COMS30127: Computational Neuroscience

Lecture 11: Firing rates and receptive fields (f)

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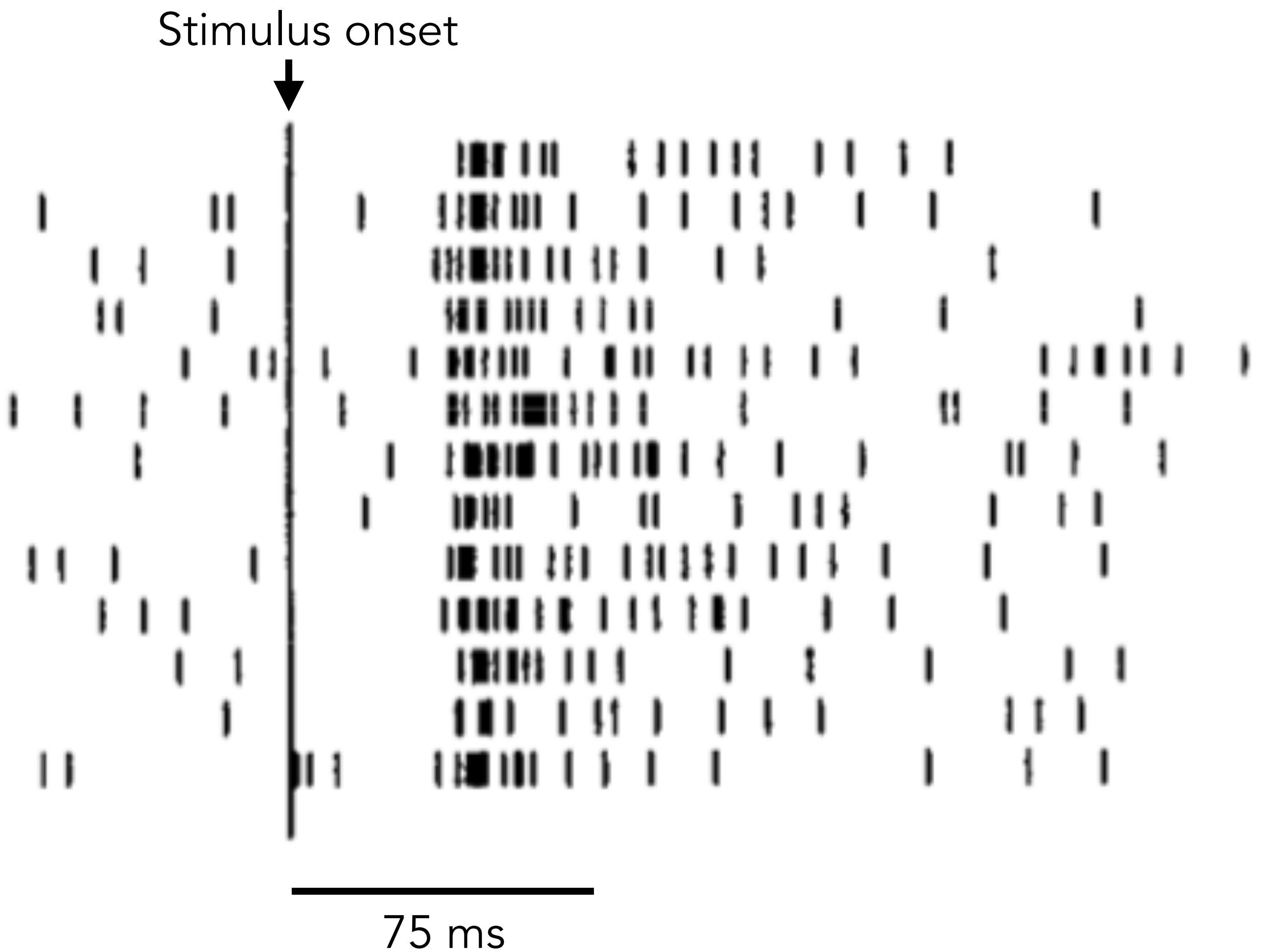
What we will cover today

- What are firing rates?
- How do we measure them?
- How do we model them?
- What is rate coding?
- Tuning curves and receptive fields.
- Rate decoding.

What are firing rates?



Raster plot of spikes from a single monkey visual cortex neuron from repeated presentations (each row) of a visual stimulus (oriented grating).

Note the increase in the neuron's firing rate ~50 ms after stimulus onset.

[Motter, *J Neurophysiol*, 1993]

Properties of a rate

- Non-negative (can't fire at less than 0 Hz).
- Continuous, $\in \mathbb{R}_{\geq 0}$
- Usually latent (hidden) variables rather than directly measurable.

Properties of neural firing rates

- Typically low on average (0.1— 10 spikes per second; Hz)
- Varies systematically across brain regions (pyramidal cells in superficial somatosensory cortex fire ~0.1 Hz, while Purkinje neurons in the cerebellum fire ~50 Hz spontaneously).
- Very heterogeneous even within a population of neurons of the same type (typically follows a log-normal distribution)

How do we measure firing rates?

