MOOSIC

EVALUATING MACHINE LEARNING FOR PLAYLIST CREATION

Group 3:
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Introduction

Moosic is a growing startup with increasing demand for playlist creation. This raises the question: **Can machine learning generate playlists as effectively as humans?**

Objective:

- Compare human-made playlists with automated ones using K-Means clustering.
- Evaluate whether Spotify's audio features can accurately group songs by mood and style.

Questions

1. **Are Spotify's audio features effective in identifying similar songs?**
   Can these features (tempo, energy, danceability, etc.) detect similarities the way humans do?

2. **Is K-Means a suitable method for playlist creation?**
   Should we refine the approach or explore alternative models?

Creating the Prototype

Data Collection

5,235 Spotify tracks with features like tempo, danceability, energy, and loudness.

Processing / Data Cleaning

Removed duplicates, chose features, scaled all features with MinMaxScaler for consistency.

Model Selection

We used **K-Means** clustering to group the songs based on their audio features.

Model Training

K-Means was applied to eight features of 5,171 tracks, with different cluster numbers tested to optimize the results.

Overview Of The Chosen Song Features

Loudness
Overall perceived loudness of a track in decibels (dB).

Tempo 🎵⏱️🎵
Overall estimated tempo of a track in beats per minute (BPM).

Energy 🧘‍♀️🤘
Perceptual measure of intensity and activity.

Danceability 🕺💃
How suitable a track is for dancing.

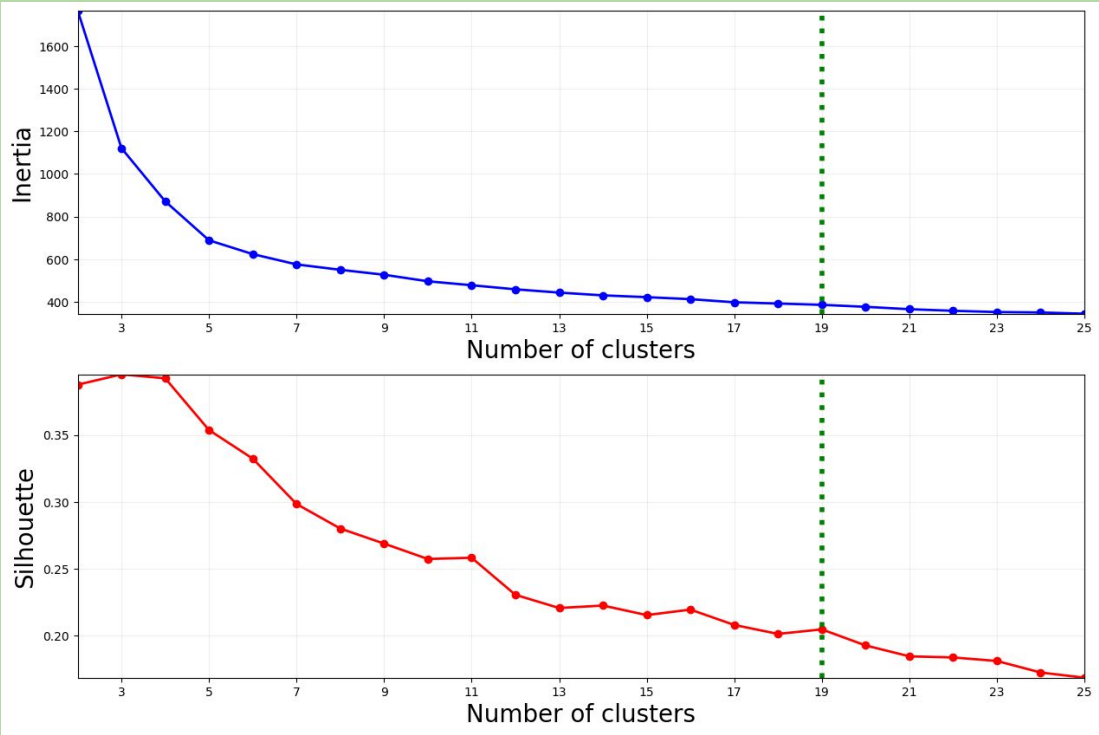
Speeechiness 🎶🗣️
Detects the presence of spoken words in a track.

