ANALYSING ROCK MUSIC BETWEEN THE YEARS 1956 - 1999

In this project, I am working with a dataset of rock music tracks from Spotify, which contains information about 5,000+ songs including their name, artist, release year, popularity score, and various audio features such as energy, danceability, etc

The dataset was collected from Kaggle Link to the dataset and focuses on some of the most well-known rock tracks from different decades.

The main goal of this analysis is to explore how the popularity of rock music has changed over time, and to understand what factors make certain songs stand the test of time. In other words, I want to find patterns that explain why some songs remain popular even after decades.

For this project, I am using:

- Python for coding
- Numpy and Pandas for data cleaning and analysis
- Matplotlib and Seaborn for data visualisation

By the end of this project, I aim to highlight key trends in rock music popularity, the influence of different audio features, and the artists and songs that continue to resonate with listeners today.

Imports and Reading Data

In [ ]:

```
# Importing all required python libraries and setting global seaborn style
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('ggplot')
```

In [2]:

```
# Reading the CSV dataset file into a Pandas dataframe
```

```python
df = pd.read_csv('./history-of-rock-spotify.csv')
```

Data Understandling

Before starting the analysis, let's first explore the dataset to understand its structure and contents.

In [3]:
```python
df.shape
```

Out[3]:
```
(5484, 18)
```

In [4]:
```python
df.head()
```

Out[4]:

	index	name	artist	release_date	length	popularity	danceability	acousticness	danceability.1	energy	instrumenta
0	0	Smells Like Teen Spirit	Nirvana	1991	5.032000	74	0.502	0.000025	0.502	0.912	0.0(
1	1	Stairway to Heaven - Remaster	Led Zeppelin	1971	8.047167	78	0.338	0.580000	0.338	0.340	0.00
2	2	Bohemian Rhapsody - Remastered 2011	Queen	1975	5.905333	74	0.392	0.288000	0.392	0.402	0.00
3	3	Imagine - Remastered 2010	John Lennon	1971	3.131100	77	0.547	0.907000	0.547	0.257	0.18
4	4	(I Can't Get No) Satisfaction - Mono Version	The Rolling Stones	1965	3.713550	77	0.723	0.038300	0.723	0.863	0.0:

In [5]:
```python
df.columns
```

Out[5]:
```
Index(['index', 'name', 'artist', 'release_date', 'length', 'popularity',
       'danceability', 'acousticness', 'danceability.1', 'energy',
       'instrumentalness', 'key', 'liveness', 'loudness', 'speechiness',
       'tempo', 'time_signature', 'valence'],
      dtype='object')
```

In [6]:
```
df.dtypes
```

Out[6]:
```
index                 int64
name                 object
artist               object
release_date          int64
length              float64
popularity            int64
danceability        float64
acousticness        float64
danceability.1      float64
energy              float64
instrumentalness    float64
key                   int64
liveness            float64
loudness            float64
speechiness         float64
tempo               float64
time_signature        int64
valence             float64
dtype: object
```

In [7]:
```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5484 entries, 0 to 5483
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   index             5484 non-null   int64  
 1   name              5484 non-null   object 
 2   artist            5484 non-null   object 
 3   release_date      5484 non-null   int64  
 4   length            5484 non-null   float64
 5   popularity        5484 non-null   int64  
 6   danceability      5484 non-null   float64
 7   acousticness      5484 non-null   float64
 8   danceability.1    5484 non-null   float64
 9   energy            5484 non-null   float64
 10  instrumentalness  5484 non-null   float64
 11  key               5484 non-null   int64  
 12  liveness          5484 non-null   float64
 13  loudness          5484 non-null   float64
 14  speechiness       5484 non-null   float64
 15  tempo             5484 non-null   float64
 16  time_signature    5484 non-null   int64  
 17  valence           5484 non-null   float64
dtypes: float64(11), int64(5), object(2)
memory usage: 771.3+ KB
```

Out[7]:

	index	release_date	length	popularity	danceability	acousticness	danceability.1	energy	instrumen
count	5484.000000	5484.000000	5484.000000	5484.000000	5484.000000	5484.000000	5484.000000	5484.000000	5484.
mean	2741.500000	1991.196389	4.148302	49.413202	0.511047	0.173019	0.511047	0.715642	0.
std	1583.238769	15.331628	1.496269	17.317263	0.147916	0.242596	0.147916	0.204980	0.
min	0.000000	1956.000000	0.162533	0.000000	0.000000	0.000001	0.000000	0.003830	0.
25%	1370.750000	1978.000000	3.302100	40.000000	0.413000	0.003658	0.413000	0.584000	0.
50%	2741.500000	1993.000000	3.945442	52.000000	0.515000	0.048400	0.515000	0.758000	0.
75%	4112.250000	2004.000000	4.680271	62.000000	0.611000	0.260250	0.611000	0.885000	0.
max	5483.000000	2020.000000	24.091767	84.000000	0.987000	0.995000	0.987000	0.998000	0.

- `df.shape` tells us about number of rows and columns in the dataframe (rows,columns)
- `df.head()` - shows first 5 rows of the DataFrame
- `df.columns` - shows all column names
- `df.dtypes` - shows data type of each column
- `df.info()` - summary of DataFrame (rows, columns, data types, memory use)
- `df.describe()` - gives statistical summary (mean, min, max, etc.) for numeric columns

Data Preparation

Data preparation includes cleaning and organizing the dataset before analysis.

In [ ]:
```
df = df[[#'index',
        'name', 'artist', 'release_date', 'length', 'popularity',
       'danceability', 'acousticness',
       #'danceability.1',
       'energy',
       #'instrumentalness', 'key', 'liveness', 'loudness', 'speechiness',
       #'tempo', 'time_signature', 'valence'
       ]]
```

The above lines of code helps us to select only the required columns (features) with which we wish to perform the analysis.

The details for the selected columns are given below:

- `name` - Name of song.
- `artist` - Name of artist.
- `release_date` - Year song was released (1956-2020).
- `length` - Duration of song in minutes.
- `popularity` - The popularity of the track. The value will be between 0 and 100, with 100 being the most popular.
- `danceability` - Describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm.
- `acousticness` - A confidence measure from 0.0 to 1.0 of whether the track is acoustic.
- `energy` - A measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic.

