CS598PS – Machine Learning for Signal Processing

Underconstrained Signal Separation

22 October 2020

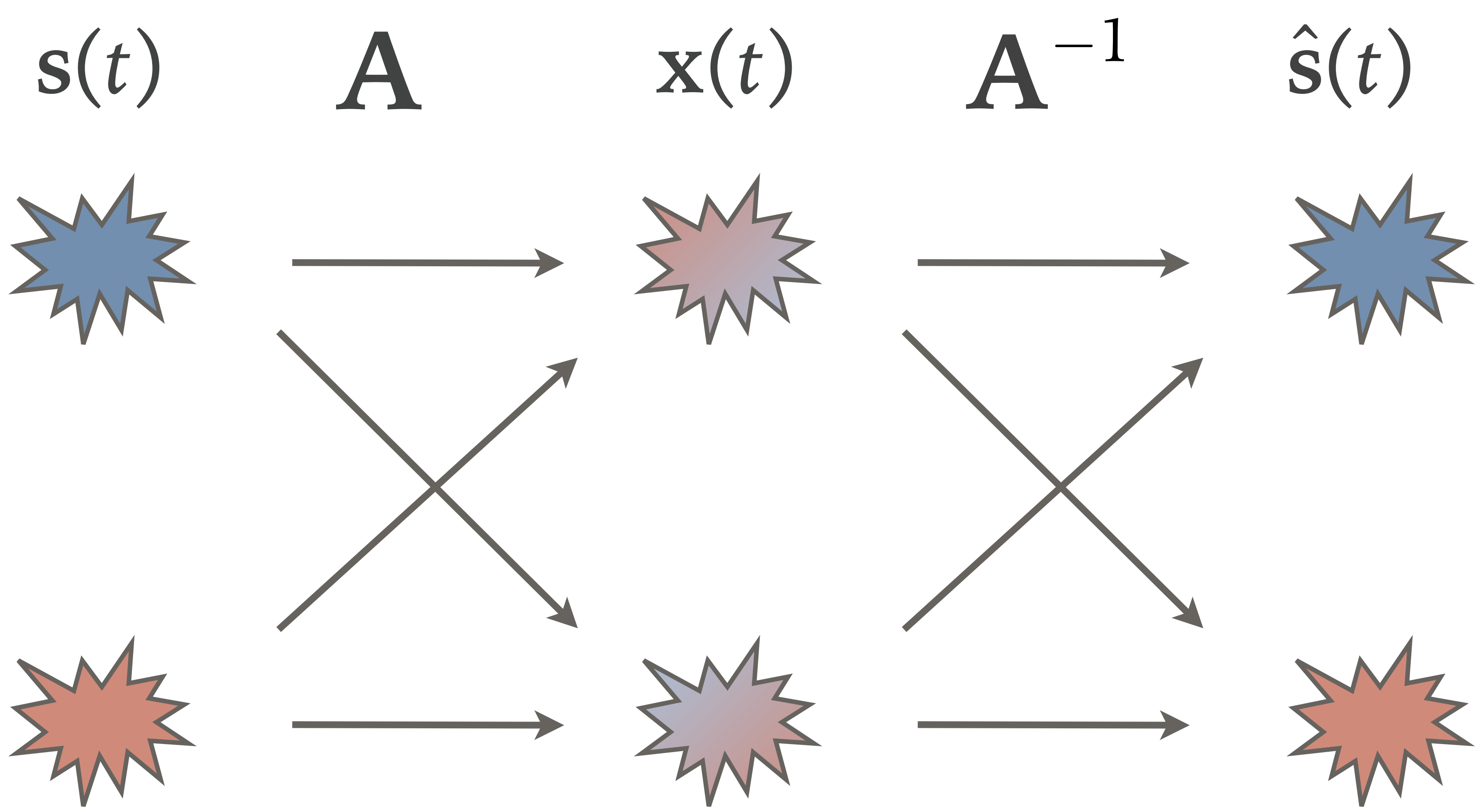
University of Illinois at Urbana-Champaign

Today's lecture

- Underconstrained signal separation
- Single-channel signal separation

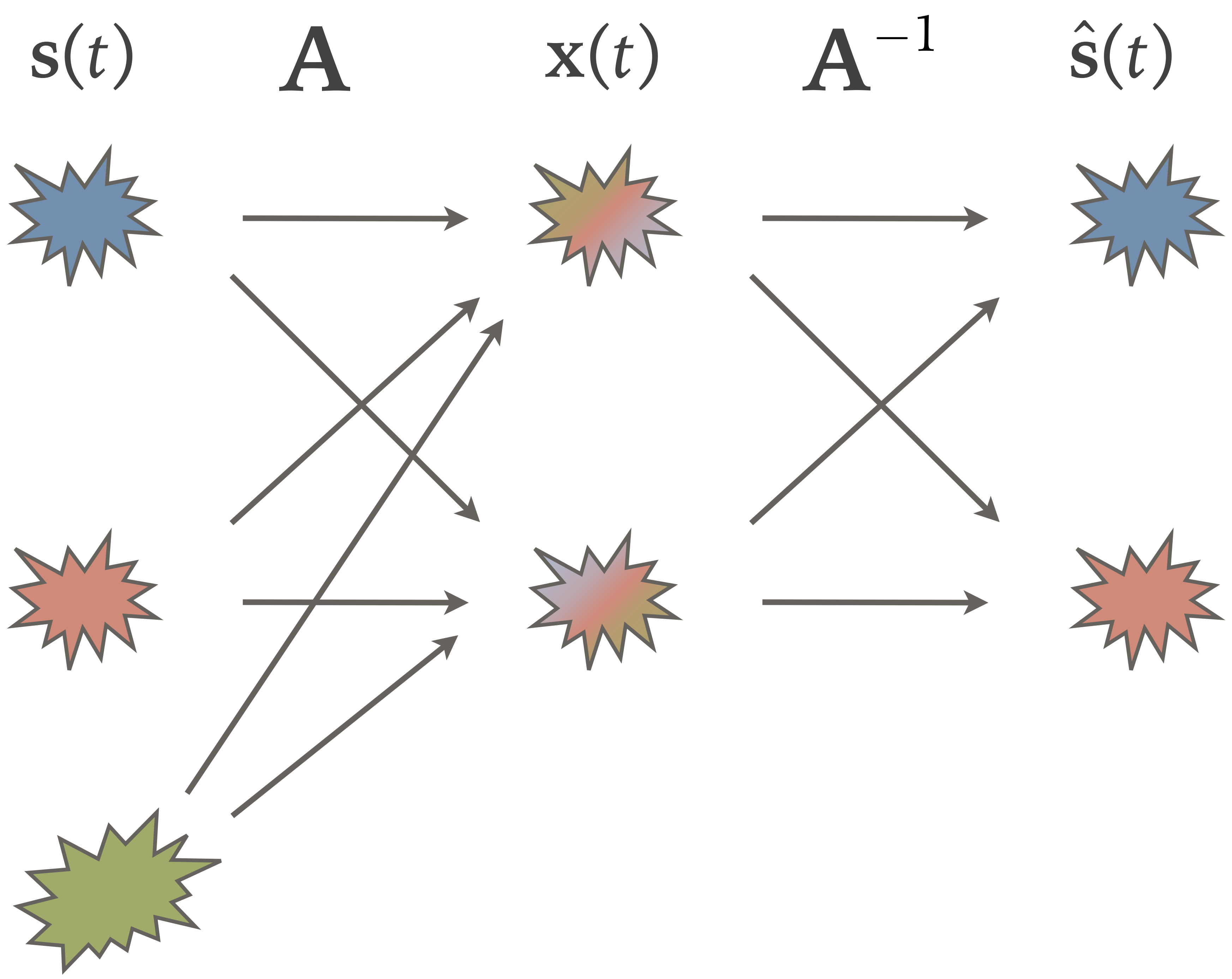
N-in / N-out separation

- Using ICA we can resolve N-sources by using N-sensors



N-in / N-out separation

- More sources create non-invertible mixing
  - A problem!



Underconstrained separation

- When we have fewer sensors than sources

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix} \cdot \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \end{bmatrix} = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}$$

- Ill-defined problem

$$\begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{bmatrix} \cdot \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} s_1(t) \\ s_2(t) \\ s_3(t) \end{bmatrix}$$

Straightforward solutions

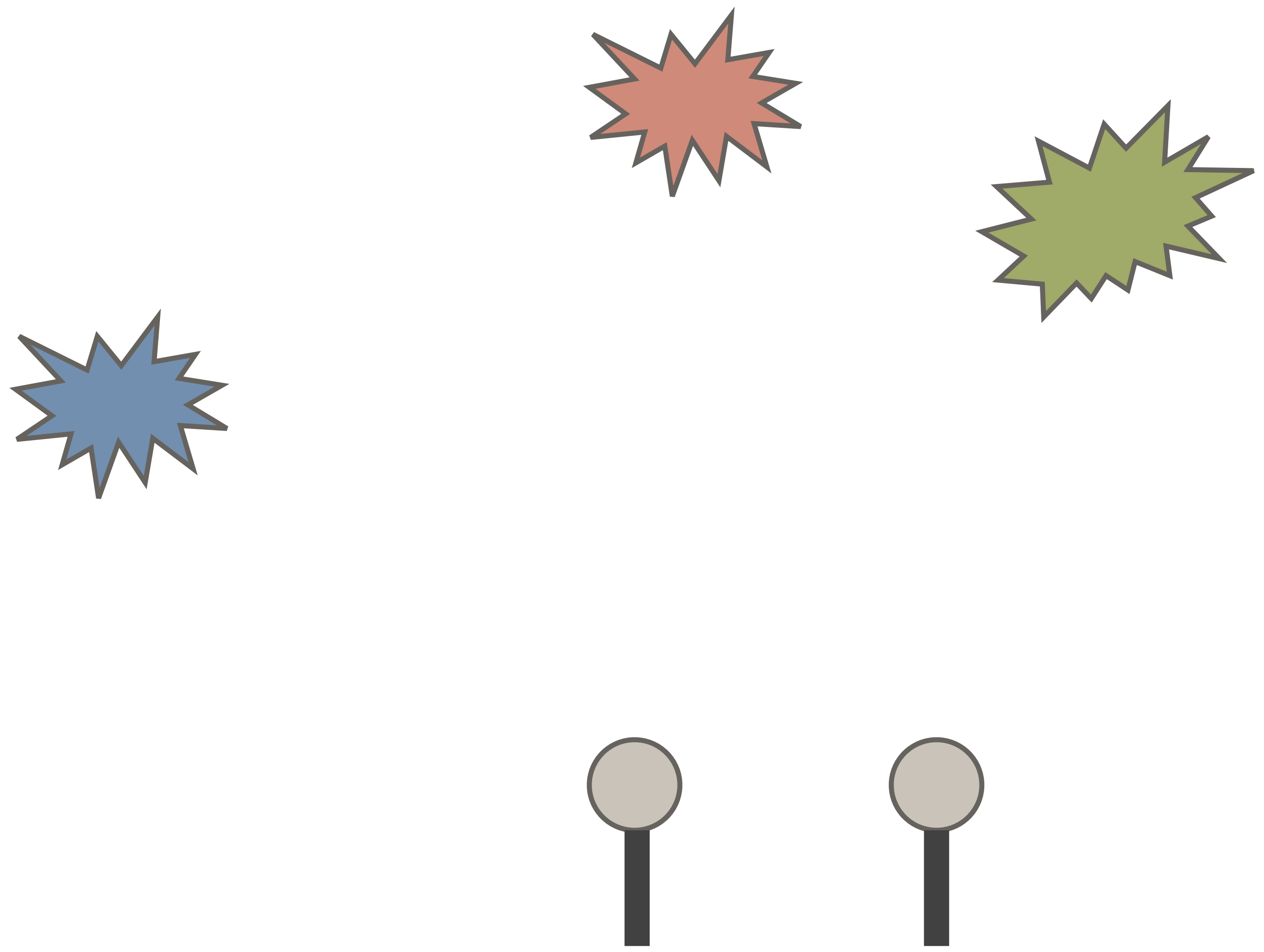
- Beamforming
  - Boosts one signal, but does not separate
- Source properties
  - Known statistics of source characteristics
- Deflation methods
  - Extract one source at a time

But we live in a harsh world ...

- Let's say you only get two sensors
  - Sensors are expensive!
- What can we do to resolve mixtures now?

Using the audio case again

- Put two microphones in a room
  - More than two sources present
- How can we recover the sources?



An alternative way to unmix

- With ICA we try to undo the mixing
  - We invert the mixing process
  - Tough and tedious for complex mixtures

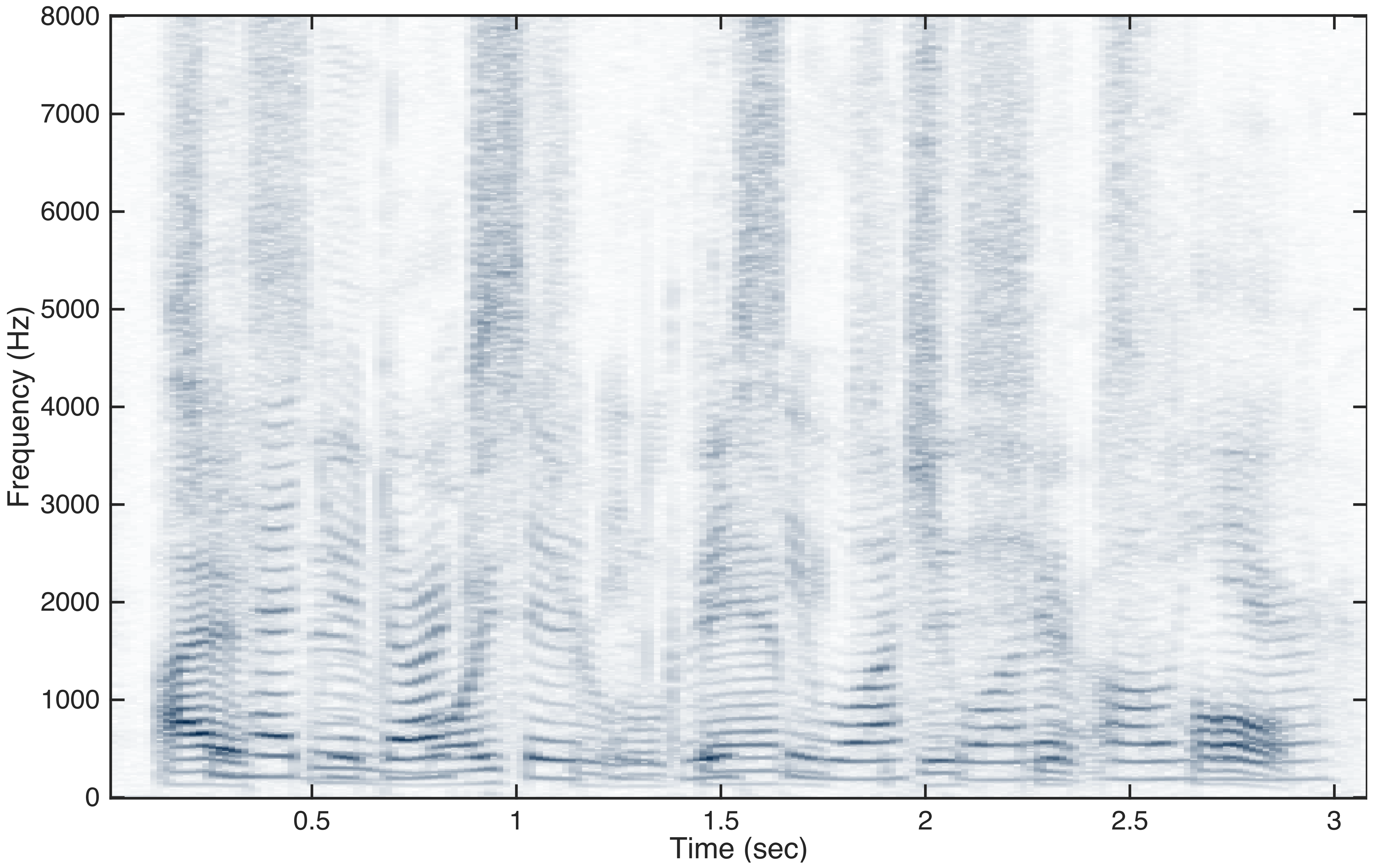
- Masking alternative
  - Using binary masks on spectrograms we can isolate desired sources
  - The optimal masks are not derived from mixing conditions
    - Convolutive mixing, etc. are not an issue

Masking

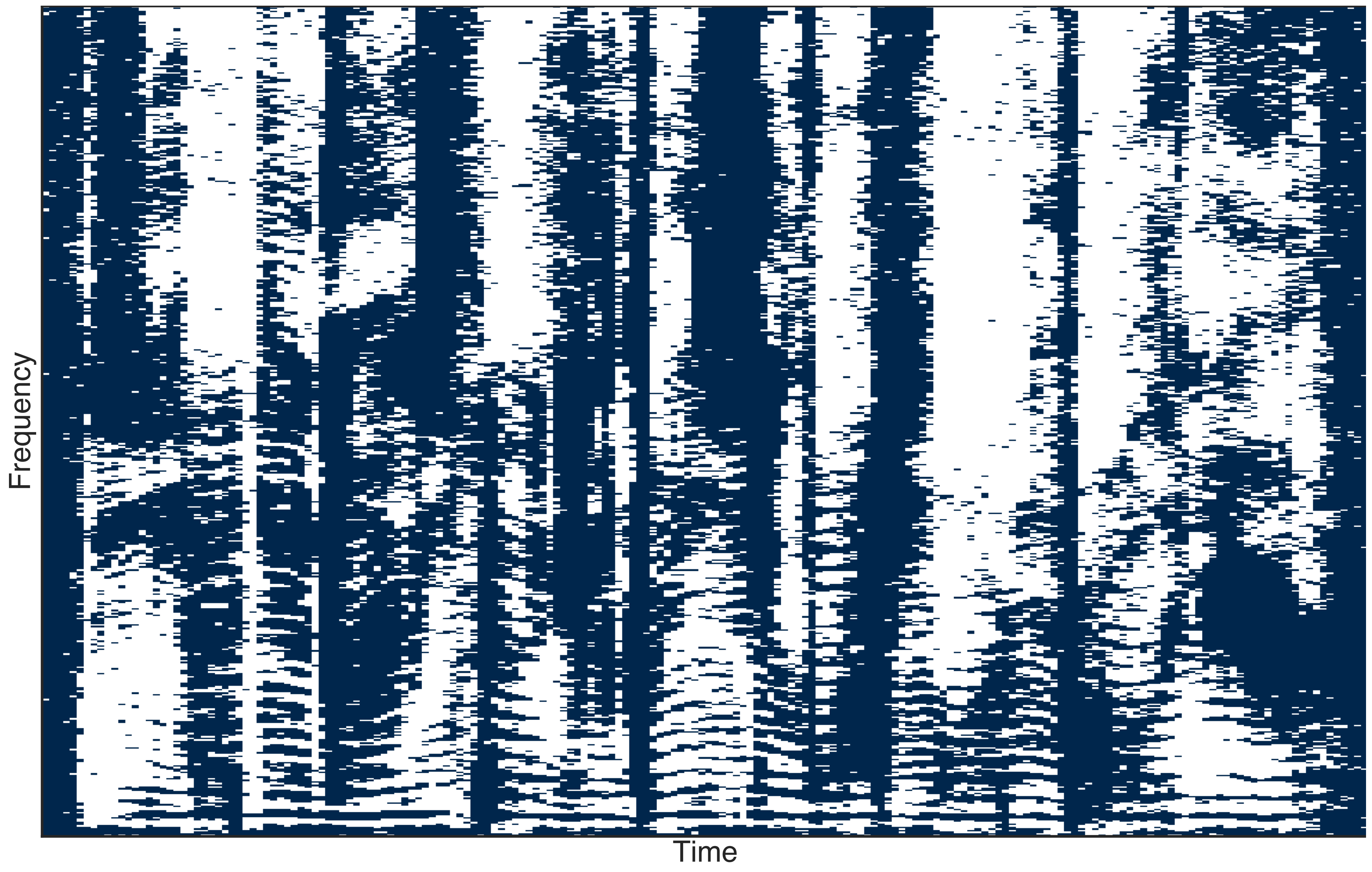
- Two simultaneous sources

- What are the chances the two source spectrograms coincide at any pixel?

- We can pick only certain "pixels" from the spectrogram to get each source

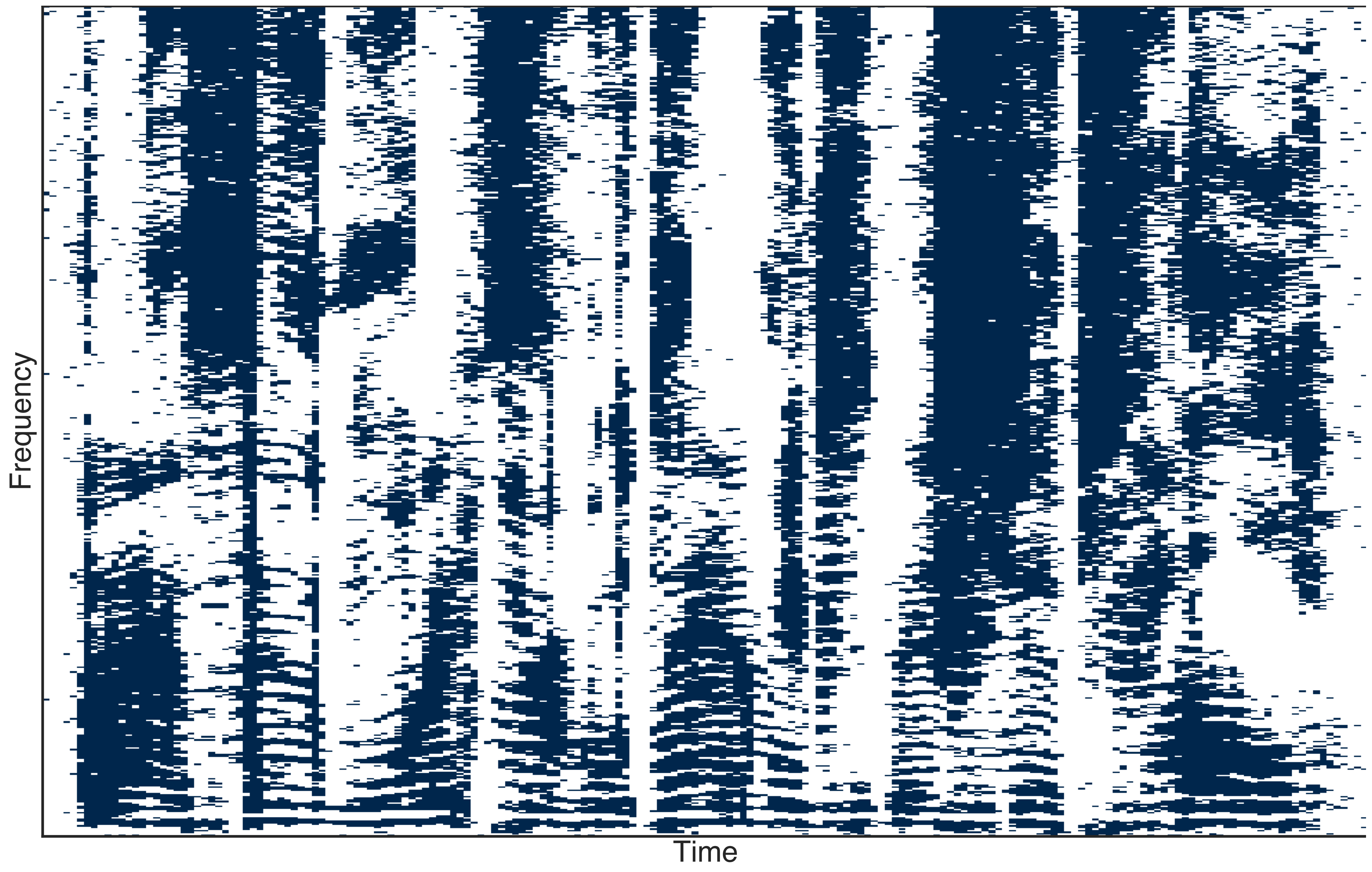


Mask examples



Mask for which:

$$|F_{source1}(f, t)| > |F_{source2}(f, t)|$$

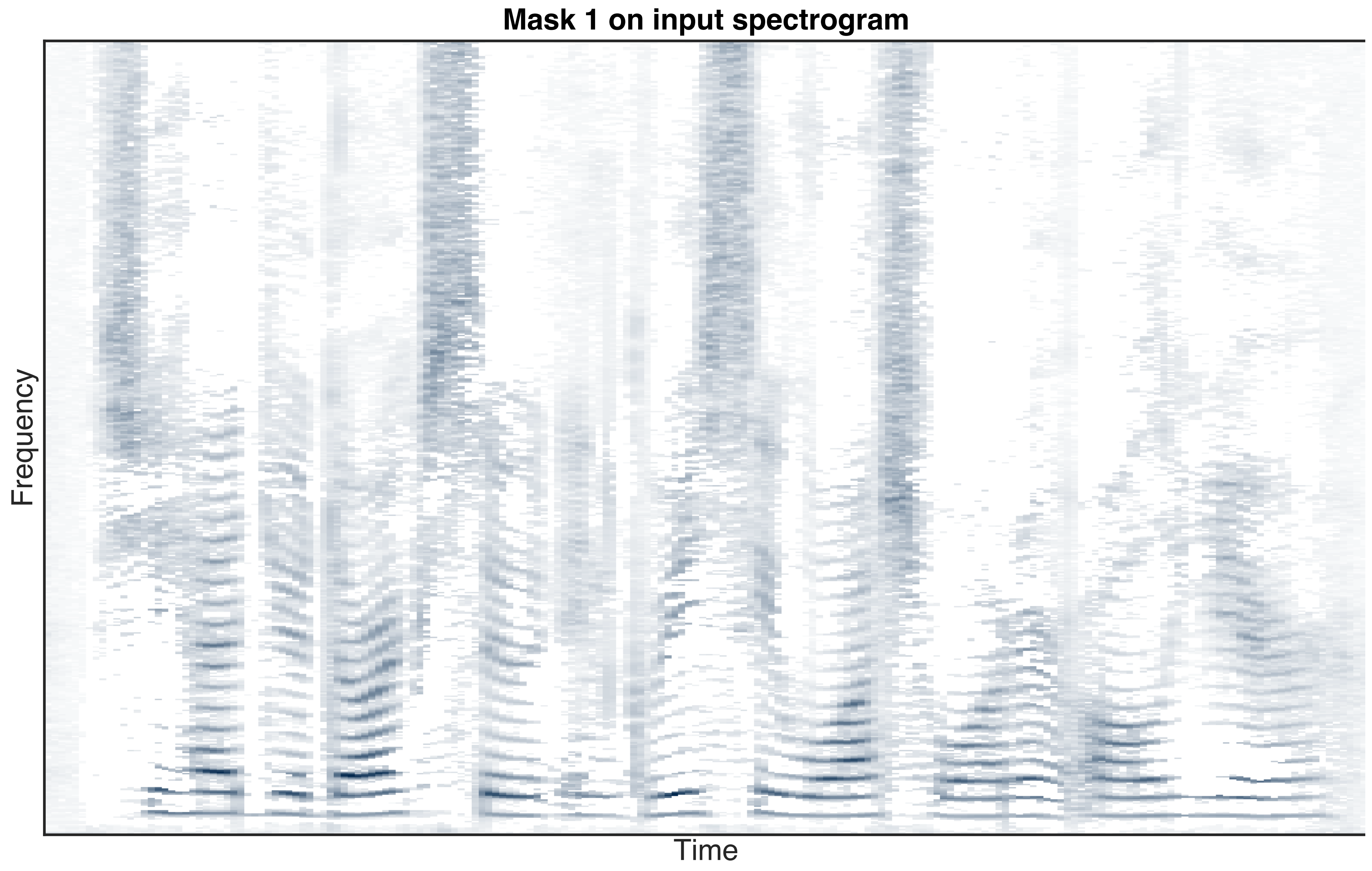


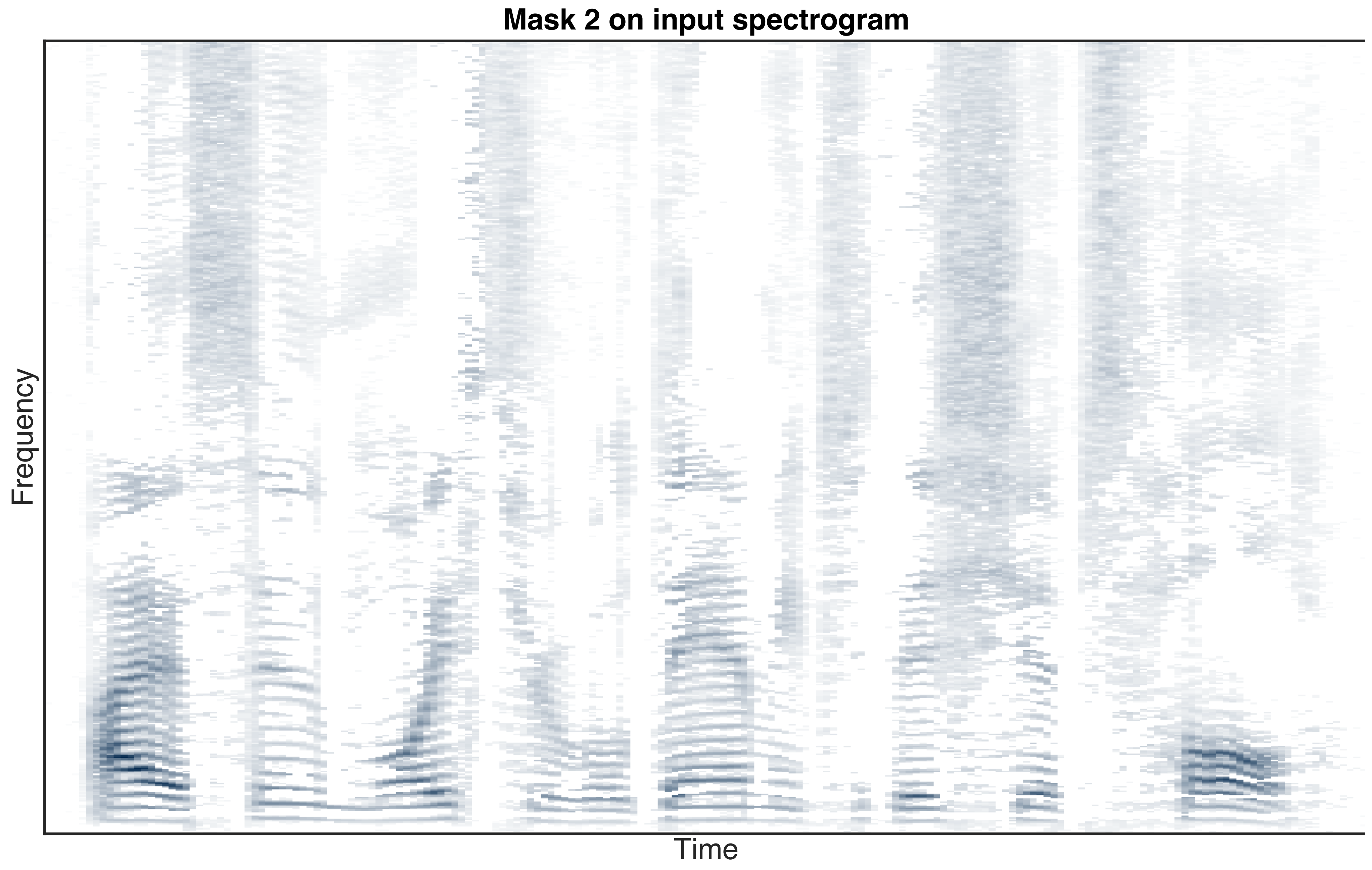
Mask for which:

$$|F_{source1}(f, t)| < |F_{source2}(f, t)|$$

Masks applied on mixture

- When applied on mixture spectrogram, masks produce good approximations of the two source spectrograms





Mixture

Extracted source 1

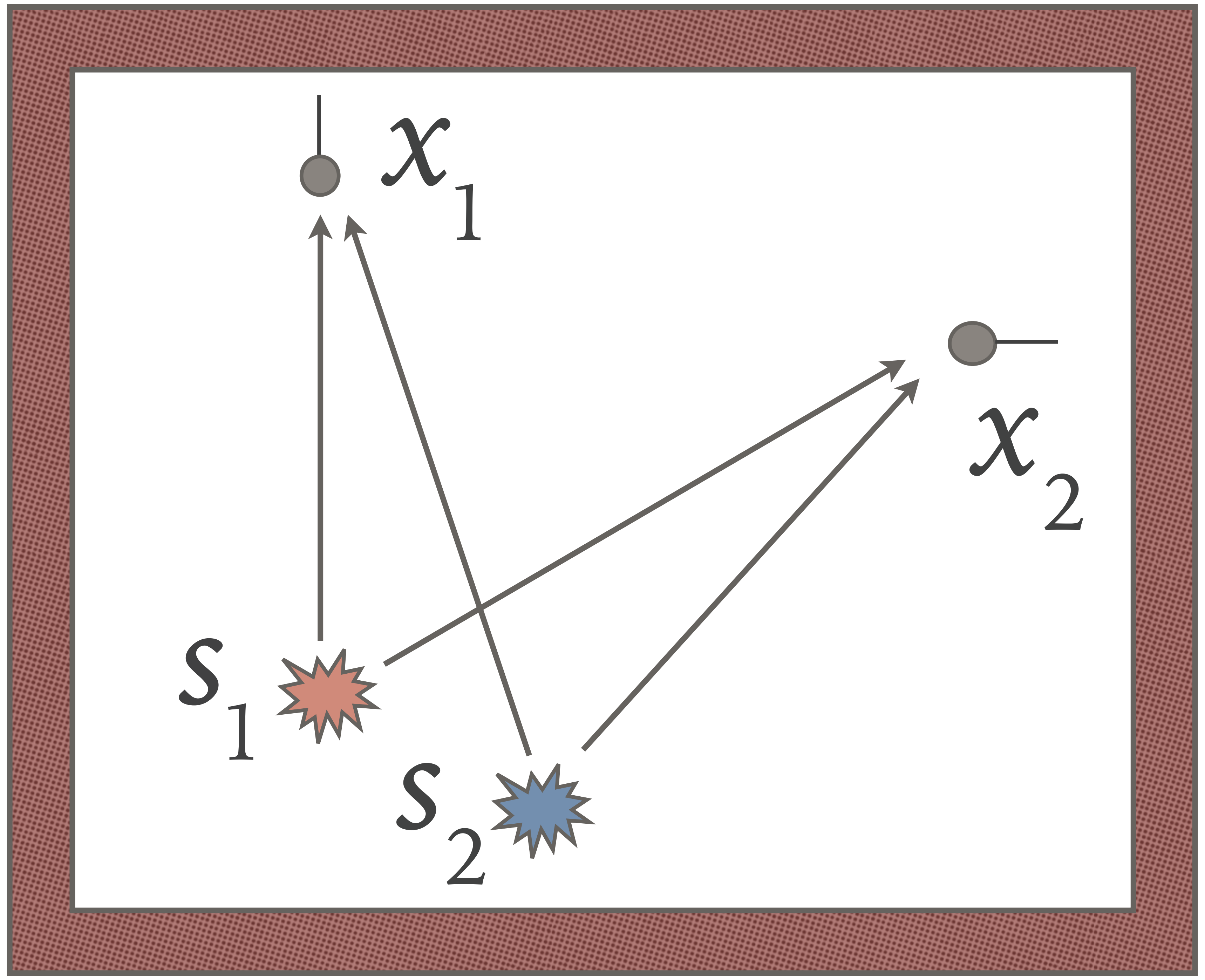
Extracted source 2

How do we get the proper masks?

- Spatial information can help us discover the appropriate source masks
  - Time-frequency cells indicating the same direction of arrival get on the same mask
- A plus: No constraint on number of sources and sensors!
  - We can apply multiple masks on a single spectrogram

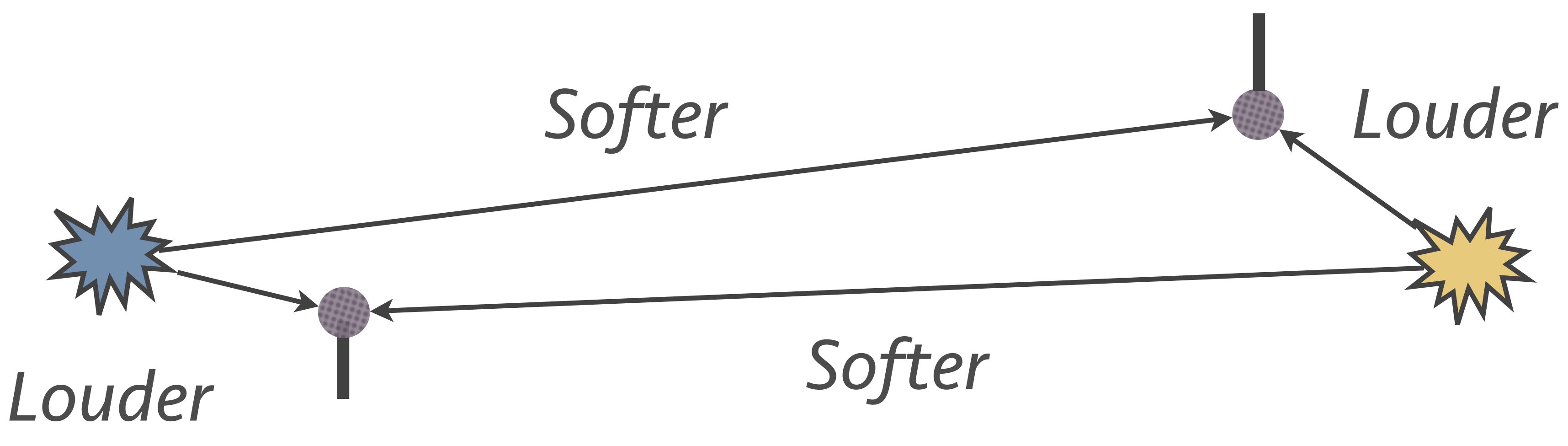
Spatial cues for masks

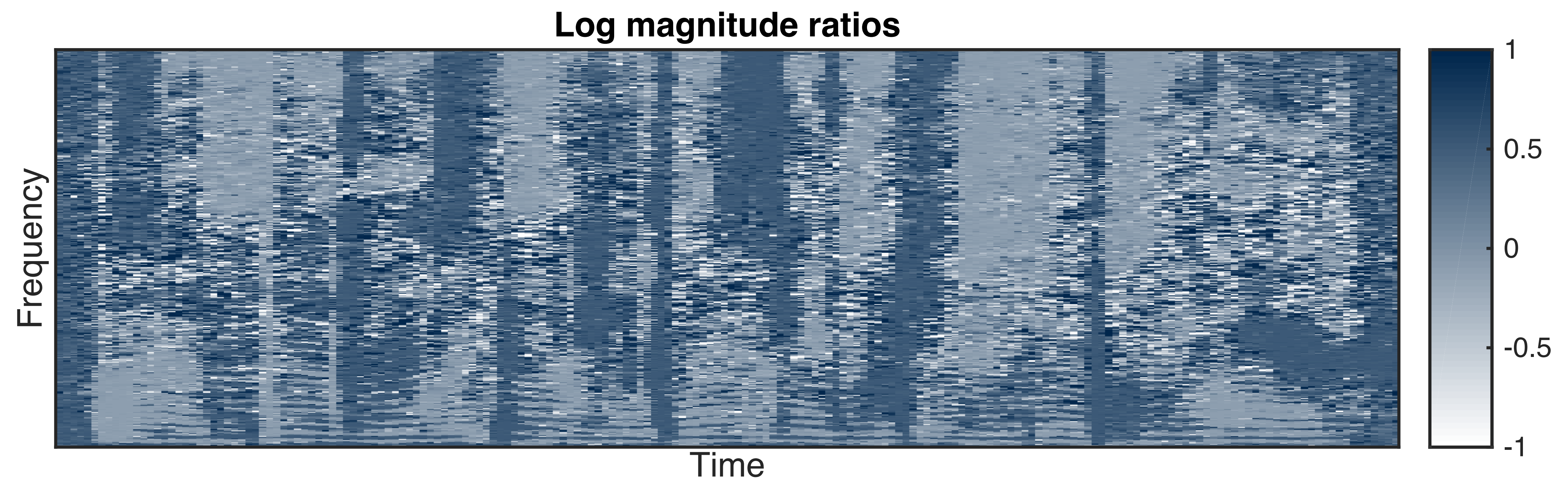
- Gather spatial statistics for each time-frequency point
  - Amplitude ratios
  - Phase differences
- Cluster cells with similar statistics to form masks
  - Each location would have its own set of features



Magnitude ratios as spatial features

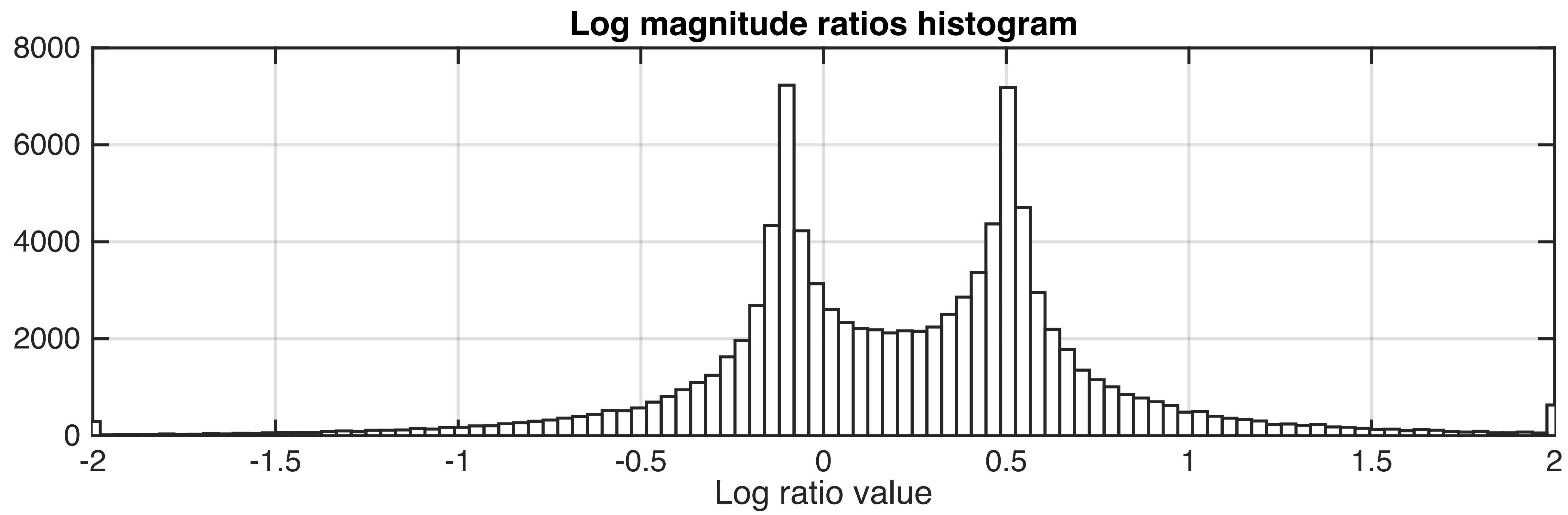
- Time/frequency bin ratios between the sensors will be different depending on a source's position





- We extract these as:

$$\alpha(\tau,\omega) = \log\left\|\frac{F_2(\tau,\omega)}{F_1(\tau,\omega)}\right\|$$

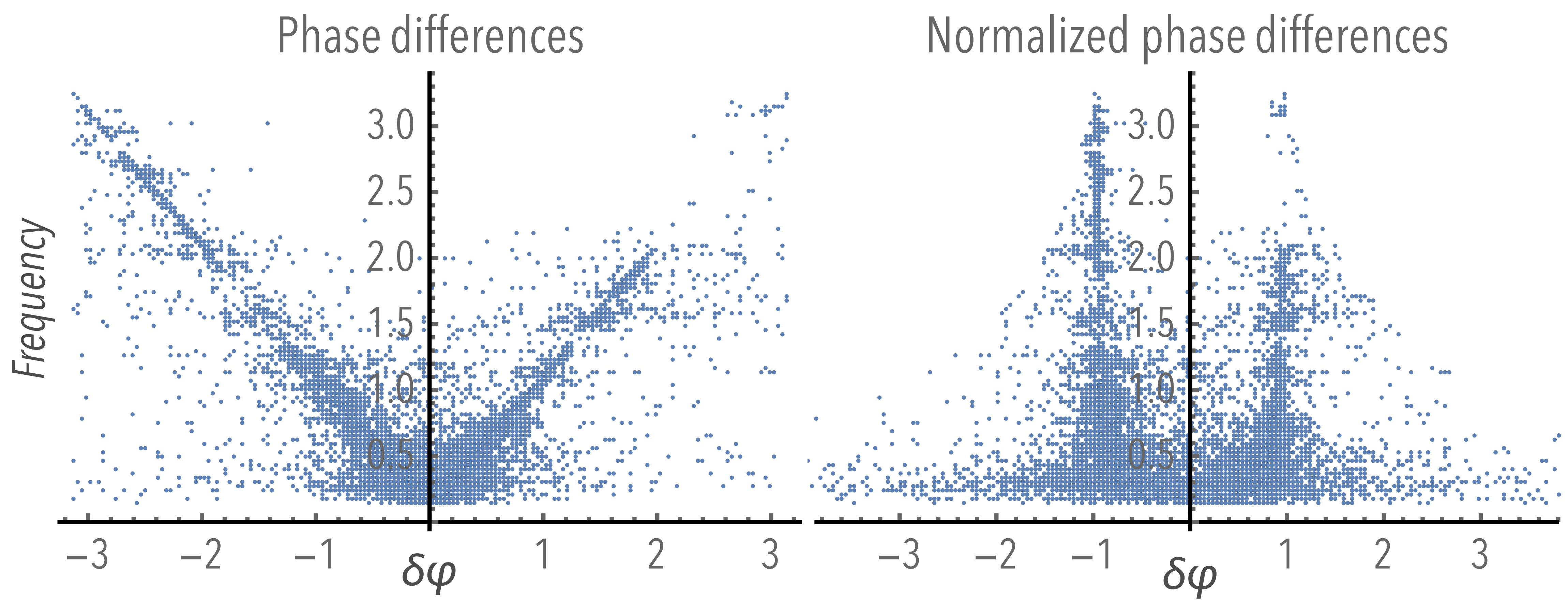


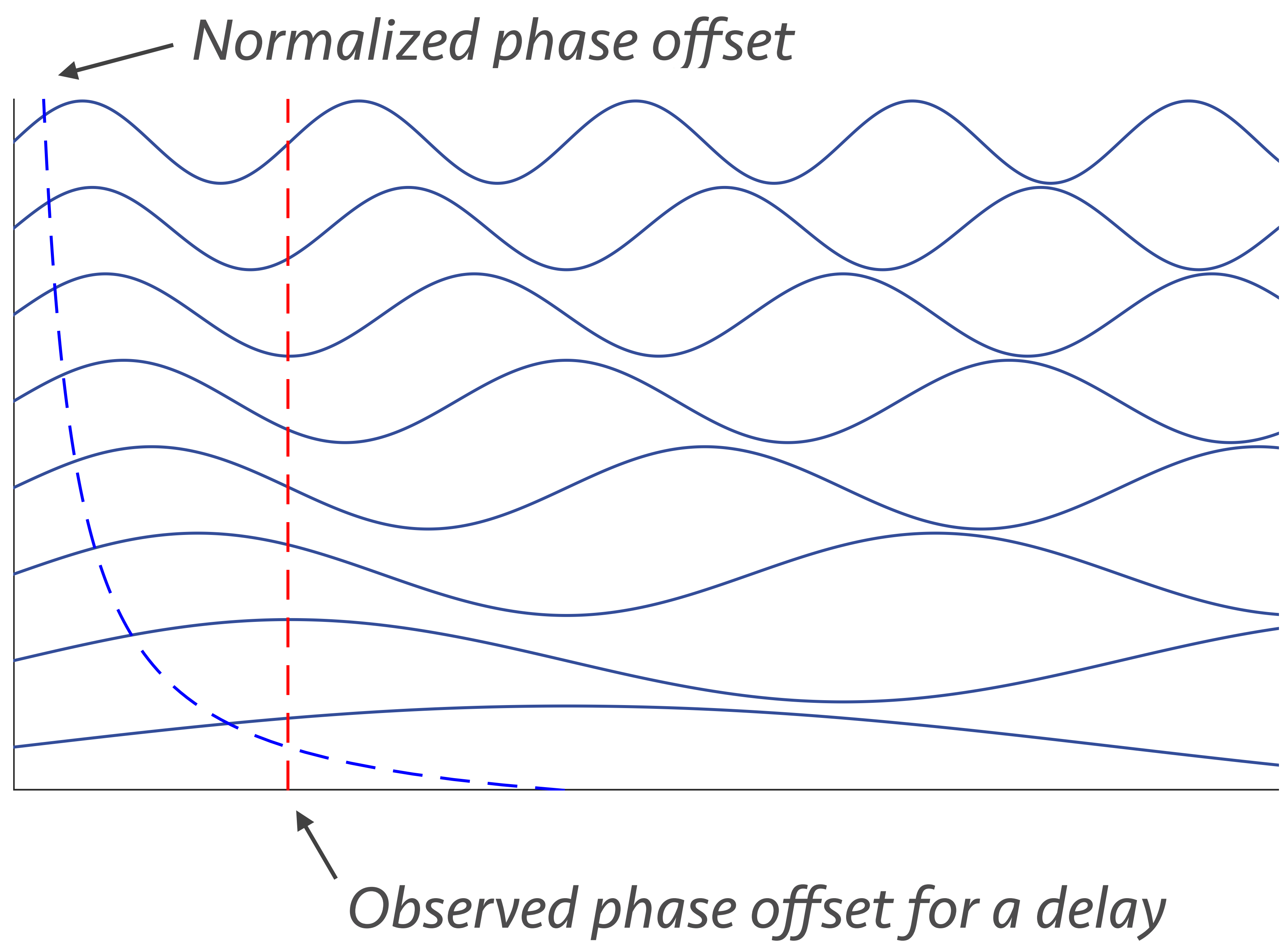
Normalized phase differences

- Use per-bin phase differences
  - But they depend on frequency
- Instead we can normalize:

$$\delta(\tau,\omega) = \frac{1}{\omega}\left(\angle F_2(\tau,\omega) - \angle F_1(\tau,\omega)\right)$$

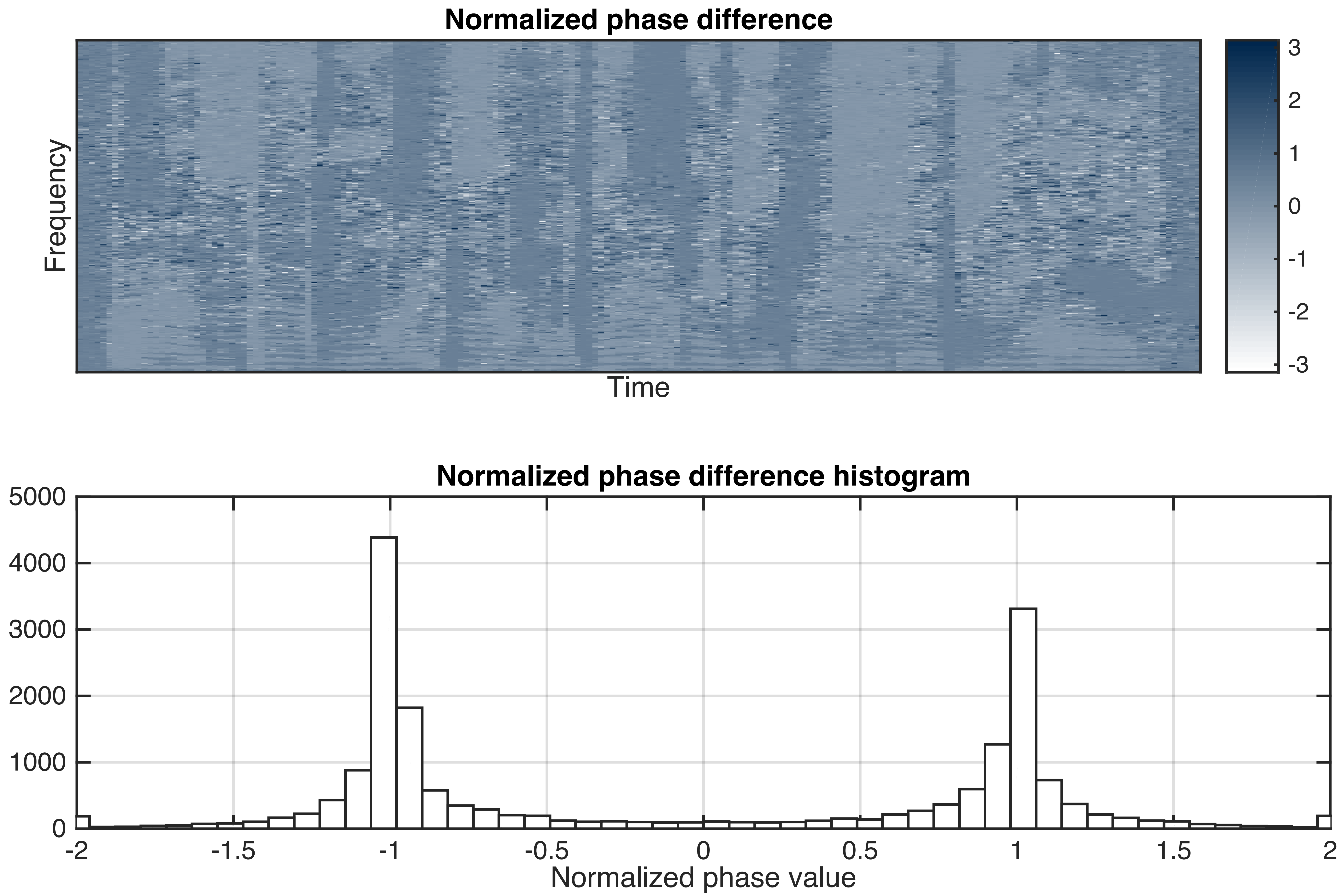
  - Which gives us a "delay" value
- Only works if the delay is less than a period though!





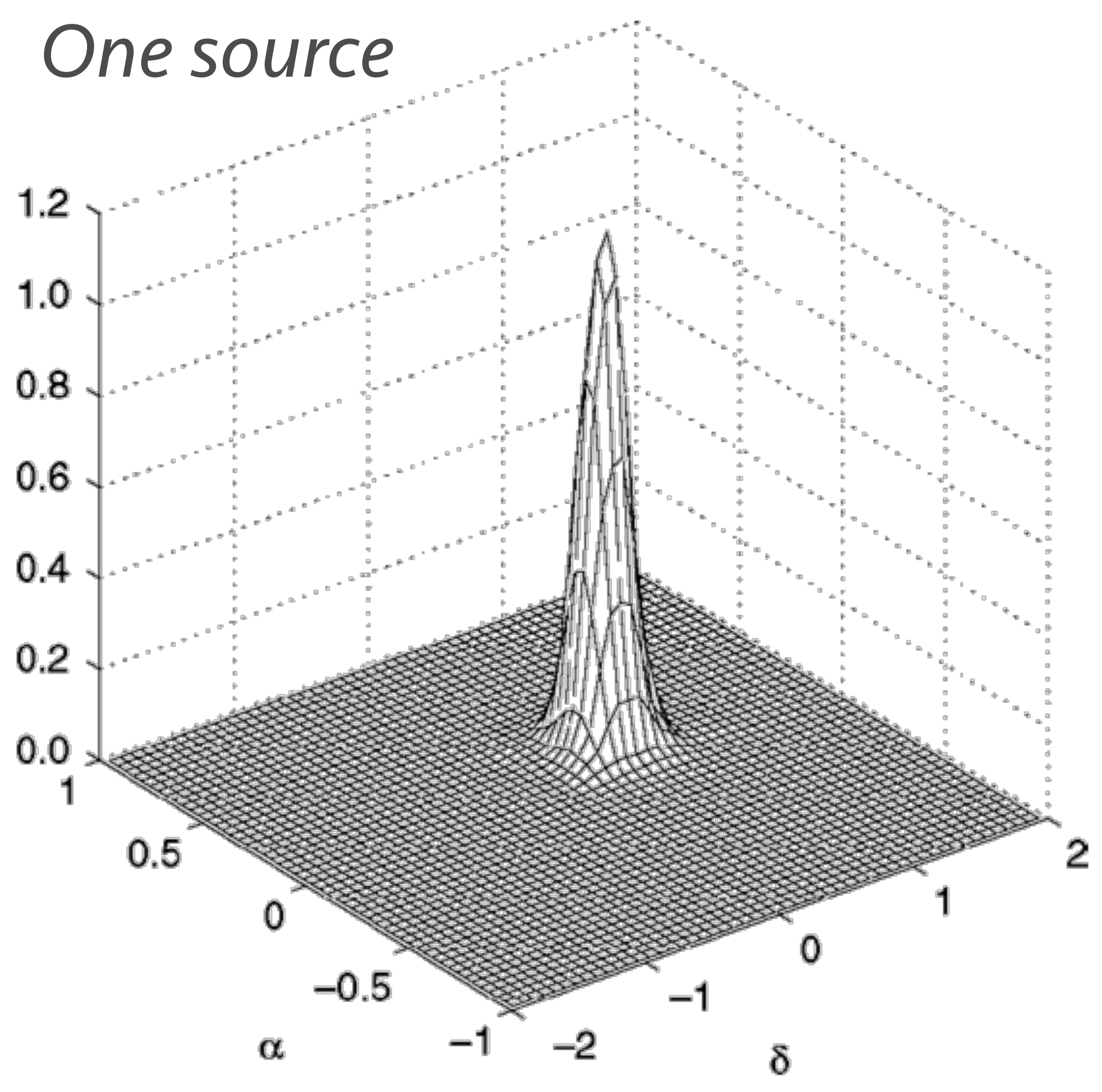
Normalized phases as spatial features

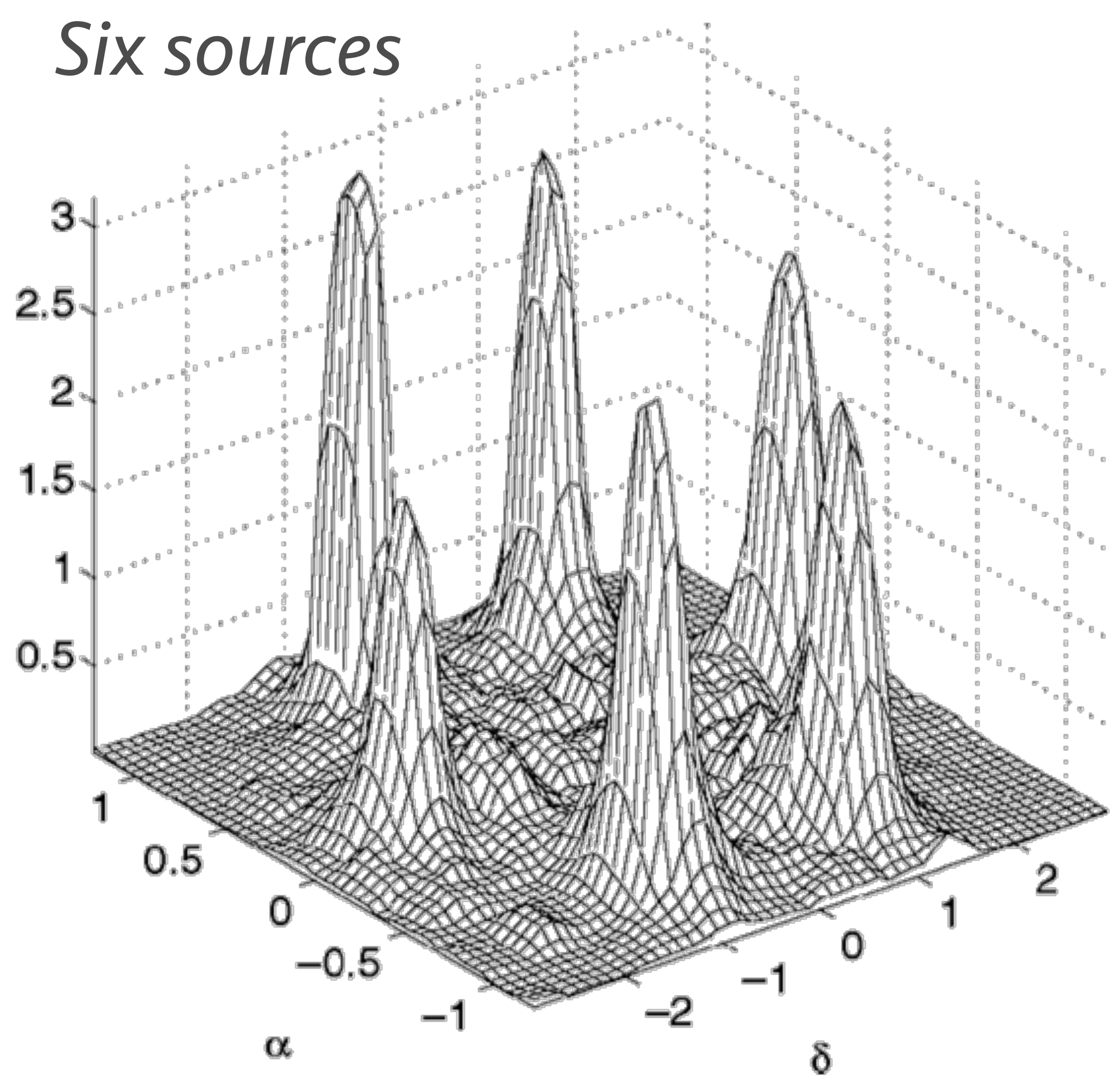
- Each spatial location will generate a unique value
- We will get clear peaks for each location's contribution



Clustering the location statistics

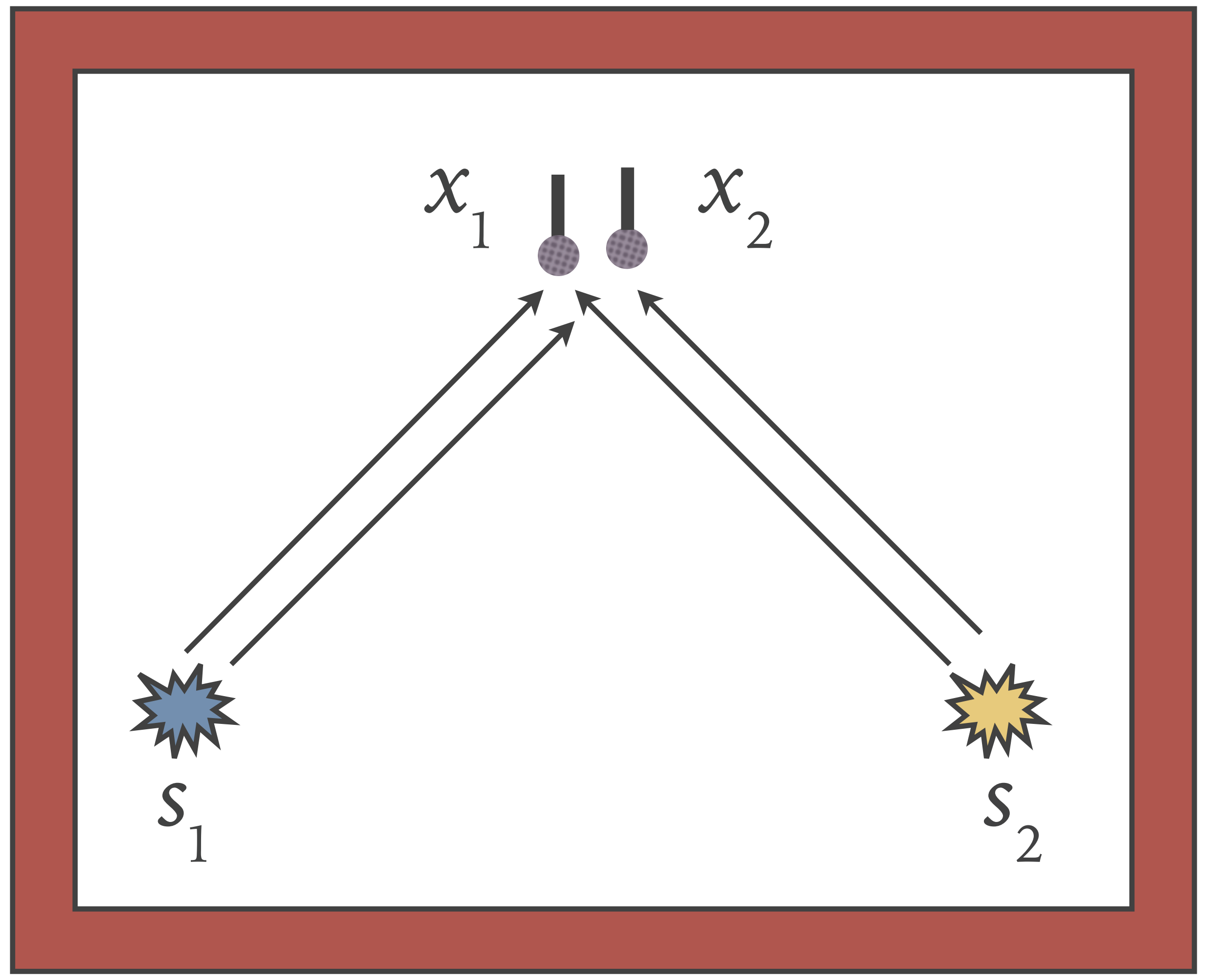
- Histogram all these measurements in the joint parameter space
- Peaks are spatially separate sources
  - N sources will result in N peaks
- Each peak corresponds to a location
  - We can now group time-frequency "pixels" according to the peaks
  - Each mask is made out of the time-freq "pixels" which are closest to a mode

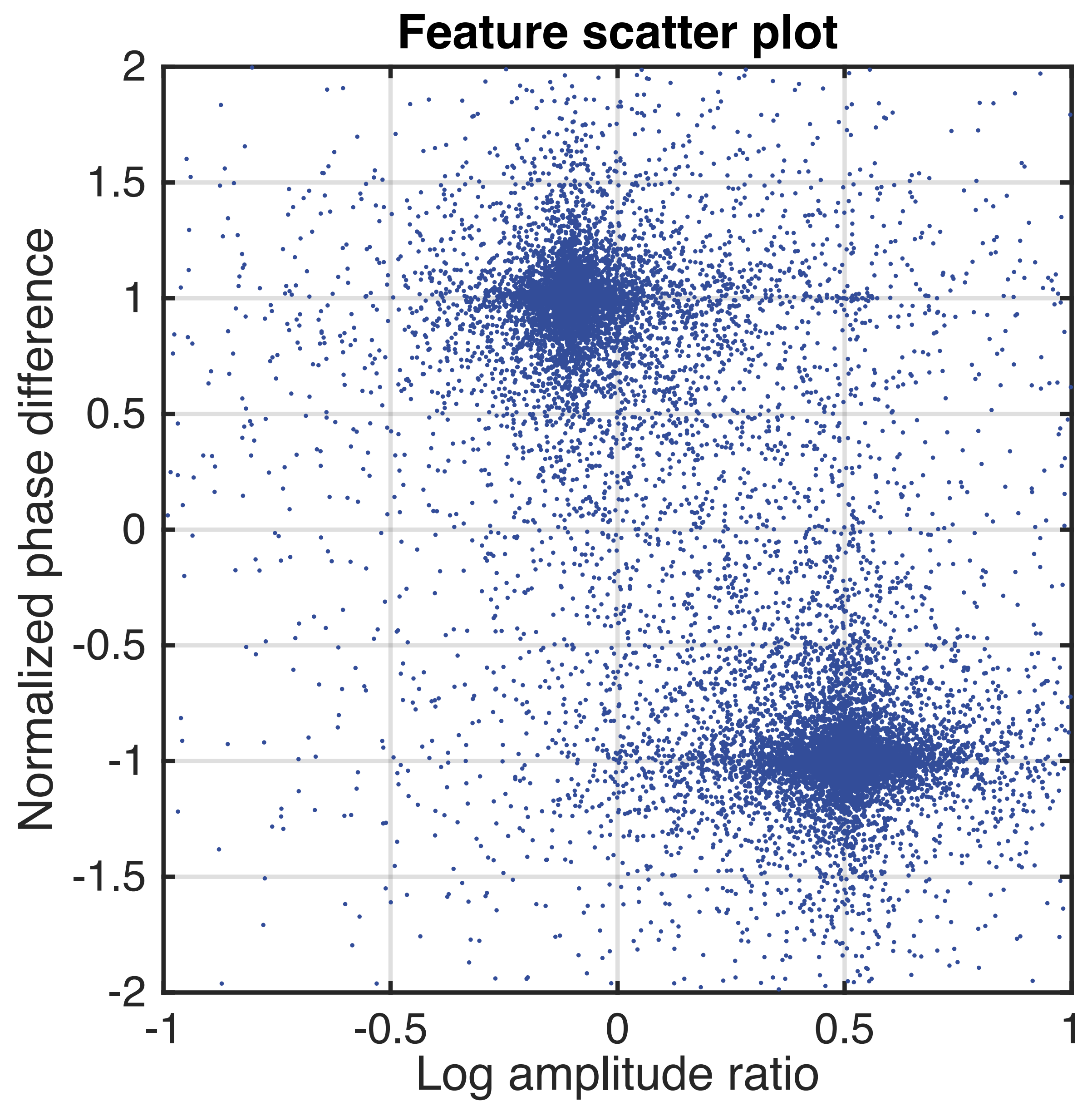


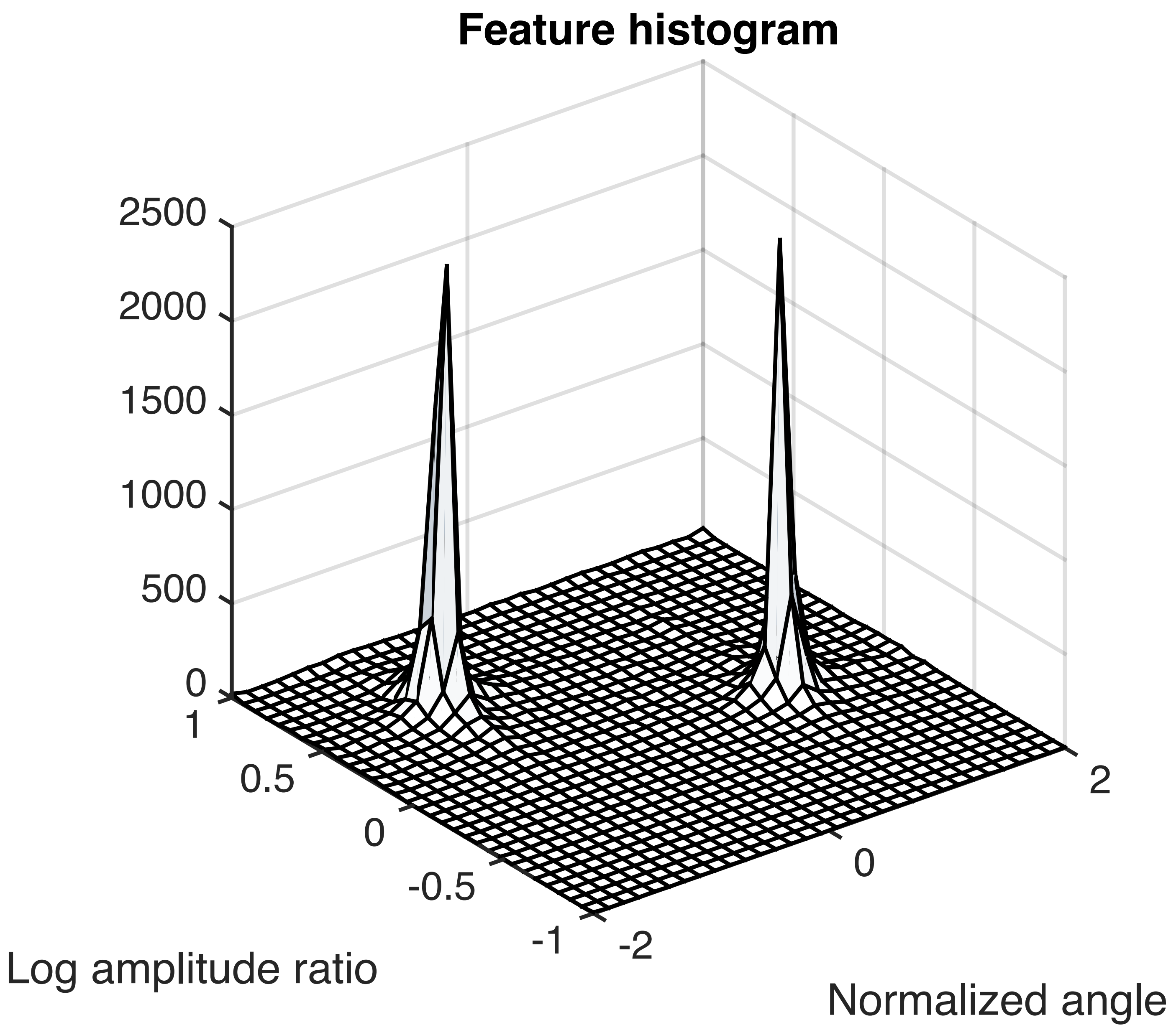


2 microphone example

- Closely spaced mics, symmetric sources
  - Each source creates a cluster with a unique center

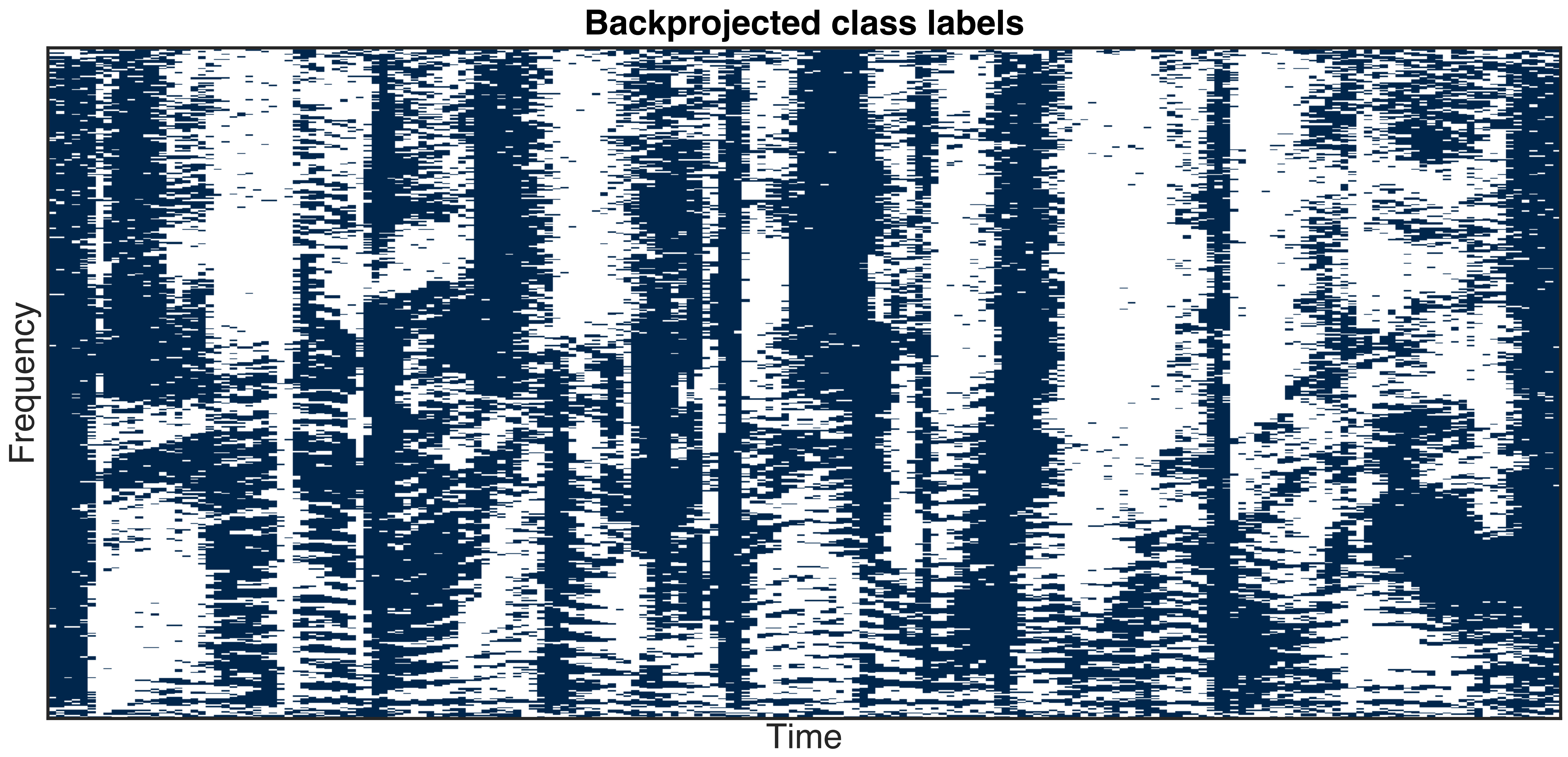






Back-projecting to the spectrograms

- Use the cluster labels to assign each point to a source
  - Place back into spectrogram and you get the desired binary mask

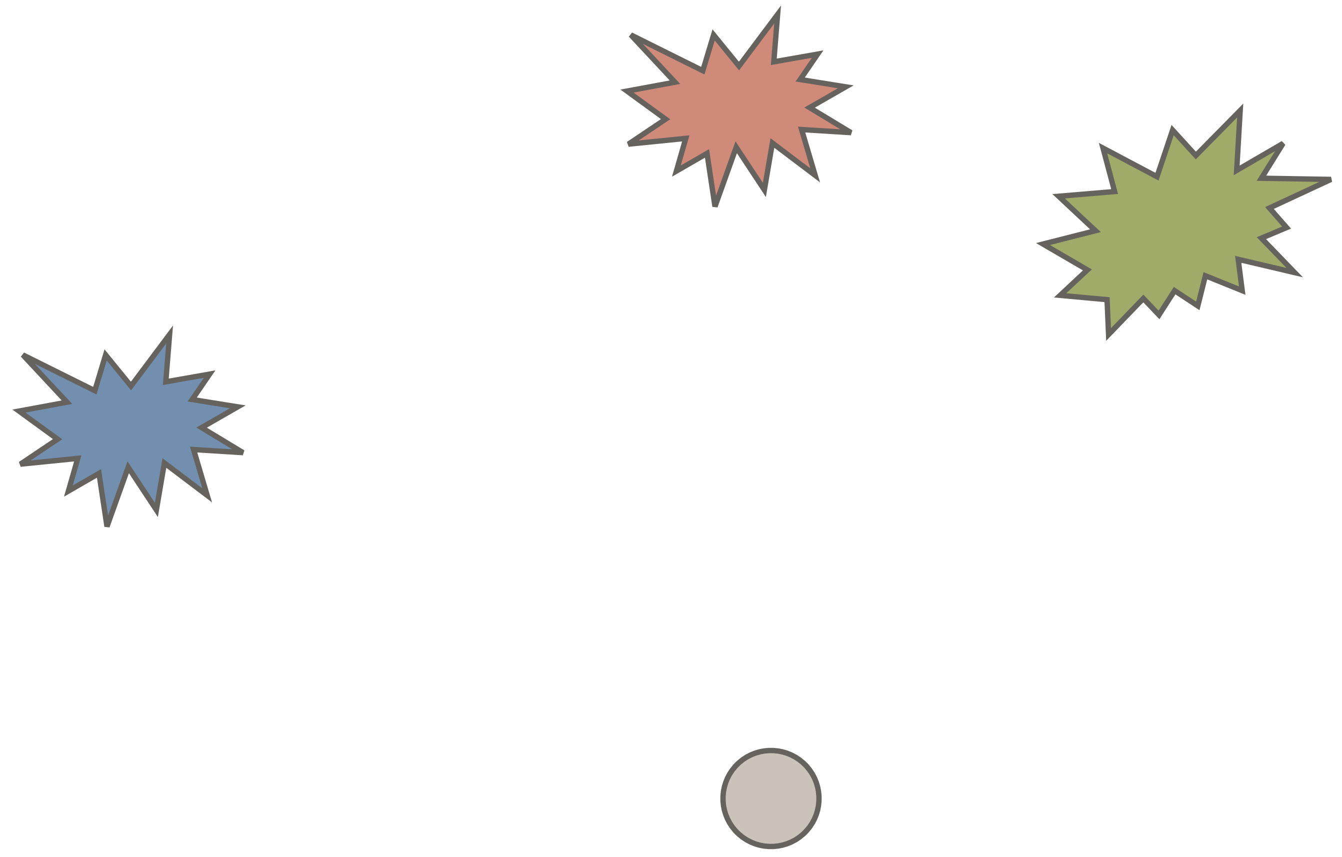


Female speaker

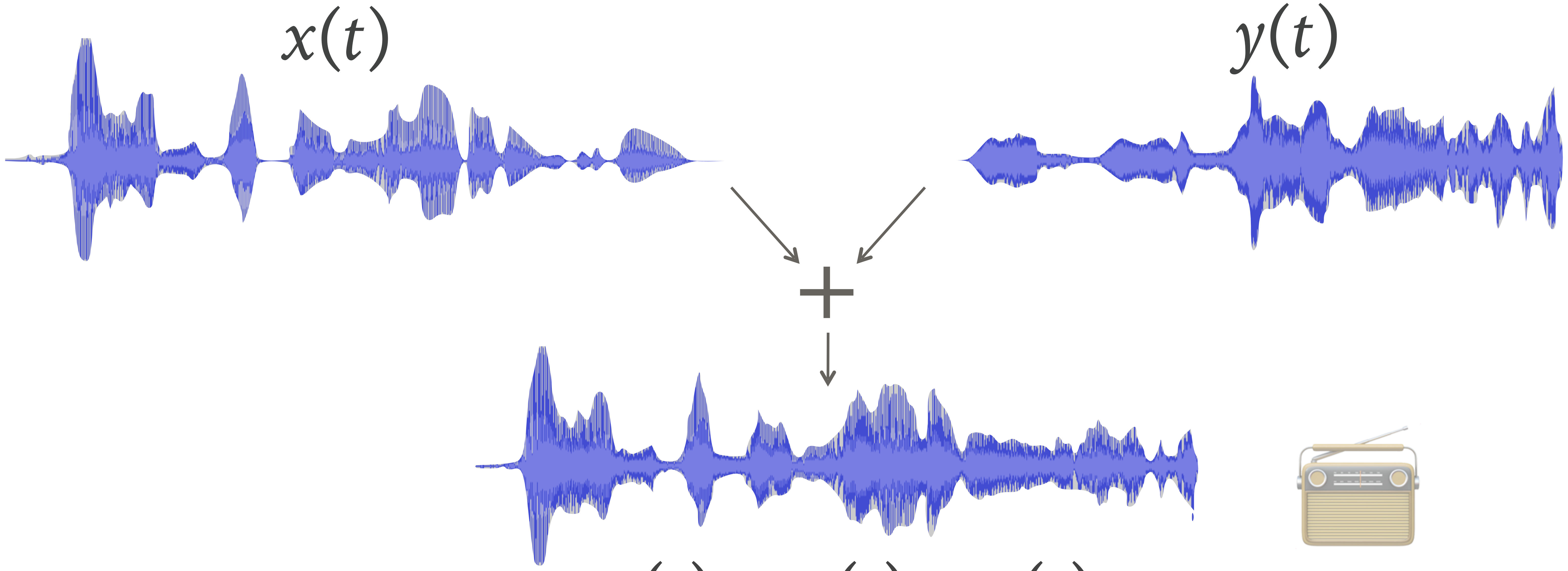
Male speaker

But sensors are so expensive …

- What if we don’t have an array at all?
  - One sensor – multiple inputs case



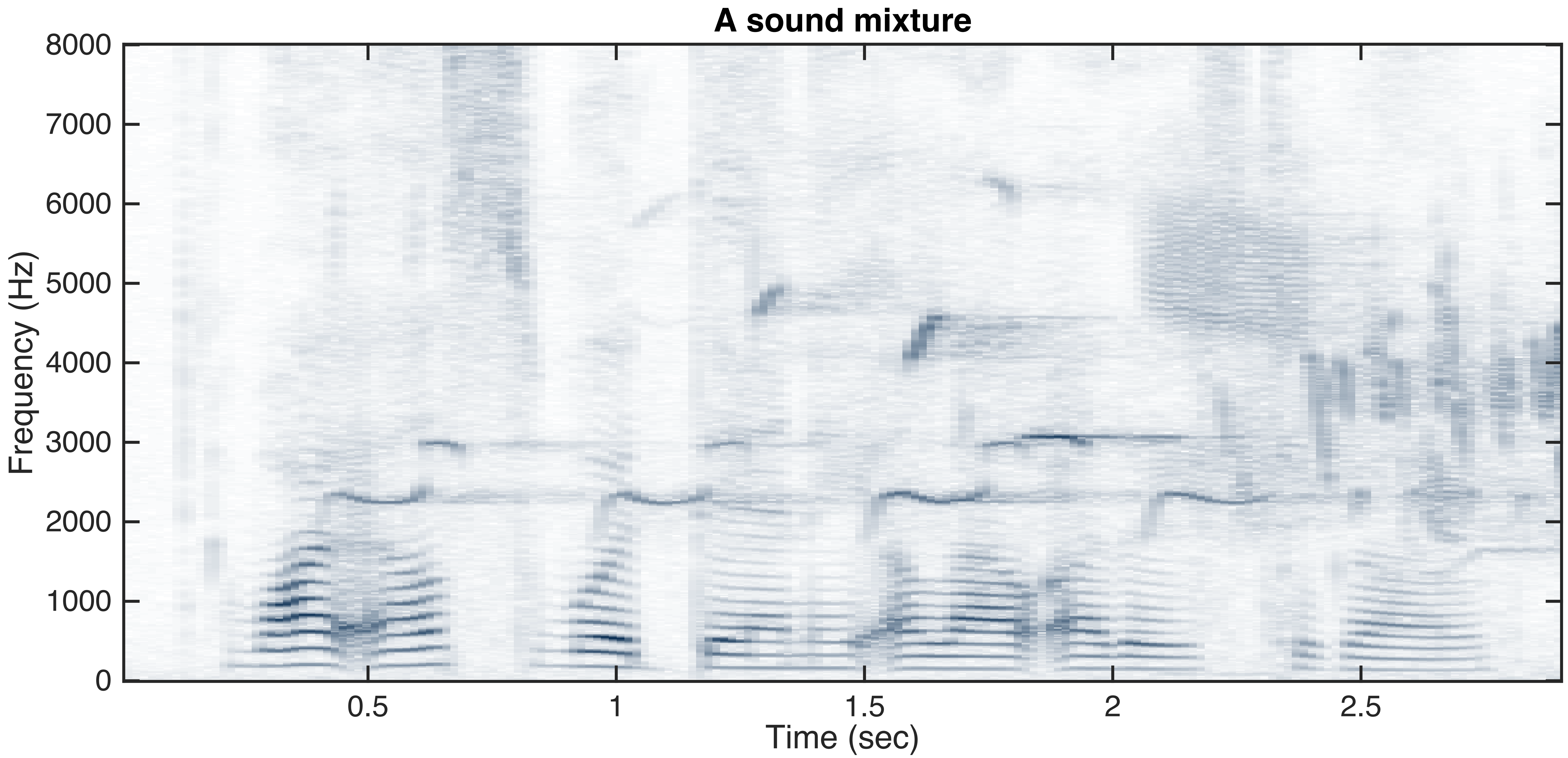
Single-channel source separation



$$m(t) = x(t) + y(t)$$

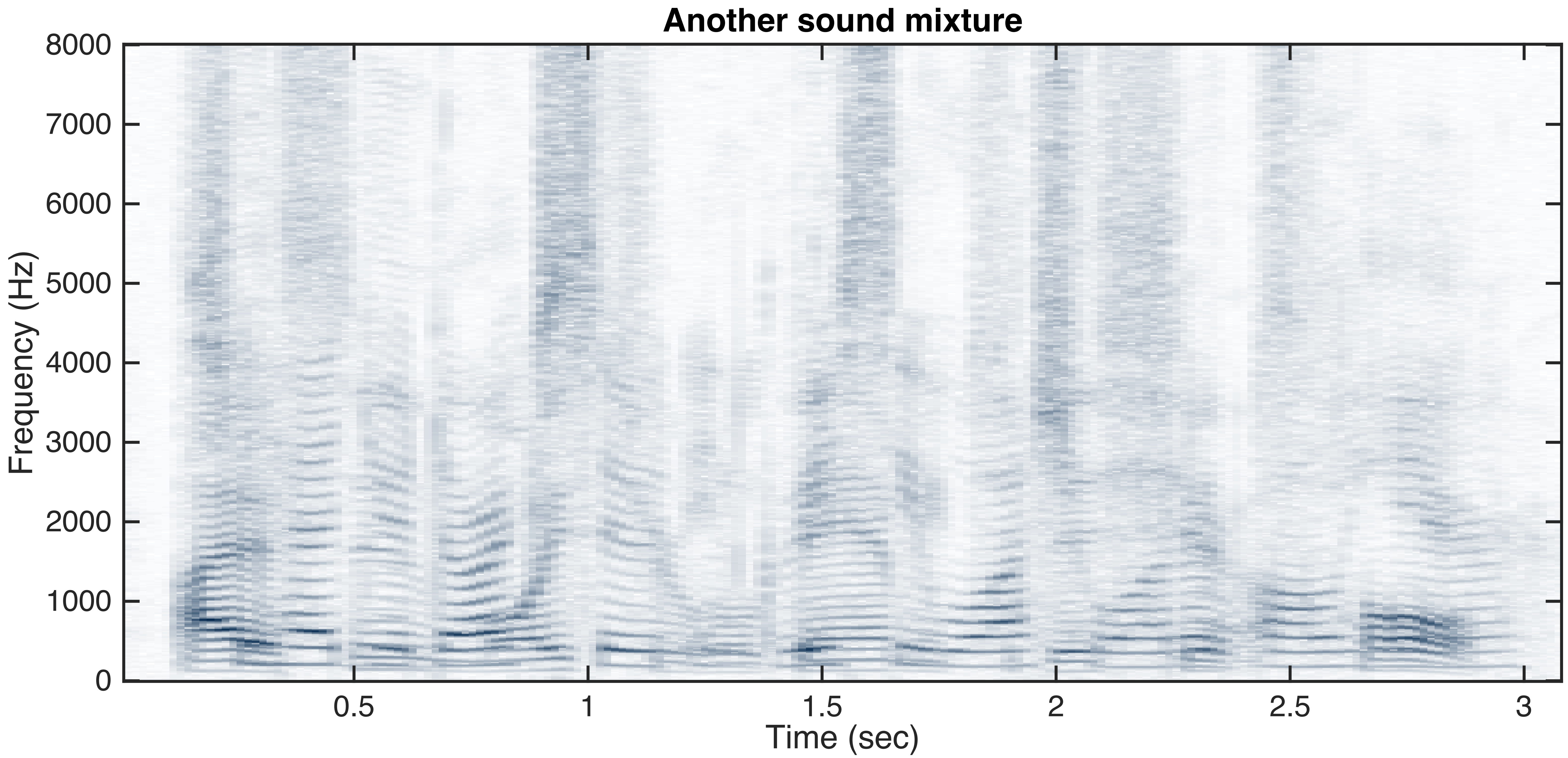
- Another ill-defined problem!

The name of the game



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

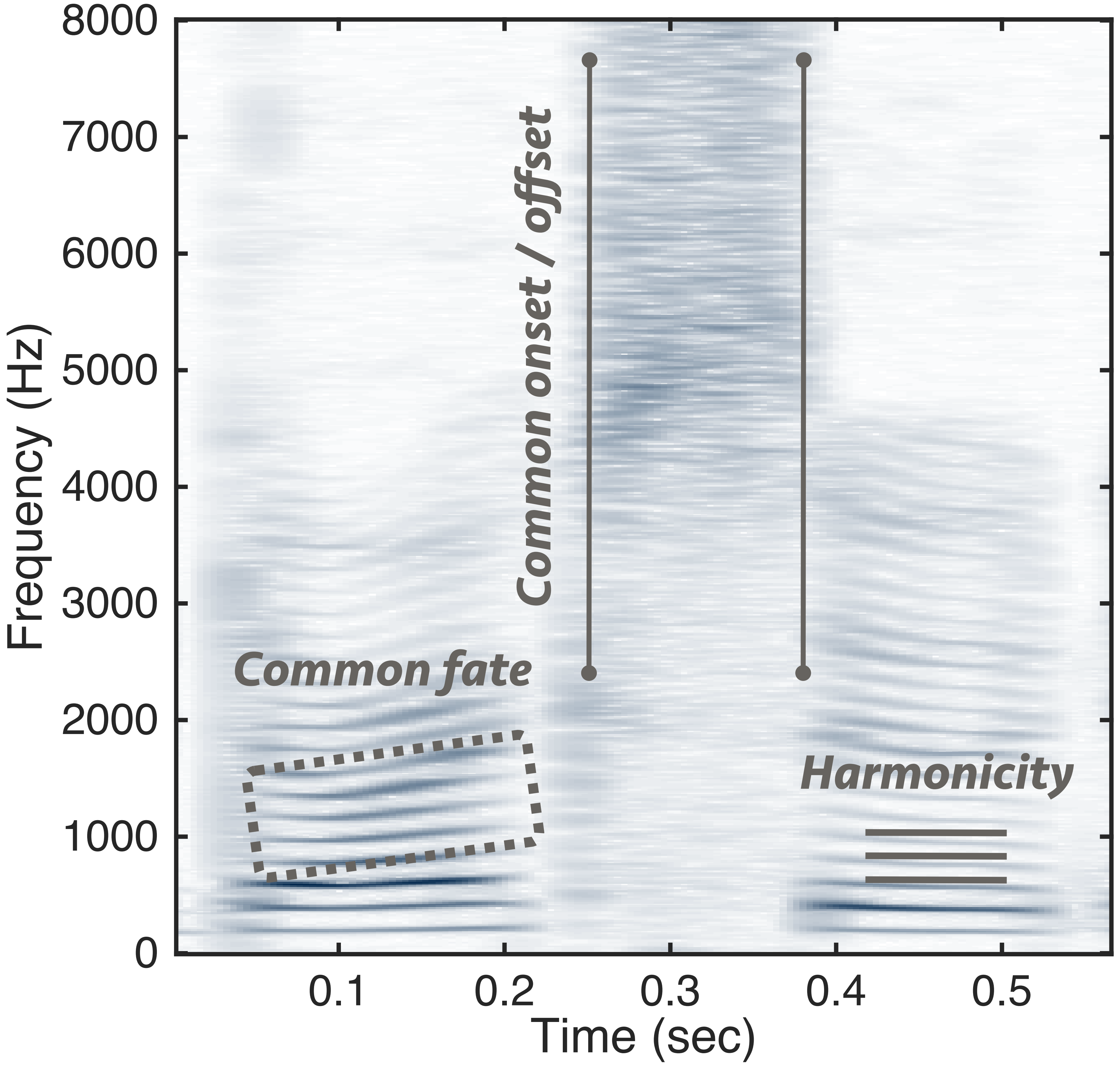
The name of the game



- 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 mix  *Sep* 

Ellis mix  *Sep* 

Wang mix  *Sep* 

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 …

Mix  *Sep* 

Mix  *Sep* 

Mix  *Sep* 

Mix  *Sep* 

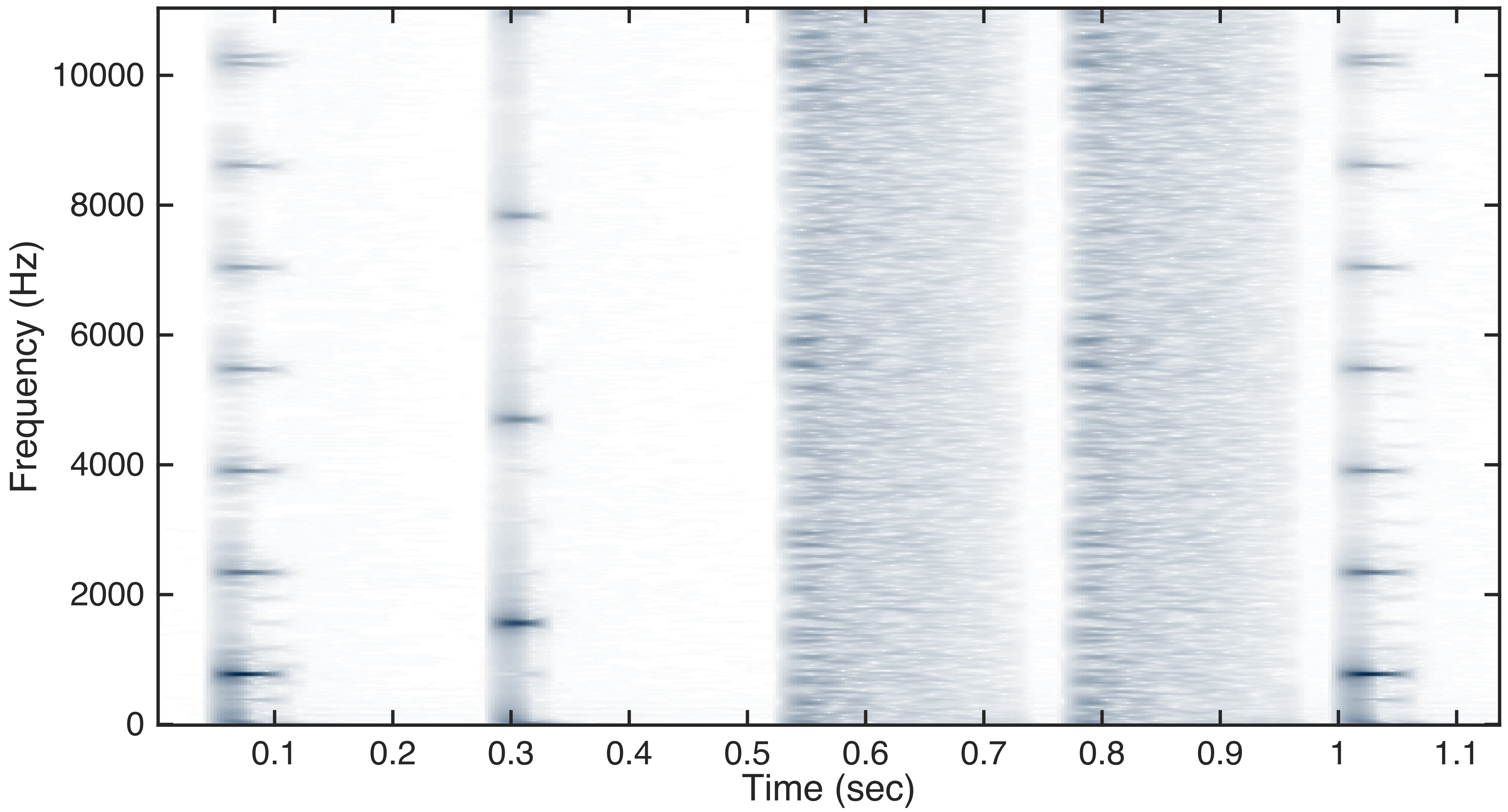
Forgoing unsupervised methods

- It is hard to define source structure
  - We should learn it instead

- Supervised source separation
  - Use training data as hints on what you want

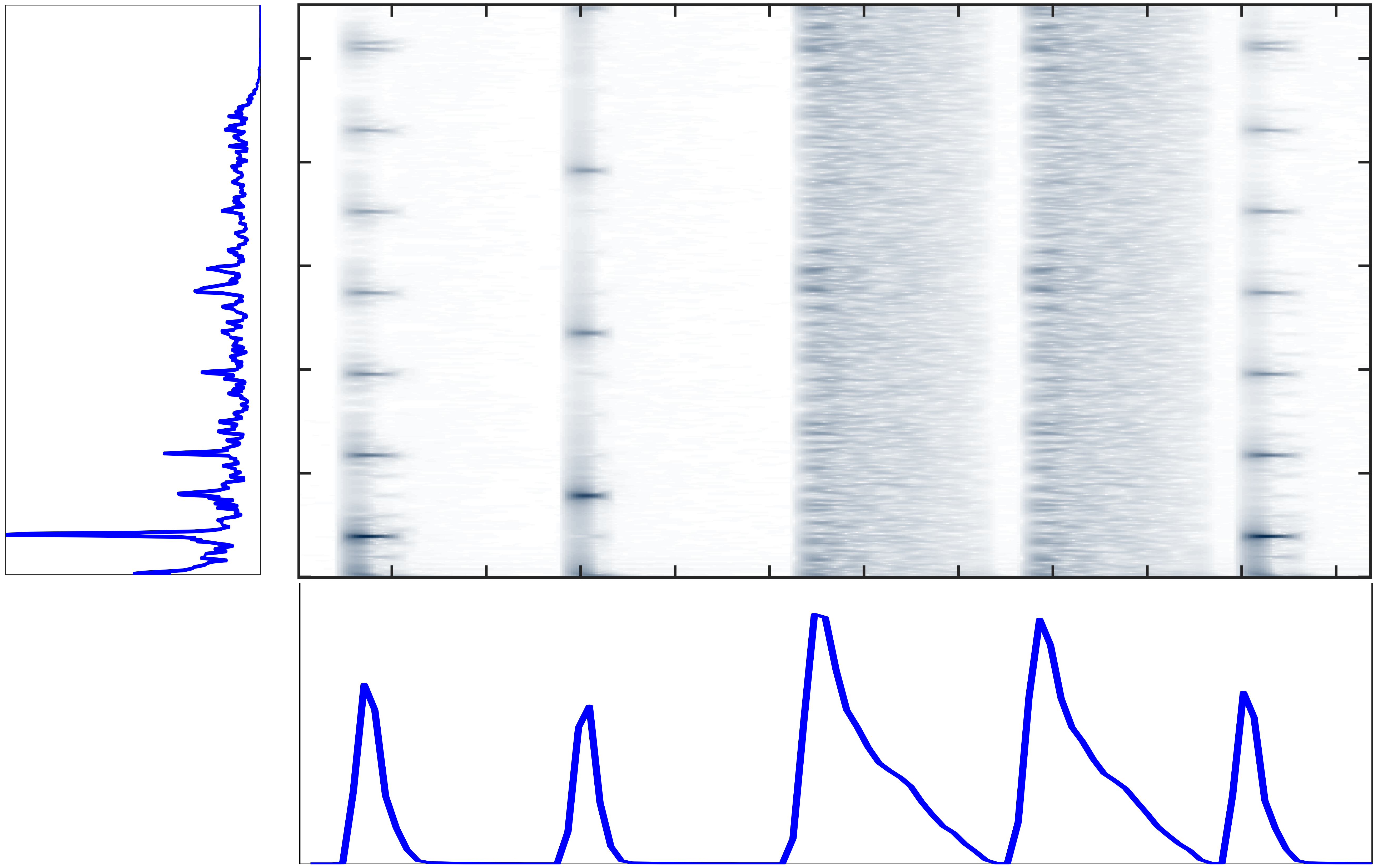
Learning models of sounds

- Starting with a sound having simple elements



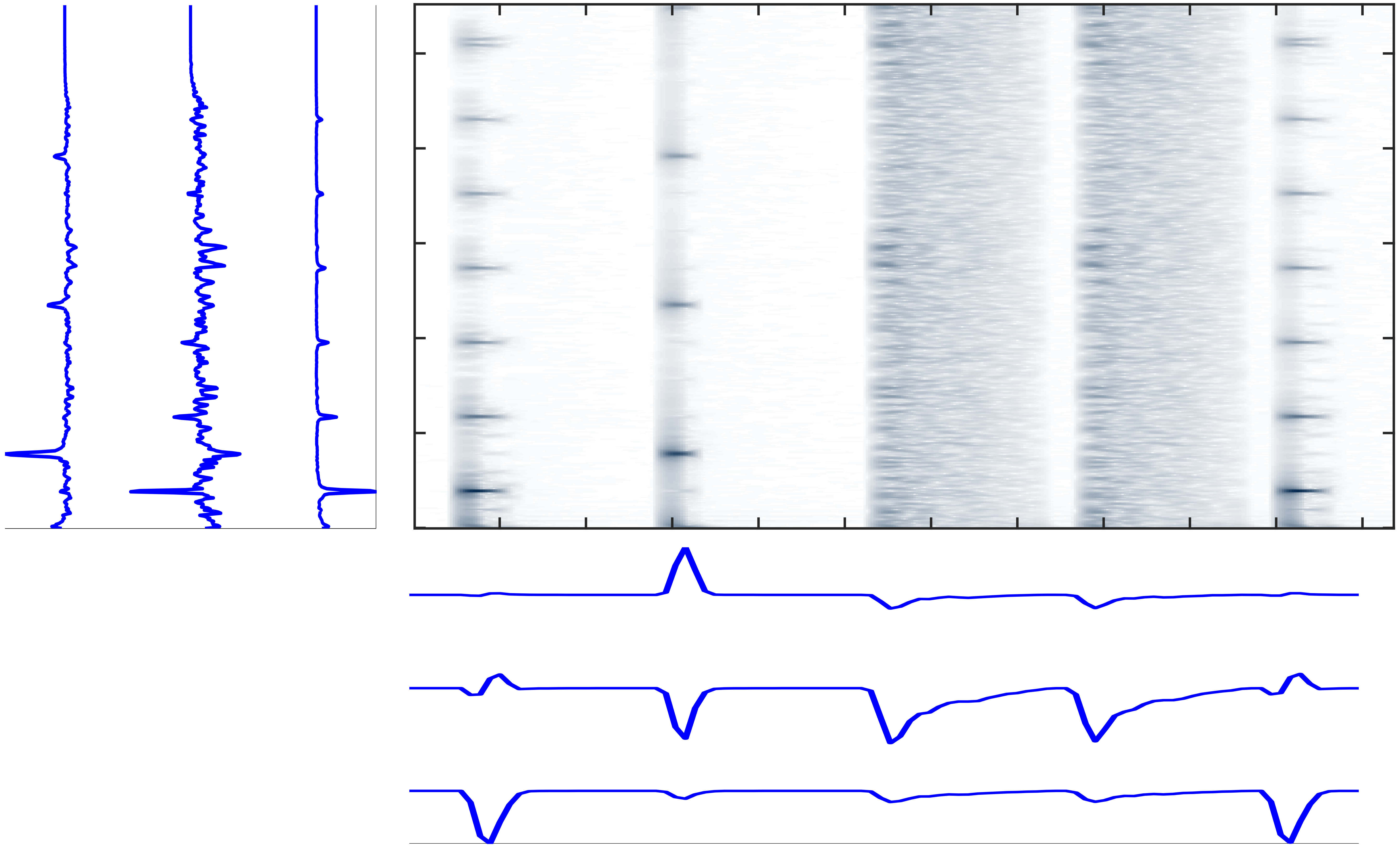
A simple factorization model

- Factor input as: $\mathbf{F} = \mathbf{w} \cdot \mathbf{h}$



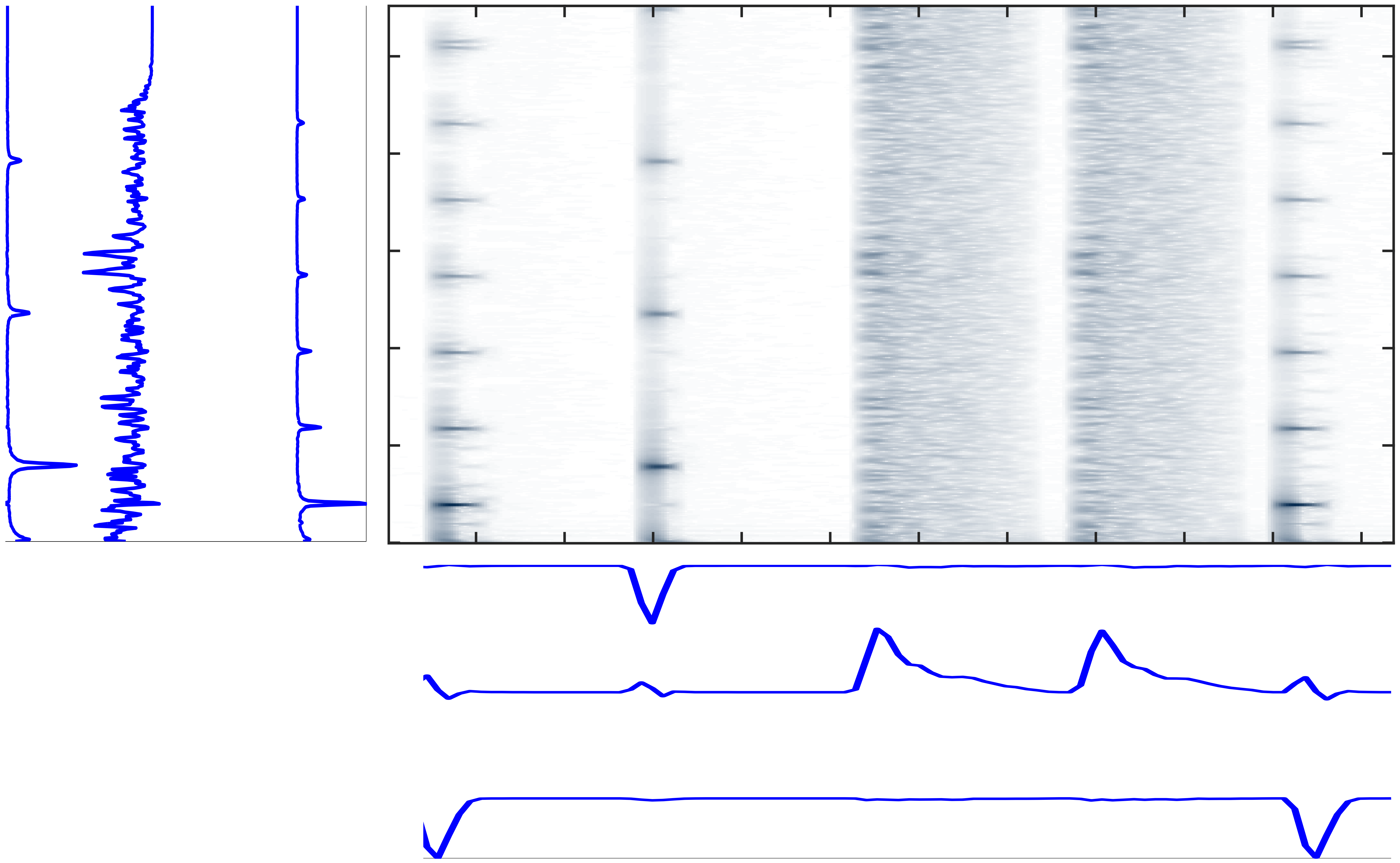
Upping the rank

- Use PCA instead: $\mathbf{F} = \mathbf{W} \cdot \mathbf{H}$



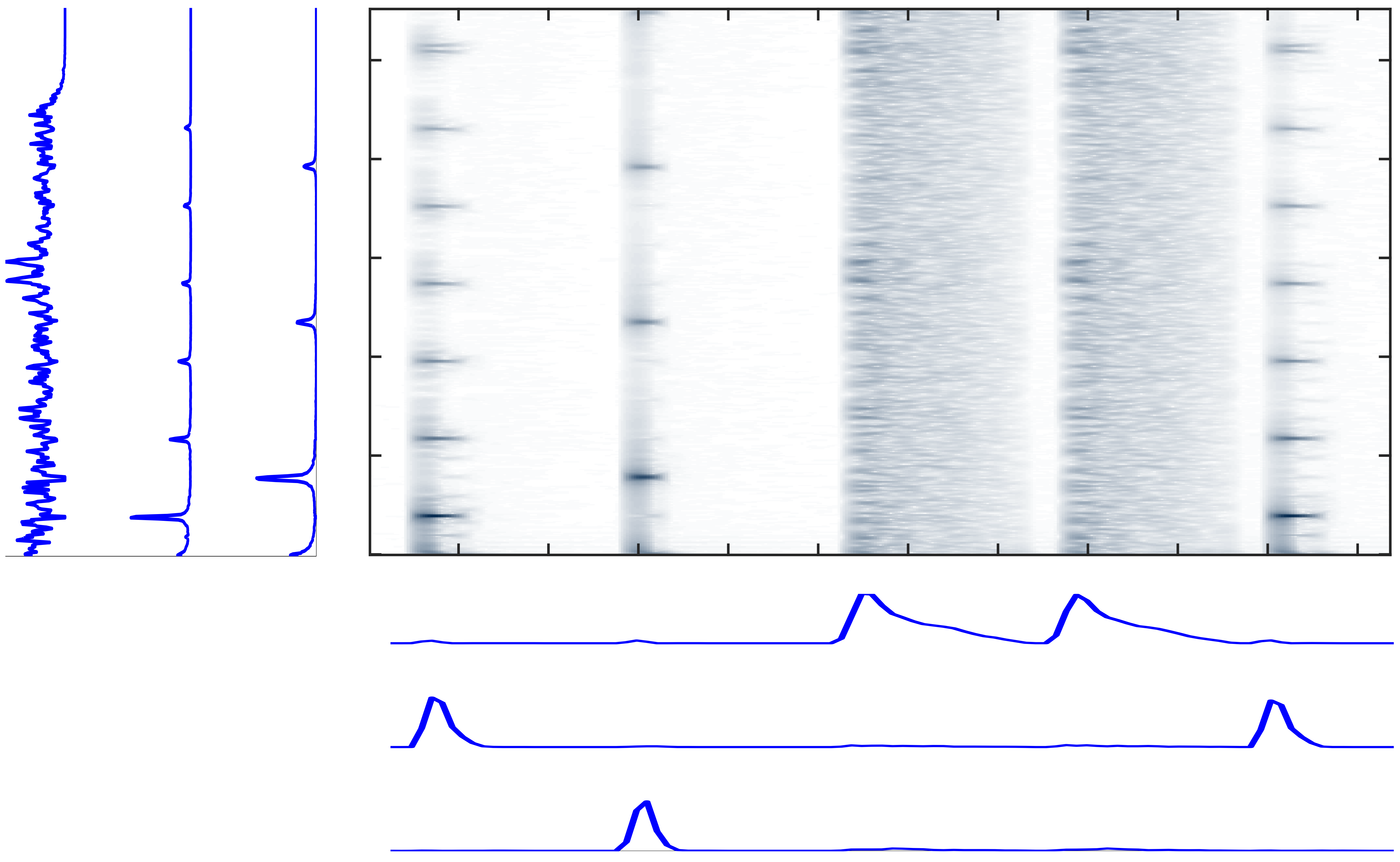
Trying something else

- Use ICA instead: $\mathbf{F} = \mathbf{W} \cdot \mathbf{H}$



One last try ...

- Use NMF instead: $\mathbf{F} = \mathbf{W} \cdot \mathbf{H}$



Interpreting the model

- Rank-R model returns R components

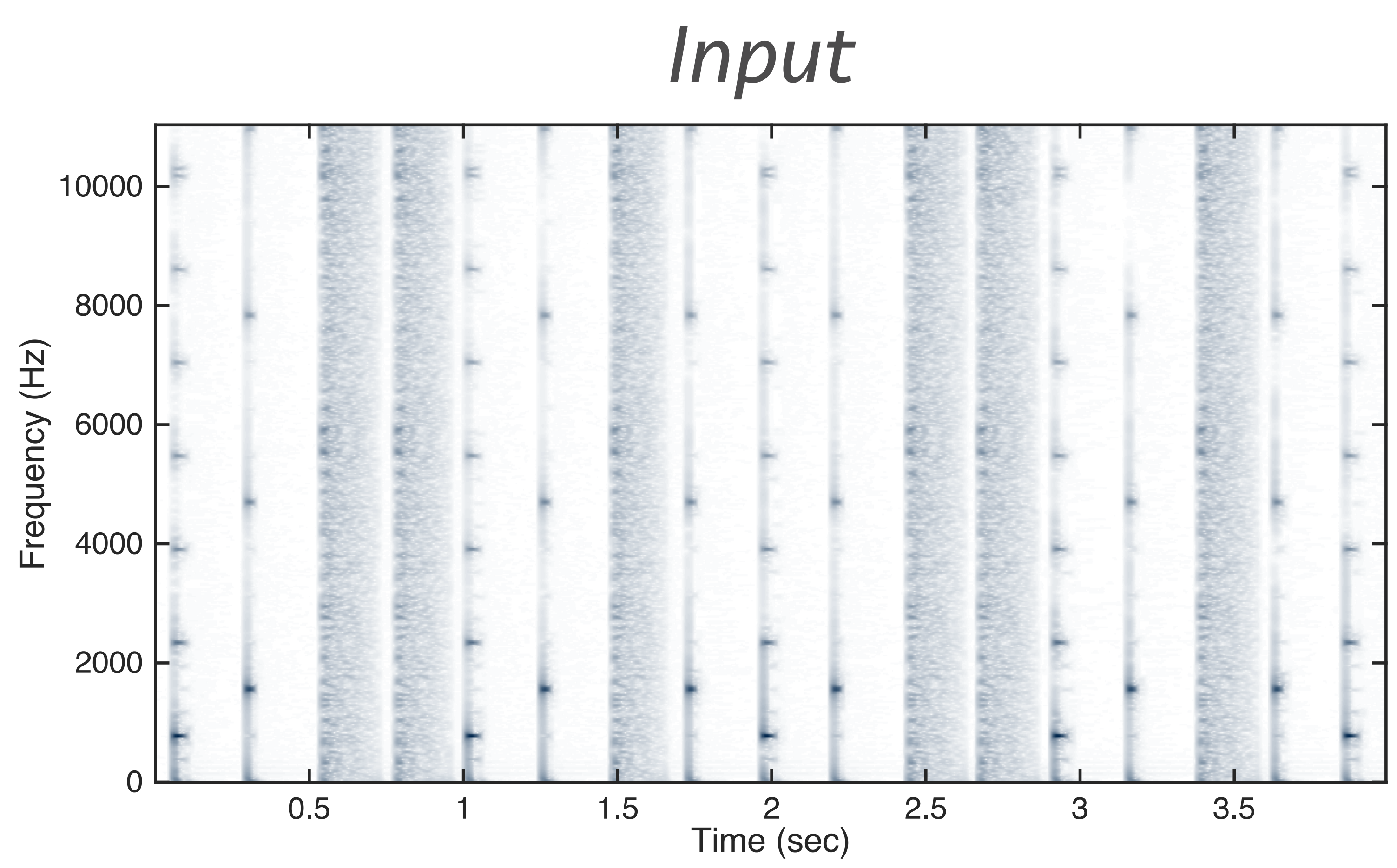
$$\mathbf{F} = \mathbf{W} \cdot \mathbf{H}$$

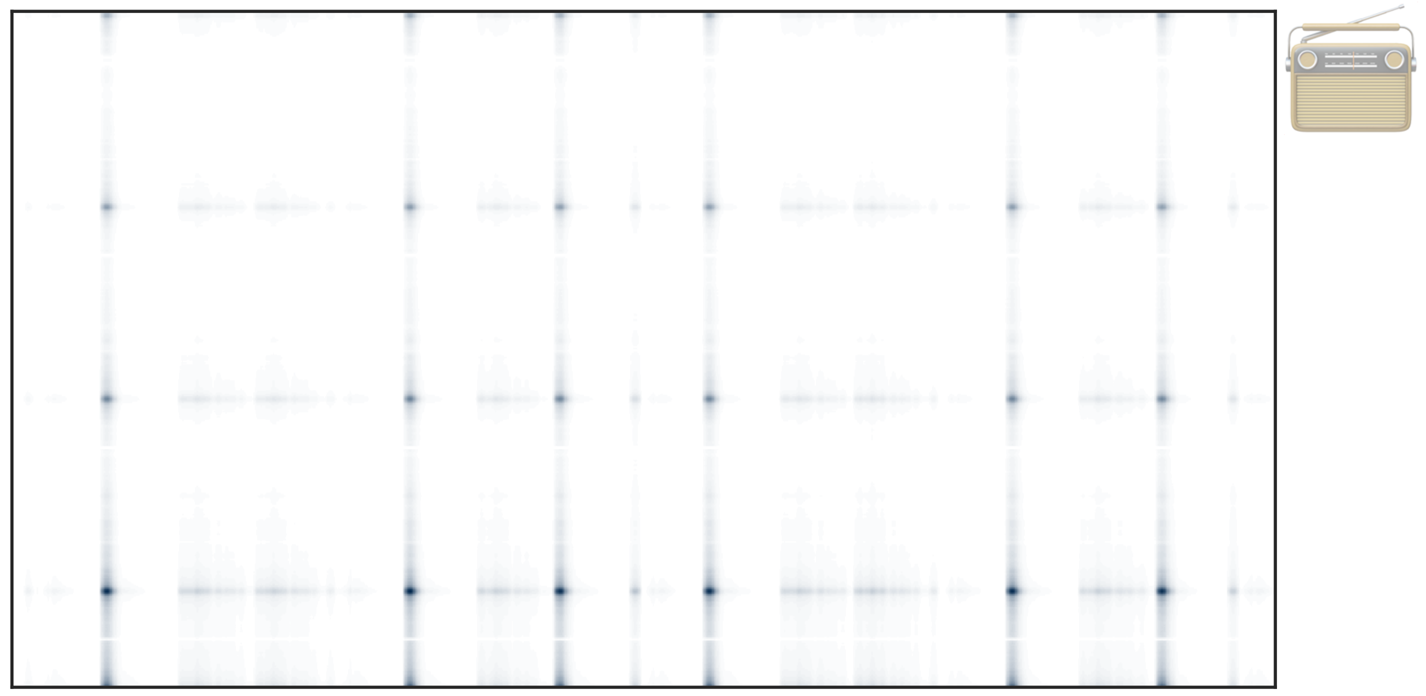
$$\mathbf{F} \in \mathbb{R}^{M \times N, \geq 0}, \mathbf{W} \in \mathbb{R}^{M \times R, \geq 0}, \mathbf{H} \in \mathbb{R}^{R \times N, \geq 0}$$

- $\mathbf{W}$ matrix holds spectral templates
  - vertical structure
- $\mathbf{H}$ matrix their time activations
  - horizontal structure
- Or vice-versa!

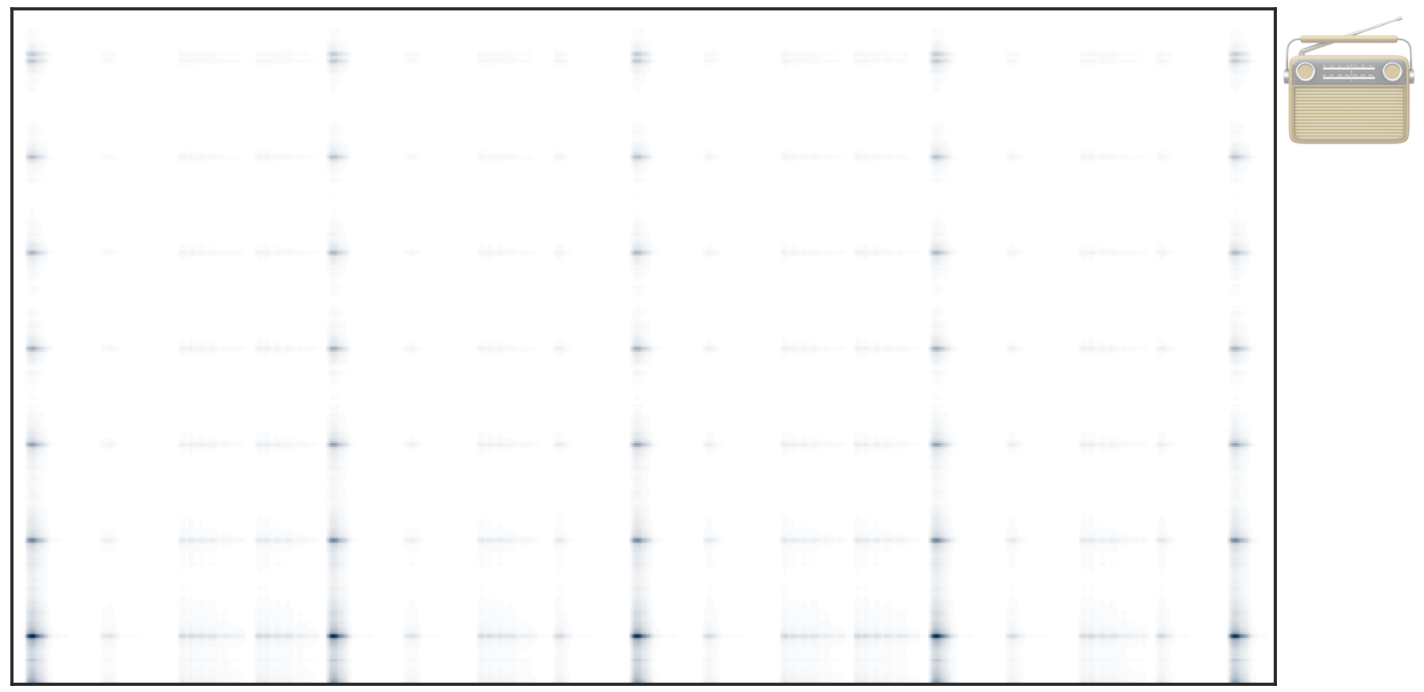
Element-wise reconstructions

- Each component latches to a "subsound"
  - and can then be isolated!

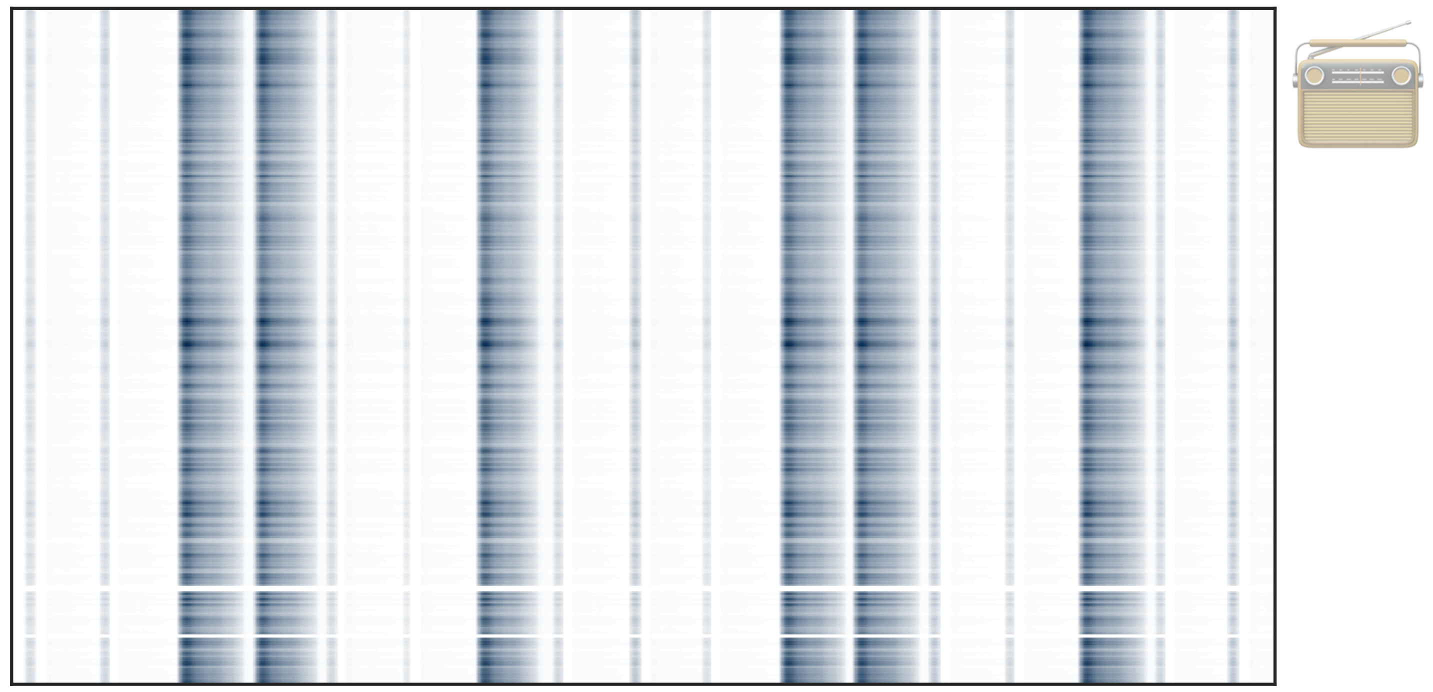




$\mathbf{W}_{:,1} \cdot \mathbf{H}_{1,:}$

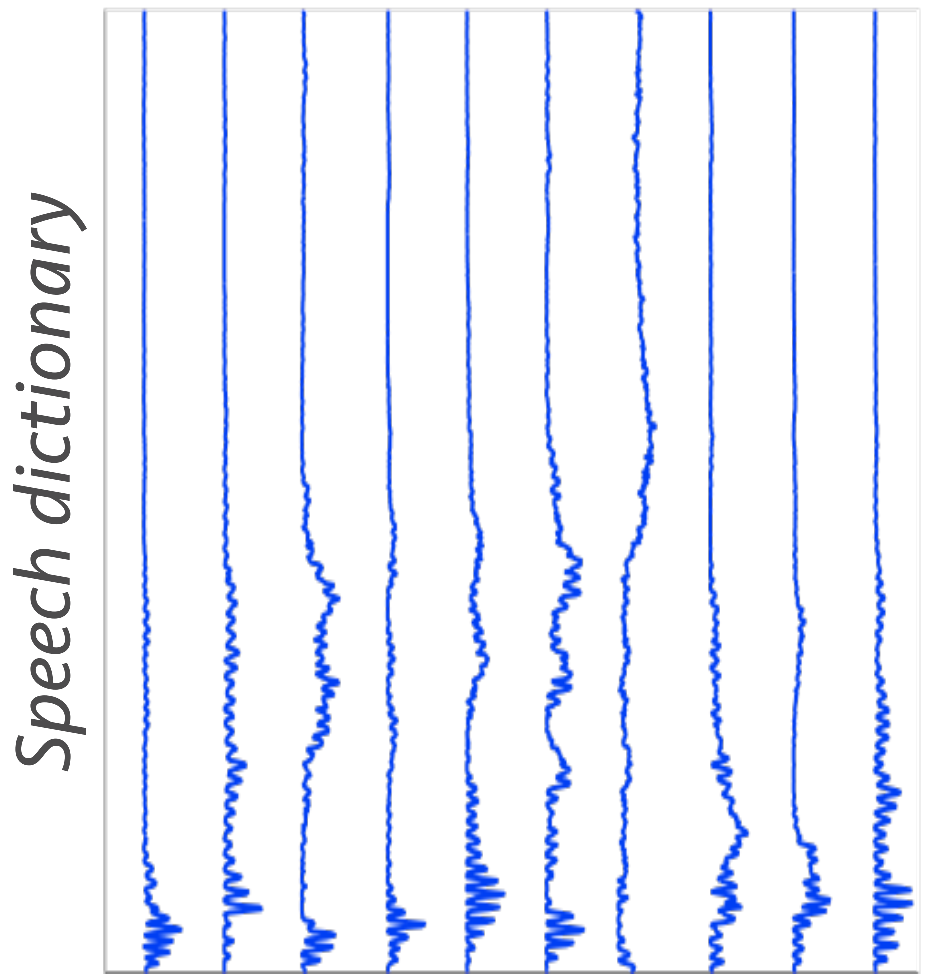


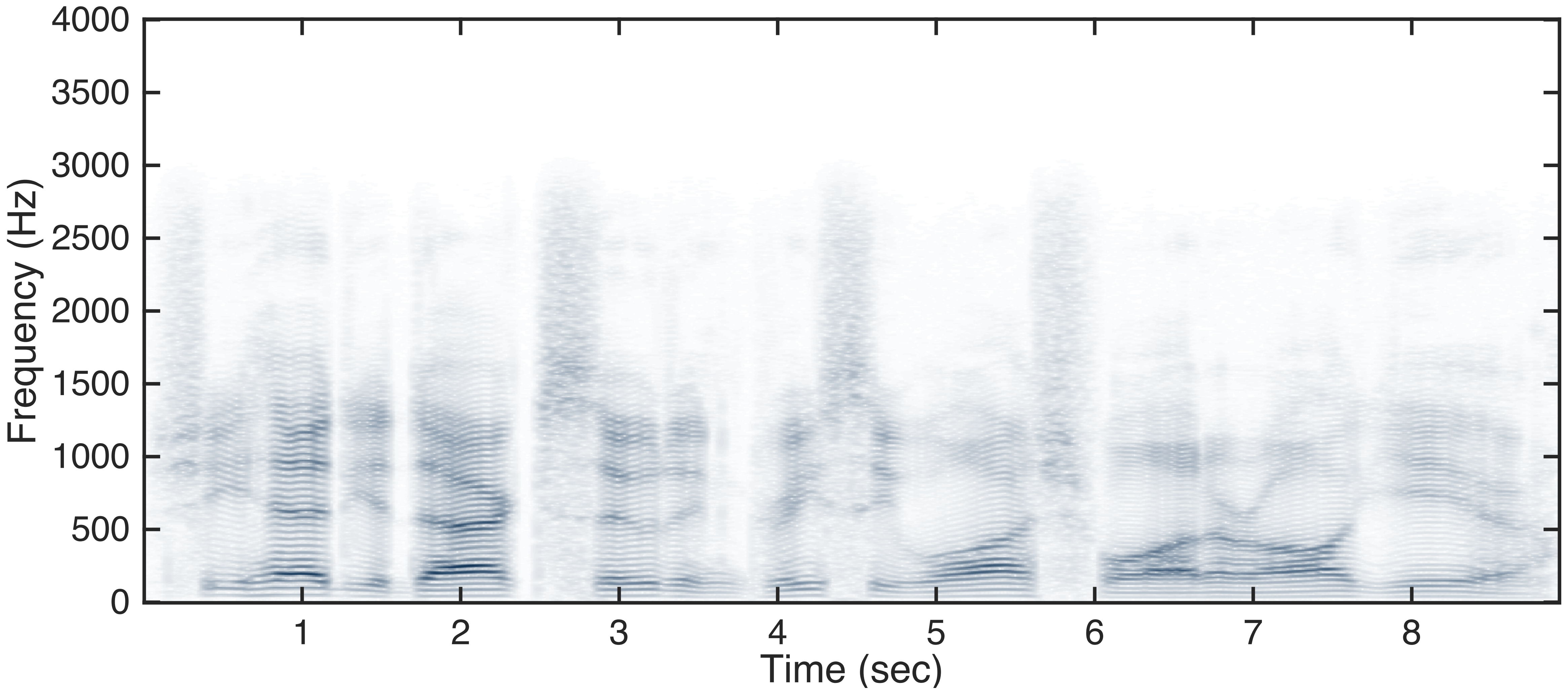
$\mathbf{W}_{:,2} \cdot \mathbf{H}_{2,:}$



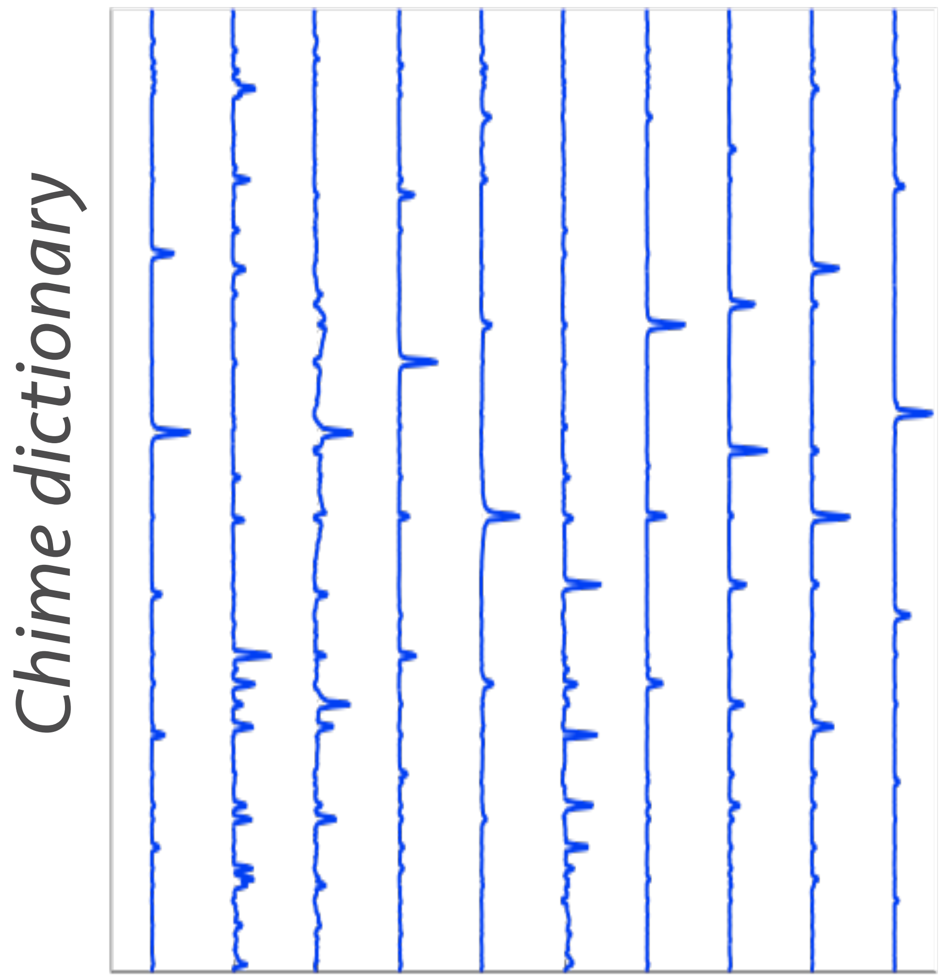
$\mathbf{W}_{:,3} \cdot \mathbf{H}_{3,:}$

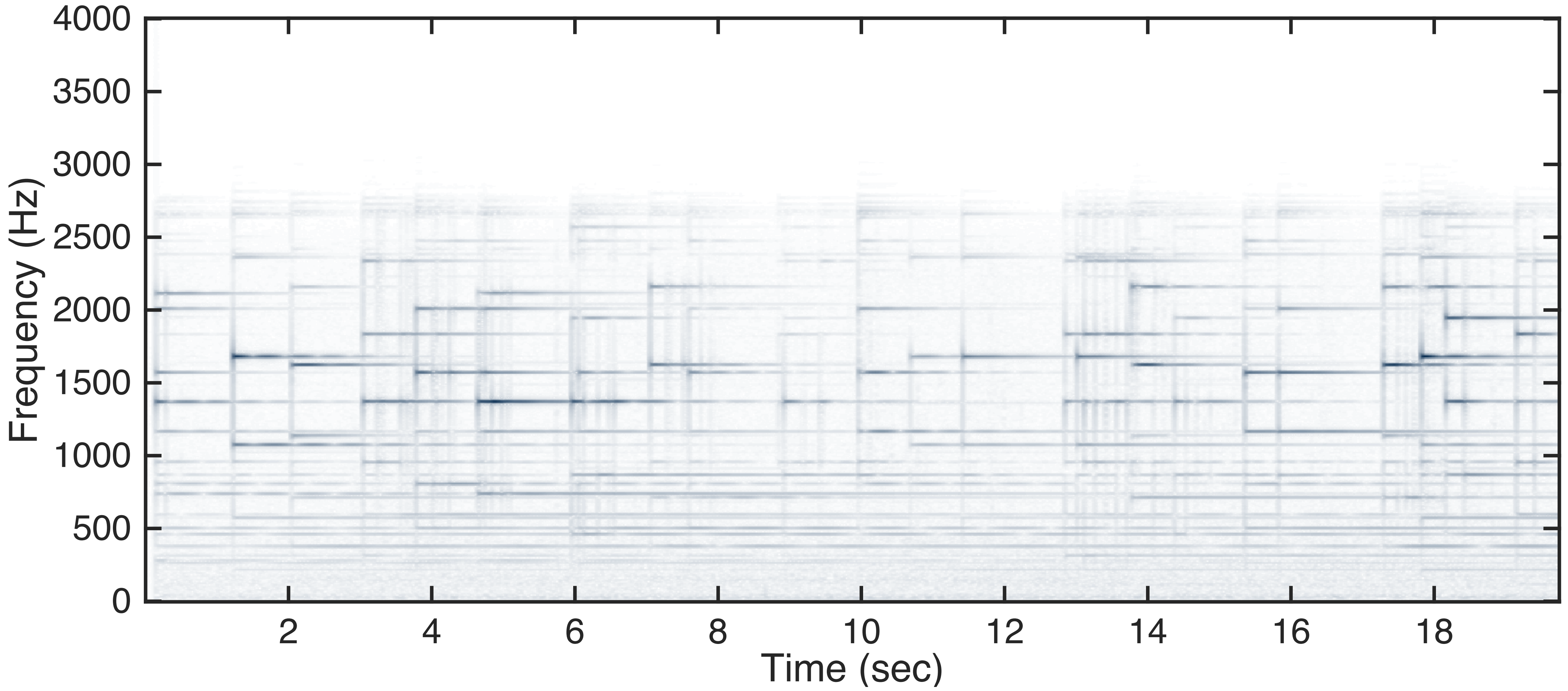
Making NMF sound models





Speech recording





Chime recording

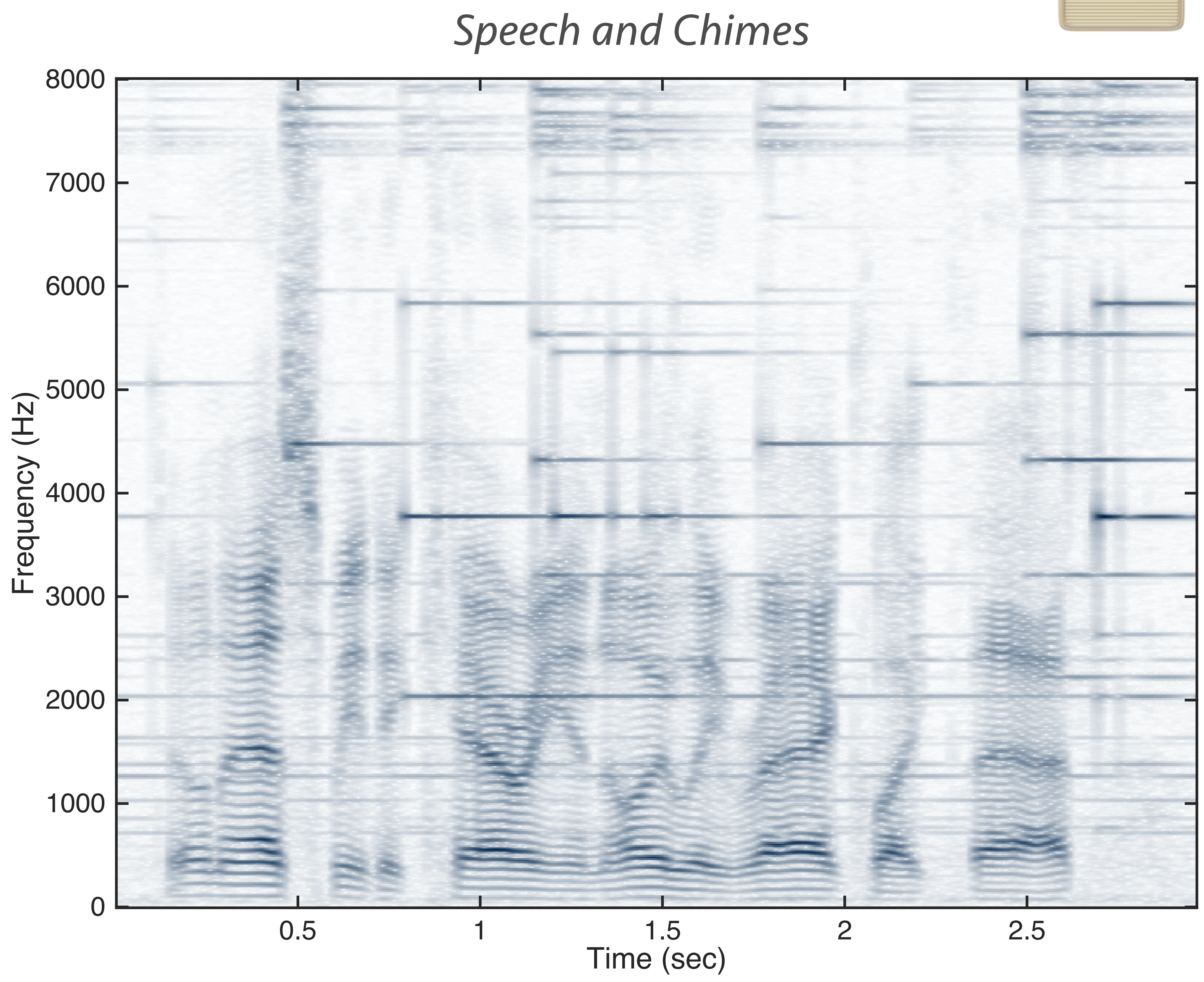
Mixtures of sounds

- Use spectrogram additivity
    - combine models to explain mixture

$$\mathbf{F} = \begin{bmatrix} \mathbf{W}_{chimes} & \mathbf{W}_{speech} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{H}_{chimes} \\ \mathbf{H}_{speech} \end{bmatrix}$$

Known/fixed *Estimated*

- We estimate only the weights
- The known bases claim only the parts that they can fit best



Separation

- Recompose sources individually

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

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

Mixture

Extracted speech

Extracted chimes

- And convert spectrograms to time domain
  - Use the phase of the mixture
  - Unlike before this is a soft mask

Two problems

- Sounds in mixture have to be distinct
  - but not my much!

Speech & speech mixture

Extracted speaker 1

Extracted speaker 2

- What are the chances we know all sounds?
  - Usually we know a target or a noise

Separation with unknown sounds

- Same as before, use only one model:

$$\mathbf{F} = \begin{bmatrix} \mathbf{W}_{known} & \mathbf{W}_{unknown} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{H}_{known} \\ \mathbf{H}_{unknown} \end{bmatrix}$$

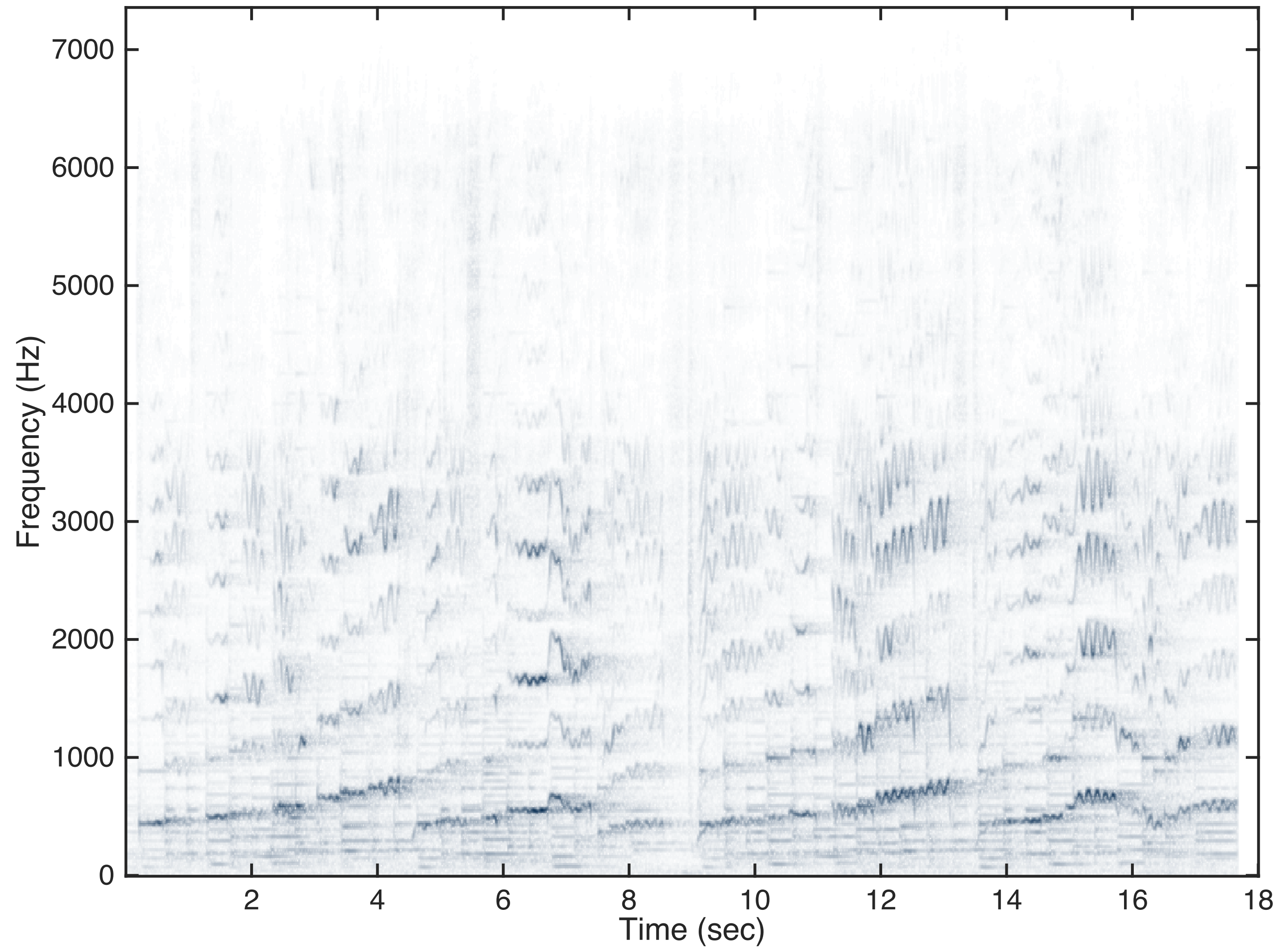
Known/fixed

Estimated

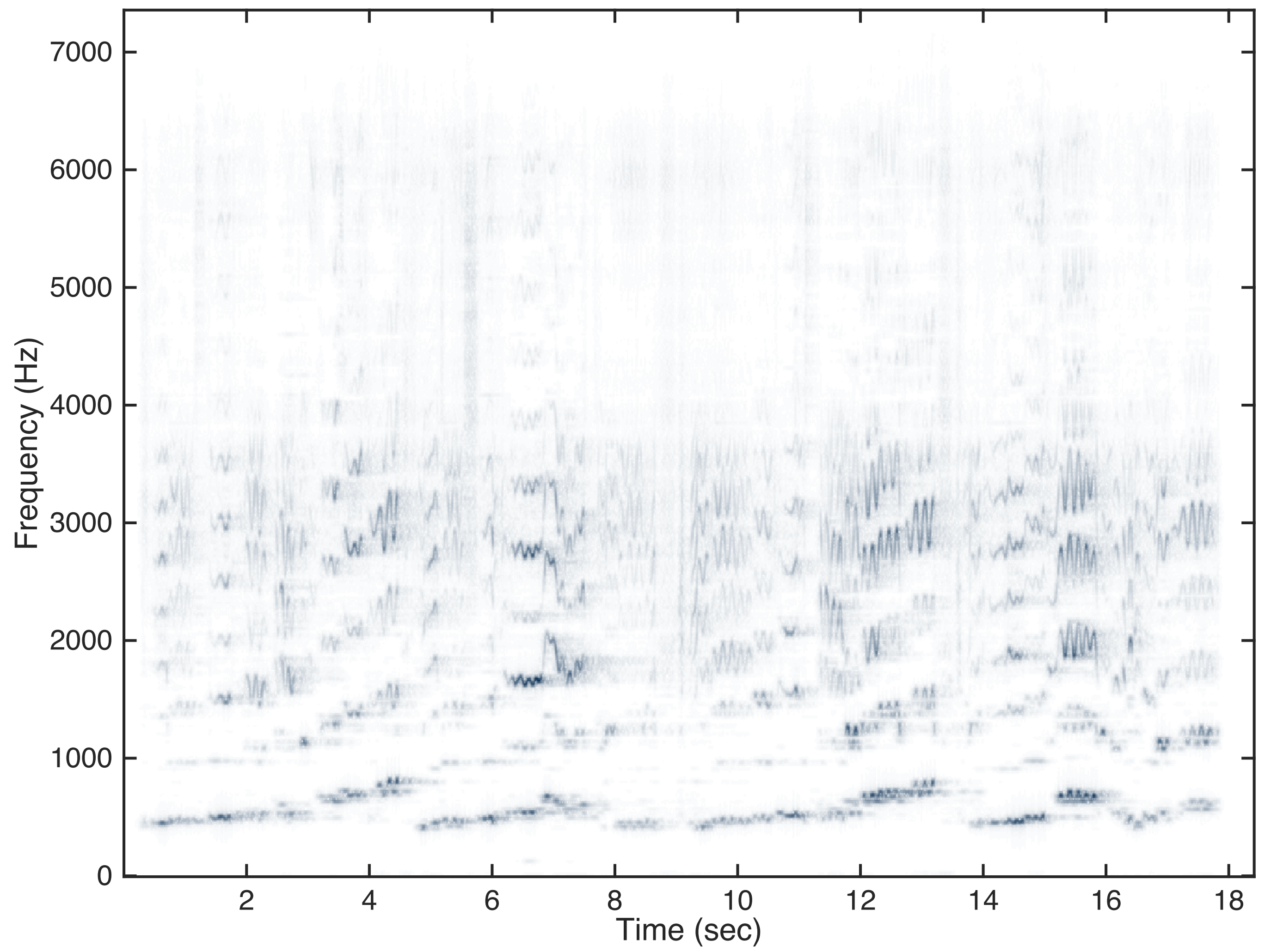
- Learn weights and unknown bases
  - Unknown bases converge to the unknown parts in the mixture

Soprano & Piano  *Extracted soprano* 

Soprano+Piano



Extracted soprano



Setting up the problem

- Can be done in two ways
  - Have model of noise, extract extras
  - Have model of target, remove extras
- All cases can be binary
  - What you want vs. the rest
- Can be applied to denoising
  - Can deal with non-stationary noise

Speech + the beauty of mechanics

Wideband noise

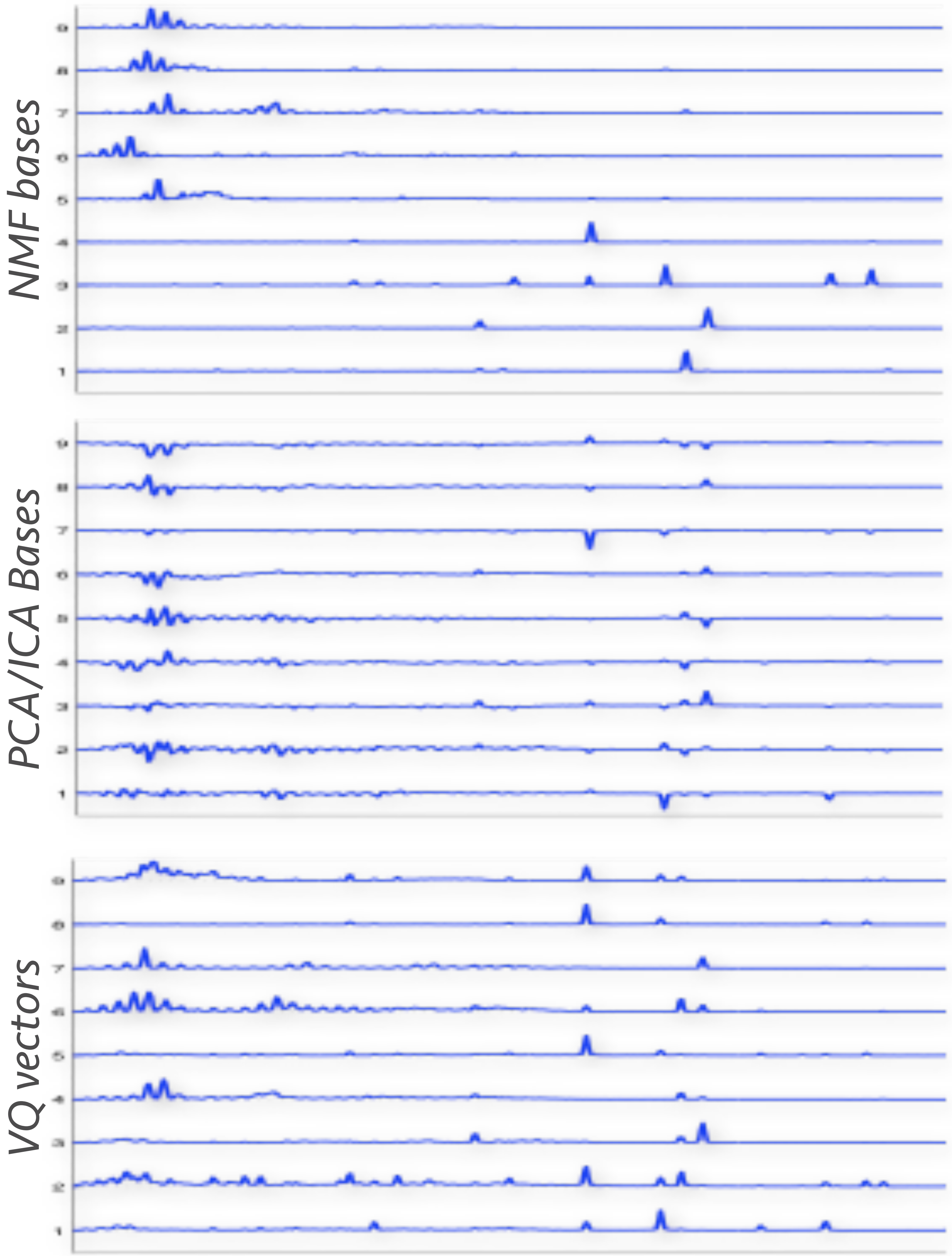
Extracted speech

Loosely correlated "noise"

Denoised sound

Why this model?

- We need to measure the *presence* of something
  - Therefore our domain is inherently non-negative
- PCA, ICA, etc don't work
  - The use of cross-cancellation gives nonsensical results
- K-means is not additive
  - Can't model mixing effects
- NMF is best at this

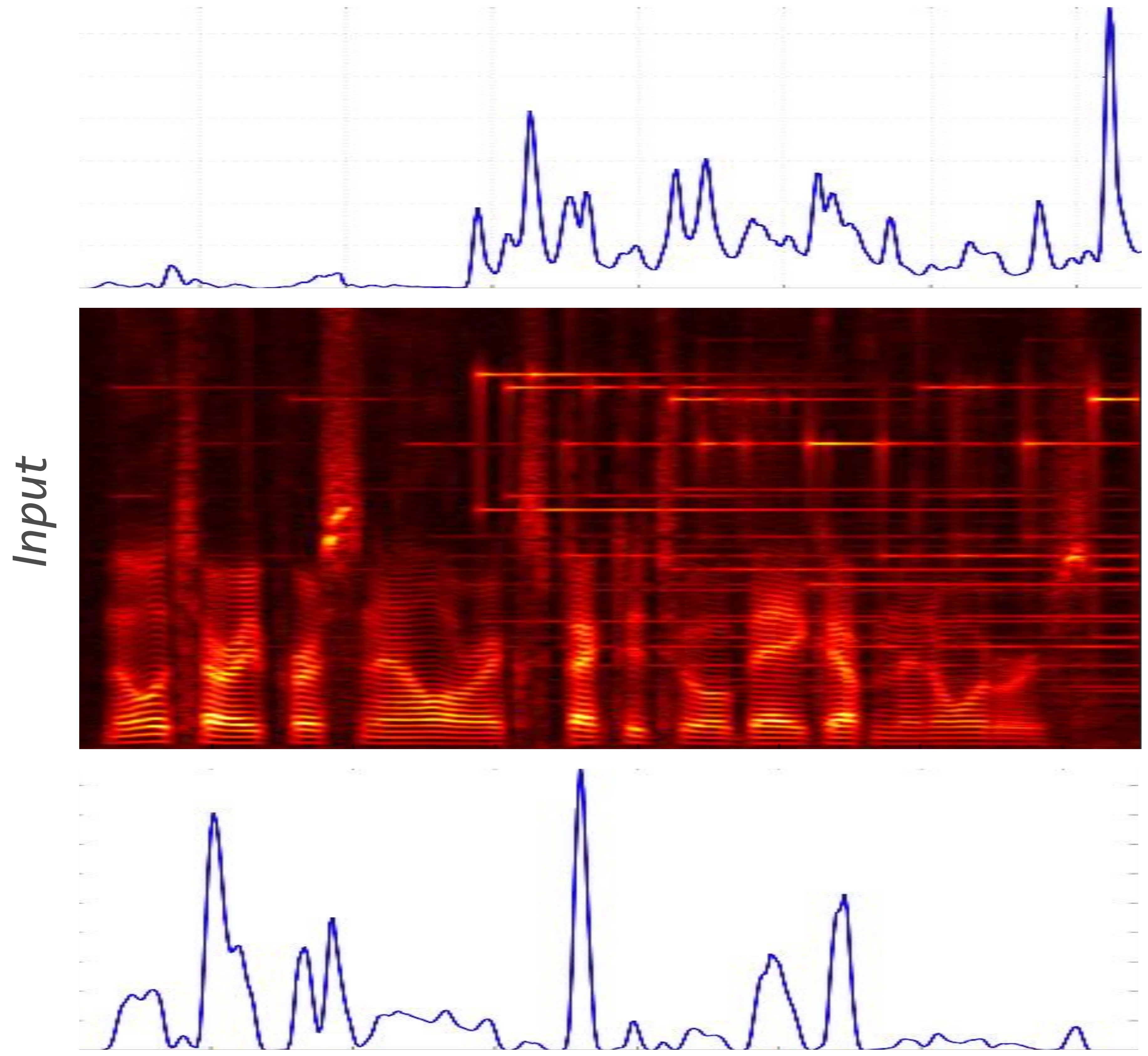


Measuring presence

- Recognition in mixtures
  - We can't use classifiers!
  - No hard answer
    - Not even a soft one …

- Measuring source presence
  - Observe source weights
  - Deduce amount of sounds

Overall energy of chime time weights



Overall energy of speech time weights

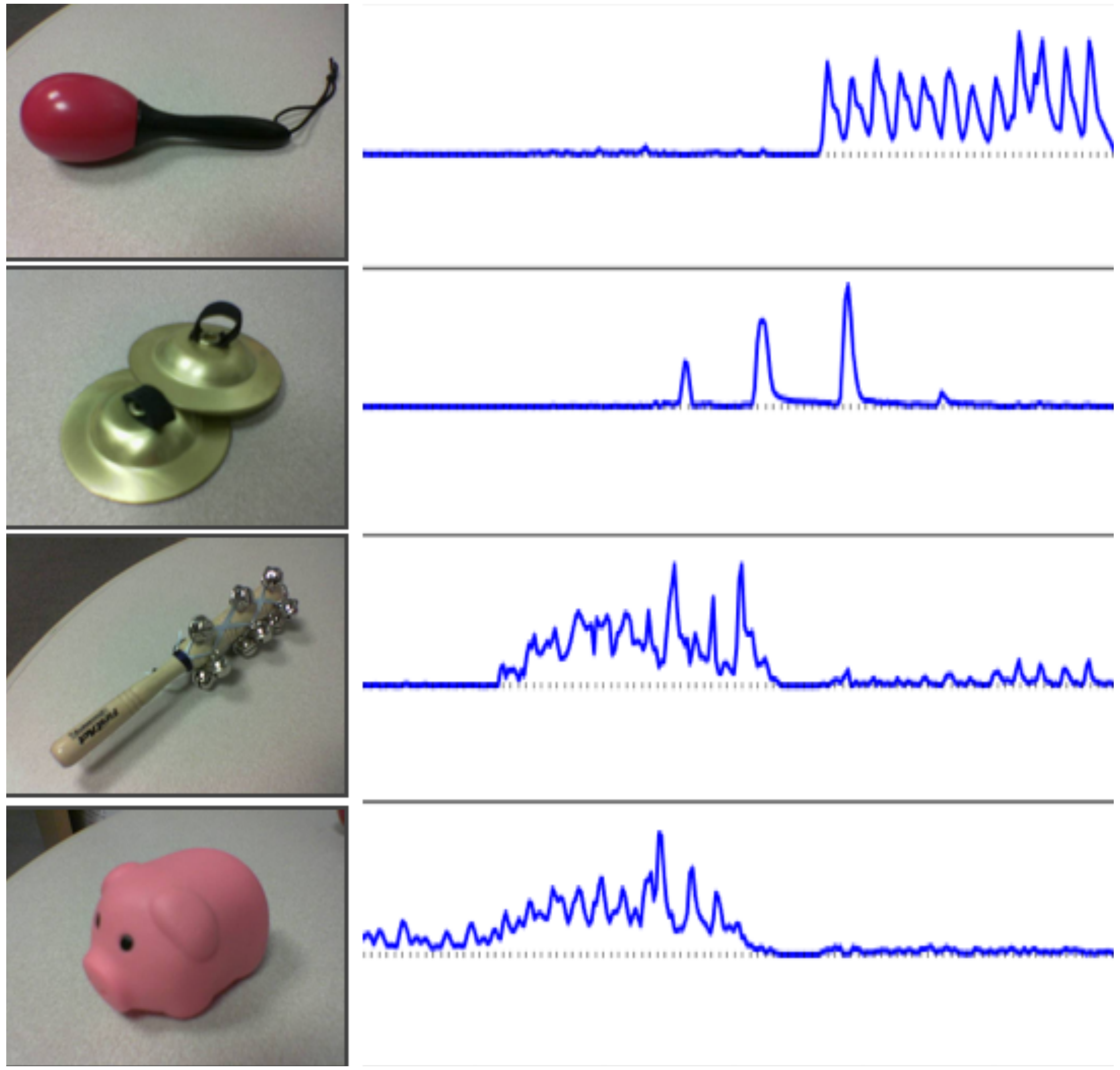
Sound recognition in mixtures

- Use known models to estimate presence of these sounds in a mixture

$$\mathbf{F} = \begin{bmatrix} \mathbf{W}_{shaker} & \mathbf{W}_{cymbals} & \mathbf{W}_{jingles} & \mathbf{W}_{pig} \end{bmatrix} \cdot \begin{bmatrix} \mathbf{H}_{shaker} \\ \mathbf{H}_{cymbals} \\ \mathbf{H}_{jingles} \\ \mathbf{H}_{pig} \end{bmatrix}$$

Known/fixed

Estimated

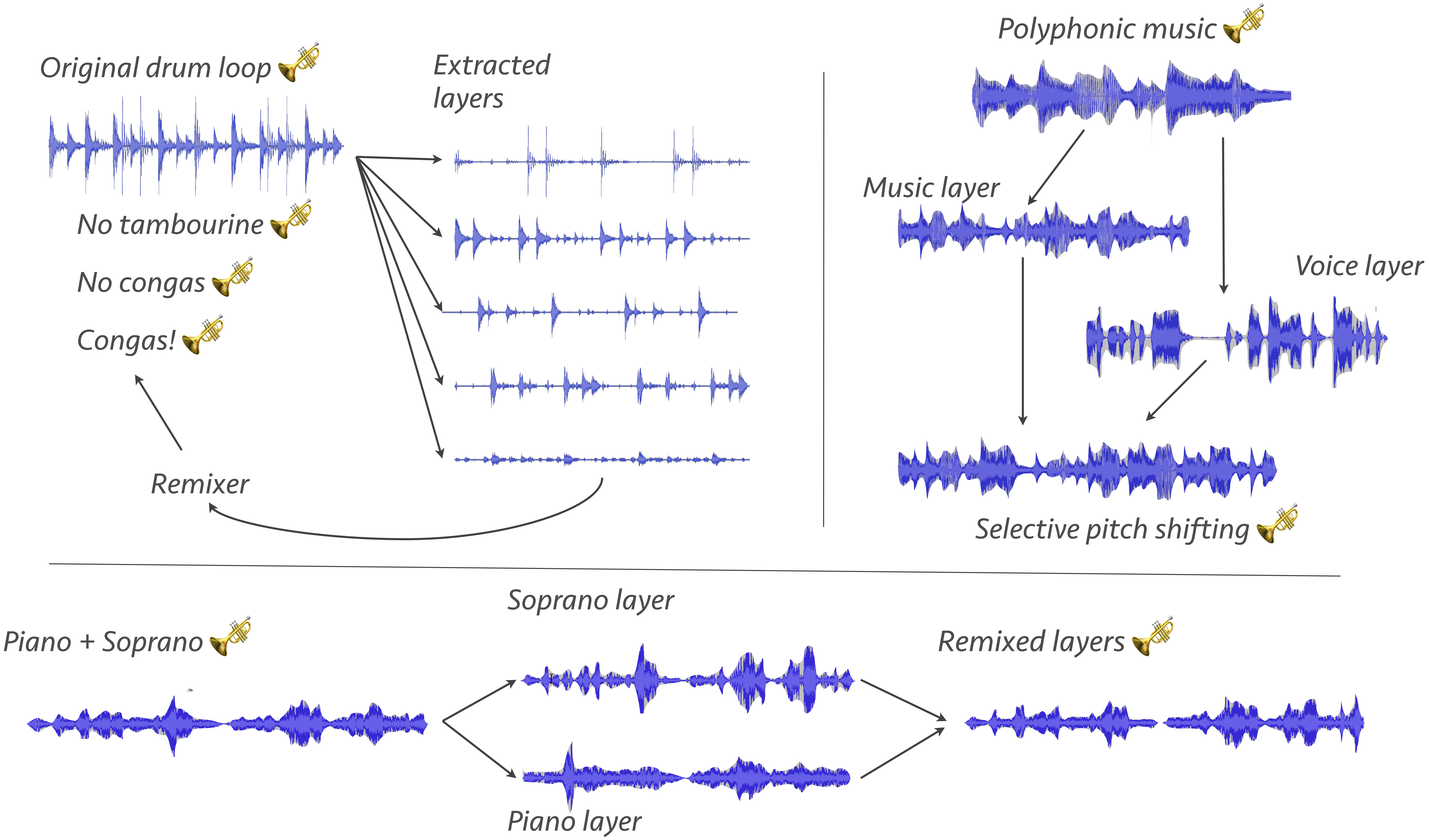


- We are explaining the mixture, not doing simple classification

Video Content Analysis

- Detecting sounds in mixtures
  - We learn dictionaries offline and explain the movie soundtrack

Audio layer editing



Using priors

- We can bias the NMF models while learning
- In each iteration we can add a bias term to the estimate of the two factors

$$\mathbf{W} = \mathbf{W} + \alpha \mathbf{B}_{\mathbf{W}}$$ *How we want $\mathbf{W}$ to be*

$$\mathbf{H} = \mathbf{H} + \beta \mathbf{B}_{\mathbf{H}}$$ *How we want $\mathbf{H}$ to be*

  - Forces them to assume a specific form
  - This allows using user guidance in learning

User-guided sound selection

Recap

- Under-constrained signal separation
  - The DUET algorithm
- Single-channel separation
  - Spectral factorizations

Reading

- The DUET algorithm
  - https://www.researchgate.net/profile/Scott_Rickard/publication/3318963_Blind_Separation_of_Speech_Mixtures_via_Time-Frequency_Masking/links/02bfe51277499a70da000000.pdf
- Spectral factorizations for separation
  - http://paris.cs.illinois.edu/pubs/smaragdis-FA2005.pdf
  - http://paris.cs.illinois.edu/pubs/smaragdis-ica07.pdf
  - http://www.merl.com/reports/docs/TR2004-104.pdf