Music Genre Recognition Report

Group 8: Ian Lowe, Christian Martinez, Martin Ronquillo, and Sabrina Ferras

---

Introduction

Many things need to be categorized, but it is challenging to do so without textual or numerical data. One particularly interesting problem is the categorization of audio data. Using our dataset, which contains textual lyric data as well as descriptive features that were quantified by Spotify, ***we aim to classify the genre of a song based on features such as loudness, danceability, mood, and lyrical content.*** To accomplish this, we'll be utilizing many of sci-kit learn's classification estimators including KNN, Decision Trees, and Random Forest to attempt to determine the genre of any given song based on lyrical data.

Selection of Data

Dataset

The dataset from Mendeley is a .csv which contains over 28,000 entries of songs. It also contains music metadata (e.g. sadness, danceability, loudness) and the songs are from 1950 to 2019. The data was collected using the Echo Nest API and the spotipy Python package. The lyrics were obtained using the Lyrics Genius API, based on the song title and artist name.

Characteristics of Data

The main attributes that would be a good focus of interest for this project are Genre, Lyrics, and Artist. There are a total of 7 different genres in the dataset: rock, reggae, jazz, blues, hip hop, country, and pop. There is an associated paper about this dataset titled "Temporal Analysis and Visualisation of Music." This paper goes in depth about characteristics of the data and its calculations. For example, there is an attribute "Acousticness" which is defined in the paper as having the "Presence of acoustic instruments."

Dataset: https://data.mendeley.com/datasets/3t9vbwxgr5/3

Associated Analysis Paper: https://sol.sbc.org.br/index.php/eniac/article/view/12155/12020

In [2]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import rcParams
```

```
rcParams['figure.figsize'] = 8,6
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import PolynomialFeatures
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from warnings import simplefilter
simplefilter(action='ignore', category=FutureWarning)

df = pd.read_csv("https://raw.githubusercontent.com/ChrisMart21/383-Group-Project-ML-M
```

Target

In [3]:
```
# Our goal is to predict the music 'genre'
# 7 total Genres
target = ['genre']
df['genre'].value_counts()
```

Out[3]:
```
pop         7042
country     5445
blues       4604
rock        4034
jazz        3845
reggae      2498
hip hop      904
Name: genre, dtype: int64
```

Predictors

This data contains a total of 22 numeric predictors for each song/genre entry. These predictors can be broadly split into two main categories, '***Song Topic Scoring***' and '***Musical Features Scoring***' each ranging from 0 to 1. We will leverage this detailed data to generate 3 different models consisting of predictors 'A', 'B', 'A+B'

In [4]:
```
#predictor 'A'
predictor_topics = ['dating', 'violence', 'world/life', 'night/time',
                    'shake the audience', 'family/gospel', 'romantic',
                    'communication', 'obscene', 'music', 'movement/places',
                    'light/visual perceptions', 'family/spiritual','like/girls',
                    'sadness', 'feelings']
#predictor 'B'
predictor_music_features = ['danceability', 'loudness', 'acousticness',
                            'instrumentalness', 'valence', 'energy']
#both 'A + B'
predictor_all = predictor_topics + predictor_music_features
```

Preliminary work - Data Preparations

In [5]:
```
#Removing data from before or from 2017 due to they style of music changing a lot sinc
df = df[(df['release_date'] >= 2017) & ((df['genre'] != 'reggae') & (df['genre'] != 'h

# One Hot Encoding
```

```python
# encoder = OneHotEncoder(handle_unknown='ignore')
# target_one_hot = pd.DataFrame(encoder.fit_transform(df[target]).toarray())
# target_one_hot.columns = df['genre'].unique()

#Label Encoder
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
target_le = pd.DataFrame(le.fit_transform(np.ravel(df[target]))) #using .ravel() to re


# topic data prep
topic_features = df[predictor_topics]
music_features = df[predictor_music_features]
all_features = df[predictor_all]
```

Preliminary work - Data Exploration and Visualization

Data Exploration

In [26]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1278 entries, 19341 to 80960
Data columns (total 30 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   artist_name               1278 non-null   object 
 1   track_name                1278 non-null   object 
 2   release_date              1278 non-null   int64  
 3   genre                     1278 non-null   object 
 4   lyrics                    1278 non-null   object 
 5   len                       1278 non-null   int64  
 6   dating                    1278 non-null   float64
 7   violence                  1278 non-null   float64
 8   world/life                1278 non-null   float64
 9   night/time                1278 non-null   float64
 10  shake the audience        1278 non-null   float64
 11  family/gospel             1278 non-null   float64
 12  romantic                  1278 non-null   float64
 13  communication             1278 non-null   float64
 14  obscene                   1278 non-null   float64
 15  music                     1278 non-null   float64
 16  movement/places           1278 non-null   float64
 17  light/visual perceptions  1278 non-null   float64
 18  family/spiritual          1278 non-null   float64
 19  like/girls                1278 non-null   float64
 20  sadness                   1278 non-null   float64
 21  feelings                  1278 non-null   float64
 22  danceability              1278 non-null   float64
 23  loudness                  1278 non-null   float64
 24  acousticness              1278 non-null   float64
 25  instrumentalness          1278 non-null   float64
 26  valence                   1278 non-null   float64
 27  energy                    1278 non-null   float64
 28  topic                     1278 non-null   object 
 29  age                       1278 non-null   float64
dtypes: float64(23), int64(2), object(5)
memory usage: 309.5+ KB
```

