Erasmus School of Economics

What music are you in the mood for?

A hierarchical cluster analysis on music attributes and recommendations for mood playlists

EBB5

Group 3

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Agenda

1. Recap of hierarchical clustering theory

2. Research aim and data

3. Model diagnostics

4. Analysis and results

5. Application and conclusion

6. Discussion and future research

Theory recap: Hierarchical Clustering

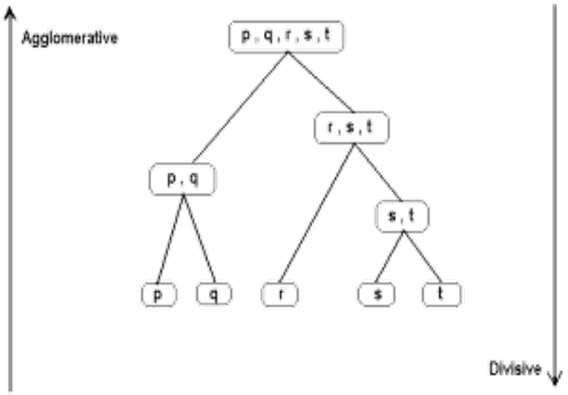
Hierarchical clustering

"Hierarchical methods proceed by stages producing a sequence of partitions, each corresponding to a different number of clusters" (Fraley & Raftery, 1998)

As opposed to K-means clustering, hierarchical clustering does **not require pre-specification** of the number of clusters K.

Agglomerative clustering

- Known as AGNES
- Bottom-up approach



Divisive clustering

- Known as DIANA
- Top-down approach

Measuring (dis)similarity between two clusters

There are various linkage methods to measure (dis)similarity:

	Method	Formula	Description
1	**Single (minimum) Linkage**	$D_{12} = min_{ij} d(X_i, Y_j)$	This is the distance between the **closest** members of the two clusters
2	**Complete (maximum) Linkage**	$D_{12} = max_{ij} d(X_i, Y_j)$	This is the distance between the members that are **farthest** apart (most dissimilar)
3	**Average (mean) Linkage**	$D_{12} = \frac{1}{kl} \sum_{i=1}^{k} \sum_{j=1}^{l} d(X_i, Y_j)$	This method involves looking at the distances between **all pairs and averages all** of these distances
4	**Ward's Method**	$D_{12} = \sqrt{\frac{2.\|k\|.\|l\|}{\|k\| + \|l\|}} . \|\|\bar{x} - \bar{y}\|\|$	This method minimizes the **total within-cluster variance.** Those clusters are combined whose merger results in minimum information loss

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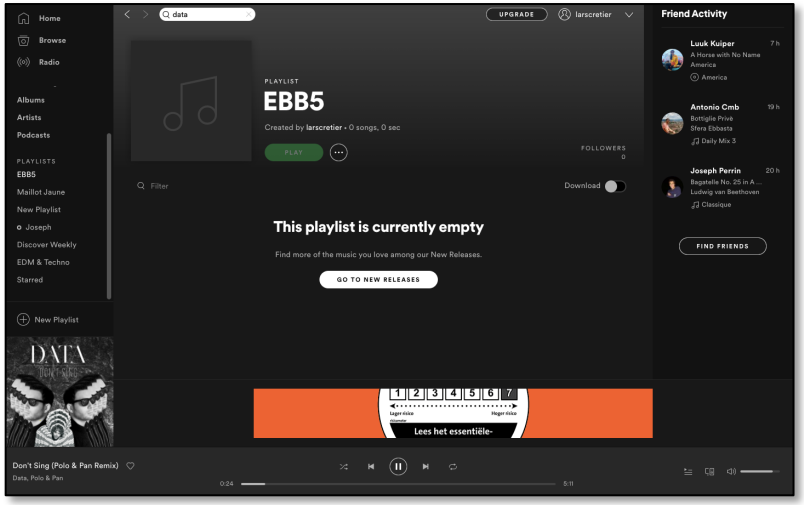
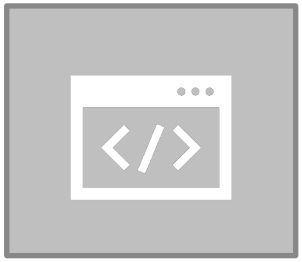
Research aim

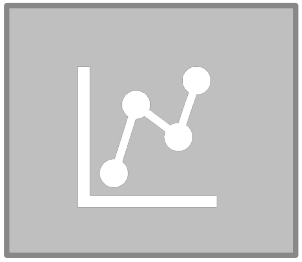
1. To provide a music recommendation approach by clustering music based on multiple attributes
2. To create music playlists for customers based on moods



Data



- Available on Kaggle
- With a developer account, you can scrape the data from Spotify



- Top 10 songs from 2010 to 2019 by year
- Worldwide

- Dataset contains 603 observations
- 14 variables in dataset

Variables

No. included of variables: 9

Variable	Explanation	Min	Max
BPM	Beats Per Minute (BPM): tempo of the song	43	206
Energy	Energy of the song by a combination of intensity and activity (100 is high energy)	4	98
Danceability	The suitability of a track for dancing based on multiple musical elements (100 is very danceable)	23	97
Loudness (dB)	The average loudness of a track in decibels (0 is loud)	-15	-2
Liveness	The presence of an audience (100 is high prob. of being live track)	2	74
Valence	The positiveness of the track (100 is very positive)	4	98
Duration	Duration of track in seconds	134	424
Acousticness	Confidence interval of the track being acoustic (100 is high prob. of being acoustic song)	0	99
Speechiness	The degree of spoken words (100 is only spoken)	3	48

Source: Spotify Developer

Data preparation

1

Cleaning the data

- **Remove NA's** and impossible values
- **Remove duplicate values** (even if it occurs multiple times in the top 50 charts)

2

Scaling the data

- Values must be **comparable** and should be measured in the **same unit**
- If variables are measured in different units, some can become **more influential** in the clustering process

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Model diagnostics

1. Suitability of clustering the data
    - Hopkins Statistic
2. Choosing the appropriate linking method
    - Complete, Single, Average, Ward
    - Cophenetic correlation coefficient
3. Choosing the optimal number of K clusters
    - Within cluster sum of squares
    - Average silhouette width
    - Gap statistic

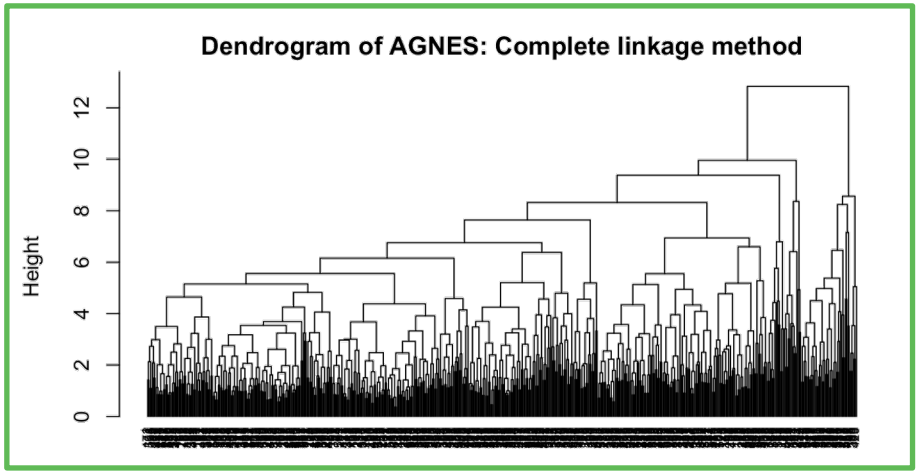
1 Suitability of clustering: Hopkins Statistic

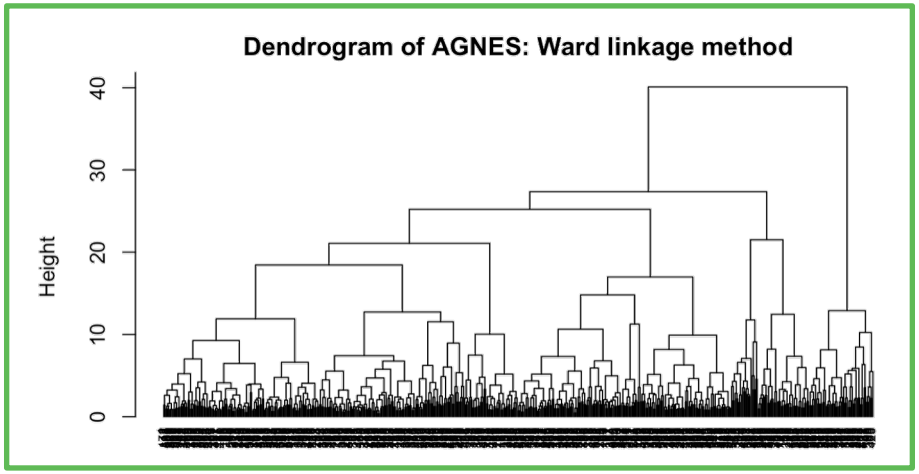
Hopkins criterion tests whether data results from a uniform random distribution.

