USING CLUSTERING TO PREDICT THE MUSIC GENRE OF SONGS WITH THE GIVEN FEATURES OF THE DATASET

INTRODUCTION TO THE PROBLEM
The problem is to find if it is possible to accurately cluster groups of songs together based on their genre without knowing what there genre is.

WHAT IS CLUSTERING AND HOW DOES IT WORK?

INTRODUCTION OF THE DATASET
The data set is taken from kaggle from user 'vicsuperman'. The data set include columns: instance_id, artist_name, track_name, popularity, acousticness, danceability, duration_ms, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, obtained_date, valence, music_genre. Columns deemed neccesarry to predict what genre of music a song is were: 'acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo', 'valence'. These characteristics were labeled as 'features' in the code. The 'music_genre' column was used to test the accuracy of using the clustering method for guessing the music genre of different songs.

DATA UNDERSTANDING/VISUALIZATION

PRE-PROCESSING THE DATA
To preprocess the data all null values were dropped from the dataset as any rows containing with null would mess with the output. Some columns had data as a '?' instead of a number which would cause issues with inputing the data into the model so that data was converted to N/A before dropping of N/A values took place so all of these unusable rows could be removed in one go.

MODELING (CLUSTERING)

STORYTELLING (CLUSTERING ANALYSIS)

IMPACT SECTION
Clustering is not commonly used for creating models for unsupervised learning. Music recommendation apps like Spotify use many different types of AI and ML instead of just one technique to find which song to recommend to a user. If recommendation systems can use another technique to help create more accurate recommendations for users than they should do so to give users the best experience. Completeing a project like this with a less common technique for recommendations could create discussion around new techniques to help create better recommendation systems in the future.

REFERENCES
https://www.kaggle.com/datasets/vicsuperman/prediction-of-music-genre/data

CODE

import pandas as pd import numpy as np from sklearn.preprocessing import StandardScaler from sklearn.cluster import KMeans from sklearn.metrics import confusion_matrix, classification_report from sklearn.decomposition import PCA import matplotlib.pyplot as plt

In [68]:
```
df = pd.read_csv("music_genre.csv")
```

In [69]:
```
df.replace('?', np.nan, inplace=True)

df = df.dropna()

features = df[['acousticness', 'danceability', 'energy', 'instrumentalness', 'liven

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)

df_features_scaled = pd.DataFrame(scaled_features, columns=features.columns)
```

In [72]:
```
kmeans = KMeans(n_clusters=10, n_init=10, random_state=42)
df['predicted_genre'] = kmeans.fit_predict(scaled_features)
clusters = kmeans.fit_predict(scaled_features)
```

In [73]:
```
cluster_to_genre = df.groupby('predicted_genre')['music_genre'].agg(lambda x: x.val

df['predicted_genre'] = df['predicted_genre'].map(cluster_to_genre)

print(classification_report(df['music_genre'], df['predicted_genre'], zero_division
```

```
              precision    recall  f1-score   support

 Alternative       0.20      0.24      0.22      4495
       Anime       0.19      0.27      0.22      4497
       Blues       0.22      0.12      0.15      4470
   Classical       0.64      0.81      0.71      4500
     Country       0.17      0.28      0.21      4486
  Electronic       0.38      0.29      0.33      4466
     Hip-Hop       0.40      0.41      0.40      4520
        Jazz       0.23      0.26      0.24      4521
         Rap       0.25      0.27      0.26      4504
        Rock       0.00      0.00      0.00      4561

    accuracy                           0.29     45020
   macro avg       0.27      0.29      0.28     45020
weighted avg       0.27      0.29      0.28     45020
```

In [74]:
```
features = df[['acousticness', 'danceability', 'energy', 'instrumentalness', 'liven

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)
```

In [75]:
```
n_clusters = 12  # adjust based on your dataset and domain knowledge

kmeans = KMeans(n_clusters=n_clusters, n_init=10, random_state=42)
df['cluster'] = kmeans.fit_predict(scaled_features)
```

