

spotify_songs

September 10, 2023

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2 *****Creating Cohorts of Songs Project Machine Learning Project*****

```
import pandas as pd import numpy as np import matplotlib.pyplot as plt
```

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

```
[2]: dataframe = pd.read_csv("1673873388_rolling_stones_spotify.csv")
```

```
[3]: # printing the available columns in the csv file
print(dataframe.columns.tolist())
```

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

```
[4]: # printing the duplicates in a csv file
duplicate_rows = dataframe[dataframe.duplicated()]
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [Unnamed: 0, name, album, release_date, track_number, id, uri,
acousticness, danceability, energy, instrumentalness, liveness, loudness,
speechiness, tempo, valence, popularity, duration_ms]
Index: []
```

```
[5]: # Removing the duplicates in a csv file
dataframe = dataframe.drop_duplicates()
print(dataframe)
```

```
      Unnamed: 0              name          album \
0          0  Concert Intro Music - Live  Licked Live In NYC
1          1  Street Fighting Man - Live  Licked Live In NYC
2          2        Start Me Up - Live  Licked Live In NYC
3          3  If You Can't Rock Me - Live  Licked Live In NYC
```

4	4	Don't Stop - Live Licked Live In NYC						
...						
1605	1605		Carol	The Rolling Stones				
1606	1606		Tell Me	The Rolling Stones				
1607	1607	Can I Get A Witness		The Rolling Stones				
1608	1608	You Can Make It If You Try		The Rolling Stones				
1609	1609	Walking The Dog		The Rolling Stones				
		release_date	track_number		id	\		
0	6/10/2022		1	2IEkywLJ4ykbhi1yRQvmsT				
1	6/10/2022		2	6GVgVJBKkGJoRfarYRvGTU				
2	6/10/2022		3	1Lu761pZ0dBTGpzxaQoZNW				
3	6/10/2022		4	1agTQzOTUnGNggycxEqiDH				
4	6/10/2022		5	7piGJR8YndQBQWVXv6KtQw				
...			
1605	4/16/1964		8	0817M5UpRnffG10FyuRiQZ				
1606	4/16/1964		9	3JZ11QBstTM6WwoJdzFDLhx				
1607	4/16/1964		10	0t2qvfSBQ3Y081zRRoVTdb				
1608	4/16/1964		11	5ivIs5vwSj0RCh0Iv1Y3On				
1609	4/16/1964		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:1agTQzOTUnGNggycxEqiDH			0.5670	0.369			
4	spotify:track:7piGJR8YndQBQWVXv6KtQw			0.4000	0.303			
...			
1605	spotify:track:0817M5UpRnffG10FyuRiQZ			0.1570	0.466			
1606	spotify:track:3JZ11QBstTM6WwoJdzFDLhx			0.0576	0.509			
1607	spotify:track:0t2qvfSBQ3Y081zRRoVTdb			0.3710	0.790			
1608	spotify:track:5ivIs5vwSj0RCh0Iv1Y3On			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]

```
[6]: # Checking for missing values in a csv
missing_values = dataframe.isnull().sum()
print(missing_values)
```

```

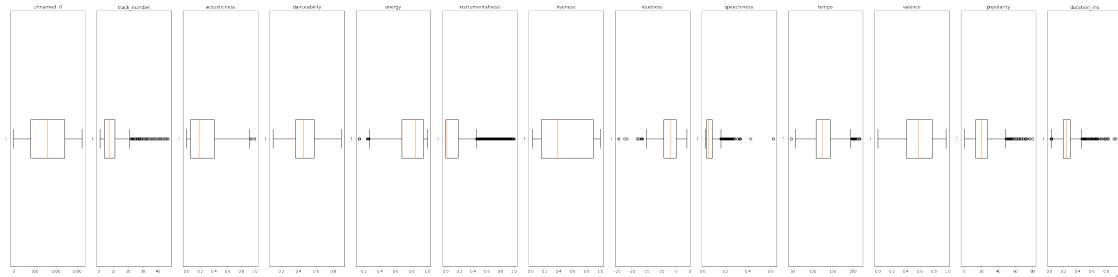
Unnamed: 0          0
name              0
album             0
release_date      0
track_number      0
id                0
uri               0
acousticness      0
danceability      0
energy            0
instrumentalness 0
liveness          0
loudness          0
speechiness       0
tempo             0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

