A decorative graphic on the left side of the slide consisting of a grid of squares in various shades of blue and purple, arranged in a stepped pattern.

jSymbolic: Demonstration and Tutorial

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Topics

- Introduction to “features”
- Introduction to jSymbolic
- jSymbolic demo and tutorial

What are “features”?

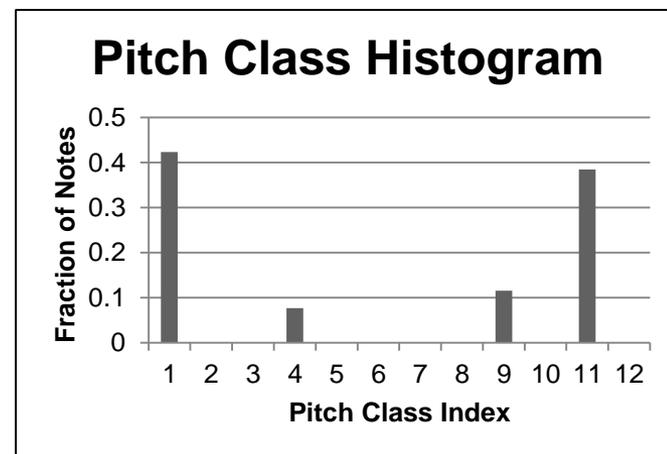
- Pieces of information that can **characterize something** (e.g. a piece of music) in a **simple way**
- Usually **numerical values**
 - A feature can be a **single value**, or it can be a **set of related values** (e.g. a histogram)
- Can be extracted from pieces **as a whole**, or from **segments**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

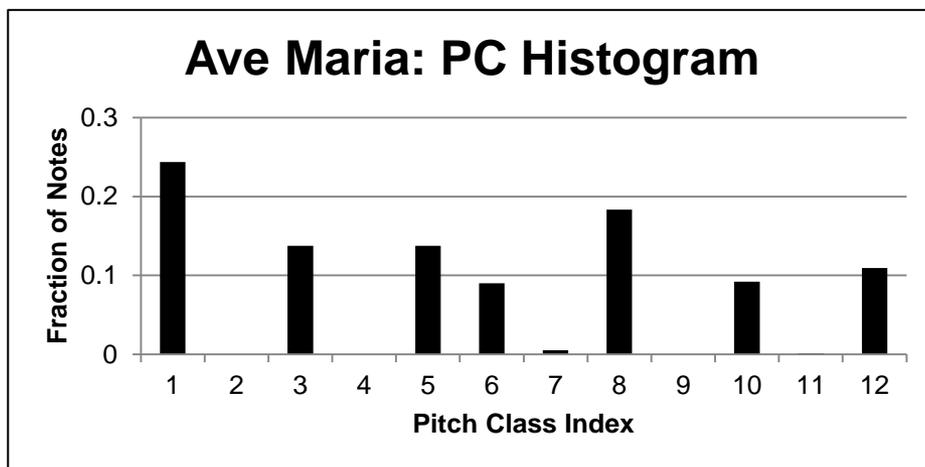


Josquin's *Ave Maria... Virgo serena*

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

Ave Maria... Virgo serena
Motet
Josquin Des Prez
(1440 - 1521)

The image shows a musical score for Josquin Des Prez's motet 'Ave Maria... Virgo serena'. It features four vocal parts: Superius (Soprano), Altus (Alto), Tenor, and Bassus (Bass). The lyrics are: 'A - ve - Ma - ri - a, Gra - ti - a - ple - na, Do - mi - nus te - cum, Vir - go se - re - na, se - re - na, se - re - na.' The score includes measure numbers 5, 10, 15, 20, and 25. A speaker icon is located in the top right corner of the score area.



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

Kyrie



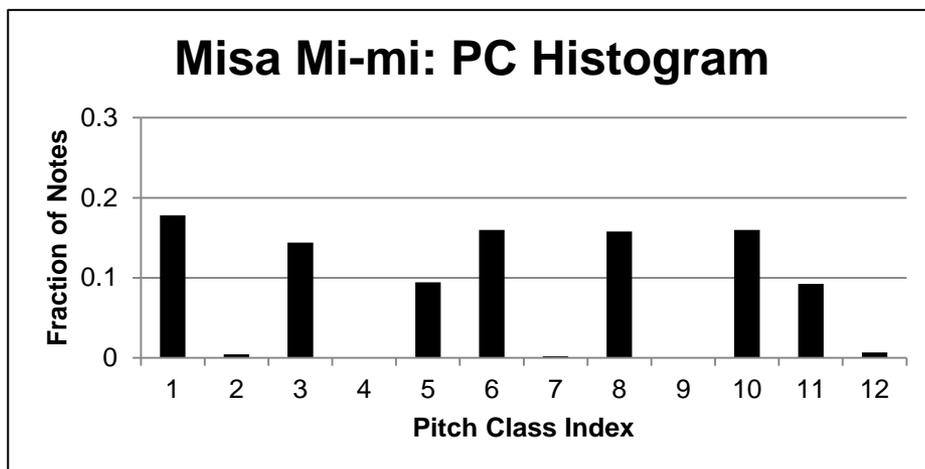
- Range: 26
- Repeated notes: 0.084
- Vertical perfect 4^{ths}: 0.109
- Rhythmic variability: 0.042
- Parallel motion: 0.076

