Analysis of Everyday Sounds

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1. Personal and Consumer Audio
2. Segmenting & Clustering
3. Special-Purpose Detectors
4. Generic Concept Detectors
5. Challenges & Future

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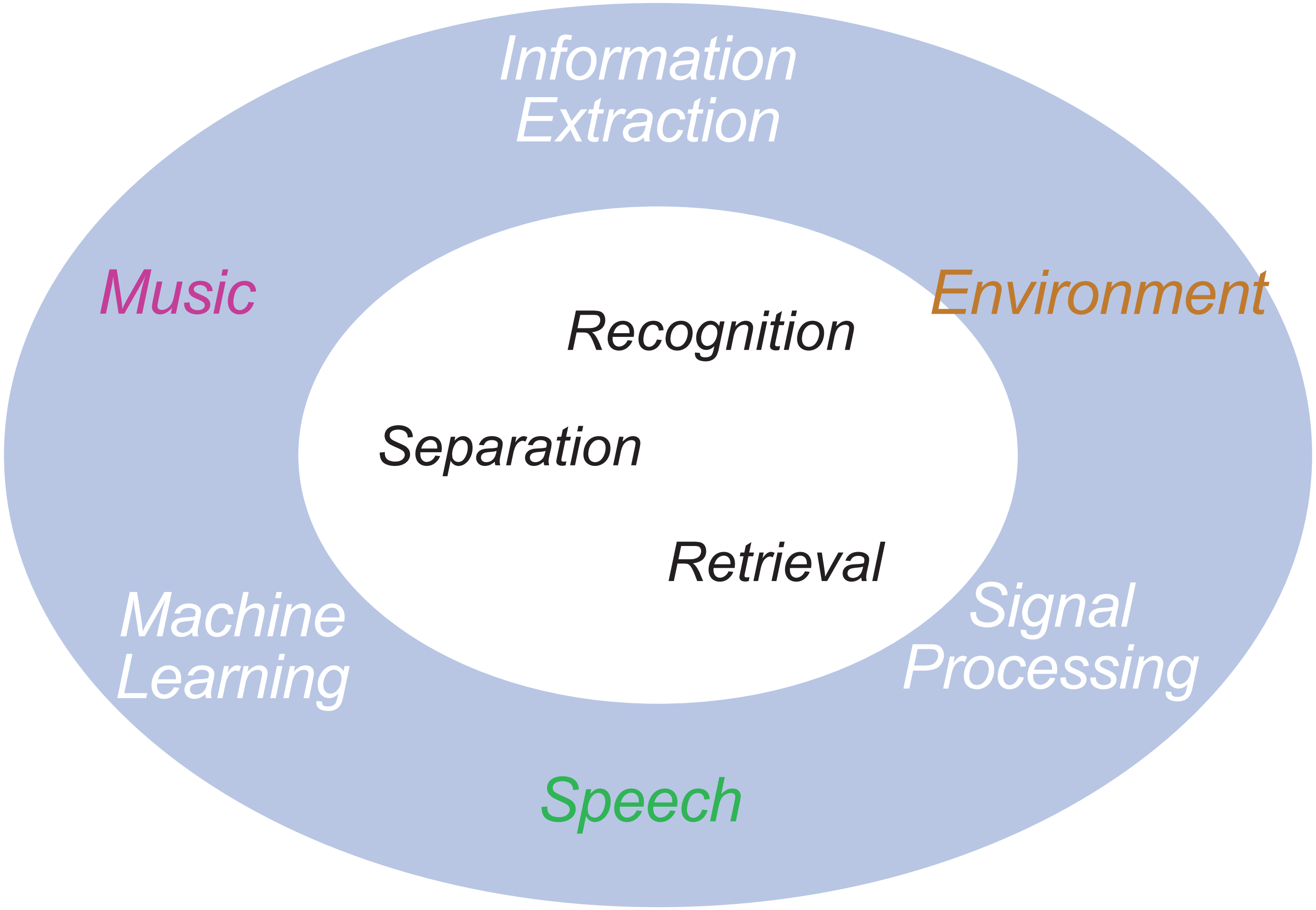
LabROSA Overview



1. Personal Audio Archives

- Easy to record everything you hear
  - <2GB / week @ 64 kbps
- Hard to find anything
  - how to scan?
  - how to visualize?
  - how to index?
- Need automatic analysis
- Need minimal impact

Personal Audio Applications

- Automatic appointment-book history
  - fills in when & where of movements
- "Life statistics"
  - how long did I spend in meetings this week?
  - most frequent conversations
  - favorite phrases?
- Retrieving details
  - what exactly did I promise?
  - privacy issues...
- Nostalgia
- ... or what?

Consumer Video

- Short video clips as the evolution of snapshots
    - 10-60 sec, one location, no editing
    - browsing?
- More information for indexing...
    - video + audio
    - foreground + background

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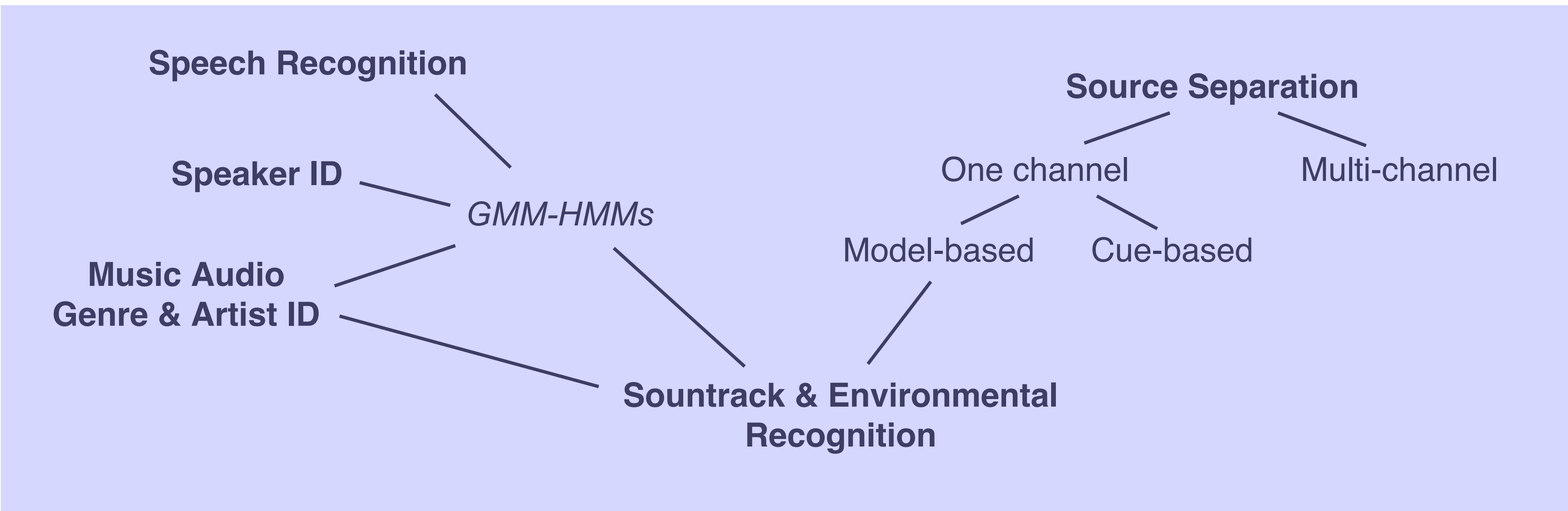
Information in Audio

- **Environmental recordings contain info on:**
  - location – type (restaurant, street, ...) and specific
  - activity – talking, walking, typing
  - people – generic (2 males), specific (Chuck & John)
  - spoken content ... maybe
- **but not:**
  - what people and things "looked like"
  - day/night ...
  - ... except when correlated with audible features

A Brief History of Audio Processing

- Environmental sound classification draws on earlier sound classification work
  - as well as source separation...

