SPOTIFY DATA ANALYTICS

Objective:

Analyze Spotify data to uncover insights about music trends,user preferences, and song characteristics.

```python
# importing mojor libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
from textblob import TextBlob

# addition libraries
import warnings
warnings.filterwarnings('ignore')
```

Task 1.1: Overview of the Project and Its Objectives

This project focuses on analyzing Spotify music data to uncover meaningful patterns, trends, and insights related to songs, artists, genres, and listener preferences. With the rapid growth of digital music streaming, platforms like Spotify generate vast amounts of data that can be used to understand what makes songs popular, how musical styles evolve over time, and how user tastes vary across genres and artists.

The main goal of this project is to apply exploratory data analysis (EDA) and data-driven techniques to examine the characteristics of tracks and identify relationships between audio features and popularity. By analyzing attributes such as danceability, energy, tempo, loudness, and valence, the project aims to understand how musical properties influence audience engagement and trends.

Objectives

- Explore and clean the Spotify datasets for analysis
- Analyze track-level audio features and their distributions
- Identify trends across artists, genres, and years
- Examine how musical characteristics affect popularity
- Discover patterns in listener preferences and genre performance
- Generate insights and recommendations using data visualization and statistical analysis

Overall, the project demonstrates how data analytics can be used to better understand the music industry and listener behavior.

Task 1.2: Explanation of the Dataset Used

The project uses multiple Spotify datasets containing detailed information about tracks, artists, genres, and yearly trends. These datasets provide both musical attributes and metadata that support comprehensive analysis.

Datasets Included

1. Track-level Dataset (data.csv)

This dataset contains information about individual songs available on Spotify. Each row represents a track with various audio and popularity features.

Key attributes include:

- Track name and artist
- Popularity score
- Duration
- Danceability
- Energy
- Loudness
- Speechiness
- Acousticness
- Instrumentalness
- Liveness
- Valence (musical positivity)
- Tempo

This dataset is primarily used to analyze how audio characteristics influence song popularity and listener engagement.

2. Artist-level Dataset (data_by_artist.csv)

This dataset aggregates features at the artist level by averaging track characteristics for each artist.

Used to:

- Compare artists based on their musical style
- Identify high-performing or popular artists
- Analyze consistency in audio features across an artist’s songs

3. Genre-level Dataset (data_by_genres.csv)

This dataset groups tracks by genre and provides averaged audio features.

Used to:

- Study differences between musical genres
- Identify dominant genre traits (e.g., energetic vs acoustic genres)
- Compare genre popularity

4. Yearly Dataset (data_by_year.csv)

This dataset summarizes music trends over time by year.

Used to:

- Analyze how music characteristics evolve across years
- Observe changes in popularity, tempo, or energy over time
- Detect historical trends in the music industry

5. Tracks with Genres Dataset (data_w_genres.csv)

This dataset links tracks with their associated genres, enabling more detailed analysis.

Used to:

- Connect individual tracks to genre categories
- Perform combined track + genre analysis
- Improve genre-based recommendations and comparisons

Summary

Together, these datasets provide a comprehensive view of Spotify music data at multiple levels — track, artist, genre, and time. This multi-dimensional structure enables deeper insights into musical patterns, listener preferences, and evolving trends in the music industry.

```
tracks = pd.read_csv('data.csv')
artist = pd.read_csv('data_by_artist.csv')
genres = pd.read_csv('data_by_genres.csv')
year = pd.read_csv('data_by_year.csv')
tracks_genres = pd.read_csv('data_w_genres.csv')
```

Data Collection and Preprocessing

Task 2.1: Load the dataset into the Jupyter notebook.

Task 2.2: Inspect and clean the data (handle missing values, duplicates, etc.).

Task 2.3: Perform exploratory data analysis (EDA) to understand the basic characteristics of the data

```
artist.head()
```

```
   mode  count  acousticness  \
0     1      9      0.590111
1     1     26      0.862538
2     1      7      0.856571
3     1     27      0.884926
4     1      7      0.510714

                                             artists  danceability  \
0                    "Cats" 1981 Original London Cast      0.467222
1                           "Cats" 1983 Broadway Cast      0.441731
2         "Fiddler On The Roof" Motion Picture Chorus      0.348286
3      "Fiddler On The Roof" Motion Picture Orchestra      0.425074
4  "Joseph And The Amazing Technicolor Dreamcoat"...      0.467143

     duration_ms    energy  instrumentalness  liveness   loudness  \
0  250318.555556  0.394003          0.011400  0.290833 -14.448000
1  287280.000000  0.406808          0.081158  0.315215 -10.690000
2  328920.000000  0.286571          0.024593  0.325786 -15.230714
3  262890.962963  0.245770          0.073587  0.275481 -15.639370
4  270436.142857  0.488286          0.009400  0.195000 -10.236714

   speechiness       tempo   valence  popularity  key
0     0.210389  117.518111  0.389500   38.333333    5
1     0.176212  103.044154  0.268865   30.576923    5
2     0.118514   77.375857  0.354857   34.857143    0
3     0.123200   88.667630  0.372030   34.851852    0
4     0.098543  122.835857  0.482286   43.000000    5
```

```
genres.head()
```

```
   mode                  genres  acousticness  danceability
duration_ms  \
0     1  21st century classical      0.979333      0.162883
1.602977e+05
1     1                   432hz      0.494780      0.299333
1.048887e+06
2     1                   8-bit      0.762000      0.712000
1.151770e+05
3     1                      []      0.651417      0.529093
2.328809e+05
4     1              a cappella      0.676557      0.538961
1.906285e+05

     energy  instrumentalness  liveness   loudness  speechiness
tempo  \
0  0.071317          0.606834  0.361600 -31.514333     0.040567
75.336500
1  0.450678          0.477762  0.131000 -16.854000     0.076817
```

```
120.285667
2  0.818000          0.876000  0.126000  -9.180000     0.047000
133.444000
3  0.419146          0.205309  0.218696 -12.288965     0.107872
112.857352
4  0.316434          0.003003  0.172254 -12.479387     0.082851
112.110362

    valence  popularity  key
0  0.103783   27.833333    6
1  0.221750   52.500000    5
2  0.975000   48.000000    7
3  0.513604   20.859882    7
4  0.448249   45.820071    7
```

```
year.head()
```

```
   mode  year  acousticness  danceability    duration_ms    energy  \
0     1  1921      0.886896      0.418597  260537.166667  0.231815
1     1  1922      0.938592      0.482042  165469.746479  0.237815
2     1  1923      0.957247      0.577341  177942.362162  0.262406
3     1  1924      0.940200      0.549894  191046.707627  0.344347
4     1  1925      0.962607      0.573863  184986.924460  0.278594

   instrumentalness  liveness   loudness  speechiness       tempo
valence  \
0          0.344878  0.205710 -17.048667     0.073662  101.531493
0.379327
1          0.434195  0.240720 -19.275282     0.116655  100.884521
0.535549
2          0.371733  0.227462 -14.129211     0.093949  114.010730
0.625492
3          0.581701  0.235219 -14.231343     0.092089  120.689572
0.663725
4          0.418297  0.237668 -14.146414     0.111918  115.521921
0.621929

   popularity  key
0    0.653333    2
1    0.140845   10
2    5.389189    0
3    0.661017   10
4    2.604317    5
```

```
tracks_genres.head()
```

```
           genres
artists  \
0  ['show tunes']                  "Cats" 1981 Original London Cast

1              []                         "Cats" 1983 Broadway Cast
```

```
2              []       "Fiddler On The Roof” Motion Picture Chorus

3              []     "Fiddler On The Roof” Motion Picture Orchestra

4              []  "Joseph And The Amazing Technicolor Dreamcoat"...


   acousticness  danceability    duration_ms    energy
instrumentalness  \
0      0.590111      0.467222  250318.555556  0.394003
0.011400
1      0.862538      0.441731  287280.000000  0.406808
0.081158
2      0.856571      0.348286  328920.000000  0.286571
0.024593
3      0.884926      0.425074  262890.962963  0.245770
0.073587
4      0.510714      0.467143  270436.142857  0.488286
0.009400

   liveness   loudness  speechiness       tempo   valence  popularity
key  \
0  0.290833 -14.448000     0.210389  117.518111  0.389500   38.333333
5
1  0.315215 -10.690000     0.176212  103.044154  0.268865   30.576923
5
2  0.325786 -15.230714     0.118514   77.375857  0.354857   34.857143
0
3  0.275481 -15.639370     0.123200   88.667630  0.372030   34.851852
0
4  0.195000 -10.236714     0.098543  122.835857  0.482286   43.000000
5

   mode  count
0     1      9
1     1     26
2     1      7
3     1     27
4     1      7

tracks.head()

   valence  year  acousticness  \
0   0.0594  1921         0.982
1   0.9630  1921         0.732
2   0.0394  1921         0.961
3   0.1650  1921         0.967
4   0.2530  1921         0.957
```

```
                                             artists  danceability  \
0  ['Sergei Rachmaninoff', 'James Levine', 'Berli...         0.279
1                                     ['Dennis Day']         0.819
2  ['KHP Kridhamardawa Karaton Ngayogyakarta Hadi...         0.328
3                                   ['Frank Parker']         0.275
4                                     ['Phil Regan']         0.418

   duration_ms  energy  explicit                      id
instrumentalness  \
0       831667   0.211         0  4BJqT0PrAfrxzMOxytFOIz
0.878000
1       180533   0.341         0  7xPhfUan2yNtyFG0cUWkt8
0.000000
2       500062   0.166         0  1o6I8BglA6ylDMrIELygv1
0.913000
3       210000   0.309         0  3ftBPsC5vPBKxYSee08FDH
0.000028
4       166693   0.193         0  4d6HGyGT8e121BsdKmw9v6
0.000002

   key  liveness  loudness  mode  \
0   10     0.665   -20.096     1
1    7     0.160   -12.441     1
2    3     0.101   -14.850     1
3    5     0.381    -9.316     1
4    3     0.229   -10.096     1

                                                name  popularity
release_date  \
0  Piano Concerto No. 3 in D Minor, Op. 30: III. ...           4
1921
1                            Clancy Lowered the Boom           5
1921
2                                          Gati Bali           5
1921
3                                          Danny Boy           3
1921
4                        When Irish Eyes Are Smiling           2
1921

   speechiness    tempo
0       0.0366   80.954
1       0.4150   60.936
2       0.0339  110.339
3       0.0354  100.109
4       0.0380  101.665

print(tracks.info())
print('-'*50)
print(artist.info())
```

```python
print('-'*50)
print(genres.info())
print('-'*50)
print(year.info())
print('-'*50)
print(tracks_genres.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 170653 entries, 0 to 170652
Data columns (total 19 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   valence           170653 non-null  float64
 1   year              170653 non-null  int64
 2   acousticness      170653 non-null  float64
 3   artists           170653 non-null  object
 4   danceability      170653 non-null  float64
 5   duration_ms       170653 non-null  int64
 6   energy            170653 non-null  float64
 7   explicit          170653 non-null  int64
 8   id                170653 non-null  object
 9   instrumentalness  170653 non-null  float64
 10  key               170653 non-null  int64
 11  liveness          170653 non-null  float64
 12  loudness          170653 non-null  float64
 13  mode              170653 non-null  int64
 14  name              170653 non-null  object
 15  popularity        170653 non-null  int64
 16  release_date      170653 non-null  object
 17  speechiness       170653 non-null  float64
 18  tempo             170653 non-null  float64
dtypes: float64(9), int64(6), object(4)
memory usage: 24.7+ MB
None
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28680 entries, 0 to 28679
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   mode              28680 non-null  int64
 1   count             28680 non-null  int64
 2   acousticness      28680 non-null  float64
 3   artists           28680 non-null  object
 4   danceability      28680 non-null  float64
 5   duration_ms       28680 non-null  float64
 6   energy            28680 non-null  float64
 7   instrumentalness  28680 non-null  float64
 8   liveness          28680 non-null  float64
 9   loudness          28680 non-null  float64
```

```
 10  speechiness       28680 non-null  float64
 11  tempo             28680 non-null  float64
 12  valence           28680 non-null  float64
 13  popularity        28680 non-null  float64
 14  key               28680 non-null  int64
dtypes: float64(11), int64(3), object(1)
memory usage: 3.3+ MB
None
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2973 entries, 0 to 2972
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   mode              2973 non-null   int64
 1   genres            2973 non-null   object
 2   acousticness      2973 non-null   float64
 3   danceability      2973 non-null   float64
 4   duration_ms       2973 non-null   float64
 5   energy            2973 non-null   float64
 6   instrumentalness  2973 non-null   float64
 7   liveness          2973 non-null   float64
 8   loudness          2973 non-null   float64
 9   speechiness       2973 non-null   float64
 10  tempo             2973 non-null   float64
 11  valence           2973 non-null   float64
 12  popularity        2973 non-null   float64
 13  key               2973 non-null   int64
dtypes: float64(11), int64(2), object(1)
memory usage: 325.3+ KB
None
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   mode              100 non-null    int64
 1   year              100 non-null    int64
 2   acousticness      100 non-null    float64
 3   danceability      100 non-null    float64
 4   duration_ms       100 non-null    float64
 5   energy            100 non-null    float64
 6   instrumentalness  100 non-null    float64
 7   liveness          100 non-null    float64
 8   loudness          100 non-null    float64
 9   speechiness       100 non-null    float64
 10  tempo             100 non-null    float64
 11  valence           100 non-null    float64
```

```
 12  popularity        100 non-null    float64
 13  key               100 non-null    int64
dtypes: float64(11), int64(3)
memory usage: 11.1 KB
None
--------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28680 entries, 0 to 28679
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   genres            28680 non-null  object
 1   artists           28680 non-null  object
 2   acousticness      28680 non-null  float64
 3   danceability      28680 non-null  float64
 4   duration_ms       28680 non-null  float64
 5   energy            28680 non-null  float64
 6   instrumentalness  28680 non-null  float64
 7   liveness          28680 non-null  float64
 8   loudness          28680 non-null  float64
 9   speechiness       28680 non-null  float64
 10  tempo             28680 non-null  float64
 11  valence           28680 non-null  float64
 12  popularity        28680 non-null  float64
 13  key               28680 non-null  int64
 14  mode              28680 non-null  int64
 15  count             28680 non-null  int64
dtypes: float64(11), int64(3), object(2)
memory usage: 3.5+ MB
None
```

```python
print(tracks.isnull().sum())
print('-'*50)
print(artist.isnull().sum())
print('-'*50)
print(genres.isnull().sum())
print('-'*50)
print(year.isnull().sum())
print('-'*50)
print(tracks_genres.isnull().sum())
```

```
valence             0
year                0
acousticness        0
artists             0
danceability        0
duration_ms         0
energy              0
explicit            0
id                  0
```

