

A Preliminary Analyzation of Grammy Album of the Year History with Spotify API

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```
## Warning: package 'knitr' was built under R version 4.0.1
```

Background and Data Extraction:

Grammy nominations and winners can be somewhat predictable. It's easy to place bets on who's going to get nominated or win based on streaming history, top-charts, or artist popularity. However, it is interesting to consider if the Recording Academy has a specific taste for music. This project intends to explore the trends in audio features for the nominations and winners of Album of the Year. To do this, I have generated a brief python application that connects to Spotify database. Spotify's open database returns various information about release history, artist popularity, streaming, history, etc. Amongst the features available from the Spotify Developer's page, you can request a track's audio features. Audio features are 13 Spotify-deemed and/or factual values that rate a track based on sonic characteristics. Each data point is an audio feature summary of each track in the album; Note Spotify does not offer this data- my Python application summarized each album (see a detailed explanation in the .py file). In addition to the audio features from Spotify I've included Spotify's Album name and ID, Spotify's Artist name and ID, the year of nomination, the number of tracks in the album, and a binary variable for if the album won in the year of respective nomination. The data frame includes every nomination from 1961 to 2021. Using this data frame I will look at how audio features have changed overtime and how those audio features can be used to model the Recording Academy's 'taste' for music.

Series in the data frame:

album_name: Album Name

album_id: Spotify's unique Album ID

artist_name: Primary artist of the Album

artist_id: Spotify's unique Artist ID

year: year of Grammy nomination number_track: Number of Tracks in the album

win: 1{won the year of nomination}, 0{otherwise}

danceability: Average measure from 0.0 to 1.0 of how danceable the tracks are (1.0 being most energetic)

energy: Average measure from 0.0 to 1.0 of how energetic the album's tracks are (1.00 being most energetic)

key: average of factor variable from -1.0 to 11.0 for the key of the album's tracks

loudness: Average overall loudness in decibels of the album's tracks.

mode: 1{major}, 0{minor}

speechiness: Average measure from 0.0 to 1.0 of whether the album's tracks are a speech recording (1.00 being exclusively speech)

acousticnes: Average measure from 0.0 to 1.0 of whether the album's track is acoustic (1.00 being most acoustic)

instrumentalnes: Average measure from 0.0 to 1.0 of whether the album's tracks are instrumental (1.00 being exclusively instrumental with no vocals)

liveness: Average from 0.0 to 1.0 of whether the album's tracks is a live recording/presence of an audience in recording (1.00 being most acoustic)

valence: Average measure from 0.0 to 1.0 of whether the album's tracks are "positive and happy" sounding (1.00 being most valent sounding)

tempo:The average beats per minute of the the album's tracks

duration_ms:The average duration the album's track

time_signature: average of factor variable from 3 to 7 that indicates the album's tracks time signature

Data frame snippet:

```
library(readr)
master_data <- read_csv("master_data.csv")

## Warning: Missing column names filled in: 'X1' [1]

## Parsed with column specification:
## cols(
##   .default = col_double(),
##   album_name = col_character(),
##   album_id = col_character(),
##   artist_name = col_character(),
##   artist_id = col_character()
## )

## See spec(...) for full column specifications.
df<-master_data[,-c(1)]
df

## # A tibble: 308 x 20
##   album_name album_id artist_name artist_id year number_tracks win
##   <chr>      <chr>    <chr>      <chr>    <dbl>      <dbl> <dbl>
## 1 The Butto~ 7hXOR0e~ Bob Newhart 49mU7S19~ 1961         6     1
## 2 Belafonte~ 26UI9qe~ Harry Bela~ 6Tw1ktF4~ 1961        19     0
## 3 Nice 'n' ~ 2Xp6c80~ Frank Sina~ 1Mxqyy3p~ 1961        16     0
## 4 Puccini: ~ 3eTeuie~ Giacomo Pu~ 00zxPXyo~ 1961        37     0
## 5 Wild Is L~ 5k1MBVD~ Nat King C~ 7v4imS0m~ 1961        14     0
## 6 Judy At C~ 3MORdVA~ Judy Garla~ 0hItVPjw~ 1962        26     1
## 7 Breakfast~ 53mCG3m~ Henry Manc~ 2EExdpjU~ 1962        15     0
## 8 Genius + ~ 1VTSotS~ Ray Charles 1eYhYunl~ 1962        10     0
## 9 Great Ban~ 52a7wxV~ The Si Zen~ 1eUYmq0o~ 1962        12     0
## 10 The Nat K~ 3NoP1if~ Nat King C~ 7v4imS0m~ 1962        36     0
## # ... with 298 more rows, and 13 more variables: danceability <dbl>,
## #   energy <dbl>, key <dbl>, loudness <dbl>, mode <dbl>, speechiness <dbl>,
## #   acousticness <dbl>, instrumentalness <dbl>, liveness <dbl>, valence <dbl>,
## #   tempo <dbl>, duration_ms <dbl>, time_signature <dbl>
```

What makes a nominee (summary of all nominations including winners):