```

```
[7]: # Graphical representation of outliers using box and whisker plots
numeric_columns = dataframe.select_dtypes(include=['number'])

plt.figure(figsize=(40, 10))
for column in numeric_columns.columns:
    plt.subplot(1, len(numeric_columns.columns), numeric_columns.columns.
    ↪get_loc(column) + 1)
    plt.boxplot(dataframe[column], vert=False)
    plt.title(column)
```

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



2.2 Depending on your findings, clean the data for further processing.

```
[8]: dataframe.fillna(dataframe.mean())
dataframe.dropna(axis=1)
```

/tmp/ipykernel_236/3033724010.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction.

```
dataframe.fillna(dataframe.mean())
```

```
[8]:      Unnamed: 0           name          album \
0          0  Concert Intro Music - Live  Licked Live In NYC
1          1  Street Fighting Man - Live  Licked Live In NYC
2          2           Start Me Up - Live  Licked Live In NYC
3          3  If You Can't Rock Me - Live  Licked Live In NYC
4          4           Don't Stop - Live  Licked Live In NYC
...
1605        ...           ...
1605        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       6/10/2022           1  2IEkywLJ4ykbhi1yRQvmsT
1       6/10/2022           2  6GVgVJBKkGJoRfarYRvGTU
2       6/10/2022           3  1Lu761pZ0dBTGpzxaQoZNW
3       6/10/2022           4  1agTQzOTUnGNggycEqiDH
4       6/10/2022           5  7piGJR8YndQBQWVXv6KtQw
...
1605        ...           ...
1605        4/16/1964           8  0817M5UpRnffGlOFyuRiQZ
```

1606	4/16/1964	9	3JZl1QBstM6WwoJdzFDLhx					
1607	4/16/1964	10	0t2qvfSBQ3Y081zRRoVTdb					
1608	4/16/1964	11	5ivIs5vwSj0RCh0IvlY30n					
1609	4/16/1964	12	43SkTJJ2xleDaeiE4TIM70					
								\
0	spotify:track:2IEkywLJ4ykbhi1yRQvmsT			0.0824		0.463		
1	spotify:track:6GVgVJBKkGJoRfarYRvGTU			0.4370		0.326		
2	spotify:track:1Lu761pZ0dBTGpzxQoZNW			0.4160		0.386		
3	spotify:track:1agTQz0TUngNggycEqiDH			0.5670		0.369		
4	spotify:track:7piGJR8YndQBQWVXv6KtQw			0.4000		0.303		
...	
1605	spotify:track:0817M5UpRnffG10FyuRiQZ			0.1570		0.466		
1606	spotify:track:3JZl1QBstM6WwoJdzFDLhx			0.0576		0.509		
1607	spotify:track:0t2qvfSBQ3Y081zRRoVTdb			0.3710		0.790		
1608	spotify:track:5ivIs5vwSj0RCh0IvlY30n			0.2170		0.700		
1609	spotify:track:43SkTJJ2xleDaeiE4TIM70			0.3830		0.727		
								\
0	energy	instrumentalness	liveness	loudness	speechiness	tempo		
1	0.993	0.996000	0.9320	-12.913	0.1100	118.001		
2	0.965	0.233000	0.9610	-4.803	0.0759	131.455		
3	0.969	0.400000	0.9560	-4.936	0.1150	130.066		
4	0.985	0.000107	0.8950	-5.535	0.1930	132.994		
...	
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		
								\
0	valence	popularity	duration_ms					
1	0.0302	33	48640					
2	0.3180	34	253173					
3	0.3130	34	263160					
4	0.1470	32	305880					
...	
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]

```
[9]: # Removing the outliers
Q1 = dataframe.quantile(0.25)
Q3 = dataframe.quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
dataframe[(dataframe >= lower_bound) & (dataframe <= upper_bound)].
    dropna(axis=1)
```

/tmp/ipykernel_236/787857994.py:7: FutureWarning: Automatic reindexing on DataFrame vs Series comparisons is deprecated and will raise ValueError in a future version. Do `left, right = left.align(right, axis=1, copy=False)` before e.g. `left == right`
 dataframe[(dataframe >= lower_bound) & (dataframe <= upper_bound)].dropna(axis=1)

```
[9]:      Unnamed: 0  danceability  liveness  valence
 0          0       0.463     0.9320   0.0302
 1          1       0.326     0.9610   0.3180
 2          2       0.386     0.9560   0.3130
 3          3       0.369     0.8950   0.1470
 4          4       0.303     0.9660   0.2060
 ...
 1605      1605     0.466     0.3240   0.9670
 1606      1606     0.509     0.5160   0.4460
 1607      1607     0.790     0.0669   0.8350
 1608      1608     0.700     0.1660   0.5320
 1609      1609     0.727     0.0965   0.9690
```