Instrumentalness 🧜‍♀️🎸🎷
Predicts if a track has no vocals, treating "ooh" and "aah" sounds as instrumental.

Acousticness 🎛️🎻
Measures the likelihood of a track being acoustic, with low scores indicating electronic or digitally produced music.

Valence ☹️😀
Measures a track's musical positiveness, with higher values indicating happiness or euphoria and lower values indicating negativity like sadness or anger.

How many playlists (Clusters) should be?

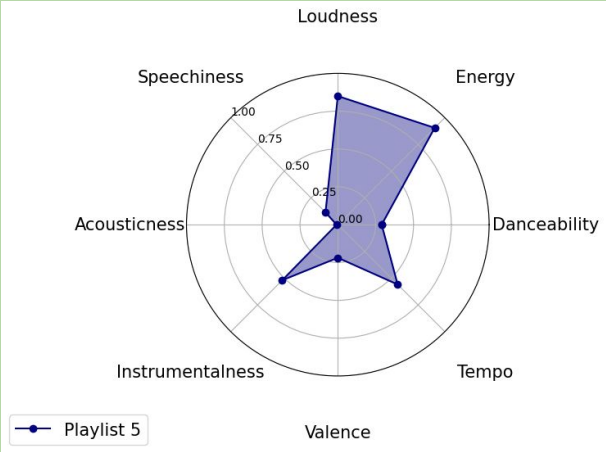


MinMax scaling

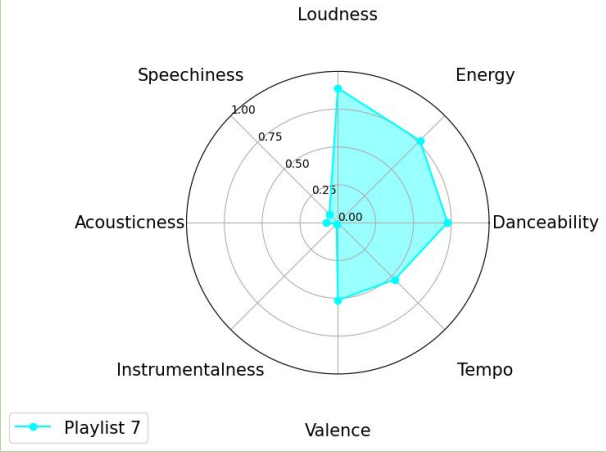
k = 19
N_iter = 69
Inertia ~ 385
Silhouette ~ 0.2

Without scaling

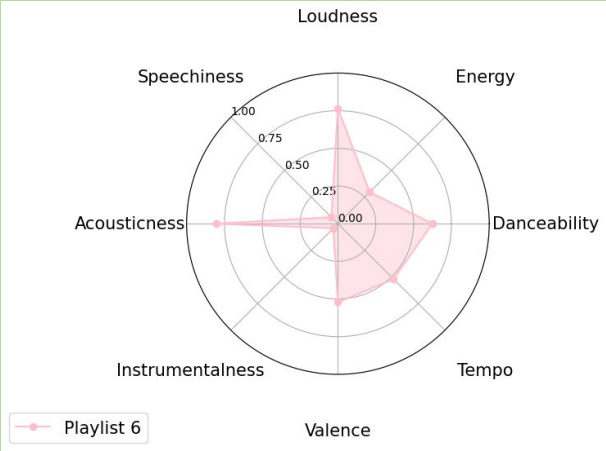
k = 12
N_iter = 32
Inertia ~ 190024
Silhouette ~ 0.4



