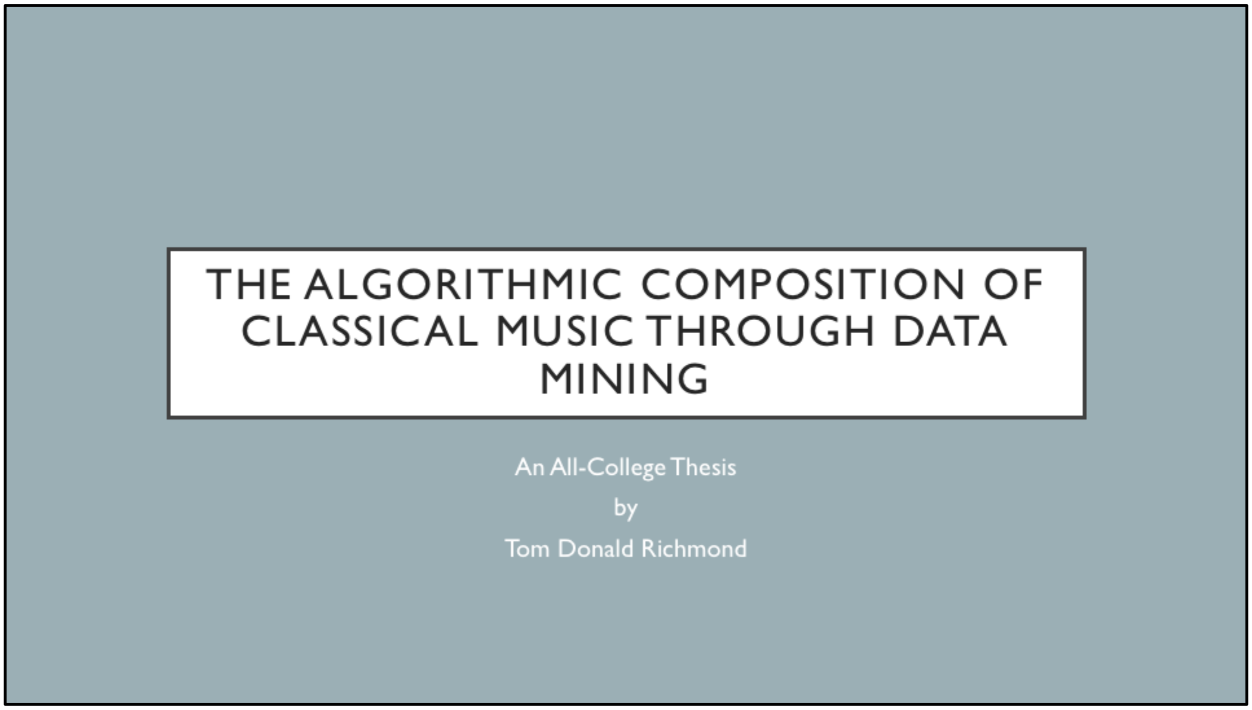
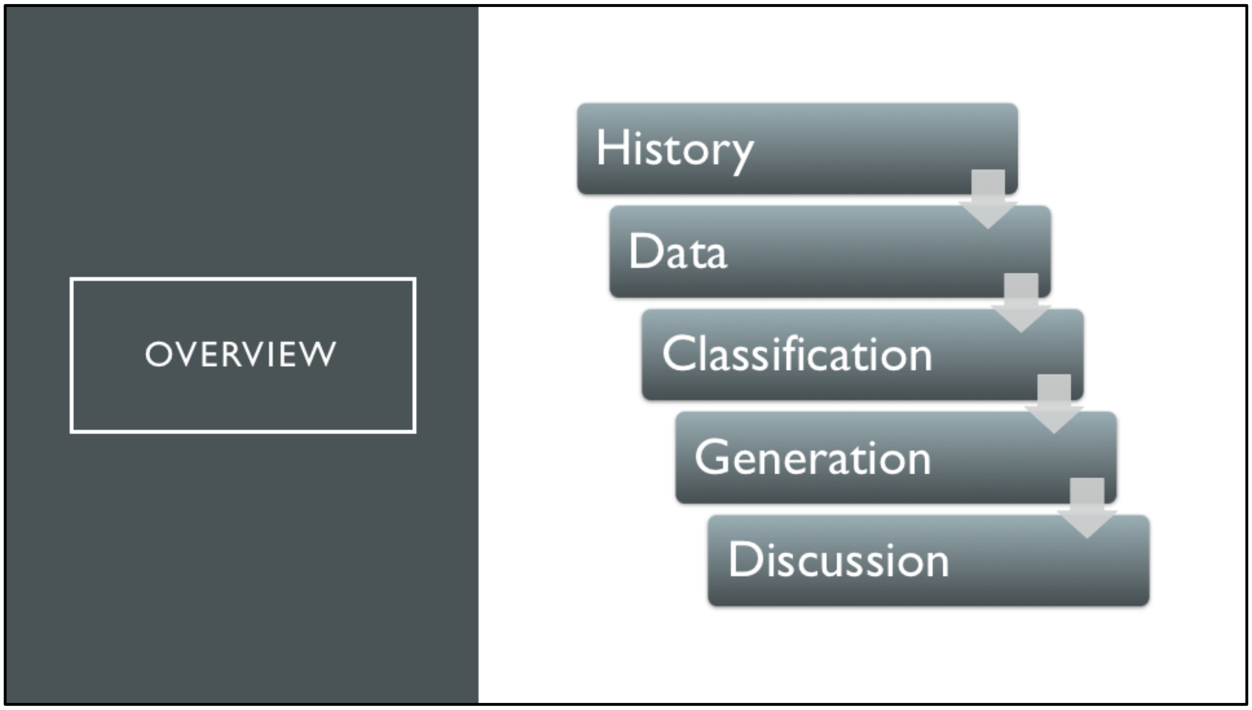


