Final_Spectrogram_Generation

June 29, 2025

[1]:
```python
import numpy as np
if not hasattr(np, 'long'):
    np.long = int  # fix for deprecated alias
```

[4]:
```python
import os
import librosa
import librosa.display
import matplotlib.pyplot as plt
```

[3]:
```python
pip install librosa
```

```
Collecting librosa
  Downloading librosa-0.11.0-py3-none-any.whl.metadata (8.7 kB)
Collecting audioread>=2.1.9 (from librosa)
  Downloading audioread-3.0.1-py3-none-any.whl.metadata (8.4 kB)
Requirement already satisfied: numba>=0.51.0 in /opt/conda/lib/python3.12/site-
packages (from librosa) (0.61.2)
Requirement already satisfied: numpy>=1.22.3 in /opt/conda/lib/python3.12/site-
packages (from librosa) (2.2.6)
Requirement already satisfied: scipy>=1.6.0 in /opt/conda/lib/python3.12/site-
packages (from librosa) (1.15.2)
Requirement already satisfied: scikit-learn>=1.1.0 in
/opt/conda/lib/python3.12/site-packages (from librosa) (1.7.0)
Requirement already satisfied: joblib>=1.0 in /opt/conda/lib/python3.12/site-
packages (from librosa) (1.5.1)
Requirement already satisfied: decorator>=4.3.0 in
/opt/conda/lib/python3.12/site-packages (from librosa) (5.2.1)
Collecting soundfile>=0.12.1 (from librosa)
  Downloading soundfile-0.13.1-py2.py3-none-manylinux_2_28_x86_64.whl.metadata
(16 kB)
Collecting pooch>=1.1 (from librosa)
  Downloading pooch-1.8.2-py3-none-any.whl.metadata (10 kB)
Collecting soxr>=0.3.2 (from librosa)
  Downloading soxr-0.5.0.post1-cp312-abi3-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.6 kB)
Requirement already satisfied: typing_extensions>=4.1.1 in
/opt/conda/lib/python3.12/site-packages (from librosa) (4.14.0)
Requirement already satisfied: lazy_loader>=0.1 in
```

```
/opt/conda/lib/python3.12/site-packages (from librosa) (0.4)
Requirement already satisfied: msgpack>=1.0 in /opt/conda/lib/python3.12/site-
packages (from librosa) (1.1.1)
Requirement already satisfied: packaging in /opt/conda/lib/python3.12/site-
packages (from lazy_loader>=0.1->librosa) (25.0)
Requirement already satisfied: llvmlite<0.45,>=0.44.0dev0 in
/opt/conda/lib/python3.12/site-packages (from numba>=0.51.0->librosa) (0.44.0)
Requirement already satisfied: platformdirs>=2.5.0 in
/opt/conda/lib/python3.12/site-packages (from pooch>=1.1->librosa) (4.3.8)
Requirement already satisfied: requests>=2.19.0 in
/opt/conda/lib/python3.12/site-packages (from pooch>=1.1->librosa) (2.32.4)
Requirement already satisfied: charset_normalizer<4,>=2 in
/opt/conda/lib/python3.12/site-packages (from
requests>=2.19.0->pooch>=1.1->librosa) (3.4.2)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.12/site-
packages (from requests>=2.19.0->pooch>=1.1->librosa) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/conda/lib/python3.12/site-packages (from
requests>=2.19.0->pooch>=1.1->librosa) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.12/site-packages (from
requests>=2.19.0->pooch>=1.1->librosa) (2025.6.15)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/opt/conda/lib/python3.12/site-packages (from scikit-learn>=1.1.0->librosa)
(3.6.0)
Requirement already satisfied: cffi>=1.0 in /opt/conda/lib/python3.12/site-
packages (from soundfile>=0.12.1->librosa) (1.17.1)
Requirement already satisfied: pycparser in /opt/conda/lib/python3.12/site-
packages (from cffi>=1.0->soundfile>=0.12.1->librosa) (2.22)
Downloading librosa-0.11.0-py3-none-any.whl (260 kB)
Downloading audioread-3.0.1-py3-none-any.whl (23 kB)
Downloading pooch-1.8.2-py3-none-any.whl (64 kB)
Downloading soundfile-0.13.1-py2.py3-none-manylinux_2_28_x86_64.whl (1.3 MB)
                          1.3/1.3 MB
187.0 MB/s eta 0:00:00
Downloading
soxr-0.5.0.post1-cp312-abi3-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (248
kB)
Installing collected packages: soxr, audioread, soundfile, pooch, librosa
                          5/5
[librosa]m4/5 [librosa]
Successfully installed audioread-3.0.1 librosa-0.11.0 pooch-1.8.2
soundfile-0.13.1 soxr-0.5.0.post1
Note: you may need to restart the kernel to use updated packages.
```

