IST_718_Final_Project_Chose_another_song

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[ ]:
```
# Make the format such that figures will display nicely in the pdf of this␣
↪document.
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('pdf', 'svg')
```

1 Introduction

For our group project, we chose to look at information available from Spotify on what people are currently listening to. To do this, we utilized a data set off of Kaggle; previous students had organized Spotify data into csv files containing streaming information from 2017 to 2020. We built off their project to focus on exploring what Spotify could tell us about the streaming music industry.

Each year in the US, over 34 thousand new people claim to be singers or musicians on their tax returns. This means that there are far more than 34K people who are entering the music industry each year. However, studies show that only 1% of musicians stay in their field after the first year; this represents the huge amount of turnover and competition in the market. We wanted to utilize the Spotify data to get a better feel for that market.

One of the aspects of streaming platforms like Spotify is the ability to easily discover new music. Spotify's recommendation system is based off the sound qualities of the music you listen to but especially the genre of music. We chose to dive into an exploration of the relationship between Genre and music qualities, country, year, and a few other attributes.

2 Libraries

[ ]:
```
import pandas as pd
from pandas.core.algorithms import quantile
pd.set_option('display.max_columns', None)
import numpy as np
import seaborn as sns
```

```
import matplotlib.pyplot as plt
import re
import datetime
import six

from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import KMeans
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
```

3 Data Sources

The Kaggle data had two data sources: a final csv and a csv to calculate popularity. Between them, they contain all songs that made it into Spotify's top 200 daily for the years 2017 through 2020 for each of 35 Countries as well as a Global category. The data is a mix of numeric and categorical variables numbering 151 attributes and > 170,000 rows in the final csv and 8 attributes by > 9,800,000 rows in the popularity csv. The students who put together these data sources provided fairly clean csv files; predominately, the "cleaning" you wil see below is deciding which columns to keep as well as how to deal with NaN values.

The majority of our attention was focused on the final csv though we did use the popularity csv for some EDA and initial exploration of song Genre related to song Position.

3.1 Connect to Drive and set wd

[ ]:
```
#Mount google drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
#Change the directory to our google Drive
  #Elissa
%cd /content/drive/My\ Drive/
```

```
/content/drive/My Drive
```

3.2 Data Munging

3.2.1 Final CSV

Read in data and look at basic descriptive statistics.

[ ]:
```
#Read in Final Database csv
finalDat = pd.read_csv("Final database.csv")
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2718:
DtypeWarning: Columns (7,8,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25) have
mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

[ ]:
```
#print(finalDat.head(n=2))
#print(finalDat.describe())
print(finalDat.shape)
```

```
(170633, 151)
```

Clean final csv to remove unwanted columns.

[ ]:
```
#Remove all columns from 109 (bing_norm_negative) to 112 (Argentina) to 146␣
 ↪(USA)
noDummies = finalDat.drop(finalDat.iloc[:,109:147], axis = 1)
noDummies.drop(noDummies.iloc[:,74:100], axis = 1, inplace=True) #anger_norm to␣
 ↪Positive_Bayes
noDummies.drop(noDummies.iloc[:,55:58], axis = 1, inplace=True)␣
 ↪#syuzhet_norm         to nrc_norm
noDummies.drop(noDummies.iloc[:,29:31], axis = 1, inplace=True) #explicit_false␣
 ↪and explicit_true
```

[ ]:
```
# Change the column names with a slash
noDummies = noDummies.rename(columns={'Album/Single': 'AlbumSingle', 'mode':␣
 ↪'trackMode', 'dance/electronic': 'danceElectronic'})

# Transform the data types
noDummies['Country'] = noDummies.Country.astype('category')
noDummies['AlbumSingle'] = noDummies.AlbumSingle.astype('category')
noDummies['Genre'] = noDummies.Genre.astype('category')
noDummies['Artist_followers'] = pd.to_numeric(noDummies.Artist_followers,␣
 ↪errors='coerce')
noDummies['Explicit'] = noDummies.Explicit.astype('category')
noDummies['Release_date'] = pd.to_datetime(noDummies.Release_date,␣
 ↪format='%Y-%m-%d', errors='coerce')
noDummies['Track_number'] = pd.to_numeric(noDummies.Track_number,␣
 ↪errors='coerce')
noDummies['Tracks_in_album'] = pd.to_numeric(noDummies.Tracks_in_album,␣
 ↪errors='coerce')
```

```
noDummies['danceability'] = pd.to_numeric(noDummies.danceability,␣
 ↪errors='coerce')
noDummies['energy'] = pd.to_numeric(noDummies.energy, errors='coerce')
noDummies['key'] = pd.to_numeric(noDummies.key, errors='coerce')
noDummies['loudness'] = pd.to_numeric(noDummies.loudness, errors='coerce')
noDummies['trackMode'] = pd.to_numeric(noDummies.trackMode, errors='coerce')
noDummies['speechiness'] = pd.to_numeric(noDummies.speechiness, errors='coerce')
noDummies['acoustics'] = pd.to_numeric(noDummies.acoustics, errors='coerce')
noDummies['instrumentalness'] = pd.to_numeric(noDummies.instrumentalness,␣
 ↪errors='coerce')
noDummies['liveliness'] = pd.to_numeric(noDummies.liveliness, errors='coerce')
noDummies['valence'] = pd.to_numeric(noDummies.valence, errors='coerce')
noDummies['tempo'] = pd.to_numeric(noDummies.tempo, errors='coerce')
noDummies['duration_ms'] = pd.to_numeric(noDummies.duration_ms, errors='coerce')
noDummies['Popu_max'] = pd.to_numeric(noDummies.Popu_max, errors='coerce')
noDummies['Top10_dummy'] = pd.to_numeric(noDummies.Top10_dummy, errors='coerce')
noDummies['Top50_dummy'] = pd.to_numeric(noDummies.Top50_dummy, errors='coerce')
noDummies['Cluster'] = noDummies.Cluster.astype('category')
noDummies['Genre_new'] = noDummies.Genre_new.astype('category')

#noDummies.info() #This is almost certainly too long to keep in our final␣
 ↪submission.
```

[ ]:
```
# Display the data shape and null values for each column

print('Null Values:', )
print()
print(noDummies.isnull().sum())
print()
print('Data Shape:')
print()
print(noDummies.shape)
```

```
Null Values:

Country            0
Uri                0
Popularity         0
Title              0
Artist             0
               ...
Thug           98767
Popu_max           0
Top10_dummy        0
Top50_dummy        0
Cluster            0
Length: 82, dtype: int64
```

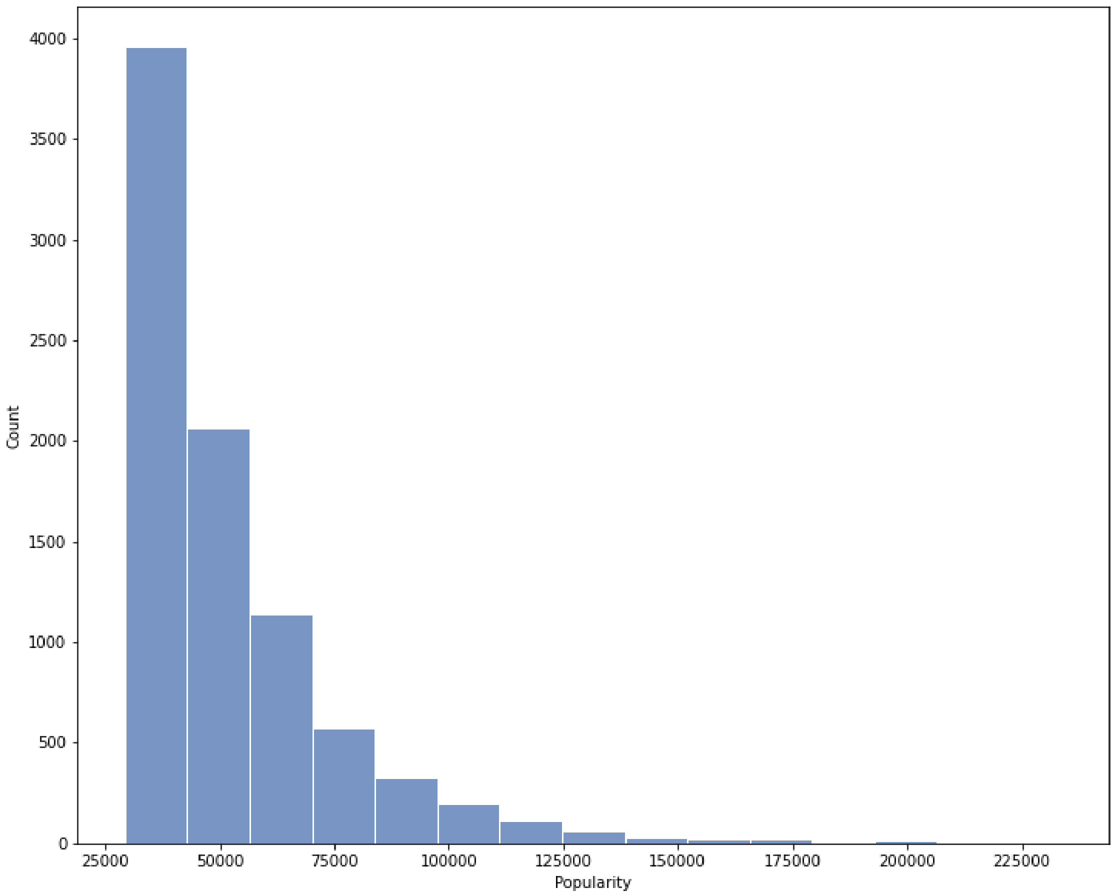
```
Data Shape:

(170633, 82)
```

Visualize outliers and remove all with Popularity values above the 95% quantile.

```
[ ]: # Calculate Interquartile Range
Q95 = quantile(noDummies['Popularity'], 0.95)
print("95th Percentile:", Q95)

# Subset the Outliers
outlierDAT = noDummies[(noDummies['Popularity'] > 29287)]
# Sort the Outliers
outlierDAT.sort_values(by=['Popularity'], inplace=True, ascending=False)
#print(outlierDAT.shape)

# Histogram of Outlier Popularity values
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
sns.histplot(data=outlierDAT, x='Popularity', bins = 15)
```

```
95th Percentile: 29287.55999999999

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff63885de50>
```




```
[ ]: # Remove Outliers from noDummies
noDummies_outliersRemoved = noDummies[(noDummies['Popularity'] < 29287)]

print(noDummies_outliersRemoved.shape)
```

```
(162100, 82)
```

Finally, subset the data set into 5 separate ones for each of the countries of interest.

```
[ ]: # Subset by Country
globalDat = noDummies_outliersRemoved[(noDummies_outliersRemoved["Country"] ==␣
 ↪"Global")]
usaDat = noDummies_outliersRemoved[(noDummies_outliersRemoved["Country"] ==␣
 ↪"USA")]
finlandDat = noDummies_outliersRemoved[(noDummies_outliersRemoved["Country"] ==␣
 ↪"Finland")]
singaporeDat = noDummies_outliersRemoved[(noDummies_outliersRemoved["Country"]␣
 ↪== "Singapore")]
newZealandDat =noDummies_outliersRemoved[(noDummies_outliersRemoved["Country"]␣
 ↪== "New Zealand")]
```

3.2.2 Popularity CSV

Bring in data, remove unwanted columns, and rename columns to match formatting in the final csv.

[ ]:
```
#Bring in the csv
popularityRAW = pd.read_csv("Database to calculate popularity.csv")
#Make a copy to play with
pop = popularityRAW

#Remove columns we aren't interested in
pop = pop.drop(columns={'Unnamed: 0'})
#Rename colums to match format.
pop = pop.rename(columns={'country':'Country','date':'Date','position':
↪'Position', 'uri':'Uri','track':'Track','title':'Title','artist':'Artist'})
```

3.2.3 Join each final country subset with position data from the popularity csv.

[ ]:
```
#We want Country and Uri for joining. The only unique information we are trying␣
↪to bring over is the position. Date, Track, Title, and Artist are already␣
↪present.
pop = pop.drop(columns=['Track', 'Title', 'Artist'])

## Join pop with each Country subset on Uri and Country

#Select countries of interest
countries = ['USA', 'Global', 'Finland', 'Singapore', 'New Zealand']
pop_CountrySelection = pop[pop['Country'].isin(countries)]

# Join the datasets
globalJoin = pop_CountrySelection.merge(globalDat, on=['Uri', 'Country'])
usaJoin = pop_CountrySelection.merge(usaDat, on=['Uri', 'Country'])
finlandJoin = pop_CountrySelection.merge(finalDat, on=['Uri', 'Country'])
singaporeJoin = pop_CountrySelection.merge(singaporeDat, on=['Uri', 'Country'])
newZealandJoin = pop_CountrySelection.merge(newZealandDat, on=['Uri',␣
↪'Country'])
```

4 Exploratory Data Analysis

4.1 Popularity csv

Start by creating a single joined data frame that represents our 5 countries in one.

[ ]:
```
# Generate merged data frame with all countries of interest
finalComb = noDummies_outliersRemoved[['Country','Genre','Uri', 'Artist',␣
↪'Popularity']]
#Select countries of interest
countries = ['USA', 'Global', 'Finland', 'Singapore', 'New Zealand']
```

```
finalComb = finalComb[finalComb['Country'].isin(countries)]
spotJoin = pop.merge(finalComb, on=['Uri', 'Country'])

#Go ahead and drop Uri
spotJoin = spotJoin.drop(columns='Uri')
spotJoin.head(n=1)
```

[ ]:
```
  Country        Date  Position  Genre                   Artist  Popularity
0  Global  05/11/2020       1.0  latin  Bad Bunny - Jhay Cortez      3160.6
```

Extract the year and month to use for grouping.

[ ]:
```
#Change to datetime
spotJoin['Date'] = pd.to_datetime(spotJoin.Date)

#Extract (https://www.interviewqs.com/ddi-code-snippets/
 ↪extract-month-year-pandas)
spotJoin['Year'] = pd.DatetimeIndex(spotJoin['Date']).year
spotJoin['Month'] = pd.DatetimeIndex(spotJoin['Date']).month
```

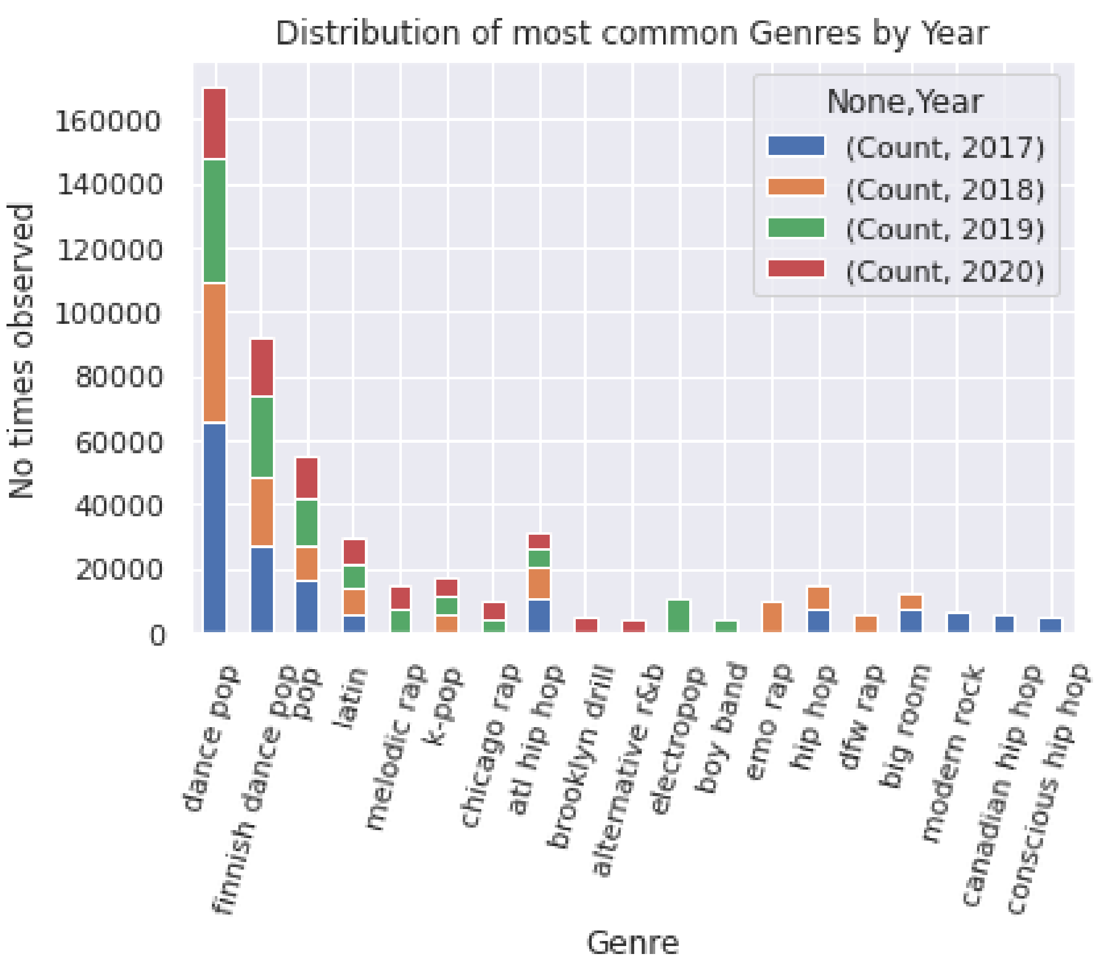
- **Are there any differences by Year for the counts of the Genres?**

[ ]:
```
#Groupby appriate columns of interest.
YearGenre = spotJoin.groupby(['Year', 'Genre']).size().reset_index()
YearGenre.columns = ['Year', 'Genre', 'Count']

#Look at results numerically by Count
YG = YearGenre.sort_values(['Year','Count'], ascending=False)

# Seperate out each year
YG_2020 = YG[YG.Year==2020]
YG_2019 = YG[YG.Year==2019]
YG_2018 = YG[YG.Year==2018]
YG_2017 = YG[YG.Year==2017]

#Use pandas nlargest and nsmallest to select the largest and smallest rows␣
 ↪based on the Count column.
L2020 = YG_2020.nlargest(10, 'Count')
L2019 = YG_2019.nlargest(10, 'Count')
L2018 = YG_2018.nlargest(10, 'Count')
L2017 = YG_2017.nlargest(10, 'Count')

S2020 = YG_2020.nsmallest(10, 'Count')
S2019 = YG_2019.nsmallest(10, 'Count')
S2018 = YG_2018.nsmallest(10, 'Count')
S2017 = YG_2017.nsmallest(10, 'Count')
```

[ ]:
```
##For the most commonly seen genres##
```

```
#Combine all largest values for the years
frames = [L2020, L2019, L2018, L2017]
result = pd.concat(frames)

#Let's create a new structure to this where each year gets its own column and␣
 ↪is filled by count.
play = result.set_index('Genre')
play2 = play.pivot(columns='Year')
play2.plot(kind='bar', stacked='True')
plt.ylabel('No times observed')
plt.title('Distribution of most common Genres by Year')
plt.xticks(rotation=75, horizontalalignment="center")
#plt.savefig('Distribution of most common Genres by Year',␣
 ↪orientation='landscape', bbox_inches='tight')
```

[ ]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18]), <a list of 19 Text major ticklabel objects>)
```



There are a few genres that are highly represented in each year. These are dance pop, finish dance pop, pop, and latin. The other highly represented genres are far lower than these and normally just present in one or two years.

k-pop though us represented in the last three consecutive years.

