SpotifyClassifier

ELEN E6893 Big Data Analytics
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Project Overview

- Track Genre Classification
- Used Spotify Dev API to create our own dataset
- Predicts genre from name only!
- No need for mp3 file of song to classify

Fig 1. Spotify - source for song metadata

Business Value

- Users are curious about 'Spotify Wrapped' genre listening patterns
- Spotify API only provides genre labels for artists, not tracks
- Some artists have many genres

Example

- You enjoy 'Ronin (Taylor's Version)'
- *What genre is it?*
- Taylor Swift has written pop, country, folk, rap, and more!
- We provide labels for individual tracks!

Fig 2. Red (Taylor's Version) vs. Reputation album comparison

New Dataset

- Queried Spotify for recommendations across 73 subgenres
- ~500 tracks labelled for each subgenre
- Collected Spotify metadata for individual tracks, added subgenre labels
- Grouped 73 subgenres ->11 'super-genres' for simpler classification

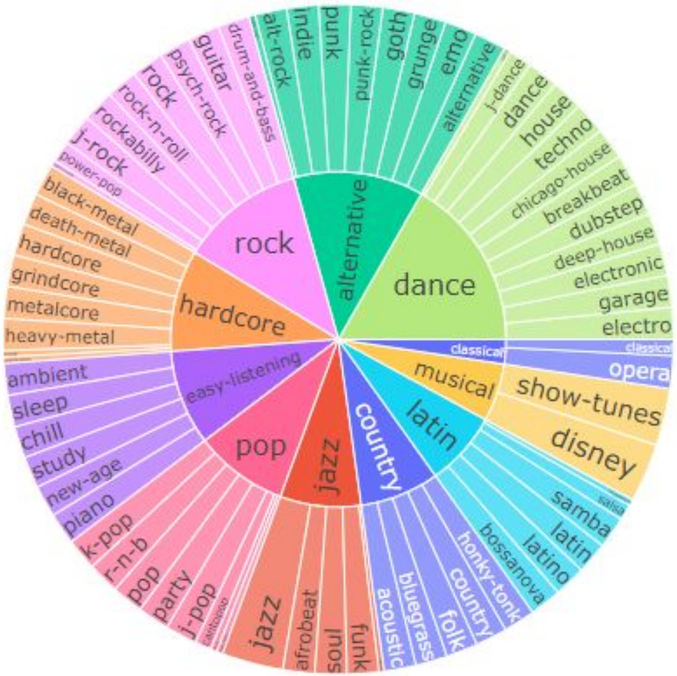


Fig 3. Our dataset hierarchy

Feature Variety

- Combined Spotify audio features and audio analysis
- Averaged pitch and timbre vectors over all song segments
- Included other miscellaneous metrics (popularity, date of release, explicit lyrics)

