Inter-/intra-performer similarity

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Quantitative approaches to performance analysis.

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Experiments with solo vocalists.

Conclusions 4
Summary and future directions.

Introduction

Similarity in performance

- **Modeling style**
  - style as self- or group-similarity
  - relationship between inter-performer similarity and intra-performer consistency
  - the need to sound spontaneous
    - Chaffin, Lemieux, Chen (2007)

Introduction

What do I mean by studying performance?

- **Using (live) recorded performances**
- **Measuring performance parameters**
  - timing
  - dynamics
  - **tuning**
  - timbre
- **Assessing relationship between performance of various parameters and musical materials**

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Quantitative Performance Analysis

A brief history

Pioneers
Binet and Courtier
Sears
Miller

1895–1930 | 1920–40s | 1960s | 1980s and 90s | 1990s and 2000s

Quantitative Performance Analysis

A brief history

Pioneers

Binet and Courtier
Sears
Miller

1895–1930 | 1920–40s | 1960s | 1980s and 90s | 1990s and 2000s

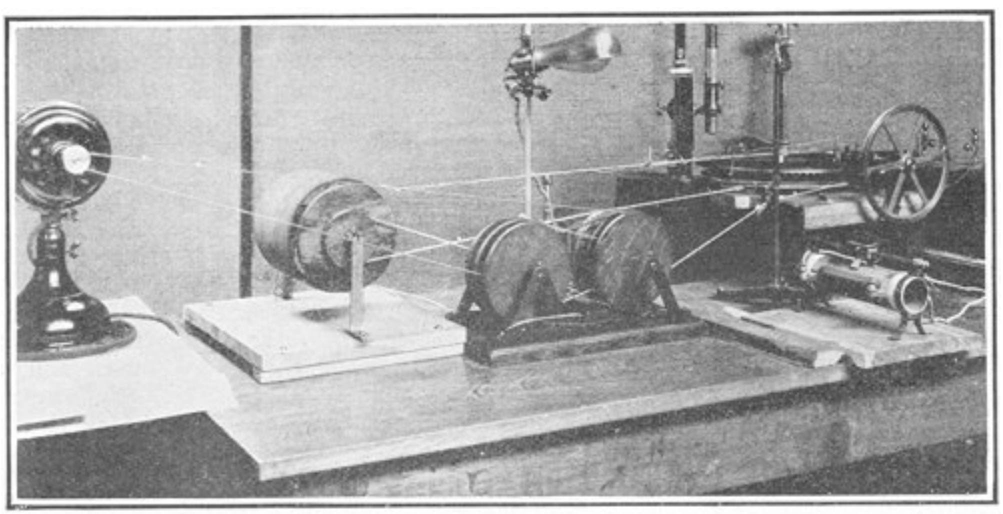
University of Iowa

Seashore and colleagues

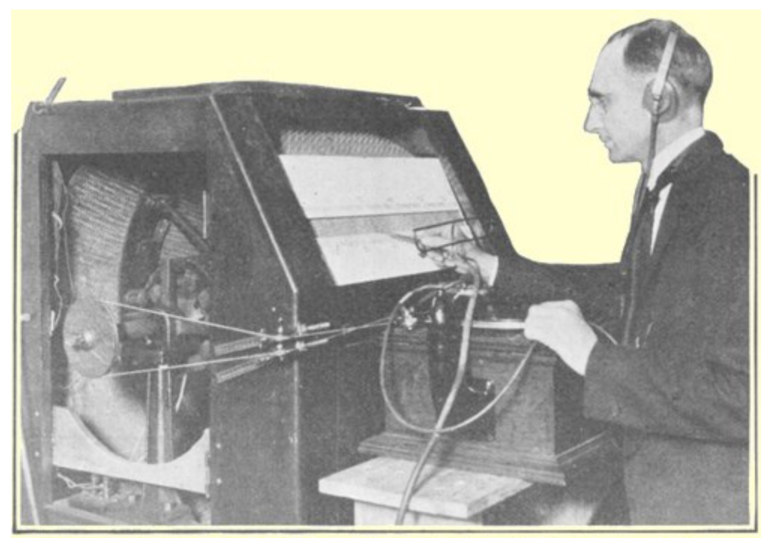
Quantitative Performance Analysis

University of Iowa

- **Carl Seashore (1938) and colleagues studied timing, dynamics, intonation, and vibrato in pianists, violinists, and singers**
  - artistic performance conceived as deviations from the exact



Wave recorder for use with disk phonograph; the lever, acting like a pantograph, traces the waves on a revolving smoked drum

