A Markov Model for Analysis of Musical Genre

John O. Brickley[a], Wolfgang Olsson[b], and Martin Cenek[c]

[a]jobrickley@alaska.edu, Department of Philosophy
[b]wqolsson@alaska.edu, Department of Music (Minor)
[c]mcenek@uaa.alaska.edu, Department of Computer Science and Engineering

Hypothesis

We hypothesize that 'flattening' of pieces of music to linear sequences of notes while tallying occurrences of each pair will yield probabilistic transition matrices enabling automated grouping of analyzed pieces into established musical genres.

Approach

1. Assembled a corpus of classical, gospel, and folk music for analysis.
2. Processed selected pieces to produce a list of note letters.
3. Generated matrices of each note-pair's occurrence.
4. Calculated mean square error for each pair of matrices.
5. Created a force-directed graph with clustering of pieces inversely proportional to mean square error.
6. Checked against hypothesis.

Advantages

- Quantification of similarity between pieces of music.
- Analysis independent of external data sets.
- Domain agnostic approach with potential applications in other fields.

Disadvantages

- Factorial growth in number of comparisons between pieces may lead to computational inefficiency.
- Exclusion of potentially relevant features from analysis.

Transition Matrices

The probability of each note-pair's occurrence was calculated and these probabilities were input to a 12×12 matrix where rows were first- and columns were second-notes in each pair.

	C	C#	D	D#	E	F	F#	G	G#	A	A#	B
C	0.0106	0	0.0213	0	0.0904	0.0319	0.0071	0.023	0	0.0106	0	0.0035
C#	0	0	0	0	0.0035	0.0018	0	0.0018	0	0	0	0
D	0.0053	0	0.0035	0	0	0.0337	0.0142	0.0479	0.0018	0.0142	0	0.0089
D#	0	0	0	0	0	0	0	0	0	0	0	0
E	0.016	0	0.0018	0	0	0.0071	0.0035	0.0691	0.0018	0.0213	0	0.0106
F	0.0089	0	0.0089	0	0.0035	0.0035	0	0.0408	0.0035	0.0284	0	0.0142
F#	0.0106	0	0	0	0	0	0	0.0035	0	0.0106	0	0
G	0.0762	0.0071	0.0319	0	0.0142	0.0035	0	0.0106	0	0	0	0.0603
G#	0	0	0.0035	0	0	0.0035	0	0	0	0	0	0
A	0.0461	0	0.0284	0	0.0071	0.0035	0	0	0	0.0035	0	0
A#	0	0	0	0	0	0	0	0	0	0	0	0
B	0.0248	0	0.0301	0	0.0124	0.023	0	0.0071	0	0	0	0

Figure 1: Transition matrix for Das Wohltemperierte Klavier Prelude No. 1

Flattening

1. Pieces were transposed to a common key (C) to ease comparison.

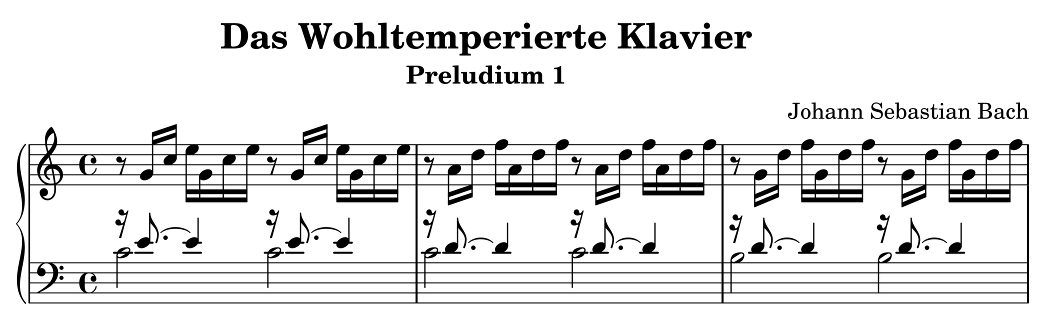

Figure 2: One of the pieces which was processed.

2. Notes from each piece were then extracted and arranged in a list ordered according to time, pitch, and other features such as accidentals. For example, the notes in Figure 3 were converted to the list *C, E, G, C, E, G, C, E, C, E, G, C, E, G, C, E, E.*

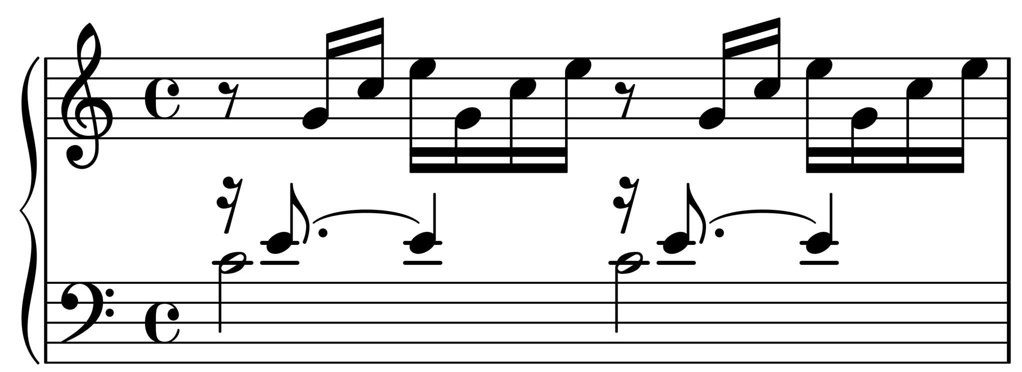

Figure 3: A transposed, but unflattened section.