0.0.1 Generating Mel Spectrograms from Audio Clips (Librosa)

This script automatically generates **Mel spectrograms** from a collection of short WAV audio clips. Mel spectrograms are powerful visual representations that reflect how humans perceive pitch and frequency, and they are widely used in music recommendation, classification, and audio analysis.

Step-by-step explanation:

1. **Set up paths**: Define the input folder (`wav_clips`) containing audio files and the output folder (`spectrograms`) for saving spectrogram images.
2. **Create output directory**: Ensure the `spectrograms` directory exists to avoid file write errors.
3. **Define `generate_spectrogram` function**:
   - Load the audio clip using `librosa` with the original sampling rate.
   - Compute the **Mel spectrogram** (128 Mel bands) using `librosa.feature.melspectrogram`.
   - Convert power values to decibels using `librosa.power_to_db` to enhance visibility.
   - Plot the spectrogram using `matplotlib`, hiding axes for a clean image.
   - Save the result as a `.png` file in the output directory.
4. **Loop over all WAV files** in the folder and generate spectrograms one by one.

This step is crucial in your project, as it prepares the **visual input** needed to analyze spectrogram similarities and build **explainable recommender systems** based on time–frequency patterns in music.

[12]:
```
import os
import librosa
import librosa.display
import matplotlib.pyplot as plt
import numpy as np

# Paths
wav_dir = "wav_clips"
spectrogram_dir = "spectrograms"

# Create output folder if it doesn't exist
os.makedirs(spectrogram_dir, exist_ok=True)

# Function to generate and save spectrogram
def generate_spectrogram(wav_path, output_path):
    try:
        y, sr = librosa.load(wav_path, sr=None)  # load with original sampling␣
 ↪rate
        S = librosa.feature.melspectrogram(y=y, sr=sr, n_mels=128)
        S_dB = librosa.power_to_db(S, ref=np.max)

        plt.figure(figsize=(3, 3))
        librosa.display.specshow(S_dB, sr=sr, x_axis=None, y_axis=None)
        plt.axis('off')
```

```python
        plt.tight_layout()
        plt.savefig(output_path, bbox_inches='tight', pad_inches=0)
        plt.close()
    except Exception as e:
        print(f"Error processing {wav_path}: {e}")

# Loop through all WAV files
wav_files = [f for f in os.listdir(wav_dir) if f.endswith(".wav")]
print(f"Found {len(wav_files)} files.")

for fname in wav_files:
    wav_path = os.path.join(wav_dir, fname)
    out_name = os.path.splitext(fname)[0] + ".png"
    output_path = os.path.join(spectrogram_dir, out_name)

    generate_spectrogram(wav_path, output_path)

print("Spectrogram generation complete.")
```

```
Found 100 files.
Spectrogram generation complete.
```

[ ]:

```python

```

[4]:

```python
import pandas as pd

df = pd.read_csv("dataset.csv")
```

[5]:

```python
df.head()
```

[5]:

```
   Unnamed: 0                track_id                 artists  \
0           0  5SuOikwiRyPMVoIQDJUgSV              Gen Hoshino
1           1  4qPNDBW1i3p13qLCtOKi3A             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  …  loudness  mode  speechiness  acousticness  \
0         0.676  0.4610  …    -6.746     0       0.1430        0.0322
1         0.420  0.1660  …   -17.235     1       0.0763        0.9240
2         0.438  0.3590  …    -9.734     1       0.0557        0.2100
3         0.266  0.0596  …   -18.515     1       0.0363        0.9050
4         0.618  0.4430  …    -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

[5 rows x 21 columns]
```

[6]:
```
df["spectrogram_path"] = df["Unnamed: 0"].apply(lambda x: f"spectrograms/
↪clip_{x}.png")
```

