Algorithmic Composition of Classical Music through Data Mining

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**Abstract**

The desire to teach a computer how to algorithmically compose music has been a hot topic in the world of computer science since the 1950’s, with roots of computer-less algorithmic composition dating back to the days of Mozart and a pair of dice. One of the biggest limitations of algorithmically composing music to date has been the difficulty of limiting the amount of human intervention required to achieve a musically homogenous, computer-generated composition. We attempt to remedy this issue by teaching a computer how the rules of composition differ between the six distinct eras of classical music by having it examine a dataset of musical scores, rather than explicitly telling the computer the formal rules of composition. To pursue this automation of the algorithmic composition process, we examined the intersectionality of algorithmic composition with the machine learning concept of classification. Using a Naïve Bayes classifier system, the computer learns to classify pieces of classical music into their respective musical era based upon a number of explicit attributes extracted from the data. It then attempts to primitively recreate each of these six musical styles using a technique inspired by cellular-automata, with rules informed by the output of the classifier. The success of this process is twofold determined by feeding samples of its compositions as a test set into a number of classifiers deemed to have a high success rate among a training set of traditionally composed pieces, as well as by analysis of the pieces performed by studied musicians. We concluded that the process adequately replicates the attributes on which the classifier focuses. It shows the potential of further hybridization of classification techniques – ones which focus on different attributes within classical music – with composition techniques. This hybridization could potentially further remove human intervention from the process, and result in more wholly homogenous generated pieces of music.

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1. **Introduction**

Of all major art forms, music has historically relied most upon scientific and mathematical devices in its creation. While many other forms of art are often lauded for breaking the rules, and these avant-garde approaches often find themselves at the forefront of popularity, the most praised and well-respected pieces of music always seem to find themselves firmly grounded in the formal rules of composition that have been widely accepted for centuries.

The reason behind this can be easily attributed to the notion that music is very well founded in the world of mathematics, and the rules of music theory are indeed built upon it. Both the relations between pitches and durations are best defined by numbers and ratios. In fact, because of its reliance on precise measurement, music was considered until fairly recently a branch of science (Wieners). This fact makes it very tempting to both analyze and create music through a scientific approach, and it is indeed a venture that has been attempted many times over the course of human history, making great strides since the beginning of the digital age.

**1.1 Early Exploration**

The intersection of mathematics and music predates the computing age quite considerably. The topic of algorithmically composing music saw its initial explorations as early as 500 B.C. in the times of Pythagoras (Boethius), when he developed the concept of “music of the spheres”, in which he drew a connection of significance between the world of music and mathematics. Of course, Pythagoras could not have known what he was pioneering would one day spawn the algorithmic composition of music, as the term ‘algorithm’ wasn’t even invented until 1120 (Niederhaus). From this point on, the world of music was situated comfortably in the middle of the mathematical spectrum, and a millennium later, Flavius Cassiodorus (ca. 485-575) described mathematics as a union of the four disciplines: arithmetic, music, geometry and astronomy (Diaz).

Once the medieval period came around, composers began to formulate rules by which pitch relations and combinations were governed, laying the groundwork for music theory as a practice that would be followed and expanded upon for centuries (Duckles). It was in the 1700’s with a game called Musikalische Würfelspiel (Fernandez), which translates from German to ‘musical dice game’, that the rules were put to use in an algorithmic fashion. The game’s most popular iteration, allegedly devised by Mozart himself, saw the user roll a pair of dice, and their composition would proceed based on the outcome being mapped to a ruleset Mozart outlined. These early experiments laid the ground work for algorithmic music to come.

**1.2 The Data-Driven Intelligence Age**

With the framework of algorithmic music already laid centuries before, it was only natural that the concepts were brought into the world of computing as early as the 1950’s at the genesis of the information age. The most famous example from this time is Hiller and Isaacson’s *Illiac Suite*, which used rule systems and Markov chains, a stochastic predictive system with no memory, to predict the next successive note based solely on the current note. As the work was expanded upon by colleagues and interested parties, the chains were designed to implement an *n*th-order technique, which allows the process to consider the last *n* notes, rather than only the most recent (Vico). This initial work with Markov chains became the springboard of computerized algorithmic compositions.

