Machine Learning and Music Composition

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Introduction

Bringing music composition to everyone

Outline

Background
- Music
- Machine Learning

Methods
- Random Forests
- Markov Chains

Training

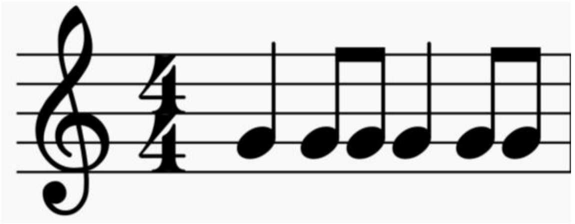
Evaluation

Results

Conclusion

Rhythm and Melodic Progression

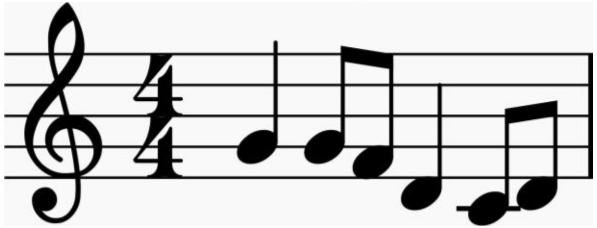
Changes in note length
Changes from long to short or visa versa



A melodic progress is the interval between two notes

Melody

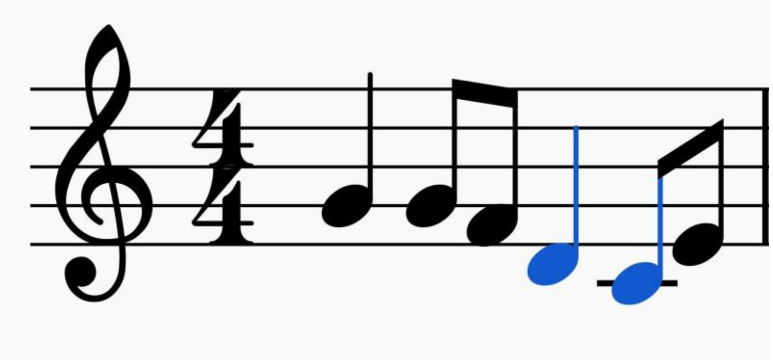
Combining several intervals together gives us a melody



General Framework

All of the following methods share the a similar method of producing the next note

- **-Set of previous notes**
- **-Key signature**
- **-Word frequency**
- **-Many more**



