

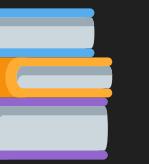
Predicting Song Suggestions Based on Track Metrics

Data 144 Fall 2021

Day 2 Session 1

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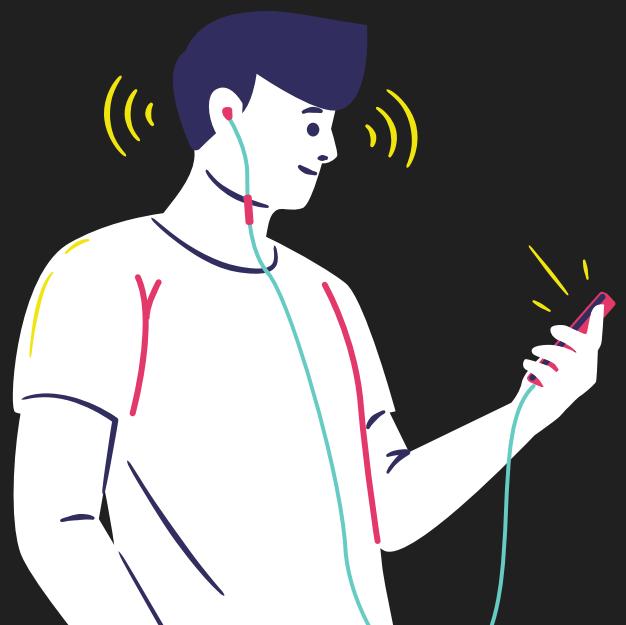
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Introduction

- **Can we accurately predict suggested songs following a playlist, based on the characteristics of a song?**
- Being able to predict songs that have a similar "vibe" can boost creative input, as well as an eclectic music taste
- Ability to "blend" any number of user's songs to recommend tracks that have the highest similarity across all user songs'.



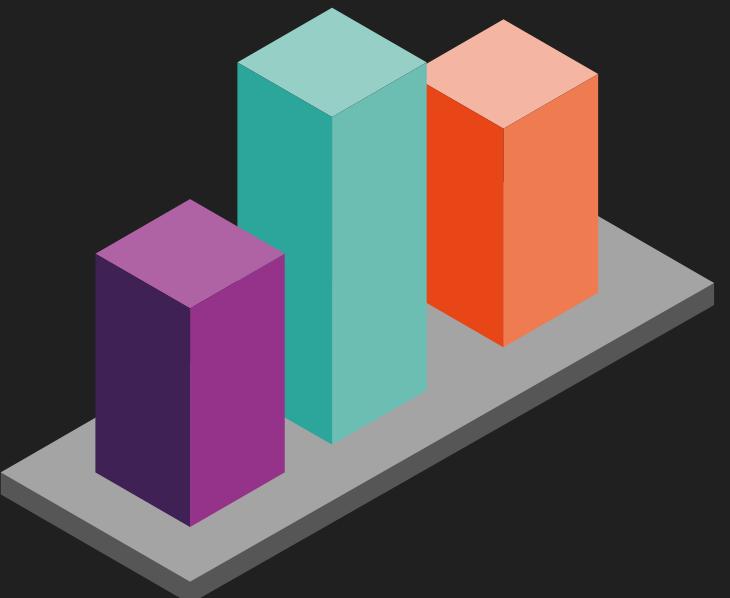
Dataset

- Raw data extracted from Spotify API [database](#)
- Web API has several endpoints, containing parameters relating to albums, artists, tracks, and playlists
- Includes categorical features like artist and album name, as well as more niche features like "danceability" and "energy"



Dataset

- Since we want to predict song suggestions based on playlist tracks, we meshed playlists together to make one playlist that's large enough to model on
- Created a CSV file consisting of four distinct users, each with their own distinct playlist(s)
- 4539 rows (tracks) x 17 columns (song attributes)