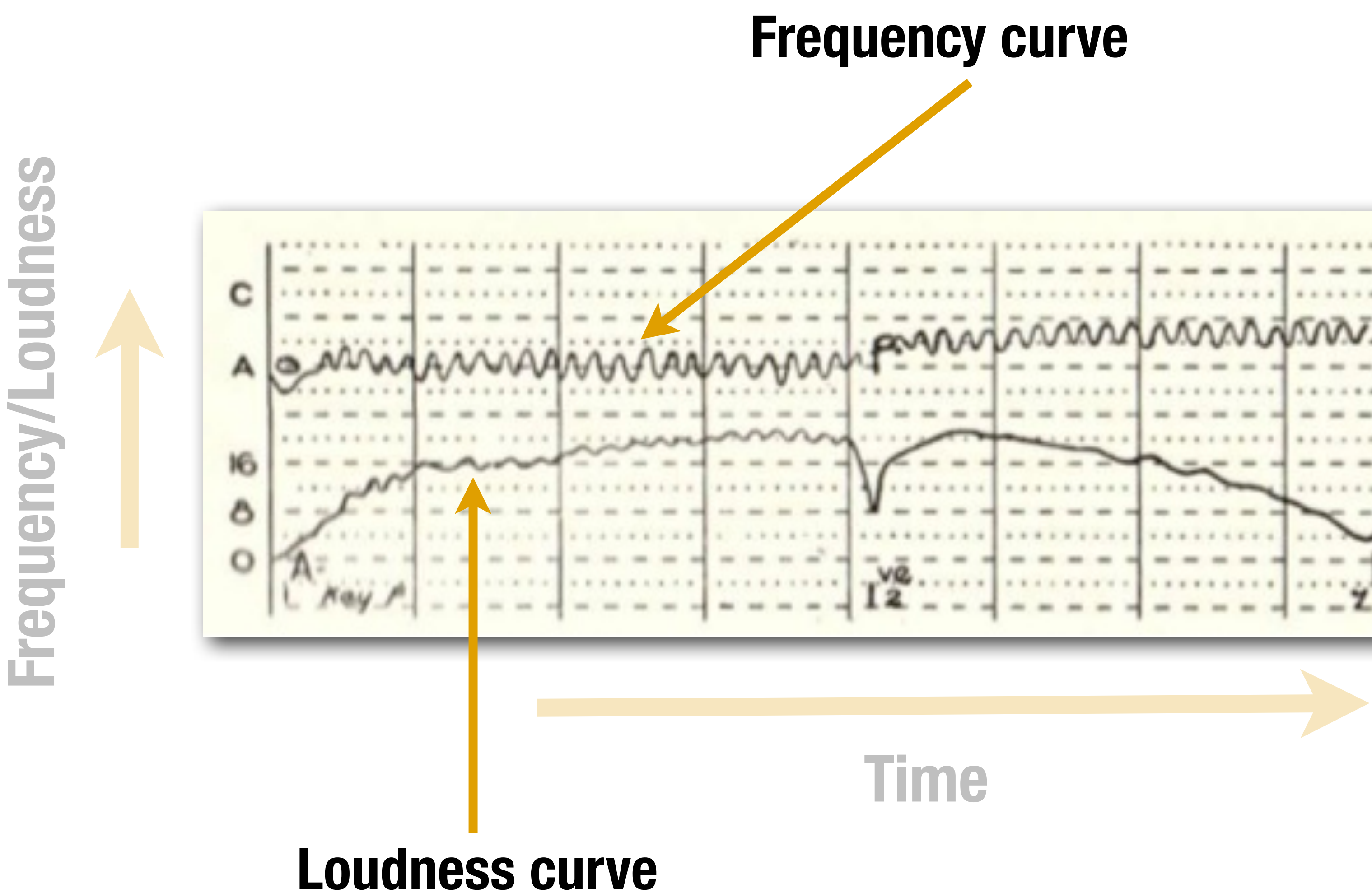


The tonoscope for analyzing the pitch of the tones on a disk phonograph record

Cary (1922)

Performance Scores

University of Iowa



Seashore (1936)

How did Seashore model data?

Statistical methods used in Seashore's lab

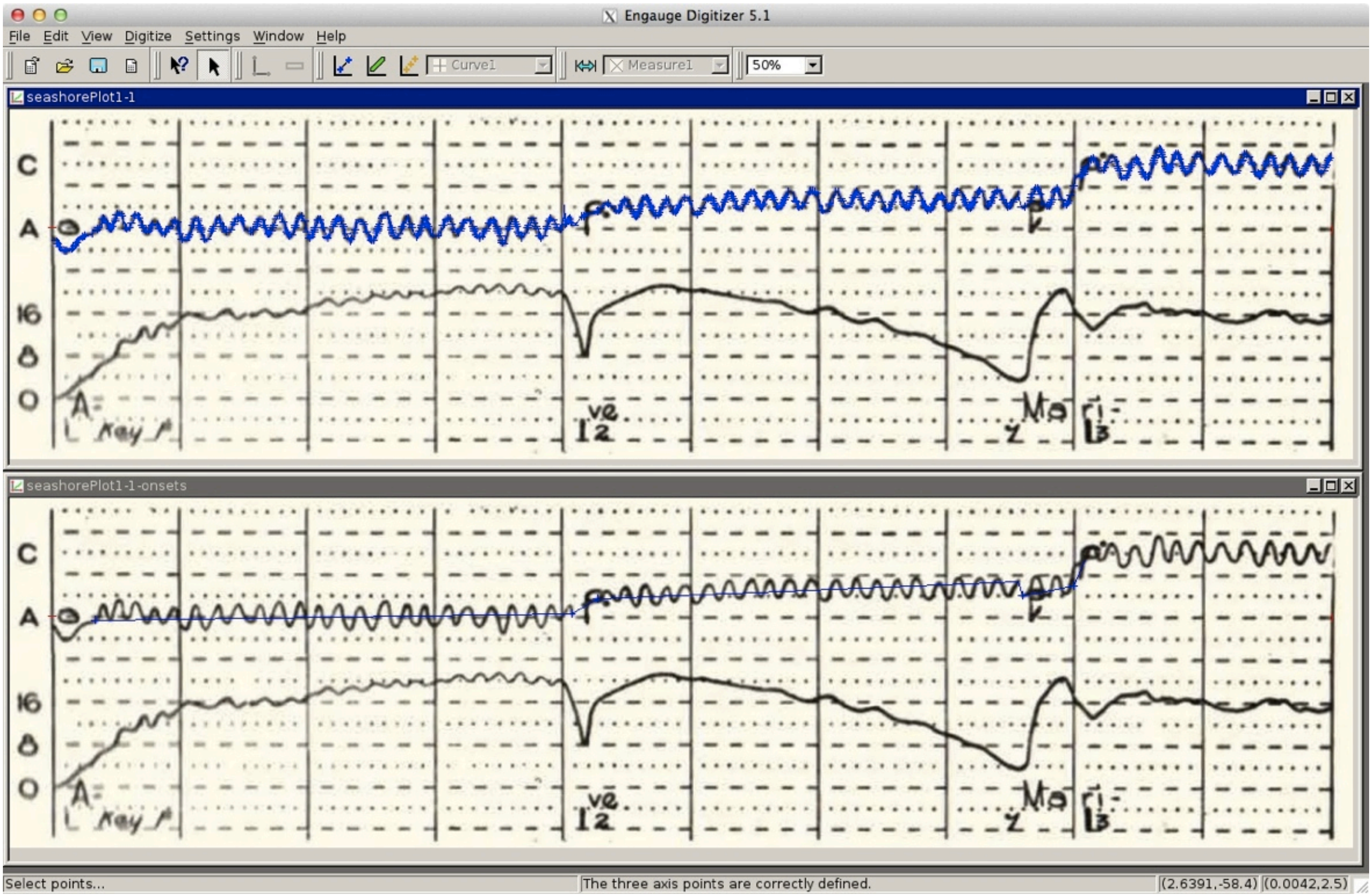
Table III. Cycle-to-cycle regularity of extent and rate of vibrato

