Mini project

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Contents

1 Introduction to project

(Please not that this introduction to the project was written last, upon completion of the project, by summarising the entire text with the assistance of ChatGPT. I then curated and paraphrased the text myself.)

This project will explore the user experiences and perceptions of the Spotify music streaming service, particularly among users who are new to online subscription services, and how the transparency of recommender systems could be improved so as to provide users with adequate information on their functioning.

The introduction will highlight the origins of recommender systems in the 1990s and their prevalence in combating information overload on the internet. The text will discuss the basic concept of personal recommendations presented as ranked lists of products and how recommender systems gather data from users to understand their preferences. It then explore the importance of system feedback and explanation in recommender systems. It explains how providing justifications for recommendations can increase user adoption and understanding of the system's output. The text also discusses different types of feedback and opinion extraction methods, such as explicit and implicit feedback gathering, and suggests improvements to engage users in providing explicit feedback.
The subsequent section chronicles my own experience, which could be applied to other users with a persona similar to mine, with the Spotify music streaming service and highlights some user interface issues and confusion with the terminology used.
The problem of the "black box" in recommender systems is addressed, where the algorithms used are opaque and provide little information on how predictions are made. The text emphasises the need for transparency in these systems and highlights the benefits it brings, such as better user interaction and trust. It also mentions one approach to solving the black box problem by providing explanations to users.
Overall, the project will provide an overview of recommender systems, their history, the im-

portance of transparency, and the challenges associated with system feedback and explanation.

2 Introduction to recommender systems

(Please note that this part of the project contains text which was intially paraphrase from the original papers with the assistance of ChatGPT. I subsequently paraphrased the text a second time myself.)

In the 1990s, the prevalence of the internet lead to the creation of recommender systems that made use of what is known as "collaborative filtering" to help users combat information overload. In order to forecast how much users would enjoy a big collection of products, these systems developed prediction models. Some systems used reader ratings to compile forecasts based on Usenet News articles. Similarly, other systems used innovations by means of filtering to recommend music or videos to suggest materials through e-mail and web-based platforms among enthusiasts. The use of recommender systems soon spread throughout academia and industries. Recommender engines were widely advertised by 1996, and several universities hosted research workshops on the topic by that time (Konstan and Riedl, 2012).

A very straightforward observation that lead to the advancement of these recommender systems was how people depend on suggestions from others while making ordinary decisions. For instance, people sometimes rely on recommendations from their friends when choosing a book to read, employers frequently use recommendation letters in hiring decisions, and people often read and rely on movie reviews written by movie critics that appear in magazines when choosing something to watch.
Personal recommendations are presented as ranked lists of products in their most basic form. Based on the user's choices and limitations, the systems attempt to forecast the best items or services while performing these ratings. For the purpose of accomplishing such tasks, recommender systems gather data from users on their preferences, which are either openly communicated by means of product ratings, or are inferred through analysing the user's be-

haviours. For example of the latter case, a recommender system might have the ability to interpret a user's action to certain products as an implied appeal of the goods (Ricci, Rokach and Shapira, 2015).

3 Data extraction for recommender algorithms

(Please note that this part of the project contains text which was intially paraphrase from the original papers with the assistance of ChatGPT. I subsequently paraphrased the text a second time myself.)

Individuals' subjective feelings and emotions, which may be considered a form of opinions, can be a form of feedback. Such feedback can be communicated in a variety of ways, including through short text or longer written materials as well as other means. Opinion retrieval may be separated into two processes, namely the selection of pertinent materials, and their subsequent re-ranking in accordance with opinion scores. Customer review analysis is the most popular method for obtaining opinions and has recently become a major area of research.

To address the challenges involved in extracting opinions through machines, researchers have proposed a user feedback-based approach where individuals serve as appraisers in order to establish their opinions of products and services based on available reviews, this serves as opinion data. This approach leverages human expertise to accurately extract opinions about products and correctly rank them differently. By obtaining feedback from appraiser, who are ultimately the users, genuine opinion data can be obtained about a product. Two primary methods exist for collecting feedback from users. They are known as explicit feedback and implicit feedback.

Explicit feedback gathering methods involve querying users to complete a feedback datasheet where they provide their opinions about certain products based on considered reviews presented to them. The feedback provided is then scored and weighted, and products are ranked accordingly. However, obtaining accurate feedback can be challenging as this type of mechanism requires effort from the user. This method might also pose challenges as uninterested or facetious users may either not wish to undertake the feedback process whatsoever, or might not take seriously, leading to incomplete or frivolous feedback data.

On the other hand, implicit feedback gathering methods are means of obtaining user feedback by observing the actions of users. Rather than asking the users to fill out a feedback form, their actions are monitored to infer their feedback. This method falls under the area of online data extraction, which is a subset of web mining (Sohail, Siddiqui and Ali, 2014).

3.1 Suggestions to engage users in providing implicit and explicit feedback

This part of the project will provide advices on potential improvements to engage users with the recommendation system, as well as improvements in regards to customization. The following wireframes and suggestions could be applied to music streaming services that supply personalised music recommendations, such as Spotify (Please note that these suggestions were initially suggested with the assistance of ChatGPT. The suggestions were subsequently examined by myself, and so was the text provided, and I subsequently paraphrased the text. The wireframes were provided by ChatGPT as ASCII art and I subsequently modified the content of the wireframes accordingly).

