In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples,silhouette_score

import warnings
warnings.filterwarnings('ignore')
```

Importing Data

In [2]:
```
df=pd.read_csv('rolling_stones_spotify.csv')
df.head()
```

Out[2]:

	Unnamed: 0	name	album	release_date	track_number	id	uri	acousticness	danceat
0	0	Concert Intro Music - Live	Licked Live In NYC	2022-06-10	1	2IEkywLJ4ykbhi1yRQvmsT	spotify:track:2IEkywLJ4ykbhi1yRQvmsT	0.0824	0
1	1	Street Fighting Man - Live	Licked Live In NYC	2022-06-10	2	6GVgVJBKkGJoRfarYRvGTU	spotify:track:6GVgVJBKkGJoRfarYRvGTU	0.4370	0
2	2	Start Me Up - Live	Licked Live In NYC	2022-06-10	3	1Lu761pZ0dBTGpzxaQoZNW	spotify:track:1Lu761pZ0dBTGpzxaQoZNW	0.4160	0
3	3	If You Can't Rock Me - Live	Licked Live In NYC	2022-06-10	4	1agTQzOTUnGNggyckEqiDH	spotify:track:1agTQzOTUnGNggyckEqiDH	0.5670	0
4	4	Don't Stop - Live	Licked Live In NYC	2022-06-10	5	7piGJR8YndQBQWVXv6KtQw	spotify:track:7piGJR8YndQBQWVXv6KtQw	0.4000	0

In [3]:
```
df.columns
```

Out[3]:
```
Index(['Unnamed: 0', 'name', 'album', 'release_date', 'track_number', 'id',
       'uri', 'acousticness', 'danceability', 'energy', 'instrumentalness',
       'liveness', 'loudness', 'speechiness', 'tempo', 'valence', 'popularity',
       'duration_ms'],
      dtype='object')
```

In [4]:
```
df.shape
```

Out[4]:
```
(1610, 18)
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1610 entries, 0 to 1609
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Unnamed: 0        1610 non-null   int64  
 1   name              1610 non-null   object 
 2   album             1610 non-null   object 
 3   release_date      1610 non-null   object 
 4   track_number      1610 non-null   int64  
 5   id                1610 non-null   object 
 6   uri               1610 non-null   object 
 7   acousticness      1610 non-null   float64
 8   danceability      1610 non-null   float64
 9   energy            1610 non-null   float64
 10  instrumentalness  1610 non-null   float64
 11  liveness          1610 non-null   float64
 12  loudness          1610 non-null   float64
 13  speechiness       1610 non-null   float64
 14  tempo             1610 non-null   float64
 15  valence           1610 non-null   float64
 16  popularity        1610 non-null   int64  
 17  duration_ms       1610 non-null   int64  
dtypes: float64(9), int64(4), object(5)
memory usage: 226.5+ KB
```

In [6]:
```
continuous_var=[x for x in df if df[x].dtypes != 'O']
```

In [7]:
```
categorical_var=[x for x in df if x not in continuous_var]
```

In [8]:
```
print(continuous_var)
print('-----------------------')
print(categorical_var)
```

```
['Unnamed: 0', 'track_number', 'acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'loudness', 's
peechiness', 'tempo', 'valence', 'popularity', 'duration_ms']
-----------------------
['name', 'album', 'release_date', 'id', 'uri']
```

In [9]:
```
df.drop(['id','uri','Unnamed: 0'],axis=1,inplace=True)
```

In [10]:
```
df.shape
```

Out[10]:
```
(1610, 15)
```

In [11]:
```
df_excel=pd.read_excel('Data Dictionary - Creating cohorts of songs.xlsx')
df_excel
```

Out[11]:

	Variable	Description
0	name	the name of the song
1	album	the name of the album
2	release_date	the day month and year the album was released
3	track number	the order the song appears on the album
4	id	the Spotify id for the song
5	uri	the Spotify uri for the song
6	acousticness	A confidence measure from 0.0 to 1.0 of whethe...
7	danceability	Danceability describes how suitable a track is...
8	energy	Energy is a measure from 0.0 to 1.0 and repres...
9	instrumentalness	Predicts whether a track contains no vocals. "...
10	liveness	Detects the presence of an audience in the rec...
11	loudness	The overall loudness of a track in decibels (d...
12	speechiness	detects the presence of spoken words in a trac...
13	tempo	The overall estimated tempo of a track in beat...
14	valence	A measure from 0.0 to 1.0 describing the music...
15	popularity	the popularity of the song from 0 to 100
16	duration_ms	The duration of the track in milliseconds.

Data inpection and cleaning

In [12]:
```
df[df.duplicated()==True]
```

Out[12]:

	name	album	release_date	track_number	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo
928	Some Girls - Remastered	Some Girls (Deluxe Version)	1978-06-09	4	0.5270	0.474	0.938	0.520000	0.299	-2.643	0.0898	71.99
929	Lies - Remastered	Some Girls (Deluxe Version)	1978-06-09	5	0.4370	0.382	0.997	0.950000	0.617	-1.568	0.1880	162.42
935	Claudine	Some Girls (Deluxe Version)	1978-06-09	1	0.0144	0.439	0.977	0.022100	0.383	-4.386	0.1280	105.12
939	No Spare Parts	Some Girls (Deluxe Version)	1978-06-09	5	0.2400	0.594	0.762	0.000015	0.712	-5.145	0.0292	72.64
940	Don't Be A Stranger	Some Girls (Deluxe Version)	1978-06-09	6	0.0610	0.720	0.867	0.029700	0.385	-5.871	0.0390	127.32
946	Petrol Blues	Some Girls (Deluxe Version)	1978-06-09	12	0.7690	0.835	0.621	0.114000	0.116	-8.007	0.0406	115.87

In [13]:
```
df=df.drop_duplicates()
df
```

Out[13]:

	name	album	release_date	track_number	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	v
0	Concert Intro Music - Live	Licked Live In NYC	2022-06-10	1	0.0824	0.463	0.993	0.996000	0.9320	-12.913	0.1100	118.001	
1	Street Fighting Man - Live	Licked Live In NYC	2022-06-10	2	0.4370	0.326	0.965	0.233000	0.9610	-4.803	0.0759	131.455	
2	Start Me Up - Live	Licked Live In NYC	2022-06-10	3	0.4160	0.386	0.969	0.400000	0.9560	-4.936	0.1150	130.066	
3	If You Can't Rock Me - Live	Licked Live In NYC	2022-06-10	4	0.5670	0.369	0.985	0.000107	0.8950	-5.535	0.1930	132.994	
4	Don’t Stop - Live	Licked Live In NYC	2022-06-10	5	0.4000	0.303	0.969	0.055900	0.9660	-5.098	0.0930	130.533	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1605	Carol	The Rolling Stones	1964-04-16	8	0.1570	0.466	0.932	0.006170	0.3240	-9.214	0.0429	177.340	
1606	Tell Me	The Rolling Stones	1964-04-16	9	0.0576	0.509	0.706	0.000002	0.5160	-9.427	0.0843	122.015	
1607	Can I Get A Witness	The Rolling Stones	1964-04-16	10	0.3710	0.790	0.774	0.000000	0.0669	-7.961	0.0720	97.035	
1608	You Can Make It If You Try	The Rolling Stones	1964-04-16	11	0.2170	0.700	0.546	0.000070	0.1660	-9.567	0.0622	102.634	
1609	Walking The Dog	The Rolling Stones	1964-04-16	12	0.3830	0.727	0.934	0.068500	0.0965	-8.373	0.0359	125.275	

1604 rows × 15 columns

In [14]:
```
df.shape
```

Out[14]:
```
(1604, 15)
```

- **Duplicate entries is dropped from the dataframe.**

In [15]:
```
df.isna().sum()
```

Out[15]:
```
name                0
album               0
release_date        0
track_number        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
```

- **THERE IS NO MISSING VALUES.**

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1604 entries, 0 to 1609
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   name              1604 non-null   object 
 1   album             1604 non-null   object 
 2   release_date      1604 non-null   object 
 3   track_number      1604 non-null   int64  
 4   acousticness      1604 non-null   float64
 5   danceability      1604 non-null   float64
 6   energy            1604 non-null   float64
 7   instrumentalness  1604 non-null   float64
 8   liveness          1604 non-null   float64
 9   loudness          1604 non-null   float64
 10  speechiness       1604 non-null   float64
 11  tempo             1604 non-null   float64
 12  valence           1604 non-null   float64
 13  popularity        1604 non-null   int64  
 14  duration_ms       1604 non-null   int64  
dtypes: float64(9), int64(3), object(3)
memory usage: 200.5+ KB
```

