Classy Muse: Music Classification

Prachi Varma, Robert Turnage, Grant Wilson

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Problem and Objective

Problem Statement:

- Traditionally, music streaming services, such as Spotify, are provided musical genre metadata by labels and publishers. While this is generally reliable, it is not uncommon for metadata from smaller/indie publishers to be incorrect, leading to a bad user experience.

Objective:

- We want to build an ML model that will classify different musical genres by audio analysis
    - Defining the many community described music genres we will attempt to classify by analyzing audio features of frequency and time alongside metrics of track “energy”, tempo, and speed.

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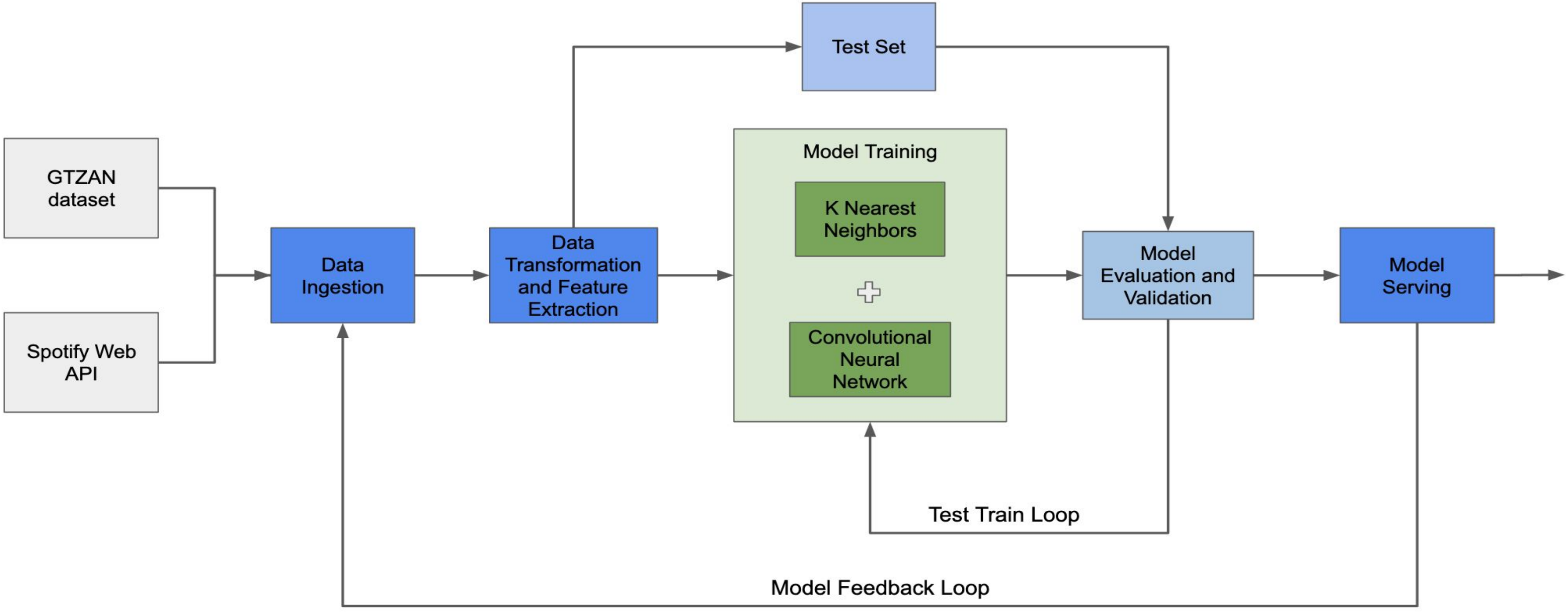
Methodology

We want to train a model based on features that important in audio and specifically in music.

