Final Project

Majorz

```r
library(tidyverse)
library(tidymodels)
library(glmnet)
library(Stat2Data)
library(ggcorrplot)
spotify <- read_csv("data/tf_mini.csv")
```

Introduction and Data

With recent features on music apps such as Spotify Wrapped gaining massive popularity, understanding users' music taste for personalized recommendations and music trend analysis have become a critical challenge for streaming companies. To categorize and analyze the countless songs on these platforms, each are dissected into various musical elements ranging from duration and tempo to loudness and danceability. Using a real database of song tracks compiled and released by Spotify for data engineering purposes, we wanted to see whether common trends could be observed between different musical elements. Modes of songs, specifically, were of our interest since they determine the mood of the music — songs in major modes sound more bright and uplifting while those in minor modes are more calm and even sadder. We wanted to explore if musical aspects such as bounciness or tempo would be correlated to the song's mode in some way, with some of our example hypotheses being that minor songs would be slower and/or less danceable but more acoustic than major songs. Hence, we set the following:

Research question: How do different musical elements affect whether a song is in major or minor mode?

This data was collected from the Spotify for Developers website, as the data set was published to be used as part of an open data science challenge. With no null values and well-categorized variables, our data was already cleaned and ready to be used for a complete case analysis. Minor data cleaning processes that we conducted were deleting irrelevant variables such as acoustic vectors and adding a new variable "new_mode" to express major and minor modes numerically as 1 and 0.

Data source: https://www.aicrowd.com/challenges/spotify-sequential-skip-prediction-challenge/dataset_files (need to create an account and log in to access the dataset)

Some of our key variables included:

- duration: length of the song in seconds
- release_year: year of song released
- key: song key starting from C major (0) to B minor (11)
- mode: song mode (major or minor)
- new_mode: song mode numerized (1 = major, 0 = minor)
- tempo: speed of song in beats per minute (bpm)
- time signature: number of quarter notes in each measure

