# Using statistical feature extraction and machine learning in musicological research

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# Topics

- Introduction to "features" (from a machine learning perspective)
  - And how they can be useful for musicologists
- jSymbolic2
  - And how it can be useful to musicologists
- Composer attribution study
- ELVIS database feature annotation

# Empiricism, software & statistics

- Empiricism, automated software tools and statistical analysis techniques allow us to:
  - Study huge quantities of music very quickly
    - More than any human could reasonably look at
  - Empirically validate (or repudiate) our theoretical suspicions
  - Do purely exploratory studies of music
  - See music from fresh perspectives
    - Can inspire new ways of looking at music

# Human involvement is crucial

- Of course, computers certainly cannot replace the expertise and insight of musicologists and theorists
  - Computers instead serve as powerful tools and assistants that allow us to greatly expand the scope and reliability of our work
- Computers do not understand musical experience
  - We must pose the research questions for them to investigate
  - We must interpret the results they present us with
- Music is, after all, defined by human experience, not some “objective” externality

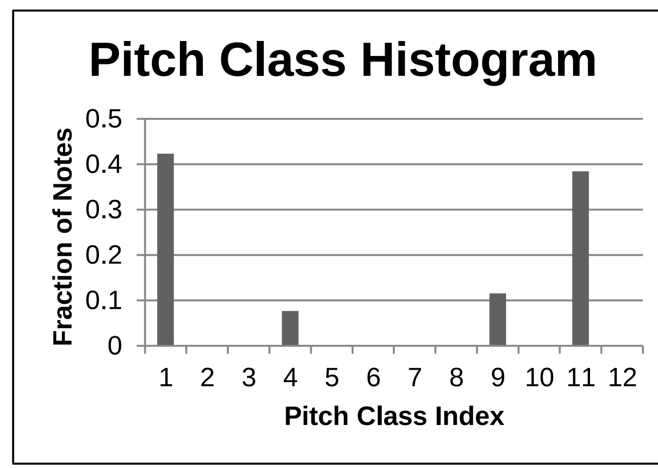
# What are "features"?

- Pieces of information that can characterize something (e.g. a piece of music) in a simple way
- Usually numerical values
  - A feature can be a single value, or it can be a set of related values (e.g. a histogram)
- Can be extracted from pieces as a whole, or from segments of pieces

# Example: Two basic features

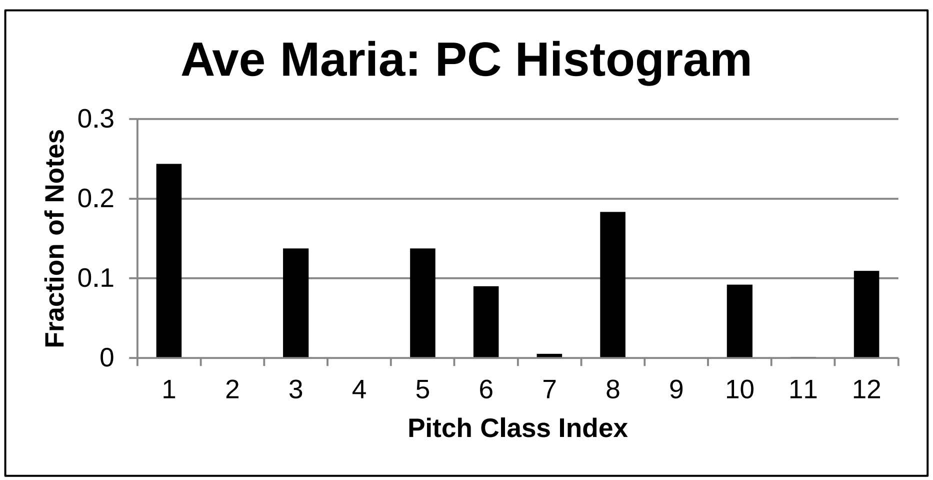
- Range (1-D): Difference in semitones between the highest and lowest pitches.
- Pitch Class Histogram (12-D): Each of its 12 values represents the fraction of notes with a particular pitch class. The first value corresponds to the most common pitch class, and each following value to a pitch class a semitone higher than the previous.

