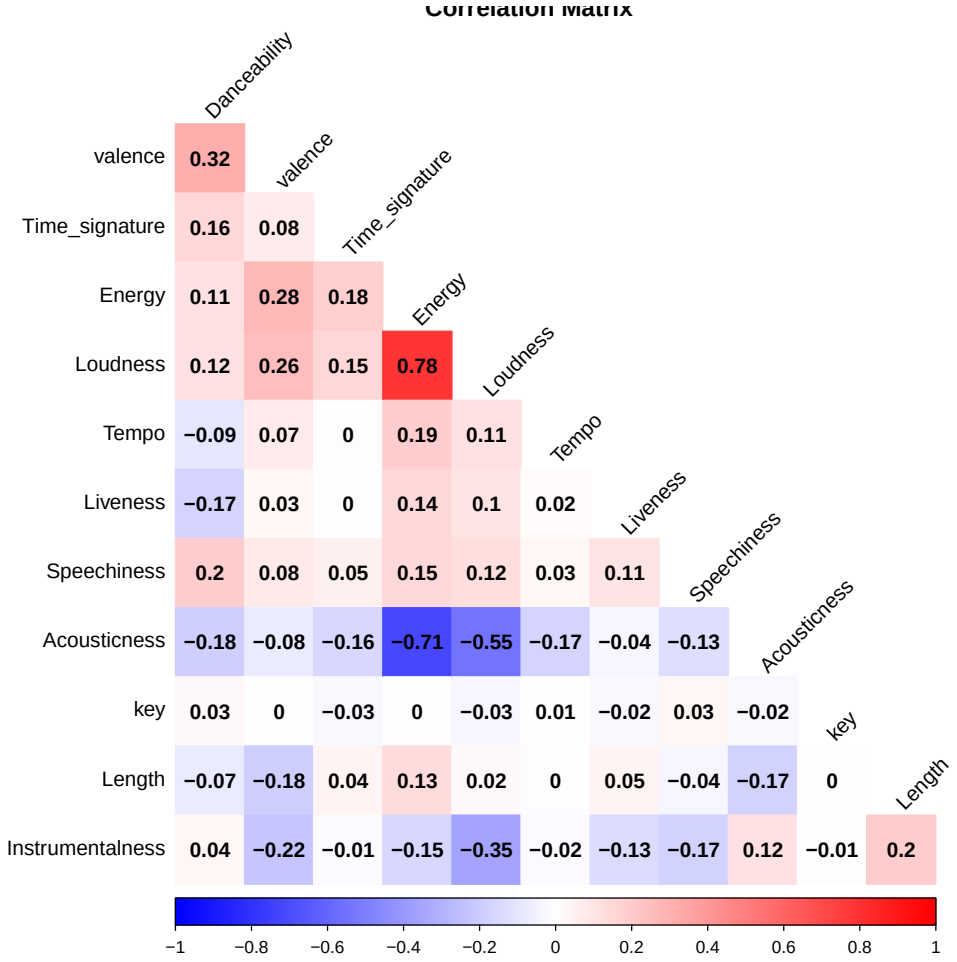

Histogram of Tempo
Frequency
0
2000
0
50
100
150
200
250
Tempo


Q−Q Plot of Tempo
Sample Quantiles
0
250
−4
−2
0
2
4
Theoretical Quantiles



6.1.3. Check Correlation

```
library(corrplot)
numeric_df <- df_features[sapply(df_features, is.numeric)]
correlation_mat <- cor(numeric_df, use = "complete.obs")
corrplot(correlation_mat, method = "color", type = "lower", # Focusing on the lower triangle
         order = "hclust",
         addCoef.col = "black",
         tl.col = "black", tl.srt = 45,
         diag = FALSE,
         na.label = "",
         col = colorRampPalette(c("blue", "white", "red"))(200),
         title = "Correlation Matrix"
         )
```



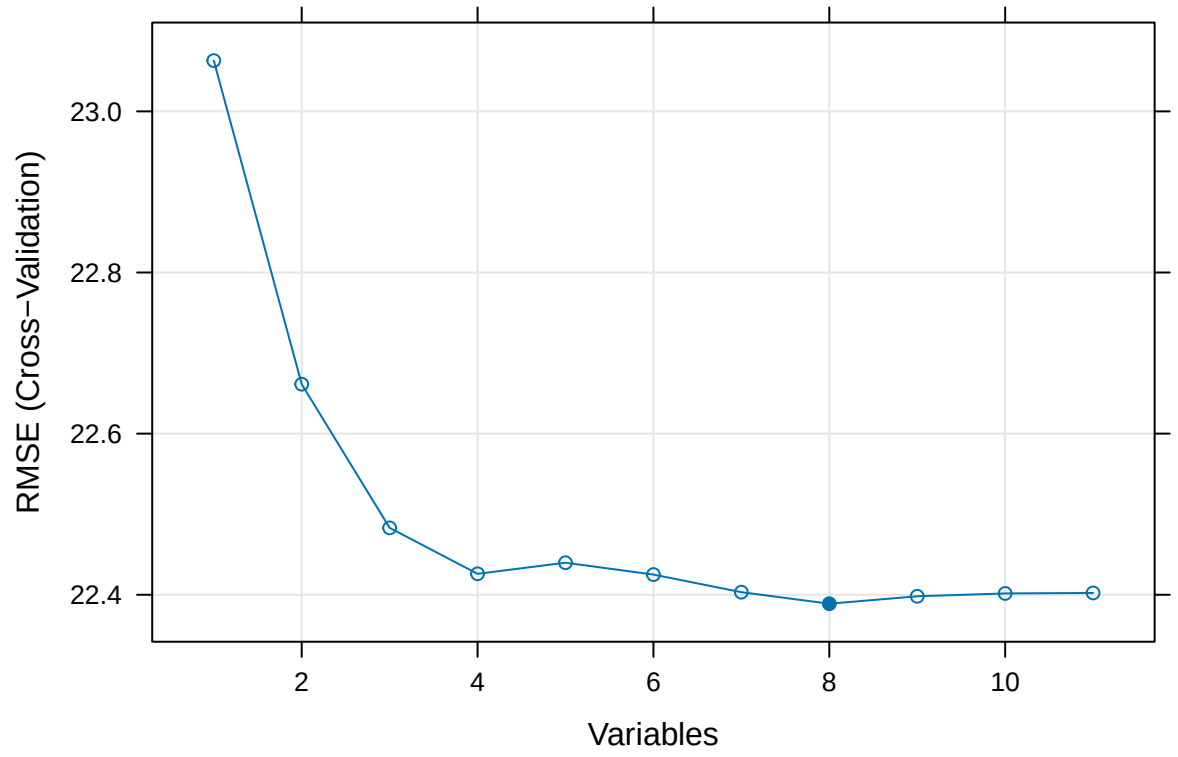
According to the correlation diagram, we found that the energy column has the high correlation with other variables, and we decide to drop it.

```
#drop energy
numeric_df <- numeric_df[, !(names(numeric_df) %in% c("Energy"))]
```

6.2 Regression: Feature Selection

```
library(caret)

set.seed(123)

X_scaled <- as.data.frame(scale(numeric_df))
y <- df_y

scale <- data.frame(X_scaled, Popularity = y)

control <- rfeControl(functions=lmFuncs, method="cv", number=10)

results <- rfe(x=scale[, -ncol(scale)], y=scale$Popularity, sizes=1:ncol(scale[, -ncol(scale)]), rfeCon
```

```r
plot(results, type=c("o", "g"))
```



Select the best Variables

```r
# The best subset of variables is in
bestVars <- results$optVariables
print(bestVars)
```

```
## [1] "Acousticness"     "Instrumentalness" "Loudness"         "Danceability"
## [5] "Liveness"         "valence"          "Length"           "Time_signature"
```

6.3 Regression: Build Model

```r
finalModel <- lm(Popularity ~ ., data=data[, c(bestVars, "Popularity")])
# Summary of the final model
summary(finalModel)
```

```
##
## Call:
## lm(formula = Popularity ~ ., data = data[, c(bestVars, "Popularity")])
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -30.267 -16.036  -7.043   7.825  74.447
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       2.261e+01  2.971e+00   7.610 3.08e-14 ***
## Acousticness     -1.397e+01  9.756e-01 -14.323  < 2e-16 ***
## Instrumentalness -1.039e+01  8.415e-01 -12.350  < 2e-16 ***
## Loudness          7.268e-01  7.095e-02  10.244  < 2e-16 ***
## Danceability      1.004e+01  1.826e+00   5.501 3.91e-08 ***
## Liveness         -5.334e+00  1.592e+00  -3.350 0.000813 ***
## valence          -3.409e+00  1.180e+00  -2.889 0.003874 **
## Length           -7.492e-06  2.603e-06  -2.878 0.004009 **
## Time_signature    1.556e+00  6.679e-01   2.330 0.019822 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22.39 on 7253 degrees of freedom
## Multiple R-squared:  0.1423, Adjusted R-squared:  0.1413
## F-statistic: 150.4 on 8 and 7253 DF,  p-value: < 2.2e-16
```

Our first linear regression model. The minimum residual is -30.267, and the maximum is 74.447 The Adjusted R-squared is really low. This model does not have a high predictive power,an alternative models is need for research.

6.4 Classification: Feature Selection

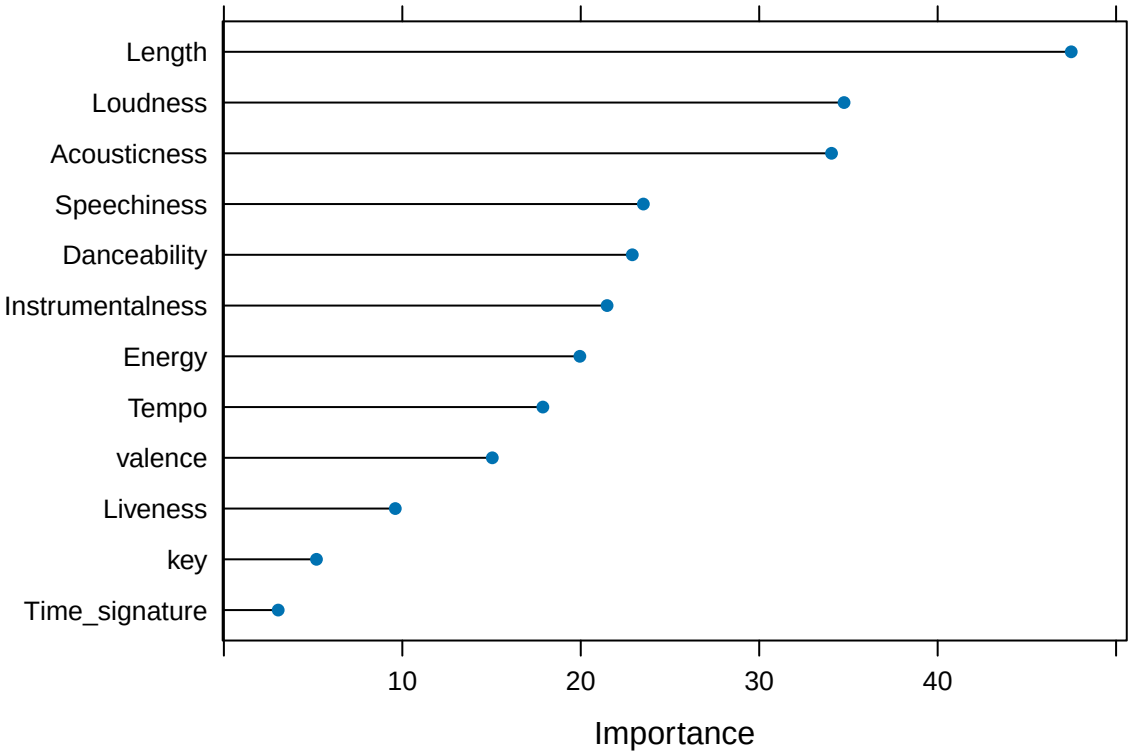
Our Classification model mutates popularity base on its average. If a popularity value is greater than 16(the average of the variable), it returns a 1. If it is smaller than 16, it returns a 0.