To get a gist of what our data was presenting, we fitted an initial logistic model using all variables as predictors.

```
spotify_mode <- spotify |>
  mutate(new_mode = if_else(mode == "major", 1, 0),
         new_mode = as.numeric(new_mode))

spotify_mode |> drop_na(new_mode)
```

```
# A tibble: 50,704 x 31
   track_id      durat~1 relea~2 us_po~3 acous~4 beat_~5 bounc~6 dance~7 dyn_r~8
   <chr>           <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
 1 t_a540e552-1~    110.    1950   100.    0.458   0.519   0.505   0.400    7.51
 2 t_67965da0-1~    188.    1950   100.    0.916   0.419   0.546   0.491    9.10
 3 t_0614ecd3-a~    161.    1951    99.6   0.813   0.426   0.508   0.492    8.37
 4 t_070a63a0-7~    175.    1951    99.7   0.397   0.401   0.360   0.552    5.97
 5 t_d6990e17-9~    370.    1951   100.    0.729   0.371   0.335   0.483    5.80
 6 t_fcb90952-0~    178.    1951   100.    0.186   0.549   0.579   0.744    8.67
 7 t_20675f8a-3~    166.    1952   100.    0.519   0.592   0.640   0.741    9.53
 8 t_7577ca53-5~    198.    1952    99.5   0.787   0.472   0.448   0.427    6.91
 9 t_8a461a4e-6~    215.    1954   100.    0.155   0.526   0.566   0.523    8.63
10 t_ae523005-8~    281.    1954    97.4   0.941   0.233   0.209   0.242    4.83
# ... with 50,694 more rows, 22 more variables: energy <dbl>, flatness <dbl>,
#   instrumentalness <dbl>, key <dbl>, liveness <dbl>, loudness <dbl>,
#   mechanism <dbl>, mode <chr>, organism <dbl>, speechiness <dbl>,
#   tempo <dbl>, time_signature <dbl>, valence <dbl>, acoustic_vector_0 <dbl>,
#   acoustic_vector_1 <dbl>, acoustic_vector_2 <dbl>, acoustic_vector_3 <dbl>,
```

```
#   acoustic_vector_4 <dbl>, acoustic_vector_5 <dbl>, acoustic_vector_6 <dbl>,
#   acoustic_vector_7 <dbl>, new_mode <dbl>, and abbreviated variable names ...
```

```
glm_all_mode <- glm(new_mode ~ us_popularity_estimate + duration + release_year + acoustic
     beat_strength + bounciness + danceability + dyn_range_mean + energy +
     flatness + instrumentalness + key + liveness + loudness + mechanism +
       organism + speechiness + tempo + time_signature + valence,
     data = spotify_mode,
     family = "binomial")
summary(glm_all_mode)
```

```
Call:
glm(formula = new_mode ~ us_popularity_estimate + duration +
    release_year + acousticness + beat_strength + bounciness +
    danceability + dyn_range_mean + energy + flatness + instrumentalness +
    key + liveness + loudness + mechanism + organism + speechiness +
    tempo + time_signature + valence, family = "binomial", data = spotify_mode)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3569  -1.2543   0.7625   0.9493   1.8185

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
(Intercept)            32.2683808  2.3096693  13.971  < 2e-16 ***
us_popularity_estimate -0.0112941  0.0085642  -1.319 0.187249
duration               -0.0008868  0.0001370  -6.472 9.68e-11 ***
release_year           -0.0145826  0.0010562 -13.807  < 2e-16 ***
acousticness            0.4800550  0.1339125   3.585 0.000337 ***
beat_strength           2.3227249  0.3798220   6.115 9.64e-10 ***
bounciness             -4.2116774  0.5087117  -8.279  < 2e-16 ***
danceability            0.2508033  0.1611182   1.557 0.119556
dyn_range_mean          0.1188409  0.0200062   5.940 2.85e-09 ***
energy                 -0.5804580  0.1072094  -5.414 6.15e-08 ***
flatness                0.7082200  0.3348900   2.115 0.034448 *
instrumentalness       -0.3421403  0.0522757  -6.545 5.95e-11 ***
key                    -0.0930592  0.0026793 -34.733  < 2e-16 ***
liveness                0.3261005  0.0588139   5.545 2.95e-08 ***
loudness                0.0223914  0.0043966   5.093 3.53e-07 ***
mechanism              -0.8263282  0.2122943  -3.892 9.93e-05 ***
```

```
organism               -0.3927748  0.3168700  -1.240 0.215144
speechiness            -1.0627013  0.0967583 -10.983  < 2e-16 ***
tempo                   0.0027563  0.0004504   6.120 9.37e-10 ***
time_signature         -0.2081995  0.0260103  -8.005 1.20e-15 ***
valence                 0.5394631  0.0506272  10.656  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 66141  on 50703  degrees of freedom
Residual deviance: 63327  on 50683  degrees of freedom
AIC: 63369

Number of Fisher Scoring iterations: 4
```

