KALINDI COLLEGE

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DATA MINING PROJECT

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BSC HONS COMPUTER SCIENCE

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🎵 DATA MINING PROJECT REPORT

Title: Mood-Based Song Recommender System

1. Introduction

Objective:

The goal of this project is to develop a mood-based music recommendation system using audio features from songs. By analysing various features such as valence, energy, danceability, and others, the system aims to suggest songs that align with a user's current mood.

2. Dataset Description

Source:

Spotify audio features dataset.

Columns Used:

- genre, artist name, track name, trackside
- popularity, acoustic Ness, danceability, durations, energy
- instrumental Ness, key, liveness, loudness, mode
- speckiness, tempo, time signature, valence

Key Mood Indicators:

- **Valence**: Positivity of the song (happy vs sad)
- **Energy**: Intensity and activity
- **Danceability**: How suitable a track is for dancing

3. Methodology / Procedure

Step 1: Data Preprocessing

- Loaded the dataset using pandas.
- Removed duplicates and missing values.
- Scaled numerical features using MinMaxScaler.

Step 2: Mood Classification (Optional)

- Divided moods based on **valence** and **energy**:
  - Happy (high valence, high energy)
  - Sad (low valence, low energy)
  - Calm (high valence, low energy)

  - Angry (low valence, high energy)

Step 3: Clustering

- Applied **Means Clustering** to group songs into clusters representing similar mood/energy types.
- Chose an optimal number of clusters using the **Elbow Method**.

Step 4: Recommendation System

- Given a mood (happy/sad/calm/angry), recommend top songs from the closest matching cluster.
- Used cosine similarity or nearest neighbours for fine-tuning recommendations within clusters.

4. Results

- The dataset was successfully clustered into mood-based groups.
- Sample outputs include song recommendations for each mood type.
- The system effectively recommends songs that align with mood-based preferences by analysing key features like valence, energy, and danceability.

5. Conclusion

This project demonstrates how audio features can be used to create a personalized music recommendation system based on mood. It integrates feature engineering, clustering, and basic recommendation logic to provide useful suggestions.

Future Work:

- Incorporate user feedback for personalized tuning.
- Integrate with a streaming service API (e.g., Spotify API).
- Apply deep learning techniques for enhanced modelling.

