jSymbolic 2: New Developments and Research Opportunities

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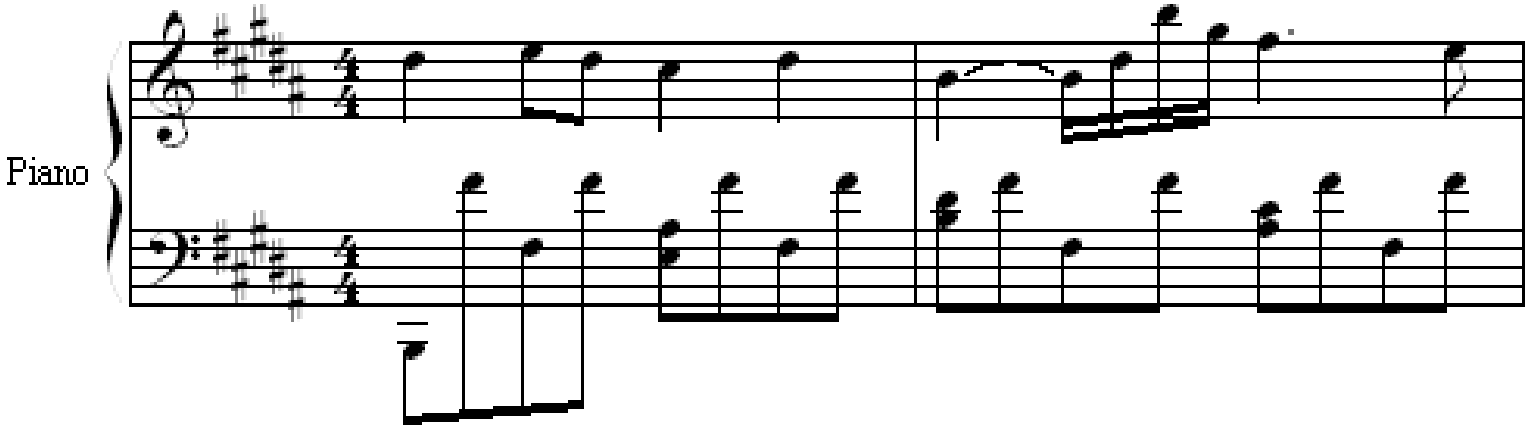
Topics

- Introduction to “features” (from a machine learning perspective)
  - And how they can be useful for musicologists and music theorists
- jSymbolic2
  - What it is
  - How it’s useful to music theorists and musicologists

What are “features”?

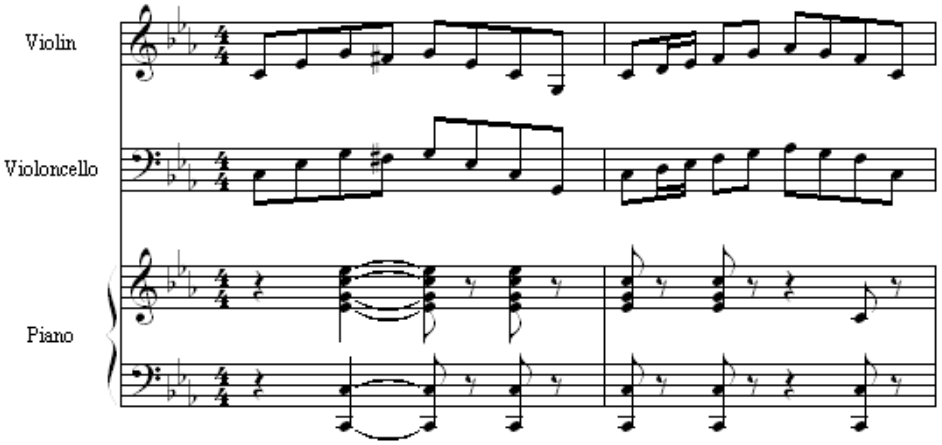
- Pieces of information that can characterize something (e.g. a piece of music) in a (usually) simple way
- (Usually) numerical values
  - Can be single values or can be vectors of related values
  - Histograms are a common type of vector
- (Usually) represent a piece as a whole
  - Or at least regularly spaced windows / musical segments within the piece

Chopin's *Nocturne in B, Op. 32, No. 1*



- Average Note To Note Dynamics Change: 6.03
- Chromatic Motion: 0.0769
- Dominant Spread: 3
- Harmonicity of Two Strongest Rhythmic Pulses: 1
- Importance of Bass Register: 0.2
- Interval Between Strongest Pitch Classes: 3
- Most Common Pitch Class Prevalence: 0.433
- Note Density: 3.75
- Number of Common Melodic Intervals: 3
- Number of Strong Pulses: 5
- Orchestral Strings Fraction: 0
- Overall Dynamic Range: 62
- Pitch Class Variety: 7
- Range: 48
- Relative Strength of Most Common Intervals: 0.5
- Size of Melodic Arcs: 11
- Stepwise Motion: 0.231
- Strength of Strongest Rhythmic Pulse: 0.321
- Variability of Note Duration: 0.293
- Variation of Dynamics: 16.4

