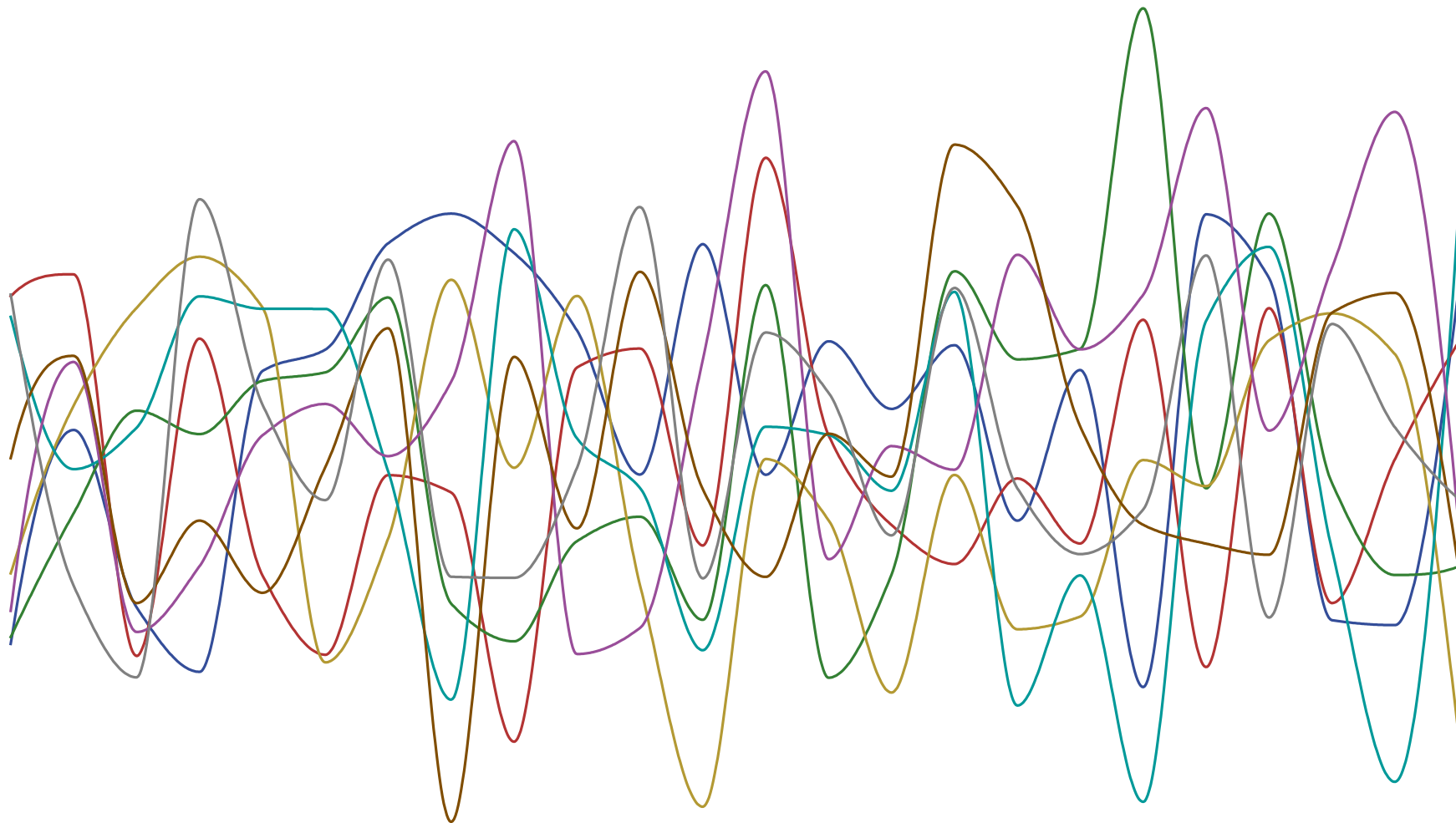




Fun with audio mixtures

(or why DSP is actually useful)

Paris Smaragdis

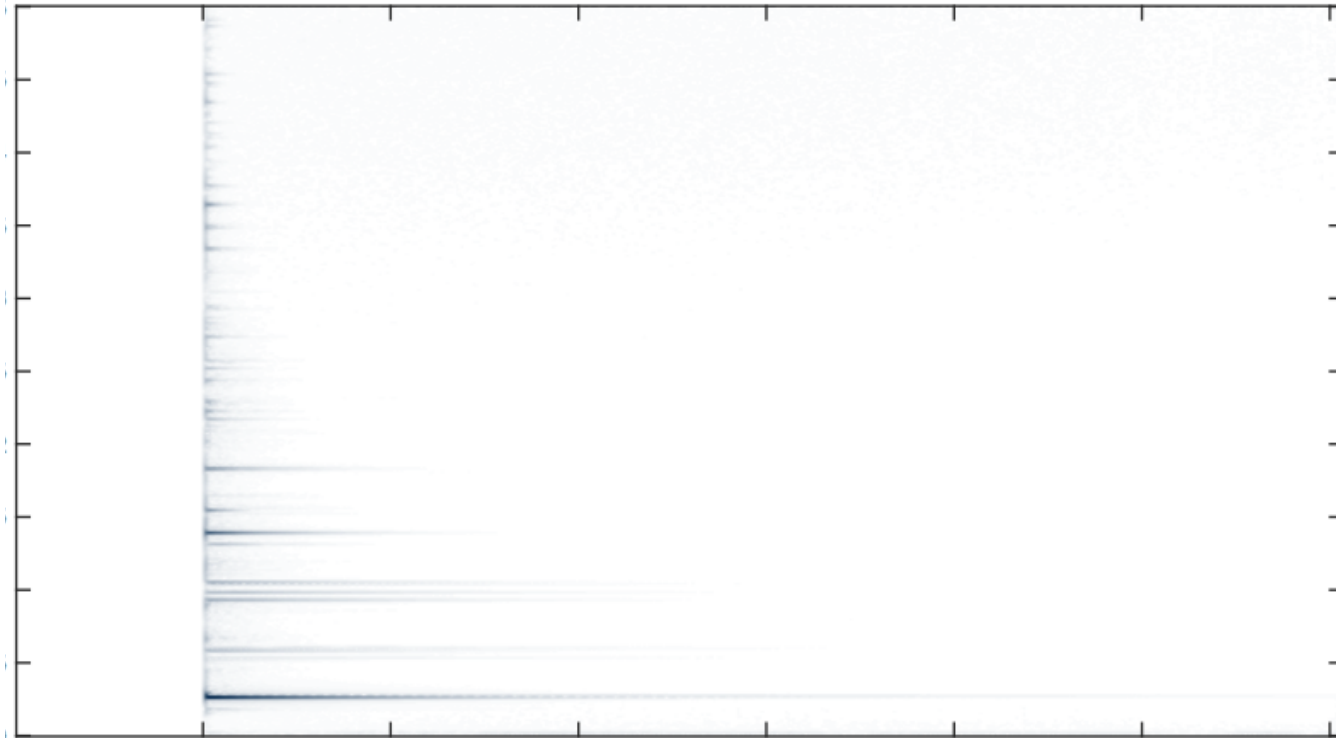
paris@illinois.edu

What fun?

- Audio mixture problems
 - Scene analysis
 - Separation
 - Denoising
 - Manipulation
 - Classification and detection
 - ...

A starter

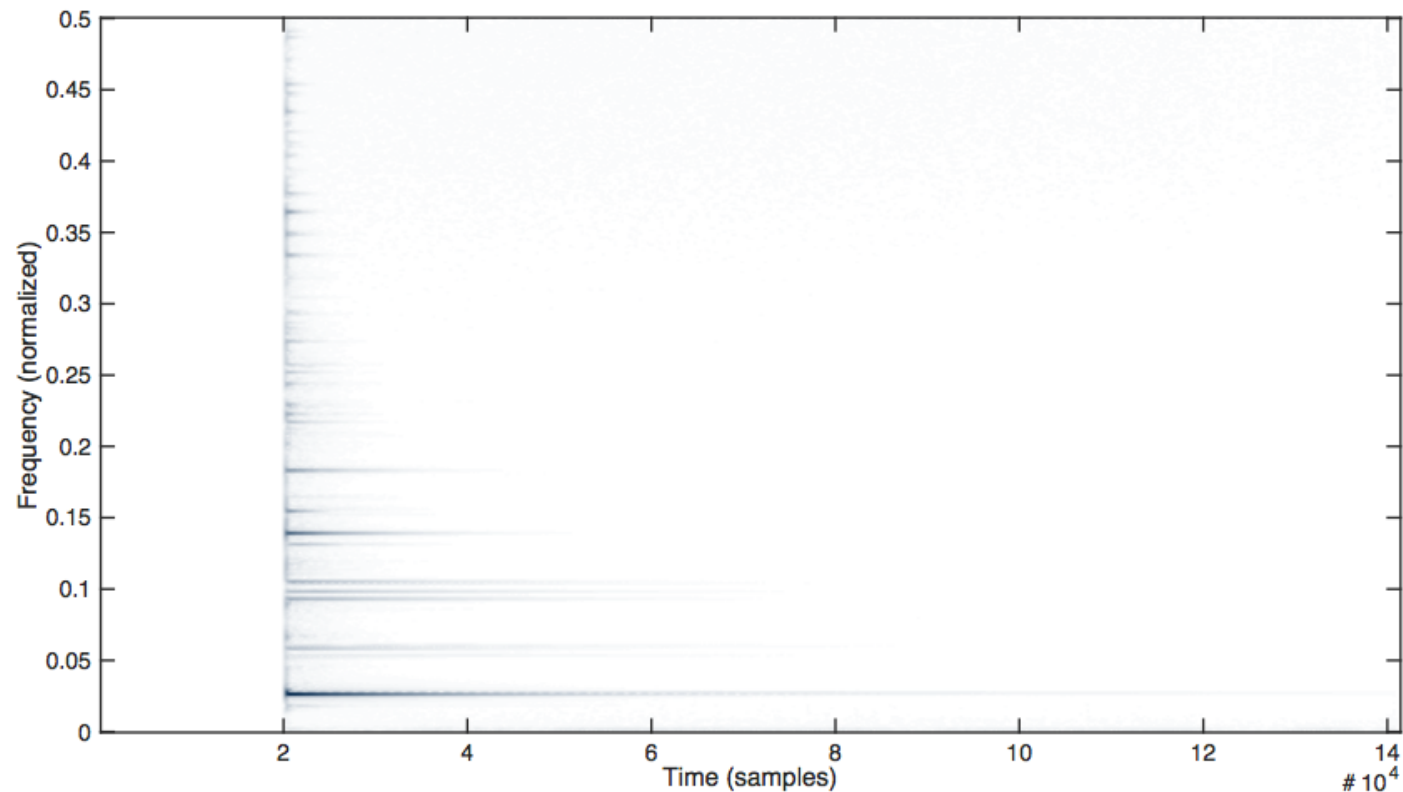
- What's this?



A spectrogram



- Representing energy in time/frequency



Factorizing a spectrogram

- We can approximate the 2D magnitude spectrogram as a product of two 1D functions
 - A “frequency function” and a “time function”

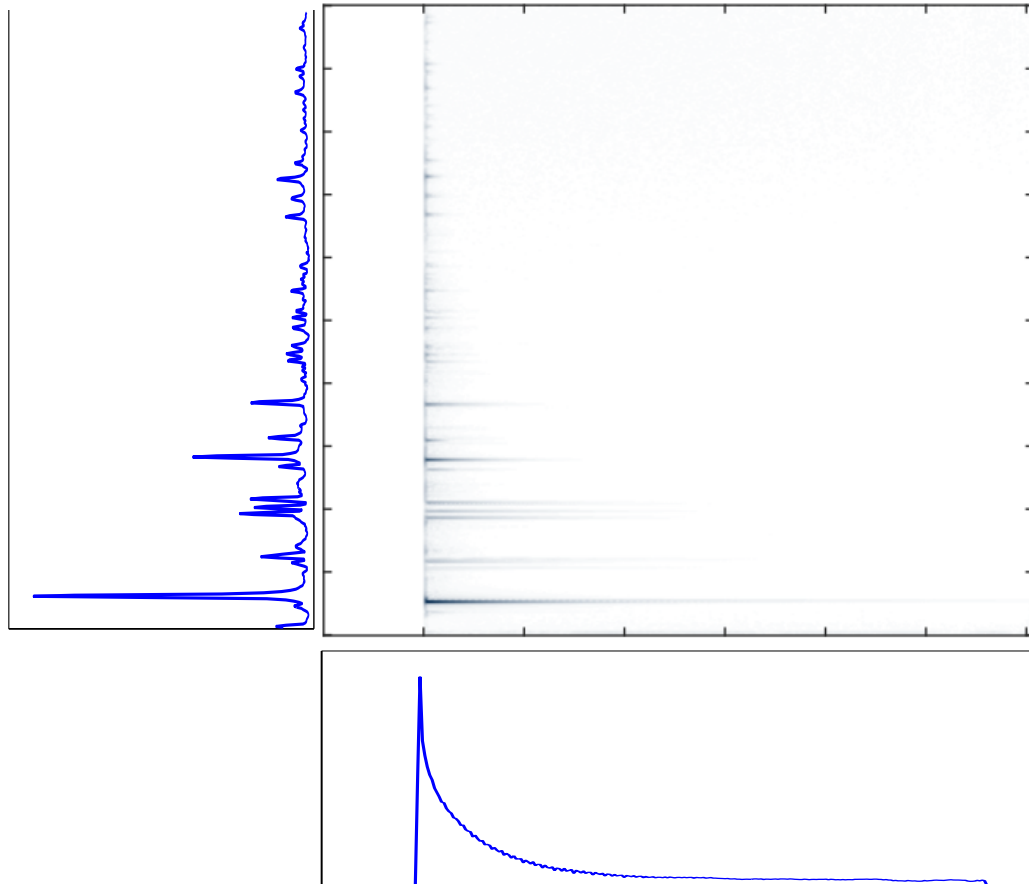
$$S(\omega, \tau) = F(\omega)A(\tau)$$

Spectrogram *Frequency function* *Time function*

The diagram illustrates the factorization of a spectrogram. The equation $S(\omega, \tau) = F(\omega)A(\tau)$ is shown. Below the equation, three labels are positioned: 'Spectrogram' under $S(\omega, \tau)$, 'Frequency function' under $F(\omega)$, and 'Time function' under $A(\tau)$. Arrows point from each label to its corresponding term in the equation.

Estimating the factors

- We integrate over each dimension



Nothing new here

- Frequency factor == Power spectrum
 - Energy distribution across frequency

$$F(\omega) = \int S(\omega, \tau) d\tau$$

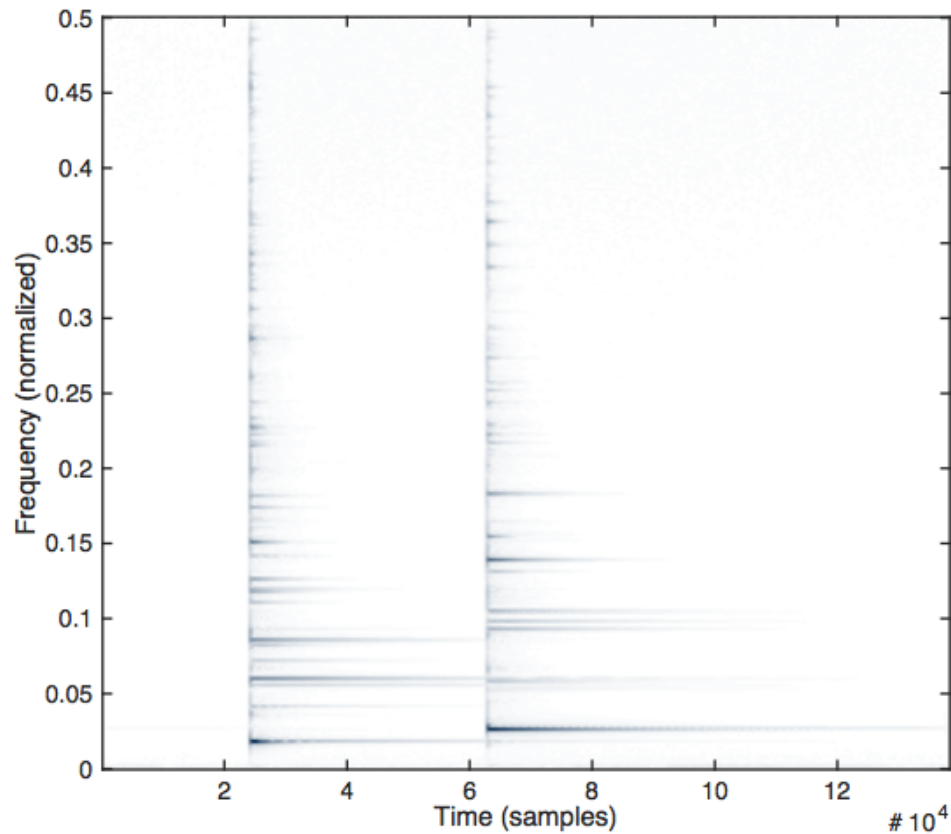
- Time factor == Time envelope
 - Energy distribution across time

$$A(\tau) = \int S(\omega, \tau) d\omega$$

Another example

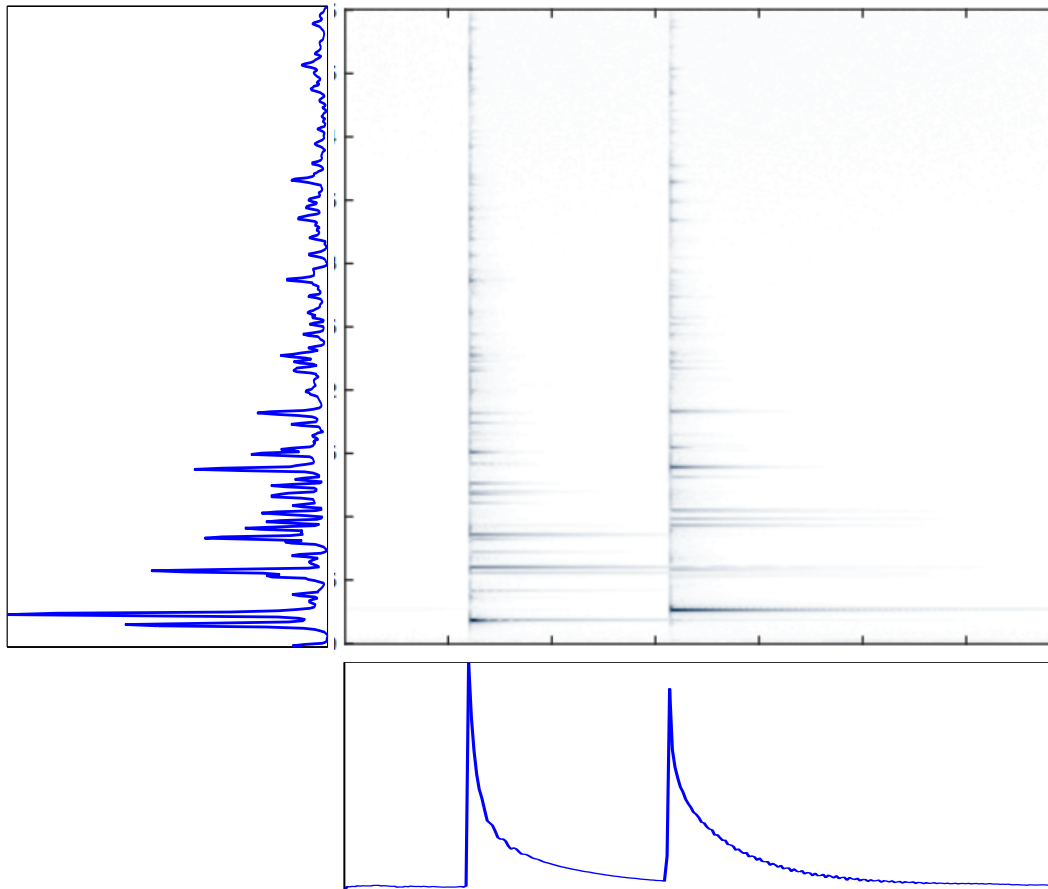


- What now?



Not as useful this time

- The factors are “mixed”



What if?

- Could we get two sets of factors?
 - One for each sound

- Initial factorization model:

$$S(\omega, \tau) = F(\omega)A(\tau)$$

- A “multiple factors” model:

$$S(\omega, \tau) = F_1(\omega)A_1(\tau) + F_2(\omega)A_2(\tau)$$

Learning this model

- Simple two-stage process

- 1. "Assign blame"

$$\gamma_i(\omega, \tau) = \frac{F_i(\omega)A_i(\tau)}{F_1(\omega)A_1(\tau) + F_2(\omega)A_2(\tau)}$$

- 2. Re-estimate

$$F_i(\omega) = \int \gamma_i(\omega, \tau) S(\omega, \tau) d\tau$$

$$A_i(\tau) = \int \gamma_i(\omega, \tau) S(\omega, \tau) d\omega$$

- Repeat ...

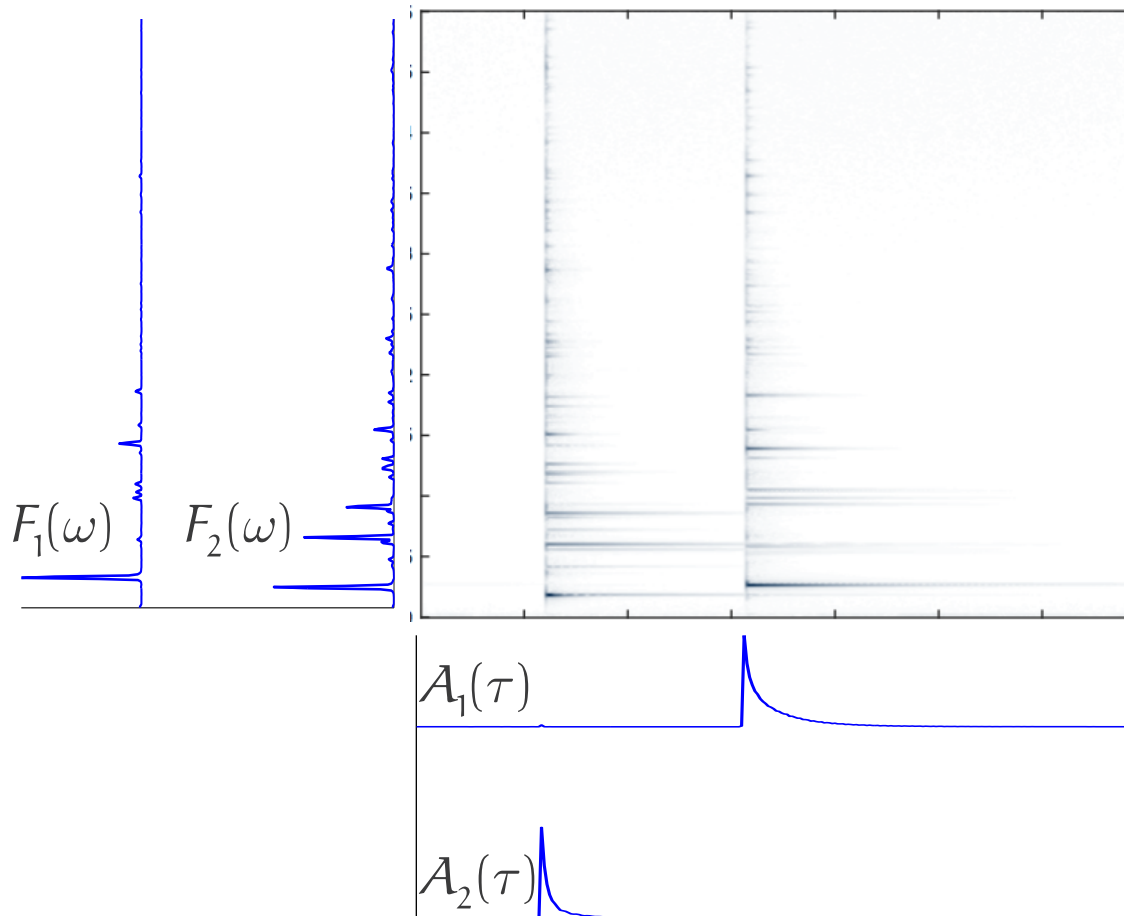
MATLAB code:

```
for i = 1:100
    g = s ./ (f * a);
    f = f .* (s * g');
    a = a .* (f' * g);
end
```

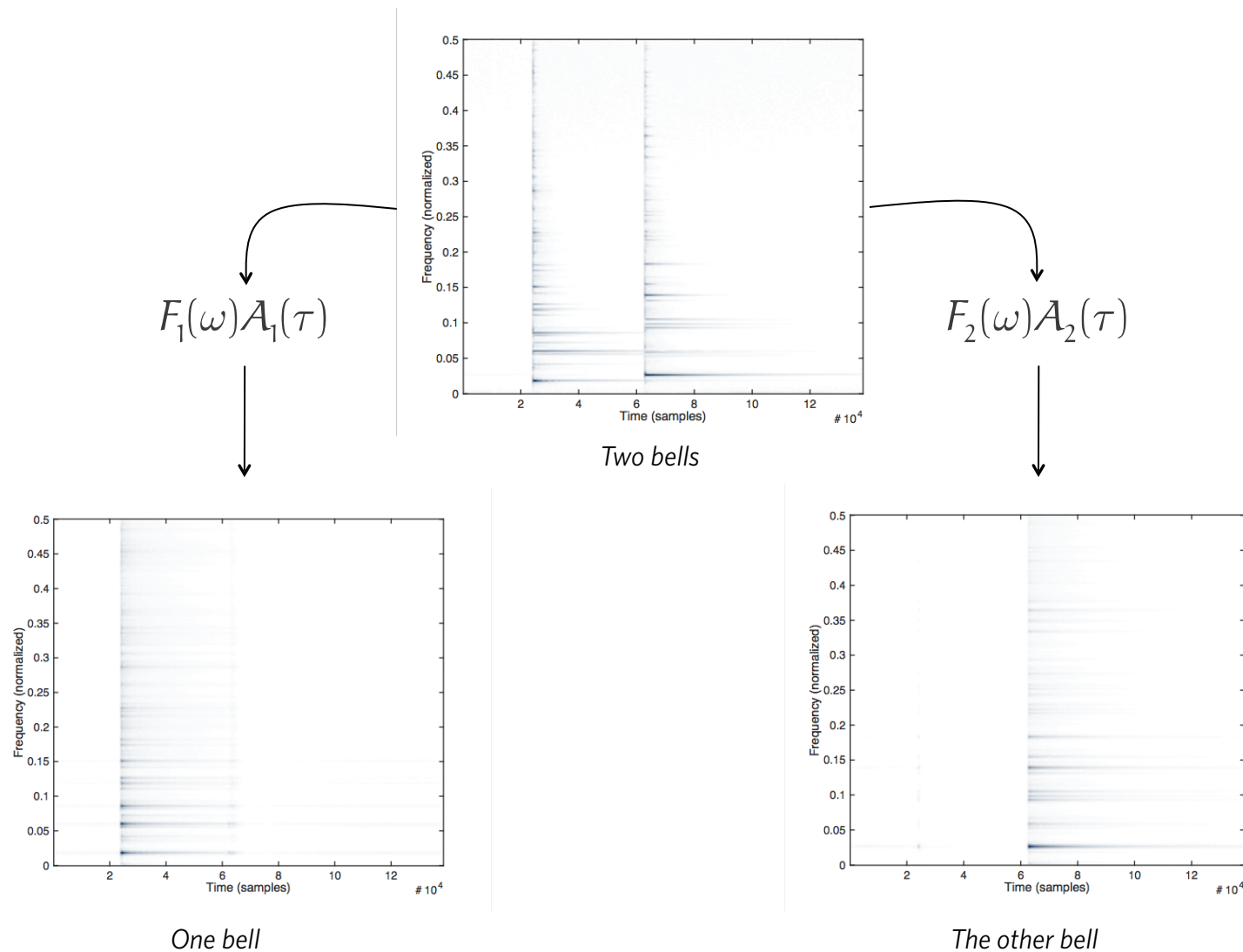


What does this do?

- More useful representation!



Factors learn sources



Going back to time

- Original input had amplitude *and* phase

$$S(\omega, \tau) = |\text{STFT } x(t)|$$

$$\Phi(\omega, \tau) = \angle \text{STFT } x(t)$$

- To get each source assume:

$$|\text{STFT } y_i(t)| = F_i(\omega) \mathcal{A}_i(\tau)$$

$$\angle \text{STFT } y_i(t) = \Phi(\omega, \tau)$$

- So now we can extract each bell:

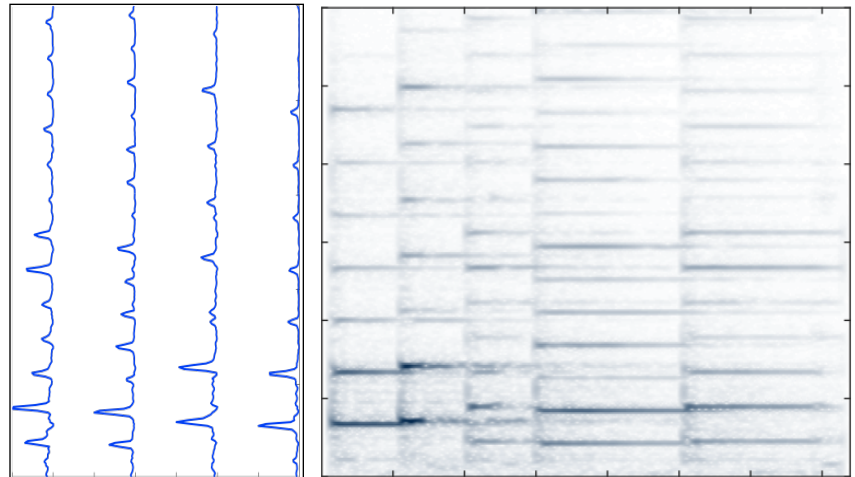


Let's try some music

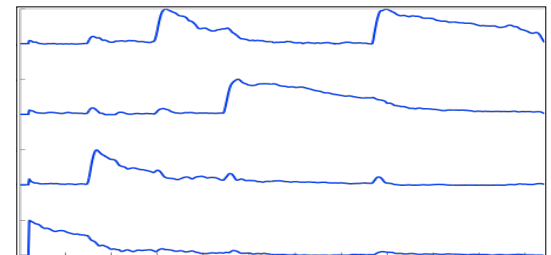


- Use more factors
 - Four in this case
- What do they correspond to?

A bit of Bach



*4 piano notes
5 instances*



General algorithm

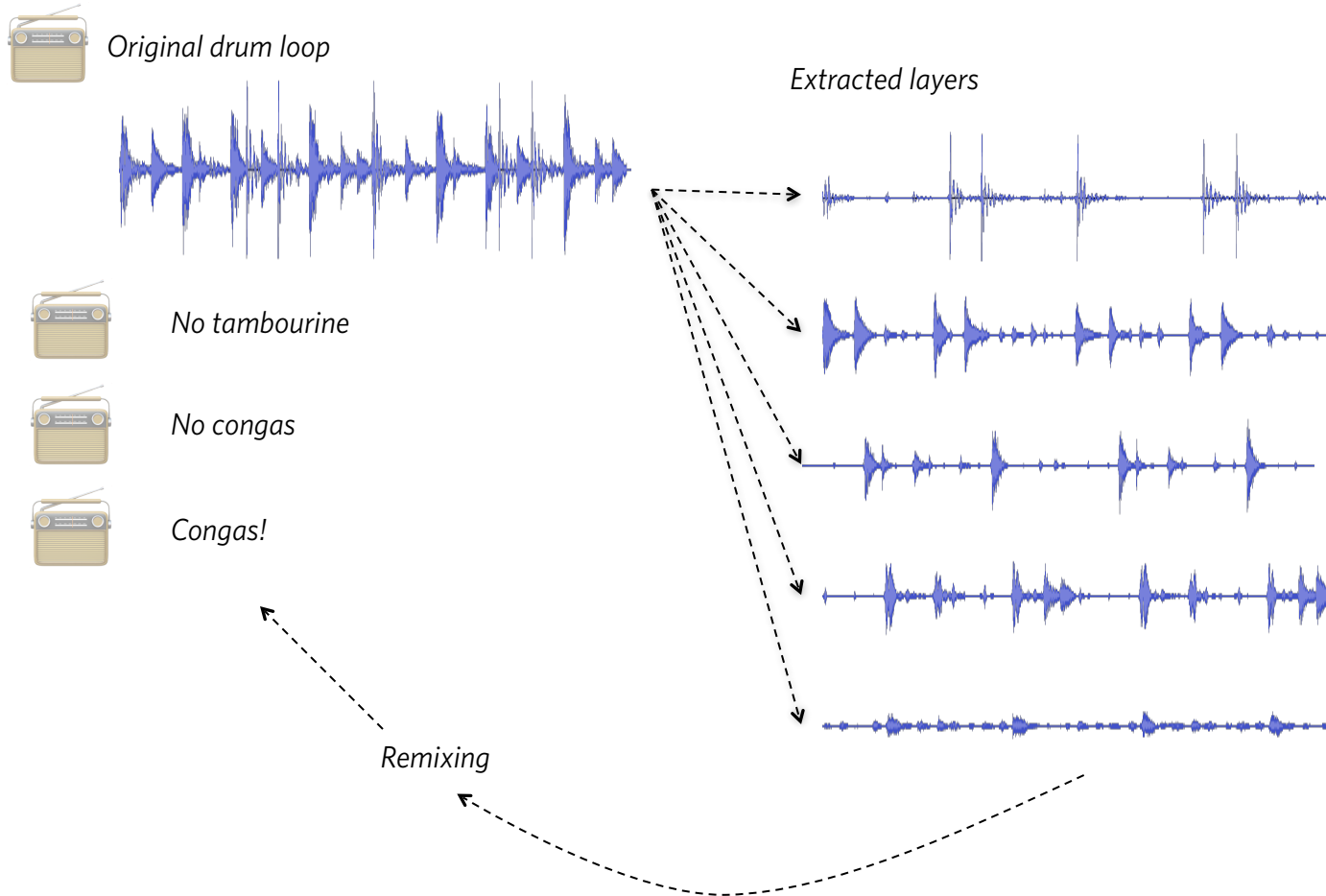
- If you like linear algebra:
 - Non-negative Matrix Factorization

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

- If you like probability:
 - Probabilistic Latent Component Analysis

$$P(\omega, \tau) = \sum_z P(z)P(\omega | z)P(\tau | z)$$

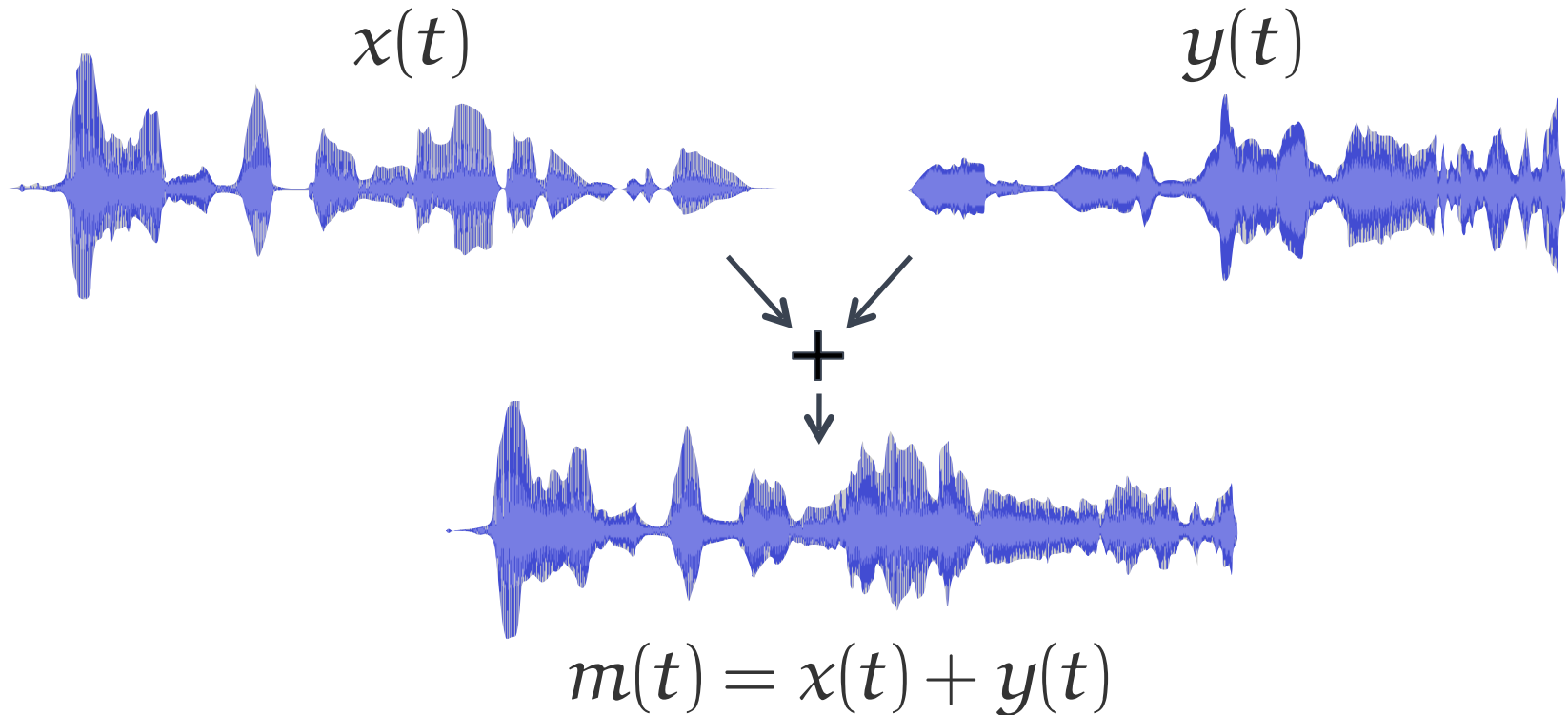
Audio remixing



But ...

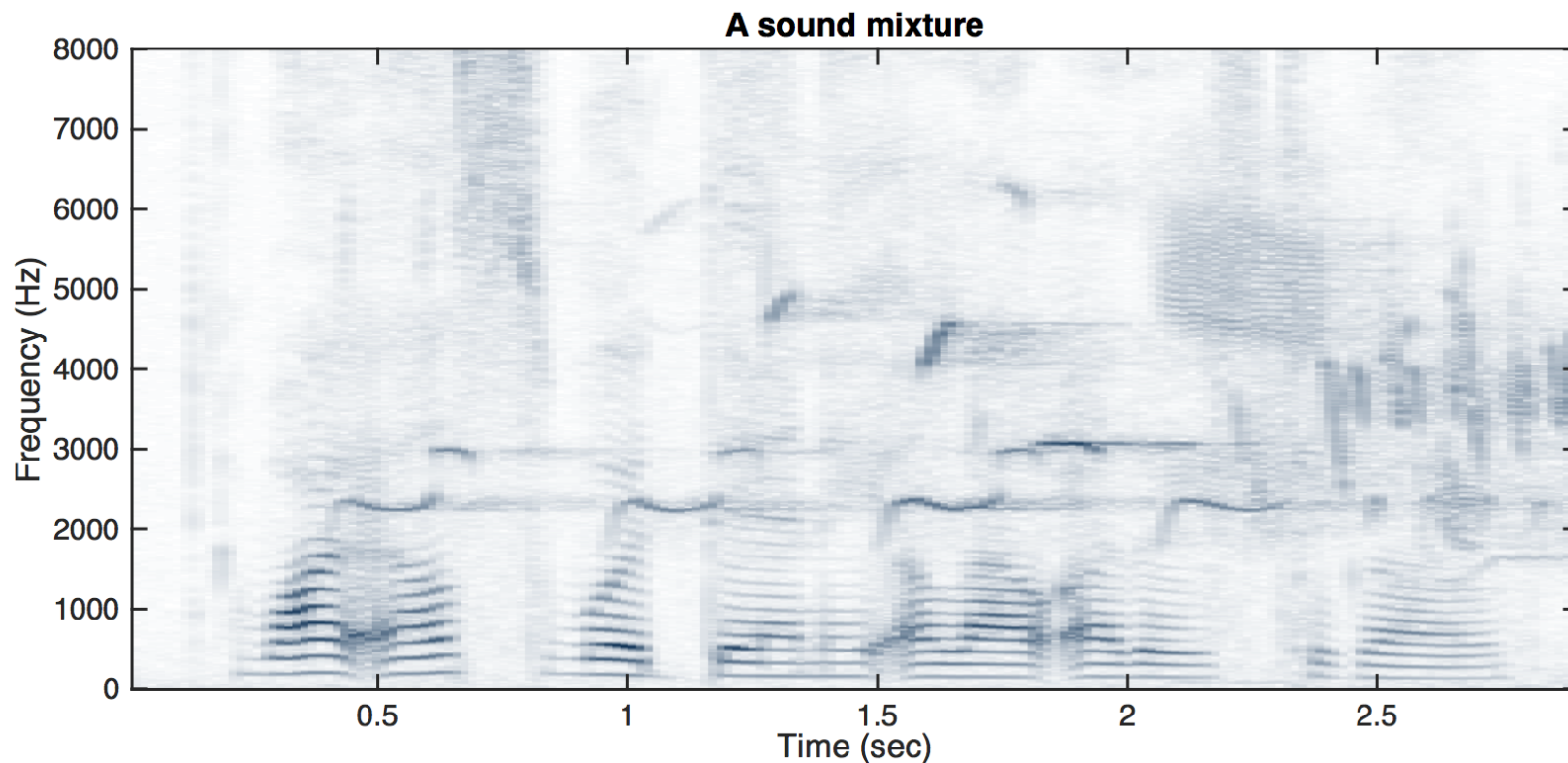
- We can only deal with simple sounds
 - Why?
- Let's look at real-world source separation

Defining the problem



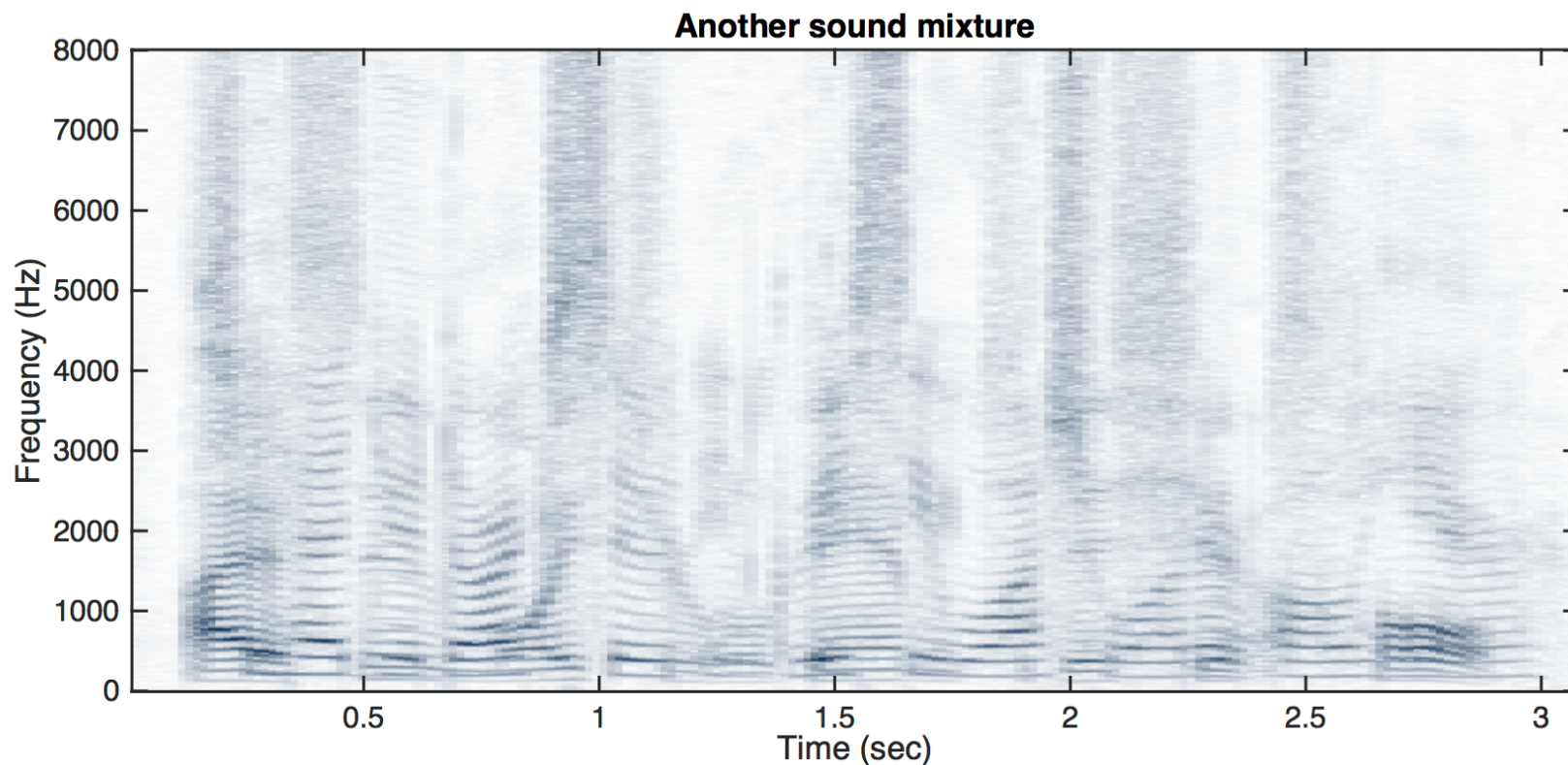
- An ill-defined problem!
 - “Single-channel source separation”

The name of the game



- Finding signal priors to perform separation
 - School a: Perceptually-minded approaches
 - School b: Statistical approaches

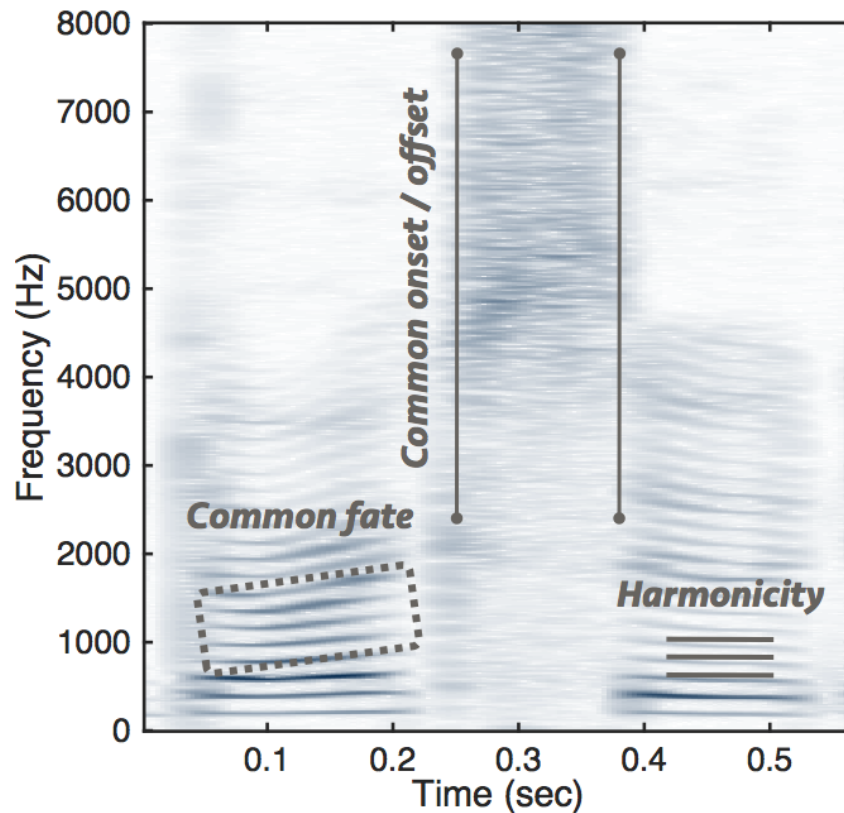
The name of the game



- Finding signal priors to perform separation
 - School a: Perceptually-minded approaches
 - School b: Statistical approaches

Perceptual approaches

- “Computational Auditory Scene Analysis”
 - Driven by psychoacoustic experiments



Brown



Ellis



Wang



Some (general) statistical approaches

- Approaches with general source assumptions
 - Lee and Jang
 - ICA dictionaries of time waveforms
 - Reyes, Jojic and Ellis
 - Graphical model on TF distributions
 - Lagrange, et al.
 - Normalized cuts
 - Bach and Jordan
 - Spectral clustering for perceptual grouping
- Things aren't great ...

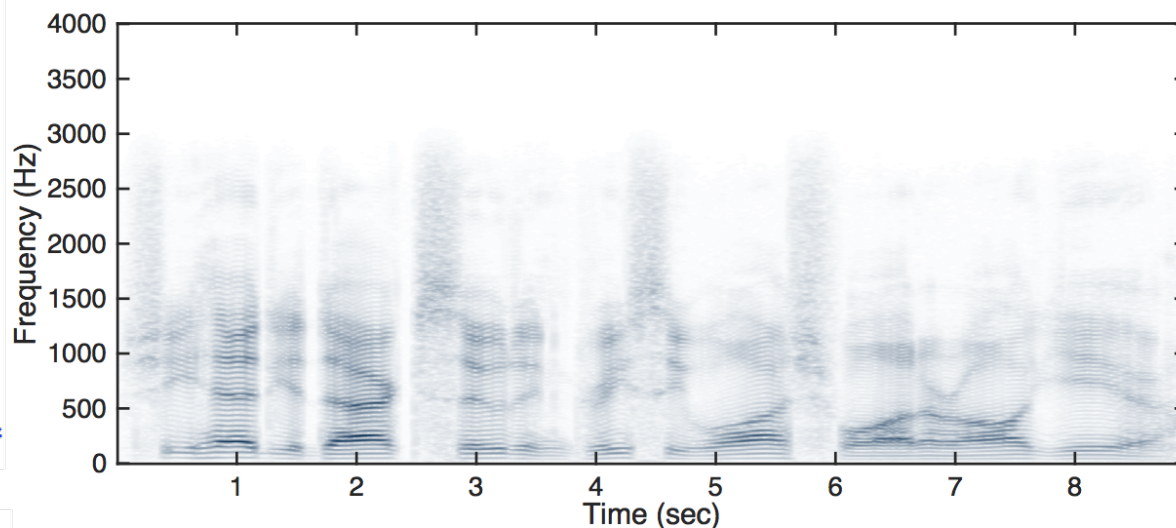
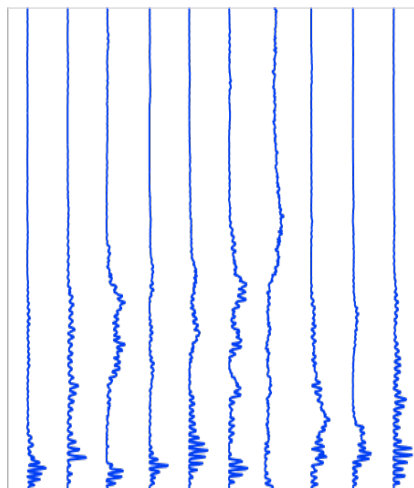


Forgetting unsupervised methods

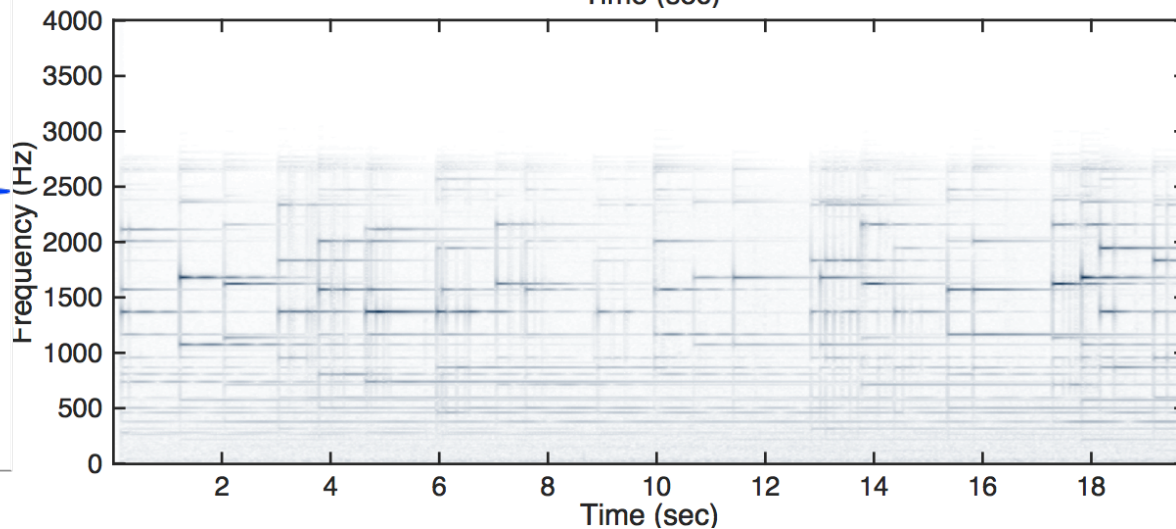
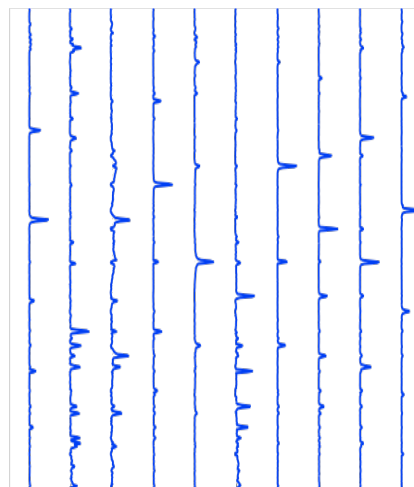
- It is hard to define source structure
 - We should learn it instead
- Supervised source separation
 - Use training data to hints what you want

Learning factor dictionaries

Speech example



Chime example



Mixtures of sounds

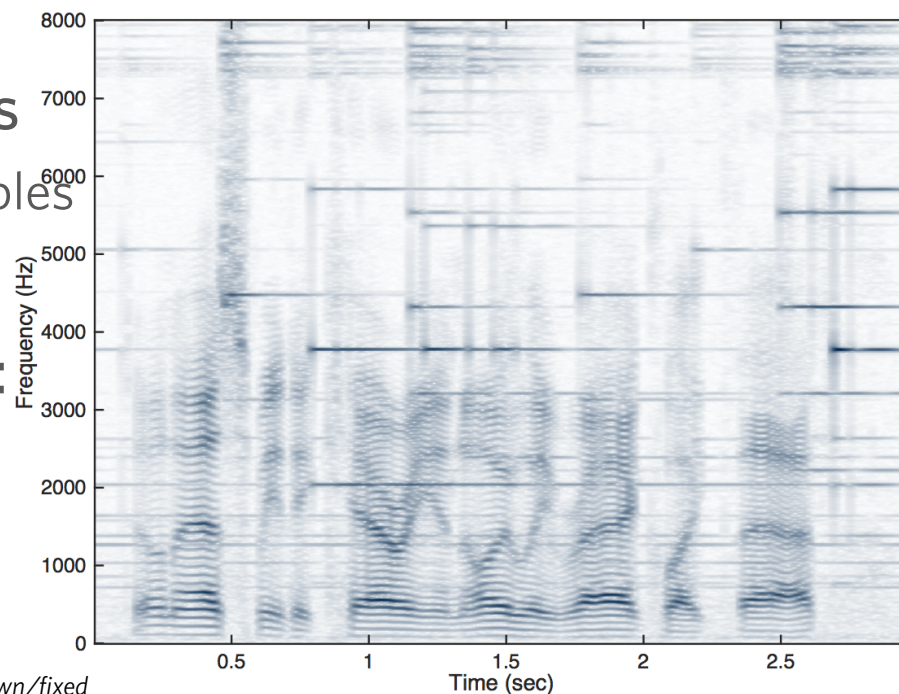


- Assumption: Sound mixtures are composed by frequency factors of the included sounds
 - Which we can learn from examples
- To separate estimate their proportions from the mixture:

$$\underline{S(\omega, \tau)} = \sum_i \underline{F(\omega, i)} \underline{A(\tau, i)}$$

$$F(\omega, i) = \begin{cases} F_{chimes}(\omega, i) \\ F_{speech}(\omega, i) \end{cases}$$

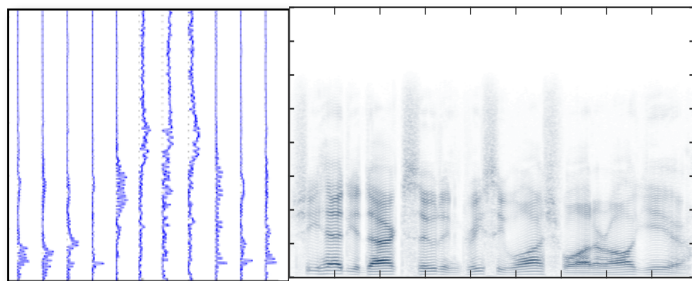
— Known/fixed
— Estimated



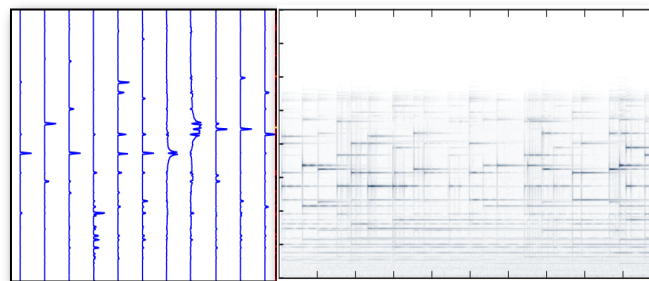
Speech and Chimes

Huh?

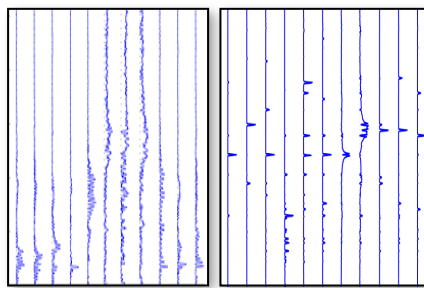
Learn speech dictionary



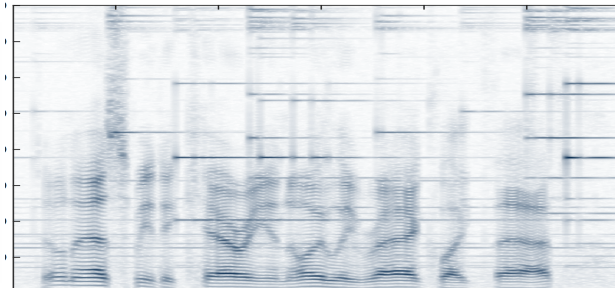
Learn chime dictionary



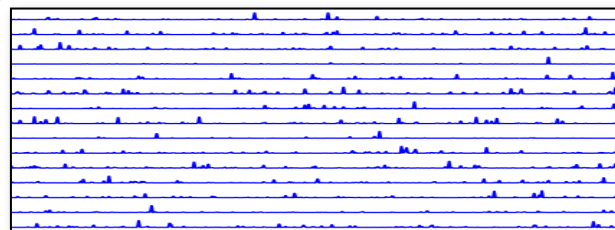
Keep fixed



Mixture of speech and chimes



Learn only the weights



Speech and Chimes



Speech and Speech



What if we don't have models?

- We usually don't know the frequency dictionary of all sounds in a mixture
 - We might know only some
- Complementary learning:

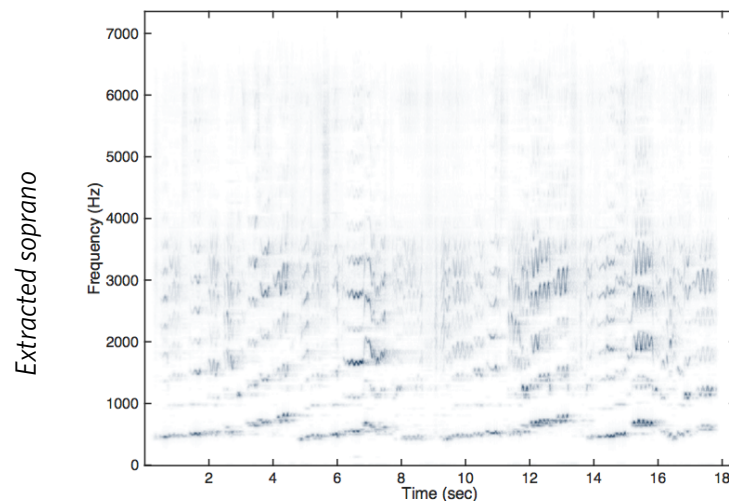
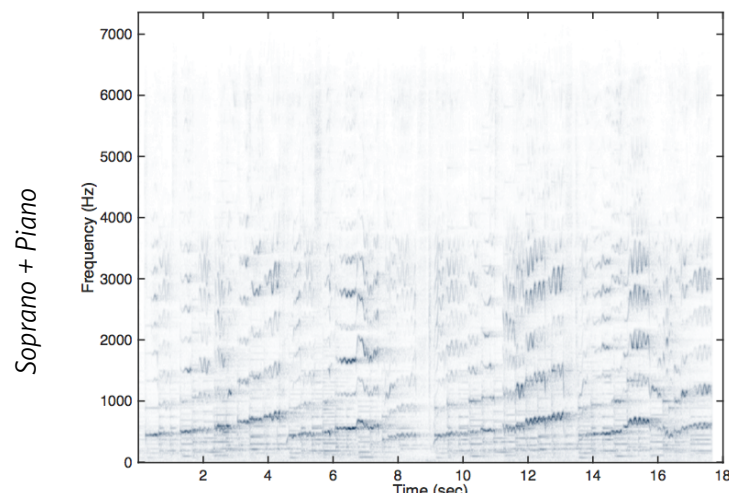
$$\underline{S(\omega, \tau)} = \sum_i \underline{F(\omega, i)} \underline{A(\tau, i)}$$

— Known/fixed
— Estimated

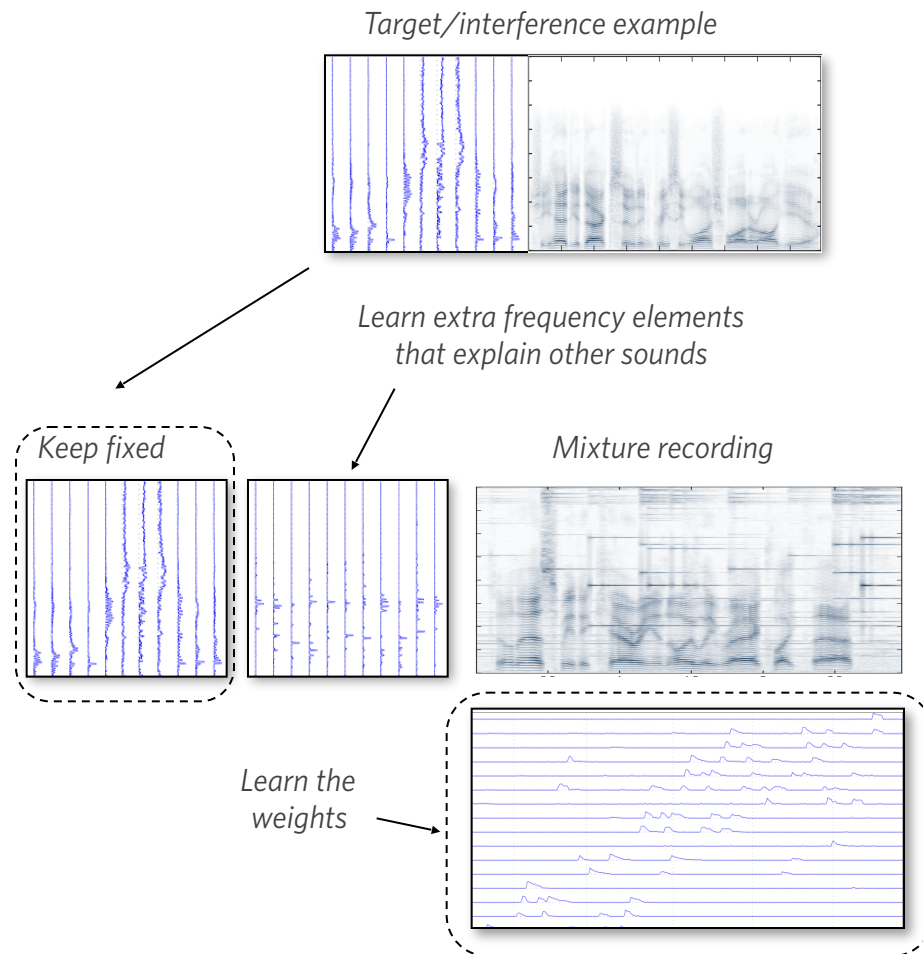
$$F(\omega, i) = \begin{cases} F_{\text{known}}(\omega, i) \\ F_{\text{unknown}}(\omega, i) \end{cases}$$

Soprano + Piano 

Soprano 



Huh again?



Use in denoising

- Two cases
 - Have noise model, extract target
 - E.g. noise is street ambience
 - Have target, remove noise
 - E.g. cell phone knows your voice
- Denoising, Separation, Karaoke, ...

Speech & the beauty of mechanics



Wideband noise

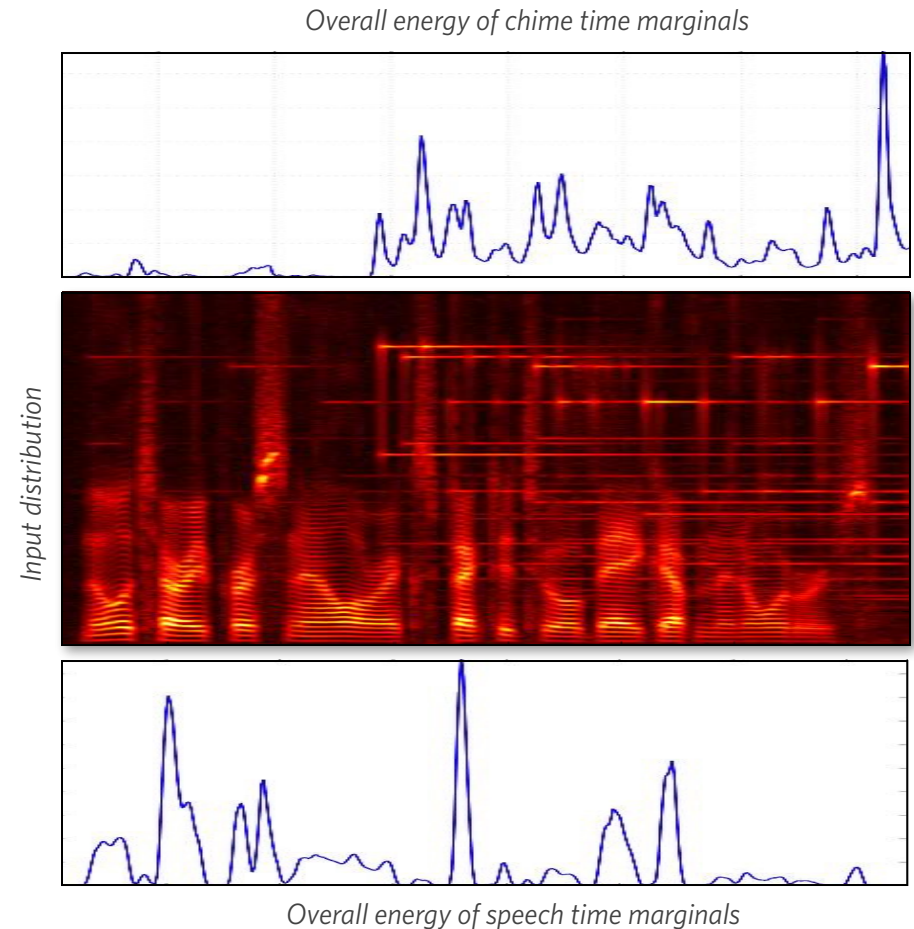


*Noise removal
example*



Presence of factors

- Time factors indicate amount of presence of a sound in a mixture
- This is very useful for analyzing scenes where we care to find sounds



Sound recognition in mixtures

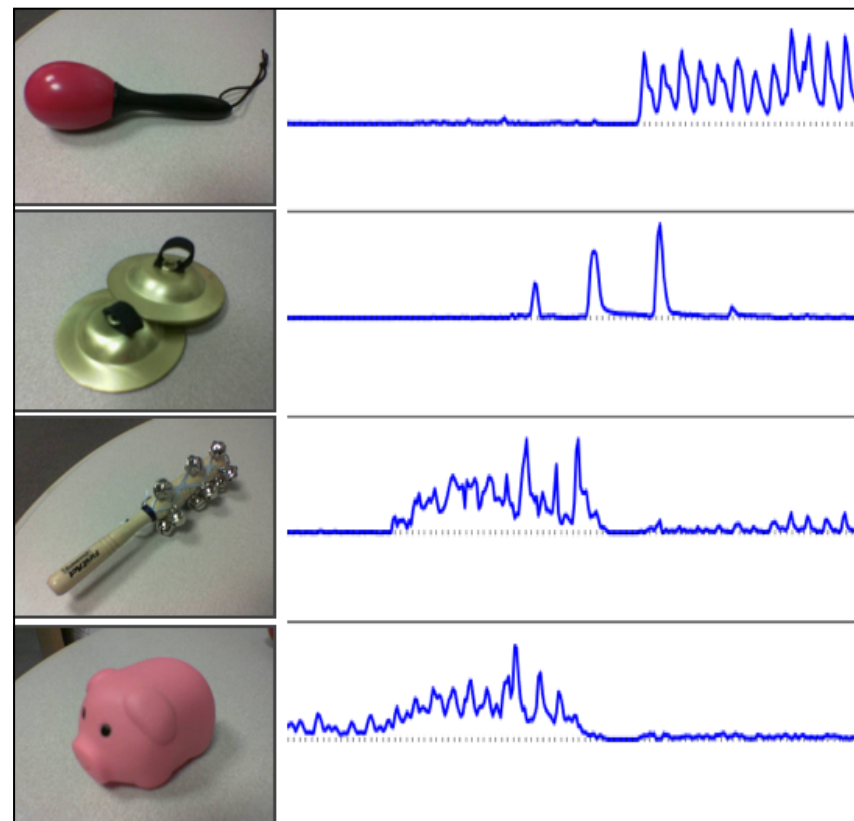


- Sound classification is very poorly defined in machine learning
 - Uses winner-takes-all approach
 - But we have simultaneous sounds
- Mixed sound recognition model

$$\mathcal{S}(\omega, \tau) = \sum_i \begin{bmatrix} \underline{P_{shaker}(\omega, i)} \\ P_{cymbals}(\omega, i) \\ P_{jingles}(\omega, i) \\ \underline{P_{pig}(\omega, i)} \end{bmatrix} \cdot \begin{bmatrix} P_{shaker}(\tau, i) \\ P_{cymbals}(\tau, i) \\ P_{jingles}(\tau, i) \\ \underline{P_{pig}(\tau, i)} \end{bmatrix}$$

— Known/fixed
— Estimated

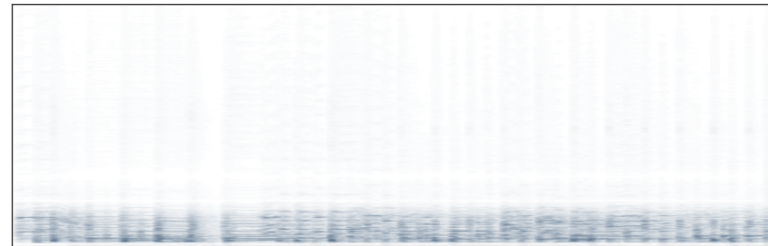
Estimated source likelihoods



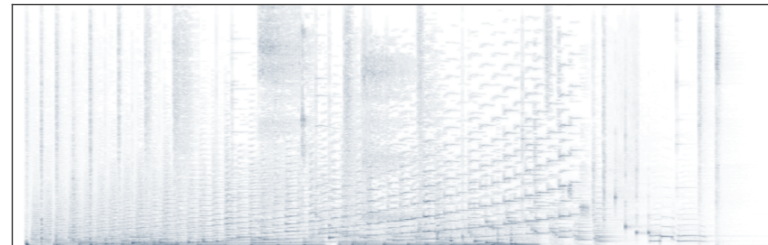
Audio superresolution

- Problem: We are missing some frequency bands
 - And lost frequencies are gone
 - forever ...
- Upsampling by example
 - Fit sound class frequency factors to bandlimited data
 - Reconstruct from learned factors using full frequency range

Bandlimited recording



Example sounds

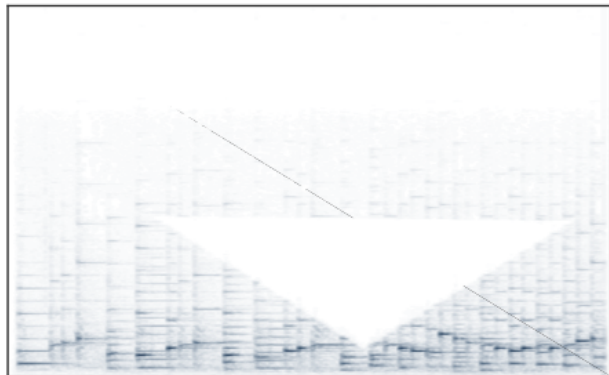


Expanded recording

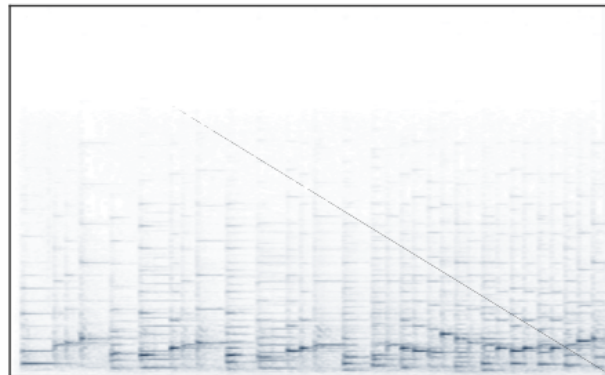


Ditto for missing data

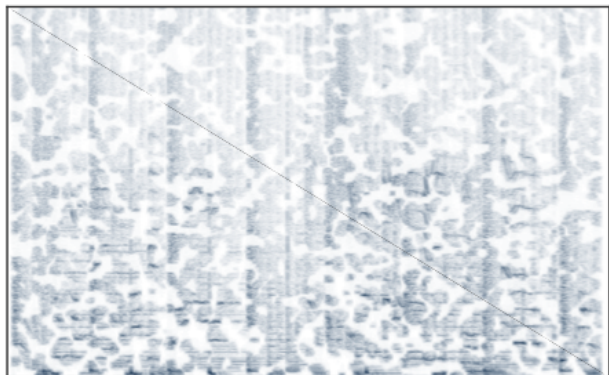
Large gap missing data input



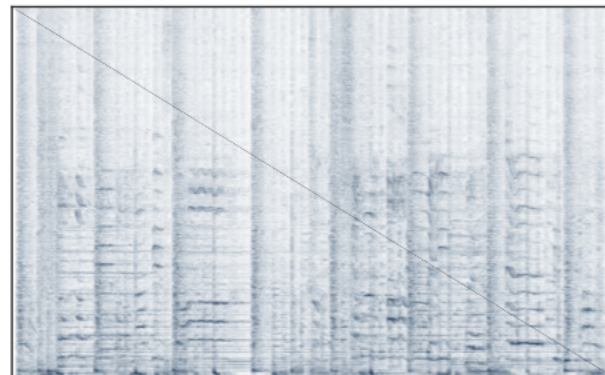
Recovered output



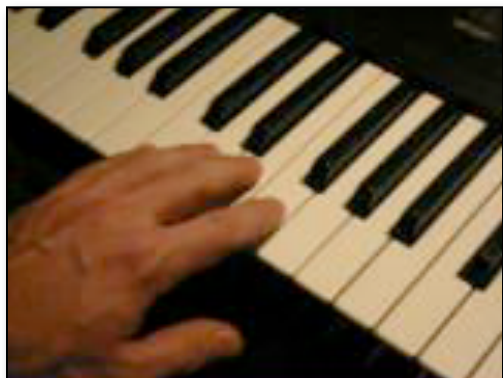
Random mask missing data input



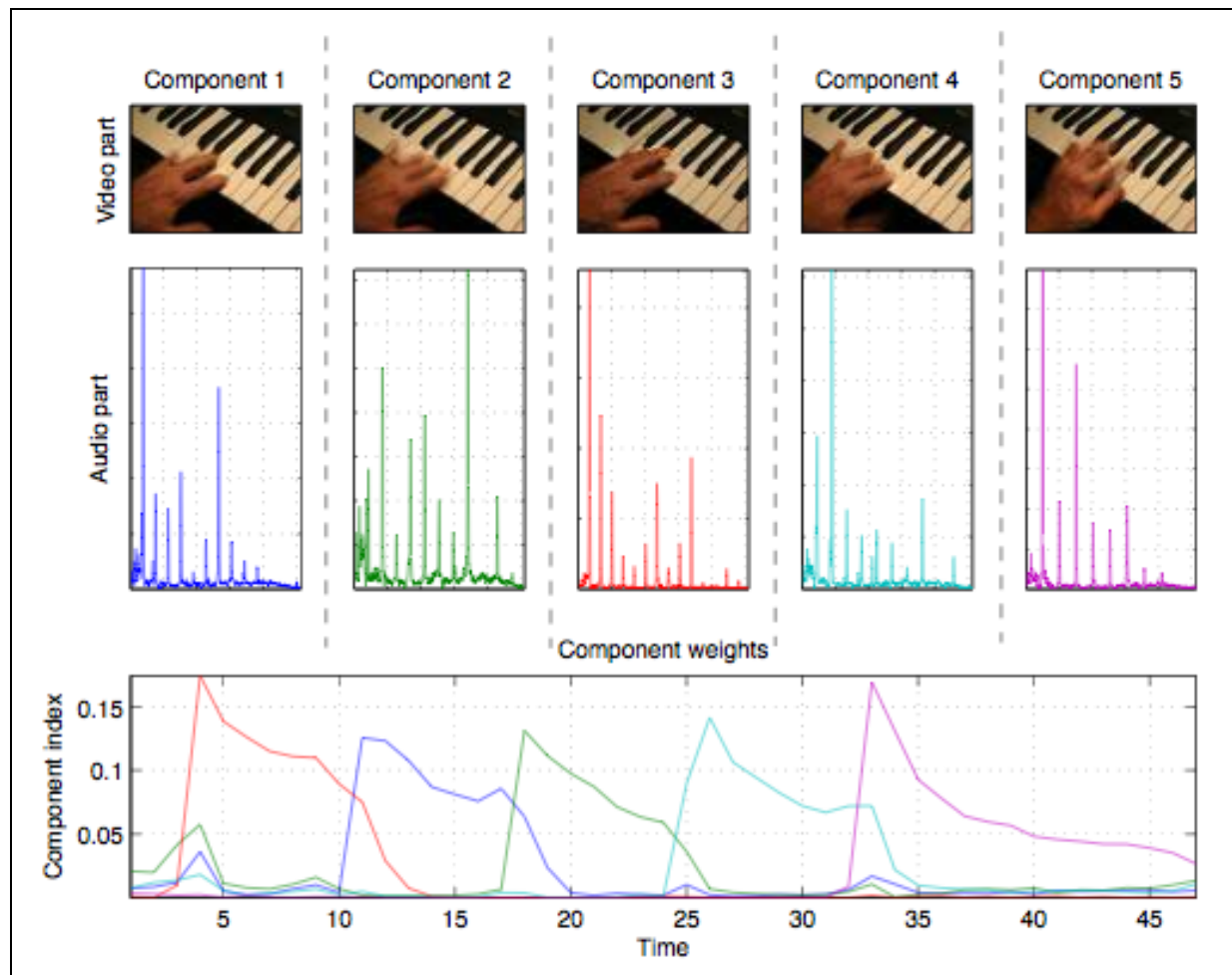
Recovered output



Audio-visual example



- Input with correlated images and pictures



All that's neat, but why?

- So far we focused on simple problems
 - Good for writing papers, but not for real-life
- Let's use this technology in the real-world
 - Sensing using audio
 - Being invariant to mixture issues

Video Content Analysis

- Audio is a strong cue for detecting various events in video
- Classify sounds to perform semantic analysis on video
 - Specific subclasses for type of broadcast (e.g. for news we use male and female speech, for sports use cheering, etc)
- Build in high-end Mitsubishi PVRs, TV sets and "HDTV cell phones"

Hard computer vision problems



Was there a goal?



Sad or funny clip?

Real-time movie sound parsing



Traffic Monitoring

- “Interesting” event discovery
 - Very hard/demanding visual task
 - Easier on the audio domain
- Reliable performance
 - ~5% false negatives,
 - ~4% false positives
- Hopefully we saved a life
(or an insurance company ...)

Examples of actual detected “interesting” parts



Normal crash



Hard-to-see crash



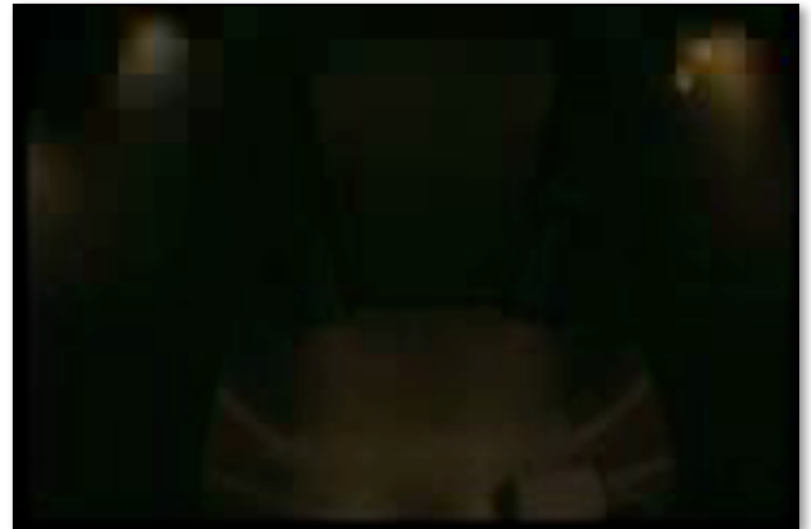
Near crash



Notable (?) event

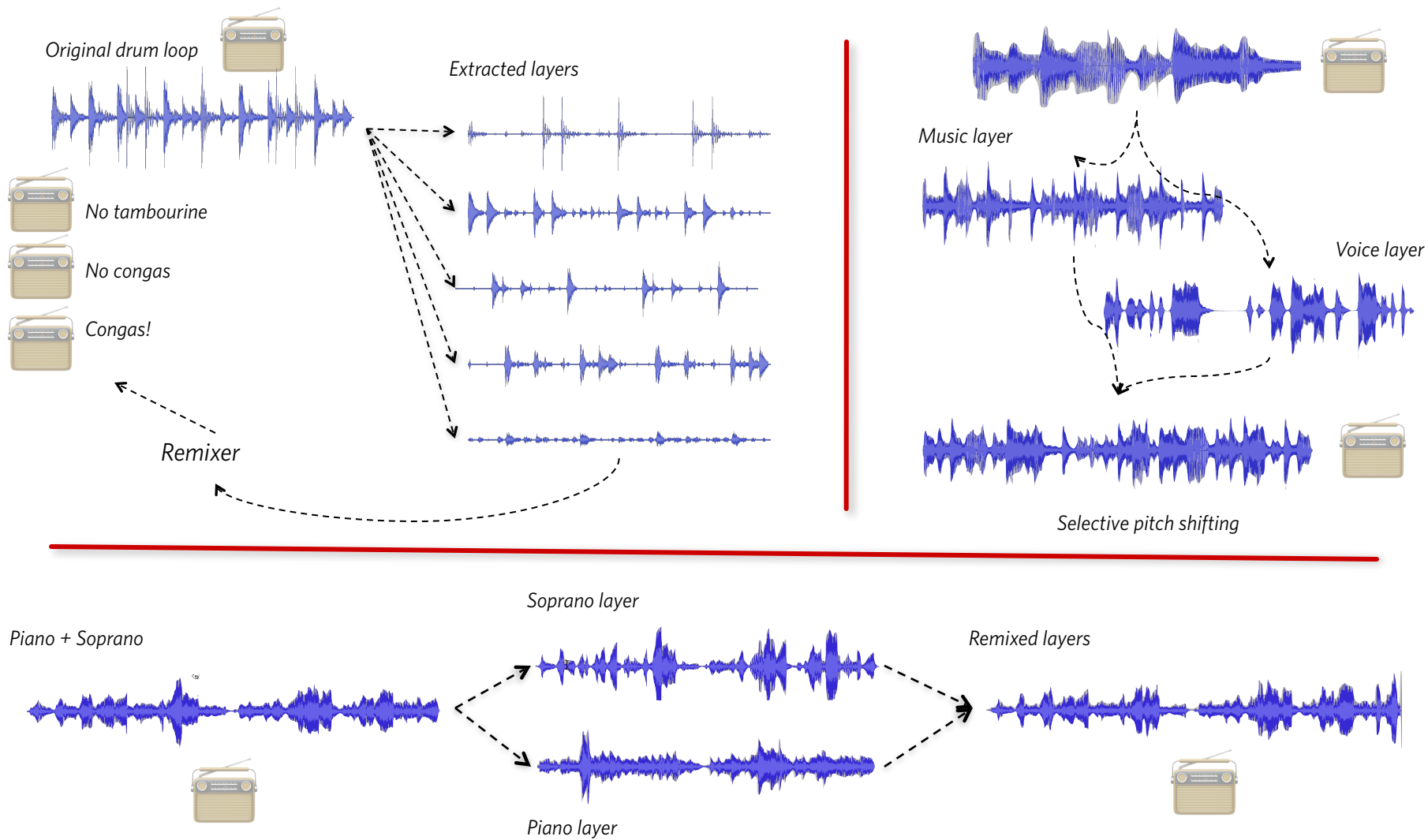
Security Surveillance

- Detect sounds in elevators
 - Normal speech, excited speech, footsteps, thumps, door open & close, screams, etc.
- When detecting suspicious sounds we can raise an alert
 - 96% accuracy in elevator test recordings with actors

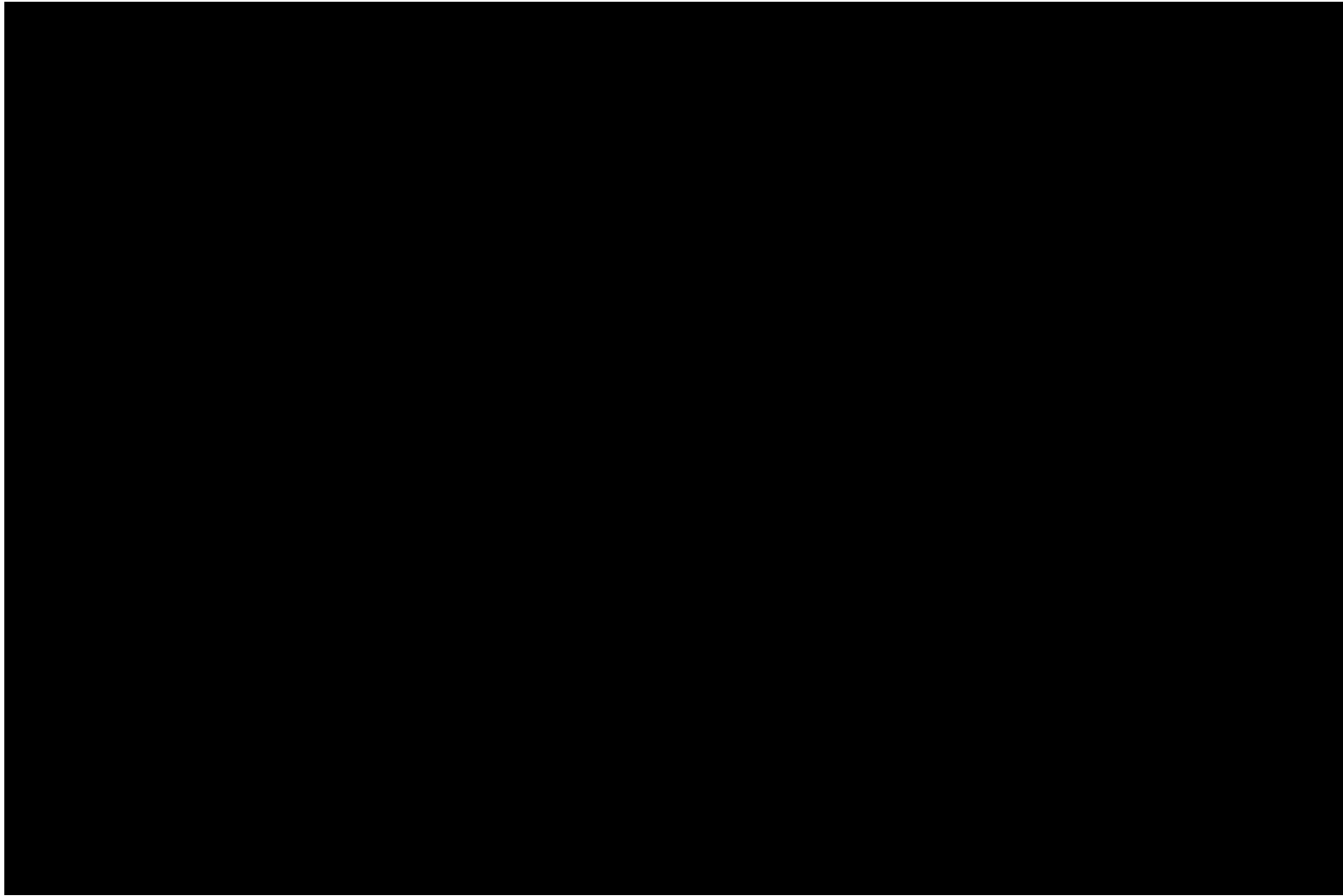


Elevators are a dark environment with poor visual analysis prospects

Audio layer editing



User-guided sound selection



Audio/visual editing

Input sequences



Output sequences



Many more things to do ...

- Mixtures are everywhere in DSP
 - Medical data, mechanical readings, ...
- I only talked about audio here
 - Lots of work to do in the field of mixtures
 - Lots of cool things coming out recently