Music is unique in that, of all major art forms, it has historically relied most upon scientific and mathematical devices in its creation.
The reason behind this can be easily attributed to the notion that music is well founded in the world of mathematics, and the rules of music theory are infact built upon it.
Both the relations between pitches and durations are best defined by numbers and ratios.
This fact makes it tempting to both analyze and create music through a scientific approach, and it is a venture that has been attempted many times over the course of history



During the course of our research, we took our own venture into world of algorithmic composition by means of machine learning.
Over the next thirty minutes, we'll explore the history that inspired our research
Data used
How we arrived at our selected classification technique,
How we used its output craft our composition software
Discussion of findings and potential

EARLY EXPLORATIONS

- Music as a discipline of mathematics
  - Pythagoras and the Music of the Spheres [2] - ~500 BC
  - Music Theory [5] - 6th Century
  - Musikalisches Würfelspiel [6] - 18th Century

Musikalisches Würfelspiel

Table of Measure Numbers

Part One

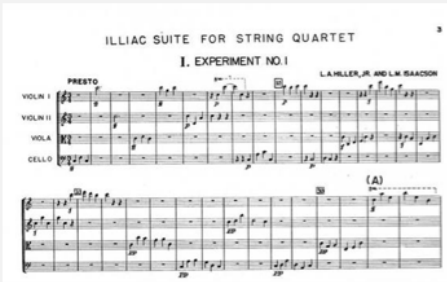
	I	II	III	IV	V	VI	VII	VIII
2	96	22	141	41	105	122	11	30
3	32	6	128	63	146	46	134	81
4	69	95	158	13	153	55	110	24
5	40	17	113	85	161	2	159	100
6	148	74	163	45	80	97	36	107
7	104	157	27	167	154	68	118	91
8	152	60	171	53	99	133	21	127
9	119	84	114	50	140	86	169	94
10	98	142	42	156	75	129	62	123
11	3	87	165	61	135	47	147	33
12	54	130	10	103	28	37	106	5

Part Two

	I	II	III	IV	V	VI	VII	VIII
2	70	121	26	9	112	49	109	14
3	117	39	126	56	174	18	116	83
4	66	139	15	132	73	58	145	79
5	90	176	7	34	67	160	52	170
6	25	143	64	125	76	136	1	93
7	138	71	150	29	101	162	23	151
8	16	155	57	175	43	168	89	172
9	120	88	48	166	51	115	72	111
10	65	77	19	82	137	38	149	8
11	102	4	31	164	144	59	173	78
12	35	20	108	92	12	124	44	131

Table of Measures

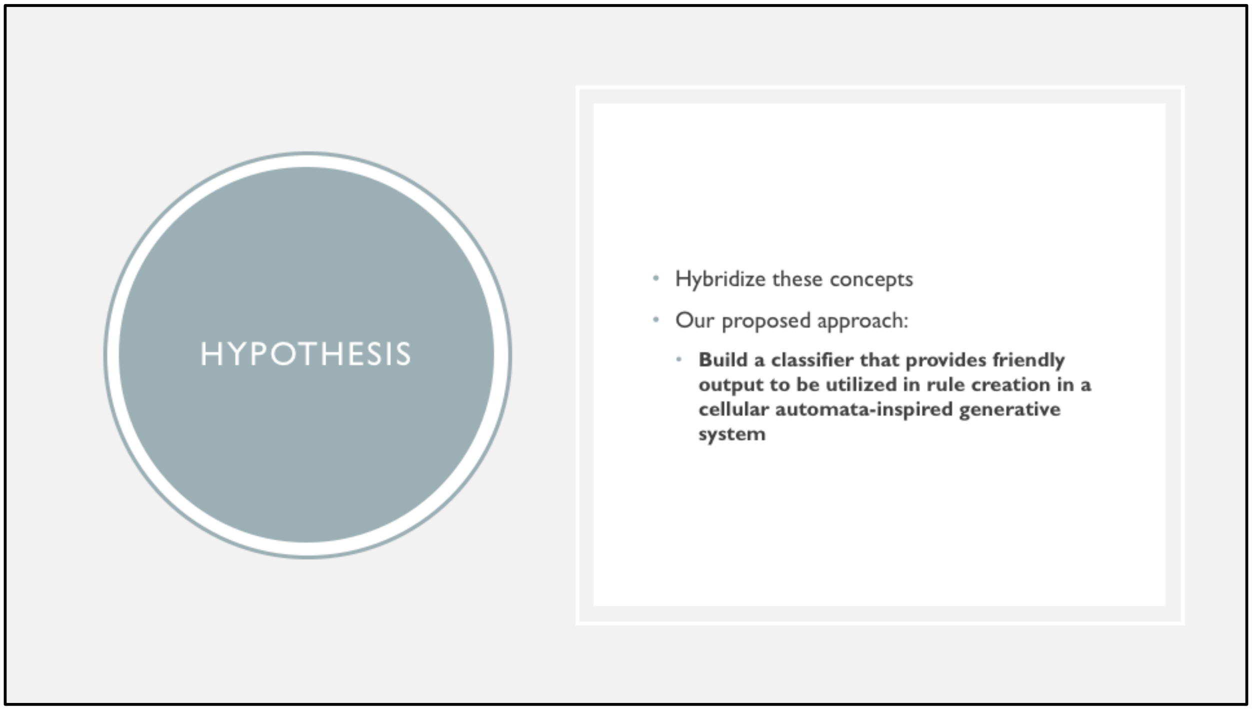
Intersection of math, science and music has a rich history
The groundwork laid as far back as 500 bc
First significant connections drawn between mathematics and music through movements of celestial bodies
It wasn’t until the medieval period that formal rules to govern pitch relations were laid, and music theory was born.
And we saw the very beginnings of algorithmic composition in the 18th century
Allegedly devised by Mozart himself