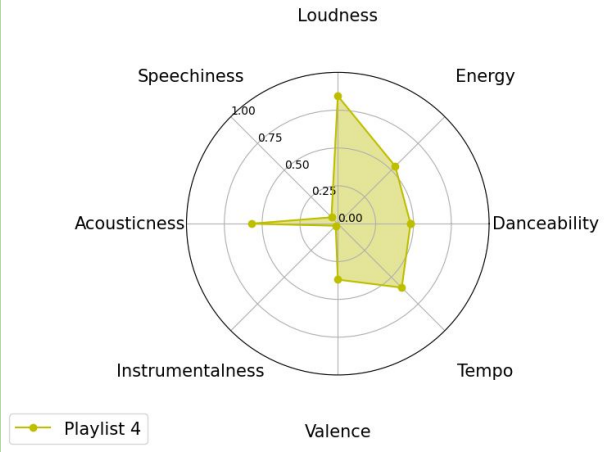
#	Titre	Album
1	Vale of Tears - remastered 2012 Gorement	The Ending Quest
2	Ceremony Of Shiva Behemoth	Satanica
3	Wasteland of Terror Asphyx	The Rack
4	The Holocaust Incarnate Aborted	Engineering the dead (Re-release)



#	Titre	Album
1	Au Revoir (feat. Sido) Mark Forster, Sido	Bauch und Kopf
2	So bist Du - Radio Edit Oli. P	Lebenslauf - Seine Gold- & Platin
3	Counting Stars OneRepublic	Native
4	Since U Been Gone Kelly Clarkson	Since U Been Gone