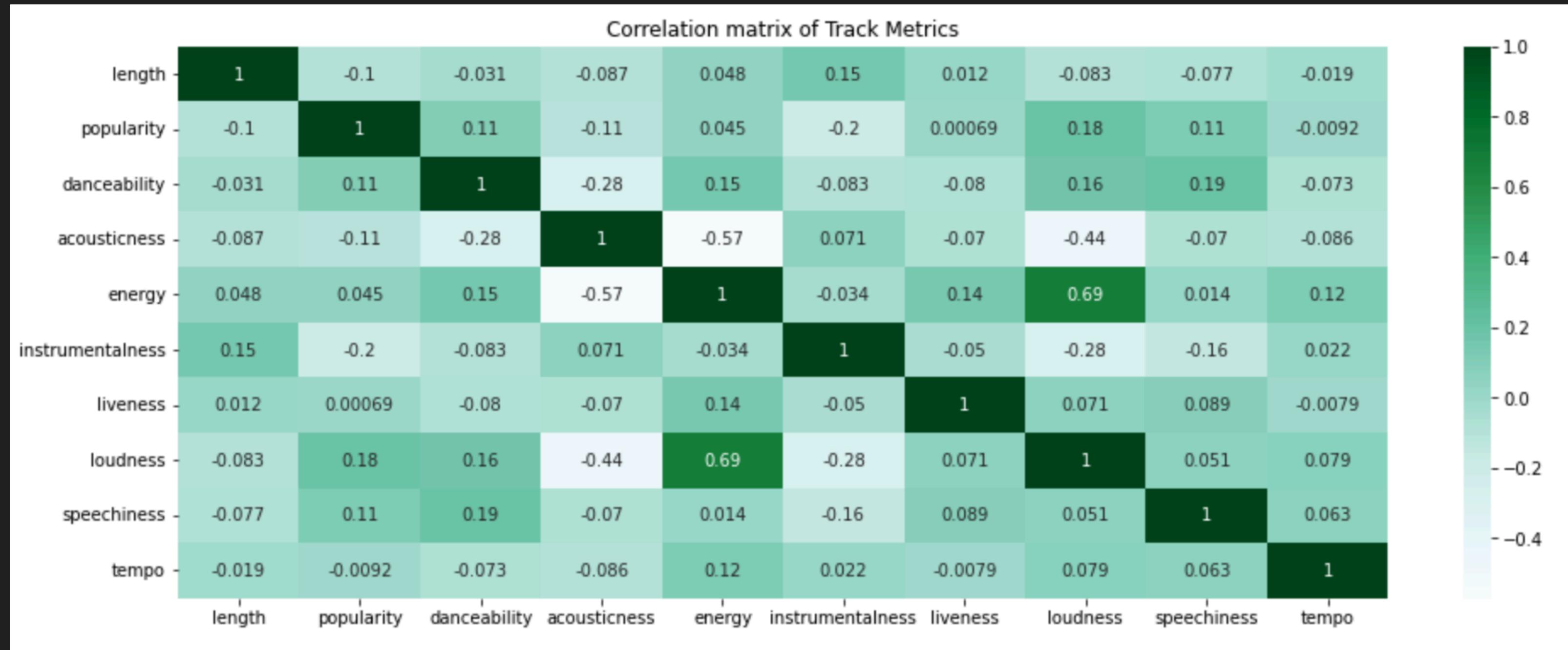


Dataset

- Song data was pulled from three distinct Spotify users, all of whom have different styles of music.