DATA DRIVEN INTELLIGENCE ERA

- *Illiac Suite* [7] – 1958
  - Markov Chains, stochastic system
  - Expanded upon by interested parties
- Generation
  - Splinted thereafter into groups
- Classification
  - Variety of styles and classes [8], [9]

The beginning of the digital age ushered in an intense interest in algorithmic music
It all started in 1958 with Hiller and Isaacson's Illiac Suite
Markovian chains, a stochastic predictive system with a memory of one
Interested parties adapted their work to include an nth order technique
Thereafter, algorithmic composition was splintered into many distinct categories of generation
(6 Gerhard Nierhaus: generative grammars, transition networks, genetic algorithms, cellular automata, artificial neural networks (ANNs) and artificial intelligence [3])
Computer music has also shown much interest in classification, Many successful classification experiments



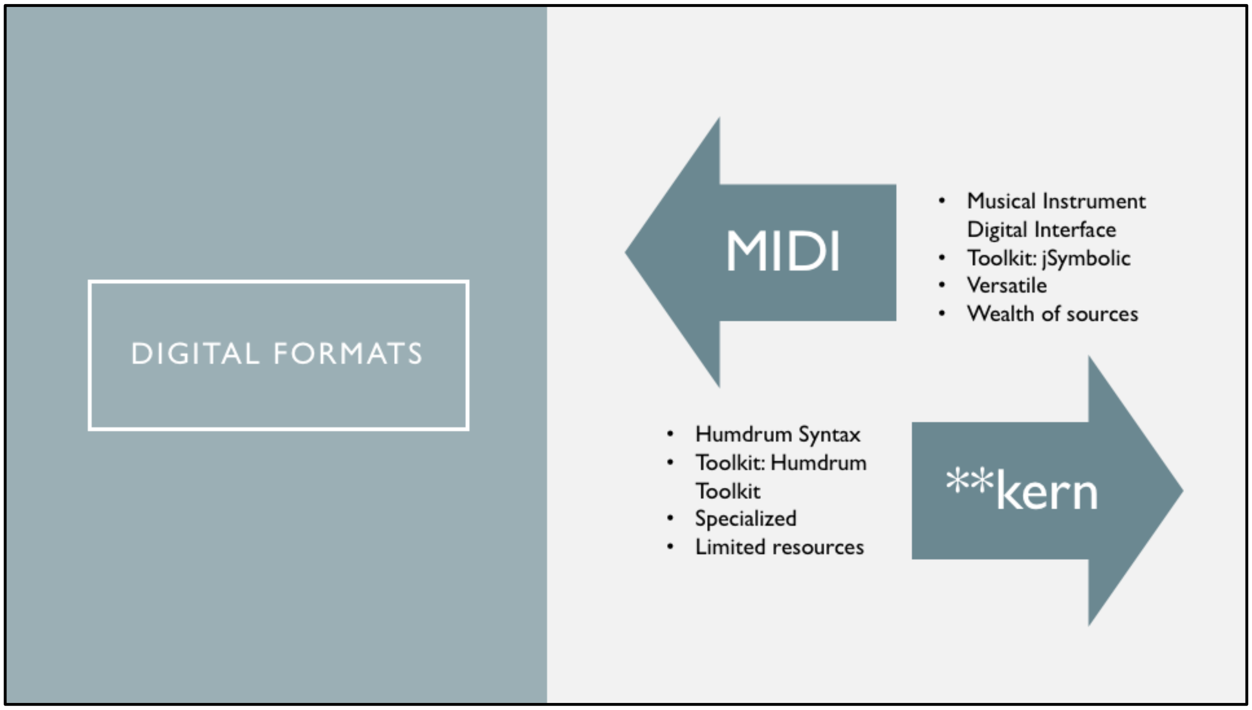
These experiments were the basis upon which we built the idea of our experiments, with the goal of improving algorithmic composition by utilizing the power of predictive classification methodologies to fuel rule based algorithmic composition techniques

With any venture into data mining, the most important step is to select your data

