Machine Learning and Music Composition

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ABSTRACT

in the background section,introduce topics: Decision Trees, Over Fitting, Machine Learning, Finite Automata and others.

1. INTRODUCTION

2. BACKGROUND

We use this section to introduce important terminology for the rest of the paper.

2.1 Music

In this section we explain the terminology that is important to the music side of the paper.

2.1.1 Melody

Melodic progression is the breaking down of the 8 note octave into equal parts. Either whole steps of the 12 half steps or semitones. Melody is the pitches and rhythm that are used to be aesthetically pleasing. Thus a melodic progression uses various intervals- the whole steps or half steps in combinations that are pleasing, we hope, to the listener.

2.2 Computer Science

In this section we describe the terms that are important for understand the terminology related to computer science.

2.2.1 Decision Trees

Consider inserting an image about decsion trees if deemed necessary?

Decision trees are a structure that repesent the tests and outcome of an algorith. Every node on the decision tree represents a possible test or choice that an algorithm can make. The resulting branches from that come from that node represent all of the possible outcomes of that test. This can easily be repesented by flipping a coin multiple times in a row. Every time the coin is flipped, a node is created in the descision tree. In this instance, the two nodes for the coin flip are heads and tails. For every subsequent coin flip, a new set of nodes and leaves are generated. This allows the decision tree to contain all possible out comes for the Nth coin flip.

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2.2.2 Overfitting

Overfitting is possible side effect that can occur with decision trees. When a decision tree is made and trained for an application, it can become too complex and dependant on the particular set of data that it was trained upon. This occurs when a tree gains too many parameters, making the tree too specific to the data that it was trained on, or the nodes the tree branches from are inconsequential to the actual results. A concequence of overfitting happens when the tree is then tried on data different from what is was trained on. The tree looses its accurecy at prodicting what the possible results may be.

2.3 Machine Learning

2.4 General Framework

All of the methods described in this paper share a similar framework that would be usefull to understand. The commonality between all of the methods is that every note is generated in relation to a cache of previous notes. Meaning that every note is dependant upon a set of notes before it, whether it is only the previous note or a larger set of notes. This allows the program to determine a melodic progression for the music.

3. METHODS

In this section, we will be describing three seperate subcategories of machine learning. The three subcategories of machine learning that we will be describing are *random forests*, *markov chains*, and *neural networks*.

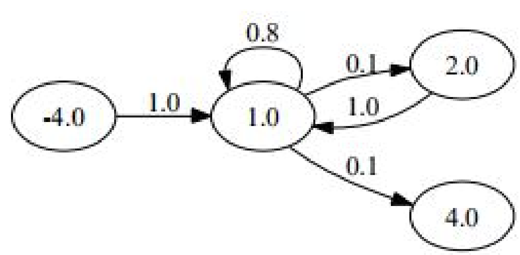

Figure 1: Finite automata detailing the Markov Generated in Automatic Composition of Music with Methods of Computational Intelligence

First, we discuss the use of random forests. Random forests operate by generating and altering a large collection of decision trees. The generated output of the random forest is the result of the average answer of all of the decision trees in the forest. As with all machine learning a set of amount of time is required to teach the algorithm to properly generate answers. For the case of random forest, each decision tree is made on only a small part of the set of data, with overlap among all of the trees. This overlap in the data that the trees are built on helps to reduce over fitting of the trees to the data. When it comes to music we discuss a program known as ALYSIA, that uses two random forests to generate music from a given set of lyrics.

Next, markov chains function fundamentally differently than random forests. Markov chains use a state machine and a statistical models to predict the next value. Figure 1 shows a simple finite automata for a markov chain, containing only the possibility of having quarter, half, or whole notes, that was generated fo the paper Automatic Composition of Music with Methods of Computational Intelligence. The automata visualizes the way the markov chain uses probabilistic determination to predict what the next note or value will be. In the terms of music this means that for each state in the automata it has a percentage chance of moving to each of the other nodes in the automata. In this case, the first note will be a quarter note with an 80% chance of having a repeated quarter note, and only a 10% chance of having a half note following.

Neural networks offer yet another approach to using computers to generate music, this time being a deterministic style of algorithm.

Need to add much more to the section on neural networks.

4. METHODS AND MUSIC

In this section, we will discussing how the previously stated methods can be applied to the composition of music with specific examples.

4.1 ALYSIA

ALYSIA, Automated LYrical Song-writing Application, is a program that uses random forests to generate songs and melodies for a given set of pop lyrics. ALYSIA contains two different random forests that work in tandem: one to produce rhythm, the other to produce pitch values. [ALYSIA] Random forests can provide some inherent benefits over Markov chains. Even though both models work from a cache of previous notes and both predict what the next note should be. Markov chains offer only a statistical probability of what the next note should be, while random forests include a reasoning to what the next note should be.

4.2 Citations

4.3

Acknowledgments

Fix the section heards because currently they are not organized in a way that makes sense.