spotifyml

December 15, 2023

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[2]:
```
# Import Libraries


import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

[3]:
```
# Import dataset for our enviroment

df = pd.read_csv("/content/drive/MyDrive/dataset1/rolling_stones_spotify.csv")
```

[4]:
```
df
```

[4]:

	Unnamed: 0	name	album	\
0	0	Concert Intro Music - Live	Licked Live In NYC	
1	1	Street Fighting Man - Live	Licked Live In NYC	
2	2	Start Me Up - Live	Licked Live In NYC	
3	3	If You Can't Rock Me - Live	Licked Live In NYC	
4	4	Don’t Stop - Live	Licked Live In NYC	
…	…	…	…	
1605	1605	Carol	The Rolling Stones	
1606	1606	Tell Me	The Rolling Stones	
1607	1607	Can I Get A Witness	The Rolling Stones	
1608	1608	You Can Make It If You Try	The Rolling Stones	
1609	1609	Walking The Dog	The Rolling Stones	

	release_date	track_number	id	\
0	2022-06-10	1	2IEkywLJ4ykbhi1yRQvmsT	
1	2022-06-10	2	6GVgVJBKkGJoRfarYRvGTU	
2	2022-06-10	3	1Lu761pZ0dBTGpzxaQoZNW	
3	2022-06-10	4	1agTQzOTUnGNggyckEqiDH	

```
4      2022-06-10              5  7piGJR8YndQBQWVXv6KtQw
…           …           …                       …
1605   1964-04-16              8  08l7M5UpRnffGl0FyuRiQZ
1606   1964-04-16              9  3JZllQBsTM6WwoJdzFDLhx
1607   1964-04-16             10  0t2qvfSBQ3Y08lzRRoVTdb
1608   1964-04-16             11  5ivIs5vwSj0RChOIvlY3On
1609   1964-04-16             12  43SkTJJ2xleDaeiE4TIM70

                                        uri  acousticness  danceability  \
0     spotify:track:2IEkywLJ4ykbhi1yRQvmsT        0.0824         0.463
1     spotify:track:6GVgVJBKkGJoRfarYRvGTU        0.4370         0.326
2     spotify:track:1Lu761pZ0dBTGpzxaQoZNW        0.4160         0.386
3     spotify:track:1agTQzOTUnGNggyckEqiDH        0.5670         0.369
4     spotify:track:7piGJR8YndQBQWVXv6KtQw        0.4000         0.303
…                                      …           …           …
1605  spotify:track:08l7M5UpRnffGl0FyuRiQZ        0.1570         0.466
1606  spotify:track:3JZllQBsTM6WwoJdzFDLhx        0.0576         0.509
1607  spotify:track:0t2qvfSBQ3Y08lzRRoVTdb        0.3710         0.790
1608  spotify:track:5ivIs5vwSj0RChOIvlY3On        0.2170         0.700
1609  spotify:track:43SkTJJ2xleDaeiE4TIM70        0.3830         0.727

      energy  instrumentalness  liveness  loudness  speechiness    tempo  \
0      0.993          0.996000    0.9320   -12.913       0.1100  118.001
1      0.965          0.233000    0.9610    -4.803       0.0759  131.455
2      0.969          0.400000    0.9560    -4.936       0.1150  130.066
3      0.985          0.000107    0.8950    -5.535       0.1930  132.994
4      0.969          0.055900    0.9660    -5.098       0.0930  130.533
…      …                …       …       …           …       …
1605   0.932          0.006170    0.3240    -9.214       0.0429  177.340
1606   0.706          0.000002    0.5160    -9.427       0.0843  122.015
1607   0.774          0.000000    0.0669    -7.961       0.0720   97.035
1608   0.546          0.000070    0.1660    -9.567       0.0622  102.634
1609   0.934          0.068500    0.0965    -8.373       0.0359  125.275

      valence  popularity  duration_ms
0      0.0302          33        48640
1      0.3180          34       253173
2      0.3130          34       263160
3      0.1470          32       305880
4      0.2060          32       305106
…       …          …           …
1605   0.9670          39       154080
1606   0.4460          36       245266
1607   0.8350          30       176080
1608   0.5320          27       121680
1609   0.9690          35       189186
```

```
[1610 rows x 18 columns]
```

[5]:
```
df.rename(columns={"Unnamed: 0" : "Master_id"}, inplace=True  )
```

[6]:
```
df
```

[6]:
```
      Master_id                         name              album release_date  \
0             0   Concert Intro Music - Live  Licked Live In NYC   2022-06-10
1             1   Street Fighting Man - Live  Licked Live In NYC   2022-06-10
2             2           Start Me Up - Live  Licked Live In NYC   2022-06-10
3             3  If You Can't Rock Me - Live  Licked Live In NYC   2022-06-10
4             4            Don’t Stop - Live  Licked Live In NYC   2022-06-10
…           …                           …                 …           …
1605       1605                        Carol  The Rolling Stones   1964-04-16
1606       1606                     Tell Me  The Rolling Stones   1964-04-16
1607       1607          Can I Get A Witness  The Rolling Stones   1964-04-16
1608       1608   You Can Make It If You Try  The Rolling Stones   1964-04-16
1609       1609               Walking The Dog  The Rolling Stones   1964-04-16

      track_number                      id  \
0                1  2IEkywLJ4ykbhi1yRQvmsT
1                2  6GVgVJBKkGJoRfarYRvGTU
2                3  1Lu761pZOdBTGpzxaQoZNW
3                4  1agTQzOTUnGNggyckEqiDH
4                5  7piGJR8YndQBQWVXv6KtQw
…              …                       …
1605             8  0817M5UpRnffGlOFyuRiQZ
1606             9  3JZllQBsTM6WwoJdzFDLhx
1607            10  0t2qvfSBQ3YO8lzRRoVTdb
1608            11  5ivIs5vwSjORChOIvlY3On
1609            12  43SkTJJ2xleDaeiE4TIM70

                                    uri  acousticness  danceability  \
0     spotify:track:2IEkywLJ4ykbhi1yRQvmsT        0.0824         0.463
1     spotify:track:6GVgVJBKkGJoRfarYRvGTU        0.4370         0.326
2     spotify:track:1Lu761pZOdBTGpzxaQoZNW        0.4160         0.386
3     spotify:track:1agTQzOTUnGNggyckEqiDH        0.5670         0.369
4     spotify:track:7piGJR8YndQBQWVXv6KtQw        0.4000         0.303
…                                      …             …             …
1605  spotify:track:0817M5UpRnffGlOFyuRiQZ        0.1570         0.466
1606  spotify:track:3JZllQBsTM6WwoJdzFDLhx        0.0576         0.509
1607  spotify:track:0t2qvfSBQ3YO8lzRRoVTdb        0.3710         0.790
1608  spotify:track:5ivIs5vwSjORChOIvlY3On        0.2170         0.700
1609  spotify:track:43SkTJJ2xleDaeiE4TIM70        0.3830         0.727

      energy  instrumentalness  liveness  loudness  speechiness    tempo  \
0      0.993          0.996000    0.9320   -12.913       0.1100  118.001
```