MUSICAL DATA

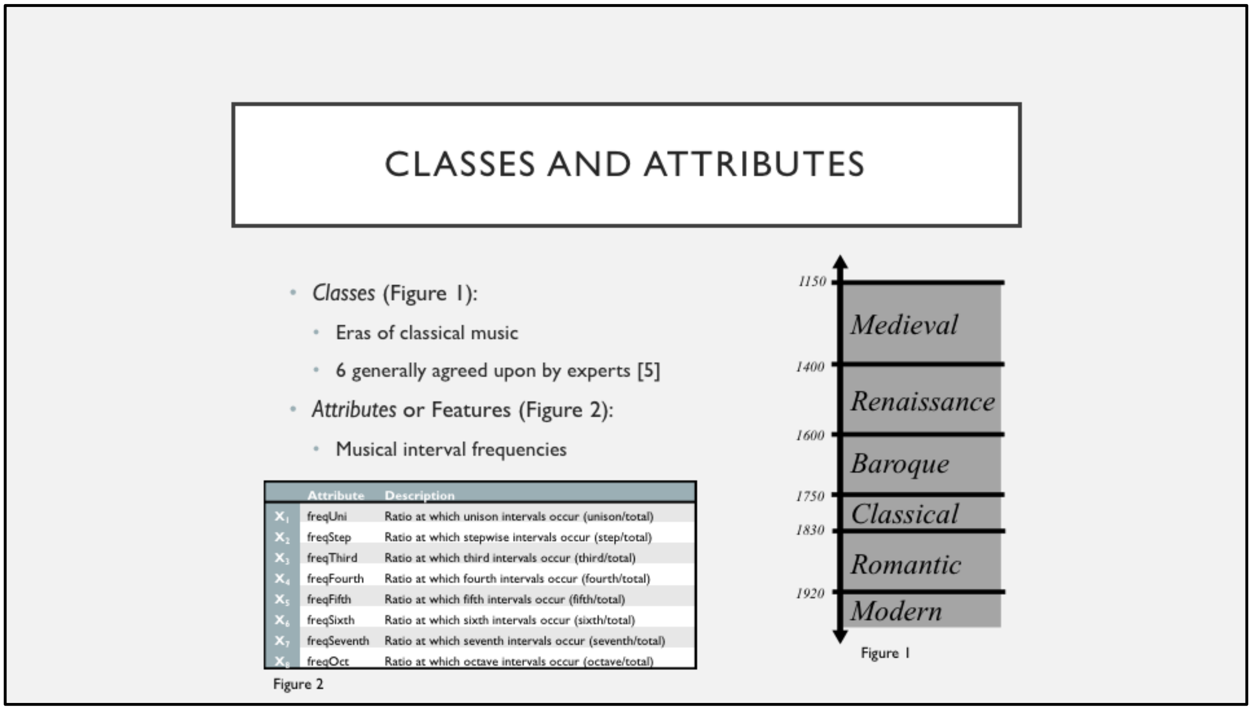
- *Musical score*, or sheet music
  - Visual representation of music, symbols and key words
- 9^{th} century monks popularized the practice [10]
- Stable backlog of written music across history

Luckily for us, there is a large amount of available musical data
For centuries, this data has been recorded by means of musical score or sheet music
Comprised of various symbols and key words that are capable of representing numerous features, such as dynamics, durations, pitches, tempo, etc
This idea saw its start in ancient Greek and Middle Eastern civilizations, where they began using basic music symbols as written reminders
9^{th} century monks began practice of recording music by virtue of these symbols on sheets, and the practice exploded



While sheet music is ideal for human use, the dawn of computer music research helped realize the necessity of a new representation of music for computer use was realized
This was due to the visual nature of sheet music, and the challenge that provides a computer to parse it for pertinent information
Two most popular forms are MIDI and **kern.
Kern described by creator as "general-purpose software system intended to assist musical research" [12],

The term data mining is rather broad, being defined as “The process of discovering useful information in large data repositories” [13]
Has led to a variety of approaches being developed to accomplish this singular goal
We will be focusing on classification, the task of assigning objects to one of several pre-defined categories or *classes* based upon a variety of features, or attributes
Trained classifiers are then able to predict the classes of newly introduced data



This makes the task of selected classes and attributes important to the success of a classifier

For the sake of our experiment, we chose to separate the data into the six distinct classical music eras

Our musical data presented us with a large number of features to draw upon
We were looking for attributes that benefit both generative process and classification process
For this reason, we zeroed in on the notion of musical intervals, and the frequency at which they appeared during the piece.