Johannes Ockeghem

1
Ky - ri - e e - le - i - son.
2
Ky - ri - e e - le - i - son.
3
Ky - ri - e e - le - i - son.
4
Ky - ri - e e - le - i - son.

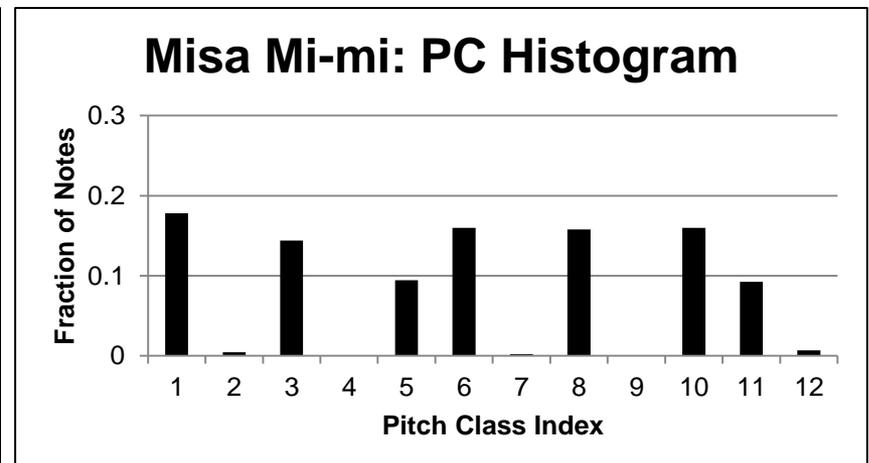
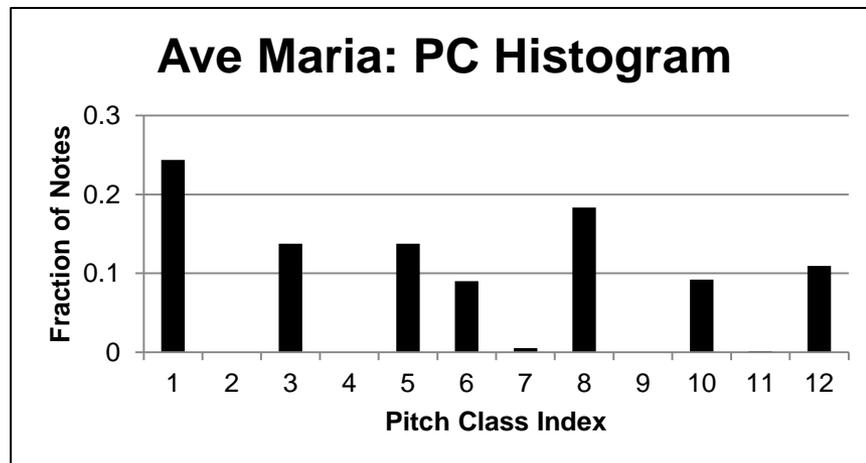
5
i - son, e - le - i - son.
6
son, e - le - i - son.
7
son, e - le - i - son.
8
i - son, e - le - i - son.

12
Chri - ste e - le - i - son, e - le - i - son.
13
Chri - ste e - le - i - son, e - le - i - son.
14
Chri - ste e - le - i - son, e - le - i - son.
15
Chri - ste e - le - i - son, e - le - i - son.



Feature value comparison

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



Feature visualization: Histograms (1/4)