- **There are no irrelevant entries.**

In [17]:
```
def outlier(df,x):
    q1=df[x].quantile(0.25)
    q3=df[x].quantile(0.75)
    iqr=q3-q1
    df=df.loc[~((df[x]<(q1-1.5*iqr))|(df[x]>(q3+1.5*iqr))),]
    return df
```

In [18]:
```
df=outlier(df,'instrumentalness')
df=outlier(df,'popularity')
df=outlier(df,'loudness')
df=outlier(df,'duration_ms')
df=outlier(df,'loudness')
df=outlier(df,'liveness')
df=outlier(df,'speechiness')
df=outlier(df,'danceability')
df=outlier(df,'acousticness')
df=outlier(df,'tempo')
df=outlier(df,'valence')
```

In [19]:
```
df.shape
```

Out[19]:
```
(1122, 15)
```

- **All the outliers have been removed from the data.**

Exploratory Data Analysis and Feature Engineering

The 2 most recommended albums

In [20]:
```
df_album=df.groupby(['album'])['popularity'].mean()
df_album
```

Out[20]:
```
album
12 X 5                               32.428571
12 x 5                                5.125000
A Bigger Bang (2009 Re-Mastered)     27.062500
A Bigger Bang (Live)                 18.000000
Aftermath                            35.333333
                                       ...
Undercover                           19.857143
Undercover (2009 Re-Mastered)        24.666667
Voodoo Lounge (Remastered 2009)      33.076923
Voodoo Lounge Uncut (Live)           11.861111
got LIVE if you want it!             16.000000
Name: popularity, Length: 88, dtype: float64
```

In [21]:
```
df_album=df_album.reset_index()
df_album
```

Out[21]:

	album	popularity
0	12 X 5	32.428571
1	12 x 5	5.125000
2	A Bigger Bang (2009 Re-Mastered)	27.062500
3	A Bigger Bang (Live)	18.000000
4	Aftermath	35.333333
...	...	...
83	Undercover	19.857143
84	Undercover (2009 Re-Mastered)	24.666667
85	Voodoo Lounge (Remastered 2009)	33.076923
86	Voodoo Lounge Uncut (Live)	11.861111
87	got LIVE if you want it!	16.000000

88 rows × 2 columns

In [22]:
```
df_album=pd.DataFrame(df_album)
df_album
```

Out[22]:

	album	popularity
0	12 X 5	32.428571
1	12 x 5	5.125000
2	A Bigger Bang (2009 Re-Mastered)	27.062500
3	A Bigger Bang (Live)	18.000000
4	Aftermath	35.333333
...	...	...
83	Undercover	19.857143
84	Undercover (2009 Re-Mastered)	24.666667
85	Voodoo Lounge (Remastered 2009)	33.076923
86	Voodoo Lounge Uncut (Live)	11.861111
87	got LIVE if you want it!	16.000000