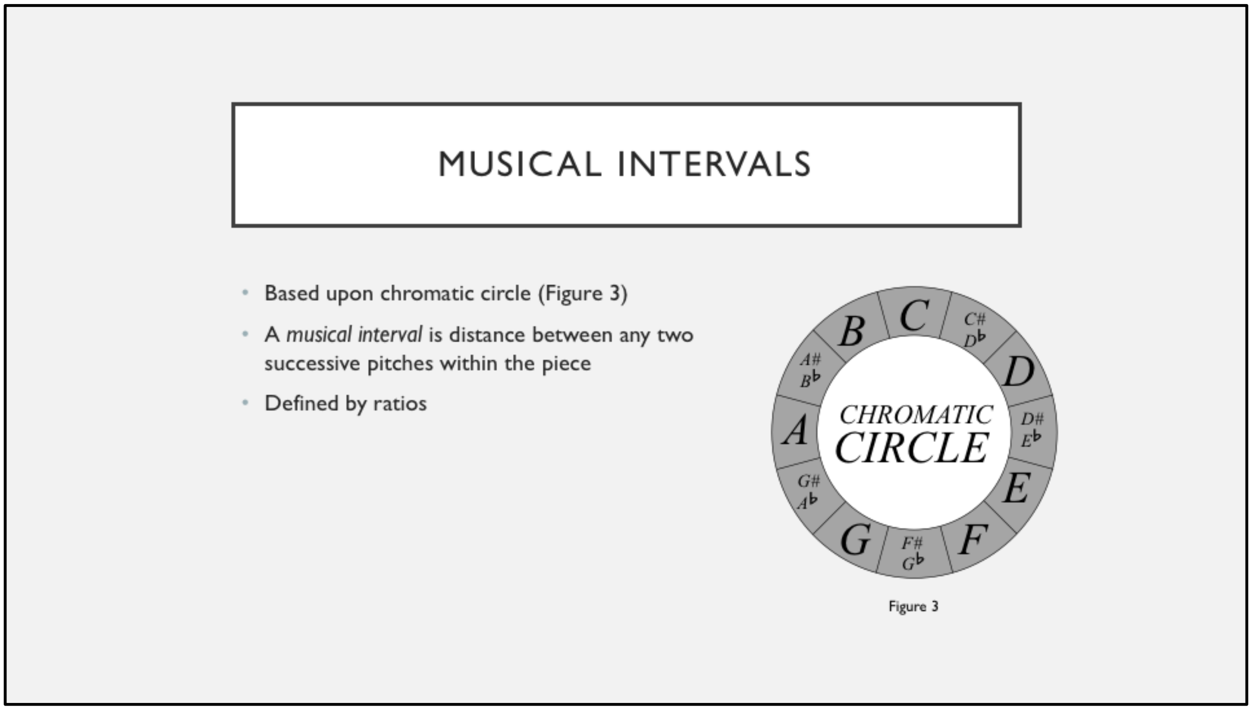
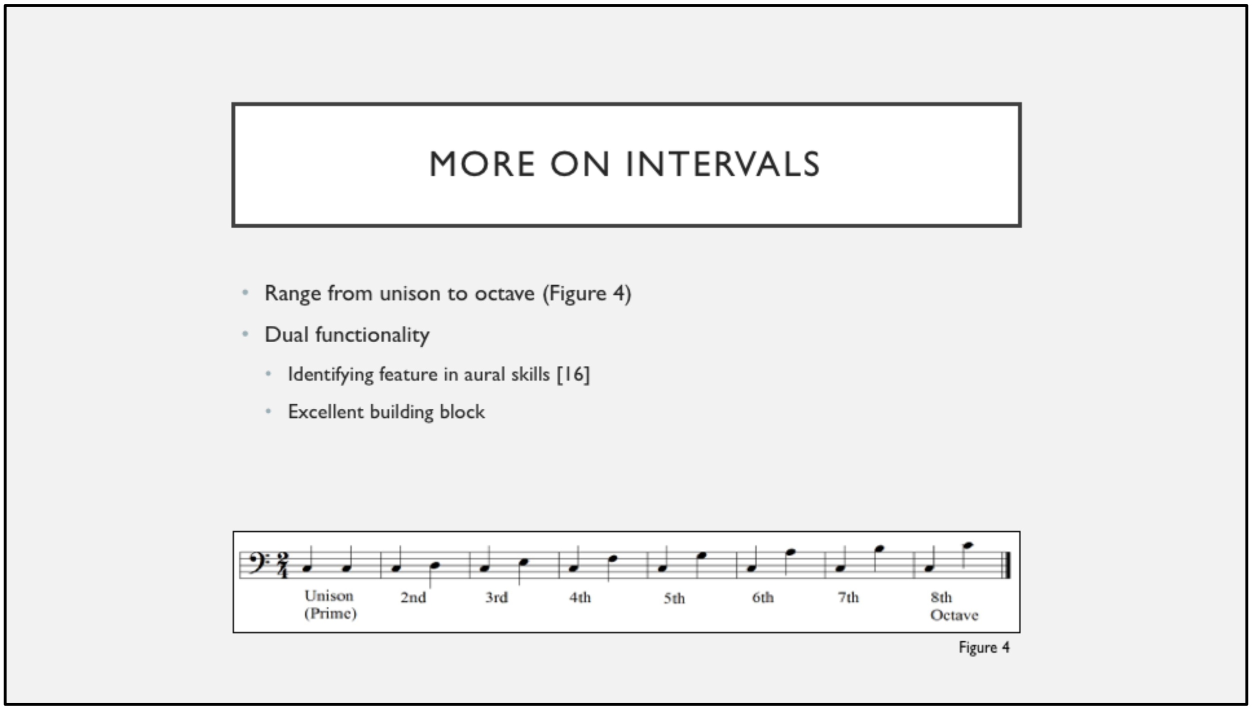


Figure 3

The concept of a musical interval is based upon chromatic circle, an equal temperament, cyclical scale, which makes up the backbone of western music
Between any two adjacent pitches on circle is half a step
An octave is the distance between identical notes after a single cycle. This interval has a 2:1 hertz ratio, thus 440hz, 220hz and 110hz all signify the pitch ‘A’



From this scale, we can derive a ratio between any two successive notes
Our features range from unison, meaning there is no distance between the two pitches, to the octave.
The selection of these features was twofold
It presents us with an identifying feature of music, which is often cited in aural listening skills when distinguishing between eras
It also provides us with features which can be imitated and used as an excellent building block for our generative process.