In [ ]:
```
df['length_minutes'] = pd.to_timedelta(df['length'],unit='m')\
    .dt.components.minutes
```

- Converts the `length` column (in minutes) to a timedelta and extracts only the minutes part into a new column `length_minutes`.

In [ ]:
```
def name_clean(name):
    cleaned_name = name.split('-')[0].strip()
    return cleaned_name
df['song_name'] = df['name'].apply(name_clean)
```

- `name_clean` function removes everything after `-` in the `name` column and extra spaces.

- `df['song_name'] = df['name'].apply(name_clean)` → applies this function to create a new `song_name` column.

In [ ]:
```
df.drop(['name'],axis=1,inplace=True)
```

- Drops the `name` column from the DataFrame permanently (`inplace=True`).

In [ ]:
```
df = df[['artist','song_name','length_minutes','release_date','popularity','danceability','acousticness','energy']]
df
```

Out[ ]:

	artist	song_name	length_minutes	release_date	popularity	danceability	acousticness	energy
0	Nirvana	Smells Like Teen Spirit	5	1991	74	0.502	0.000025	0.912
1	Led Zeppelin	Stairway to Heaven	8	1971	78	0.338	0.580000	0.340
2	Queen	Bohemian Rhapsody	5	1975	74	0.392	0.288000	0.402
3	John Lennon	Imagine	3	1971	77	0.547	0.907000	0.257
4	The Rolling Stones	(I Can't Get No) Satisfaction	3	1965	77	0.723	0.038300	0.863
...	...	...	...	...	...	...	...	...
5479	King Gizzard & The Lizard Wizard	I'm In Your Mind	3	2014	47	0.296	0.005910	0.776
5480	King Gizzard & The Lizard Wizard	Cellophane	3	2014	44	0.432	0.002130	0.887
5481	King Gizzard & The Lizard Wizard	Hot Water	3	2014	40	0.627	0.860000	0.609
5482	CAN	Vitamin C	3	1972	52	0.643	0.006690	0.644
5483	Touché Amoré	~	1	2011	0	0.222	0.000258	0.959

5484 rows × 8 columns

- Reorders and keeps only the specified columns in the DataFrame.

In [ ]:
```
df.loc[df.duplicated(subset=['song_name','artist','release_date'])]
```

Out[ ]:

	artist	song_name	length_minutes	release_date	popularity	danceability	acousticness	energy
625	Iron Maiden	Run to the Hills	3	1982	71	0.249	0.028600	0.943
2189	Sinéad O'Connor	Nothing Compares 2 U	4	1990	75	0.511	0.042500	0.574
2474	The Bravery	An Honest Mistake	3	2005	56	0.460	0.000003	0.889
3187	Metallica	Don't Tread On Me	4	1991	55	0.674	0.004530	0.833
3200	Pink Floyd	The Great Gig in the Sky	4	1973	66	0.275	0.768000	0.216
3283	The Shangri-Las	Remember (Walkin' In The Sand)	2	1996	52	0.285	0.733000	0.513
3437	Bryan Adams	Heaven	4	1984	77	0.382	0.046500	0.589
3552	Edward Sharpe & The Magnetic Zeros	Home	5	2009	72	0.545	0.320000	0.590
3674	Godsmack	Voodoo	4	1998	65	0.778	0.170000	0.613
3713	Creed	One Last Breath	3	2001	69	0.386	0.008410	0.677
3844	The Smiths	Ask	3	1987	58	0.453	0.387000	0.986
4289	The Polyphonic Spree	Soldier Girl	3	2002	38	0.443	0.202000	0.584
5345	The Kooks	Naive	3	2006	61	0.547	0.068800	0.816
5352	The Smashing Pumpkins	Cherub Rock	4	1993	64	0.382	0.000006	0.867
5425	Led Zeppelin	D'yer Mak'er	4	1973	49	0.525	0.262000	0.929
5431	Talking Heads	Born Under Punches (The Heat Goes On)	5	1980	37	0.731	0.312000	0.709
5432	Van Halen	Jump	3	1984	0	0.547	0.074500	0.822
5433	Van Halen	Panama	3	1984	0	0.515	0.001350	0.987
5472	King Gizzard & The Lizard Wizard	Rattlesnake	7	2017	45	0.582	0.030900	0.962

- Finds duplicate rows based on `song_name`, `artist`, and `release_date` columns.

In [ ]:
```
df.query('song_name == "Jump"')
```

Out[ ]:

	artist	song_name	length_minutes	release_date	popularity	danceability	acousticness	energy
66	Van Halen	Jump	4	1984	79	0.572	0.1710	0.835
5432	Van Halen	Jump	3	1984	0	0.547	0.0745	0.822

- To check all rows where `song_name` is `"Jump"` to inspect duplicates before dropping them. Since `"Jump"` is a duplicate value in column `song_name`

In [20]:
```
df = df.loc[~df.duplicated(subset=['song_name','artist','release_date'])]\
    .reset_index(drop=True).copy()
df
```

Out[20]:

	artist	song_name	length_minutes	release_date	popularity	danceability	acousticness	energy
0	Nirvana	Smells Like Teen Spirit	5	1991	74	0.502	0.000025	0.912
1	Led Zeppelin	Stairway to Heaven	8	1971	78	0.338	0.580000	0.340
2	Queen	Bohemian Rhapsody	5	1975	74	0.392	0.288000	0.402
3	John Lennon	Imagine	3	1971	77	0.547	0.907000	0.257
4	The Rolling Stones	(I Can't Get No) Satisfaction	3	1965	77	0.723	0.038300	0.863
...	...	...	...	...	...	...	...	...
5460	King Gizzard & The Lizard Wizard	I'm In Your Mind	3	2014	47	0.296	0.005910	0.776
5461	King Gizzard & The Lizard Wizard	Cellophane	3	2014	44	0.432	0.002130	0.887
5462	King Gizzard & The Lizard Wizard	Hot Water	3	2014	40	0.627	0.860000	0.609
5463	CAN	Vitamin C	3	1972	52	0.643	0.006690	0.644
5464	Touché Amoré	~	1	2011	0	0.222	0.000258	0.959

5465 rows × 8 columns

- Removes duplicate rows based on `song_name`, `artist`, and `release_date`.
- Resets the index and creates a clean copy of the DataFrame.