Audio Features

- Frequency
- Wavelength
- Amplitude
- Pitch patterns



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Data

1. GTZAN genre classification dataset (10 genres with 100 .wav files)
2. Spotify Web API/ Everynoise.com

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EDA and Feature Extraction

- Librosa for feature extraction from audio files
  - Waveforms
  - Mel-Frequency Cepstral Coefficients Spectrographs
  - Chroma Frequencies

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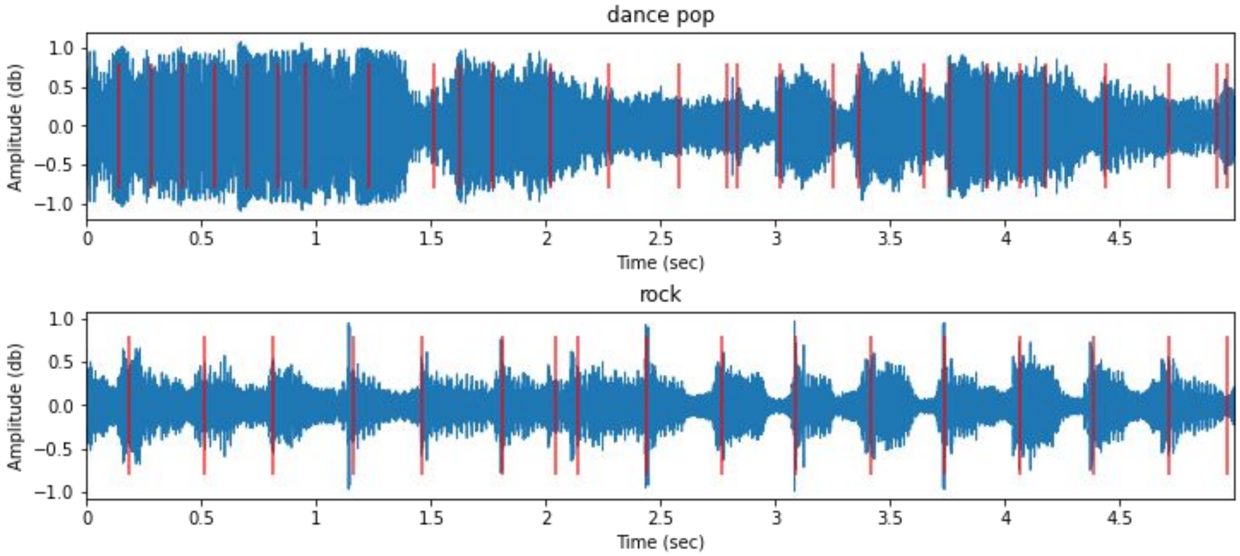
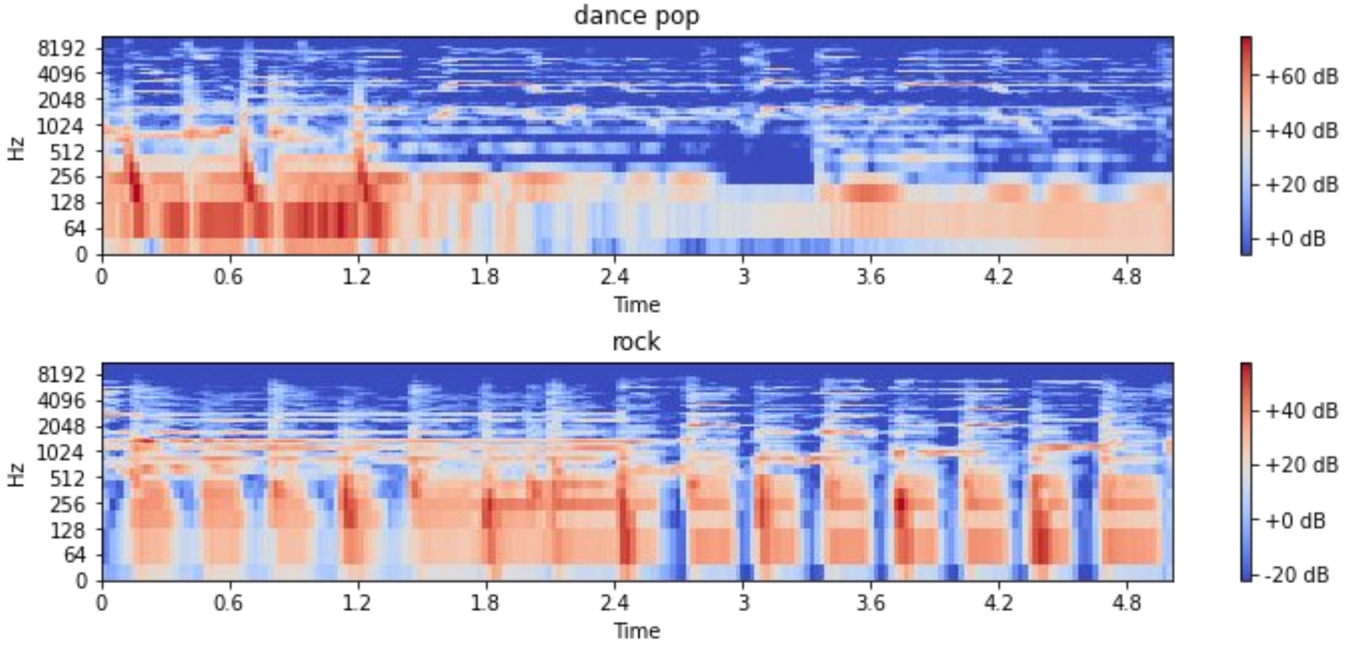
Waveforms