In [7]:

```
df.describe()
```

Out[7]:

	release_date	len	dating	violence	world/life	night/time	shake the audience	fa
count	1278.000000	1278.000000	1278.000000	1278.000000	1278.000000	1278.000000	1278.000000	
mean	2017.933490	86.089202	0.018776	0.142754	0.105924	0.054130	0.029147	
std	0.787205	45.783015	0.043383	0.189347	0.162829	0.103597	0.052656	
min	2017.000000	1.000000	0.000315	0.000315	0.000301	0.000346	0.000342	
25%	2017.000000	49.000000	0.000752	0.000927	0.000835	0.000822	0.000993	
50%	2018.000000	80.000000	0.001350	0.036336	0.003010	0.001880	0.002149	
75%	2019.000000	117.000000	0.004785	0.305575	0.148849	0.064782	0.036330	
max	2019.000000	199.000000	0.362900	0.927126	0.766905	0.735489	0.402632	

8 rows × 25 columns

In [8]:

```
df.corr()
```

Out[8]:

	release_date	len	dating	violence	world/life	night/time	shake the audience	fam
release_date	1.000000	0.000599	-0.021424	-0.008955	-0.008615	0.021668	0.040296	
len	0.000599	1.000000	0.041516	-0.136853	-0.174779	-0.060549	0.224751	
dating	-0.021424	0.041516	1.000000	-0.096495	-0.064834	0.016264	-0.002099	
violence	-0.008955	-0.136853	-0.096495	1.000000	-0.206975	-0.118914	-0.098632	
world/life	-0.008615	-0.174779	-0.064834	-0.206975	1.000000	-0.116900	-0.052357	
night/time	0.021668	-0.060549	0.016264	-0.118914	-0.116900	1.000000	-0.058860	
shake the audience	0.040296	0.224751	-0.002099	-0.098632	-0.052357	-0.058860	1.000000	
family/gospel	0.030347	0.009925	-0.005780	-0.018016	-0.013319	-0.004434	-0.027790	
romantic	-0.044471	-0.091255	0.025130	-0.072353	-0.041029	-0.007233	-0.046684	
communication	-0.033837	-0.010120	-0.035637	-0.112843	-0.097527	-0.026458	-0.044599	
obscene	0.040415	0.453468	-0.013736	-0.274653	-0.252029	-0.126810	0.149482	
music	0.005952	-0.050636	-0.042560	-0.119723	-0.075264	-0.026247	-0.070108	
movement/places	0.047721	0.185904	-0.042267	-0.138008	-0.045384	-0.075488	-0.011722	
light/visual perceptions	0.027188	-0.069044	-0.074946	0.017065	-0.003751	-0.015246	-0.103583	
family/spiritual	0.025389	-0.060082	-0.064565	0.097941	0.023699	-0.039966	-0.057722	
like/girls	0.004294	0.097607	0.005282	-0.098260	-0.044062	0.007468	-0.023804	
sadness	-0.040235	-0.131278	0.049147	-0.219773	-0.159474	-0.101217	-0.067673	
feelings	-0.031198	-0.033126	-0.004244	-0.079927	-0.031918	-0.003229	-0.047537	
danceability	0.018391	0.392302	0.014236	-0.175856	-0.126299	-0.006735	0.092519	
loudness	0.051561	0.158529	0.012287	-0.002213	-0.071862	0.017789	0.064995	
acousticness	-0.072207	-0.092432	-0.014306	-0.095886	0.070819	-0.037953	-0.055265	
instrumentalness	-0.008167	-0.140661	-0.017386	0.133918	-0.023776	0.012624	-0.072925	
valence	0.021728	0.150815	0.058645	-0.079593	-0.074164	0.074184	-0.024530	
energy	0.071666	0.067195	-0.012866	0.117018	-0.069936	0.071475	0.038864	
age	-1.000000	-0.000599	0.021424	0.008955	0.008615	-0.021668	-0.040296	

