In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
features=pd.read_csv(r"C:\Users\SURYA K\OneDrive\Desktop\jupyter lab\SpotifyFeature
tracks=pd.read_csv(r"C:\Users\SURYA K\OneDrive\Desktop\jupyter lab\archive\tracks.c
```

In [3]:
```
tracks.head()
```

Out[3]:

| | id | name | popularity | duration_ms | explicit | artists | |
|---|---|---|---|---|---|---|---|
| **0** | 35iwgR4jXetI318WEWsa1Q | Carve | 6 | 126903 | 0 | ['Uli'] | |
| **1** | 021ht4sdgPcrDgSk7JTbKY | Capítulo 2.16 - Banquero Anarquista | 0 | 98200 | 0 | ['Fernando Pessoa'] | [' |
| **2** | 07A5yehtSnoedViJAZkNnc | Vivo para Quererte - Remasterizado | 0 | 181640 | 0 | ['Ignacio Corsini'] | [' |
| **3** | 08FmqUhxtyLTn6pAh6bk45 | El Prisionero - Remasterizado | 0 | 176907 | 0 | ['Ignacio Corsini'] | [' |
| **4** | 08y9GfoqCWfOGsKdwojr5e | Lady of the Evening | 0 | 163080 | 0 | ['Dick Haymes'] | |

In [4]:
```
features.head()
```

Out[4]:

| | genre | artist_name | track_name | track_id | popularity | acousticness | da |
|---|---|---|---|---|---|---|---|
| **0** | Movie | Henri Salvador | C'est beau de faire un Show | 0BRjO6ga9RKCKjfDqeFgWV | 0 | 0.611 | |
| **1** | Movie | Martin & les fées | Perdu d'avance (par Gad Elmaleh) | 0BjC1NfoEOOusryehmNudP | 1 | 0.246 | |
| **2** | Movie | Joseph Williams | Don't Let Me Be Lonely Tonight | 0CoSDzoNIKCRs124s9uTVy | 3 | 0.952 | |
| **3** | Movie | Henri Salvador | Dis-moi Monsieur Gordon Cooper | 0Gc6TVm52BwZD07Ki6tIvf | 0 | 0.703 | |
| **4** | Movie | Fabien Nataf | Ouverture | 0IuslXpMROHdEPvSl1fTQK | 4 | 0.950 | |

In [5]:
```
tracks.shape
```

Out[5]:
```
(586672, 20)
```

In [6]:
```
features.shape
```

Out[6]:
```
(232725, 18)
```

In [7]:
```
#checking null
pd.isnull(tracks).sum()
```

Out[7]:
```
id                  0
name               71
popularity          0
duration_ms         0
explicit            0
artists             0
id_artists          0
release_date        0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
time_signature      0
dtype: int64
```

In [8]:
```
pd.isnull(features).sum()
```

Out[8]:
```
genre              0
artist_name        0
track_name         1
track_id           0
popularity         0
acousticness       0
danceability       0
duration_ms        0
energy             0
instrumentalness   0
key                0
liveness           0
loudness           0
mode               0
speechiness        0
tempo              0
time_signature     0
valence            0
dtype: int64
```

In [9]:
```
#checking info
tracks.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
```

In [10]:
```
#checking info
features.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
```

In [11]:
```
#finding 10 least popular songs in the spotify dataset
least_songs=tracks.sort_values('popularity',ascending=True)[0:10]
least_songs[['name','popularity']]
```

Out[11]:

| | name | popularity |
|---|---|---|
| **32** | The Dear Little Shamrock | 0 |
| **78** | Pobre Cotorro - Remasterizado | 0 |
| **77** | Entrerriana - Remasterizado | 0 |
| **76** | Capítulo 2.9 - Banquero Anarquista | 0 |
| **75** | Capítulo 1.9 - Banquero Anarquista | 0 |
| **74** | Capítulo 1.7 - Banquero Anarquista | 0 |
| **73** | The Girl That I Marry | 0 |
| **72** | Capítulo 2.14 - Banquero Anarquista | 0 |
| **71** | Capítulo 2.4 - Banquero Anarquista | 0 |
| **70** | Capítulo 1.21 - Banquero Anarquista | 0 |

In [12]:
```
#descriptive statistics of tracks
tracks.describe().transpose()
```

Out[12]:

| | count | mean | std | min | 25% | 50 |
|---|---|---|---|---|---|---|
| **popularity** | 586672.0 | 27.570053 | 18.370642 | 0.0 | 13.0000 | 27.0000 |
| **duration_ms** | 586672.0 | 230051.167286 | 126526.087418 | 3344.0 | 175093.0000 | 214893.0000 |
| **explicit** | 586672.0 | 0.044086 | 0.205286 | 0.0 | 0.0000 | 0.0000 |
| **danceability** | 586672.0 | 0.563594 | 0.166103 | 0.0 | 0.4530 | 0.5770 |
| **energy** | 586672.0 | 0.542036 | 0.251923 | 0.0 | 0.3430 | 0.5490 |
| **key** | 586672.0 | 5.221603 | 3.519423 | 0.0 | 2.0000 | 5.0000 |
| **loudness** | 586672.0 | -10.206067 | 5.089328 | -60.0 | -12.8910 | -9.2430 |
| **mode** | 586672.0 | 0.658797 | 0.474114 | 0.0 | 0.0000 | 1.0000 |
| **speechiness** | 586672.0 | 0.104864 | 0.179893 | 0.0 | 0.0340 | 0.0443 |
| **acousticness** | 586672.0 | 0.449863 | 0.348837 | 0.0 | 0.0969 | 0.4220 |
| **instrumentalness** | 586672.0 | 0.113451 | 0.266868 | 0.0 | 0.0000 | 0.0000 |
| **liveness** | 586672.0 | 0.213935 | 0.184326 | 0.0 | 0.0983 | 0.1390 |
| **valence** | 586672.0 | 0.552292 | 0.257671 | 0.0 | 0.3460 | 0.5640 |
| **tempo** | 586672.0 | 118.464857 | 29.764108 | 0.0 | 95.6000 | 117.3840 |
| **time_signature** | 586672.0 | 3.873382 | 0.473162 | 0.0 | 4.0000 | 4.0000 |

In [13]:
```
#descriptive of feature
features.describe().transpose()
```

Out[13]:

| | count | mean | std | min | 25% | |
|---|---|---|---|---|---|---|
| **popularity** | 232725.0 | 41.127502 | 18.189948 | 0.00000 | 29.0000 | 43 |
| **acousticness** | 232725.0 | 0.368560 | 0.354768 | 0.00000 | 0.0376 | 0 |
| **danceability** | 232725.0 | 0.554364 | 0.185608 | 0.05690 | 0.4350 | 0 |
| **duration_ms** | 232725.0 | 235122.339306 | 118935.909299 | 15387.00000 | 182857.0000 | 220427 |
| **energy** | 232725.0 | 0.570958 | 0.263456 | 0.00002 | 0.3850 | 0 |
| **instrumentalness** | 232725.0 | 0.148301 | 0.302768 | 0.00000 | 0.0000 | 0 |
| **liveness** | 232725.0 | 0.215009 | 0.198273 | 0.00967 | 0.0974 | 0 |
| **loudness** | 232725.0 | -9.569885 | 5.998204 | -52.45700 | -11.7710 | -7 |
| **speechiness** | 232725.0 | 0.120765 | 0.185518 | 0.02220 | 0.0367 | 0 |
| **tempo** | 232725.0 | 117.666585 | 30.898907 | 30.37900 | 92.9590 | 115 |
| **valence** | 232725.0 | 0.454917 | 0.260065 | 0.00000 | 0.2370 | 0 |

In [14]:
```
#finding top 10 popular songs in the spotify dataset
least_songs=tracks
popular_songs=least_songs[least_songs['popularity']>90].sort_values('popularity',as
popular_songs[['name','popularity','artists']]
```

Out[14]:

| | name | popularity | artists |
|---|---|---|---|
| **93802** | Peaches (feat. Daniel Caesar & Giveon) | 100 | ['Justin Bieber', 'Daniel Caesar', 'Giveon'] |
| **93803** | drivers license | 99 | ['Olivia Rodrigo'] |
| **93804** | Astronaut In The Ocean | 98 | ['Masked Wolf'] |
| **92811** | telepatía | 97 | ['Kali Uchis'] |
| **92810** | Save Your Tears | 97 | ['The Weeknd'] |
| **92813** | Blinding Lights | 96 | ['The Weeknd'] |
| **93805** | Leave The Door Open | 96 | ['Bruno Mars', 'Anderson .Paak', 'Silk Sonic'] |
| **92814** | The Business | 95 | ['Tiësto'] |
| **91866** | Streets | 94 | ['Doja Cat'] |
| **93806** | Fiel | 94 | ['Los Legendarios', 'Wisin', 'Jhay Cortez'] |

In [15]:
```
#Make the Release Date Column as the Index Column.
tracks['release_date'] = pd.to_datetime(tracks['release_date'], dayfirst=True, erro
tracks.set_index('release_date',inplace=True)
tracks.index=pd.to_datetime(tracks.index)
tracks.head()
```

Out[15]:

| release_date | id | name | popularity | duration_ms | explicit | |
|---|---|---|---|---|---|---|
| **1922-02-22** | 35iwgR4jXetI318WEWsa1Q | Carve | 6 | 126903 | 0 | |
| **1922-06-01** | 021ht4sdgPcrDgSk7JTbKY | Capítulo 2.16 - Banquero Anarquista | 0 | 98200 | 0 | ['F |
| **1922-03-21** | 07A5yehtSnoedViJAZkNnc | Vivo para Quererte - Remasterizado | 0 | 181640 | 0 | |
| **1922-03-21** | 08FmqUhxtyLTn6pAh6bk45 | El Prisionero - Remasterizado | 0 | 176907 | 0 | |
| **NaT** | 08y9GfoqCWfOGsKdwojr5e | Lady of the Evening | 0 | 163080 | 0 | H |

In [16]:
```
#Find the Name of the Artist Present in the specific Row of the Dataset.
tracks[['artists']].iloc[24]
```

Out[16]:
```
artists    ['Fernando Pessoa']
Name: 1922-06-01 00:00:00, dtype: object
```

In [17]:
```
print("Unique Genre")
print(features['genre'].unique())
print("Unique Artists")
print(tracks['artists'].unique())
```

```
Unique Genre
['Movie' 'R&B' 'A Capella' 'Alternative' 'Country' 'Dance' 'Electronic'
 'Anime' 'Folk' 'Blues' 'Opera' 'Hip-Hop' "Children's Music"
 'Children’s Music' 'Rap' 'Indie' 'Classical' 'Pop' 'Reggae' 'Reggaeton'
 'Jazz' 'Rock' 'Ska' 'Comedy' 'Soul' 'Soundtrack' 'World']
Unique Artists
["['Uli']" "['Fernando Pessoa']" "['Ignacio Corsini']" ... "['阿YueYue']"
 "['ROLE MODEL']" "['Gentle Bones', 'Clara Benin']"]
```

In [18]:
```
#Converting the Duration of the Songs From Milliseconds to Seconds.
tracks['duration'] = tracks['duration_ms'].apply (lambda x : round(x/1000))
tracks.drop('duration_ms', inplace = True, axis=1)
tracks.duration.head()
```

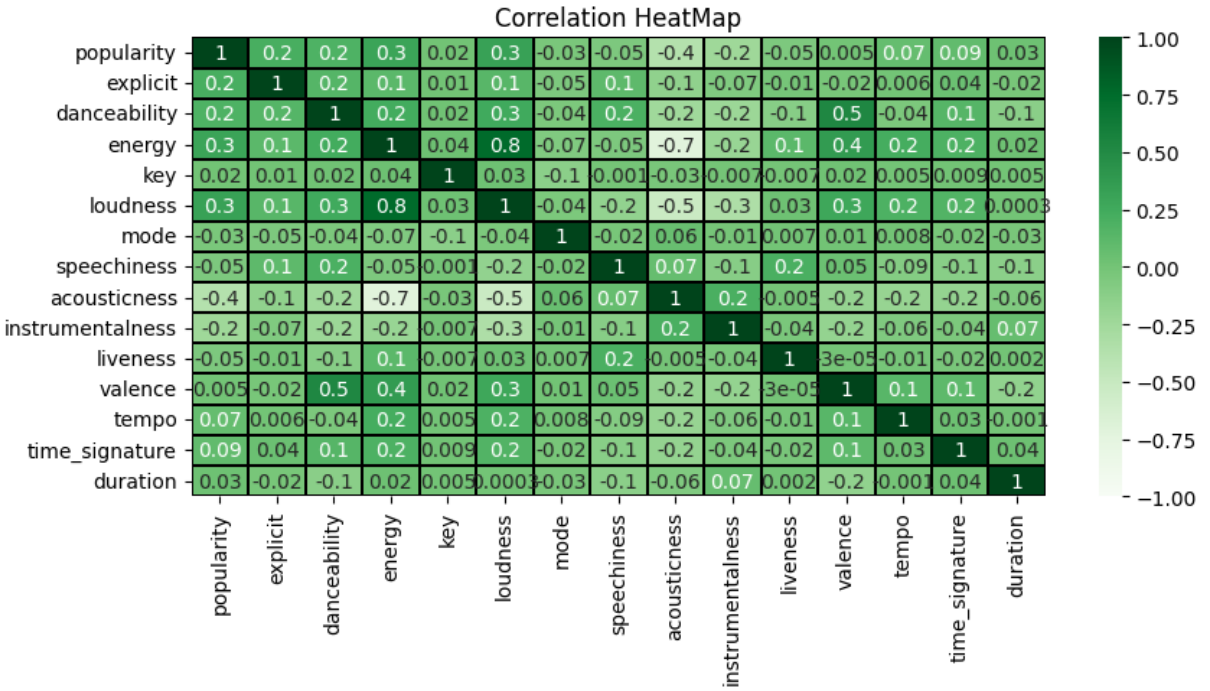
Out[18]:
```
release_date
1922-02-22    127
1922-06-01     98
1922-03-21    182
1922-03-21    177
NaT           163
Name: duration, dtype: int64
```

In [19]:
```
#Most Common Artists in the Dataset
top_artists = tracks['artists'].value_counts().head(10)
print(top_artists)
```