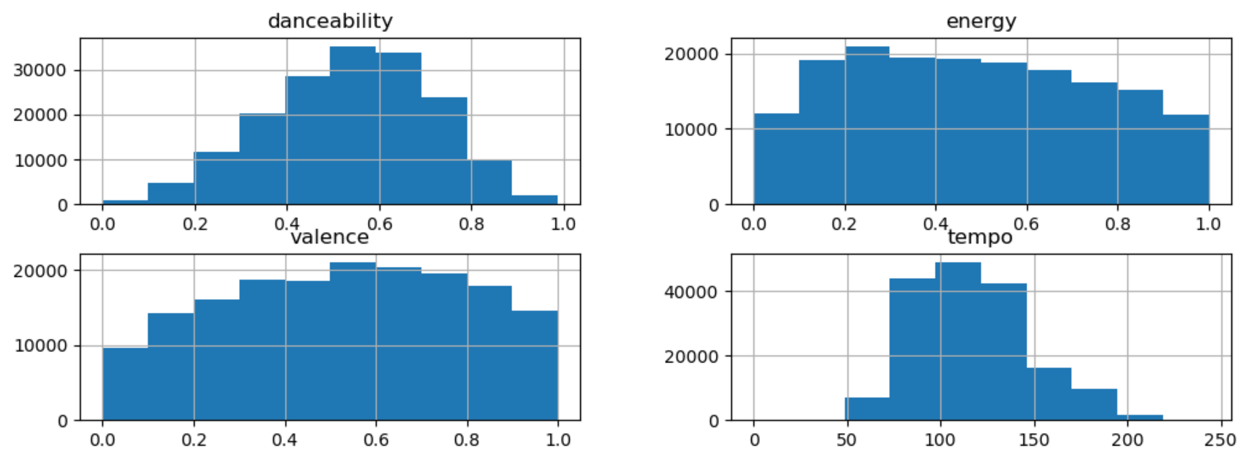
```
instrumentalness    0
key                 0
liveness            0
loudness            0
mode                0
name                0
popularity          0
release_date        0
speechiness         0
tempo               0
dtype: int64
--------------------------------------------------
mode                0
count               0
acousticness        0
artists             0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
key                 0
dtype: int64
--------------------------------------------------
mode                0
genres              0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
key                 0
dtype: int64
--------------------------------------------------
mode                0
year                0
acousticness        0
danceability        0
```

```
duration_ms         0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
key                 0
dtype: int64
--------------------------------------------------
genres              0
artists             0
acousticness        0
danceability        0
duration_ms         0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
key                 0
mode                0
count               0
dtype: int64

# Fill numeric missing values with mean
tracks.fillna(tracks.mean(numeric_only=True), inplace=True)
artist.fillna(artist.mean(numeric_only=True), inplace=True)
genres.fillna(genres.mean(numeric_only=True), inplace=True)
year.fillna(year.mean(numeric_only=True), inplace=True)

# Remove duplicates
tracks.drop_duplicates(inplace=True)
artist.drop_duplicates(inplace=True)
genres.drop_duplicates(inplace=True)
year.drop_duplicates(inplace=True)
tracks_genres.drop_duplicates(inplace=True)

# Data type corrections
tracks['year'] = tracks['year'].astype(int)
tracks['popularity'] = tracks['popularity'].astype(int)
year['year'] = year['year'].astype(int)

# Basic dataset overview
print(tracks.shape)
```

```
print('-'*50)
print(artist.shape)
print('-'*50)
print(genres.shape)
print('-'*50)
print(year.shape)
print('-'*50)
print(tracks_genres.shape)
```

```
(170653, 19)
--------------------------------------------------
(28680, 15)
--------------------------------------------------
(2973, 14)
--------------------------------------------------
(100, 14)
--------------------------------------------------
(28680, 16)
```

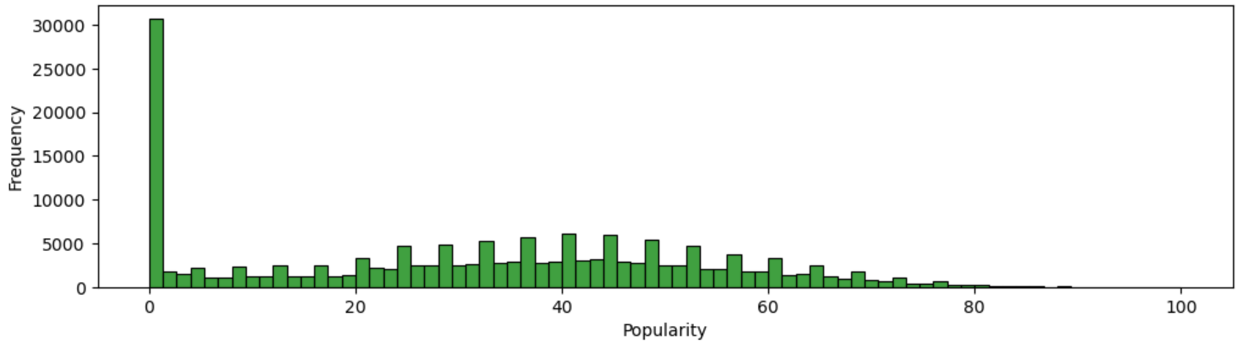
```
# Distribution of audio features
tracks[['danceability','energy','valence','tempo']].hist(figsize=(12,4
))
plt.show()
```



