CS_M148_Checkin5

November 14, 2025

[ ]:
```python
# Imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score,␣
↪calinski_harabasz_score
import requests
import io
```

[9]:
```python
# Display and plotting defaults
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 100)
sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)

# Load dataset from Hugging Face - direct CSV download
# Using direct download to avoid glob pattern issues with datasets library
url = "https://huggingface.co/datasets/maharshipandya/spotify-tracks-dataset/
↪resolve/main/dataset.csv"
print("Downloading dataset from Hugging Face...")
response = requests.get(url, timeout=30)
response.raise_for_status()
df = pd.read_csv(io.StringIO(response.text))
print("Dataset loaded successfully!")

# Basic cleaning: drop obvious duplicates and reset index
df = df.drop_duplicates().reset_index(drop=True)

print(f"\nDataset shape: {df.shape}")
print(f"Number of columns: {len(df.columns)}")
print(f"Column names: {list(df.columns)}")
print("\nFirst few rows:")
df.head()
```

```
Downloading dataset from Hugging Face…
Dataset loaded successfully!

Dataset shape: (114000, 21)
Number of columns: 21
Column names: ['Unnamed: 0', 'track_id', 'artists', 'album_name', 'track_name',
'popularity', 'duration_ms', 'explicit', 'danceability', 'energy', 'key',
'loudness', 'mode', 'speechiness', 'acousticness', 'instrumentalness',
'liveness', 'valence', 'tempo', 'time_signature', 'track_genre']

First few rows:
```

[9]:

```
   Unnamed: 0                track_id                 artists  \
0           0  5SuOikwiRyPMVoIQDJUgSV              Gen Hoshino
1           1  4qPNDBW1i3p13qLCt0Ki3A             Ben Woodward
2           2  1iJBSr7s7jYXzM8EGcbK5b  Ingrid Michaelson;ZAYN
3           3  6lfxq3CG4xtTiEg7opyCyx             Kina Grannis
4           4  5vjLSffimiIP26QG5WcN2K        Chord Overstreet

                                          album_name  \
0                                             Comedy
1                                   Ghost (Acoustic)
2                                     To Begin Again
3  Crazy Rich Asians (Original Motion Picture Sou…
4                                            Hold On

                   track_name  popularity  duration_ms  explicit  \
0                      Comedy          73       230666     False
1            Ghost - Acoustic          55       149610     False
2              To Begin Again          57       210826     False
3  Can't Help Falling In Love          71       201933     False
4                     Hold On          82       198853     False

   danceability  energy  key  loudness  mode  speechiness  acousticness  \
0         0.676  0.4610    1    -6.746     0       0.1430        0.0322
1         0.420  0.1660    1   -17.235     1       0.0763        0.9240
2         0.438  0.3590    0    -9.734     1       0.0557        0.2100
3         0.266  0.0596    0   -18.515     1       0.0363        0.9050
4         0.618  0.4430    2    -9.681     1       0.0526        0.4690

   instrumentalness  liveness  valence    tempo  time_signature track_genre
0          0.000001    0.3580    0.715   87.917               4    acoustic
1          0.000006    0.1010    0.267   77.489               4    acoustic
2          0.000000    0.1170    0.120   76.332               4    acoustic
3          0.000071    0.1320    0.143  181.740               3    acoustic
4          0.000000    0.0829    0.167  119.949               4    acoustic
```

[10]:

```python
# Prepare numeric features for PCA and clustering
# Select audio features that are numeric and relevant for analysis
num_features = [
    'danceability', 'energy', 'loudness', 'speechiness', 'acousticness',
    'instrumentalness', 'liveness', 'valence', 'tempo', 'duration_ms'
]

available = [c for c in num_features if c in df.columns]
missing = sorted(set(num_features) - set(available))
if missing:
    print('Missing columns skipped:', missing)

# Keep rows with no NaNs in used columns
model_df = df.dropna(subset=available).copy()

X = model_df[available].copy()

print(f"Features used: {available}")
print(f"Data shape after cleaning: {X.shape}")
print(f"\nFeature statistics:")
X.describe()
```

```
Features used: ['danceability', 'energy', 'loudness', 'speechiness',
'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
'duration_ms']
Data shape after cleaning: (114000, 10)

Feature statistics:
```

