Spotify

March 12, 2024

1 Machine Learning

1.0.1 Course-End Project Problem Statement

Course-End Project: Creating Cohorts of Songs

1.0.2 Problem Scenario:

The customer always looks forward to specialized treatment, whether shopping over an e-commerce website or watching Netflix. They want what they might like to see. To keep the customers engaged, it is also crucial for companies to always present the most relevant information. Spotify is a Swedish audio streaming and media service provider. The company has over 456 million active monthly users, including over 195 million paying subscribers, as of September 2022. The company intends to create cohorts of different songs that will aid in the recommendation of songs to users based on various relevant features. Each cohort would contain similar types of songs. ### Problem Objective: 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.

- Note: Download Data Dictionary – Creating cohorts of songs.xlsx from the course resource section in the LMS.

Data Description: This dataset contains data from Spotify's API about all albums for the Rolling Stones listed on Spotify. It is important to note that all songs have unique IDs.

Variable Description

- name It is the name of the song.
- album It is the name of the album.
- release_date It is the day, month, and year the album was released.
- track number It is the order the song appears on the album.
- id It is the Spotify id for the song.
- uri It is the Spotify URI for the song.
- acousticness A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.

- danceability It describes how suitable a track is for dancing based on a combination of musical elements, including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is the least danceable, and 1.0 is the most danceable.
- energy It is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
- instrumentalness It predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.
- liveness It detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides a strong likelihood that the track is live.
- loudness The overall loudness of a track in decibels (dB) and loudness values are averaged across the entire track and are useful for comparing the relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 dB.
- speechiness It detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g., talk show, audiobook, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.
- tempo The overall estimated tempo of a track is in beats per minute (BPM), and in musical terminology, the tempo is the speed or pace of a given piece and derives directly from the average beat duration.
- valence A measure from 0.0 to 1.0 describes the musical positiveness conveyed by a track, and tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g., sad, depressed, angry).
- popularity It is the popularity of the song from 0 to 100.
- duration_ms It is the duration of the track in milliseconds.

Steps to Perform:

Initial data inspection and data cleaning: Check whether the data has duplicates, missing values, irrelevant (erroneous entries) values, or outliers.

Depending on your findings, clean the data for further processing. ##### Perform Exploratory Data Analysis and Feature Engineering: Use appropriate visualizations to find out which two albums should be recommended to anyone based on the number of popular songs in an album.

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

Discover how a song's popularity relates to various factors and how this has changed over time. Comment on the importance of dimensionality reduction techniques, share your ideas and explain your observations. ##### Perform Cluster Analysis: Identify the right number of clusters Use appropriate clustering algorithm Define each cluster based on the features

[1]:
```python
# Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import warnings
```

[2]:
```python
# Suppressing the warnings
warnings.filterwarnings('ignore')
```

[3]:
```python
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

1.1 Data Inspection and Data Cleaning

[4]:
```python
# Load Data
df = pd.read_excel('1673873388_rolling_stones_spotify.xlsx')
df.head()
```

[4]:
```
   Unnamed: 0                         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          Donâ€ t Stop - Live  Licked Live In NYC   2022-06-10

   track_number                      id                                   uri  \
0             1  2IEkywLJ4ykbhi1yRQvmsT  spotify:track:2IEkywLJ4ykbhi1yRQvmsT
1             2  6GVgVJBKkGJoRfarYRvGTU  spotify:track:6GVgVJBKkGJoRfarYRvGTU
2             3  1Lu761pZ0dBTGpzxaQoZNW  spotify:track:1Lu761pZ0dBTGpzxaQoZNW
3             4  1agTQzOTUnGNggyckEqiDH  spotify:track:1agTQzOTUnGNggyckEqiDH
4             5  7piGJR8YndQBQWVXv6KtQw  spotify:track:7piGJR8YndQBQWVXv6KtQw

   acousticness  danceability  energy  instrumentalness  liveness  loudness  \
0        0.0824         0.463   0.993          0.996000     0.932   -12.913
1        0.4370         0.326   0.965          0.233000     0.961    -4.803
```

```
2        0.4160          0.386   0.969          0.400000     0.956    -4.936
3        0.5670          0.369   0.985          0.000107     0.895    -5.535
4        0.4000          0.303   0.969          0.055900     0.966    -5.098

   speechiness    tempo  valence  popularity  duration_ms
0       0.1100  118.001   0.0302          33        48640
1       0.0759  131.455   0.3180          34       253173
2       0.1150  130.066   0.3130          34       263160
3       0.1930  132.994   0.1470          32       305880
4       0.0930  130.533   0.2060          32       305106
```

[5]:
```
# Creating a backup dataframe and dropping unneccssary solumns
df_bak = df.copy(deep=1)

df.drop(['Unnamed: 0', 'id', 'uri', 'duration_ms', 'track_number'], axis = 1,␣
 ↪inplace = True)
```

[6]:
```
print(f'>>> Shape  : {df.shape}\n')
print(f'>>> Info : ')
df.info()
```

```
>>> Shape  : (1610, 13)

>>> Info :
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1610 entries, 0 to 1609
Data columns (total 13 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   acousticness      1610 non-null   float64
 4   danceability      1610 non-null   float64
 5   energy            1610 non-null   float64
 6   instrumentalness  1610 non-null   float64
 7   liveness          1610 non-null   float64
 8   loudness          1610 non-null   float64
 9   speechiness       1610 non-null   float64
 10  tempo             1610 non-null   float64
 11  valence           1610 non-null   float64
 12  popularity        1610 non-null   int64
dtypes: datetime64[ns](1), float64(9), int64(1), object(2)
memory usage: 163.6+ KB
```

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

[7]:
```
                   count        mean        std        min         25%  \
acousticness      1610.0    0.250475   0.227397   0.000009    0.058350
danceability      1610.0    0.468860   0.141775   0.104000    0.362250
energy            1610.0    0.792352   0.179886   0.141000    0.674000
instrumentalness  1610.0    0.164170   0.276249   0.000000    0.000219
liveness          1610.0    0.491730   0.349100   0.021900    0.153000
loudness          1610.0   -6.971615   2.994003 -24.408000   -8.982500
speechiness       1610.0    0.069512   0.051631   0.023200    0.036500
tempo             1610.0  126.082033  29.233483  46.525000  107.390750
valence           1610.0    0.582165   0.231253   0.000000    0.404250
popularity        1610.0   20.788199  12.426859   0.000000   13.000000

                        50%        75%      max
acousticness        0.18300    0.40375    0.994
danceability        0.45800    0.57800    0.887
energy              0.84850    0.94500    0.999
instrumentalness    0.01375    0.17900    0.996
liveness            0.37950    0.89375    0.998
loudness           -6.52300   -4.60875   -1.014
speechiness         0.05120    0.08660    0.624
tempo             124.40450  142.35575  216.304
valence             0.58300    0.77800    0.974
popularity         20.00000   27.00000   80.000
```

[8]:
```python
# Checking for the Null Values
df.isna().sum(axis=0)
```

[8]:
```
name                0
album               0
release_date        0
acousticness        0
danceability        0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
dtype: int64
```

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

[9]:
```
Index(['name', 'album', 'release_date', 'acousticness', 'danceability',
       'energy', 'instrumentalness', 'liveness', 'loudness', 'speechiness',
       'tempo', 'valence', 'popularity'],
```