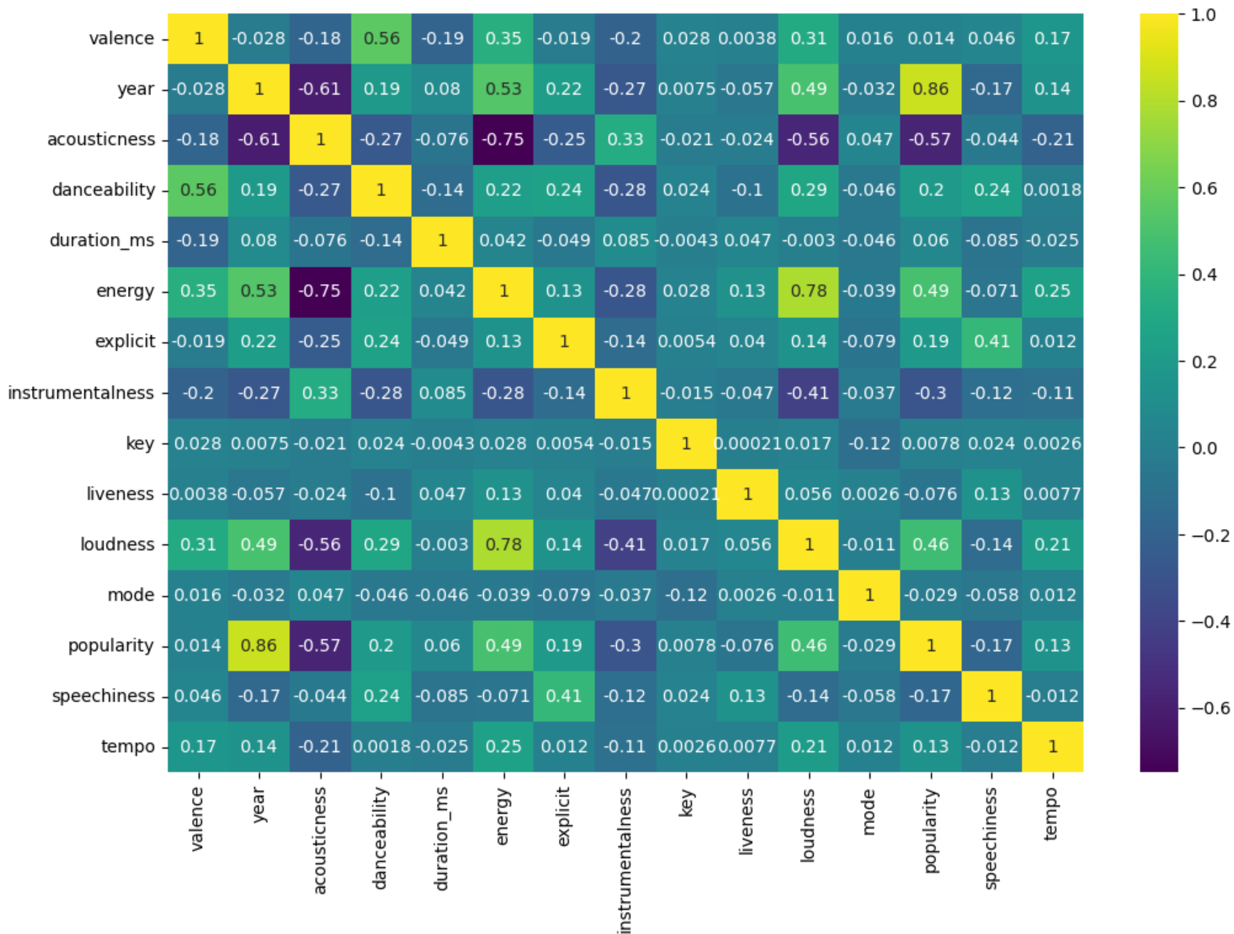

```
# Popularity analysis
print(tracks['popularity'].describe())
plt.figure(figsize=(12,3))
sns.histplot(data=tracks,x='popularity',color='green')
plt.xlabel("Popularity")
plt.ylabel("Frequency")
plt.show()
```

```
count    170653.000000
mean         31.431794
std          21.826615
```

```
min            0.000000
25%           11.000000
50%           33.000000
75%           48.000000
max          100.000000
Name: popularity, dtype: float64
```




```python
# Correlation between features
plt.figure(figsize=(12,8))
sns.heatmap(tracks.corr(numeric_only=True),annot=True,cmap='viridis')
plt.show()
```




```
# Genre analysis
genres.sort_values('popularity', ascending=False).head(10)
```

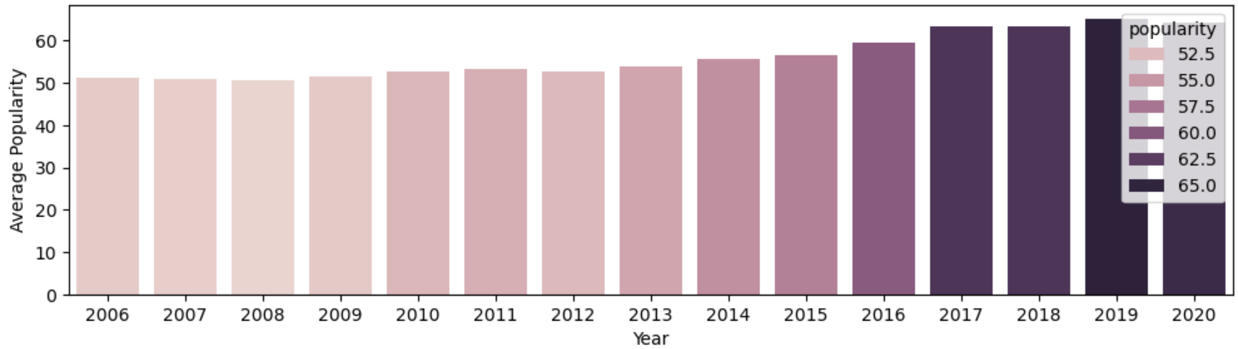
```
      mode                genres  acousticness  danceability
duration_ms  \
237      1              basshall      0.213167       0.81800
169799.166667
2755     1        trap venezolano      0.044600       0.87700
231848.000000
2533     1   south african house      0.043833       0.84700
311854.333333
2778     0            turkish edm      0.008290       0.69800
186700.000000
46       0        alberta hip hop      0.330000       0.88500
144000.000000
536      0     chinese electropop      0.002570       0.66000
217088.000000
37       0              afroswing      0.318450       0.71175
179995.375000
1381     1           indie triste      0.946000       0.83000
207400.000000
```

```
1239     1            guaracha      0.009030       0.74500
189818.000000
2383     1       russian dance      0.005610       0.65300
198095.000000

        energy  instrumentalness  liveness   loudness  speechiness  \
237   0.630167          0.000020  0.081067  -6.627833     0.134833
2755  0.777000          0.000035  0.086300  -4.246000     0.117000
2533  0.562333          0.130339  0.075133  -7.719000     0.050733
2778  0.719000          0.000004  0.326000  -4.923000     0.045500
46    0.685000          0.000000  0.148000  -6.429000     0.062700
536   0.787000          0.000000  0.323000  -4.592000     0.032000
37    0.580187          0.000258  0.189950  -7.016687     0.195563
1381  0.159000          0.000020  0.362000 -14.461000     0.038300
1239  0.972000          0.465000  0.297000  -3.506000     0.077400
2383  0.945000          0.915000  0.439000  -2.634000     0.096000

           tempo   valence  popularity  key
237   115.092500  0.588667   80.666667    2
2755  102.020000  0.706000   80.000000    1
2533  123.676333  0.834333   80.000000    1
2778  120.062000  0.364000   80.000000    0
46     99.954000  0.937000   78.500000   11
536   142.018000  0.199000   78.500000    1
37     83.250125  0.676625   77.312500   11
1381  104.950000  0.189000   77.000000    1
1239  128.031000  0.556000   77.000000    7
2383  126.093000  0.326000   77.000000    5
```

```python
# Artist analysis
artist.sort_values('popularity', ascending=False).head(10)
```

```
       mode  count  acousticness          artists  danceability
duration_ms  \
20966     0      2      0.056300      Ritt Momney      0.399000
210463.0
14354     1      1      0.090700        Lele Pons      0.905000
155825.0
15070     0      2      0.310000  Los Legendarios      0.823000
213314.0
11764     1      2      0.819000         Jerry Di      0.854000
197587.0
7463      0      2      0.068600           Emilee      0.674000
176547.0
28263     1      2      0.424000      salem ilese      0.738000
136839.0
23687     0      1      0.068600        Surf Mesa      0.674000
176547.0
213       0      3      0.166633              A7S      0.742667
168293.0
```