- Feedback interface: Users of the music streaming service could have access to a feedback section where they may post criticisms of certain songs or albums that were suggested to them. The recommendation system would subsequently fine tune future suggesstions based on such feedback (Figure 1).

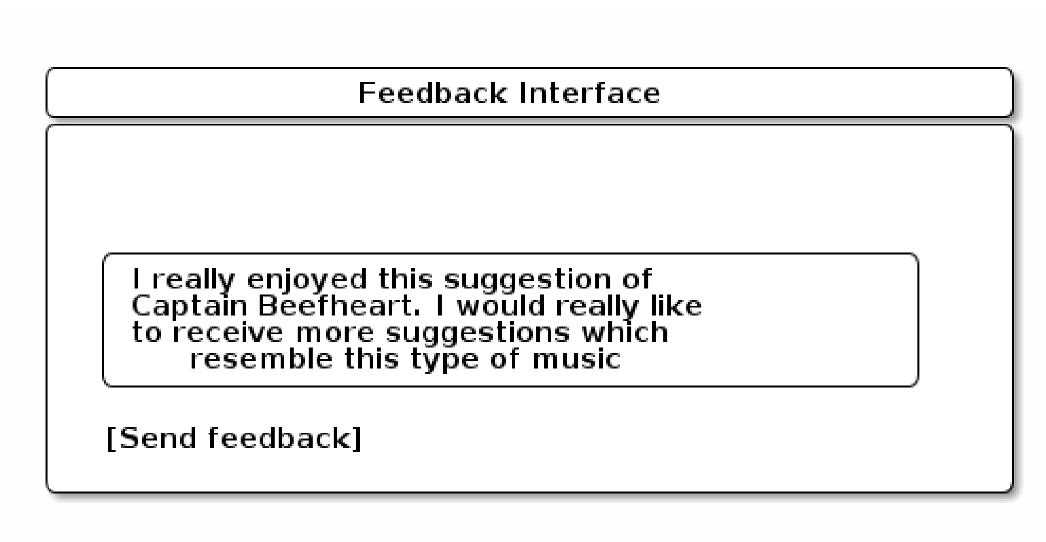


Figure 1: Feedback interface.

- Preference customisation interface: Users may be given controls to customise the factors that affect the recommendations, such as preferred genres, artists, moods, or even certain musical characteristics including tempo or energy level. They could also be given the choice of whether they would prefer to receive recommendations for entire albums or individual songs (Figure 2).

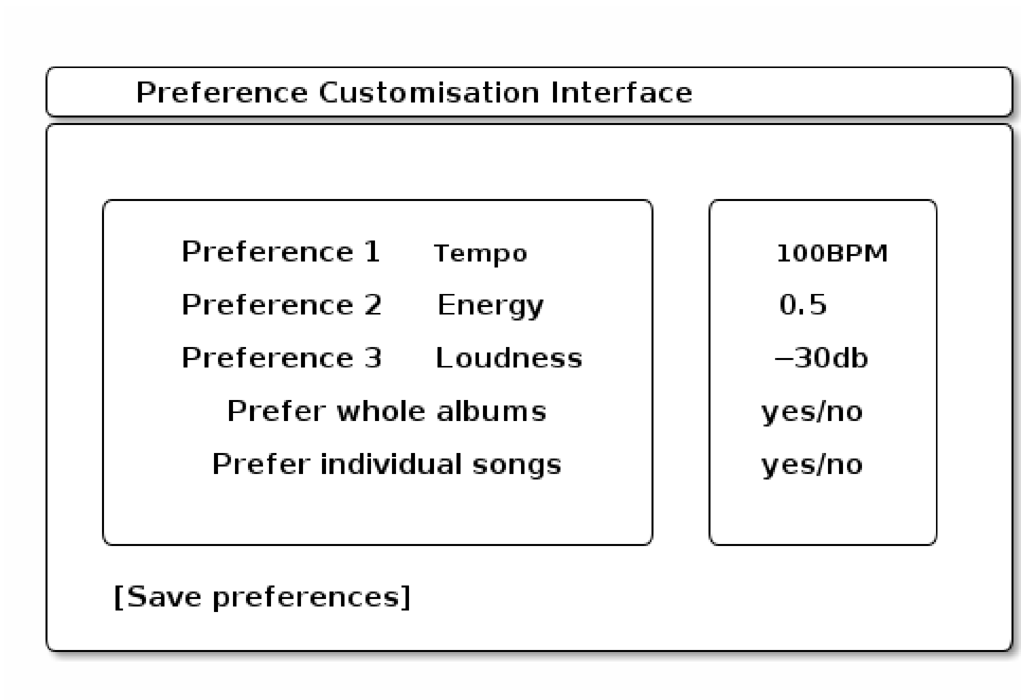


Figure 2: Preference customisation interface.