```
      dtype='object')
```

[10]:
```
a1 = []
a2 = list(np.sort(df['album'].unique()))

b1 = ["12 X 5", "December's Children", "England's Newest Hit Makers", "Get Yer␣
↪Ya-Ya's Out", "Get Yer Ya-Ya's Out"]
b2 = ["12 x 5", "Decemberâ€ s Children", "Englandâ€ s Newest Hitmakers", "Get␣
↪Yer Ya Yas Out", "Get Yer Ya-Ya's Out!"]

for i in np.sort(df['album'].unique()):
    a1.append(i.split(' (')[0].split(' - ')[0])

df['album'] = [i if i not in a2 else a1[a2.index(i)] for i in df['album']]
df['album'] = [i if i not in b2 else b1[b2.index(i)] for i in df['album']]
```

[11]:
```
# Checking for the duplicatesNull Values
df[df[['name', 'album']].duplicated()]
```

[11]:
```
                                  name                        album  \
92        Start Me Up - Remastered 2021                   Tattoo You
93          Hang Fire - Remastered 2021                   Tattoo You
94              Slave - Remastered 2021                   Tattoo You
95        Little T&A - Remastered 2021                   Tattoo You
96     Black Limousine - Remastered 2021                   Tattoo You
…                                  …                           …
1592                     I'm A King Bee  England's Newest Hit Makers
1593                              Carol  England's Newest Hit Makers
1595                Can I Get A Witness  England's Newest Hit Makers
1596          You Can Make It If You Try  England's Newest Hit Makers
1597                    Walking The Dog  England's Newest Hit Makers

     release_date  acousticness  danceability  energy  instrumentalness  \
92     2021-10-22        0.0302         0.555   0.956          0.367000
93     2021-10-22        0.0136         0.421   0.927          0.079700
94     2021-10-22        0.1300         0.558   0.898          0.306000
95     2021-10-22        0.1560         0.497   0.953          0.042900
96     2021-10-22        0.1220         0.480   0.934          0.198000
…             …           …            …      …                …
1592   1964-05-30        0.0160         0.884   0.554          0.005620
1593   1964-05-30        0.1480         0.599   0.939          0.007470
1595   1964-05-30        0.3120         0.783   0.783          0.000000
1596   1964-05-30        0.2010         0.699   0.554          0.000051
1597   1964-05-30        0.3960         0.724   0.942          0.064800

      liveness  loudness  speechiness    tempo  valence  popularity
92      0.0753    -2.147       0.0577  121.752    0.933          12
```

```
93     0.2640   -1.734       0.0345  151.096    0.922            11
94     0.0562   -4.314       0.0515  133.338    0.853            11
95     0.6670   -1.978       0.0328  135.453    0.801            13
96     0.7010   -1.382       0.0715  108.894    0.825             9
…       …        …        …     …       …          …
1592   0.0786  -10.899       0.0636  105.536    0.884             0
1593   0.3200   -9.223       0.0390   88.645    0.967             1
1595   0.0763   -7.981       0.0741   97.018    0.842             0
1596   0.1070   -9.465       0.0529  102.508    0.582             0
1597   0.1160   -8.357       0.0354  125.331    0.967             0

[371 rows x 13 columns]
```

[12]:
```python
df.drop(df.index[df[df[['name', 'album']].duplicated()].index], inplace= True)
df[df[['name', 'album']].duplicated()]
```

[12]:
```
Empty DataFrame
Columns: [name, album, release_date, acousticness, danceability, energy,
instrumentalness, liveness, loudness, speechiness, tempo, valence, popularity]
Index: []
```

[13]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1239 entries, 0 to 1609
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              1239 non-null   object
 1   album             1239 non-null   object
 2   release_date      1239 non-null   datetime64[ns]
 3   acousticness      1239 non-null   float64
 4   danceability      1239 non-null   float64
 5   energy            1239 non-null   float64
 6   instrumentalness  1239 non-null   float64
 7   liveness          1239 non-null   float64
 8   loudness          1239 non-null   float64
 9   speechiness       1239 non-null   float64
 10  tempo             1239 non-null   float64
 11  valence           1239 non-null   float64
 12  popularity        1239 non-null   int64
dtypes: datetime64[ns](1), float64(9), int64(1), object(2)
memory usage: 135.5+ KB
```

[14]:
```python
df.head()
```

[14]:
```
                           name              album release_date  acousticness  \
0   Concert Intro Music - Live  Licked Live In NYC   2022-06-10        0.0824
1   Street Fighting Man - Live  Licked Live In NYC   2022-06-10        0.4370
2           Start Me Up - Live  Licked Live In NYC   2022-06-10        0.4160
3  If You Can't Rock Me - Live  Licked Live In NYC   2022-06-10        0.5670
4          Donâ€ t Stop - Live  Licked Live In NYC   2022-06-10        0.4000

   danceability  energy  instrumentalness  liveness  loudness  speechiness  \
0         0.463   0.993          0.996000     0.932   -12.913       0.1100
1         0.326   0.965          0.233000     0.961    -4.803       0.0759
2         0.386   0.969          0.400000     0.956    -4.936       0.1150
3         0.369   0.985          0.000107     0.895    -5.535       0.1930
4         0.303   0.969          0.055900     0.966    -5.098       0.0930

     tempo  valence  popularity
0  118.001   0.0302          33
1  131.455   0.3180          34
2  130.066   0.3130          34
3  132.994   0.1470          32
4  130.533   0.2060          32
```

feature_list = ['acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo', 'valence']

[15]:
```python
feature_list = ['acousticness', 'danceability', 'energy', 'instrumentalness',
 ↪'liveness', 'loudness', 'speechiness', 'tempo', 'valence']
features_df = pd.DataFrame(df[feature_list])
features_df.head()
```

[15]:
```
   acousticness  danceability  energy  instrumentalness  liveness  loudness  \
0        0.0824         0.463   0.993          0.996000     0.932   -12.913
1        0.4370         0.326   0.965          0.233000     0.961    -4.803
2        0.4160         0.386   0.969          0.400000     0.956    -4.936
3        0.5670         0.369   0.985          0.000107     0.895    -5.535
4        0.4000         0.303   0.969          0.055900     0.966    -5.098

   speechiness    tempo  valence
0       0.1100  118.001   0.0302
1       0.0759  131.455   0.3180
2       0.1150  130.066   0.3130
3       0.1930  132.994   0.1470
4       0.0930  130.533   0.2060
```