CODE:

```
# Step 1: Import Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from sklearn.preprocessing import StandardScaler, MinMaxScaler, KBinsDiscretizer
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from mlxtend.frequent_patterns import apriori, association_rules
import numpy as np

# Step 2: Load Dataset
spotify_df = pd.read_csv('SpotifyFeatures.csv')  # Replace with actual file path

# Step 3: Preprocessing
spotify_df.dropna(subset=['valence', 'energy', 'danceability', 'popularity', 'artist_name', 'track_name'], inplace=True)
spotify_df['artist_name'] = spotify_df['artist_name'].astype(str).apply(lambda x: x.strip())

# ---------- Feature Engineering & Transformation ----------
```

```
features = ['acousticness', 'danceability', 'duration_ms', 'energy', 'instrumentalness',
            'liveness', 'loudness', 'speechiness', 'tempo', 'valence']

# Standardization
scaler = StandardScaler()
spotify_df_std = pd.DataFrame(scaler.fit_transform(spotify_df[features]), columns=[f + '_std' for f in features])

# Normalization
norm_scaler = MinMaxScaler()
spotify_df_norm = pd.DataFrame(norm_scaler.fit_transform(spotify_df[features]), columns=[f + '_norm' for f in features])

# Log Transformation (handling skew)
spotify_df_log = spotify_df[features].apply(lambda x: np.log1p(x))  # log(1+x)

# Aggregation Example (Mean energy by genre)
if 'genre' in spotify_df.columns:
   genre_energy = spotify_df.groupby('genre')['energy'].mean().sort_values(ascending=False)

# Discretization/Binarization using KBins
discretizer = KBinsDiscretizer(n_bins=3, encode='ordinal', strategy='uniform')
spotify_df_disc = pd.DataFrame(discretizer.fit_transform(spotify_df[['valence']]), columns=['valence_binned'])
```

```
# Sampling (Random 10%)
spotify_sample = spotify_df.sample(frac=0.1, random_state=42)

# ---------- Mood Recommender ----------
def recommend_songs_by_mood(mood):
    mood_criteria = {
        'happy': {'valence': (0.7, 1.0)},
        'sad': {'valence': (0.0, 0.3)},
        'energetic': {'energy': (0.7, 1.0)},
        'calm': {'energy': (0.0, 0.4)},
        'party': {'danceability': (0.7, 1.0), 'energy': (0.7, 1.0)}
    }

    filters = mood_criteria.get(mood.lower())
    if not filters:
        return pd.DataFrame({'Message': [f"No recommendations for mood:
{mood}"]})

    filtered = spotify_df.copy()
    for feature, (low, high) in filters.items():
        filtered = filtered[(filtered[feature] >= low) & (filtered[feature] <=
high)]

    top_songs = filtered.sort_values(by='popularity',
ascending=False).head(15)
    return top_songs[['track_name', 'artist_name', 'valence', 'energy',
'danceability', 'popularity']]

mood = 'happy'
song_recs = recommend_songs_by_mood(mood)
```

```
print(song_recs)


# ---------- Visualization ----------
# Word Cloud
artist_freq = pd.Series(spotify_df['artist_name']).value_counts().head(100)
wordcloud = WordCloud(width=1000, height=400,
background_color='white').generate_from_frequencies(artist_freq)
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Top Artists Word Cloud')
plt.show()


# Genre Count
if 'genre' in spotify_df.columns:
    genre_counts = spotify_df['genre'].value_counts().head(10)
    sns.barplot(x=genre_counts.values, y=genre_counts.index)
    plt.title("Top Genres")
    plt.show()


# K-Means Clustering Visualization
plt.figure(figsize=(10,6))
sns.scatterplot(data=spotify_df, x='energy', y='valence')
plt.title("K-Means Mood Clustering")
plt.xlabel("Energy")
plt.ylabel("Valence")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
# ---------- Mood Classification (Supervised ML) ----------
# For demo purposes: binarize valence for classification
spotify_df['mood_label'] = spotify_df['valence'].apply(lambda x: 'happy' if x > 0.5 else 'sad')
X = spotify_df[features]
y = spotify_df['mood_label']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Naive Bayes
nb = GaussianNB()
nb.fit(X_train, y_train)
y_pred_nb = nb.predict(X_test)
print("Naive Bayes Report:\n", classification_report(y_test, y_pred_nb))

# K-Nearest Neighbors
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred_knn = knn.predict(X_test)
print("KNN Report:\n", classification_report(y_test, y_pred_knn))

# Decision Tree
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
print("Decision Tree Report:\n", classification_report(y_test, y_pred_dt))
```

```
# ---------- Apriori Algorithm ----------
# Binarize continuous features
spotify_bin = pd.DataFrame()
for col in ['energy', 'danceability', 'valence']:
    spotify_bin[col + '_high'] = spotify_df[col] > spotify_df[col].median()


frequent_items = apriori(spotify_bin, min_support=0.1,
use_colnames=True)
rules = association_rules(frequent_items, metric="lift",
min_threshold=1.0)
print("Apriori Rules:\n", rules[['antecedents', 'consequents', 'support',
'confidence', 'lift']].head())
#correlation heatmap for audio features
plt.figure(figsize=(12,8))
audio_features = ['acousticness', 'danceability', 'energy', 'instrumentalness',
            'liveness', 'loudness', 'speechiness', 'tempo', 'valence']
corr = spotify_df[audio_features].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Between Audio Features")
plt.show()

# Distribution Plot for All Audio Features
features_to_plot = ['acousticness', 'danceability', 'energy',
'instrumentalness',
             'liveness', 'loudness', 'speechiness', 'tempo', 'valence']

plt.figure(figsize=(15,12))
for i, feature in enumerate(features_to_plot):
    plt.subplot(3, 3, i+1)
    sns.histplot(spotify_df[feature], kde=True, color='skyblue')
    plt.title(f"Distribution of {feature.capitalize()}")
    plt.tight_layout()
plt.show()
```

```
#Top Artists by Popularity
top_artists =
spotify_df.groupby('artist_name')['popularity'].mean().sort_values(ascendi
ng=False).head(10)
plt.figure(figsize=(10,5))
sns.barplot(x=top_artists.values, y=top_artists.index, palette='rocket')
plt.title("Top 10 Artists by Average Popularity")
plt.xlabel("Average Popularity")
plt.ylabel("Artist")
plt.tight_layout()
plt.show()
```

