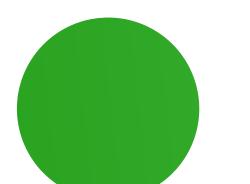


WOOOSCO

Data Detectives: Cracking the Playlist Case with
Audio Clues and K-Means



THE SOUND OF SIMILARITY: CAN ALGORITHMS MATCH HUMAN INTUITION?

 Yes! K-Means successfully grouped songs in a way that aligns with human perception of similarity.

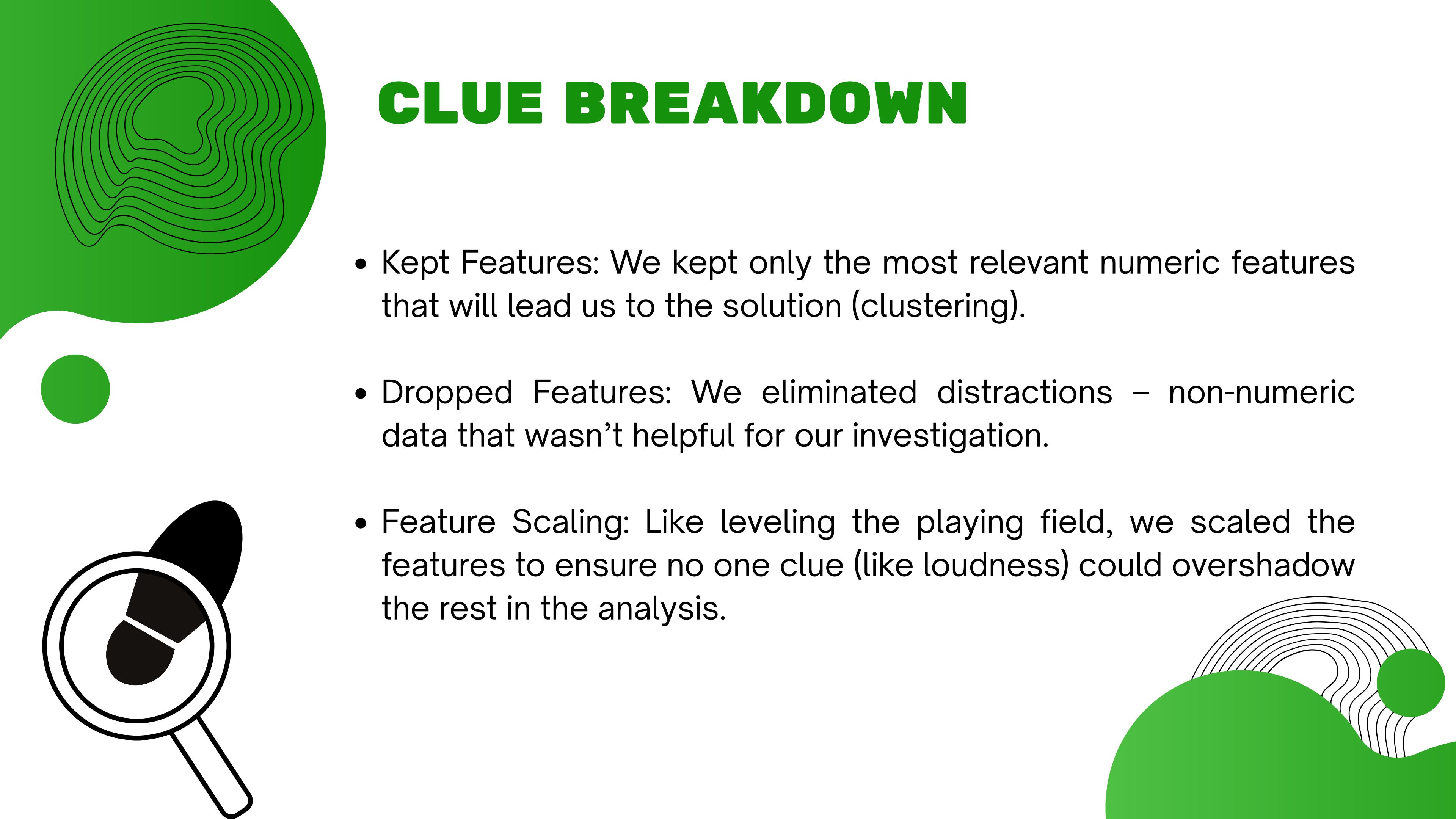
- Audio features like tempo, energy, and valence helped cluster songs with shared characteristics.
- Clustered songs conveyed similar moods.
- Human review confirmed a very high degree of perceptual similarity within clusters.