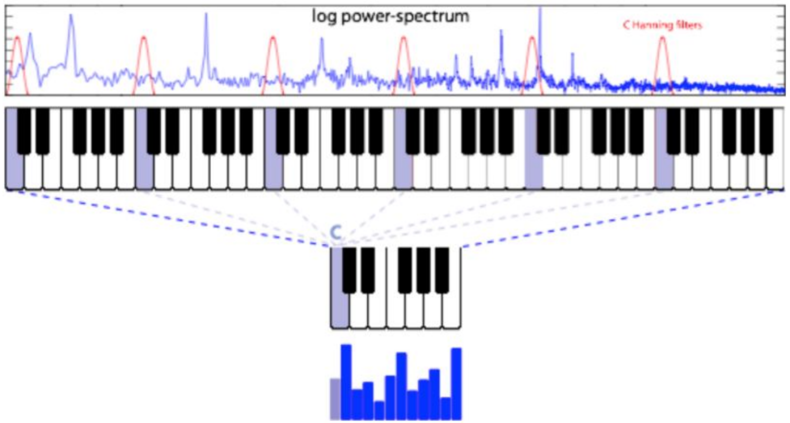


Fig 4. Pitch feature vector

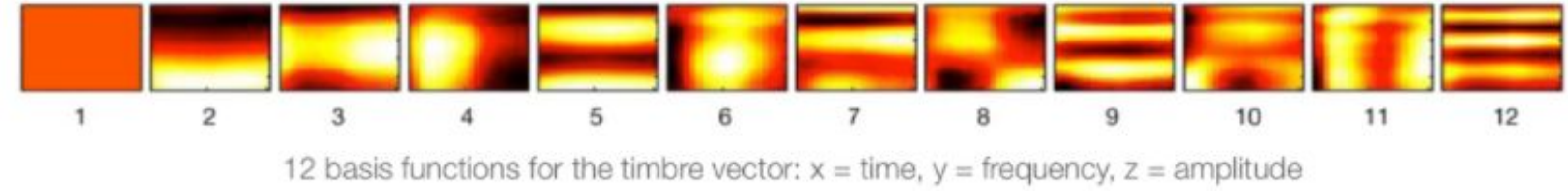


Fig 5. Timbre feature vector

Model Architecture

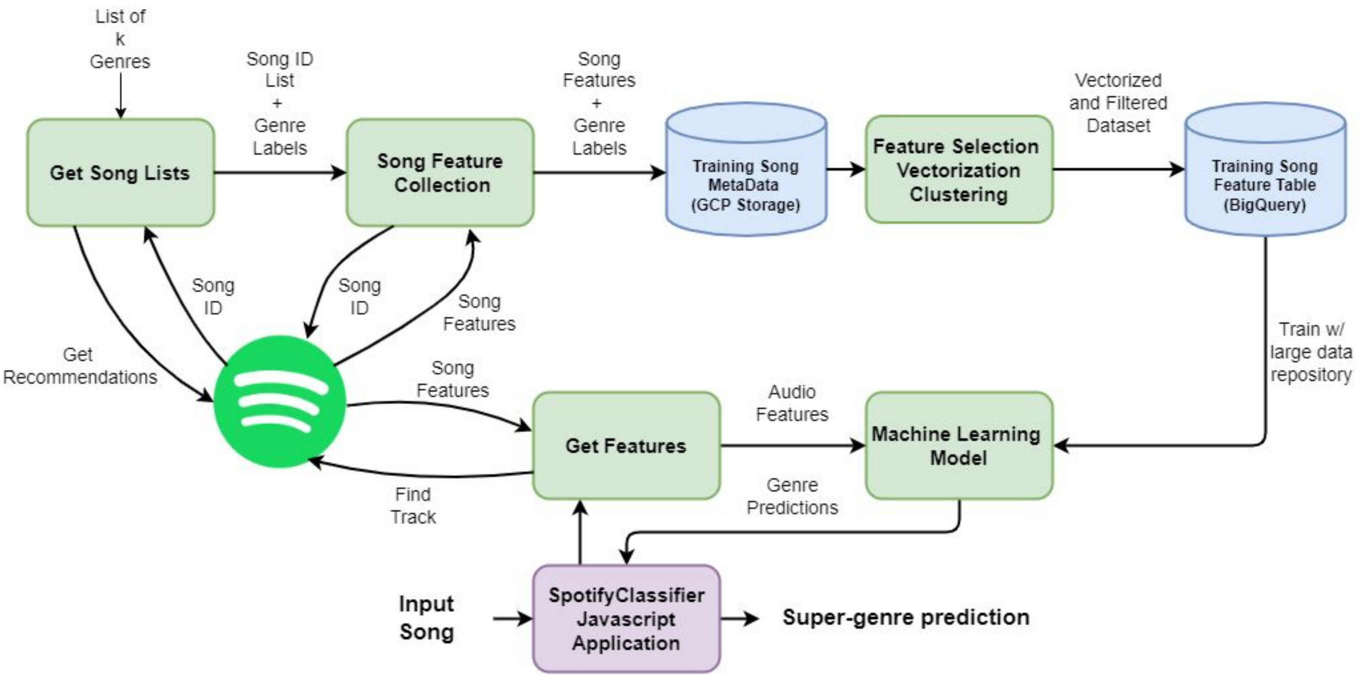


Fig 6. System Diagram

Model Performance

Tested models

- Random Forest Classifier. Accuracy: 0.4765
- Decision Tree Classifier. Accuracy: 0.4156
- Logistic Regression. Accuracy: 0.5518
- LinearSVC. Accuracy: 0.4796
- GBT Classifier Accuracy: 0.6223

GBT results

- Test set F1-Score: 0.6217
- Test set Precision: 0.6238
- Test set Recall: 0.6223
- Test set Accuracy: 0.6223

As a benchmark, human accuracy averages around 70% for this kind of genre classification work [1].

[1] Mingwen Dong. Convolutional neural network achieves human-level accuracy in music genre classification. CoRR, abs/1802.09697, 2018.