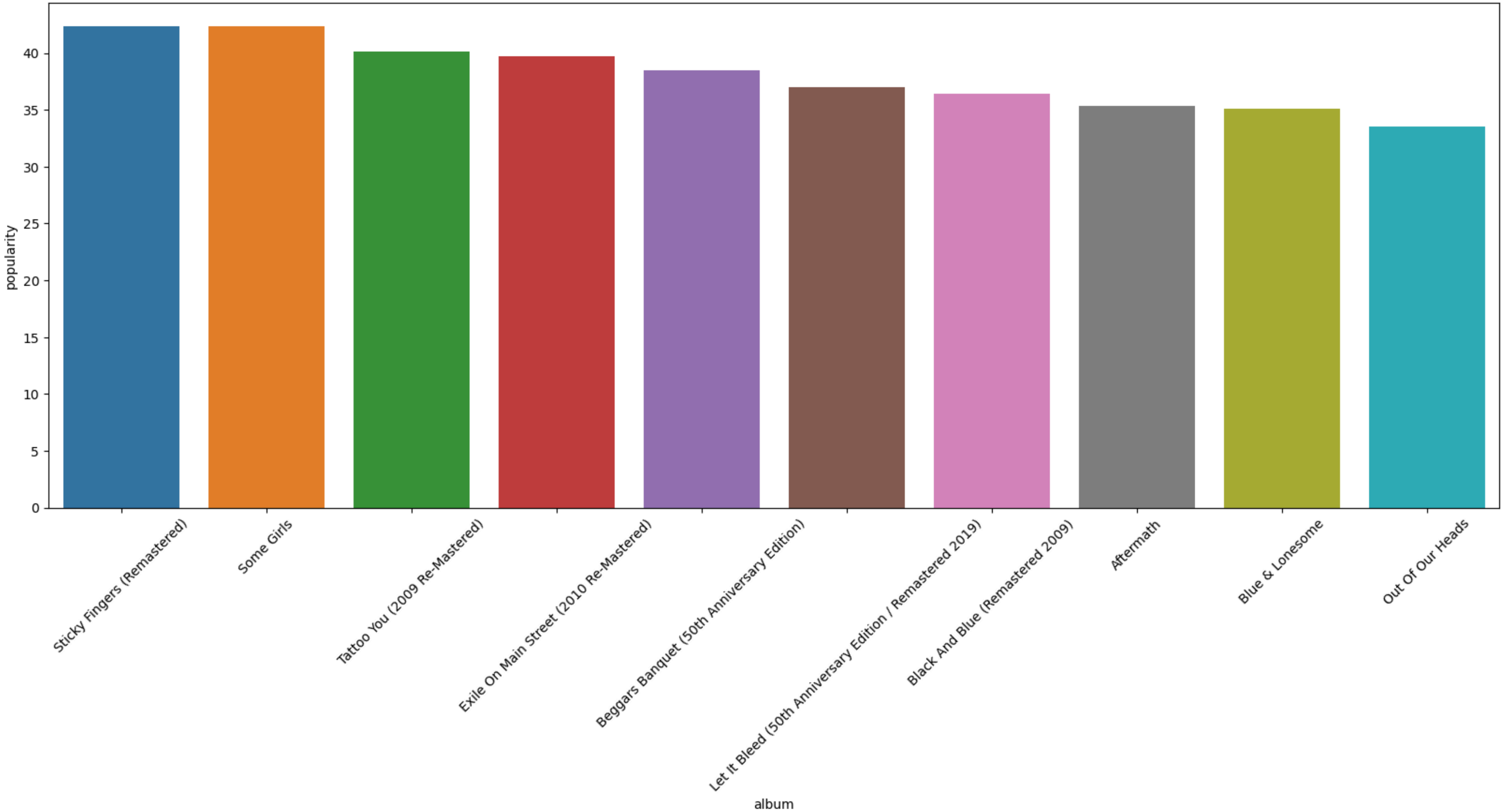
88 rows × 2 columns

In [23]:
```
df_album=df_album.sort_values('popularity',ascending=0)
df_album=df_album.head(10)
df_album
```

Out[23]:

	album	popularity
66	Sticky Fingers (Remastered)	42.333333
59	Some Girls	42.333333
72	Tattoo You (2009 Re-Mastered)	40.125000
26	Exile On Main Street (2010 Re-Mastered)	39.750000
7	Beggars Banquet (50th Anniversary Edition)	38.500000
44	Let It Bleed (50th Anniversary Edition / Remas...	37.000000
12	Black And Blue (Remastered 2009)	36.428571
4	Aftermath	35.333333
13	Blue & Lonesome	35.125000
55	Out Of Our Heads	33.500000

In [24]:
```
plt.figure(figsize=(20,7))
sns.barplot(data=df_album,x='album',y='popularity',estimator=np.sum)
plt.xticks(rotation=45)
plt.show()
```



- **Sticky Fingers (Remastered) and Some Girls are the two albums that should be recommended to anyone.**

Features and patterns of songs

- **The features are from the 5th column of the dataframe, so visualising them using iloc function.**