Add if_popularity, should return 1 and 0s

```
df_y2 <- as.data.frame(as.factor(ifelse(data$Popularity > 16, 1, 0)))
names(df_y2)[names(df_y2) == "as.factor(ifelse(data$Popularity > 16, 1, 0))"] <- "popularity_01"
df_features2=subset(df_features, select = -c(genre))
df_model <- cbind(df_y2, df_features2)
```

Before building models, we identify the most relevant features for predicting our target variable. This will take roughly 10min to run.

```
library(caret)
set.seed(123)

# Train a Random Forest model to assess feature importance
control = trainControl(method = "cv", number = 5)
model <- train(popularity_01~., data=df_model, method="rf", importance=TRUE, trControl = control)

# Plot the variable importance
# Extracting variable importance
importance <- varImp(model, scale=FALSE)

# Plotting variable importance
plot(importance)
```

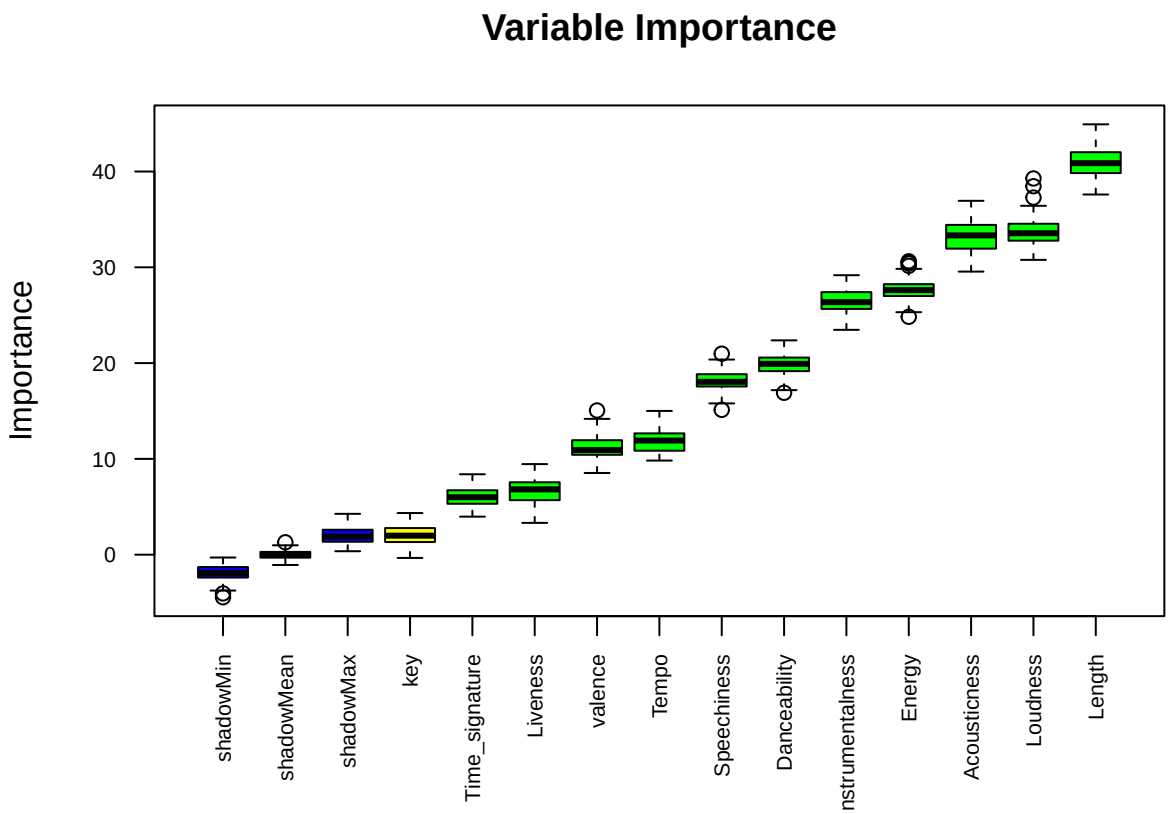


This chunk runs on High CPU occupation

```
library(randomForest)
library(Boruta)
# Run Boruta
set.seed(123)  # For reproducibility
boruta_output <- Boruta(popularity_01 ~ ., data = df_model, doTrace = 0)

# Print the results
print(boruta_output)
```

```
## Boruta performed 99 iterations in 1.596476 mins.
##  11 attributes confirmed important: Acousticness, Danceability, Energy,
## Instrumentalness, Length and 6 more;
##  No attributes deemed unimportant.
##  1 tentative attributes left: key;
```

```
# Plot the results for visualization
plot(boruta_output, cex.axis=.7, las=2, xlab="", main="Variable Importance")
```




```
# Get the final decision of which variables were confirmed as important
final_vars <- getSelectedAttributes(boruta_output, withTentative = FALSE)
```

List all the improtant varibles

```
final_vars_with_target <- c("popularity_01", final_vars)
selected_features_df <- df_model[, final_vars_with_target]
print(final_vars)
```

```
##  [1] "Length"           "Acousticness"     "Danceability"     "Energy"
##  [5] "Instrumentalness" "Liveness"         "Loudness"         "Speechiness"
##  [9] "Tempo"            "Time_signature"   "valence"
```

6.5 Classification: Build Model

Describe the models you have built, including any assumptions or choices made in the process.

6.5.1. Model 1: Random Forest

```
# Split the data into training and testing sets
index <- createDataPartition(selected_features_df$popularity_01, p=0.8, list=FALSE)
trainData <- selected_features_df[index, ]
```

```r
testData <- selected_features_df[-index, ]

param_grid <- expand.grid(mtry = c(2, 4, 6) )

# Model 1: Random Forest
rfModel <- train(popularity_01 ~ ., data=trainData,method = "rf", trControl = trainControl(method = "cv
rfModel$bestTune
```

```
##   mtry
## 2    4
```

```r
rfModel <- rfModel$finalModel

rfPredictions <- predict(rfModel, newdata=testData)
rfConfMatrix <- confusionMatrix(rfPredictions, testData$popularity_01)
print("Random Forest Model Results:")
```

```
## [1] "Random Forest Model Results:"
```

```r
print(rfConfMatrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 905 295
##          1 100 151
##
##                Accuracy : 0.7278
##                  95% CI : (0.7041, 0.7505)
##     No Information Rate : 0.6926
##     P-Value [Acc > NIR] : 0.001855
##
##                   Kappa : 0.2722
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9005
##             Specificity : 0.3386
##          Pos Pred Value : 0.7542
##          Neg Pred Value : 0.6016
##              Prevalence : 0.6926
##          Detection Rate : 0.6237
##    Detection Prevalence : 0.8270
##       Balanced Accuracy : 0.6195
##
##        'Positive' Class : 0
##
```

Overall, the model demonstrates reasonably good performance in terms of overall accuracy, but there are notable differences in performance between sensitivity and specificity, indicating potential future direction of analysis. This also result the balanced accuracy to be relatively low compare to the accuracy.

6.5.2. Model 2: Generalized Linear Model

```
library(boot)
```

```
##
## Attaching package: 'boot'
```

```
## The following object is masked from 'package:lattice':
##
##     melanoma
```

```
iindex <- createDataPartition(df_model$popularity_01, p=0.8, list=FALSE)
trainData <- df_model[index, ]
testData <- df_model[-index, ]

glmFit <- function(data, indices) {
  fit <- glm(popularity_01 ~ ., data=data[indices, ], family=binomial())
  return(fit)
}

glmModel <- glm(popularity_01 ~ ., data=trainData, family=binomial())
cvResults <- cv.glm(trainData, glmModel, K=10)


glmPredictions <- predict(glmModel, newdata=testData, type="response")
glmPredictionsClass <- ifelse(glmPredictions > 0.5, 1, 0)
glmConfMatrix <- confusionMatrix(as.factor(glmPredictionsClass), testData$popularity_01)

print(glmConfMatrix)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 934 340
##          1  71 106
##
##                Accuracy : 0.7167
##                  95% CI : (0.6928, 0.7398)
##     No Information Rate : 0.6926
##     P-Value [Acc > NIR] : 0.0242
##
##                   Kappa : 0.2007
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9294
##             Specificity : 0.2377
##          Pos Pred Value : 0.7331
##          Neg Pred Value : 0.5989
##              Prevalence : 0.6926
```

```
##          Detection Rate : 0.6437
##    Detection Prevalence : 0.8780
##       Balanced Accuracy : 0.5835
##
##        'Positive' Class : 0
##
```

the GLM model exhibits similar patterns to the Random Forest model, with relatively good sensitivity but lower specificity which indicates a tendency to correctly identify positive instances but struggles with accurately identifying negatives.

6.6 Model Selection

```
# Random Forest Metrics
rfAccuracy <- rfConfMatrix$overall['Accuracy']
rfSensitivity <- rfConfMatrix$byClass['Sensitivity']
rfSpecificity <- rfConfMatrix$byClass['Specificity']
rfBalanced = rfConfMatrix$byClass['Balanced Accuracy']
# GLM Metrics
glmAccuracy <- glmConfMatrix$overall['Accuracy']
glmSensitivity <- glmConfMatrix$byClass['Sensitivity']
glmSpecificity <- glmConfMatrix$byClass['Specificity']
glmBalanced = glmConfMatrix$byClass['Balanced Accuracy']
# Print the metrics
print(paste("Random Forest Accuracy:", rfAccuracy))
```

```
## [1] "Random Forest Accuracy: 0.727773949000689"
```

```
print(paste("Random Forest Sensitivity:", rfSensitivity))
```

```
## [1] "Random Forest Sensitivity: 0.900497512437811"
```

```
print(paste("Random Forest Specificity:", rfSpecificity))
```

```
## [1] "Random Forest Specificity: 0.338565022421525"
```

```
print(paste("Random Forest Balanced Accuracy:", rfBalanced))
```

```
## [1] "Random Forest Balanced Accuracy: 0.619531267429668"
```

```
print(paste("GLM Accuracy:", glmAccuracy))
```

```
## [1] "GLM Accuracy: 0.716747070985527"
```

```
print(paste("GLM Sensitivity:", glmSensitivity))
```

```
## [1] "GLM Sensitivity: 0.929353233830846"
```

```r
print(paste("GLM Specificity:", glmSpecificity))
```

```
## [1] "GLM Specificity: 0.237668161434978"
```

```r
print(paste("GLM Balanced Accuracy:", glmBalanced))
```

```
## [1] "GLM Balanced Accuracy: 0.583510697632912"
```

```r
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
# Random Forest AUC
rfProbabilities <- predict(rfModel, newdata=testData, type="prob")
rfROC <- roc(response=testData$popularity_01, predictor=rfProbabilities[,2])
```

```
## Setting levels: control = 0, case = 1

## Setting direction: controls < cases
```

```r
rfAUC <- auc(rfROC)

# GLM AUC
glmProbabilities <- predict(glmModel, newdata=testData, type="response")
glmROC <- roc(response=testData$popularity_01, predictor=glmProbabilities)
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
glmAUC <- auc(glmROC)

# Print AUC values
print(paste("Random Forest AUC:", rfAUC))
```

```
## [1] "Random Forest AUC: 0.762561631305357"
```