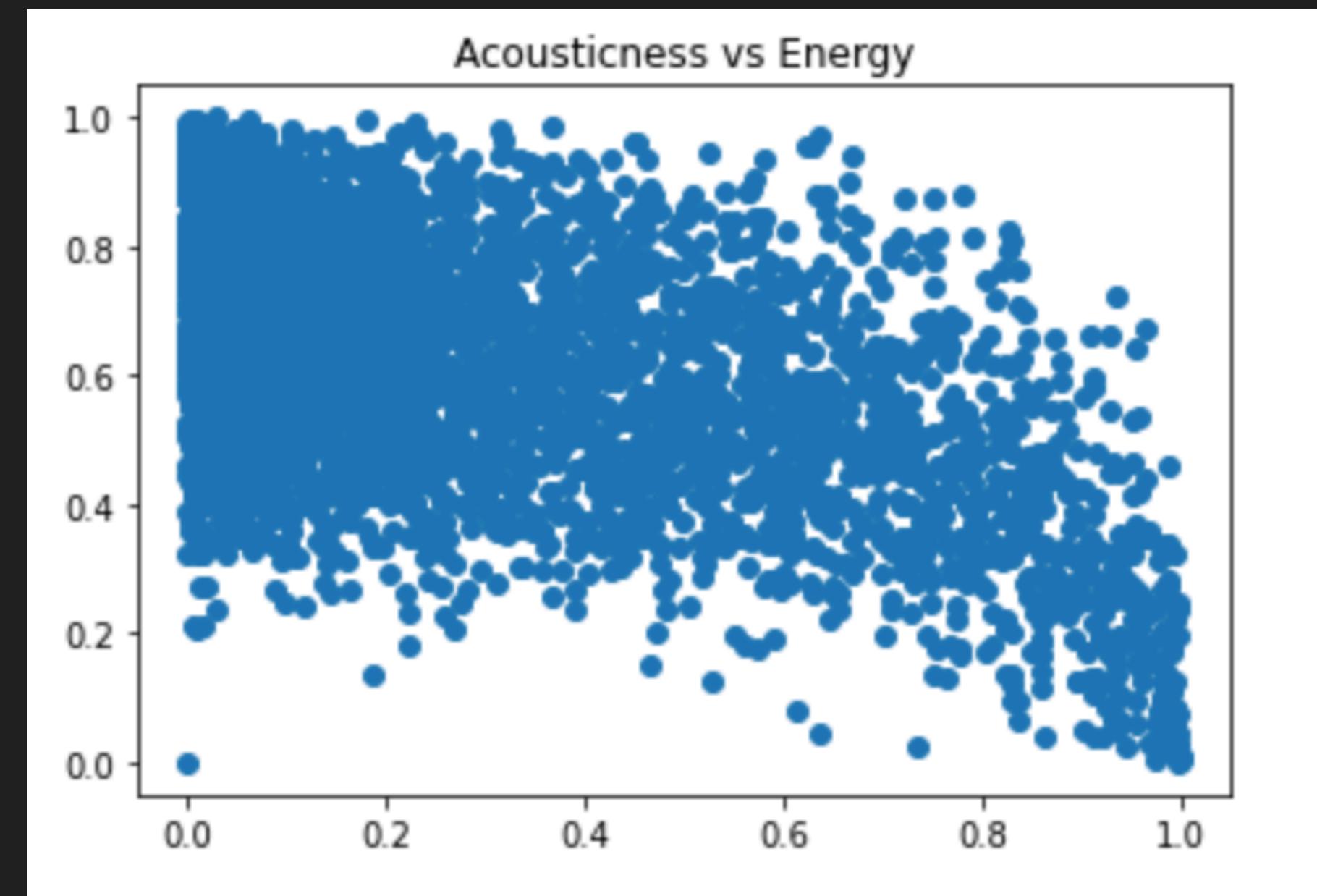
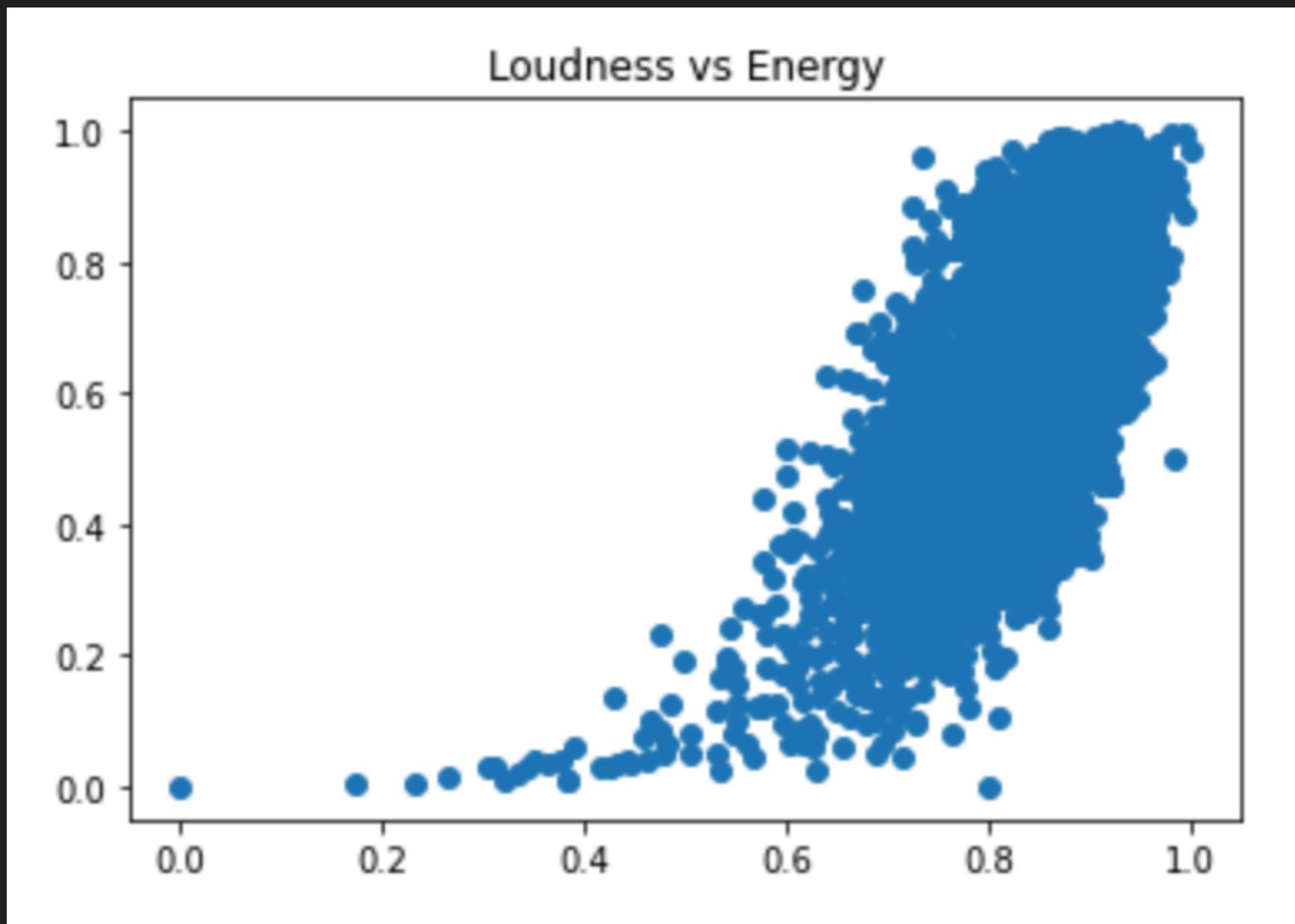
name	object	album	object	artist	object	release_date	object	length	int64	popularity	int64	danceability	float64	acousticness	float
Have Yourself a Memorable Christmas	0.1%	R&B: From Doo-Wop ...	0.8%	Various Artists	10.8%	2012-01-01	1.7%	3056 - 4747301	0 - 98	0 - 98	0.0 - 0.983	0.0 - 0.996	0.0 - 0.996	
Winter Wonderland	0.1%	Isles Of Wonder: Music	0.8%	Prince	1.7%	2013-01-01	1.3%	1865 others	97.1%	1865 others	0.874	0.874	0.874	
4377 others	99.8%	3271 others	98.4%	1860 others	87.6%	1865 others	97.1%	1865 others	97.1%	1865 others	0.182	0.182	0.182	
Fight Night	No Label II	Migos				2014-06-03		216247	68			0.874		0.182	
Versace (Remix)	Versace (feat. Drake) [Remix] - Single	Migos				2015-01-06		246047	59			0.845		0.0218	
Love Songs - Bonus	Parked Car Convos	Kaash Paige				2019-11-15		148640	74			0.641		0.831	
Cognac Queen	Tina Snow	Megan Thee Stallion				2018-12-21		222752	74			0.79		0.0593	
Wat U Sed (feat. Iamdoechii & Kal Banx)	The House Is Burning	Isaiah Rashad				2021-07-30		176682	64			0.838		0.101	