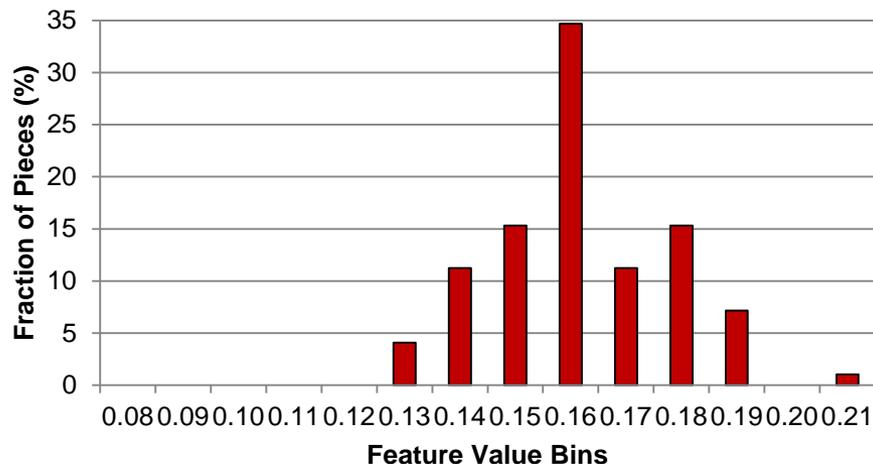
- **Histograms** are one good way to visualize how the values of a feature are distributed across a corpus **as a whole**
 - As opposed to focusing on individual pieces
- The **x-axis** corresponds to a series of bins, with each corresponding to a **range of values** for a given feature
 - e.g. the first bin could correspond to Parallel Motion feature values between 0 and 0.1, the next bin to Parallel Motion values between 0.1 and 0.2, etc.
- The **y-axis** indicates the **fraction of all pieces** that have a feature value within the range of each given bin
 - e.g. if 30% of pieces in the corpus have Parallel Motion values between 0.1 and 0.2, then this bin (0.1 to 0.2) will have a y-coordinate of 30% (or, equivalently, 0.3)

Feature visualization: Histograms (2/4)

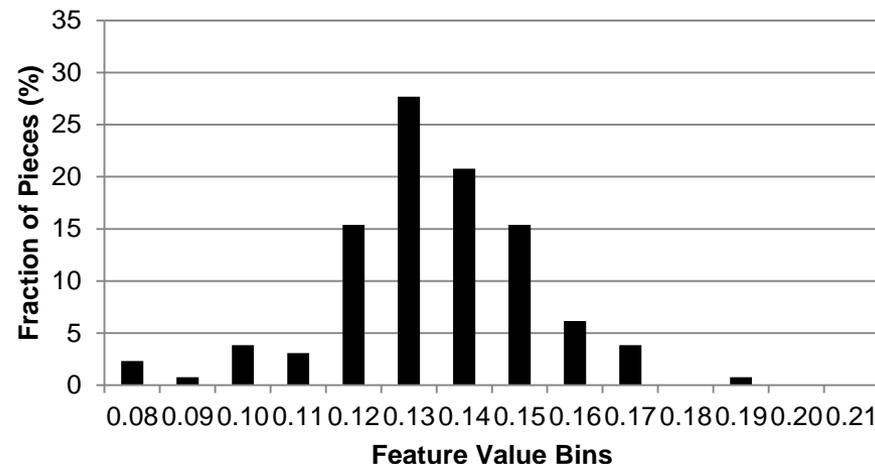
- In other words:
 - Each bar on a histogram represents the fraction of pieces in a corpus with a feature value falling in that bar's range of feature values
- **Clarification:** I am speaking here about a way to visualize a 1-dimensional feature as it is distributed across a corpus of interest
 - This is distinct from the multi-dimensional histogram features discussed earlier
 - e.g. Pitch Class Histograms
 - Although both are equally histograms, of course

Feature visualization: Histograms (3/4)

