Spotify: A Deeper Dive

Analyzing my listening habits on Spotify through EDA & PCA.

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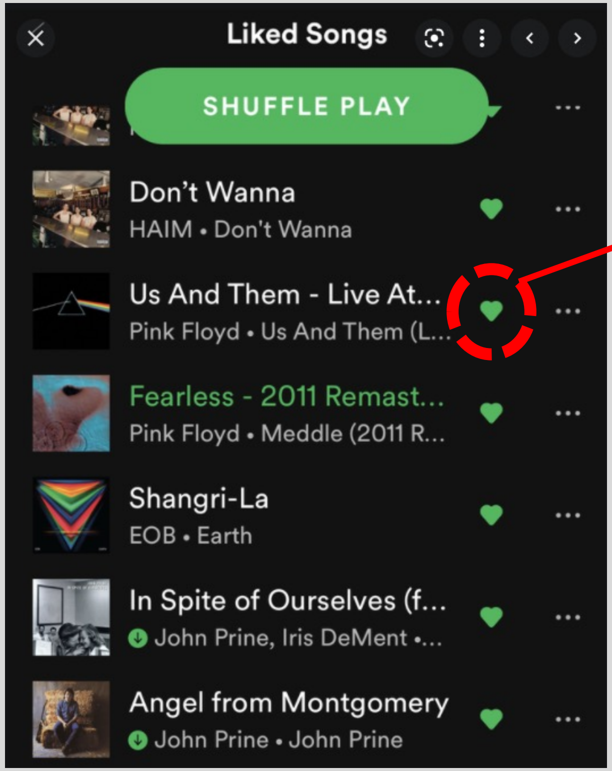
The Objective?



Using my "Liked" songs on Spotify, quantify and visualize my listening habits.

Identify trends, correlations, and insights that can be made from my "liked" music history.

Data Extraction

- Use *SpotifyR* to query my profile's playlist
- Iterate through each track's ID to extract features
- Combine identification & features into single data frame

SpotifyR package

get_playlist( )

get_track_audio_features( )

Features

Identifier

Danceability	Energy	key	Loudness	mode	Speechiness	Acousticness	Instrumentalness	Liveness	Valence	tempo	track_id	duration_ms	time_signature	track_name	artist_name	artist_id
0.806	0.913	6	-4.825	0	0.0467	0.00266	0.0932	0.0855	0.627	125.012	5jV0kgwhWafAdeJPVFcZpQ	263160	4	Want It	Black V Neck	2l0xOjnrmYsxNoQ0QI3G5a
0.806	0.638	8	-5.698	1	0.0424	0.149	0.0000137	0.119	0.858	104.976	2E7R8kXD7qZpvfW25F7gUW	195413	4	Prosecco	Patrik Jean	5QCf1Qb08Q4E3EPnyo8mw1
0.684	0.913	11	-4.203	0	0.0673	0.0395	0.39	0.0911	0.249	127.992	683i8O9hKQK1j9ai3mCo5M	355093	4	Funhouse - Digital Dog Remix	P!nk	1KCSPY1glIKqW2TotWuXOR
0.866	0.954	10	-7.38	1	0.0636	0.0953	0.429	0.123	0.9	124.965	7uIsUgH28J66pUa6nL2uSU	212000	4	Break Ya Neck	Sloth	5iD9mn2inFzm1u3jvr9egi
0.747	0.749	0	-6.337	1	0.0558	0.0798	0.00000179	0.318	0.914	121.964	2LAtELE0xGyMKcvNlxiyF3	138200	4	1 Day 2 Nights	HRVY	28y6CyJNkGNjJQKrlx4AmN
0.626	0.826	4	-4.474	0	0.0574	0.000482	0	0.335	0.461	122.976	1vZPWU4KC0Ao1XlIlJntL6	193840	4	Disco Love	The Saturdays	15qI5w4XJFLRMwOp2VrlD5
0.762	0.775	2	-4.348	1	0.034	0.0603	0	0.119	0.834	121.023	1HxcMzgxGXvteXSrTBbpu7	179507	4	Ego	The Saturdays	15qI5w4XJFLRMwOp2VrlD5

