

# The Neural Code:

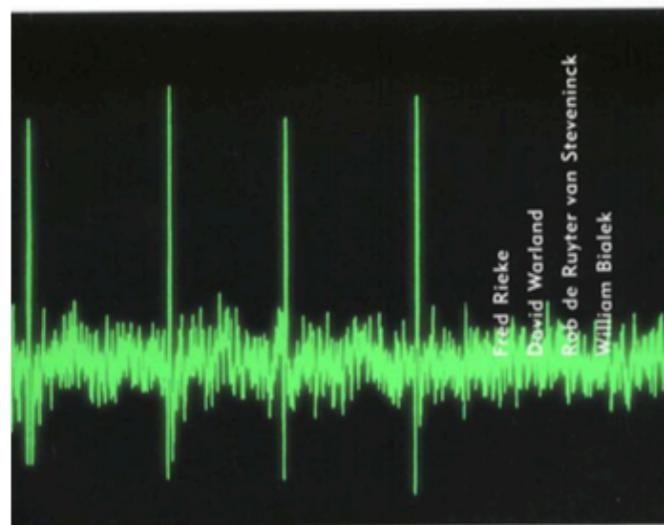
## From temporal to rate coding, and single neurons to networks.



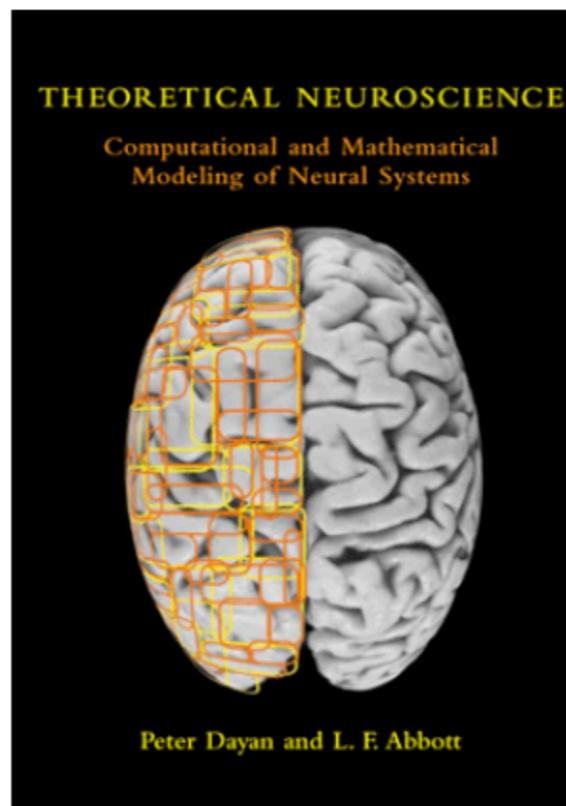
Introduction to Neuroinformatics.  
Benjamin F. Grewe  
Thursday, Nov. 7th, 2019

# Literature/Books:

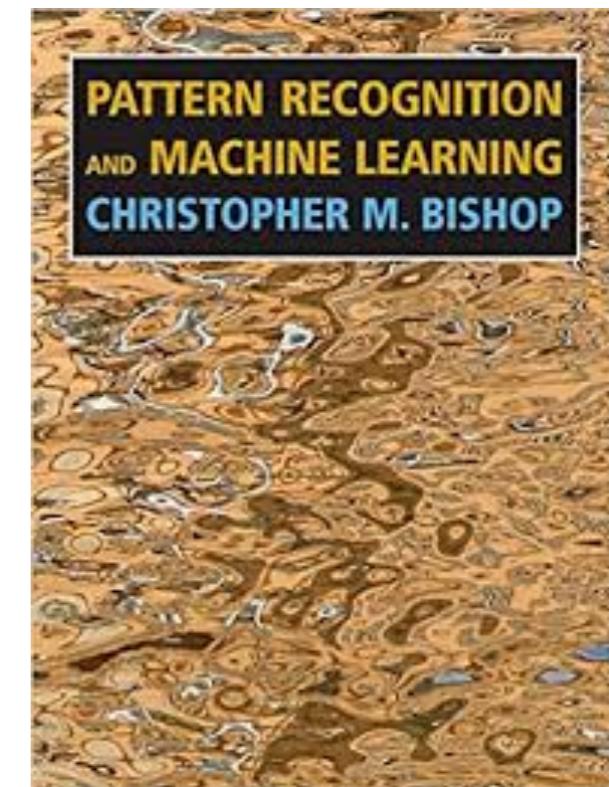
**S P I K E S**  
EXPLORING THE NEURAL CODE



Rieke et al. 1997



Dayan and Abbott

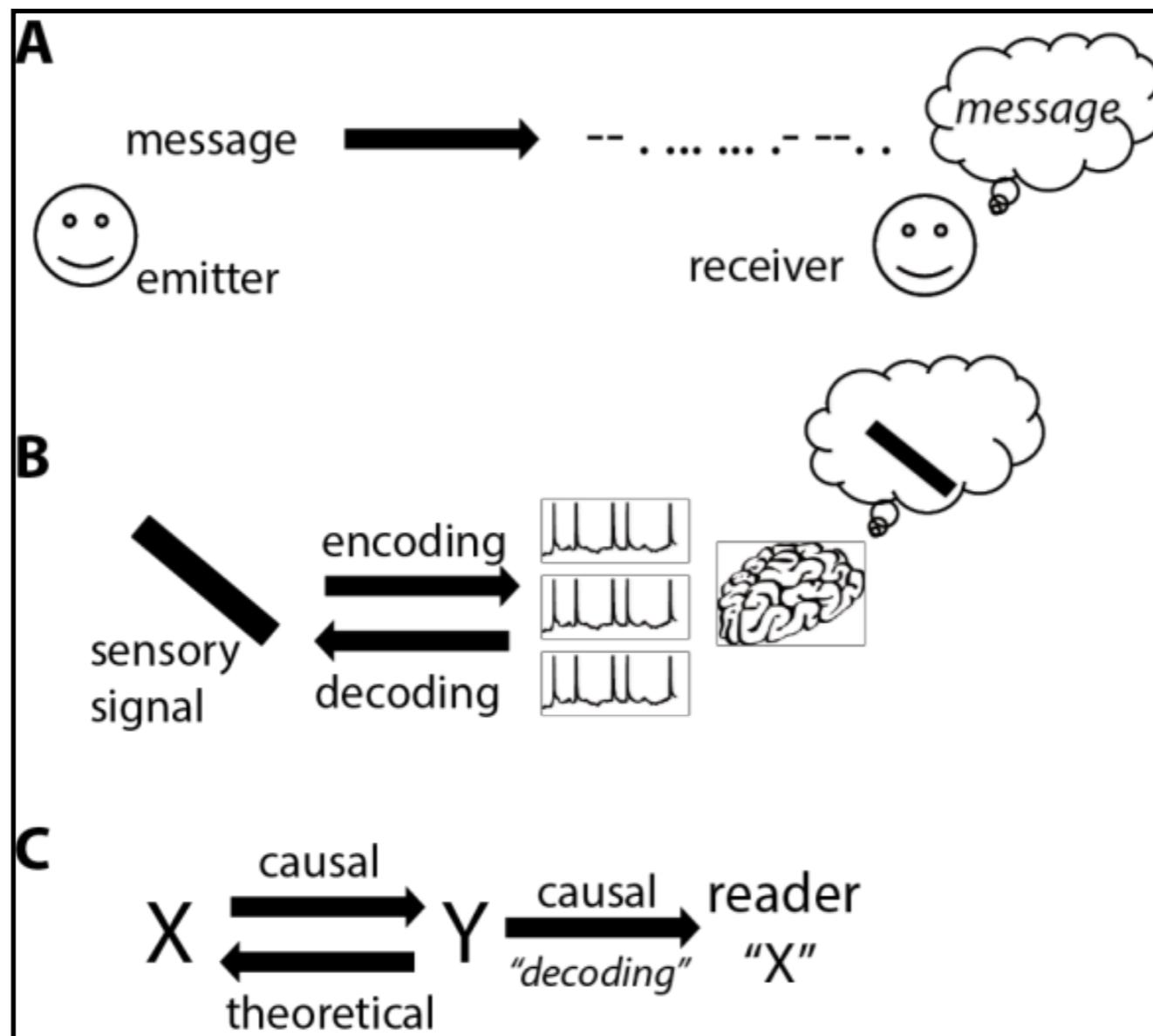


Bishop 2011

# Paper and Reviews:

- **Brette 2017, 10.1101/168237**
- **deCharms and Zador, 2000, 10.1146/annurev.neuro.23.1.613**
- **Perkel and Bullock, 1968, <https://ntrs.nasa.gov/search.jsp?R=19690022317>**
- **Quiroga et al, 2005, 10.1038/nature03687**
- **Georgopoulos et al., 1988, [10.1523/JNEUROSCI.08-08-02928](https://doi.org/10.1523/JNEUROSCI.08-08-02928)**
- **Grewé et al., 2017, [10.1038/nature21682](https://doi.org/10.1038/nature21682)**

# The Coding Metaphor.



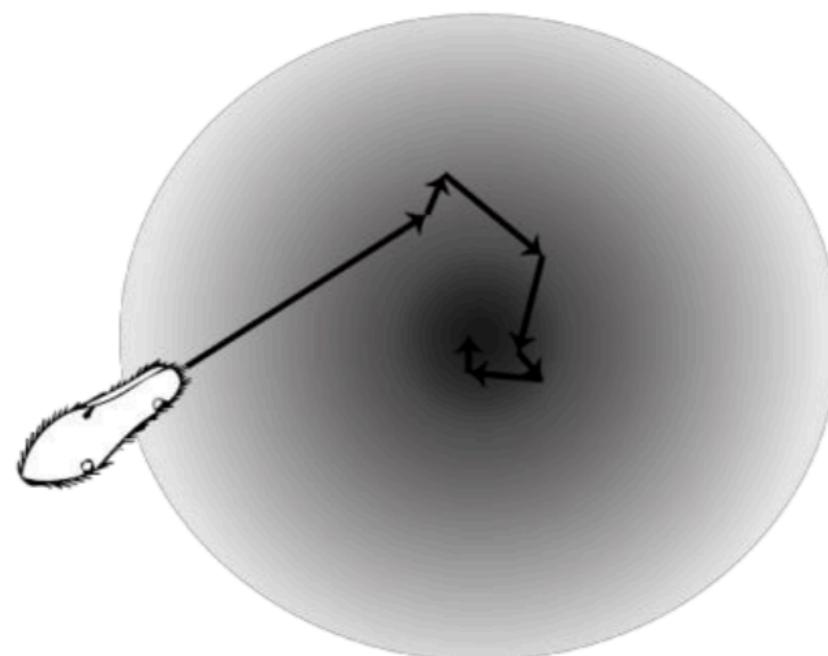
Brette, 2017, bioarxiv

**Perkel and Bullock (1968): The problem of neural coding is to elucidate “the representation and transformation of information in the nervous system.”**

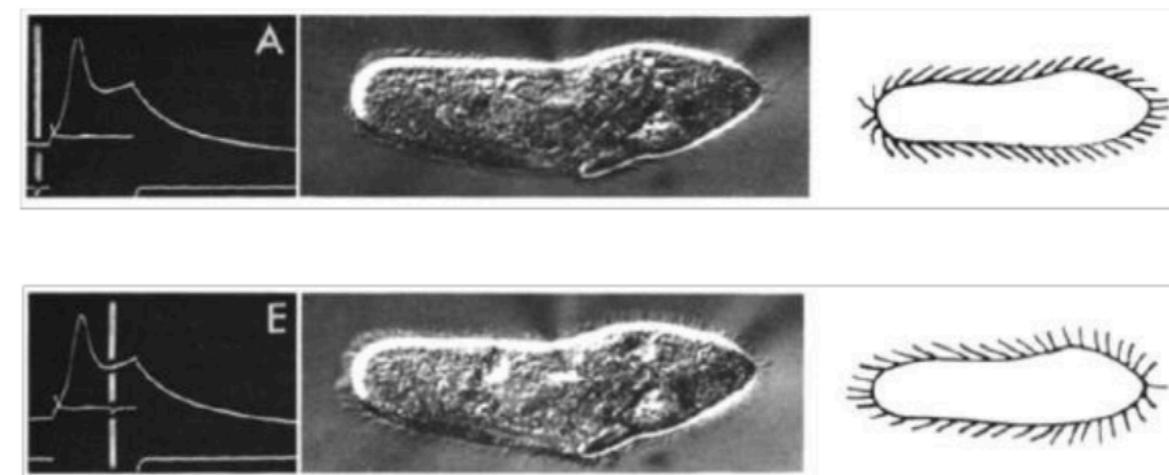
# Representation and Transformation of Information.

## The Paramecium a ‘*Swimming Neuron*’.

**A**

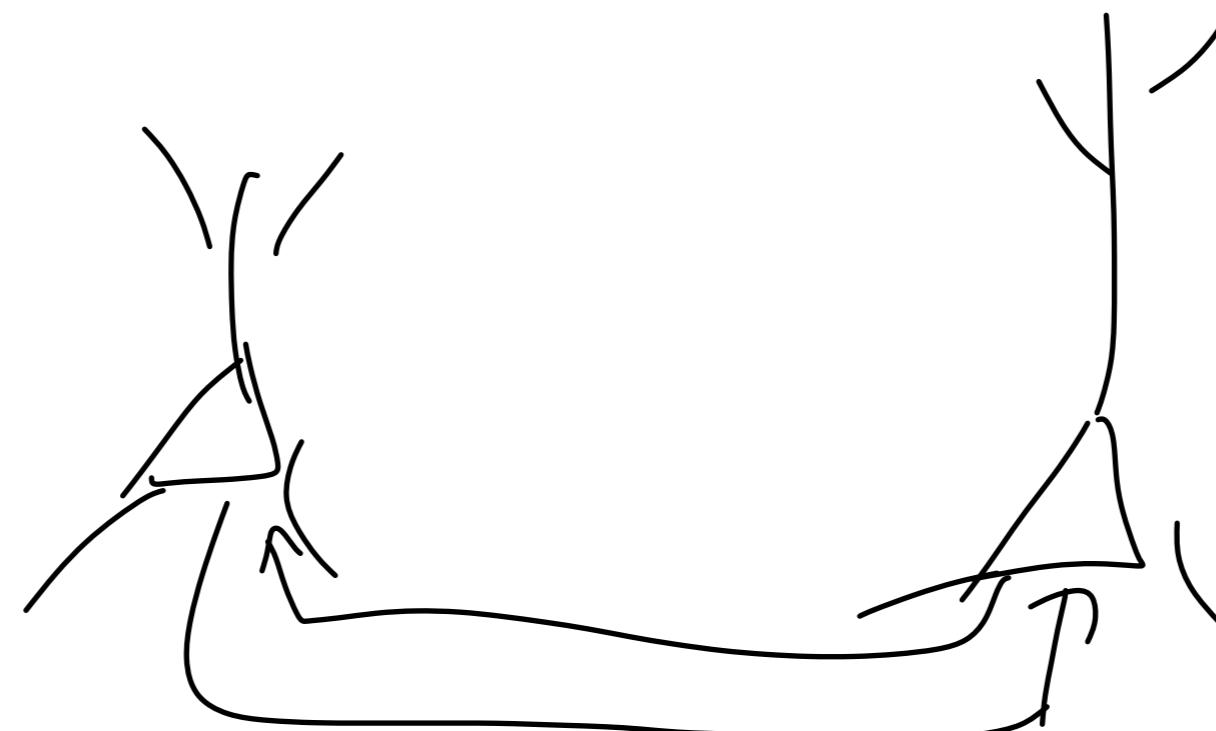


**B**



Brette, 2017, bioarxiv

# Representation and Transformation of Information.



# The Coding Metaphor.

**Considering three elements (correspondence, representation, causality):**

1. The technical sense of a code is a correspondence between two domains, e.g. visual signals and spike trains. We call this relation a code to mean that spike trains specify the visual signals, as in a cipher: one can theoretically reconstruct the original message (visual signals) from the encoded message (spike trains) with some accuracy, a process called *decoding*.
2. Not all cases of correlations in nature are considered instances of coding. Climate scientists, for example, rarely ask how rain encodes atmospheric pressure.
3. Finally, we would not say that visual signals encode retinal spike trains, even though this would comply with the technical sense. The reason is the communication metaphor implicitly assumes a causal relation between the original message and the encoded message; here, spike trains result from visual signals by a causal process (transduction).

# Encoding and Decoding of Information.

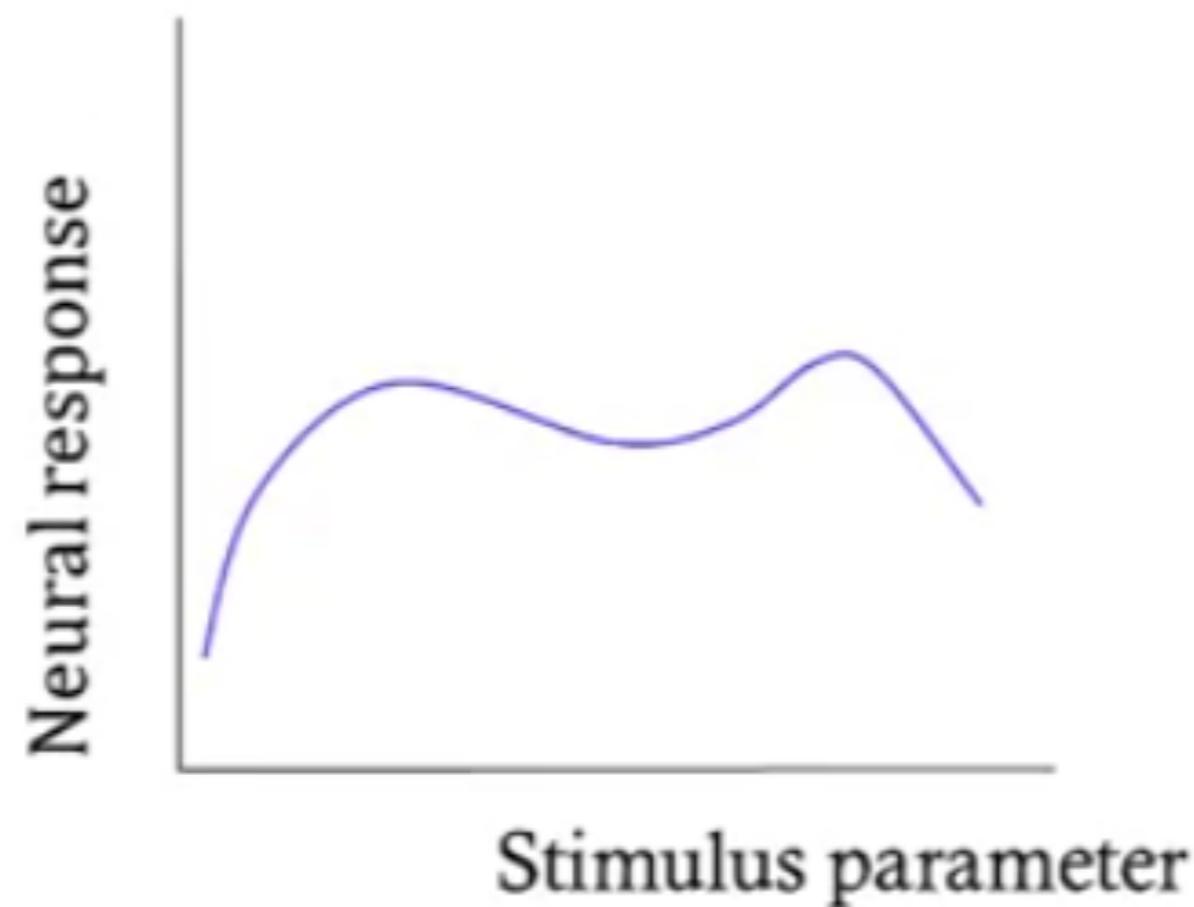
**Encoding:** How does a stimulus cause a pattern of responses?

- Building an approximate mechanistic model of the world.

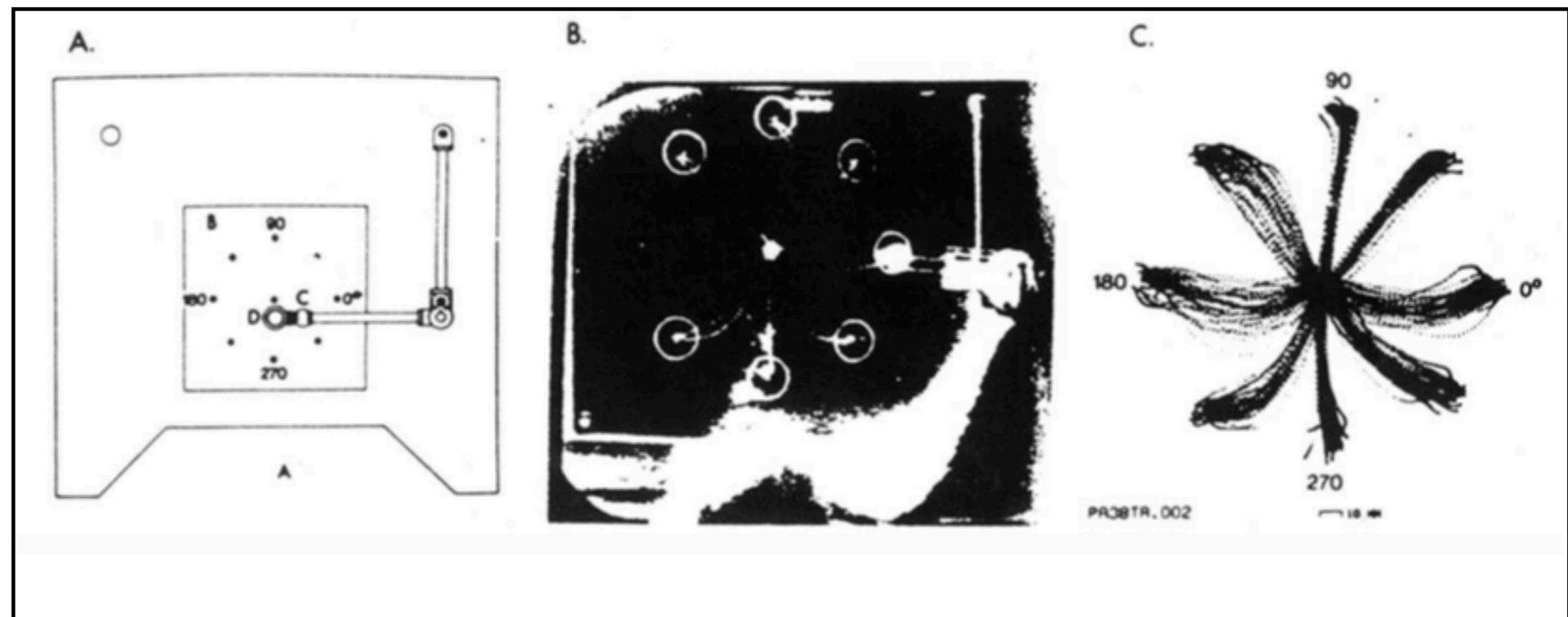
**Decoding:** What do the responses tell us about the stimulus?

- How can we reconstruct the stimulus?

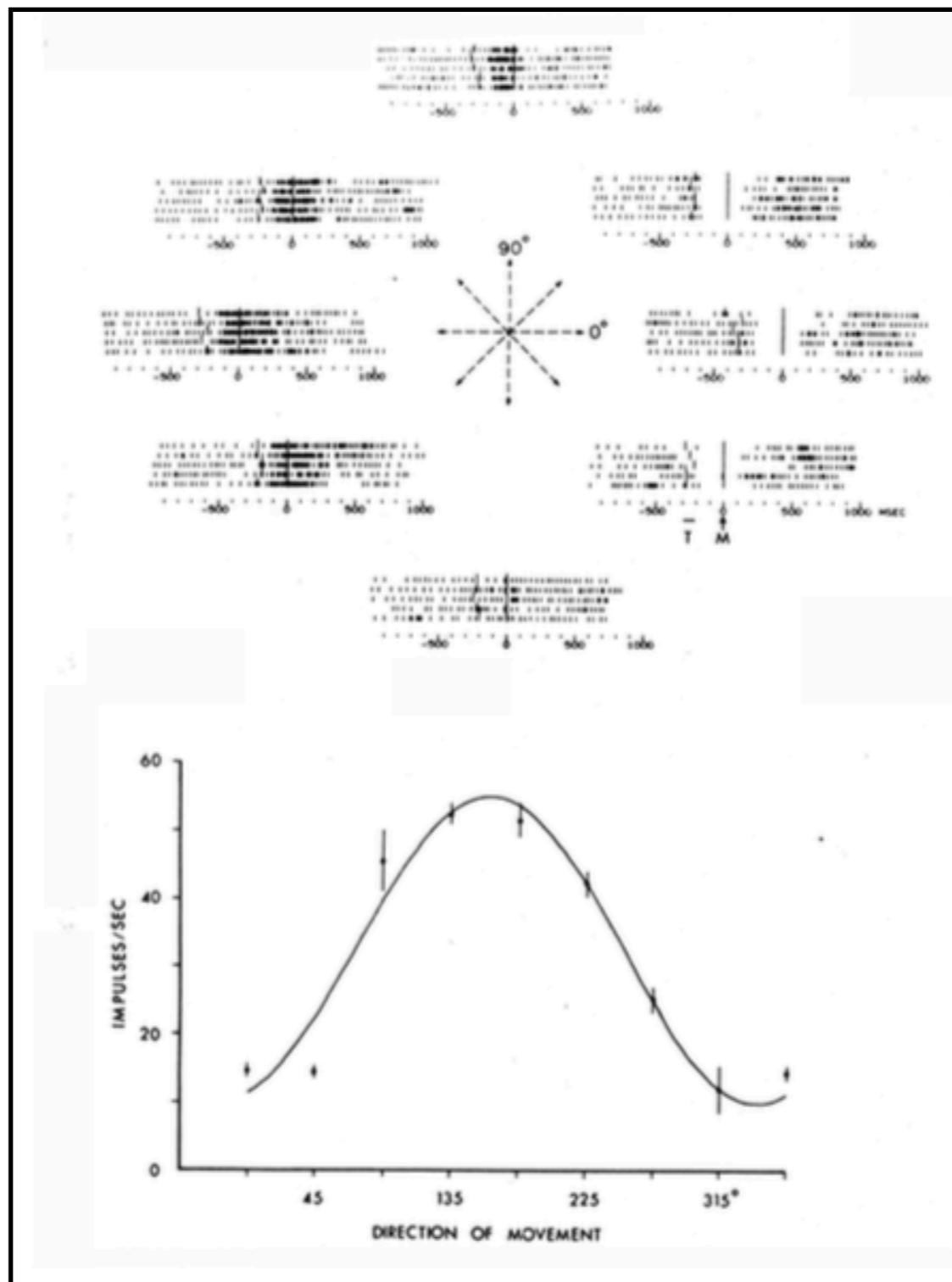
# Finding the Stimulus-Response Relation.