HOW DID WE APPROACH THIS MYSTERY?

-  Step 1: Load the Evidence (5,000 Songs) in a CSV format
-  Step 2: Scaled the continuous, numerical features (Danceability, Energy, etc.).
-  Step 3: Using K-Means clustering, we grouped songs based on their shared features and perceived similarities.
-  Step 4: Assigned thematic playlist names based on cluster centroids.
-  Step 5: Uploaded playlists to Spotify via API

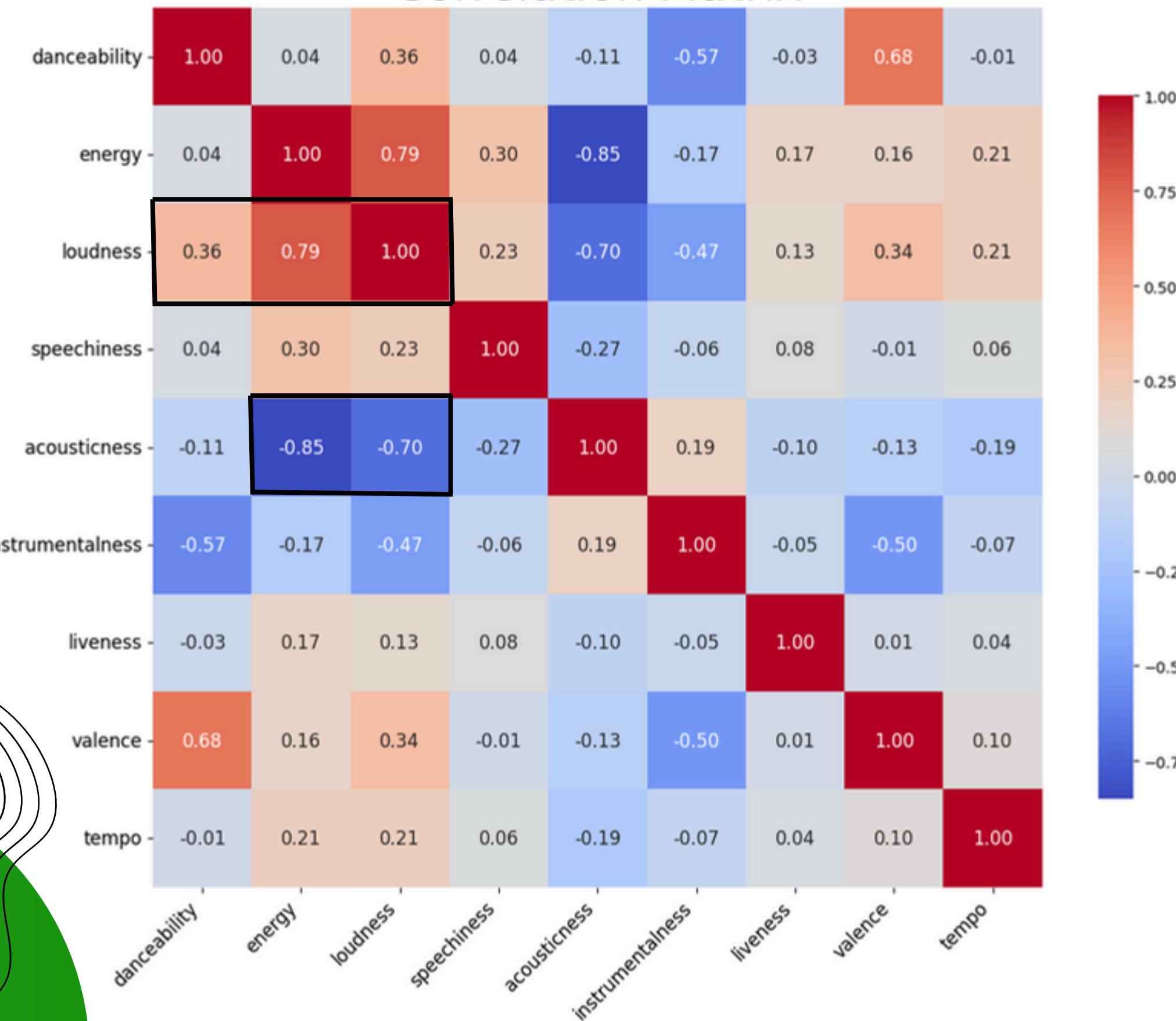




CLUE BREAKDOWN

- Kept Features: We kept only the most relevant numeric features that will lead us to the solution (clustering).
- Dropped Features: We eliminated distractions – non-numeric data that wasn't helpful for our investigation.
- Feature Scaling: Like leveling the playing field, we scaled the features to ensure no one clue (like loudness) could overshadow the rest in the analysis.

Correlation Matrix



Positive Correlations:

loudness & energy
danceability & valence

Negative Correlations:

acousticness & energy

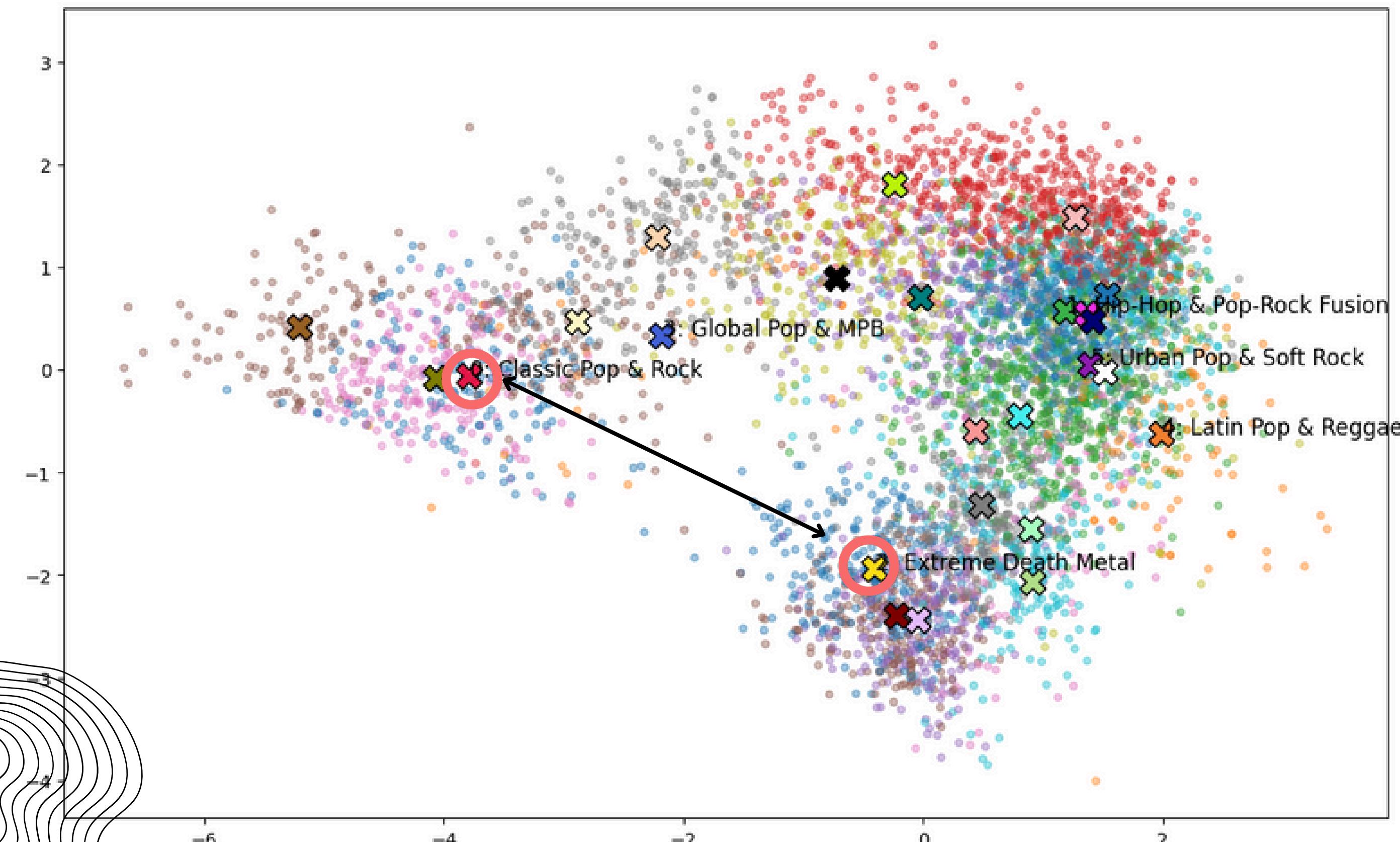
acousticness & loudness

instrumentalness & danceability

First Analysis:

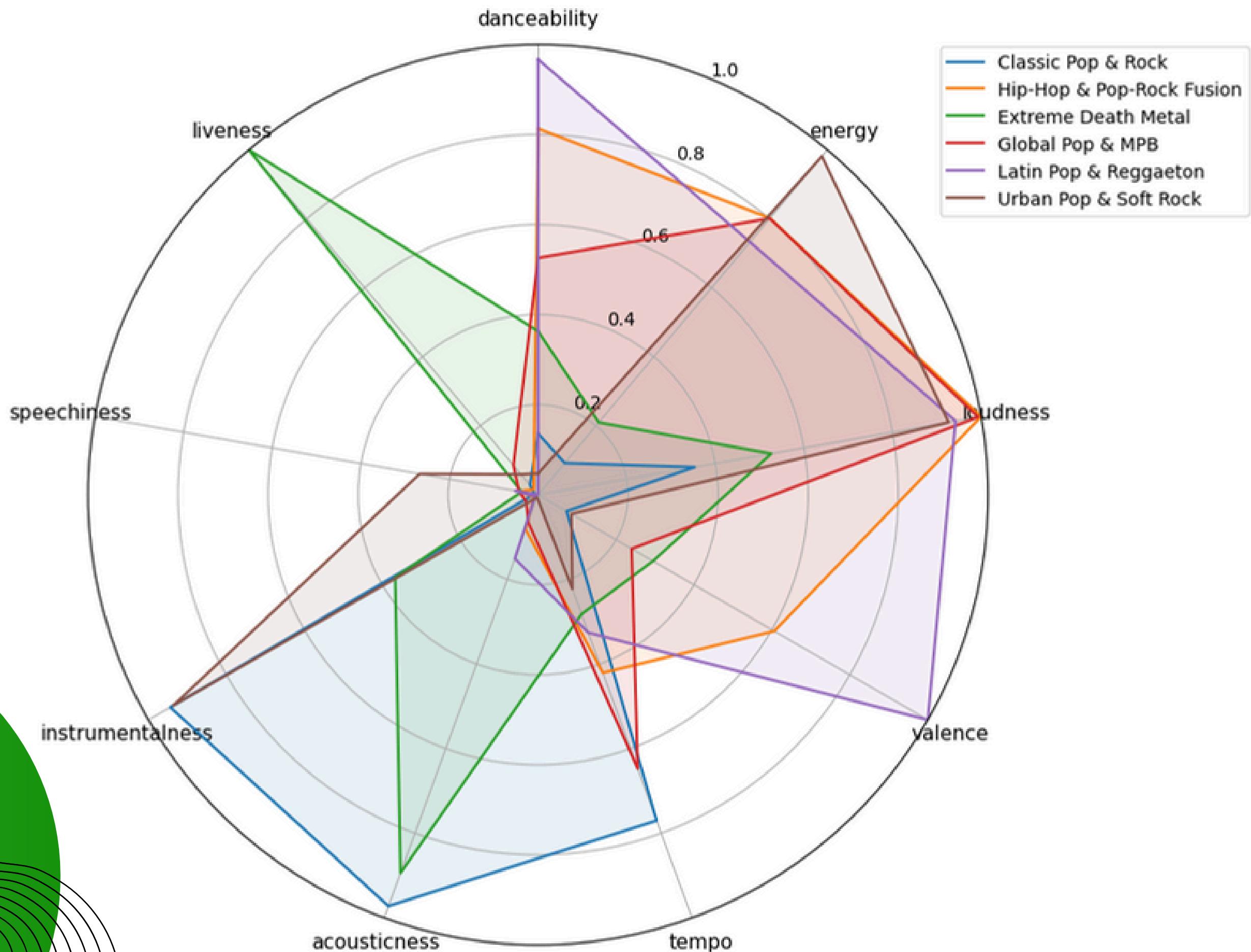
- Energetic tracks tend to be loud
- acoustic and instrumental tracks are generally quieter and less energetic