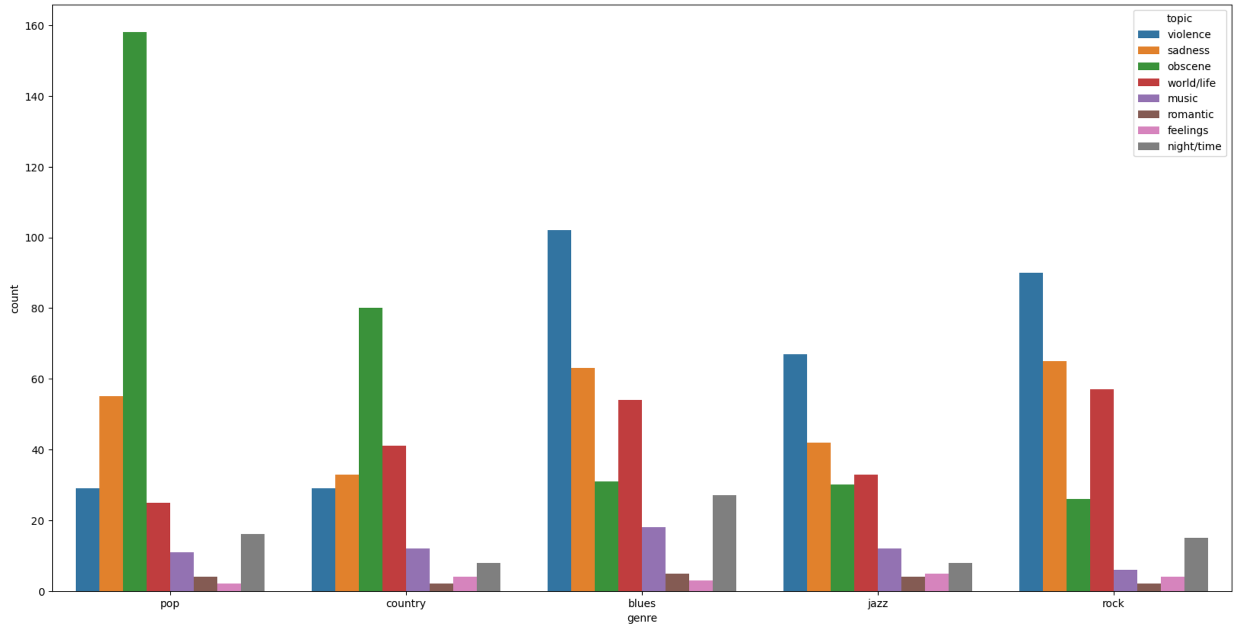
25 rows × 25 columns

Visualization

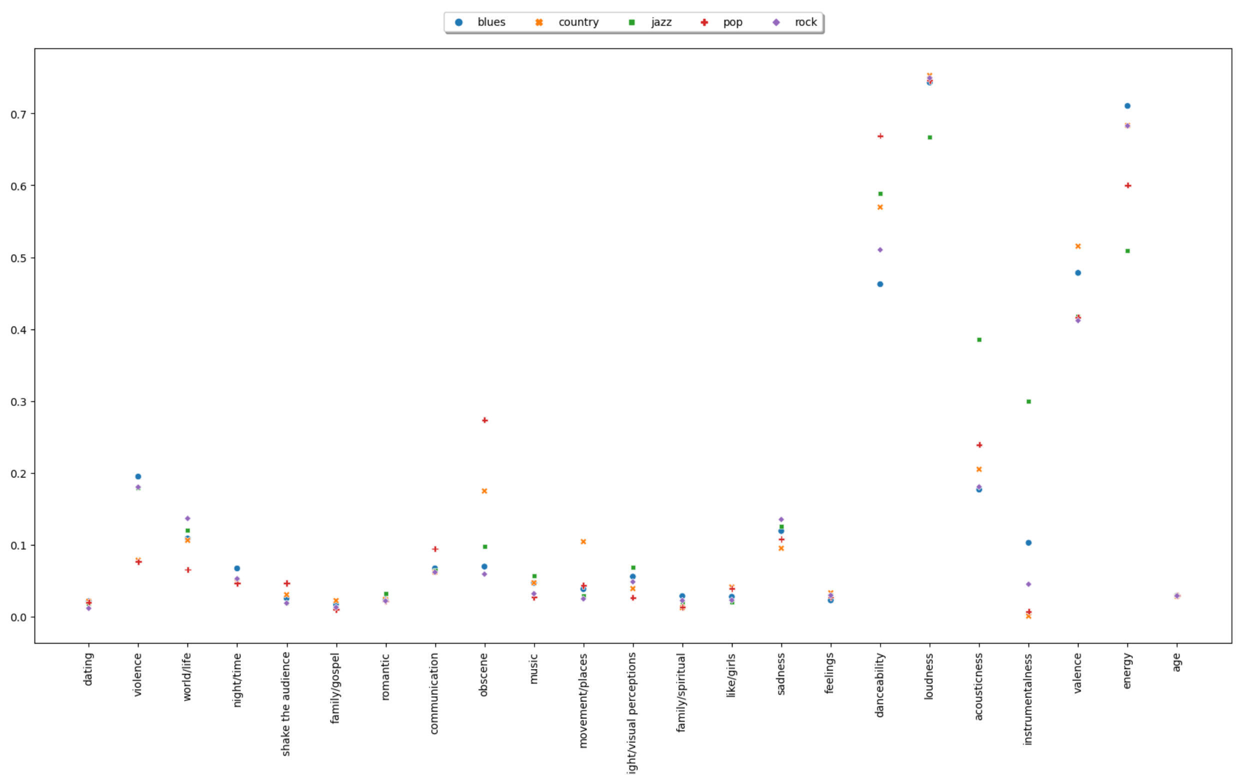
In [9]:

```
# some exploration and visualization
fig, ax = plt.subplots(figsize=(20, 10))
```

```python
sns.countplot(x='genre', data=df, hue='topic');
```