1.2 Scaling And Decoposing

[16]:
```
from sklearn.manifold import TSNE
from sklearn.preprocessing import StandardScaler

# scale the data for better results
features_df = StandardScaler().fit_transform(features_df)

features_df_tsne = TSNE(learning_rate=100).fit_transform(features_df)

features_df_tsne
```

[16]:
```
array([[-19.618046, -33.72533 ],
       [-28.162659,  16.59559 ],
       [-30.906765, -22.013271],
       …,
       [ 23.98327 , -10.512095],
       [ 39.72409 ,  -8.797641],
       [ 23.788965,  -5.317569]], dtype=float32)
```

Decomposing the features as there are too many features for the clustering of the songs. Reducing the number of features to two where the features don;t really loose any of the reduced values

[17]:
```
features_df = pd.DataFrame(data = features_df,
                           columns = feature_list)
features_df.head()
```

[17]:

	acousticness	danceability	energy	instrumentalness	liveness	loudness	\
0	-0.711916	0.029653	1.054720	3.071082	1.162032	-2.045796	
1	0.853867	-0.939624	0.898093	0.263934	1.244453	0.672496	
2	0.761138	-0.515123	0.920468	0.878342	1.230242	0.627917	
3	1.427898	-0.635398	1.009969	-0.592902	1.056873	0.427146	
4	0.690488	-1.102349	0.920468	-0.387634	1.258664	0.573619	

	speechiness	tempo	valence
0	0.733260	-0.277206	-2.316806
1	0.075820	0.182247	-1.076932
2	0.829659	0.134813	-1.098472
3	2.333480	0.234803	-1.813619
4	0.405504	0.150761	-1.559440

2 DATA VISUALISATION

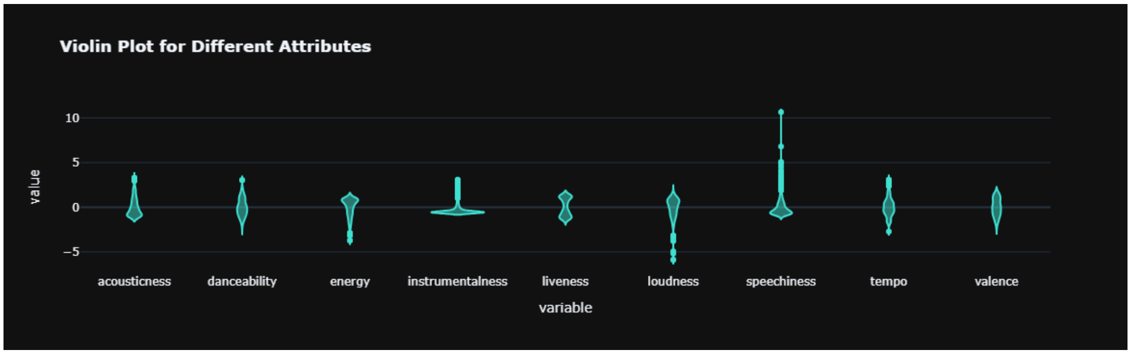
- Feature Distribution

[18]:
```
fig = make_subplots(rows = 3,
                    cols = 3,
```

```
                    subplot_titles=[f'<i>{i.title()}' for i in feature_list])
l = len(feature_list)
for i in range(l):
    fig.add_trace(go.Histogram(x = features_df[feature_list[i]]),
                  col = i % 3 + 1,
                  row = i // 3 +1)

fig.update_layout(height = 900,
                width = 900,
                title_text = '<b>Feature Distribution',
                template = 'plotly_dark',
                title_x = 0.5,
                showlegend=False)


fig.show()
```

- Violin Plot for Different Attributes

[19]:
```
px.violin(data_frame= features_df,
          y = feature_list,
              color_discrete_sequence = ['turquoise'],
              template = 'plotly_dark',
              title = '<b>Violin Plot for Different Attributes')
```



[20]:
```
def outliers(feature_list, dataset) :

    l = len(feature_list)
    row = 3
    col = l//row
    fig = make_subplots(rows = row,
                        cols = col,
                        subplot_titles=[f'<i>{i.title()}' for i in␣
 ↪feature_list])
    for i in range(l):
        fig.add_trace(go.Box(x = dataset[feature_list[i]]),
                      col = i % col + 1,
                      row = i // row +1)

    fig.update_layout(height = 900,
                      width = 900,
                      title_text = '<b>Feature Distribution')

    fig.update_layout(template = 'plotly_dark',
                      title_x = 0.5)
    fig.update_layout(showlegend=False)

    fig.show()

outliers(feature_list, df )
```

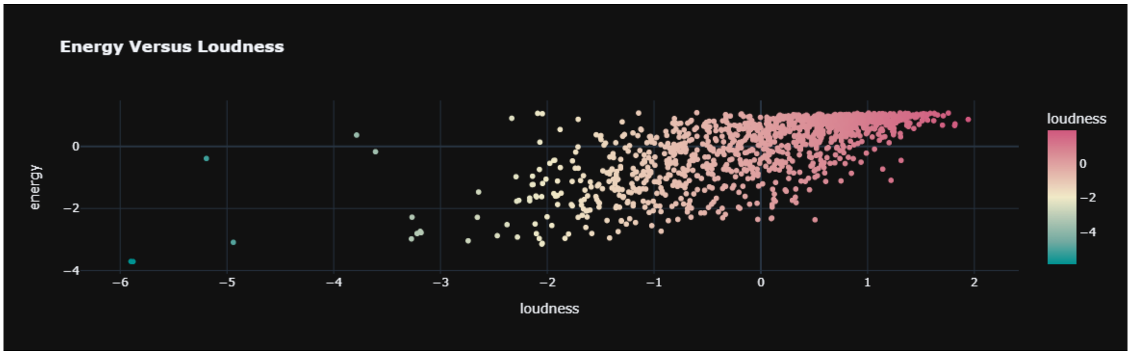
We won't be removing outliers as outlying part of one feature is major part of another as can be seen from Instrmentalenes and Speechiness

- Heat Map for Different Attributes

[21]:
```
fig = px.imshow(features_df.corr(),
            text_auto =True,
            height =1000,
            template = 'plotly_dark',
            title = '<b>Heat Map for Different Attributes')
fig.show()
```

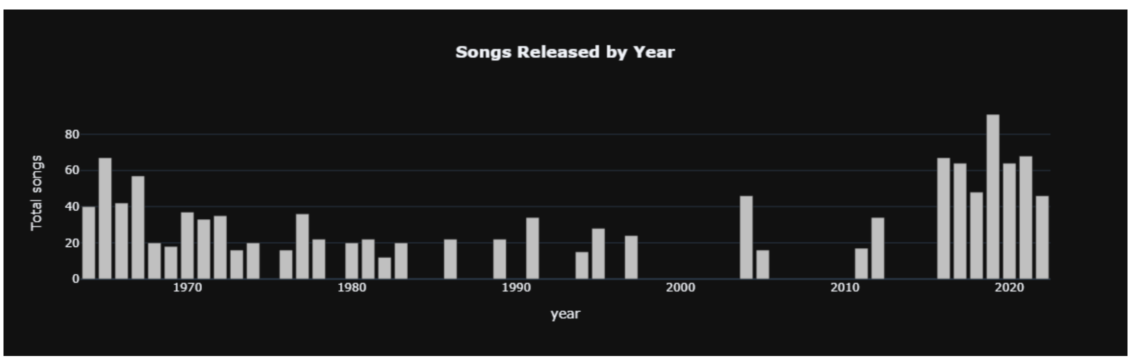
- No Strong correlation found except for between Loudness and Energy
- Energy Versus Loudness