	N cycles	Differences in extent: Average	%.1 step and less	%.2 step and less	Differences in rate: Average	%.5 c.p.s. and less	%1.0 c.p.s. and less
Baker	583	.07	90	95	.53	70	95
Homer	207	.06	90	95	.46	80	95
Kraft 1	168	.14	60	85	.53	65	90
Kraft 2	201	.14	60	80	.57	70	90
Marsh	428	.07	85	95	.50	70	95
Seashore	303	.09	75	90	.51	70	90
Stark	436	.07	90	95	.50	70	95
Thompson	163	.09	80	95	.60	75	85
Tibbett	260	.06	85	95	.56	65	90

Seashore (1936)

Performance Scores

Digitizing the data



Quantitative Performance Analysis

A brief history

Pioneers
Binet and Courtier
Sears
Miller

Ethnomusicology
Charles Seeger

1895–1930 **1920–40s** **1960s** **1980s and 90s** **1990s and 2000s**

University of Iowa
Seashore and colleagues

Quantitative Performance Analysis

A brief history

Pioneers
Binet and Courtier
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Ethnomusicology
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1895–1930 | 1920–40s | 1960s | 1980s and 90s | 1990s and 2000s

University of Iowa
Seashore and colleagues

Piano
Gabrielsson
Todd
Clarke
Repp

Quantitative Performance Analysis

Popularity of the piano

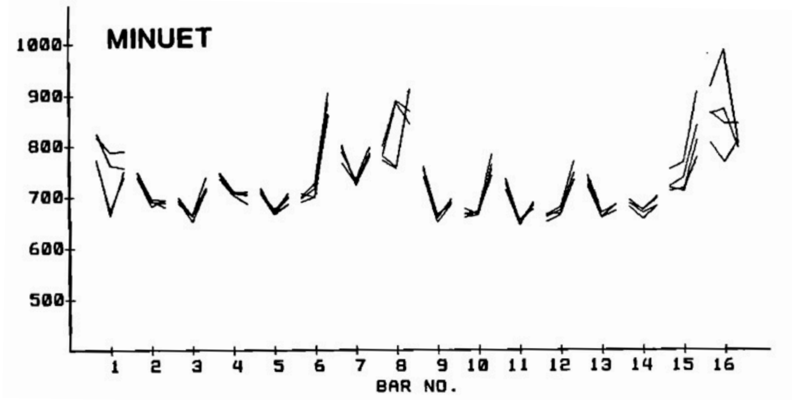
- Large amount of solo repertoire
- Instrument's percussive nature
- Feasibility of using specially equipped pianos (e.g., MIDI)
    - cannot study existing recordings
    - new recordings are typically done in a lab environment

Bosendorfer SE piano at BRAMS, Montreal

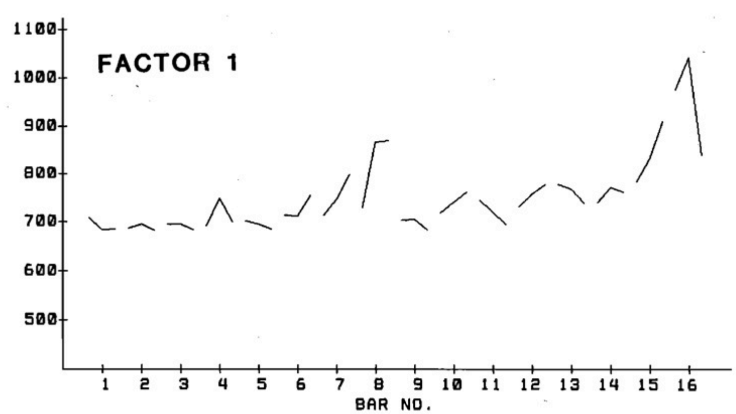
How did these psychologists model data?

Statistical methods used in Repp's piano studies

Averaging performances



Factor analysis



Qualitative descriptions

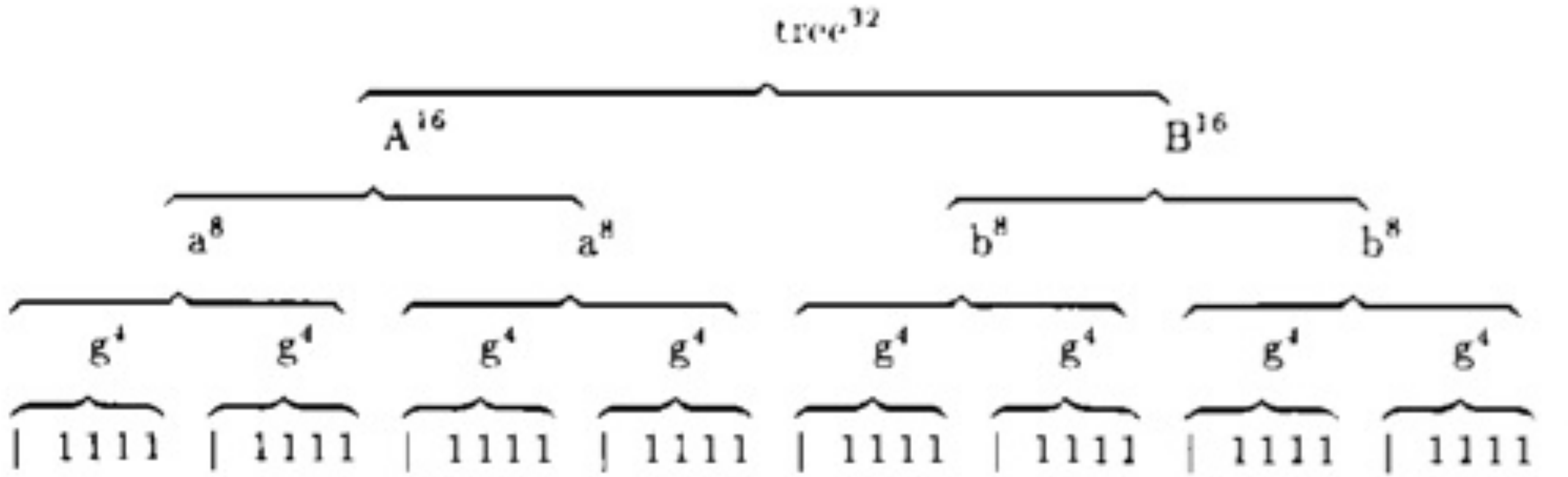
Beethovenian	un-Beethovenian
Fast	slow
Expressive	inexpressive
Relaxed	tense
Superficial	deep
Cold	warm
Powerful	weak
Serious	playful
Pessimistic	optimistic
Smooth	rough
Spontaneous	deliberate
Consistent	variable
Coherent	incoherent
Sloppy	precise
Excessive	restrained
Rigid	flexible
Effortful	facile
Soft	hard
Realistic	idealistic
Usual	unusual

Repp (1990)

How did these psychologists model data?

Statistical methods used in Todd's piano studies

Regression analysis



"the faster the louder, the slower the softer"

Todd (1992)

Quantitative Performance Analysis

A brief history

1895–1930

Pioneers
Binet and Courtier
Sears
Miller

1920–40s

University of Iowa
Seashore and colleagues

1960s

Ethnomusicology
Charles Seeger

1980s and 90s

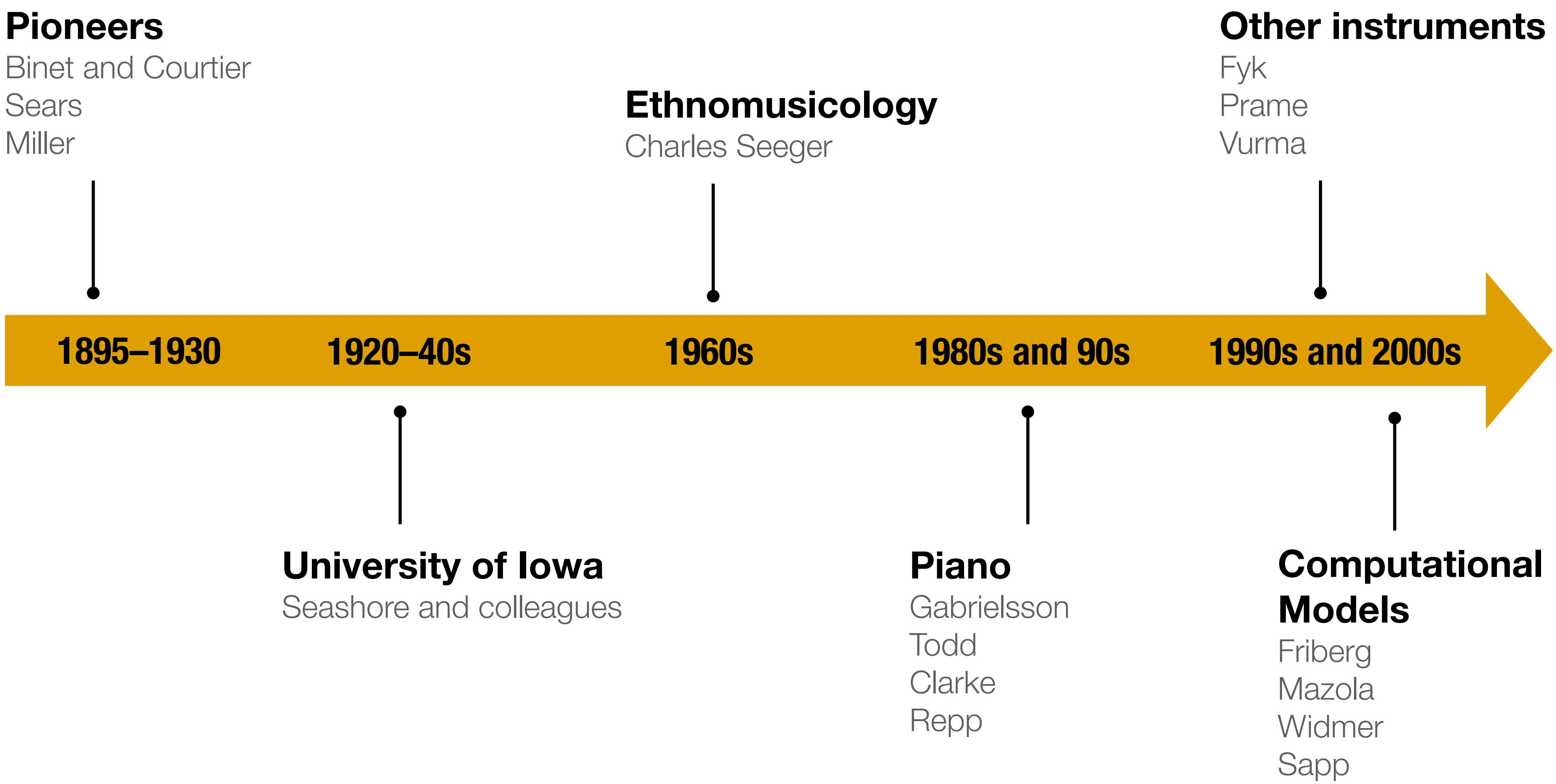
Piano
Gabrielsson
Todd
Clarke
Repp

1990s and 2000s

Other instruments
Fyk
Prame
Vurma

Quantitative Performance Analysis

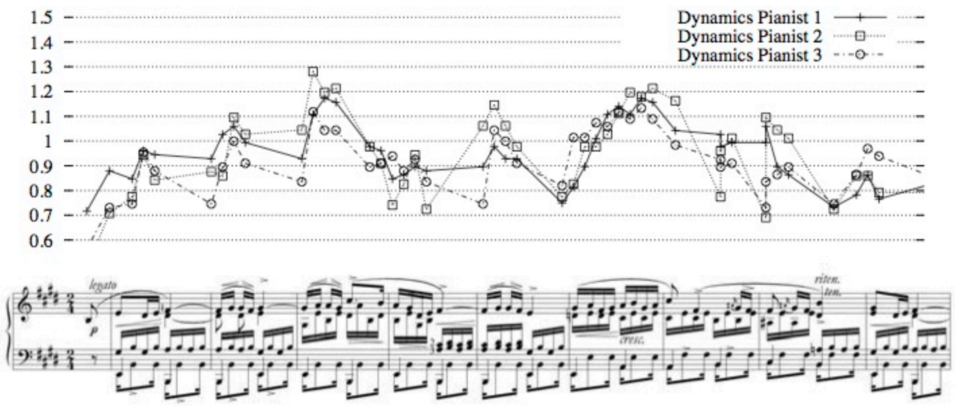
A brief history



How do computer scientists model data?

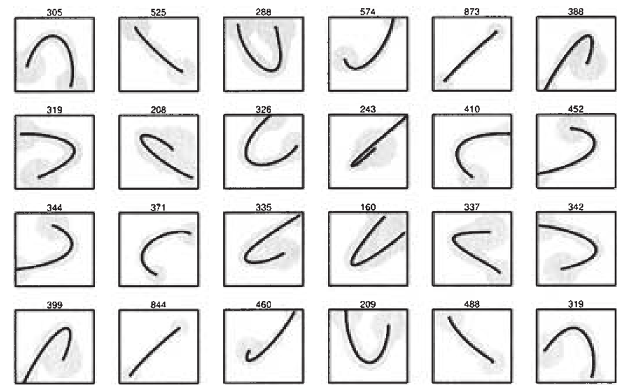
Summary of statistical approaches used by Widmer et al.

Case-based reasoning



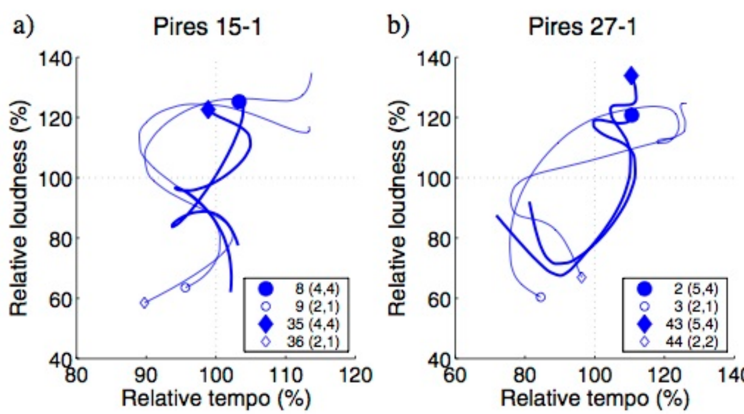
Tobudic and Widmer 2003

Performance alphabets



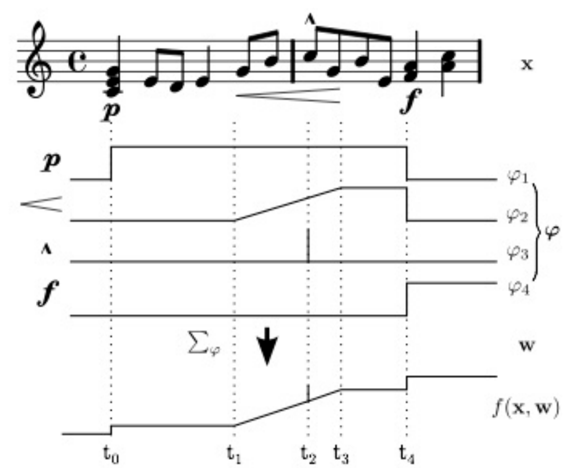
Widmer and Goebl 2004

Performance worms



Goebl, Pampalk, and Widmer 2004

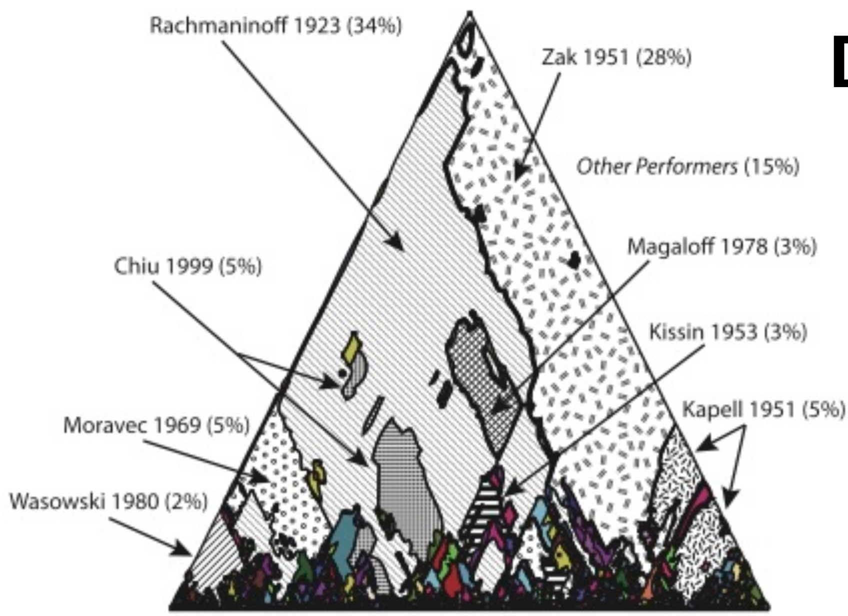
Linear-basis functions



Grachten and Widmer 2012

How do computer scientists model data?

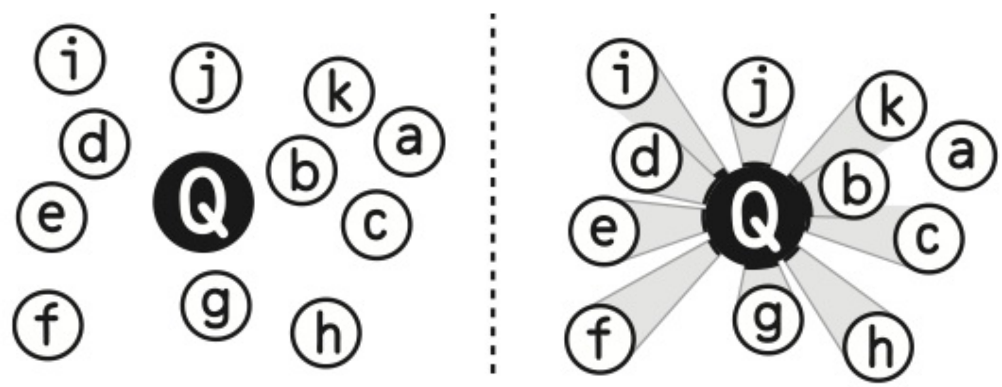
Summary of statistical approaches used by Sapp



Dynascape for Horowitz 1949
mazurka 63/3 (57 performances)

Dynascapes

Nearest-Neighbour



Sapp 2008

Piano data sets

What do they contain?

- **Vienna datasets (Bosendorfer)**
  - Magaloff performing the complete Chopin piano works
  - Batik performing 13 complete Mozart sonatas
- **Mazurka dataset (Commercial)**
  - 2926 recordings, between ~45–100 recordings per Chopin Mazurka – one recording per performer per era
  - Commercial recordings are a curated product

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Experiments with Singers

Overview

- Intonation in trained singers in the Western Art Music tradition
- Various aspect of the work was done in collaboration with Dan Ellis (Columbia), Ichiro Fujinaga (McGill), Michael Mandel (Ohio State), and Jon Wild (McGill)

Overview

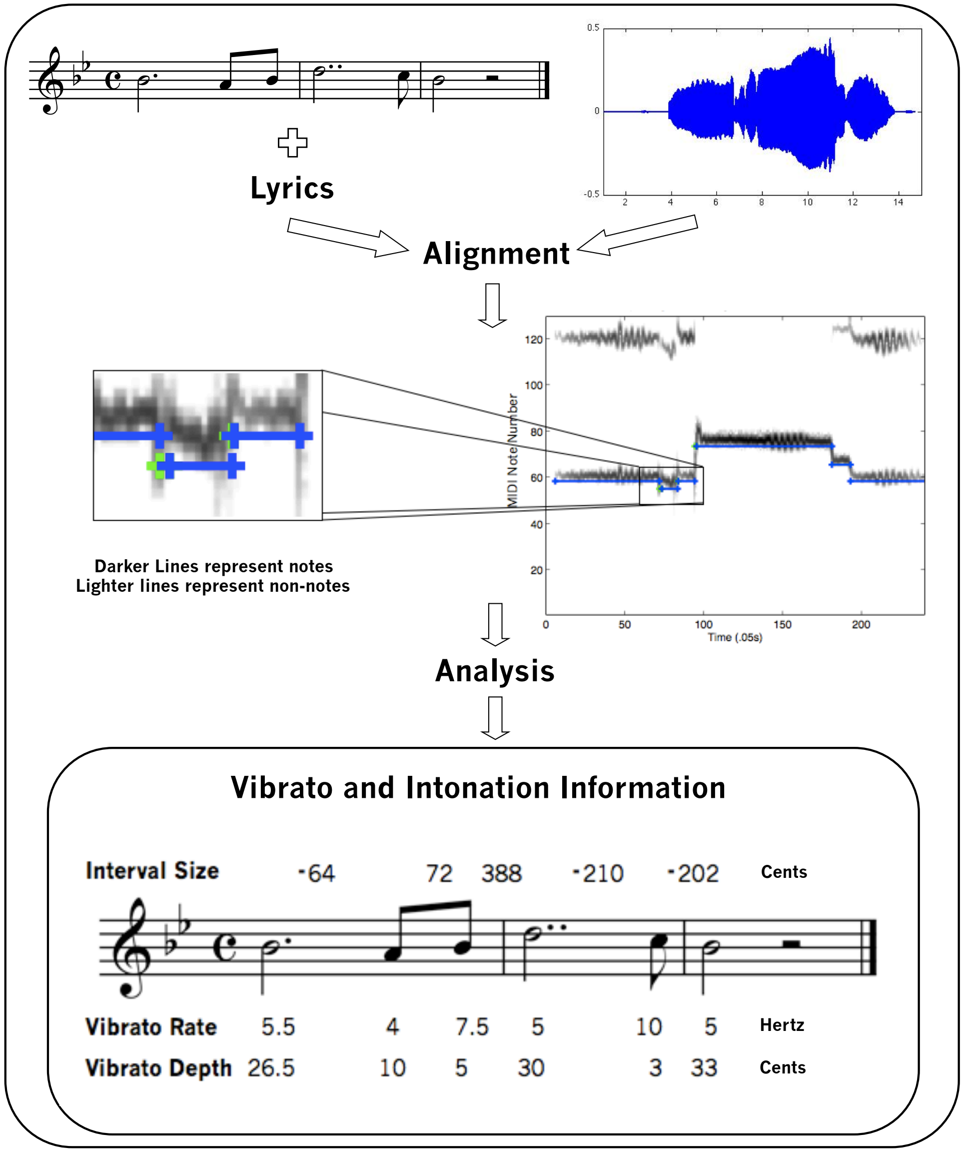
Experiment design

- Musical Material
  - Schubert's "Ave Maria"
    - 3x a cappella & 3x accompanied
- Singers
  - 6 non-professional singers: undergraduate vocal majors
  - 6 professional singers: possess at least one graduate-level degree in voice performance
- Melodic semitones and whole tones analyzed
- Singers listened to and approved their own recordings

Devaney, Mandel, Ellis and Fujinaga (2011)
Devaney, Wild, and Fujinaga (2011)

Data Extraction

Using MIDI-audio alignment



Loudness: Glasberg and Moore (2002)

F_0 Estimation: de Cheveigné and Kawahara (2002)

Pitch: Gockel, Moore, and Carlyon (2001)

Slope/Curvature: Devaney, Mandel and Fujinaga (2011)

AMPACT

www.ampact.org

Devaney, Mandel, and Fujinaga (2012)

Data Analysis

Linear regression

- **Dependent variable**
  - interval size in cents
- **Independent variables**
  - direction
  - singer or level of experience
  - harmonic context
    - leading tone or not
  - accompaniment
    - versus *a cappella*

Commonality between performers

Observable trends

- **General tuning trends**
  - No strict adherence, on average smaller than equal temperament (more so for semitones than whole tones)
  - Ascending semitones were significantly larger on average than descending semitones

- **Harmonic context**
  - Non-pros exhibited a significant difference between semitones in leading tone and non-leading tone contexts
    - semitones in a leading context were significantly smaller on average

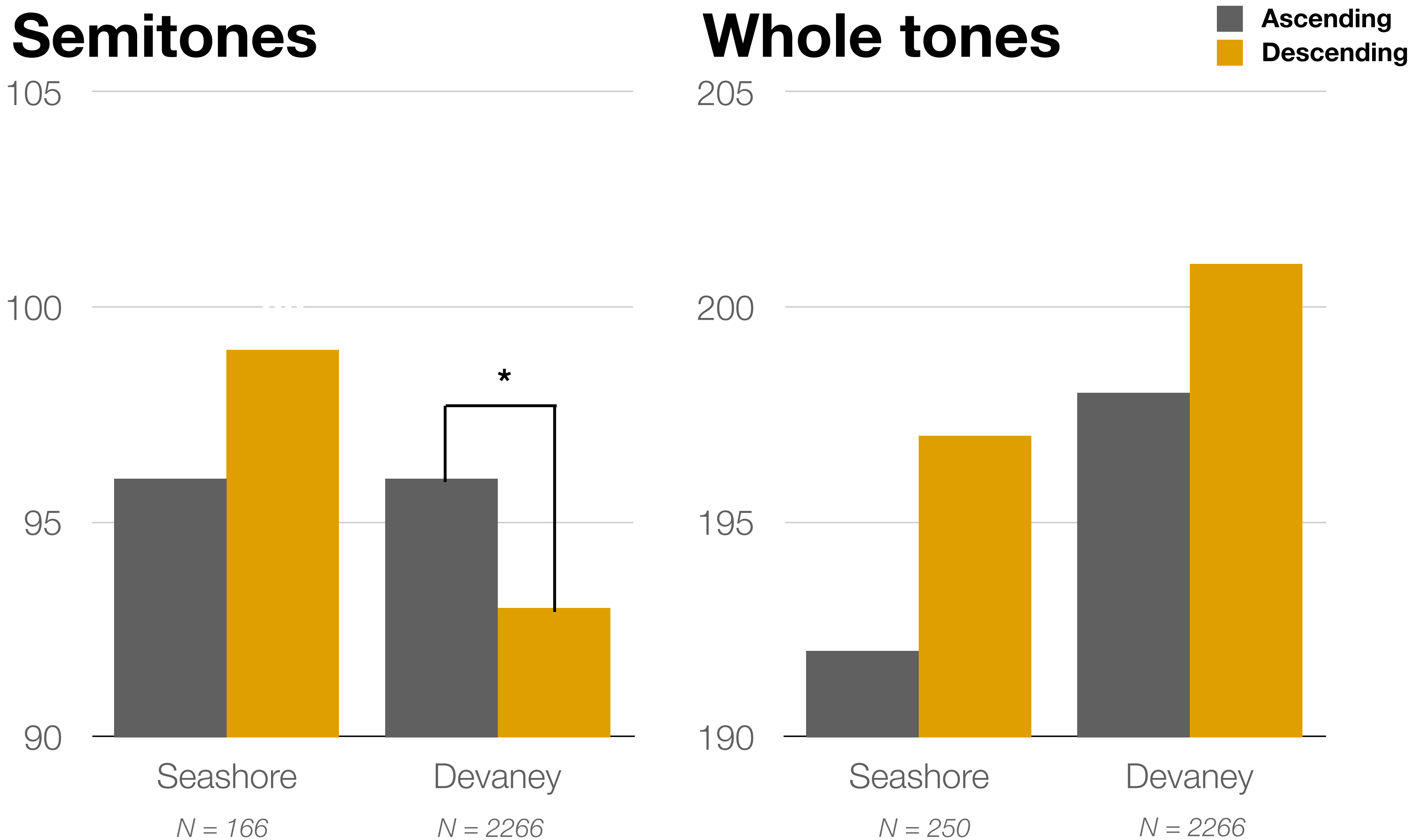
Is there an effect of training?

Professionals versus non-professionals

- **Effect of training**
  - **Accompaniment**
    - Solo non-pros’ accompanied semitones were 3 cents larger on average than their *a cappella* semitones
  - **Consistency**
    - Pros were more consistent with one another
  - **Interval size**
    - Pros’ semitones were significantly larger on average (closer to equal temperament)

Incorporating Seashore data

Comparative analysis of Seashore and contemporary data



Singer Identity

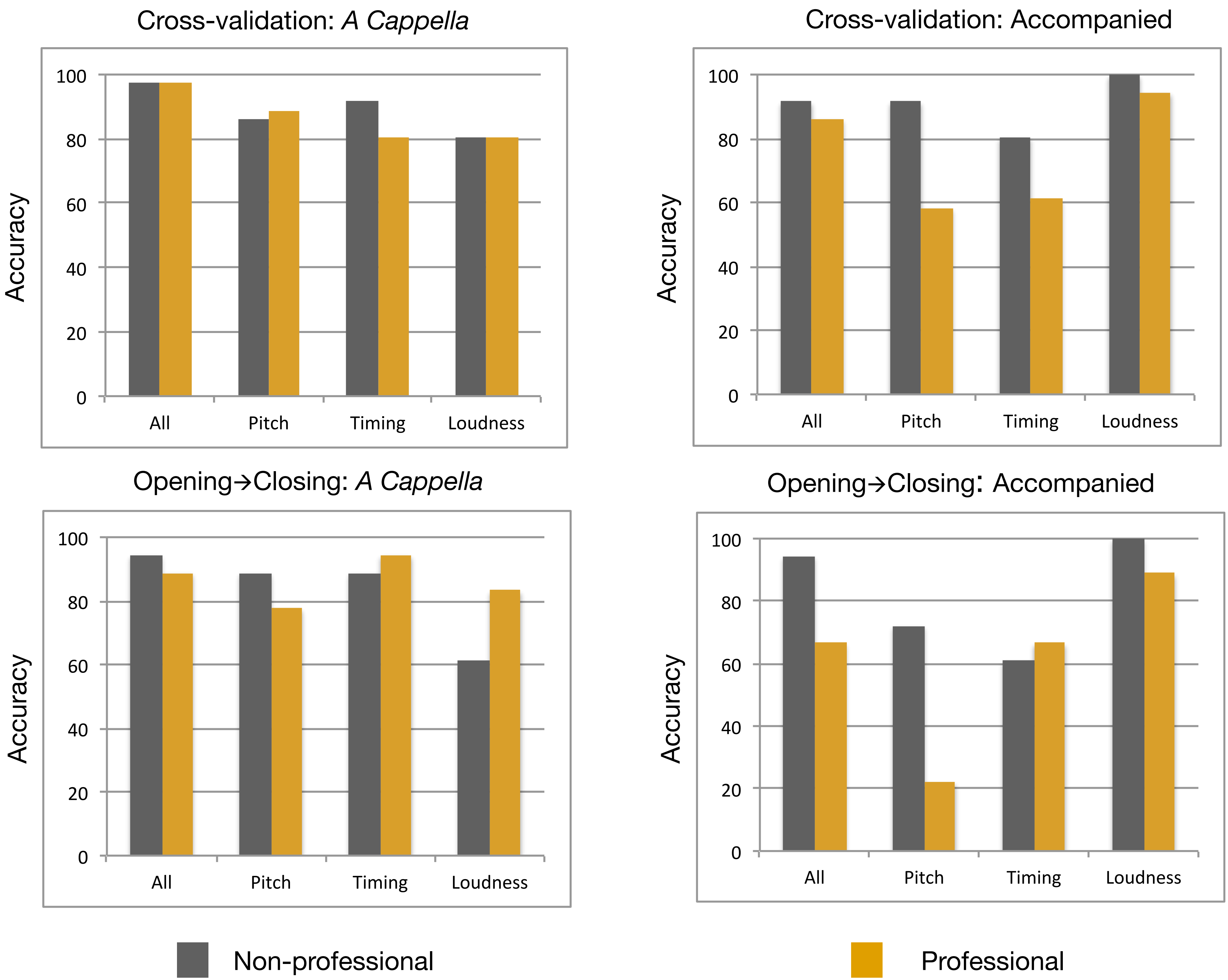
Framing as a classification problem

- **Experiments**
  - Predicting singer identity within openings and closings using cross=validation
  - Predicting singer identity of closing trained on opening
- **Support vector machine, with L1-regularization**
  - using the feature vectors for feature selection

Singer Identity

Framing as a classification problem

Pitch	Timing	Loudness
Interval size	Inter-onset interval	Long-term loudness
Distance from opening note	Duration	
Slope		
Curvature		
Vibrato extent		
Vibrato rate		


Cross-validation: A Cappella
Cross-validation: Accompanied
Opening→Closing: A Cappella
Opening→Closing: Accompanied
Accuracy
100
80
60
40
20
0
All
Pitch
Timing
Loudness
Non-professional
Professional

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Summary

Where we have been

- **This talk has**
  - provided a brief overview of the history of quantitative performance analysis with a particular focus on performance modeling
  - described the results of descriptive and predictive analysis of data from an experiment with twelve singers to explore inter- and intra-singer similarity

Future Work

Where might we be going?

- **Different features**
    - timbre
- **More sophisticated musical models**
    - looking at variance at particular points in the piece
- **categorical perception**
- **Integrating more qualitative information**
    - performer intentionality
    - listener perception/reception
        - categorical perception of features – mid-level representation?

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- School of Music and College of Arts and Sciences (OSU)
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Thank you!

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