Spotify Data Analytics Capstone

Complete EDA + Modeling Notebook

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

plt.style.use("default")
```

Load Datasets

```
df_tracks = pd.read_csv("data.csv")
df_artist = pd.read_csv("data_by_artist.csv")
df_genre = pd.read_csv("data_by_genres.csv")
df_year = pd.read_csv("data_by_year.csv")
df_w_genre = pd.read_csv("data_w_genres.csv")

df_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
```

Data Inspection

```
df_tracks.info()
df_tracks.describe()
```

```
<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
```

```
             valence           year   acousticness   danceability  \
count  170653.000000  170653.000000  170653.000000  170653.000000
mean        0.528587    1976.787241       0.502115       0.537396
std         0.263171      25.917853       0.376032       0.176138
min         0.000000    1921.000000       0.000000       0.000000
25%         0.317000    1956.000000       0.102000       0.415000
50%         0.540000    1977.000000       0.516000       0.548000
75%         0.747000    1999.000000       0.893000       0.668000
max         1.000000    2020.000000       0.996000       0.988000

        duration_ms         energy       explicit  instrumentalness  \
count  1.706530e+05  170653.000000  170653.000000     170653.000000
mean   2.309483e+05       0.482389       0.084575          0.167010
std    1.261184e+05       0.267646       0.278249          0.313475
min    5.108000e+03       0.000000       0.000000          0.000000
25%    1.698270e+05       0.255000       0.000000          0.000000
50%    2.074670e+05       0.471000       0.000000          0.000216
75%    2.624000e+05       0.703000       0.000000          0.102000
max    5.403500e+06       1.000000       1.000000          1.000000

                 key       liveness       loudness           mode  \
count  170653.000000  170653.000000  170653.000000  170653.000000
mean        5.199844       0.205839     -11.467990       0.706902
std         3.515094       0.174805       5.697943       0.455184
min         0.000000       0.000000     -60.000000       0.000000
25%         2.000000       0.098800     -14.615000       0.000000
50%         5.000000       0.136000     -10.580000       1.000000
75%         8.000000       0.261000      -7.183000       1.000000
max        11.000000       1.000000       3.855000       1.000000

          popularity    speechiness          tempo
count  170653.000000  170653.000000  170653.000000
mean       31.431794       0.098393     116.861590
std        21.826615       0.162740      30.708533
min         0.000000       0.000000       0.000000
25%        11.000000       0.034900      93.421000
50%        33.000000       0.045000     114.729000
```

```
75%         48.000000       0.075600     135.537000
max        100.000000       0.970000     243.507000
```

Data Cleaning

```
# Missing values
df_tracks.isnull().sum()