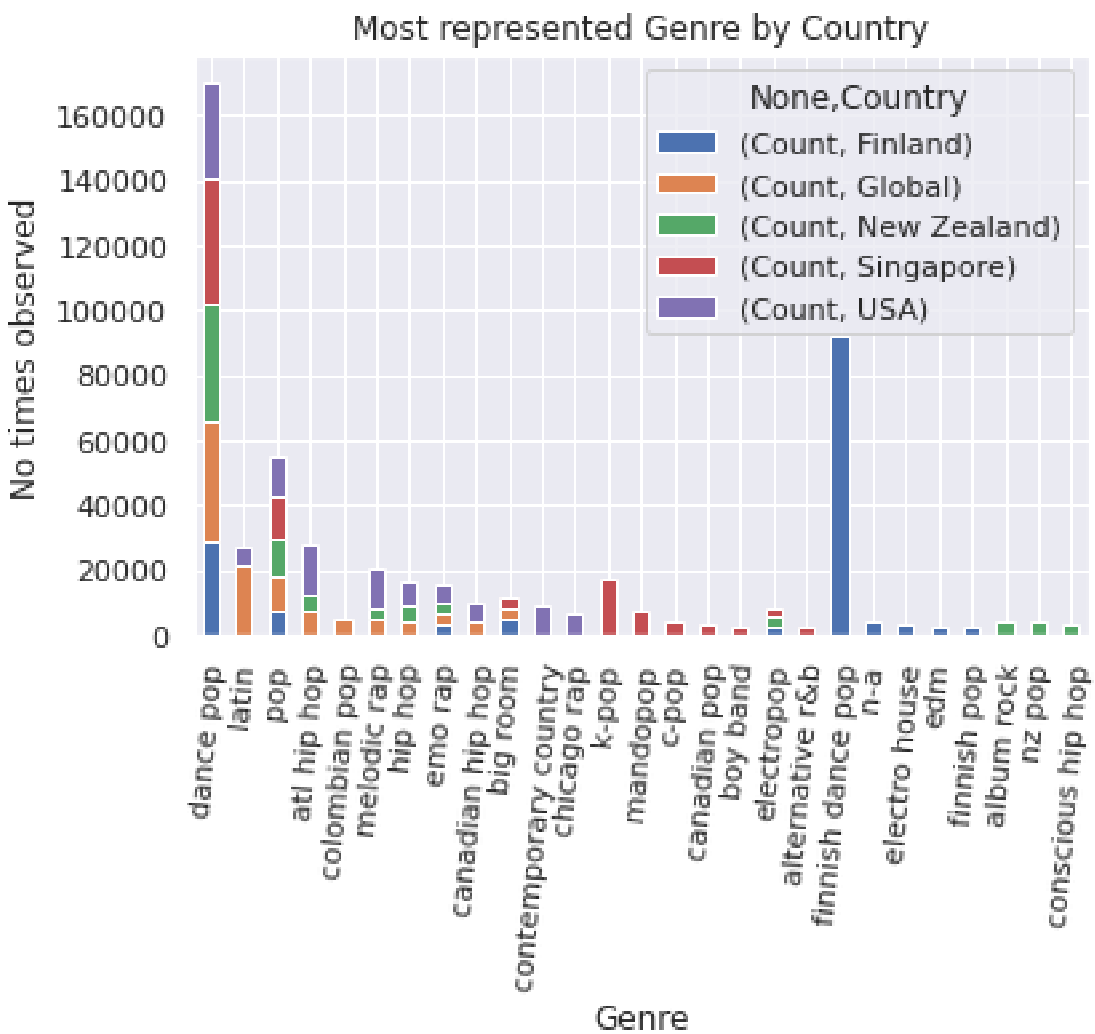
- **Are there differences by Country for the counts in each Genre?**

[ ]:
```
#We will start back with spotJoin
spotJoin.head()

#Group by country and then get counts by Genre
CountryGenre = spotJoin.groupby(['Country', 'Genre']).size().reset_index()
CountryGenre.columns = ['Country', 'Genre', 'Count']

#Look at results numerically by Count
CG = CountryGenre.sort_values(['Country','Count'], ascending=False)
CG

# Seperate out each country
CG_Global = CG[CG.Country=='Global']
CG_USA = CG[CG.Country=='USA']
CG_Singapore = CG[CG.Country=='Singapore']
CG_Finland = CG[CG.Country=='Finland']
CG_NewZ = CG[CG.Country=='New Zealand']

#Use pandas nlargest and nsmallest to select the largest and smallest rows␣
↪based on the Count column.
LGlob = CG_Global.nlargest(10, 'Count')
LUSA = CG_USA.nlargest(10, 'Count')
LSing = CG_Singapore.nlargest(10, 'Count')
LFin = CG_Finland.nlargest(10, 'Count')
LNZ = CG_NewZ.nlargest(10, 'Count')

SGlob = CG_Global.nsmallest(10, 'Count')
SUSA = CG_USA.nsmallest(10, 'Count')
SSing = CG_Singapore.nsmallest(10, 'Count')
SFin = CG_Finland.nsmallest(10, 'Count')
SNZ = CG_NewZ.nsmallest(10, 'Count')
```

[ ]:
```
##For the most commonly seen genres##

#Combine all largest values for the years
frames = [LGlob, LUSA, LSing, LFin, LNZ]
result = pd.concat(frames)

#Let's create a new structure to this where each year gets its own column and␣
↪is filled by count.
play = result.set_index('Genre')
```

```
play2 = play.pivot(columns='Country')
play2.plot(kind='bar', stacked='True')
plt.ylabel('No times observed')
plt.title('Most represented Genre by Country')
plt.xticks(rotation=85, horizontalalignment="center")
#plt.savefig('Distribution of most common Genres by Country',␣
 ↪orientation='landscape', bbox_inches='tight')
```

[ ]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26]),
 <a list of 27 Text major ticklabel objects>)
```



- All 5 countries have dance pop and pop genres highly represented.
- Genres with high representation in 4 countries:

- dfw rap & emo rap are represented in Finlad, Global, New Zealand, and USA.
- electo pop is represented in Finlad, Global, New Zealand, and Singapore.
- **Look at Distribution of Position by Genre**

While it is useful to get an idea of which genres are highly and lowly represented in our data, our main point of this analysis is less on being present and more on where you rank when you are present.

For this next section, we are going to try to help artists understand how best to market their work in order to appear in the top 10 songs and to avoid being in the bottom 10 songs. * When trying to look at the top 10 and bottom 10 songs, there were too many rows to make graphing easily legible by genre. * I chose next to just look at all songs in the top and bottom 5 positions.

[ ]:
```
# Select all rows where position is between 190 and 200
posHigh = spotJoin.loc[spotJoin['Position'] >= 190]

#Select all rows where position is between 1 and 10.
posLow = spotJoin.loc[spotJoin['Position'] <= 10]
```

[ ]:
```
#Option to make pandas dataframes into presentable images (https://
↪stackoverflow.com/questions/26678467/
↪export-a-pandas-dataframe-as-a-table-image)
def render_mpl_table(data, col_width=3.0, row_height=0.625, font_size=14,
                     header_color='#40466e', row_colors=['#f1f1f2', 'w'],␣
↪edge_color='w',
                     bbox=[0, 0, 1, 1], header_columns=0,
                     ax=None, **kwargs):
    if ax is None:
        size = (np.array(data.shape[::-1]) + np.array([0, 1])) * np.
↪array([col_width, row_height])
        fig, ax = plt.subplots(figsize=size)
        ax.axis('off')

    mpl_table = ax.table(cellText=data.values, bbox=bbox, colLabels=data.
↪columns, **kwargs)

    mpl_table.auto_set_font_size(False)
    mpl_table.set_fontsize(font_size)

    for k, cell in  six.iteritems(mpl_table._cells):
        cell.set_edgecolor(edge_color)
        if k[0] == 0 or k[1] < header_columns:
            cell.set_text_props(weight='bold', color='w')
            cell.set_facecolor(header_color)
        else:
            cell.set_facecolor(row_colors[k[0]%len(row_colors) ])
    return ax
```

Counts of Genres by average top 10 Position and bottom 10 position

[ ]:
```
#How many genres are represented in each Country in their top 10 songs?
df = posHigh.groupby('Country', as_index=False).agg({"Genre": "nunique"})
#Call the function
render_mpl_table(df, header_columns=0, col_width=2.0)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff633b2e0d0>

Country	Genre
Finland	193
Global	219
New Zealand	182
Singapore	161
USA	167

[ ]:
```
df = posLow.groupby('Country', as_index=False).agg({"Genre": "nunique"})
#Call the function
render_mpl_table(df, header_columns=0, col_width=2.0)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff6320643d0>

Country	Genre
Finland	48
Global	34
New Zealand	40
Singapore	28
USA	47

4.2 Final csv

We contiued our analysis by comparing the summary statistics of the five geographic subsets.

[ ]:
```
# Descriptive Statistics for the Global segment
globalDat.describe()
```

[ ]:

	Popularity	Artist_followers	Track_number	Tracks_in_album
count	5232.000000	5.231000e+03	5232.000000	5232.000000
mean	2771.490424	1.079109e+07	4.609518	10.173930
std	5344.398426	1.267602e+07	4.869453	9.613539
min	0.800000	9.000000e+00	1.000000	1.000000
25%	63.200000	2.394814e+06	1.000000	1.000000
50%	391.100000	5.647016e+06	2.000000	11.500000
75%	2454.787500	1.430398e+07	7.000000	16.000000
max	29198.150000	7.178310e+07	71.000000	349.000000

	danceability	energy	key	loudness	trackMode
count	5232.000000	5232.000000	5232.000000	5232.000000	5232.000000
mean	0.680593	0.636534	5.203364	-6.448142	0.573586
std	0.147821	0.169608	3.665930	2.624988	0.494603
min	0.125000	0.013700	0.000000	-34.475000	0.000000
25%	0.591000	0.535000	1.000000	-7.576750	0.000000
50%	0.697000	0.651000	5.000000	-6.064500	1.000000
75%	0.789000	0.760000	8.000000	-4.759000	1.000000
max	0.974000	0.996000	11.000000	1.509000	1.000000

	speechiness	acoustics	instrumentalness	liveliness	valence
count	5232.000000	5232.000000	5232.000000	5232.000000	5232.000000
mean	0.137576	0.222247	0.012460	0.181380	0.480203
std	0.123152	0.240845	0.076994	0.140136	0.224046
min	0.023500	0.000002	0.000000	0.019700	0.026200
25%	0.046800	0.038100	0.000000	0.097600	0.305000
50%	0.084400	0.132000	0.000000	0.126000	0.474000
75%	0.197250	0.323000	0.000036	0.216000	0.652000
max	0.966000	0.994000	0.956000	0.988000	0.982000

	tempo	duration_ms	Days_since_release	Released_after_2017
count	5232.000000	5232.000000	5168.000000	5168.000000
mean	122.680178	205678.423165	1234.231811	0.885642
std	29.878289	52133.580024	2591.972035	0.318276
min	45.780000	30133.000000	9.000000	0.000000
25%	97.985750	176409.500000	371.750000	1.000000
50%	120.933000	201141.000000	745.000000	1.000000
75%	143.983000	228917.750000	1135.000000	1.000000
max	216.334000	943529.000000	28798.000000	1.000000

	album	compilation	single	bolero	boy band	\
count	5232.000000	5232.000000	5232.000000	5232.000000	5232.000000	
mean	0.606460	0.010703	0.382836	0.000382	0.016055	
std	0.488581	0.102912	0.486125	0.019550	0.125699	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	0.000000	1.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	country	danceElectronic	else	funk	hip hop	\
count	5232.000000	5232.000000	5232.000000	5232.000000	5232.000000	
mean	0.005161	0.025994	0.020260	0.010512	0.267966	
std	0.071658	0.159132	0.140902	0.101999	0.442942	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	house	indie	jazz	k-pop	latin	\
count	5232.000000	5232.000000	5232.0	5232.000000	5232.000000	
mean	0.022362	0.012424	0.0	0.022745	0.062309	
std	0.147873	0.110777	0.0	0.149103	0.241739	
min	0.000000	0.000000	0.0	0.000000	0.000000	
25%	0.000000	0.000000	0.0	0.000000	0.000000	
50%	0.000000	0.000000	0.0	0.000000	0.000000	
75%	0.000000	0.000000	0.0	0.000000	0.000000	
max	1.000000	1.000000	0.0	1.000000	1.000000	

	metal	opm	pop	r&b/soul	rap	reggae	\
count	5232.000000	5232.0	5232.000000	5232.000000	5232.000000	5232.0	
mean	0.015482	0.0	0.306002	0.031537	0.127485	0.0	
std	0.123470	0.0	0.460874	0.174780	0.333547	0.0	
min	0.000000	0.0	0.000000	0.000000	0.000000	0.0	
25%	0.000000	0.0	0.000000	0.000000	0.000000	0.0	
50%	0.000000	0.0	0.000000	0.000000	0.000000	0.0	
75%	0.000000	0.0	1.000000	0.000000	0.000000	0.0	
max	1.000000	0.0	1.000000	1.000000	1.000000	0.0	

	reggaeton	rock	trap	nrc_norm	syuzhet	\
count	5232.000000	5232.000000	5232.000000	2984.000000	2984.000000	
mean	0.005161	0.037271	0.010894	-0.002011	-0.313304	
std	0.071658	0.189442	0.103816	0.928194	3.347492	
min	0.000000	0.000000	0.000000	-1.000000	-19.650000	
25%	0.000000	0.000000	0.000000	-1.000000	-2.062500	

50%	0.000000	0.000000	0.000000	0.000000	-0.050000
75%	0.000000	0.000000	0.000000	1.000000	1.750000
max	1.000000	1.000000	1.000000	1.000000	12.100000

	bing	afinn	nrc	anger	anticipation \
count	2984.000000	2984.000000	2984.000000	2984.000000	2984.000000
mean	-1.477882	-4.164209	-0.167225	3.225536	3.398458
std	4.153626	11.679735	3.967330	3.180945	2.722206
min	-31.000000	-63.000000	-18.000000	0.000000	0.000000
25%	-3.000000	-9.000000	-2.000000	1.000000	1.000000
50%	-1.000000	-1.000000	0.000000	2.000000	3.000000
75%	1.000000	3.000000	2.000000	5.000000	5.000000
max	13.000000	26.000000	18.000000	25.000000	19.000000

	disgust	fear	joy	sadness	surprise \
count	2984.000000	2984.000000	2984.000000	2984.000000	2984.000000
mean	2.247989	3.340147	3.400134	3.032172	2.054625
std	2.301342	3.196952	2.530951	2.661411	1.809212
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	1.000000	2.000000	1.000000	1.000000
50%	2.000000	2.000000	3.000000	2.000000	2.000000
75%	3.000000	5.000000	5.000000	4.000000	3.000000
max	17.000000	28.000000	21.000000	24.000000	11.000000

	trust	negative	positive	n_words	Celebrate \
count	2984.000000	2984.000000	2984.000000	2984.000000	2984.000000
mean	3.569370	6.130027	5.962802	331.929960	0.050938
std	3.121285	5.198041	4.517217	169.616566	0.219909
min	0.000000	0.000000	0.000000	3.000000	0.000000
25%	1.000000	2.000000	3.000000	212.000000	0.000000
50%	3.000000	5.000000	5.000000	300.000000	0.000000
75%	5.000000	8.000000	8.000000	414.000000	0.000000
max	26.000000	44.000000	35.000000	1707.000000	1.000000

	Desire	Explore	Fun	Hope	Love \
count	2984.000000	2984.000000	2984.000000	2984.000000	2984.000000
mean	0.077748	0.173257	0.052279	0.240617	0.143767
std	0.267819	0.378533	0.222626	0.427530	0.350912
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	Nostalgia	Thug	Popu_max	Top10_dummy	Top50_dummy
count	2984.000000	2984.000000	5232.000000	5232.000000	5232.000000
mean	0.066354	0.195040	94.712920	0.051797	0.274083

```
std        0.248941     0.396298     57.484207     0.221637     0.446093
min        0.000000     0.000000      1.000000     0.000000     0.000000
25%        0.000000     0.000000     46.000000     0.000000     0.000000
50%        0.000000     0.000000     91.000000     0.000000     0.000000
75%        0.000000     0.000000    143.000000     0.000000     1.000000
max        1.000000     1.000000    200.000000     1.000000     1.000000
```

[ ]:
```
# Descriptive Statistics for the USA segment
usaDat.describe()
```

[ ]:
```
         Popularity  Artist_followers  Track_number  Tracks_in_album  \
count   6437.000000      6.437000e+03   6437.000000      6437.000000
mean    2353.953208      9.561874e+06      5.285226        11.402206
std     4834.307276      1.198242e+07      5.143864         9.447639
min        0.800000      1.200000e+01      1.000000         1.000000
25%       73.600000      2.374492e+06      1.000000         1.000000
50%      340.000000      5.177309e+06      3.000000        13.000000
75%     1890.100000      1.144079e+07      8.000000        16.000000
max    29097.450000      7.178310e+07     76.000000       349.000000

       danceability       energy          key     loudness    trackMode  \
count   6437.000000  6437.000000  6437.000000  6437.000000  6437.000000
mean       0.676263     0.619871     5.183937    -6.736003     0.600280
std        0.150422     0.168739     3.668780     2.663256     0.489879
min        0.125000     0.005430     0.000000   -34.475000     0.000000
25%        0.578000     0.515000     1.000000    -7.909000     0.000000
50%        0.689000     0.633000     5.000000    -6.285000     1.000000
75%        0.787000     0.741000     8.000000    -4.976000     1.000000
max        0.980000     0.996000    11.000000     0.175000     1.000000

       speechiness   acoustics  instrumentalness   liveliness      valence  \
count  6437.000000  6437.000000       6437.000000  6437.000000  6437.000000
mean      0.149964     0.220258          0.013990     0.182406     0.458003
std       0.131850     0.243991          0.086168     0.137415     0.219410
min       0.022900     0.000002          0.000000     0.021500     0.026200
25%       0.047000     0.035100          0.000000     0.099500     0.284000
50%       0.093000     0.126000          0.000000     0.126000     0.450000
75%       0.230000     0.323000          0.000023     0.219000     0.620000
max       0.966000     0.994000          0.960000     0.963000     0.982000

             tempo    duration_ms  Days_since_release  Released_after_2017  \
count  6437.000000    6437.000000         6352.000000          6352.000000
mean    122.287746  204638.707783         1259.876889             0.885233
std      29.849923   53849.743200         2683.506858             0.318766
min      45.780000   30133.000000            9.000000             0.000000
25%      97.020000  174358.000000          365.000000             1.000000
50%     122.011000  200594.000000          744.000000             1.000000
75%     144.065000  228707.000000         1142.000000             1.000000
```