```
df_nom <- df[,-c(1:5,7)]
summary(df_nom)

## number_tracks  danceability      energy      key      loudness
## Min.   : 1.0    Min.   :0.230    Min.   :0.108    Min.   :2.00    Min.   : -21.37
## 1st Qu.:11.0    1st Qu.:0.477    1st Qu.:0.399    1st Qu.:4.41    1st Qu.: -13.44
## Median :12.0    Median :0.561    Median :0.534    Median :5.08    Median : -10.17
## Mean   :14.2    Mean   :0.556    Mean   :0.517    Mean   :5.15    Mean   : -10.56
## 3rd Qu.:15.2    3rd Qu.:0.642    3rd Qu.:0.638    3rd Qu.:5.77    3rd Qu.:  -7.54
```

```
## Max. :92.0 Max. :0.844 Max. :0.917 Max. :9.00 Max. : -2.50
## mode speechiness acousticness instrumentalness
## Min. :0.143 Min. :0.0286 Min. :0.0001 Min. :0.0000
## 1st Qu.:0.583 1st Qu.:0.0385 1st Qu.:0.1928 1st Qu.:0.0006
## Median :0.714 Median :0.0466 Median :0.3284 Median :0.0120
## Mean :0.704 Mean :0.0813 Mean :0.3857 Mean :0.0675
## 3rd Qu.:0.833 3rd Qu.:0.0755 3rd Qu.:0.5363 3rd Qu.:0.0726
## Max. :1.000 Max. :0.9438 Max. :0.9565 Max. :0.7257
## liveness valence tempo duration_ms
## Min. :0.0627 Min. :0.125 Min. : 72.6 Min. : 93034
## 1st Qu.:0.1342 1st Qu.:0.388 1st Qu.:108.5 1st Qu.:205304
## Median :0.1703 Median :0.498 Median :117.0 Median :239282
## Mean :0.1988 Mean :0.497 Mean :116.3 Mean :239447
## 3rd Qu.:0.2185 3rd Qu.:0.599 3rd Qu.:123.1 3rd Qu.:273878
## Max. :0.9123 Max. :0.917 Max. :149.8 Max. :427333
## time_signature
## Min. :3.27
## 1st Qu.:3.81
## Median :3.91
## Mean :3.87
## 3rd Qu.:4.00
## Max. :4.10
```

What makes a winner (summary of all winners):

```
df_win<-df[df$win==1,]
df_win<-df_win[-c(1:5,7)]
summary(df_win)
```

```
## number_tracks danceability energy key loudness
## Min. : 6.0 Min. :0.230 Min. :0.150 Min. :2.64 Min. : -18.68
## 1st Qu.:11.0 1st Qu.:0.483 1st Qu.:0.388 1st Qu.:4.57 1st Qu.: -13.92
## Median :13.0 Median :0.568 Median :0.514 Median :5.32 Median : -11.33
## Mean :13.9 Mean :0.551 Mean :0.493 Mean :5.32 Mean : -11.26
## 3rd Qu.:15.0 3rd Qu.:0.617 3rd Qu.:0.618 3rd Qu.:6.24 3rd Qu.: -9.02
## Max. :40.0 Max. :0.808 Max. :0.792 Max. :8.44 Max. : -4.22
## mode speechiness acousticness instrumentalness
## Min. :0.154 Min. :0.0303 Min. :0.0416 Min. :0.0000
## 1st Qu.:0.518 1st Qu.:0.0391 1st Qu.:0.2405 1st Qu.:0.0008
## Median :0.727 Median :0.0455 Median :0.4022 Median :0.0104
## Mean :0.688 Mean :0.0945 Mean :0.4357 Mean :0.0551
## 3rd Qu.:0.822 3rd Qu.:0.0672 3rd Qu.:0.6430 3rd Qu.:0.0729
## Max. :1.000 Max. :0.9438 Max. :0.9292 Max. :0.3736
## liveness valence tempo duration_ms
## Min. :0.0717 Min. :0.152 Min. : 88.4 Min. :127590
## 1st Qu.:0.1248 1st Qu.:0.380 1st Qu.:105.2 1st Qu.:215952
## Median :0.1584 Median :0.472 Median :114.6 Median :254571
## Mean :0.2227 Mean :0.484 Mean :114.3 Mean :251343
## 3rd Qu.:0.2110 3rd Qu.:0.578 3rd Qu.:121.1 3rd Qu.:282508
## Max. :0.9123 Max. :0.789 Max. :139.7 Max. :413925
## time_signature
## Min. :3.33
## 1st Qu.:3.74
```