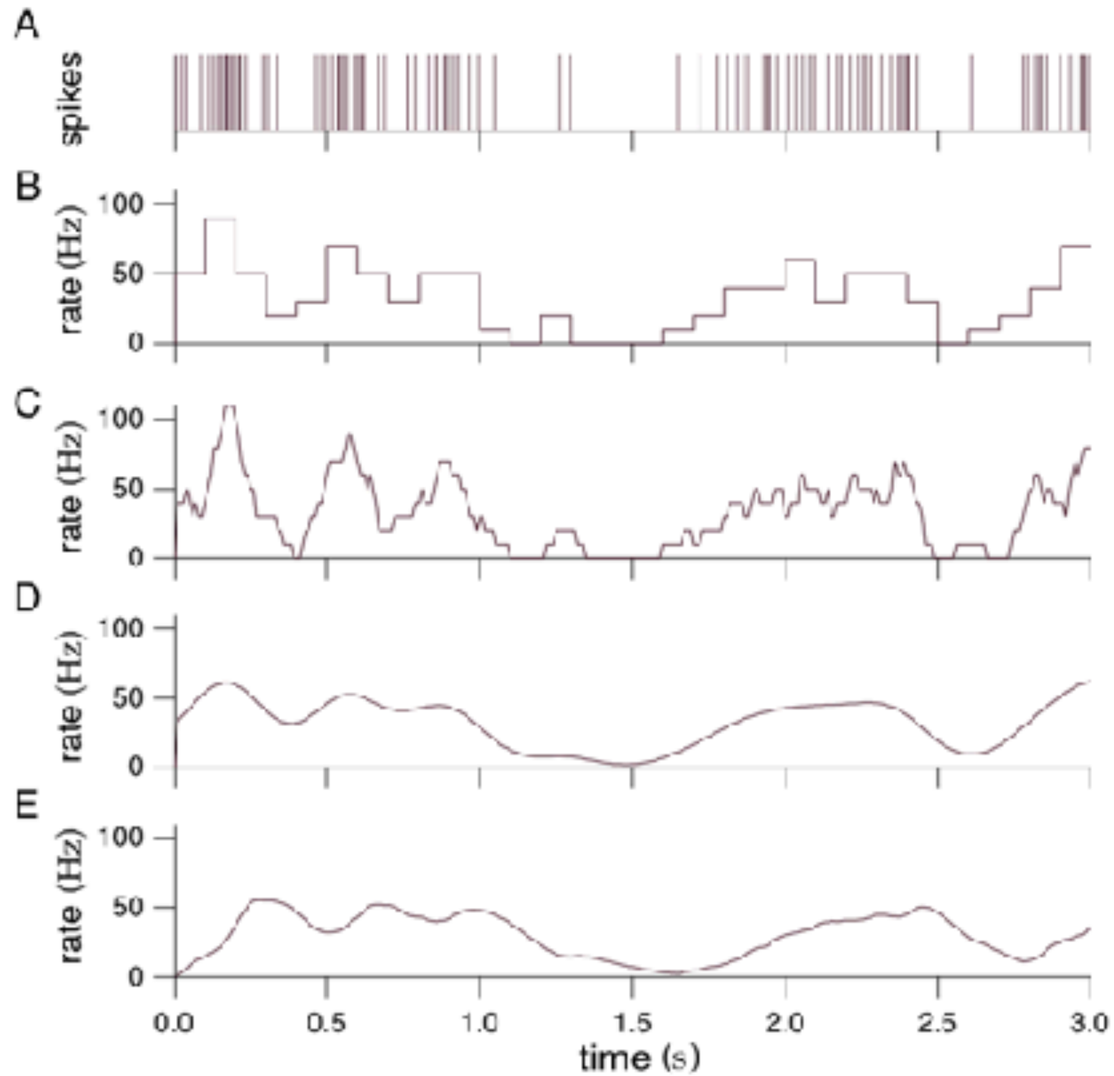


Figure 1.4: Firing rates approximated by different procedures. A) A spike train from a neuron in the inferior temporal cortex of a monkey recorded while that animal watched a video on a monitor under free viewing conditions. B) Discrete-time firing rate obtained by binning time and counting spikes with $\Delta t = 100$ ms. C) Approximate firing rate determined by sliding a rectangular window function along the spike train with $\Delta t = 100$ ms. D) Approximate firing rate computed using a Gaussian window function with $\sigma_t = 100$ ms. E) Approximate firing rate for an α function window with $1/\alpha = 100$ ms. (Data from Baddeley et al., 1997.)

[Dayan & Abbott, 2001]

How do we model firing rates?

- Represent a neuron's firing rate as a scalar variable, usually denoted x or r.
- Typically we are interested in studying the dynamics of a network of such neurons.
- Write down equation for the dynamics, for example:

$$\tau \frac{dx_i}{dt} = -x_i + g\left(\sum_{j \neq i}^{N} w_{ij} x_j\right)$$

where τ is a time constant, w_{ij} is the strength of the synapse from neuron j to neuron i, and g is some nonlinear function, often a sigmoid such as tanh.

Rate coding

https://www.youtube.com/watch?v=lfNVv0A8QvI

Rate coding

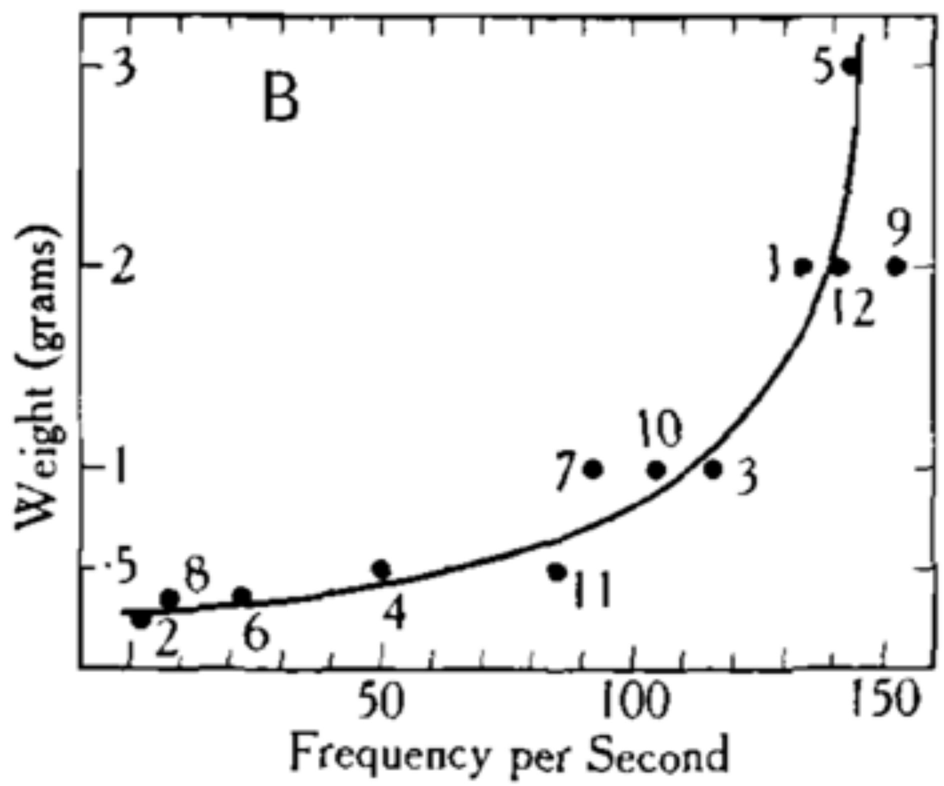
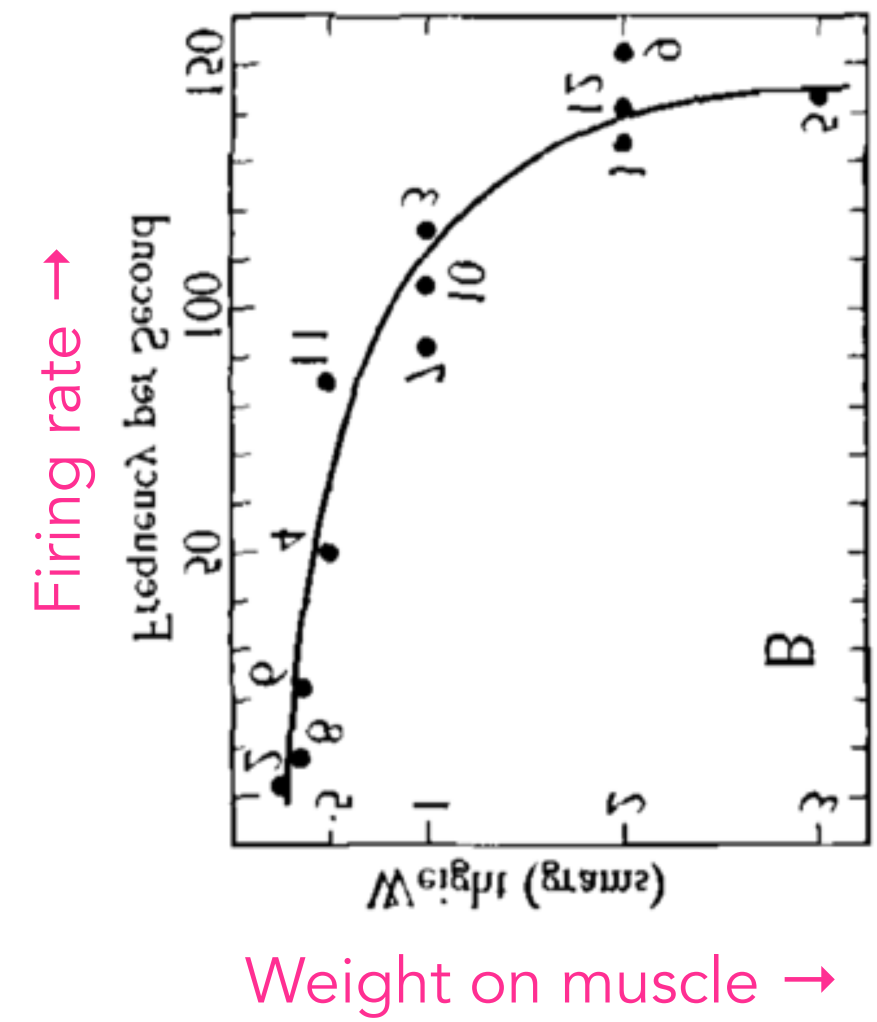


