

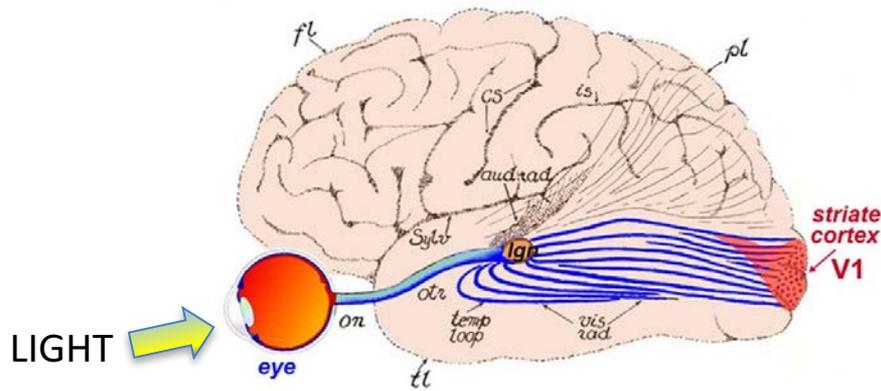
# Introduction to Neural Computation

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Prof. Michale Fee  
MIT BCS 9.40 — 2018

Lecture 9 — Receptive fields

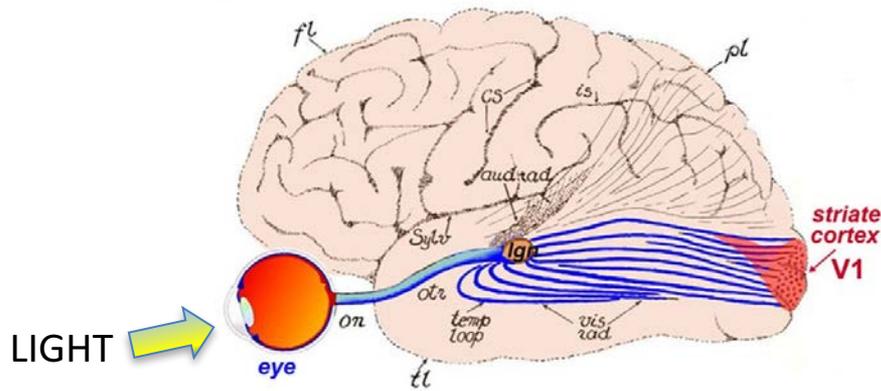
# Spatial receptive fields



Video of visual neurons of a cat from Hubel & Wiesel's experiments.

Ali Moeeny. "[Hubel & Wiesel – LGN Neuron.](#)" April 23, 2011. YouTube.

# Spatial receptive fields



Video of visual neurons of a cat – simple and complex cells - from Hubel & Wiesel's experiments.

Ali Moeeny. "[Hubel & Wiesel – Cortical Neuron – V1.](#)" April 23, 2011. YouTube.

# Learning objectives for Lecture 9

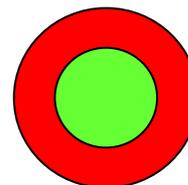
- To be able to mathematically describe a neural response as a linear filter followed by a nonlinear function.
  - A correlation of a spatial receptive field with the stimulus
  - A convolution of a temporal receptive field with the stimulus
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# Spatial receptive fields

- How do we represent receptive fields mathematically?
- At the simplest level, we think of the receptive field (RF) as the region of visual space that causes the neuron to spike.
- But a visual neuron doesn't respond to any stimulus within this RF. It responds selectively to certain 'features' in the stimulus.
- We can think of a neuron as having a filter (G) that passes certain features in both space and time.
- The better the stimulus 'overlaps' with the filter, the more the neuron will spike.



# Spatial receptive fields

- How do we represent receptive fields mathematically?

Start by describing the spatial part of this filter.

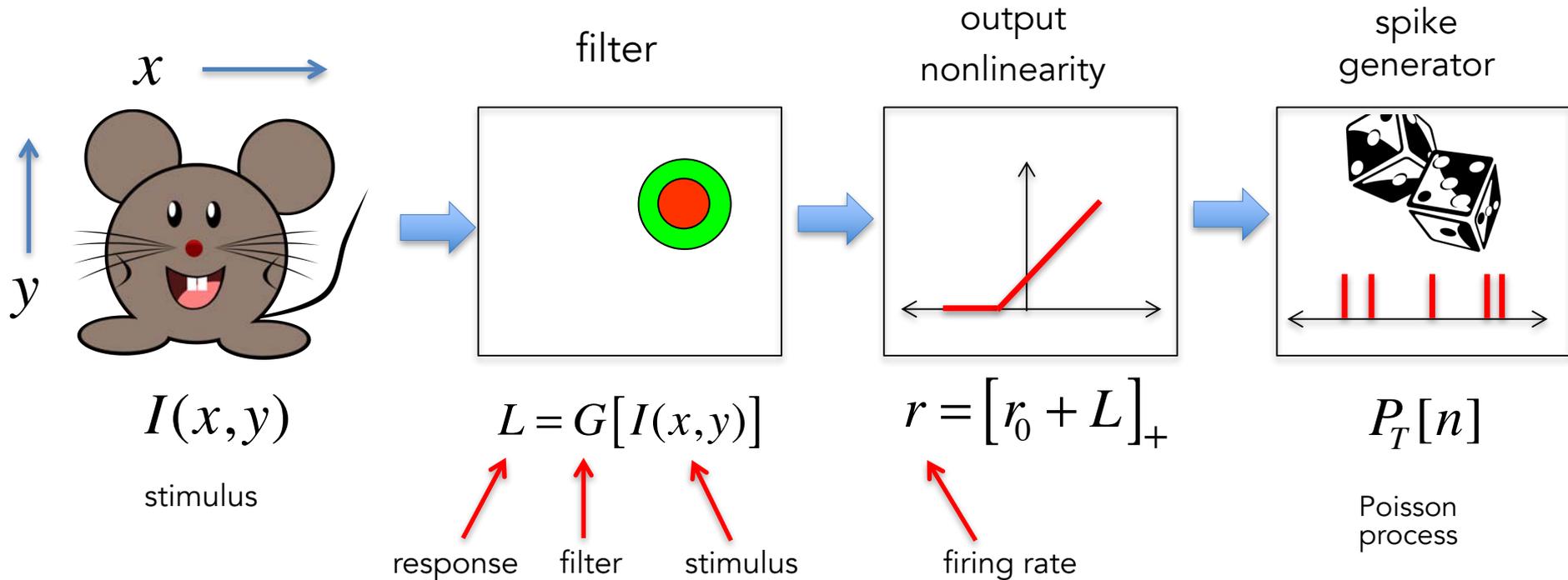


Image of mouse in public domain.

# Spatial receptive fields

- How do we represent receptive fields mathematically?

We are going to consider the simplest case in which the response of a neuron is given by a linear filter acting on the stimulus.

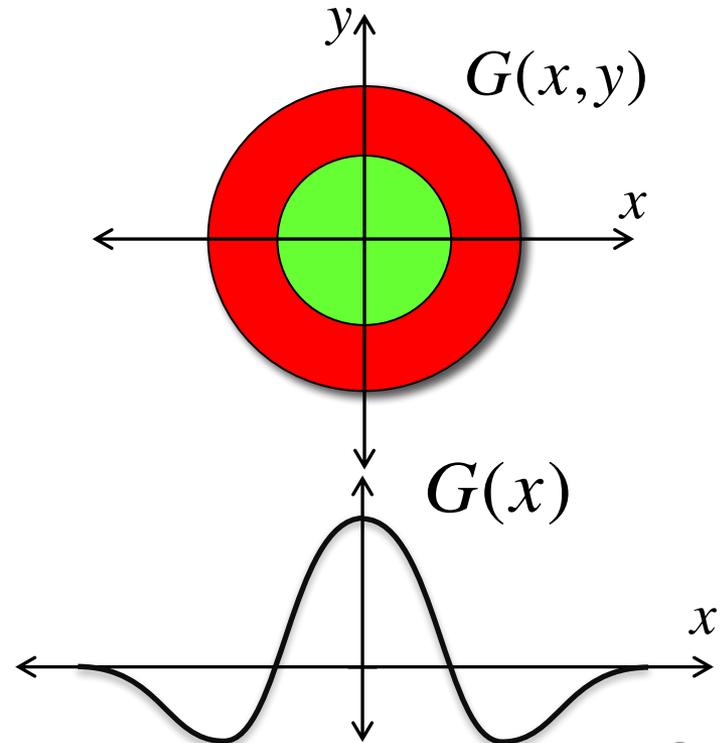
$$r = r_0 + \iint G(x,y)I(x,y)dx dy$$

Let's look at this in one dimension

$$r = r_0 + \int G(x)I(x)dx$$

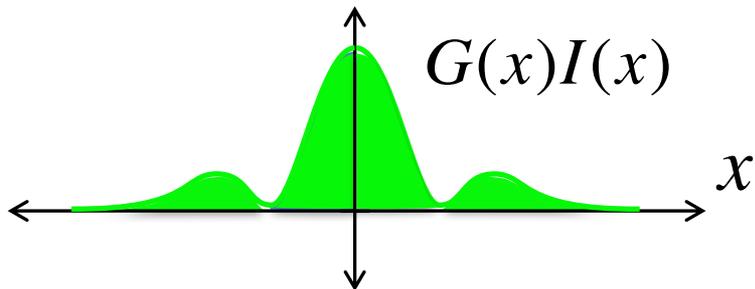
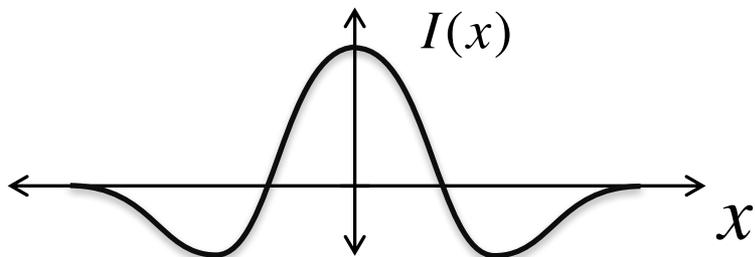
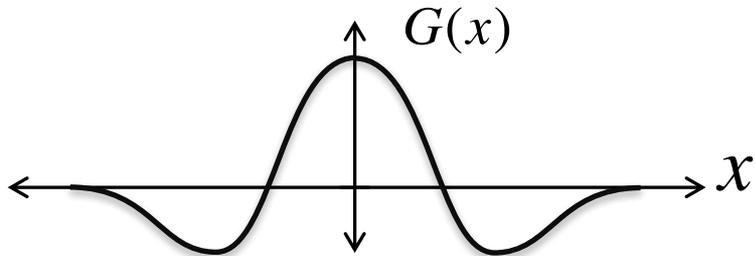
Like a correlation