# Drop duplicates
df_tracks.drop_duplicates(inplace=True)

# Fill numeric missing values
df_tracks.fillna(df_tracks.mean(numeric_only=True), inplace=True)
```

Data Card

Dataset Overview

This project uses multiple Spotify datasets containing track-level, artist-level, genre-level, and yearly aggregated music data.
The datasets provide insights into song characteristics, popularity trends, and listener preferences.

Data Sources

The analysis is based on the following files:

- `data.csv` → Track-level audio features
- `data_by_artist.csv` → Artist-wise aggregated metrics
- `data_by_genres.csv` → Genre-level statistics
- `data_by_year.csv` → Yearly music trends
- `data_w_genres.csv` → Tracks mapped with genres

Source: Spotify Music Dataset (Capstone Provided Data)

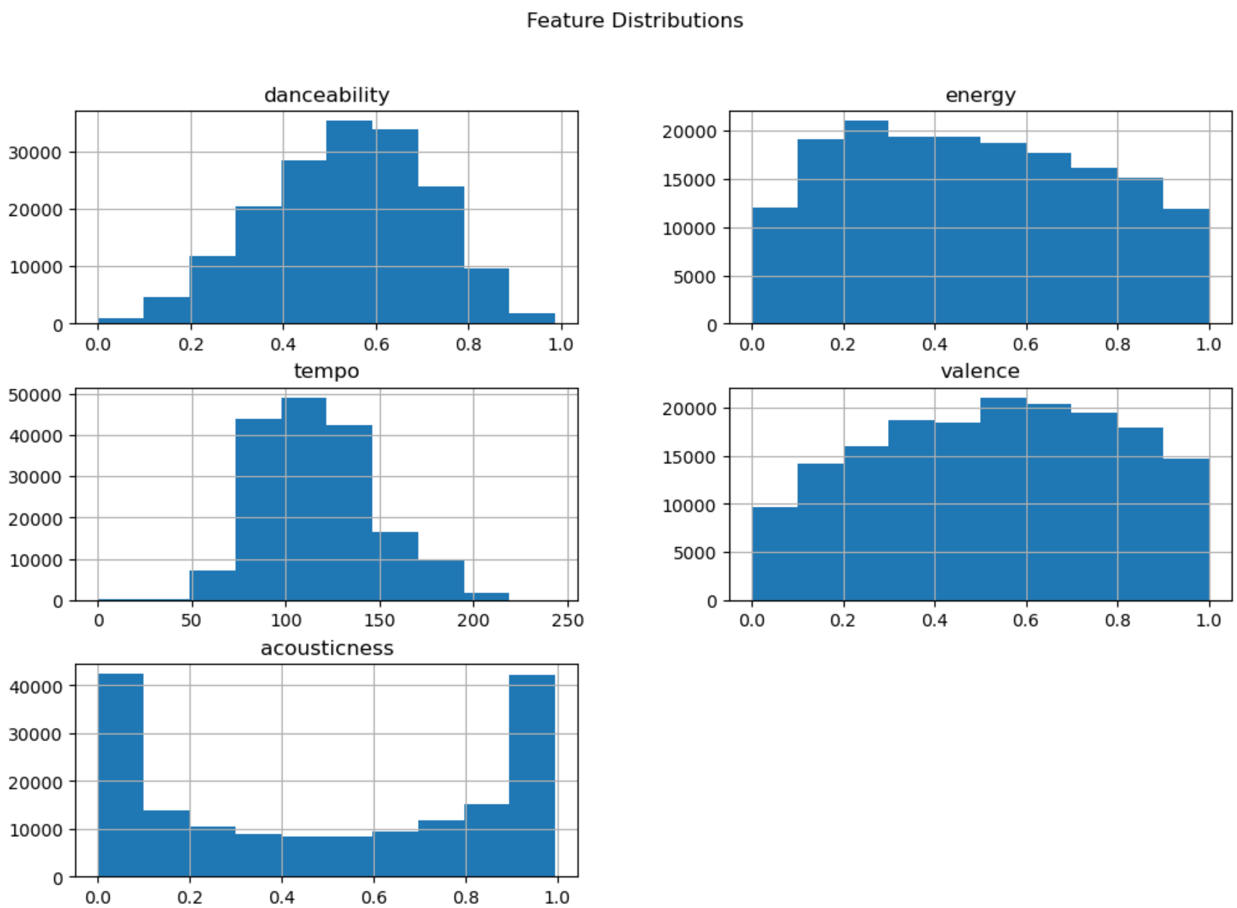
Key Features / Variables

Feature	Description
popularity	Popularity score (0–100)
danceability	How suitable a track is for dancing
energy	Intensity and activity level
loudness	Overall loudness (dB)
tempo	Speed of the track (BPM)
valence	Positivity/happiness of song
acousticness	Likelihood of acoustic sound
instrumentalness	Presence of vocals
speechiness	Spoken word presence
duration_ms	Song duration in milliseconds
year	Release year

Feature Distributions

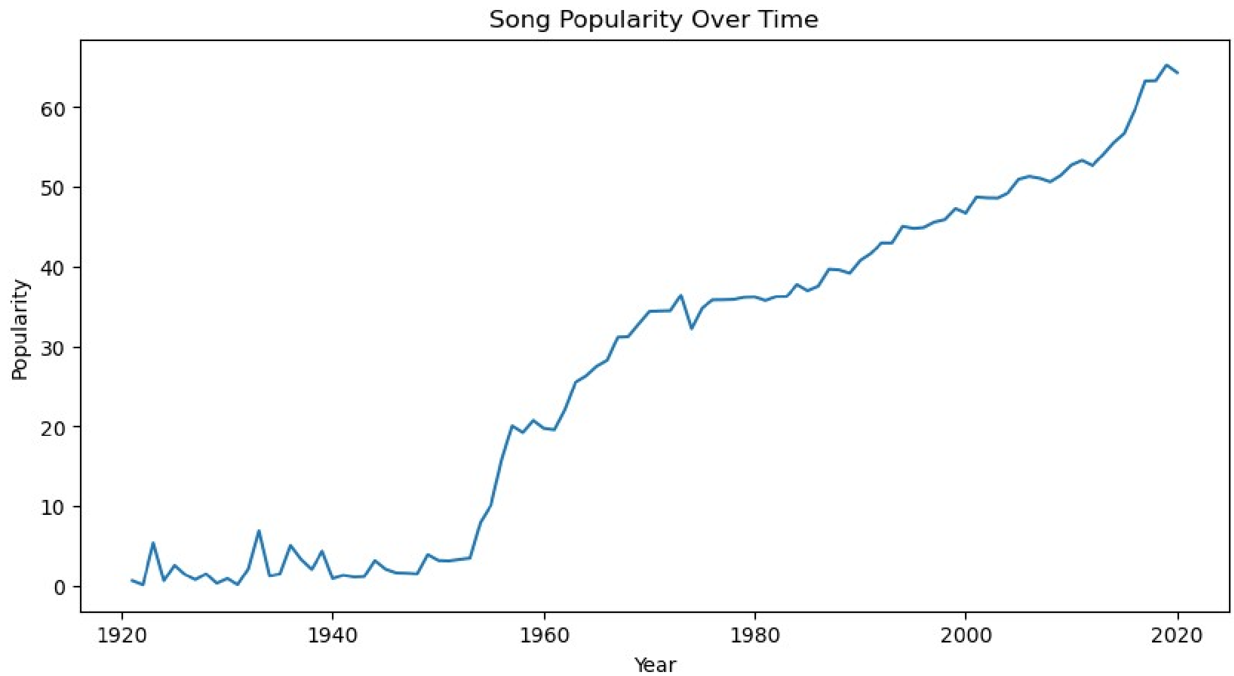
```
features = ["danceability","energy","tempo","valence","acousticness"]