FIG. 25. FROG'S STERNO-CUTANEOUS PREPARATION. RELATION BETWEEN INTENSITY OF STIMULUS (WEIGHT ON MUSCLE) AND FREQUENCY OF DISCHARGE.



[*The Basis of Sensation*, Adrian, 1928]

Rate coding over time

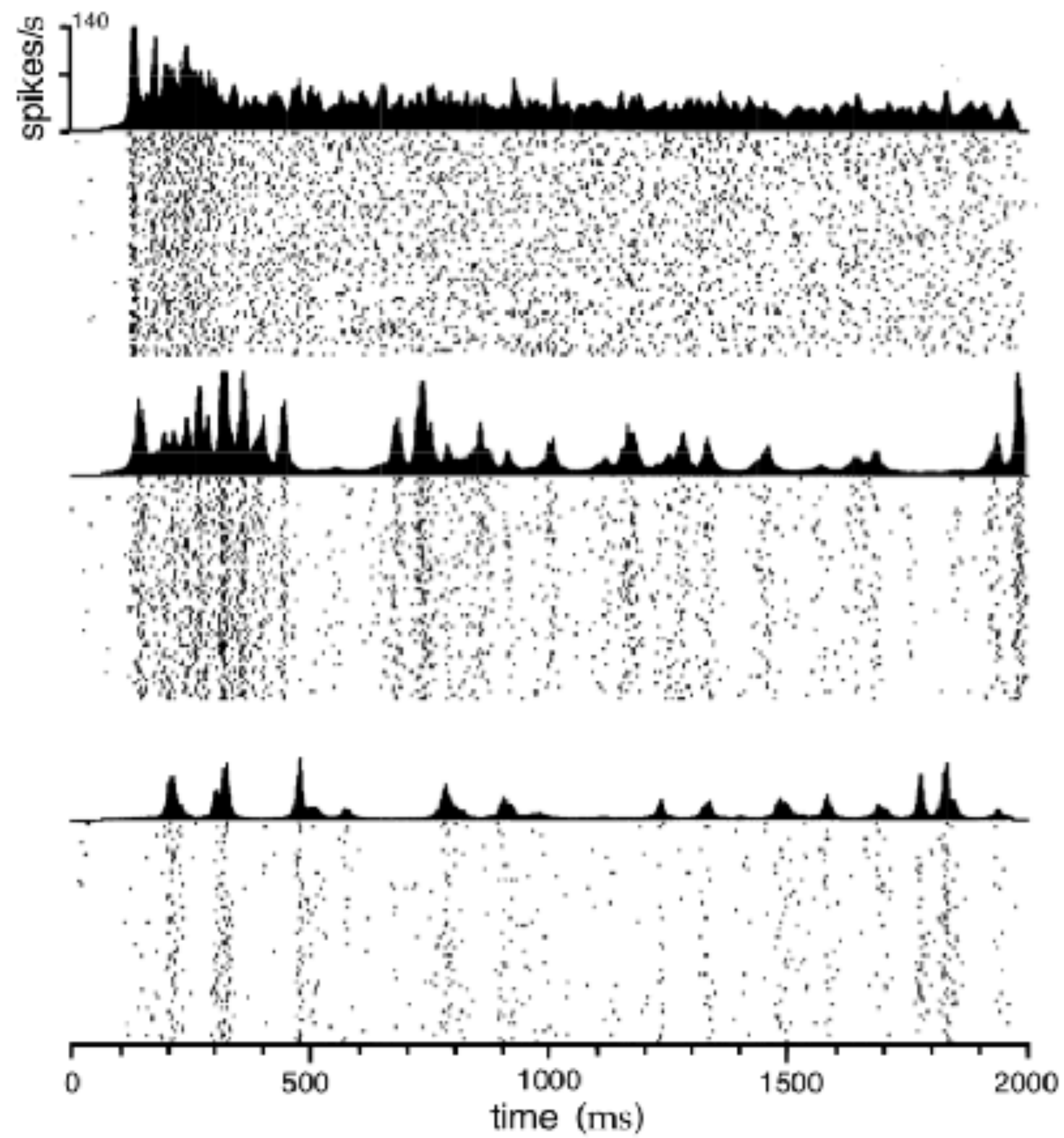
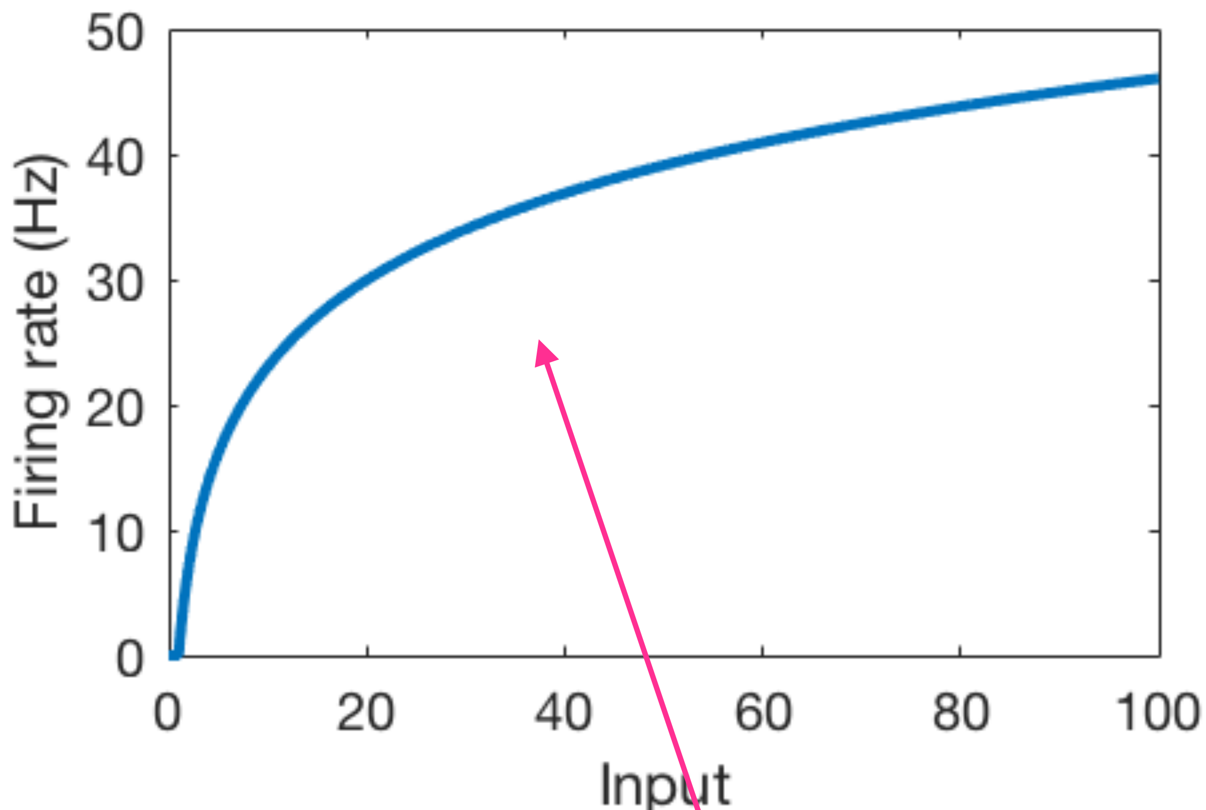