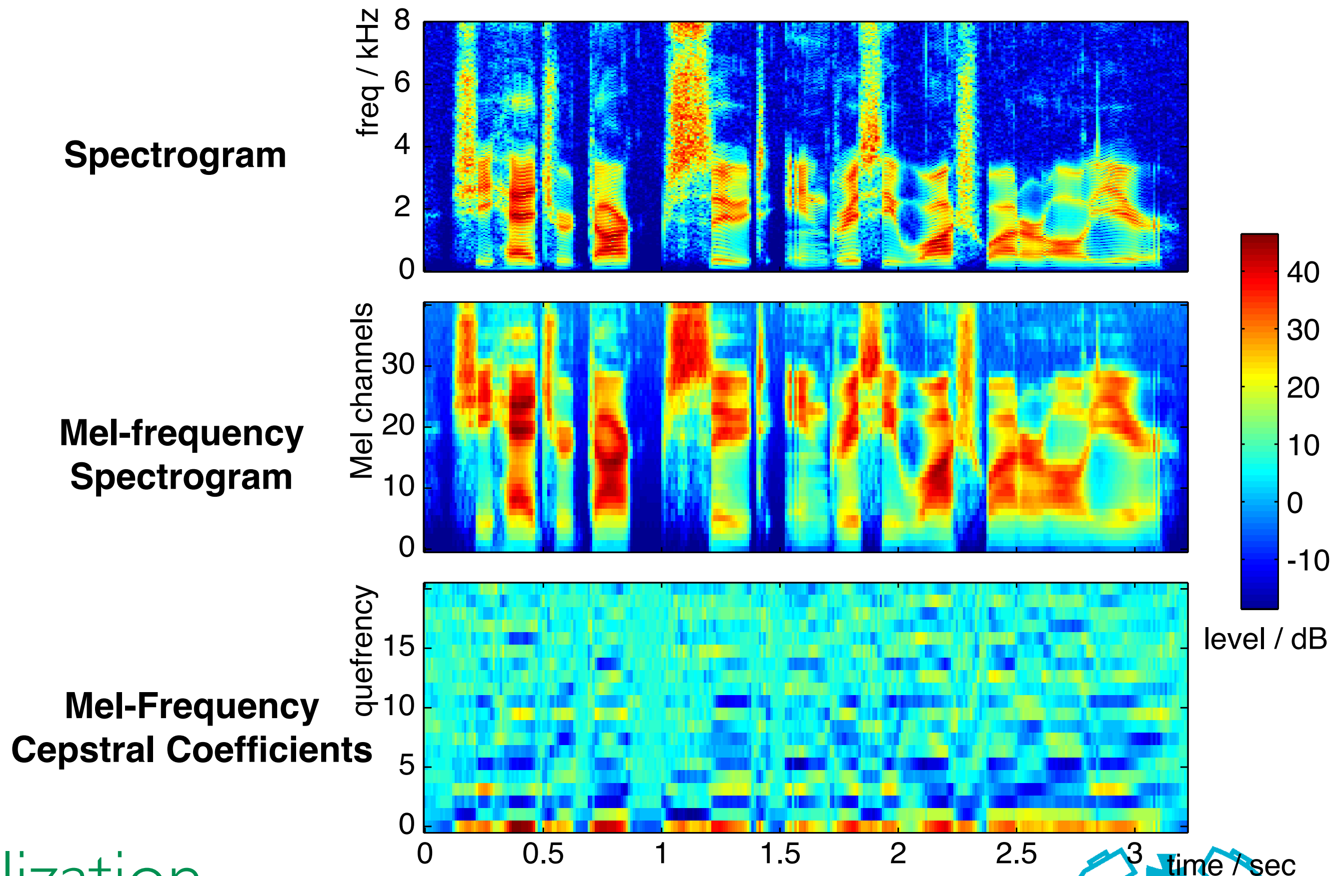


2. Segmentation & Clustering

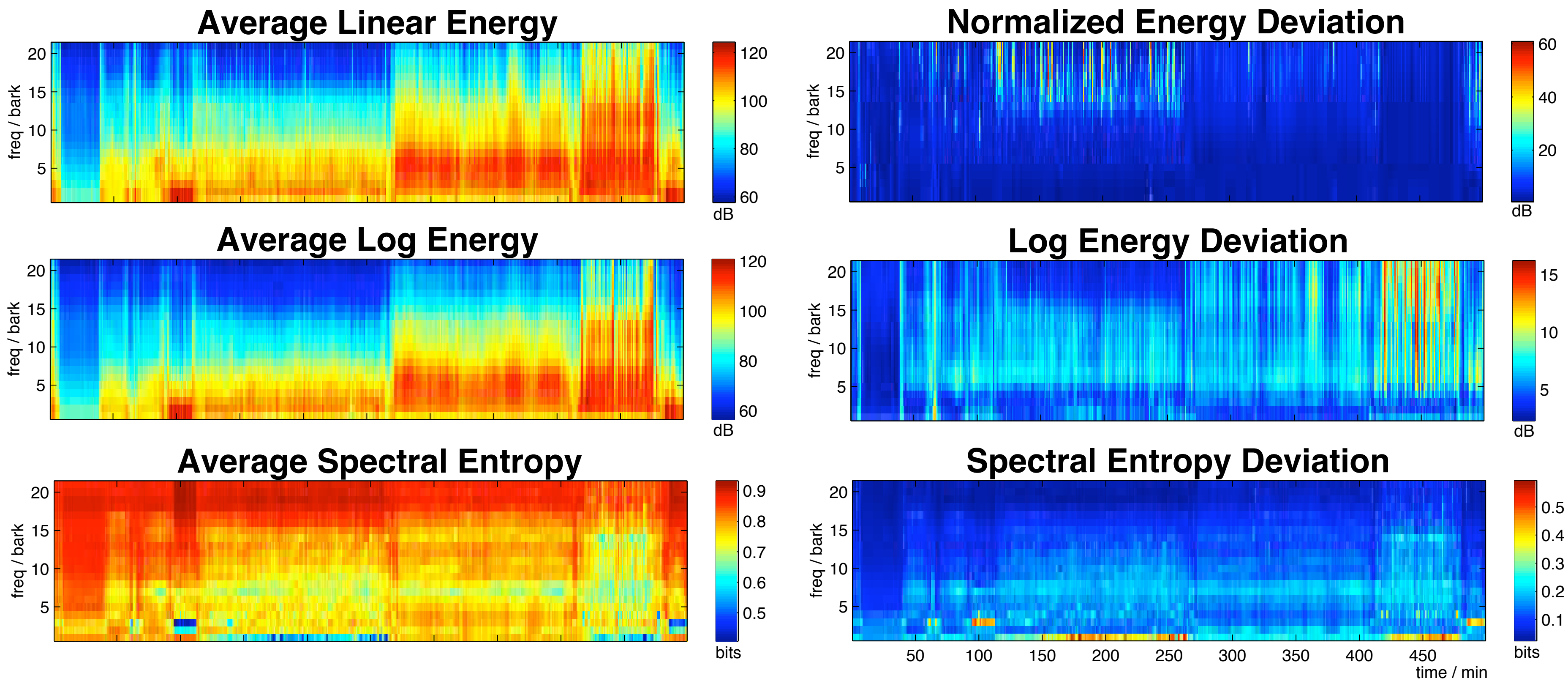
- Top-level structure for long recordings: Where are the major boundaries?
  - e.g. for diary application
  - support for manual browsing
- Length of fundamental time-frame
  - 60s rather than 10ms?
  - background more important than foreground
  - average out uncharacteristic transients
- Perceptually-motivated features
  - .. so results have perceptual relevance
  - broad spectrum + some detail

MFCC Features

- Need "timbral" features:
  Mel-Frequency Cepstral Coeffs (MFCCs)
  - auditory-like frequency warping
  - log-domain
  - discrete cosine transform = orthogonalization



Long-Duration Features

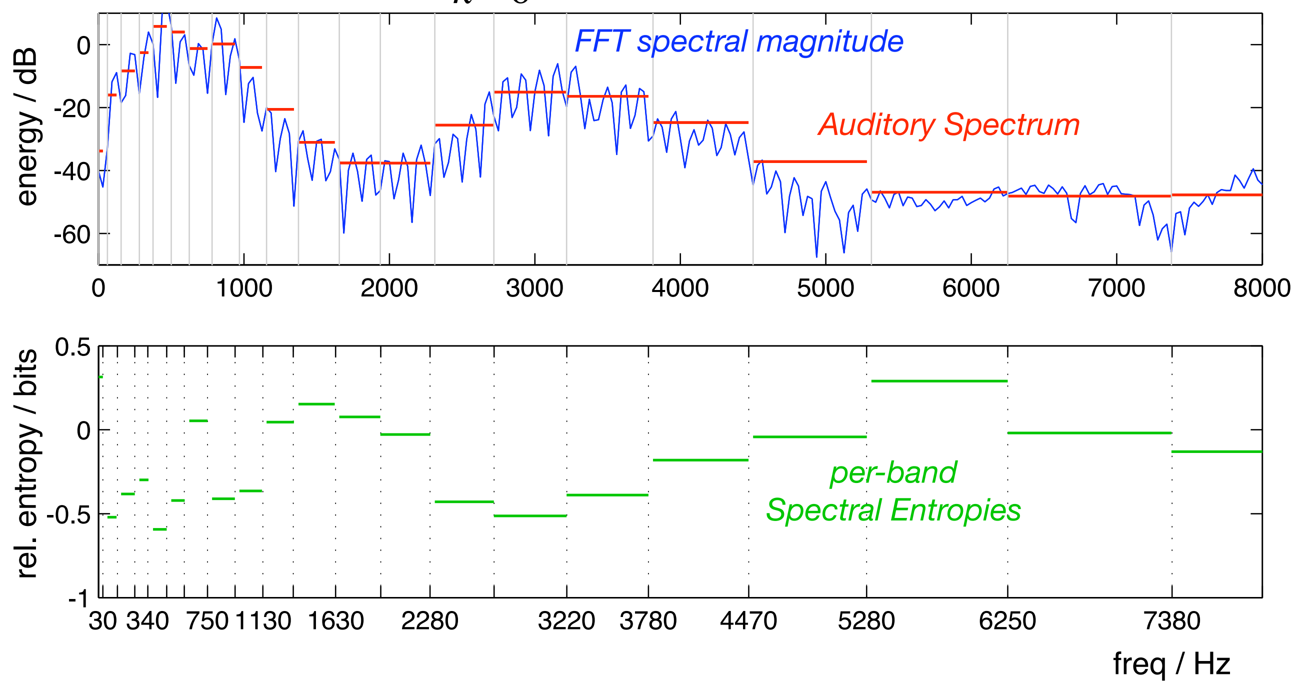


- Capture both average and variation
- Capture a little more detail in subbands...

Spectral Entropy

- Auditory spectrum: $A[n,j] = \sum_{k=0}^{N_F} w_{jk} X[n,k]$
- Spectral entropy ≈ 'peakiness' of each band:

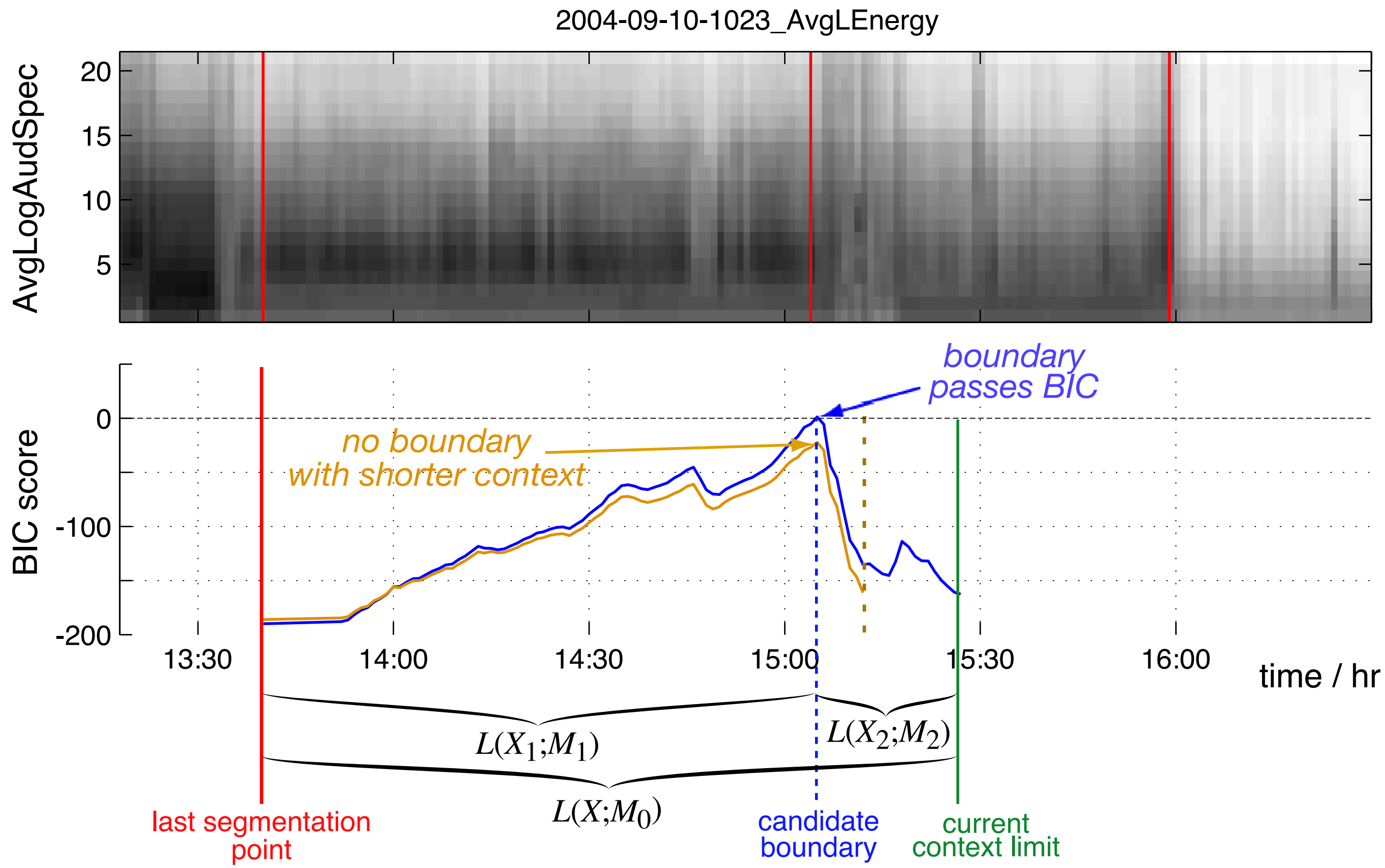
$$H[n,j] = -\sum_{k=0}^{N_F} \frac{w_{jk} X[n,k]}{A[n,j]} \cdot log\left(\frac{w_{jk} X[n,k]}{A[n,j]}\right)$$