[1610 rows x 4 columns]

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

```
[24]: import matplotlib.pyplot as plt
import seaborn as sns

# Summary statistics
print(dataframe.describe())

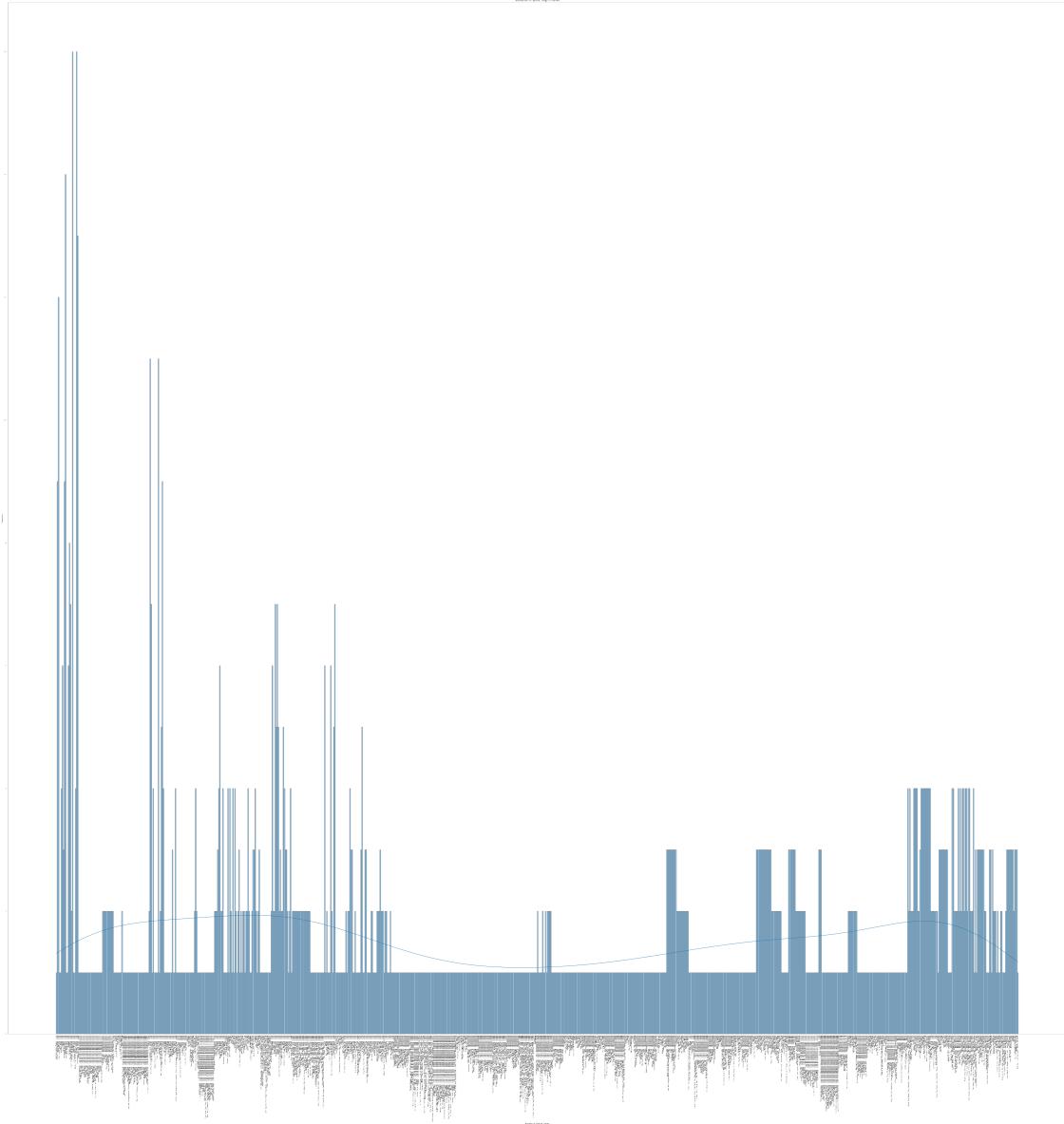
# Distribution of popular songs
plt.figure(figsize=(100, 100))
sns.histplot(data=dataframe.dropna(axis=1), x='name', bins=100, kde=True)
plt.xlabel('Number of Popular Songs')
plt.ylabel('Frequency')
plt.xticks(rotation=90)
```

```
plt.title('Distribution of Popular Songs in Albums')
plt.show()
```

