Spotify: A Brief Analysis

Pedro Monteiro 97484
Eduardo Fernandes 98512
Tiago Matos 98134
Vitor Dias 98396
André Gomes 97541

Aspetos Profissionais e Sociais da Engenharia Informática

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1 Introduction

Nowadays, more and more people, from the youngest to the oldest, like to listen to music. From listening to music to relax and distract from surroundings to listening to music to concentrate while studying, the role of music has become more and more important as the days go by.
This assignment will focus on the Spotify platform, understand what it is, how it works, its recommendation service, and also Autoplay.
Our goal is to dig deeper into Spotify system and algorithms that provide all those features.

2 Spotify Platform

As mentioned before, the use of Spotify is constantly growing these days, but what is this platform really? And how it works?

2.1 What is and how it works?

Spotify is a digital music, podcast and video service that provides access to millions of songs and other content from creators around the world.
Basic functions like playing music are totally free, but is also possible choose to upgrade to Spotify Premium.
Spotify is available across a range of devices, including computers, phones, tablets, speakers, TVs, and cars.

With Spotify (premium or not) it is possible:

- get recommendations based on your taste;
- build collections of music and podcasts;
- and more!

The company licenses tracks from major and minor record labels for its extensive music library. It pays the rights holders an amount based on the number of times people listen to each track.
Listening to music on Spotify is entirely free, like was said before, but there are some banner ads within the official apps and there are even occasional ads between songs as a trade-off.
It is possible to listen to entire albums on Spotify in addition to playlists curated by Spotify staff, artists, and other users. Likewise, the user can create Spotify playlists and share them with friends and community.

2.2 Spotify Free vs. Spotify Premium

Spotify Free is an ad-supported tier that allows to access all songs, including podcasts. However, it is needed to endure banner and audio ads alongside it.

Aside from these, here are a few other things expected from Spotify Free:

- Four audio quality levels capped at 160kbit/s for both desktop and mobile apps;
- No offline listening for music, but podcasts are available to download;
- Access to personalized playlists.

Spotify Premium is a paid subscription tier that gives full access to everything the app has to offer.
The Premium tier is also completely ad-free and offers on-demand playback for all playlists. With Spotify Premium, users can take music anywhere in the world. And if the user is going somewhere with no WiFi, they can also download as much as 10,000 songs and podcasts for offline listening. Last but not least, Premium subscribers also get better audio quality of 320kbit/s on both desktop and mobile apps.

2.3 How it compares to other services?

Mobile music streaming apps have turned into a highly competitive business. There are a lot of applications, such as Spotify, Pandora, iTunes, Google Music, and many others.
Spotify was one of the first music streaming apps of its kind to offer users access to a large catalogue of music in just a few clicks, and year after year, has been able to improve its mobile app design, usability, streaming quality, and music sharing capabilities.
Inevitably, due to the platform revolutionising, the way we consume music nowadays and gaining global success, competition has risen from other industry-leading mobile technology companies.
Spotify's competitors for the best music streaming service includes:

- TIDAL - offers a tiered subscription-based mobile app development platform that houses a large music library. Its claim among the best music apps is that it pays artists better than all other music streaming services.
- Apple Music - has a similar platform to Tidal, but has a slew of radio mixes by high-profile musicians and DJ's. As a top music app for iPhone, Apple is already the leading podcast platform and houses essentially every podcast out there.
- Google Play Music/YouTube Music - have recently merged into one, as Google owns YouTube and the platform already has millions of dedicated users. The music streaming service integrates perfectly into both the mobile app design and flow of YouTube, so user knows exactly what product you're using.

But, with all of this competition pressuring them, what makes Spotify the King when it comes to the best music streaming app?

- Spotify offers everything that all of its music streaming app competitors have and more. It has a library of millions of songs (over 40 million) and a massive number of playlists created by both mobile app users and Spotify's own algorithm system;

- Discovery Through Data - from its mobile machine-learning, artificial intelligence and data sifting technology, Spotify analyses user's listening habits and builds out customised recommendations. This includes playlists and music suggestions based on the genres and artists users are listening to regularly;

- Discover Weekly Feature - this playlist is refreshed every Monday with 30 new songs that users have most likely never heard of but will probably love because they are chosen based on user most recent listening habits;

- Collaboration On Music Streaming Apps - Spotify has sharing capabilities that make playlists social as well. It's just another way it stands out as the best music streaming app for Android and iPhone. If users create a playlist, they can invite friends to collaborate, which lets everyone included add songs to the playlist. This makes for a more shared experience with the mobile application, which is how music is generally best enjoyed.

3 Spotify Streaming

3.1 Streaming

In the digital world, we often hear the word Streaming referring to streaming platforms, streaming music, streaming video games, and a lot of other content. But what does it mean and what is the difference between streaming and downloading, something we are used to doing.

