How to milkify the music *K*ow?
OR
How suitable are spotify's audio features for creating curated playlists using *K*-means?

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Research by
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MAIN QUESTIONS

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- Are Spotify's audio features able to identify "similar songs", as defined by humanly detectable criteria?

- Is K-Means a good method to create playlists?

DATA

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- Data of 5000 songs from spotify
- 8 Features for analysis:
  - **Danceability**: describes how suitable a track is for dancing
  - **Energy**: represents a perceptual measure of intensity and activity
  - **Loudness**: overall loudness of a track in decibels (dB)
  - **Speechiness**: detects the presence of spoken words in a track
  - **Acousticness**: confidence measure whether the track is acoustic
  - **Instrumentalness**: predicts whether a track contains no vowels
  - **Valence**: describes the musical positiveness conveyed in a track
  - **Tempo**: overall estimated tempo of a track in beats per minute (BPM)

SCALING

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	danceability	energy	loudness	speechiness	acousticness	instrumentalness	valence	tempo
count	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000
mean	0.509503	0.653565	-9.338098	0.083178	0.290043	0.257337	0.443596	118.721407
std	0.218041	0.288335	6.294850	0.071193	0.355985	0.370686	0.277725	28.568463
min	0.000000	0.000000	-60.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.309000	0.479000	-11.337000	0.039000	0.002450	0.000001	0.196000	96.174000
50%	0.539000	0.738000	-7.338000	0.055800	0.095400	0.001880	0.417000	119.180000
75%	0.688000	0.893000	-5.264000	0.098650	0.565500	0.643000	0.677000	134.019000
max	0.967000	1.000000	1.342000	0.918000	0.996000	0.985000	0.985000	213.990000

Before scaling

After Min-Max scaling

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	valence	tempo
count	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000	5235.000000
mean	0.526890	0.653565	0.825893	0.090608	0.291208	0.261255	0.450352	0.554799
std	0.225482	0.288335	0.102619	0.077552	0.357414	0.376331	0.281954	0.133504
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.319545	0.479000	0.793306	0.042484	0.002460	0.000001	0.198985	0.449432
50%	0.557394	0.738000	0.858498	0.060784	0.095783	0.001909	0.423350	0.556942
75%	0.711479	0.893000	0.892309	0.107462	0.567771	0.652792	0.687310	0.626286
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

CLUSTERING SONGS USING K-MEANS

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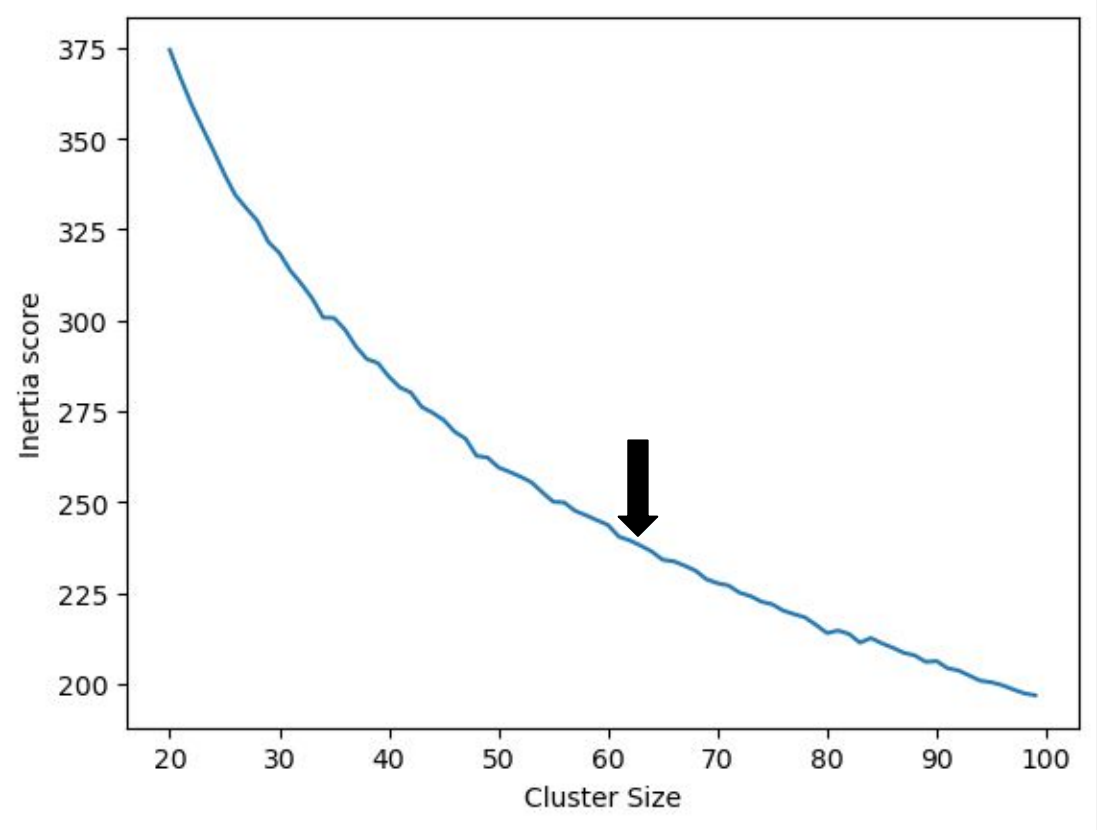