dance pop
Amplitude (db)
1.0
0.5
0.0
−0.5
−1.0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
Time (sec)
rock
Amplitude (db)
1.0
0.5
0.0
−0.5
−1.0
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
Time (sec)

MFCC



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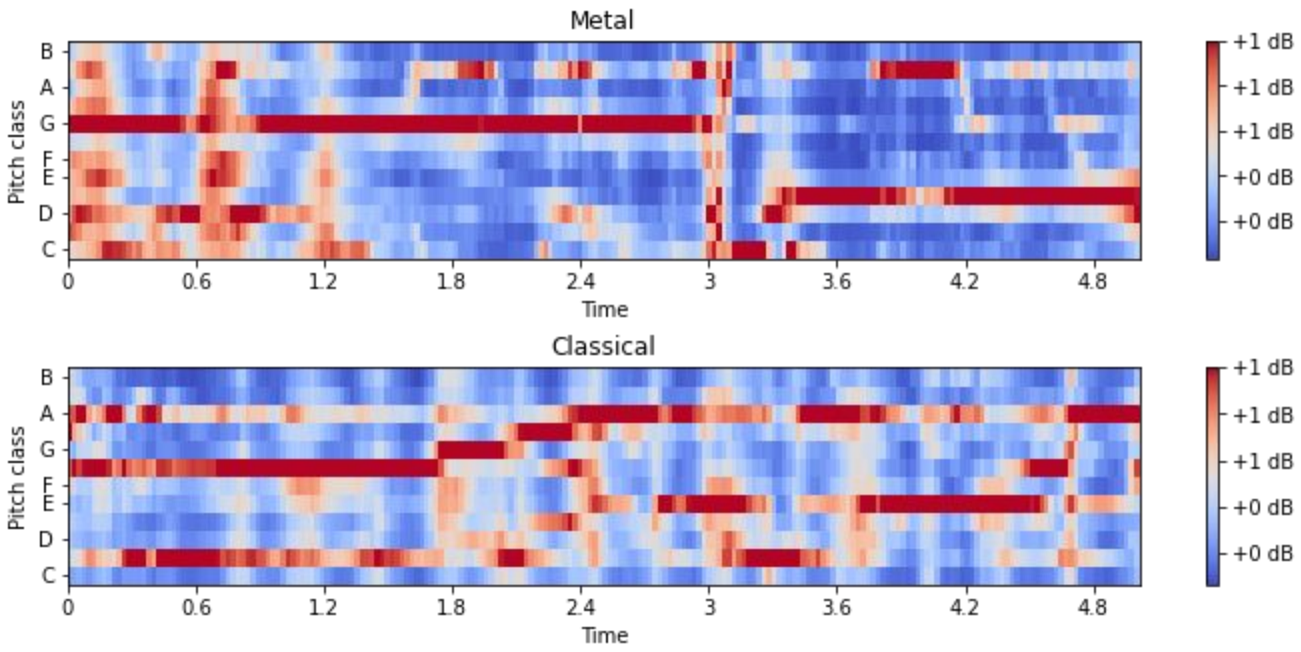
Chroma Frequencies