```
artists
['Die drei ???']                            3856
['TKKG Retro-Archiv']                       2006
['Benjamin Blümchen']                       1503
['Bibi Blocksberg']                         1472
['Lata Mangeshkar']                         1373
['Bibi und Tina']                            927
['Tintin', 'Tomas Bolme', 'Bert-Åke Varg']    905
['Francisco Canaro']                         891
['Ella Fitzgerald']                          870
['Tadeusz Dolega Mostowicz']                 838
Name: count, dtype: int64
```

In [20]:
```
# Keep only numeric columns for correlation
numeric_tracks = tracks.select_dtypes(include=['number'])

# Calculate correlation
correlation = numeric_tracks.corr(method='pearson')

# Plot heatmap
```

```
plt.figure(figsize=(9,5))
hmap = sns.heatmap(correlation, annot=True, fmt='.1g', vmin=-1, vmax=1, center=0, c
hmap.set_title('Correlation HeatMap')
hmap.set_xticklabels(hmap.get_xticklabels(), rotation=90)
plt.tight_layout()
plt.show()
```

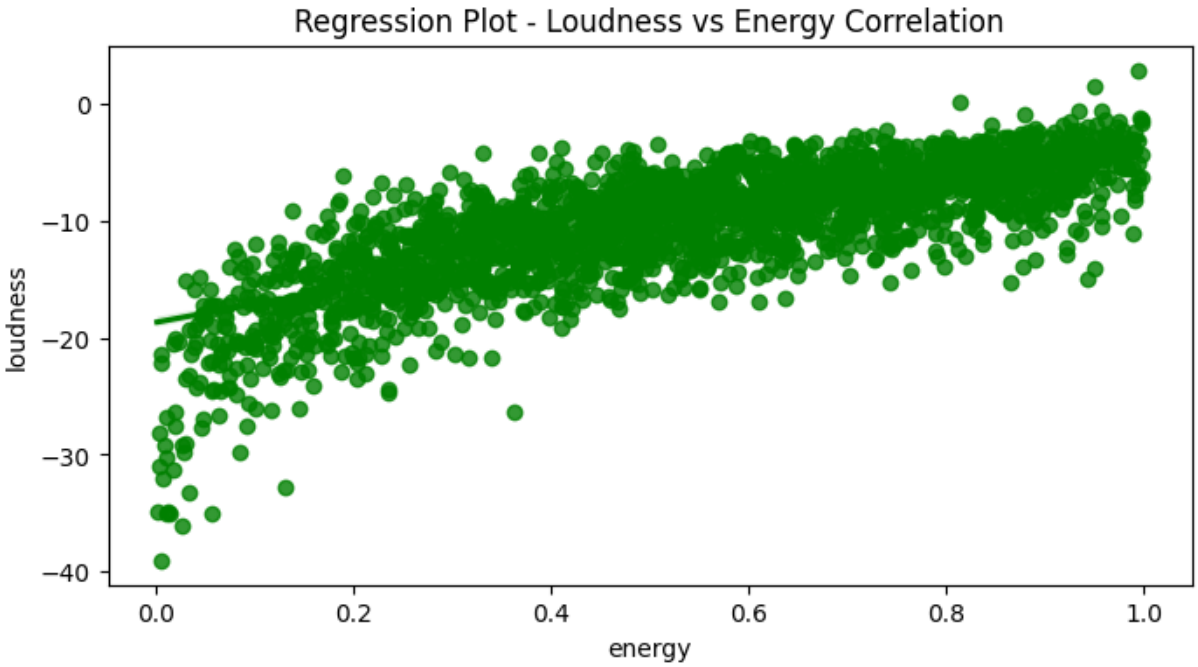



In [21]:
```
#Sample Only 4 Percent of the Whole Dataset.
sample=tracks.sample(int(0.004*len(tracks)))
print(len(sample))
```

2346

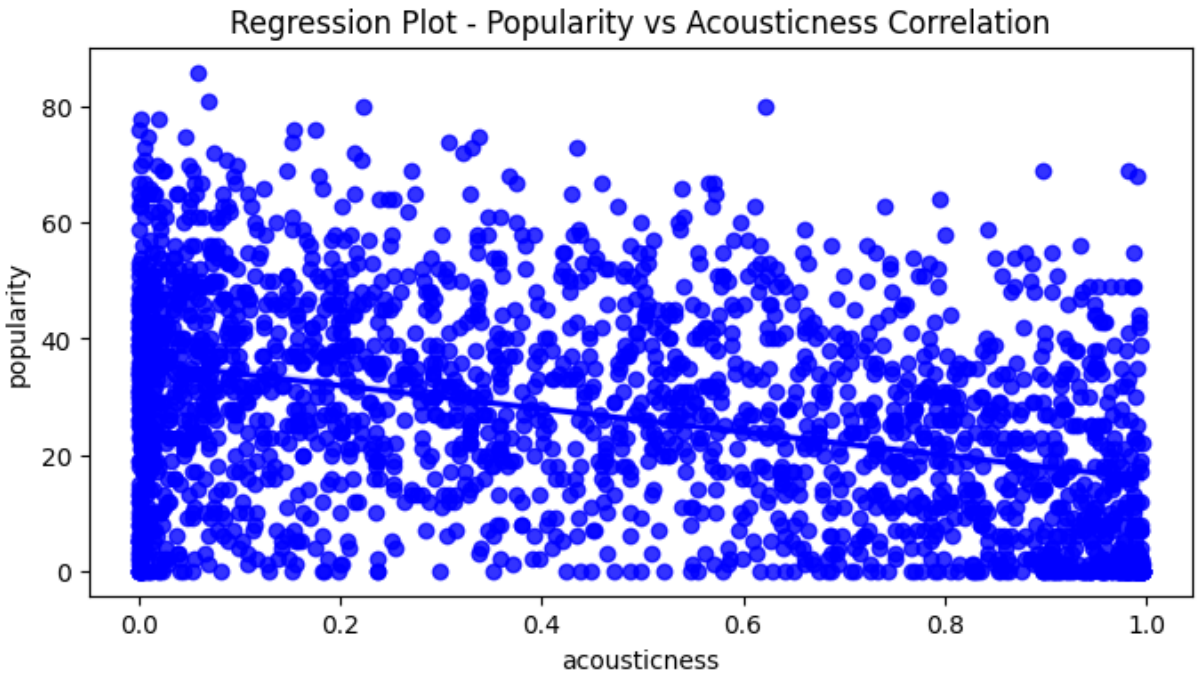
In [22]:
```
#Create a Regression Plot Between Loudness and Energy. Let's Plot It  in the Form o
plt.figure(figsize=(8,4))
sns.regplot(data=sample, y='loudness', x='energy', color='green').set(title='Regres
```

Out[22]: [Text(0.5, 1.0, 'Regression Plot - Loudness vs Energy Correlation')]




In [23]:
```
#Create a Regression Plot Between Popularity and Acousticness in the Form of a Regr
plt.figure(figsize=(8,4))
