



Behavior Modes for Machine-Learning Enabled Performance Technologies

Jason Palamara, PhD Scott Deal, DMA

Machine Musician Lab, Donald Tavel Arts and Technology Research Center

Department of Music and Arts Technology

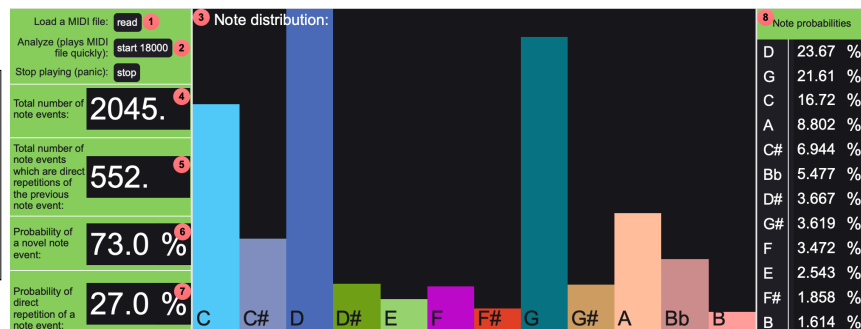
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Abstract

This project illuminates the use of and approach to behavior modes in the AVATAR musical improvisation software which employ machine-learning data in different ways, approximating human performance. While the list of possibilities for ways to play a grouping of notes on a given instrument is practically infinite, a much smaller number of behaviors is regularly used by any one performer. With the goal of the AVATAR project being an interconnected system of softwares, which maps to a real-life human model, these behavior modes have been modeled after the improvisation style of the project's primary model, composer-percussionist Scott Deal.

A behavior mode is here defined as "observed tendencies which a given performer returns to with regularity." Once observed and catalogued, it is our hope that these tendencies may be used proscriptively to generate new musical material which adheres closer to the original musical dataset than that generated by a standard Markov model from the same dataset.

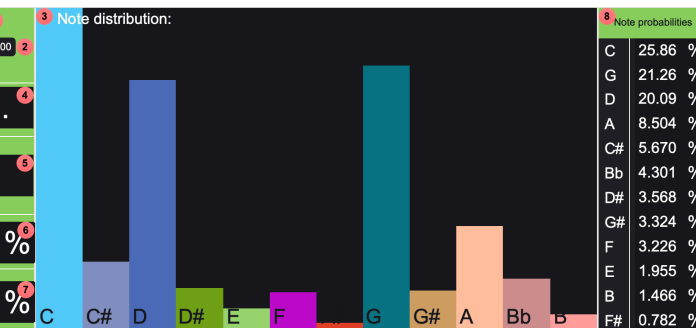
Example 1.
Machine analysis of an improvisation on vibraphone, by Scott Deal, July 8, 2020.



Observing Behavior Modes

AVATAR's performance schema previously began by building a Markov model from a concatenated MIDI file of multiple improvised performances. Here, MIDI files have been analyzed by a Max patch for characteristics which may be referred to as elements of style. In the example to the right (1.), the algorithm has identified most the four most common pitches in the sample as being D, G, C and A. The analysis also shows a 73% chance that any note will be repeated before moving on to a novel note choice, and the system also provides an in-depth analysis of the probabilities for all twelve pitches possible.

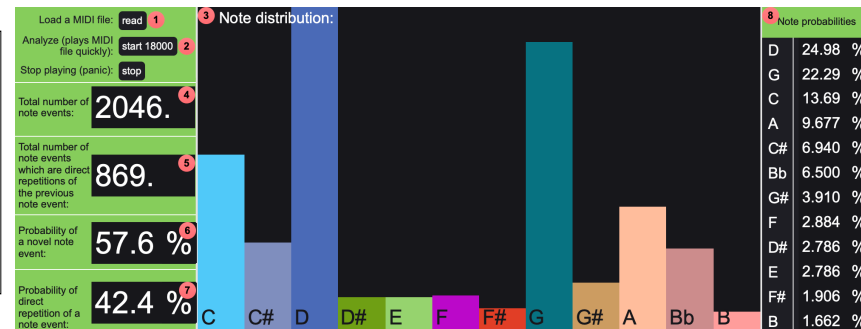
Example 2.
Machine analysis of music generated via a Markov-chain, order 2, resulting in a significantly less repetitive music, with a different tonal emphasis.



Simple Markov-Chain Generated Music

In the next example (2.), a new MIDI file music was generated via a Markov model of the original MIDI file with the same number of notes and the file was subsequently analyzed by the same patch for repetition and tonal percentages. While this process did map closely to some notable characteristics of the original model (for instance the four most common notes are the same), the level of repetition is significantly varied, as are the probabilities of each note choice giving the generated music a different tonal emphasis.

Example 3.
Machine analysis of music generated via a Markov-chain (order 2), using a Behavior mode filter. While tonal emphasis shows improvement, more work is needed to improve the probability of direct repetition.



A Markov-Chain, with a 'Behavior Mode' Filter

In the third example (3.), another new MIDI file music of similar length was again generated via a Markov model of the original MIDI file but this time the Markov generation process was 'filtered' for repetitions, using the probability of repetition from the original MIDI file. While this process has significantly skewed the probability of direct repetition, it has simultaneously improved the distribution of notes and thus maps closer to the tonal emphasis or centrality of the original dataset.