Summary

Project Title
Spotify Deep Dive - Coding on The Weeknd

Team Members
- Riona Espedido
- Tasha Do
- Mark Peck
- Sri Penumatcha

Project Description/Outline
Using the Spotify API to analyse trends and patterns relating to albums, artists, playlists and songs.

Q1	Tasha Do
Q2	Riona Espedido
Q3	Sri Penumatcha
Q4	Mark Peck

Datasets to be Used
https://developer.spotify.com/documentation/web-api

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1. Q1 - Genre vs Audio Features

Research question: what genre dominates which audio feature and what analysis can be provided?

1.1 Source

Spotify playlists require you to choose Playlist to extrapolate their tracks and their data.This is through identifying their playlist “Playlist ID”. The chosen playlists and their corresponding “Playlist ID” are as follows:

Genre	Playlist Name	{playlist_iD}
Country	Country Mix	37i9dQZF1EQmPV0vrce2QZ
Death-metal	Death Metal Mix	37i9dQZF1EIf78r65WuXwA
Drum-and-bass	Drum and Bass Mix	37i9dQZF1EIherXksVvnrN
Hip-hop	Hip Hop Mix	37i9dQZF1EQnqst5TRi17F
Pop	Pop Mix	37i9dQZF1EQncLwOalG3K7
Rock	Rock Mix	37i9dQZF1EQpj7X7UK8OOF

The following provides a brief description for each Spotify audio feature used in the following analysis.

Genre	Type	Description
Loudness	dB	The overall loudness of a track in decibels (dB). Values typically range between -60 and 0 db
Tempo	BPM	The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.
Acousticness	0.0 to 1.0 Scale	A confidence measure of whether the track is acoustic.
Danceability		Describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity.
Energy		Represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.
Instrumentalness		Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal".
Valence		describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

1.2 Top Genre by Audio Feature Average

The below table provides the average audio feature for each genre where:

Genre	Danceability	Energy	Loudness	Acousticness	Instrumentalness	Liveness	Valence	Tempo
country	0.56784	0.57468	-7.28798	0.351710	0.001955	0.146506	0.474560	119.95554
death_metal	0.35016	0.93722	-5.76456	0.000344	0.413084	0.228660	0.268878	118.39464
drum_and_bass	0.55230	0.87058	-3.14776	0.049614	0.098785	0.215868	0.336012	139.86554
hip-hop	0.74594	0.66716	-6.66886	0.176523	0.002311	0.215512	0.557440	114.93276
pop	0.63748	0.68478	-5.01192	0.164444	0.000129	0.160110	0.519116	115.83242
rock	0.51538	0.75504	-7.07282	0.101358	0.031590	0.170108	0.532900	128.62016

Figure 1.1 Average Audio Feature Value by Genre

From looking at this summary of the average aggregation of each audio feature, we can find that the top genre for each audio feature are as follows, to 2 decimal places:

Audio Feature	Top Genre	Type	Value
Danceability	Hip Hop	Linear scale (0.00 to 1.00)	0.75
Energy	Death Metal	Linear scale (0.00 to 1.00)	0.94
Loudness	Drum and Bass	dB	-3.15
Acousticness	Country	Linear scale (0.00 to 1.00)	-0.35
Instrumentalness	Death Metal	Linear scale (0.00 to 1.00)	0.41
Liveness	Death Metal	Linear scale (0.00 to 1.00)	0.29
Valence	Hip Hop	Linear scale (0.00 to 1.00)	0.56
Tempo	Drum and Bass	BPM	139.87

Figure 1.2 Top Genre for each Audio Feature

1.3 Track Distribution of the *"Danceability"* Audio Feature

Exploring the Danceability audio feature, we can understand the distribution of this audio feature for all audio tracks of a specific genre. This is seen in the below box plot.