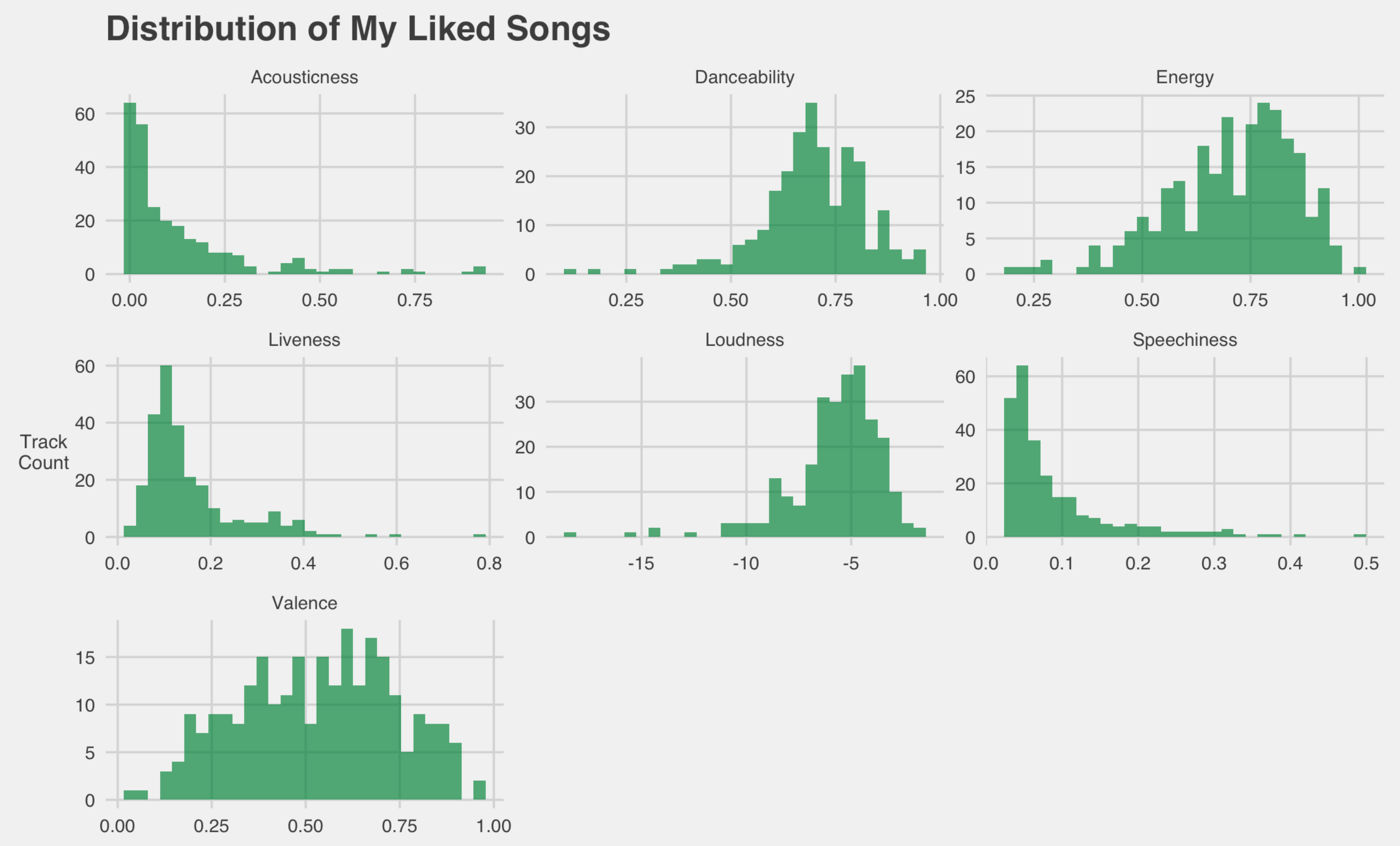
Exploratory Analysis

259 Tracks

221 Artists

Based on distributions, I tend to prefer more **danceable** and **energetic** tracks, rather than acoustic or “speechy” tracks.

