EDA_Final_Project_Code

December 13, 2022

1 EECE 5644 - Intro to Machine Learning - Final Project: EDA and Musical Genre Classification

1.1 Tyler's Code

Imports

[ ]:
```
import os
os.environ["OMP_NUM_THREADS"] = "4" # export OMP_NUM_THREADS=4
os.environ["OPENBLAS_NUM_THREADS"] = "4" # export OPENBLAS_NUM_THREADS=4
os.environ["MKL_NUM_THREADS"] = "6" # export MKL_NUM_THREADS=6
os.environ["VECLIB_MAXIMUM_THREADS"] = "4" # export VECLIB_MAXIMUM_THREADS=4
os.environ["NUMEXPR_NUM_THREADS"] = "6" # export NUMEXPR_NUM_THREADS=6
# Audio Processing and Display Modules
import IPython.display as ipy       # Playing Audio Samples
import librosa as lib               # Spectrograms
import librosa.display as libdis    # Wavefrom Plots
import seaborn as sns               # Additional Plotting
import sweetviz as sv               # Visual Aid
# Machine Learning Modules
import sklearn
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.linear_model import SGDClassifier, LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.neural_network import MLPClassifier
import xgboost as xgb
from xgboost import XGBClassifier, XGBRFClassifier
from xgboost import plot_tree, plot_importance, to_graphviz
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.metrics import plot_confusion_matrix, confusion_matrix,␣
↪accuracy_score, roc_auc_score, roc_curve
from sklearn.metrics import balanced_accuracy_score, make_scorer
```

```
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪cross_val_score, StratifiedKFold, KFold
from sklearn.linear_model import Lasso
from sklearn.decomposition import PCA
from sklearn.feature_selection import RFE
# Standard Python Modules
import pandas as pd
import random as rnd
import numpy as np
import matplotlib.pylab as plt
plt.style.use('ggplot')
pd.options.display.max_columns = 60
pd.options.display.max_rows = 50
```

Function for Model Evaluation

[ ]:
```
def model_assess(model, X_train, y_train, X_test, y_test, title = "Default"):
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    #print(confusion_matrix(y_test, preds))
    print('Accuracy', title, ':', round(accuracy_score(y_test, preds), 5), '\n')
```

Functions

[ ]:
```
def SampleRandomSong(df, song):
    idx = rnd.randint(0,99)
    df = df.query(r'label == "{val}"'.format(val = song)).
↪reset_index(drop=True).iloc[idx]
    audio_path = r"C:\Users\tmcke\OneDrive\Desktop\NORTHEASTERN\Fall 2022\Intro␣
↪to Machine Learning\Python Files\GTZAN␣
↪Dataset\genres_original\{val1}\{val2}".format(val1 = song,val2 = str(df[0]))
    return df, audio_path
# Normalising the spectral centroid for visualisation
def normalize(x, axis=0):
    return sklearn.preprocessing.minmax_scale(x, axis=axis)
```

Input GTZAN Datasets (3 sec and 30 sec)

[ ]:
```
# Read CSV file of 10 genres of Music
df = pd.read_csv('features_3_sec.csv')
df_30sec = pd.read_csv('features_30_sec.csv')
```

[ ]:
```
# Display Dataframe
df_30sec
```

[ ]:
```
# Dimensions of 3 sec features dataframe
df.shape
# List the dtype for each column of Dataframe
#df.dtypes
```

[ ]: (9990, 60)

[ ]:
```
# List all the columns of Dataframe
df.columns
```

1.1.1 Listen to Random Music Tracks from GTZAN Dataset

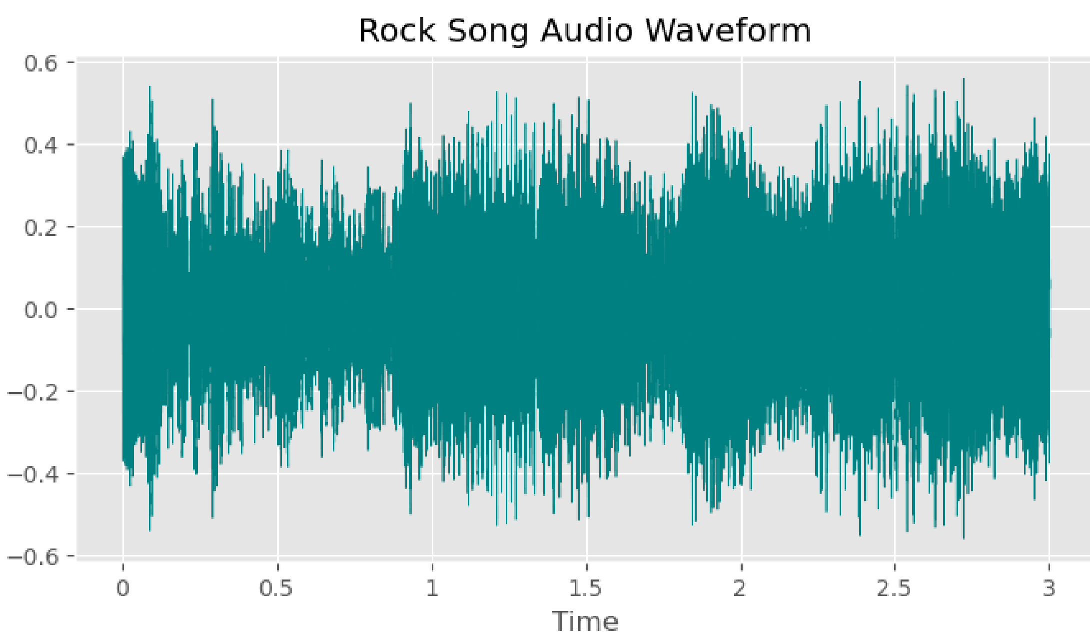
1.1.2 Rock Song

[ ]:
```
seriesRock, audioPath = SampleRandomSong(df_30sec,"rock")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

Time-Domain Waveform: Rock Song

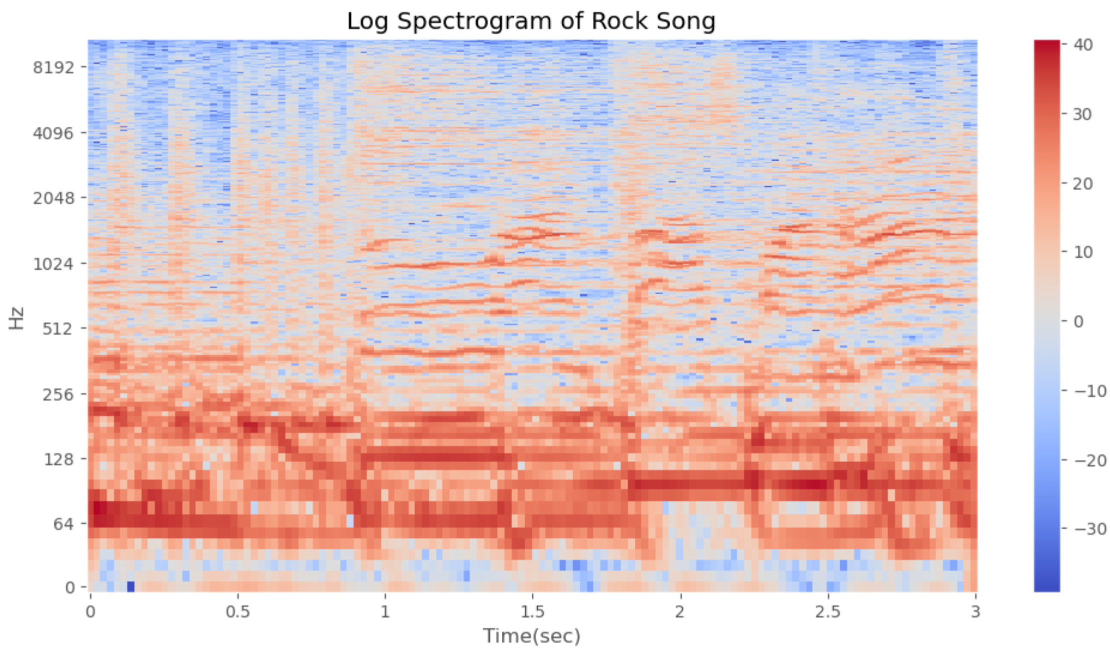
[ ]:
```
# Sample first 3 seconds from random genre song
x1 = x[0:66139]
plt.figure(figsize=(8,4))
libdis.waveshow(x1,sr=sr, color = 'teal')
plt.title('Rock Song Audio Waveform')
plt.show()
```



Spectrogram: Rock Song

- Visual representation of the spectrum of frequencies versus time.
- Intensity of signal at various frequencies over time

```
[ ]: X = lib.stft(x1)                                         # Compute␣
      ↪Spectrogram of 3 sec Rock Sample
     Xdb = lib.amplitude_to_db(abs(X))                         # Convert Amplitude␣
      ↪to Decibels
     plt.figure(figsize=(12, 6))
     libdis.specshow(Xdb, sr=sr, x_axis='time', y_axis='log')    # Librosa Display␣
      ↪Log Spectrogram
     plt.colorbar()
     plt.xlabel('Time(sec)')
     plt.ylabel('Hz')
     plt.title('Log Spectrogram of Rock Song')
     plt.show()
```



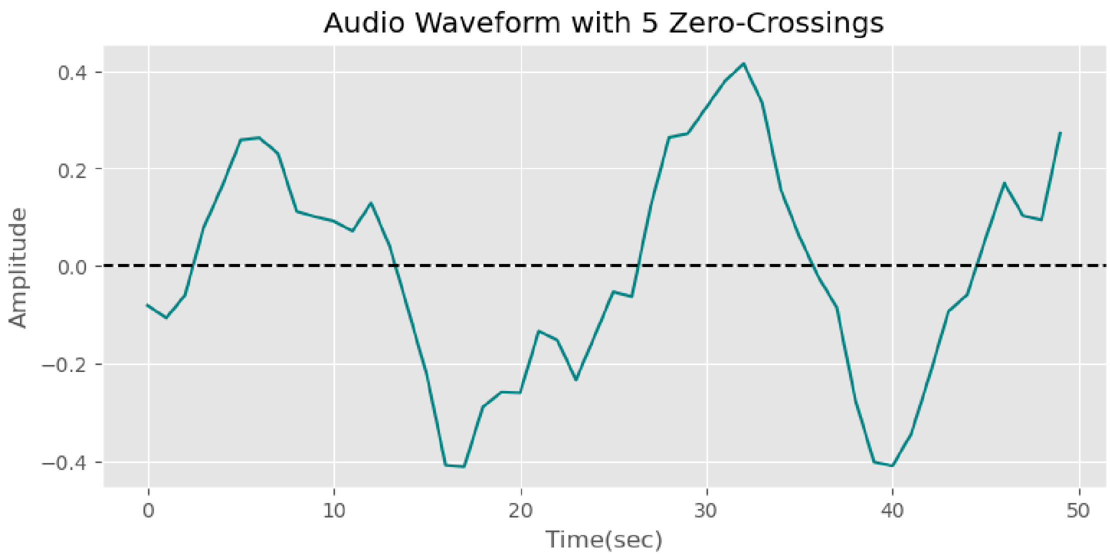
Zero-Crossing Rate (Zoomed-In Section of 3 sec Audio)

- Rate of sign-changes of signal
- Rate at which the audio signal changes from positive to negative and back

```
[ ]: # Zooming in
     n0 = 5050
     n1 = 5100
     numZeroCross = sum(lib.zero_crossings(x1[n0:n1], pad=False))
     print(r"The Number of Zero-Crossings for Zoomed-In Audio Waveform is: {val}".
      ↪format(val = numZeroCross))
     plt.figure(figsize=(9, 4))
     plt.plot(x1[n0:n1], color = 'teal')
```

```
plt.axhline(y=0, color='k', linestyle='--')
plt.xlabel('Time(sec)')
plt.ylabel('Amplitude')
plt.title(r"Audio Waveform with {val} Zero-Crossings".format(val =␣
↪numZeroCross))
plt.grid(True)
```

```
The Number of Zero-Crossings for Zoomed-In Audio Waveform is: 5
```

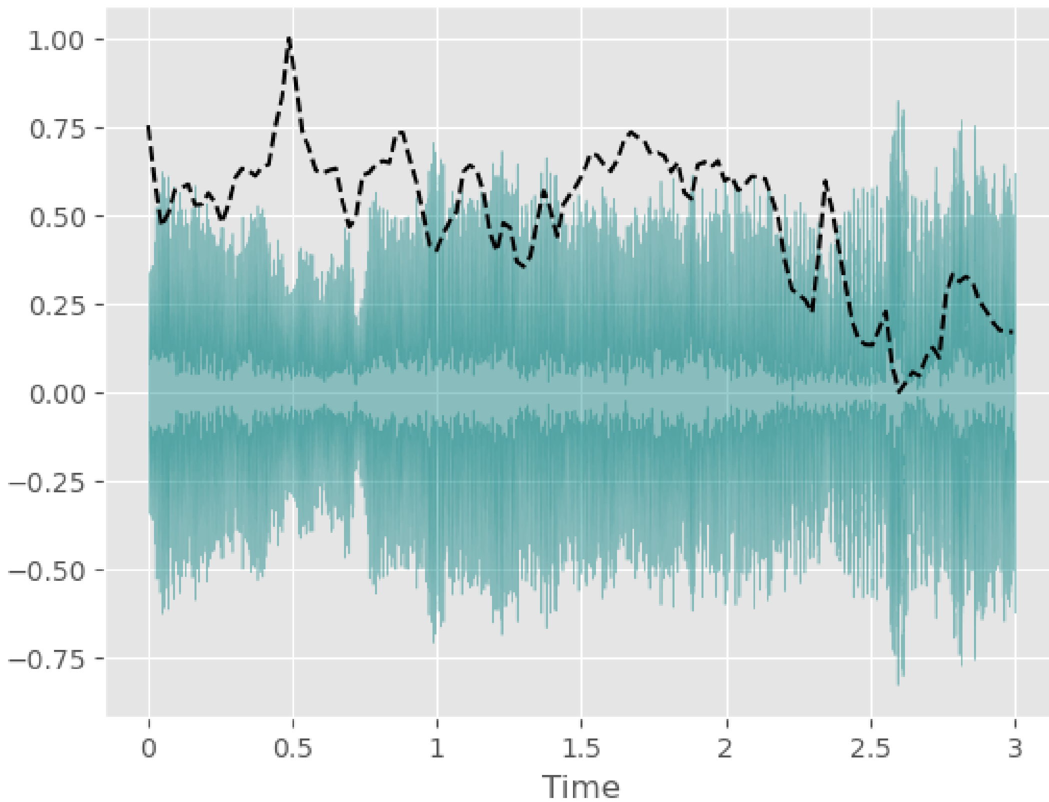


Spectral Centroids

- Indicates where the centroid of the audio spectrogram is located
- Calculated as weighted mean of frequencies present in the audio

[ ]:
```
spectral_centroids = lib.feature.spectral_centroid(x1, sr=sr)[0]
# Computing the time variable for visualization
frames = range(len(spectral_centroids))
t = lib.frames_to_time(frames)
#Plotting the Spectral Centroid along the waveform
libdis.waveshow(x1, sr=sr, alpha=0.4, color = 'teal')
plt.plot(t, normalize(spectral_centroids), color='k',linestyle = '--')
plt.show()
```

```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_25904\3320952454.py:1:
FutureWarning: Pass y=[0.3352661  0.1633606  0.08322144 … 0.37353516
0.40194702 0.42190552] as keyword args. From version 0.10 passing these as
positional arguments will result in an error
  spectral_centroids = lib.feature.spectral_centroid(x1, sr=sr)[0]
```

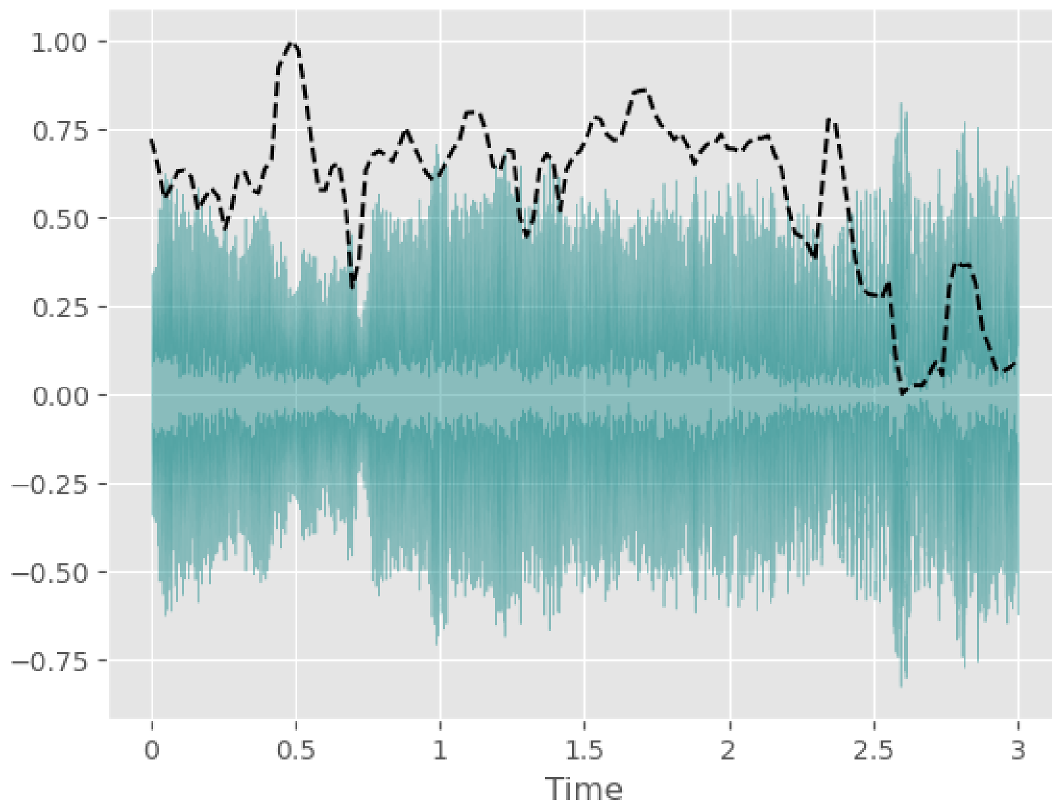


Spectral Rolloff

- Measurement of the shape of audio
- Represents frequency below a specified percentage of total spectral energy

[ ]:
```
spectral_rolloff = lib.feature.spectral_rolloff(x1+0.01, sr=sr)[0]
lib.display.waveshow(x1, sr=sr, alpha=0.4, color = 'teal')
plt.plot(t, normalize(spectral_rolloff), color='k',linestyle = '--')
plt.show()
```