Decision Trees

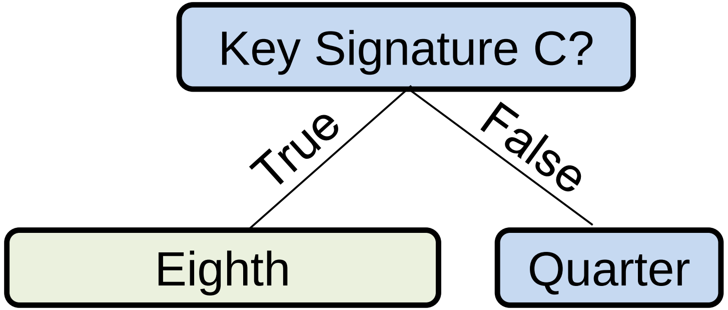
Branching tree like structure

-Nodes represent choices

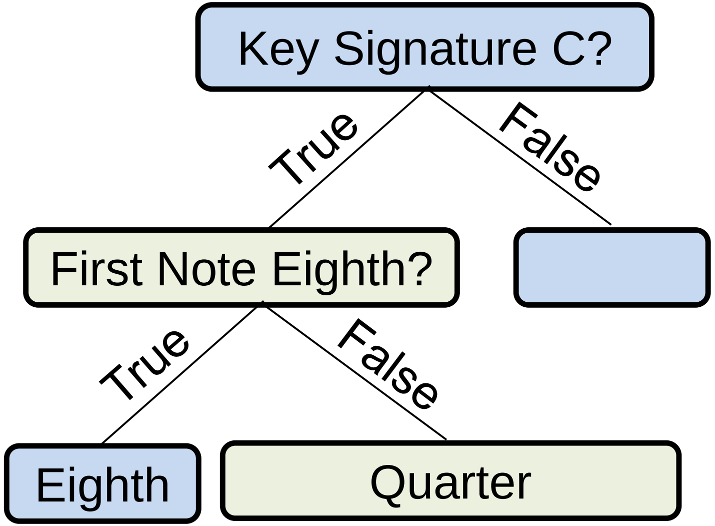
-Branches represent the outcomes

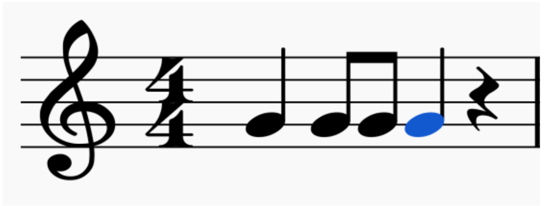
Represents all tests and every possible outcome from the tests

Decision Trees

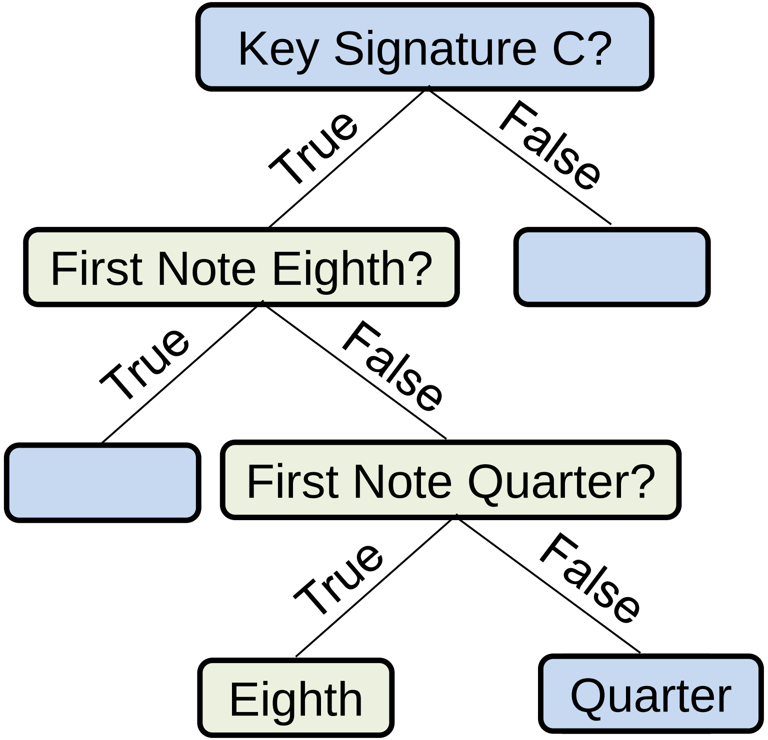


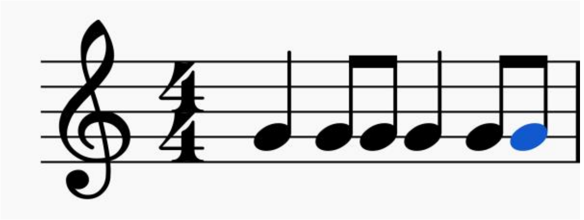
Decision Trees





Decision Trees





Random Forests

A collection of decision trees makes a random forests

Final answer is the “most popular” vote

ALYSIA

Produced by Ackerman et al. [1]