# Encoding Motor Output in Primates.



# Encoding Motor Output in Primates.

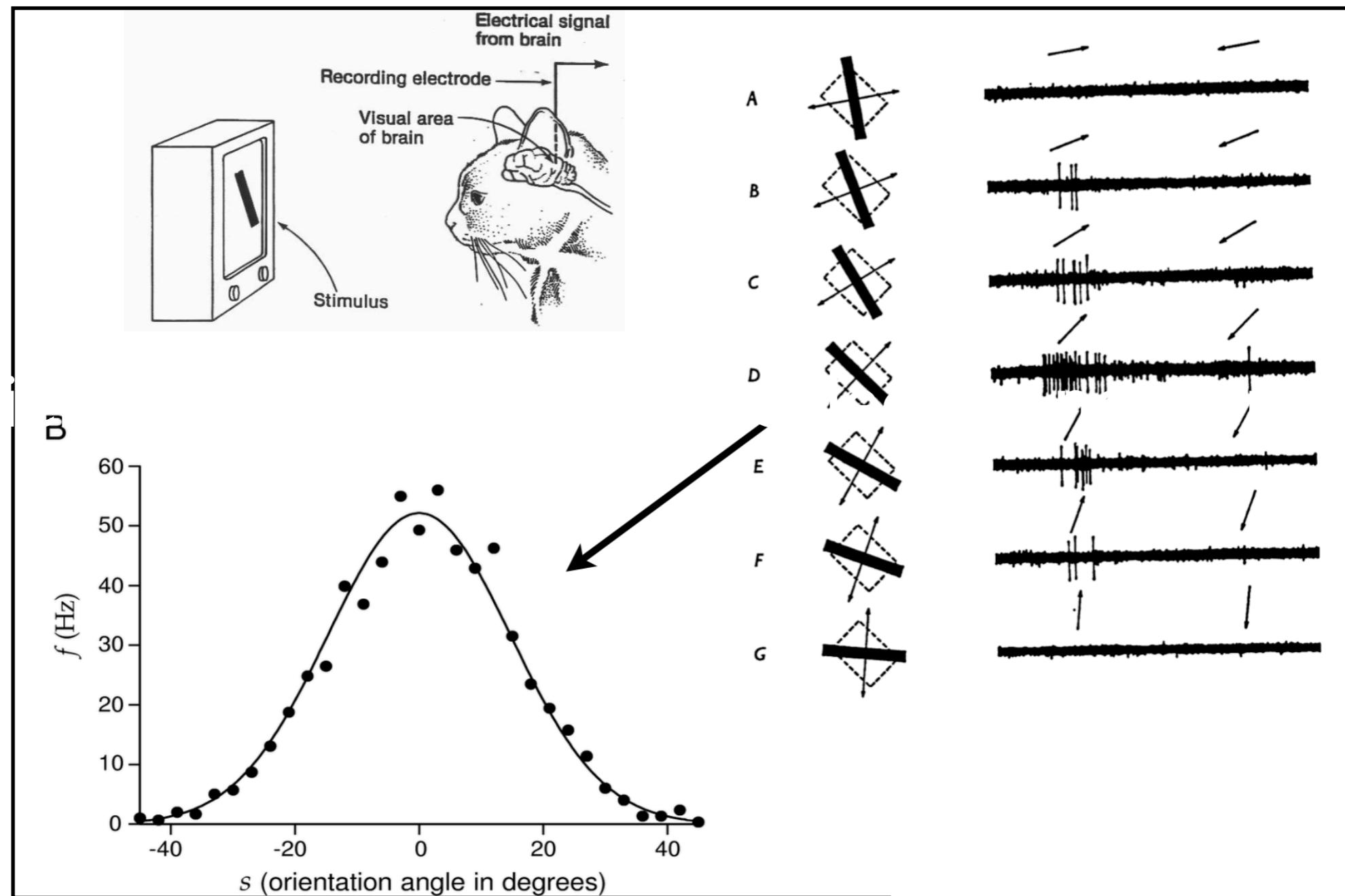


# Recording Neuronal Responses in Cat V1

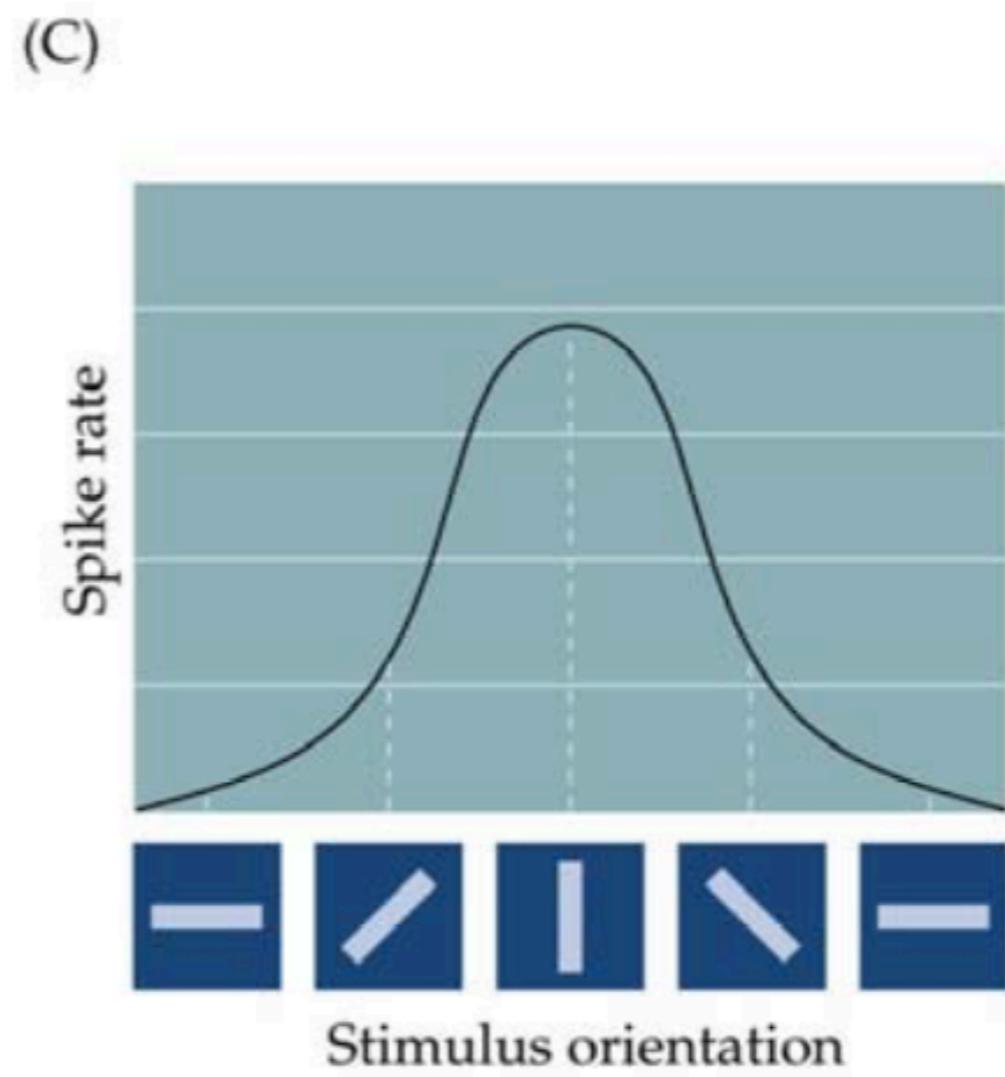
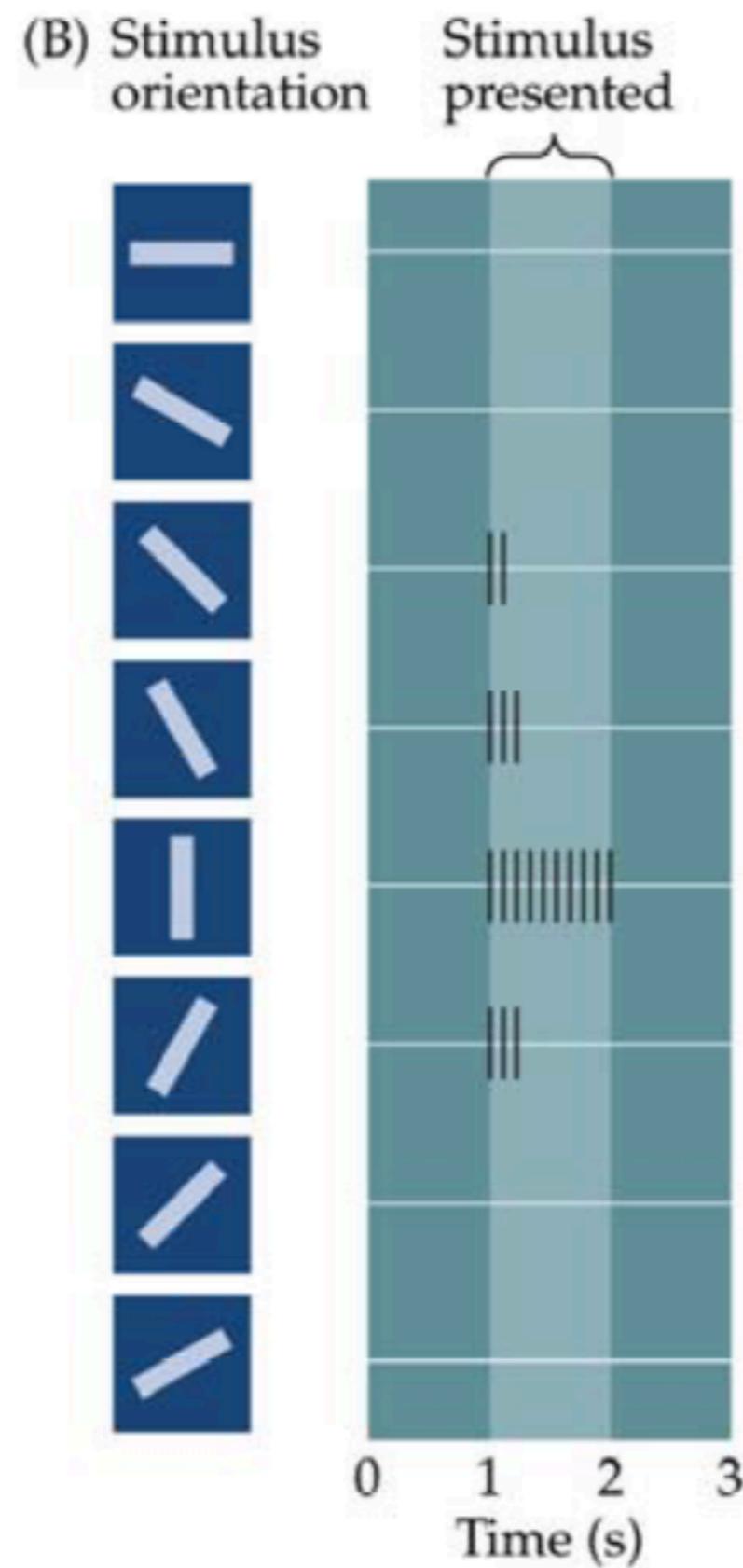
**What is the stimulus parameter encoded by V1 neurons?**



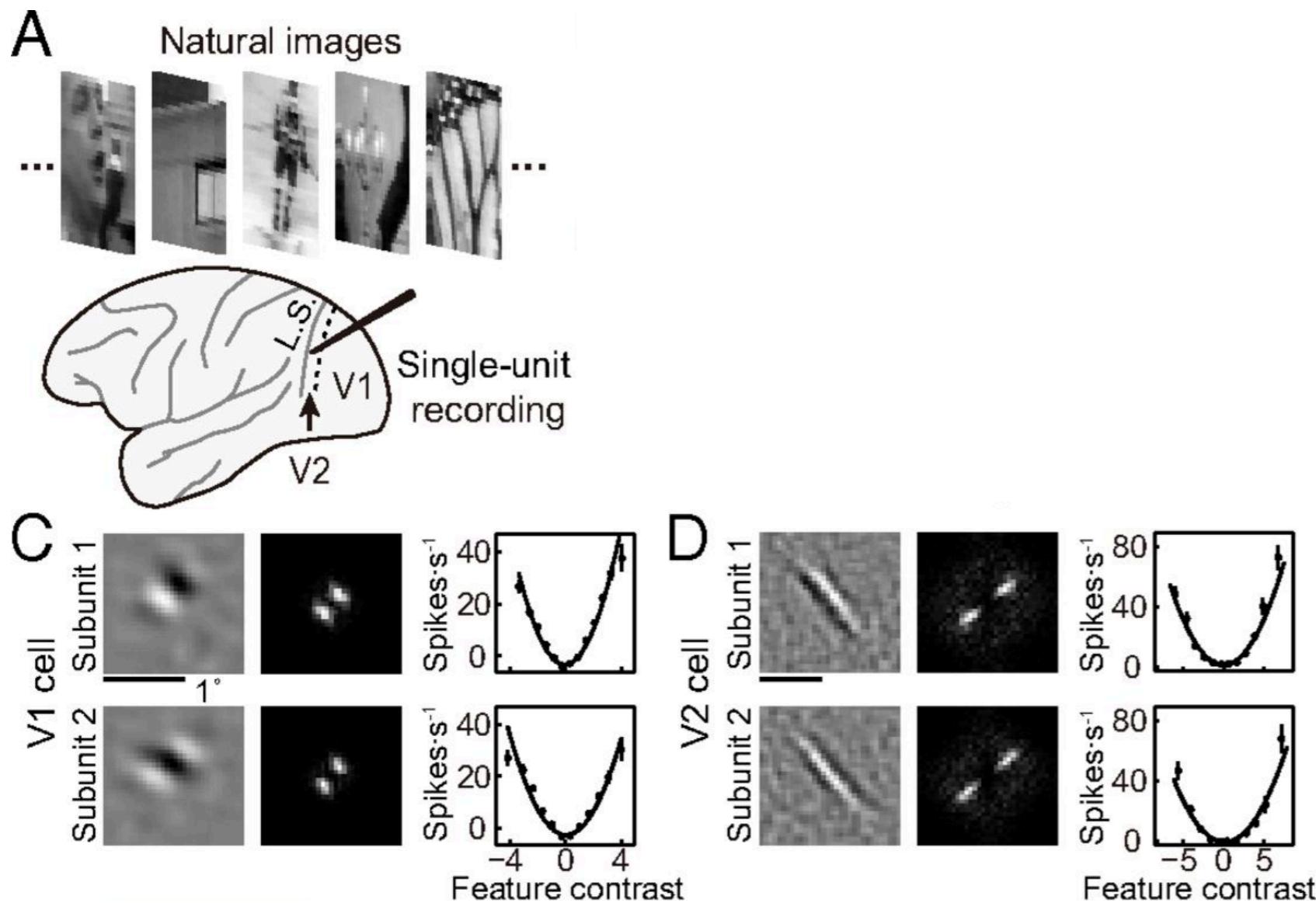
# Orientation and Direction selective Neurons in VI.



# Orientation and Direction selective Neurons in VI.



# Edge Filters in Primate Visual Cortex.



**Spatial structure of neuronal receptive field in awake monkey secondary visual cortex (V2)**

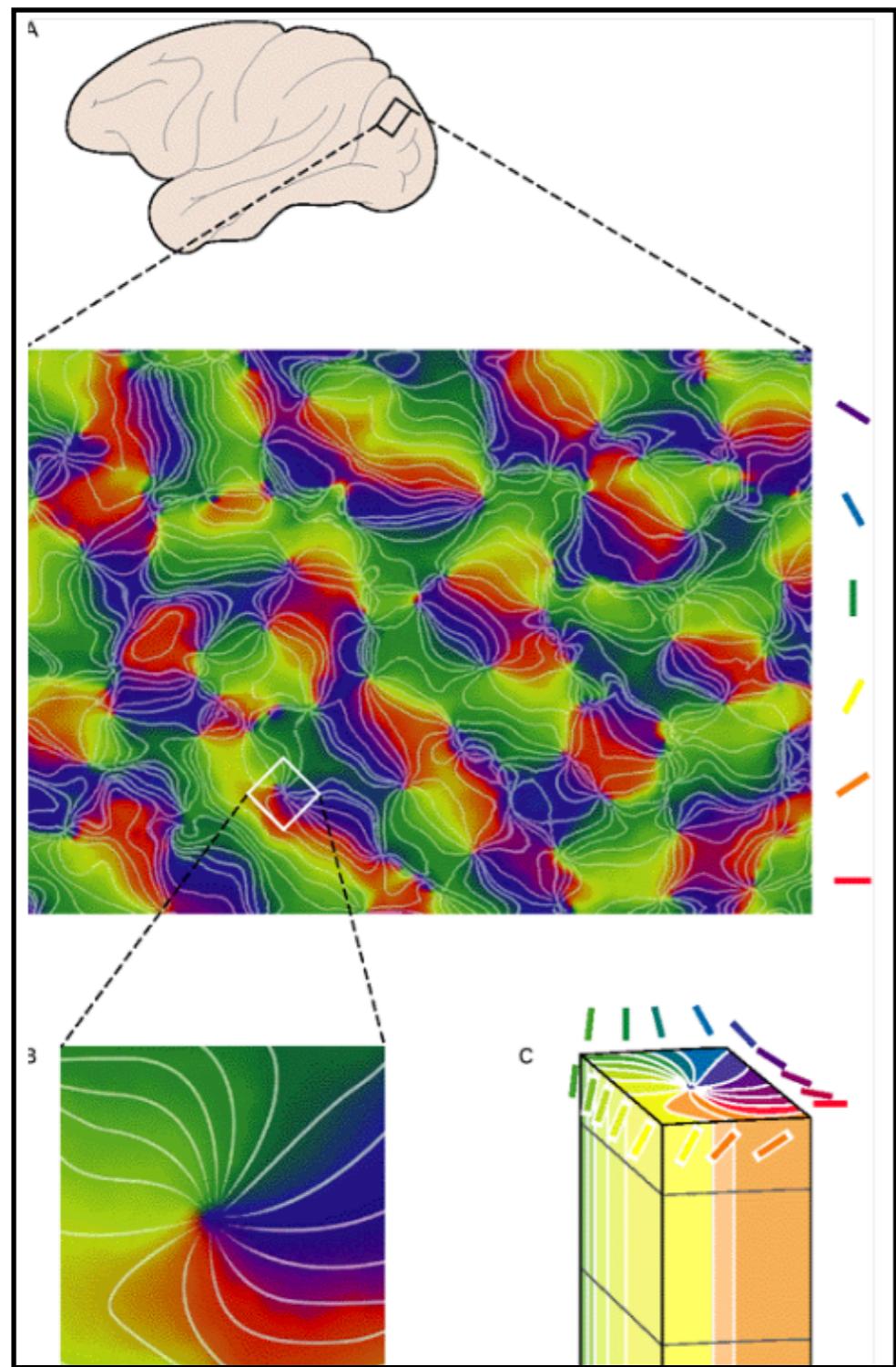


Lu Liu, Liang She, Ming Chen, Tianyi Liu, Haidong D. Lu, Yang Dan, and Mu-ming Poo

PNAS February 16, 2016 113 (7) 1913-1918; first published February 2, 2016 <https://doi.org/10.1073/pnas.1525505113>

Contributed by Mu-ming Poo, January 6, 2016 (sent for review October 12, 2015; reviewed by Judith Hirsch and Doris Y. Tsao)

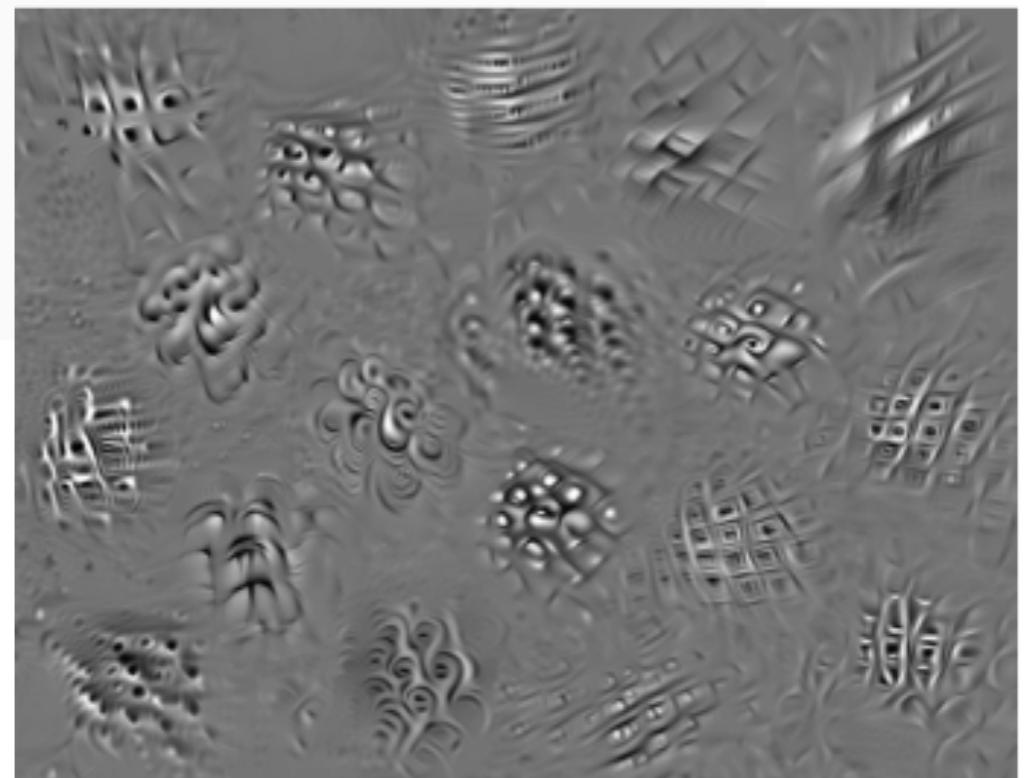
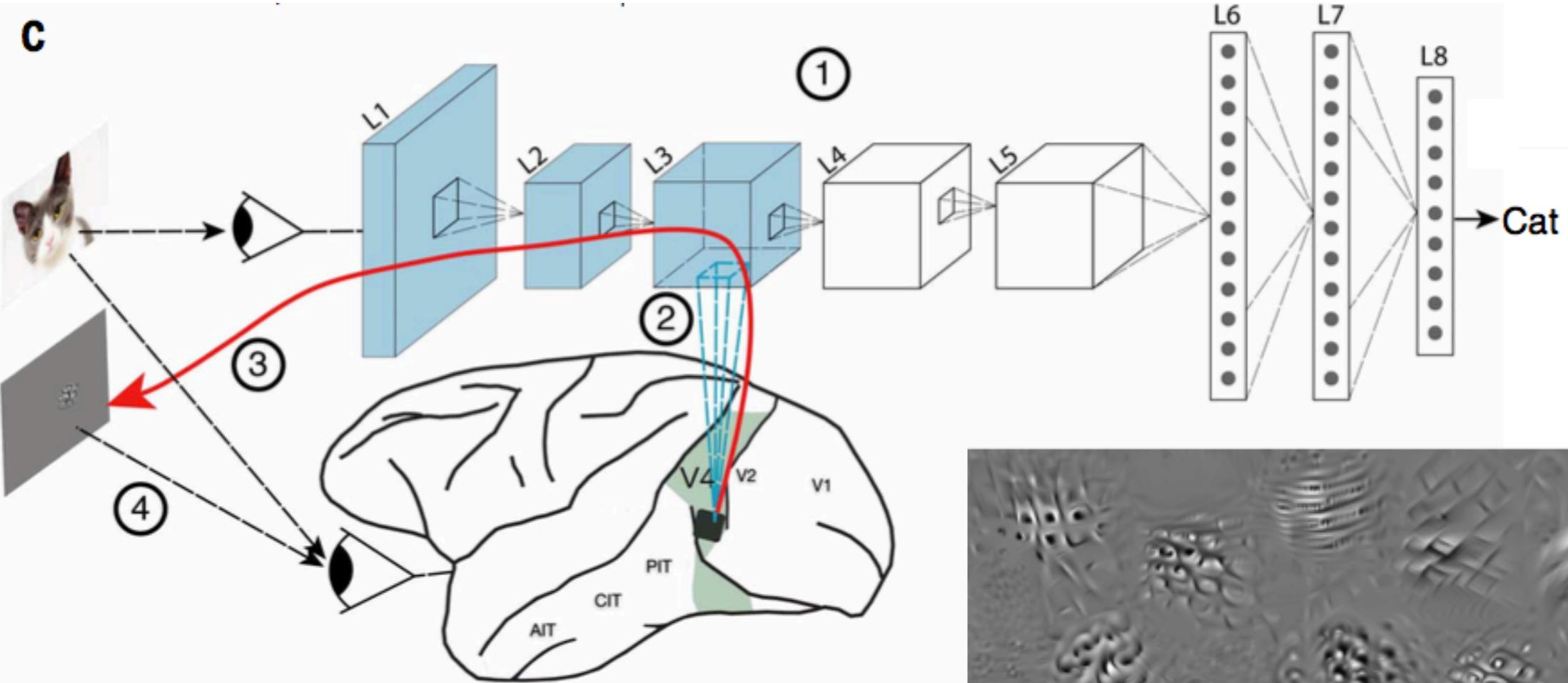
# Orientation Specific Organization in Cat VI



**Pinwheel structure.**



# Encoding complex Stimuli in Primate V4



RESEARCH

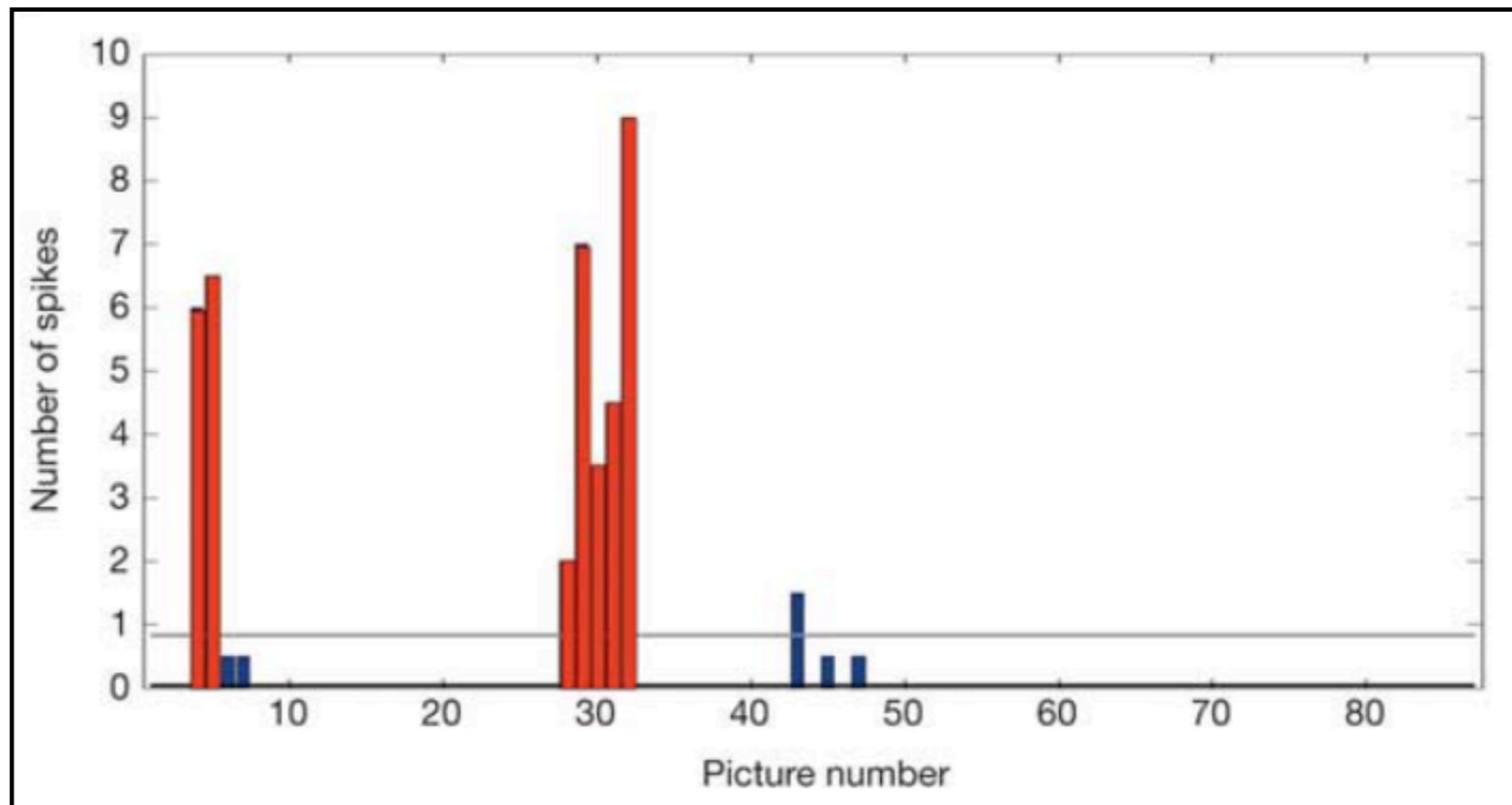
RESEARCH ARTICLE SUMMARY

NEUROSCIENCE

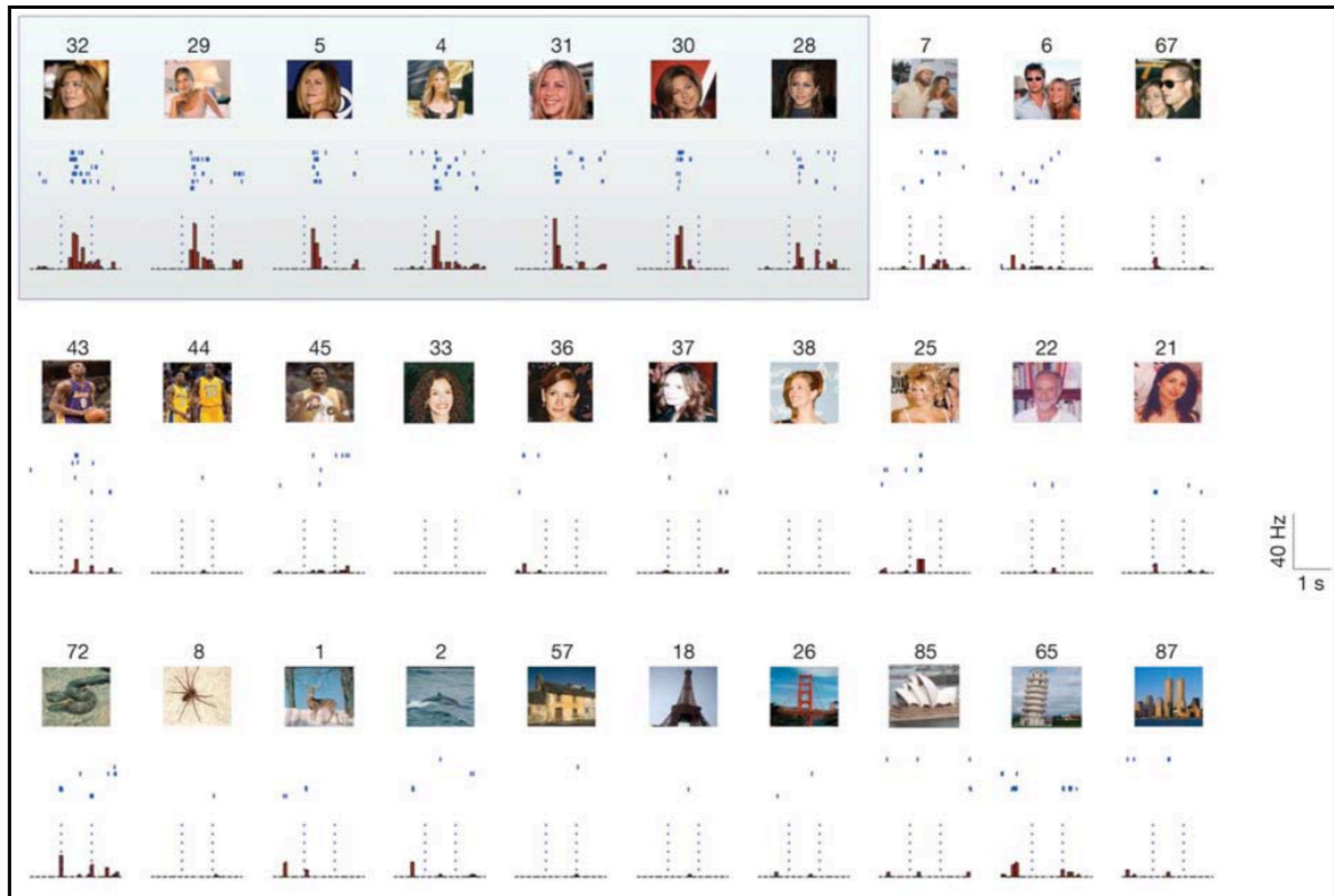
**Neural population control via deep image synthesis**

