spotify-audio-analysis

October 30, 2024

1 Spotify Audio Analysis

1.1 Project Introduction

About Spotify: Founded in 2006, Spotify has grown into a global leader in music streaming, offering access to millions of songs, podcasts, and other audio content. Through cutting-edge technology and advanced data analytics, Spotify provides personalized listening experiences to users, supporting both a free, ad-based model and a premium subscription service.

Industry Scope: Spotify operates within the realms of music streaming, podcasting, audio content, technology, and advertising, positioning itself as a pivotal player in the digital audio space.

Purpose of the Analysis: The goal of this analysis is to uncover key insights from Spotify's extensive audio data, identifying patterns that contribute to a track's popularity. By examining features like danceability, energy, acousticness, and valence, this project aims to determine which elements make songs resonate with listeners and how these attributes vary across different genres and time frames.

Dataset Overview: For this project, we utilize two robust datasets:

1. **tracks.csv** from Spotify Datasets, containing 586,672 entries. This dataset includes:
    - **Track Details:** Track ID, song title, popularity score, duration, explicit content flag, and artist information.
    - **Audio Features:** Danceability, energy, loudness, speechiness, acousticness, instrumentalness, valence, and tempo.
    - **Additional Attributes:** Release date, key, mode, and time signature.
2. **SpotifyFeatures.csv** from Spotify Tracks DB, comprising 232,725 entries. This dataset includes:
    - **Genre Information:** Genre classification for each track.
    - **Artist and Track Data:** Artist name, track title, and track ID.
    - **Audio Features:** Acousticness, danceability, energy, liveness, loudness, speechiness, valence, and tempo.
    - **Additional Attributes:** Key, mode, duration, and time signature.

Using these datasets, this analysis delves into how audio characteristics influence track popularity, providing insights into listener preferences across different genres and time periods.

2 1: Import Libraries and Load Data

Import Libraries

[60]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set plot style
sns.set_style("whitegrid")
```

Data Load

[61]:
```
from google.colab import drive
drive.mount('/content/drive')

# Load data from Google Drive
df_tracks = pd.read_csv('/content/drive/MyDrive/Data Analysis/Python Project/
 ↪Spotify Music Analysis/Tracks.csv')
df_genre = pd.read_csv('/content/drive/MyDrive/Data Analysis/Python Project/
 ↪Spotify Music Analysis/SpotifyFeatures.csv')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

3 2. Data Overview

Preview Data Structure

[62]:
```
# Display the first rows of each dataset
print("Tracks.csv Preview:")
df_tracks.head()

print("SpotifyFeatures.csv Preview:")
df_genre.head()
```

```
Tracks.csv Preview:
SpotifyFeatures.csv Preview:
```

[62]:
```
   genre        artist_name                        track_name  \
0  Movie     Henri Salvador       C'est beau de faire un Show
1  Movie  Martin & les fées  Perdu d'avance (par Gad Elmaleh)
2  Movie    Joseph Williams    Don't Let Me Be Lonely Tonight
3  Movie     Henri Salvador    Dis-moi Monsieur Gordon Cooper
4  Movie       Fabien Nataf                         Ouverture
```

```
                track_id  popularity  acousticness  danceability  \
0  0BRjO6ga9RKCKjfDqeFgWV           0         0.611         0.389   
1  0BjC1NfoEOOusryehmNudP           1         0.246         0.590   
2  0CoSDzoNIKCRs124s9uTVy           3         0.952         0.663   
3  0Gc6TVm52BwZD07Ki6tIvf           0         0.703         0.240   
4  0IuslXpMROHdEPvSl1fTQK           4         0.950         0.331   

   duration_ms  energy  instrumentalness key  liveness  loudness   mode  \
0        99373   0.910             0.000  C#    0.3460    -1.828  Major   
1       137373   0.737             0.000  F#    0.1510    -5.559  Minor   
2       170267   0.131             0.000   C    0.1030   -13.879  Minor   
3       152427   0.326             0.000  C#    0.0985   -12.178  Major   
4        82625   0.225             0.123   F    0.2020   -21.150  Major   

   speechiness    tempo time_signature  valence  
0       0.0525  166.969            4/4    0.814  
1       0.0868  174.003            4/4    0.816  
2       0.0362   99.488            5/4    0.368  
3       0.0395  171.758            4/4    0.227  
4       0.0456  140.576            4/4    0.390  
```

Summary Information on Each Dataset

[63]:
```python
# Summary information of datasets
print("Tracks.csv Info:")
print(df_tracks.info())

print("SpotifyFeatures.csv Info:")
print(df_genre.info())
```

```
Tracks.csv Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 586672 entries, 0 to 586671
Data columns (total 20 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   id                586672 non-null  object 
 1   name              586601 non-null  object 
 2   popularity        586672 non-null  int64  
 3   duration_ms       586672 non-null  int64  
 4   explicit          586672 non-null  int64  
 5   artists           586672 non-null  object 
 6   id_artists        586672 non-null  object 
 7   release_date      586672 non-null  object 
 8   danceability      586672 non-null  float64
 9   energy            586672 non-null  float64
 10  key               586672 non-null  int64  
 11  loudness          586672 non-null  float64
```

```
 12  mode              586672 non-null  int64
 13  speechiness       586672 non-null  float64
 14  acousticness      586672 non-null  float64
 15  instrumentalness  586672 non-null  float64
 16  liveness          586672 non-null  float64
 17  valence           586672 non-null  float64
 18  tempo             586672 non-null  float64
 19  time_signature    586672 non-null  int64
dtypes: float64(9), int64(6), object(5)
memory usage: 89.5+ MB
None
SpotifyFeatures.csv Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 232725 entries, 0 to 232724
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   genre             232725 non-null  object
 1   artist_name       232725 non-null  object
 2   track_name        232724 non-null  object
 3   track_id          232725 non-null  object
 4   popularity        232725 non-null  int64
 5   acousticness      232725 non-null  float64
 6   danceability      232725 non-null  float64
 7   duration_ms       232725 non-null  int64
 8   energy            232725 non-null  float64
 9   instrumentalness  232725 non-null  float64
 10  key               232725 non-null  object
 11  liveness          232725 non-null  float64
 12  loudness          232725 non-null  float64
 13  mode              232725 non-null  object
 14  speechiness       232725 non-null  float64
 15  tempo             232725 non-null  float64
 16  time_signature    232725 non-null  object
 17  valence           232725 non-null  float64
dtypes: float64(9), int64(2), object(7)
memory usage: 32.0+ MB
None
```

4 3. Data Cleaning

Handle Missing Values

[64]:
```
# Drop rows with missing 'name' or 'track_name'
df_tracks.dropna(subset=['name'], inplace=True)
df_genre.dropna(subset=['track_name'], inplace=True)
```