```
1       0.965          0.233000    0.9610    -4.803       0.0759  131.455
2       0.969          0.400000    0.9560    -4.936       0.1150  130.066
3       0.985          0.000107    0.8950    -5.535       0.1930  132.994
4       0.969          0.055900    0.9660    -5.098       0.0930  130.533
…       …                …       …         …            …       …
1605    0.932          0.006170    0.3240    -9.214       0.0429  177.340
1606    0.706          0.000002    0.5160    -9.427       0.0843  122.015
1607    0.774          0.000000    0.0669    -7.961       0.0720   97.035
1608    0.546          0.000070    0.1660    -9.567       0.0622  102.634
1609    0.934          0.068500    0.0965    -8.373       0.0359  125.275

      valence  popularity  duration_ms
0      0.0302          33        48640
1      0.3180          34       253173
2      0.3130          34       263160
3      0.1470          32       305880
4      0.2060          32       305106
…       …          …           …
1605   0.9670          39       154080
1606   0.4460          36       245266
1607   0.8350          30       176080
1608   0.5320          27       121680
1609   0.9690          35       189186

[1610 rows x 18 columns]
```

[7]:
```
df.shape
```

[7]:
```
(1610, 18)
```

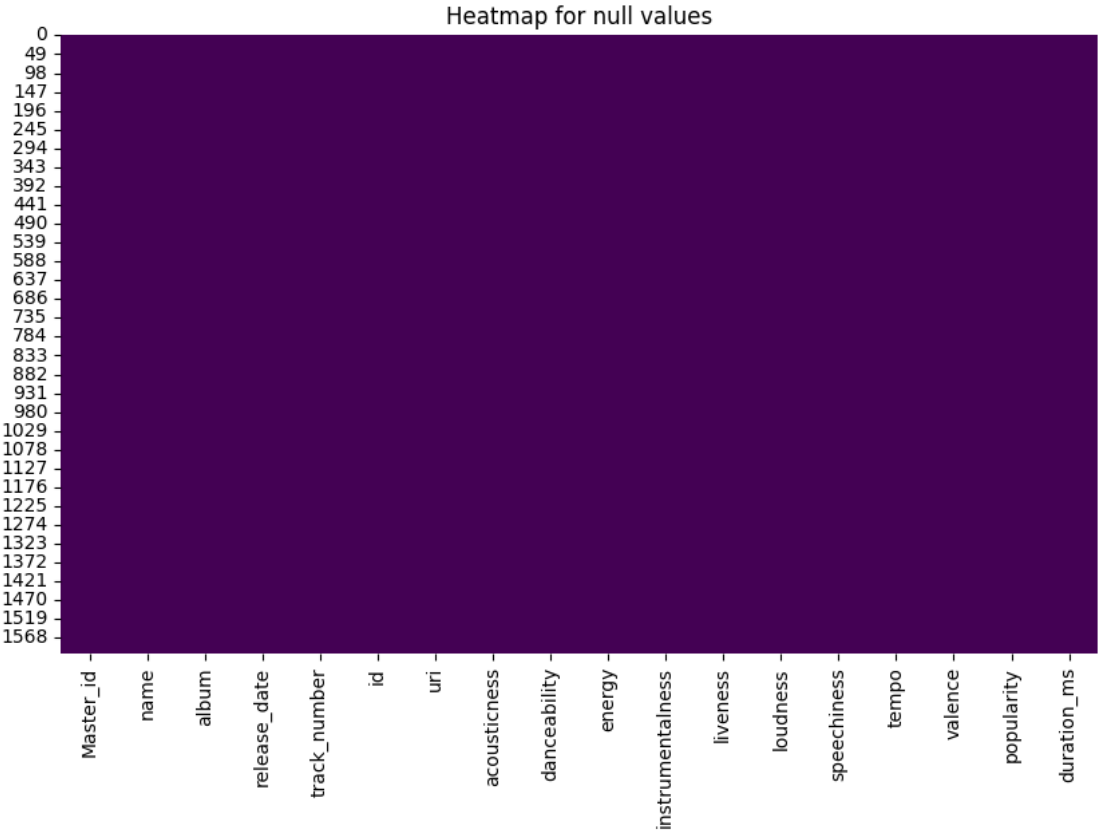
[8]:
```
df.dtypes
```

[8]:
```
Master_id             int64
name                 object
album                object
release_date         object
track_number          int64
id                   object
uri                  object
acousticness        float64
danceability        float64
energy              float64
instrumentalness    float64
liveness            float64
loudness            float64
speechiness         float64
tempo               float64
```

```
valence             float64
popularity            int64
duration_ms           int64
dtype: object
```

[9]:
```
df['release_date'] = pd.to_datetime(df['release_date'], errors='coerce')
```

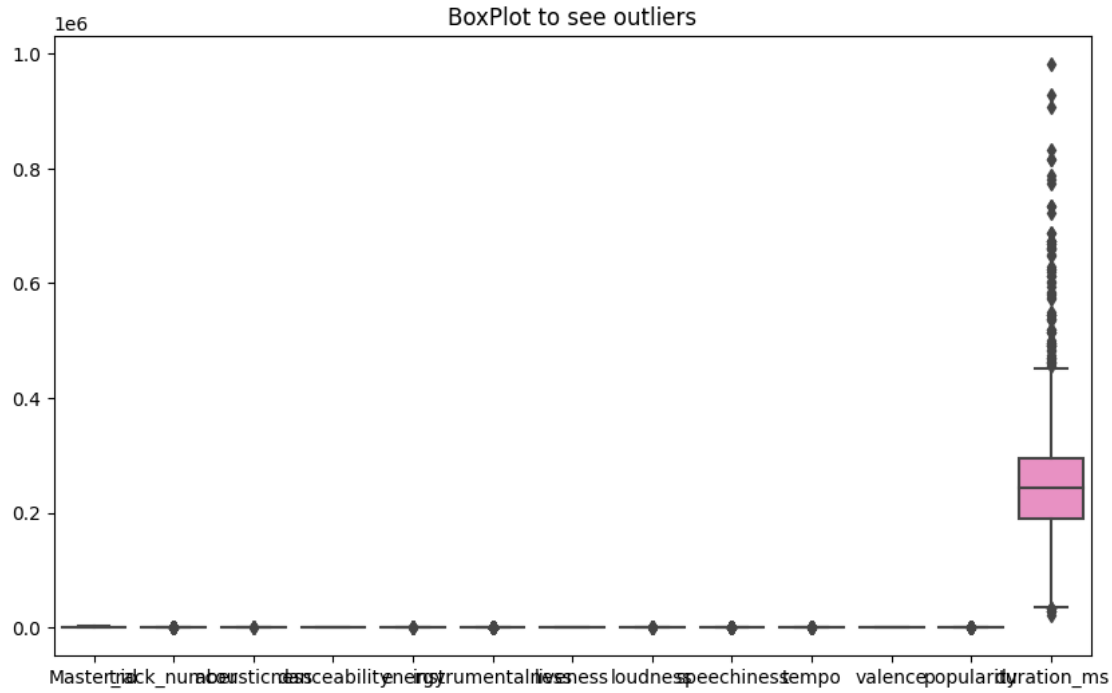
[10]:
```
# Data cleaning


