main

April 12, 2025

# 1 Music Recommendation System with Spotify Data

### 1.0.1 1. Loading Data :

[12]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import MinMaxScaler

file_path = 'data/spotify_data.csv'
df_raw = pd.read_csv(file_path)

print("Original data shape:", df_raw.shape)
print("Original data head:\n", df_raw.head())
```

```
Original data shape: (1159764, 20)
Original data head:
    Unnamed: 0    artist_name        track_name                track_id  \
0           0     Jason Mraz  I Won't Give Up  53QF56cjZA9RTuuMZDrSA6
1           1     Jason Mraz  93 Million Miles  1s8tP3jP4GZcyHDsjvw218
2           2  Joshua Hyslop  Do Not Let Me Go  7BRCa8MPiyuvr2VU3O9W0F
3           3   Boyce Avenue          Fast Car  63wsZUhUZLlh1OsyrZq7sz
4           4   Andrew Belle  Sky's Still Blue  6nXIYClvJAfi6ujLiKqEq8

   popularity  year     genre  danceability  energy  key  loudness  mode  \
0          68  2012  acoustic         0.483   0.303    4   -10.058     1
1          50  2012  acoustic         0.572   0.454    3   -10.286     1
2          57  2012  acoustic         0.409   0.234    3   -13.711     1
3          58  2012  acoustic         0.392   0.251   10    -9.845     1
4          54  2012  acoustic         0.430   0.791    6    -5.419     0

   speechiness  acousticness  instrumentalness  liveness  valence    tempo  \
0       0.0429        0.6940          0.000000    0.1150    0.139  133.406
1       0.0258        0.4770          0.000014    0.0974    0.515  140.182
2       0.0323        0.3380          0.000050    0.0895    0.145  139.832
3       0.0363        0.8070          0.000000    0.0797    0.508  204.961
4       0.0302        0.0726          0.019300    0.1100    0.217  171.864
```

```
   duration_ms  time_signature
0       240166               3
1       216387               4
2       158960               4
3       304293               4
4       244320               4
```

### 1.0.2 2. Initial Cleaning & Preprocessing :

[13]:
```python
print("Missing values before dropping:\n", df_raw.isnull().sum())
df_clean = df_raw.dropna().copy() # Use .copy() to avoid SettingWithCopyWarning
print("\nShape before dropping NA:", df_raw.shape)
print("\nShape after dropping NA:", df_clean.shape)


# Checking for duplicates
print("\nDuplicate rows:", df_clean.duplicated().sum())
```

```
Missing values before dropping:
 Unnamed: 0          0
artist_name        15
track_name          1
track_id            0
popularity          0
year                0
genre               0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
duration_ms         0
time_signature      0
dtype: int64

Shape before dropping NA: (1159764, 20)

Shape after dropping NA: (1159748, 20)

Duplicate rows: 0
```

### 1.0.3 3. Feature Selection and Overview

The dataset contains various audio features from Spotify. For our similarity model, we'll focus on intrinsic audio characteristics rather than metadata.

**Selected Features for Modeling:**

| Feature | Description | Range |
|---|---|---|
| **Danceability** | Suitability for dancing based on rhythm and beat | 0.0-1.0 |
| **Energy** | Intensity and activity level | 0.0-1.0 |
| **Key** | Musical key (requires one-hot encoding) | -1 to 11 |
| **Loudness** | Overall loudness (requires scaling) | -60 to 0 dB |
| **Mode** | Major (1) or Minor (0) key (requires one-hot encoding) | 0 or 1 |
| **Speechiness** | Presence of spoken words | 0.0-1.0 |
| **Acousticness** | Likelihood of being acoustic | 0.0-1.0 |
| **Instrumentalness** | Likelihood of having no vocals | 0.0-1.0 |
| **Liveness** | Presence of audience/live recording | 0.0-1.0 |
| **Valence** | Musical positiveness/mood | 0.0-1.0 |
| **Tempo** | Speed in BPM (requires scaling) | Varies |

We exclude metadata (artist_name, track_name, track_id, genre, year), popularity, duration_ms, and time_signature as they're less relevant for audio similarity.

[14]:
```
features = ['danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',␣
↪'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo']

df = df_clean[features]
print("\nSelected features shape:", df.shape)