```
max     212.058000  943529.000000       28798.000000            1.000000

             album  compilation       single  bolero     boy band  \
count  6437.000000  6437.000000  6437.000000  6437.0  6437.000000
mean      0.679820     0.008389     0.311791     0.0     0.016001
std       0.466582     0.091214     0.463261     0.0     0.125490
min       0.000000     0.000000     0.000000     0.0     0.000000
25%       0.000000     0.000000     0.000000     0.0     0.000000
50%       1.000000     0.000000     0.000000     0.0     0.000000
75%       1.000000     0.000000     1.000000     0.0     0.000000
max       1.000000     1.000000     1.000000     0.0     1.000000

           country  danceElectronic         else         funk      hip hop  \
count  6437.000000      6437.000000  6437.000000  6437.000000  6437.000000
mean      0.036042         0.023303     0.028119     0.002175     0.297654
std       0.186408         0.150875     0.165325     0.046589     0.457262
min       0.000000         0.000000     0.000000     0.000000     0.000000
25%       0.000000         0.000000     0.000000     0.000000     0.000000
50%       0.000000         0.000000     0.000000     0.000000     0.000000
75%       0.000000         0.000000     0.000000     0.000000     1.000000
max       1.000000         1.000000     1.000000     1.000000     1.000000

             house       indie         jazz        k-pop        latin  \
count  6437.000000  6437.000000  6437.000000  6437.000000  6437.000000
mean      0.013982     0.008700     0.000155     0.015535     0.023769
std       0.117424     0.092873     0.012464     0.123678     0.152340
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

             metal     opm          pop     r&b/soul          rap  \
count  6437.000000  6437.0  6437.000000  6437.000000  6437.000000
mean      0.010875     0.0     0.270157     0.038061     0.172285
std       0.103721     0.0     0.444075     0.191359     0.377657
min       0.000000     0.0     0.000000     0.000000     0.000000
25%       0.000000     0.0     0.000000     0.000000     0.000000
50%       0.000000     0.0     0.000000     0.000000     0.000000
75%       0.000000     0.0     1.000000     0.000000     0.000000
max       1.000000     0.0     1.000000     1.000000     1.000000

            reggae    reggaeton         rock         trap     nrc_norm  \
count  6437.000000  6437.000000  6437.000000  6437.000000  4363.000000
mean      0.000311     0.001554     0.033090     0.008234    -0.030484
std       0.017625     0.039387     0.178885     0.090372     0.931755
min       0.000000     0.000000     0.000000     0.000000    -1.000000
```

25%	0.000000	0.000000	0.000000	0.000000	-1.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	syuzhet	bing	afinn	nrc	anger \
count	4363.000000	4363.000000	4363.00000	4363.000000	4363.000000
mean	-0.498602	-1.672473	-5.24639	-0.299106	3.468943
std	3.531078	4.349078	12.49253	4.089683	3.299665
min	-22.500000	-31.000000	-70.00000	-25.000000	0.000000
25%	-2.350000	-4.000000	-12.00000	-3.000000	1.000000
50%	-0.150000	-1.000000	-2.00000	0.000000	3.000000
75%	1.650000	1.000000	3.00000	2.000000	5.000000
max	12.100000	13.000000	26.00000	18.000000	25.000000

	anticipation	disgust	fear	joy	sadness \
count	4363.000000	4363.000000	4363.000000	4363.000000	4363.000000
mean	3.578730	2.413477	3.576209	3.548247	3.207426
std	2.790142	2.393350	3.351808	2.613082	2.748068
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2.000000	1.000000	1.000000	2.000000	1.000000
50%	3.000000	2.000000	3.000000	3.000000	3.000000
75%	5.000000	4.000000	5.000000	5.000000	4.000000
max	19.000000	17.000000	28.000000	21.000000	24.000000

	surprise	trust	negative	positive	n_words \
count	4363.000000	4363.000000	4363.000000	4363.000000	4363.000000
mean	2.165482	3.804492	6.572771	6.273665	340.372221
std	1.902273	3.262975	5.413520	4.700065	171.100087
min	0.000000	0.000000	0.000000	0.000000	3.000000
25%	1.000000	1.000000	3.000000	3.000000	216.000000
50%	2.000000	3.000000	5.000000	5.000000	310.000000
75%	3.000000	5.000000	9.000000	9.000000	431.000000
max	14.000000	26.000000	44.000000	45.000000	1707.000000

	Celebrate	Desire	Explore	Fun	Hope \
count	4363.000000	4363.000000	4363.000000	4363.000000	4363.000000
mean	0.038964	0.074948	0.171442	0.046069	0.228742
std	0.193531	0.263338	0.376938	0.209659	0.420071
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	Love	Nostalgia	Thug	Popu_max	Top10_dummy \
count	4363.000000	4363.000000	4363.000000	6437.000000	6437.000000

```
mean     0.123539     0.078157     0.238139    86.798509     0.082958
std      0.329092     0.268450     0.425993    58.103709     0.275840
min      0.000000     0.000000     0.000000     1.000000     0.000000
25%      0.000000     0.000000     0.000000    36.000000     0.000000
50%      0.000000     0.000000     0.000000    79.000000     0.000000
75%      0.000000     0.000000     0.000000   136.000000     0.000000
max      1.000000     1.000000     1.000000   200.000000     1.000000

       Top50_dummy
count  6437.000000
mean      0.329657
std       0.470125
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
max       1.000000
```

[ ]:
```python
# Descriptive Statistics for the Finland segment
finlandDat.describe()
```

[ ]:
```
         Popularity  Artist_followers  Track_number  Tracks_in_album  \
count   6597.000000      6.595000e+03   6597.000000      6597.000000
mean    2788.186426      6.152822e+06      3.409732         7.095801
std     5272.758521      1.202754e+07      3.966611         7.221370
min        0.800000      0.000000e+00      1.000000         1.000000
25%       72.000000      1.476300e+04      1.000000         1.000000
50%      422.200000      1.338760e+05      1.000000         3.000000
75%     2690.450000      6.170158e+06      5.000000        12.000000
max    29210.950000      7.178310e+07     41.000000       100.000000

       danceability       energy          key     loudness    trackMode  \
count   6597.000000  6597.000000  6597.000000  6597.000000  6597.000000
mean       0.643373     0.671831     5.284978    -6.511686     0.532666
std        0.145042     0.177448     3.634454     2.518634     0.498970
min        0.062800     0.005430     0.000000   -26.956000     0.000000
25%        0.553000     0.569000     2.000000    -7.528000     0.000000
50%        0.657000     0.691000     5.000000    -6.068000     1.000000
75%        0.747000     0.801000     8.000000    -4.897000     1.000000
max        0.974000     0.999000    11.000000     0.175000     1.000000

       speechiness   acoustics  instrumentalness   liveliness      valence  \
count  6597.000000 6597.000000       6597.000000  6597.000000  6597.000000
mean      0.100014    0.187159          0.024550     0.186028     0.489976
std       0.095042    0.229932          0.118973     0.139018     0.224135
min       0.023100    0.000004          0.000000     0.013800     0.026200
25%       0.039600    0.021500          0.000000     0.097700     0.319000
50%       0.059700    0.090200          0.000000     0.131000     0.481000
```

75%	0.121000	0.266000	0.000133	0.241000	0.659000
max	0.966000	0.995000	0.987000	0.988000	0.978000

	tempo	duration_ms	Days_since_release	Released_after_2017	\
count	6597.000000	6597.000000	6479.000000	6479.000000	
mean	121.734349	206163.283614	1165.744096	0.863251	
std	28.273975	48101.999332	2012.356572	0.343609	
min	45.529000	30133.000000	15.000000	0.000000	
25%	99.946000	180953.000000	386.500000	1.000000	
50%	120.056000	202206.000000	778.000000	1.000000	
75%	140.020000	225021.000000	1191.000000	1.000000	
max	216.334000	943529.000000	28798.000000	1.000000	

	album	compilation	single	bolero	boy band	\
count	6597.000000	6597.000000	6597.000000	6597.0	6597.000000	
mean	0.451114	0.013491	0.535395	0.0	0.007428	
std	0.497642	0.115373	0.498783	0.0	0.085869	
min	0.000000	0.000000	0.000000	0.0	0.000000	
25%	0.000000	0.000000	0.000000	0.0	0.000000	
50%	0.000000	0.000000	1.000000	0.0	0.000000	
75%	1.000000	0.000000	1.000000	0.0	0.000000	
max	1.000000	1.000000	1.000000	0.0	1.000000	

	country	danceElectronic	else	funk	hip hop	\
count	6597.000000	6597.000000	6597.000000	6597.000000	6597.000000	
mean	0.000455	0.026376	0.077611	0.000758	0.083371	
std	0.021322	0.160262	0.267579	0.027522	0.276463	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	house	indie	jazz	k-pop	latin	\
count	6597.000000	6597.000000	6597.000000	6597.000000	6597.000000	
mean	0.033500	0.020312	0.000455	0.010005	0.003486	
std	0.179952	0.141077	0.021322	0.099529	0.058947	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	metal	opm	pop	r&b/soul	rap	\
count	6597.000000	6597.0	6597.000000	6597.000000	6597.000000	
mean	0.056844	0.0	0.558587	0.014855	0.066849	
std	0.231562	0.0	0.496593	0.120983	0.249778	

```
min       0.000000     0.0     0.000000     0.000000     0.000000
25%       0.000000     0.0     0.000000     0.000000     0.000000
50%       0.000000     0.0     1.000000     0.000000     0.000000
75%       0.000000     0.0     1.000000     0.000000     0.000000
max       1.000000     0.0     1.000000     1.000000     1.000000

            reggae    reggaeton         rock         trap     nrc_norm  \
count  6597.000000  6597.000000  6597.000000  6597.000000  2079.000000
mean      0.000455     0.000152     0.035016     0.003486    -0.004329
std       0.021322     0.012312     0.183834     0.058947     0.922649
min       0.000000     0.000000     0.000000     0.000000    -1.000000
25%       0.000000     0.000000     0.000000     0.000000    -1.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     1.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

           syuzhet         bing        afinn          nrc        anger  \
count  2079.000000  2079.000000  2079.000000  2079.000000  2079.000000
mean     -0.181818    -1.308321    -2.927369    -0.132275     2.873978
std       3.410808     4.246573    11.052679     3.978686     2.955638
min     -19.950000   -31.000000   -63.000000   -23.000000     0.000000
25%      -1.850000    -3.000000    -7.000000    -2.000000     1.000000
50%       0.100000    -1.000000    -1.000000     0.000000     2.000000
75%       1.850000     1.000000     4.000000     2.000000     4.000000
max      12.100000    11.000000    26.000000    18.000000    22.000000

       anticipation      disgust         fear          joy      sadness  \
count   2079.000000  2079.000000  2079.000000  2079.000000  2079.000000
mean       3.177489     2.023569     3.088504     3.197210     2.846080
std        2.555025     2.175841     3.059226     2.404394     2.538704
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        1.000000     1.000000     1.000000     1.000000     1.000000
50%        3.000000     1.000000     2.000000     3.000000     2.000000
75%        4.000000     3.000000     4.000000     4.000000     4.000000
max       19.000000    17.000000    28.000000    15.000000    20.000000

          surprise        trust     negative     positive      n_words  \
count  2079.000000  2079.000000  2079.000000  2079.000000  2079.000000
mean      1.909572     3.201058     5.577682     5.445406   312.963444
std       1.674556     2.807761     4.855229     4.151577   157.274931
min       0.000000     0.000000     0.000000     0.000000    30.000000
25%       1.000000     1.000000     2.000000     3.000000   205.000000
50%       2.000000     3.000000     4.000000     4.000000   282.000000
75%       3.000000     4.000000     7.000000     7.000000   386.000000
max      10.000000    20.000000    40.000000    34.000000  1344.000000

         Celebrate       Desire      Explore          Fun         Hope  \
```

count	2079.000000	2079.000000	2079.000000	2079.000000	2079.000000
mean	0.063011	0.081289	0.194324	0.048581	0.247715
std	0.243041	0.273344	0.395775	0.215042	0.431789
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	Love	Nostalgia	Thug	Popu_max	Top10_dummy \
count	2079.000000	2079.000000	2079.000000	6597.000000	6597.000000
mean	0.166426	0.069264	0.129389	88.079278	0.082007
std	0.372552	0.253964	0.335711	57.442179	0.274396
min	0.000000	0.000000	0.000000	1.000000	0.000000
25%	0.000000	0.000000	0.000000	39.000000	0.000000
50%	0.000000	0.000000	0.000000	81.000000	0.000000
75%	0.000000	0.000000	0.000000	136.000000	0.000000
max	1.000000	1.000000	1.000000	200.000000	1.000000

	Top50_dummy
count	6597.000000
mean	0.299530
std	0.458087
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

[ ]:
```
# Descriptive Statistics for the Singapore segment
singaporeDat.describe()
```

[ ]:

	Popularity	Artist_followers	Track_number	Tracks_in_album \
count	3380.000000	3.378000e+03	3379.000000	3379.000000
mean	3393.934615	1.134634e+07	4.014501	9.167209
std	5727.489706	1.418691e+07	4.514705	10.711880
min	0.800000	0.000000e+00	1.000000	1.000000
25%	102.400000	1.416818e+06	1.000000	1.000000
50%	639.550000	5.087482e+06	2.000000	9.000000
75%	3893.912500	1.713281e+07	6.000000	14.000000
max	29263.150000	7.178310e+07	54.000000	349.000000

	danceability	energy	key	loudness	trackMode \
count	3379.000000	3379.000000	3379.000000	3379.000000	3379.000000
mean	0.633497	0.626987	5.191181	-6.400888	0.622078
std	0.143963	0.184445	3.610413	2.677267	0.484940
min	0.125000	0.036700	0.000000	-23.657000	0.000000
25%	0.538000	0.505000	2.000000	-7.640000	0.000000

50%	0.650000	0.642000	5.000000	-5.954000	1.000000
75%	0.735000	0.768000	8.000000	-4.642500	1.000000
max	0.968000	0.995000	11.000000	0.175000	1.000000

	speechiness	acoustics	instrumentalness	liveliness	valence	\
count	3379.000000	3379.000000	3379.000000	3379.000000	3379.000000	
mean	0.090515	0.254537	0.015774	0.177065	0.460929	
std	0.089127	0.268209	0.097406	0.134363	0.217626	
min	0.023300	0.000002	0.000000	0.015100	0.033700	
25%	0.037450	0.039900	0.000000	0.095200	0.285000	
50%	0.054800	0.145000	0.000000	0.124000	0.452000	
75%	0.102000	0.405000	0.000020	0.215500	0.620000	
max	0.966000	0.994000	0.959000	0.988000	0.978000	

	tempo	duration_ms	Days_since_release	Released_after_2017	\
count	3379.000000	3379.000000	3320.000000	3320.000000	
mean	120.213488	209513.197988	1348.186747	0.821084	
std	28.177781	41732.458226	2379.909075	0.383339	
min	46.718000	35240.000000	11.000000	0.000000	
25%	98.196000	185897.000000	435.000000	1.000000	
50%	118.994000	206067.000000	872.500000	1.000000	
75%	139.641500	229549.500000	1276.000000	1.000000	
max	208.225000	526387.000000	28798.000000	1.000000	

	album	compilation	single	bolero	boy band	\
count	3380.000000	3380.000000	3380.000000	3380.0	3380.000000	
mean	0.523373	0.022485	0.453846	0.0	0.023669	
std	0.499527	0.148277	0.497939	0.0	0.152037	
min	0.000000	0.000000	0.000000	0.0	0.000000	
25%	0.000000	0.000000	0.000000	0.0	0.000000	
50%	1.000000	0.000000	0.000000	0.0	0.000000	
75%	1.000000	0.000000	1.000000	0.0	0.000000	
max	1.000000	1.000000	1.000000	0.0	1.000000	

	country	danceElectronic	else	funk	hip hop	\
count	3380.000000	3380.000000	3380.000000	3380.000000	3380.000000	
mean	0.002367	0.026036	0.036982	0.000592	0.078698	
std	0.048600	0.159264	0.188746	0.024322	0.269307	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	house	indie	jazz	k-pop	latin	\
count	3380.000000	3380.000000	3380.000000	3380.000000	3380.000000	
mean	0.035503	0.030178	0.000296	0.145562	0.005325	

```
std        0.185075     0.171101     0.017201     0.352719     0.072792
min        0.000000     0.000000     0.000000     0.000000     0.000000
25%        0.000000     0.000000     0.000000     0.000000     0.000000
50%        0.000000     0.000000     0.000000     0.000000     0.000000
75%        0.000000     0.000000     0.000000     0.000000     0.000000
max        1.000000     1.000000     1.000000     1.000000     1.000000

             metal     opm          pop    r&b/soul          rap  reggae  \
count  3380.000000  3380.0  3380.000000  3380.000000  3380.000000  3380.0
mean      0.014497     0.0     0.464497     0.039053     0.061243     0.0
std       0.119545     0.0     0.498812     0.193750     0.239810     0.0
min       0.000000     0.0     0.000000     0.000000     0.000000     0.0
25%       0.000000     0.0     0.000000     0.000000     0.000000     0.0
50%       0.000000     0.0     0.000000     0.000000     0.000000     0.0
75%       0.000000     0.0     1.000000     0.000000     0.000000     0.0
max       1.000000     0.0     1.000000     1.000000     1.000000     0.0

         reggaeton         rock         trap     nrc_norm      syuzhet  \
count  3380.000000  3380.000000  3380.000000  1851.000000  1851.000000
mean      0.000296     0.034320     0.000888    -0.001621     0.140005
std       0.017201     0.182076     0.029783     0.922100     3.028486
min       0.000000     0.000000     0.000000    -1.000000   -19.650000
25%       0.000000     0.000000     0.000000    -1.000000    -1.500000
50%       0.000000     0.000000     0.000000     0.000000     0.300000
75%       0.000000     0.000000     0.000000     1.000000     1.950000
max       1.000000     1.000000     1.000000     1.000000    10.100000

              bing        afinn          nrc        anger  anticipation  \
count  1851.000000  1851.000000  1851.000000  1851.000000   1851.000000
mean     -0.866559    -1.372771     0.033495     2.488385      2.882766
std       3.878983     9.516779     3.630496     2.631668      2.326761
min     -31.000000   -63.000000   -20.000000     0.000000      0.000000
25%      -3.000000    -5.000000    -2.000000     1.000000      1.000000
50%      -1.000000     0.000000     0.000000     2.000000      2.000000
75%       1.000000     4.000000     2.000000     3.000000      4.000000
max      11.000000    26.000000    18.000000    18.000000     19.000000