```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_25904\407351742.py:1: FutureWarning:
Pass y=[0.3452661  0.1733606  0.09322143 … 0.38353515 0.411947   0.4319055 ]
as keyword args. From version 0.10 passing these as positional arguments will
result in an error
  spectral_rolloff = lib.feature.spectral_rolloff(x1+0.01, sr=sr)[0]
```



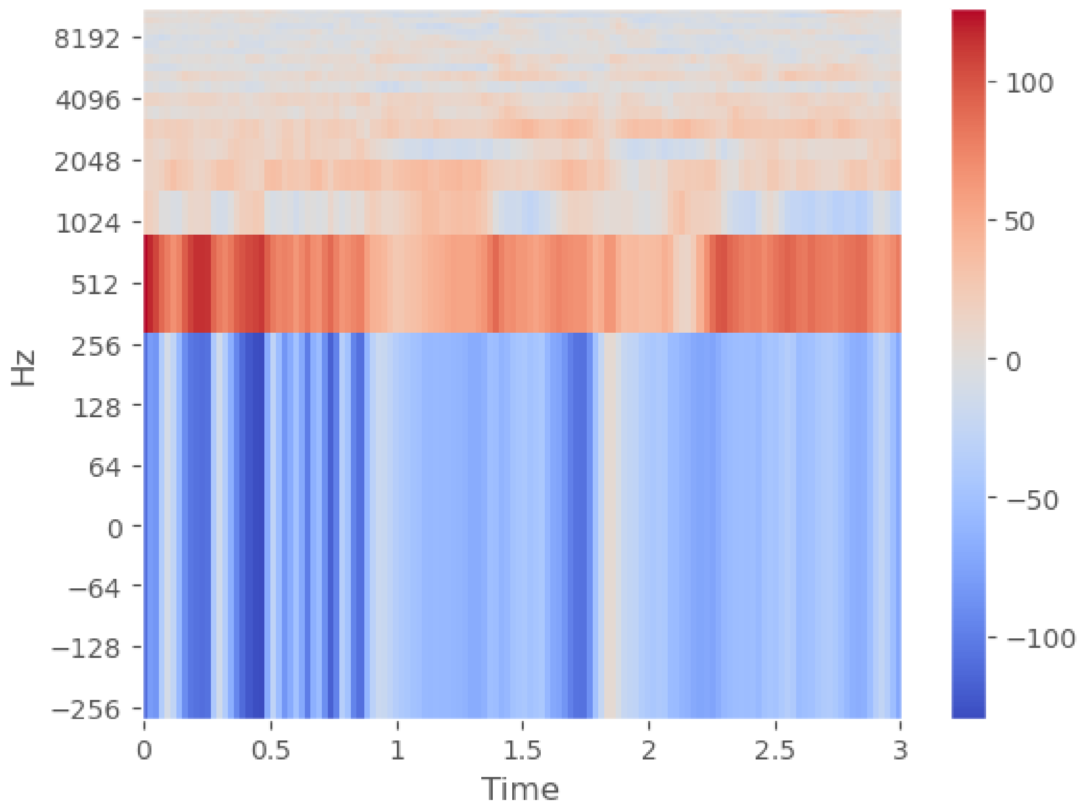
Mel-Frequency Cepstral Coefficients

- Small set of features (btw 10-20)
- Concisely describe the overall shape of spectral envelope
- Models characteristics of the human voice

[ ]:
```
mfccs = lib.feature.mfcc(x1, sr=sr)
print(mfccs.shape)
#Displaying  the MFCCs:
lib.display.specshow(mfccs, sr=sr, x_axis='time', y_axis = 'log')
plt.colorbar()
plt.show()
```

```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_2744\512006153.py:1: FutureWarning:
Pass y=[0.07925415 0.05932617 0.03930664 … 0.03674316 0.05004883 0.13900757]
as keyword args. From version 0.10 passing these as positional arguments will
result in an error
  mfccs = lib.feature.mfcc(x1, sr=sr)
```

```
(20, 130)
```

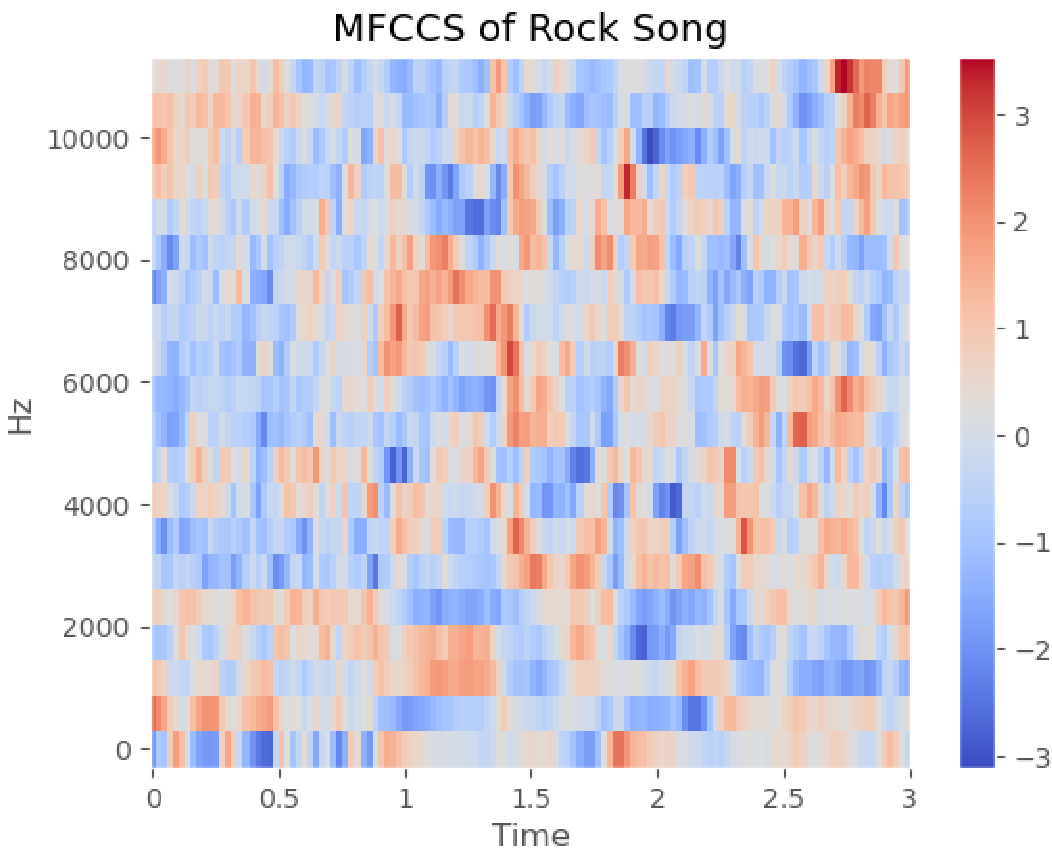



```
[ ]: # Scale the MFCCs
mfccs = sklearn.preprocessing.scale(mfccs, axis=1)
mfccs_mean = mfccs.mean()
mfccs_var = mfccs.var()
print(r"The Mean for the Mel-Frequency Cepstral Coefficients are: {val}".
  ↪format(val = mfccs_mean))
print(r"The Variance for the Mel-Frequency Cepstral Coefficients are: {val}".
  ↪format(val = mfccs_var))
lib.display.specshow(mfccs, sr=sr, x_axis='time', y_axis = 'hz')
plt.title('MFCCS of Rock Song')
plt.colorbar()
plt.show()
```

```
c:\Users\tmcke\anaconda3\lib\site-packages\sklearn\preprocessing\_data.py:239:
UserWarning: Numerical issues were encountered when centering the data and might
not be solved. Dataset may contain too large values. You may need to prescale
your features.
  warnings.warn(
c:\Users\tmcke\anaconda3\lib\site-packages\sklearn\preprocessing\_data.py:258:
UserWarning: Numerical issues were encountered when scaling the data and might
not be solved. The standard deviation of the data is probably very close to 0.
```

```
  warnings.warn(
```

```
The Mean for the Mel-Frequency Cepstral Coefficients are: -7.335956286880219e-10
The Variance for the Mel-Frequency Cepstral Coefficients are: 1.0
```



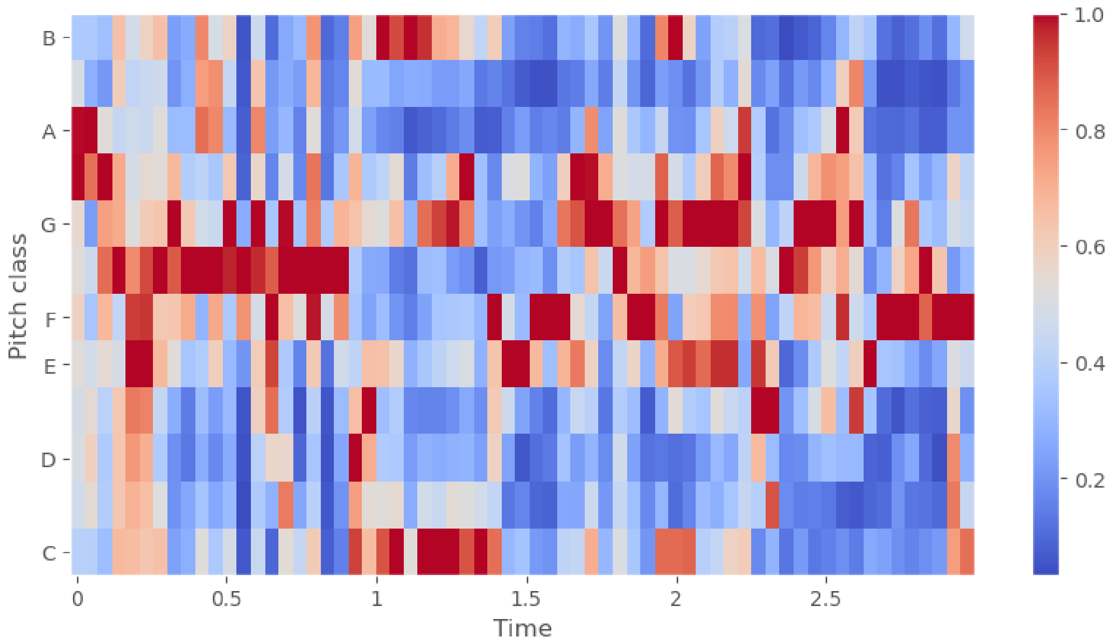
Chroma Frequencies

- Entire spectrum is projected onto 12 bins representing the 12 semitones of musical octave
- Chords/Notes into certain Pitch Class (A-G) over time

[ ]:
```
hop_length = 1024
chromagram = lib.feature.chroma_stft(x1, sr=sr, hop_length=hop_length)
plt.figure(figsize=(10, 5))
libdis.specshow(chromagram, x_axis='time', y_axis='chroma',␣
 ↪hop_length=hop_length, cmap='coolwarm')
plt.colorbar()
plt.show()
```

```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_2744\2138767856.py:2: FutureWarning:
Pass y=[0.07925415 0.05932617 0.03930664 … 0.03674316 0.05004883 0.13900757]
as keyword args. From version 0.10 passing these as positional arguments will
```

```
result in an error
  chromagram = lib.feature.chroma_stft(x1, sr=sr, hop_length=hop_length)
```

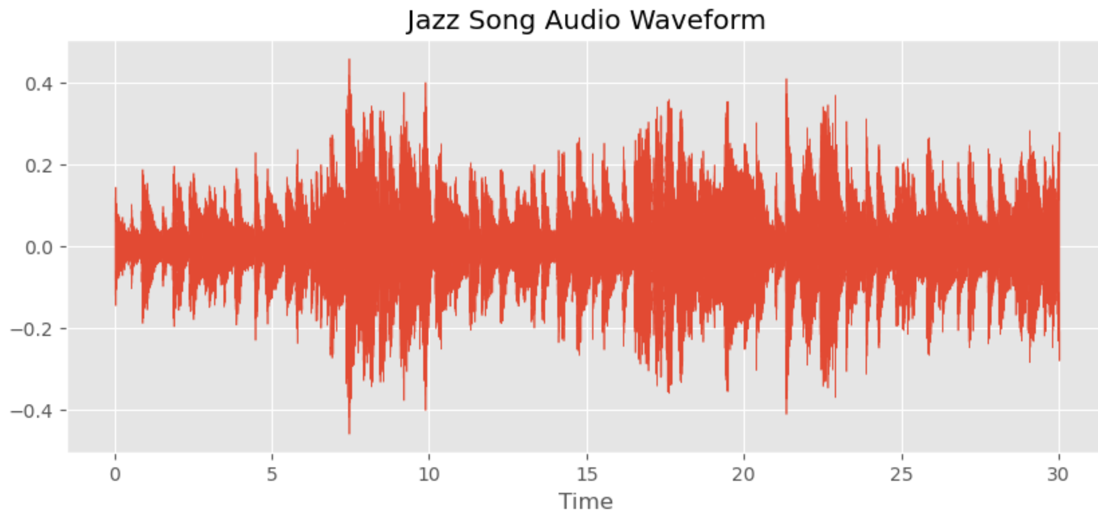


1.1.3 Jazz Song

[ ]:
```
seriesJazz, audioPath = SampleRandomSong(df_30sec,"jazz")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Jazz Song Audio Waveform')
plt.show()
```

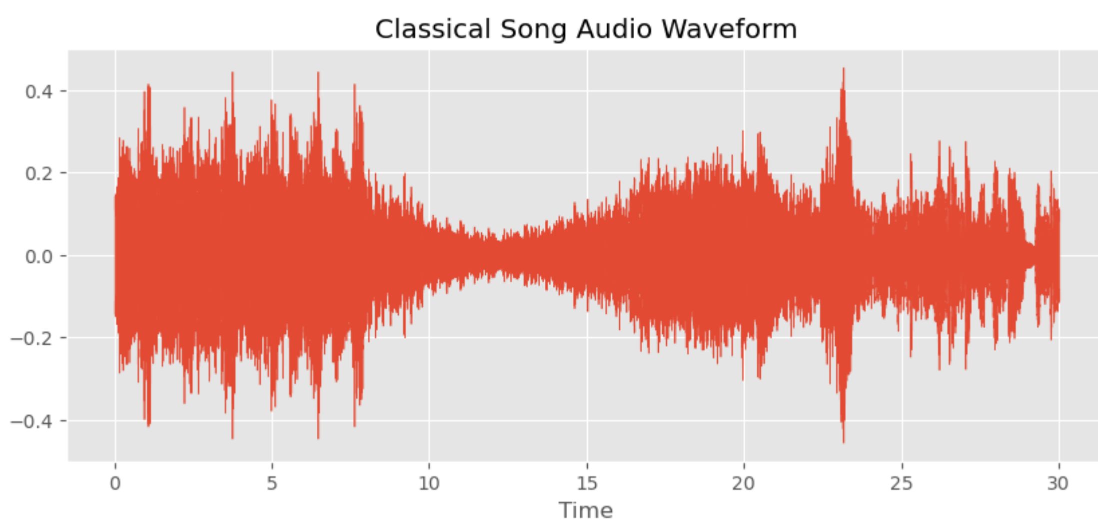


1.1.4 Classical Song

[ ]:
```
seriesClassical, audioPath = SampleRandomSong(df_30sec,"classical")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Classical Song Audio Waveform')
plt.show()
```

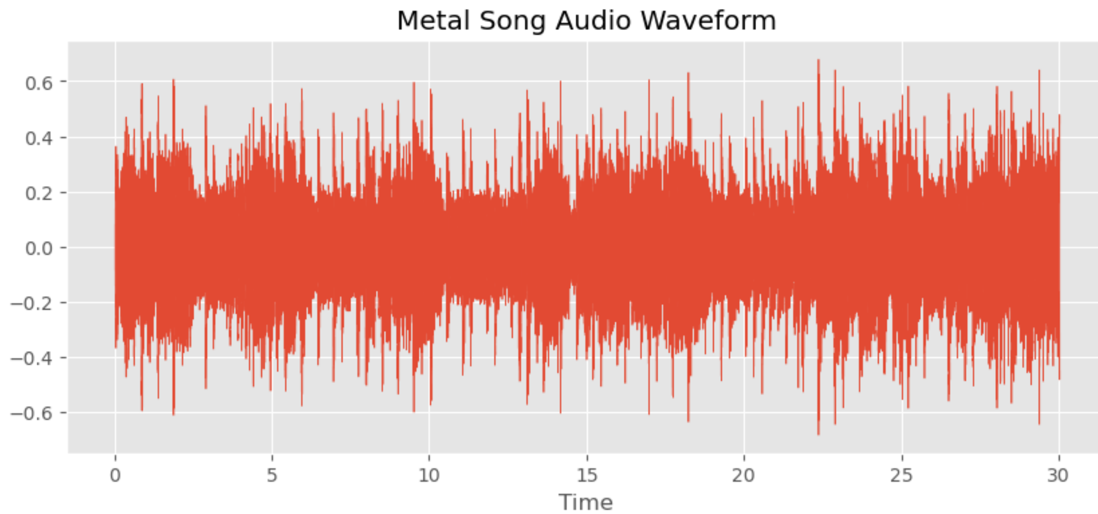


1.1.5 Metal Song

[ ]:
```
seriesMetal, audioPath = SampleRandomSong(df_30sec,"metal")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Metal Song Audio Waveform')
plt.show()
```

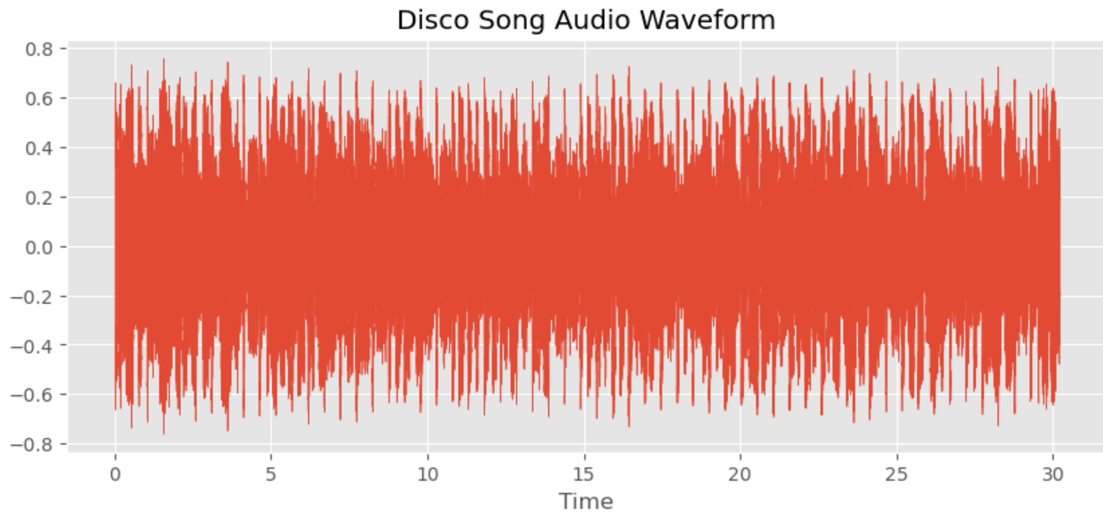


1.1.6 Disco Song

[ ]:
```
df_disco, audioPath = SampleRandomSong(df_30sec,"disco")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Disco Song Audio Waveform')
plt.show()
```

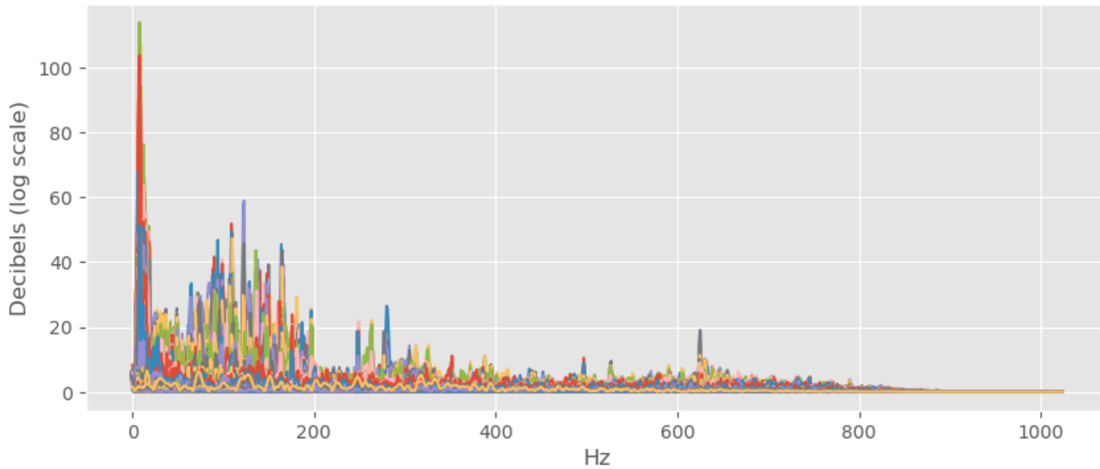


Fourier Transform of Disco Song