In [21]:

```
new_df = df[~df['release_date'].isin(range(2000,2021))].reset_index(drop=True)
new_df
```

Out[21]:

	artist	song_name	length_minutes	release_date	popularity	danceability	acousticness	energy
0	Nirvana	Smells Like Teen Spirit	5	1991	74	0.502	0.000025	0.912
1	Led Zeppelin	Stairway to Heaven	8	1971	78	0.338	0.580000	0.340
2	Queen	Bohemian Rhapsody	5	1975	74	0.392	0.288000	0.402
3	John Lennon	Imagine	3	1971	77	0.547	0.907000	0.257
4	The Rolling Stones	(I Can't Get No) Satisfaction	3	1965	77	0.723	0.038300	0.863
...	...	...	...	...	...	...	...	...
3492	Minutemen	The Politics of Time	1	1984	24	0.541	0.003560	0.638
3493	The B-52's	Planet Claire	4	1979	46	0.715	0.052900	0.549
3494	The Stooges	I Wanna Be Your Dog	3	1969	59	0.523	0.087800	0.941
3495	The Grumpies	Everyday	1	1998	1	0.109	0.452000	0.966
3496	CAN	Vitamin C	3	1972	52	0.643	0.006690	0.644

3497 rows × 8 columns

- Creates `new_df` by keeping only rows where `release_date` is between (1956-1999).
- Resets the index after filtering.

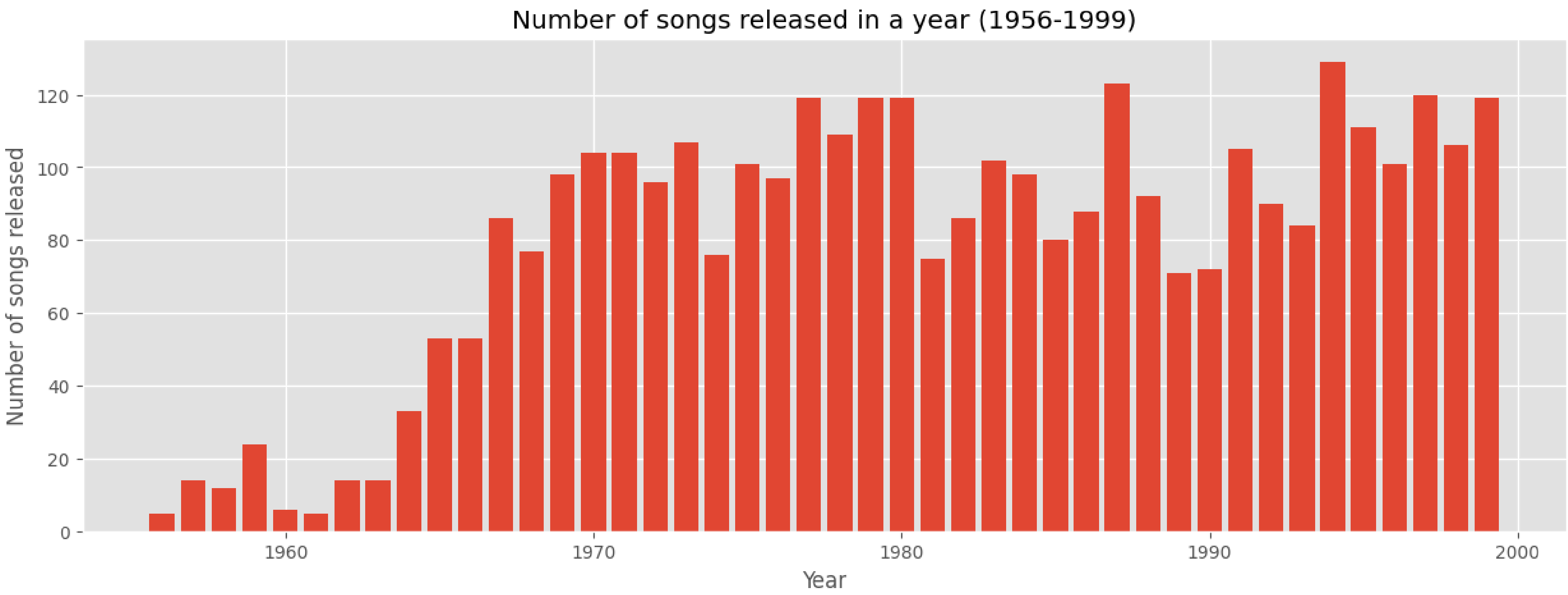
Exploratory Analysis and Visualization

Here we understand the data patterns, trends, and relationships also use statistics and visualizations (like plots and charts) to explore the dataset.

In [22]:

```
year_song_count = new_df['release_date'].value_counts()
plt.figure(figsize=(15, 5))
plt.bar(year_song_count.index, year_song_count.values)
plt.xlabel("Year")
```

```
plt.ylabel("Number of songs released")
plt.title("Number of songs released in a year (1956-1999)")
plt.show()
```