sns.regplot(data=sample, y='popularity', x='acousticness', color='blue').set(title=
```

Out[23]:
```
[Text(0.5, 1.0, 'Regression Plot - Popularity vs Acousticness Correlation')]
```



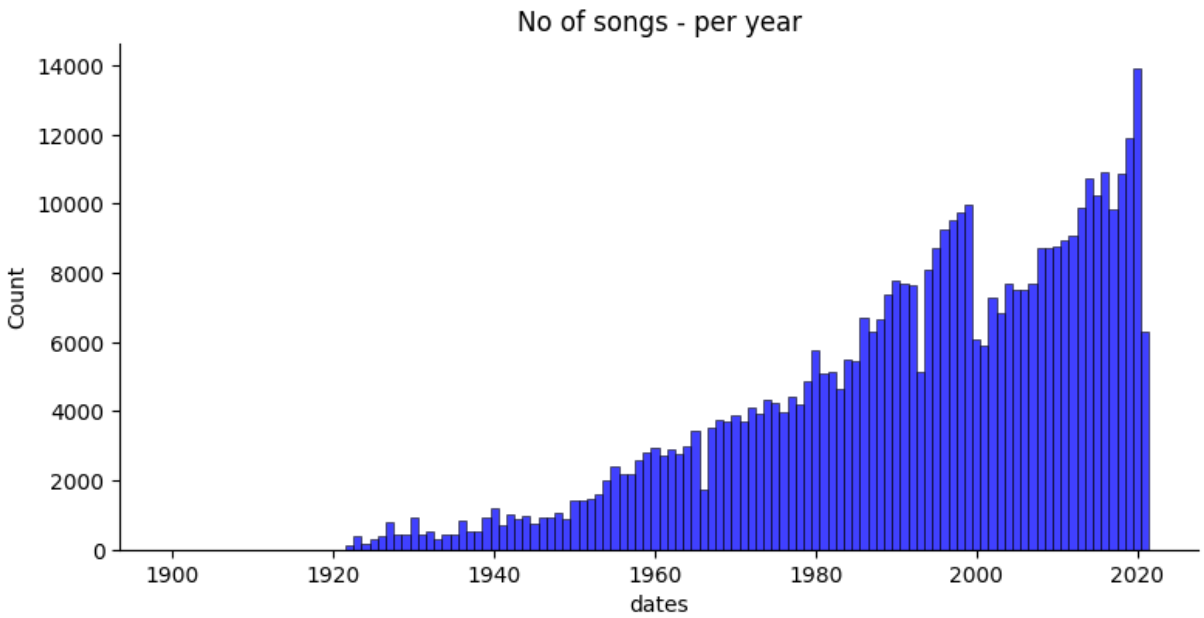

In [24]:
```
#creating new column in tracks table
tracks['dates']=tracks.index.get_level_values('release_date')
tracks.dates=pd.to_datetime(tracks.dates)
years=tracks.dates.dt.year
tracks.head()
```

Out[24]:

| release_date | id | name | popularity | explicit | artists | |
|---|---|---|---|---|---|---|
| **1922-02-22** | 35iwgR4jXetI318WEWsa1Q | Carve | 6 | 0 | ['Uli'] | |
| **1922-06-01** | 021ht4sdgPcrDgSk7JTbKY | Capítulo 2.16 - Banquero Anarquista | 0 | 0 | ['Fernando Pessoa'] | ['14jt |
| **1922-03-21** | 07A5yehtSnoedViJAZkNnc | Vivo para Quererte - Remasterizado | 0 | 0 | ['Ignacio Corsini'] | ['5LiC |
| **1922-03-21** | 08FmqUhxtyLTn6pAh6bk45 | El Prisionero - Remasterizado | 0 | 0 | ['Ignacio Corsini'] | ['5LiC |
| **NaT** | 08y9GfoqCWfOGsKdwojr5e | Lady of the Evening | 0 | 0 | ['Dick Haymes'] | ['3 |

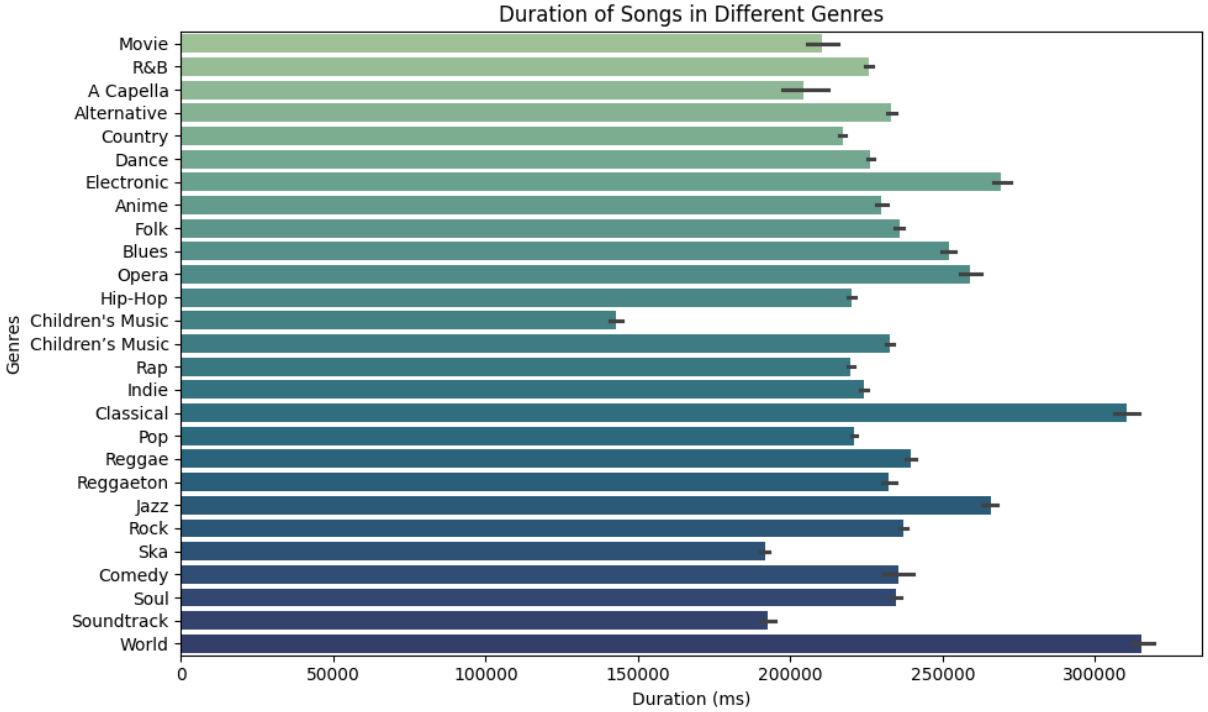
In [25]:
```
#Number of Songs per Year
sns.displot(years, discrete=True, aspect=2, height=4, kind='hist',color='blue').set
```

Out[25]: <seaborn.axisgrid.FacetGrid at 0x25354629160>

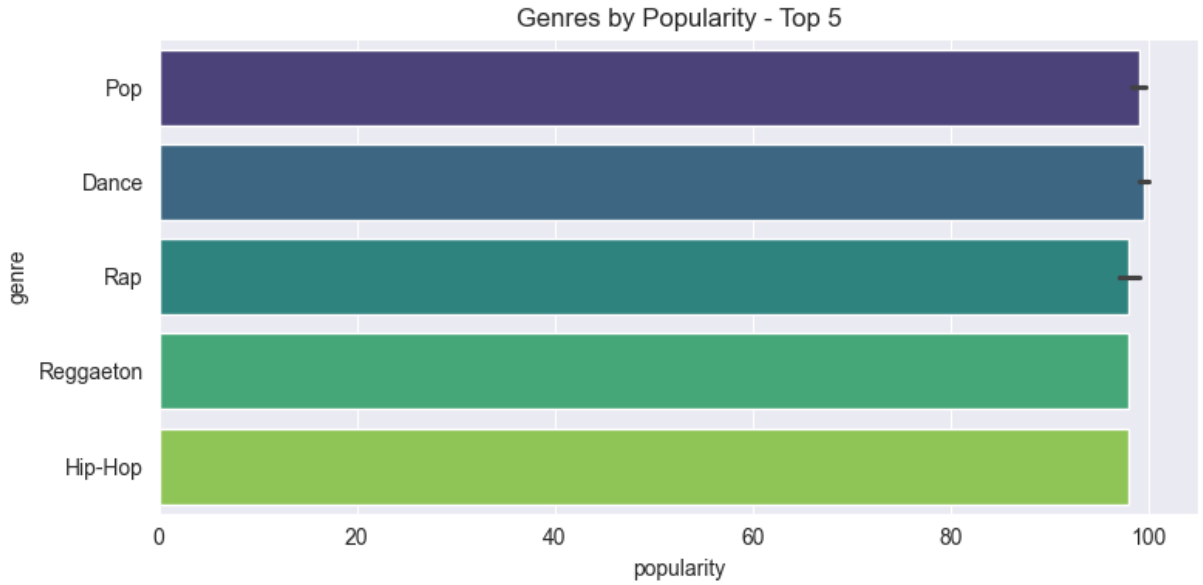



In [ ]:

In [26]:
```
#spotify feature analysis
#Horizontal Bar Plot: Song Duration Across Different Genres
plt.figure(figsize=(10,6))
plt.title('Duration of Songs in Different Genres')
sns.barplot(y='genre', x='duration_ms', data=features, hue='genre', palette='crest'
plt.xlabel('Duration (ms)')
plt.ylabel('Genres')
plt.tight_layout()
plt.show()
```

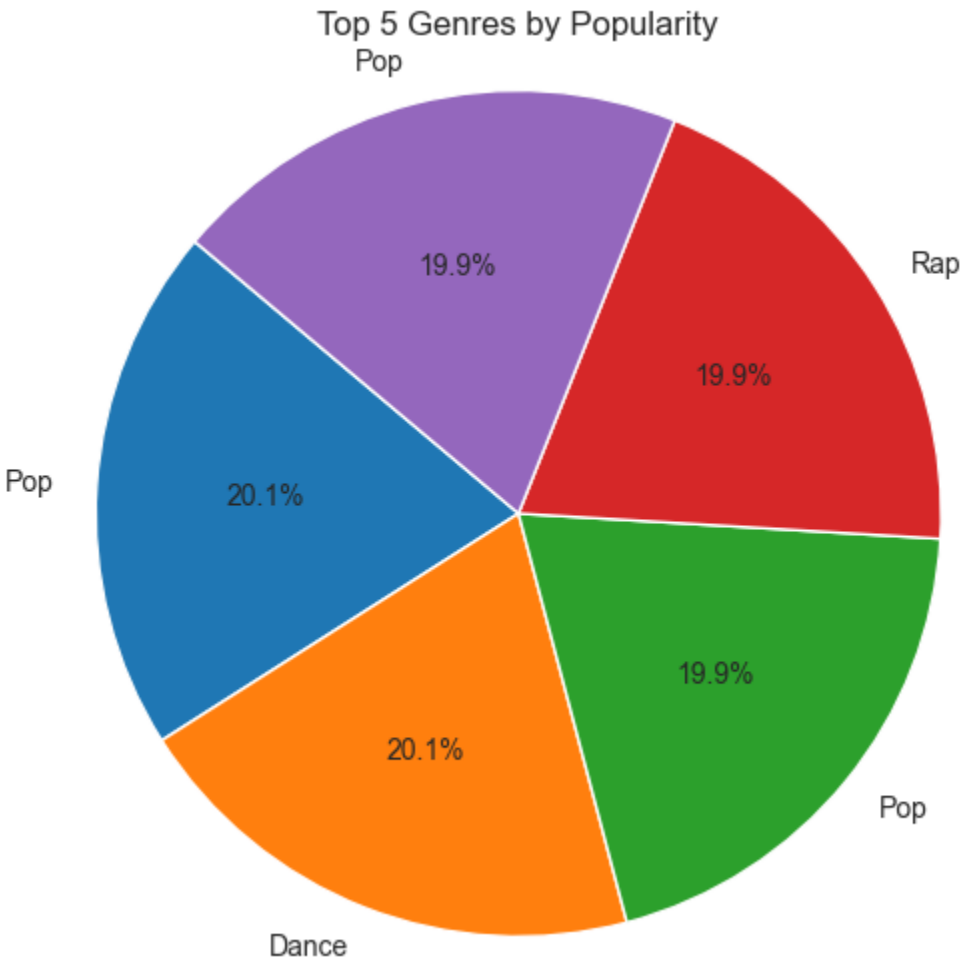



