ML Project 3 - Creating Cohorts of Songs

February 13, 2023

1 ML Project 3 - Creating Cohorts of Songs

1.0.1 As a data scientist, you should perform exploratory data analysis and perform cluster analysis to create cohorts of songs. The goal is to gain a better understanding of the various factors that contribute to creating a cohort of songs.

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

2 EDA - Exploratory Data Analysis

[2]:
```
df = pd.read_excel('1673873388_rolling_stones_spotify.xlsx')
```

[3]:
```
df
```

[3]:
```
      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          Donâ€ 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]
```

[4]:
```
df = df.drop(['Unnamed: 0'],axis=1)
```

[5]:
```
df.shape
```

[5]:
```
(1610, 17)
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1610 entries, 0 to 1609
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              1610 non-null   object
 1   album             1610 non-null   object
 2   release_date      1610 non-null   datetime64[ns]
 3   track_number      1610 non-null   int64
 4   id                1610 non-null   object
 5   uri               1610 non-null   object
 6   acousticness      1610 non-null   float64
 7   danceability      1610 non-null   float64
 8   energy            1610 non-null   float64
 9   instrumentalness  1610 non-null   float64
 10  liveness          1610 non-null   float64
 11  loudness          1610 non-null   float64
 12  speechiness       1610 non-null   float64
 13  tempo             1610 non-null   float64
 14  valence           1610 non-null   float64
 15  popularity        1610 non-null   int64
 16  duration_ms       1610 non-null   int64
dtypes: datetime64[ns](1), float64(9), int64(3), object(4)
memory usage: 214.0+ KB
```

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

[7]:

	track_number	acousticness	danceability	energy	\
count	1610.000000	1610.000000	1610.000000	1610.000000	
mean	8.613665	0.250475	0.468860	0.792352	
std	6.560220	0.227397	0.141775	0.179886	
min	1.000000	0.000009	0.104000	0.141000	
25%	4.000000	0.058350	0.362250	0.674000	
50%	7.000000	0.183000	0.458000	0.848500	
75%	11.000000	0.403750	0.578000	0.945000	
max	47.000000	0.994000	0.887000	0.999000	

	instrumentalness	liveness	loudness	speechiness	tempo	\
count	1610.000000	1610.00000	1610.000000	1610.000000	1610.000000	
mean	0.164170	0.49173	-6.971615	0.069512	126.082033	

```
std            0.276249     0.34910     2.994003     0.051631    29.233483
min            0.000000     0.02190   -24.408000     0.023200    46.525000
25%            0.000219     0.15300    -8.982500     0.036500   107.390750
50%            0.013750     0.37950    -6.523000     0.051200   124.404500
75%            0.179000     0.89375    -4.608750     0.086600   142.355750
max            0.996000     0.99800    -1.014000     0.624000   216.304000

            valence   popularity    duration_ms
count  1610.000000  1610.000000    1610.000000
mean      0.582165    20.788199  257736.488199
std       0.231253    12.426859  108333.474920
min       0.000000     0.000000   21000.000000
25%       0.404250    13.000000  190613.000000
50%       0.583000    20.000000  243093.000000
75%       0.778000    27.000000  295319.750000
max       0.974000    80.000000  981866.000000
```

[8]:
```
df.isnull().sum()
```

[8]:
```
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
```

[9]:
```
df.columns
```

[9]:
```
Index(['name', 'album', 'release_date', 'track_number', 'id', 'uri',
       'acousticness', 'danceability', 'energy', 'instrumentalness',
       'liveness', 'loudness', 'speechiness', 'tempo', 'valence', 'popularity',
       'duration_ms'],
      dtype='object')
```

[10]:
```
df.dtypes
```

[10]:
```
name                        object
album                       object
release_date        datetime64[ns]
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
```

[11]:
```
df
```

[11]:

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

      track_number                      id  \
0                1  2IEkywLJ4ykbhi1yRQvmsT
1                2  6GVgVJBKkGJoRfarYRvGTU
2                3  1Lu761pZ0dBTGpzxaQoZNW
3                4  1agTQzOTUnGNggyckEqiDH
4                5  7piGJR8YndQBQWVXv6KtQw
…              …                       …
1605             8  0817M5UpRnffGl0FyuRiQZ
1606             9  3JZllQBsTM6WwoJdzFDLhx
1607            10  0t2qvfSBQ3Y08lzRRoVTdb
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
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4     spotify:track:7piGJR8YndQBQWVXv6KtQw        0.4000         0.303
…                                      …             …            …
1605  spotify:track:08l7M5UpRnffGlOFyuRiQZ        0.1570         0.466
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1607  spotify:track:0t2qvfSBQ3Y08lzRRoVTdb        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
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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
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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 17 columns]
```
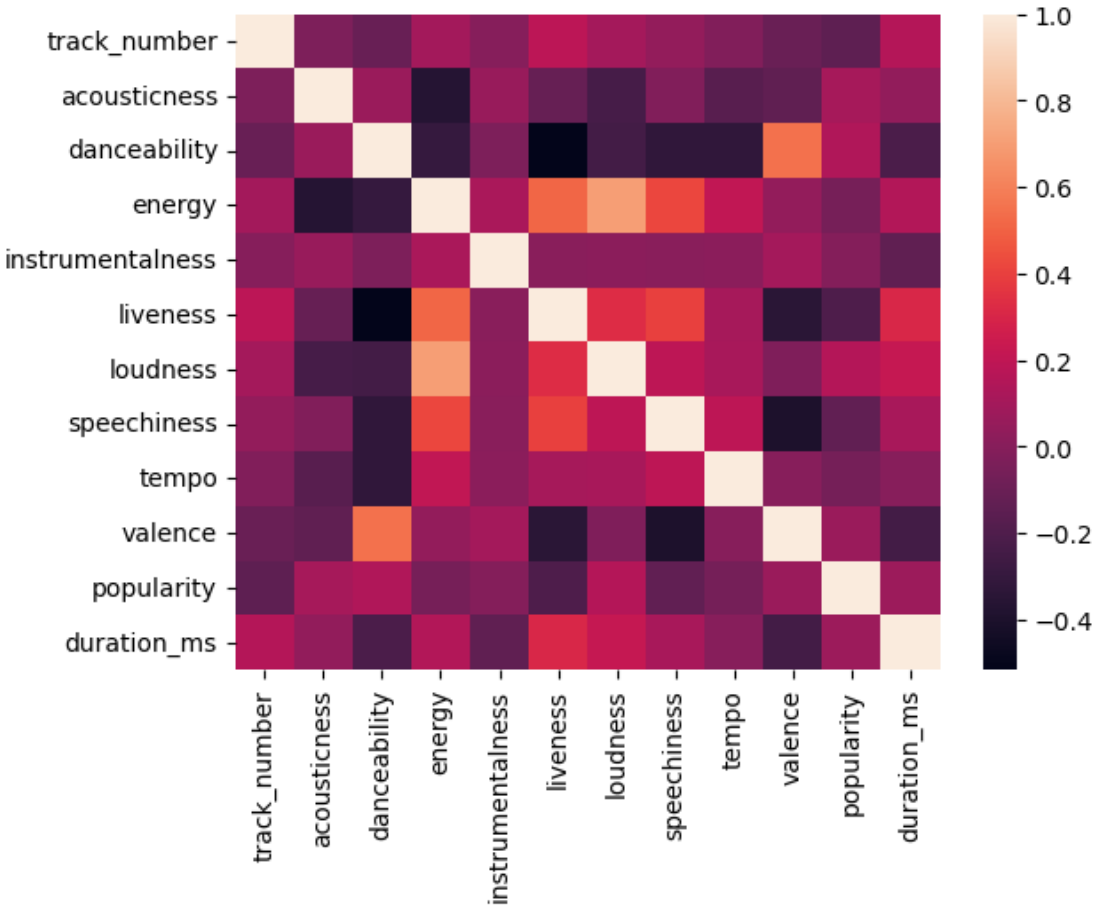

[12]:
```
df.corr()
```

[12]:
```
                track_number  acousticness  danceability    energy  \
track_number        1.000000     -0.035675     -0.112004  0.096314
acousticness       -0.035675      1.000000      0.070017 -0.363819
danceability       -0.112004      0.070017      1.000000 -0.300536
```

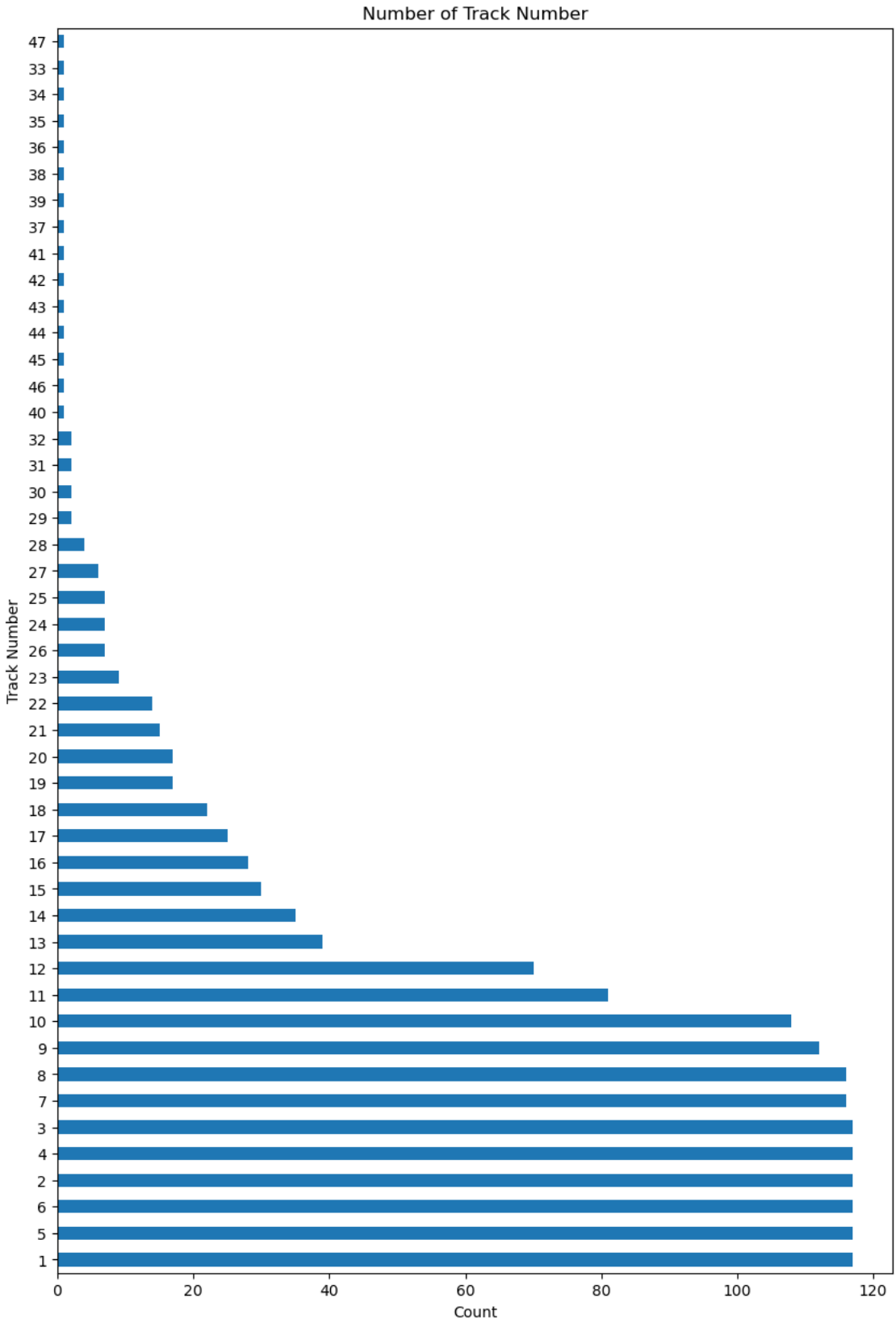
```
energy                0.096314     -0.363819     -0.300536  1.000000
instrumentalness     -0.002772      0.061403     -0.031812  0.120261
liveness              0.188351     -0.117739     -0.516387  0.511188
loudness              0.100835     -0.237083     -0.249406  0.698039
speechiness           0.040617     -0.021774     -0.322684  0.417214
tempo                -0.023934     -0.171003     -0.324398  0.201885
valence              -0.104567     -0.138803      0.546210  0.046217
popularity           -0.145115      0.108046      0.141205 -0.057272
duration_ms           0.156455      0.039128     -0.220045  0.148876

                  instrumentalness  liveness  loudness  speechiness     tempo  \
track_number              -0.002772  0.188351  0.100835     0.040617 -0.023934
acousticness               0.061403 -0.117739 -0.237083    -0.021774 -0.171003
danceability              -0.031812 -0.516387 -0.249406    -0.322684 -0.324398
energy                     0.120261  0.511188  0.698039     0.417214  0.201885
instrumentalness           1.000000  0.008873  0.012524     0.009586  0.010961
liveness                   0.008873  1.000000  0.327036     0.400018  0.108855
loudness                   0.012524  0.327036  1.000000     0.189904  0.112837
speechiness                0.009586  0.400018  0.189904     1.000000  0.192687
tempo                      0.010961  0.108855  0.112837     0.192687  1.000000
valence                    0.103480 -0.347451 -0.027571    -0.399751  0.000558
popularity                -0.010612 -0.205845  0.156323    -0.136745 -0.061061
duration_ms               -0.137599  0.304735  0.221558     0.114546  0.001465