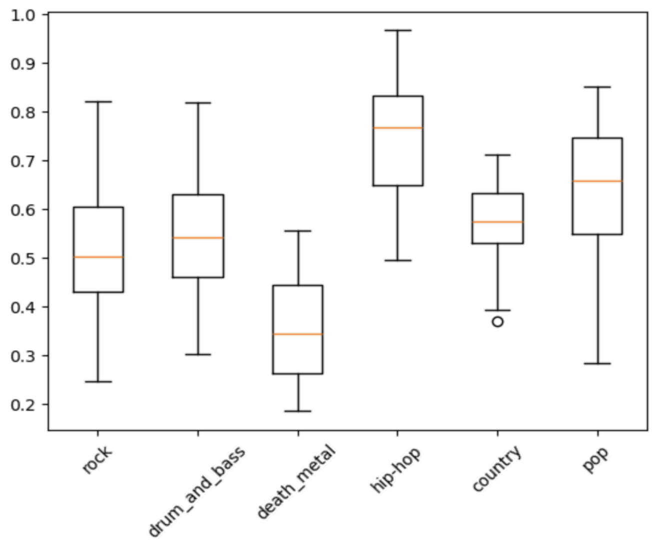

Figure 1.3 Genre by Danceability Audio Feature (0.00 to 1.00)

It can be seen that the distribution of Hip-Hop tracks is scaled much higher than the other genres.

1.4 Genre with Highest Total Variance

The following analysis identified the genre with the most variance in their audio features; concluding which genre of music is the most diverse.

Total variance is calculated by summing the variance of each parameter, in this case, each audio feature (i.e. Var(X + Y) = Var(X) + Var(Y)). This has been calculated as per the below table, under heading “Total Var. Incl. Loudness and Tempo”.

Although, knowing that Loudness and Tempo are calculated using dB and BPM respectively, this skews our data as the other audio features utilise the linear scale (0.00 to 1.00) to quantify their measurement. To avoid skewing this data, we can remove the variance for Loudness and Tempo to generate an updated genre total variance under the heading “Total Var. Excl. Loudness and Tempo”.

Additional columns are provided to show the rank of lowest to highest total variance for each genre.

	Genre	Total Var. Incl. Loudness and Tempo	Rank Incl. Loudness and Tempo	Total Var. Excl. Loudness and Tempo	Rank Excl. Loudness and Tempo
0	country	1075.244994	2	0.166542	2
1	death_metal	548.593037	5	0.203888	1
2	drum_and_bass	1836.976728	1	0.140738	4
3	hip-hop	1069.295923	3	0.155203	3
4	pop	507.444116	6	0.119054	6
5	rock	790.422618	4	0.127796	5

Figure 1.4 Total variance by Genre

From this table, we can see the genre Drum and Bass was ranked number 1 in the most diverse genre of music, but then became number 4. Death Metal becomes number 1 when removing Loudness and Tempo in the calculation of audio features.

These are also plotted graphically for reference here:

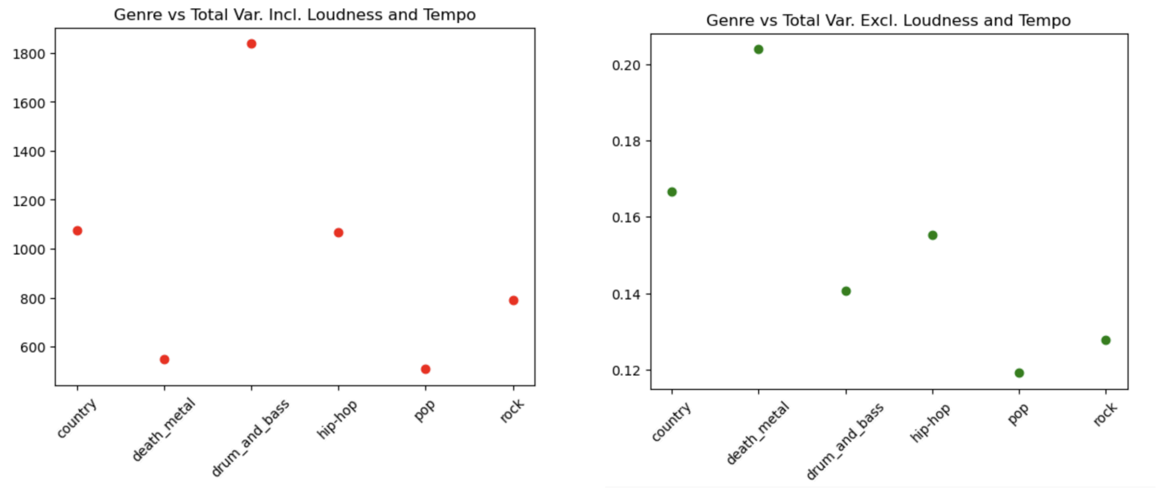

Figure 1.5 Comparison of total variance: Total variance including loudness and tempo (left), Total variance excluding loudness and tempo (right)

1.5 Analysis

From the chosen 6 genres:

- Death Metal dominates the most Spotify audio features as per the following table summary. The type of audio features that Death Metal dominates, indicates that Death Metal is certainly the most extreme type of music compared to the other genres.

