

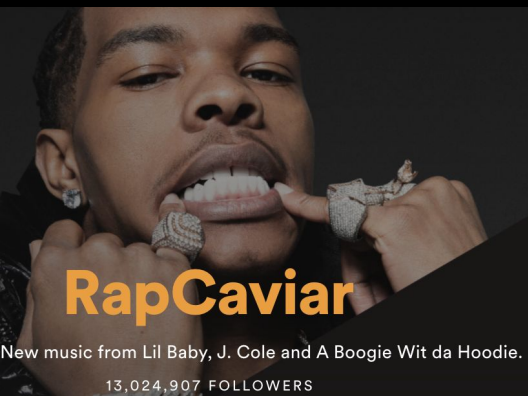
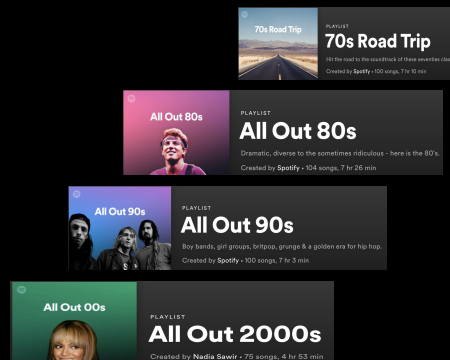
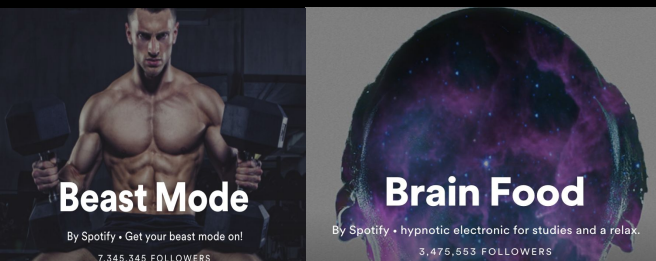


Thematically Sequenced Playlist

Georgetown Analytics
Cohort 19

By: Nick Merkling, Adam Goldstein, Patricia Merino, and Navneet Sandhu

Introduction



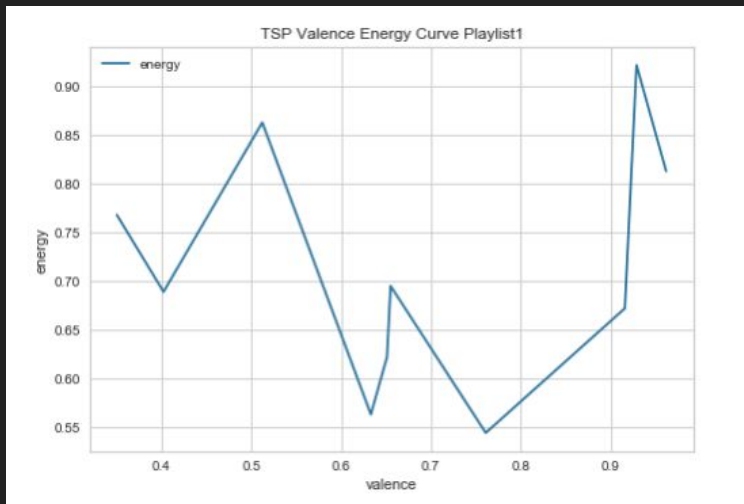
- 286 Million Monthly active Spotify users (130 million premium users)
- 36% of global streaming market
- Average of 25 listening hours a month per user
- Over 50 million tracks available on Spotify (lqbar)

Spotify Audio Features

1. Valence - Music Positivity or Reflectiveness
2. Energy - Intensity or Activity
3. Danceability - How Suitable for Dancing
4. Acousticness - How confident an acoustic instrument is present
5. Liveness - Detects presence of an audience
6. Speechiness - Detects presence of speech
7. Instrumentalness - Predicts whether a track has no vocals or vocals
8. Key - Scale the track is played in
9. Mode - Indicates major or minor scale
10. Tempo - Beats Per Minute
11. Time Signature - How many beats per minute

Hypothesis

- We believe that creating playlists driven by lyrical content can give the user a glimpse into thematic sequences that exist within their “liked” tracks.
- Additionally, we believe that the sonic variation of a playlist, ordered according to a valence-energy curve, provides the user with a captivating listening experience.