- Rewards interface: The streaming music service could implement a rewards programme to encourage customer feedback. For sharing their opinions on the suggested music users can receive rewards, such as a hard copy of an album, by earning "feedback points". In this manner, the service would promote user participation and interest in the feedback process (Figure 3).

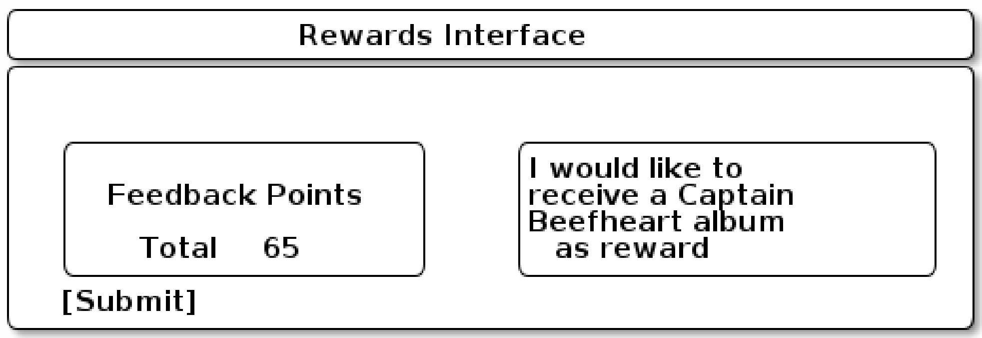


Figure 3: Rewards interface.

These suggestions may assist music streaming industries make their services more engaging. Users have the option to offer input, personalise their recommendations and earn rewards. By implementing these ideas, personalisation may be improved and user involvement raised.

4 User personas and journey through the streaming service Spotify

As someone who does not use recommender systems very much, I decided as an experiment for this project to explore how they might work and provide assistance to potential users. For this I chose the Spotify music streaming service. It is worth keeping in mind that my own persona could be generalised and assumed to be the persona of several users, namely the persona of people who:

- Do not like to be tracked on the internet.
- Have no experience with paid subscriptions over online services.
- Do not understand the idea behind services such as Spotify.
- Only have experience in listening to music over the radio, or via a stereo installation.
- Like to own a solid copy (i.e. a CD) of the media they own or purchase.
- Will listen to an album from start to finish i.e. not switch album right in the middle of listening to said album, or not switch tune one after another.
- Want to potentially share a hard copy of the music they own with a friend.
- Are computer literate.
- Embrace the idea of Free Software.
- For the most part of their use access the internet via computers, not via mobile devices.
- Do not do their computing over mobile devices but with laptop or desktop computers.

It is worth noting that although the idea of this project is to understand how the recommendation system might work and how the user is informed about it, there are several steps that need to be taken in order to get to that point. Therefore my own journey will also describe how I find the navigating over the Spotify interface.

As a starting point as a user with no experience with online subscription services whatsoever, I find that logging in the system provides a bland interface, this is something which I quite like as it makes me think that I might be able to customise it to my liking. However the system in my view is not bland enough. To explain what I mean by this is that prior to this project I had to make use of this newly created Spotify account in order to complete an assignment for this course. The completing of this assignment went fine but the system somehow kept a history of my past searches and at this stage the home page displays a history of my past searches i.e. the music which I have recently played and another list which is titled "Your top mixes" (Figure 4).

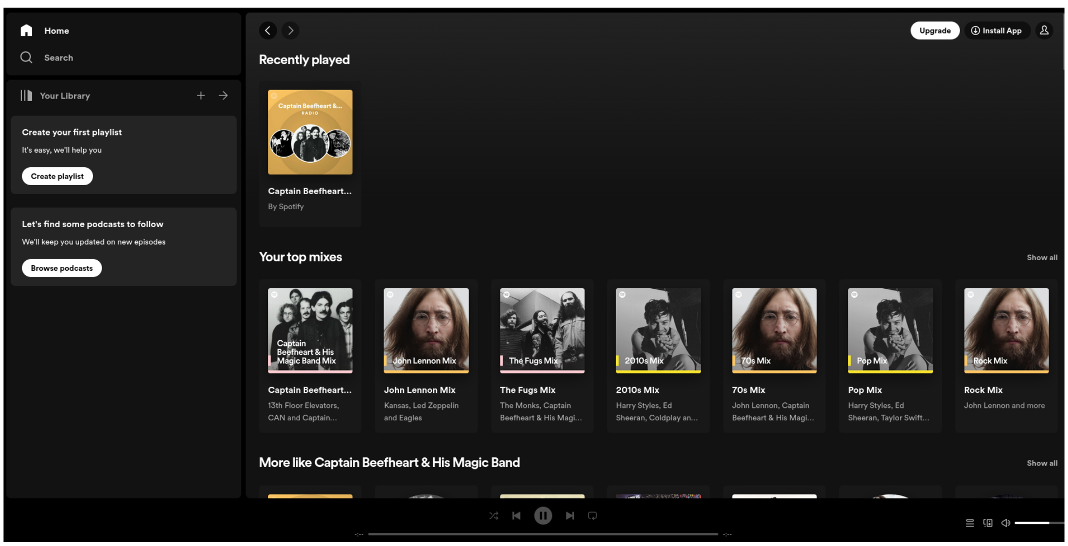


Figure 4: Home page.