Since this advent, the topic’s exploration has increased drastically, and has branched into many different realms, with new techniques and structures being used as the basic building block of the composition process. In his book “Algorithmic Composition: Paradigms of Automated Music Generation”, Gerhard Nierhaus split the topic into several distinct categories, including generative grammars, transition networks, genetic algorithms, cellular automata, artificial neural networks (ANNs) and artificial intelligence (Nierhaus). As these fields grow further apart, greater strides and achievements are being made within each.

The intersection of music and computing becomes even more pronounced when you approach the topic of data mining. Many have explored the potential of classifying music of all varieties, and results have been quite successful. Researchers Lebar, Chang & Yu used classifiers to distinguish between different classical composers using stylistic features as attributes. Basili, Serafini and Stellato tackled the topic of popular music when they classified a set of music into six distinct genres based on features such as intervals, instruments used and meter changes. The basic structure of this study has been conducted by many, receiving respectable results overall.

**1.3 Study Overview**

While it is clear that this topic has been explored in many facets, there is still a gap when it comes to what a computer is capable of producing, and some of the most recent studies in the field still find themselves labeled as composition inspiration software (Vico). The idea of hybridizing multiple of these concepts has therefore become attractive, in an effort to achieve the best generative characteristics from multiple approaches. For this reason, we find it worthwhile to explore new avenues, and see what kind of new directions we can bring to the topic of algorithmic composition.

It became evident during the course of our research that one such hybridization comes from the potential of using the field of data mining to inform the decisions made during certain algorithmic composition techniques. Intersecting these two concepts has the potential of creating a smarter generative process, capable of replicating nuanced differences between several different categories of music, adapting to new forms of music being introduced, and minimizing the amount of human intervention required for some techniques, such as generative grammars and cellular automata, which in their current state require a large amount of human input to inform the computer of what rules to follow. It is under the guide of this general framework that we began our work.

1. **Data**

With any venture into the world of data mining, the first and most important task you must address is the data that you wish to use within the experiment. The topic of music presents a particular challenge in this respect, as the data at hand is not nearly as friendly for computer use as something like stock numbers or attendance projections may be. For this reason, a substantial amount of time needed to be dedicated to understanding the data of music, discovering what kind of characteristics are desirable to use from the data, and what kind of computer-friendly representations we have as options moving forward.

**2.1 Musical Representation**

In order to properly understand the data, it is important to first have a firm background in the formalities of music. For the sake of this experiment, we will be narrowing the scope of our focus entirely upon classical music. The main reason for this decision is classical music’s written consistency across history (Duckles). Music has evolved and expanded greatly since the days of Mozart and Bach and as a result, much of what is being created today in popular music has abandoned the concept of formally creating a written representation of the music. Recent years have seen the greatest decline in non-educational production of sheet music (Tawa). Luckily, classical music, by virtue of its creation for performances by individuals other than those composing, as well as its educational value, has a rich history of written representation. It is still most widely recorded in this manner today, and thus provides us with a much more stable and wide backlog for analyzation.

This backlog of classical musical literature is comprised almost entirely within the medium of musical scores, or sheet music. Sheet music is a visual representation of music made up of many components, most notably measures that contain notes with duration values. This manor of recording music started as early as the ancient Greek and Middle Eastern civilizations where they began using basic music symbols as written reminders. It wasn’t until the 9th century that Christian Monks began recording music on sheets. From this point on, the practice exploded in popularity, and has maintained the same basic structure (Tawa).

The information recorded on a piece of sheet music is extensive and is able to encompass the entirety of a musical piece. Everything from notes to volume to the speed at which it is played is all represented with various symbols and key words across the page. It takes a trained musician to know how to get the necessary information off the page.

**2.2 Digital Formats**

For hundreds of years, western music has been represented by means of these musical scores. This has been relatively unchanged because it is an ideal notation for a musician to read and perform, and as a product, reproducibility was at a premium (Tawa). With the advent of the digital age, the necessity for a new representation of written music was realized. This was due to the complex nature of musical scores. It is quite difficult to teach a computer to parse through the various symbols and notations of music, making the task of retrieving the data necessary for processing challenging. As a result, the computer science community was met with the challenge of creating a new representation of music that could be more easily processed for the studies to come. Though many were proposed, two have risen above the others in the world of research, MIDI and \*\*kern musical files. Both have their own unique advantages and disadvantages.