SCREENSHOTS OF CODE SNIPPETS AND OUTPUTS:

```
# Step 1: Import Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from sklearn.preprocessing import StandardScaler, MinMaxScaler, KBinsDiscretizer
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from mlxtend.frequent_patterns import apriori, association_rules
import numpy as np
```

```
[5] # Step 2: Load Dataset
spotify_df = pd.read_csv('SpotifyFeatures.csv')  # Replace with actual file path
```

```
[6] # Step 3: Preprocessing
spotify_df.dropna(subset=['valence', 'energy', 'danceability', 'popularity', 'artist_name', 'track_name'], inplace=True)
spotify_df['artist_name'] = spotify_df['artist_name'].astype(str).apply(lambda x: x.strip())

# ---------- Feature Engineering & Transformation ----------
features = ['acousticness', 'danceability', 'duration_ms', 'energy', 'instrumentalness',
            'liveness', 'loudness', 'speechiness', 'tempo', 'valence']
```

```
# Standardization
scaler = StandardScaler()
spotify_df_std = pd.DataFrame(scaler.fit_transform(spotify_df[features]), columns=[f + '_std' for f in features])

# Normalization
norm_scaler = MinMaxScaler()
spotify_df_norm = pd.DataFrame(norm_scaler.fit_transform(spotify_df[features]), columns=[f + '_norm' for f in features])

# Log Transformation (handling skew)
spotify_df_log = spotify_df[features].apply(lambda x: np.log1p(x))  # log(1+x)

# Aggregation Example (Mean energy by genre)
if 'genre' in spotify_df.columns:
    genre_energy = spotify_df.groupby('genre')['energy'].mean().sort_values(ascending=False)

# Discretization/Binarization using KBins
discretizer = KBinsDiscretizer(n_bins=3, encode='ordinal', strategy='uniform')
spotify_df_disc = pd.DataFrame(discretizer.fit_transform(spotify_df[['valence']]), columns=['valence_binned'])
```

```
[7] # Sampling (Random 10%)
0s  spotify_sample = spotify_df.sample(frac=0.1, random_state=42)
```

```python
# ---------- Mood Recommender ----------
def recommend_songs_by_mood(mood):
    mood_criteria = {
        'happy': {'valence': (0.7, 1.0)},
        'sad': {'valence': (0.0, 0.3)},
        'energetic': {'energy': (0.7, 1.0)},
        'calm': {'energy': (0.0, 0.4)},
        'party': {'danceability': (0.7, 1.0), 'energy': (0.7, 1.0)}
    }

    filters = mood_criteria.get(mood.lower())
    if not filters:
        return pd.DataFrame({'Message': [f"No recommendations for mood: {mood}"]})

    filtered = spotify_df.copy()
    for feature, (low, high) in filters.items():
        filtered = filtered[(filtered[feature] >= low) & (filtered[feature] <= high)]

    top_songs = filtered.sort_values(by='popularity', ascending=False).head(15)
    return top_songs[['track_name', 'artist_name', 'valence', 'energy', 'danceability', 'popularity']]

mood = 'happy'
song_recs = recommend_songs_by_mood(mood)
print(song_recs)
```