```
## Median :3.90
## Mean   :3.85
## 3rd Qu.:4.00
## Max.   :4.00
```

Audio Features Overtime:

RED: Winners

GREEN: Nominations (not including winners)

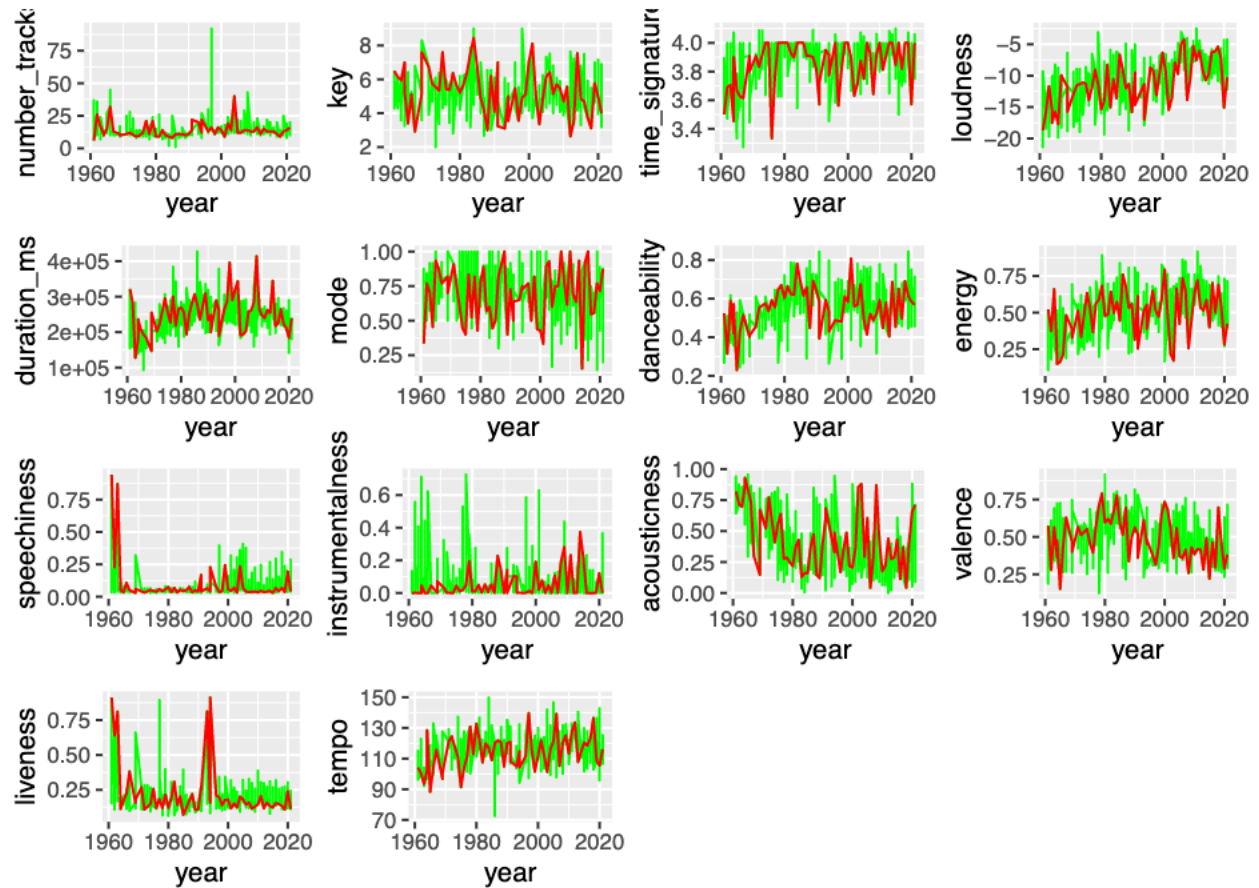
```
df_nom1<-df[df$win==0,]
df_nom1 <-df[-c(1:4,7)]
df_win1<-df[df$win==1,]
df_win1<-df_win1[-c(1:4,7)]
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 4.0.1

