

This notebook contains codes executed for Assignment-3 (**Descriptive Data Mining**) for the course **CSIT558\_01SP25** by:

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```
# Importing the required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA

from google.colab import files

# Uploading the file
dataset = files.upload()

<IPython.core.display.HTML object>

Saving Spotify_Youtube.csv to Spotify_Youtube.csv

# Loading the data into a dataframe
df = pd.read_csv("Spotify_Youtube.csv")

df.shape
(20718, 28)

print(list(df.columns))

['Unnamed: 0', 'Artist', 'Url_spotify', 'Track', 'Album',
'Album_type', 'Uri', 'Danceability', 'Energy', 'Key', 'Loudness',
'Speechiness', 'Acousticness', 'Instrumentalness', 'Liveness',
'Valence', 'Tempo', 'Duration_ms', 'Url_youtube', 'Title', 'Channel',
'Views', 'Likes', 'Comments', 'Description', 'Licensed',
'official_video', 'Stream']

df.head()

{"type":"dataframe","variable_name":"df"}

# Checking the missing values
print(df.isnull().sum())
```

```

# Very few records with null values
# Removing missing values
df = df.dropna()

Unnamed: 0          0
Artist              0
Url_spotify        0
Track               0
Album               0
Album_type          0
Uri                 0
Danceability       2
Energy              2
Key                 2
Loudness            2
Speechiness         2
Acousticness        2
Instrumentalness   2
Liveness            2
Valence             2
Tempo               2
Duration_ms         2
Url_youtube        470
Title               470
Channel             470
Views               470
Likes               541
Comments            569
Description         876
Licensed            470
official_video      470
Stream              576
dtype: int64

print("Before dropping duplicates: ", df.shape)
# Dropping the duplicate rows
df.drop_duplicates(inplace=True)
print("After dropping duplicates: ", df.shape)

Before dropping duplicates: (20718, 28)
After dropping duplicates: (20718, 28)

# Selecting the numerical values to analyze the correlation
df_num = df.select_dtypes(include=["number"])
df_num.info()

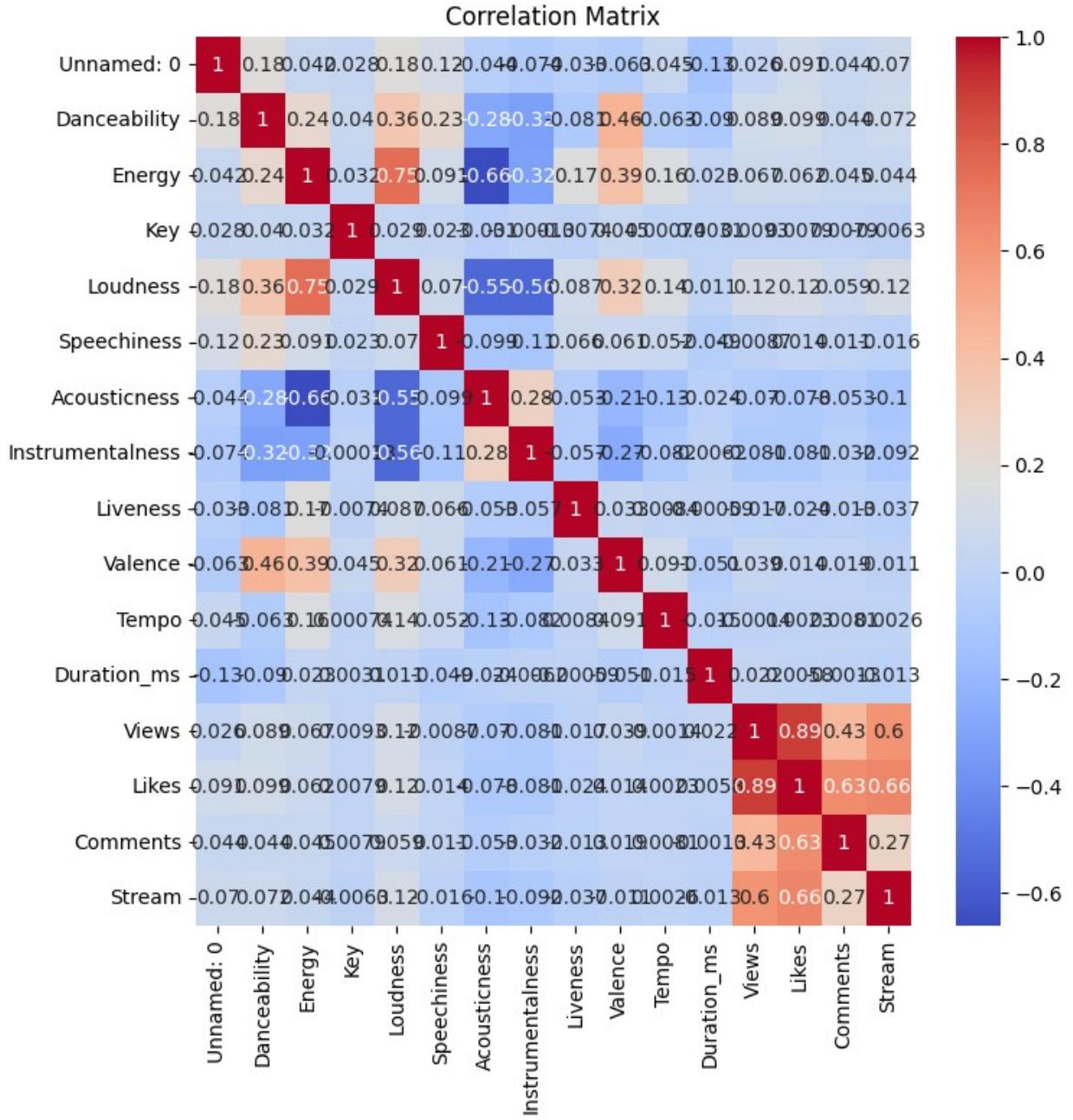
<class 'pandas.core.frame.DataFrame'>
Index: 19170 entries, 0 to 20717
Data columns (total 16 columns):

```

```
#   Column      Non-Null Count   Dtype  
--- 
0   Unnamed: 0      19170 non-null   int64  
1   Danceability    19170 non-null   float64 
2   Energy          19170 non-null   float64 
3   Key             19170 non-null   float64 
4   Loudness        19170 non-null   float64 
5   Speechiness     19170 non-null   float64 
6   Acousticness    19170 non-null   float64 
7   Instrumentalness 19170 non-null   float64 
8   Liveness        19170 non-null   float64 
9   Valence         19170 non-null   float64 
10  Tempo           19170 non-null   float64 
11  Duration_ms     19170 non-null   float64 
12  Views           19170 non-null   float64 
13  Likes           19170 non-null   float64 
14  Comments         19170 non-null   float64 
15  Stream          19170 non-null   float64 

dtypes: float64(15), int64(1)
memory usage: 2.5 MB
```

```
# Analyrizing the correlation between the quantitative attributes
correlation_matrix = df_num.corr()
plt.figure(figsize=(8, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



```
# Selecting numerical features for clustering
features = ['Loudness', 'Energy', 'Danceability', 'Valence',
'Tempo', 'Speechiness',
'Acousticness', 'Instrumentalness', 'Liveness', 'Views',
'Likes', 'Stream']

df_selected = df[features]
```