[22]:
```
fig = px.scatter(features_df,
        x = 'loudness',
        y = 'energy',
        color = 'loudness',
        color_continuous_scale = 'tealrose',
        template = 'plotly_dark',
        title = f'<b>Energy Versus Loudness')
fig.show()
```



- Songs Released by Year

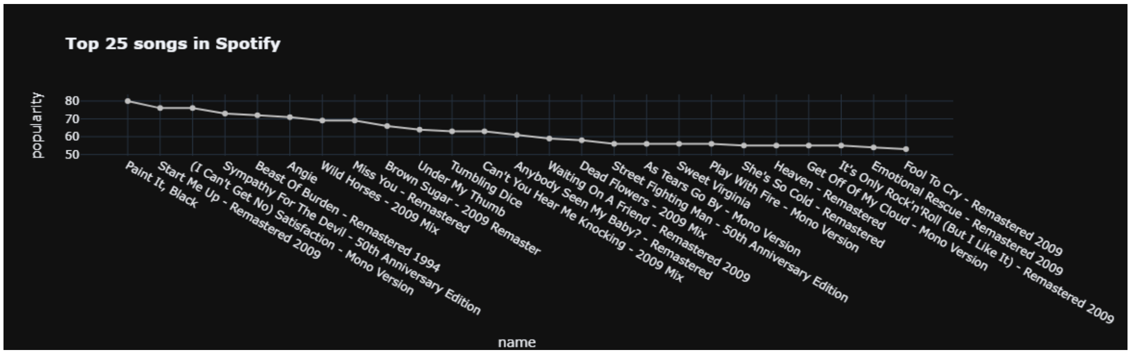
[23]:
```
df['year'] = pd.DatetimeIndex(df['release_date']).year

fig = px.bar(data_frame = df.groupby('year',as_index=False).count().
 ↪sort_values(by='name',ascending=False).sort_values(by='year'),
             x = 'year',
             y = 'name',
             labels = {'name':'Total songs'},
             color_discrete_sequence = ['silver'],
             template = 'plotly_dark',
             title = '<b>Songs Released by Year')
fig.update_layout(hovermode = 'x',
                  title_x = 0.5)
```



- Top 25 songs in Spotify

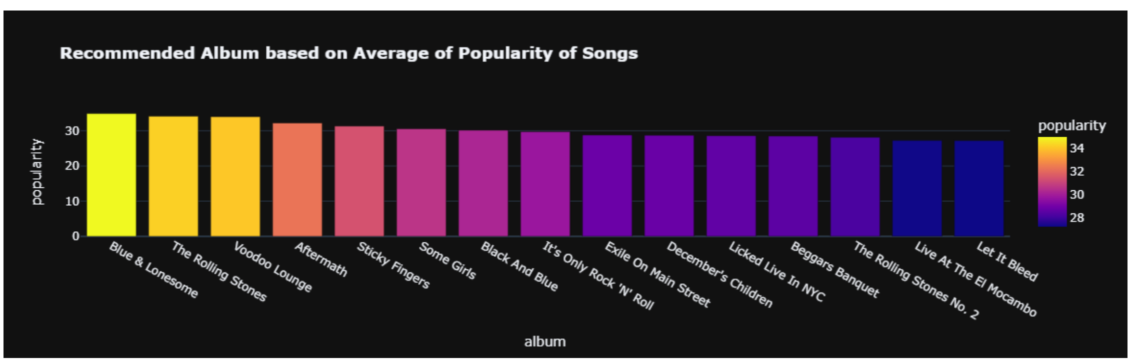
[24]:
```
fig = px.line(df.sort_values(by='popularity',
                             ascending=False).head(25),
             x = 'name',
             y = 'popularity',
             hover_data = ['album'],
```

```
                 color_discrete_sequence = ['silver'],
                 template = 'plotly_dark',
                 markers = True,
                 title = '<b> Top 25 songs in Spotify',
                 )
fig.show()
```



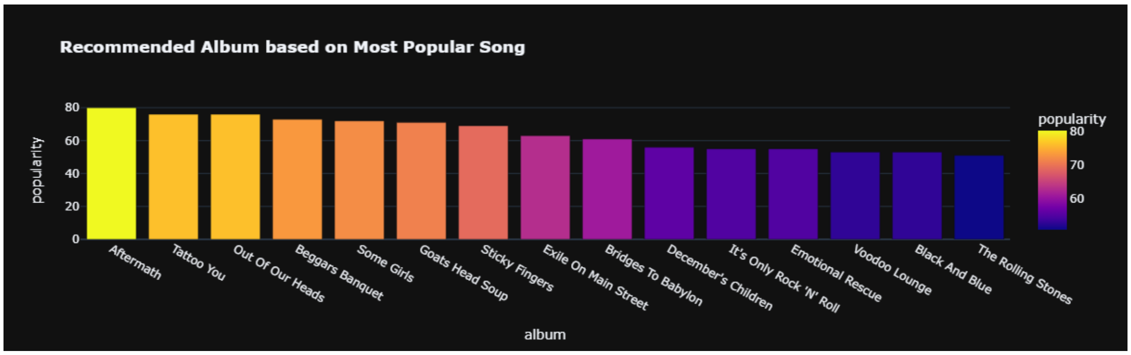
- Recommended Album based on Average of Popularity of Songs

[25]:
```
by_mean = df.groupby('album')['popularity'].mean().sort_values(ascending =␣
 ↪False).head(15)
fig = px.bar(by_mean,
       y = 'popularity',
       color = 'popularity',
       color_continuous_scale = 'plasma',
       template = 'plotly_dark',
       title = f'<b>Recommended Album based on Average of Popularity of Songs')
fig.show()
```