Our Data Science Pipeline

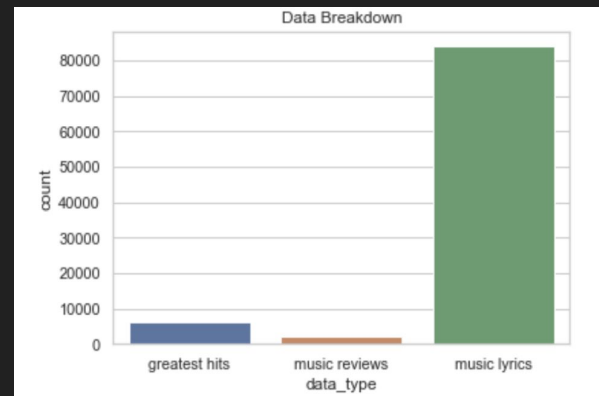
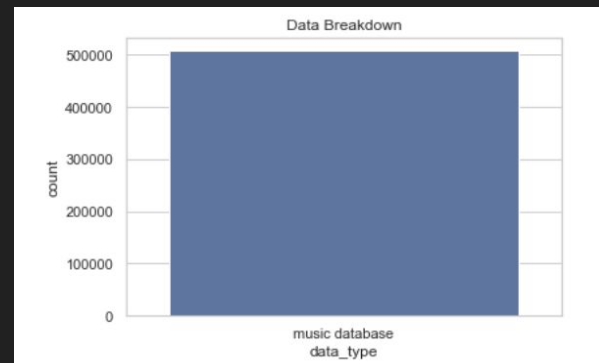
Tools that we used:

- Spotify API
- AWS S3 Storage
- Python 3
 - Jupyter Notebook
 - Yellowbrick
 - NLTK



Ingestion Phase

- Retrieved data from 4 different sources including:
 - Personal Music database
 - Kaggle file which includes song lyrics
 - Spotify's Greatest hits per Decade (1960s-2010s)
 - Critically Acclaimed Albums over the last 50 years
- Why?
 - Personal touch, legal acquisition of song lyrics to bypass web scraping methods, notable music based off popular Spotify playlists, and to introduce expert perspectives of target parameters