Mendelssohn's *Piano Trio No. 2*

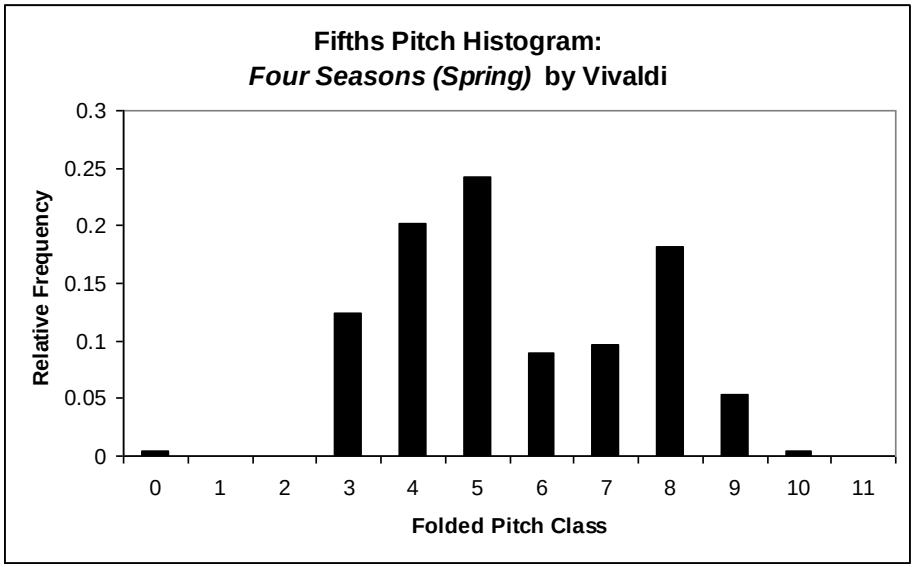


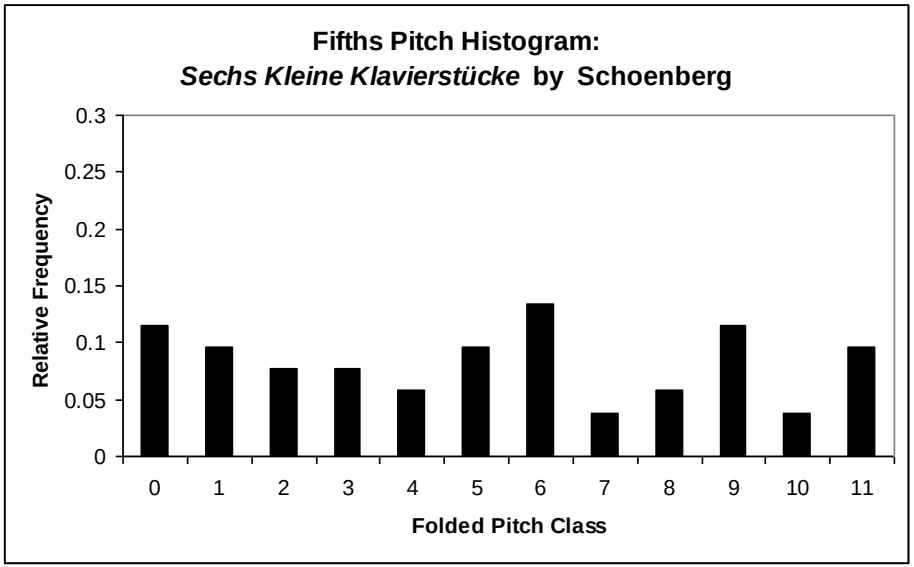
- Average Note To Note Dynamics Change: 1.46
- Chromatic Motion: 0.244
- Dominant Spread: 2
- Harmonicity of Two Strongest Rhythmic Pulses: 1
- Importance of Bass Register: 0.373
- Interval Between Strongest Pitch Classes: 7
- Most Common Pitch Class Prevalence: 0.39
- Note Density: 29.5
- Number of Common Melodic Intervals: 6
- Number of Strong Pulses: 6
- Orchestral Strings Fraction: 0.56
- Overall Dynamic Range: 22
- Pitch Class Variety: 7
- Range: 39
- Relative Strength of Most Common Intervals: 0.8
- Size of Melodic Arcs: 7.27
- Stepwise Motion: 0.439
- Strength of Strongest Rhythmic Pulse: 0.173
- Variability of Note Duration: 0.104
- Variation of Dynamics: 5.98