Pouya Bashivan\*, Kohitij Kar\*, James J. DiCarlo†

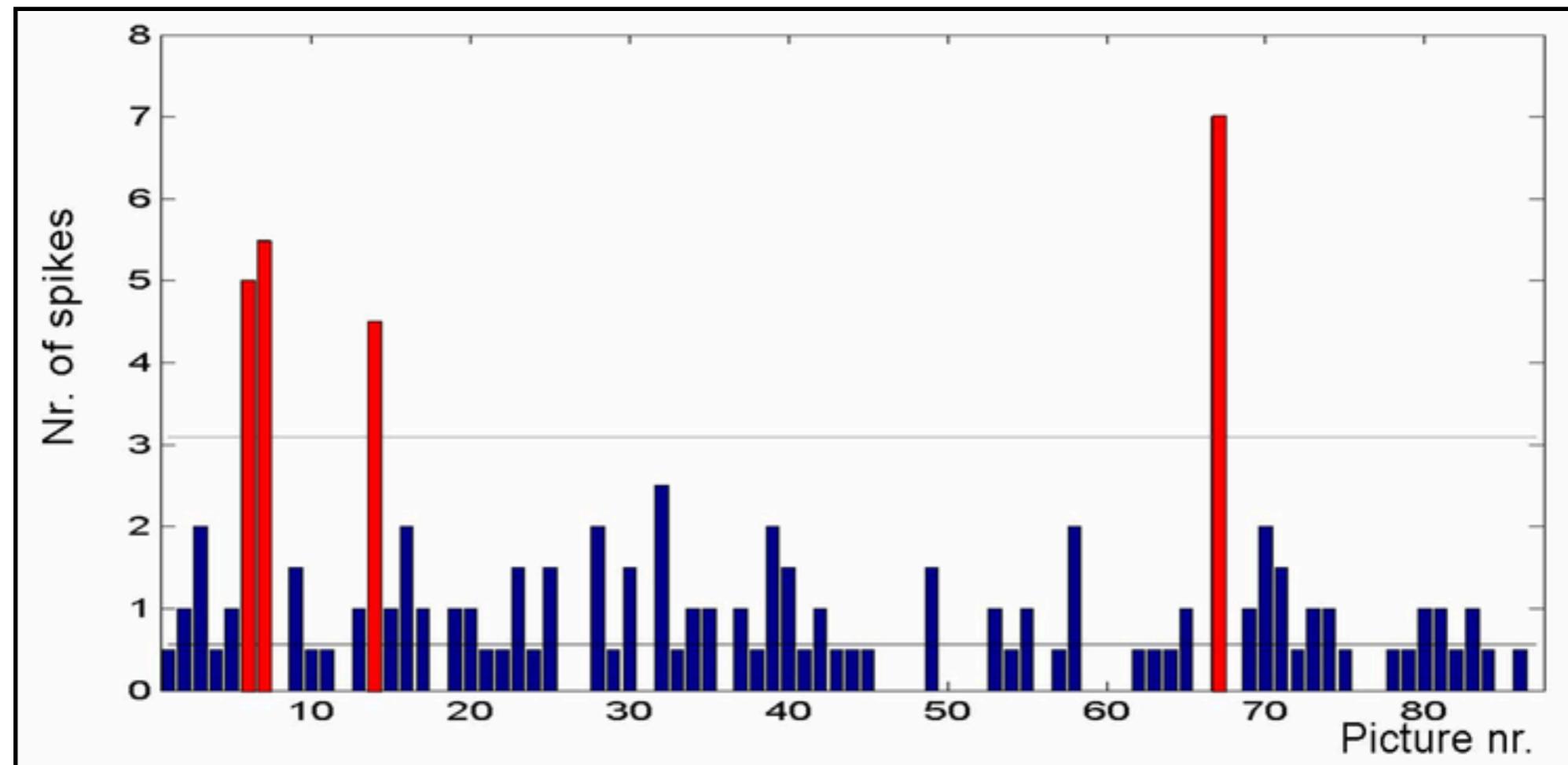
# Encoding Visual Stimuli in the Human Brain (area MTL)



# Encoding Visual Stimuli in the Human Brain (area MTL)



# Encoding Visual Stimuli in the Human Brain (area MTL)



# Encoding Visual Stimuli in the Human Brain (area MTL)



# Encoding Spatial Information in Rat Hippocampus.

The Nobel Prize in Physiology or Medicine 2014  
John O'Keefe, May-Britt Moser, Edvard Moser

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## The Nobel Prize in Physiology or Medicine 2014

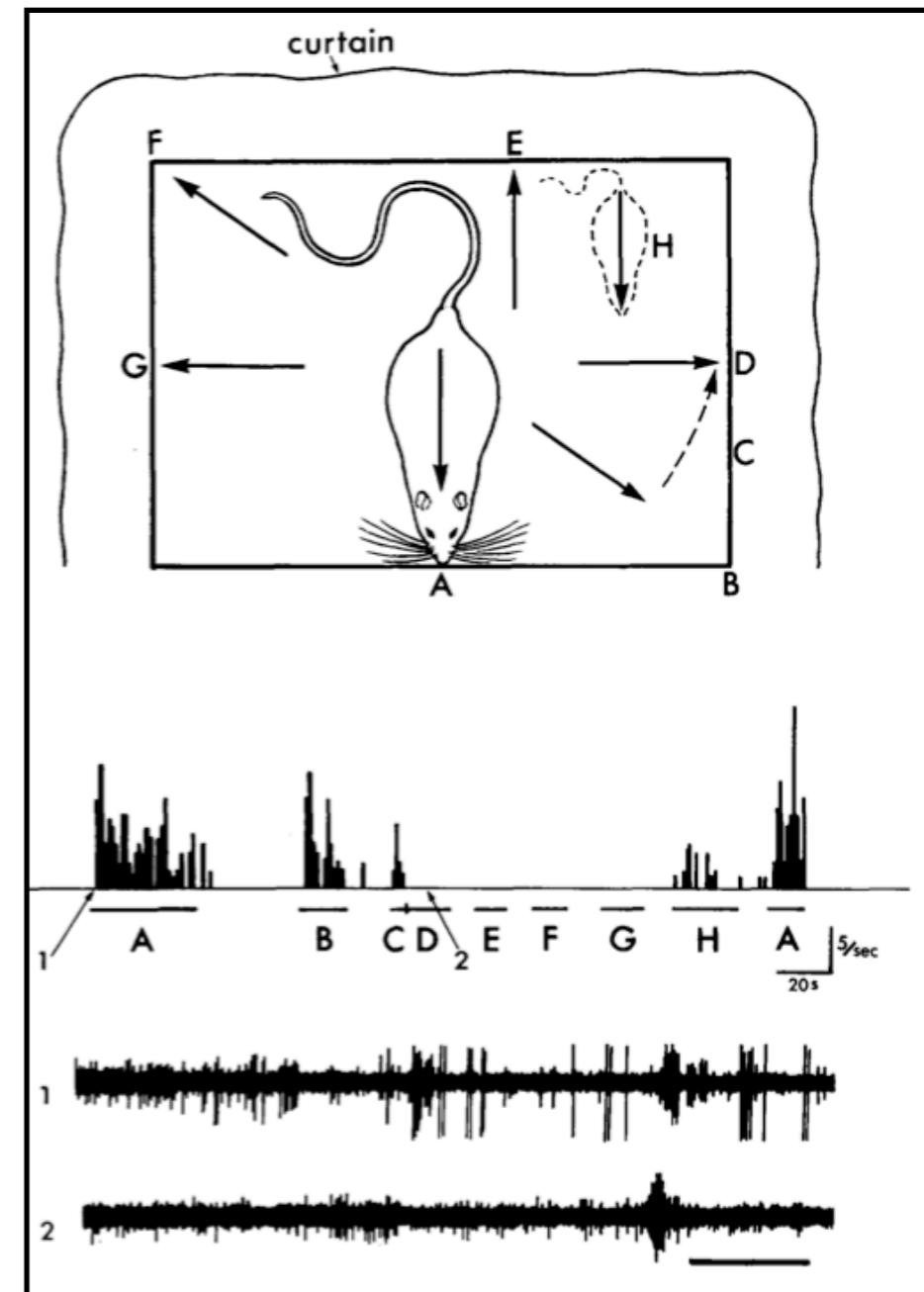
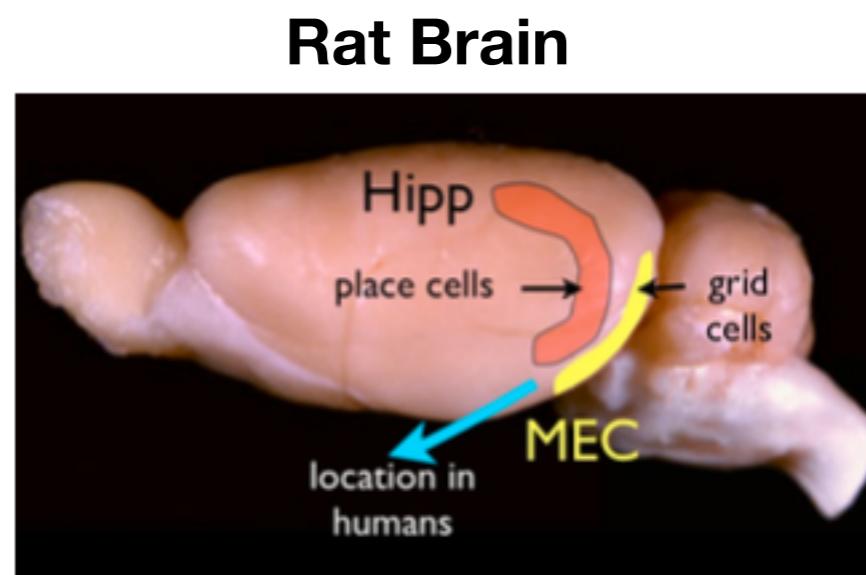


Photo: David Bishop, UCL  
**John O'Keefe**  
Prize share: 1/2

Photo: G. Mogen/NTNU  
**May-Britt Moser**  
Prize share: 1/4

Photo: G. Mogen/NTNU  
**Edvard I. Moser**  
Prize share: 1/4

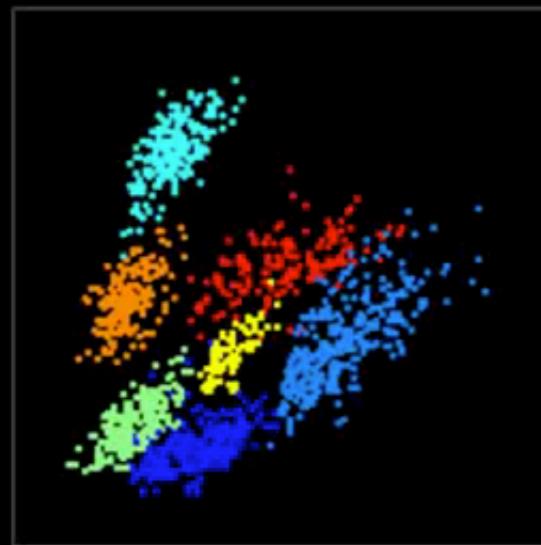
# Encoding Spatial Information in Rat Hippocampus.



# Encoding Space via Hippocampal Place Cells

cell activity

overall



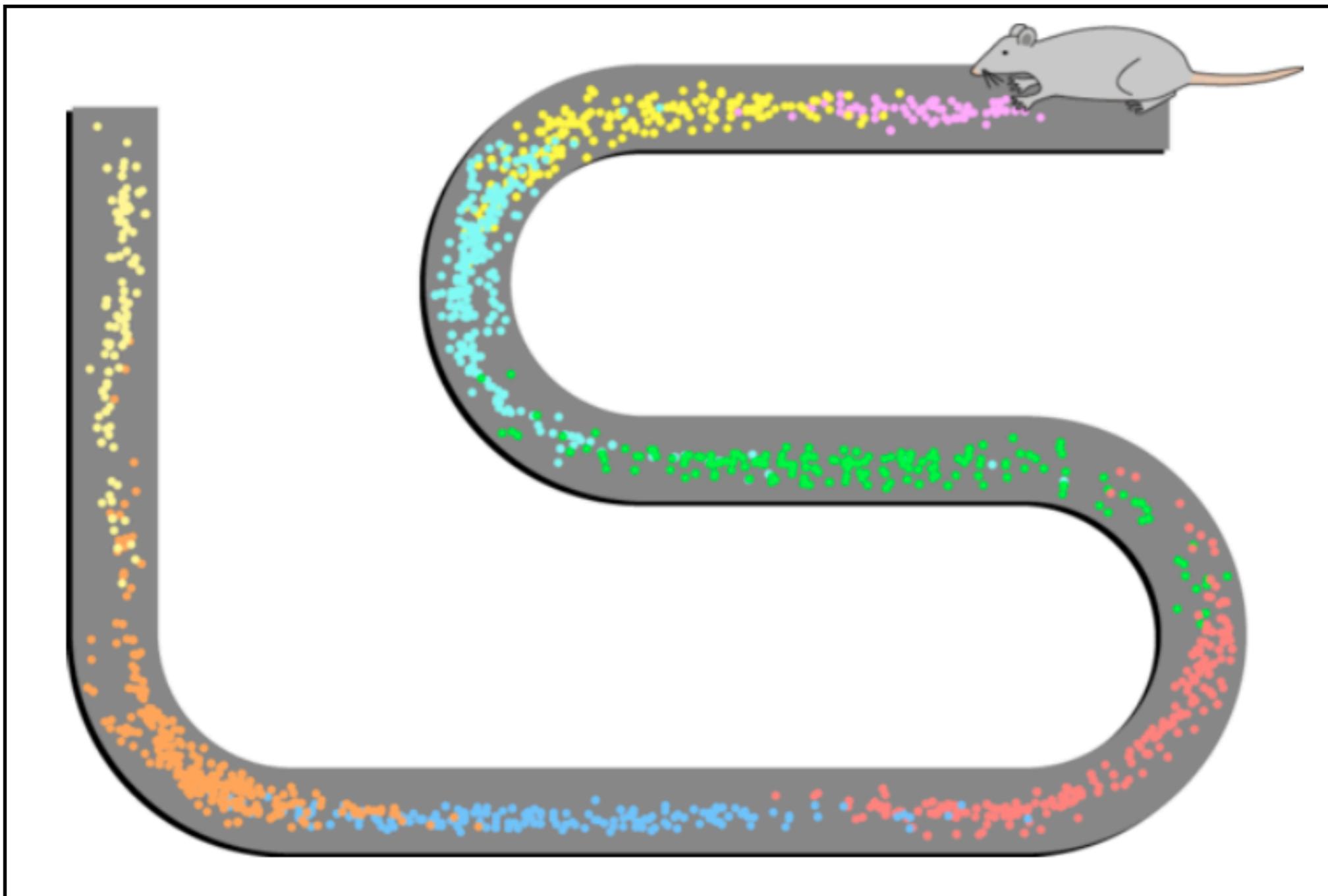
ongoing



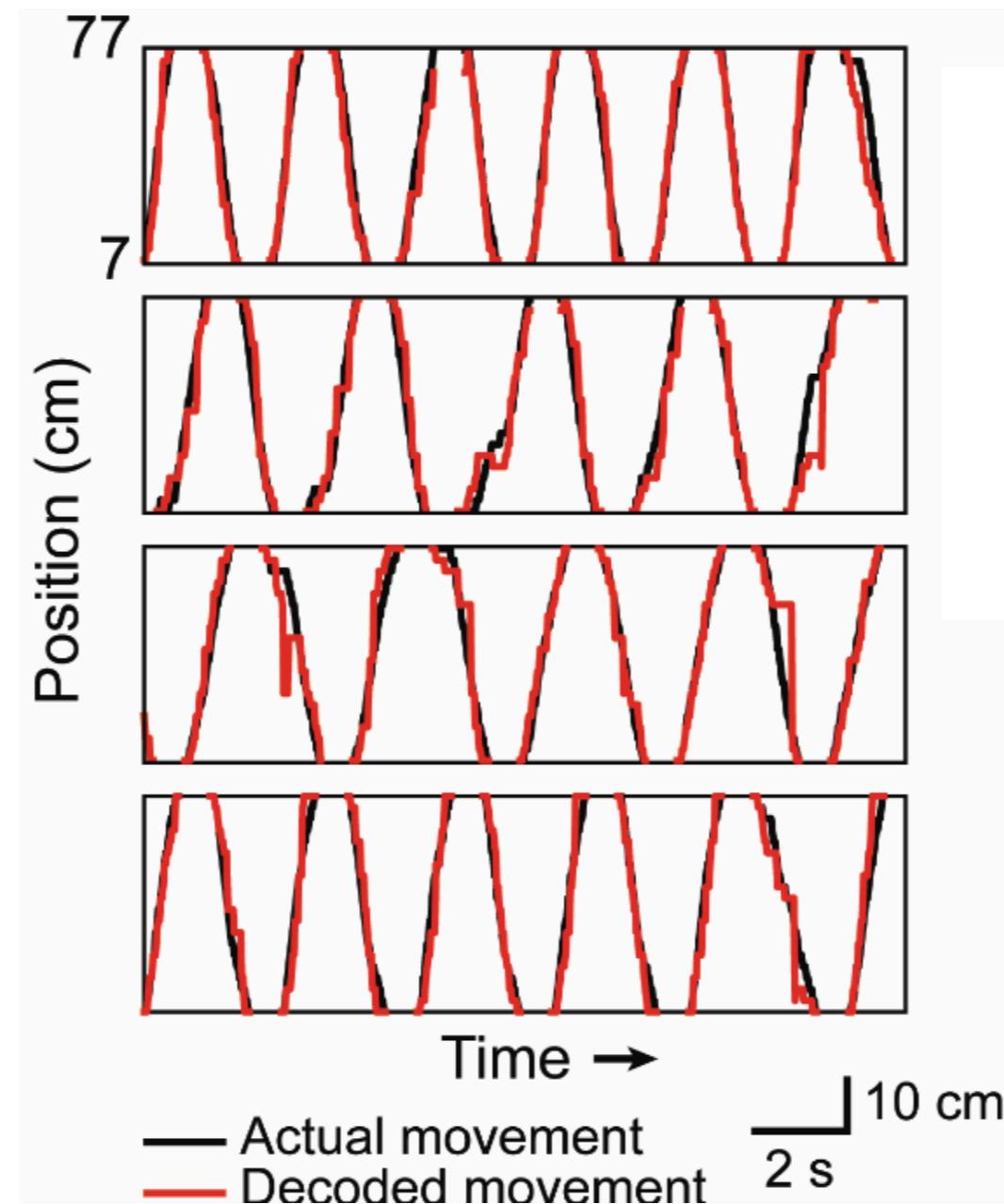
behavior



# Encoding Space via Hippocampal Place Cells



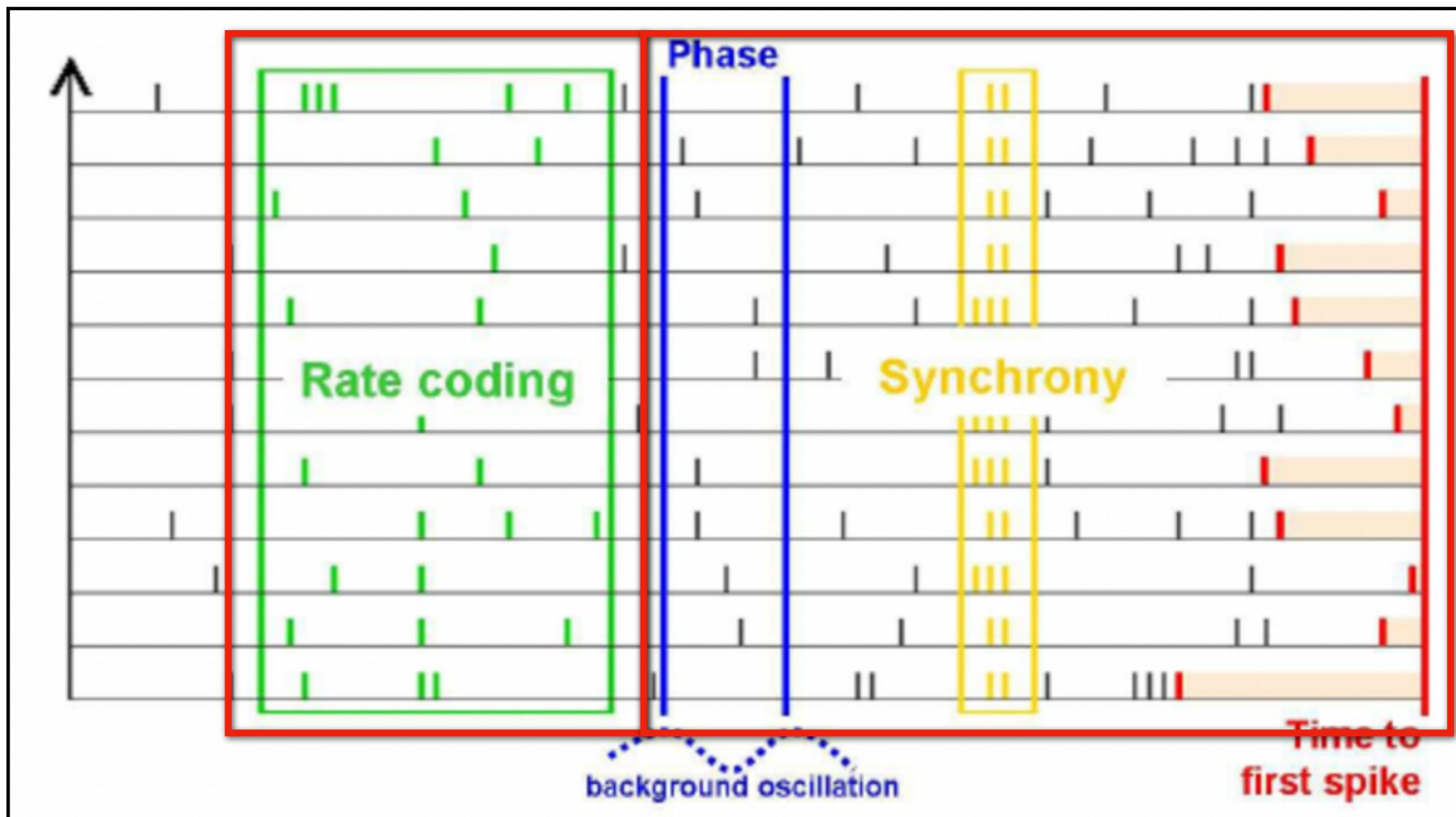
# Decoding the Rats Position from Population Activity.



Ziv and Schnitzer, 2013

# Which Features of the Spike Trains are the Signal?

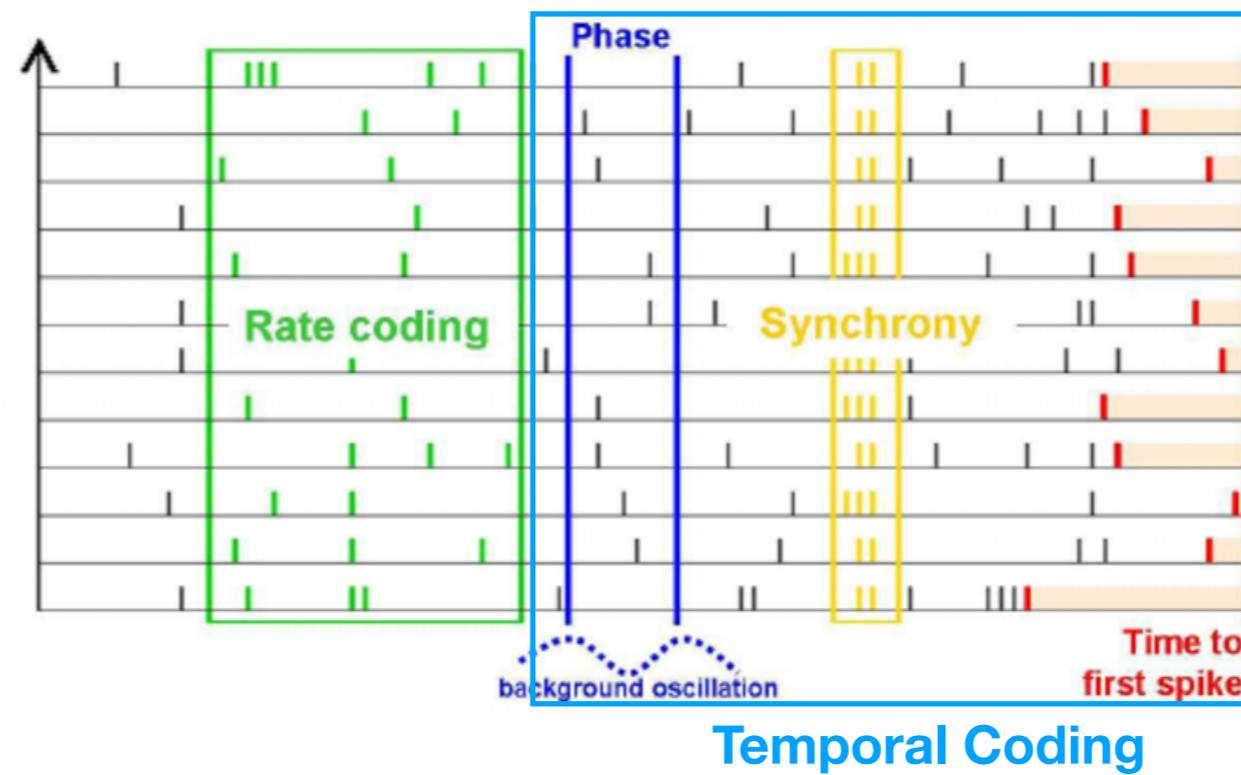
Temporal Code



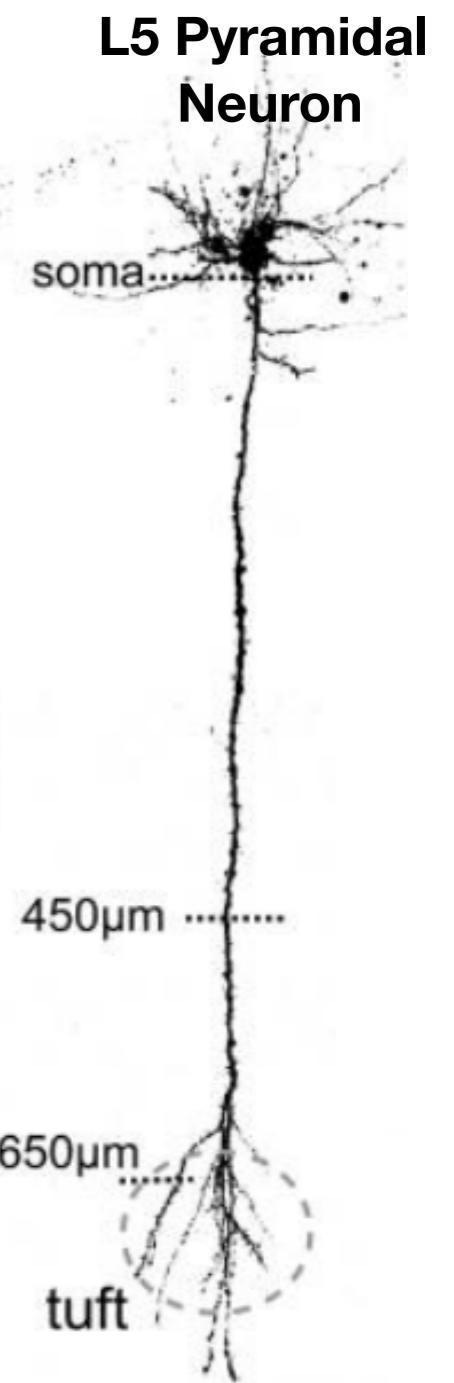
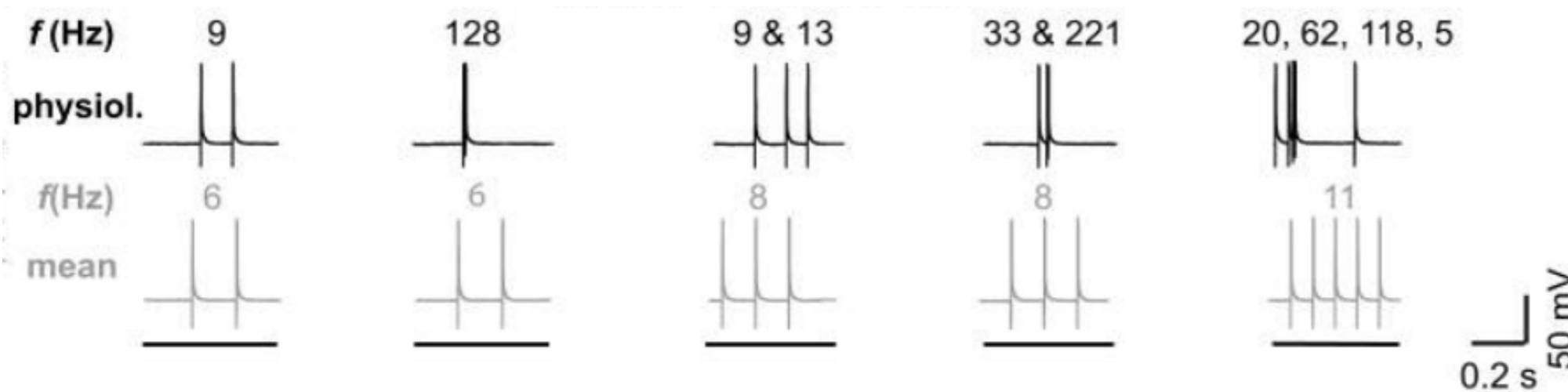
# Temporal v.s. Rate Code.