# Null values
df_null = df.isnull()

plt.figure(figsize=(10, 6))
sns.heatmap(df_null, cbar=False,cmap='viridis')

plt.title("Heatmap for null values")

plt.show()
```



[11]:
```
print(df_null.sum())
```

```
Master_id           0
name                0
album               0
release_date        0
track_number        0
id                  0
uri                 0
acousticness        0
danceability        0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
duration_ms         0
dtype: int64
```

[12]:
```
# outliers

plt.figure(figsize=(10,6))
sns.boxplot(data=df)
plt.title("BoxPlot to see outliers")
plt.show()
```



[24]:
```
df['release_Year'] = df['release_date'].dt.year
df
```

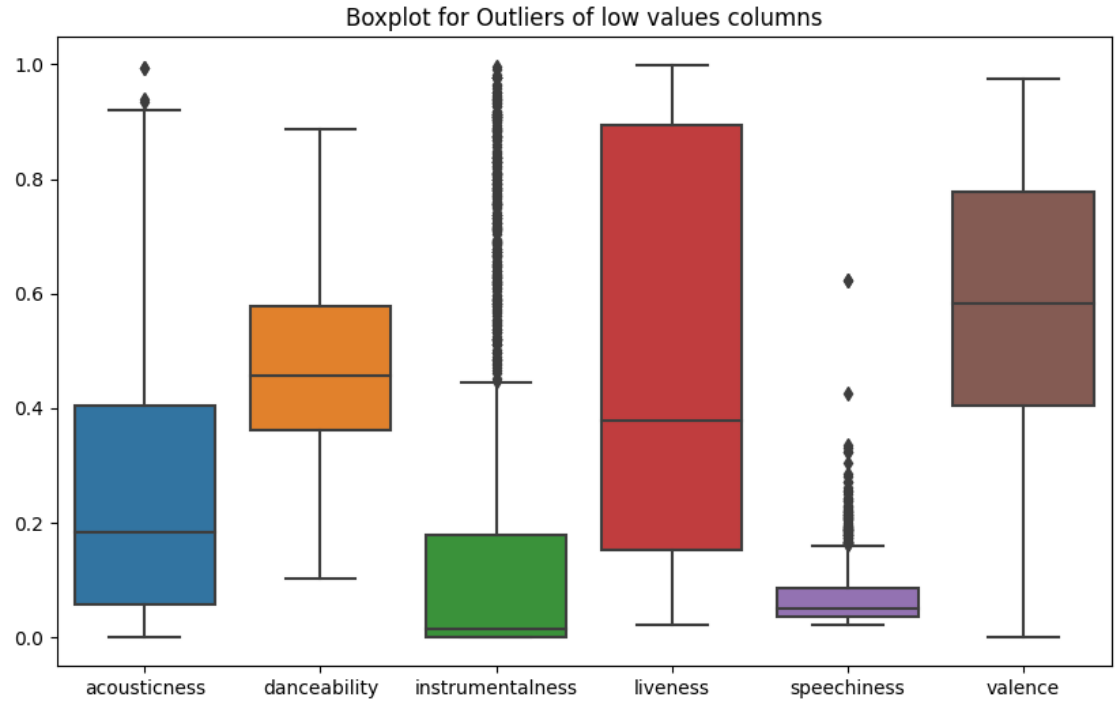
[24]:

	Master_id	name	album	release_date	track_number	id
0	0	Concert Intro Music - Live	Licked Live In NYC	2022-06-10	1	2IEkywLJ4ykbhi1yRQvmsT
1	1	Street Fighting Man - Live	Licked Live In NYC	2022-06-10	2	6GVgVJBKkGJoRfarYRvGTU
2	2	Start Me Up - Live	Licked Live In NYC	2022-06-10	3	1Lu761pZOdBTGpzxaQoZNW
3	3	If You Can't Rock Me - Live	Licked Live In NYC	2022-06-10	4	1agTQzOTUnGNggyckEqiDH
4	4	Don’t Stop - Live	Licked Live In NYC	2022-06-10	5	7piGJR8YndQBQWVXv6KtQw
…	…	…	…	…	…	…
1605	1605	Carol	The Rolling Stones	1964-04-16	8	08l7M5UpRnffGl0FyuRiQZ
1606	1606	Tell Me	The Rolling Stones	1964-04-16		
1607	1607	Can I Get A Witness	The Rolling Stones	1964-04-16		
1608	1608	You Can Make It If You Try	The Rolling Stones	1964-04-16		
1609	1609	Walking The Dog	The Rolling Stones	1964-04-16		

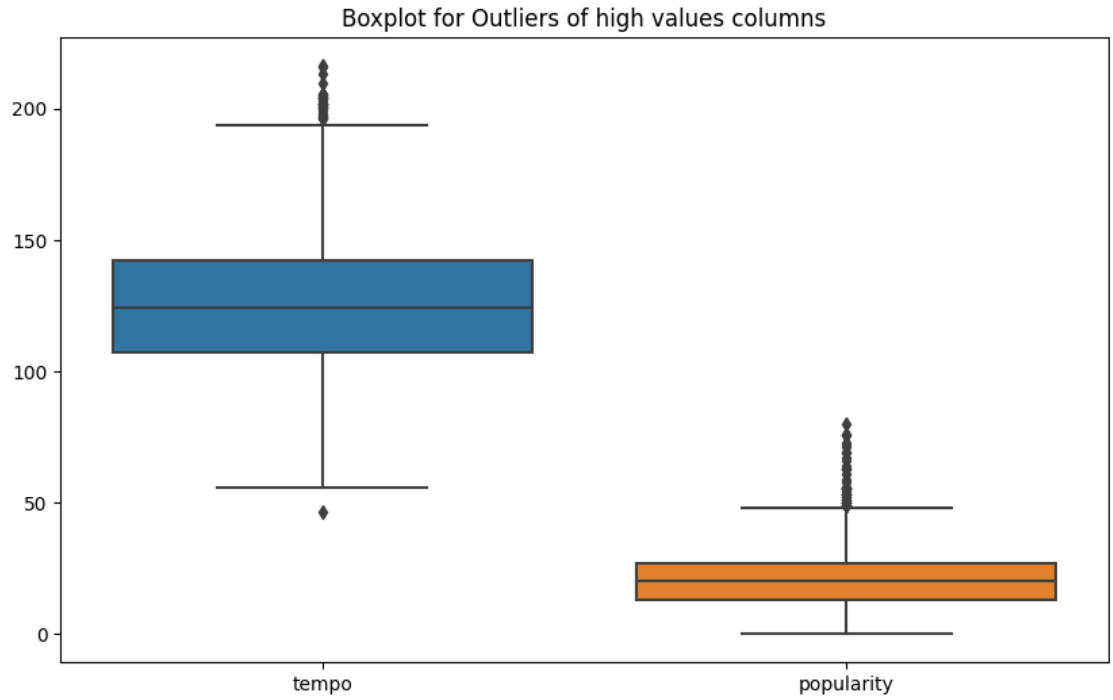
```
1606             9  3JZllQBsTM6WwoJdzFDLhx
1607            10  0t2qvfSBQ3YO8lzRRoVTdb
1608            11  5ivIs5vwSj0RChOIvlY3On
1609            12  43SkTJJ2xleDaeiE4TIM70

