Of all the art forms in existence, music is one that has seen widespread influence and success like few others. Even though TV shows and movies have a ‘visual’ advantage over music, the latter still thrives in the modern age, raking in 31.2 billion USD for FY2022. This success is not just a fluke though. There definitely is something to be said about the ability of music to transcend the failings of spoken language through means of varied instrumentation and above all, the sheer genius of certain artists to manipulate voices and instruments to make songs transcendent of their time. For example, the song Bohemian Rhapsody by British band Queen stops me in my tracks just as much today as it did 5 years ago when I first discovered it. A lot of memories (be they happy or sad) are likely associated with certain songs as well, making music an integral part of the lives of many people.

The seeming nobility of music is swiftly brought down by the nature of the ‘industry’ that generates it. Yes, I use the word ‘generates’ quite consciously, and this is most certainly the result of musical endeavors being treated more as commercial opportunities rather than a means of expression. Instead of moving into the clear negatives created as a result of the , it would be more fitting to talk about one of the benefits of commercializing music: accessibility. This brings us to music-streaming services, the modern embodiment of accessibility. These services offer at a nominal price, the access to digital libraries of a vast ocean of music from different genres. The biggest player in this space is Spotify, a company started in 2006 by Swedish entrepreneurs Daniel Ek and Martin Lorentzon. As of 2023, the service has over 210 million paid subscribers and 510 million monthly active users worldwide. Our data was taken from Tidy Tuesday’s compilation of Spotify’s internal metrics on different aspects of songs such as danceability, key, mode, duration of time, instrumentalness, liveness, and valence, amongst other things. The intention is to use this data to answer the question:

**What qualities of a song are the most important contributers to its danceability score?**

Before proceeding, here is a small list of the aforementioned song traits, courtesy of Tidy Tuesday’s readme page:

| | | |
|---|---|---|
| danceability | double | A value of 0.0 is least danceable and 1.0 is most danceable. |
| energy | double | Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. |
| key | double | The estimated overall key of the track. If no key was detected, the value is -1. |
| loudness | double | The overall loudness of a track in decibels (dB). Values typically range between -60 and 0 db. |
| mode | double | Mode indicates the modality (major or minor) of a track. Major is represented by 1 and minor is 0. |

If interested, the explanations for other such traits can be found here.

All in all, there were 32833 observations and 23 columns (16 of which are numeric) in the dataset as imported from Tidy Tuesday. There was no cleaning that needed to be performed, as the data was structured perfectly by default and it is mentioned here that we will randomly sample 10000 observations to use for our tests.