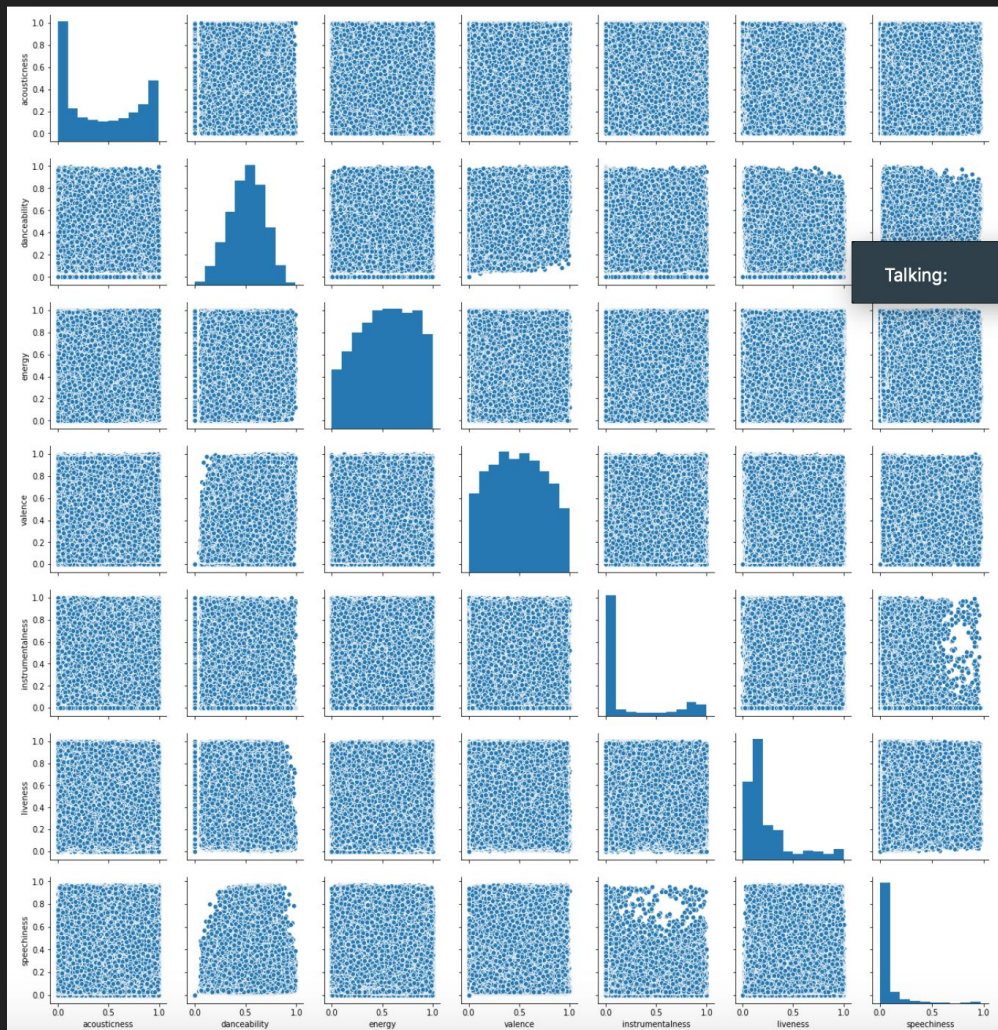


Wrangling Phase

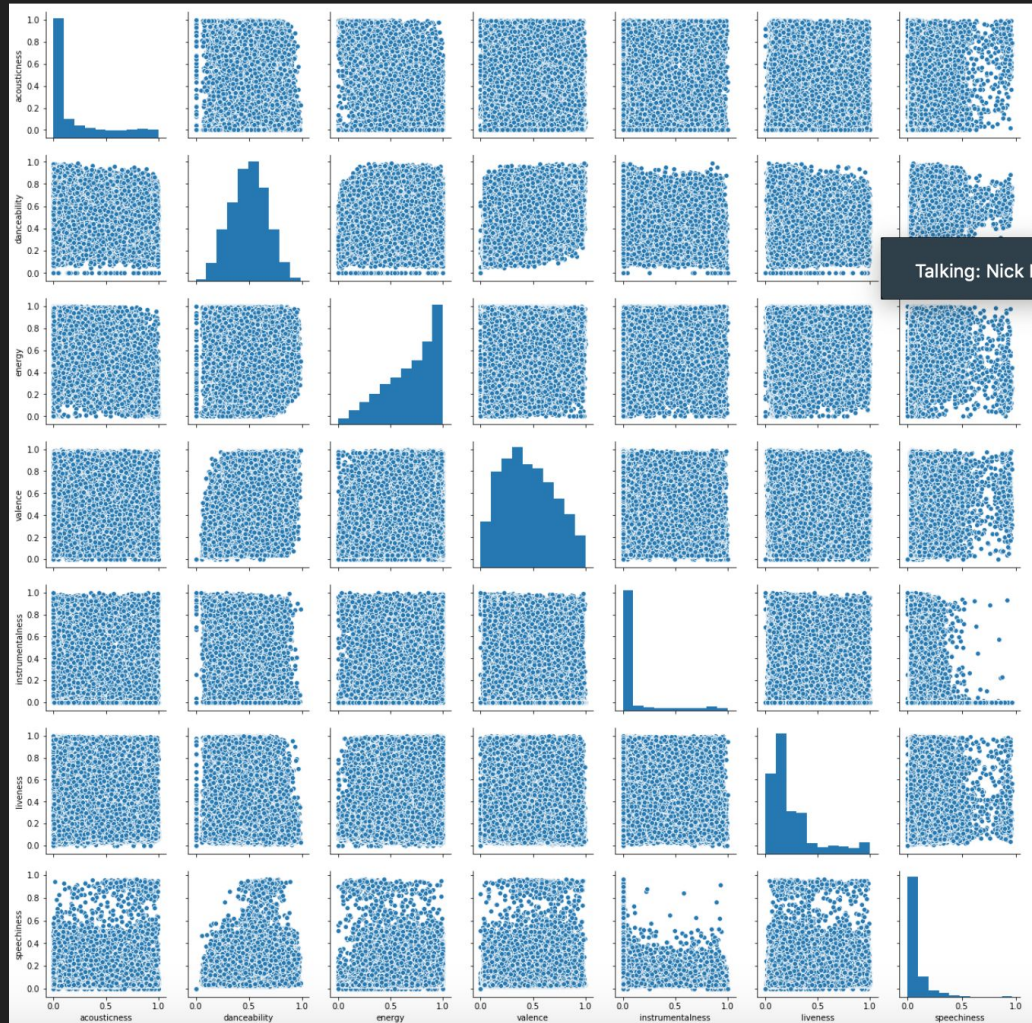
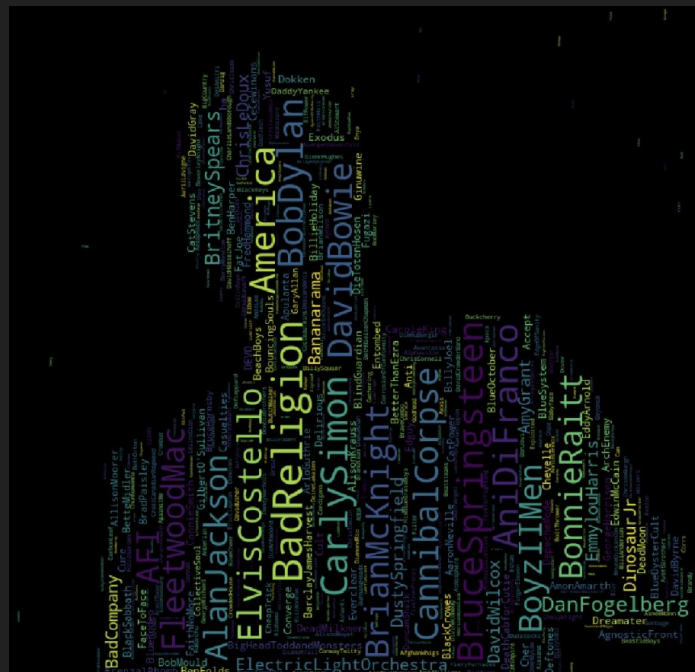
- Navigated Spotify API file's JSON tree to locate useful data fields
 - Music database, Spotify Greatest Hits playlists, and critically acclaimed albums
- Mapped Kaggle data to track uri from Spotify API
 - Validated the match using Python library, fuzzymatch
 - Set threshold at 96% probability (4% error)
 - Dataset is dramatically reduced using a 1-to-1 match
- 3 phases of lyric cleaning:
 - Spacy Lemmatization, NLTK tokenization, and removal of stop words using NLTK, as well as other .txt file resources