In [27]:
```
#Find top five genres by Popularity and polting a barplot for the same.
top_genres = features.sort_values('popularity', ascending=False).head(10)
sns.set_style('darkgrid')
plt.figure(figsize=(8,4))
sns.barplot(y='genre',x='popularity',data=top_genres,hue='genre',palette='viridis',
plt.tight_layout()
plt.show()
```

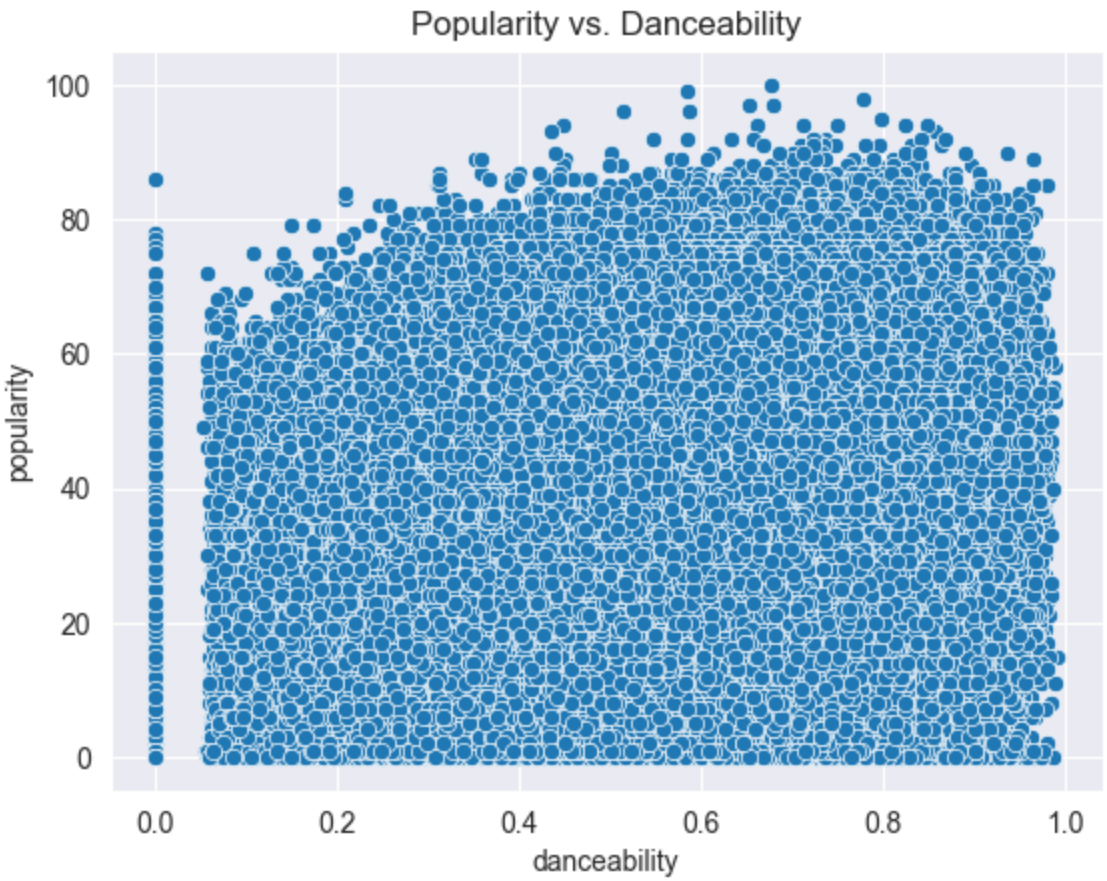



In [28]:
```
# Get top 5 genres by popularity
Top = features.sort_values('popularity', ascending=False).head(5)
# Create pie chart
plt.figure(figsize=(6,6))
plt.pie(Top['popularity'], labels=Top['genre'], autopct='%1.1f%%', startangle=140)
plt.title('Top 5 Genres by Popularity')
plt.axis('equal')  # Equal aspect ratio ensures the pie is a circle
```

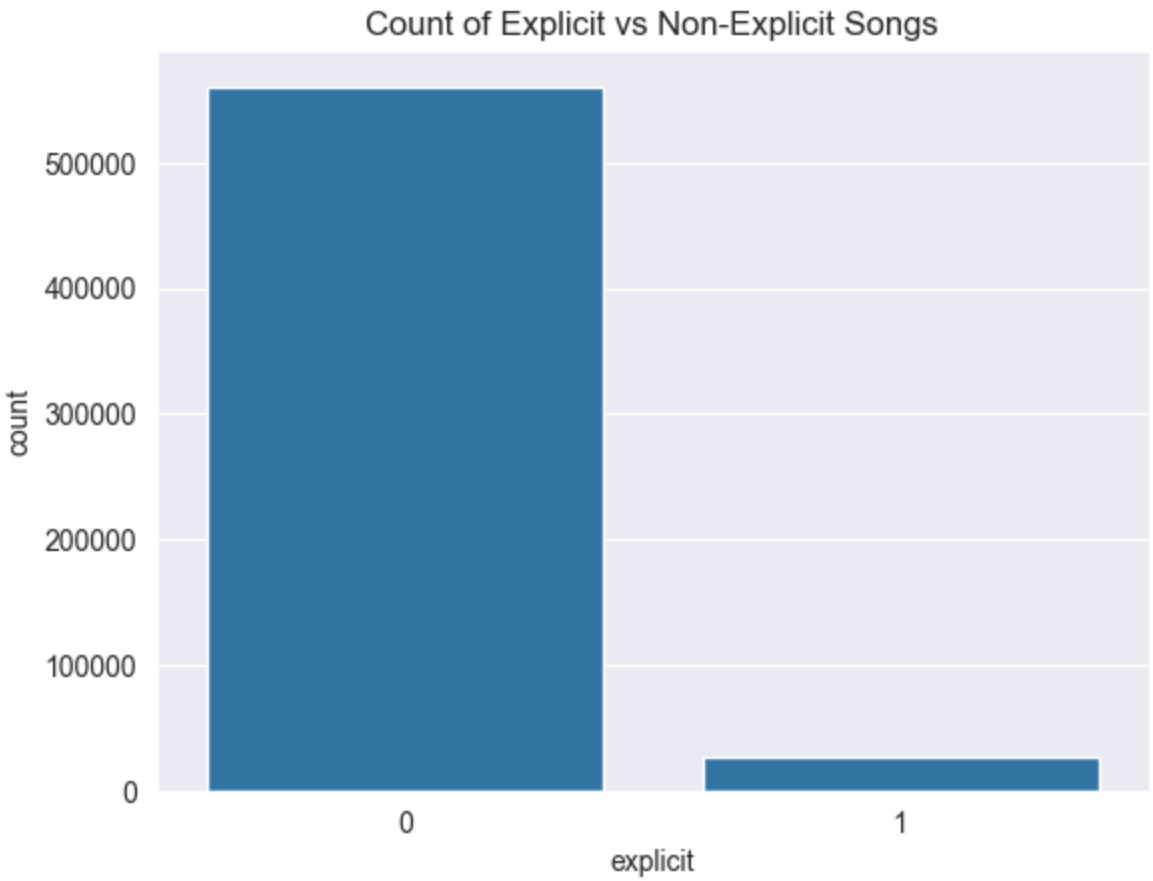
```
plt.show()
```




In [29]:
```
sns.scatterplot(x='danceability', y='popularity', data=tracks)
plt.title('Popularity vs. Danceability')
plt.show()
```

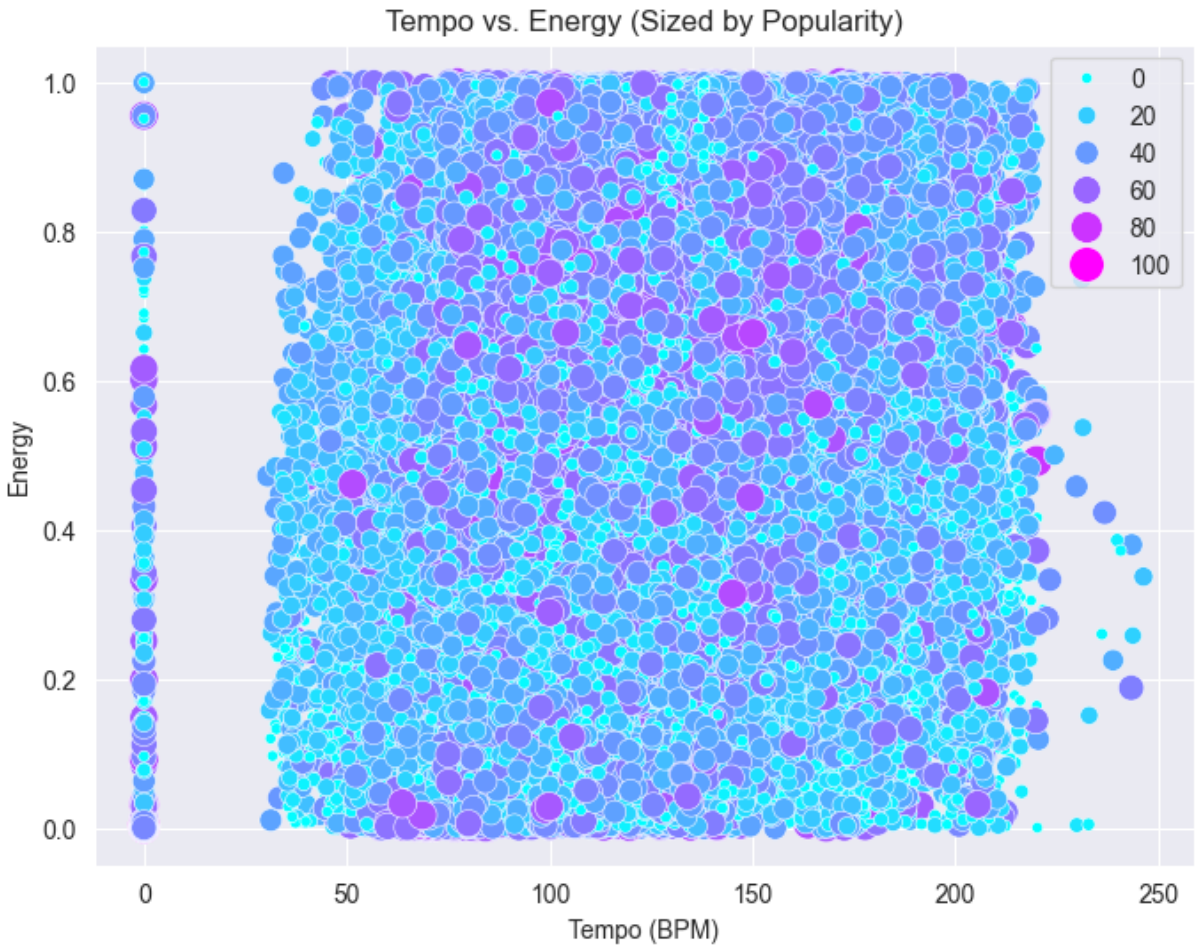



In [30]:
```
sns.countplot(x='explicit', data=tracks)
plt.title('Count of Explicit vs Non-Explicit Songs')
plt.show()
```

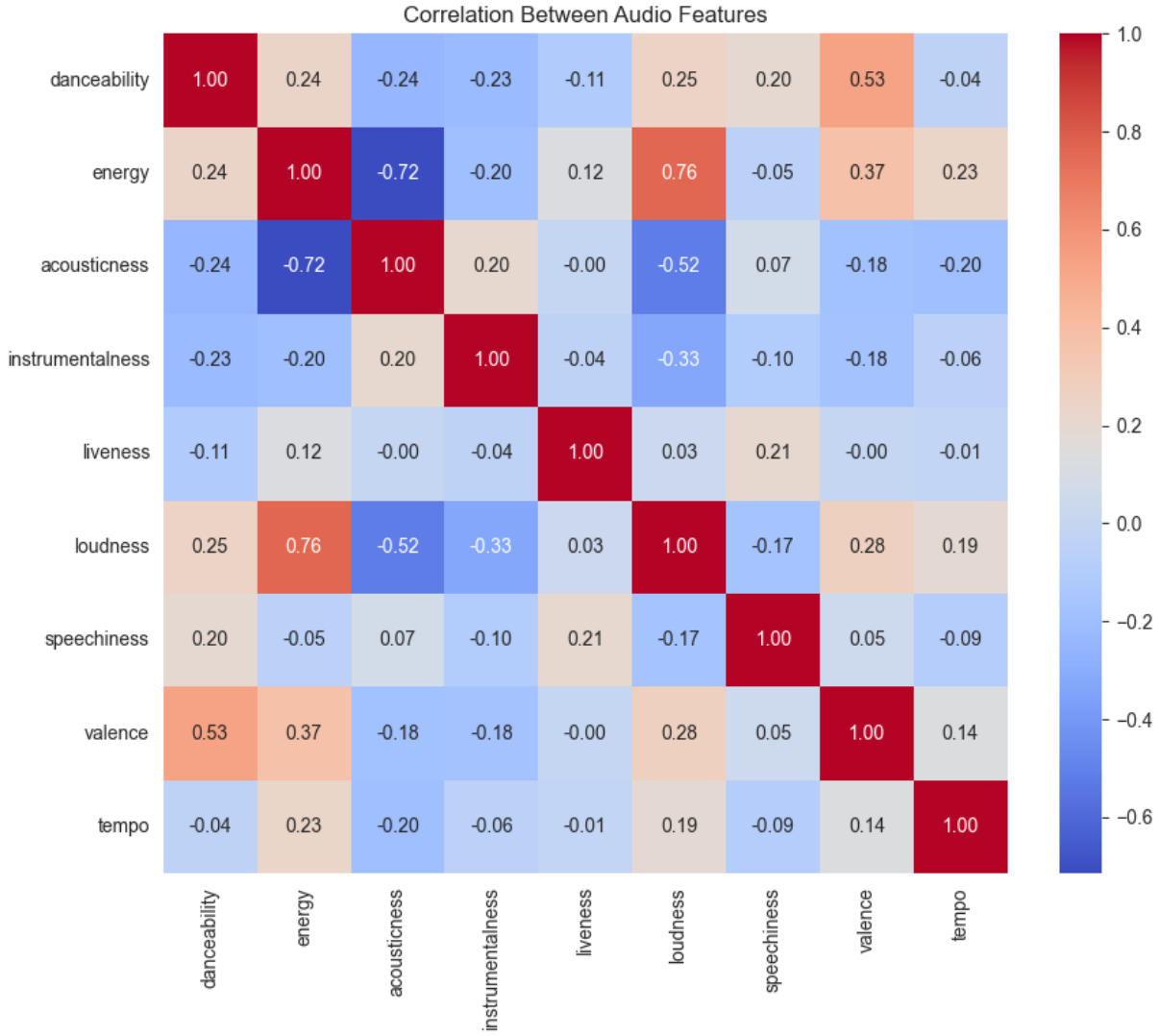



In [31]:
```
#Tempo vs Energy Scatter Plot
plt.figure(figsize=(8,6))
sns.scatterplot(x='tempo', y='energy', data=tracks, hue='popularity', palette='cool
plt.title('Tempo vs. Energy (Sized by Popularity)')
plt.xlabel('Tempo (BPM)')
plt.ylabel('Energy')
plt.legend()
plt.show()
```

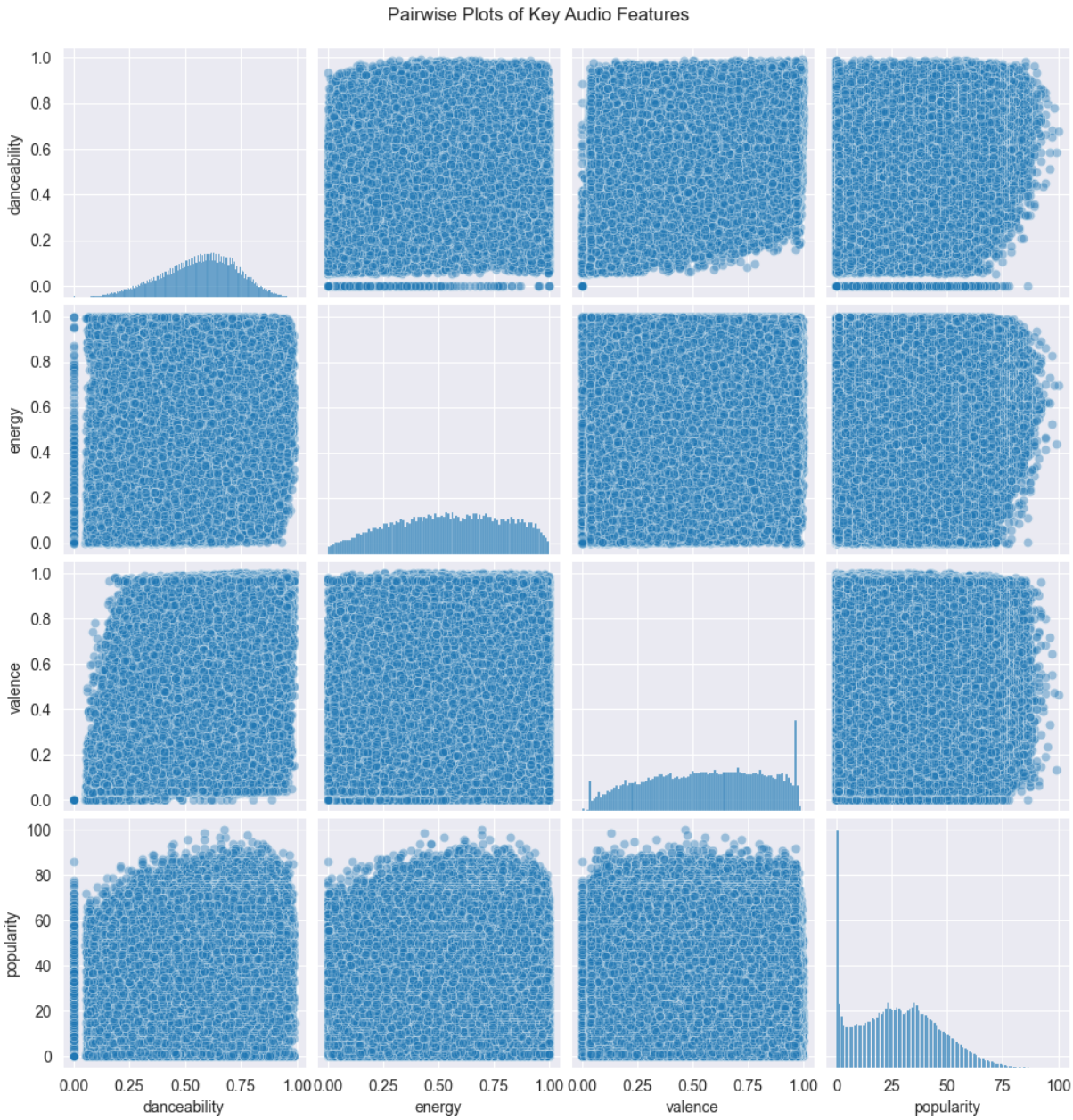
```
C:\Program Files\Python313\Lib\site-packages\IPython\core\pylabtools.py:170: UserWar
ning: Creating legend with loc="best" can be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```