```
[ ]: # Default FFT window size
n_fft = 2048 # FFT window size
hop_length = 512 # number audio of frames between STFT columns (looks like a␣
↪good default)

# Short-time Fourier transform (STFT)
D = np.abs(lib.stft(x, n_fft = n_fft, hop_length = hop_length))

print('Shape of D object:', np.shape(D))
```

```
Shape of D object: (1025, 1293)
```

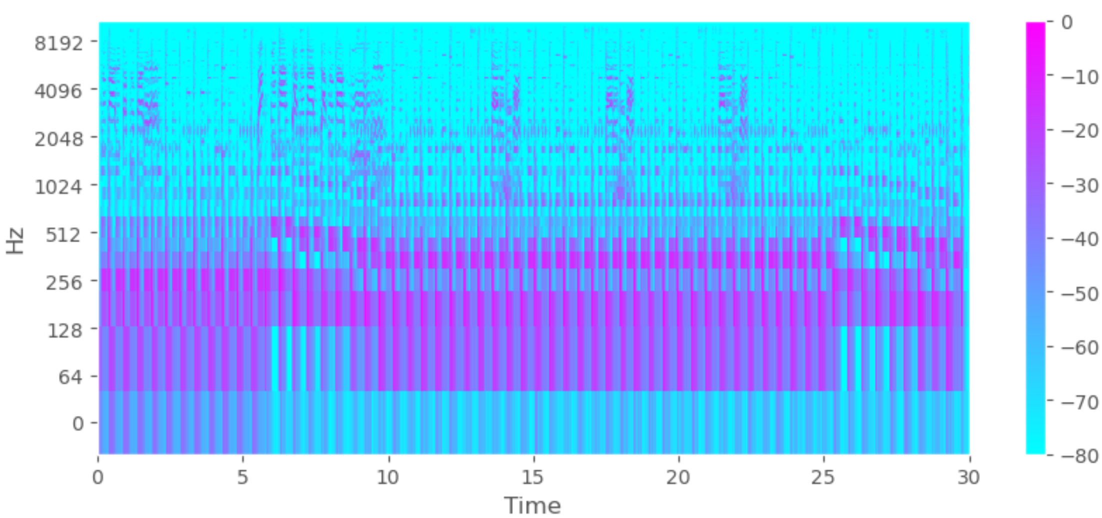
```
[ ]: plt.figure(figsize = (10, 4))
plt.plot(D);
plt.xlabel('Hz')
plt.ylabel('Decibels (log scale)')
plt.show()
```



Mel-Spectrogram of Disco Song

```
[ ]: X_Mel = lib.feature.melspectrogram(x,sr=sr)
X_Mel_dB = lib.amplitude_to_db(X_Mel, ref=np.max)
plt.figure(figsize = (10, 4))
libdis.specshow(X_Mel_dB, sr=sr, hop_length=hop_length, x_axis = 'time', y_axis␣
 ↪= 'log',cmap = 'cool')
plt.colorbar()
plt.show()
```

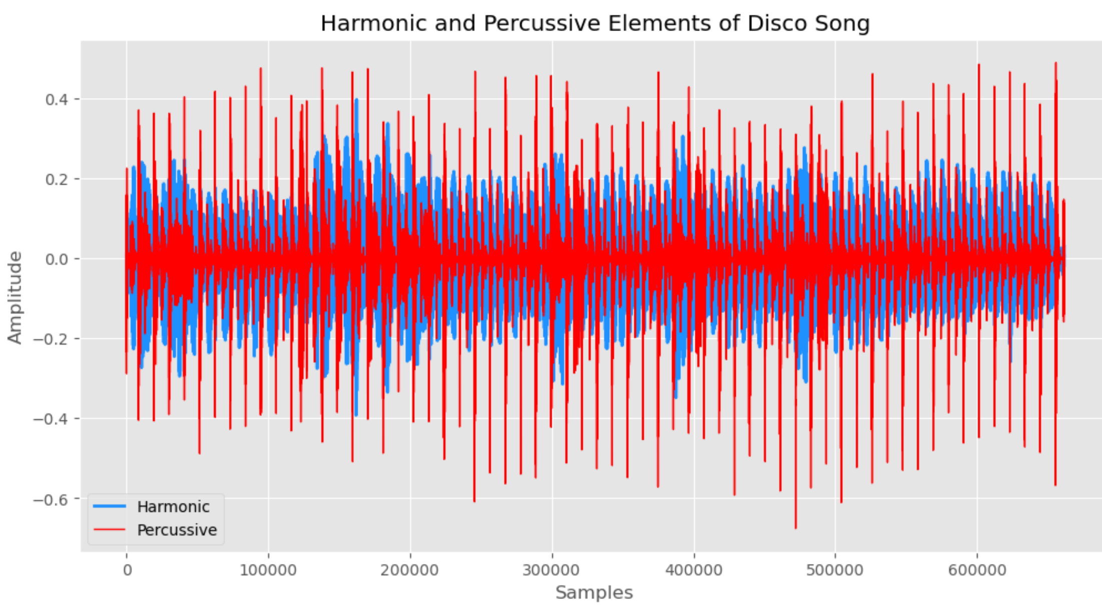
```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_25904\1899063832.py:1:
FutureWarning: Pass y=[ 0.03314209  0.00604248  0.03399658 …  0.04415894
-0.00759888
 -0.03445435] as keyword args. From version 0.10 passing these as positional
arguments will result in an error
  X_Mel = lib.feature.melspectrogram(x,sr=sr);
```



Harmonics and Perceptrual of Disco Song

- Harmonics represent the sound color of music
- Perceptrual represents the sound rhythm and emotion

[ ]:
```
x_harm, x_perc = lib.effects.hpss(x)
plt.figure(figsize = (12, 6))
plt.plot(x_harm, color = 'dodgerblue', linewidth = 2, label = 'Harmonic')
plt.plot(x_perc, color = 'red', linewidth = 1, label = 'Percussive')
plt.xlabel('Samples')
plt.ylabel('Amplitude')
plt.title('Harmonic and Percussive Elements of Disco Song')
plt.legend()
plt.show()
```



Tempo of Disco Song

[ ]:
```
tempo, _ = lib.beat.beat_track(x, sr=sr)
print('The Tempo for the Disco Song: {val} bpm'.format(val = tempo))
```

```
C:\Users\tmcke\AppData\Local\Temp\ipykernel_16744\4117489929.py:1:
FutureWarning: Pass y=[-0.18777466 -0.23693848 -0.15542603 …  0.03741455
0.10574341
  0.09619141] as keyword args. From version 0.10 passing these as positional
arguments will result in an error
  tempo, _ = lib.beat.beat_track(x, sr=sr)
```

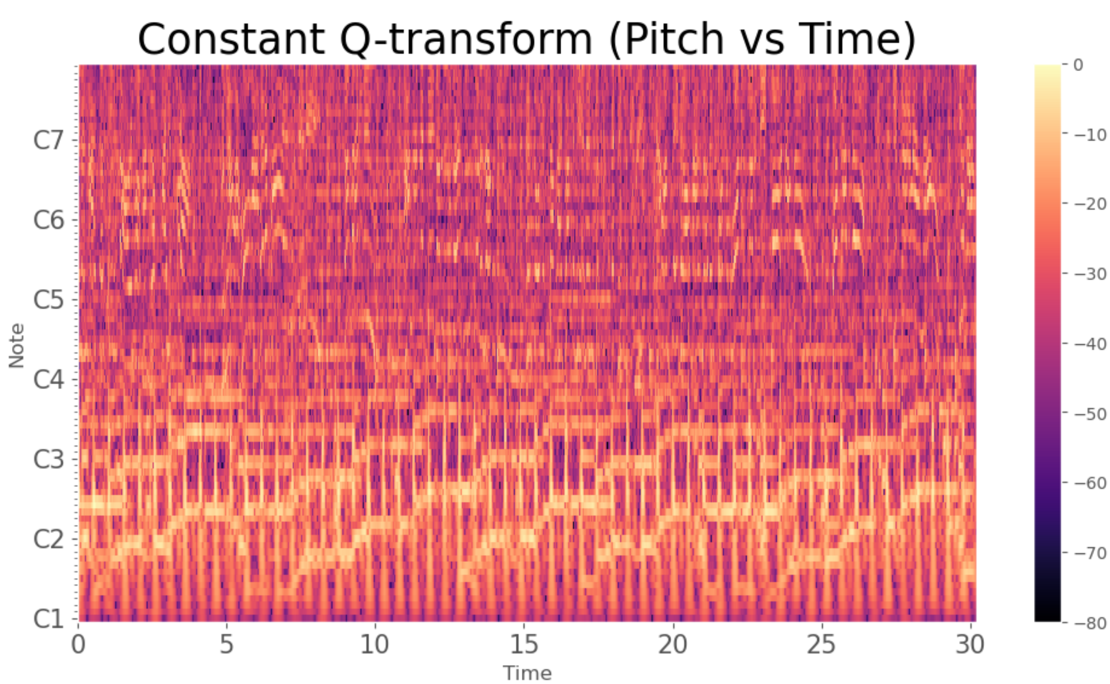
```
The Tempo for the Disco Song: 117.45383522727273 bpm
```

Constant Q-Transform (CQT) of Disco Song

- CQT meaures the energy in each pitch

```
[ ]: C = lib.cqt(x, sr=sr)
plt.figure(figsize = (12, 6))

# getting the original colormap using cm.get_cmap() function
orig_map=plt.cm.get_cmap('viridis')

# reversing the original colormap using reversed() function
rmap = orig_map.reversed()

libdis.specshow(lib.amplitude_to_db(C, ref=np.max),sr=sr, x_axis = 'time',␣
 ↪y_axis = 'cqt_note', cmap ='magma')
plt.colorbar()
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.title('Constant Q-transform (Pitch vs Time)', fontsize = 25)
plt.show()
```

```
c:\Users\tmcke\anaconda3\lib\site-packages\librosa\util\decorators.py:88:
UserWarning: amplitude_to_db was called on complex input so phase information
will be discarded. To suppress this warning, call amplitude_to_db(np.abs(S))
instead.
  return f(*args, **kwargs)
```

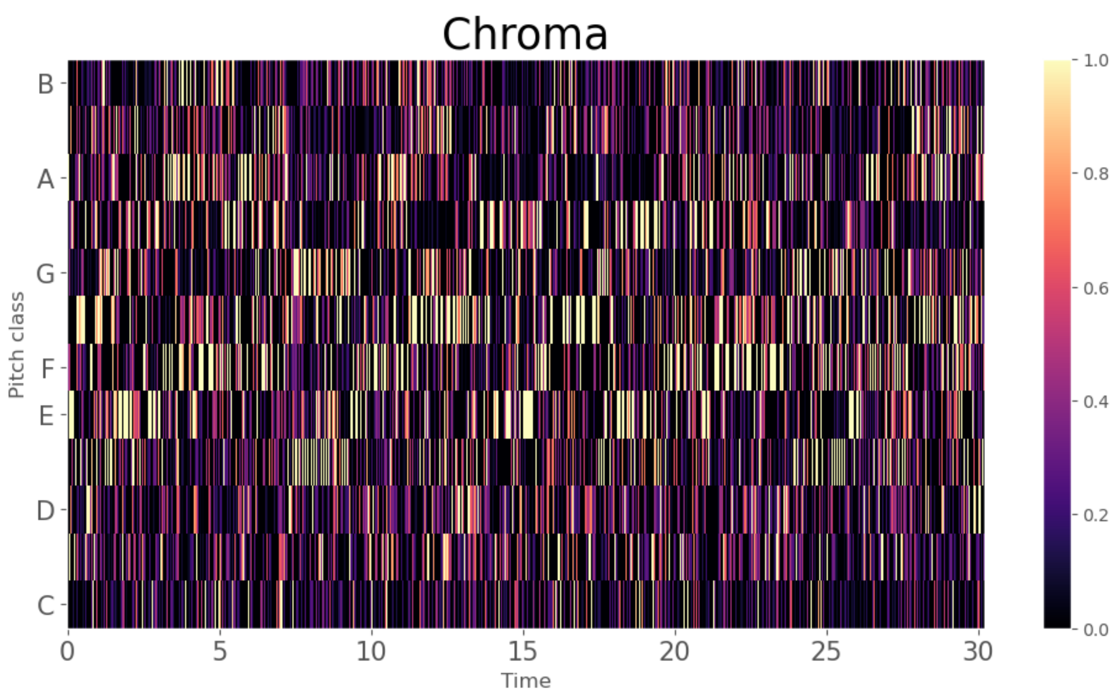


Pitch vs Pitch Class using CQT and Chroma

- CQT measures the energy in each pitch
- Chroma measures the energy in each pitch class

[ ]:
```
chroma = lib.feature.chroma_cqt(C=C, sr=sr)
plt.figure(figsize = (12, 6))

# getting the original colormap using cm.get_cmap() function
orig_map=plt.cm.get_cmap('magma')

# reversing the original colormap using reversed() function
reversed_map = orig_map.reversed()

libdis.specshow(chroma, x_axis = 'time', y_axis = 'chroma', cmap = 'magma')
plt.colorbar()
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.title('Chroma', fontsize = 25)
plt.show()
```

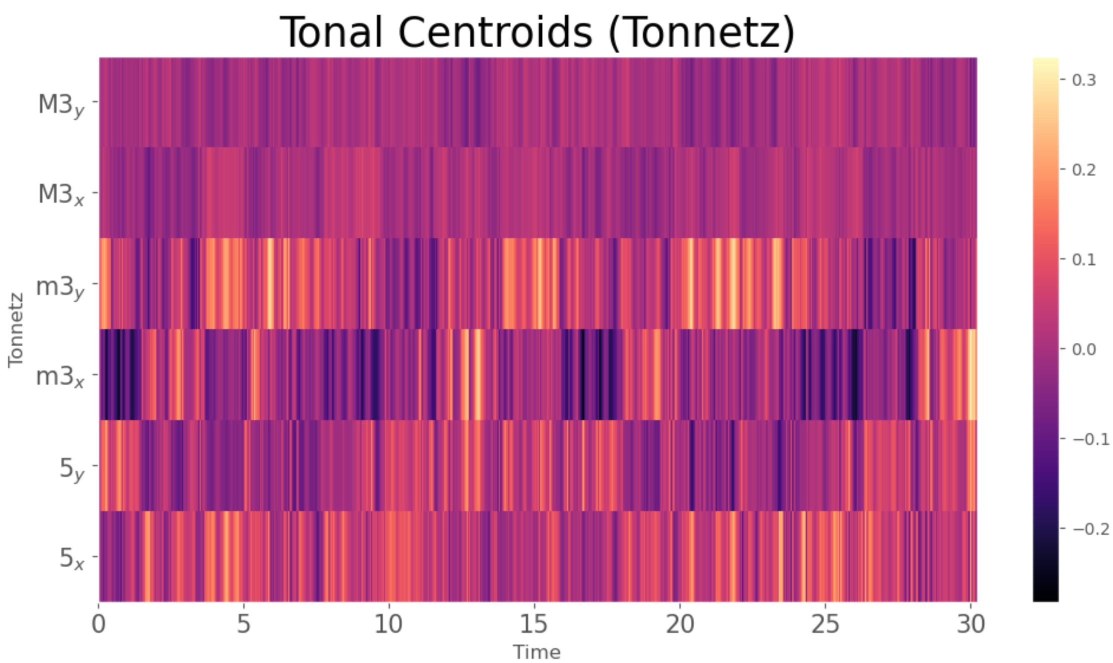
```
c:\Users\tmcke\anaconda3\lib\site-packages\librosa\util\decorators.py:88:
UserWarning: Trying to display complex-valued input. Showing magnitude instead.
  return f(*args, **kwargs)
```



Tonnetz of Disco Song

- representation of projected chroma features onto a 6-dimensional basis representing the perfect fifth, minor third, and major third each as two-dimensional coordinates

[ ]:
```
tonnetz = lib.feature.tonnetz(y=x,sr=sr)
plt.figure(figsize = (12, 6))
lib.display.specshow(tonnetz,y_axis='tonnetz', x_axis='time', cmap = 'magma')
plt.colorbar()
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.title('Tonal Centroids (Tonnetz)', fontsize = 25)
plt.show()
```



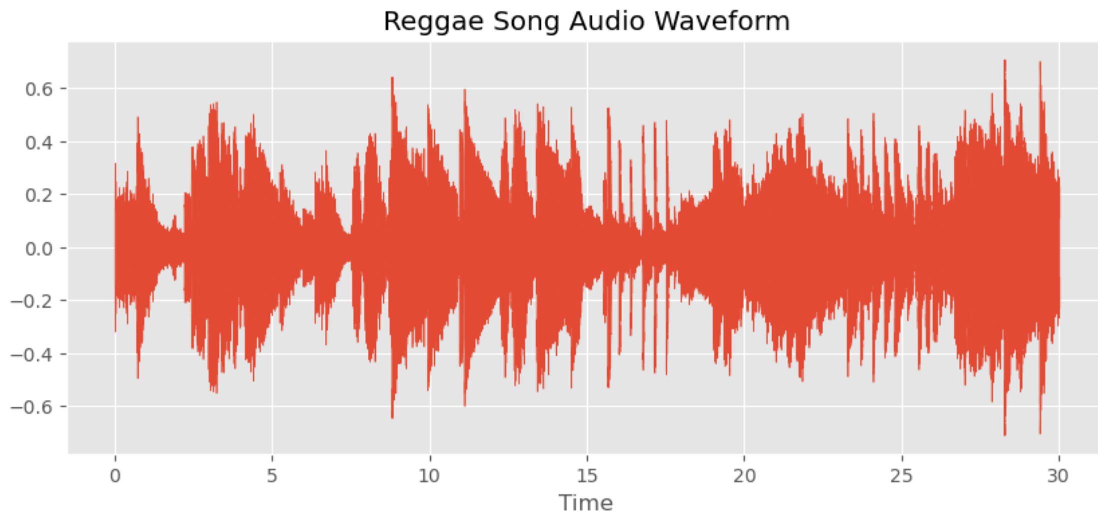
1.1.7 Reggae Song

[ ]:
```
df_reggae, audioPath = SampleRandomSong(df_30sec,"reggae")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
```

