Cognitively motivated representations of symbolic music

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Introduction

- This talk will discuss the early stages of a project that uses a top-down approach to develop a robust representation(s) of symbolic music data
- Such a representation would be useful for a number of analytic applications, including
 - harmonic analysis
 - provenance assignment
 - similarity analysis

(Some) Existing Approaches

Predicting Phrase Labels

(Some) Existing Approaches

Predicting Phrase Labels

Next Steps

(Some) Existing Approaches

Predicting Phrase Labels

Next Steps

Conclusions

Ultimate Goal

- To develop a representation for western art music scores that is
 - cognitively meaningful
 - computationally accessible
 - able to capture temporal relationships
 - able to facilitate the analysis of multiple levels of musical structure

Motivation

- Existing representations have shown limited success for harmonic and higher-level musical analysis
- Multi-level model employed in music theory pedagogy may be useful in developing new representations

Motivation

A pedagogical approach

Formal Structure

Higher

Phrase-level Function

Roman Numerals (Harmonic Analysis)

Notes (Musical Surface)

Lower

Motivation

Speech recognition

Higher-level music analysis

"Language model"

Functional analysis

Phonemes

MFCCs and representations

Representation

Acoustic signal

Musical surface

- Piano-roll notation
 - David Temperley's preference rules (2001)
- Vertical slices of polyphonic music to form "chords"
 - Quinn and Mavromatis (2011) with extension to incorporate voice leading
 - Chris White's chord-based function model
- Martin Rohmeier's scale degree, function, and phraselevel representations (2011)

- Large-scale analysis approaches are heavily influenced by text retrieval methods, namely N-grams (sequences of N contiguous symbols)
- N-grams work well for
 - melody retrieval in monophonic contexts (Pickens 2001)
 - chord retrieval in polyphonic contexts when the chords occur as distinct units (Scholz et al. 2009)
 - e.g., peachnote.com's N-gram viewer (Viro 2011)

- N-gram representations encounter problems with more complex textures
 - e.g., where the notes of chords are not played simultaneously
- N-grams do not distinguish between what is structurally significant and what is not
 - e.g., between what is a chord-tone and what is a non-chord tone/ornamentation.



"Language Model" for Music

- Harmonic/Roman numeral analysis is a hard task when working from the musical surface
- A model of phrase-level function and its relationship to roman numeral labels (the "language model") facilitates a top-down approach
 - This approach also allows for
 - the evaluation of existing representations
 - the development of learned representations

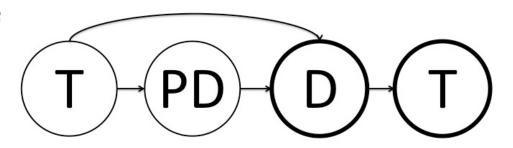
Musical Phrases

- Complete musical statements built from the ordered presentation of three harmonic functions
 - tonic, pre-dominant, and dominant functions
- End with a cadence
 - remaining on the dominant function for a half cadence
 - returning to the tonic function for an authentic or a deceptive cadence

Predicting Phrase Labels

Hidden Markov model (HMM)

State space



- Encoded chord label and function for all examples from Laitz's textbook The Complete Musician (2011) into digital representation
 - used to train HMM transition probabilities and evaluate model

This part of the project was undertaken with Daniel Shananan

Predicting Phrase Labels

- Evaluation
 - 80/20 split of textbook data: 94.3% overall accuracy
 - tonic: 93%, pre-dominant: 93%, dominant: 89%
 - Workbook exercises: 87.5% overall accuracy
 - tonic: 96%, pre-dominant: 83%, dominant: 52%**
 - ** 36% of phrases ended with a dominant function in the workbook versus 17% in the training set

This part of the project was undertaken with Daniel Shananan

Next Steps

- Experiment with both hierarchical hidden Markov models (HHMM) and conditional random fields (CRF)
- HHMM implementation
 - 3-state phrase-level function HMM will sit on top of a lower-level roman numeral HMM
- CRF implementation
 - each state will have a roman numeral and a function
 - advantage over HHMMs in this context: ability to utilize temporal context, including metrical position and features from previous time frames

Next Steps

- Once the "language model" has been implemented different existing representations will be evaluated along with learned representations
- A successful representation must be able to capture
 - information about note duration and metrical strength across different time scales
 - temporal relationships between pitch classes and chords

Conclusions

- This talk has described an ongoing project for developing a multi-level model for western art music analysis
- The model is inspired by
 - music theory pedagogy
 - speech recognition
- The ultimate goal of this project is to develop a representation of the musical surface that is both utilitarian and related to human musical information processing

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