EDA Music Database

Word cloud visualization of music database content, featuring prominent names like Duke Ellington, His Orchestra, and Young, along with other artists like Hank Thompson, Smokey Robinson, and The Beatles.

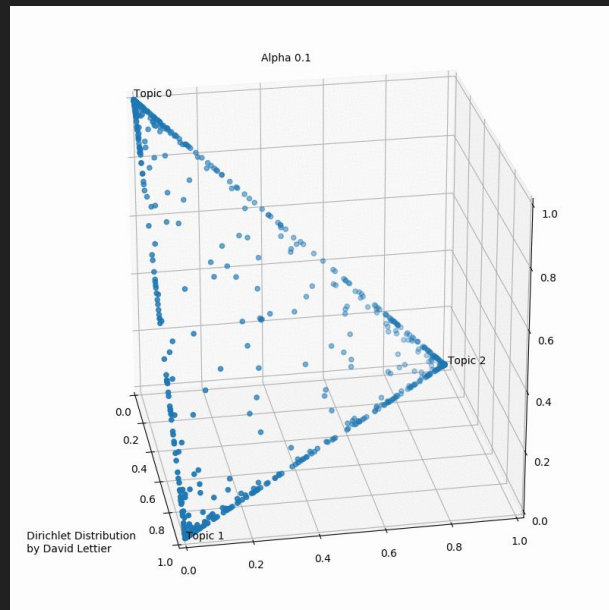


EDA Lyric Dataset



Topic Modeling

- Sklearn LatentDirichletAllocation/LDA Topic Modeling
- CountVectorizer to convert lyrics to tokens/terms
- Fitted the LDA model on our vectorized data
 - Output `n_topics` and `n_words`
- Fine tuned hyperparameters to produce coherent topics
- Determined probability of each document fitting with in a topic



Logic to Creating Playlists Using Topic Analyses

Return all playlist that meet the following criteria:

- $10 \leq \text{Playlist length} \leq 20$
- Only return track_uris that have a probability of 0.65 or more for a topic.