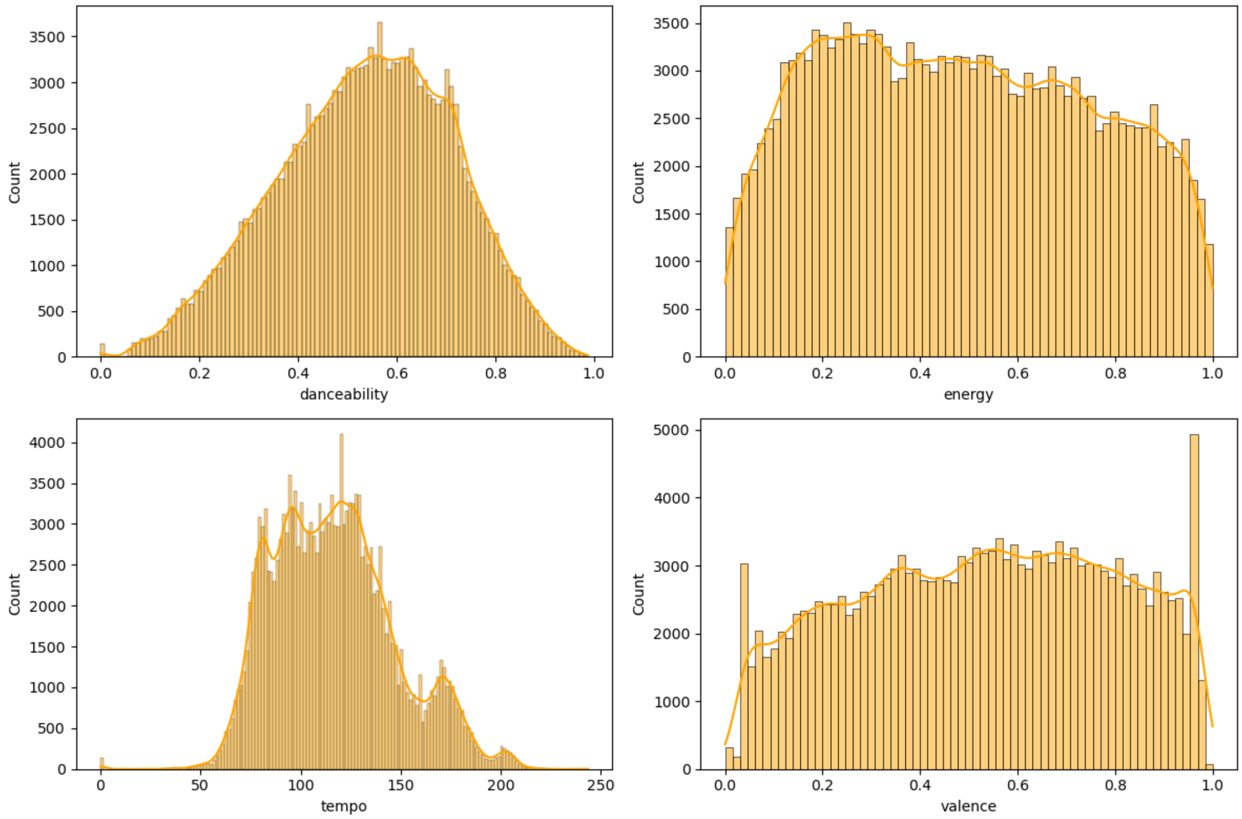
```
14378     0      2      0.254000     Lenny Santos      0.752000
206760.0
16453     1      1      0.018500        Master KG      0.880000
342613.0

       energy  instrumentalness  liveness   loudness  speechiness
tempo  \
20966   0.491          0.000890  0.110000 -10.778000       0.0538
91.066000
14354   0.686          0.000000  0.266000  -3.152000       0.0664
103.013000
15070   0.821          0.000004  0.143000  -3.402000       0.1660
99.999000
11764   0.525          0.000000  0.146000  -4.426000       0.2140
97.054000
7463    0.774          0.001880  0.393000  -7.567000       0.0892
112.050000
28263   0.621          0.000007  0.692000  -7.313000       0.0486
113.968000
23687   0.774          0.001880  0.393000  -7.567000       0.0892
112.050000
213     0.726          0.000000  0.154667  -5.921333       0.1980
121.296333
14378   0.716          0.000000  0.243000  -5.200000       0.0325
117.007000
16453   0.483          0.000009  0.060700  -7.012000       0.0504
124.009000

        valence  popularity  key
20966  0.151000        93.0    6
14354  0.963000        92.0    0
15070  0.791000        90.0    8
11764  0.630000        89.0    1
7463   0.330000        88.0   11
28263  0.715000        88.0    0
23687  0.330000        88.0   11
213    0.554667        87.0    8
14378  0.553000        86.0   10
16453  0.827000        86.0    1

# Yearly trends
plt.figure(figsize=(12,3))
sns.barplot(data=year.tail(15),x='year',y='popularity',hue='popularity
')
plt.xlabel("Year")
plt.ylabel("Average Popularity")
plt.show()
```



Data Analysis

Task 3.1: Distribution of Features (danceability, energy, tempo)

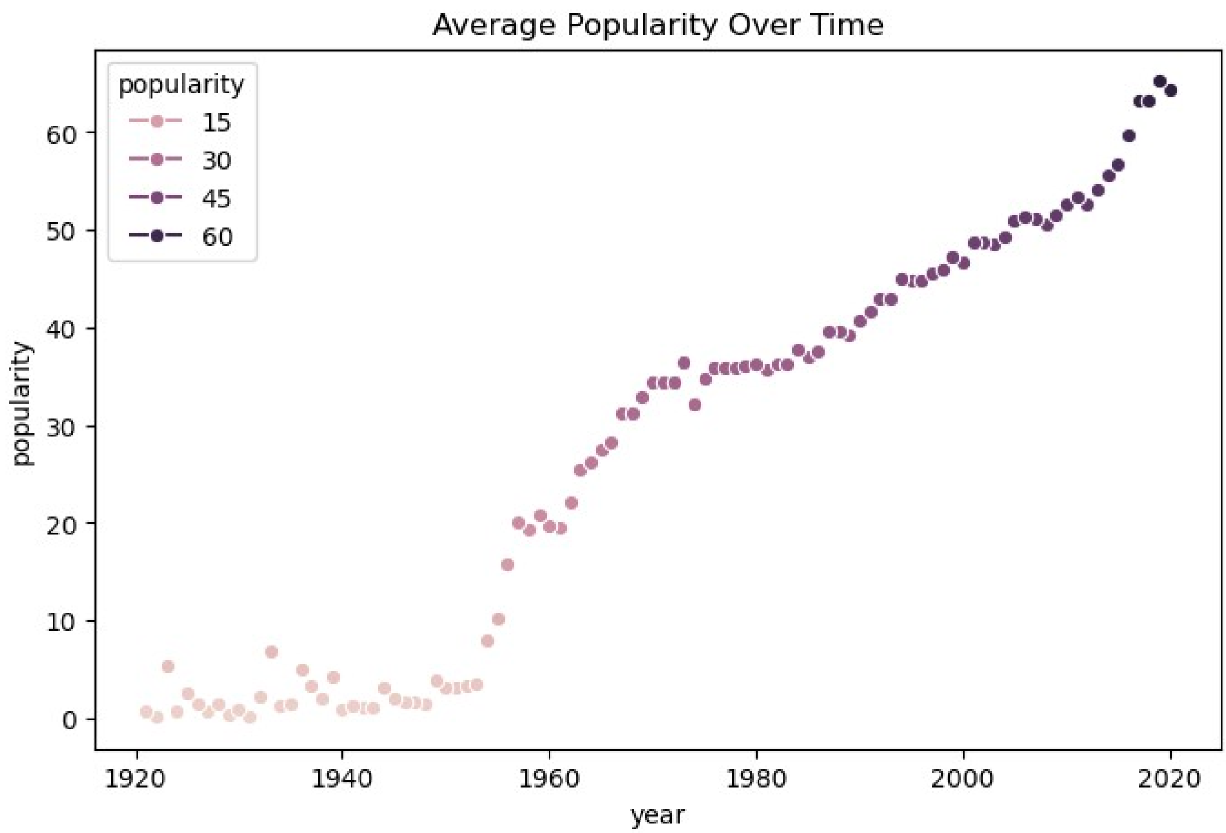
```
# Histograms with KDE
features = ['danceability', 'energy', 'tempo', 'valence']
plt.figure(figsize=(12,8))
for i, col in enumerate(features, 1):
    plt.subplot(2,2,i)
    sns.histplot(tracks[col],kde=True,color='orange')
plt.tight_layout()
plt.show()
```



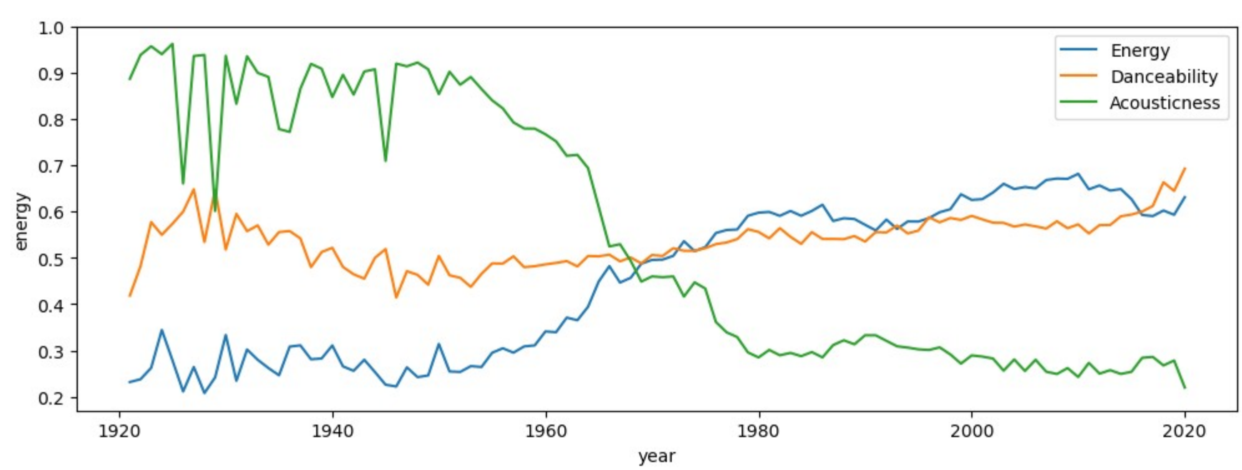
Task 3.2: Trends Over Time

Using data_by_year.csv to observe how music changes historically.