# ALGORITHM EXECUTION

Value of k - Silhouette Scores

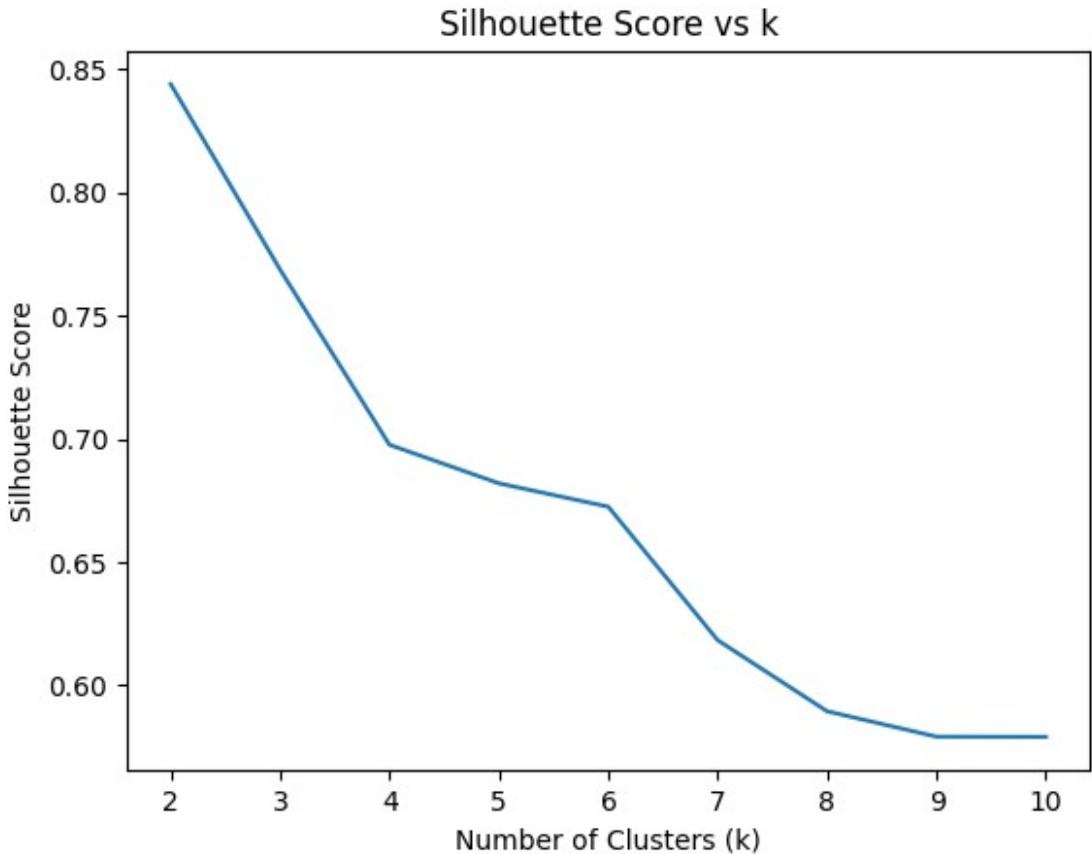
```
silhouette_list = []
# Checking for k between 2 and 10
k_range = range(2, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(df_selected)
    silhouette_list.append(silhouette_score(df_selected,
kmeans.labels_))

# Printing the silhouette scores
print(silhouette_list)

# Plotting the silhouette scores for different k values
plt.plot(k_range, silhouette_list)
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score vs k')
plt.show()

[0.843987884130402, 0.7686954086867869, 0.6975975600927531,
0.681949666560278, 0.6724521919555116, 0.618290878120718,
0.5894443917009909, 0.5791376172678511, 0.5790619254658479]
```



Value of k - Elbow Method

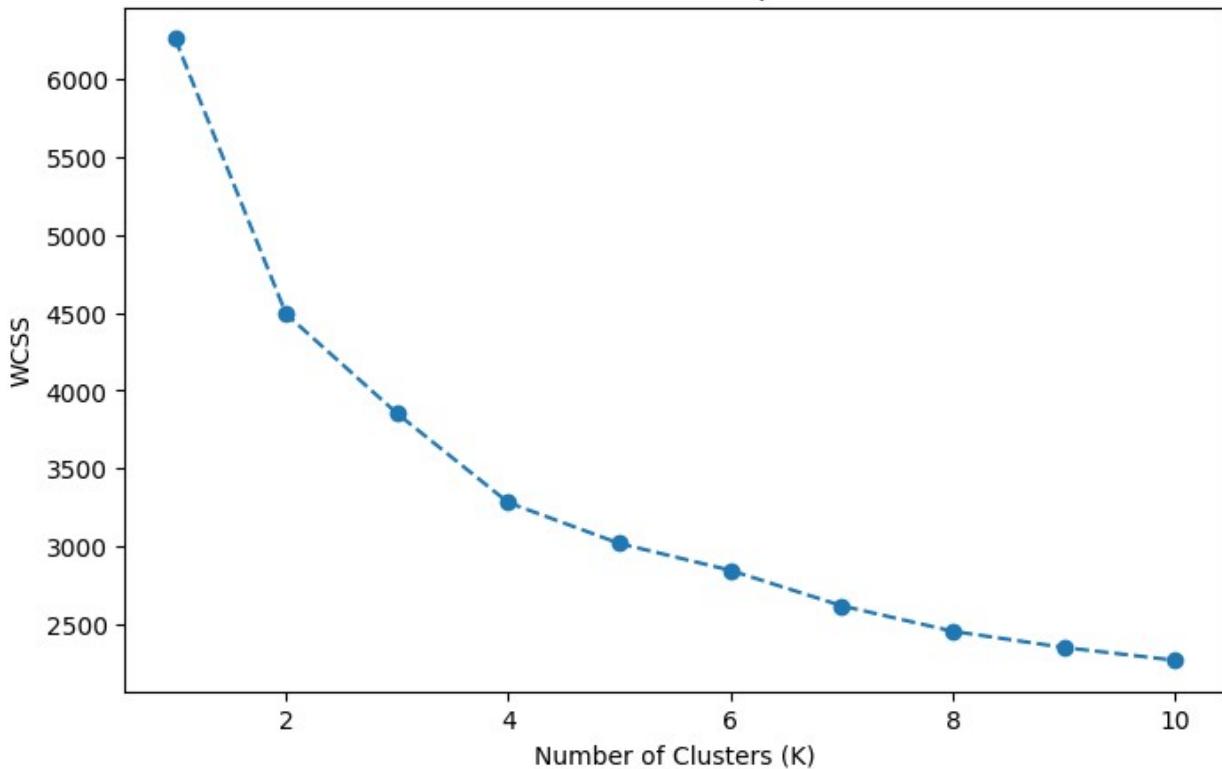
### MinMaxScaler

```
# Bringing all the values of the selected features into a common
# standard
scaler_minmax = MinMaxScaler()
df_scaled_minmax = scaler_minmax.fit_transform(df_selected)

wcss_minmax = [] # Within-cluster sum of squares
for k in range(1, 11):
    kmeans_minmax = KMeans(n_clusters=k, random_state=42)
    kmeans_minmax.fit(df_scaled_minmax)
    wcss_minmax.append(kmeans_minmax.inertia_) # Inertia is the sum
# of squared distances to the nearest centroid

# Plot the elbow curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss_minmax, marker='o', linestyle='--')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('WCSS')
plt.title('Elbow Method for Optimal K')
plt.show()
```