Feature value comparison

Feature	*Nocturne*	*Trio*
Average Note To Note Dynamic Change	6.03	1.46
Overall Dynamic Range	62	22
Variation of Dynamics	16.4	5.98
Note Density	3.75	29.5
Orchestral Strings Fraction	0	**0.56**
Variability of Note Duration	**0.293**	0.104
Chromatic Motion	0.077	**0.244**
Range	48	39

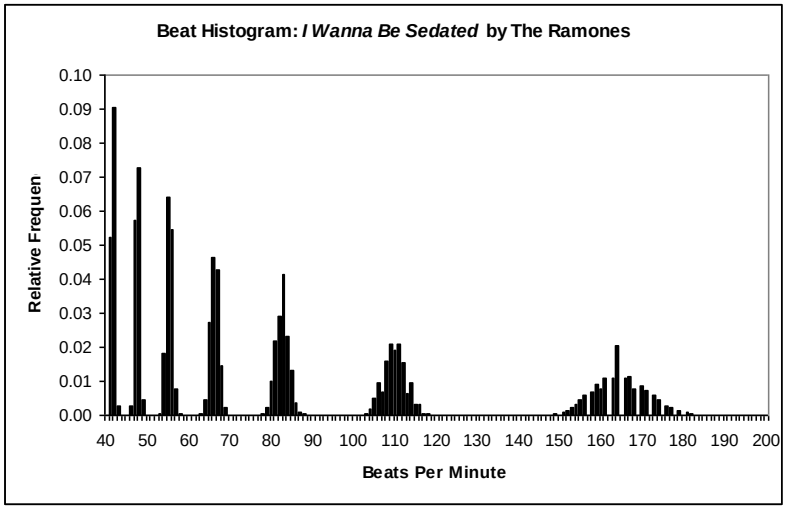
Fifths pitch class histogram

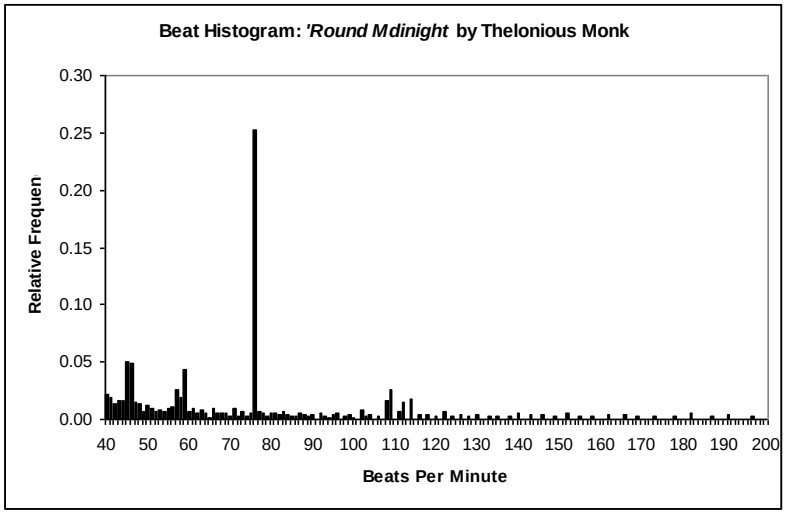




Beat histogram

- Beat histograms use a technique called "autocorrelation" to calculate the relative strengths of different beat periodicities
- "I Wanna Be Sedated" by The Ramones (top)
  - Several harmonic peaks with large spreads around them
- "'Round Midnight" by Thelonious Monk (bottom)
  - Only one strong peak, with a large low-level spread
- Histograms like this can be used directly, or other features may be derived from them
  - e.g. peak statistics





