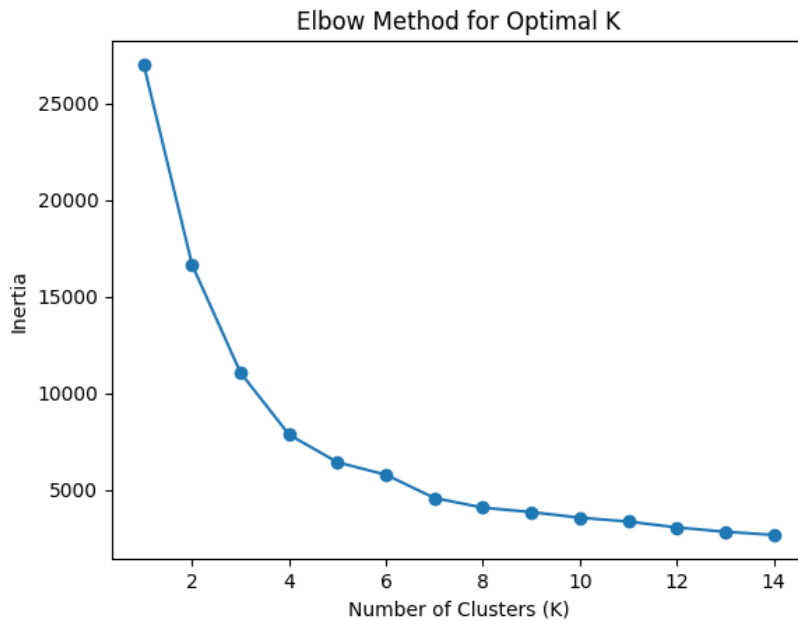


In this assignment, we analyzed audio characteristics from the Spotify/YouTube dataset by focusing on three key features: liveness (recording type), energy (track intensity), and loudness (volume level). Both K-means clustering (with 3D visualization) and hierarchical clustering (individual dimensions) were utilized to identify meaningful patterns in the data.

For K-Means Clustering, the dataset was pre-processed and scaled for optimal k determination. The elbow graph below suggested K=5 as the optimal number of clusters, as the inertia curve starts to flatten at K=5, meaning that the addition of clusters provides less significant improvements in segmentation.



After selecting the number of clusters, K-MEANS clustering was performed to segment the dataset. Here is the semantic cluster interpretation based on their characteristics:

1. Cluster 0

- Characterized as low liveness, moderate energy, moderate loudness
- Labelled as 'Moderate Studio Recording'

2. Cluster 1

- Characterized as low liveness, high energy, high loudness
- Labelled as 'High-Energy Studio Banger'

3. Cluster 2

- Characterized as low liveness, low energy, low loudness
- Labelled as 'Quiet Ambient'