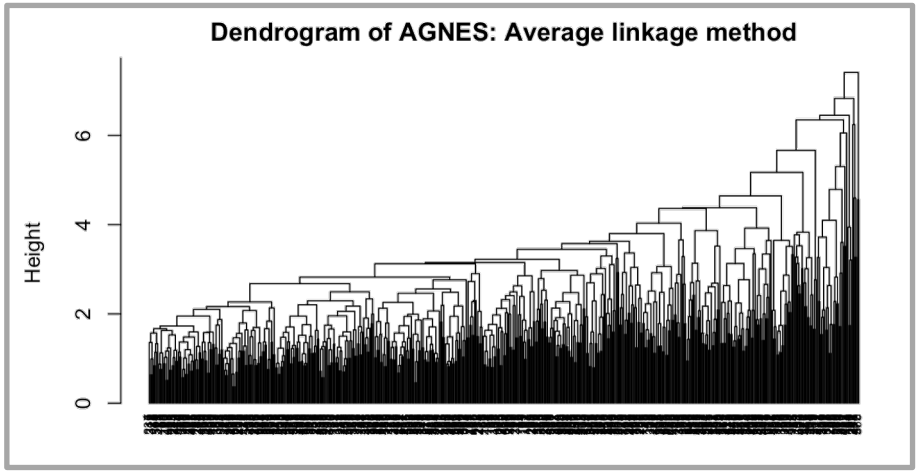
H ≈ 0.75

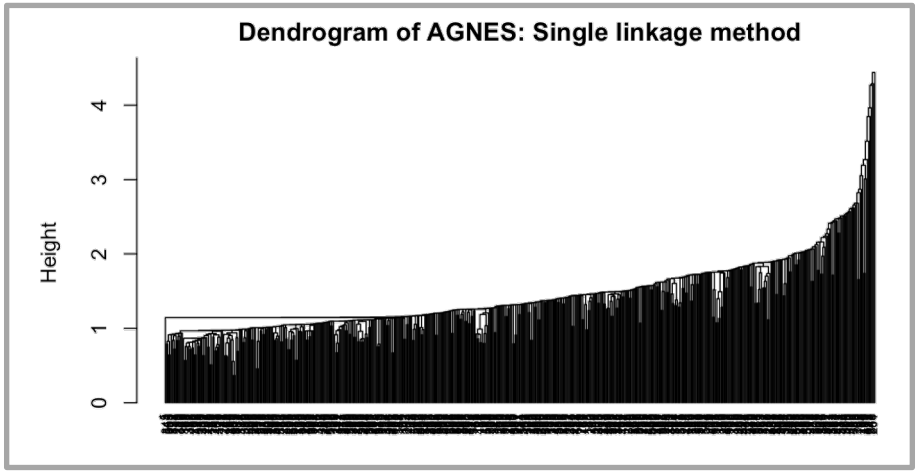
- Null hypothesis: H < 0.5, data is randomly **uniformly distributed**.
- Null hypothesis is rejected, and data contains **meaningful clusters.**

2 Choosing the appropriate linkage method









From the dendrograms, the **Complete** and the **Ward** linkage method appear to be best for interpretation purposes.

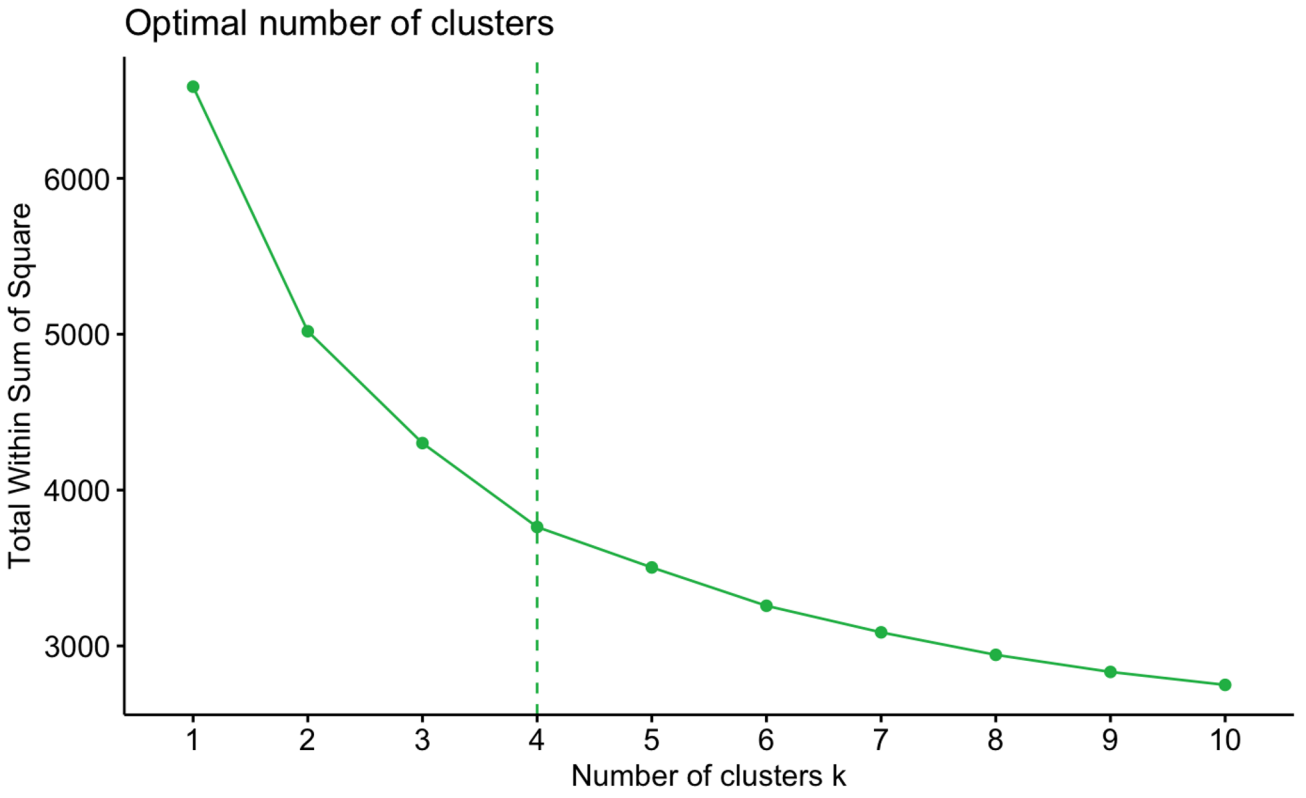
2 Choosing the appropriate linkage method

Linkage methods			
Complete	Single	Average	Ward
0.89	0.70	0.80	**0.96**

- The **cophenetic correlation coefficient** indicates how accurately the cluster tree represents dissimilarities between observations.
- From the cophenetic correlation coefficients, the **Ward linkage** method appears to be the best method.