Exploratory Data Analysis



Most notable correlations are between the "energy" and "loudness" features (skew positive) and "energy" with "acousticness" (skew negative)

Exploratory Data Analysis

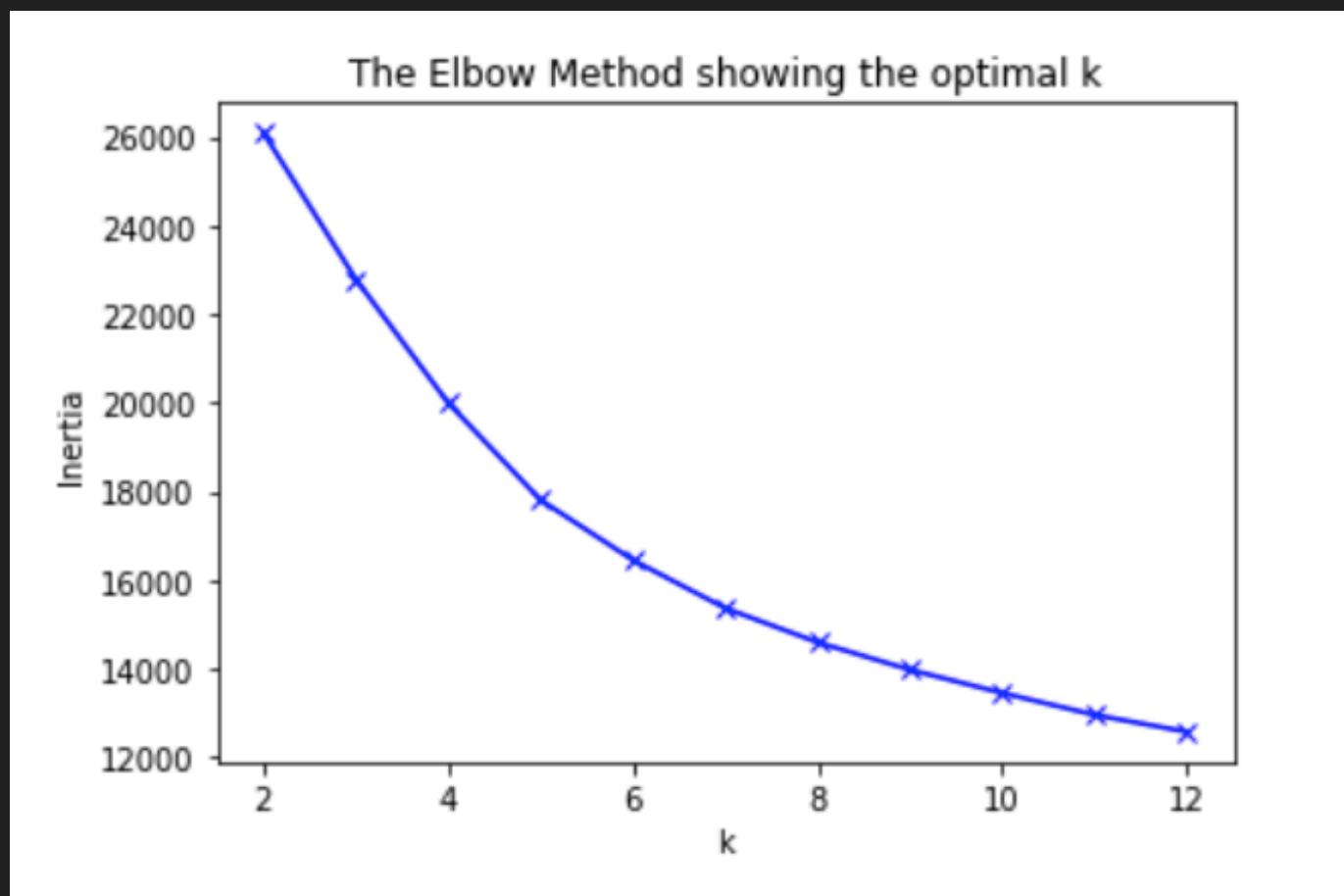




Modeling

Clustering

- To begin our cluster analysis, we used the elbow method to find the optimal number of clusters
- We found that the optimal number of clusters was five
- Given this value, we used sklearn's clustering algorithm on our dataset, creating a table of the cluster labels, dimensional feature values, and track info for each data point or track
- Created a table of cluster centers for use in the recommendation part of our analysis