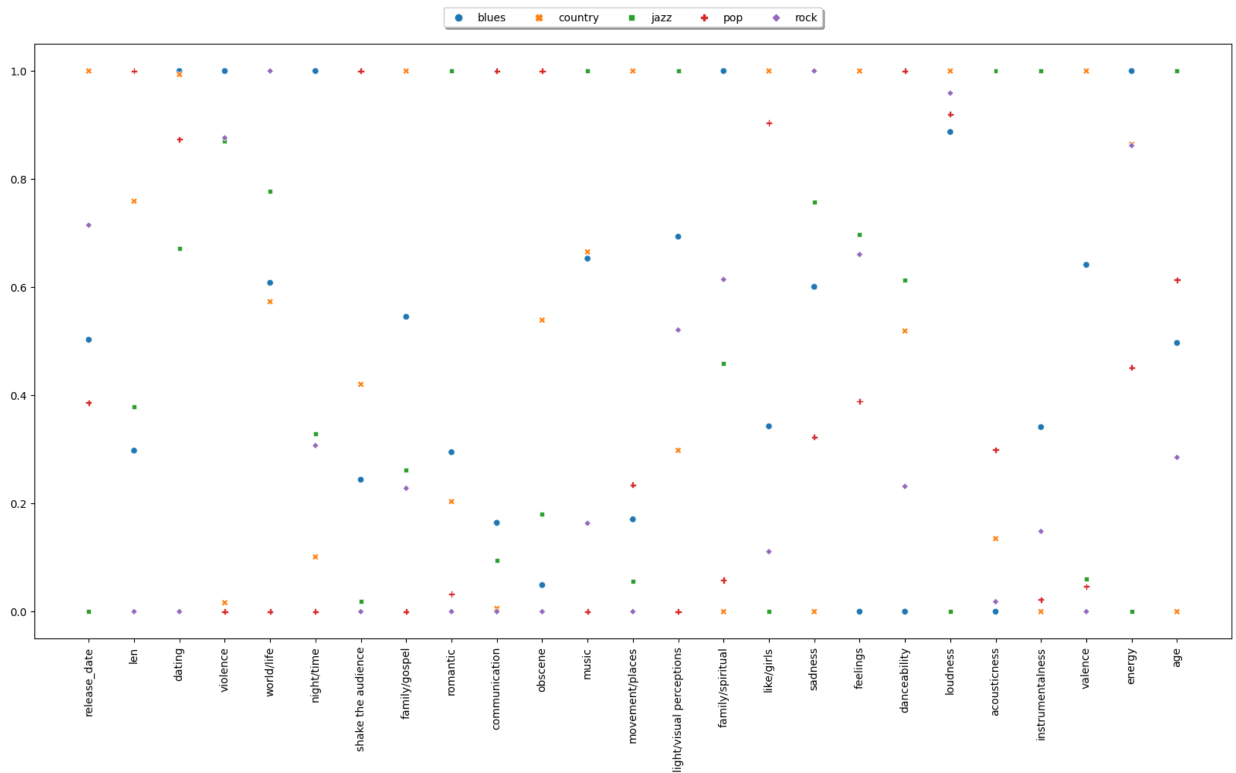


In [10]:
```python
data = df.groupby('genre').mean(numeric_only=True).drop(['release_date','len'], axis=1
fig, ax = plt.subplots(figsize=(20, 10))
sns.scatterplot(data=data.T)
plt.xticks(rotation=90)
plt.legend(loc='upper center', bbox_to_anchor=(.5, 1.07),
          ncol=7, fancybox=True, shadow=True);
```

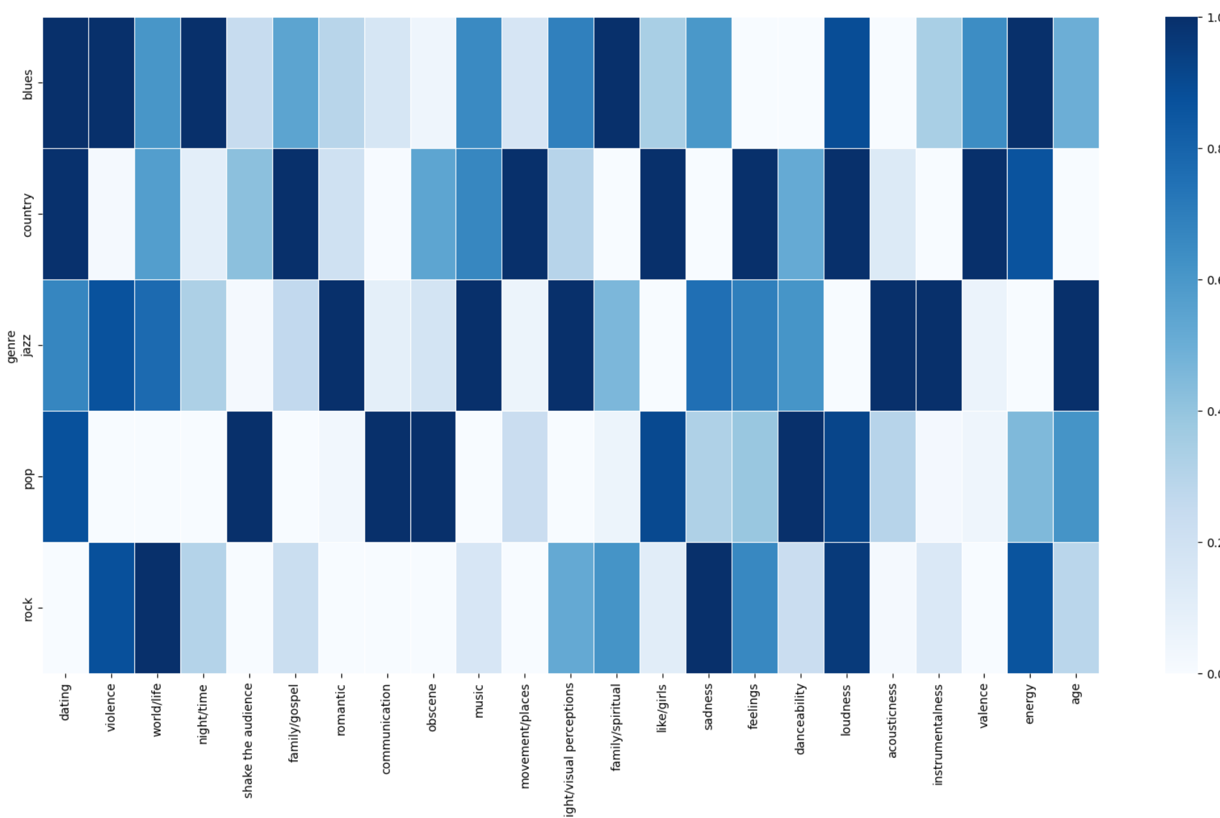


In [11]:
```python
#min max scaling data
data = df.groupby('genre').mean(numeric_only=True)
data = (data - data.min())/(data.max()-data.min())
fig, ax = plt.subplots(figsize=(20, 10))
sns.scatterplot(data=data.T)
plt.xticks(rotation=90)
```

```
plt.legend(loc='upper center', bbox_to_anchor=(.5, 1.07),
           ncol=7, fancybox=True, shadow=True);
```