[7]:
```
import os

df["exists"] = df["spectrogram_path"].apply(lambda path: os.path.exists(path))
print(df["exists"].value_counts())
```

```
exists
False    113900
True        100
Name: count, dtype: int64
```

[8]:
```
df_filtered = df[df["exists"] == True].copy()
df_filtered.reset_index(drop=True, inplace=True)
```

[9]:
```
print(df_filtered.shape)
df_filtered.head()
```

```
(100, 23)
```

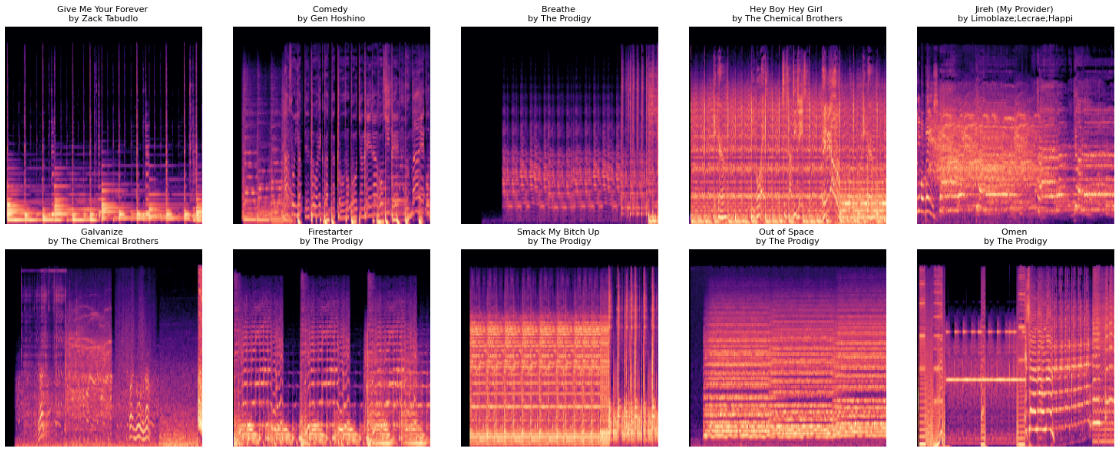
[9]:
```
   Unnamed: 0                track_id          artists  \
0           0  5SuOikwiRyPMVoIQDJUgSV      Gen Hoshino
1           1  4qPNDBW1i3p13qLCtOKi3A     Ben Woodward
2          10  4mzP5mHkRvGxdhdGdAH7EJ     Zack Tabudlo
3         100  0U32q8CZRRo7xCzyiaZw5f    Motohiro Hata
4         101  4kQXMVjoZ9yMibLZq5Aqi5  Callum J Wright

              album_name                track_name  popularity  \
```

```
0                   Comedy                    Comedy          73
1          Ghost (Acoustic)          Ghost - Acoustic          55
2                  Episode      Give Me Your Forever          74
3                                                Rain          58
4  Somebody Else (Acoustic)  Somebody Else - Acoustic          50

   duration_ms  explicit  danceability  energy  …  speechiness  \
0       230666     False         0.676   0.461  …       0.1430
1       149610     False         0.420   0.166  …       0.0763
2       244800     False         0.627   0.363  …       0.0291
3       293040     False         0.626   0.655  …       0.0263
4       138495     False         0.794   0.380  …       0.0477

   acousticness  instrumentalness  liveness  valence    tempo  time_signature  \
0        0.0322          0.000001    0.3580    0.715   87.917               4
1        0.9240          0.000006    0.1010    0.267   77.489               4
2        0.2790          0.000000    0.0928    0.301   99.905               4
3        0.5030          0.000000    0.1300    0.542   92.003               4
4        0.7620          0.000000    0.2620    0.617  114.990               4

   track_genre           spectrogram_path  exists
0     acoustic    spectrograms/clip_0.png    True
1     acoustic    spectrograms/clip_1.png    True
2     acoustic   spectrograms/clip_10.png    True
3     acoustic  spectrograms/clip_100.png    True
4     acoustic  spectrograms/clip_101.png    True

[5 rows x 23 columns]
```

