MUSIC RECOMENDATION SYSTEM

In [1]:
```python
#importing all relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics.pairwise import cosine_similarity
import seaborn as sns
import statsmodels.api as sm
from warnings import filterwarnings
import os
from scipy.spatial.distance import pdist, squareform
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

filterwarnings('ignore')
```

In [2]:
```python
#loading my dataset
data_main = pd.read_csv('top 100 streamed songs.csv').drop(columns=['id'])
data = data_main.drop(columns=['name'])
data_main.head()
```

Out[2]:

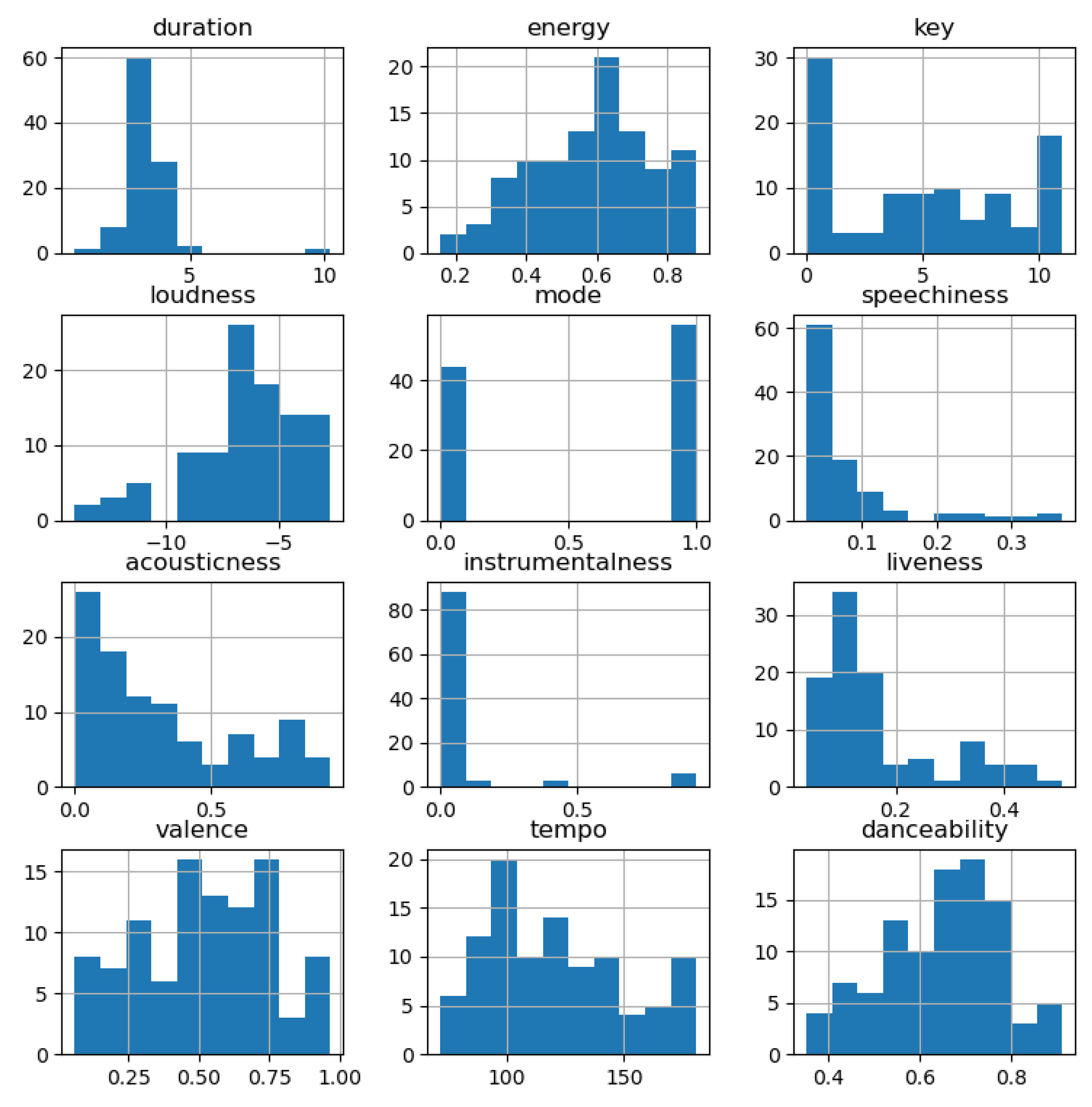
	name	duration	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	danceability
0	Good 4 U Olivia Rodrigo	2.97	0.664	9	-5.044	1	0.1540	0.33500	0.000	0.0849	0.688	166.928	0.563
1	Stay The Kid LAROI & Justin Bieber	2.30	0.506	8	-11.275	1	0.0589	0.37900	0.868	0.1100	0.454	170.054	0.564
2	Levitating Dua Lipa feat. DaBaby	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000	0.0674	0.915	102.977	0.702
3	Peaches Justin Bieber feat. Daniel Caesar & Gi...	3.30	0.696	0	-6.181	1	0.1190	0.32100	0.000	0.4200	0.464	90.030	0.677
4	Montero (Call Me By Your Name) Lil Nas X	2.30	0.503	8	-6.725	0	0.2200	0.29300	0.000	0.4050	0.710	178.781	0.593

