Understanding the Language of Music:

from an Etude Generation Perspective

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Abstract

In recent years there has been a focus on the accessibility and equity of music instruction in under-served communities. The value of private/guided instruction is clear, but the question of reaching students from lower economic classes presents challenges our current educational system struggles to address. The Blugold Computational Music Suite is a system that supports novice to intermediate musicians in their musical goals by giving them access to computer generated lessons that mimic what a private instructor would assign to them.

This work investigates methods for automatically generating musical etudes that are derived from a given musical selection. We compare various methods implemented from the current literature by quantifying the similarities between the generated music and the original selection. Using the similarity results, we make recommendations for which methods should be considered when generating etudes for musical instruction.

Background

In recent years, there has been a focus on the accessibility and equity of music instruction in undeserved communities [1, 2, 3, 4]. The value of private and guided instruction is clear [5, 6, 7], but the question of reaching students in a low-economic class or rural regions presents challenges our current educational system struggles to address. The BCMS is a system that can supports novice to intermediate musicians in their musical goals by giving them access to computer generated lessons which mimics what a private instructor would *assign*.

A common practice in music instruction mirrors a Socratic approach commonly employed in the classroom. An instructor will consider the goal of the student musician (*i.e.*, a target musical selection wished to be preformed, and break it down into a set of etudes for the student to practice based on the properties of the musical selection (*e.g.*, rhythm, dynamics, range, *etc.*). As the student masters the various etudes, the instructor will present more difficult ones, or address other aspects of the musical selection; eventually preparing the student to master the desired selection of music. This approach to assisting the student musician is the corner-stone of the BCMS project.

Figure 1 Shows an example musical selection used as input to the feature extraction and generation system.

Approach

Markov Chain

First-Order Markov Chains is a simple statically based model. Each state has a set of possible transitions based on the probability of their occurrence. For this work, the note properties are the states and the transitions are the probabilities of those states extracted from the original musical selection.

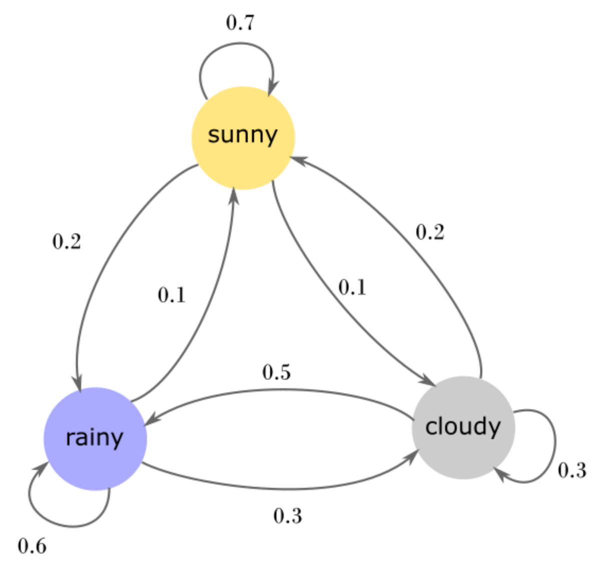

Figure 2 Shows an example First-Order Markov Chain.

Results

Figure 3 Shows an example generated etude from the Hidden Markov Model representing only rhythm properties.

All results were generated using a First-Order Markov Chain that was generated by extracting the frequencies of all possible note pith and duration from the original musical selection. Future work will consider higher order models to account for musical phrasing.