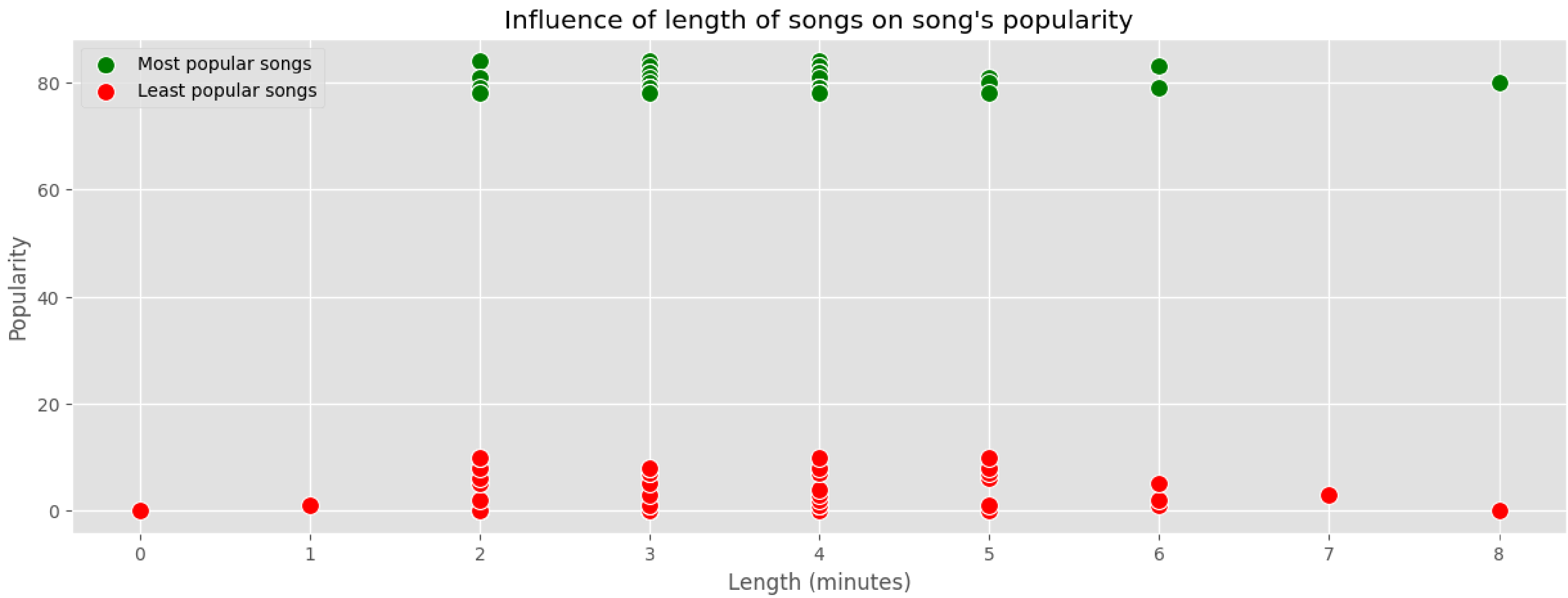
It appears that number of rock songs released started increasing in the 1960s and remained in the range 100-120 songs released every year since mid 1960

Possible reasons:

- Rise of rock culture and popular bands in the 1960s
- Growth of music industry and record production
- Increased youth interest in rock music during that era

In [25]:
```
top_songs = new_df.sort_values(by='popularity', ascending=False).head(50)
bottom_songs = new_df.sort_values(by='popularity', ascending=True).head(50)
plt.figure(figsize=(15, 5))
sns.scatterplot(x=top_songs['length_minutes'], y=top_songs['popularity'], color='green', s=100)
sns.scatterplot(x=bottom_songs['length_minutes'], y=bottom_songs['popularity'], color='red', s=100)
```

```
plt.xlabel("Length (minutes)")
plt.ylabel("Popularity")
plt.title("Influence of length of songs on song's popularity")
plt.legend(['Most popular songs','Least popular songs'])
plt.show()
```



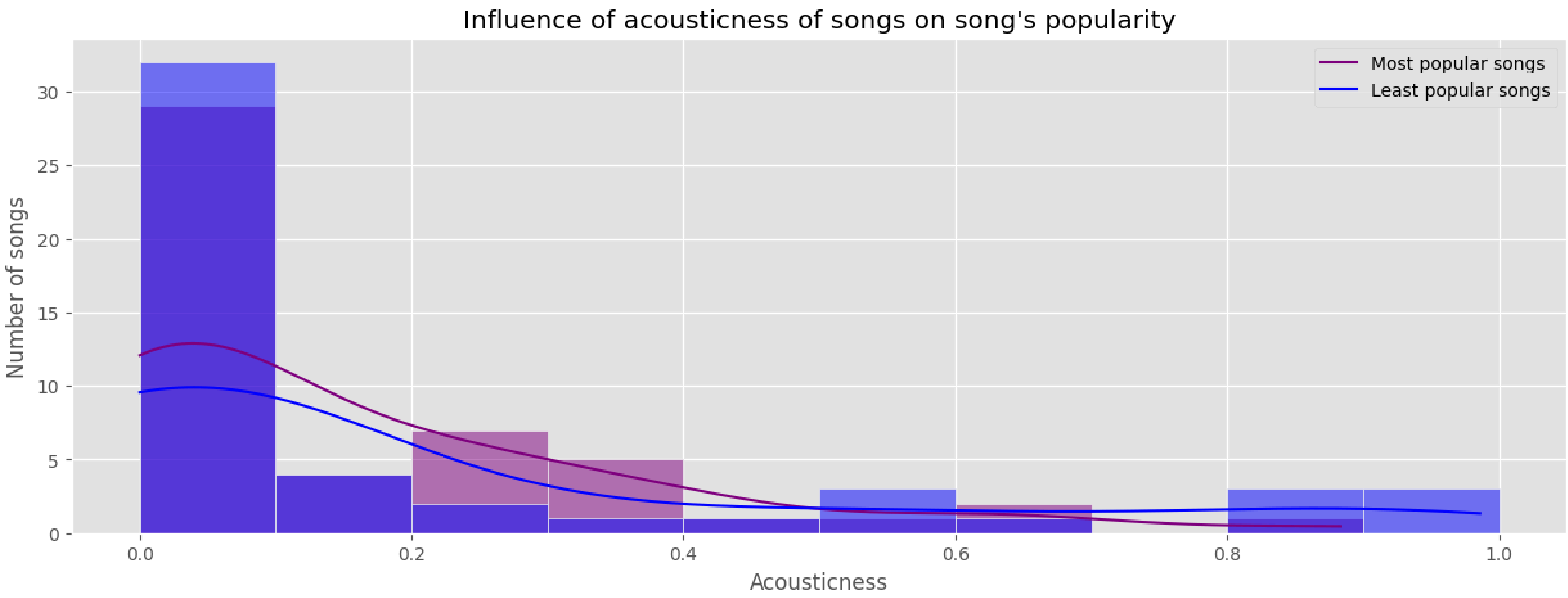
We can infer from the above scatterplot that length of songs didn't seem to have an effect on the popularity of the songs. As an almost equal number of songs both popular and unpopular are present in a range of song length.