Convert Data Types

[65]:
```
# Convert release date columns to datetime
df_tracks['release_date'] = pd.to_datetime(df_tracks['release_date'],␣
↪errors='coerce')

# Convert 'mode' to binary (0 for Minor, 1 for Major)
df_genre['mode_binary'] = df_genre['mode'].map({'Minor': 0, 'Major': 1})
```

Convert Duration from Milliseconds to Seconds

[66]:
```
# Convert duration from milliseconds to seconds
df_tracks['duration'] = df_tracks['duration_ms'] / 1000
df_genre['duration'] = df_genre['duration_ms'] / 1000

# Drop original duration columns
df_tracks.drop('duration_ms', axis=1, inplace=True)
df_genre.drop('duration_ms', axis=1, inplace=True)
```

5 Exploratory Data Analysis (EDA)

Summary Statistics

[67]:
```
print("Summary Statistics for Tracks.csv:")
df_genre.describe()
```

```
Summary Statistics for Tracks.csv:
```

[67]:
```
          popularity   acousticness   danceability         energy  \
count  232724.000000  232724.000000  232724.000000  232724.000000
mean       41.127490       0.368562       0.554366       0.570958
std        18.189986       0.354768       0.185608       0.263456
min         0.000000       0.000000       0.056900       0.000020
25%        29.000000       0.037600       0.435000       0.385000
50%        43.000000       0.232000       0.571000       0.605000
75%        55.000000       0.722000       0.692000       0.787000
max       100.000000       0.996000       0.989000       0.999000

       instrumentalness       liveness       loudness    speechiness  \
count     232724.000000  232724.000000  232724.000000  232724.000000
mean           0.148302       0.215010      -9.569896       0.120765
std            0.302769       0.198273       5.998215       0.185519
min            0.000000       0.009670     -52.457000       0.022200
25%            0.000000       0.097400     -11.771000       0.036700
50%            0.000044       0.128000      -7.762000       0.050100
75%            0.035800       0.264000      -5.501000       0.105000
max            0.999000       1.000000       3.744000       0.967000

               tempo        valence    mode_binary       duration
```

```
count  232724.000000  232724.000000  232724.000000  232724.000000
mean      117.666494       0.454919       0.652030     235.121846
std        30.898942       0.260065       0.476328     118.935926
min        30.379000       0.000000       0.000000      15.387000
25%        92.959000       0.237000       0.000000     182.856250
50%       115.777500       0.444000       1.000000     220.427000
75%       139.054500       0.660000       1.000000     265.768000
max       242.903000       1.000000       1.000000    5552.917000
```

[68]:
```python
print("Summary Statistics for SpotifyFeatures.csv:")
df_tracks.describe()
```

```
Summary Statistics for SpotifyFeatures.csv:
```

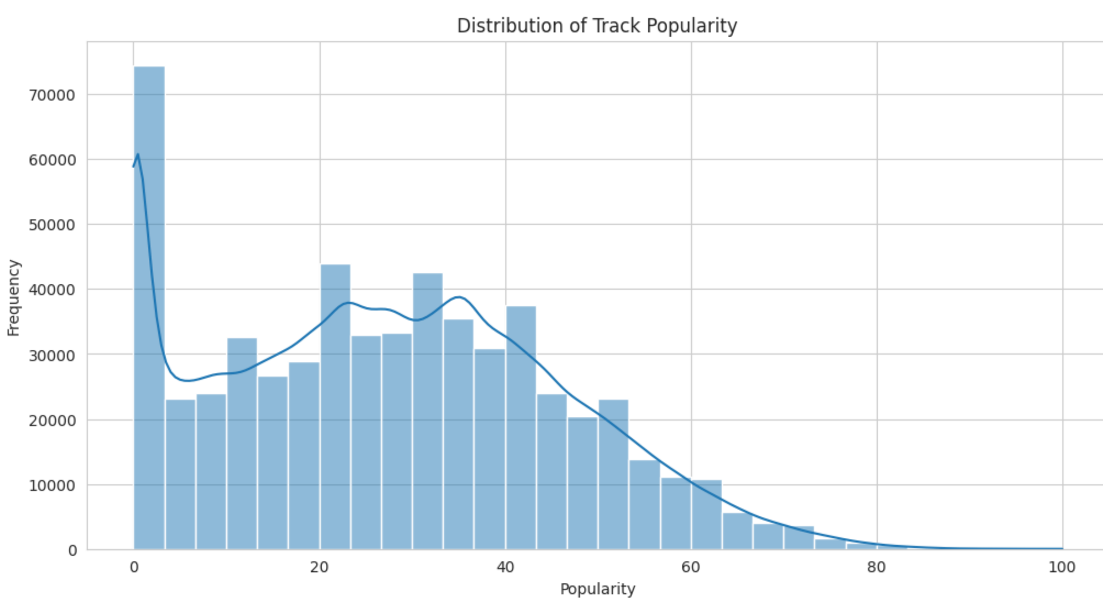
[68]:
```
          popularity       explicit                   release_date  \
count  586601.000000  586601.000000                         448010
mean       27.573212       0.044091  1993-03-23 09:16:40.761590016
min         0.000000       0.000000            1900-01-01 00:00:00
25%        13.000000       0.000000            1980-01-01 00:00:00
50%        27.000000       0.000000            1997-01-01 00:00:00
75%        41.000000       0.000000            2011-01-01 00:00:00
max       100.000000       1.000000            2021-04-16 00:00:00
std        18.369417       0.205298                            NaN

        danceability         energy            key       loudness  \
count  586601.000000  586601.000000  586601.000000  586601.000000
mean        0.563612       0.542071       5.221594     -10.205789
min         0.000000       0.000000       0.000000     -60.000000
25%         0.453000       0.343000       2.000000     -12.891000
50%         0.577000       0.549000       5.000000      -9.242000
75%         0.686000       0.748000       8.000000      -6.481000
max         0.991000       1.000000      11.000000       5.376000
std         0.166101       0.251910       3.519420       5.089422

                mode    speechiness   acousticness  instrumentalness  \
count  586601.000000  586601.000000  586601.000000     586601.000000
mean        0.658797       0.104870       0.449803          0.113425
min         0.000000       0.000000       0.000000          0.000000
25%         0.000000       0.034000       0.096900          0.000000
50%         1.000000       0.044300       0.422000          0.000024
75%         1.000000       0.076300       0.784000          0.009550
max         1.000000       0.971000       0.996000          1.000000
std         0.474114       0.179902       0.348812          0.266843

            liveness        valence          tempo  time_signature  \
count  586601.000000  586601.000000  586601.000000   586601.000000
mean        0.213933       0.552306     118.467930        3.873410
```

```
min          0.000000       0.000000       0.000000         0.000000
25%          0.098300       0.346000      95.606000         4.000000
50%          0.139000       0.564000     117.387000         4.000000
75%          0.278000       0.769000     136.324000         4.000000
max          1.000000       1.000000     246.381000         5.000000
std          0.184328       0.257673      29.762942         0.473112

             duration
count   586601.000000
mean       230.054853
min          3.344000
25%        175.083000
50%        214.907000
75%        263.867000
max       5621.218000
std        126.532825
```