pl_count<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=number_tracks), color='green') +
  geom_line(data=df_win1, aes(x=year, y=number_tracks), color='red')
pl_key<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=key), color='green') +
  geom_line(data=df_win1, aes(x=year, y=key), color='red')
pl_ts<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=time_signature), color='green') +
  geom_line(data=df_win1, aes(x=year, y=time_signature), color='red')
pl_loudness<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=loudness), color='green') +
  geom_line(data=df_win1, aes(x=year, y=loudness), color='red')
pl_tempo<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=tempo), color='green') +
  geom_line(data=df_win1, aes(x=year, y=tempo), color='red')

pl_duration<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=duration_ms), color='green') +
  geom_line(data=df_win1, aes(x=year, y=duration_ms), color='red')
pl_mode<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=mode), color='green') +
  geom_line(data=df_win1, aes(x=year, y=mode), color='red')
pl_dance<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=danceability), color='green') +
  geom_line(data=df_win1, aes(x=year, y=danceability), color='red')
pl_energy<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=energy), color='green') +
  geom_line(data=df_win1, aes(x=year, y=energy), color='red')
pl_speech<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=speechiness), color='green') +
  geom_line(data=df_win1, aes(x=year, y=speechiness), color='red')
pl_instr<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=instrumentalness), color='green') +
  geom_line(data=df_win1, aes(x=year, y=instrumentalness), color='red')
pl_acoust<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=acousticness), color='green') +
  geom_line(data=df_win1, aes(x=year, y=acousticness), color='red')
pl_valence<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=valence), color='green') +
  geom_line(data=df_win1, aes(x=year, y=valence), color='red')
pl_liveness<-ggplot()+geom_line(data=df_nom1, aes(x=year, y=liveness), color='green') +
  geom_line(data=df_win1, aes(x=year, y=liveness), color='red')

library(gridExtra)
grid.arrange(pl_count, pl_key, pl_ts, pl_loudness, pl_duration,
             pl_mode, pl_dance, pl_energy, pl_speech, pl_instr,
             pl_acoust, pl_valence, pl_liveness, pl_tempo)
```



There are no outstanding trends in terms of the difference between those that win and those that were nominated. However, we can see here that there are some noticeable relationships between year and audio features. There is an upward trend in loudness, danceability, and energy. There is a downward trend in acousticness and liveness. This is an interesting facet to explore the social implications surrounding the decades. Other contributing factors to these trends could also be the technology surrounding the time (e.g. better technology implies louder decibel recordings).

OLS Regression:

```
mod <- lm(formula=win~loudness+duration_ms+danceability+energy+speechiness+
           instrumentalness+acousticness+valence+liveness+tempo+factor(year), data=df)
summary(mod)
```