Here are some summary statistics of danceability:

```
Favstats mosaic

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min         0.0000
Q1          0.5630
median      0.6720
Q3          0.7610
max         0.9830
mean        0.6548
sd          0.1451
n       32833.0000
missing     0.0000

----------------
```
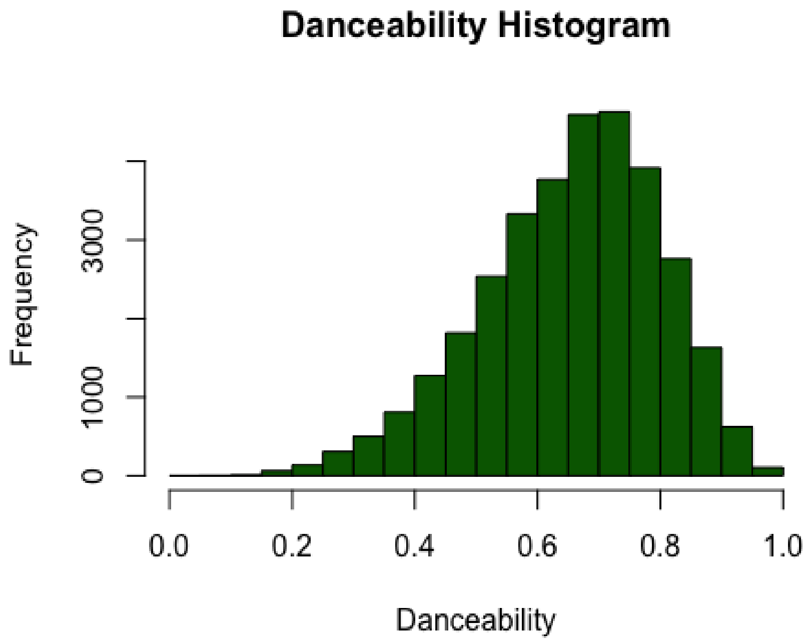
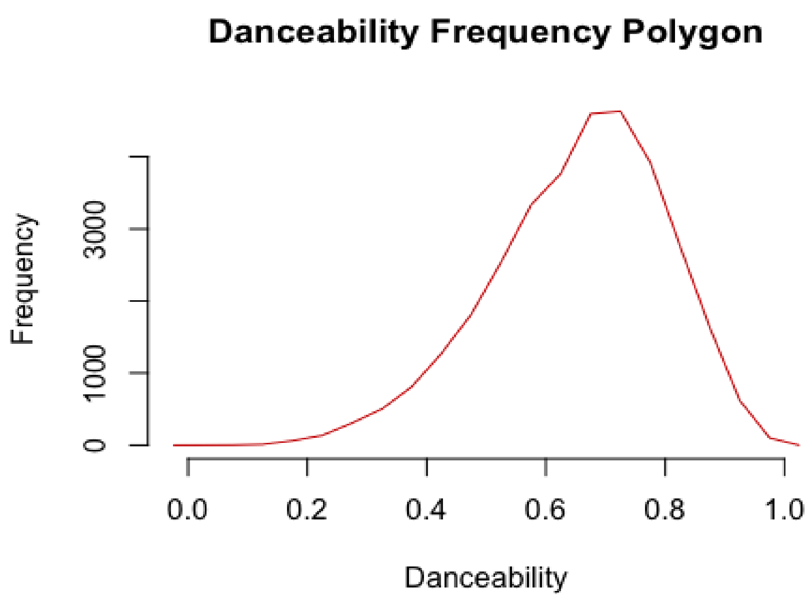

Here is a histogram and frequency polygon of the danceability trait for ease of visualization. We notice a left skew present in the plot and it is unimodal as well.




## Methodology & Results:

First, we will fit an additive multiple linear regression model and proceed from there. We initialize our sampled data and remove the non-numeric parameters. While most of the columns are classified correctly, we correct for "mode" and "key" as factors. This is because "mode" is a 0 or 1 entry and "key" represents the 11 keys in music.

Naive Linear Model:

Here is our model and ANOVA table:

```
Call:
lm(formula = danceability ~ ., data = music_reduced)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.59813 -0.07675  0.01342  0.08896  0.36148 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       9.010e-01  1.417e-02  63.599  < 2e-16 ***
track_popularity  2.197e-04  5.280e-05   4.161 3.20e-05 ***
energy           -2.393e-01  1.131e-02 -21.168  < 2e-16 ***
key1              2.491e-02  5.382e-03   4.629 3.72e-06 ***
key2             -1.986e-03  5.848e-03  -0.340   0.7342    
key3             -3.809e-02  8.444e-03  -4.511 6.52e-06 ***
key4             -1.423e-02  6.302e-03  -2.258   0.0240 *  
key5              3.523e-03  6.080e-03   0.579   0.5623    
key6              2.180e-03  6.013e-03   0.363   0.7169    
key7              6.869e-03  5.651e-03   1.216   0.2242    
key8              2.612e-03  6.136e-03   0.426   0.6704    
key9             -1.184e-02  5.737e-03  -2.063   0.0391 *  
key10             4.289e-03  6.293e-03   0.682   0.4956    
key11            -3.504e-03  5.792e-03  -0.605   0.5453    
loudness          9.068e-03  6.018e-04  15.068  < 2e-16 ***
mode1            -1.541e-02  2.697e-03  -5.711 1.15e-08 ***
speechiness       2.480e-01  1.279e-02  19.386  < 2e-16 ***
acousticness     -1.009e-01  6.973e-03 -14.478  < 2e-16 ***
instrumentalness  7.322e-02  6.112e-03  11.980  < 2e-16 ***
liveness         -8.817e-02  8.415e-03 -10.477  < 2e-16 ***
valence           2.292e-01  5.685e-03  40.322  < 2e-16 ***
tempo            -9.035e-04  4.758e-05 -18.990  < 2e-16 ***