**Rate coding** refers to information being carried by the firing rate. It is often argued, or assumed, that firing rate captures essentially all relevant information.

**Temporal coding** may refer to several quite different ideas: (i) Much of the information may be transmitted by a neuron during certain small intervals of time, (ii) synchronous, or what one could call quasi-synchronous, firing of neurons within and across ensembles may carry important information, (iii) the precise timing, or pattern, of spikes may carry information.

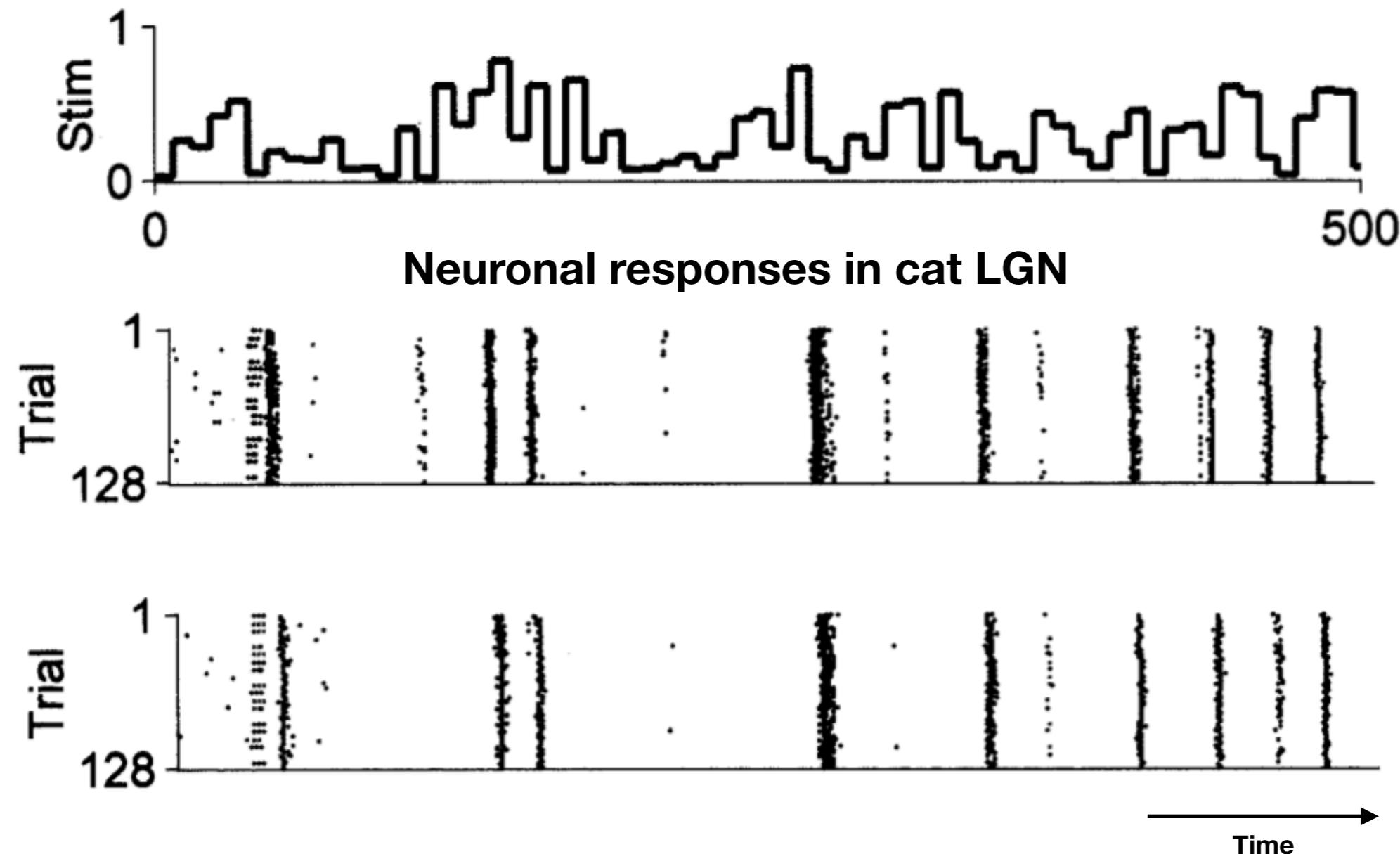


# Temporal v.s. Rate Code.

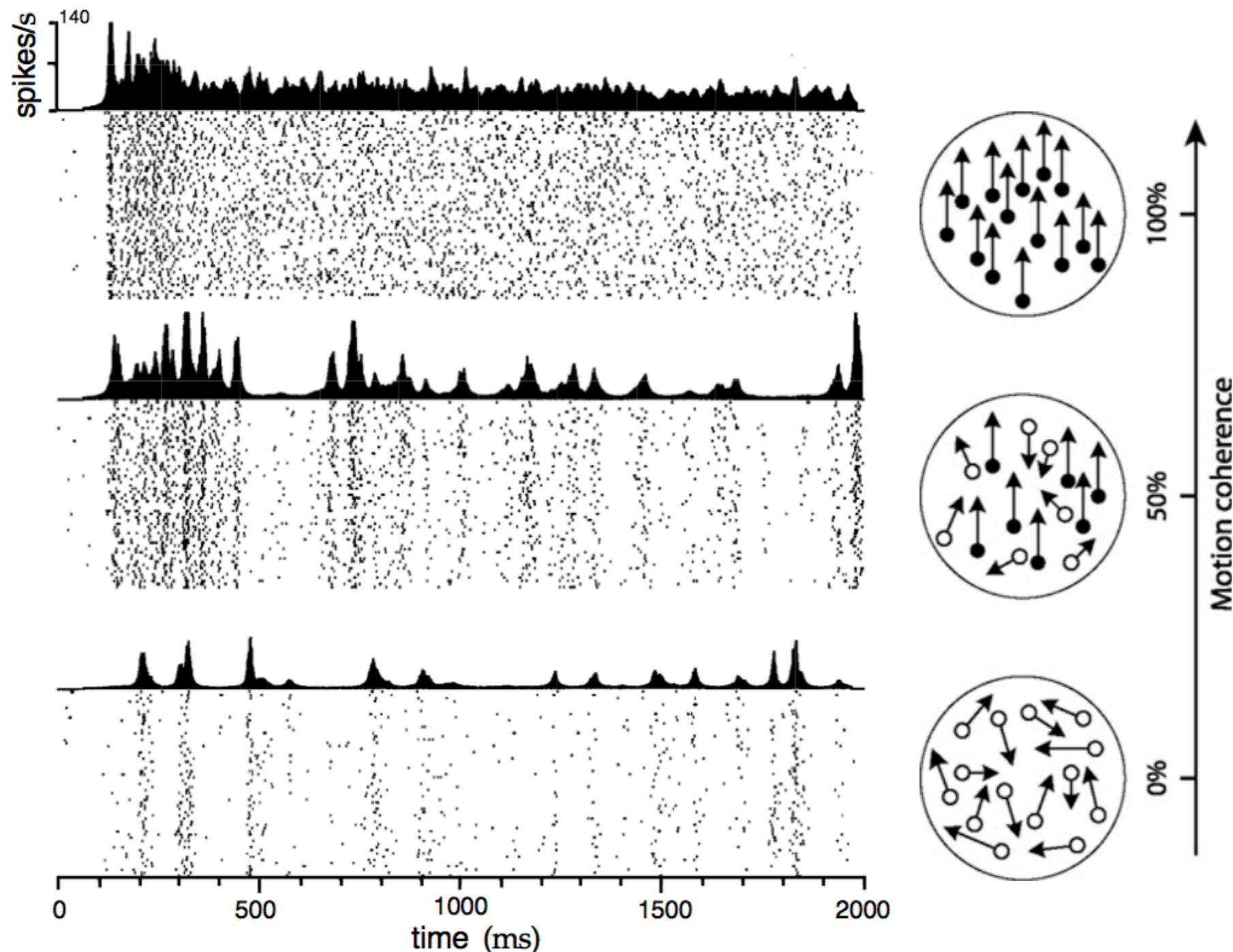


Grawe et al., 2010

# Temporal v.s. Rate Code - QUIZ!

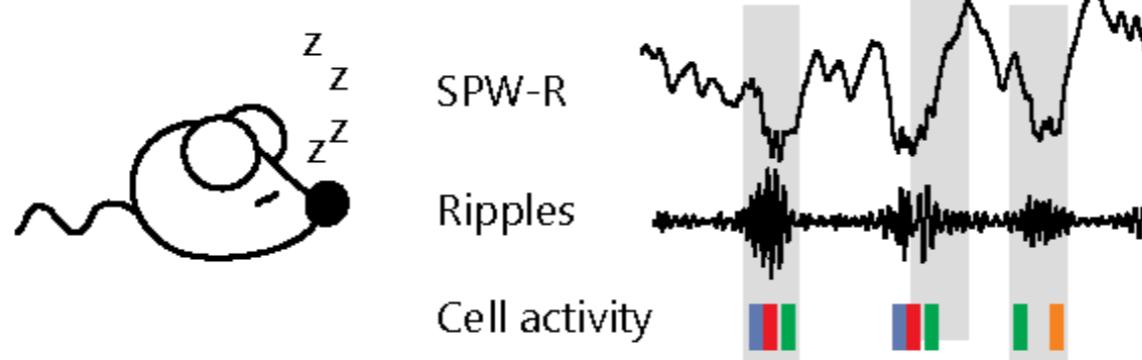
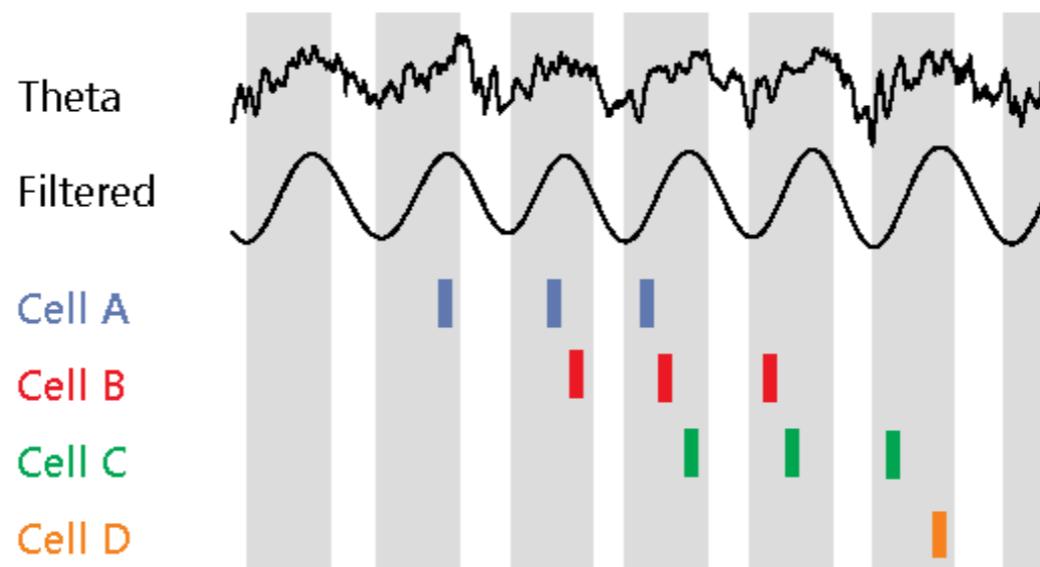
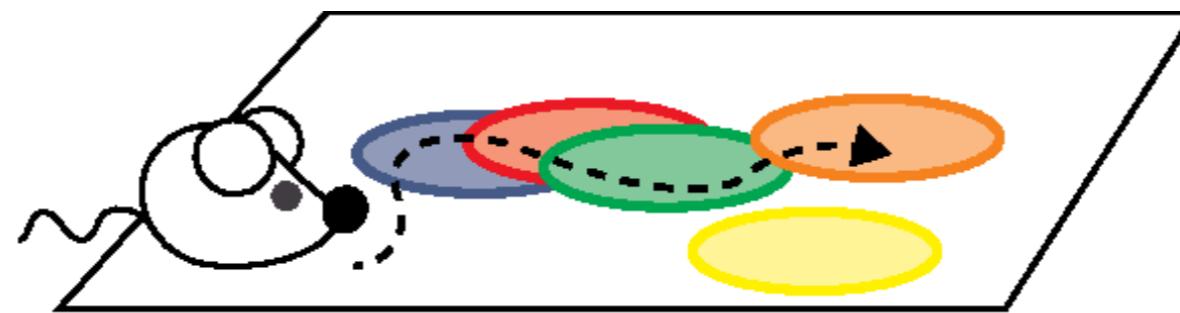


# Temporal v.s. Rate Code - QUIZ!

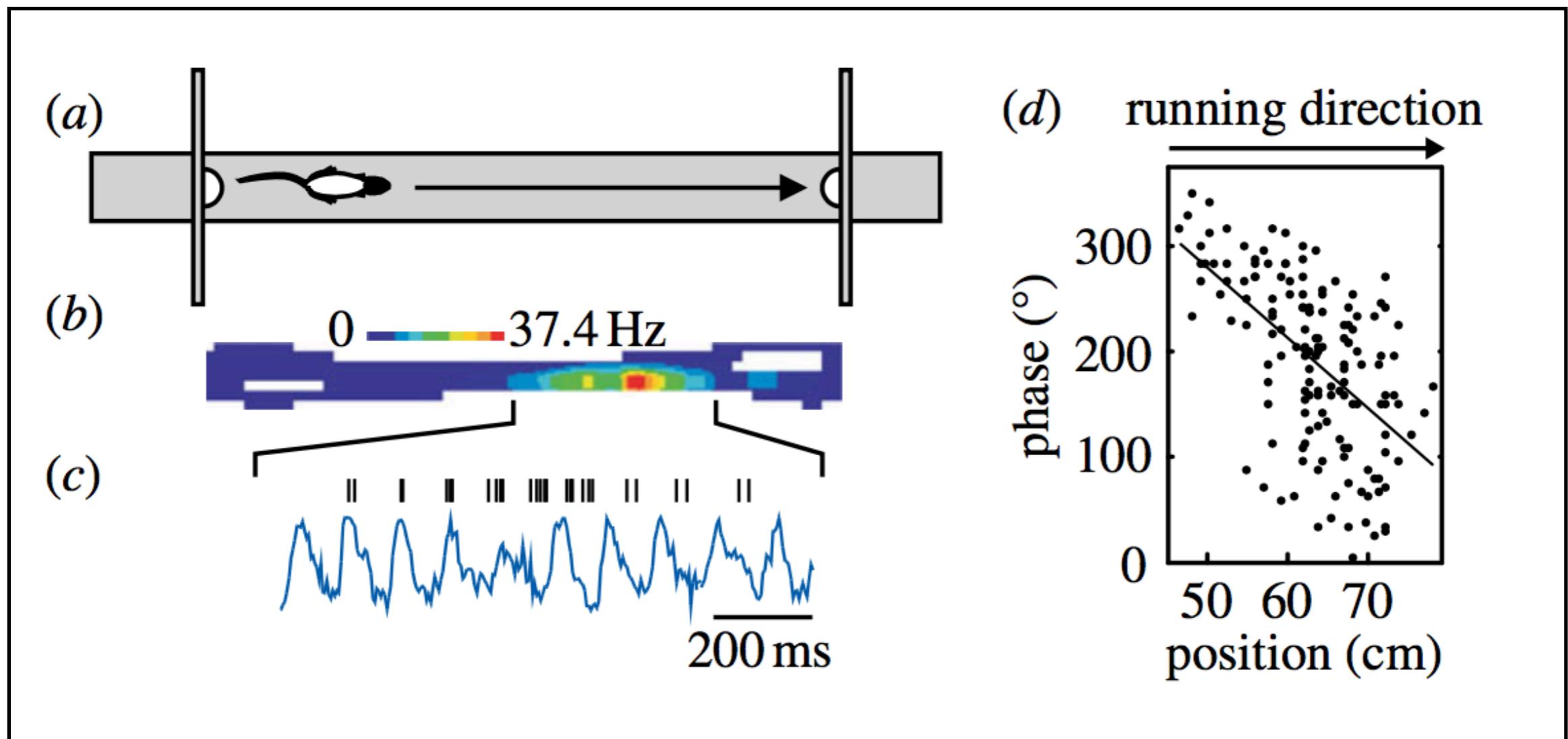


Bair and Koch, 1996

# Phase Coding in Hippocampus.

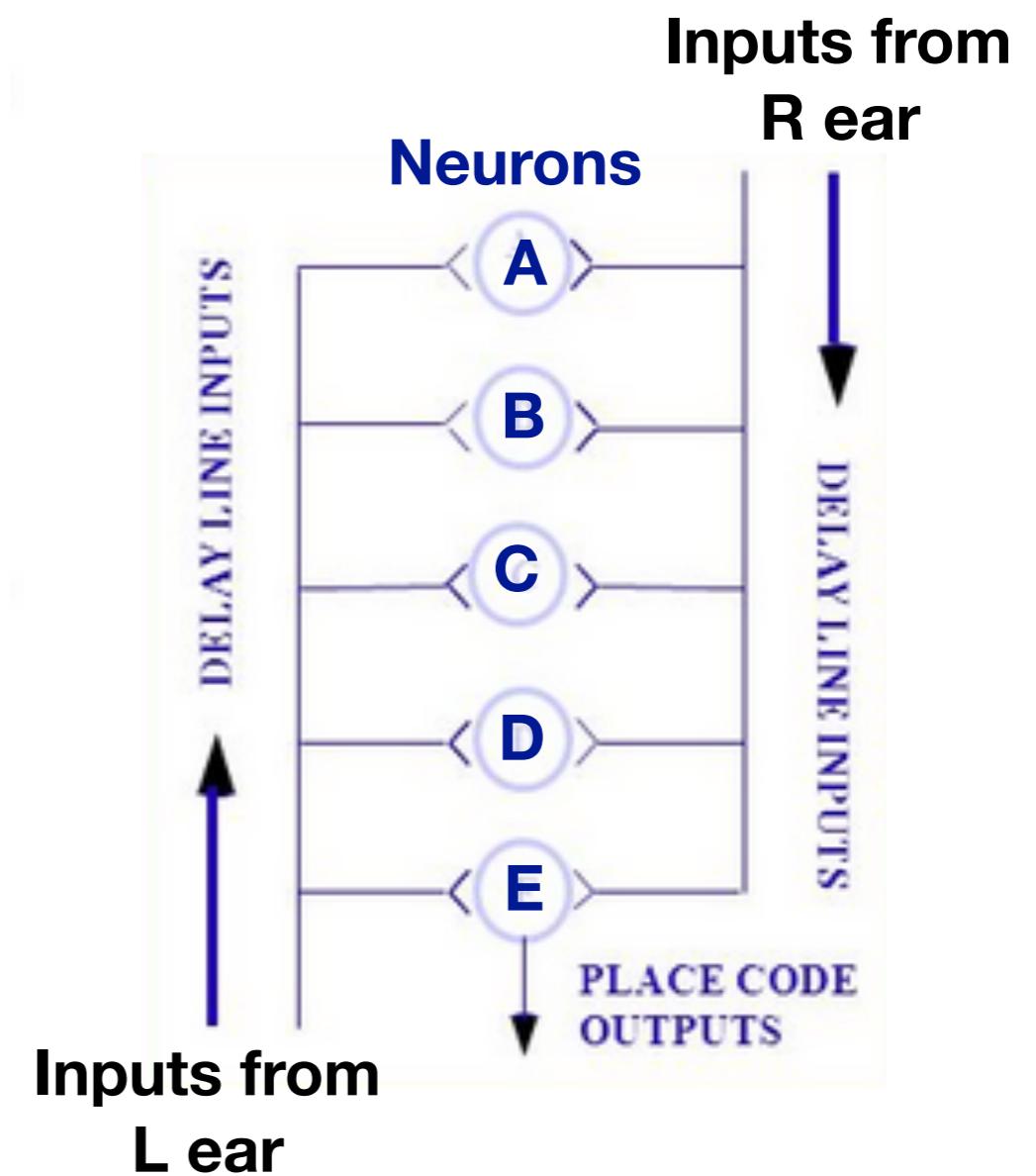
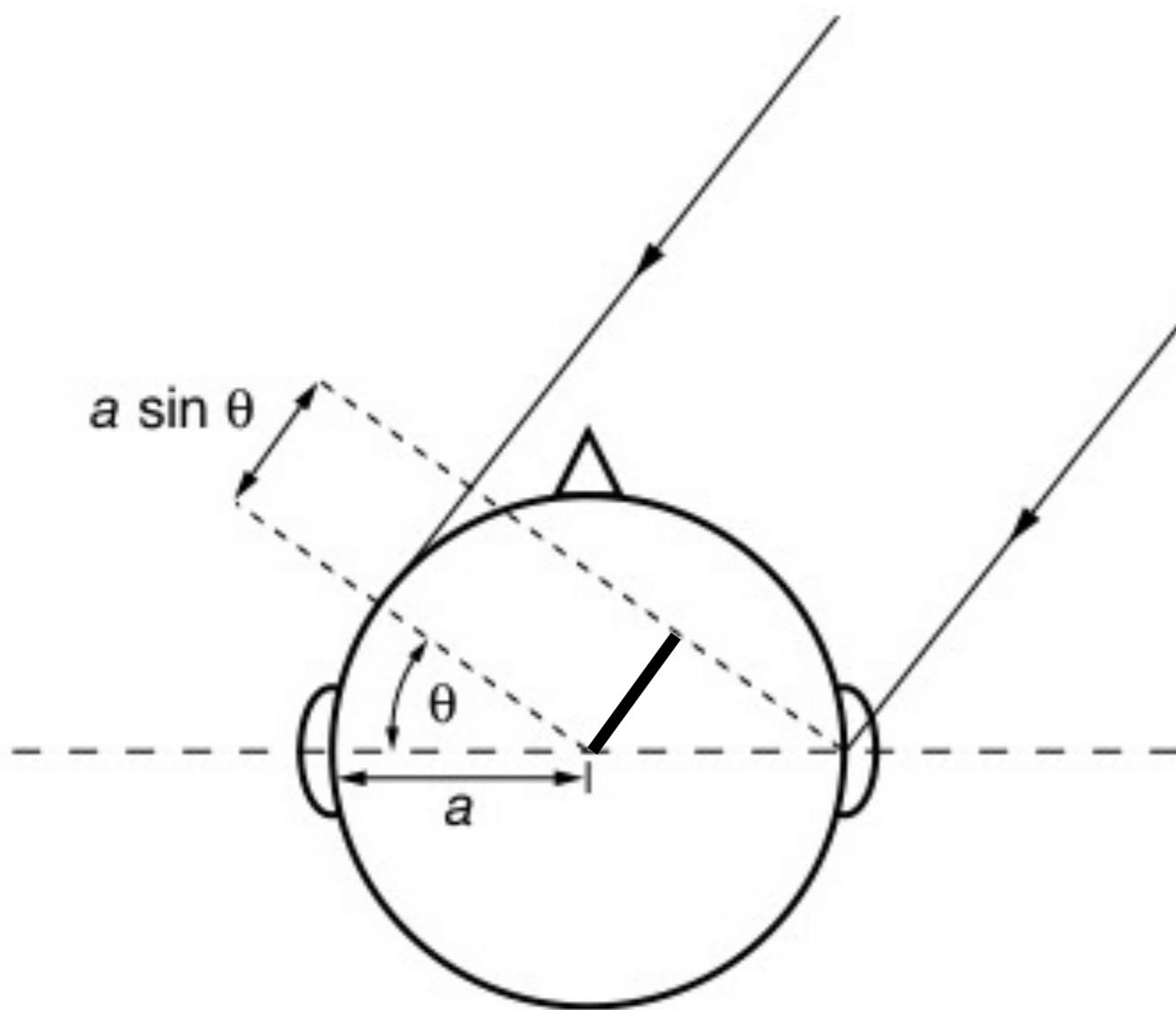