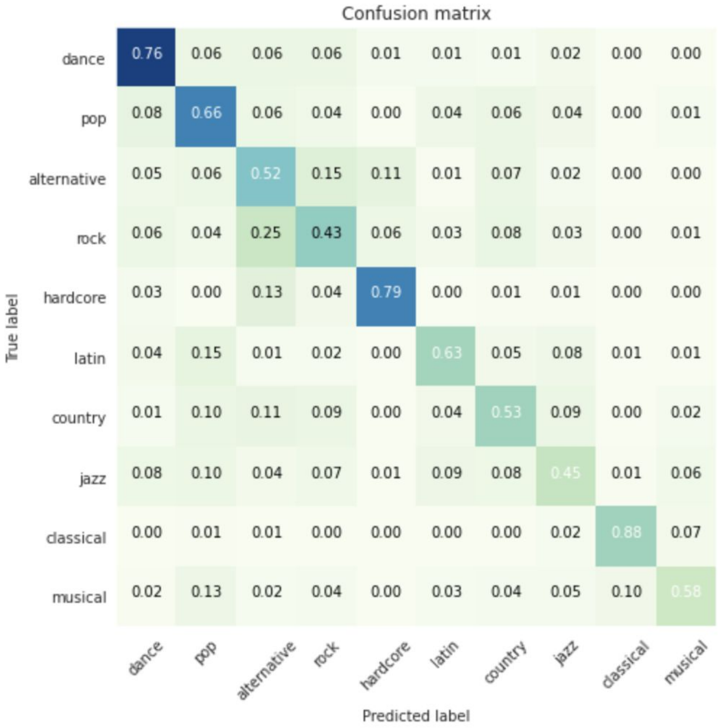


Fig 7. Test Set Confusion Matrix

Model Performance

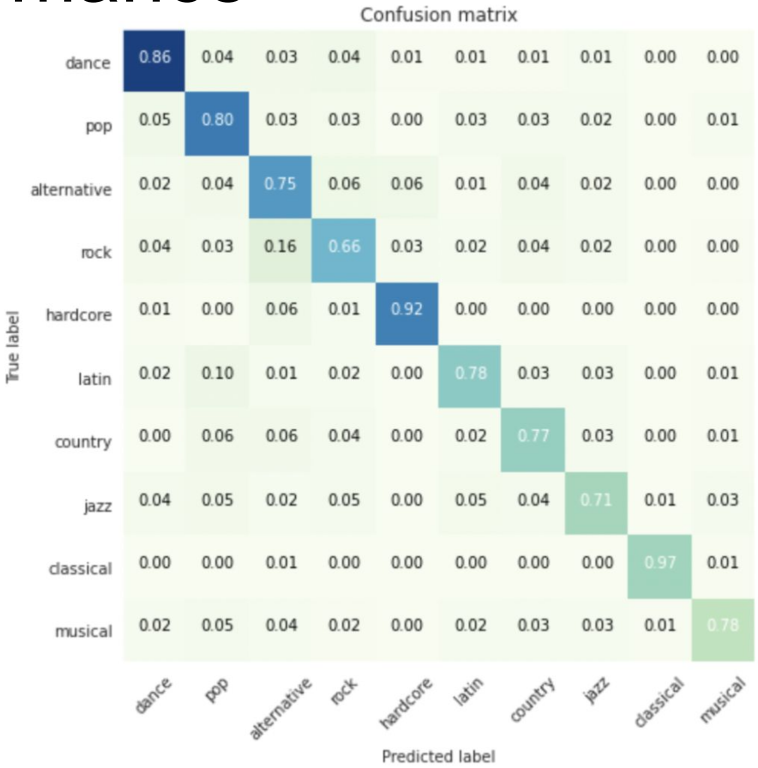


Fig 8. Train Set Confusion Matrix

Analysis: What is this, a crossover episode?

'12qZHAeOyTf93YAWvGDTat': ['alternative', 'emo', 'garage', 'grunge', 'guitar', 'party', 'punk-rock', 'rock-n-roll', 'study']

'1MUQ6LtYIw6sSGQJEoIi2X': ['acoustic', 'alternative', 'bluegrass', 'chill', 'folk', 'sleep', 'study']

'3FtYbEfBqAlGO46NUDQSAt': ['alternative', 'chill', 'indie-pop', 'party', 'study', 'techno']

Super-Genres as a Graph

- Maybe 'super-genre' hierarchy model was an oversimplification
- Perhaps some subgenres belong to more than one cluster
- Ex: "alt-rock" = "rock"&"alternative"
- We set out to find more representative super-genres
- Also want to identify problematic (highly interconnected) subgenres