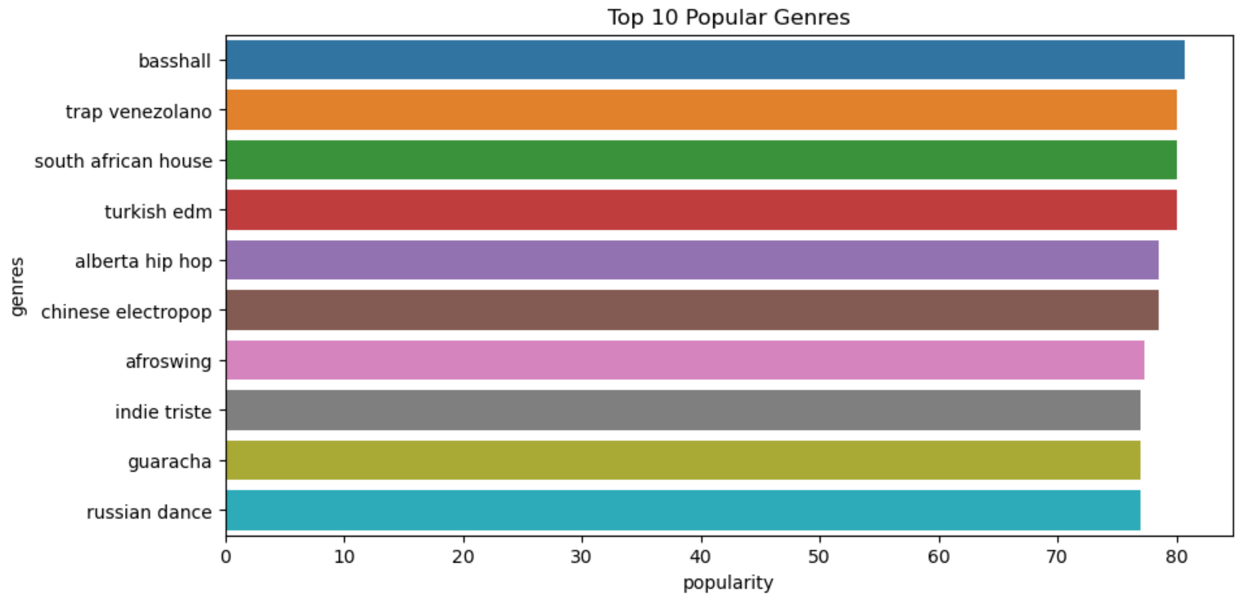
```
# Popularity trend line
plt.figure(figsize=(8,5))
sns.lineplot(data=year,x='year',y='popularity',marker='o',hue='popular
ity')
plt.title("Average Popularity Over Time")
plt.show()
```




```python
# Feature evolution over time
plt.figure(figsize=(12,4))
sns.lineplot(data=year,x='year',y='energy',label='Energy')
sns.lineplot(data=year,x='year',y='danceability',label='Danceability')
sns.lineplot(data=year,x='year',y='acousticness',label='Acousticness')
plt.legend()
plt.show()
```

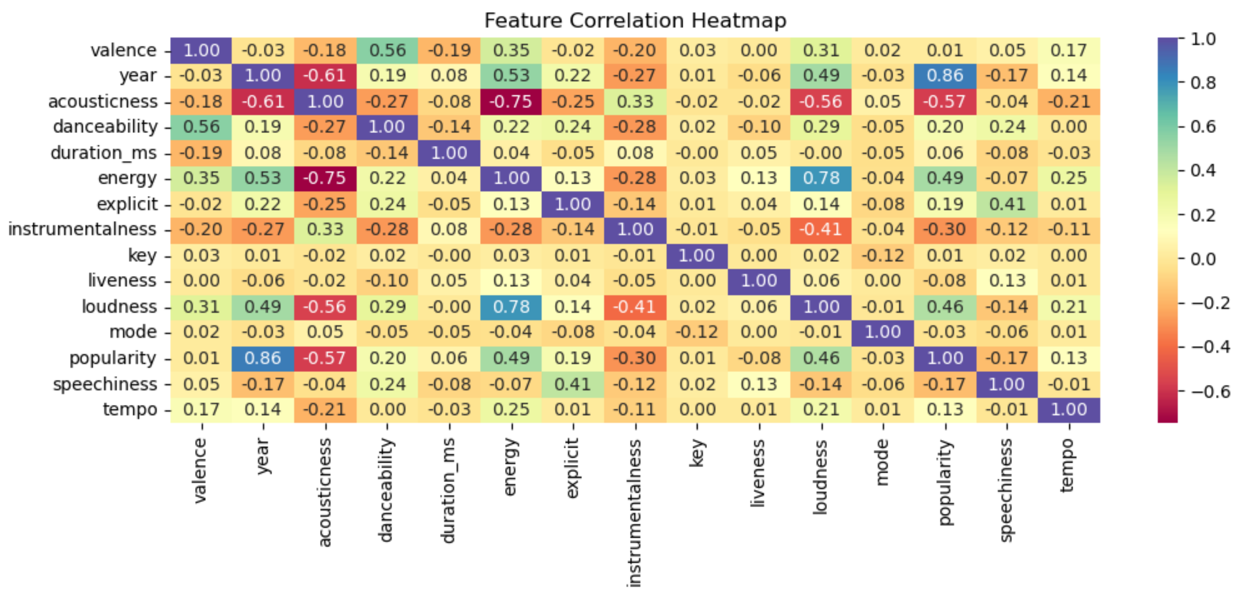


```python
# Most popular genres
top_genres = genres.sort_values('popularity',ascending=False).head(10)
plt.figure(figsize=(10,5))
sns.barplot(data=top_genres,x='popularity',y='genres',hue='genres')
plt.title('Top 10 Popular Genres')
plt.show()
```

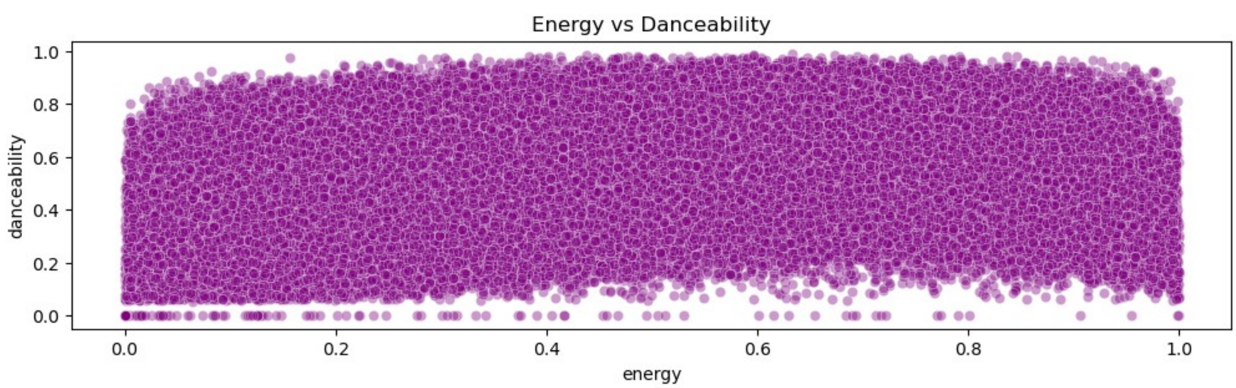


Task 3.3: Correlation Between Features

```python
# Correlation heatmap
plt.figure(figsize=(12,4))
corr = tracks.corr(numeric_only=True)
sns.heatmap(corr,annot=True,cmap='Spectral',fmt='.2f')
plt.title('Feature Correlation Heatmap')
plt.show()
```



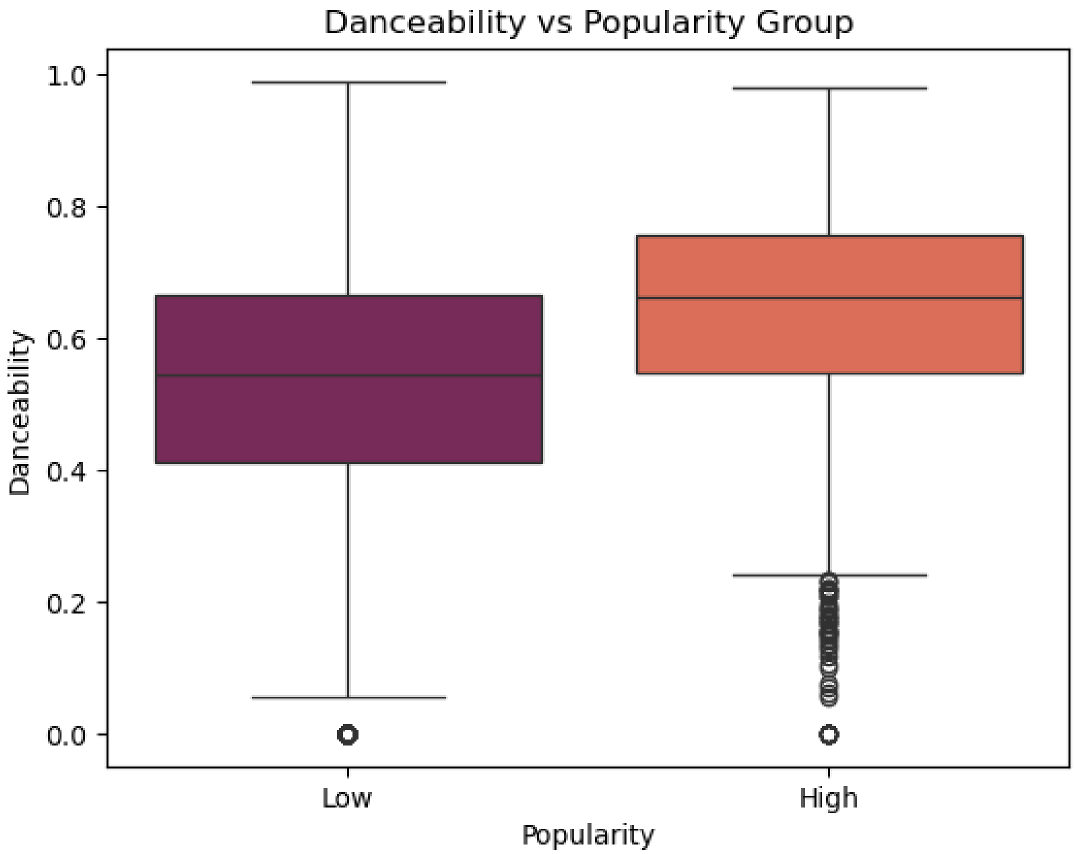

```
# Energy vs Danceability scatter
plt.figure(figsize=(12,3))
sns.scatterplot(data=tracks,x='energy',y='danceability',alpha=0.4,colo
r='purple')
plt.title('Energy vs Danceability')
plt.show()
```