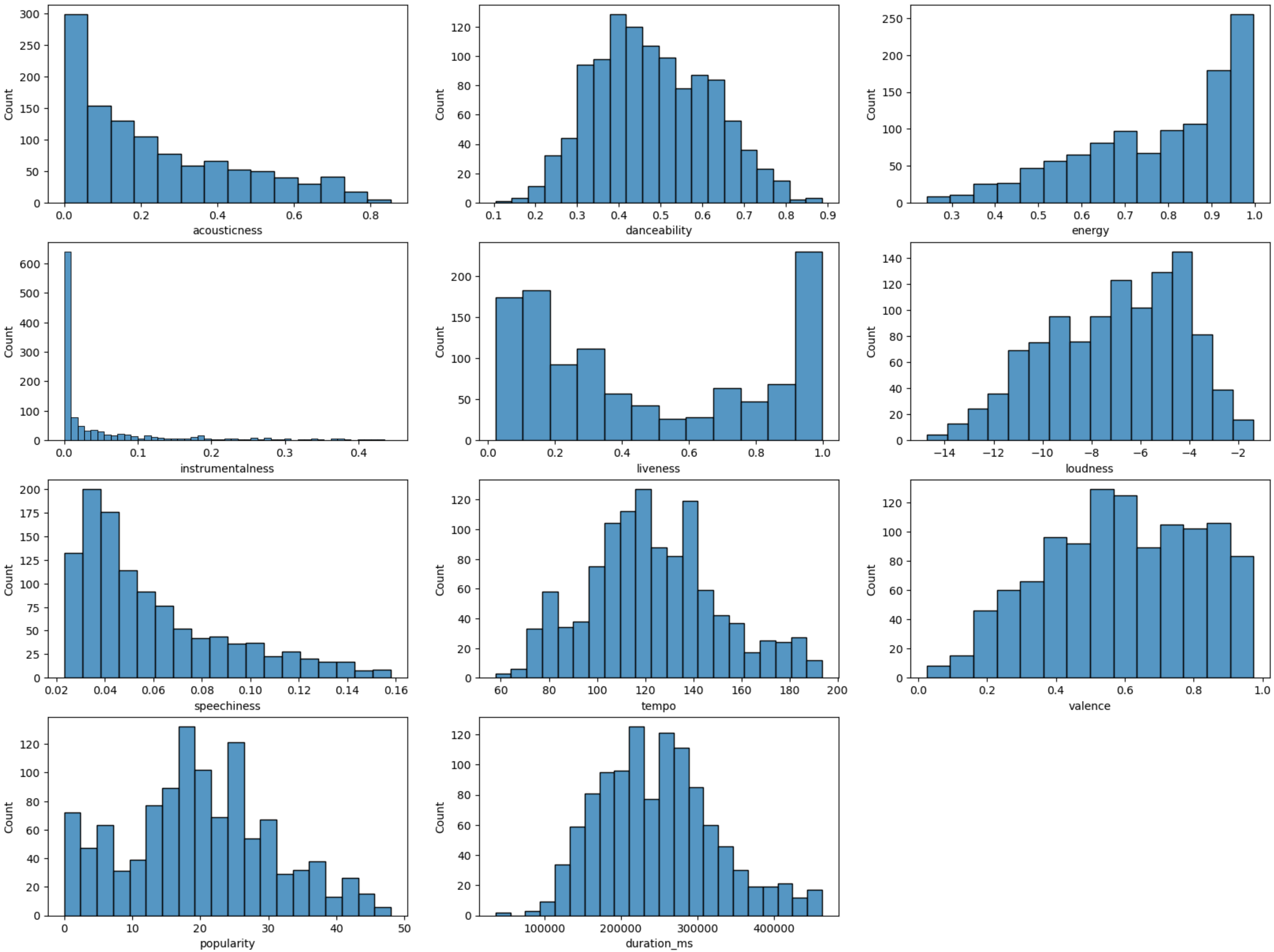
In [25]:
```
df_ftr=df.iloc[:,4:15]
df_ftr
```

Out[25]:

	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity	duration_ms
1	0.4370	0.326	0.965	0.233000	0.9610	-4.803	0.0759	131.455	0.318	34	253173
2	0.4160	0.386	0.969	0.400000	0.9560	-4.936	0.1150	130.066	0.313	34	263160
4	0.4000	0.303	0.969	0.055900	0.9660	-5.098	0.0930	130.533	0.206	32	305106
5	0.2750	0.340	0.956	0.125000	0.7410	-5.539	0.0915	101.628	0.125	31	244293
6	0.5610	0.262	0.810	0.000003	0.9720	-6.851	0.0969	77.520	0.394	31	245506
...	...	...	...	...	...	...	...	...	...	...	...
1605	0.1570	0.466	0.932	0.006170	0.3240	-9.214	0.0429	177.340	0.967	39	154080
1606	0.0576	0.509	0.706	0.000002	0.5160	-9.427	0.0843	122.015	0.446	36	245266
1607	0.3710	0.790	0.774	0.000000	0.0669	-7.961	0.0720	97.035	0.835	30	176080
1608	0.2170	0.700	0.546	0.000070	0.1660	-9.567	0.0622	102.634	0.532	27	121680
1609	0.3830	0.727	0.934	0.068500	0.0965	-8.373	0.0359	125.275	0.969	35	189186

1122 rows × 11 columns

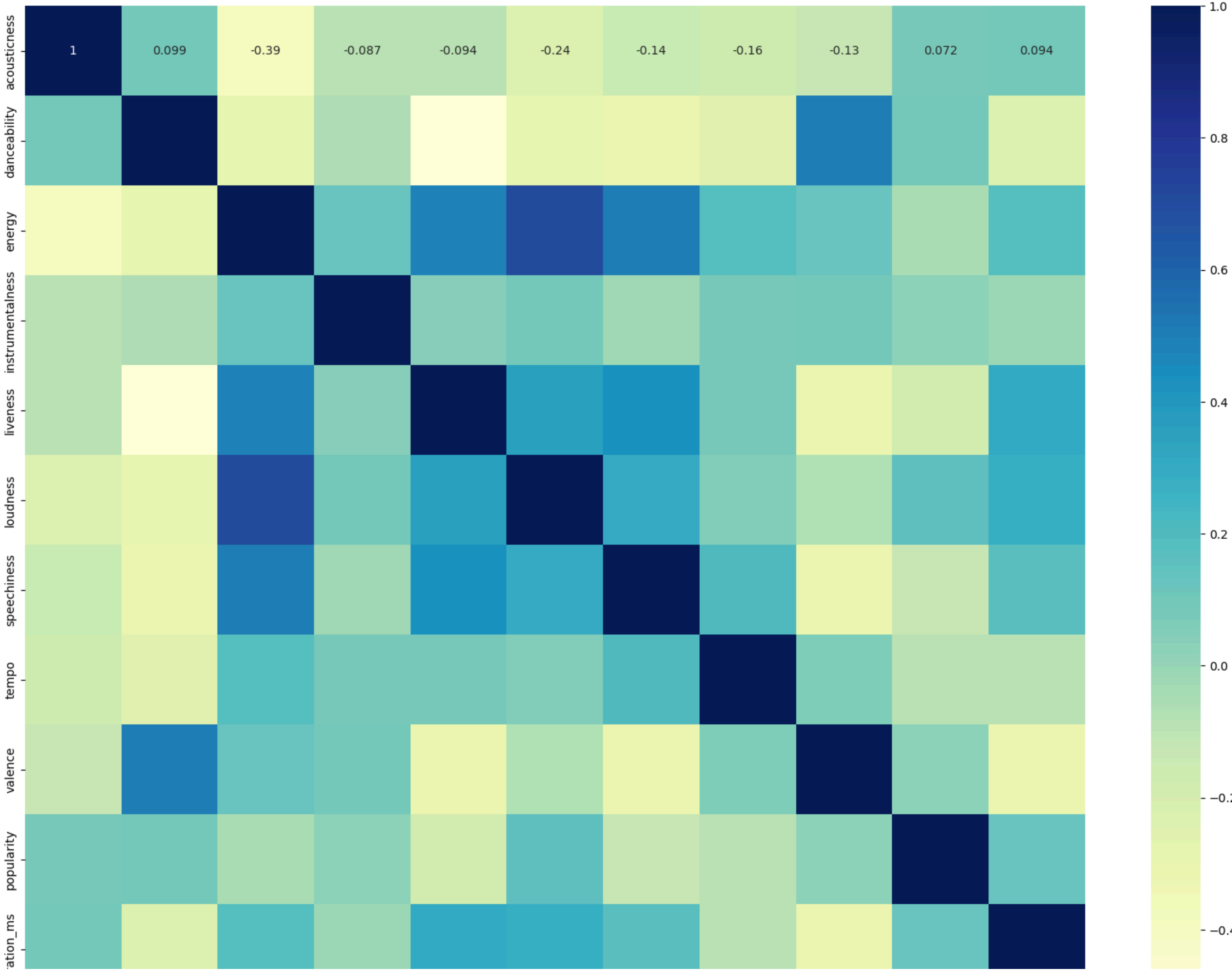
In [26]:
```
plt.figure(figsize=(20,15))
for i,column in enumerate(df_ftr.columns,1):
    plt.subplot(4,3,i)
    sns.histplot(df_ftr[column])
plt.show()
```