In [3]:
```python
#viewing the first rows in our dataset
data.head()
```

Out[3]:

	duration	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	danceability
0	2.97	0.664	9	-5.044	1	0.1540	0.33500	0.000	0.0849	0.688	166.928	0.563
1	2.30	0.506	8	-11.275	1	0.0589	0.37900	0.868	0.1100	0.454	170.054	0.564
2	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000	0.0674	0.915	102.977	0.702
3	3.30	0.696	0	-6.181	1	0.1190	0.32100	0.000	0.4200	0.464	90.030	0.677
4	2.30	0.503	8	-6.725	0	0.2200	0.29300	0.000	0.4050	0.710	178.781	0.593

In [4]:
```python
#plotting distribution plots of our data
data.hist(figsize = (9,9));
```



In [5]:
```python
#having a general description of our data
data.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
duration	100.0	3.404900	0.927022	0.73000	2.910000	3.3700	3.630000	10.220
energy	100.0	0.587650	0.168273	0.15700	0.477750	0.6090	0.707750	0.883
key	100.0	5.050000	3.825420	0.00000	1.000000	5.0000	8.000000	11.000
loudness	100.0	-6.577120	2.447338	-14.06700	-7.676250	-6.2625	-4.786750	-2.724
mode	100.0	0.560000	0.498888	0.00000	0.000000	1.0000	1.000000	1.000
speechiness	100.0	0.075461	0.068065	0.02530	0.036100	0.0518	0.080650	0.368
acousticness	100.0	0.314539	0.281076	0.00028	0.090750	0.2385	0.519750	0.941
instrumentalness	100.0	0.070682	0.221947	0.00000	0.000000	0.0000	0.000083	0.941
liveness	100.0	0.161737	0.112657	0.03410	0.088375	0.1200	0.205250	0.509
valence	100.0	0.517354	0.237512	0.05920	0.329000	0.5420	0.711500	0.967
tempo	100.0	121.548260	29.148613	71.88400	97.476250	117.0375	141.733750	180.917
danceability	100.0	0.647900	0.126942	0.35200	0.566750	0.6635	0.734000	0.910

Approach 1: Recomendation with Eucledian Distance

In [ ]:

In [6]:
```python
#select features
data_features = data.iloc[:,1:]
#scale
data_features_scaled =  StandardScaler().fit_transform(data_features)

def n_nearest_row(dataframe,input_row,n=5):
    print("Input song:\n",pd.DataFrame(data.iloc[input_row,:]).T)

    distances = pdist(dataframe.values, metric='euclidean')
    dist_matrix = squareform(distances)
    distances_from_input_row = pd.DataFrame(dist_matrix)[input_row].sort_values()

    distances_from_input_row = distances_from_input_row[1:n+1].sort_index()
    nearest_rows = data_main[data.index.isin(distances_from_input_row.index)]

    output_df = pd.concat((nearest_rows,distances_from_input_row),axis=1)

    columns = list(data_main.columns)
    columns.append("distance")
    output_df.columns=columns

    return output_df



nearest_5_row = n_nearest_row(data_features,96) # we will examine the first index
print("\n\nNearest songs: ")
nearest_5_row
```