From the Verizon website, an American wireless network operator, Streaming is " the technology of transmitting audio and video files in a continuous flow over a wired or wireless internet connection". This means if we want to watch a movie but not the whole movie, we can use streaming and we do not need to load it all, unlike downloads. We get real-time access to the content.

Obviously this requires access to the internet while we want to get the media and also may require a rather strong connection mainly for video streaming since a lot of data is being transmitted. Without a good connection, breakings will probably occur thus the experience might not be as desired. Gladly this problem is almost mitigated in the most developed countries, with faster internet.

3.2 Spotify Streaming

As in Sweden the broadband Internet system is one of the fastest, Spotify wanted to decrease the use of illegal websites that managed to share files such as music, since those websites provided fast access to the content using the fast broadband. So, Spotify grew up using some technologies from those websites to share their music.

Once we hit the play button, the music shall play almost immediately. In fact it takes more or less 256 ms to start playing the music. There is almost no buffering in the streaming, something they prioritize.

Before, when we requested a track, the initial part would come from the Spotify servers.

Then it tried to search for the remainder of the music searching peer-to-peer (P2P), the way those illegal websites work. If it did not find the required data, it would switch back to the Spotify servers, and then again try P2P. When the music is reaching its end, the next track is prefetched.
This P2P method allowed the app to avoid fetching from the servers and use less bandwidth and better up time. The user only uploaded data from the Web and Computer apps. The mobile app would not upload data. Nowadays, with the company growth, they abandoned the P2P system and now rely only on their servers, that increased in number.
Besides all of this, there is also the cache, with the recommended size of 1GB, where a lot of music is stored. In fact, the cache is the main source of the data.

Back when they used P2P, the music origin would be:

- **55.4% from caches**
- **35.8% from P2P**
- **8.8% from servers**

3.3 Spotify Theoretical Bandwidth

Spotify has different bandwidth settings for different music qualities and platforms. It also has a Automatic option that adapts to the network in use.
The mobile and desktop app have four different quality settings:

- Free
  - **Low:** 24 kb/s
  - **Normal:** 96 kb/s
  - **High:** 160 kb/s
- Premium
  - **Very High:** 320 kb/s

The web player has two options:

- Free
  - 128 kb/s
- Premium
  - 256 kb/s

Podcasts quality is approximately 96kbit/s except for the web player where it is 128 kbit/s

3.4 Spotify Bandwidth Measurement

In order to test Spotify bandwidth in our devices, we played a song and calculated the bandwidth dividing the amount of data received by the time the music has.

3.4.1 Methodology

In order to measure the bandwidth of the desktop application, we utilized Glasswire to capture the network activity and size of packets received during the playtime of a song. In the Desktop application, the music is loaded all at once in the beggining.

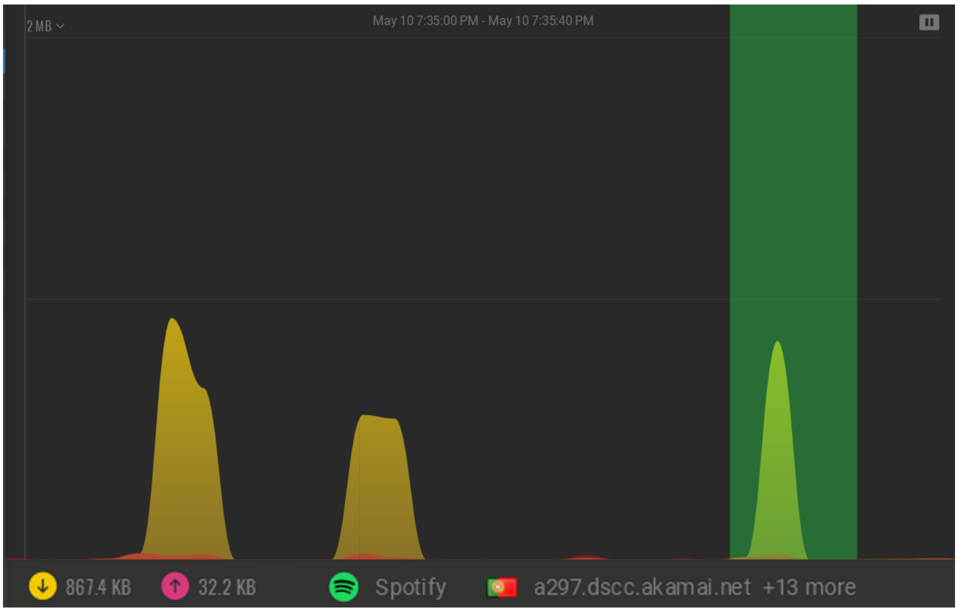


Figure 1: Graph of the network activity for the Spotify desktop application with ”Low” quality. Highlighted in green is the duration of the music fetching and below is the size of packets received.