6 Key EDA Visualizations

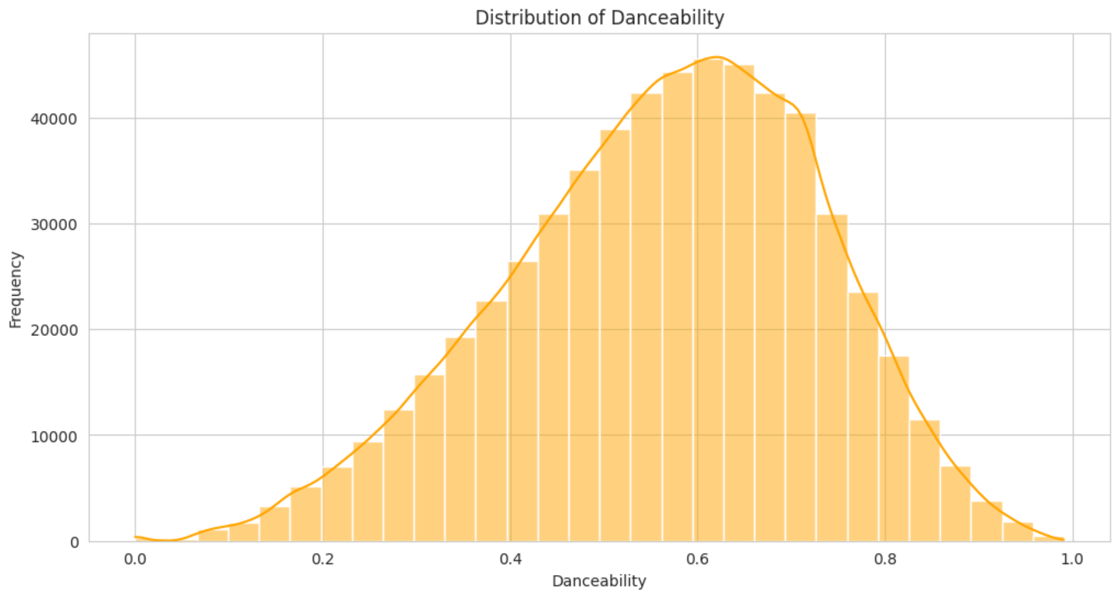
** Distribution of Track Popularity **

[69]:
```
plt.figure(figsize=(12, 6))
sns.histplot(df_tracks['popularity'], bins=30, kde=True)
plt.title('Distribution of Track Popularity')
plt.xlabel('Popularity')
plt.ylabel('Frequency')
plt.show()
```



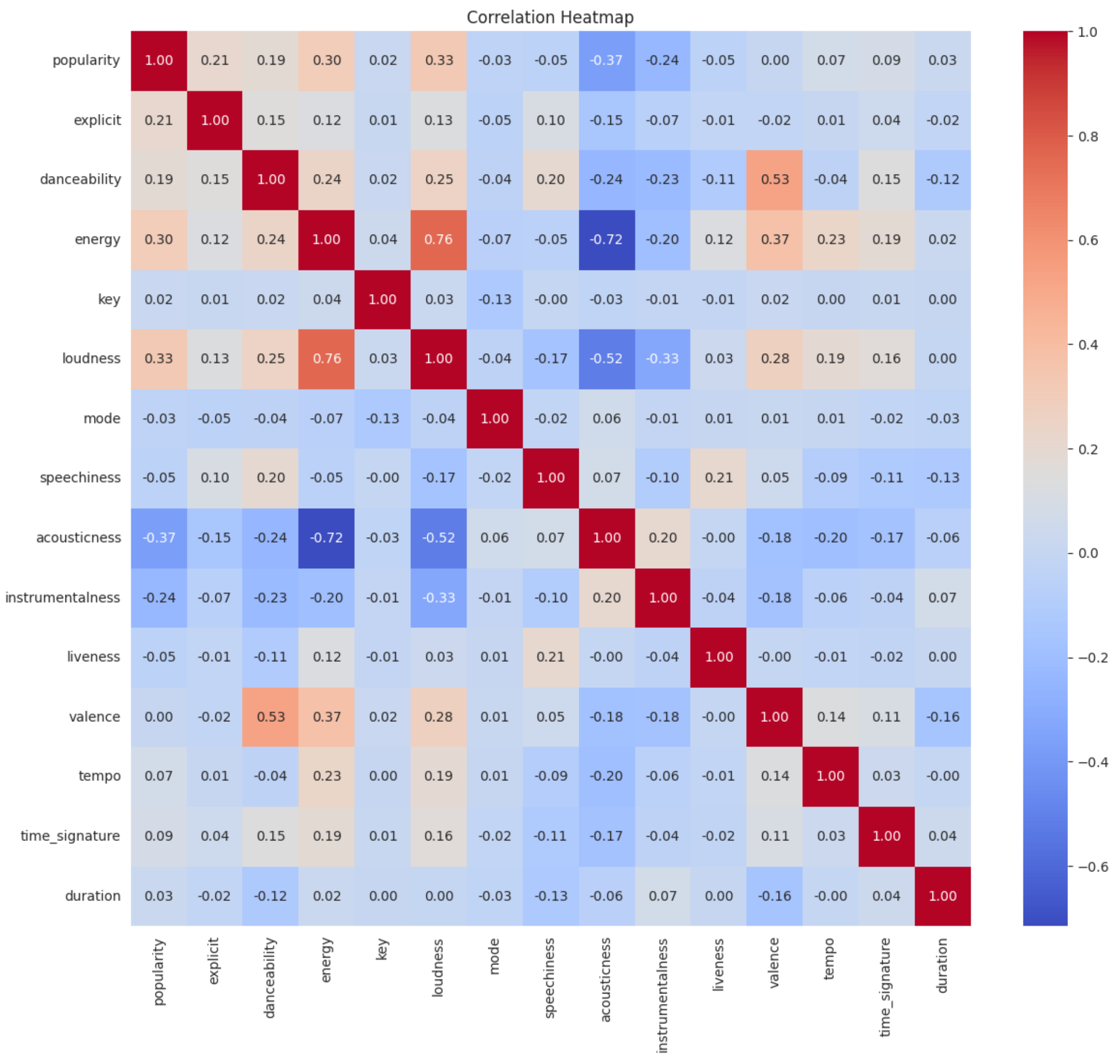
Distribution of Danceability

[70]:
```
plt.figure(figsize=(12, 6))
sns.histplot(df_tracks['danceability'], bins=30, kde=True, color='orange')
plt.title('Distribution of Danceability')
plt.xlabel('Danceability')
plt.ylabel('Frequency')
plt.show()
```