                                      uri  acousticness  danceability  \
0     spotify:track:2IEkywLJ4ykbhi1yRQvmsT        0.0824         0.463
1     spotify:track:6GVgVJBKkGJoRfarYRvGTU        0.4370         0.326
2     spotify:track:1Lu761pZ0dBTGpzxaQoZNW        0.4160         0.386
3     spotify:track:1agTQzOTUnGNggyckEqiDH        0.5670         0.369
4     spotify:track:7piGJR8YndQBQWVXv6KtQw        0.4000         0.303
…                                      …             …             …
1605  spotify:track:08l7M5UpRnffGl0FyuRiQZ        0.1570         0.466
1606  spotify:track:3JZllQBsTM6WwoJdzFDLhx        0.0576         0.509
1607  spotify:track:0t2qvfSBQ3YO8lzRRoVTdb        0.3710         0.790
1608  spotify:track:5ivIs5vwSj0RChOIvlY3On        0.2170         0.700
1609  spotify:track:43SkTJJ2xleDaeiE4TIM70        0.3830         0.727

      energy  instrumentalness  liveness  loudness  speechiness    tempo  \
0      0.993          0.996000    0.9320   -12.913       0.1100  118.001
1      0.965          0.233000    0.9610    -4.803       0.0759  131.455
2      0.969          0.400000    0.9560    -4.936       0.1150  130.066
3      0.985          0.000107    0.8950    -5.535       0.1930  132.994
4      0.969          0.055900    0.9660    -5.098       0.0930  130.533
…      …                …       …       …         …          …       …
1605   0.932          0.006170    0.3240    -9.214       0.0429  177.340
1606   0.706          0.000002    0.5160    -9.427       0.0843  122.015
1607   0.774          0.000000    0.0669    -7.961       0.0720   97.035
1608   0.546          0.000070    0.1660    -9.567       0.0622  102.634
1609   0.934          0.068500    0.0965    -8.373       0.0359  125.275

      valence  popularity  duration_ms  release_year  release_Year
0      0.0302          33        48640          2022          2022
1      0.3180          34       253173          2022          2022
2      0.3130          34       263160          2022          2022
3      0.1470          32       305880          2022          2022
4      0.2060          32       305106          2022          2022
…       …         …           …             …           …
1605   0.9670          39       154080          1964          1964
1606   0.4460          36       245266          1964          1964
1607   0.8350          30       176080          1964          1964
1608   0.5320          27       121680          1964          1964
1609   0.9690          35       189186          1964          1964

[1610 rows x 20 columns]
```

[25]:
```
# because we have a big diference betewen values lats make more detalied


#separate dataset
low_float_columns =␣
 ↪['acousticness','danceability','instrumentalness','liveness','speechiness','valence']
high_int_float = ['tempo','popularity']
others_columns = ['loudness','duration_ms']
last_columns = ['Master_id','release_Year']

df_low = df[low_float_columns]
df_high = df[high_int_float]
df_others = df[others_columns]
df_last = df[last_columns]
```

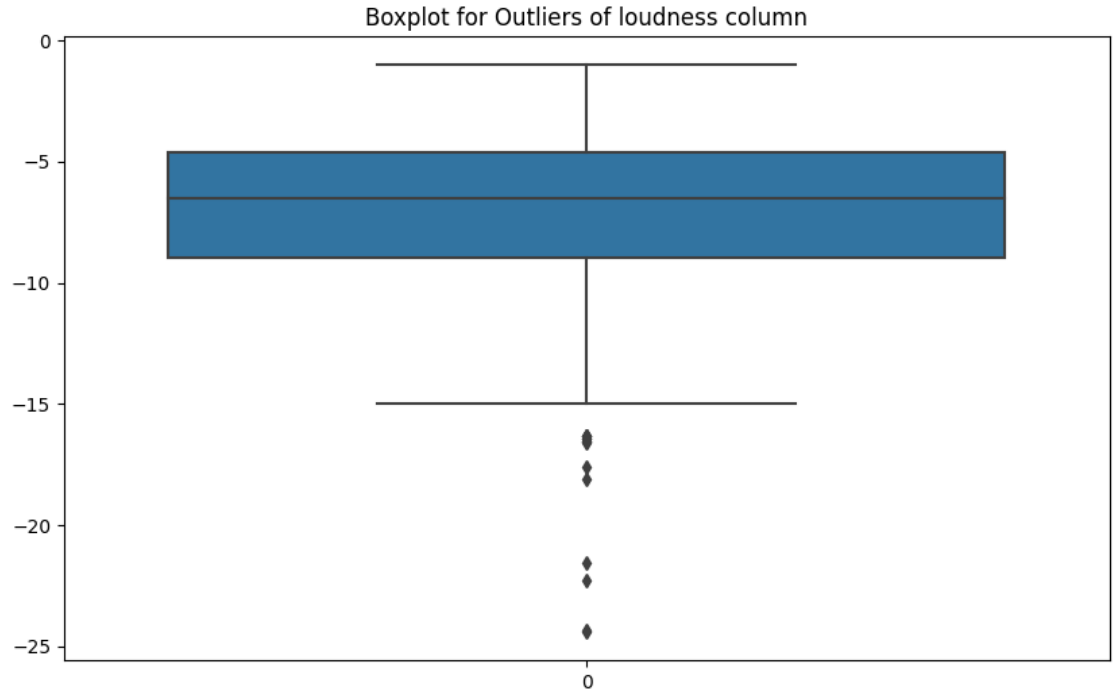
[26]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df_low)
plt.title("Boxplot for Outliers of low values columns")
plt.show()
```