Audio Feature	Top Genre	Type	Value
Energy	Death Metal	Linear scale (0.00 to 1.00)	0.94
Instrumentalness	Death Metal	Linear scale (0.00 to 1.00)	0.41
Liveness	Death Metal	Linear scale (0.00 to 1.00)	0.29

- Hip-hop scores the highest on Danceability, with the scoring distribution of hip-hops tracks significantly higher than the other genres. This could mean that hip-hop tracks are more utilised by dancing studios and clubs.
- Drum and Bass have the highest score of total variance if including the tempo and loudness audio features, whereas Death metal does if excluding the aforementioned audio features. This indicates that these genres have the more varied and diverse type of music.

4. Q4.1 - User Data vs Daily Mix

Research question: Does Spotify glean from user data to generate recommended mixes and how faithful are they to that data?

4.1.1 Source

User data called “Top Tracks” was selected as these were the tracks that Spotify considered my favourite. These were compared to the 6 “Daily Mix” offerings generated by Spotify. All were called through the API and converted into DataFrames.The “features” of each track are numerical representations of a track’s qualities. Some are typical, like tempo, and others are generated by Spotify, such as “danceability”.

Selecting track metadata to feature ‘feaures’:

	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo	duration_ms
0	0.399	0.7610	9	-6.318	1	0.0334	0.000105	0.0456	0.0757	0.2430	140.084	304907
1	0.252	0.1880	1	-11.648	1	0.0456	0.329000	0.1210	0.1000	0.0302	86.997	113773
2	0.404	0.4070	5	-11.843	1	0.0299	0.492000	0.0338	0.3910	0.0848	106.547	189293
3	0.430	0.2560	2	-15.737	1	0.0607	0.161000	0.8520	0.1470	0.2080	96.704	330905
4	0.213	0.0695	11	-14.832	1	0.0409	0.018500	0.9580	0.1240	0.0382	112.192	106213

Figure 4.1.1 Track audio features DataFrame

4.1.2 Visual Analysis

Example violin plot showing the different distributions of data. This assisted in the manual selection of data for running the tests. This was to avoid running huge amounts of data when a small sample of the data would suffice. The Indie Mix and the Upbeat Mix appeared quite similar and different to my User Top Tracks, respectively.

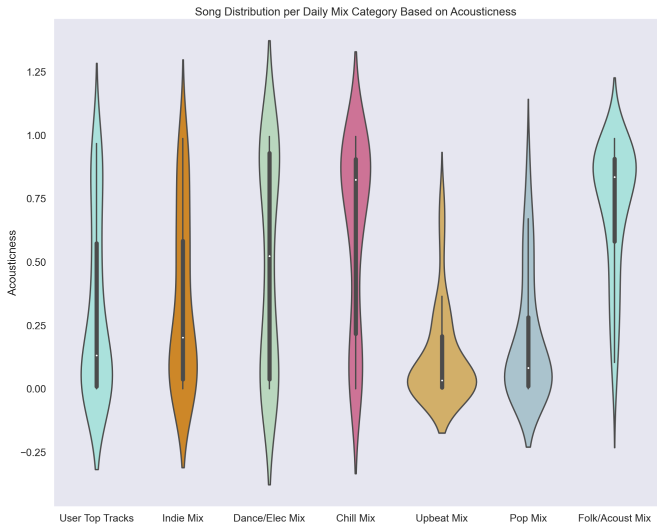

Figure 4.1.2 Violin Plot of all data

4.1.3 ANOVA Test

Running ANOVA test on all data sets (user data and 6 daily mixes):

	ANOVA Score	P Value
Danceability	20.573458	1.376305e-20
Energy	26.219777	1.156735e-25
Acousticness	25.849988	2.431911e-25

Figure 4.1.3 ANOVA Score

4.1.4 T Test

Running T test on manually selected daily mixes and manually selected features:

	T Score	P Value
Indie Danceability	-2.910622	4.465015e-03
Indie Energy	-1.956052	5.330610e-02
Indie Acousticness	-0.515548	6.073311e-01
Upbeat Danceability	-7.768563	7.881566e-12
Upbeat Energy	-6.256453	1.036904e-08
Upbeat Acousticness	3.276788	1.452878e-03

Figure 4.1.4 T Test

4.1.5 Pearson Regression

Running Pearson regression on the same manually selected categories:

	Pearson R Score	P Value
Indie Danceability	0.024543	0.865653
Indie Energy	-0.041358	0.775513
Indie Acousticness	-0.048103	0.740095
Upbeat Danceability	-0.036797	0.799726
Upbeat Energy	-0.165771	0.249933
Upbeat Acousticness	-0.189392	0.187742

Figure 4.1.5 Pearson Regression Test

4.1.6 Conclusion:

Where the scores for the statistical tests show a greater difference, the p values are below the necessary 0.05 alpha. Where the test scores are similar to the mean or show no correlation, showing a lesser difference, the p values are very high. This suggests that we can reject the null hypothesis and conclude that Spotify is likely introducing variance into the mixes, which should be interpreted as novelty.

Q4.2 Track Recommendation Program: Coding on The Weeknd

4.2.1 Research Question

Can I reverse the original question in order to create my own miniature program to recommend a track to listen to?

4.2.2 Method

In order to create a small program within the time frame, an individual artist was selected, and that artist’s top tracks were called from the Spotify API.

Using the same audio “features” as before, they were all standardised as Z scores. Then they were compared by using the function “cosine similarity” and a matrix was generated.

4.2.3 Similarity Matrix

```
# Create matrix using cosine similarity function
similarity_matrix = cosine_similarity(top_weeknd_z_scores.values, features_z_score.values)

# build dataframe for display
similarity_df = pd.DataFrame(similarity_matrix, index=top_weeknd_z_scores.index, columns=features_z_sc
similarity_df
```

	0	1	2	3	4	5	6	7	8	9
0	0.153647	-0.100868	-0.088900	-0.284247	0.177419	0.547879	0.225539	-0.036782	-0.616390	0.204620
1	0.402101	-0.262322	-0.255256	0.210272	0.123630	-0.208126	-0.020619	0.376442	0.049501	-0.502087
2	-0.122630	-0.255833	0.015568	0.206217	-0.440012	-0.225308	-0.162235	0.502341	0.567624	-0.006296
3	0.589635	-0.106175	-0.273008	-0.357188	-0.001530	0.404514	-0.096364	0.276595	-0.126206	-0.033196
4	0.144072	-0.073902	-0.191192	0.149430	-0.176201	0.034012	0.134174	-0.326447	0.066837	0.199747
5	-0.522558	0.457095	0.185955	0.394205	0.683569	-0.675209	-0.256042	-0.557009	0.055456	-0.221833
6	0.119960	-0.401715	0.280017	-0.269796	-0.489835	0.208302	0.034956	0.302678	0.213802	0.206813
7	-0.322536	0.406763	0.263235	-0.135957	-0.337470	0.043581	-0.026239	-0.212431	-0.048910	0.507025
8	-0.150868	0.287781	-0.108203	0.026373	-0.054031	0.362283	0.238673	-0.343011	-0.375437	0.179432
9	0.118062	-0.102270	-0.127394	-0.415042	0.126486	0.360543	0.421124	0.074626	-0.184547	-0.294974

Figure 4.2.3 Similarity matrix

4.2.4 Heatmap

The matrix now visualised in a heatmap.

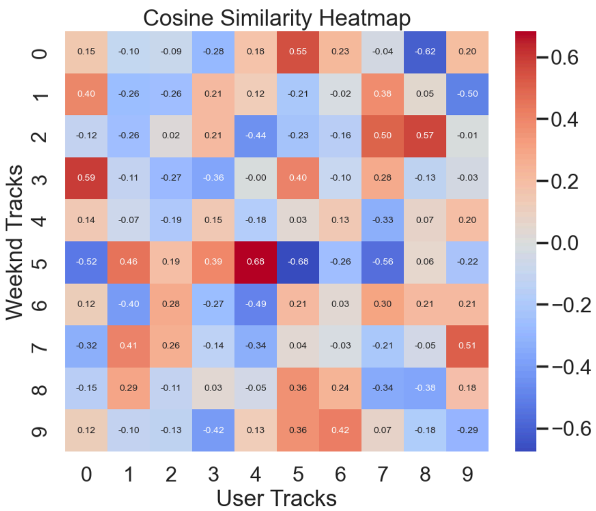

Figure 4.2.4 Similarity matrix heatmap

One track stood out as the most similar, and its ID number was fed back into the API, resulting in a track title: “Starboy”

4.2.5 Conclusion

Conclusion:
The track “Starboy” is acceptable to listen to, and it deserves the score of 0.68 out of 1.