```
plt.title('Reggae Song Audio Waveform')
plt.show()
```



1.1.8 Blues Song

```
[ ]: df_blues, audioPath = SampleRandomSong(df_30sec,"blues")
     x,sr = lib.load(audioPath)
     ipy.Audio(audioPath)
```

```
[ ]: <IPython.lib.display.Audio object>
```

```
[ ]: plt.figure(figsize=(10,4))
     libdis.waveshow(x,sr=sr)
     plt.title('Blues Song Audio Waveform')
     plt.show()
```

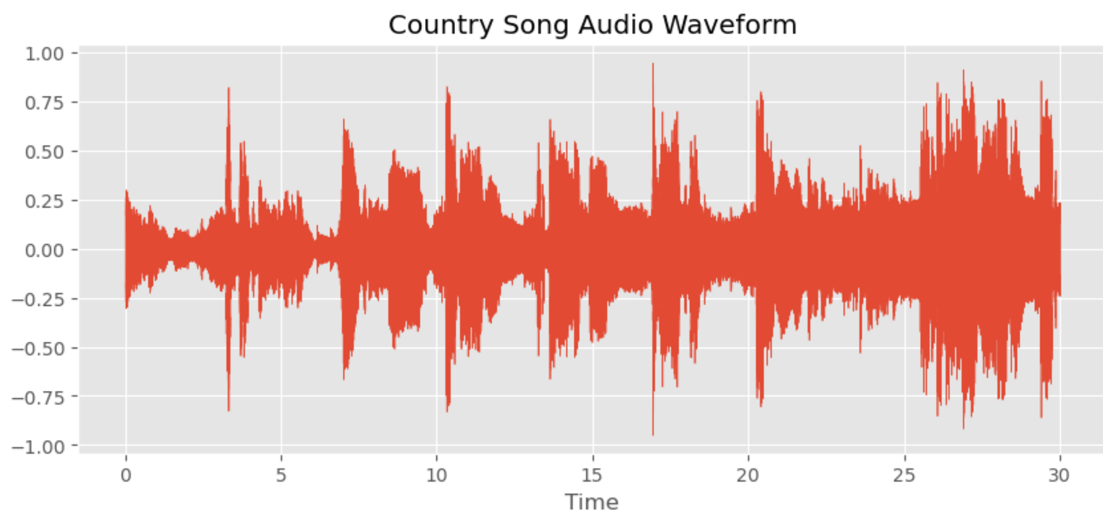
```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In [1], line 1
----> 1 plt.figure(figsize=(10,4))
      2 libdis.waveshow(x,sr=sr)
      3 plt.title('Blues Song Audio Waveform')

NameError: name 'plt' is not defined
```

1.1.9 Country Song

[ ]:
```
df_country, audioPath = SampleRandomSong(df_30sec,"country")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Country Song Audio Waveform')
plt.show()
```

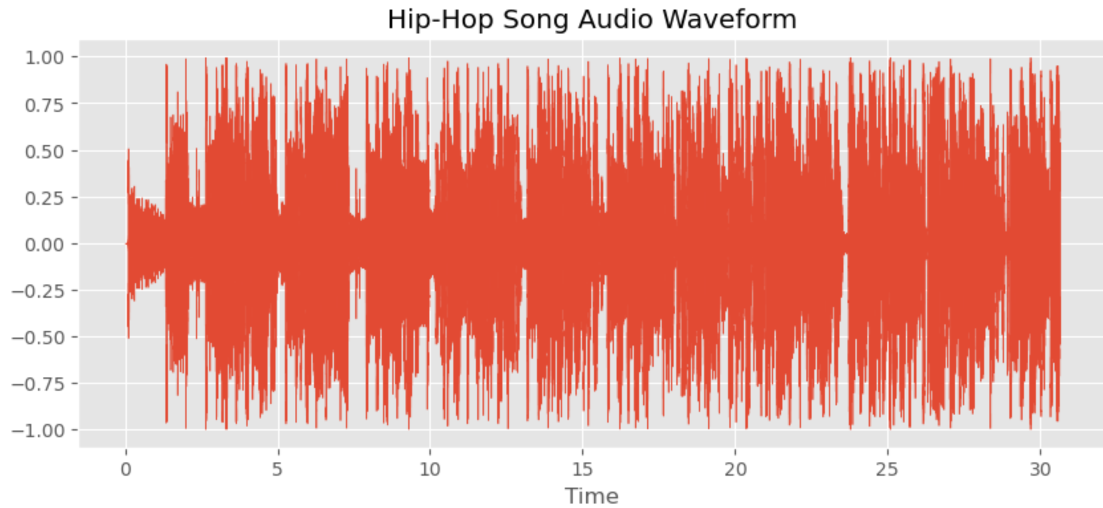


1.1.10 Hip-Hop Song

[ ]:
```
df_hiphop, audioPath = SampleRandomSong(df_30sec,"hiphop")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Hip-Hop Song Audio Waveform')
plt.show()
```

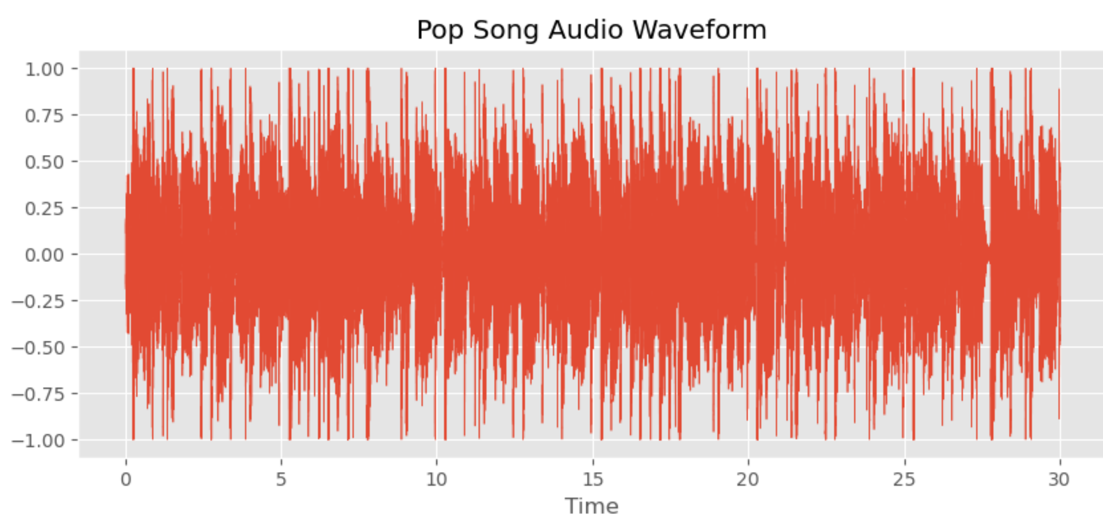


1.1.11 Pop Song

[ ]:
```
df_pop, audioPath = SampleRandomSong(df_30sec,"pop")
x,sr = lib.load(audioPath)
ipy.Audio(audioPath)
```

[ ]: <IPython.lib.display.Audio object>

[ ]:
```
plt.figure(figsize=(10,4))
libdis.waveshow(x,sr=sr)
plt.title('Pop Song Audio Waveform')
plt.show()
```



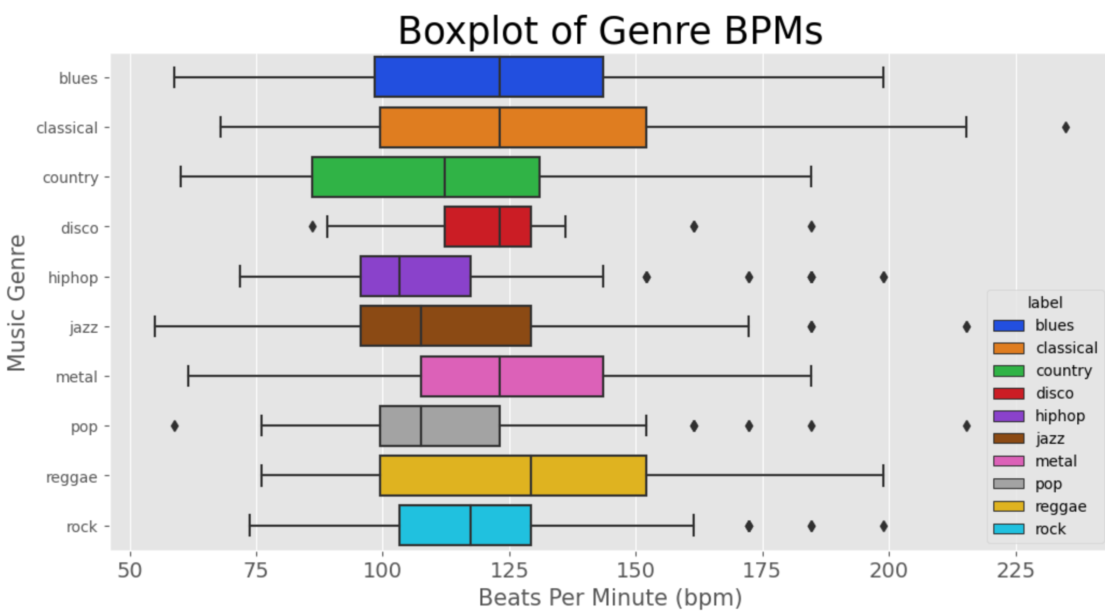
1.2 Exploratory Data Analysis

- Primarily going to use the 30 sec features of GTZAN Dataset
- Contains 10 genres with 100 songs each and 60 features

[ ]:
```
df = pd.read_csv('features_30_sec.csv')
df
```

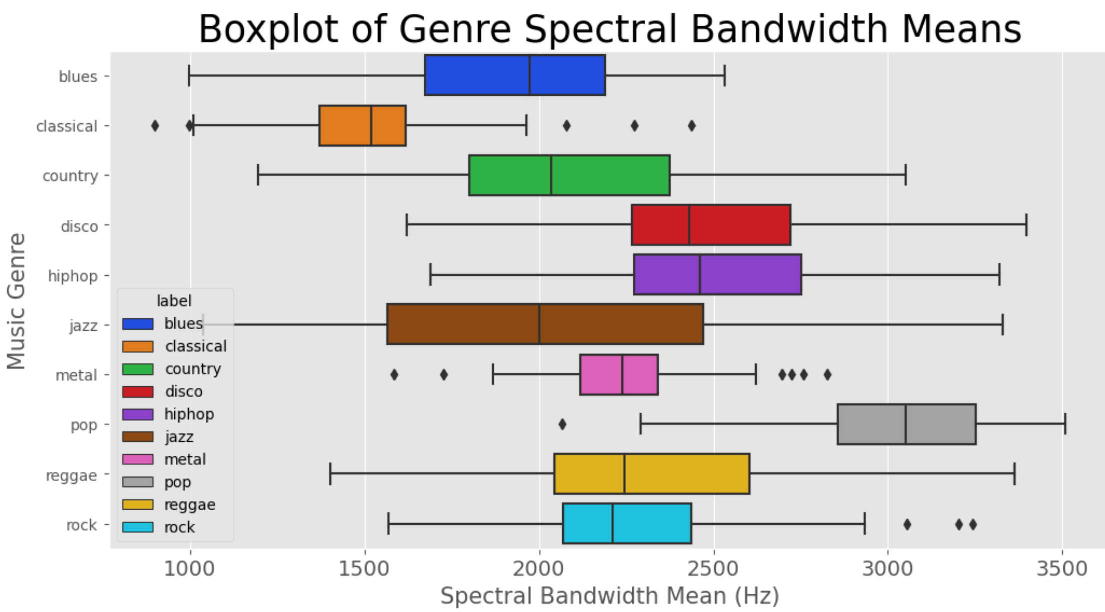
1.2.1 Boxplot of Genre Distributions

[ ]:
```
# Extract Tempo and Genre Labels and show distribution of Genre Tempos
tempoData = df[['label','tempo']]

fig, ax = plt.subplots(figsize = (12, 6))
sns.boxplot(x = "tempo", y = "label", data = tempoData, palette = 'bright',hue␣
 ↪= 'label',dodge = False);

plt.title('Boxplot of Genre BPMs', fontsize = 25)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10)
plt.xlabel('Beats Per Minute (bpm)', fontsize = 15)
plt.ylabel('Music Genre', fontsize = 15)
plt.show()
```



[ ]:
```
# Extract Tempo and Genre Labels and show distribution of Genre Tempos
BandwidthData = df[['label','spectral_bandwidth_mean']]
```

```
fig, ax = plt.subplots(figsize = (12, 6))
sns.boxplot(x = "spectral_bandwidth_mean", y = "label", data = BandwidthData,␣
↪palette = 'bright',hue = 'label',dodge = False);

plt.title('Boxplot of Genre Spectral Bandwidth Means', fontsize = 25)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10)
plt.xlabel('Spectral Bandwidth Mean (Hz)', fontsize = 15)
plt.ylabel('Music Genre', fontsize = 15)
plt.show()
```



1.2.2 Principal Component Analysis & K-Means Clustering

1.2.3 Principal Component Analysis

1. Normalization
2. Extract Principal Components
3. Visualization

[ ]:
```
# Read CSV file of 10 genres of Music
#df = pd.read_csv('features_3_sec.csv')
df = pd.read_csv('features_30_sec.csv')
# Use PCA to reduce dimensionality
X = df.drop(['filename','length','label'], axis=1)
y = df['label']

# Normalize
```

```
cols = X.columns
scaler = preprocessing.MinMaxScaler()
np_scaled = scaler.fit_transform(X)
X = pd.DataFrame(np_scaled, columns = cols)

# PCA - 2 Components
pca = PCA(n_components=2)
components = pca.fit_transform(X)
temp_df = pd.DataFrame(data = components, columns = ['Principal Component 1',␣
↪'Principal Component 2'])
print(pca.explained_variance_ratio_)

# Concatenate with target label
OG_PCA_df = pd.concat([temp_df, y], axis=1)
#pca.explained_variance_ratio_
OG_PCA_df
```

```
[0.24644968 0.22028192]
```

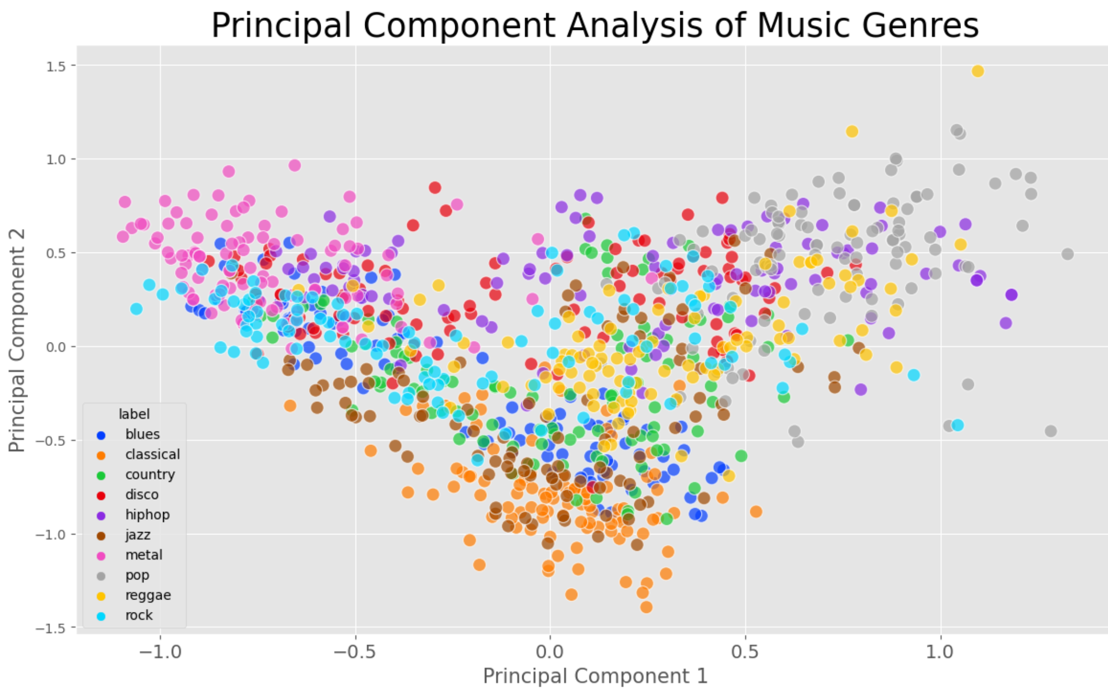
[ ]:

```
     Principal Component 1  Principal Component 2  label
0                -0.394212              -0.116145  blues
1                 0.052019              -0.270757  blues
2                -0.479184              -0.224616  blues
3                 0.017145              -0.439886  blues
4                -0.160395              -0.508617  blues
..                     …                     …    …
995              -0.754452              -0.039476   rock
996              -0.810739              -0.031233   rock
997              -0.845324              -0.007202   rock
998              -0.234262              -0.372666   rock
999              -0.399060              -0.276561   rock

[1000 rows x 3 columns]
```

[ ]:

```
# Visualize the Principal Components of GTZAN Dataset
plt.figure(figsize = (14, 8))
sns.scatterplot(x = "Principal Component 1",
                y = "Principal Component 2",
                data = OG_PCA_df,
                hue = "label",
                palette = 'bright',
                alpha = 0.7,
                s = 100);
plt.title('Principal Component Analysis of Music Genres', fontsize = 25)
plt.xticks(fontsize = 14)
plt.yticks(fontsize = 10)
plt.xlabel('Principal Component 1', fontsize = 15)
plt.ylabel('Principal Component 2', fontsize = 15)
```

```
plt.grid(True)
plt.show()
```



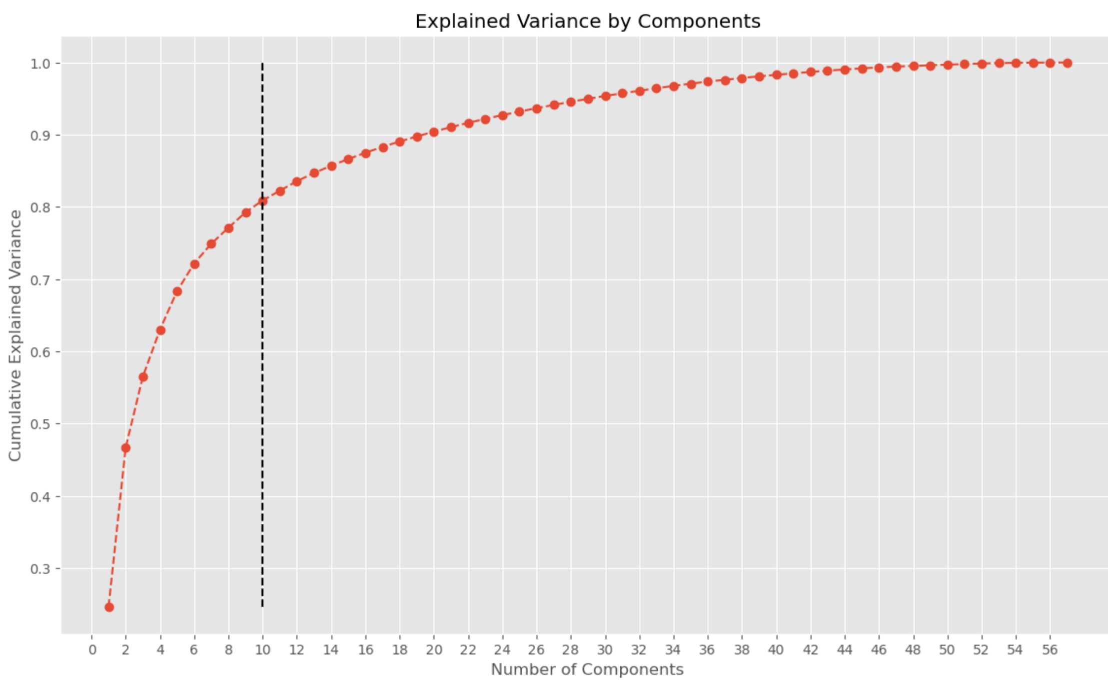
1.2.4 K-Means Clustering

[ ]:
```
# Read CSV file of 10 genres of Music
#df = pd.read_csv('features_3_sec.csv')
df = pd.read_csv('features_30_sec.csv')
# Use PCA to reduce dimensionality
X = df.drop(['filename','length','label'], axis=1)
y = df['label']

# Normalize
cols = X.columns
scaler = preprocessing.MinMaxScaler()
X = scaler.fit_transform(X)

# PCA - 2 Components
pca = PCA()
pca.fit(X)
print(pca.explained_variance_ratio_)
```

[ ]:
```
# Decide how many features to keep based on Cumulative Variance plot
a = range(1,len(pca.explained_variance_ratio_)+1)
```

```python
b = pca.explained_variance_ratio_.cumsum() >= 0.8
c = np.sum(b == False)
n_components = a[c]
print(f"The Number of Components estimated to preserve 80% of Variance =␣
↪{n_components}")
plt.figure(figsize=(14,8))
plt.plot(a, pca.explained_variance_ratio_.cumsum(), marker = 'o', linestyle =␣
↪'--')
plt.vlines(a[c], ymin=np.min(pca.explained_variance_ratio_.cumsum()), ymax=np.
↪max(pca.explained_variance_ratio_.cumsum()), color = 'k',␣
↪linestyles='dashed')
plt.xticks(range(0,len(pca.explained_variance_ratio_),2))
plt.title('Explained Variance by Components')
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.show()
```

```
The Number of Components estimated to preserve 80% of Variance = 10
```

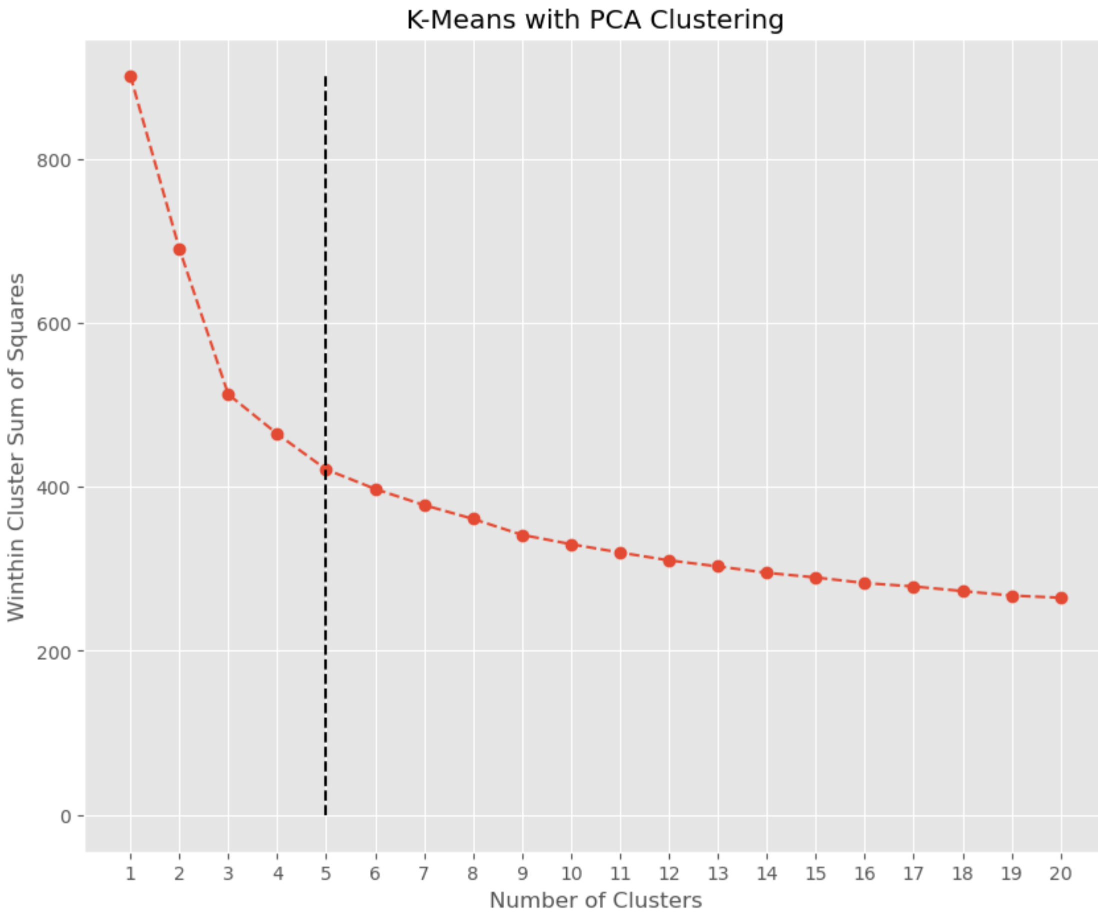


[ ]:
```python
# Reduce dimensionality using PCA from n = 57 to value calculated above that␣
↪preserves 80% of variance
pca = PCA(n_components=n_components)
pca.fit(X)
scores_pca = pca.transform(X)
```

[ ]:
```
from kneed import KneeLocator
# Determine how many clustering solutions to test
wcss = []
max_clusters = 21
for i in range(1,max_clusters):
    kmeans_pca = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans_pca.fit(scores_pca)
    wcss.append(kmeans_pca.inertia_)

# programmatically locate the elbow
n_clusters = KneeLocator([i for i in range(1, max_clusters)], wcss,␣
 ↪curve='convex', direction='decreasing').knee
print("Optimal number of clusters =", n_clusters)
```

```
Optimal number of clusters = 5
```

[ ]:
```
# Plot WCSS against the number of components on graph
plt.figure(figsize=(10,8))
plt.plot(range(1,21), wcss, marker = 'o', linestyle = '--')
plt.vlines(n_clusters, ymin=0, ymax=max(wcss), color = 'k', linestyles='dashed')
plt.title('K-Means with PCA Clustering')
plt.xlabel('Number of Clusters')
plt.xticks(range(1,max_clusters))
plt.ylabel('Winthin Cluster Sum of Squares')
plt.show()
```



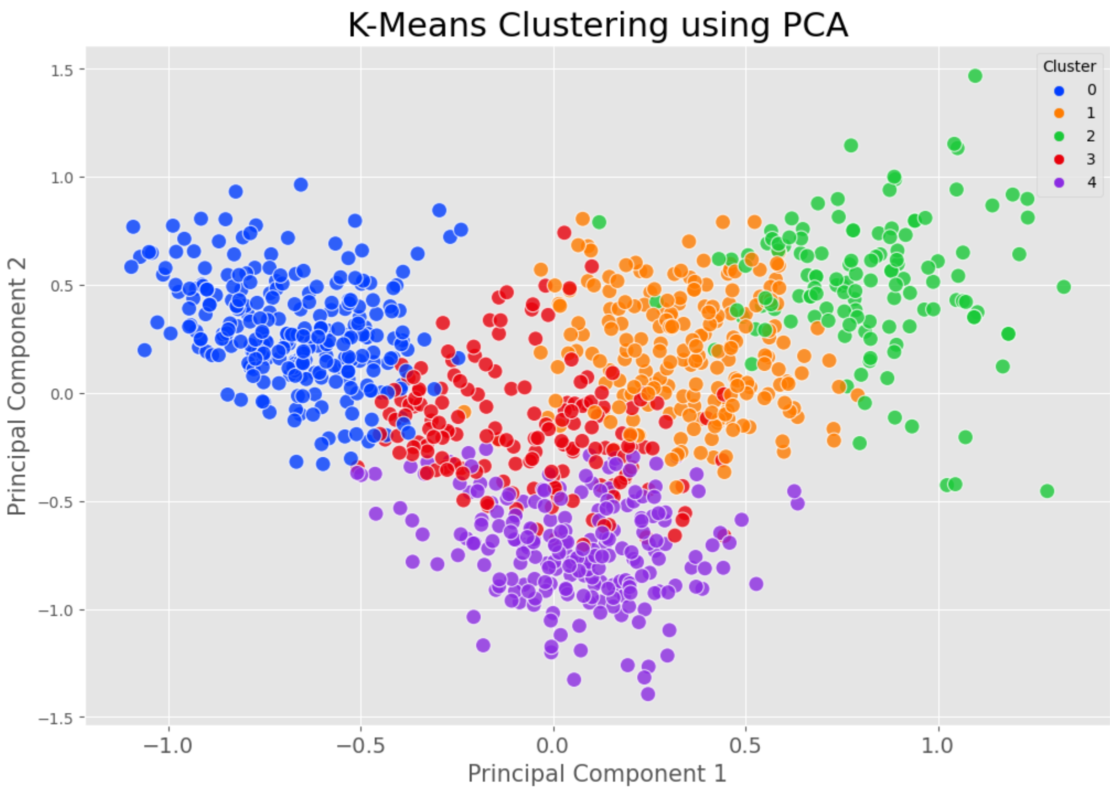
[ ]:
```
kmeans_pca = KMeans(n_clusters = n_clusters, init = 'k-means++', random_state =␣
  ↪42)
kmeans_pca.fit(scores_pca)
df['Cluster'] = kmeans_pca.labels_
df
```

[ ]:
```
genres = df['Cluster']
X = df.loc[:,df.columns != 'label']
# PCA - 2 Components
pca = PCA(n_components=2)
components = pca.fit_transform(scores_pca)
temp_df = pd.DataFrame(data = components, columns = ['Principal Component 1',␣
  ↪'Principal Component 2'])

# Concatenate with target label
PCA_df = pd.concat([temp_df, genres], axis=1)
#pca.explained_variance_ratio_
PCA_df
```

```
[ ]:      Principal Component 1  Principal Component 2  Cluster
     0                -0.394212              -0.116145        0
     1                 0.052019              -0.270757        3
     2                -0.479184              -0.224616        0
     3                 0.017145              -0.439886        4
     4                -0.160395              -0.508617        4
     ..                     …                     …       …
     995              -0.754452              -0.039476        0
     996              -0.810739              -0.031233        0
     997              -0.845324              -0.007202        0
     998              -0.234262              -0.372666        3
     999              -0.399060              -0.276561        3

     [1000 rows x 3 columns]
```

```
[ ]: # Visualize the Principal Components of GTZAN Dataset
     plt.figure(figsize = (12, 8))
     sns.scatterplot(x = "Principal Component 1",y = "Principal Component 2",data =␣
      ↪OG_PCA_df,hue = "label",palette = 'bright',alpha = 0.8,s = 100);
     plt.title('Principal Component Analysis of Music Genres', fontsize = 22)
     plt.xticks(fontsize = 14)
     plt.yticks(fontsize = 10)
     plt.xlabel('Principal Component 1', fontsize = 15)
     plt.ylabel('Principal Component 2', fontsize = 15)
     plt.grid(True)
     plt.show()
```

```
[ ]: # Visualize the Principal Components of GTZAN Dataset
     plt.figure(figsize = (12, 8))
     sns.scatterplot(x = "Principal Component 1",y = "Principal Component 2",data =␣
      ↪PCA_df,hue = "Cluster",palette = 'bright',alpha = 0.8,s = 100);
     plt.title('K-Means Clustering using PCA', fontsize = 22)
     plt.xticks(fontsize = 14)
     plt.yticks(fontsize = 10)
     plt.xlabel('Principal Component 1', fontsize = 15)
     plt.ylabel('Principal Component 2', fontsize = 15)
     plt.grid(True)
     plt.show()
```



1.3 Classification of Music Genres

1.3.1 Convert Genre Labels into Numerical Values from 0 - 9 for all 10 Genres

[ ]:
```
# Read CSV file of 10 genres of Music
#df = pd.read_csv('features_3_sec.csv')
df = pd.read_csv('features_30_sec.csv')
```

[ ]:
```
df['label'] = df['label'].replace('blues',0)
df['label'] = df['label'].replace('classical',1)
df['label'] = df['label'].replace('country',2)
df['label'] = df['label'].replace('disco',3)
df['label'] = df['label'].replace('hiphop',4)
df['label'] = df['label'].replace('jazz',5)
df['label'] = df['label'].replace('metal',6)
df['label'] = df['label'].replace('pop',7)
df['label'] = df['label'].replace('reggae',8)
df['label'] = df['label'].replace('rock',9)
```

1.3.2 Normalize Columns of Dataframe

[ ]:
```
# Remove irrelevant columns and parse target column from dataset
X = df.drop(['filename','length','label'], axis=1)
y = df['label']

# Normalize so everything is on the same scale.
cols = X.columns
scaler = preprocessing.MinMaxScaler()
np_scaled = scaler.fit_transform(X)

# new data frame with the new scaled data.
X = pd.DataFrame(np_scaled, columns = cols)
X
```

1.3.3 Split Dataframe into Training-Test Sets

[ ]:
```
# Specify Ratio of Training/Testing and Split into separate sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