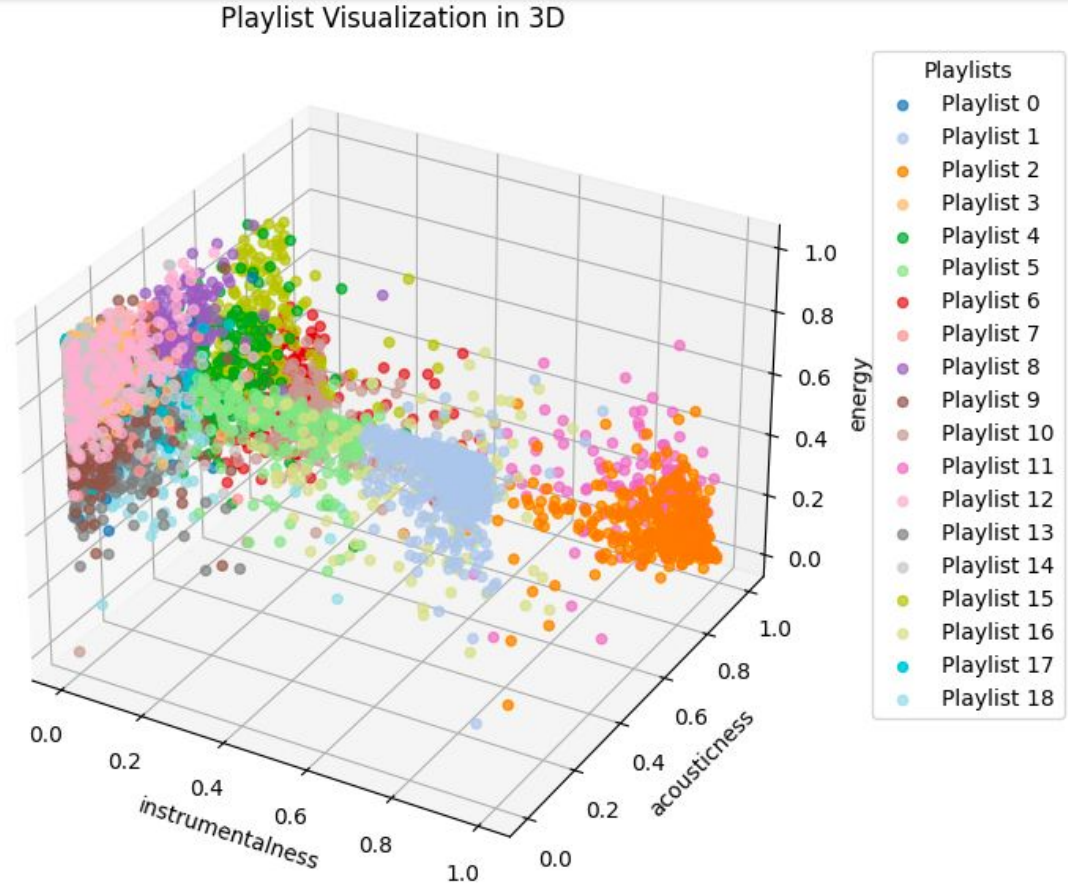


#	Titre	Album
1	To Love Somebody Bee Gees	Bee Gees' 1st
2	Mean To Me - Remastered/1998 Dean Martin	This Time I'm Swingin'
3	Windows Chick Corea	The Best Of Chick Corea
4	Teach Me Tonight Dinah Washington	The Complete Dinah Washington

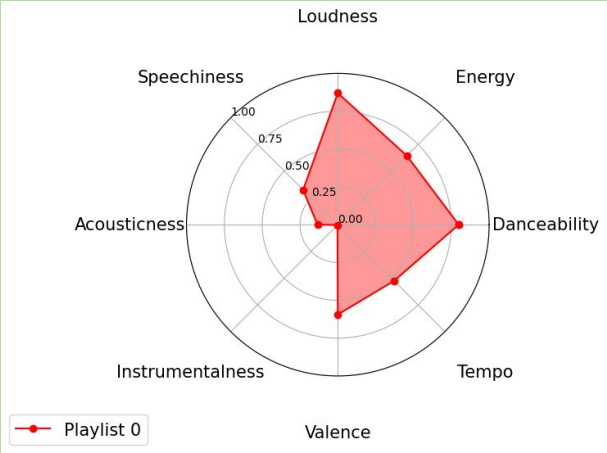


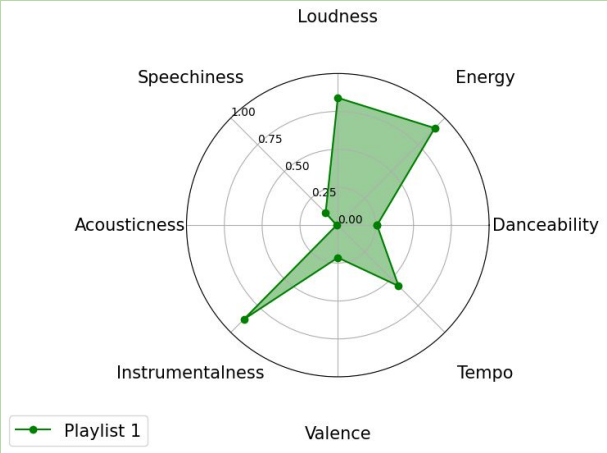
#	Titre	Album
1	Where Do You Go To (My Lovely) Peter Sarstedt	Playlist: The Best Of Peter Sars
2	Chove Chuva Jorge Ben Jor	Favourites: From Samba Esque
3	Will You Be There - Single Version Michael Jackson	The Essential Michael Jackson
4	Blue World John Coltrane	Blue World