# Set the index to track_id from the original dataframe
df.index = df_clean['track_id'].values
df.index.name = 'track_id'
```

```
Selected features shape: (1159748, 11)
```

### 1.0.4 4. Feature Engineering & Transformation:

[15]:
```
from sklearn.preprocessing import MinMaxScaler
import pandas as pd

# Apply min-max scaling to tempo
print("\nTempo statistics before scaling:")
print(df['tempo'].describe())
scaler_tempo = MinMaxScaler()
df['tempo'] = scaler_tempo.fit_transform(df[['tempo']])
```

```python
print("\nTempo statistics after scaling:")
print(df['tempo'].describe())

# One-hot encode key
key_dummies = pd.get_dummies(df['key'], prefix='key', drop_first=False) # Keep␣
↪all keys
df = pd.concat([df, key_dummies], axis=1)

# One-hot encode mode
mode_dummies = pd.get_dummies(df['mode'], prefix='mode', drop_first=False) #␣
↪Keep both 0 and 1
df = pd.concat([df, mode_dummies], axis=1)

# Drop original categorical columns
df.drop(['key', 'mode'], axis=1, inplace=True)

print("\nProcessed features head (after OHE):\n", df.head())
print("Processed features shape (after OHE):", df.shape)
print("Index check:", df.index.name)

# Create some music-specific Meaningful composite features
df['energy_to_acousticness_ratio'] = df['energy'] / (df['acousticness'] + 0.01)
df['vocal_character'] = df['speechiness'] * (1 - df['instrumentalness'])
```

```
Tempo statistics before scaling:
count    1.159748e+06
mean     1.213775e+02
std      2.977964e+01
min      0.000000e+00
25%      9.879800e+01
50%      1.219310e+02
75%      1.399030e+02
max      2.499930e+02
Name: tempo, dtype: float64

Tempo statistics after scaling:
count    1.159748e+06
mean     4.855236e-01
std      1.191219e-01
min      0.000000e+00
25%      3.952031e-01
50%      4.877377e-01
75%      5.596277e-01
max      1.000000e+00
Name: tempo, dtype: float64
```

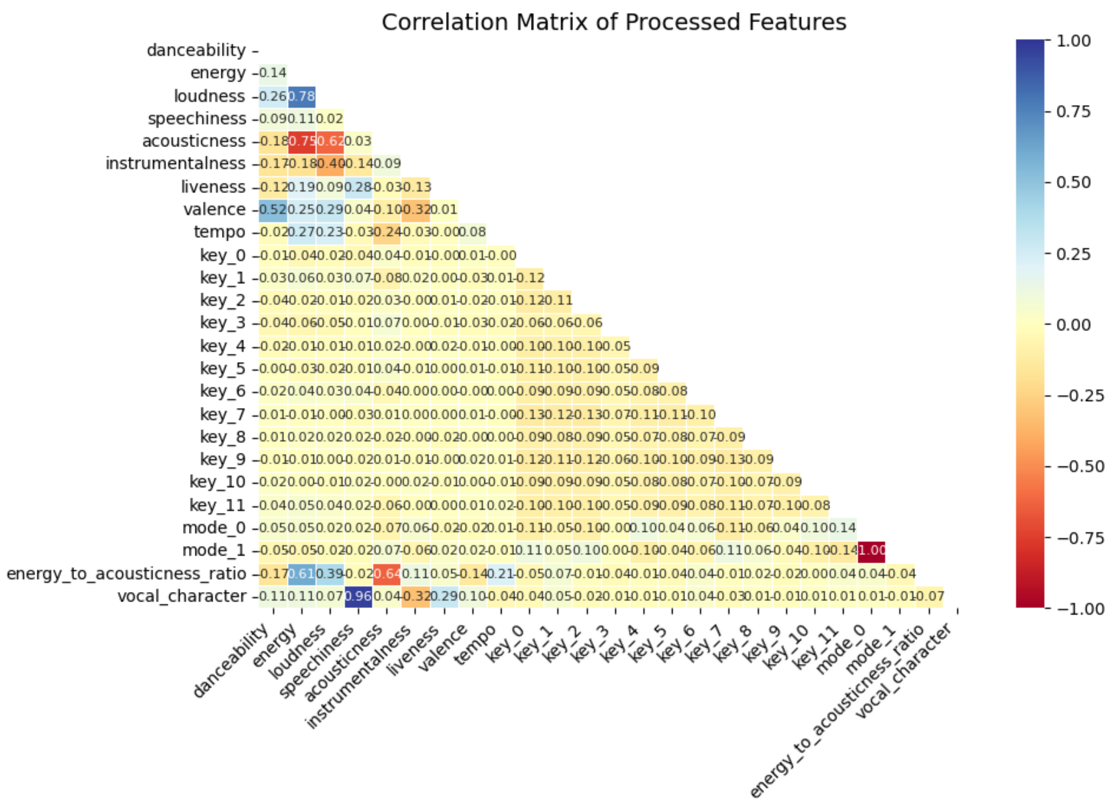
```
/var/folders/93/lcr499bs33s3sbz5nld5dwvc0000gn/T/ipykernel_919/3461003564.py:8:
```