Count
acousticness
Count
danceability
Count
energy
Count
instrumentalness
Count
liveness
Count
loudness
Count
speechiness
Count
tempo
Count
valence
Count
popularity
Count
duration_ms

- **The above graphs show that instrumentalness and speechiness are skewed where the data mostly lies around 0.**

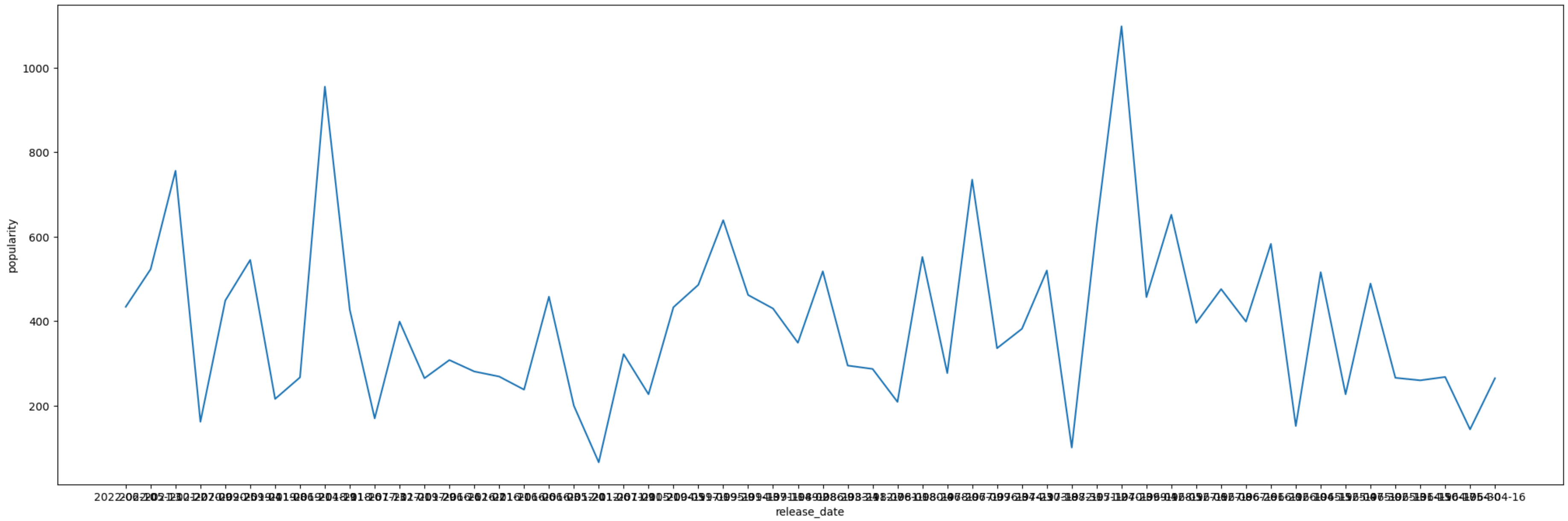
Correlation of song popularity with other factors

In [27]:
```
plt.figure(figsize=(20,15))
sns.heatmap(df_ftr.corr(),annot=True,cmap='YlGnBu')
plt.show()
```


acousticness
danceability
energy
instrumentalness
liveness
loudness
speechiness
tempo
valence
popularity
ation_ms
1
0.099
-0.39
-0.087
-0.094
-0.24
-0.14
-0.16
-0.13
0.072
0.094
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

- **There is hardly any correlation of popularity with the other factors as shown in the above heatmap.**

In [28]:
```
plt.figure(figsize=(25,8))
sns.lineplot(data=df,x='release_date',y='popularity',estimator=np.sum,ci=None)
plt.show()
```



- **The popularity is average from release_date.It doesn't depict any particular trend.**

Dimensionality Reduction Techniques

Dimensionality reduction is defined as a method of reducing variables in a training dataset used to develop machine learning models.

Dimensionality reduction helps with high dimensional data problems, while trying to preserve most of the relevant information in the data needed to learn accurate, predictive models. There are often too many factors on the basis of which the final prediction is done. These factors are basically variables called features. The higher the number of features, the harder it gets to visualize the training set and then work on it. Sometimes, most of these features are correlated, and hence redundant. This is where dimensionality reduction algorithms come into play.

When the number of features/variables is very large relative to the number of observations in your dataset, certain algorithms struggle to train effective models. This is called the “Curse of Dimensionality”.