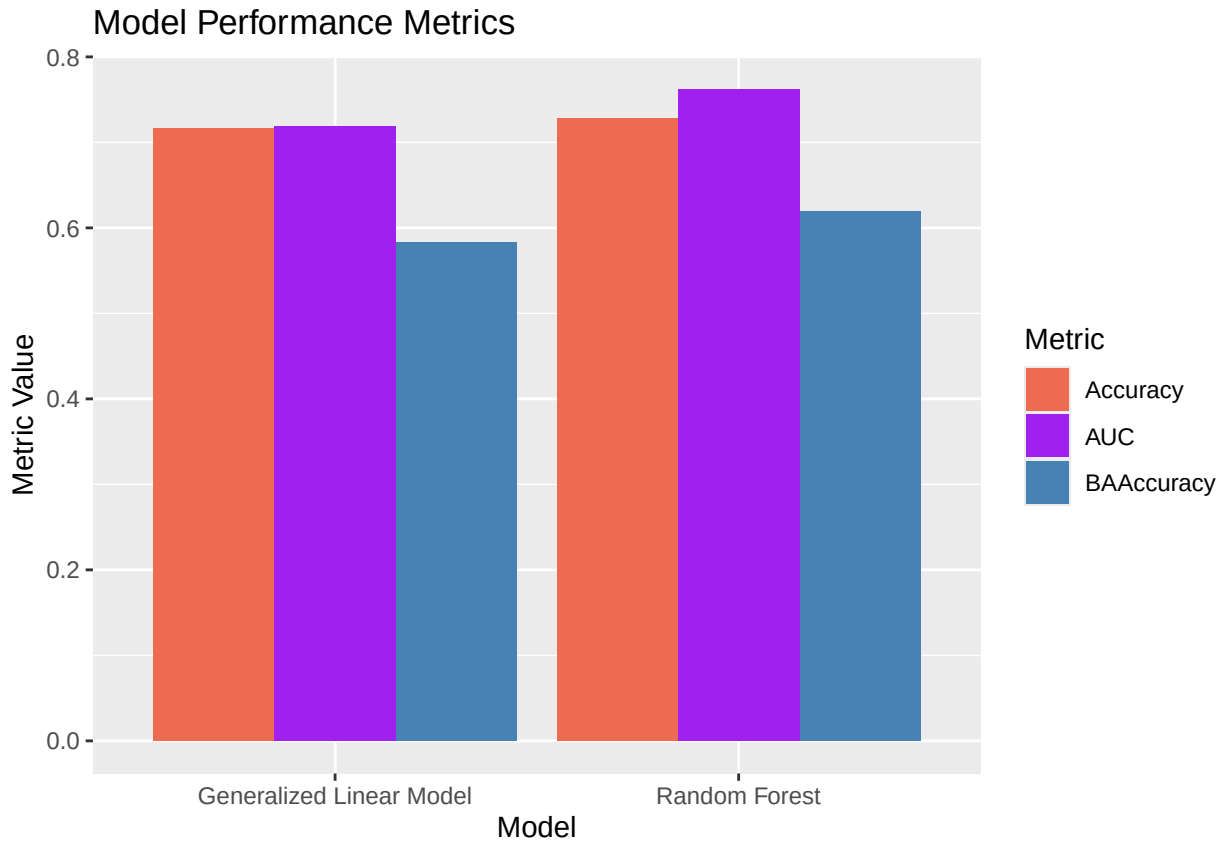
```r
print(paste("GLM AUC:", glmAUC))
```

```
## [1] "GLM AUC: 0.718577516007407"
```

```r
print(glmROC)
```

```
##
## Call:
## roc.default(response = testData$popularity_01, predictor = glmProbabilities)
##
## Data: glmProbabilities in 1005 controls (testData$popularity_01 0) < 446 cases (testData$popularity_
## Area under the curve: 0.7186
```

```r
data_for_plot =  data.frame(Model = c("Random Forest", "Generalized Linear Model"),
 Accuracy = c(rfAccuracy,glmAccuracy), BAAccuracy = c(rfBalanced,glmBalanced), AUC = c(auc(rfROC), auc(g
df_long <- pivot_longer(data_for_plot, cols = c(Accuracy, BAAccuracy, AUC), names_to = "Metric", values_
ggplot(df_long, aes(x = Model, y = Value, fill = Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(x = "Model", y = "Metric Value", title = "Model Performance Metrics") +
  scale_fill_manual(values = c("Accuracy" = "coral2", "BAAccuracy" = "steelblue", "AUC" = "purple"))
```




```r
# Summary for GLM model
summary(glmModel)
```

```
##
## Call:
## glm(formula = popularity_01 ~ ., family = binomial(), data = trainData)
##
```

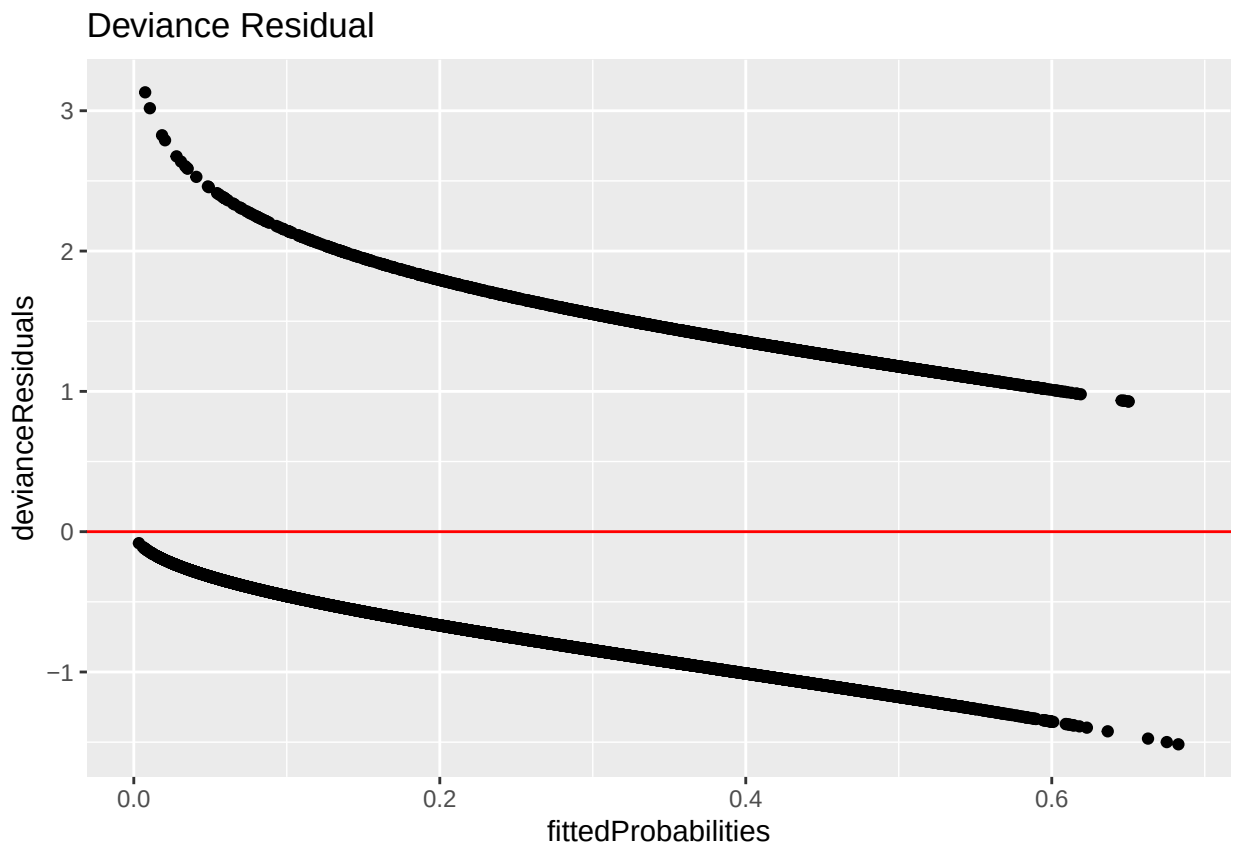
```
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -9.783e-01  5.128e-01  -1.908 0.056412 .
## Length           -7.539e-07  3.538e-07  -2.131 0.033091 *
## Acousticness     -1.303e+00  1.453e-01  -8.966  < 2e-16 ***
## Danceability      8.688e-01  2.212e-01   3.927 8.59e-05 ***
## Energy            2.701e-02  2.625e-01   0.103 0.918060
## Instrumentalness -8.423e-01  1.172e-01  -7.190 6.48e-13 ***
## Liveness         -6.787e-01  1.917e-01  -3.540 0.000400 ***
## Loudness          9.955e-02  1.346e-02   7.396 1.40e-13 ***
## Speechiness       1.159e-01  2.874e-01   0.403 0.686643
## Tempo            -3.927e-04  1.133e-03  -0.347 0.728940
## Time_signature    3.840e-01  1.027e-01   3.741 0.000184 ***
## key               1.797e-04  8.413e-03   0.021 0.982959
## valence          -3.592e-01  1.420e-01  -2.530 0.011410 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 7173.6  on 5810  degrees of freedom
## Residual deviance: 6432.2  on 5798  degrees of freedom
## AIC: 6458.2
##
## Number of Fisher Scoring iterations: 5
```

Length, Acousticeness, Danceability, Instrumentalness, Liveness, Loudness, Time_Signature and valence are important predictors of the outcome variable.

6.7 Other features

```r
# Assuming logistic regression model

# Calculating fitted probabilities
fittedProbabilities <- predict(glmModel, type = "response")
# Extracting deviance residuals
devianceResiduals <- residuals(glmModel, type = "deviance")


# Plotting deviance residuals against fitted probabilities
ggplot() +geom_point(aes( x = fittedProbabilities, y = devianceResiduals)) + geom_abline(h= 0,slope = 0
```

```
## Warning in geom_abline(h = 0, slope = 0, col = "red"): Ignoring unknown
## parameters: 'h'
```

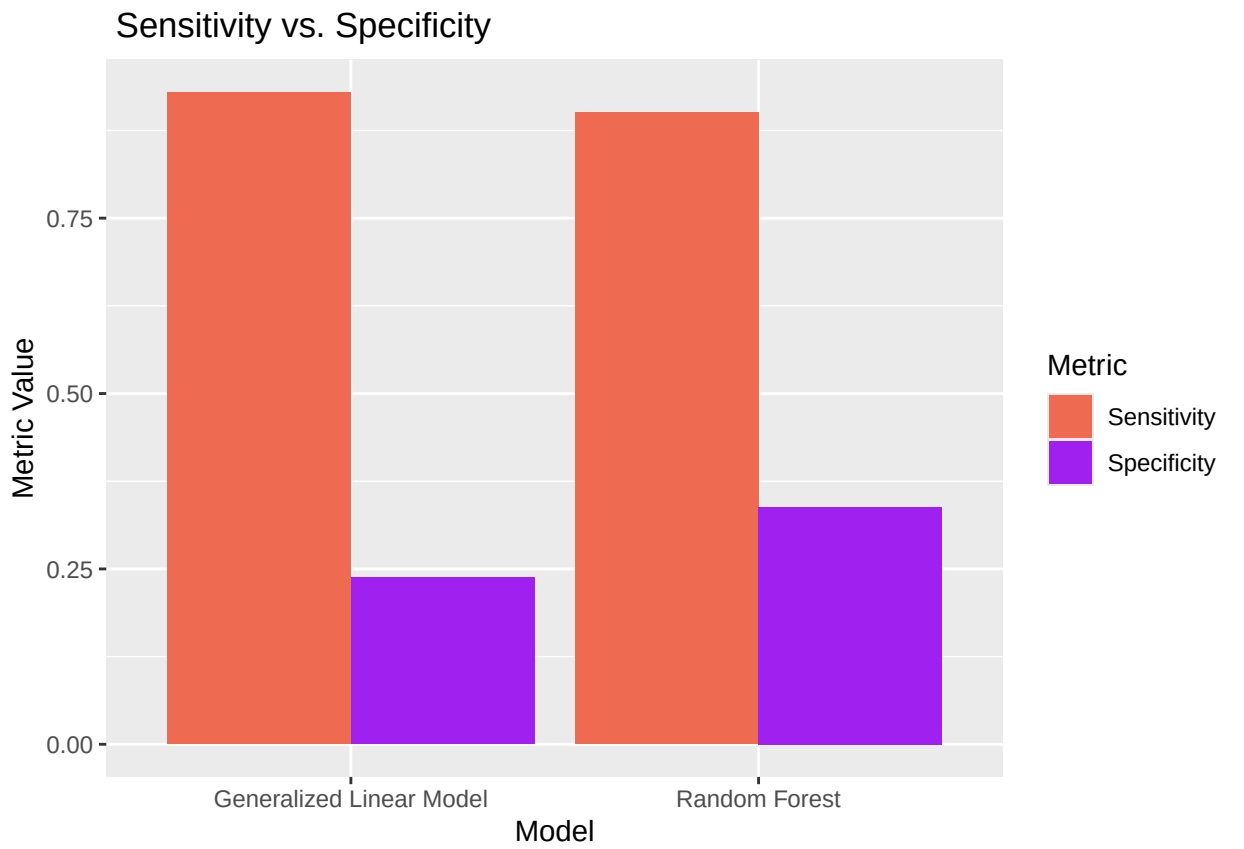


This plot can reveal patterns in the residuals, indicating potential issues with the model. We can see the as the fitted probability grows, the model has a lower positive residual, which means the model is better on the assignment on predicting positive class (1). But when as the fitted probability grows, the negative residual also grows. Indicating the model is not doing well on predicting negative class (0).