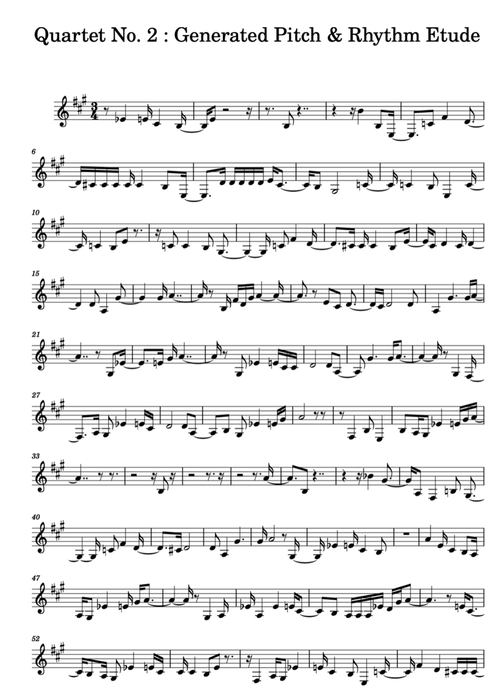

Figure 5 Shows an example generated etude from the Hidden Markov Model representing both pitch and rhythm properties.

Figure 4 Shows an example generated etude from the Hidden Markov Model representing only pitch properties.

Similarity Metrics

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(y_i - x_i)^2}$$

Euclidean

$$EMD = \sum_{i=1}^{m}\sum_{j=1}^{n} M_{ij}d_{ij}$$

Earth Movers

$$\cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Cosine Similarity

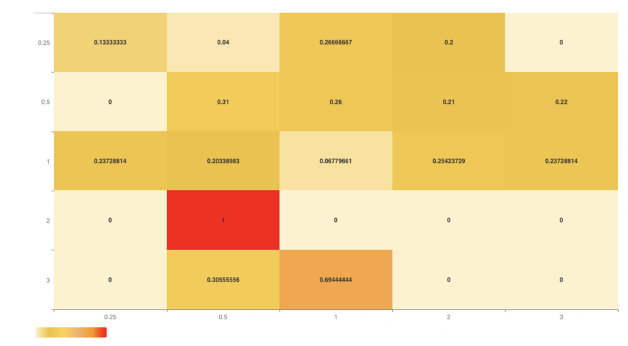

Figure 5 Quartet No. 2 Duration Matrix Heat-map

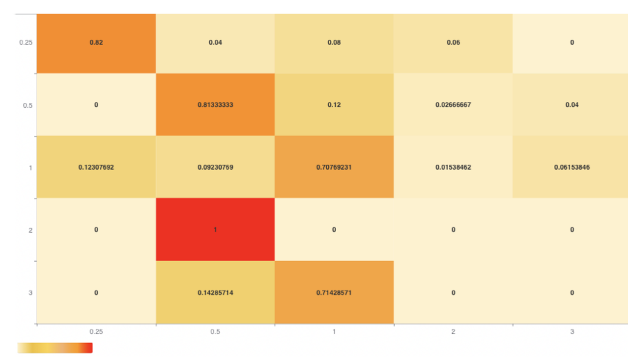

Figure 6 Generated Rhythm Etude Duration Matrix Heat-map.

Future Works

Future work will

- investigate the value of similarity metrics in regard to generating music for practice versus, creating similar musical selections.
- expand the number and type of properties that are used for the generation of etudes.
- investigate how the various proprieties interact in the generation process and if they can be treated independently in regard to musical study.

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References

[1] A. Wilson, *et al.* Widening the gap? The challenges for equitable music education in Scotland. *Support for Learning*, 35(4):473-492, 2020.
[2] R. MacLeod, *et al. Near-peer mentorship: A model for private music instruction in an underserved community. String Research Journal,* 10(1): 45-60, 2020.
[3] B. Nichols. Equity in music education: Access to learning during the pandemic and beyond. *Music Educators Journal*. 107(1):68-70, 2020.
[4] K. Salvador *et al*. Access to music education with regard to race in to urban areas. *Arts Education Policy Review*, 115(3):82-92, 2014.
[5] G. Nierman. The role of private music instruction in the development of high school music students' ability to describe musical events. *Bulletin of the Council for Research in Music education*, 15 - 27, 1983.
[6] N. Seipp. A Comparison of Class and Private Music Instruction. West Virginia University, 1976.
[7] J. Davidson *et al*. "private teaching, private learning". An exploration of music instrument learning in the private studio, junior and senior conservatories. *International handbook of research in arts education*, 729 - 755. Springer, 2007.