Dimensionality reduction techniques can further broadly classified into two categories: 1. Feature selection - Feature selection is a method introduced to remove less significant features from the data,so that the model is trained only on the features that contribute most to the prediction(dependent) variable. It includes methods such as Filter, Wrapper and Embedded. 2. Feature extraction - Feature extraction is a process by which an initial set of raw data is reduced to more manageable groups for processing. It is basically done with image and text data, where only the important feature is extracted and sent ahead for processing instead of taking the whole data. It includes methods such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Kernel PCA (K-PCA), and Quadratic Discriminant Analysis (QCA).

Importance of Dimensionality reduction techniques are: 1. It helps data compression by reducing features. 2. It makes machine learning algorithms computationally efficient. 3. It allows the data to take up less storage space as well as it reduces the computation times. 4. It helps in removing multi-collinearity in data which improves the interpretation of the parameters of the machine learning model. 5. It reduces the data to 2d or 3d array which becomes easier to visualise the data. 6. It avoids the curse of dimensionality.

There are significant usage of these techniques but using them may lead to the loss of information, which might impact the other algorithms later on.

Cluster Analysis

- **For cluster analysis we need to select the required columns.**

In [29]:
```
df2=df[['danceability','energy','loudness','speechiness','acousticness','instrumentalness','liveness','tempo','valence',
df2
```

Out[29]:

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	liveness	tempo	valence	popularity	duration_ms
1	0.326	0.965	-4.803	0.0759	0.4370	0.233000	0.9610	131.455	0.318	34	253173
2	0.386	0.969	-4.936	0.1150	0.4160	0.400000	0.9560	130.066	0.313	34	263160
4	0.303	0.969	-5.098	0.0930	0.4000	0.055900	0.9660	130.533	0.206	32	305106
5	0.340	0.956	-5.539	0.0915	0.2750	0.125000	0.7410	101.628	0.125	31	244293
6	0.262	0.810	-6.851	0.0969	0.5610	0.000003	0.9720	77.520	0.394	31	245506
...	...	...	...	...	...	...	...	...	...	...	...
1605	0.466	0.932	-9.214	0.0429	0.1570	0.006170	0.3240	177.340	0.967	39	154080
1606	0.509	0.706	-9.427	0.0843	0.0576	0.000002	0.5160	122.015	0.446	36	245266
1607	0.790	0.774	-7.961	0.0720	0.3710	0.000000	0.0669	97.035	0.835	30	176080
1608	0.700	0.546	-9.567	0.0622	0.2170	0.000070	0.1660	102.634	0.532	27	121680
1609	0.727	0.934	-8.373	0.0359	0.3830	0.068500	0.0965	125.275	0.969	35	189186

1122 rows × 11 columns

In [30]:
```
df2.columns
```

Out[30]:
```
Index(['danceability', 'energy', 'loudness', 'speechiness', 'acousticness',
       'instrumentalness', 'liveness', 'tempo', 'valence', 'popularity',
       'duration_ms'],
      dtype='object')
```

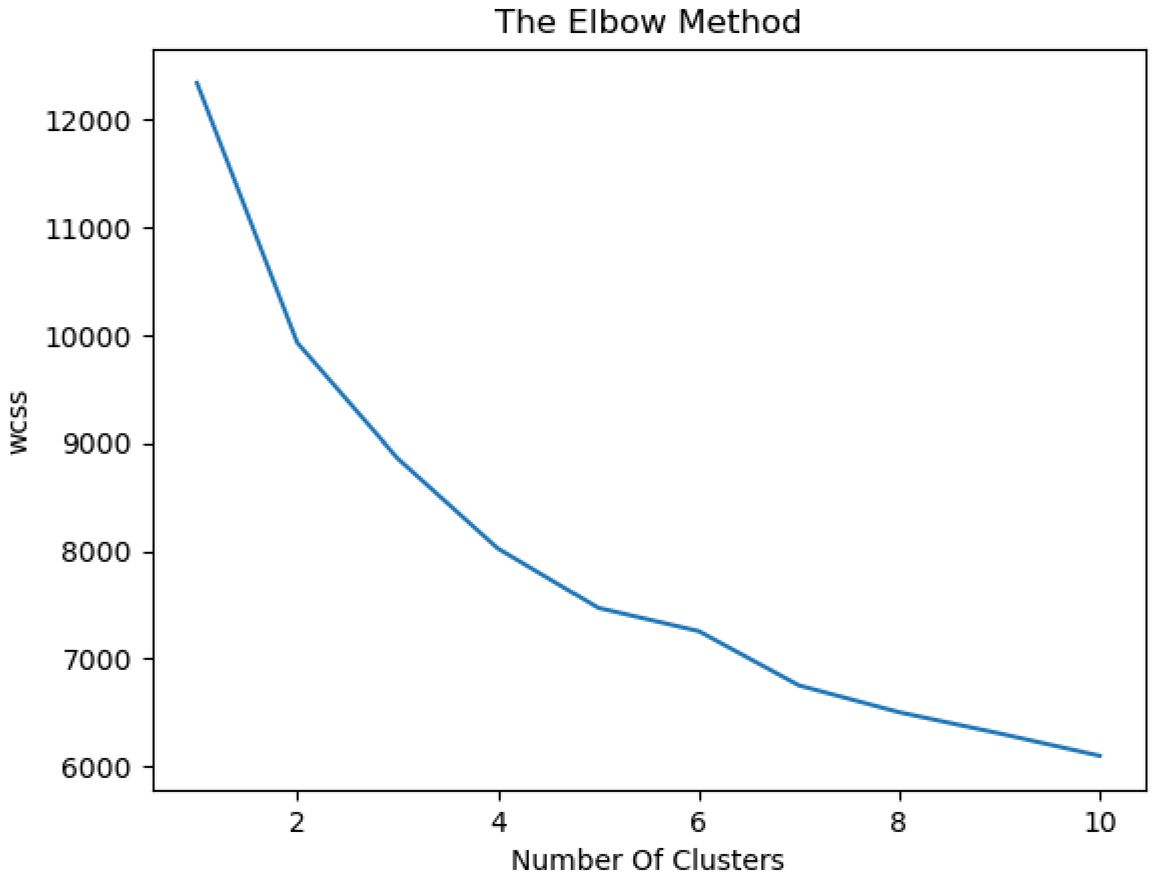
- **Scaling the data for better results.**