	Unnamed: 0	track_number	acousticness	danceability	energy	\
count	1610.000000	1610.000000	1610.000000	1610.000000	1610.000000	
mean	804.500000	8.613665	0.250475	0.468860	0.792352	
std	464.911282	6.560220	0.227397	0.141775	0.179886	
min	0.000000	1.000000	0.000009	0.104000	0.141000	
25%	402.250000	4.000000	0.058350	0.362250	0.674000	
50%	804.500000	7.000000	0.183000	0.458000	0.848500	
75%	1206.750000	11.000000	0.403750	0.578000	0.945000	
max	1609.000000	47.000000	0.994000	0.887000	0.999000	

	instrumentalness	liveness	loudness	speechiness	tempo	\
count	1610.000000	1610.000000	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

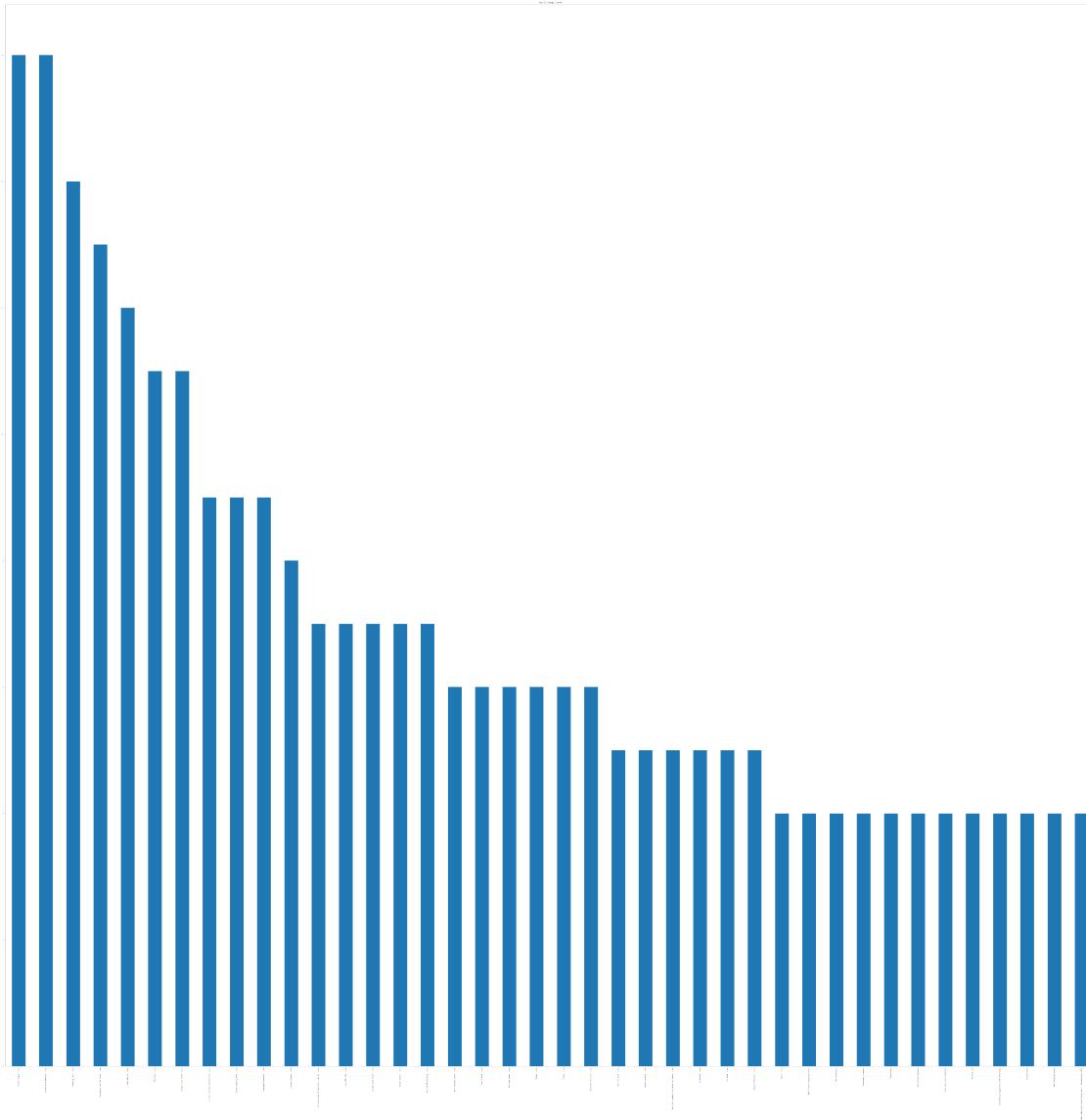


2.4 Perform exploratory data analysis to dive deeper into different features of songs and identify the pattern.

2.5 Bivariate and Multivariate Analysis

```
[36]: # Bar Plots data analysis  
  
plt.figure(figsize=(100, 100))  
  
artist_counts = dataframe['name'].value_counts()  
artist_counts[:40].plot(kind='bar')
```

```
plt.xlabel('Artist')
plt.ylabel('Count')
plt.title('Top 40 Songs Count')
plt.show()
```



2.6 ****Linear regression to predicting the popularity of a song based on danceability and energy****

```