I personally found my homepage irritating at this point as I did not want to have a history of my past searches displayed. Unfortunately there seem to be no straightforward way of resetting the history from this very homepage. The other thing which strikes me is the jargon used. As a new user to this type of services, I am unfamiliar with terms such as "playlist" or "podcast" and I do not know what they might be. Yet there are two buttons on the left of the panel that call to create a playlist or to browse podcasts. Above these two buttons is located another "Your library" button which when I click on it collapses the panel on the left side (Figure 5).

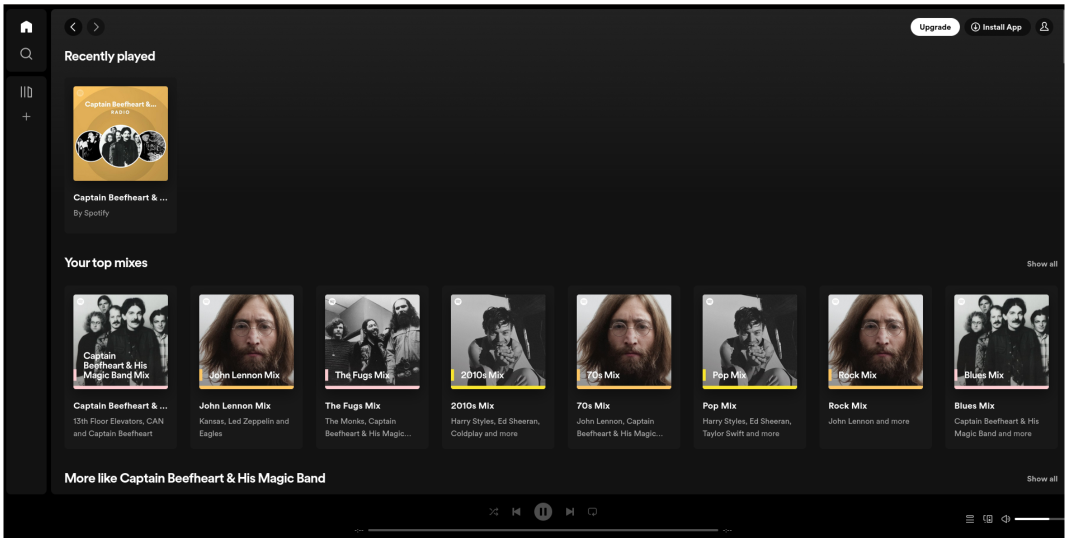


Figure 5: Home page with left side collapsed.

After clicking on this button I found myself confused and I did not know how to return to the previous format. Other than collapsing the left side of the panel, this also had the effects of enlarging the icons/images displayed on the page and made me realise that there was an icon which displayed "2010s Mix". I could not understand why this was there as my previous searches were only related to music from between 1970 to 1980. Out of curiosity, I right clicked on this icon to find out if there might be a way to remove it from my homepage. This action brought up the following contextual menu (Figure 6).

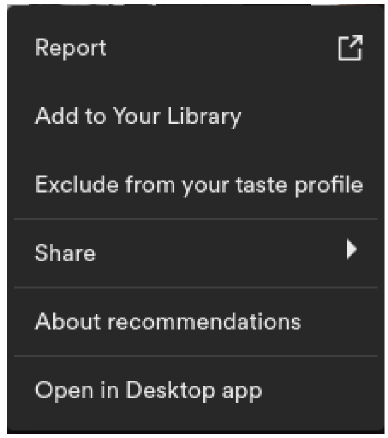


Figure 6: Contextual menu 1.

Here are my views on this contextual menu:

- Report: I do not know what this means.
- Add to your library: At this stage I do not know what this would imply
- Exclude from your taste profile: This is an option which makes it clear as to what it will do. However I do not particularly like the words employed such as "taste", and in particular the word "profile" exasperates me as I have a great dislike of being profiled. In my view this type of wording ought to have a way of being configured so as to not incensitise users .
- Share: brings up a submenu with options to "copy link to playlist" and "embed playlist". Once again at this stage I've yet to understand what a playlist might be, so these options are confusing to me.
- About recommendations: I'm guessing this might take me to a page which might explain something about recommendations.
- Open in desktop app: I find this one borderline insulting. As a computer enthusiast, I do not use "apps", instead I use programs and software. Moreover I do not use a desktop computer but a laptop, therefore I think this might not apply for my use. In line with this point I should also note that something similar is displayed at the top right of the

homepage, under a button which calls to "Install app". The problem with this is that the word "app" is usually used to refer to programs which are designed to run on mobile devices, as such it makes me feel like this interface is not designed to be accessed from a computer.