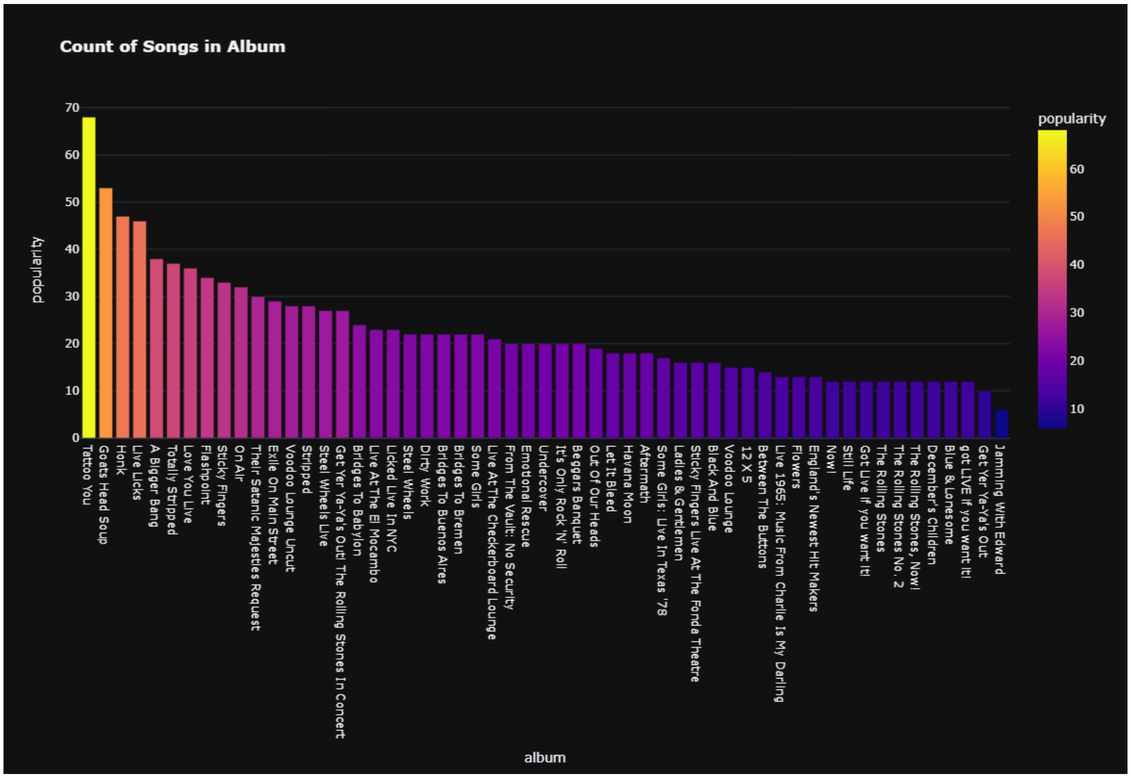
- Recommended Album based on Most Popular Song

[26]:
```
by_max = df.groupby('album')['popularity'].max().sort_values(ascending = False).
↪head(15)
fig = px.bar(by_max,
        y = 'popularity',
        color = 'popularity',
        color_continuous_scale = 'plasma',
        template = 'plotly_dark',
        title = f'<b>Recommended Album based on Most Popular Song')
fig.show()
```



- Song Count

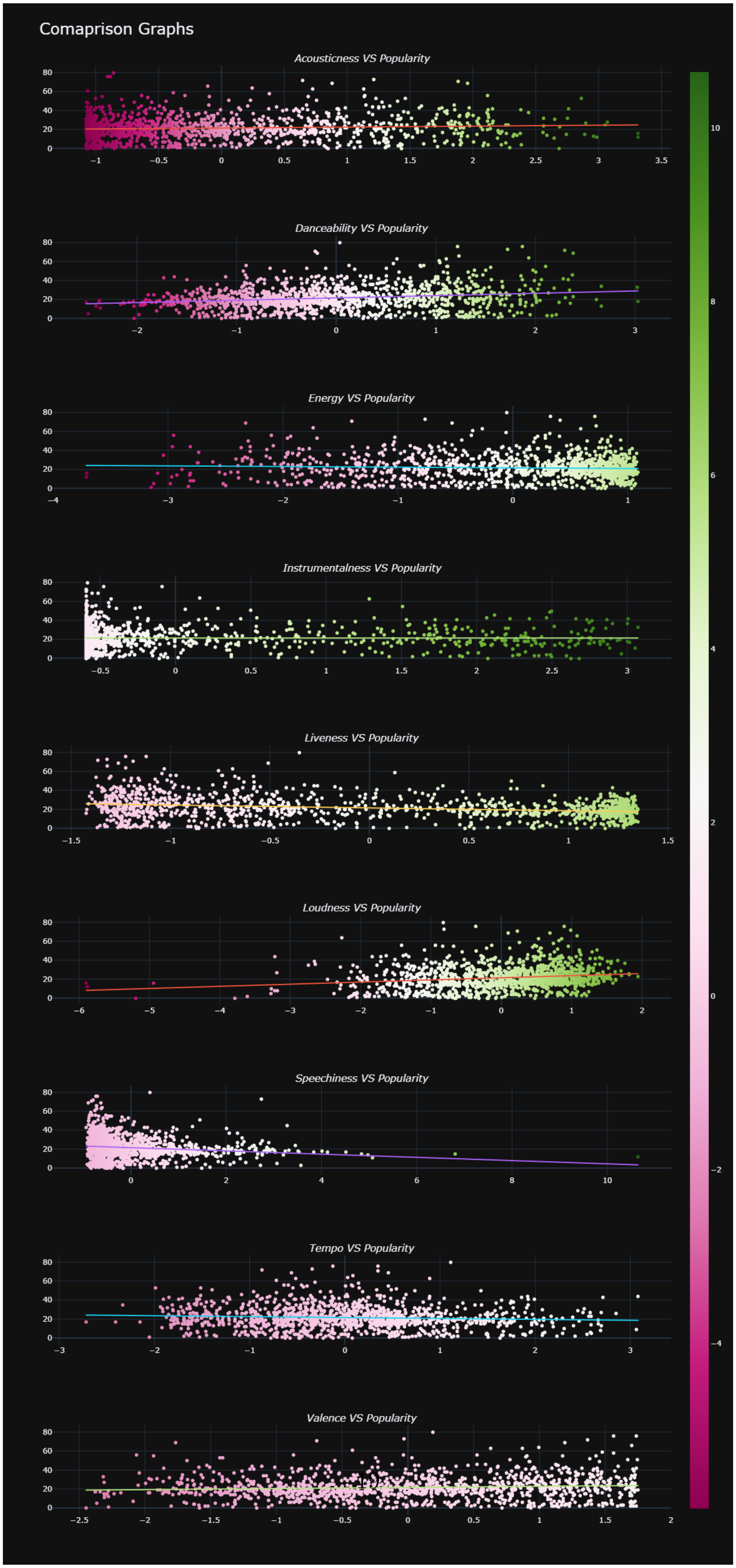
[27]:
```
by_count = df.groupby('album')['popularity'].count().sort_values(ascending =␣
↪False)
fig = px.bar(by_count,
        y = 'popularity',
        color = 'popularity',
        color_continuous_scale = 'plasma',
        template = 'plotly_dark',
        height = 800,
        title = f'<b>Count of Songs in Album')
fig.show()
```