**2.2.1 MIDI**

First seeing its start in 1981 (Anderton), the Musical Instrument Digital Interface (MIDI) format is one of the most widely used digital musical formats that exist. By virtue of its creation for use with electronic synthesizers, MIDI files contain representations of the musical score that are often recorded via humans playing the score with a synthesizer, though you can also find hand compiled MIDI representations. When hand encoded, these files serve as a kind of hybrid between performed music and written music, as it is a strict representation of how a musical piece would be performed without any human error or embellishment.

Over time, this format has been adapted for use in scholarly research, with many toolkits being developed, such as jSymbolic (Basili), to extract data from the MIDI files. Because of its widespread use for a variety of functions, the backlog of MIDI scores to be used for potential research is vast, but also unreliable. This is due to the fact that anyone with an electronic keyboard can plug it into a computer and create these files, regardless of their accuracy level. Despite this, we found throughout our survey of previous studies that MIDI is the most widely used file type in academic research concerning computer music.

**2.2.2 \*\*kern**

While the MIDI format was created for a wide variety of computer music purposes, a format known as \*\*kern was created with a much narrower intention. \*\*kern files are musical representation files which fit within a broader syntax known as ‘Humdrum’. Described by its creator David Huron as a “general-purpose software system intended to assist musical research” (Huron), the software was quite literally designed for use in projects like this. Researchers Lebar, Chang & Yu used this format when attempting to classify musical scores by composer, while researchers Mearns, Tidar and Dixon used this file type to characterize composers into different classical styles.

The Humdrum software can be split up into two separate entities: The Humdrum Syntax and the Humdrum Toolkit (Huron). Humdrum Syntax is a grammar by which any file that falls under its guise must adhere to. \*\*kern is a single file type under this syntax, and indeed the most widely used of them, designed to represent the core information for common Western Music. The format is capable of representing nearly every nuance found within a musical score, down to the direction the stem of a note is facing on the page. The other half of the equation, the Humdrum Toolkit, is described by Huron as a toolbox of ‘utilities’, with over 70 inter-related software tools, which can be used to manipulate any data that conforms to the Humdrum syntax. These tools, combined with the vast number of features that can be represented using the Humdrum Syntax, make it a very attractive option in the realm of data mining.

While this format offers many advantages, there are certainly drawbacks to it as well. Because of its rather limited usage (being designed specifically for research purposes), the amount of data available in this file type is sparse. There have been a number of people who have contributed a large number of scores encoded in \*\*kern format, however the encoding process, which must be done entirely by hand, is a tedious one (though perhaps lends itself to a greater attention to detail), and there will never be a rich well of files to choose from. Another drawback is that the \*\*kern format does not offer a playback function like its MIDI file alternative. While this is not a drawback from an analytical standpoint, it does make it difficult to determine whether a piece has been accurately encoded and puts us at the whim of those who encoded the data.

Despite these deficiencies, we found the format of \*\*kern to be most compatible with the task at hand. The Humdrum toolkit offers us an effective way to extract any and all information about the score we may find useful, and the textual representation is also much friendlier to interpret on a visual level. With this decision, we began our work in data mining.

1. **Data Mining**

Data mining has exploded in recent years as an emerging concept in the area of computational intelligence. The applications of this new and intellectually stimulating field are plentiful, diverse, and exciting for those focusing on the topic. The phrase ‘data mining’ itself defines a rather broad idea, simply described as “sifting through very large amounts of data for useful information” (Business Dictionary). In the pursuit of achieving this goal, this topic has been approached using several other distinct methodologies, such as classification, clustering and association, among others (Tan).

While each of these data mining methods have merit, and some may indeed be useful in future works while attempting to improve the algorithmic music composition challenge, this study has chosen to focus its attention on the topic of classification. Classification is defined as “the task of assigning objects to one of several predefined categories” (Tan). This objective is achieved through the use a learning scheme that generates a set of rules for classifying instances into these predefined classes. The trained classifier is then able to predict the classes or categories based on the generated rules (Suh). The predictive power of this form of data mining is one of the driving forces behind the decision, as a predictive rule-based system provides us a nice backbone upon which to build a music generator.