```
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['tempo'] = scaler_tempo.fit_transform(df[['tempo']])


Processed features head (after OHE):
                        danceability  energy  loudness  speechiness  \
track_id
53QF56cjZA9RTuuMZDrSA6         0.483   0.303   -10.058       0.0429
1s8tP3jP4GZcyHDsjvw218         0.572   0.454   -10.286       0.0258
7BRCa8MPiyuvr2VU3O9W0F         0.409   0.234   -13.711       0.0323
63wsZUhUZLlh1OsyrZq7sz         0.392   0.251    -9.845       0.0363
6nXIYClvJAfi6ujLiKqEq8         0.430   0.791    -5.419       0.0302

                        acousticness  instrumentalness  liveness  valence  \
track_id
53QF56cjZA9RTuuMZDrSA6        0.6940          0.000000    0.1150    0.139
1s8tP3jP4GZcyHDsjvw218        0.4770          0.000014    0.0974    0.515
7BRCa8MPiyuvr2VU3O9W0F        0.3380          0.000050    0.0895    0.145
63wsZUhUZLlh1OsyrZq7sz        0.8070          0.000000    0.0797    0.508
6nXIYClvJAfi6ujLiKqEq8        0.0726          0.019300    0.1100    0.217

                           tempo  key_0  …  key_4  key_5  key_6  key_7  \
track_id                                …
53QF56cjZA9RTuuMZDrSA6  0.533639  False  …   True  False  False  False
1s8tP3jP4GZcyHDsjvw218  0.560744  False  …  False  False  False  False
7BRCa8MPiyuvr2VU3O9W0F  0.559344  False  …  False  False  False  False
63wsZUhUZLlh1OsyrZq7sz  0.819867  False  …  False  False  False  False
6nXIYClvJAfi6ujLiKqEq8  0.687475  False  …  False  False   True  False

                        key_8  key_9  key_10  key_11  mode_0  mode_1
track_id
53QF56cjZA9RTuuMZDrSA6  False  False   False   False   False    True
1s8tP3jP4GZcyHDsjvw218  False  False   False   False   False    True
7BRCa8MPiyuvr2VU3O9W0F  False  False   False   False   False    True
63wsZUhUZLlh1OsyrZq7sz  False  False    True   False   False    True
6nXIYClvJAfi6ujLiKqEq8  False  False   False   False    True   False

[5 rows x 23 columns]
Processed features shape (after OHE): (1159748, 23)
Index check: track_id
```

### 1.0.5 5. Exploratory Data Analysis :

[16]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

print("\nCalculating Correlation Matrix...")
correlation_matrix = df.corr()

plt.figure(figsize=(10, 7))
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))
sns.heatmap(correlation_matrix, annot=True, cmap='RdYlBu', fmt='.2f',␣
 ↪linewidths=0.5, vmin=-1, vmax=1, mask=mask, annot_kws={"size": 8})
plt.title('Correlation Matrix of Processed Features', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```