           disgust         fear          joy      sadness     surprise  \
count  1851.000000  1851.000000  1851.000000  1851.000000  1851.000000
mean      1.733117     2.701783     2.994598     2.567261     1.712588
std       1.995693     2.743187     2.264646     2.350201     1.544143
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     1.000000     1.000000     1.000000     1.000000
50%       1.000000     2.000000     3.000000     2.000000     1.000000
75%       2.000000     4.000000     4.000000     4.000000     2.000000
max      17.000000    28.000000    14.000000    18.000000     9.000000
```

	trust	negative	positive	n_words	Celebrate
count	1851.000000	1851.000000	1851.000000	1851.000000	1851.000000
mean	2.889249	4.947596	4.981091	302.684495	0.067531
std	2.486536	4.350205	3.739514	150.385267	0.251007
min	0.000000	0.000000	0.000000	3.000000	0.000000
25%	1.000000	2.000000	2.000000	203.000000	0.000000
50%	2.000000	4.000000	4.000000	276.000000	0.000000
75%	4.000000	7.000000	7.000000	362.500000	0.000000
max	17.000000	40.000000	25.000000	1344.000000	1.000000

	Desire	Explore	Fun	Hope	Love
count	1851.000000	1851.000000	1851.000000	1851.000000	1851.000000
mean	0.085359	0.188006	0.042680	0.297137	0.179363
std	0.279491	0.390823	0.202188	0.457121	0.383759
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	1.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	Nostalgia	Thug	Popu_max	Top10_dummy	Top50_dummy
count	1851.000000	1851.000000	3380.000000	3380.000000	3380.000000
mean	0.055646	0.084279	94.173964	0.052663	0.279586
std	0.229298	0.277881	57.887272	0.223392	0.448862
min	0.000000	0.000000	1.000000	0.000000	0.000000
25%	0.000000	0.000000	43.750000	0.000000	0.000000
50%	0.000000	0.000000	91.000000	0.000000	0.000000
75%	0.000000	0.000000	144.000000	0.000000	1.000000
max	1.000000	1.000000	200.000000	1.000000	1.000000

[ ]:
```
# Descriptive Statistics for the New Zealand segment
newZealandDat.describe()
```

[ ]:

	Popularity	Artist_followers	Track_number	Tracks_in_album
count	3330.000000	3.330000e+03	3330.000000	3330.000000
mean	3689.195676	1.197809e+07	4.697898	10.615916
std	6155.711812	1.455671e+07	4.820605	8.888207
min	0.800000	4.000000e+01	1.000000	1.000000
25%	121.600000	1.733956e+06	1.000000	1.000000
50%	753.700000	5.910376e+06	3.000000	12.000000
75%	3988.875000	1.693157e+07	7.000000	16.000000
max	29160.200000	7.178310e+07	54.000000	131.000000

	danceability	energy	key	loudness	trackMode
count	3330.000000	3330.000000	3330.000000	3330.000000	3330.000000
mean	0.658583	0.618444	5.159459	-6.841457	0.602402
std	0.149349	0.174097	3.665756	2.786117	0.489475
min	0.151000	0.012900	0.000000	-34.475000	0.000000

25%	0.570000	0.508000	1.000000	-8.060500	0.000000
50%	0.672000	0.634000	5.000000	-6.354000	1.000000
75%	0.761000	0.744000	8.000000	-5.027750	1.000000
max	0.974000	0.993000	11.000000	1.634000	1.000000

	speechiness	acoustics	instrumentalness	liveliness	valence \
count	3330.000000	3330.000000	3330.000000	3330.000000	3330.000000
mean	0.123437	0.228744	0.017537	0.180313	0.466307
std	0.120758	0.250149	0.097172	0.136712	0.219035
min	0.023100	0.000018	0.000000	0.021900	0.026200
25%	0.042225	0.034225	0.000000	0.096800	0.297000
50%	0.067500	0.129500	0.000000	0.124000	0.458000
75%	0.170000	0.344000	0.000060	0.220000	0.625000
max	0.966000	0.995000	0.956000	0.944000	0.982000

	tempo	duration_ms	Days_since_release	Released_after_2017 \
count	3330.000000	3330.000000	3243.000000	3243.000000
mean	120.569568	209258.564565	1768.914277	0.791551
std	29.198042	55429.153631	3277.131840	0.406262
min	45.780000	30133.000000	11.000000	0.000000
25%	97.956750	179405.000000	463.000000	1.000000
50%	119.628500	204737.000000	884.000000	1.000000
75%	140.092750	232553.250000	1307.000000	1.000000
max	207.476000	943529.000000	28798.000000	1.000000

	album	compilation	single	bolero	boy band \
count	3330.000000	3330.000000	3330.000000	3330.0	3330.000000
mean	0.634835	0.014715	0.350450	0.0	0.021922
std	0.481549	0.120427	0.477183	0.0	0.146451
min	0.000000	0.000000	0.000000	0.0	0.000000
25%	0.000000	0.000000	0.000000	0.0	0.000000
50%	1.000000	0.000000	0.000000	0.0	0.000000
75%	1.000000	0.000000	1.000000	0.0	0.000000
max	1.000000	1.000000	1.000000	0.0	1.000000

	country	danceElectronic	else	funk	hip hop \
count	3330.000000	3330.000000	3330.000000	3330.000000	3330.000000
mean	0.003604	0.033033	0.038138	0.004505	0.180480
std	0.059931	0.178750	0.191558	0.066974	0.384645
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

	house	indie	jazz	k-pop	latin \
count	3330.000000	3330.000000	3330.0	3330.000000	3330.000000

mean	0.018919	0.012913	0.0	0.021021	0.003003
std	0.136259	0.112916	0.0	0.143476	0.054726
min	0.000000	0.000000	0.0	0.000000	0.000000
25%	0.000000	0.000000	0.0	0.000000	0.000000
50%	0.000000	0.000000	0.0	0.000000	0.000000
75%	0.000000	0.000000	0.0	0.000000	0.000000
max	1.000000	1.000000	0.0	1.000000	1.000000

	metal	opm	pop	r&b/soul	rap \
count	3330.000000	3330.0	3330.000000	3330.000000	3330.000000
mean	0.022823	0.0	0.394294	0.043243	0.128228
std	0.149361	0.0	0.488772	0.203435	0.334394
min	0.000000	0.0	0.000000	0.000000	0.000000
25%	0.000000	0.0	0.000000	0.000000	0.000000
50%	0.000000	0.0	0.000000	0.000000	0.000000
75%	0.000000	0.0	1.000000	0.000000	0.000000
max	1.000000	0.0	1.000000	1.000000	1.000000

	reggae	reggaeton	rock	trap	nrc_norm \
count	3330.000000	3330.0	3330.000000	3330.000000	2340.000000
mean	0.009009	0.0	0.050751	0.014114	0.012821
std	0.094501	0.0	0.219521	0.117979	0.926918
min	0.000000	0.0	0.000000	0.000000	-1.000000
25%	0.000000	0.0	0.000000	0.000000	-1.000000
50%	0.000000	0.0	0.000000	0.000000	0.000000
75%	0.000000	0.0	0.000000	0.000000	1.000000
max	1.000000	0.0	1.000000	1.000000	1.000000

	syuzhet	bing	afinn	nrc	anger \
count	2340.000000	2340.000000	2340.000000	2340.000000	2340.000000
mean	-0.125342	-1.263675	-3.115385	-0.054701	2.938034
std	3.312103	4.236909	11.186377	3.963547	3.035349
min	-19.650000	-31.000000	-63.000000	-18.000000	0.000000
25%	-1.800000	-3.000000	-7.250000	-2.000000	1.000000
50%	0.050000	-1.000000	-1.000000	0.000000	2.000000
75%	1.850000	1.000000	4.000000	2.000000	4.000000
max	10.100000	11.000000	26.000000	18.000000	25.000000

	anticipation	disgust	fear	joy	sadness \
count	2340.000000	2340.000000	2340.000000	2340.000000	2340.000000
mean	3.245726	2.058547	3.112821	3.291026	2.871368
std	2.557731	2.266451	3.052779	2.445368	2.622646
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	1.000000	2.000000	1.000000
50%	3.000000	1.000000	2.000000	3.000000	2.000000
75%	4.000000	3.000000	4.000000	5.000000	4.000000
max	19.000000	17.000000	28.000000	15.000000	24.000000

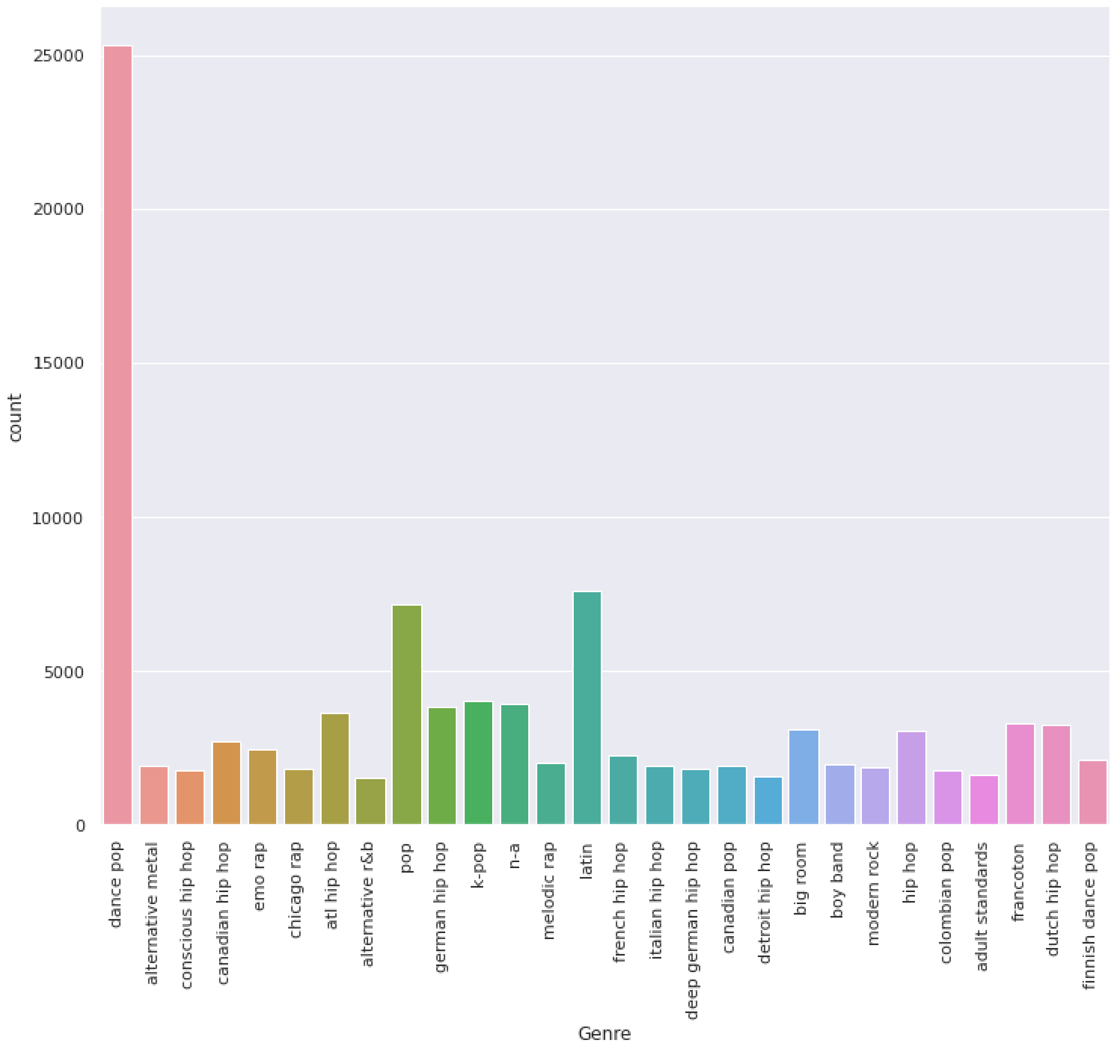
```
        surprise        trust     negative     positive      n_words  \
count  2340.000000  2340.000000  2340.000000  2340.000000  2340.000000
mean      1.959402     3.370085     5.739316     5.684615   317.824786
std       1.702191     2.950606     5.058486     4.280725   161.974159
min       0.000000     0.000000     0.000000     0.000000     3.000000
25%       1.000000     1.000000     2.000000     3.000000   205.000000
50%       2.000000     3.000000     4.000000     5.000000   285.500000
75%       3.000000     5.000000     8.000000     8.000000   390.000000
max      10.000000    23.000000    44.000000    29.000000  1344.000000

         Celebrate       Desire      Explore          Fun         Hope  \
count  2340.000000  2340.000000  2340.000000  2340.000000  2340.000000
mean      0.062393     0.080342     0.197863     0.050427     0.241453
std       0.241920     0.271880     0.398474     0.218872     0.428056
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

              Love    Nostalgia         Thug     Popu_max  Top10_dummy  \
count  2340.000000  2340.000000  2340.000000  3330.000000  3330.000000
mean      0.154274     0.067521     0.145726    90.782282     0.050751
std       0.361288     0.250976     0.352907    55.977512     0.219521
min       0.000000     0.000000     0.000000     1.000000     0.000000
25%       0.000000     0.000000     0.000000    45.000000     0.000000
50%       0.000000     0.000000     0.000000    84.000000     0.000000
75%       0.000000     0.000000     0.000000   137.000000     0.000000
max       1.000000     1.000000     1.000000   200.000000     1.000000

       Top50_dummy
count  3330.000000
mean      0.278378
std       0.448268
min       0.000000
25%       0.000000
50%       0.000000
75%       1.000000
max       1.000000
```

Additionally we examined the Genres for each of the country subsets. Specifically, it was important to see how genres were distributed. We made two observations.

- In most subsets 'dance pop' makes up a significant percentage of the observations
- Genres can be so specific that common genres like "hip hop" are separated into multiple genres (e.g. concious hip hop, Canadian hip hop, Atlanta hip hop).

[ ]:
```
# Filter out genres with less than 1500 observations
finalDatGenreCT = noDummies.groupby("Genre").filter(lambda x: len(x) > 1500)

finalDatGenreCT['Genre'] = finalDatGenreCT.Genre.astype(str)

# Genre bar chart
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = finalDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

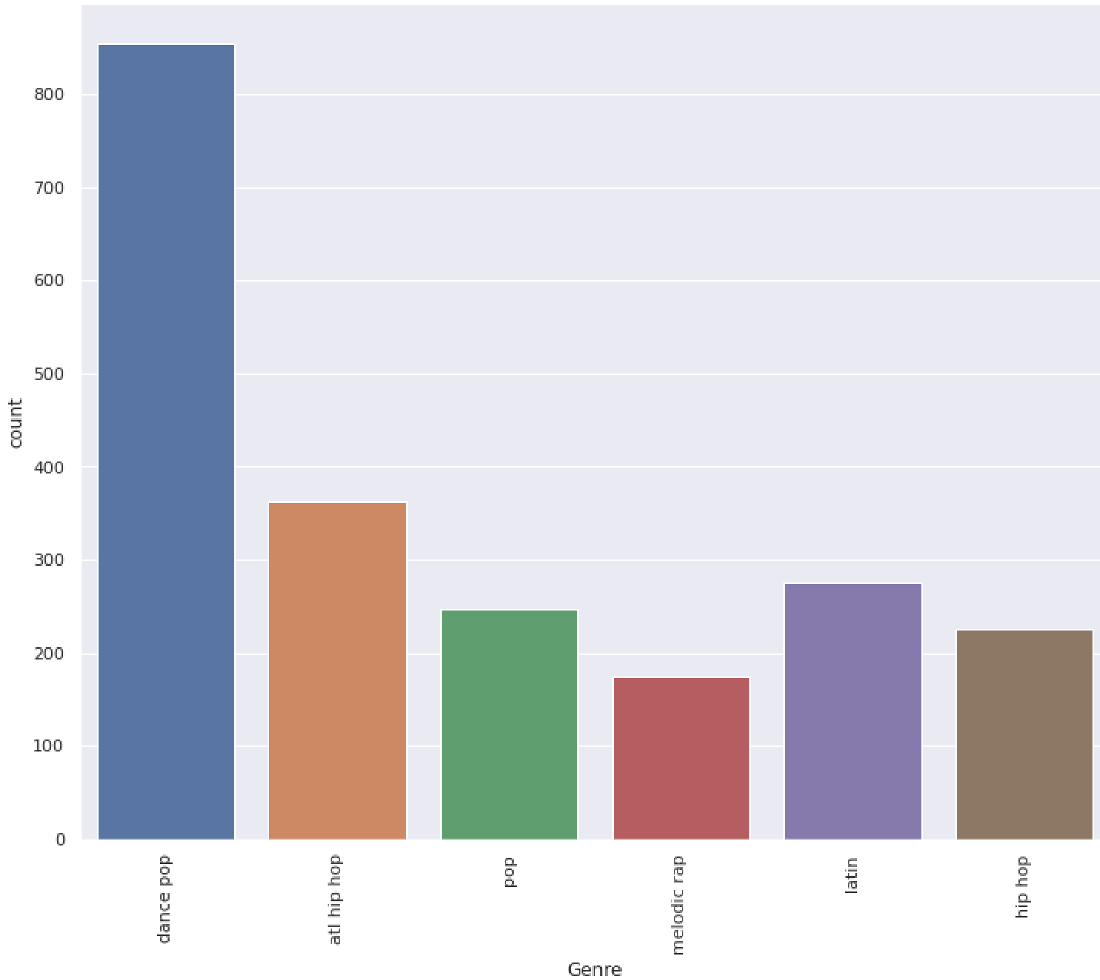
[ ]:
```
[Text(0, 0, 'dance pop'),
 Text(0, 0, 'alternative metal'),
 Text(0, 0, 'conscious hip hop'),
 Text(0, 0, 'canadian hip hop'),
 Text(0, 0, 'emo rap'),
 Text(0, 0, 'chicago rap'),
 Text(0, 0, 'atl hip hop'),
 Text(0, 0, 'alternative r&b'),
 Text(0, 0, 'pop'),
 Text(0, 0, 'german hip hop'),
 Text(0, 0, 'k-pop'),
 Text(0, 0, 'n-a'),
 Text(0, 0, 'melodic rap'),
 Text(0, 0, 'latin'),
 Text(0, 0, 'french hip hop'),
 Text(0, 0, 'italian hip hop'),
 Text(0, 0, 'deep german hip hop'),
 Text(0, 0, 'canadian pop'),
 Text(0, 0, 'detroit hip hop'),
 Text(0, 0, 'big room'),
 Text(0, 0, 'boy band'),
 Text(0, 0, 'modern rock'),
 Text(0, 0, 'hip hop'),
 Text(0, 0, 'colombian pop'),
 Text(0, 0, 'adult standards'),
 Text(0, 0, 'francoton'),
 Text(0, 0, 'dutch hip hop'),
 Text(0, 0, 'finnish dance pop')]
```



[ ]:
```python
# Filter out genres with less than 150 observations
globalDatGenreCT = globalDat.groupby("Genre").filter(lambda x: len(x) > 150)

globalDatGenreCT['Genre'] = globalDatGenreCT.Genre.astype(str)

# Genre bar chart
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = globalDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

[ ]:
```
[Text(0, 0, 'dance pop'),
 Text(0, 0, 'atl hip hop'),
 Text(0, 0, 'pop'),
 Text(0, 0, 'melodic rap'),
 Text(0, 0, 'latin'),
```

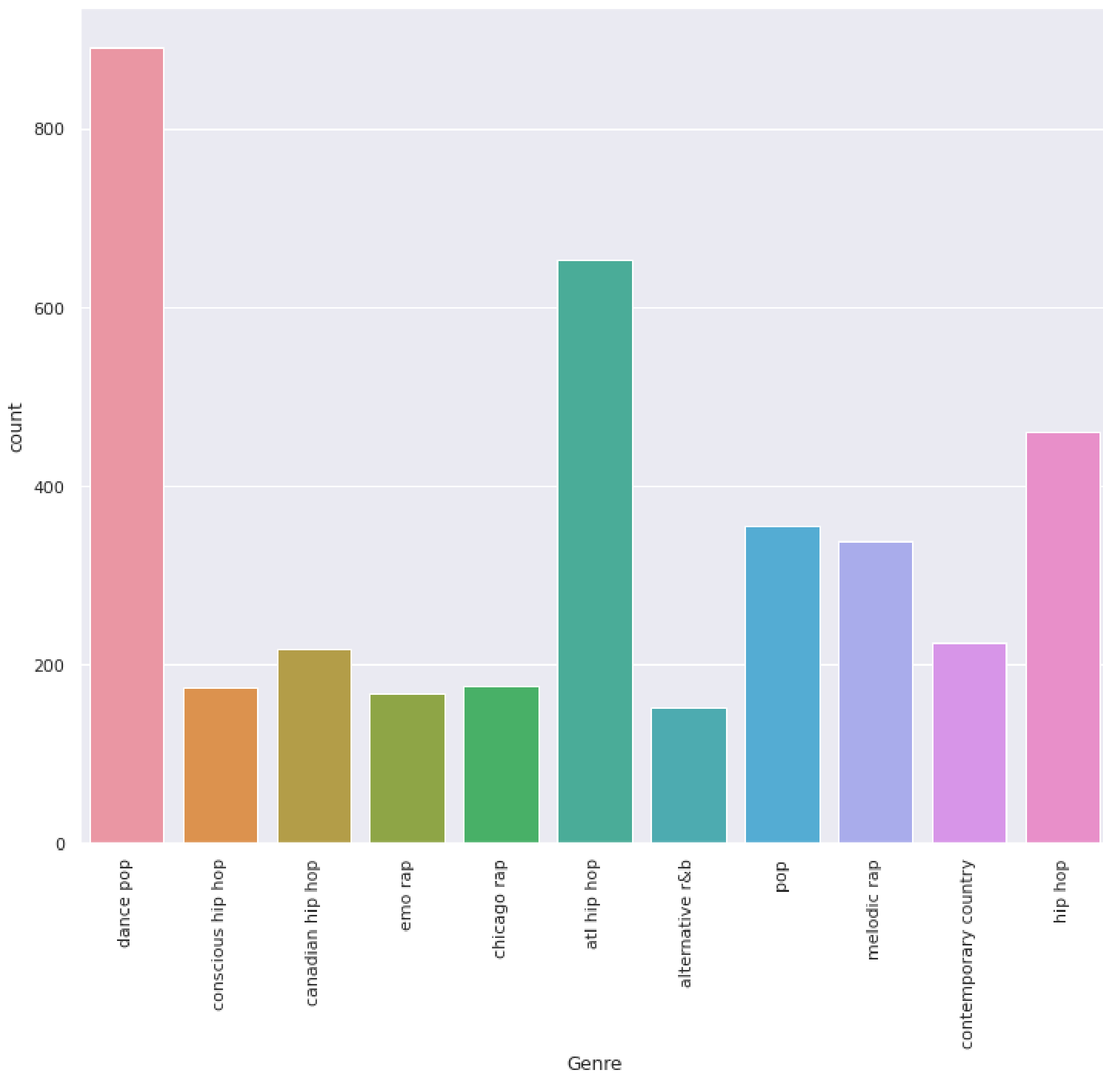
```
Text(0, 0, 'hip hop')]
```



[ ]:
```python
# Filter out genres with less than 150 observations
usaDatGenreCT = usaDat.groupby("Genre").filter(lambda x: len(x) > 150)

usaDatGenreCT['Genre'] = usaDatGenreCT.Genre.astype(str)