                   valence  popularity  duration_ms
track_number     -0.104567   -0.145115     0.156455
acousticness     -0.138803    0.108046     0.039128
danceability      0.546210    0.141205    -0.220045
energy            0.046217   -0.057272     0.148876
instrumentalness  0.103480   -0.010612    -0.137599
liveness         -0.347451   -0.205845     0.304735
loudness         -0.027571    0.156323     0.221558
speechiness      -0.399751   -0.136745     0.114546
tempo             0.000558   -0.061061     0.001465
valence           1.000000    0.065333    -0.244833
popularity        0.065333    1.000000     0.074102
duration_ms      -0.244833    0.074102     1.000000
```

[13]:
```
sns.heatmap(df.corr())
```

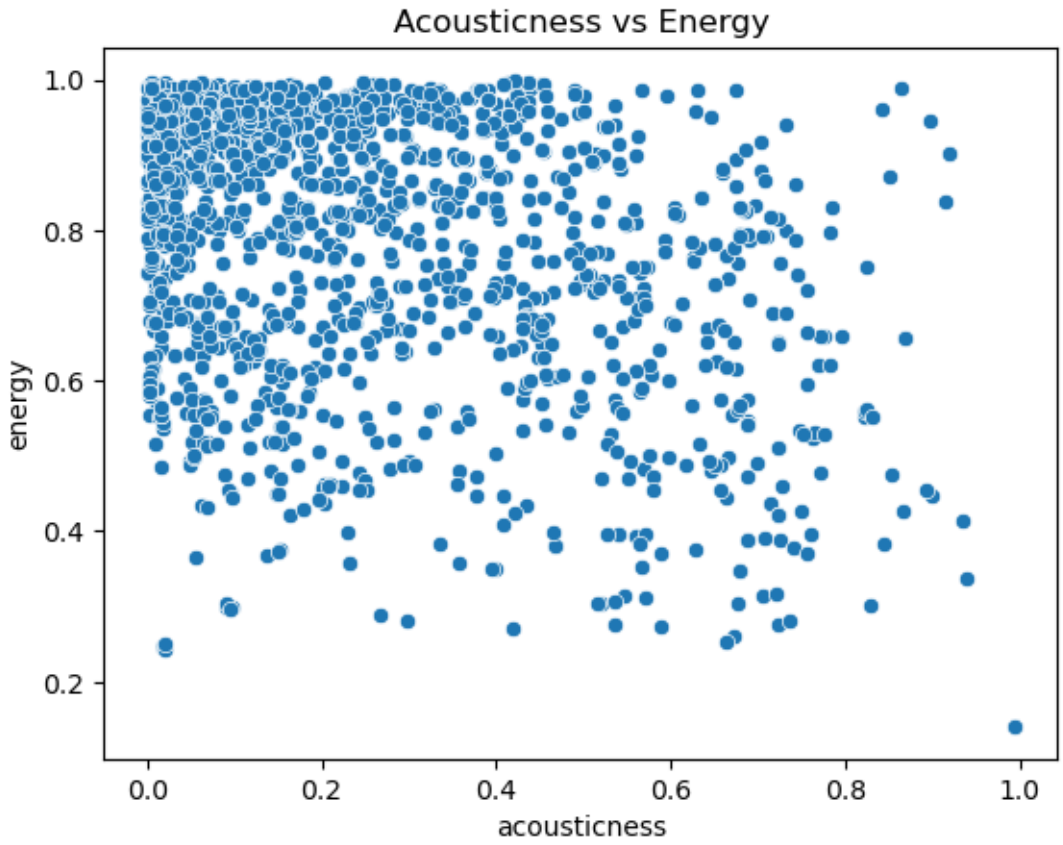
[13]: <AxesSubplot:>



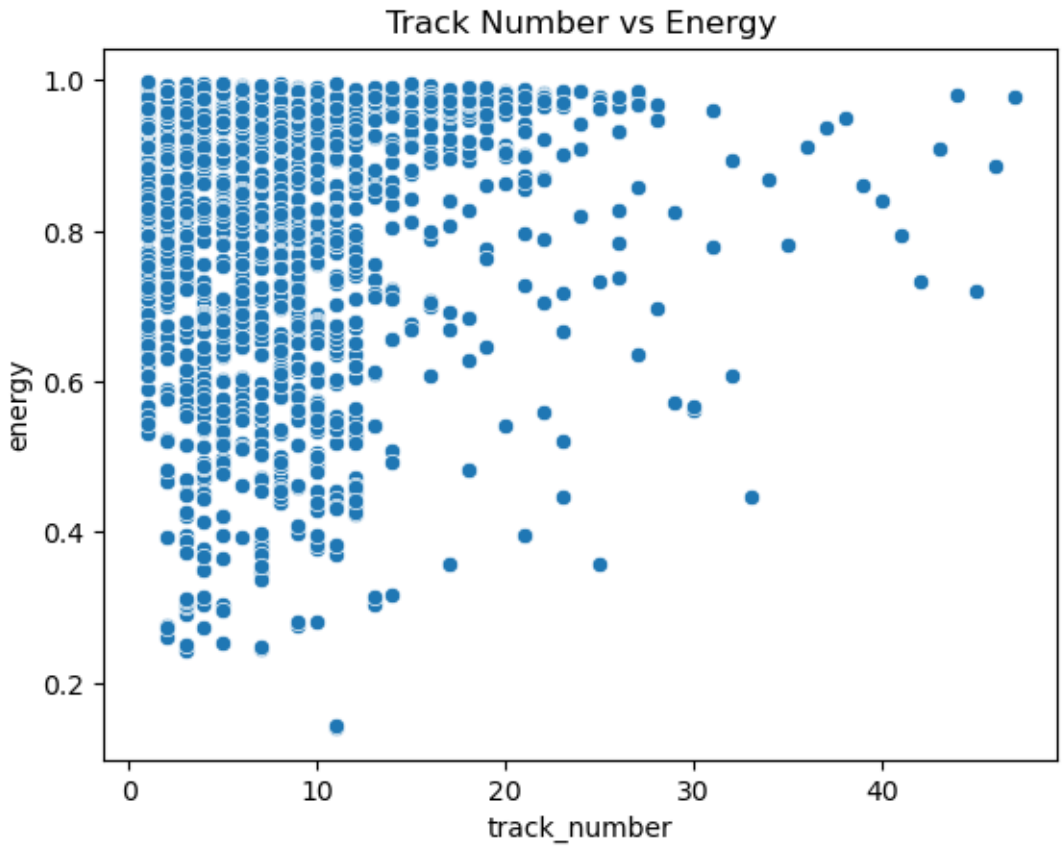
[14]:
```
df['track_number'].value_counts().plot(kind='barh',figsize=(10,15))
plt.xlabel('Count')
plt.ylabel('Track Number')
plt.title('Number of Track Number')
