

Briefly put yourself in the not-so-distant past. Your favorite band had just released a new album, and you hurry to the store to purchase a CD before it's sold out. A few years later, you're amazed to find that all your music can be stored digitally on a single device, the iPod. Now, with the dawn of the iPhone and other application-enabled smartphones, music has become more mainstream than ever (Song et al., 2012). This is especially true with the introduction of subscription-based music platforms. These services have opened new avenues for consumption of musical media. Instead of waiting for a new release from your favorite band, the constant accessibility to music has bred an interesting question for the purveyors of these services: How can we maintain user retention beyond what we know this user will listen to? The answer lies in music recommendation engines.

Music recommendation engines are the underlying algorithms which allow music services to personalize content for individual users. The underlying idea to these algorithms is simple. Getting down to it, there are two pieces in this puzzle: the user and the music. The user has some inherent preferences that characterize their listening. There are those that like to explore, those that stick to what they like, and many who characterize themselves as a blend of the two. The advantage to understanding the user is knowing the depths of exploration that they are willing to make. A more adventurous listener might be exposed to more experimental recommendations that someone more stuck in their ways. The musical aspect of recommendations comes from data like artist and genre. This also includes more technical metadata such as tempo and pitch (Song et al., 2012). The latter of these two, the acoustic metadata, is applied in signal processing contexts to automatically characterize genre and mood of music in a process called Music Information Retrieval (MIR) (Schedl, 2019). However, these signal processing techniques are not limited to characterization and have been shown to be effective in recommendation engines through spectral analysis (Magno & Sable, 2008).

This paper will compare the use of content-based engines in music recommendation versus spectrum-based analysis done on sound data. Moreover, the goal of this paper is to determine which method is more effective in recommending music specific to a user. Part of this entails some desire in the MIR field for the need of a standardized metric to characterize a successful recommendation (Schedl, 2019).

To be able to conduct this project, I will need to draw on my skills from my time series and physics courses. For instance, the method I will consider for spectral analysis uses the Fast Fourier Transform (FFT) to analyze the fundamental frequencies in the acoustic data. From here, the spectrograms of different songs can be compared using some distance-based correlation metric. It's my understanding that standardization will not be necessary, to preserve frequency magnitudes, an important aspect in potentially comparing the tone and pitch of a song. In terms of content-based engines, I will explore methods that have shown promise, including decision trees, clustering algorithms, and Monte Carlo Sampling. As for data, Last.fm is a reputable source for analyses in Spotify, and would offer me the capabilities that I'm looking for in the analysis that will be attempted in this paper.

## Works Cited

Magno, Terence & Sable, Carl. (2008). A Comparison of Signal Based Music Recommendation to Genre Labels, Collaborative Filtering, Musicological Analysis, Human Recommendation and Random Baseline.

Schedl, Markus. (2019). Deep Learning in Music Recommendation Systems.

Song, Yading & Dixon, Simon & Pearce, Marcus. (2012). A Survey of Music Recommendation Systems and Future Perspectives.