BIC Segmentation

- BIC (Bayesian Info. Crit.) compares models:

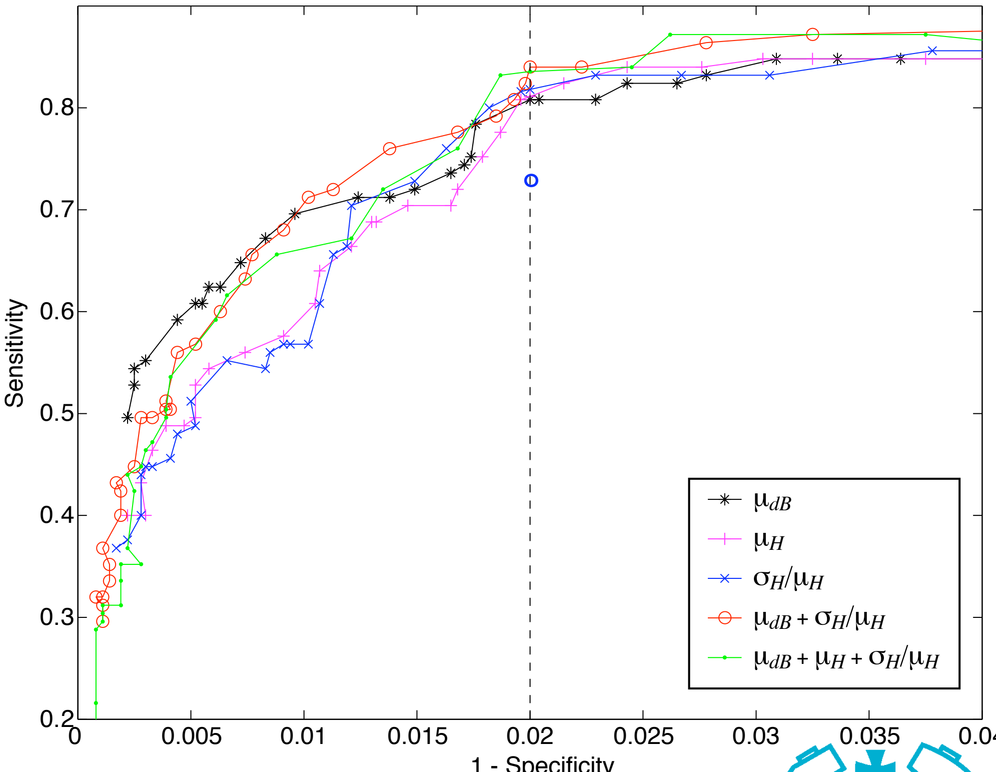
$$\log \frac{L(X_1;M_1)L(X_2;M_2)}{L(X;M_0)} \gtrless \frac{\lambda}{2} \log(N)\Delta\#(M)$$



BIC Segmentation Results

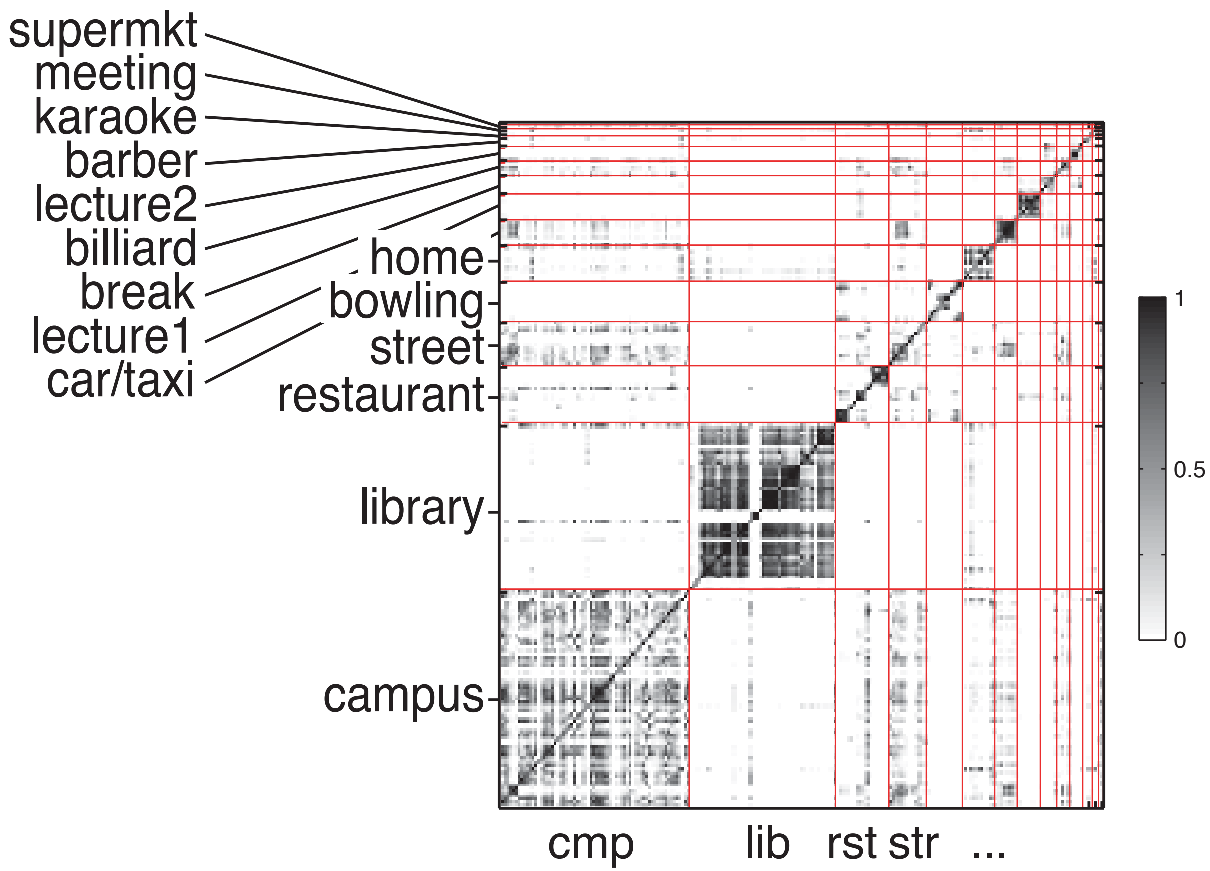
- **Evaluate: 62 hr hand-marked dataset**
  - 8 days, 139 segments, 16 categories
  - measure Correct Accept % @ False Accept = 2%:

Feature	*Correct Accept*
μ_{dB}	80.8%
μ_{H}	81.1%
σ_H/μ_H	81.6%
$\mu_{dB} + \sigma_H/\mu_H$	84.0%
$\mu_{dB} + \sigma_H/\mu_H + \mu_H$	83.6%
mfcc	73.6%