* 1. **Data Extraction**

In order to get the most out of the data mining process, there is a large amount of preparatory work that must be done to ensure that the information received as consequence of our work is valuable and significant. Our results are only as valuable as the system from which they were derived, so it is important to ensure we make the correct decisions leading up to the actual data mining taking place. Some of these decisions include dictating which pre-defined classes to supply our classifier as it categorizes the data, which features we would like our classifier to look at in making these categorizations, and the preprocessing and data extraction required to make the data accessible for the actual data mining process.

**3.1.1 Classes**

The first thing we needed to do when prepping our data for processing was select the pre-defined classes by which to separate the data, as the classification methodology necessitates. In musical classification, there have been studies that have done this in several manors, whether it be by composer, genre, or even decade. For the sake of our study, we found it most appropriate to separate the classes based upon musical era within the classical spectrum.

There have been several eras by which the style of a classical piece can be defined, roughly outlined in figure 1. The years in which these eras transitioned between one another have been debated by experts, however it is generally accepted that there are six distinct eras, ranging from the beginnings of formally composed music in the medieval era to the wildly innovative and often atonal modern era of classical music. Moreover, students and scholars of music are able to use their training in aural skills, such as identifying the interval between any two successive notes, among other musical features, to identify which of these eras a piece of classical music belongs to. This suggests that there are quantifiable differences in their structure that make it so, and provide us great reason to believe a computer will be able to identify these differences as well.



Figure 1 – A timeline displaying the order and generally agreed upon

dates of the various eras of classical music

**3.1.2 Attributes**

Our next step was to decide which attributes we would be basing our classification upon. In data mining techniques utilizing classification, these attributes – or features – are analyzed in a variety of ways in an attempt to generate rules for separating the data into the pre-defined classes it has been given. It is therefore important to choose features that are both indicative of the stylistic-era under which the piece was composed, as well as replicable for the future generative process. The features decided upon after consideration of a number of factors, presented in figure 2, are based upon the notion of a musical interval. The task of choosing these attributes came with two major challenges; one musical and one computational.

|  |  |  |
| --- | --- | --- |
|  | **Attribute** | **Description** |
| X1 | freqUni | Ratio at which unison intervals occur (unison/total) |
| X2 | freqStep | Ratio at which stepwise intervals occur (step/total) |
| X3 | freqThird | Ratio at which third intervals occur (third/total) |
| X4 | freqFourth | Ratio at which fourth intervals occur (fourth/total) |
| X5 | freqFifth | Ratio at which fifth intervals occur (fifth/total) |
| X6 | freqSixth | Ratio at which sixth intervals occur (sixth/total) |
| X7 | freqSeventh | Ratio at which seventh intervals occur (seventh/total) |
| X8 | freqOct | Ratio at which octave intervals occur (octave/total) |

Figure 2 - List of attributes used in classification

By merit of the musical data we are using, there were countless numbers of attributes through which we had to sift in order to choose our features. As described above, a piece of sheet music contains a vast amount of information, and our selected \*\*kern format does little to narrow down that scope, as it does such an excellent job of preserving all the information recorded in a traditional score. Our chosen attributes must be indicative of the era the piece represents, so as to allow the classifier to accurately and practically determine which era the piece came from.

Secondly, from a computational standpoint, we wanted to consider features that would lend themselves to both the classification process, as well as the generation process in the next step of our research. Classification mandates that each feature within its system be flat rather than structural – meaning that the value can be defined by either a numeric or discrete value (Suh). Because of music’s reliance on mathematics, this factor is not terribly delimiting, but it does help suggest which features may lend themselves best to the process: those which are finite and numerically categorized. It behooved us to focus on features which we could see as easily replicable in a future generative process, meaning features like dynamics would do little good on their own.

After consideration of these factors, the decision was made to focus upon the frequency with which certain musical intervals occur within the pieces of music. Before we delve into why exactly we made this decision, it is important to understand what an interval is.



Figure 3 – A visual representation of the Chromatic

Circle, the backbone on which western music has been created.

