spotify-genre-report

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Introduction

We are tasked with an individual project to demonstrate our ability to apply machine learning techniques on publicly available datasets.

I've chosen to use the "Dataset of songs in Spotify" available from Kaggle which consists of audio features of songs provided by Spotify and the task is to use these features to predict the genre of the song.

Here's a link to the dataset:

https://www.kaggle.com/mrmorj/dataset-of-songs-in-spotify

We will be attempting different machine learning algorithms to achieve this.

Analysis

We first examine the dataset and perform data wrangling and data visualization on the dataset to gain more insight to the features available to us and prepare the data for machine learning.

Data Wrangling

Import the dataset into an object "spotify" from the excel sheet to RStudio, the file is saved in the same working directory as the script so relative path is used.

```r
spotify <- read.csv("genres_v2.csv")
```

We then examine the dataset with the head and summary functions:

```
##   danceability energy key loudness mode speechiness acousticness
## 1        0.831  0.814   2   -7.364    1      0.4200       0.0598
## 2        0.719  0.493   8   -7.230    1      0.0794       0.4010
## 3        0.850  0.893   5   -4.783    1      0.0623       0.0138
## 4        0.476  0.781   0   -4.710    1      0.1030       0.0237
## 5        0.798  0.624   2   -7.668    1      0.2930       0.2170
## 6        0.721  0.568   0  -11.295    1      0.4140       0.0452
##   instrumentalness liveness valence   tempo           type
## 1         1.34e-02   0.0556  0.3890 156.985 audio_features
## 2         0.00e+00   0.1180  0.1240 115.080 audio_features
## 3         4.14e-06   0.3720  0.0391 218.050 audio_features
## 4         0.00e+00   0.1140  0.1750 186.948 audio_features
## 5         0.00e+00   0.1660  0.5910 147.988 audio_features
```

```
## 6        2.12e-01   0.1280  0.1090 144.915 audio_features
##                       id                                  uri
## 1 2Vc6NJ9PW9gD9q343XFRKx spotify:track:2Vc6NJ9PW9gD9q343XFRKx
## 2 7pgJBLVz5VmnL7uGHmRj6p spotify:track:7pgJBLVz5VmnL7uGHmRj6p
## 3 0vSWgAlfpye0WCGeNmuNhy spotify:track:0vSWgAlfpye0WCGeNmuNhy
## 4 0VSXnJqQkwuH2ei1nOQ1nu spotify:track:0VSXnJqQkwuH2ei1nOQ1nu
## 5 4jCeguq9rMTlbMmPHuO7S3 spotify:track:4jCeguq9rMTlbMmPHuO7S3
## 6 6fsypiJHyWmeINsOLC1cos spotify:track:6fsypiJHyWmeINsOLC1cos
##                                                 track_href
## 1 https://api.spotify.com/v1/tracks/2Vc6NJ9PW9gD9q343XFRKx
## 2 https://api.spotify.com/v1/tracks/7pgJBLVz5VmnL7uGHmRj6p
## 3 https://api.spotify.com/v1/tracks/0vSWgAlfpye0WCGeNmuNhy
## 4 https://api.spotify.com/v1/tracks/0VSXnJqQkwuH2ei1nOQ1nu
## 5 https://api.spotify.com/v1/tracks/4jCeguq9rMTlbMmPHuO7S3
## 6 https://api.spotify.com/v1/tracks/6fsypiJHyWmeINsOLC1cos
##                                                       analysis_url duration_ms
## 1 https://api.spotify.com/v1/audio-analysis/2Vc6NJ9PW9gD9q343XFRKx      124539
## 2 https://api.spotify.com/v1/audio-analysis/7pgJBLVz5VmnL7uGHmRj6p      224427
## 3 https://api.spotify.com/v1/audio-analysis/0vSWgAlfpye0WCGeNmuNhy       98821
## 4 https://api.spotify.com/v1/audio-analysis/0VSXnJqQkwuH2ei1nOQ1nu      123661
## 5 https://api.spotify.com/v1/audio-analysis/4jCeguq9rMTlbMmPHuO7S3      123298
## 6 https://api.spotify.com/v1/audio-analysis/6fsypiJHyWmeINsOLC1cos      112511
##   time_signature     genre                                 song_name
## 1              4 Dark Trap                        Mercury: Retrograde
## 2              4 Dark Trap                                  Pathology
## 3              4 Dark Trap                                   Symbiote
## 4              3 Dark Trap ProductOfDrugs (Prod. The Virus and Antidote)
## 5              4 Dark Trap                                      Venom
## 6              4 Dark Trap                                    Gatteka
##   Unnamed..0 title
## 1         NA
## 2         NA
## 3         NA
## 4         NA
## 5         NA
## 6         NA

##   danceability        energy              key          loudness
##  Min.   :0.0651   Min.   :0.000243   Min.   : 0.00   Min.   :-33.357
##  1st Qu.:0.5240   1st Qu.:0.632000   1st Qu.: 1.00   1st Qu.: -8.161
##  Median :0.6460   Median :0.803000   Median : 6.00   Median : -6.234
##  Mean   :0.6394   Mean   :0.762516   Mean   : 5.37   Mean   : -6.465
##  3rd Qu.:0.7660   3rd Qu.:0.923000   3rd Qu.: 9.00   3rd Qu.: -4.513
##  Max.   :0.9880   Max.   :1.000000   Max.   :11.00   Max.   :  3.148
##
##       mode         speechiness      acousticness       instrumentalness
##  Min.   :0.0000   Min.   :0.0227   Min.   :0.0000011   Min.   :0.00000
##  1st Qu.:0.0000   1st Qu.:0.0491   1st Qu.:0.0017300   1st Qu.:0.00000
##  Median :1.0000   Median :0.0755   Median :0.0164000   Median :0.00594
##  Mean   :0.5495   Mean   :0.1366   Mean   :0.0961605   Mean   :0.28305
##  3rd Qu.:1.0000   3rd Qu.:0.1930   3rd Qu.:0.1070000   3rd Qu.:0.72200
##  Max.   :1.0000   Max.   :0.9460   Max.   :0.9880000   Max.   :0.98900
##
##     liveness         valence           tempo            type
```

```
##  Min.   :0.0107   Min.   :0.0187   Min.   : 57.97   Length:42305
##  1st Qu.:0.0996   1st Qu.:0.1610   1st Qu.:129.93   Class :character
##  Median :0.1350   Median :0.3220   Median :144.97   Mode  :character
##  Mean   :0.2141   Mean   :0.3571   Mean   :147.47
##  3rd Qu.:0.2940   3rd Qu.:0.5220   3rd Qu.:161.46
##  Max.   :0.9880   Max.   :0.9880   Max.   :220.29
##
##       id                uri             track_href        analysis_url
##  Length:42305       Length:42305       Length:42305       Length:42305
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   duration_ms     time_signature     genre             song_name
##  Min.   : 25600   Min.   :1.000   Length:42305       Length:42305
##  1st Qu.:179840   1st Qu.:4.000   Class :character   Class :character
##  Median :224760   Median :4.000   Mode  :character   Mode  :character
##  Mean   :250866   Mean   :3.973
##  3rd Qu.:301133   3rd Qu.:4.000
##  Max.   :913052   Max.   :5.000
##
##    Unnamed..0       title
##  Min.   :    0   Length:42305
##  1st Qu.: 5256   Class :character
##  Median :10480   Mode  :character
##  Mean   :10484
##  3rd Qu.:15709
##  Max.   :20999
##  NA's   :21525
```