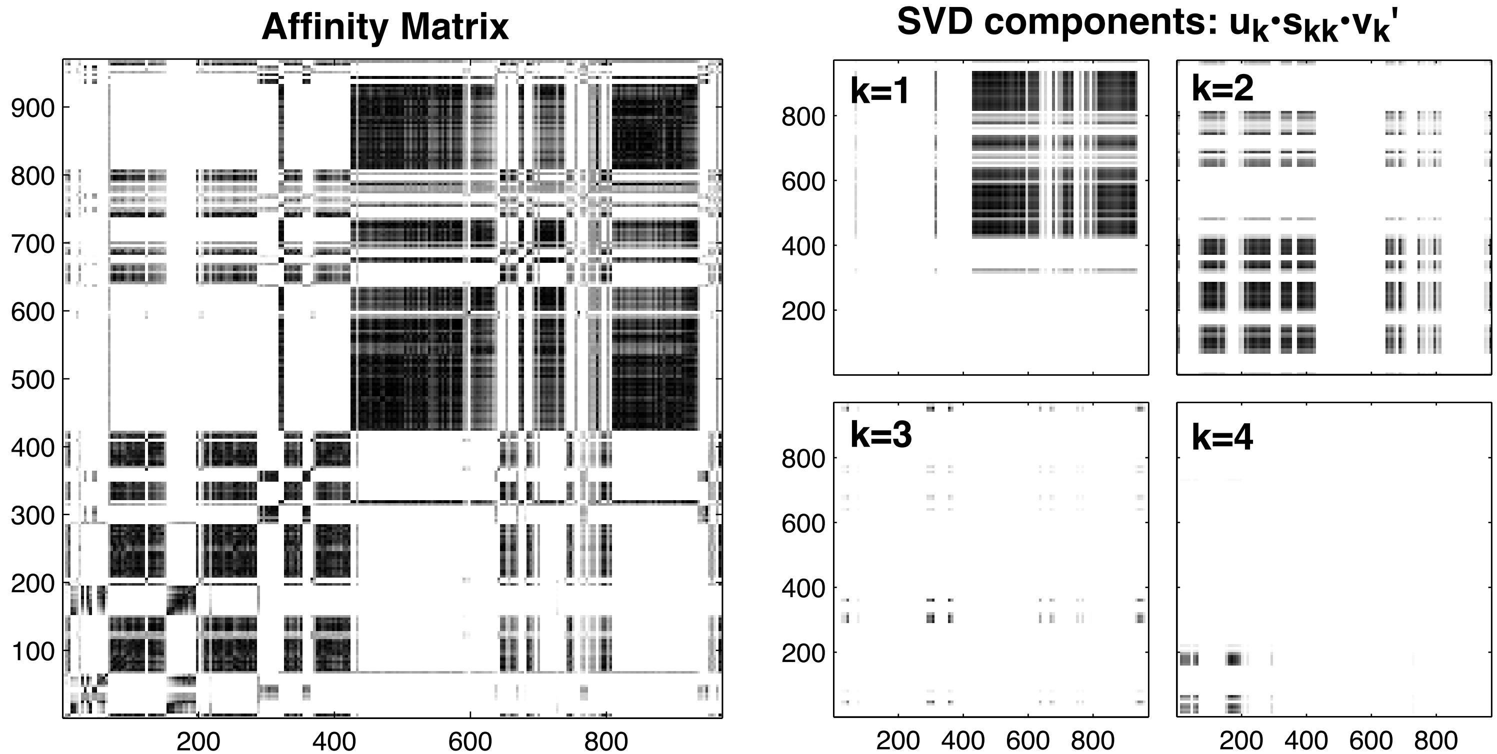
Segment Clustering

- Daily activity has lots of repetition:
  Automatically cluster similar segments
  - 'affinity' of segments as KL2 distances



Spectral Clustering

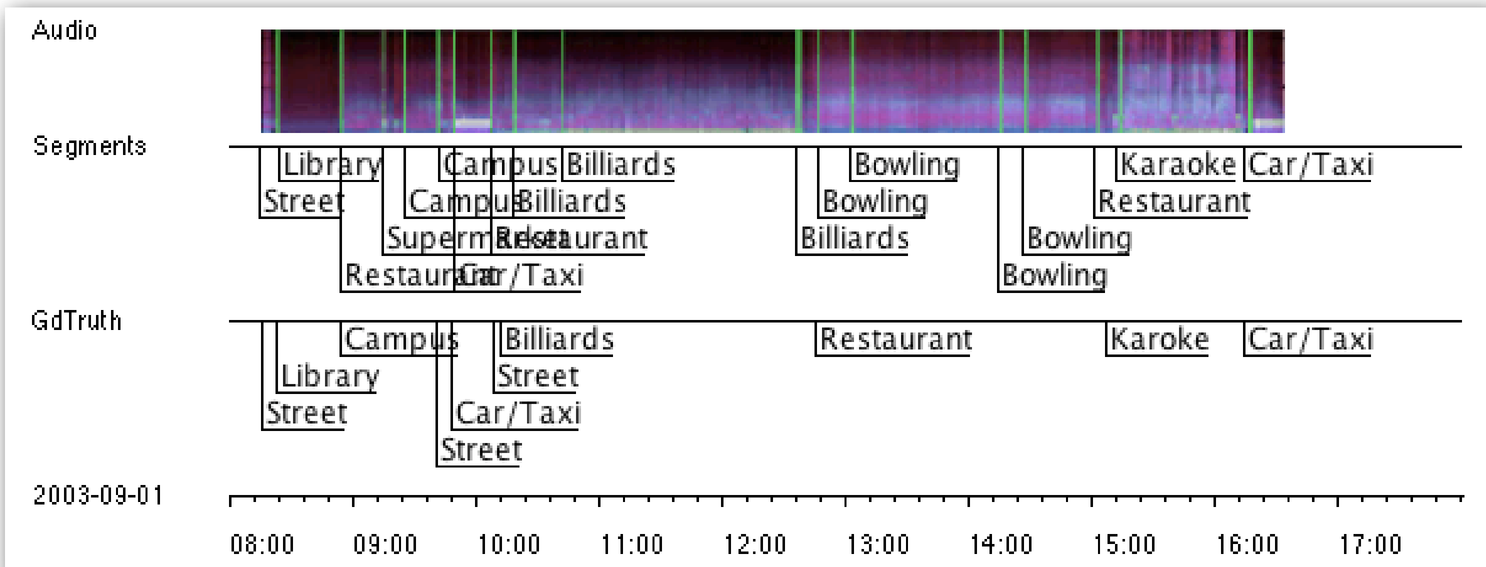
- Eigenanalysis of affinity matrix: $A = U \bullet S \bullet V'$



  - eigenvectors v_k give cluster memberships
- Number of clusters?

Clustering Results

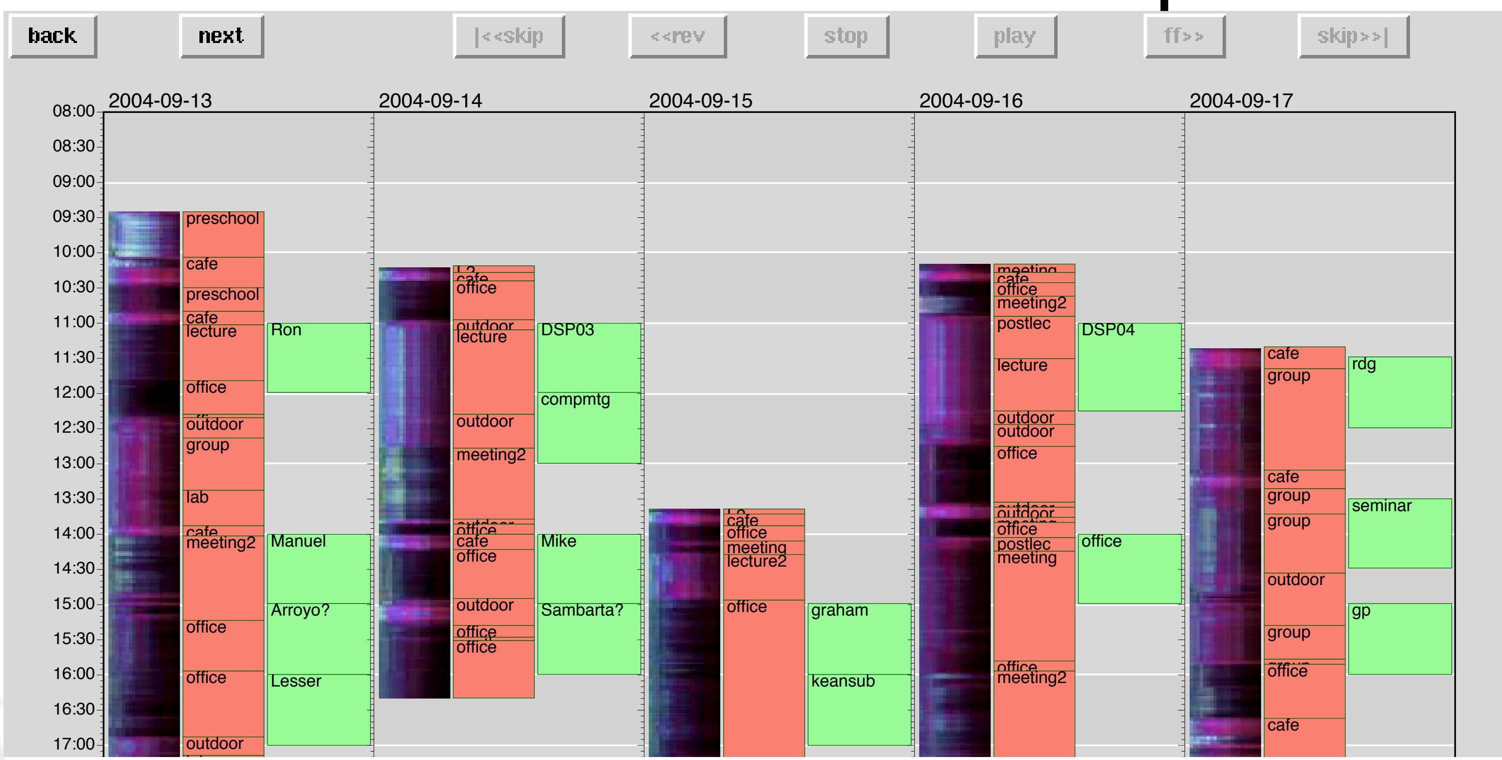
- Clustering of automatic segments gives 'anonymous classes'
  - BIC criterion to choose number of clusters
  - make best correspondence to 16 GT clusters



- Frame-level scoring gives ~70% correct
  - errors when same 'place' has multiple ambiences

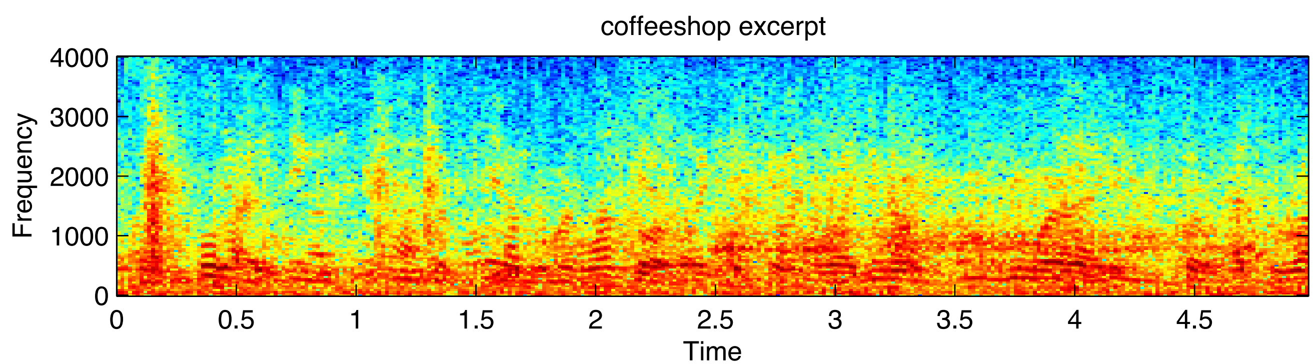
Browsing Interface

- Browsing / Diary interface
  - links to other information (diary, email, photos)
  - synchronize with note taking? *(Stifelman & Arons)*
  - audio thumbnails
- Release Tools + "how to" for capture