Figure 1.19: Time-dependent firing rates for different stimulus parameters. The rasters show multiple trials during which an MT neuron responded to the same moving random dot stimulus. Firing rates, shown above the raster plots, were constructed from the multiple trials by counting spikes within discrete time bins and averaging over trials. The three different results are from the same neuron but using different stimuli. The stimuli were always patterns of moving random dots but the coherence of the motion was varied (see chapter 3 for more information about this stimulus). (Adapted from Bair and Koch, 1996.)

[Dayan & Abbott, 2001]

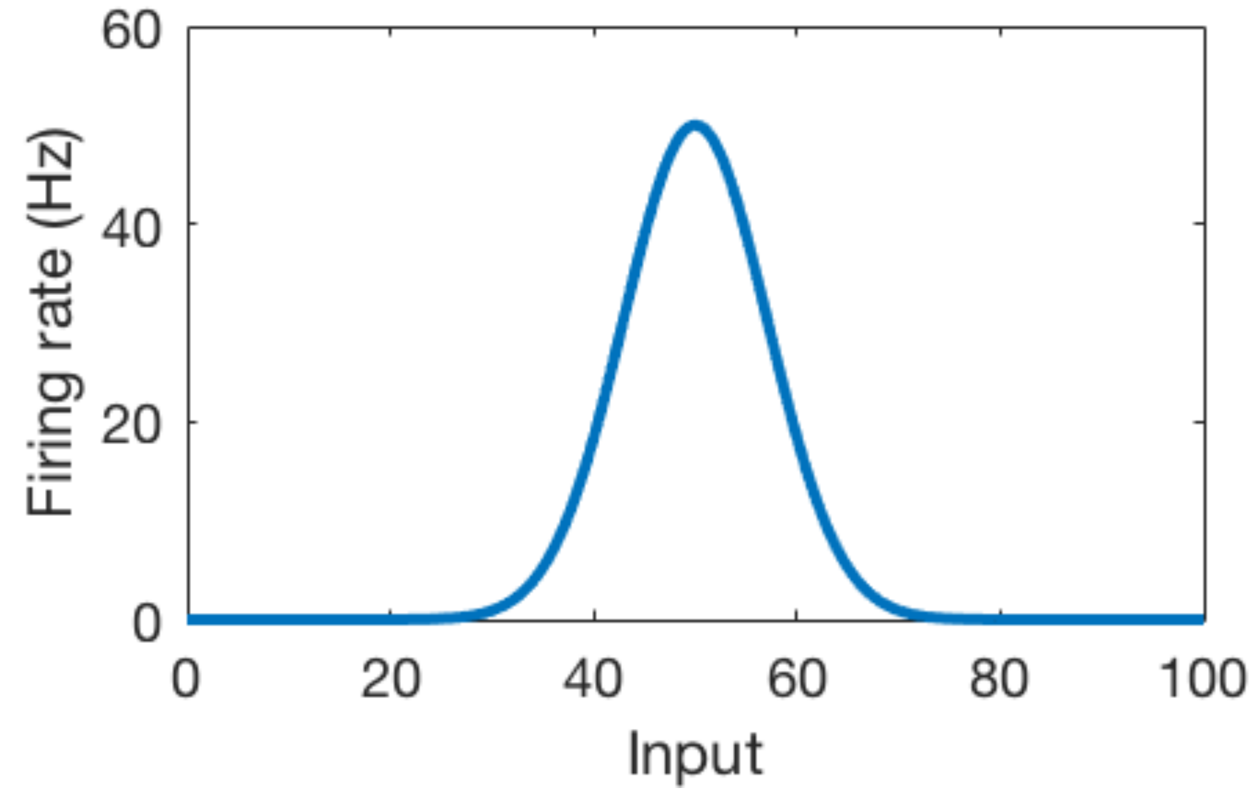
Modelling rate coding, in single neurons

$$r(x) = \alpha \log(x)$$



e.g. mechanoreceptors, visual image contrast

$$r(x) = \alpha e^{-\left(\frac{x-\mu}{\sigma}\right)^2}$$



e.g. visual stimulus orientation, place fields

Can account for Weber's law:
humans are sensitive to relative rather than absolute stimulus changes.

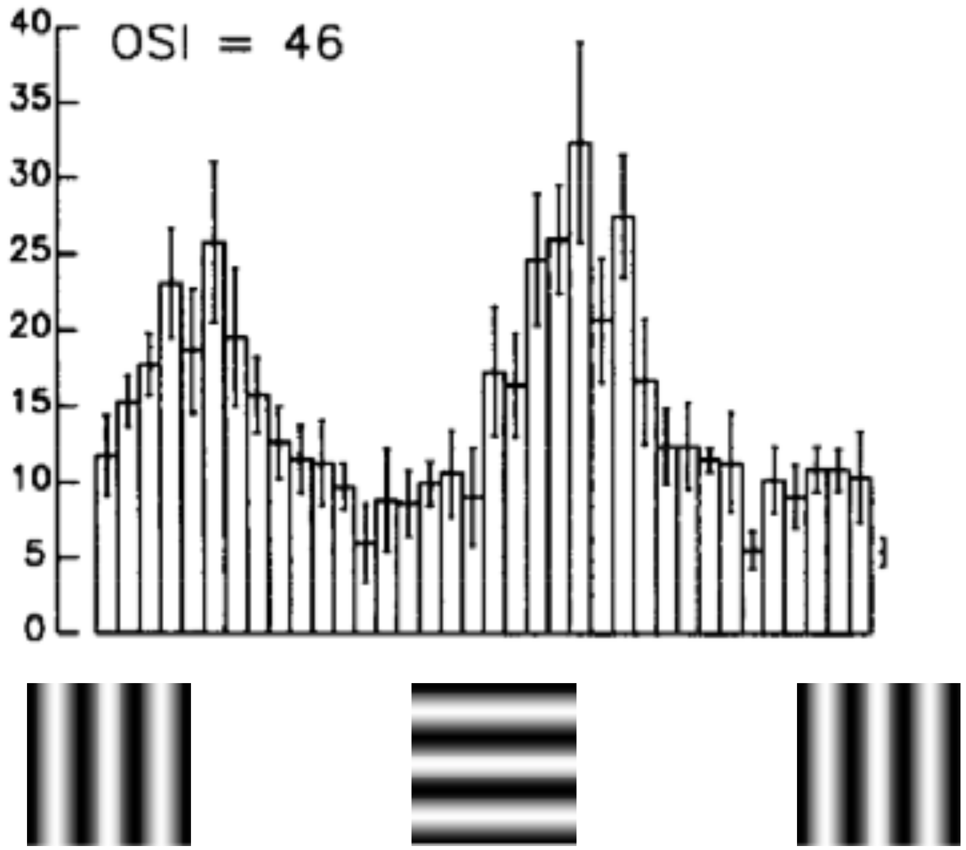
Tuning curves and receptive fields

- Some neurons in the brain respond to certain aspects of sensory stimuli by firing action potentials. Tuning curves and receptive fields are compact descriptions of these stimulus-response relationships.

- A neuron's tuning curve is a description of its firing rate as a function of some property of the stimulus.

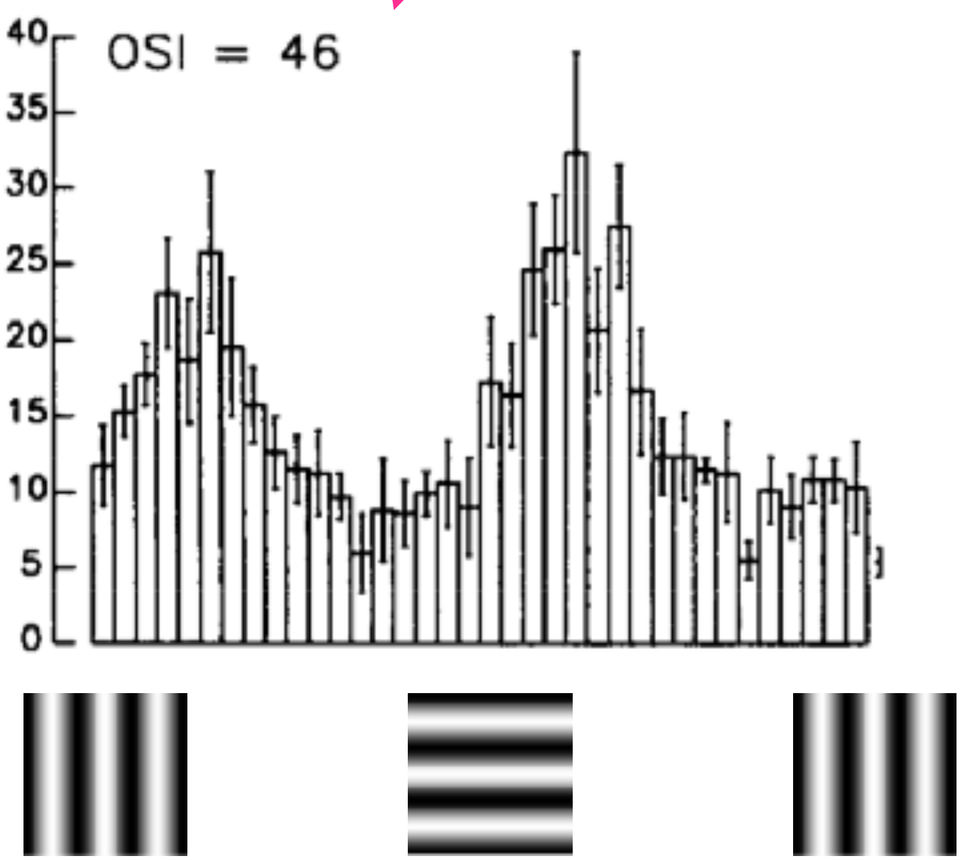
- A neuron's receptive field is the subset of the stimulus space that the neuron responds to.

Tuning curves and receptive fields



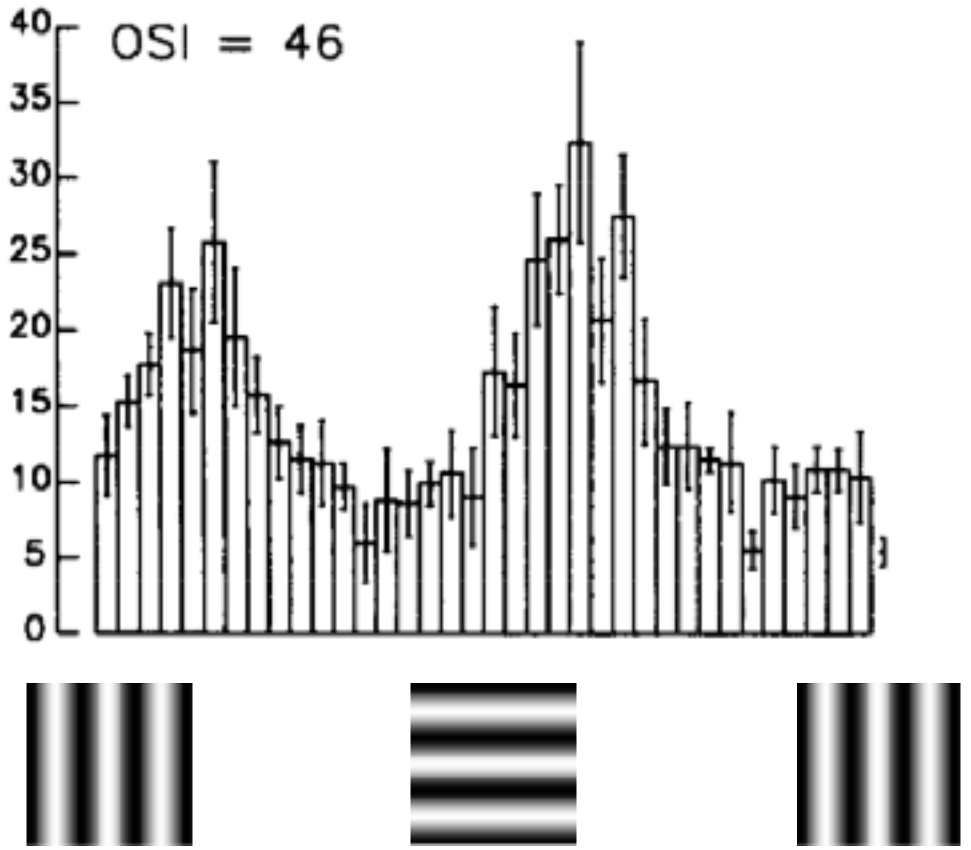
[Chapman & Stryker, *J Neurosci*, 1993]

Tuning curves and receptive fields

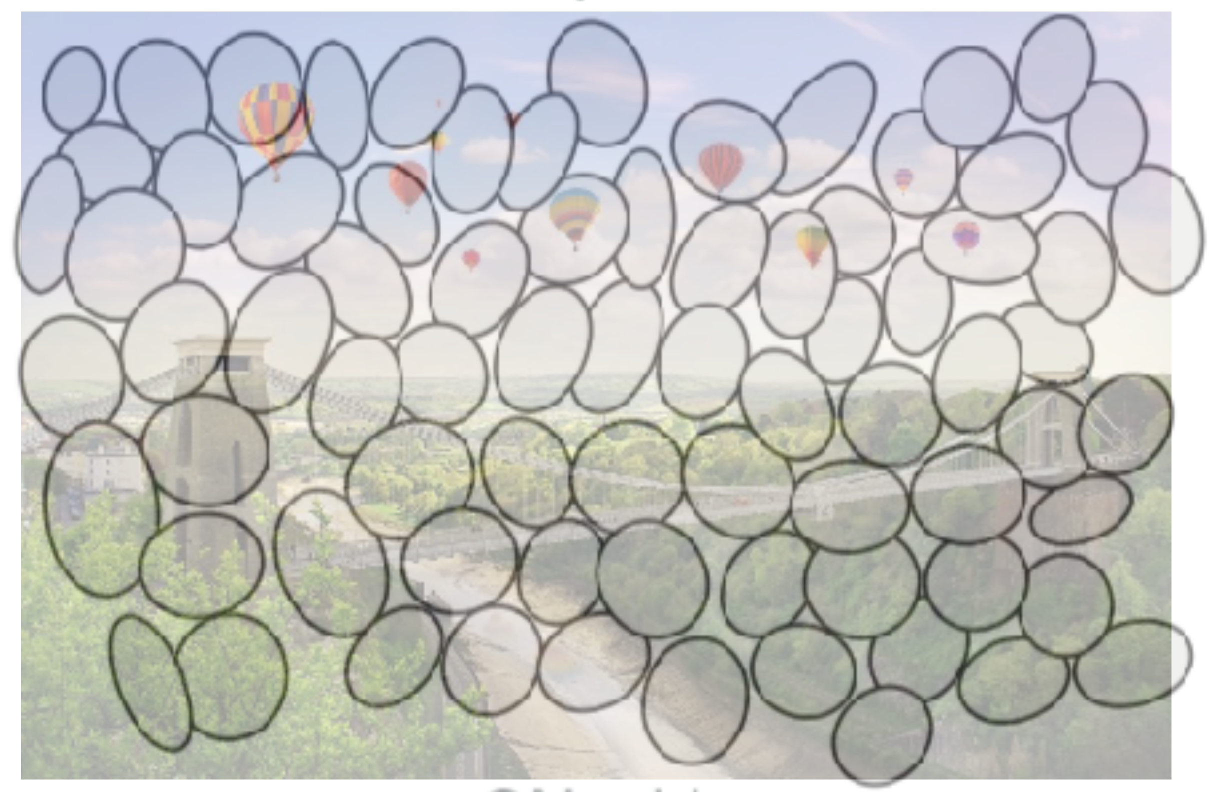


[Chapman & Stryker, *J Neurosci*, 1993]

Tuning curves and receptive fields

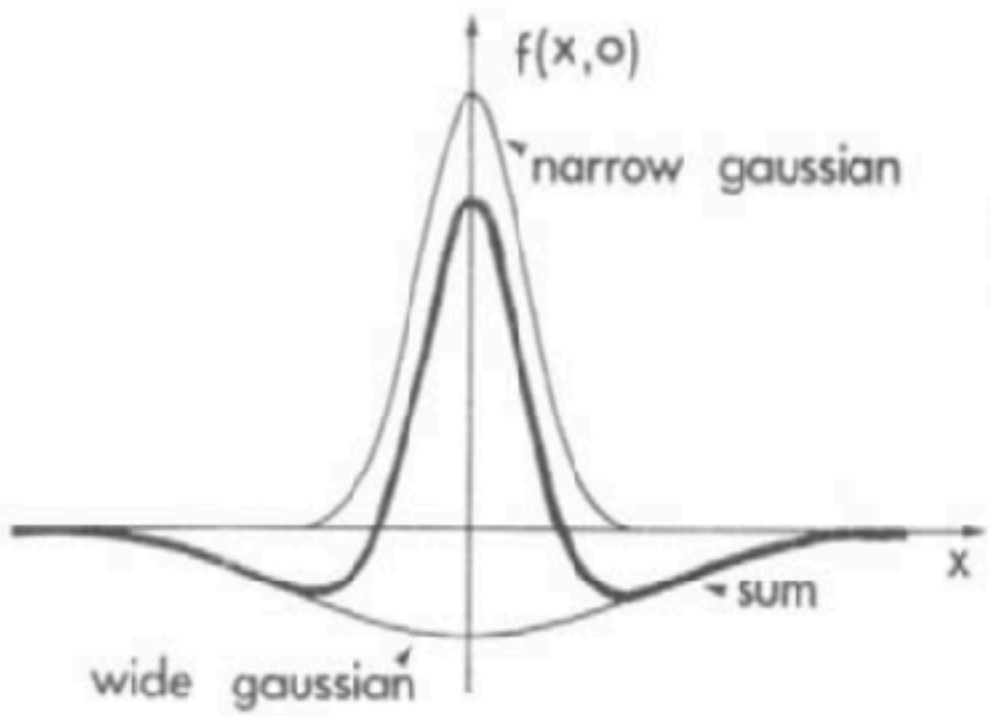


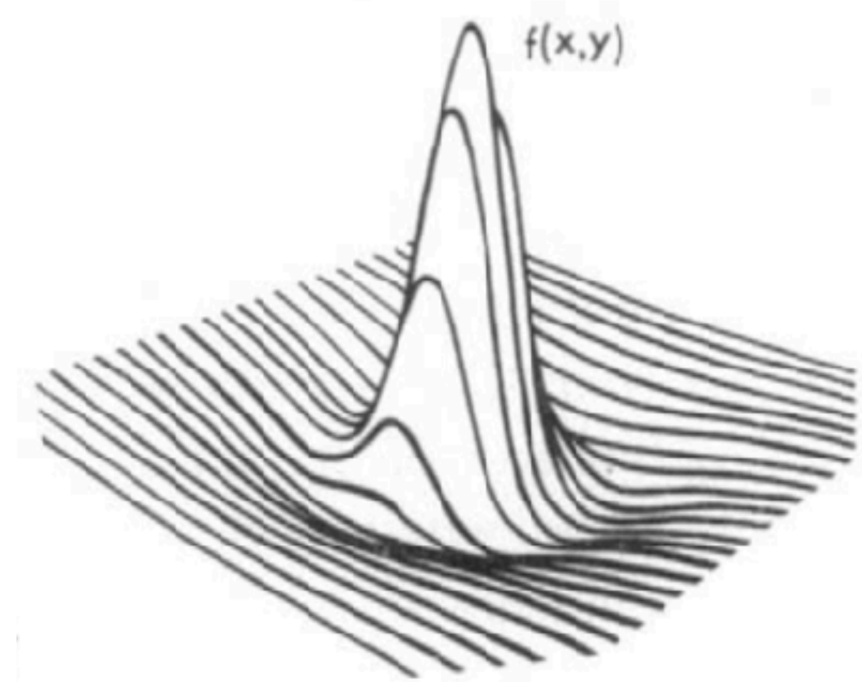
[Chapman & Stryker, *J Neurosci*, 1993]



[Field & Chichilnisky, *Annu Rev Neurosci*, 2007]

Modelling receptive fields



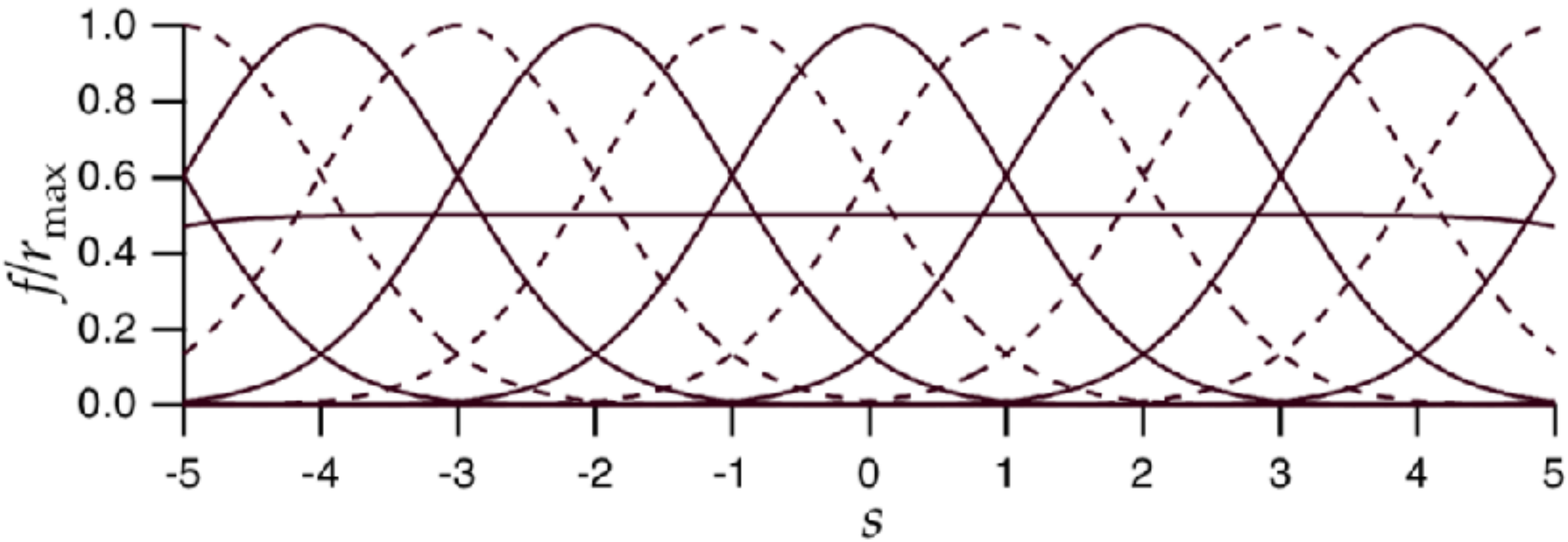


$$f(x, y) = g_1\sigma_1{}^{-2}\pi^{-1}.\exp(-(x^2 + y^2)/\sigma_1{}^{-2}) - g_2\sigma_2{}^{-2}\pi^{-1}.\exp(-(x^2 + y^2)/\sigma_2{}^{-2})$$

Models ‘ON’ centre region and ‘OFF’ surround region, typical of retinal ganglion cells.

[Rodieck, *Vision Res*, 1965]

Modelling rate coding, in populations of neurons



- A population of neurons, each with identical gaussian tuning curves for a 1D stimulus, but with each neuron having its peak response to a different preferred stimulus value.
- Here the neurons are assumed to be homogeneous and tile input space uniformly.
- However, real biological neurons tend to have multiple forms of heterogeneity:
  - Peak firing rates
  - Tuning curve shape (many not tuned at all)
  - Non-uniform preferred stimulus values
  - Varying degrees of trial-to-trial response reliability ("noise")

[Dayan & Abbott, 2001]

Rate decoding

- Up to now we have considered neural (en)coding: asking what the brain's response is to stimuli.
  $P(r|s) = ?$

- Decoding is the opposite of encoding.

- Decoding takes the "brain's-eye view": trying to estimate the stimulus from the neural activity.
  $P(s|r) = ?$

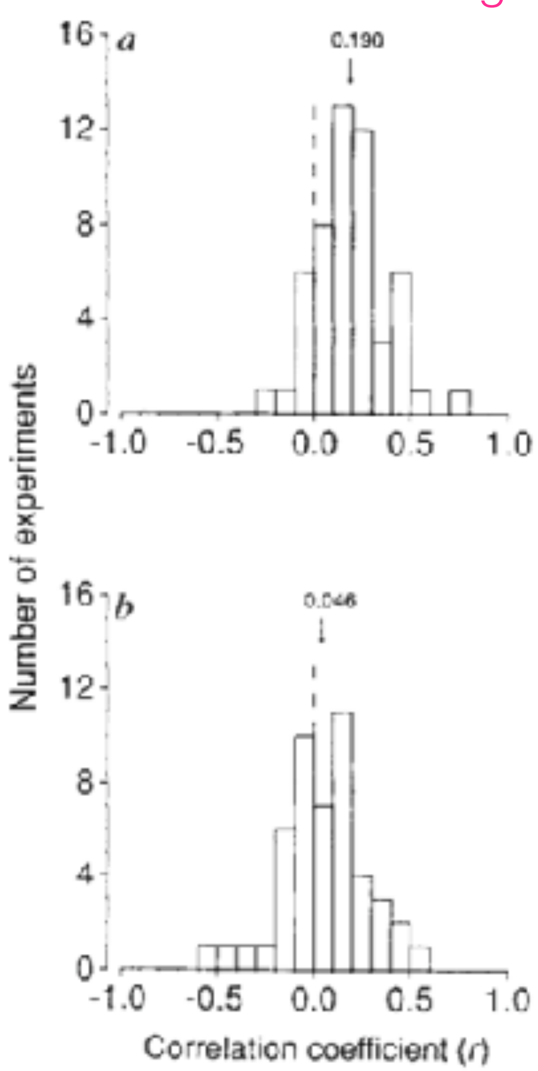
Rate decoding

- Various schemes have been proposed for decoding neural activity, including:
  - Population vector [Theunissen and Miller, *J Neurophysiol*, 1991]
  - Optimal linear estimator [Salinas and Abbott, *J Comput Neurosci*,1994]
  - Maximum likelihood and Bayesian decoding [e.g. Zhang et al., J Neurophysiol, 1996]

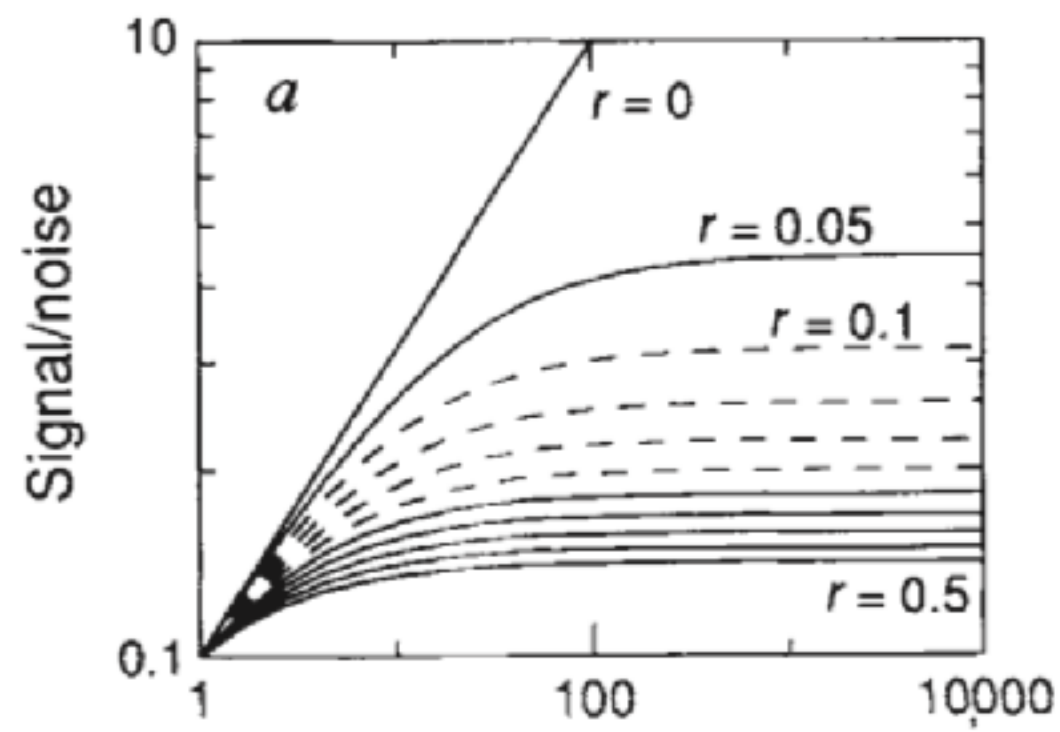
The noise correlation problem

- Neurons' activities are not conditionally independent given the stimulus. Instead, they exhibit correlated trial-to-trial variability, a.k.a. "noise correlations".
- This correlated variability implies that you can arbitrarily increase the signal/noise ratio by simply averaging over multiple neurons.

Neurons with similar tuning curves



Neurons with dissimilar tuning curves



[Zohary et al., *Nature*, 1994]

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