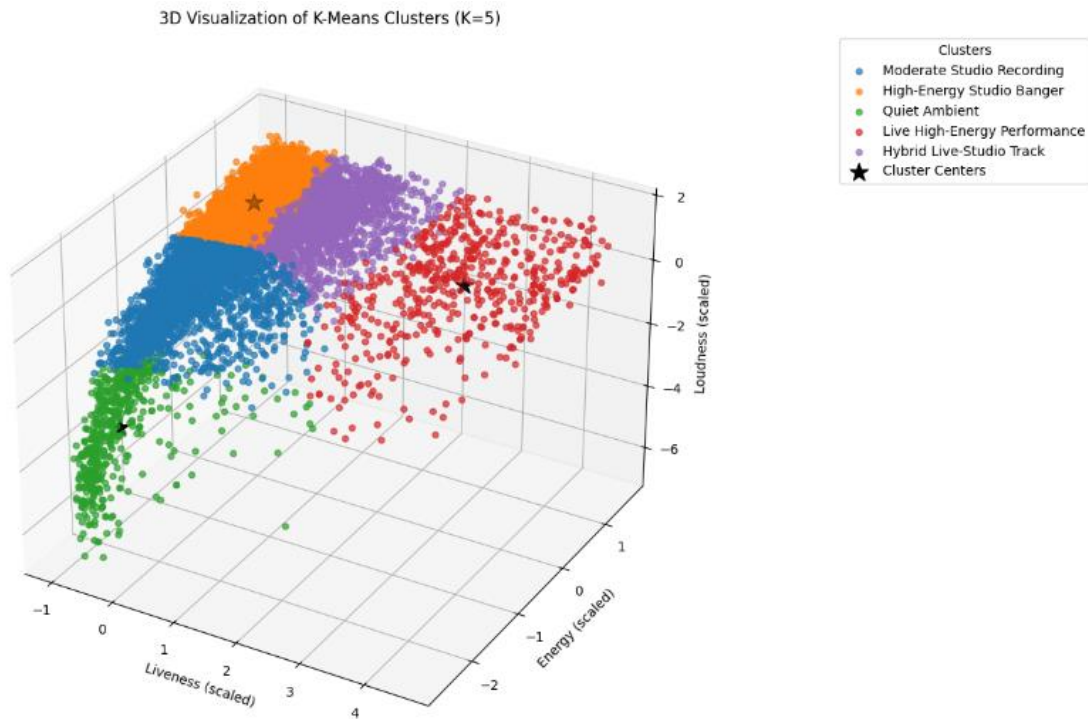
4. Cluster 3

- Characterized as high liveness, moderate-to-high energy, high loudness
- Labelled as 'Live High-Energy Performance'

5. Cluster 4

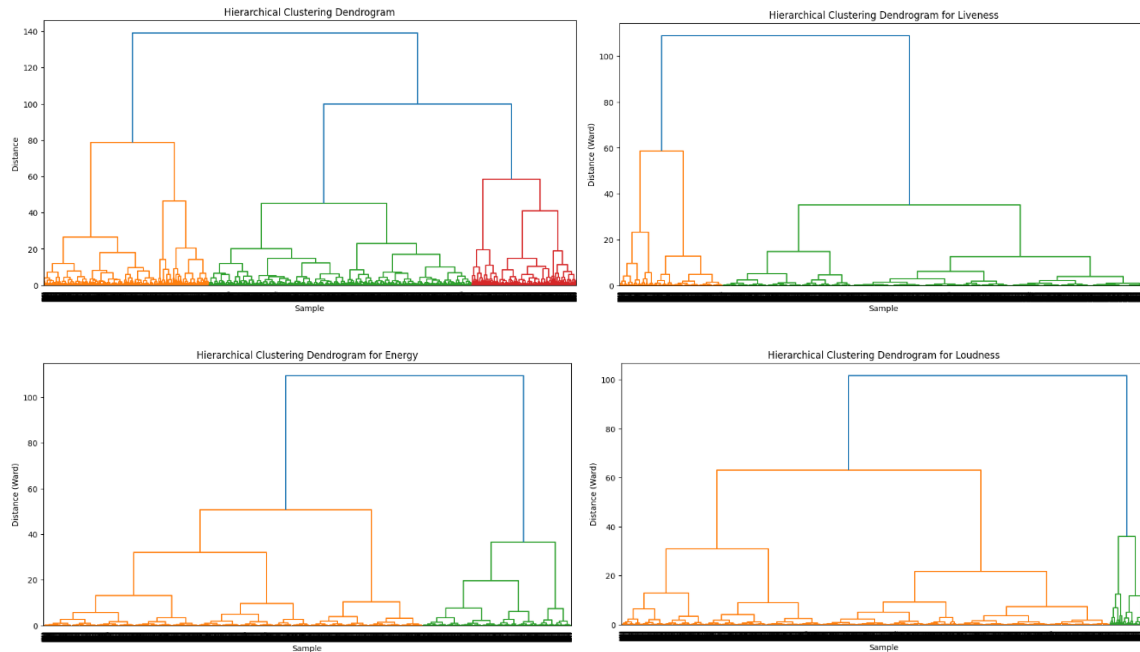
- Characterized as moderate liveness, high energy, high loudness
- Labelled as 'Hybrid Live-Studio Track'

To better visualize the clustering results, a 3D scatter plot was then implemented with cluster centers and interpretable labels. The x-axis is liveness, y-axis for energy, and z-axis for loudness, with all three features pre-scaled. Each data point represents a song, colored by its own cluster.

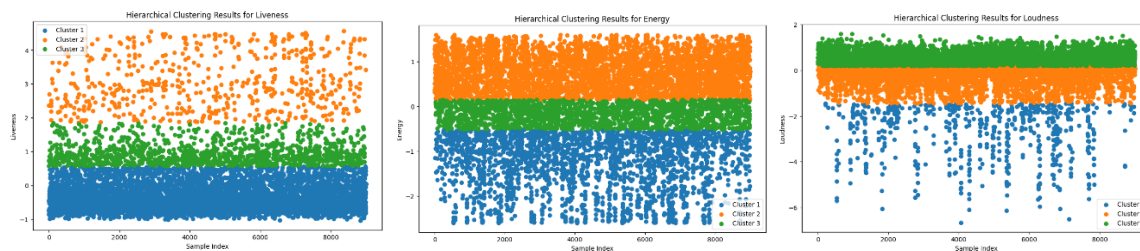


For hierarchical clustering, we performed on each individual dimension (liveness, energy, and loudness). To begin with, the dendrogram analysis was performed on all three features and each of the individual columns respectively.