PRE-PROCESSING

- 262 **kern scores (Figure 5)
- Musical intervals extracted via command line
- Each frequency appended to Attribute-Related File Format (.arff) file, along with class

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

Figure 5

We were able to find 262 unique **kern scores from the medieval through modern eras for our experiment. It is worth noting that the data is not evenly distributed, as some eras have withstood the test of time better than others, and have more available data.

Using the humdrum toolkit and egrep in a linux command line, we were able to extract the number of occurrences of each interval, and divide it by the total number of intervals.

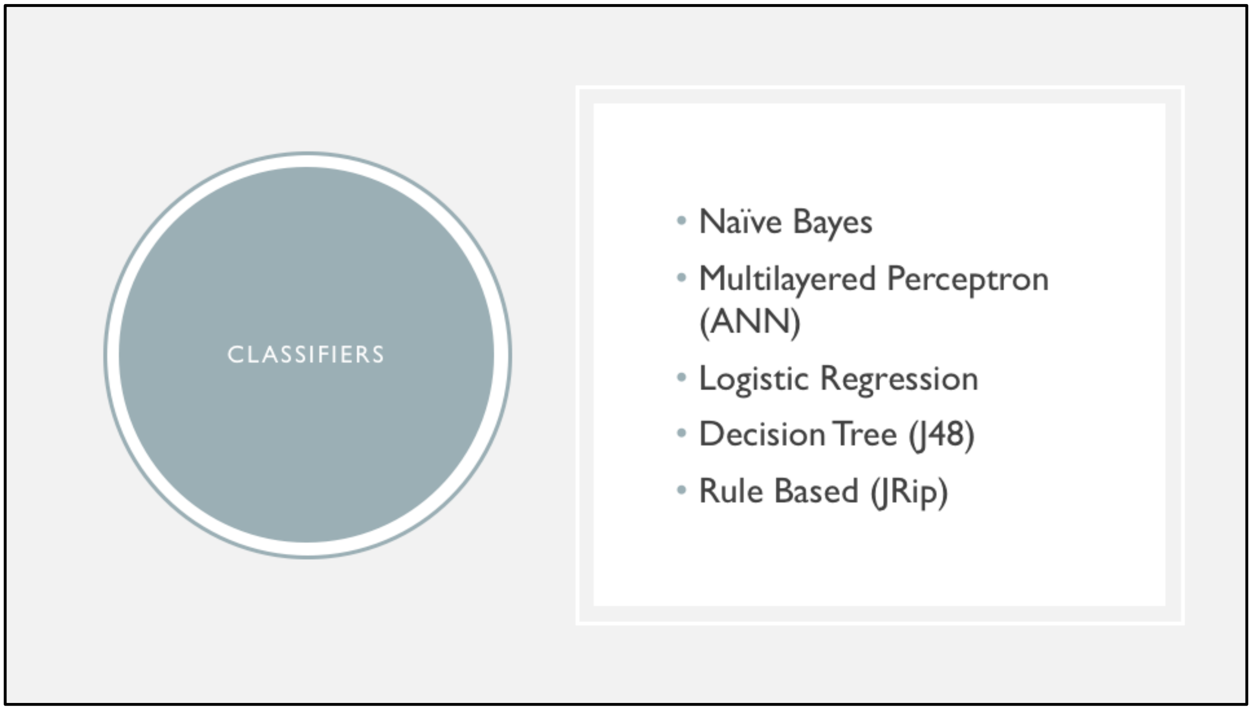
We appended these frequencies to a single arff file, along with the class it is associated with

```
@RELATION kern

@ATTRIBUTE freqUni     NUMERIC
@ATTRIBUTE freqTwos    NUMERIC
@ATTRIBUTE freqThirds  NUMERIC
@ATTRIBUTE freqFourths   NUMERIC
@ATTRIBUTE freqFifths  NUMERIC
@ATTRIBUTE freqSixths   NUMERIC
@ATTRIBUTE freqSevenths  NUMERIC
@ATTRIBUTE freqOctaves   NUMERIC

@ATTRIBUTE class        {Medieval, Renaissance, Baroque, Classical, Romantic, Modern}
```

CLASSES AND ATTRIBUTES



Using this arff file, we began out classification.
There were countless techniques that fit the classification schema to choose from
These five techniques selected for the sake of their diversity, ranging greatly in both complexity and output.