Ock: Vertical 6ths Histogram



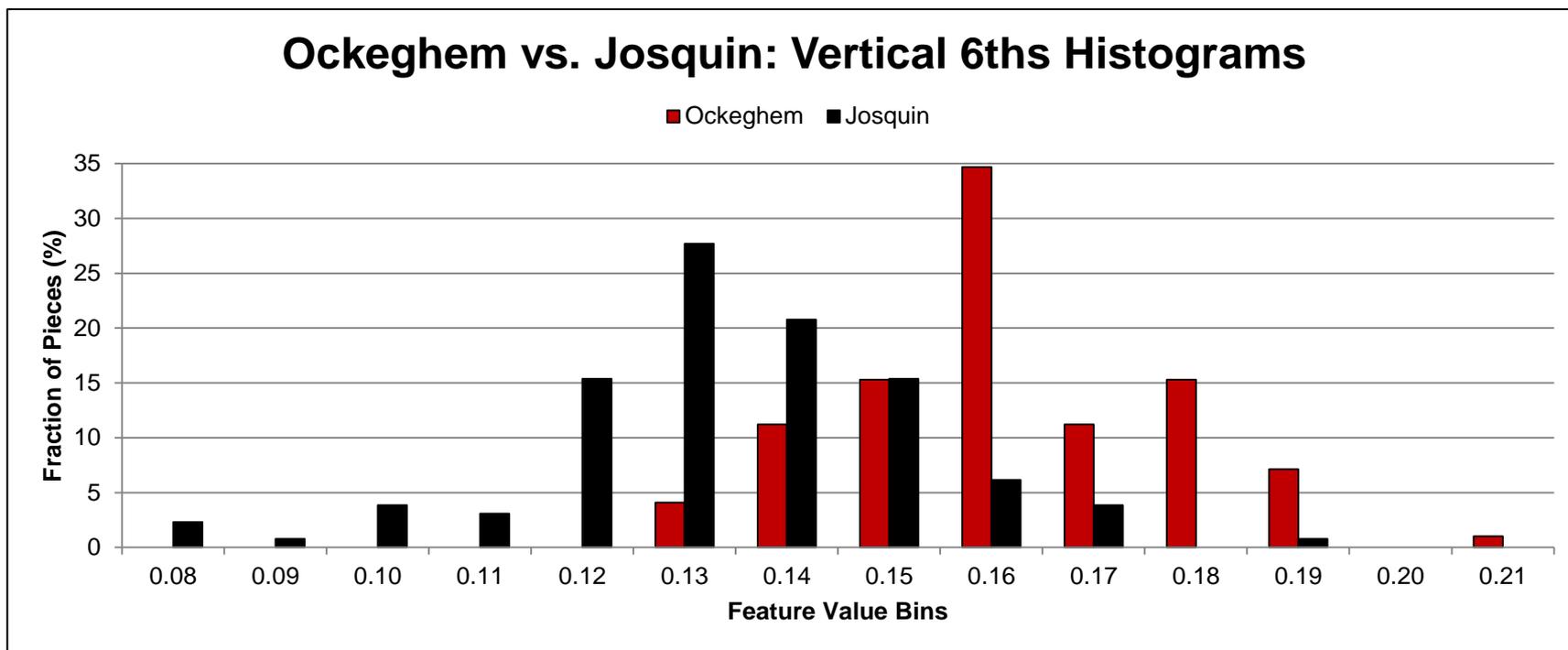
Jos: Vertical 6ths Histogram



- These histograms show that **Ockeghem tends to have more vertical 6^{ths} (between all pairs of voices) than Josquin**
 - Ockeghem peaks in the 0.16 to 0.17 bin
 - Josquin peaks in the 0.13 to 0.14 bin
- Of course, there are also clearly **many exceptions**
 - This feature is helpful, but is limited if only considered alone

Feature visualization: Histograms (4/4)

- The histograms for both composers can also be superimposed onto a single chart:

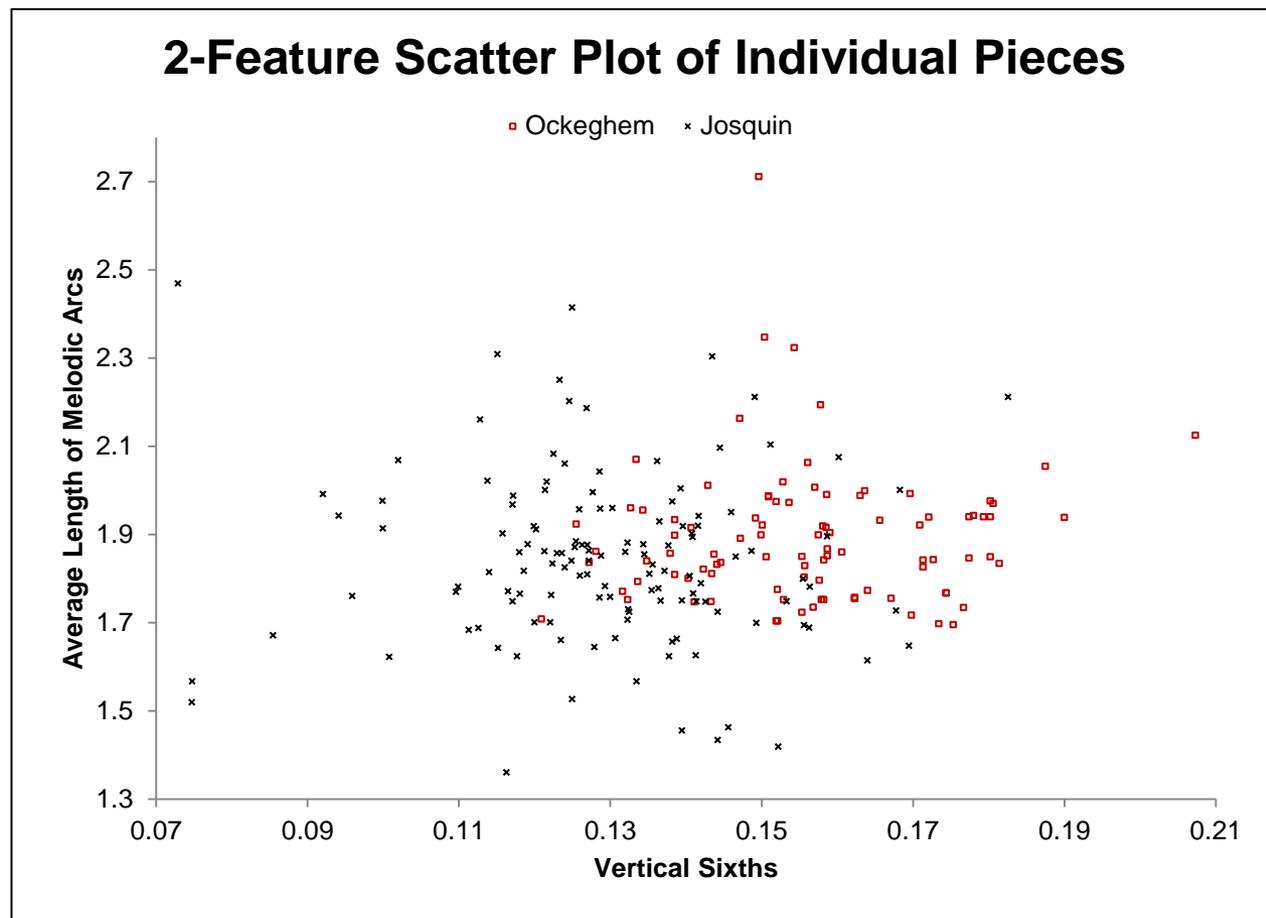


Feature visualization: Scatter plots (1/6)

- **Scatter plots** are another good way to visualize feature data
 - The **x-axis** represents one feature
 - The **y-axis** represents some other feature
 - Each **point** represents the values of these two features for a single piece
- Scatter plots let you see pieces **individually**, rather than aggregating them into bins like histograms
 - Scatter plots also let you see more clearly how the two features **divide** the different composers
- To make them easier to read, scatter plots typically have just **2 dimensions**
 - Computer classifiers, in contrast, work with **n-dimensional** scatterplots (one dimension per feature)

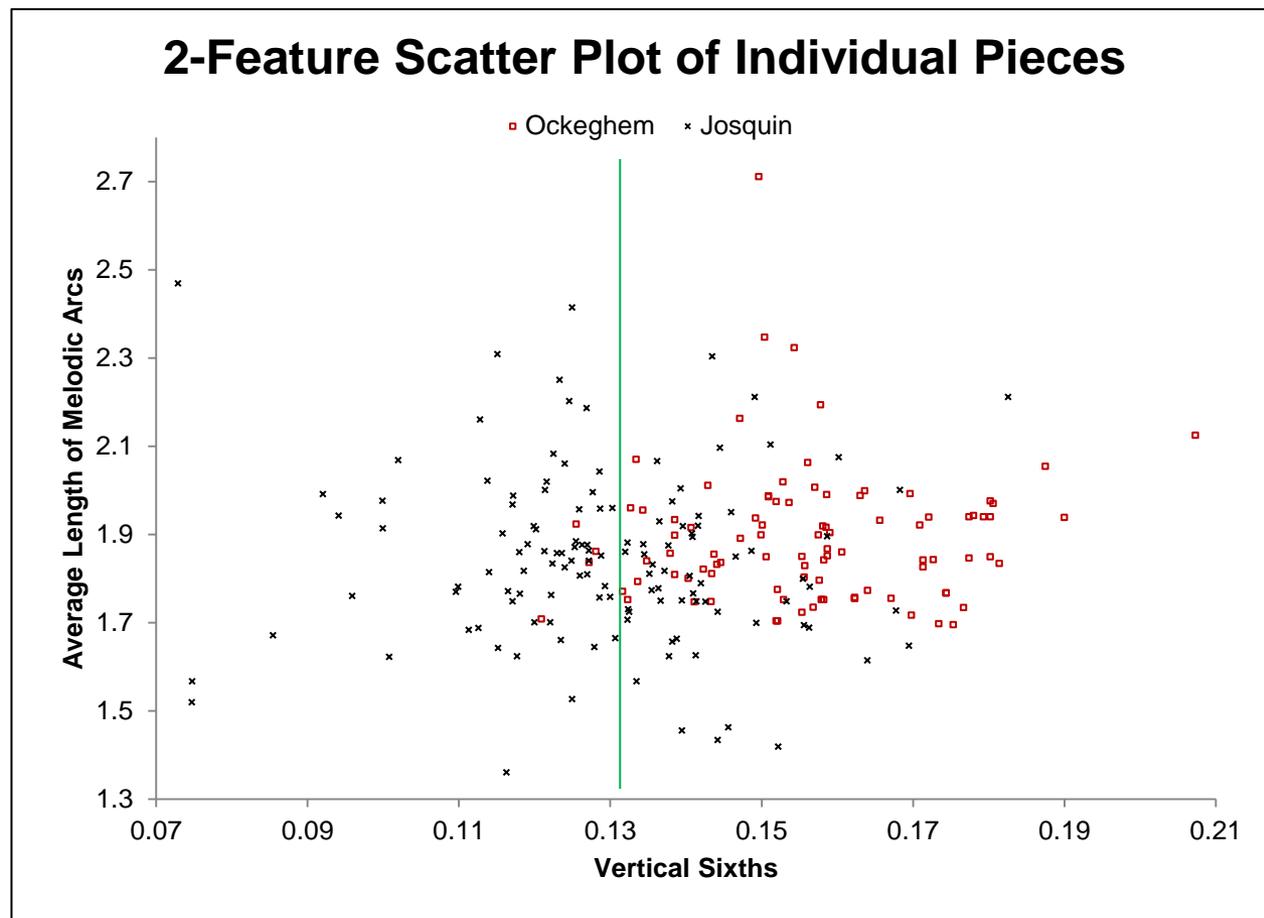
Feature visualization: Scatter plots (2/6)