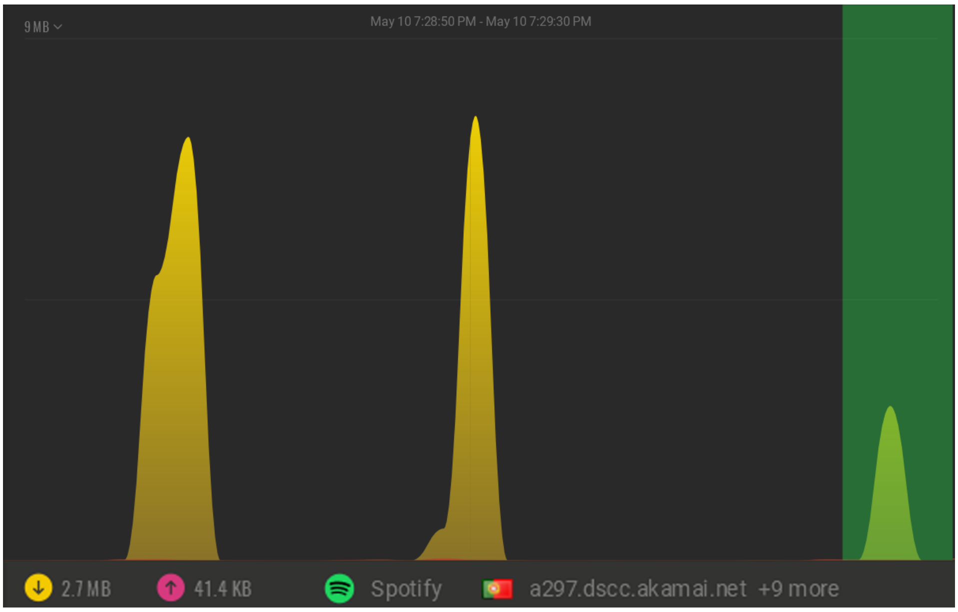


Figure 2: Graph of the network activity for the Spotify desktop application with ”Medium” quality. Highlighted in green is the duration of the music fetching and below is the size of packets received.

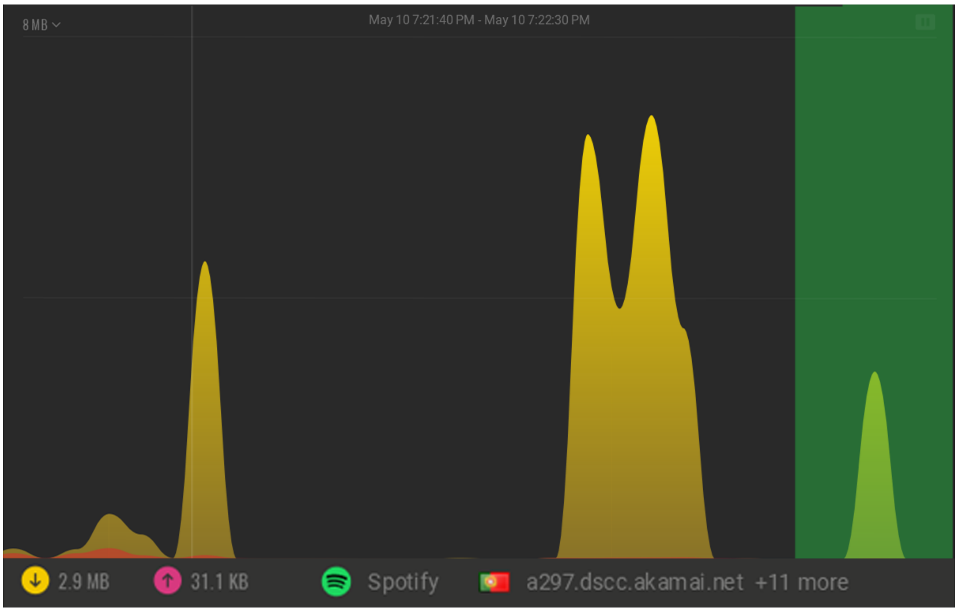


Figure 3: Graph of the network activity for the Spotify desktop application with ”High” quality. Highlighted in green is the duration of the music fetching and below is the size of packets received.