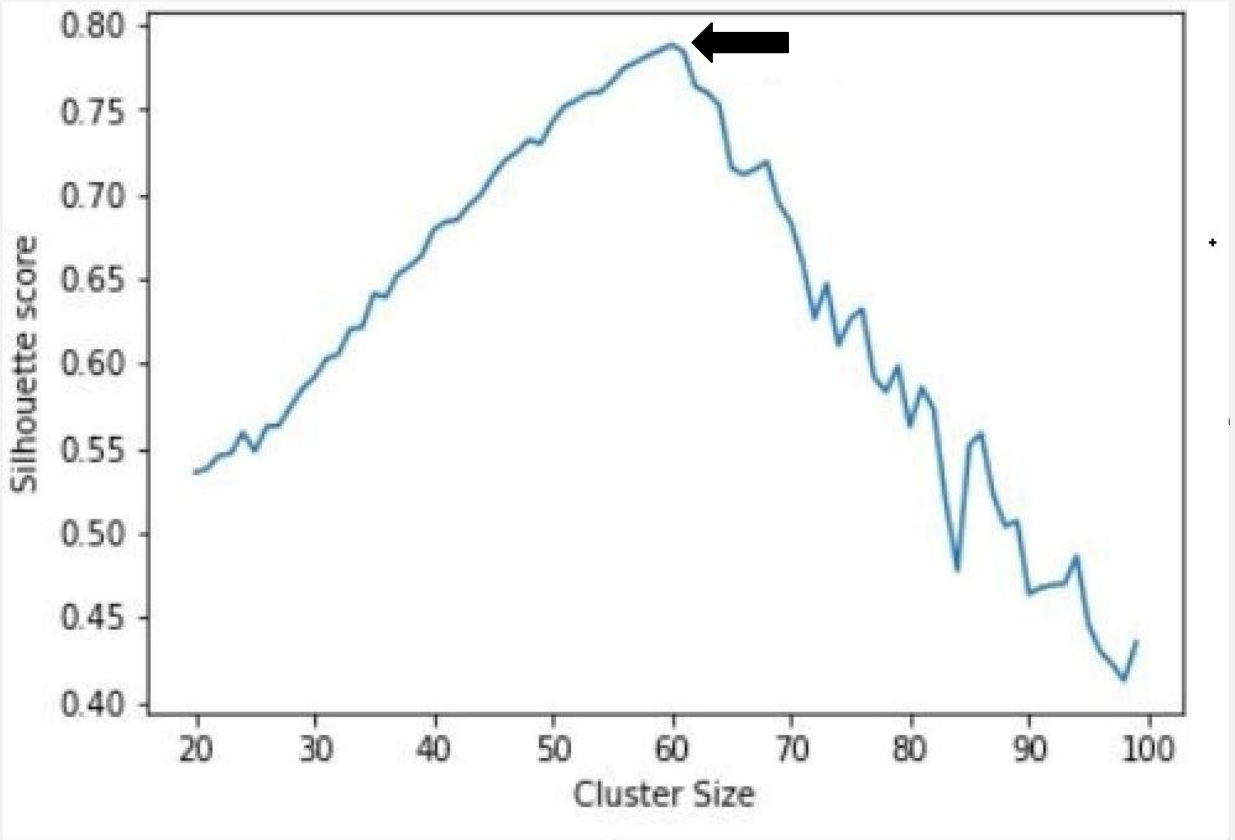

CLUSTER ANALYSIS

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- Out of 60 clusters, we randomly took 2 clusters (0, 38) for further analysis
- We compared the two clusters with regard to their features
- In order to decide if the clusters are coherent, we randomly listened to some of the songs from each cluster
- To proof our intuitions, we have collected data on genres through web scraping