From these tables, we can see that the type, id, uri, track_href, analysis_url, title, unnamed title columns are not very useful for us, hence we will be removing those columns and use the remaining features to predict the genre.

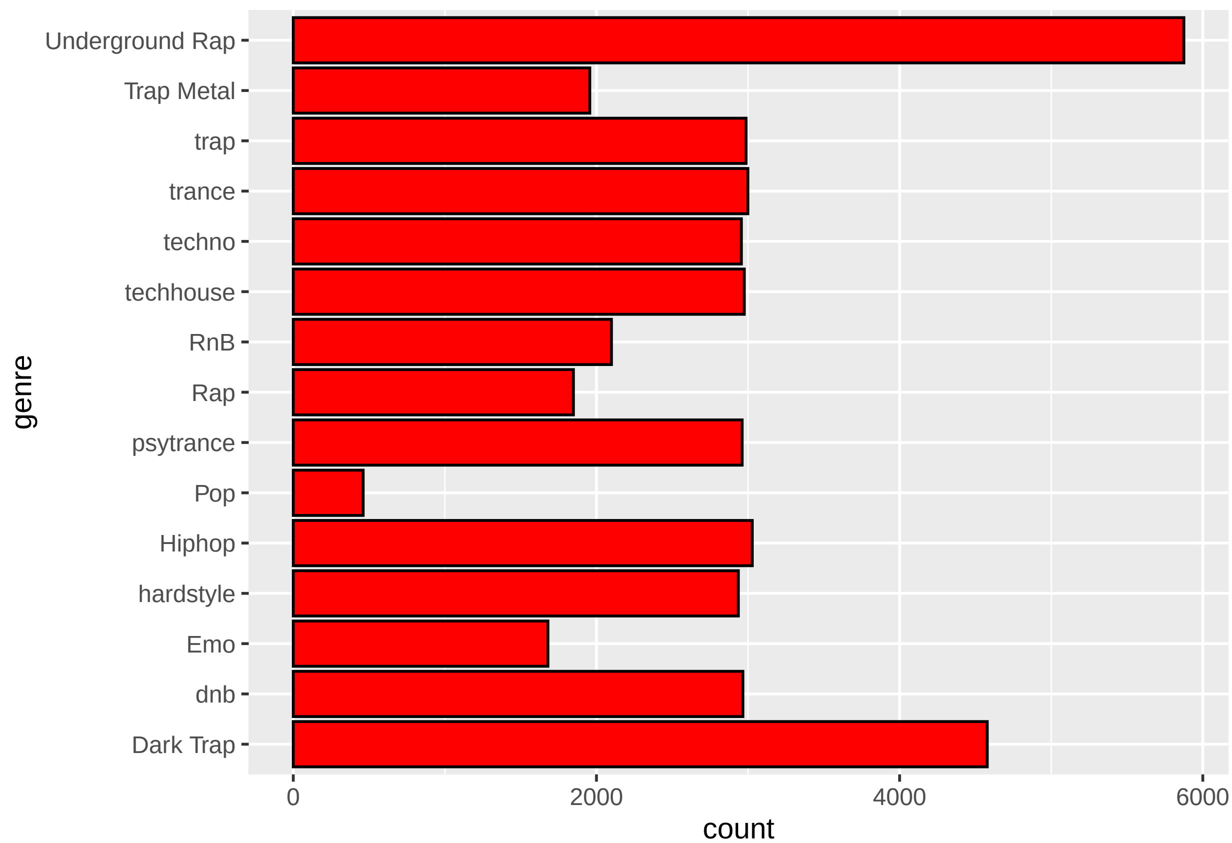
```
spotify <- spotify %>%
  select(danceability, energy, key, loudness, speechiness, acousticness, instrumentalness, liveness, va
```

```
##   danceability energy key loudness speechiness acousticness instrumentalness
## 1        0.831  0.814   2   -7.364      0.4200       0.0598         1.34e-02
## 2        0.719  0.493   8   -7.230      0.0794       0.4010         0.00e+00
## 3        0.850  0.893   5   -4.783      0.0623       0.0138         4.14e-06
## 4        0.476  0.781   0   -4.710      0.1030       0.0237         0.00e+00
## 5        0.798  0.624   2   -7.668      0.2930       0.2170         0.00e+00
## 6        0.721  0.568   0  -11.295      0.4140       0.0452         2.12e-01
##   liveness valence   tempo duration_ms time_signature     genre
## 1   0.0556  0.3890 156.985      124539              4 Dark Trap
## 2   0.1180  0.1240 115.080      224427              4 Dark Trap
## 3   0.3720  0.0391 218.050       98821              4 Dark Trap
## 4   0.1140  0.1750 186.948      123661              3 Dark Trap
## 5   0.1660  0.5910 147.988      123298              4 Dark Trap
## 6   0.1280  0.1090 144.915      112511              4 Dark Trap
```

Data visualization

We now use data visualization techniques to explore the dataset visually. FIrst we look at the genre distribution,

