Spotify Sequential Skip Prediction Challenge

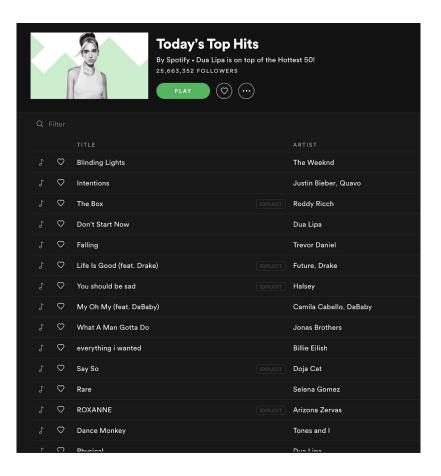
Austin Poor

Introduction

"Spotify has over 190 million active users interacting with over 40 million tracks"

The Challenge

Goal: Predict the likelihood of a user skipping any given song during a listening session



Methodology

The Data

- 10-20 song sessions
- Song and user data was anonymized
- Balanced classes (0.517 skips)
- 350GB of CSV data
- Used subset of the data
 - 100k Session Rows
 - o 50k Track Rows
- Stored data in PostgreSQL DB

training_set		
session_id	text	
session_position	bigint	
session_length	bigint	
track_id_clean	text	H
skip_1	boolean	
skip_2	boolean	
skip_3	boolean	
not_skipped	boolean	
context_switch	bigint	
no_pause_before_play	bigint	
short_pause_before_play	bigint	
long_pause_before_play	bigint	
hist_user_behavior_n_seekfwd	bigint	
hist_user_behavior_n_seekback	bigint	
hist_user_behavior_is_shuffle	boolean	
hour_of_day	bigint	
date	text	
premium	boolean	
context_type	text	
hist_user_behavior_reason_start	text	
hist_user_behavior_reason_end	text	

track_features	
track_id	text
duration	double
release_year	bigint
us_popularity_estimate	double
acousticness	double
beat_strength	double
bounciness	double
danceability	double
dyn_range_mean	double
energy	double
flatness	double
instrumentalness	double
key	bigint
liveness	double
loudness	double
mechanism	double
mode	text
organism	double
speechiness	double
tempo	double
time_signature	bigint

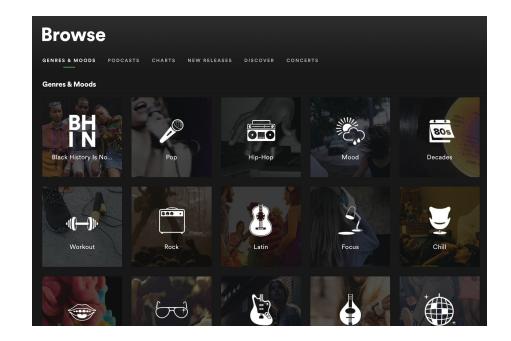
double

acoustic_vectors	
track_id	text
acoustic_vector_0	double
acoustic_vector_1	double
acoustic_vector_2	double
acoustic_vector_3	double
acoustic_vector_4	double
acoustic_vector_5	double
acoustic_vector_6	double
acoustic vector 7	double