	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9
2s4VgvPiR53zdL3J5MaQN21115	0	0.12	0	0	0	0	0.05	0	0	0.4
08r7EUSkvCw7SKCSCPn5jg2828	0	0	0	0	0	0	0.16	0	0	0
5uiWMRE1tpoGaurztqRMvs709	0	0	0.01	0.14	0	0	0	0	0	0.82
1HFD2CepjuRBQmDg4pvfoW108	0	0	0	0	0	0	0.74	0	0	0.06
4Fy4iEL2IHJWVFYEG9Otcv572	0	0.23	0	0	0	0	0	0	0	0.02
7eJwdZaLJxvmXEZOpojPbe1614	0	0	0	0	0	0.1	0.32	0	0	0.04
62JldCeeRjVIR1mf5pveKh299	0	0	0	0	0	0	0	0	0	0
6bj9T3EwskyDxpuMiqKDW7921	0	0	0	0	0	0.06	0	0	0	0.13
0S2P5gXlwnicD5hsBCYxc2598	0	0	0.05	0.05	0	0	0	0	0	0
6EWgcAqvGNvJmA94XUUoNZ1257	0	0	0	0	0	0	0	0	0	0
5Cpbdd5vnNA3hu3BU44vGT677	0	0	0	0	0.07	0	0.16	0	0	0

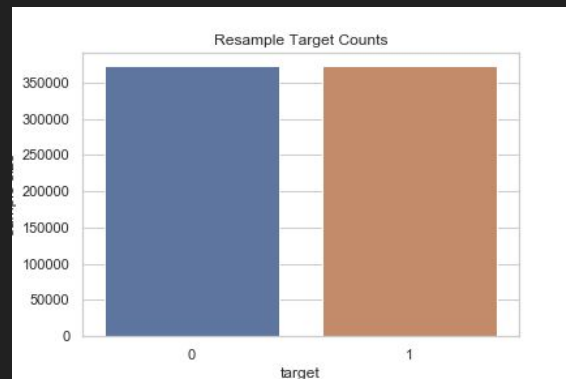
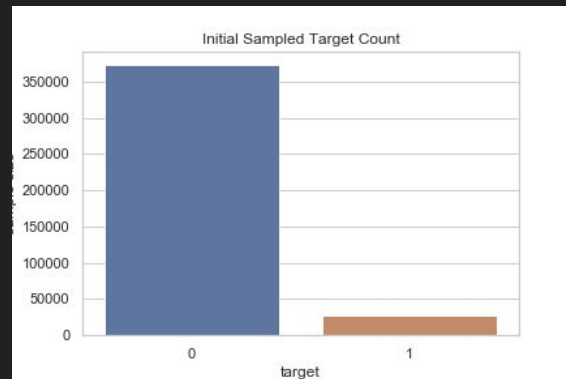
Binary Classification: Setting Target Parameter

- Set our target as good or bad playlist
 - (1 or 0) using binary classification
 - Set thresholds for Valence, Energy, Danceability feature values
- Parameters (mean)
 - Valence ≥ 0.45
 - Energy ≥ 0.65
 - Danceability ≥ 0.52