I also like louder music.

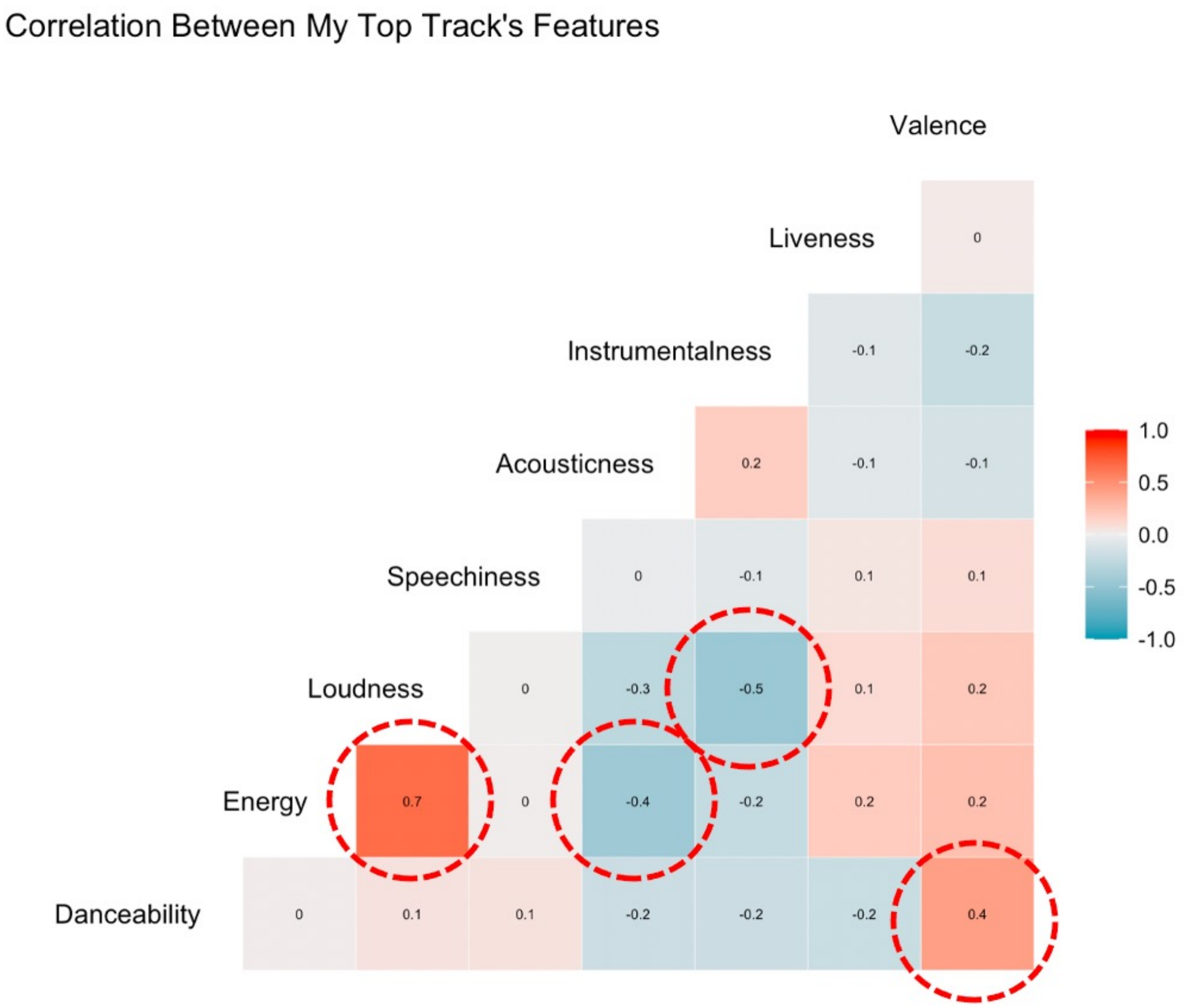


Feature Correlation

Correlation shows how close variables are to having a linear relationship with each other.