In [12]:
```
data = df.groupby('genre').mean(numeric_only=True).drop(['release_date','len'], axis=
data = (data - data.min())/(data.max()-data.min())
fig, ax = plt.subplots(figsize=(20, 10))
sns.heatmap(data, linewidths=.5, cmap='Blues');
```



Preliminary work - Machine Learning

Train Test Split and Standard Scaler

In [13]:
```
# TOPIC_FEATURES
X_topic_train_raw, X_topic_test_raw, y_topic_train, y_topic_test = train_test_split(
    topic_features, target_le, test_size=.30, random_state=0
)

#use standard scaler for topic
scaler_topic = StandardScaler()
X_topic_train = scaler_topic.fit_transform(X_topic_train_raw)
X_topic_test = scaler_topic.transform(X_topic_test_raw)

# MUSIC_FEATURES
X_mFeatures_train_raw, X_mFeatures_test_raw, y_mFeatures_train, y_mFeatures_test = tra
    music_features, target_le, test_size=.30, random_state=0
)


#use standard scaler
scaler_features = StandardScaler()
X_mfeatures_train = scaler_features.fit_transform(X_mFeatures_train_raw)
X_mfeatures_test = scaler_features.transform(X_mFeatures_test_raw)


# ALL_FEATURES
X_allFeatures_train_raw, X_allFeatures_test_raw, y_allFeatures_train, y_allFeatures_te
    all_features, target_le, test_size=.30, random_state=0
)


#use standard scaler
scaler_allFeatures = StandardScaler()
X_allFeatures_train = scaler_features.fit_transform(X_allFeatures_train_raw)
X_allFeatures_test = scaler_features.transform(X_allFeatures_test_raw)
```

Methods - Machine Learning

We implemented three machine learning algorithms to predict the genre of a song based off given lyrical characteristics. The machine learning algorithms we used below are KNN, Decsion Tree, and Random Forest.

KNN Classifier

Topic Features

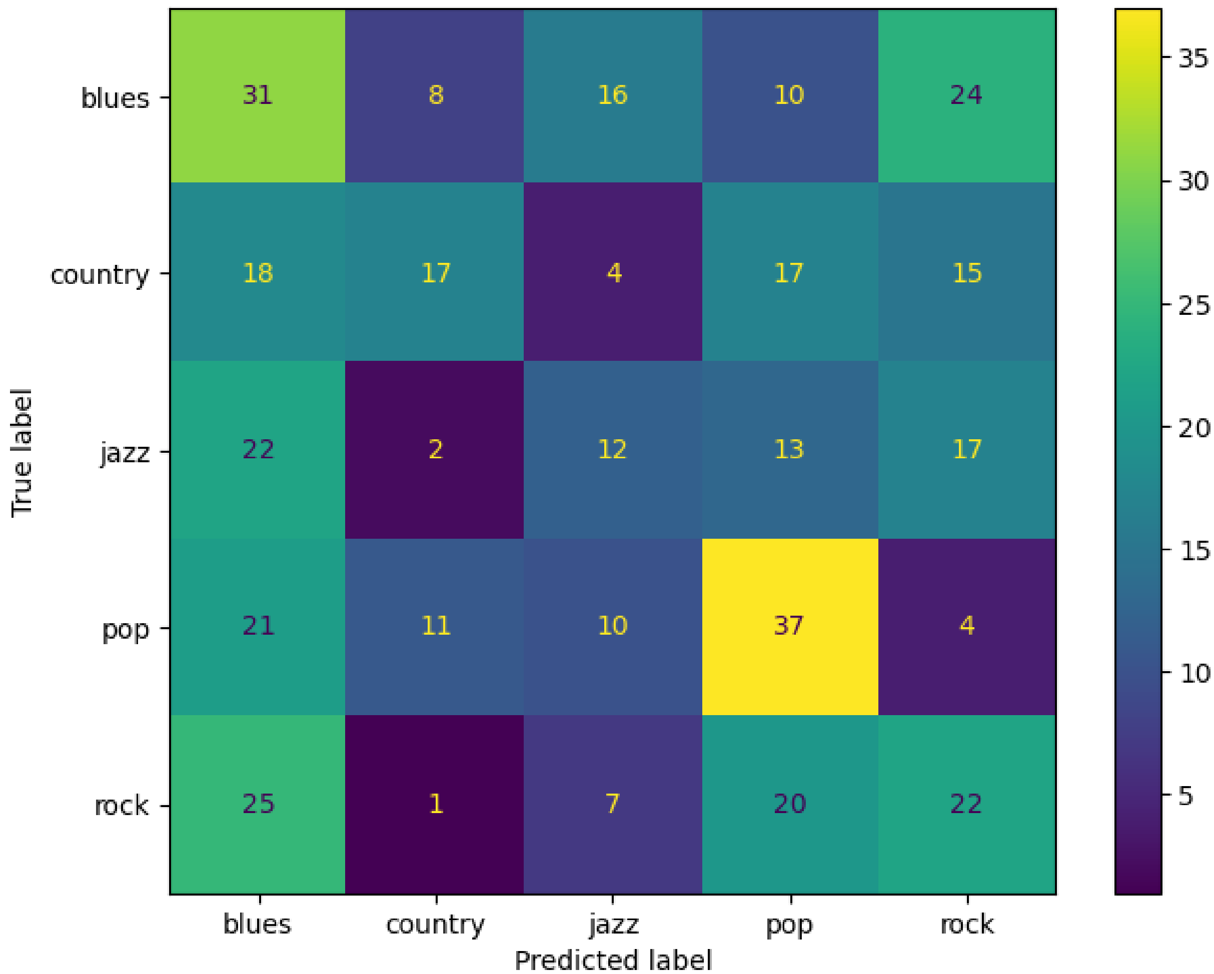
In [14]:
```
# TOPIC_FEATURES
from sklearn.metrics import accuracy_score
knn = KNeighborsClassifier()
knn.fit(X_topic_train, np.ravel(y_topic_train))
```

```
predictions = knn.predict(X_topic_test)
print(accuracy_score(y_topic_test, predictions))
```

```
0.3098958333333333
```