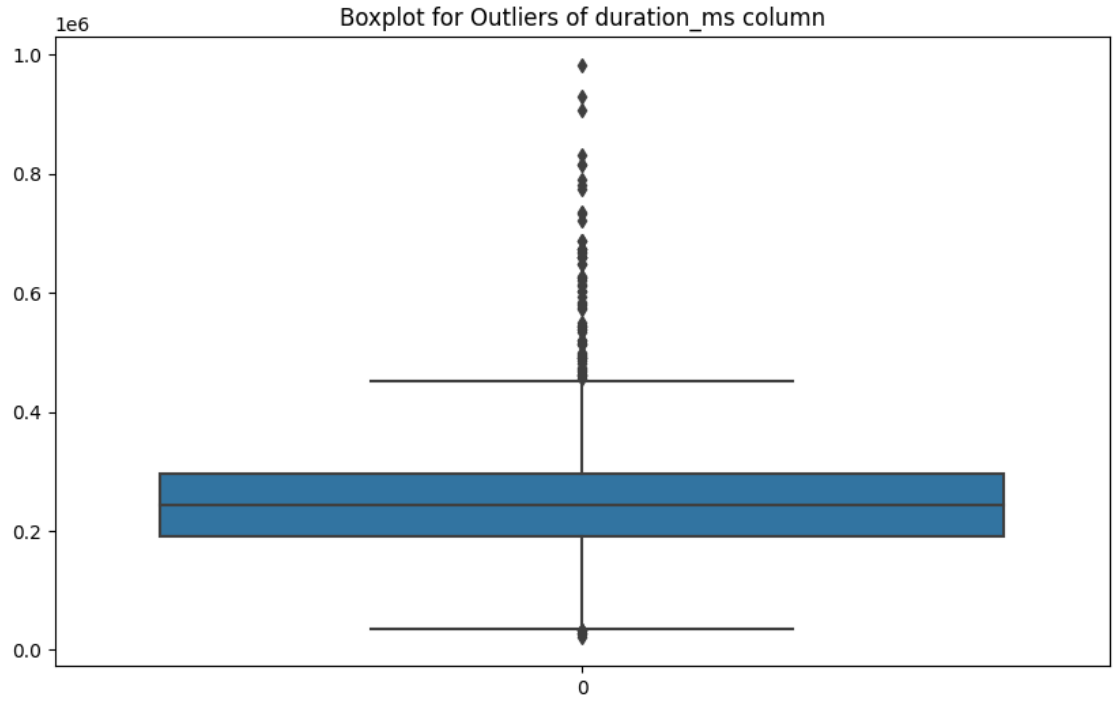
[27]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df_high)
plt.title("Boxplot for Outliers of high values columns")
plt.show()
```



[28]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df['loudness'])
plt.title('Boxplot for Outliers of loudness column')
plt.show()
```



[29]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df['duration_ms'])
plt.title('Boxplot for Outliers of duration_ms column')
plt.show()
```



[30]:
```
df_numeric = pd.concat([df_low,df_high,df_others,df_last], axis=1)
```

[31]:
```
df_numeric.describe()
```

[31]:

	acousticness	danceability	instrumentalness	liveness	speechiness	\
count	1610.000000	1610.000000	1610.000000	1610.00000	1610.000000	
mean	0.250475	0.468860	0.164170	0.49173	0.069512	
std	0.227397	0.141775	0.276249	0.34910	0.051631	
min	0.000009	0.104000	0.000000	0.02190	0.023200	
25%	0.058350	0.362250	0.000219	0.15300	0.036500	
50%	0.183000	0.458000	0.013750	0.37950	0.051200	
75%	0.403750	0.578000	0.179000	0.89375	0.086600	
max	0.994000	0.887000	0.996000	0.99800	0.624000	

	valence	tempo	popularity	loudness	duration_ms	\
count	1610.000000	1610.000000	1610.000000	1610.000000	1610.000000	
mean	0.582165	126.082033	20.788199	-6.971615	257736.488199	

```
std       0.231253    29.233483    12.426859     2.994003  108333.474920
min       0.000000    46.525000     0.000000   -24.408000   21000.000000
25%       0.404250   107.390750    13.000000    -8.982500  190613.000000
50%       0.583000   124.404500    20.000000    -6.523000  243093.000000
75%       0.778000   142.355750    27.000000    -4.608750  295319.750000
max       0.974000   216.304000    80.000000    -1.014000  981866.000000

         Master_id  release_Year
count  1610.000000   1610.000000
mean    804.500000   1991.745963
std     464.911282     22.440296
min       0.000000   1964.000000
25%     402.250000   1970.000000
50%     804.500000   1986.000000
75%    1206.750000   2017.000000
max    1609.000000   2022.000000
```

[32]:
```
# verify duplicates in dataset

duplicatas = df.duplicated().any()

if duplicatas:
    print("There are duplicates in the DataFrame.")
else:
    print("There are no duplicates in the DataFrame.")
```

```
There are no duplicates in the DataFrame.
```

[33]:
```
# data analysis
```

o Use appropriate visualizations to find out which two albums should be recommended to anyone based on the number of popular songs in an album.

what would it be like an album that everyone should like the average would be great ,maybe there are no extraordinary songs among them but in general all the songs should be good.

[34]:
```
count_popularity = df.groupby('album')['popularity'].sum().reset_index()
```

[35]:
```
top_5_album = count_popularity.sort_values(by='popularity',ascending=False).
↪head(5)
```

[36]:
```
print(top_5_album['album'])
```