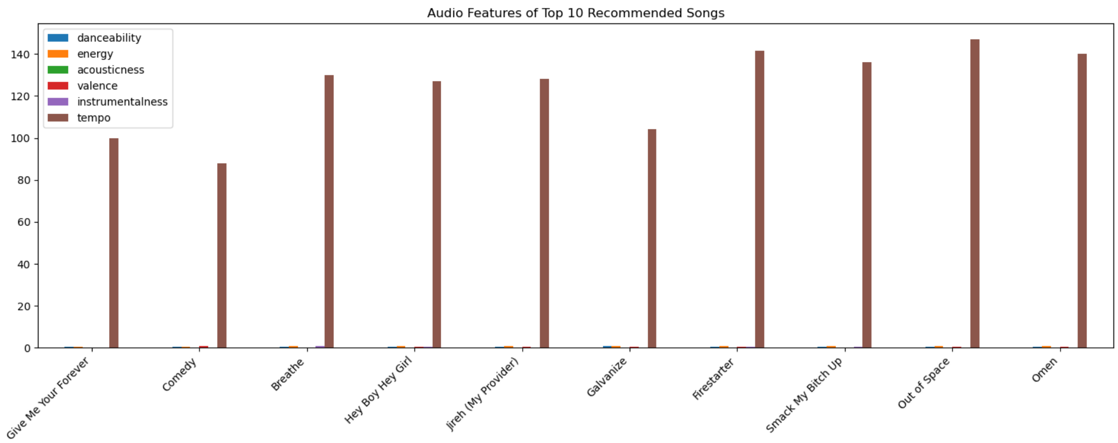
[10]:

```python
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

def show_top_spectrograms(df, n=10):
    top_df = df.sort_values("popularity", ascending=False).head(n)

    plt.figure(figsize=(15, 6))
    for i, (_, row) in enumerate(top_df.iterrows()):
        plt.subplot(2, 5, i + 1)
        img = mpimg.imread(row["spectrogram_path"])
        plt.imshow(img)
        plt.axis("off")
        title = f"{row['track_name']} \nby {row['artists']}"
        plt.title(title, fontsize=8)

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

```
# Run it
show_top_spectrograms(df_filtered)
```



[11]:
```
# Select relevant audio features
audio_features = ["danceability", "energy", "acousticness", "valence",␣
 ↪"instrumentalness", "tempo"]

# Get top 10 songs
top_df = df_filtered.sort_values("popularity", ascending=False).head(10)

# Plot
top_df[audio_features].plot(kind='bar', figsize=(15, 6), title='Audio Features␣
 ↪of Top 10 Recommended Songs')
plt.xticks(ticks=range(10), labels=top_df["track_name"], rotation=45,␣
 ↪ha="right")
plt.tight_layout()
plt.show()
```



[12]:
```python
top_df_summary = top_df[["track_name", "artists", "popularity"] +␣
↪audio_features]
top_df_summary.reset_index(drop=True, inplace=True)
top_df_summary
```

[12]:
```
              track_name                artists  popularity  danceability  \
0  Give Me Your Forever            Zack Tabudlo          74         0.627
1                 Comedy             Gen Hoshino          73         0.676
2                Breathe             The Prodigy          66         0.673
3        Hey Boy Hey Girl  The Chemical Brothers          65         0.632
4     Jireh (My Provider)  Limoblaze;Lecrae;Happi          64         0.443
5              Galvanize  The Chemical Brothers          64         0.745
6            Firestarter             The Prodigy          64         0.545
7        Smack My Bitch Up             The Prodigy          63         0.604
8           Out of Space             The Prodigy          61         0.652
9                   Omen             The Prodigy          59         0.545