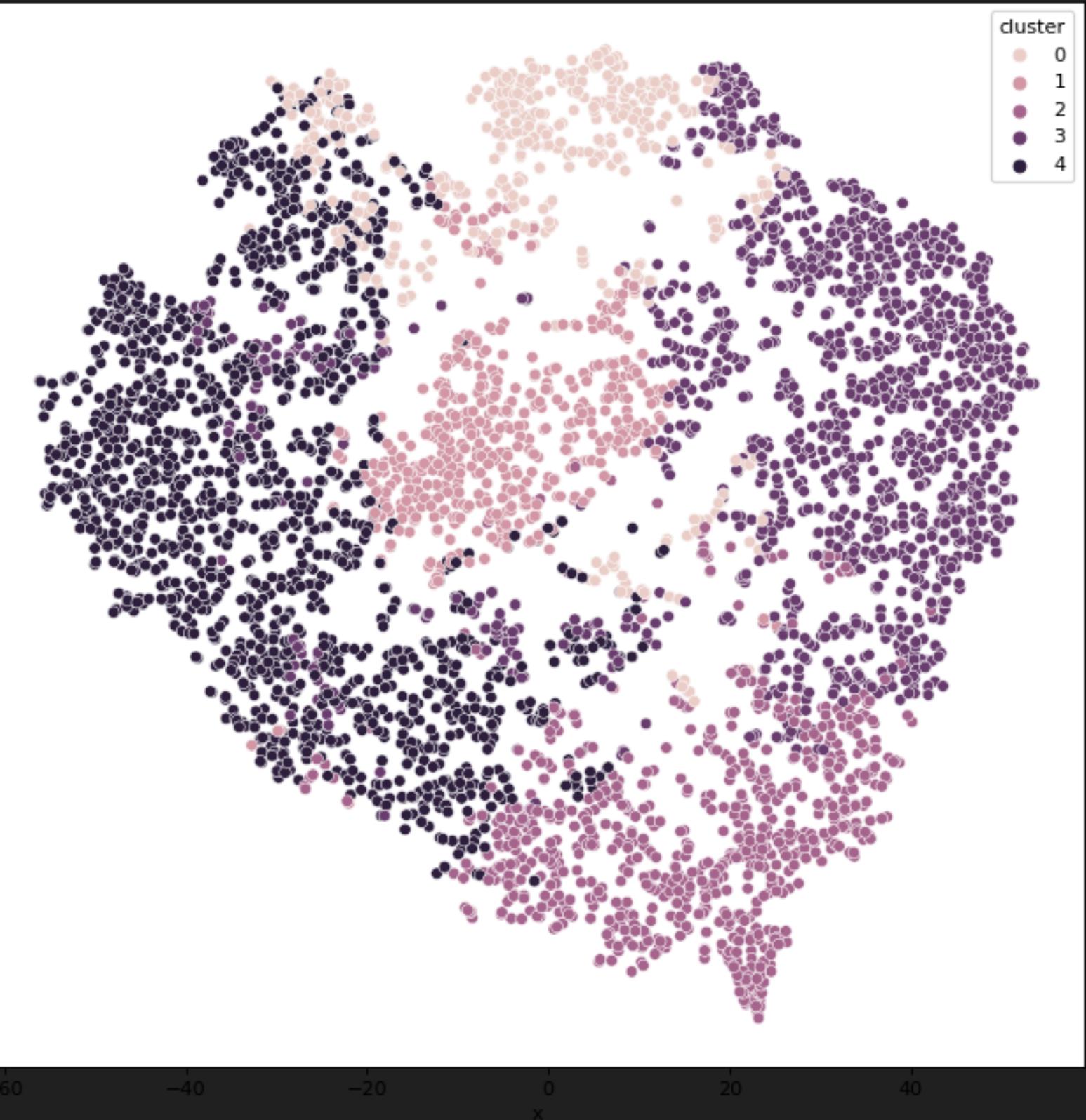


t-SNE

- t-SNE, or t-distributed stochastic neighbor embedding, is a machine learning technique that performs dimensionality reduction on our data
- Given a large number of features, dimensionality reduction helps to downsize this number into a number of components that can easily be graphed
- We used t-SNE to reduce the dimensions of our data point table and cluster center table
- This allowed us to better visualize, analyze, and understand how each data point fit into a given cluster