duration_ms      -1.193e-07  2.189e-08  -5.451 5.13e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1275 on 9977 degrees of freedom
Multiple R-squared:  0.2497,	Adjusted R-squared:  0.248 
F-statistic: 150.9 on 22 and 9977 DF,  p-value: < 2.2e-16

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Analysis of Variance Table

Response: danceability
                   Df  Sum Sq Mean Sq  F value    Pr(>F)    
track_popularity    1   1.451  1.4510   89.309 < 2.2e-16 ***
```
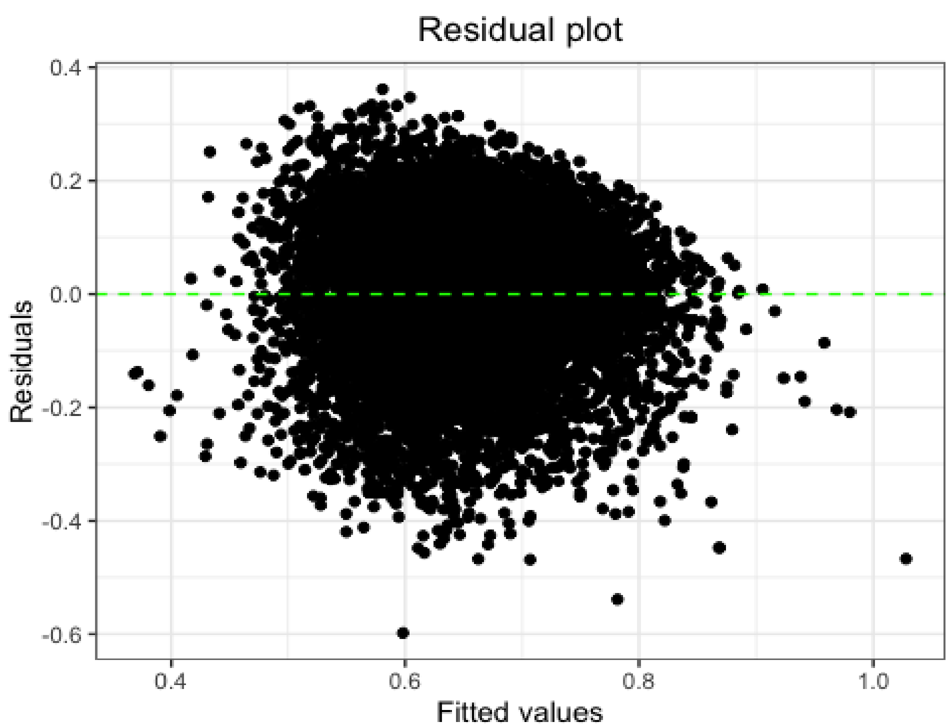

```
energy               1   1.090  1.0903   67.109 2.883e-16 ***
key                 11   3.059  0.2781   17.118 < 2.2e-16 ***
loudness             1   2.125  2.1252  130.809 < 2.2e-16 ***
mode                 1   0.762  0.7616   46.877 8.002e-12 ***
speechiness          1   6.245  6.2447  384.368 < 2.2e-16 ***
acousticness         1   1.704  1.7043  104.902 < 2.2e-16 ***
instrumentalness     1   0.334  0.3342   20.569 5.820e-06 ***
liveness             1   2.729  2.7293  167.990 < 2.2e-16 ***
valence              1  28.140 28.1402 1732.057 < 2.2e-16 ***
tempo                1   5.818  5.8179  358.101 < 2.2e-16 ***
duration_ms          1   0.483  0.4827   29.713 5.128e-08 ***
Residuals         9977 162.093  0.0162
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

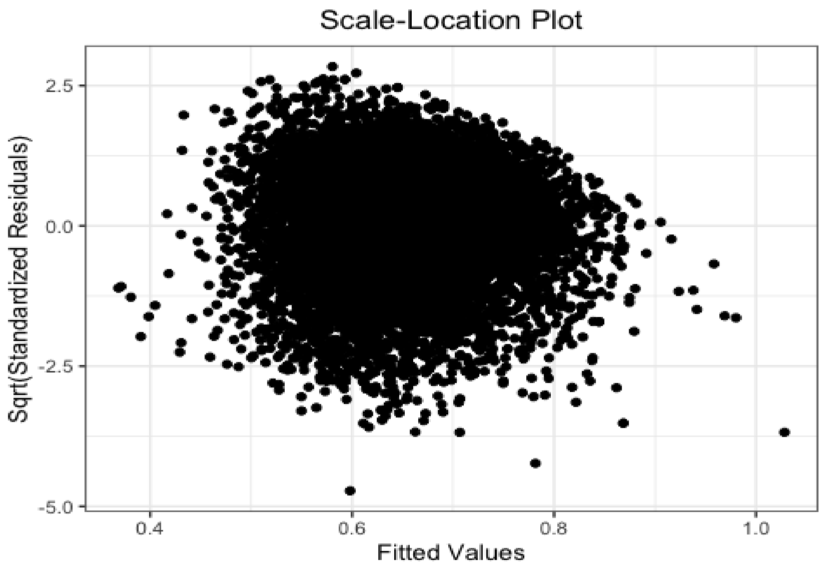
Technically, we get the answer to our question here by noticing from the ANOVA that all the predictors are highly significant. The model iteslf is also significant. However, in regards to model utility, the $R^2_{adj}$ doesn't seem convincing as it implies that our model is only able to explain 24.8% of the data.