6.8 Results Analysis

Discuss the results of your models, including any important metrics and how they compare to your objectives.

```
model_metrics <- data.frame(
  Model = c(rep("Random Forest", 2), rep("Generalized Linear Model", 2)),
  Metric = c(rep(c("Sensitivity", "Specificity"), 2)),
  Value = c(rfSensitivity, rfSpecificity, glmSensitivity, glmSpecificity))
ggplot(model_metrics, aes(x = Model, y = Value, fill = Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = " Sensitivity vs. Specificity", y = "Metric Value")+
  scale_fill_manual(values = c("Sensitivity" = "coral2", "Specificity" = "purple"))
```



Our model has a high Sensitivity but a low specificity. It indicates that the model is good at correctly identifying positive cases but tends to incorrectly classify negative cases as positive. Apply to our case, the model is good at predicting popular songs but it's falsely identifying less popular songs with high popularity. The model has a decent accuracy and AUC which indicates certain strengths of it. We need to further refine the model to achieve a better balance between sensitivity and specificity. This could involve adjusting the model's threshold, feature selection, or gathering more balanced datasets.This also makes sense because less popular song are indeed more prevalent than hit songs. For important varibles: Length, Acousticeness, Danceability, Instrumentalness, Liveness, Loudness, Time_Signature, Some of them are very intuitive; Song with more danceability and liveness indicate a certain feature of Pop and electronic songs, and popularity is literally the definition of pop songs. Loudness and liveness are the key feature of Rock and hip-hop songs. Most importantly, Length is a key feature of all songs in the streaming age. A song with longer duration tends to have less streams (fast paced world).

A Reasonable doubt: we have many 0s and low popularity values in the dataset. In fact, the dataset is not balanced, and the number of tracks with popularity values smaller than the average is much higher than the number of tracks with higher popularity. Class imbalance occurs when one class (in this case, tracks with lower popularity) is significantly more prevalent than another class.

7. Objective 2: Predict song genres by audio features from Spotify data

```r
# for the year column, mostly of raw data is in the format of m/d/yyyy, however, some tracks have only
# to make it consistent,we only extract the release year
data$Release_year <- sub(".*([0-9]{4})$", "\\1", data$Release_date)
```

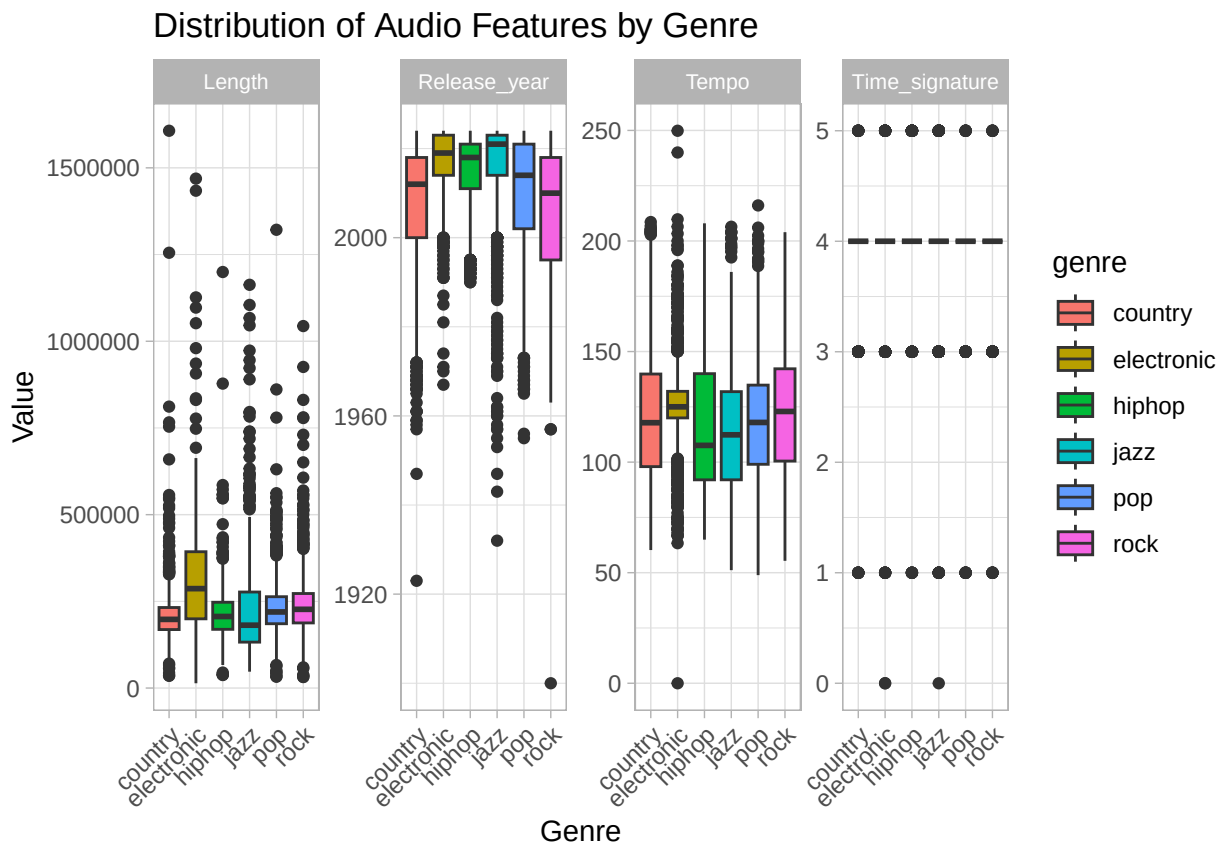
```r
data$Release_year <- as.numeric(data$Release_year)
#make genre a factor
genre_data = data[ , 7:21]
genre_data$genre <- as.factor(genre_data$genre)
genre_data = select(genre_data, - Popularity)
str(genre_data)
```

```
## 'data.frame':    7262 obs. of  14 variables:
##  $ Length          : num  208306 197411 253906 131999 179123 ...
##  $ Acousticness    : num  0.113 0.0965 0.417 0.0642 0.383 0.153 0.0305 0.151 0.0106 0.521 ...
##  $ Danceability    : num  0.762 0.458 0.637 0.892 0.505 0.377 0.676 0.621 0.783 0.846 ...
##  $ Energy          : num  0.692 0.561 0.69 0.503 0.694 0.584 0.926 0.792 0.636 0.652 ...
##  $ Instrumentalness: num  0.00 0.00 0.00 0.00 0.00 0.00 6.58e-04 1.83e-06 0.00 2.33e-04 ...
##  $ Liveness        : num  0.094 0.156 0.211 0.102 0.16 0.0662 0.0771 0.077 0.283 0.0814 ...
##  $ Loudness        : num  -3.97 -4.82 -3.21 -7.09 -5.42 ...
##  $ Speechiness     : num  0.0438 0.0269 0.0693 0.178 0.0295 0.0495 0.0425 0.037 0.0614 0.0333 ...
##  $ Tempo           : num  115 150 140 140 154 ...
##  $ Time_signature  : int  4 3 4 4 4 4 4 4 4 4 ...
##  $ key             : int  5 10 9 6 2 2 0 0 7 7 ...
##  $ valence         : num  0.397 0.206 0.103 0.615 0.406 0.444 0.818 0.375 0.745 0.888 ...
##  $ genre           : Factor w/ 6 levels "country","electronic",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ Release_year    : num  2008 2018 2009 2023 2023 ...
```

7.1 EDA

Firstly, I try to visualize the distribution of audio features across different music genres using **box plots**.

```r
music_data_long <- pivot_longer(genre_data,
                                cols = c(Length, Release_year,Tempo, Time_signature),
                                names_to = "Feature",
                                values_to = "Value")

ggplot(music_data_long, aes(x = genre, y = Value, fill = genre)) +
  geom_boxplot() +
  facet_wrap(~ Feature, scales = "free", ncol = 4) +
  theme_light() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.text.x = element_text(size = 8)) +
  labs(title = "Distribution of Audio Features by Genre",
       x = "Genre", y = "Value")
```



Length: Electronic music (yellow) has the highest median song length, indicating that it typically has longer tracks. Country has the most outliers above the upper whisker, highlighting the presence of significantly longer tracks in this genre.

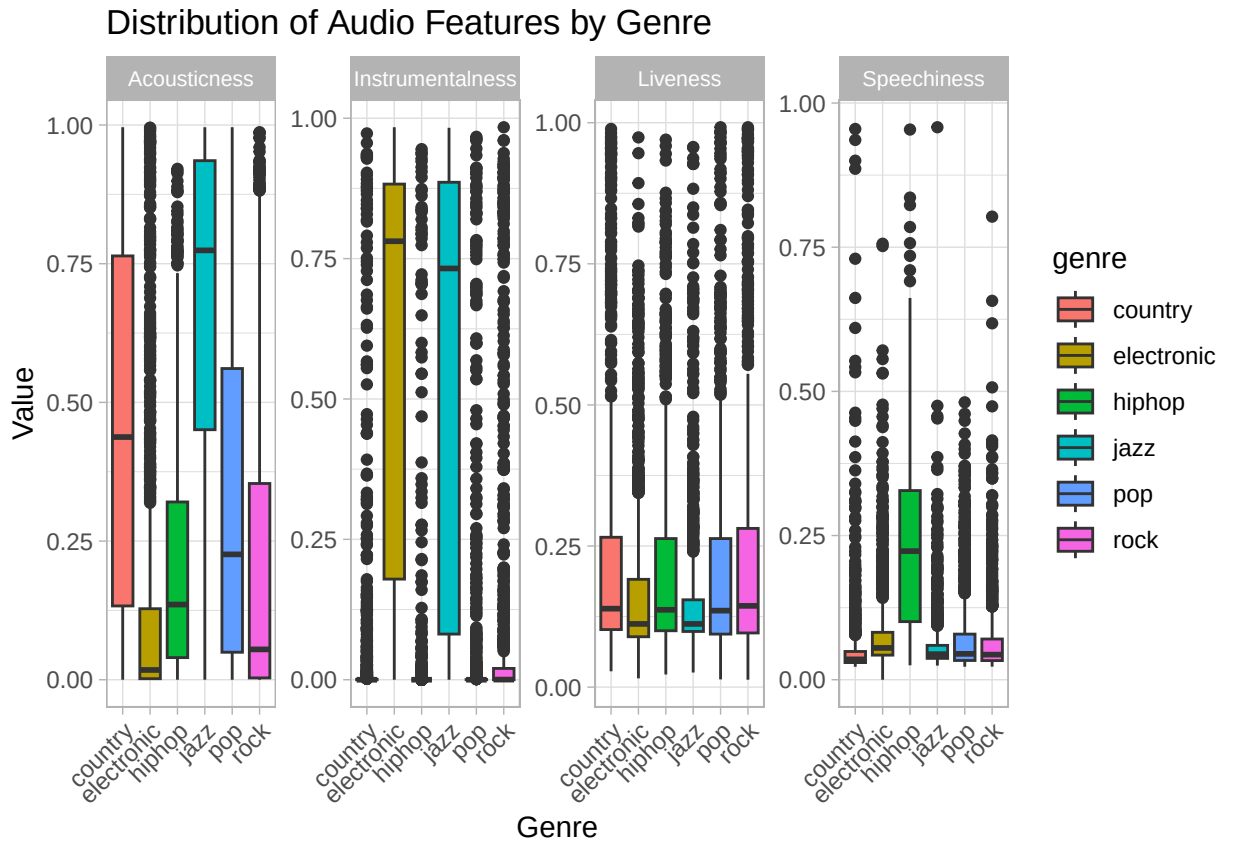
Release_year: The IQR for electronic (yellow) is the most compact, indicating less variation in the release years, while rock (pink) has a broader IQR, indicating more diversity in the release years of its tracks.Rock (pink) reaches back to the earliest years, indicating a history of older releases in this genre.