Two random forests

-one for rhythm

-one for pitch

Lyric based system

Co-creative or autonomous process

ALYSIA: Order

The random forests could be run in any order

Either
Rhythm -> Pitch
Or
Pitch -> Rhythm

The melody benefits best from generating the rhythm first

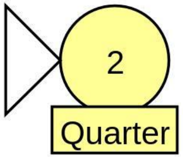
Markov Chains

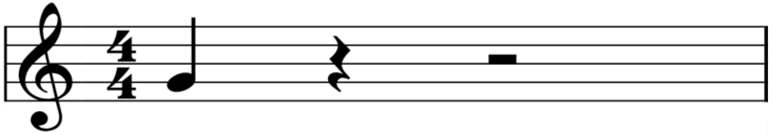
Produced by Klinger et al. [2]

Uses probability and previous note instead of conducting tests

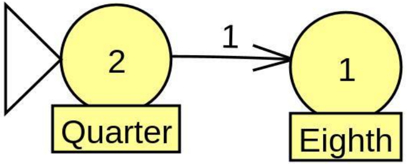
The method used uses two chains one for pitch and one for rhythm, similar to ALYSIA

Markov Chains

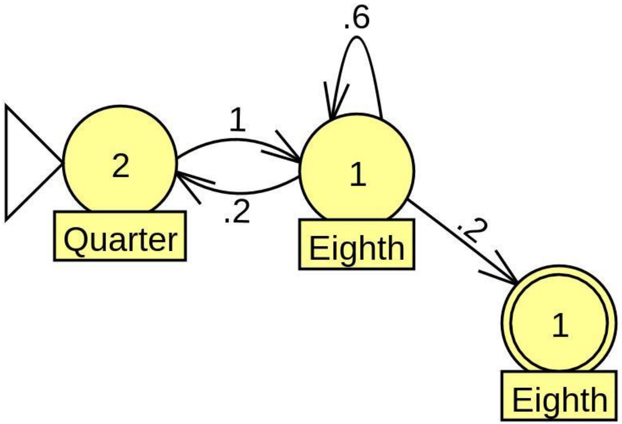




Markov Chains

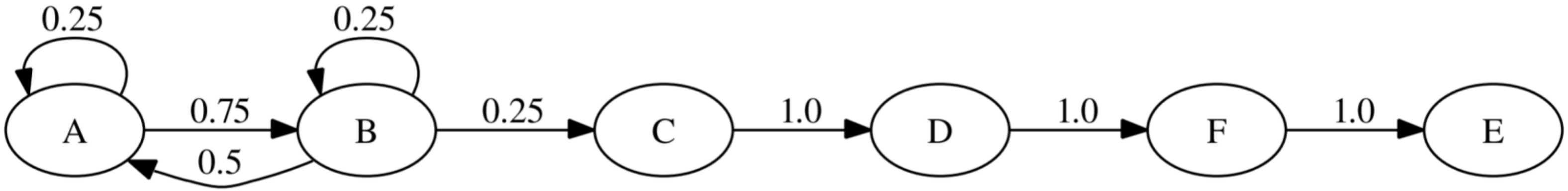


Markov Chains



Markov Chains: Pitch

Absolute Pitch



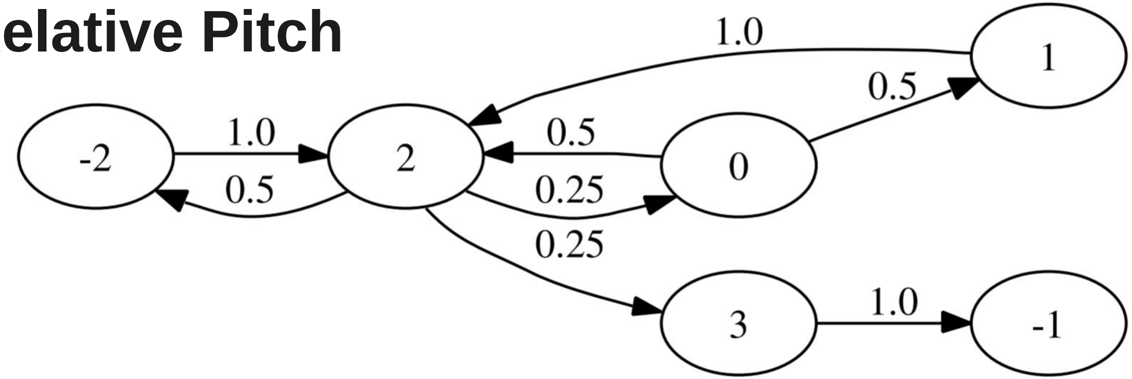
Works with direct note values (CDEFGABC)

More simple and easy to follow

Input needs to be in correct key.