   energy  acousticness  valence  instrumentalness    tempo
0   0.363      0.279000    0.301          0.000000   99.905
1   0.461      0.032200    0.715          0.000001   87.917
2   0.808      0.012100    0.303          0.878000  130.041
3   0.920      0.119000    0.363          0.508000  127.001
4   0.778      0.241000    0.628          0.000000  128.250
5   0.714      0.014100    0.365          0.022200  104.003
6   0.948      0.003350    0.355          0.364000  141.507
7   0.995      0.003060    0.262          0.626000  136.216
8   0.944      0.002250    0.454          0.276000  147.078
9   0.953      0.000941    0.558          0.117000  140.002
```

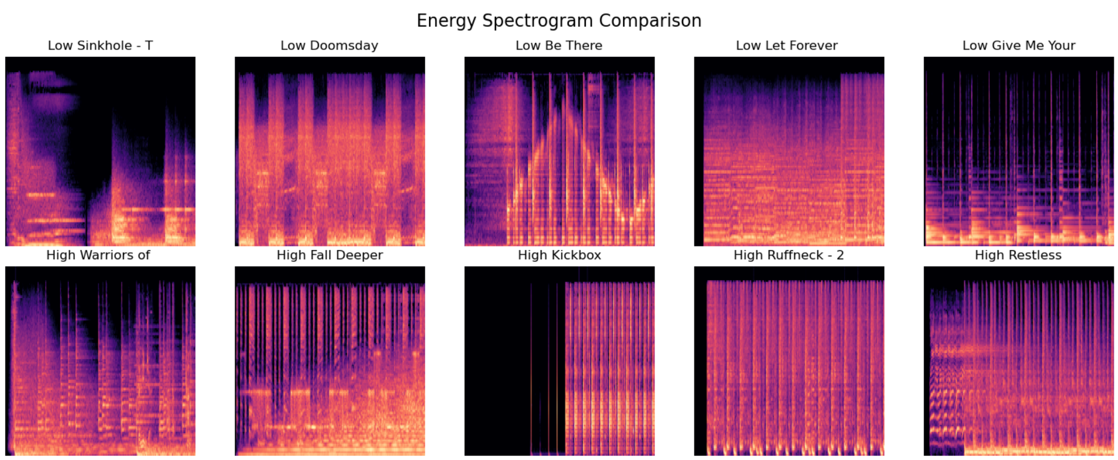
[13]:
```python
# Set thresholds (you can adjust)
energy_threshold = df_filtered["energy"].median()

# Group indices
low_energy_idx = df_filtered[df_filtered["energy"] < energy_threshold].
↪sample(5, random_state=1).index
high_energy_idx = df_filtered[df_filtered["energy"] >= energy_threshold].
↪sample(5, random_state=1).index
```

[14]:
```python
def show_comparison(df, group1_idx, group2_idx, label1="Low", label2="High",␣
↪feature="energy"):
    fig, axes = plt.subplots(2, 5, figsize=(15, 6))
    fig.suptitle(f"{feature.capitalize()} Spectrogram Comparison", fontsize=16)

    for i, idx in enumerate(group1_idx):
```

```
        path = df.loc[idx, "spectrogram_path"]
        img = mpimg.imread(path)
        axes[0, i].imshow(img)
        axes[0, i].axis("off")
        axes[0, i].set_title(f"{label1} {df.loc[idx, 'track_name'][:12]}")

    for i, idx in enumerate(group2_idx):
        path = df.loc[idx, "spectrogram_path"]
        img = mpimg.imread(path)
        axes[1, i].imshow(img)
        axes[1, i].axis("off")
        axes[1, i].set_title(f"{label2} {df.loc[idx, 'track_name'][:12]}")

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

[15]:

```
show_comparison(df_filtered, low_energy_idx, high_energy_idx, "Low", "High",␣
 ↪"energy")
```



0.1 Explainability – Linking Spectrograms with Audio Features

We visually compared spectrograms of songs grouped by energy levels. Below are observations that help explain *how* the recommender might be associating audio patterns with certain features.

Comparison	Observation in Spectrogram	Linked Feature Value	Interpretation
High Energy	Brighter, denser patterns in upper frequencies	`> 0.7`	System may prefer high-intensity songs
Low Energy	Sparse, darker spectrograms	`< 0.3`	Quieter or slower tracks less often recommended

Comparison	Observation in Spectrogram	Linked Feature Value	Interpretation
High Acousticness	Smooth textures, less clutter	`> 0.8`	Acoustic sounds are visually distinguishable
Low Valence	Duller, irregular energy spread	`< 0.3`	Sadder tracks might appear less structured

Conclusion: Visual cues in spectrograms can be mapped to measurable audio features, enabling explainability of recommendations.

