1. Overview

We performed clustering on music data from the Spotify–YouTube dataset, focusing on three main acoustic features:

- **Liveness**
- **Energy**
- **Loudness**

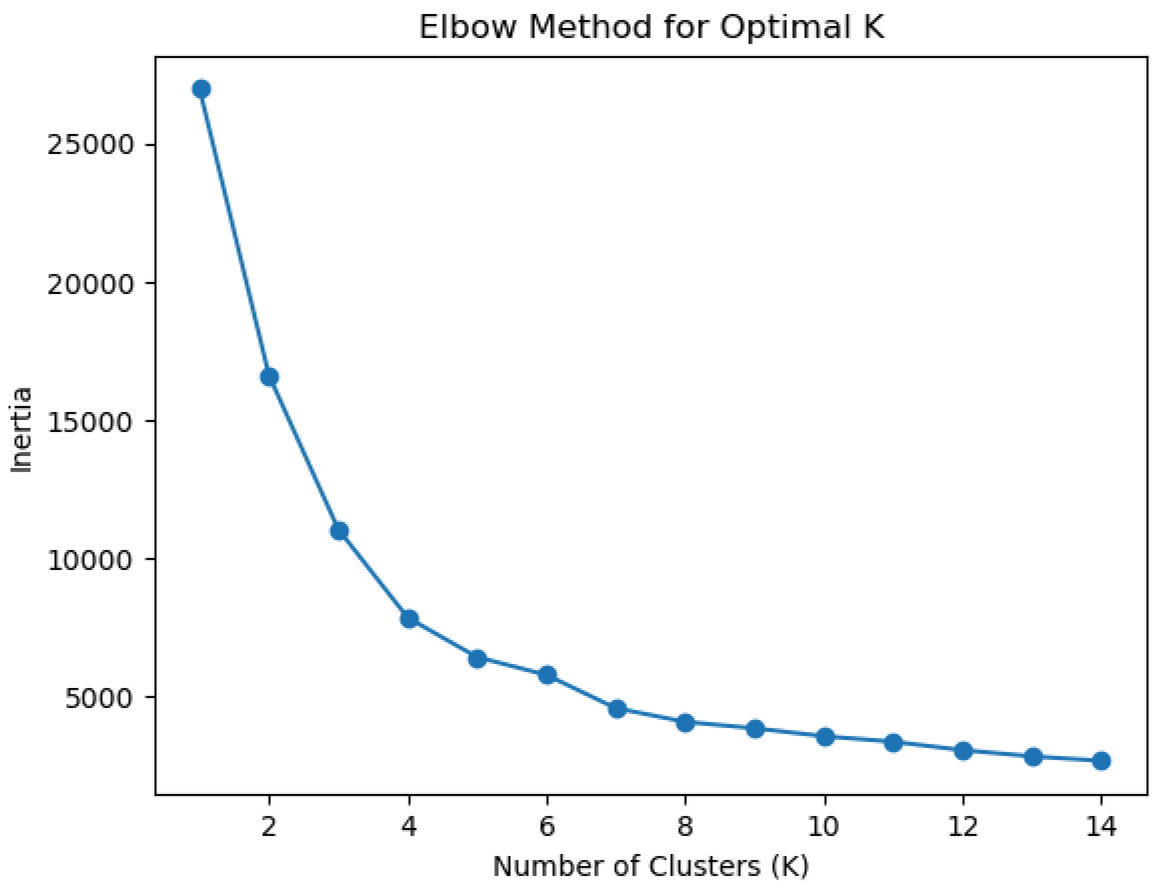
Two clustering methods were employed:

1. **K-Means** with $k = 5$ (determined via the elbow method).
2. **Hierarchical Clustering** (also yielding *5* clusters for consistency and observation from dendrogram).

2. K-Means Clustering Results

2.1 Elbow Method

The elbow method indicated that **5 clusters** offer a balanced trade-off between distinct group separation and avoiding excessive fragmentation. The inertia curve flattening out near $k = 5$ supports this choice.



2.2 K-Means Cluster Centers (Original Scale)

After scaling the features (so each contributes equally), we used K-Means and then **inverse-transformed** the resulting cluster centers back to the original scale. Below is a table of these means:

Cluster	Liveness	Energy	Loudness (dB)
0	0.143	0.420	-11.159
1	0.334	0.779	-6.005
2	0.111	0.758	-6.014
3	0.126	0.085	-25.135
4	0.746	0.692	-7.775

2.3 Cluster Labels for K-Means

Based on inspection of these average values, we assigned the following **descriptive labels**:

```python
cluster_labels = {
    0: "Quiet, Moderate Energy (Studio Feel)",
    1: "High Energy, Loud (Medium–Live Feel)",
    2: "High Energy, Loud (Studio–Focused)",
    3: "Very Quiet, Very Low Energy (Ambient/Minimal)",
    4: "High–Liveness, Moderate–High Energy (Live Performances)"
}
```