Elbow Method for Optimal K



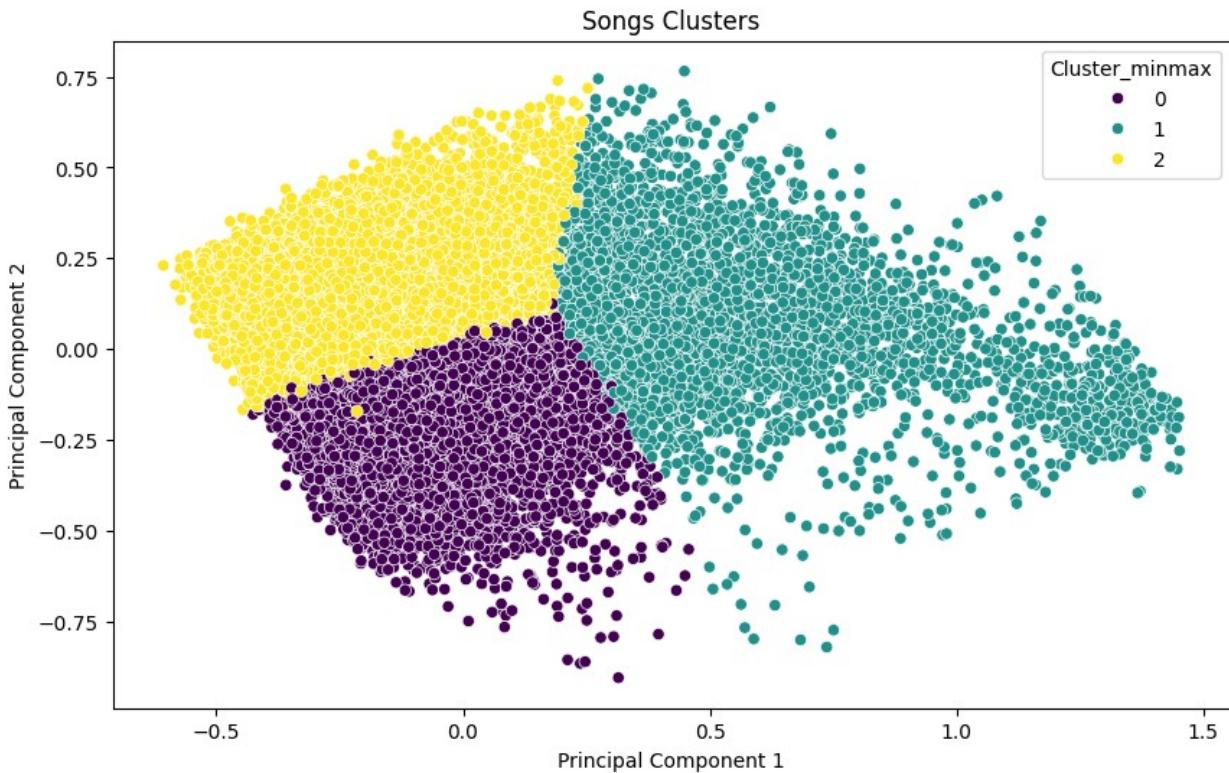
### KMeans When k=3 and algorithm = 'elkan'

```
k = 3 # Update based on elbow method
algorithm='elkan' # Testing with 'elkan' algortihm

# Creating the K-Means clustering
kmeans_minmax = KMeans(n_clusters=k, algorithm=algorithm,
random_state=42)
df['Cluster_minmax'] = kmeans_minmax.fit_predict(df_scaled_minmax)

# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_minmax)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

# Visualizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_minmax', data=df,
palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()
```



## KMeans When k=3 and algorithm = 'lloyd'

```

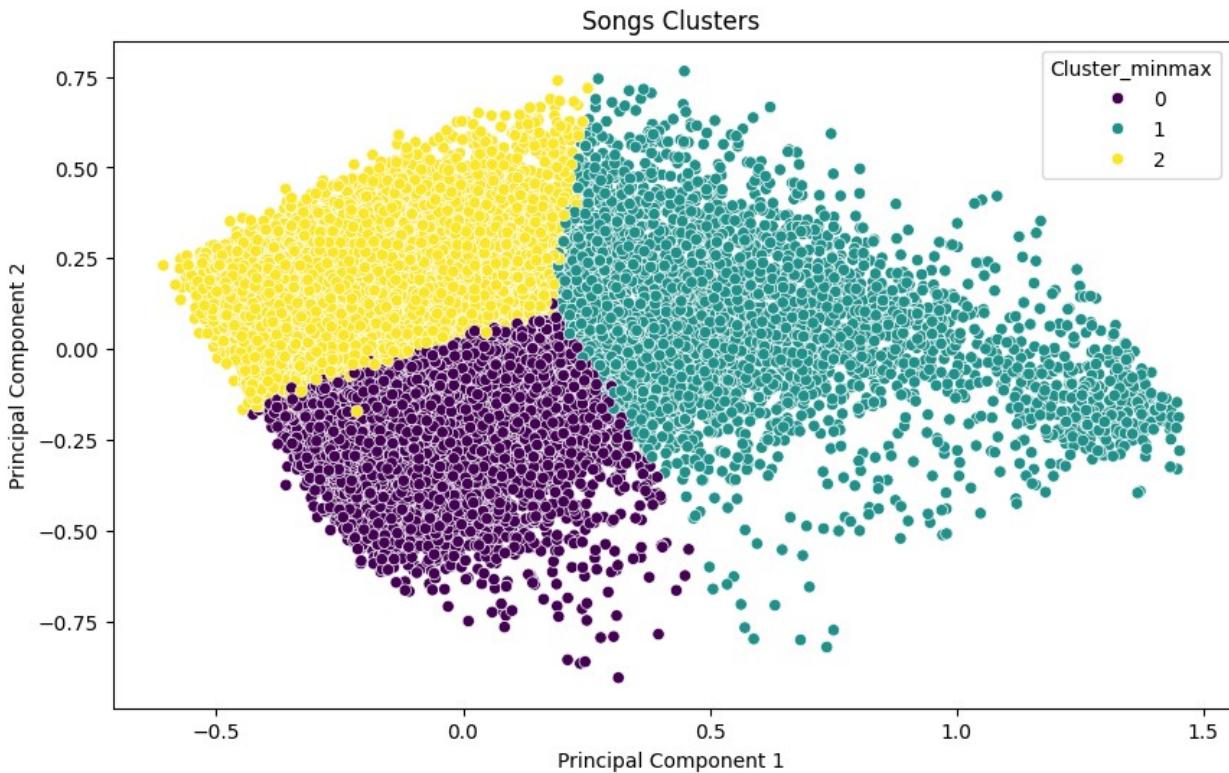
k = 3 # Update based on elbow method
algorithm='lloyd' # Testing with 'lloyd' algortihm

# Creating the K-Means clustering
kmeans_minmax = KMeans(n_clusters=k, algorithm=algorithm,
random_state=42)
df['Cluster_minmax'] = kmeans_minmax.fit_predict(df_scaled_minmax)

# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_minmax)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

# Visulaizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_minmax', data=df,
palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()