[10]:

	danceability	energy	loudness	speechiness
count	114000.000000	114000.000000	114000.000000	114000.000000
mean	0.566800	0.641383	-8.258960	0.084652
std	0.173542	0.251529	5.029337	0.105732
min	0.000000	0.000000	-49.531000	0.000000
25%	0.456000	0.472000	-10.013000	0.035900
50%	0.580000	0.685000	-7.004000	0.048900
75%	0.695000	0.854000	-5.003000	0.084500
max	0.985000	1.000000	4.532000	0.965000

	acousticness	instrumentalness	liveness	valence
count	114000.000000	114000.000000	114000.000000	114000.000000
mean	0.314910	0.156050	0.213553	0.474068
std	0.332523	0.309555	0.190378	0.259261
min	0.000000	0.000000	0.000000	0.000000
25%	0.016900	0.000000	0.098000	0.260000
50%	0.169000	0.000042	0.132000	0.464000
75%	0.598000	0.049000	0.273000	0.683000
max	0.996000	1.000000	1.000000	0.995000

```
                tempo   duration_ms
count  114000.000000  1.140000e+05
mean      122.147837  2.280292e+05
std        29.978197  1.072977e+05
min         0.000000  0.000000e+00
25%        99.218750  1.740660e+05
50%       122.017000  2.129060e+05
75%       140.071000  2.615060e+05
max       243.372000  5.237295e+06
```

0.1 Part 1: Principal Component Analysis (PCA)

[11]:

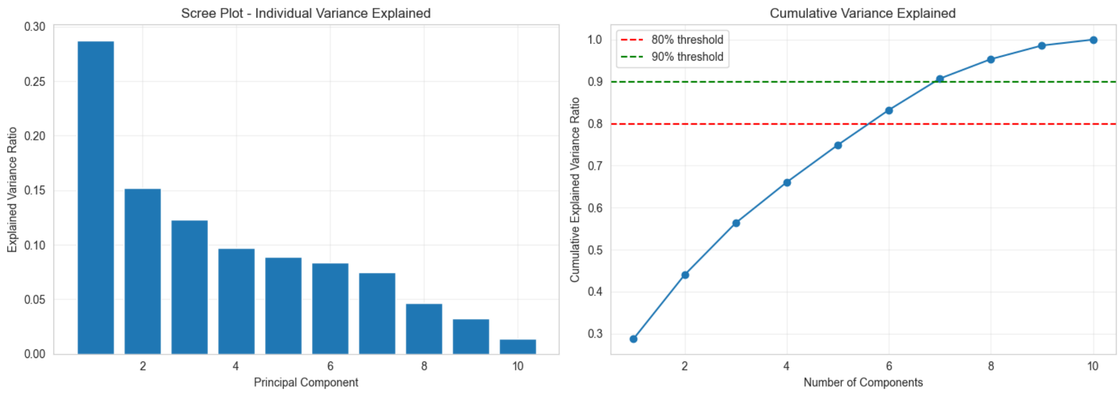
```python
# Standardize features before PCA
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA - keep all components to analyze variance
pca = PCA()
X_pca = pca.fit_transform(X_scaled)

# Calculate cumulative explained variance
cumulative_variance = np.cumsum(pca.explained_variance_ratio_)

print("Explained variance ratio per component:")
for i, var in enumerate(pca.explained_variance_ratio_, 1):
    print(f"PC{i}: {var:.4f} ({var*100:.2f}%)")

print(f"\nCumulative explained variance:")
for i, cum_var in enumerate(cumulative_variance, 1):
    print(f"PC1-PC{i}: {cum_var:.4f} ({cum_var*100:.2f}%)")
```

```
Explained variance ratio per component:
PC1: 0.2874 (28.74%)
PC2: 0.1524 (15.24%)
PC3: 0.1234 (12.34%)
PC4: 0.0971 (9.71%)
PC5: 0.0887 (8.87%)
PC6: 0.0834 (8.34%)
PC7: 0.0748 (7.48%)
PC8: 0.0463 (4.63%)
PC9: 0.0325 (3.25%)
PC10: 0.0140 (1.40%)

Cumulative explained variance:
PC1-PC1: 0.2874 (28.74%)
PC1-PC2: 0.4398 (43.98%)
PC1-PC3: 0.5632 (56.32%)
```

```
PC1-PC4: 0.6603 (66.03%)
PC1-PC5: 0.7490 (74.90%)
PC1-PC6: 0.8323 (83.23%)
PC1-PC7: 0.9071 (90.71%)
PC1-PC8: 0.9535 (95.35%)
PC1-PC9: 0.9860 (98.60%)
PC1-PC10: 1.0000 (100.00%)
```