When my songs were **loud**, they tended to be more energetic and less instrumental.

The more danceable songs also tended to have a higher valence *(positivity conveyed by track).*



= "hotspot" relationships

PCA

INFO SLIDE:

Unsupervised method to reduce dimensions of data set

Collapse track features into **Principal Components** to more easily visualize

= PC1, PC2, PC3, PC4 …

PC1 Explains highest variation between features

Visual Example:

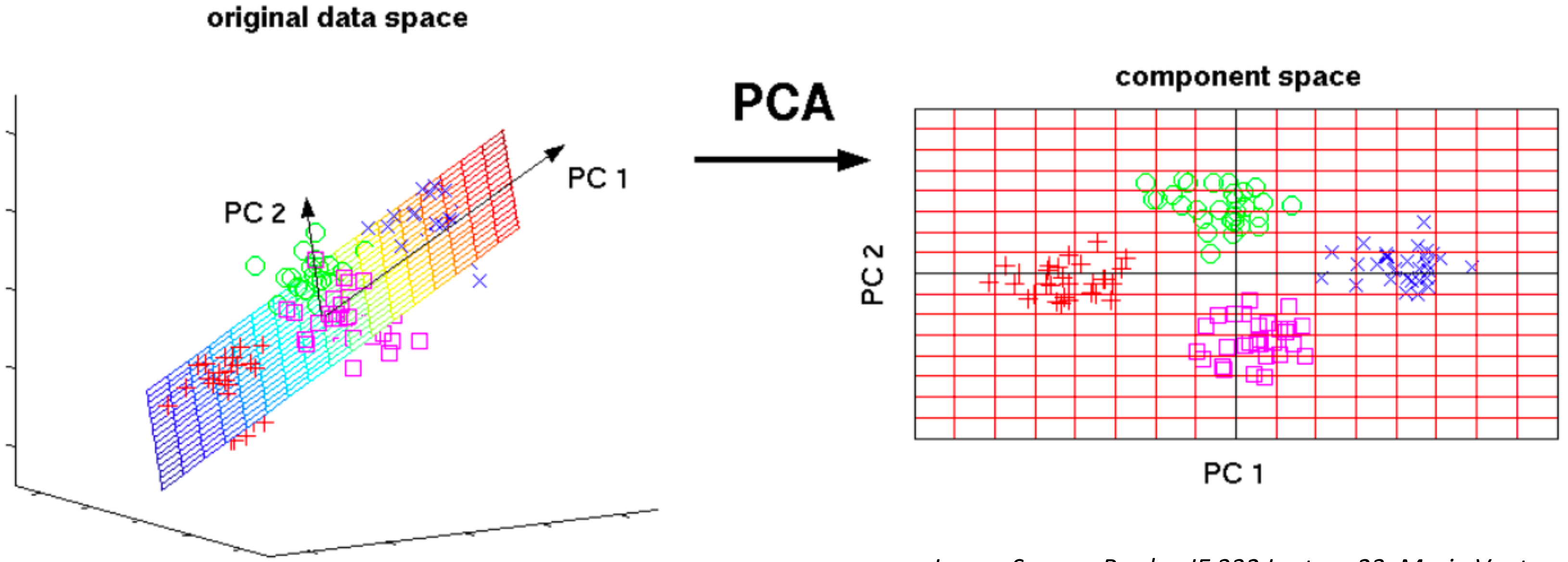
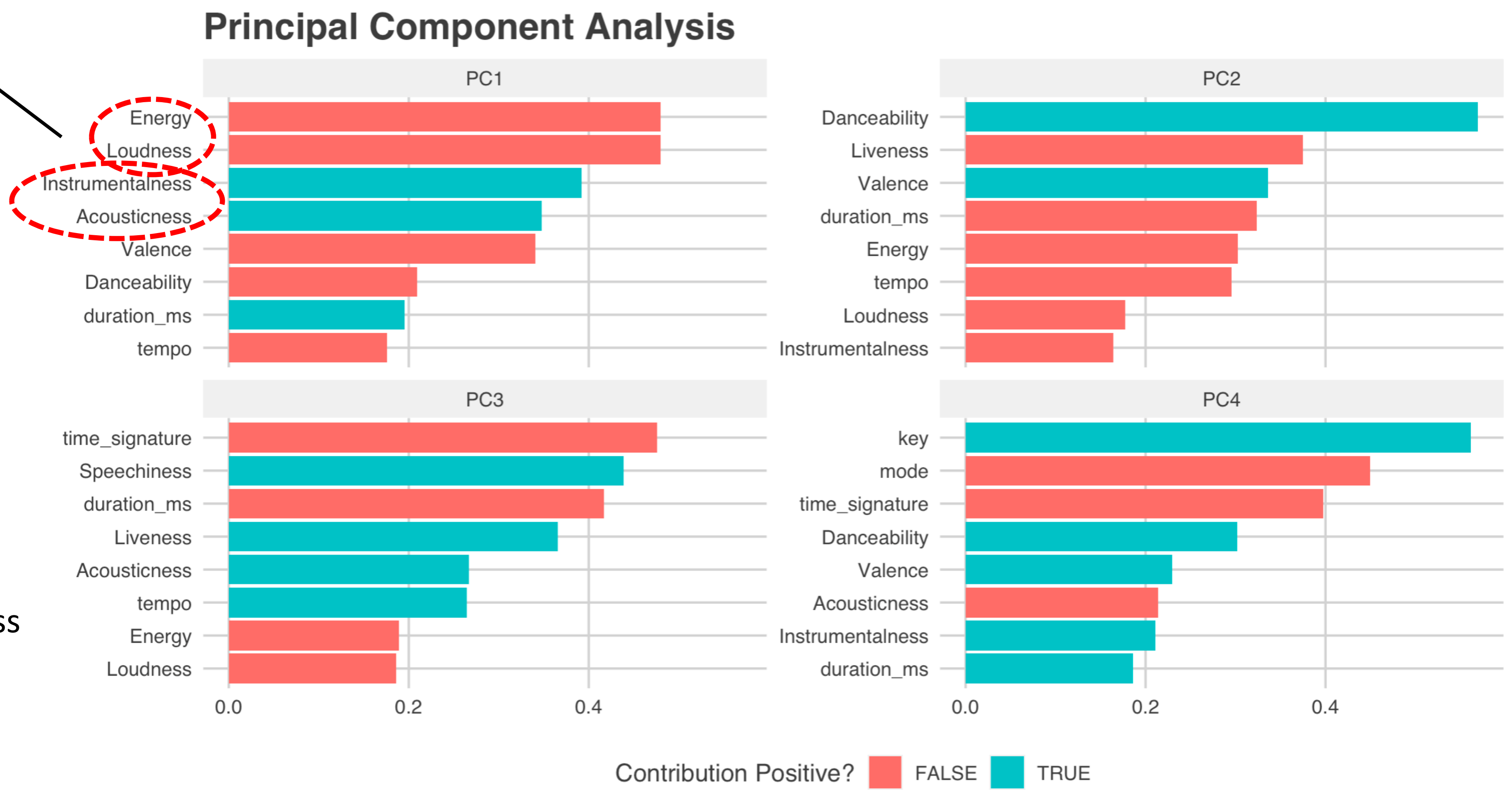


Image Source: Purdue IE 332 Lecture 23, Mario Ventresca

PCA

Correlated features explain variation in opposing directions



Features with high correlations tender to have a similar effect on variance explanation