# Specify number of K-Folds when performing Cross-Validation
k = 10

# Create an instance of StratifiedKFold which can be used to get indices of␣
 ↪different training and test folds
skfold = StratifiedKFold(n_splits=k)
kfold = KFold(n_splits=k, shuffle=True)
scores = []
```

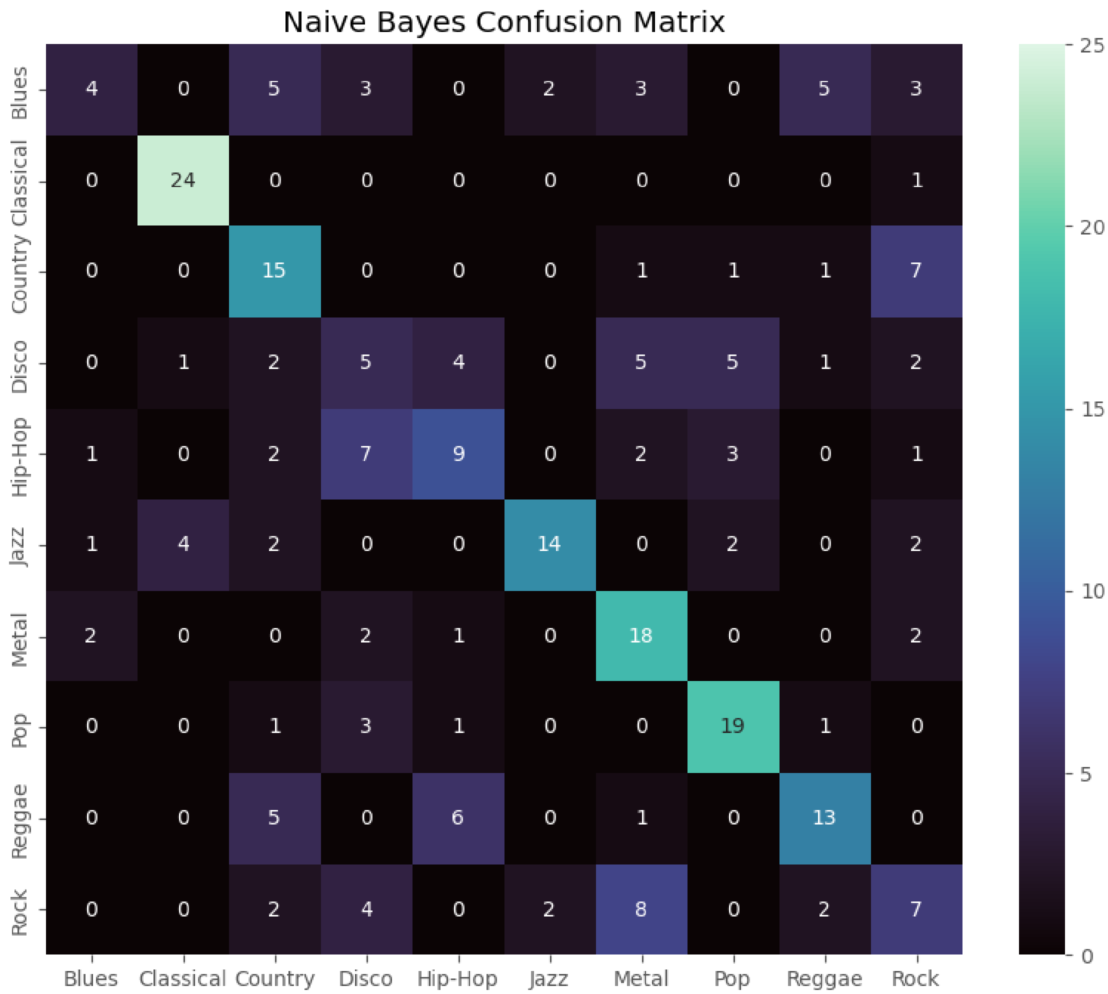
1.3.4 Perform K-Fold Cross Validation using Different Classifier Models

1.3.5 Naive Bayes Model

[ ]:
```
# Naive Bayes Model
nb = GaussianNB()

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), nb)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(nb,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(nb,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
nb.fit(X_train,y_train)
y_pred = nb.predict(X_test)

# Naive Bayes
model_assess(nb, X_train, y_train, X_test, y_test, "Naive Bayes")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('Naive Bayes Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.49333333 0.46666667 0.57333333 0.53333333
0.50666667 0.62666667
 0.64       0.49333333 0.50666667 0.49333333]
Cross Validation accuracy: 0.533 +/- 0.057
K-fold CV average score: 0.52 with K = 10
Stratified K-fold CV average score: 0.53
Accuracy Naive Bayes : 0.512
```

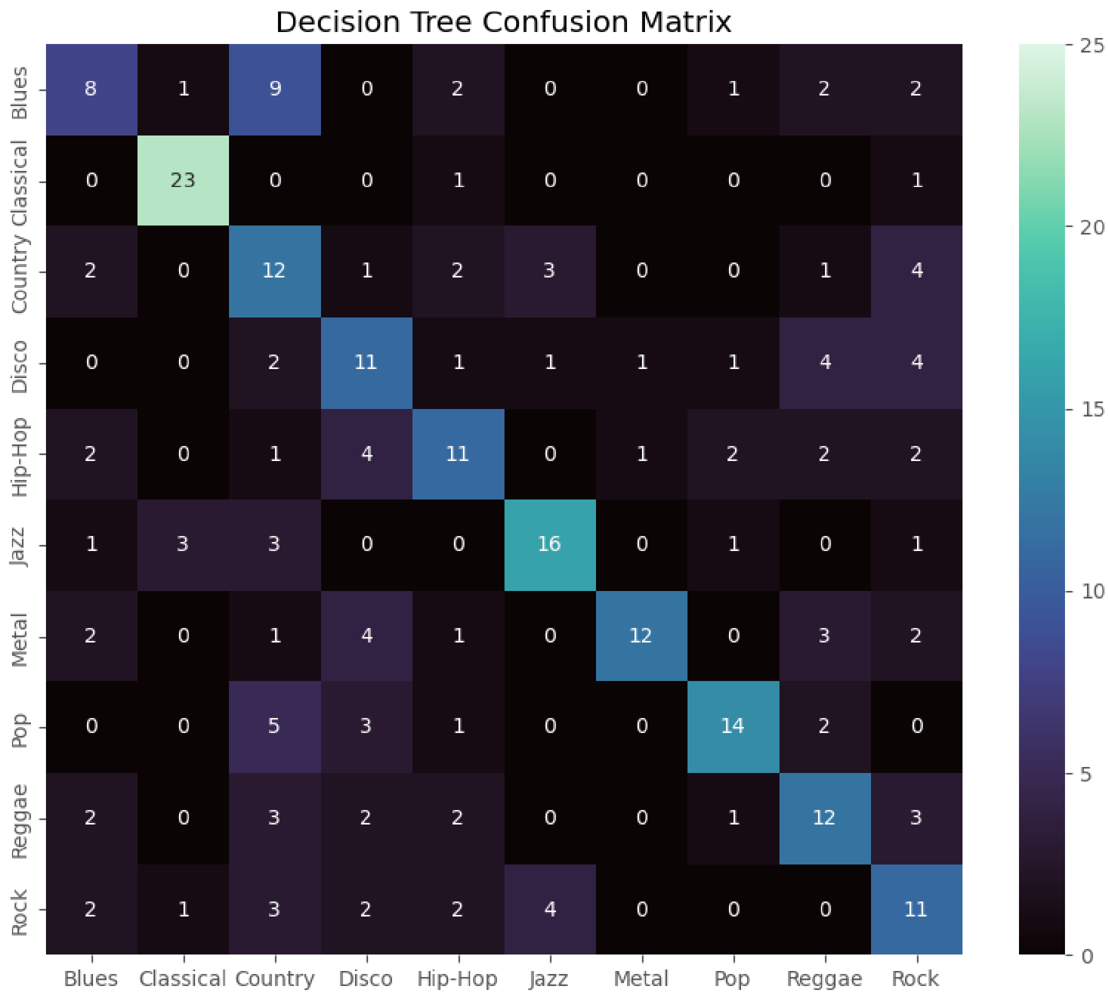


1.3.6 Decision Tree Model

```
[ ]: # Decision Tree Model
dt = DecisionTreeClassifier(criterion = 'entropy')

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), dt)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))
```

```
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(dt,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(dt,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
dt.fit(X_train,y_train)
y_pred = dt.predict(X_test)

# Decision Tree
model_assess(dt,X_train, y_train, X_test, y_test, "Decision Tree")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('Decision Tree Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.45333333 0.57333333 0.49333333 0.61333333
0.53333333 0.48
 0.53333333 0.57333333 0.42666667 0.57333333]
Cross Validation accuracy: 0.525 +/- 0.057
K-fold CV average score: 0.51 with K = 10
Stratified K-fold CV average score: 0.53
Accuracy Decision Tree : 0.516
```

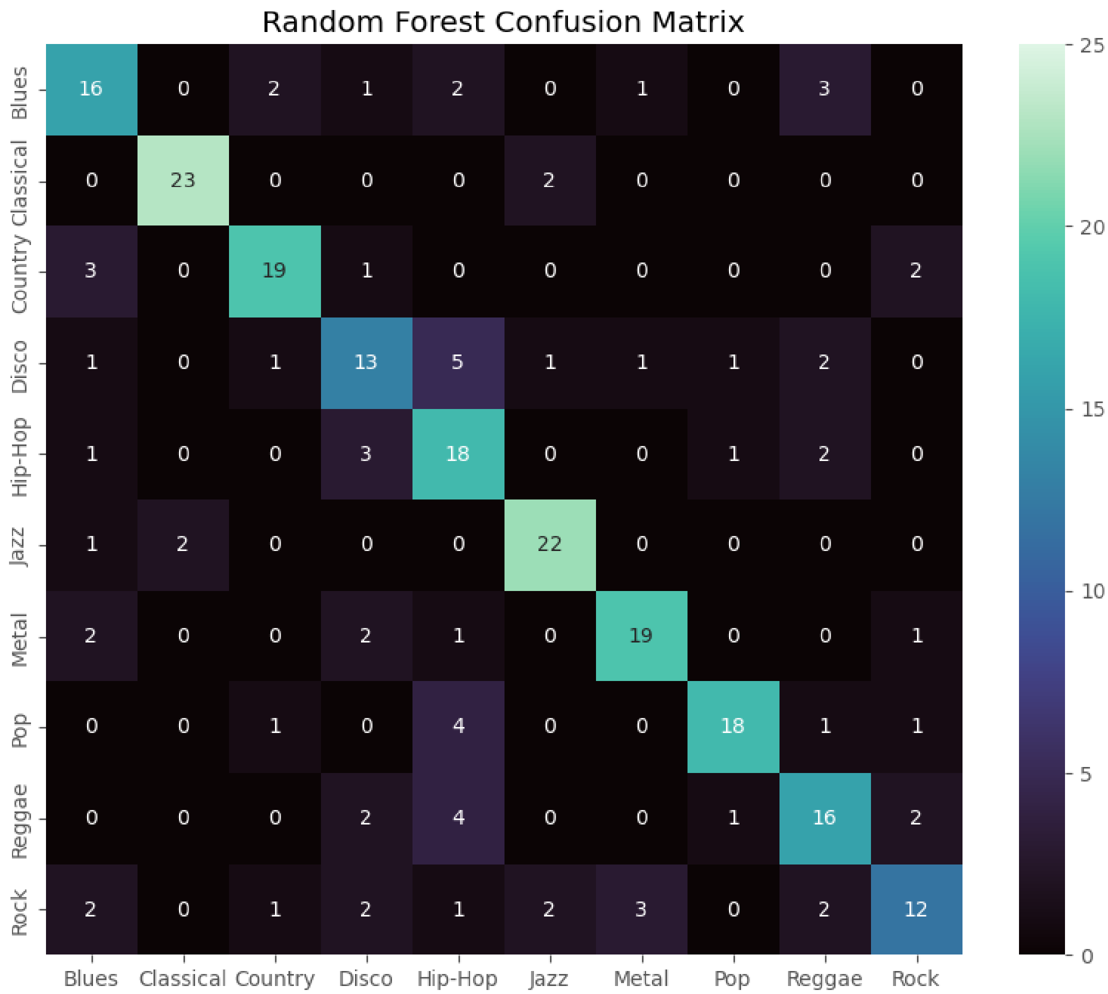


1.3.7 Random Forest Model

[ ]:
```python
# Decision Tree Model
rf = RandomForestClassifier(criterion = 'entropy')

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), rf)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
    ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(rf,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(rf,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
rf.fit(X_train,y_train)
y_pred = rf.predict(X_test)

# Random Forest
model_assess(rf, X_train, y_train, X_test, y_test, "Random Forest")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('Random Forest Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.66666667 0.68       0.74666667 0.70666667
0.66666667 0.68
 0.74666667 0.61333333 0.69333333 0.69333333]
Cross Validation accuracy: 0.689 +/- 0.037
K-fold CV average score: 0.68 with K = 10
Stratified K-fold CV average score: 0.69
Accuracy Random Forest : 0.708
```

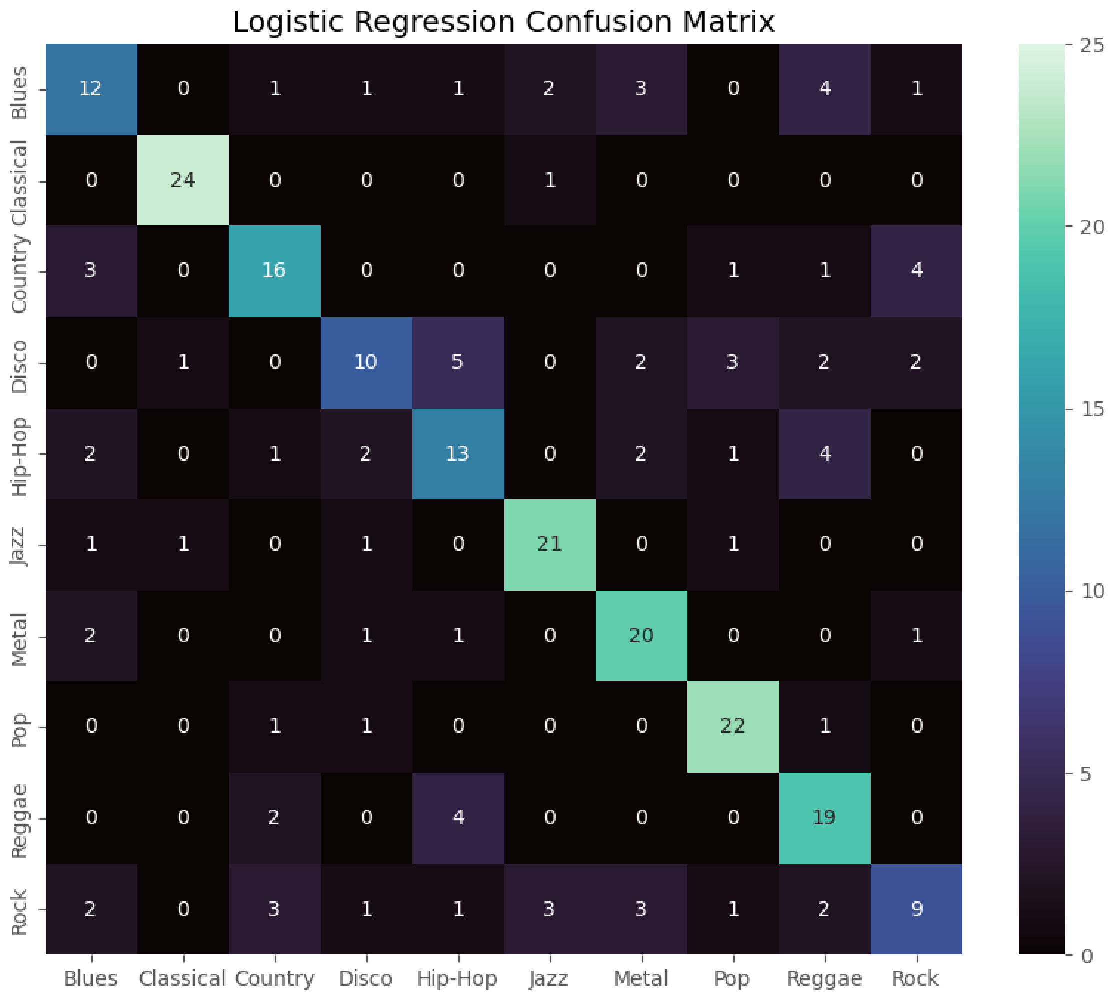


1.3.8 Logistic Regression Model

[ ]:
```
# Logistic Regression Model
lrg = LogisticRegression(random_state=42, multi_class='auto',max_iter=500)

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), lrg)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
    ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(lrg,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(lrg,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
lrg.fit(X_train,y_train)
y_pred = lrg.predict(X_test)

# Logistic Regression
model_assess(lrg, X_train, y_train, X_test, y_test, "Logistic Regression")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('Logistic Regression Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.6        0.6        0.64       0.77333333
0.70666667 0.73333333
 0.68       0.62666667 0.66666667 0.61333333]
Cross Validation accuracy: 0.664 +/- 0.056
K-fold CV average score: 0.64 with K = 10
Stratified K-fold CV average score: 0.65
Accuracy Logistic Regression : 0.664
```

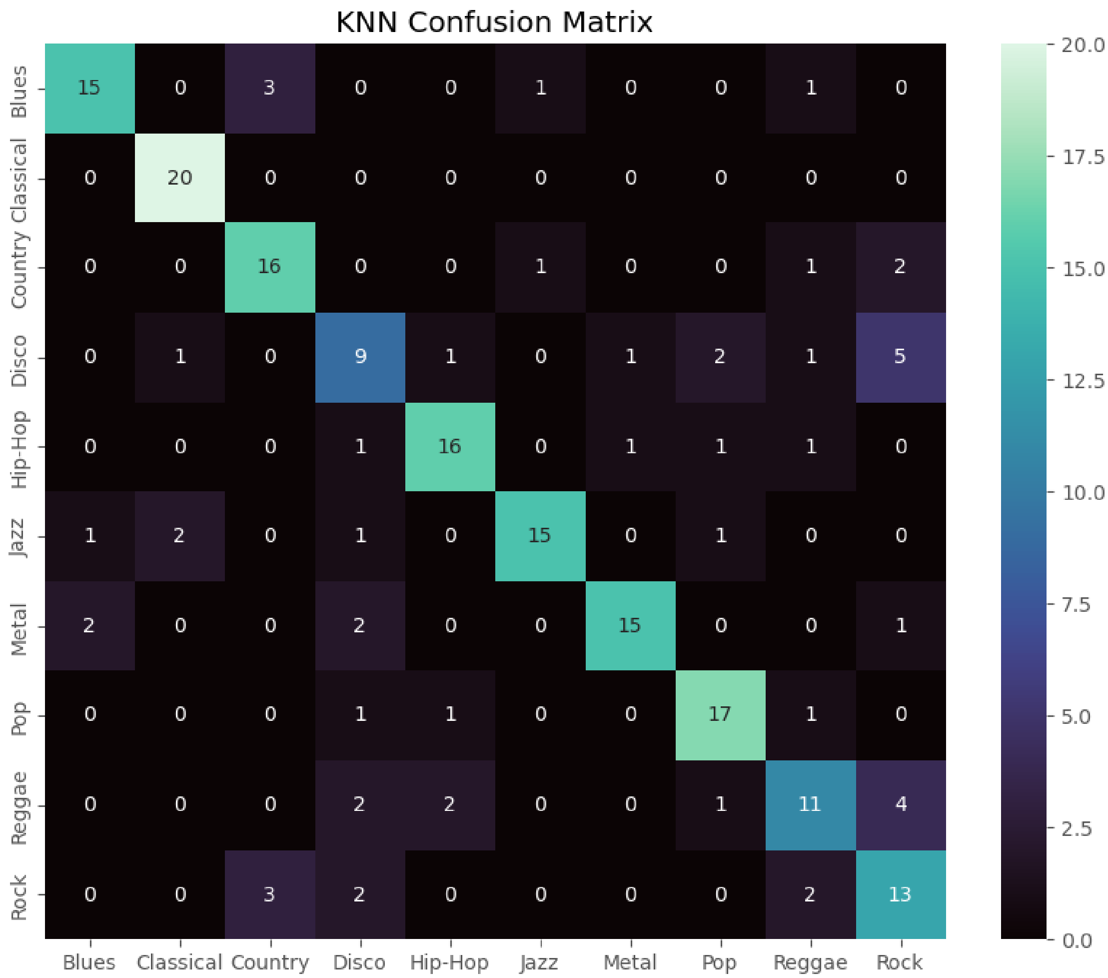


1.3.9 K-Nearest Neighbors Model

[ ]:
```python
# K-Nearest Neighbor Model
knn = KNeighborsClassifier(weights = 'distance')