[12]:

```python
# Scree plot
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Individual variance explained
axes[0].bar(range(1, len(pca.explained_variance_ratio_) + 1),
            pca.explained_variance_ratio_)
axes[0].set_xlabel('Principal Component')
axes[0].set_ylabel('Explained Variance Ratio')
axes[0].set_title('Scree Plot - Individual Variance Explained')
axes[0].grid(True, alpha=0.3)

# Cumulative variance explained
axes[1].plot(range(1, len(cumulative_variance) + 1),
             cumulative_variance, marker='o')
axes[1].axhline(y=0.8, color='r', linestyle='--', label='80% threshold')
axes[1].axhline(y=0.9, color='g', linestyle='--', label='90% threshold')
axes[1].set_xlabel('Number of Components')
axes[1].set_ylabel('Cumulative Explained Variance Ratio')
axes[1].set_title('Cumulative Variance Explained')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Find number of components for common thresholds
n_80 = np.argmax(cumulative_variance >= 0.80) + 1
n_90 = np.argmax(cumulative_variance >= 0.90) + 1
print(f"\nComponents needed for 80% variance: {n_80}")
print(f"Components needed for 90% variance: {n_90}")
```




```
Components needed for 80% variance: 6
Components needed for 90% variance: 7
```

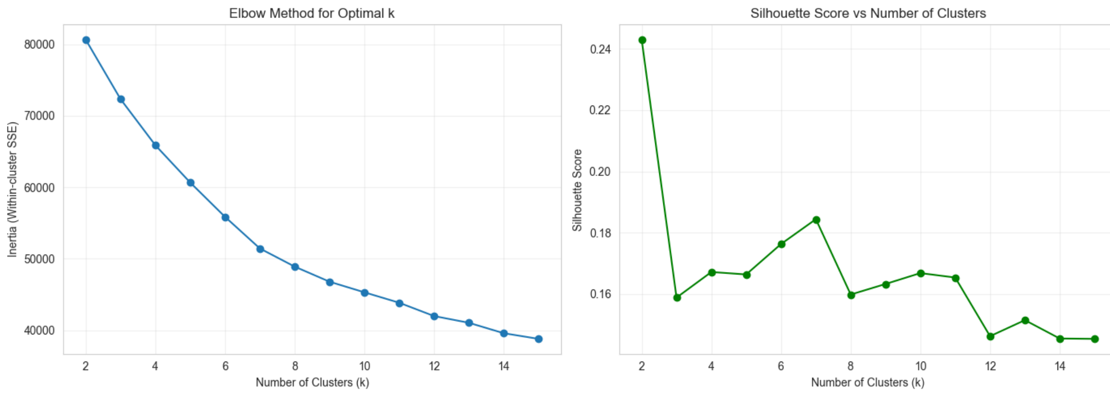
0.2 Part 2: Clustering (K-Means)

