Developing a symbolic music representation inspired by speech recognition

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Goal and Motivation

Prior Work

Predicting Phrase Labels

Next Steps

Conclusions

Goal

- Develop a symbolic representation that
  - provides an estimate of which notes are structurally significant
  - works for a range of musical textures
  - captures temporal relationships
  - facilitates the analysis of multiple levels of musical structure
  - is computationally tractable

Motivation

Speech recognition	↔	**Higher-level music analysis**
“Language model”	↔	Functional analysis
Phonemes	↔	Harmonic analysis
MFCCs and other representations	↔	*Representation*
Acoustic signal	↔	Musical surface

Prior Work: Representations

- Vertical slices of polyphonic music to form “chords”
  - per event (Quinn 2010)
  - per beat (Radicioni and Espositio, 2006)
- Working from chord labels (when available)
  - de Haas et. al (2011)

Prior Work: N-grams

- 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)

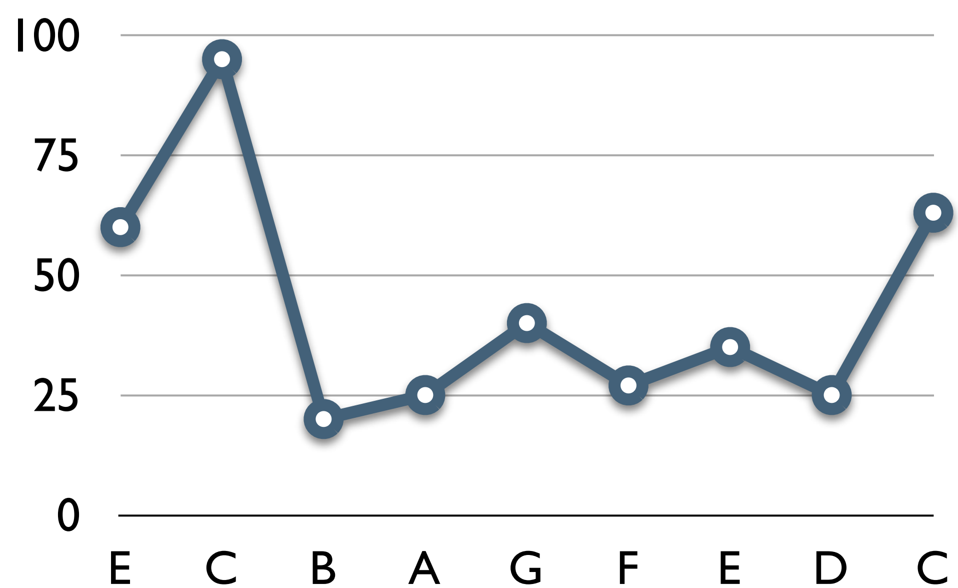
Prior Work: N-grams

- N-gram representations encounter problems with more complex textures
  - e.g., where the notes of chords are not played simultaneously

- N-grams cannot 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.

This needs to be encoded in the representation

What might this look like?



“Language Model” for Music

Functional harmonic analysis may be flawed but it can be useful

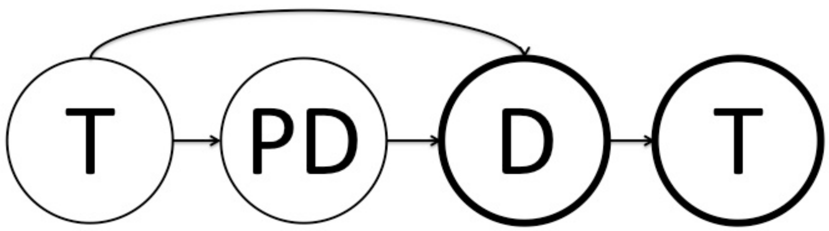
A model of phrase-level function and its relationship to roman numeral labels can be used as a “language model”

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

Conditional Random Fields

- Like HMMs, CRFs are probabilistic, temporal models
- HMM observations are isolated, only containing information about its own label
  - i.e., uses a joint distribution over both label and observation sequences
- CRFs encode information about temporal context, including metrical position and features from previous time frames
  - i.e., uses conditional probability over label sequences given an observation sequence

Conditional Random Fields

- CRF Implementation
  - observations will be the output of a multi-layer perceptron run on the musical surface
  - states will have chord and function label
  - outputs possible state sequences
- Representation
  - the musical surface with likely structurally significant notes highlighted
  - additional processing will be needed to achieve this

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 can capture temporal relationships and works for a range of musical textures

Thank You!

References

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