As the goal of this project is to investigate how recommendations can be made transparent to users, I decided to click on the "About recommendations" option of this contextual menu. This had the following effect (Figure 7)

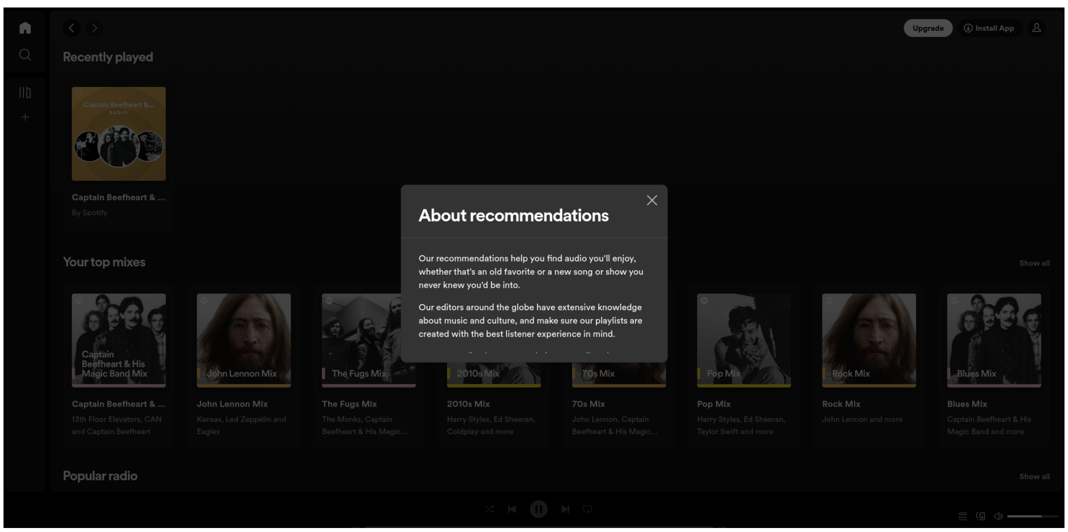


Figure 7: About recommendations.

The side effect which took place was that of a "pop up" type, darkening most of the screen and displaying a very small light gray frame in the middle of it. This frame contains text, the frame has to be scrolled through and reads the following:

> *Our recommendations help you find audio you'll enjoy, whether that's an old favorite or a new song or show you never knew you'd be into.*
>
> *Our editors around the globe have extensive knowledge about music and culture, and make sure our playlists are created with the best listener experience in mind.*

> *Our personalized recommendations are tailored to your unique taste, taking into account a variety of factors, such as what you're listening to and when, the listening habits of people who have similar taste in music and podcasts, and the expertise of our music and podcast specialists.*
>
> *In some cases, commercial considerations may influence our recommendations, but listener satisfaction is our priority and we only ever recommend content we think you'll want to hear. Our recommendations rely on signals from you, so keep on listening to the songs and podcasts you love!*

The first thing I would like to point out is that I would personally prefer to be taken a dedicated web-page instead of having a pop up being presented on my screen. Moreover, as someone who is computer literate and familiar with the way in which recommender systems work, I already know before reading this 147 words long paragraph that this word count will be nowhere near enough to provide a user who might be interested in the matter, how the Spotify recommender algorithm works. Indeed after having read the paragraph I can confirm that not once the words "algorithm" or "machine learning" are spoken of. Instead the text sways the reader into believing that humans might be working behind the scenes so as to provide users with recommendations. In my view this is not only unfair but it also give the impression that the reader my be a simpleton. The next part of this essay will delve into the way in which recommender systems work in general, not only in music recommender systems.

5 System feedback explanation to users

5.1 The benefits of explaining to users

(Please note that this part of the project contains text which was intially paraphrase from the original papers with the assistance of ChatGPT. I subsequently paraphrased the text a second time myself.)

As explained in the introduction, by categorising and ranking items in a personalised way, recommender systems can help users quickly find interesting goods and other materials. A number of these systems do not stop at creating customised lists of products, they also provide justifications for why a certain product is suggested and why the system presumes the user would be interested in it. Providing such explanations can increase the system's adoption, perceived quality, and efficacy in addition to helping users understand the output and logic. Studies in how to create and communicate system-generated explanations have received more attention in recent years. Some elemental explanation functions are now built into online retailing platforms. There are several ways to explain recommendations, involving non-personalised and personalised ones. The "Customers who bought this item also bought..." (Gedikli, Jannach and Ge, 2014) stickers that appears alongside a list of suggestions is an example of a recommendation that is not personalised but that carries an explanation. The extent of the explanations offered by a recommender system are often based on algorithms employed to create the suggestion catalogue. In explanations established on knowledge-based advising methods, an expert's subject knowledge and expressly obtained user preferences are often included in the rule base. Different explanation strategies have been put forth for what is known as collaborative filtering recommenders by several researchers. Furthermore, these researchers have shown that explanations to users can improve a recommender system's general acceptability. In the context of recommender systems, an explanation is a segment of intelligence to advance different purposes, such as providing the rationale for a recommendation or enabling better interchange between a commerce and a customer. However, there is currently no universally accepted denotation of the word "explanation" in relation to recommender systems. It has been suggested that in recommender systems, explanations are commonly used to justify recommendations (Gedikli, Jannach and Ge, 2014).

5.2 Explanations in Spotify

Following on with my journey into the Spotify recommendation system, I wanted to delve one step deeper into its system so as to find relevant information. At this stage I was still on my homepage and noticed an icon located at the top right of the page which I hadn't inspected so far (Figure 8).