```



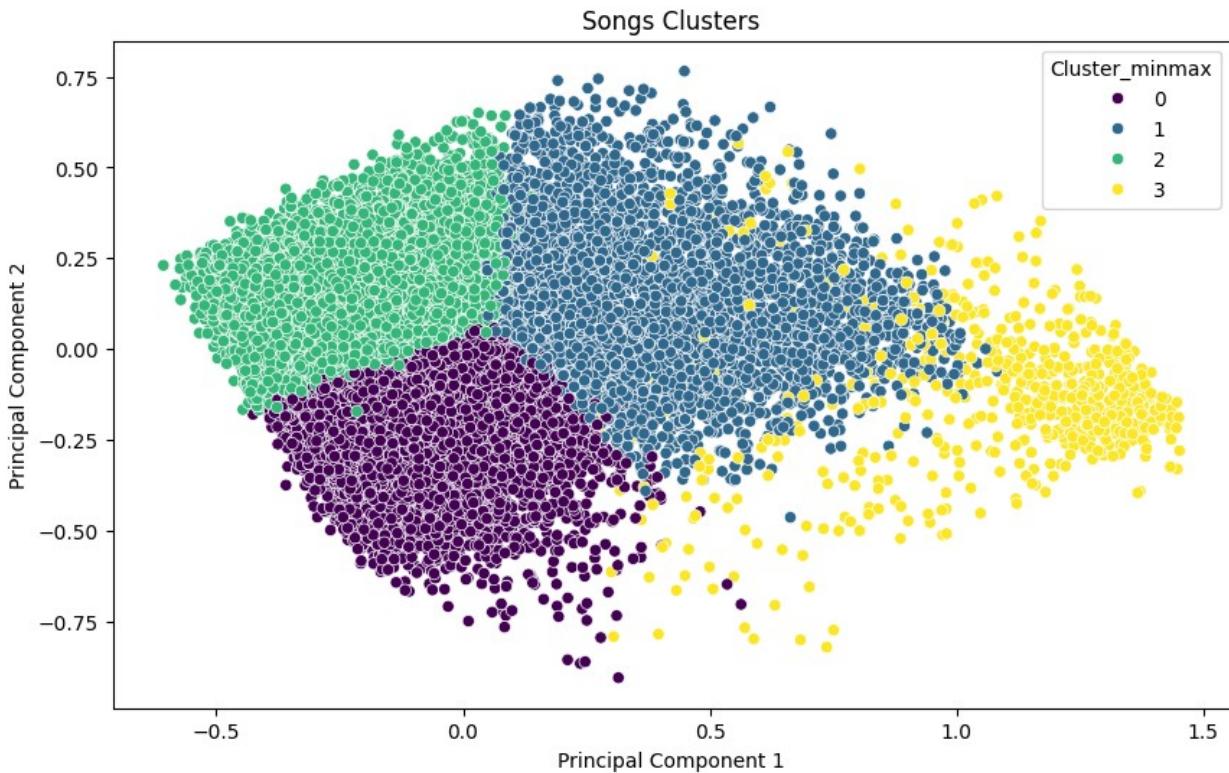
## KMeans When k=4 and algorithm = 'elkan'

```
# Testing with k=4
k = 4
algorithm='elkan' # Testing with 'elkan' algortihm

# Creating the K-Means clustering
kmeans_minmax = KMeans(n_clusters=k, random_state=42)
df['Cluster_minmax'] = kmeans_minmax.fit_predict(df_scaled_minmax)

# Visualizing k=4
# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_minmax)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

# Visulaizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_minmax', data=df,
palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()
```



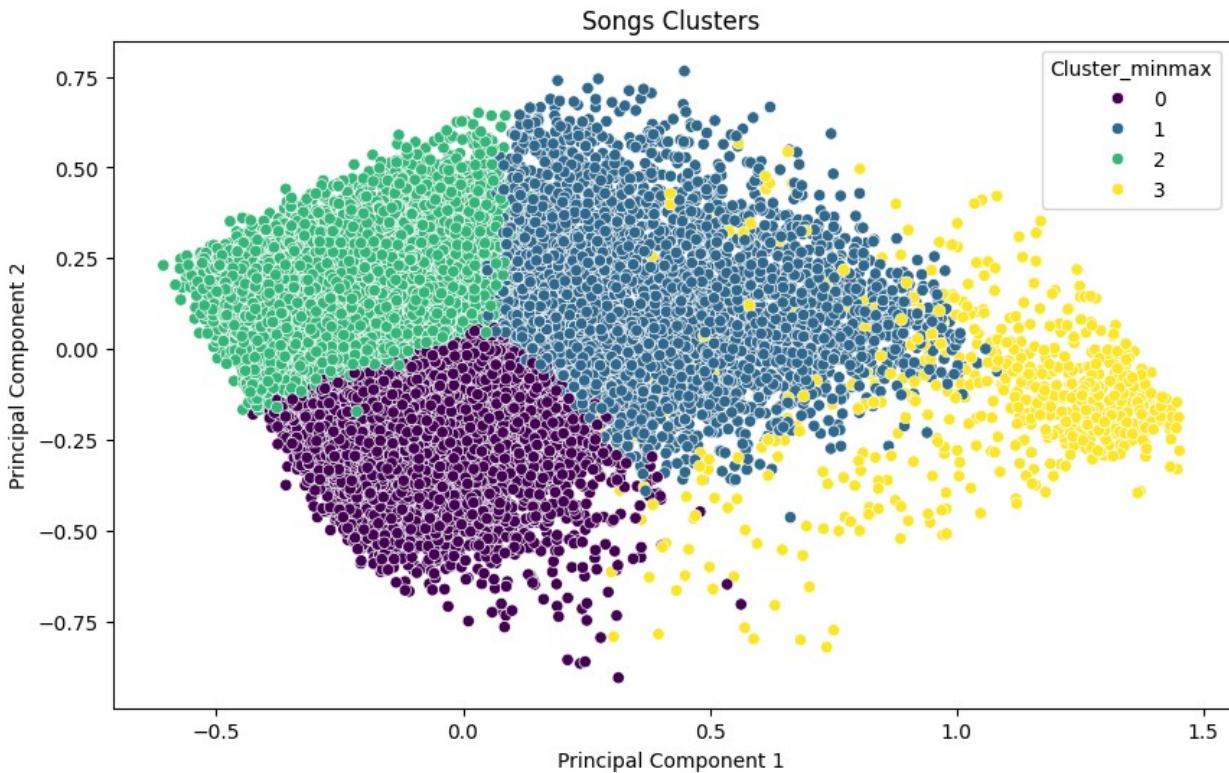
## KMeans When k=3 and algorithm = 'lloyd'

```
# Testing with k=4
k = 4
algorithm='lloyd' # Testing with 'lloyd' algortihm

# Creating the K-Means clustering
kmeans_minmax = KMeans(n_clusters=k, random_state=42)
df['Cluster_minmax'] = kmeans_minmax.fit_predict(df_scaled_minmax)

# Visualizing k=4
# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_minmax)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

# Visulaizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_minmax', data=df,
palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()
```



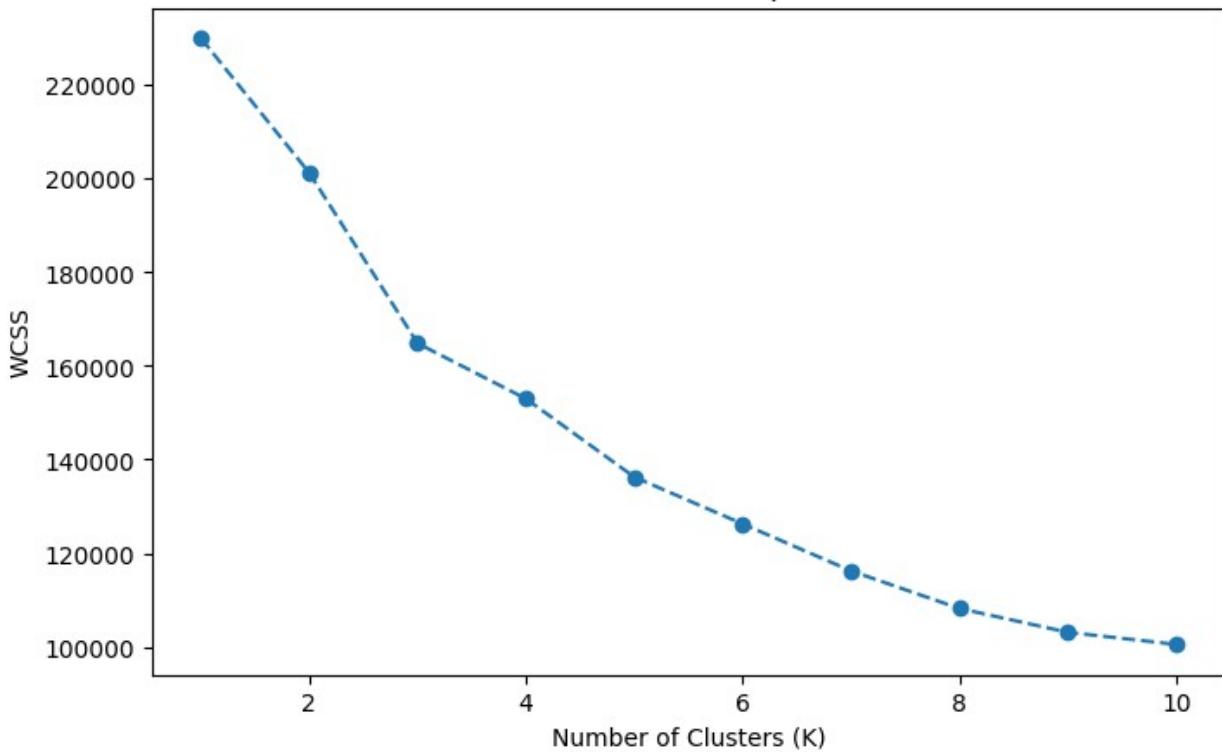
## StandardScaler

```
# Bringing all the values of the selected features into a common standard
scaler_standard = StandardScaler()
df_scaled_standard = scaler_standard.fit_transform(df_selected)

wcss_standard = [] # Within-cluster sum of squares
for k in range(1, 11):
    kmeans_standard = KMeans(n_clusters=k, random_state=42)
    kmeans_standard.fit(df_scaled_standard)
    wcss_standard.append(kmeans_standard.inertia_) # Inertia is the sum of squared distances to the nearest centroid

# Plot the elbow curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss_standard, marker='o', linestyle='--')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('WCSS')
plt.title('Elbow Method for Optimal K')
plt.show()
```