plt.show()
```


Number of Track Number
Track Number
47
33
34
35
36
38
39
37
41
42
43
44
45
46
40
32
31
30
29
28
27
25
24
26
23
22
21
20
19
18
17
16
15
14
13
12
11
10
9
8
7
3
4
2
6
5
1
0
20
40
60
80
100
120
Count

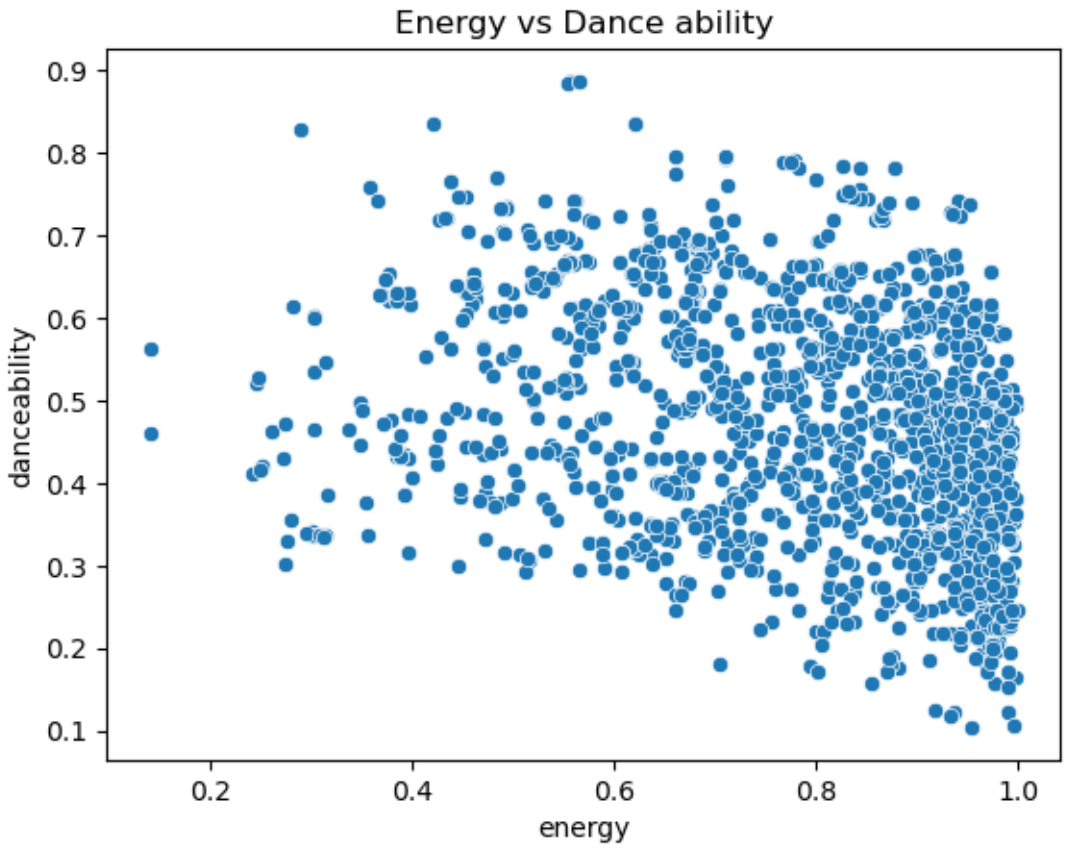
[15]:
```
sns.scatterplot(x=df['acousticness'],y=df['energy'])
plt.title('Acousticness vs Energy')
plt.show()
```



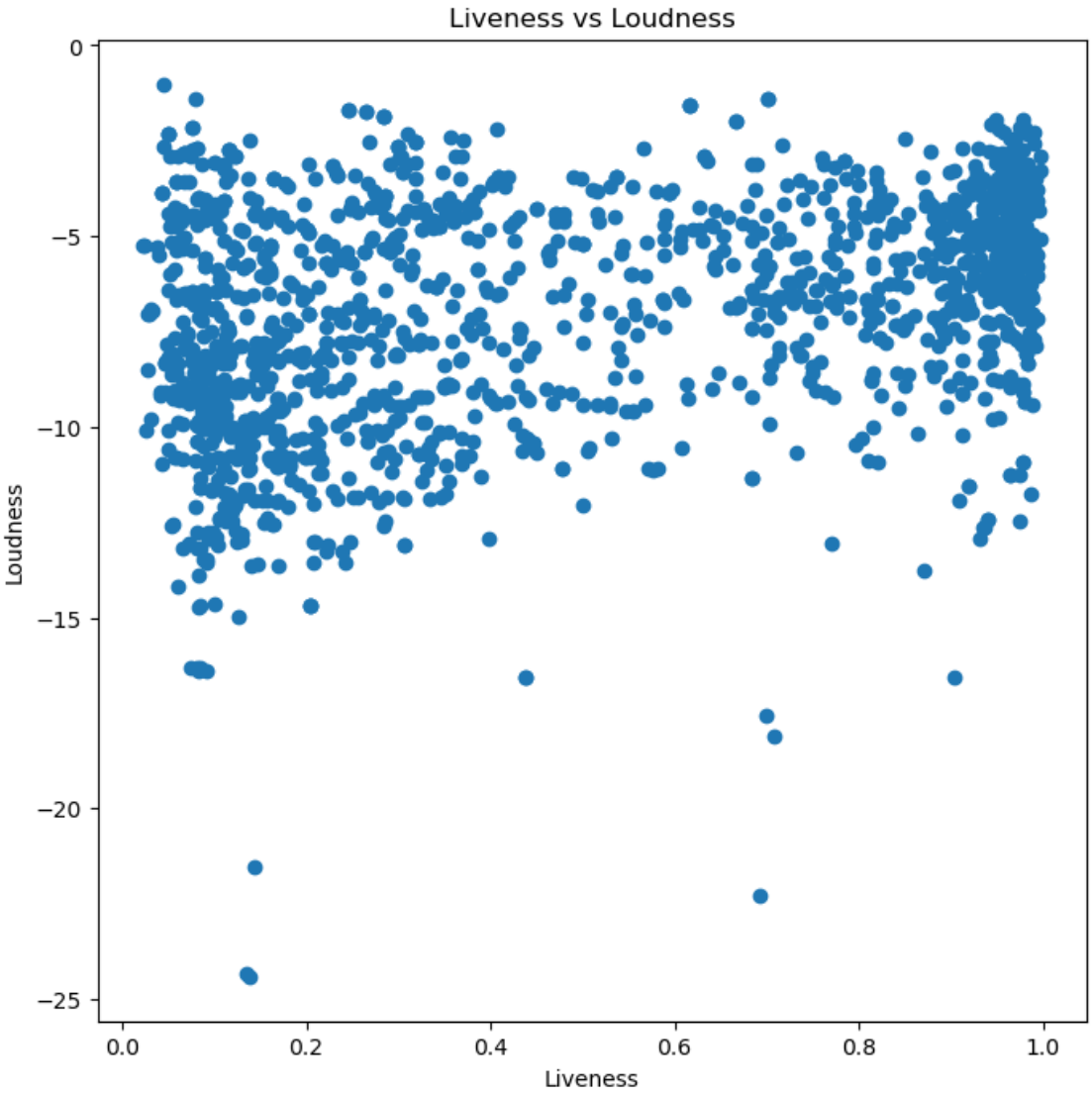
[16]:
```
sns.scatterplot(x=df['track_number'],y=df['energy'])
plt.title('Track Number vs Energy')
plt.show()
```



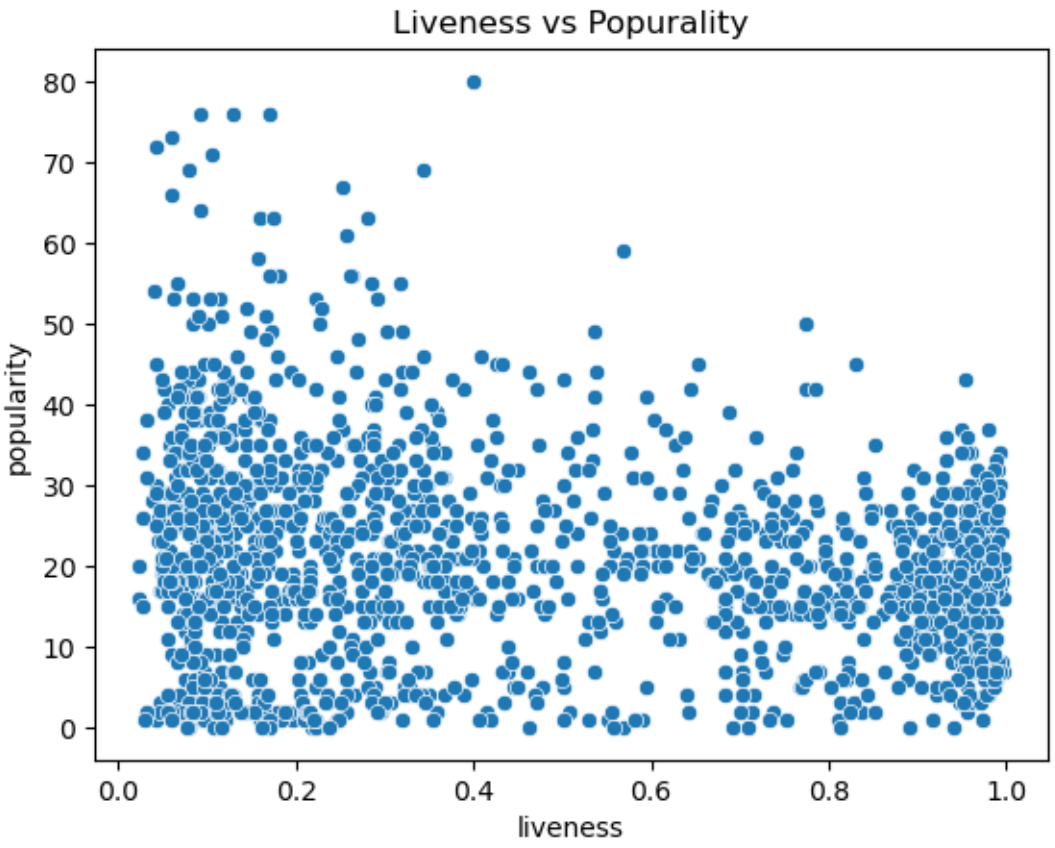
[17]:
```
sns.scatterplot(x=df['energy'],y=df['danceability'])
plt.title('Energy vs Dance ability')
plt.show()
```



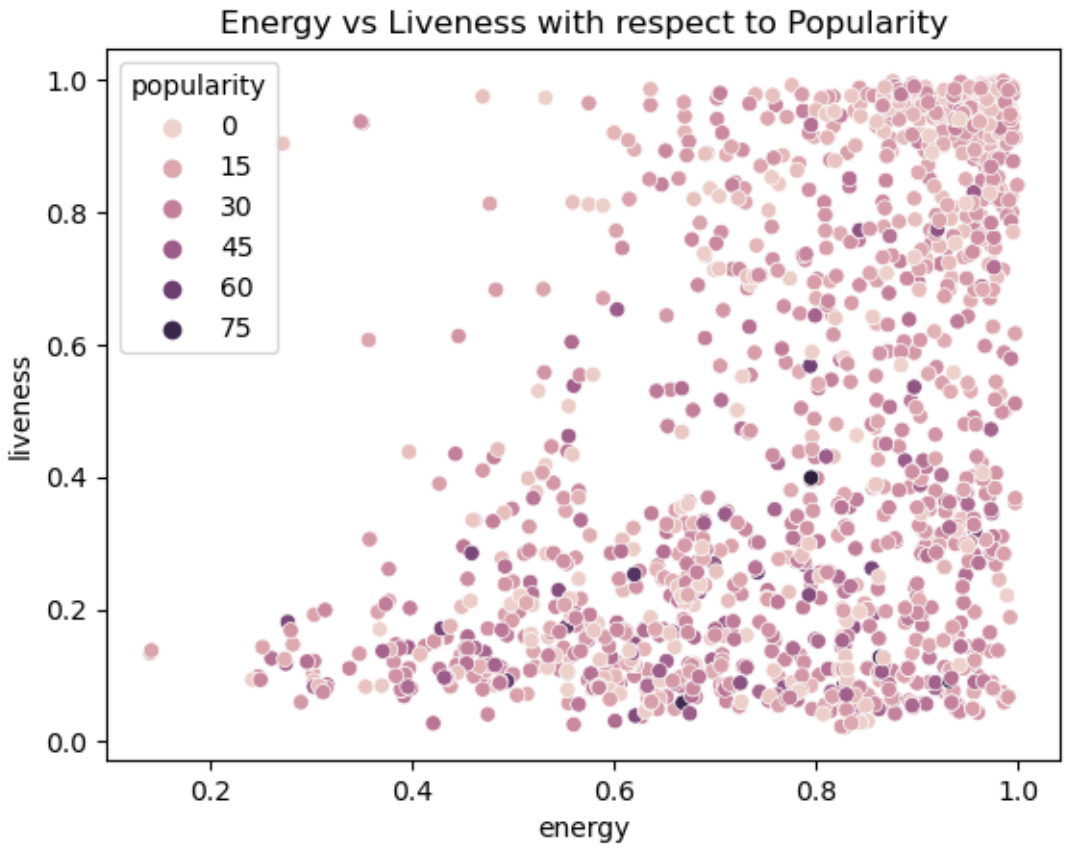
[18]:
```
plt.figure(figsize=(8,8),dpi=100)
plt.scatter(x=df['liveness'],y=df['loudness'])
plt.xlabel('Liveness')
plt.ylabel('Loudness')
plt.title('Liveness vs Loudness')
plt.show()
```



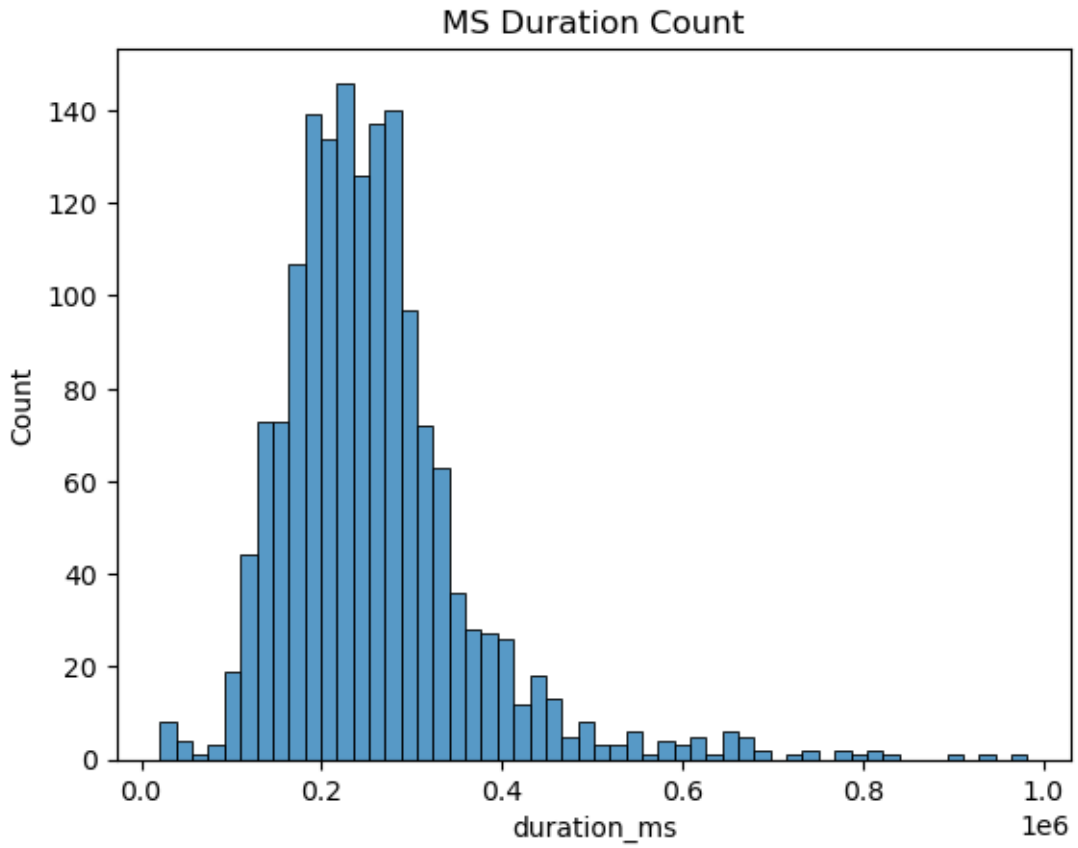
[19]:
```