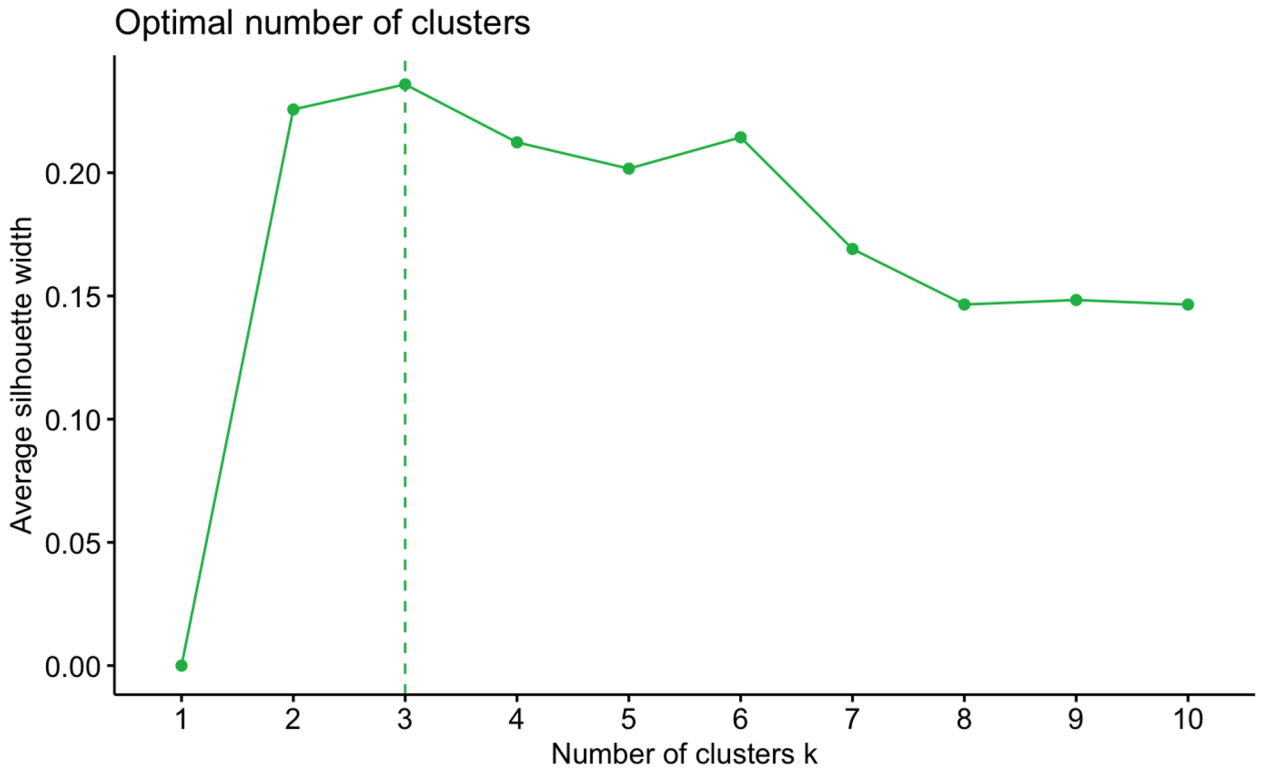
Notes: See appendix 1 for a correlation table showing the similarity in linkage method dendrogram outcomes

3 Number of K clusters: within cluster sum of squares



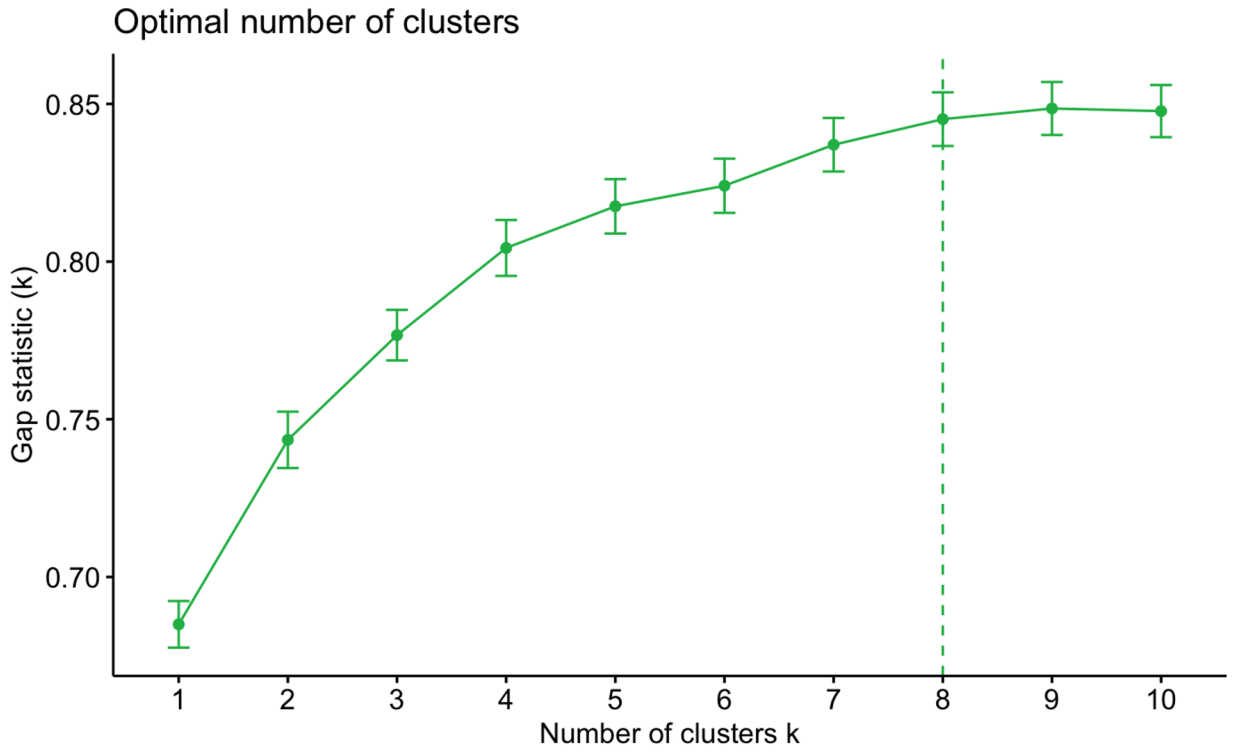
A true **'elbow'** can not be observed. However, one could argue that there is change in slope at 4 clusters, after which including 5 clusters does not add much improvement to a model that includes 4 clusters regarding the variation accounted for.

3 Number of K clusters: average silhouette



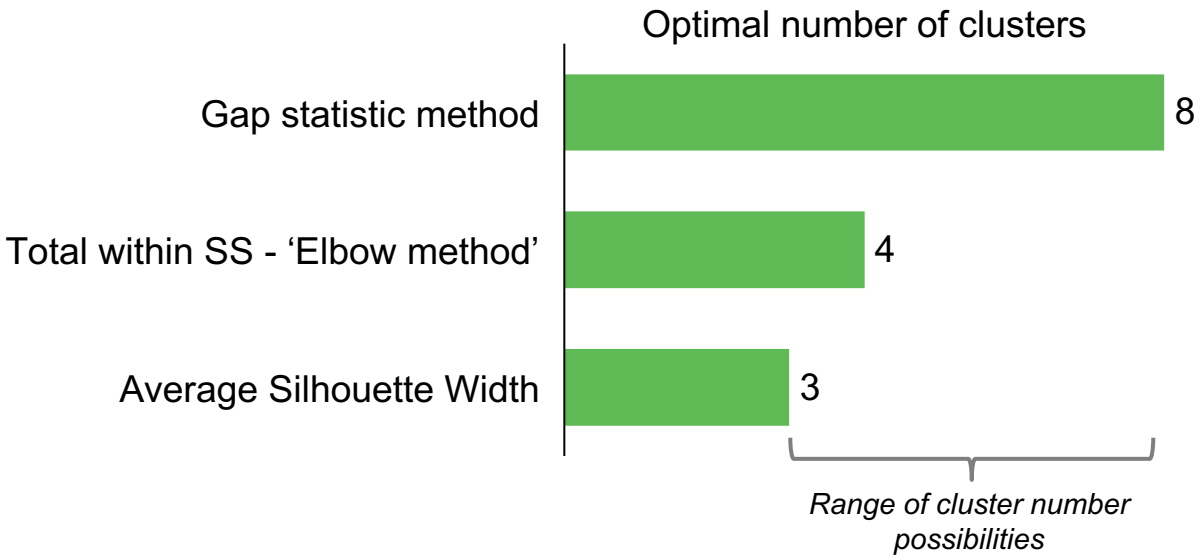
The optimal number of clusters is 3 based on the **average silhouette width**, which describes the **cohesion** of each observation within the cluster compared to the **separation** with other clusters.

3 Number of K clusters: gap statistic



The gap statistic indicates the use of **8 clusters**. The gap statistic compares the change between **within-cluster sum of squares** or variation with **expected values** under an appropriate null reference distribution.

3 Number of K clusters per diagnostic



- All methods point at a **different** optimal number of clusters.
- As the interest lies in a large number of clusters, we average the methods and **use 6 clusters**.
- Also, 6 clusters has a relative **high average silhouette width** and a **small change in the slope** of the within-cluster variation.