RESULTS

- Ten-Fold Cross Validation
- Success based on AUC (area under the curve) of a Receiver Operating Characteristic graph
- Naïve Bayes selected based on statistical output and excellent AUC values

	Medieval	Renaissance	Baroque	Classical	Romantic	Modern	Average
MLP	0.964	0.958	0.854	0.988	0.836	0.996	0.933
LR	0.981	0.951	0.808	0.921	0.885	0.927	0.885
Naïve	0.938	0.931	0.73	0.889	0.853	0.871	0.838
JRip	0.705	0.841	0.73	0.874	0.704	0.836	0.773
J48	0.798	0.777	0.681	0.804	0.741	0.753	0.753

Figure 6

9/10ths used as training set, 1/10th as test set. Reiterated ten times over
The Receiver Operating Characteristic (ROC) 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 precision rate, which may be skewed as a result of the uneven distribution of data.
A perfectly classified set of data would have an AUC of 1.
As you can see, our classifiers performed admirably, ranging from .933 to .753 AUC values
In the end, we selected Naïve bayes by virtue of its statistical output

GENERATION

- Challenge:
  - Based upon output of Naïve Bayes (Figure 7), build a generation technique
- Statistically inspire cellular automata progression

freqTwos	Medieval	Renaissance	Baroque	Classical	Romantic	Modern
mean	0.4837	0.424	0.3562	0.3924	0.2786	0.2111
std. dev.	0.0864	0.1258	0.1272	0.0718	0.0734	0.0964
weight sum	12	28	79	52	72	31

Figure 7

With our classification process completed, our next challenge was to build a generative process.
We decided the concept of cellular automata presented us with a nice opportunity to use the statistical output of Naïve bayes to inspire its generation

CELLULAR AUTOMATA

- Grid of cells, each containing one of a finite number of states
- Cell state shifts based transitionary rules
- Shift dictated by predetermined 'neighborhood' of cells
- Wolfram Algorithm (Figure 8) [18]

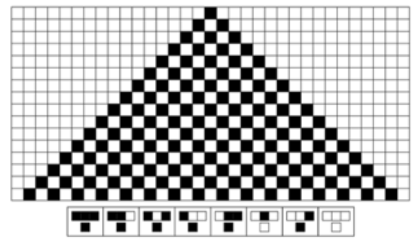


Figure 8

Cellular Automata, based upon the cellular replication process.
Devised by John von Neumann (50s), it has been utilized by some of the biggest names in math and computing, including Stephen Wolfram and John Horton Conway
A cellular automata is comprised of a grid of cells, each of which being one of a finite number of state. With each shift in time, each cell shifts states based on the state of surrounded cells known as a neighborhood
This concept has been used in basic music composition as a way to create chaos and patterns within music

ADAPTED MUSICAL MODEL

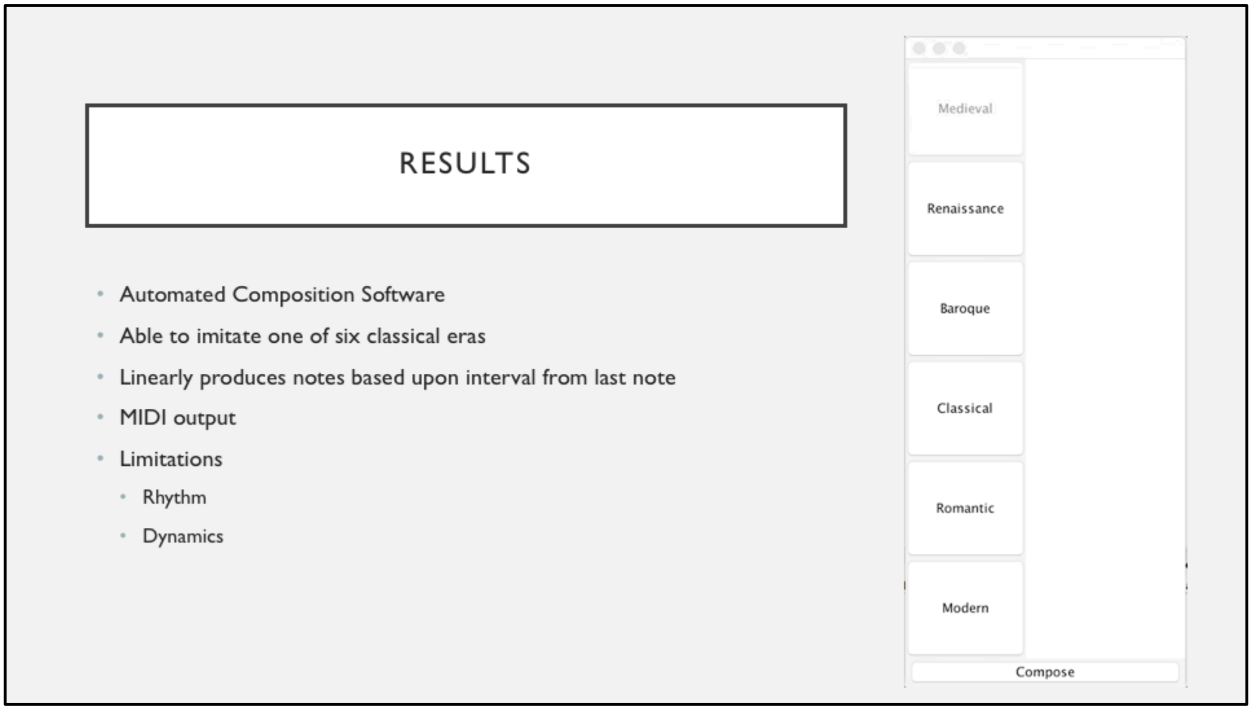
Binary Represenation of Notes

0000	START
0001	C
0010	C#/D♭
0011	D
0100	D#/E♭
0101	E
0110	F
0111	F#/G♭
1000	G
1001	G#/A♭
1010	A
1011	A#/B♭
1100	D
1101	C
1110	Rest
1111	TERMINATE