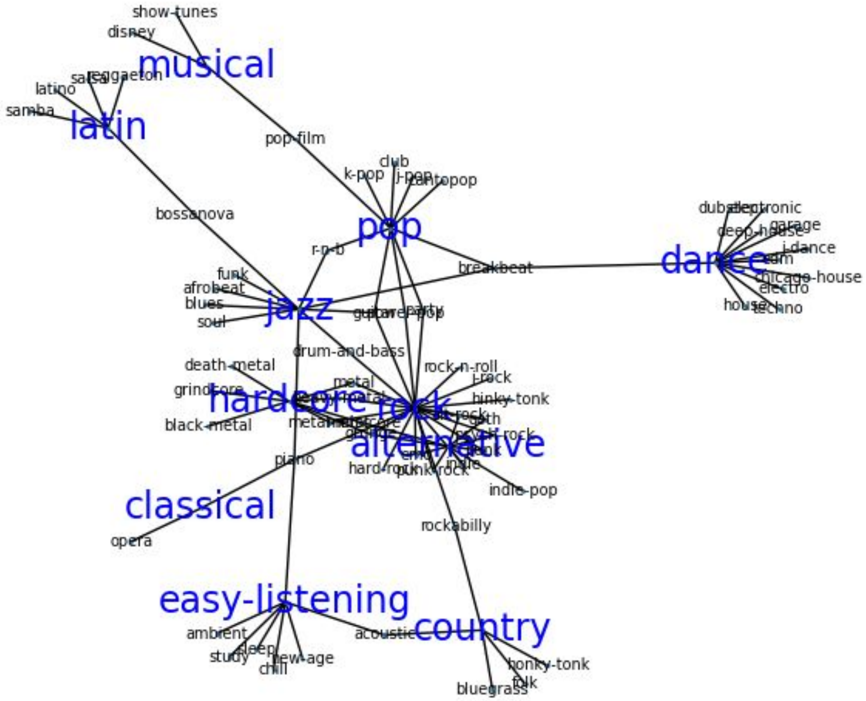
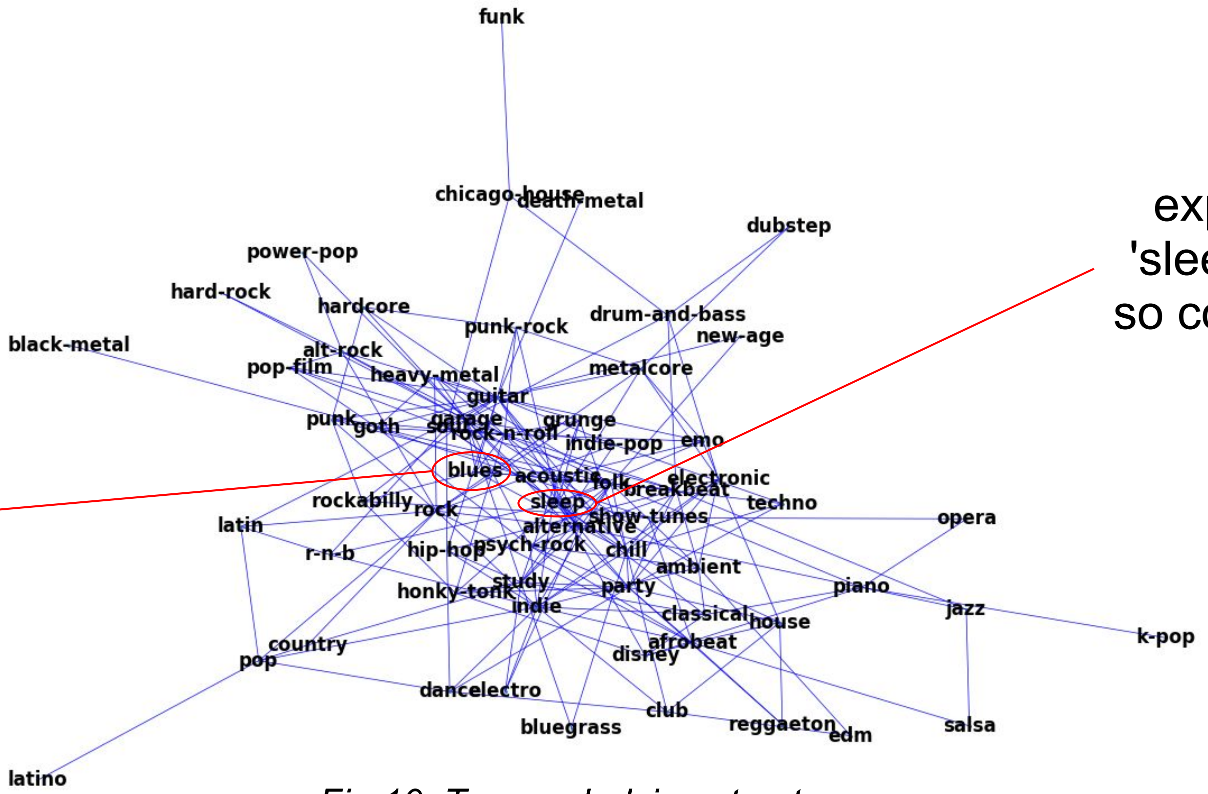


Fig 9. Our expected underlying structure

Genre Interconnectedness



Unsurprising 'blues' is central

Not expecting 'sleep' to be so connected

Fig 10. True underlying structure

Most Interconnected Subgenres

- Ranked based on subgenre overlap
- 'chill', 'study', and 'sleep', rounded out the top 3
- Interestingly, these were all part of our 'easy-listening' super-genre
- 'guitar', 'party, and 'acoustic' are unsurprising offenders, as they are vague