```
Calculating Correlation Matrix…
```



## 1.1 Correlation Analysis Findings

The correlation matrix reveals several highly correlated feature pairs:

| Feature Pair | Correlation Coefficient |
|---|---|
| energy and loudness | 0.781 |
| energy and acousticness | -0.753 |
| speechiness and vocal_character | 0.965 |
| mode_0 and mode_1 | -1.000 |

These strong correlations suggest potential redundancy in our feature set, which may impact model performance.
The perfect negative correlation between mode_0 and mode_1 is expected since they are one-hot encoded from the same categorical variable.

[17]:
```
# Drop highly correlated features to reduce redundancy
print("\nDropping highly correlated features...")
features_to_drop = ['mode_1', 'vocal_character', 'acousticness', 'loudness']
df = df.drop(columns=features_to_drop)

print(f"Features dropped: {features_to_drop}")
print(f"Remaining features: {df.columns.tolist()}")
print("Original dataframe shape:", df_raw.shape)
print(f"New dataframe shape: {df.shape}")
```

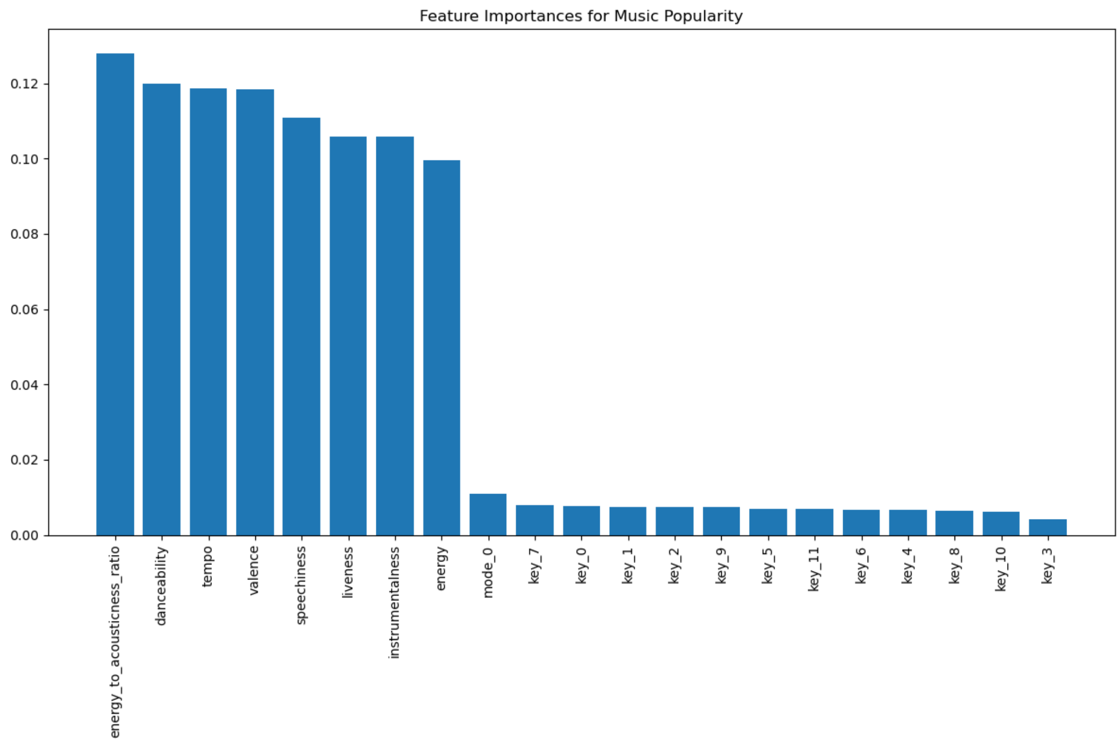
```
Dropping highly correlated features…
Features dropped: ['mode_1', 'vocal_character', 'acousticness', 'loudness']
Remaining features: ['danceability', 'energy', 'speechiness',
'instrumentalness', 'liveness', 'valence', 'tempo', 'key_0', 'key_1', 'key_2',
'key_3', 'key_4', 'key_5', 'key_6', 'key_7', 'key_8', 'key_9', 'key_10',
'key_11', 'mode_0', 'energy_to_acousticness_ratio']
Original dataframe shape: (1159764, 20)
New dataframe shape: (1159748, 21)
```

**Feature Importance Analysis**

[18]:
```
print("\nEvaluating feature importance using Random Forest...")
from sklearn.ensemble import RandomForestRegressor
import multiprocessing