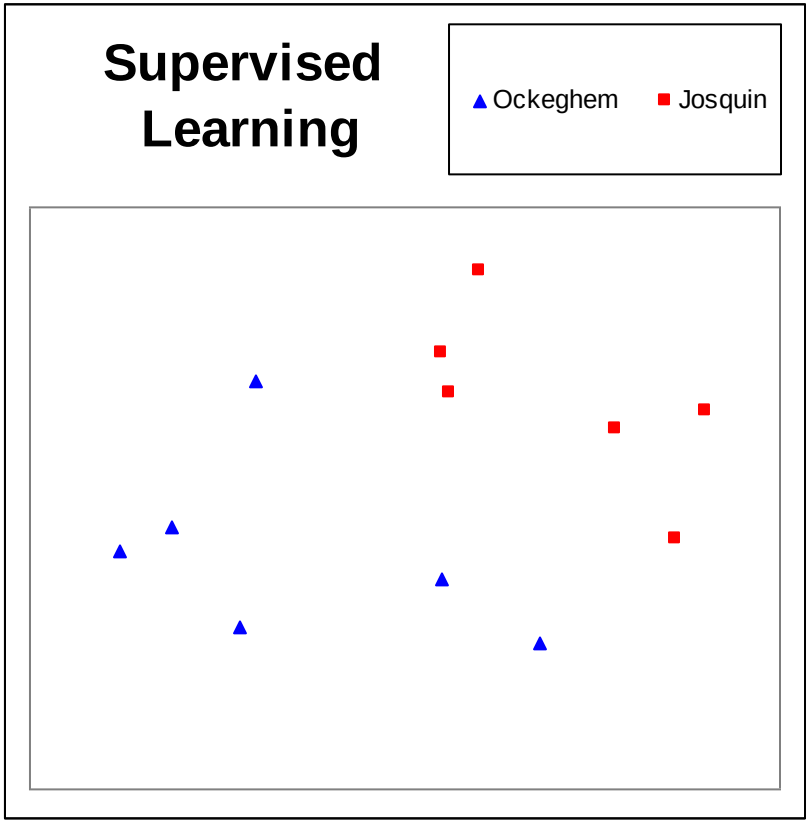
How can features be useful?

- Sophisticated searches of large musical databases
  - e.g. find all pieces with no more than X amount of chromaticism, and less than Y amount of parallel motion
  - ELVIS database + Musiclibs
- Using statistical analysis and visualization tools to study the empirical musical importance of various features when extracted from large datasets
  - e.g. features based on instrumentation were most effective for distinguishing genres (McKay & Fujinaga 2005)
- Using machine learning to classify or cluster music
  - Supervised or unsupervised learning
  - e.g. identify the composers of unattributed musical pieces

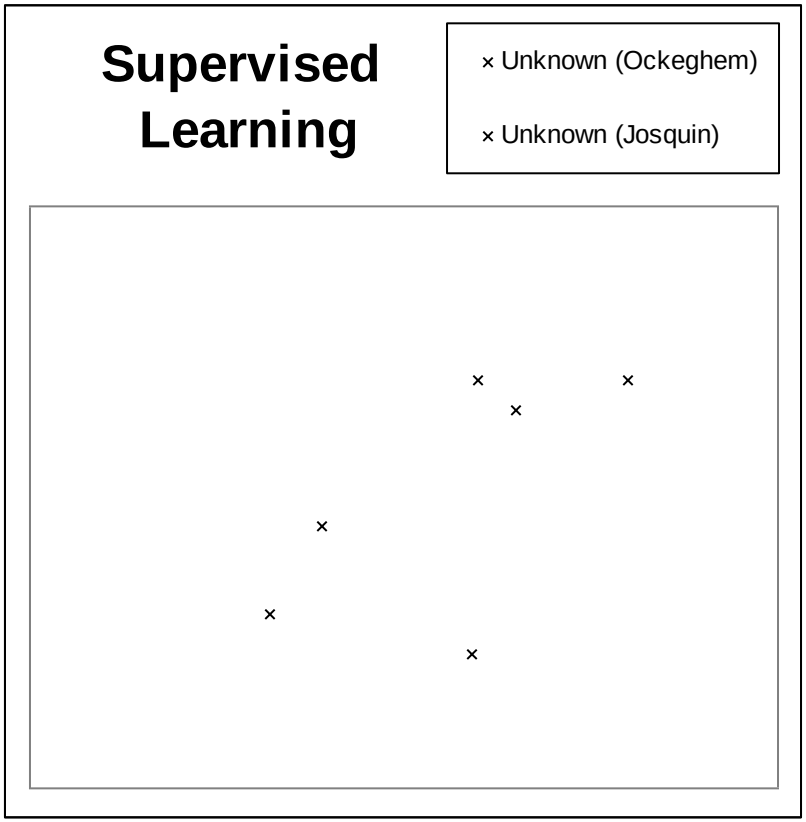
Sample expert system

```
if ( parallel_fifths == 0 &&
     landini_cadences == 0 )
   then composer → Palestrina
else composer → Machaut
```

