

Measurement and Classification of Acoustic Signals

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Longterm Autonomous Recording (Now Readily Available)

Chief Advantage

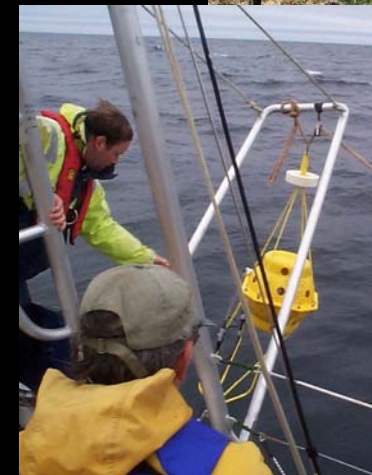
Rich in biological information

- Species + / -
- Spatial distribution
- Patterns of calling
- Repertoires & behavior

Chief Constraint

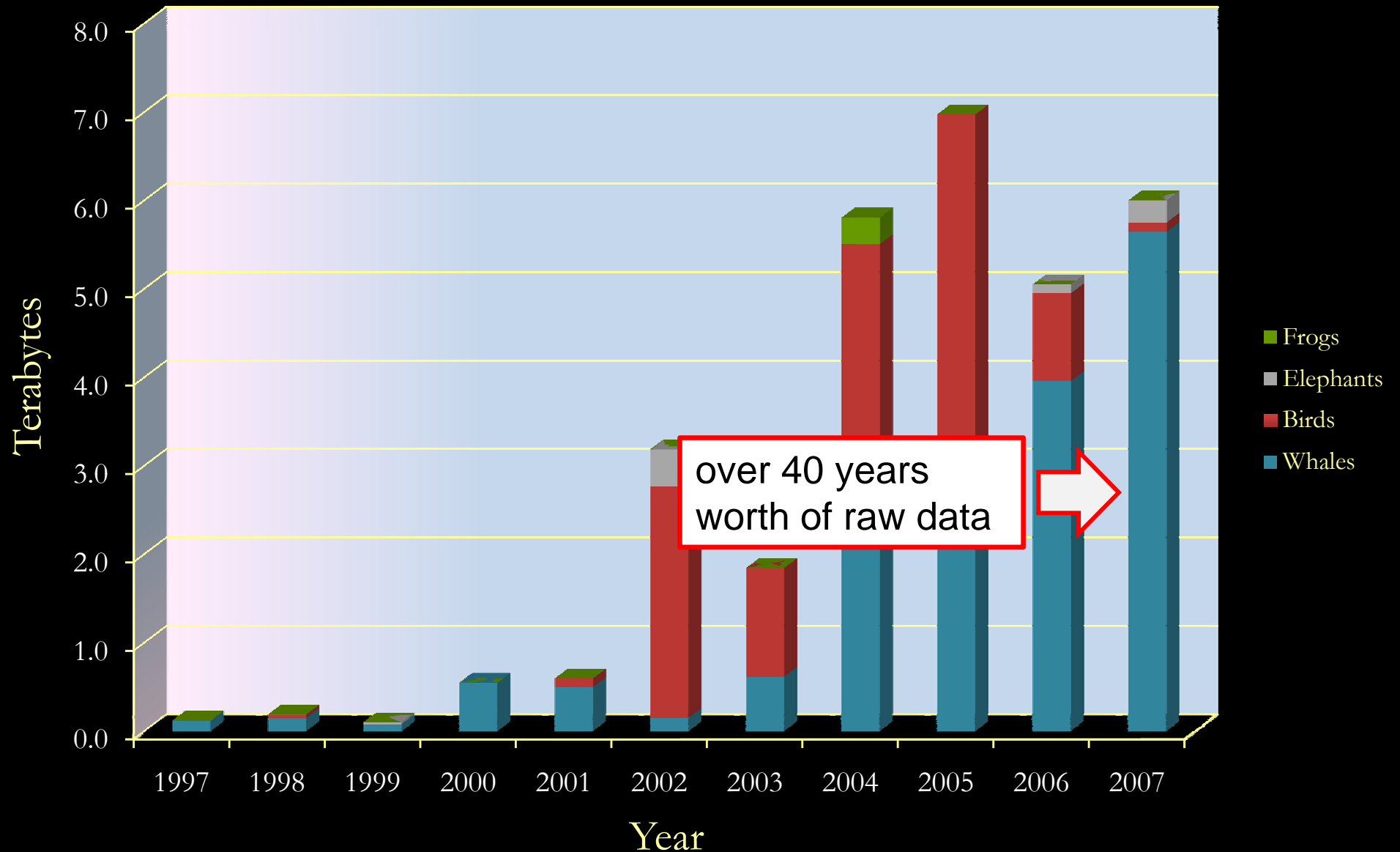
Sophisticated tools required

- Long data streams → Automatic processing



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Terabytes of Data Collected



Elements of Signal Extraction

- Detection
 - distinguish signals from background noise
- Classification
 - associate signal transients with group labels

Approaches to Classification

- Instance-based
 - training data → library of exemplars
 - proximity determines class
- Model-based
 - training data informs model
 - model output determines class

Instance-based Learning

Requirements

- Expert labeling
- Spanning set
- Proximity metric
- Neighbor-based rule

$$L = \{ (x_1, \theta_{x_1}), (x_2, \theta_{x_2}), \dots, (x_n, \theta_{x_n}) \}$$

$$\delta_{NN} = \min \{ \|x_i - x\| \}$$

$$NN \text{ Rule} \Rightarrow \theta_x = \theta_{NN}$$

Instance-based Learning

Requirements

- Proximity metric

Distance between two
attribute vectors

$$x_1 = \{ a_{11}, a_{21}, \dots, a_{p1} \}$$

$$x_2 = \{ a_{12}, a_{22}, \dots, a_{p2} \}$$

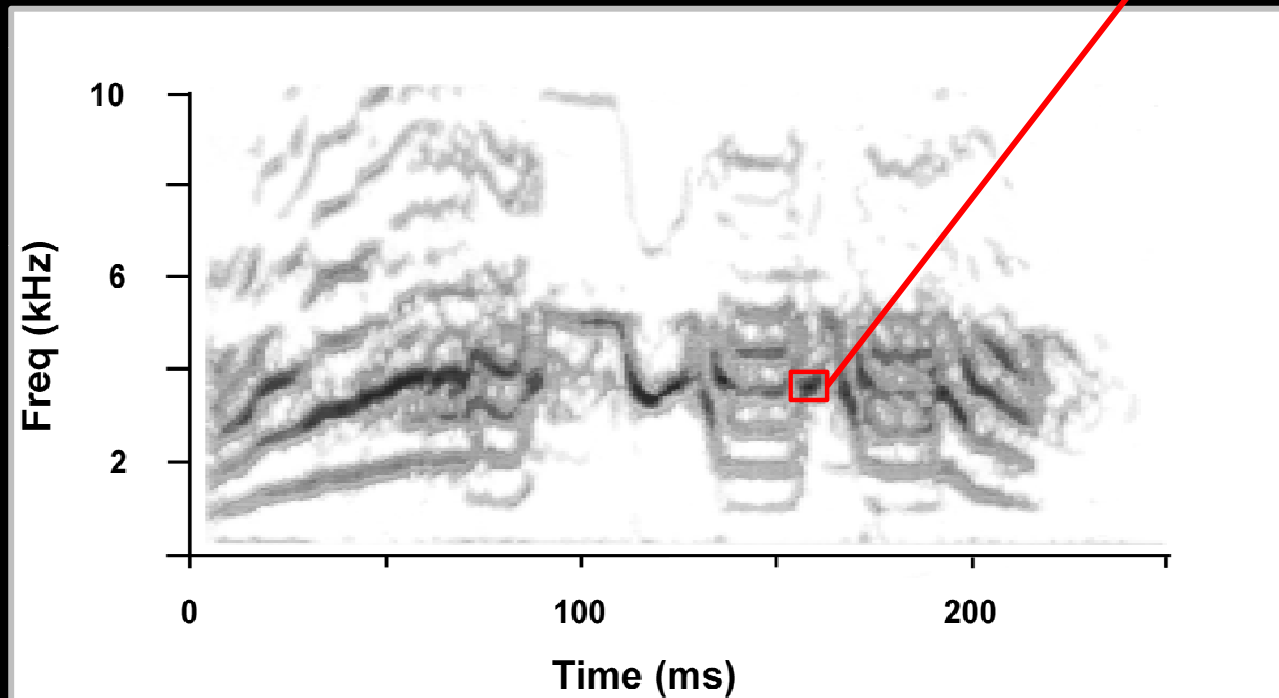
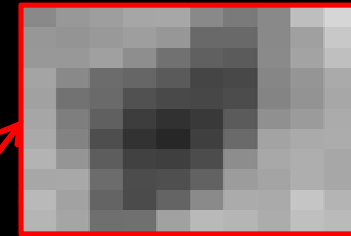
$$D = \|x_1 - x_2\|$$

$$= \sqrt{(a_{11} - a_{12})^2 + (a_{21} - a_{22})^2 + \dots + (a_{p1} - a_{p2})^2}$$

STFT Signal Decomposition

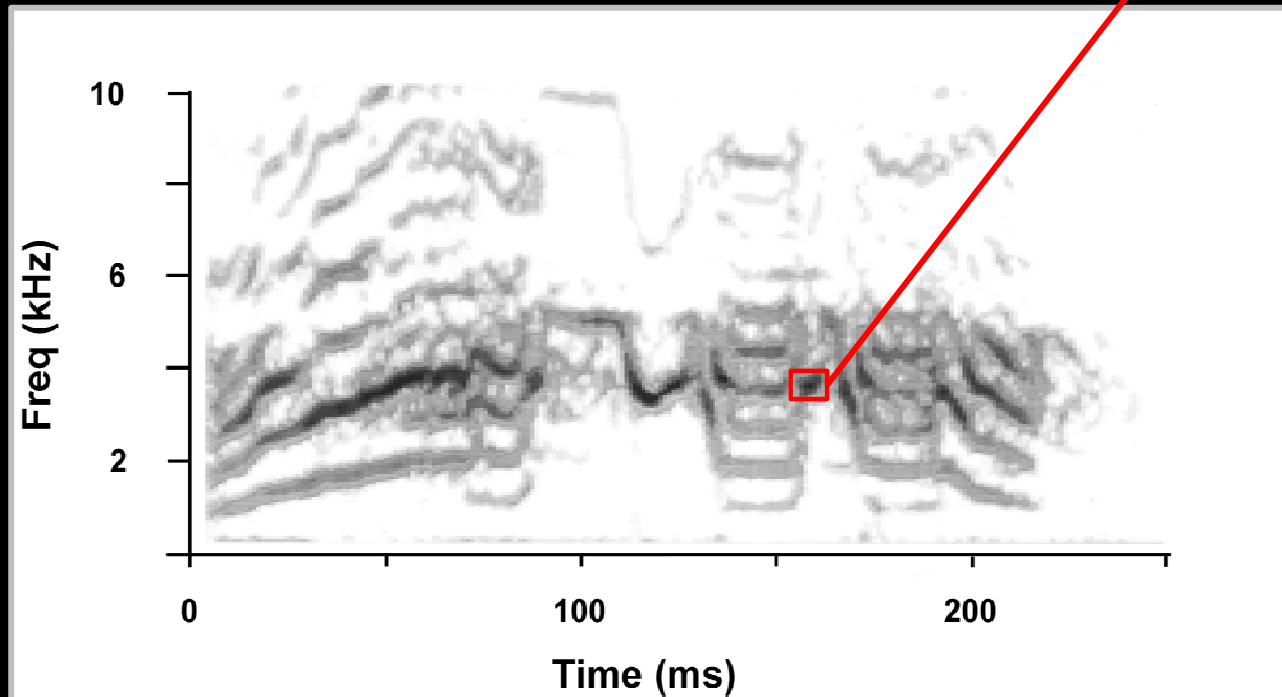
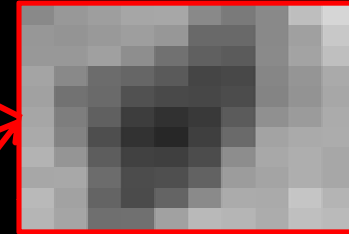
$$\Delta f = \frac{F_s}{N_{FFT}}$$

$$\Delta t = \frac{N_{win}}{F_s}, \quad \Delta_{grid} = \frac{N_{inc}}{F_s}$$

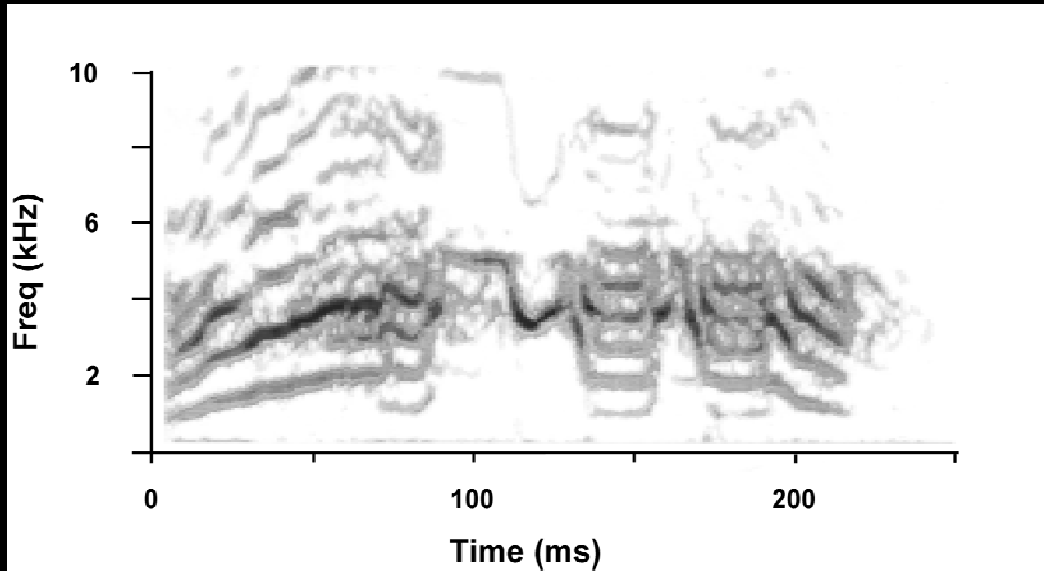


- FFT size
- Data window size
- Window increment
- Taper function
- Sample Rate

118	118	103	97	89	88	118	133	118	65	41
104	104	107	102	97	104	150	150	118	95	55
103	103	103	95	113	142	159	164	117	92	64
91	91	118	147	153	165	186	183	121	106	85
94	94	141	149	174	182	184	179	123	108	88
89	89	129	159	194	206	198	164	111	100	84
85	85	124	177	205	216	192	149	92	85	83
76	76	106	162	190	192	179	114	87	81	88
88	88	87	147	179	176	157	99	91	81	88
70	70	93	155	180	155	117	84	85	58	75
74	74	90	144	143	94	70	74	83	64	69



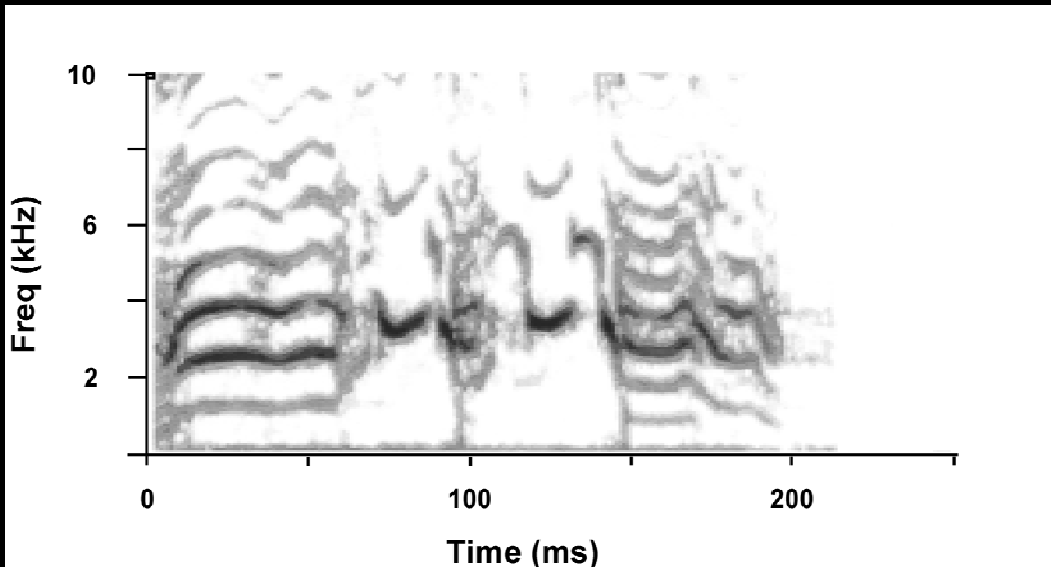
X =



Spectrogram Cross Correlation

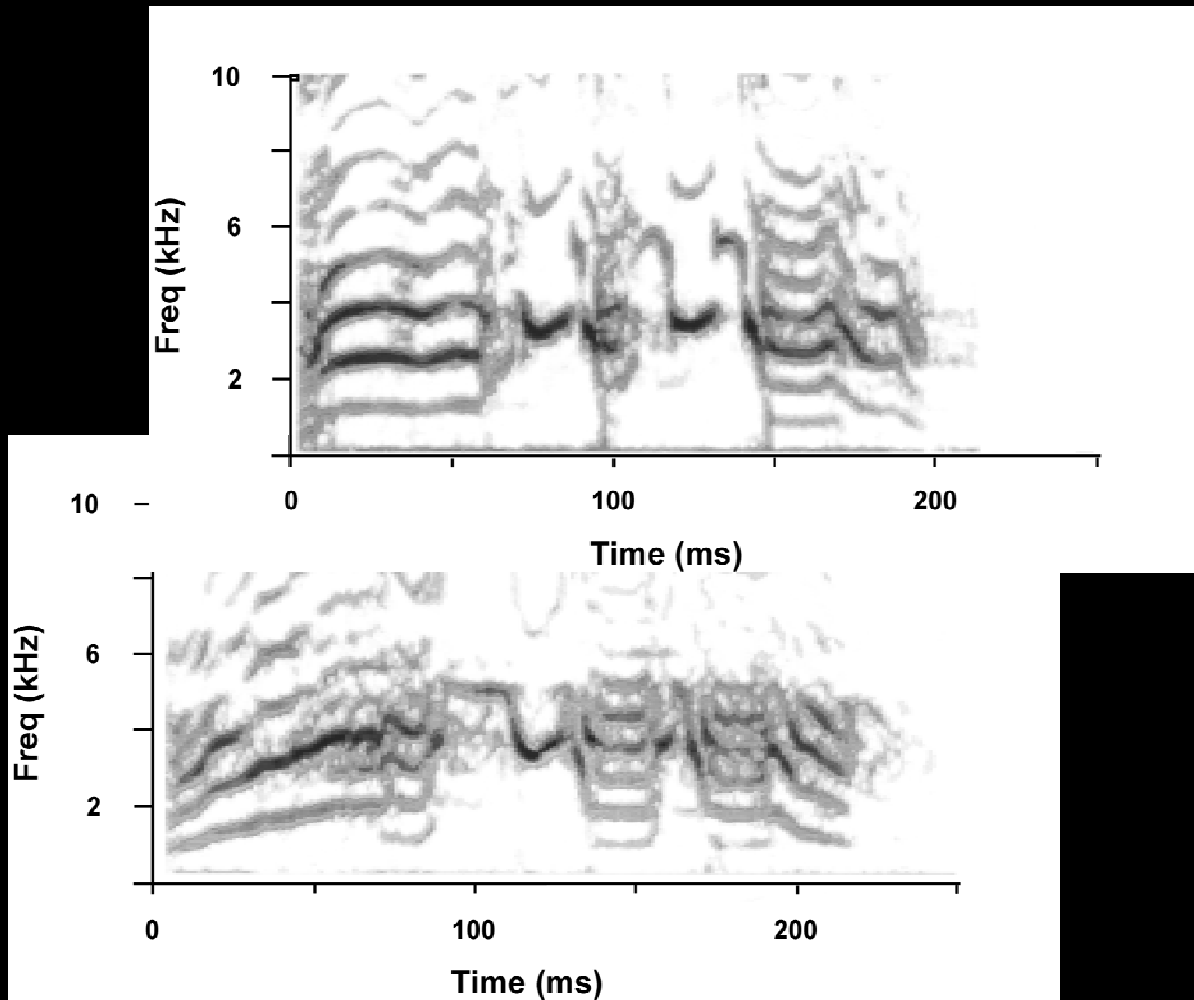
$$\rho = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \\ = \frac{E((X - \mu_X)(Y - \mu_Y))}{\sigma_X \sigma_Y}$$

Y =



Time and frequency
shifting achieves
optimal alignment

Spectrogram Cross Correlation



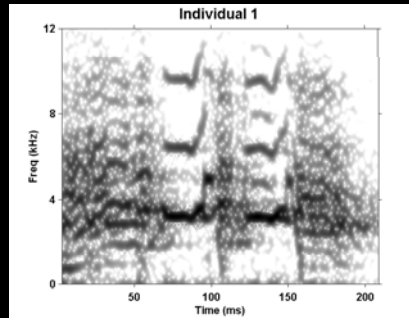
$$\rho = \frac{\sum_{i,j} (x_{ij} - \bar{x})(y_{ij} - \bar{y})}{\sqrt{\sum_{i,j} (x_{ij} - \bar{x})^2 \sum_{i,j} (y_{ij} - \bar{y})^2}}$$

Time and frequency
shifting achieves
optimal alignment

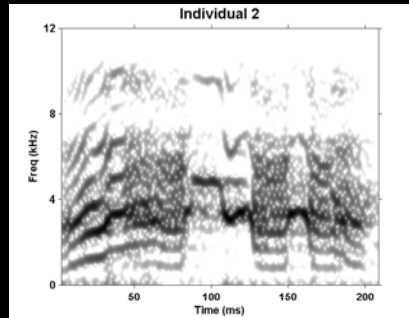
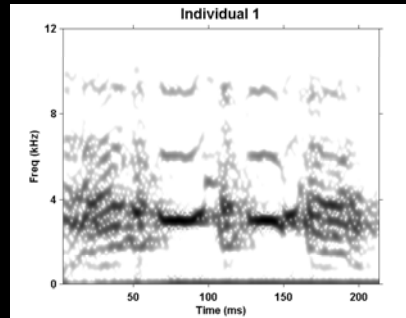
SPCC to Assess Structural Hierarchy

Contact Call Examples

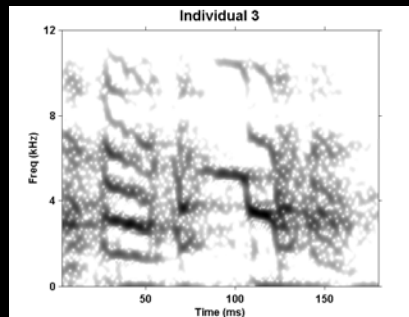
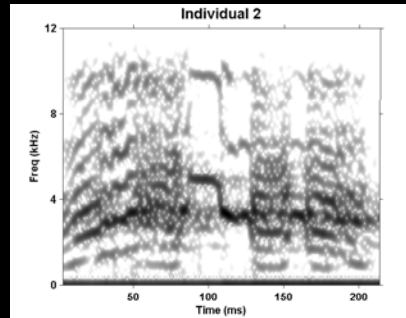
Ind 1
Ind 2
Ind 3
Pair 1
Pair 2



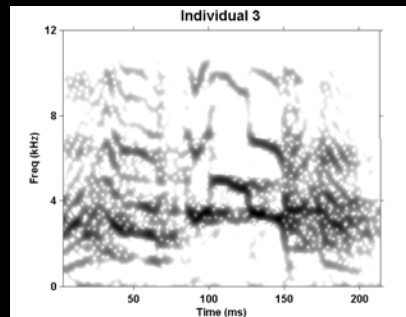
...



...



...



...

...



Pairwise Correlation Matrix

Call Object →

Call Object →

	id1 ₁	id1 ₂	id1 ₃	...	id2 ₁	id2 ₂	id2 ₃	...	idk ₁	idk ₂	idk ₃	...
id1 ₁	1.00	0.61	0.44	...	0.20	0.22	0.24	...	0.23	0.21	0.18	...
id1 ₂	0.61	1.00	0.38	...	0.21	0.20	0.25	...	0.20	0.22	0.16	...
id1 ₃	0.44	0.38	1.00	...	0.22	0.22	0.23	...	0.18	0.20	0.15	...
...
id2 ₁	0.20	0.21	0.22	...	1.00	0.55	0.54	...	0.18	0.21	0.19	...
id2 ₂	0.22	0.20	0.22	...	0.55	1.00	0.54	...	0.17	0.17	0.19	...
id2 ₃	0.24	0.25	0.23	...	0.54	0.54	1.00	...	0.16	0.19	0.17	...
...
idk ₁	0.23	0.20	0.18	...	0.18	0.17	0.16	...	1.00	0.51	0.34	...
idk ₂	0.21	0.22	0.20	...	0.21	0.17	0.19	...	0.51	1.00	0.33	...
idk ₃	0.18	0.16	0.15	...	0.19	0.19	0.17	...	0.34	0.33	1.00	...
...

Square symmetric

$$\frac{N(N-1)}{2}$$

Unique pairwise values

PCO Analysis

1. start with pairwise distance matrix

$$\mathbf{D} = \begin{matrix} & n \text{ obj} \rightarrow \\ \begin{matrix} n \text{ obj} \\ \downarrow \end{matrix} & \begin{pmatrix} d_{11} & d_{21} & \cdots & d_{n1} \\ d_{12} & d_{22} & \cdots & d_{n2} \\ \vdots & \vdots & & \vdots \\ d_{1n} & d_{2n} & \cdots & d_{nn} \end{pmatrix} \end{matrix}$$

2. transform distance values

$$b_{ij} = -\frac{1}{2} \left(d_{ij}^2 - \sum_{i=1}^n d_{ij}^2 - \sum_{j=1}^n d_{ij}^2 + \sum_{i=1}^n \sum_{j=1}^n d_{ij}^2 \right)$$

$$\Rightarrow \mathbf{B} = \mathbf{X}\mathbf{X}^t \quad \text{where, } \mathbf{X} = \begin{matrix} & p \text{ var} \rightarrow \\ \begin{matrix} n \text{ obj} \\ \downarrow \end{matrix} & \begin{pmatrix} x_{11} & x_{21} & \cdots & x_{p1} \\ x_{12} & x_{22} & \cdots & x_{p2} \\ \vdots & \vdots & & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{pn} \end{pmatrix} \end{matrix}$$

3. perform eigen decomposition

$$\mathbf{B} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^t = (\mathbf{u}_1 \quad \mathbf{u}_2 \quad \cdots \quad \mathbf{u}_n) \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} \begin{pmatrix} \mathbf{u}_1^t \\ \mathbf{u}_2^t \\ \vdots \\ \mathbf{u}_n^t \end{pmatrix}$$

$$\Rightarrow \mathbf{X} = (\sqrt{\lambda_1}\mathbf{u}_1 \quad \sqrt{\lambda_2}\mathbf{u}_2 \quad \cdots \quad \sqrt{\lambda_n}\mathbf{u}_n) = \begin{matrix} & p \text{ var} \rightarrow \\ \begin{matrix} n \text{ obj} \\ \downarrow \end{matrix} & \begin{pmatrix} \sqrt{\lambda_1}u_{11} & \sqrt{\lambda_2}u_{21} & \cdots & \sqrt{\lambda_n}u_{p1} \\ \sqrt{\lambda_1}u_{12} & \sqrt{\lambda_2}u_{22} & \cdots & \sqrt{\lambda_n}u_{p2} \\ \vdots & \vdots & & \vdots \\ \sqrt{\lambda_1}u_{1n} & \sqrt{\lambda_2}u_{2n} & \cdots & \sqrt{\lambda_n}u_{pn} \end{pmatrix} \end{matrix}$$

Ordination using PCO

Object \rightarrow

Pairwise Correlation Matrix

Object \rightarrow

	id1 ₁	id1 ₂	id1 ₃	...	id2 ₁	id2 ₂	id2 ₃	...	idk ₁	idk ₂	idk ₃	...
id1 ₁	1.00	0.61	0.44	...	0.20	0.22	0.24	...	0.23	0.21	0.18	...
id1 ₂	0.61	1.00	0.38	...	0.21	0.20	0.25	...	0.20	0.22	0.16	...
id1 ₃	0.44	0.38	1.00	...	0.22	0.22	0.23	...	0.18	0.20	0.15	...
...
id2 ₁	0.20	0.21	0.22	...	1.00	0.55	0.54	...	0.18	0.21	0.19	...
id2 ₂	0.22	0.20	0.22	...	0.55	1.00	0.54	...	0.17	0.17	0.19	...
id2 ₃	0.24	0.25	0.23	...	0.54	0.54	1.00	...	0.16	0.19	0.17	...
...
idk ₁	0.23	0.20	0.18	...	0.18	0.17	0.16	...	1.00	0.51	0.34	...
idk ₂	0.21	0.22	0.20	...	0.21	0.17	0.19	...	0.51	1.00	0.33	...
idk ₃	0.18	0.16	0.15	...	0.19	0.19	0.17	...	0.34	0.33	1.00	...
...

Ordination using PCO

Attribute →

Object-Attribute Table

Object →

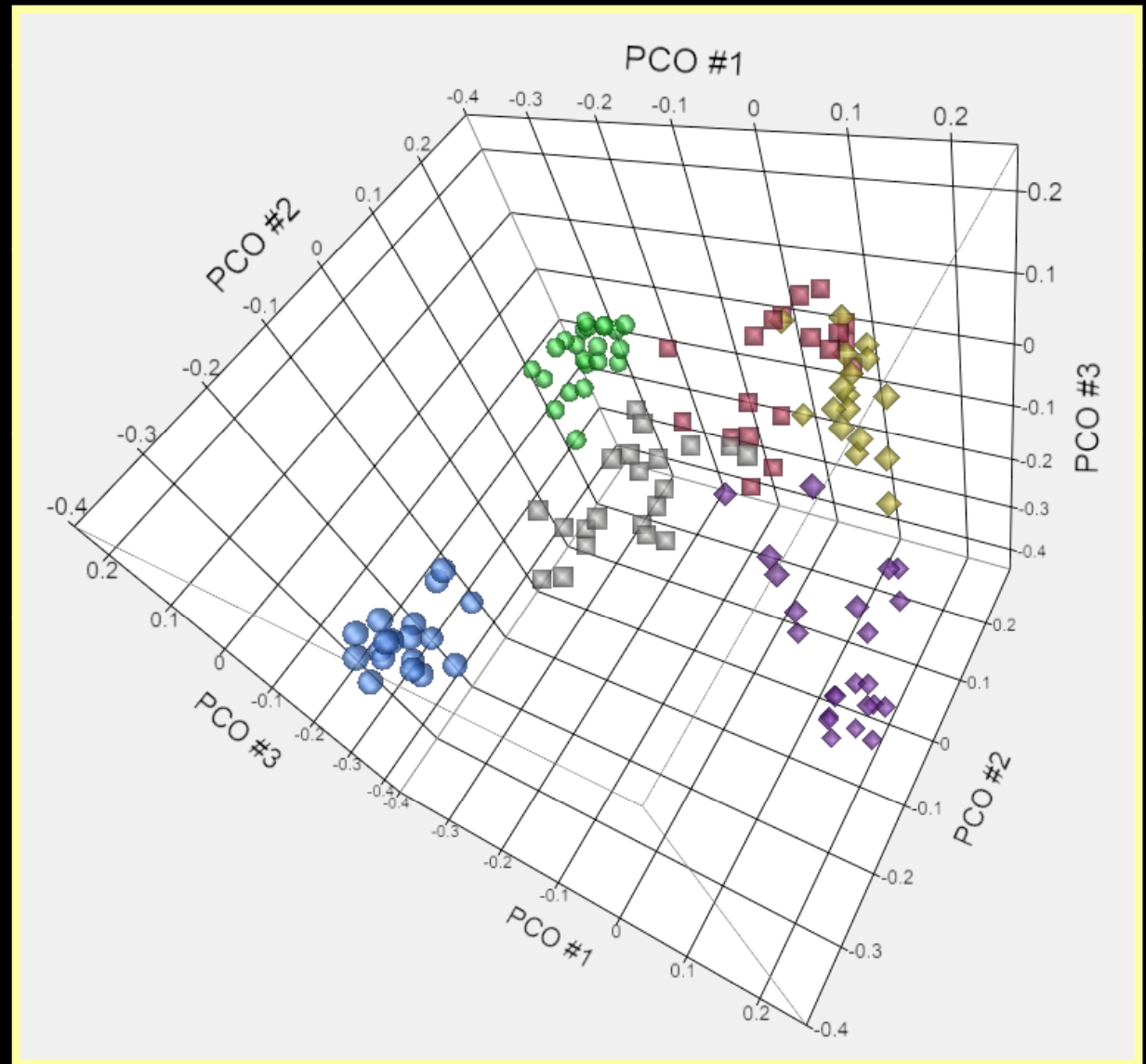
	pc1	pc2	pc3	pc4	pc5	pc6	pc7	pc8	pc9	pc10	...	pc k
id1 ₁	-0.293	0.215	-0.087	0.015	-0.009	0.055	-0.133	0.051	-0.009	0.116	...	0
id1 ₂	-0.268	0.170	-0.086	-0.001	-0.002	0.032	-0.145	-0.040	0.017	0.100	...	0
id1 ₃	-0.287	0.208	-0.072	0.016	-0.022	-0.021	-0.016	-0.008	0.040	0.089	...	0
...
id2 ₁	-0.174	-0.353	0.061	-0.050	0.086	-0.081	0.099	0.022	0.020	0.060	...	0
id2 ₂	-0.195	-0.330	0.060	-0.027	0.070	-0.106	0.068	0.030	-0.010	0.029	...	0
id2 ₃	-0.160	-0.300	0.028	0.013	-0.001	-0.172	0.114	0.032	-0.023	0.117	...	0
...
id k ₁	0.162	0.156	0.091	-0.249	-0.004	0.013	0.032	0.208	-0.005	0.099	...	0
id k ₂	0.150	0.135	0.116	-0.272	-0.052	0.054	0.044	0.063	0.016	0.125	...	0
id k ₃	0.200	0.046	0.098	-0.210	0.009	-0.058	-0.110	0.145	-0.073	-0.018	...	0
...

SPCC-PCO for examining call structure and identity

3D PCO Space

6 individuals

3 social pairs

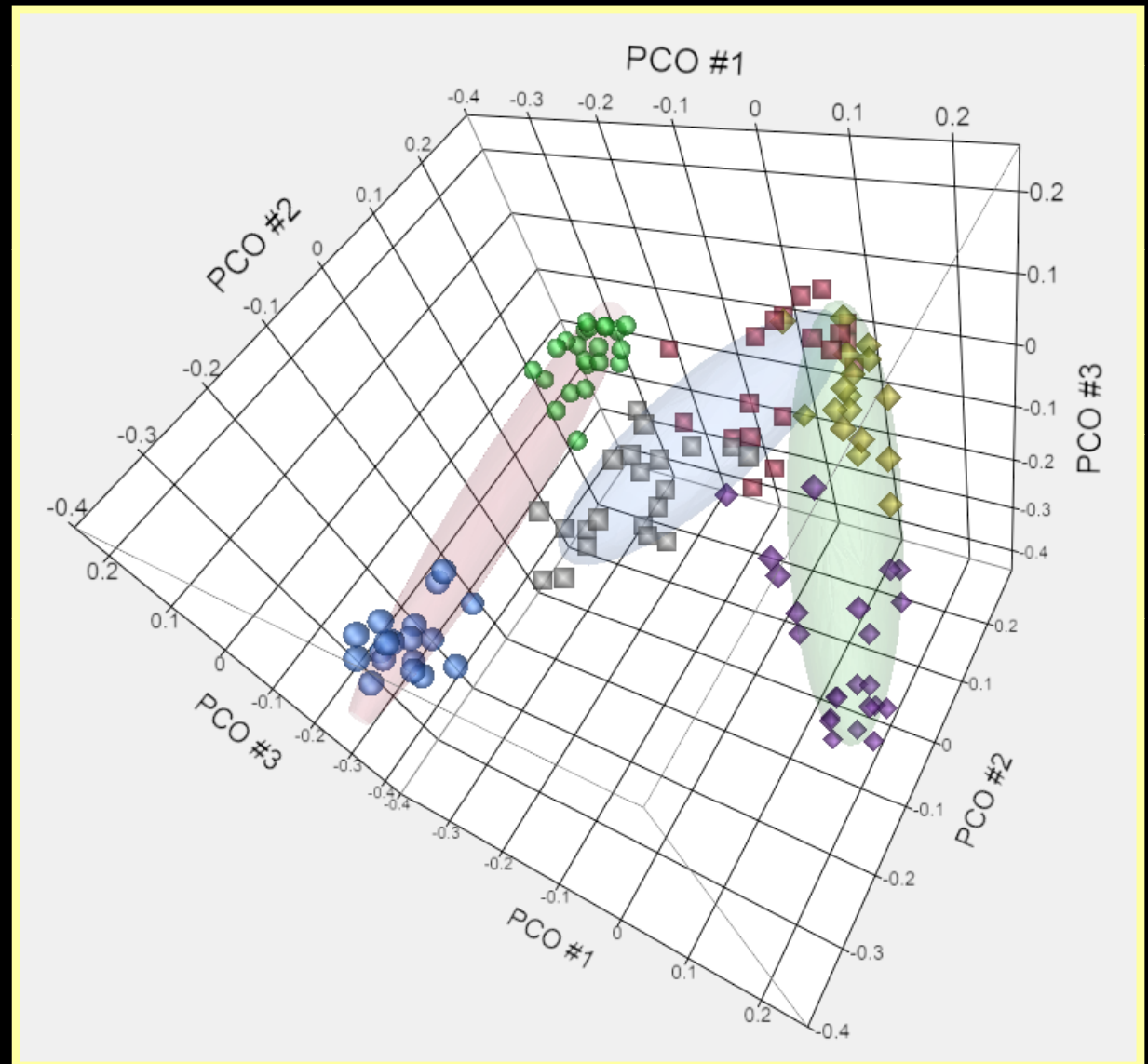


SPCC-PCO for examining call structure and identity

3D PCO Space

6 individuals

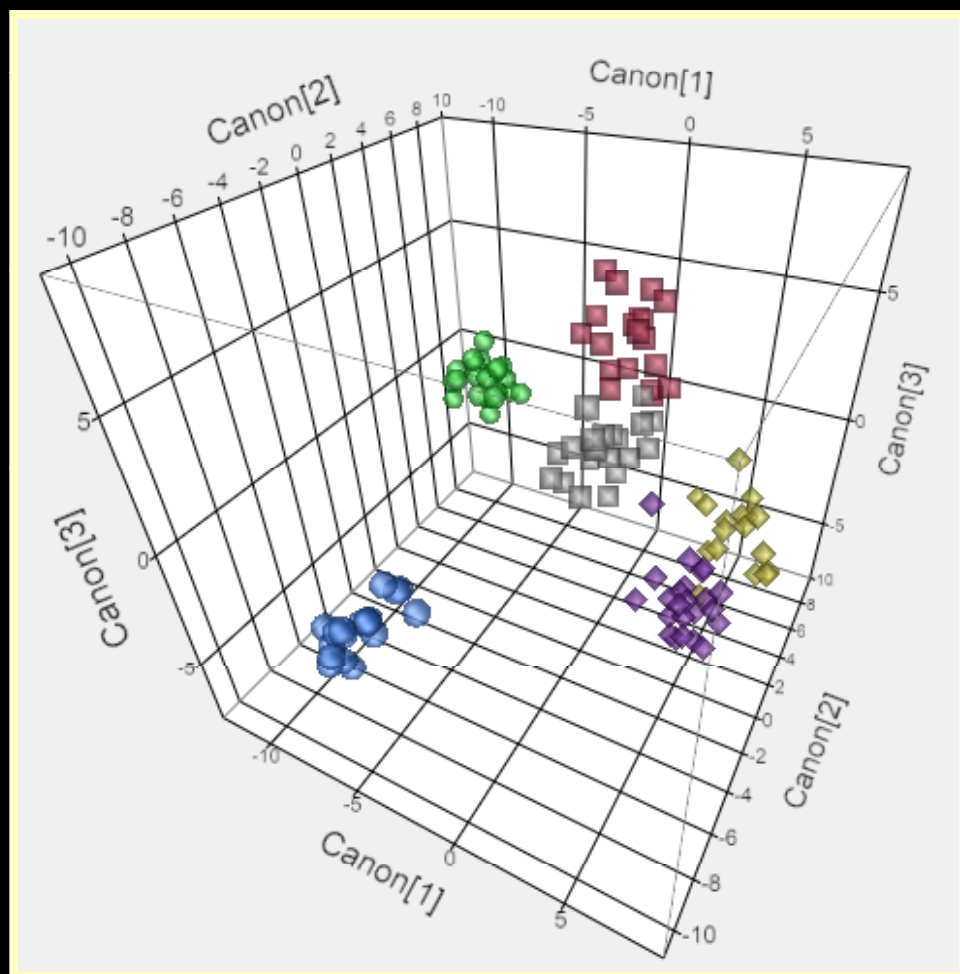
3 social pairs



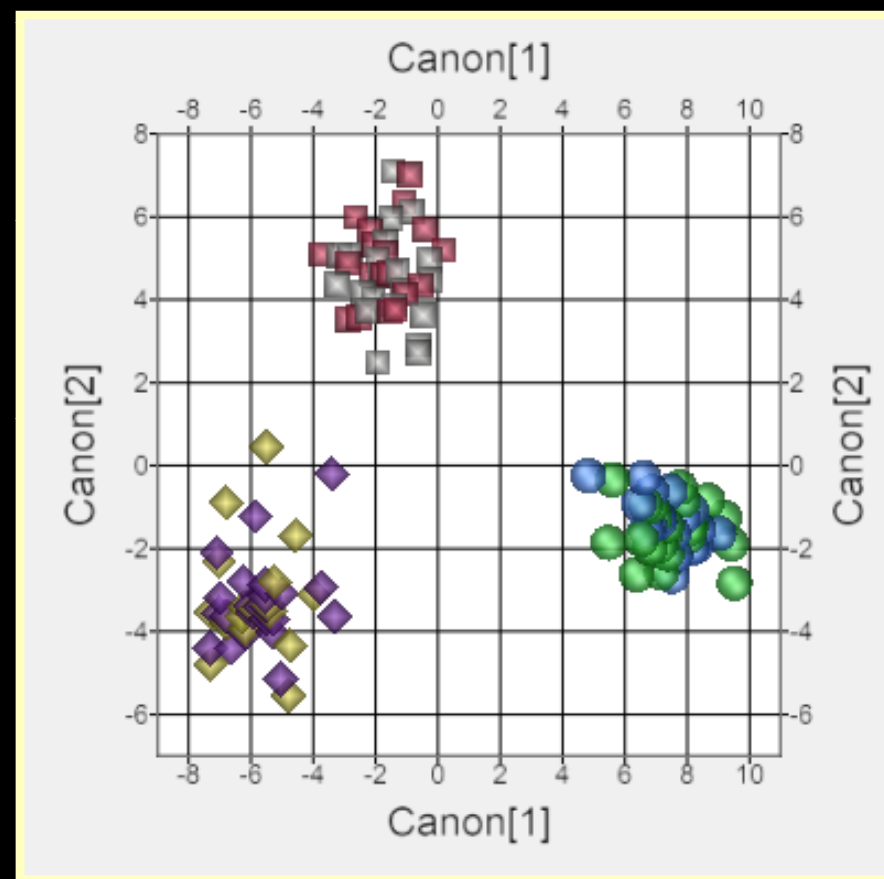
LDA using latent PCO measures

PCO 1-14, 90% variation explained

By Individual



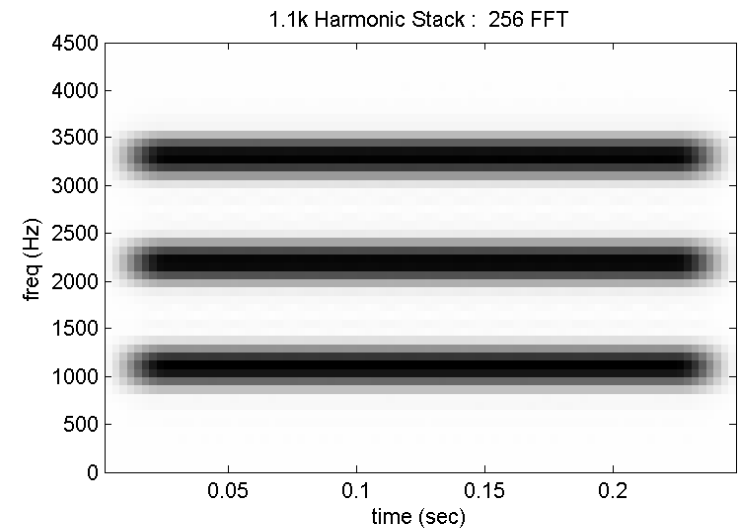
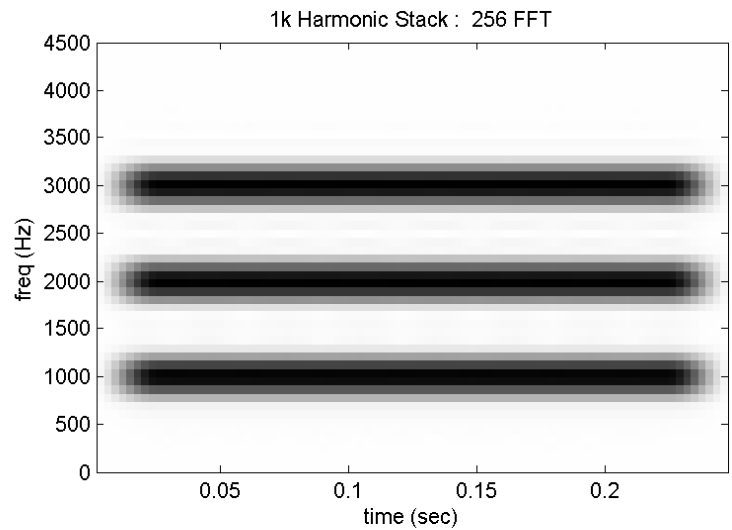
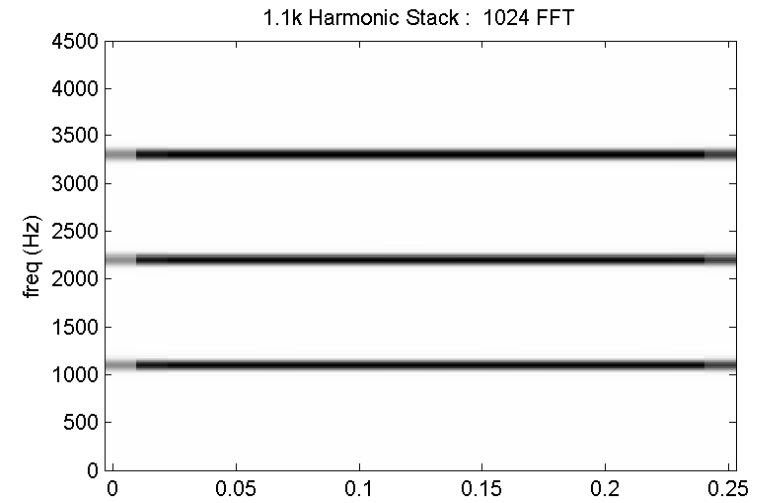
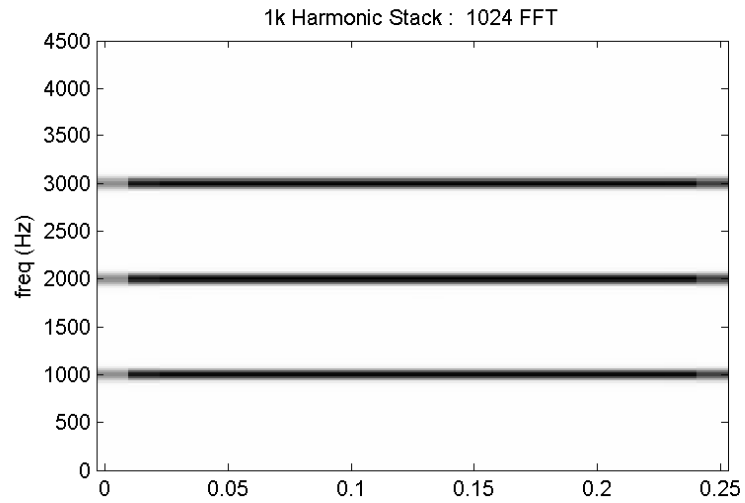
By Pair



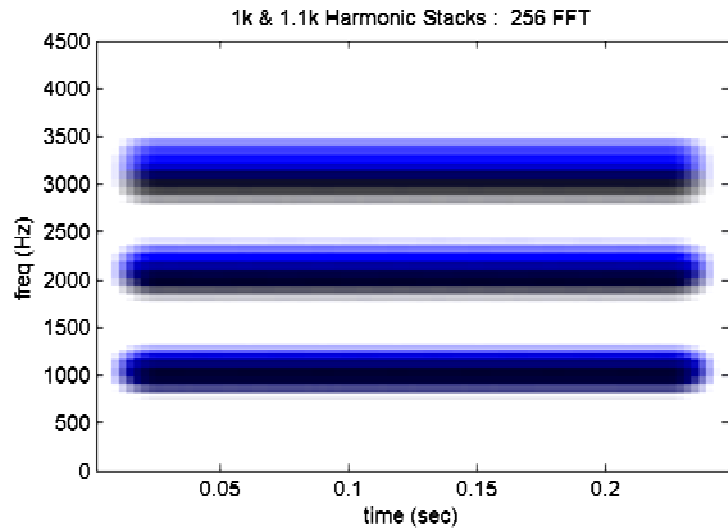
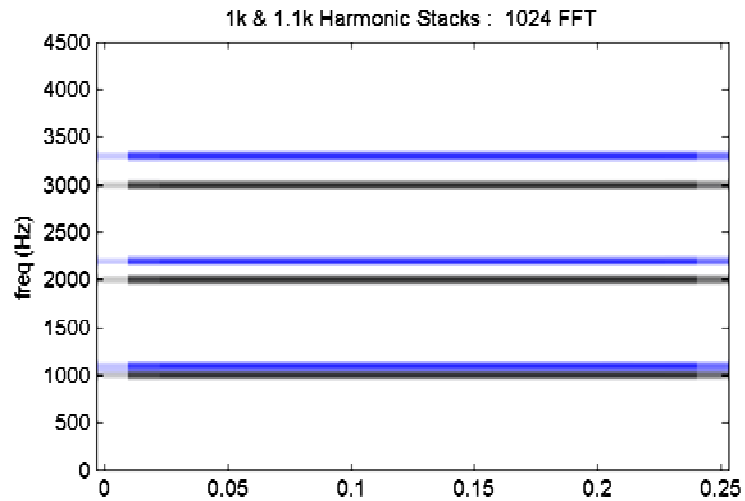
SPCC & SPCC-PCO Considerations

- Variable timing patterns
unless using dynamic warping...
- Decomposition parameters
patterns can be revealed or obscured...
- Signal clutter / overlap
can affect correlation results...
- Latent measures are relative
all data must be available up front...

Importance of Decomposition Parameters



Importance of Decomposition Parameters



1024 pt FFT	1 KHz Stack	1.1 KHz Stack
1 KHz Stack	1.000	0.000
1.1 KHz Stack	0.000	1.000

256 pt FFT	1 KHz Stack	1.1 KHz Stack
1 KHz Stack	1.000	0.751
1.1 KHz Stack	0.751	1.000

Model-based Learning

Requirements

- Expert labeling
- Spanning set
- Measured attributes
- Modeling paradigm

$$L = \{ (x_1, \theta_{x_1}), (x_2, \theta_{x_2}), \dots, (x_p, \theta_{x_n}) \}$$

$$x_i = \{ a_{1i}, a_{2i}, \dots, a_{pi} \}$$

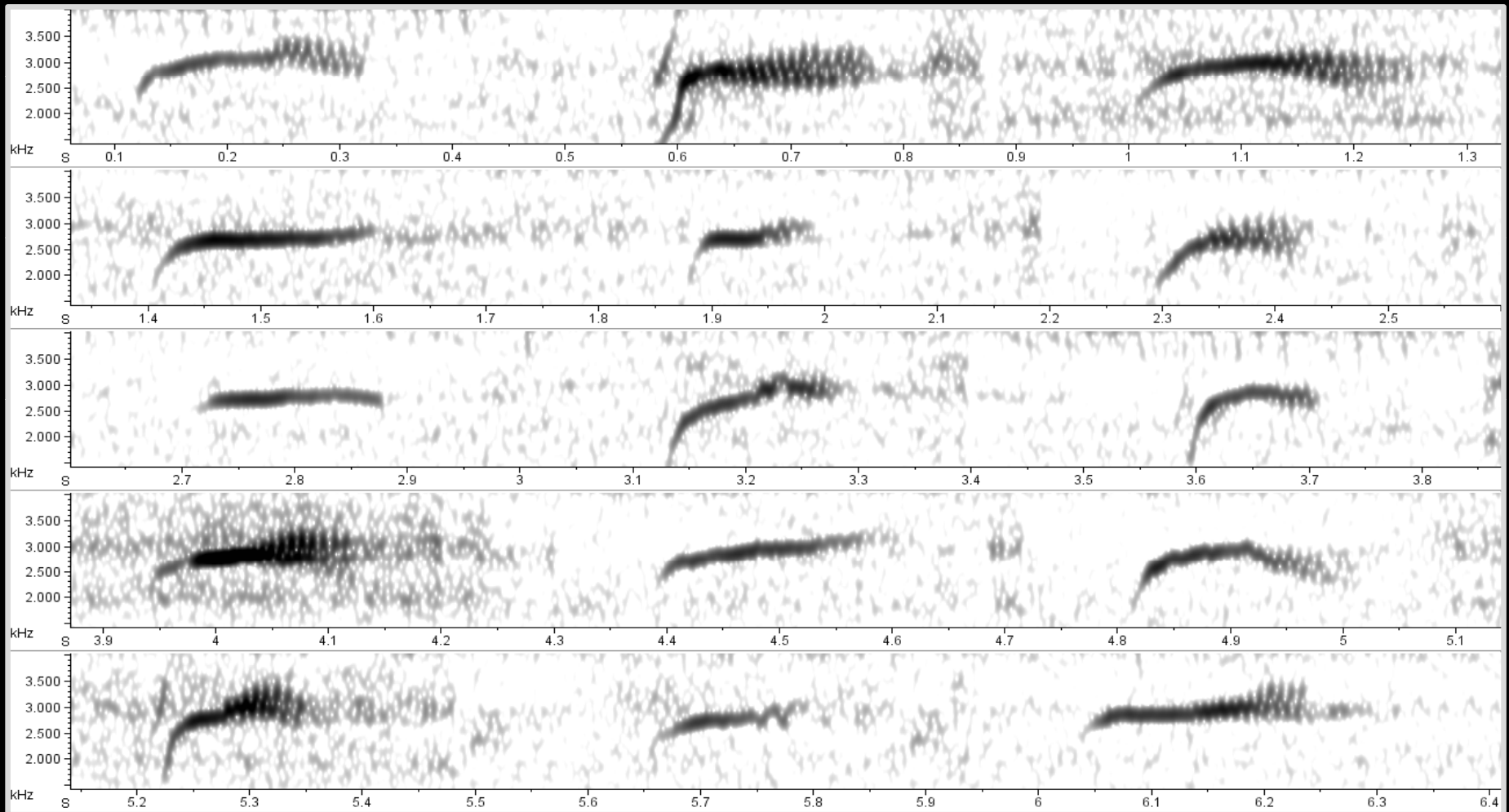
$$L \Rightarrow \text{Model}$$

Exploring Biological Variability



Swainson's Thrush

Species-specific flight calls
→ relatively low variability



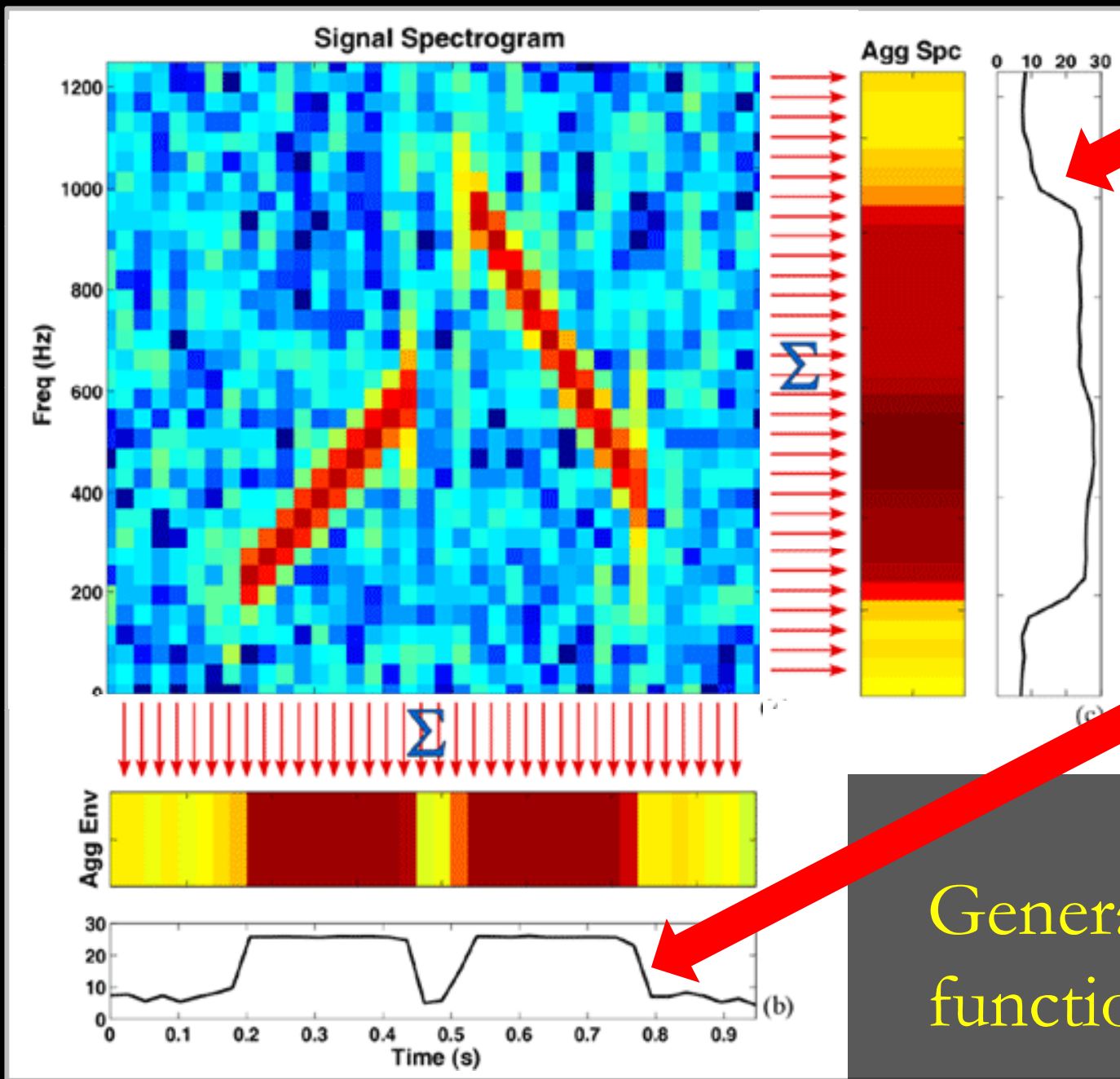
Model Types

- Rule Sets
 - 1R, PRISM, PART
- Decision Trees
 - ID3, C4.5, Random Tree
- Statistical Models
 - LDA, Bayes, Gaussian mixtures, HMM, Neural networks
- Meta Learners
 - Bagging, boosting, stacking

Attribute Generation

- Energy distribution measurement
 - Generically applicable

- Contour extraction & measurement
 - Targeted to FM signals

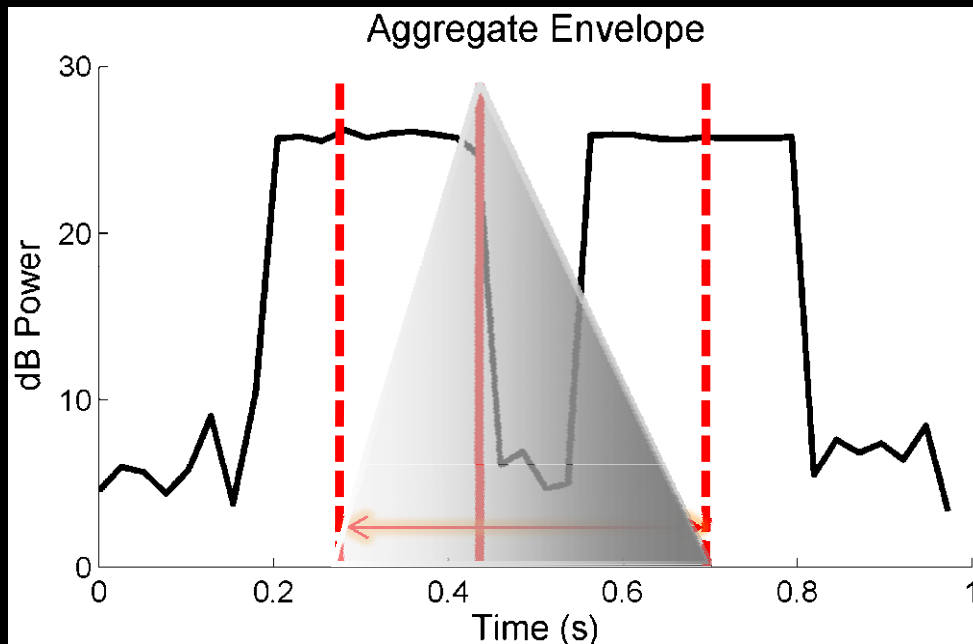


Aggregate Spectrum

Aggregate Envelope

Generating energy functions

Measuring Distributions

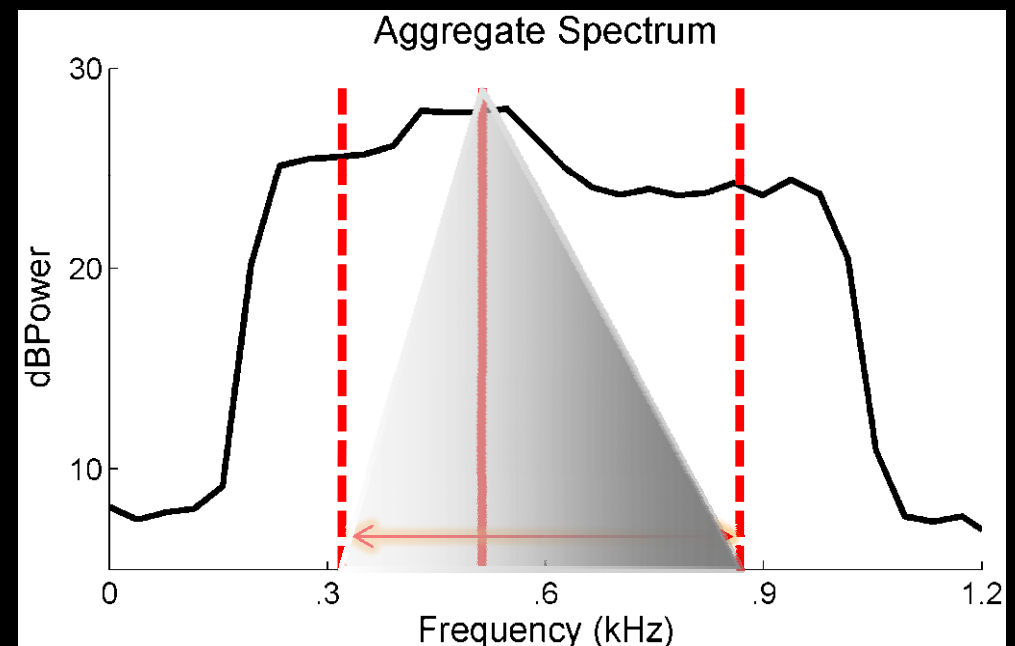


Estimator

- Median
- Quartile (p -Percentile) Range
- Skewness

Signal Feature

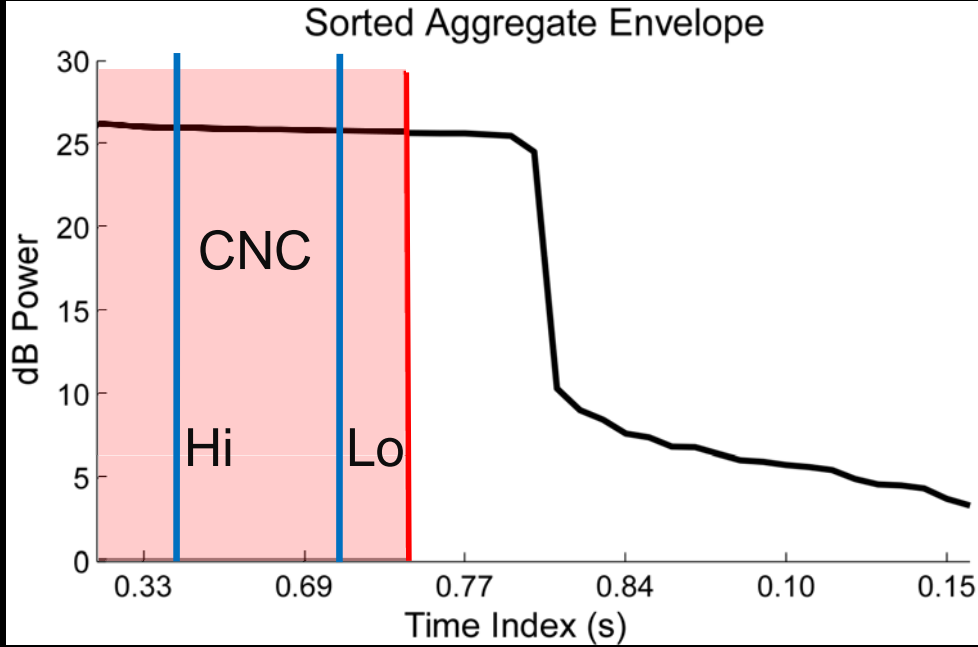
- Central Time / Frequency
- Duration / Bandwidth
- Signal Symmetry



More measures

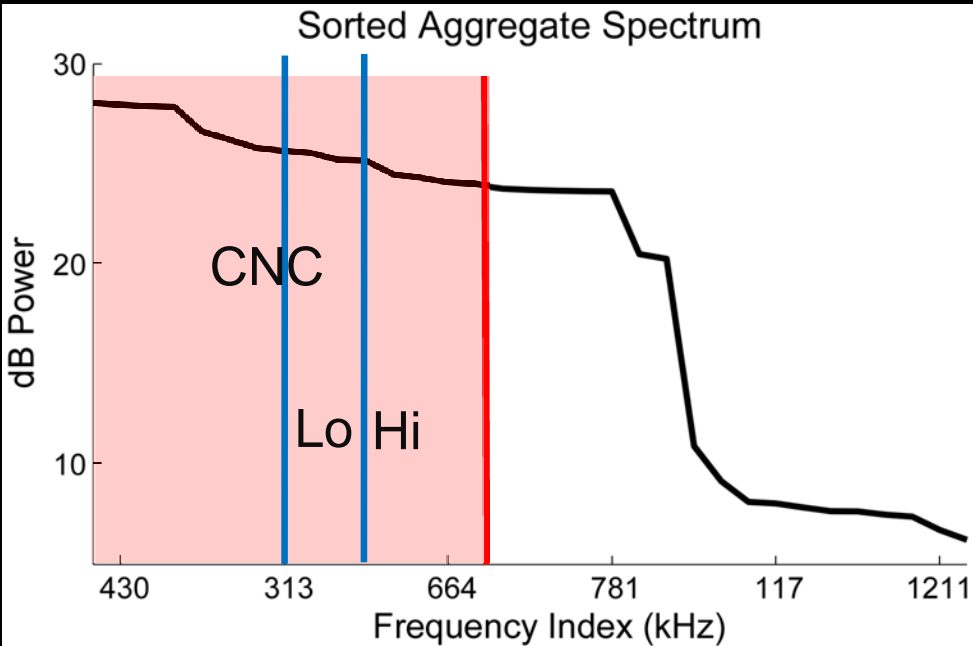
Estimator

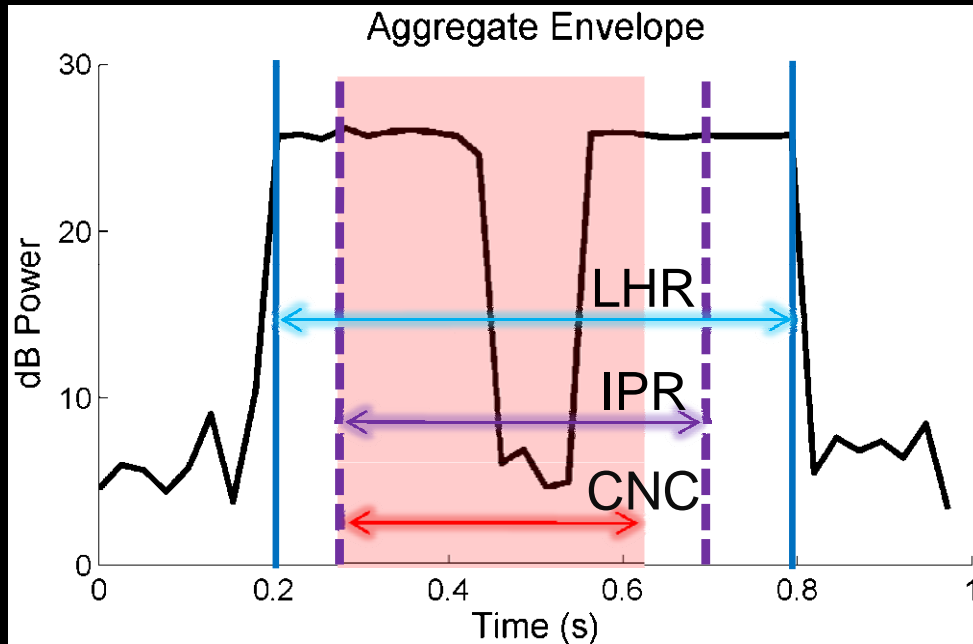
- Bins to Median (p -Percentile)
- Index Range in CNC Bins



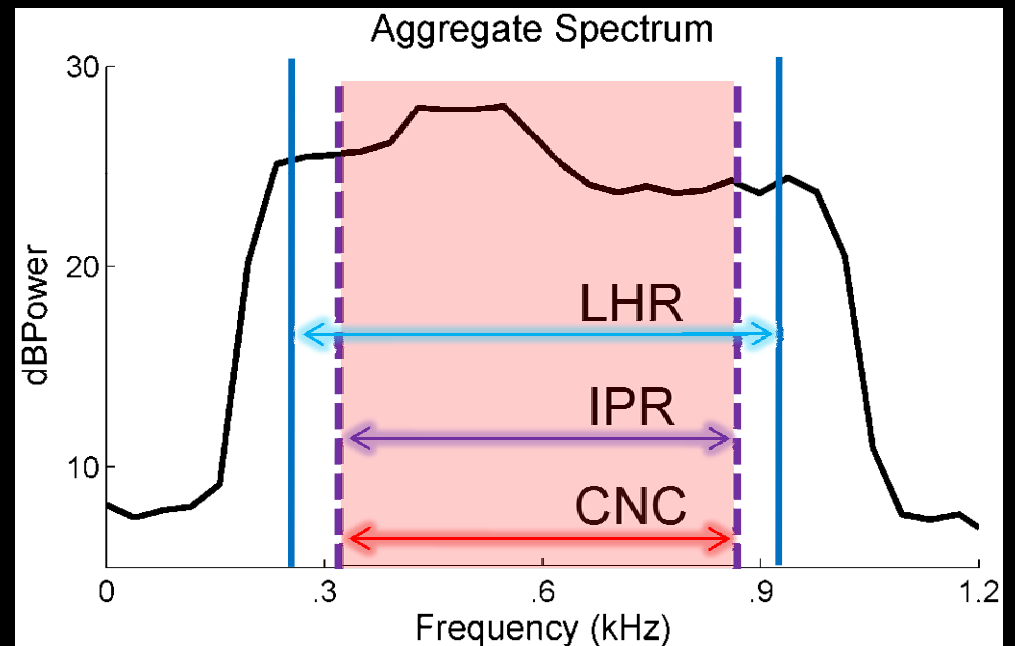
Signal Feature

- Collapsed Dur / BW
- Expanded Dur / BW

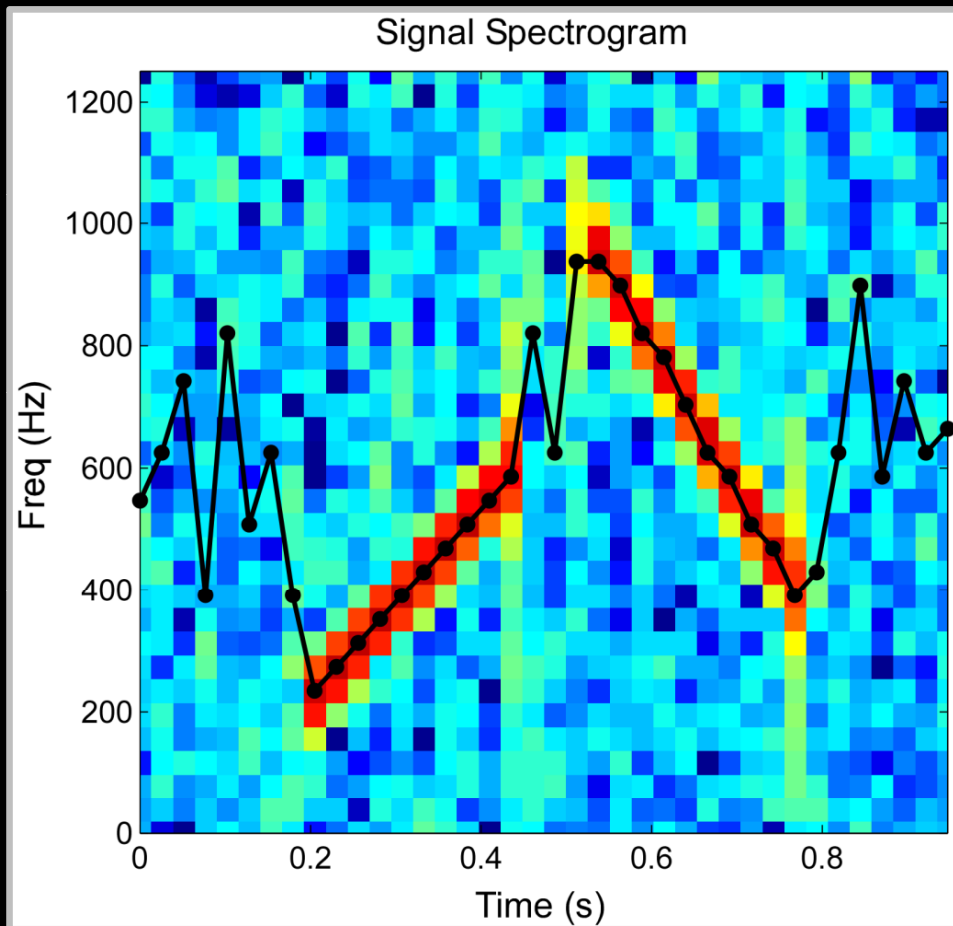




A suite of duration / bandwidth metrics



Extracting Frequency Contours



STFT Approaches

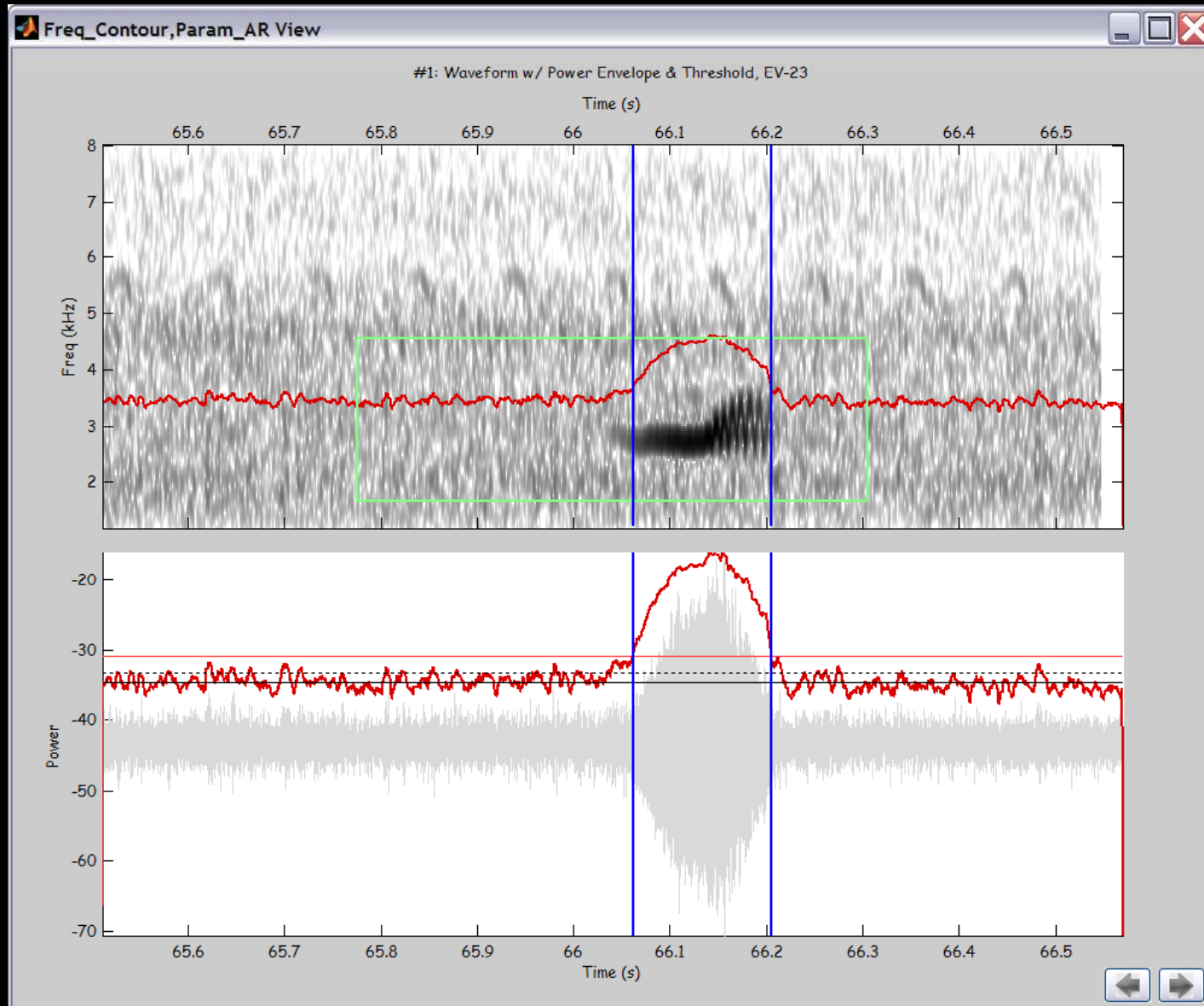
Track of short-time
medians

Parametric Frequency
Estimation & Tracking

Something entirely
different...

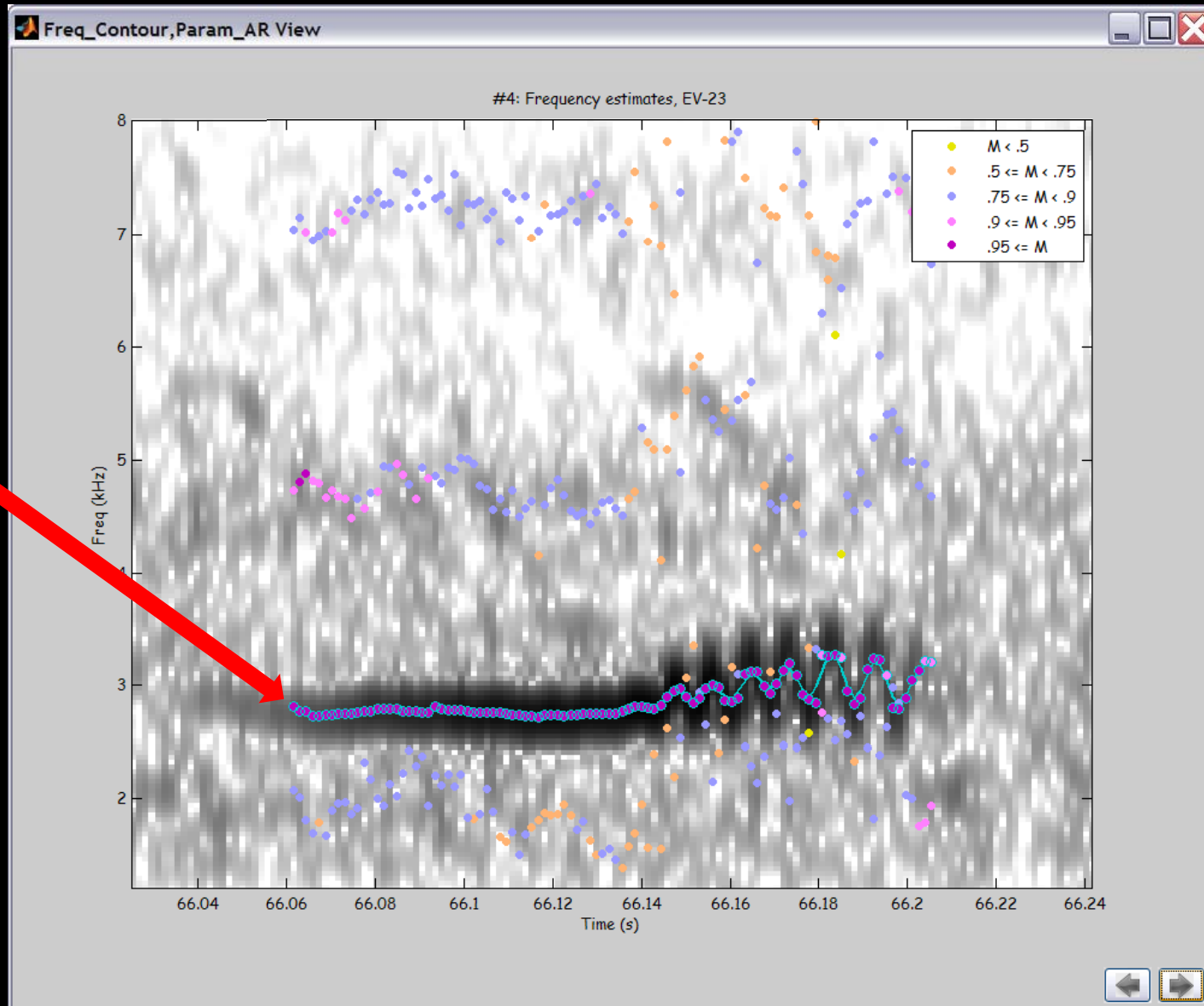
Contour Measurement

Duration Estimation



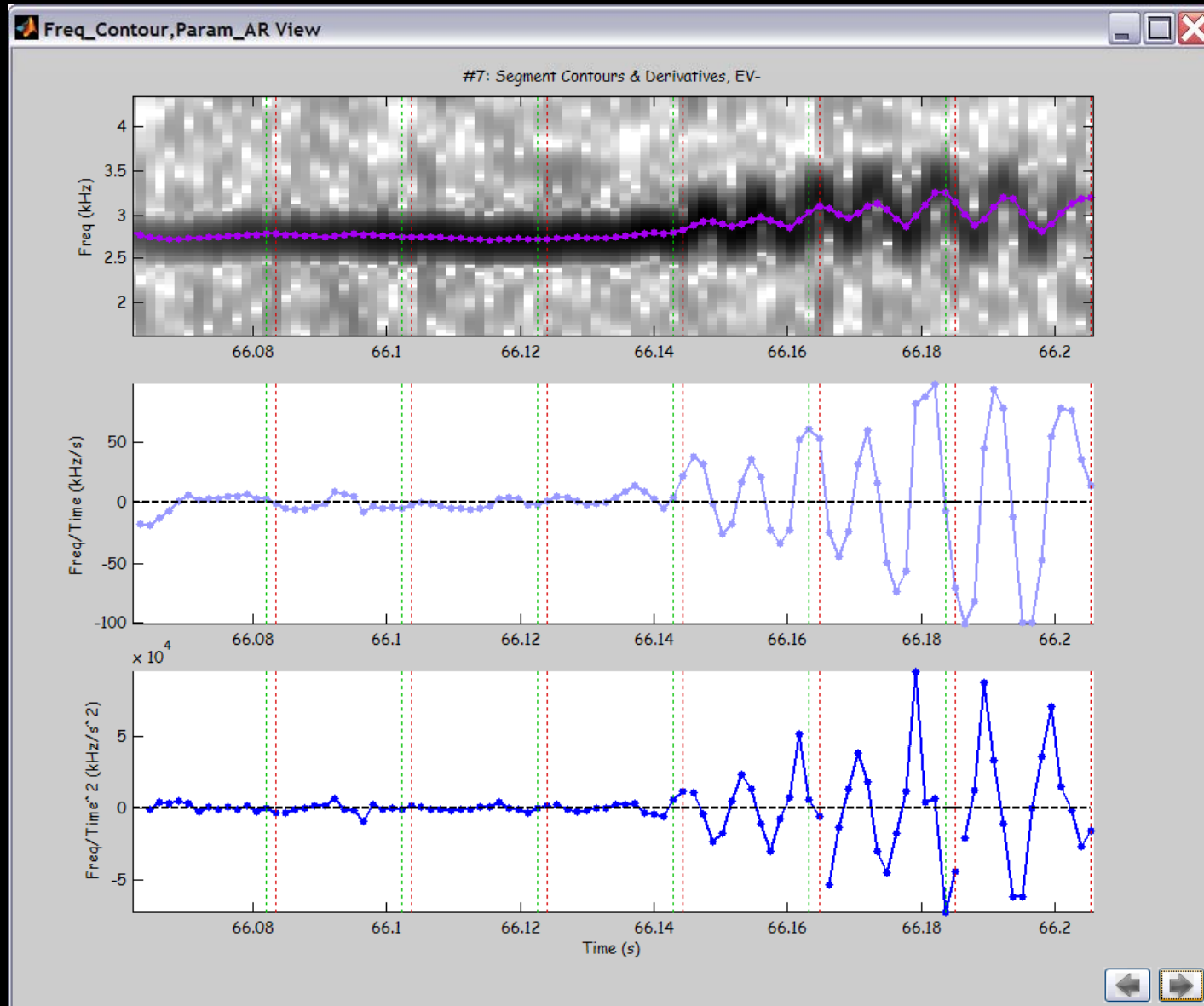
Contour Measurement

Frequency Estimation & Tracking



Contour Measurement

Contour Summarization

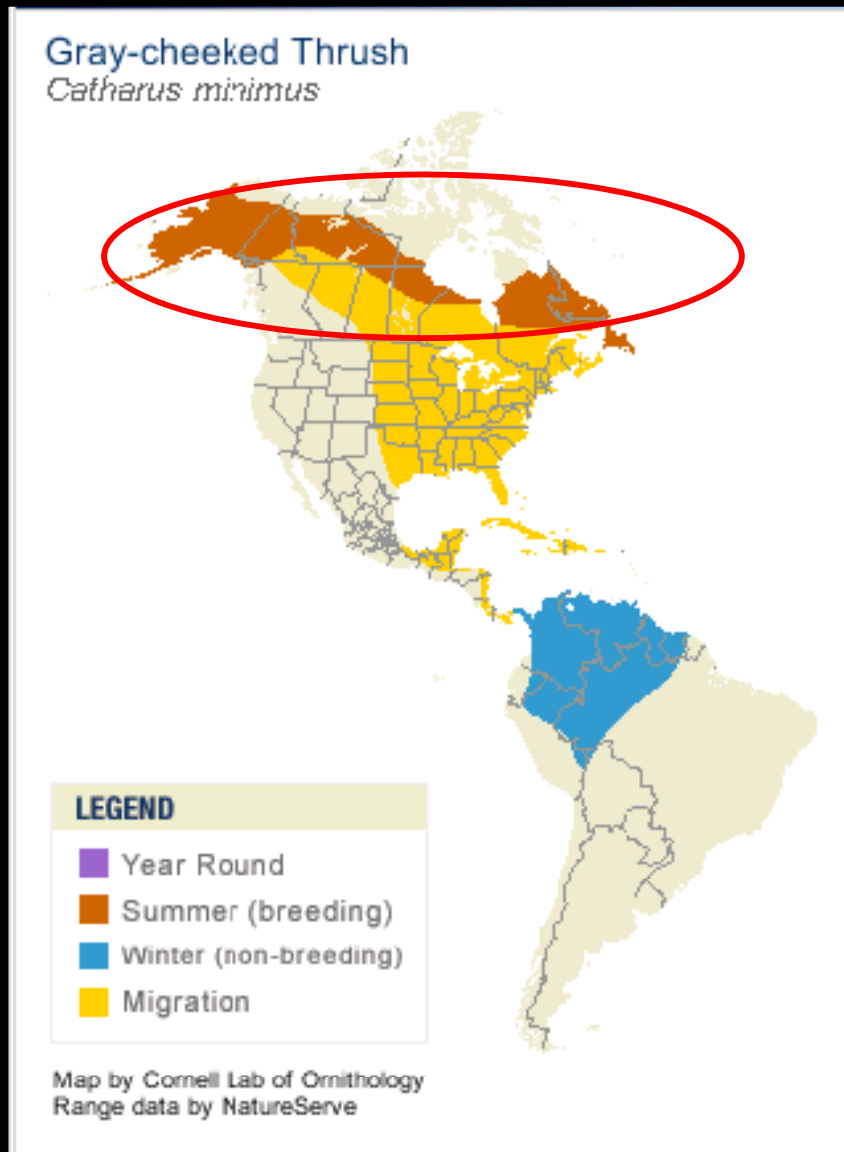


Contour

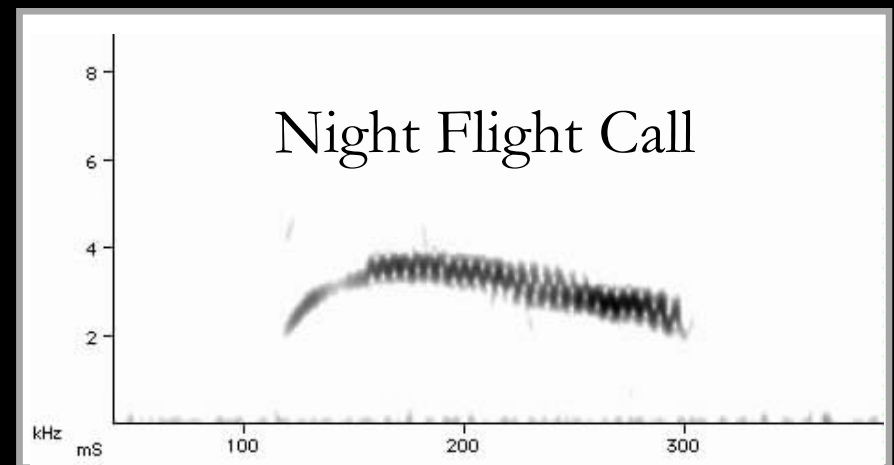
1st
Derivative

2nd
Derivative

Monitoring nocturnal bird migration

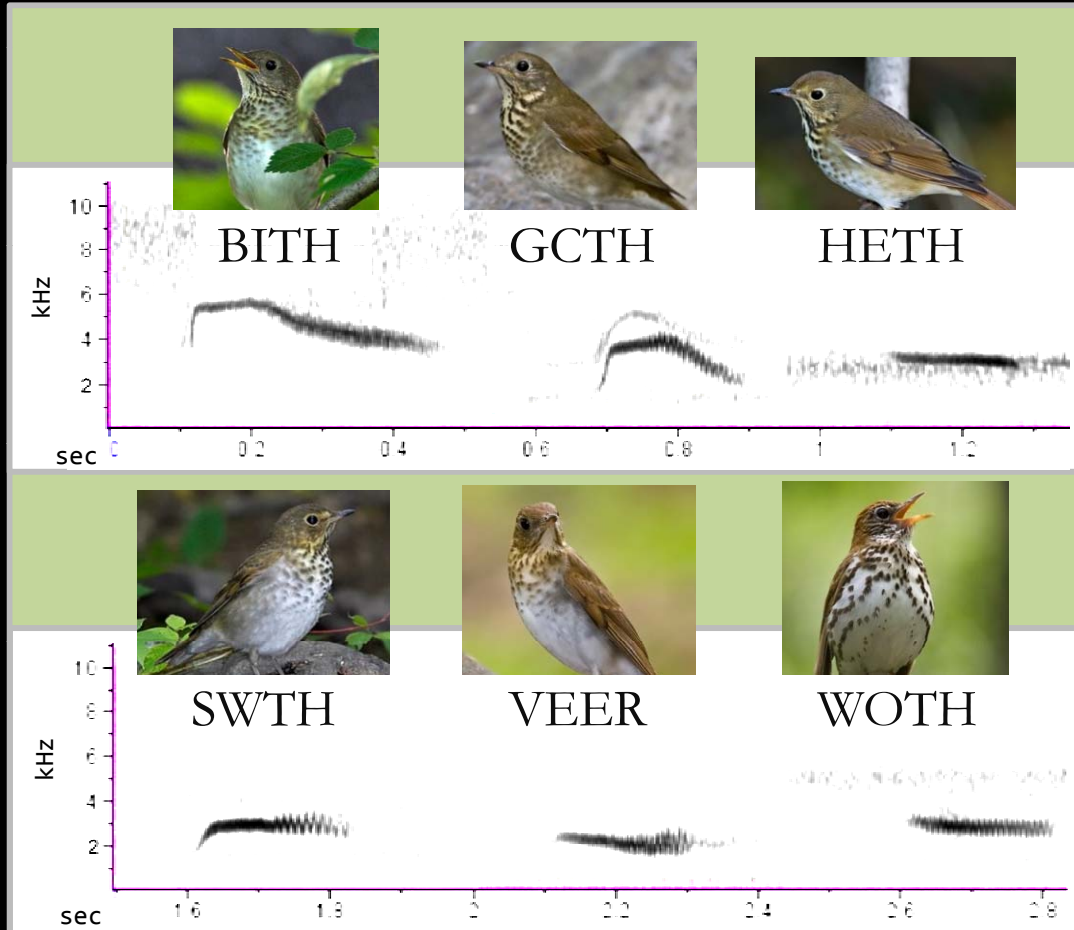
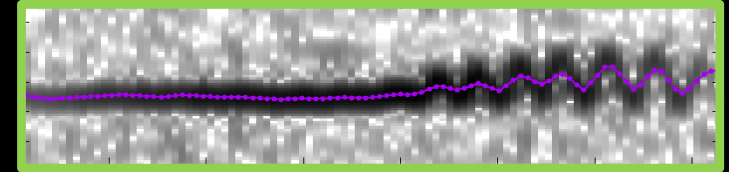


Gray-cheeked Thrush



Identifying nocturnal migrants

using contour extraction



6 Thrush species

Frequency modulated calls
with varying range, pattern & modulation rate

Photographs ©

Lloyd Spitalnick

Random Forest Classification

100 trees, 7 random attributes of 98 total, 10-fold cross validation

Predicted Class

Actual Class

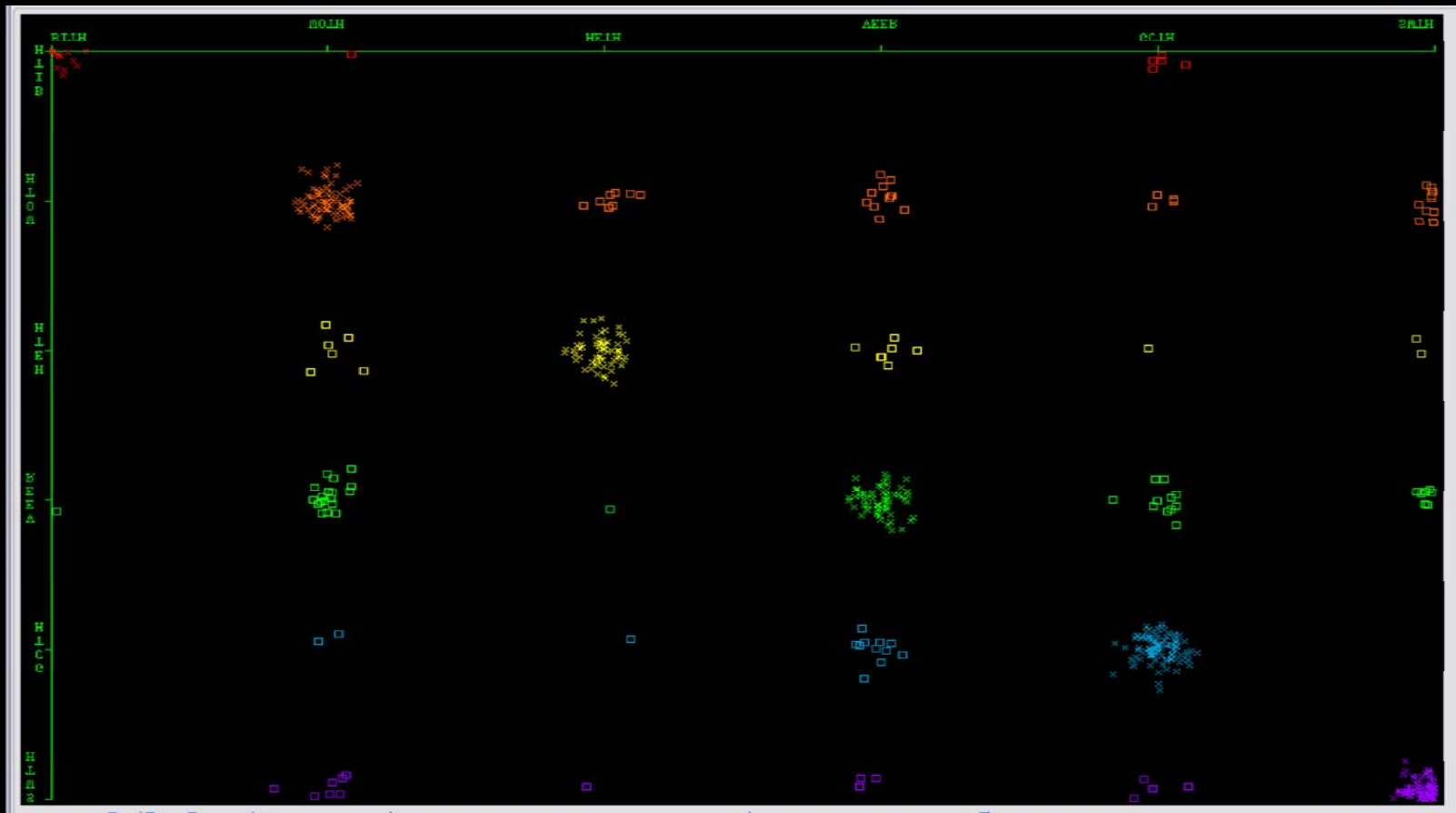
	BITH	WOTH	HETH	VEER	GCTH	SWTH	Recall
BITH	13	1	0	0	5	0	.68
WOTH	0	83	8	11	5	10	.71
HETH	0	6	66	7	1	2	.81
VEER	1	18	1	67	11	7	.64
GCTH	0	2	1	11	106	0	.88
SWTH	0	7	1	3	4	105	.88
Precision	.93	.71	.86	.68	.80	.85	

Random Forest Classification

100 trees, 7 random attributes of 98 total, 10-fold cross validation

Predicted Class

Actual Class



Attribute Sets

Requirements

- Quantifiable
- Repeatable
- Robust
- Discriminating

Whether physically intuitive
or hopelessly abstract...

Thank you

with thanks to

Russell Charif

& collaborators

Andrew Farnsworth

Kurt Fristrup

Jack Bradbury