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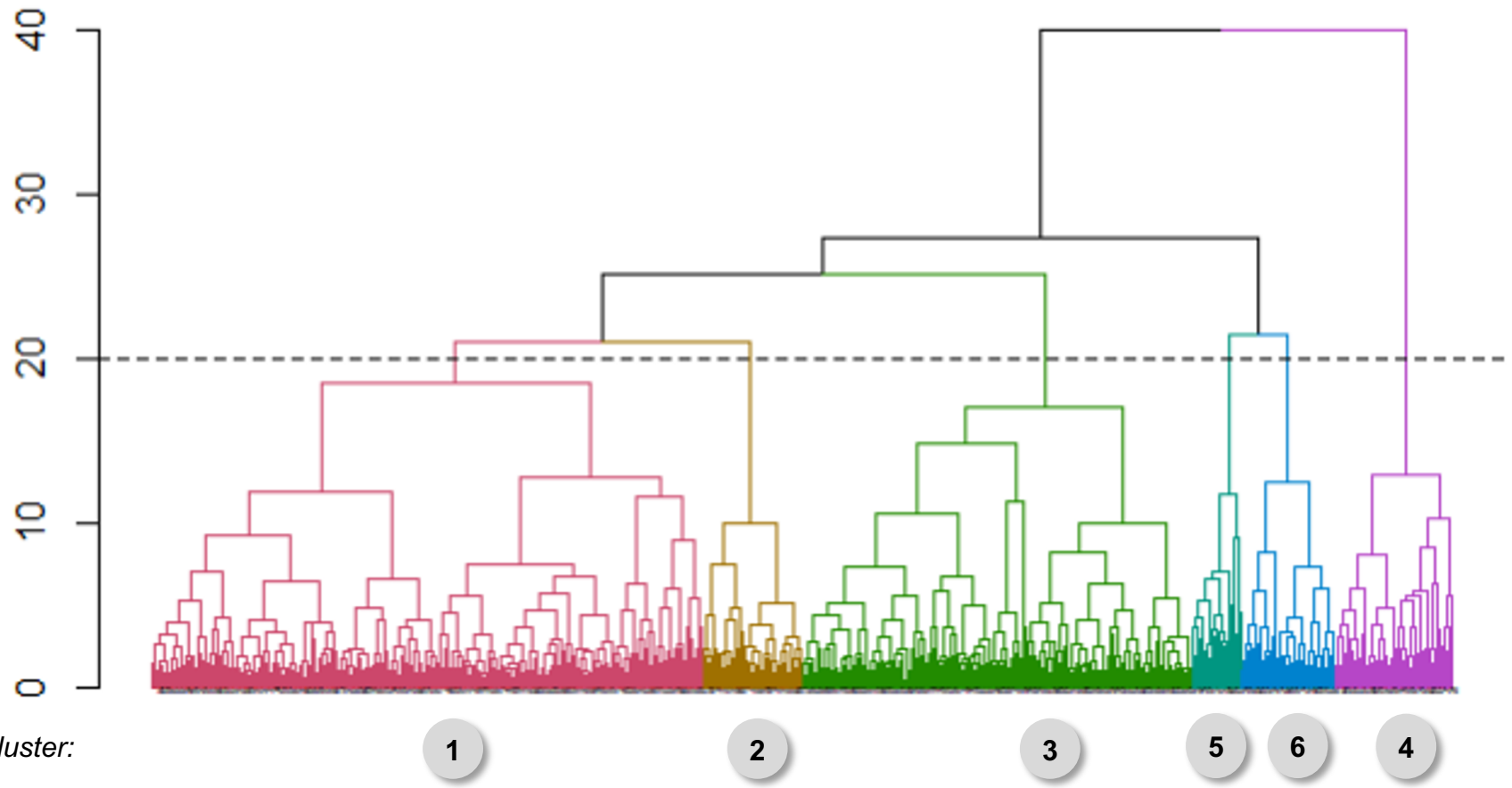
Results

Dendrogram of clusters from the analysis

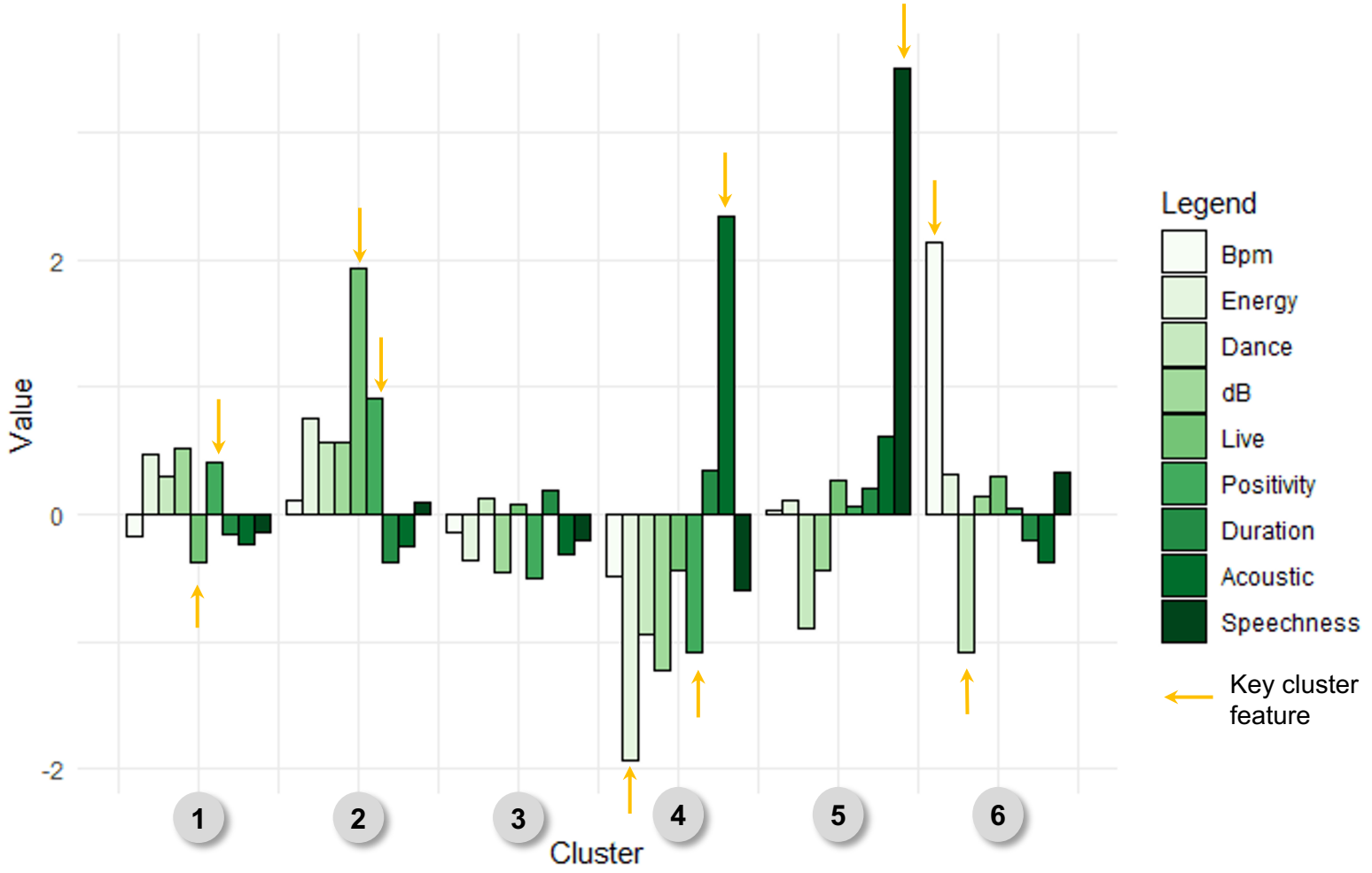
Agglomerative Clustering: Join similar clusters bottom-up



Notes: See appendix 2 and 3 for clustering outcomes with k = 4

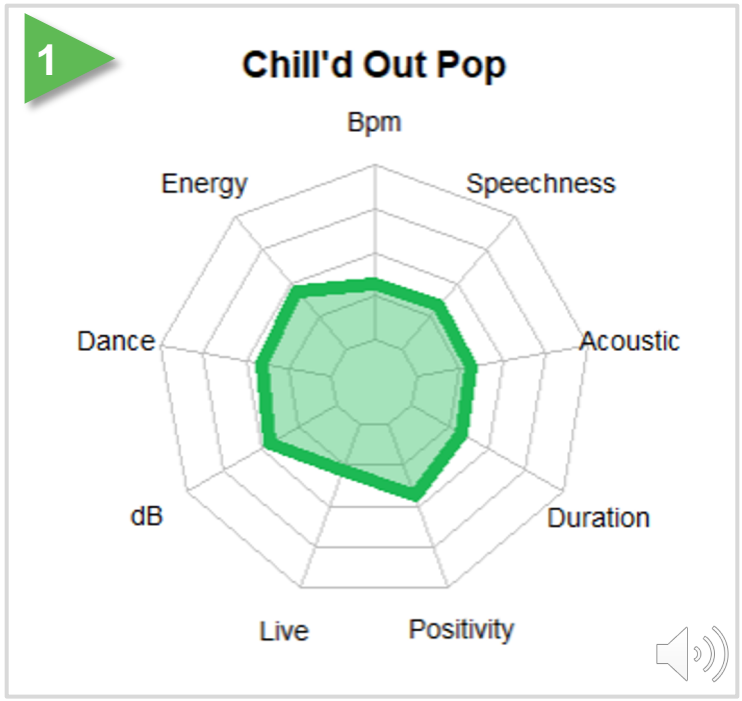
The clusters are clearly distinguishable

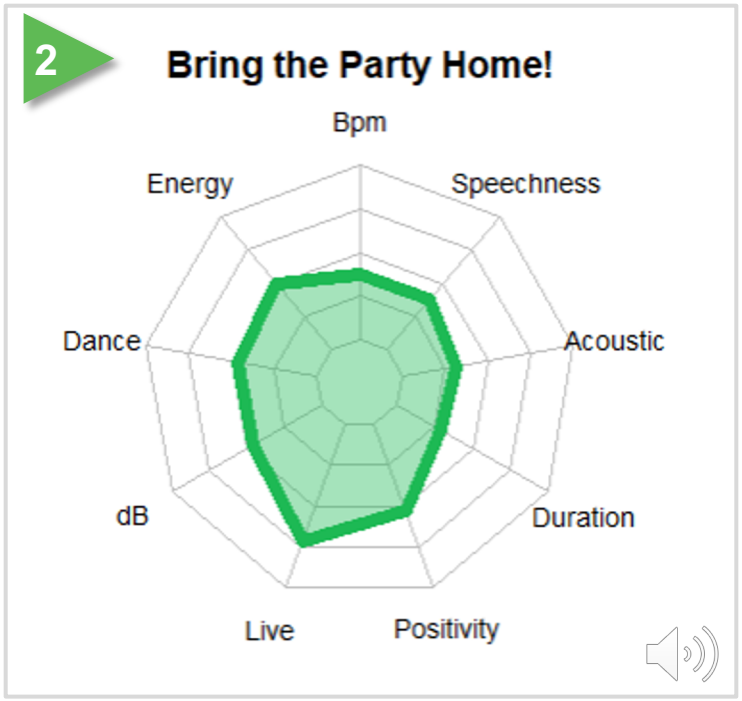
Bar plot of (scaled) cluster characteristic values



The determined clusters demonstrate **relevant and distinguishable** characteristics

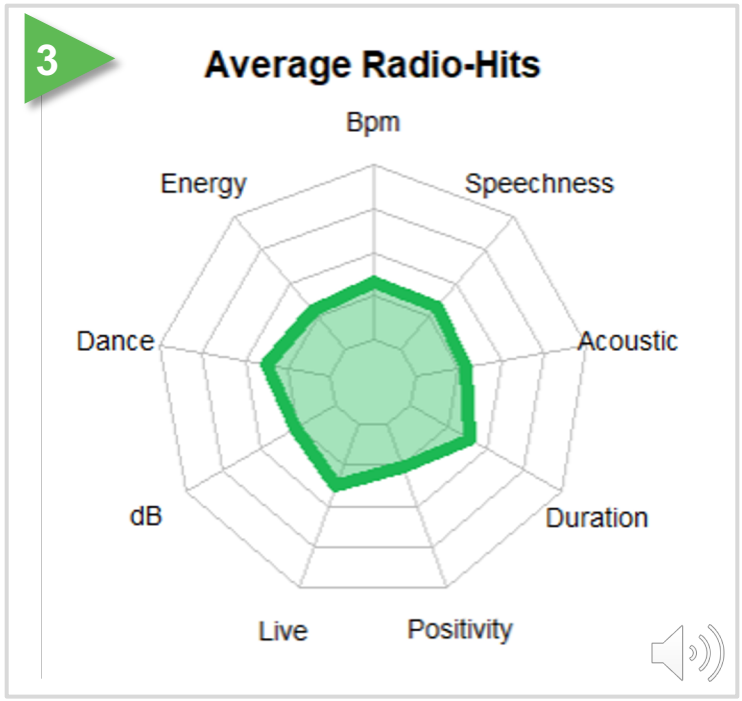
Cluster Comparison 1 and 2

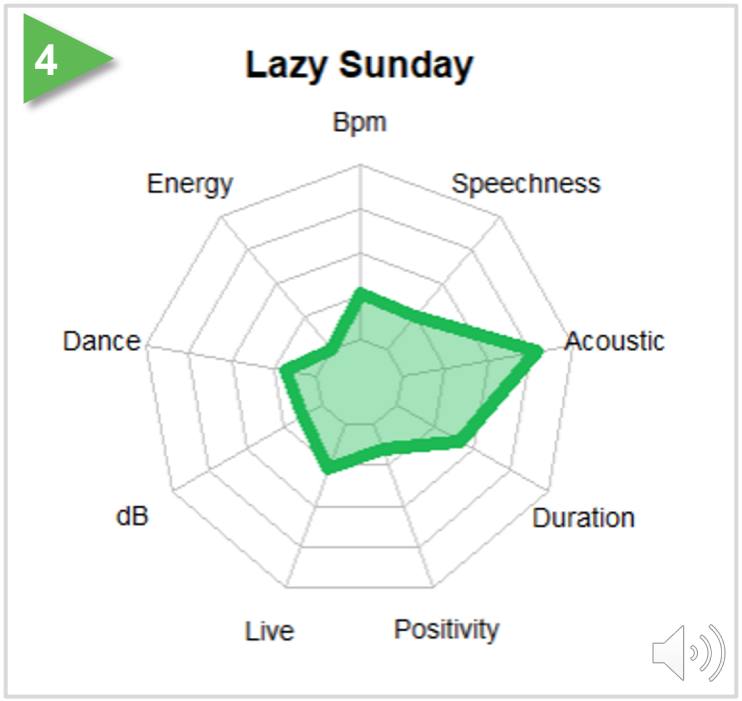




	Chill'd Out Pop	Bring the Party Home!
Size	237 obs.	44 obs.
Genre	Dance Pop (63%)	Dance Pop (64%)
Artist	Bruno Mars, Rihanna, Katy Perry	Pitbull, Jennifer Lopez, Kesha

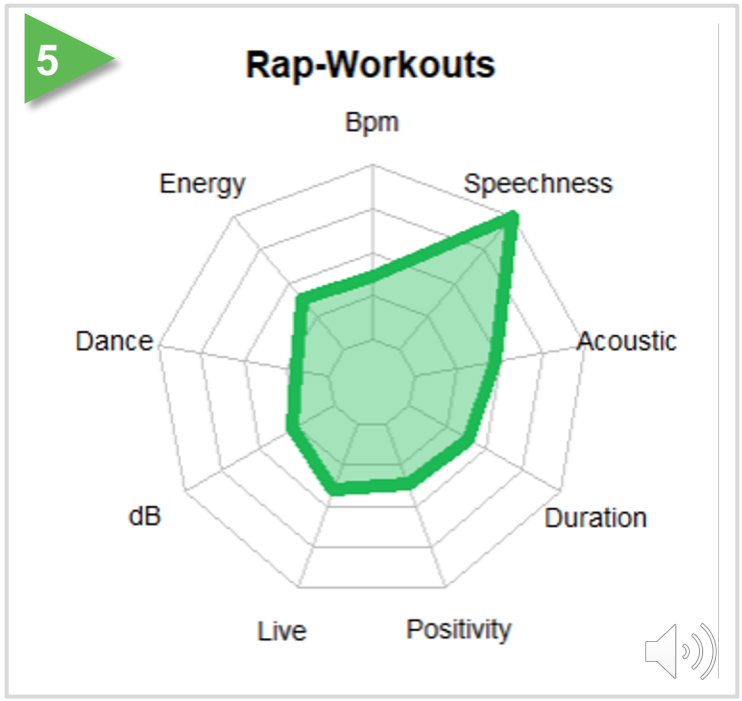
Cluster Comparison 3 and 4

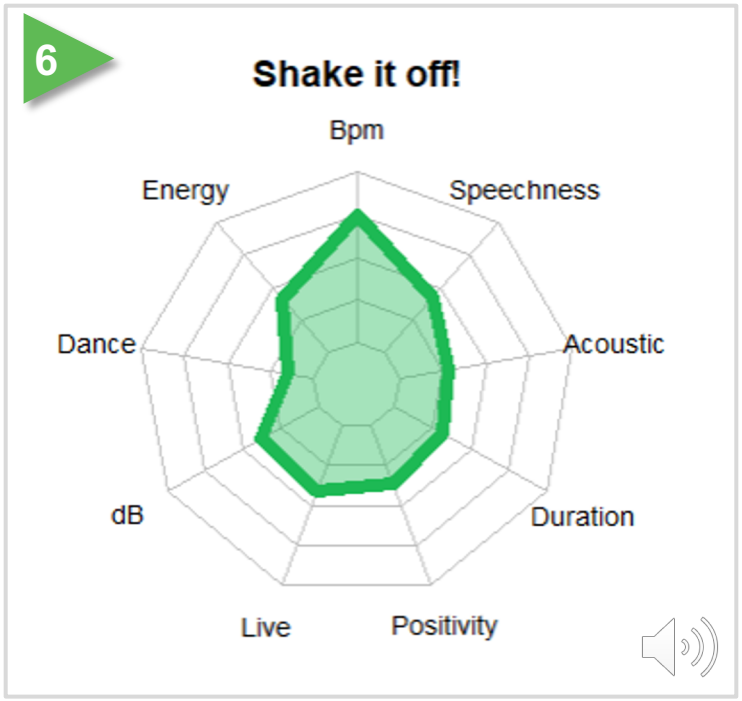




	Average Radio-Hits	Lazy Sunday
Size	175 obs.	53 obs.
Genre	Dance Pop (54%)	Dance Pop (30%)
Artist	Chainsmokers, Maroon 5	Adele, Ed Sheeran, John Legend