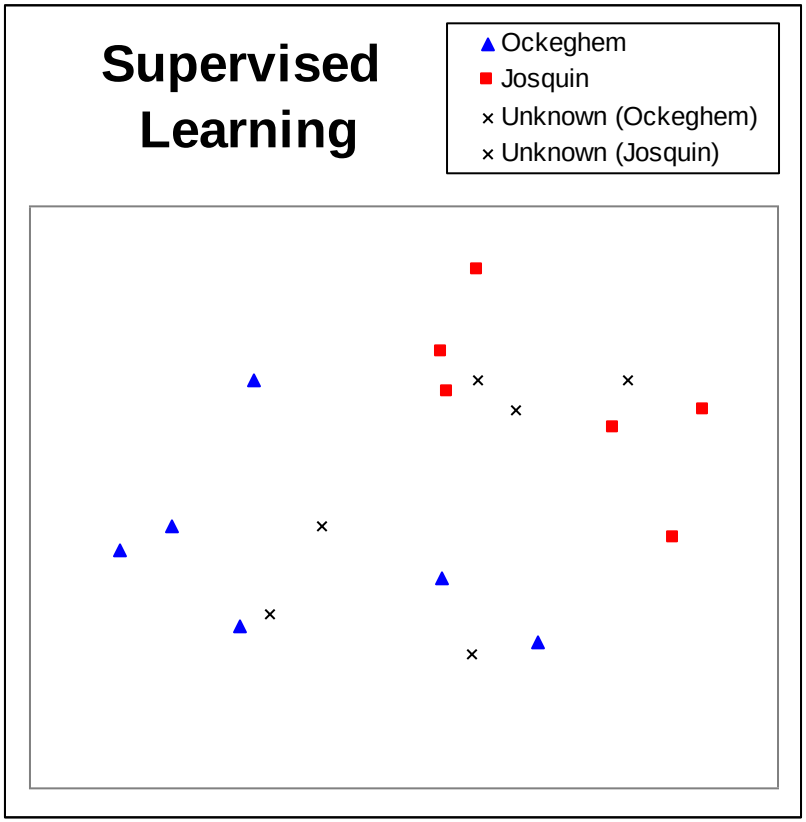
Sample supervised learning



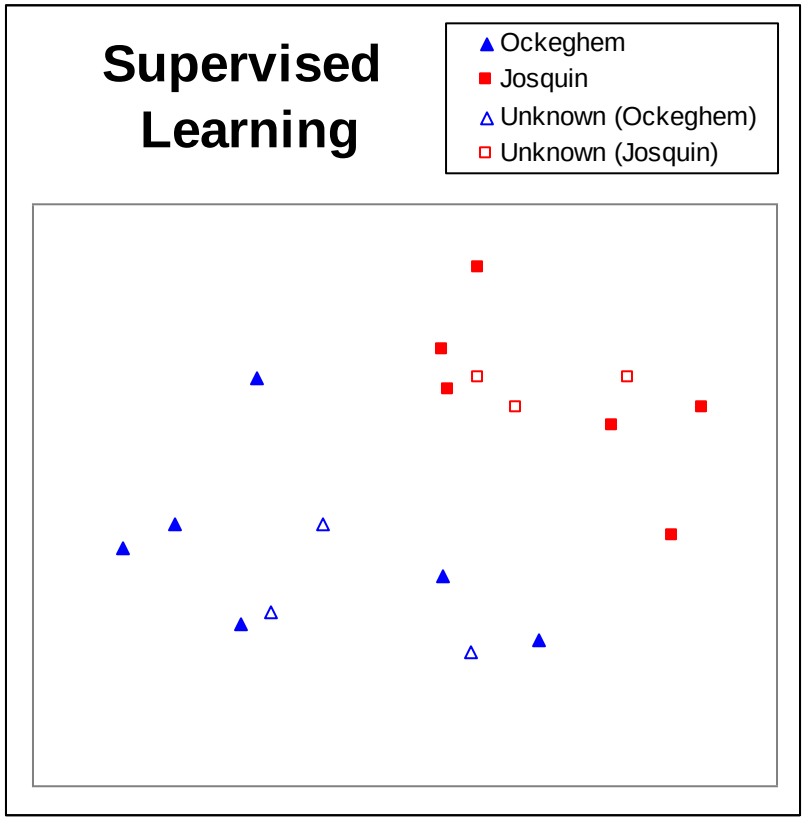
Sample supervised learning



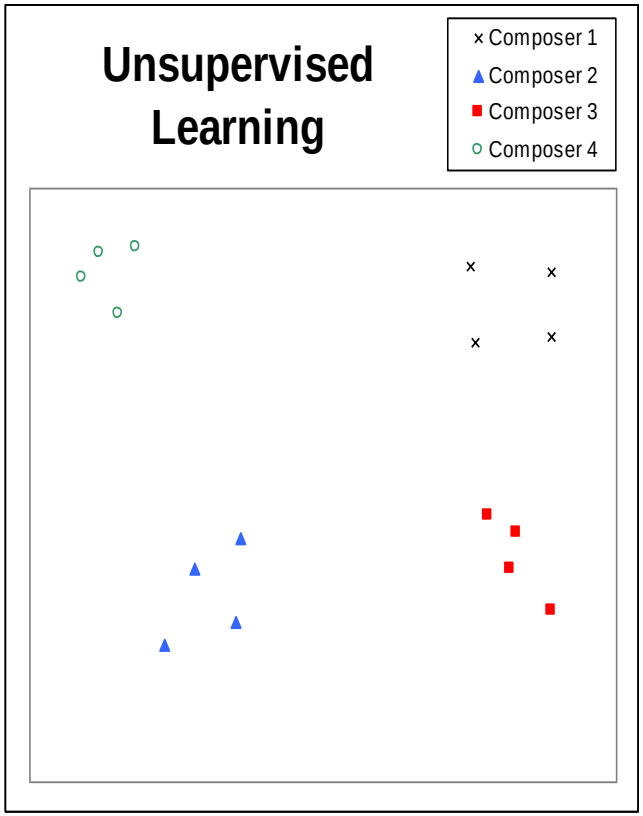
Sample supervised learning



Sample supervised learning



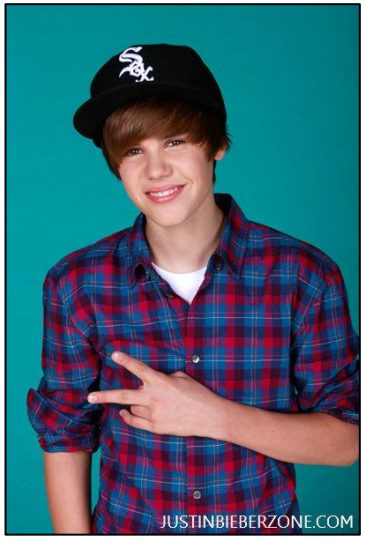
Sample unsupervised learning



Benefits of features and machine learning

- Can quickly perform consistent empirical studies involving thousands of pieces
- Can be applied to diverse types of music
- Can simultaneously consider thousands of features and their interrelationships
  - And can statistical condense many features into low-dimensional spaces when needed
- No need to formally specify any heuristics or queries before beginning analyses
  - Unless you want to, of course
- Can avoid (or validate) potentially incorrect ingrained biases and assumptions

jSymbolic's lineage



- Bodhidharma (2004)
  - Specialized feature extraction and machine learning for genre classification research
- jSymbolic (2006)
  - General-purpose feature extraction
  - Part of jMIR
- jSymbolic2 (2016)
  - Bigger and better!

What does jSymbolic2 do?

- Extracts 158 features
- Some of these are multi-dimensional histograms, including:
  - Pitch and pitch class histograms
  - Melodic interval histogram
  - Vertical interval histograms
  - Chord types histogram
  - Beat histogram
  - Instrument histograms

jSymbolic2's feature types (1/2)