Clustering and Mapping Music Genres with KMeans and PCA



- Each point is a Song colored by Cluster
- KMeans clustering ($k=25$) to group songs with similar sound profiles.
- PCA to reduce feature space to 2D for visualization.
- Large "X" = Centroids
- 6 clusters labeled for clarity
- Distant Clusters: distinct styles (Metal vs. Classic Pop & Rock)

Comparison between different genres & features



A few observations:

- “**Hip-Hop & Pop-Rock Fusion**” has high speechiness and energy but low acousticness, indicating a vocal-driven, energetic, loud style with high danceability.
- “**Urban Pop & Soft Rock**” has a high level of energy, loudness and instrumentalness => this can speak for a great diversity in the genre
- “**Latin Pop & Reggaeton**” has a high level of danceability, loudness and valence

HOW DID WE APPROACH THIS STUDY

METHODOLOGY

- Grouping songs with numerical features only
- Data scaling: using the Min Max approach, range [0,1]
- Clustering with KMeans ($k = 25$)
- `random_state=42` ensures reproducibility
- We opted for K-means:
 1. fits the Unsupervised ML - no need for data labels
 2. data labels
 3. Easy to implement
 4. Fast for large data sets
 5. Easy to interpret



This approach does not use genre labels — it's purely based on sound features.

HOW DID WE APPROACH THIS STUDY

METHODOLOGY (2)

- Thematic Playlists names assignment:
 1. Artist profiling using ChatGPT
 - Pl 0: “Classic Pop & Rock”
 - Pl 1: “Hip-Hop & Pop-Rock Fusion”
(Sample: Appendix, Table 1)
 2. Manual checking of each genre
- Number of centroids (k) was determined using:
 - The Silhouette score (Appendix, graph 1)
 - backed with, the Elbow method (Appendix, graph2)

PROTOTYPE EFFECTIVENESS

METHODOLOGY (3)

	artist	cluster		html
Unnamed: 0				
1029	Dusty Springfield	0	https://open.spotify.com/track/1uLwVWTOpMqNkBs...	
4880	Revolverheld	0	https://open.spotify.com/track/55VQvOY6dT63vHm...	
2161	Eminem	1	https://open.spotify.com/track/4dK00wCxIqWEeN8...	
4807	Tokio Hotel	1	https://open.spotify.com/track/2qQj72YfEUQ98t7...	

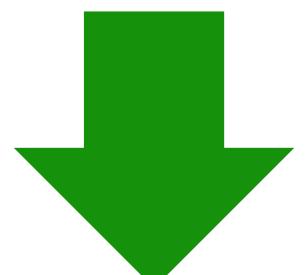
- Sampled 2 songs per playlist:
- Pl0: “Classic Pop & Rock”
- Pl1: “Hip-Hop & Pop-Rock Fusion”
- Playlists show strong cohesion

CONCLUSION & NEXT STEPS

- Spotify's **audio features** can detect musical similarities recognizable by human listeners.
- **K-Means** is a good baseline for playlist generation, but exploring more advanced models can yield better personalization and musical flow.