Tempo: The median tempo is similar across genres, but electronic (yellow) and rock (pink) have slightly higher median tempos, which could indicate a tendency for these genres to have faster beats. And electronic (yellow) has a narrower IQR, indicating more consistency in tempo.

Time_signature: The median for all genres appears to be 4, indicating a standard beat pattern across genres. The IQR for all genres is very narrow or non-existent. The absence of outliers indicates that it is rare for songs in these genres to deviate from the common 4/4 time signature.

```
music_data_long <- pivot_longer(genre_data,
                                cols = c(Acousticness, Instrumentalness,
                                         Liveness, Speechiness),
                                names_to = "Feature",
                                values_to = "Value")

ggplot(music_data_long, aes(x = genre, y = Value, fill = genre)) +
  geom_boxplot() +
  facet_wrap(~ Feature, scales = "free", ncol = 4) +
  theme_light() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.text.x = element_text(size = 8)) +
```

```
  labs(title = "Distribution of Audio Features by Genre",
       x = "Genre", y = "Value")
```



Acousticness: Jazz (light blue) has the highest median, indicating that on average, jazz songs have a higher degree of acousticness. Electronic (yellow) has the lowest median, suggesting that electronic music typically has less acoustic sound. Electronic music have a narrower IQR, suggesting more consistency in their levels of acousticness.

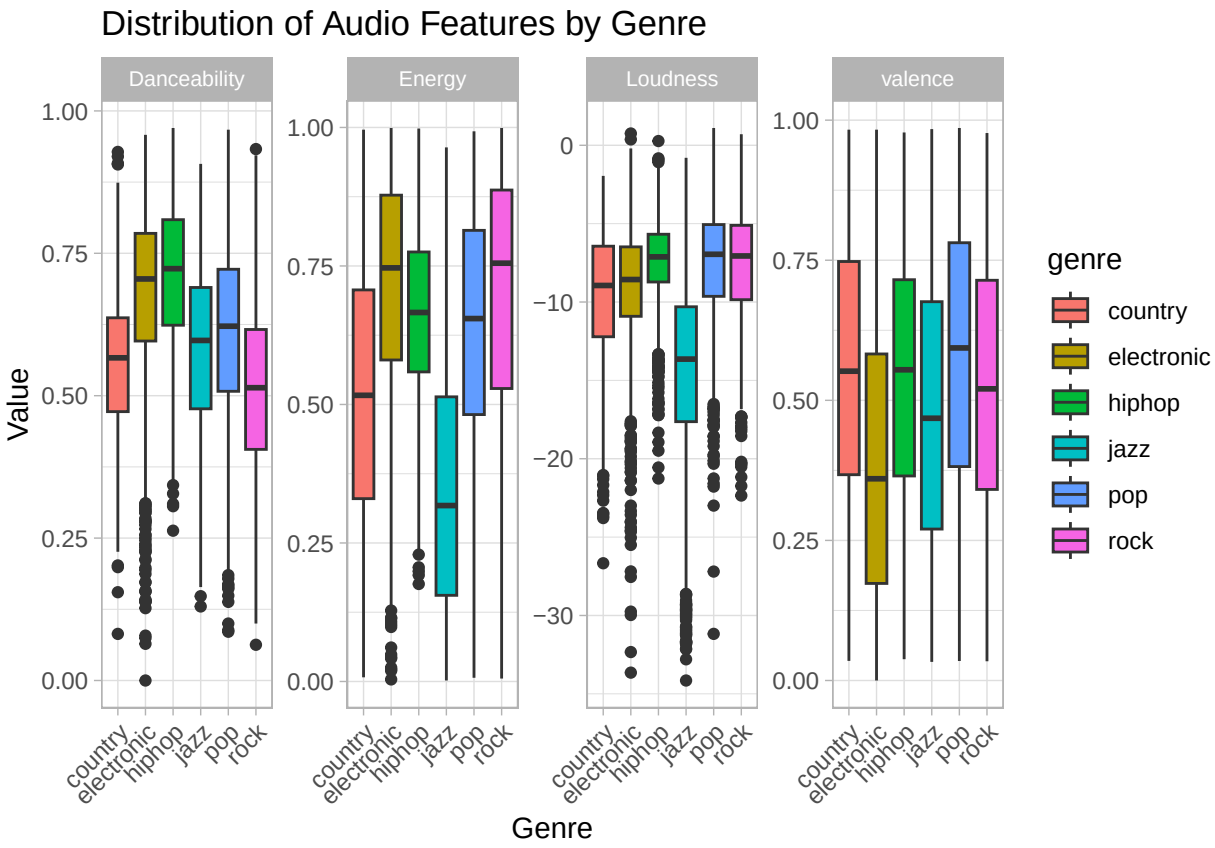
Instrumentalness: The jazz genre has a large IQR, showing a broad range of instrumentalness, suggesting varying levels of instrumental elements in jazz music. Rock and country exhibit a significant number of outliers, emphasizing tracks that are predominantly instrumental.

Liveness: The IQR is narrow for all genres, with rock (pink) being slightly wider, indicating a modest variation in the live aspect of their tracks. There are a few outliers, particularly in jazz and country, showing some tracks with higher liveness.

Speechiness: Hip-hop (green) has the highest median, which is expected due to the spoken word element of the genre. Hip-hop has a wide IQR, indicating a range of speechiness, from songs with more instrumental parts to those with spoken words. Also, Hip-hop shows the longest whiskers, reflecting a broad spread of speechiness in the genre.

```
music_data_long <- pivot_longer(genre_data,
                                cols = c(Danceability, Energy, Loudness,valence),
                                names_to = "Feature",
                                values_to = "Value")

ggplot(music_data_long, aes(x = genre, y = Value, fill = genre)) +
```

```
geom_boxplot() +
facet_wrap(~ Feature, scales = "free", ncol = 4) +
theme_light() +
theme(axis.text.x = element_text(angle = 45, hjust = 1),
      strip.text.x = element_text(size = 8)) +
labs(title = "Distribution of Audio Features by Genre",
     x = "Genre", y = "Value")
```



Danceability: Hip-hop (green) has the highest median, indicating its songs are generally the most danceable. Rock (pink) has the lowest median, suggesting it is less danceable on average than other genres. The whiskers indicate the overall range of danceability, with hip-hop showing a broad spread, indicating diversity in this aspect.

Energy: Jazz have lower median value, which suggests this genre' songs are typically much less energetic. There are outliers for several genres, with electronic (yellow) showing songs with particularly low energy levels.

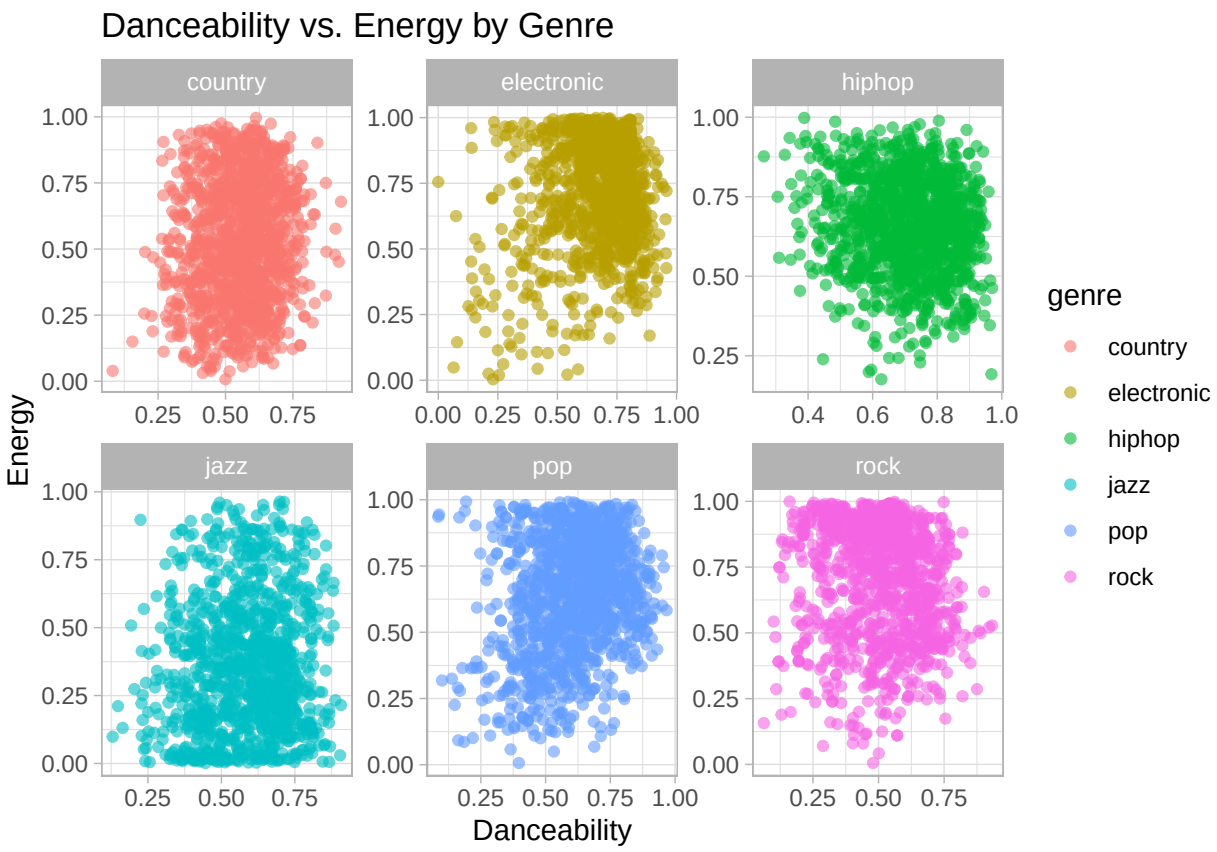
Loudness: The median loudness levels are fairly central across all genres, with jazz (light blue) slightly higher, implying it tends to quieter. Jazz again shows a wide IQR, suggesting a varied loudness range within the genre.

valence: Pop (purple) has one of the highest median valence scores, suggesting its songs often have a more positive mood. In contrast, electronic (yellow) has a lower median, indicating a generally less positive mood.