In [32]:
```
audio_features = ['danceability', 'energy', 'acousticness', 'instrumentalness',
                  'liveness', 'loudness', 'speechiness', 'valence', 'tempo']

plt.figure(figsize=(10,8))
sns.heatmap(tracks[audio_features].corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Between Audio Features')
plt.show()
```

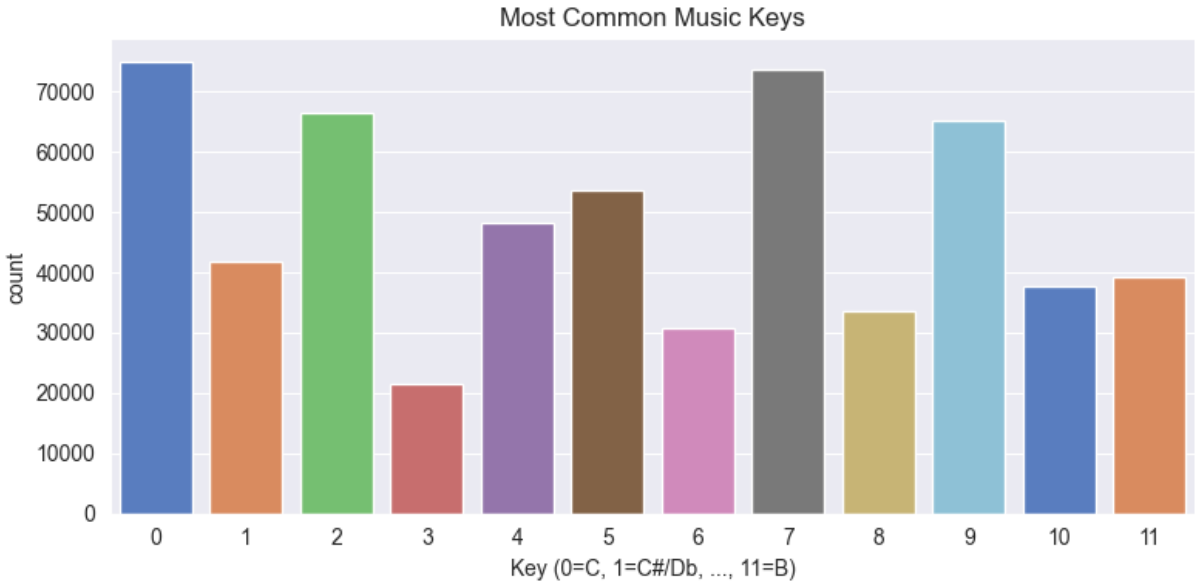



In [35]:
```
sns.pairplot(tracks[['danceability', 'energy', 'valence', 'popularity']], kind='sca
plt.suptitle('Pairwise Plots of Key Audio Features', y=1.02)
plt.show()
```

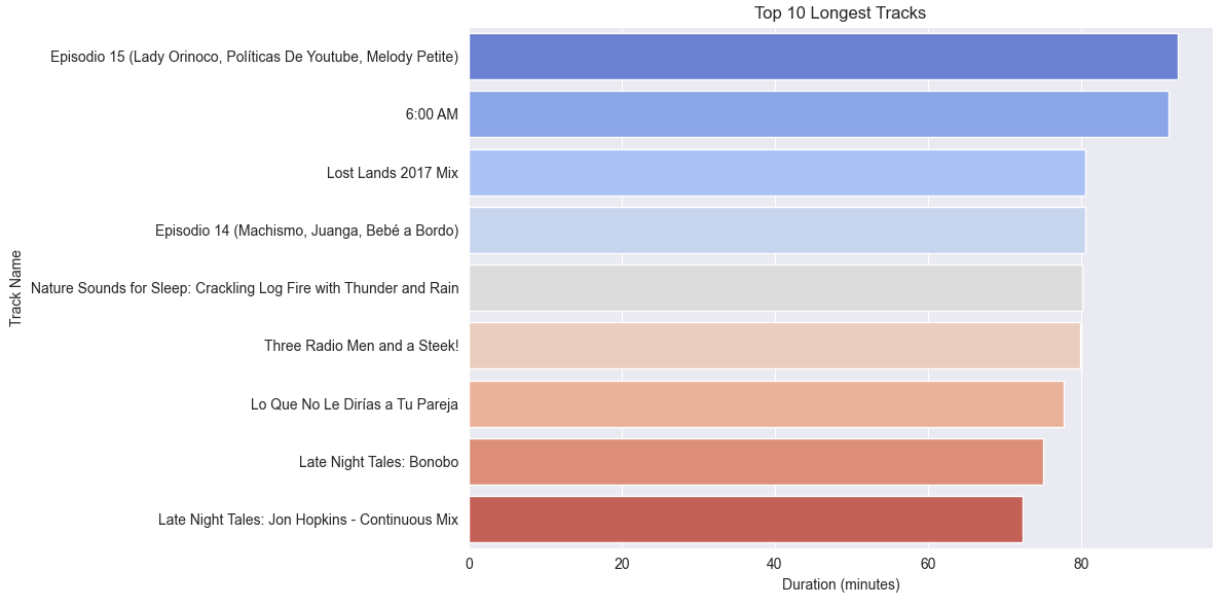



In [ ]:
```
#Number of Songs Released Per Year
tracks['year'] = pd.to_datetime(tracks['release_date']).dt.year
print(tracks['year'])
```

In [36]:
```
plt.figure(figsize=(8,4))
sns.countplot(x='key', data=tracks, hue='key', palette='muted', legend=False)
plt.title('Most Common Music Keys')
plt.xlabel('Key (0=C, 1=C#/Db, ..., 11=B)')
plt.tight_layout()
plt.show()
```




In [37]:
```
# Convert duration from milliseconds to minutes
features['duration_min'] = features['duration_ms'] / 60000

# Get top 10 longest tracks
longest_tracks = features.sort_values(by='duration_min', ascending=False).head(10)

# Plot with hue to avoid warning
plt.figure(figsize=(12,6))
sns.barplot(
    x='duration_min',
    y='track_name',
    data=longest_tracks,
    hue='track_name',       # add hue
    palette='coolwarm',
    dodge=False,
    legend=False            # hide redundant legend
)
plt.title('Top 10 Longest Tracks')
plt.xlabel('Duration (minutes)')
plt.ylabel('Track Name')
plt.tight_layout()
plt.show()
```



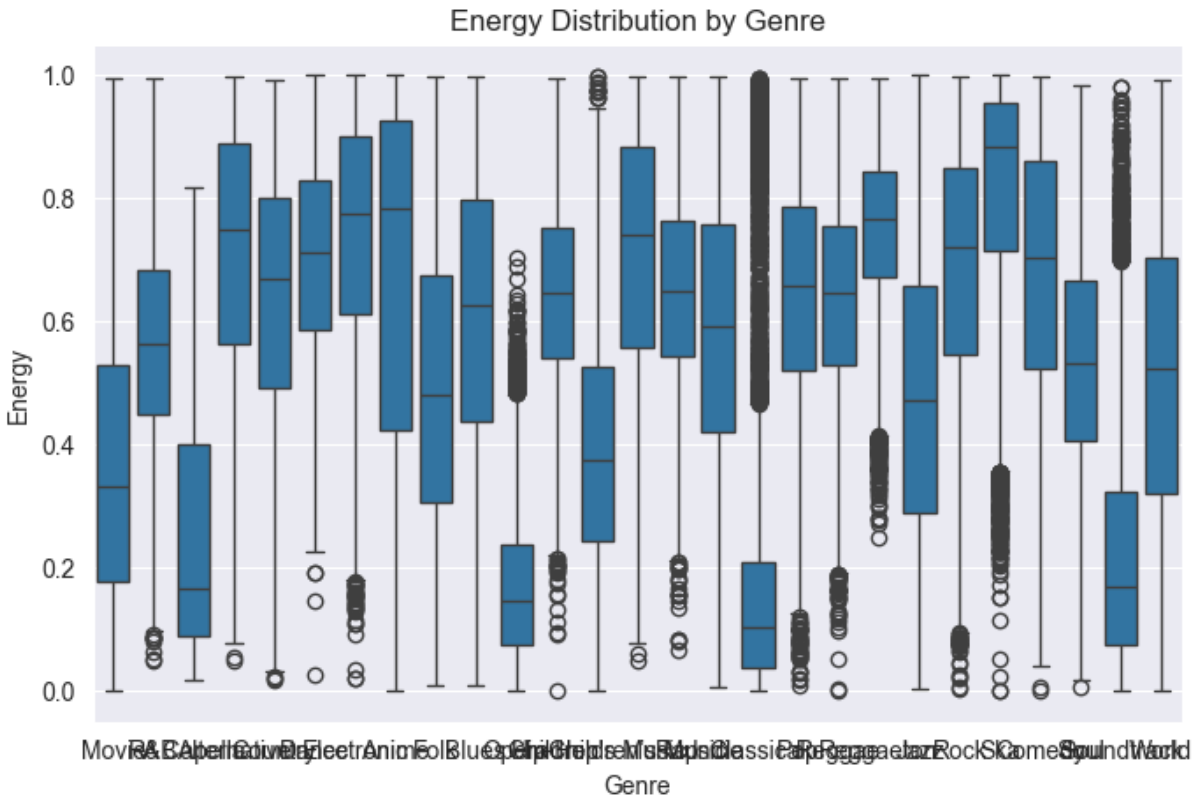

In [38]:
```
print(tracks.columns.tolist())
```

```
['id', 'name', 'popularity', 'explicit', 'artists', 'id_artists', 'danceability', 'e
nergy', 'key', 'loudness', 'mode', 'speechiness', 'acousticness', 'instrumentalness'
, 'liveness', 'valence', 'tempo', 'time_signature', 'duration', 'dates']
```