```
Input song:
     duration  energy   key  loudness  mode  speechiness  acousticness  \
96      3.37   0.748  11.0    -5.922   0.0       0.0589         0.305

    instrumentalness  liveness  valence    tempo  danceability
96               0.0    0.0811    0.964  163.984         0.672


Nearest songs: 
```

Out[6]:

	name	duration	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	danceability	distance
0	Good 4 U Olivia Rodrigo	2.97	0.664	9	-5.044	1	0.1540	0.3350	0.000000	0.0849	0.688	166.928	0.563	3.813541
1	Stay The Kid LAROI & Justin Bieber	2.30	0.506	8	-11.275	1	0.0589	0.3790	0.868000	0.1100	0.454	170.054	0.564	8.751547
47	Cover Me In Sunshine P!nk & Willow Sage Hart	2.37	0.488	5	-11.276	1	0.0568	0.0142	0.900000	0.1560	0.107	160.013	0.543	9.118828
58	Stressed Out twenty one pilots	3.37	0.637	4	-5.677	0	0.1410	0.0462	0.000023	0.0602	0.648	169.977	0.734	9.228556
80	rockstar (feat. 21 Savage) Post Malone	3.64	0.520	5	-6.136	0	0.0712	0.1240	0.000070	0.1310	0.129	159.801	0.585	7.371259

In [7]:
```python
data_main.shape
```

Out[7]:
```
(100, 13)
```

In [8]:
```python
data.shape
```

Out[8]:
```
(100, 12)
```

Aproach2: Recomendation withK-Nearest

in order to find the optimal values of K for our classification, we used KMeans from the scikit-learn library and the elbow visualizer for the yellow brick bibrary.

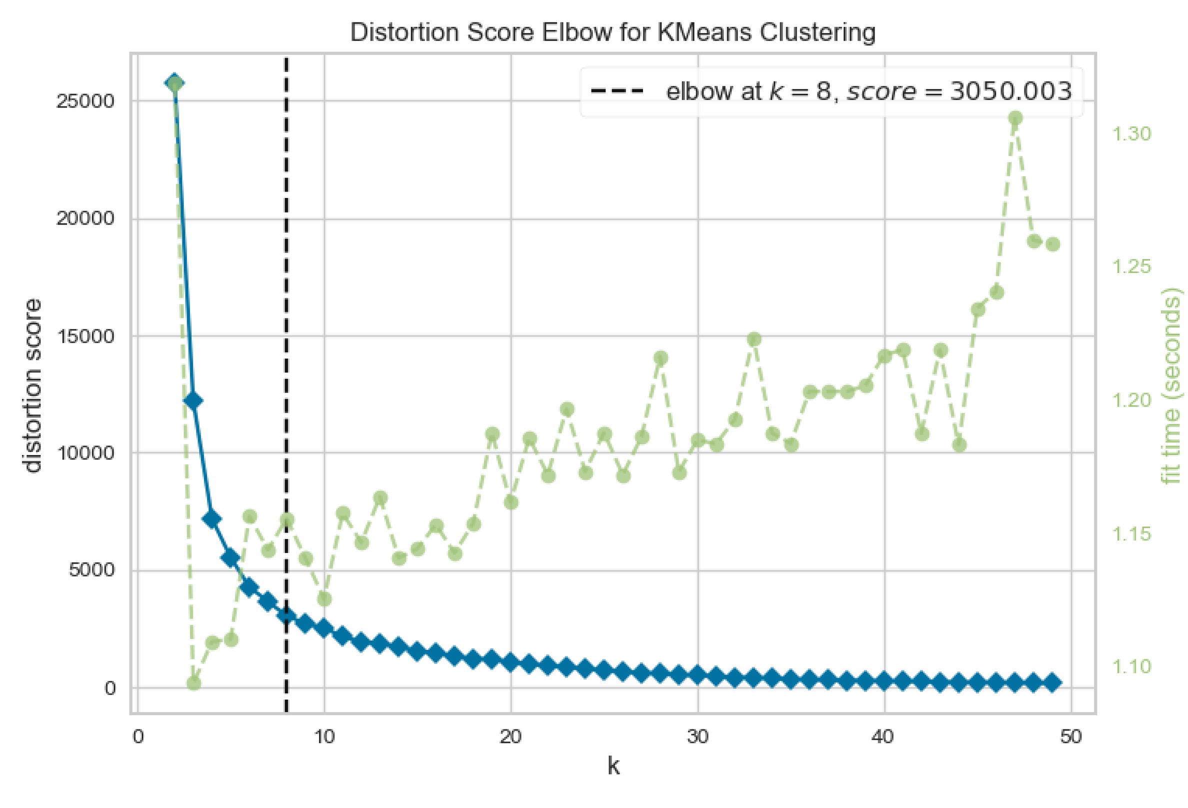
In [9]:
```python
!pip install yellowbrick
```