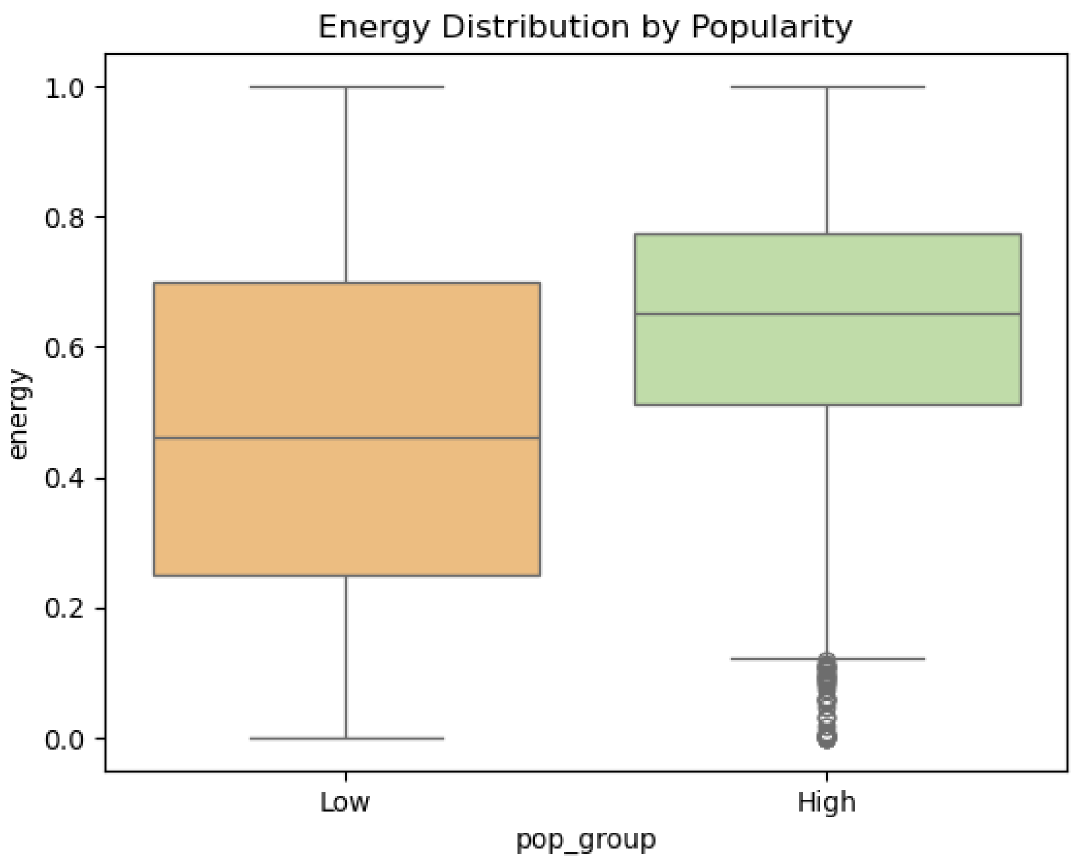
Task 3.4: User Preferences & Listening Habits

```
# Popular vs less popular songs (boxplot comparison)
tracks['pop_group'] = tracks['popularity'].apply(
    lambda x: 'High' if x >= 70 else 'Low')

sns.boxplot(data=tracks,x='pop_group',y='danceability',palette='rocket
')
plt.xlabel('Popularity')
plt.ylabel('Danceability')
```

```
plt.title('Danceability vs Popularity Group')
plt.show()
```



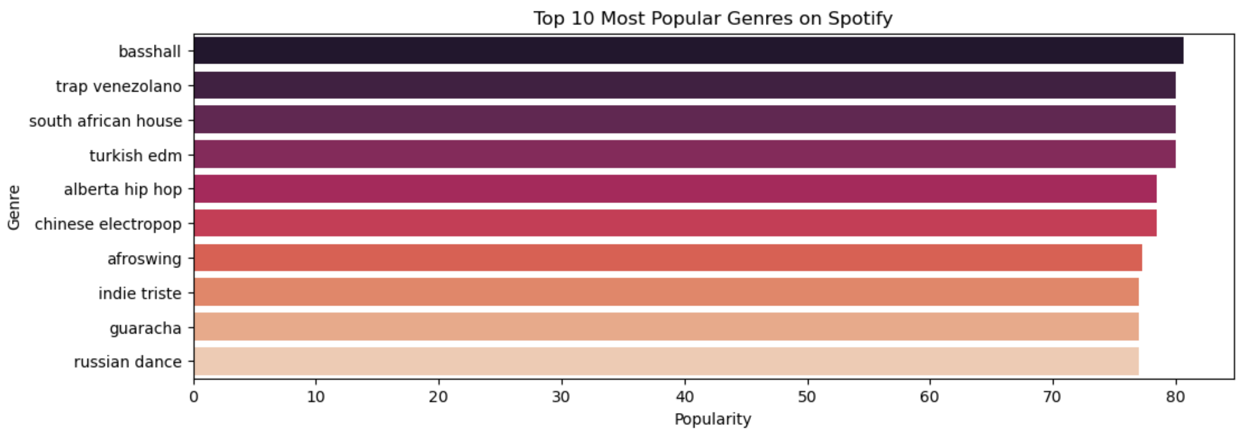

```
# Feature comparison for popularity
sns.boxplot(data=tracks,x='pop_group',y='energy',palette='Spectral')
plt.title("Energy Distribution by Popularity")
plt.show()
```



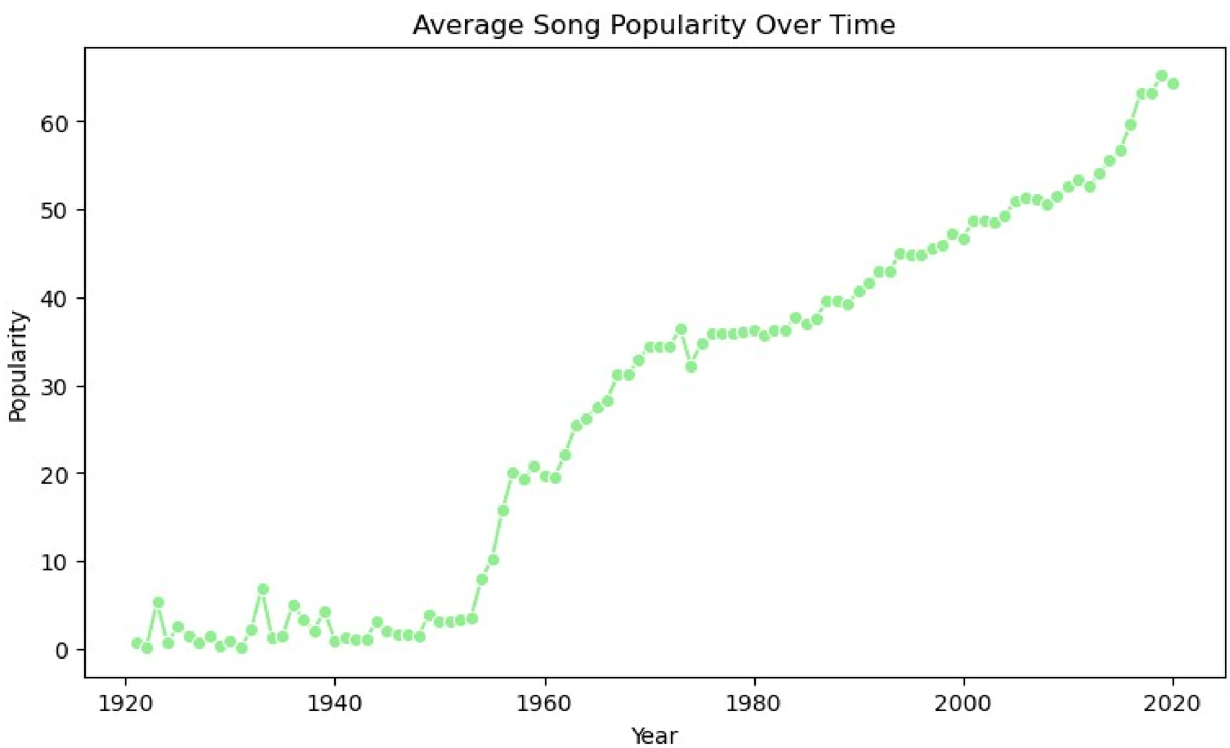
Visualization

Task 4.1: Basic Visualizations (Bar, Line, Scatter)

```
# Bar Chart – Top 10 Popular Genres
top_genres = genres.sort_values('popularity',
ascending=False).head(10)
plt.figure(figsize=(12,4))
sns.barplot(data=top_genres,x='popularity',y='genres',palette='rocket'
)
plt.title("Top 10 Most Popular Genres on Spotify")
plt.xlabel("Popularity")
plt.ylabel("Genre")
plt.show()
```