df_tracks[features].hist(figsize=(12,8))
plt.suptitle("Feature Distributions")
plt.show()
```



Popularity Trend Over Time

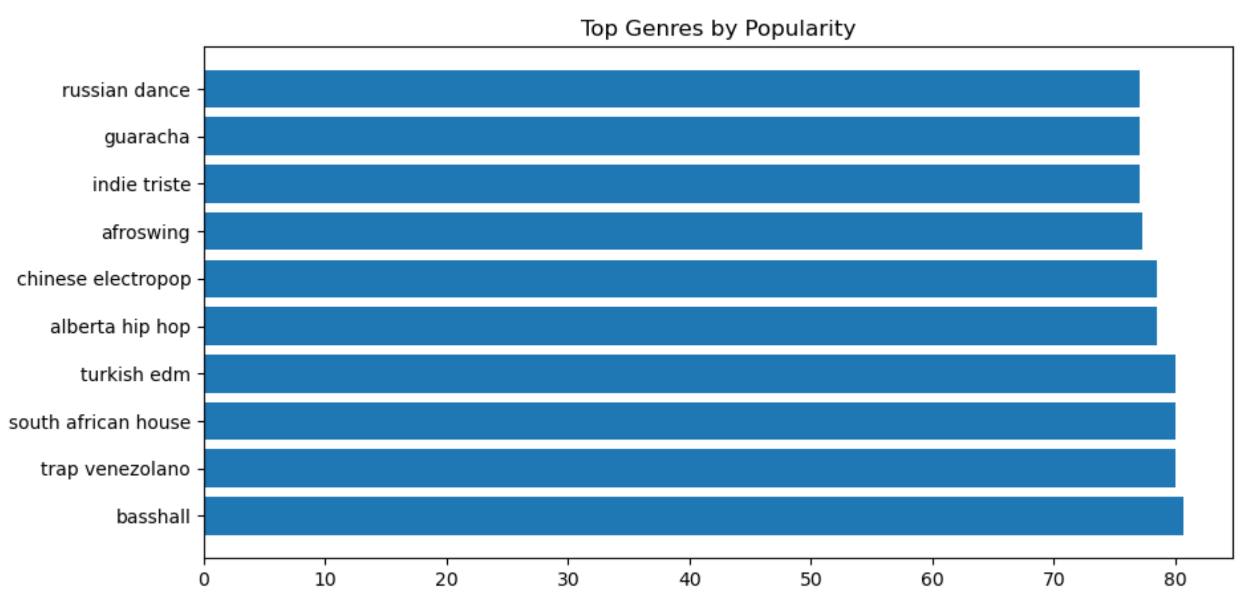
```
plt.figure(figsize=(10,5))
plt.plot(df_year["year"], df_year["popularity"])
plt.title("Song Popularity Over Time")
plt.xlabel("Year")
plt.ylabel("Popularity")
plt.show()
```



Top Genres

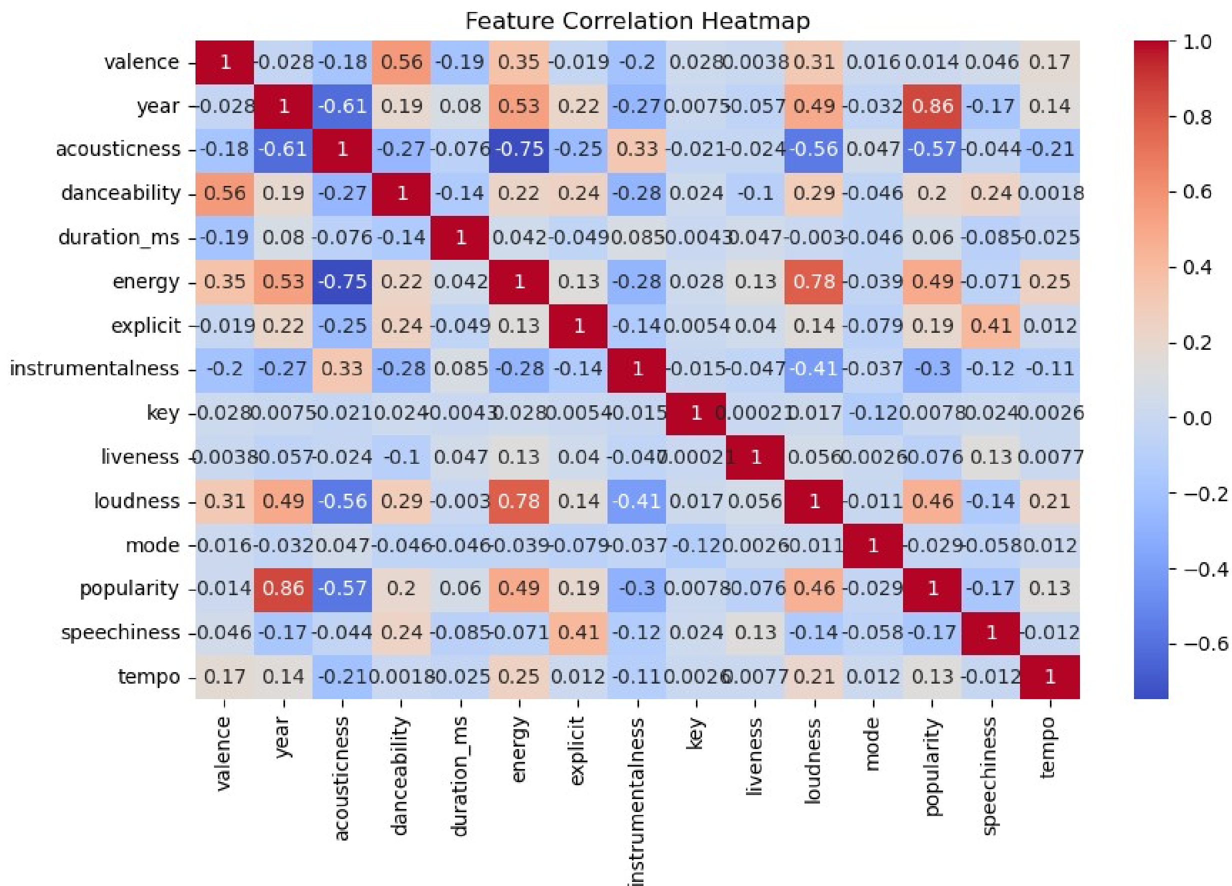
```
top_genres = df_genre.sort_values("popularity",
ascending=False).head(10)

