

# **BILLBOARD HOT 100 ANALYSIS**

**WHAT MAKES A SONG POPULAR?**

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# INTRODUCTION

- Context
- The Dataset
- Data Prep
- Data Model
- Conclusion
- Appendix



A decorative graphic on the left side of the slide consisting of three parallel, wavy vertical lines. The outermost line is white, the middle line is a light blue color, and the innermost line is white. They are positioned on the left side of the dark blue background.

# CONTEXT



# THE QUESTION

Can characteristics of a song be used to determine **when** the song appeared on the Billboard Hot 100 Chart?



# THE BILLBOARD HOT 100

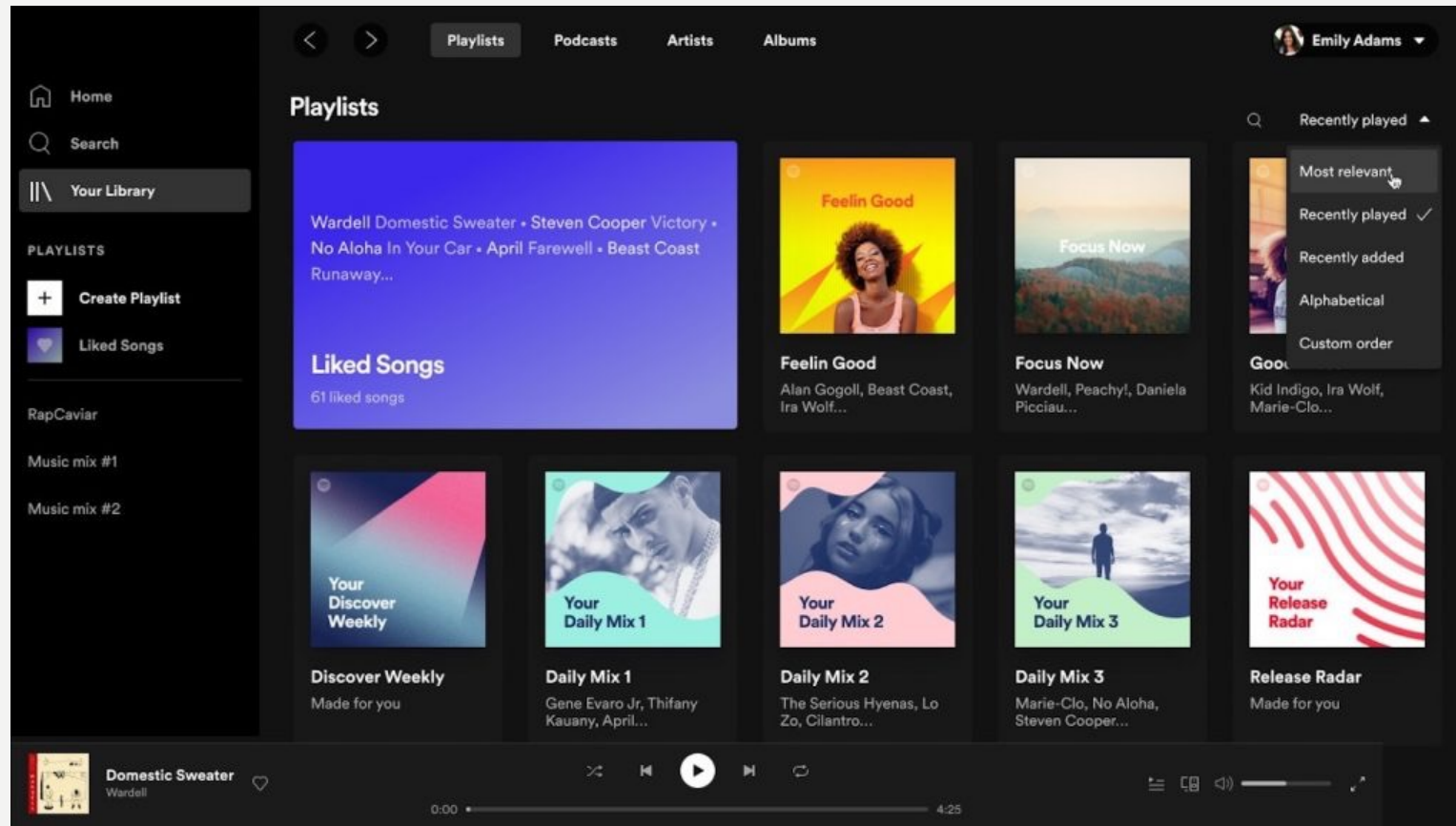
## billboard HOT 100

|    | SONG                           | ARTIST                        |
|----|--------------------------------|-------------------------------|
| 1  | Permission To Dance            | BTS                           |
| 2  | good 4 u                       | Olivia Rodrigo                |
| 3  | Stay                           | The Kid LAROI & Justin Bieber |
| 4  | Levitating                     | Dua Lipa ft. DaBaby           |
| 5  | Kiss Me More                   | Doja Cat ft. SZA              |
| 6  | Bad Habits                     | Ed Sheeran                    |
| 7  | Butter                         | BTS                           |
| 8  | Montero (Call Me By Your Name) | Lil Nas X                     |
| 9  | Save Your Tears                | The Weeknd & Ariana Grande    |
| 10 | deja vu                        | Olivia Rodrigo                |