$$\sum_i G_i I_i$$

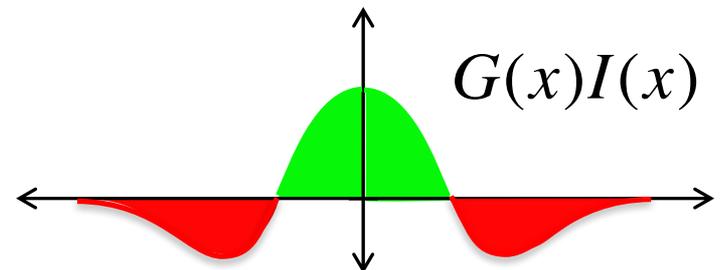
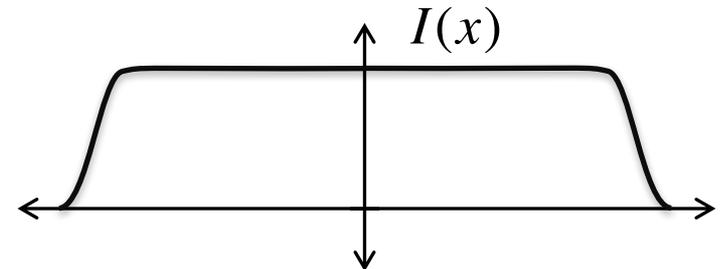
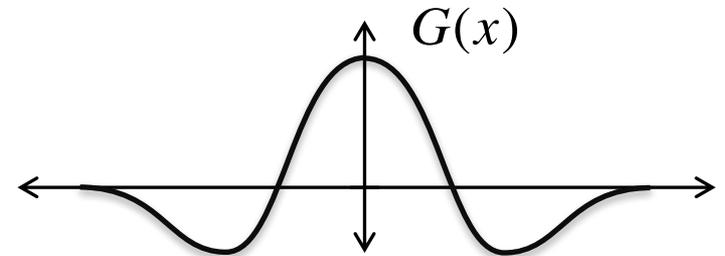


# Spatial receptive fields

- How do we represent receptive fields mathematically?



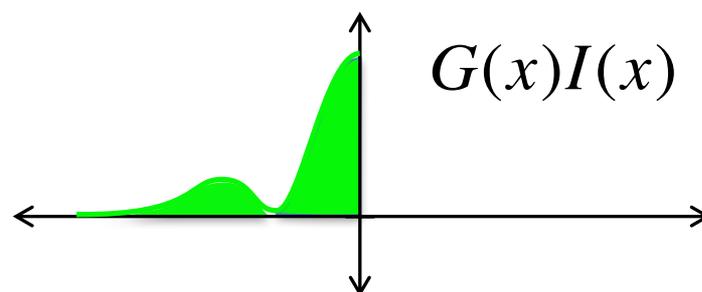
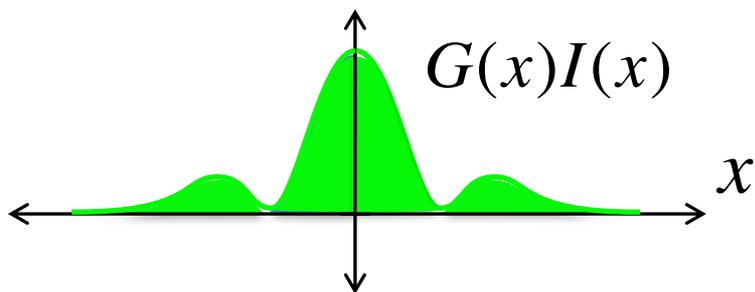
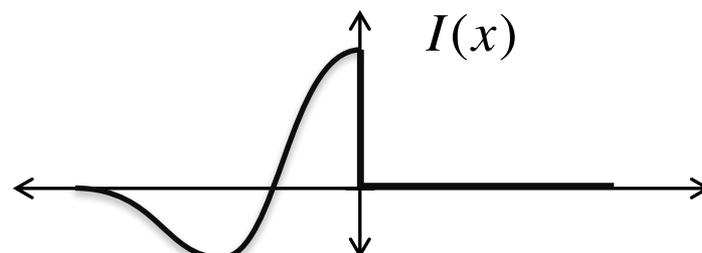
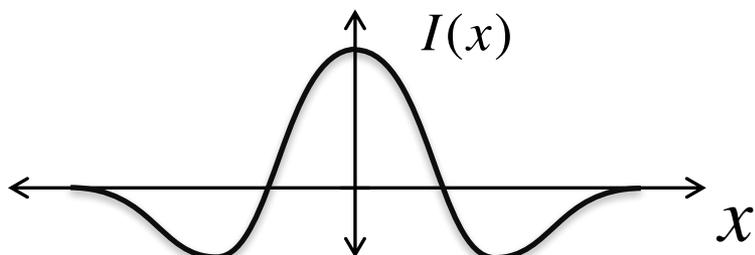
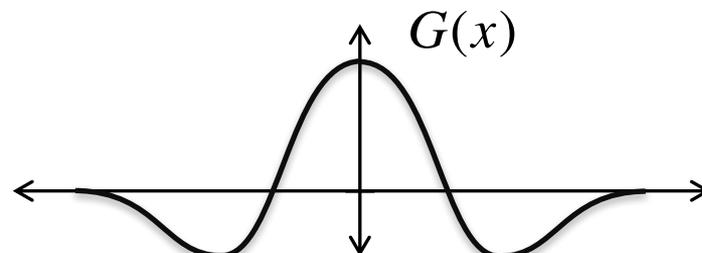
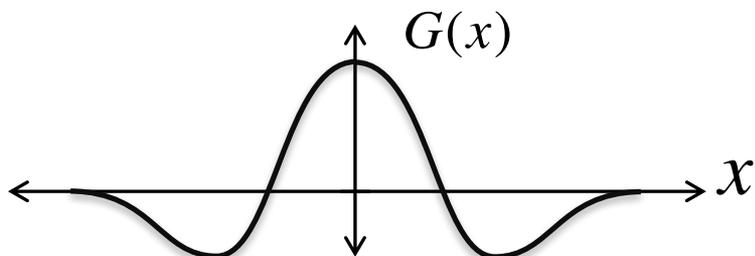
$$\int G(x)I(x)dx \text{ big}$$



$$\int G(x)I(x)dx \text{ small}$$

# Linearity

- Response varies linearly with overlap



$$\int G(x)I(x)dx \text{ big}$$

$$\int G(x)I(x)dx \text{ half as big}$$

# Temporal receptive fields

- We can also think of the response of a neuron as some function of the temporal variations in the stimulus.

$$r(t) = r_0 + D[S(t)]$$

Time-dependent firing rate

Spontaneous firing rate

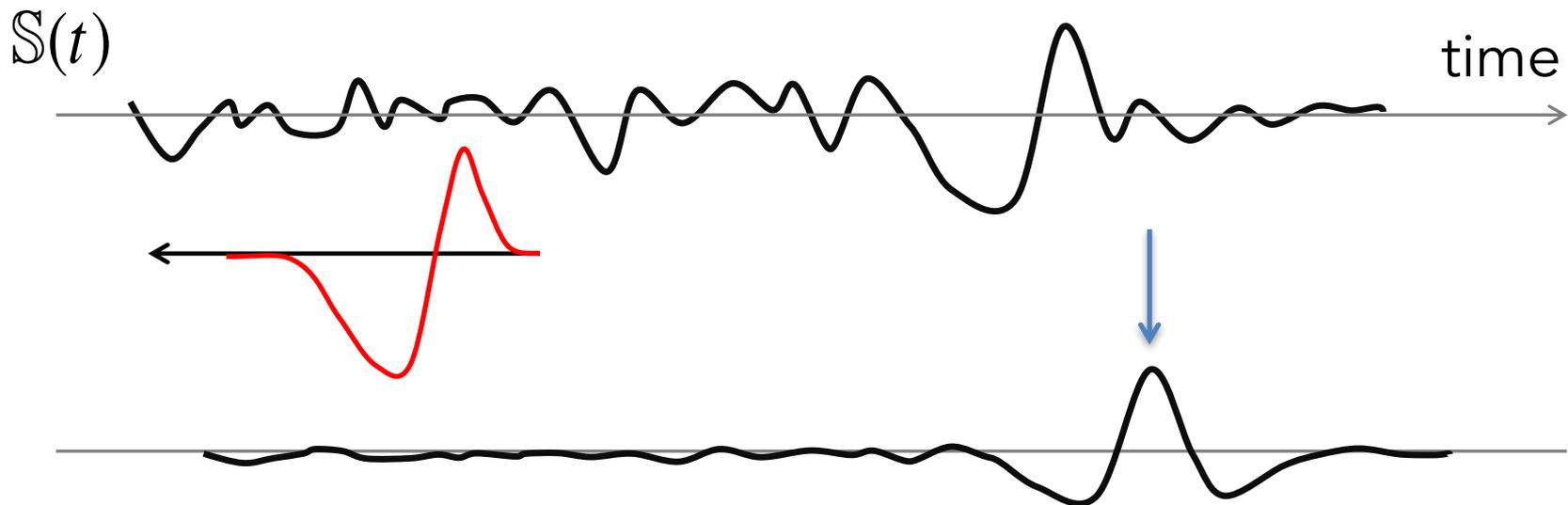
Filter

Stimulus

The diagram illustrates the equation  $r(t) = r_0 + D[S(t)]$ . Four blue arrows point from labels below to specific parts of the equation: from 'Time-dependent firing rate' to  $r(t)$ , from 'Spontaneous firing rate' to  $r_0$ , from 'Filter' to  $D$ , and from 'Stimulus' to  $S(t)$ .

# Temporal receptive fields

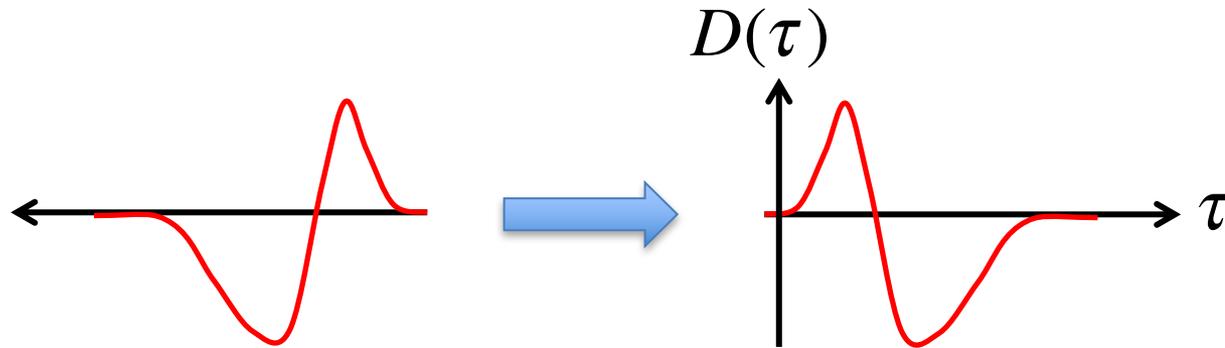
- We can think of 'overlap' in the time domain! That there is a particular 'temporal profile' of a stimulus that makes a neuron spike.