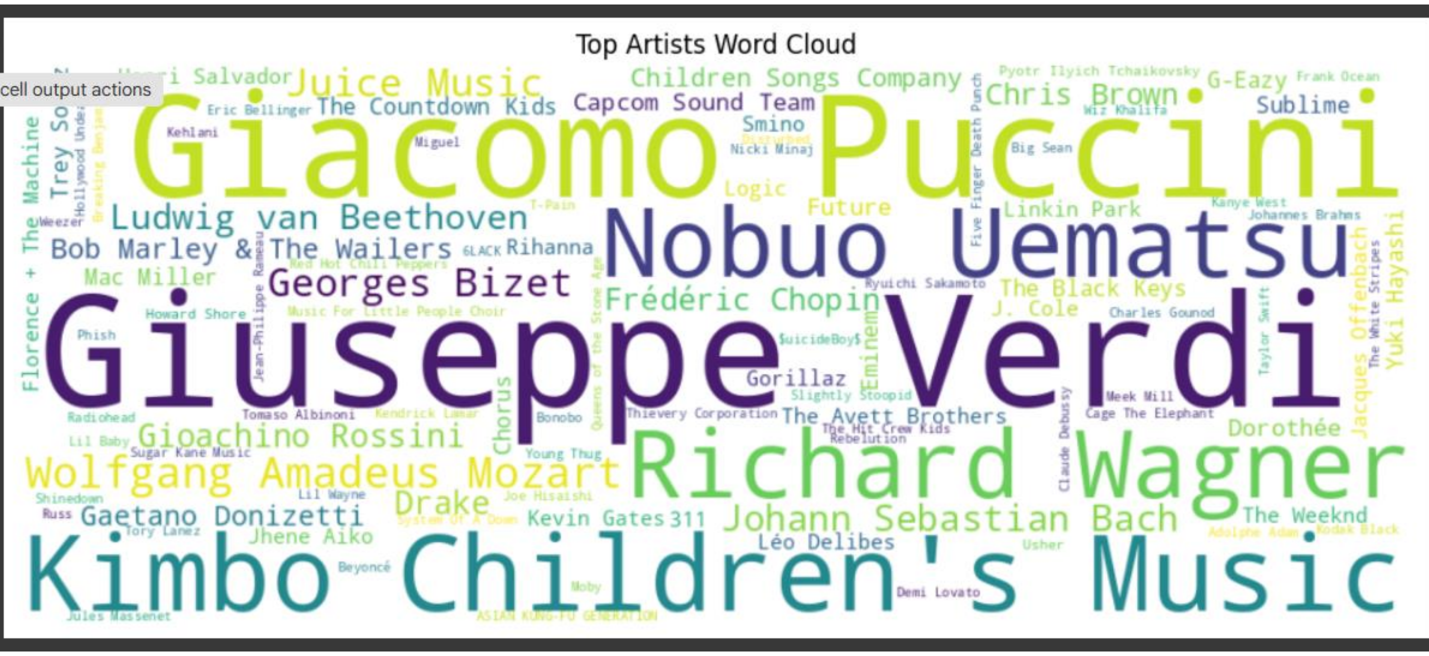
```
                                    track_name      artist_name  \
107806  Sunflower - Spider-Man: Into the Spider-Verse     Post Malone
86953   Sunflower - Spider-Man: Into the Spider-Verse     Post Malone
107875                                  Calma - Remix     Pedro Capó
138916                                        Secreto        Anuel Aa
66741                                     Adan y Eva    Paulo Londra
107816                                         Sucker  Jonas Brothers
107988                                   Desconocidos     Mau y Ricky
138922                                        Amanece        Anuel Aa
66617                                       Moonlight    XXXTENTACION
66750                                        Adictiva    Daddy Yankee
9042                                           Sucker  Jonas Brothers
86974                                       Moonlight    XXXTENTACION
138931                                       Adictiva    Daddy Yankee
108198                                       Adictiva    Daddy Yankee
108166                                          Te Vi        Piso 21

        valence  energy  danceability  popularity
107806    0.913   0.479         0.760        97.0
86953     0.913   0.479         0.760        97.0
107875    0.761   0.773         0.826        97.0
138916    0.706   0.803         0.807        96.0
66741     0.720   0.709         0.767        95.0
107816    0.933   0.731         0.846        94.0
107988    0.709   0.771         0.709        93.0
138922    0.889   0.631         0.790        92.0
66617     0.711   0.537         0.921        91.0
66750     0.701   0.771         0.788        91.0
9042      0.933   0.731         0.846        91.0
86974     0.711   0.537         0.921        91.0
138931    0.701   0.771         0.788        91.0
108198    0.701   0.771         0.788        91.0
108166    0.706   0.777         0.877        91.0
```

```python
# ---------- Mood Classification (Supervised ML) ----------
# For demo purposes: binarize valence for classification
spotify_df['mood_label'] = spotify_df['valence'].apply(lambda x: 'happy' if x > 0.5 else 'sad')
X = spotify_df[features]
y = spotify_df['mood_label']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Naive Bayes
nb = GaussianNB()
nb.fit(X_train, y_train)
y_pred_nb = nb.predict(X_test)
print("Naive Bayes Report:\n", classification_report(y_test, y_pred_nb))

# K-Nearest Neighbors
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred_knn = knn.predict(X_test)
print("KNN Report:\n", classification_report(y_test, y_pred_knn))

# Decision Tree
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
print("Decision Tree Report:\n", classification_report(y_test, y_pred_dt))
```