# Use a simple target like popularity
target = df_clean['popularity']

# Train a random forest model to get feature importance with parallel processing
rf = RandomForestRegressor(n_estimators=100, random_state=42, n_jobs=-1)
rf.fit(df, target)
```

```python
# Get feature importances
importances = rf.feature_importances_
indices = np.argsort(importances)[::-1]

# Plot feature importances
plt.figure(figsize=(12, 8))
plt.title('Feature Importances for Music Popularity')
plt.bar(range(df.shape[1]), importances[indices], align='center')
plt.xticks(range(df.shape[1]), [df.columns[i] for i in indices], rotation=90)
plt.tight_layout()
plt.show()

# Keep only top features
importance_threshold = 0.05  # This will capture the most significant features␣
↪based on your graph
important_indices = [i for i, imp in enumerate(importances) if imp >␣
↪importance_threshold]
top_features = [df.columns[i] for i in indices if importances[i] >␣
↪importance_threshold]
print(f"Features with importance > {importance_threshold}: {top_features}")
df_important = df[top_features]

# Let's also keep the custom ratio features since they're highly important
if 'energy_to_acousticness_ratio' not in df_important.columns and␣
↪'energy_to_acousticness_ratio' in df.columns:
    df_important['energy_to_acousticness_ratio'] =␣
↪df['energy_to_acousticness_ratio']

if 'vocal_character' not in df_important.columns and 'vocal_character' in df.
↪columns:
    df_important['vocal_character'] = df['vocal_character']

print(f"Refined feature set shape: {df_important.shape}")
```

```
Evaluating feature importance using Random Forest…
```

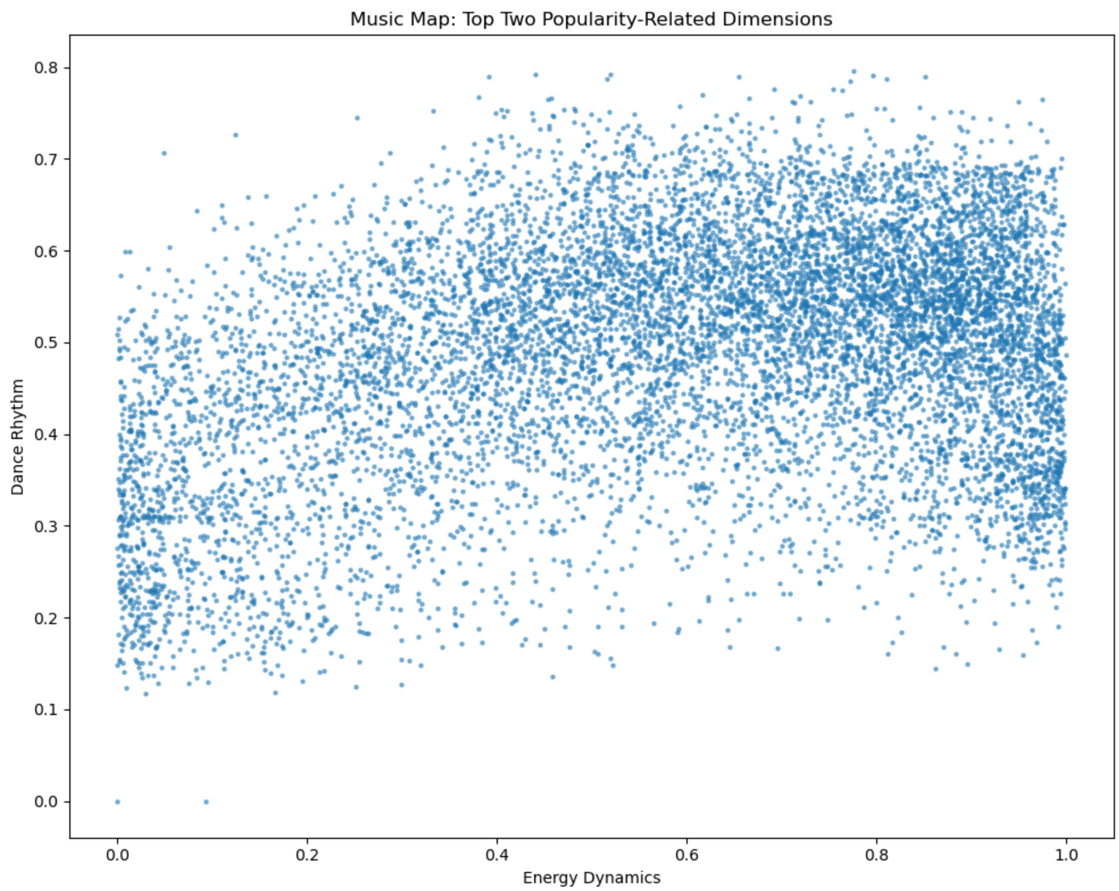