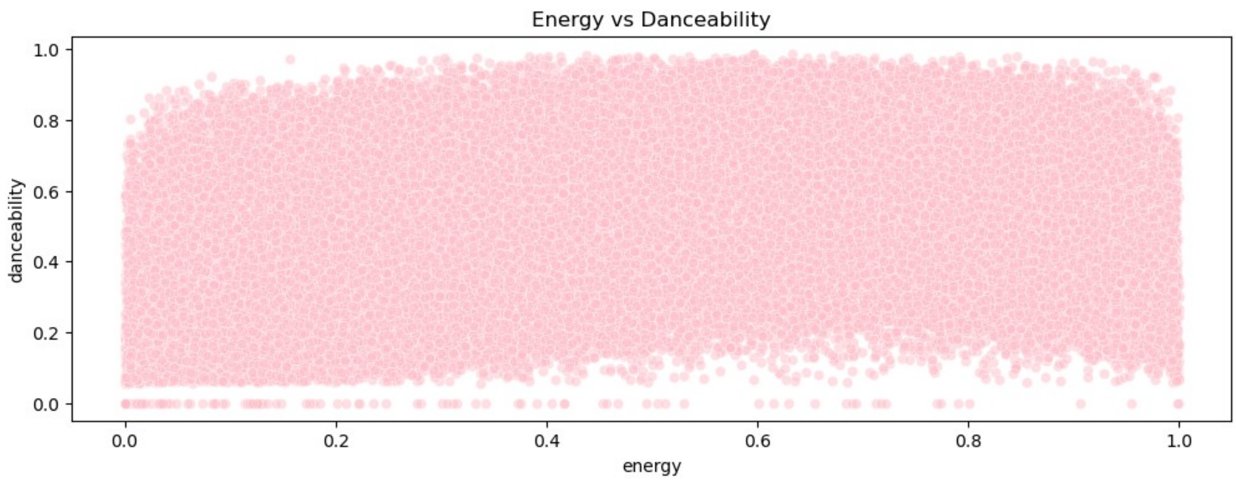



```
# Line Graph – Popularity Trend Over Time
plt.figure(figsize=(9,5))
sns.lineplot(data=year,x='year',y='popularity',marker='o',color='light
green')
plt.title("Average Song Popularity Over Time")
plt.xlabel("Year")
plt.ylabel("Popularity")
plt.show()
```



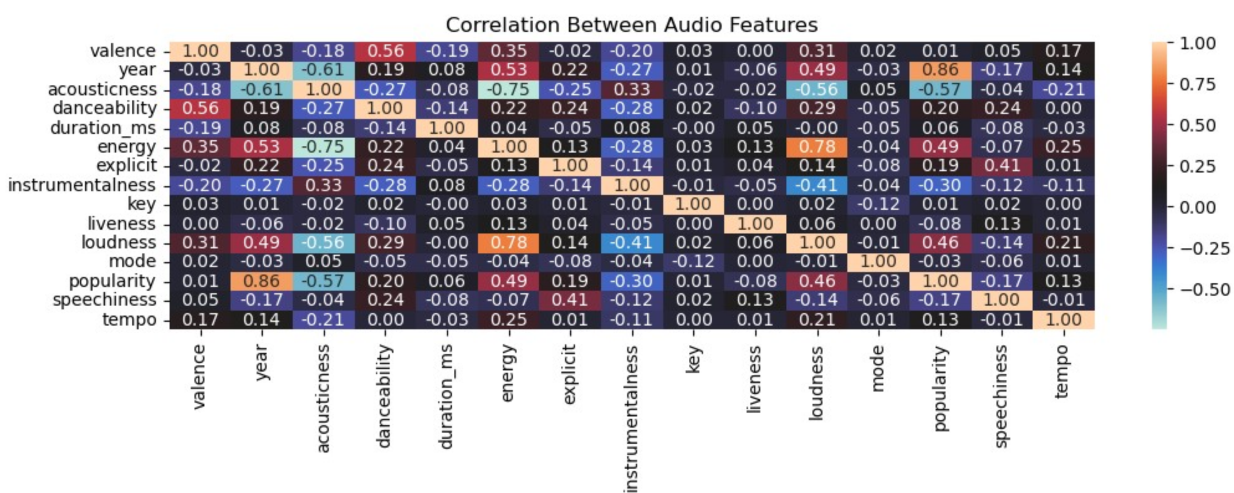

```
# Scatter Plot – Energy vs Danceability
plt.figure(figsize=(12,4))
sns.scatterplot(data=tracks,x='energy',y='danceability',alpha=0.5,colo
```

```
r='pink')
plt.title("Energy vs Danceability")
plt.show()
```



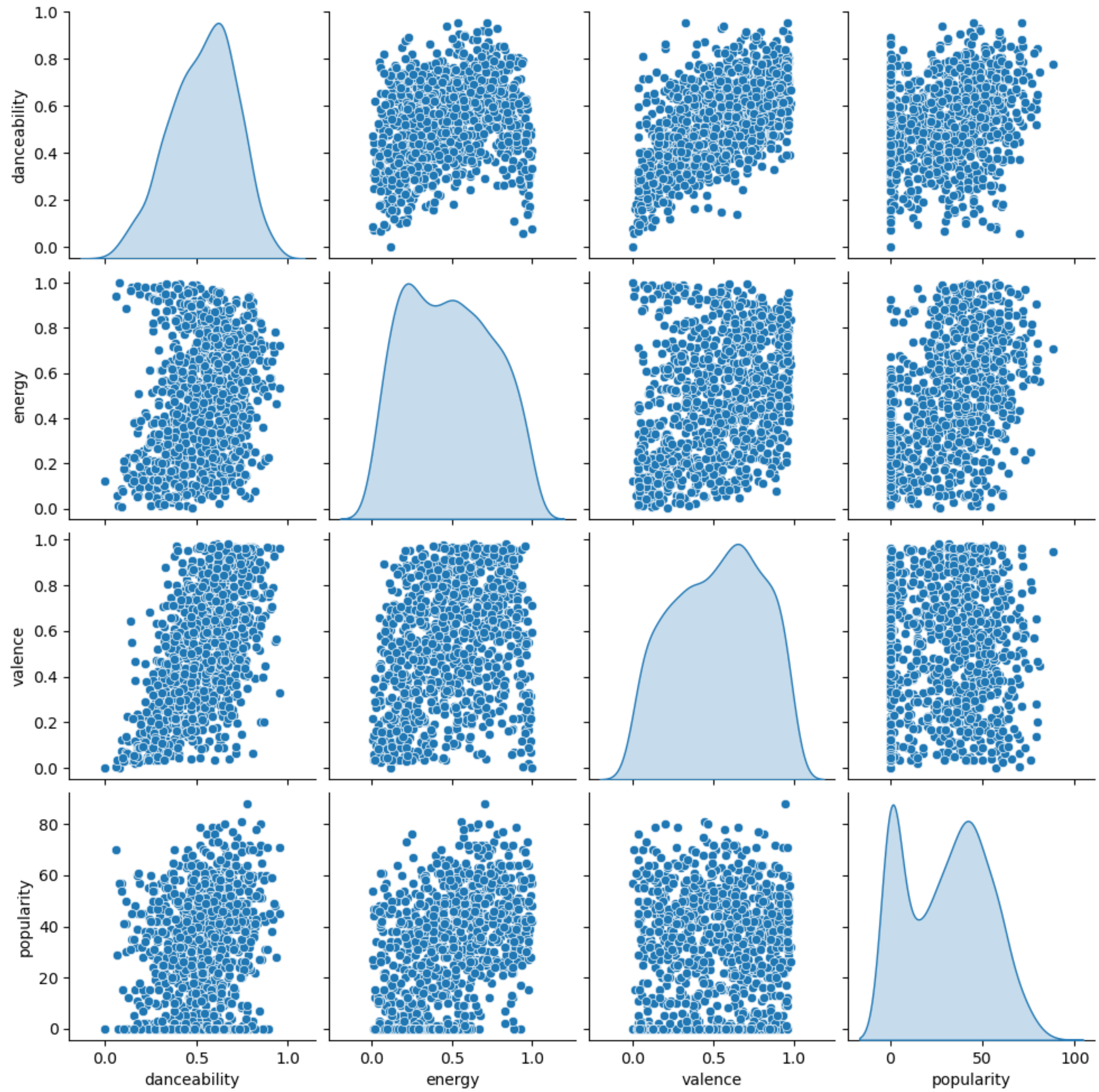
Task 4.2: Advanced Visualizations (Heatmaps, Pair Plots)

```
# Correlation Heatmap
plt.figure(figsize=(12,3))
corr = tracks.corr(numeric_only=True)
sns.heatmap(corr,annot=True,cmap='icefire',fmt='.2f')
plt.title('Correlation Between Audio Features')
plt.show()
```




```
# Pair Plot (Feature Relationships)
sample_tracks = tracks.sample(1000)  # speed up plotting
```

```python
sns.pairplot(sample_tracks[['danceability','energy','valence','popular
ity']],diag_kind='kde')
plt.show()
```



