Sparse Representations
in
Biology and Signal Processing

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Outline

Sparse representations ...

- as generic representational trick
- for acoustic source separation
- as model of neuronal sensory processing
- as predictive model of neuronal auditory processing

Intel *vs* The Brain

- Brain is made of snot (lipids and sugars and protein)

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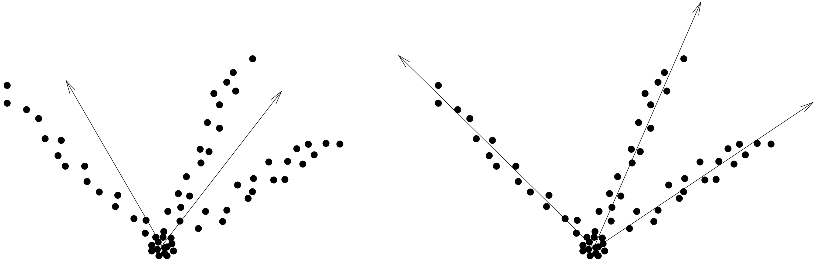
- Brain sensory inference regime: noise limit of sensors across entire dynamic range and all ecological conditions
- Computer sensory inference regime: tuned systems sometimes work in carefully controlled demos

Sparse Representation

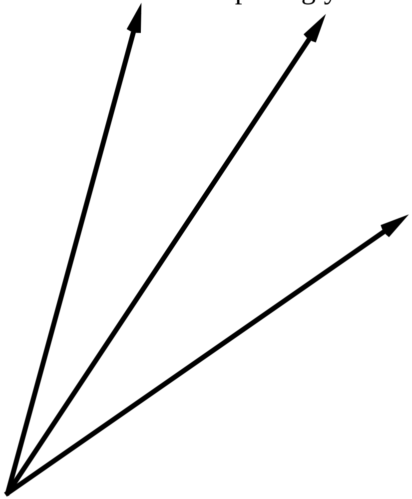
Using an *overcomplete basis* allows a sparseness assumption to capture surprisingly sophisticated statistical structure.



Complete basis (left), overcomplete basis (right).

Sparseness in Higher Dimensions

"At most two" sparseness in 3D is surprisingly rich



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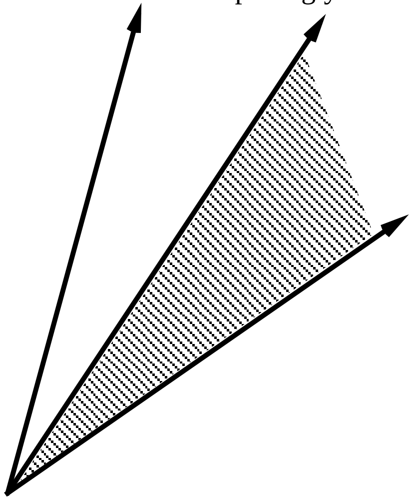

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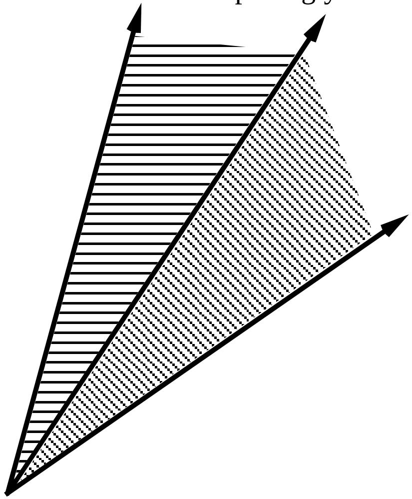

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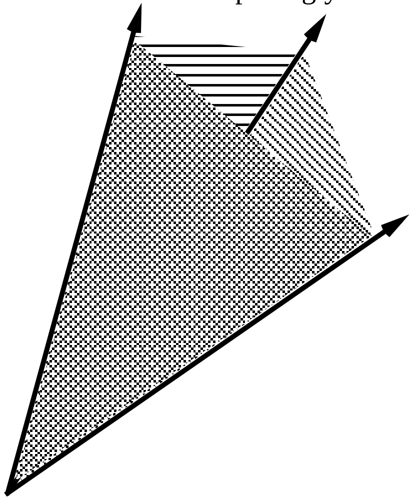

Sparseness

Conflicting representational requirements:

- strong prior information
- efficient optimisation

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Fortunately:

- Sparse representations can efficiently represent statistical structure (Simoncelli and Olshausen, 2001).
- Sparse representations are found in the brain: V1 (Vinje and Gallant, 2000), A1 (DeWeese et al., 2003), *etc.*

Source Separation

$\mathbf{x}(t) = \mathbf{A}(\tau) * \mathbf{s}(t) + \text{noise}$

Think: $\mathbf{s}$ is sources $s_j(t)$
$\mathbf{x}$ is sensors $x_i(t)$
$a_{ij}(\tau)$ is filter $s_j \longmapsto x_i$

Problem: Given $\mathbf{x}$, recover $\mathbf{s}$.

Solution: Prior information; Bayes Rule.

Methods: generally indirect (find inverse map).

This Algorithm

One Microphone.

Direct Method.

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Just separation. Not localisation.

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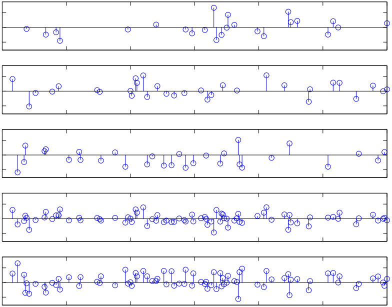
(But looks straightforward to extend...)

Instantaneous Mixture

1. Move to basis where signals are sparse.
2. Columns of **A** are apparent (clustering, EM).
3. Sparse decomposition finds coefficients.



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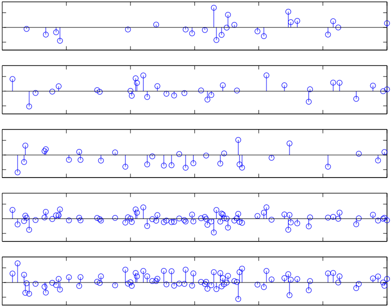
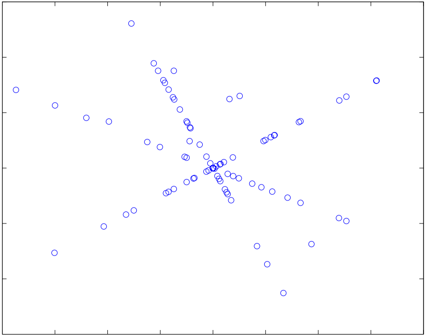
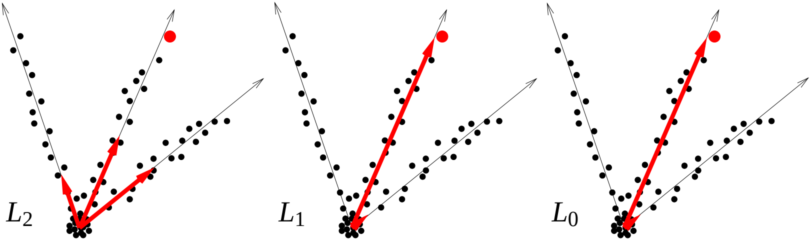




Coefficients via L_1 Optimisation

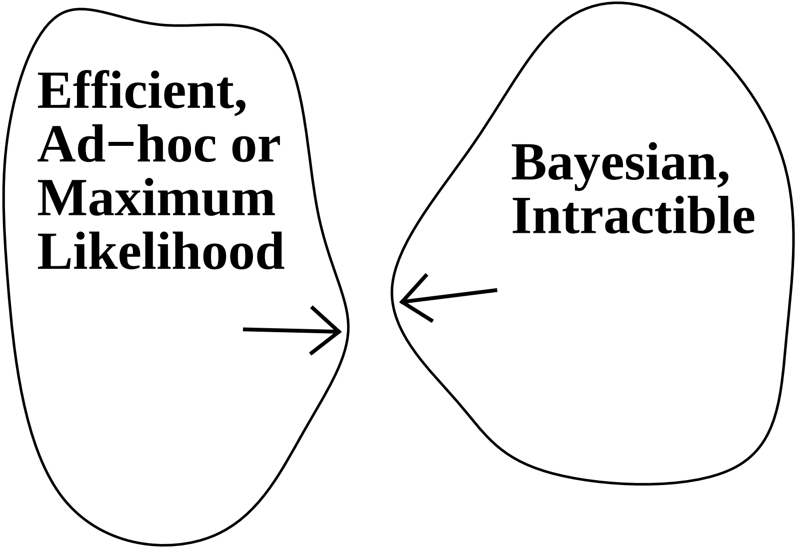


Formulation: $\min_{\mathbf{c}} \|\mathbf{c}\|_p$ subject to $\mathbf{D}\mathbf{c} = \mathbf{x}$ for some L_p

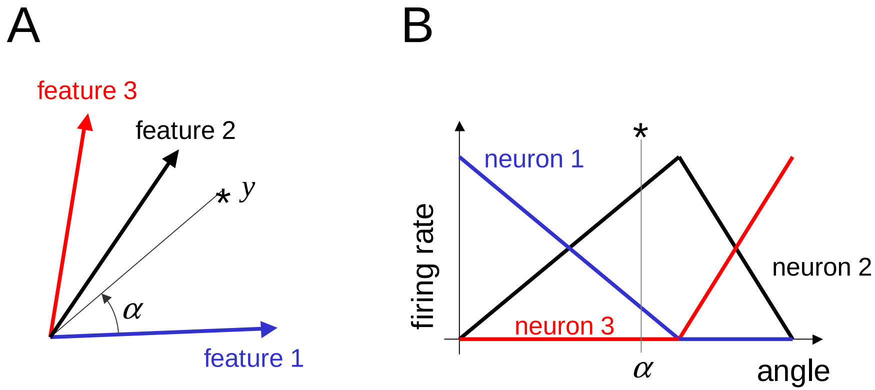
L_1-opt: convex approx. of L_0 (Chen et al., 1998).

L_2: pseudoinverse; L_0: NP-complete; L_1: Linear Programming.

Algorithm Development Philosophies



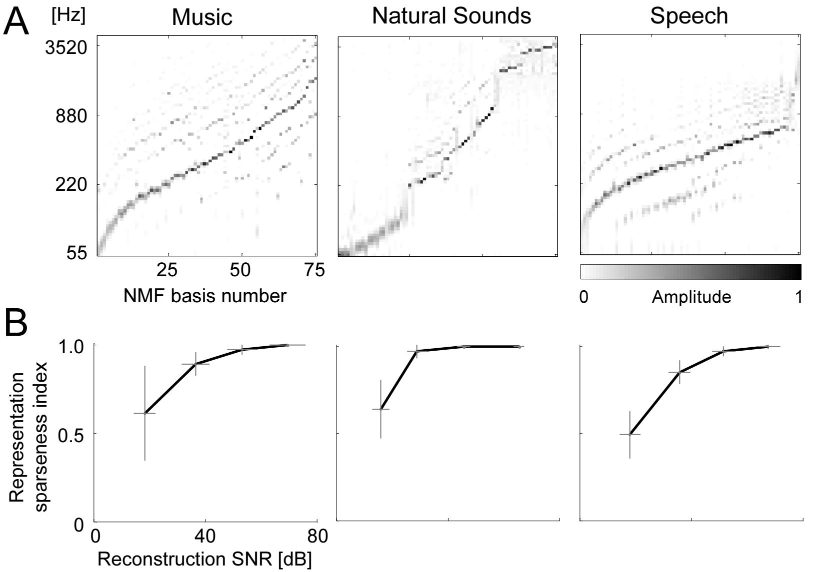
Piecewise Linear Encoding



(A) Encode input data '∗' in overcomplete basis (3 in 2D).

(B) Tuning curves: continuous, piecewise linear.

Finding a Sparse Overcomplete Spectral Basis



Sparse overcomplete spectral basis via NMF, using window size of one frame.

One-Ear Source Separation

Sensor vector becomes scalar:

$$x(t) = \sum_j s_j(t)$$

Hard! Two-microphone tricks don't work.

Known techniques use very strong priors.

- Factorial HMMs (Roweis, 2001)
- Basis/nonlinearity (Hochreiter and Mozer, 2001)
- Per-source basis (Jang and Lee, 2003)

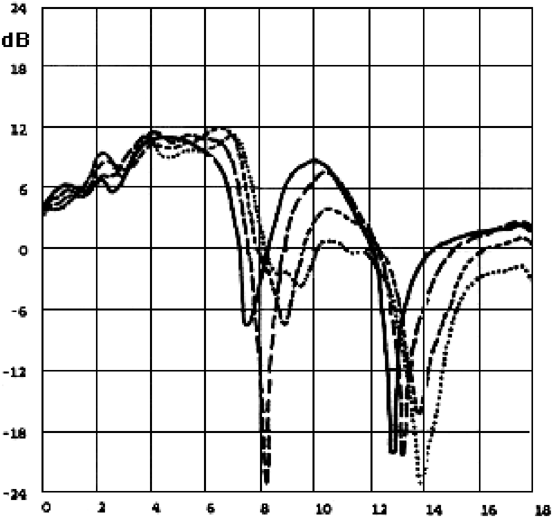
The HRTF

Animals use a variety of binaural and monaural cues for sound localisation, including intra-aural intensity and phase disparity, and monaural spectral filtering by the head and pinnae (head-related transfer function, or HRTF.)

$$x(t) = \sum_j h_j(\tau) * s_j(t)$$

HRTF studied for localisation of single source (Bregman, 1990; Yost et al., 1996) but not for separation of multiple sources.

Actual HRTFs



Different linear filters $h_j(\omega)$ for different angles of arrival.

HRTF-Based Sparse Separation

Monaural source separation with **pinnae**.

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Assume sources sparse in signal dictionary:

$$s_j(t) = \sum_k c_{jk}\, d_k(t)$$

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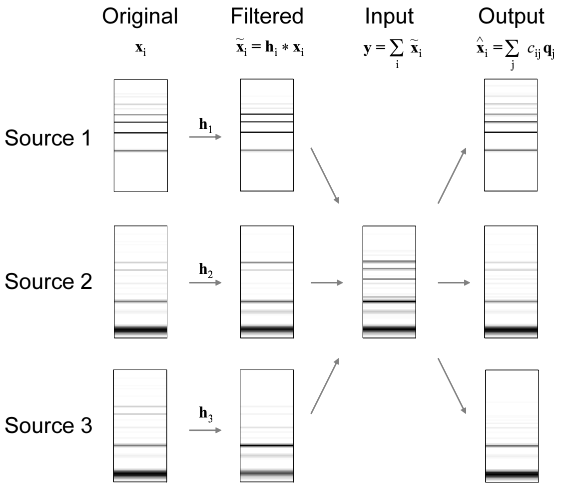
Reconstruct in source space (deconvolution):

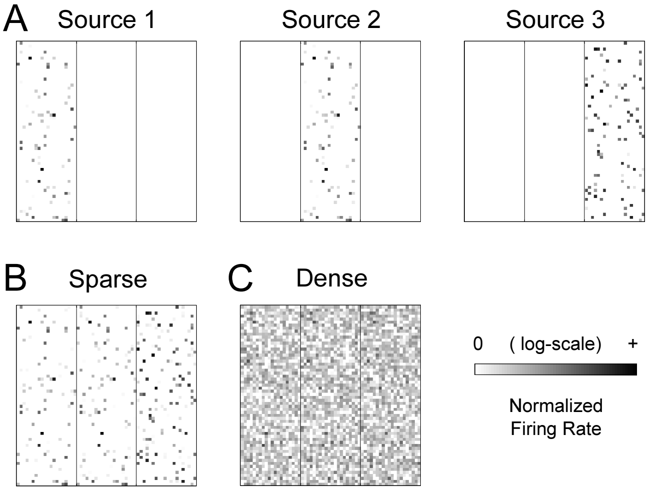
$$s_j(t) = \sum_k c_{jk}\, d_k(t)$$

HRTF-Based Sparse Separation (Cartoon)



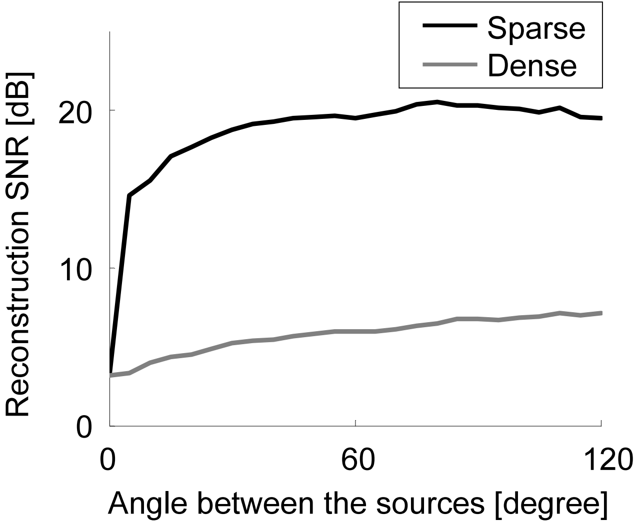
HRTF filters "colour" spectral features, allowing separation by sparse decomposition over basis HRTFs $*$ source dictionary elements.

Sparse *vs* Dense Coefficients



Coefficients recovered with min L_1-norm from three sources processed individually (top), their mixture (bottom left), and using the L_2-norm (bottom right).

Separation Performance



Noise

L_1-norm optimisation sensitive to noise.

Fix by including slop

$$\underset{\mathbf{c}}{\text{minimise}}\ \|\mathbf{c}\|_1 \text{ s.t. } \|\mathbf{Dc} - \mathbf{y}\|_p \leq \beta$$

Noise level is β, norm is $p = 1$, 2, or ∞.

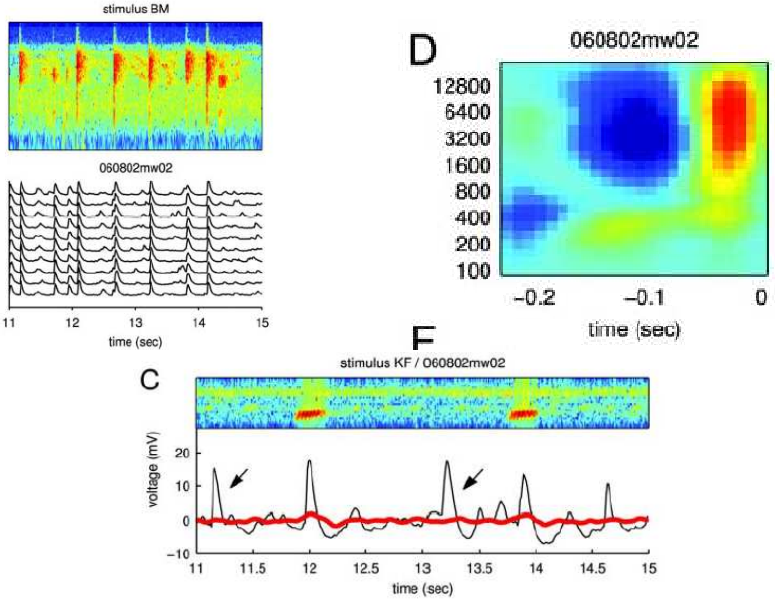
Gaussian ($p = 2$) using L_1+L_2, conic, or SDP.

Solve $p = 1$ or ∞ using linear programming.

Flexible Framework

- instantaneous and convolutive mixing
- binaural information (multiple ears)
- per-source dictionaries
- noise
- temporal structure on coefficients
- convolutive dictionaries
- adaptive signal dictionaries/filters
- room for advances in optimisation
- stronger prior? bigger dictionary!
- **contact with biology**

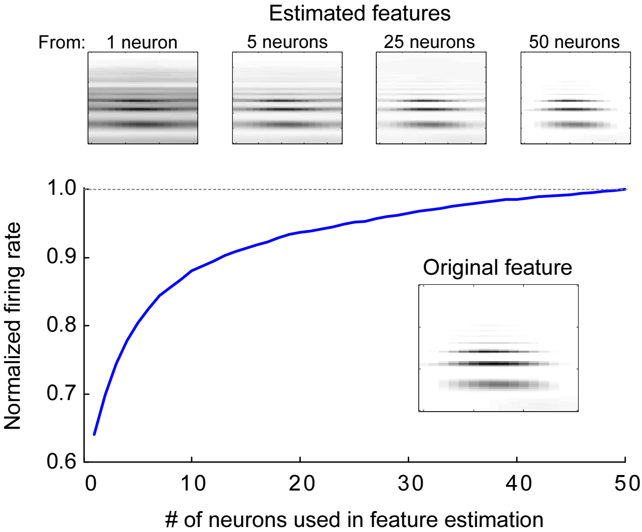
Physiology


stimulus BM
060802mw02
11
12
13
14
15
time (sec)
D
060802mw02
12800
6400
3200
1600
800
400
200
100
−0.2
−0.1
0
time (sec)
F
stimulus KF / 060802mw02
C
voltage (mV)
20
10
0
−10
11
11.5
12
12.5
13
13.5
14
14.5
15
time (sec)

Predictions

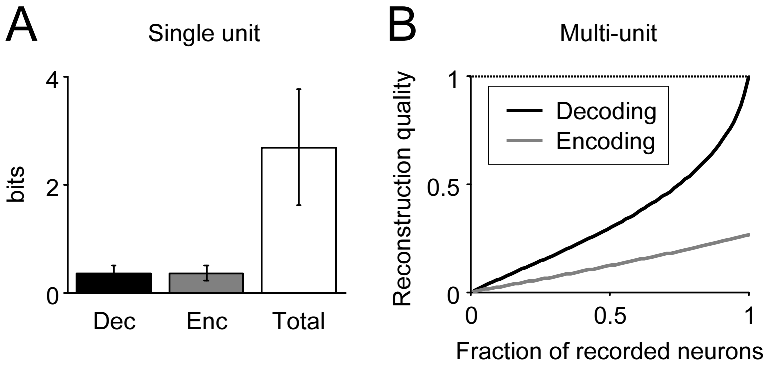
- Sparse activity
- **$>$#Neurons $\rightarrow$ Better Linear Stimulus Optimisation**
- **Linear decoding outperforms linear encoding (in bits)**
- **STRF depends on context**
- $\mathbf{r}(k\,\mathbf{x}) = k\,\mathbf{r}(\mathbf{x})$
- $\|\mathbf{r}(\mathbf{x}_1 + \mathbf{x}_2)\|_1 \leq \|\mathbf{r}(\mathbf{x}_1) + \mathbf{r}(\mathbf{x}_2)\|_1$
- Response shifts opposed to HRTF changes

Stimulus Optimisation



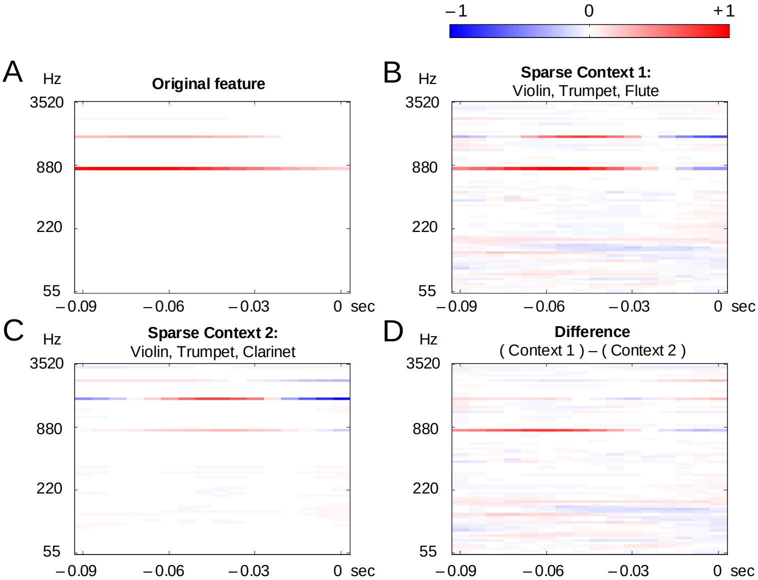
Ability of estimated stimulus to drive neuron improves with #neurons.
"Optimal feature" estimation requires multi-neuron recordings.

Linear Decoding vs Nonlinear Encoding



Linear decoding outperforms linear encoding for multi-neuron but not single neuron experiments.

Context-Dependence of STRF



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- ... are used in state-of-the-art signal processing.
- ... can make novel neuronal *pre*dictions.

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Other domains:

- Control (*e.g.* switching)
- Statistics (*e.g.* sparse weights, shrinkage)
- Bayesian reasoning (*e.g.* explaining away)

Collaborators

- Anthony M. Zador
- Hiroki Asari
- Rasmus Olsson

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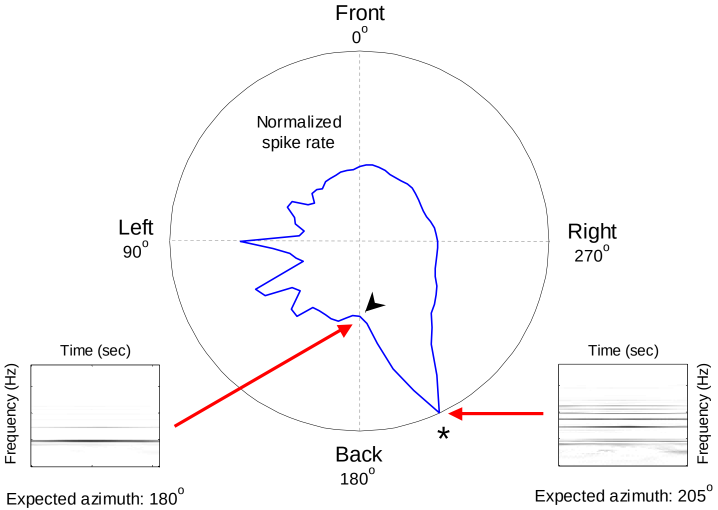
Top-Down Neuronal Modulation



Normalised response of coefficient tuned to cello feature at 205° azimuth (‘∗’).

Sensory Substitution/Augmentation

Present sensory data using somatosensory modality: electrode array on tongue (Tyler et al., 2003).

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Potential applications: oscillopsia, blindness, hearing loss, new senses (magnetic, radar), data visualisation.

Need Good Signal Dictionaries

- separation and de-mixing performance depend on dictionary
- need dictionary optimisation algorithms for:
  - sparseness
  - separation
  - perceptual quality with lossy encoder
  - speech, music, video
  - particular acoustic sources
  - rapid dictionary adaptation

Current Dictionary Work

Goal: automatically find optimal dictionaries.

- NMF on spectra (Hiro Asari)
- Subspace clustering (O'Grady and Pearlmutter, 2004)
- Alg. Diff. of LP (Vamsi Potluru):
  $\nabla_{\mathbf{D}} \langle \| \mathsf{L1opt}(\mathbf{s}, \mathbf{D}) \|_1 \rangle$
  $\nabla_{\mathbf{D}} \| \mathsf{sparse\_separate}(\mathbf{A} * \mathbf{s}, \mathbf{D}) - \mathbf{s} \|_2^2$

Distant future: joint estimation of sources, HRTF, acoustic environment; adaptive source models.

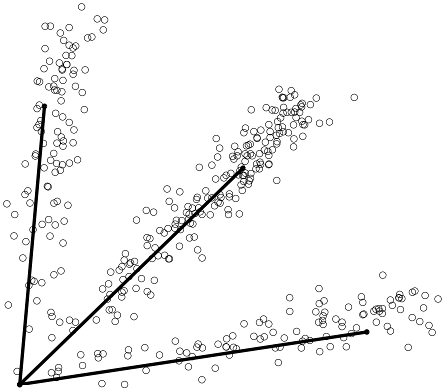
AD of Linear Programming

$$\begin{aligned}
\text{L1opt}(\mathbf{y}, \mathbf{D}) &= \begin{bmatrix}\mathbf{I} & -\mathbf{I}\end{bmatrix} \text{lp}\left(\mathbf{1}, -\mathbf{I}, \mathbf{0}, \mathbf{D}\begin{bmatrix}\mathbf{I} & -\mathbf{I}\end{bmatrix}, \mathbf{y}\right) \\
\text{lp}(\mathbf{w}, \mathbf{A}, \mathbf{a}, \mathbf{B}, \mathbf{b}) &= \arg\min_{\mathbf{z}} \ \mathbf{w}^\top \mathbf{z} \text{ s.t. } \mathbf{A}\mathbf{z} \le \mathbf{a} \ \& \ \mathbf{B}\mathbf{z} = \mathbf{b} \\
&= \text{lq}\left(\begin{bmatrix}\mathbf{P}_\alpha & 0 \\ 0 & \mathbf{P}_\beta\end{bmatrix}\begin{bmatrix}\mathbf{A} \\ \mathbf{B}\end{bmatrix}, \begin{bmatrix}\mathbf{P}_\alpha & 0 \\ 0 & \mathbf{P}_\beta\end{bmatrix}\begin{bmatrix}\mathbf{a} \\ \mathbf{b}\end{bmatrix}\right) \\
\text{lq}(\mathbf{M}, \mathbf{m}) &= \mathbf{z} \quad \text{s.t. } \ \mathbf{M}\mathbf{z} = \mathbf{m} \\
\overleftarrow{\text{lq}}(\mathbf{M}, \mathbf{m}, \mathbf{z}, \grave{\mathbf{z}}) &= \begin{bmatrix}\grave{\mathbf{M}} & \grave{\mathbf{m}}\end{bmatrix} \\
\grave{\mathbf{m}} &= \text{lq}(\mathbf{M}^\top, \grave{\mathbf{z}}) \\
\grave{\mathbf{M}} &= -\grave{\mathbf{m}}\mathbf{z}^\top
\end{aligned}$$

Dictionary Optimisation

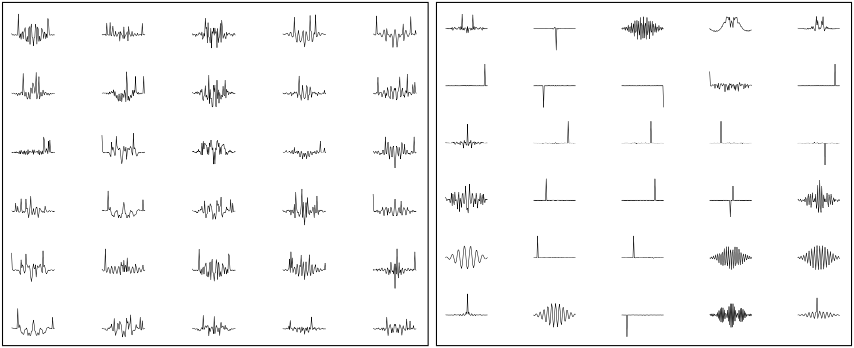
1. Draw $\mathbf{y}$ from signal distribution.
2. Calculate $E_{\mathbf{y}} = \|\text{L1opt}(\mathbf{y}, \mathbf{D})\|_1$
3. Calculate $\nabla_{\mathbf{D}} E_{\mathbf{y}}$ using $\overleftarrow{\text{L1opt}}(\cdot)$.
4. Step $\mathbf{D} := \mathbf{D} - \eta \nabla_{\mathbf{D}} E_{\mathbf{y}}$.
5. Normalise columns $\mathbf{d}_i$ of $\mathbf{D}$ with $\mathbf{d}_i := \mathbf{d}_i / \|\mathbf{d}_i\|_2$.
6. Repeat to convergence of $\mathbf{D}$.

Learnt Dictionary (1)



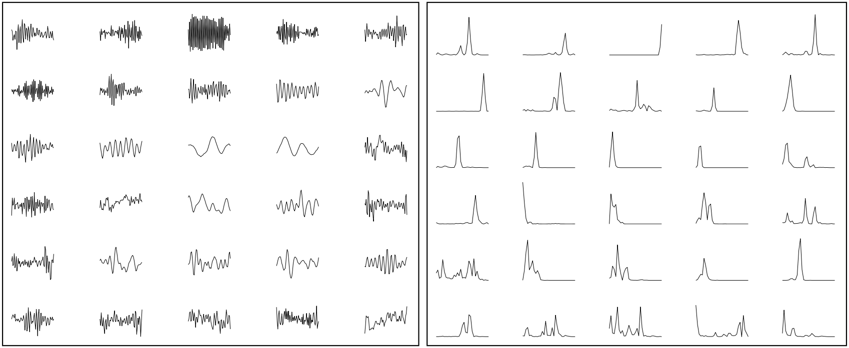
Overcomplete basis for 2D test data.
Noise biases basis towards regions of less coverage; fix with noise term.

Learnt Dictionary (2)



Artificial signal ensemble (left); learnt dictionary elements (right).
Data: sparse combinations of Gabor functions and delta pulses.
$\mathbf{D}$: 64×128.

Learnt Dictionary (3)



Learnt dictionary for speech: William Butler Yeats reciting *Coole Park and Ballylee* and *The Lake Isle of Innisfree*, 8 ms windows, $\mathbf{D} : 64 \times 128$. Dictionary elements (left) and power spectra 0–4 kHz (right).

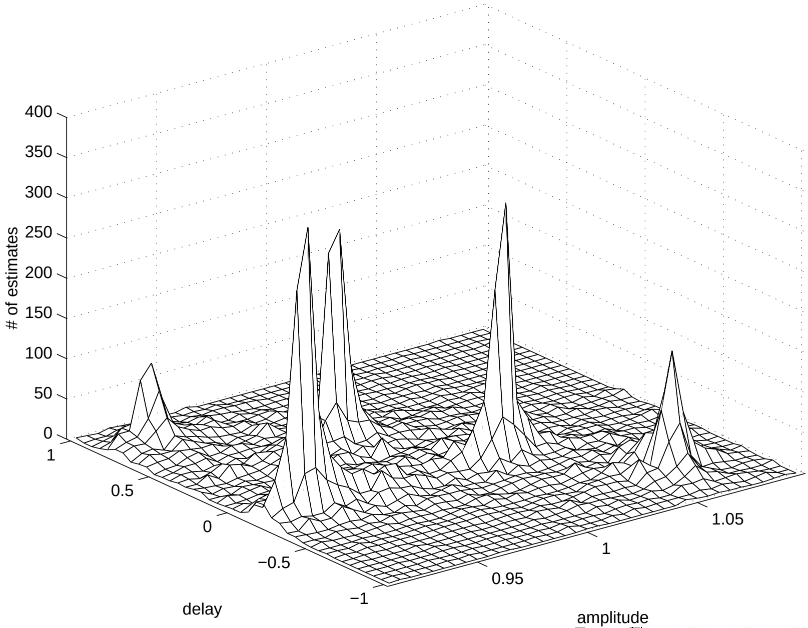
DUET algorithm

Anechoic mixture (Rickard and Dietrich, 2000). Assume narrowband: delays $|\delta_j| < $ wavelength.

$$x_1(t) = \sum_j s_j(t) \qquad x_2(t) = \sum_j a_j\, s_j(t - \delta_j)$$

- Mixing/delay parameters found by clustering in time-frequency domain (short-time DFT).
- Can recover #sources $>$ #mixtures.
- Practical almost-real-time algorithm.

DUET Coefficient Clusters



To Add

block diagram
more cells in cortex than in cochlea