[14]:

```python
# Determine optimal number of clusters using elbow method
# Use a sample for faster computation when finding optimal k
sample_size = min(10000, len(X_scaled))
if sample_size < len(X_scaled):
    print(f"Using sample of {sample_size} points for faster computation...")
    np.random.seed(42)
    sample_indices = np.random.choice(len(X_scaled), size=sample_size,␣
↪replace=False)
    X_sample = X_scaled[sample_indices]
else:
    X_sample = X_scaled

# Test k from 2 to 15
k_range = range(2, 16)
inertias = []
silhouette_scores = []

print("Testing different k values...")
for k in k_range:
    print(f"  Testing k={k}...", end=' ')
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=5)  # Reduced n_init␣
↪for speed
    kmeans.fit(X_sample)
    inertias.append(kmeans.inertia_)
    # Use sample_size parameter to speed up silhouette calculation
    sil_score = silhouette_score(X_sample, kmeans.labels_,␣
↪sample_size=min(5000, len(X_sample)))
```

```
    silhouette_scores.append(sil_score)
    print(f"silhouette={sil_score:.4f}")

# Plot elbow curve and silhouette scores
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

axes[0].plot(k_range, inertias, marker='o')
axes[0].set_xlabel('Number of Clusters (k)')
axes[0].set_ylabel('Inertia (Within-cluster SSE)')
axes[0].set_title('Elbow Method for Optimal k')
axes[0].grid(True, alpha=0.3)

axes[1].plot(k_range, silhouette_scores, marker='o', color='green')
axes[1].set_xlabel('Number of Clusters (k)')
axes[1].set_ylabel('Silhouette Score')
axes[1].set_title('Silhouette Score vs Number of Clusters')
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Find optimal k (highest silhouette score)
optimal_k = k_range[np.argmax(silhouette_scores)]
print(f"Optimal number of clusters (highest silhouette score): k = {optimal_k}")
print(f"Silhouette score at k={optimal_k}: {max(silhouette_scores):.4f}")
```

```
Using sample of 10000 points for faster computation…
Testing different k values…
  Testing k=2… silhouette=0.2430
  Testing k=3… silhouette=0.1588
  Testing k=4… silhouette=0.1672
  Testing k=5… silhouette=0.1664
  Testing k=6… silhouette=0.1763
  Testing k=7… silhouette=0.1844
  Testing k=8… silhouette=0.1598
  Testing k=9… silhouette=0.1632
  Testing k=10… silhouette=0.1668
  Testing k=11… silhouette=0.1653
  Testing k=12… silhouette=0.1462
  Testing k=13… silhouette=0.1514
  Testing k=14… silhouette=0.1454
  Testing k=15… silhouette=0.1453
```

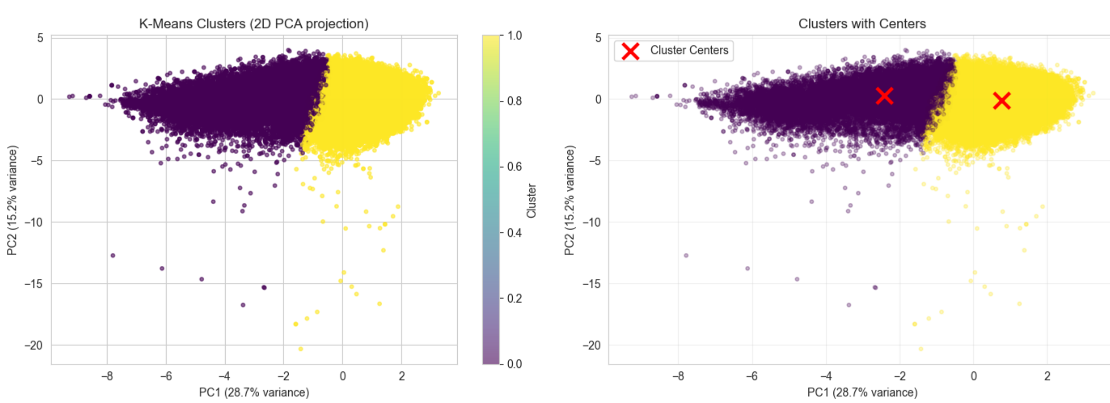



```
Optimal number of clusters (highest silhouette score): k = 2
Silhouette score at k=2: 0.2430
```

[15]:
```python
# Apply K-Means with optimal k
kmeans_final = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
cluster_labels = kmeans_final.fit_predict(X_scaled)

# Add cluster labels to dataframe
model_df['cluster'] = cluster_labels

# Calculate clustering evaluation metrics
silhouette = silhouette_score(X_scaled, cluster_labels)
davies_bouldin = davies_bouldin_score(X_scaled, cluster_labels)
calinski_harabasz = calinski_harabasz_score(X_scaled, cluster_labels)

print("Clustering Evaluation Metrics:")
print(f"Silhouette Score: {silhouette:.4f} (higher is better, range: -1 to 1)")
print(f"Davies-Bouldin Index: {davies_bouldin:.4f} (lower is better)")
print(f"Calinski-Harabasz Index: {calinski_harabasz:.4f} (higher is better)")

print(f"\nCluster sizes:")
print(model_df['cluster'].value_counts().sort_index())
```