# Genre bar chart
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = usaDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

[ ]:
```
[Text(0, 0, 'dance pop'),
 Text(0, 0, 'conscious hip hop'),
 Text(0, 0, 'canadian hip hop'),
 Text(0, 0, 'emo rap'),
```

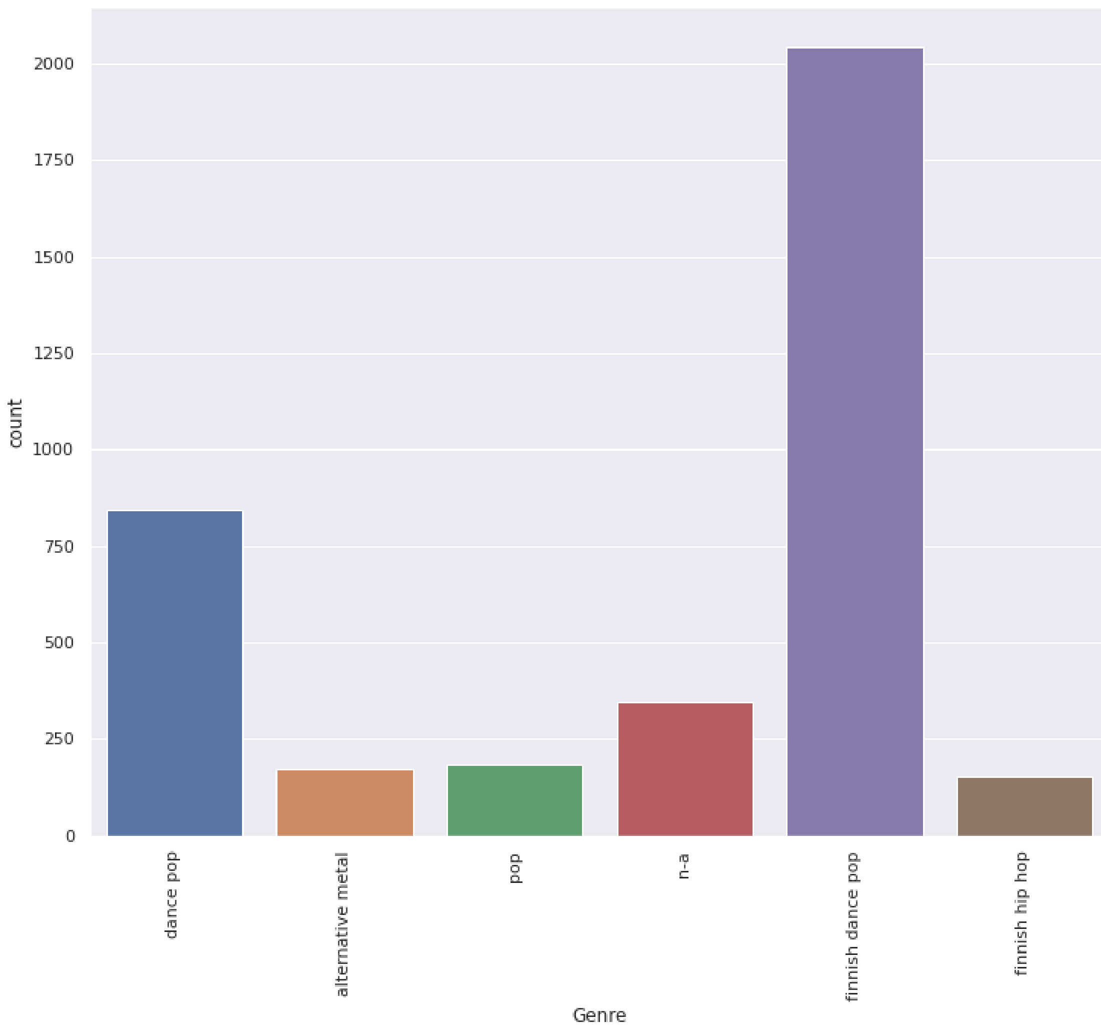
```
 Text(0, 0, 'chicago rap'),
 Text(0, 0, 'atl hip hop'),
 Text(0, 0, 'alternative r&b'),
 Text(0, 0, 'pop'),
 Text(0, 0, 'melodic rap'),
 Text(0, 0, 'contemporary country'),
 Text(0, 0, 'hip hop')]
```



[ ]:
```python
# Filter out genres with less than 150 observations
finlandDatGenreCT = finlandDat.groupby("Genre").filter(lambda x: len(x) > 150)

finlandDatGenreCT['Genre'] = finlandDatGenreCT.Genre.astype(str)

# Genre bar chart
```

```
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = finlandDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

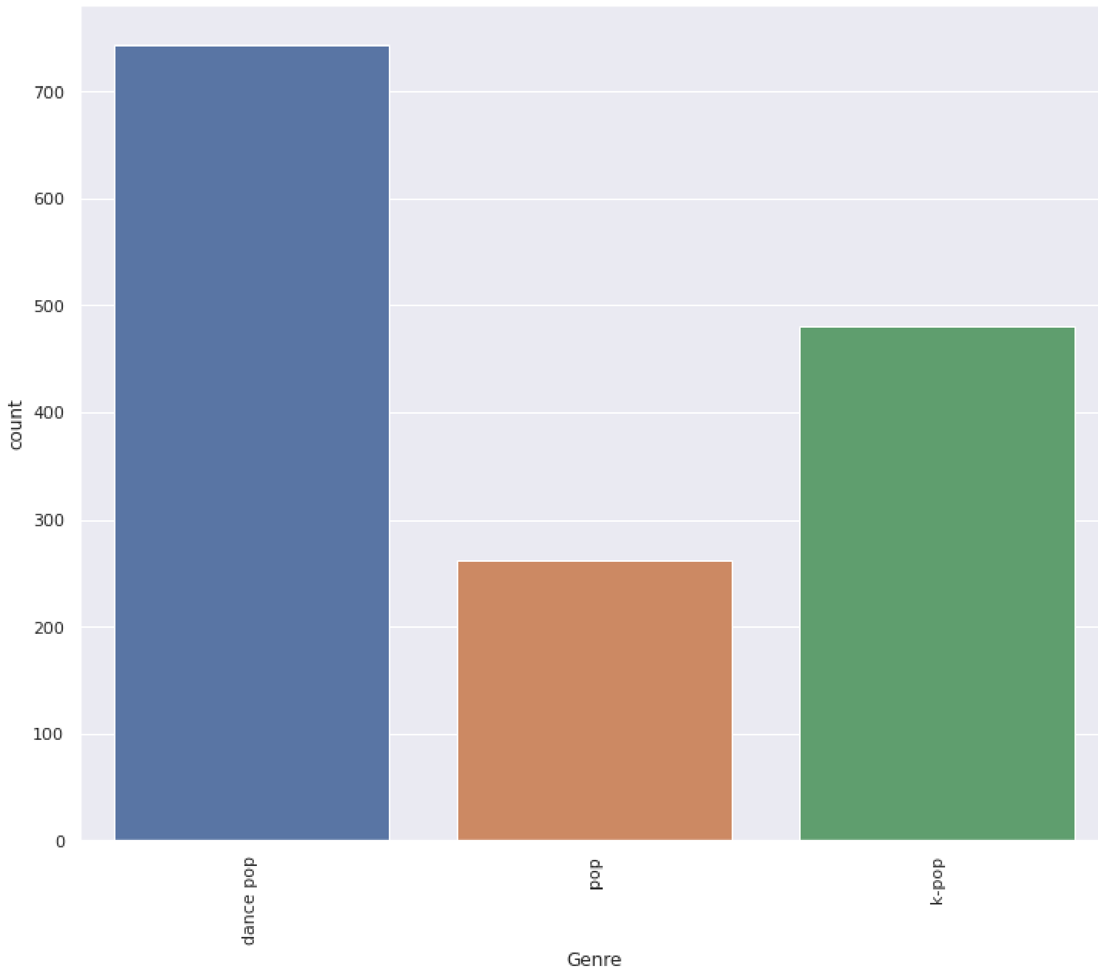
[ ]:
```
[Text(0, 0, 'dance pop'),
 Text(0, 0, 'alternative metal'),
 Text(0, 0, 'pop'),
 Text(0, 0, 'n-a'),
 Text(0, 0, 'finnish dance pop'),
 Text(0, 0, 'finnish hip hop')]
```



[ ]:
```
# Filter out genres with less than 150 observations
singaporeDatGenreCT = singaporeDat.groupby("Genre").filter(lambda x: len(x) >
 ↪150)
```

```
singaporeDatGenreCT['Genre'] = singaporeDatGenreCT.Genre.astype(str)

# Genre bar chart
fig, ax = plt.subplots(figsize=(12, 10))
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = singaporeDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

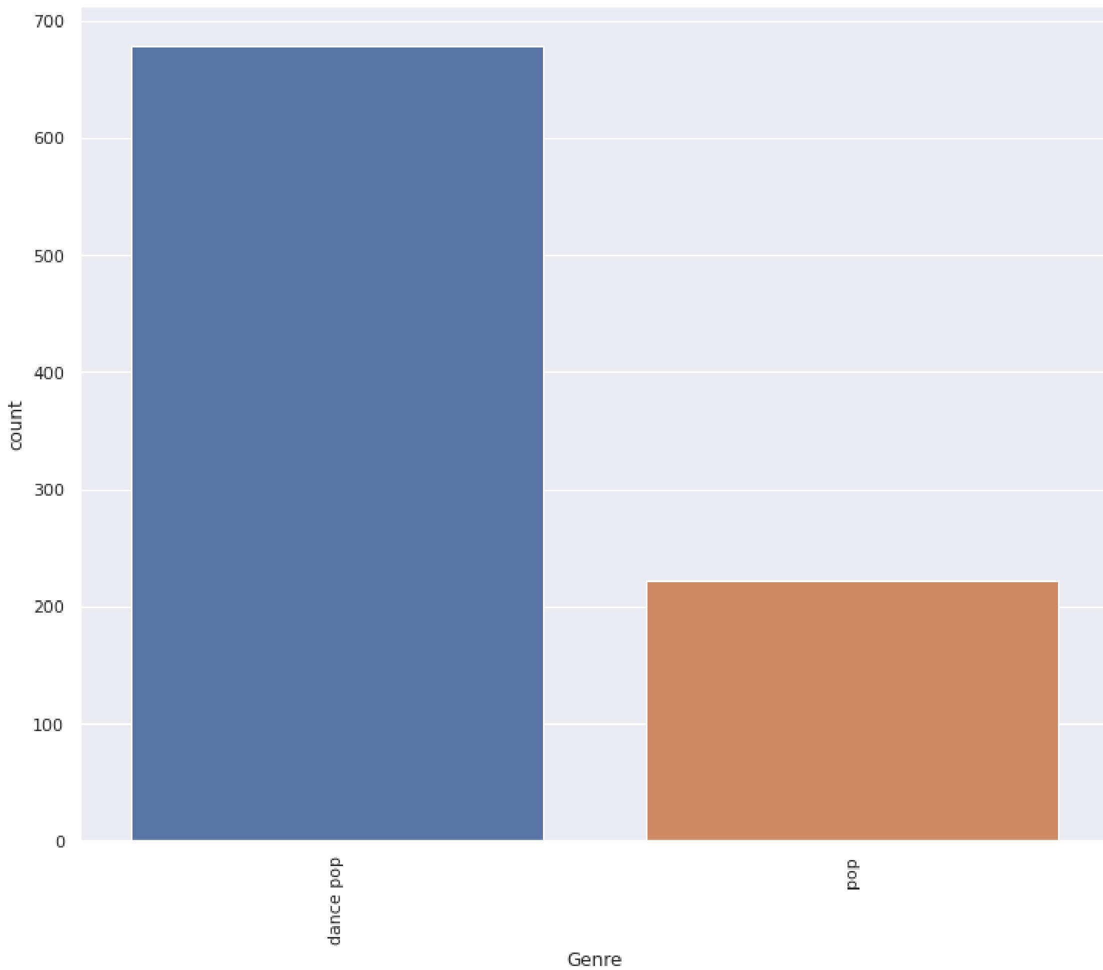
[ ]: [Text(0, 0, 'dance pop'), Text(0, 0, 'pop'), Text(0, 0, 'k-pop')]



[ ]:
```
# Filter out genres with less than 150 observations
newZealandDatGenreCT = newZealandDat.groupby("Genre").filter(lambda x: len(x) >␣
↪150)

newZealandDatGenreCT['Genre'] = newZealandDatGenreCT.Genre.astype(str)

# Genre bar chart
fig, ax = plt.subplots(figsize=(12, 10))
```

```
sns.set_theme(style="darkgrid")
ax = sns.countplot(x="Genre", data = newZealandDatGenreCT)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```

[ ]: [Text(0, 0, 'dance pop'), Text(0, 0, 'pop')]



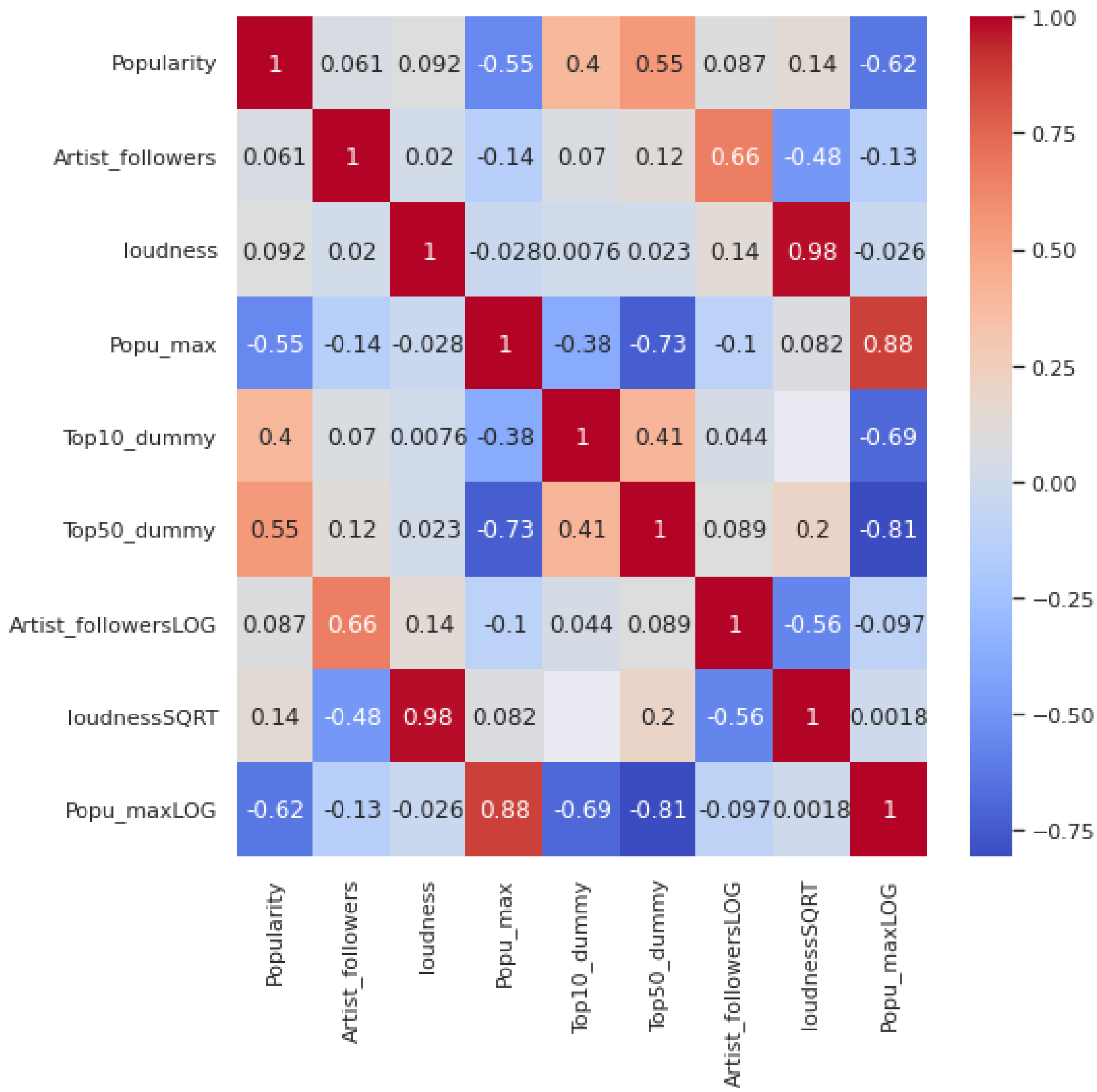
We also looked at the correlation of most of the numeric variables. The correlation matrix below shows some of the more significant or representative variables.

[ ]:
```
dataCorr = noDummies_outliersRemoved[['Popularity', 'Artist_followers',␣
 ↪'loudness', 'Popu_max'
                            , 'Top10_dummy', 'Top50_dummy']]
dataCorr = dataCorr.dropna()


dataCorr['Artist_followersLOG'] = np.log10(dataCorr['Artist_followers'])
dataCorr['loudnessSQRT'] = np.sqrt(dataCorr['loudness'])
dataCorr['Popu_maxLOG'] = np.log10(dataCorr['Popu_max'])
```

```
plt.figure(figsize=(8,8))
sns.heatmap(dataCorr.corr(), annot=True, cmap='coolwarm')
```

```
/usr/local/lib/python3.7/dist-packages/pandas/core/series.py:726:
RuntimeWarning: divide by zero encountered in log10
  result = getattr(ufunc, method)(*inputs, **kwargs)
/usr/local/lib/python3.7/dist-packages/pandas/core/series.py:726:
RuntimeWarning: invalid value encountered in sqrt
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff628c244d0>



One exploratory approach that was taken was to use the qualities and features of the music to categorize them by genre. A subset was created and vizualied to enhance our understanding of the relationships between genres. Genre is such a broad category it was necessary to limit the analysis to four genres, "rock", "hip hop", "latin" and "country". Attempts to analyze up to 12 genres did not result in any significant conclusions.

