a mobile application to refine music suggestions based upon user preferences and feedback

[date]

**Abstract**

**Declaration**

*I certify that all material in this dissertation which is not my own work has been identified.*

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# **1 Introduction**

### **Motivation**

Music is a central part of a huge number of people’s lives. People listen to music when working, exercising, partying and during so many other daily activities. Searching for new music has evolved in the past 50 years away from vinyl record shops to digital formats such as CD’s, MP3 players and now streaming services. An (IFPI, 2018) study found that global average music consumption per week sits at almost 18 hours a week – or 2.5 hours a day. It also forms a huge economic industry; Spotify disclosed an annual revenue of almost $6 Billion in 2018, with total users standing at over 200 million in the fourth quarter of that year (Spotify Technology, S.A, 2018).

The way in which users can be exposed to new music content has changed along with the evolution in consumption. During the days of vinyl records, shopkeepers would recommend fresh music they have recently taken into stock. Now, modern music platforms such as Spotify or Deezer provide suggestions or recommendations to users on new music to listen to in the form of a recommendation engine. Platform-curated recommendations often form a significant chunk of consumption; (Economic Times, 2018) established a figure of 15% for the Gaana music platform. These recommendations are often based upon user feedback – known as collaborative filtering.

Whilst this technique is likely to result in a majority of listeners receiving desired results, making it reliable, it is often limited outside of the generic listeners use-case. Music tracks have attributes which aren’t created in artificial big-data situations; for example, signal frequencies can be analysed. The Spotify API is a fantastic case study of this; it stores data on danceability, valence and energy to give some examples, as well as storing more traditional, collaborative attributes such as popularity (Spotify, 2019). These content-based attributes can be combined with collaborative ones in order to provide more interesting and demand-specific suggestions.

Considering use cases, the initial motivation for this project came from a personal interest in discovering music based upon similarities in the content, rather than music that was popular in the genre I was listening to or the region I was listening in. As a DJ, I have found that traditional collaborative recommendations typically show me music I am already aware of. In designing a platform to discover music based upon its content, I hope to be able to enhance my ability to discover more unknown music which would fit into a specific vibe with which I am attempting to play.

### **Aims & Objectives**

In the broadest terms, the aim of this project is to design and implement a platform to create refined music suggestions using a recommendation engine biased towards a content-based filtering technique, against the industry-preferred collaborative filtering approach. The (IFPI, 2018) study referenced earlier also finds that 27% of total music listening time is on mobile devices; accounting for the continued use of non on-demand services such as radios, that suggests that a mobile application would be the most commercially sensible development platform. In order to provide ease-of-use to users of the application, and to take advantage of the huge amount of resources available for developing such an application through music platforms, tying the application to (at least) one platform through an API should be another of the broad objectives.

# **Literature & Specification**

### **Literature Review Summary**

Recommendations engines for music are inherently a big data problem; (Sagiroglu & Sinanc, 2013) define big data as ‘data sets large, more varied and complex structure with the difficulties of storing, analysing and visualizing for further processes’. Using earlier figures, users listen to just 22.5 minutes of recommended music a day, showing the challenge in creating good concise recommendations. Considering the four key areas of big data, volume clearly presents the biggest challenge; (Spotify, 2019) has over 50 million individual tracks stored. Veracity is interesting in the context of generated attributes being subjective.

Data characteristics in music can be split into ‘content-based’ and ‘collaborative’ (Lin, et al., 2014). Content-based attributes, such as ‘danceability’, refer to the content of music, whereas collaborative attributes, such as ‘popularity’, denote user preferences. Content-based attributes can be split into factual (musical key) and subjective (energy). Subjective attributes are the result of complex analysis to generate comparative values; the above examples are results from the Spotify API (Spotify, 2019).

The ‘cold start problem’ is a common issue facing recommendation engines, described as the ‘need to accumulate personal information in advance’; industry leaders such as Spotify & Apple Music face this problem (Wang, et al., 2014) (Jenkins & Yang, 2016). Existing literature shows the requirement of engines to use a combination of both techniques. One example would be to store users’ listening history to prevent repeat recommendations - (O'Bryant, 2017) proposes use of such data in making informed recommendations.

Existing literature on designing music recommendation engines spans from complex mathematical designs to linear, iterative ones. (Kodama, et al., 2005) discuss a system defining a ‘mood’ of a song by extracting values including tonality, dispersion of chords and signal levels; they then proceed to ask a user to select from ‘reference words’ to describe how the song makes them feel. (Kaji, et al., 2005) discuss a system utilising a three-stage system to generate and refine playlists through generation, transcoding and data analysis.

Often discussed in literature is the tendency of collaborative-biased engines to favour ‘popular’ music. (Celma, 2008) uses Amazon’s website as an example of this. (Soleymani, et al., 2015) propose a heavily mathematical, content-based solution to the cold-start problem, using ‘modulation analysis to extract timbral features’. They argue that use of attributes more complicated than genre provide better results for users.

### **Project Specification**

# **Design**

As a project heavily leaning towards software engineering, as opposed to research, design decisions should be made with a commercial viewpoint at the forefront of the process.

### **Pathways & UI**

### **Recommendation Engine**

# **Development Lifecycle**

# **Implementation**

# **Testing & Evaluation**

# **Critical Discussion & Conclusion**

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