Possible reasons:

- Both short and long songs can become hits if they resonate with listeners.

In [26]:
```
plt.figure(figsize=(15, 5))
sns.histplot(top_songs['acousticness'], bins = np.arange(0,1,0.1) ,color='purple', kde=True)
sns.histplot(bottom_songs['acousticness'], bins = np.arange(0,1.01,0.1), color='blue',kde = True)
plt.xlabel("Acousticness")
plt.ylabel("Number of songs")
```

```
plt.title("Influence of acousticness of songs on song's popularity")
plt.legend(['Most popular songs','Least popular songs'])
plt.show()
```



It appears that numbers of both popular and unpopular songs decreases as the song's acousticness increases. So similar to song length, acousticness doesn’t seem to strongly affect a song’s popularity.

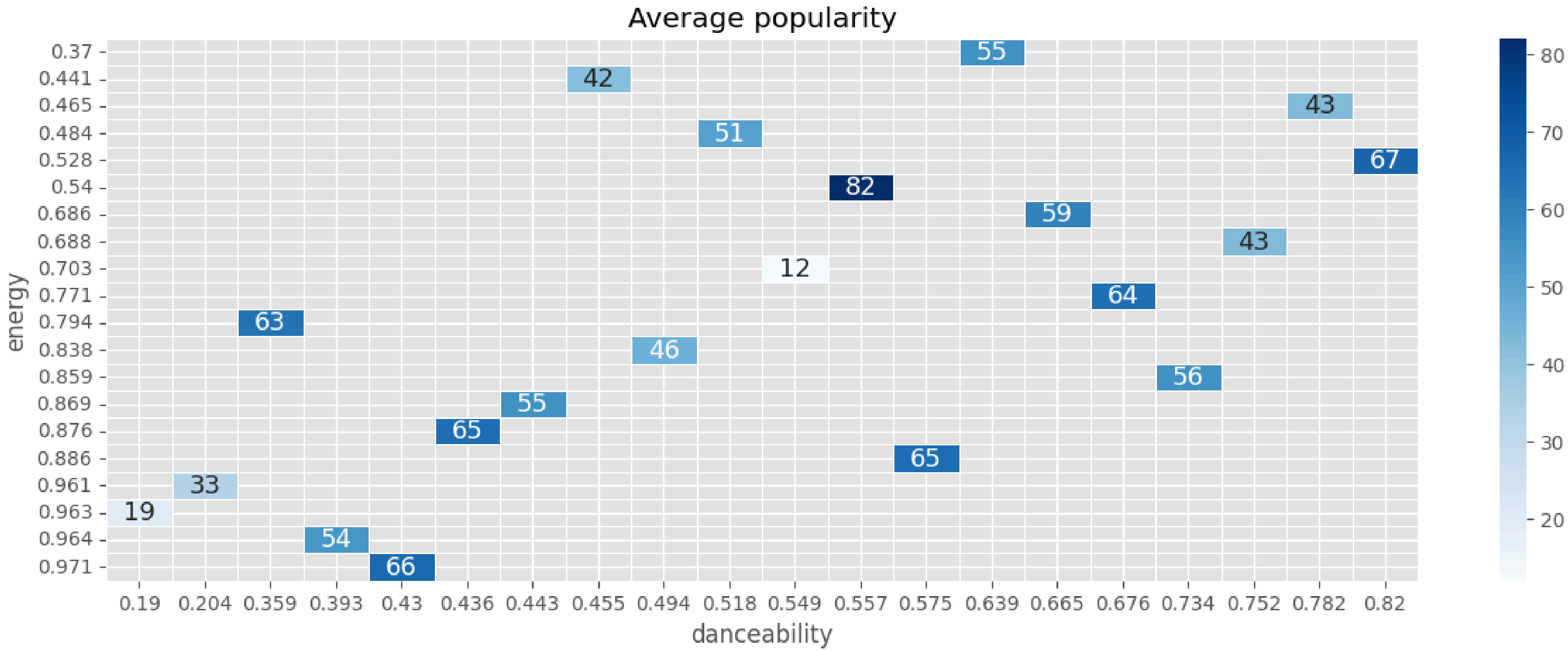
Possible reasons:

- As acousticness increases, songs are more mellow or soft.
- Rock music usually favors energetic, electric sounds, so fewer songs (both popular and unpopular) have very high acousticness.

In [27]:
```
plt.figure(figsize=(15, 10))
sample_df = new_df.sample(20)
sample_input = sample_df.pivot_table(index='energy', columns='danceability', values='popularity', aggfunc='mean')
plt.figure(figsize=(15, 5))
sns.heatmap(sample_input, annot = True, linewidths=.5, cmap='Blues', annot_kws={"fontsize":13})
```

```
plt.title('Average popularity')
plt.show()
```

```
<Figure size 1500x1000 with 0 Axes>
```