chart dated July 24, 2021



# SONG CHARACTERISTICS FROM SPOTIFY



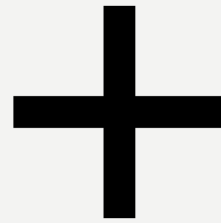
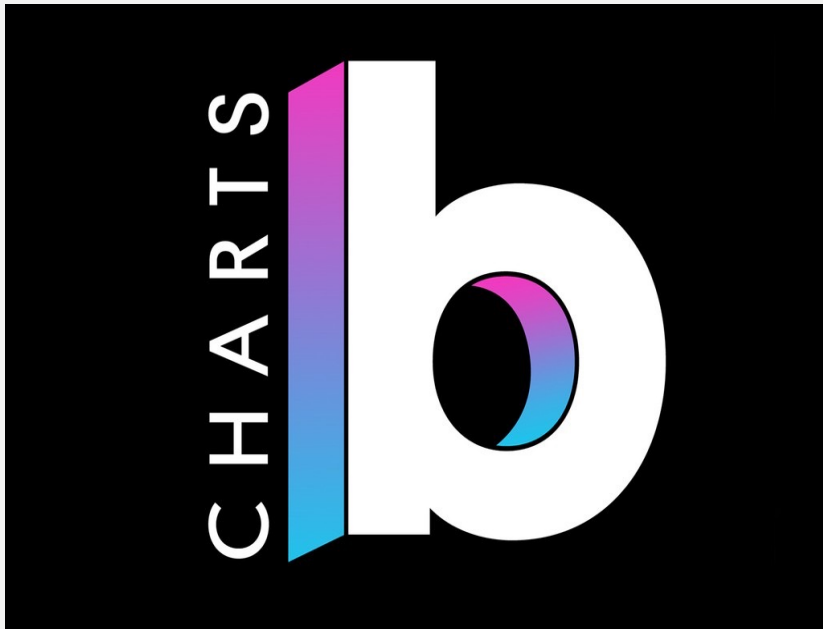