In [31]:
```
df2_scaled=preprocessing.scale(df2)
df2_scaled
```

Out[31]:
```
array([[-1.12374274,  1.03769966,  0.79311787, ..., -1.23686702,
         1.32089452,  0.06571664],
       [-0.68686651,  1.05991678,  0.74529973, ..., -1.25941854,
         1.32089452,  0.19648624],
       [-1.29121196,  1.05991678,  0.68705509, ..., -1.74202113,
         1.13478996,  0.74572645],
       ...,
       [ 2.25476675, -0.02316758, -0.3422932 , ...,  1.09496045,
         0.9486854 , -0.9437378 ],
       [ 1.59945241, -1.28954314, -0.91970618, ..., -0.27166184,
         0.66952856, -1.65605047],
       [ 1.79604671,  0.86551702, -0.49042156, ...,  1.69934127,
         1.4139468 , -0.77212805]])
```

In [32]:
```
wcss=[]
for i in range(1,11):
    df2_kmeans=KMeans(n_clusters=i,init='k-means++',random_state=42)
    df2_kmeans.fit(df2_scaled)
    wcss.append(df2_kmeans.inertia_)
```

In [33]:
```
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number Of Clusters')
plt.ylabel('wcss')
plt.show()
```



- **The above graph doesn't have a significant difference among the clusters, which means this is not a ideal data cluster analysis. Lets try it again by using the pca and reducing the dimensions.**

In [34]:
```
pca=PCA(n_components=2).fit(df2_scaled)
pca
```

Out[34]:
```
▾ PCA
PCA(n_components=2)
```

In [35]:
```
df2_pca=pca.transform(df2_scaled)
df2_pca
```

Out[35]:
```
array([[ 2.21956482,  0.57172049],
       [ 2.68907547,  0.08218135],
       [ 2.66851331,  1.55267133],
       ...,
       [-2.17254773, -0.89817802],
       [-2.40444331,  0.01252812],
       [-2.00512304, -1.77282898]])
```

In [36]:
```
df2.shape,df2_pca.shape
```

Out[36]:
```
((1122, 11), (1122, 2))
```

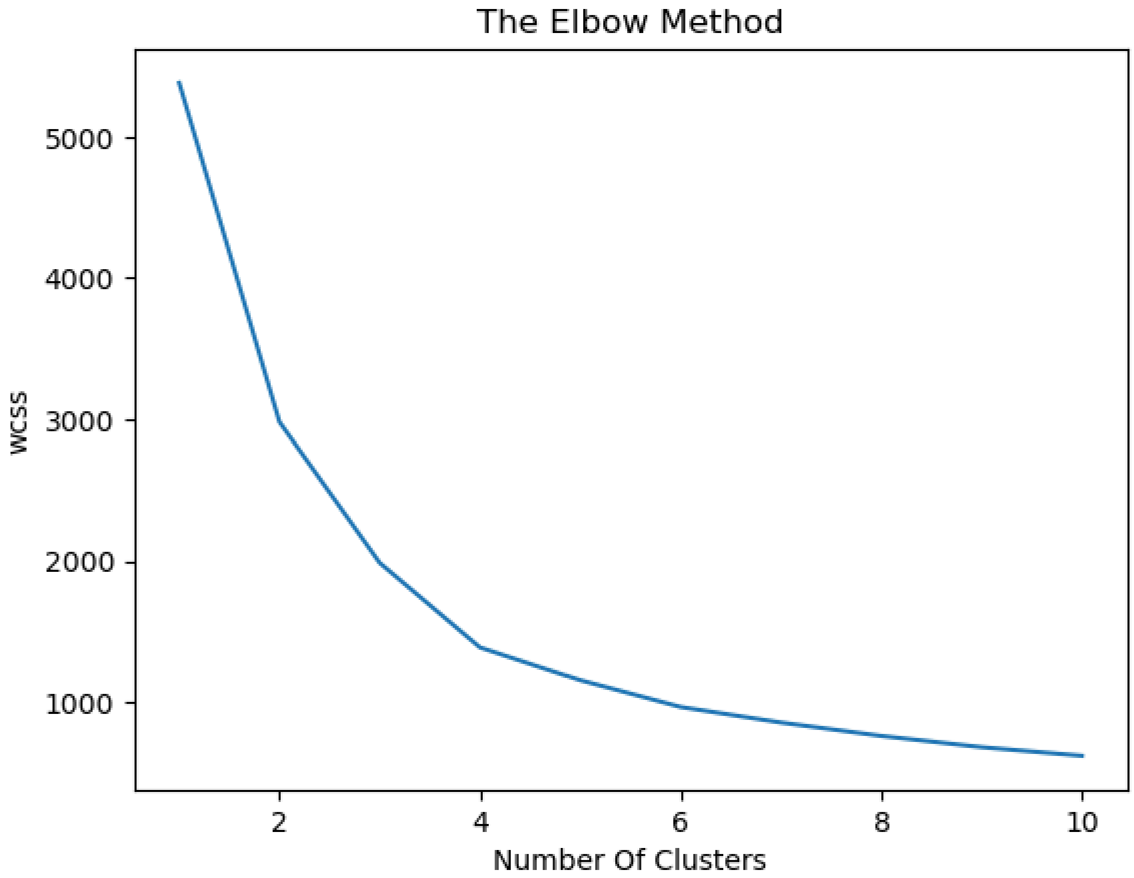
In [37]:
```
wcss=[]
for i in range(1,11):
    df2_kmeans=KMeans(n_clusters=i,init='k-means++',random_state=42)
    df2_kmeans.fit(df2_pca)
    wcss.append(df2_kmeans.inertia_)
```

In [38]:
```
wcss
```

Out[38]:
```
[5380.633871637081,
 2983.853997070694,
 1989.2931198674028,
 1391.4262683589227,
 1158.606235319844,
 969.6574093051321,
 859.8470581471136,
 765.3418409157769,
 685.8253032212612,
 625.0939499265012]
```