sns.scatterplot(x=df['liveness'],y=df['popularity'])
plt.title('Liveness vs Popurality')
plt.show()
```



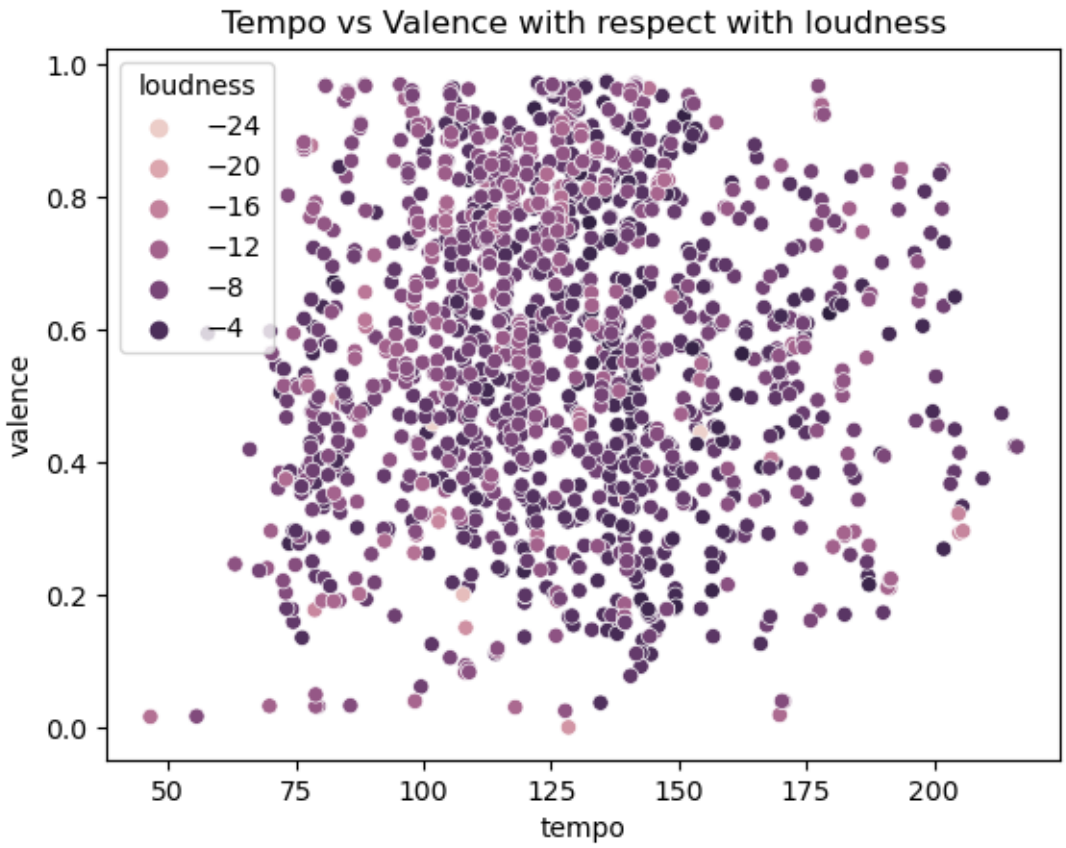
[20]:
```
sns.scatterplot(x=df['energy'],y=df['liveness'],hue=df['popularity'])
plt.title('Energy vs Liveness with respect to Popularity')
plt.show()
```



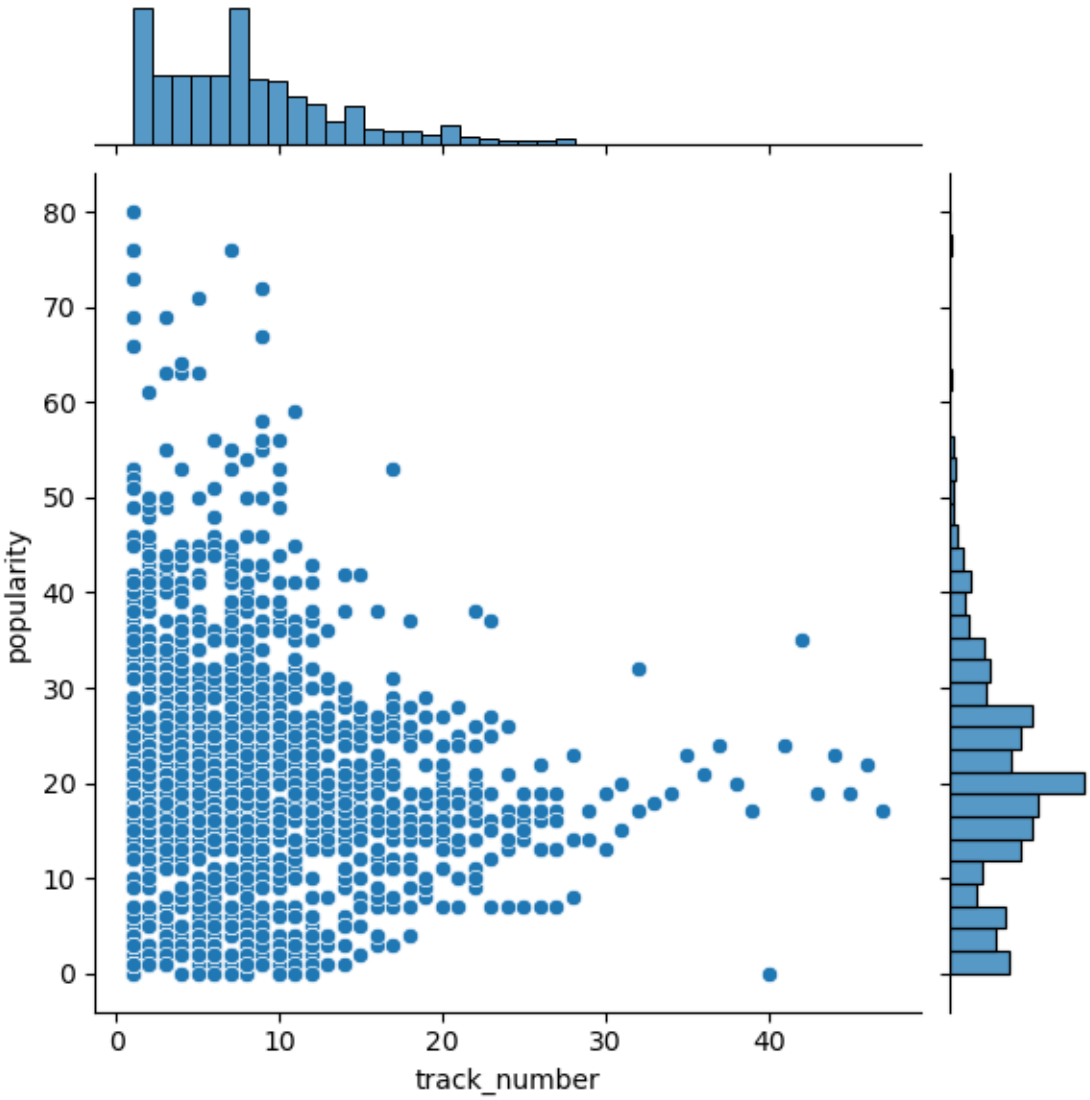
[21]:
```
sns.histplot(df['duration_ms'])
plt.title('MS Duration Count')
plt.show()
```



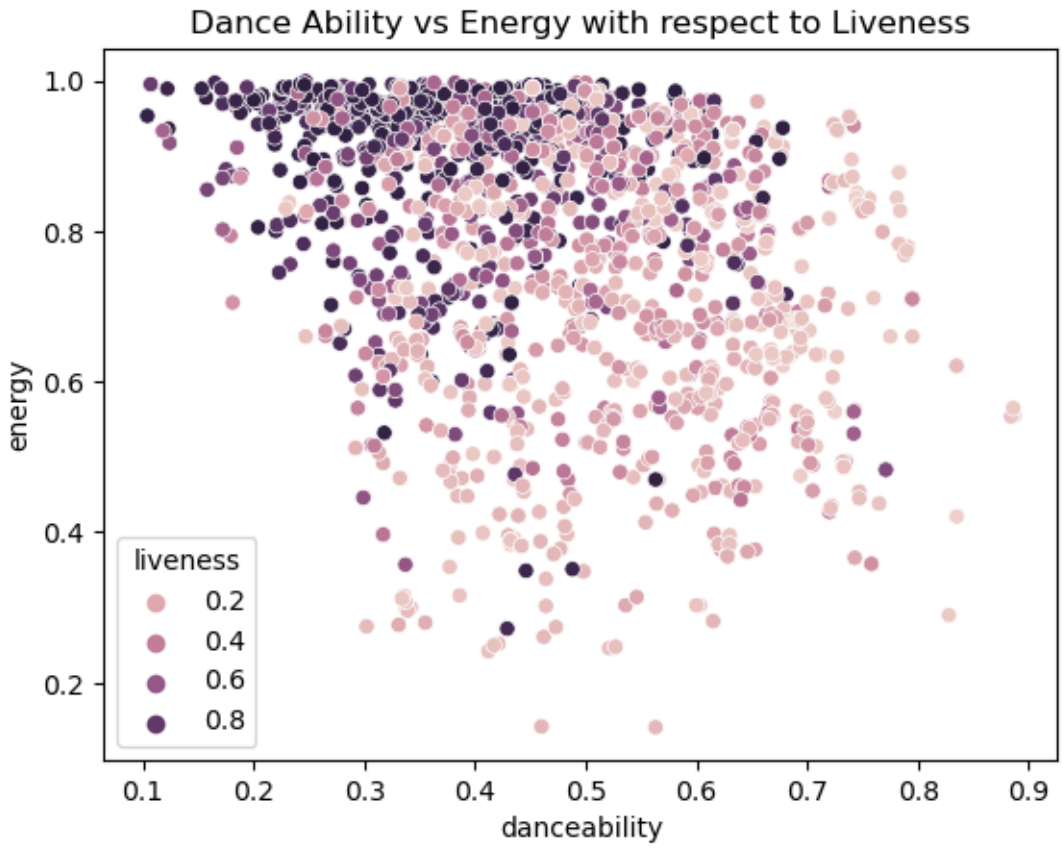
[22]:
```
sns.scatterplot(x=df['tempo'],y=df['valence'],hue=df['loudness'])
plt.title('Tempo vs Valence with respect with loudness')
plt.show()
```



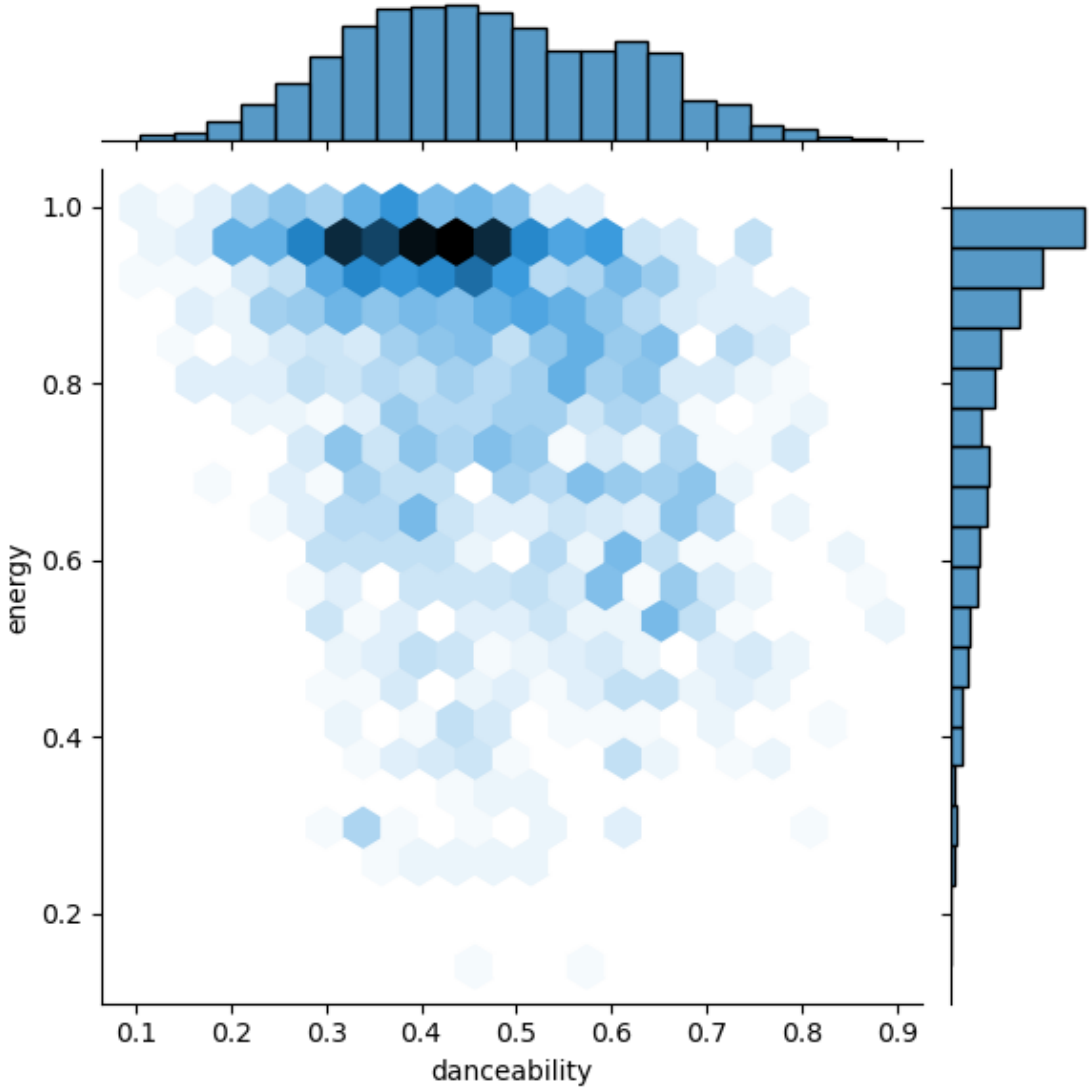
[23]:
```
sns.jointplot(x=df['track_number'],y=df['popularity'])
plt.show()
```



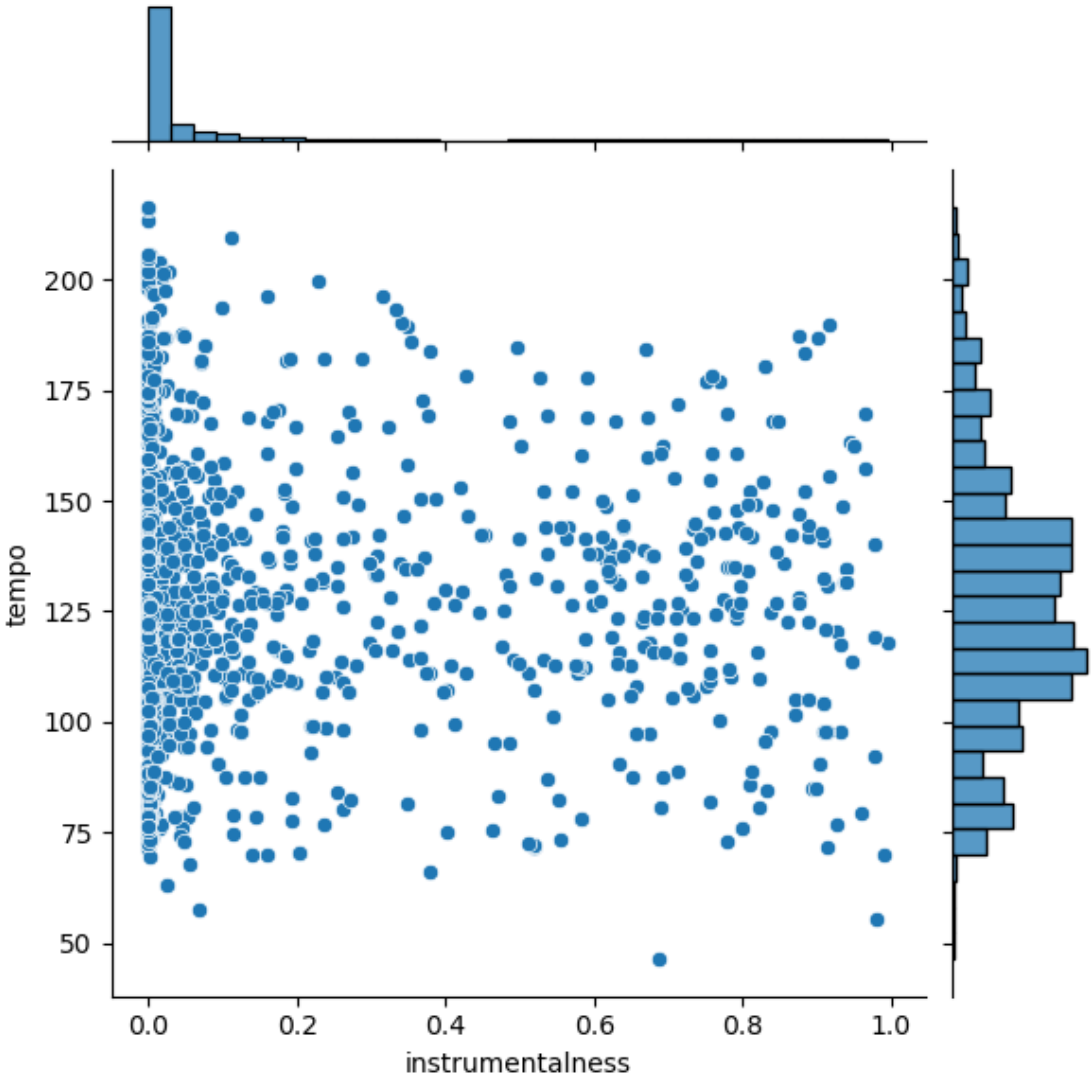
[24]:
```
sns.scatterplot(x=df['danceability'],y=df['energy'],hue=df['liveness'])
plt.title('Dance Ability vs Energy with respect to Liveness')
plt.show()
```



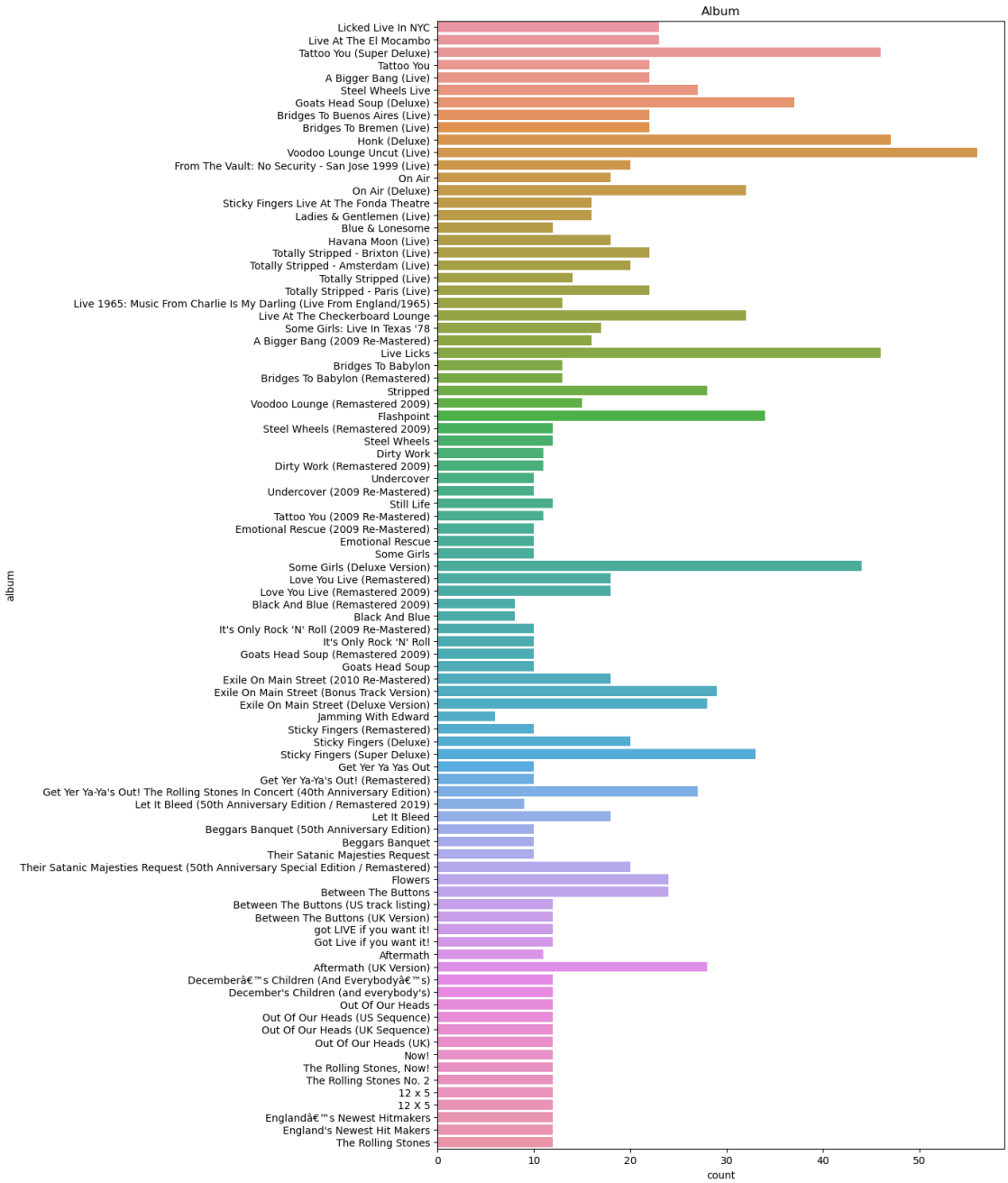
[25]:
```