# INTRODUCING THE DATASET



# DATASET ORIGIN

Characteristics of how the public received it

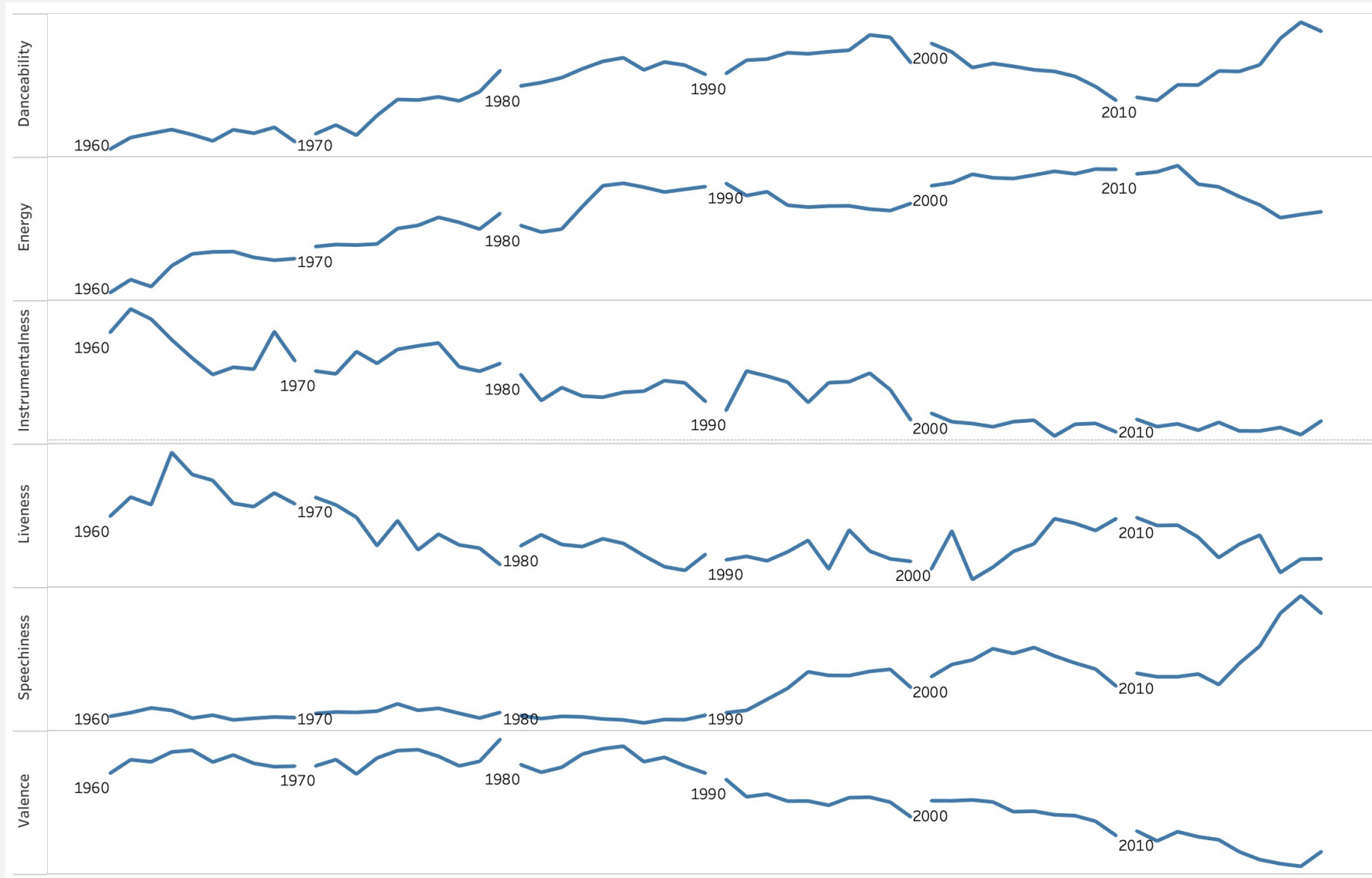


Characteristics of it's sound





# MUSIC CHARACTERISTICS OVER TIME



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# DATA PREP



# CLEANING THE DATA

## Removed

- Highly correlated columns
- Empty Rows (no metadata)
- Columns where all the values were the same

## Added

- Season (Fall, Spring, etc.)
- Isolated Year from Week value

## Modified

- Min Max scaling rows
- Dummy Variables





# THE MODEL

LGBM REGRESSOR



# FINAL MODEL STATS

## INPUTS

**Learning Rate**

0.1

**Max\_Depth**

-1

**N\_Estimators**

300

**Num\_Leaves**

56

## OUTPUTS

**RMSE**

9.0

**MAE**

6.4

**r2**

77.7

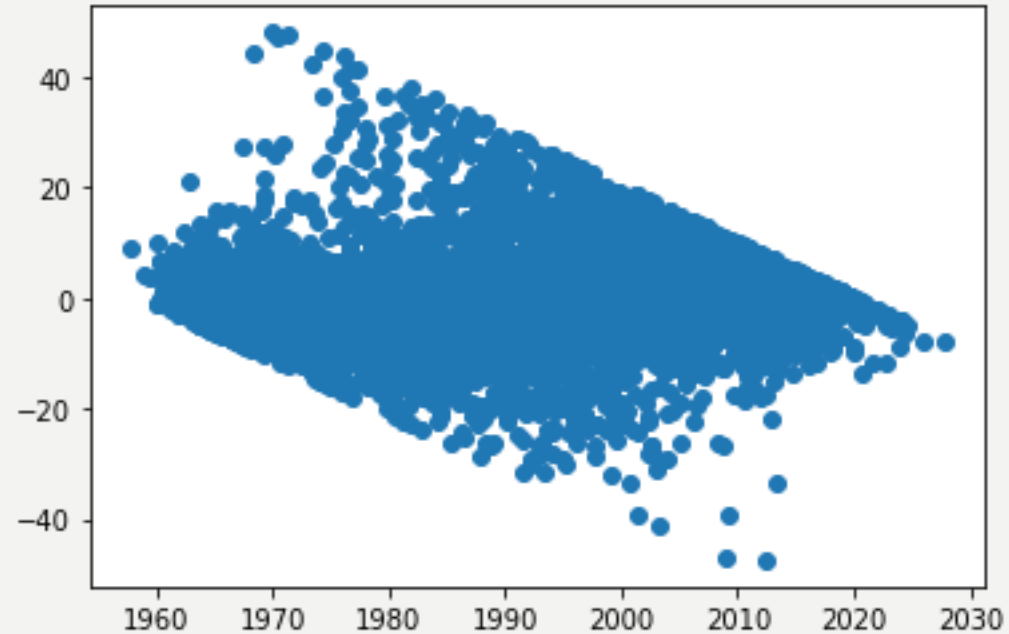


# IMPORTANT VARIABLES

The song's **duration**, **speechiness**, and **loudness** were among the most important characteristics along with **how long it charted** and **how high**.