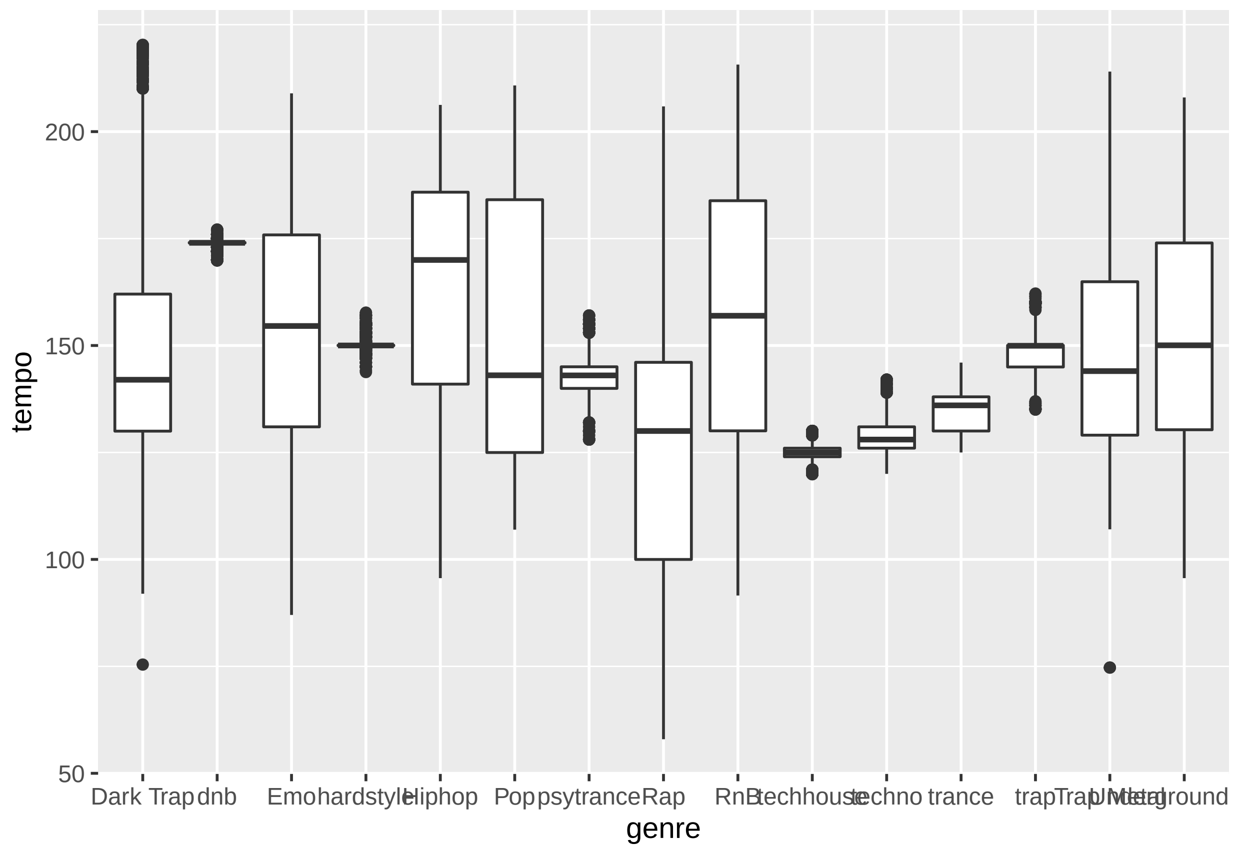
```
#investigate genre distribution
spotify %>%
  group_by(genre) %>%
  ggplot(aes(genre)) +
  geom_bar(fill = "red", color = "black") +
  coord_flip()
```



We can see a list of the genres that are present in the dataset, it is worth noting that the genres in the dataset are not evenly distributed with a lot of the songs belonging to the Underground Rap genre and very few belong to the Pop genre.

We then examine the tempo distribution and average tempo by genre

```
#investigate tempo distribution by genre
spotify %>%
  group_by(genre) %>%
  ggplot(aes(genre, tempo)) +
  geom_boxplot()
```



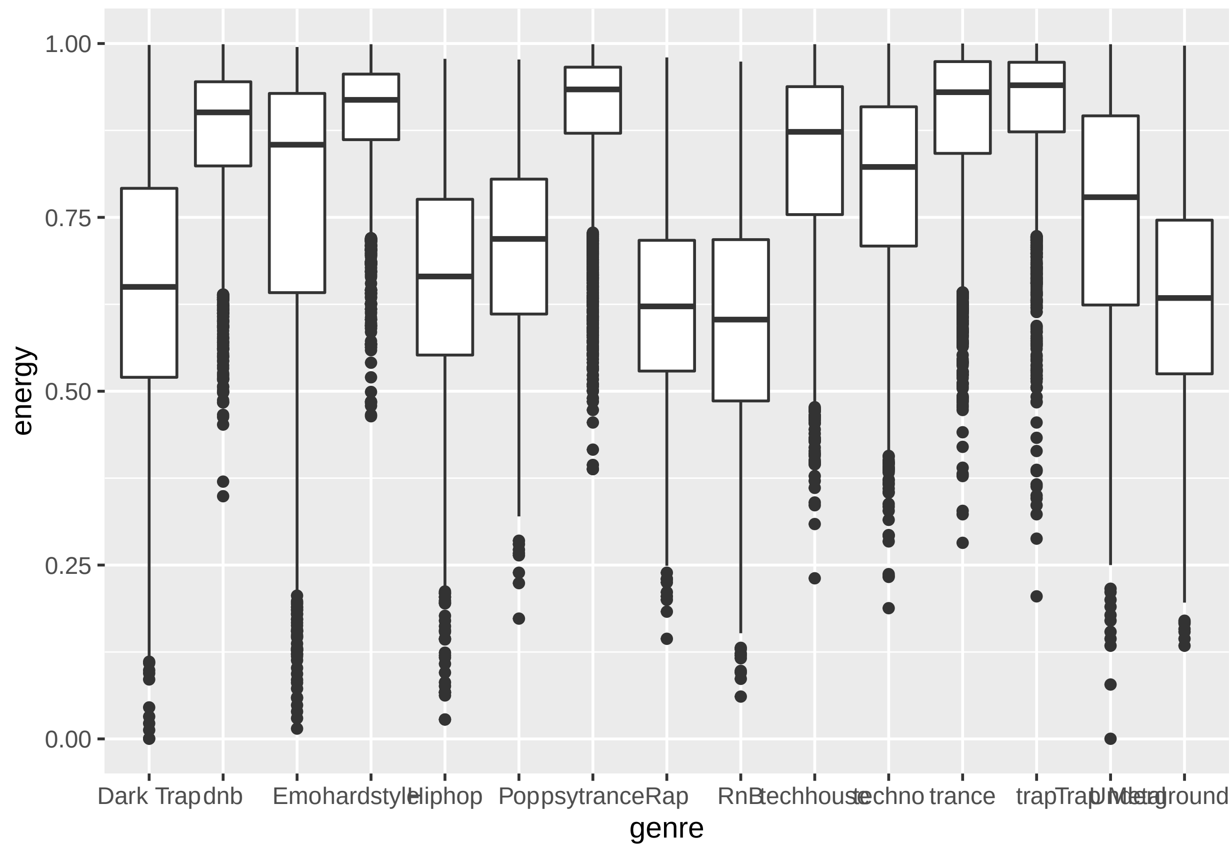

```r
#investigate the average tempo by genre
spotify %>%
  group_by(genre) %>%
  summarise(mean_tempo = mean(tempo)) %>%
  arrange(desc(mean_tempo))
```

```
## # A tibble: 15 x 2
##    genre           mean_tempo
##    <chr>                <dbl>
##  1 dnb                   174.
##  2 Hiphop                163.
##  3 RnB                   158.
##  4 Emo                   154.
##  5 Underground Rap       153.
##  6 Pop                   152.
##  7 hardstyle             151.
##  8 Dark Trap             150.
##  9 Trap Metal            149.
## 10 trap                  148.
## 11 psytrance             143.
## 12 trance                135.
## 13 techno                129.
## 14 Rap                   126.
## 15 techhouse             125.
```