- Range = G - C = 7 semitones
- Pitch Class Histogram: see graph ->
  - Note counts: C: 3, D: 10, E: 11, G: 2
  - Most common note: E (11/26 notes)
    - Corresponding to 0.423 of the notes
  - E is thus pitch class 1, G is pitch class 4, C is pitch class 9, D is pitch class 11



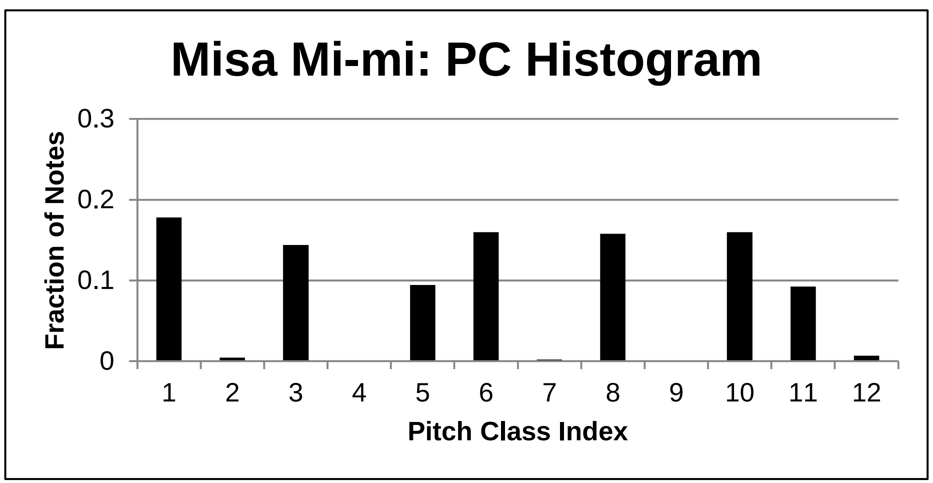
# Josquin’s *Ave Maria... Virgo serena*

- Range: 34
- Repeated notes: 0.181
- Vertical perfect 4$^{\text{ths}}$: 0.070
- Rhythmic variability: 0.032
- Parallel motion: 0.039



