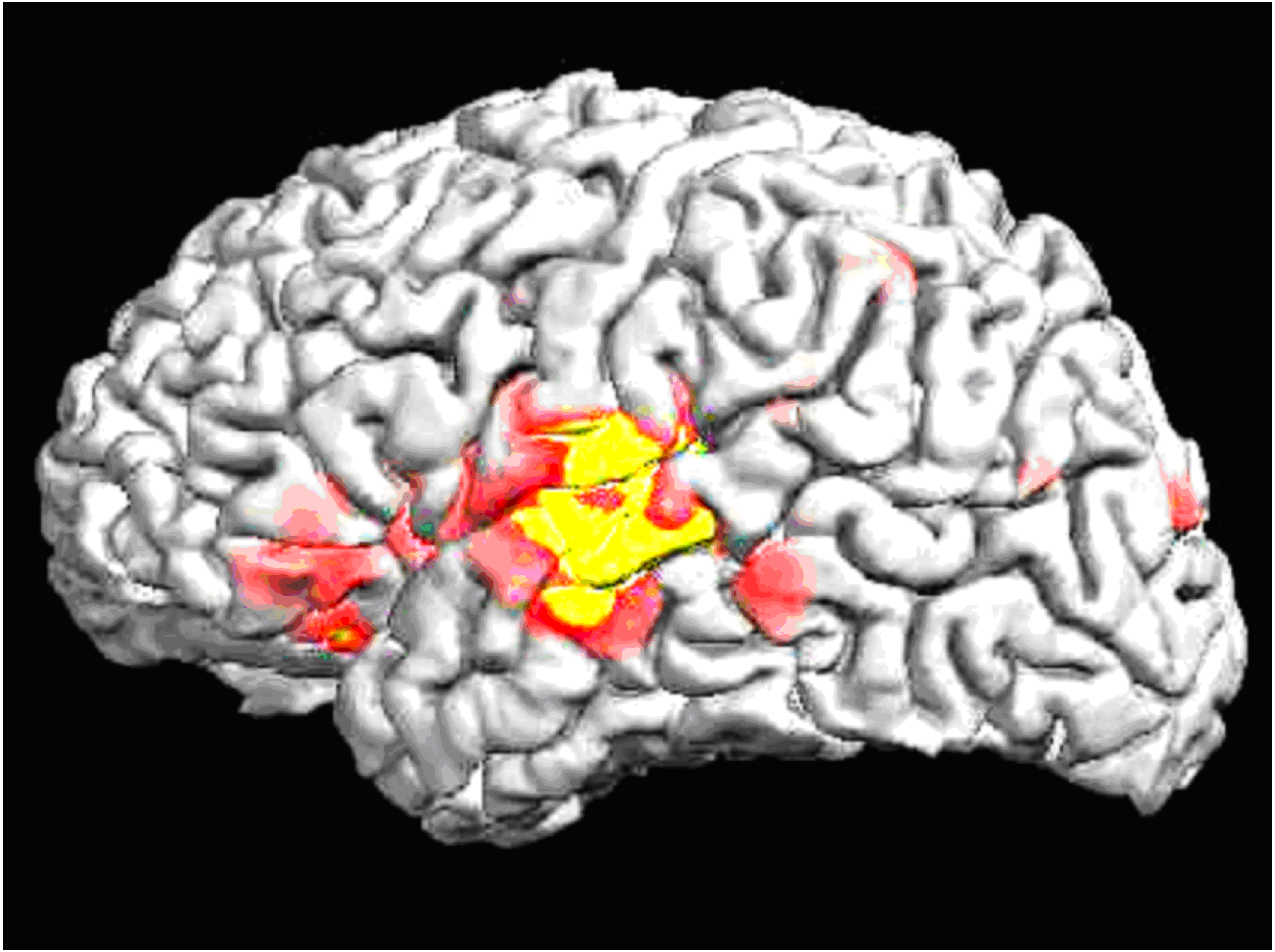
Computational neuroscience

"Neurotechnology"

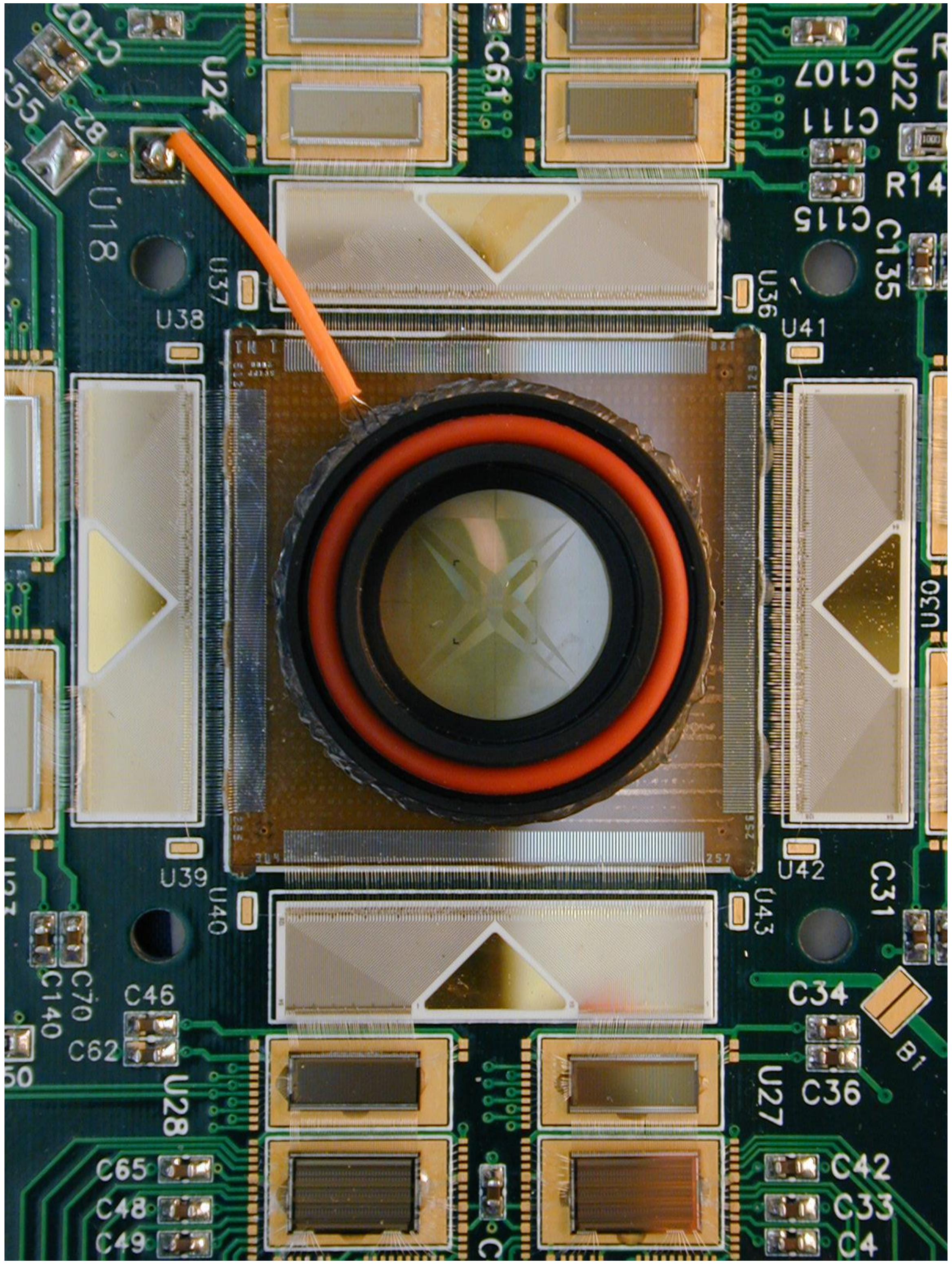


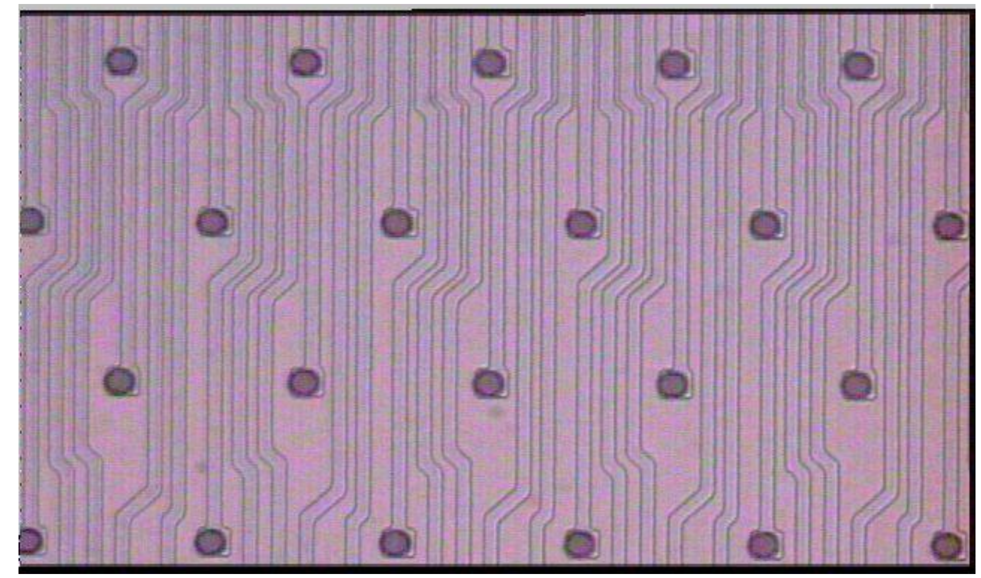
http://www.lce.hut.fi/research/cogntech/neurophysiology

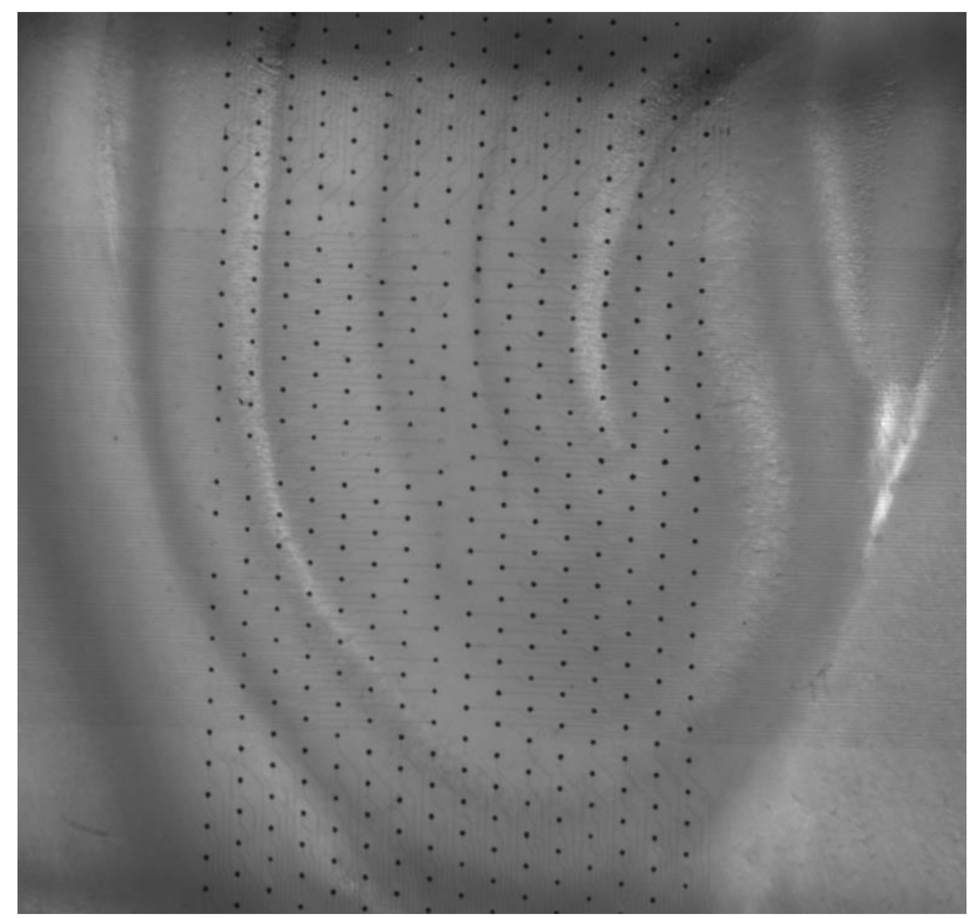
Recording from the brain

Recording from the brain

Reading out the neural code

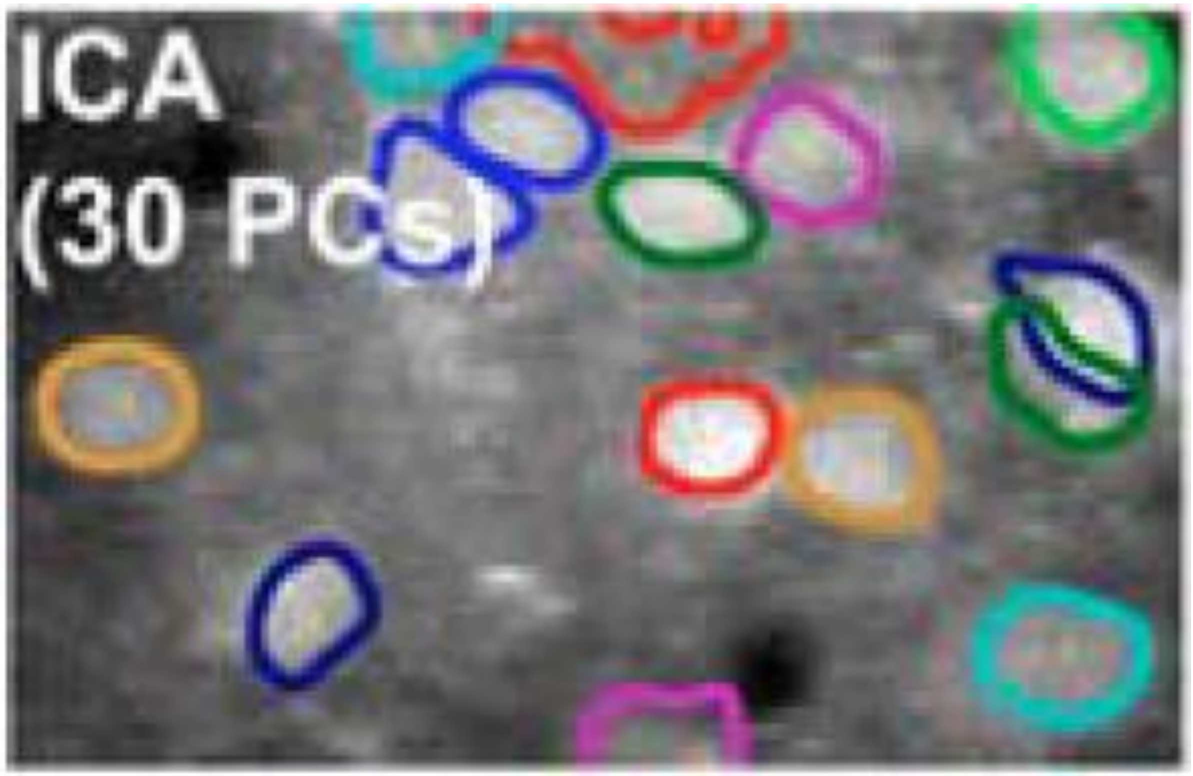


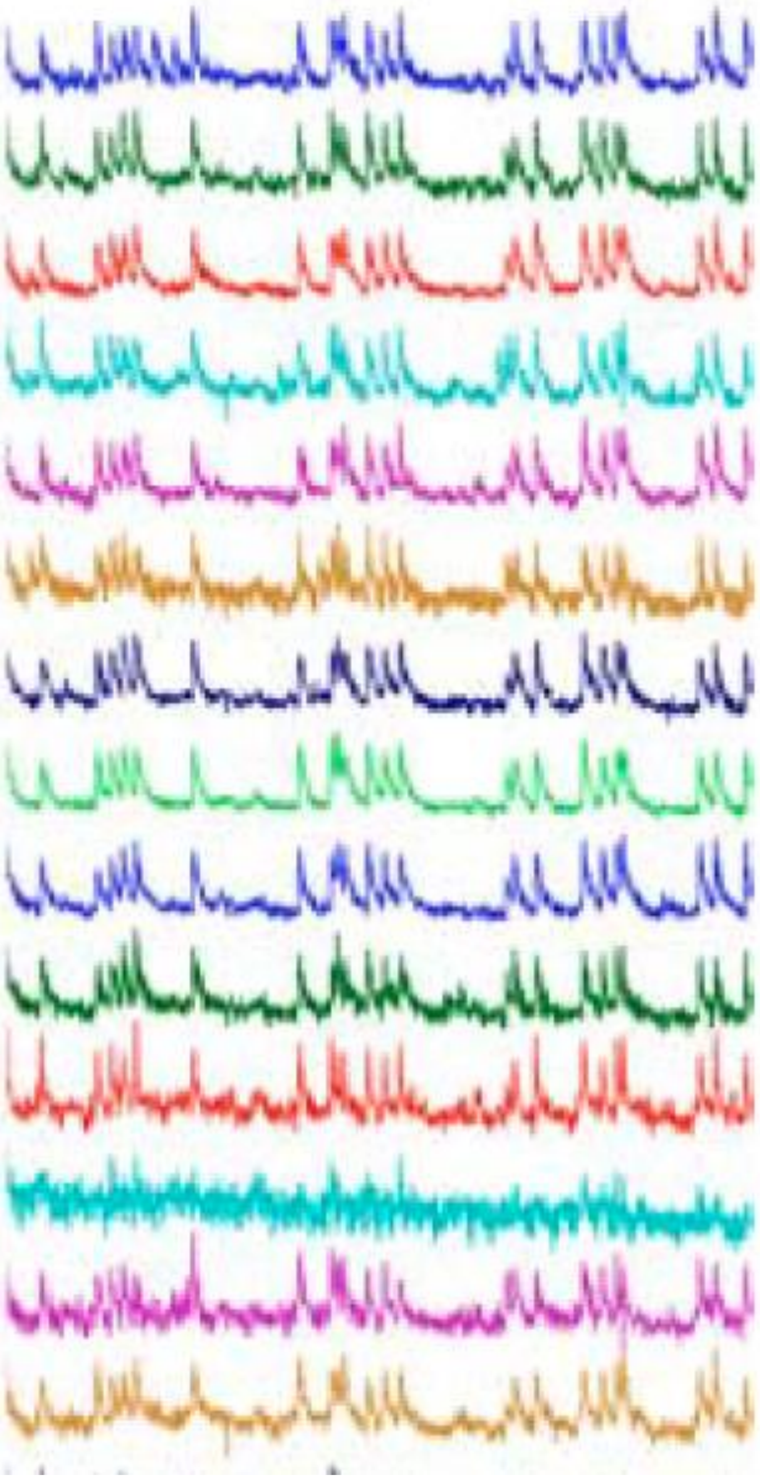




Reading out the neural code

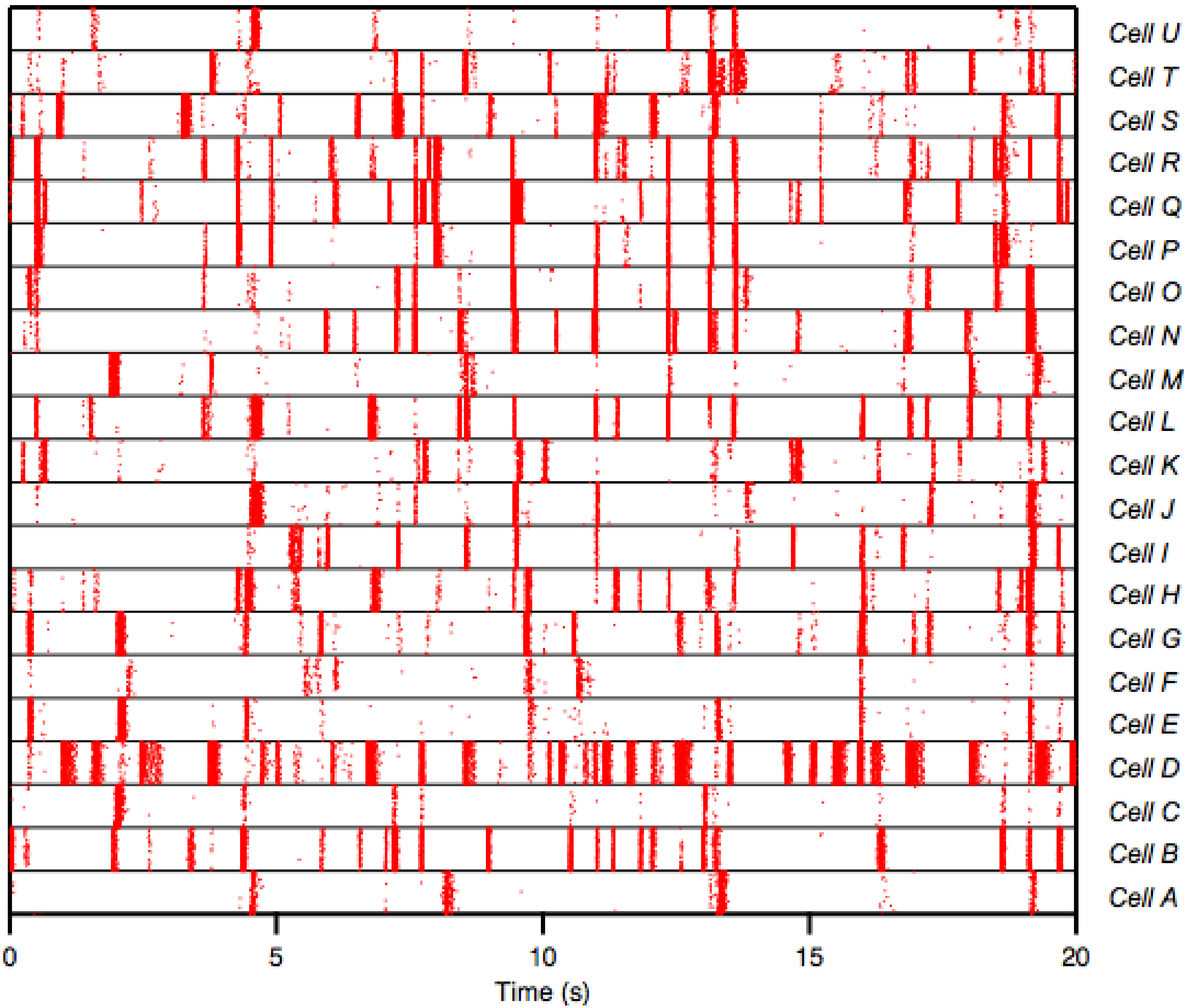
Reading out the neural code





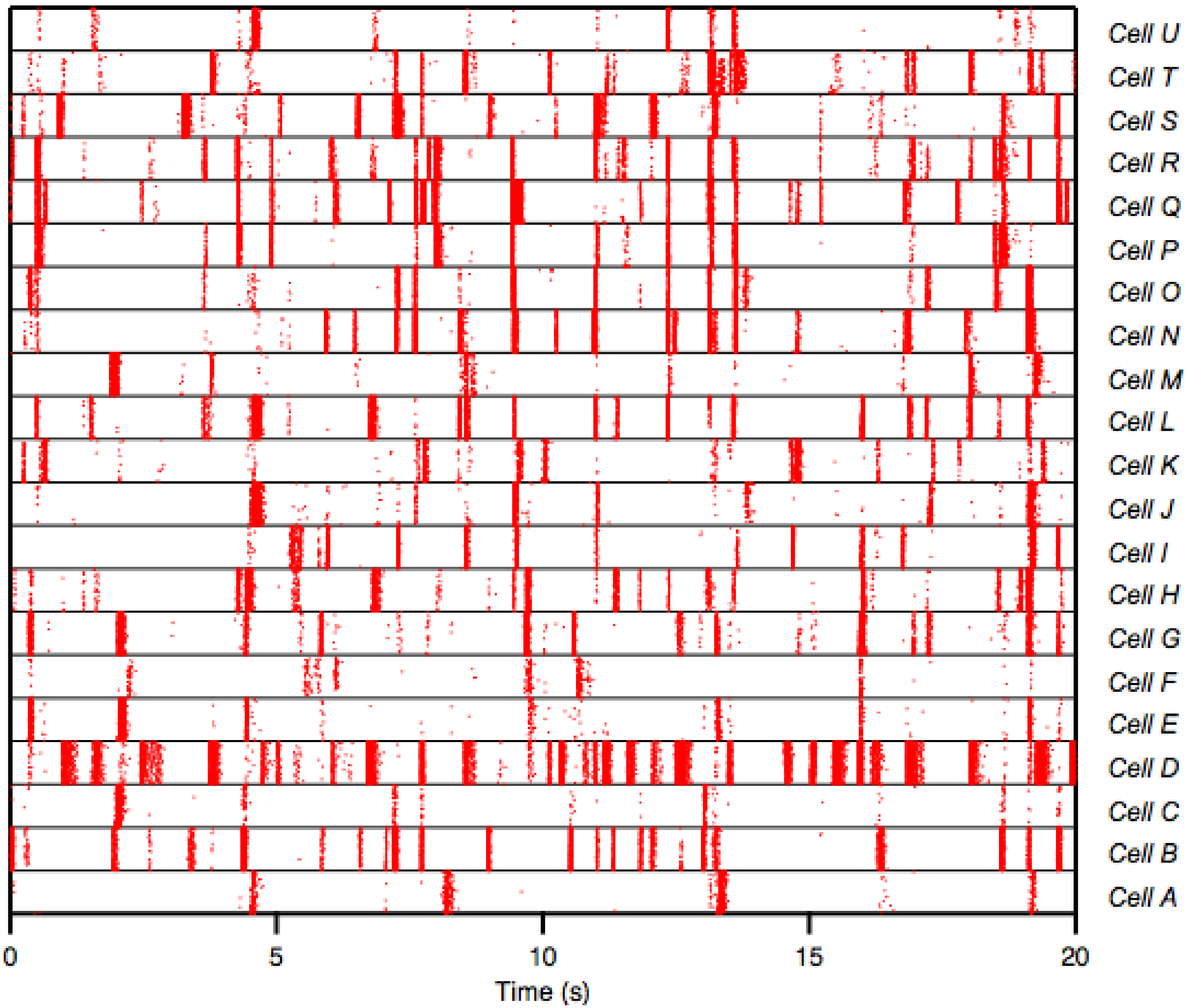
Kwan, HFSP 2010

What is the neural code?



M. Berry

What is the neural code?



Single neurons

Populations

Encoding and decoding

Encoding: how does a stimulus cause a pattern of responses?

- what are the responses and what are their characteristics?
- neural models:
  - -- from stimulus to response
  - -- descriptive ←→ mechanistic models

Decoding: what do these responses tell us about the stimulus?

- Implies some kind of decoding algorithm
- How to evaluate how good our algorithm is?

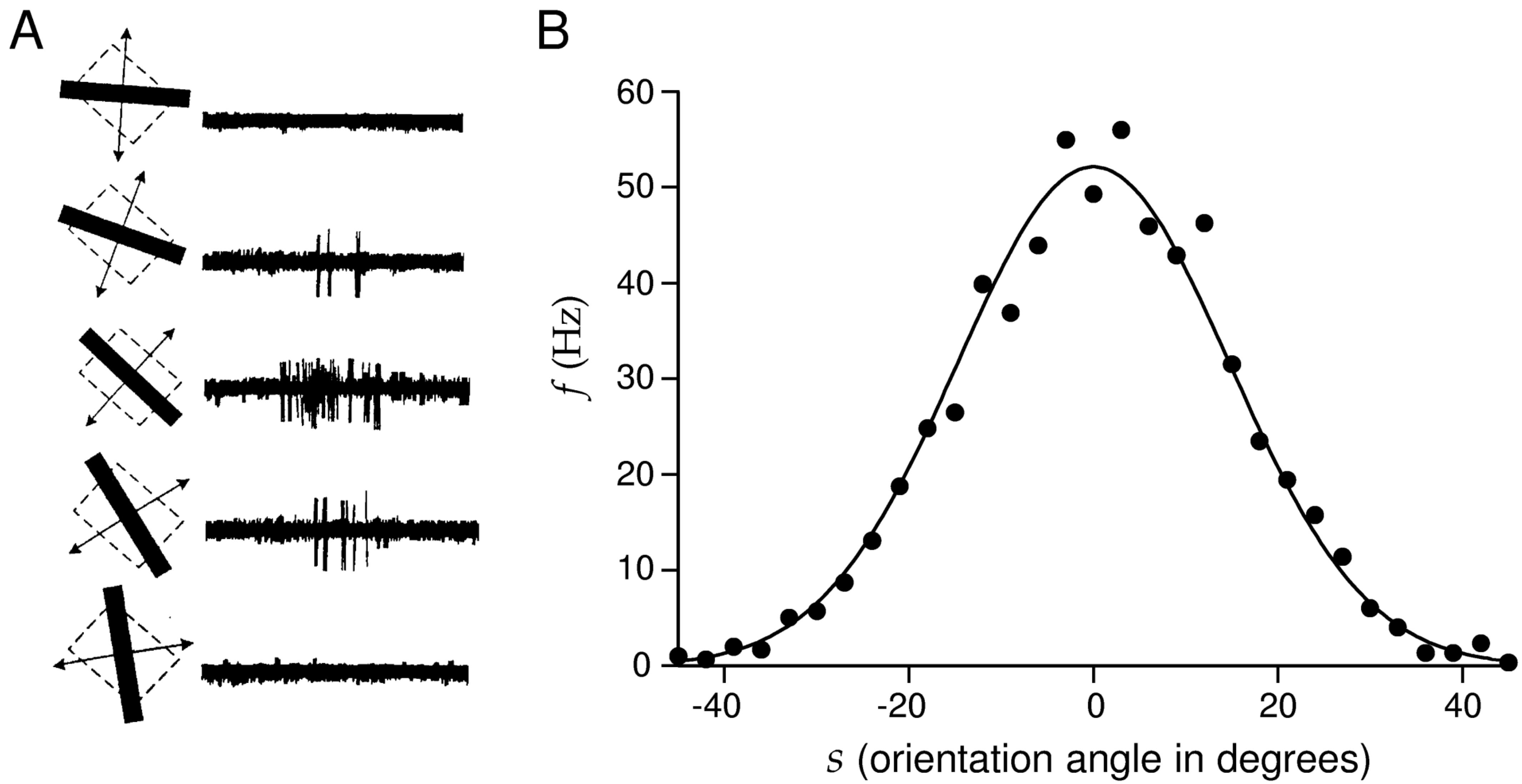
Encoding and decoding

$\boxed{\text{P(response | stimulus)}}$ *encoding*

$\boxed{\text{P(stimulus | response)}}$ *decoding*

- What is response?
- What is stimulus?
- What is the function P?

