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COMPUTER SCIENCE

PRODUCTIVITY PLAYLIST

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Introduction

We listen to music for enjoyment, distraction, joy, comfort, and focus. People curate music playlists to reflect and affect their own moods. Popular music platforms like Spotify also create playlists of songs with similar moods by feeding data on a song's characteristics to machine learning models which create personalized playlists for users. The music from these playlists is not optimized to steer users to productivity, and often distracts instead. Previous affective music studies create playlists of songs with a similar emotional state, but those playlists were not dynamic based on mood [1]. We create a "productivity playlist," an intelligent algorithm that creates playlists that automatically adjust based on the user's current mood to lead them towards a happier or more productive state.

Dataset

We use the Arousal-Valence circumplex model of emotions since its continuous nature allows for a path to traverse its two-dimensional space [3]. We found two datasets containing many songs and their associated points in this model: the DEAM 2016 and the Deezer 2018 datasets [2, 4]. After statistically comparing the Deezer and DEAM datasets, we chose the Deezer 2018 dataset since it contains more songs (18,000+) with a wider spread of emotional points. This will allow us to create large playlists that can travel through a greater range of emotions.

Methods

Our algorithm, given a starting song, a target song, and a desired length, creates a smooth, linear path with consistent steps through the Arousal-Valence space. We use a K-Nearest Neighbors (KNN) machine learning model to interpolate this path. The algorithm moves from a current song towards the destination in consistent steps, finding the nearest neighbors to a "target" point. We find the smoothest next song out of these points using a distance metric and repeat until we reach the destination.

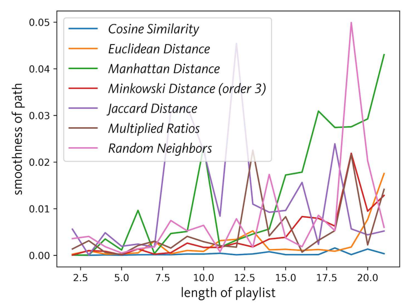

Figure 1: A comparison of various distance metrics in creating smooth playlists of various lengths with our algorithm. Each playlist was compared with MSE to a "perfect" line from the origin to the destination.

Results

To ensure our playlists are as smooth as possible, we chose several popular distance metrics to compare and used mean-squared error to evaluate our playlists (see Figure 1). After discovering that Cosine Similarity produced the smoothest playlists, we used our algorithm to create smooth dynamic playlists in the Arousal-Valence space to bridge the emotions between given starting and target songs (see Figure 2).

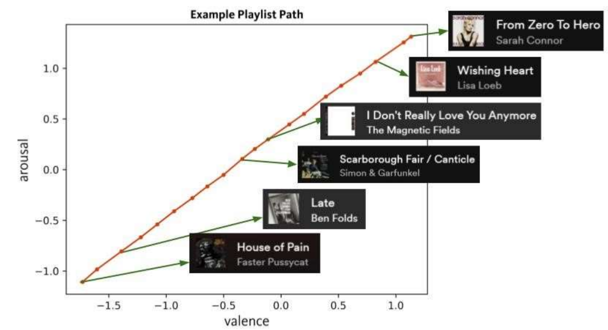

Figure 2: A 21-song playlist created by the algorithm. It moves smoothly from depression to excitement.

Discussion

This work is a starting point for further research. Currently, we are examining ways to detect a user's emotional state using facial recognition, to automatically tune playlists from a user's emotion. We are also examining Spotify's built-in audio feature data to create dynamic playlists with similar genres. Playlists made by our algorithm could be powerful tools in mental health and productivity, gently guiding users to happier or more focused states of mind.

References

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[2] Remi Delbouys, Romain Hennequin, Francesco Piccoli, Jimena Royo-Letelier, and Manuel Moussallam. 2018. MUSIC MOOD DETECTION BASED ON AUDIO AND LYRICS WITH DEEP NEURAL NET. (2018), 6.

[3] Jonathan Posner, James A Russell, and Bradley S Peterson. 2005. The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. Dev. Psychopathol. 17, 3 (2005), 715–734. DOI:https://doi.org/10.1017/S0954579405050340

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