Here are the residual plots to help with checking model assumptions:

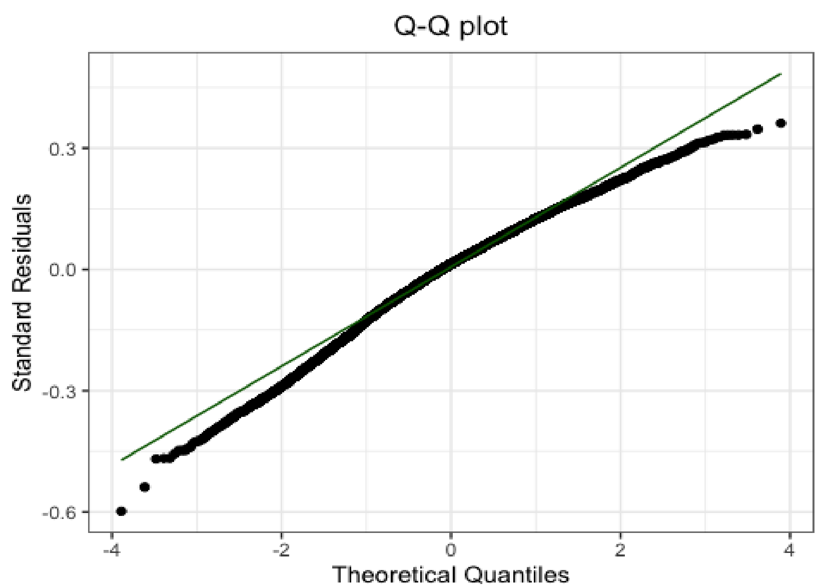
1. **<u>Independence</u>**: This assumption is clearly violated as there are multiple songs by the same individual in the dataset. Even though we have randomly sampled our set, there is a non-zero probability of this happening. So, our data is not independent.
2. **<u>Linearity</u>**: From the residual plot below, we don't see any non-linear pattern that would raise any flags. So, we consider this assumption to hold.



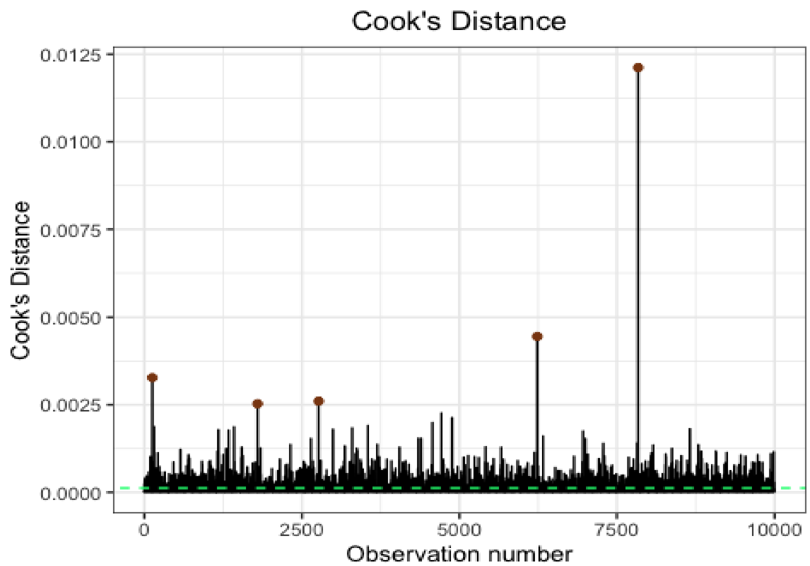
3. **Homoscedasticity**: Again, using the same residual plot, we notice the lack of a funnel-like shape here. So, this assumption is not violated.




4. **Normality**: As we have more than 5000 observations, solely relying on a quantitative test of normality would not be the best way to go here. This is because normality tests can be overly sensitive at large sample sizes. So, we will rely on a qualitative way to check this assumption. Using the plot below, we see that there is noticeable deviation at the tails. While one can go either way on this, we will consider this a violation of the assumption.




5. **Cook's distance (Influential points and outliers)**: Clearly, there are issues with influential points in our model. I have marked the top five most influential points with brown dots, but even if you ignored these points, there are multiple other points that lie beyond the green threshold.