- Josquin pieces tend to be **left** and **low** on this graph



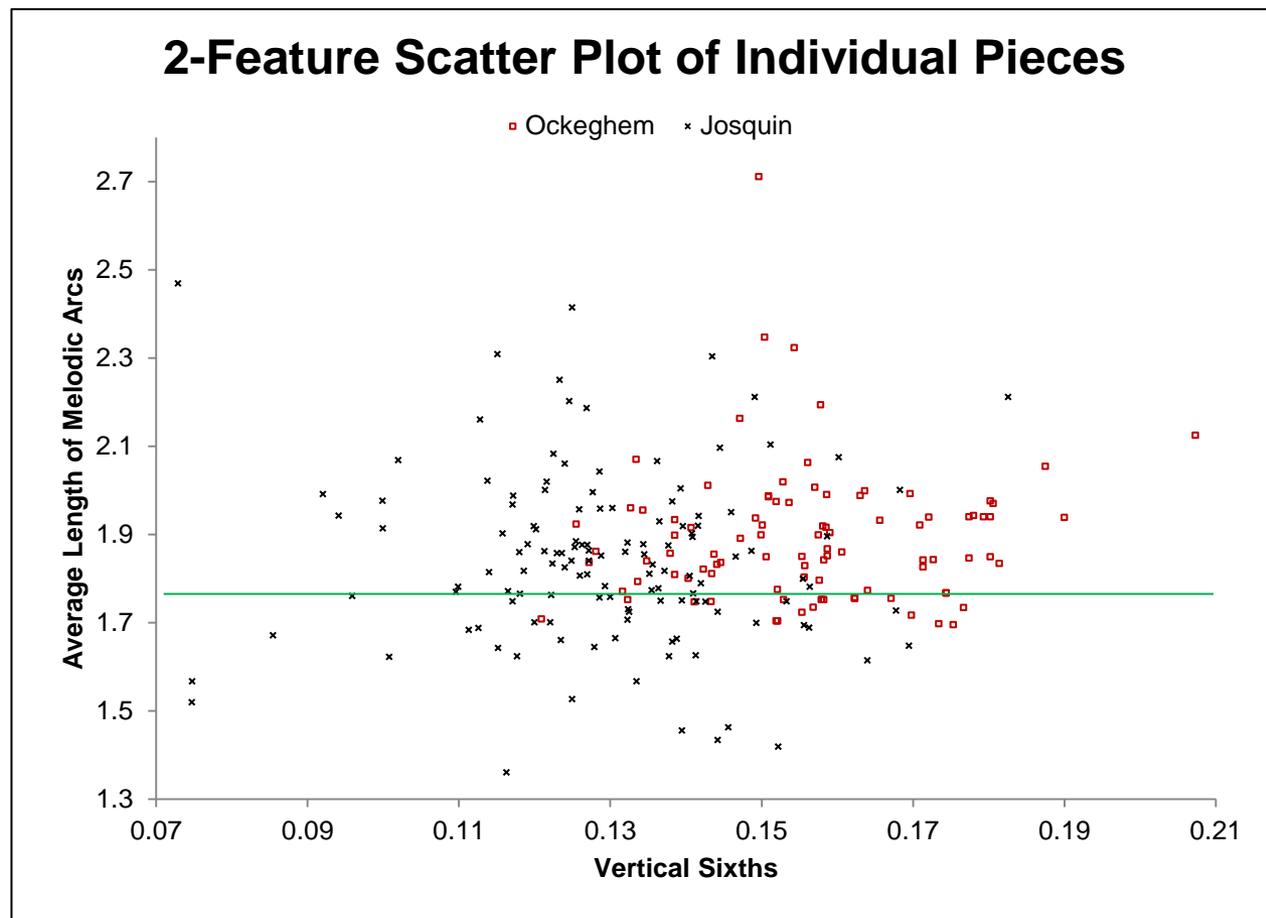
Feature visualization: Scatter plots (3/6)

- Simply drawing a single 1-D dividing line (“**discriminant**”) results in a not entirely terrible classifier based only on **Vertical Sixths**!
 - But many pieces would still be misclassified
 - Get **62%** classification accuracy using an SVM and just this one feature



