Final Project

Majorz

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

```r
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
```

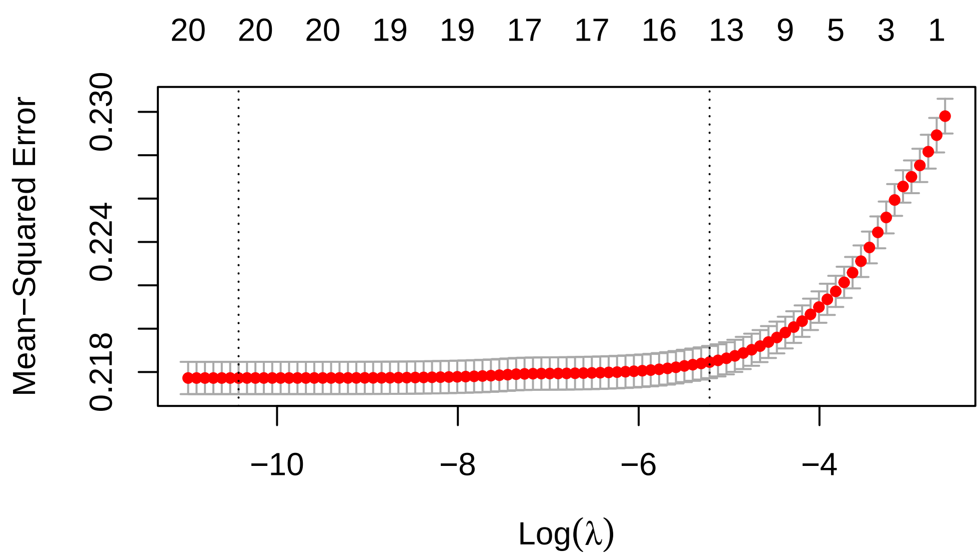
```r
y <- spotify_mode$new_mode
x <- model.matrix(new_mode ~ us_popularity_estimate + duration + release_year +
                acousticness + beat_strength + bounciness + danceability +
                  dyn_range_mean + energy + flatness + instrumentalness + key +
                  liveness + loudness + mechanism + organism + speechiness +
                  tempo + time_signature + valence,
                  data = spotify_mode, family = "binomial")
lasso_sc <- cv.glmnet(x, y, alpha = 1)
best_lambda <- lasso_sc$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 -0.0023559636
duration               -0.0001813693
release_year           -0.0027568279
acousticness            0.0792094381
beat_strength           0.4315404261
bounciness             -0.8109519946
danceability            0.0525710194
dyn_range_mean          0.0224876823
energy                 -0.1262305883
flatness                0.1267500250
```

```
instrumentalness       -0.0766624599
key                    -0.0204687650
liveness                0.0688576817
loudness                0.0046671053
mechanism              -0.1423437972
organism               -0.0337463830
speechiness            -0.2431275494
tempo                   0.0005642049
time_signature         -0.0409951623
valence                 0.1198012139
```

LASSO kept all of the predictors.

```
plot(lasso_sc)
```



not sure if this is needed or not^

Introduction and Data

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 ______.

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