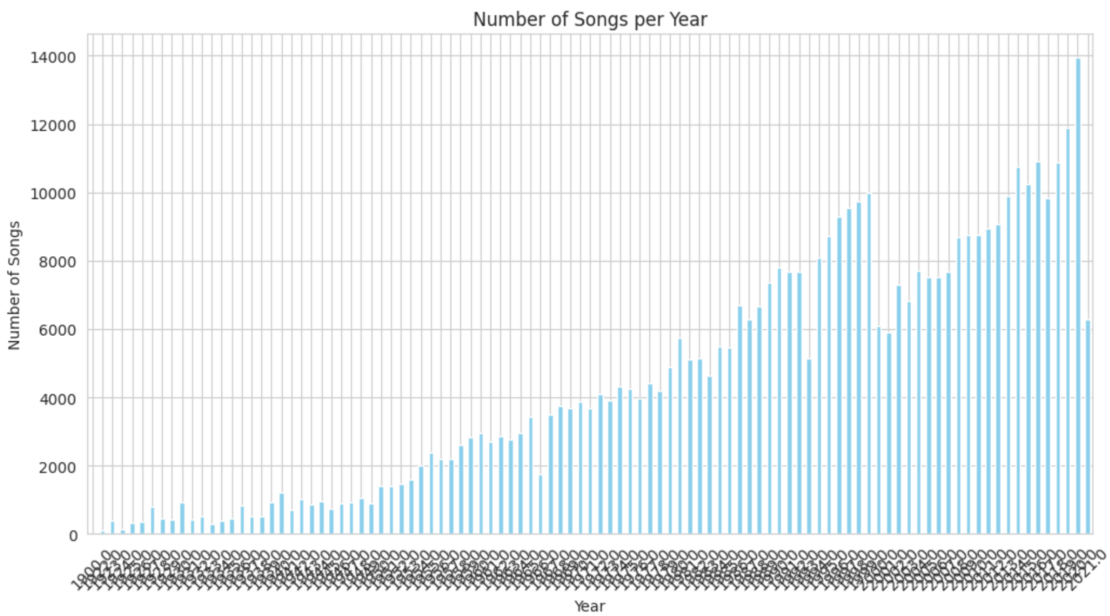
Correlation Heatmap

[71]:
```
numeric_df = df_tracks.select_dtypes(include=[np.number])
plt.figure(figsize=(14, 12))
sns.heatmap(numeric_df.corr(), annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



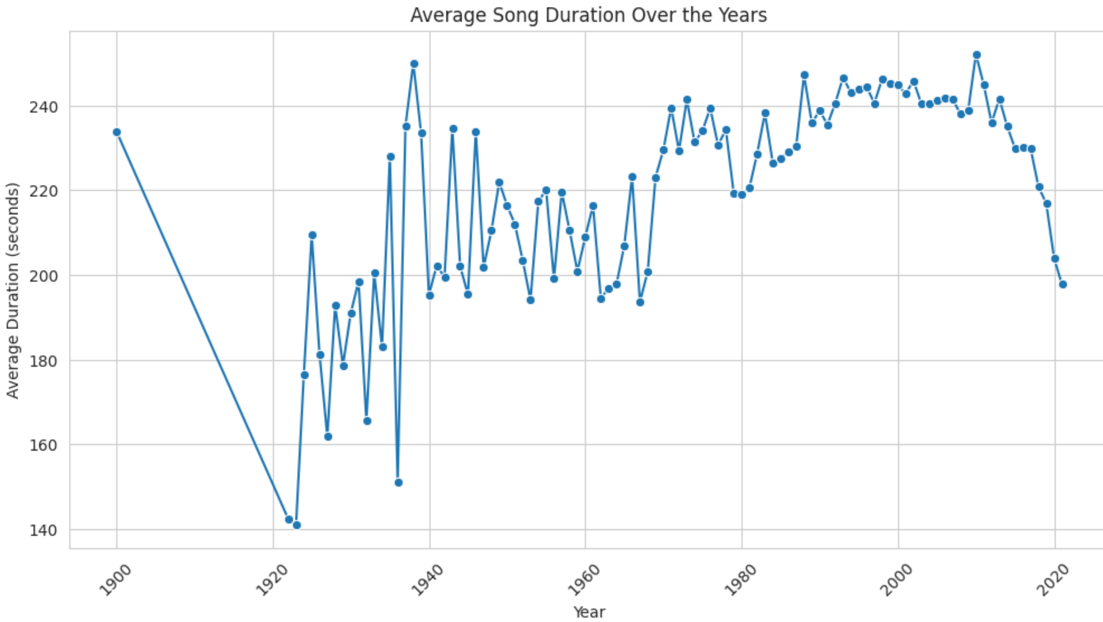
Number of Songs per Year

[91]:
```python
# Count the number of songs per year
songs_per_year = df_tracks['year'].value_counts().sort_index()

# Plotting the number of songs per year
plt.figure(figsize=(12, 6))
songs_per_year.plot(kind='bar', color='skyblue')
plt.title('Number of Songs per Year')
plt.xlabel('Year')
plt.ylabel('Number of Songs')
plt.xticks(rotation=45)
plt.show()
```



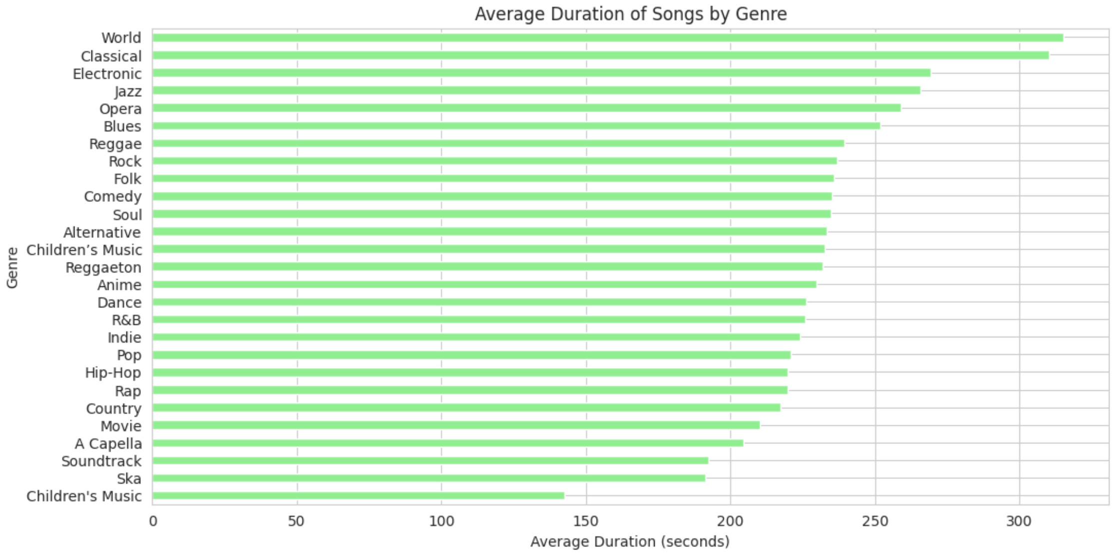
Year vs. Duration