[38]: from statsmodels.formula.api import ols

model = ols('popularity ~ danceability + energy', data=dataframe).fit()
```

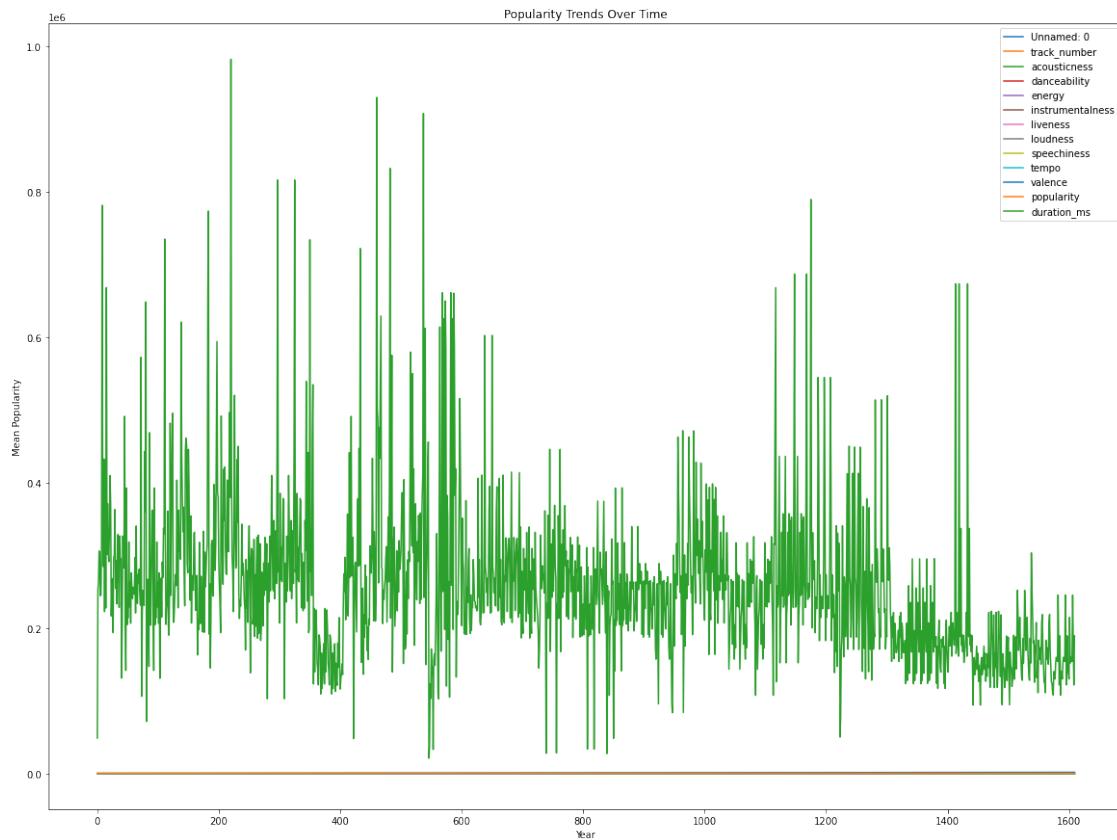
```
print(model.summary())
```

```
OLS Regression Results
=====
Dep. Variable: popularity R-squared: 0.020
Model: OLS Adj. R-squared: 0.019
Method: Least Squares F-statistic: 16.55
Date: Sun, 10 Sep 2023 Prob (F-statistic): 7.69e-08
Time: 13:23:25 Log-Likelihood: -6324.6
No. Observations: 1610 AIC: 1.266e+04
Df Residuals: 1607 BIC: 1.267e+04
Df Model: 2
Covariance Type: nonrobust
=====
            coef    std err      t      P>|t|      [0.025      0.975]
-----
Intercept   16.0793   2.035     7.902     0.000    12.088    20.070
danceability 11.9473   2.269     5.265     0.000     7.496    16.398
energy      -1.1266   1.788    -0.630     0.529    -4.635    2.381
=====
Omnibus: 180.283 Durbin-Watson: 0.609
Prob(Omnibus): 0.000 Jarque-Bera (JB): 316.500
Skew: 0.744 Prob(JB): 1.87e-69
Kurtosis: 4.582 Cond. No. 13.7
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[48]: # Visualization
dataframe.plot(kind='line', figsize=(20, 15))
plt.xlabel('Year')
plt.ylabel('Mean Popularity')
plt.title('Popularity Trends Over Time')
plt.show()
```