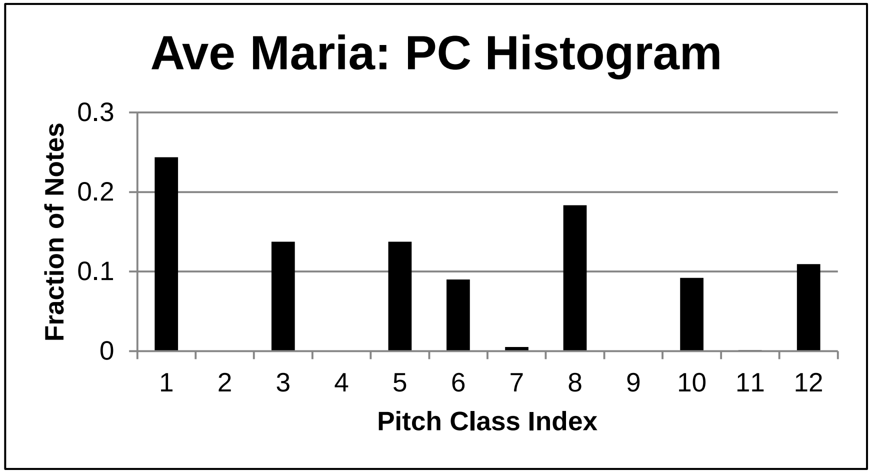

# Ockeghem's *Missa Mi-mi* (Kyrie)

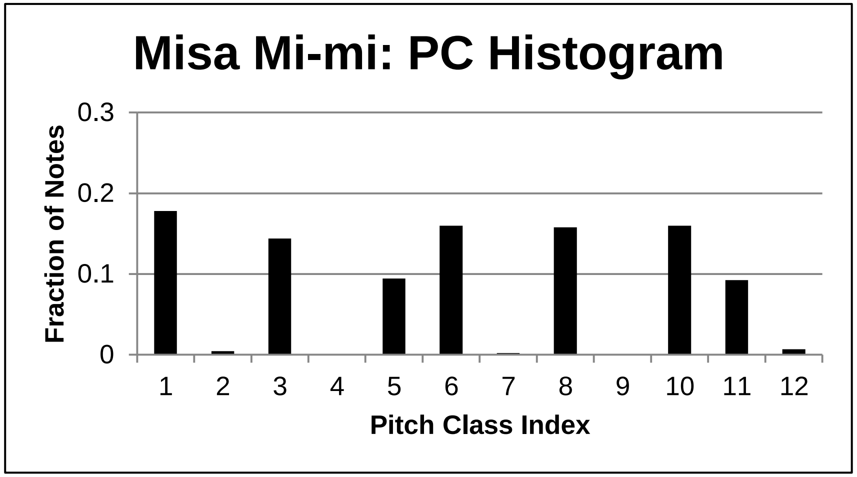
- Range: 26
- Repeated notes: 0.084
- Vertical perfect 4ths: 0.109
- Rhythmic variability: 0.042
- Parallel motion: 0.076




# Feature value comparison

| Feature | Ave Maria | Misa Mi-mi |
|---|---|---|
| Range | 34 | 26 |
| Repeated notes | 0.181 | 0.084 |
| Vertical perfect 4ths | 0.070 | 0.109 |
| Rhythmic variability | 0.032 | 0.042 |
| Parallel motion | 0.039 | 0.076 |



# How can we use features?

- Use machine learning to classify or cluster music
  - e.g. identify the composers of unattributed musical pieces
- Apply statistical analysis and visualization tools to features extracted from large collections of music
  - Look for patterns
- Perform sophisticated searches of large musical databases
  - e.g. find all pieces with less than X amount of chromaticism and more than Y amount of contrary motion

# jSymbolic2: Introduction

- jSymbolic2 is a software platform we have implemented for extracting features from symbolic music
  - Part of our much larger jMIR package

# What does jSymbolic2 do?

- Extracts 172 unique features
- Some of these are multi-dimensional histograms, including:
  - Pitch and pitch class histograms
  - Melodic interval histograms
  - Vertical interval histograms
  - Chord types histograms
  - Beat histograms
  - Instrument histograms
- In all, extracts a total of 1230 separate values

# jSymbolic2: Feature types (1/2)

- 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 / horizontal intervals:
  - 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 / vertical intervals:
  - What vertical intervals are present?
  - What types of chords do they represent?
  - How much harmonic movement is there?

# jSymbolic2: Feature types (2/2)

- 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?

# Composer attribution study

- We used jSymbolic2 features to automatically classify pieces of Renaissance music by composer
  - As an example of the kinds of things that can be done with jSymbolic2
  - As a meaningful research project in its own right

# RenComp7 dataset

- Began by constructing our "RenComp7" dataset:
  - 1584 MIDI pieces
  - By 7 Renaissance composers
- Combines:
  - Top right: Music drawn from the Josquin Research Project (Rodin, Sapp and Bokulich)
  - Bottom right: Music by Palestrina (John Miller) and Victoria (Sigler, Wild and Handelman 2015)

| Composer | Pieces |
|---|---|
| Busnoys | 69 |
| Josquin *(only includes the 2 most secure Jesse Rodin groups)* | 131 |
| La Rue | 197 |
| Martini | 123 |
| Ockeghem | 98 |