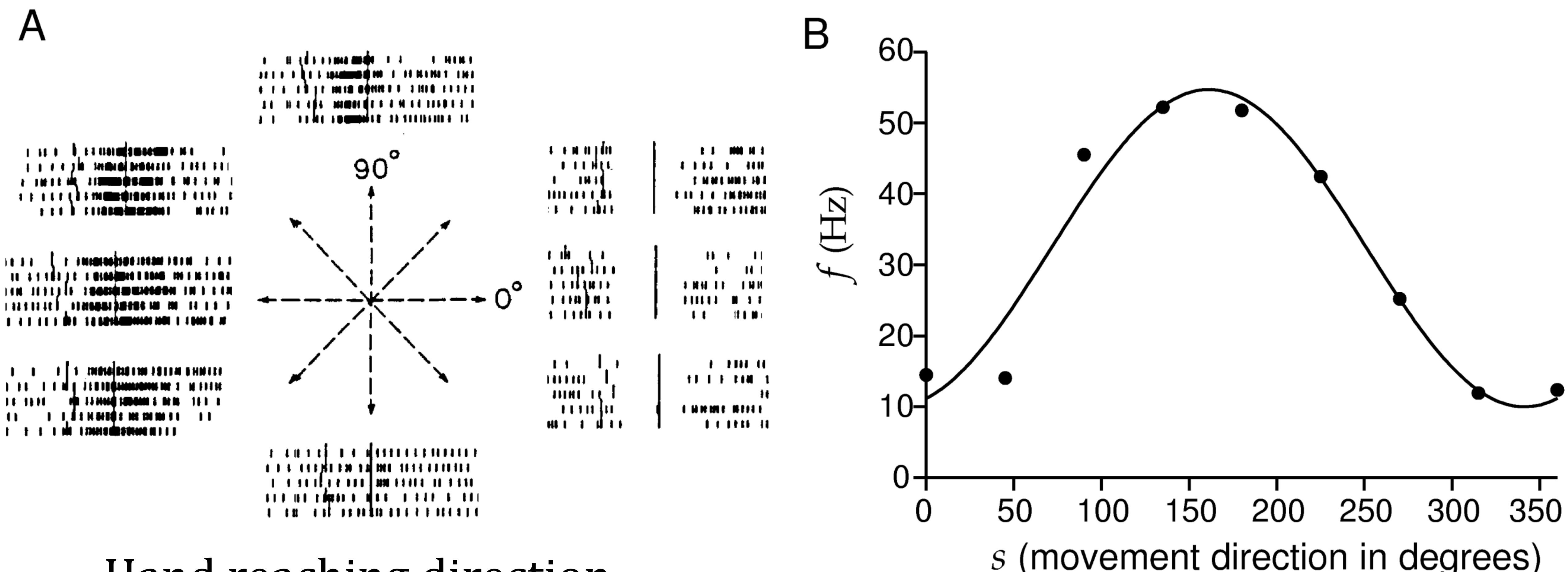
Tuning curves



Nonlinear function: r = g(s)

Gaussian tuning curve of a cortical (V1) neuron

Tuning curves

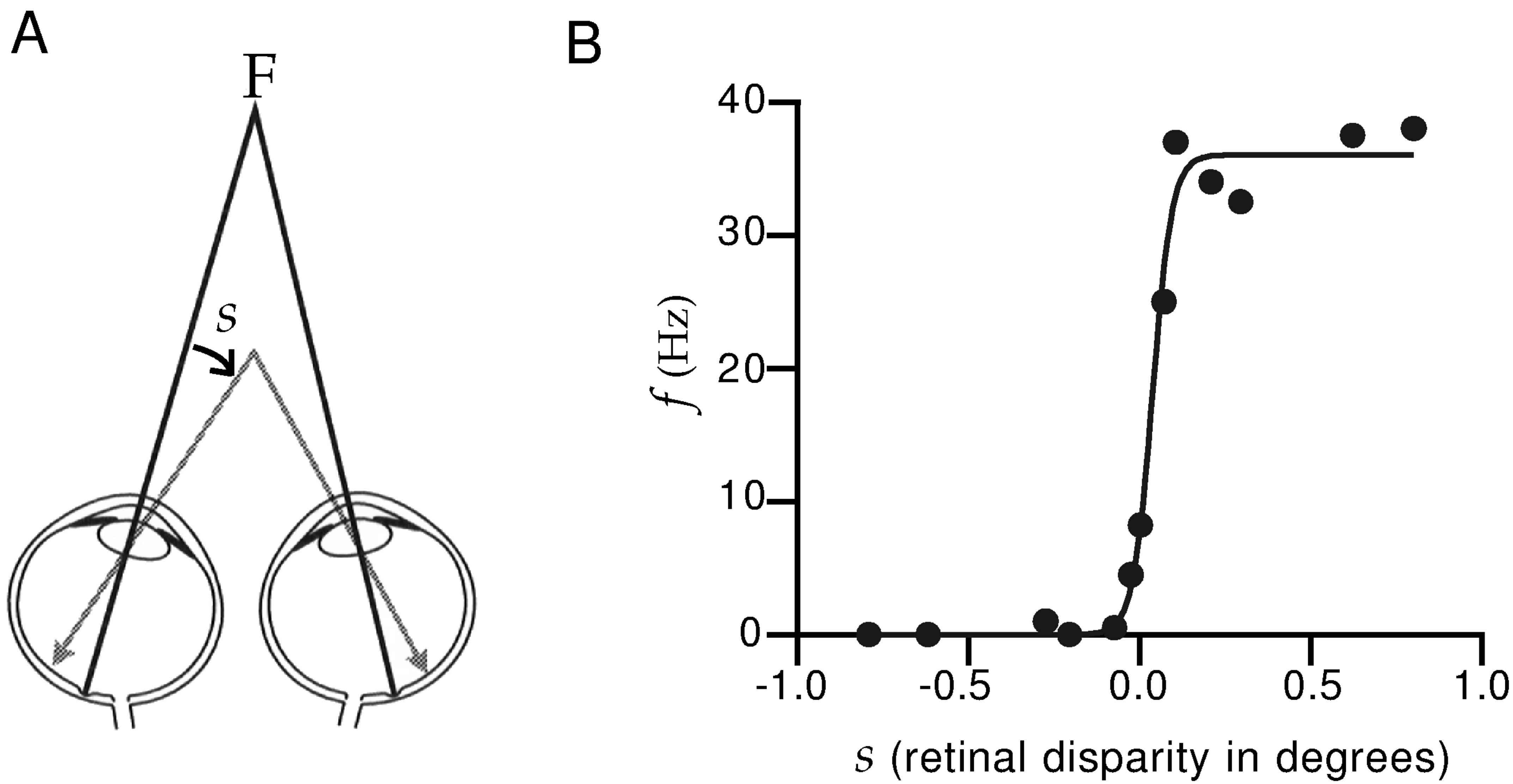


Hand reaching direction

Nonlinear function: $r = g(s)$

Cosine tuning curve of a motor cortical neuron

Tuning curves

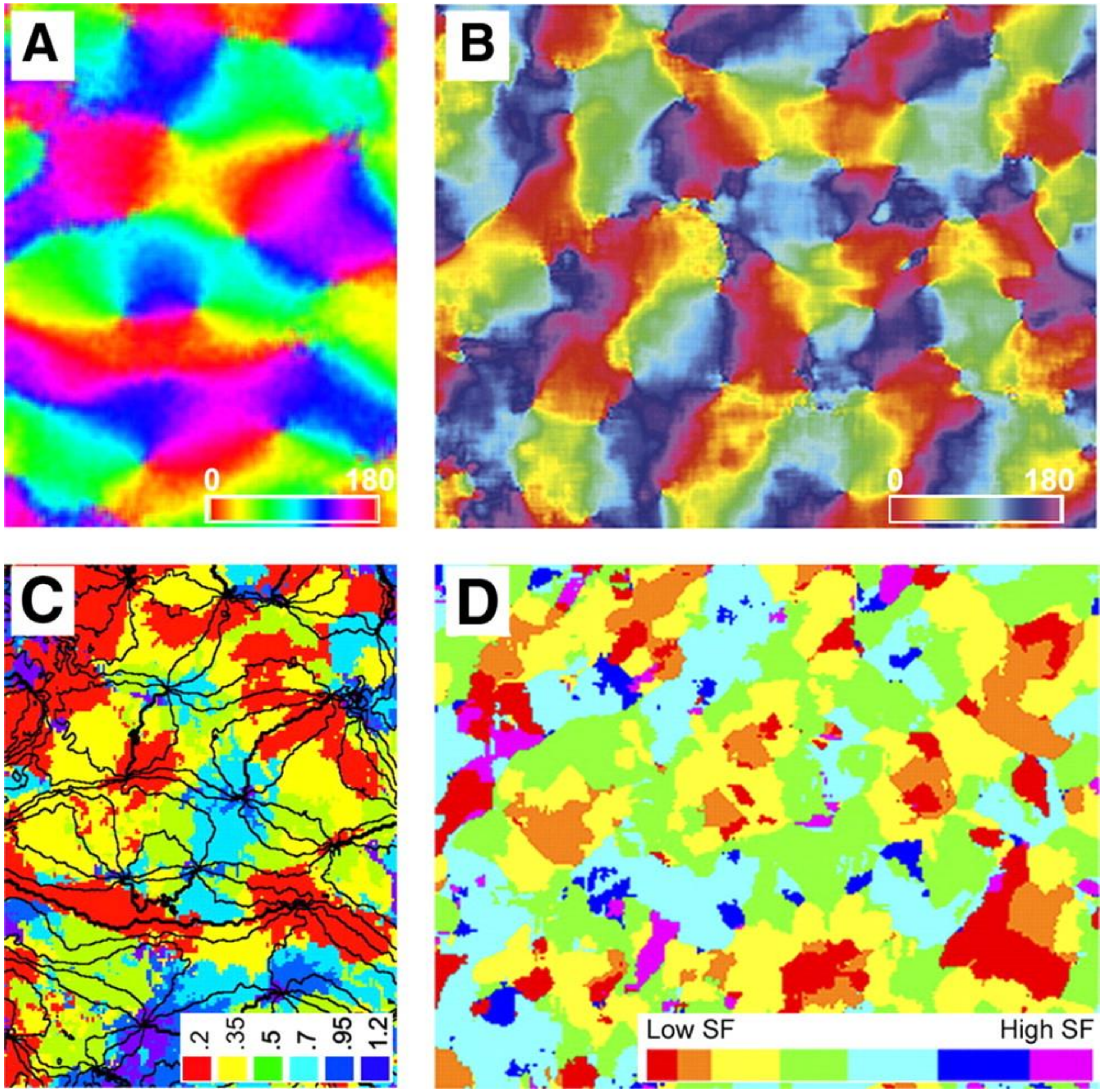


Nonlinear function: r = g(s)

Sigmoidal tuning curve of a V1 cortical neuron

Map of feature selectivity in primary visual cortex

Cat

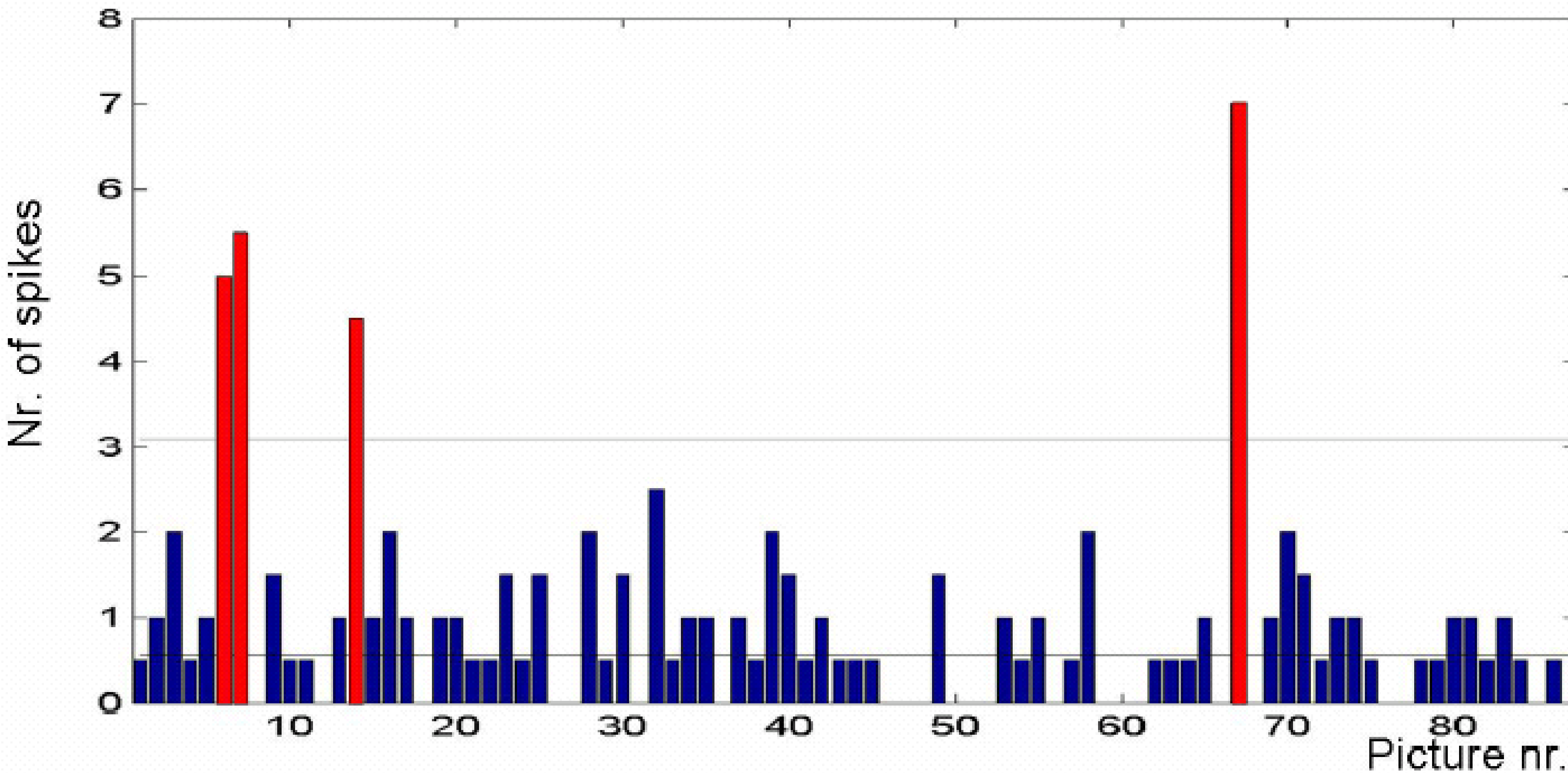


Bush baby

Issa N P et al. J Neurophysiol 2008;99:2745-2754

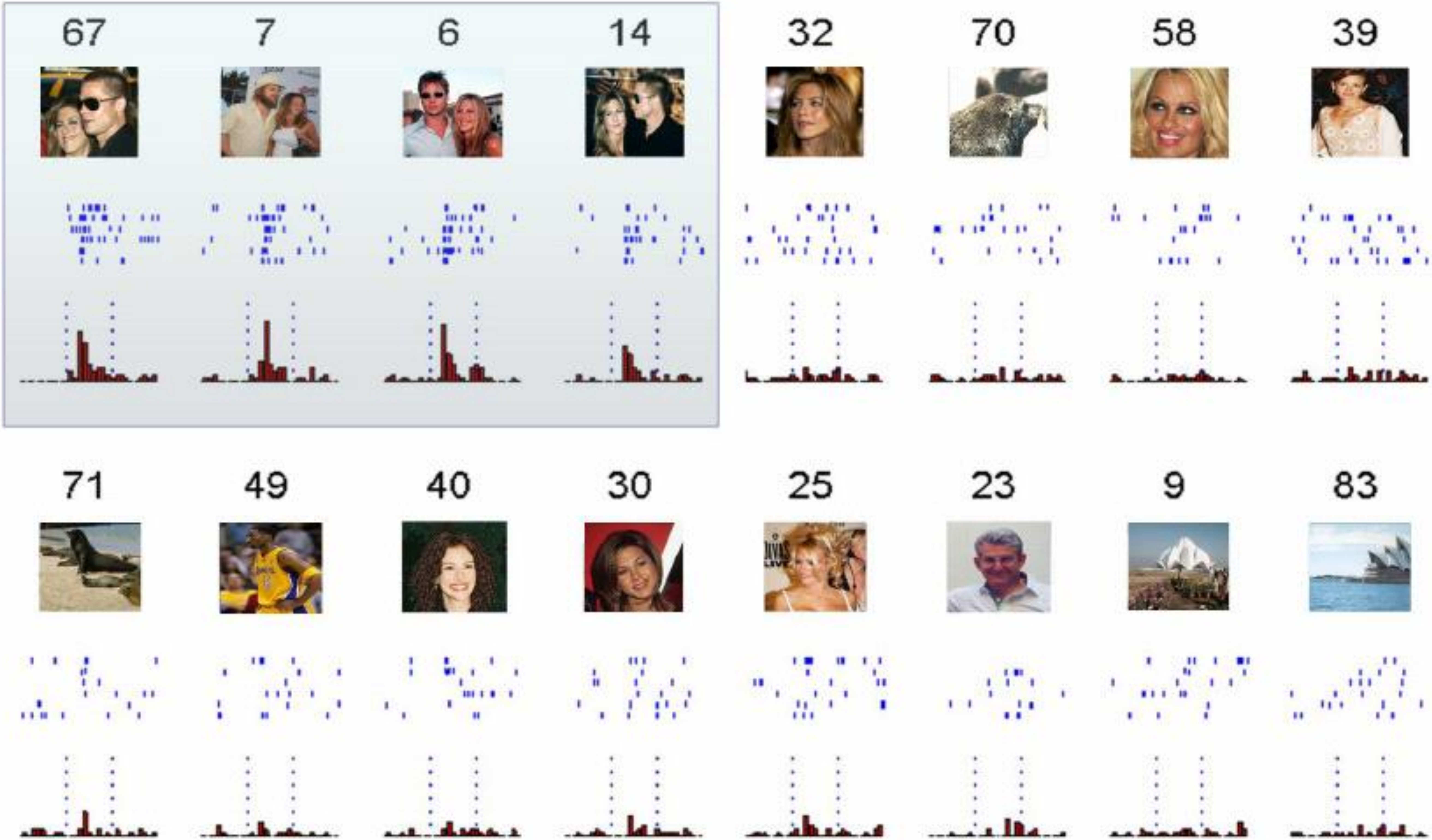
Journal of Neurophysiology

“Tuning curves”

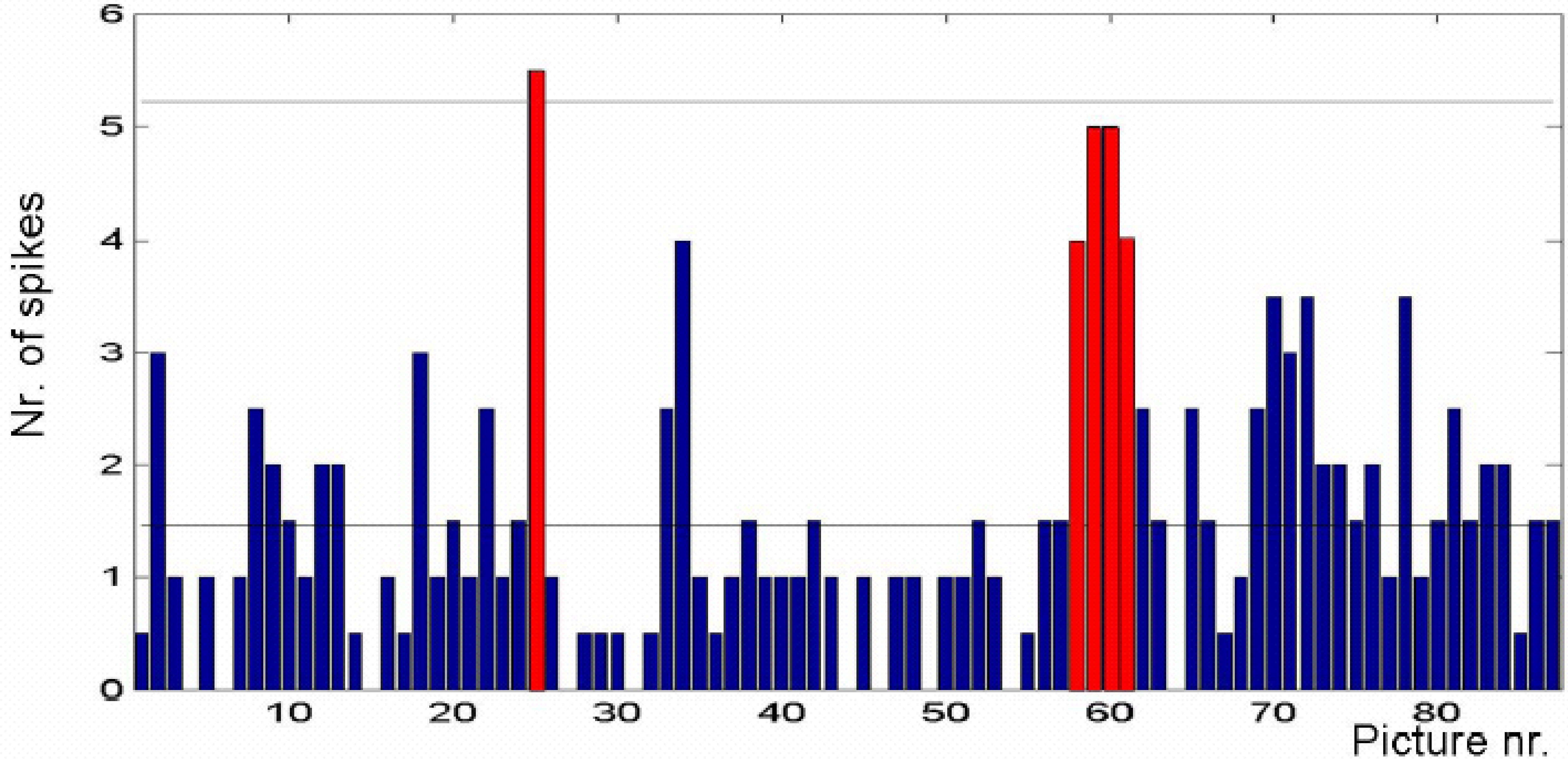


Quian Quiroga, Reddy, Kreiman, Koch and Fried, *Nature* (2005)

What is s?

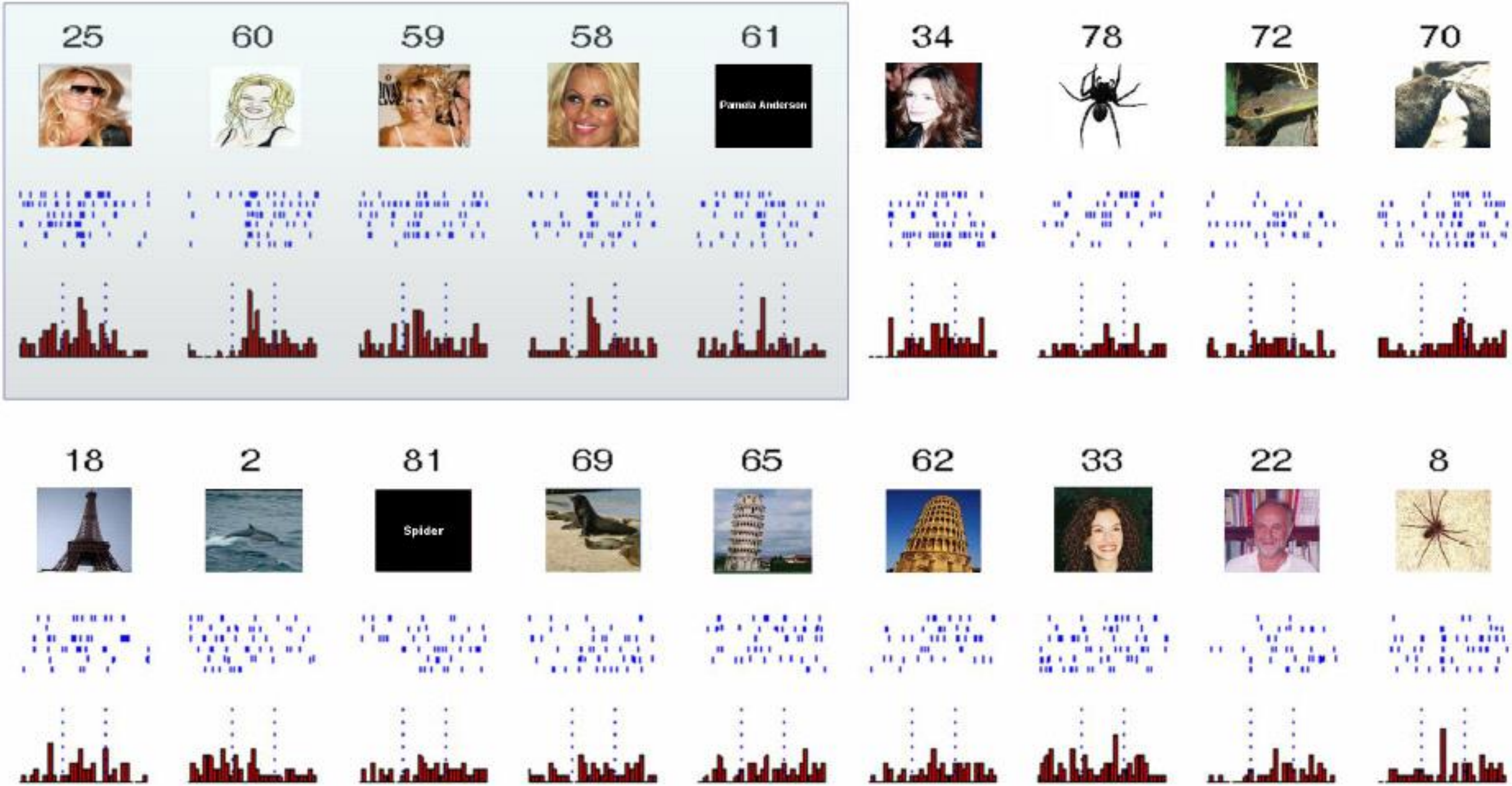


Tuning curves

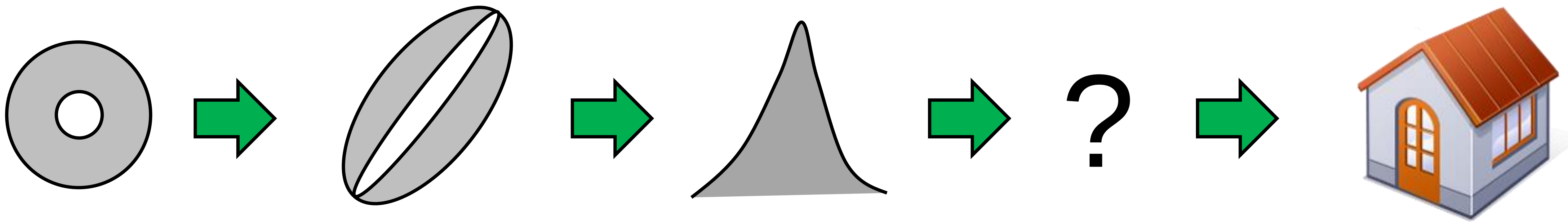


Quian Quiroga, Reddy, Kreiman, Koch and Fried, *Nature* (2005)

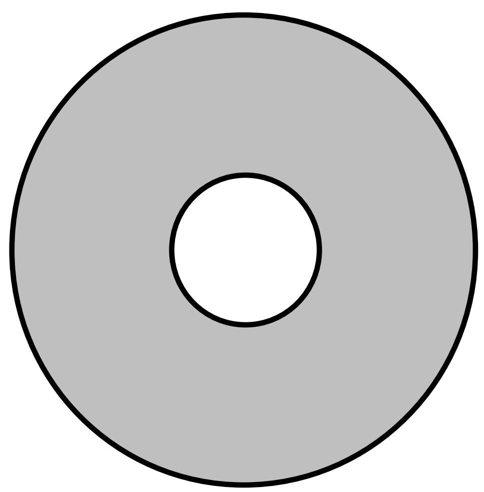
What is *s*?