```
Requirement already satisfied: yellowbrick in c:\users\lenovo\anaconda3\lib\site-packages (1.5)
Requirement already satisfied: numpy>=1.16.0 in c:\users\lenovo\anaconda3\lib\site-packages (from yellowbrick) (1.23.5)
Requirement already satisfied: cycler>=0.10.0 in c:\users\lenovo\anaconda3\lib\site-packages (from yellowbrick) (0.11.0)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in c:\users\lenovo\anaconda3\lib\site-packages (from yellowbrick) (3.7.0)
Requirement already satisfied: scipy>=1.0.0 in c:\users\lenovo\anaconda3\lib\site-packages (from yellowbrick) (1.10.0)
Requirement already satisfied: scikit-learn>=1.0.0 in c:\users\lenovo\anaconda3\lib\site-packages (from yellowbrick) (1.2.1)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.0.5)
Requirement already satisfied: pillow>=6.2.0 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (9.4.0)
Requirement already satisfied: packaging>=20.0 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (22.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.4.4)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (4.25.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.8.2)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\lenovo\anaconda3\lib\site-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.0.9)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\lenovo\anaconda3\lib\site-packages (from scikit-learn>=1.0.0->yellowbrick) (2.2.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\lenovo\anaconda3\lib\site-packages (from scikit-learn>=1.0.0->yellowbrick) (1.2.0)
Requirement already satisfied: six>=1.5 in c:\users\lenovo\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.
16.0)
```

In [10]:
```python
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer

kmeans = KMeans()
visualizer = KElbowVisualizer(kmeans, k=(2,50))