- **WCSS is the sum of squares wihin the cluster.**

In [39]:
```
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number Of Clusters')
plt.ylabel('wcss')
plt.show()
```



- **The elbow point on the above graph is near 4. So,the right number of clusters is 4.**

In [40]:
```
kmeans=KMeans(n_clusters=4,init='k-means++',random_state=42)
```

In [41]:
```
df2_pred=kmeans.fit_predict(df2_pca)
df2_pred
```

Out[41]:
```
array([1, 1, 1, ..., 3, 3, 3])
```

In [42]:
```
df2_pred.shape
```

Out[42]:
```
(1122,)
```

In [43]:
```
centroids=kmeans.cluster_centers_
centroids
```

Out[43]:
```
array([[-0.85484076,  1.85421384],
       [ 2.31158746,  0.34702541],
       [ 0.29414372, -1.06618595],
       [-1.95642005, -0.4414307 ]])
```

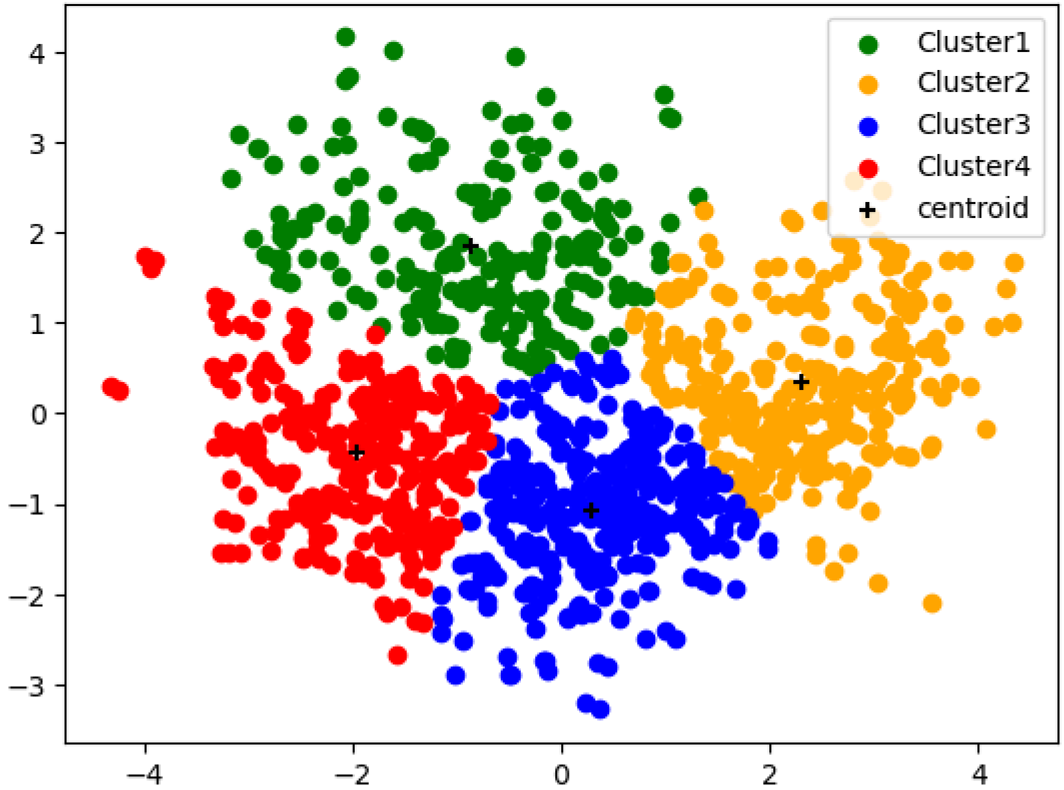
In [44]:
```
df2['cluster'] = kmeans.labels_
df2
```

Out[44]:

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	liveness	tempo	valence	popularity	duration_ms	cluster
1	0.326	0.965	-4.803	0.0759	0.4370	0.233000	0.9610	131.455	0.318	34	253173	1
2	0.386	0.969	-4.936	0.1150	0.4160	0.400000	0.9560	130.066	0.313	34	263160	1
4	0.303	0.969	-5.098	0.0930	0.4000	0.055900	0.9660	130.533	0.206	32	305106	1
5	0.340	0.956	-5.539	0.0915	0.2750	0.125000	0.7410	101.628	0.125	31	244293	1
6	0.262	0.810	-6.851	0.0969	0.5610	0.000003	0.9720	77.520	0.394	31	245506	1
...	...	...	...	...	...	...	...	...	...	...	...	...
1605	0.466	0.932	-9.214	0.0429	0.1570	0.006170	0.3240	177.340	0.967	39	154080	2
1606	0.509	0.706	-9.427	0.0843	0.0576	0.000002	0.5160	122.015	0.446	36	245266	2
1607	0.790	0.774	-7.961	0.0720	0.3710	0.000000	0.0669	97.035	0.835	30	176080	3
1608	0.700	0.546	-9.567	0.0622	0.2170	0.000070	0.1660	102.634	0.532	27	121680	3
1609	0.727	0.934	-8.373	0.0359	0.3830	0.068500	0.0965	125.275	0.969	35	189186	3

1122 rows × 12 columns

In [45]:
```
plt.scatter(df2_pca[df2_pred==0,0],df2_pca[df2_pred==0,1],c='green',label='Cluster1')
plt.scatter(df2_pca[df2_pred==1,0],df2_pca[df2_pred==1,1],c='orange',label='Cluster2')
plt.scatter(df2_pca[df2_pred==2,0],df2_pca[df2_pred==2,1],c='blue',label='Cluster3')
plt.scatter(df2_pca[df2_pred==3,0],df2_pca[df2_pred==3,1],c='red',label='Cluster4')
plt.scatter(centroids[:,0],centroids[:,1],c='black',marker='+',label='centroid')
plt.legend()
plt.show()
```



In [46]:
```
df2_sil=silhouette_score(df2_pca,df2_pred,metric='euclidean')
df2_sil
```

Out[46]: 0.4018130721337812

- **Using KMeans and silhouette_score as the clustering algorithms.**