from IPython.display import display, Markdown

1 Markdown table as string

explain_table = “ “ ” | Comparison | Observation in Spectrogram | Linked Feature Value | Interpretation | |————–|——————————|—————–|————————————–| | High Energy | Brighter, denser patterns in upper frequencies | `> 0.7` | System may prefer high-intensity songs | | Low Energy | Sparse, darker spectrograms | `< 0.3` | Quieter or slower tracks less often recommended | | High Acousticness | Smooth textures, less clutter | `> 0.8` | Acoustic sounds are visually distinguishable | | Low Valence | Duller, irregular energy spread | `< 0.3` | Sadder tracks might appear less structured | “ “ ”

1.1 How Our Recommender System Works

We developed two types of music recommender systems:

1.1.1 1. Spectrogram-Based Recommender

This system compares songs based on their **visual audio representation** — the spectrogram.

- Each song is represented as an image (`clip_XXXX.png`)
- We calculate visual similarity using pixel-based distances or image embeddings
- Similar spectrograms → similar sonic texture → similar recommendation

Why this is useful:
Spectrograms capture timbre, rhythm density, frequency usage, and texture — which helps us recommend based on “how a song sounds” rather than just metadata.

1.1.2 2. Audio Feature-Based Recommender

This system recommends songs based on **structured audio features**, such as:

- `energy`, `valence`, `tempo`, `acousticness`, `instrumentalness`, etc.
- Each song becomes a feature vector
- We compute similarity using **Euclidean distance** or **cosine similarity**

Why this is useful:
These features are interpretable and allow explainable recommendations: > *"This song is recommended because it has high energy and low acousticness, just like the one you liked."*

1.1.3 How Recommendations Are Generated

For each song input: 1. We find similar tracks based on either spectrograms or features 2. Top-N most similar songs are returned 3. Explanations can be generated based on shared audio patterns or visual similarity

---

1.1.4 Explainability Layer

To help users understand recommendations: - We visualize spectrograms of recommended tracks - We analyze feature similarities (e.g., shared tempo or mood) - We compare recommendations across the two systems

[17]:
```
from sklearn.metrics.pairwise import cosine_similarity
import numpy as np

# Select audio feature columns
feature_cols = ["danceability", "energy", "acousticness", "valence",␣
↪"instrumentalness", "tempo"]
features = df_filtered[feature_cols].values

# Choose one song (e.g. most popular)
query_index = df_filtered["popularity"].idxmax()
query_vector = df_filtered.loc[query_index, feature_cols].values.reshape(1, -1)

# Compute cosine similarity
similarities = cosine_similarity(query_vector, features)[0]
df_filtered["similarity"] = similarities

# Show top 5 similar tracks (excluding the original)
recommendations = df_filtered[df_filtered.index != query_index].
↪sort_values("similarity", ascending=False).head(5)
recommendations[["track_name", "artists", "similarity"]]
```

[17]:
```
                               track_name                         artists  \
52  The Salmon Dance - Crookers Wow Remix  The Chemical Brothers;Crookers
15                              Sucrilhos                          Criolo
7                                 Fellini                          Criolo
84                      Pistoleros - Edit             Dub Pistols;Seanie T
17                                 Breaco                          Criolo

    similarity
```