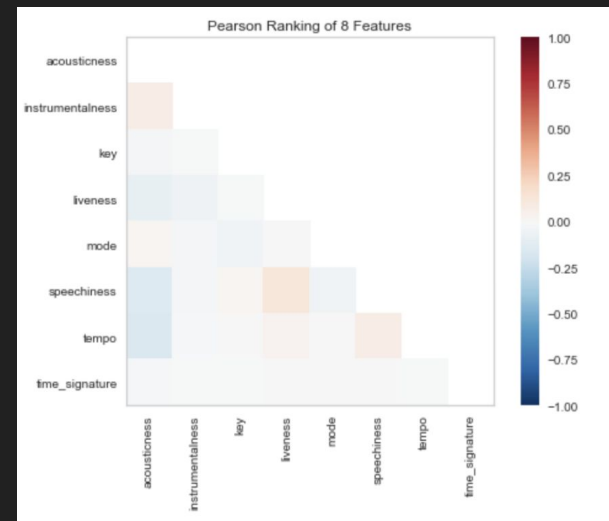
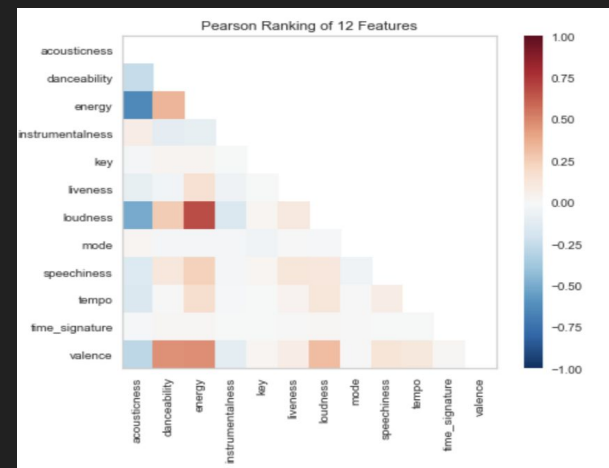
Binary Classification: Class Imbalance

- 1 = “Good Playlist”
- 0 = “Bad Playlist”
- Initially had massive class imbalance, but used Sci-kit learn’s resample utility to create a 50/50 split between our binary classification



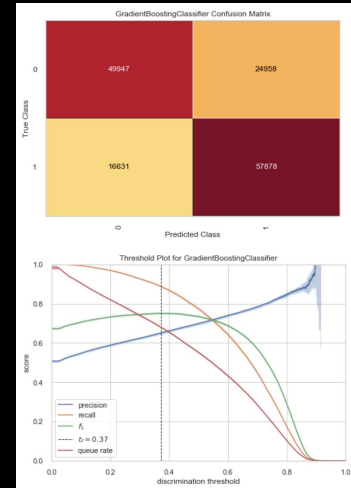
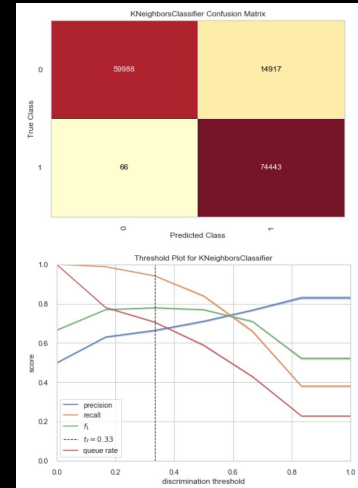
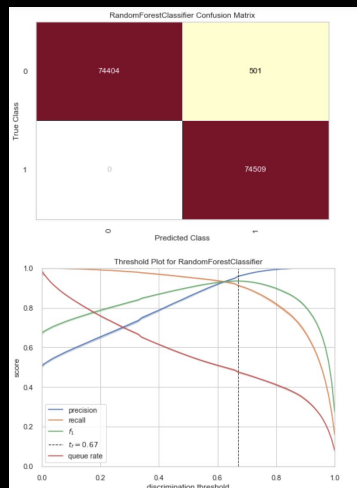
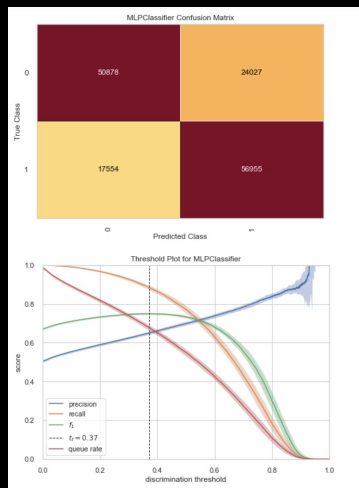
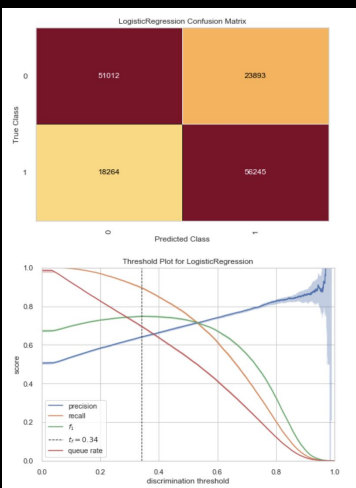
Feature Selection