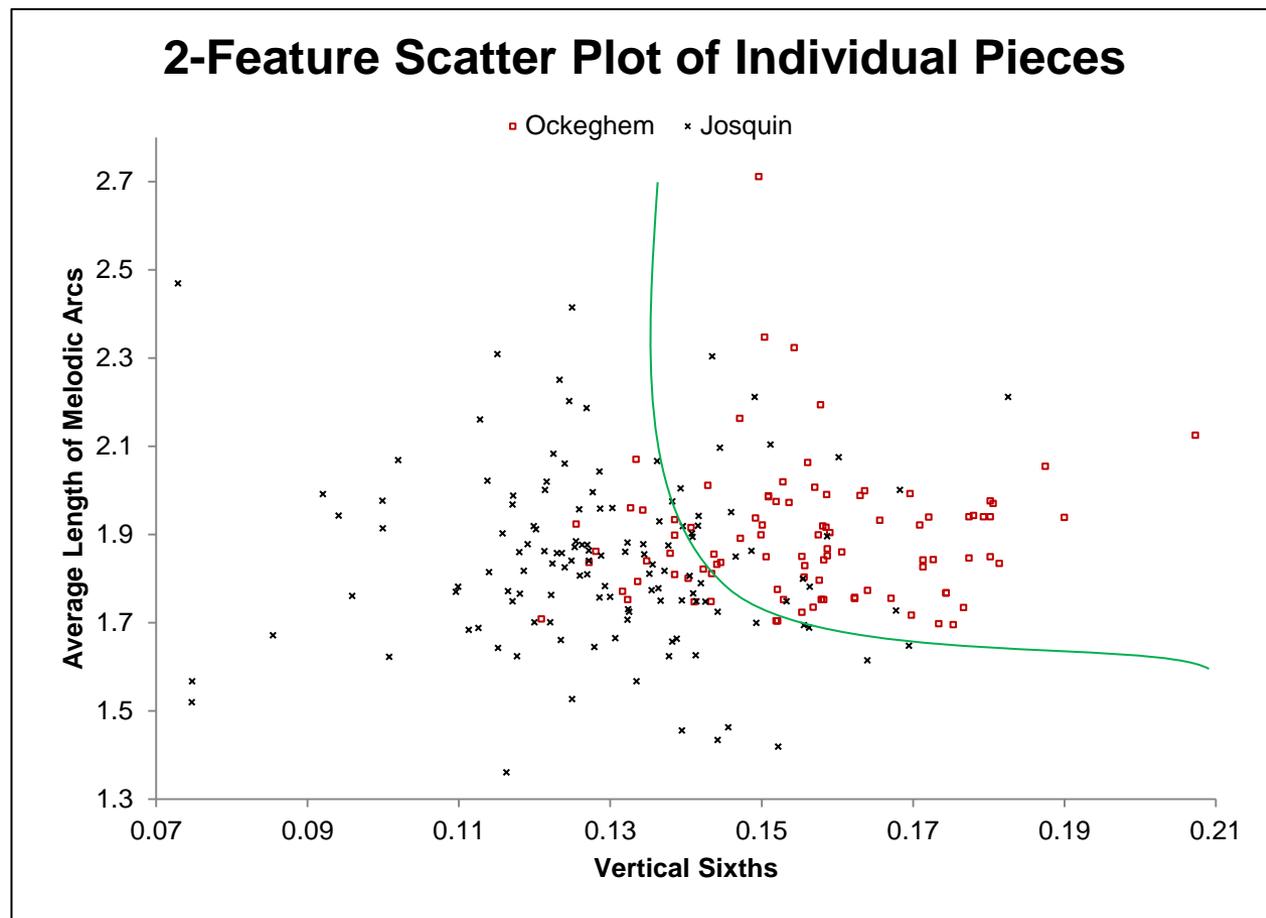
Feature visualization: Scatter plots (4/6)

- Could alternatively draw a 1-D discriminant dividing the pieces based only on the **Average Length of Melodic Arcs**
 - Get **57%** classification accuracy using an SVM and just this one feature
 - Not as good as the **Vertical Sixths** discriminant (62%)