Modeling and Predictions

Task 5.1: Build Predictive Models to Forecast Song Popularity

```
# Prepare the data
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
# Select numeric features only
features = [
    'danceability','energy','loudness','speechiness',
    'acousticness','instrumentalness','liveness',
    'valence','tempo','duration_ms'
]

X = tracks[features]
y = tracks['popularity']
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
# Scale features (important for regression)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Task 5.2: Evaluate Different Models

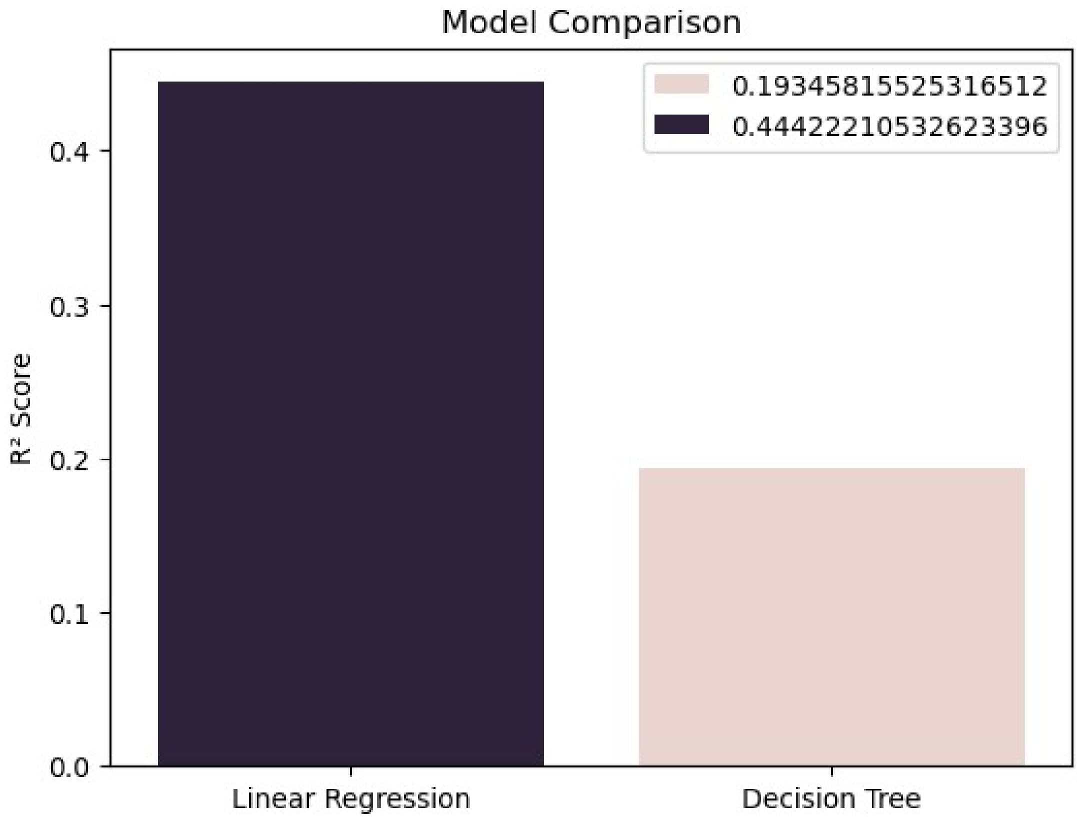
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

lr = LinearRegression()
lr.fit(X_train, y_train)

y_pred_lr = lr.predict(X_test)

print("Linear Regression Results:")
print("MAE:", mean_absolute_error(y_test, y_pred_lr))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_lr)))
print("R2:", r2_score(y_test, y_pred_lr))
```

```
Linear Regression Results:
MAE: 13.11202616522743
RMSE: 16.307952651171533
R2: 0.44422210532623396
```

```python
# Decision Tree
from sklearn.tree import DecisionTreeRegressor
dt = DecisionTreeRegressor(random_state=42)
dt.fit(X_train, y_train)

y_pred_dt = dt.predict(X_test)

print("Decision Tree Results:")
print("MAE:", mean_absolute_error(y_test, y_pred_dt))
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_dt)))
print("R2:", r2_score(y_test, y_pred_dt))
```

```
Decision Tree Results:
MAE: 14.255713769495962
RMSE: 19.645462578647304
R2: 0.19345815525316512
```

```python
# Compare Model Performance (Visualization)
models = ['Linear Regression','Decision Tree']
r2_scores = [
    r2_score(y_test, y_pred_lr),
    r2_score(y_test, y_pred_dt)
]
sns.barplot(x=models,y=r2_scores,hue=r2_scores)
plt.ylabel("R² Score")
plt.title("Model Comparison")
plt.show()
```



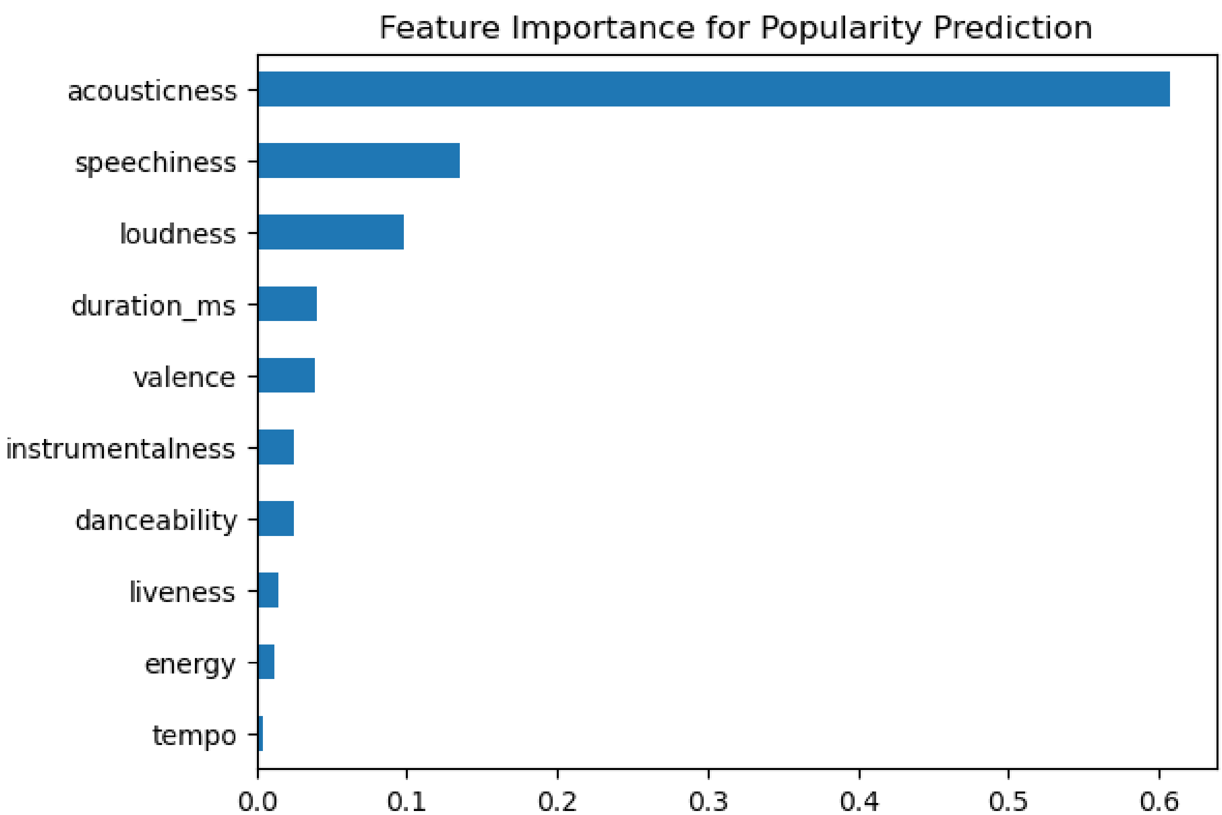
Task 5.3: Fine-Tune Models to Improve Accuracy

```
from sklearn.model_selection import GridSearchCV

params = {
    'max_depth': [5, 10, 20, None],
    'min_samples_split': [2, 5, 10]
}

grid = GridSearchCV(
    DecisionTreeRegressor(random_state=42),
    params,
    cv=5,
    scoring='r2'
)

grid.fit(X_train, y_train)

best_dt = grid.best_estimator_

y_pred_best = best_dt.predict(X_test)
```

```
print("Best Parameters:", grid.best_params_)
print("Tuned R2:", r2_score(y_test, y_pred_best))
```

```
Best Parameters: {'max_depth': 10, 'min_samples_split': 10}
Tuned R2: 0.5415446259348499
```

```
# Feature Importance (Very useful insight)
importance = pd.Series(best_dt.feature_importances_, index=features)
importance.sort_values().plot(kind='barh')
plt.title("Feature Importance for Popularity Prediction")
plt.show()
```



Conclusion

Task 6.1: Key Findings

The analysis of Spotify's dataset revealed several important patterns in music trends, user preferences, and track characteristics. Popular tracks generally exhibit higher energy, danceability, and loudness, indicating that upbeat and engaging songs tend to attract more listeners. Certain genres consistently dominate streaming counts, suggesting strong audience loyalty toward specific music styles. Additionally, newer releases show higher engagement levels compared to older tracks, highlighting the impact of recency on streaming behavior. Correlation analysis also indicated relationships between audio features (such as energy and loudness) and popularity scores.

Task 6.2: Implications of the Results

These findings have practical implications for artists, producers, and music streaming platforms. Understanding which features contribute to track popularity can help artists tailor their music to audience preferences. Record labels can make data-driven decisions regarding genre investments and release strategies. For Spotify, insights into listener behavior can enhance recommendation systems, personalized playlists, and targeted promotions, ultimately improving user satisfaction and platform engagement.

Task 6.3: Future Research Directions

Future research could explore deeper user-level analytics, such as individual listening patterns and personalized recommendation accuracy. Time-series analysis may help identify evolving trends and seasonal listening habits. Incorporating sentiment analysis of lyrics or social media feedback could provide richer context for popularity prediction. Additionally, applying machine learning models to predict hit songs based on audio features would further enhance predictive capabilities.