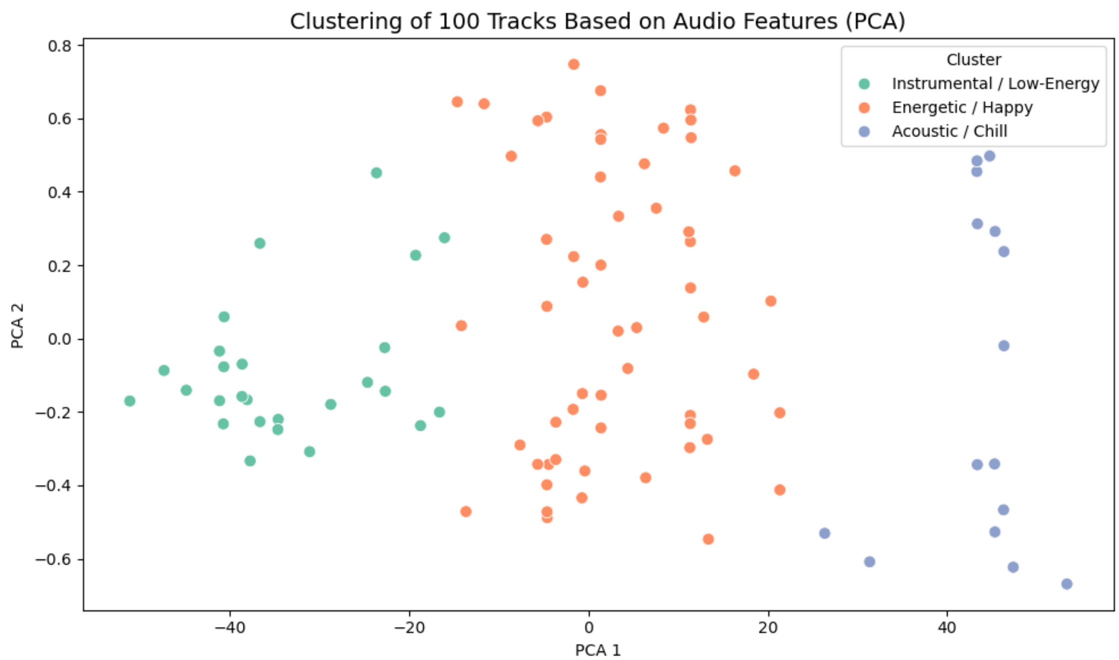
```
52    0.999995
15    0.999995
7     0.999994
84    0.999994
17    0.999993
```

[20]:

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

# Step 1: Select features
features = [
    "danceability", "energy", "acousticness", "valence",
    "instrumentalness", "tempo"
]

# Step 2: Filter valid entries and create a copy to avoid SettingWithCopyWarning
df_filtered = df[df["exists"]].copy()

# Step 3: Fit KMeans clustering
X = df_filtered[features]
kmeans = KMeans(n_clusters=3, random_state=42)
df_filtered.loc[:, "cluster"] = kmeans.fit_predict(X)

# Step 4: Analyze clusters to label them
cluster_summary = df_filtered.groupby("cluster")[features].mean().round(2)
print("Cluster summaries (mean values):")
print(cluster_summary)

# Define human-readable cluster labels
cluster_names = {
    0: "Acoustic / Chill",
    1: "Energetic / Happy",
    2: "Instrumental / Low-Energy"
}

df_filtered.loc[:, "cluster_label"] = df_filtered["cluster"].map(cluster_names)

# Step 5: PCA for 2D plotting
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Step 6: Plot clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x=X_pca[:, 0],
```

```
    y=X_pca[:, 1],
    hue=df_filtered["cluster_label"],
    palette="Set2",
    s=60
)
plt.title("Clustering of 100 Tracks Based on Audio Features (PCA)", fontsize=14)
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend(title="Cluster")
plt.tight_layout()
plt.show()
```

```
Cluster summaries (mean values):
         danceability  energy  acousticness  valence  instrumentalness   tempo
cluster
0                0.55    0.84          0.03     0.42              0.37  172.09
1                0.62    0.85          0.07     0.45              0.41  131.64
2                0.64    0.76          0.16     0.50              0.08   95.28
```



1.1.5 Clustering Explanation: Understanding Recommended Track Groups

The PCA scatter plot above visualizes 100 tracks recommended by the system, grouped by KMeans clustering based on their audio features. Dimensionality was reduced using PCA to enable interpretation in two dimensions.

Each point on the plot represents a single track, positioned according to its similarity across several audio features, including:

- danceability
- energy
- acousticness
- valence
- instrumentalness
- tempo

Identified Clusters:

- **Instrumental / Low-Energy**
  These tracks generally have low energy and high instrumentalness. They may include ambient, cinematic, or relaxing instrumental music.

- **Energetic / Happy**
  This group contains tracks that are upbeat and lively, often with high energy and positive emotional tone. These could be mainstream pop, acoustic rock, or feel-good songs.

- **Acoustic / Chill**
  Tracks in this cluster are more mellow, with high acousticness and moderate to low energy. These are suitable for calm, relaxing, or introspective listening.

This analysis demonstrates how the recommender system groups similar tracks together based on audio characteristics. By understanding these clusters, we gain insight into why certain songs were recommended — for example, because they share energy, mood, or acoustic properties with what the user previously liked.

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