Elbow Method for Optimal K



## KMeans When k=3

```
# TEST
k = 6 # Update based on elbow method

# Creating the K-Means clustering
kmeans_standard = KMeans(n_clusters=k, random_state=42)
df['Cluster_standard'] =
kmeans_standard.fit_predict(df_scaled_standard)

k = 3 # Update based on elbow method

# Creating the K-Means clustering
kmeans_standard = KMeans(n_clusters=k, random_state=42)
df['Cluster_standard'] =
kmeans_standard.fit_predict(df_scaled_standard)

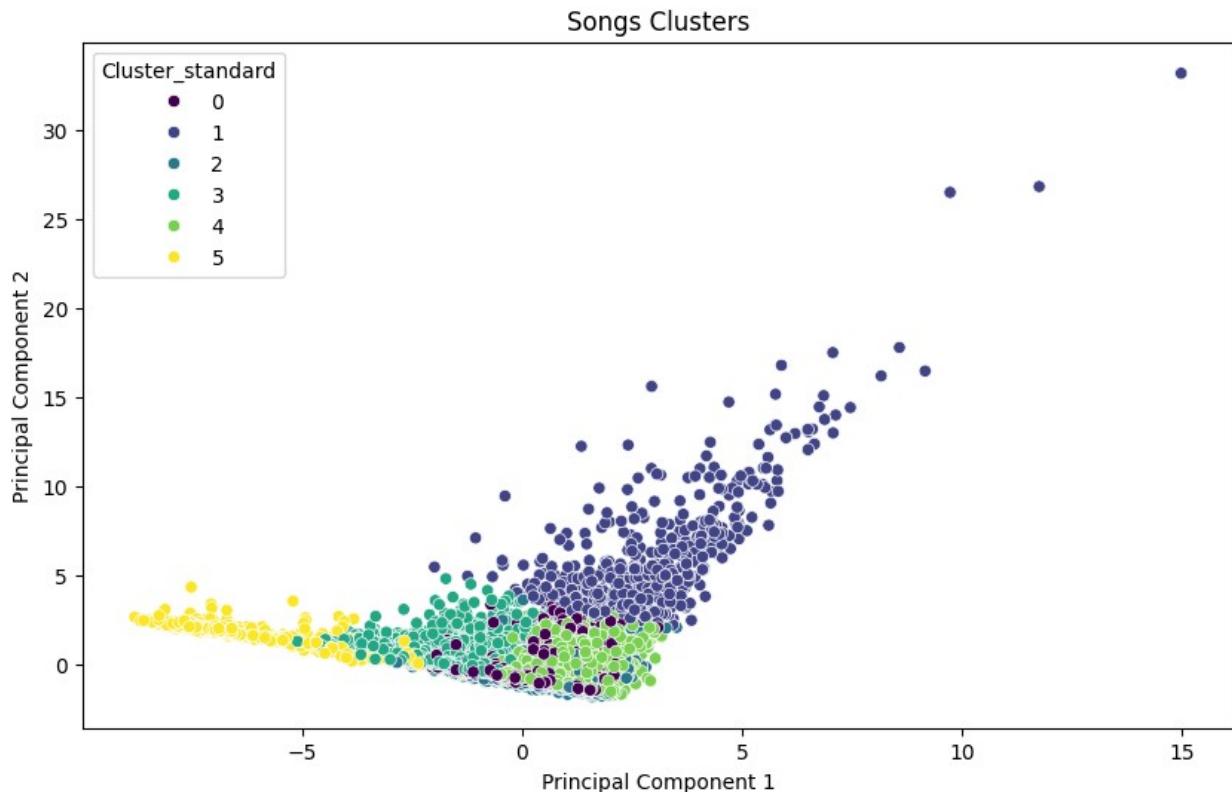
# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_standard)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

# Visualizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_standard', data=df,
```

```

palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()

```



## KMeans When k=4

```

# Testing k=4
k = 4

# Creating the K-Means clustering
kmeans_standard = KMeans(n_clusters=k, random_state=42)
df['Cluster_standard'] =
kmeans_standard.fit_predict(df_scaled_standard)

#Visualizing k=4
# PCA
pca = PCA(n_components=2)
df_pca = pca.fit_transform(df_scaled_standard)
df['PCA1'] = df_pca[:, 0]
df['PCA2'] = df_pca[:, 1]

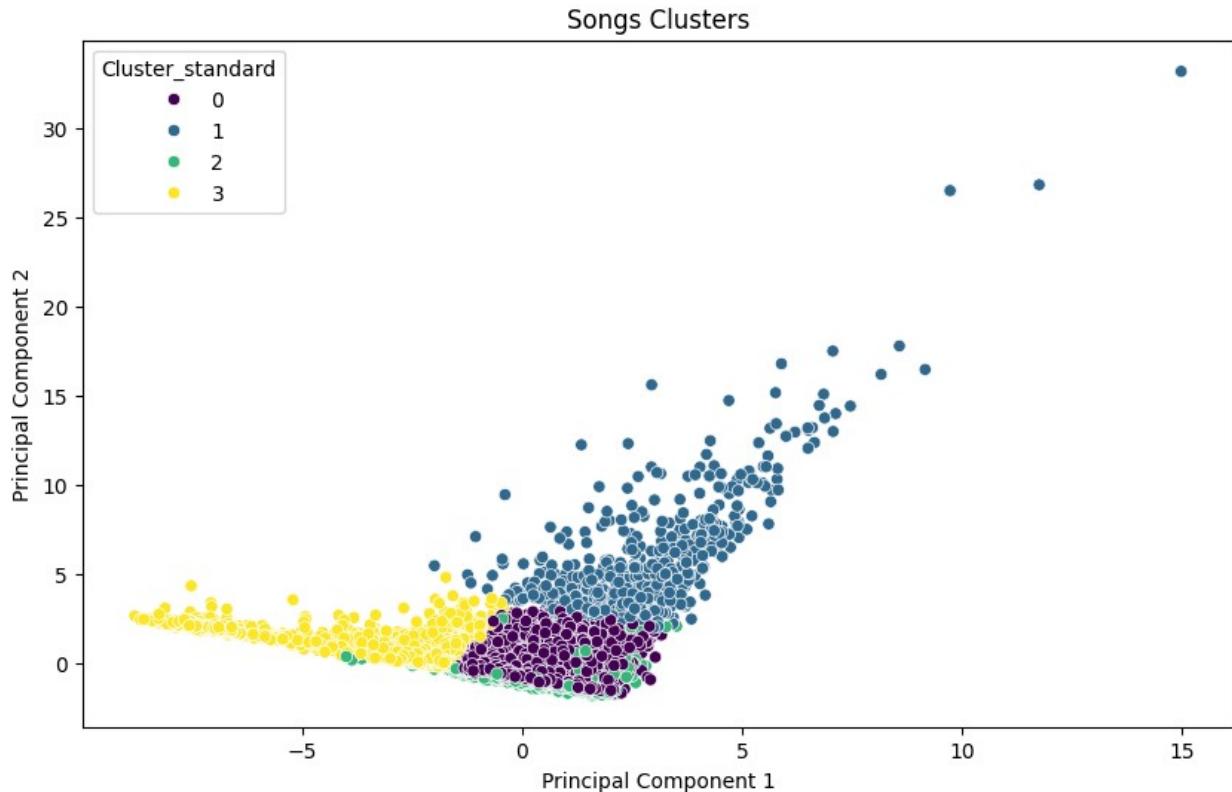
# Visulaizing the clusters
plt.figure(figsize=(10, 6))