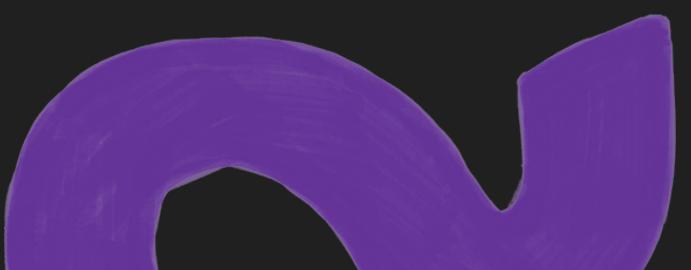
Clustering

- Performed t-SNE embedding on our dimension reduced data to give us five clusters (from optimal k-mean cluster)



Random Track Subsetting

- We needed to randomly select a large dataset of new songs from Spotify's API
- Created a function which called on Spotify's search endpoint, adding a random letter to the final query string
- We used a wildcard character (%), randomly entering it after or on both sides of the random letter within the final query string (e.g. 'd%' or '%d%')
 - Allowed us to search for any song that matched the random letter that was entered
- Randomly selected the offset parameter, which specified where in the returned data, to start picking songs from
- Ended with a new dataset of 1,000+ randomly selected songs



Recommendation Analysis

```
column_names = [ "name", "album", "artist", "distance"]
# test_centers_trimmed = test_centers.iloc[:,4:]

# calculate the Euclidean distance between two vectors
def euclidean_distance(row1, row2):
    distance = 0.0
    for i in range(len(row1)-1):
        distance += (row1[i] - row2[i])**2
    return np.sqrt(distance)

#finds the distance to the closest cluster for a given song
def find_distance_from_centers(song, centers):
    distances = []
    for i in range(len(centers)):
        distance = euclidean_distance(song, centers.iloc[i, :])
        distances.append(distance)
    return min(distances)

#create a dataframe that includes a best distant column
def near_cluster_centers(centers, songs):
    songs_distances = pd.DataFrame(columns = column_names)
    for i in range(len(songs)):
        song_trimmed = songs.iloc[i, 5:12]
        best_distance = find_distance_from_centers(song_trimmed, centers)

        songs_distances.loc[i, "name"] = songs.iloc[i, 0]
        songs_distances.loc[i, "album"] = songs.iloc[i, 1]
        songs_distances.loc[i, "artist"] = songs.iloc[i, 2]
        songs_distances.loc[i, "distance"] = best_distance

    return songs_distances

distance_df = near_cluster_centers(cluster_center_table, random_songs_df)
distance_df.sort_values("distance")
```

- After gathering random Spotify tracks, we needed to write a function that measured the distance to the closest cluster for any given song
- Songs closest to our 5 cluster centroids had the highest similarity across all of our metrics
- The songs with the smallest distance were then recommended