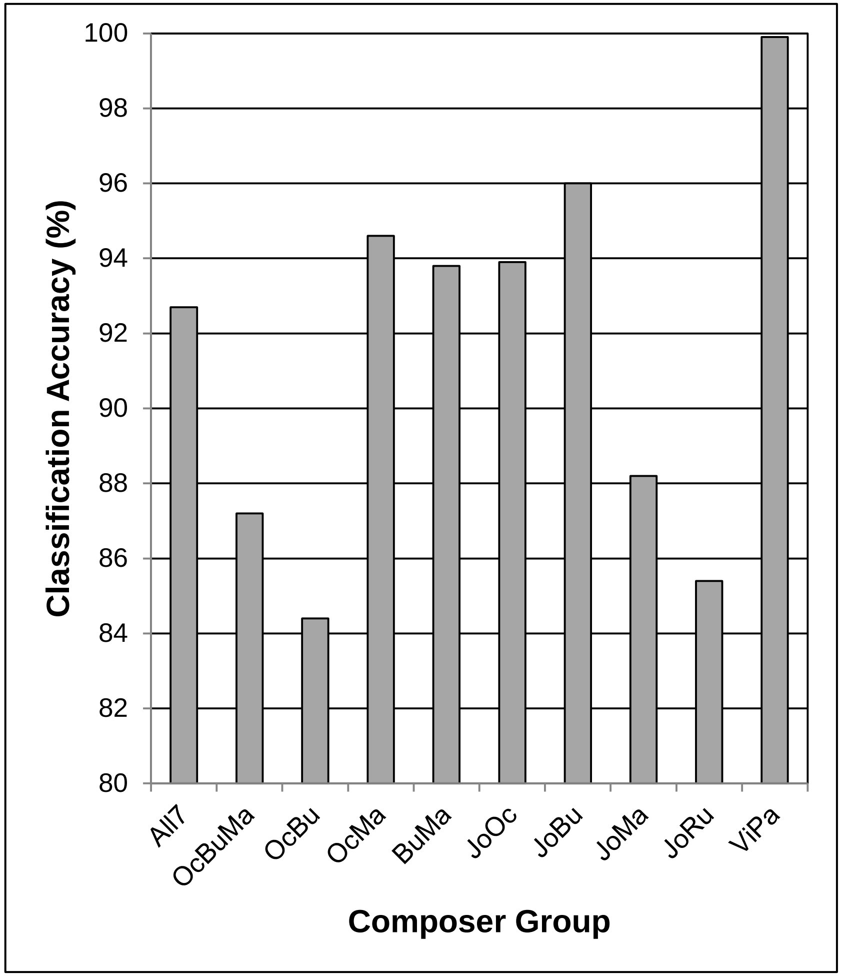
| Composer | Pieces |
|---|---|
| Palestrina | 705 |
| Victoria | 261 |

# Methodology

- Extracted 721 feature values from each of the 1584 RenComp7 pieces using jSymbolic2
- Used machine learning to teach a classifier to automatically distinguish the music of the composers
  - Based on the jSymbolic2 features
- Used statistical analysis to gain insight into relative compositional styles
- Performed several versions of this study
  - Classifying amongst all 7 composers
  - Focusing only on smaller subsets of composers
    - Some more similar, some less similar

# Classification results

| Composer Group | Classification Accuracy |
|---|---|
| All 7 | 92.7% |
| Ockeghem / Busnoys / Martini | 87.2% |
| Ockeghem / Busnoys | 84.4% |
| Ockeghem / Martini | 94.6% |
| Busnoys / Martini | 93.8% |
| Josquin / Ockeghem | 93.9% |
| Josquin / Busnoys | 96.0% |
| Josquin / Martini | 88.2% |
| Josquin / La Rue | 85.4% |
| Victoria / Palestrina | 99.9% |



# Direct applications of such work

- Validating existing suspected but uncertain attributions
- Helping to resolve conflicting attributions
- Suggesting possible attributions of currently unattributed scores

# How do the composers differ?

- Some interesting questions:
  - What musical insights can we learn from the jSymbolic2 feature data itself?
  - In particular, what can we learn about how the music of the various composers differ from one another?
- Chose to focus on two particular pairs:
  - Josquin vs. Ockeghem: Relatively different
  - Josquin vs. La Rue: Relatively similar

# A priori expectations (1/2)

- What might an expert musicologist expect to differentiate the composers?
  - Before actually examining the feature values
- Once formulating these expectations, we can then see if the feature data confirms or repudiates these expectations
  - Both are useful!
- I consulted one musicologist (Julie Cumming) and one theorist (Peter Schubert), both experts in the period . . .