Does this look familiar?

# Temporal receptive fields

Convolution!!  $r(t) = r_0 + \int_{-\infty}^{\infty} D(\tau)S(t - \tau)d\tau$



Linear temporal response kernel. (Or 'temporal kernel')

It is linear in the sense that if we make the stimulus partial, or weaker, the response changes linearly.

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# Spatio-temporal receptive fields

- Now we are going to put the temporal receptive field and the spatial receptive field together in a single object.
- This is called the spatio-temporal receptive field (STRF).
- Let's imagine a stimulus that is a function of space and time, like the light falling on a retina:  $I(x, y, t)$
- But now we are going to simplify things by considering only one spatial dimension:  $I(x, t)$

$$r(t) = r_0 + \int_{-\infty}^{\infty} dx d\tau D(x, \tau) I(x, t - \tau)$$

# Spatio-temporal receptive fields

Here we are doing a correlation and a convolution at the same time!  
Correlation in the integral over space and a convolution in the integral over time!

$$r(t) = r_0 + \iint dx d\tau D(x, \tau) I(x, t - \tau)$$

correlation

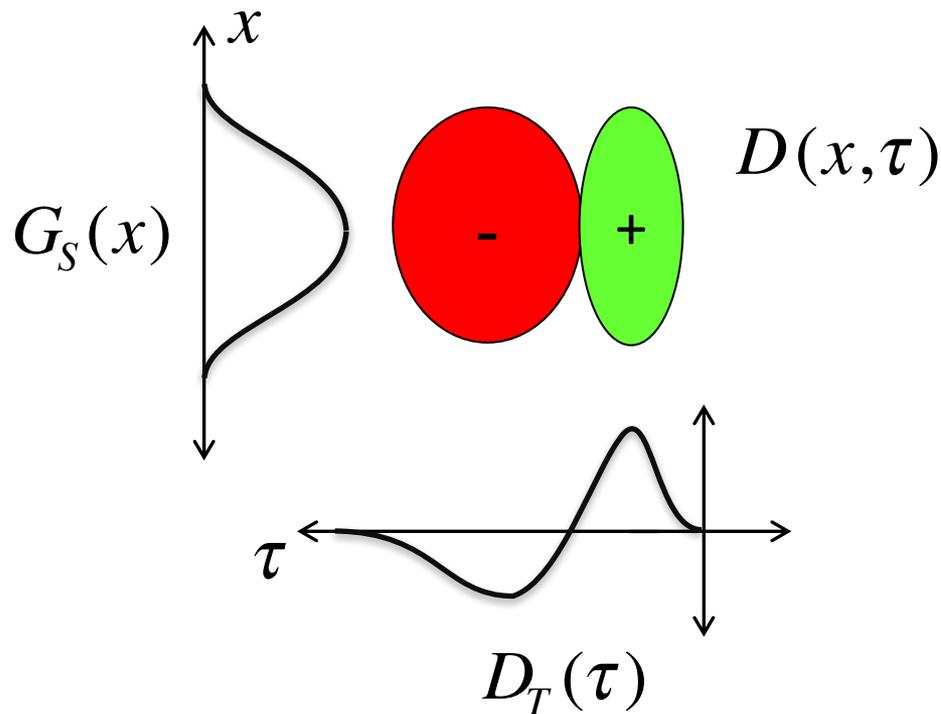
$$r(t) = r_0 + \int_{-\infty}^{\infty} d\tau \int_{-\infty}^{\infty} dx D(x, \tau) I(x, t - \tau)$$

convolution

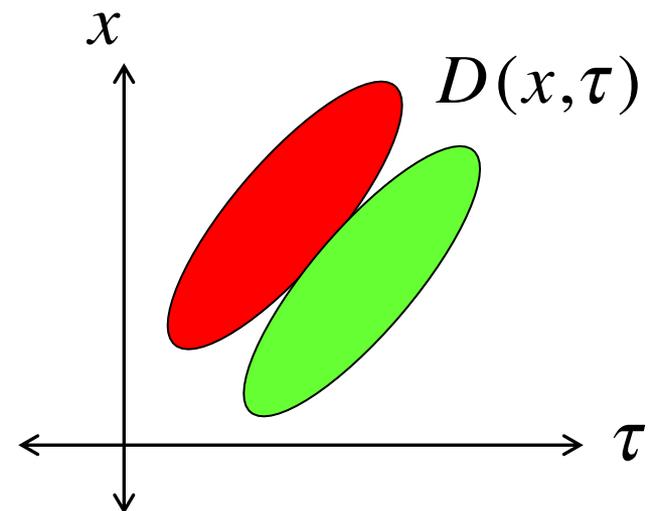
# Separability

- If a receptive field is separable in space and time, then we can decompose it into a spatial receptive field and a temporal receptive field.

Separable



Inseparable



# Separability

- If a receptive field is separable in space and time, then we can decompose it into a spatial receptive field and a temporal receptive field:

$$r(t) = r_0 + \int_{-\infty}^{\infty} dx \int_{-\infty}^{\infty} d\tau D(x, \tau) I(x, t - \tau)$$

$$D(x, \tau) = G_S(x) D_T(\tau)$$

$$\mathbb{S}(t) = \int_{-\infty}^{\infty} dx G(x) I(x, t) \quad \text{Correlation}$$

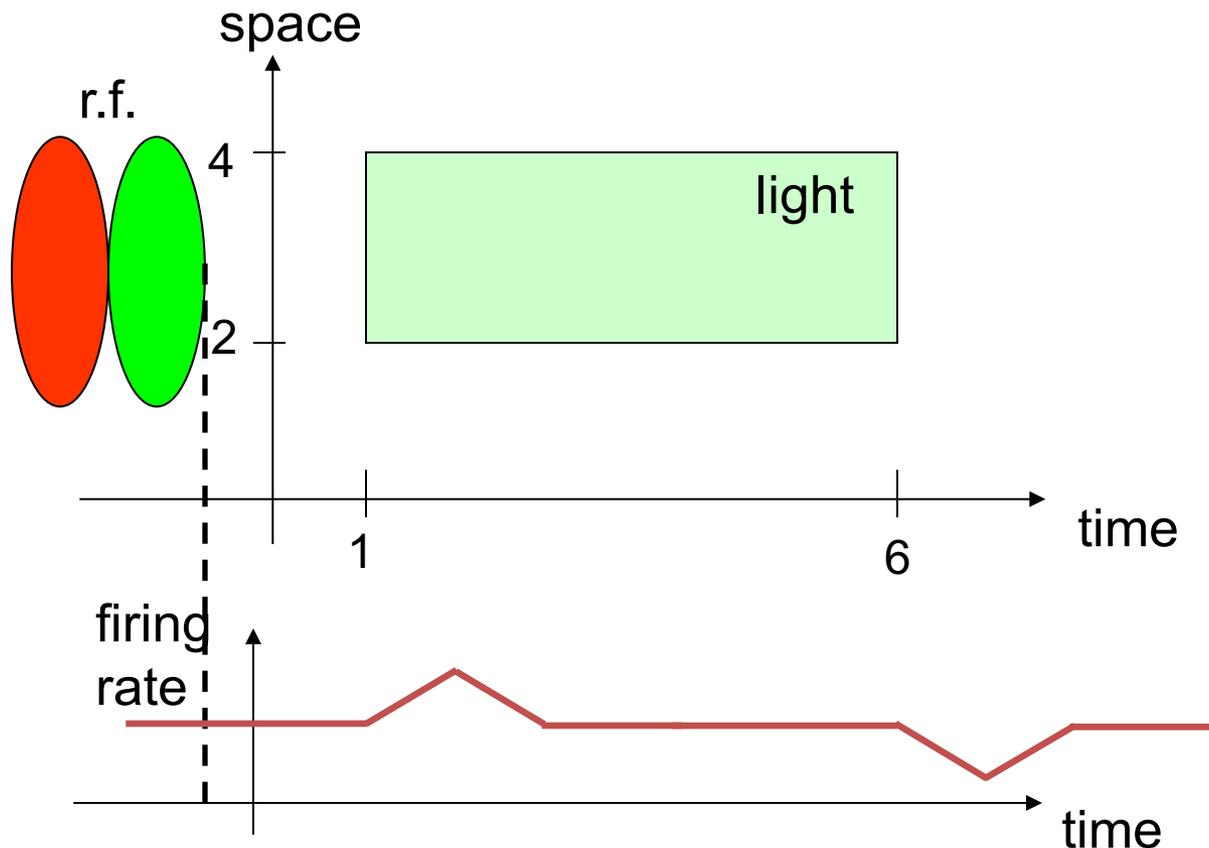
where

$$r(t) = r_0 + \int_{-\infty}^{\infty} d\tau D_T(\tau) \mathbb{S}(t - \tau) \quad \text{Convolution}$$