# Phase Coding in Hippocampus.

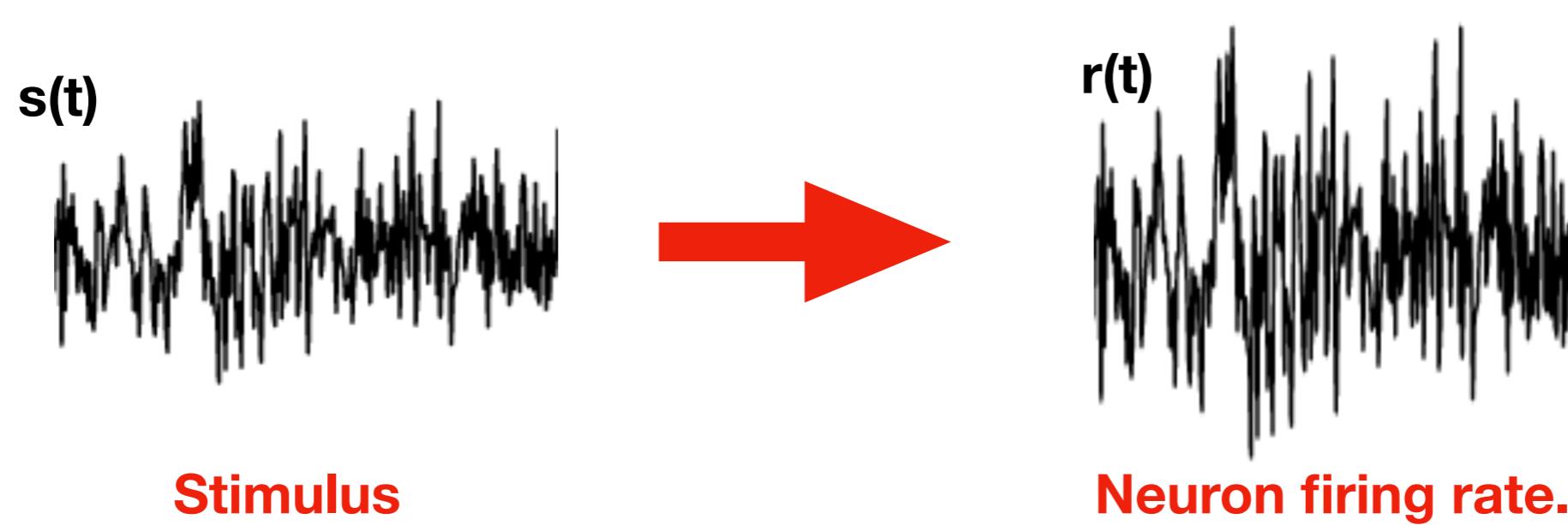


O'Keefe and Recce, 1993

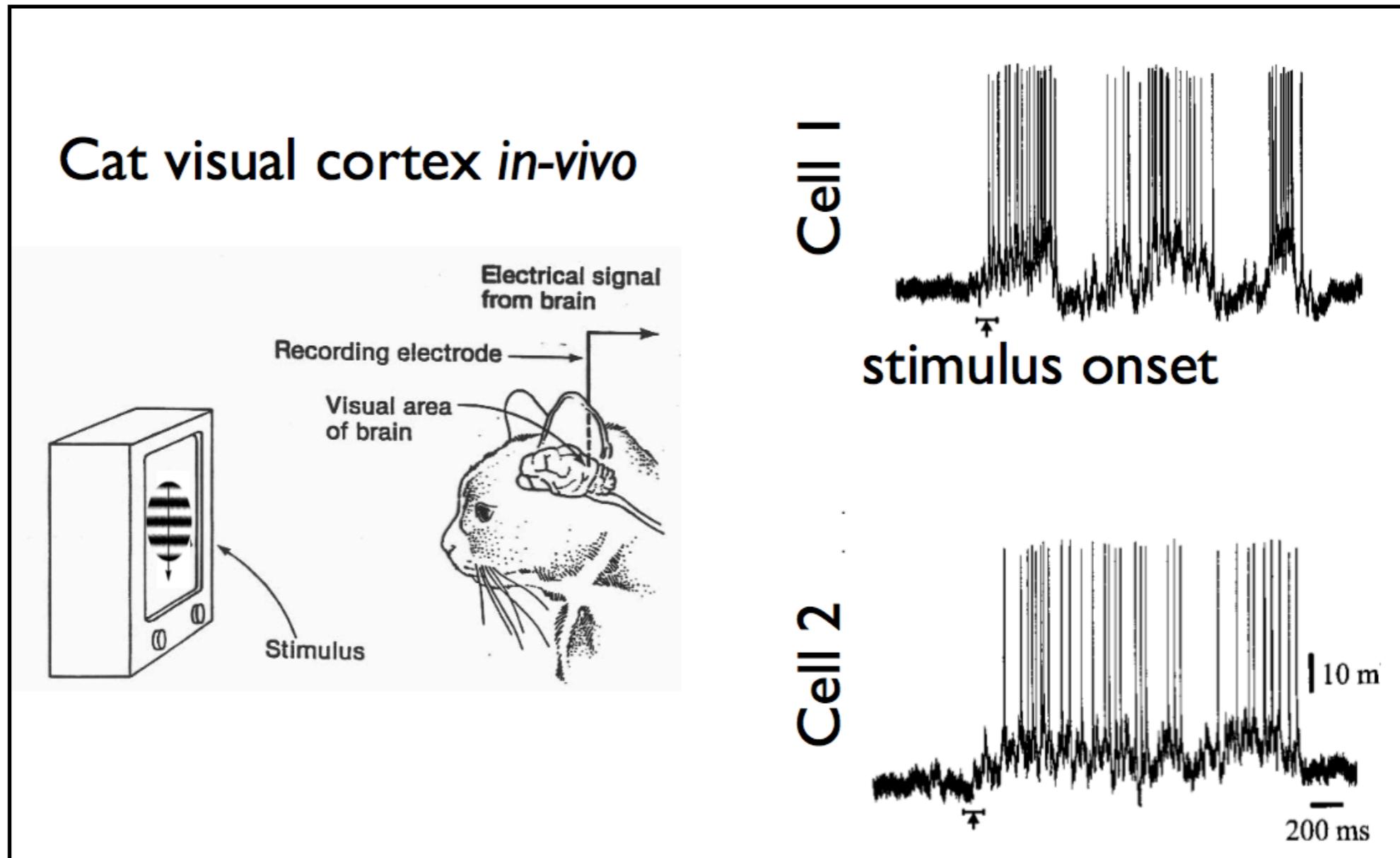
# Sound Localization by measuring the Interaural Time Difference (ITD)



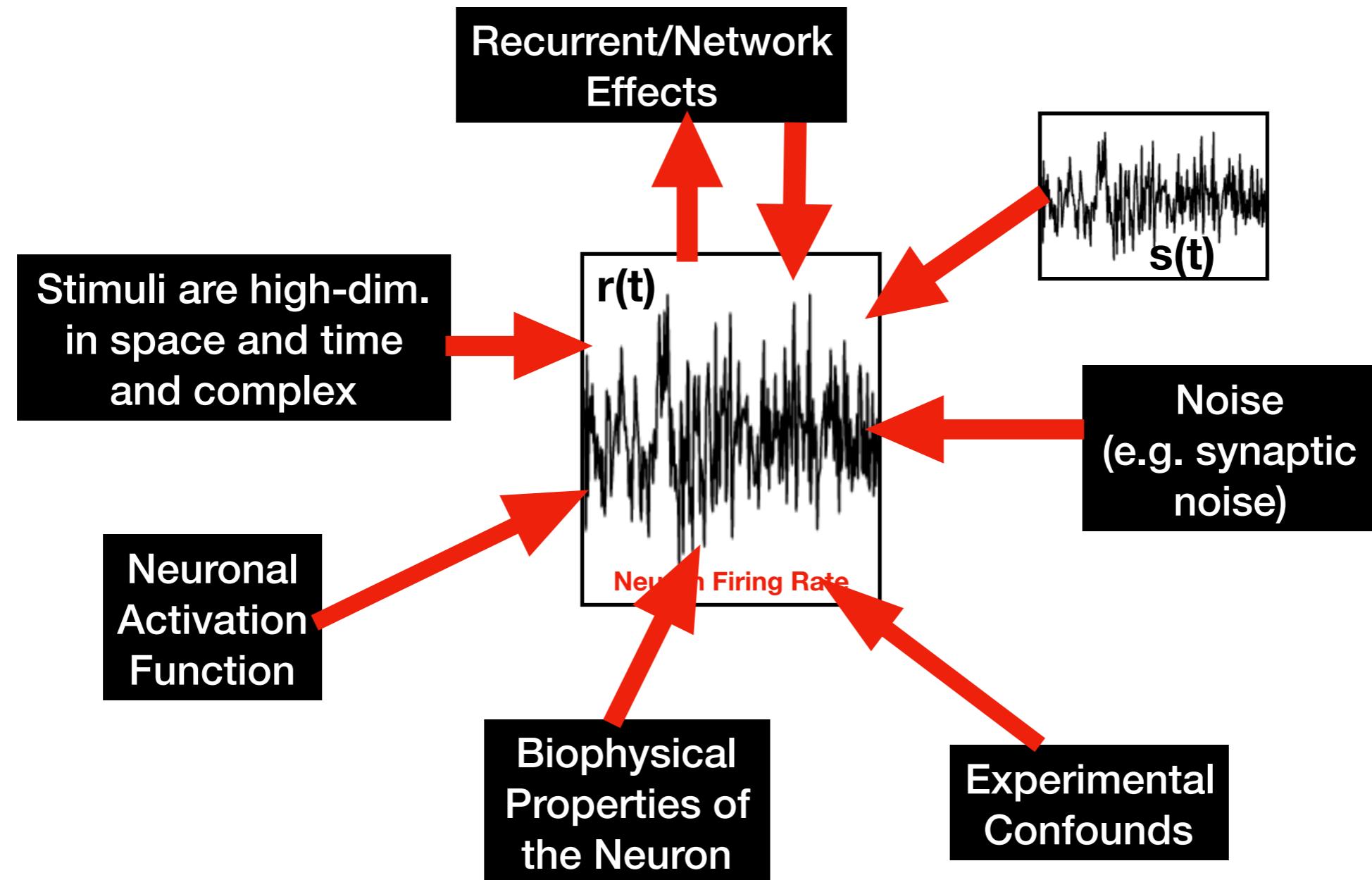
# How to investigate the Stimulus Encoding of a Neuron?



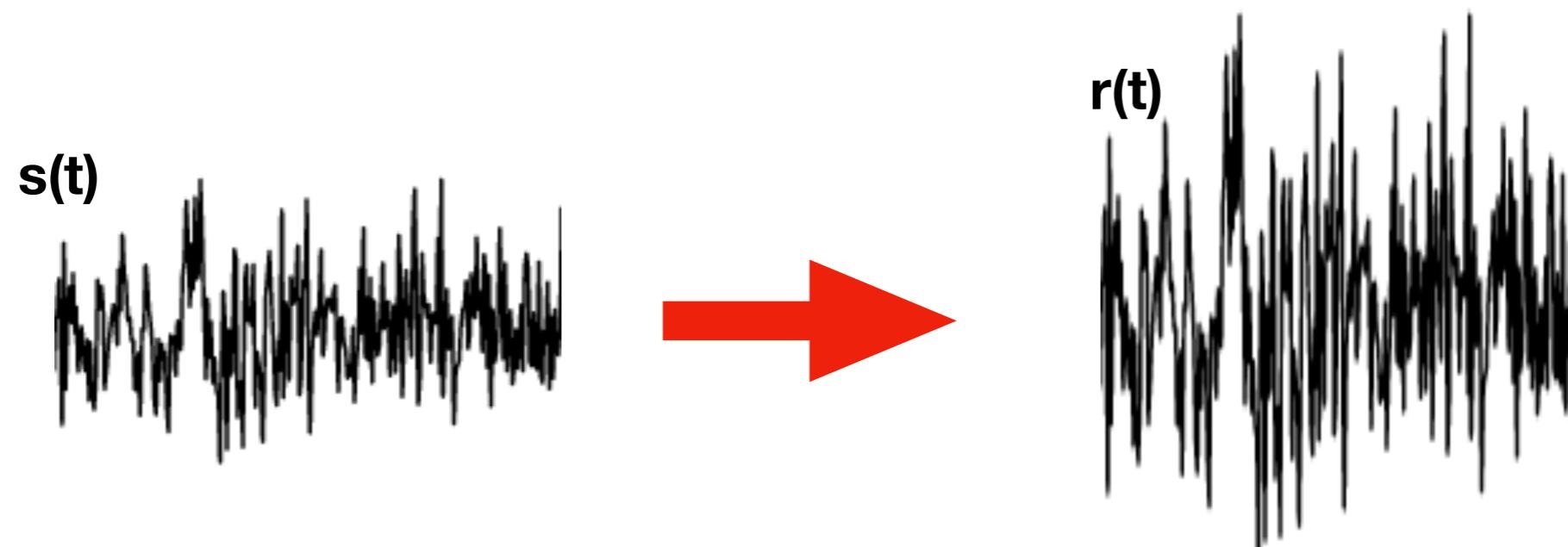
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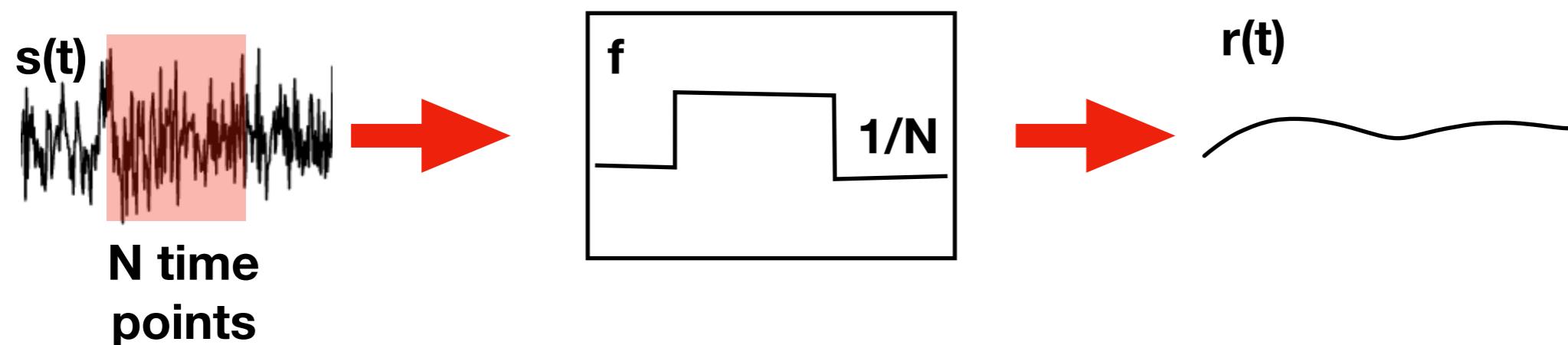
# The Neuron as Temporal Filter.



Linear Temporal Filter:  $r(t) = \sum_{k=0}^n s_{t-k} f_k$

$$r(t) = \int_{-\infty}^t d\tau s(t - \tau) f(\tau)$$

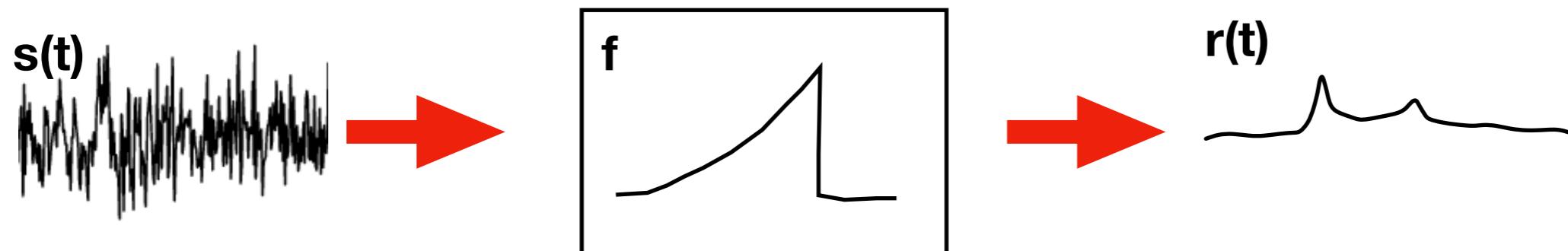
# Example #1: The Running AVG Filter.



Linear Temporal Filter:  $r(t) = \sum_{k=0}^n s_{t-k} f_k$

$$r(t) = \int_{-\infty}^t d\tau s(t - \tau) f(\tau)$$

## Example #2: The Leaky AVG Filter.

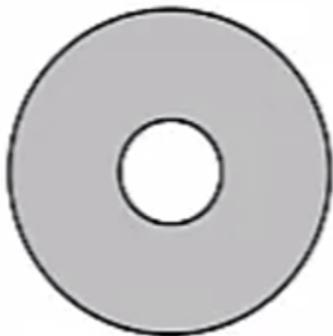


### Example II: The Leaky Avg. Filter

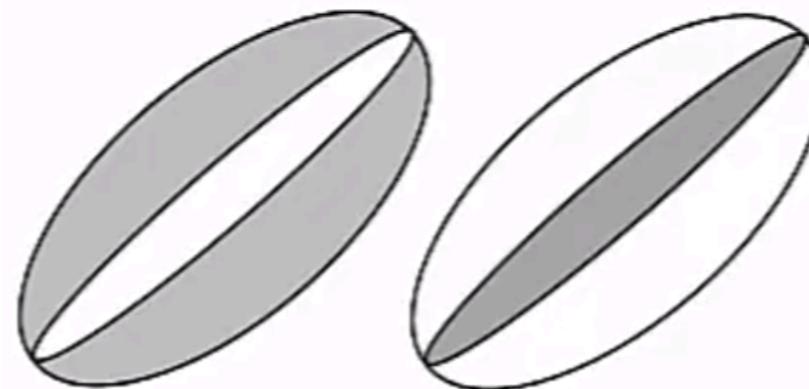
Linear Temporal Filter:  $r(t) = \sum_{k=0}^n s_{t-k} f_k$

$$r(t) = \int_{-\infty}^t d\tau s(t - \tau) f(\tau)$$

# Basic Model of Linear Spatial Filtering.



**Retina Ganglion Cell**

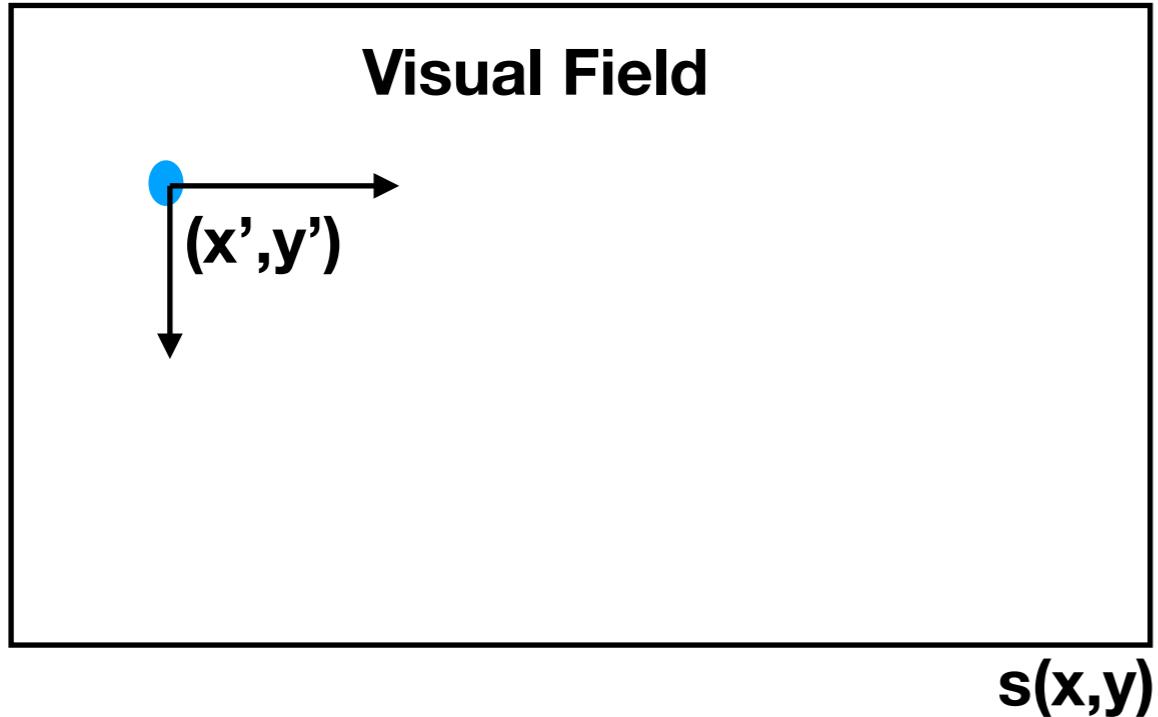


**V1 Pyramidal Cell**

$$\text{Linear Filter: } r(t) = \sum_{k=0}^n s_{t-k} f_k$$

$$r(t) = \sum_{x=n, y=n}^n s_{x-x', y-y'} f_{x', y'}$$

# Basic Model of Linear Spatial Filtering.

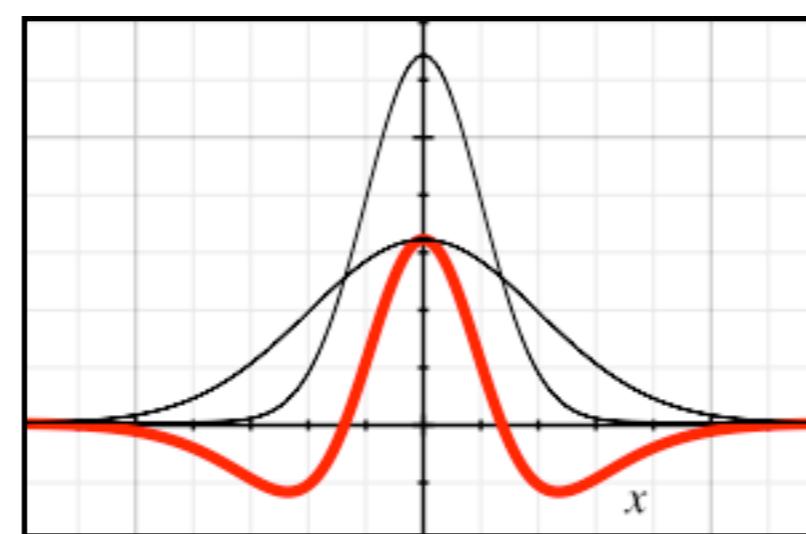
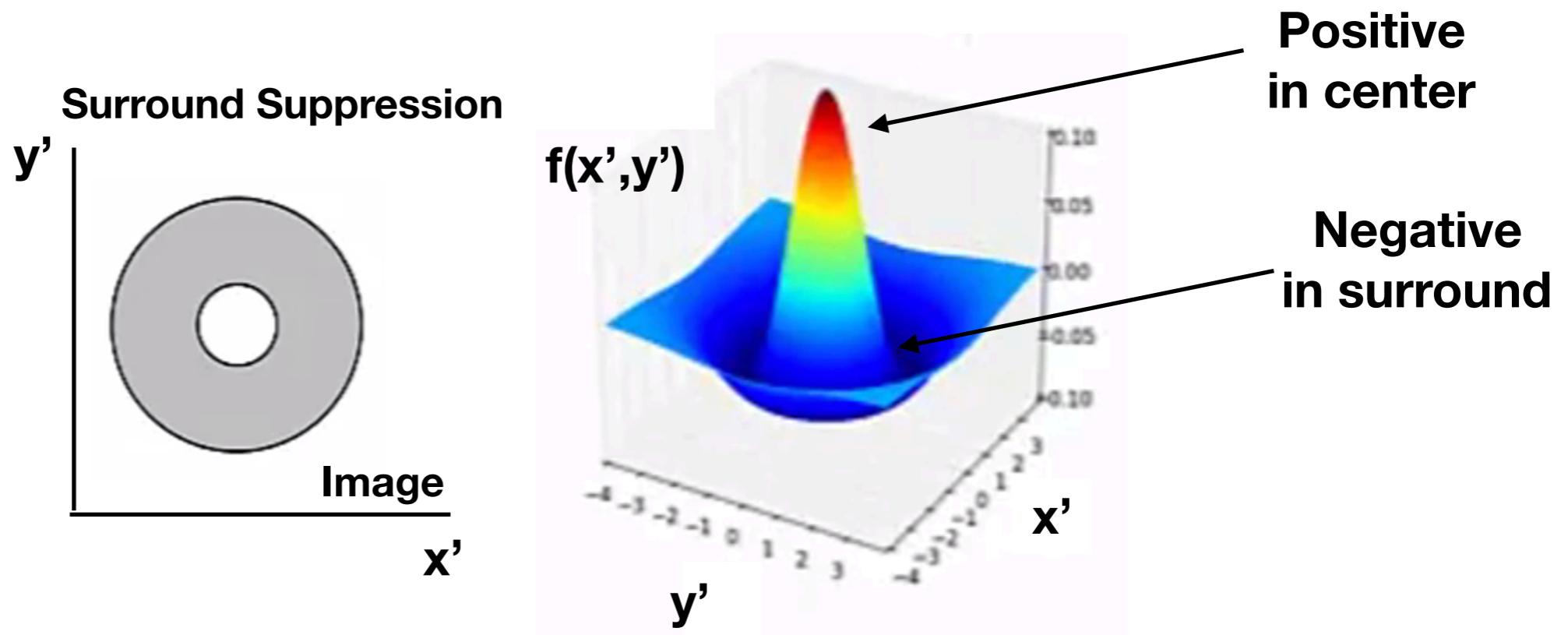


$$r(t) = \sum_{x=n, y=n}^n s_{x-x', y-y'} f_{x', y'}$$

Spatial Filter f

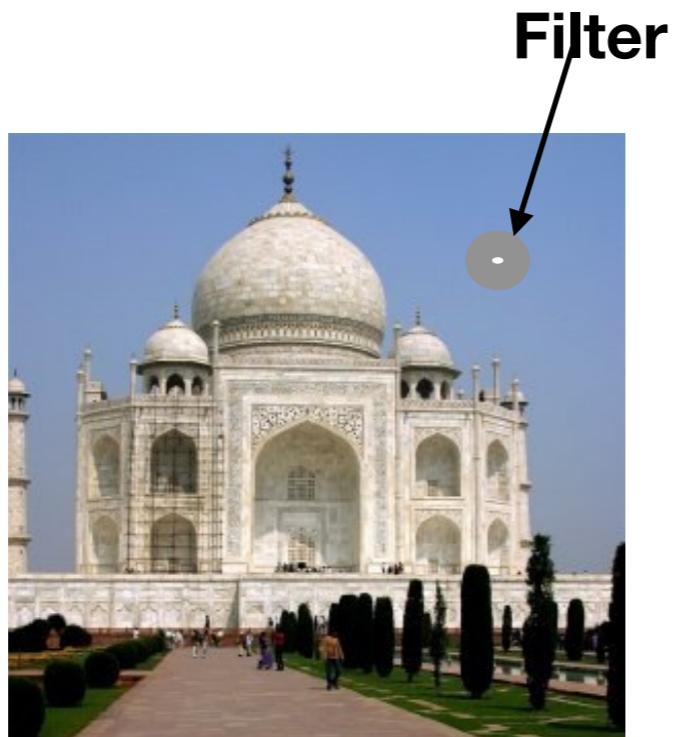
$$r(t) = \int_{-\infty}^{\infty} dx' dy' s(x - x', y - y') f(x', y')$$

# Basic Model of Linear Spatial Filtering.



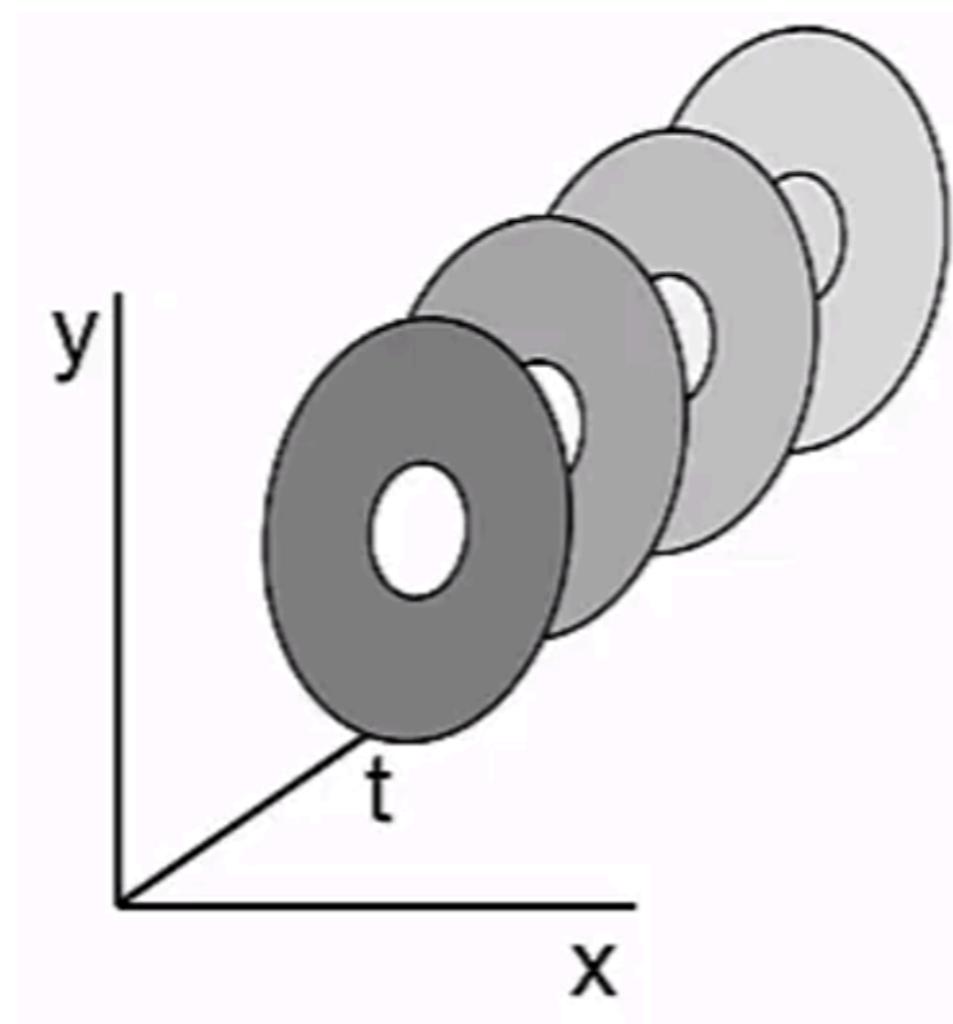
**Difference of Gaussians Filter**

# Example #1: Linear Spatial Filtering.



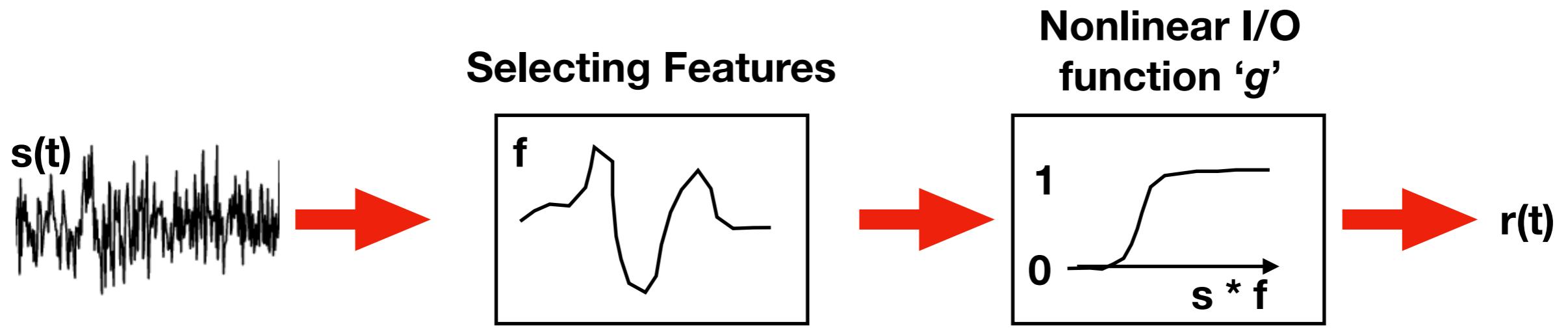
**Original Image**

# Combining Temporal and Spatial Filtering.



$$r_{x,y}(t) = \iiint dx' dy' d\tau f(x', y', \tau) s(x - x', y - y', t - \tau)$$

# Combining Filtering with a Nonlinearity.



- Can spike rates be negative?
- What happens if the stimulus becomes stronger and stronger?  
Can firing rates increase indefinitely?