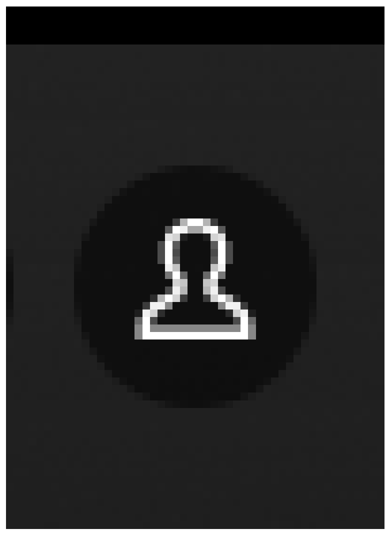


Figure 8: Top right icon.

Clicking on this icon brought up a contextual menu with options for "Account", "Profile", "Upgrade to Premium", "Settings" and "Log out" (Figure 9).

From then I decided that the options which might be of interest to me would be the "Account", "Profile" and "Settings". I started by the "Account" option which took me to an "Account overview" page (Figure 10).

This page had no information whatsoever which could interest me in my research. I then went

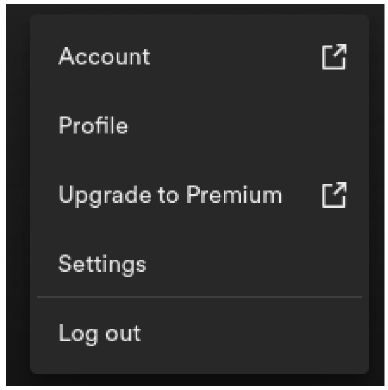


Figure 9: Contextual menu 2.

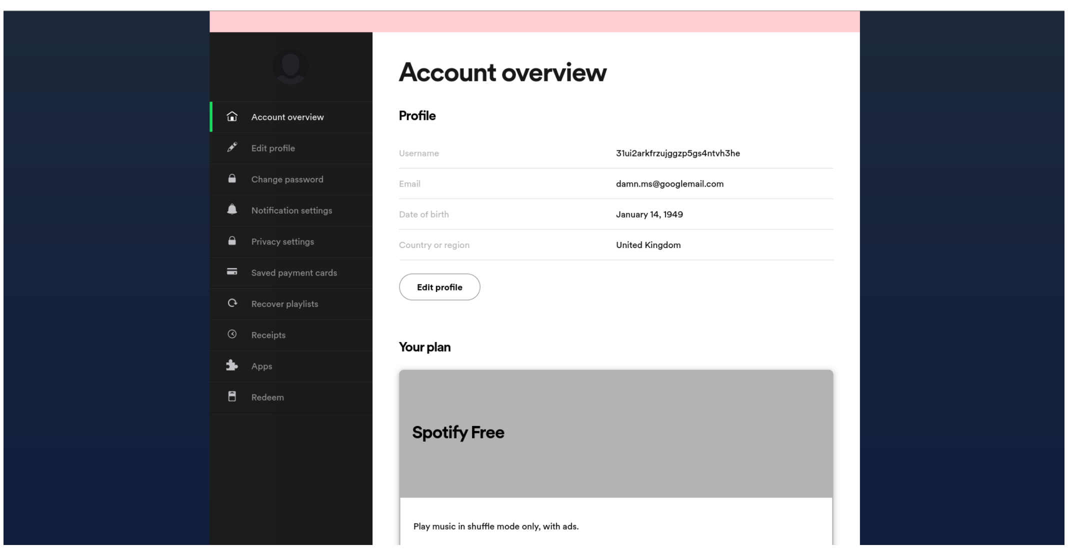


Figure 10: Account overview.

to my "Profile" page (Figure 11).

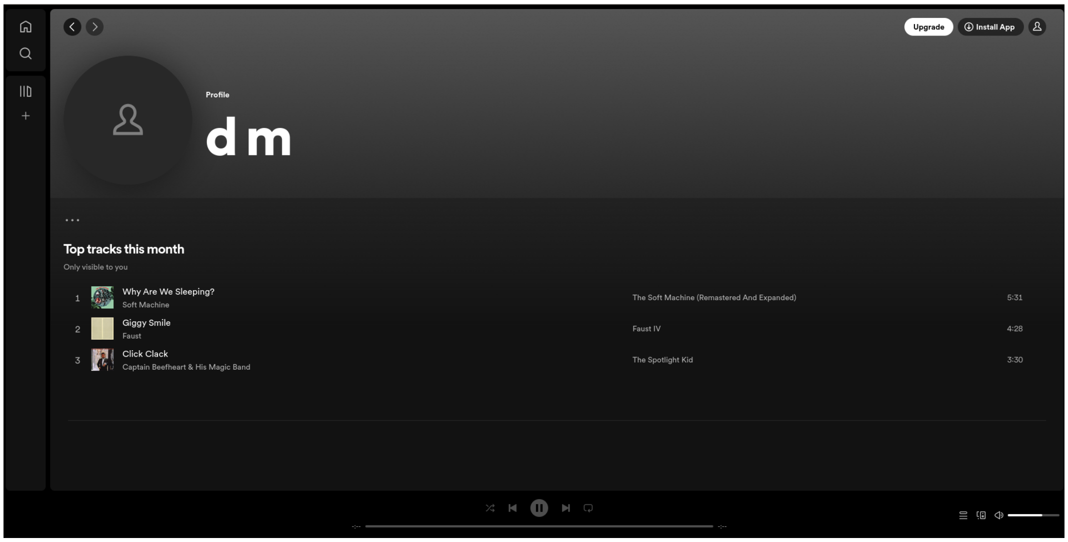


Figure 11: Profile.