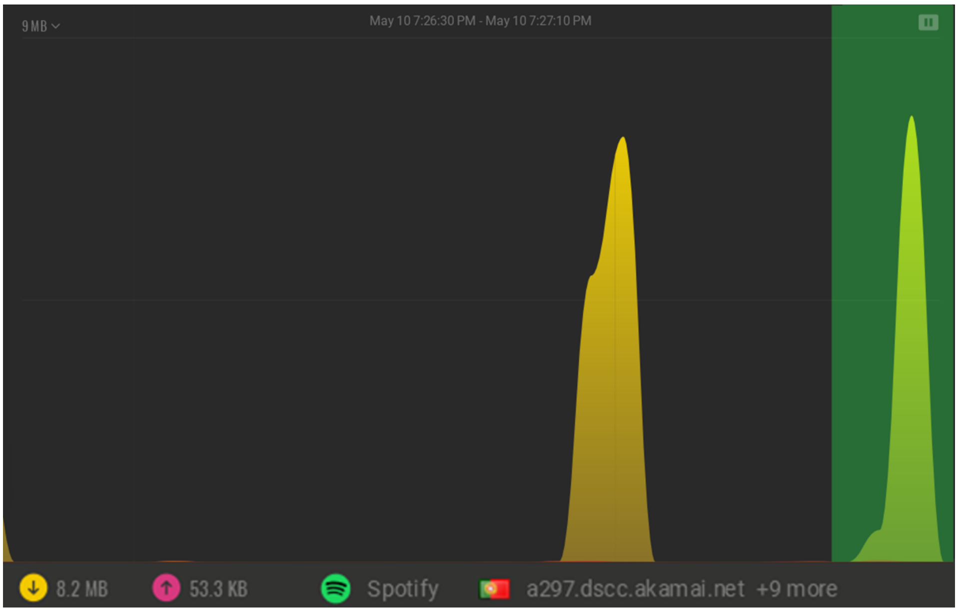


Figure 4: Graph of the network activity for the Spotify desktop application with "Very High" quality. Highlighted in green is the duration of the music fetching and below is the size of packets received.

Regarding the Web Application, we used the "Network" tab in the Chrome Browser Developer Tools. In the Web App, the music does not get fetched all at once but according to the needs so we receive packets until the end of the song.

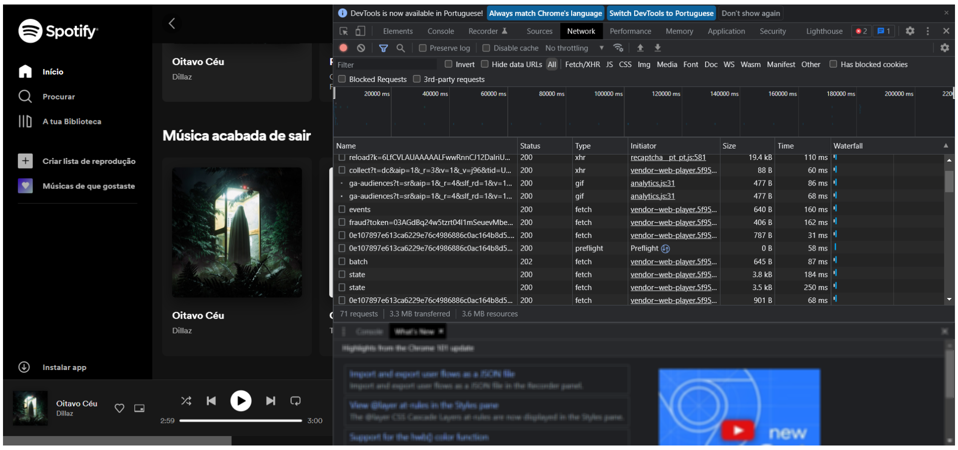


Figure 5: Spotify web app using a Free Account with the music played and the "Network" tab opened.

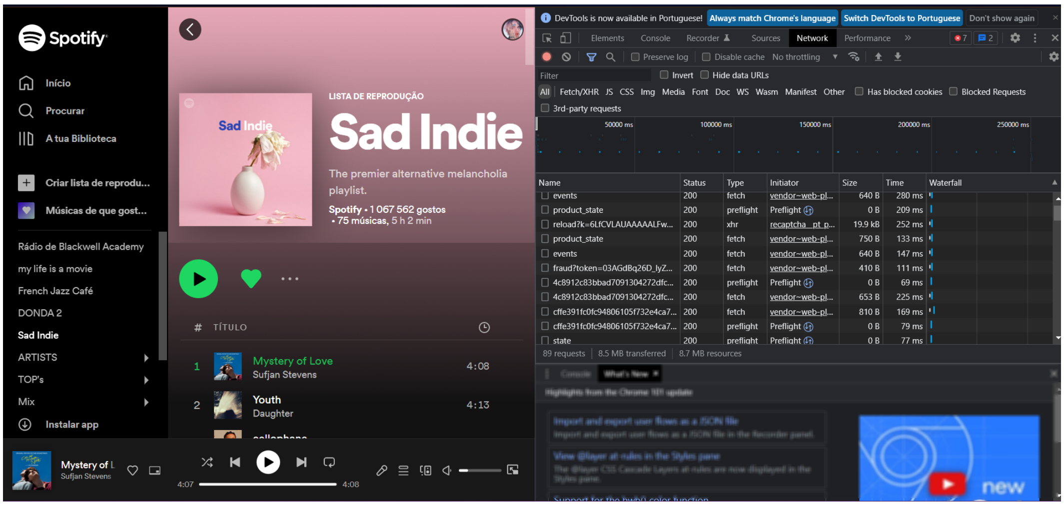


Figure 6: Spotify web app using a Premium Account with the music played and the "Network" tab opened.

3.4.2 Results

The observed results were as follows:

Client	Music duration (minutes-seconds)	Packets Received (MB)	kB/s	Kbits/s	Expected
App - Low Quality	3:53	0.8674	3.7	29.6	24 kbits/s
App – Medium Quality	3:46	2.7	11.9	95.57	96 kbits/s
App – High Quality	2:28	2.9	19.6	156.75	160 kbits/s
App – Very High	3:22	8.2	40.6	324.75	320 kbits/s
Web – Free	3:00	3.3	18.3	146.7	128 kbits/s
Web - Premium	4:08	8.5	34.3	274.19	256 kbits/s

Figure 7: Table of the packets measurement

Since using the desktop/laptop we usually use wi-fi, the bandwidth is not a problem. However on the mobile app, since it is often used with mobile data, thus may spend unexpected data. However this is easily solved with the app settings that allow setting the quality according to the source of the internet.

4 Spotify recommendation system

As we move ahead into the 2020s, an ever-increasing share of music consumption and discovery is going to be mediated by AI-driven recommendation systems. On Spotify over one third of all new artist discoveries happen through "Made for You" recommendation sessions. Music professionals rely on recommender systems across platforms like Spotify to amplify the ad budgets, connect with the new audiences, and all-around execute successful release campaigns, while often having no clear vision of how these systems operate and how to leverage them to amplify artist discovery.

4.1 How recommendation and music discovery works on Spotify?

In a lot of ways, Spotify's recommendation engine is playing the matchmaker between the artists and fans on a two-sided marketplace. So first, to understand this topic we will start by understanding how the algorithms are approached in this application.
The recommendation landscape on Spotify is much more diverse than on some of the other consumption platforms. Just consider the range of Spotify features that are generated with the help of the recommendation engine:

- **Discover Weekly Release Radar playlists**
- **Your Daily Mix playlists**
- **Artist / Decade / Mood / Genre Mix playlists**
- **Special personalized playlists (Your Time Capsule, On Repeat, Repeat Rewind, etc.)**
- **Personalized editorial playlists**
- **Personalized browse section**
- **Personalized search results**
- **Playlist suggestions enhance playlist feature**
- **Artist/song radio and autoplay features**

In one way or another, all these diverse spaces are mediated by the recommender engine, but each of them is running on a separate algorithm with its own inner logic and reward system. The track and user representation form a sort of universal foundation for these algorithms, providing a shared model layer designed to answer the common questions of feature-specific algorithms, such as:

- **User-entity affinity**: *"How much does user X like artist A or track B? What are the favorite artists/tracks of user Y?"*
- **Item similarity**: *How similar are artist A artist B? What are the 10 tracks most similar to track C?"*
- **Item clustering**: *"How would we split these 50 tracks/artists into separate groups?"*

Figure 8: Cloud of similarities

The feature-specific algorithms can then tap into these unified models to generate recommendations optimized for a given consumption space/context. For instance, the algorithm behind Your Time Capsule playlists would primarily engage with user-entity affinity data to try and find the tracks that users love but haven't listened to in a while. On the other hand, Discover Weekly algorithms would employ a mix of affinity and similarity data to find tracks similar to the user's preferences, which they haven't heard yet. Finally, generating Your Daily Mix playlists would involve all three methods — first, clustering the user's preferences into several groups and then expanding these lists with similar tracks.

4.2 The goals and rewards of Spotify recommendation algorithms

The overarching goal of the Spotify recommender system has to do primarily with retention, time spent on the platform, and general user satisfaction. However, these top-level goals are way too broad to devise a balanced reward system for ML algorithms serving content recommendations across a variety of features and contexts, and so the definition of success for the algorithms will largely depend on where and why the user engages with the system.

In some cases, Spotify would employ a set of algorithms just to devise the reward functions for a specific feature. For example, Spotify has trained a separate ML model to predict user satisfaction with Discover Weekly (with the training set sourced by user surveys). This model would look at the entire wealth of user interaction data, user past Discover Weekly behavior, and user goal clusters (i.e., if the user engaged with Discover Weekly as a background, to search for new music, save music or later, etc.), and then produce a unified satisfaction metric based on all that activity.

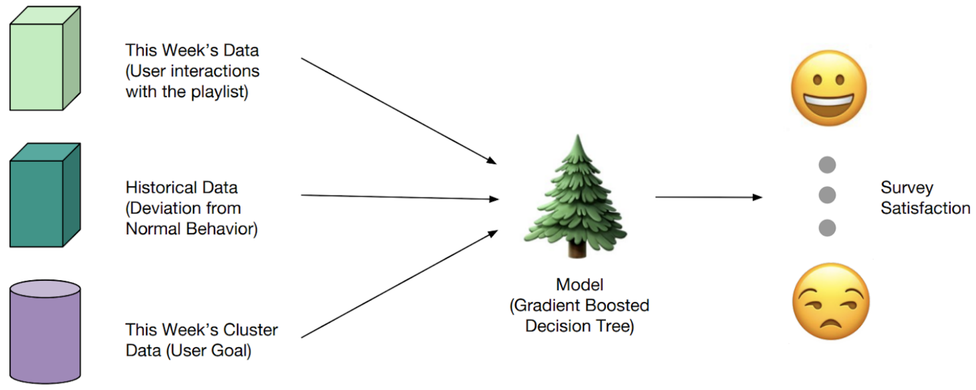


Figure 9: Procedure that return satisfaction prediction

The satisfaction prediction produced by the model is then, in turn, used as the reward for the algorithm that would compose Discover Weekly playlists, thus building a comprehensive reward system that doesn't rely on potentially ambiguous user signals.

The Spotify recommender system is an extremely complex and intricate system, with dozens (if not hundreds) of algorithms and ML models employed across various levels, all working together to create one of the most advanced recommendation experiences on the music streaming market. This system has been developed and iterated on for close to 12 years now — growing in size, capabilities, and complexity.

4.3 Behind the algorithm: understanding music and user tastes

In broad strokes, at the core of any AI recommender system, there's an ML model optimized for the key business goals: user retention, time spent on the platform, and, ultimately, generated revenue. For this recommendation system to work, it needs to understand the content it recommends and the users it recommends it to. On each side of that proposition, Spotify employs several independent ML models and algorithms to generate item representations and user representations.

For Spotify we just need the algorithm to make the perfect match between track and user representation and find the right track for the right person (and the right moment).

Spotify's approach to track representation is made up of two primary components:

- **Content-based filtering**, aiming to describe the track by examining the content itself
- **Collaborative filtering**, aiming to describe the track in its connection with other tracks on the platform by studying user-generated assets

The recommendation engine needs data generated by both methods to get a holistic view of the content on the platform and solve the cold start problems when dealing with newly uploaded tracks.

4.4 Content-based Filtering

4.4.1 Analyzing artist-sourced metadata

As soon as Spotify ingests the new track, an algorithm will analyze all the general song metadata provided by the distributor and metadata specific to Spotify (sourced through the Spotify for Artist pitch form). In the ideal scenario, where all the metadata is filled correctly and makes its way to the Spotify database, this list should include various specifications such as Track title, Release title, Artist name and much more.

The artist-sourced metadata is then passed downstream, as input into other content-based models and the recommender system itself.

4.4.2 Analyzing raw audio signals

The second step of the content-based filtering is the raw audio analysis, which runs as soon as the audio files, accompanied by the artist-soured metadata, are ingested into Spotify's database. The audio features data available through Spotify API consists of 12 metrics describing the sonic characteristics of the track. However, on top of these "objective" audio attributes, Spotify generates at least three perceptual, high-level features designed to reflect how the track sounds like in a more holistic way:

- **Danceability**, describing how suitable a track is for dancing based on a combination of musical elements, including tempo, rhythm stability, beat strength, and overall regularity.
- **Energy**, representing "a perceptual measure of intensity and activity", based on the track's dynamic range, perceived loudness, timbre, onset rate, and general entropy.
- **Valence**, describing "the musical positiveness of the track". Generally speaking, tracks with high valence sound more positive (e.g., happy, cheerful, euphoric), while songs with low valence sound more negative (e.g., sad, depressed, angry).

In addition to the audio feature extraction, a separate algorithm will also analyze the track's temporal structure and split the audio into different segments of varying granularity from sections (defined by significant shifts in the song timbre or rhythm, that highlight transitions between key parts of the track such as verse, chorus, bridge, solo, etc.) down to tatums (representing the smallest cognitively meaningful subdivision of the main beat).

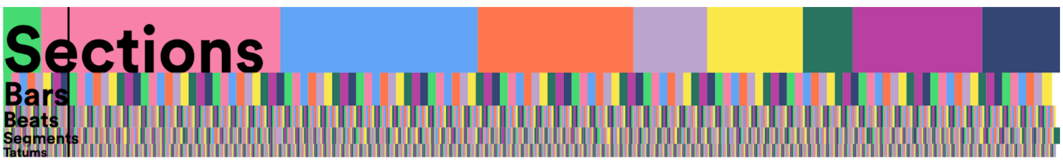


Figure 10: Temporal Audio Analysis for Lil Nas X – Industry Baby (feat. Jack Harlow) (Visualization by Spotify Audio Analysis)

4.4.3 Analyzing text with Natural Language Processing models

The final component of the content-based track representation is the Natural Language Processing models, employed to extract semantic information describing the track/artist from music-related text content. These models are applied in three primary contexts:

- **User-generated playlists**. The NLP algorithms run against the user-generated playlists featuring the track on Spotify to uncover additional insights into the song's mood, style, and genre. "If the song appears on a lot of playlists with "sad" in the title, it is a sad song."
- **Lyrics analysis**. The primary goal here is to establish the prominent themes and the general meaning of the song's lyrics while also scanning for potential "clues" that might be useful down the road, such as locations, brands, or people mentioned throughout the text.
- **Web-crawled data**. Running NLP models against web-crawled data allows Spotify to uncover how people (and gatekeepers) describe music online by analyzing the terms and adjectives that have the most co-occurrence with the song's title or the artist's name.

The NLP models allow Spotify to tap into the track's cultural context and expand on the sonic analysis of how the song sounds with a social dimension of how the song is perceived.

The three components outlined above, artist-sourced metadata, audio analysis, and NLP models make up the content-based approach of the track representation within Spotify's recommender system.

4.5 Collaborative Filtering

To better understand how collaborative filtering works, we must first take a look at what user modelling is and how it works.

4.5.1 What is user modelling?

User modelling/profiling is a subdivision of human-computer interaction (HCI) which has a wide range of uses and can be broadly defined as the "process of acquiring, extracting and representing the features of users", as stated by Zhou et al. [10]. These models are essential for many modern user-facing services that rely on recommendation algorithms. To enable the recommender systems used in these services, each user has a log of interactions that is analysed to gather information on their behaviours and interests. When discussing the case of user modelling in music streaming platforms, we can point out some more specific challenges and objectives that arise.

4.5.2 The usage of user modelling on Spotify

User modelling is a core component of Spotify's recommendation system as it enables the creation of a profile that describes the users' interests and preferences. By pinpointing features such as genres, artists and audio features and combining those with interaction logs it is possible to associate the user's preferences with certain kinds of music. User interaction logs might include information like library saves, adding tracks to playlists, following artists or how much time is spent listening to a specific song. This information and more can be used to create a user taste profile like the one in Figure 11.

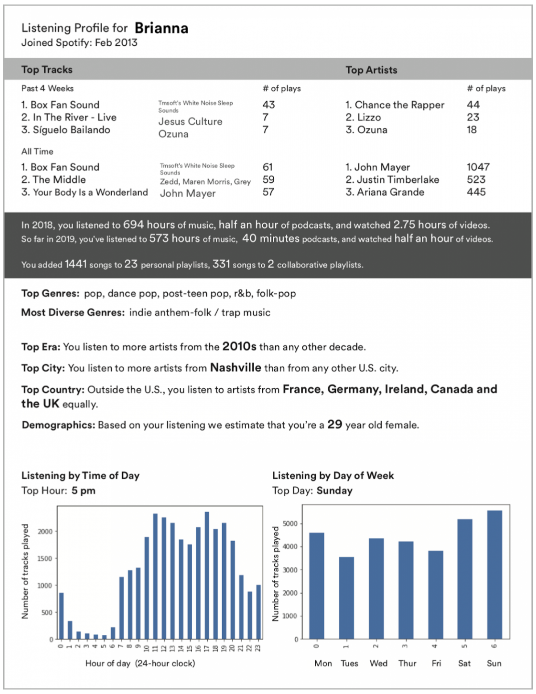


Figure 11: Example of a personal data profile [9].

4.5.3 Collaborative Filtering on Spotify

The kind of model mentioned previously allows for a "simple" recommendation system which can lead to conclusions like "Users who like A tend to like B as well" [7] which is known as Collaborative Filtering (CF) [6]. In Spotify's system, CF is used to create clustering of items and to measure similarity between items, creating embeddings, as illustrated in Figure 12. From the figure, it is possible to observe how an artist can be easily compared to another. For example, if a user listens to songs from The Beatles frequently, that same user is most likely to enjoy a song by Prince than one by Rihanna. The recommender system can easily take advantage of this clusters and similarity assessment by taking a user's most liked artists and arranging a few novelty songs from similar artists.