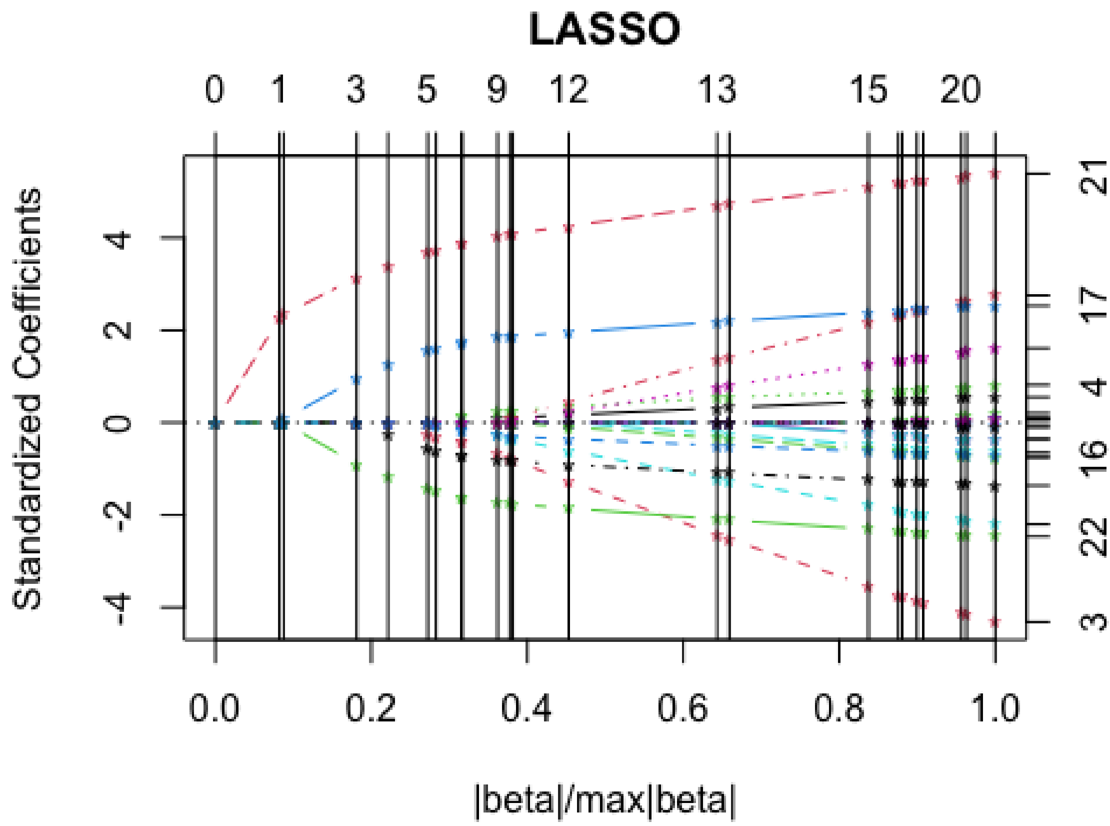



Here is the largest influential points from our sampled data. Interestingly, it is a four second song by Japanese band DREAMS COME TRUE, who have 1.5 Million followers as of 11/29/2023.

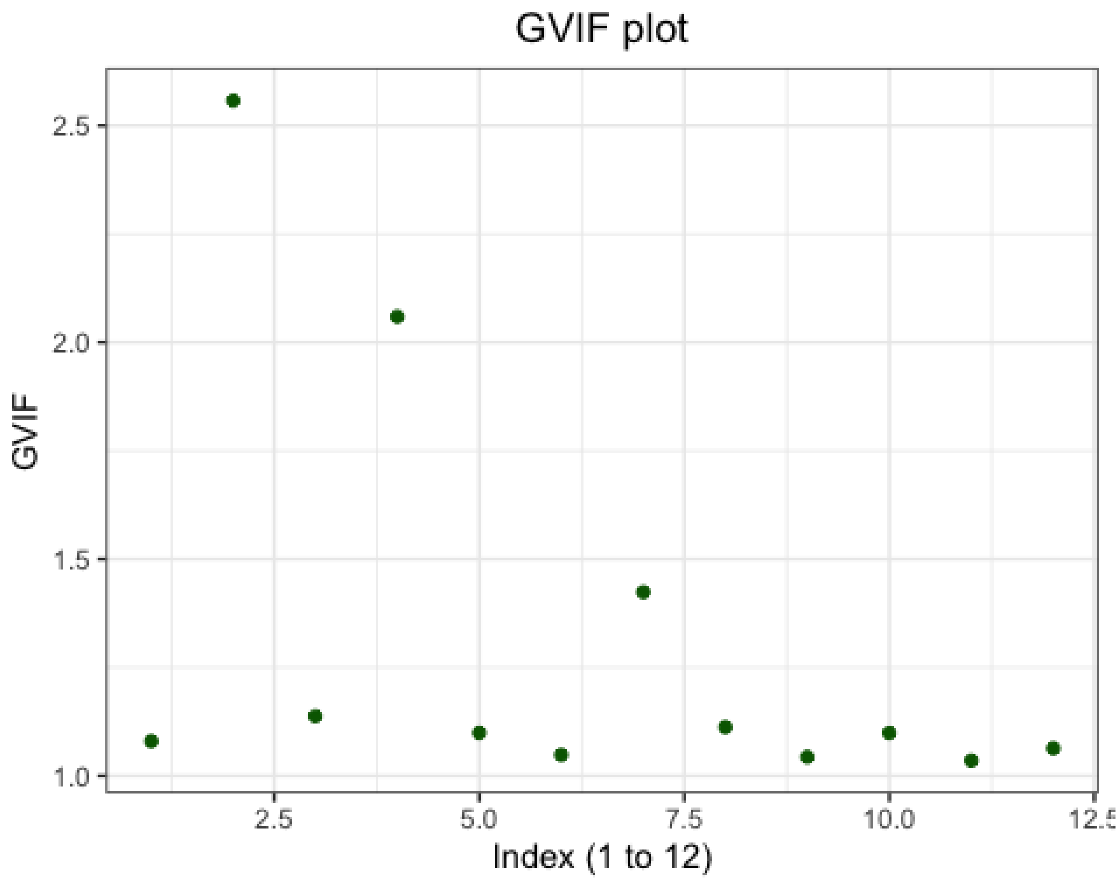
```
1w6nRCU68klqNfYaaVP2j        <- track_id
Hi, How're You Doin'?        <- track_name
DREAMS COME TRUE             <- track_artist
0                            <- track_popularity
4wdK52JVu5GzhxW3RCZ3AV       <- track_album_id
Dreams Come True             <- track_album_name
1989-03-21                   <- track_album_release_date
City Pop 1985 シティーポップ  <- playlist_name
3j2osvmecEao5nmo9jZ5df       <- playlist_id
rock                         <- playlist_genre
album rock                   <- playlist_subgenre
0                            <- danceability
0.315                        <- energy
1                            <- key
-26.087                      <- loudness
1                            <- mode
0                            <- speechiness
0                            <- acousticness
0                            <- instrumentalness
0                            <- liveness
0                            <- valence
0                            <- tempo
4000                         <- duration_ms
```

Overall, the point of fitting the linear model was in order to ‘test the waters.’ To improve upon this, we will use a lasso selection process, which will appropriately inflate/deflate the $\beta$’s depending upon their relative importance/unimportnace.