Energy & Loudness

Instrumentalness & Acousticness

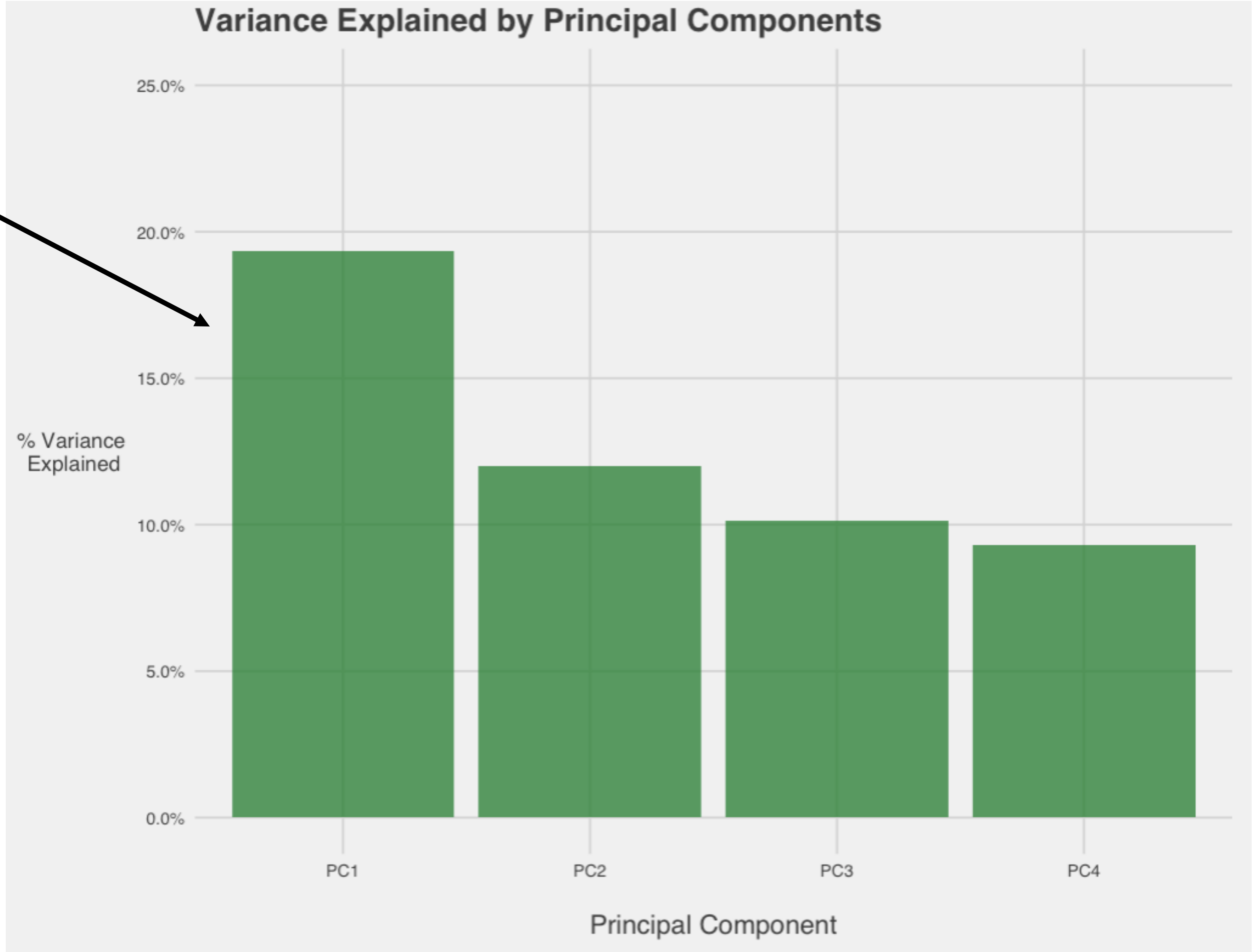
Valence & Danceability

PCA

PC1 only explains ~19% of variance, PC2 drops to ~12% *(31% total)*

Similarity of track features may cause minimal component explanation

My "Liked" songs are not that different?