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Modeling

Convolutional Neural Network

- MFCC Spectrograph log transformation of data
  - Test Set: 400 files
  - Train Set: 100 files
- Constant Q Transform Chromagram
  - Test Set: 400 files
  - Train Set: 100 files

KNN, Logistic Regression, GPC

- DataFrame of 500 Spotify tracks

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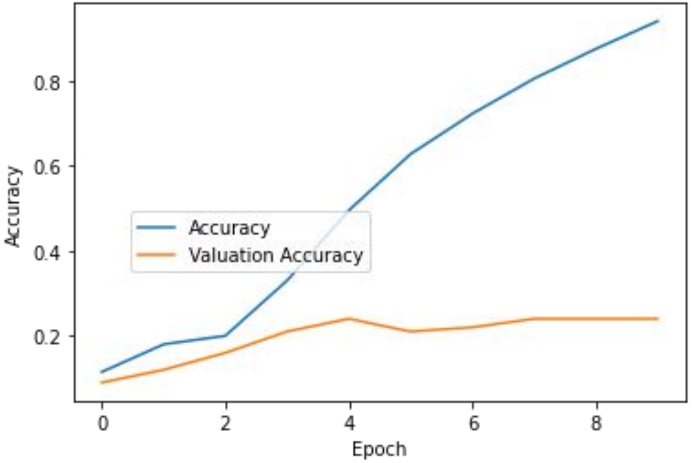
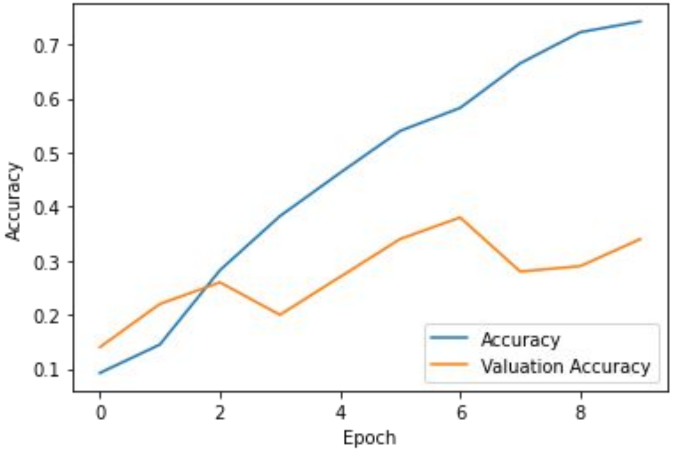
CNN Results

CNN - Chroma CQT



CNN - MFCC Spectrogram



KNN Results

```
[ ]  search = GridSearchCV(pipe, param_grid, n_jobs=-1)
     search.fit(X_train, y_train)
     print("Best parameter (CV score=%0.3f):" % search.best_score_)
     print(search.best_params_)
```

```
Best parameter (CV score=0.307):
{'knn__leaf_size': 5, 'knn__n_neighbors': 10}
```

```
[ ]  print(f"Train Score: {search.score(X_train, y_train)}")
     print(f"Test Score: {search.score(X_test, y_test)}")
```

```
Train Score: 0.4272151898734177
Test Score: 0.29245283018867924
```

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Limitations and Future Work

- Limitations
  - 30 second audio snippets of much longer tracks may leave out significant features
  - Spotify doesn't allow queries based on genres, so data was pulled from a derivative of genre
    - Everynoise.com
  - Overfitting of the CNN due to the complexity of having multiple pooling and convolutional layers
- Future Work
  - Content-based music recommendation systems
  - Mood-based playlist creation

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Questions?

Appendix

Standards

- Librosa
- Scipy
- Sklearn
- tensorflow / Keras
- Pandas
- numpy