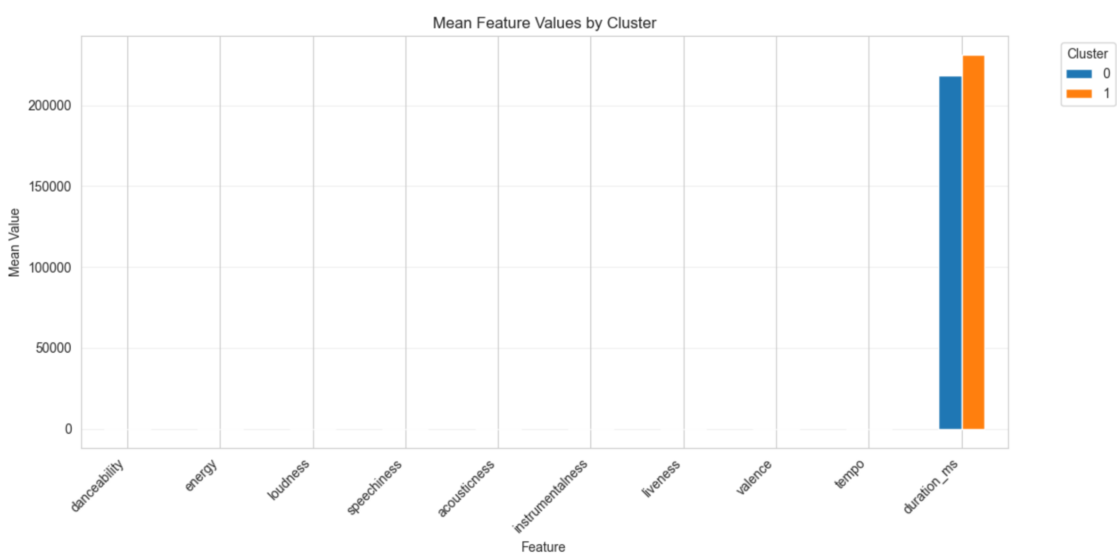
```
Clustering Evaluation Metrics:
Silhouette Score: 0.2508 (higher is better, range: -1 to 1)
Davies-Bouldin Index: 1.6517 (lower is better)
Calinski-Harabasz Index: 27345.0761 (higher is better)

Cluster sizes:
cluster
0    27916
1    86084
Name: count, dtype: int64
```

```
[16]: # Visualize clusters using first two principal components
pca_2d = PCA(n_components=2)
X_pca_2d = pca_2d.fit_transform(X_scaled)

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Scatter plot colored by cluster
scatter = axes[0].scatter(X_pca_2d[:, 0], X_pca_2d[:, 1],
                          c=cluster_labels, cmap='viridis', alpha=0.6, s=10)
axes[0].set_xlabel(f'PC1 ({pca_2d.explained_variance_ratio_[0]*100:.1f}% variance)')
axes[0].set_ylabel(f'PC2 ({pca_2d.explained_variance_ratio_[1]*100:.1f}% variance)')
axes[0].set_title('K-Means Clusters (2D PCA projection)')
plt.colorbar(scatter, ax=axes[0], label='Cluster')

# Cluster centers in PCA space
cluster_centers_pca = pca_2d.transform(kmeans_final.cluster_centers_)
axes[1].scatter(X_pca_2d[:, 0], X_pca_2d[:, 1],
                c=cluster_labels, cmap='viridis', alpha=0.3, s=10)
axes[1].scatter(cluster_centers_pca[:, 0], cluster_centers_pca[:, 1],
                c='red', marker='x', s=200, linewidths=3, label='Cluster Centers')
axes[1].set_xlabel(f'PC1 ({pca_2d.explained_variance_ratio_[0]*100:.1f}% variance)')
axes[1].set_ylabel(f'PC2 ({pca_2d.explained_variance_ratio_[1]*100:.1f}% variance)')
axes[1].set_title('Clusters with Centers')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

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



[17]:
```
# Analyze cluster characteristics
print("Cluster characteristics (mean values):")
cluster_means = model_df.groupby('cluster')[available].mean()
print(cluster_means.round(3))