The tempo/mean tempo distribution provide an interesting insight as some genres (techhouse) have very small inter quartile ranges whilst genres like pop has large inter quartile ranges. Furthermore, there is quite a range when exploring the mean tempo, varying from 125.techhouse to 174.dnb which can be a good predictor for genres.

We then examine the energy distribution and average energy by genre

```r
#investigate energy distribution by genre
spotify %>%
  group_by(genre) %>%
  ggplot(aes(genre, energy)) +
  geom_boxplot()
```



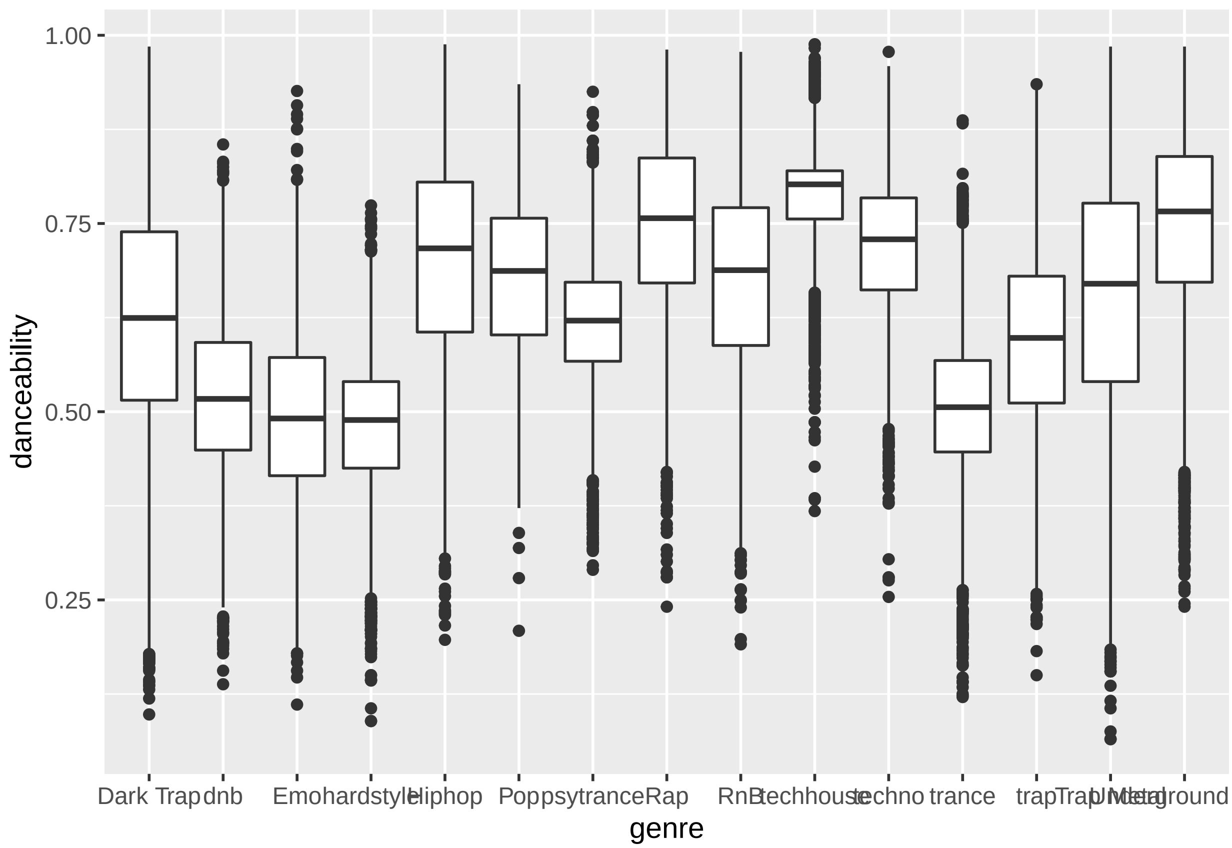

```r
#investigate the average energy level by genre
spotify %>%
  group_by(genre) %>%
  summarise(mean_energy = mean(energy)) %>%
  arrange(desc(mean_energy))
```