sns.jointplot(x=df['danceability'],y=df['energy'],kind='hex')
plt.show()
```



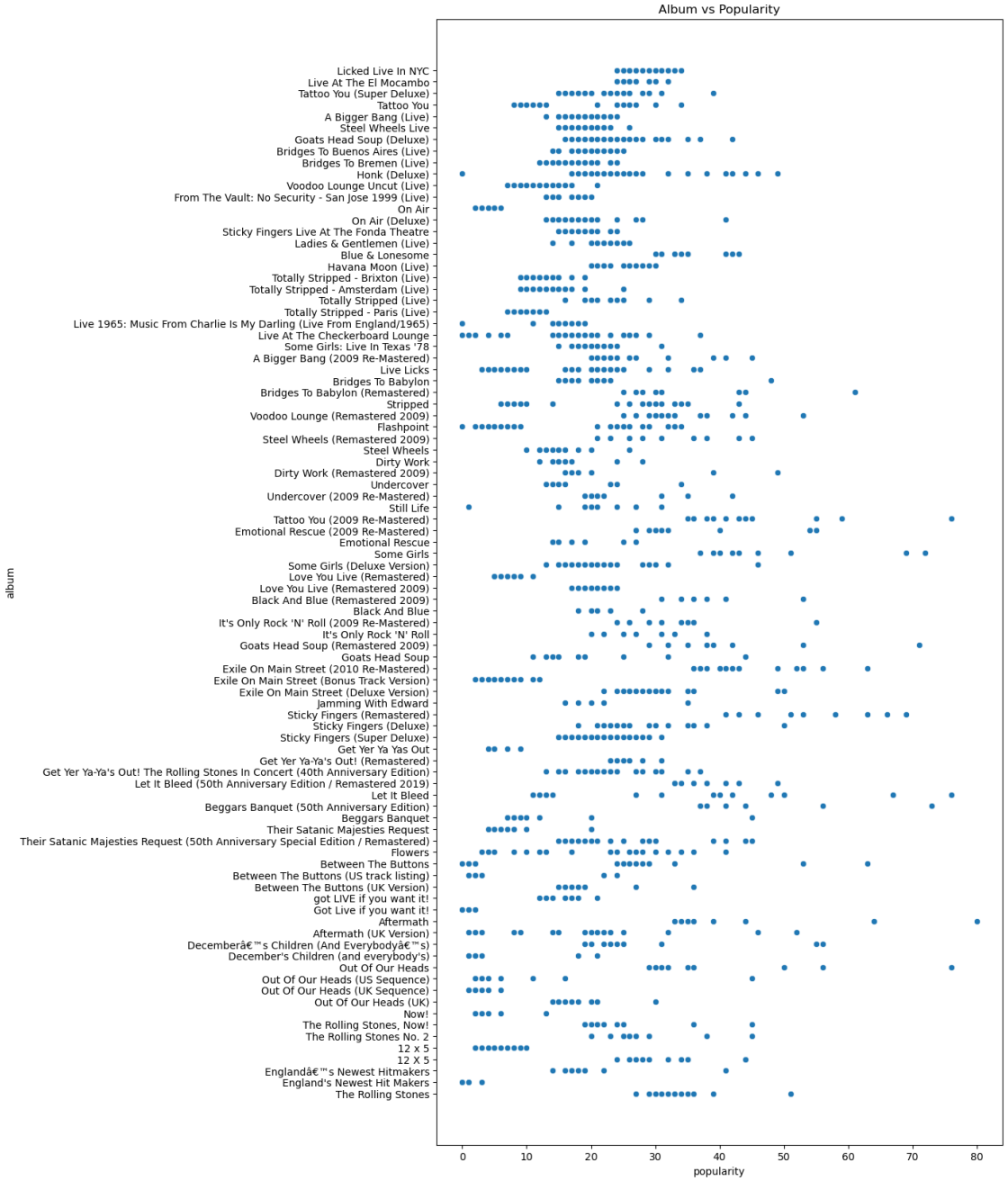
[26]:
```
sns.jointplot(x=df['instrumentalness'],y=df['tempo'])
plt.show()
```



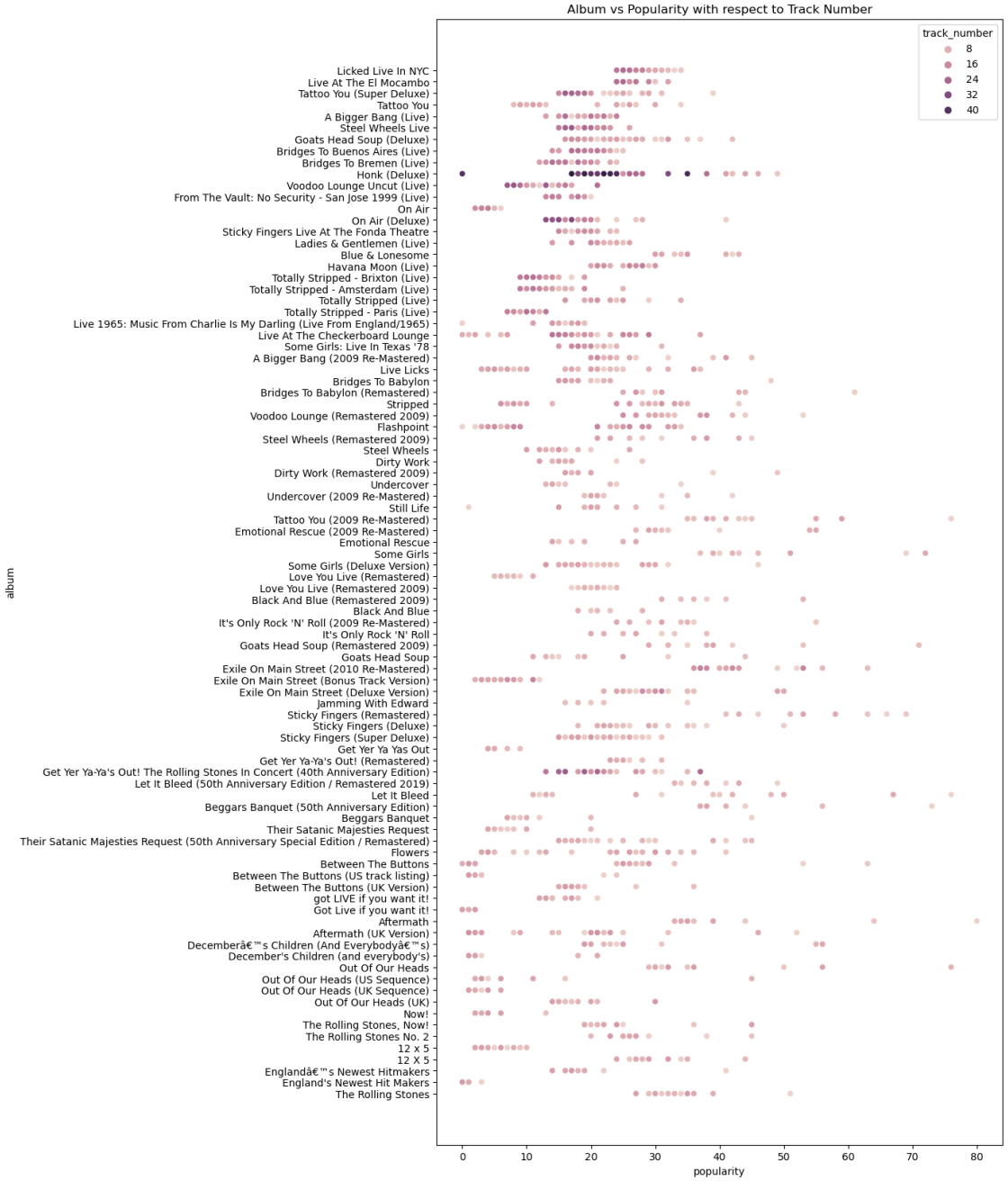
[27]:
```
plt.figure(figsize=(10,20))
sns.countplot(y=df['album'])
plt.title('Album')
plt.show()
```



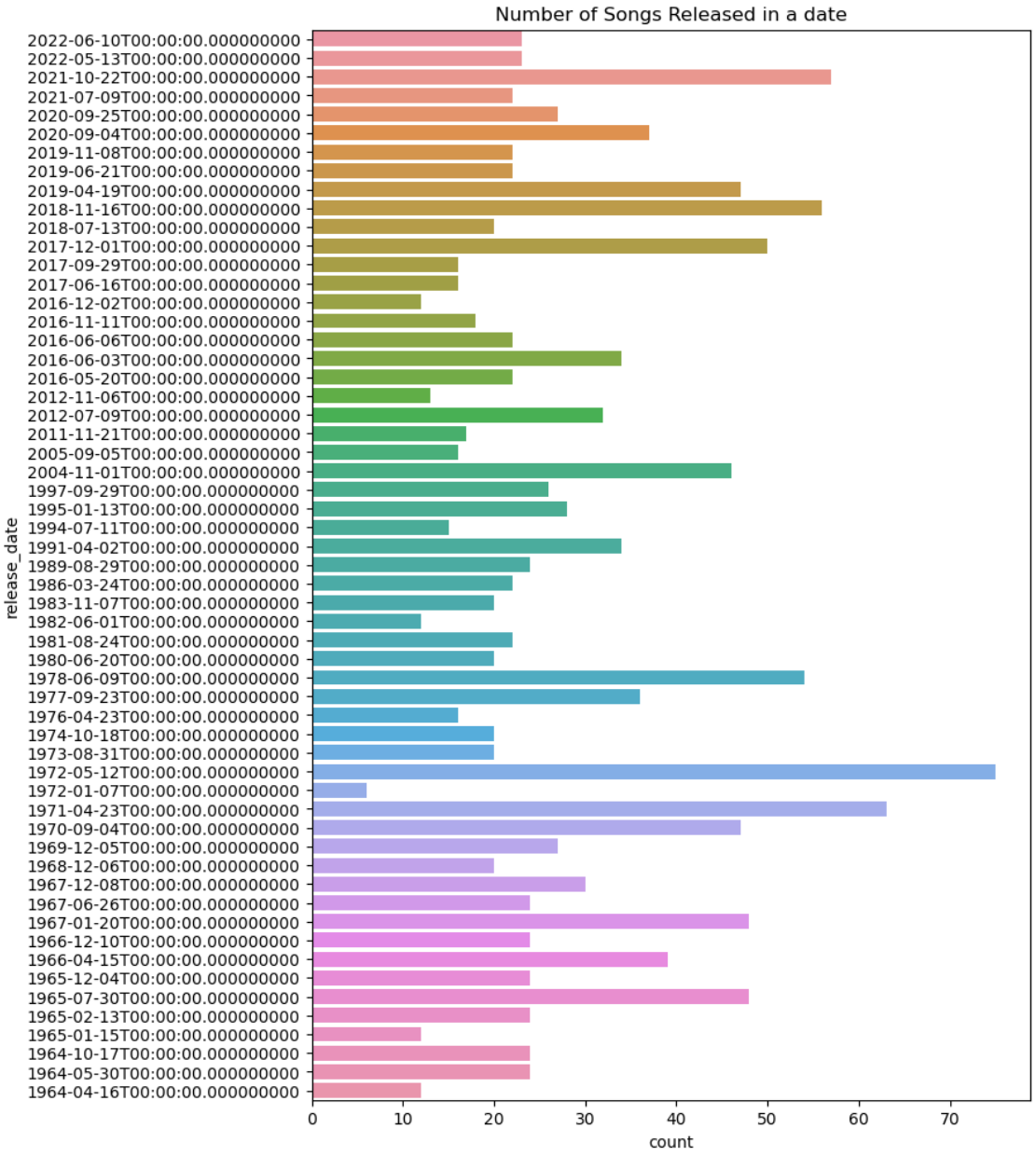
[28]:
```
plt.figure(figsize=(10,20))
sns.scatterplot(y=df['album'],x=df['popularity'])
plt.title('Album vs Popularity')
plt.show()
```



[29]:
```
plt.figure(figsize=(10,20))
sns.scatterplot(y=df['album'],x=df['popularity'],hue=df['track_number'])
plt.title('Album vs Popularity with respect to Track Number')
plt.show()
```

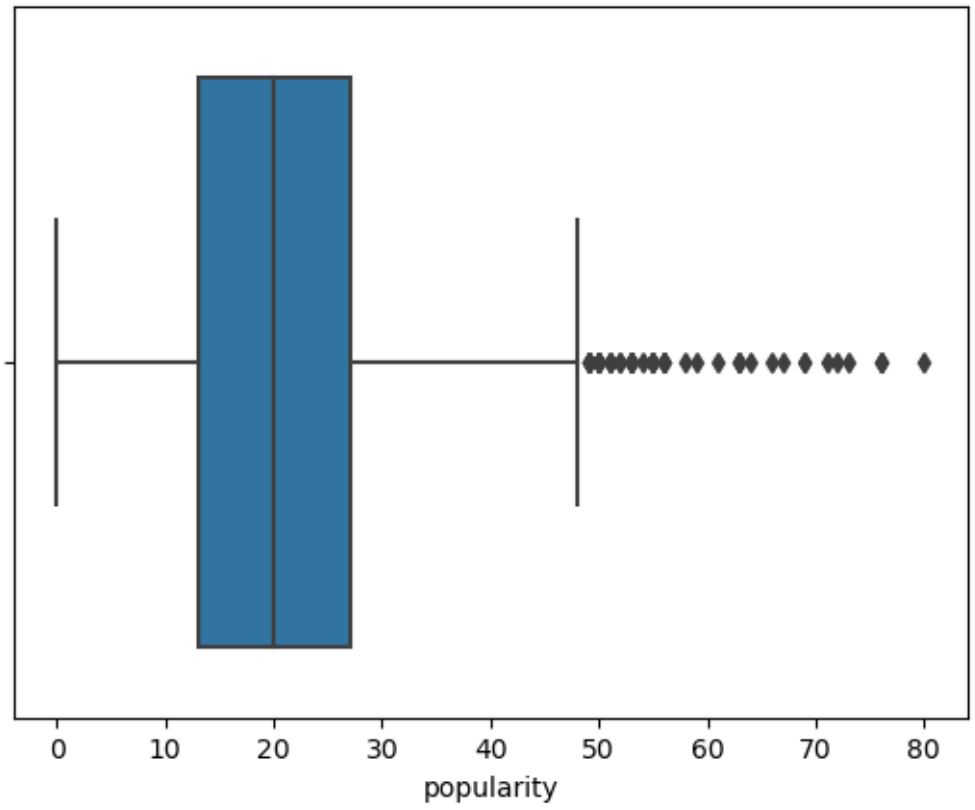


[30]:
```
plt.figure(figsize=(8,12))
sns.countplot(y=df['release_date'])
plt.title('Number of Songs Released in a date')
plt.show()
```

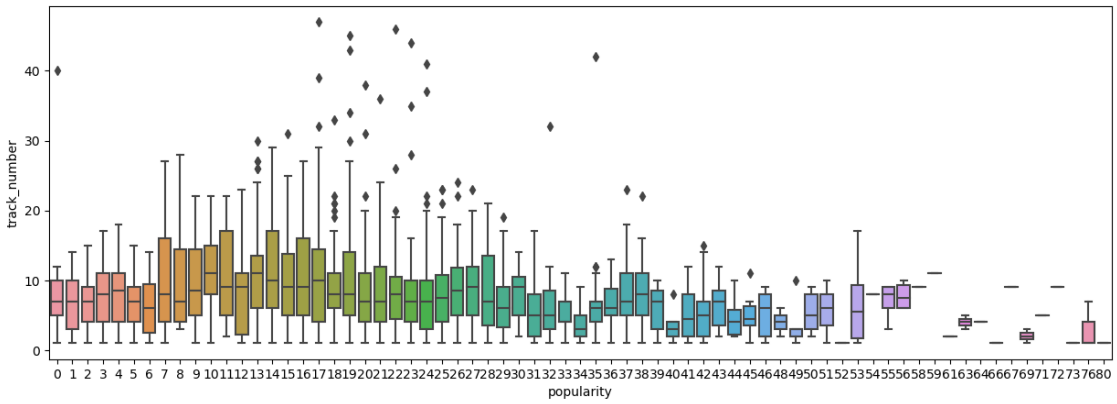


[31]:
```
sns.boxplot(df['popularity'])
plt.show()
```