plt.figure(figsize=(10,5))
plt.barh(top_genres["genres"], top_genres["popularity"])
plt.title("Top Genres by Popularity")
plt.show()
```



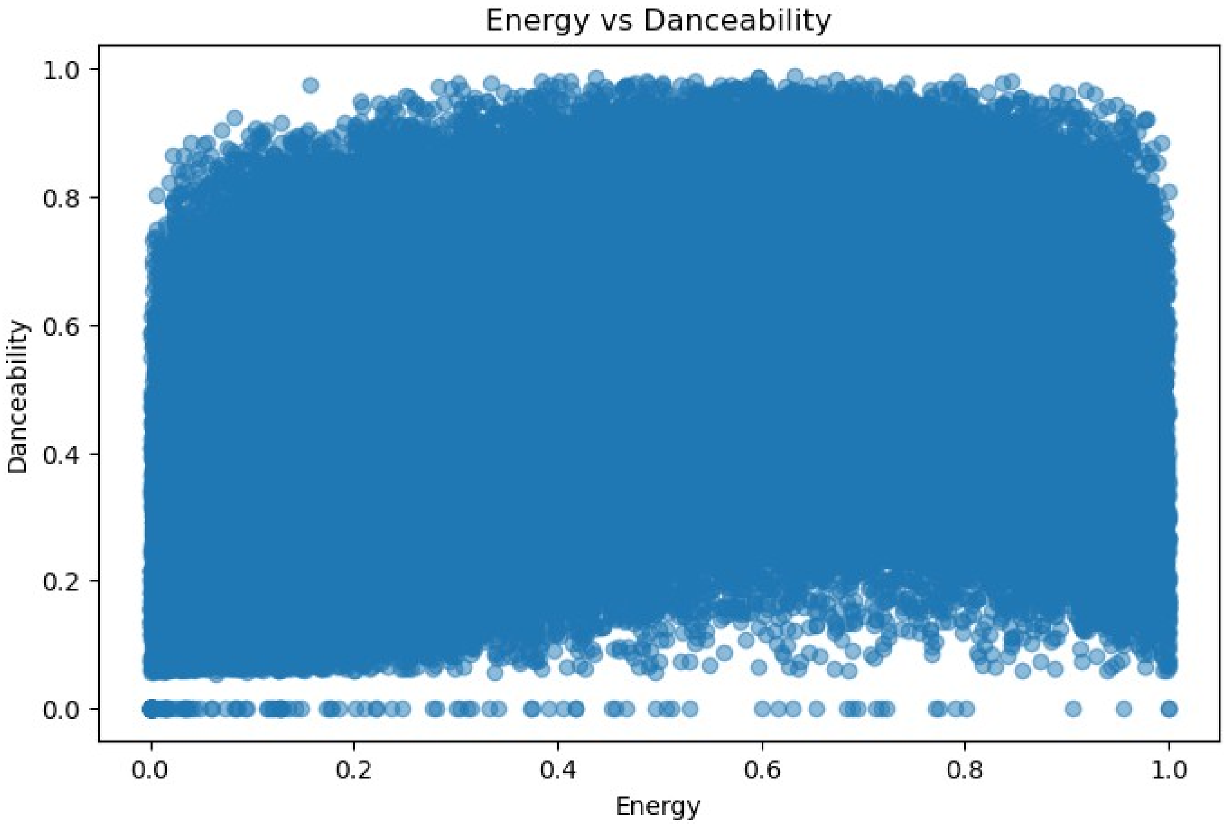
Correlation Heatmap