```
[92]: # Calculate the average duration of songs per year
avg_duration_per_year = df_tracks.groupby('year')['duration'].mean()

# Plotting the average duration of songs per year
plt.figure(figsize=(12, 6))
sns.lineplot(x=avg_duration_per_year.index, y=avg_duration_per_year.values,␣
↪marker='o')
plt.title('Average Song Duration Over the Years')
plt.xlabel('Year')
plt.ylabel('Average Duration (seconds)')
plt.xticks(rotation=45)
plt.show()
```



Duration of Songs in Different Genres

[93]:
```
# Calculate the average duration of songs by genre
avg_duration_by_genre = df_genre.groupby('genre')['duration'].mean().
    ↪sort_values()

# Plotting the average duration of songs by genre
plt.figure(figsize=(12, 6))
avg_duration_by_genre.plot(kind='barh', color='lightgreen')
plt.title('Average Duration of Songs by Genre')
plt.xlabel('Average Duration (seconds)')
plt.ylabel('Genre')
plt.show()
```

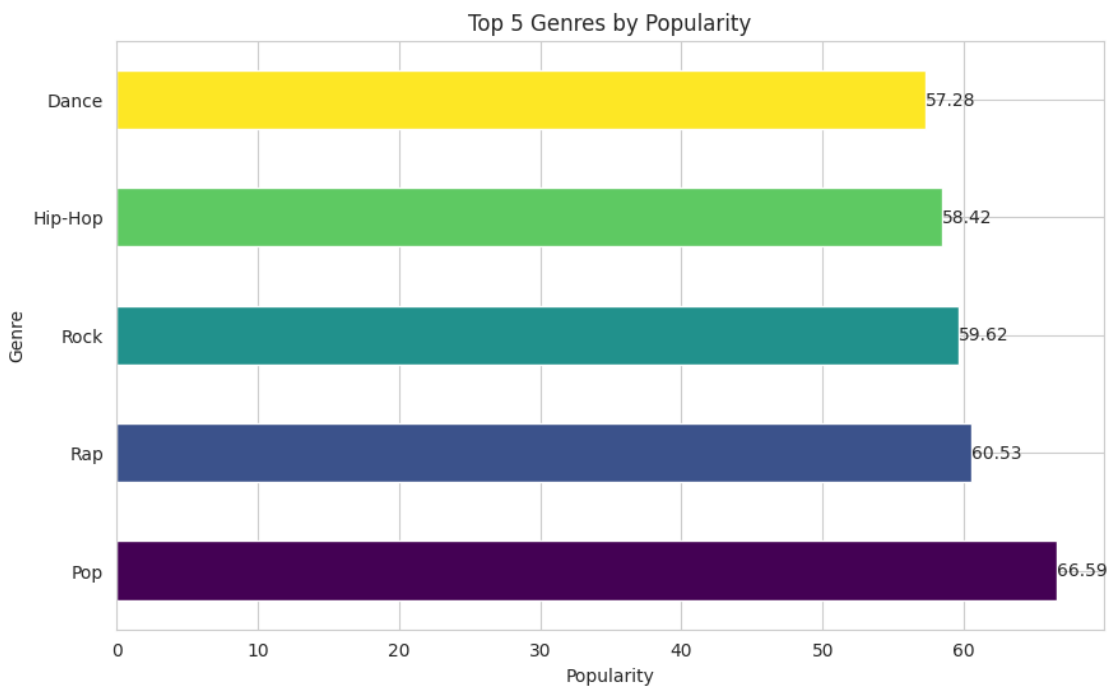


7 Genre Popularity Analysis

Top Genres by Popularity

[72]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Sample DataFrame definition (if you haven't defined df_genre)
# Uncomment and modify as needed
# data = {
#     'genre': ['Pop', 'Rock', 'Hip-Hop', 'Jazz', 'Classical', 'Electronic'],
#     'popularity': [75, 80, 90, 70, 60, 85]
# }
# df_genre = pd.DataFrame(data)

# Calculate the top 5 genres by average popularity
top_genres = df_genre.groupby('genre')['popularity'].mean().
 ↪sort_values(ascending=False).head(5)

# Create a horizontal bar chart
plt.figure(figsize=(10, 6))
colors = plt.cm.viridis(np.linspace(0, 1, len(top_genres)))  # Generate␣
 ↪different colors

# Plot the horizontal bar chart
top_genres.plot(kind='barh', color=colors)
```

```python
# Set the title and labels
plt.title("Top 5 Genres by Popularity")
plt.xlabel("Popularity")
plt.ylabel("Genre")

# Add data labels on top of the bars
for index, value in enumerate(top_genres):
    plt.text(value, index, f'{value:.2f}', ha='left', va='center')

# Show the plot
plt.show()
```



