In my analysis of my personal Spotify playlist, I look at approximately 25% of the playlist (as it is more than 400 songs-long) in which I tackled Task 2 and 3 of the class lab Jupyter Notebook.

With Task 2, I created five subsets of the features based on different aspects of songs that could be looked at by a recommendation algorithm. Looking at the features related to music theory (e.g. time signature and key), the results were relatively predictable. For instance, songs with a fast tempo had high cosine similarities irrespective of genre. With this subset, very similar songs would only be the same in the way the music is composed/produced. Some subsets proved to be useless in finding similar songs; using a subset with file features (e.g. song duration) could not tell me much about the songs apart from them either having the same length or volume. A subset based on the 'speechiness' and 'instrumentalness' of songs had the greatest number of similarities. As expected, more instrumental heavy songs were more like each other than more lyrical songs (with some exceptions) – it seems that with this subset, the similarity scores are dependent on the ratio between a song's lyricism and instrumentals (according to Spotify's algorithm). The best subsets were the ones with features pertaining to the overall atmosphere the song produced. One subset looked at a song's valence and energy, the songs with high similarity scores were very similar in how energetic they are and how they make the listener feel. For example, calmer music that were still high energy matched with similar songs; the same happened with songs that were also high energy but more on the excitable side.

In Task 3, I used the audio features to create a recommendation algorithm based on the feature subset used. The seed track was 'vs. Eve' by Funk Fiction – a *psydub* song (electronic music that has its roots in psychedelic trance and dub music). It is the more unique song in the sample set from my playlist so it was interesting to see what I could make of the recommended songs. The first attempt used random features; the songs given were not very similar which showed that I would need to make the criteria stricter. Using a more instrumental approach, the recommended songs were not strictly instrumental, but they were similar in tone and tempo. The final attempt contained a subset of features that could look at songs that gave the same vibe, which ended up working the best. From the tests, I observed that using too many features made the recommendations too vague whilst too little made recommending very difficult. The 'acousticness' feature proved to be not the best feature to use – I expected it help in finding more electronic music, while it did bring up low acoustic songs, these were not necessarily electronic music. Getting the top 20 songs was sufficient as anything above 30 would have produced very irrelevant results.