```
40                            Honk (Deluxe)
75                Tattoo You (Super Deluxe)
36                 Goats Head Soup (Deluxe)
62              Some Girls (Deluxe Version)
28    Exile On Main Street (Deluxe Version)
```

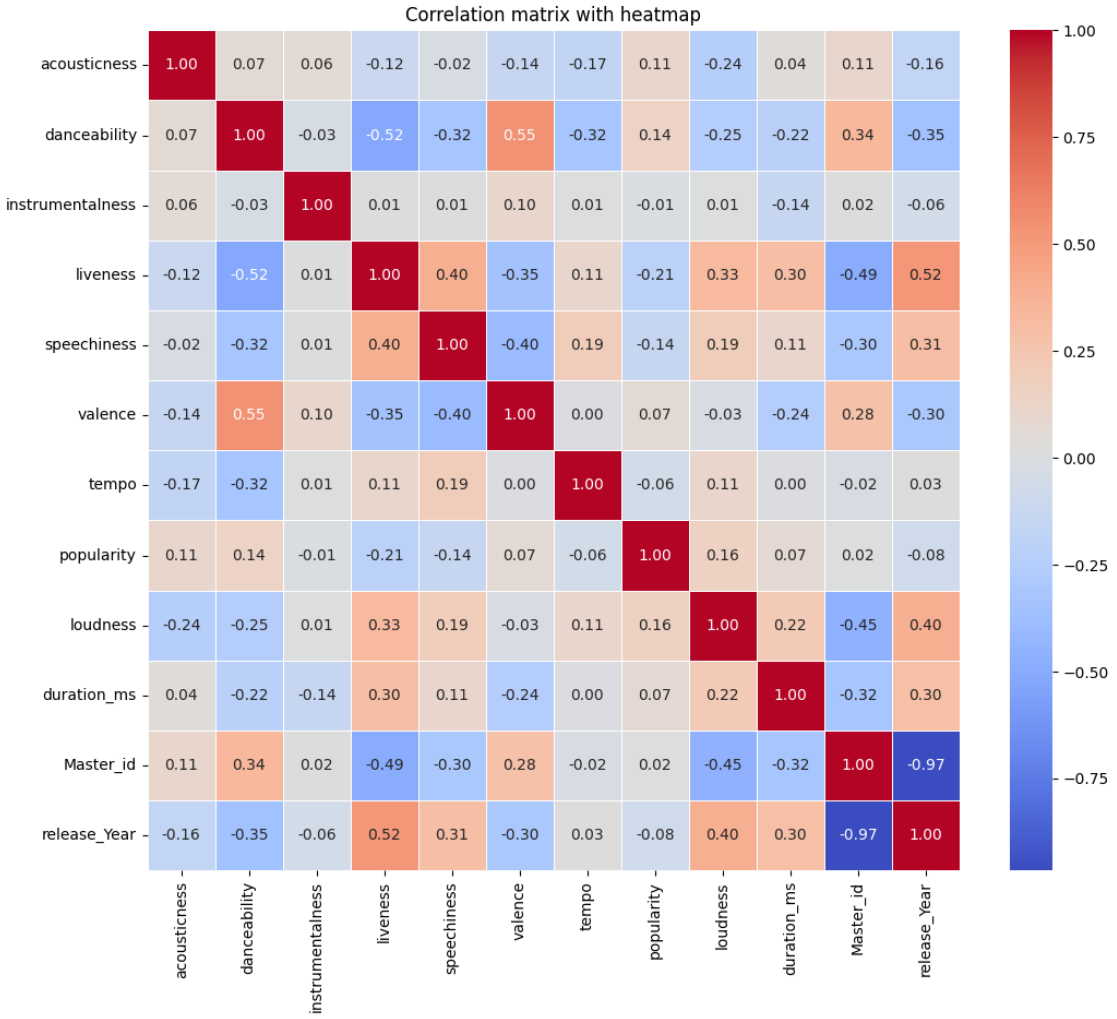
```
Name: album, dtype: object
```

1.Honk (Deluxe) ## 2.Tattoo You (Super Deluxe)
3.Goats Head Soup (Deluxe)
4.Some Girls (Deluxe Version) ## 5.Exile On Main Street (Deluxe Version)

1 Perform exploratory data analysis to dive deeper into different features of songs and identify the pattern.

[37]:
```
# Let's start by looking at the relationship between numerical variables

correlation_matrix = df_numeric.corr()
```

[38]:
```
plt.figure(figsize=(12,10))
sns.heatmap(data=correlation_matrix,annot=True,cmap='coolwarm',linewidths=0.
↪5,fmt=".2f")
plt.title('Correlation matrix with heatmap')
plt.show()
```



In this correlation matrix, unfortunately, I can't see much of what can make a song more or less popular.

but we have a correlation regarding valance and danceability, which was already expected, happiest songs are the most danceable.

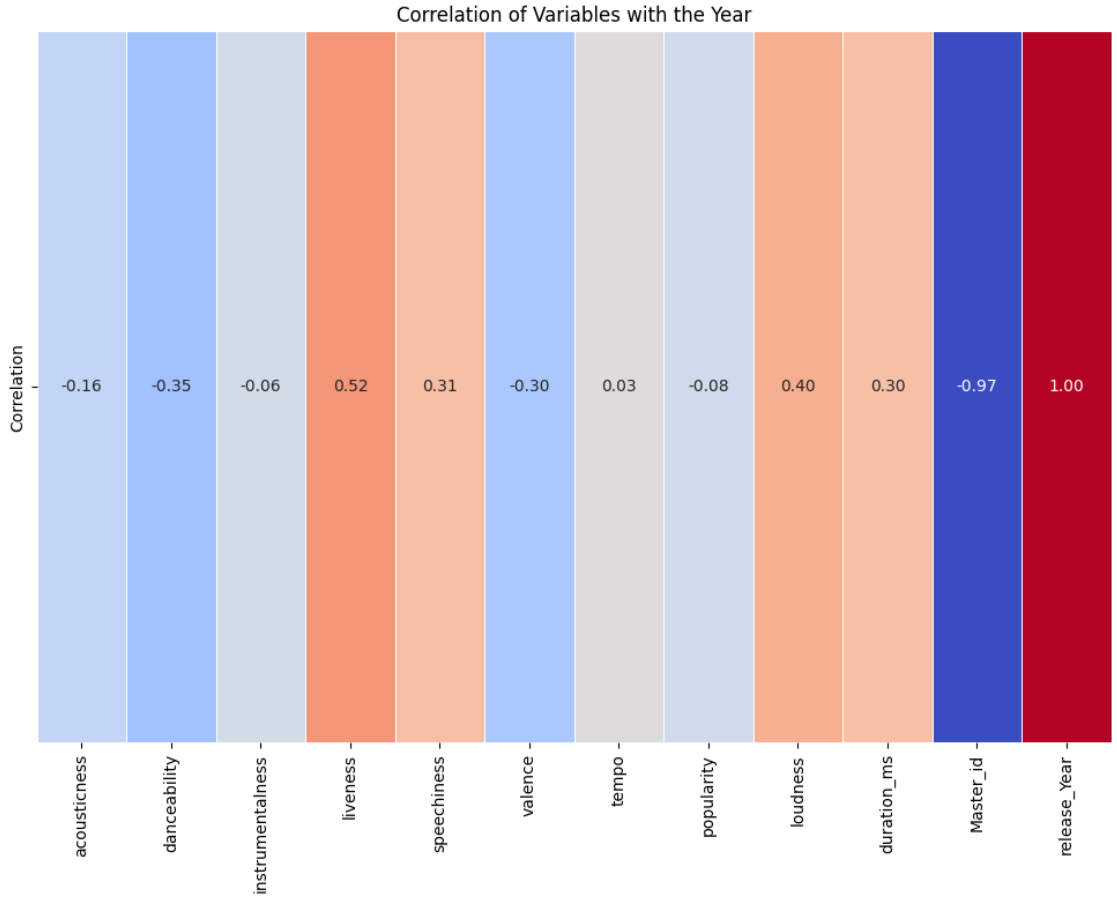
- valance-danceability
- speechiness-liveness

2 Discover how a song's popularity relates to various factors and how this has changed over time.

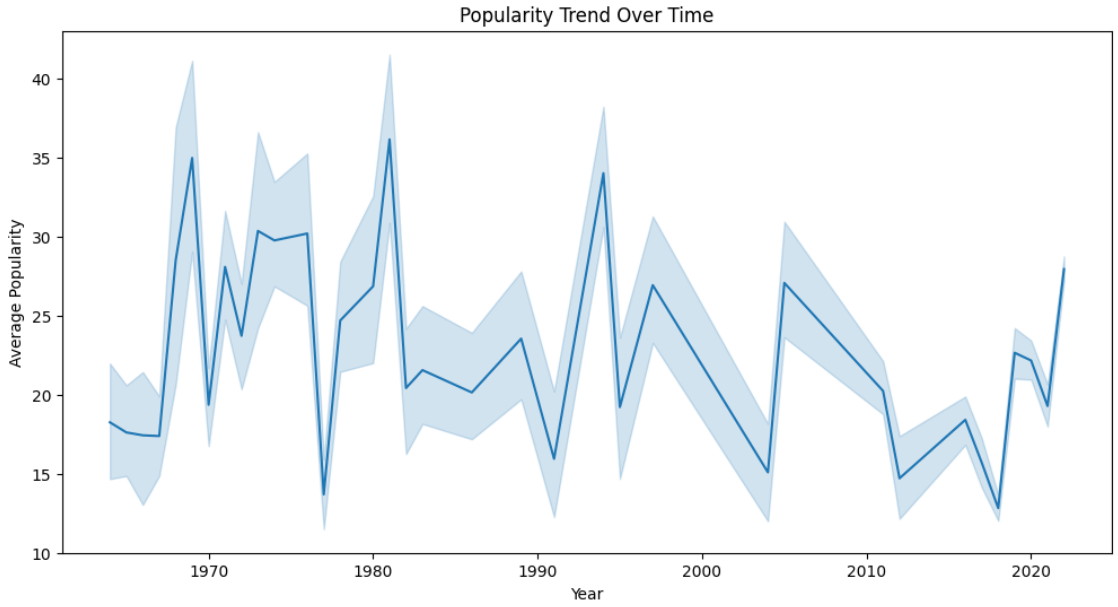
[39]:
```
# correlation of all variables with the year of release