25
60
59
58
61
Pamela Anderson
34
78
72
70
18
2
81
Spider
69
65
62
33
22
8

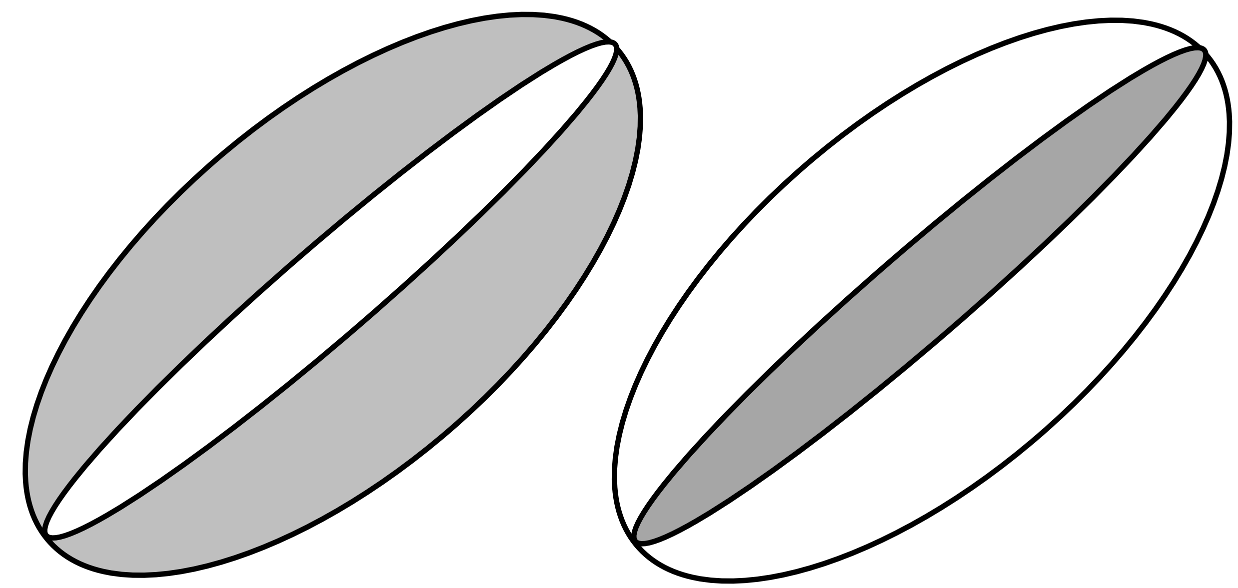
Building up complex selectivity



Basic coding model: linear filtering



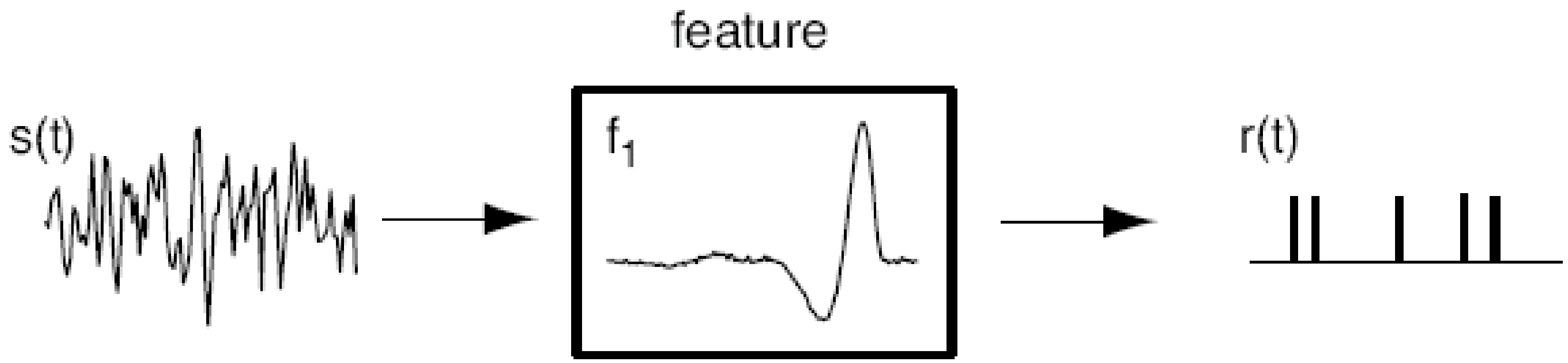
retina



Visual cortex

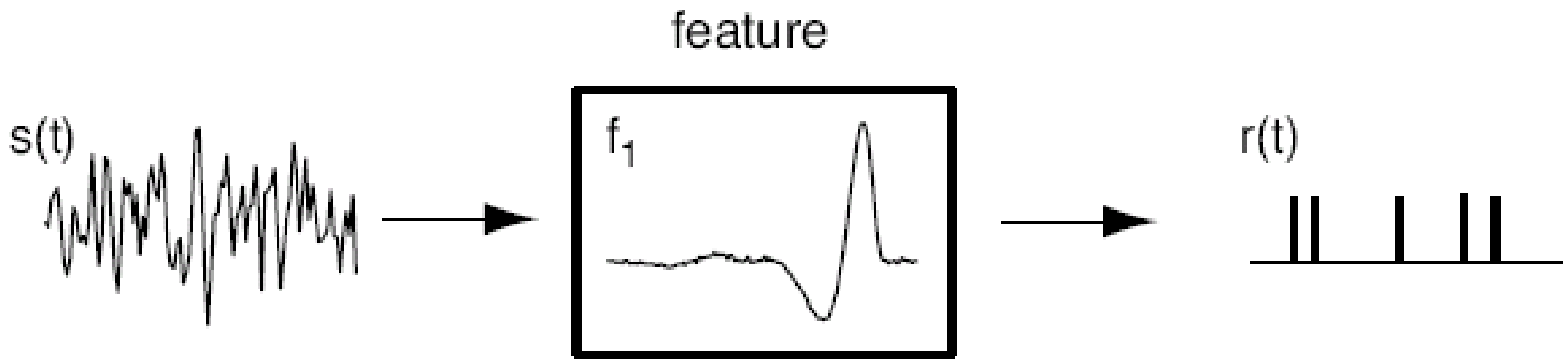
Spatial filter: $r = \iint f(x,y)\, I(x_0-x, y_0-y)\, dx\, dy$

Basic coding model: temporal filtering



Linear filter: $r(t) = \int s(t-\tau)\, f(\tau)\, dt$

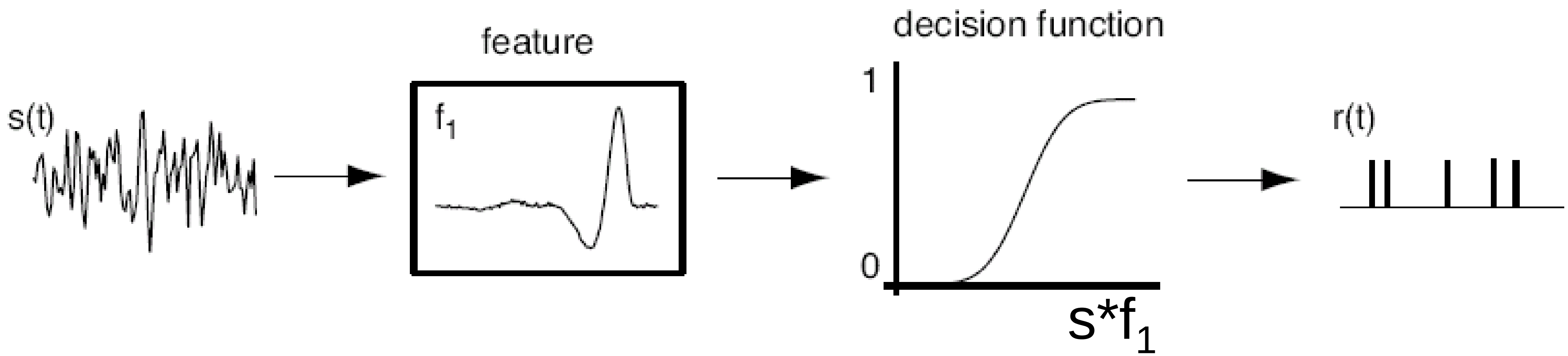
Basic coding model: temporal filtering



Linear filter: $r(t) = \int s(t-\tau)\, f(\tau)\, d\tau$

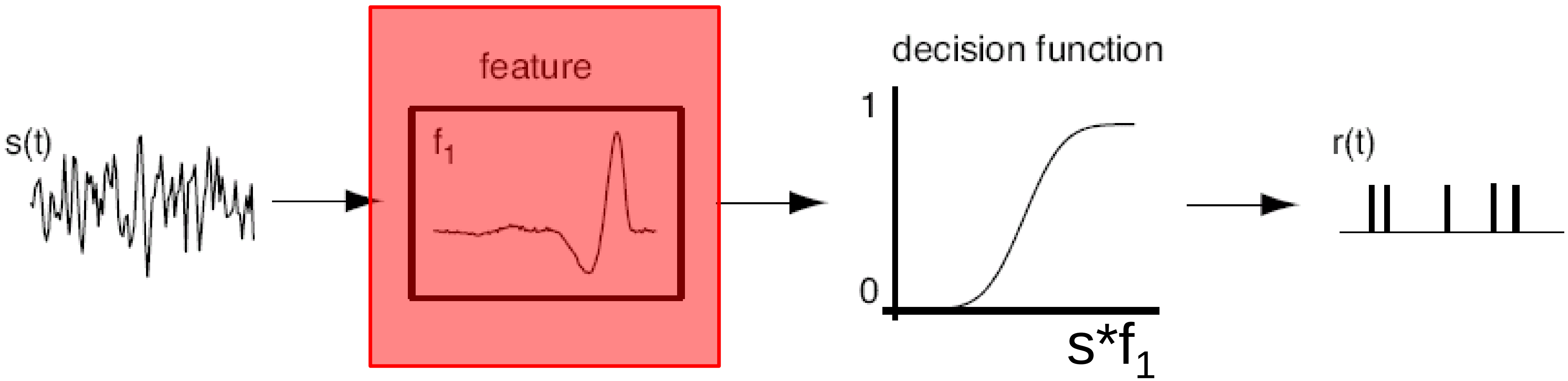
…shortcomings?

Next most basic coding model



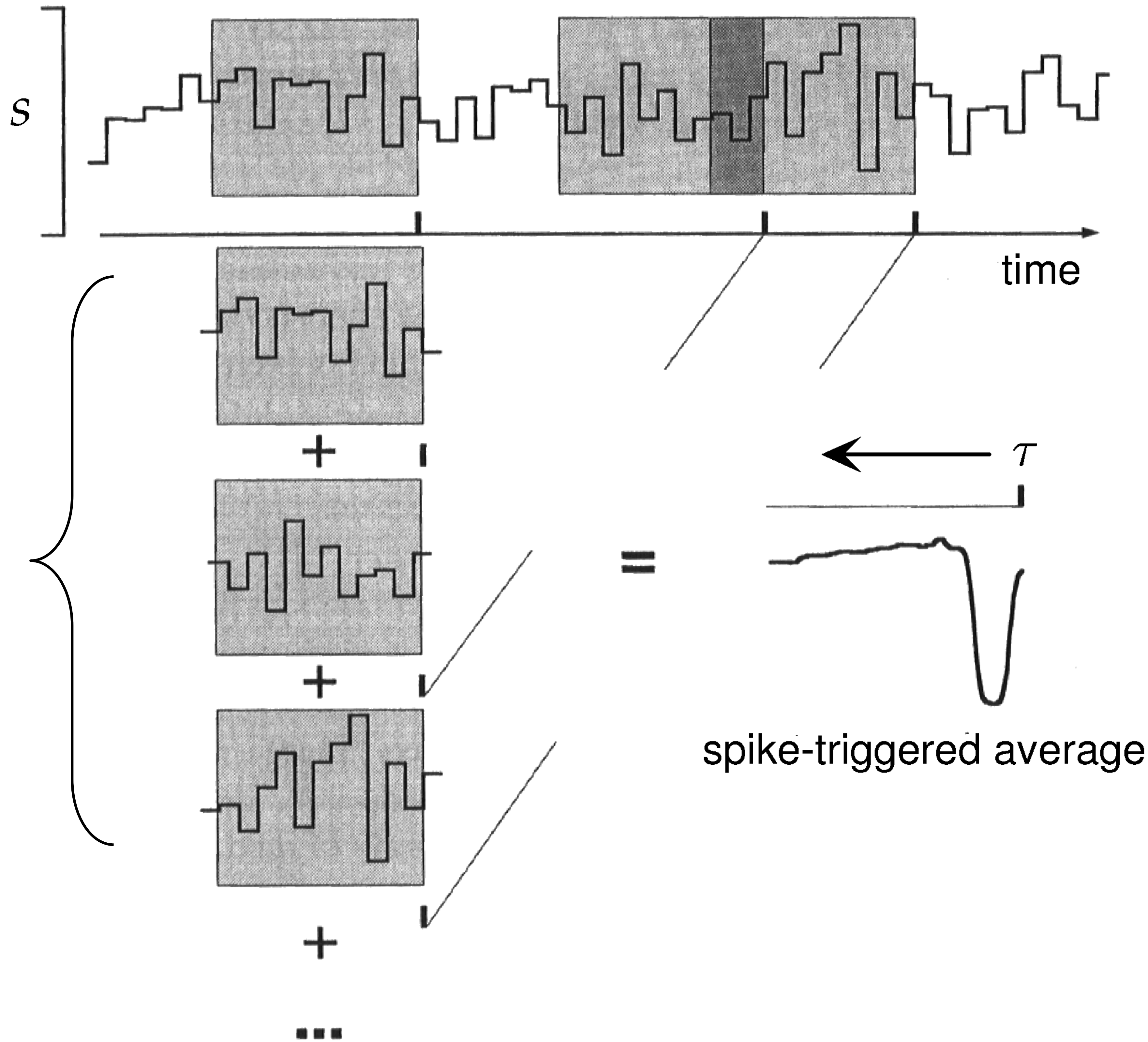
Linear filter & nonlinearity: $r(t) = g(\int s(t-\tau)\, f(\tau)\, d\tau)$

How to find the components of this model

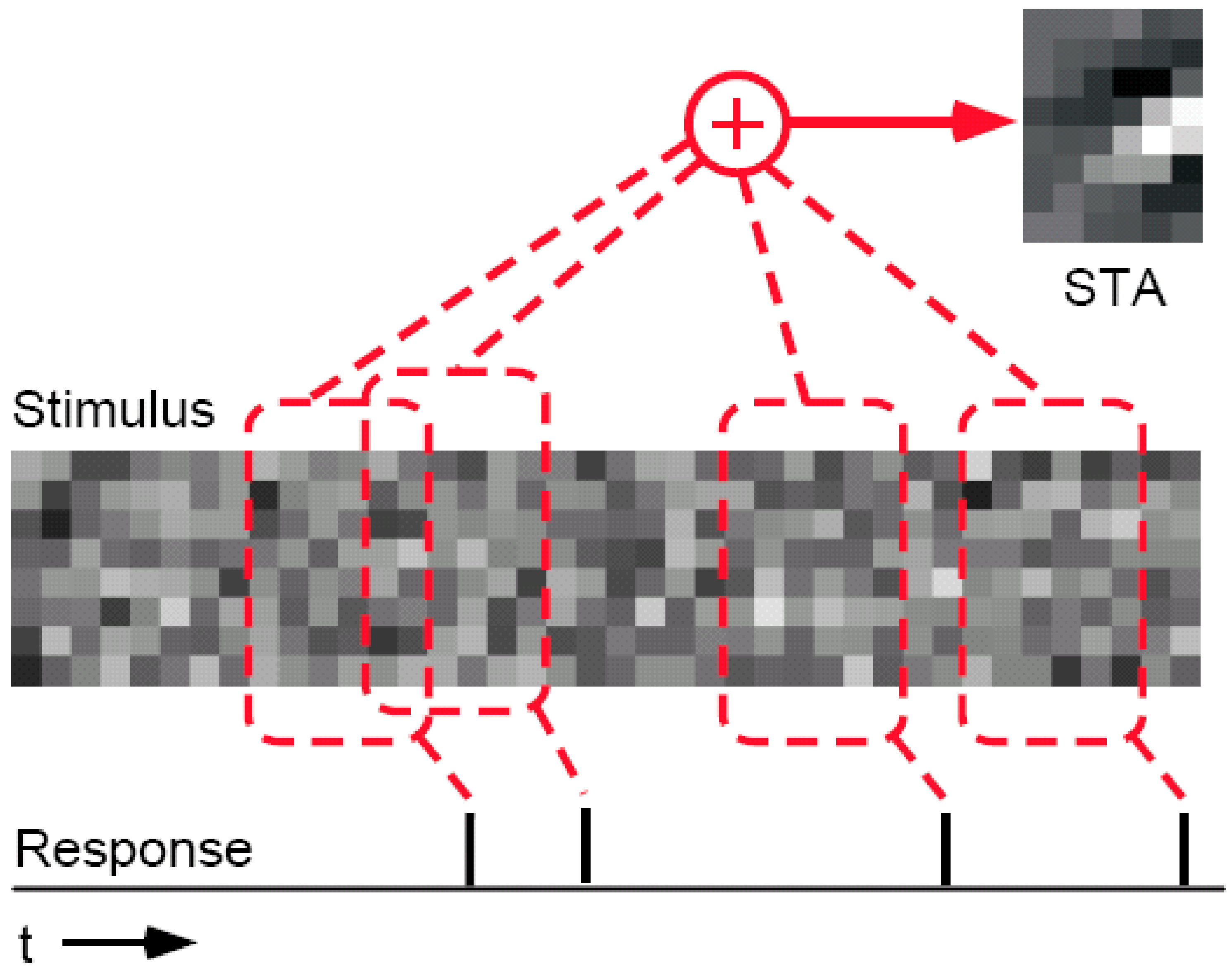


Reverse correlation: the spike-triggered average

Spike-
conditional
ensemble



The spike-triggered average

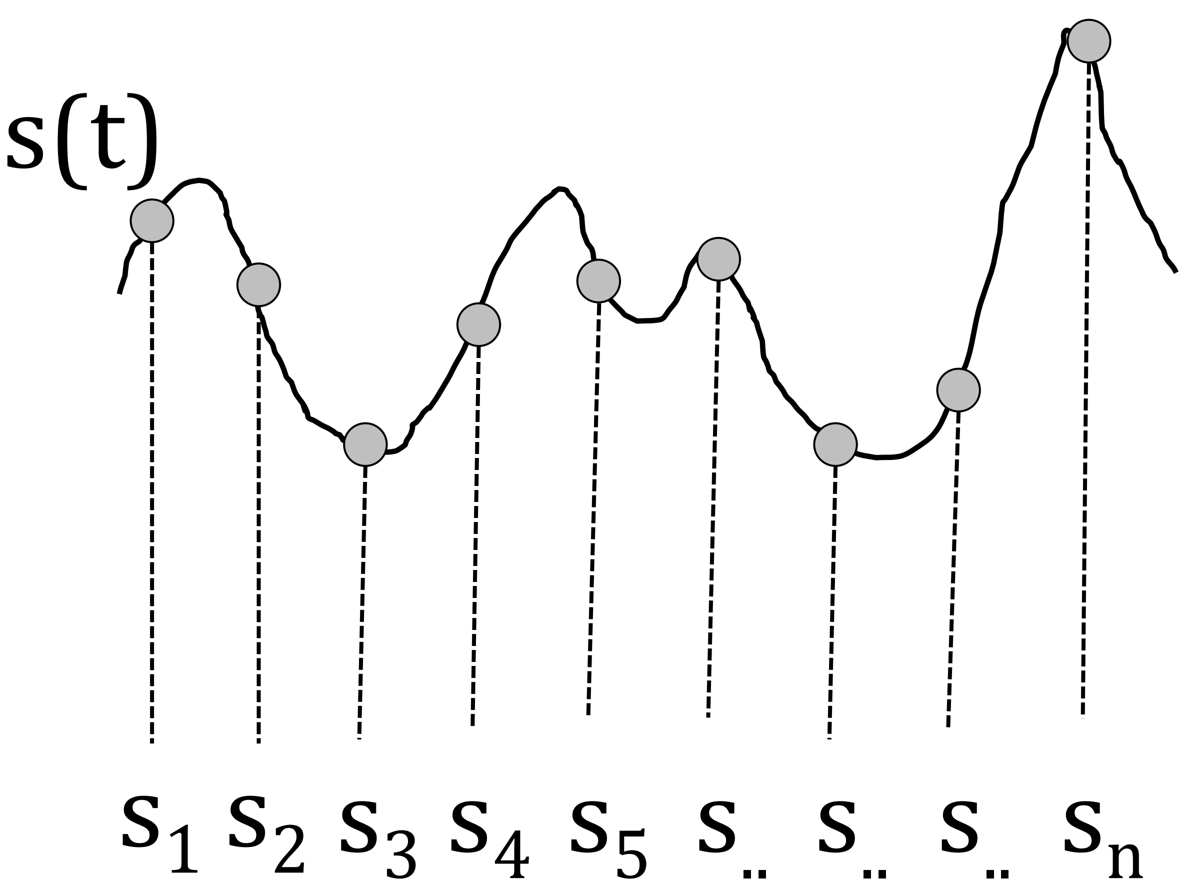


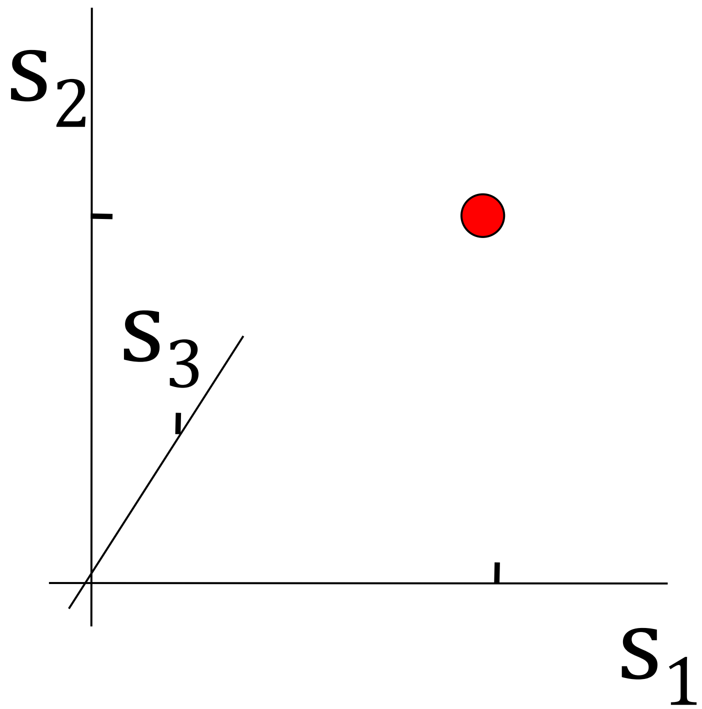
Dimensionality reduction

More generally, one can conceive of the action of the neuron or neural system as *selecting a low dimensional subset* of its inputs.

$$P(\text{response} \mid \text{stimulus}) \rightarrow P(\text{response} \mid s_1, s_2, .., s_n)$$

Start with a very high dimensional description (eg. an image or a time-varying waveform) and pick out a small set of relevant dimensions.

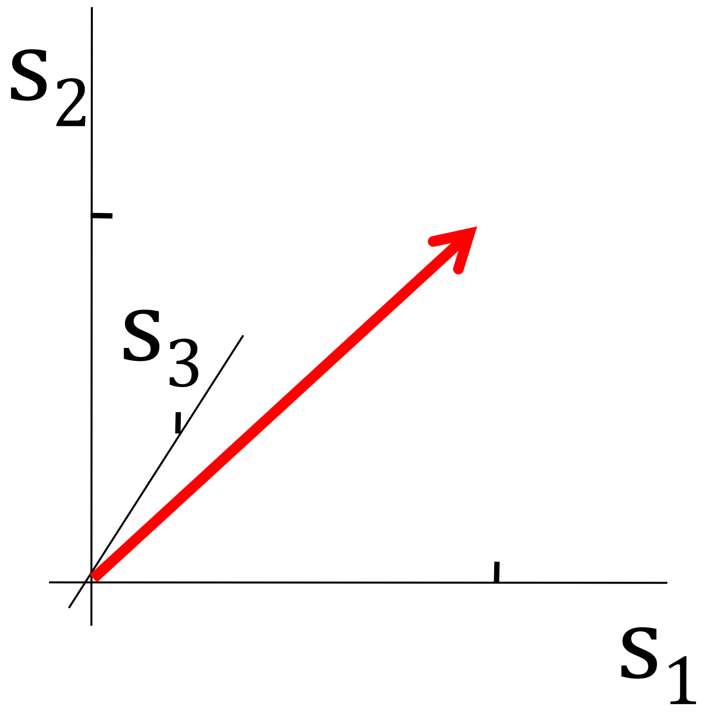




$$S(t) = (S_1, S_2, S_3, \ldots, S_n)$$

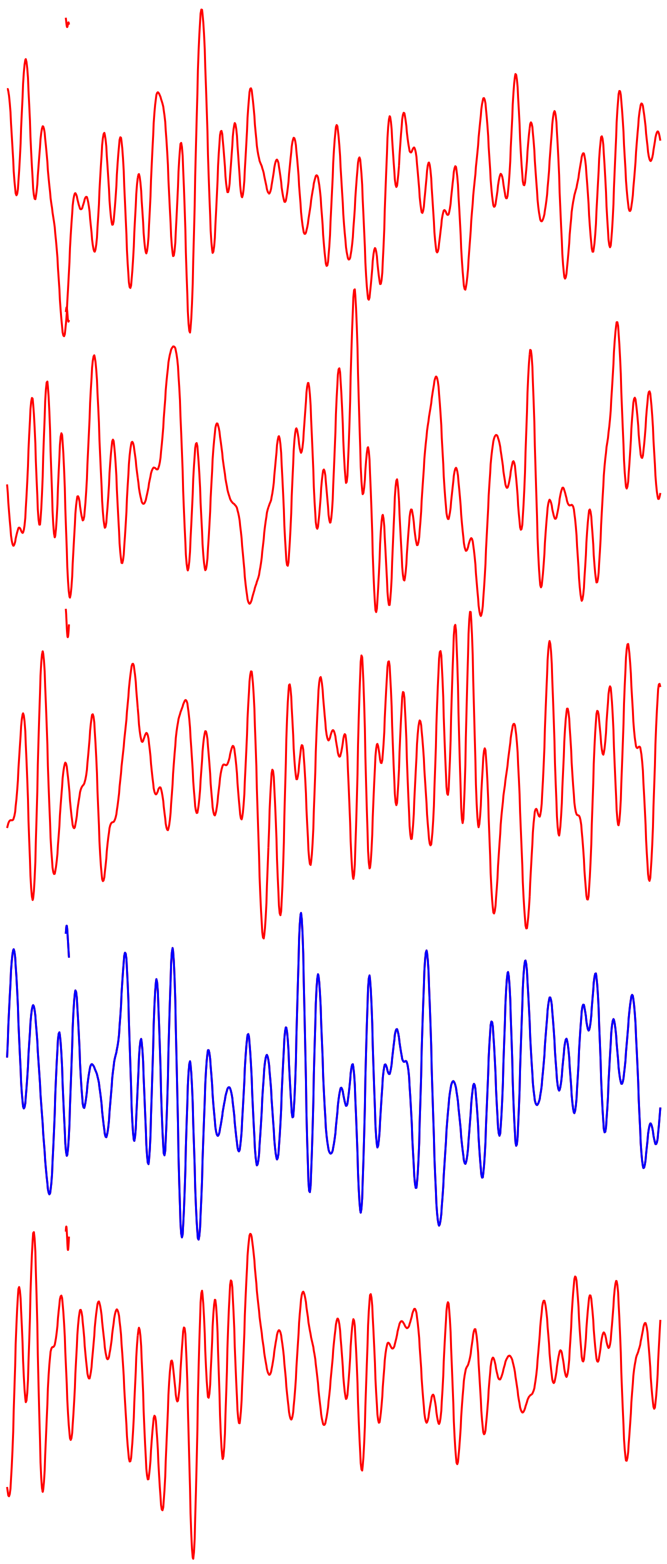
Linear filtering

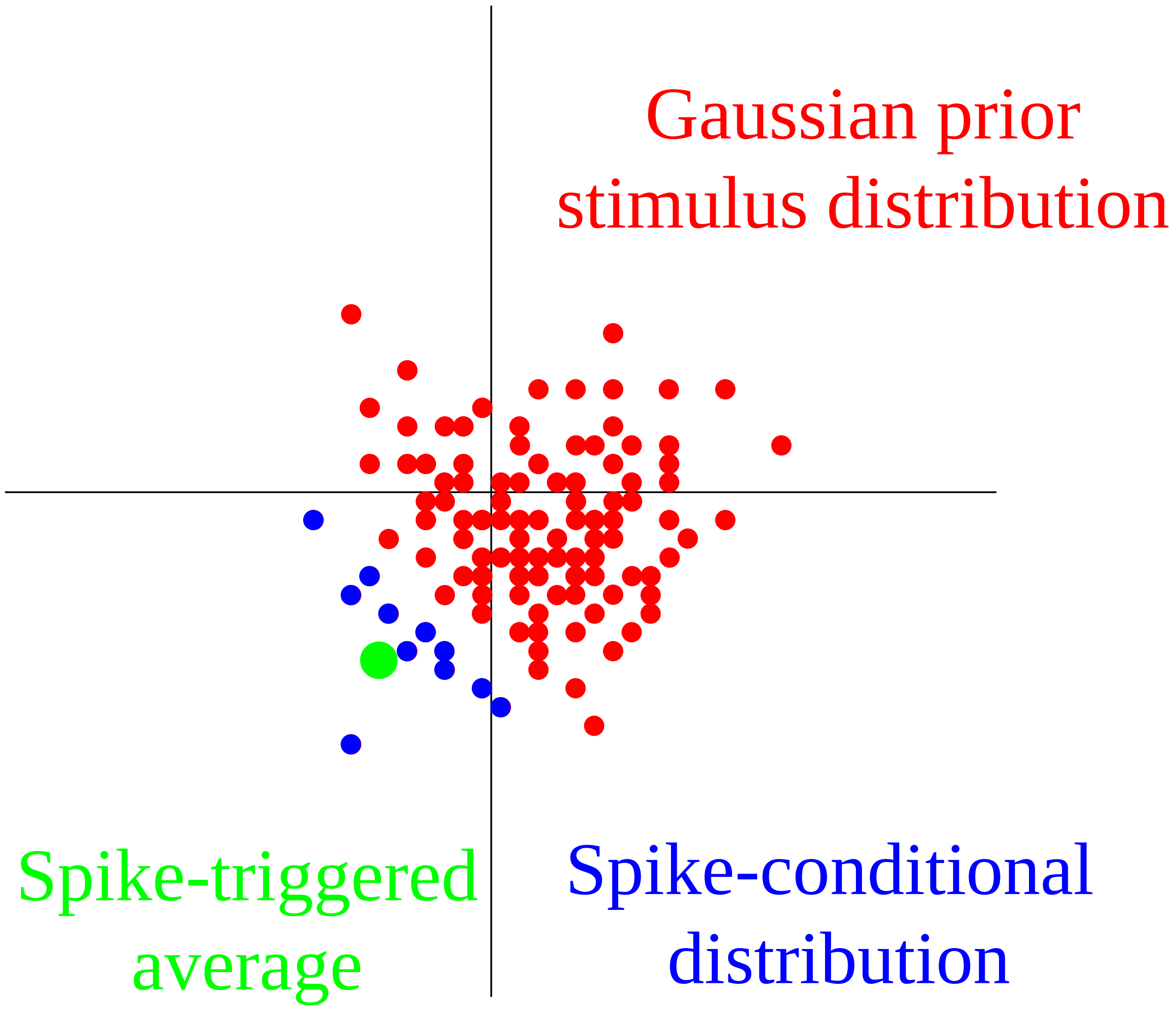
Linear filtering = convolution = projection