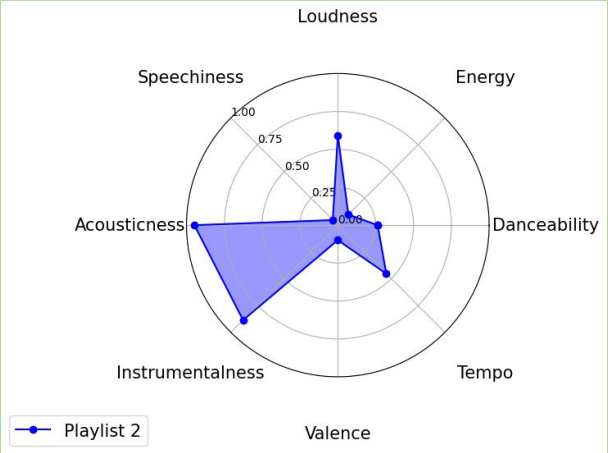
Visualizing three features

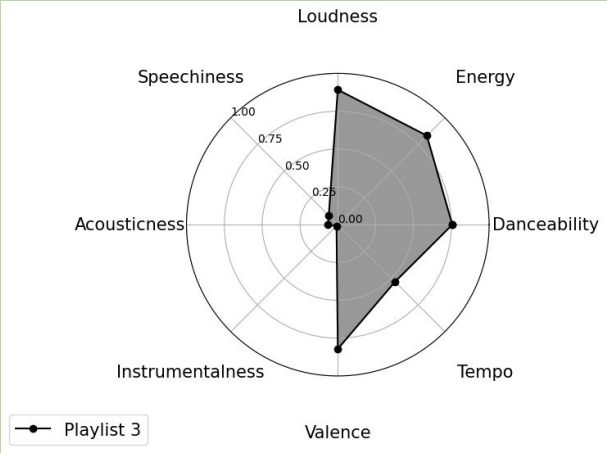


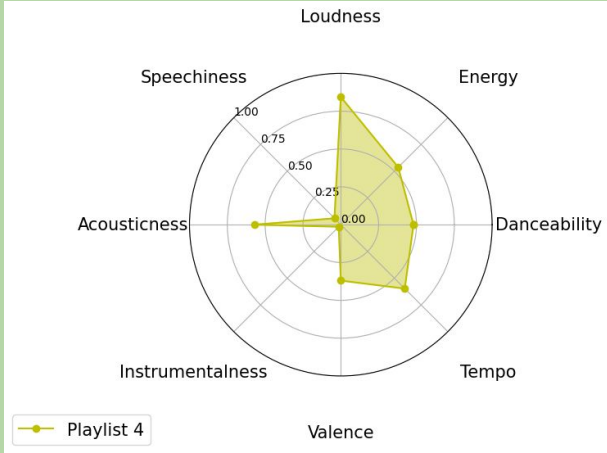
Concierto de Aranjuez for Guitar and Orches	2
Three Pieces for Orchestra, Op. 6 (1929 Revi	2
Symphony No. 9 in E Minor, Op. 95, B. 178,	2
Concerto for Orchestra, BB 123: I. Introduzic	2
A Lake	2
Moments In Love	2
Gilded	2
Suite Pour L'invisible	2
Photo With Grey Sky, White Clouds	2
Yanagiwara	2
Wind On Wind	2
Pop 2	2
Tosca / Act 3: "E lucevan le stelle"	2
Pagliacci / Act 1: "Recitar!...Vesti la giubba"	2
An Ending (Ascent) - Remastered 2005	2
#3	2
Night Time Peace	2
Sadness - Carlos Cipa Rework	2
Piano Sonata No. 13 in A Major, D. 664: II. A	2
Candle in the Wind	2
Concierto de Aranjuez: II. Adagio [Excerpt]	2
Suite for Variety Orchestra: Waltz 2 (Arr. for 1	2
Hide and Seek	2
Sonata in A Minor, K.109: Adagio	2
Sunrise in Montmartre	2