Interpretations:

1. **Cluster 0: "Quiet, Moderate Energy (Studio Feel)"**
   - Low liveness (~0.14), moderate energy (~0.42), quieter loudness (~-11.16 dB).
   - Typically, calmer studio tracks with a mild energy level.
2. **Cluster 1: "High Energy, Loud (Medium-Live Feel)"**
   - Medium liveness (~0.33), high energy (~0.78), quite loud (~-6 dB).
   - Tracks possibly well-suited to workouts or parties, with some live ambiance.
3. **Cluster 2: "High Energy, Loud (Studio-Focused)"**
   - Lowest liveness (~0.11), high energy (~0.76), loud (~-6 dB).
   - Similar loudness and energy to Cluster 1, but with a studio, less 'live' vibe.
4. **Cluster 3: "Very Quiet, Very Low Energy (Ambient/Minimal)"**
   - Very low energy (~0.085), extremely quiet (~-25 dB), minimal liveness (~0.13).
   - Likely ambient, acoustic, or minimalistic recordings.
5. **Cluster 4: "High-Liveness, Moderate-High Energy (Live Performances)"**
   - Significantly higher liveness (~0.75), moderate-to-high energy (~0.69), moderately loud (~-7.78 dB).
   - Strongly suggests live concert recordings or "live session" tracks.

3. Hierarchical Clustering Results

For comparison, we also applied **Hierarchical Clustering** (Ward linkage, Euclidean metric) and cut the dendrogram at *n* = *5* clusters. While it naturally merges or splits tracks based on similarity, the overarching distribution is broadly similar to K-Means. However, the exact grouping of individual tracks can differ because hierarchical clustering does not rely on "centroids" but on incremental merging of closest items or subclusters.

3.1 Hierarchical Clustering Labels

We labeled the Hierarchical clusters in a way that roughly corresponds to the K-Means categories, but recognized they may not match perfectly:

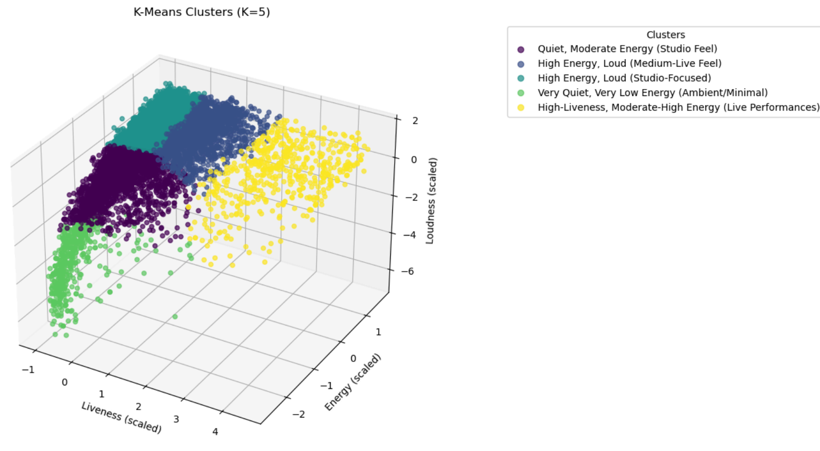
```
legend_labels_hc = [
    "HC: Quiet, Moderate (Similar to K0?)",
    "HC: High Energy, Loud (Similar to K1?)",
    "HC: High Energy, Loud (Studio?)",
    "HC: Very Quiet & Low Energy",
    "HC: High-Liveness, Mod-High Energy"
]
```

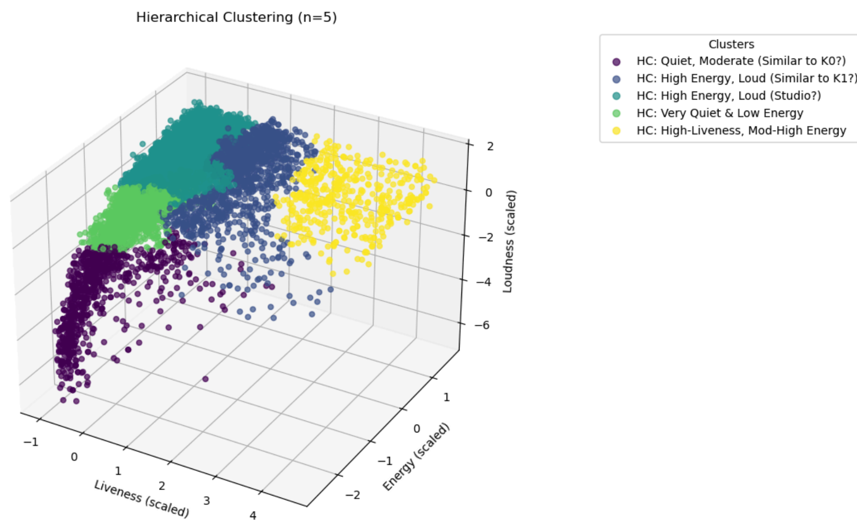
Observations:

- Tracks in the **“Quiet, Moderate”** cluster share similarities with K-Means Cluster 0 (lower loudness, moderate energy).
- A **“High Energy, Loud”** cluster correlates with K-Means Clusters 1 or 2, though hierarchical might blend certain edge cases differently.
- The **“Very Quiet & Low Energy”** grouping aligns well with K-Means Cluster 3.
- A **“High-Liveness, Moderately High Energy”** group typically aligns with K-Means Cluster 4.