Feature Engineering

Generate features to account for a user's listening history

Added previous track features, including if that track was skipped

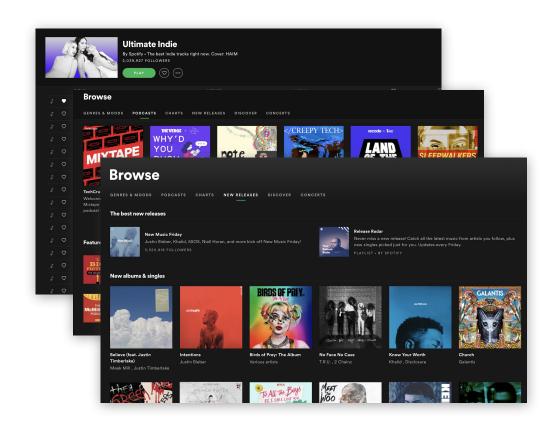


Model Selection

Target Metric **Accuracy** per competition guidelines

Baselined with Logistic Regression

Moved to tree-based models which would automatically handle feature interactions

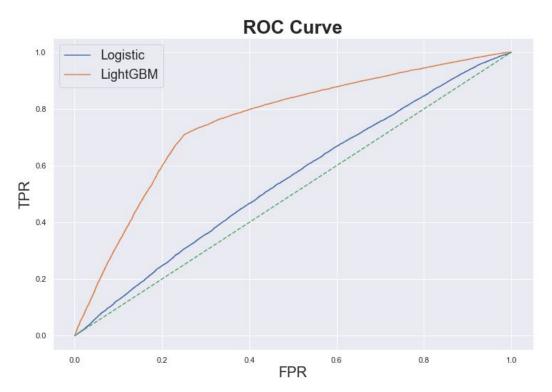


Results

Model Results

Best Test Accuracy: **0.73** (with LightGBM)

Error Analysis: No clear trend in the model residuals



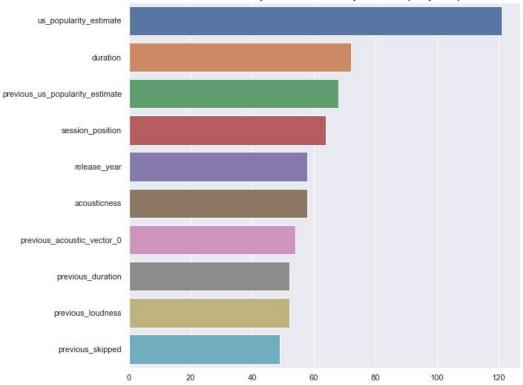
Conclusions

Conclusions

us_popularity_estimate had the highest feature importance followed by duration and then previous_us_popularity_estimate

Model results are pretty good but with room for improvement

LightGBM Model Feature Importance Comparison (Top 10)



Future Work

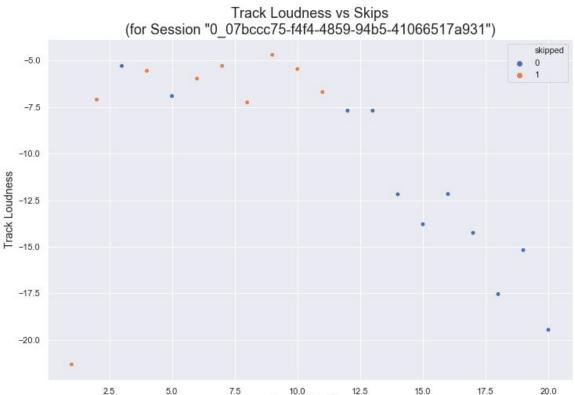
Future Work

- Test other types of algorithms:
 - Unsupervised Learning to cluster songs
 - RNN to predict based on the sequence of tracks
- Supplement the dataset with more data from the Spotify API
- Create a Flask app to visualize predictions using D3