```
Features with importance > 0.05: ['energy_to_acousticness_ratio',
'danceability', 'tempo', 'valence', 'speechiness', 'liveness',
'instrumentalness', 'energy']
Refined feature set shape: (1159748, 8)
```

[24]:
```
# Define more musically meaningful components based on feature importance
df_important.loc[:, 'energy_dynamics'] = df['energy']
df_important.loc[:, 'dance_rhythm'] = 0.6*df['danceability'] + 0.4*df['tempo']
df_important.loc[:, 'emotional_content'] = df['valence']
df_important.loc[:, 'vocal_presence'] = df['speechiness'] - 0.
 ↪5*df['instrumentalness']
df_important.loc[:, 'performance_style'] = df['liveness']

print("Improved music-specific components (first 5 rows):")
print(df_important.head())

# Visualize top dimensions
plt.figure(figsize=(10, 8))
sample_size = min(10000, len(df_important))
plt.scatter(
    df_important['energy_dynamics'].iloc[:sample_size],
    df_important['dance_rhythm'].iloc[:sample_size],
    alpha=0.5, s=5
```

```python
)
plt.xlabel('Energy Dynamics')
plt.ylabel('Dance Rhythm')
plt.title('Music Map: Top Two Popularity-Related Dimensions')
plt.tight_layout()
plt.show()
```

```
Improved music-specific components (first 5 rows):
                        energy_to_acousticness_ratio  danceability     tempo  \
track_id
53QF56cjZA9RTuuMZDrSA6                      0.430398         0.483  0.533639
1s8tP3jP4GZcyHDsjvw218                      0.932238         0.572  0.560744
7BRCa8MPiyuvr2VU309W0F                      0.672414         0.409  0.559344
63wsZUhUZLlh1OsyrZq7sz                      0.307222         0.392  0.819867
6nXIYClvJAfi6ujLiKqEq8                      9.576271         0.430  0.687475

                        valence  speechiness  liveness  instrumentalness  \
track_id
53QF56cjZA9RTuuMZDrSA6    0.139       0.0429    0.1150          0.000000
1s8tP3jP4GZcyHDsjvw218    0.515       0.0258    0.0974          0.000014
7BRCa8MPiyuvr2VU309W0F    0.145       0.0323    0.0895          0.000050
63wsZUhUZLlh1OsyrZq7sz    0.508       0.0363    0.0797          0.000000
6nXIYClvJAfi6ujLiKqEq8    0.217       0.0302    0.1100          0.019300

                        energy  energy_dynamics  dance_rhythm  \
track_id
53QF56cjZA9RTuuMZDrSA6   0.303            0.303      0.503256
1s8tP3jP4GZcyHDsjvw218   0.454            0.454      0.567497
7BRCa8MPiyuvr2VU309W0F   0.234            0.234      0.469137
63wsZUhUZLlh1OsyrZq7sz   0.251            0.251      0.563147
6nXIYClvJAfi6ujLiKqEq8   0.791            0.791      0.532990

                        emotional_content  vocal_presence  performance_style
track_id
53QF56cjZA9RTuuMZDrSA6              0.139        0.042900             0.1150
1s8tP3jP4GZcyHDsjvw218              0.515        0.025793             0.0974
7BRCa8MPiyuvr2VU309W0F              0.145        0.032275             0.0895
63wsZUhUZLlh1OsyrZq7sz              0.508        0.036300             0.0797
6nXIYClvJAfi6ujLiKqEq8              0.217        0.020550             0.1100
```




### 1.1.1 6. Standard Scaling:

We'll initially scale all features to have zero mean and unit variance. This is important for distance-based algorithms like K-Means and PCA..

[21]:
```
# Import StandardScaler from sklearn.preprocessing
from sklearn.preprocessing import StandardScaler