# RESIDUAL PLOT



The linear pattern may be due to a missing variable



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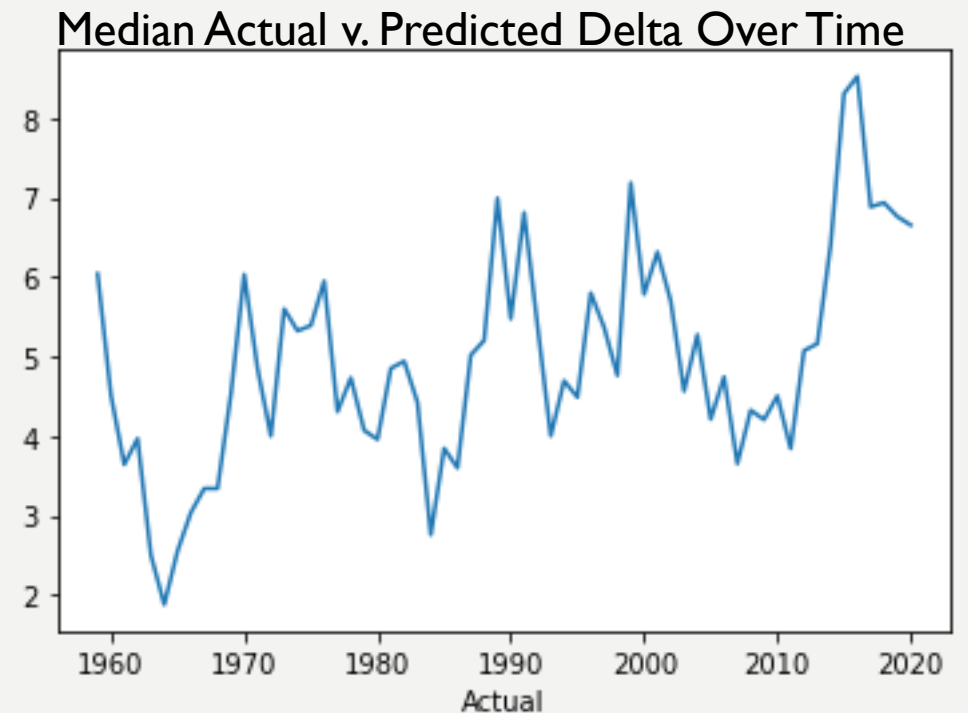
# CONCLUSION





# SO CAN I PREDICT IT?

- To a certain extent, if the song doesn't resemble songs from previous decades
  - Lots of music is derivative and sound is cyclical



# NEXT STEPS...

- Include genre once reducing cardinality, see if that addresses the residual plot
- Tag and remove song covers
- Look at it from a derivation standpoint – who sounds like who?



# THANK YOU!

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A decorative graphic on the left side of the page consisting of two parallel, wavy vertical lines. The inner line is a light blue color, and the outer line is white. They start from the top left and extend towards the bottom left, creating a stylized, organic shape.

# APPENDIX

ALL THE EXTRA STUFF, ANNOTATED

# LINKS

- Data.World Datasets: <https://data.world/kcmillersean/billboard-hot-100-1958-2017>
- GitHub: <https://github.com/lcagney/MSDS-Practicum-2>
- YouTube: <https://youtu.be/Q3zYRNRokrc>

# SPOTIFY DEFINITIONS

| Term             | Definition   |
|------------------|--|
| Acousticness     | A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic. |
| Instrumentalness | Predicts whether a track contains no vocals.   |
| Key              | The key the track is in.   |
| Liveness         | Detects the presence of an audience in the recording.  |
| Loudness         | The overall loudness of a track in decibels (dB).  |
| Mode             | Mode indicates the modality (major or minor) of a track, the type of scale from which its melodic content is derived.        |
| Speechiness      | Speechiness detects the presence of spoken words in a track.   |
| Tempo            | The overall estimated tempo of a track in beats per minute (BPM).  |
| Valence          | A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track.   |