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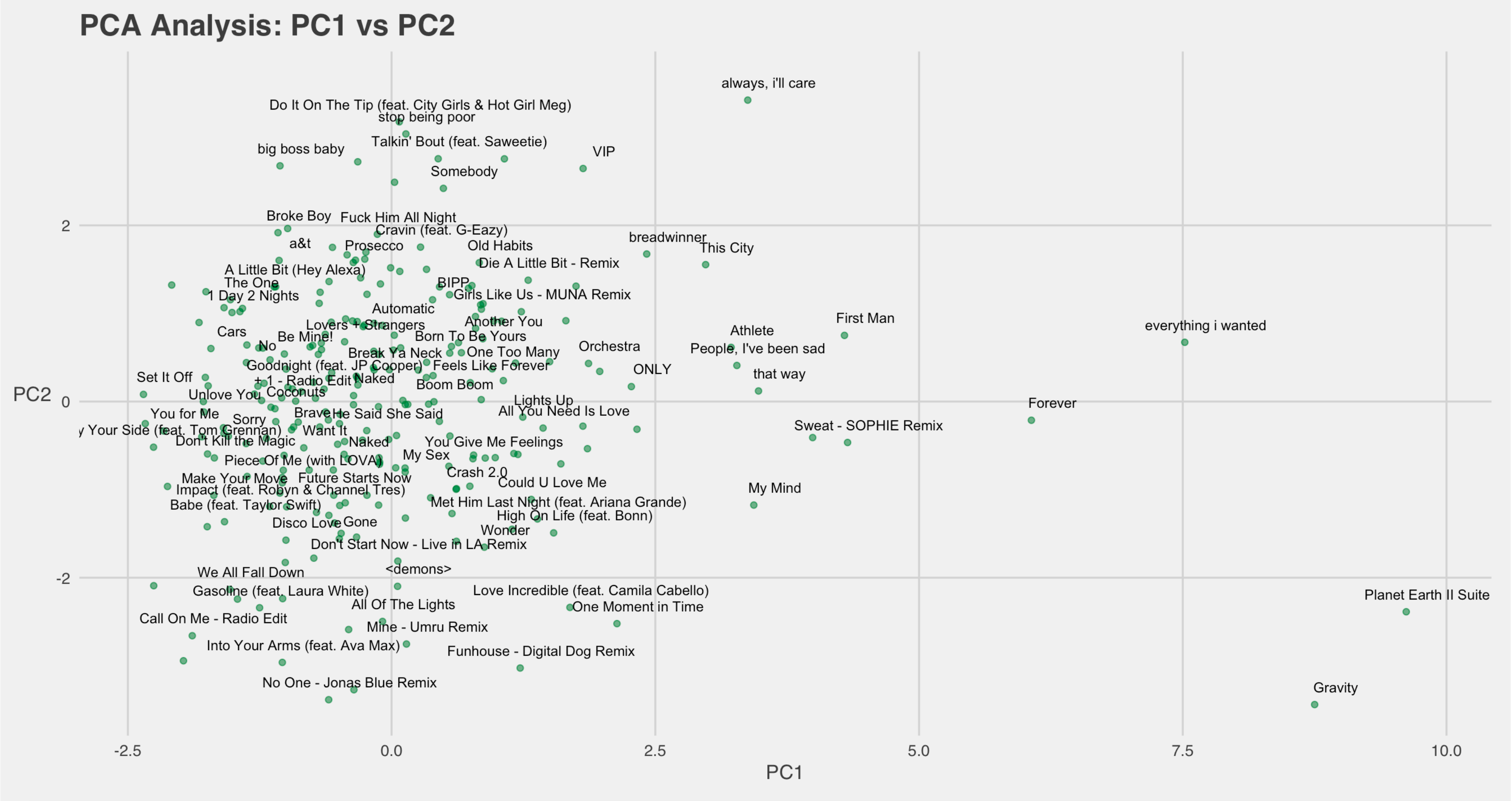
PC1 vs PC2 scatterplot (2D)

Tracks are not well defined by 2 PC's & are far from 2D subspace

For modelling, use a different dimensionality reduction method or include more features



PCA

Factor Mapping on PC1 vs PC2

Illustrates relationship between features & components

⇩

Most of my “liked” songs are energetics + loud