# Visualize cluster characteristics
fig, ax = plt.subplots(figsize=(12, 6))
cluster_means.T.plot(kind='bar', ax=ax)
ax.set_xlabel('Feature')
ax.set_ylabel('Mean Value')
ax.set_title('Mean Feature Values by Cluster')
ax.legend(title='Cluster', bbox_to_anchor=(1.05, 1), loc='upper left')
ax.grid(True, alpha=0.3, axis='y')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
Cluster characteristics (mean values):
         danceability  energy  loudness  speechiness  acousticness  \
cluster
0               0.471   0.304   -14.146        0.058         0.743
1               0.598   0.751    -6.350        0.093         0.176

         instrumentalness  liveness  valence    tempo  duration_ms
cluster
0                   0.299     0.178    0.318  110.158   218611.338
1                   0.110     0.225    0.525  126.036   231083.237
```



0.3 Explanation: How PCA is Used in the Project

Dimensionality Reduction and Structure Learning:

PCA is applied to the Spotify audio features to reduce dimensionality and uncover underlying structure in the data. The analysis reveals:

1. **Dimensionality Reduction**: The scree plot shows that the first few principal components capture most of the variance. For example, if the first 3-4 components explain 80-90% of variance, we can reduce from 10 features to 3-4 components while retaining most information. This is useful for:
   - Visualizing high-dimensional data in 2D/3D space
   - Reducing computational complexity for downstream tasks
   - Removing noise and focusing on the most important patterns
2. **Structure Discovery**: The principal components reveal which combinations of audio features vary together. For instance:
   - PC1 might capture a "energy-danceability" axis (high energy + high danceability vs. low energy + low danceability)
   - PC2 might capture an "acoustic-instrumental" axis
   - This helps understand the main dimensions along which songs differ
3. **Application in Project**: PCA components can be used as:
   - Input features for regression/classification models (reduced dimensionality)
   - Visualization tool to explore song similarities
   - Preprocessing step before clustering (as demonstrated in the cluster visualization above)

0.4 Explanation: How Clustering is Used in the Project

Determining Number of Clusters:

The optimal number of clusters (k) was determined using two complementary methods:

1. **Elbow Method**: Plots the within-cluster sum of squares (inertia) against k. The "elbow" point where the curve bends indicates diminishing returns from adding more clusters. However, the elbow can be subjective.

2. **Silhouette Score**: A more objective metric that measures how similar samples are to their own cluster compared to other clusters. Values range from -1 to 1, with higher values indicating better-defined clusters. We selected k with the highest silhouette score from the tested range (k=2 to 15).

Quantitative Evaluation:

Three metrics were used to evaluate clustering quality: - **Silhouette Score**: Measures cluster cohesion and separation (higher is better, range: -1 to 1) - **Davies-Bouldin Index**: Measures average similarity ratio between clusters (lower is better) - **Calinski-Harabasz Index**: Ratio of between-cluster to within-cluster variance (higher is better)

Learning About Data Structure:

Clustering reveals natural groupings in the Spotify dataset:

1. **Music Genre Discovery**: Clusters may correspond to different music styles (e.g., high-energy dance tracks vs. acoustic ballads vs. instrumental pieces). By examining cluster char-

acteristics (mean feature values), we can identify:
   - Which audio features distinguish each cluster
   - Whether clusters align with known genres or reveal new patterns
   - How songs are distributed across different musical styles
2. **Application in Project**: The clusters can be used for:
   - **Recommendation Systems**: Songs in the same cluster are similar and can be recommended together
   - **Market Segmentation**: Understanding different listener preferences based on audio characteristics
   - **Feature Engineering**: Cluster labels can be added as categorical features to regression/classification models
   - **Data Exploration**: Identifying outliers (songs that don't fit well in any cluster) or discovering new music categories

The combination of PCA and clustering provides both dimensionality reduction and meaningful segmentation of the music dataset, enabling deeper insights into the structure of audio features and song similarities.