Year_corr = df_numeric.corr()['release_Year'].values
print(Year_corr)
```

```
[-0.16119325 -0.353826   -0.06296395  0.51830649  0.30688814 -0.30066067
  0.0308757  -0.08164804  0.39927011  0.30006646 -0.96539861  1.        ]
```

[40]:
```
# heatmap for correlation of all numeric varibles with release_Year

Year_corr_df = pd.DataFrame(Year_corr, index=df_numeric.columns,␣
 ↪columns=['Correlation'])


plt.figure(figsize=(12, 8))
sns.heatmap(data=Year_corr_df.T, annot=True, cmap="coolwarm", fmt='.2f',␣
 ↪linewidths=0.5, cbar=False)
plt.title('Correlation of Variables with the Year')
plt.show()
```



[41]:
```
plt.figure(figsize=(12, 6))
sns.lineplot(data=df, x='release_Year', y='popularity')
plt.title('Popularity Trend Over Time')
plt.xlabel('Year')
plt.ylabel('Average Popularity')
plt.show()
```



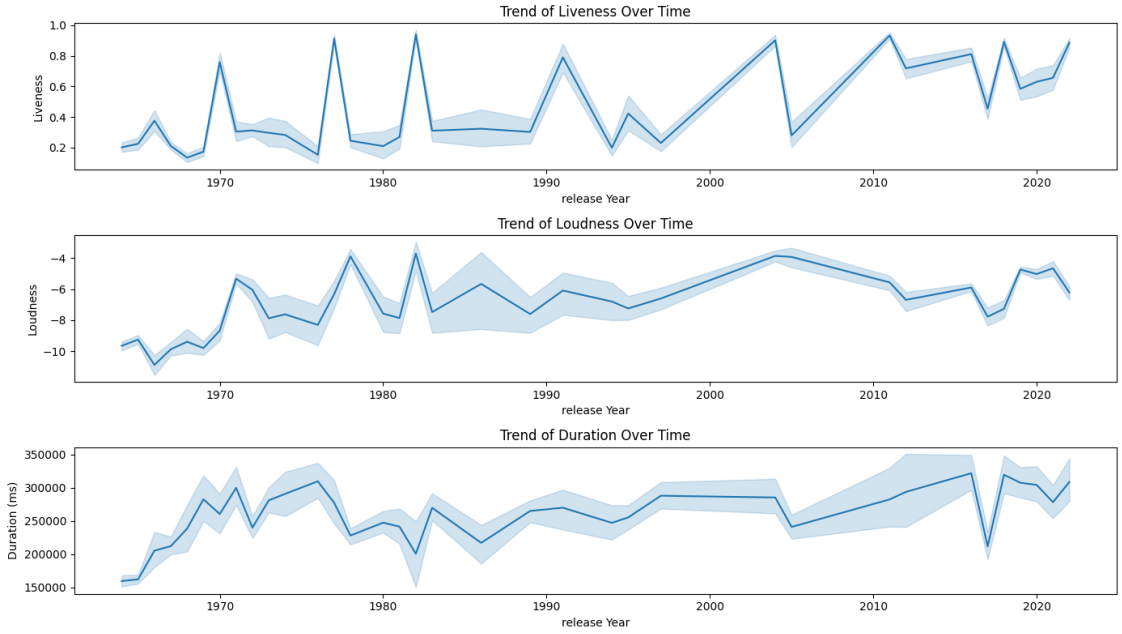
[42]:
```
mean_music_popularity_per_year = df.groupby(df['release_Year'])['popularity'].
↪mean().nlargest(5)
```

[43]:
```
print(mean_music_popularity_per_year)
```