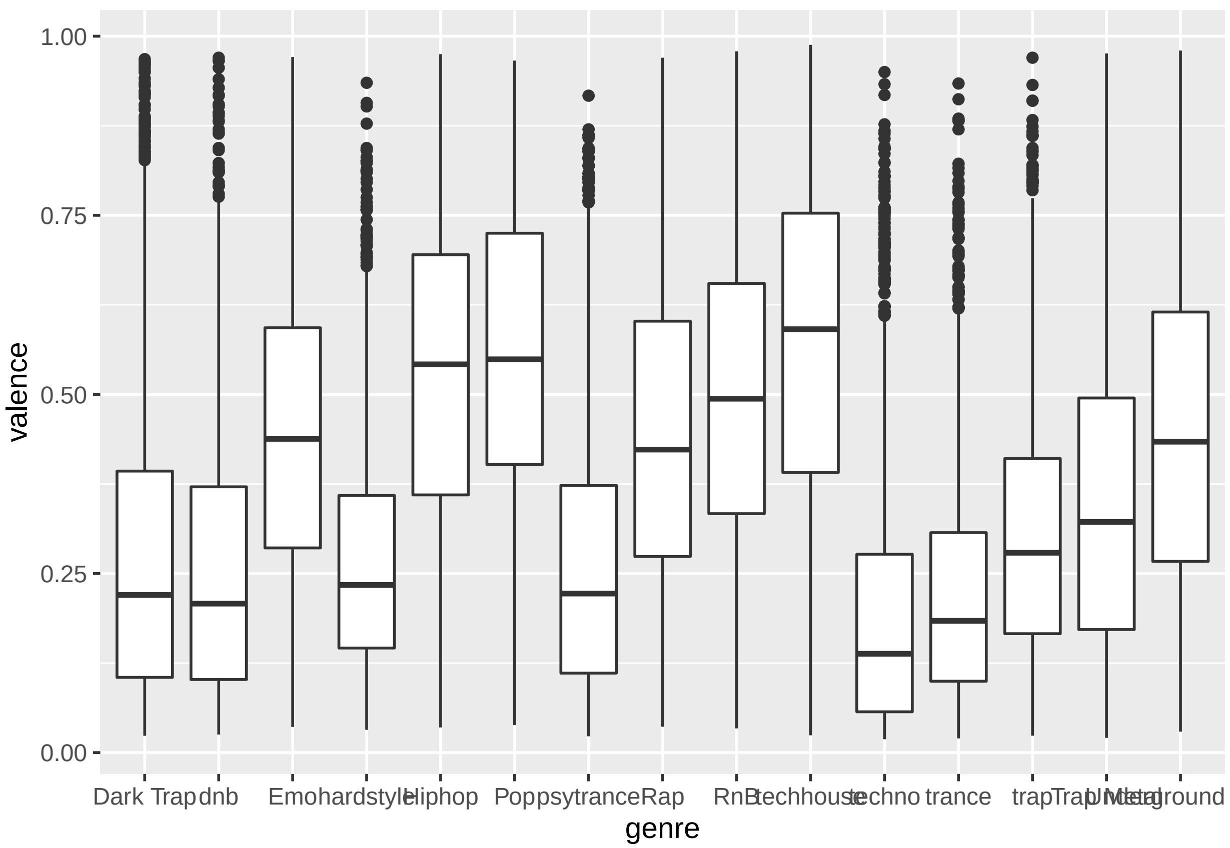
```
## # A tibble: 15 x 2
##    genre          mean_energy
##    <chr>                <dbl>
##  1 trap                 0.906
##  2 psytrance            0.902
##  3 hardstyle            0.896
##  4 trance               0.892
##  5 dnb                  0.873
```

```
##  6 techhouse            0.834
##  7 techno               0.796
##  8 Emo                  0.761
##  9 Trap Metal           0.749
## 10 Pop                  0.698
## 11 Hiphop               0.654
## 12 Dark Trap            0.647
## 13 Underground Rap      0.636
## 14 Rap                  0.620
## 15 RnB                  0.599
```

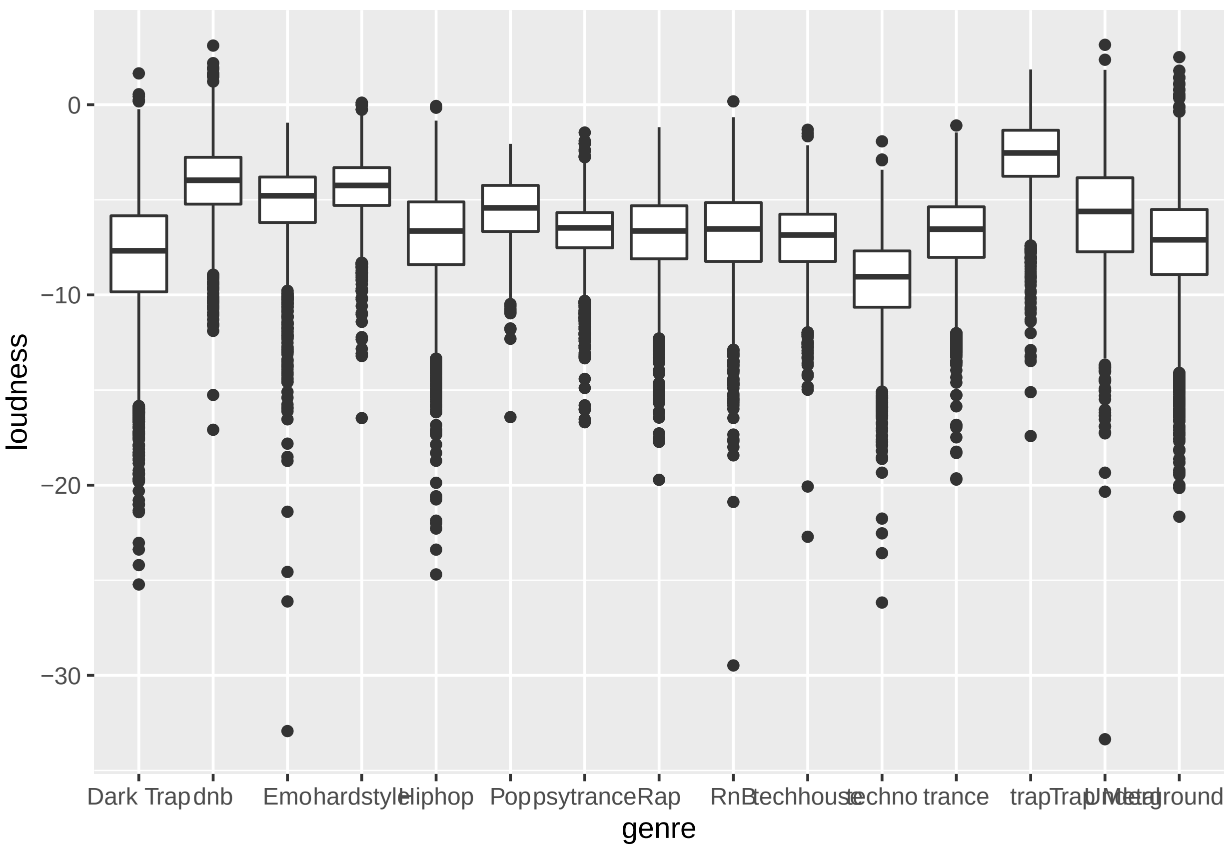
The energy level distribution is more condense as all genres have an average above 0.5.