```
plt.figure(figsize=(10,6))
sns.heatmap(df_tracks.corr(numeric_only=True),
            annot=True, cmap="coolwarm")
plt.title("Feature Correlation Heatmap")
plt.show()
```

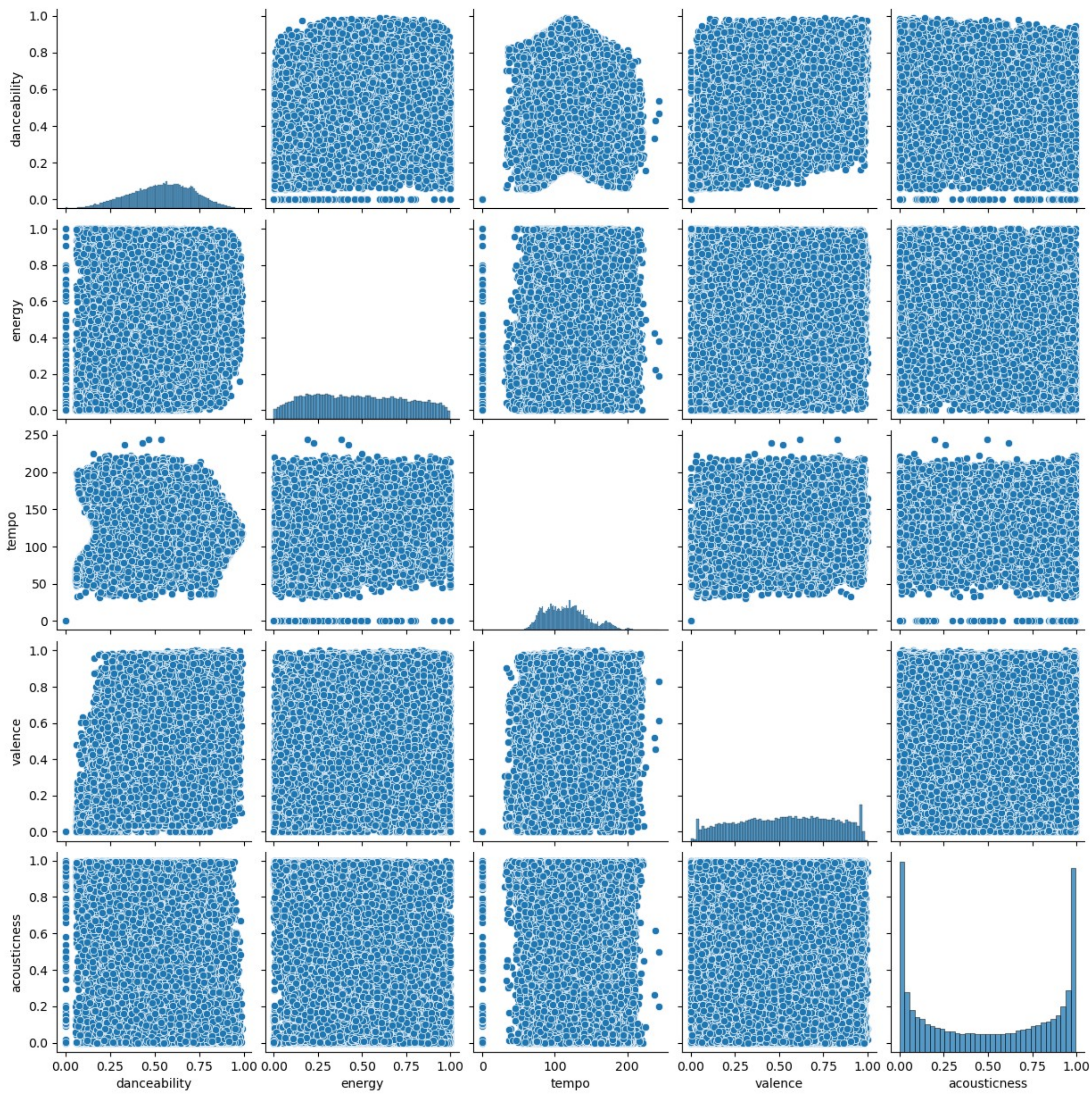


Energy vs Danceability