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), knn)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(knn,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(knn,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)

# KNN
model_assess(knn, X_train, y_train, X_test, y_test, "KNN")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('KNN Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.675  0.75   0.7    0.6625 0.725  0.775  0.6
0.65   0.6375 0.7   ]
Cross Validation accuracy: 0.688 +/- 0.051
K-fold CV average score: 0.70 with K = 10
Stratified K-fold CV average score: 0.70
Accuracy KNN : 0.735
```

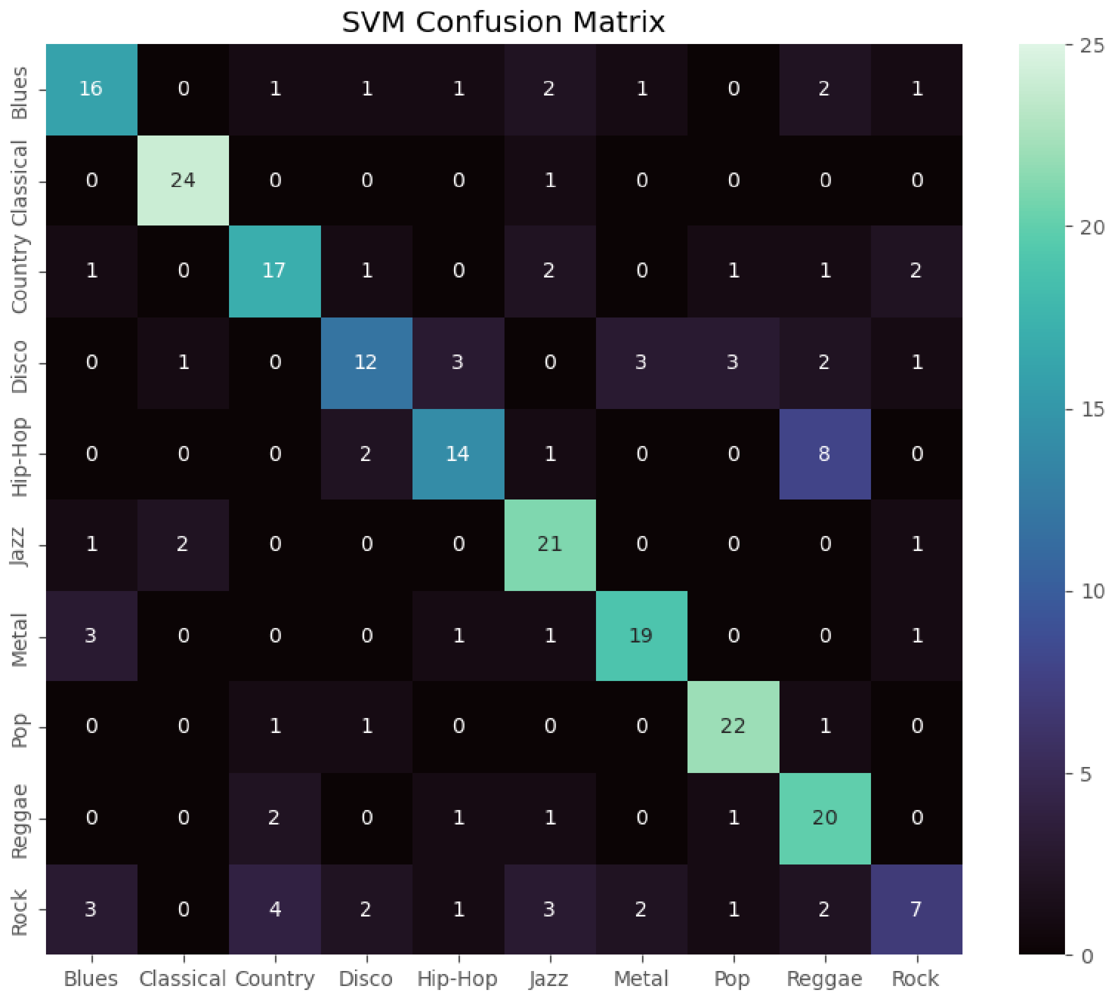


1.3.10 Support Vector Machine Model

[ ]:
```python
# Support Vector Machine Model
#svm = SVC(kernel = 'poly', decision_function_shape="ovr")
svm = LinearSVC(random_state = 42)

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), svm)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(svm,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(svm,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
svm.fit(X_train,y_train)
y_pred = svm.predict(X_test)

# Support Vector Machine
model_assess(svm, X_train, y_train, X_test, y_test, "Support Vector Machine")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('SVM Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.66666667 0.66666667 0.66666667 0.84
0.72       0.69333333
 0.73333333 0.68       0.69333333 0.68      ]
Cross Validation accuracy: 0.704 +/- 0.050
K-fold CV average score: 0.70 with K = 10
Stratified K-fold CV average score: 0.70
Accuracy Support Vector Machine : 0.688
```

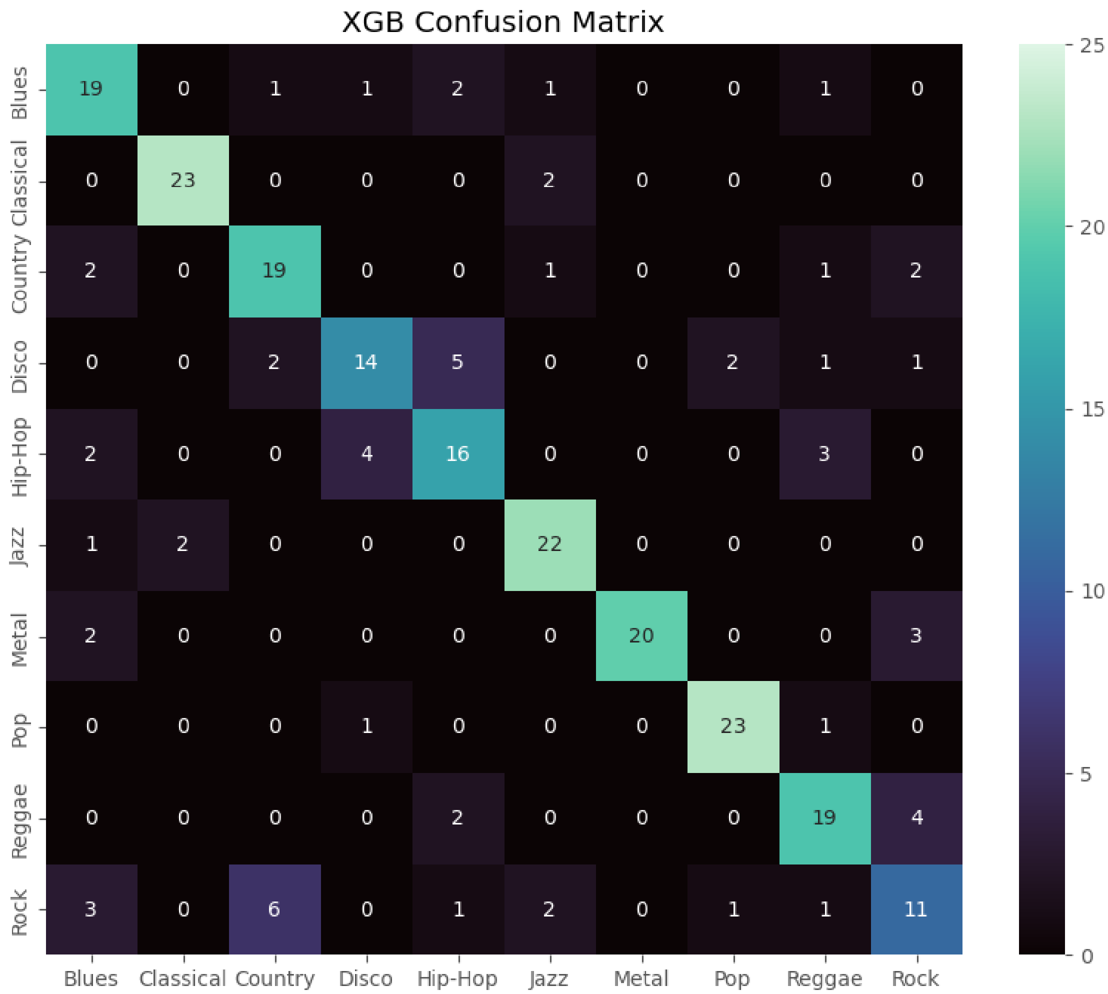


1.3.11 Cross Gradient Boost Model

[ ]:
```
# Cross Gradient Booster
xgb = XGBClassifier()

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), xgb)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))
```

```python
# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(xgb,X_train,y_train,cv=kfold)
skf_cv_scores = cross_val_score(xgb,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
xgb.fit(X_train,y_train)
y_pred = xgb.predict(X_test)

# Cross Gradient Booster
model_assess(xgb, X_train, y_train, X_test, y_test, "Cross Gradient Booster")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True, cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('XGB Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.66666667 0.69333333 0.69333333 0.74666667
0.66666667 0.77333333
 0.73333333 0.74666667 0.68       0.74666667]
Cross Validation accuracy: 0.715 +/- 0.037
K-fold CV average score: 0.71 with K = 10
Stratified K-fold CV average score: 0.71
Accuracy Cross Gradient Booster : 0.744
```



1.4 Optimization Methods

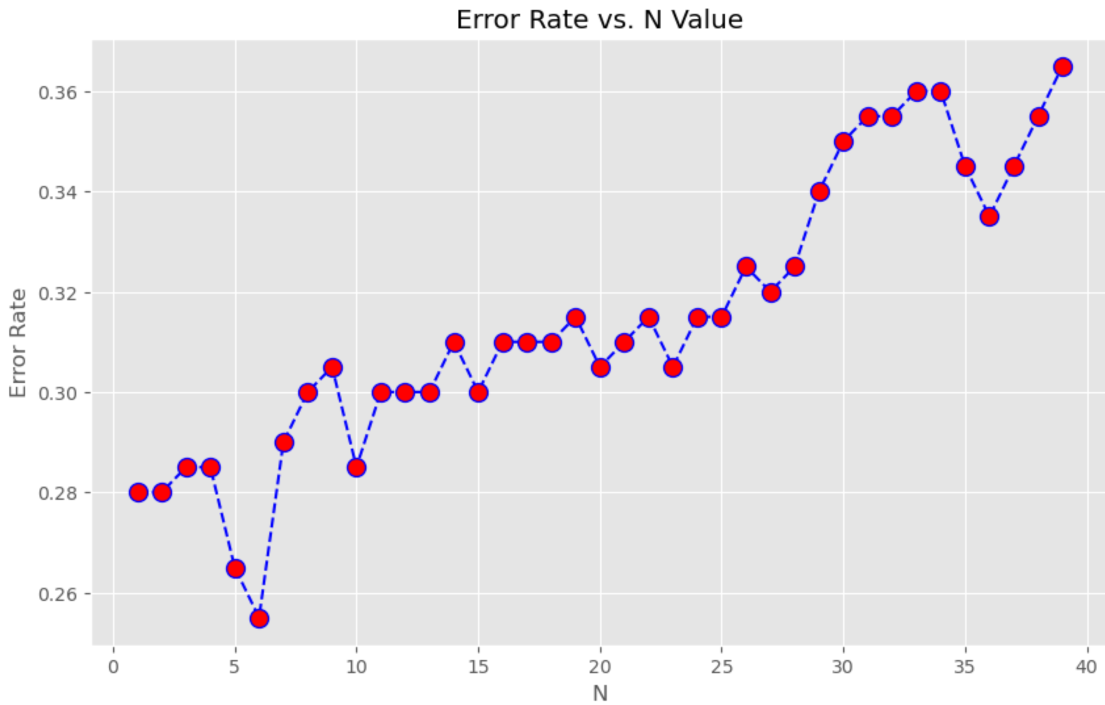
1.4.1 Find Optimal value N for KNN Model

[ ]:
```
error_rate = []
for i in range(1,40):
 knn = KNeighborsClassifier(n_neighbors=i,weights = 'distance')
 knn.fit(X_train,y_train)
 pred_i = knn.predict(X_test)
 error_rate.append(np.mean(pred_i != y_test))
```

[ ]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue',␣
↪linestyle='dashed',marker='o',markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. N Value')
plt.xlabel('N')
```

```
plt.ylabel('Error Rate')
opt_k_value = error_rate.index(min(error_rate))+1
print("Minimum error:",min(error_rate),"at N =",opt_k_value)
```

```
Minimum error: 0.255 at N = 6
```

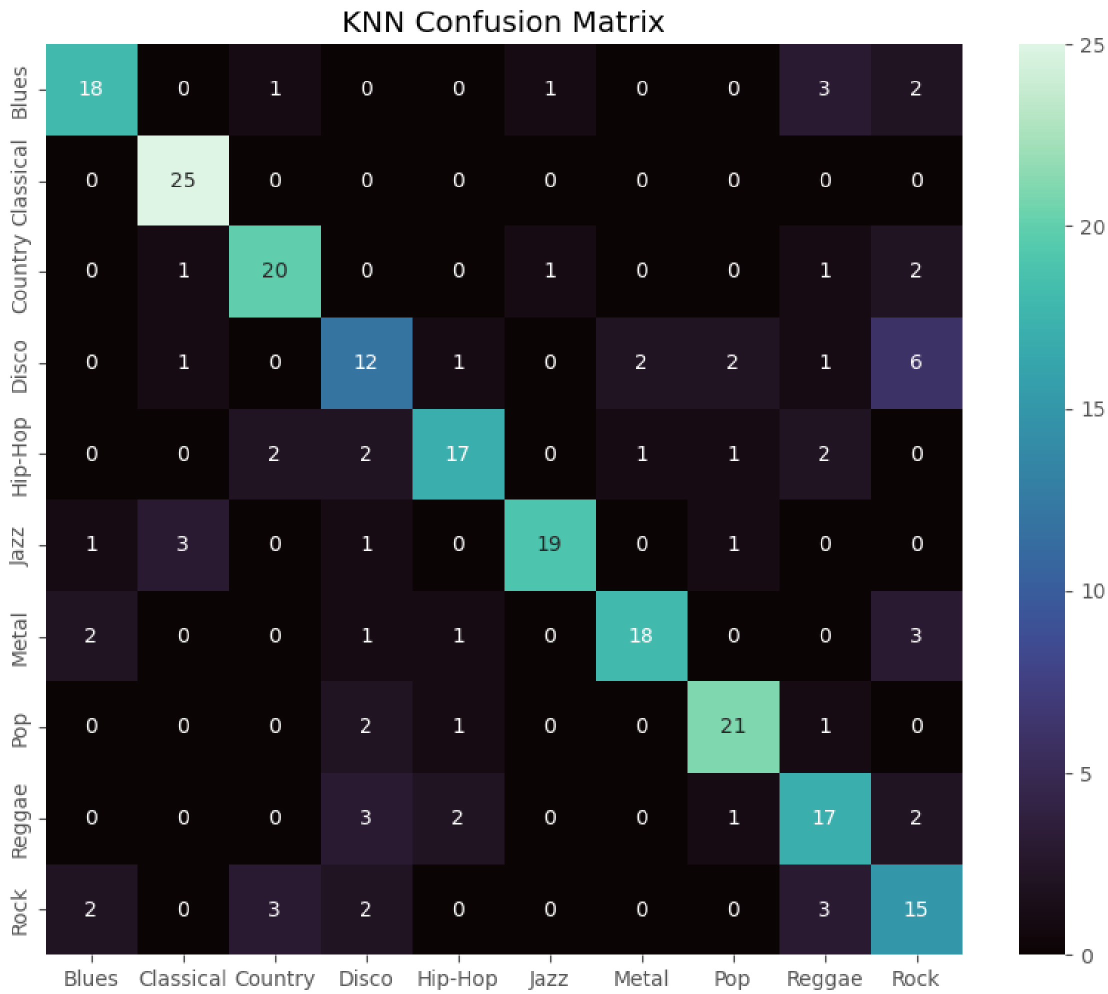


1.5 Optimized KNN Model

```
[ ]: # K-Nearest Neighbor Model
knn = KNeighborsClassifier(n_neighbors = opt_k_value,weights = 'distance')

# Create an instance of Pipeline
pipeline = make_pipeline(MinMaxScaler(), knn)

# Compute Cross-Validation Scores and Print the Average Accuracy Score
scores = cross_val_score(pipeline, X=X_train, y=y_train, cv=k, n_jobs=1)

# Print Accuracy Scores from K-Fold Cross Validation
print('Cross Validation accuracy scores: %s' % scores)
print('Cross Validation accuracy: %.3f +/- %.3f' % (np.mean(scores),np.
 ↪std(scores)))

# use KFold CV and print mean accuracy scores
kf_cv_scores = cross_val_score(knn,X_train,y_train,cv=kfold)
```

```python
skf_cv_scores = cross_val_score(knn,X_train,y_train,cv=skfold)
print(f"K-fold CV average score: %.2f with K = {k}" % kf_cv_scores.mean())
print(f"Stratified K-fold CV average score: %.2f" % skf_cv_scores.mean())

# Predict using Model and Plot the Confusion Matrix
knn.fit(X_train,y_train)
y_pred = knn.predict(X_test)

# KNN
model_assess(knn, X_train, y_train, X_test, y_test, "KNN")
plt.figure(figsize = (10,8))
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True,  cmap = 'mako',
            xticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            yticklabels =␣
 ↪['Blues','Classical','Country','Disco','Hip-Hop','Jazz','Metal','Pop','Reggae','Rock'],
            vmin = 0, vmax = len(y_test)/10)
plt.title('KNN Confusion Matrix')
plt.show()
```

```
Cross Validation accuracy scores: [0.64       0.70666667 0.72       0.70666667
0.68       0.72
 0.68       0.65333333 0.61333333 0.68      ]
Cross Validation accuracy: 0.680 +/- 0.034
K-fold CV average score: 0.68 with K = 10
Stratified K-fold CV average score: 0.67
Accuracy KNN : 0.728
```