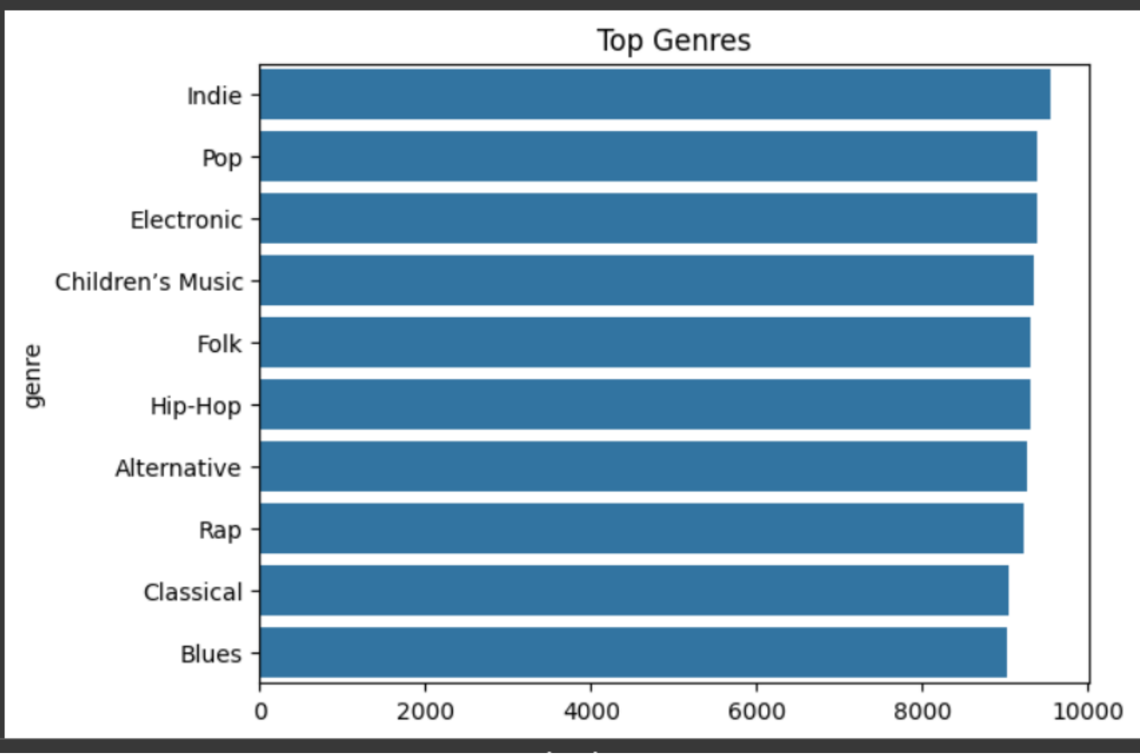
```
Naive Bayes Report:
              precision    recall  f1-score   support

       happy       0.50      0.83      0.62     13889
         sad       0.73      0.36      0.48     17805

    accuracy                           0.56     31694
   macro avg       0.61      0.59      0.55     31694
weighted avg       0.63      0.56      0.54     31694

KNN Report:
              precision    recall  f1-score   support

       happy       0.59      0.56      0.58     13889
         sad       0.67      0.69      0.68     17805

    accuracy                           0.64     31694
   macro avg       0.63      0.63      0.63     31694
weighted avg       0.63      0.64      0.63     31694

Decision Tree Report:
              precision    recall  f1-score   support

       happy       1.00      1.00      1.00     13889
         sad       1.00      1.00      1.00     17805

    accuracy                           1.00     31694
   macro avg       1.00      1.00      1.00     31694
weighted avg       1.00      1.00      1.00     31694
```

```python
# ---------- Visualization ----------
# Word Cloud
artist_freq = pd.Series(spotify_df['artist_name']).value_counts().head(100)
wordcloud = WordCloud(width=1000, height=400, background_color='white').generate_from_frequencies(artist_freq)
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Top Artists Word Cloud')
plt.show()
```