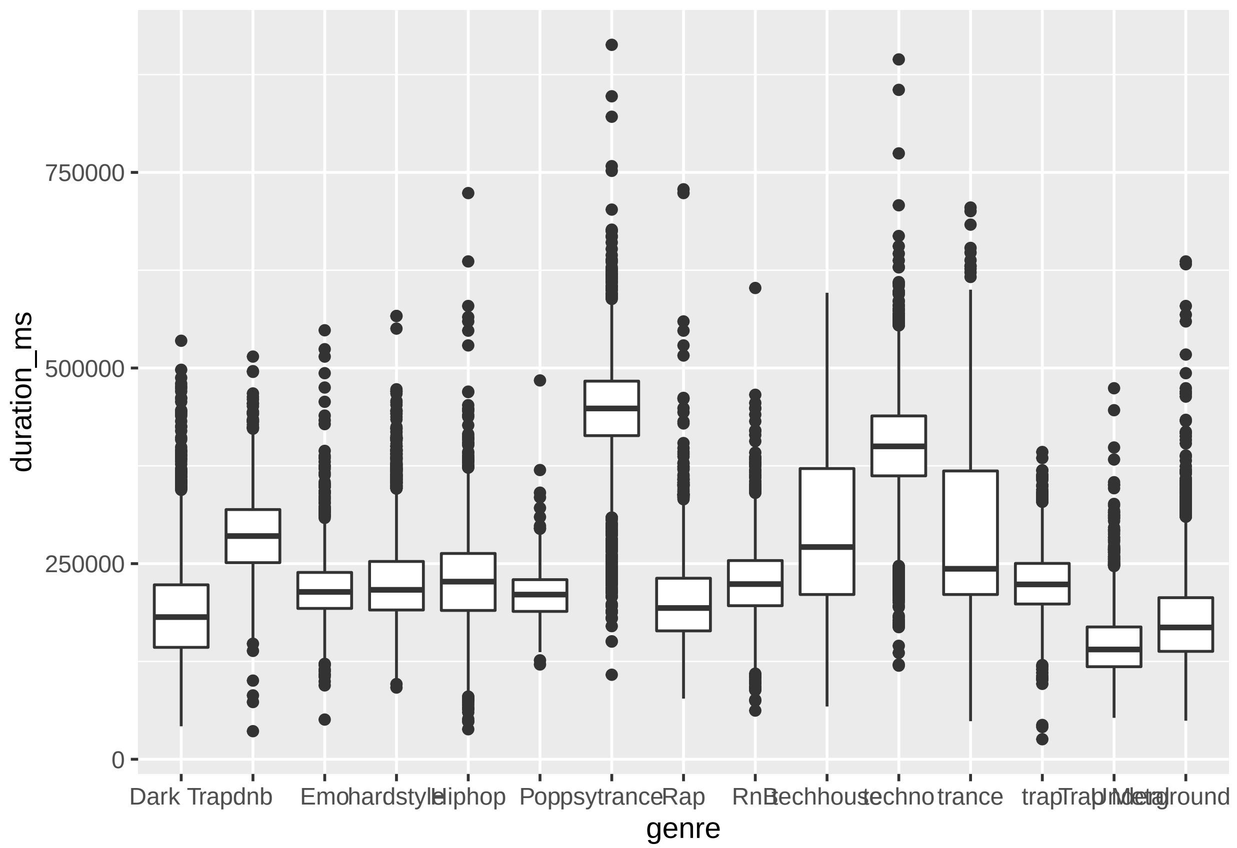
We also look at danceability, valence, loudness and duration distributions by genre:





valence
1.00
0.75
0.50
0.25
0.00
Dark Trap
dnb
Emo
hardstyle
Hiphop
Pop
psytrance
Rap
RnB
techhouse
techno
trance
trap
genre


0
−10
−20
−30
loudness
Dark Trap
dnb
Emo
hardstyle
Hiphop
Pop
psytrance
Rap
RnB
techhouse
techno
trance
trap
Trap Metal
Underground R
genre



From the plots, we can see that danceability, valence are more distributed between genres than loudness and duration, suggesting they are stronger predictors for analysis later.

Separating training, test, and validation dataset

We then move on to creating training, test and validation dataset from the spotify dataset. The validation dataset is strictly used for evaluation only and was not used for training in any way. When working on different algorithms, training dataset is used to train our algorithm and tested on the test dataset.

The validation dataset consists of 20% of the spotify dataset, the remaining 80% is distributed as follows: training 80%, testing 20%.

As the original spotify dataset consists of 42305 observations (songs) it allows for 20% going to the validation dataset as we have enough observations for training. I avoided splitting it into 90%:10% as that will increase computational cost and time.

During the training process, the algorithms are evaluated on the test set.

Later in the report, the final evaluation will be performed on the validation dataset, which was not used in the training process in any way.

```
set.seed(7, sample.kind = "Rounding")
```

```
## Warning in set.seed(7, sample.kind = "Rounding"): non-uniform 'Rounding' sampler
## used
```

```r
verify_index <- createDataPartition(spotify$genre, times = 1, p = 0.2, list = FALSE)
analysis <- spotify[-verify_index,]
temp <- spotify[verify_index,]

validation <- temp %>%
  semi_join(analysis, by = "genre")

removed <- anti_join(temp, validation)
```

```
## Joining, by = c("danceability", "energy", "key", "loudness", "speechiness", "acousticness", "instrum
```

```r
analysis <- rbind(analysis, removed)

set.seed(7, sample.kind = "Rounding")
```

```
## Warning in set.seed(7, sample.kind = "Rounding"): non-uniform 'Rounding' sampler
## used
```

```r
test_index <- createDataPartition(analysis$genre, times = 1, p = 0.2, list = FALSE)
training_set <- analysis[-test_index,]
test_set <- analysis[test_index,]

rm(removed, temp, verify_index, analysis, test_index)
```

Machine learning

We will be using a range of machine learning algorithms to predict the genre of the song using the audio features available to us.