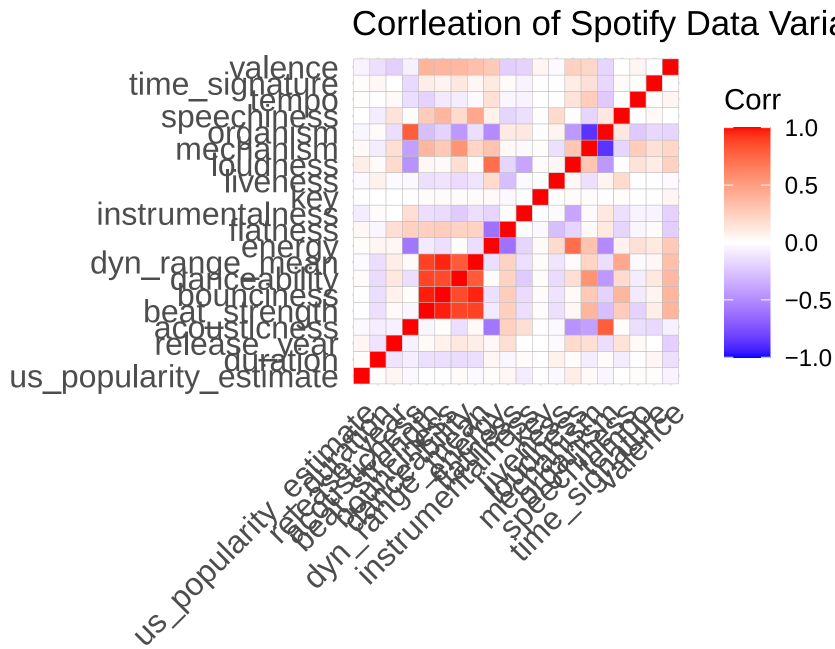
As demonstrated by the regression model above, there are many predictors that are statistically significant, using the significance level of $\alpha = 0.5$. However, it is critical to improve this baseline model in the following ways:

1) Confirm that there are not instances of multicollinearity (or model overfitting)
2) Ensure that the variables included are meaningfully contributing to the model
3) Optimize the model and determine if interactions or changes are appropriate

```
spotify_cor <- spotify_mode|>
  select(us_popularity_estimate, duration, release_year, acousticness,
     beat_strength, bounciness, danceability, dyn_range_mean, energy,
     flatness,instrumentalness, key, liveness, loudness, mechanism,
       organism, speechiness, tempo, time_signature, valence)

cor_spotify <- cor(spotify_cor)

ggcorrplot(cor_spotify)+
  labs(title = "Corrleation of Spotify Data Variables")
```



Source used: http://www.sthda.com/english/wiki/ggcorrplot-visualization-of-a-correlation-matrix-using-ggplot2#:~:text=The%20easiest%20way%20to%20visualize,ggcorr()%20in%20ggally%20package

Examining the correlation plot above, it appears there are variables that have a high positive correlation with each other. This causes great concern with multicollinearity as the model may be overfitted. For example,

- beat_strength is highly correlated with
  - dyn_range_mean
  - danceability
  - bounciness

Therefore, to prevent overfitting in our regression model, the following variables should be removed:

1) beat_strength

2) dyn_range_mean

3) danceability

4) bounciness

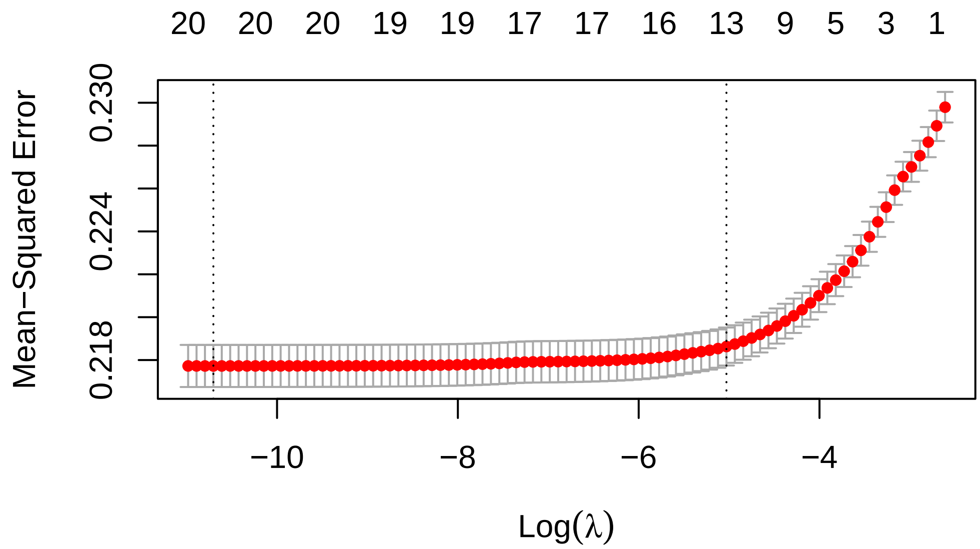
In addition to removing variables due to extremely high correlations, it is also important to select variables that make an impact on the model. For example, some variables may be replicated or not meaningful by nature to the outcome of interest; therefore, removal is essential. In this analysis, we decided to use a LASSO model to select variables that are essential to the model.

```
y <- spotify_mode$new_mode
x <- model.matrix(new_mode ~ us_popularity_estimate + duration + release_year +
                acousticness + beat_strength + bounciness + danceability +
                  dyn_range_mean + energy + flatness + instrumentalness + key +
                  liveness + loudness + mechanism + organism + speechiness +
                  tempo + time_signature + valence,
                  data = spotify_mode, family = "binomial")
lasso_sc <- cv.glmnet(x, y, alpha = 1)
best_lambda <- lasso_sc$lambda.min
lasso_final <- glmnet(x, y, alpha = 1, lambda = best_lambda)
lasso_final$beta
```

```
21 x 1 sparse Matrix of class "dgCMatrix"
                                  s0
(Intercept)                .
us_popularity_estimate -0.0023637916
duration               -0.0001814763
release_year           -0.0027557208
acousticness            0.0805640127
beat_strength           0.4370267283
bounciness             -0.8190123058
danceability            0.0535792890
dyn_range_mean          0.0227053898
energy                 -0.1261802580
flatness                0.1274372536
instrumentalness       -0.0765744138
key                    -0.0204709028
liveness                0.0689080471
loudness                0.0046734630
mechanism              -0.1449917751
organism               -0.0369852549
speechiness            -0.2429662033
tempo                   0.0005675704
time_signature         -0.0409752274
valence                 0.1198630481
```

LASSO kept all of the predictors.

```
plot(lasso_sc)
```



not sure if this is needed or not^

Methodology

Evaluating assumptions:

figure out to make this smaller or how to get charts to show^

There had to be less data points for some of the predictors because there was only so many different values and enough of them to be able to get the empirical logits. For example, with key there is only 12 unique values, but not all of them had enough values to be calculated, so we did 10 groups. I eliminated the titles to make the plots more clear and because they were repetitive. In summary, we concluded that linearity is met for _________ because there is no major pattern in empirical logits. Linearity was not met for ______ because ______.

```
glm_aug <- glm_aug |>
  mutate(prob = exp(.fitted)/(1 + exp(.fitted)),
         pred_mode = ifelse(prob > 0.5, "Major", "Minor")) |>
```

```
  select(.fitted, prob, pred_mode, new_mode)

table(glm_aug$pred_mode, glm_aug$new_mode)
```

Using our logistic regression model as a classifier for any infection by using a threshold of 0.5 predicted probability, we are able to calculate the following values:

Prevalence:

Sensitivity:

Specificity:

Positive predicted value:

Negative predicted value:

This implies that _____

```
glm_aug |>
  roc_auc(truth = as.factor(new_mode),
          prob,
          event_level = "second") |>
  autoplot()

glm_aug |>
  roc_auc(truth = as.factor(new_mode),
          prob,
          event_level = "second")
```

Results

HOW to pick which predictors are the best???

One predictor that makes sense to interpret is key because key has changes in whole numbers while many of the other predictors are within tenths of differences of each other amongst observations. Holding all other predictors constant, for every one (unit) increase in key, we expect the log-odds of a song being major rather than minor to increase by approximately 0.0931. So, when holding all other predictors constant, we for every one number increase in key (find what this means), the odds of the patient getting any infection is predicted to be multiplied by $e^{0.0931} = 1.0976$. For an example, while holding all other predictors constant, the relative odds of a song being major rather than minor comparing a song with key 10 vs a song with key 2 is $e^{8*0.0931}$ is 2.106.

to be continued

Discussion