- With 12 initial features saw recognized leakage between Valence, Energy, and Danceability
- Removed loudness because there was some collinearity found and did not provide



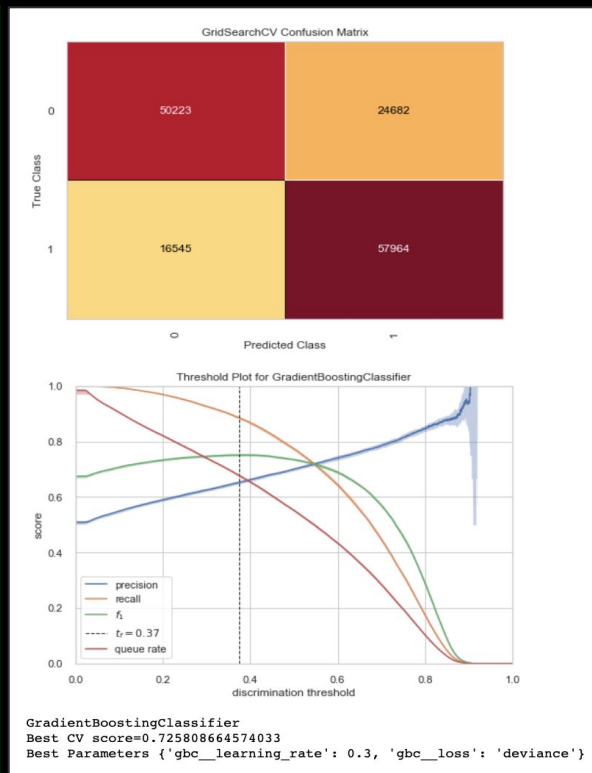
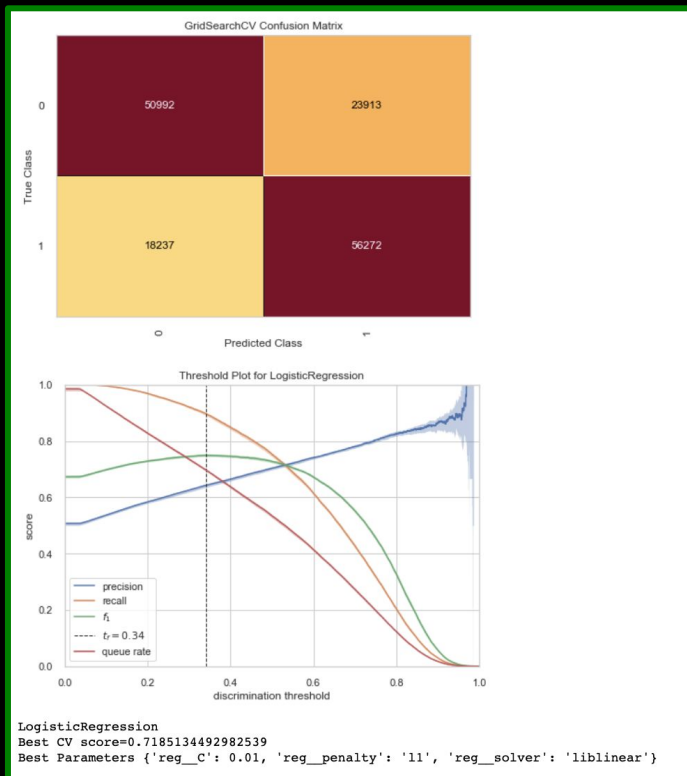
Model Selection

	Model	Transformer	Test Model Score	F1 Score	Precision Score	Recall Score
0	LogisticRegression()	StandardScaler()	0.713683	0.728371	0.704087	0.754391
1	MLPClassifier()	StandardScaler()	0.717967	0.734750	0.706671	0.765153
2	(DecisionTreeClassifier(max_features='auto', r...	StandardScaler()	0.883880	1.000000	1.000000	1.000000
3	(DecisionTreeClassifier(max_depth=1, random_st...	StandardScaler()	0.717231	0.732461	0.701124	0.766731
4	KNeighborsClassifier()	StandardScaler()	0.741291	0.934033	0.876336	0.999863
5	(DecisionTreeRegressor(criterion='friedman_ms...	StandardScaler()	0.719606	0.738309	0.702361	0.778135