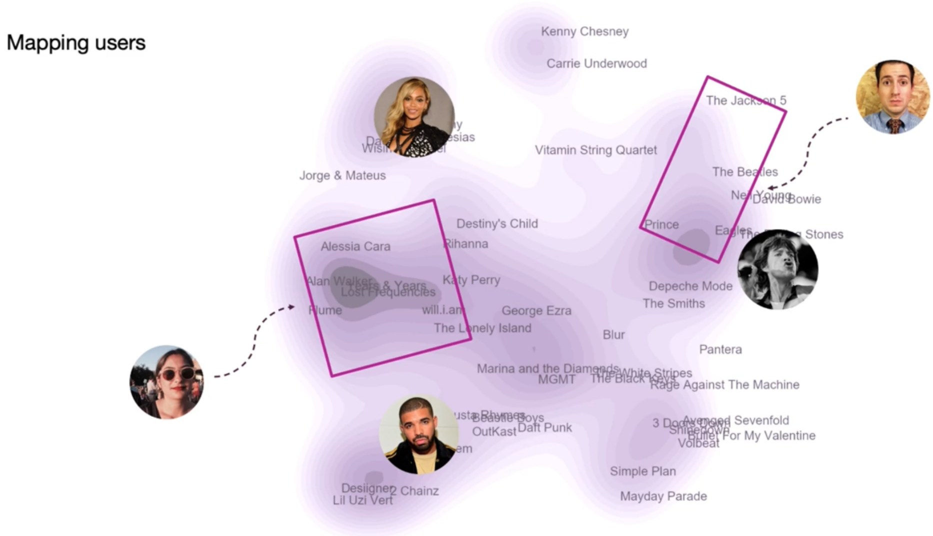


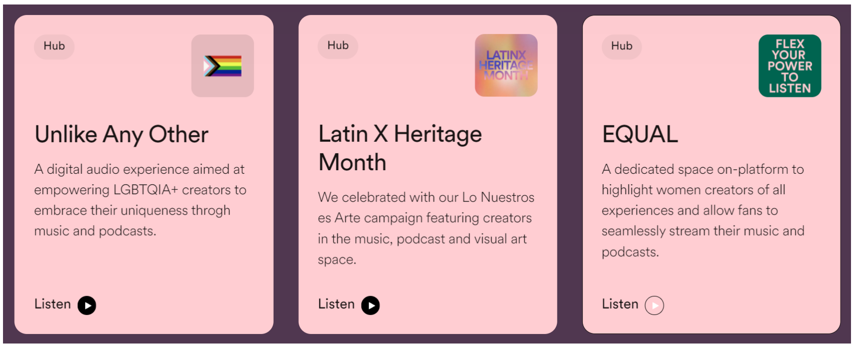
Figure 12: Hypothetical illustration of the Spotify musical artist embedding space [4].

5 Social Impacts

As a global brand, Spotify impacts the world, the music industry, and their users every single day. With this, comes a great responsibility. Spotify tries to use their platform to uplift marginalized voices and amplify important causes. To educate and motivate. To get behind the big social issues and raise awareness of the solutions. This is done by advising Spotify's creators and partners on how they can achieve ambitious social goals, pushing culture, acceptance and truth forward.

In order to achieve their goals, such as amplifying important causes, Spotify organises summits and training sessions, as well as working with other brands and partners. Most recently, their work with HeadCount, BallotReady, Election Protection Hotline and Civic Alliance contributed to historic youth turnout at the 2020 US election.

Spotify is also driving equity on their platform by spotlighting underrepresented artists and creators and ensuring their content is easy for their listeners to discover. They also invest in uplift programs like Sound Up, per example, their global initiative providing education, workshops and support for aspiring podcasters. Adding to this, Spotify as also created "Hubs" to their platform, as exemplified bellow:



Spotify has also created a program called "Spotify Gives Back", focused on supporting the people and causes they believe in. The program includes:

- **Employee Donation Match**, providing a platform for employees to double their charitable contributions to organizations they care about;
- **Dollars for Doers**, rewarding employees who volunteer with financial donations to the organizations they are supporting;
- **Volunteering**, giving employees the tools and resources to give back;
- **Pro Bono ads**, supporting not-for-profit partners with pro-bono ad inventory;

6 Conclusion

In this analysis, we "scratched the surface" on the complex system that is Spotify, one of the most recognizable streaming platforms. We also discussed the system as a music streaming platform, explained how the system works in terms of architecture and compared the theoretical bandwidths with the ones that are used. From that discussion, we could observe that the bandwidths disclosed by Spotify were mainly accurate to reality for both the Premium and the free versions.
When explaining the immense system that is used for recommendations, it was possible to easy to appreciate how it works. We briefly explained the three main components that are used in Spotify's recommender system, which were collaborative filtering, content-based filtering, and natural language processing. We explained how these components work together to create the perfect recommendations for each user.

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