```
release_Year
1981    36.136364
1969    34.962963
1994    34.000000
1973    30.350000
1976    30.187500
Name: popularity, dtype: float64
```

[44]:
```
plt.figure(figsize=(14, 8))

# Liveness over time
plt.subplot(3, 1, 1)
sns.lineplot(data=df_numeric, x='release_Year', y='liveness')
plt.title('Trend of Liveness Over Time')
plt.xlabel('release Year')
plt.ylabel('Liveness')

# Loudness over time
plt.subplot(3, 1, 2)
sns.lineplot(data=df_numeric, x='release_Year', y='loudness')
plt.title('Trend of Loudness Over Time')
plt.xlabel('release Year')
```

```
plt.ylabel('Loudness')

# Duration over time
plt.subplot(3, 1, 3)
sns.lineplot(data=df_numeric, x='release_Year', y='duration_ms')
plt.title('Trend of Duration Over Time')
plt.xlabel('release Year')
plt.ylabel('Duration (ms)')

plt.tight_layout()
plt.show()
```



From my studies, I concluded that perhaps music is no longer at its peak but more balanced as it was in the 70s to 90s. I believe that with the advancement of other technologies, people can spend their time doing other things like watching streams or playing games, etc.

Also how we can see over time the 'liveness', 'loudness' and 'duration_ms' which indicates the entry perhaps of podcasts.

3 Comment on the importance of dimensionality reduction techniques, share your ideas and explain your observations.

Dimensionality reduction is crucial for dealing with the "curse of dimensionality", making data analysis more efficient and preventing overfitting. These techniques simplify models, improve interpretability, and make complex patterns easier to visualize. By focusing on the most relevant features, they contribute to modeling effectiveness, reduce noise in data, and are essential for

high-dimensional datasets.

It is obvious that with the increase in technology also comes some problems with it, such as the exponential increase in data, but these problems can be solved with professionals like us who are prepared to process the data as much as possible, to the point of leaving you with only data that really matters to be studied and analyzed and of course with the increase in data also comes a good thing that is the increase in precision in decision making and thus being able to use this data to train machines to operate on gigantic data which would perhaps take a human a few hours to do. can now be done in minutes perhaps seconds and help us make accurate decisions

4 Perform Cluster Analysis:

- Identify the right number of clusters

[45]:
```
# List to store intra-cluster variation
inertia = []

# Test different values for the number of clusters
for n_clusters in range(1, 11):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    kmeans.fit(df_numeric)
    inertia.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
```

```
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
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  warnings.warn(
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  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```
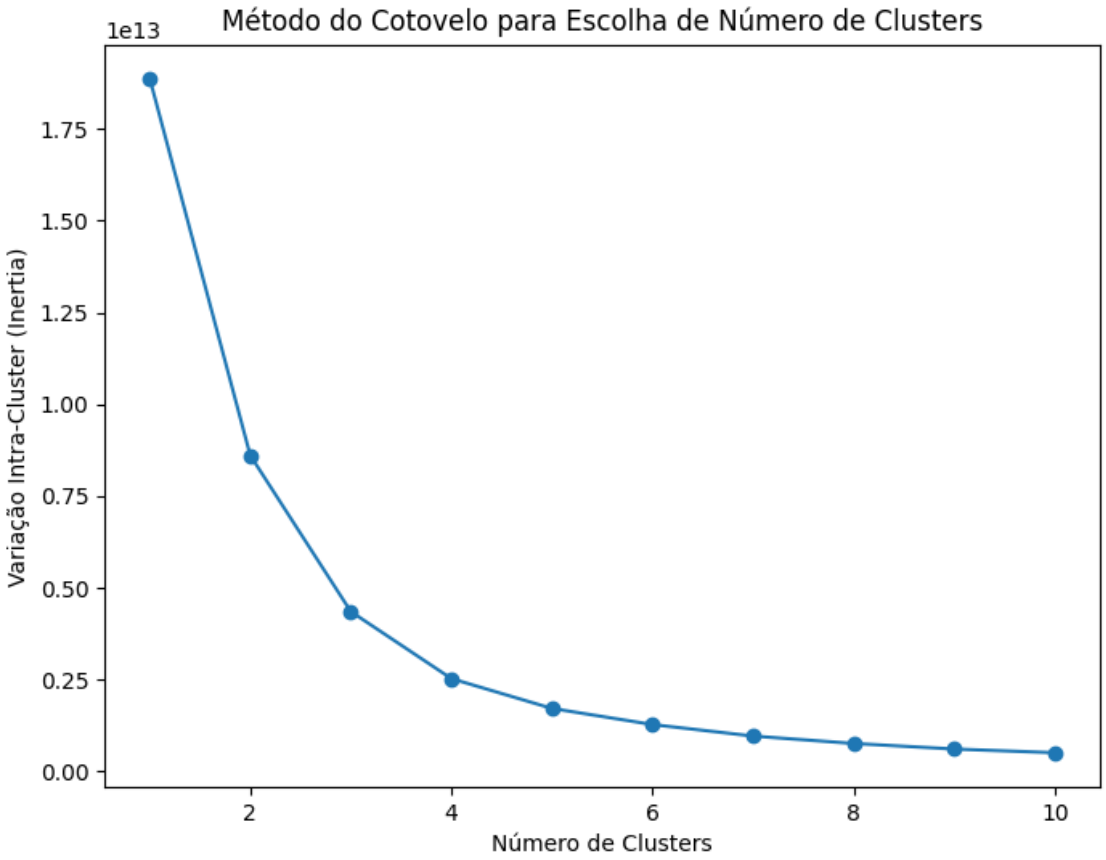

[46]:

```python
# Plot the elbow method graph

plt.figure(figsize=(8, 6))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Método do Cotovelo para Escolha de Número de Clusters')
plt.xlabel('Número de Clusters')
plt.ylabel('Variação Intra-Cluster (Inertia)')
plt.show()
```



Number of clusters - 3

[48]:
```
n_clusters = 3

# relevant characteristics for clustering
X = df[['energy', 'danceability']]

kmeans = KMeans(n_clusters=n_clusters, random_state=42)
df['cluster'] = kmeans.fit_predict(X)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[49]:
```
print(df[['energy', 'danceability', 'cluster']])
```

```
      energy  danceability  cluster
0      0.993         0.463        0
1      0.965         0.326        0
2      0.969         0.386        0
```

```
3       0.985          0.369         0
4       0.969          0.303         0
…       …              …       …
1605    0.932          0.466         0
1606    0.706          0.509         1
1607    0.774          0.790         1
1608    0.546          0.700         2
1609    0.934          0.727         1

[1610 rows x 3 columns]
```

for me ‘danceability’ and ‘energy’ are the most relevant characteristics for us to be able to create cluster divisions and be able to recommend similar music to the user