```
C:\Users\Vinosh\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

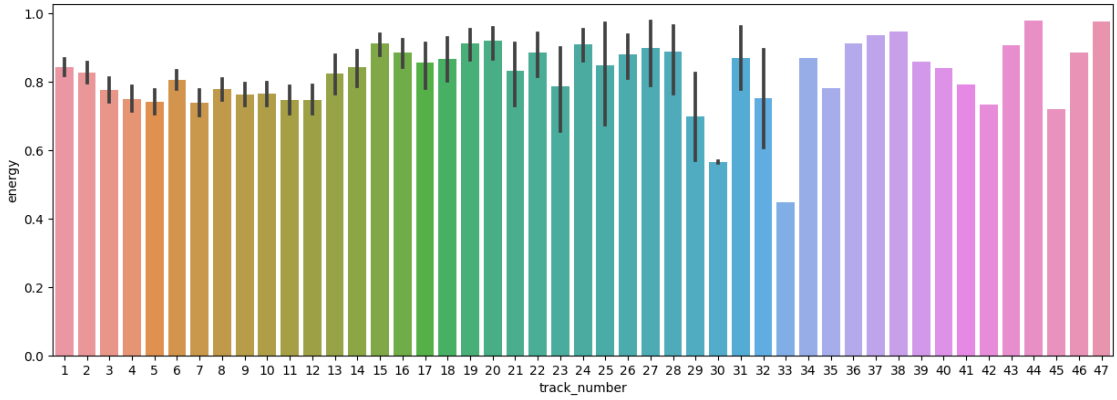


[32]:
```
plt.figure(figsize=(15,5))
sns.boxplot(x=df['popularity'],y=df['track_number'])
plt.show()
```



[33]:
```
plt.figure(figsize=(15,5))
sns.barplot(x=df['track_number'],y=df['energy'])
```