Include real-time-user feedback:

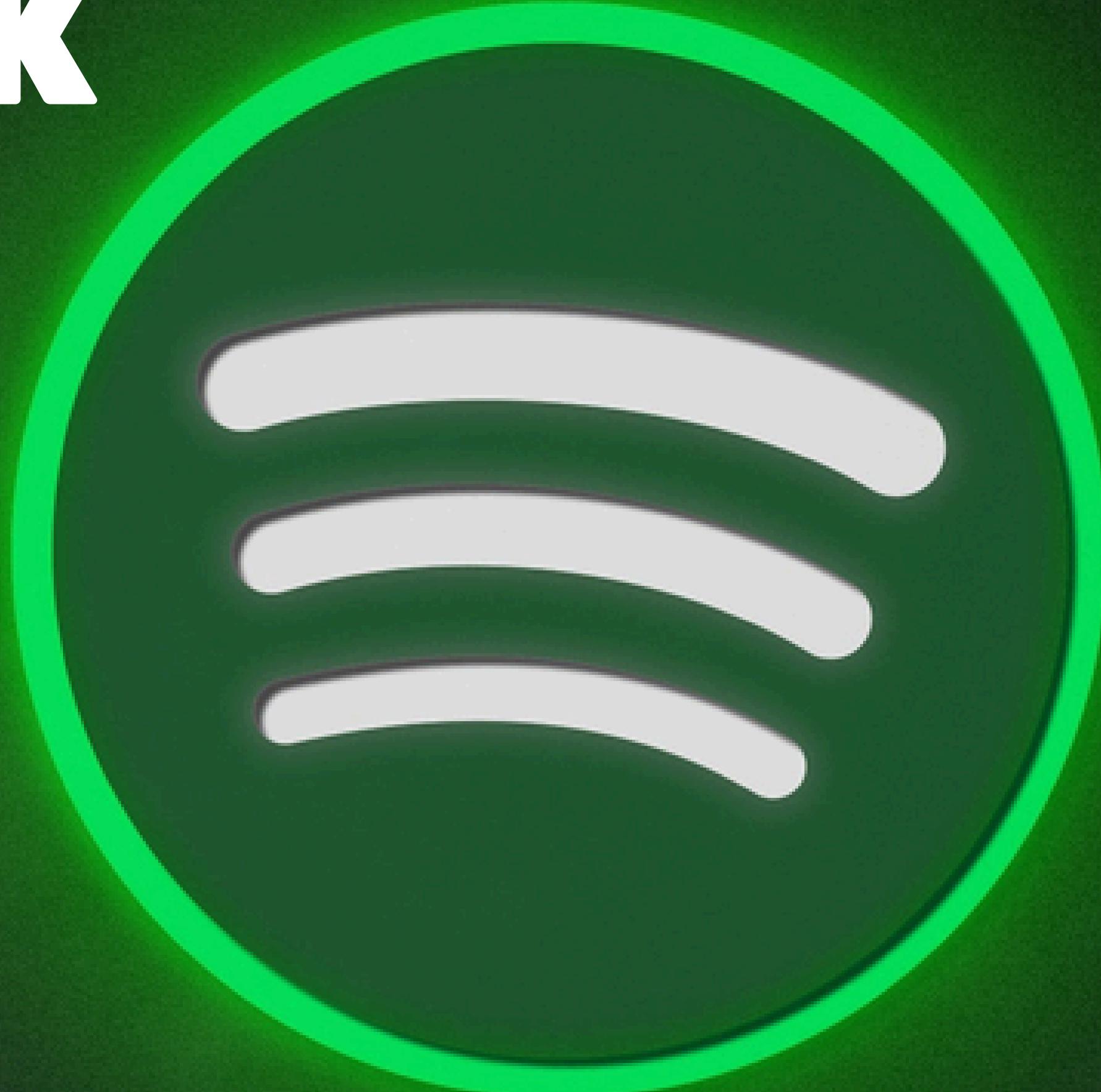
- geodata & time
- rates how often songs are skipped
- how much time spend the user listening to the playlist
- how much time spent on playlist



**Personalized Playlists for
each User Profile**



THANK YOU



APRIL, 2025

**NABIL
ANTHONY
JAN
SATYA**

SPOTIFY UPLOAD

The image shows a Spotify interface with a dark theme. On the left, a sidebar lists several playlists: 'Moosic_proj...', '+ Erstellen', 'Playlists' (selected), 'Von dir', 'Zuletzt', 'Dream Pop & Indie' (by sattyx3.sf), 'Vintage Pop & Chanson' (by sattyx3.sf), 'Jazz Legends & Piano Masterpieces' (by sattyx3.sf), 'Hardstyle' (by sattyx3.sf), 'Baroque & Jazz Classics' (by sattyx3.sf), '90s Death Metal' (by sattyx3.sf), and 'Raw Death Metal'. The main area displays a public playlist titled 'Dream Pop & Indie' by 'sattyx3.sf'. The playlist has 237 songs and a duration of approximately 15 hours. The first four songs listed are:

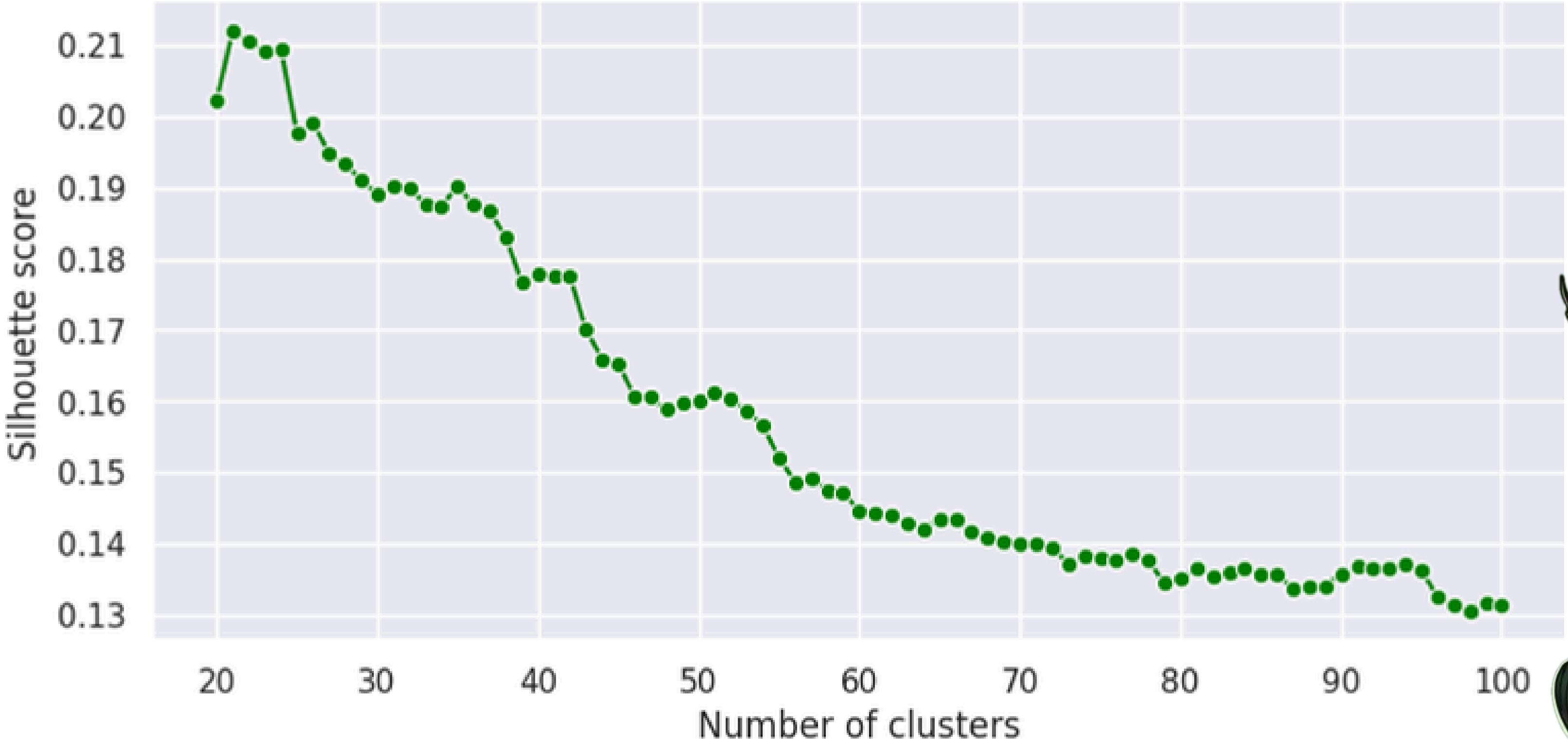
#	Titel	Album	Dauer
1	Different Pulses	Different Pulses (Editio...	4:26
2	Devil Or Angel	Places	4:04
3	Point of View - Radio Edit	Essential - Chill Out	3:50
4	The Hymn For The Cigarettes	The Fidelity Wars	3:53

At the bottom, there is a playback control bar with icons for shuffle, previous, play, next, and repeat.