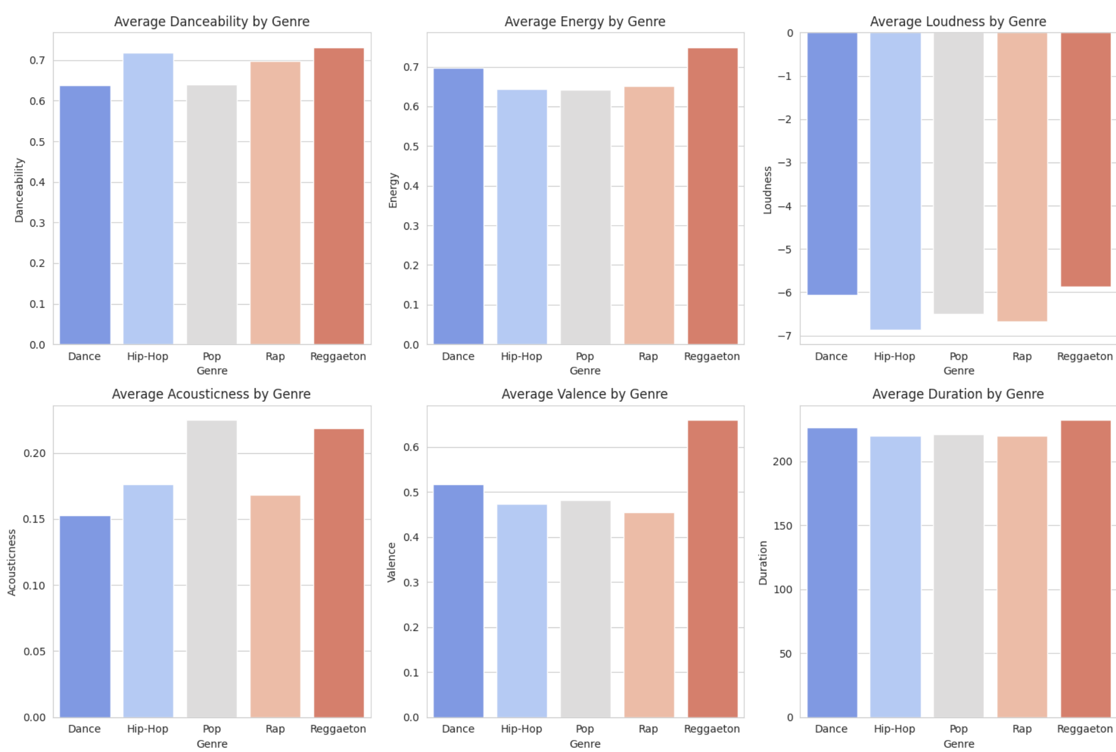
Average Audio Features by Top Genres

[73]:
```python
top_genres_list = ['Pop', 'Dance', 'Rap', 'Reggaeton', 'Hip-Hop']
filtered_df = df_genre[df_genre['genre'].isin(top_genres_list)]
genre_audio_features = filtered_df.groupby('genre').agg({
    'danceability': 'mean',
    'energy': 'mean',
    'loudness': 'mean',
    'acousticness': 'mean',
    'valence': 'mean',
    'duration': 'mean'
}).reset_index()
```

```python
# Create bar plots for each audio feature
plt.figure(figsize=(15, 10))
for i, feature in enumerate(['danceability', 'energy', 'loudness',␣
↪'acousticness', 'valence', 'duration']):
    plt.subplot(2, 3, i + 1)
    sns.barplot(data=genre_audio_features, x='genre', y=feature,␣
↪palette='coolwarm')
    plt.title(f'Average {feature.capitalize()} by Genre')
    plt.xlabel('Genre')
    plt.ylabel(f'{feature.capitalize()}')
plt.tight_layout()
plt.show()
```

```
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:
```

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-73-dc816b6a30aa>:16: FutureWarning:

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

  sns.barplot(data=genre_audio_features, x='genre', y=feature,
palette='coolwarm')
```



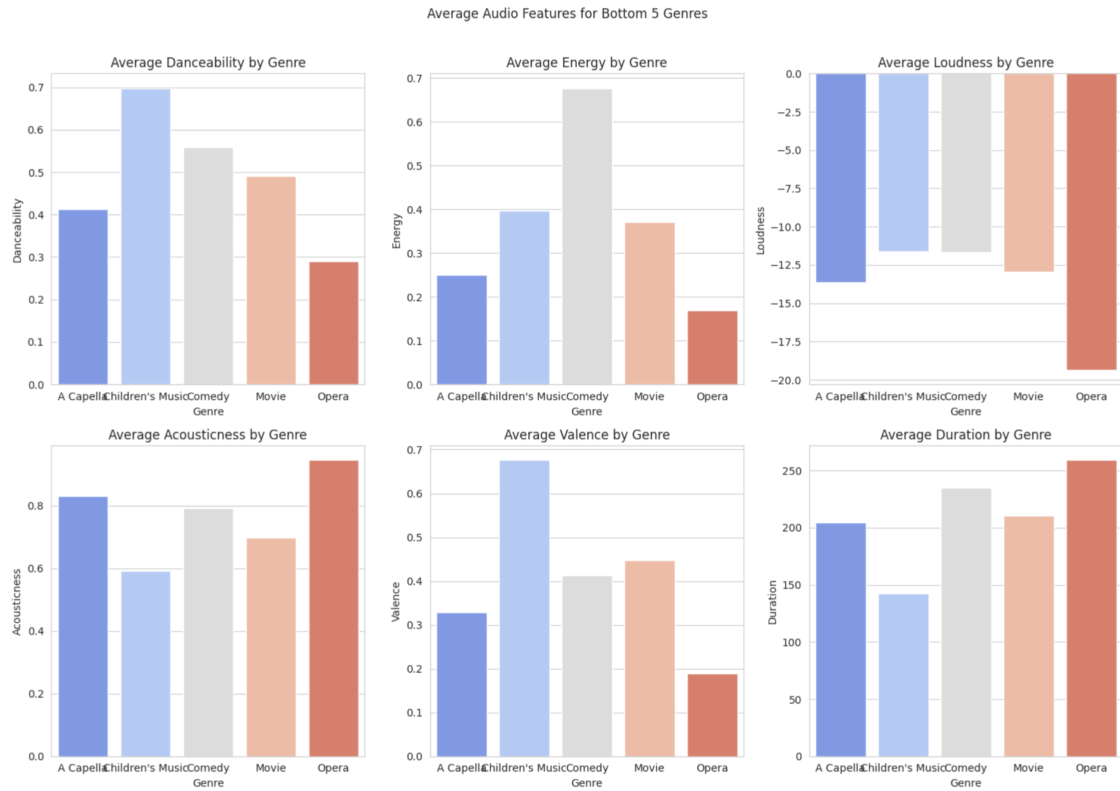
Average Audio Features by Bottom Genres

[74]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Sample DataFrame definition (if you haven't defined df_genre)
# Uncomment and modify as needed
# data = {
```

```
#     'genre': ['Pop', 'Dance', 'Rap', 'Reggaeton', 'Hip-Hop', 'Rock', 'Jazz',␣
↪'Classical', 'Country', 'Folk'],
#     'popularity': [75, 80, 90, 70, 60, 30, 20, 15, 25, 10],
#     'danceability': np.random.rand(10),
#     'energy': np.random.rand(10),
#     'loudness': np.random.rand(10) * 100 - 50,
#     'acousticness': np.random.rand(10),
#     'valence': np.random.rand(10),
#     'duration': np.random.randint(180000, 300000, size=10)  # Duration in␣
↪milliseconds
# }
# df_genre = pd.DataFrame(data)

# Identify the bottom 5 genres by average popularity
bottom_genres = df_genre.groupby('genre')['popularity'].mean().
↪sort_values(ascending=True).head(5)

# Filter the original DataFrame for these bottom genres
filtered_bottom_df = df_genre[df_genre['genre'].isin(bottom_genres.index)]

# Calculate average audio features for the bottom genres
bottom_genre_audio_features = filtered_bottom_df.groupby('genre').agg({
    'danceability': 'mean',
    'energy': 'mean',
    'loudness': 'mean',
    'acousticness': 'mean',
    'valence': 'mean',
    'duration': 'mean'
}).reset_index()

# Create bar plots for each audio feature
plt.figure(figsize=(15, 10))
for i, feature in enumerate(['danceability', 'energy', 'loudness',␣
↪'acousticness', 'valence', 'duration']):
    plt.subplot(2, 3, i + 1)
    sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,␣
↪palette='coolwarm')
    plt.title(f'Average {feature.capitalize()} by Genre')
    plt.xlabel('Genre')
    plt.ylabel(f'{feature.capitalize()}')
plt.tight_layout()
plt.suptitle("Average Audio Features for Bottom 5 Genres", y=1.05)  # Adjust␣
↪title position
plt.show()
```

```
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:
```