Plotting various features against the Popularity of the songs

[28]:
```python
# Initialising the plot variable as str
fig1 = ''
fig2 = ''
fig3 = ''
fig4 = ''
fig5 = ''
fig6 = ''
fig7 = ''
fig8 = ''
fig9 = ''

# Storing the variables in list figures
figures = [fig1, fig2, fig3, fig4, fig5, fig6, fig7, fig8, fig9]

# Creting plots using for loop
for i in range(9):
    figures[i] = px.scatter(features_df,
            x = feature_list[i],
            y = df['popularity'],
            color = feature_list[i],
            color_continuous_scale = 'plasma',
```

```
            trendline='ols')

# Storing the headers for the Names of Plots in a list
figure_names = []
for i in feature_list:
    figure_names.append(f'<i>{i.title()} VS Popularity')

# Initialising the trace list and then storing them into another list for␣
 ↪looping
figure1_traces = []
figure2_traces = []
figure3_traces = []
figure4_traces = []
figure5_traces = []
figure6_traces = []
figure7_traces = []
figure8_traces = []
figure9_traces = []

figure_traces = [figure1_traces , figure2_traces, figure3_traces,␣
 ↪figure4_traces, figure5_traces, figure6_traces, figure7_traces,␣
 ↪figure8_traces, figure9_traces]

# Taking the elements from the plots and using them to create traces for the␣
 ↪subplots
for i in range(9):
    for trace in range(len(figures[i]["data"])):
        figures[i]["data"][trace]['showlegend'] = False
        figure_traces[i].append(figures[i]["data"][trace])

# Creting the subplot Figure
comparison_figure = make_subplots(rows = 9, cols = 1, subplot_titles =␣
 ↪figure_names)

# Adding the traces to the figure
for i in range(9):
    for traces in figure_traces[i]:
        comparison_figure.append_trace(traces, row = i+1, col = 1)

comparison_figure.update_layout(height = 2500, width = 1000, title_text =␣
 ↪"Comaprison Graphs", title_font_size = 25, template = 'plotly_dark')

comparison_figure.show()
```



Comaprison Graphs
Acousticness VS Popularity
Danceability VS Popularity
Energy VS Popularity
Instrumentalness VS Popularity
Liveness VS Popularity
Loudness VS Popularity
Speechiness VS Popularity
Tempo VS Popularity
Valence VS Popularity

Through the trendline in the graphs, it can be seen that Acoustiness, Dancebility, Valence, Loudness is liked mnore at the higher levels while the rest are less popular the higher their value or no effect at all.

2.1 Training Models for predicting Popularity and testing

[29]:
```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split
```

[30]:
```
# separate the data to training and testing
X= features_df # all the features accept DV
y = df["popularity"] # the DV
X_train, X_test, y_train,y_test=train_test_split(X,y,
                                                 test_size=0.2,
                                                 random_state=0)
# save as np.array
X_train = np.array(X_train)
X_test = np.array(X_test)
y_train = np.array(y_train)
y_test = np.array(y_test)
```

[31]:
```
# create a linear regression, random forest & decision tree object
model_regression = LinearRegression()
model_random_forest = RandomForestRegressor()
model_decision_tree = DecisionTreeRegressor()
model_xgboost = XGBRegressor()
```

[32]:
```
model_regression.fit(X_train, y_train)
```

[32]:
```
LinearRegression()
```

[33]:
```
model_random_forest.fit(X_train, y_train)
```

[33]:
```
RandomForestRegressor()
```

[34]:
```
model_decision_tree.fit(X_train, y_train)
```

[34]:
```
DecisionTreeRegressor()
```

[35]:
```
model_xgboost.fit(X_train, y_train)
```

[35]:
```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
             missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, …)
```

[36]:
```
# estimate the R² score on training and testing data
# (1) Linear regression
print(model_regression.score(X_train,y_train))
print(model_regression.score(X_test,y_test))
```

```
0.19396651223160155
0.16926201652752848
```

[37]:
```
# (3) Decission Tree
print(model_decision_tree.score(X_train,y_train))
print(model_decision_tree.score(X_test,y_test))
```

```
1.0
-0.725561921406735
```

[38]:
```
# (2) Random Forest
print(model_random_forest.score(X_train,y_train))
print(model_random_forest.score(X_test,y_test))
```

```
0.8757247990646652
0.08522159574174182
```

[39]:
```
# (4) XGBOOST
print(model_xgboost.score(X_train,y_train))
print(model_xgboost.score(X_test,y_test))
```

```
0.9967689107870302
-0.08023682210155036
```

All the models have very low accuracy score

2.2 Clustering

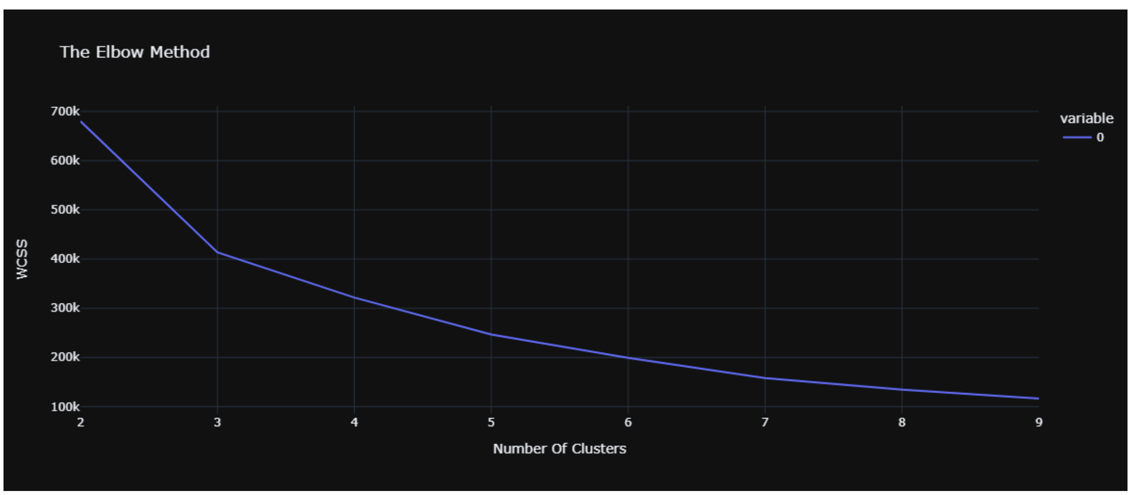
[40]:
```
color = ['red', 'green', 'yellow', 'blue', 'magenta', 'cyan', 'white', ␣
↪'gray', 'bright_red', 'bright_green', 'bright_yellow', 'bright_blue', ␣
↪'bright_magenta', 'bright_cyan', 'bright_white']
```

2.2.1 K-Means Clustering

[41]:
```
feature_arr = features_df_tsne
```

[42]:
```
#  ------------------------ k-means Clustering ---------------------

# Determining the cluster size
score_list = []
for i in range(2,10):
    kmeans_model = KMeans(n_clusters=i,
                          init = 'k-means++',
                          random_state=42).fit(feature_arr)

    score_list.append(kmeans_model.inertia_)
preds = kmeans_model.predict(feature_arr)
```