Markov Chains: Pitch

Relative Pitch



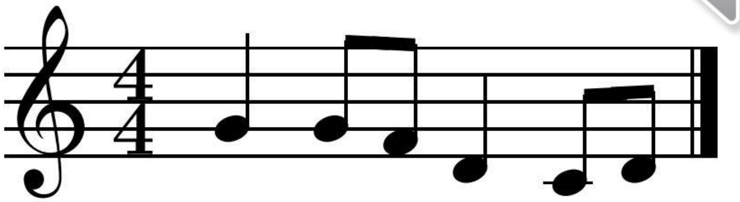
Uses interval distance

Easier to change instrument type and key afterwards.

One-point mutation

Post processing on the written melody is done to make the music more complex

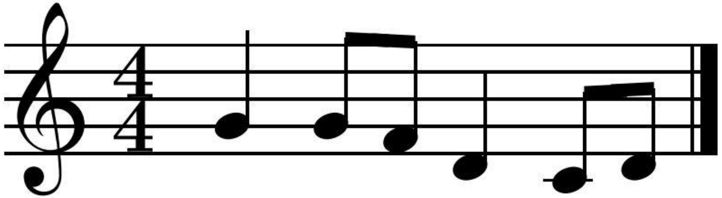
One-point mutation is an operation that traverses over the melody with a small percentage chance to change a note value

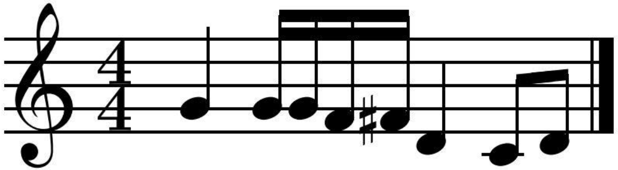


Note Splitting

Similar to one-point mutation

Duration instead of pitch





Training ALYSIA

Starts with a set of user provided songs

The songs are split along song boundaries, and subsections within song

The program then mutates itself trying to emulate the style of the music

Each mutation is evaluated, the best mutations are passed on

Training Markov Chains

Similar to ALYSIA method described

Another option, generating melodies with a random walk or pitches and rhythms

Random Markov Chains combined together and the output evaluated with existing methods

New recombinations every generation

Evaluation

How do the programs understand if they have accomplished their goal?

Methods Used

- **-Feature Extraction**
- **-Decision Trees**

Feature Extraction

Using a program to find out information about the generated song

The feature extraction is looking for features of rhythmic, pitch, pattern importance

Two methods used

-Rests on Downbeats

-Repeated Pitch

Rests on Downbeats

$$\frac{\text{\# of bars beginning with rests}}{\text{\# of bars}}$$

First line has a ratio of 0
Second line has a ratio of .75

Repeated Pitches

$$\frac{\text{\# adjacent notes with vertical intervals of size 0}}{\text{\# of notes}}$$