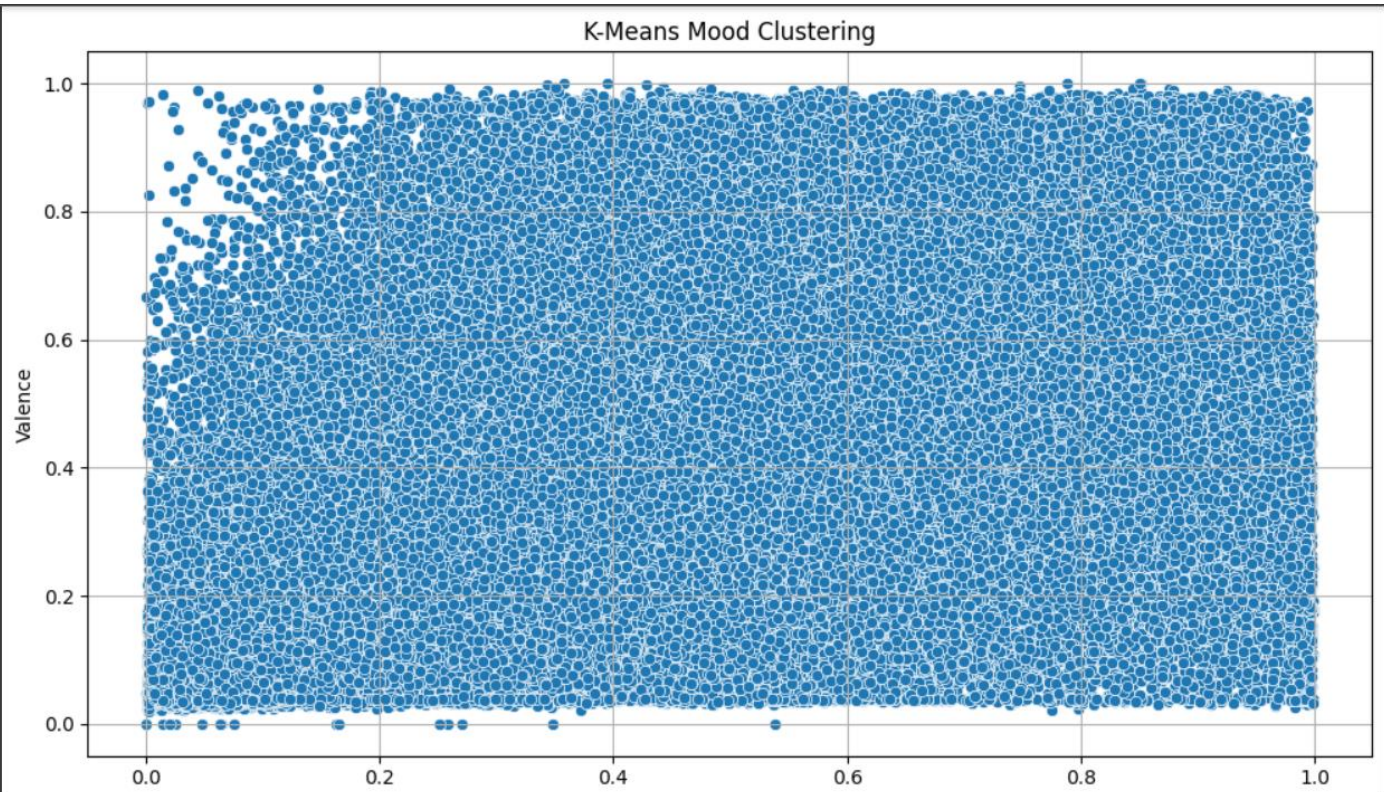
Code cell output actions




```python
# Genre Count
if 'genre' in spotify_df.columns:
    genre_counts = spotify_df['genre'].value_counts().head(10)
    sns.barplot(x=genre_counts.values, y=genre_counts.index)
    plt.title("Top Genres")
    plt.show()
```



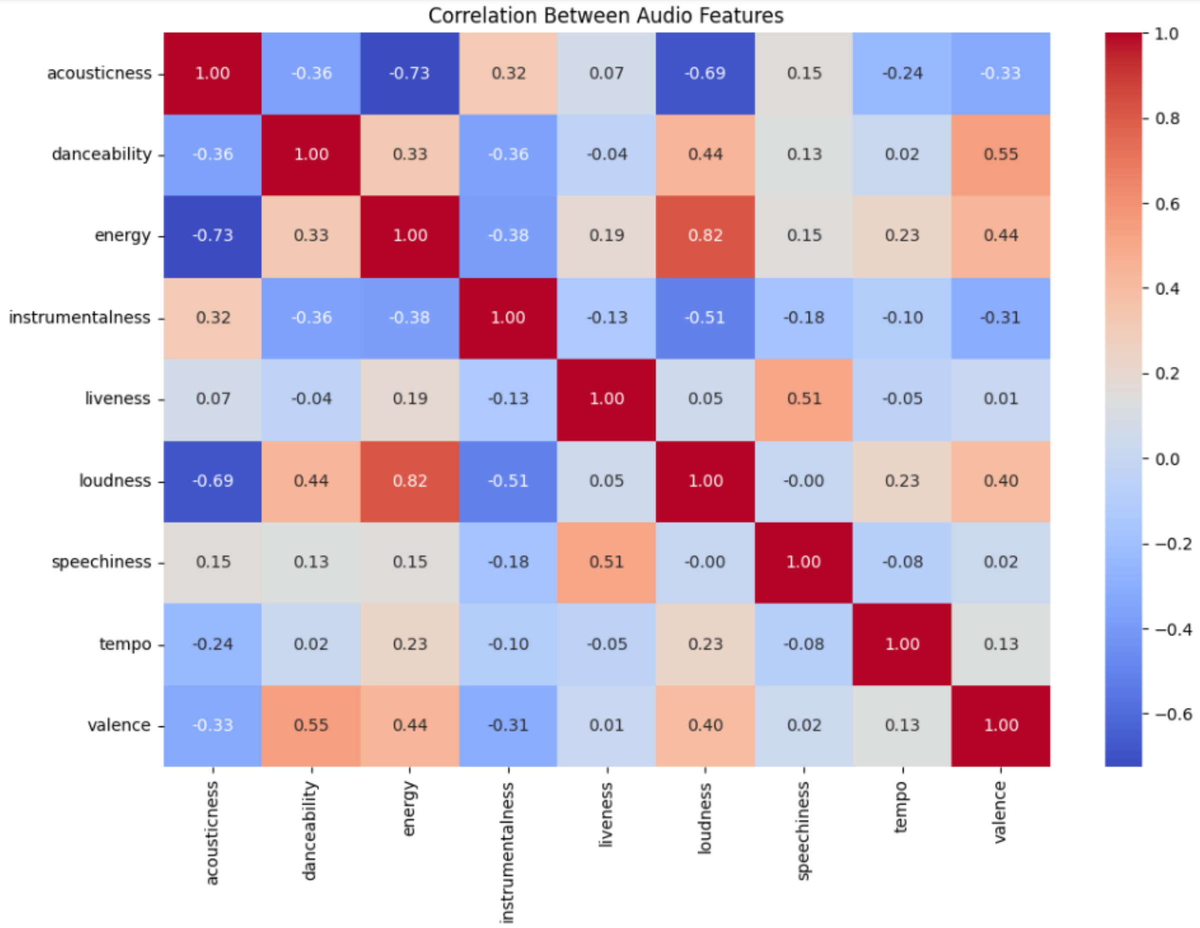
```
# K-Means Clustering Visualization
plt.figure(figsize=(10,6))
sns.scatterplot(data=spotify_df, x='energy', y='valence')
plt.title("K-Means Mood Clustering")
plt.xlabel("Energy")
plt.ylabel("Valence")
plt.grid(True)
plt.tight_layout()
plt.show()
```