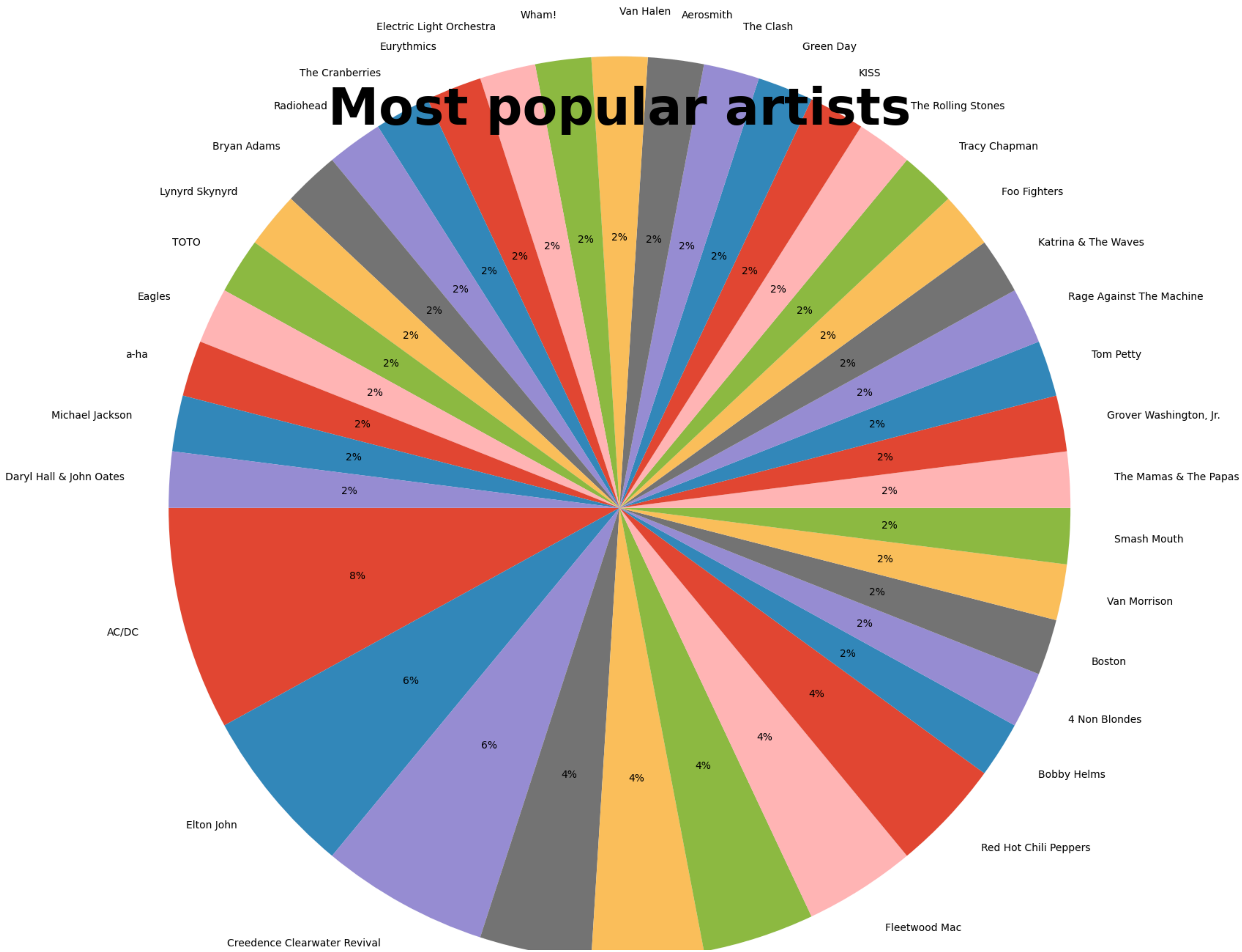
The heatmap indicates that in general popular songs had an equal balance of danceability and energy

Possible reasons-

- Popular rock songs balanced danceability and energy to appeal to listeners for both radio and live performances.
- Rise of club and festival culture encouraged songs that were energetic but still easy to dance to.
- Bands aimed for tracks that could engage audiences without being too aggressive or too mellow.

In [28]:
```
top_artists = top_songs.artist.value_counts()
plt.figure(figsize=(15, 10))
plt.pie(top_artists, labels = top_artists.index, startangle=180, radius=2, autopct='%1.0f%%')
```

```python
plt.title('Most popular artists', pad=100, fontweight='bold', fontsize=50)
plt.show()
```


Most popular artists
Van Halen
Aerosmith
The Clash
Green Day
KISS
The Rolling Stones
Tracy Chapman
Foo Fighters
Katrina & The Waves
Rage Against The Machine
Tom Petty
Grover Washington, Jr.
The Mamas & The Papas
Smash Mouth
Van Morrison
Boston
4 Non Blondes
Bobby Helms
Red Hot Chili Peppers
Fleetwood Mac
Creedence Clearwater Revival
Elton John
AC/DC
Daryl Hall & John Oates
Michael Jackson
a-ha
Eagles
TOTO
Lynyrd Skynyrd
Bryan Adams
Radiohead
The Cranberries
Eurythmics
Electric Light Orchestra
Wham!
8%
6%
6%
4%
4%
4%
4%
4%
2%

The pie chart shows the most popular artists based on number of songs they have in the top popular songs between (1956-1999). Each slice represents an artist's share of top songs

Asking and Answering Questions

Answering questions about the data using a plot or statistic.