In [15]:

```
cm = confusion_matrix(y_topic_test, predictions, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['blues', 'country',
disp.plot()
plt.show()

# sanity check that labels correspond to the right encoded values
print(target_le.value_counts())
print(df[target].value_counts())
```



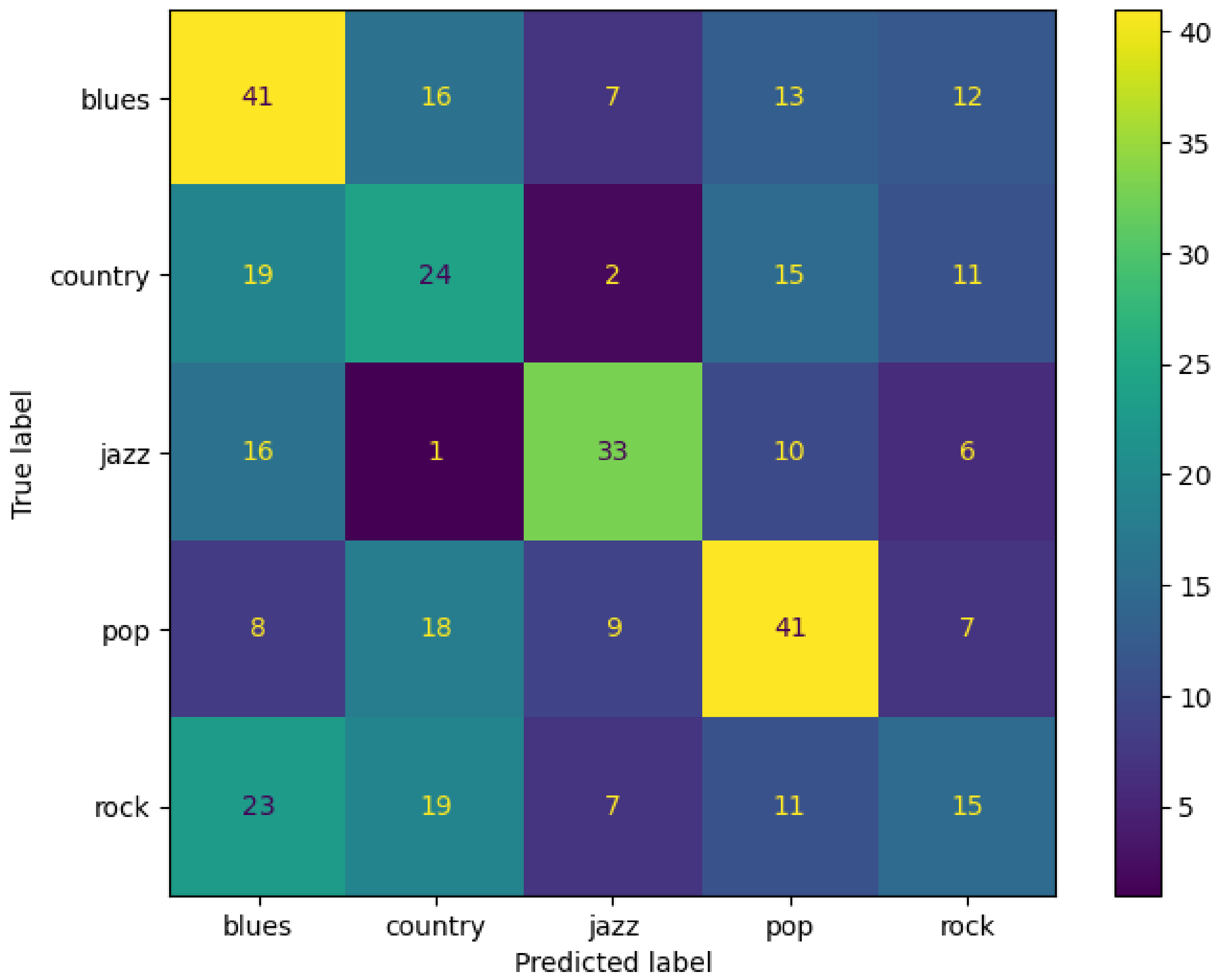

```
0    303
3    300
4    265
1    209
2    201
dtype: int64
genre
blues      303
pop        300
rock       265
country    209
jazz       201
dtype: int64
```