```

```

sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster_standard', data=df,
palette='viridis')
plt.title("Songs Clusters")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()

```



## ANALYSIS

### MinMaxScaler Analysis

```

# Analyzing the clusters through Mean
df.groupby("Cluster_minmax")[features].mean()

{"summary": {
    "name": "df",
    "rows": 3,
    "fields": [
        {
            "column": "Cluster_minmax",
            "properties": {
                "dtype": "int32",
                "num_unique_values": 3,
                "samples": [0, 1, 2],
                "semantic_type": "\",
                "description": "\n"
            }
        },
        {
            "column": "Loudness",
            "properties": {
                "dtype": "number",
                "std": 3.743019842598732,
                "min": -12.830534926958832,
                "max": -6.258135404315865,
                "num_unique_values": 3,
                "samples": [-6.440584851527758, -]
            }
        }
    ]
}}

```

```
12.830534926958832,\n          -6.258135404315865\n      ],\n  {\\"semantic_type\\": \\"\\\", \n   \"description\\": \\"\\\"\n  }\n},\n  {\n    \\"column\\": \\"Energy\\\", \n    \\"properties\\\": {\n      \\"dtype\\": \\"number\\\", \n      \\"std\\\": 0.20683997931350273,\n      \\"min\\\": 0.347898999814077,\n      \\"max\\\": 0.7211589992885938,\n      \\"num_unique_values\\\": 3,\n      \\"samples\\\": [\n        0.6889830727298809,\n        0.347898999814077,\n        0.7211589992885938\n      ],\n    {\\"semantic_type\\": \\"\\\", \n     \"description\\\": \\"\\\"\n    },\n    {\n      \\"column\\": \\"Danceability\\\", \n      \\"properties\\\": {\n        \\"dtype\\": \\"number\\\", \n        \\"std\\\": 0.10423178376969981,\n        \\"min\\\": 0.4969739176626826,\n        \\"max\\\": 0.7048240455299977,\n        \\"num_unique_values\\\": 3,\n        \\"samples\\\": [\n          0.587059274135705,\n          0.4969739176626826,\n          0.7048240455299977\n        ],\n      {\\"semantic_type\\": \\"\\\", \n       \"description\\\": \\"\\\"\n      },\n      {\n        \\"column\\": \\"Valence\\\", \n        \\"properties\\\": {\n          \\"dtype\\": \\"number\\\", \n          \\"std\\\": 0.226767993446099,\n          \\"min\\\": 0.34511065604249663,\n          \\"max\\\": 0.74656153663742,\n          \\"num_unique_values\\\": 3,\n          \\"samples\\\": [\n            0.3630819954095539,\n            0.34511065604249663,\n            0.74656153663742\n          ],\n        {\\"semantic_type\\": \\"\\\", \n         \"description\\\": \\"\\\"\n        },\n        {\n          \\"column\\": \\"Tempo\\\", \n          \\"properties\\\": {\n            \\"dtype\\": \\"number\\\", \n            \\"std\\\": 5.561508175967272,\n            \\"min\\\": 112.9524358565737,\n            \\"max\\\": 123.11102955099699,\n            \\"num_unique_values\\\": 3,\n            \\"samples\\\": [\n              123.11102955099699,\n              112.9524358565737,\n              121.95516872184018\n            ],\n            \\"semantic_type\\\": \\"\\\", \n            \\"description\\\": \\"\\\"\n          },\n          {\n            \\"column\\": \\"Speechiness\\\", \n            \\"properties\\\": {\n              \\"dtype\\": \\"number\\\", \n              \\"std\\\": 0.023294504332633657,\n              \\"min\\\": 0.06272990703851261,\n              \\"max\\\": 0.10660993597344083,\n              \\"num_unique_values\\\": 3,\n              \\"samples\\\": [\n                0.06272990703851261,\n                0.10660993597344083,\n                0.0982275426768039\n              ],\n              \\"semantic_type\\\": \\"\\\", \n              \\"description\\\": \\"\\\"\n            },\n            {\n              \\"column\\": \\"Acousticness\\\", \n              \\"properties\\\": {\n                \\"dtype\\": \\"number\\\", \n                \\"std\\\": 0.33319397164761444,\n                \\"min\\\": 0.12491309022234974,\n                \\"max\\\": 0.7433287014900398,\n                \\"num_unique_values\\\": 3,\n                \\"samples\\\": [\n                  0.7433287014900398,\n                  0.21911794928977946,\n                  0.12491309022234974\n                ],\n                \\"semantic_type\\\": \\"\\\", \n                \\"description\\\": \\"\\\"\n              },\n              {\n                \\"column\\": \\"Instrumentalness\\\", \n                \\"properties\\\": {\n                  \\"dtype\\": \\"number\\\", \n                  \\"std\\\": 0.08820459029153568,\n                  \\"min\\\": 0.017096223883092246,\n                  \\"max\\\": 0.17827469157237716,\n                  \\"num_unique_values\\\": 3,\n                  \\"samples\\\": [\n                    0.17827469157237716,\n                    0.035586541388609956,\n                    0.21911794928977946\n                  ],\n                  \\"semantic_type\\\": \\"\\\", \n                  \\"description\\\": \\"\\\"\n                }\n              }\n            }\n          }\n        }\n      }\n    }\n  }\n}\n
```

```

0.017096223883092246],\n      \\"semantic_type\\": \"\",\\n
\\\"description\\\": \"\\n      \"},\\n      {\n        \\"column\\":
\\\"Liveness\\\",\\n        \\"properties\\\": {\n          \\"dtype\\":
\\\"number\\\",\\n          \\"std\\\": 0.02017717530700346,\\n          \\"min\\":
0.16410788844621516,\\n          \\"max\\\": 0.2023756276000574,\\n
\\\"num_unique_values\\\": 3,\\n          \\"samples\\\": [\n            0.2023756276000574,\\n            0.16410788844621516,\\n
0.19433411192791084],\\n      \\"semantic_type\\\": \"\",\\n
\\\"description\\\": \"\\n      \"},\\n      {\n        \\"column\\":
\\\"Views\\\",\\n        \\"properties\\\": {\n          \\"dtype\\": \\\"number\\\",\\n
\\\"std\\\": 31359758.22461054,\\n          \\"min\\\": 53920413.45232404,\\n
\\\"max\\\": 113310754.43644771,\\n          \\"num_unique_values\\\": 3,\\n
\\\"samples\\\": [\n            101076793.9843638,\\n
53920413.45232404,\\n            113310754.43644771
],\\n      \\"semantic_type\\\": \"\",\\n      \\"description\\\": \"\\n      \"}\\n    },\\n    {\n      \\"column\\": \\\"Likes\\\",\\n      \\"properties\\\": {\n        \\"dtype\\": \\\"number\\\",\\n
\\\"std\\\": 199401.9112288662,\\n        \\"min\\\": 404759.10464807437,\\n
\\\"max\\\": 750828.494427318,\\n        \\"num_unique_values\\\": 3,\\n
\\\"samples\\\": [\n            404759.10464807437,\\n
750828.494427318
],\\n      \\"semantic_type\\\": \"\",\\n      \\"description\\\": \"\\n      \"}\\n  },\\n  {\n    \\"column\\": \\\"Stream\\\",\\n    \\"properties\\\": {\n      \\"dtype\\": \\\"number\\\",\\n
\\\"std\\\": 32505248.823813245,\\n      \\"min\\\": 97260257.17556441,\\n
\\\"max\\\": 161640483.11217904,\\n      \\"num_unique_values\\\": 3,\\n
\\\"samples\\\": [\n            161640483.11217904,\\n
97260257.17556441,\\n            137271078.84301636
],\\n      \\"semantic_type\\\": \"\",\\n      \\"description\\\": \"\\n      \"}\\n  }
],\\n  ],\\n},\\n  \\"type\\": \"dataframe\"}