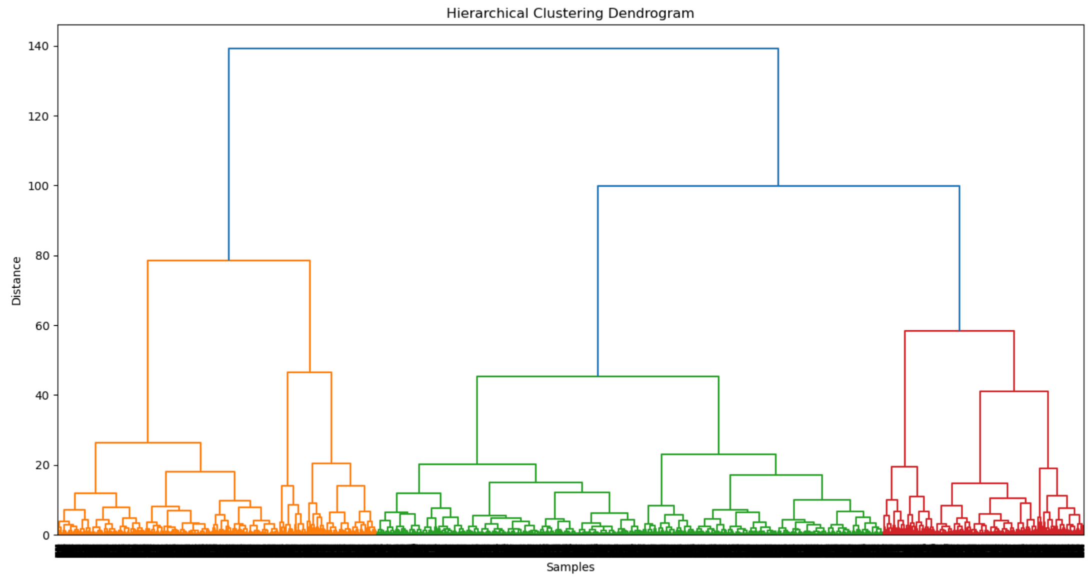
4. Visualizations

1. **3D Scatter Plots**
    - **K-Means**: Each color in the 3D scatter corresponds to one of the five clusters, and the legend maps to the descriptive labels listed above.
    - **Hierarchical**: A similar 3D visualization indicates how the five clusters form in that method.





2. **Dendrogram**
   - Shows the incremental merging of data points into clusters in the hierarchical approach. Large vertical 'jumps' often signify major divisions between groups.



5. Overall Analysis and Recommendations

1. **Distinct Cluster Profiles**
    - We effectively have five unique "sound profiles" ranging from "quiet/low-energy" to "loud/high-energy," with an additional dimension of "liveness" indicating how 'live' or 'studio-like' each track is.
2. **Use Cases**
    - **Cluster 1 & 2** (High energy, loud) can be recommended for workouts, parties, or energetic playlists.
    - **Cluster 0** sits at a more moderate midpoint, possibly suited to casual listening or background contexts.
    - **Cluster 3** is extremely quiet and low-energy, ideal for soothing or ambient environments.
    - **Cluster 4** (high liveness) caters to those seeking the excitement of live performances.
3. **Methodological Considerations**
    - **K-Means**: Useful for larger datasets; requires specifying K upfront.
    - **Hierarchical**: Offers a dendrogram for more granular insight but can be expensive on very large data.
    - In this case, both methods converge on similar musical groupings with slight differences in membership.
4. **Possible Extensions**
    - **Additional Audio/Music Features**: Incorporate Danceability, Tempo, Valence, or spectral analyses for a more nuanced classification.

- **Contextual Tagging**: Label clusters according to artist or genre for deeper insights (e.g., “High-Energy Rock” vs. “High-Energy Pop”).
- **User Preference Modeling**: Use cluster IDs as a dimension in personalized recommendation or playlist generation.

6. Conclusions

The clustering results underline that **Liveness**, **Energy**, and **Loudness** form a concise yet effective feature set to categorize music by “atmosphere” and “intensity.” The five-cluster solution reveals a gradient from very soft, minimal tracks to highly loud, energetic, and potentially live recordings. By comparing K-Means and Hierarchical outcomes, we confirm the existence of these distinct groupings across the dataset. Ultimately, these findings can inform playlist curation, targeted recommendations, or further audio analysis efforts.