Music Features

In [16]:
```
# MUSIC_FEATURES
knn = KNeighborsClassifier()
knn.fit(X_mfeatures_train, np.ravel(y_mFeatures_train))
predictions = knn.predict(X_mfeatures_test)
print(accuracy_score(y_mFeatures_test, predictions))
```

```
0.4010416666666667
```

In [17]:
```
cm = confusion_matrix(y_mFeatures_test, predictions, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['blues', 'country',
disp.plot()
plt.show()

# sanity check that labels correspond to the right encoded values
print(target_le.value_counts())
print(df[target].value_counts())
```



```
0    303
3    300
4    265
1    209
2    201
dtype: int64
genre
blues      303
pop        300
rock       265
country    209
jazz       201
dtype: int64
```

Decision Tree

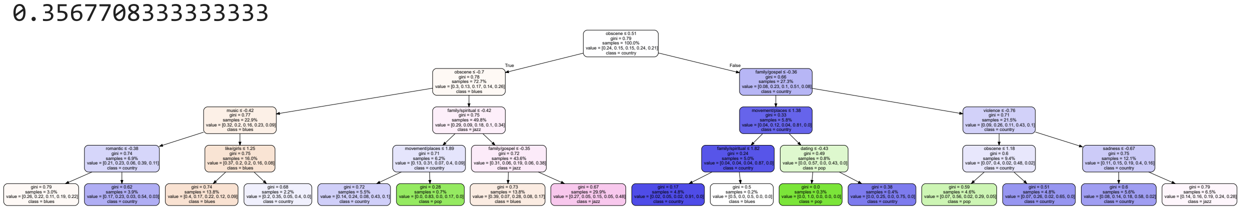
Topic Features

In [18]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
import graphviz

clf = DecisionTreeClassifier(random_state=42, max_depth=4, max_features=0.4)
clf.fit(X_topic_train, np.ravel(y_topic_train))

predictions = clf.predict(X_topic_test)
print(accuracy_score(y_topic_test, predictions))
target_names = df['genre'].value_counts().index.values
dot_data = export_graphviz(clf, precision=2,
                     feature_names=predictor_topics,
                     proportion=True,
                     class_names=target_names,
                     filled=True, rounded=True,
                     special_characters=True)

# plot it
graph = graphviz.Source(dot_data)
graph
```

```
0.35677083333333333
```

Out[18]:



Music Features

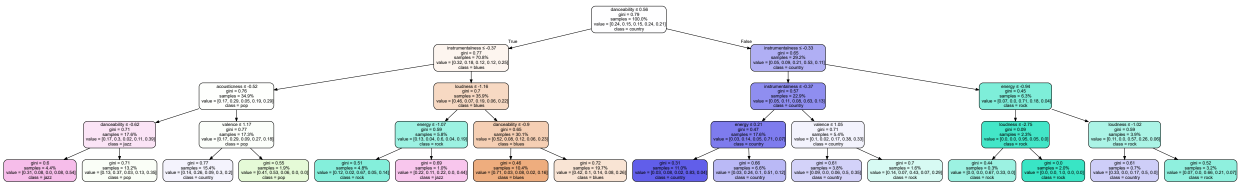
In [19]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
import graphviz
clf = DecisionTreeClassifier(random_state=42, max_depth=4)
clf.fit(X_mfeatures_train, np.ravel(y_mFeatures_train))

predictions = clf.predict(X_mfeatures_test)
print(accuracy_score(y_mFeatures_test, predictions))
target_names = df['genre'].value_counts().index.values
```

```
dot_data = export_graphviz(clf, precision=2,
                           feature_names=predictor_music_features,
                           proportion=True,
                           class_names=target_names,
                           filled=True, rounded=True,
                           special_characters=True)

# plot it
graph = graphviz.Source(dot_data)
graph
```

0.47395833333333333

Out[19]:



Random Forest

Topic Features

In [20]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics

forest = RandomForestClassifier(criterion='entropy', random_state=42, max_depth=6, max
forest.fit(X_topic_train, np.ravel(y_topic_train))
predictions = forest.predict(X_topic_test)
print("Accuracy:",metrics.accuracy_score(y_topic_test, predictions))
```

Accuracy: 0.4088541666666667

Music Features

In [21]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics

forest = RandomForestClassifier(max_depth=5, min_samples_leaf=10, n_estimators=200,
                              n_jobs=-1, random_state=42) #best params found using GridSearch
forest.fit(X_mfeatures_train, np.ravel(y_mFeatures_train))
predictions = forest.predict(X_mfeatures_test)
print("Accuracy:",metrics.accuracy_score(y_mFeatures_test, predictions))
```