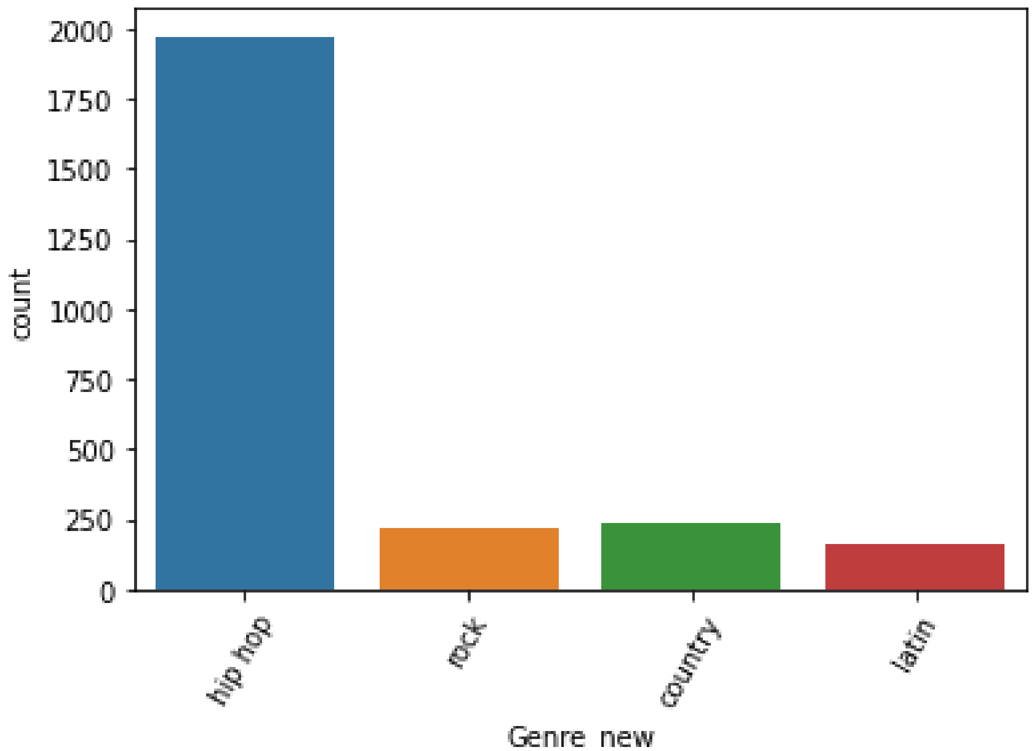
[ ]:
```
# Create a subset with four genres and weighted with equal counts
# Hip Hop, rock, Latin, Country
noDummies['Genre_new'] = noDummies.Genre_new.astype('object')
usaDat2 = noDummies[(noDummies["Country"] == "USA")]

usaGenre1 = usaDat2.iloc[:, 13:24]
usaGenre2 = usaDat2['Genre_new']

usaGenre = pd.concat([usaGenre1, usaGenre2.reindex(usaGenre1.index)], axis=1)

usaGenre = usaGenre.loc[usaGenre['Genre_new'].isin(['rock', 'hip hop', 'latin',␣
↪'country'])]



usaGenre.head(n=1)
```

[ ]:
```
       danceability  energy  key  loudness  trackMode  speechiness  acoustics  \
1             0.767   0.709  1.0    -4.470        1.0       0.3360    0.32300
107           0.827   0.522  7.0    -4.866        1.0       0.0845    0.16300
118           0.338   0.729  6.0    -6.419        0.0       0.1020    0.75800
203           0.582   0.488  2.0    -8.208        1.0       0.4550    0.00168
207           0.611   0.867  1.0    -5.298        1.0       0.0896    0.11000
...             ...     ...  ...       ...        ...          ...        ...
89400         0.734   0.468  1.0    -9.029        1.0       0.0912    0.01800
89410         0.702   0.668  9.0    -9.237        1.0       0.2140    0.51800
89423         0.615   0.871  1.0    -5.308        1.0       0.0894    0.12600
89424         0.863   0.576  5.0    -5.687        0.0       0.2390    0.12400
89426         0.512   0.580  3.0    -6.658        0.0       0.0290    0.62100

       instrumentalness  liveliness  valence    tempo Genre_new
1              0.000000      0.0676    0.720  171.993   hip hop
107            0.000001      0.1090    0.477  151.990   hip hop
118            0.000032      0.1800    0.543  184.174   hip hop
203            0.000000      0.0941    0.309   80.322   hip hop
207            0.000105      0.3460    0.336  140.032   hip hop
...                 ...         ...      ...      ...       ...
89400          0.000000      0.3820    0.285  118.001   hip hop
89410          0.000000      0.0588    0.561  116.063      rock
89423          0.000059      0.3810    0.284  140.033   hip hop
89424          0.000000      0.1430    0.832  132.054   hip hop
89426          0.000017      0.5130    0.303  159.847   country
```

```
[2582 rows x 12 columns]
```

[ ]:
```
sns.countplot(x="Genre_new", data=usaGenre)
plt.xticks(rotation = 60)
```

[ ]:
```
(array([0, 1, 2, 3]), <a list of 4 Text major ticklabel objects>)
```



[ ]:
```
usaGenre.head(n=2)
```

[ ]:
```
     danceability  energy  key  loudness  trackMode  speechiness  acoustics  \
1           0.767   0.709  1.0    -4.470        1.0       0.3360    0.32300
107         0.827   0.522  7.0    -4.866        1.0       0.0845    0.16300
118         0.338   0.729  6.0    -6.419        0.0       0.1020    0.75800
203         0.582   0.488  2.0    -8.208        1.0       0.4550    0.00168
207         0.611   0.867  1.0    -5.298        1.0       0.0896    0.11000

     instrumentalness  liveliness  valence    tempo Genre_new
1            0.000000      0.0676    0.720  171.993   hip hop
107          0.000001      0.1090    0.477  151.990   hip hop
118          0.000032      0.1800    0.543  184.174   hip hop
203          0.000000      0.0941    0.309   80.322   hip hop
207          0.000105      0.3460    0.336  140.032   hip hop
```

```
[ ]: # Create a sample with equal counts
usaGenre = usaGenre.groupby("Genre_new").sample(n=150, random_state=777)

usaGenre = usaGenre.reset_index(drop=True)

print("usaGenre Shape:", usaGenre.shape)
#usaGenre.tail()
```

```
usaGenre Shape: (600, 12)
```

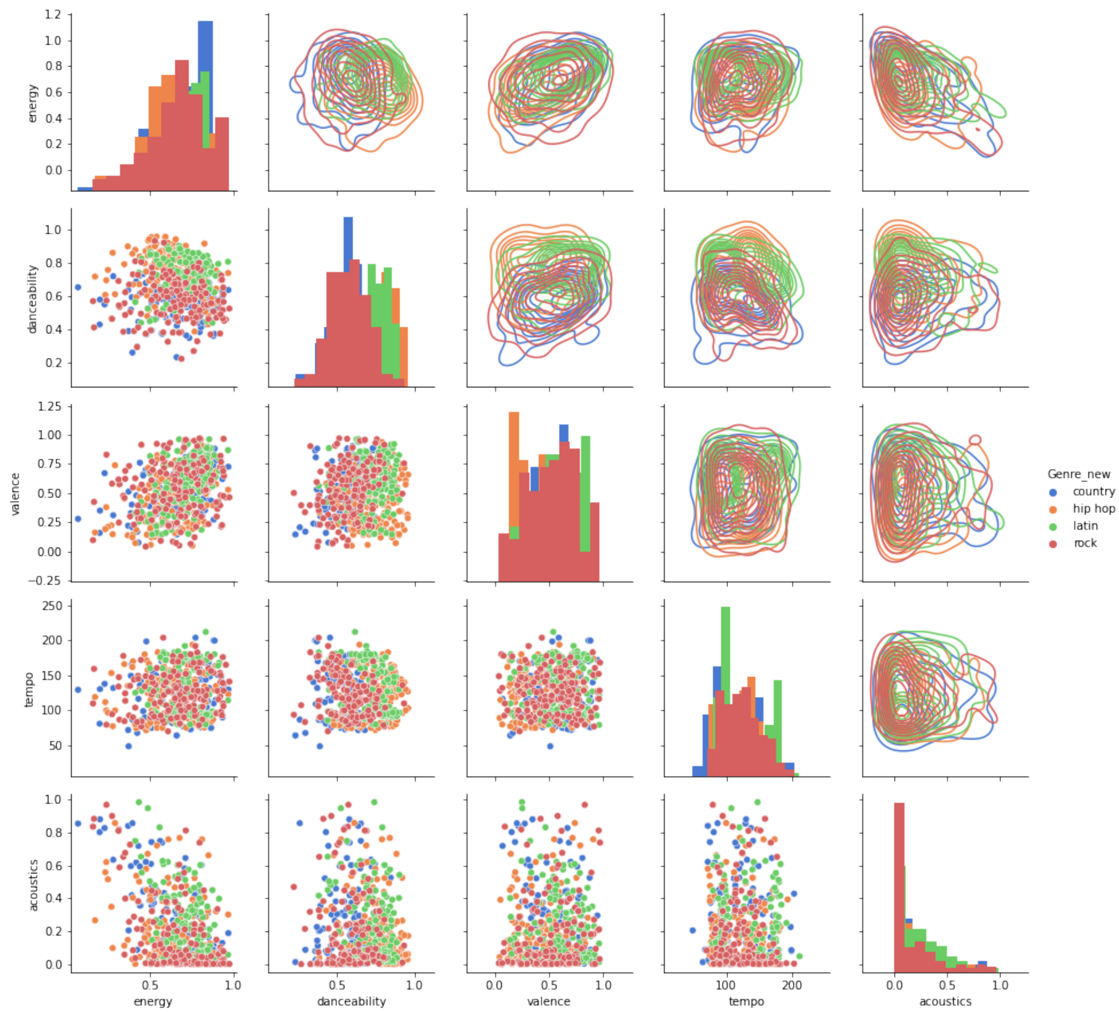
```
[ ]: usaGenre.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 600 entries, 0 to 599
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   danceability      600 non-null    float64
 1   energy            600 non-null    float64
 2   key               600 non-null    float64
 3   loudness          600 non-null    float64
 4   trackMode         600 non-null    float64
 5   speechiness       600 non-null    float64
 6   acoustics         600 non-null    float64
 7   instrumentalness  600 non-null    float64
 8   liveliness        600 non-null    float64
 9   valence           600 non-null    float64
 10  tempo             600 non-null    float64
 11  Genre_new         600 non-null    object
dtypes: float64(11), object(1)
memory usage: 56.4+ KB
```

```
[ ]: # Creates a grid using Seaborn's PairGrid()
g = sns.PairGrid(
    usaGenre,
    vars=['energy', 'danceability', 'valence', 'tempo', 'acoustics'],
    hue='Genre_new',
    diag_sharey=False,
    palette=sns.color_palette('muted', n_colors=4))

# Adds histograms on the diagonal
g.map_diag(plt.hist)

# Adds density plots above the diagonal
g.map_upper(sns.kdeplot)

# Adds scatterplots below the diagonal
```

```
g.map_lower(sns.scatterplot)

# Adds a legend
g.add_legend()
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7fe8b2de0450>



4.3 Hierarchichal Cluster Analysis

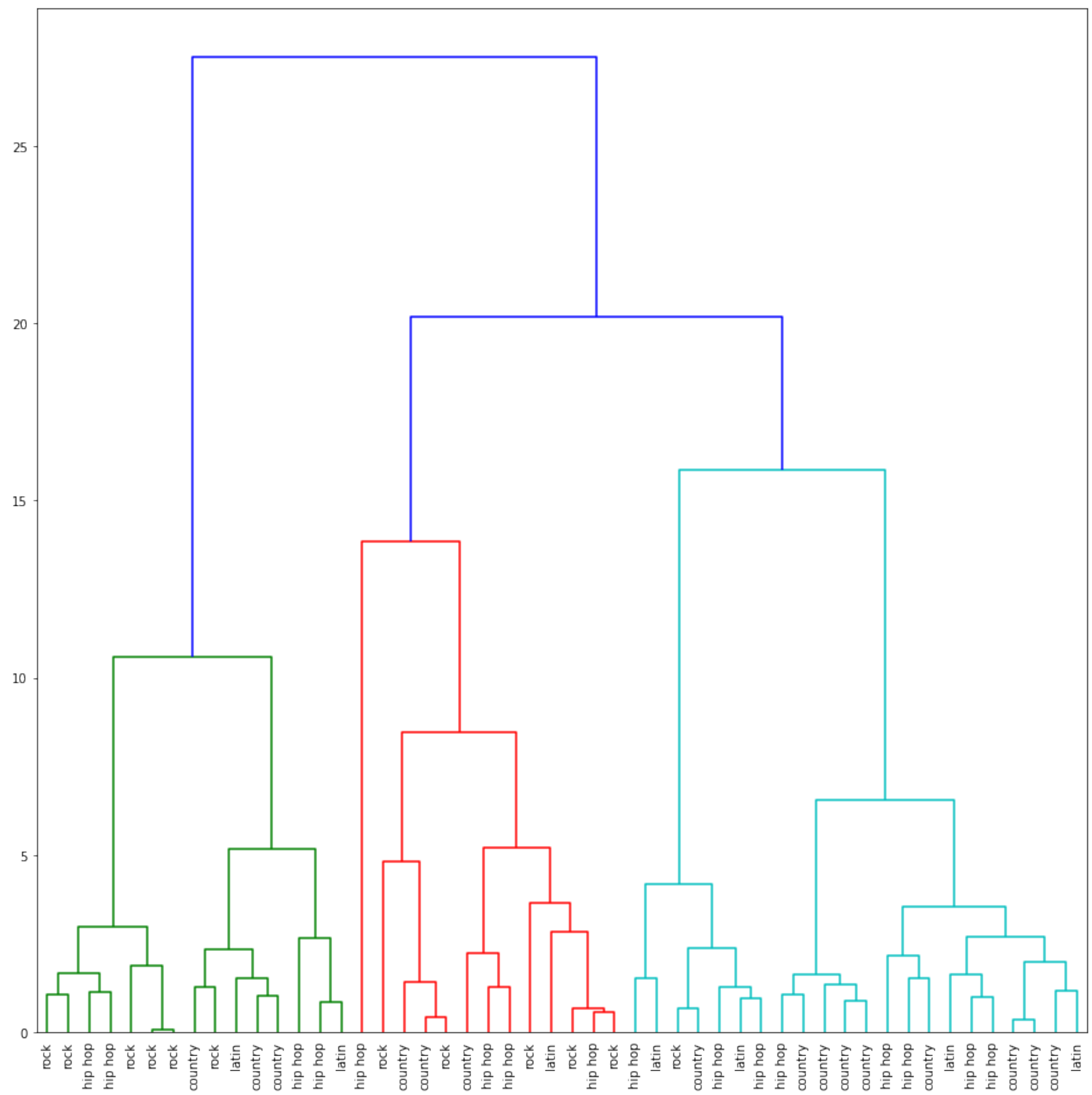
Hierarchical Cluster Analysis was performed and a dendrogram generated to visualize linkages between observations. The dendrogram shows many linkages between separate genres further proving that the music qualities of separate genres overlap in ways that make them difficult to distinguish.

[ ]:
```
# Create a sample set for Hierarchical Cluster Analysis

usaGenreSample = usaGenre.sample(50)
```

```
# Setup independant (X) and dependant (y) variables
X_hc = usaGenreSample.iloc[:, 0:10]

y_hc = usaGenreSample['Genre_new']

print('X Shape:', X_hc.shape)
```

```
X Shape: (50, 10)
```

[ ]:
```
# Performs agglomerative clustering using `ward` linkage and `euclidean` metric
hc = linkage(X_hc, method='ward', metric='euclidean')

# Sets the figure size
fig = plt.figure(figsize=(15, 15))

# Displays the dendogram
# The lambda function sets the labels of each leaf
dn = dendrogram(
    hc,
    leaf_label_func=lambda id: y_hc.values[id],
    leaf_font_size=10)
```



4.4 K-Means Cluster Analysis

A K-Means Cluster Analysis was performed ahead of the initiating predictive models. Like the agglomerative clusering, K-means clustering was used to gain insight into the relationship between genres. The scatter plots show that each of the four genres, "rock", "hip hop", "latin" and "country", are overlapping. The analysis identified four centroids and corresponding clusters, but those clusters do not correspond with the four genres in any consistancy.

[ ]:
```
# Configure the data for k-Means Cluster Analysis

# Setup independant (X) and dependant (y) variables
X_km = usaGenre.iloc[:, 0:10]
```

```
# Standardizes the values for the features
X_km = pd.DataFrame(
    StandardScaler().fit_transform(X_km),
    columns=X_km.columns)


y_km = usaGenre['Genre_new']

print('X Shape:', X_km.shape)
print('y Shape:', y_km.shape)
```

```
X Shape: (600, 10)
y Shape: (600,)
```

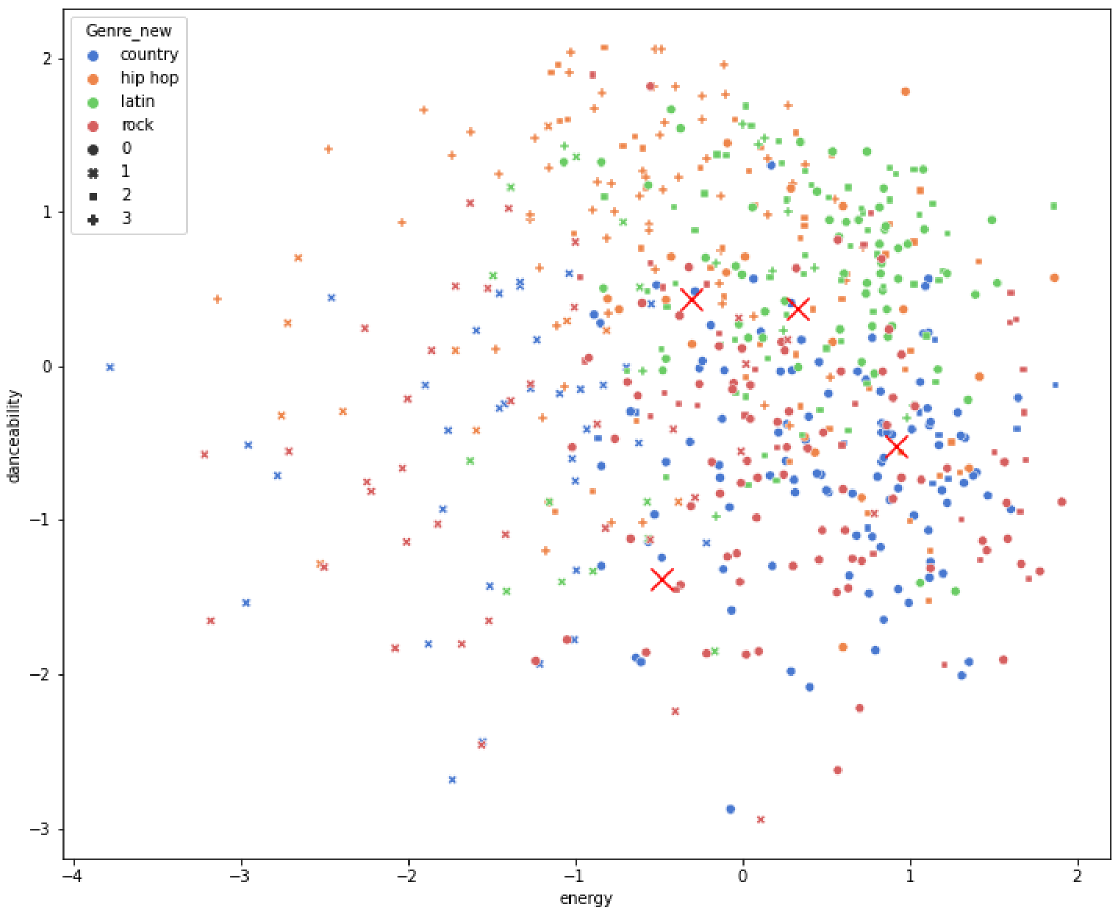
[ ]:
```
# k-Means: Train the Model

# Sets up the kMeans object
km = KMeans(
    n_clusters=4,
    random_state=1,
    init='k-means++',
    n_init=10)

# Fits the model to the data
km.fit(X_km)

# Displays the parameters of the fitted model
km.get_params()
```

[ ]:
```
{'algorithm': 'auto',
 'copy_x': True,
 'init': 'k-means++',
 'max_iter': 300,
 'n_clusters': 4,
 'n_init': 10,
 'n_jobs': None,
 'precompute_distances': 'auto',
 'random_state': 1,
 'tol': 0.0001,
 'verbose': 0}
```

[ ]:
```
# Creates a scatter plot to show clusters and centriods

fig, ax = plt.subplots(figsize=(12, 10))

sns.scatterplot(
    x='energy',
    y='danceability',
```

```
    data=X_km,
    hue=y_km,
    style=km.labels_,
    palette=sns.color_palette('muted', n_colors=4))