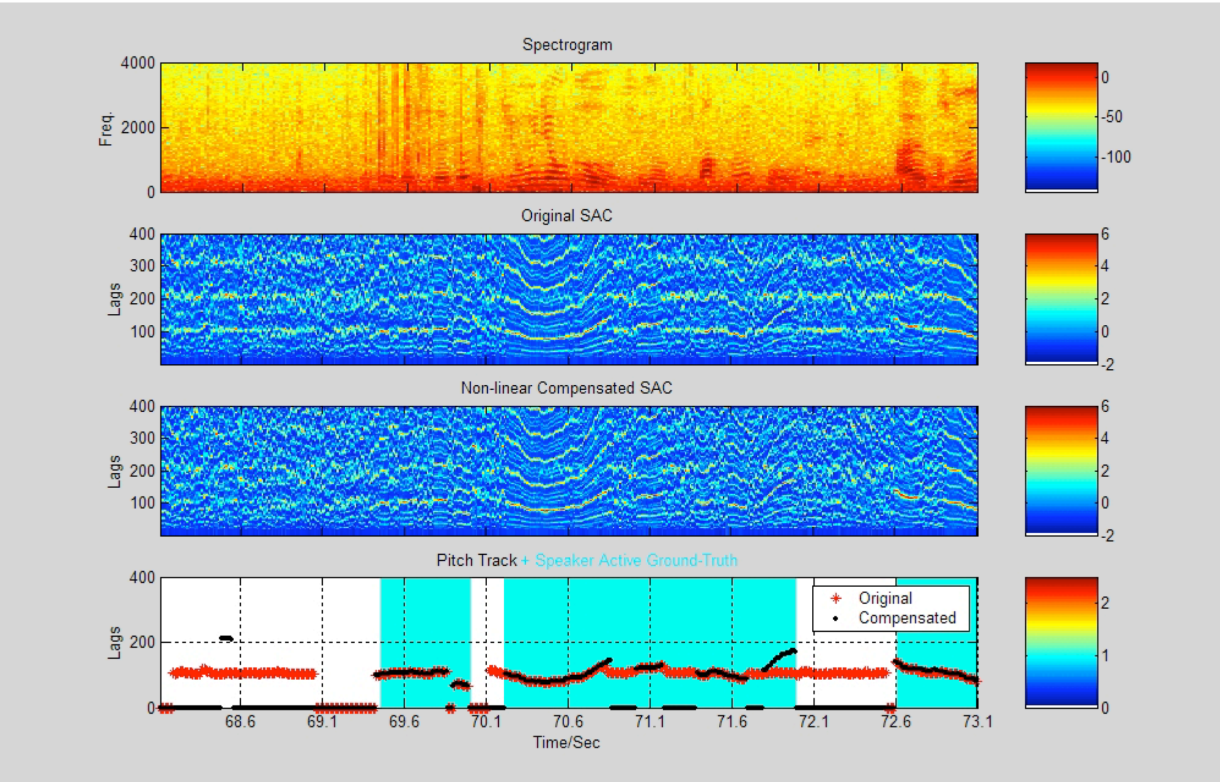
3. Special-Purpose Detectors: Speech

- Speech emerges as most interesting content
- Just identifying speech would be useful
  - goal is speaker identification / labeling
- Lots of background noise
  - conventional Voice Activity Detection inadequate
- Insight: Listeners detect pitch track (melody)
  - look for voice-like periodicity in noise



Voice Periodicity Enhancement

- Noise-robust subband autocorrelation



- Subtract local average
  - suppresses steady background e.g. machine noise
  - 15 min test set; 88% acc (no suppression: 79%)
  - also for enhancing speech by harmonic filtering

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Detecting Repeating Events

with Jim Ogle

- Recurring sound events can be informative
  - indicate similar circumstance...
  - but: define "event" – sound organization
  - define "recurring event" – how similar?
  - .. and how to find them – tractable?
- Idea: Use hashing (fingerprints)
  - index points to other occurrences of each hash; intersection of hashes points to match - much quicker search
  - use a fingerprint insensitive to background?

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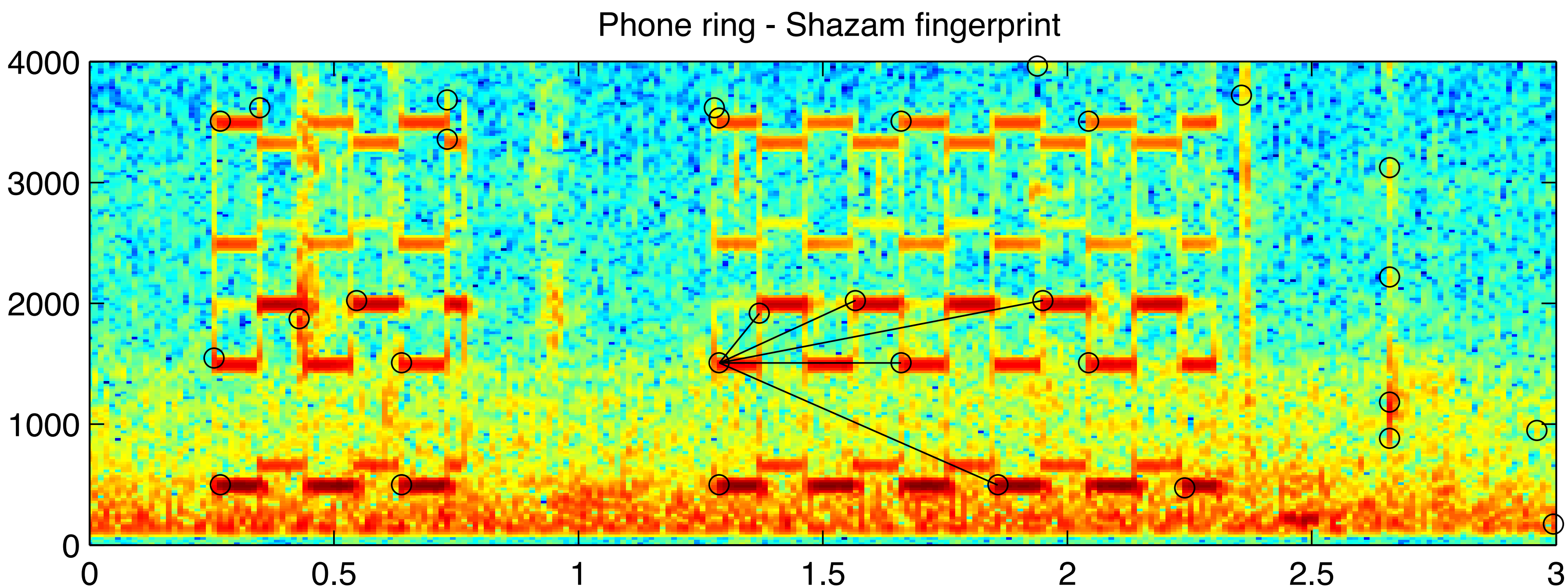
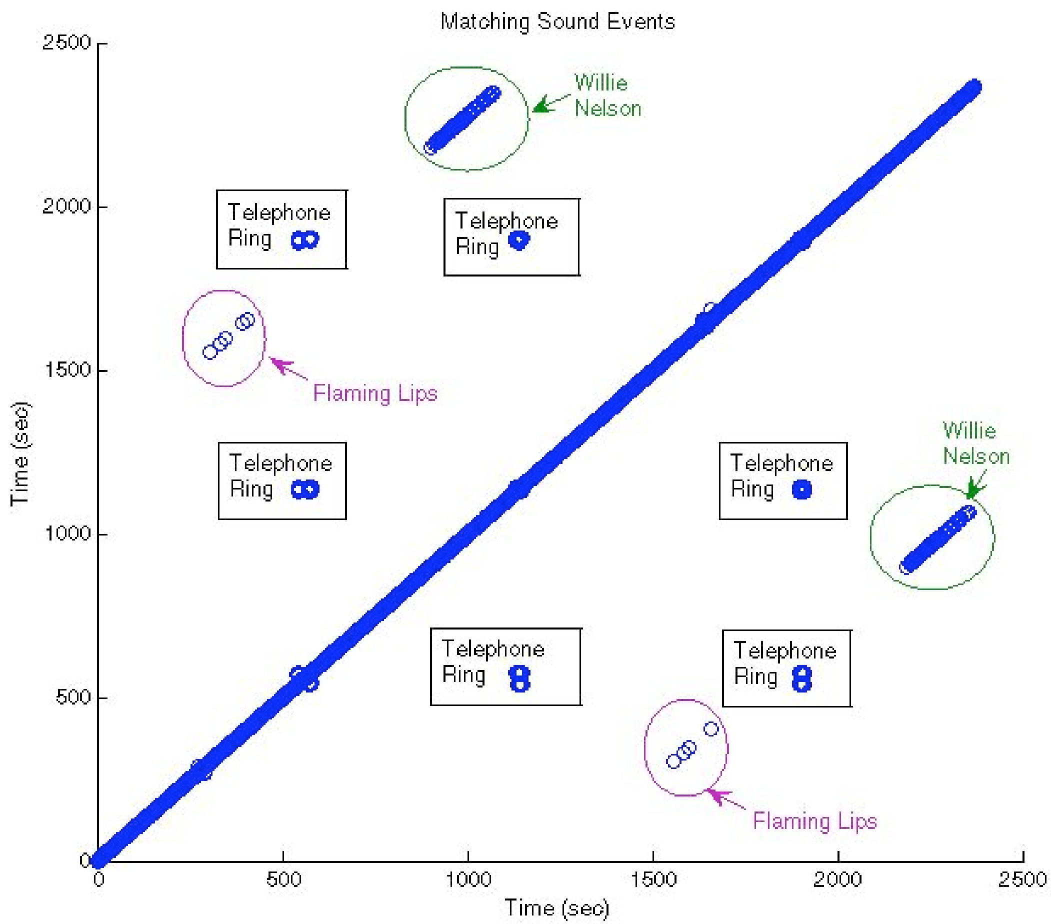
Shazam Fingerprints

- Prominent spectral onsets are landmarks;
  Use relations $\{f_1, f_2, \Delta t\}$ as hashes



  - intrinsically robust to background noise

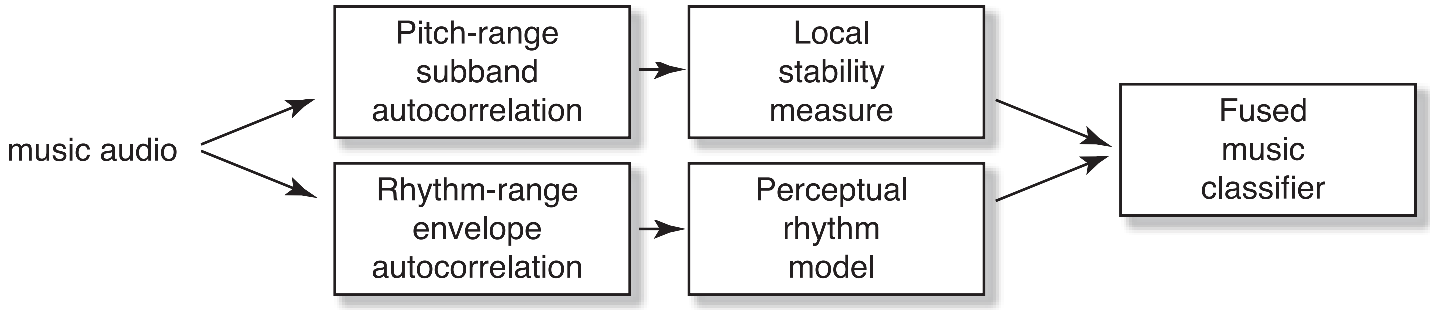
Exhaustive Search for Repeats



- More selective hashes →
  - few hits required to confirm match (faster; better precision)
  - but less robust to backgound (reduce recall)
- Works well when exact structure repeats
  - recorded music, electronic alerts
  - no good for "organic" sounds e.g. garage door

Music Detector

- Two characteristic features for music
  - strong, sustained periodicity (notes)
  - clear, rhythmic repetition (beat)
  - at least one should be present!