```

## StandardScaler Analysis

```

# Analyzing the clusters through Mean
df.groupby("Cluster_standard")[features].mean()

{"summary":{\n  \\"name\\": \\\"df\\\",\\n  \\"rows\\": 3,\\n  \\"fields\\\": [\n    {\n      \\"column\\": \\\"Cluster_standard\\\",\\n      \\"properties\\\": {\n        \\"dtype\\": \\\"int32\\\",\\n        \\"num_unique_values\\\": 3,\\n
        \\"samples\\\": [\n          0,\\n          1,\\n          2
        ],\\n        \\"semantic_type\\\": \"\",\\n        \\"description\\\": \"\\n          \"}\\n      },\\n      {\n        \\"column\\": \\\"Loudness\\\",\\n        \\"properties\\\": {\n          \\"dtype\\": \\\"number\\\",\\n
          \\"std\\\": 4.745604364128136,\\n          \\"min\\\": -14.249233238004448,\\n
          \\"max\\\": -5.750179586563307,\\n          \\"num_unique_values\\\": 3,\\n
          \\"samples\\\": [\n            -14.249233238004448,\\n
            -5.750179586563307,\\n            -6.340902288674667
          ],\\n        \\"semantic_type\\\": \"\",\\n        \\"description\\\": \"\\n          \"}\\n      },\\n      {\n        \\"column\\": \\\"Energy\\\",\\n        \\"properties\\\": {\n          \\"dtype\\": \\\"number\\\",\\n
          \\"std\\\": 1.0,\\n          \\"min\\\": 0.0,\\n          \\"max\\\": 1.0,\\n          \\"num_unique_values\\\": 2,\\n
          \\"samples\\\": [\n            0.0,\\n            1.0
          ],\\n        \\"semantic_type\\\": \"\",\\n        \\"description\\\": \"\\n          \"}\\n      }
    ]
  }
}