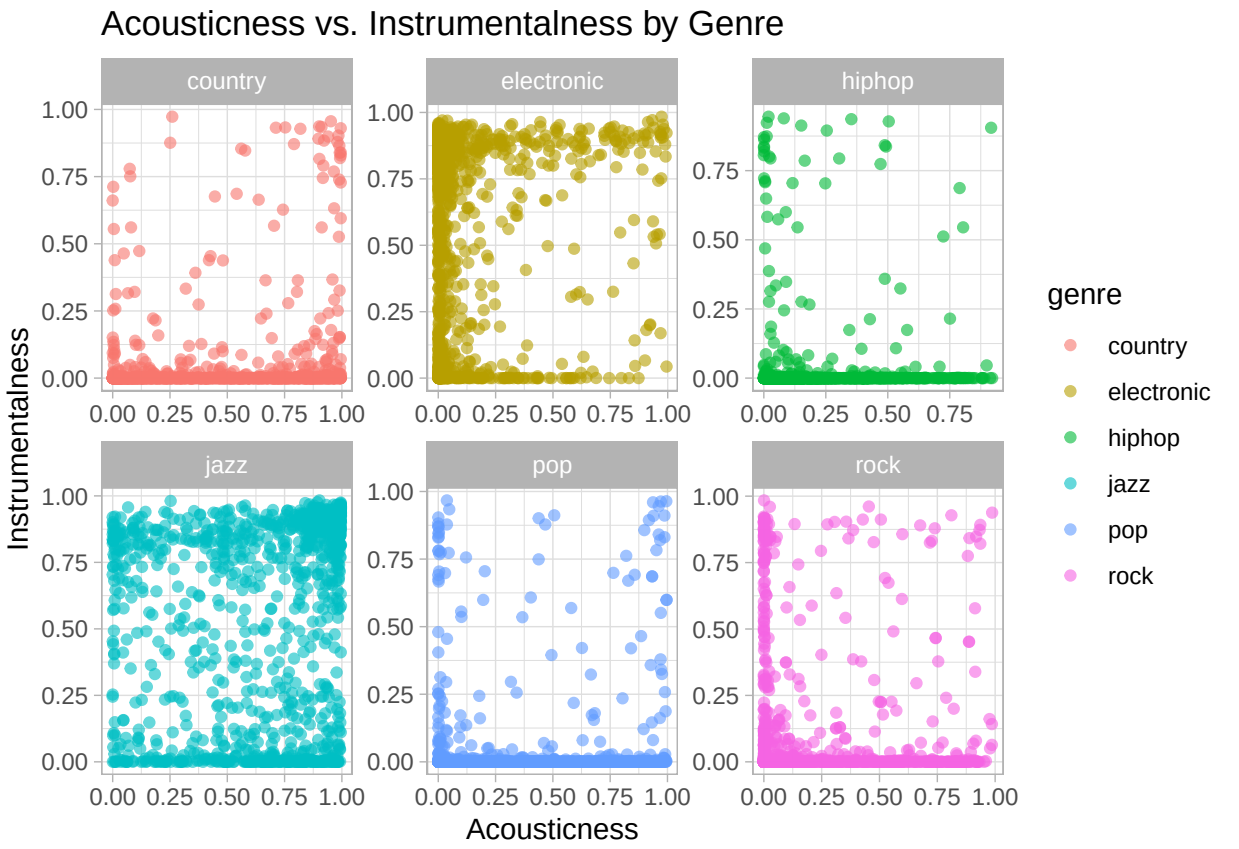
After exploring the relationship between single feature and genre, now we aim to investigate future the relationships between pairs of audio features across different music genres by **scatter plot**.

The plots are designed to uncover potential interaction effects that could be important for data engineering in the following section.

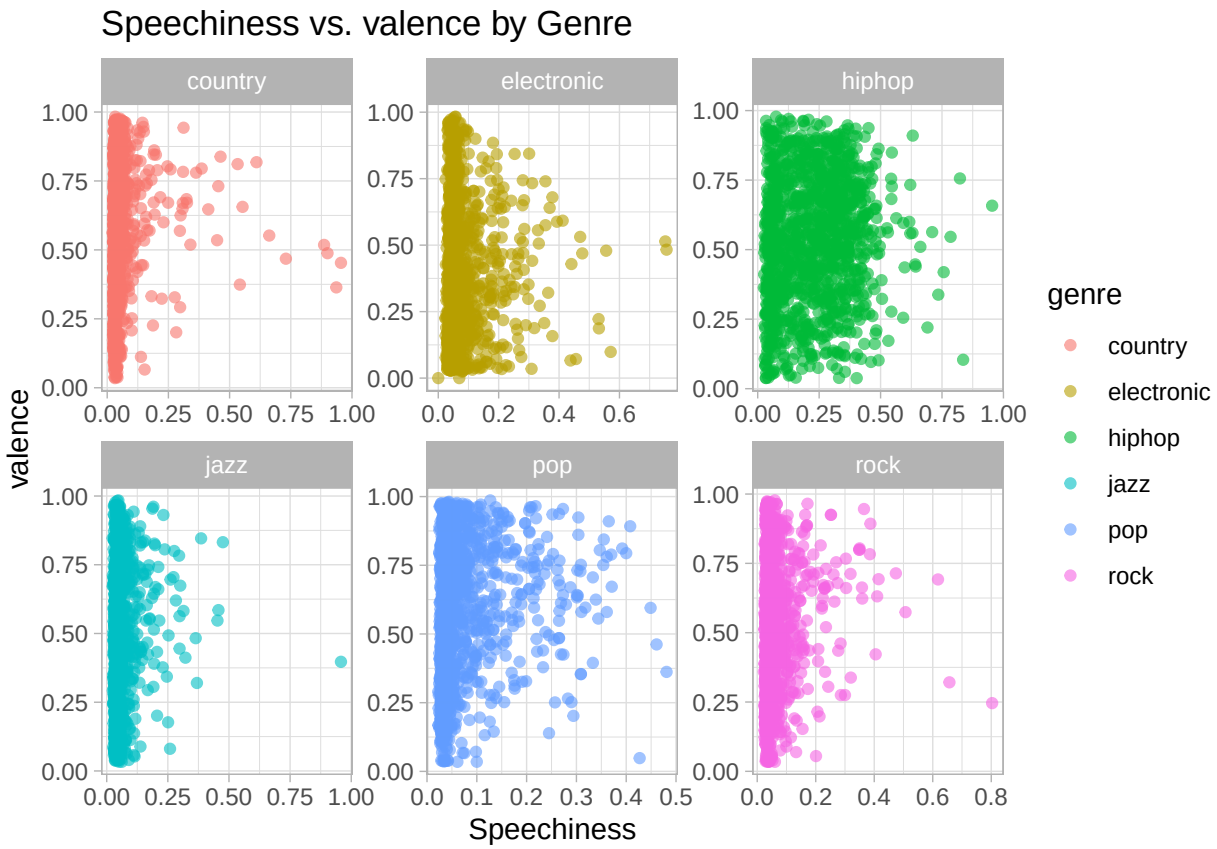
```
ggplot(genre_data, aes(x = Danceability, y = Energy, color = genre)) +
  geom_point(alpha = 0.6) +
  facet_wrap(~ genre, scales = "free") +
  theme_light() +
  labs(title = "Danceability vs. Energy by Genre",
       x = "Danceability", y = "Energy")
```




```
ggplot(genre_data, aes(x = Acousticness, y = Instrumentalness, color = genre)) +
  geom_point(alpha = 0.6) +
  facet_wrap(~ genre, scales = "free") +
  theme_light() +
  labs(title = "Acousticness vs. Instrumentalness by Genre",
       x = "Acousticness", y = "Instrumentalness")
```




```
ggplot(genre_data, aes(x = Speechiness, y = valence, color = genre)) +
  geom_point(alpha = 0.6) +
  facet_wrap(~ genre, scales = "free") +
  theme_light() +
  labs(title = "Speechiness vs. valence by Genre",
       x = "Speechiness", y = "valence")
```



- **Danceability vs. Energy by Genre**

  High danceability and energy levels are often associated with more upbeat and fast-paced music.

  Electronic and Hip-hop music are often designed for dancing and tend to have higher danceability and energy levels.

- **Acousticness vs. Instrumentalness**

  These features can help differentiate genres known for live instrumentation from those that are more electronic or vocal-heavy.

  Jazz exhibits higher levels of acousticness and instrumentalness, reflecting the genre's reliance on acoustic instruments and instrumental solos.

- **Speechiness vs. Valence**

  We think it will be interesting to explore genres that feature more lyrical content with varying emotional tones.

  Hip-hop is distinguished by its use of spoken words, resulting in higher speechiness levels. The valence in hip-hop can vary widely, reflecting the diverse emotional tones explored in the lyrics. In contrast, Jazz and Electronic music might show lower speechiness.

7.2 Data Pre-processing

7.2.1 Data Engineering

Based on the scatter plots above, we create three new features.

```r
#Energy and Danceability:
genre_data$Energy_Danceability_Interaction <-
  genre_data$Energy * genre_data$Danceability

#Acousticness and Instrumentalness
genre_data$Acousticness_Instrumentalness_Interaction <-
  genre_data$Acousticness * genre_data$Instrumentalness


#Speechiness and Valence:
genre_data$Speechiness_Valence_Interaction <-
  genre_data$Speechiness * genre_data$valence
```

7.2.2 Normalization

Because of potential classification methods in the following parts (e.g. SVM), we scale numerical features to a standard range.

The normalization formula used is **(x - min(x)) / (max(x) - min(x))**, which scales the data to a **[0, 1]** range.

Part of audio features have already in the format of [0,1], therefore, we only need to normalize the remaining numeric features.

```r
# Normalizing selected features
features_to_normalize <- c("Loudness", "Tempo", "Time_signature",
                           "key", "Release_year", "Length",
                           "Energy_Danceability_Interaction",
                           "Acousticness_Instrumentalness_Interaction",
                           "Speechiness_Valence_Interaction")

genre_data[features_to_normalize] <-
  as.data.frame(lapply(
    genre_data[features_to_normalize],
    function(x) (x - min(x, na.rm = TRUE)) /
      (max(x, na.rm = TRUE) - min(x, na.rm = TRUE))))

head(genre_data)
```

```
##       Length Acousticness Danceability Energy Instrumentalness Liveness
## 1 0.12206093       0.1130        0.762  0.692                0   0.0940
## 2 0.11522191       0.0965        0.458  0.561                0   0.1560
## 3 0.15068500       0.4170        0.637  0.690                0   0.2110
## 4 0.07416144       0.0642        0.892  0.503                0   0.1020
## 5 0.10374216       0.3830        0.505  0.694                0   0.1600
## 6 0.10504593       0.1530        0.377  0.584                0   0.0662
##    Loudness Speechiness     Tempo Time_signature       key valence genre
## 1 0.8560082      0.0438 0.4598999            0.8 0.4545455   0.397   pop
## 2 0.8320095      0.0269 0.5998599            0.6 0.9090909   0.206   pop
## 3 0.8775389      0.0693 0.5616530            0.8 0.8181818   0.103   pop
## 4 0.7677011      0.1780 0.5600480            0.8 0.5454545   0.615   pop
## 5 0.8150460      0.0295 0.6161977            0.8 0.1818182   0.406   pop
## 6 0.8549302      0.0495 0.3669041            0.8 0.1818182   0.444   pop
```

```
##   Release_year Energy_Danceability_Interaction
## 1    0.8709677                       0.6164703
## 2    0.9516129                       0.3003858
## 3    0.8790323                       0.5138538
## 4    0.9919355                       0.5245464
## 5    0.9919355                       0.4097339
## 6    0.9677419                       0.2573981
##   Acousticness_Instrumentalness_Interaction Speechiness_Valence_Interaction
## 1                                         0                      0.027700675
## 2                                         0                      0.008827653
## 3                                         0                      0.011370935
## 4                                         0                      0.174389708
## 5                                         0                      0.019079798
## 6                                         0                      0.035011757
```

7.3 Feature Selection

We would like to conduct model-based selection.

Decision tree usually works as a starting point for classification model.