# FINAL DATASET VALUES

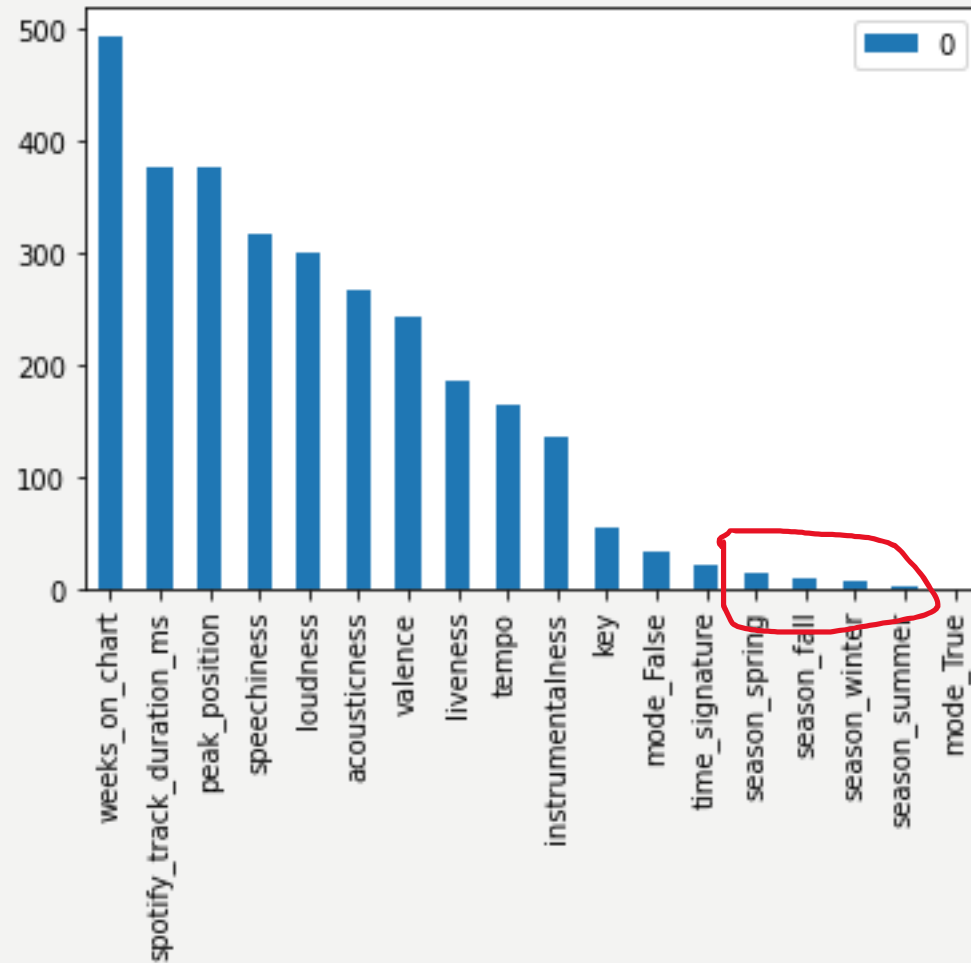
## TARGET VARIABLE

- Year

## PREDICTOR VARIABLES

- weeks\_on\_chart
- peak\_position
- spotify\_track\_duration\_ms
- acousticness
- loudness
- tempo
- time\_signature
- key
- speechiness
- instrumentalness
- liveness
- valence
- mode\_False
- mode\_True
- season\_fall
- season\_spring
- season\_summer
- season\_winter