CLUSTER ANALYSIS

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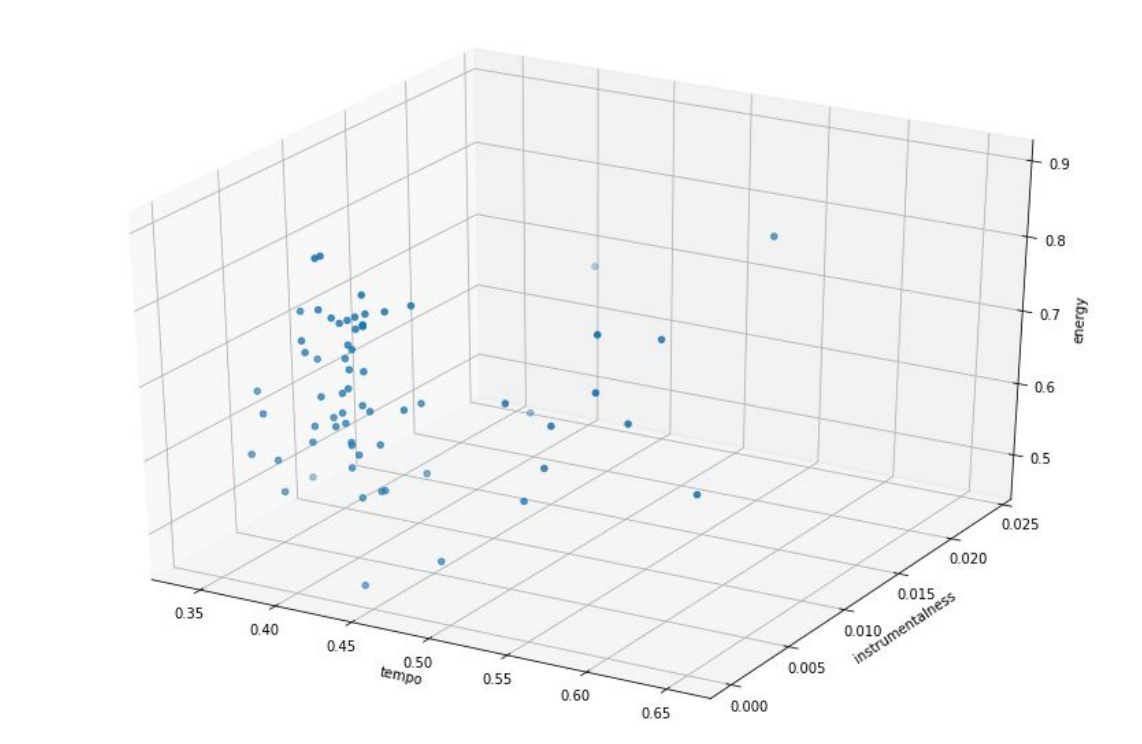
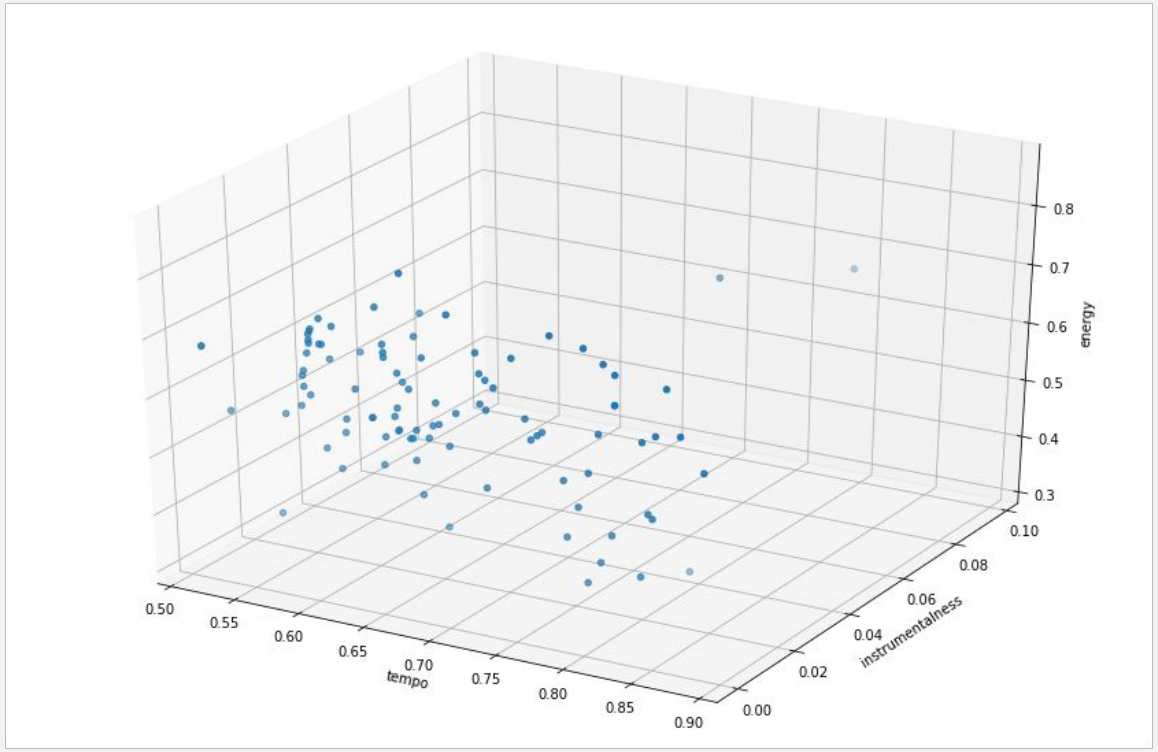
Features: Tempo, Instrumentalness, Energy