```
Call:
lars(x = music_matrix, y = music_reduced$danceability, type = "lasso",
    intercept = TRUE)
R-squared: 0.25
Sequence of LASSO moves:
     valence speechiness tempo liveness energy duration_ms key1
Var       21          17    22       20      3          23    4
Step       1           2     3        4      5           6    7
     track_popularity acousticness loudness instrumentalness mode1 key3 key9
Var                 2           18       15               19    16    6   12
Step                8            9       10               11    12   13   14
     key4 key7 key10 key11 key2 key5 key8 key6
Var     7   10    13    14    5    8   11    9
Step   15   16    17    18   19   20   21   22


LASSO Coefficients

------------------

     (Intercept) track_popularity           energy             key1
    0.000000e+00     2.196882e-04    -2.393059e-01     2.491412e-02
            key2             key3             key4             key5
   -1.985946e-03    -3.809129e-02    -1.423014e-02     3.523078e-03
            key6             key7             key8             key9
    2.180248e-03     6.868816e-03     2.611649e-03    -1.183677e-02
           key10            key11         loudness            mode1
    4.289135e-03    -3.503741e-03     9.067841e-03    -1.540652e-02
     speechiness     acousticness instrumentalness         liveness
    2.480393e-01    -1.009498e-01     7.322137e-02    -8.816558e-02
         valence            tempo      duration_ms
    2.292154e-01    -9.035249e-04    -1.193453e-07