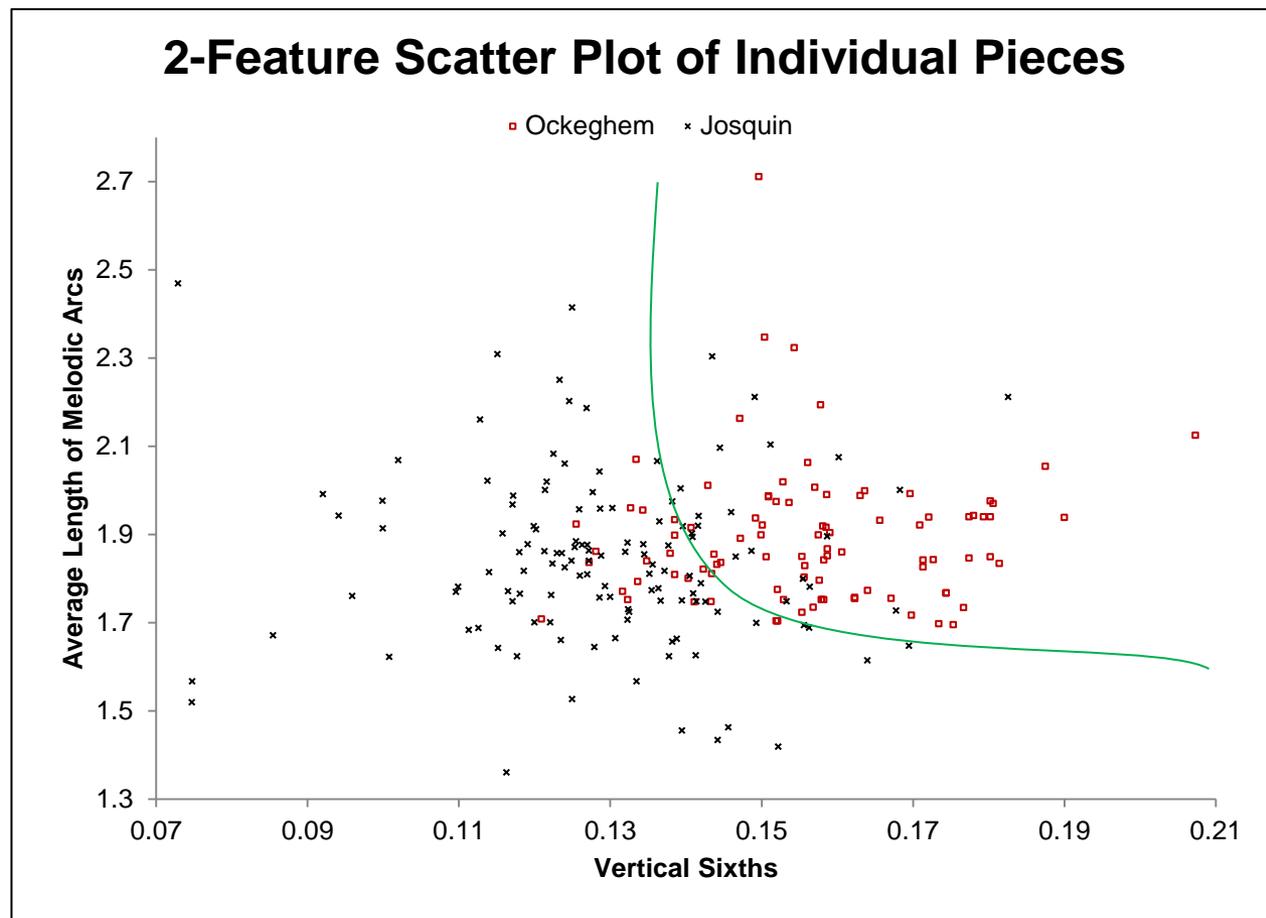
Feature visualization: Scatter plots (5/6)

- Drawing a **curve** (another kind of discriminant) divides the composers still better than either of the previous discriminants
 - Get **80%** accuracy using an SVM and just these 2 features!
- **More than 2 features are clearly needed to improve performance**



Feature visualization: Scatter plots (6/6)

- In fact, many (but not all) types of **machine learning** in effect simply learn where to place these kinds of discriminants as they train
- But typically with many **more than just two features**, of course



jSymbolic : Introduction

- **jSymbolic** is a software platform I have implemented for extracting features from symbolic music
 - Part of our much larger **jMIR** package
- Compatible with **Macs**, **PCs** and **Linux** computers
- Free and **open-source**

What does jSymbolic do?

- Extracts **246 unique features**
- Some of these are **multi-dimensional histograms**, including:
 - Pitch and pitch class histograms
 - Melodic interval histograms
 - Vertical interval histograms
 - Chord types histograms
 - Rhythmic value histograms
 - Beat histograms
 - Instrument histograms
- In all, extracts a total of **1497 separate values**

jSymbolic: Extensibility

- jSymbolic is specifically designed such that music scholars can **design their own features** and work with programmers to then very easily add these features to the jSymbolic infrastructure
 - Fully open source
 - Modular plug-in feature design
 - Automatically handles feature dependencies and scheduling
 - Very well-documented code

jSymbolic demo

- Web site
- Manual
- Tutorial
- GUI
 - API and command line interface
- Configuration files
- Manually examining features
- Analyzing features with Weka
- Looking at the code
 - Adding new features

Thanks for your attention!

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