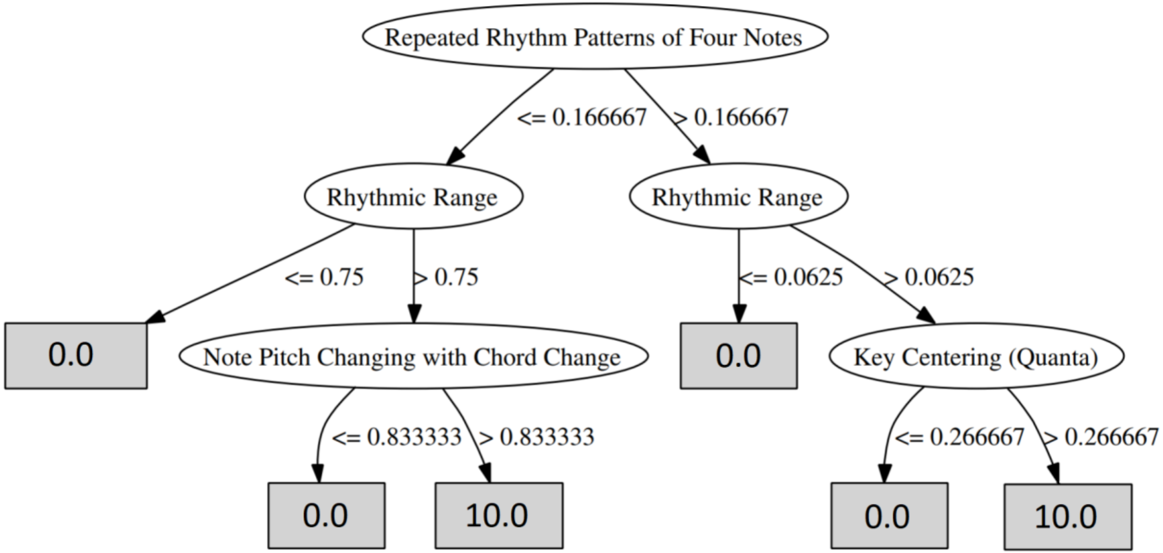
First line has a ratio of 0
Second line has a ratio of 1

Decision Trees

0 is a bad melody

10 is a potentially good melody

Constructed using methods similar to feature extraction



Results ALYSIA [1]

ALYSIA

Achieved accuracy of 86.79% and 72.28% for rhythmic and pitch accuracy to the style of training songs

Includes the reason of why the next note is what it is

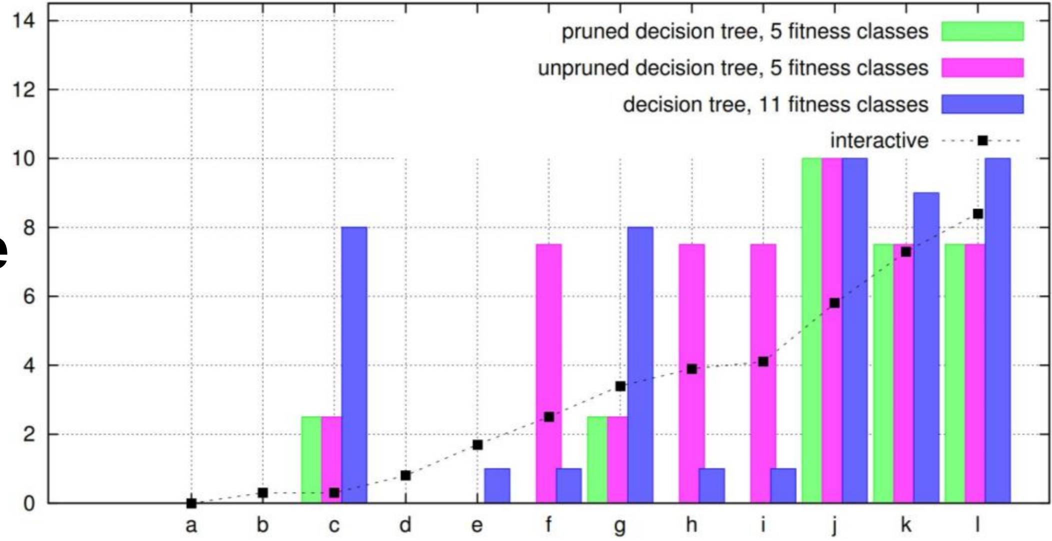
Of the 59 extractable features, examining the 5 previous notes was by far most important, key signature was a distant second

Results Markov Chains [2]