THe machine learning algorithms that we will use are:

Linear discriminant analysis (LDA) Quadratic discriminant analysis (QDA) k-nearest neighbour algorithm (kNN) Random forest (rf)

Model 1 | LDA model We first try a LDA model:

```r
train_lda <- train(genre ~ ., data = training_set, method = "lda")
s_lda <- predict(train_lda, test_set)
mean(test_set$genre == s_lda)
```

```
## [1] 0.525251
```

Model 2 | QDA model We then try a qda model:

```r
train_qda <- train(genre ~ ., data = training_set, method = "qda")
```

```
## Warning: model fit failed for Resample01: parameter=none Error in qda.default(x, grouping, ...) : ra
```

```
## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo, :
## There were missing values in resampled performance measures.
```

```
s_qda <- predict(train_qda, test_set)
mean(test_set$genre == s_qda)
```

```
## [1] 0.6107501
```

Model 3 | Random forest model 1 We now attempt a random forest model with 100 tree nodes:

```
train_rf <- train(genre ~ ., data = training_set, method = "rf",
                  tuneGrid = data.frame(mtry = seq(1:7)),
                  ntree = 100)

train_rf$bestTune
```

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

```
s_rf <- predict(train_rf, test_set)

mean(s_rf == test_set$genre)
```

```
## [1] 0.6642056
```

We can also observe the variable importance which is why "rf" is used over "rborist".

```
varImp(train_rf)
```

```
## rf variable importance
##
##                  Overall
## tempo            100.000
## duration_ms       54.237
## danceability      40.525
## instrumentalness  39.171
## loudness          33.652
## energy            32.641
## valence           28.692
## speechiness       27.340
## acousticness      25.490
## liveness          19.539
## key                9.829
## time_signature     0.000
```

As shown, tempo is the most important variable to predict genre, followed by duration and danceability. It seems time signature has no impact at predicting the genre of the song.

Model 4 | Random forest model 2 We now attempt a random forest model with 500 tree nodes to see if it improves the accuracy:

```
train_rf2 <- train(genre ~ ., data = training_set, method = "rf",
                  tuneGrid = data.frame(mtry = seq(1:7)),
                  ntree = 500)

train_rf2$bestTune
```

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

```
s_rf2 <- predict(train_rf2, test_set)

mean(s_rf2 == test_set$genre)
```

```
## [1] 0.6702599
```

again we observe the variable importance.

```
varImp(train_rf2)
```

```
## rf variable importance
##
##                   Overall
## tempo             100.000
## duration_ms        54.212
## danceability       41.160
## instrumentalness   38.669
## loudness           33.920
## energy             32.648
## valence            28.609
## speechiness        27.345
## acousticness       25.516
## liveness           19.300
## key                 9.898
## time_signature      0.000
```

The variable importance is the same as our previous random forest model.

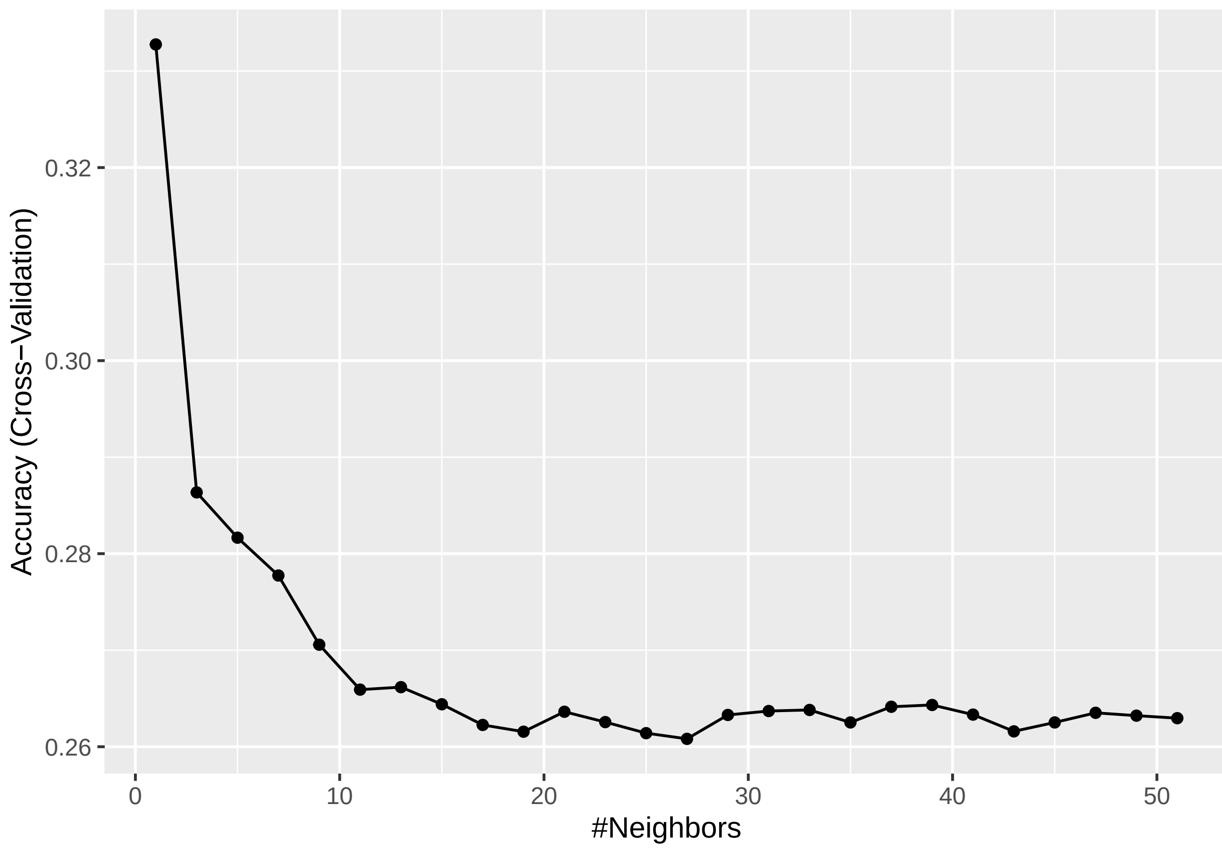
Model 5 | KNN model - All predictors We then apply the KNN model using all the predictors available to us and optimise for number of neighbours:

```
train_knn <- train(genre ~ ., data = training_set, method = "knn",
                   tuneGrid = data.frame(k = seq(1, 51, 2)),
                   trControl = trainControl(method = "cv", number=10, p=0.9))

train_knn$bestTune
```

```
##   k
## 1 1
```

```r
ggplot(train_knn)
```




```r
s_knn <- predict(train_knn, test_set)

mean(s_knn == test_set$genre)
```

```
## [1] 0.3350561
```