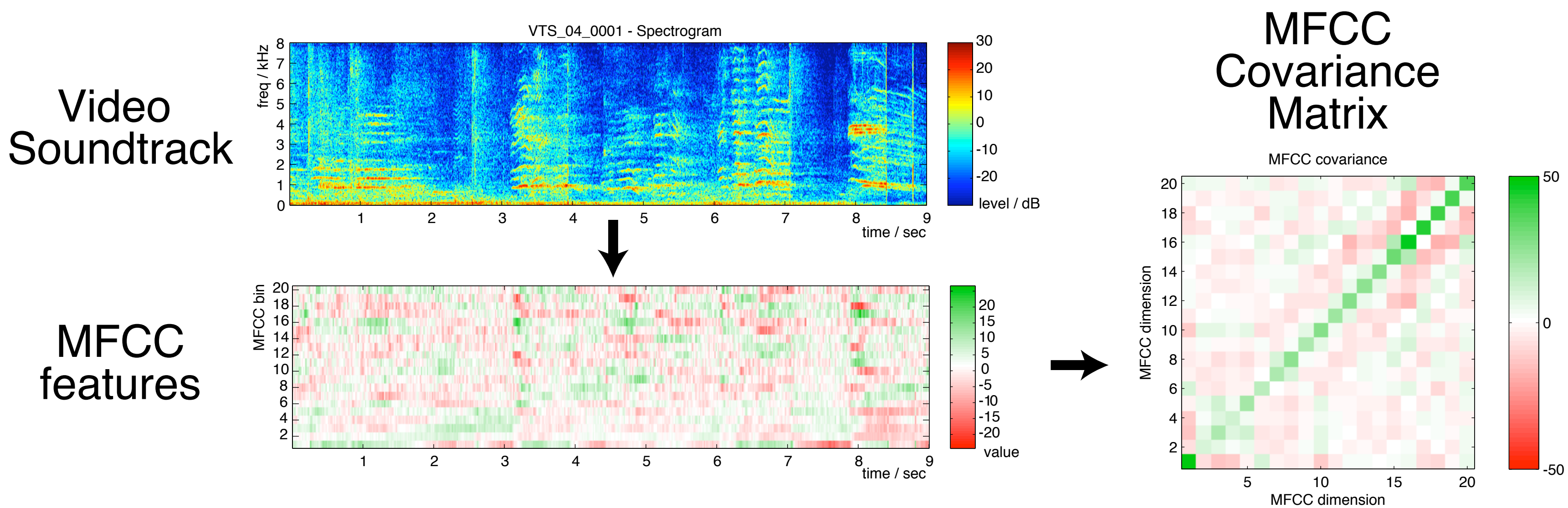
- Noise-robust pitch detector
  - looks for high-order autocorrelation
- Beat tracker
  - .. from Music IR work

4. Generic Concept Detectors

- Consumer Video application:
  How to assist browsing?
  - system automatically tags recordings
  - tags chosen by usefulness, feasibility
- Initial set of 25 tags defined:
  - "animal", "baby", "cheer", "dancing" ...
  - human annotation of 1300+ videos
  - evaluate by average precision
- Multimodal detection
  - separate audio + visual low-level detectors
  - (then fused...)

MFCC Covariance Representation

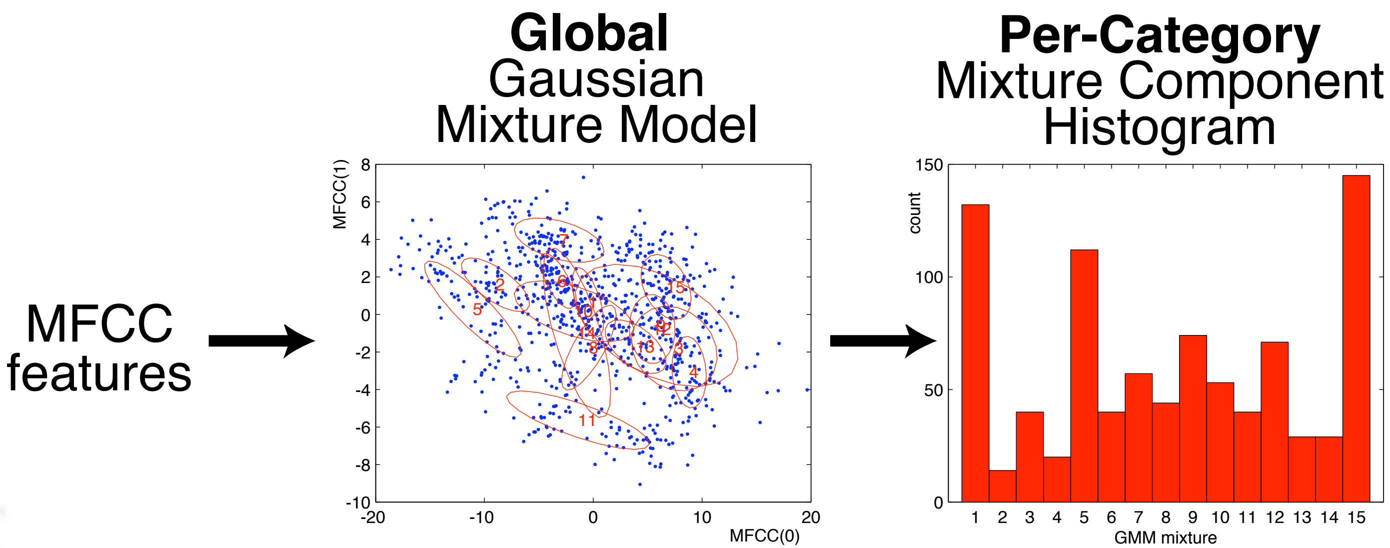
- Each clip/segment → fixed-size statistics
  - similar to speaker ID and music genre classification
- Full Covariance matrix of MFCCs
  - maps the kinds of spectral shapes present



- Clip-to-clip distances for SVM classifier
  - by KL or 2nd Gaussian model

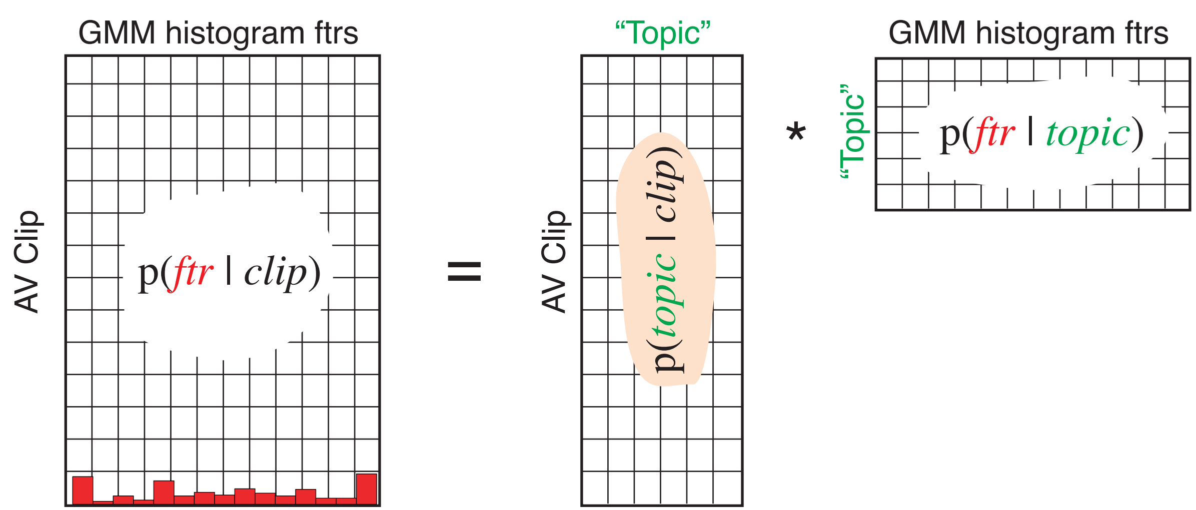
GMM Histogram Representation

- Want a more 'discrete' description
  - .. to accommodate nonuniformity in MFCC space
  - .. to enable other kinds of models...
- Divide up feature space with a single Gaussian Mixture Model
  - .. then represent each clip by the components used



Latent Semantic Analysis (LSA)