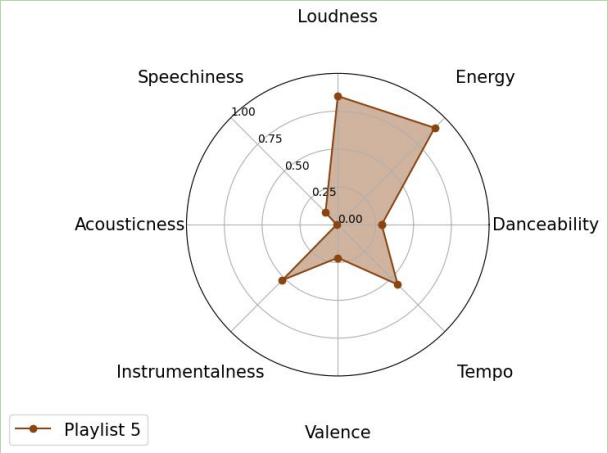

Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 0

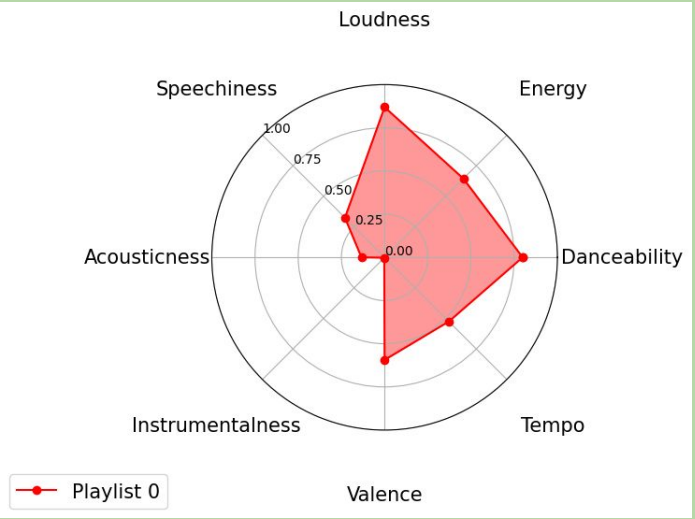

Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 1


Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 2


Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 3


Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 4


Loudness
Energy
Danceability
Tempo
Valence
Instrumentalness
Acousticness
Speechiness
1.00
0.75
0.50
0.25
0.00
Playlist 5



name	play_list	genre
My Love Is Your Love	0	dance pop, not rap
Starboy	0	Electropop
The Gangsta, The Killa And The Dope Dealer	0	gangsta rap song
Nein Mann - Radio Edit	0	german hip hop pop
Leider geil (Leider geil)	0	german hip hop, pop
I'M DEAD	0	hip hop
Heartless	0	hip hop
Hypnotize - 2007 Remaster	0	Hip Hop & Rap
Muthaf**ka Up	0	Hip Hop & Rap
Candy Shop	0	hip hop dirty rap
Drop It Like It's Hot	0	hip hop rap
Trouble On My Mind	0	Hip hop rap
Gangsta Nation	0	Hip hop rap

Assessment of K-Means Clustering

Advantages

- ✅ **Simple, easy to implement**, and computationally efficient.
- ✅ **Works well with large datasets** and provides clear, distinct clusters.
- ✅ **Scales efficiently** and is widely used in real-world applications.
- ✅ **Interpretable results**, making it useful for quick insights.

Disadvantages

- ❌ Requires predefining the number of clusters (K).
- ❌ Sensitive to initial centroid placement and outliers. No option to determine a minimal size of the clusters.
- ❌ Assumes clusters are spherical and evenly sized, which may not be realistic.
- ❌ Struggles with complex or overlapping data distributions.

Summary

Findings

K-means is a **valuable tool for organizing** music data & creating initial playlist groupings.

However **not** a perfect solution.

The subjective nature of music and the importance of context means that **human input is still essential for creating truly satisfying playlists.**

Recommendations

User based filtering:

Use listening history to improve recommendations.

User based feedback:

Allow users to tweak playlists and rate recommendations.

Language Processing:

Analyze lyrics to group songs by themes (e.g., party, romance, nostalgia).

Thank You!

Total variance and size of lists

play_list	
1	579
7	433
2	402
3	389
9	348
17	348
14	289
13	253
6	236
15	227
5	225
8	205
11	199
18	198
10	190
4	186
12	180
16	160
0	124