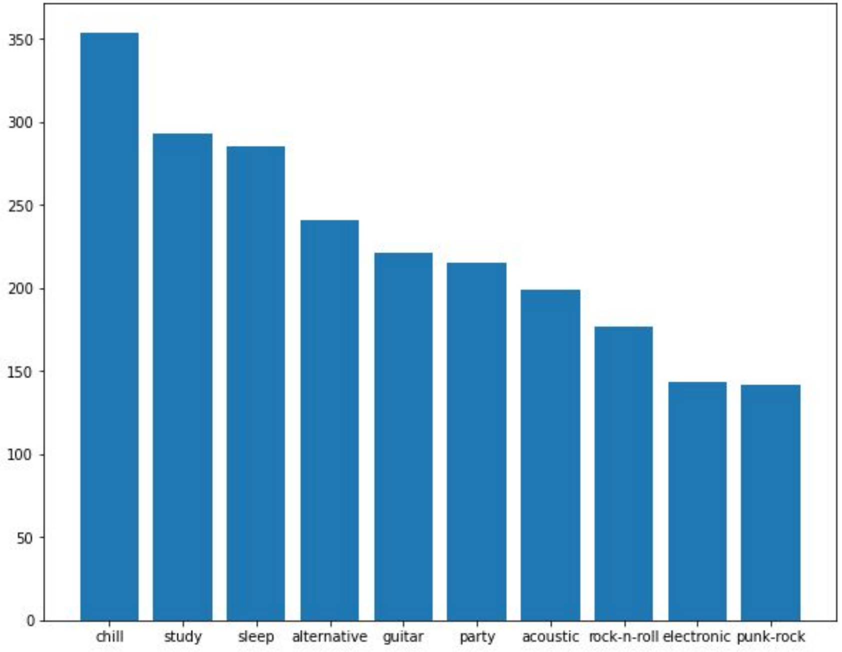


Fig 11. Top interconnected subgenres

Stretch Goals

- Didn't quite get this perfect for today
- Connect front end of website to back end
- Display album art / animation of input track
- Visualize prediction scores against our sunburst and graph clustering visuals

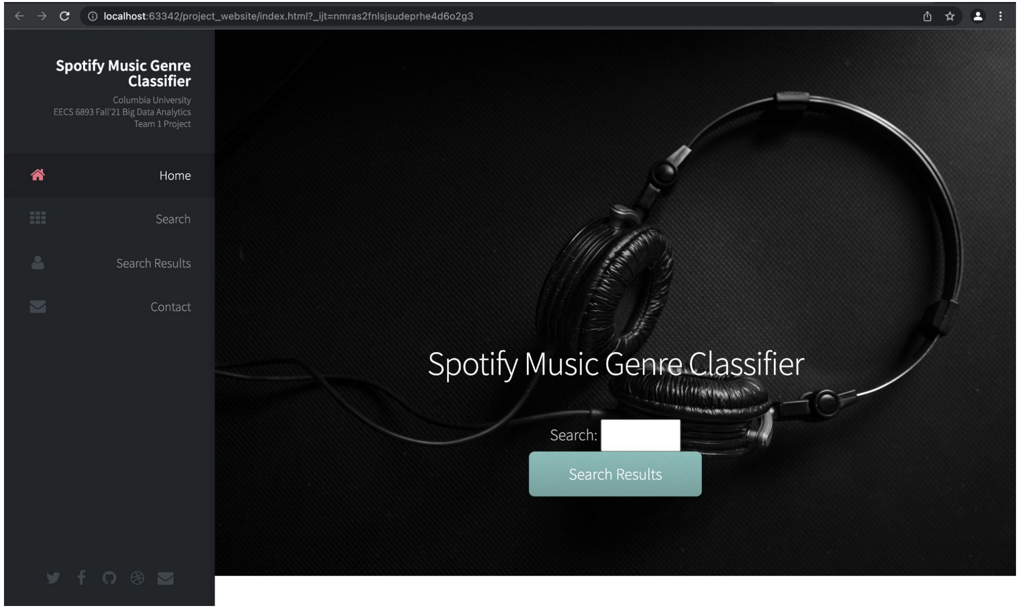


Fig 12. Website Front End

Check us out on github!

https://github.com/athornton1618/SpotifyClassifier