# FULL IMPORTANT VARIABLES

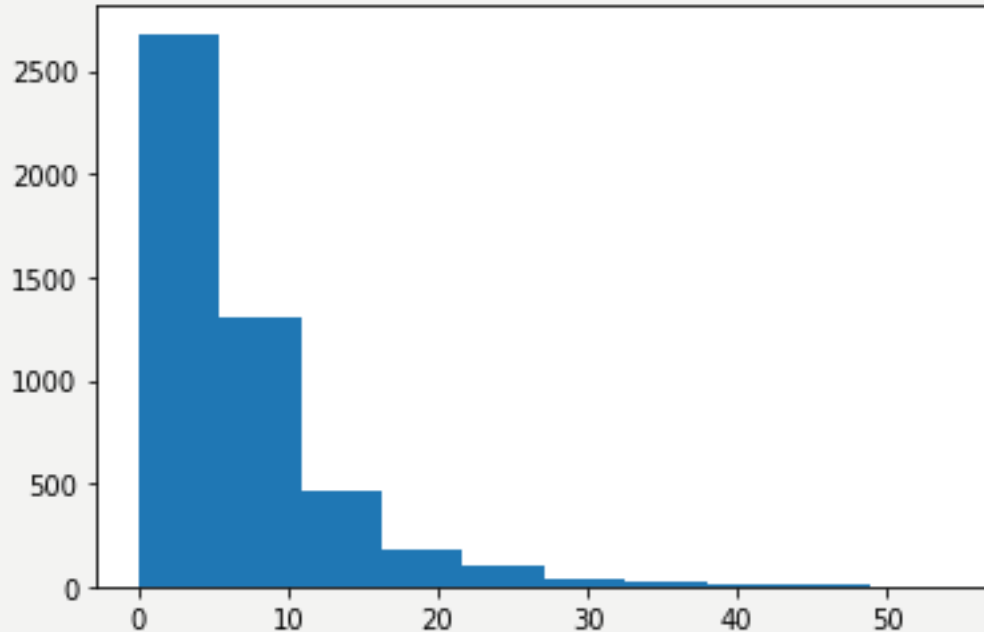


The variables I created for the dataset added virtually no predictive value



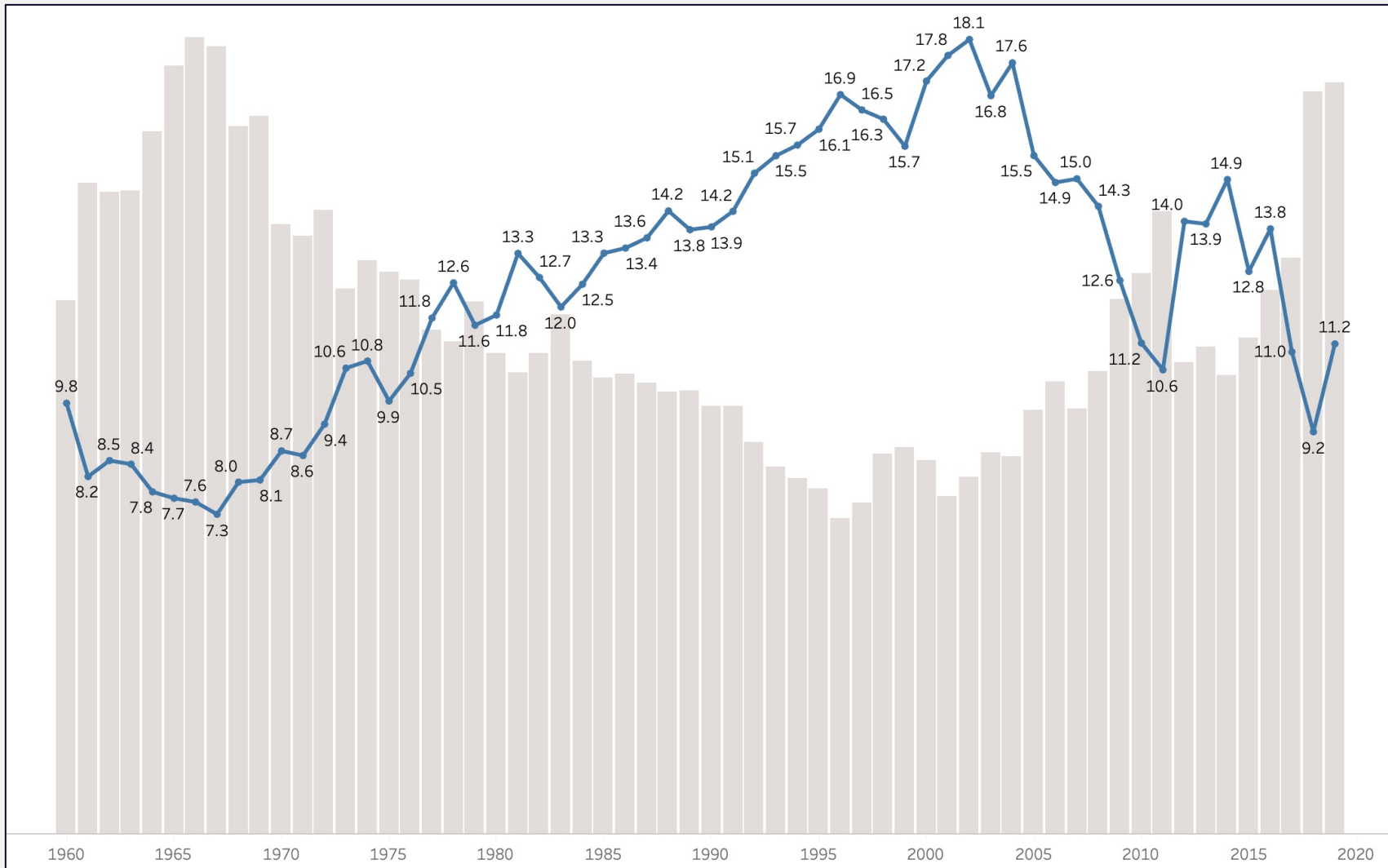
# COMPARING ACTUAL VS. PREDICTED

Delta Between Actual & Predicted



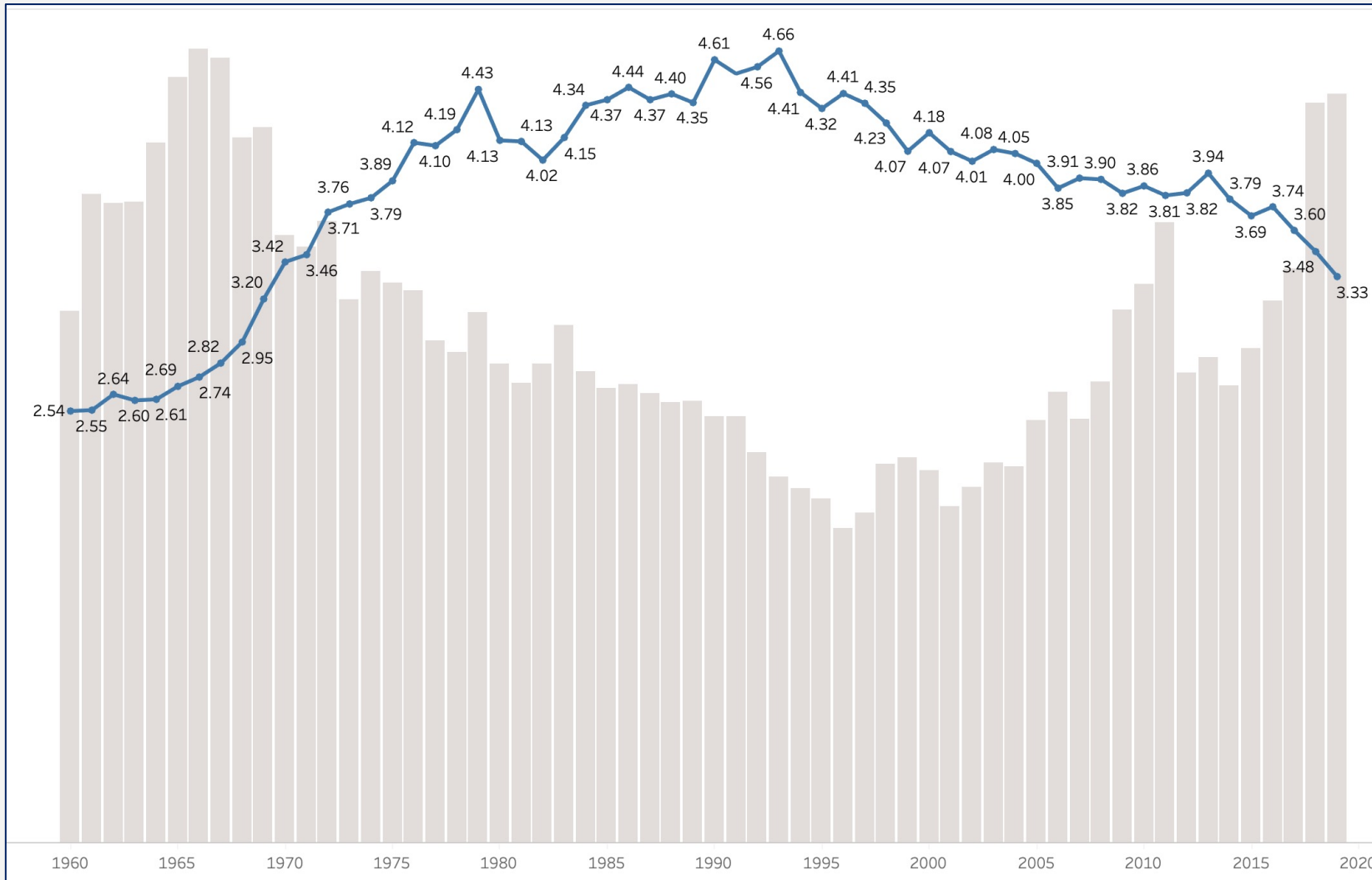
Comparing the differences between actual and predicted. More than half of the test dataset got the year correctly within a small variance; however, when the prediction was off – it was *really* off. My hypothesis is because of either covers of songs or because of throwback sounds.