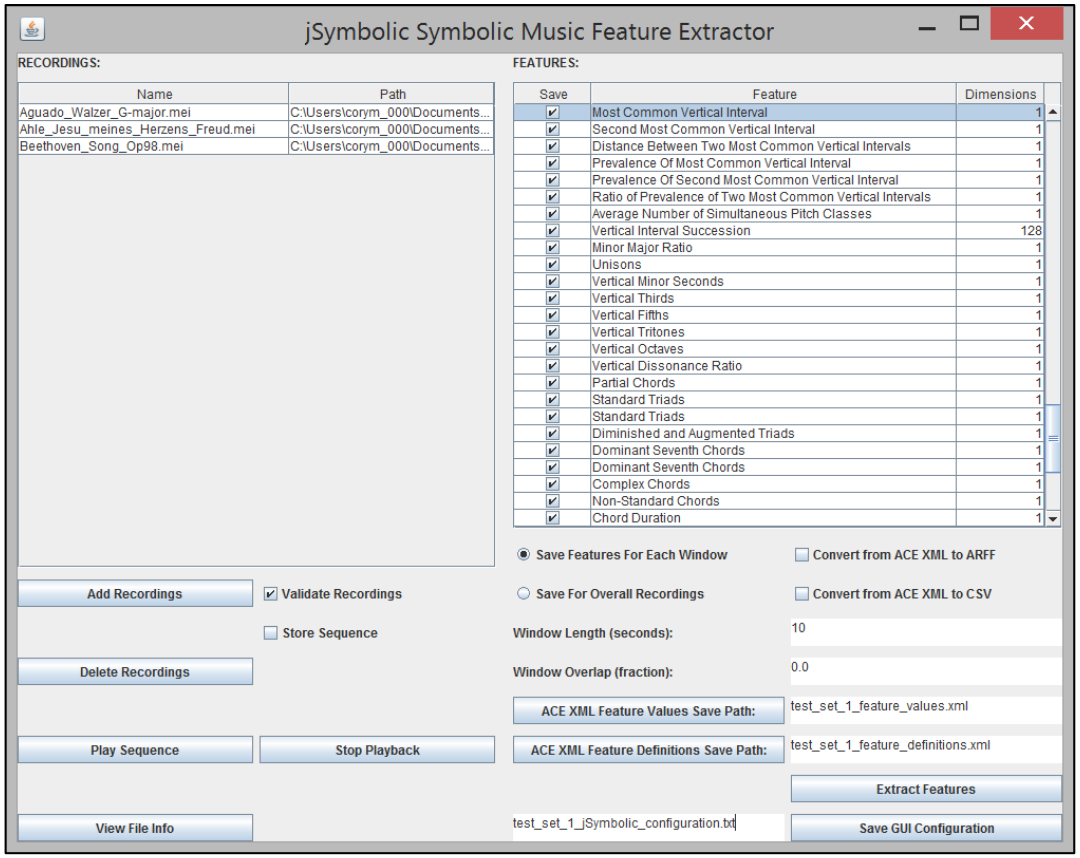
- Instrumentation:
  - What types of instruments are present and which are given particular importance relative to others?
- Texture:
  - How many independent voices are there and how do they interact (e.g., polyphonic, homophonic, etc.)?
- Rhythm:
  - Time intervals between the attacks of different notes
  - Duration of notes
  - What kinds of meters and rhythmic patterns are present?
  - Rubato?
- Dynamics:
  - How loud are notes and what kinds of dynamic variations occur?

jSymbolic feature types (2/2)

- Pitch Statistics:
  - What are the occurrence rates of different pitches and pitch classes?
  - How tonal is the piece?
  - How much variety in pitch is there?
- Melody:
  - What kinds of melodic intervals are present?
  - How much melodic variation is there?
  - What kinds of melodic contours are used?
  - What types of phrases are used?
- Chords:
  - What vertical intervals are present?
  - What types of chords do they represent?
  - How much harmonic movement is there?