Once again there was no information about system recommendations. The next and last thing to try was the "Settings" page (Figure 12).

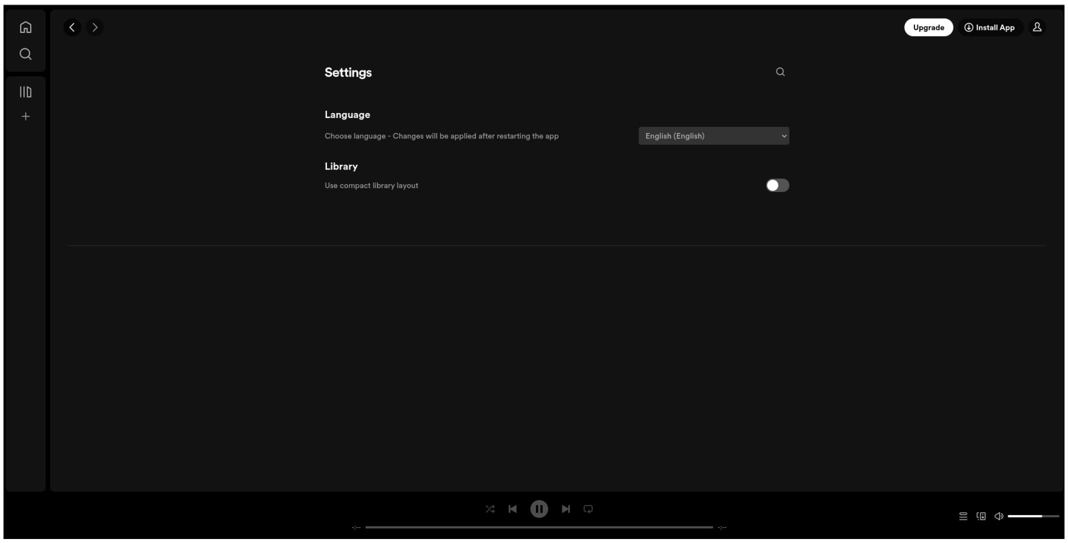


Figure 12: Settings.

I could find no information about system recommendation on this page either.
From this point, I came under the impression that Spotify was not quite au courant about the research conducted, as explained in the previous chapter, about the benefits of explaining to its users the workings of its recommendation system. However, I thought that I might have missed a web page somewhere or done something wrong, so as a last resort decide to do a google search for potential information. This proved to be unfruitful (Figure 13).

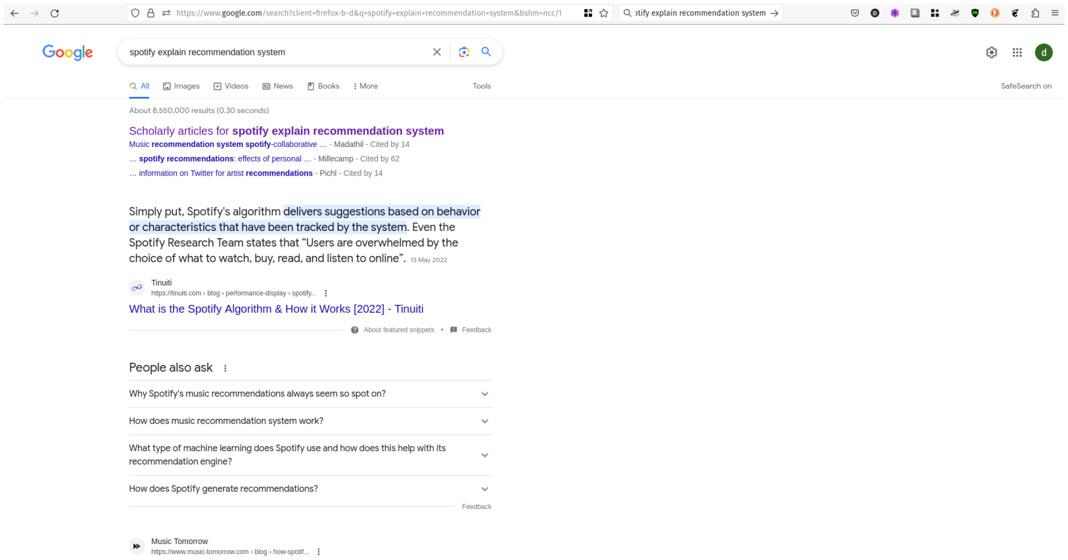


Figure 13: Google search.