```

```

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```

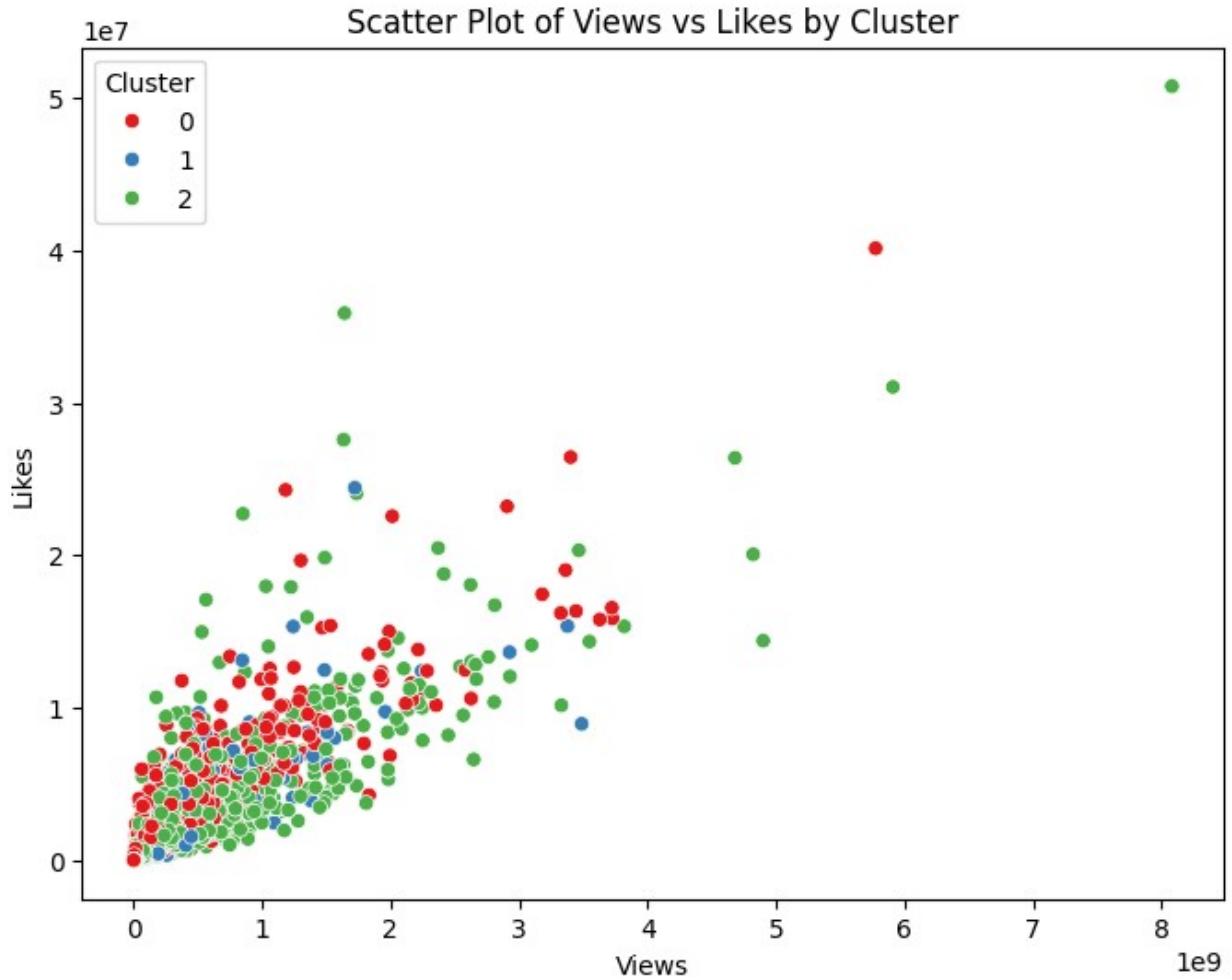
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# Scatter plot to show Views vs Likes, with different clusters as
colors
plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='Views', y='Likes', hue='Cluster_minmax',
palette='Set1')

plt.title('Scatter Plot of Views vs Likes by Cluster')
plt.xlabel('Views')
plt.ylabel('Likes')
plt.legend(title='Cluster')
plt.show()

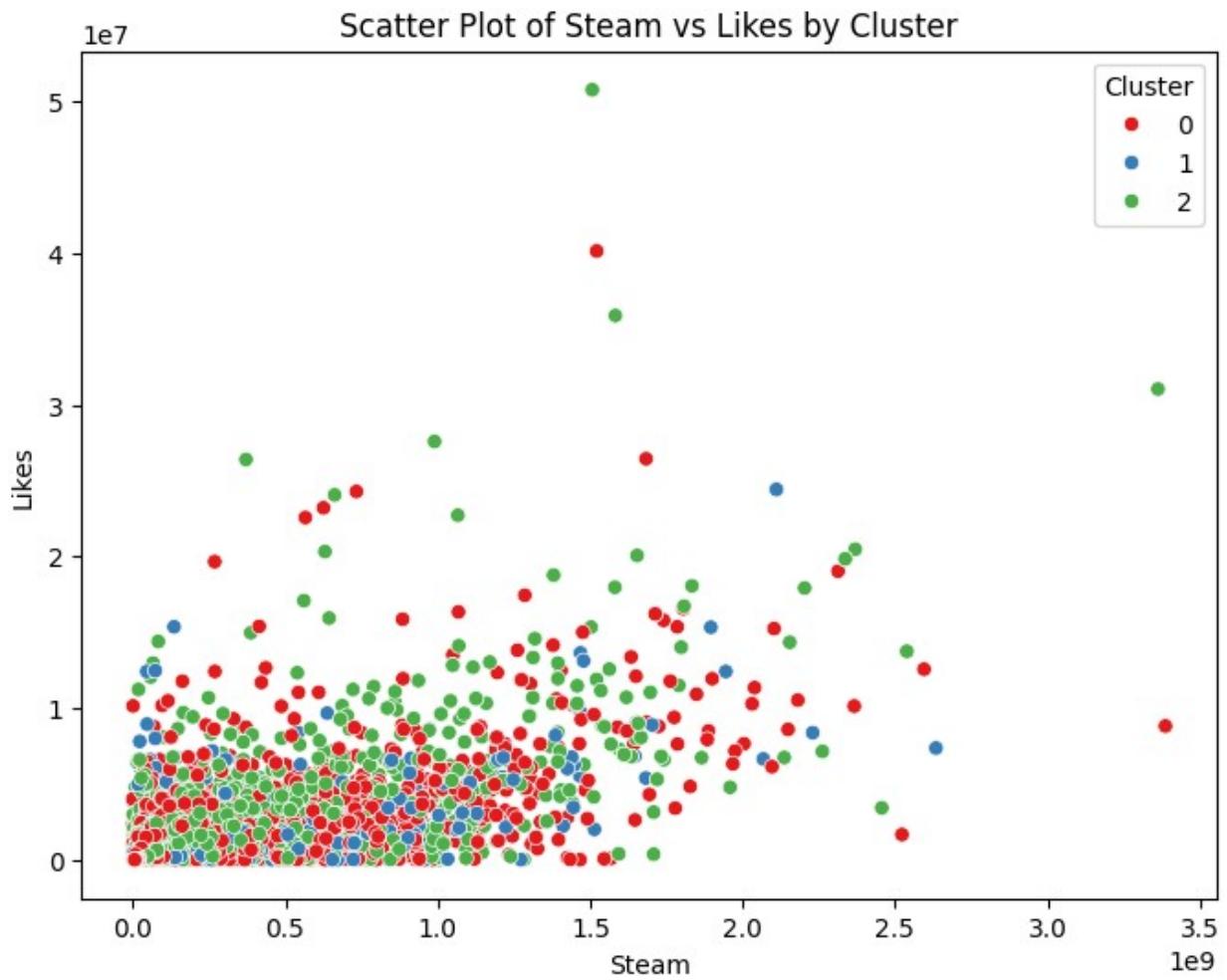
```



```
# Scatter plot to show Stream vs Likes, with different clusters as colors
plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='Stream', y='Likes', hue='Cluster_minmax',
palette='Set1')

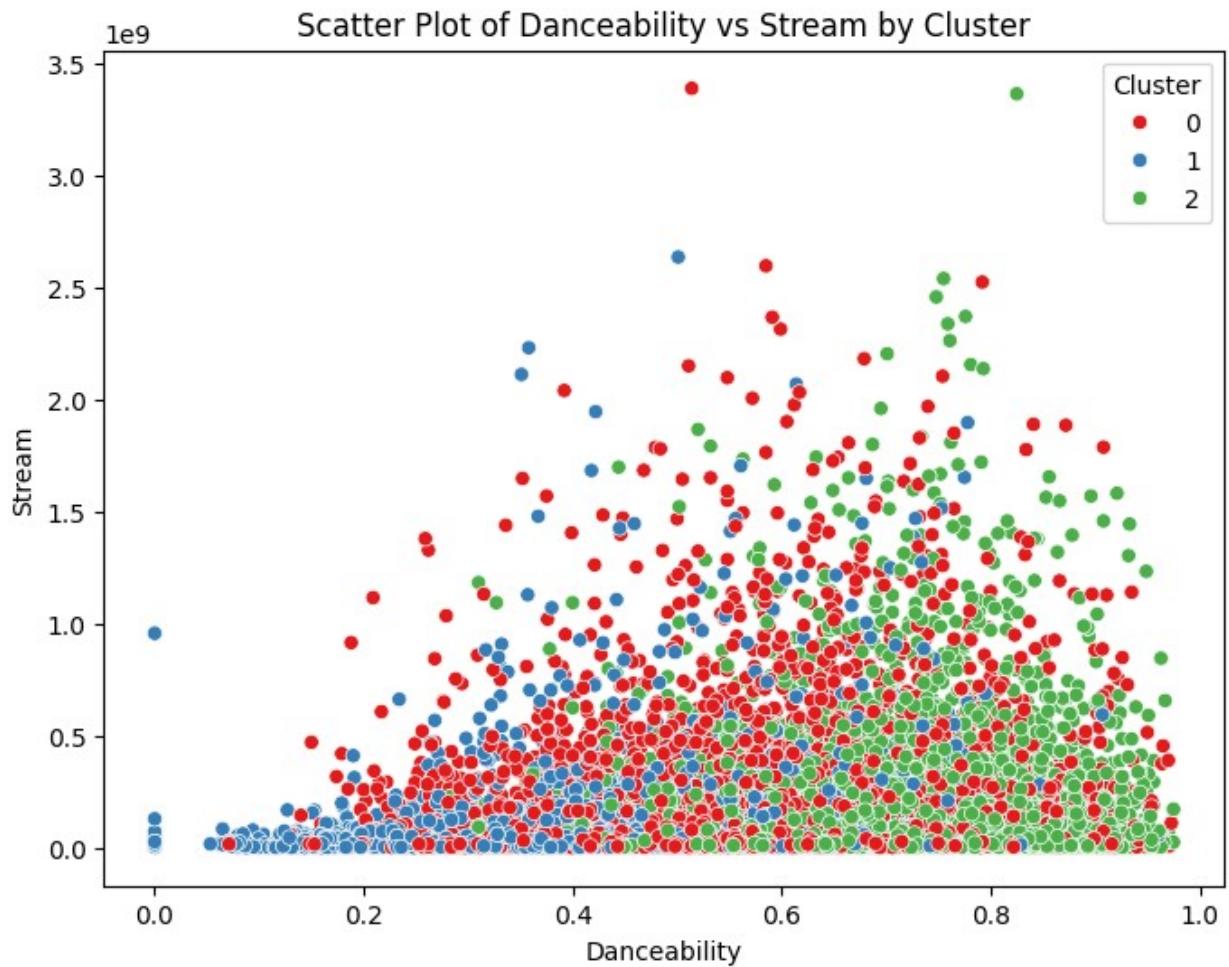
plt.title('Scatter Plot of Steam vs Likes by Cluster')
plt.xlabel('Steam')
plt.ylabel('Likes')
plt.legend(title='Cluster')
plt.show()
```



```
# Scatter plot to show Danceability vs Stream, with different clusters as colors
plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='Danceability', y='Stream',
hue='Cluster_minmax', palette='Set1')

plt.title('Scatter Plot of Danceability vs Stream by Cluster')
plt.xlabel('Danceability')
plt.ylabel('Stream')
plt.legend(title='Cluster')
plt.show()
```



```
# Scatter plot to show Loudness vs Likes, with different clusters as colors
plt.figure(figsize=(8, 6))

sns.scatterplot(data=df, x='Loudness', y='Likes',
hue='Cluster_minmax', palette='Set1')

plt.title('Scatter Plot of Loudness vs Likes by Cluster')
plt.xlabel('Loudness')
plt.ylabel('Likes')
plt.legend(title='Cluster')
plt.show()
```