How can you use jSymbolic2

- Graphical user interface
- Command line interface
- Rodan workflow
- Java API

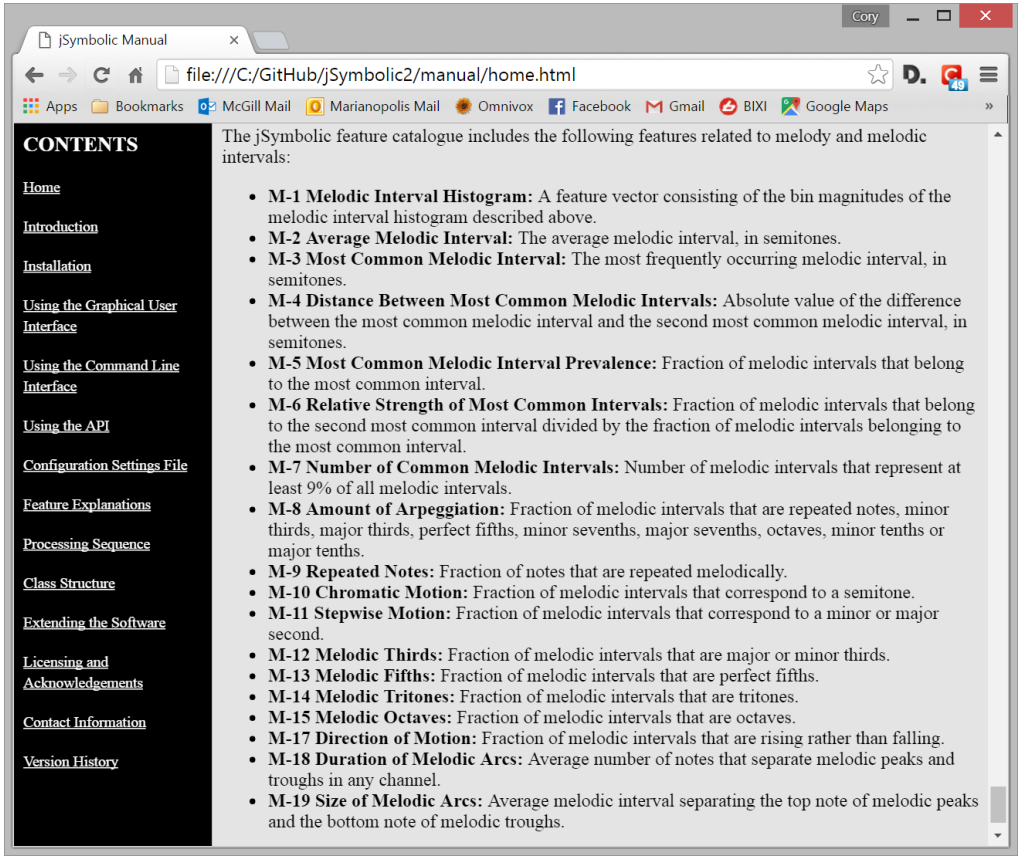


jSymbolic2's file formats

- Input:
  - MIDI
  - MEI
  - MusicXML (via Rodan workflow only)
- Output:
  - ACE XML
  - Weka ARFF
  - CSV

jSymbolic2's documentation

- Super-mega-ultra detailed manual
  - At least compared to most academic software manuals
  - In HTML
- Super-mega-ultra detailed Javadocs
  - For programmers



jSymbolic2: More great things

- Windowed feature extraction
  - Including overlapping windows
- Configuration files
  - Pre-set feature choices
  - Pre-set input and output choices
  - More
- jMei2Midi
  - Most complete MEI to MIDI converter in the universe!
  - General-purpose (not just for jSymbolic2)
  - Specialized pipeline for transmitting relevant MEI data that cannot be represented in MIDI

Exploratory simple pilot study

- Josquin vs. Ockeghem composer identification / attribution
  - 124 jSymbolic2 features extracted from the JRP data
  - 105 Josquin pieces and 98 Ockeghem
- Achieved 89.7% classification accuracy
  - 10-fold cross-validation
- Lots of room for improving results still further
  - Only used simple SVM classifier with default settings
  - No dimensionality reduction was used
    - Both expert insights and automatic analysis can be applied
  - Still more jSymbolic2 features to come
- Interesting future research applications:
  - Determine which features are most effective
    - Can analyze feature data both visually and statistically
  - Apply trained classifiers to unattributed or uncertain pieces
  - Expand scope to other composers

What you can do with jSymbolic

- Empirically study huge collections of music in new ways
  - Search music databases based on feature values
  - Analyze and visualize music based on feature values
  - Use machine learning
- Design your own custom features
  - jSymbolic2 is specifically designed to make it easy to add new custom features
  - Easy to iteratively build increasingly complex features based on existing features
- Perform multimodal research
  - Combine symbolic features with other features extracted from audio, lyrics and cultural data
  - This improves results substantially! (McKay et al. 2010)

Use jSymbolic2 with jMIR

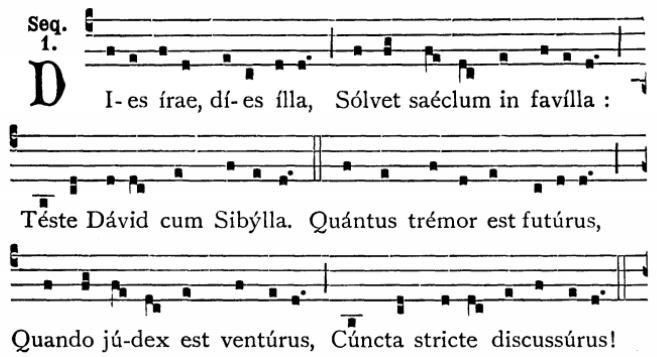
- ACE: Meta-learning classification engine
- Bodhidharma MIDI, SLAC and Codaich: datasets
- jAudio: Audio feature extraction
- jLyrics: Extracts features from lyrical transcriptions
- jWebMiner: Cultural feature extraction
- ACE XML: File formats
  - Features, feature metadata, instance metadata and ontologies
- lyricFetcher: Lyric mining
- jMusicMetaManager: Metadata management
- jSongMiner: Metadata harvesting
- jMIRUtilities: Infrastructure for conducting experiments
- jProductionCritic: Automated production error-checking

Research collaborations

- We would love to collaborate with music theorists and musicologists on their work
- We can help you apply and adapt jSymbolic to specific research projects
- We can help you come up with novel ways to study music

jSymbolic2: Currently in progress

- Final testing and debugging
- Annotation of all valid files in the ELVIS database with extracted features
  - And Musiclibs, eventually
  - Auto-annotation scripts
- MEI pre-modern notation
- Designing new features
  - Requests welcome!



Acknowledgements

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  - Implemented almost all of the new jSymbolic2 code
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Thanks for your attention

- **E-mail:** cory.mckay@mail.mcgill.ca
- **jSymbolic2:** github.com/DDMAL/jSymbolic2
- **jMIR:** jmir.sourceforge.net

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