- 2.7 ****Comment on the importance of dimensionality reduction techniques, share your ideas and explain your observations.****
- 2.8 Reduced-dimensional representations are often more interpretable, making it easier to extract meaningful insights from the data.
- 2.9 ****Perform Cluster Analysis: Identify the right number of clusters , Use appropriate clustering algorithm, Define each cluster based on the features****

```
[64]: df_encoded = pd.get_dummies(dataframe, column)
```

```
[65]: from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

numeric_columns = dataframe.select_dtypes(include=['number'])
categorical_columns = dataframe.select_dtypes(exclude=['number'])

categorical_encoded = pd.get_dummies(categorical_columns)
```

```

preprocessed_data = pd.concat([numeric_columns, categorical_encoded], axis=1)

scaler = StandardScaler()
scaled_data = scaler.fit_transform(preprocessed_data)

inertia = []

for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8, 4))
plt.plot(range(1, 11), inertia, marker='o', linestyle='--', color='b')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.grid(True)
plt.show()

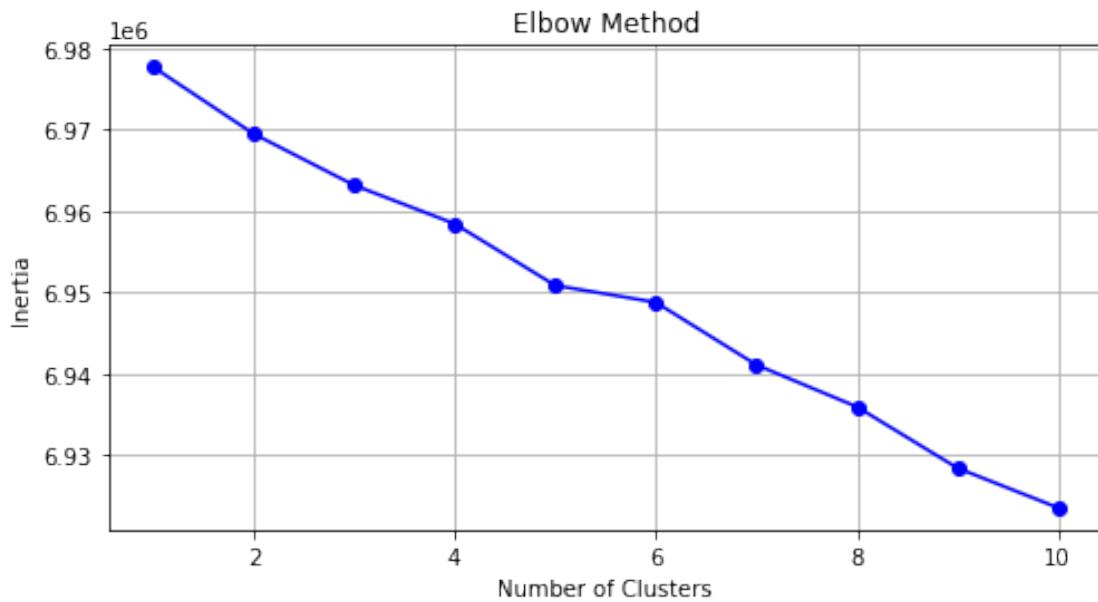
```

```

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

```

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



[]: