

Recognizing and Classifying Environmental Sounds

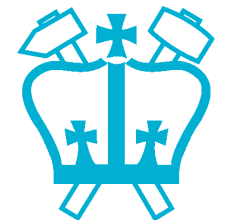
Dan Ellis

Laboratory for Recognition and Organization of Speech and Audio
Dept. Electrical Eng., Columbia Univ., NY USA

dpwe@ee.columbia.edu

<http://labrosa.ee.columbia.edu/>

1. Environmental Sound Recognition
2. Foreground Events
3. Background Retrieval
4. Labels & Annotation
5. Future Directions



COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

I. What is hearing for?



<http://news.bbc.co.uk/2/hi/science/nature/7130484.stm>

- Hearing = getting **information** from sound
 - predators/prey
 - communication
- Environmental sound recognition is **fundamental**

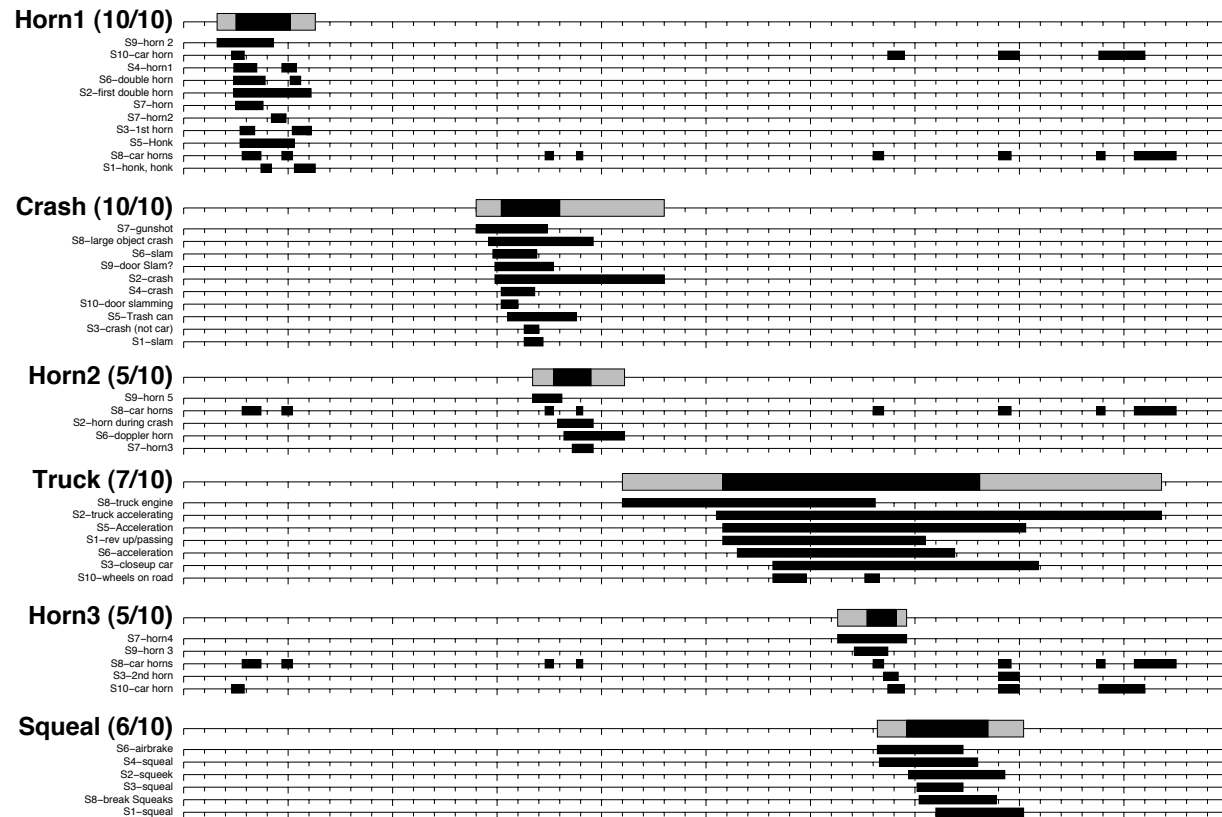
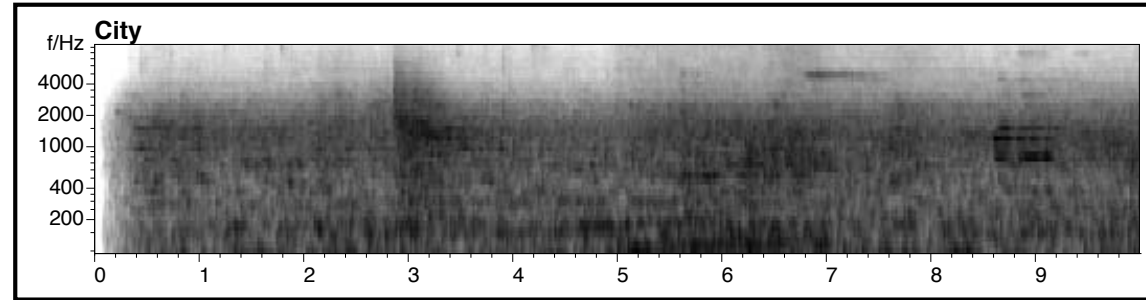
Environmental Sound Perception

Ellis 1996

- What do people hear?

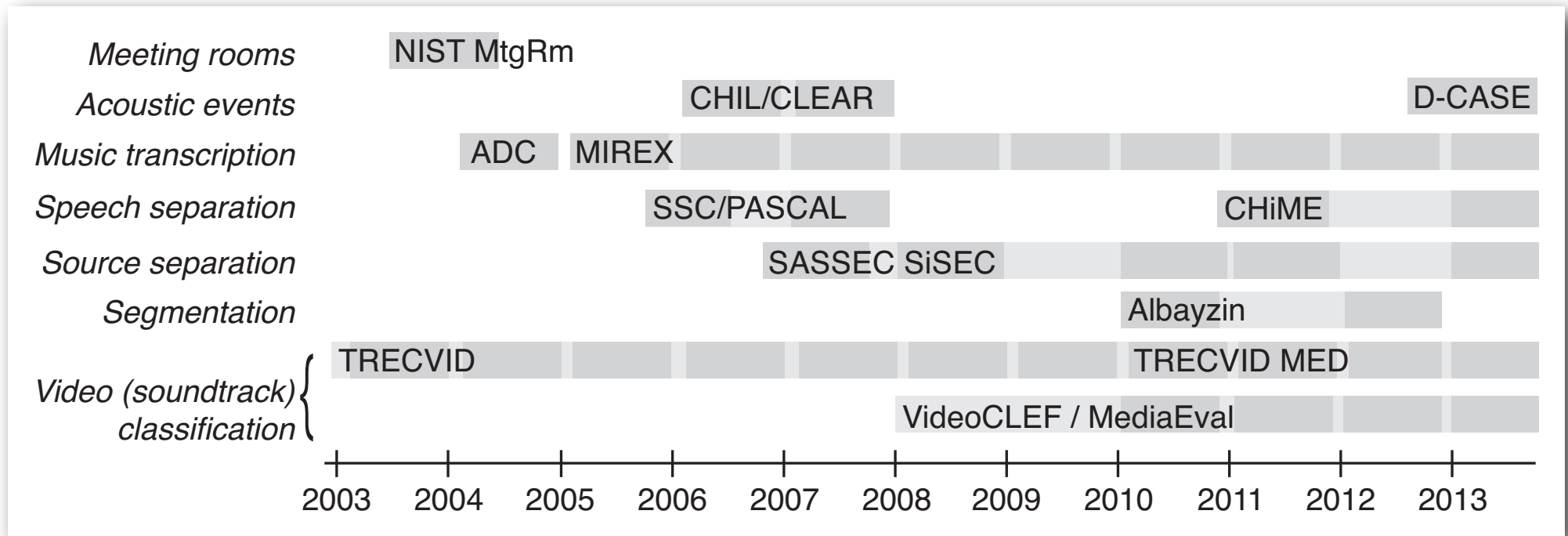
- sources
- ambience

- Mixtures are the rule



Sound Scene Evaluations

- **Evaluations** are good for research
 - help researchers, help funders
- **A decade of evaluations:**

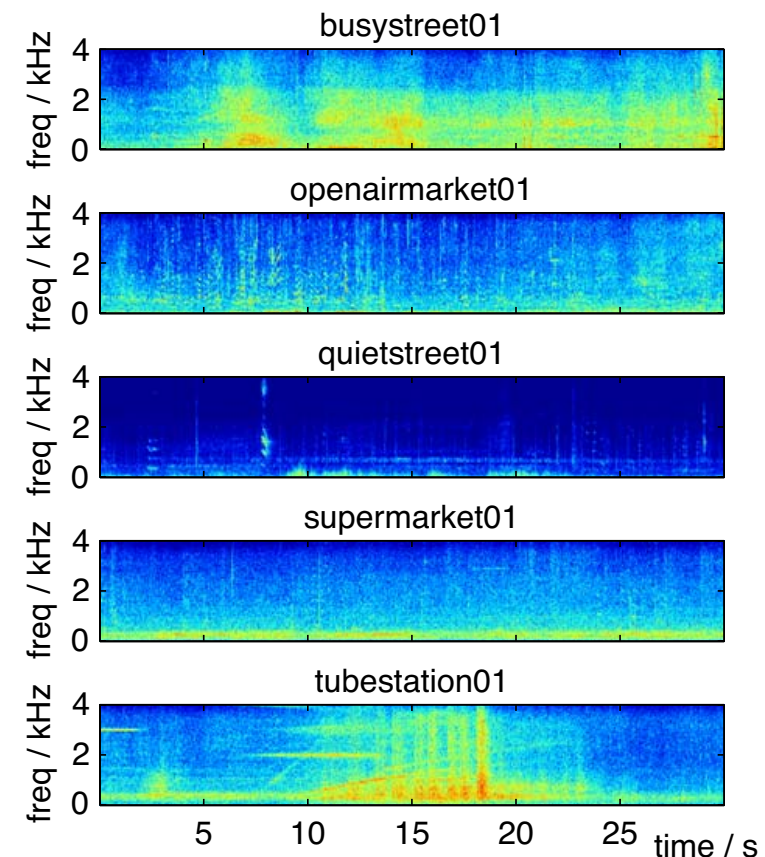


- **Metrics:** SNR, Frame Acc, Event Error Rate, mAP

DCASE (2012-2013)

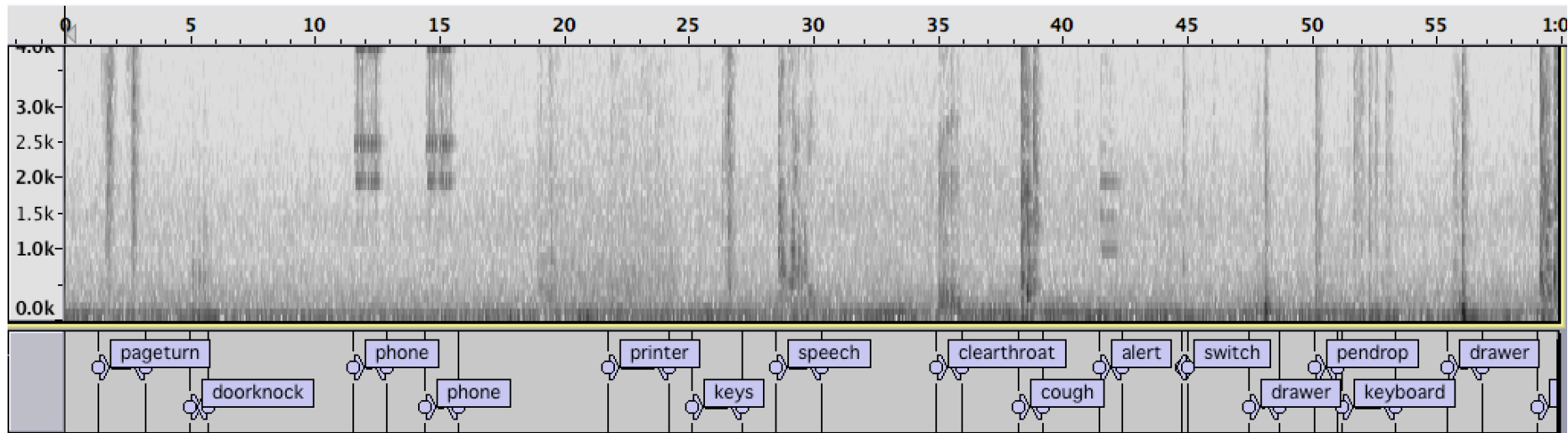
Giannoulis et al. 2013

- 2012 IEEE **AASP Challenge**:
“Detection and Classification of Acoustic Scenes and Events”
 - Systems submitted Mar 2013
 - Results at **WASPAA**, Oct 2013
 - 2 tasks...
- **Task I: Scene classification**
 - 10 classes x 10 examples x 30 s
 - street, supermarket, restaurant, office, park ...
 - evaluate on 100 examples (~1 hour total) by classification accuracy



DCASE Event Detection

- **Task 2: Event detection** (“office live”)
 - 16 events x 20 training examples (~ 20 min total)
knock, laugh, drawer, keys, phone ...
 - evaluate on ~ 15 min (?)
 - metrics: frame-level AEER
& event-level precision-recall



TRECVID MED (2010-2013)

Over et al. 2011

- “Multimedia **Event** Detection”
 - e.g. MED2011: 15 events x 200 example videos (~60s)
 - Making a sandwich, Birthday party, Parade, Flash mob
 - evaluate by mean Average Precision over 10k-100k videos (200-2,000 hours)
 - audio and video ...
 - participants have annotated ~1000 videos (> 10 h)



E009 Getting a Vehicle Unstuck

Consumer Video Dataset

Y-G. Jiang et al. 2011

- **Columbia Consumer Video (CCV)**
 - 9,317 videos / 210 hours
 - 20 concepts based on consumer user study
 - Labeled via Amazon Mechanical Turk

Mark all the categories that appear in any part of the video.

Description:

- Watch the entire video as more categories may appear over time.
- Mark all the categories that appear in any part of the video.
- Make sure the audio is on.
- If no matching category is found, mark the box in front of "None of the categories matches".
- For categories that appears to be relevant but you're not completely sure, please still mark it.
- Please move over or click on the category name for detailed description.



[Replay](#) [Continue Playing](#)

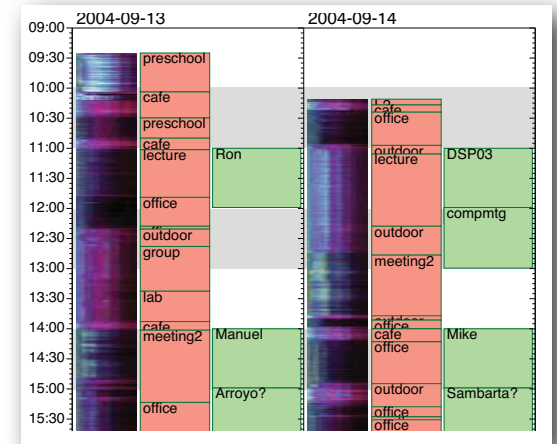
Original URL: http://www.youtube.com/watch?v=u_2dqWBd1L0

Sport	Animal	Celebration	Others
<input type="checkbox"/> Basketball	<input type="checkbox"/> Cat	<input type="checkbox"/> Graduation	<input type="checkbox"/> Music Performance
<input type="checkbox"/> Baseball	<input type="checkbox"/> Dog	<input type="checkbox"/> Birthday	<input type="checkbox"/> Non-music Performance
<input type="checkbox"/> Soccer	<input type="checkbox"/> Bird	<input type="checkbox"/> Wedding Reception	<input type="checkbox"/> Parade
<input type="checkbox"/> Ice Skate		<input type="checkbox"/> Wedding Ceremony	<input type="checkbox"/> Beach
<input type="checkbox"/> Ski		<input type="checkbox"/> Wedding Dance	<input type="checkbox"/> Playground
<input type="checkbox"/> Swim	<input type="checkbox"/> None of the categories matches.		
<input type="checkbox"/> Biking	<input type="checkbox"/> I don't see any video playing.		

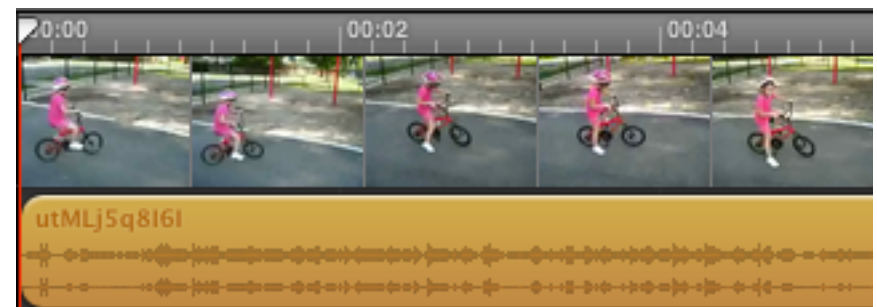
Current Time: 10 sec

Environmental Sound Motivations

- Audio **Lifelog** Diarization



- **Consumer Video** Classification & Search



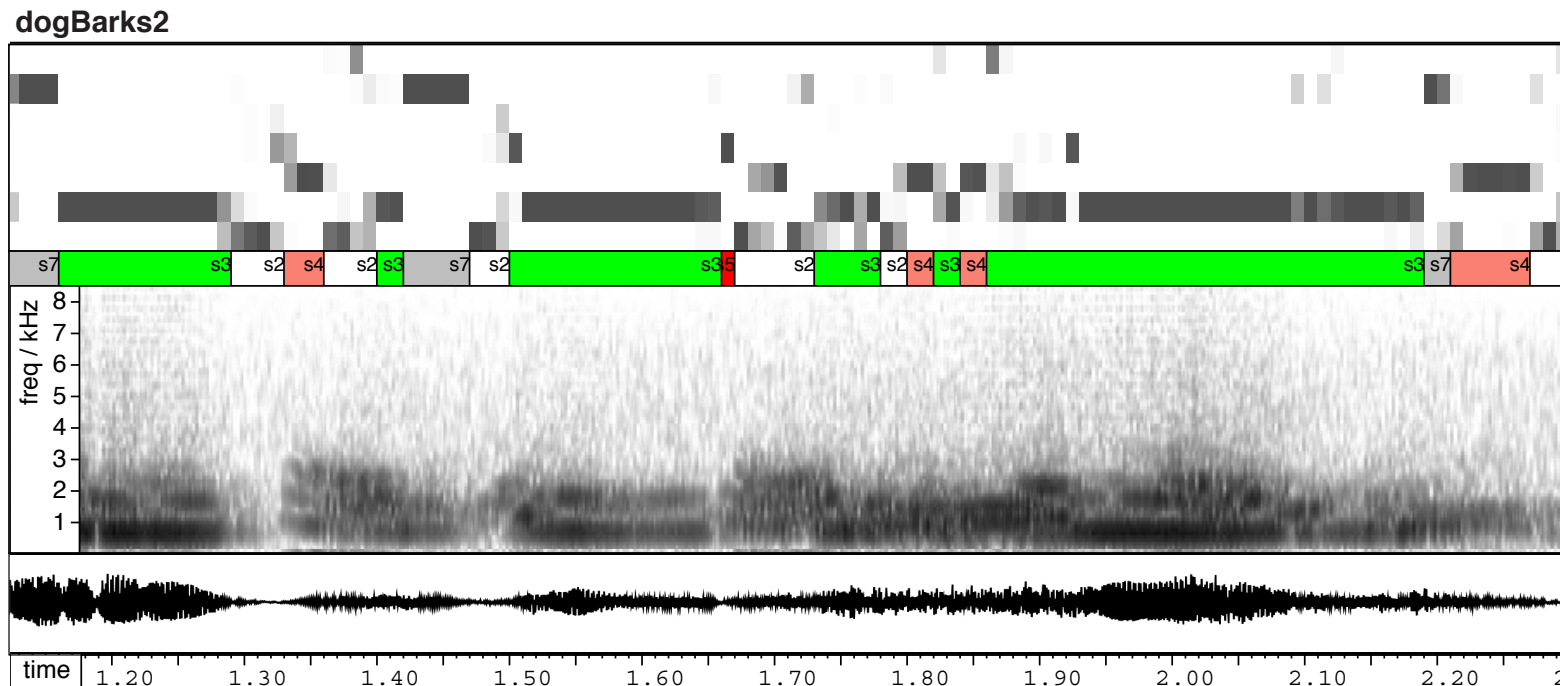
- Real-time hearing prosthesis app
- Robot environment sensitivity
- **Understanding hearing**



2. Foreground Event Recognition

Reyes-Gomes & Ellis 2003

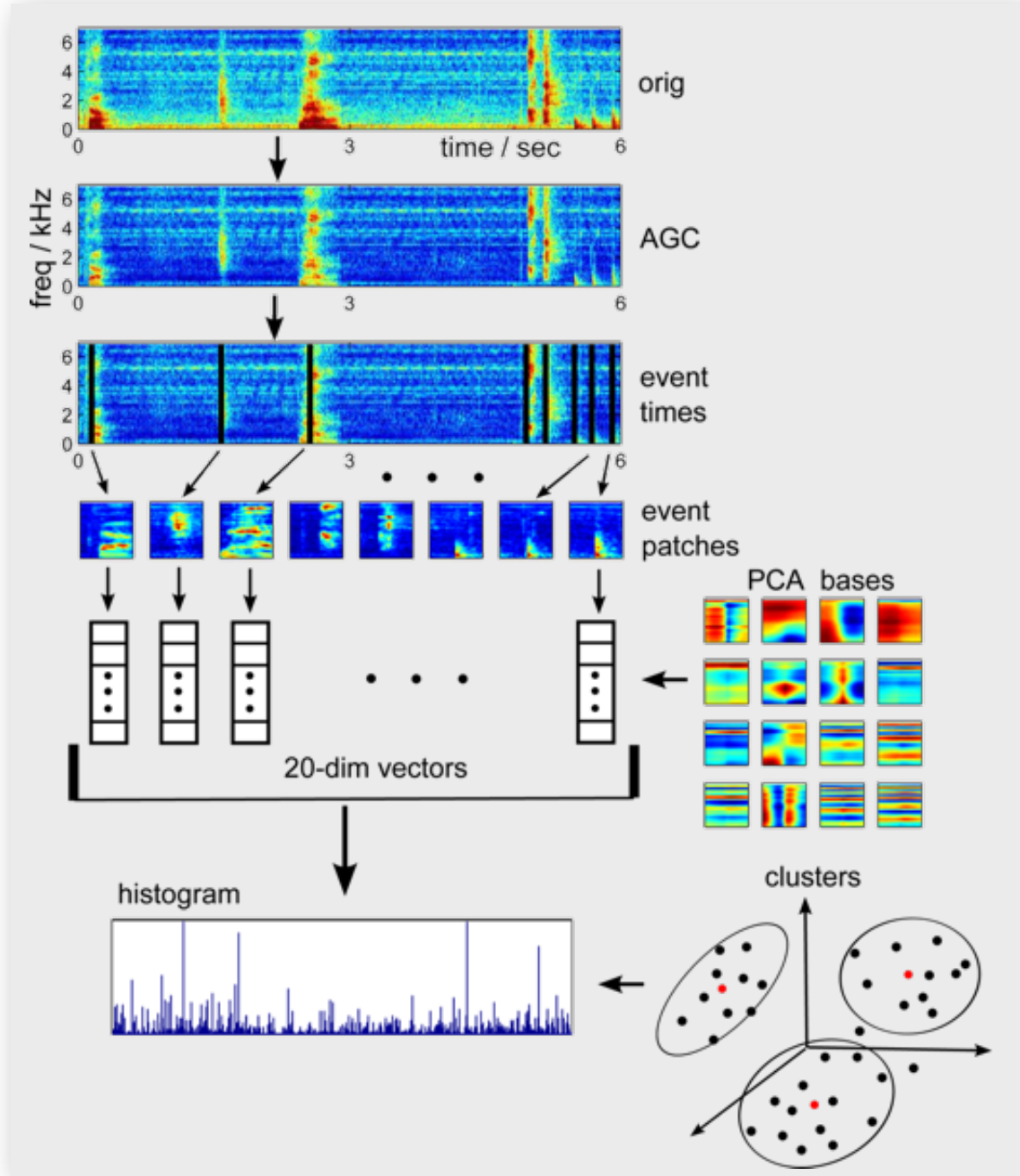
- “Events” are what we hear / notice
- ASR approach?



- events = words? what are subwords?
- need **labeled** data
- but ... **mature tools** are great

Transient Features

Cotton, Ellis, Loui '11



- Transients = foreground events?
- Onset detector finds energy bursts
 - best SNR
- PCA basis to represent each
 - 300 ms x auditory freq
- “bag of transients”

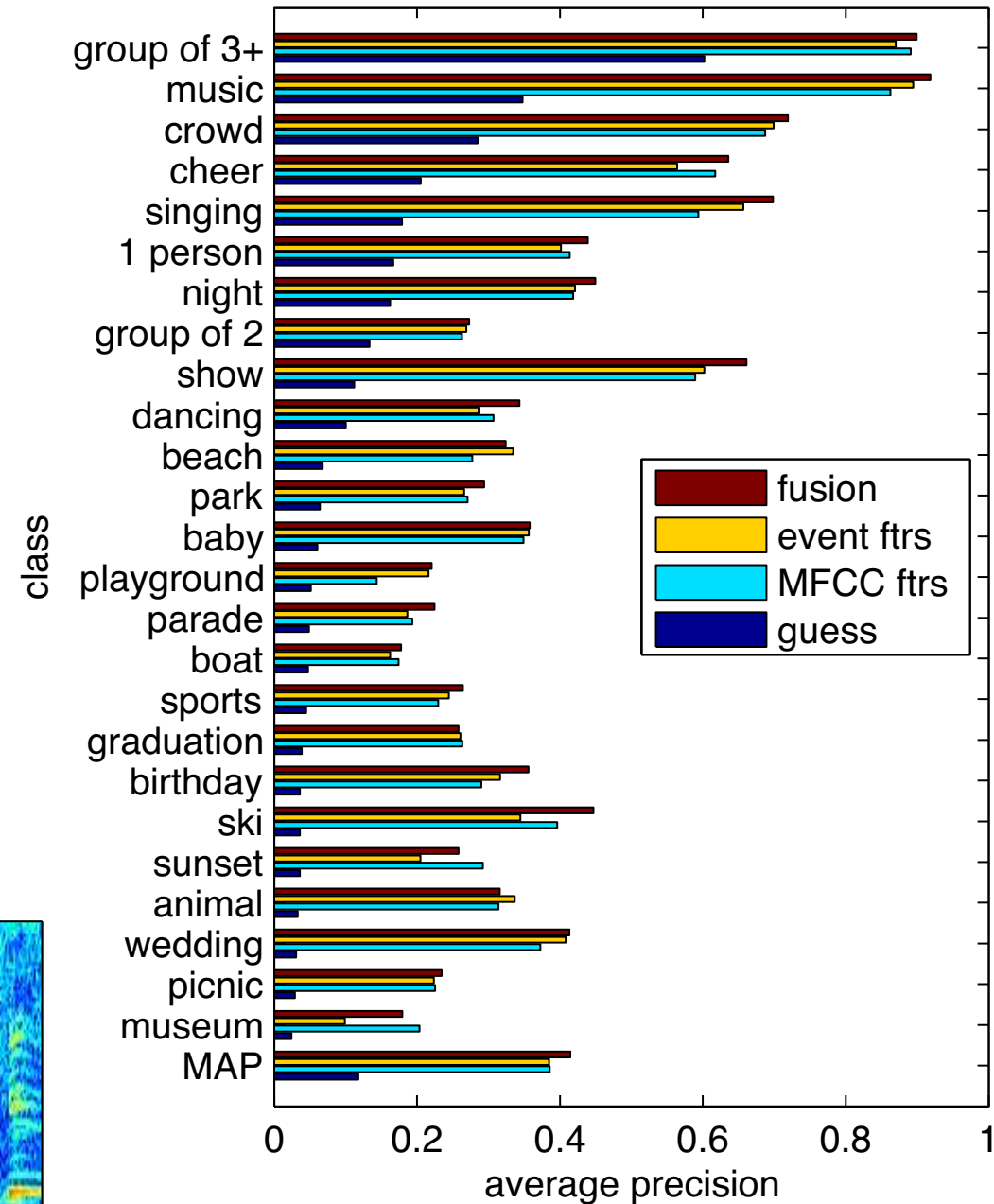
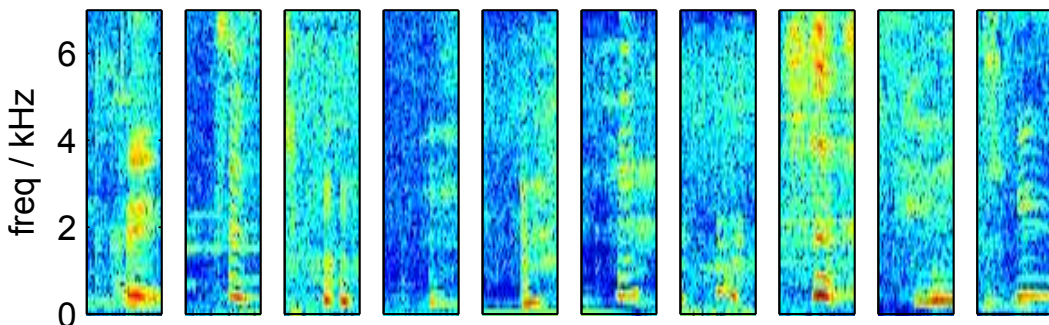
Transient Features

- Results show a **small benefit**

- similar to MFCC baseline?

- Examine **clusters**

- looking for **semantic consistency...**
- link cluster to label



NMF Transient Features

Smaragdis & Brown '03
Abdallah & Plumbley '04
Virtanen '07

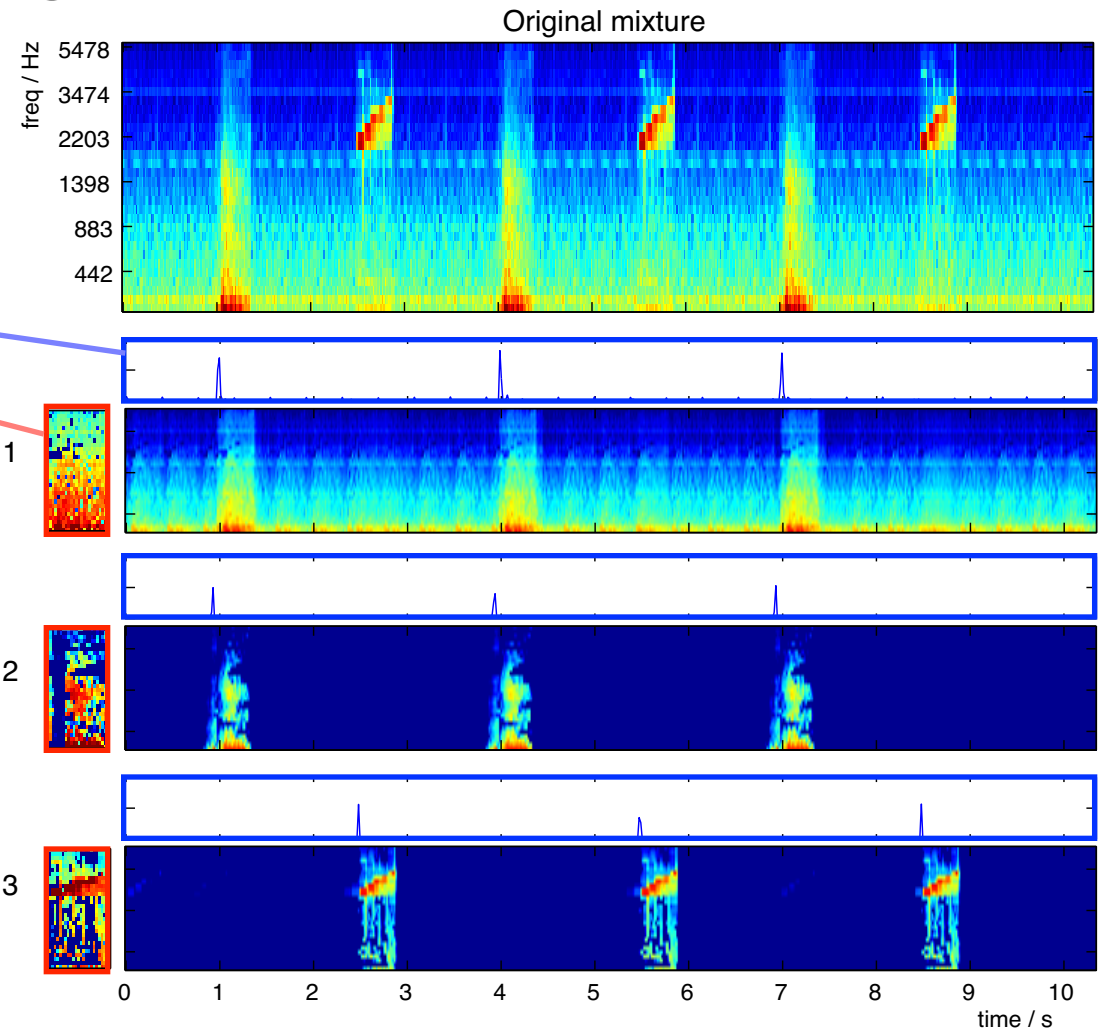
- Decompose spectrograms into

templates

+ **activation**

$$\mathbf{X} = \mathbf{W} \cdot \mathbf{H}$$

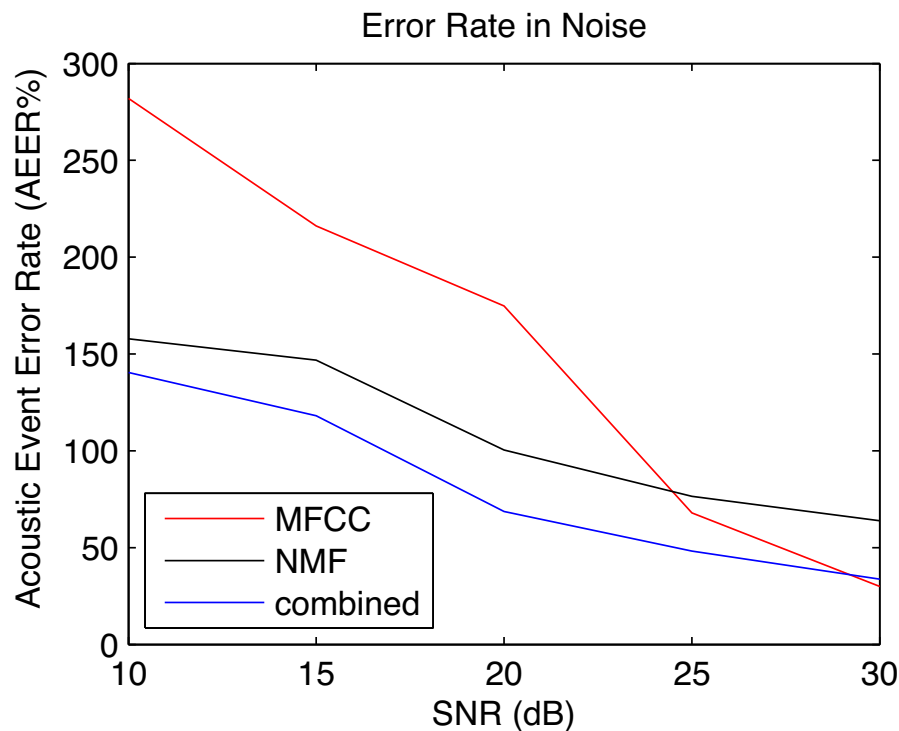
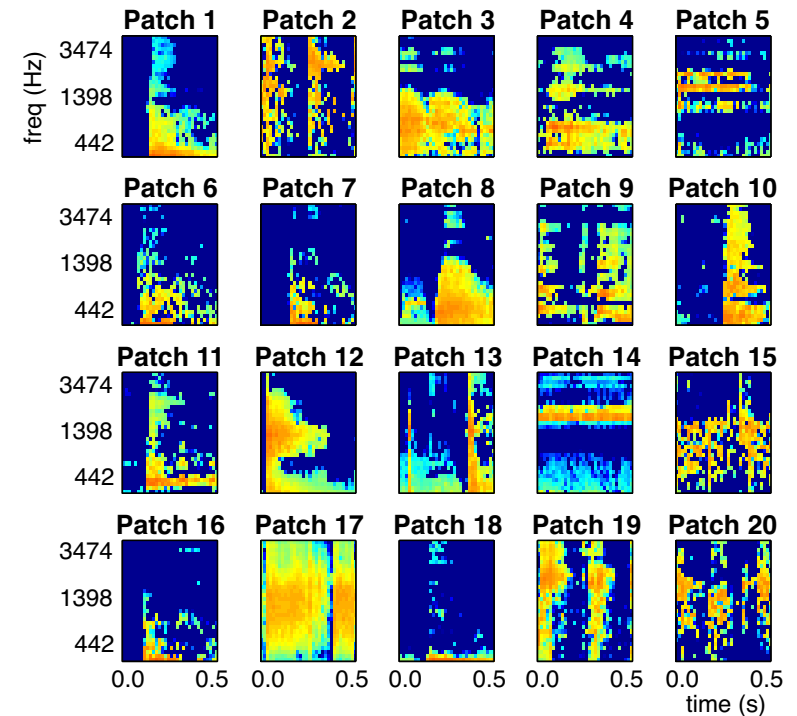
- well-behaved
gradient descent
algorithm
- 2D patches
- sparsity control
- computation time...



NMF Transient Features

Cotton & Ellis '11

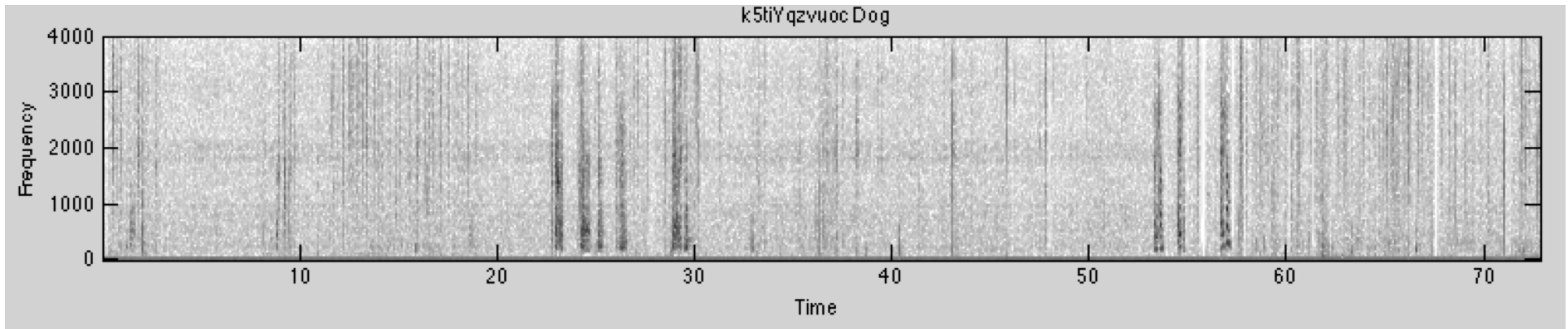
- Learn 20 patches from **CLEAR Meeting Room** events
- Compare to **MFCC-HMM** detector



- NMF more **noise-robust**
○ combines well ...

Why Are Events Hard?

- Events are **short**

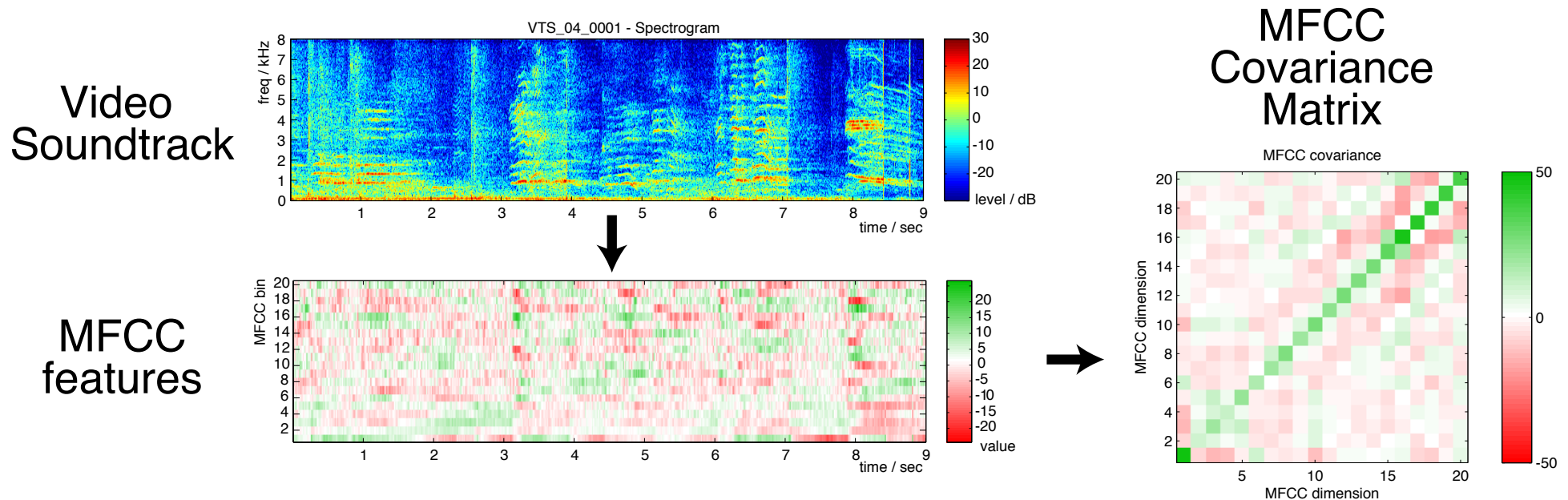


- target sounds may occupy only a few % of time
- Events are **varied**
 - what is the vocabulary? what are the prototypes?
 - source & channel variability
- **Critical information is in fine-time structure**
 - onset transient etc.
 - poor match to classic frame-spectral-envelope features

3. Background Retrieval

K. Lee & Ellis 2010

- **Baseline** for soundtrack classification
 - divide sound into short frames (e.g. 30 ms)
 - calculate features (e.g. MFCC) for each frame
 - describe clip by **statistics** of frames (mean, covariance)
 - = “**bag of features**”

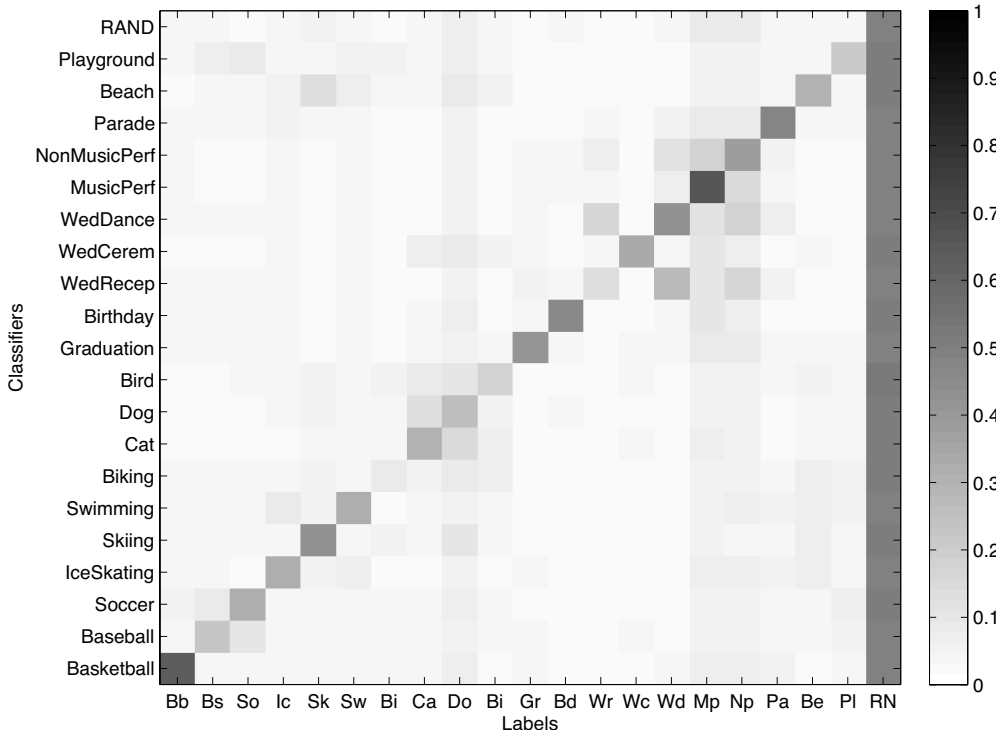


- Classify by e.g. Mahalanobis distance + **SVM**

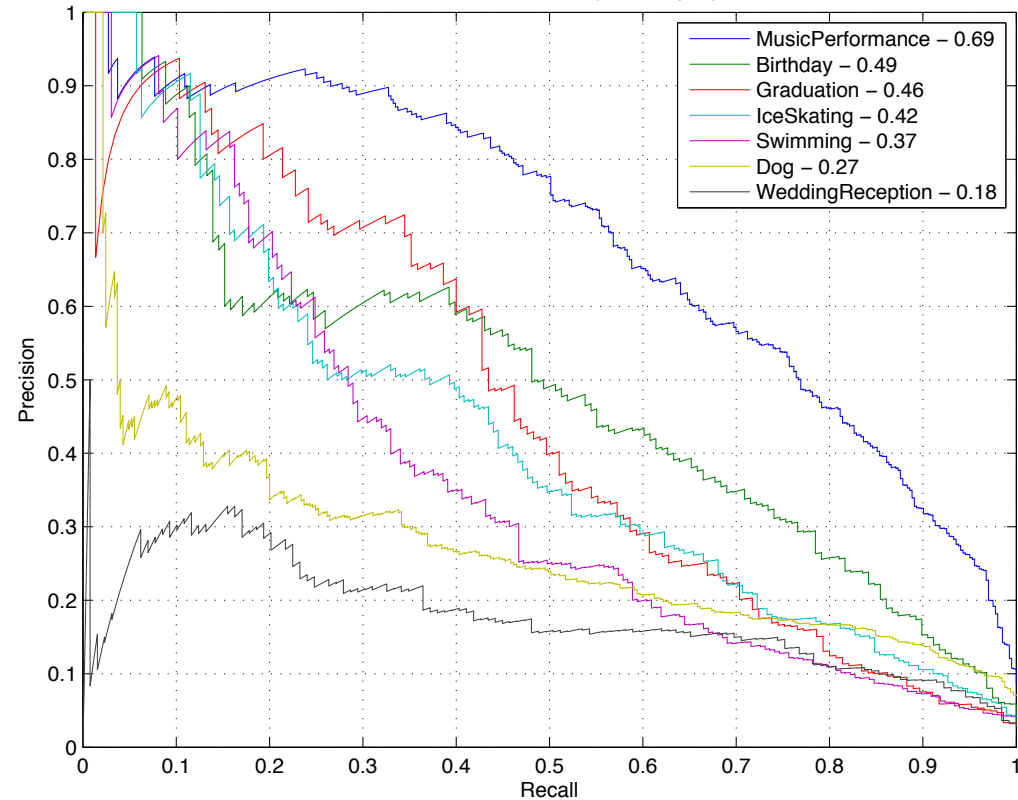
Retrieval Evaluation

- Rank large test set by match to category
- Precision-Recall

CCV Test – mfc230 – AP (mean=0.345)



CCV Precision-Recall (mfcc+sbpca)



- mean Average Precision



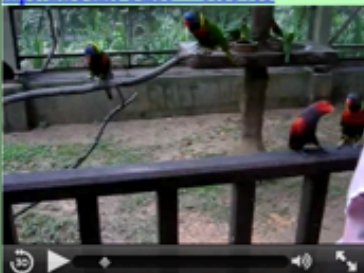



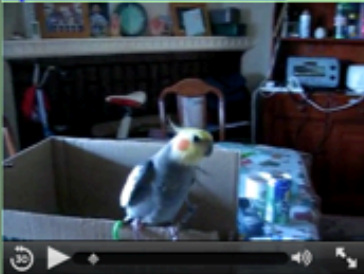
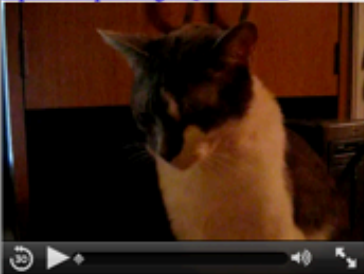



Retrieval Examples

- High precision for **top hits** (in-domain)

Bird-max P@20=0.60

file:///Users/drspeech/data/aladdin/code/genVidClassif/html/fusion/Bird-max.html

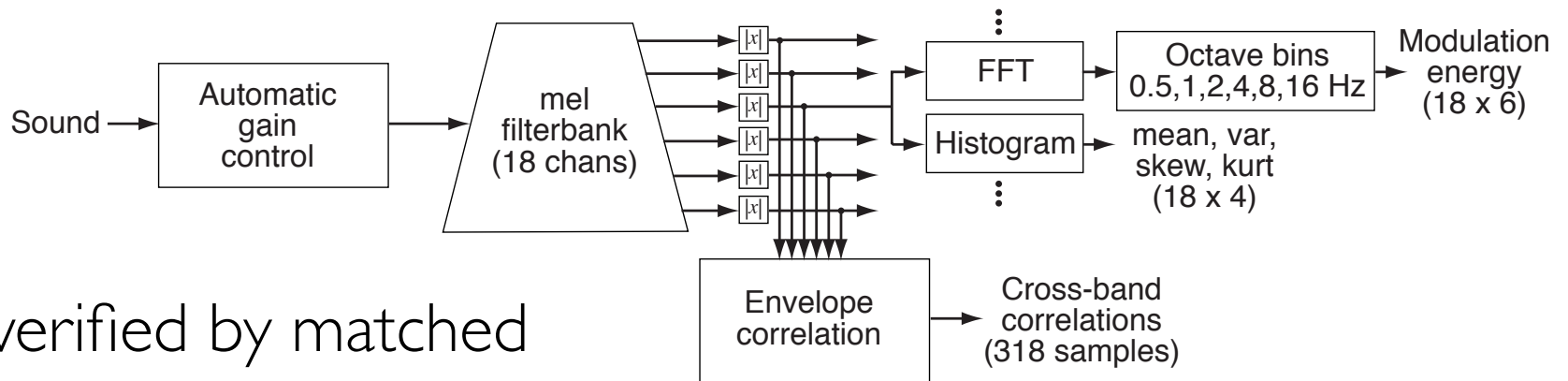
Bird-max P@20=0.60

<p>mp3/FQo-jO-4cbg - -0.49095</p> 	<p>mp3/feci_HyjFDI - -0.49797</p> 	<p>mp3/TxiOkh0YE8 - -0.68403</p> 	<p>mp3/r_d00DUbNEA - -0.82298</p> 
<p>mp3/YsQjN_3fRRQ - -0.8447</p> 	<p>mp3/lLoopvzsAMs - -1.0387</p> 	<p>mp3/NZEVLYA9Z3s - -1.0474</p> 	<p>mp3/FV6qwSZgmQ - -1.0984</p> 
<p>mp3/Btyyaila92Q - -1.1623</p> 	<p>mp3/lhaEx6XrBts - -1.1764</p> 	<p>mp3/-2ADyk_D7Ng - -1.1772</p> 	<p>mp3/ZlqV3BhElhE - -1.1934</p> <p>Loading...</p>

Sound Texture Features

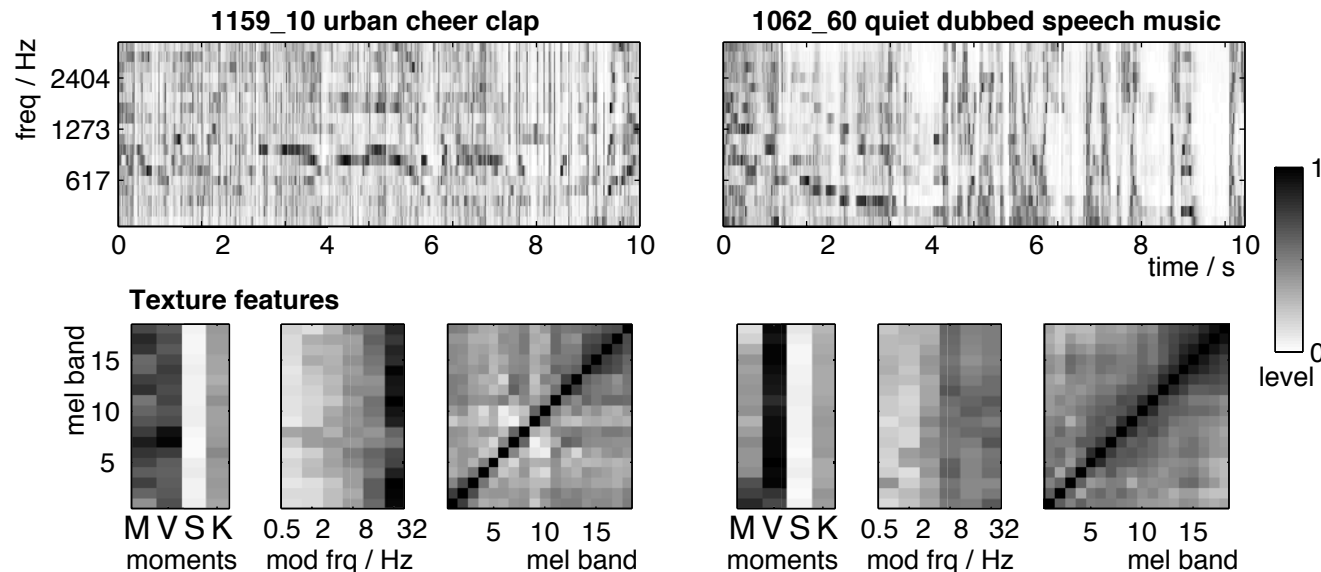
McDermott et al. '09
Ellis, Zheng, McDermott '11

- Characterize sounds by perceptually-sufficient statistics



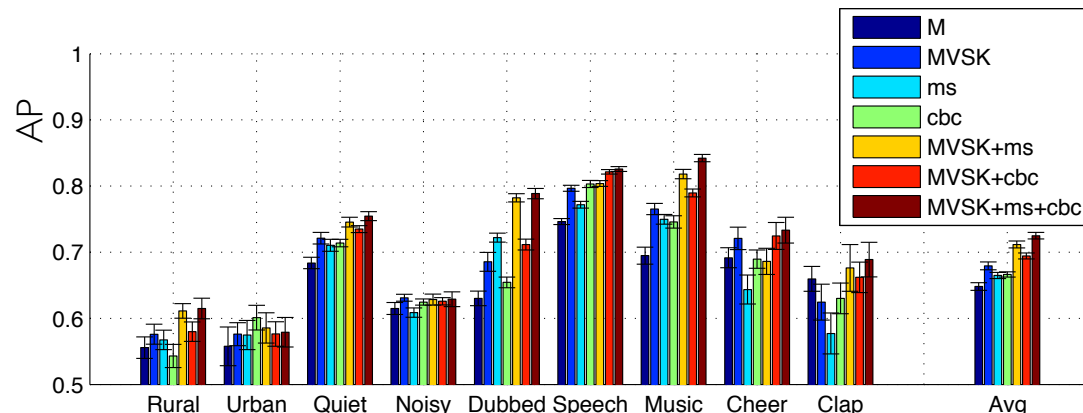
- .. verified by matched resynthesis

- Subband distributions & env x-corrs
- Mahalanobis distance ...

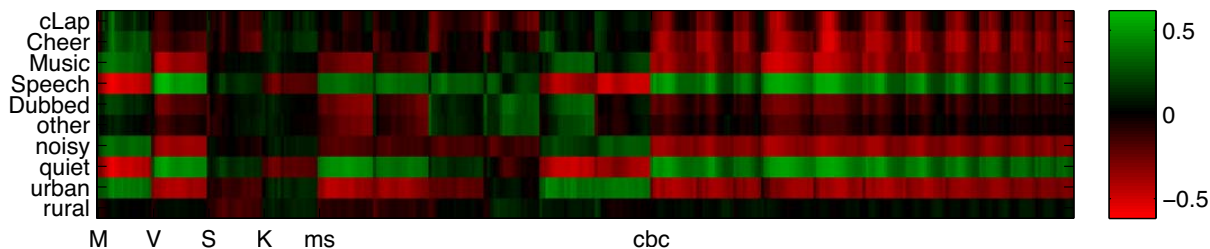


Sound Texture Features

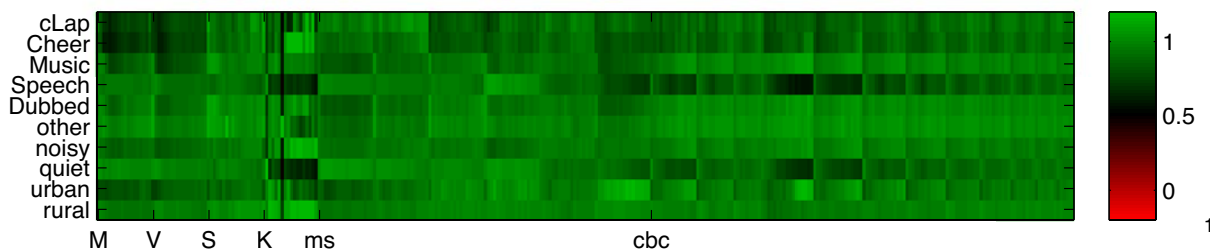
- Test on **MED 2010** development data
 - 10 audio-oriented manual labels



MED 2010 Txtr Feature (normd) means



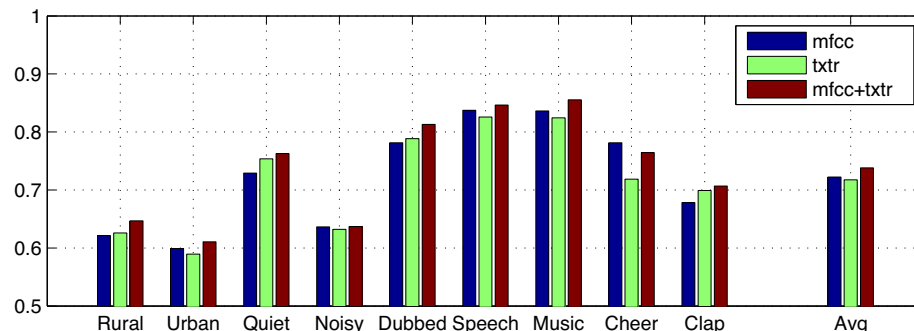
MED 2010 Txtr Feature (normd) stddevs



- **Per-class stats**

- relate dimensions to classes?

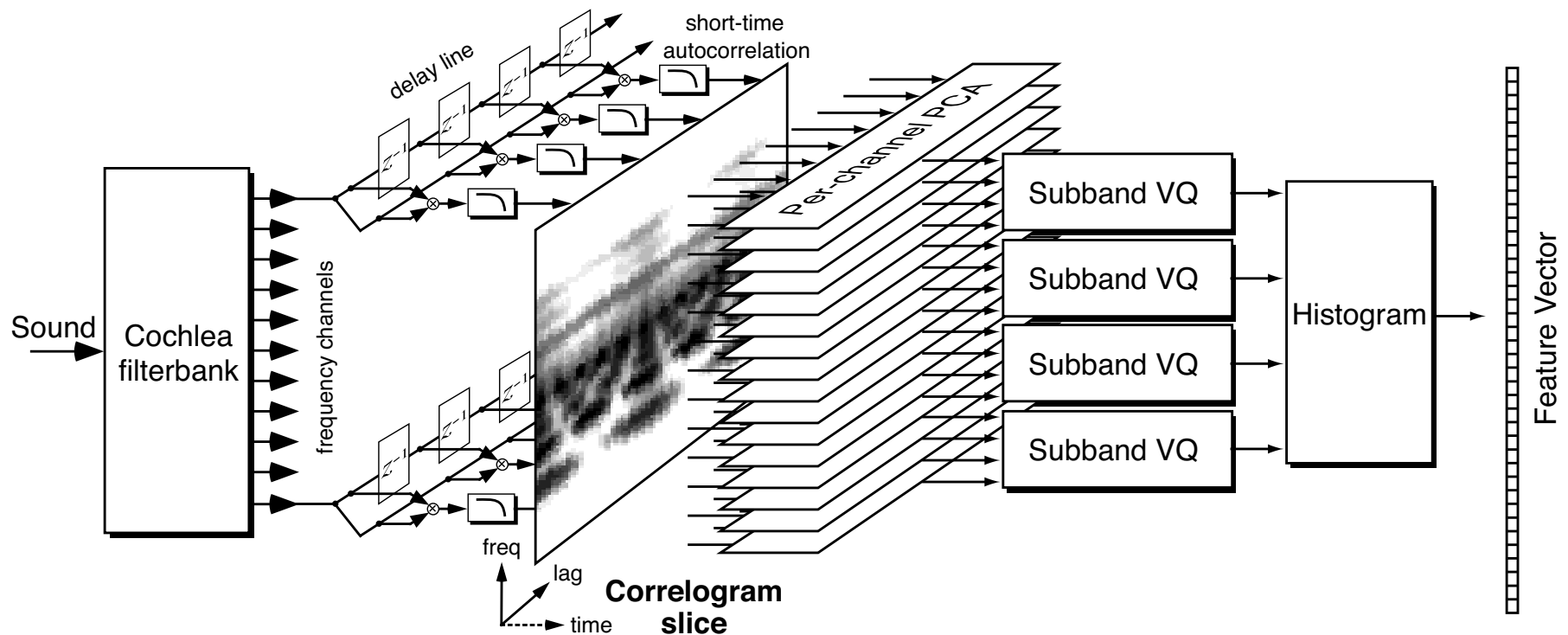
- Perform ~ same as MFCCs
 - covariance ~ texture?



Auditory Model Features

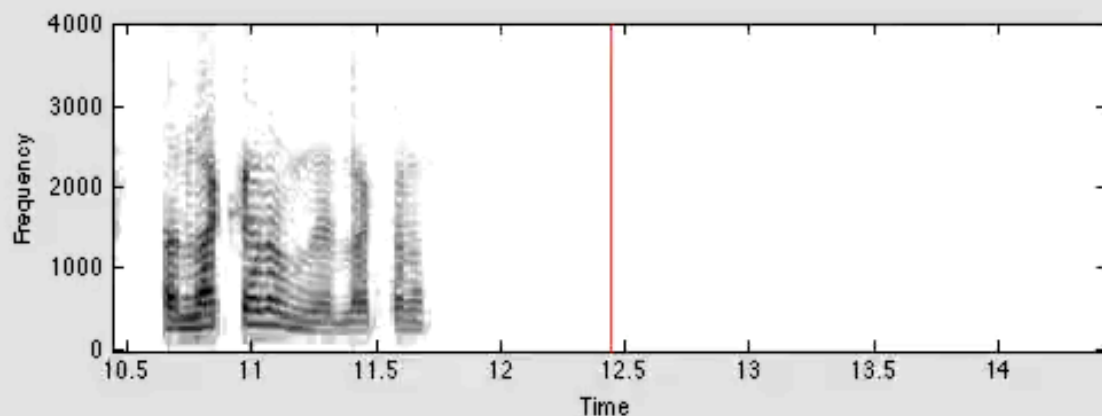
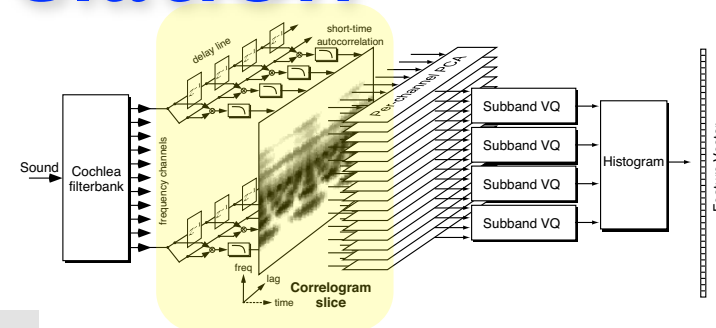
Lyon et al. 2010
Cotton & Ellis 2013

- **Subband Autocorrelation PCA (SBPCA)**
 - Simplified version of Lyon et al. system
 - 10x faster (RT \times 5 \rightarrow RT/2)
- Captures **fine time structure** in multiple bands
 - .. missing in MFCC features

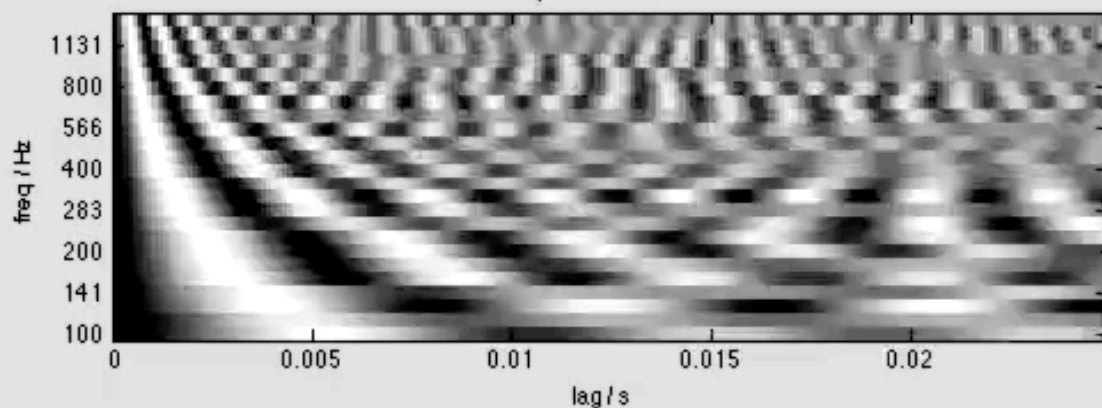


Subband Autocorrelation

- Autocorrelation **stabilizes** fine time structure



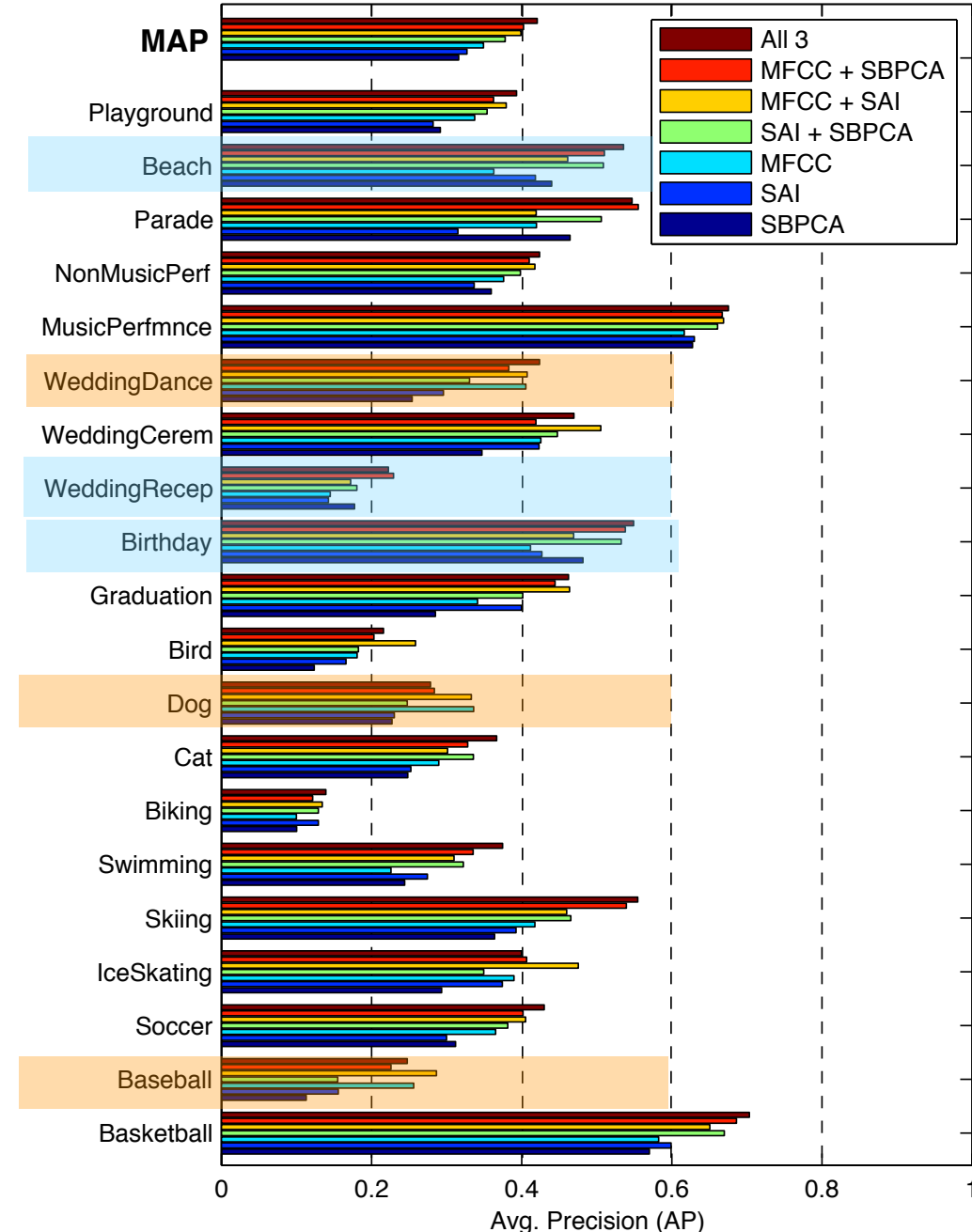
speech - 12.44



- 25 ms window, lags up to 25 ms
- calculated every 10 ms
- normalized to max (zero lag)

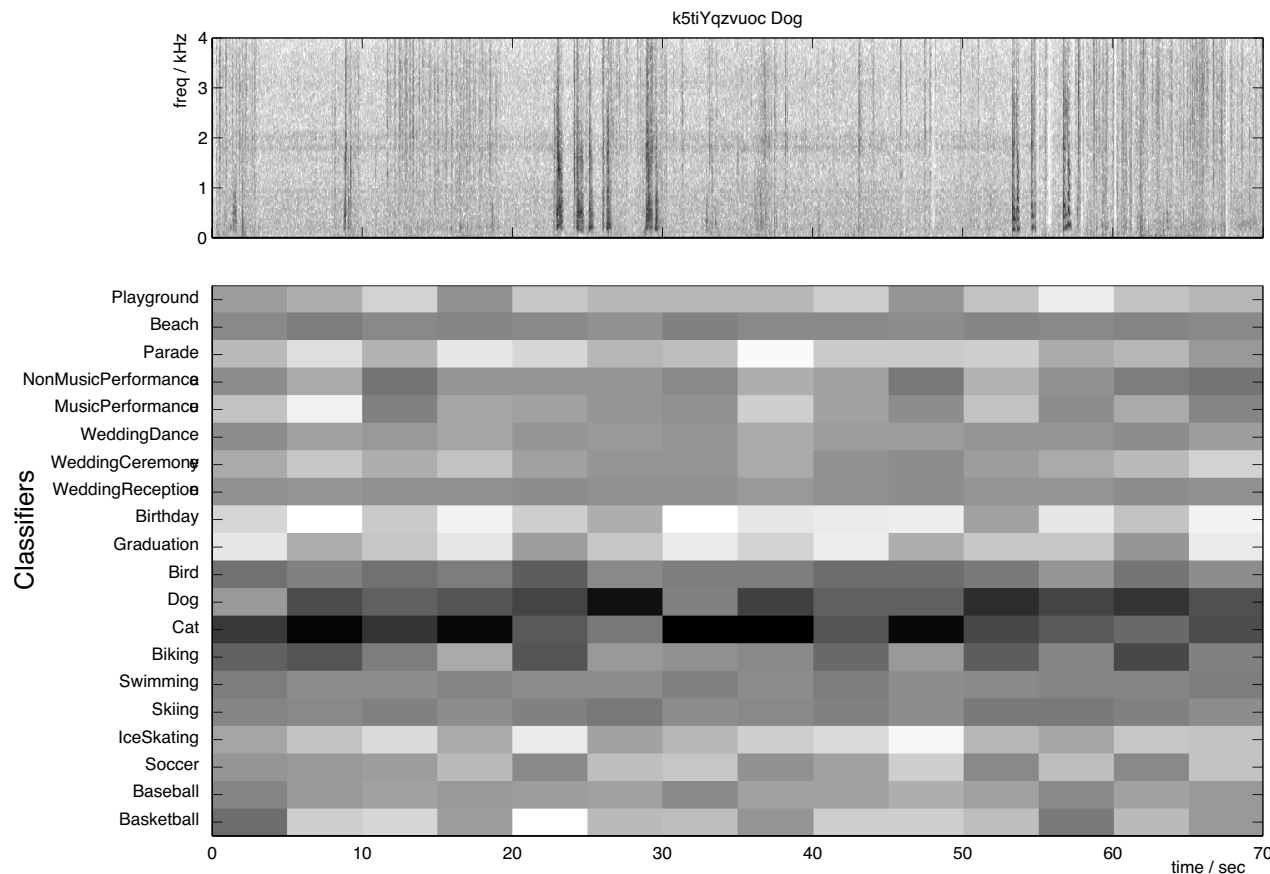
Auditory Model Feature Results

- **SAI** and **SBPCA** close to **MFCC** baseline
- **Fusing** MFCC and SBPCA improves mAP by 15% rel
 - mAP: 0.35 → 0.40
- **Calculation time**
 - **MFCC**: 6 hours
 - **SAI**: 1087 hours
 - **SBPCA**: 110 hours



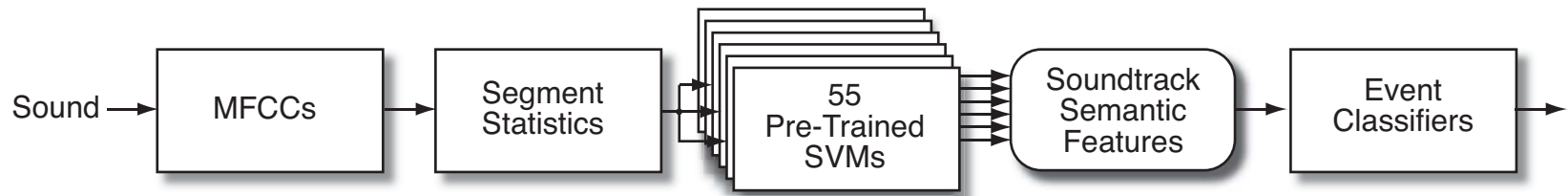
What is Being Recognized?

- Soundtracks represented by **global features**
 - MFCC covariance, codebook histograms
 - What are the **critical parts** of the sound?



Semantic Audio Features

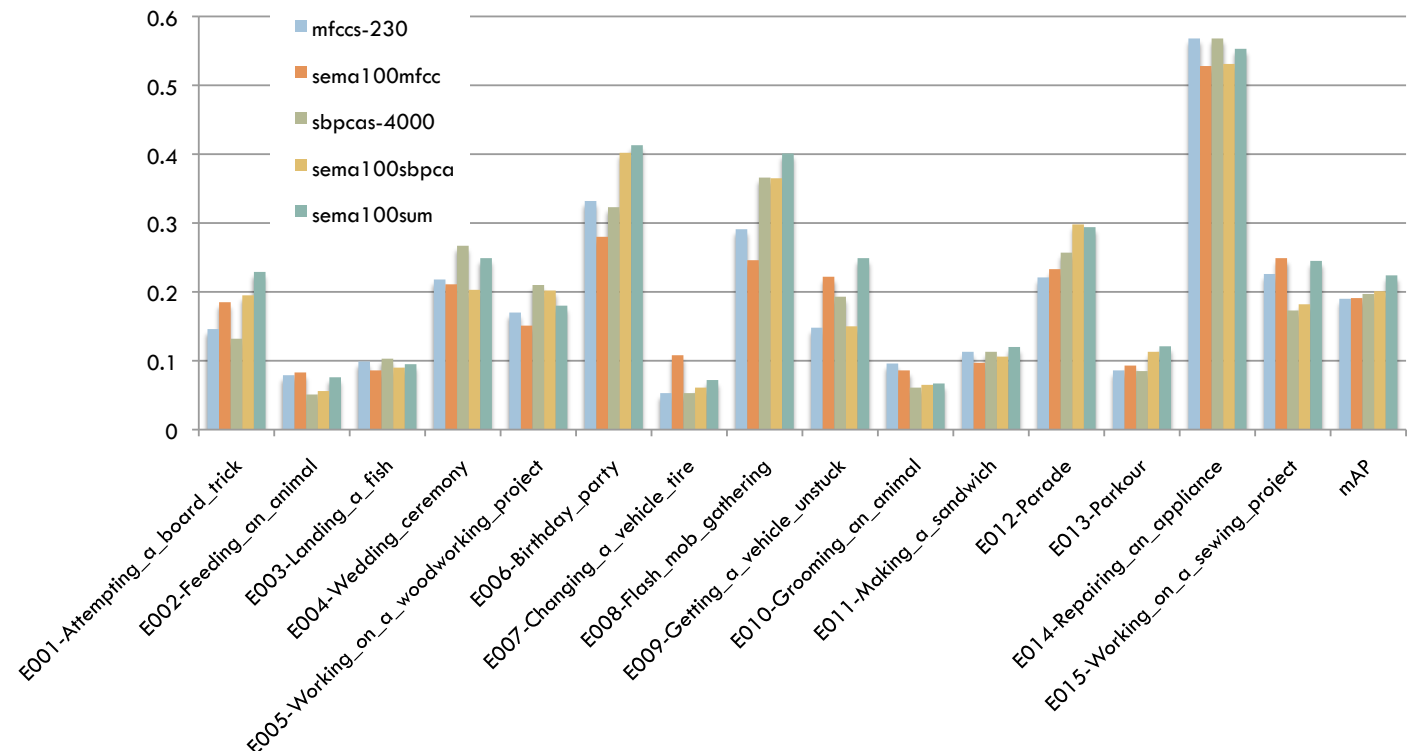
- Train **classifiers** on **related** labeled data



- defines a new “semantic” feature space

- Use for **target classifier**

- or combo



4. Labels & Annotation

Burger et al. '12

- “**Semantic Features**” are a promising approach
 - but we need good coverage...
 - how to learn more categories?
- **Annotation is expensive**
 - fine time annotation
 - > 10x real-time
 - a few hours are available
- **What to label?**
 - generic vs. task-specific

animal	singing	clatter
anim_bird	music_sing	rustle
anim_cat	music	scratch
anim_ghoat	knock	hammer
anim_horse	thud	washboard
human_noise	clap	applause
laugh	click	whistle
scream	bang	squeak
child	beep	tone
mumble	engine_quiet	sirene
speech	engine_light	water
speech_ne	power_tool	micro_blow
radio	engine_heavy	wind
white_noise	cheer	
other_creak	crowd	

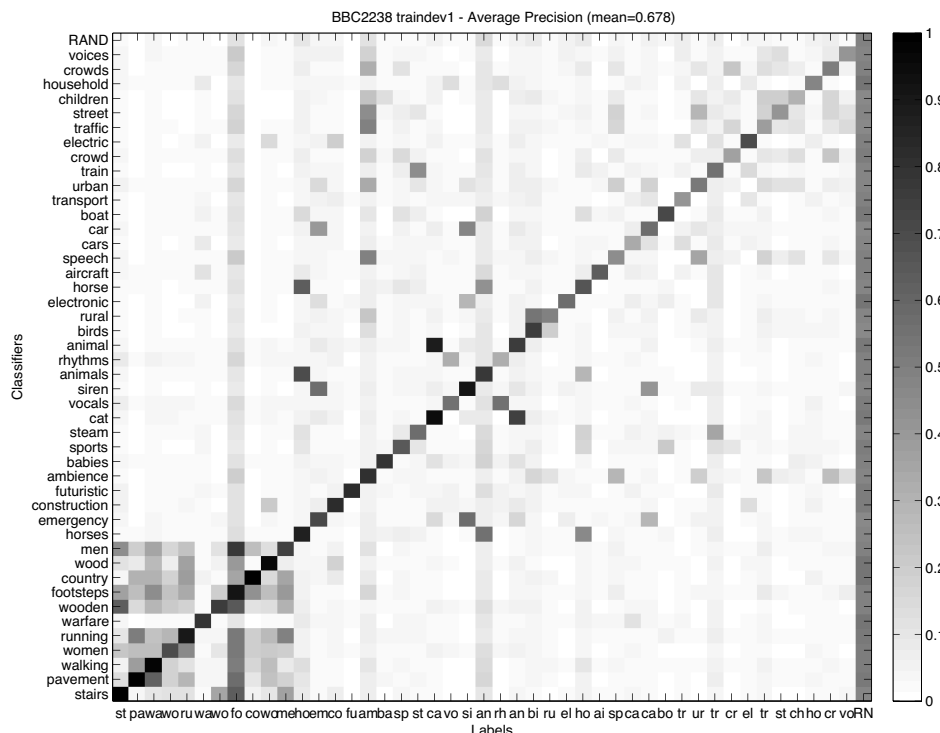
BBC Audio Semantic Classes

- **BBC Sound Effects Library**
 - 2238 tracks (60 h)
 - short descriptions
- Use **top 45 keywords**

SFX001-04-01	Wood Fire Inside Stove	5:07
SFX001-05-01	City Skyline City Skyline	9:46
SFX001-06-01	High Street With Traffic, Footsteps	
SFX001-07-01	Car Wash Automatic, Wash Phase Inside R	
SFX001-08-01	Motor Cycle Yamaha Rd 350: Motor Cycle	
SFX001-09-01	Motor Cycle Yamaha Rd 350, Rider Runs U	

↓

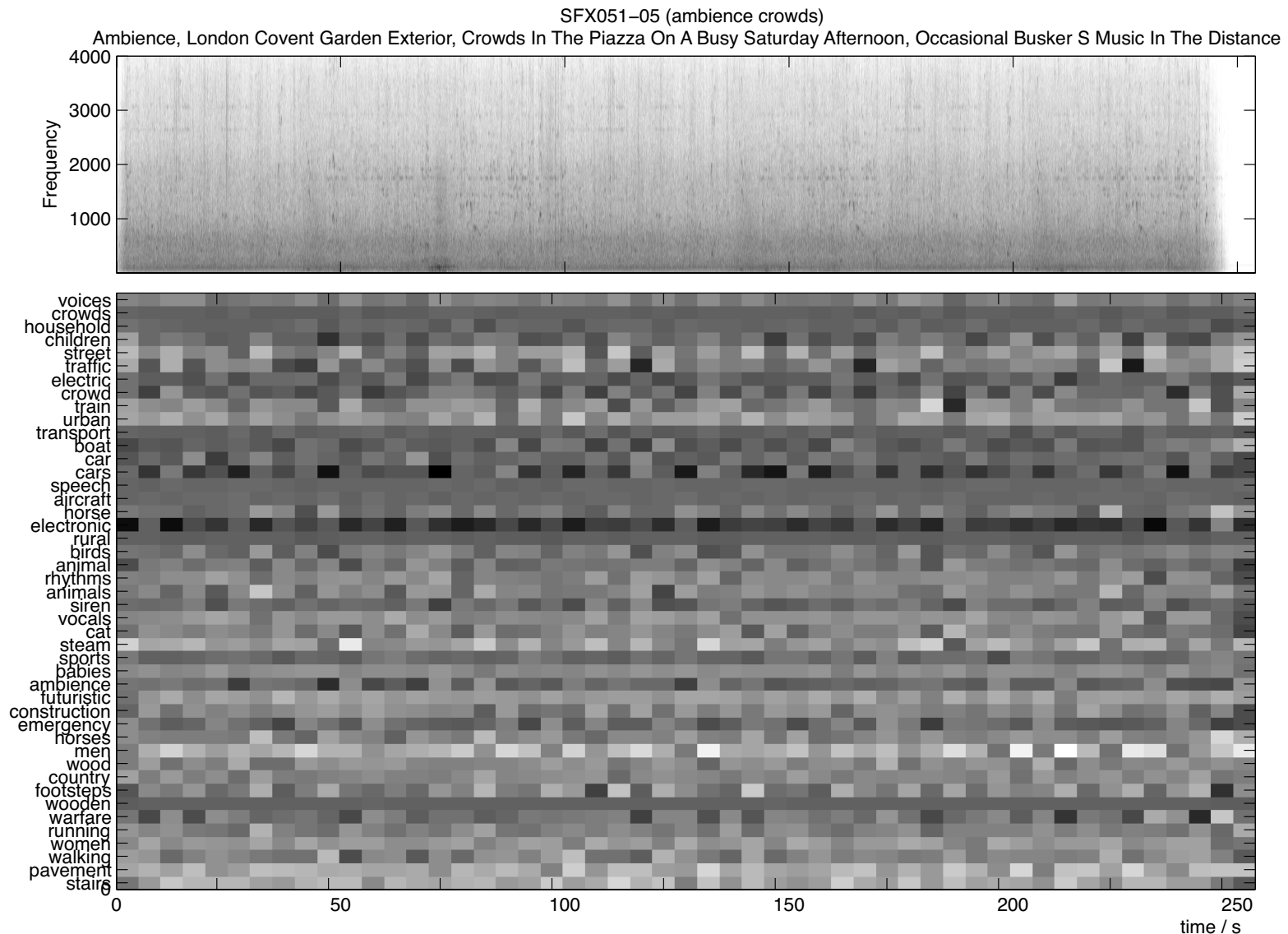
290 footsteps	59 men
267 on	59 general
240 animals	55 switch
197 ambience	53 starts
193 interior	53 crowds
...	...



- Added as **“semantic units”**
 - some redundancy visible in mutual APs

BBC Audio Semantic Classes

- Limited semantic correspondence



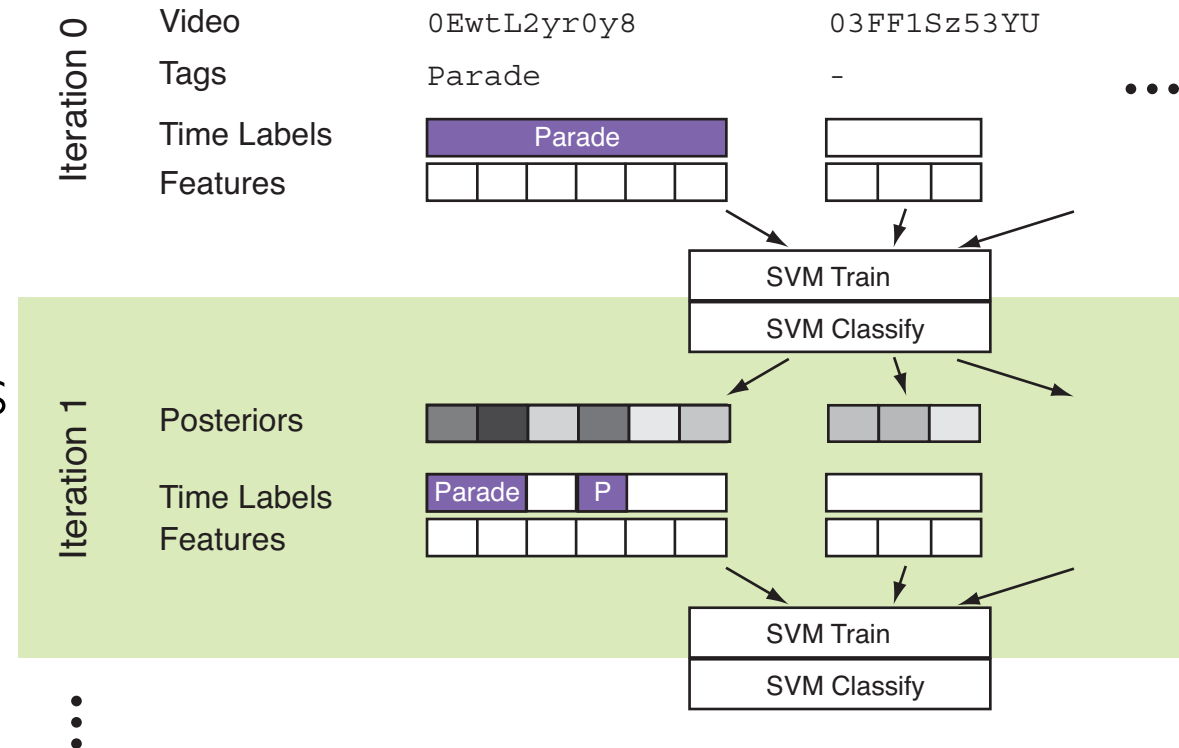
Label Temporal Refinement

K Lee, Ellis, Loui '10

- **Audio Ground Truth at coarse time resolution**
 - better-focused labels give better classifiers?
 - but little information in very short time frames

- **Train classifiers on shorter (2 sec) segments?**

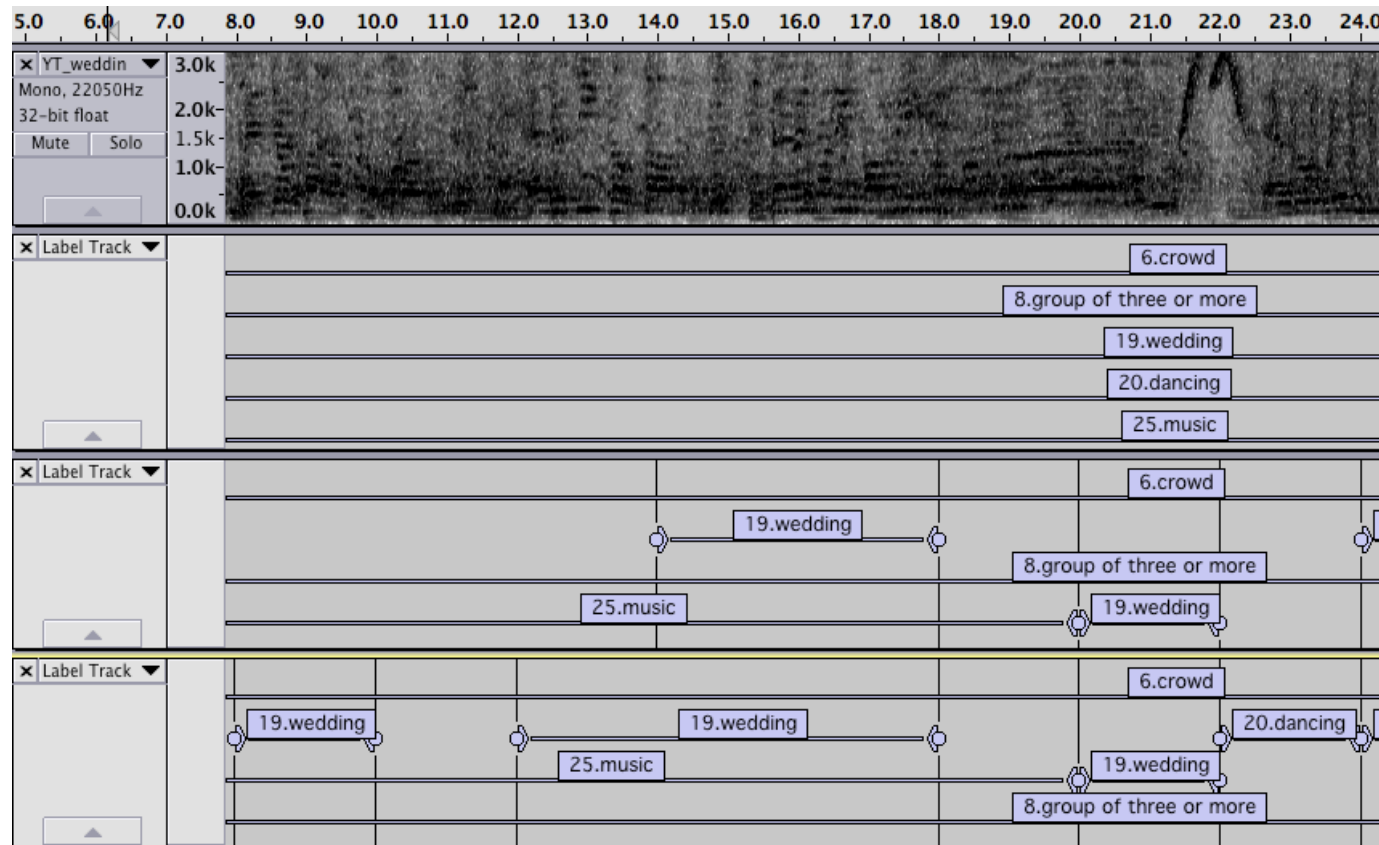
- Initial labels apply to whole clip
- **Relabel** based on most likely segments in clip
- Retrain classifier



Label Temporal Refinement

- Refining labels is “**Multiple Instance Learning**”
 - “Positive” clips have at least one +ve frame
 - “Negative” clips are all -ve
- Refine based on previous classifier’s scores

- threshold from CDFs of +ve and -ve frames
- mAP improves ~10% after a few iterations



5. Future: Tasks & Metrics

- Environmental sound recognition:
What is it **good for**?
 - media content description (“**Recounting**”)
 - environmental **awareness**

- What are the right ways to **evaluate**?
 - task-specific metrics: AEER, F-measure
 - downstream tasks: WER, mAP
 - real **applications**: archive search, aware devices

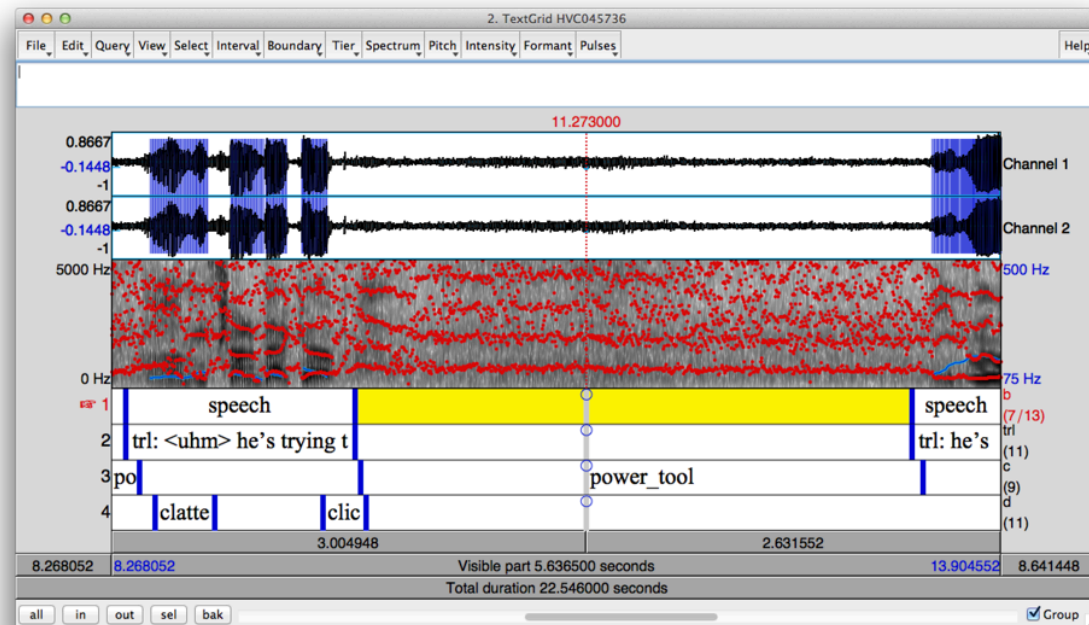


Labels & Annotations

- Training data: **quality** vs. **quantity**

- **quality** costs:
 - DCASE ~ 0.3 h
 - TRECVID MED ~ 10 h

- **quantity** always wins

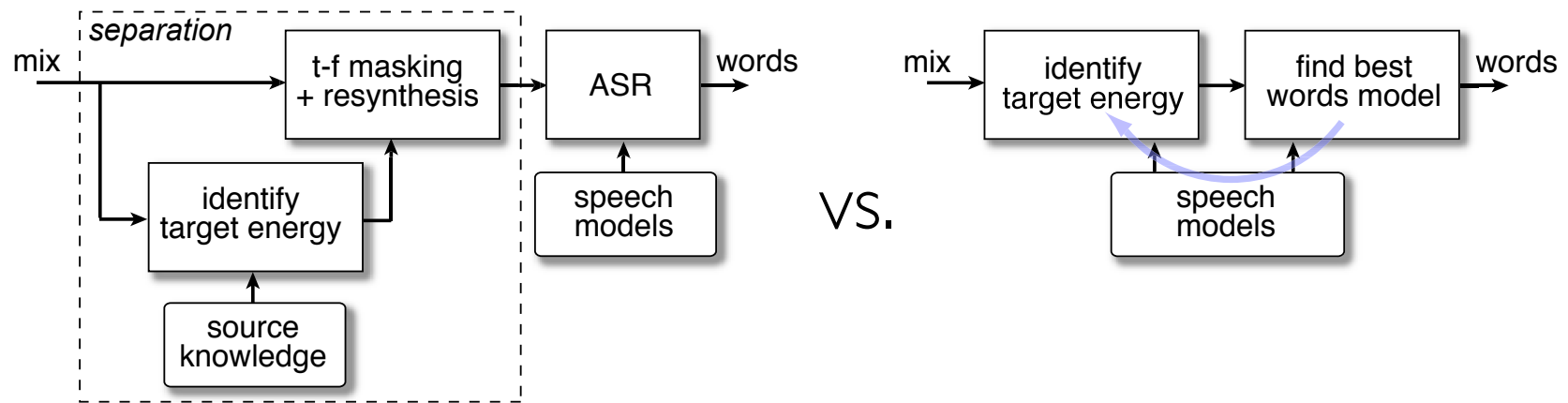


Susanne Burger CMU

- **Opportunistic labeling**
 - e.g. Sound Effects library, subtitles ...
 - need **refinement** strategies
- Existing annotations indicate **interest**

Source Separation

- Separated sources makes event detection easy
 - “separate then recognize” paradigm



- integrated solution more powerful...
- Environmental Source Separation is **ill-defined**
 - relevant “sources” are listener-defined
 - environment description addresses this
 - Environment recognition for source separation

Summary

- (Machine) Listening:
Getting useful information from sound
- Foreground event recognition
... by focusing on peak energy patches
- Background sound retrieval
... from long-time statistics
- Data, Labels, and Task
... what are the sources of interest?

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