Cluster 0



Cluster 38

CLUSTER ANALYSIS

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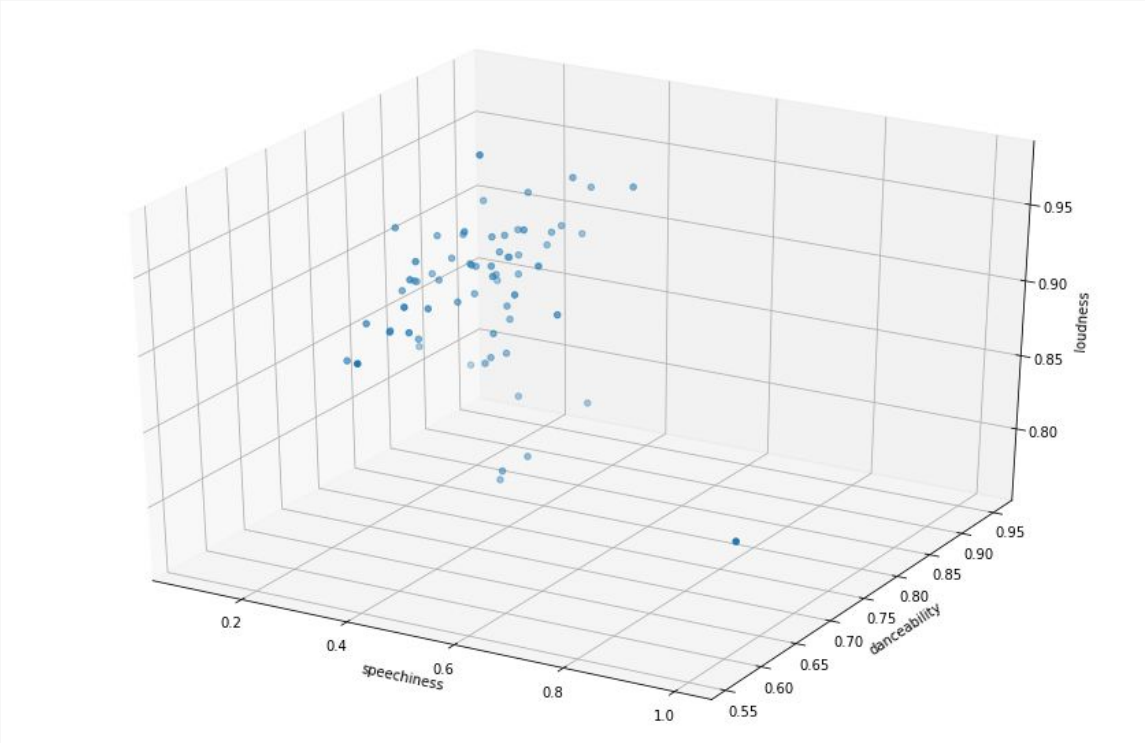
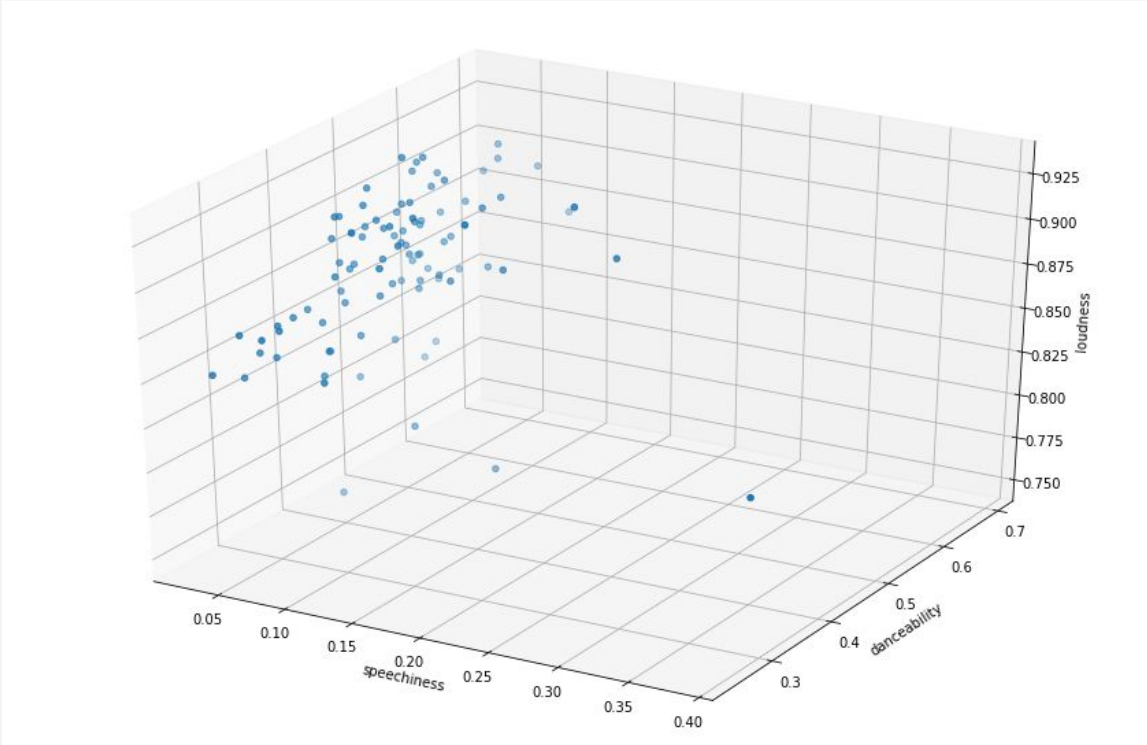
Features: Speechiness, Danceability, Loudness