These lack of findings led me to think that Spotify's recommender system works in a way which is known as a "black box" (Alshammari, Nasraoui and Sanders, 2019).

6 The problem of the "black box"

6.1 "Black box" explanation

(Please note that this part of the project contains text which was intially paraphrase from the original papers with the assistance of ChatGPT. I subsequently paraphrased the text a second time myself.)

Recommender systems have become progressively popular in addressing information overload to users of online platforms by predicting their preferences and recommending pertinent suggestions on said platforms. Among these systems collaborative filtering algorithms are considered the most advanced. However, they are opaque and provide little information on how their predictions are made. Such enigmatic systems are often referred to as "black box". Insufficient availability of information regarding recommender systems and their underlying algorithms is a prevailing issue. While a few sources claim to provide partial or complete information, the majority of respondents in the study expressed dissatisfaction with the existing information landscape. Moreover, in the event that some clues might be provided, it tends to be inadequate. The components commonly known as "why am I seeing this" which is offered by certain platforms, is widely regarded as in comprehending recommendations. This viewpoint aligns with academic research, contrasting the opposing claims made by a significant industries. Academic studies have concluded that the transparency features of some platforms are incomplete, and ambiguous. Additionally, it should be noted that the functionalities provided these services is rarely resorted to by users, due to the tricky interface conception. These concerns have often been expressed by people, emphasising the difficulty or even impossibility of accessing information (Ruohonen, 2023).

6.2 Addressing the problem of the "black box"

In order to address the problem of the "black box" in the case of Spotify, although this could be applied to platforms that employ recommender systems in general, I would propose that the service provide users with a very boldly signposted and dedicated section on their website which would allow users to delve into the innards of their recommender algorithms. This section would highlight and detail the following points, which in my view align well with the values of the type of user persona that I have simulated in the previous section:

- The recommender system is central to the Spotify streaming service.
- The recommender system analyses the user's listening history ("implicit feedback").
- The recommender system analyses the user's listening habits ("implicit feedback").
- The recommender system analyses and tracks the user's browsing habits ("implicit feedback").
- The recommender system identifies patterns between users ("implicit feedback" and "collaborative filtering").
- The recommender system identifies patterns between music genres ("content-based filtering").
- The recommender system employs methods such as "collaborative filtering" and/or "content-based filtering" in order to generate recommendations that might align with the user's preferences.
- The recommender system employs machine learning and data analysis techniques in order to improve its accuracy.

In line with the user persona which I have simulated, I believe that Spotify could also provided a dedicated section which highlights the following points:

- Spotify collects users' personal information such as email addresses and birthdays (Hern and Rankin, 2015).
- Spotify can eavesdrop through users' contacts (Hern and Rankin, 2015).
- Spotify can determine and collect users' location (Hern and Rankin, 2015).

- Spotify shares collected data with advertisers (Hern and Rankin, 2015).
- Spotify performs sentiment analysis by scrutinising users' music consumption (Mahdawi, 2018)

7 Closing thoughts

(Please note that this part of the was initially summarised with the assistance of ChatGPT and subsequently paraphrased by myself.)

This project has covered a brief historical overview of recommender systems and how they became prevalent in the 1990s and how they used innovations by means on filtering in order to suggest music and videos to potential users of online e-commerce services. The idea behind these recommenders was based on how people would sometimes rely on suggestions from their peers.

We have seen how data extraction is obtained by user feedback over online ratings ("explicit feedback"), or by analysing the actions of users over online platforms ("implicit feedback"). Suggestions which may engage users in providing explicit and implicit feedback to music streaming platforms have been offered.

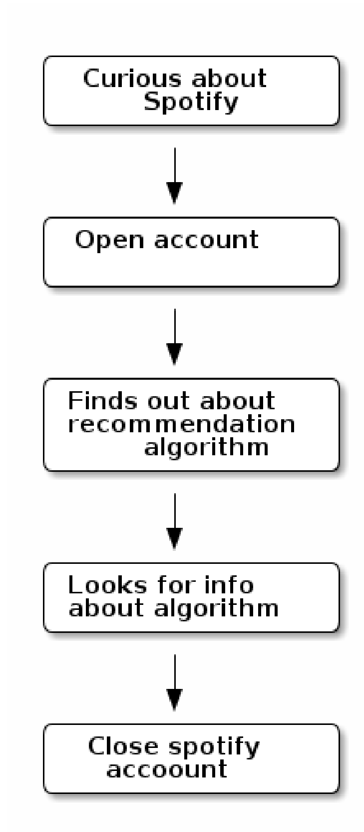
The project has simulated the persona of a user who is unfamiliar to music streaming services and how they might navigate the Spotify service in order to find out the workings of its recommendation system.

Lastly we have deduced that the Spotify system qualifies for what is known as a "black box", and have provided suggestions so as to improve its transparency.

I shall also inform the reader that upon completing this project I will be closing my Spotify account as the problem of the "black box" does not align with my values.

8 Customer journey according to user persona

(Please note that the structure of this customer journey "map" was provided by ChatGPT as ASCII art. I subsequently edited the content of the boxes accordingly.)



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