The goal is to visualize the arrangement of clusters, showing the similarities between clusters (merging at low position refers to highly similar clusters) and helping determine the optimal number of clusters (a large vertical gap between merges suggests a natural stopping point, and by cutting at that gap, the number of horizontal lines intersected by the cut corresponds to the number of clusters).



Based on dendrograms above, 3 clusters were selected to perform agglomerative clustering. The clustering was later performed with 5 clusters as well for consistency with the previous K-MEANS.



For liveness, cluster 1 with low liveness covers the majority of tracks, indicating most are studio-recorded. Cluster 2 is a small but distinct group with extremely high liveness values, likely concert recordings. Cluster 3 with moderate liveness may represent live tracks with post-processing or studio-audience mixes. Overall, cluster 2 is small but extreme category, while cluster 1 dominates - confirming that most tracks are studio-produced.

Liveness					
	Size	Min	Max	Mean	Std
Cluster 1	7247	-1.041	0.568	-0.399	0.348
Cluster 2	571	1.855	4.571	3.074	0.790
Cluster 3	1181	0.573	1.843	0.964	0.312

For energy, cluster 2 with high energy is the largest, which may suggest the given Spotify_YouTube dataset skews toward upbeat music. Cluster 1 with low energy is

distinct with wider spread, possibly representing genres like classical or lo-fi, and the cluster 3 is characterized with moderate energy.

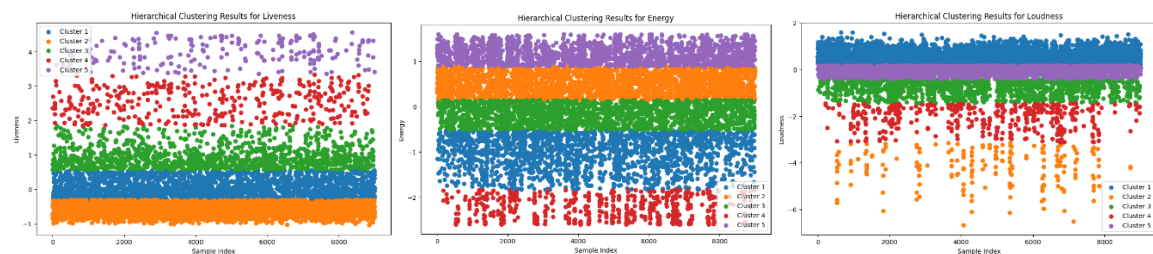
Energy					
	Size	Min	Max	Mean	Std
Cluster 1	2532	-2.601	-0.513	-1.304	0.616
Cluster 2	4536	0.150	1.604	0.801	0.392
Cluster 3	1931	-0.509	0.146	-0.171	0.192

For loudness, the cluster 3 with high loudness covers the majority, aligning with the "loudness war" trend in modern music. Cluster 1 with low loudness is the smallest cluster, indicating fewer ultra-soft recordings in the dataset, and the cluster 2 labels moderate-to-low loudness, suggesting typical of most mainstream tracks.

Loudness					
	Size	Min	Max	Mean	Std
Cluster 1	632	-6.664	-1.452	-2.757	1.165
Cluster 2	3419	-1.444	0.185	-0.378	0.435
Cluster 3	4948	0.186	1.594	0.613	0.262

Those clusters can be used for music recommendations, suggesting tracks with similar energy/loudness profiles, or genre analysis (for example, high-energy, loud tracks may correlate with specific genres like hip-hop). Besides, based on the cluster size, quiet tracks might not align with the preference of YouTube / Spotify users or caused by platform biases.

The following is the same agglomerative clustering performed with 5 clusters, with the main purpose of being consistent with the K-MEANS analysis.



For liveness, compared with the previous 3 clusters, the original low-liveness cluster is split into cluster 1 (lightly processed live tracks with near-zero mean) and cluster 2 (studio with strongly negative mean). Besides, the original high-liveness cluster is split into cluster 4 (professionally mixed live tracks with high liveness) and cluster 5 (the smallest group - unfiltered live recordings with extreme liveness). In this case, it

provides a more precise distinction between raw live, processed live, and studio tracks.

Liveness					
	Size	Min	Max	Mean	Std
Cluster 1	2177	-0.304	0.568	0.047	0.255
Cluster 2	5070	-1.041	-0.309	-0.591	0.790
Cluster 3	1181	0.573	1.843	0.964	0.312
Cluster 4	369	1.855	3.335	2.564	0.411
Cluster 5	202	3.364	4.571	4.006	0.335

For energy, the original low-energy cluster is split into cluster 1 (mildly relaxing with low energy) and cluster 4 (extreme low energy, likely ASMR). The original high-energy cluster is split into cluster 2 (balanced range with moderate-to-high energy) and cluster 5 (music with peak intensity of energy - likely death metal). Clusters 2 and cluster 3 capture the middle range in terms of energy, which can be useful for mood-based playlists. By isolating niche genres, the playlist recommendation system can be optimized, tailoring to energy extremes like workout or relaxation.