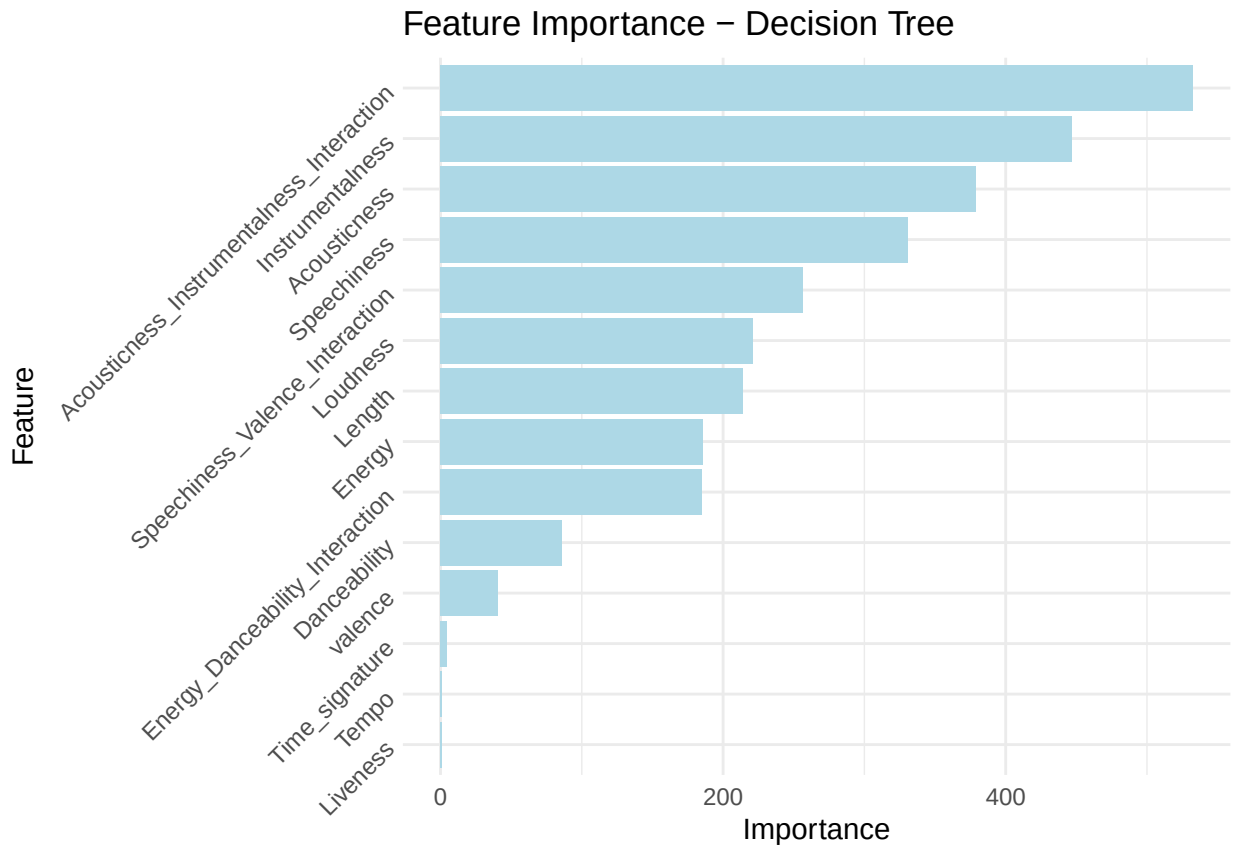
```r
#split into training and testing sets to evaluate model performance.
index <- createDataPartition(genre_data$genre, p = 0.8, list = FALSE)
traindata <- genre_data[index, ]
testdata <- genre_data[-index, ]
```

```r
#Decision tree
dt_model <- rpart(genre ~ ., data = traindata, method = "class")
dt_predictions <- predict(dt_model, newdata = testdata, type = "class")

# Evaluating model performance
confusionMatrix(dt_predictions, testdata$genre)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   country electronic hiphop jazz pop rock
##   country        119          5      9   17  50   37
##   electronic       9        173      6   35  14   34
##   hiphop          13         12    184    6  38   19
##   jazz            16         30      3  144  14    9
##   pop             83         10     48   27 124   63
##   rock            14          5      3    1  13   62
##
## Overall Statistics
##
##                Accuracy : 0.5562
##                  95% CI : (0.5302, 0.582)
##     No Information Rate : 0.1753
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4662
##
```

```
##  Mcnemar's Test P-Value : 4.79e-15
##
## Statistics by Class:
##
##                      Class: country Class: electronic Class: hiphop Class: jazz
## Sensitivity                 0.46850            0.7362        0.7273     0.62609
## Specificity                 0.90126            0.9193        0.9264     0.94094
## Pos Pred Value              0.50211            0.6384        0.6765     0.66667
## Neg Pred Value              0.88861            0.9474        0.9414     0.93025
## Prevalence                  0.17529            0.1622        0.1746     0.15873
## Detection Rate              0.08213            0.1194        0.1270     0.09938
## Detection Prevalence        0.16356            0.1870        0.1877     0.14907
## Balanced Accuracy           0.68488            0.8277        0.8268     0.78351
##                      Class: pop Class: rock
## Sensitivity              0.49012     0.27679
## Specificity              0.80686     0.97061
## Pos Pred Value           0.34930     0.63265
## Neg Pred Value           0.88208     0.88009
## Prevalence               0.17460     0.15459
## Detection Rate           0.08558     0.04279
## Detection Prevalence     0.24500     0.06763
## Balanced Accuracy        0.64849     0.62370
```

```r
# Extracting feature importance
importance <- dt_model$variable.importance
importance_df <- data.frame(Feature = names(importance), Importance = importance)
importance_df <- importance_df[order(-importance_df$Importance),]

# Visualizing the feature importance
ggplot(importance_df, aes(x = reorder(Feature, Importance), y = Importance)) +
  geom_col(fill = "lightblue") +
  coord_flip() +
  theme_minimal() +
  labs(title = "Feature Importance - Decision Tree", x = "Feature", y = "Importance") +
  theme(axis.text.y = element_text(angle = 45))
```



This horizontal bar chart shows the relative importance of different features as determined by a decision tree model used for genre classification. From the evaluation matrix, we see the decision tree model shows some ability to predict genres beyond random guessing or always choosing the most common genre, and there is definitely room for improvement.

Based on above feature importance table, it seems like **Time_signature**, **Liveness**, **Tempo** and **Release_year** are the least important features.

Dropping less important features can help simplify our model.

```
set.seed(123)
train_data_updated <-
  traindata[,
            !(names(traindata) %in% c("Time_signature", "Liveness", "Tempo","Release_year"))]

test_data_updated <-
  testdata[,
           !(names(testdata) %in% c("Time_signature", "Liveness", "Tempo","Release_year"))]
```

7.4 Build Model

Potential Model Choices: Random Forest; Support Vector Machine; Neural Network

Random Forest: Chosen for its ability to handle large data sets with many features without overfitting. Its ensemble approach, which aggregates predictions from multiple decision trees, makes it robust against noisy data.

Support Vector Machine (SVM): Preferred for its effectiveness in high-dimensional spaces, which is typical for our dataset containing various audio features. SVM is capable of defining complex decision boundaries, making it suitable for distinguishing between multiple genres.

Neural Network: Selected for its deep learning capabilities, which allow it to learn complex patterns in data. This is particularly useful in our case where the relationship between audio features and genres can be non-linear and intricate.

```
# Set up cross-validation settings

control <- trainControl(method = "cv", number = 5,
                        savePredictions = "final",
                        verboseIter = FALSE,
# for final output, we dont need to print out detailed step information
                        search = "grid")  # parameter tuning method
```

7.4.1. Model 1: Random Forest

```
# Define the tuning grid for mtry only
tuneGrid <- expand.grid(
  mtry = c(2, 3, 4, 5)
)


# Train the Random Forest model with tuning for mtry and a fixed ntree value
rf_model <- train(
  genre ~ .,
  data = train_data_updated,
  method = "rf",
  trControl = control,
  tuneGrid = tuneGrid,
  ntree = 500,
  # Set a fixed number of trees
  # we have tried different ntree, but 500 works most stable
  metric = "Accuracy"
)

# Print the model results to see the best parameters
print(rf_model)
```

```
## Random Forest
##
## 5813 samples
##   12 predictor
##    6 classes: 'country', 'electronic', 'hiphop', 'jazz', 'pop', 'rock'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 4650, 4650, 4650, 4651, 4651
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
```

```
##   2     0.6172397  0.5402205
##   3     0.6211954  0.5449625
##   4     0.6225709  0.5466424
##   5     0.6182697  0.5414593
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 4.
```

7.4.2. Model 2: SVM

Kernel 1: Radial

```r
# Define the tuning grid for svmRadial
svm_tune_grid <- expand.grid(
  sigma = c(0.001,0.01),
  C = c(10, 100, 1000)
)

# Train the SVM model using the radial basis function kernel
svm_model <- train(
  genre ~ .,
  data = train_data_updated,
  method = "svmRadial",
  trControl = control,
  tuneGrid = svm_tune_grid,
  preProcess = "scale"  # Automatically scales features for SVM
)

# Print the model results to view the best parameters and accuracy
print(svm_model)
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 5813 samples
##   12 predictor
##    6 classes: 'country', 'electronic', 'hiphop', 'jazz', 'pop', 'rock'
##
## Pre-processing: scaled (12)
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 4651, 4650, 4650, 4650, 4651
## Resampling results across tuning parameters:
##
##   sigma  C     Accuracy   Kappa
##   0.001    10  0.5759488  0.4903044
##   0.001   100  0.5864423  0.5028689
##   0.001  1000  0.5950438  0.5131494
##   0.010    10  0.5984844  0.5173110
##   0.010   100  0.6005504  0.5197930
##   0.010  1000  0.6014096  0.5207682
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 0.01 and C = 1000.
```

Kernel 2: Polynomial

```
# Define the tuning grid for svmPoly
svm_poly_tune_grid <- expand.grid(
  degree = 2,
  scale = c(0.01,0.1,1),
  C = c(5,10)
)


# Train the SVM model using the polynomial kernel
svm_poly_model <- train(
  genre ~ .,
  data = train_data_updated,
  method = "svmPoly",
  trControl = control,
  tuneGrid = svm_poly_tune_grid,
  preProcess = "scale"  # Automatically scales features for SVM
)

# Print the model results to view the best parameters and accuracy
print(svm_poly_model)
```

```
## Support Vector Machines with Polynomial Kernel
##
## 5813 samples
##   12 predictor
##    6 classes: 'country', 'electronic', 'hiphop', 'jazz', 'pop', 'rock'
##
## Pre-processing: scaled (12)
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 4650, 4651, 4650, 4651, 4650
## Resampling results across tuning parameters:
##
##   scale  C   Accuracy   Kappa
##   0.01    5  0.5893709  0.5063393
##   0.01   10  0.5938423  0.5117132
##   0.10    5  0.5993479  0.5183746
##   0.10   10  0.5979713  0.5167133
##   1.00    5  0.5977996  0.5165017
##   1.00   10  0.5950472  0.5131992
##
## Tuning parameter 'degree' was held constant at a value of 2
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 2, scale = 0.1 and C = 5.
```

In our SVM model comparison, the Radial Basis Function (RBF) kernel outperformed the Polynomial kernel in accuracy, indicating better generalization to our music genre classification dataset. The radial kernel's flexibility in handling complex data structures makes it more effective for our application, leading us to choose it for its superior performance and adaptability.