# Adds cluster centers to the same plot
plt.scatter(
    km.cluster_centers_[:,0],
    km.cluster_centers_[:,1],
    marker='x',
    s=200,
    c='red')
```

[ ]: <matplotlib.collections.PathCollection at 0x7fe8b1c8ad50>



[ ]:
```
# k-MEANS: OPTIMIZE VIA SILHOUETTE SCORES

# Sets up the custom scorer
def s2(estimator,X):
```

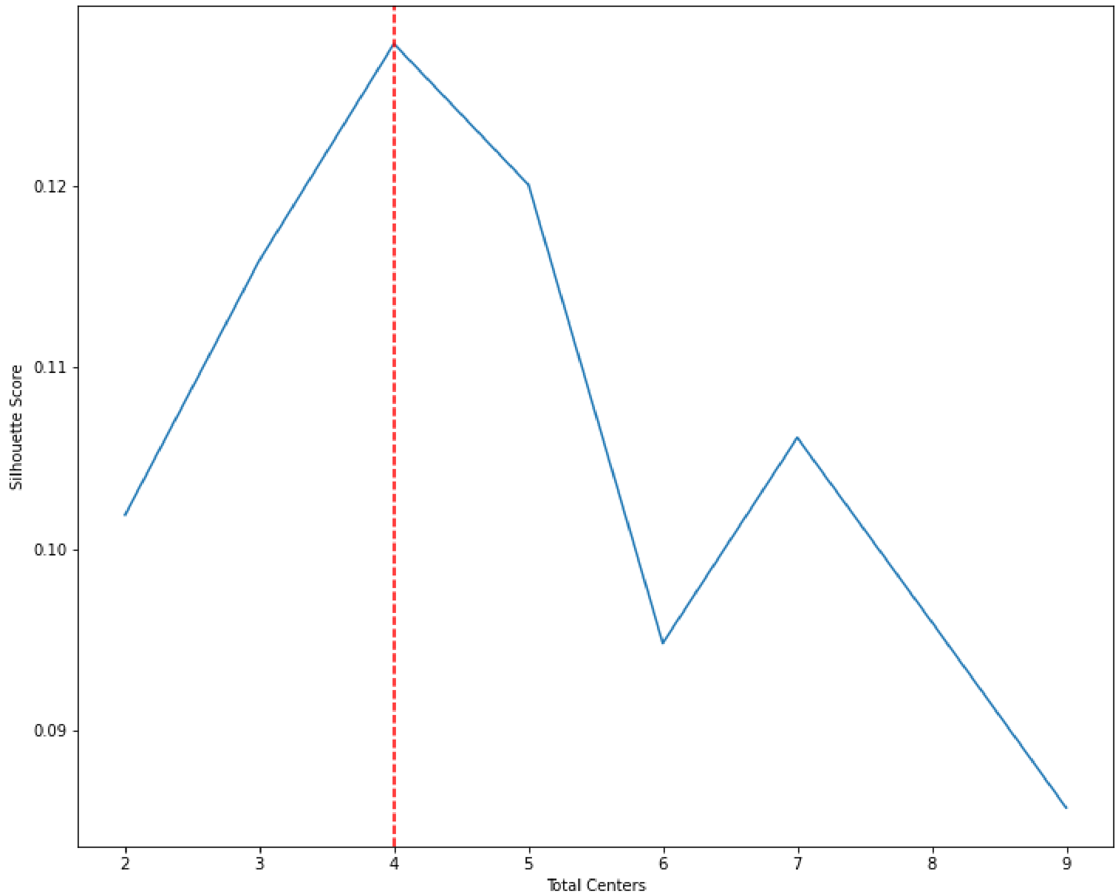
```python
    return silhouette_score(X, estimator.predict(X))

# List of values for the parameter `n_clusters`
param = range(2,10)

# KMeans object
km = KMeans(random_state=0, init='k-means++')

# Sets up GridSearchCV object and stores in grid variable
grid = GridSearchCV(
    km,
    {'n_clusters': param},
    scoring=s2,
    cv=2)

# Fits the grid object to data
grid.fit(X_km)

# Accesses the optimum model
best_km = grid.best_estimator_

# Displays the optimum model
best_km.get_params()
```

[ ]:
```
{'algorithm': 'auto',
 'copy_x': True,
 'init': 'k-means++',
 'max_iter': 300,
 'n_clusters': 4,
 'n_init': 10,
 'n_jobs': None,
 'precompute_distances': 'auto',
 'random_state': 0,
 'tol': 0.0001,
 'verbose': 0}
```

[ ]:
```python
# Plot mean_test_scores vs. n_clusters
fig, ax = plt.subplots(figsize=(12, 10))

plt.plot(
    param,
    grid.cv_results_['mean_test_score'])

# Draw a vertical line, where the best model is
plt.axvline(
    x=best_km.n_clusters,
    color='red',
    ls='--')
```

```
# Adds labels to the plot
plt.xlabel('Total Centers')
plt.ylabel('Silhouette Score')
```

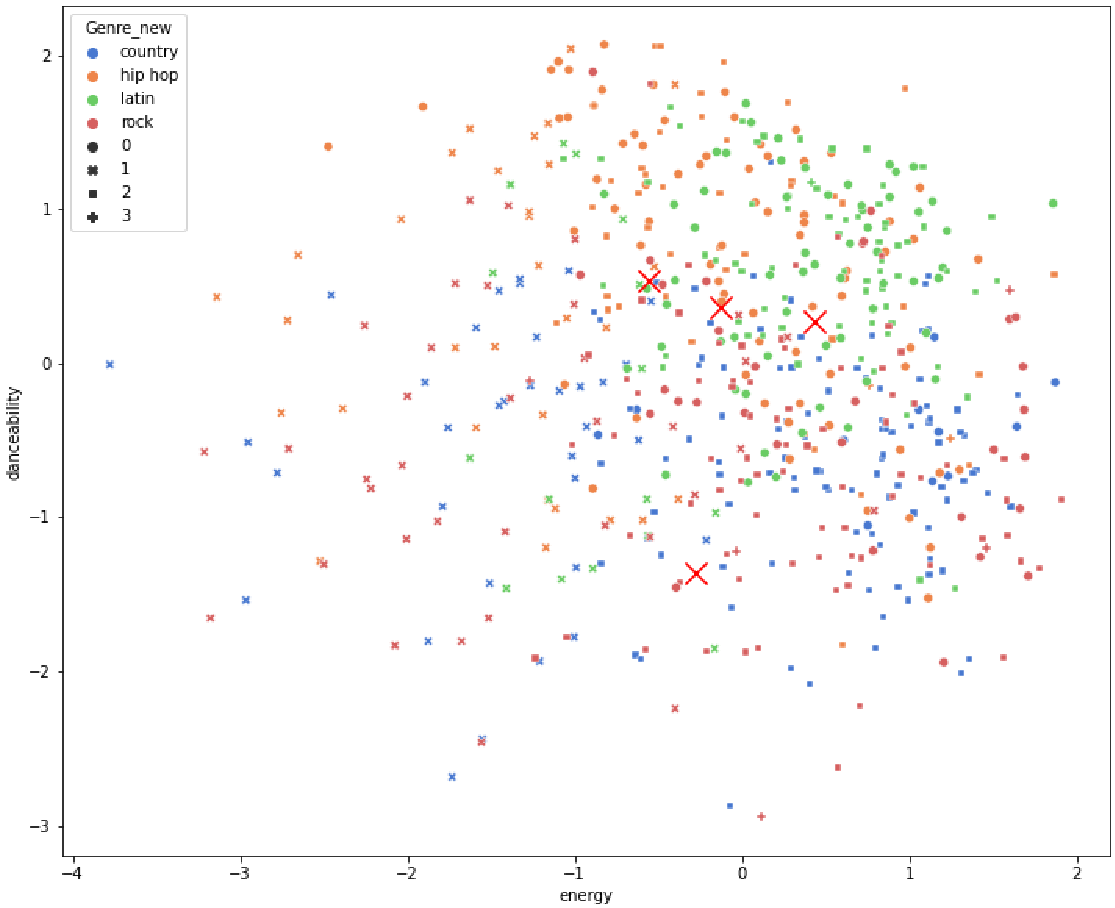
[ ]: Text(0, 0.5, 'Silhouette Score')



[ ]:
```
# Creates a scatter plot to show optimized clusters and centriods

# Creates a scatter plot
fig, ax = plt.subplots(figsize=(12, 10))

sns.scatterplot(
    x='energy',
    y='danceability',
    data=X_km,
    hue=y_km,
    style=best_km.labels_,
    palette=sns.color_palette('muted', n_colors=4))
```

```python
# Adds cluster centers to the same plot
plt.scatter(
    best_km.cluster_centers_[:, 0],
    best_km.cluster_centers_[:, 1],
    marker='x',
    s=200,
    c='red')
```

[ ]: <matplotlib.collections.PathCollection at 0x7fe8b1bf9f50>



5 Models

5.1 Assign Training and Test Data

[ ]:
```python
# Split the Training and Test data

X_train, X_test, y_train, y_test = train_test_split(usaGenre.iloc[:, 0:11],
 ↪usaGenre['Genre_new'], test_size=0.25)
```

```python
# Class labels
classLabels = ['rock', 'hip hop', 'latin', 'country']

print('X_train Shape:', X_train.shape)
print()
print('X_test Shape:', X_test.shape)
print(X_train)
```

```
X_train Shape: (450, 11)

X_test Shape: (150, 11)
     danceability  energy   key  loudness  trackMode  speechiness  acoustics  \
200         0.863   0.576   5.0    -5.687        0.0       0.2390     0.1240
464         0.388   0.338  10.0   -10.054        1.0       0.0328     0.6520
512         0.593   0.749   5.0    -5.671        1.0       0.0475     0.0116
284         0.604   0.570   7.0    -4.093        0.0       0.0331     0.1040
33          0.634   0.516   8.0    -6.050        1.0       0.0373     0.4000
..            ...     ...   ...       ...        ...          ...        ...
508         0.653   0.684   7.0    -7.052        0.0       0.1990     0.0615
113         0.569   0.807   0.0    -4.584        1.0       0.0464     0.0876
370         0.734   0.836  10.0    -4.803        0.0       0.0735     0.0170
76          0.632   0.804   7.0    -6.109        1.0       0.0503     0.1010
422         0.795   0.755   5.0    -4.788        1.0       0.0454     0.3270

     instrumentalness  liveliness  valence    tempo
200          0.000000       0.143    0.832  132.054
464          0.000004       0.248    0.477  177.784
512          0.108000       0.314    0.650  164.961
284          0.000000       0.178    0.618  140.060
33           0.000000       0.142    0.769  153.831
..                ...         ...      ...      ...
508          0.000387       0.270    0.355  110.049
113          0.000000       0.164    0.883   76.011
370          0.000016       0.179    0.623   80.002
76           0.000000       0.170    0.350   92.456
422          0.000000       0.464    0.816   92.020

[450 rows x 11 columns]
```

5.2 Naive Bayes

The Naive Bayes Classifier is a simple probabalistic classifier based on Bayes theorem and that assumes naivety (assumed independance between the predictors/features). It predicts based on conditional probability: the probability that something will happen given that something else has already occurred. This classifier will use conditional probability to decide if a songs music qualities make it more likely to be one of the genres or another.

The training accuracy for naive bayes model was 58.44%. Comparitivly the testing accuracy was 58.67% (in most trials the testing accuracy was less than the training accuracy). The confusion matrix shows that "rock" was predicted accurately, but the other genres "hip hop", "latin", and "country" were mislabled frequently.

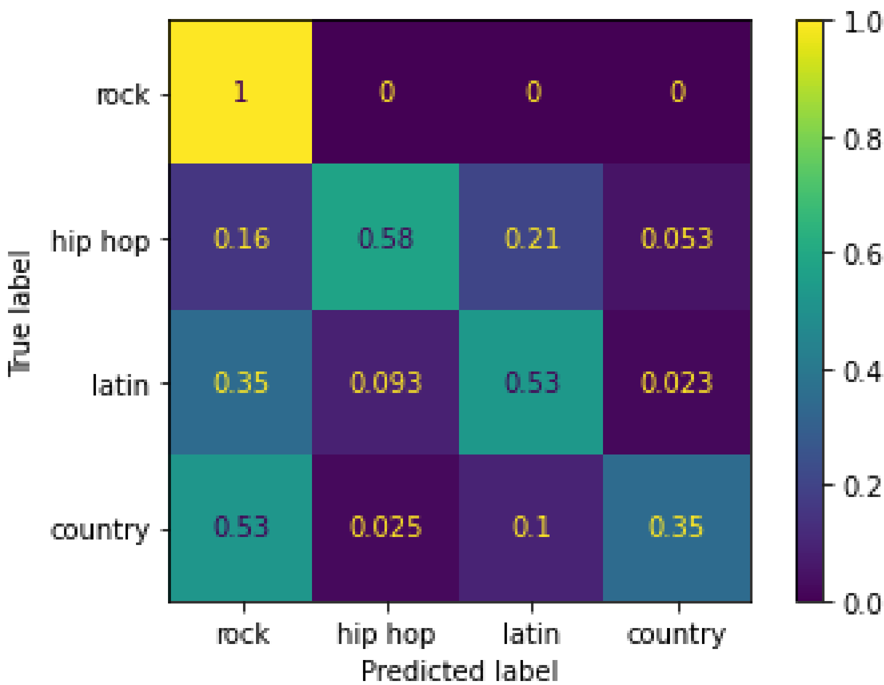
[ ]:
```
## Naive Bayes ##

# Train Model
nb = GaussianNB().fit(X_train, y_train)
```

[ ]:
```
# Calculate Mean Accuracy on Training Data

print(
    'Accuracy on training data: '
    + str("{:.2%}".format(nb.score(X_train, y_train))))
```

```
Accuracy on training data: 58.44%
```

[ ]:
```
# Test Model: Confusion Matrix

plot_confusion_matrix(
    nb, X_test, y_test,
    display_labels=classLabels,
    normalize='true')
```

[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7fe8b1b13050>
```



[ ]:
```
# Calculate Mean Accuracy on Testing Data
print(
    'Accuracy on testing data: '
    + str("{:.2%}".format(nb.score(X_test, y_test))))
```

```
Accuracy on testing data: 58.67%
```

5.3 KNN

KNN is a supervised machine learning algorithm that can be used for both classification and regression problems. K-nearest neighbors operates by assuming that similar things live near each other. It calculates this closeness (or distance) by determining the distance between points on a graph. When using KNN, we can optimize on the number of neighbors that any given data point is likely to have.

The training accuracy for this kNN model was 58.89%. Grid Search was used to optimize the model parameters, including k, the number of neighbors used to categorize each observation. The optimal k was found to be 7. The model can be compared to earlier plots that show how there is very little separation between genre clusters when comparing them based on music qualities. The test accuracy for this model was found to be 40%.

[ ]:
```
# k Nearest Neighbors Model

# Train Model
knn = KNeighborsClassifier(n_neighbors=5) \
    .fit(X_train, y_train)
```

[ ]:
```
# Calculate Mean Accuracy on Training Data

print(
    'Accuracy on training data: '
    + str("{:.2%}".format(knn.score(X_train, y_train))))
```

```
Accuracy on training data: 58.89%
```

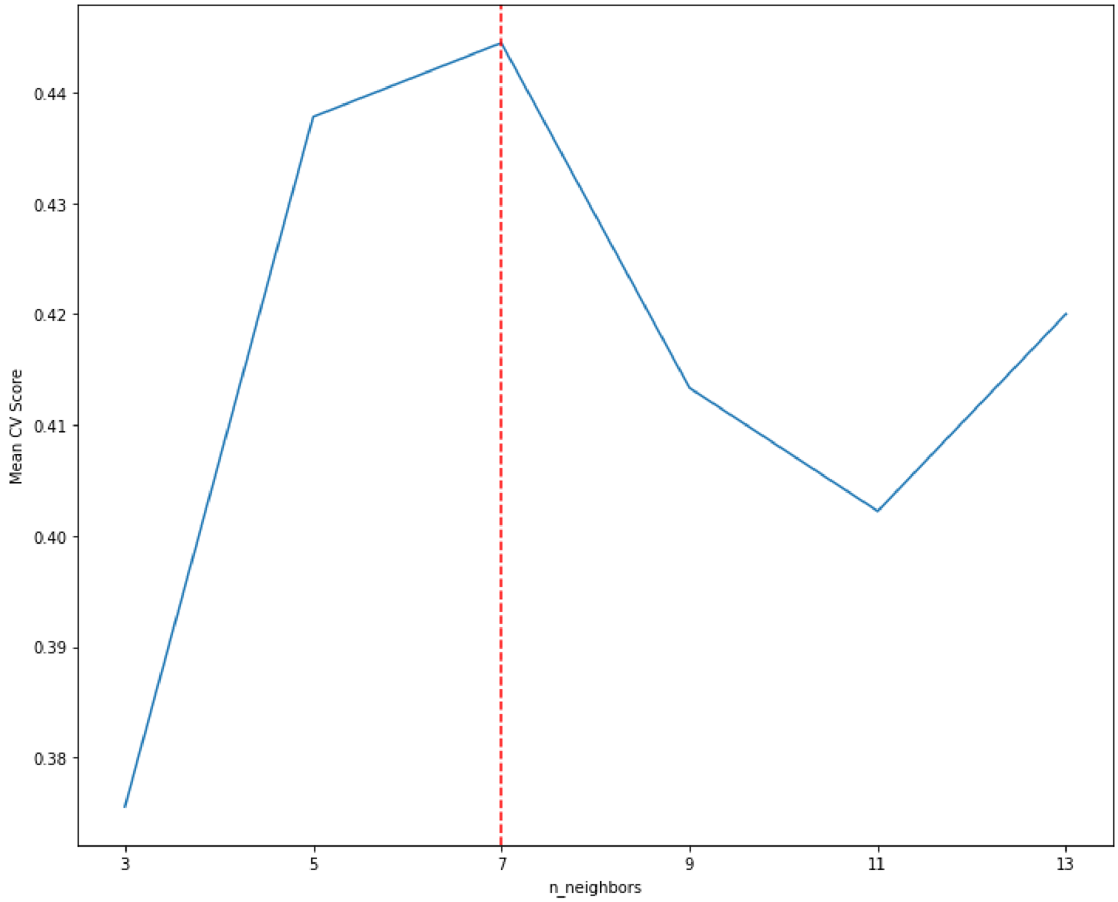
[ ]:
```
# Optimize the kNN Model

# Set up the kNN classifier object
knn = KNeighborsClassifier()

# Search parameters
param = range(3, 15, 2)

# Sets up GridSearchCV object and stores it in grid variable
grid = GridSearchCV(
    knn,
    {'n_neighbors': param})
```

```python
# Fits the grid object and gets the best model
best_knn = grid \
    .fit(X_train, y_train) \
    .best_estimator_

# Displays the optimum model
best_knn.get_params()
```

[ ]:
```
{'algorithm': 'auto',
 'leaf_size': 30,
 'metric': 'minkowski',
 'metric_params': None,
 'n_jobs': None,
 'n_neighbors': 7,
 'p': 2,
 'weights': 'uniform'}
```

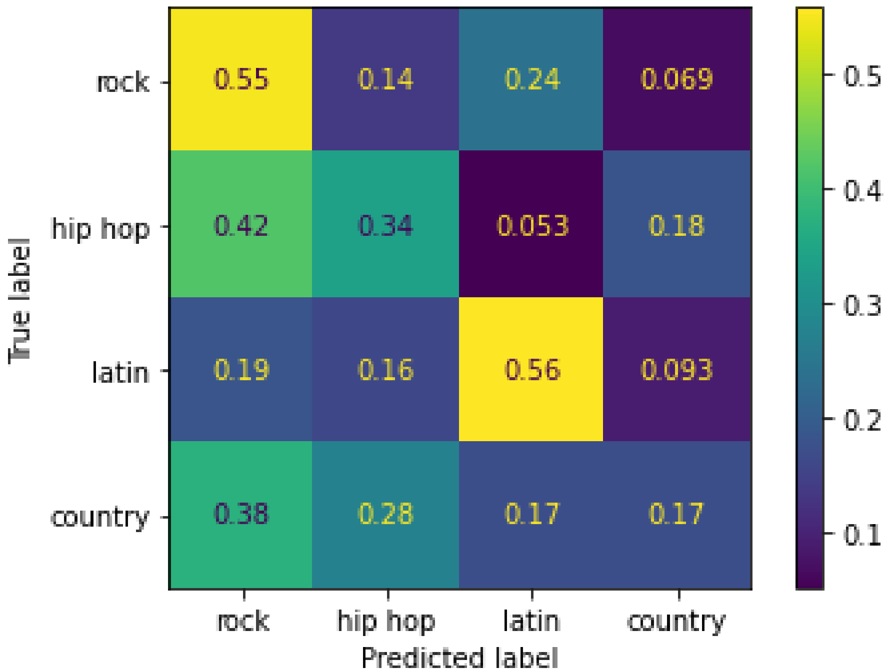
[ ]:
```python
# Plots mean_test_scores vs. total neighbors
fig, ax = plt.subplots(figsize=(12, 10))
plt.plot(
    param,
    grid.cv_results_['mean_test_score'])

# Adds labels to the plot
plt.xticks(param)
plt.ylabel('Mean CV Score')
plt.xlabel('n_neighbors')

# Draws a vertical line where the best model is
plt.axvline(
    x=best_knn.n_neighbors,
    color='red',
    ls='--')
```

[ ]:
```
<matplotlib.lines.Line2D at 0x7fe8b1a66510>
```



[ ]:
```
# Test Model: Confusion Matrix

plot_confusion_matrix(
    best_knn, X_test, y_test,
    display_labels=classLabels,
    normalize='true')
```

[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7fe8b1a5ecd0>
```




```
[ ]: # Calculate Mean Accuracy on Testing Data
     print(
         'Accuracy on testing data: '
         + str("{:.2%}".format(best_knn.score(X_test, y_test))))
```

```
Accuracy on testing data: 40.00%
```

5.4 Decision Tree

A decision tree is a branching tree-like structure in which each node represents a binary "decision" that leads to other nodes or culminates in a classification. Using a decision tree is advantages as it allows the user to visualize the critical distinctions with the model.

The training accuracy for this decision tree model was 64.44%. Grid Search was used to optimize the model parameters, entropy and gini. The first node of the model attempts to separate predicted "rock" observations from "hip hop". In comparison to the dendrogram produced earlier, it may be difficult to distinctly identify rock and hip hop based on the features. The test accuracy for this model was found to be 58.67%. The confusion matrix shows how observations were mislabled. For example "latin" observations were predicted to be "hip hop" in 26% of the "latin" observations.