```
##
## Call:
## lm(formula = win ~ loudness + duration_ms + danceability + energy +
##     speechiness + instrumentalness + acousticness + valence +
##     liveness + tempo + factor(year), data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.4886 -0.2255 -0.1499 -0.0227  0.9896
##
## Coefficients:
```


##	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	-7.77e-01	6.20e-01	-1.25	0.211
## loudness	-1.28e-02	1.96e-02	-0.66	0.512
## duration_ms	1.61e-06	6.84e-07	2.36	0.019 *
## danceability	1.73e-01	4.34e-01	0.40	0.691
## energy	2.62e-01	5.58e-01	0.47	0.639
## speechiness	-2.96e-02	3.97e-01	-0.07	0.941
## instrumentalness	-2.88e-01	2.42e-01	-1.19	0.235
## acousticness	3.73e-01	2.16e-01	1.73	0.085 .
## valence	-1.51e-01	3.61e-01	-0.42	0.677
## liveness	3.78e-01	2.97e-01	1.27	0.204
## tempo	-1.36e-03	2.79e-03	-0.49	0.626
## factor(year)1962	1.19e-01	2.70e-01	0.44	0.659
## factor(year)1963	1.67e-01	2.95e-01	0.57	0.572
## factor(year)1964	4.28e-01	2.82e-01	1.52	0.131
## factor(year)1965	2.38e-01	2.72e-01	0.88	0.381
## factor(year)1966	3.27e-01	2.88e-01	1.14	0.256
## factor(year)1967	2.21e-01	2.78e-01	0.79	0.427
## factor(year)1969	3.18e-01	2.55e-01	1.24	0.215
## factor(year)1971	3.27e-01	3.05e-01	1.07	0.284
## factor(year)1972	2.52e-01	2.90e-01	0.87	0.385
## factor(year)1973	4.40e-02	3.03e-01	0.15	0.885
## factor(year)1974	1.66e-01	2.89e-01	0.57	0.566
## factor(year)1975	2.93e-01	3.09e-01	0.95	0.344
## factor(year)1976	2.41e-01	2.93e-01	0.82	0.412
## factor(year)1977	1.81e-01	3.04e-01	0.60	0.551
## factor(year)1978	2.77e-01	2.98e-01	0.93	0.352
## factor(year)1979	2.87e-01	2.95e-01	0.97	0.331
## factor(year)1980	2.69e-01	3.03e-01	0.89	0.375
## factor(year)1981	2.52e-01	2.92e-01	0.86	0.389
## factor(year)1982	2.15e-01	2.99e-01	0.72	0.473
## factor(year)1983	3.08e-01	3.02e-01	1.02	0.308
## factor(year)1984	3.34e-01	3.05e-01	1.10	0.274
## factor(year)1985	2.80e-01	3.05e-01	0.92	0.360
## factor(year)1986	1.03e-01	3.03e-01	0.34	0.734
## factor(year)1987	1.70e-01	2.99e-01	0.57	0.569
## factor(year)1988	2.16e-01	3.02e-01	0.71	0.476
## factor(year)1989	2.14e-01	3.01e-01	0.71	0.479
## factor(year)1990	3.15e-01	3.06e-01	1.03	0.303
## factor(year)1991	2.31e-01	2.64e-01	0.87	0.383
## factor(year)1993	1.48e-01	2.94e-01	0.50	0.615
## factor(year)1994	1.81e-01	2.57e-01	0.70	0.482
## factor(year)1996	2.46e-01	3.04e-01	0.81	0.420
## factor(year)1997	2.89e-01	3.00e-01	0.96	0.336
## factor(year)1998	2.05e-01	2.98e-01	0.69	0.492
## factor(year)1999	2.70e-01	3.01e-01	0.90	0.370
## factor(year)2000	2.83e-01	2.99e-01	0.95	0.345
## factor(year)2001	2.47e-01	3.00e-01	0.82	0.412
## factor(year)2002	2.97e-01	3.08e-01	0.96	0.336
## factor(year)2003	2.72e-01	2.98e-01	0.91	0.361
## factor(year)2004	3.14e-01	2.99e-01	1.05	0.295
## factor(year)2005	3.09e-01	2.97e-01	1.04	0.300
## factor(year)2006	3.81e-01	3.06e-01	1.25	0.214
## factor(year)2007	2.79e-01	3.09e-01	0.90	0.367

```

## factor(year)2008 2.42e-01 3.00e-01 0.81 0.421
## factor(year)2009 3.25e-01 3.08e-01 1.06 0.292
## factor(year)2010 3.15e-01 3.11e-01 1.01 0.312
## factor(year)2011 3.39e-01 3.13e-01 1.08 0.279
## factor(year)2012 3.36e-01 3.13e-01 1.07 0.285
## factor(year)2013 3.66e-01 2.99e-01 1.23 0.221
## factor(year)2014 2.51e-01 3.08e-01 0.82 0.415
## factor(year)2015 2.63e-01 3.03e-01 0.87 0.386
## factor(year)2016 2.72e-01 3.04e-01 0.90 0.372
## factor(year)2017 2.93e-01 3.04e-01 0.97 0.335
## factor(year)2018 3.39e-01 3.03e-01 1.12 0.265
## factor(year)2019 2.46e-01 2.91e-01 0.85 0.398
## factor(year)2020 2.11e-01 2.78e-01 0.76 0.447
## factor(year)2021 2.42e-01 2.73e-01 0.88 0.377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.43 on 241 degrees of freedom
## Multiple R-squared:  0.0785, Adjusted R-squared:  -0.174
## F-statistic: 0.311 on 66 and 241 DF,  p-value: 1

```

This is a log linear regression. Each coefficient estimates the probability increase/decrease in winning if there is a 1 unit change in audio feature rating. However, even with this fixed effect model, using a dummy variable for year, it seems that audio features are not significant predictors for if an album will win the Album of the Year category. This could indicate that the Recording Academy has a fairly diverse taste in music: It can be observed that the album nominations involves a selection of albums that are diverse in genre and thus in audio features. Or simply, the audio features supplied by Spotify are fairly irrelevant to capturing the complex aspects of a track.

Since there is not much statistical evidence from this preliminary analysis, it may be more interesting to apply this python application elsewhere. Perhaps the python application can be used to compare user listening habits rather than make predictions. The python application is built to be changed easily to accept playlist input instead of albums. So we can use playlists as a way to sample a user's listening habits. Questions could involve: To what extent is music taste similar to my peers? How has listening changed over the years for a user (using playlists as a timestamp)? Going forward I intend to apply and adapt my Python application to suit these queries.