visualizer.fit(data_features)
visualizer.poof();
```



after fitting the visualizer to our features, we are able to determine the optimal value of k to 8.

In [11]:
```python
kmeans = KMeans(n_clusters=8)
kmeans.fit(data_features)
data_groups = pd.concat((data_main, pd.DataFrame(kmeans.labels_,columns=['Group'])), axis=1)
data_groups.head(5)
```

Out[11]:

	name	duration	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	danceability	Group
0	Good 4 U Olivia Rodrigo	2.97	0.664	9	-5.044	1	0.1540	0.33500	0.000	0.0849	0.688	166.928	0.563	6
1	Stay The Kid LAROI & Justin Bieber	2.30	0.506	8	-11.275	1	0.0589	0.37900	0.868	0.1100	0.454	170.054	0.564	6
2	Levitating Dua Lipa feat. DaBaby	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000	0.0674	0.915	102.977	0.702	5
3	Peaches Justin Bieber feat. Daniel Caesar & Gi...	3.30	0.696	0	-6.181	1	0.1190	0.32100	0.000	0.4200	0.464	90.030	0.677	1
4	Montero (Call Me By Your Name) Lil Nas X	2.30	0.503	8	-6.725	0	0.2200	0.29300	0.000	0.4050	0.710	178.781	0.593	2

In [12]:
```python
group5 = data_groups[data_groups['Group']==5]
group5
```

Out[12]:

	name	duration	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	danceability	Group
2	Levitating Dua Lipa feat. DaBaby	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000000	0.0674	0.915	102.977	0.702	5
13	Beautiful Mistakes (feat. Megan Thee Stallion)...	3.79	0.676	10	-5.483	1	0.0270	0.03770	0.000000	0.1540	0.721	99.048	0.713	5
18	Fiel Los Legendarios, Wisin & Jhay Cortez	4.27	0.430	6	-7.477	0	0.0255	0.73500	0.941000	0.1240	0.300	97.976	0.685	5
22	Levitating (feat. DaBaby) Dua Lipa	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000000	0.0674	0.915	102.977	0.702	5
26	Famous Friends Chris Young + Kane Brown	2.74	0.513	6	-8.619	1	0.0311	0.10100	0.000002	0.1310	0.685	102.040	0.717	5
32	Levitating Dua Lipa	3.38	0.825	6	-3.787	0	0.0601	0.00883	0.000000	0.0674	0.915	102.977	0.702	5
36	Tusa KAROL G & Nicki Minaj	3.37	0.701	2	-3.275	1	0.2830	0.30800	0.000078	0.0516	0.619	100.954	0.796	5
41	Therefore I Am Billie Eilish	2.91	0.340	11	-7.773	0	0.0697	0.21800	0.130000	0.0550	0.716	94.009	0.889	5
49	The Woo (feat. 50 Cent & Roddy Ricch) Pop Smoke	3.36	0.618	1	-5.655	1	0.1040	0.02210	0.000004	0.2590	0.286	99.700	0.490	5
51	You Right Doja Cat & The Weeknd	2.95	0.360	6	-11.212	1	0.0279	0.91800	0.877000	0.1650	0.756	99.956	0.699	5
57	Pretend CNCO	3.34	0.883	11	-3.862	0	0.1030	0.28400	0.000000	0.1400	0.834	101.983	0.680	5
59	Therefore I Am Billie Eilish	2.91	0.340	11	-7.773	0	0.0697	0.21800	0.130000	0.0550	0.716	94.009	0.889	5
63	Heather Conan Gray	3.30	0.425	5	-7.301	1	0.0333	0.58400	0.000000	0.3220	0.270	102.078	0.357	5
67	Dance Monkey Tones And I	3.49	0.588	6	-6.400	0	0.0924	0.69200	0.000104	0.1490	0.513	98.027	0.824	5
68	Shallow Lady Gaga & Bradley Cooper	3.60	0.385	7	-6.362	1	0.0308	0.37100	0.000000	0.2310	0.323	95.799	0.572	5
69	Memories Maroon 5	3.16	0.327	11	-7.241	1	0.0557	0.84100	0.000000	0.0821	0.595	91.050	0.775	5
75	Talking to the Moon Acoustic Bruno Mars	3.63	0.333	1	-6.423	0	0.0310	0.86700	0.000000	0.1070	0.208	99.511	0.352	5
97	Therefore I Am Billie Eilish	2.91	0.340	11	-7.773	0	0.0697	0.21800	0.130000	0.0550	0.716	94.009	0.889	5

Applying PCA in our dataset

by appling pca in the dataset may be very isefull.

In [13]:
```python
plt.rcParams['figure.figsize']=(12,6)
pca = PCA().fit(data_features_scaled)

plt.ylabel('cumulative variance')
plt.title('the number of components / variance')
plt.xlabel('number of components')

x = np.arange(1, 12)
y = np.cumsum(pca.explained_variance_ratio_)

plt.xticks(x)
plt.yticks(y)

plt.plot(x, y, marker='o', linestyle='-', color='b')

plt.hlines(y, 0, x, linestyle='--')
plt.vlines(x, 0, y, linestyle='--')

plt.show()
```