```
[ ]: # Decision Tree Model

     # Creates a DecisionTreeClassifier object
     dt = DecisionTreeClassifier(
         criterion='entropy',
         random_state=0,
```

```
    max_leaf_nodes=7)

# Fits the decision tree to training data
dt.fit(X_train,y_train)
```

[ ]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                       max_depth=None, max_features=None, max_leaf_nodes=7,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=0, splitter='best')
```

[ ]:
```
# Calculate Mean Accuracy on Training Data
print(
    'Accuracy on training data: '
    + str("{:.2%}".format(dt.score(X_train,y_train))))
```

```
Accuracy on training data: 64.44%
```

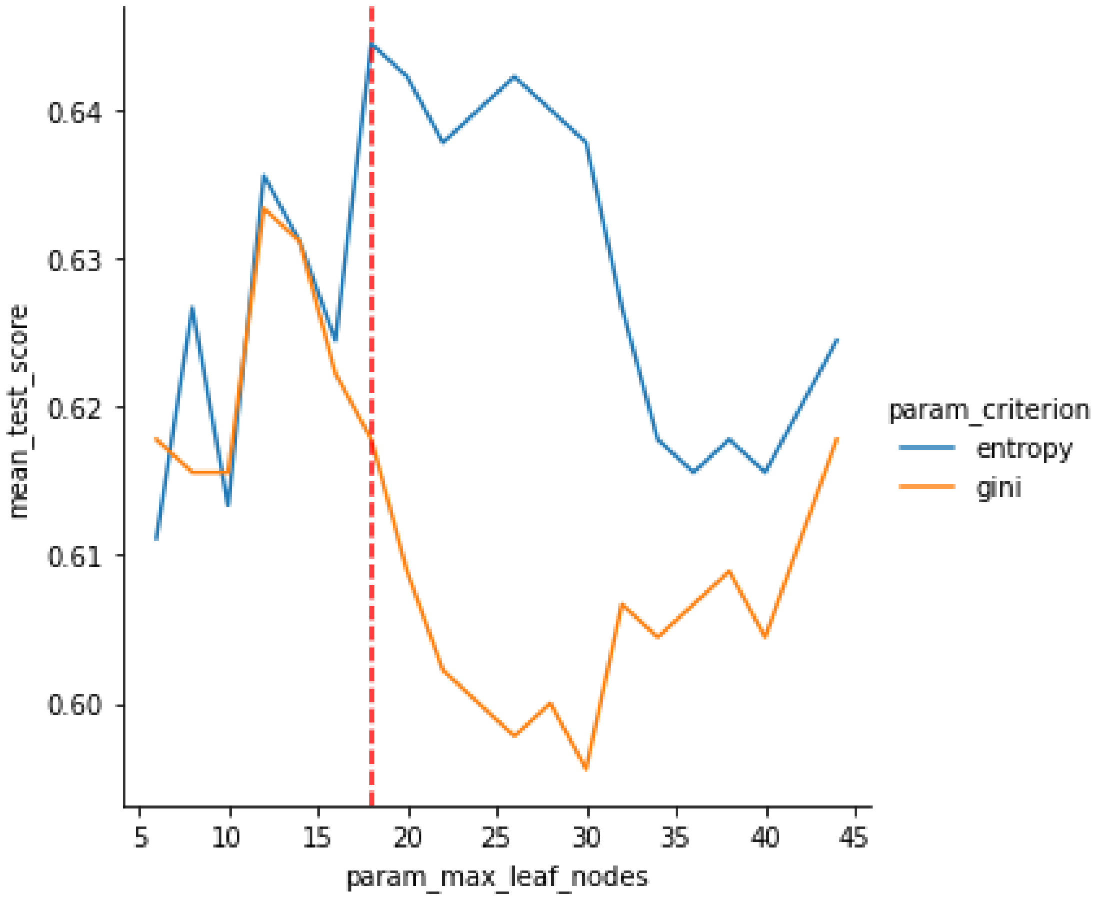
[ ]:
```
# Defines a DecisionTreeClassifier object
dt = DecisionTreeClassifier(
    random_state=1)

# Possible values for max_leaf_nodes to try
param = range(6,45,2)

# Sets up GridSearchCV object and stores it in grid variable
grid = GridSearchCV(
    dt,
    {'max_leaf_nodes': param,
     'criterion': ['entropy','gini']})

# Fits the grid to the training data
grid.fit(X_train,y_train)

# Stores the optimum model in best_dt
best_dt = grid.best_estimator_

# Displays the optimum model
best_dt.get_params()
```

[ ]:
```
{'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'entropy',
 'max_depth': None,
 'max_features': None,
 'max_leaf_nodes': 18,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
```

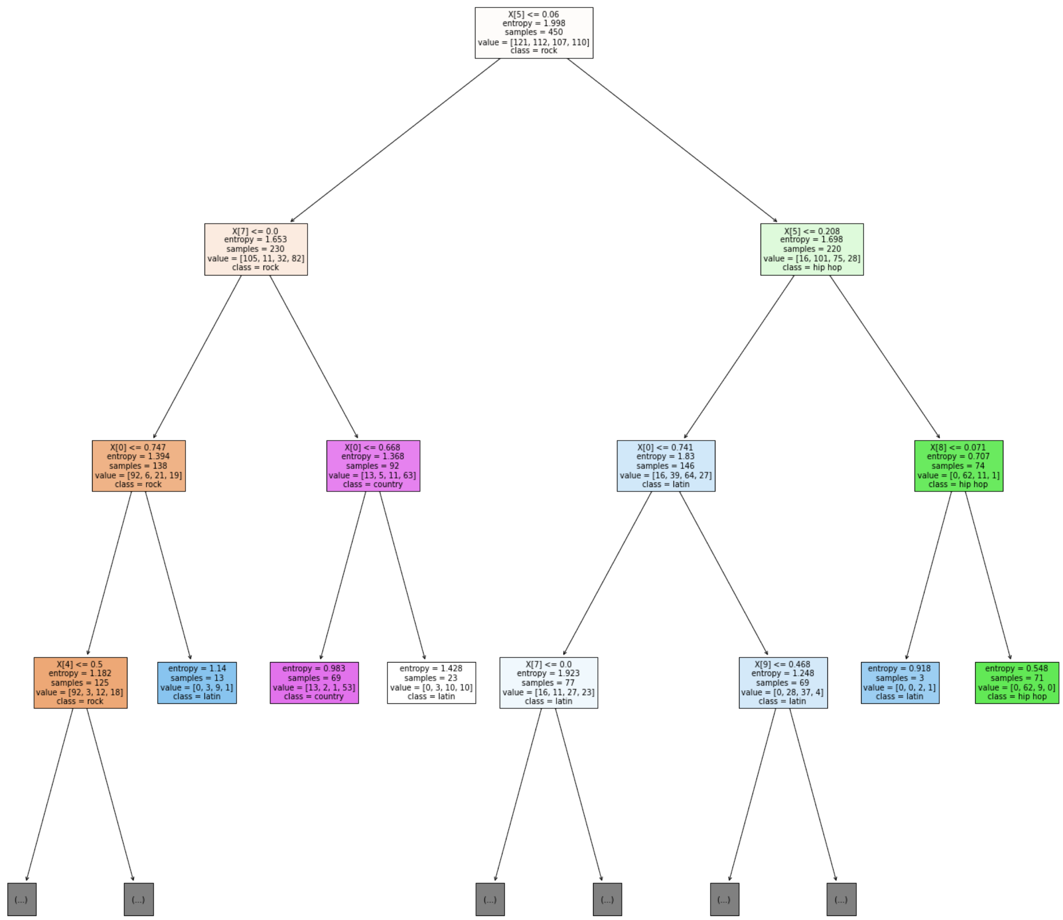
```
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': 1,
 'splitter': 'best'}
```

[ ]:
```python
# Plots the mean accuracy against max_leaf_nodes
sns.relplot(
    data=pd.DataFrame.from_dict(grid.cv_results_, orient='columns'),
    kind='line',
    x='param_max_leaf_nodes',
    y='mean_test_score',
    hue='param_criterion'
)

# Draws a vertical red line, where the best model is
plt.axvline(
    x=best_dt.max_leaf_nodes,
    color='red',
    ls='--')
```

[ ]:
```
<matplotlib.lines.Line2D at 0x7fe8b1bac210>
```

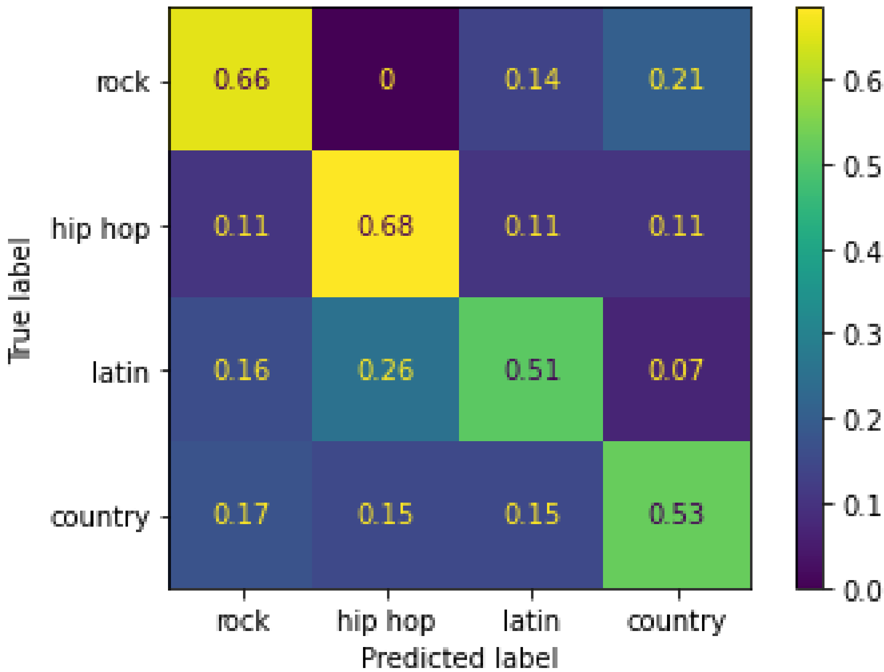


[ ]:
```
# Display the Decision Tree

# Sets the figure size
fig = plt.figure(figsize=(25, 25))



# Creates a visual display of the model.
# Keep max_depth small for better visualization
t = plot_tree(
    best_dt,
    class_names=classLabels,
    max_depth=3,
    filled=True)
```



[ ]:
```python
# Test Model: Confusion Matrix

plot_confusion_matrix(
    best_dt, X_test, y_test,
    display_labels=classLabels,
    normalize='true')
```

[ ]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fe8b1874e10>



[ ]:
```python
# Calculate Mean Accuracy on Testing Data
print(
    'Accuracy on testing data: '
    + str("{:.2%}".format(best_dt.score(X_test, y_test))))
```

```
Accuracy on testing data: 58.67%
```

5.5 Random Forest

[ ]:
```python
rf  = RandomForestClassifier(criterion= 'entropy', random_state = 137)
rf = rf.fit(X_train, y_train)
```

[ ]:
```python
# Calculate Mean Accuracy on Training Data
print(
    'Accuracy on training data: '
    + str("{:.2%}".format(rf.score(X_train,y_train))))
```

[ ]:
```python
# Confusion Matrix for RandomForest

plot_confusion_matrix(
    rf, X_test, y_test,
    display_labels=classLabels,
    normalize='true')
```

[ ]:
```python
# Calculate Mean Accuracy on Testing Data
print(
    'Accuracy on testing data: '
```

```
    + str("{:.2%}".format(rf.score(X_test, y_test))))
```

```
[ ]: rf  = RandomForestClassifier(criterion= 'gini', random_state = 137,
                                  max_depth = 150, n_estimators = 75)
     rf = rf.fit(X_train, y_train)
```

```
[ ]: # Calculate Mean Accuracy on Training Data
     print(
         'Accuracy on training data: '
         + str("{:.2%}".format(rf.score(X_train,y_train))))
```

```
[ ]: # Confusion Matrix for RandomForest

     plot_confusion_matrix(
         rf, X_test, y_test,
         display_labels=classLabels,
         normalize='true')
```

```
[ ]: # Calculate Mean Accuracy on Testing Data
     print(
         'Accuracy on testing data: '
         + str("{:.2%}".format(rf.score(X_test, y_test))))
```

5.6 Logistic Regression

Using the variables measuring the qualities of songs on a number scale, we were able to build two Logistic Regression models to predict if a song would reach the Top 50 or Top 10 on the global charts.

We split the data, 75% training and 25% testing, and after building and running the models, we found that we could accurrately predict the popularity of a song and if they will reach the Top 10 charts by up to 93.5% accurracy.

```
[ ]: # Create Top 50 Dataframe
     spotify = spotJoin

     spotify = spotify.drop(columns={'Country','Uri','Title_x',
                                     'Artist_x','AlbumSingle','Genre','Explicit',
                                     'Album','Release_date','Genre_new',
                                    ␣
       ↪'LDA_Topic','Cluster','Date','Track','Top10_dummy'})

     spotify['Top50_dummy'] = spotify.Top50_dummy.astype('category')
     spotify = spotify.dropna()
```

```
[ ]: # Create Top 50 training and test sets
     X = spotify.loc[:, spotify.columns != 'Top50_dummy']
     y = spotify.loc[:, spotify.columns == 'Top50_dummy']

     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
       ↪random_state=0)
```

```
[ ]: # Run logistic regression predicting songs in Top 50
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
```

```
[ ]: # Check results for Top 50
cm = confusion_matrix(y_test, y_pred)

sns.heatmap(cm.T, square=True, annot=True, fmt='d',
            cmap='Blues')
plt.title('Top 50')
plt.xlabel('True')
plt.ylabel('Predicted')

print('Model Accuracy:',accuracy_score(y_test, y_pred))
```

```
[ ]: # Create Top 10 Dataframe
spotify = spotJoin

spotify = spotify.drop(columns={'Country','Uri','Title_x',
                                'Artist_x','AlbumSingle','Genre','Explicit',
                                'Album','Release_date','Genre_new',
                               ␣
 ↪'LDA_Topic','Cluster','Date','Track','Top50_dummy'})

spotify['Top10_dummy'] = spotify.Top50_dummy.astype('category')
spotify = spotify.dropna()
```

```
[ ]: # Create Top 10 training and test sets
X = spotify.loc[:, spotify.columns != 'Top10_dummy']
y = spotify.loc[:, spotify.columns == 'Top10_dummy']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=0)
```

```
[ ]: # Run logistic regression predicting songs in Top 10
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
```

```
[ ]: # Check results for Top 10
cm = confusion_matrix(y_test, y_pred)

sns.heatmap(cm.T, square=True, annot=True, fmt='d',
            cmap='Blues')
plt.title('Top 10')
plt.xlabel('True')
plt.ylabel('Predicted')
```

```
print('Model Accuracy:',accuracy_score(y_test, y_pred))
```

6 Analysis

Our analysis of the Spotify dataset centered around trying to predict what makes a song popular and how we may be able to predict if a track will be popular enough to make one of the Top charting spots globally. Our hypothesis going into this project was that the popularity of a song would be best predicted by the genres most popular in each country, so we started by taking a look at the Genre data.

We used Hierarchical and K-Means Cluster Analysises to explore the relationships between genres and look for distiguishing or overlapping features. Both of these cluster analysis results showed us that the qualities of various genres do differ, but for the most part, the overlapping qualities will make it difficult for the models to distinguish between genres.

With a better understanding of the data and relationships between songs and genres, we decided to build a series of models to try to predict a tracks genre based on the music qualities, and then find the most popular genres throughout individual countries. The models we decided to work with were Naive Bayes, Decision Trees, KNN, Random Forest, and Logistic Regression.

For the Naive Bayes, Decision Trees, K-Nearest Neighbors, and Random Forest, we used the data to predict the genre of a song based on its qualities. As predicted with the EDA, the models had some trouble distinguishing between the genres, with most of the results having an accurracy around 50%. The standout model for predicting the genres ended up being the Random Forest model which was 86.8% accurrate.

With further establishment that genre can be difficult to determine and with our correlation analysis of these variables revealing a strong and positive correlation between Artist Followers and Popularity, we decided to use the track quality ratings to create a Logistic Regression model to predict whether a song would chart in the Top 50 or Top 10.

The results of the two Logistical models were highly accurrate with their predictions. We were able to determine if a track would make it to the Top 50 with 86.7% confidence and Top 10 with 93.5% confidence. The results lead us to believe that a songs popularity can't just be attributed to the genre, but the specific qualities that make up the song.

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')

!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('IST_718_Final_Project_Chose_another_song.ipynb')
```

```
Mounted at /content/drive
--2021-09-19 21:33:08--  https://raw.githubusercontent.com/brpy/colab-
pdf/master/colab_pdf.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)...
185.199.108.133, 185.199.109.133, 185.199.110.133, ...
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1864 (1.8K) [text/plain]
```

```
Saving to: colab_pdf.py

colab_pdf.py        100%[===================>]   1.82K  --.-KB/s    in 0s

2021-09-19 21:33:09 (29.2 MB/s) - colab_pdf.py saved [1864/1864]


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
```