[43]:
```
# Visualization of different cluster size performations

fig = px.line(pd.DataFrame(score_list,
             index = range(2, 10)),
        title = 'The Elbow Method')
fig.update_layout(xaxis_title = 'Number Of Clusters',
                  yaxis_title = 'WCSS',
                  template = 'plotly_dark',
                  height = 500,
                  width = 500)
fig.show()
```



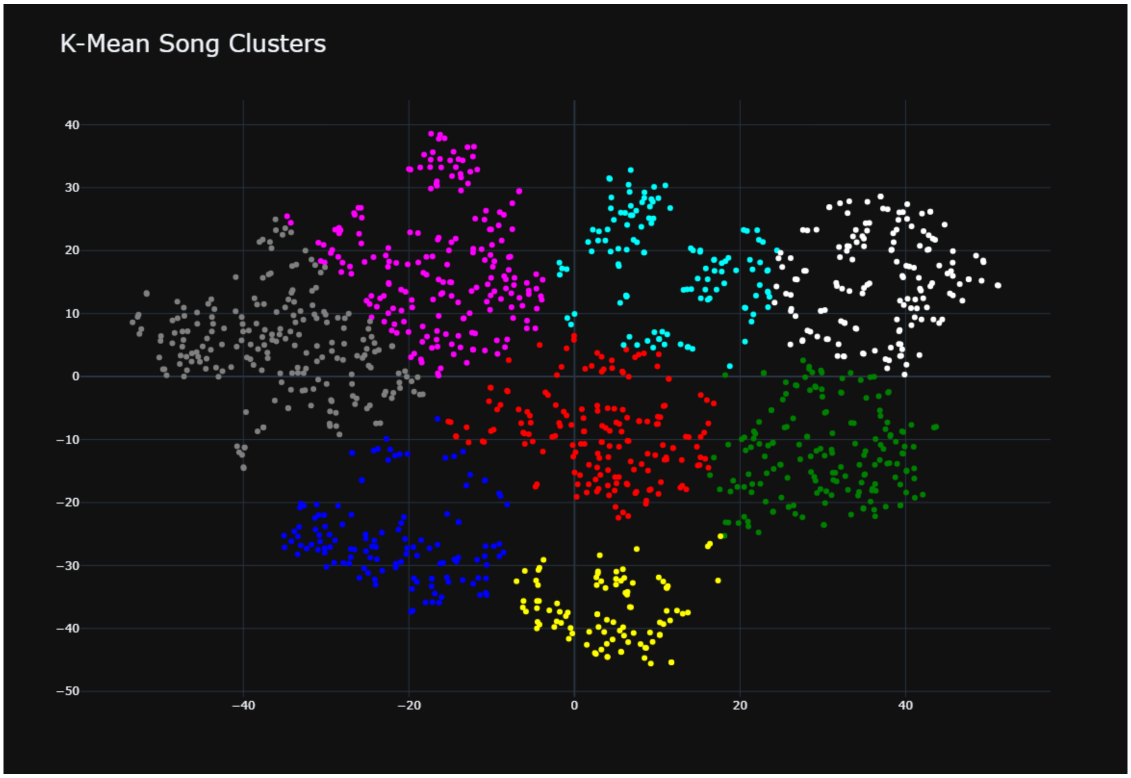
[44]:
```
cluster_i = 8
```

[45]:
```python
# Training and Predicting
k_pred = KMeans(n_clusters=cluster_i,
              init ='k-means++',
              max_iter=300,
              random_state=42).fit_predict(feature_arr)
k_pred
```

[45]: array([3, 4, 3, …, 1, 1, 1], dtype=int32)

[46]:
```python
# Initialising the plot variable as str
k_fig1 = ""
k_fig2 = ""
k_fig3 = ""
k_fig4 = ""
k_fig5 = ""
k_fig6 = ""
k_fig7 = ""
k_fig8 = ""


# Storing the variables in list figures
k_figures = [k_fig1, k_fig2, k_fig3, k_fig4, k_fig5, k_fig6, k_fig7, k_fig8]


# Creating cluster graphs using for loop
for i in range(8):
    k_figures[i] = px.scatter(x = feature_arr[k_pred == i, 0],
                            y = feature_arr[k_pred == i, 1],
                            title = f'Cluster{i}')
    k_figures[i].update_traces(marker=dict(color=color[i]))

# Initialising the trace list and then storing them into another list for␣
↪looping
k_figure1_traces = []
k_figure2_traces = []
k_figure3_traces = []
k_figure4_traces = []
k_figure5_traces = []
k_figure6_traces = []
k_figure7_traces = []
k_figure8_traces = []

k_figures_traces = [k_figure1_traces, k_figure2_traces, k_figure3_traces,␣
↪k_figure4_traces, k_figure5_traces, k_figure6_traces, k_figure7_traces,␣
↪k_figure8_traces]
```

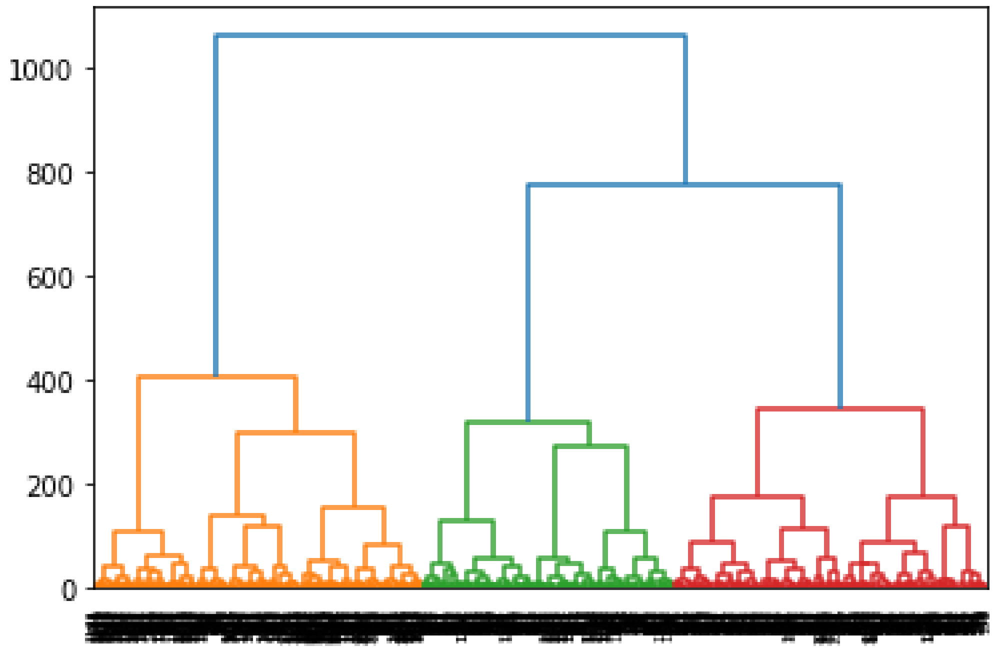
```
# Taking the elements from the plots and using them to create traces for the␣
↪subplots
for i in range(8):
    for trace in range(len(k_figures[i]["data"])):
        k_figures[i]["data"][trace]['showlegend'] = False
        k_figures_traces[i].append(k_figures[i]["data"][trace])

# Creting the subplot Figure
k_means_fig = make_subplots(rows = 1, cols = 1)

# Adding the traces to the figure
for i in range(8):
    for traces in k_figures_traces[i]:
        k_means_fig.append_trace(traces, row = 1, col = 1)

k_means_fig.update_layout(height = 800, width = 1000, title_text = "K-Mean Song␣
↪Clusters", title_font_size = 25, template = 'plotly_dark')

k_means_fig.show()
```