Results

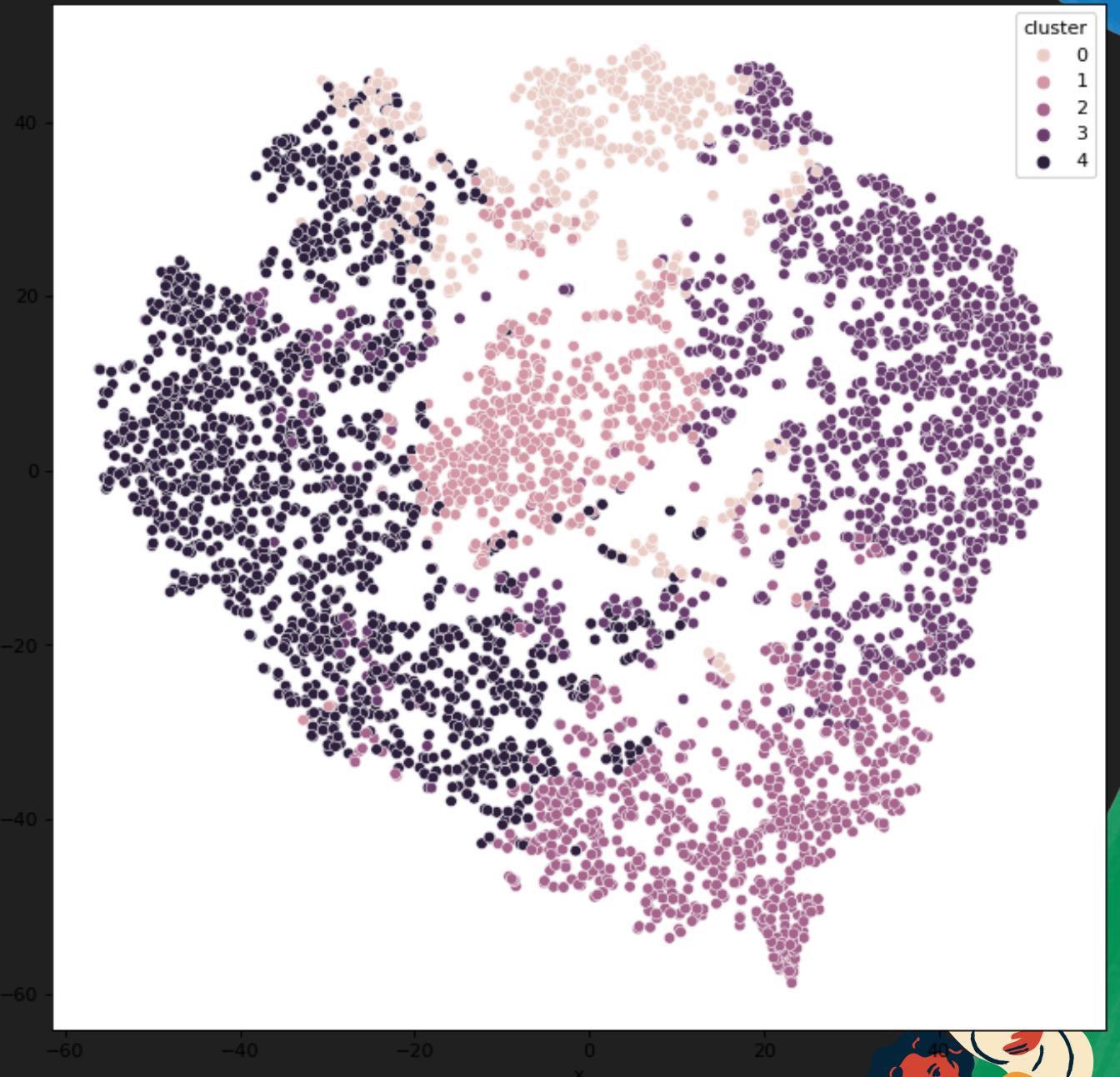
- Suggested songs relative to cluster centroids based on metrics



	name object	album object	artist object	distance object
	Quizás Si, Quizá... 0.2%	Red (Taylor's Vers... 1.9%	Taylor Sw... 3%	0.7668313278239... 0.1%
	Kings & Queens 0.2%	Fighting Demons 1.5%	Juice WRLD 3%	1.1709282284143... 0.1%
	1052 others 99.6%	844 others 96.6%	572 others ... 94%	1061 others 99.8%
351	Balance ton quoi	French Song's For New Year's Eve	Angèle	0.7668313278239661
615	The Christmas Song (Chestnuts Roasting On An Open Fire)	Christmas for Kids	Justin Bieber	1.1709282284143183
435	Lover	Music Superstars	Taylor Swift	1.2155788691666856
282	Ready	Trending Now Volume 39	Lil Baby	1.2416300444302046
356	Quihubo Cuando - En Vivo	Quihubo Cuando (En Vivo)	Carin Leon	1.281367592575012

Conclusion

- Although we modeled and analyzed a dataset with over four thousand features (tracks), more expansive data would be useful in producing more accurate predictions
- Standardizing data would help in making sense of our analyses
- Not enough memory to do more training/modeling
- Learning how to suggest more "similar" tracks is useful for user experience and stakeholder (Spotify's) profit.



Thank you!