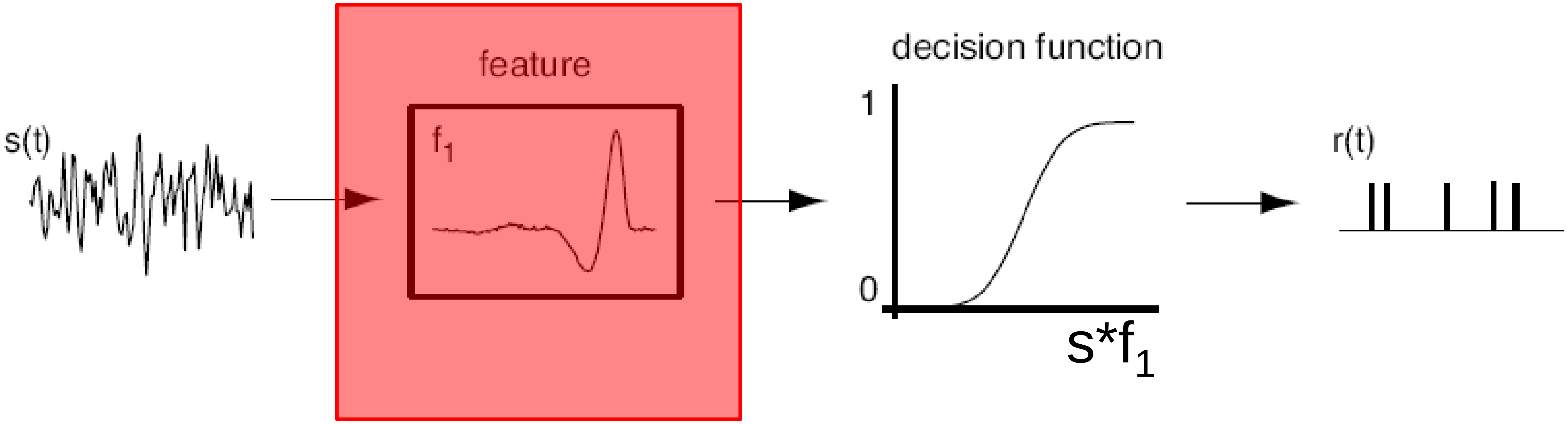
Stimulus feature is a vector in a high-dimensional stimulus space

Determining linear features from white noise





How to find the components of this model



Determining the nonlinear input/output function

The input/output function is:

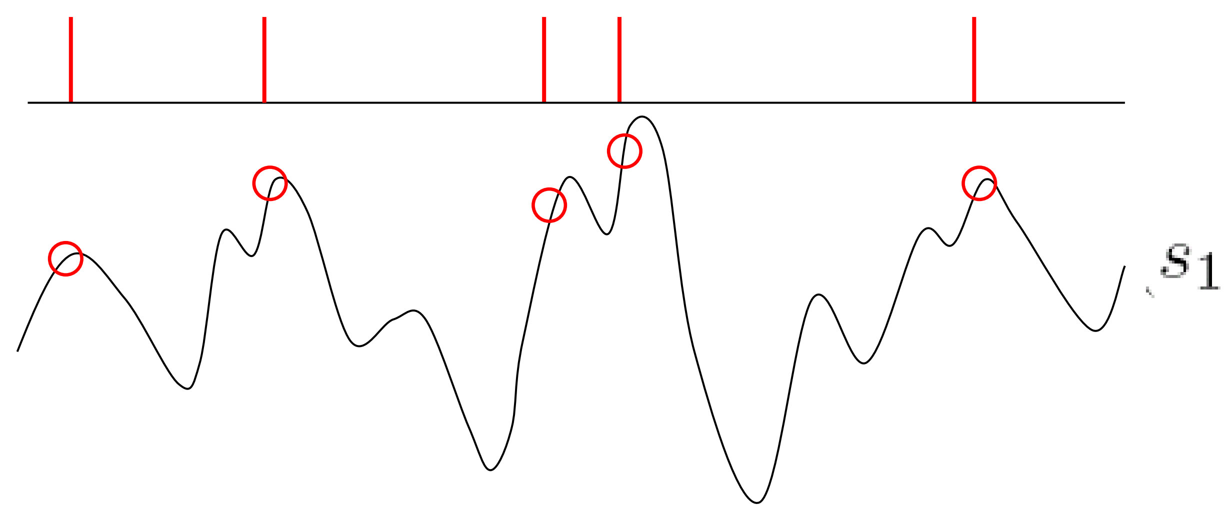
$$P(\text{spike}|\text{stimulus})$$

which can be derived from data using Bayes' rule:

$$P(\text{spike}|s_1) = \frac{P(s_1|\text{spike})P(\text{spike})}{P(s_1)}$$

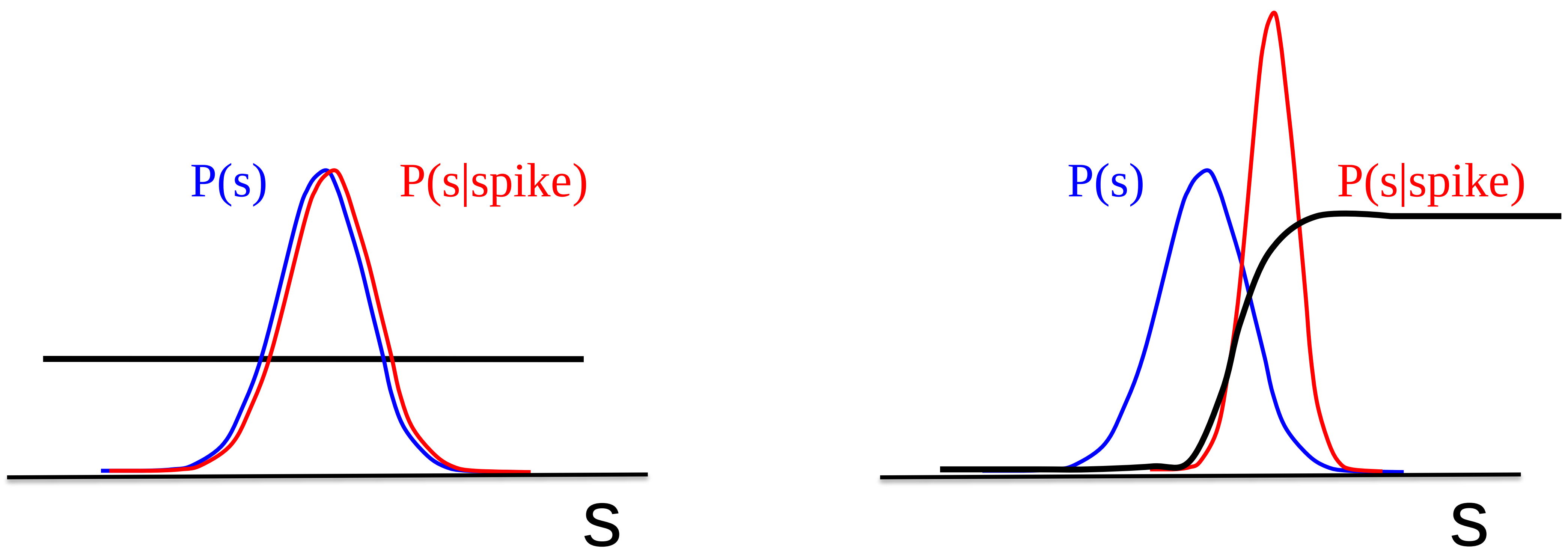
$P(s_1)$

$P(s_1|\text{spike})$

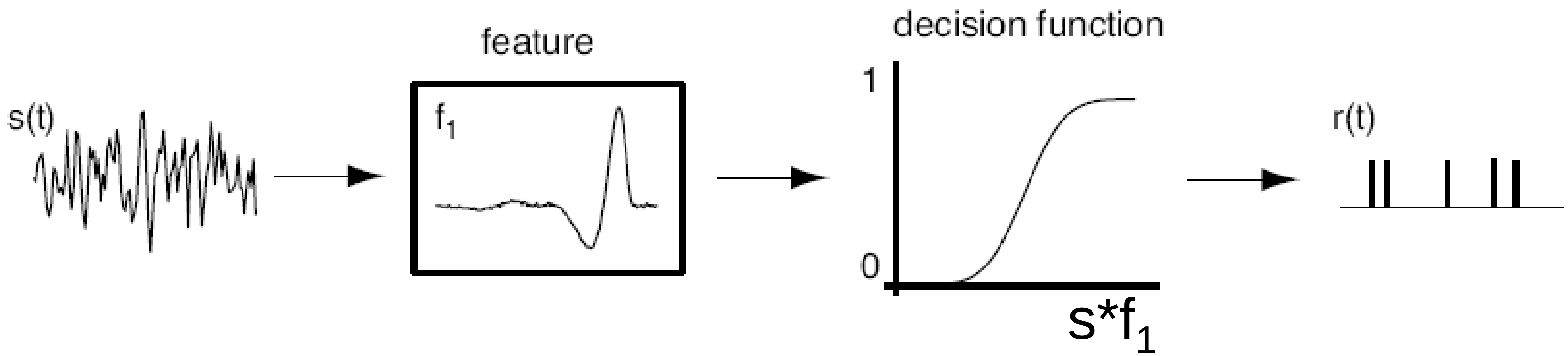


Nonlinear input/output function

Tuning curve: $P(\text{spike}|s) = P(s|\text{spike})\, P(\text{spike}) / P(s)$



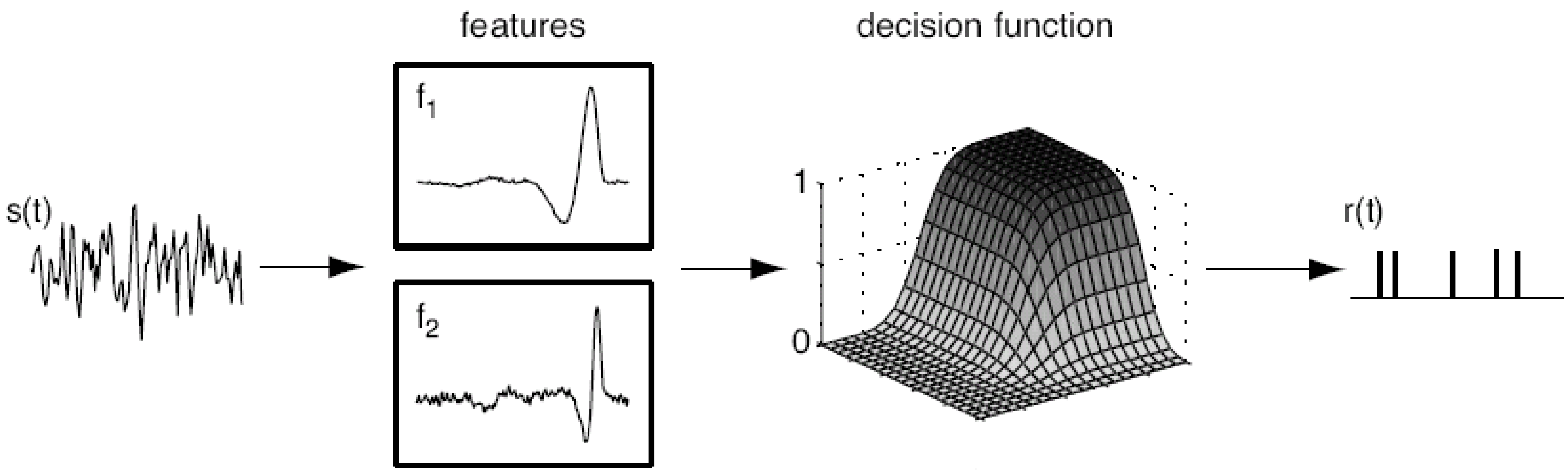
Next most basic coding model



Linear filter & nonlinearity: $r(t) = g(\int f(t-\tau)\, s(\tau)\, d\tau)$

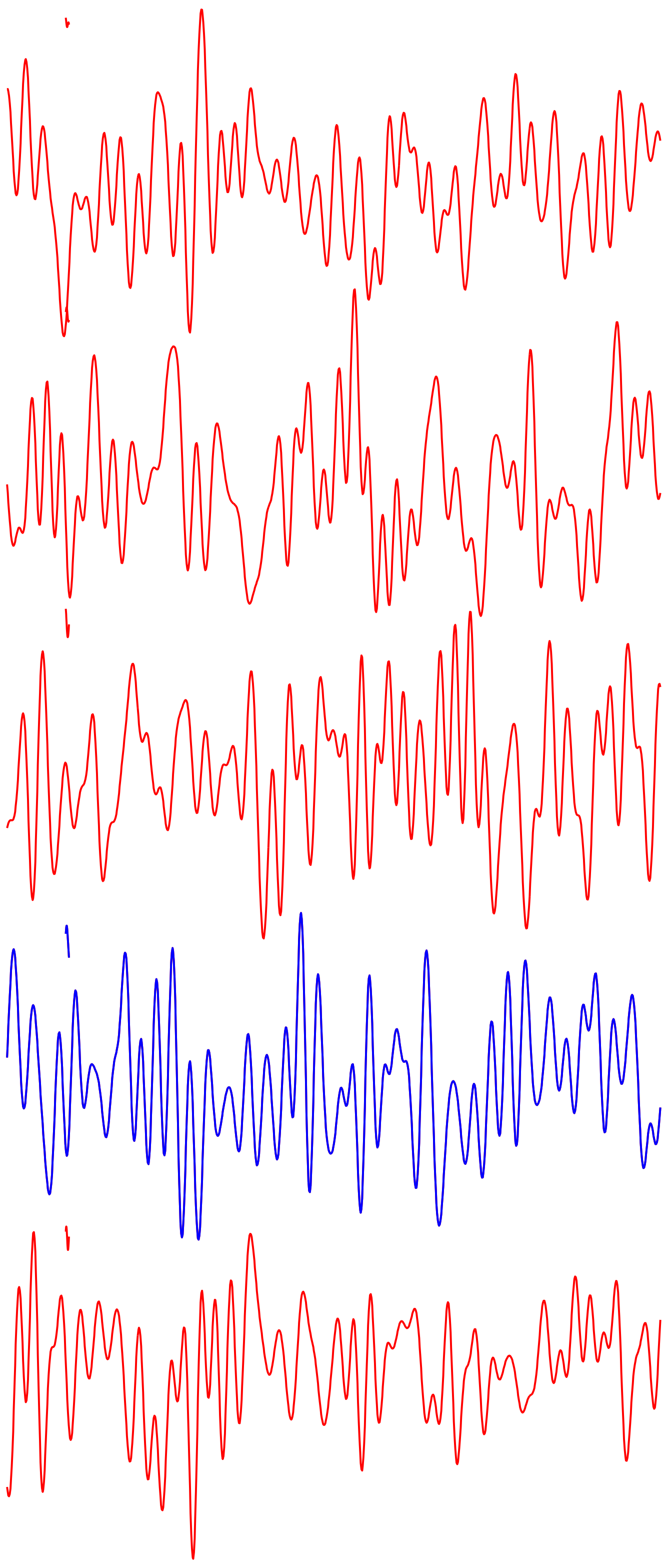
…shortcomings?

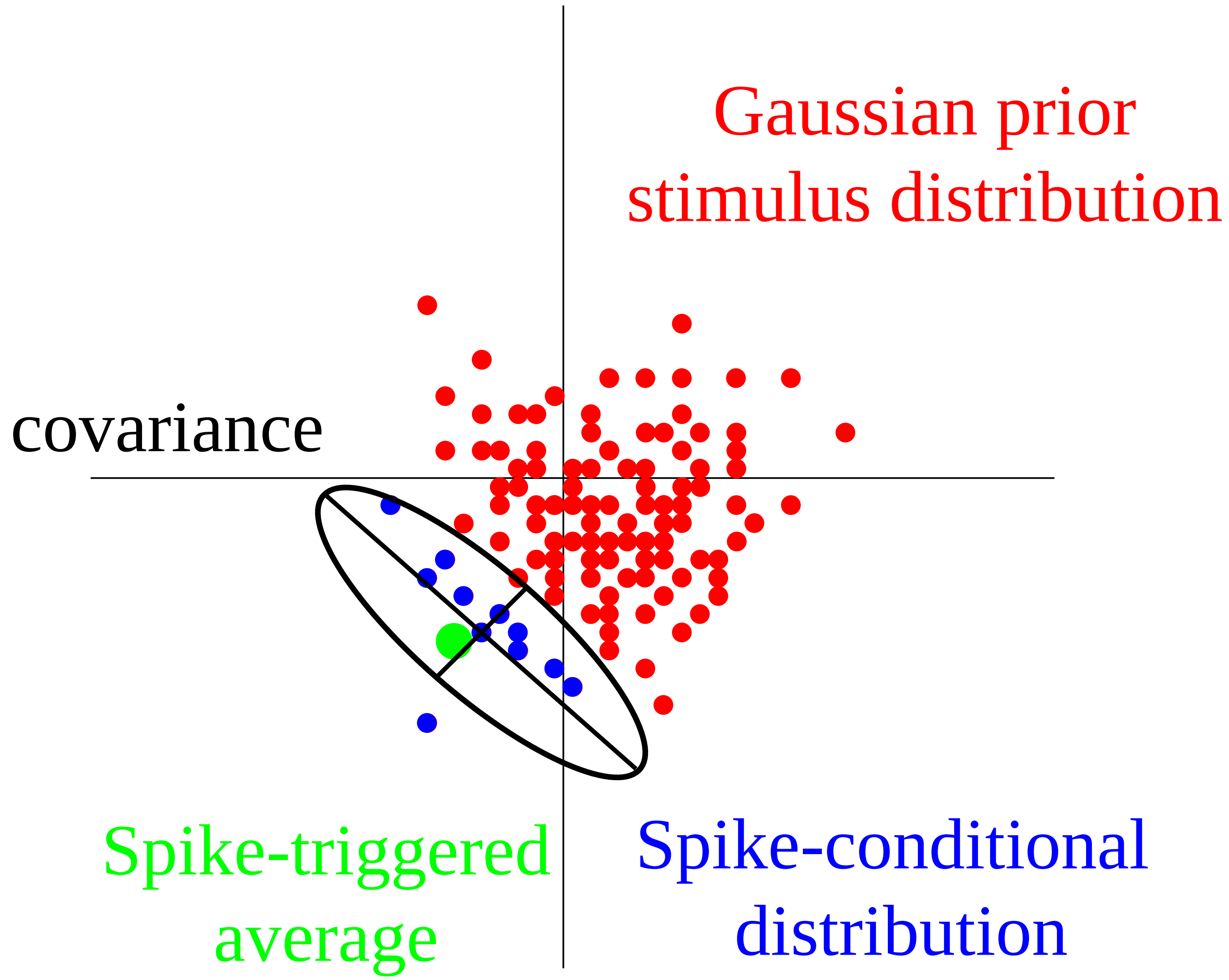
Less basic coding models



Linear filter*s* & nonlinearity: $r(t) = g(f_1{*}s, f_2{*}s, \ldots, f_n{*}s)$

Determining linear features from white noise





Identifying multiple features

The covariance matrix is

$$\boxed{C_{ij} = \langle S(t_{\text{spike}} - t_i) S(t_{\text{spike}} - t_j) \rangle - \bar{S}(t_i)\bar{S}(t_j) - \langle I(t - t_i) I(t - t_j) \rangle}$$

Spike-triggered stimulus correlation

Spike-triggered average

Stimulus prior

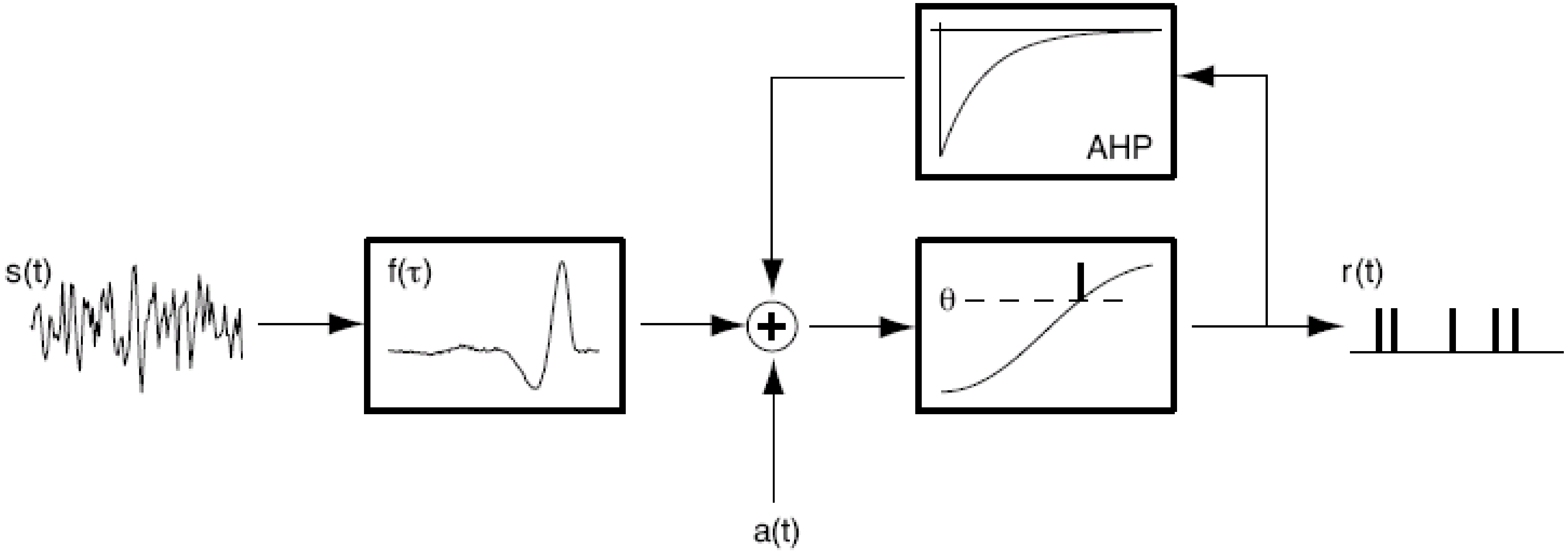
Properties:

- The number of eigenvalues significantly different from zero is the number of relevant stimulus features
- The corresponding eigenvectors are the relevant features (or span the *relevant subspace*)

Bialek et al., 1988; Brenner et al., 2000; Bialek and de Ruyter, 2005

A toy example: a filter-and-fire model

Let's develop some intuition for how this works: a filter-and-fire threshold-crossing model with AHP

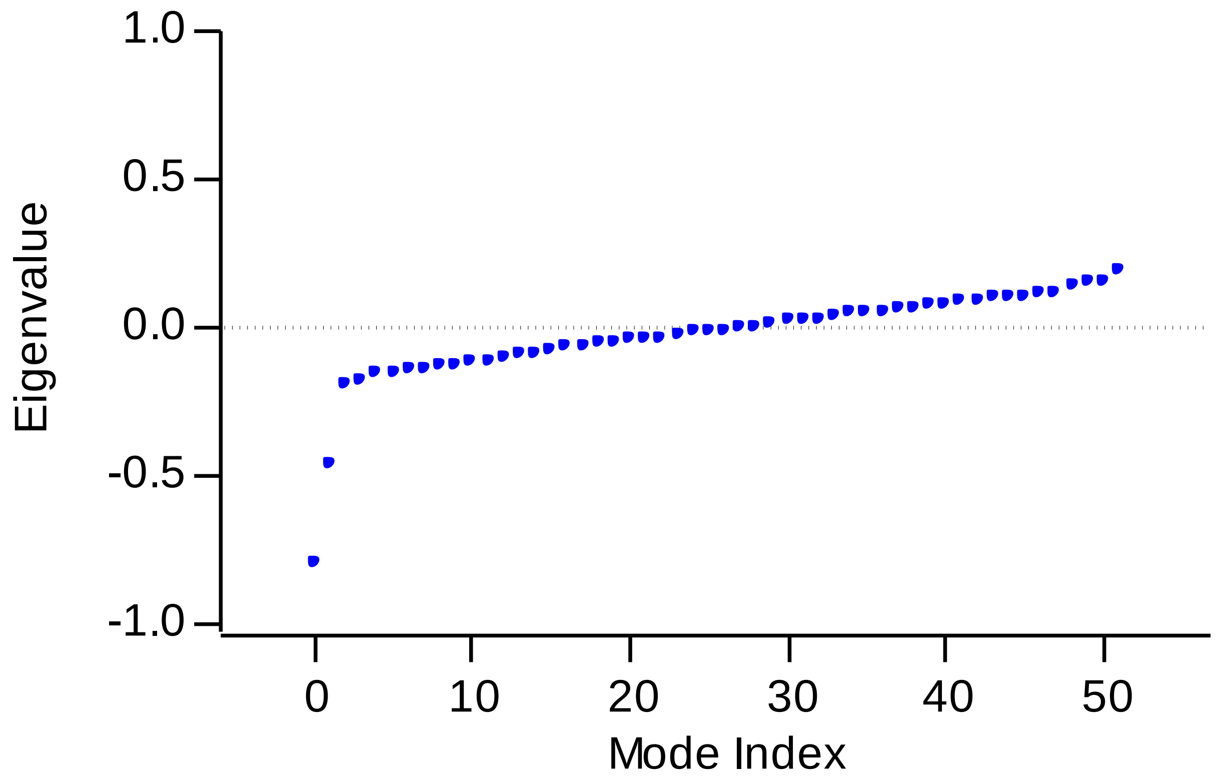


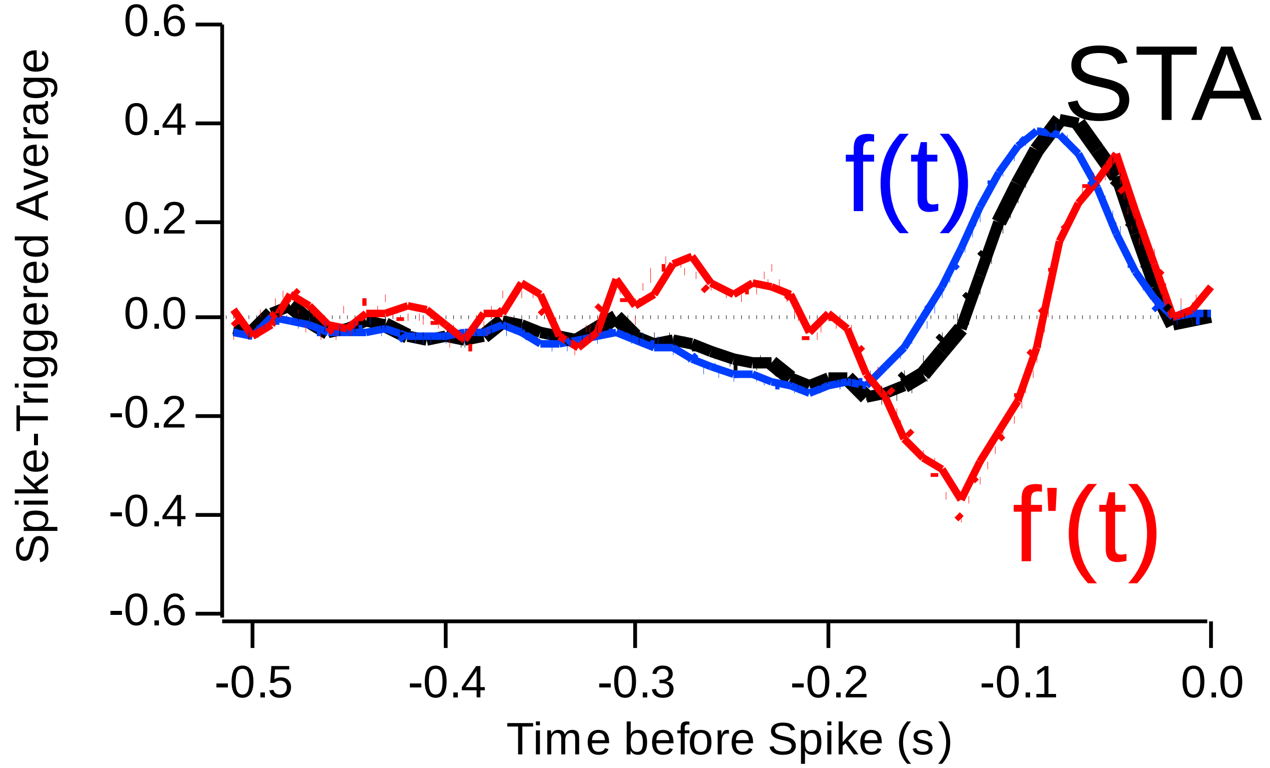
Keat, Reinagel, Reid and Meister, Predicting every spike. Neuron (2001)

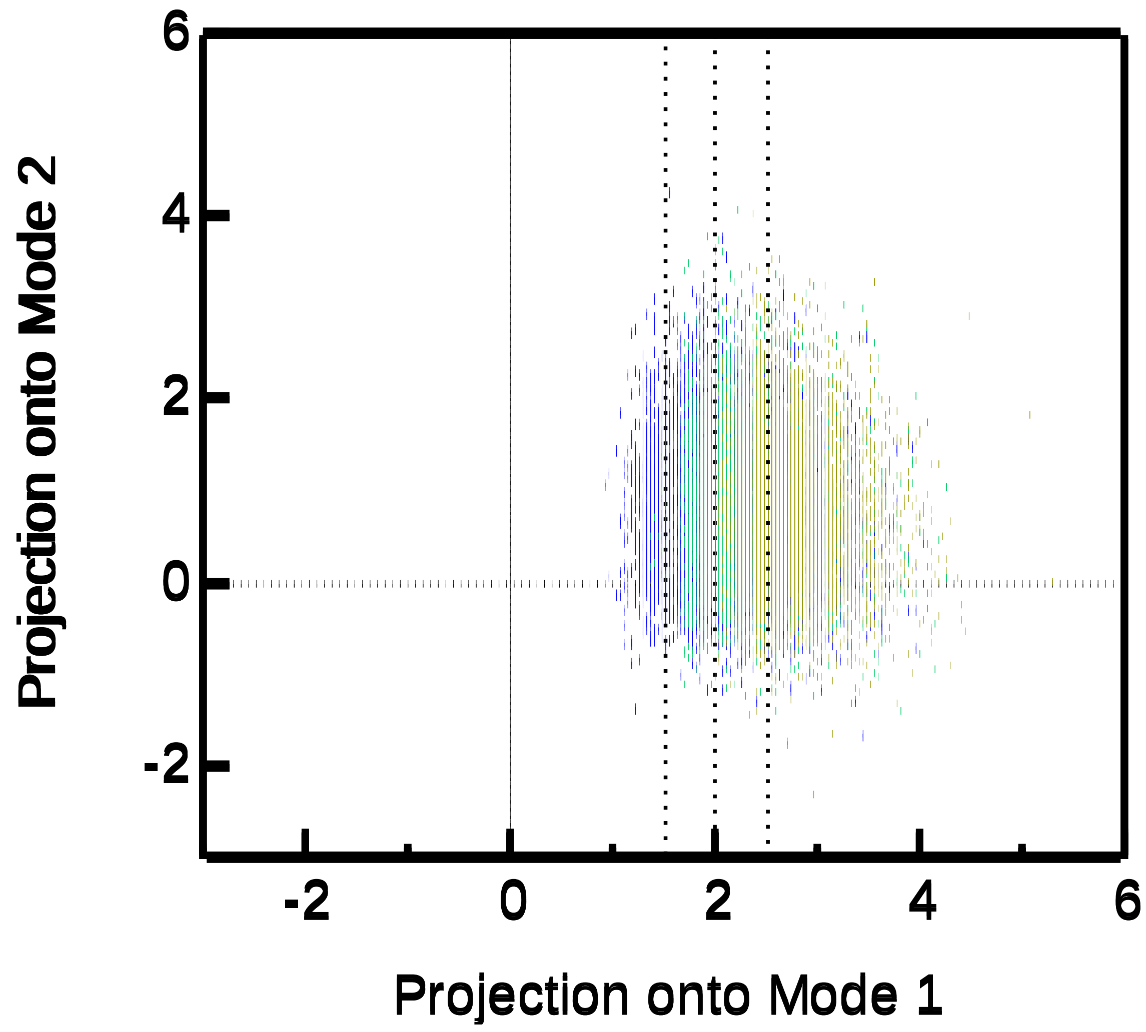
- Spiking is controlled by a single filter, *f*(t)
- Spikes happen generally on an upward threshold crossing of the filtered stimulus

➔ expect 2 **relevant features**, the filter *f*(t) and its time derivative *f'*(t)

Covariance analysis of a filter-and-fire model



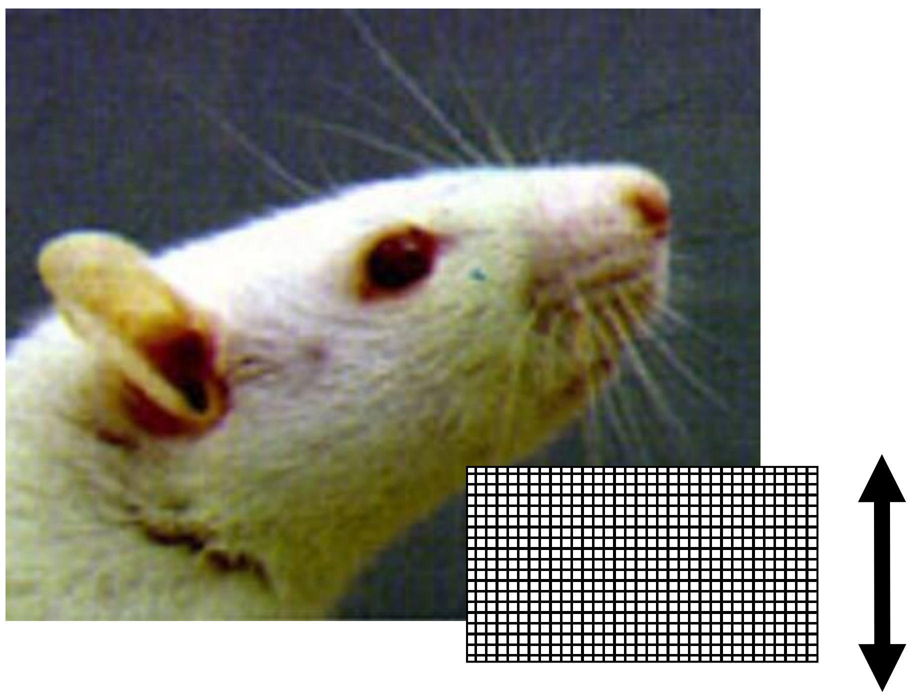




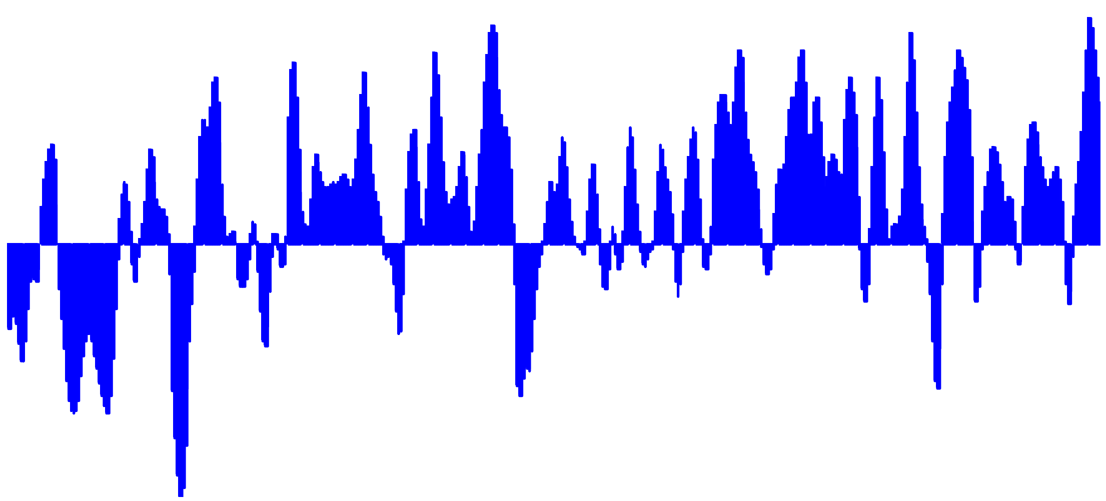
Let’s try it

Example: rat somatosensory (barrel) cortex

Rasmus Petersen and Mathew Diamond, SISSA

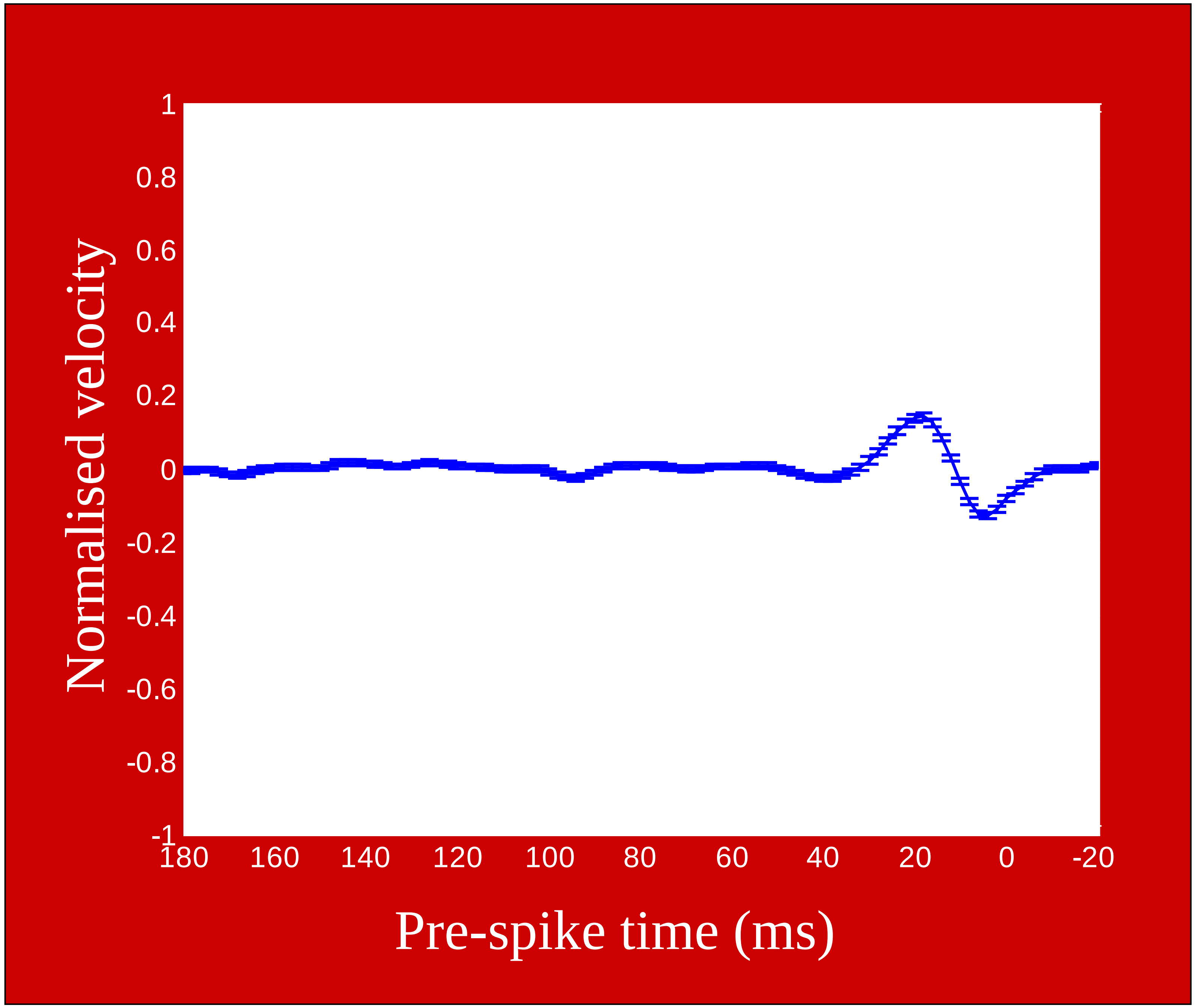


Record from single units in barrel cortex



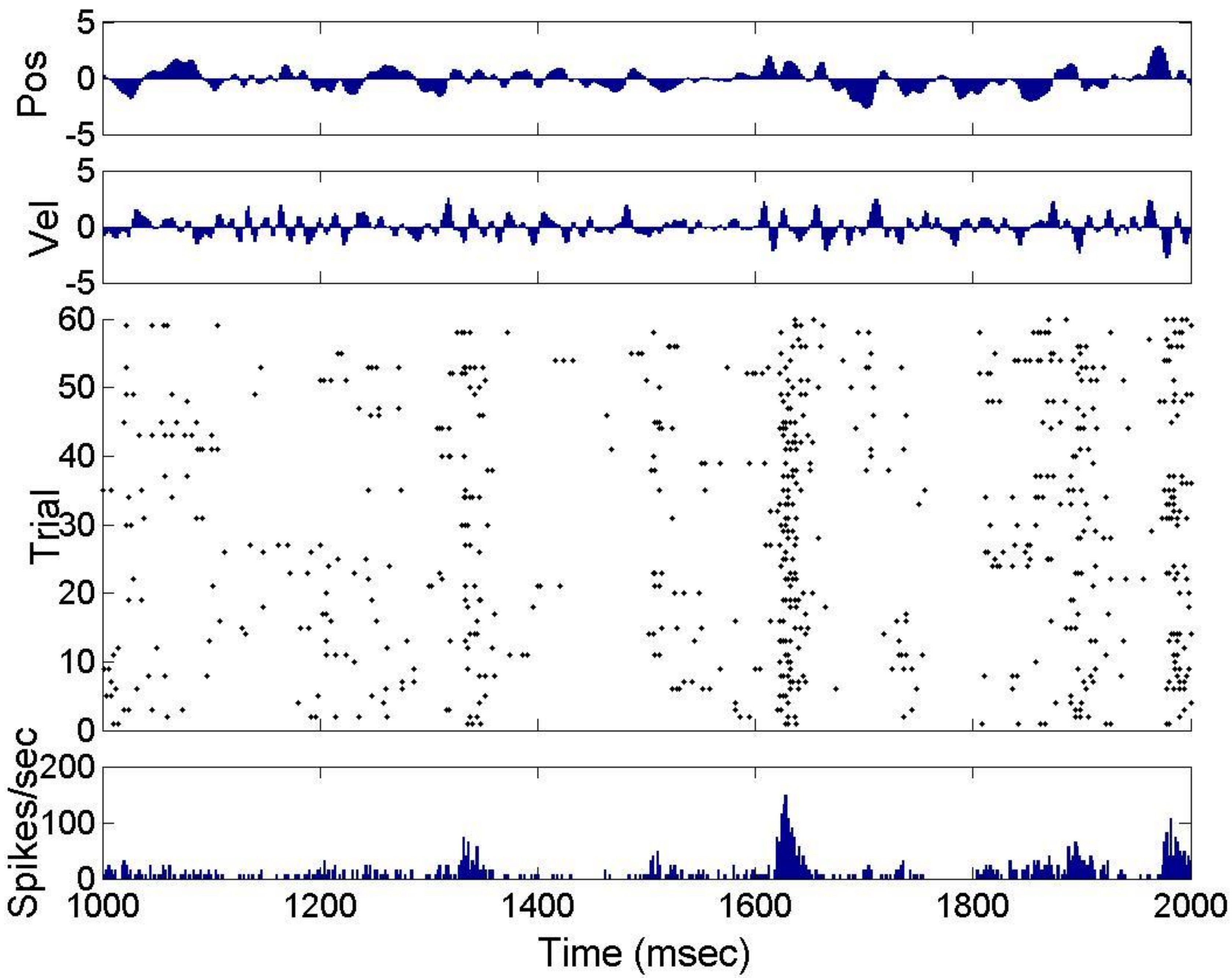
White noise analysis in barrel cortex

Spike-triggered average:



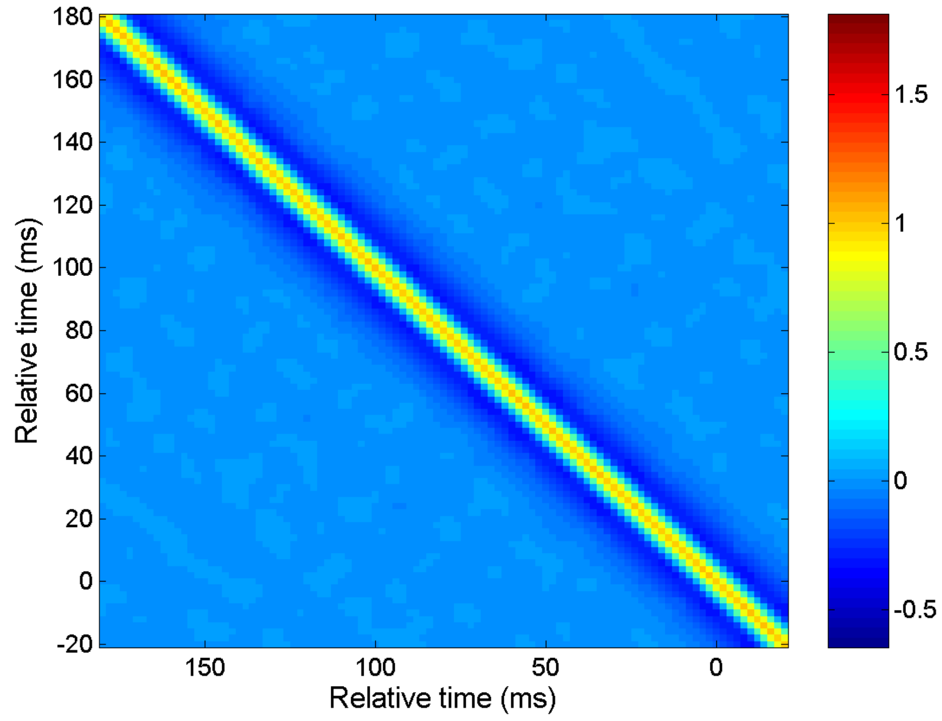
White noise analysis in barrel cortex

Is the neuron simply not very responsive to a white noise stimulus?

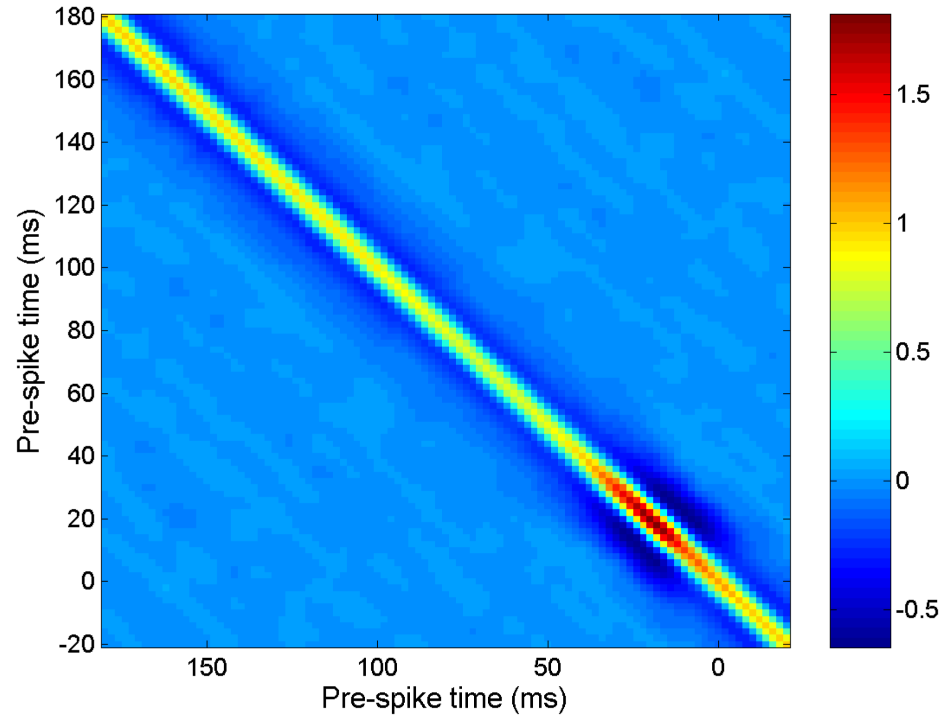


Covariance matrices from barrel cortical neurons

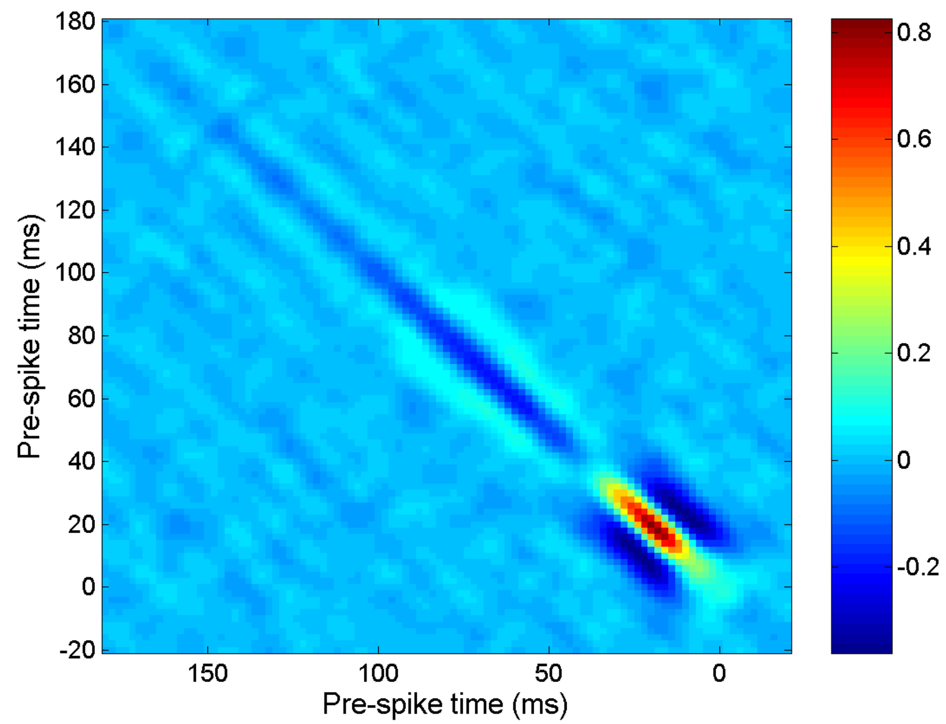
Prior



Spike-triggered



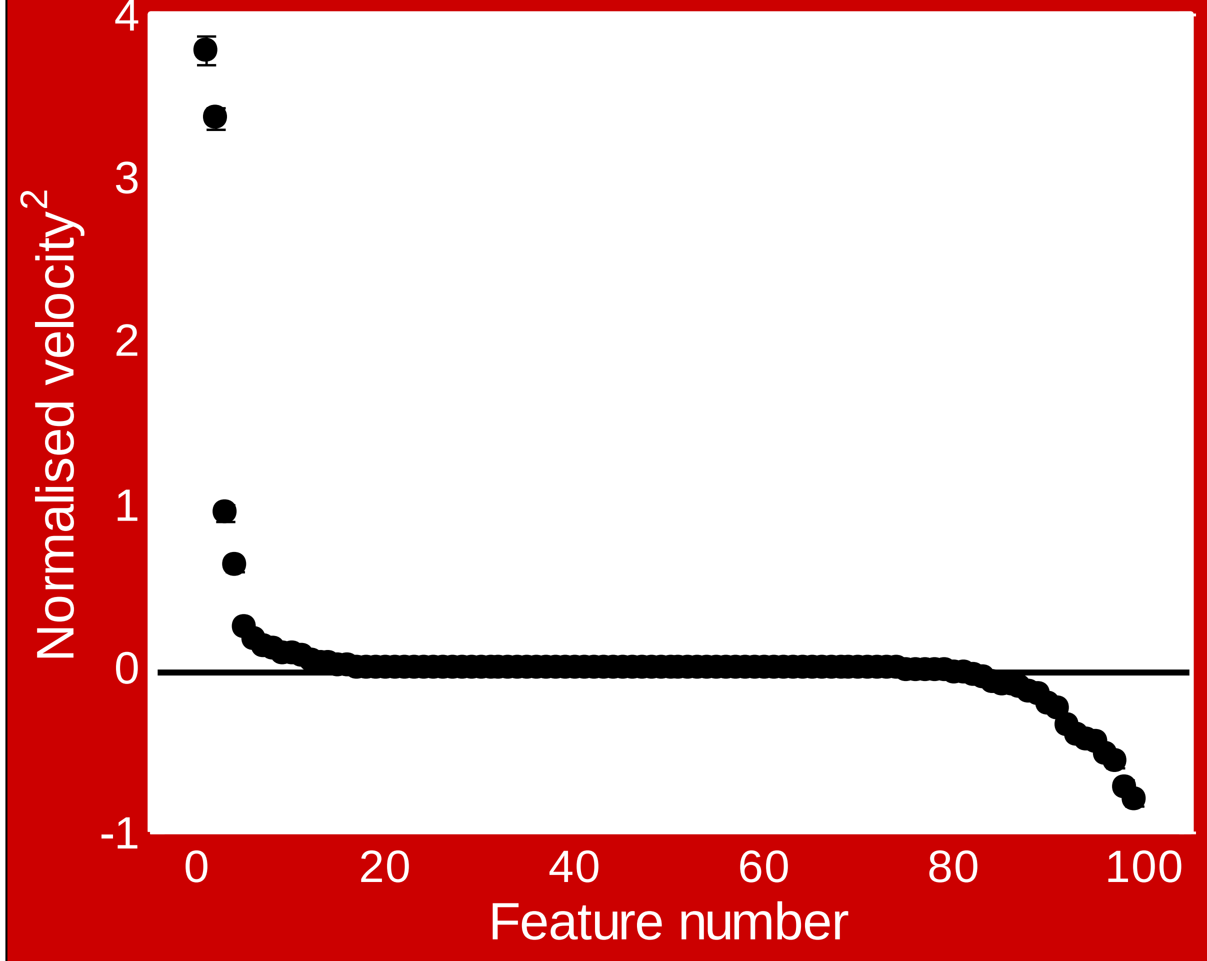
Difference

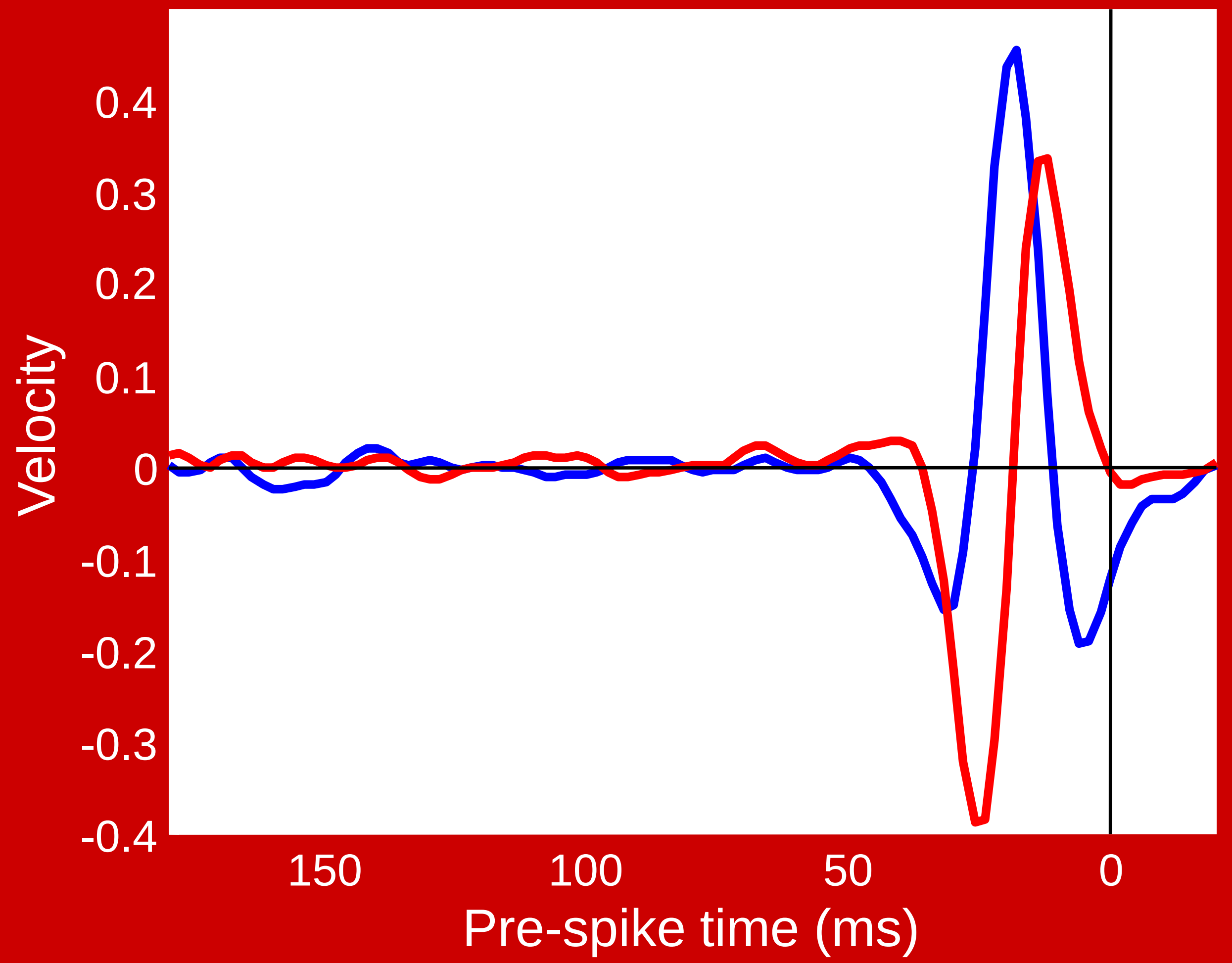


Eigenspectrum from barrel cortical neurons

Eigenspectrum

Leading modes

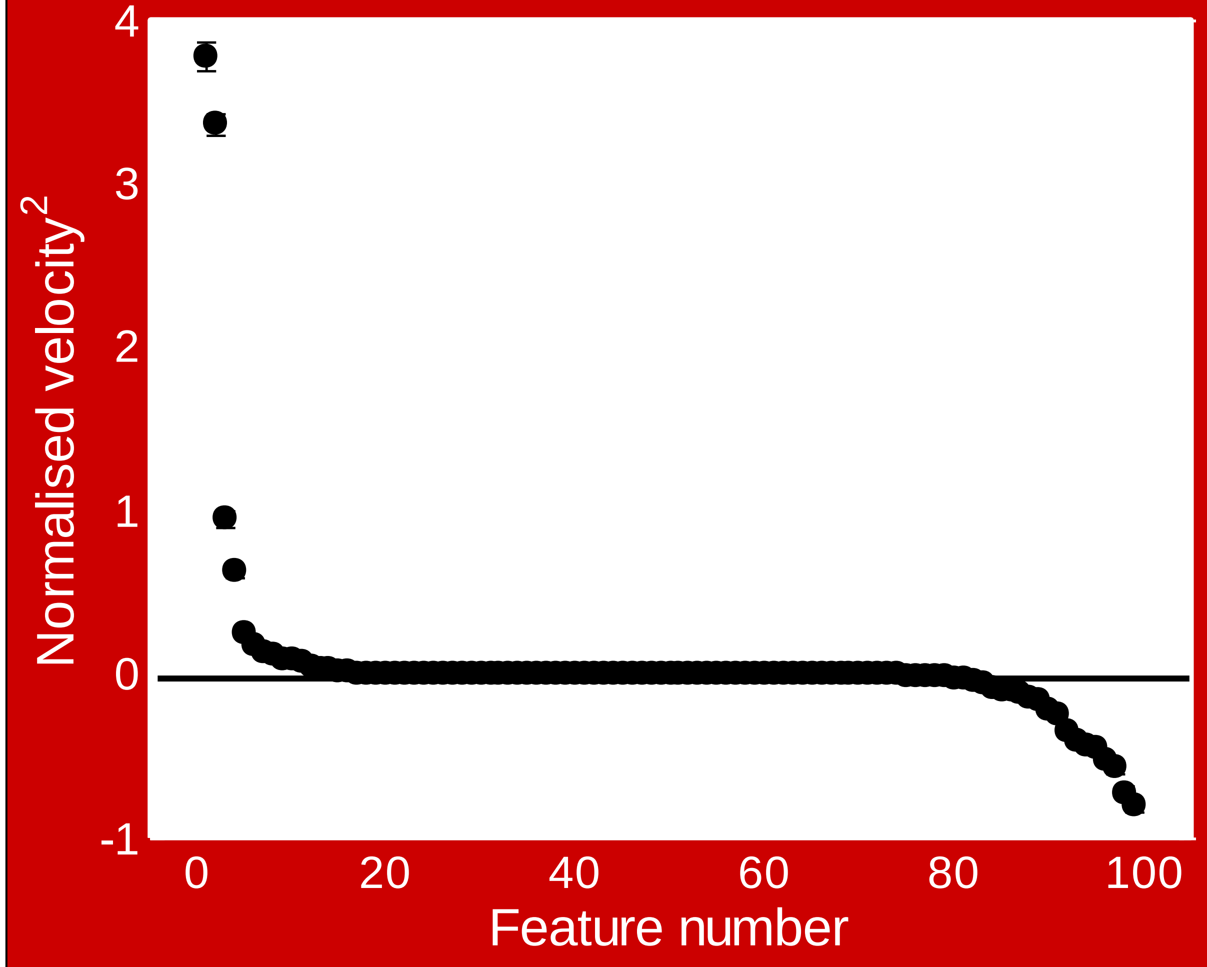


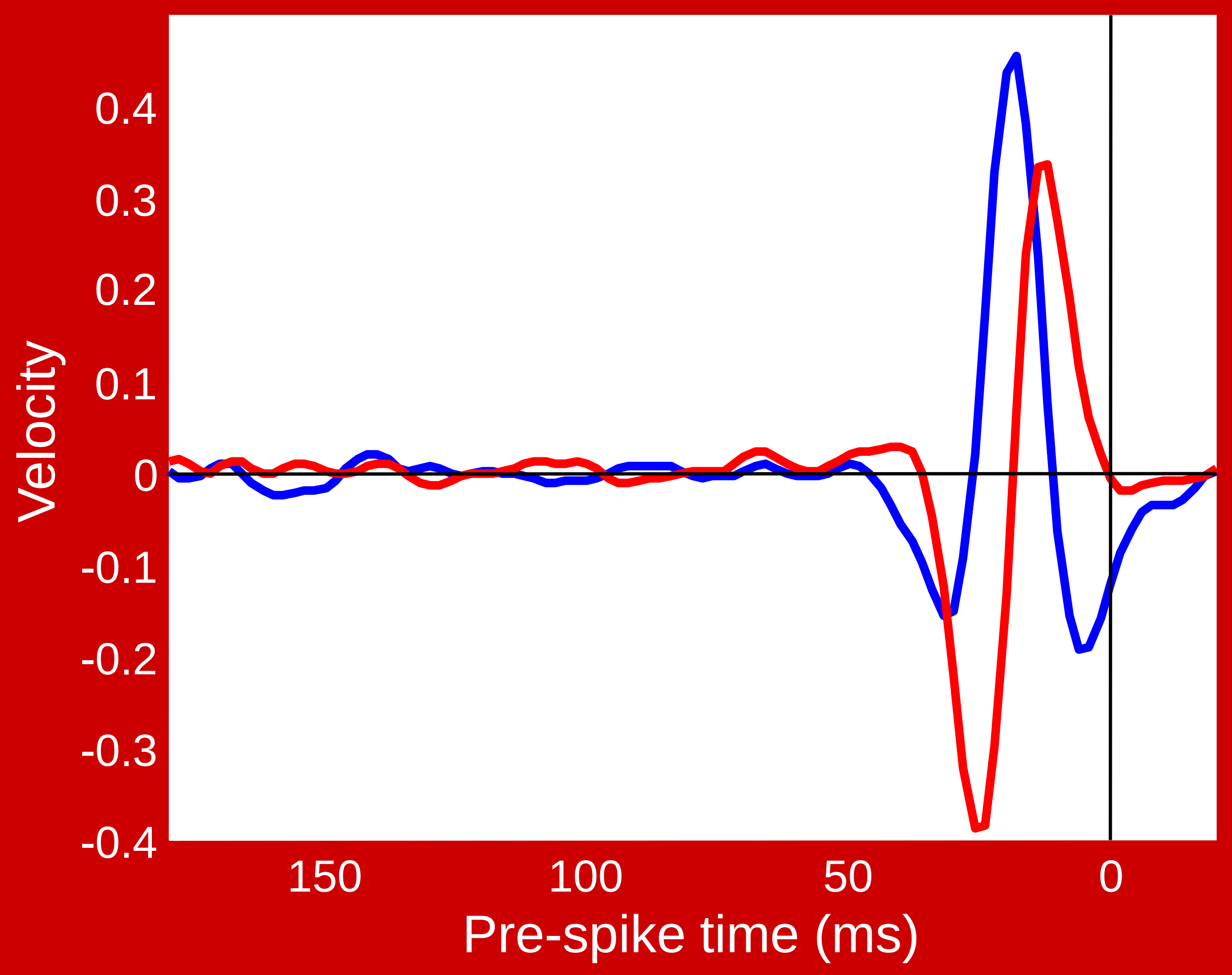


Eigenspectrum from barrel cortical neurons

Eigenspectrum

Leading modes

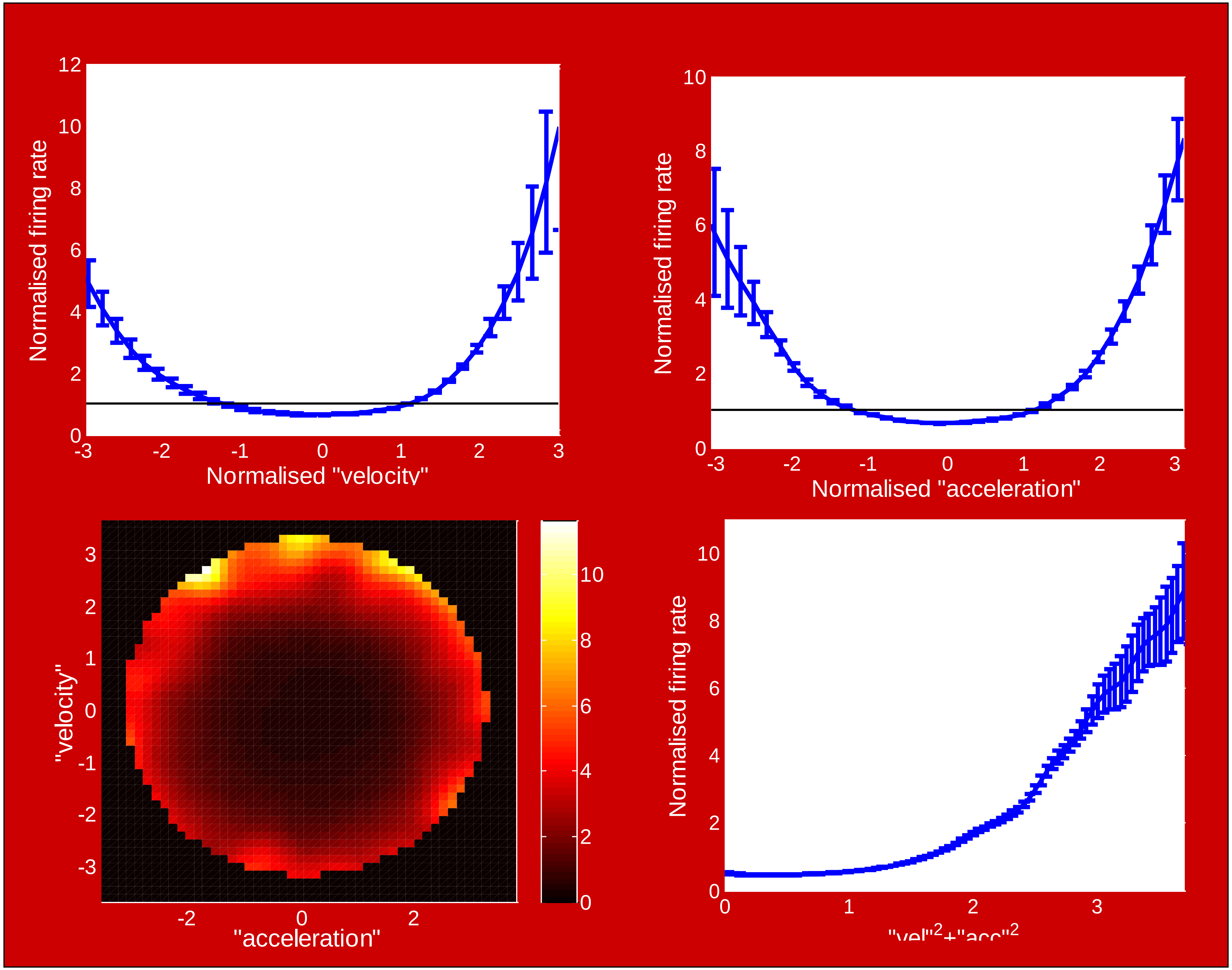




Input/output relations from barrel cortical neurons

Input/output relations wrt first two filters, alone:

and in quadrature:

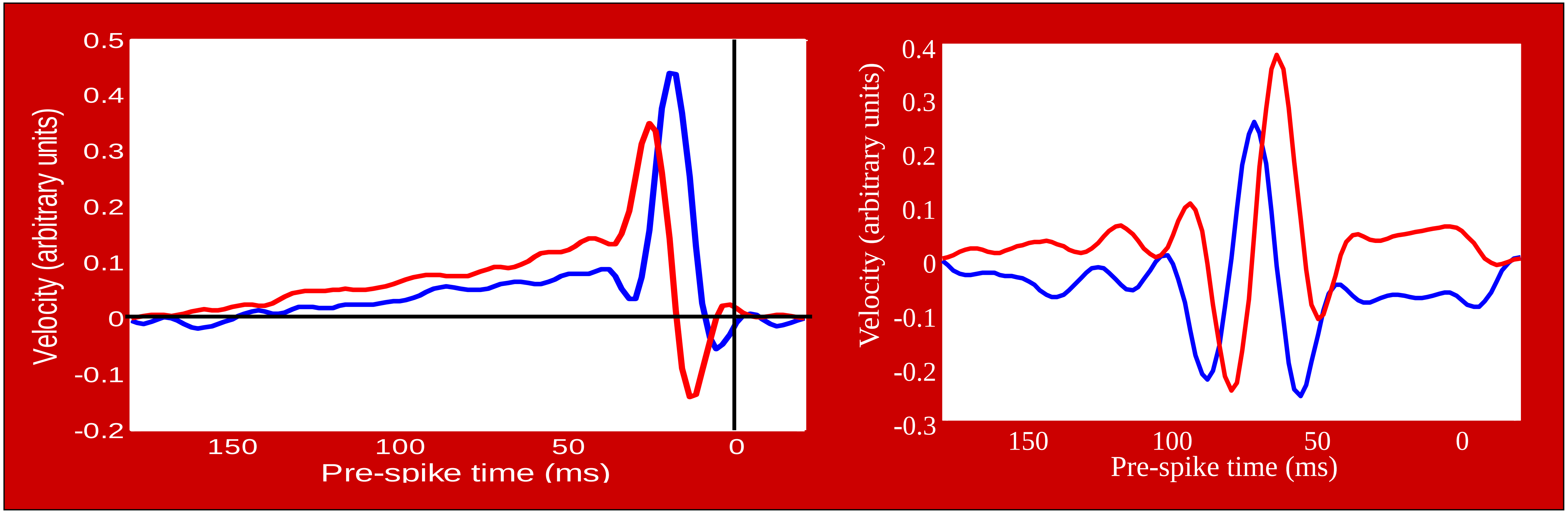


Less significant eigenmodes from barrel cortical neurons

How about the other modes?

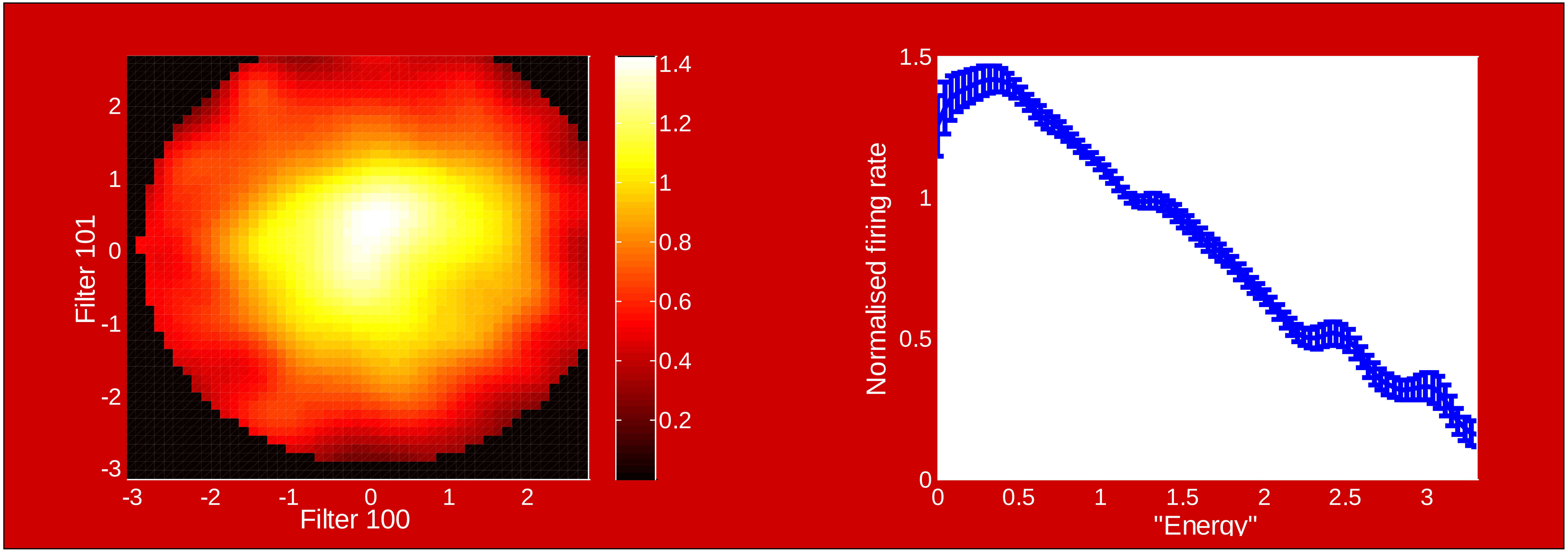
Next pair with +ve eigenvalues

Pair with -ve eigenvalues



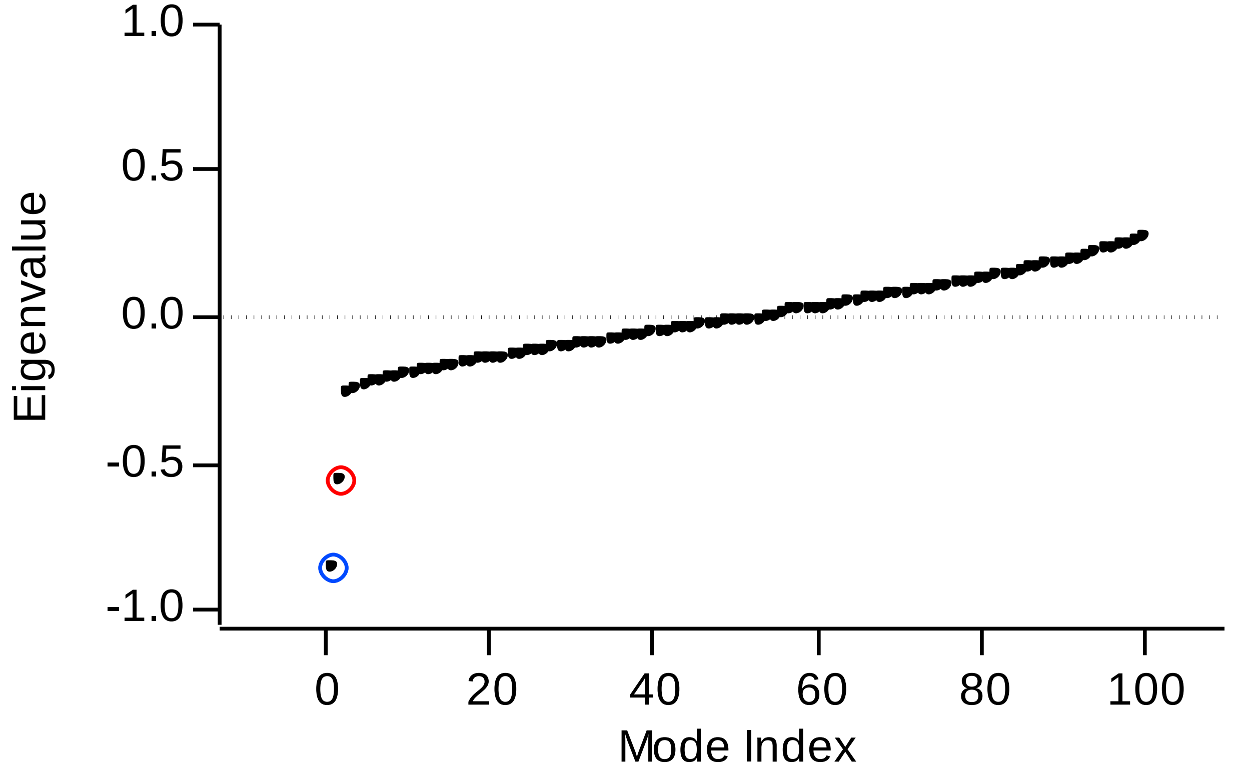
Negative eigenmode pair

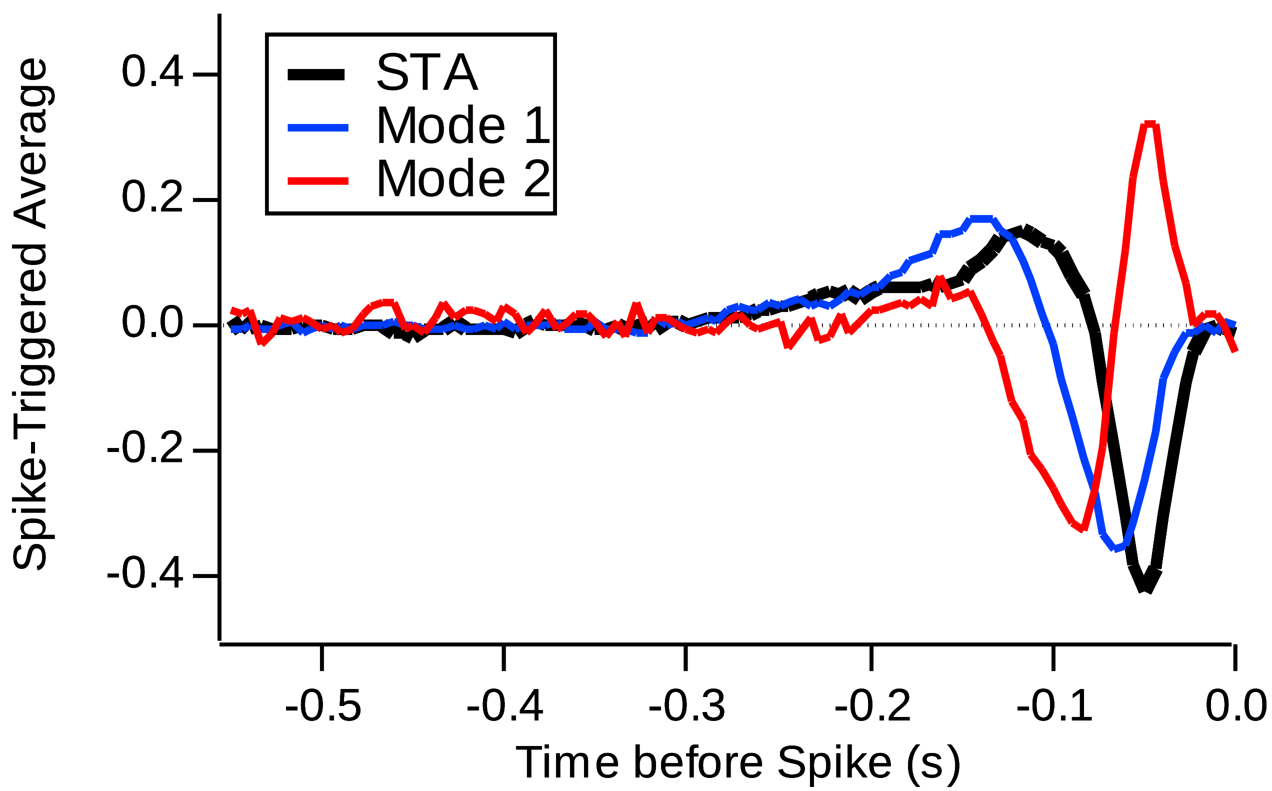
Input/output relations for negative pair

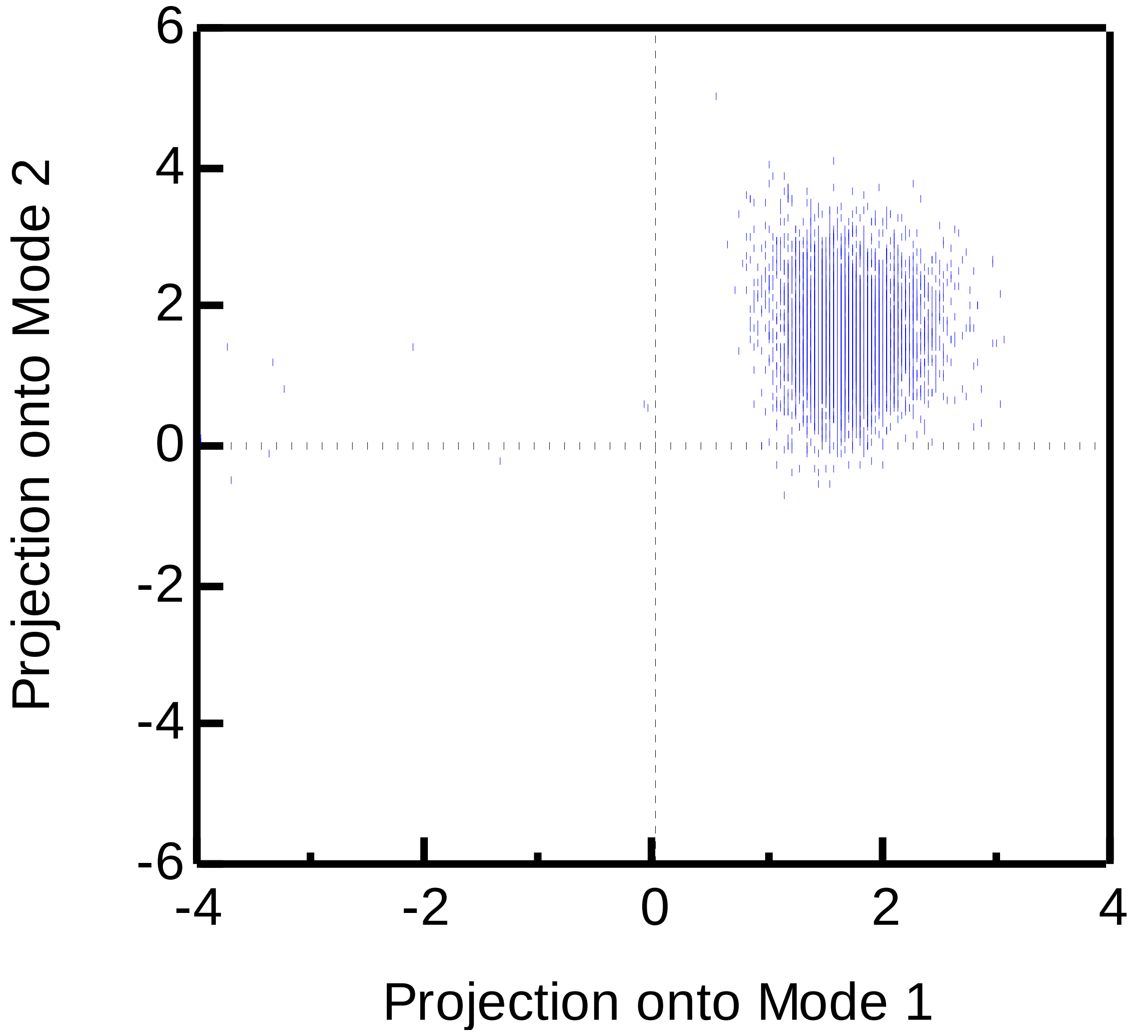


Firing rate *decreases* with increasing projection:
suppressive modes

Salamander retinal ganglion cells perform a variety of computations

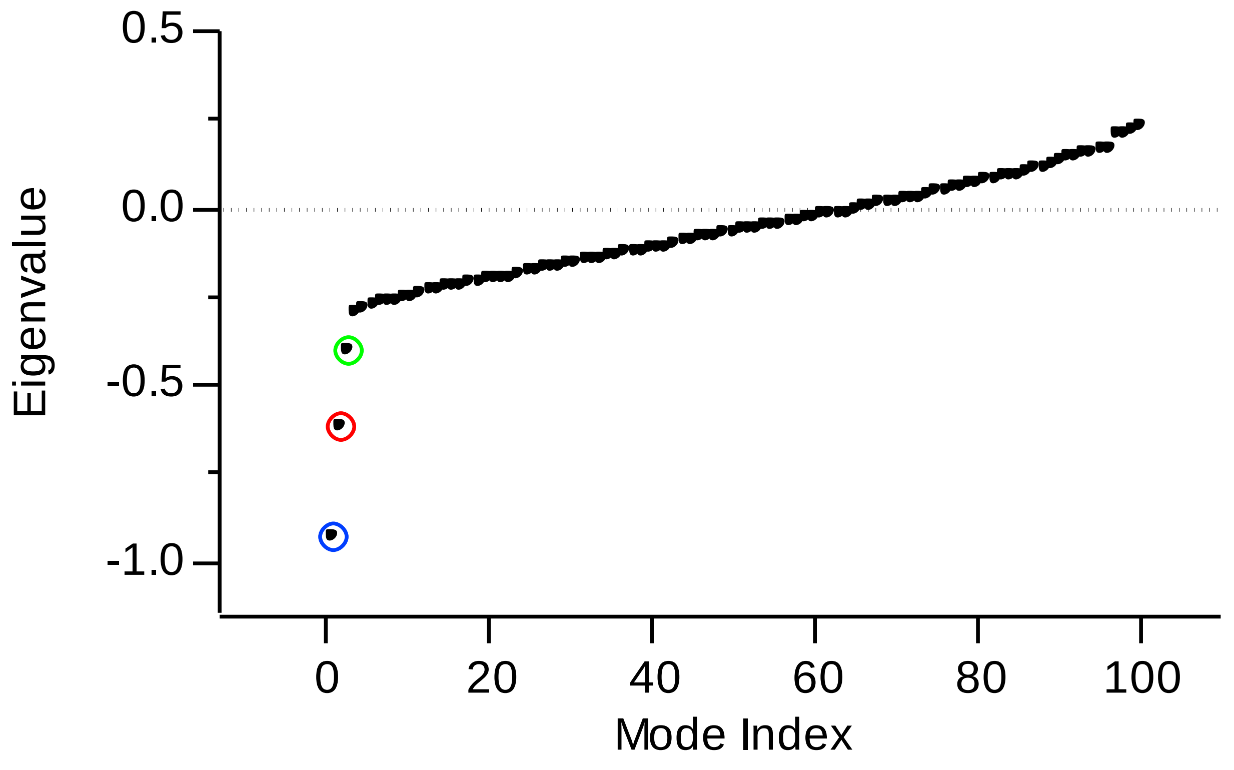


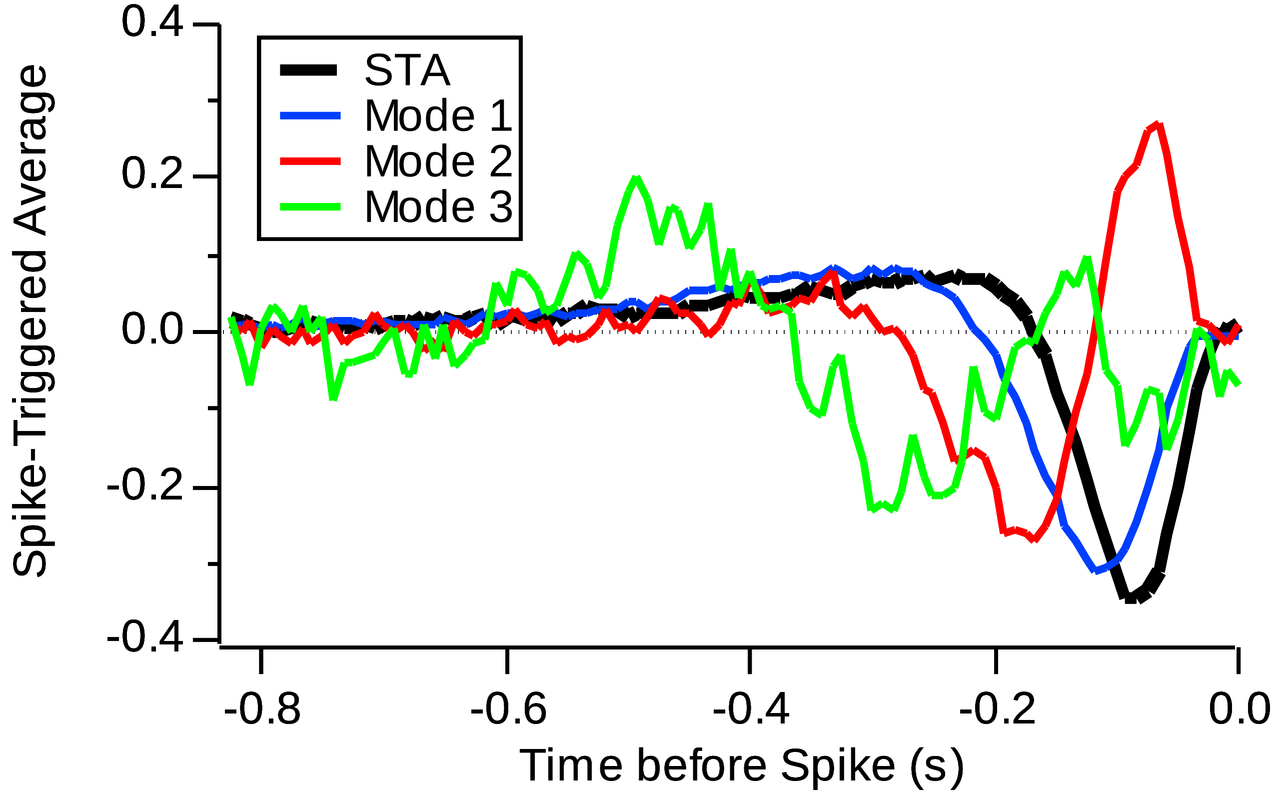


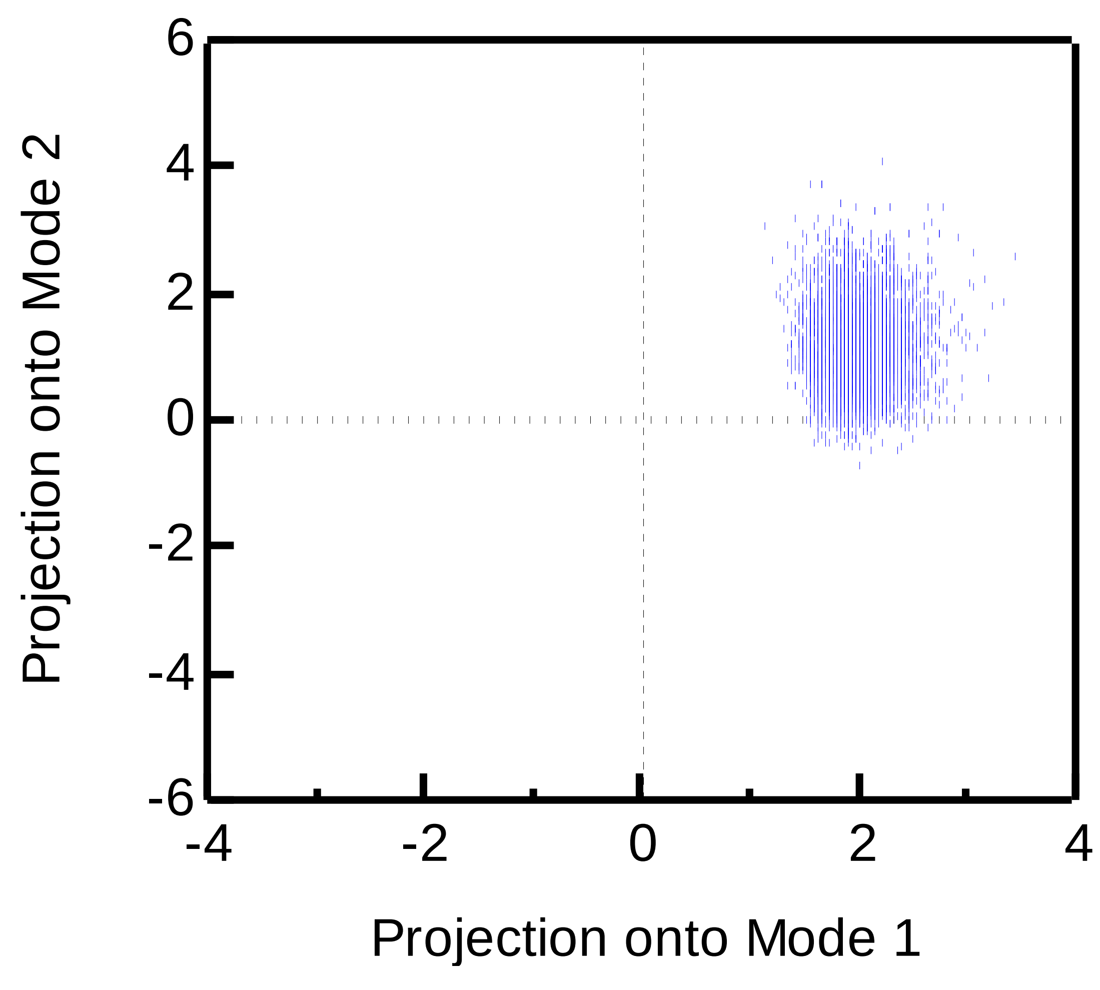


Michael Berry

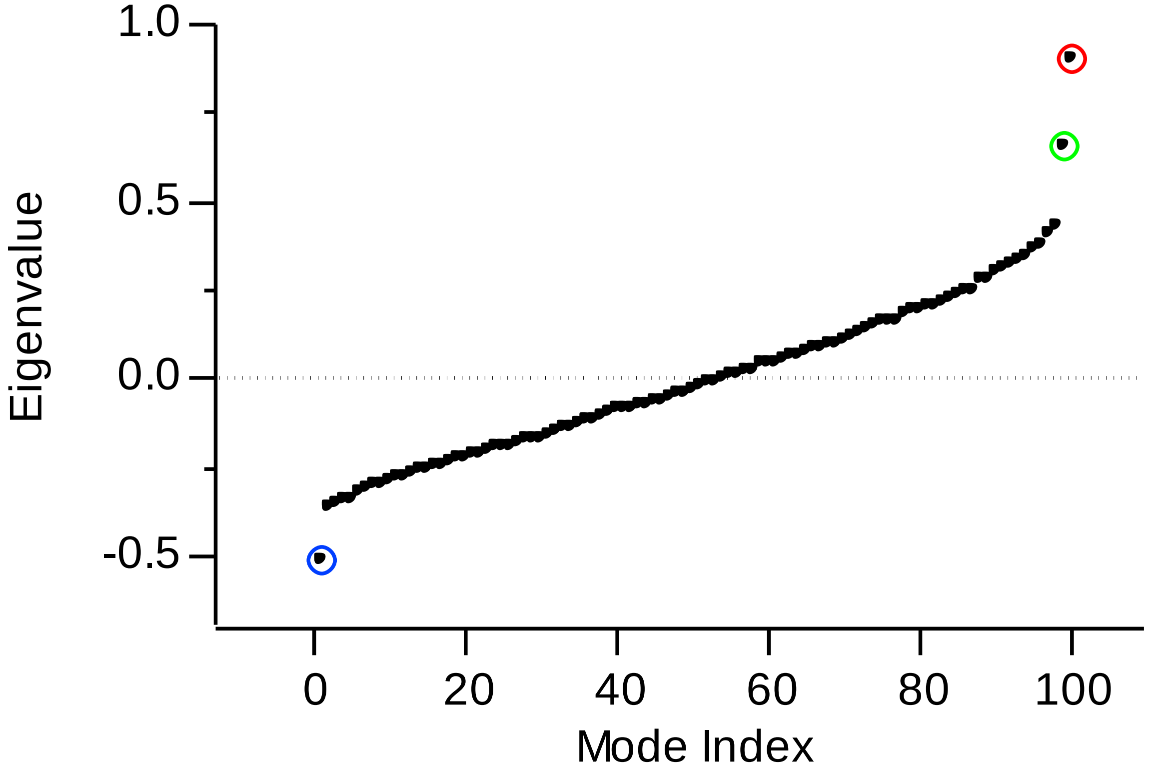
Almost filter-and-fire-like

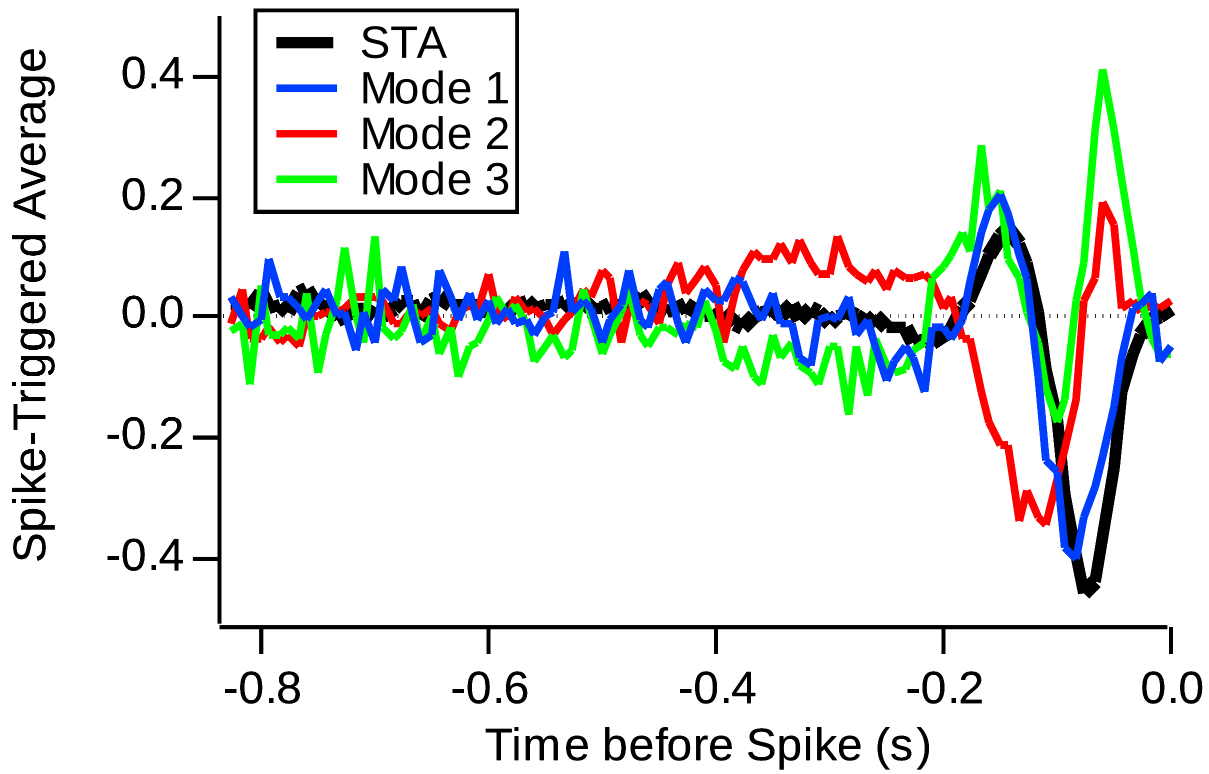


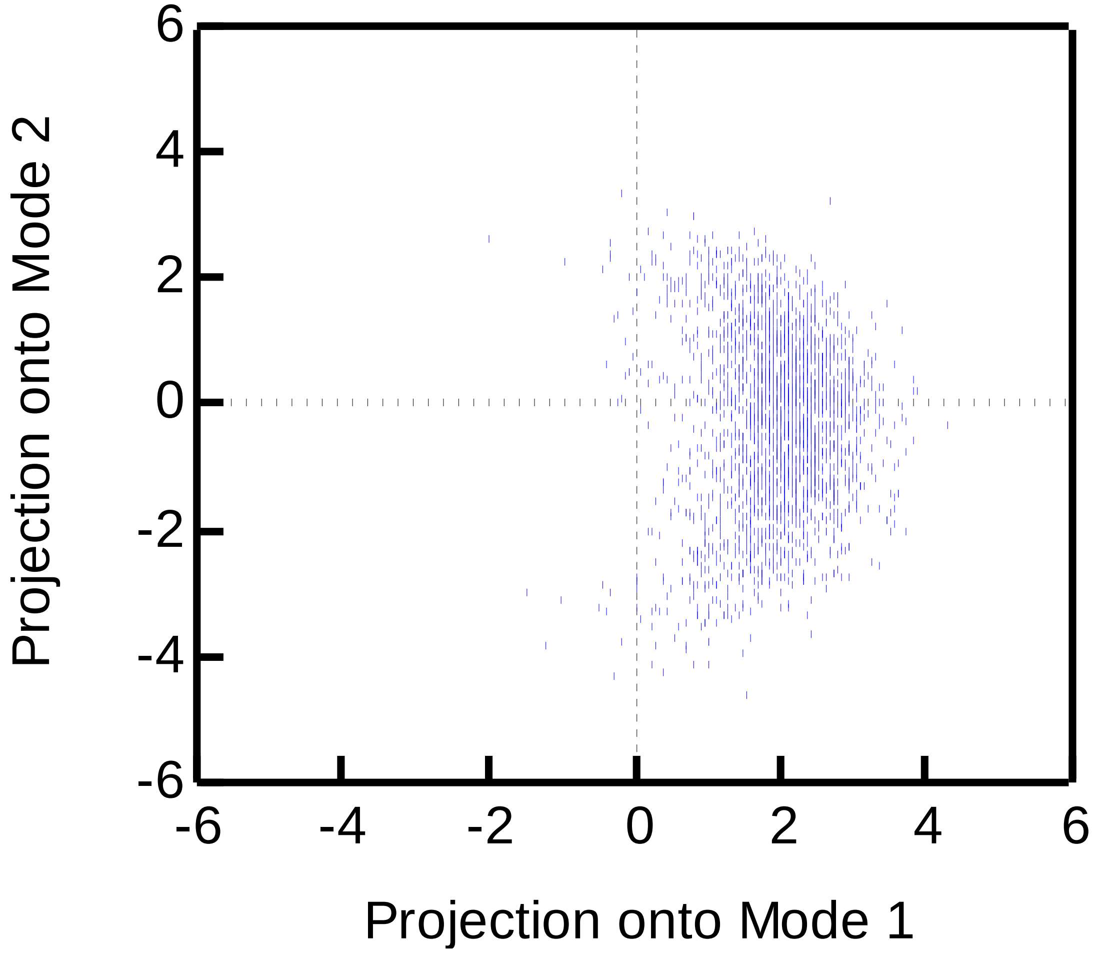




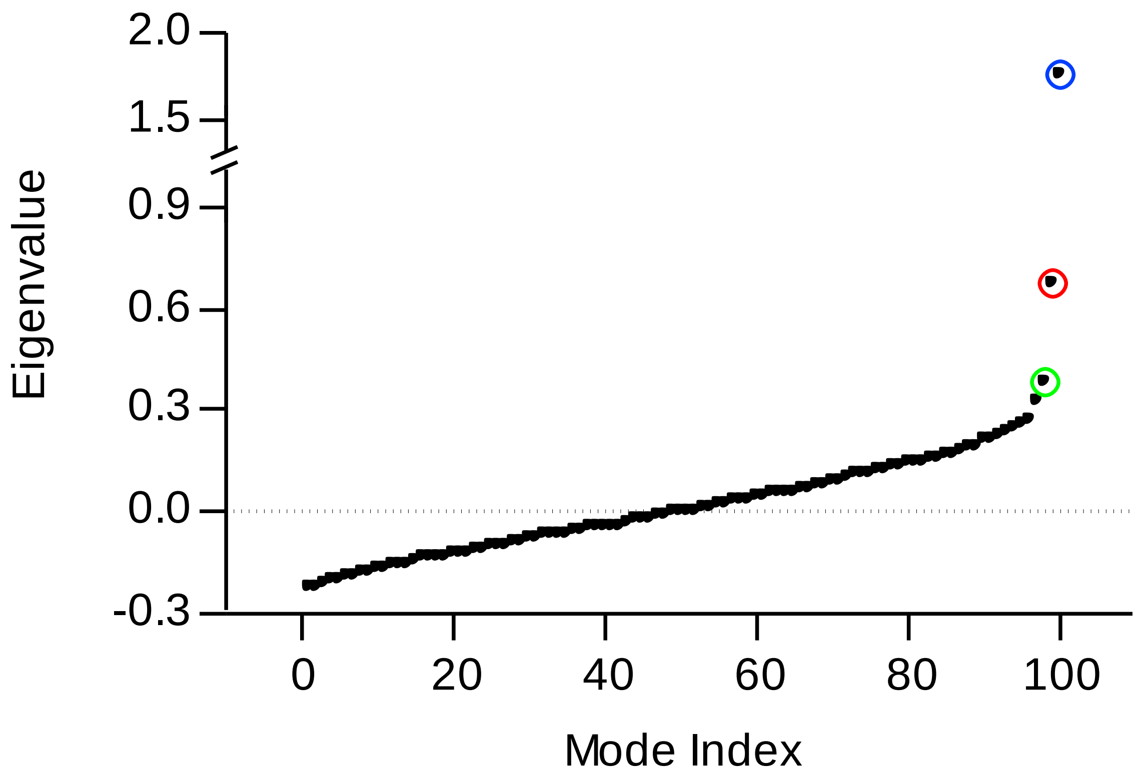
Not a threshold-crossing neuron

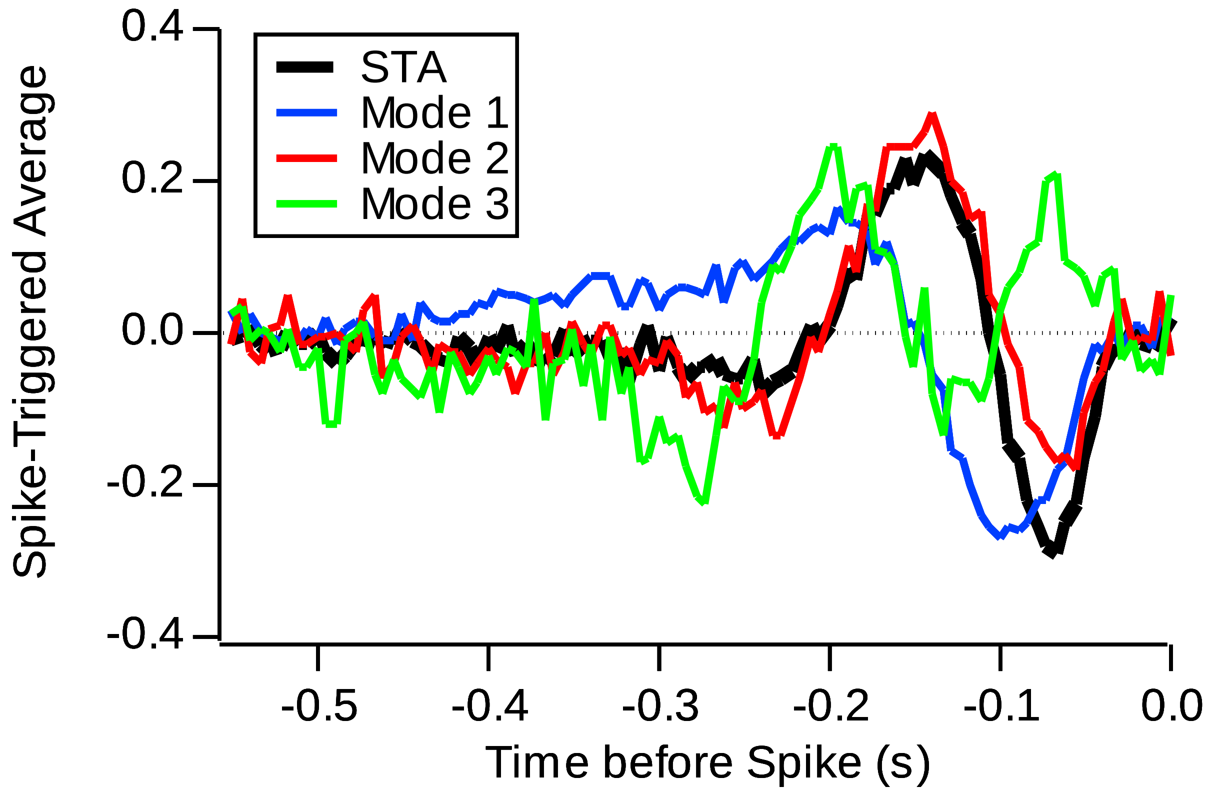


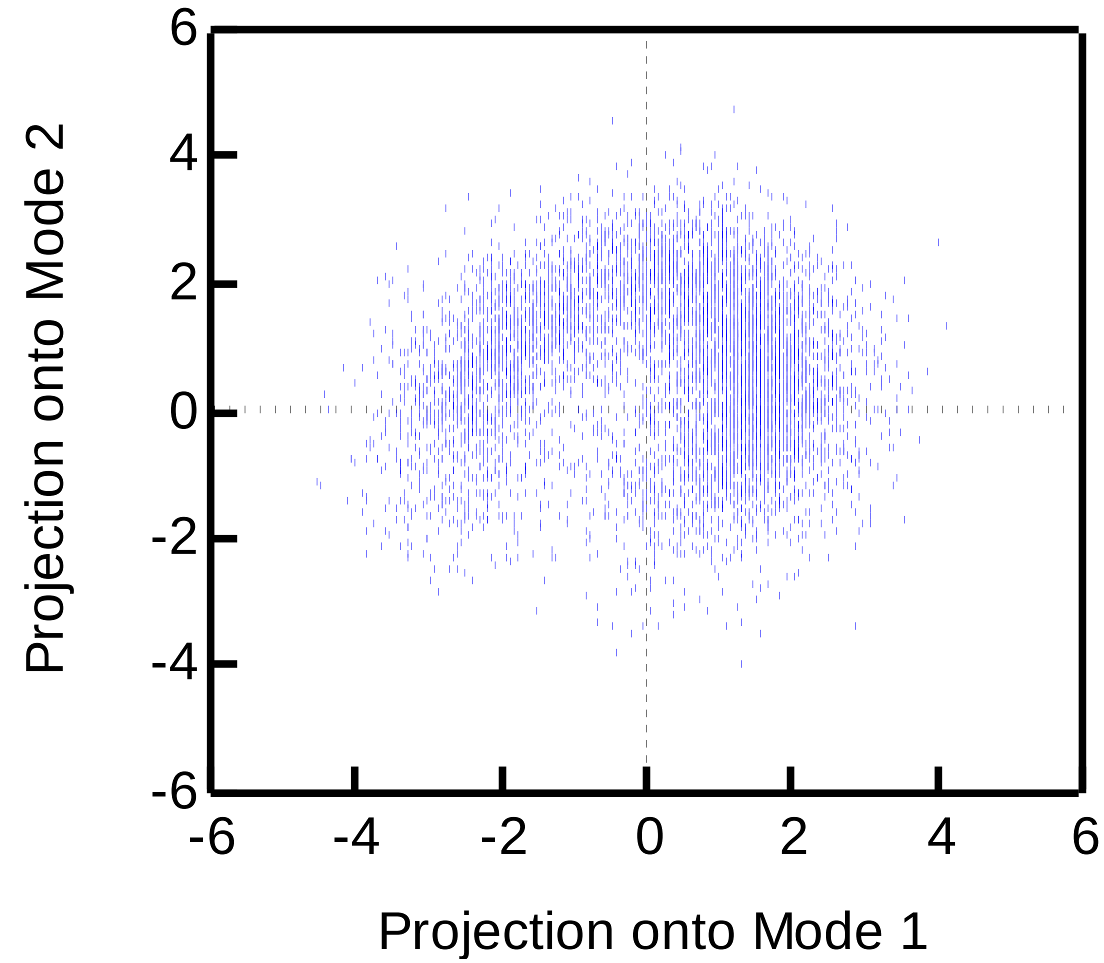




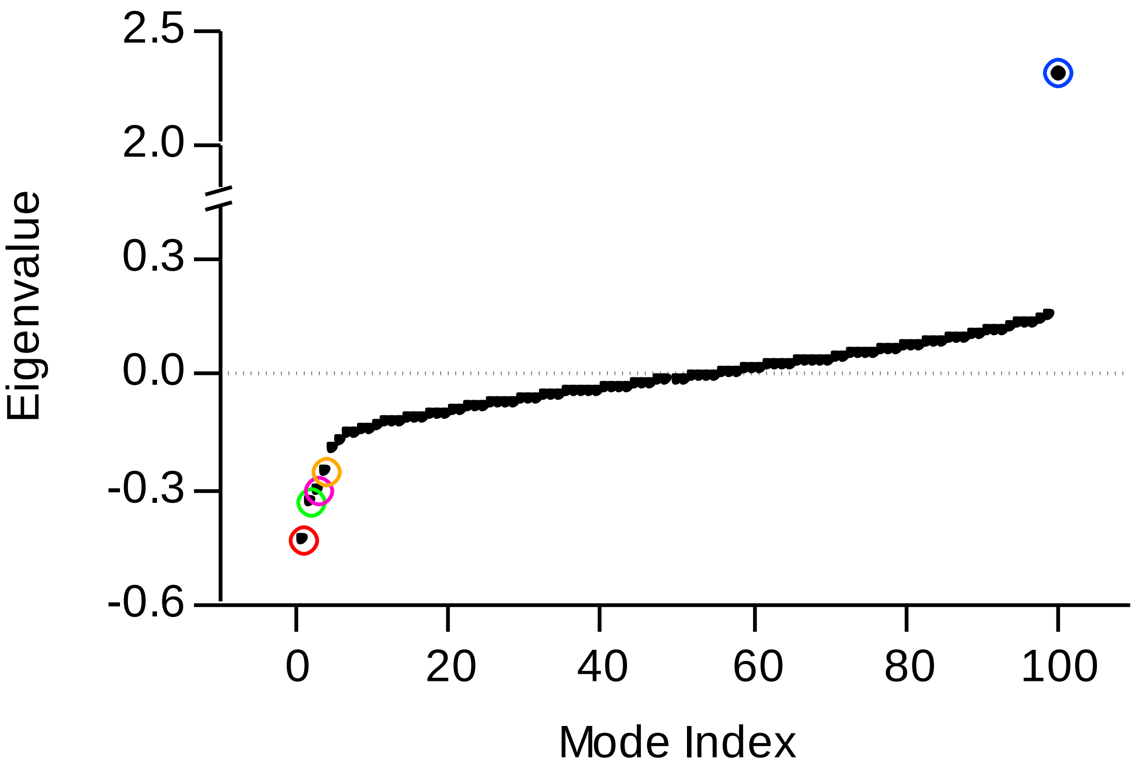
Complex cell like

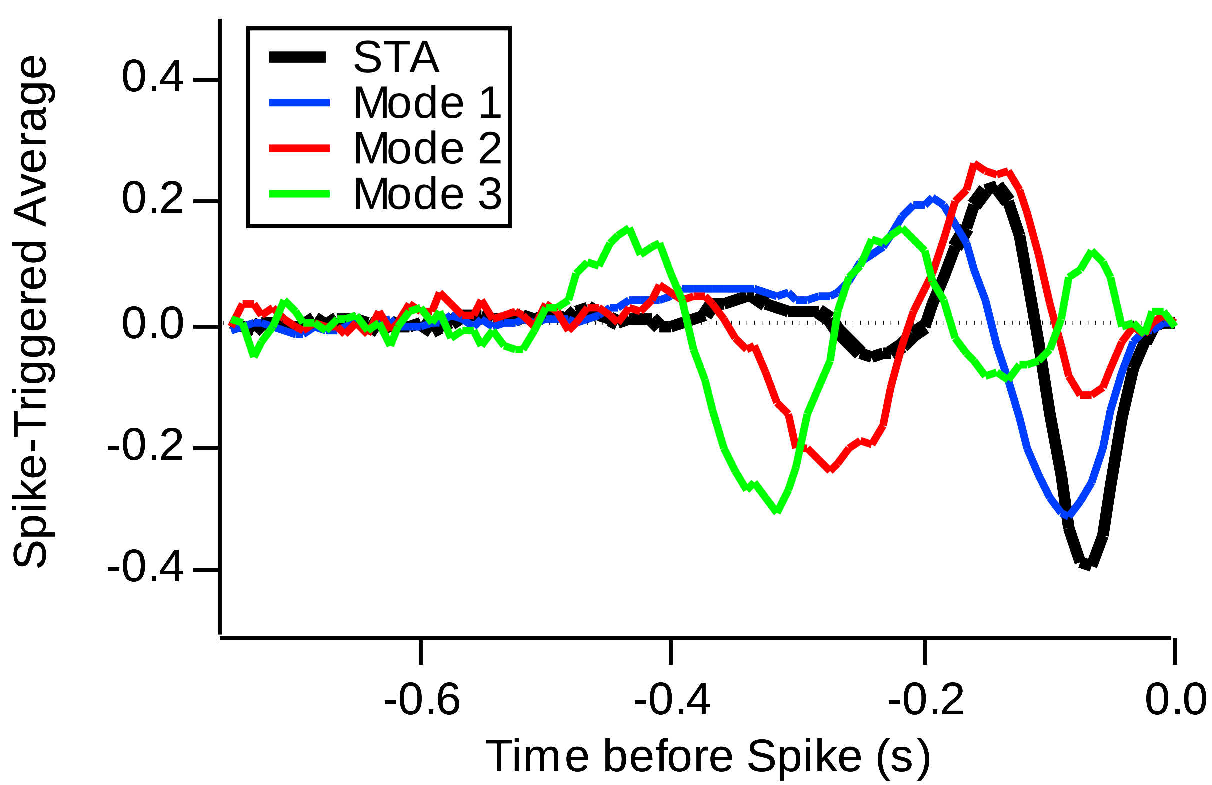


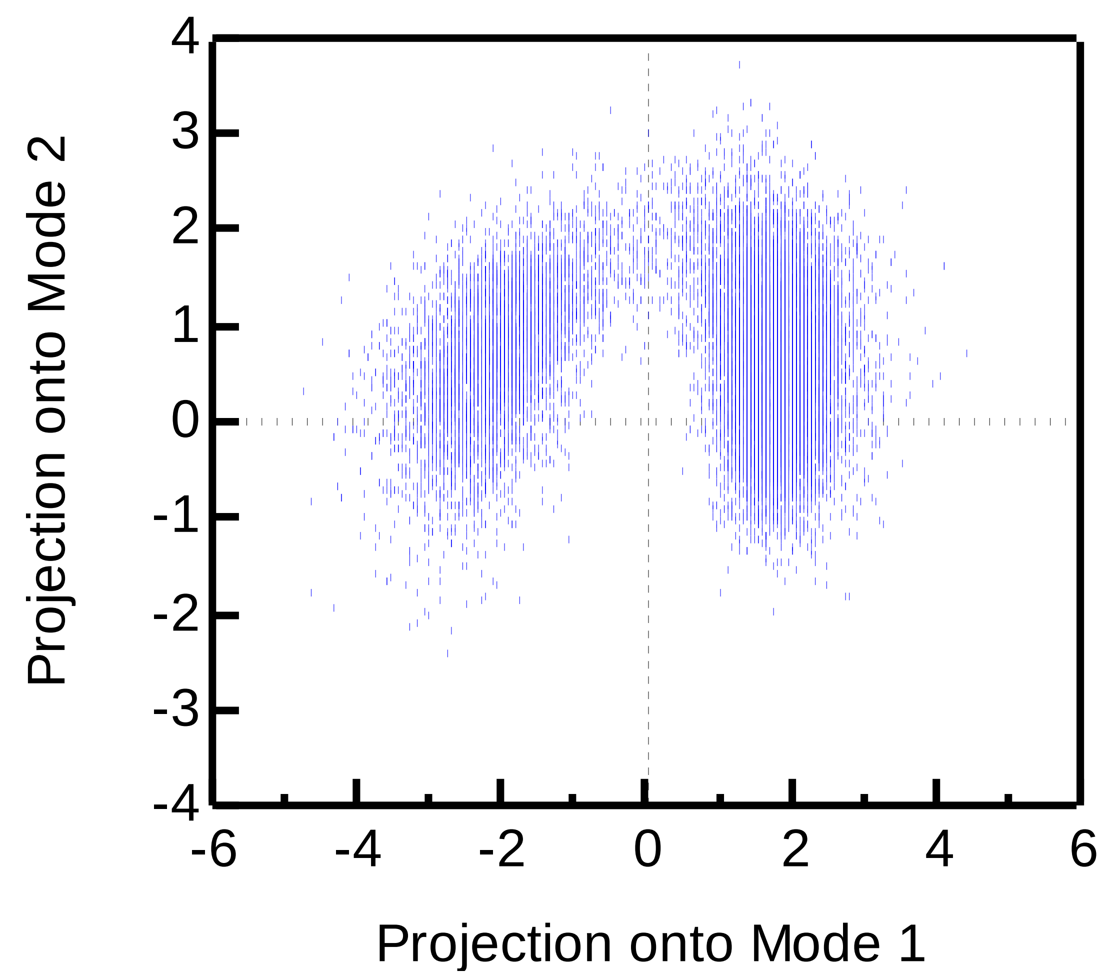




Bimodal: two separate features are encoded







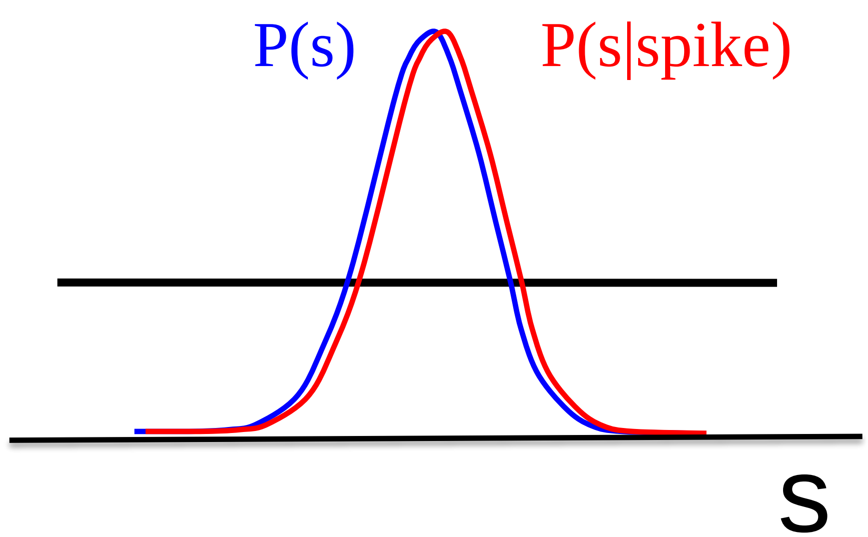
When have you done a good job?

- When the tuning curve over your variable is *interesting*.
- How to quantify interesting?

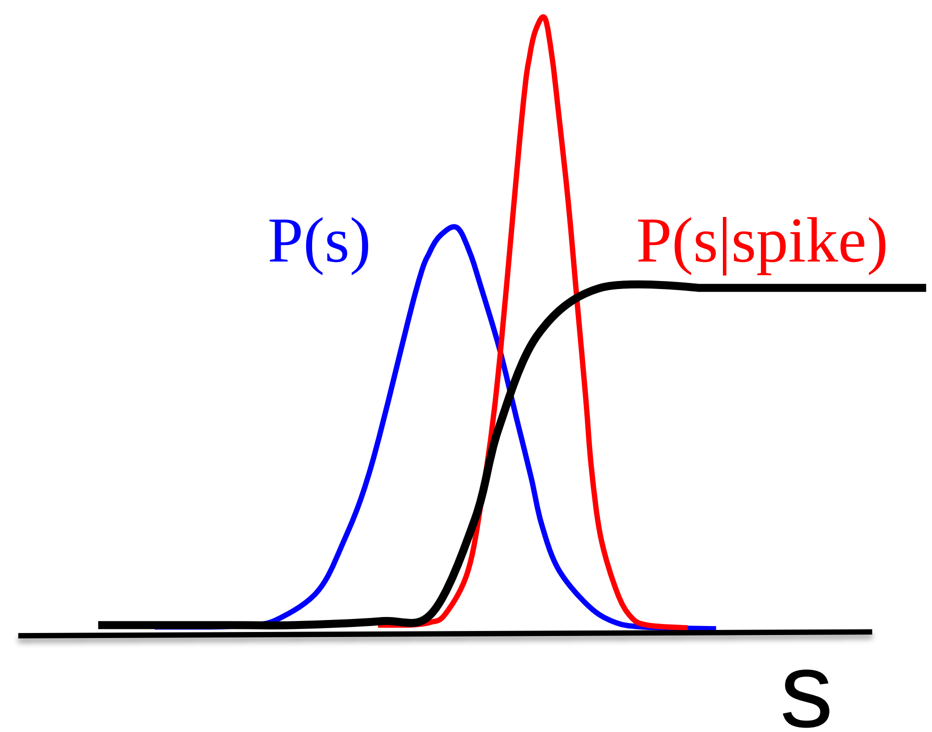
When have you done a good job?

Tuning curve: **$P(\text{spike}|s) = P(s|\text{spike})\, P(\text{spike}) / P(s)$**

Boring: spikes unrelated to stimulus



Interesting: spikes are selective

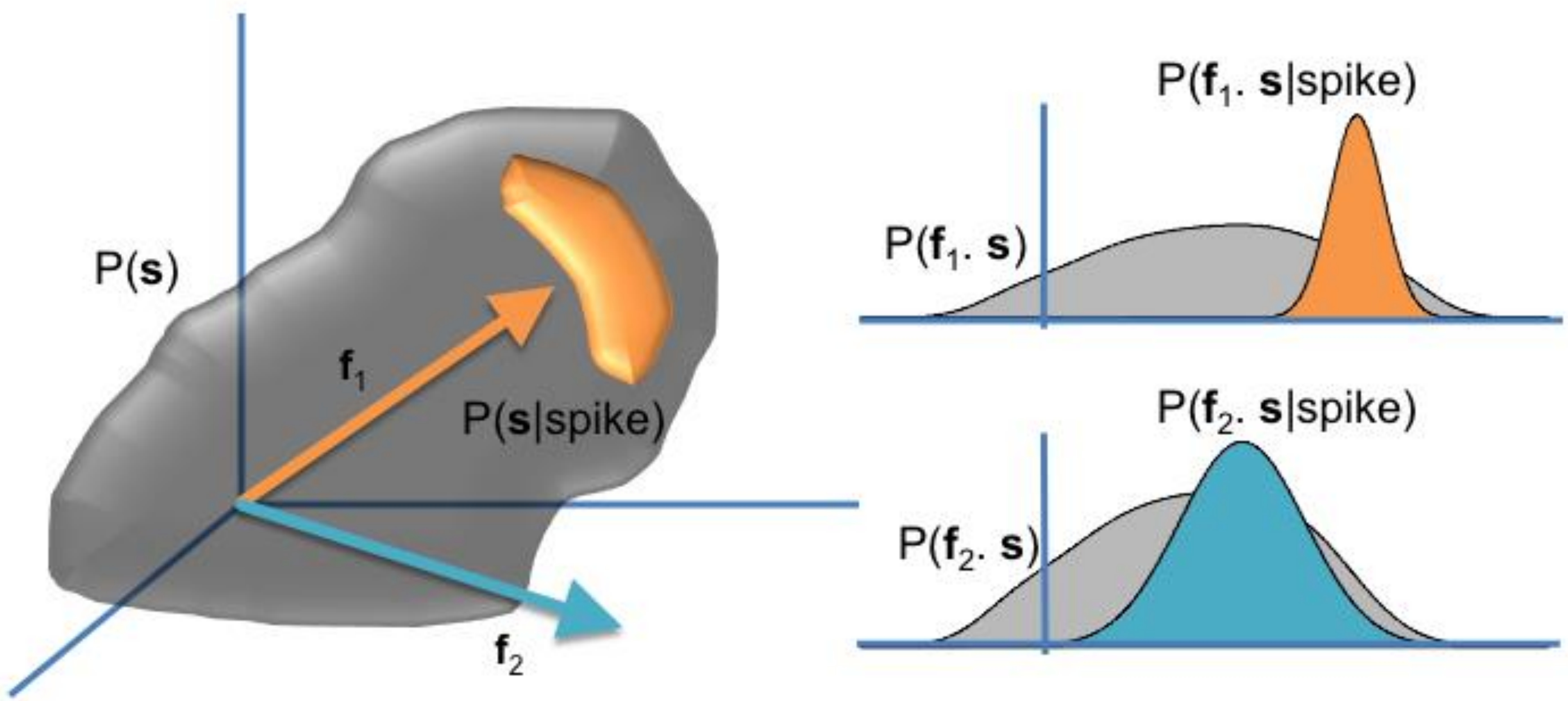


Goodness measure: $D_{KL}(P(s|\text{spike}) \mid P(s))$

Maximally informative dimensions

Sharpee, Rust and Bialek, Neural Computation, 2004

Choose filter in order to maximize D_{KL} between spike-conditional and prior distributions



Maximally informative dimensions

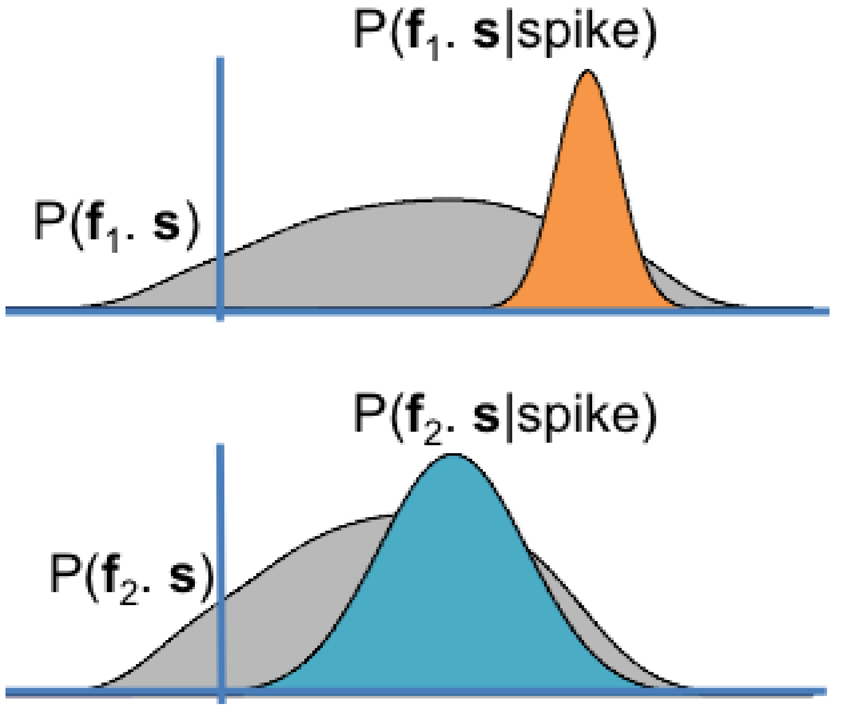
Sharpee, Rust and Bialek, Neural Computation, 2004

Choose filter in order to maximize D_{KL} between spike-conditional and prior distributions

Equivalent to maximizing mutual information between stimulus and spike

Does not depend on white noise inputs

Likely to be most appropriate for deriving models from natural stimuli

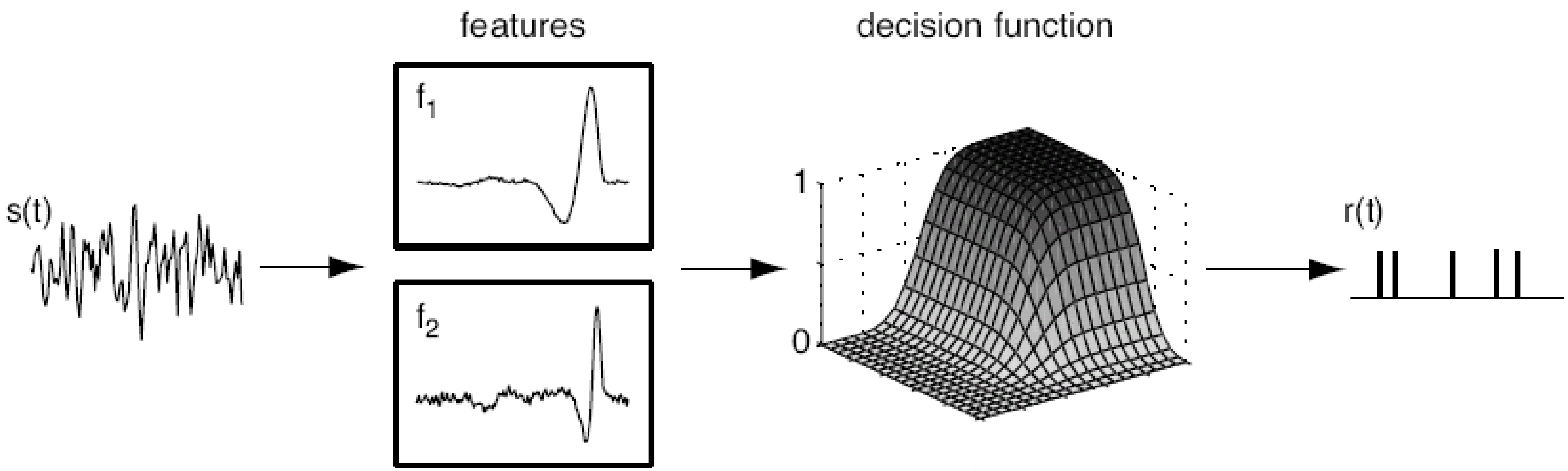


Finding relevant features

1. Single, best filter determined by the first moment
2. A family of filters derived using the second moment
3. Use the entire distribution: information theoretic methods

Removes requirement for Gaussian stimuli

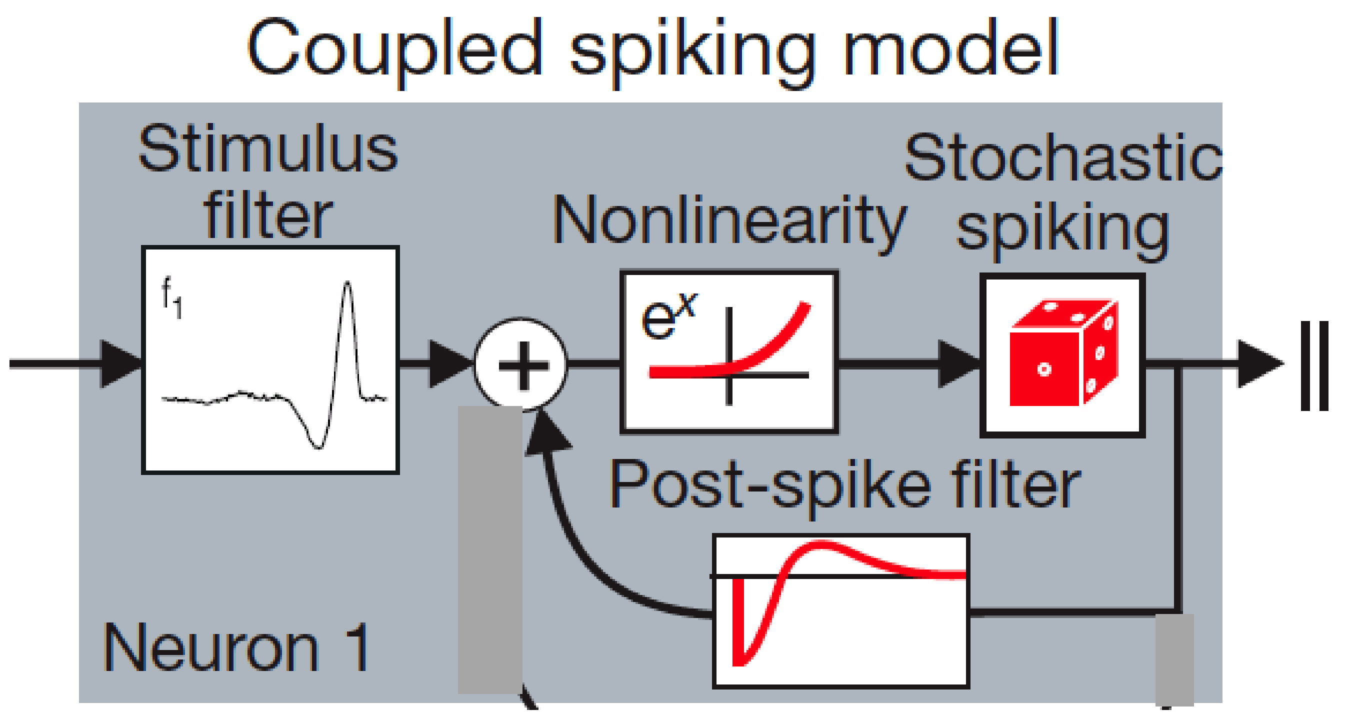
Less basic coding models



Linear filter*s* & nonlinearity: $r(t) = g(f_1{*}s, f_2{*}s, \ldots, f_n{*}s)$

…shortcomings?

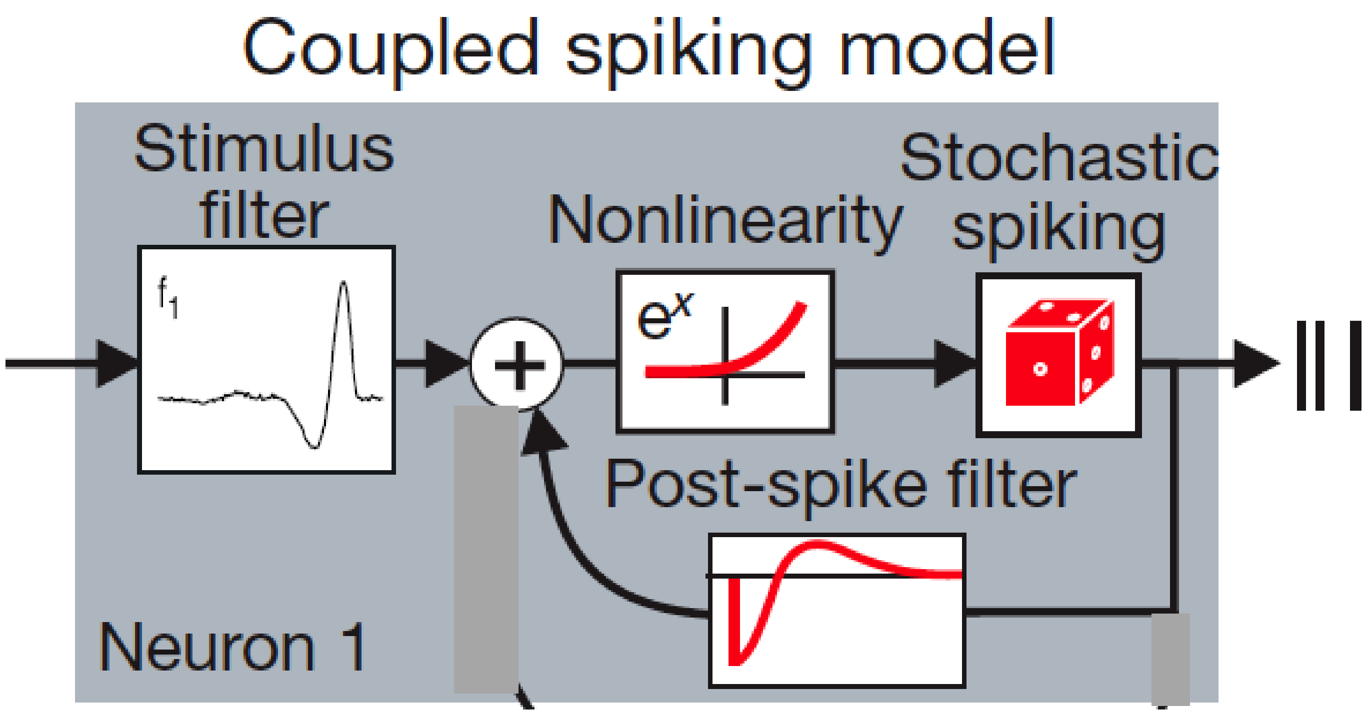
Less basic coding models



GLM: $r(t) = g(f_1 * s + f_2 * r)$

Pillow et al., *Nature* 2008; Truccolo, .., Brown, *J. Neurophysiol*. 2005

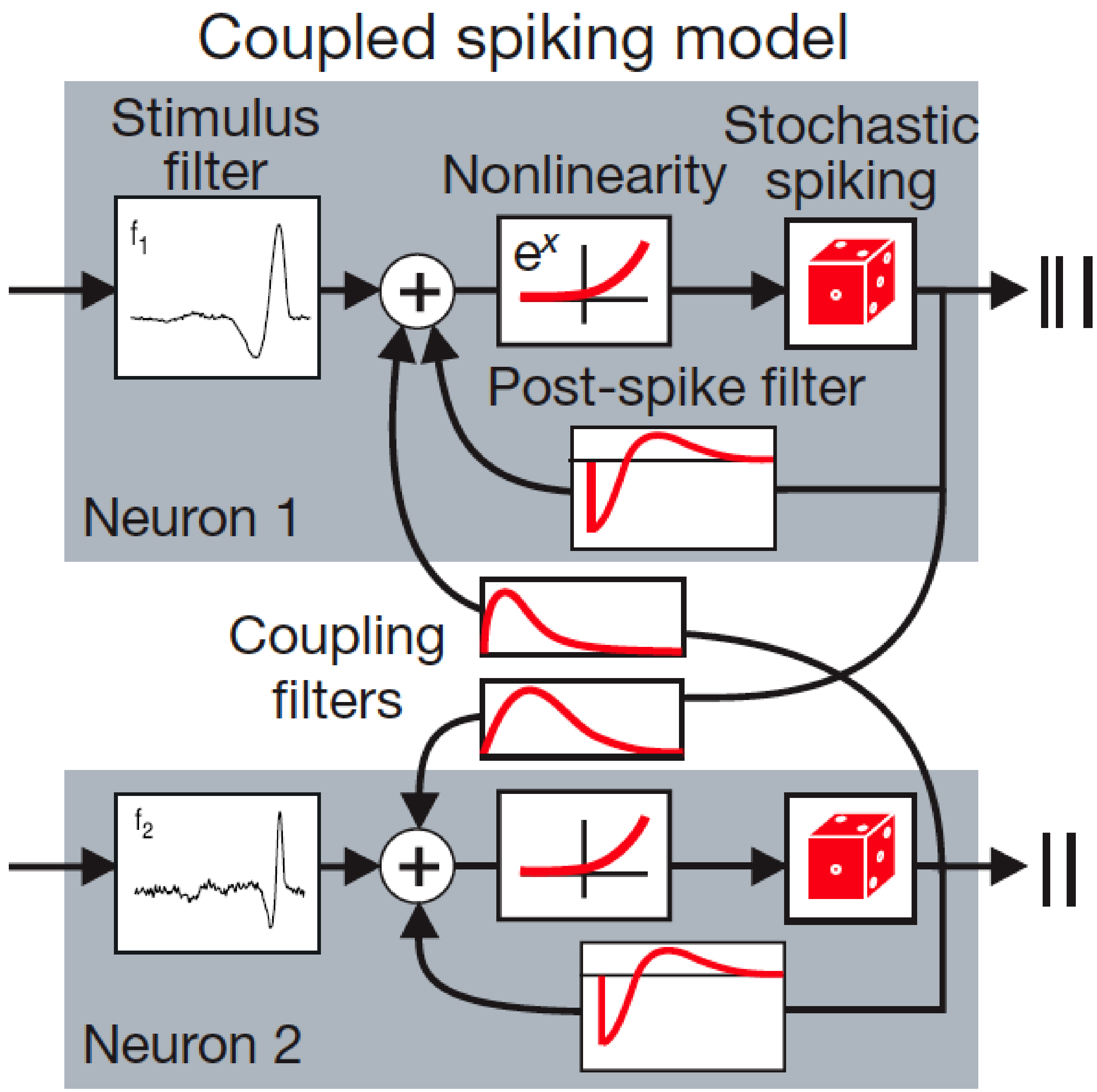
Less basic coding models



GLM: r(t) = g(f*s + h*r)

…shortcomings?

Less basic coding models



GLM: $r(t) = g(f_1 * s + h_1 * r_1 + h_2 * r_2 + \ldots)$

…shortcomings?