Cluster 0



Cluster 38

CLUSTER ANALYSIS

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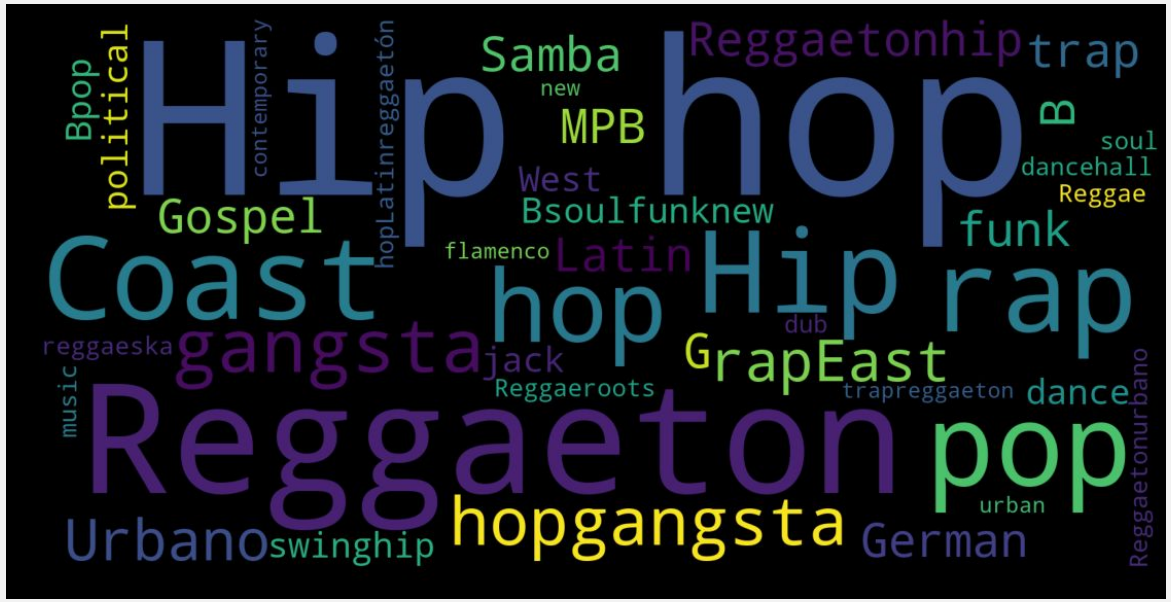
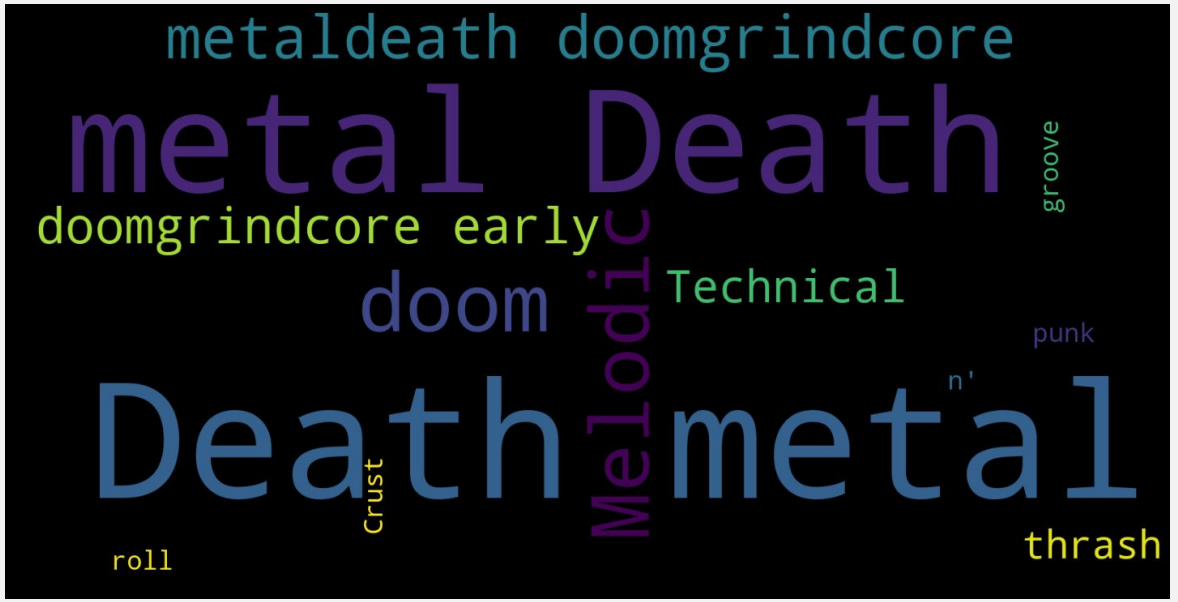
https://www.youtube.com/watch?v=FxQB1FYLu5k



Cluster 0
"Sunday morning"

https://www.youtube.com/watch?v=jo4i5mU8RV8



Cluster 38
"Messy day"

PROS AND CONS OF K-MEANS

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Pros

- Relatively simple to implement
- Scales to large datasets
- Guarantees convergence
- Can warm-start to position of centroids
- Easily adapts to new example
- Generalizes to clusters of different shapes and sizes (e.g. elliptical clusters)

Cons

- Choosing *K* manually
- Being dependent on initial values
- Clustering data of varying sizes and density
- Clustering outliers (e.g. outliers may get their on cluster instead of being ignored)
- Scaling with number of dimensions

CONCLUSION

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Coming back to our research questions:

- Are Spotify's audio features able to identify "similar songs", as defined by humanly detectable criteria? **YES!**
  - The songs in the clusters belong together
  - More features (e.g. popularity, genres) are recommended

- Is K-Means a good method to create playlists?
  - Not easy to decide, since we have to explore other methods
  - Clustering is not accurate enough

Thank you for your attention!