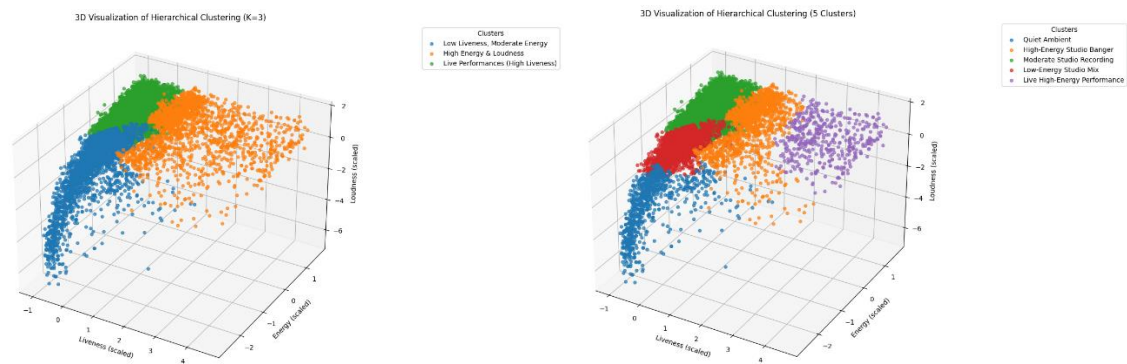
Energy					
	Size	Min	Max	Mean	Std
Cluster 1	1969	-1.836	-0.513	-1.029	0.362
Cluster 2	2626	0.150	0.890	0.515	0.212
Cluster 3	1931	-0.509	0.146	-0.171	0.192
Cluster 4	563	-2.601	-1.840	-2.266	0.244
Cluster 5	1910	0.894	1.604	1.194	0.188

For loudness, the original quiet cluster is split into cluster 2 (likely non-music content with extreme low loudness) and cluster 4 (delicate music with low loudness). The original moderate cluster is split into cluster 3 (natural dynamics like jazz with moderate quiet) and cluster 5 (nearly neutral loudness with borderline loudness). Cluster 1 covers the majority, implying the user / platform preference on loud tracks, and cluster 2 is tiny, suggesting very few soft (very quiet) tracks in the dataset. In this case, it supports more sensitive content-type detection, as cluster 2 can filter out non-music tracks, and better dynamic range awareness, as it highlights production styles.

Loudness					
	Size	Min	Max	Mean	Std
Cluster 1	4948	0.186	1.594	0.613	0.262
Cluster 2	206	-6.664	-3.149	-4.211	0.756
Cluster 3	1412	-1.444	-0.398	-0.822	0.289
Cluster 4	426	-3.120	-1.452	-2.055	0.471

Cluster 5	2007	-0.395	0.185	-0.065	0.167
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The 3D visualization was performed on the hierarchical clustering result, with 3 clusters and 5 clusters respectively.



Let's focus on the right visualization graph for consistency with the previous K-means. Cluster 0 (Quiet Ambient) is characterized with a soft vibe, which can be ideal for relaxation or background music. Cluster 1 (High-Energy Studio Bangers) covers those loud, energetic, and polished tracks, which can be a natural fit for party playlists or gym sessions. Cluster 2 (Moderate Studio Recordings) is most prevalent in the YouTube / Spotify platform with noticeable cluster size: they are energetic and loud, but more balanced compared with cluster 1 (like radio-friendly pop or rock that's designed for broad appeal rather than peak intensity). Cluster 3 (Low-Energy Studio Mix) is soft but not too sleepy, which can be ideal for focused work or winding down. Cluster 4 (Live High-Energy Performances) captures the raw excitement of concerts, which can be appealing to someone who prefers live shows.

The overall distribution generally aligns with K-MEANS results, and those breakdowns can help tailor playlists to moods, building a more precise music recommendation system.

In summary, this analysis segmented Spotify/YouTube tracks into distinct acoustic profiles using K-means and hierarchical clustering based on patterns in liveness, energy, and loudness. The K-means approach (K=5) identified five intuitive categories (from high-energy studio bangers to quiet ambient tracks), while hierarchical clustering provided granular insights into individual features, such as isolating ultra-low-energy ASMR-like tracks or raw live performances. The results align with real-world music trends (prevalence on moderate pop music) and show potential platform biases toward less energetic productions. Future data processing may include exploring genre correlations (label clusters as specific genres),

investigating user behaviors (correlate cluster attributes with user engagement), and therefore optimize the recommendation system by combining clustering with collaborative filtering.