Grid Search Results

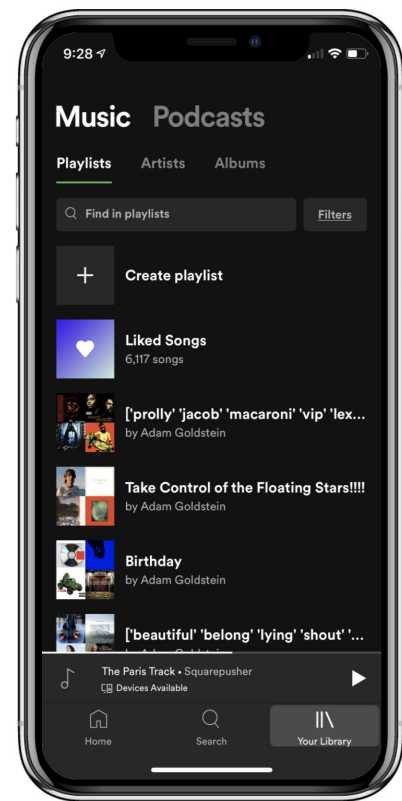
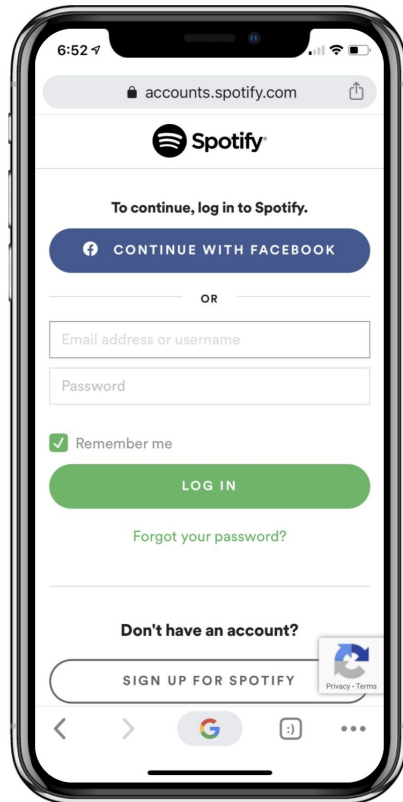
- Tested various models, opted for simplicity and favorability towards greater recall than precision



Live Jupyter Notebook Demo



Envisioned User Interface



Thanks for Listening!

Any questions?



References

Iqbal, M. (2020, May 08). Spotify Usage and Revenue Statistics (2020). Retrieved June 19, 2020, from <https://www.businessofapps.com/data/spotify-statistics/>

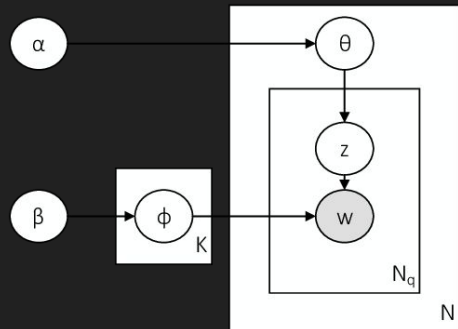
Spotify Audio Features: <https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/>

LDA: <https://www.youtube.com/watch?v=T05t-SqKArY&t=670s>

Q&A: <https://www.youtube.com/watch?v=5qap5aO4i9A>

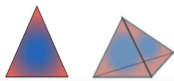
Visualization: <https://www.scikit-yb.org/en/latest/api/features/rankd.html>

Q&A: Topic Modeling



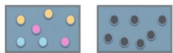
Probability of a document

$$P(\mathbf{W}, \mathbf{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta) = \prod_{j=1}^M P(\theta_j; \alpha) \prod_{i=1}^K P(\varphi_i; \beta) \prod_{t=1}^N P(Z_{j,t} | \theta_j) P(W_{j,t} | \varphi_{Z_{j,t}})$$



Topics

Words



Topics

Words

Dirichlet
Distributions

Multinomial
Distributions

Alpha