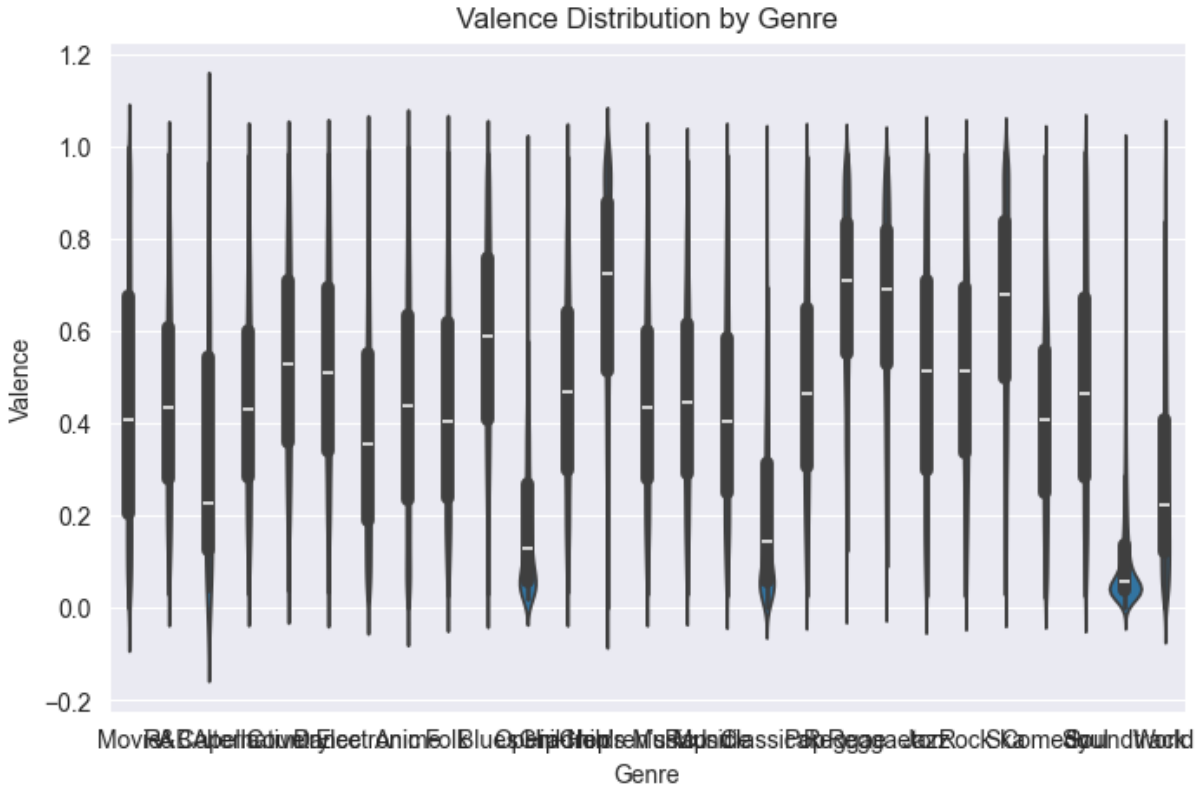
In [39]:
```
print(features.columns.tolist())
```

```
['genre', 'artist_name', 'track_name', 'track_id', 'popularity', 'acousticness', 'da
nceability', 'duration_ms', 'energy', 'instrumentalness', 'key', 'liveness', 'loudne
ss', 'mode', 'speechiness', 'tempo', 'time_signature', 'valence', 'duration_min']
```

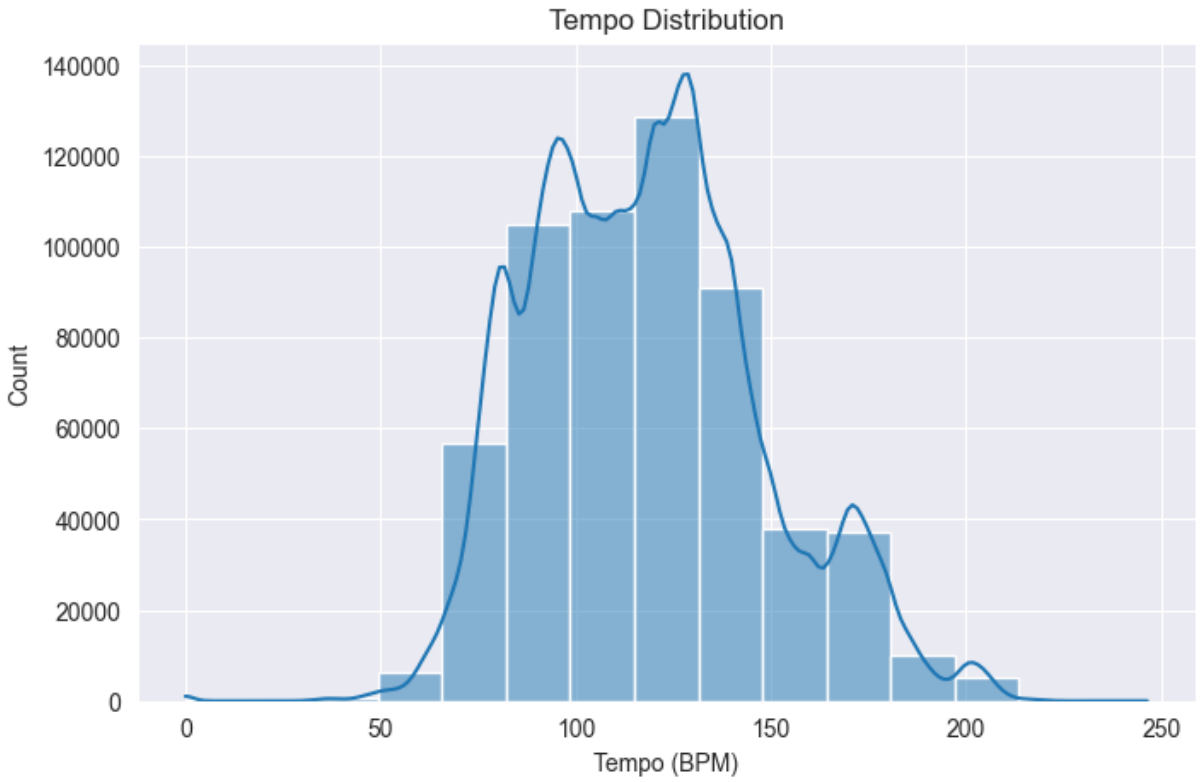
In [41]:
```
# Boxplot of Energy by Genre
# Shows how energy varies across different genres
plt.figure(figsize=(8,5))
sns.boxplot(x='genre', y='energy', data=features)
plt.title('Energy Distribution by Genre')
plt.xlabel('Genre')
plt.ylabel('Energy')
plt.show()
```



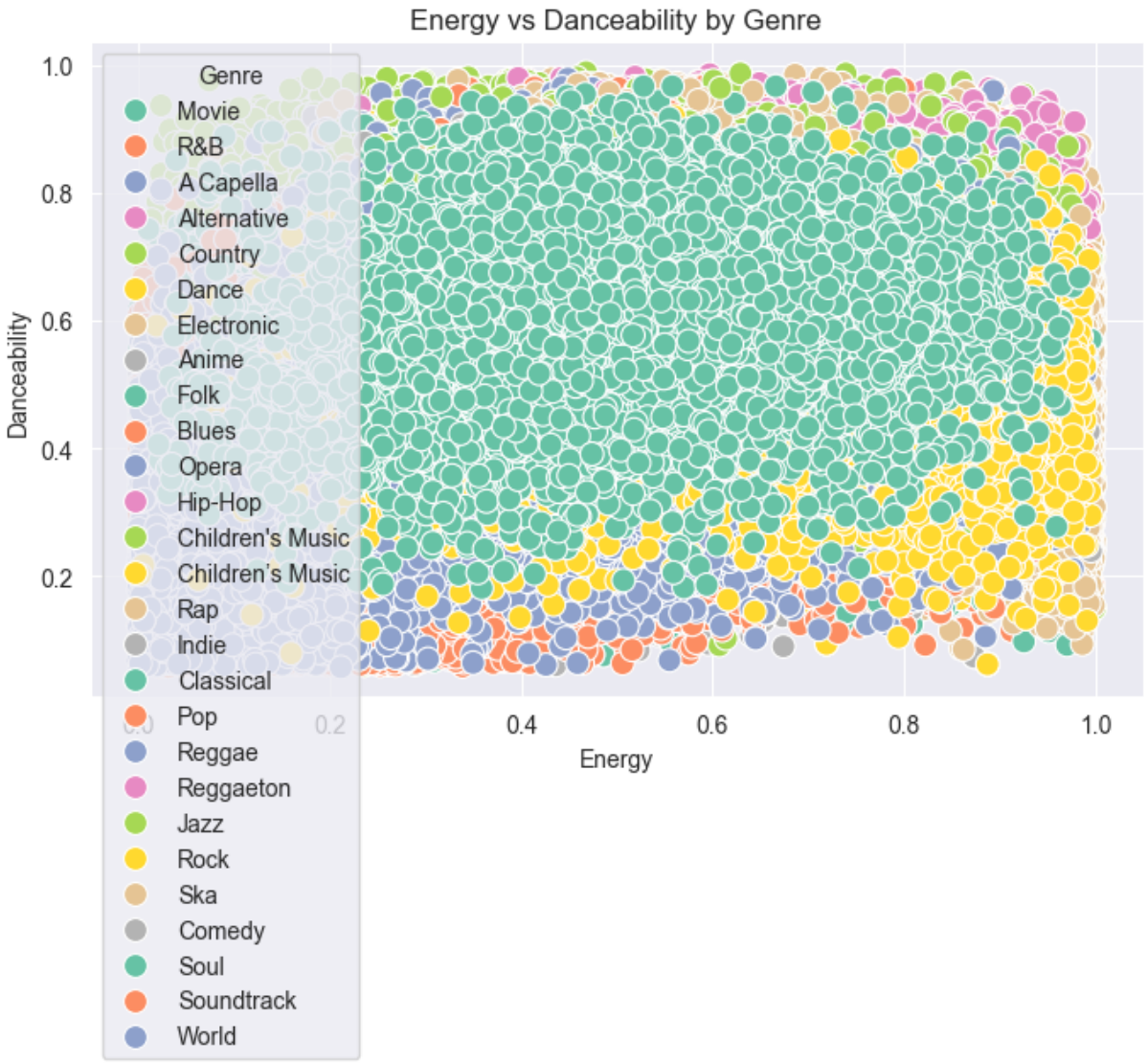

In [42]:
```
# Violin Plot of Valence (Mood) by Genre
# Visualizes the distribution and density of the valence (happiness) feature
plt.figure(figsize=(8,5))
sns.violinplot(x='genre', y='valence', data=features)
plt.title('Valence Distribution by Genre')
plt.xlabel('Genre')
plt.ylabel('Valence')
plt.show()
```