3 Heirchical Clustering

[47]:
```
data = df['popularity'].to_numpy()
```

[48]:
```
dendrogram=sch.dendrogram(sch.linkage(feature_arr,
                                      method='ward'))
```



[49]:
```
hrc_clusters = 8
```

[50]:
```
hrc=AgglomerativeClustering(n_clusters=hrc_clusters,
                            metric='euclidean',
                            linkage='ward')
```

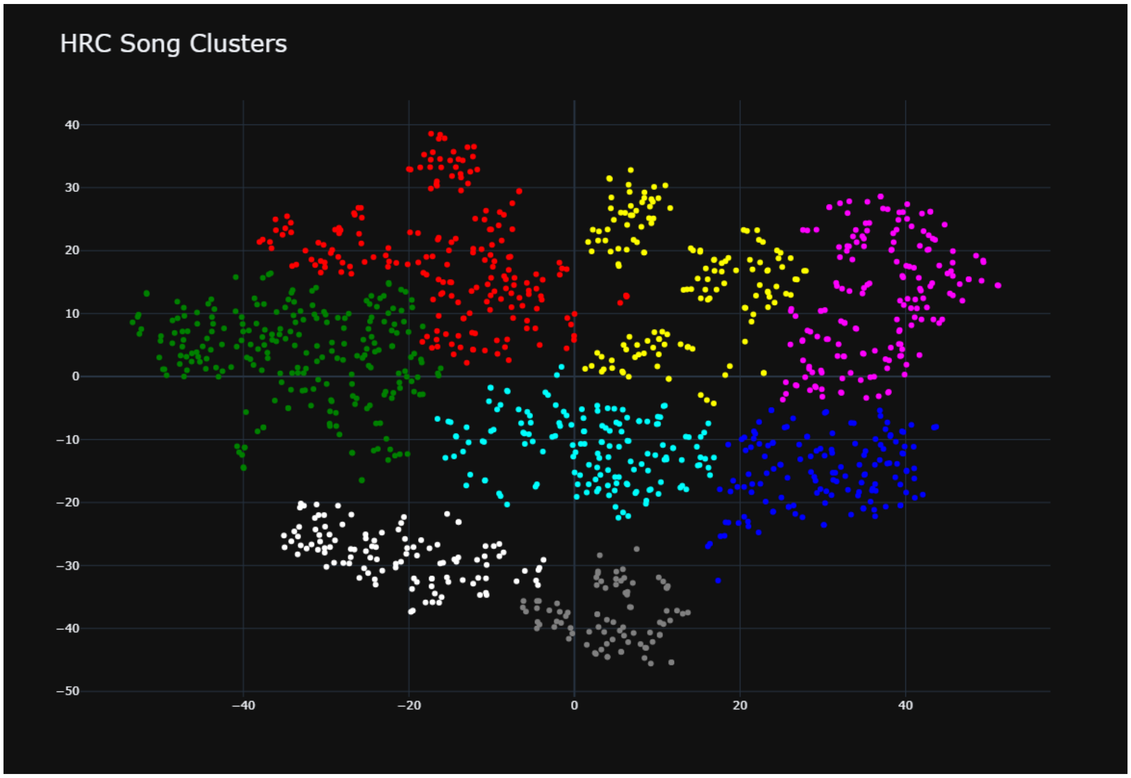
[51]:
```
pred_hrc=hrc.fit_predict(feature_arr)
pred_hrc
```

[51]: array([6, 0, 6, …, 3, 3, 3])

[52]:
```
# Initialising the plot variable as str
hrc_fig1 = ""
hrc_fig2 = ""
hrc_fig3 = ""
hrc_fig4 = ""
hrc_fig5 = ""
hrc_fig6 = ""
```

```
hrc_fig7 = ""
hrc_fig8 = ""
hrc_fig9 = ""
hrc_fig10 = ""


# Storing the variables in list figures
hrc_figures = [hrc_fig1, hrc_fig2, hrc_fig3, hrc_fig4, hrc_fig5, hrc_fig6,␣
↪hrc_fig7, hrc_fig8, hrc_fig9, hrc_fig10]


# Creating cluster graphs using for loop
for i in range(hrc_clusters):
    hrc_figures[i] = px.scatter(x = feature_arr[pred_hrc == i, 0],
                                y = feature_arr[pred_hrc == i, 1],
                                title = f'Cluster{i}')
    hrc_figures[i].update_traces(marker=dict(color=color[i]))

# Initialising the trace list and then storing them into another list for␣
↪looping
hrc_figure1_traces = []
hrc_figure2_traces = []
hrc_figure3_traces = []
hrc_figure4_traces = []
hrc_figure5_traces = []
hrc_figure6_traces = []
hrc_figure7_traces = []
hrc_figure8_traces = []
hrc_figure9_traces = []
hrc_figure10_traces = []

hrc_figures_traces = [hrc_figure1_traces, hrc_figure2_traces,␣
↪hrc_figure3_traces, hrc_figure4_traces, hrc_figure5_traces,␣
↪hrc_figure6_traces, hrc_figure7_traces, hrc_figure8_traces,␣
↪hrc_figure9_traces, hrc_figure10_traces]



# Taking the elements from the plots and using them to create traces for the␣
↪subplots
for i in range(hrc_clusters):
    for trace in range(len(hrc_figures[i]["data"])):
        hrc_figures[i]["data"][trace]['showlegend'] = False
        hrc_figures_traces[i].append(hrc_figures[i]["data"][trace])

# Creting the subplot Figure
hrc_cluster_figure = make_subplots(rows = 1, cols = 1)
```

```
# Adding the traces to the figure
for i in range(hrc_clusters):
    for traces in hrc_figures_traces[i]:
        hrc_cluster_figure.append_trace(traces, row = 1, col = 1)

hrc_cluster_figure.update_layout(height = 800, width = 1000, title_text = "HRC␣
↪Song Clusters", title_font_size = 25, template = 'plotly_dark')

hrc_cluster_figure.show()
```



[ ]:

```

```

4 Thank You