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
<ipython-input-74-1ba84ce7013c>:39: FutureWarning:

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

  sns.barplot(data=bottom_genre_audio_features, x='genre', y=feature,
palette='coolwarm')
```



Most Frequent Aritist

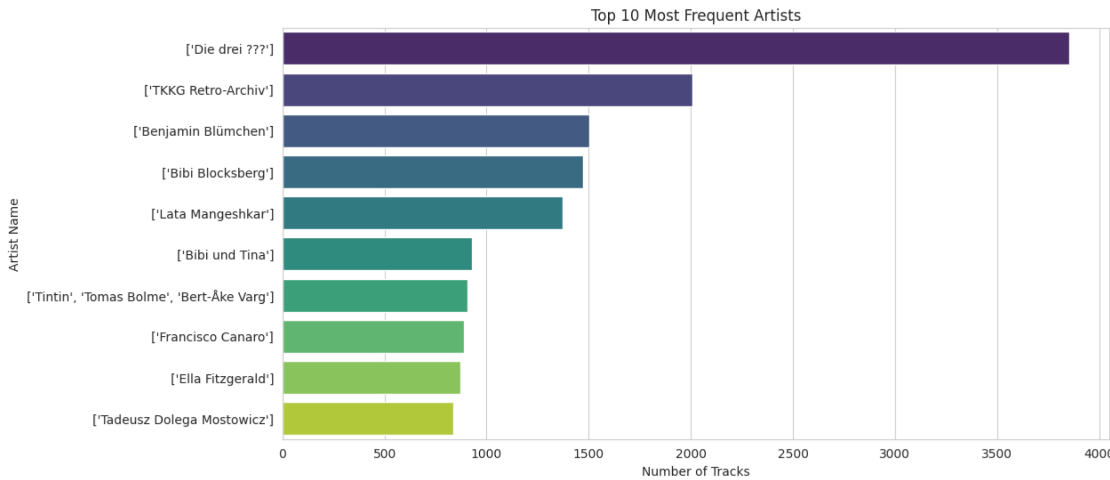
[85]:
```
# Display the columns of the df_tracks DataFrame
print(df_tracks.columns)
```

```
Index(['id', 'name', 'popularity', 'explicit', 'artists', 'id_artists',
       'danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'time_signature', 'duration', 'year'],
      dtype='object')
```

[87]:
```
# Plotting the most frequent artists
plt.figure(figsize=(12, 6))
sns.barplot(x=most_frequent_artists.values, y=most_frequent_artists.index,␣
 ↪palette='viridis')
plt.title("Top 10 Most Frequent Artists")
plt.xlabel("Number of Tracks")
plt.ylabel("Artist Name")
plt.show()
```

```
<ipython-input-87-ca8eb1a7228c>:3: 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=most_frequent_artists.values, y=most_frequent_artists.index,
palette='viridis')
```



Time-Based Analysis

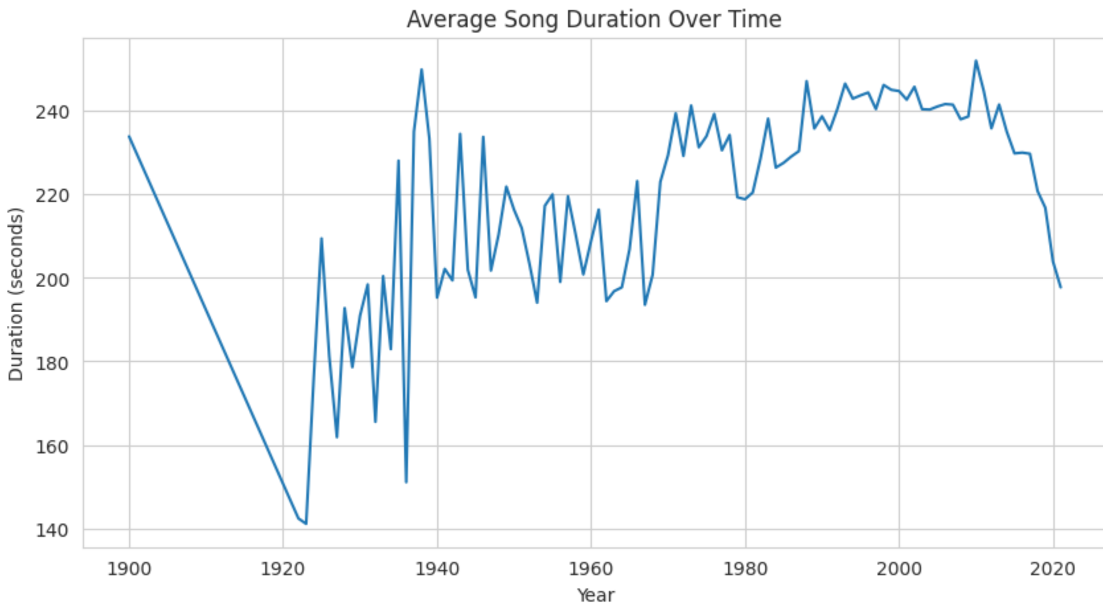
[75]:
```python
# Set release_date as the index and ensure datetime format
df_tracks.set_index('release_date', inplace=True)
```

[76]:
```python
# Extract year from the release_date
df_tracks['year'] = df_tracks.index.year
```

8 Visualize Trends Over Time

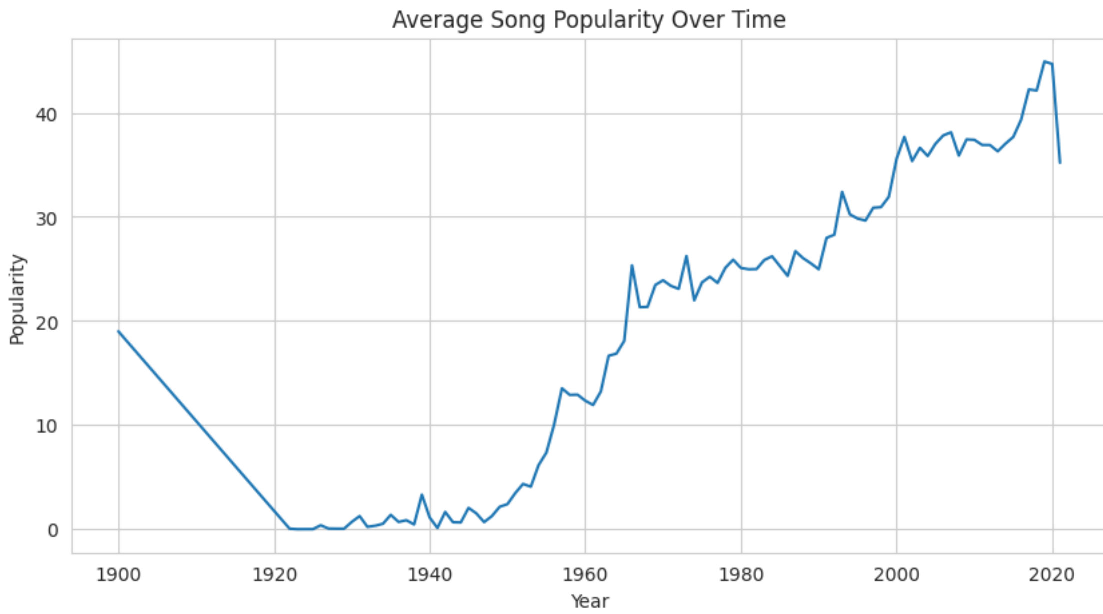
Average Song Duration Over Time

[77]:
```python
# Calculate average duration per year
avg_duration_per_year = df_tracks.groupby('year')['duration'].mean()