# A priori expectations (2/2)

- Josquin vs. Ockeghem: Ockeghem may have . . .
  - Slightly more large leaps (larger than a 5th)
  - Less stepwise motion in some voices
  - More notes at the bottom of the range
  - Slightly more chords (or simultaneities) without a third
  - Slightly more dissonance
  - A lot more triple meter
  - More varied rhythmic note values
  - More 3-voice music
  - Less music for more than 4 voices
- Josquin vs. La Rue: La Rue may have . . . Hard to say!
  - Maybe more varied repetition (melodic and contrapuntal, including rhythm)?
  - Maybe more compressed ranges?

jMIR

# Were our expectations correct?

- Josquin vs. Ockeghem: Ockeghem may have . . .
  - OPPOSITE: Slightly more large leaps (larger than a 5th)
  - SAME: Less stepwise motion in some voices
  - SAME: More notes at the bottom of the range
  - SAME: Slightly more chords (or simultaneities) without a third
  - OPPOSITE: Slightly more dissonance
  - YES: A lot more triple meter
  - SAME: More varied rhythmic note values
  - YES: More 3-voice music
  - YES: Less music for more than 4 voices
- Josquin vs. La Rue: La Rue may have . . .
  - UNKNOWN: Maybe more varied repetition (melodic and contrapuntal, including rhythm)?
  - SAME: Maybe more compressed ranges?

# Diving into the feature values

- There are a variety of statistical techniques for attempting to evaluate which features are likely to be effective in distinguishing between types of music
- We used seven of these statistical techniques to find:
  - The features and feature subsets most consistently statistically predicted to be effective at distinguishing composers
- We then manually examined these feature subsets to find the features likely to be the most musicologically meaningful

# Novel insights revealed (1/2)

- Josquin vs. Ockeghem (93.9%):
  - Rhythm-related features are particularly important
    - Josquin tends to have greater rhythmic variety
      - Especially in terms of both especially short and long notes
    - Ockeghem tends to have more triple meter
      - As expected
    - Features derived from beat histograms also have good discriminatory power
  - Ockeghem tends to have more vertical sixths
  - Ockeghem tends to have more diminished triads
  - Ockeghems tends to have longer melodic arcs

# Novel insights revealed (2/2)

- Josquin vs. La Rue (85.4%):
  - Pitch-related features are particularly important
    - Josquin tends to have more vertical unisons and thirds
    - Josquin tends to have fewer vertical fourths and octaves
    - Josquin tends to have more melodic octaves

# Research potential

- Composer attribution is just one small example of the many musicological and theoretical research domains to which features and jSymbolic2 can be applied
  - e.g. genre, such as madrigals vs. motets
  - e.g. mode identification in Renaissance music

# Database annotation

- The ELVIS database is a collection of 2852 pieces and 3358 movements by 164 composers
  - MIDI, MEI, Music XML, PDF, etc.
  - Supervised by Julie Cumming
- Work with Yaolong Ju is currently underway to:
  - Extract jSymbolic2 features from all files in ELVIS
    - And auto-extract features from new files as they are added
  - Make it possible to search ELVIS based on musical content / feature values
    - e.g. amount of chromaticism
  - Make it possible to train machine learning models on the features to allow still more sophisticated searches
    - e.g. predicted mode

# Research collaborations (1/2)

- We enthusiastically welcome research collaborations with other musicologists and theorists
- In particular, we are always looking for ideas for interesting for new features to implement
  - jSymbolic2 makes it relatively easy to add bespoke features
  - Can iteratively build increasingly complex features based on existing features

# Thanks for your attention!

- **jSymbolic2:** http://jmir.sourceforge.net
- **E-mail:** cory.mckay@mail.mcgill.ca

McGill

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École de musique Schulich

CIRMMT
Centre for Interdisciplinary Research in Music Media and Technology

Social Sciences and Humanities Research Council of Canada
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Fonds de recherche sur la société et la culture
Québec

DDMAL
Distributed Digital Music Archives & Libraries Lab

SIMSSA
Single Interface for Music Score Searching and Analysis

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