Cluster Comparison 5 and 6





	Rap-Workouts	Shake it off!
Size	22 obs.	42 obs.
Genre	Dance Pop (73%)	Dance Pop (38%)
Artist	Eminem, DJ Khaled, LMFAO	Katy Perry, Sia, Taylor Swift

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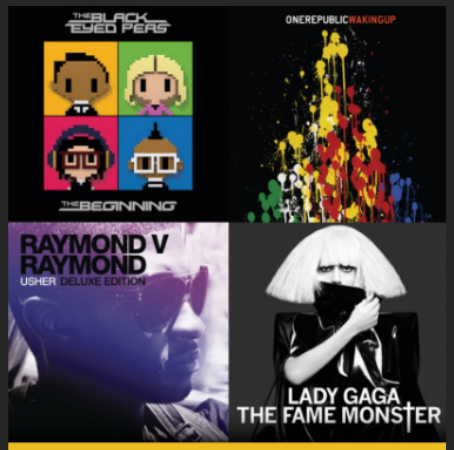
The Product

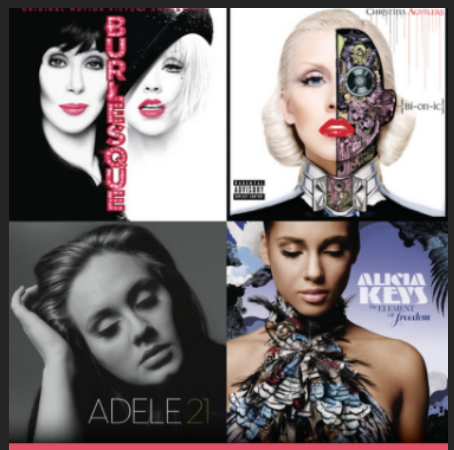
Chill'd out Pop

Bring the Party Home!

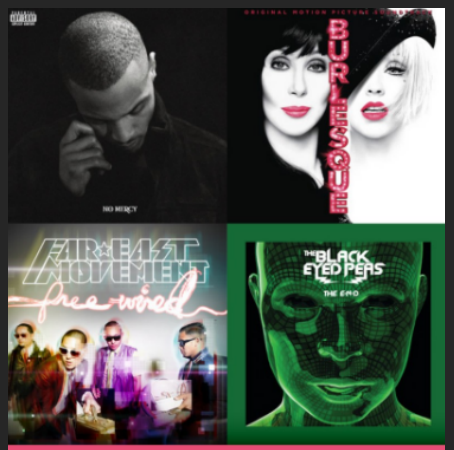
Average Radio-Hits



Lazy Sunday



Rap-Workouts



Shake it Off!

Two key outcomes with follow up steps

Conclusions

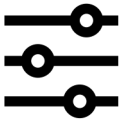
1. 6 **distinguishable clusters** based on music attributes

2. Dance music is **well represented** in the Top Charts but can be classified further

Potential next steps

1. Classification as first step to build a **recommender system**

2. **Match consumer preferences** within each cluster



3. **Detailed integratation of user-profiles** to improve matching performance

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Limitations of our analysis

	Factor	Limitation	Mitigation
1	Sub optimal classification 	• Once two objects are joined, they cannot be separated • Not a globally optimising function	Use of a genetic algorithm (GA) that seeks solution wide objective[1]
2	Computational power 	• Significant computational power required • Particularly difficult for large data sets – such as Spotify's songs database	Joint dimensionality reduction clustering to increase processing speed[2]
3	Data not representative 	• Over representation of dance pop in the charts • Data comes from Top 50 playlists.	Use data more representative including more genres

1. Cowgill et al. (1999); 2. Markos, D'Enza and van de Velden (2019)

Further potential uses of hierarchical clustering in the music industry

Simplified examples

	1 Song recommender algorithm	2 Song genre classification
Explanation	Algorithms that recommend songs based on factors specific to an individual within a cluster	Algorithm to cluster personal music collections based on the genre of the music
Method	*Generate clusters then use:* - User-KNN (personalised) - Most popular item (non-personalised)	1. Computation of Inter-Recording similarities 2. Agglomerative clustering procedure 3. Genre cluster number estimation
Paper	Aguiar Neto et al. (2020)	Tsai and Bao (2010)

Thank you for listening

Any questions?

References

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Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *63*(2), 411-423.

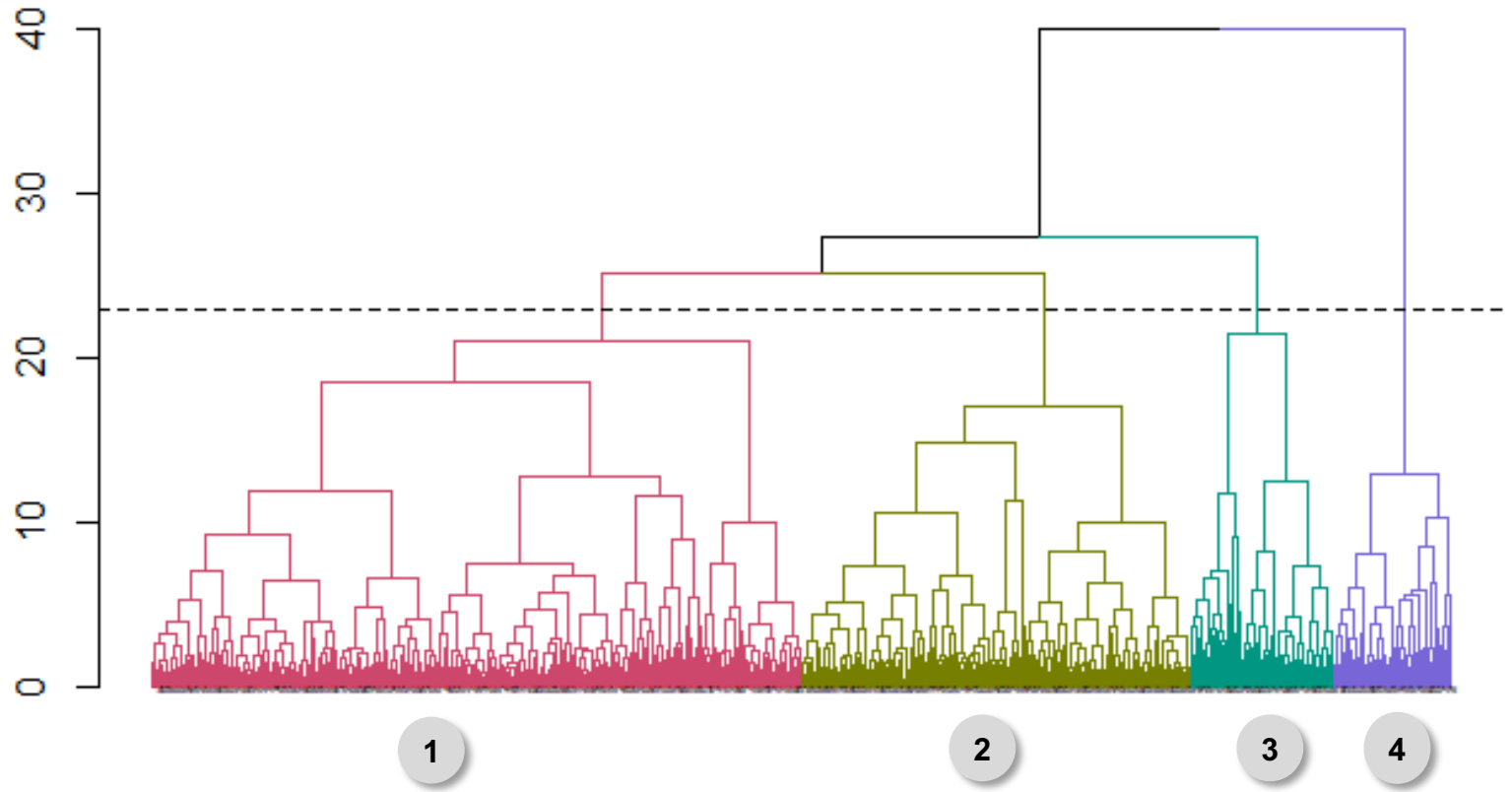
Tsai, W. and Bao, D., 2010. Clustering Music Recordings Based on Genres. *JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 26*, [online] 26, pp.2059-2074. Available at: <https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.429.6412&rep=rep1&type=pdf> [Accessed 5 November 2020].