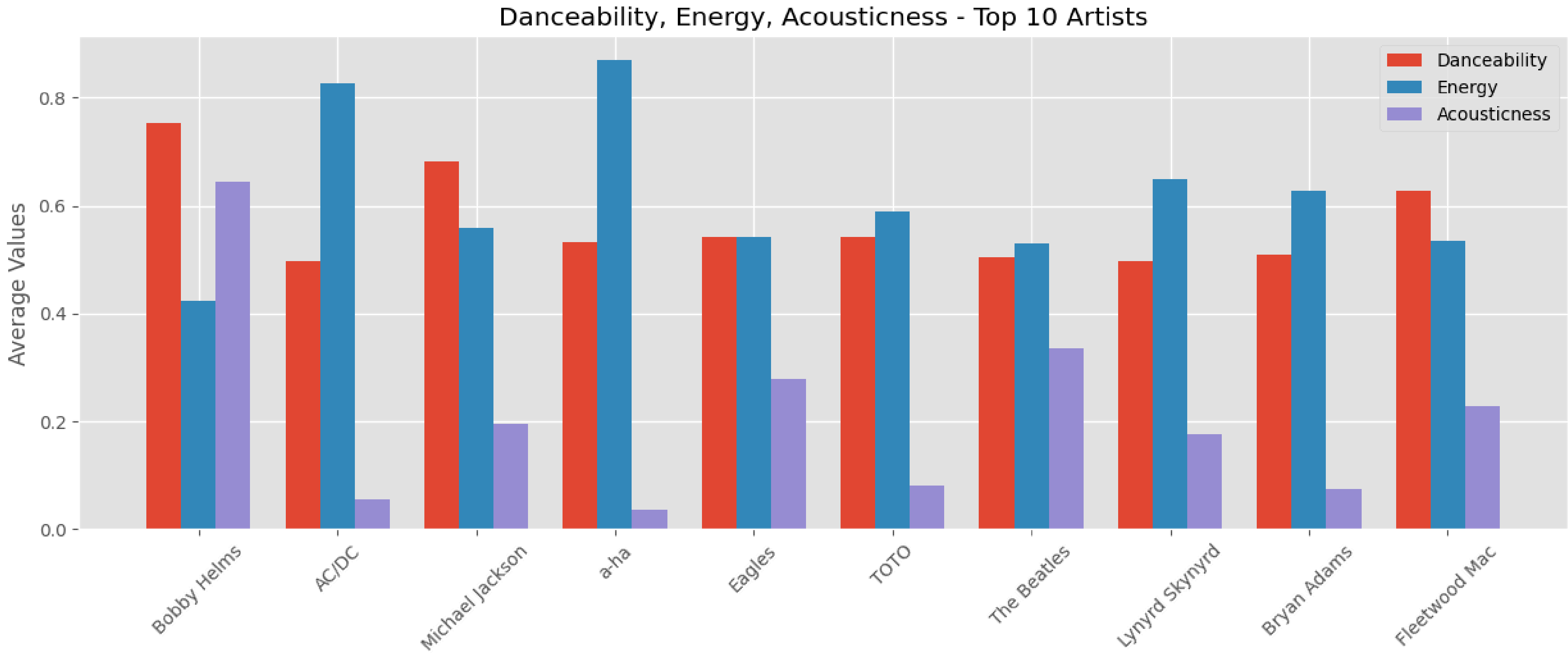
Question 1

Observe the average danceability, energy and acousticness of top 10 artists (1956-1999)

In [30]:
```
top_10 = new_df.sort_values(by='popularity', ascending = False)
top_10 = top_10.loc[~top_10.duplicated(subset=['artist'])].reset_index(drop=True).head(10)
q1_df = new_df.copy()
avg_dance = q1_df[q1_df['artist'].isin(top_10['artist'])].groupby('artist')['danceability'].agg('mean').reindex(top
avg_energy = q1_df[q1_df['artist'].isin(top_10['artist'])].groupby('artist')['energy'].agg('mean').reindex(top_10['
avg_acoustics = q1_df[q1_df['artist'].isin(top_10['artist'])].groupby('artist')['acousticness'].agg('mean').reindex
```

- `top_10` calculation:
  - Sorts `new_df` by `popularity` in descending order.
  - Removes duplicate artists so each artist appears only once.
  - Takes the top 10 most popular artists.
- `avg_dance` calculation:
  - Filters `new_df` to include only the top 10 artists.
  - Groups by artist and calculates the **mean danceability** for each artist.
  - Reorders results to match the order of `top_10`.

In [31]:
```
artists = top_10.artist
x = np.arange(len(artists))
width = 0.25
plt.figure(figsize=(15, 5))
plt.bar(x-width, avg_dance, width, label = 'Danceability')
plt.bar(x, avg_energy, width, label = 'Energy')
plt.bar(x+width, avg_acoustics, width, label = 'Acousticness')
plt.xticks(x, artists, rotation=45)
plt.ylabel("Average Values")
plt.title("Danceability, Energy, Acousticness - Top 10 Artists")
plt.legend()
plt.show()
```



Question 2

The top 3 song from 1950s, 1960s, 1970s, 1980s and 1990s

1950s

In [32]:
```
df_50s = new_df.copy()
df_50s = df_50s[df_50s['release_date'].isin(range(1956,1960))].reset_index(drop=True)
df_50s = df_50s.sort_values(by='popularity', ascending = False).reset_index(drop=True)
for i in range(3):
    print("Number {} song of 1950s is {} by {}".format(i+1, df_50s.loc[i,'song_name'], df_50s.loc[i, 'artist']))
```

```
Number 1 song of 1950s is Johnny B. Goode by Chuck Berry
Number 2 song of 1950s is Jailhouse Rock by Elvis Presley
Number 3 song of 1950s is Hound Dog by Elvis Presley
```

Note - Dataset contains data from 1956.

1960s

In [33]:
```
df_60s = new_df.copy()
df_60s = df_60s[df_60s['release_date'].isin(range(1960,1970))].reset_index(drop=True)
df_60s = df_60s.sort_values(by='popularity', ascending = False).reset_index(drop=True)
for i in range(3):
    print("Number {} song of 1960s is {} by {}".format(i+1, df_60s.loc[i,'song_name'], df_60s.loc[i, 'artist']))
```

```
Number 1 song of 1960s is Here Comes The Sun by The Beatles
Number 2 song of 1960s is Fortunate Son by Creedence Clearwater Revival
Number 3 song of 1960s is California Dreamin' by The Mamas & The Papas
```

1970s

In [34]:
```
df_70s = new_df.copy()
df_70s = df_70s[df_70s['release_date'].isin(range(1970,1980))].reset_index(drop=True)
df_70s = df_70s.sort_values(by='popularity', ascending = False).reset_index(drop=True)
for i in range(3):
    print("Number {} song of 1970s is {} by {}".format(i+1, df_70s.loc[i,'song_name'], df_70s.loc[i, 'artist']))
```

```
Number 1 song of 1970s is Highway to Hell by AC/DC
Number 2 song of 1970s is Hotel California by Eagles
Number 3 song of 1970s is The Chain by Fleetwood Mac
```

1980s

In [36]:
```
df_80s = new_df.copy()
df_80s = df_80s[df_80s['release_date'].isin(range(1980,1990))].reset_index(drop=True)
df_80s = df_80s.sort_values(by='popularity', ascending = False).reset_index(drop=True)
for i in range(3):
    print("Number {} song of 1980s is {} by {}".format(i+1, df_80s.loc[i,'song_name'], df_80s.loc[i, 'artist']))
```

```
Number 1 song of 1980s is Back In Black by AC/DC
Number 2 song of 1980s is Africa by TOTO
Number 3 song of 1980s is Billie Jean by Michael Jackson
```

1990s

In [37]:
```
df_90s = new_df.copy()
df_90s = df_90s[df_90s['release_date'].isin(range(1990,2000))].reset_index(drop=True)
df_90s = df_90s.sort_values(by='popularity', ascending = False).reset_index(drop=True)
for i in range(3):
    print("Number {} song of 1990s is {} by {}".format(i+1, df_90s.loc[i,'song_name'], df_90s.loc[i, 'artist']))
```

```
Number 1 song of 1990s is Jingle Bell Rock by Bobby Helms
Number 2 song of 1990s is Creep by Radiohead
Number 3 song of 1990s is Thunderstruck by AC/DC
```