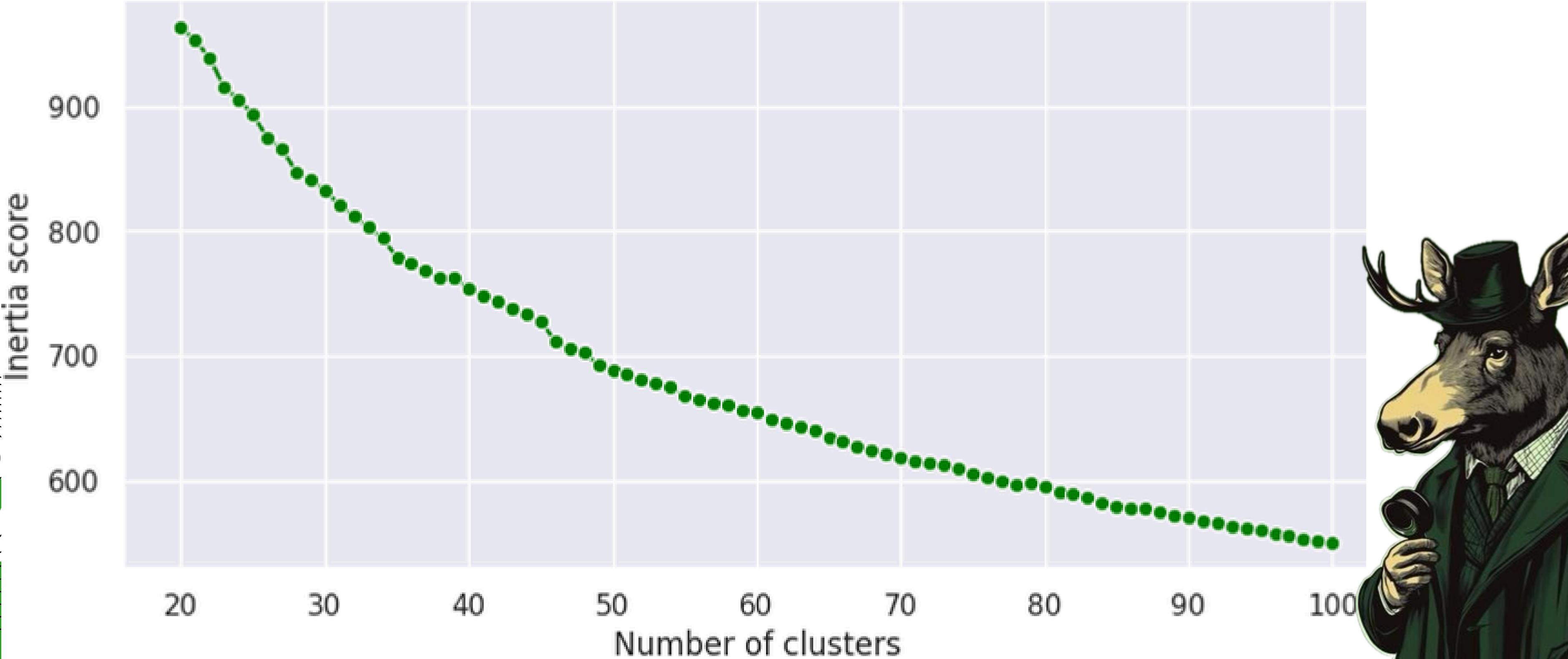
APPENDIX: GRAPH 1

Silhouette score from 20 to 100 clusters



APPENDIX: GRAPH 2

Inertia score from 20 to 100 clusters



APPENDIX: TABLE 1

Playlist	Name
0	Classic Pop & Rock
1	Hip-Hop & Pop-Rock Fusion
2	Jazz & Neo-Classical Piano
3	Extreme Death Metal
4	Indie & World-Beat
5	Old-School Death Metal
6	Global Pop & MPB
7	Classical Masters
8	Country & Folk Rock Classics