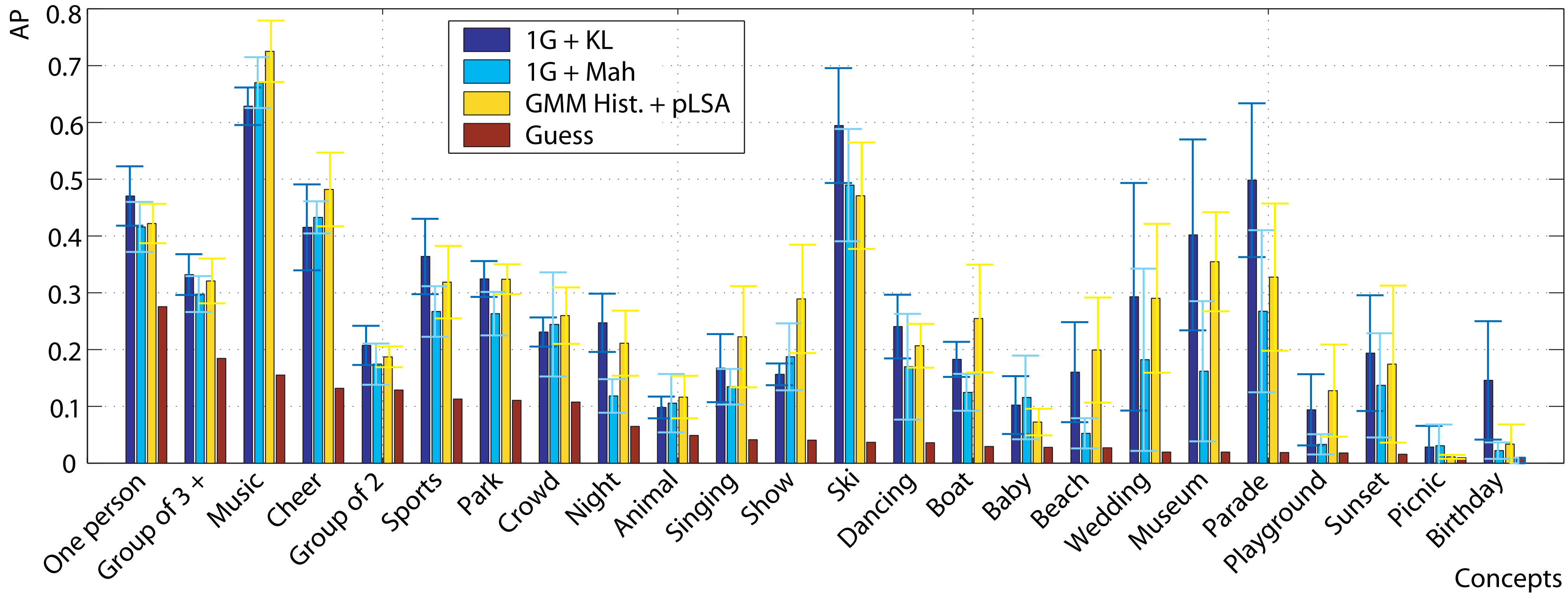
- Probabilistic LSA (pLSA) models each histogram as a mixture of several 'topics'
  - .. each clip may have several things going on
- Topic sets optimized through EM
  - $p(ftr \mid clip) = \sum_{topics} p(ftr \mid topic)\, p(topic \mid clip)$



  - use $p(topic \mid clip)$ as per-clip features

Audio-Only Results

- Wide range of results:

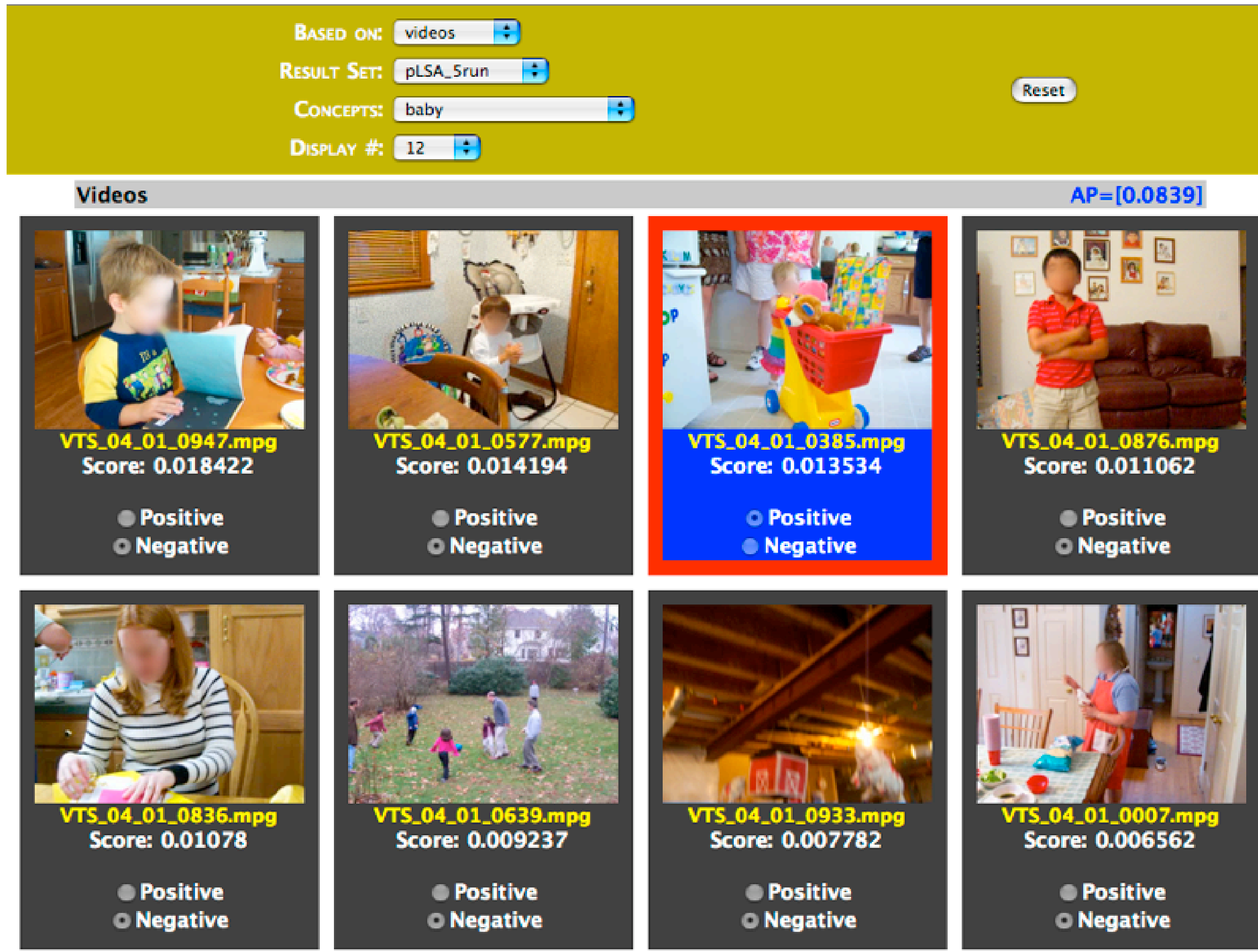


  - audio (music, ski) vs. non-audio (group, night)
  - large AP uncertainty on infrequent classes

How does it ‘feel’?

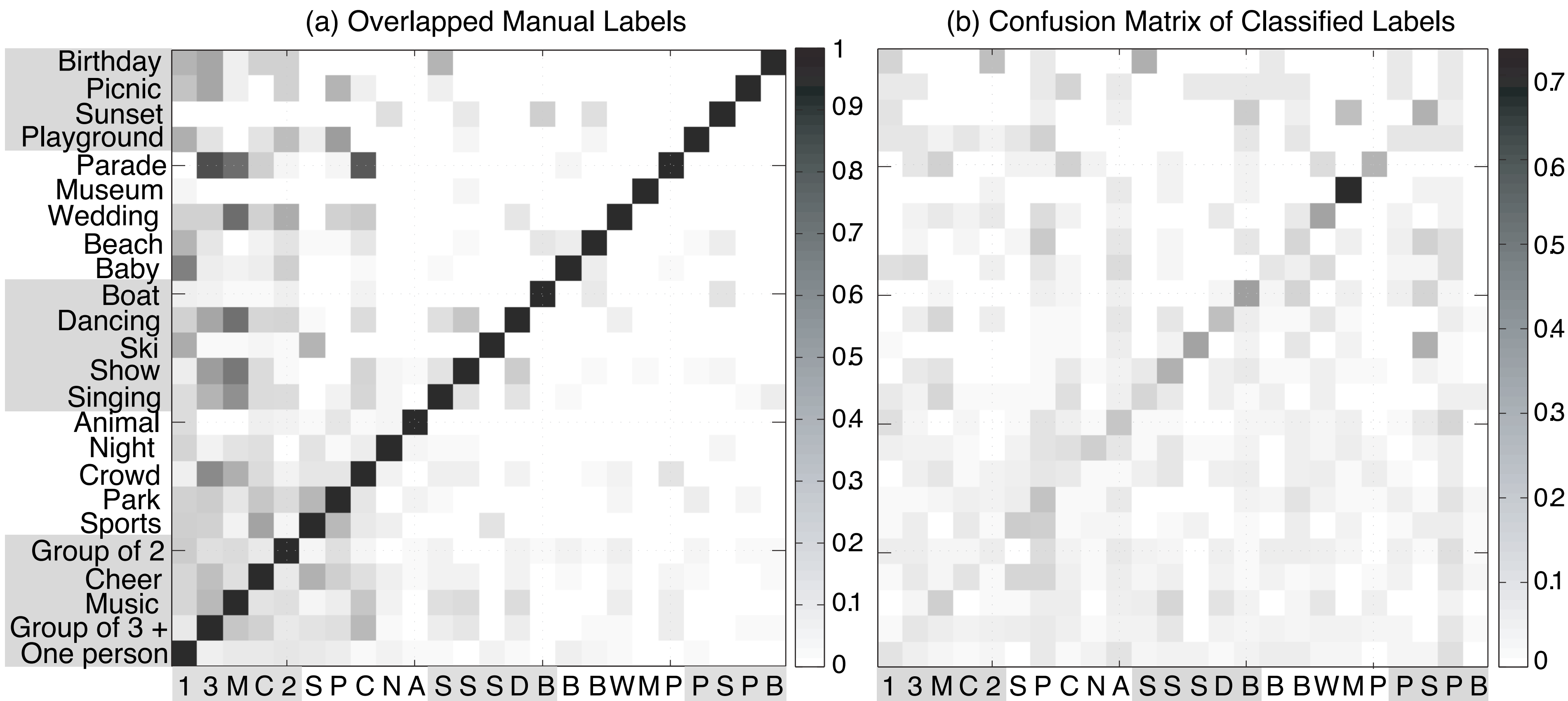
- Browser impressions: How wrong is wrong?