1.5.1 Feature Selection using Lasso Regression

[ ]:
```
# Read CSV file of 10 genres of Music
#df = pd.read_csv('features_3_sec.csv')
df = pd.read_csv('features_30_sec.csv')
df['label'] = df['label'].replace('blues',0)
df['label'] = df['label'].replace('classical',1)
df['label'] = df['label'].replace('country',2)
df['label'] = df['label'].replace('disco',3)
df['label'] = df['label'].replace('hiphop',4)
df['label'] = df['label'].replace('jazz',5)
df['label'] = df['label'].replace('metal',6)
df['label'] = df['label'].replace('pop',7)
df['label'] = df['label'].replace('reggae',8)
df['label'] = df['label'].replace('rock',9)
```

[ ]:
```
# Remove irrelevant columns and parse target column from dataset
X = df.drop(['filename','length','label'], axis=1)
y = df['label']

GTZAN_features = X.columns.tolist()
X = X.to_numpy()
y = y.to_numpy()
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)
```

[ ]:
```
pipeline = Pipeline([
                     ('scaler',StandardScaler()),
                     ('model',Lasso())
])
```

[ ]:
```
search = GridSearchCV(pipeline,
                      {'model__alpha':np.arange(0.1,10,0.1)},
                      cv = 5, scoring="neg_mean_squared_error",verbose=3
                      )
```

[ ]:
```
search.fit(X_train,y_train)
search.best_params_
```

[ ]:
```
coefficients = search.best_estimator_.named_steps['model'].coef_
importance = np.abs(coefficients)
importance
```

[ ]:
```
array([0.0997671 , 0.        , 0.        , 0.19146871, 0.49974584,
       0.07241983, 0.        , 0.        , 0.        , 0.68442517,
       0.        , 0.        , 0.04028613, 0.        , 0.        ,
       0.        , 0.06477752, 0.26346261, 0.        , 0.        ,
       0.        , 0.17202732, 0.        , 0.        , 0.        ,
       0.        , 0.07950544, 0.        , 0.        , 0.01652186,
       0.14651762, 0.        , 0.        , 0.28075513, 0.        ,
       0.        , 0.        , 0.        , 0.07871675, 0.20027255,
       0.08965554, 0.        , 0.2149307 , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.13242113, 0.        , 0.        , 0.        ,
       0.        , 0.        ])
```

[ ]:
```
col_Names = np.array(GTZAN_features)[importance > 0]
col_Names
```

1.5.2 Now reduce Dataframe to only the Valueable Features determined from Lasso Regression

[ ]:
```
X = df[col_Names]
X
```

1.6 George's Code

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from timeit import default_timer
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪StratifiedKFold
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import Lasso
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs


def main():

    filename = 'features_30_sec.csv'
    kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

    print(f'\nfile used: {filename}')
    print(f'Validation method: K-fold cross-validation ({kf.get_n_splits()}␣
↪splits, stratified)')

    csv = pd.read_csv(filename)
    data = csv.drop(['filename', 'length', 'label'], axis=1)  # remove␣
↪filename, number of samples from data.
    labels = csv.loc[:,'label'] # extract labels.

    cols = data.columns # preprocessing stuff
    scaler = preprocessing.MinMaxScaler()
    scaled_X = scaler.fit_transform(data)
    data = pd.DataFrame(scaled_X, columns=cols)
```

```python
    # models
    nb = GaussianNB()
    svm_L = SVC(kernel = 'linear', decision_function_shape="ovr")
    lr = LogisticRegression(random_state=42, multi_class='auto',max_iter=500)
    k = 6 # hardcoded in, was very slow to compute everytime using SFS
    knn = KNeighborsClassifier(n_neighbors=k, weights = 'distance')



    print(f'\n-------------------------------------\nInital Feature Comparision\n-------------------------------------')
    sorted_feature_list = get_sorted_features(data, labels, nb, kf)
    print(f'classifying genres pairwise, using the best feature: {sorted_feature_list[:1]}')
    compare_genres_pairwise(data[sorted_feature_list[:1]], labels, nb, 'Naive Bayes', kf) # all features


    print(f'\n-------------------------------------\nModel Comparision\n-------------------------------------')
    _, _, best_f_nb, _ = plot_SFS_for_model(nb, 'Naive Bayes', data, labels, kf)
    _, _, best_f_svm, _ = plot_SFS_for_model(svm_L, 'SVM (linear)', data, labels, kf)
    _, _, best_f_lr, _ = plot_SFS_for_model(lr, 'Logistic Regression', data, labels, kf)
    _, _, best_f_knn, _ = plot_SFS_for_model(knn, f'K Neighbors (k = {k})', data, labels, kf)

    compare_genres_pairwise(data[best_f_nb], labels, nb, 'Naive Bayes', kf) # compare pairwise between NB and KNN
    compare_genres_pairwise(data[best_f_knn], labels, knn, f'K Neighbors (k = {k})', kf) # all features


    print(f'\n-------------------------------------\nFinal Feature Comparision\n-------------------------------------')
    combined_list = np.concatenate((best_f_nb, best_f_svm, best_f_lr, best_f_knn))
    combined_list_u, counts = np.unique(combined_list, return_counts=True)
    feature_count = dict(zip(combined_list_u, counts))
    print(f"\nbest features overall: (contributed to the maximum values for all 4 classifiers")
    for i in [k for k,v in feature_count.items() if v == 4]:
        print(i)

    # LASSO coefficients
```

```
    # had to hardcode this, was getting a bug
    sorted_features_LASSO = ['rolloff_var', 'spectral_centroid_mean',␣
 ↪'mfcc1_mean', 'spectral_centroid_var',
                             'mfcc9_mean', 'mfcc12_mean', 'rms_var',␣
 ↪'mfcc3_mean', 'mfcc13_var', 'mfcc18_mean',
                             'chroma_stft_mean', 'mfcc12_var', 'mfcc7_mean',␣
 ↪'harmony_mean', 'mfcc5_var', 'mfcc11_var',
                             'mfcc7_var', 'spectral_bandwidth_var', 'tempo']
    print(f'\nThe best features according to the LASSO coefficients␣
 ↪({len(sorted_features_LASSO)} nonzero coefficents):\n')
    print(sorted_features_LASSO)
    print(f'\nusing the classifiers with these features:\n')

    print(f'\nmodel: Naive Bayes')
    print(f'average accuracy: {classify(nb, data[sorted_features_LASSO],␣
 ↪labels, kf):.3f}')

    print(f'\nmodel: SVM (linear)')
    print(f'average accuracy: {classify(svm_L, data[sorted_features_LASSO],␣
 ↪labels, kf):.3f}')

    print(f'\nmodel: Logistic Regression')
    print(f'average accuracy: {classify(lr, data[sorted_features_LASSO],␣
 ↪labels, kf):.3f}')

    print(f'\nmodel: K Neighbors (k = 6)')
    print(f'average accuracy: {classify(knn, data[sorted_features_LASSO],␣
 ↪labels, kf):.3f}')


    #print(f'\nmodel: K Neighbors') # really slow, computed req_k_value once␣
 ↪and then hardcoded it
    #req_k_value, max_acc_knn = get_k(data, labels, kf, verbose=True, disp=True)
    #print(f'average accuracy: {max_acc_knn:.3f}, K={req_k_value}')
    #knn = KNeighborsClassifier(n_neighbors=req_k_value, weights = 'distance')


    return


def plot_SFS_for_model(model, model_name, data, labels, cv, tol=0.95,␣
 ↪disp=True, progress=True, verbose=False):
    #http://rasbt.github.io/mlxtend/user_guide/feature_selection/
 ↪SequentialFeatureSelector/
 ↪#sequentialfeatureselector-the-popular-forward-and-backward-feature-selection-approaches-in
    print(f'\nmodel: {model_name}\n')
```

```python
    if progress:
        sfs_verbose = 1
    else:
        sfs_verbose = 0

    sfs = SFS(model,
            k_features=57,
            forward=True,
            floating=True,
            verbose=sfs_verbose,
            scoring='accuracy',
            n_jobs=3,
            cv=cv)
    t1 = default_timer()
    sfs.fit(data, labels)
    t2 = default_timer()
    print(f'\nElapsed time: {t2-t1:.1f} s, {(t2-t1)/60:.1f} m \n') # time␣
↪results(slow function)

    results = pd.DataFrame.from_dict(sfs.get_metric_dict()).T # process␣
↪results, fixes bug
    results['avg_score'] = pd.to_numeric(results['avg_score'])
    if verbose:
        print(results['avg_score'])
        print()

    all_feature_acc = (results.loc[57]).loc['avg_score']

    n_features_opt = results['avg_score'].idxmax() # calculate best␣
↪values(max_acc, optimal # features)
    best_result = results.loc[n_features_opt]
    max_acc = best_result.loc['avg_score']
    best_features = list(best_result.loc['feature_names'])

    threshold = tol*max_acc # calculate 'close enough' value, with less features
    threshold_idx = 0
    threshold_acc = 0
    for count, acc in enumerate(results['avg_score']):
        if acc > threshold:
            threshold_acc = acc
            threshold_idx = count+1
            break
    thrs_result = results.loc[threshold_idx]
    thrs_features = list(thrs_result.loc['feature_names'])

    print(f'accuracy with all features: {all_feature_acc:.3f}\n')
```

```
    print(f'max accuracy = {max_acc:.3f}, at {n_features_opt} features:
↪\n{best_features}\n' )
    print(f'thresh. accuracy = {threshold_acc:.3f}, at {threshold_idx} features:
↪\n{thrs_features}\n' )

    if disp:
        fig1 = plot_sfs(sfs.get_metric_dict(), kind='std_dev')
        plt.plot(n_features_opt, max_acc, color='black',␣
↪markerfacecolor='springgreen', marker='D', markersize=7, label='max acc.')
        plt.plot(threshold_idx, threshold_acc, color='black',␣
↪markerfacecolor='darkorange', marker='D', markersize=7, label='thr acc.')
        plt.plot(range(1, 58), np.ones(57)*threshold, color='darkorange',␣
↪linestyle='dashed', label=f'{tol*100}% of max acc.')
        plt.title(f'SFS (w. StdDev)\nModel: {model_name}')
        plt.xticks(ticks=range(5, 58, 5))
        plt.xlim([1, 57])
        plt.ylabel('Accuracy')
        plt.grid()
        plt.legend(loc = 'lower right')
        plt.show()

    return max_acc, threshold_acc, best_features, thrs_features


def get_sorted_features(data, labels, model, kf, verbose=False):

    feature_accuracy_dict = {}
    for feature in data.columns:
        feature_data = data[[feature, ]]
        feature_accuracy = classify(model, feature_data, labels, kf)
        feature_accuracy_dict.update({feature:feature_accuracy})

    best_feature = max(feature_accuracy_dict, key=feature_accuracy_dict.get)

    print(f'\nclassifying between all genres using a single feature:')
    print(f'average single-feature accuracy: {sum(feature_accuracy_dict.
↪values())/len(feature_accuracy_dict.values()):.3f}')
    print(f'best feature: {best_feature}, accuracy: {max(feature_accuracy_dict.
↪values()):.3f}\n')

    if verbose:
        print('all results:')

    sorted_feature_list = []
    for feature in sorted(feature_accuracy_dict, key=feature_accuracy_dict.get,␣
↪reverse=True):
```

```python
        sorted_feature_list.append(feature) # get top features, put in list
        if verbose:
            print(f'{feature}: {feature_accuracy_dict[feature]:.3f}')
    print()

    return sorted_feature_list


def compare_genres_pairwise(data, labels, model, model_name, cv, verbose=False, disp=True):

    genres = ['blues', 'classical', 'country', 'disco', 'hiphop', 'jazz', 'metal', 'pop', 'reggae', 'rock' ]
    genre_accuracy_dict = {}
    heatmap = np.empty((len(genres),len(genres)))
    for i in range(len(genres)):
        for j in range(i+1, len(genres)):
            class1 = genres[i]
            class2 = genres[j]
            avg = compare_two_classes(data, labels, class1, class2, model, cv)
            heatmap[j, i] = avg
            heatmap[i, j] = avg
            genre_accuracy_dict.update({class1+' and '+class2:avg})

    best_genres = max(genre_accuracy_dict, key=genre_accuracy_dict.get)
    worst_genres = min(genre_accuracy_dict, key=genre_accuracy_dict.get)
    print(f'average accuracy: {sum(genre_accuracy_dict.values())/len(genre_accuracy_dict.values()):.3f}')
    print(f'best performance between {best_genres}, accuracy: {max(genre_accuracy_dict.values()):.3f}')
    print(f'worst performance between {worst_genres}, accuracy: {min(genre_accuracy_dict.values()):.3f}\n')

    if verbose:
        print(f'all results:')
        for w in sorted(genre_accuracy_dict, key=genre_accuracy_dict.get, reverse=True):
            print(f'{w}: {genre_accuracy_dict[w]:.3f}')
        print()

    if disp:
        mask = np.zeros_like(heatmap) # mask top corner
        mask[np.triu_indices_from(mask)] = True
        #mask[np.diag_indices_from(mask)] = True
        ax = sns.heatmap(heatmap, linewidth=0.5, mask=mask, annot=True, fmt=".2f", cmap='mako_r', vmin=0.5, vmax=1.0)
```

```
        n_feat_title = len(data.columns) # used to title the graph
        ax.set_title(f"Accuracy, pairwise genre classification\n Model:␣
 ↪{model_name} \n{n_feat_title} feature(s)")
        plt.yticks(np.arange(0, len(genres))+0.5, genres, rotation='horizontal')
        plt.xticks(np.arange(0, len(genres))+0.5, genres, rotation='horizontal')
        for label in ax.get_xticklabels():
            label.set_horizontalalignment('center')
        plt.show()
        ax.cla()

    return


def compare_two_classes(data, labels, class1, class2, model, cv):

    data_class1 = data.loc[labels==class1]
    data_class2 = data.loc[labels==class2]
    data_2classes = pd.concat([data_class1, data_class2])

    labels_class1 = labels.loc[labels==class1]
    labels_class2 = labels.loc[labels==class2]
    labels_2classes = pd.concat([labels_class1, labels_class2])

    avg = classify(model, data_2classes, labels_2classes, cv)

    return avg


def classify(model, data, labels, cv):
    #print('using K-fold cross validation')
    avg_acc = 0
    for train_index, test_index in cv.split(data, labels):
        #print("TRAIN:", train_index, "TEST:", test_index)
        X_train, X_test = data.iloc[train_index], data.iloc[test_index]
        y_train, y_test = labels.iloc[train_index], labels.iloc[test_index]

        #print(f"\nTRAIN:\n", X_train, f"\nTEST:\n", X_test)
        avg_acc += model_assess(model, X_train, y_train, X_test, y_test)/cv.
 ↪get_n_splits()

    return avg_acc


def model_assess(model, X_train, y_train, X_test, y_test):
    model.fit(X_train,y_train)
    preds=model.predict(X_test)
```

```
    accuracy = accuracy_score(y_test, preds)
    return accuracy

# getting a bug where this changes the labels variable in the main function,␣
 ↪not really worth it to fix it.
def get_sorted_features_LASSO(csv, printout=False):
    # copied from Tyler's code
    #df = pd.read_csv('features_30_sec.csv')
    df = csv
    df['label'] = df['label'].replace('blues',0)
    df['label'] = df['label'].replace('classical',1)
    df['label'] = df['label'].replace('country',2)
    df['label'] = df['label'].replace('disco',3)
    df['label'] = df['label'].replace('hiphop',4)
    df['label'] = df['label'].replace('jazz',5)
    df['label'] = df['label'].replace('metal',6)
    df['label'] = df['label'].replace('pop',7)
    df['label'] = df['label'].replace('reggae',8)
    df['label'] = df['label'].replace('rock', 9)
    X = df.drop(['filename', 'length', 'label'], axis=1)
    y = df['label']
    GTZAN_features = X.columns.tolist()
    X = X.to_numpy()
    y = y.to_numpy()
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
    pipeline = Pipeline([('scaler',StandardScaler()), ('model',Lasso())])
    search = GridSearchCV(pipeline, {'model__alpha':np.arange(0.1,10,0.1)}, cv␣
 ↪= 5, scoring="neg_mean_squared_error")
    search.fit(X_train,y_train)
    coefficients = search.best_estimator_.named_steps['model'].coef_
    importance = np.abs(coefficients)

    feature_importance_dict = {}
    for i, feature in enumerate(GTZAN_features):
        feature_importance_dict.update({feature:importance[i]})

    if printout:
        print(f'\nLASSO coefficients:')
    sorted_feature_LASSO = []
    for w in sorted(feature_importance_dict, key=feature_importance_dict.get,␣
 ↪reverse=True):
        if printout:
            print(f'{w}: {feature_importance_dict[w]:.3f}')
        if feature_importance_dict[w] > 0.0:
            sorted_feature_LASSO.append(w)
```

```python
    return sorted_feature_LASSO


def get_k(data, labels, kf, verbose=False, disp=True, fast=True):
    # implementation from tyler's code.
    knn_accuracy = []
    n_k = 20
    for k in range(1, n_k+1):
        knn = KNeighborsClassifier(n_neighbors=k, weights = 'distance')

        if fast: # fast gives = 5, slow gives k = 6
            max_acc = classify(knn, data, labels, kf)
        else: # this is super slow, prob shouldn't use it.
            max_acc, _, _, _ = plot_SFS_for_model(knn, 'K Neigbors', data,␣
 ↪labels, kf, disp=False, progress=False) # do some feature reduction

        if verbose:
            print(f'for k  = {k}, average accuracy was {max_acc:.3f}')
        knn_accuracy.append(max_acc)

    req_k_value = knn_accuracy.index(max(knn_accuracy))+1
    max_acc_knn = max(knn_accuracy)

    if disp:
        plt.plot(range(1,n_k+1), knn_accuracy, color='blue',␣
 ↪linestyle='dashed',marker='o',markerfacecolor='red', markersize=5)
        plt.title('Accuracy vs. K Value')
        plt.xlabel('K')
        plt.ylabel('Accuracy')
        plt.xlim([1, n_k])
        plt.xticks(ticks=range(1,n_k+1))
        plt.grid()
        plt.show()

    return req_k_value, max_acc_knn


if __name__ == '__main__':
    main()
```