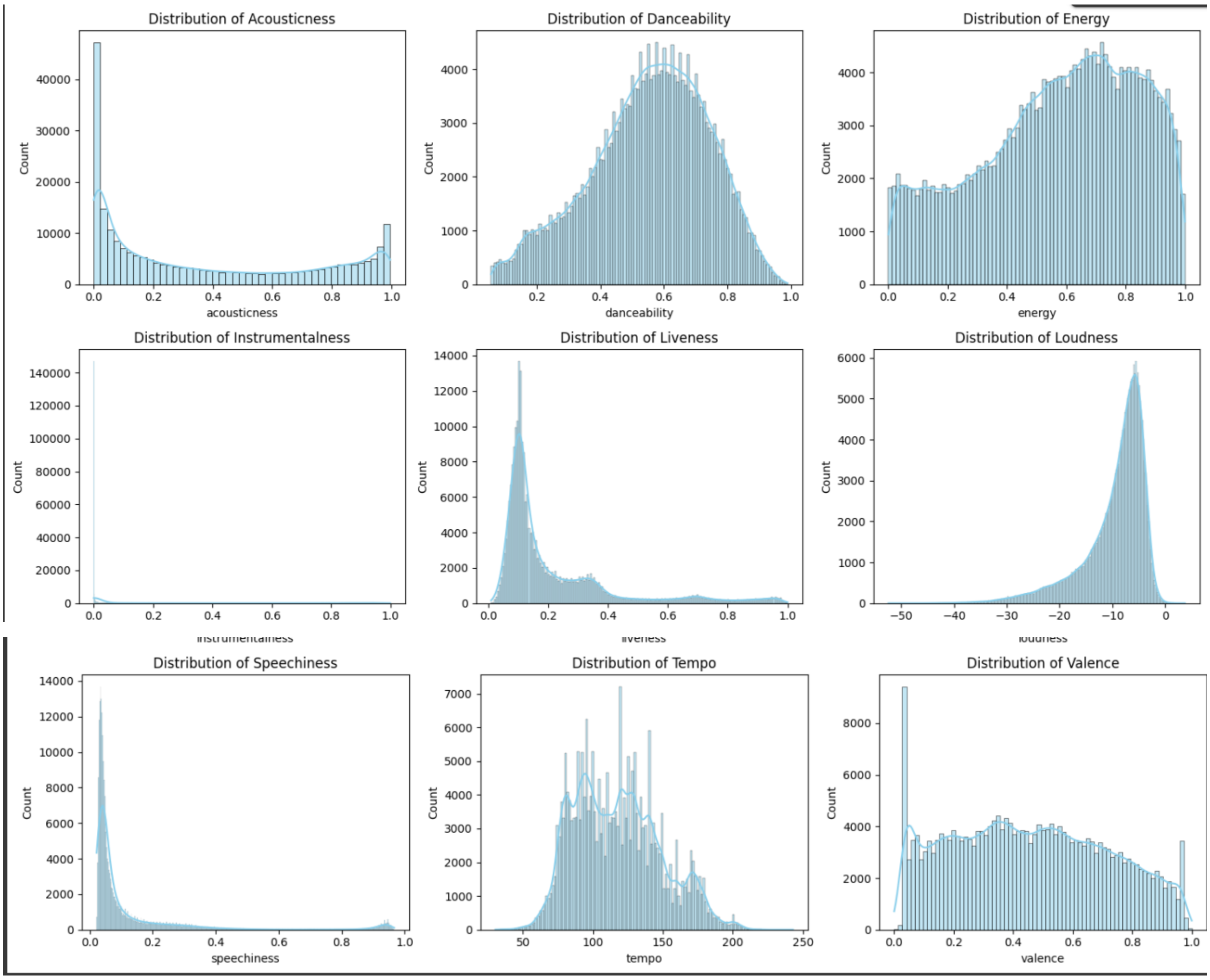
[16]
```
# ---------- Apriori Algorithm ----------
# Binarize continuous features
spotify_bin = pd.DataFrame()
for col in ['energy', 'danceability', 'valence']:
    spotify_bin[col + '_high'] = spotify_df[col] > spotify_df[col].median()

frequent_items = apriori(spotify_bin, min_support=0.1, use_colnames=True)
rules = association_rules(frequent_items, metric="lift", min_threshold=1.0)
print("Apriori Rules:\n", rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']].head())
```

```
Apriori Rules:
           antecedents          consequents   support  confidence      lift
0        (energy_high)  (danceability_high)  0.270843    0.541912  1.085181
1  (danceability_high)        (energy_high)  0.270843    0.542364  1.085181
2       (valence_high)        (energy_high)  0.318449    0.638365  1.277261
3        (energy_high)       (valence_high)  0.318449    0.637164  1.277261
4       (valence_high)  (danceability_high)  0.330559    0.662640  1.326938
```

```python
#correlation heatmap for audio features
plt.figure(figsize=(12,8))
audio_features = ['acousticness', 'danceability', 'energy', 'instrumentalness',
                  'liveness', 'loudness', 'speechiness', 'tempo', 'valence']
corr = spotify_df[audio_features].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Between Audio Features")
plt.show()
```