Top 8 hits for “Baby”



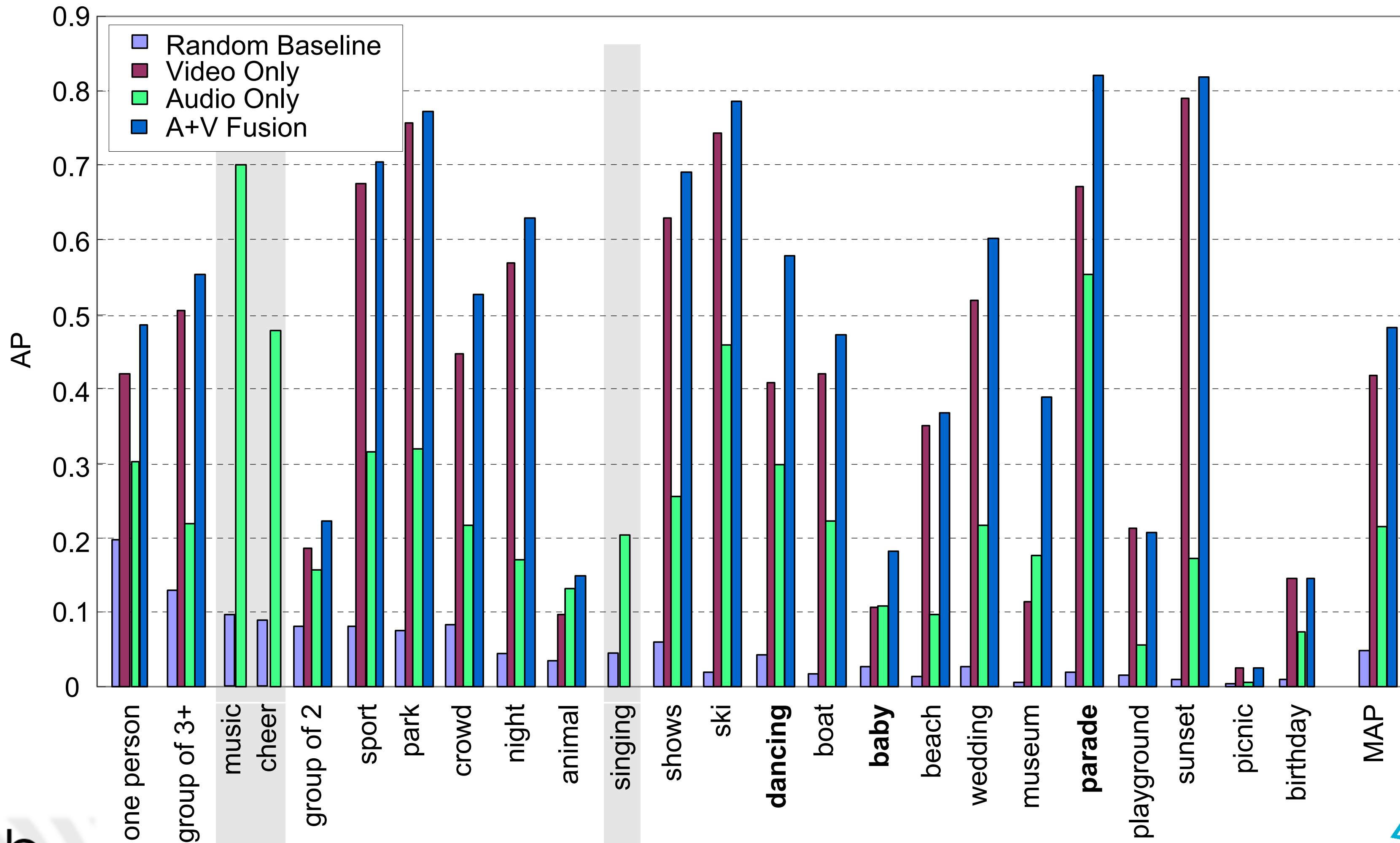
Confusion analysis

- Where are the errors coming from?



Fused Results - AV Joint Boosting

- Audio helps in many classes



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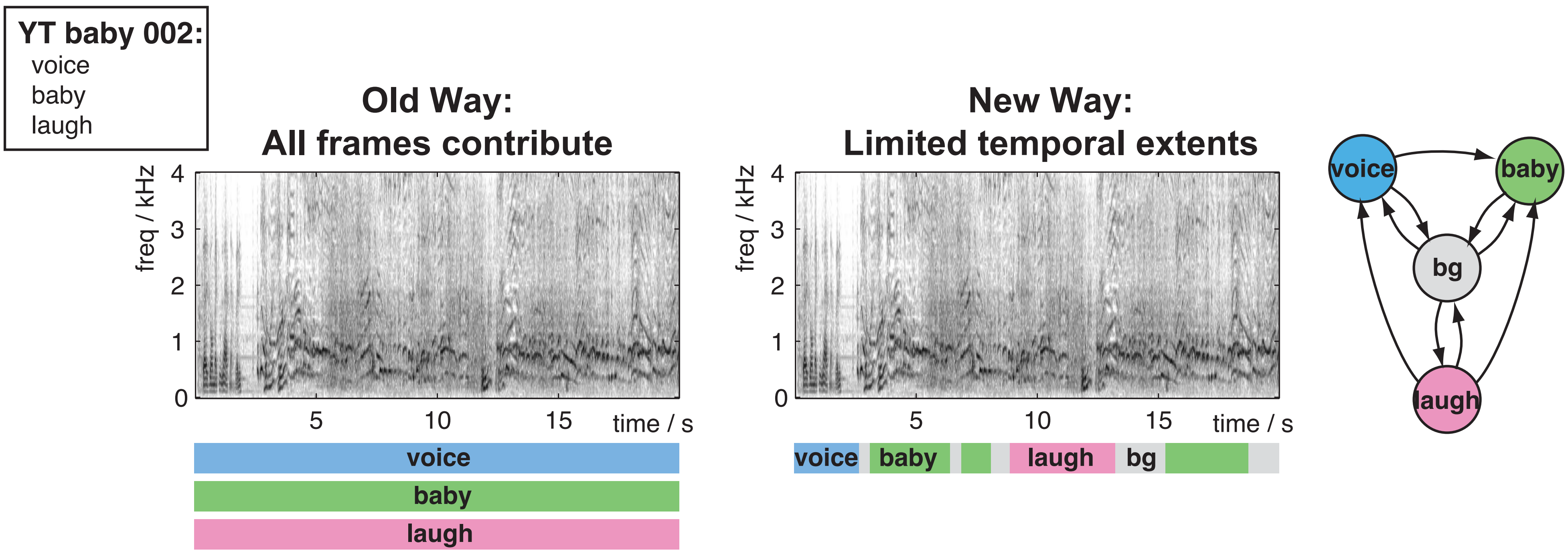
5. Future: Temporal Focus

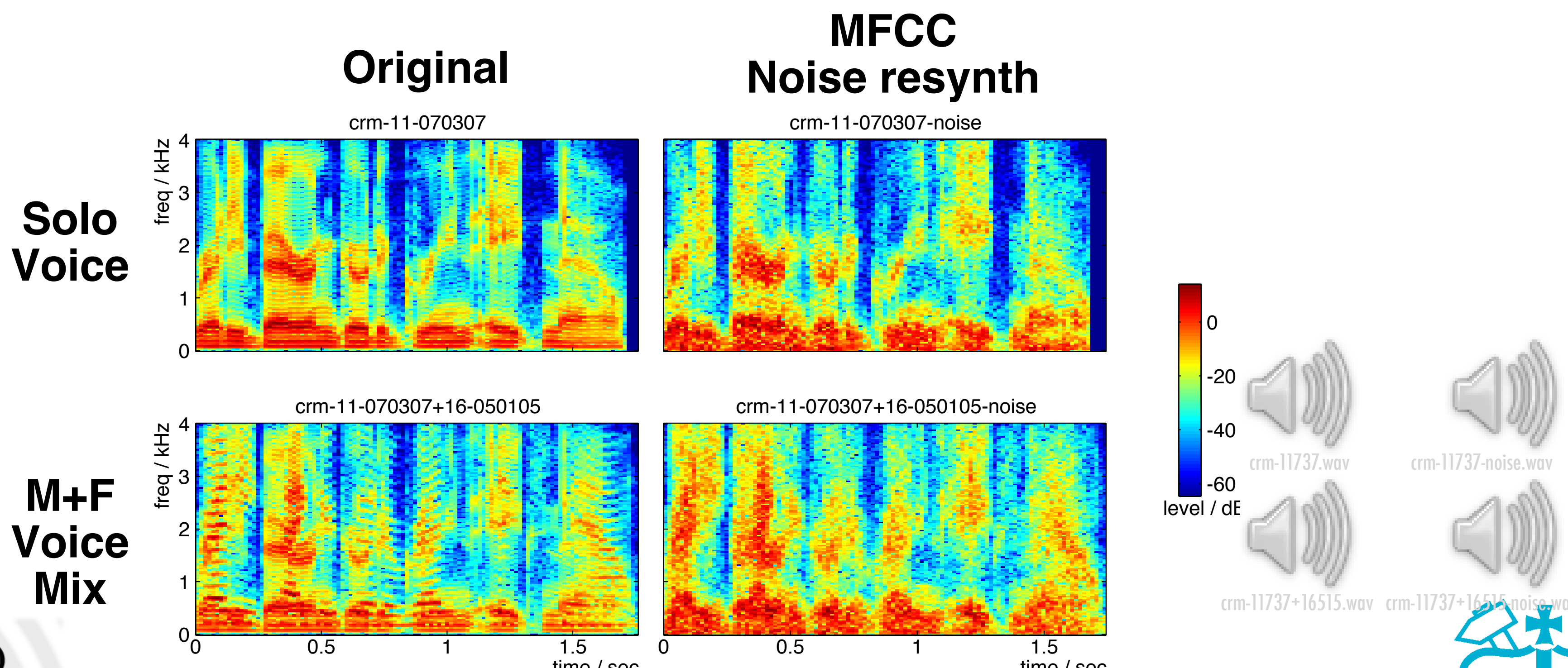
- Global vs. local class models
  - tell-tale acoustics may be 'washed out' in statistics
  - try iterative realignment of HMMs:



  - "background" (bg) model shared by all clips

Handling Sound Mixtures

- MFCCs of mixtures ≠ mix of MFCCs
  - recognition despite widely varying background?
  - factorial models / Nonnegative Matrix Factorization
  - sinusoidal / landmark techniques



Larger Datasets

- **Many detectors are visibly data-limited**
  - getting data is ~ hard
  - labeling data is expensive
- **Bootstrap from YouTube etc.**
  - lots of web video is edited/dubbed...
    - need a "consumer video" detector?
- **Preliminary YouTube results disappointing**
  - downloaded data needed extensive clean-up
  - models did not match Kodak data
- **(Freely available data!)**

Conclusions

- Environmental sound contains information
  - .. that's why we hear!
  - .. computers can hear it too
- Personal audio can be segmented, clustered
  - find specific sounds to help navigation/retrieval
- Consumer video can be 'tagged'
  - .. even in unpromising cases
  - audio is complementary to video
- Interesting directions for better models