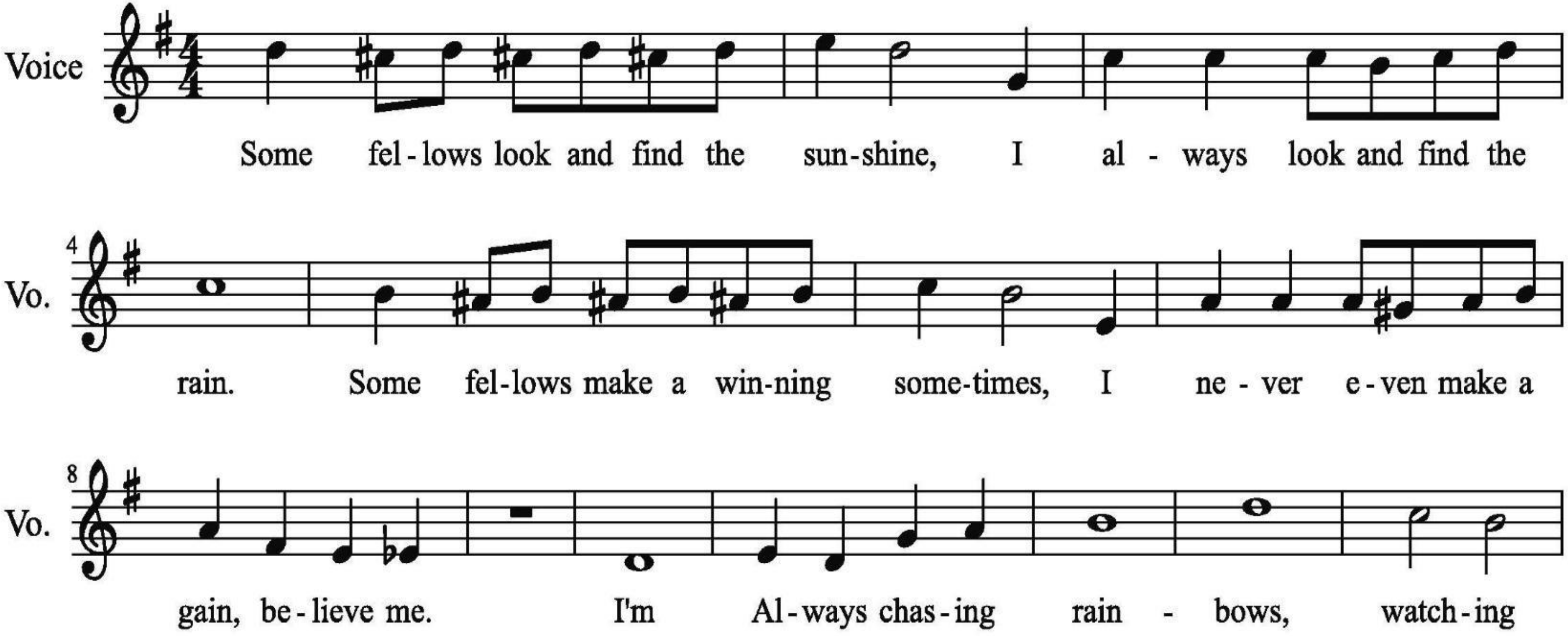
Comparison between decision tree evaluation and human response

12 comparisons taken as the training happened

General upward growth in listener approval



Original Song: I'm Always Chasing Rainbows



ALYSIA Song Conversion

Markov chain example

Conclusion

The melodies from machine learning methods lack a sense of direction to them

The post processing used by the markov chain method could have benefited the random forests

How would these methods work with music from other cultures?

Questions?

Sources

1) **M. Ackerman and D. Loker. Algorithmic Songwriting with ALYSIA. EvoStar MusArt Conference 2017.**
2) **R. Klinger and G. Rudolph. Automatic Composition of Music with Methods of Computational Intelligence. WSEAS TRANS 2007.**
3) **http://kuow.org/post/strange-composition-classical-music-meets-bioterror-orfeo (introduction picture)**