Accuracy: 0.53125

All Features

In [22]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics

forest = RandomForestClassifier(max_depth=10, min_samples_leaf=5, n_estimators=30,
                              n_jobs=-1, random_state=42) #best params found using GridSearch
forest.fit(X_allFeatures_train, np.ravel(y_allFeatures_train))
predictions = forest.predict(X_allFeatures_test)
print("Accuracy:",metrics.accuracy_score(y_allFeatures_test, predictions))
```

Accuracy: 0.5520833333333334

Results

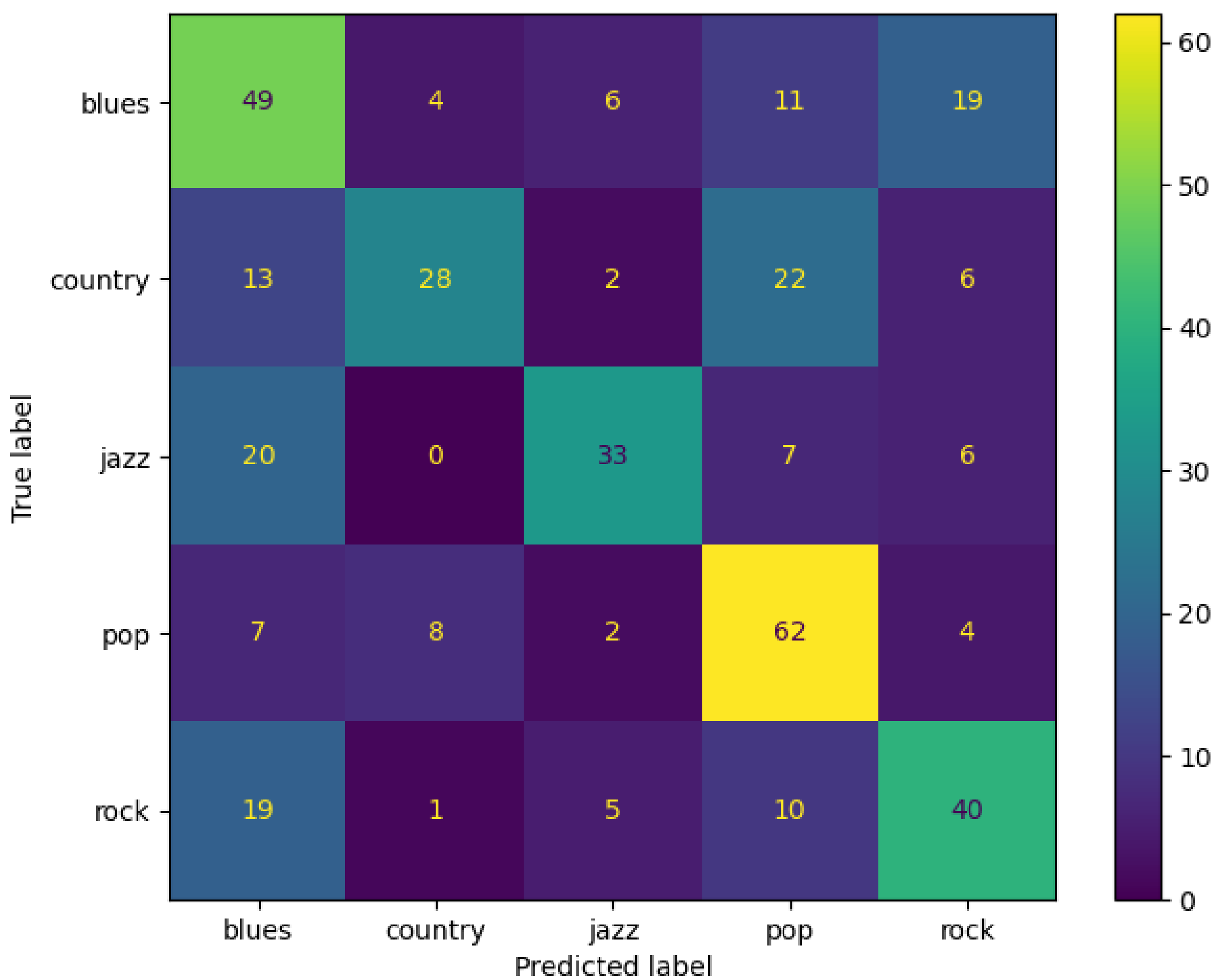
What answer was found to the research question; what did the study find? Was the tested hypothesis true? Any visualizations?

In our quest to classify the genre of songs in our dataset we ran into some issues in terms of representing our target variable. Initially used sklearn's one-hot encoder to represent our target variable, but ultimately this encoder was causing inaccuracies with the machine learning algorithms. Using one-hot encoder we were getting around an 8% accuracy with the Random Forest machine learning algorithm. By switching to sklearn's Label Encoder we were able to get the accuracy up to 55% using sklean's for the same algorithm. This showed us the importance of how we represent out target variable and the issues that can occur when dealing with a classification machine learning.

Confusion Matrix for Highest accuracy Model

In [23]:

```
cm = confusion_matrix(y_allFeatures_test, predictions, labels=forest.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['blues', 'country',
disp.plot()
plt.show()
```



Discussion

What might the answer imply and why does it matter? How does it fit in with what other researchers have found? What are the perspectives for future research? Survey about the tools investigated for this assignment.

The level of accuracy we attained implies the need for further research to be able to increase the accuracy of the predictions made. Some ideas for future research could include a more thorough analysis of the lyrical content of the songs in our dataset, as well as more characteristics on them such as rhythm. For this project we were able to use a variety of tools. Some of the tools we utilized were pandas for holding our data in a data frame and some visualization tools we used were seaborn and matplotlib. Finally we also implemented sklearn for separating the training and test data as well as some of their machine learning algorithms.

Summary

Most important findings.

In this project we sought out a way to use classification to identify the genre of a song based on its associated features. We used Scikit-Learn's classification estimators to get these predictions. The degree of accuracy was not to our initial expectation, but it gave us good practice in trying to identify different ways of increasing our accuracy. One of our most important findings was figuring out which features should be included. We made three sets of predictors; first being the features associated with the topic of the songs, next being the features associated with the characteristics of the songs (such as danceability), and lastly we had both together. We found that the predictors with the highest accuracy was the last set which included both the topic and characteristics. Another important finding was that using songs after 2017 also increased our accuracy, this is most likely due to music changing so much in the years prior. Lastly a very important finding was which classification machine learning algorithm would yield the highest accuracy and we found that to be the Random Forest Classification.