# Plotting average duration per year
plt.figure(figsize=(10, 5))
sns.lineplot(x=avg_duration_per_year.index, y=avg_duration_per_year.values)
plt.title("Average Song Duration Over Time")
plt.xlabel("Year")
plt.ylabel("Duration (seconds)")
plt.show()
```



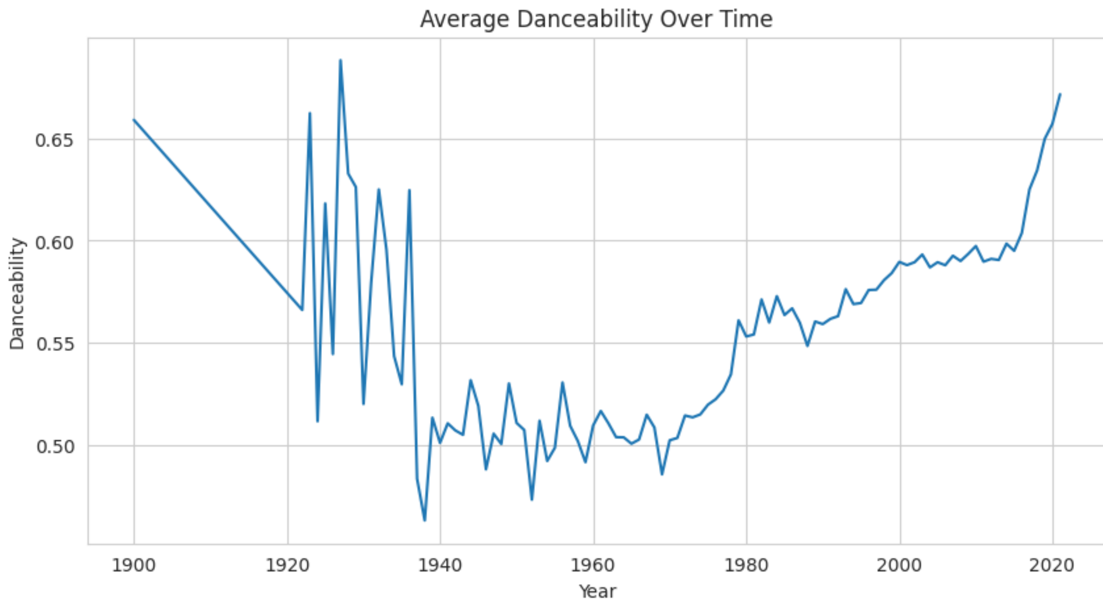
Average Popularity Over Time

[78]:
```
# Calculate average popularity per year
avg_popularity_per_year = df_tracks.groupby('year')['popularity'].mean()

# Plotting average popularity per year
plt.figure(figsize=(10, 5))
sns.lineplot(x=avg_popularity_per_year.index, y=avg_popularity_per_year.values)
plt.title("Average Song Popularity Over Time")
plt.xlabel("Year")
plt.ylabel("Popularity")
plt.show()
```



Average Danceability Over Time

[79]:
```
# Calculate average danceability per year
avg_danceability_per_year = df_tracks.groupby('year')['danceability'].mean()

# Plotting average danceability per year
plt.figure(figsize=(10, 5))
sns.lineplot(x=avg_danceability_per_year.index, y=avg_danceability_per_year.
 ↪values)
plt.title("Average Danceability Over Time")
plt.xlabel("Year")
plt.ylabel("Danceability")
plt.show()
```



8.0.1 Conclusions

This comprehensive analysis of Spotify's audio data reveals significant trends and patterns that highlight the evolving nature of music consumption. Here are the key takeaways:

- **Popularity Trends**: The upward trajectory of average track popularity over the years indicates a growing engagement with Spotify's offerings, suggesting that the platform's music selection is resonating increasingly well with listeners. This trend emphasizes the importance of continuously updating and diversifying music catalogs to cater to user preferences.

- **Evolution of Musical Characteristics**: The increase in average song duration and danceability in recent years suggests a shift towards more upbeat and rhythm-driven tracks. This could reflect listeners' preferences for music that enhances social experiences, such as dancing and gatherings. The data implies that music creators may be responding to these trends, potentially impacting the styles and formats of new releases.

- **Genre-Specific Insights**: Analysis of genre dynamics reveals that popular genres are characterized by high energy and loudness, while genres such as classical tend to have longer durations and lower energy levels. This distinction is crucial for understanding listener preferences and can guide playlist curation and recommendation systems, ensuring that users receive tailored music experiences that align with their tastes.

- **Implications for Music Recommendation Systems**: The insights gained from this analysis can inform the development of more sophisticated music recommendation algorithms. By leveraging patterns in popularity, duration, and genre characteristics, platforms can enhance user satisfaction and retention, ultimately leading to a more engaged audience.

In summary, this analysis not only uncovers trends within Spotify's catalog but also provides actionable insights for music producers, marketers, and platform developers. By understanding user preferences and the characteristics of popular music, stakeholders can make informed decisions that enhance the overall music experience on the platform.