------------------
```




Here, we see that our $R^2_{adj}$ has unfortunately only improved slightly (0.25) compared to the previous model (0.248). Could there be an issue of multicollinearity? To test this, we plot the GVIF's (Generalized Variance Inflation Factor) for each predictor.




The largest GVIF is approximately 2.5, which implies moderate correlation to other predictors. For most predictors the GVIF is marginally above 1, implying little to no correlation with other predictors. Thus, with a little hand-waving, we can scratch out multicollinearity as being a problem here.

## Discussion & Conclusion

So, where does that leave us? Well, not far from where we started! LASSO did not lead us to a better place (in terms of $R^2_{adj}$ at least) as we had hoped. With that said, issues such as those of normality and influential points are not straightforward to solve and are to be handled with a lot of care. Finally, our decision to use the predictors that ended up in our naive model was a choice that was well-deliberated. The assumption was that different aspects of a song (be they instrumental or otherwise) ultimately contribute to its danceability metric. However, we are aware of the possibility that this may not be the best move. Perhaps people consider shorter songs to be more danceable. Or something else like so. The mentality of a culture is much more difficult to predict, and a more in-depth analysis would be required to understand this complex effect.

Assuming one wants to still work with our model as it is now, there are three remedies that would be use: Response transformations, considering interaction terms, and trying a non-parametric model. We will briefly present our reasoning for the viability of the three processes.

1. **Response transformations**: One would go about this by first conducting a boxcox procedure, which would suggest an appropriate transformation on the response and then create a new linear model using the transformed response. What's the problem here? Well, boxcox needs strictly positive values in the response. Even zeroes are not allowed. Unfortunately there are many songs here that have zeroes for their danceability score. Thus, unless you're okay with deleting a chunk of songs, this approach is not recommended at all.

   Here's a sample of what happense if you use R to do the boxcox procedure.

```
MASS:: boxcox(object = music_lm_naive)

Error in boxcox.default(object = music_lm_naive): response variable mus
t be positive
```

2. **Considering Interaction terms**: This approach is a double edged sword in our opinion. On one hand, the $R^2_{adj}$ shoots up proportional to the order of interactions in the model. For example, we ran the linear model with first order interactions and the new model was able to explain 31% of the total variation, which is about a 10% increase from before. Here's that in R:

```
# Neat little trick to generate first order interactions without writin
g everything out in R
music_lm_interact <- lm(danceability~.^2,data = music_reduced)
summ <- summary(object = music_lm_interact)
# Adjusted R squared
summ$adj.r.squared

[1] 0.3109649
```

Running the LASSO on this model, the $R^2_{adj}$ increases to about 35%. All seems great so far. However, one big problem is in regards to overfitting the model with useless predictors. Take a look at the last ten predictors and compare it to our naive model from before:

```
tail(anova(music_lm_interact),10)

Analysis of Variance Table

Response: danceability
                              Df  Sum Sq Mean Sq F value    Pr(>F)
instrumentalness:valence       1   0.303 0.30255 20.3229 6.617e-06 ***
instrumentalness:tempo         1   0.039 0.03913  2.6284    0.1050
instrumentalness:duration_ms   1   0.491 0.49129 33.0012 9.485e-09 ***
liveness:valence               1   0.007 0.00746  0.5014    0.4789
liveness:tempo                 1   0.039 0.03949  2.6525    0.1034
liveness:duration_ms           1   0.001 0.00060  0.0400    0.8415
valence:tempo                  1   0.008 0.00782  0.5251    0.4687
valence:duration_ms            1   0.588 0.58832 39.5193 3.387e-10 ***
tempo:duration_ms              1   0.002 0.00189  0.1269    0.7217
Residuals                   9801 145.907 0.01489
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Thus, one should use this to make selective interactions that would strengthen the overall model.

3. **<u>Non-parametric model</u>**: This is much more random suggestion as compared to previous two. However, using the logic mentioned in (1), one should be able to see why a non-parametric approach may be beneficial.

<Add overall conclusions>