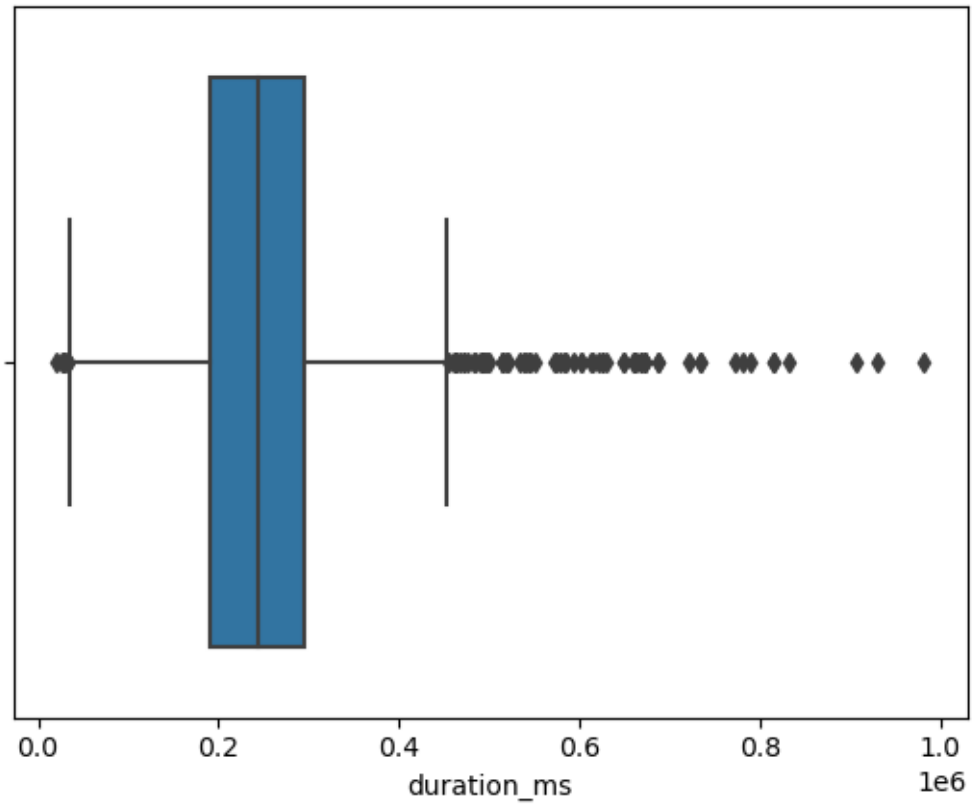
```
plt.show()
```



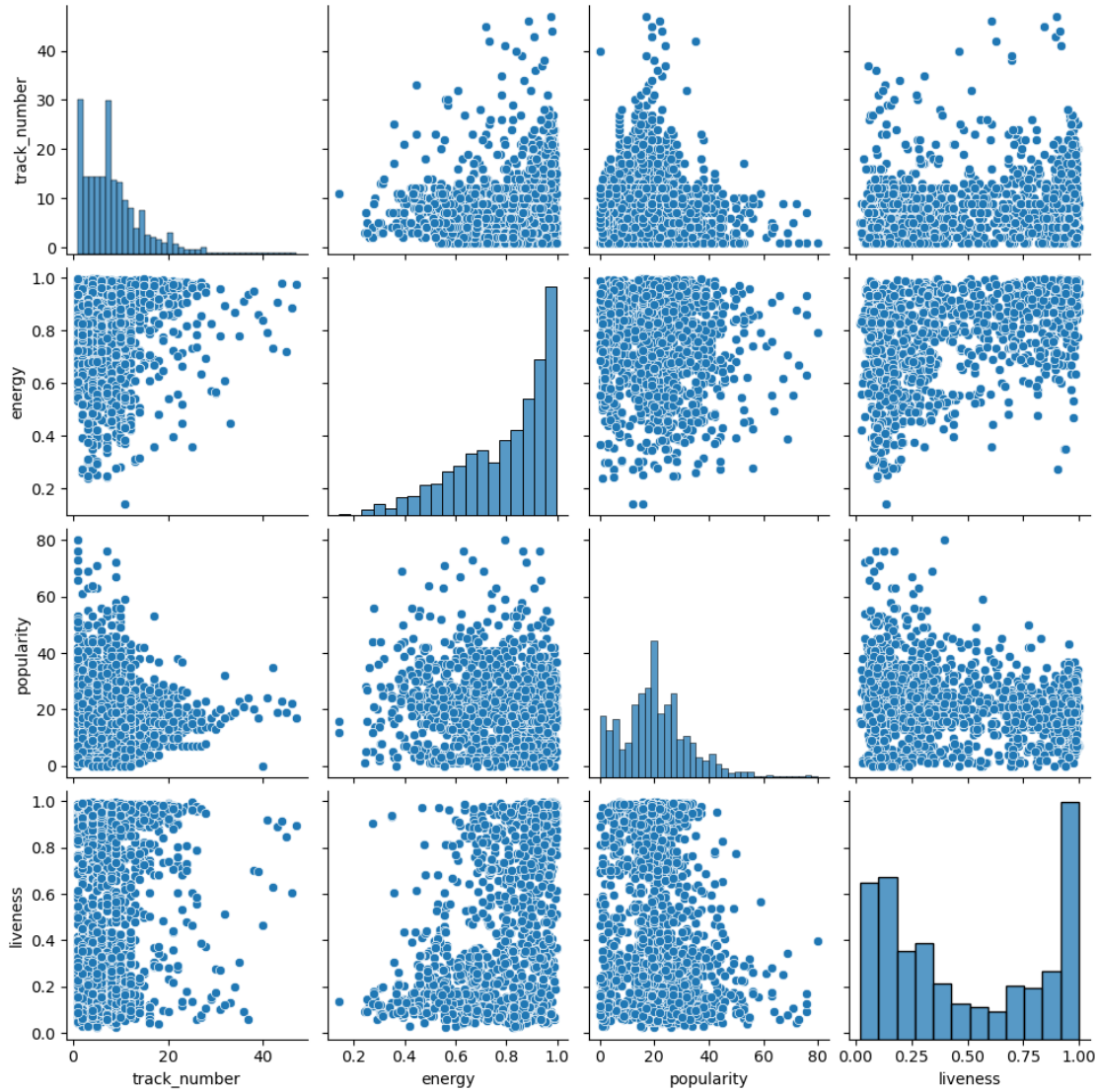
[34]:
```
sns.boxplot(df['duration_ms'])
```

```
C:\Users\Vinosh\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

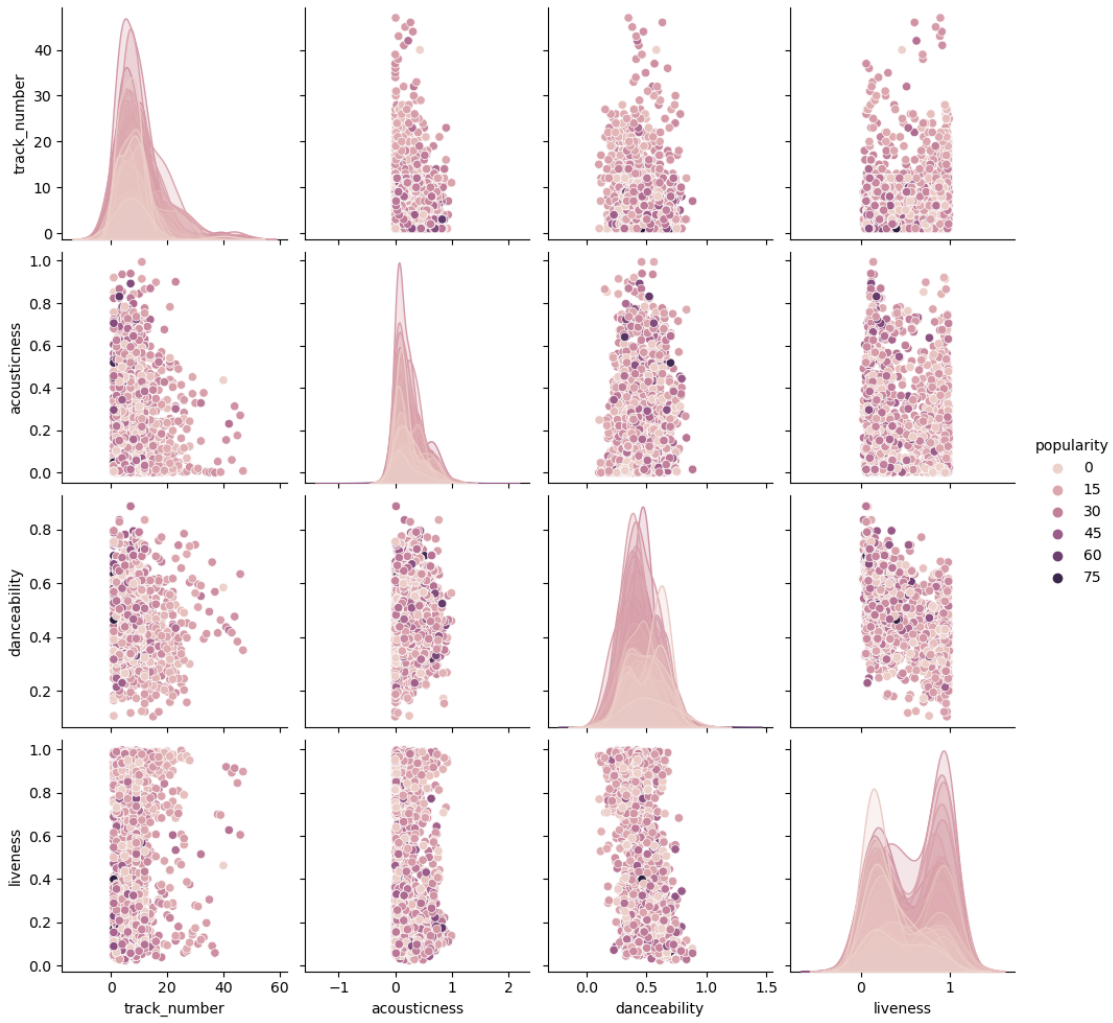
[34]:
```
<AxesSubplot:xlabel='duration_ms'>
```



[35]:
```
cols = ['track_number','energy','popularity','liveness']
sns.pairplot(df,vars=cols)
plt.show()
```

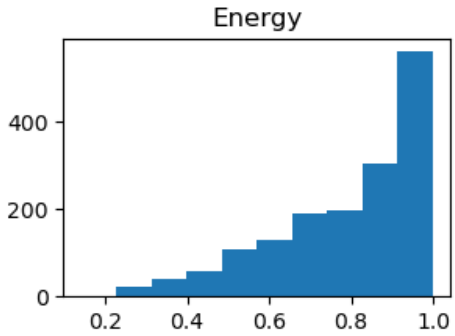


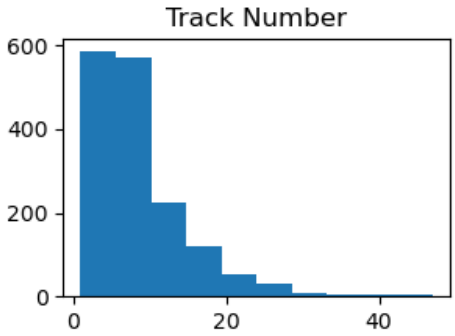
[36]:
```
cols = ['track_number','acousticness','danceability','liveness']
sns.pairplot(df,vars=cols,hue='popularity')
plt.show()
```

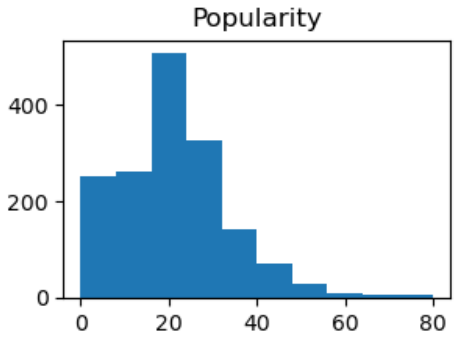


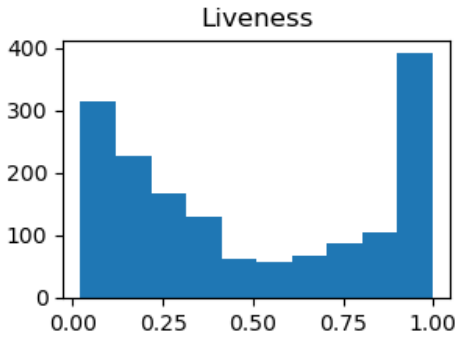
[37]:
```
plt.figure(figsize=(8,15))
plt.subplots_adjust(hspace=0.5,wspace=0.5)

plt.subplot(5,2,1)
plt.hist(df['energy'])
plt.title('Energy')

plt.subplot(5,2,2)
plt.hist(df['track_number'])
plt.title('Track Number')

plt.subplot(5,2,3)
plt.hist(df['popularity'])
plt.title('Popularity')
```

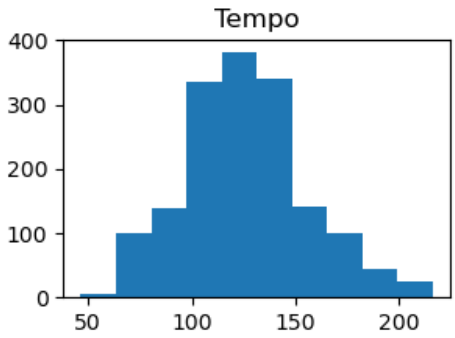
```
plt.subplot(5,2,4)
plt.hist(df['liveness'])
plt.title('Liveness')

plt.subplot(5,2,5)
plt.hist(df['tempo'])
plt.title('Tempo')

plt.subplot(5,2,6)
plt.hist(df['duration_ms'])
plt.title('Duration MS')

plt.subplot(5,2,7)
plt.hist(df['instrumentalness'])
plt.title('Instrumentalness')

plt.subplot(5,2,8)
plt.hist(df['danceability'])
plt.title('Danceability')

plt.subplot(5,2,9)
plt.hist(df['loudness'])
plt.title('Loudness')