# INVERSE RELATIONSHIP BETWEEN LENGTH ON CHART AND NUMBER OF SONGS



Average length on chart on line chart and number of songs by year on bar plot

# SIMILAR PATTERN WITH LENGTH OF SONG AND YEAR



Length of song on  
line chart and count  
of year on bar plot

# LAZY PREDICT REGRESSION RESULTS

| Model                         | Adjusted R-Squared | R-Squared | RMSE \ |
|-------------------------------|--------------------|-----------|--------|
| LGBMRegressor                 | 0.77               | 0.77      | 9.09   |
| HistGradientBoostingRegressor | 0.77               | 0.77      | 9.10   |
| XGBRegressor                  | 0.77               | 0.77      | 9.14   |
| ExtraTreesRegressor           | 0.75               | 0.75      | 9.49   |
| RandomForestRegressor         | 0.75               | 0.75      | 9.55   |
| GradientBoostingRegressor     | 0.74               | 0.74      | 9.72   |
| BaggingRegressor              | 0.73               | 0.73      | 9.97   |
| SVR                           | 0.65               | 0.65      | 11.22  |
| NuSVR                         | 0.65               | 0.65      | 11.23  |
| KNeighborsRegressor           | 0.62               | 0.62      | 11.73  |
| LinearRegression              | 0.56               | 0.56      | 12.65  |
| TransformedTargetRegressor    | 0.56               | 0.56      | 12.65  |
| PoissonRegressor              | 0.56               | 0.56      | 12.66  |
| LassoLarsIC                   | 0.56               | 0.56      | 12.66  |
| LassoCV                       | 0.56               | 0.56      | 12.66  |
| ElasticNetCV                  | 0.56               | 0.56      | 12.66  |
| BayesianRidge                 | 0.56               | 0.56      | 12.66  |
| RidgeCV                       | 0.56               | 0.56      | 12.66  |
| Ridge                         | 0.56               | 0.56      | 12.66  |
| LarsCV                        | 0.56               | 0.56      | 12.66  |
| LassoLarsCV                   | 0.56               | 0.56      | 12.66  |
| Lars                          | 0.56               | 0.56      | 12.66  |
| SGDRegressor                  | 0.56               | 0.56      | 12.66  |
| HuberRegressor                | 0.55               | 0.56      | 12.71  |
| Lasso                         | 0.53               | 0.53      | 13.06  |
| LinearSVR                     | 0.53               | 0.53      | 13.09  |
| OrthogonalMatchingPursuitCV   | 0.51               | 0.51      | 13.35  |
| ElasticNet                    | 0.50               | 0.50      | 13.54  |

Could have really gone  
with any of the top 3

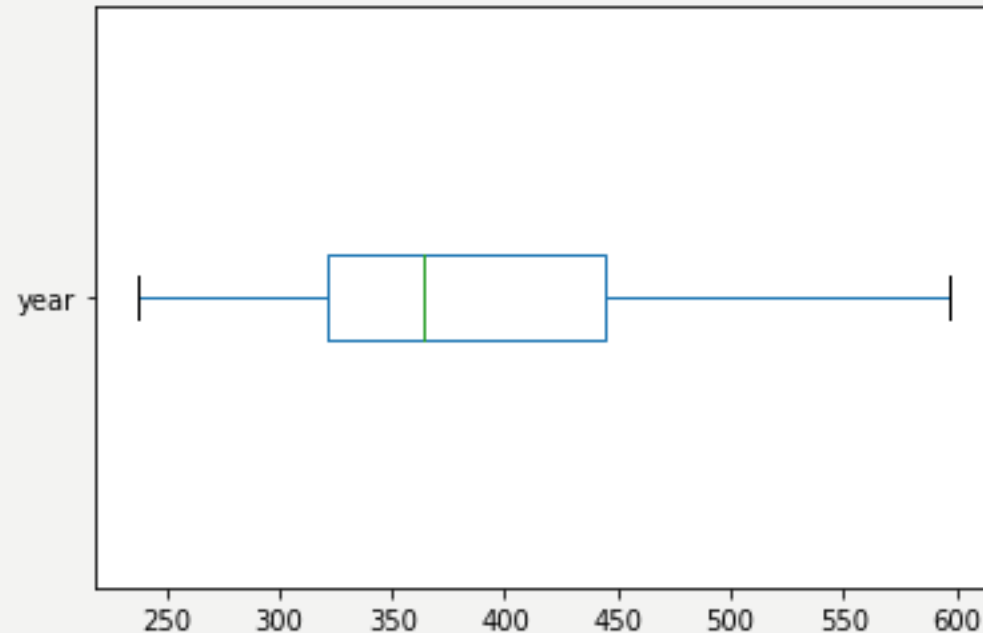
# WORD CLOUD- TOP ARTISTS SINCE 1960

Glee ruled the charts when it was releasing their covers in the early 2010s



# SONG COUNT DISTRIBUTION BY YEAR

MEDIAN IS AROUND 360 SONGS



Slightly right skewed, with some years charting an abnormally large amount of songs.

# SQL STATEMENT TO COMBINE DATASET FROM DATA.WORLD

```
SELECT a.weekid as weekid, week_position, a.song as song, a.performer as performer, weeks_on_chart, peak_position
, spotify_track_duration_ms, spotify_track_explicit, danceability, energy, c.key, loudness, mode, speechiness
, acousticness, instrumentalness, liveness, valence, tempo, time_signature
FROM hot_stuff_2 as a
join(
    SELECT max(weekid) as weekid, songid
    FROM hot_stuff_2
    GROUP BY songid) as b
on b.weekid = a.weekid and b.songid = a.songid
join hot_100_audio_features as c
on c.songid = a.songid
```