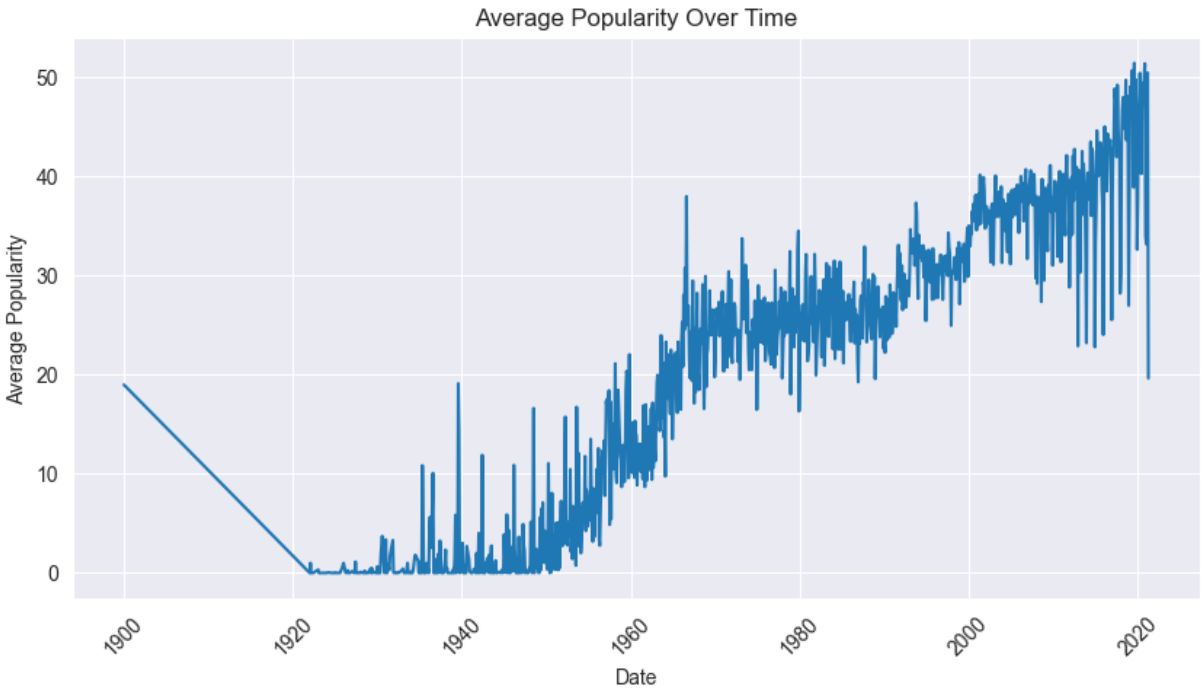

In [49]:
```
# Histogram of Tempo with KDE
# Shows tempo (BPM) distribution with a smooth KDE line
plt.figure(figsize=(8,5))
sns.histplot(tracks['tempo'], bins=15, kde=True)
plt.title('Tempo Distribution')
plt.xlabel('Tempo (BPM)')
plt.ylabel('Count')
plt.show()
```



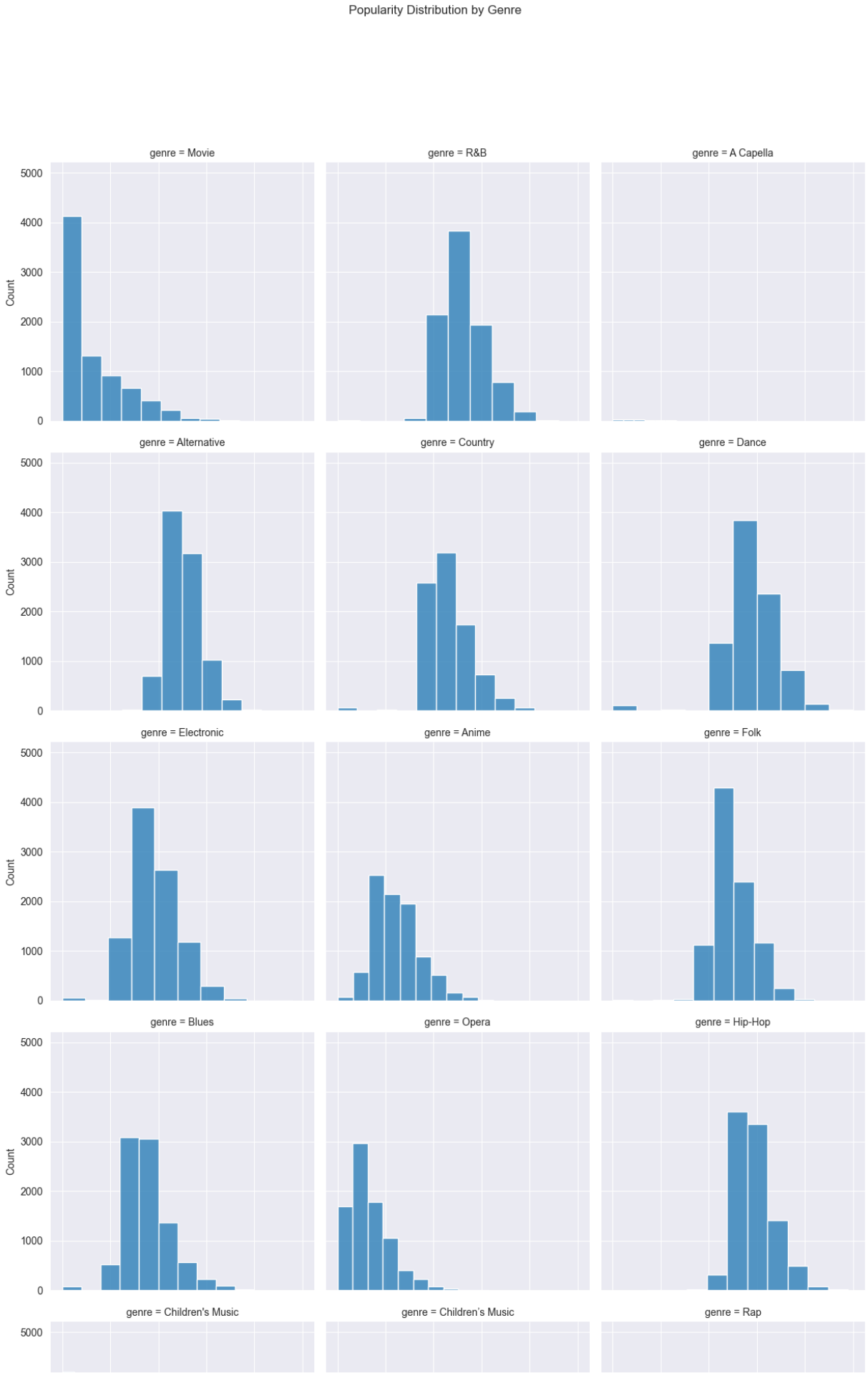

In [50]:
```
# Scatter Plot for Energy vs Danceability colored by Genre
# Helps see clustering of genres in energy and danceability space
plt.figure(figsize=(8,5))
sns.scatterplot(x='energy', y='danceability', hue='genre', data=features, palette='
plt.title('Energy vs Danceability by Genre')
plt.xlabel('Energy')
plt.ylabel('Danceability')
plt.legend(title='Genre')
plt.show()
```

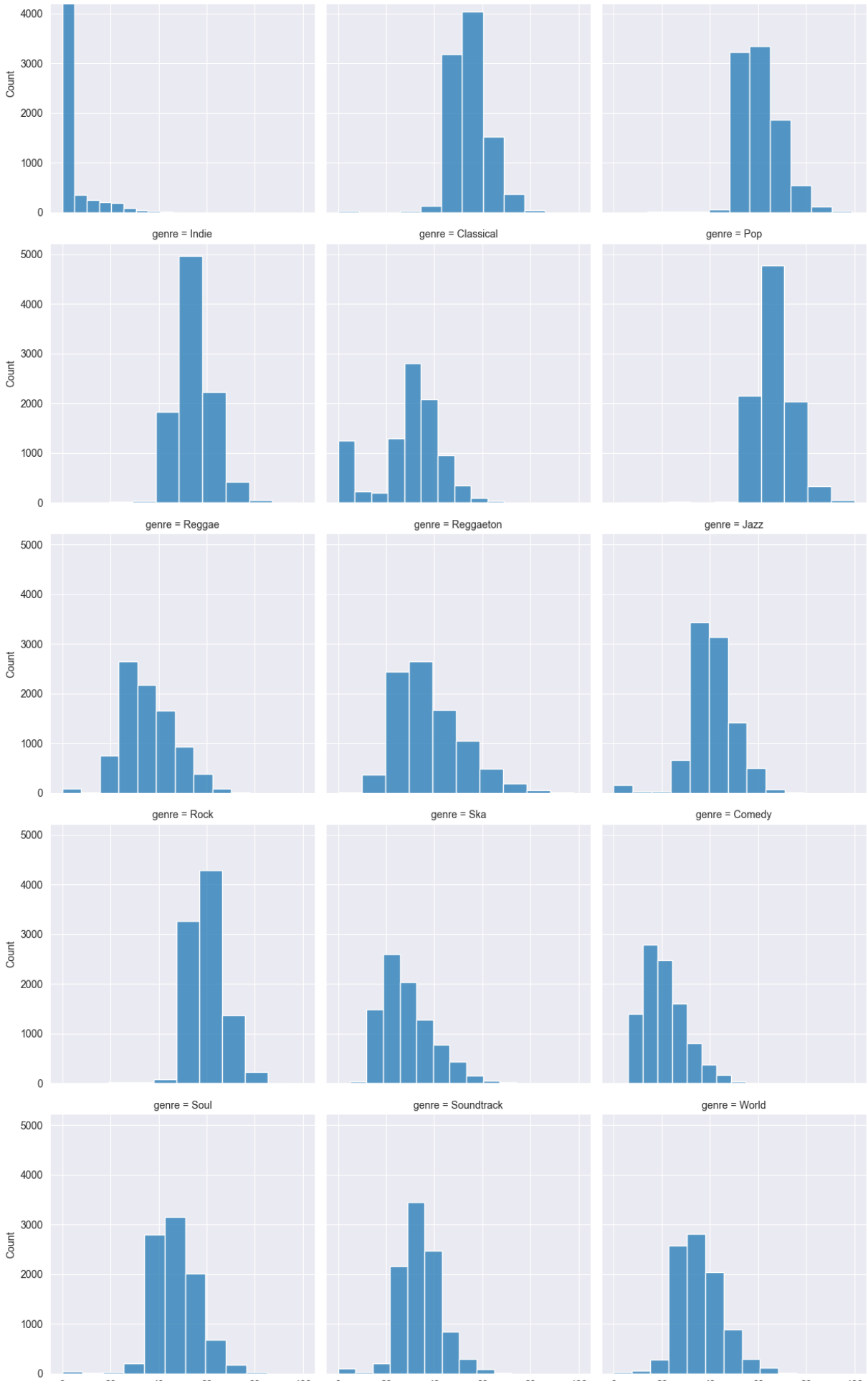



In [53]:
```
# Line Plot: Popularity Over Time
# If you have a dates column (e.g., release dates), plot how average popularity cha
tracks['dates'] = pd.to_datetime(tracks['dates'])

pop_over_time = tracks.groupby(tracks['dates'].dt.to_period('M'))['popularity'].mea
pop_over_time['dates'] = pop_over_time['dates'].dt.to_timestamp()

plt.figure(figsize=(10,5))
sns.lineplot(x='dates', y='popularity', data=pop_over_time)
plt.title('Average Popularity Over Time')
plt.xlabel('Date')
plt.ylabel('Average Popularity')
plt.xticks(rotation=45)
plt.show()
```

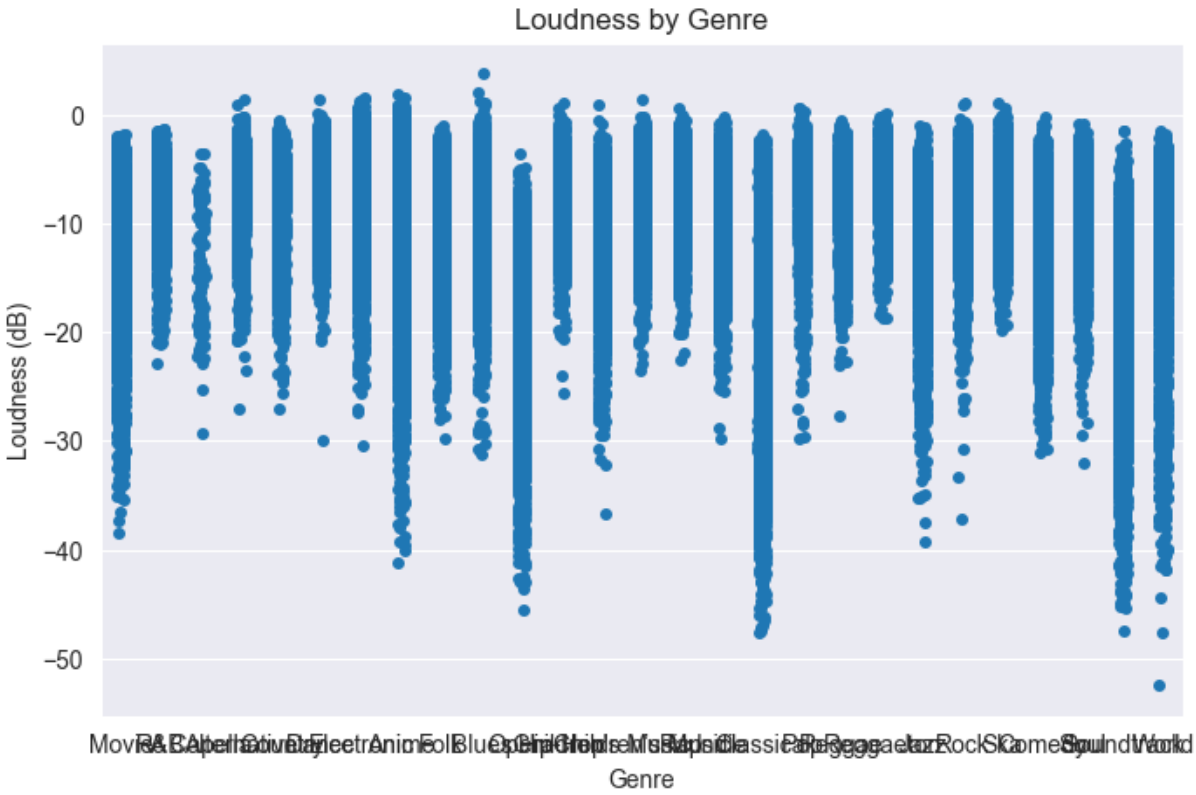



In [54]:
```
 # FacetGrid: Popularity Distribution by Genre
# Shows histograms of popularity, split by genre
g = sns.FacetGrid(features, col='genre', col_wrap=3, height=4)
g.map(sns.histplot, 'popularity', bins=10)
g.fig.suptitle('Popularity Distribution by Genre', y=1.05)
plt.show()
```