# Representing stimulus and receptive fields in space and time

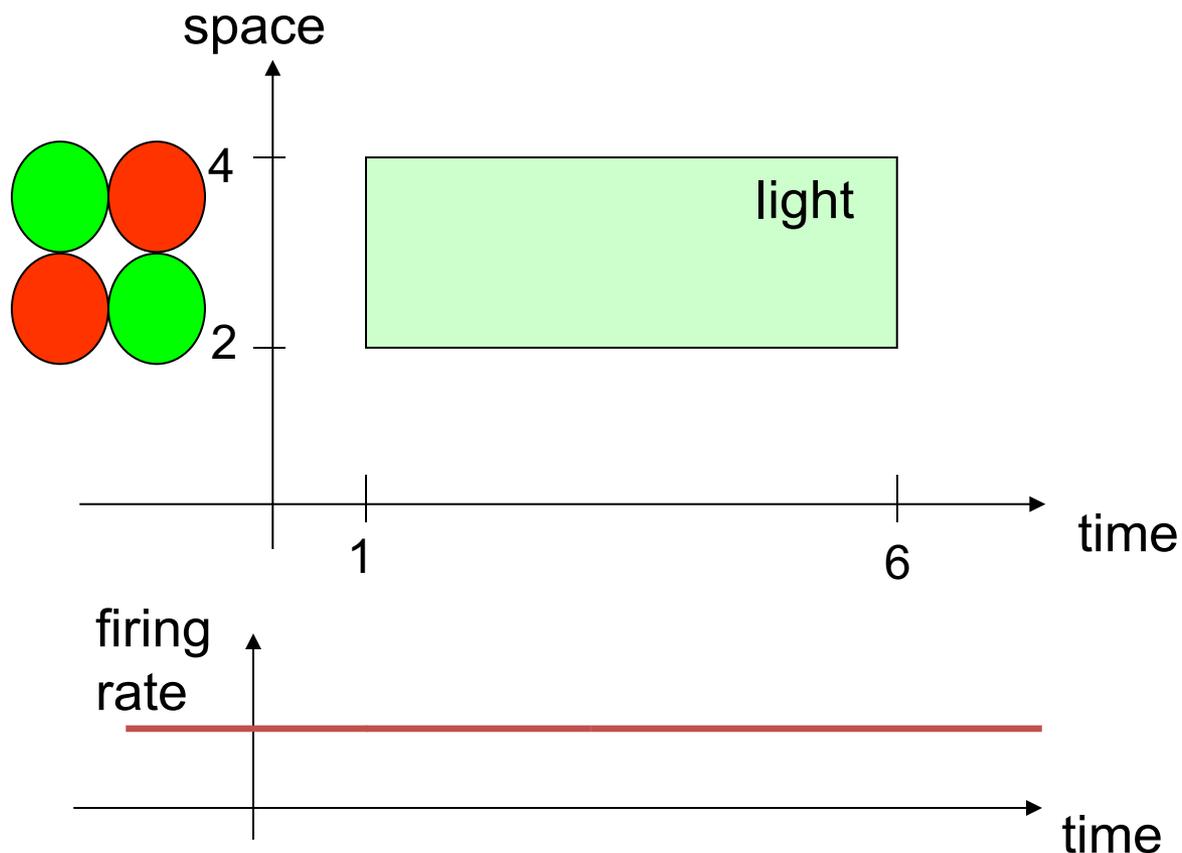
Suppose our stimulus is a bar of light extending from  $x=2$  to  $x=4$  and that is turned on for times from  $t=1$  to  $t=6$

We represent it on a space-time plot as follows:



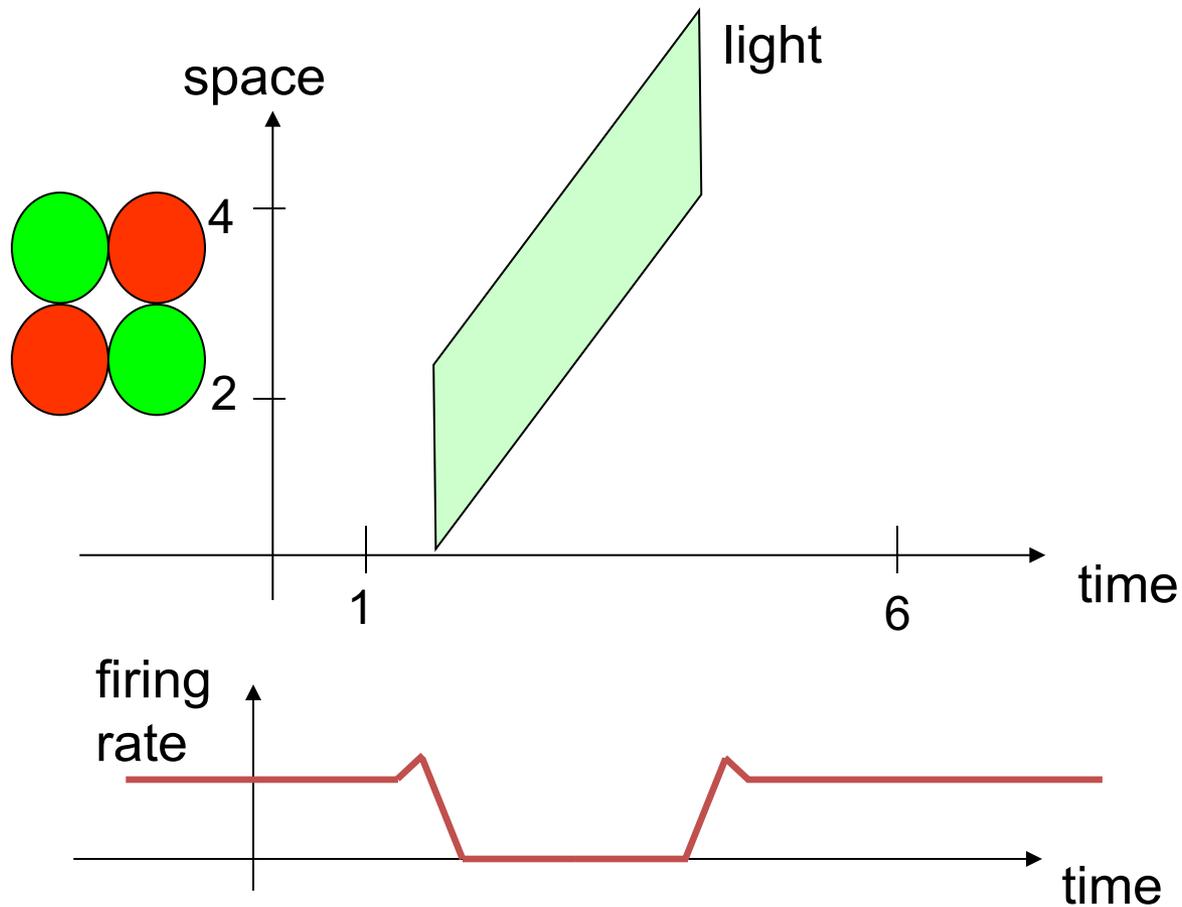
# Representing stimulus and receptive fields in space and time

Suppose we now consider a receptive field  $D(t,x)$  with spatial as well as temporal structure (but 'space-time separable' :  $D(t,x) = D(t)D(x)$  )



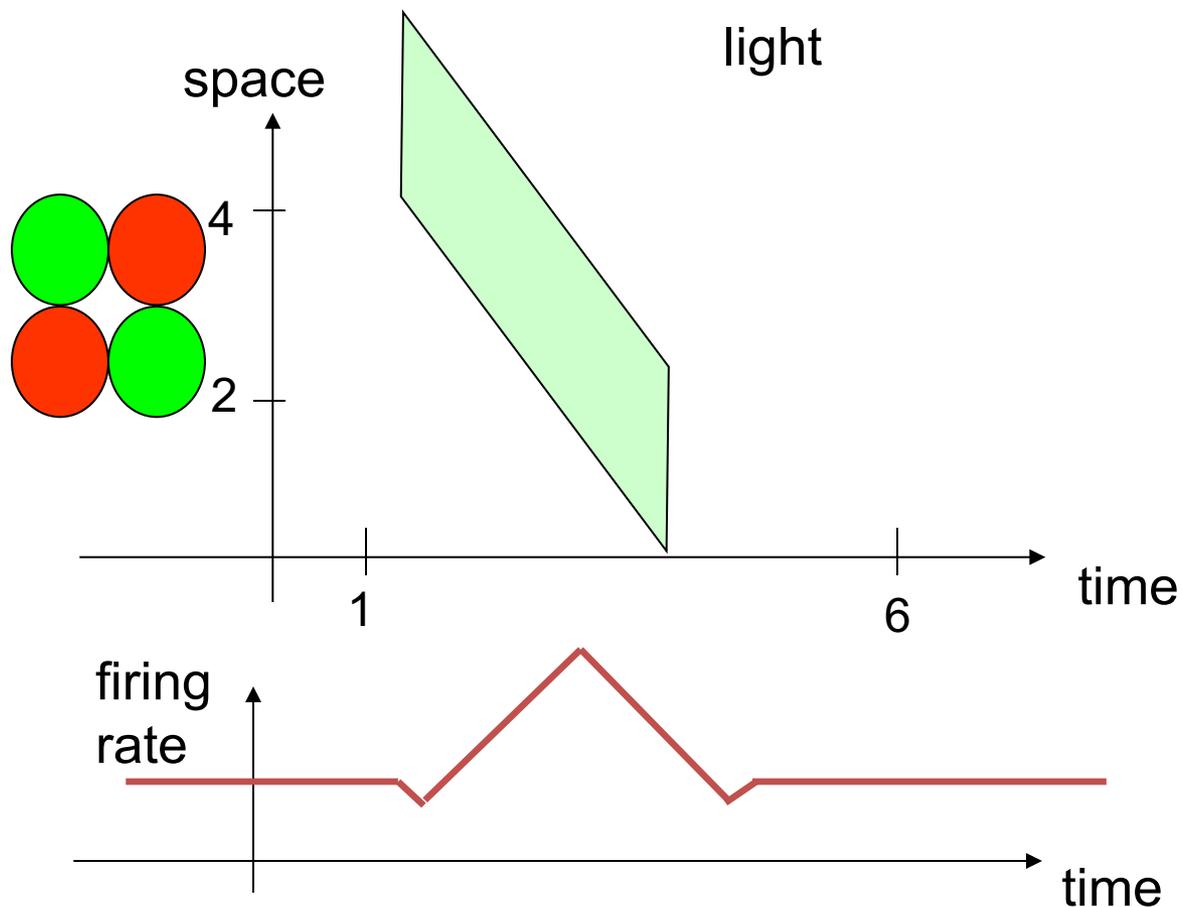
# Response to a moving bar of light

Now suppose our stimulus is moving:



# Response to a moving bar of light

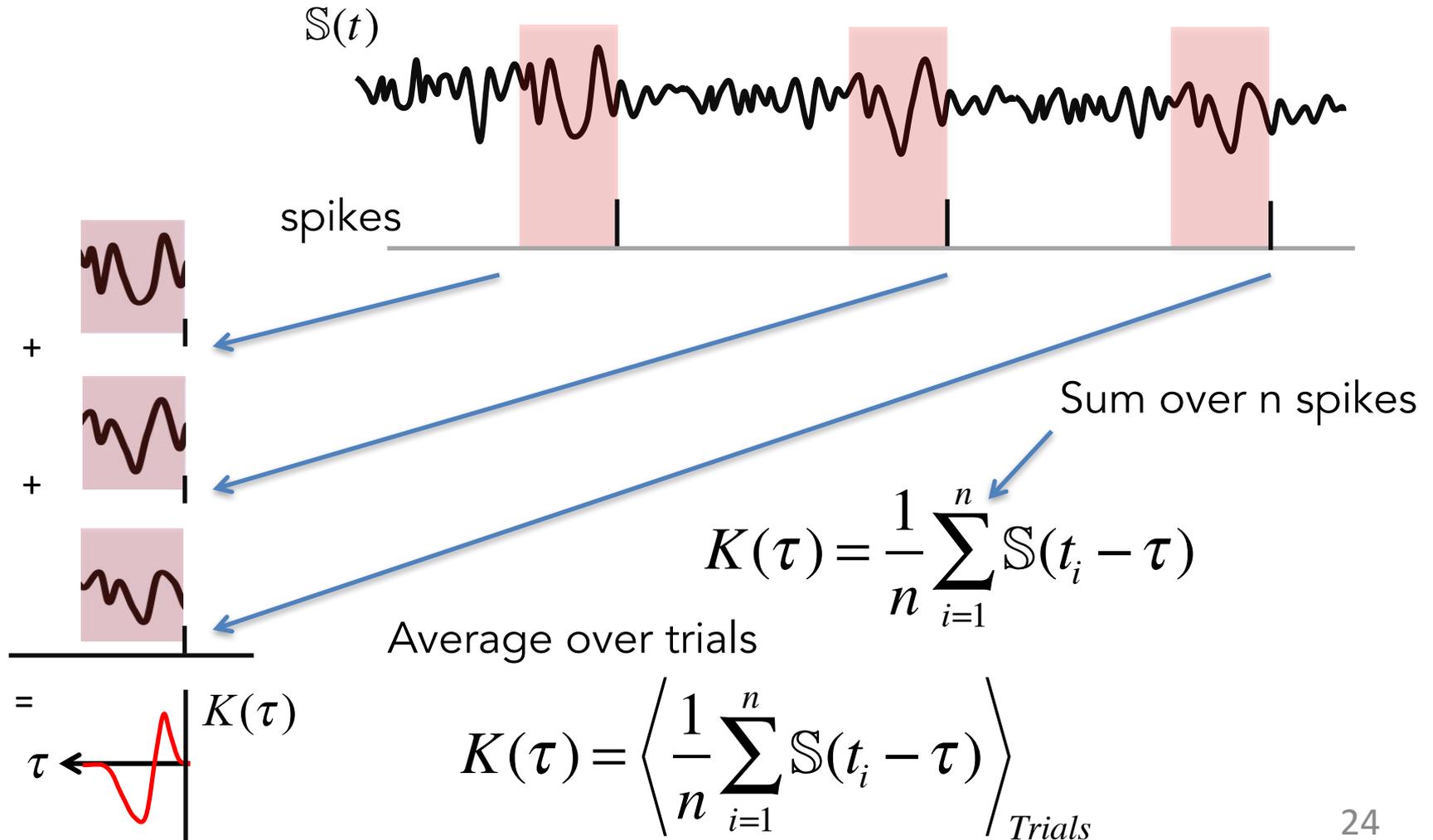
Now suppose our stimulus is moving in opposite direction:



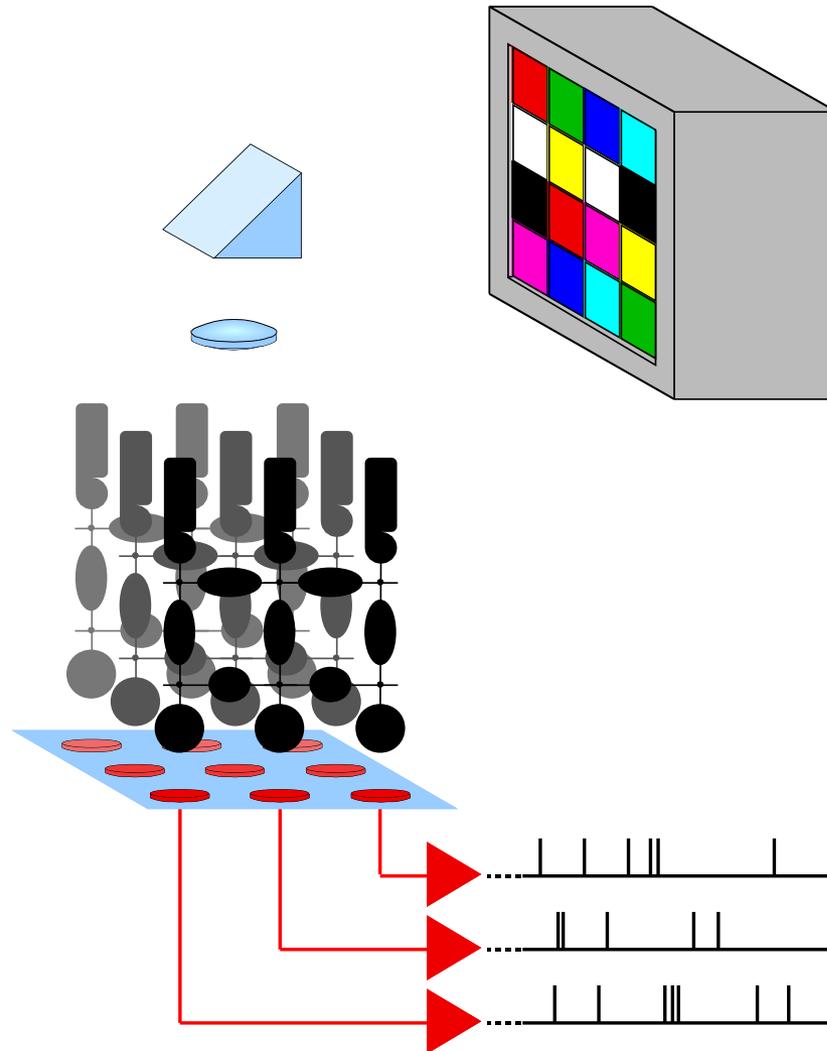
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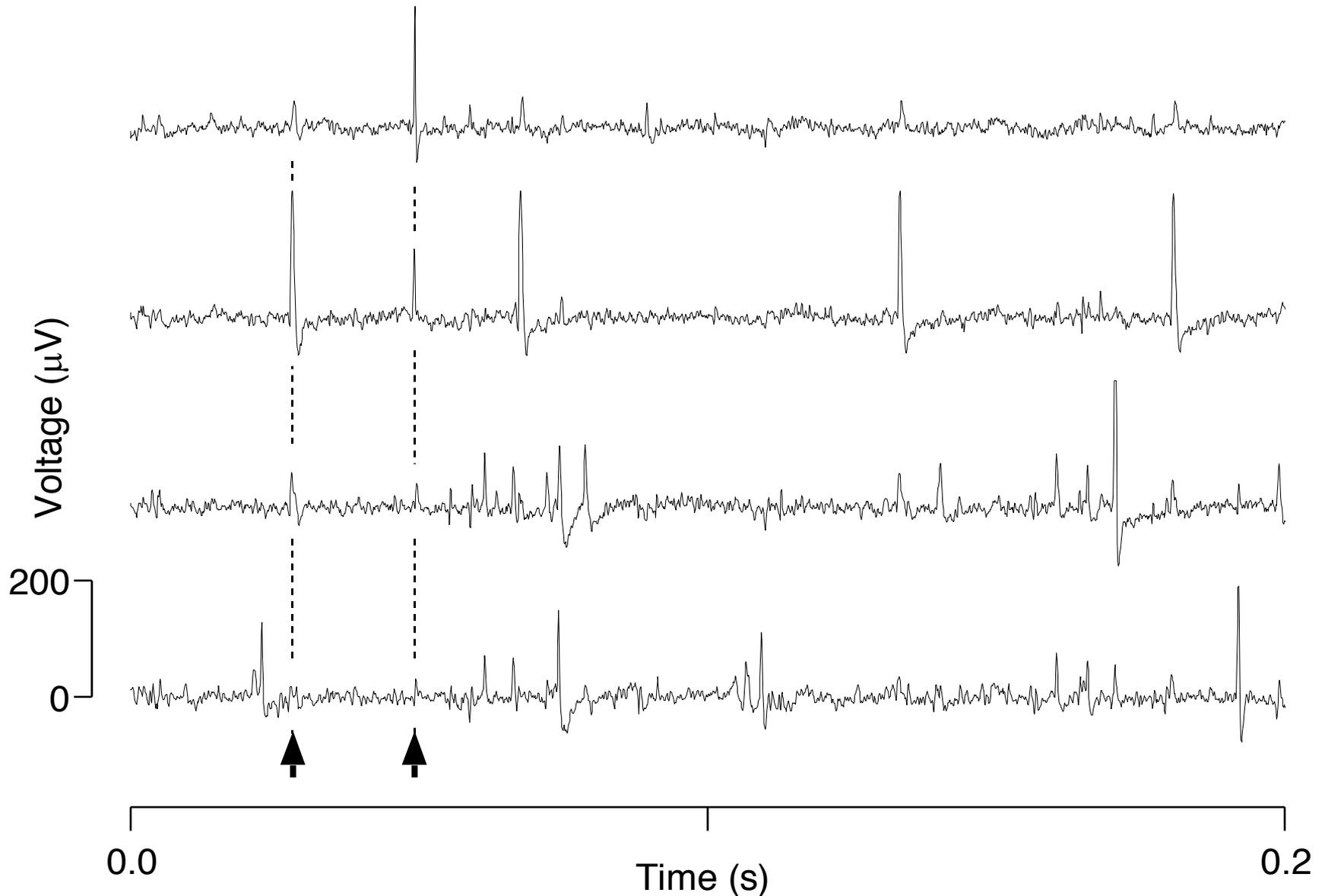
# Spike-Triggered Average