plt.subplot(5,2,10)
plt.hist(df['speechiness'])
plt.title('Speechiness')
plt.show()
```

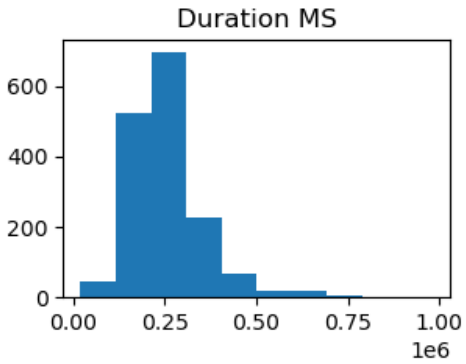

Energy
0
200
400
0.2
0.4
0.6
0.8
1.0

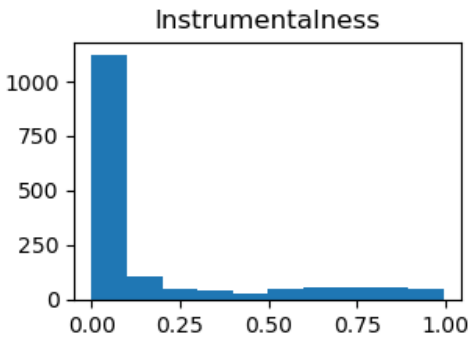

Track Number
0
200
400
600
0
20
40

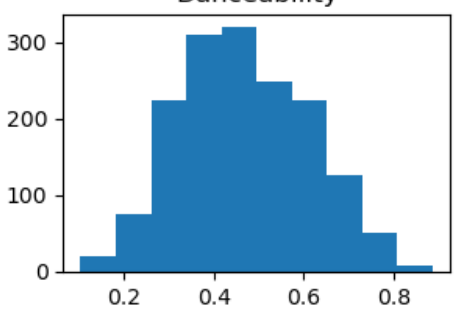

Popularity
0
200
400
0
20
40
60
80

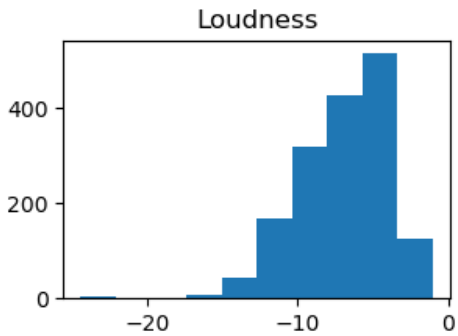

Liveness
0
100
200
300
400
0.00
0.25
0.50
0.75
1.00

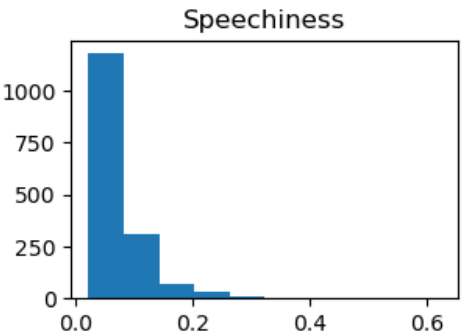

Tempo
0
100
200
300
400
50
100
150
200


Duration MS
0
200
400
600
0.00
0.25
0.50
0.75
1.00
1e6


Instrumentalness
0
250
500
750
1000
0.00
0.25
0.50
0.75
1.00


Danceability
0
100
200
300
0.2
0.4
0.6
0.8


Loudness
0
200
400
−20
−10
0


Speechiness
0
250
500
750
1000
0.0
0.2
0.4
0.6

3 Cluster Analysis

[38]:
```
df
```

[38]:
```
                            name               album release_date  \
0      Concert Intro Music - Live  Licked Live In NYC   2022-06-10
1      Street Fighting Man - Live  Licked Live In NYC   2022-06-10
2              Start Me Up - Live  Licked Live In NYC   2022-06-10
3     If You Can't Rock Me - Live  Licked Live In NYC   2022-06-10
4             Donâ€ t Stop - Live  Licked Live In NYC   2022-06-10
…                             …                 …          …
1605                      Carol  The Rolling Stones   1964-04-16
1606                   Tell Me  The Rolling Stones   1964-04-16
1607         Can I Get A Witness  The Rolling Stones   1964-04-16
1608   You Can Make It If You Try  The Rolling Stones   1964-04-16
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  08l7M5UpRnffGlOFyuRiQZ
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:08l7M5UpRnffGlOFyuRiQZ        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 17 columns]
```

[39]:
```
df.dtypes
```

[39]:
```
name                        object
album                       object
release_date        datetime64[ns]
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
```

[40]:
```
X = df.drop(['name','release_date','id','uri'],axis=1)
```

[41]:
```
X
```

[41]:

```
                    album  track_number  acousticness  danceability  energy  \
0     Licked Live In NYC              1        0.0824         0.463   0.993
1     Licked Live In NYC              2        0.4370         0.326   0.965
2     Licked Live In NYC              3        0.4160         0.386   0.969
3     Licked Live In NYC              4        0.5670         0.369   0.985
4     Licked Live In NYC              5        0.4000         0.303   0.969
…                    …            …             …             …       …
1605  The Rolling Stones              8        0.1570         0.466   0.932
1606  The Rolling Stones              9        0.0576         0.509   0.706
1607  The Rolling Stones             10        0.3710         0.790   0.774
1608  The Rolling Stones             11        0.2170         0.700   0.546
1609  The Rolling Stones             12        0.3830         0.727   0.934

      instrumentalness  liveness  loudness  speechiness    tempo  valence  \
0             0.996000    0.9320   -12.913       0.1100  118.001   0.0302
1             0.233000    0.9610    -4.803       0.0759  131.455   0.3180
2             0.400000    0.9560    -4.936       0.1150  130.066   0.3130
3             0.000107    0.8950    -5.535       0.1930  132.994   0.1470
4             0.055900    0.9660    -5.098       0.0930  130.533   0.2060
…                    …         …         …            …       …        …
1605          0.006170    0.3240    -9.214       0.0429  177.340   0.9670
1606          0.000002    0.5160    -9.427       0.0843  122.015   0.4460
1607          0.000000    0.0669    -7.961       0.0720   97.035   0.8350
1608          0.000070    0.1660    -9.567       0.0622  102.634   0.5320
1609          0.068500    0.0965    -8.373       0.0359  125.275   0.9690

      popularity  duration_ms
0             33        48640
1             34       253173
2             34       263160
3             32       305880
4             32       305106
…            …            …
1605          39       154080
1606          36       245266
1607          30       176080
1608          27       121680
1609          35       189186

[1610 rows x 13 columns]
```

[42]:
```
y = df['popularity']
```

[43]:
```
y
```

[43]:
```
0       33
1       34
2       34
3       32
4       32
        ..
1605    39
1606    36
1607    30
1608    27
1609    35
Name: popularity, Length: 1610, dtype: int64
```

[44]:
```
from sklearn.preprocessing import LabelEncoder
```

[45]:
```
le = LabelEncoder()
```

[46]:
```
X['album'] = le.fit_transform(X['album'])
```

[47]:
```
X.head()
```

[47]:

	album	track_number	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity	duration_ms
0	47	1	0.0824	0.463	0.993	0.996000	0.932	-12.913	0.1100	118.001	0.0302	33	48640
1	47	2	0.4370	0.326	0.965	0.233000	0.961	-4.803	0.0759	131.455	0.3180	34	253173
2	47	3	0.4160	0.386	0.969	0.400000	0.956	-4.936	0.1150	130.066	0.3130	34	263160
3	47	4	0.5670	0.369	0.985	0.000107	0.895	-5.535	0.1930	132.994	0.1470	32	305880
4	47	5	0.4000	0.303	0.969	0.055900	0.966	-5.098	0.0930	130.533	0.2060	32	305106

[48]:
```
from sklearn.preprocessing import MinMaxScaler
```

[49]:
```
ms = MinMaxScaler()
```

[50]:
```
cols = X.columns
```

[51]:
```
X = ms.fit_transform(X)
```

[52]:
```
X
```

[52]:
```
array([[0.52808989, 0.        , 0.08288914, …, 0.03100616, 0.4125    ,
        0.02876572],
       [0.52808989, 0.02173913, 0.43963279, …, 0.32648871, 0.425     ,
        0.24162891],
       [0.52808989, 0.04347826, 0.41850584, …, 0.32135524, 0.425     ,
        0.25202265],
       …,
       [0.85393258, 0.19565217, 0.3732338 , …, 0.85728953, 0.375     ,
        0.16139607],
       [0.85393258, 0.2173913 , 0.21830283, …, 0.54620123, 0.3375    ,
        0.10478048],
       [0.85393258, 0.23913043, 0.38530634, …, 0.99486653, 0.4375    ,
        0.17503585]])
```

[53]:
```
X = pd.DataFrame(X,columns=cols)
```

[54]:
```
X
```

[54]:

	album	track_number	acousticness	danceability	energy	\
0	0.528090	0.000000	0.082889	0.458493	0.993007	
1	0.528090	0.021739	0.439633	0.283525	0.960373	
2	0.528090	0.043478	0.418506	0.360153	0.965035	
3	0.528090	0.065217	0.570419	0.338442	0.983683	
4	0.528090	0.086957	0.402409	0.254151	0.965035	
…	…	…	…	…	…	
1605	0.853933	0.152174	0.157940	0.462324	0.921911	
1606	0.853933	0.173913	0.057939	0.517241	0.658508	
1607	0.853933	0.195652	0.373234	0.876117	0.737762	
1608	0.853933	0.217391	0.218303	0.761175	0.472028	
1609	0.853933	0.239130	0.385306	0.795658	0.924242	

	instrumentalness	liveness	loudness	speechiness	tempo	valence	\
0	1.000000	0.932384	0.491365	0.144474	0.420994	0.031006	
1	0.233936	0.962094	0.838035	0.087716	0.500239	0.326489	
2	0.401606	0.956972	0.832350	0.152796	0.492057	0.321355	
3	0.000107	0.894478	0.806745	0.282623	0.509303	0.150924	
4	0.056124	0.967216	0.825425	0.116178	0.494808	0.211499	
…	…	…	…	…	…	…	
1605	0.006195	0.309497	0.649483	0.032790	0.770502	0.992813	
1606	0.000002	0.506198	0.640378	0.101698	0.444637	0.457906	
1607	0.000000	0.046102	0.703044	0.081225	0.297504	0.857290	
1608	0.000070	0.147628	0.634393	0.064913	0.330483	0.546201	
1609	0.068775	0.076427	0.685432	0.021138	0.463838	0.994867	

	popularity	duration_ms
0	0.4125	0.028766
1	0.4250	0.241629

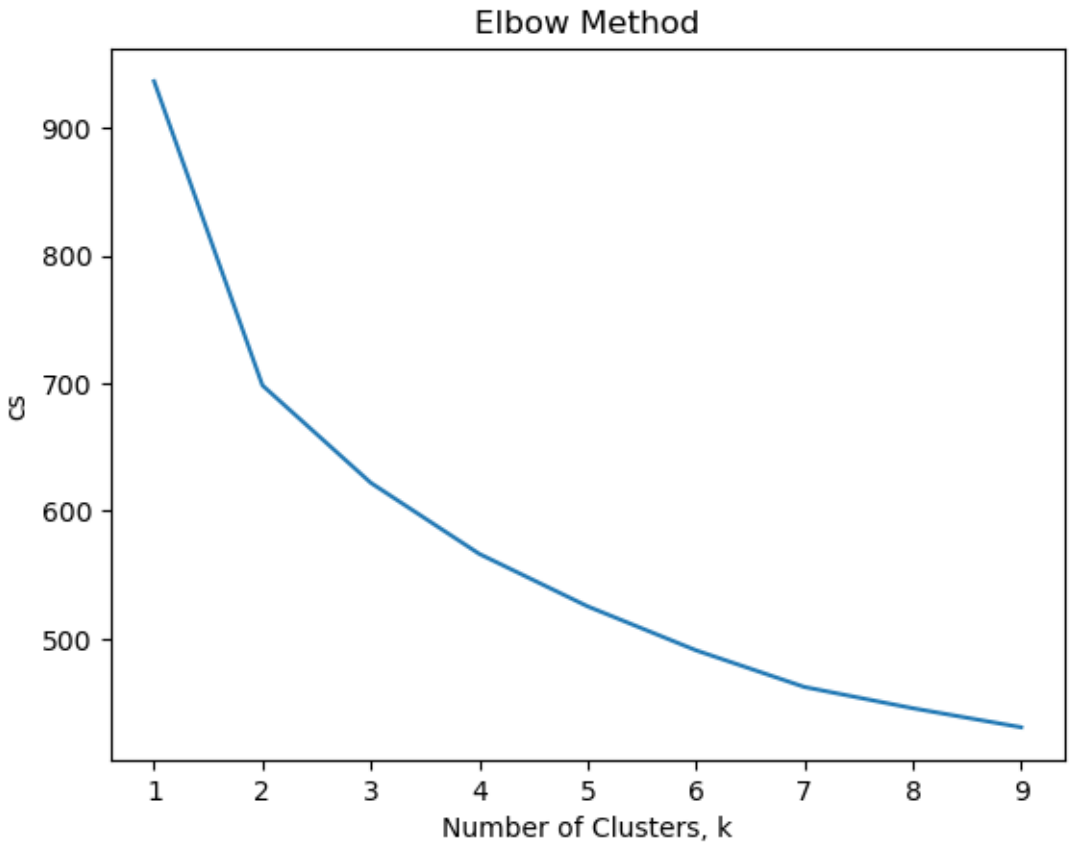
```
2          0.4250     0.252023
3          0.4000     0.296483
4          0.4000     0.295677
…             …          …
1605       0.4875     0.138500
1606       0.4500     0.233400
1607       0.3750     0.161396
1608       0.3375     0.104780
1609       0.4375     0.175036

[1610 rows x 13 columns]
```

[55]:
```
from sklearn.cluster import KMeans
```

[56]:
```
cs = []
for i in range(1,10):
    kmeans =␣
 ↪KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=0)
    kmeans.fit(X)
    cs.append(kmeans.inertia_)
```

```
C:\Users\Vinosh\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting the
environment variable OMP_NUM_THREADS=7.
  warnings.warn(
```

[57]:
```
plt.plot(range(1,10),cs)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters, k')
plt.ylabel('cs')
plt.show()
```



[58]:
```
kmeans = KMeans(n_clusters=2,random_state=0)
```

[59]:
```
kmeans.fit(X)
```

[59]:
```
KMeans(n_clusters=2, random_state=0)
```

[60]:
```
labels = kmeans.labels_
```

[61]:
```
correct_labels = sum(y==labels)
```

[62]:
```
print('Results {} out of {} samples were correctly lables'.
  ↪format(correct_labels,y.size))
```

```
Results 33 out of 1610 samples were correctly lables
```

[63]:
```
print('Accuracy Score : {0:0.2f}'.format(correct_labels/float(y.size)))
```

```
Accuracy Score : 0.02
```

[ ]:
```

```