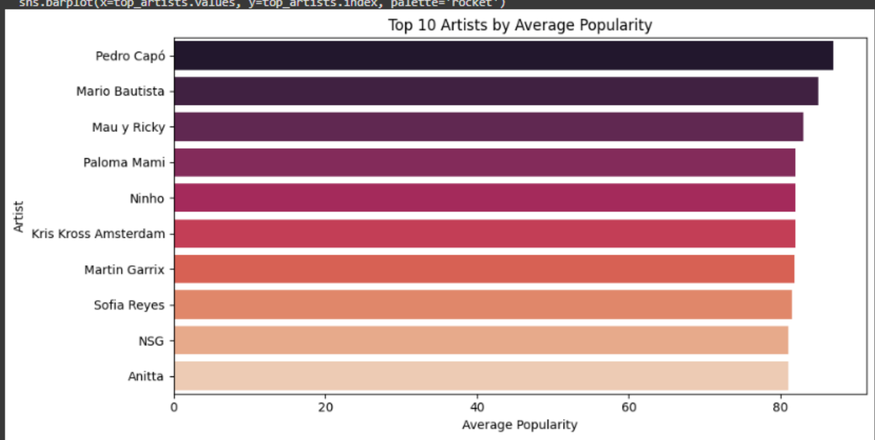



```python
# Distribution Plot for All Audio Features
features_to_plot = ['acousticness', 'danceability', 'energy', 'instrumentalness',
                    'liveness', 'loudness', 'speechiness', 'tempo', 'valence']

plt.figure(figsize=(15,12))
for i, feature in enumerate(features_to_plot):
    plt.subplot(3, 3, i+1)
    sns.histplot(spotify_df[feature], kde=True, color='skyblue')
    plt.title(f"Distribution of {feature.capitalize()}")
    plt.tight_layout()
plt.show()
```




```
[41] #Top Artists by Popularity
     top_artists = spotify_df.groupby('artist_name')['popularity'].mean().sort_values(ascending=False).head(10)
     plt.figure(figsize=(10,5))
     sns.barplot(x=top_artists.values, y=top_artists.index, palette='rocket')
     plt.title("Top 10 Artists by Average Popularity")
     plt.xlabel("Average Popularity")
     plt.ylabel("Artist")
     plt.tight_layout()
     plt.show()
```

```
<ipython-input-41-137e4a242a36>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_artists.values, y=top_artists.index, palette='rocket')
```




Thank you