# Measuring STRFs in the retina

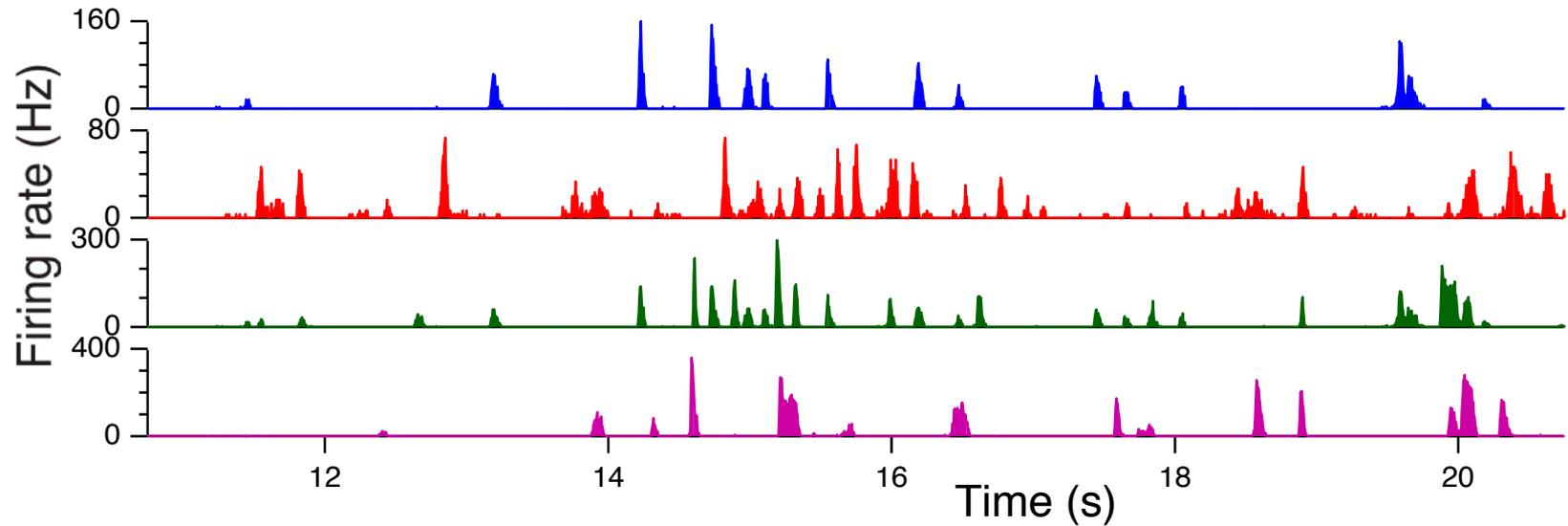


# Simultaneous Recording from Retinal Ganglion Cells

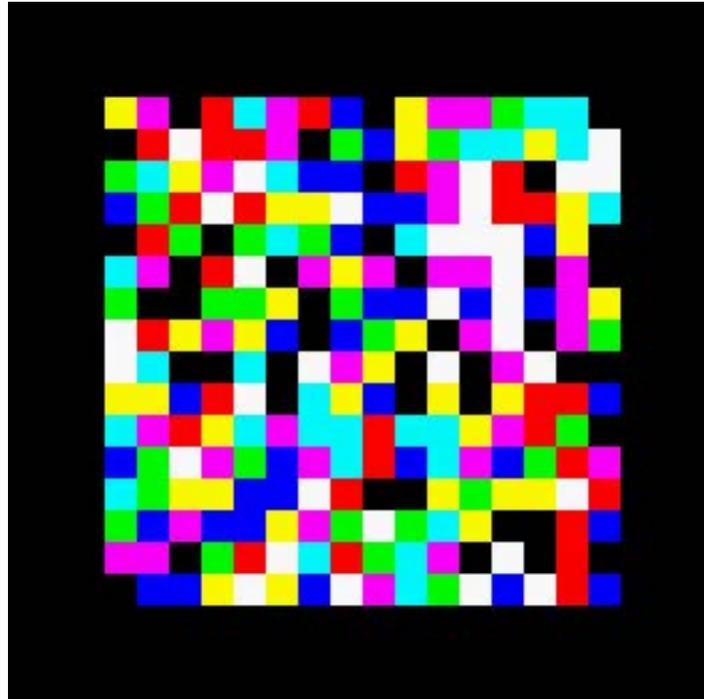


# Rabbit ganglion cells responding to a natural movie

“Trees swaying in the breeze”

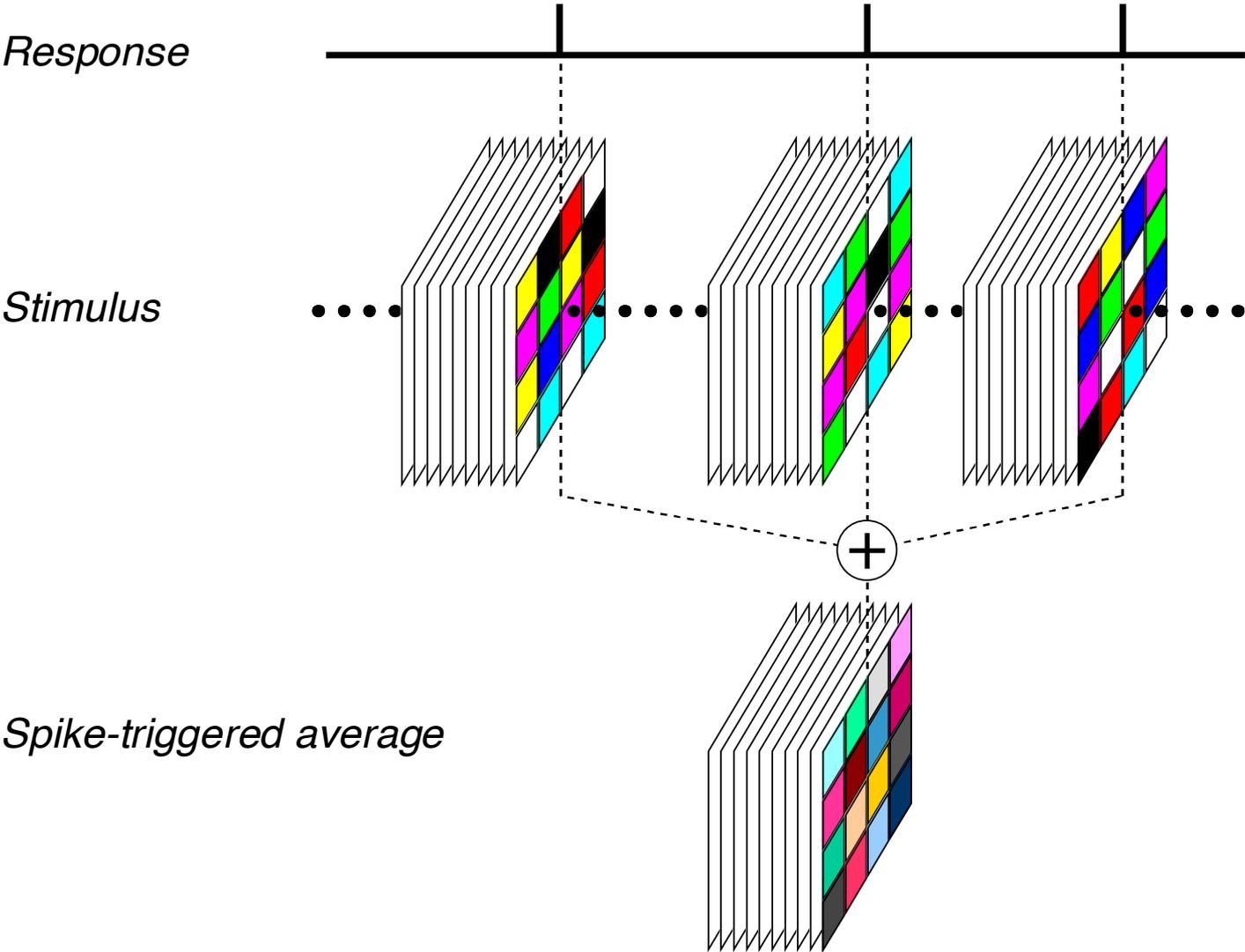


# Measuring STRFs in the retina

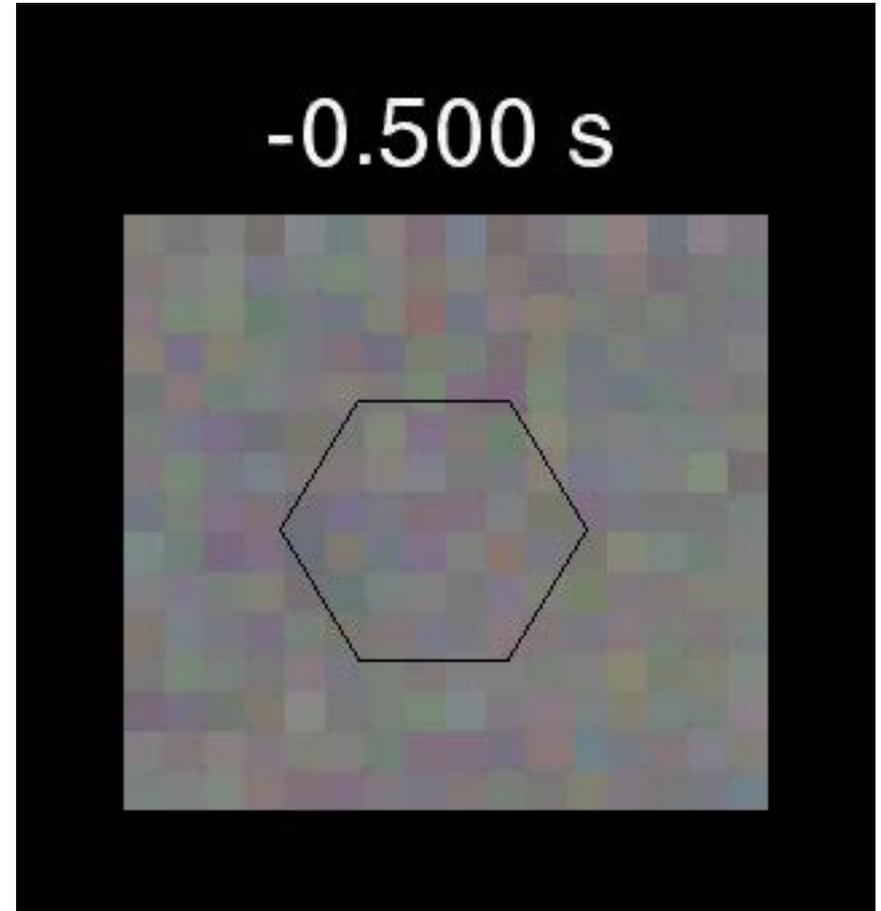
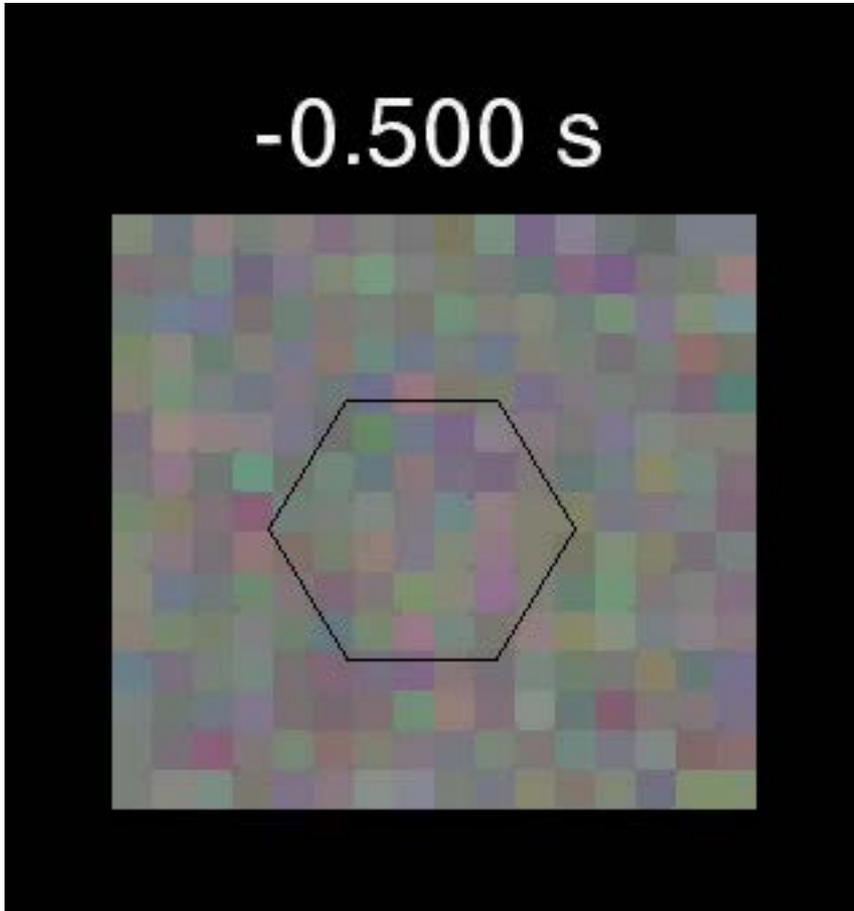