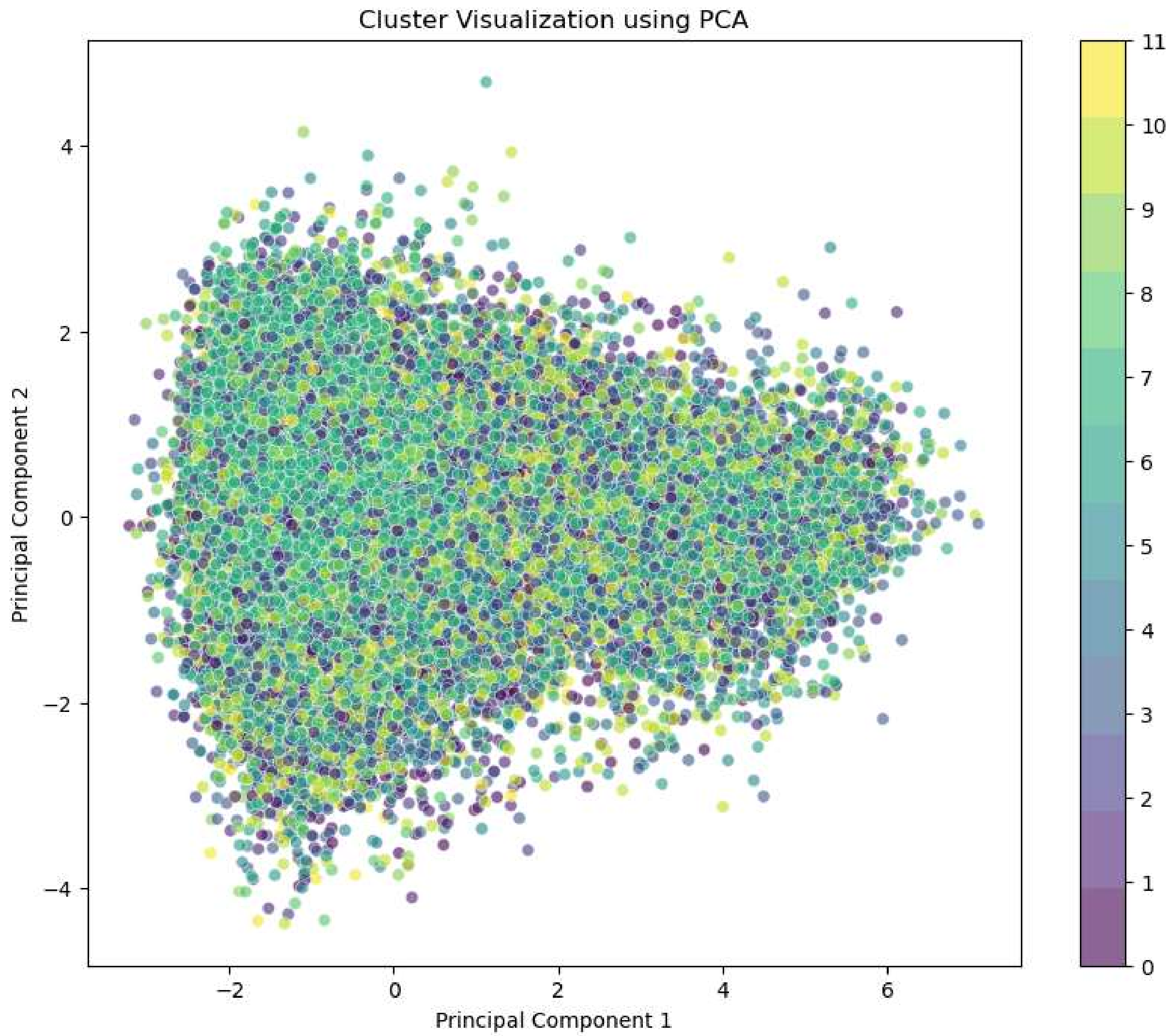
In [76]:
```
pca = PCA(n_components=2)
principal_components = pca.fit_transform(scaled_features)

pca_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])
pca_df['cluster'] = df['cluster']
```

In [77]:
```
plt.figure(figsize=(10, 8))
colors = plt.cm.get_cmap('viridis', n_clusters)

scatter = plt.scatter(pca_df['PC1'], pca_df['PC2'], c=pca_df['cluster'], cmap=color
plt.title('Cluster Visualization using PCA')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(scatter, ticks=range(n_clusters))
plt.show()
```

```
C:\Users\Holden\AppData\Local\Temp\ipykernel_2236\2663688093.py:2: MatplotlibDepreca
tionWarning: The get_cmap function was deprecated in Matplotlib 3.7 and will be remo
ved two minor releases later. Use ``matplotlib.colormaps[name]`` or ``matplotlib.col
ormaps.get_cmap(obj)`` instead.
  colors = plt.cm.get_cmap('viridis', n_clusters)
```


Cluster Visualization using PCA
Principal Component 1
Principal Component 2
−2
0
2
4
6
−4
−2
0
2
4
0
1
2
3
4
5
6
7
8
9
10
11