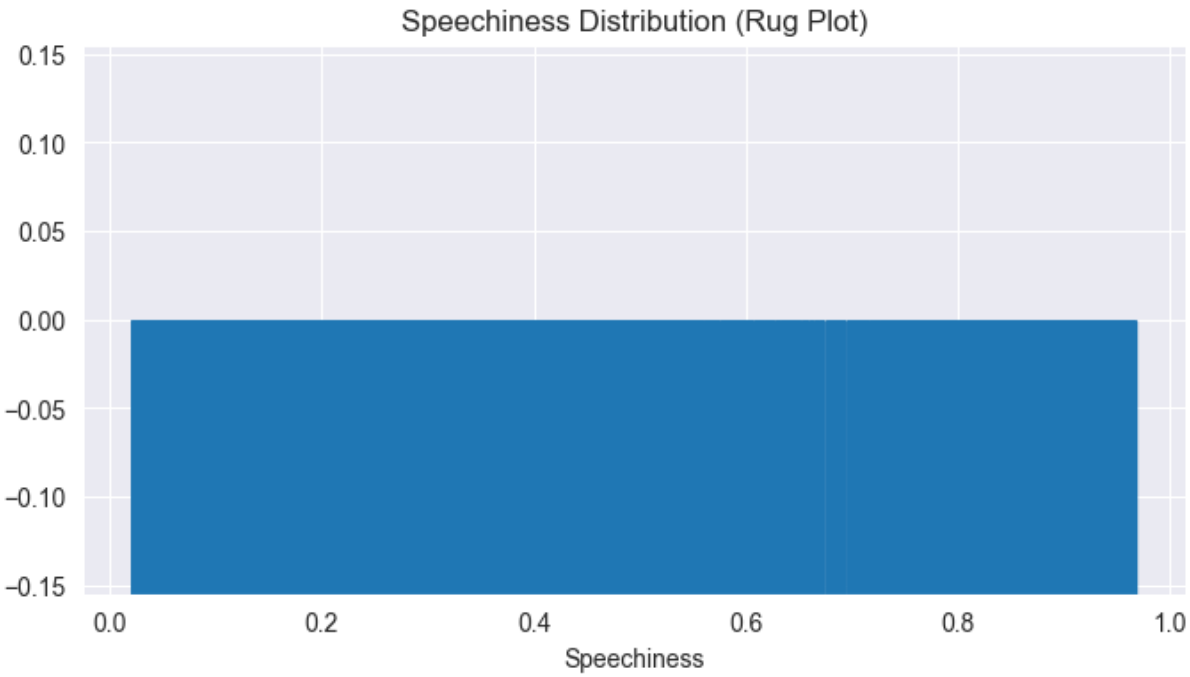

Popularity Distribution by Genre
genre = Movie
genre = R&B
genre = A Capella
genre = Alternative
genre = Country
genre = Dance
genre = Electronic
genre = Anime
genre = Folk
genre = Blues
genre = Opera
genre = Hip-Hop
genre = Children's Music
genre = Children's Music
genre = Rap
Count
0
1000
2000
3000
4000
5000


genre = Indie
genre = Classical
genre = Pop
genre = Reggae
genre = Reggaeton
genre = Jazz
genre = Rock
genre = Ska
genre = Comedy
genre = Soul
genre = Soundtrack
genre = World
Count

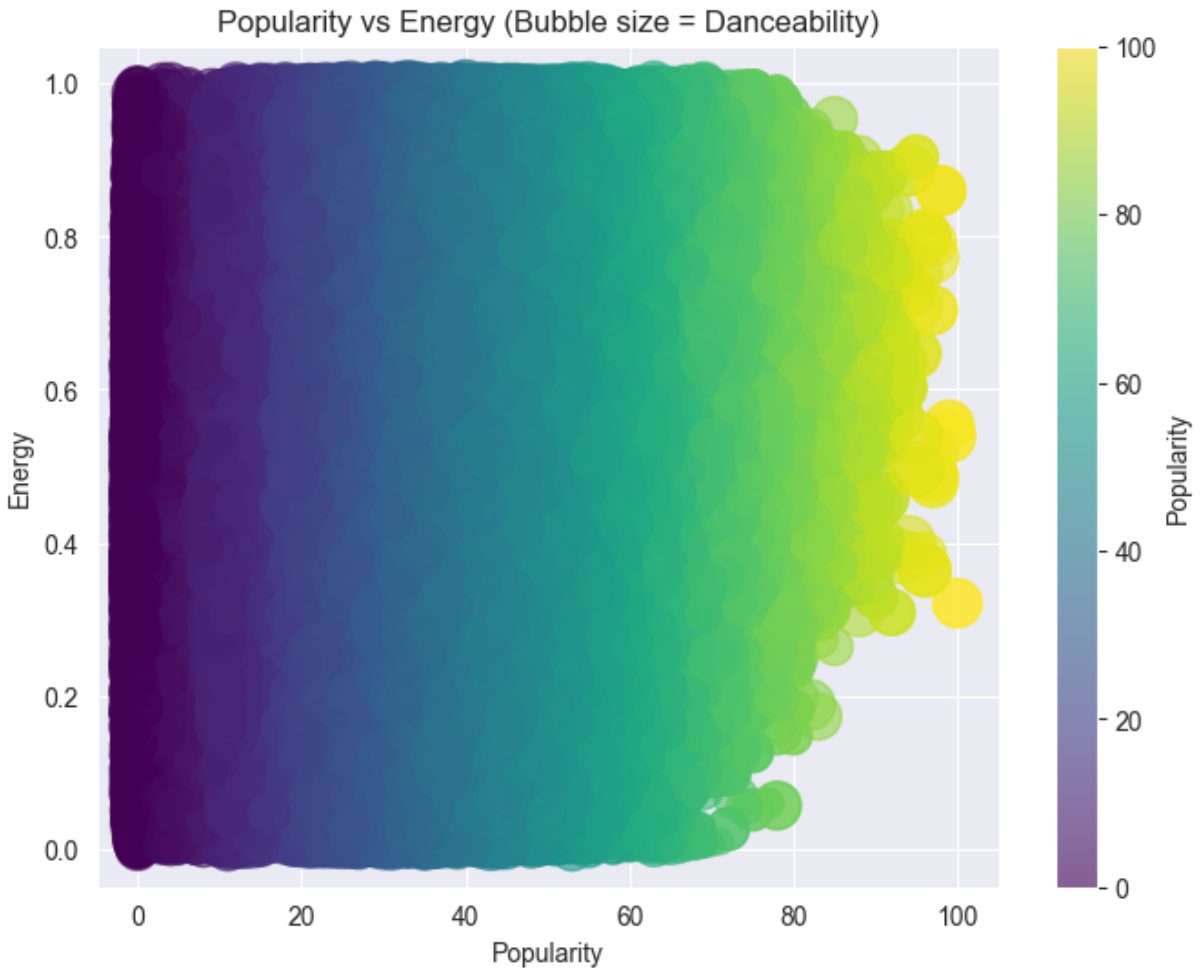

In [55]:
```
# Strip Plot: Loudness by Genre
# Shows all data points for loudness per genre
plt.figure(figsize=(8,5))
sns.stripplot(x='genre', y='loudness', data=features, jitter=True)
plt.title('Loudness by Genre')
plt.xlabel('Genre')
plt.ylabel('Loudness (dB)')
plt.show()
```




In [56]:
```
# Rug Plot: Speechiness Distribution
# Rug plots show data points along an axis, useful for distributions
plt.figure(figsize=(8,4))
sns.rugplot(features['speechiness'], height=0.5)
plt.title('Speechiness Distribution (Rug Plot)')
plt.xlabel('Speechiness')
plt.show()
```




In [57]:
```
# Bubble Plot: Popularity vs Energy with Danceability as Bubble Size
# Visualizing three dimensions together
plt.figure(figsize=(8,6))
sizes = features['danceability'] * 500

plt.scatter(features['popularity'], features['energy'], s=sizes, alpha=0.6, c=featu
plt.colorbar(label='Popularity')
plt.title('Popularity vs Energy (Bubble size = Danceability)')
plt.xlabel('Popularity')
plt.ylabel('Energy')
plt.show()
```




In [63]:
```
# Filter tracks with high energy and high danceability above 75th percentile
energy_thresh = np.percentile(features['energy'], 75)
dance_thresh = np.percentile(features['danceability'], 75)

high_energy_dance = features[(features['energy'] > energy_thresh) & (features['danc
high_energy_dance[['track_name', 'genre', 'energy', 'danceability']]
```

Out[63]:

| | track_name | genre | energy | danceability |
|---|---|---|---|---|
| **17** | Ultra Man 80 | Movie | 0.953 | 0.744 |
| **22** | Monsieur Boum Boum | Movie | 0.804 | 0.704 |
| **30** | A ty się śmiejesz ze mnie | Movie | 0.941 | 0.711 |
| **36** | For the Game | Movie | 0.826 | 0.848 |
| **159** | SLOW DANCING IN THE DARK - Loud Luxury Remix | R&B | 0.883 | 0.752 |
| **...** | ... | ... | ... | ... |
| **232634** | Ohh My Ghosts | Soul | 0.801 | 0.772 |
| **232646** | Who Cares? | Soul | 0.883 | 0.703 |
| **232682** | Me and Baby Brother | Soul | 0.795 | 0.783 |
| **232684** | Back Together Again (feat. Donny Hathaway) | Soul | 0.937 | 0.776 |
| **232704** | Put Your Hands On Me | Soul | 0.830 | 0.875 |

10904 rows × 4 columns

In [69]:
```
# Categorize tempo into bins using numpy digitize
bins = [0, 80, 120, 160, 200]
labels = ['Slow', 'Medium', 'Fast', 'Very Fast']

features['tempo_category'] = pd.cut(features['tempo'], bins=bins, labels=labels, ri
features[['track_name', 'tempo', 'tempo_category']].head()
```

Out[69]:

| | track_name | tempo | tempo_category |
|---|---|---|---|
| **0** | C'est beau de faire un Show | 166.969 | Very Fast |
| **1** | Perdu d'avance (par Gad Elmaleh) | 174.003 | Very Fast |
| **2** | Don't Let Me Be Lonely Tonight | 99.488 | Medium |
| **3** | Dis-moi Monsieur Gordon Cooper | 171.758 | Very Fast |
| **4** | Ouverture | 140.576 | Fast |

In [74]:
```
# Find the top N artists by number of tracks
top_artists = tracks['artists'].value_counts().head(10)
print(top_artists)
```

```
artists
['Die drei ???']                              3856
['TKKG Retro-Archiv']                         2006
['Benjamin Blümchen']                         1503
['Bibi Blocksberg']                           1472
['Lata Mangeshkar']                           1373
['Bibi und Tina']                              927
['Tintin', 'Tomas Bolme', 'Bert-Åke Varg']     905
['Francisco Canaro']                           891
['Ella Fitzgerald']                            870
['Tadeusz Dolega Mostowicz']                   838
Name: count, dtype: int64
```

In [ ]:

In [ ]: