Sound Organization By Source Models in Humans and Machines

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1. Mixtures and Models
2. Human Sound Organization
3. Machine Sound Organization
4. Research Questions

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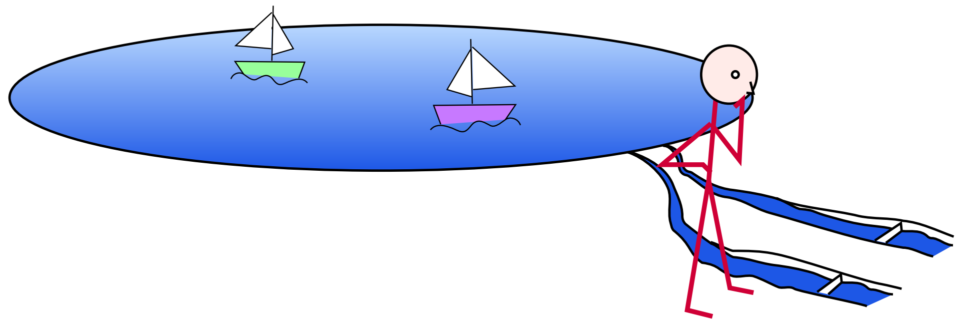
The Problem of Mixtures

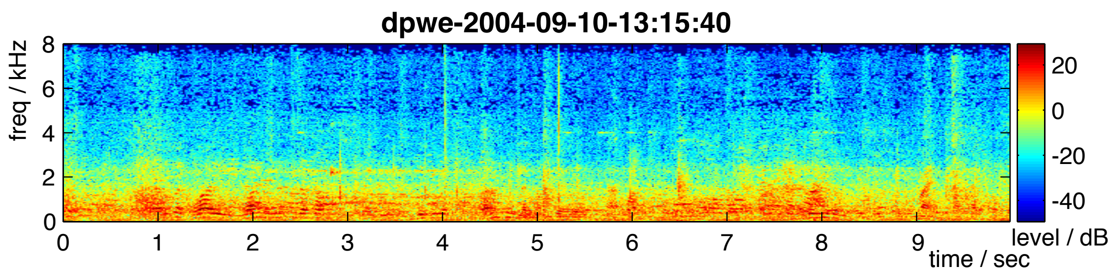


"Imagine two narrow channels dug up from the edge of a lake, with handkerchiefs stretched across each one. Looking only at the motion of the handkerchiefs, you are to answer questions such as: How many boats are there on the lake and where are they?" (after Bregman'90)

- Received waveform is a mixture
  - 2 sensors, N sources - underconstrained
- Undoing mixtures: hearing's primary goal?
  - .. by any means available

Sound Organization Scenarios

- Interactive voice systems
  - human-level understanding is expected
- Speech prostheses
  - crowds: #1 complaint of hearing aid users
- Archive analysis
  - identifying and isolating sound events



pa-2004-09-10-131540.wav

- Unmixing/remixing/enhancement...

How Can We Separate?

- By between-sensor differences (spatial cues)
  - 'steer a null' onto a compact interfering source
  - the filtering/signal processing paradigm
- By finding a 'separable representation'
  - spectral? sources are broadband but sparse
  - periodicity? maybe – for pitched sounds
  - something more signal-specific...
- By inference (based on knowledge/models)
  - acoustic sources are redundant
    → use part to guess the remainder
    - limited possible solutions

Separation vs. Inference

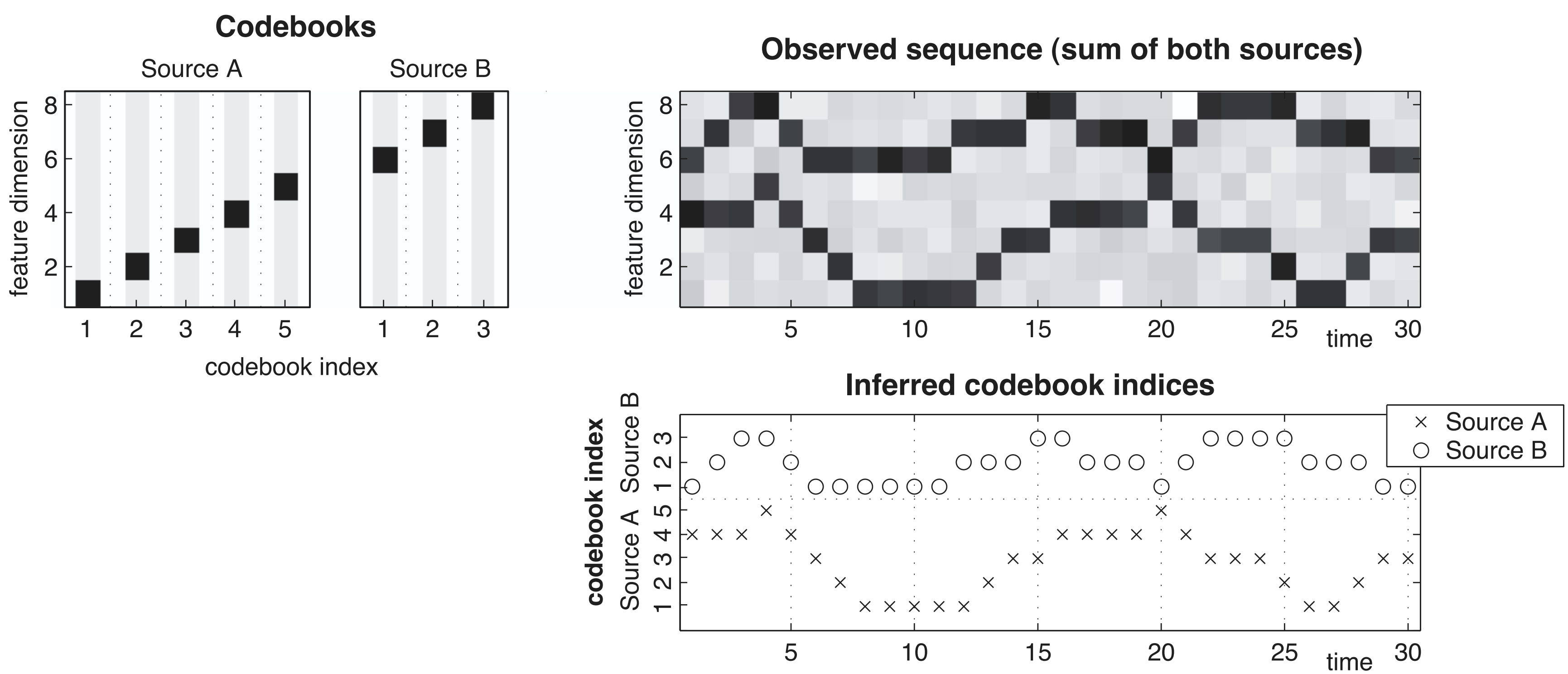
- Ideal separation is rarely possible
  - i.e. no projection can completely remove overlaps
- Overlaps → Ambiguity
  - scene analysis = find "most reasonable" explanation
- Ambiguity can be expressed probabilistically
  - i.e. posteriors of sources $\{S_i\}$ given observations X:

$$P(\{S_i\}|\,X) \propto \underbrace{P(X\,|\{S_i\})}_{\text{combination physics}}\ \underbrace{P(\{S_i\})}_{\text{source models}}$$

- Better source models → better inference
  - .. learn from examples?

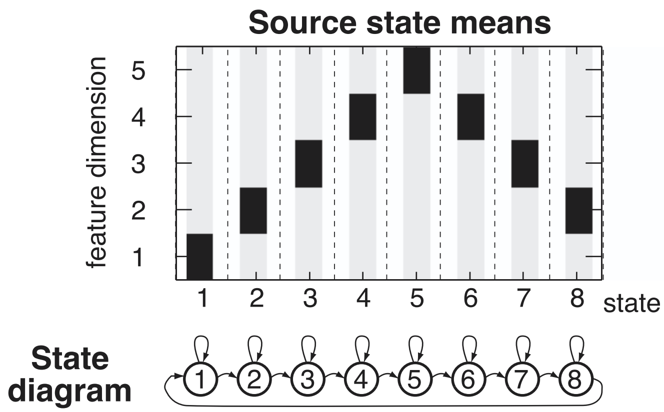
A Simple Example

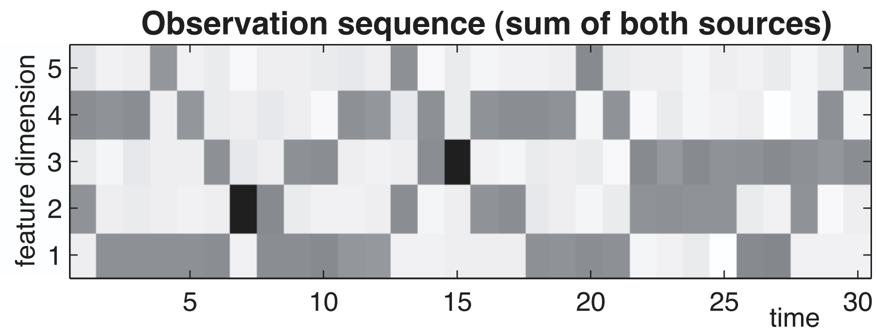
- Source models are codebooks from separate subspaces

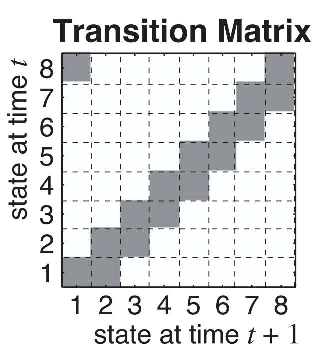


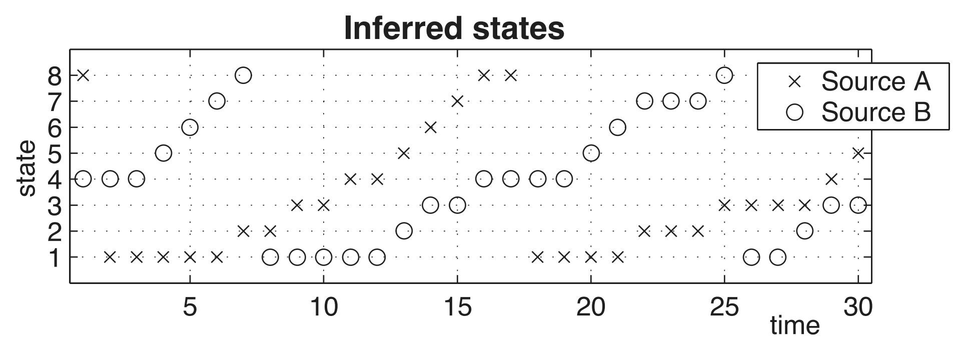
A Slightly Less Simple Example

- Sources with Markov transitions





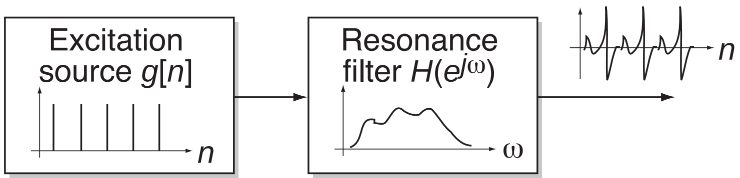




What is a Source Model?

- **Source Model describes signal behavior**
  - encapsulates constraints on form of signal
  - (any such constraint can be seen as a model...)

- **A model has parameters**
  - model + parameters
    → instance



- **What is *not* a source model?**
  - detail not provided in instance
    e.g. using phase from original mixture
  - constraints on interaction between sources
    e.g. independence, clustering attributes

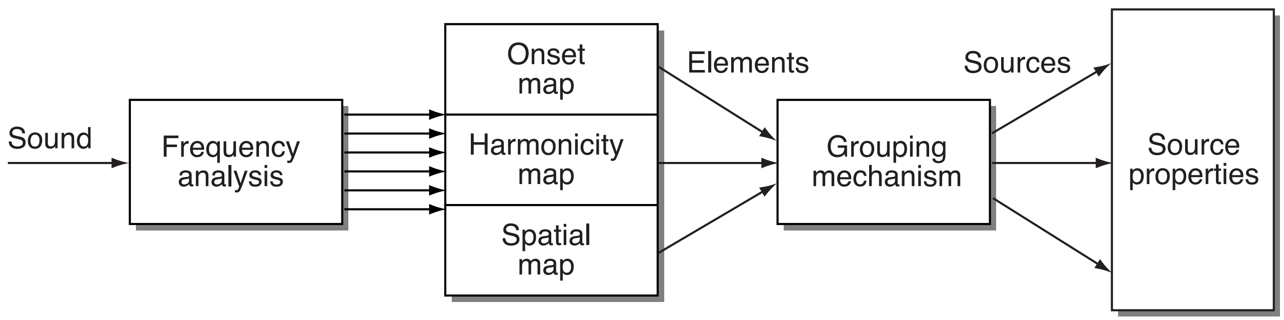
Outline

1. Mixtures and Models
2. Human Sound Organization
   - Auditory Scene Analysis
   - Using source characteristics
   - Illusions
3. Machine Sound Organization
4. Research Questions

Auditory Scene Analysis

Bregman'90
Darwin & Carlyon'95

- **How do people analyze sound mixtures?**
  - break mixture into small elements (in time-freq)
  - elements are grouped in to sources using cues
  - sources have aggregate attributes
- **Grouping rules (Darwin, Carlyon, ...):**
  - cues: common onset/modulation, harmonicity, ...

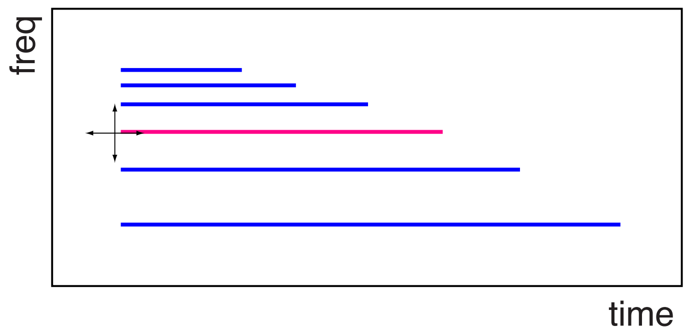


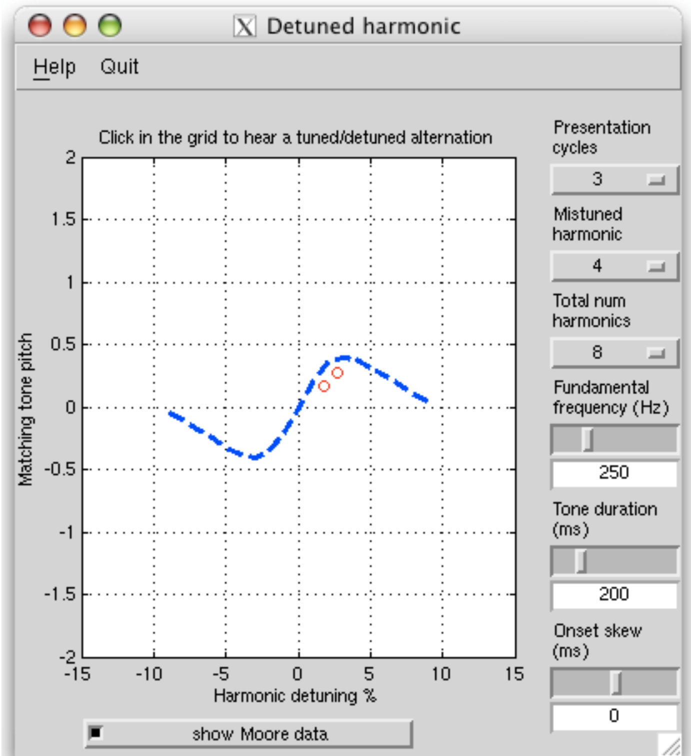
(after Darwin 1996)

- **Also learned "schema" (for speech etc.)**

Perceiving Sources

- Harmonics distinct in ear, but perceived as one source ("fused"):

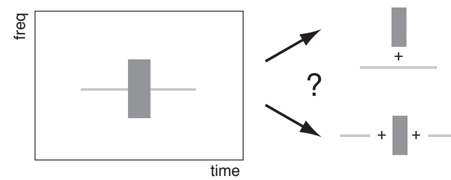


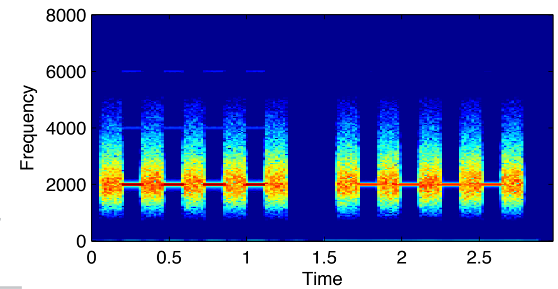


  - depends on common onset
  - depends on harmonics
- Experimental techniques
  - ask subjects "how many"
  - match attributes e.g. pitch, vowel identity
  - brain recordings (EEG "mismatch negativity")

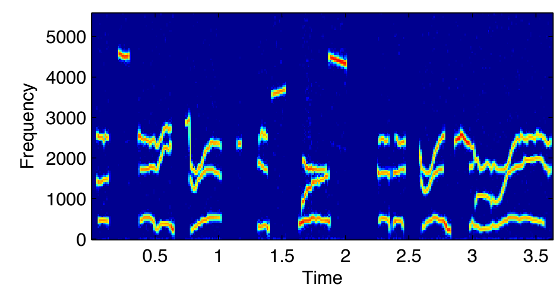
Auditory "Illusions"

- How do we explain illusions?
  - pulsation threshold

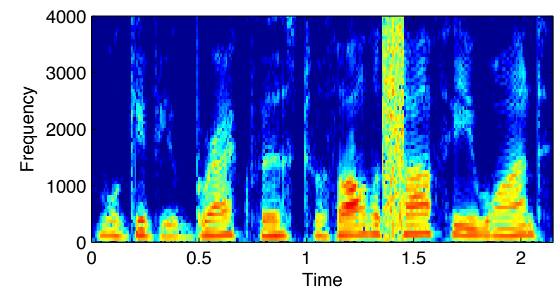




  - sinewave speech



  - phonemic restoration



- Something is providing the missing (illusory) pieces ... source models

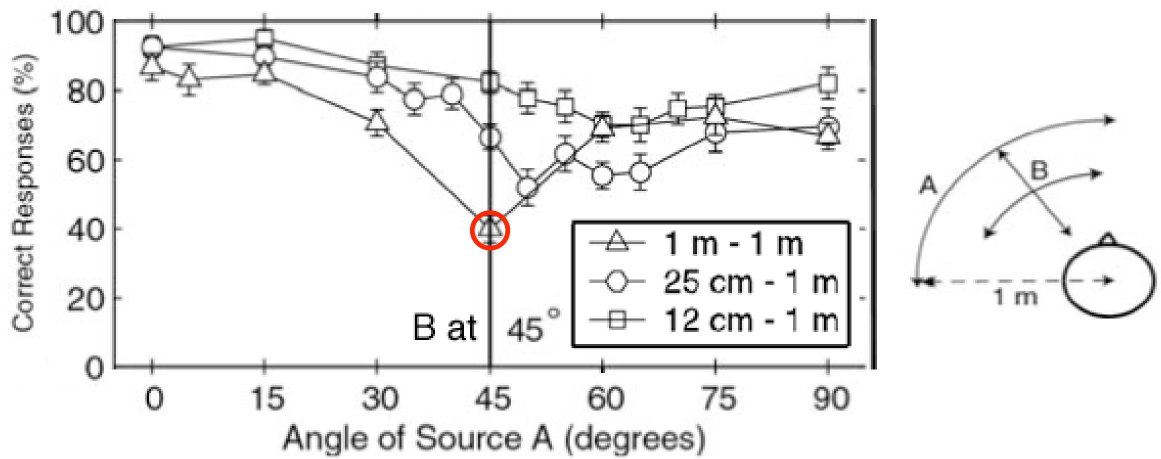
Human Speech Separation

Brungart et al.'02

- Task: Coordinate Response Measure
  - "Ready Baron go to green eight now"
  - 256 variants, 16 speakers
  - correct = color and number for "Baron"

crm-11737+16515.wav

- Accuracy as a function of spatial separation:



  - A, B same speaker
  - Range effect

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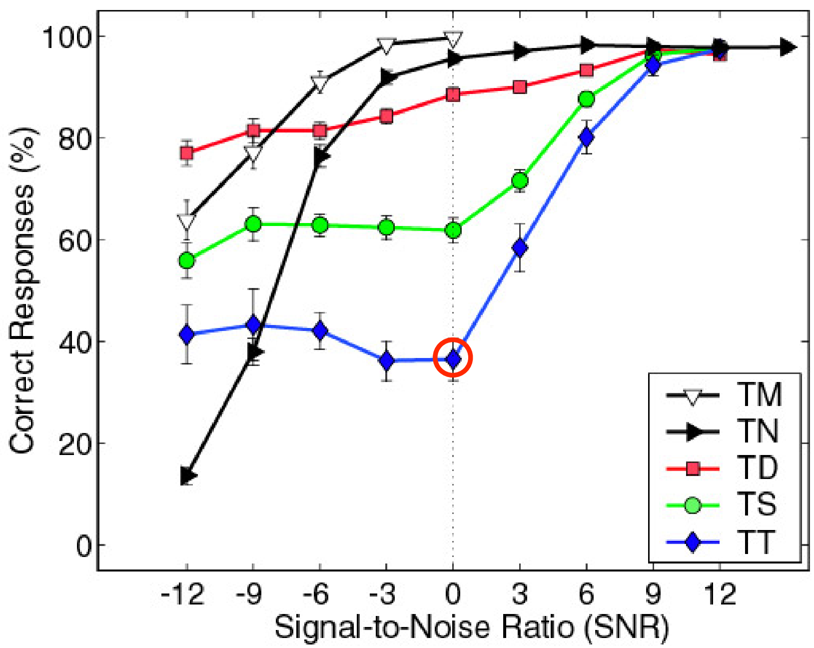
Separation by Vocal Differences

Brungart et al.'01

- CRM varying the level and voice character



(same spatial location)

  - energetic vs. informational masking
  - more than pitch .. source models

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1. Mixtures and Models
2. Human Sound Organization
3. **Machine Sound Organization**
   - Computational Auditory Scene Analysis
   - Dictionary Source Models
4. Research Questions

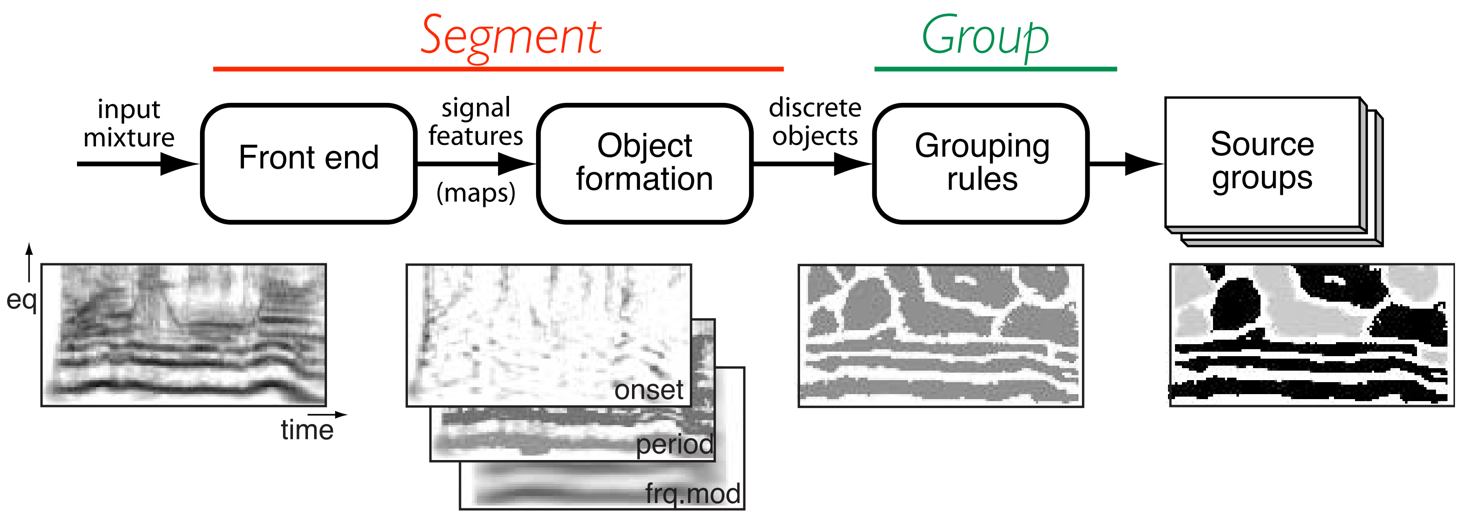
Source Model Issues

- Domain
    - parsimonious expression of constraints
    - nice combination physics
- Tractability
    - size of search space
    - tricks to speed search/inference
- Acquisition
    - hand-designed vs. learned
    - static vs. short-term
- Factorization
    - independent aspects
    - hierarchy & specificity

Computational Auditory Scene Analysis

Brown & Cooke'94
Okuno et al.'99
Hu & Wang'04 ...

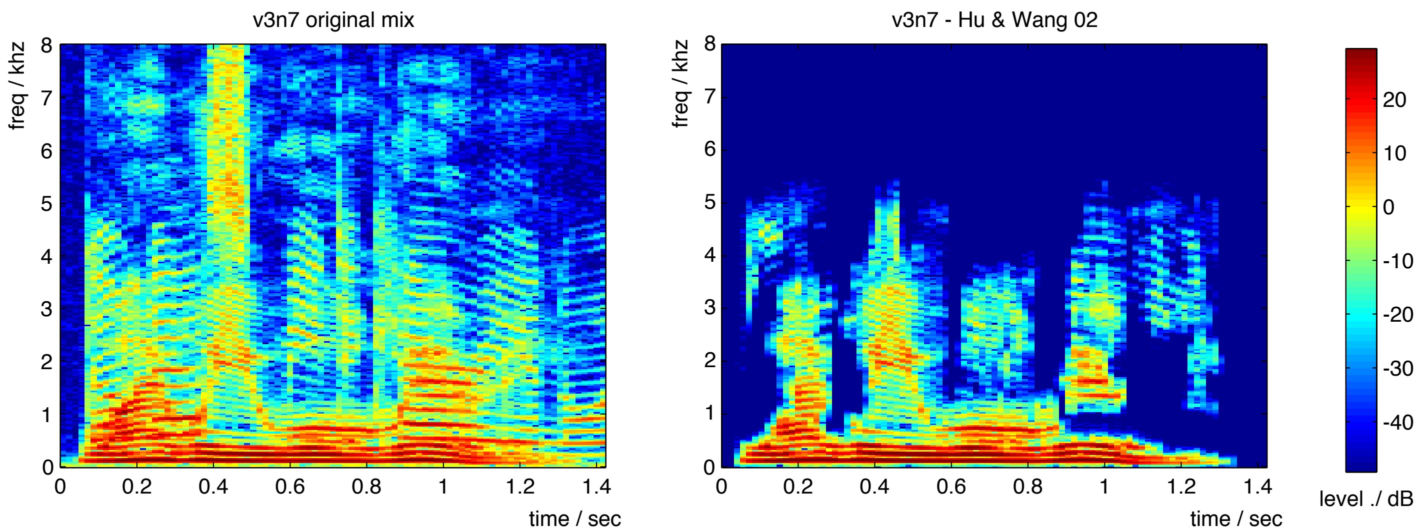
- Central idea:
  Segment time-frequency into sources based on perceptual grouping cues



  - ... principal cue is harmonicity

CASA limitations

- Limitations of T-F masking
  - cannot undo overlaps – leaves gaps



from Hu & Wang '04

huwang-v3n7.wav

- Driven by local features
  - limited model scope → no inference or illusions
- Does not learn from data

Basic Dictionary Models

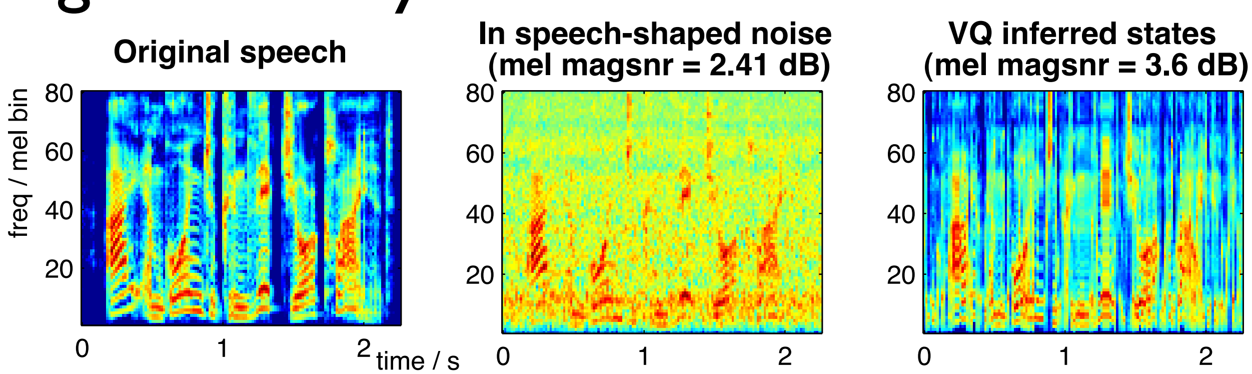
Roweis '01, '03
Kristjannson '04, '06

- Given models for sources,
  find "best" (most likely) states for spectra:

$$p(\mathbf{x}|i_1, i_2) = \mathcal{N}(\mathbf{x}; \mathbf{c}_{i1} + \mathbf{c}_{i2}, \Sigma)$$ combination model

$$\{i_1(t), i_2(t)\} = argmax_{i_1,i_2} p(\mathbf{x}(t)|i_1, i_2)$$ inference of source state

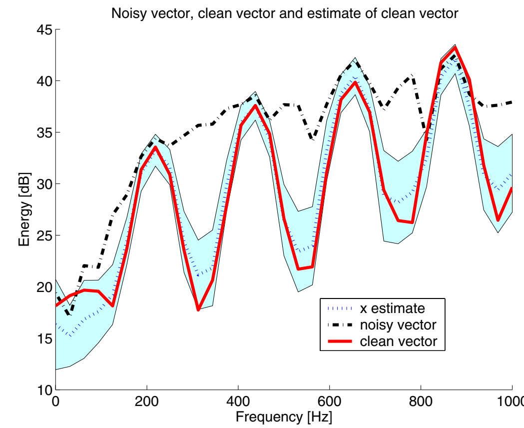
  - can include sequential constraints...
  - different domains for combining $\mathbf{c}$ and defining Σ
- E.g. stationary noise:



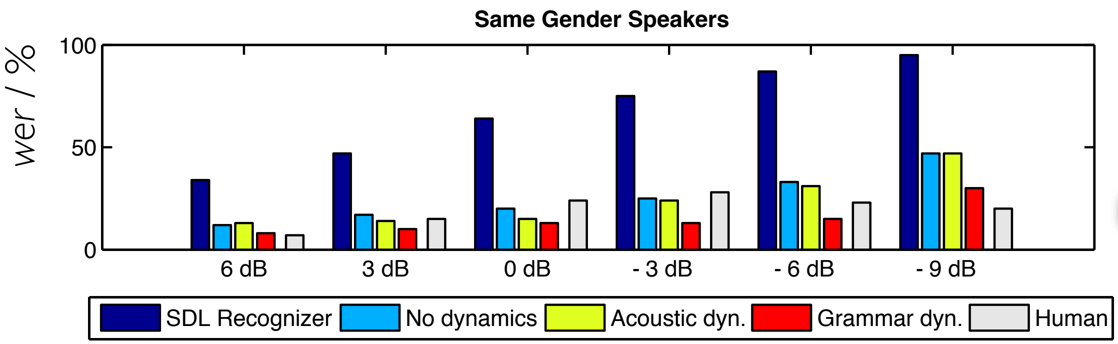
Deeper Models: Iriquois

Kristjansson, Hershey et al. '06

- Optimal inference on mixed spectra
  - speaker-specific models (e.g. 512 mix GMM)
  - Algonquin inference



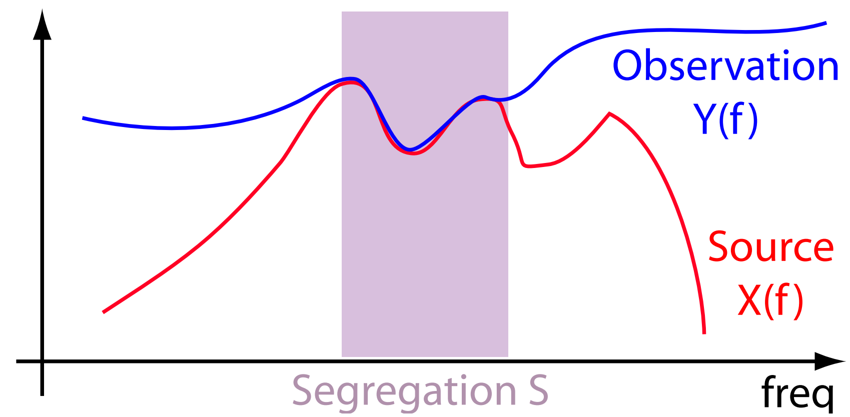
- .. for Speech Separation Challenge (Cooke/Lee'06)
  - exploit grammar constraints - higher-level dynamics



Faster Search: Fragment Decoder

Barker et al. '05

- Match 'uncorrupt' spectrum to ASR models using **missing data recognition**
  - easy if you know the segregation mask S



- Joint search for model M and segregation S to maximize:

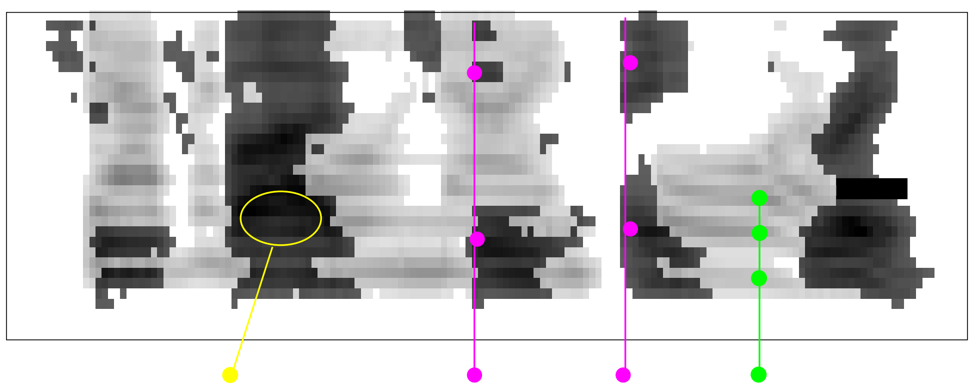
$$P(M, S|Y) = P(M)\int P(X|M) \cdot \frac{P(X|Y,S)}{P(X)} dX \cdot P(S|Y)$$

Isolated Source Model *Segregation Model*

CASA in the Fragment Decoder

$$P(M,S|Y) = P(M)\int P(X|M)\cdot \frac{P(X|Y,S)}{P(X)}dX \cdot P(S|Y)$$

- CASA can help search
  - consider only segregations made from CASA chunks
- CASA can rate segregation
  - construct $P(S|Y)$ to reward CASA qualities:

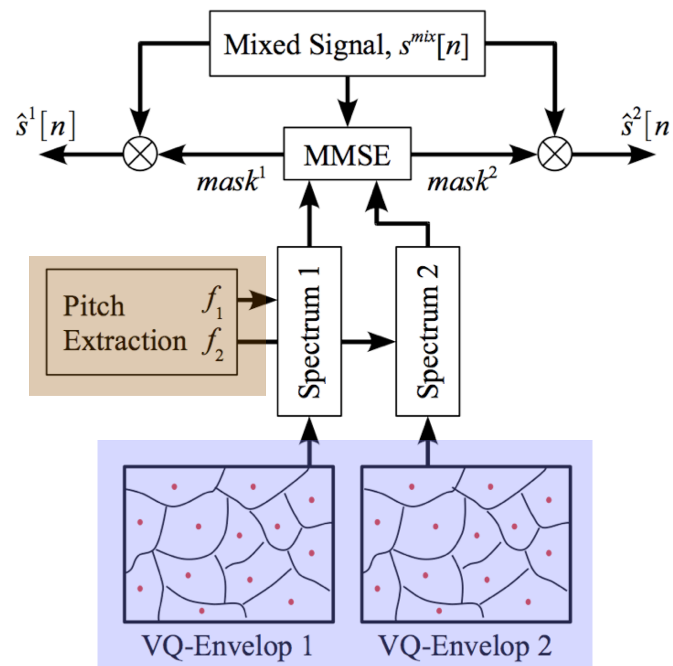


(Pitch) Factored Dictionaries

Ghandi & Has-John. '04
Radfar et al. '06

- Separate representations for "source" (pitch) and "filter"
  - NM codewords from $N+M$ entries
  - but: overgeneration...

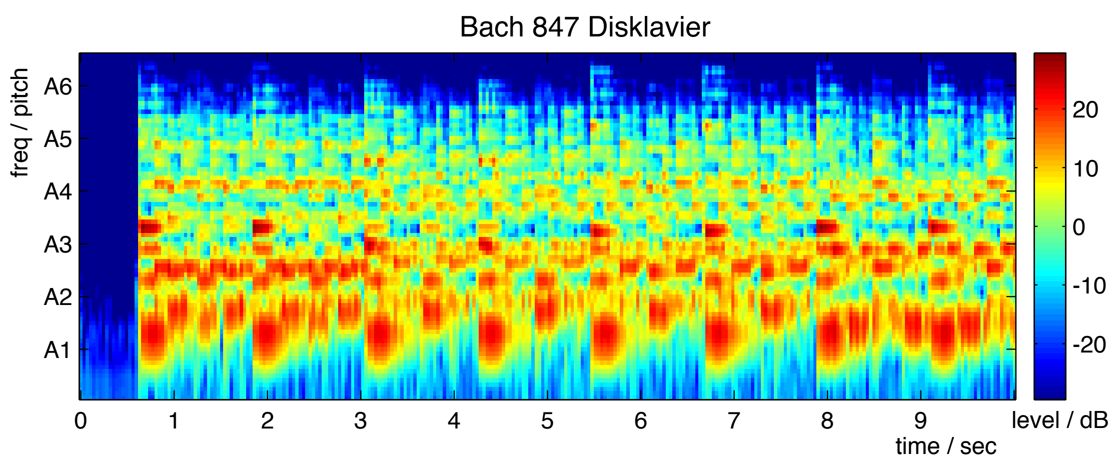
- Faster search
  - direct extraction of pitches
  - immediate separation of (most of) spectra



Discriminant Models for Music

Poliner & Ellis '06

- Transcribe piano recordings by classification
  - train SVM detectors for every piano note
  - 88 separate detectors, independent smoothing
- Trained on player piano recordings



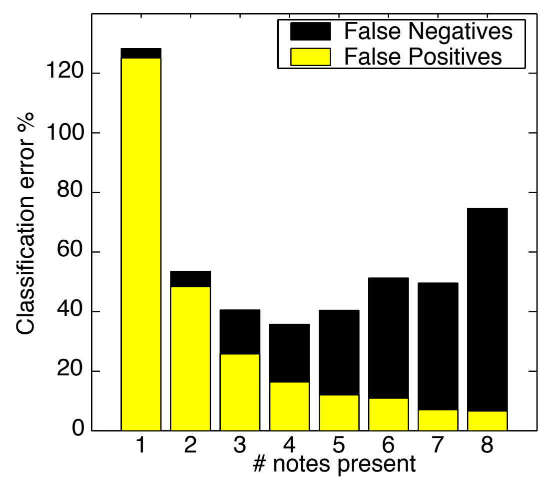
- Can resynthesize from transcript...

Piano Transcription Results

- Significant improvement from classifier:
  - frame-level accuracy results:

Algorithm	Errs	False Pos	False Neg	d'
SVM	43.3%	27.9%	15.4%	3.44
Klapuri&Ryynänen	66.6%	28.1%	38.5%	2.71
Marolt	84.6%	36.5%	48.1%	2.35

  - Breakdown by frame type:
  -

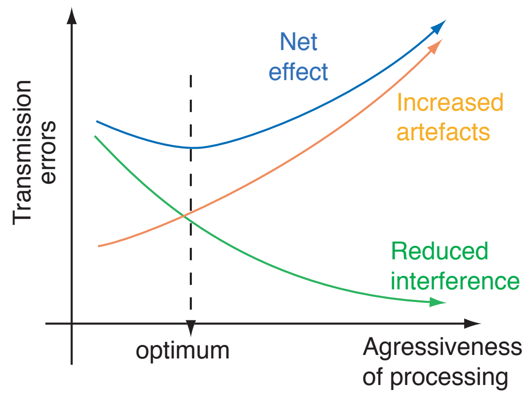


Outline

1. Mixtures & Models
2. Human Sound Organization
3. Machine Sound Organization
4. **Research Questions**
    - Task and Evaluation
    - Generic vs. Specific

Task & Evaluation

- How to measure separation performance?
  - depends what you are trying to do
- SNR?
  - energy (and distortions) are not created equal
  - different nonlinear components *[Vincent et al. '06]*
- Human Intelligibility?
  - rare for nonlinear processing to improve intelligibility
  - listening tests expensive

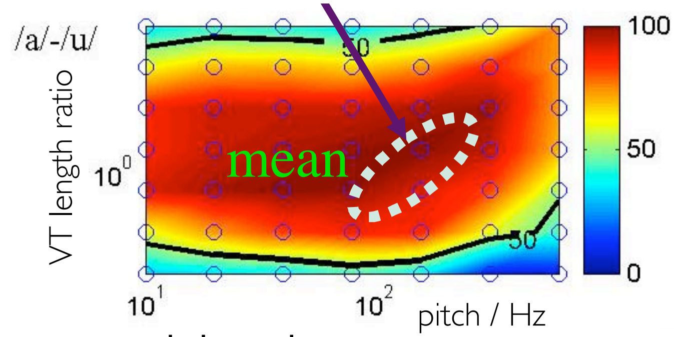


- ASR performance?
  - separate-then-recognize too simplistic; ASR needs to accommodate separation

How Many Models?

- More specific models → better separation
  - need individual dictionaries for "everything"??
- Model adaptation and hierarchy
  - speaker adapted models : base + parameters
  - extrapolation beyond normal

Smith, Patterson et al. '05



  - generic-specific: pitched → piano → this piano
- Time scales of model acquisition
  - innate/evolutionary (hair-cell tuning)
  - developmental (mother tongue phones)
  - dynamic - the "slung mugs" effect; Ozerov

Summary & Conclusions

- **Listeners do well separating sound mixtures**
  - using signal cues (location, periodicity)
  - using source-property variations
- **Machines do less well**
  - difficult to apply enough constraints
  - need to exploit signal detail
- **Models capture constraints**
  - learn from the real world
  - adapt to sources
- **Separation feasible only sometimes**
  - describing source properties is easier