Appendix 1: Choosing the **appropriate linking method**

Correlation table of linking methods				
	Complete	Single	Average	Ward
Complete	1.00	*N/A*	*N/A*	*N/A*
Single	0.50	1.00	*N/A*	*N/A*
Average	0.69	0.79	1.00	*N/A*
Ward	0.67	0.32	0.58	1.00

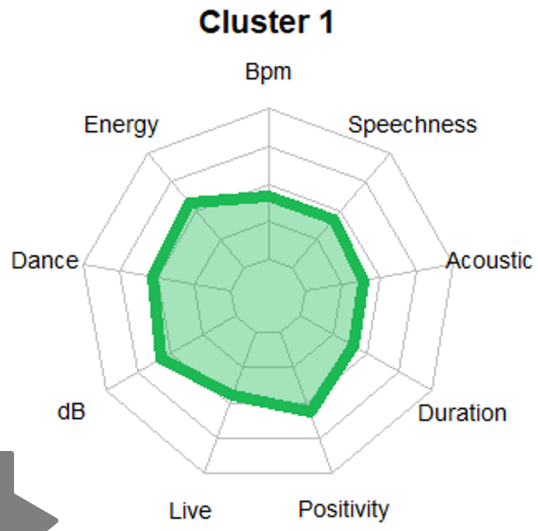
Appendix 2: Dendrogram 4-Clusters

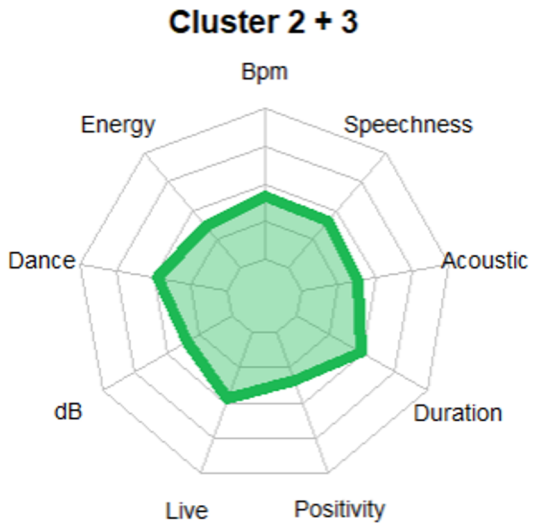
Higher dissimilarity value for clusters compared to 6 clusters