Random flicker stimulus

# Reverse-Correlation to a Random Flicker Stimulus

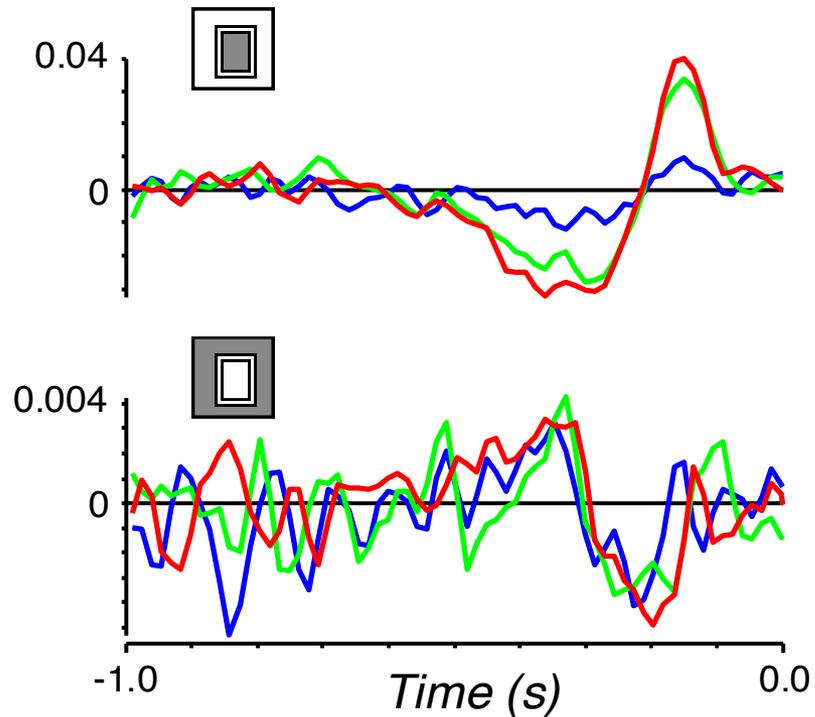
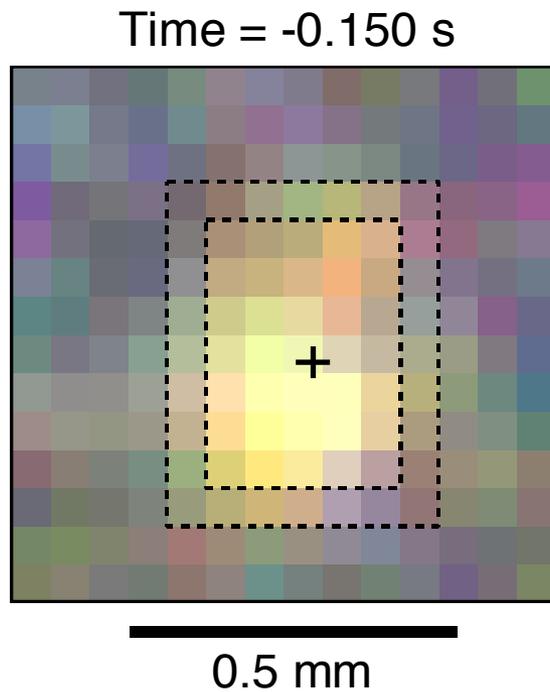
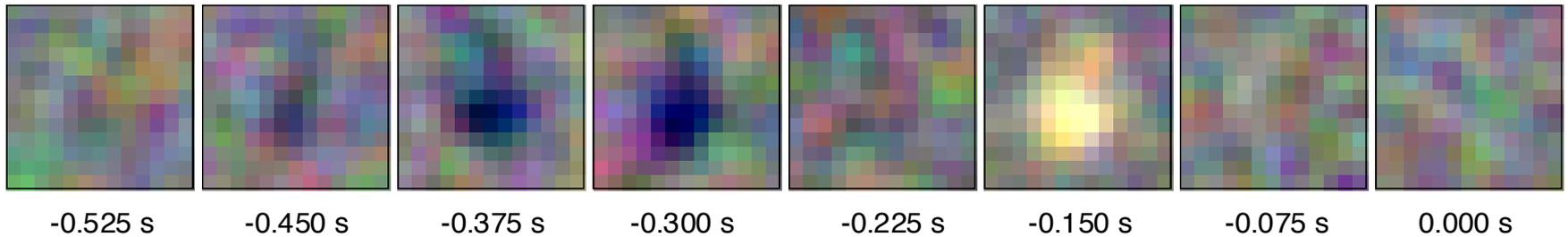


# Spatio-Temporal Receptive Fields (STRF)



See Lecture 9 video to view the above clips.

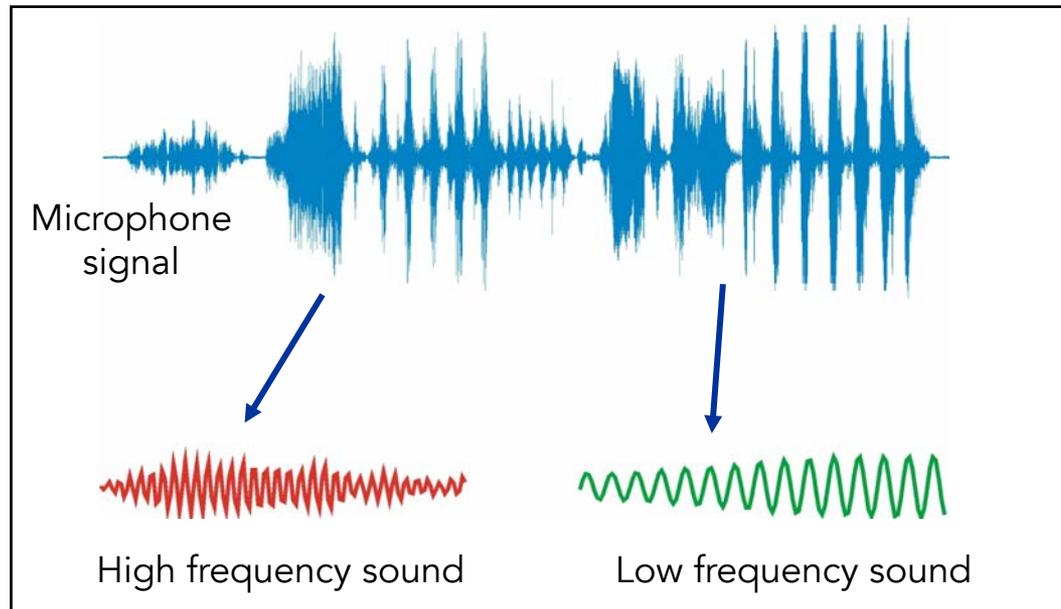
# Mean Effective Stimulus for an ON cell



# Spectro-temporal receptive fields

We can use this same approach to describe the responses of neurons in the auditory system.

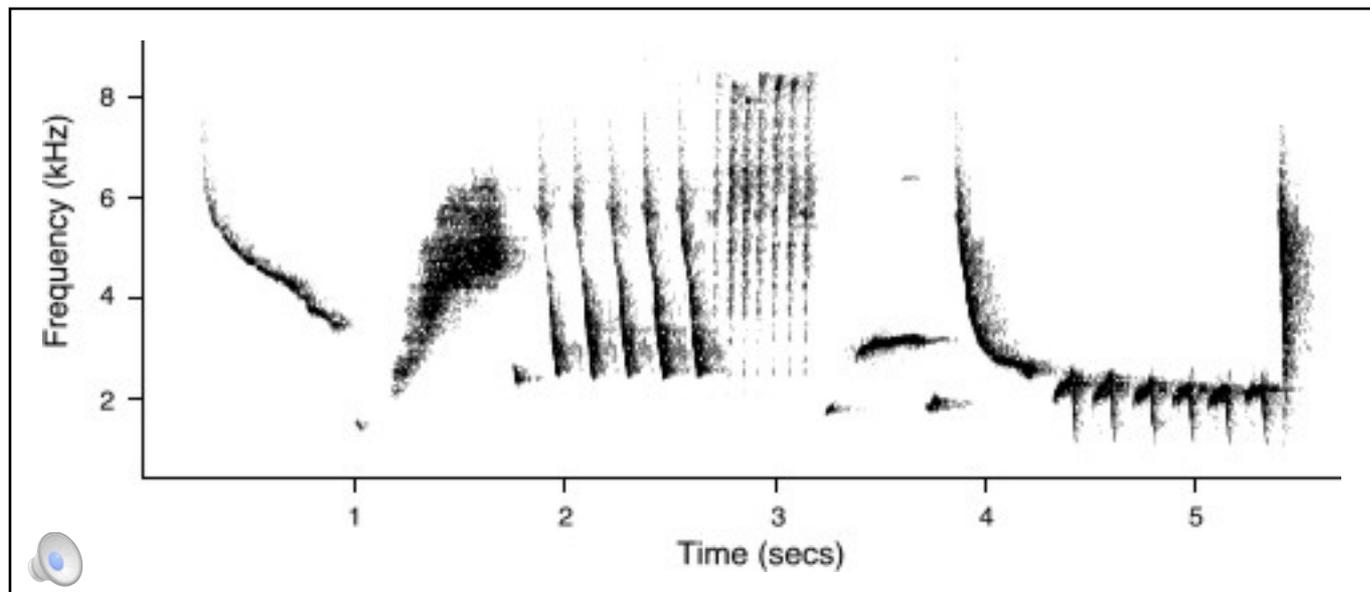
We start by representing sounds in a spectral representation.



# Spectrogram

A spectrogram shows how much power there is in a sound at different frequencies and at different times.

$$S(f, t)$$



# Spectro-temporal receptive fields

Spectro-temporal receptive fields from A1 in monkey.

Figures removed due to copyright restrictions. See Lecture 9 video or Figure 1 in deCharms, R.C., D.T. Blake and M.M. Merzenich. "[Optimizing Sound Features for Cortical Neurons.](#)" *Science* 280 No. 5368 (1998): 1439-1444.

# Spectro-temporal receptive fields

Spectro-temporal receptive fields from A1 in monkey.

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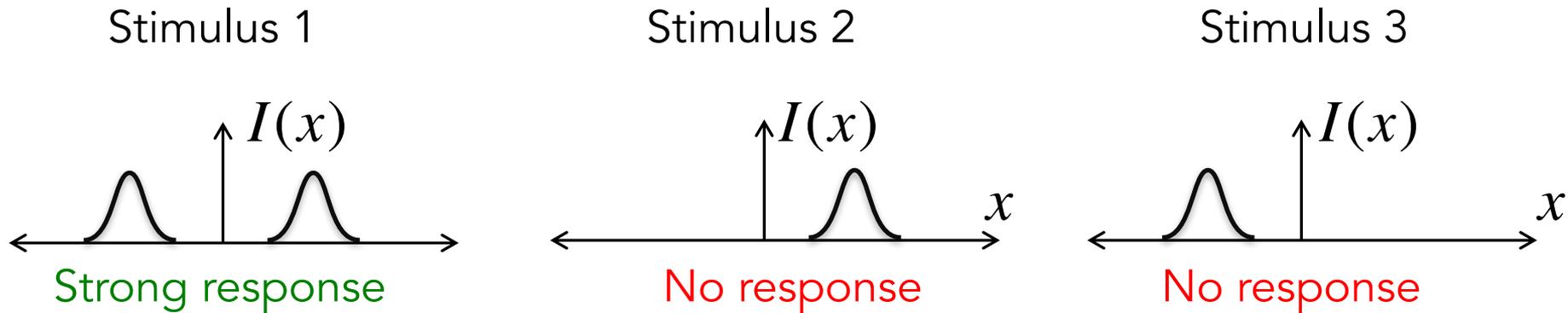
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# Extra slides on nonlinear receptive fields

# Non-linearities

Imagine a neuron with these responses to the following stimuli.



Is this neuron linear?

$$r = r_0 + \int G_1(x)I(x)dx$$

If this response was captured by a linear kernel, then, the response to Stimulus 2 and 3 would be half as large as to Stimulus 1. Thus...

$$G_1(x) = 0$$

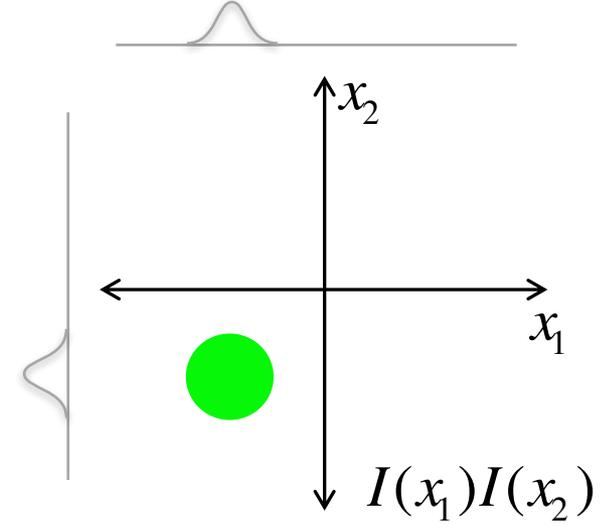
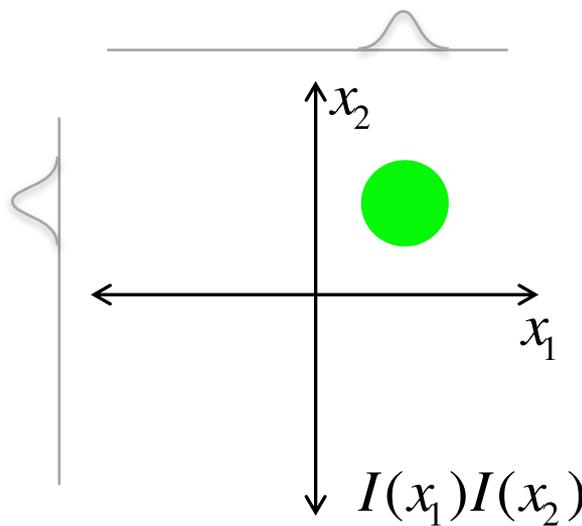
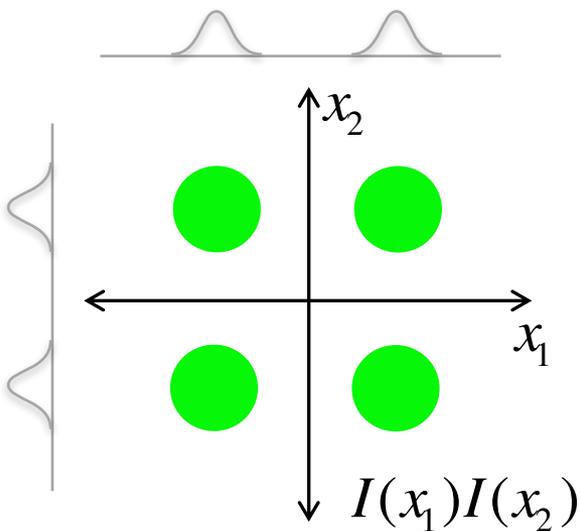
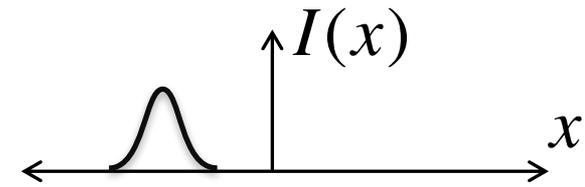
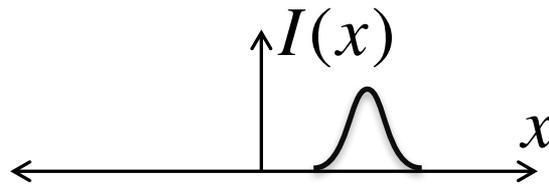
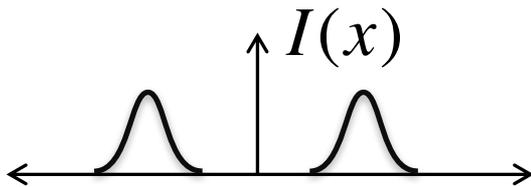
# Non-linearities

$$r = r_0 + \int dx_1 dx_2 G_2(x_1, x_2) I(x_1) I(x_2)$$

Stimulus 1

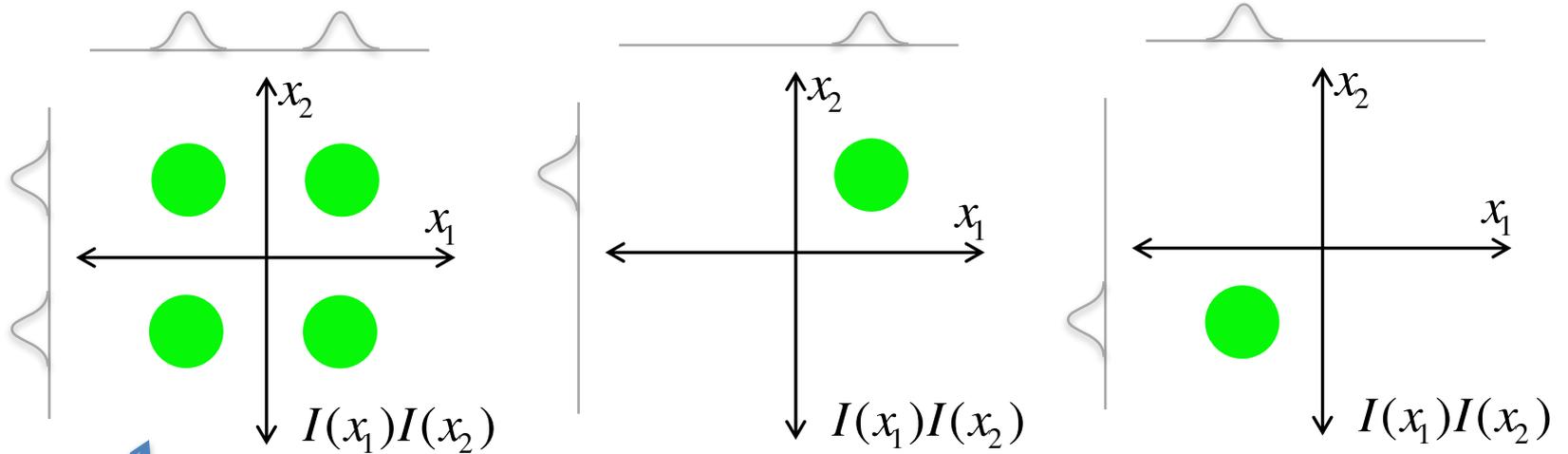
Stimulus 2

Stimulus 3

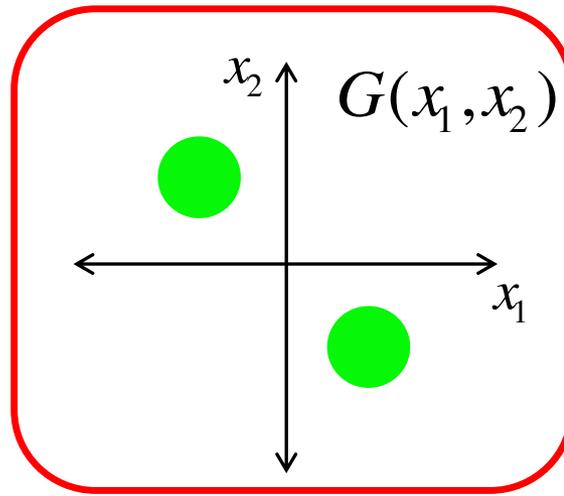


# Non-linearities

$$r = r_0 + \int dx_1 dx_2 G_2(x_1, x_2) I(x_1) I(x_2)$$



Stimulus 1 is the only one that has overlap with this nonlinear kernel.



This kernel implements an AND operation!

# Non-linearities

The Weiner-Volterra expansion is like a Taylor-series expansion for functions:

$$\begin{aligned} r &= r_0 + \int G_1(x)I(x)dx \\ &+ \int dx_1 dx_2 G_2(x_1, x_2)I(x_1)I(x_2) \\ &+ \iiint dx_1 dx_2 dx_3 G_3(x_1, x_2, x_3)I(x_1)I(x_2)I(x_3) \\ &+ \dots \end{aligned}$$

# Spike-Triggered Average

- One can show that the spike triggered average is just the cross correlation of firing rate and the stimulus

$$K(\tau) = \frac{1}{n} \sum_{i=1}^n S(t_i - \tau)$$

$$K(\tau) = \int_{-\infty}^{\infty} r(t) S(t - \tau) dt$$

reverse correlation



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