Interestingly, this variation of kNN model performed very poorly, worst than both LDA and QDA, a likely cause can be due to the nature of the predictors, we will attempt to use only a subset of the predictors, in particular the "important" variables we obtained from the random forest model earlier which are:

tempo + duration + danceability + instrumentalness + loudness

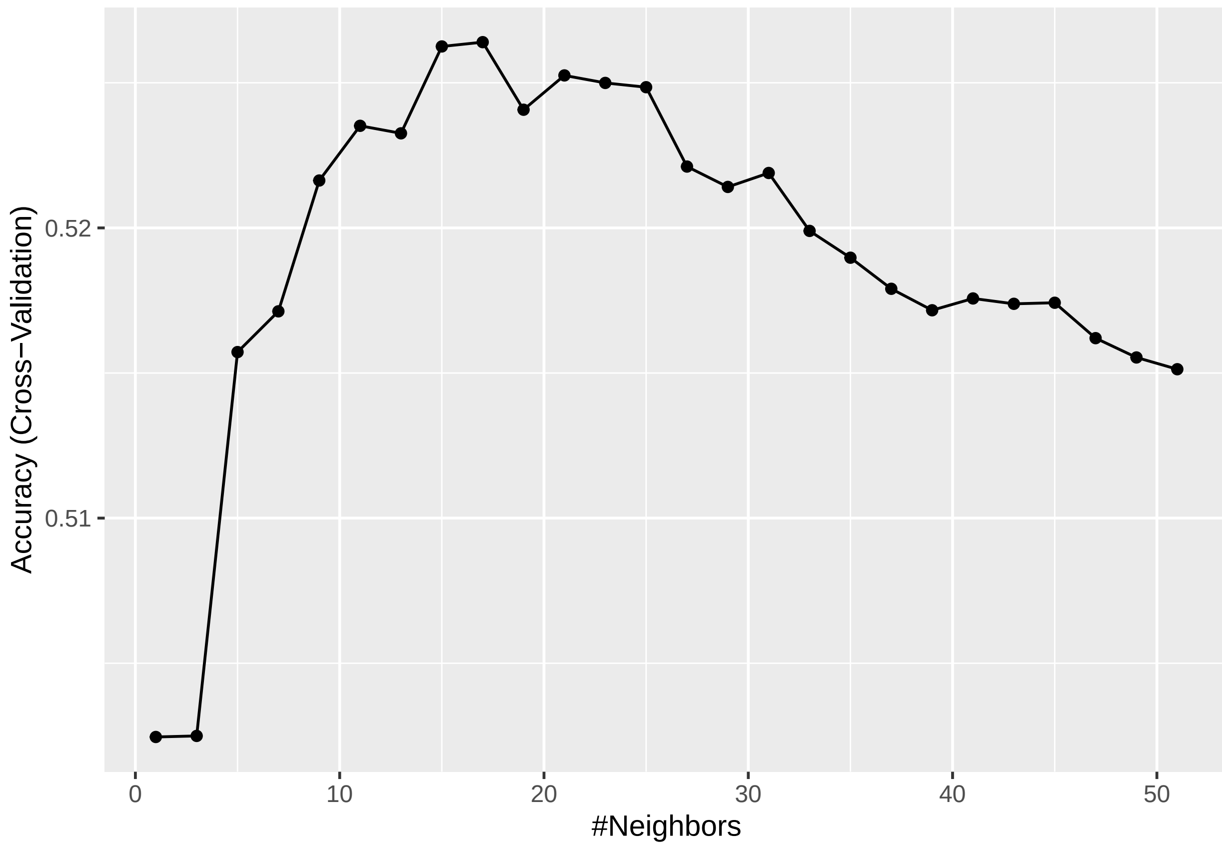
Model 6 | kNN model - important variable An interesting observation, when duration is used as a predictor, the accuracy is still as low as 0.3391908, but when duration is removed as a predictor, we achieved a better accuracy:

```r
train_knn2 <- train(genre ~ tempo + danceability + instrumentalness + loudness, data = training_set, me
                    tuneGrid = data.frame(k = seq(1, 51, 2)),
                    trControl = trainControl(method = "cv", number=10, p=0.9))

train_knn2$bestTune
```

```
##    k
## 9 17
```

```r
ggplot(train_knn2)
```




```r
s_knn2 <- predict(train_knn2, test_set)

mean(s_knn2 == test_set$genre)
```

```
## [1] 0.5316007
```

Results

Here are our final results applying the trained algorithms on the validation set:

```
## Warning in `==.default`(validation$genre, s_lda): longer object length is not a
## multiple of shorter object length

## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## Warning in `==.default`(validation$genre, s_qda): longer object length is not a
## multiple of shorter object length
```

```
## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## Warning in `==.default`(validation$genre, s_rf): longer object length is not a
## multiple of shorter object length

## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## Warning in `==.default`(validation$genre, s_rf2): longer object length is not a
## multiple of shorter object length

## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## Warning in `==.default`(validation$genre, s_knn): longer object length is not a
## multiple of shorter object length

## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## Warning in `==.default`(validation$genre, s_knn2): longer object length is not a
## multiple of shorter object length

## Warning in is.na(e1) | is.na(e2): longer object length is not a multiple of
## shorter object length

## # A tibble: 6 x 2
##   Method                          Accuracy
##   <chr>                              <dbl>
## 1 LDA model                          0.129
## 2 Random forest model (500 nodes)    0.128
## 3 Random forest model (100 nodes)    0.125
## 4 QDA model                          0.120
## 5 kNN model - important variable     0.105
## 6 kNN model - all predictors         0.102
```

The best performing algorithm is the random forest models, with 0.668 and 0.663 accuracy respectively for 100 and 500 nodes.

The kNN model have relatively low accuracy which is unexpected as the QDA model outperforms it by a margin.

Conclusion

We have attempted to use different machine learning algorithms to predict the genre of songs from a Spotify dataset, using audio features available to us as predictors.

There are some interesting observations, such as the negative impact of "duration" as a predictor on a kNN model, and tempo being the best predictor for genre according to the variable importance from random forest model.

One of the reason why the accuracy across different models are lower than expected is because the genre distribution are not evenly distributed and a lot of the genres in the dataset have overlapping similarities, as demonstrated from the data visualization earlier with a lot of features overlapping in ranges, with very few distinct features to separate the songs.