This concept of musical intervals is built upon the very foundation of western music: the chromatic circle (figure 3), a cyclical scale of equal temperament made up of 12 total pitches (Hall). A piece of music is comprised of a finite number of these 12 pitches in linear progression. A musical interval is the distance between any two successive pitches within the piece, typically ranging from unison to octave (Figure 4). The most basic of these intervals is defined as an octave, which corresponds to a 2:1 ratio. For instance, we perceive a pitch at 110 Hz to be an octave below a 220 Hz, both of which represent the note ‘A’ (Hall). Human beings perceive these ratios to be the same pitch, only at a higher or lower frequency, allowing for the cyclical nature of the scale. We can therefore identify the ratio between any two successive notes based upon this scale. While it is not unheard of to have music that utilizes other pitches note represented on the chromatic scale (this is a practice that is observed in many traditional forms of music in the eastern hemisphere), this scale is truly the backbone of western music.



Figure 4 - Visual representation of musical intervals

The first reason for this selection comes from the realm of aural skills, in which it is common to use musical intervals as a way to identify differences between eras (source). Though there are a number of features which are often cited when it comes to aurally distinguishing between eras, intervals are always presented as evidence in such efforts, and their status as a cornerstone of music theory make them an obvious answer to our query. Secondly, we found that the basis of intervals is an excellent building block upon which to build a generative system, which will be touched upon in greater detail later in our discussion.

**3.1.3 Pre-Processing**

Once all of these decisions have been made, it is time to clean the data, and extract the features that have been decided upon. In our search, we found a large number of kern scores to use within the

The first step was to collect the data to be used. Though the wealth of \*\*kern scores are not as vast as desired, we were able to 262 unique pieces of classical music from a variety of eras through two humdrum databases. The split was between these eras were not as even as one may like, as there are far less pieces of medieval music that have been encoded using \*\*kern format that eras such as the classical or romantic era, which feature much more notable composers and pieces which have endured the test of time.

|  |  |
| --- | --- |
| **Class** | **Number of Data Entries** |
| Medieval | 10 |
| Renaissance | 26 |
| Baroque | 77 |
| Classical | 50 |
| Romantic | 70 |
| Modern | 29 |
| **Total** | **262** |

Figure 5 – Distribution of data between class types

The next step was to extract the features that I desired to use in the classification process. This was perhaps the most tedious task, though I was able to do so in a Linux command line window with a combination of both the Humdrum toolkit, designed for the \*\*kern file format (and other formats following the Humdrum Syntax), as well as pattern matching using egrep. I first used a command upon all files called ‘mint’ found within the humdrum toolkit that translated the files to display the musical interval between each successive note, rather than the notes themselves. This command made it easy to retrieve the rest of the necessary information using pattern matching, keeping a variable to count how many times I encountered each kind of interval. In the end, I created a ratio between these numbers and the total number of intervals encountered and stored these values of classification.

I appended the recently calculated percentages to the end of an .arff file with appropriate headings, as well as the era with which the piece is categorized. Doing this in a loop, I was able to create one file with all 262 musical scores represented. It is with this document that I begin my classification.

**3.2 Classification**

Not all classification methods are equal, with a large variety of methods being implemented in order to achieve the same goal. It became obvious that we would need to test of dataset with a variety of classification methods in order to receive the best results possible, and we began work on feeding the data into five different classification approaches of different levels of sophistication.

**3.2.1 High level**

SVMs

Logistic Regression

**3.2.2 Low Level**

While Naïve Bayes falls into the category of a lower level classifier, it perhaps deserves a little more recognition than the title suggests. While it does not use sophisticated algorithms like the above outlined SVMs and Logistic Regression models, it is a very well-respected model in the data mining community, and it indeed performs just as well or better than sophisticated models in some instances. The premise of it is simple, based upon Bayes theorem, which provides a way of calculating the posterior probability of an attribute fitting a defined class. The success of this algorithm lies in the fact that each attribute is considered independent of one another, and these probabilities are then multiplied against each other to determine the actual probability.