Question 3

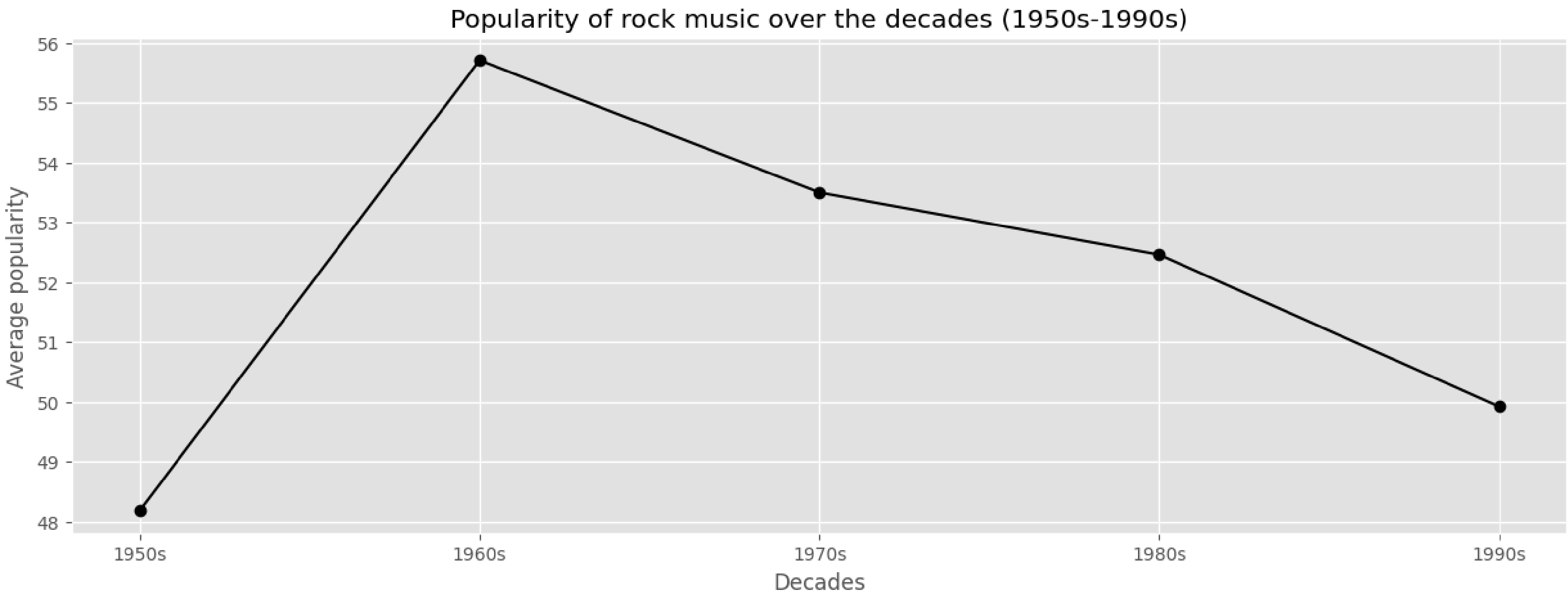
Observe popularity of rock music by decades 1950s, 1960s, 1970s, 1980s, and 1990s

In [39]:
```
pop_50s = new_df[new_df['release_date'].isin(range(1956,1960))]['popularity'].agg('mean').round(2)
pop_60s = new_df[new_df['release_date'].isin(range(1960,1970))]['popularity'].agg('mean').round(2)
pop_70s = new_df[new_df['release_date'].isin(range(1970,1980))]['popularity'].agg('mean').round(2)
pop_80s = new_df[new_df['release_date'].isin(range(1980,1990))]['popularity'].agg('mean').round(2)
pop_90s = new_df[new_df['release_date'].isin(range(1990,2000))]['popularity'].agg('mean').round(2)
popularity_decade = np.array([pop_50s, pop_60s, pop_70s, pop_80s, pop_90s])
```

`pop_50s = new_df[new_df['release_date'].isin(range(1956,1960))]['popularity'].agg('mean').round(2)` this line:

- Filters `new_df` to include only songs released between 1956 and 1959.
- Calculates the average popularity of these songs using `.agg('mean')`.
- Rounds the result to 2 decimal places with `.round(2)`.

In [40]:
```
decades = np.array(['1950s', '1960s', '1970s', '1980s', '1990s'])
plt.figure(figsize=(15, 5))
plt.plot(decades, popularity_decade, 'k-o')
plt.title('Popularity of rock music over the decades (1950s-1990s)')
plt.xlabel('Decades')
plt.ylabel('Average popularity')
plt.show()
```



Note - Dataset contains data from 1956, that might be the reason for low popularity of rock songs in 1950s in the above line chart.

We can observe that popularity of rock music is on a decline between the decades (1960s-1990s)

Inferences and Conclusions

Inferences

- Number of rock songs increased from the 1960s and stabilized around 100-120 per year.
- Song **length** and **acousticness** did not strongly affect popularity.
- Popular songs balanced **danceability** and **energy**, likely influenced by live performances and club/festival culture.
- Certain artists consistently produced more popular songs.
- Average popularity showed slight variation across decades, reflecting changing listener preferences.

Conclusions

Popularity of songs didn't depend on song length and acousticness, that means artists could experiment with their songs creating unconventional songs and still become popular. Balanced energy and danceability help songs appeal to a wider audience. Understanding these trends can help in music production and predicting potential hits. Also there has been an alarming decline in rock music's popularity with the decades, which shows rooms for improvement.

Long Live Rock n Roll!

References and Future Work

References

- Dataset source: History of rock
- Python libraries: Numpy, Pandas, Matplotlib, Seaborn

Future Work

- Analyze songs from 2000 onwards to see modern trends.
- Include other genres for comparison with rock music.
- Explore additional features like `loudness`, `instrumentalness`, `speechiness`, `liveness`, etc.