Thank you

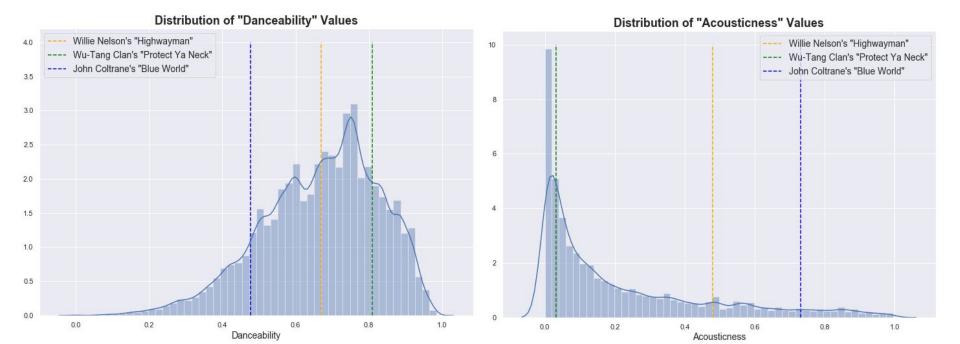
Appendix

Visualizing a Listening Session

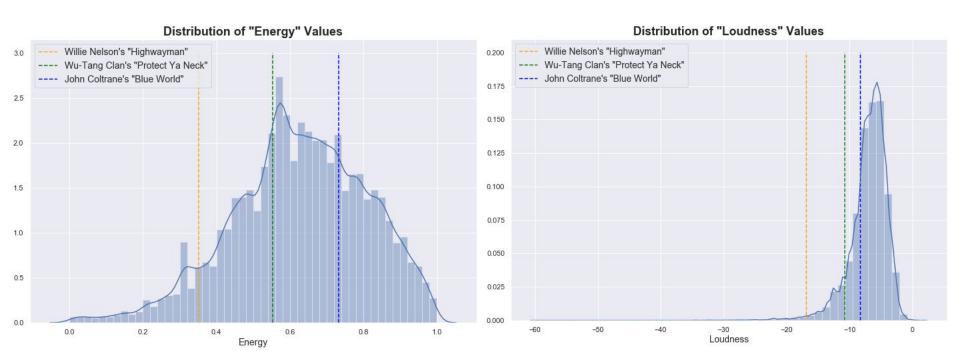


Session Position

Exploring Features



Exploring Features

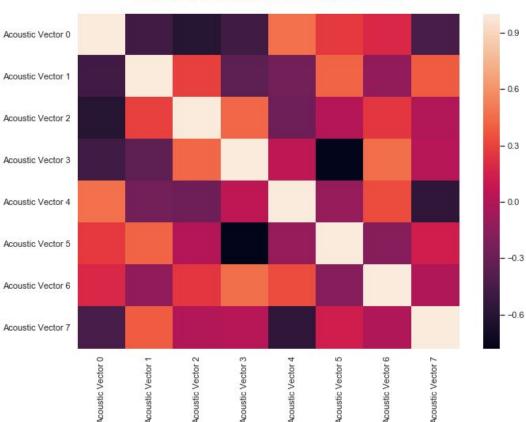


Exploring Features

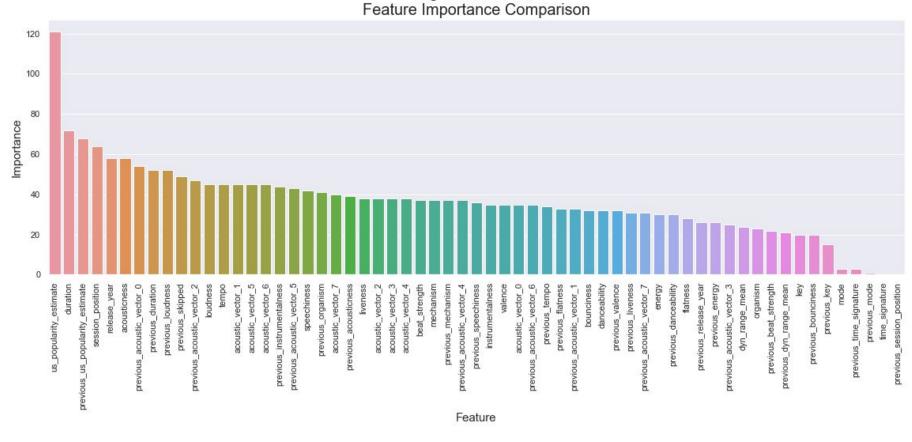
Feature	Description
Acousticness	Likelihood a track is acoustic
Danceability	Describes how suitable a track is for dancing
Energy	Measure of a track's intensity
Valence	Level of "positiveness" conveyed by a track
Speachiness	Detects the presence of spoken word

Correlation Matrix for Acoustic Vectors

Acoustic Vector Correlations



LightGBM Model Feature Importance Comparison



Flask App with D3 Visualizations