The lowest levels of classification used fall into the category of decision tree predictors and rule-based predictors. Both of these algorithms use low level blah blah blah

**3.3 Results**

Show charts, talk about why certain methods are preferred to others

TALK ABOUT 10-FOLD VERIFICATION

The charts outlined in Figure 6 show a complete picture of the results received from each of the five aforementioned methods of classification. In analyzing the results, we chose to focus on the value of the area under the ROC curve as an indication of the success of our classifiers. This is due to the inconsistent number of data pieces between each class represented (Figure 5). The ROC (Receiver Operating Characteristic) Curve maps the True Positive Rate (true positives / all positives) against the False Positive Rate (false positives / all positives). This produces a curve that will represent how often a piece is mistakenly identified as other than its proper class, rather than produce a true procession rate, which may be skewed as a result of the uneven distribution of data.

As seen in the charts, the five classifiers performed at varying levels of accuracy. The highest-level algorithm used, the Support Vector Machine model, produced AUC rates of .933, while our decision tree classifier lagged behind with an AUC of .753. Based on the complexity of each algorithm, it didn’t come as a surprise that the results fell the way they did. Higher level algorithms such as SVMs or Logistic Regression have a natural head start on decision tree or rule-based algorithms. Perhaps the biggest outlier in the classifiers presented is the Naïve Bayes model, with an excellent AUC rate of .838, despite the algorithm being quite simple and intuitive.

**4. Generation**

After analyzing the results of the classifiers, the first step in creating our algorithmic composition software was to choose one classifier to use going forward in the hybridization process. Of the five classifiers, it was clear that the true rule-based and decision tree approaches were simply not of the same accuracy as their higher-level counterparts. The benefits that were supplied by their easy to understand outputs simply did not outweigh their lack of performance, and we chose to eliminate these methods.

Of our three remaining classifiers, we chose next to eliminate the higher-level classifiers, Support Vector Machines and Logistic Regression. Despite these algorithms doing a statistically better job of classifying the musical scores, SVMs and Logistic Regression are very complex algorithms which do not output any sort of digestible information to inform you of why the classifier made the decisions it made, even for the most studied in the topic. For this reason, it is hard to conceive of a way to use these classifiers to inform the generative process of any algorithmic composition software.

We decided to proceed using the Naïve Bayes approach because it supplied us with a nice middle ground between the previously mentioned choices. It provides for us an easy, statistical output to use in our generative process, as well as respectable results in the classification process. It also provides us with a much more respectable ROC value (83.8%) than the lower-level algorithms of J48 (75.2%) and JRip (77.3%).

**4.1 Method**

In perhaps our most contributory work, we move to the generation process of the experiment. The task laid ahead of us was to find a way to utilize the intelligence gained from our Naïve Bayes classifier to inspire the algorithmic composition of music. After consideration of the classifier results and output, we decided to turn our attention to an avenue of algorithmic composition that has been less explored than some others such as artificial neural networks and formal grammars: Cellular Automata.

**4.1.1 Cellular Automata**

The concept of Cellular Automata (Singular: Automaton) was first proposed by John von Neumann in the 1950’s and reached a new peak in popularity during the 70’s due to John Conway’s now famous “Game of Life” 3-D cellular automata model (Ti). Based upon the biological cellular replication process, a cellular automata model is represented by a grid of cells, each of which is represented as one of a finite number of states (i.e. “ON” or “OFF”). This grid can be of any finite number of dimensions. The grid progresses in temporally-linear fashion, with each cell shifting states at any given step in time. This shift of the cell’s state is based upon two factors: the states of the surrounding cells in a pre-defined area defined as it’s neighborhood, and a set of transition rules which dictate the outcome based on that neighborhood (Ti). One of the most famous example of a cellular automata, the Wolfram Elementary Algorithms (Figure 7), adds a new line of cells below the previous generated line with each sequential step in time, with the states of these new cells based upon a neighborhood of the three cells directly above it, and a pre-determined rule set (Wolfram). With 256 possible rule sets, there are countless possibilities of how the algorithm can compose the sequence of cells, and it makes for some very interesting patterns.