7.4.3. Model 3: Neural Network

```
# Define the tuning grid
nn_tune_grid <- expand.grid(size = c(5, 10, 15),
                            decay = c(0.001, 0.01, 0.1))

# Train the model with tuning
nn_model <- train(genre ~ .,
                  data = train_data_updated,
                  method = "nnet",  # Ensure to use method 'nnet' for neural networks in caret
                  trControl = control,
                  tuneGrid = nn_tune_grid,
                  MaxNWts = 1000,    # Maximum allowable weights (to avoid overly complex models)
                  trace = FALSE,     # Optionally turn off training progress
                  linout = FALSE,
                  maxit = 500)

# View the results
print(nn_model)
```

```
## Neural Network
##
## 5813 samples
##   12 predictor
##    6 classes: 'country', 'electronic', 'hiphop', 'jazz', 'pop', 'rock'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 4651, 4651, 4650, 4650, 4650
## Resampling results across tuning parameters:
##
##   size  decay  Accuracy   Kappa
##    5    0.001  0.5867906  0.5034989
##    5    0.010  0.5924683  0.5103011
##    5    0.100  0.5828339  0.4987270
##   10    0.001  0.6050253  0.5254016
##   10    0.010  0.6019295  0.5216845
##   10    0.100  0.6039902  0.5240438
##   15    0.001  0.6007261  0.5201847
##   15    0.010  0.6007234  0.5201912
##   15    0.100  0.6045094  0.5246689
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were size = 10 and decay = 0.001.
```

7.4 Model Evaluation

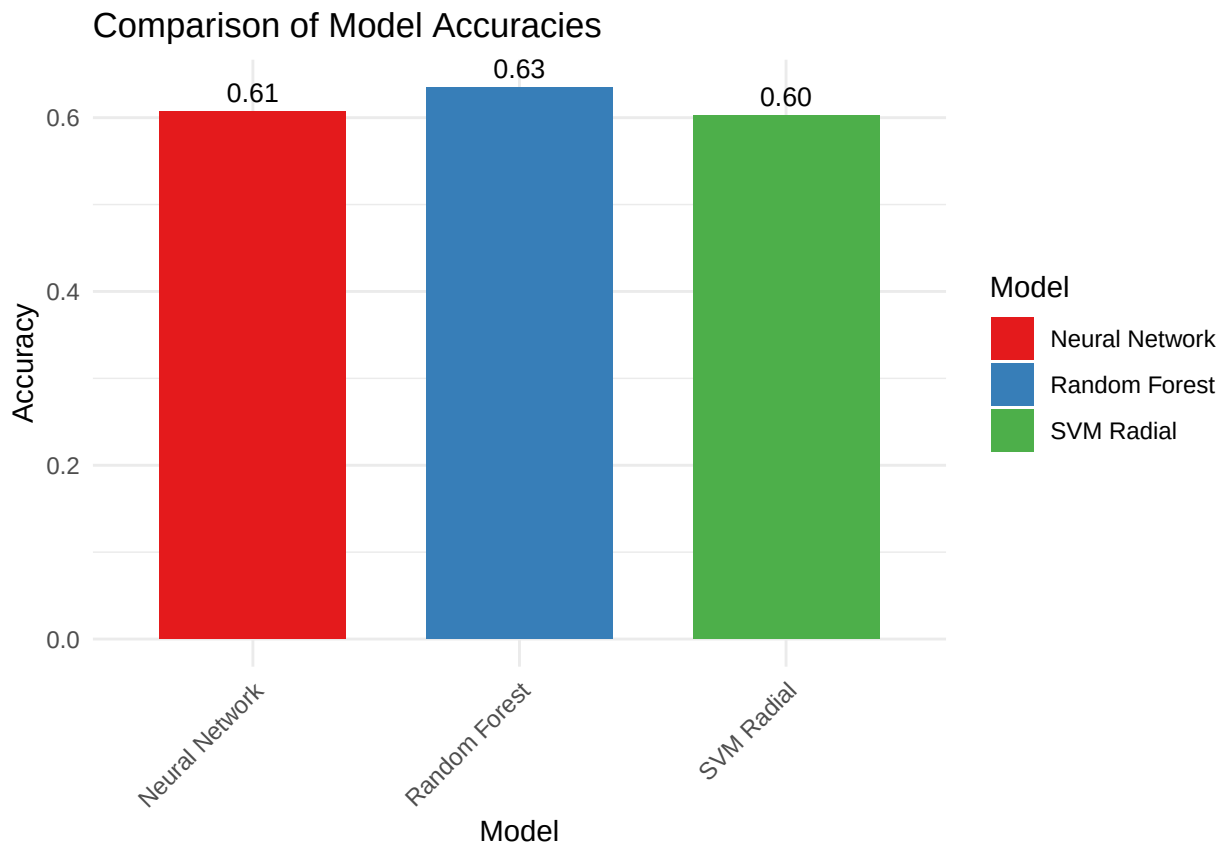
```
# Random Forest Prediction and Evaluation
rf_predictions <- predict(rf_model, newdata = test_data_updated)
rf_accuracy <- mean(rf_predictions == test_data_updated$genre)
cm_rf <- confusionMatrix(rf_predictions, test_data_updated$genre)
```

```r
# SVM Radial Prediction and Evaluation
svm_radial_predictions <- predict(svm_model, newdata = test_data_updated)
svm_radial_accuracy <- mean(svm_radial_predictions == test_data_updated$genre)
cm_svm <- confusionMatrix(svm_radial_predictions, test_data_updated$genre)


# Neural Network Prediction and Evaluation
nn_predictions <- predict(nn_model, newdata = test_data_updated)
nn_accuracy <- mean(nn_predictions == test_data_updated$genre)
cm_nn <- confusionMatrix(nn_predictions, test_data_updated$genre)
```

```r
# Create a data frame to compare model performance
model_comparison <- data.frame(
  Model = c("Random Forest", "SVM Radial", "Neural Network"),
  Accuracy = c(rf_accuracy, svm_radial_accuracy, nn_accuracy)
)

# Print the comparison table
print(model_comparison)
```

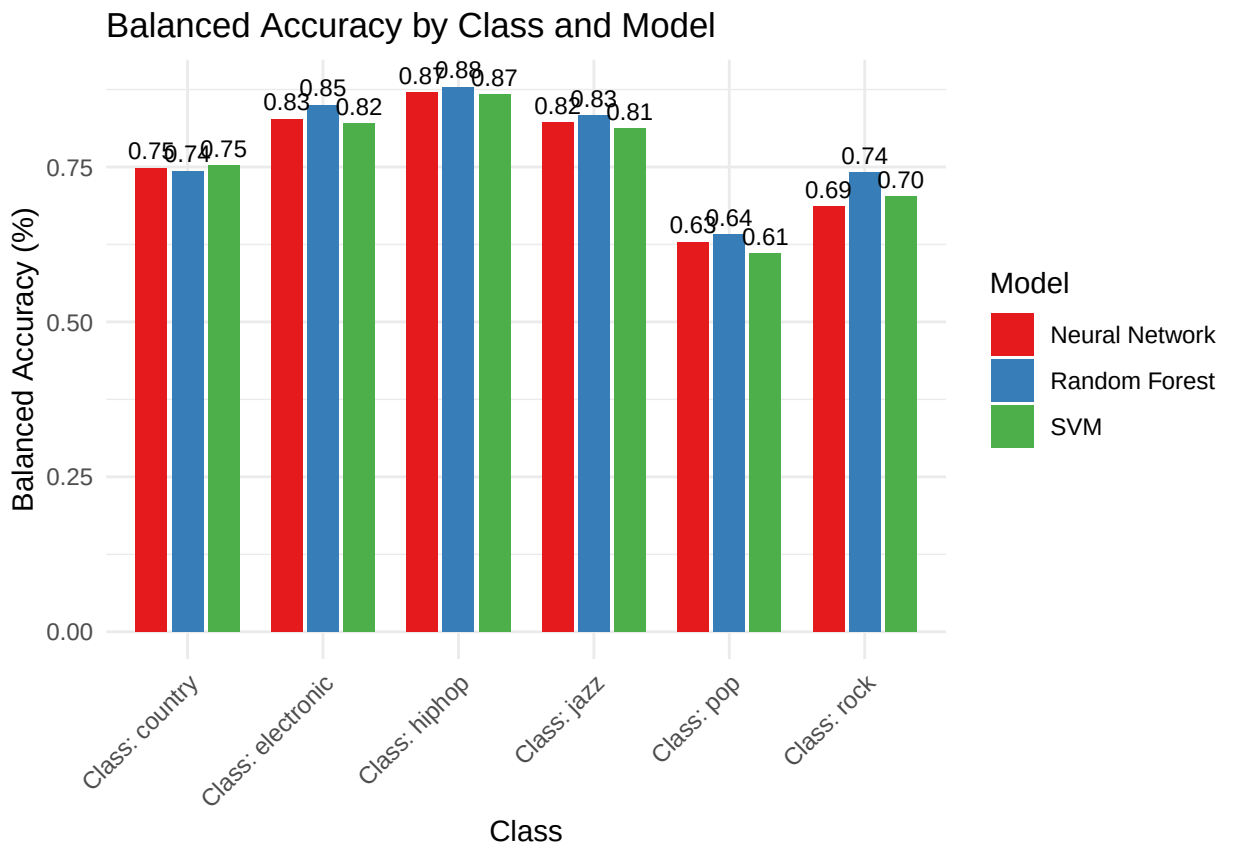
```
##            Model  Accuracy
## 1  Random Forest 0.6349206
## 2     SVM Radial 0.6024845
## 3 Neural Network 0.6073154
```

```r
# Plot the accuracy of each model
library(ggplot2)
ggplot(model_comparison, aes(x = Model, y = Accuracy, fill = Model)) +
  geom_bar(stat = "identity", position = position_dodge(), width = 0.7) +
  geom_text(aes(label = sprintf("%.2f", Accuracy)), vjust = -0.5, size = 3.5) +
  labs(title = "Comparison of Model Accuracies", x = "Model", y = "Accuracy") +
  theme_minimal() +
  scale_fill_brewer(palette = "Set1") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



This simple table presents the overall accuracy of the three models. Although the accuracy rates are somewhat close, the slight advantage of the Random Forest model could generally provide a more robust prediction by reducing the likelihood of overfitting.

```
# Combine balanced accuracy data from different models
df_balanced_accuracy_rf <- data.frame(Class = rownames(cm_rf$byClass), Balanced_Accuracy = cm_rf$byClass
df_balanced_accuracy_svm <- data.frame(Class = rownames(cm_svm$byClass), Balanced_Accuracy = cm_svm$byC
df_balanced_accuracy_nn <- data.frame(Class = rownames(cm_nn$byClass), Balanced_Accuracy = cm_nn$byClass

combined_balanced_accuracy <- rbind(df_balanced_accuracy_rf, df_balanced_accuracy_svm, df_balanced_accu

# Visualize the balanced accuracy for each class and model
library(ggplot2)
ggplot(combined_balanced_accuracy, aes(x = Class, y = Balanced_Accuracy, fill = Model)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8), width = 0.7) +
  geom_text(aes(label = sprintf("%.2f", Balanced_Accuracy)), position = position_dodge(width = 0.8), vju
  theme_minimal() +
  labs(title = "Balanced Accuracy by Class and Model", y = "Balanced Accuracy (%)", x = "Class") +
  scale_fill_brewer(palette = "Set1") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Balanced Accuracy by Class and Model: This bar chart compares the balanced accuracy of three different machine learning models - Neural Network, Random Forest, and SVM (Support Vector Machine) - for predicting different music genres. The chart indicates that genres like electronic and hip-hop have distinguishing features that are captured well by the models, while other genres might be more challenging to differentiate due to overlapping characteristics or less distinct features.

8. Conclusion

Our project undertook an innovative task where we utilized Spotify's audio features to predict song popularity and genre, demonstrating the intersection of musicology and data science. Through extensive data preprocessing, exploratory data analysis (EDA), and model building, we identified certain audio features that indicate song popularity and genre classification. Exploratory data analysis (EDA) reveals the distribution of features such as danceability, energy, and acousticity across genres, while regression and classification models attempt to quantify these relationships. In terms of predicting song popularity, our work highlights the challenges of modeling with diverse datasets, as evidenced by the range of performance of the models and their predictive accuracy. The models achieved varying degrees of success, with Random Forests and Generalized Linear Models (GLMs) showing potential in capturing the complex dynamics that lead to song popularity on Spotify. Further work needs to be conducted regarding the specificity and sensitivity of these two models. Improving false positive will be a potential topic of our next stage. In terms of genre classification, our innovative approach to feature selection and engineering (e.g., creating interaction terms and normalizing selected features) paved the way for building nuanced models that are able to distinguish between genres with reasonable accuracy. The application of models such as Random Forests, SVMs, and Neural Networks in predicting genres illustrates a comprehensive attempt to leverage Spotify's rich dataset to understand music trends.

9. Future Work

Enhanced Feature Engineering: We might try to explore deeper into creating more complex interaction terms and investigating unsupervised learning techniques for feature extraction.Maybe we could uncover hidden patterns within the audio features which significantly impact both genre classification and song popularity.

Model Exploration and Optimization:We will also try to experiment with advanced modeling techniques, including some ensemble methods for sequential analysis of songs.

Handling Class Imbalance: We will consider resampling Techniques like Oversampling or undersampling. Aim tp mitigate the impact of imbalance and improve the performance of our models.

User-Centric Applications: Last but not least, we might explore the development of user-centric applications such as personalized song recommendations and dynamic genre classification tools. In this way, we could leverage the insights and models developed in this project to enhance music discovery and curation on streaming platforms.