Figure 9

- Each cell has one of two states: 'ON' or 'OFF'
- Binary interpretation of cell sequence mapped to note values (Figure 9)
- Four-cell wide grid (16 values)
- Transitionary rules determine the most likely interval from the previous four-cell sequence to the next based upon Naïve Bayes output

With this model as a framework, we shift focus to our most contributory work
Using binary states of 'on and off', it is possible to represent each individual note with a four byte sequence.
The transitionary rules were then created based upon the aforementioned statistics provided by the classifier.
These transitionary rules vary depending on the desired replicated era



The fruit of our labour is an automated composition software capable of imitating one of six classical music eras.
The system progresses linearly, one note per 750 ms, outputted via a MIDI feature in java.
Currently, the system has a number of limitations, including the lack of rhythm and dynamic consideration.

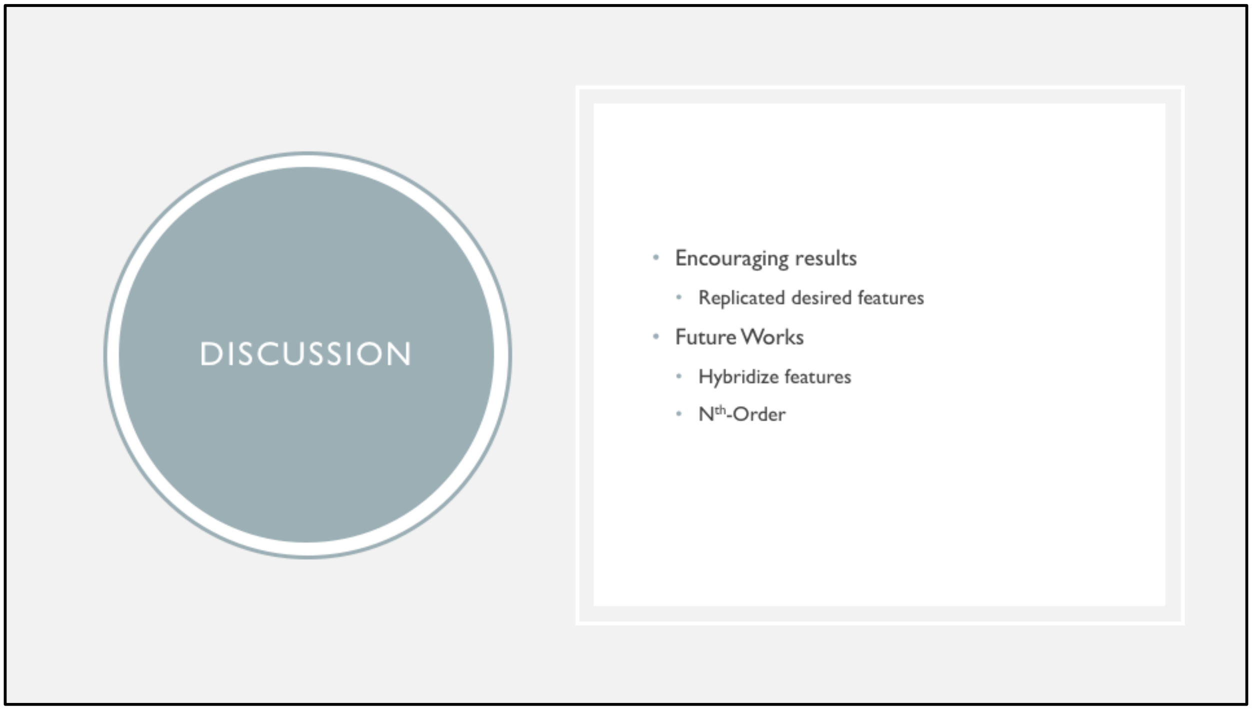
ANALYSIS

- Indirect
  - Composed 60 scores of 100 notes, 10 from each respective era
  - Used as test set to previous training set with previous classifiers
  - Tests performed admirably next to results of original classification process
- Direct
  - Composed three 10-second clips from each era
  - Presented to five scholars of music with a variety of experiential backgrounds

	Medieval	Renaissance	Baroque	Classical	Romantic	Modern	Average
MLP	0.942	0.9	0.858	0.918	0.754	0.986	0.893
LR	0.978	0.938	0.824	0.946	0.836	0.998	0.92
JRip	0.852	0.753	0.662	0.816	0.582	0.786	0.742
J48	0.812	0.757	0.757	0.8	0.678	0.826	0.772

Figure 10

In an attempt to analyze our results, we took two approaches.
In an indirect approach, we composed ten scores from each era, each with the length of 100 notes. We fed these compositions as a test set into the classifiers from earlier, and results were almost identical to the ability of our classifiers to identify traditionally composed music
From a direct perspective, we composed three 10-second clips from each of the respective eras. We packaged these clips in a random order and presented them to five musical scholars. Results were not as encouraging as the indirect approach, with only about 30% precision when presented all six options.



No surprise that indirect vs direct yielded a tale of two stories.
Features like instrumentation, rhythm, harmony
Future of algorithmic composition is wide open

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