Network Graph

Preliminary graphs such as that shown in Figure 4 have been generated for small corpora of music. The network graph shows clustering between similar pieces and distance between dissimilar pieces, which supports our hypothesis.

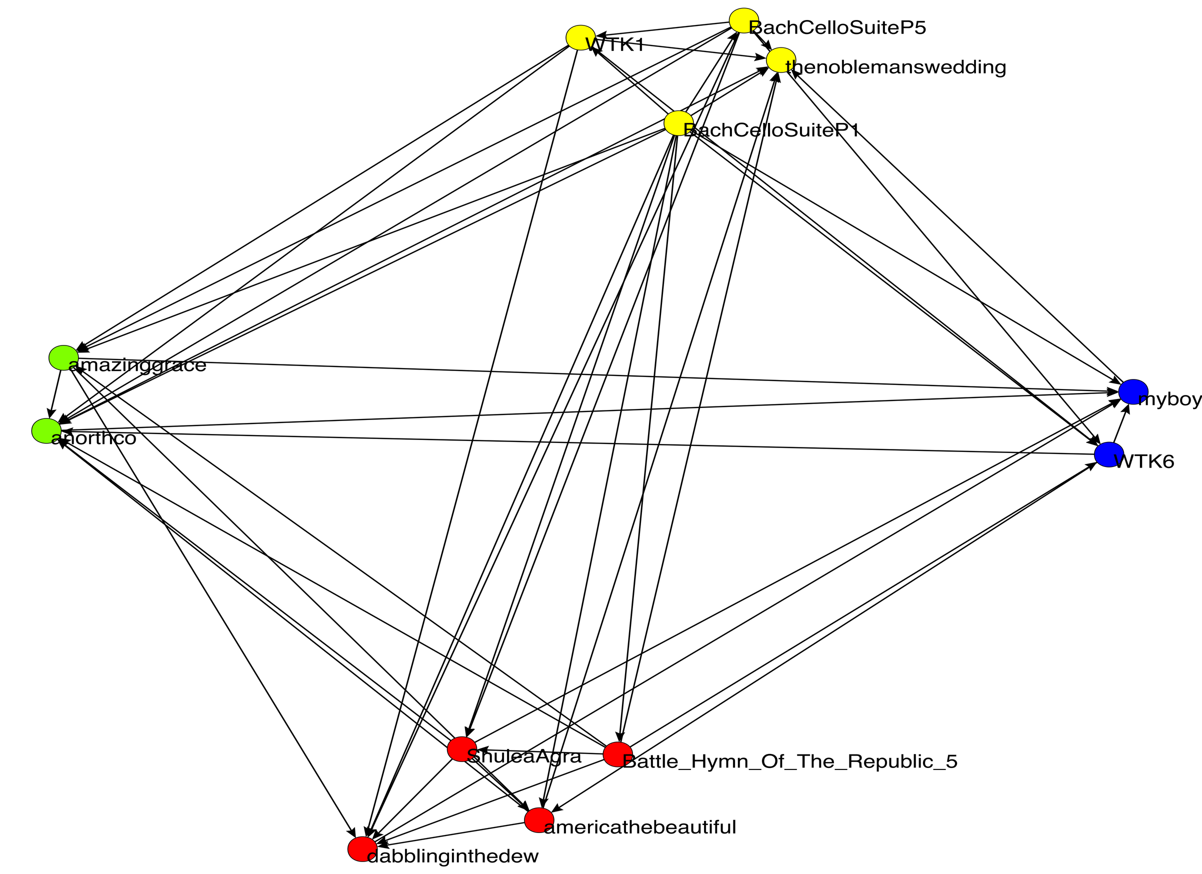

Figure 4: An example network graph for a small corpora of pieces.

Results & Analysis

The results of the analysis recapitulated accepted genre classifications. In Wohltemperierte Klavier Prelude No. 1, for example, the analysis matched the expected high density of G-C, C-E, and E-G transitions. Furthermore, in A North Country Maiden (ANCM) there was a high probability of transition between elements of the Dominant and Tonic chords. From this we conclude that the preliminary model correctly generated the transition tables which confirm common knowledge of music theory.

Conclusions

- Automatic detection of high-level features such as genre in music is possible, even given relatively small data sets.
- This model has the ability to recognize features common to established musical genres.
- The techniques used may also prove useful in fields such as linguistics, especially in areas such as fine-grained Sociolinguistic Dialect analysis and classification.

Selected References

[1] J. C. González-Avella, V. M. Eguíluz, M. G. Cosenza, K. Klemm, J. L. Herrera, and M. S. Miguel. Local versus global interactions in nonequilibrium transitions: A model of social dynamics. Physical Review, 73, 2006.

[2] R. Axelrod. The dissemination of culture: A model with local convergence and global polarization. The Journal of Conflict Resolution, 41(2):203-226, April 1997.

[3] J. Håkansson and W. Nordström. Finding clusters of similar artists: analysis of dbscan and k-means clustering. April 2012.

[4] B. Jurish. bang: Pure Data, chapter Music as a Formal Language. First edition, 2006.

[5] G. E. Poliner and D. P. Ellis. A classification approach to melody transcription. In ISMIR 2005: 6th International Conference on Music Information Retrieval: Proceedings: Variation 2: Queen Mary, University of London & Goldsmiths College, University of London, 11-15 September, 2005, pages 161-166. Queen Mary, University of London, 2005.

Acknowledgements

We would like to acknowledge Brendan Babb, of UAA's Computer Science and Mathematics departments, whose assistance with this project proved invaluable. Additionally, we thank the maintainers of the Music21 and Natural Language Toolkit libraries for the Python language.