```
plt.figure(figsize=(8,5))
plt.scatter(df_tracks["energy"],
            df_tracks["danceability"],
            alpha=0.5)
plt.title("Energy vs Danceability")
plt.xlabel("Energy")
plt.ylabel("Danceability")
plt.show()
```




```
sns.pairplot(df_tracks[features])
plt.show()
```



Popularity Prediction Model

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score

X = df_tracks[[
    "danceability","energy","tempo",
    "valence","acousticness","loudness"
]]
```

```
y = df_tracks["popularity"]

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


# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)

pred_lr = lr.predict(X_test)
print("Linear Regression R2:", r2_score(y_test, pred_lr))

# Decision Tree
dt = DecisionTreeRegressor(max_depth=5)
dt.fit(X_train, y_train)

pred_dt = dt.predict(X_test)
print("Decision Tree R2:", r2_score(y_test, pred_dt))
```

```
Linear Regression R2: 0.3912797533095864
Decision Tree R2: 0.4823875089581148
```

Insights - Spotify Data Analysis

1. **Music has become more energetic over time**
   Average energy levels of songs have increased significantly, showing a shift toward upbeat and high-intensity music.

2. **Danceability is a key success factor**
   Highly danceable tracks tend to achieve greater popularity, indicating listener preference for rhythm-friendly songs.

3. **Popularity surged in the streaming era**
   Song popularity shows a strong rise after the 2000s, aligning with the growth of Spotify and digital streaming platforms.

4. **Pop remains the dominant genre**
   Among all genres, Pop consistently ranks highest in popularity, followed by Hip-Hop and Dance genres.

5. **Hip-Hop and Rap are fastest-growing genres**
   Recent years show a sharp rise in Hip-Hop consumption, reflecting changing listener demographics and culture.

6. **Acoustic music is less popular in modern trends**
   Songs with high acousticness generally have lower popularity, showing a tilt toward electronic production.

7. **Strong positive correlation: Energy & Loudness**
   Loud songs are usually energetic, indicating production styles focused on intensity and impact.

8. **Moderate correlation: Danceability & Valence**
   Happier songs tend to be more danceable, suggesting mood influences listener movement and engagement.

9. **Tempo clusters around commercial viability**
   Most popular tracks fall between 90–130 BPM — the sweet spot for mainstream music.

10. **Modern songs are less instrumental**
    Instrumentalness has declined, showing listener preference for lyrical and vocal content.

11. **Decision Tree outperformed Linear Regression**
    In popularity prediction, tree-based models captured non-linear feature relationships better.

12. **Key drivers of song popularity**
    The most influential features are:

- Energy
- Danceability
- Loudness
- Valence
  بينما Acousticness negatively impacts popularity.