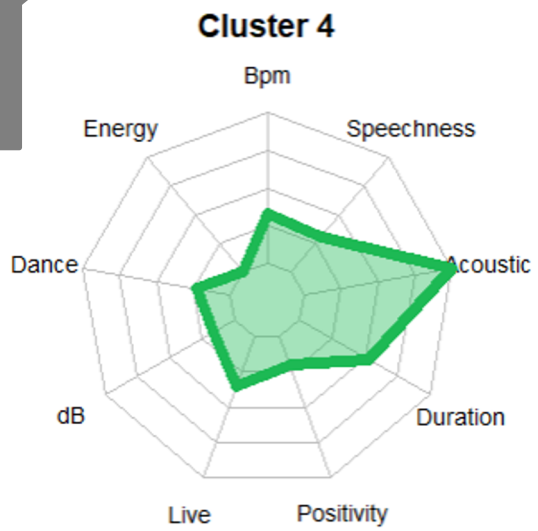


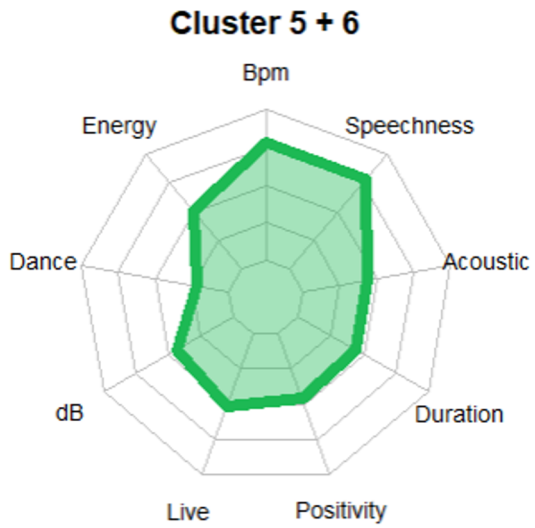
Appendix 3: 4 Cluster Alternatives

Clusters maintain distinguishable and interpretable characteristics

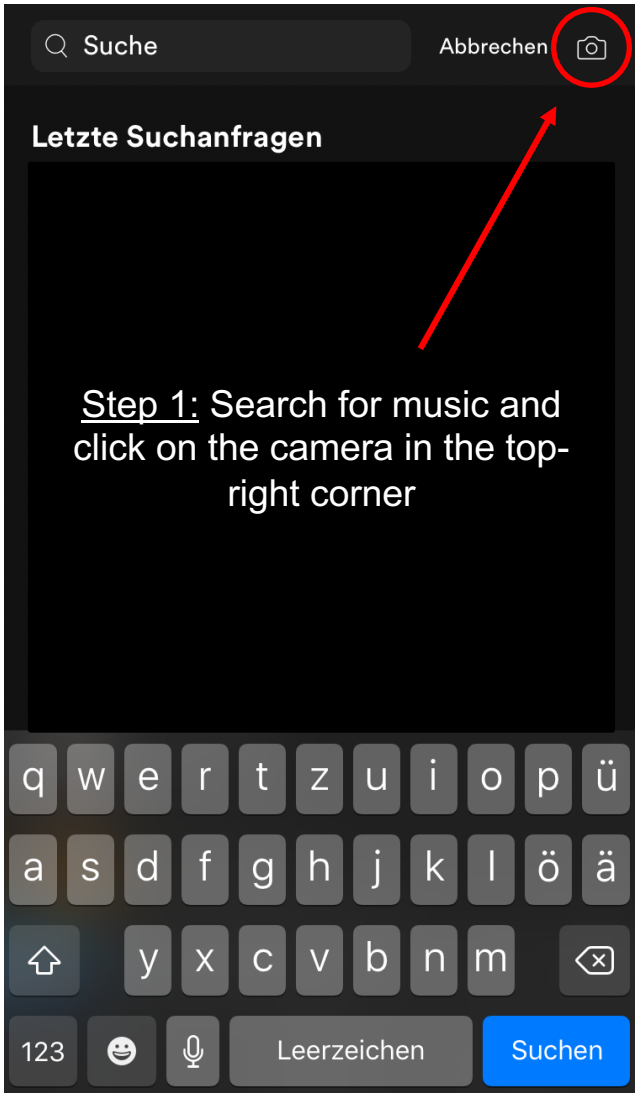


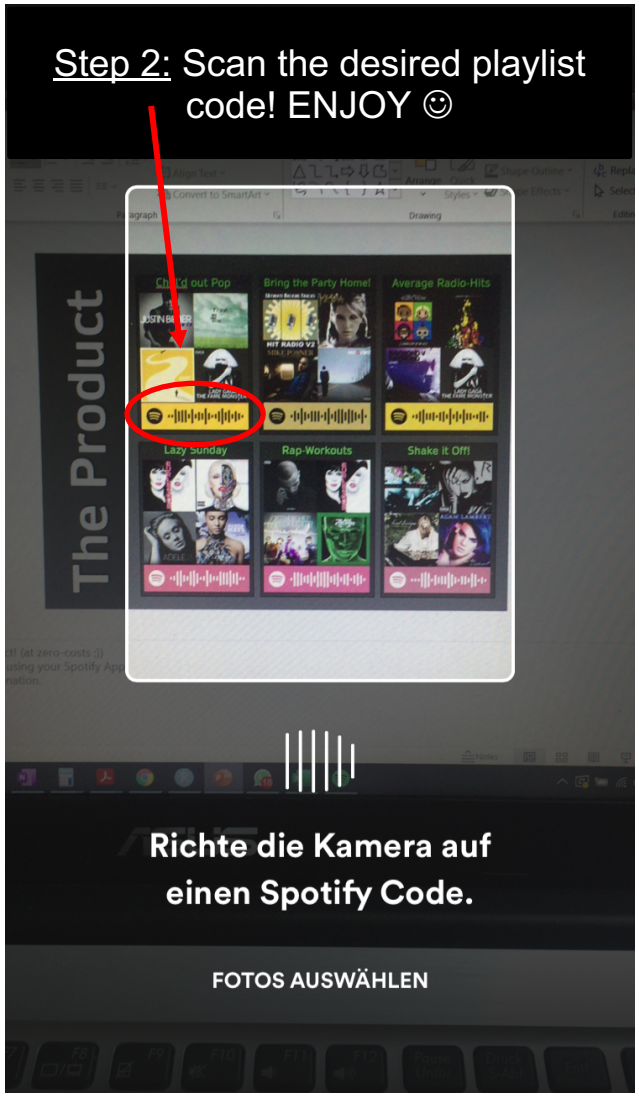




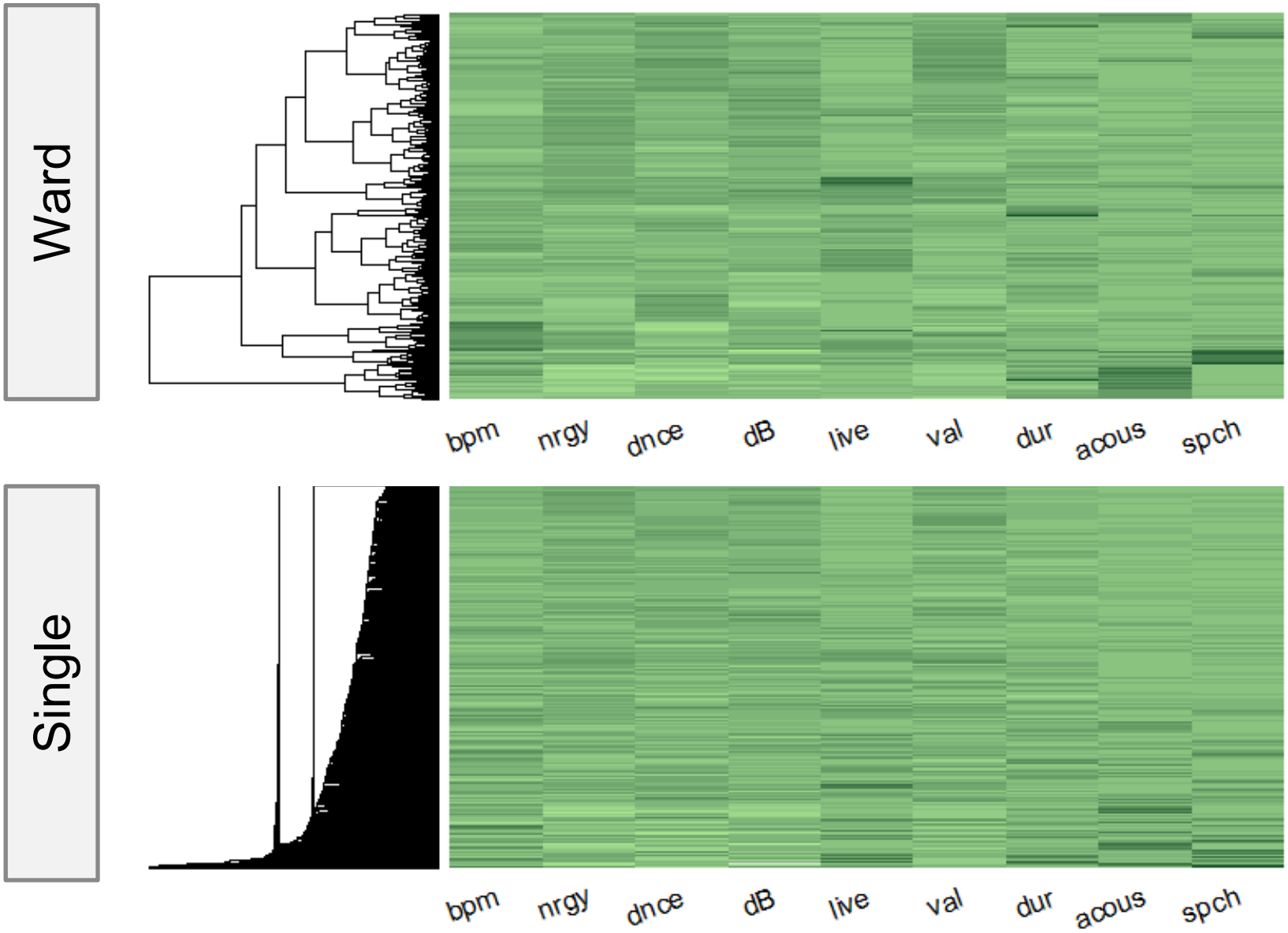


Appendix 4: Scan the Playlists

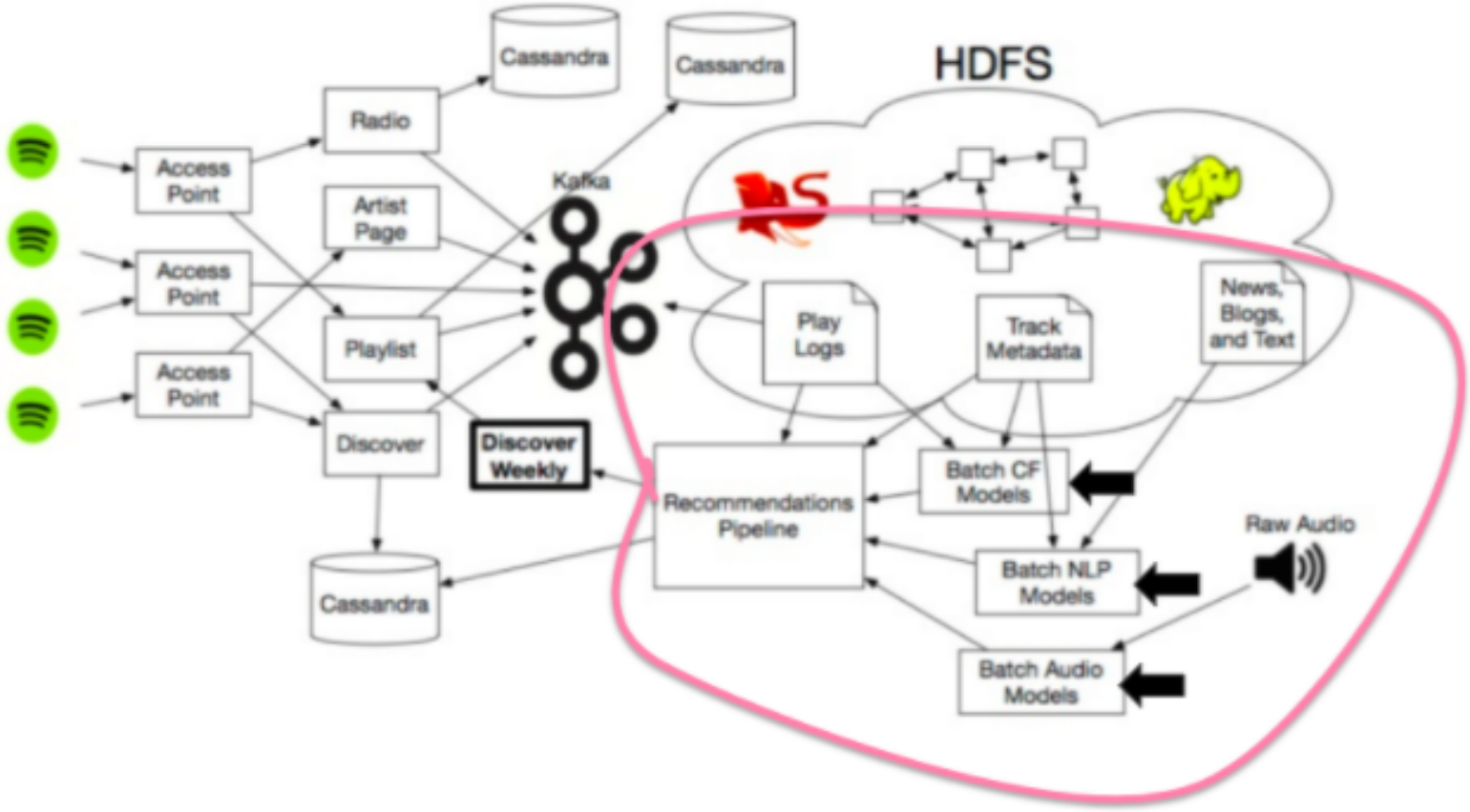




Appendix 5: Dissimilarity Matrices



Appendix 6: How Spotify actually creates its music playlists



Source: The Next Big What