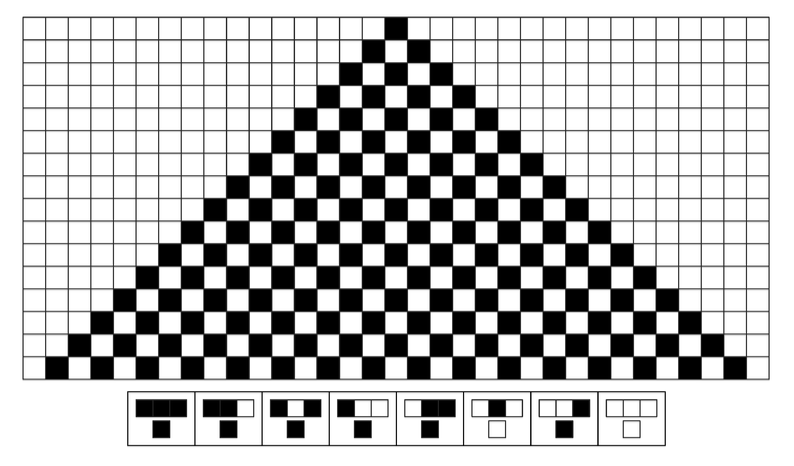


Figure 7 - Rule 250 in the Wolfram Elementary Algorithm Suite

Rule model’s such as Wolfram’s provide an interesting avenue of exploration for musical composition. The patterns found within these automata rules provide a built-in approach to chaotic music composition. However, those preliminary cellular automata models were only able to create music in an “uncontrolled” way and resulted in music that was not necessarily homogenous with any preconceived style (Vico). The next natural step was to create transitionary rules that were informed by music theory, so as to control the music being generated.

**4.2.2 Adapted Musical Model**

In an attempt to explore this avenue of musically informed cellular automata rule generation, we devised of a system inspired by the aforementioned Wolfram Algorithm. In a four-wide grid, each cell has one of two states: “On” and “Off”. These states allow for us to interpret a four-cell phrase as a binary sequence. We chose to map these binary sequences (16 sequences for a four-byte binary number) to the 12 notes of the chromatic circle (Figure 8). While this rudimentary system does not take into account rhythm, a rest character was also encoded for potential future works.



Figure 8 – A table mapping the values of a four-bit binary sequence to

the values within the chromatic circle for use in conjunction with

Cellular Automata musical composition

After the groundwork of our Cellular Automata model was fully laid out, it was time to create transitionary rules inspired by the intelligence gained through our classification process. Before each shift in states, a random float value between 0 and 1 was generated. Using the output from our Naïve Bayes classifier, which gave us statistical probabilities of each musical interval occurring at a given skip in time for a given era, this random float was mapped to one of the eight interval possibilities. The states of each cell in the four-byte sequence would then transition from the previous states to a new sequence of differing states based on this mapping. The distance between the old sequence and new would therefore be equivalent to the musical distance of the determined interval. We are essentially generating the interval between the notes, rather than the note itself. Along with creating more aurally pleasing musical phrases, this helps ease the challenges of representing key signatures within pieces of music.

To further demonstrate the potentials of this system, the software is able to switch between eras at the will of the user. Based upon the values output by the Naïve Bayes classifier, the system will replace the statistical values for the generated rule to each respective era of classical music at the click of a button, so as to encourage the system to follow the tendencies of the desired era. This feature helps the software stand out and puts to use the predictive power of our classification approach to rule generation.

The last feature we implemented was a range-check system. In preliminary testing, we found that allowing the note to change in ascending or descending fashion on a 50-50 basis, while relatively common sight within the world of music, was not controlled enough for our experiment, as the true randomness allowed for many algorithmic compositions to get out of hand in terms of range. We therefore found the average distance between the highest note and lowest note within an era of music and dictated that the composition software stay within that range when composing. This allows music that has traditionally had more range to flourish in this sense, while static pieces from earlier eras stick within a more contained range of notes.

**4.2 Results**

The result of our efforts is a composition software that is able to imitate any one of six distinct eras of classical music. The system linearly produces a sequence of successive notes based upon the intervals between the previous note and the newly generated note. The pitches are outputted as they are generated using a Java MIDI import at a constant rate that can be changed in the code (currently set to one note every 750 milliseconds).

With the system functioning in the desired fashion, our next step was to analyze just how well our composition software was able to imitate the various classical eras. We chose to implement two different methods of analyzation, to see how well the system was able to reproduce the various eras in both a mathematical and an aural fashion.