# Apply standard scaling to the reduced feature set
scaler_opt = StandardScaler()
df_important_scaled = scaler_opt.fit_transform(df_important)
df_important_scaled = pd.DataFrame(df_important_scaled, index=df.index,␣
↪columns=df_important.columns)
```

### 1.1.2 7. Dimensionality Reduction:

We'll use PCA on the scaled data to reduce the number of features while retaining most of the information (variance).

[27]:
```python
from sklearn.decomposition import PCA
import numpy as np

# Apply PCA with 6 components
n_components = 6
pca = PCA(n_components=n_components)
df_pca_improved = pca.fit_transform(df_important_scaled)
df_pca_improved = pd.DataFrame(df_pca_improved,
                               index=df.index,
                               columns=[f'PC{i+1}' for i in range(n_components)])

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

print(f"Using {n_components} components for dimensionality reduction")
print(f"Total explained variance: {cumulative_variance[-1]:.4f}")
print("Explained variance by component:")
for i, var in enumerate(explained_variance):
    print(f"PC{i+1}: {var:.4f} - Cumulative: {cumulative_variance[i]:.4f}")

print("\nPCA data shape:", df_pca_improved.shape)
print("First 5 rows of PCA-transformed data:")
df_pca_improved.head()
```

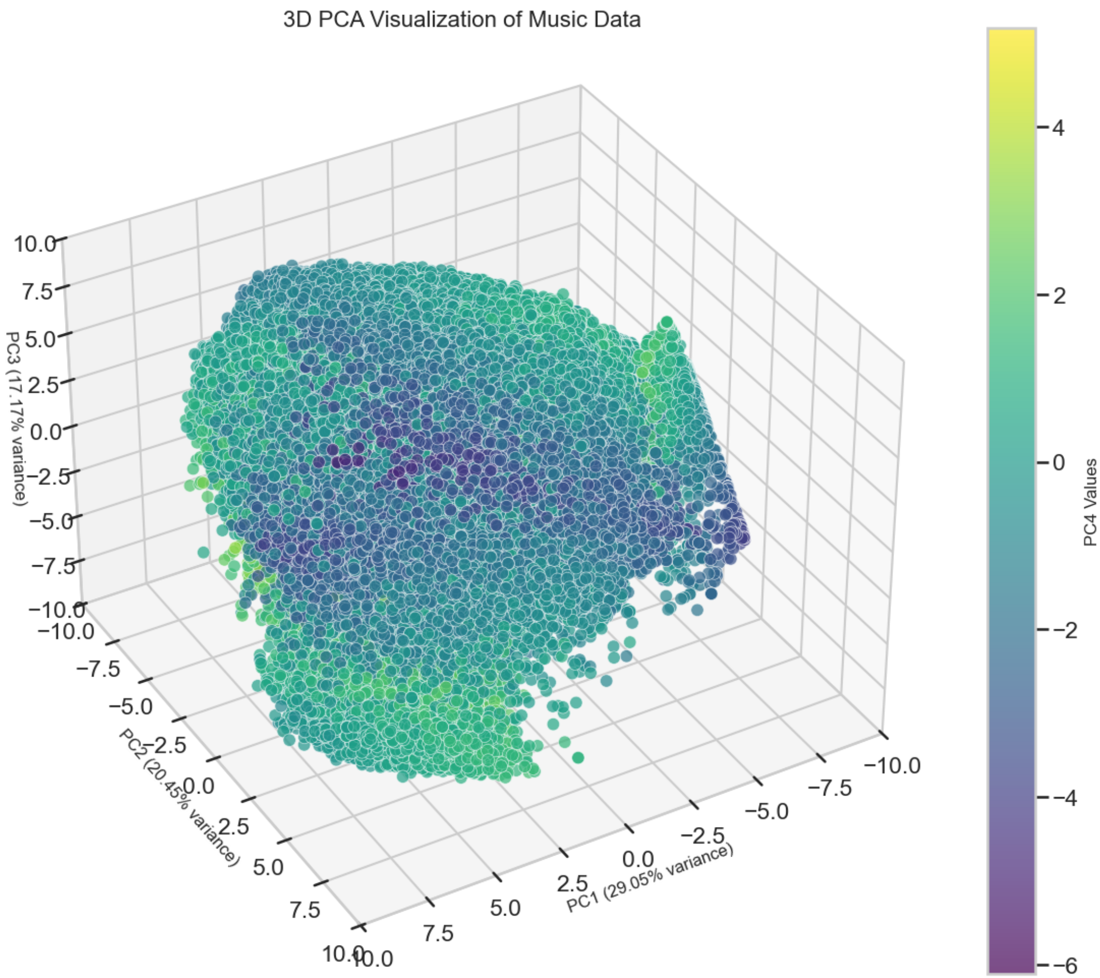
```
Using 6 components for dimensionality reduction
Total explained variance: 0.9199
Explained variance by component:
PC1: 0.2905 - Cumulative: 0.2905
PC2: 0.2045 - Cumulative: 0.4950
PC3: 0.1717 - Cumulative: 0.6668
PC4: 0.1028 - Cumulative: 0.7695
PC5: 0.0806 - Cumulative: 0.8501
PC6: 0.0697 - Cumulative: 0.9199