Linear Filter + Nonlinearity:

$$r(t) = g\left( \int s(t - \tau) f(\tau) d\tau \right)$$

# Recap QUIZ.

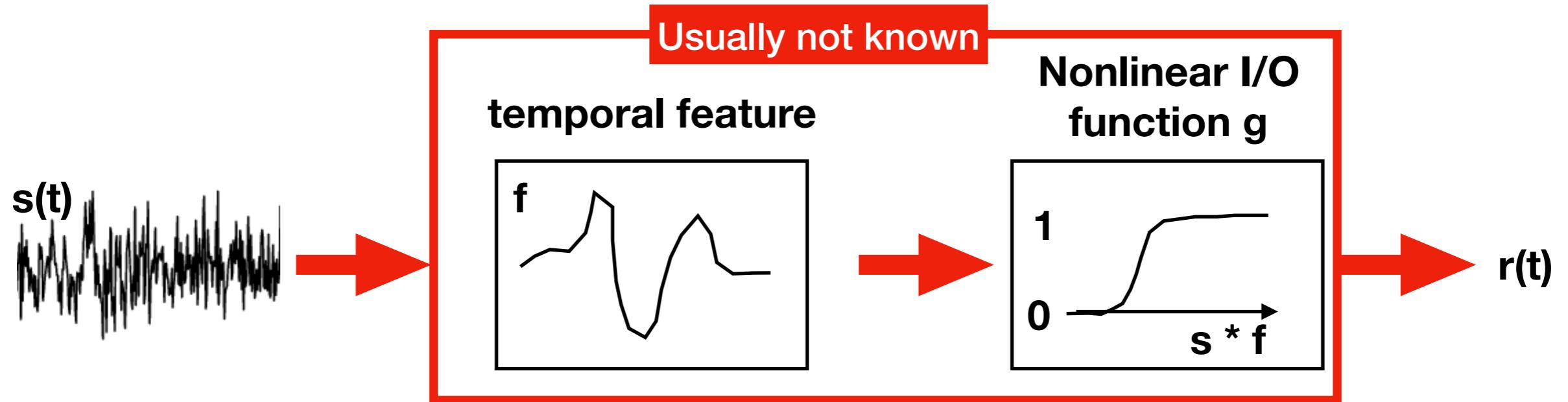
**Since this is a linear system, which of the following will always be true?**

1. The weighting coefficients always lie on a straight line.
2. If you scale the input by a constant, the output will be scaled by the same constant.
3. The output of a sum of different inputs is equal to the sum of the outputs of each of the individual inputs.
4. The filter is a linear function of the input.

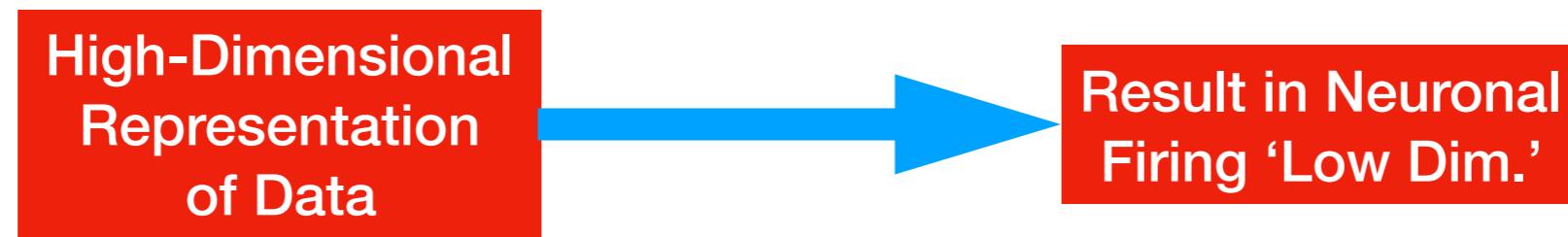
**Which of the following inputs might cause a linear system with a positive filter to predict a negative rate?**

1. An input that slowly varies between a large positive value and a large negative value.
2. A positive input that decays to zero over time.
3. A positive input with a discontinuity.
4. None of these.

# Taking into Account Spatio-temporal Features.



# Taking into Account Spatio-temporal Features.

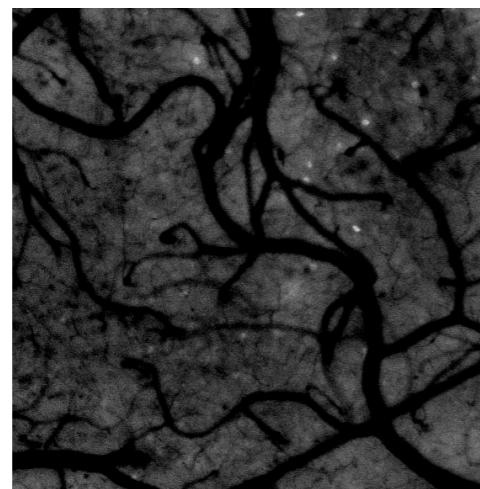


# Taking into Account Spatio-temporal Features.

**Complex  
Stimulus**



**Neuronal  
Population  
Activity**



**How does a neuron  
encode  
stimulus input?**

**Activity of the Output  
Neuron  $r(t)$**

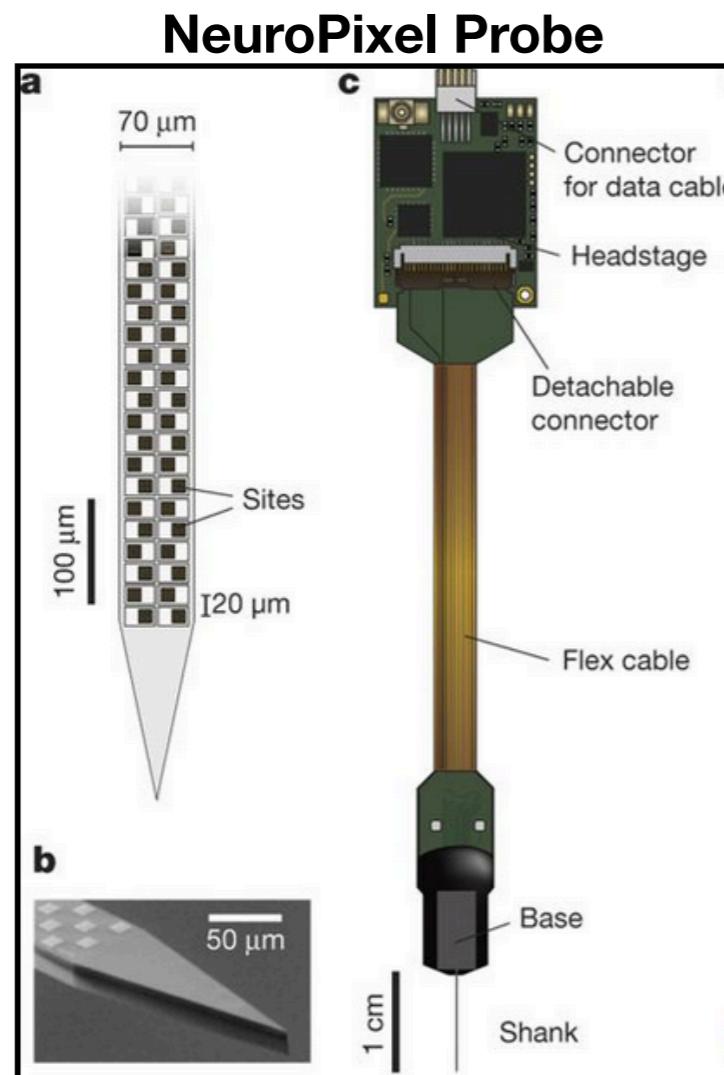


**How does a neuronal  
population  
encode behavior?**

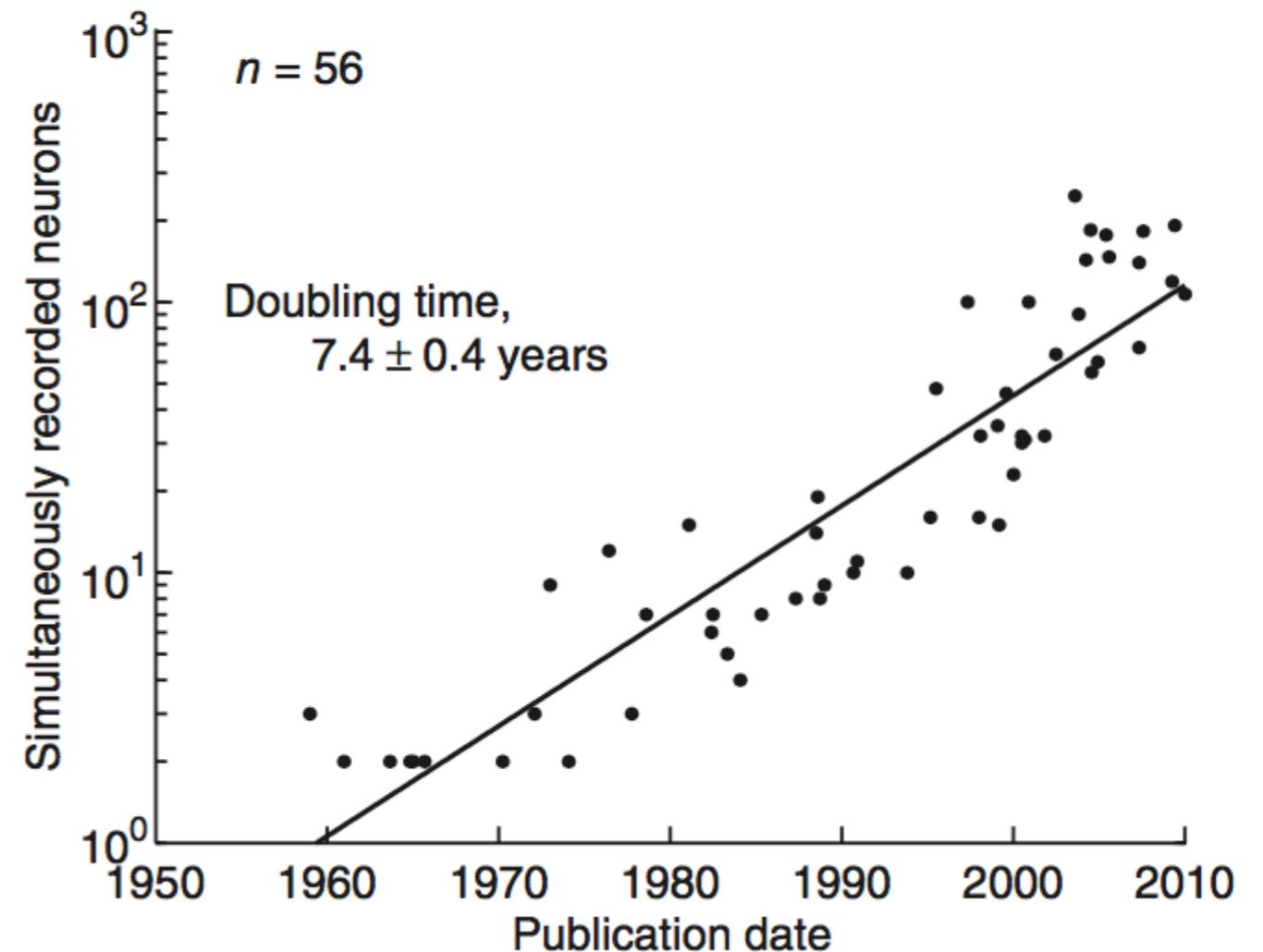
**Behavior output  
of the Animal  $a(t)$**



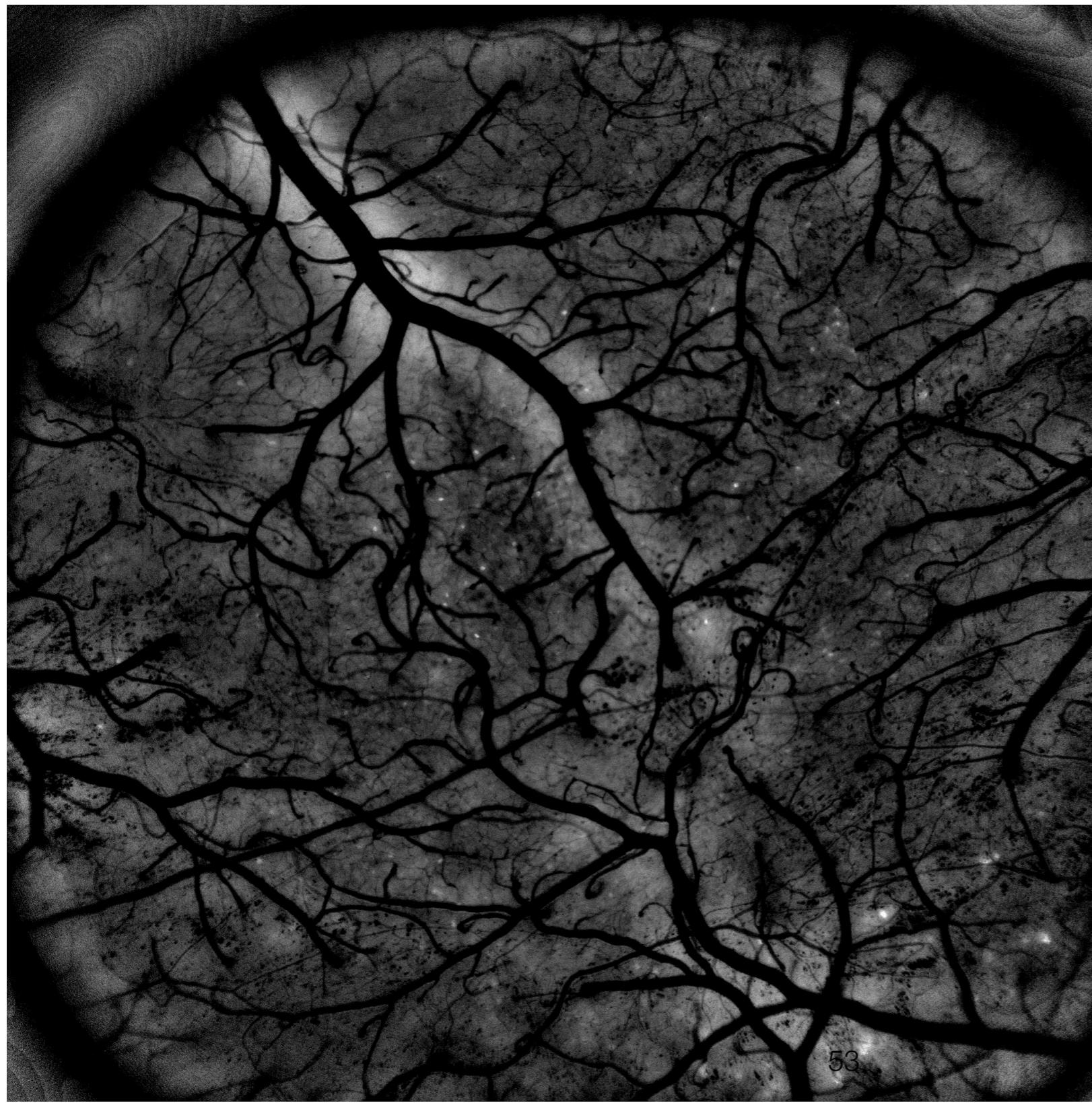
# Measuring Population Activity *in vivo* using Electrodes.



**Jun et al., 2017**



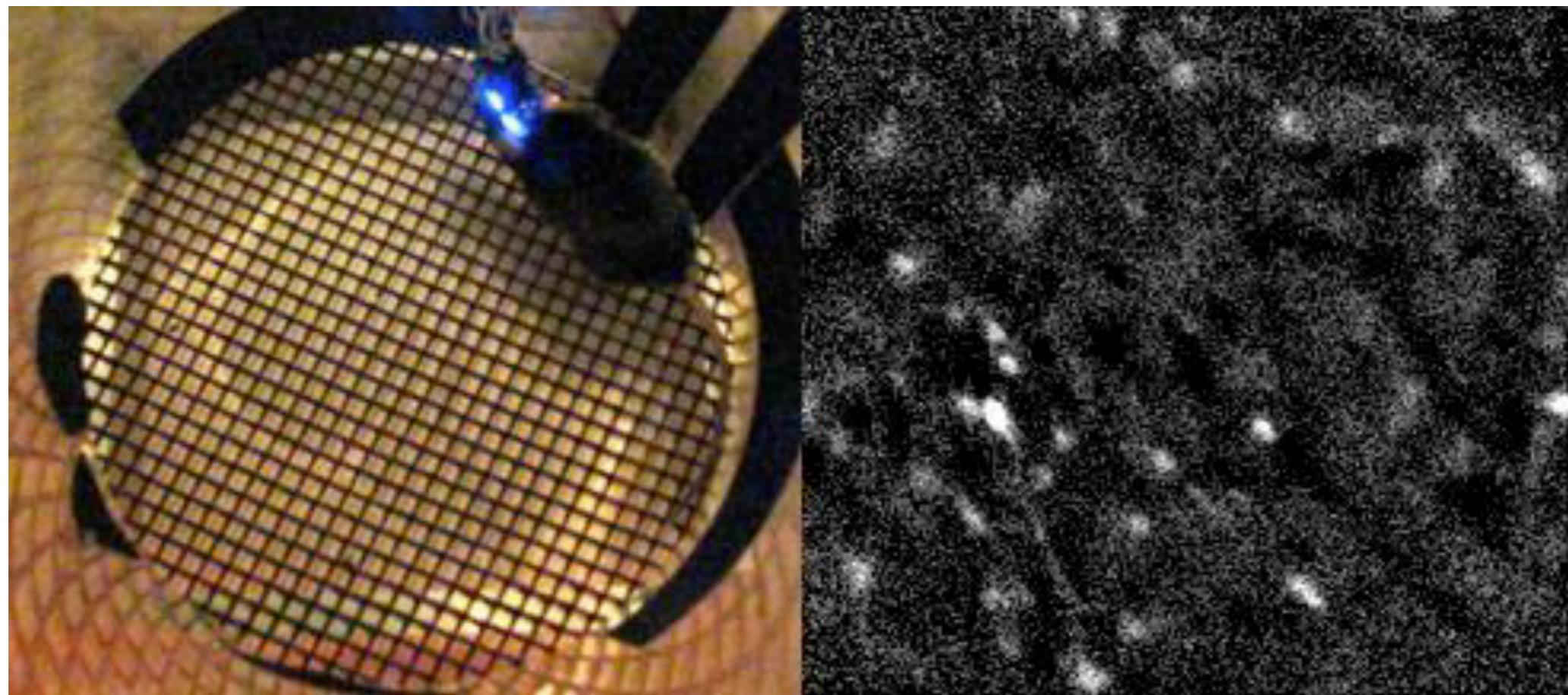
# Measuring Population Activity *in vivo* with $Ca^{2+}$ Imaging.



**In vivo population  
calcium imaging in mouse  
cortex.**

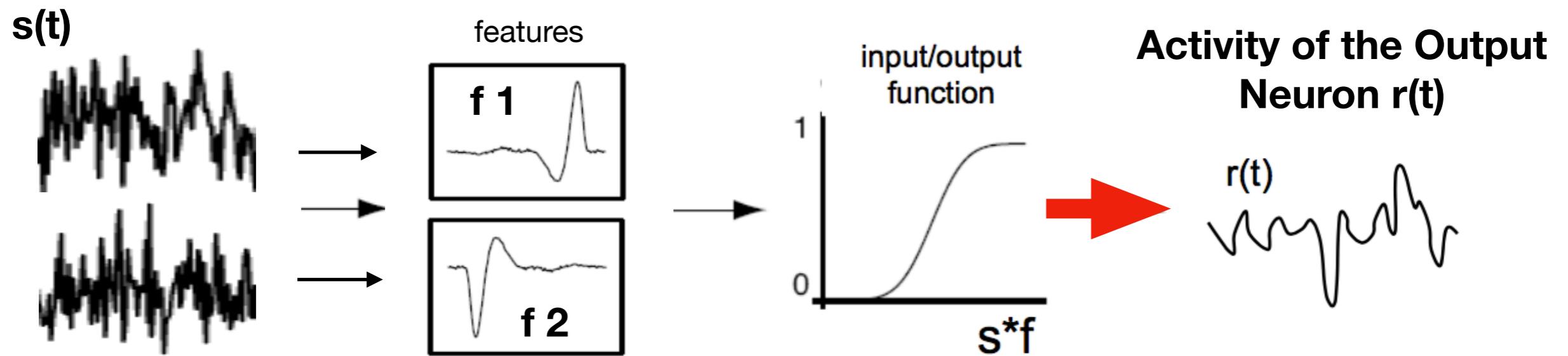
# Measuring Population Activity *in vivo* with $Ca^{2+}$ Imaging.

**In vivo population  
calcium imaging in freely moving mice.**

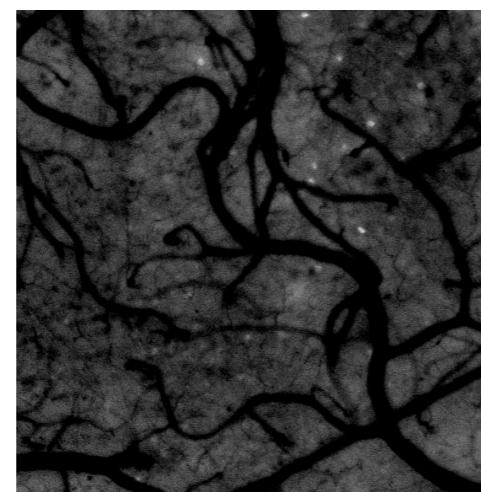


**What is the neural ‘population’ code that determines behavior?**

# Taking into Account Spatio-temporal Features.



**Neuronal Population Activity**

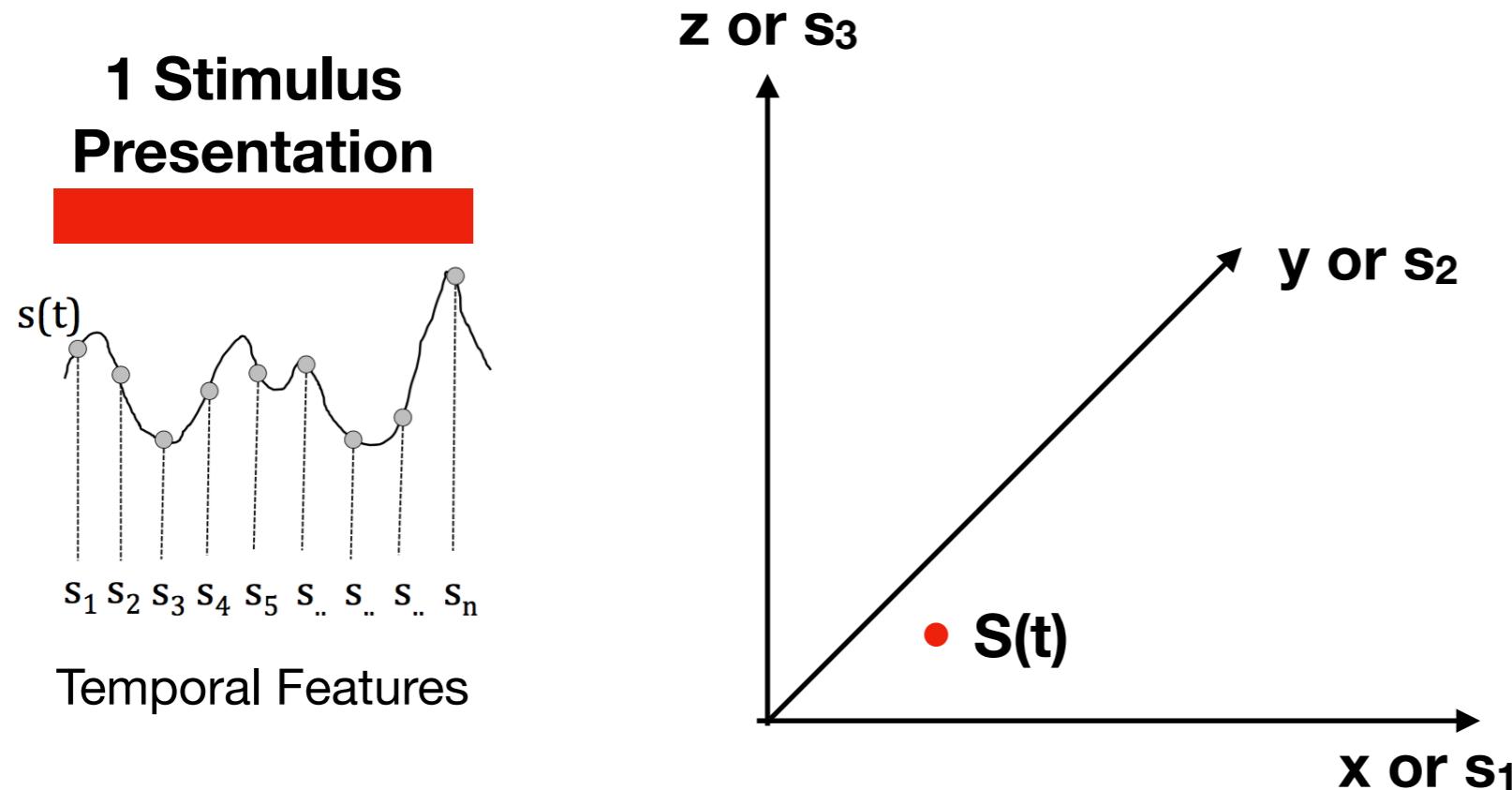


**How does a neuronal population encode behavior?**



**Behavior output of the Animal  $a(t)$**

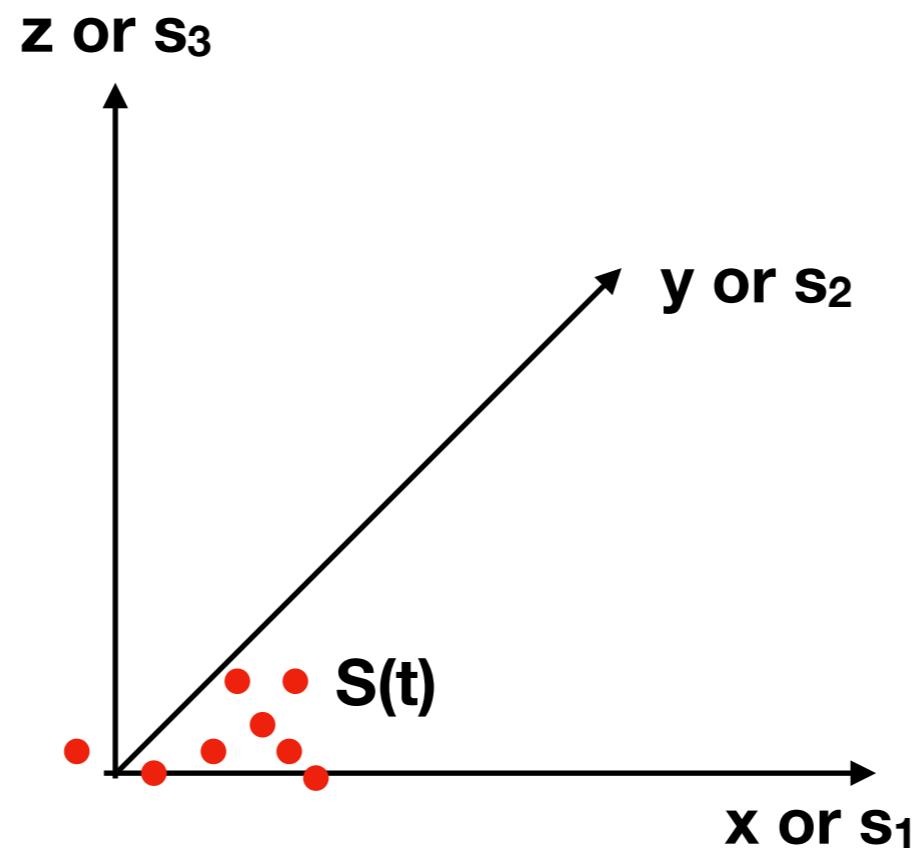
# Taking into Account Spatio-temporal Features.



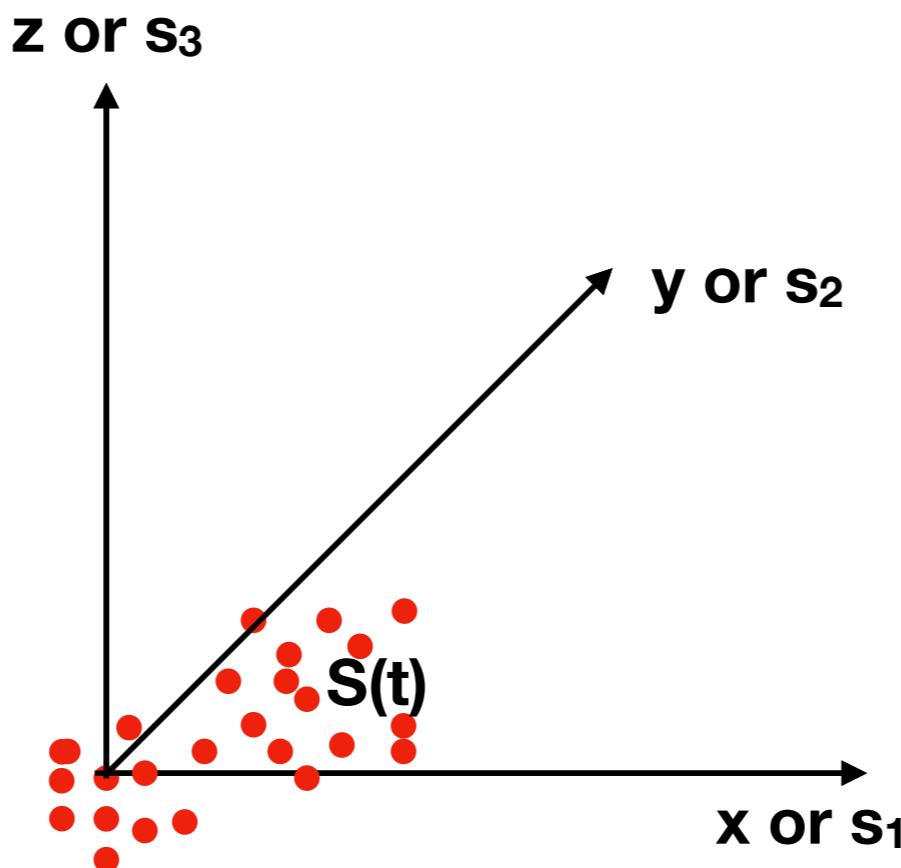
Now we want to repeatedly sample the responses to a variety of stimuli so that we can characterize what feature combination triggers a spike or a behavior.

$$P(\text{response} \mid \text{stimulus}) = P(\text{response} \mid s_1, s_2, s_3, \dots, s_n)$$

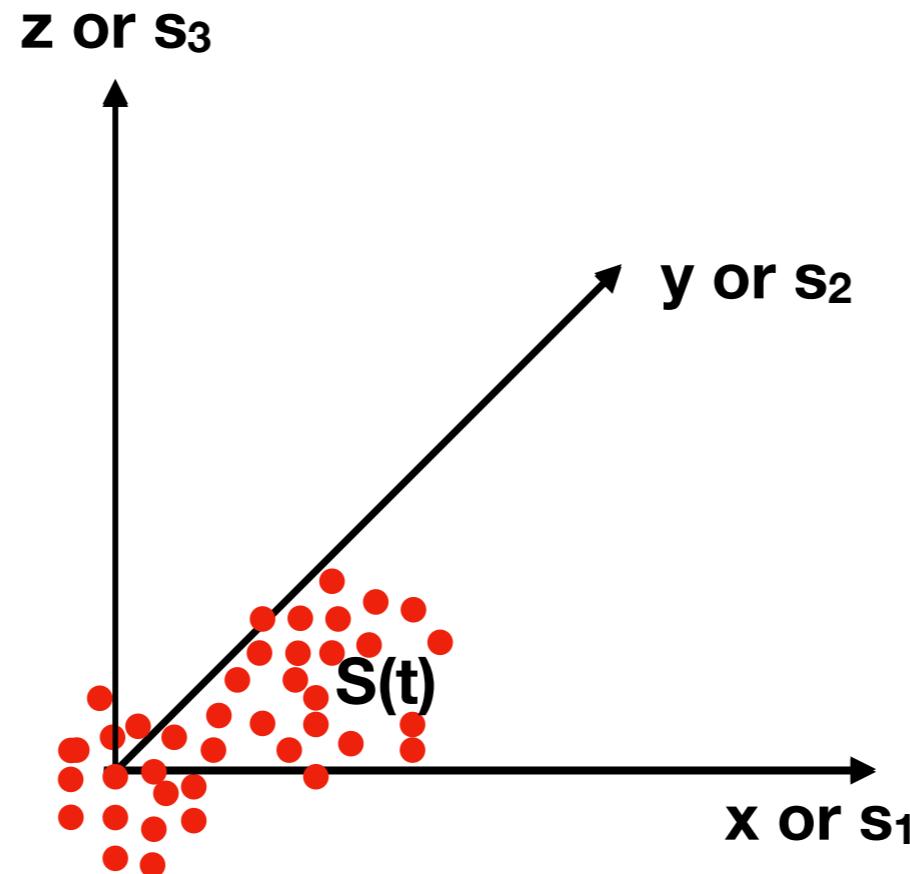
# Finding the mean Population Response Vector.



# Finding the mean Population Response Vector.



# Finding the mean Population Response Vector.



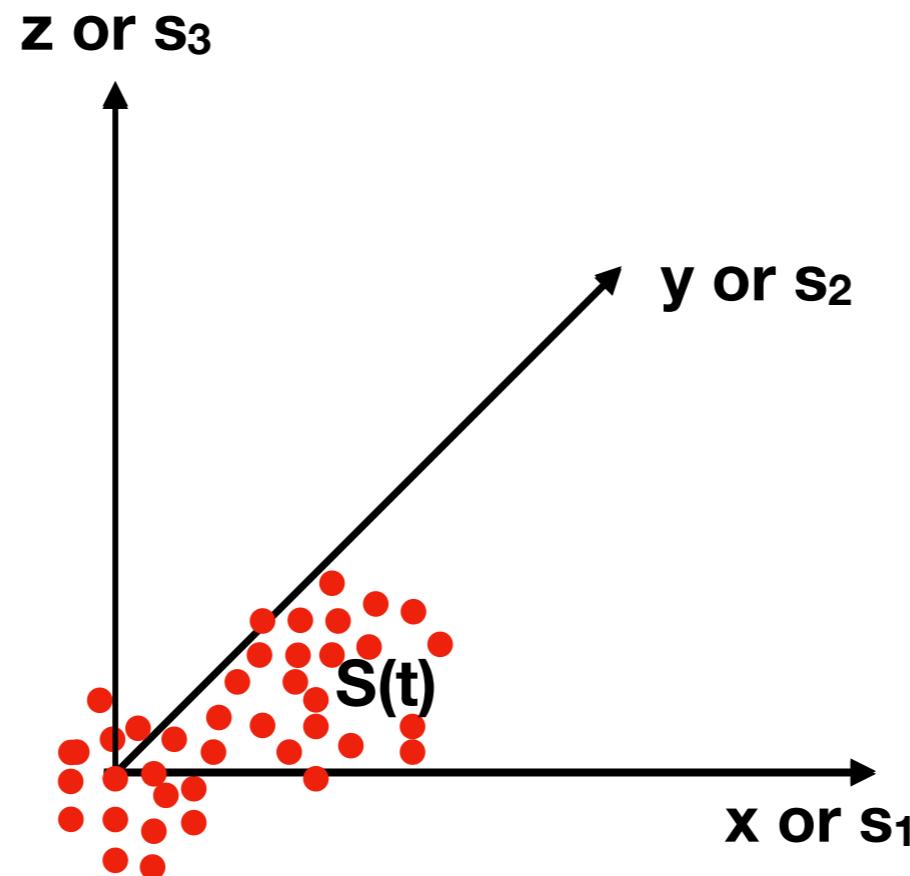
**What do we do next? Two possibilities.**

**1. We don't know the important features.**

**We don't have any labels for the stimuli.**

Unsupervised/clustering  
Approaches

# Finding the mean Population Response Vector.



**What do we do next? Two possibilities.**

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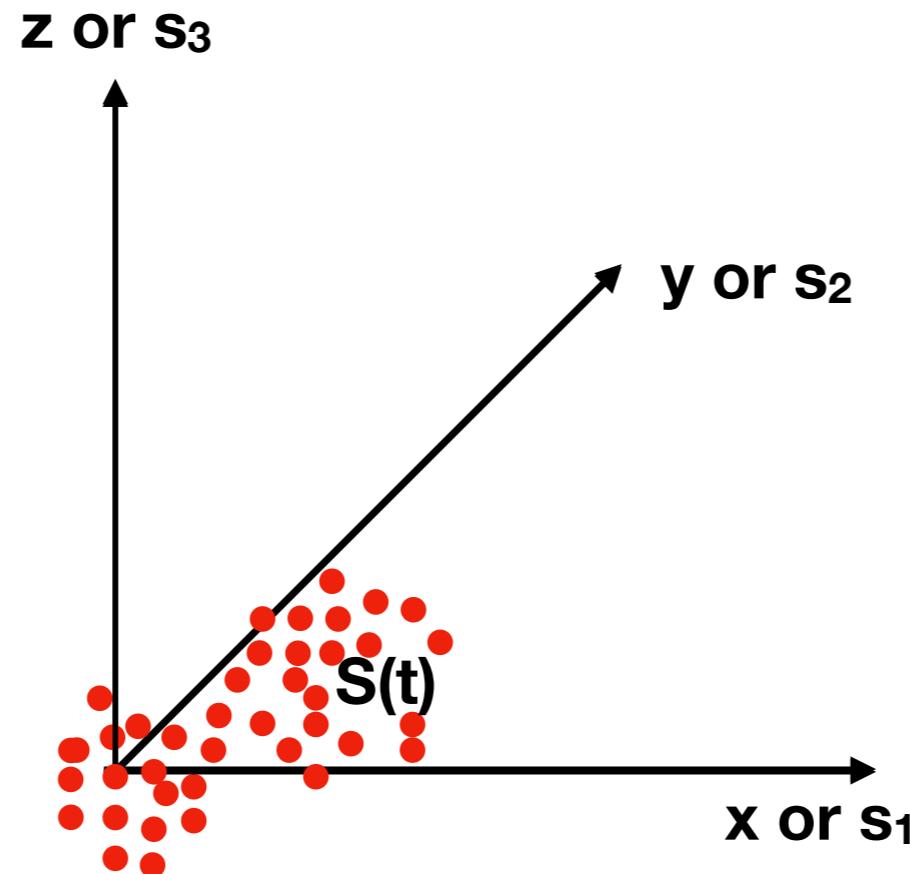
**2. We have labels for all stimuli classes.**

**We know the features of interest.**

Unsupervised/clustering  
Approaches

Supervised  
Approaches

# Finding the mean Population Response Vector.



**What do we do next? Two possibilities.**

**1. We don't know the important features.**

**We don't have any labels for the stimuli.**

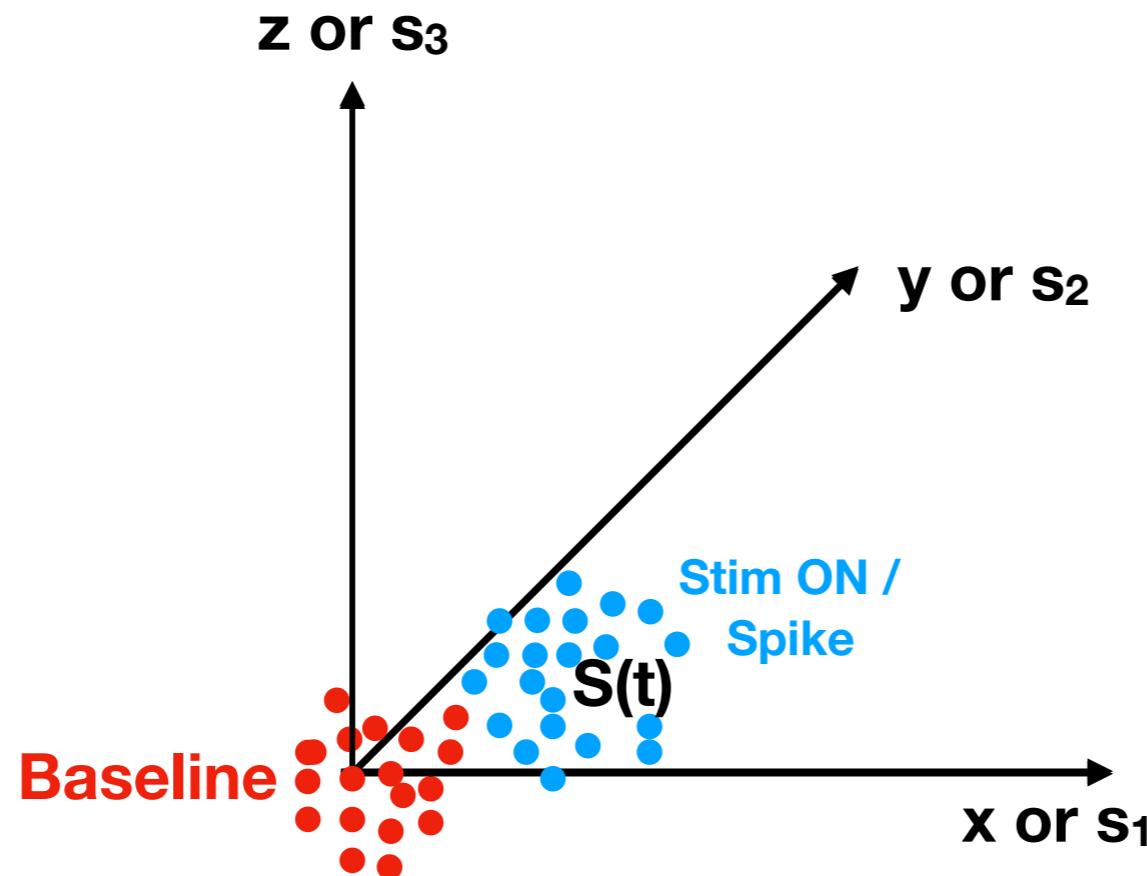
**2. We have labels for all stimuli classes.**

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Unsupervised/clustering  
Approaches

Supervised  
Approaches

# Finding the mean Population Response Vector.



**What do we do next? Two possibilities.**

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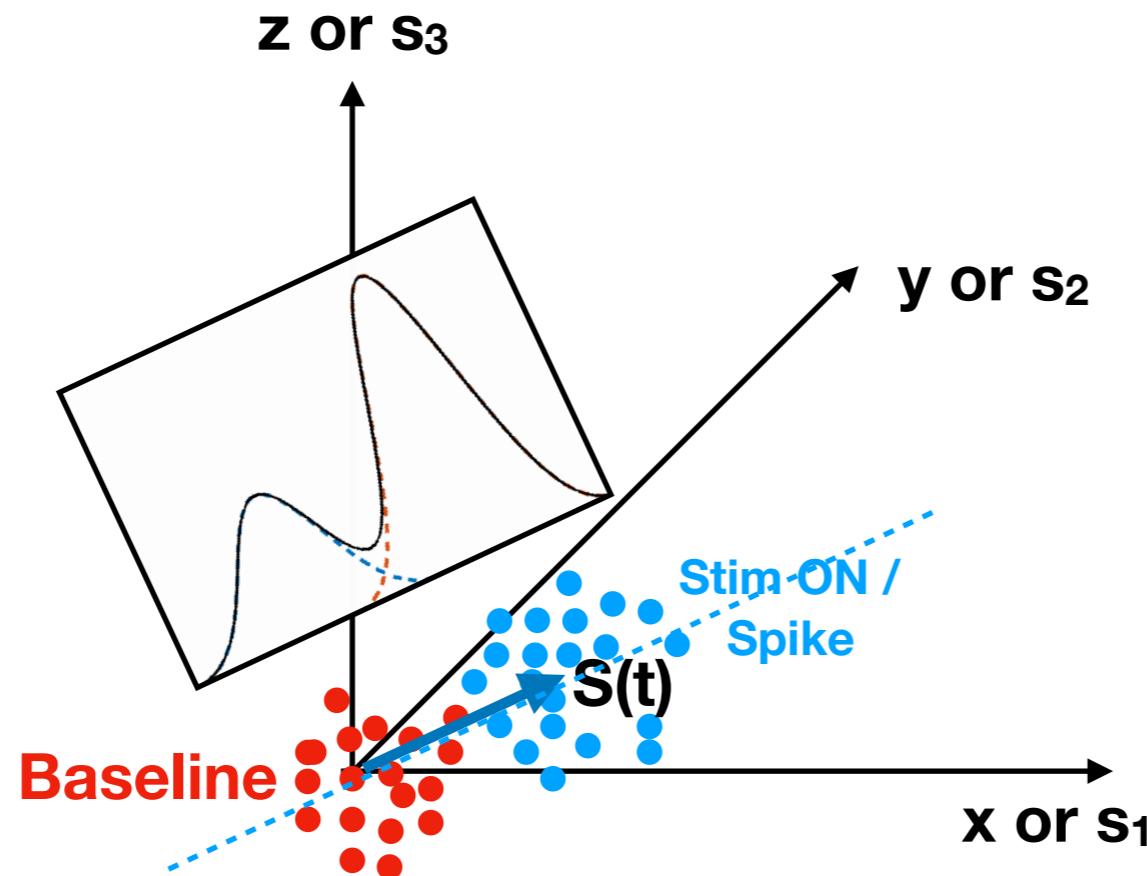
**2. We have labels for all stimuli classes.**

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Unsupervised/clustering  
Approaches

Supervised  
Approaches

# Finding the mean Population Response Vector.



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**1. We don't know the important features.**

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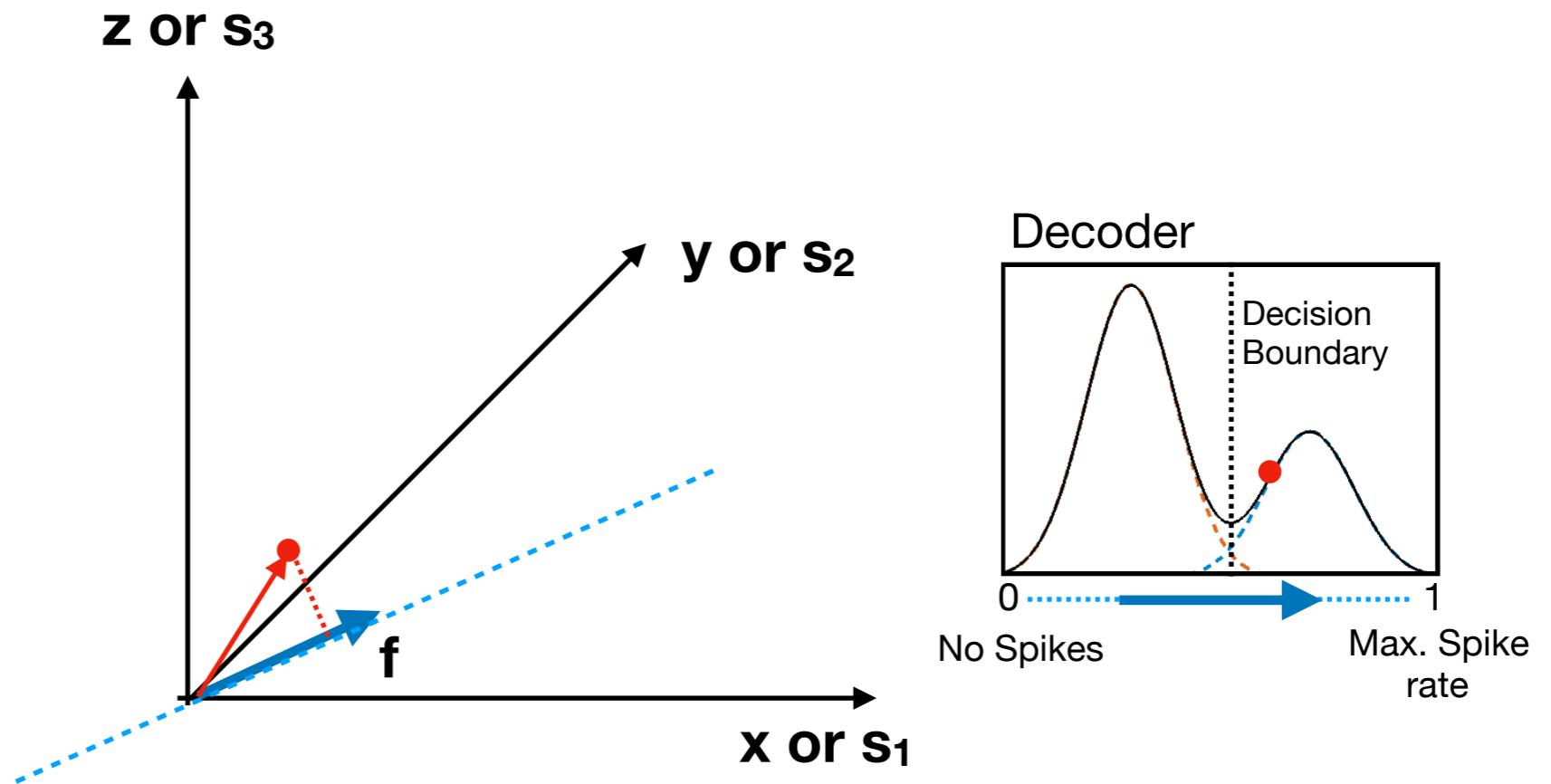
**2. We have labels for all stimuli classes.**

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Unsupervised/clustering  
Approaches

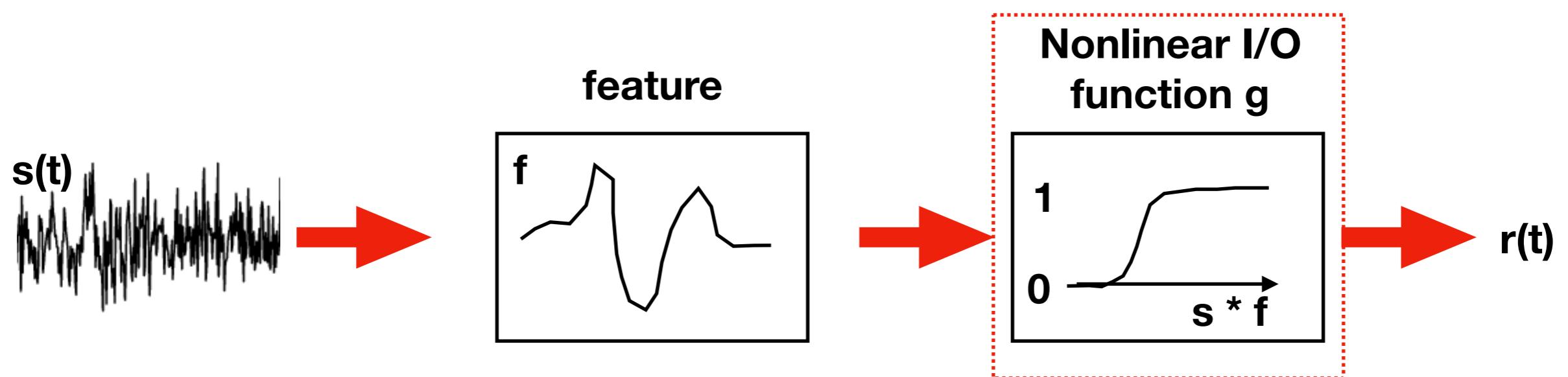
Supervised  
Approaches

# Projecting Stimuli in the direction of Neur. Responses.



Projecting Stimuli into the Direction of the Neuronal Response  
(Encoding/Filtering).

# Finding the I/O Function for a Single Neuron.



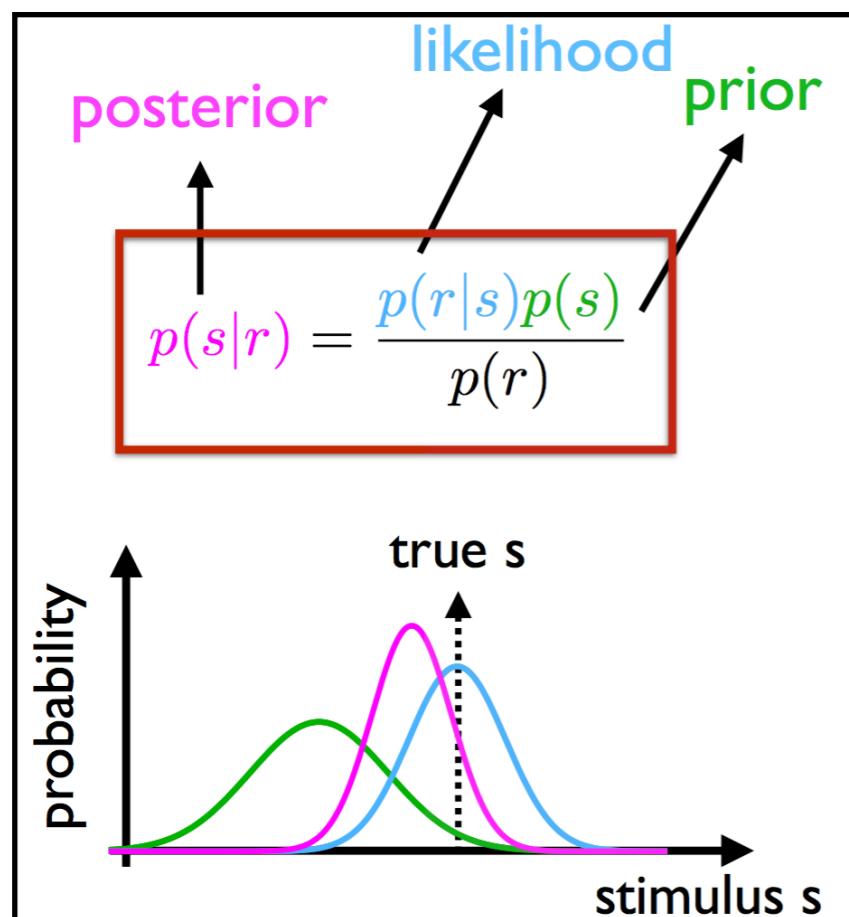
The I/O function is:

$$P(\text{spike} \mid \text{stimulus}) = P(\text{spike} \mid s_1)$$

S1 as identified  
by our linear filter

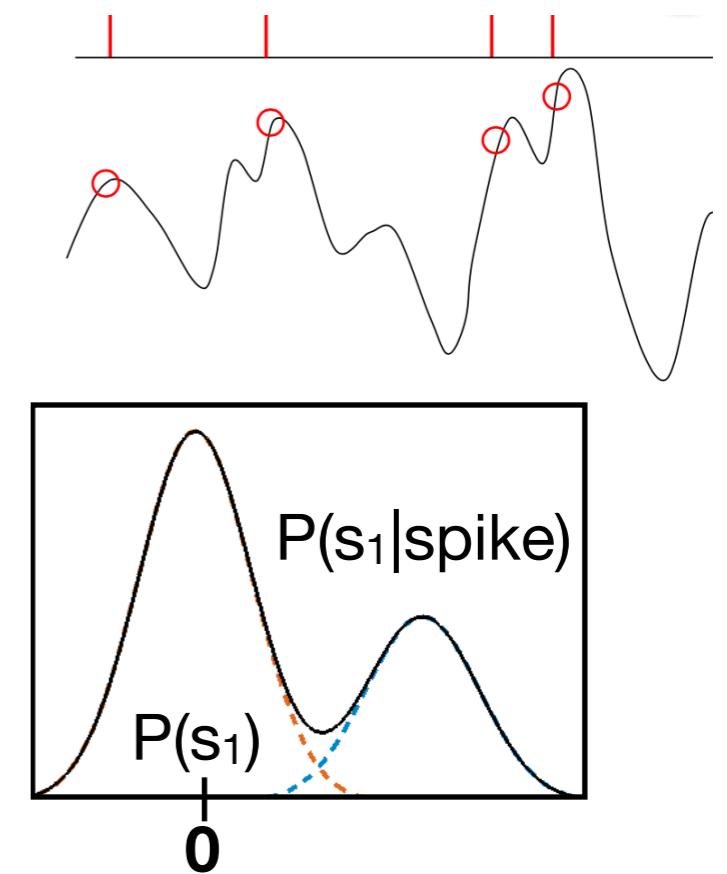
# Finding the I/O Function for a Single Neuron.