**4.2.1 Indirect Analyzation**

In our first of two efforts to analyze the results of our compositions, we used an indirect approach closely tied to the ways in which we created the software – classification. While we previously described a ‘ten-fold verification’ approach during our initial classification process, we decided upon using a ‘test set’ approach for the following exercise. In this approach, we feed the classifier a set of data points known as a training set to develop its knowledge on what distinguishes the different classes, and then feed it a set of data points known as a test set to see how accurately it is able to classify those pieces within the given classes.

To do this, we generated sixty pieces of algorithmically composed music; ten within each era and each with a length of 100 notes. We extracted from these compositions the same features we outlined in section 2.1.2, and translated the results into an .arff file mirroring the structure of our previously used .arff file. We then used this file as our test set and provided the file from our initial classification exercise as a training set. We ran these classification techniques on four of the five classifiers used in our original exercise, excluding the Naïve Bayes classifier we used to inform the composition software, as it would provide an unnaturally insightful look into the data, resulting in skewed results. The classifiers’ results are displayed in the chart below (Figure 9).

It is easy to see that the classifiers performed quite well in determining the era which our composition software was attempting to replicate. In fact, the classifiers success rates were nearly identical to the success rates they experienced with traditionally composed pieces of music, with their short comings being seen in the same categories. The only classifier that saw significant changes in performance was that of the logistic regression approach, which saw the average ROC percentage jump from 88.5% to 92%. These results alone are highly encouraging.

**4.2.2 Direct Analyzation**

To double down on our analysis, we decided to take a direct approach to the matter as well and consulted a number of experts in music. In total, five scholars of music took part in a survey to determine how well they could distinguish the success of our classifier. The exercise was simple: We generated three 15 second clips of music from each era and presented them together in a random order to the experts. We asked at the conclusion of each triplet for the experts to indicate which era they believed the composition software was meant to represent, and their confidence on a scale from 1-5. We also gave the experts an opportunity to explain how they arrived at that answer, and why they gave the confidence level they did.

The results of our direct method of analysis were not as encouraging as the indirect method. Of our experts, only one was able to predict 50% of the eras correctly, and one failed to predict a single era. The confidence levels hovered between 1 and 3 for most answers, with a distinct increase in both confidence and accuracy with the modern era, of which four of our five experts correctly predicted.

It is clear that the results of our direct method of analysis tell a very different story than the indirect method. While our classifiers were able to tell which era of music was being replicated with our composition software, experts in music had a much harder time doing so, with a success rate of below 50% when presented the option of all six eras. The results here can be

**5. Discussion**

It is clear that the results of our direct method of analysis tell a very different story than the indirect method. While our classifiers were able to tell which era of music was being replicated with our composition software to a high level of accuracy, experts in music had a much harder time doing so, with a success rate of below 30% when presented the option of all six eras.

Because of the nature of the process, it comes as no surprise that our direct and indirect methods of analysis yielded such different results. This is likely because of the limited scope with which we approached the problem, deciding to focus on a very select number of features, even though the differences in musical styles between the eras is defined by many more features, such as rhythm and harmony (A distinction many of our experts pointed out during their survey), as well as the types of instruments being used in the pieces, which is ignored by using a MIDI output. However, it is certainly promising that the features we did choose to use in the experiment yielded such high results in our indirect method of analysis. This suggests that, even if the music is not very aurally identifiable yet, trained AI has the ability to distinguish the differences. This result suggests that the project has potential moving forward, and direct results may be achieved by hybridizing this method with others designed to take rhythm and harmony into account.

**5.1 Applications**

For now, it seems the application of this software lays firmly in the category of ‘composition inspiration software’ that encompasses so much of the work that has been done in the field, though it certainly shows signs that it has the potential to be more. The success of our classifiers in determining which era the piece was meant to replicate

**5.2 Future Works**

At the end of the study, our thoughts on moving forward are much the same as they were when we began. The prospect of hybridizing the various methods of algorithmic music composition with data mining is a vast well of potential of which this study has only began to scratch the surface. The experts’ opinions that the intervals alone are not enough to fully encompass the eras which they are attempting to replicate point to the study of integrating rhythm and harmony into the process, which could be achieved in a variety of ways.

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