PCA data shape: (1159748, 6)
First 5 rows of PCA-transformed data:
```

[27]:
```
                             PC1       PC2       PC3       PC4       PC5  \
track_id
53QF56cjZA9RTuuMZDrSA6 -1.749151 -0.675105 -0.963789  1.070585  0.905743
1s8tP3jP4GZcyHDsjvw218  0.015828 -1.457013 -0.441531  0.478776  0.204161
7BRCa8MPiyuvr2VU3O9W0F -2.155084 -0.735199 -1.013651  1.193784  0.763185
63wsZUhUZLlh1OsyrZq7sz -0.511750 -1.510278 -0.427134  0.608818  1.182305
6nXIYClvJAfi6ujLiKqEq8 -0.227597  0.293794  0.927159  1.192396  0.897316

                             PC6
track_id
```

```
53QF56cjZA9RTuuMZDrSA6  0.991398
1s8tP3jP4GZcyHDsjvw218  1.063358
7BRCa8MPiyuvr2VU309W0F  1.379218
63wsZUhUZLlh1OsyrZq7sz  3.115824
6nXIYClvJAfi6ujLiKqEq8  1.579808
```

[37]:

```python
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler

# Create a 3D plot for the first 3 principal components
fig = plt.figure(figsize=(12, 10))
ax = fig.add_subplot(111, projection='3d')

# Scale data for better visualization
scaler = MinMaxScaler(feature_range=(-10, 10))
viz_data = scaler.fit_transform(df_pca_improved[['PC1', 'PC2', 'PC3']])

# Create scatter plot
scatter = ax.scatter(
    viz_data[:, 0], viz_data[:, 1], viz_data[:, 2],
    c=df_pca_improved['PC4'],
    cmap='viridis', alpha=0.7, s=80,
    edgecolors='w', linewidth=0.5
)

# Add labels and styling
plt.colorbar(scatter).set_label('PC4 Values', fontsize=12)
ax.set_xlabel(f'PC1 ({explained_variance[0]:.2%} variance)', fontsize=12)
ax.set_ylabel(f'PC2 ({explained_variance[1]:.2%} variance)', fontsize=12)
ax.set_zlabel(f'PC3 ({explained_variance[2]:.2%} variance)', fontsize=12)
plt.title('3D PCA Visualization of Music Data', fontsize=16)

# Set view properties
ax.grid(True, alpha=0.3)
ax.view_init(elev=35, azim=60)
ax.set_xlim(-10, 10); ax.set_ylim(-10, 10); ax.set_zlim(-10, 10)

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


3D PCA Visualization of Music Data
PC1 (29.05% variance)
PC2 (20.45% variance)
PC3 (17.17% variance)
PC4 Values
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
4
2
0
−2
−4
−6