The I/O function can be found from data using the Bayes' rule:



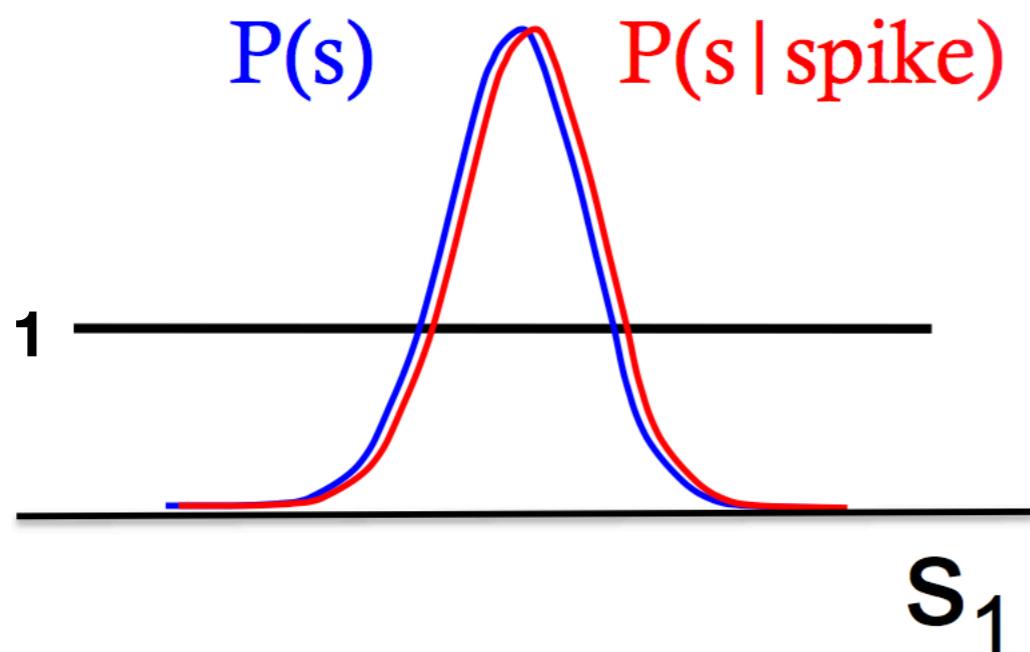
$$P(\text{spike}|s_1) = \frac{P(s_1|\text{spike})P(\text{spike})}{P(s_1)}$$

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

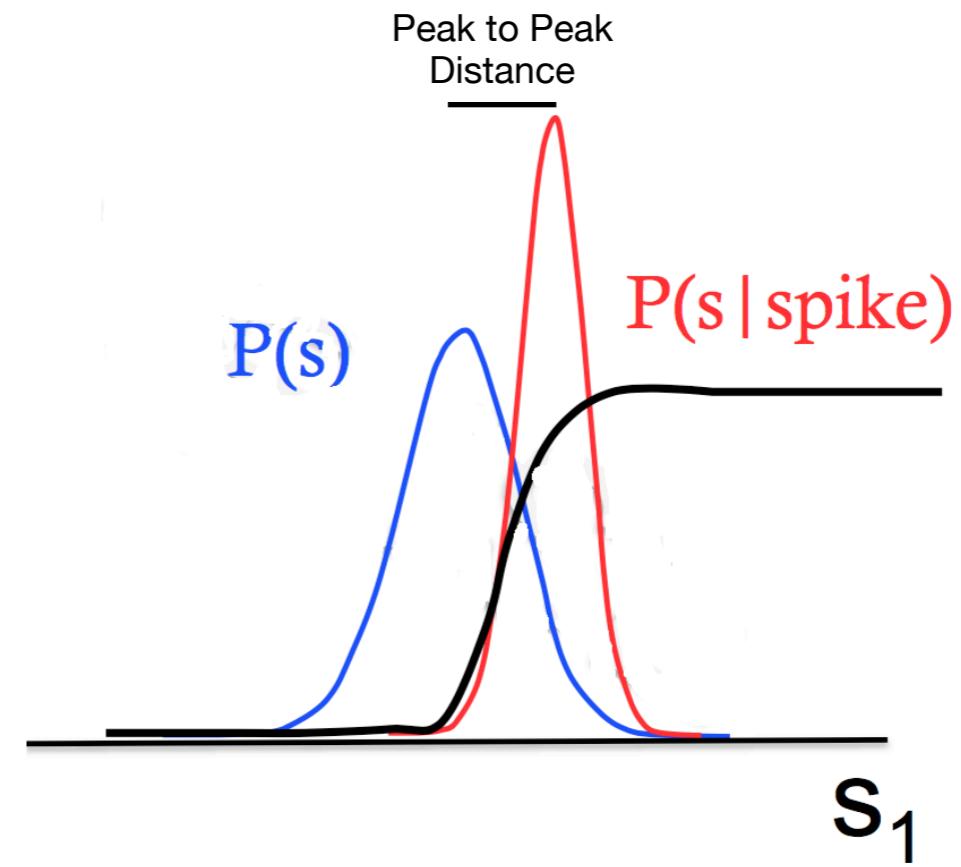


# Finding the I/O Function for a Single Neuron.

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

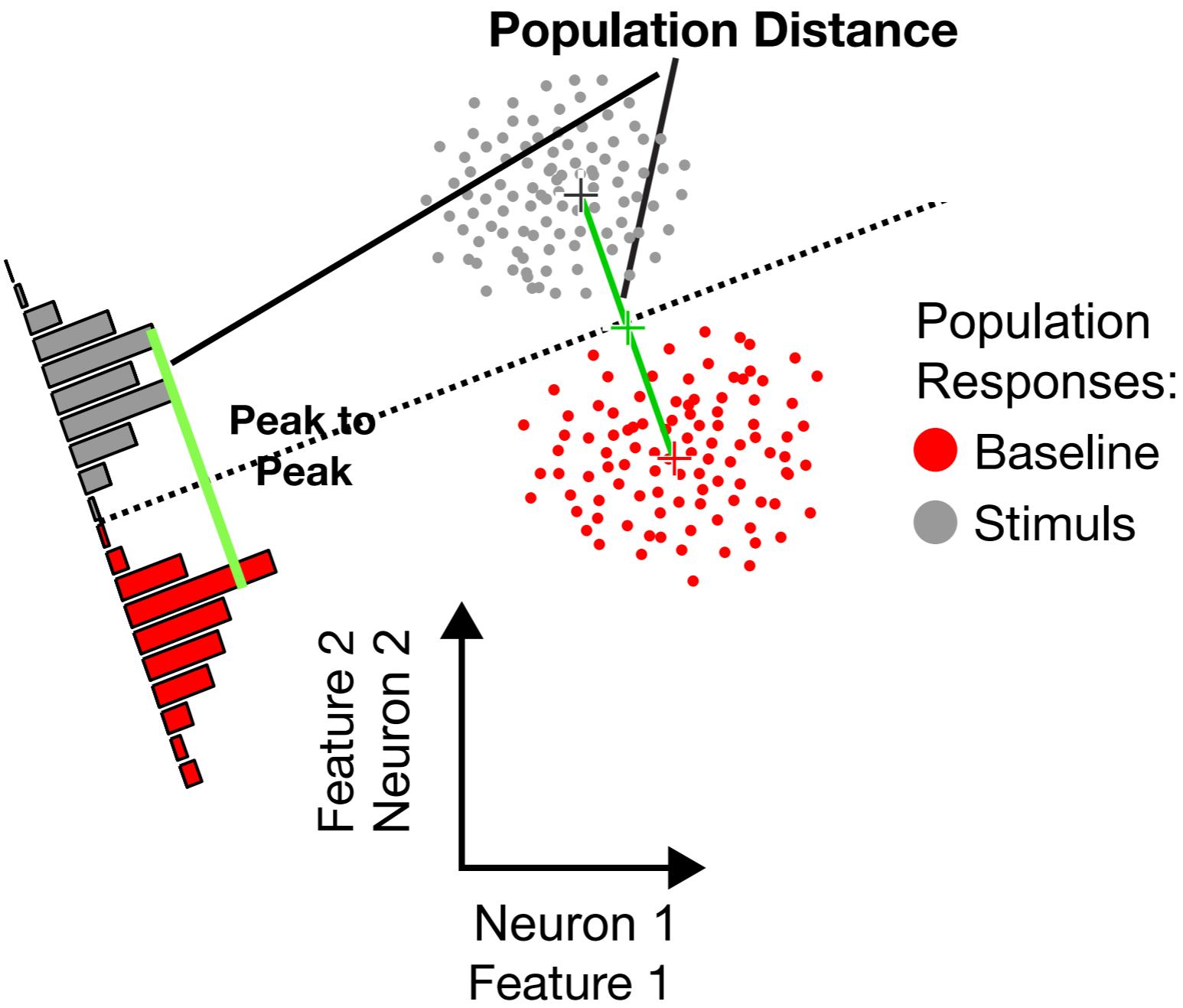


Spikes are unrelated to stimulus.

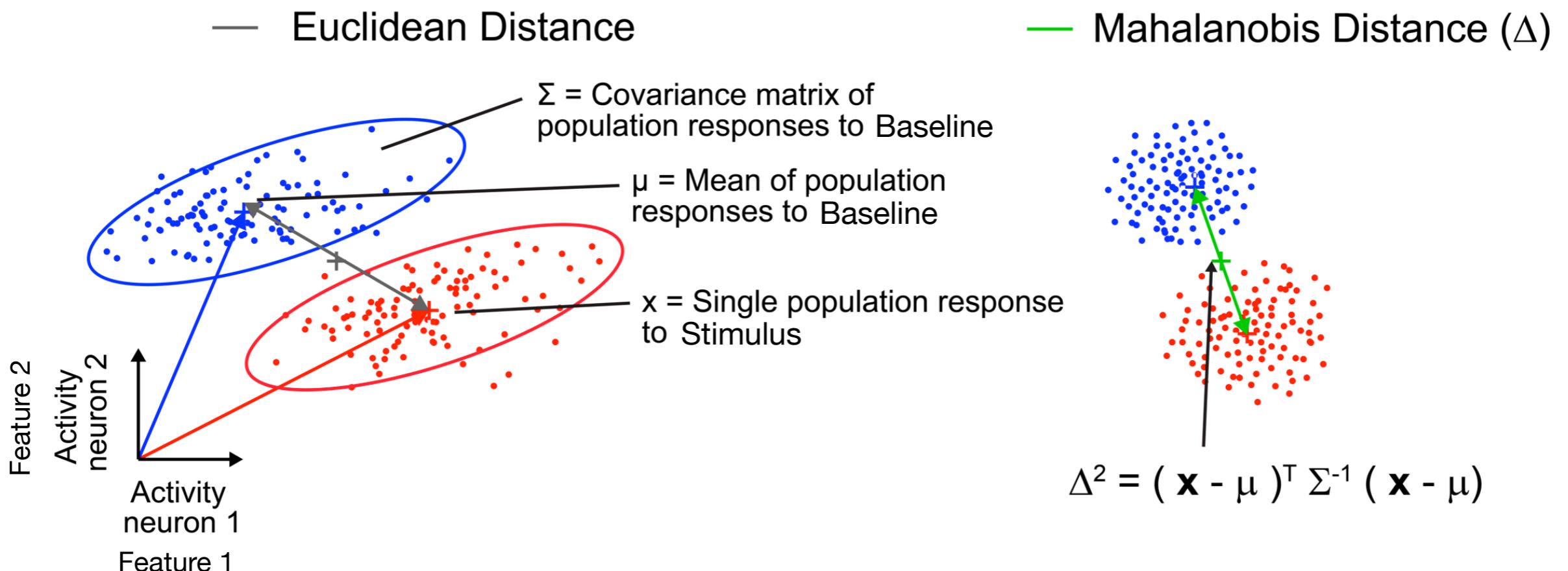


Spikes are selective!

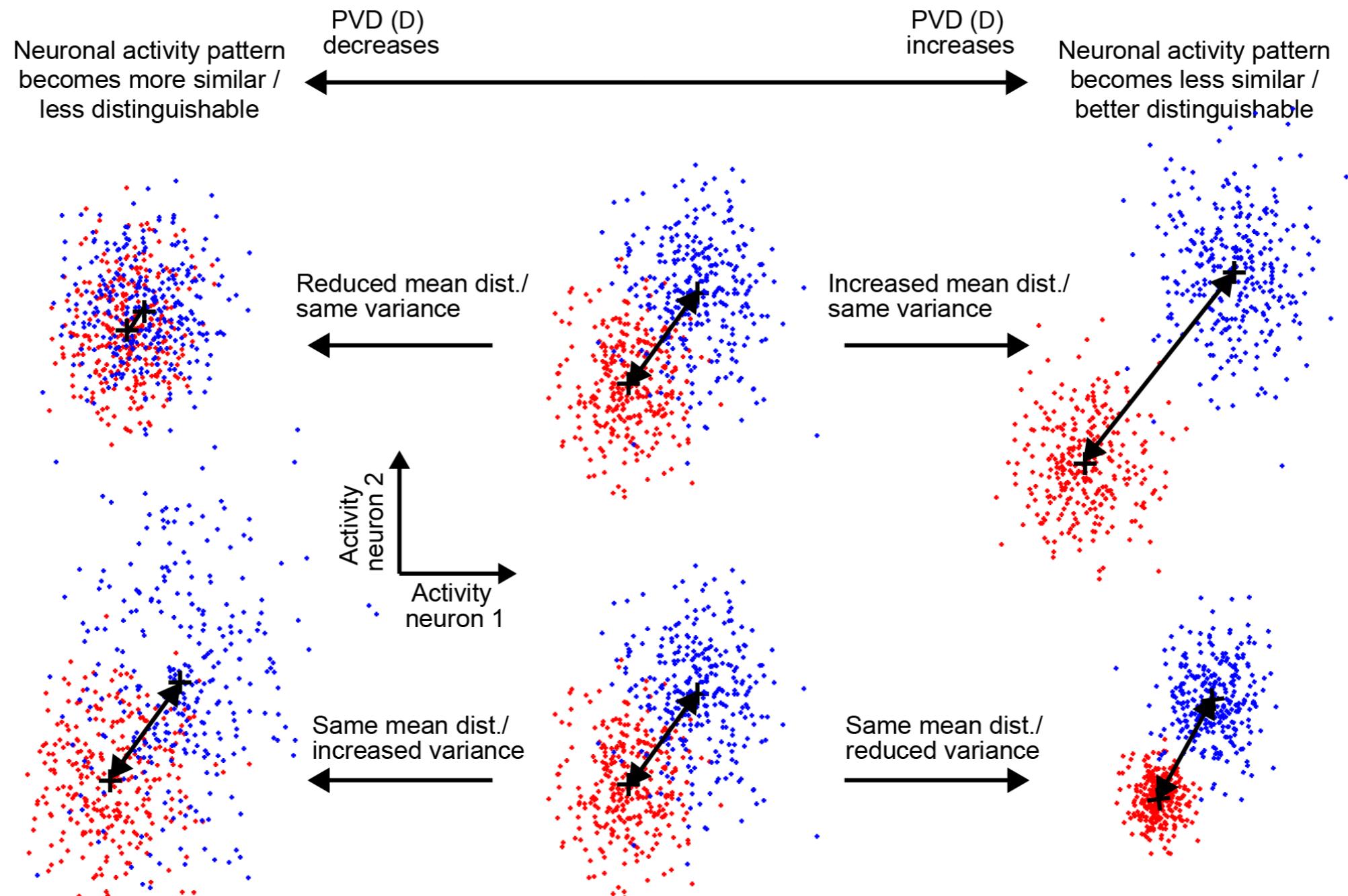
# Population Distance Metrics.



# Population Distance Metrics.

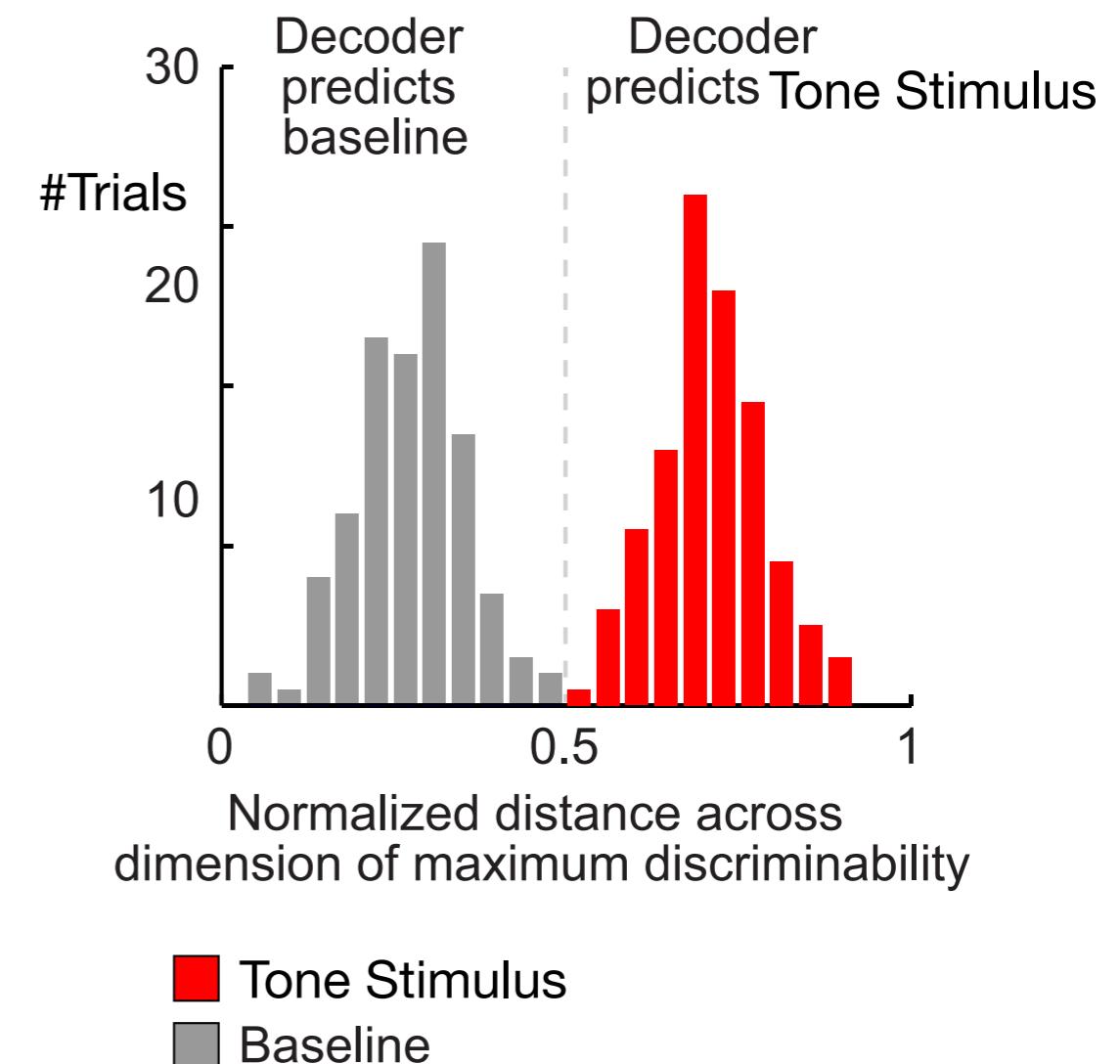
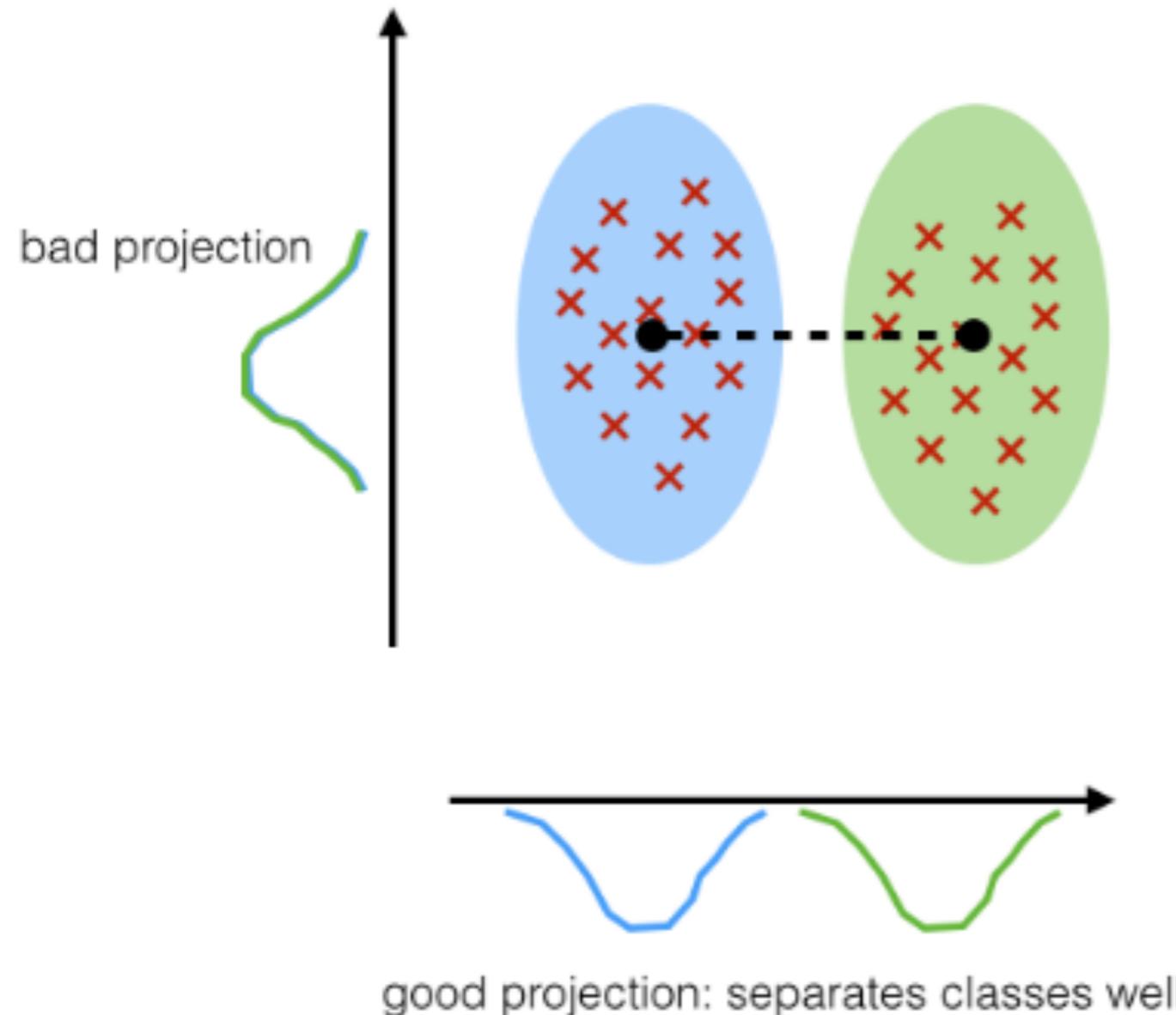


# Population Distance Metrics.



# Supervised Decoding via LDA

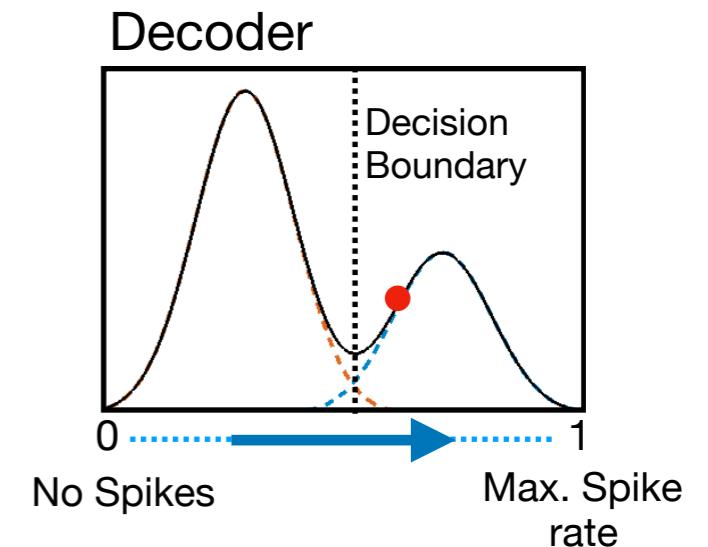
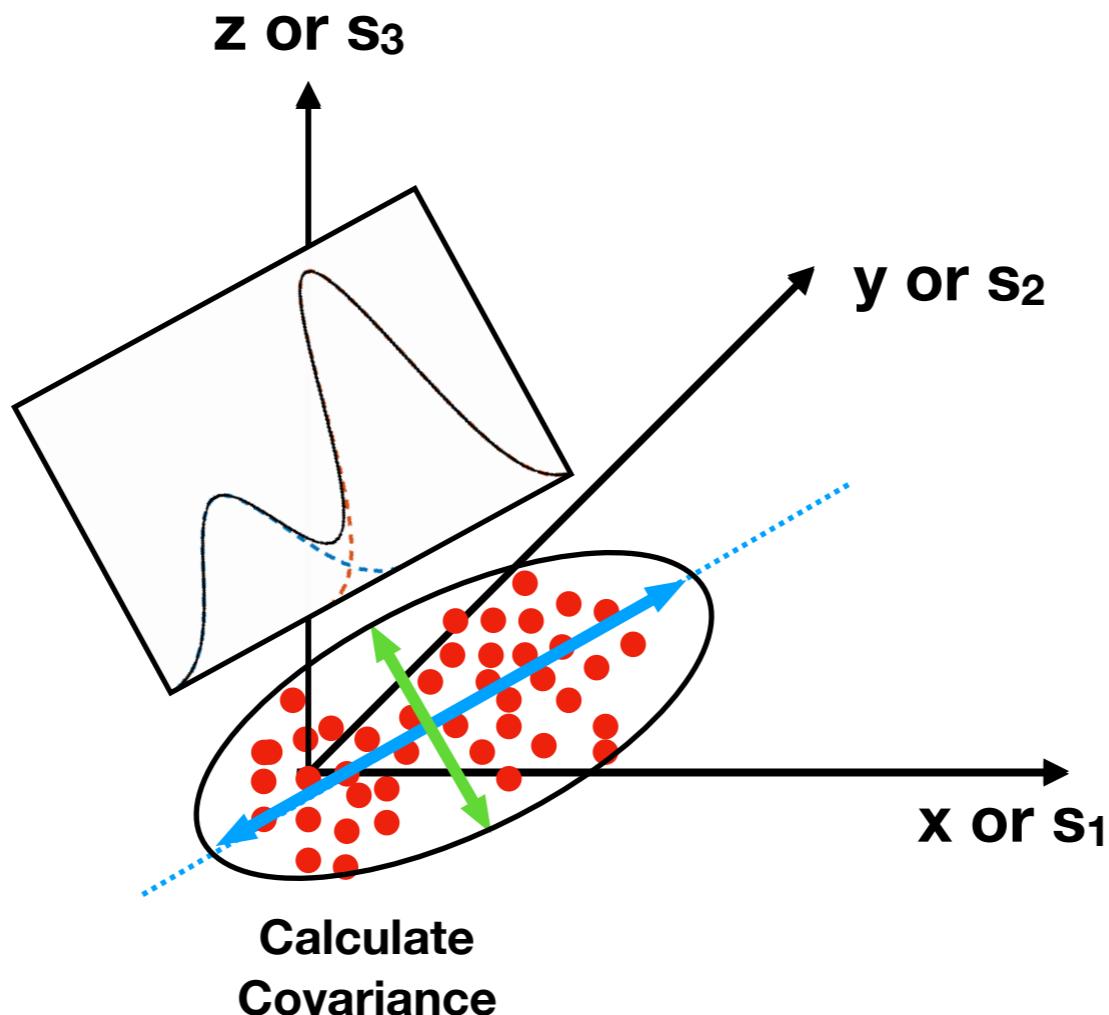
## LDA: Linear Discriminant Analysis



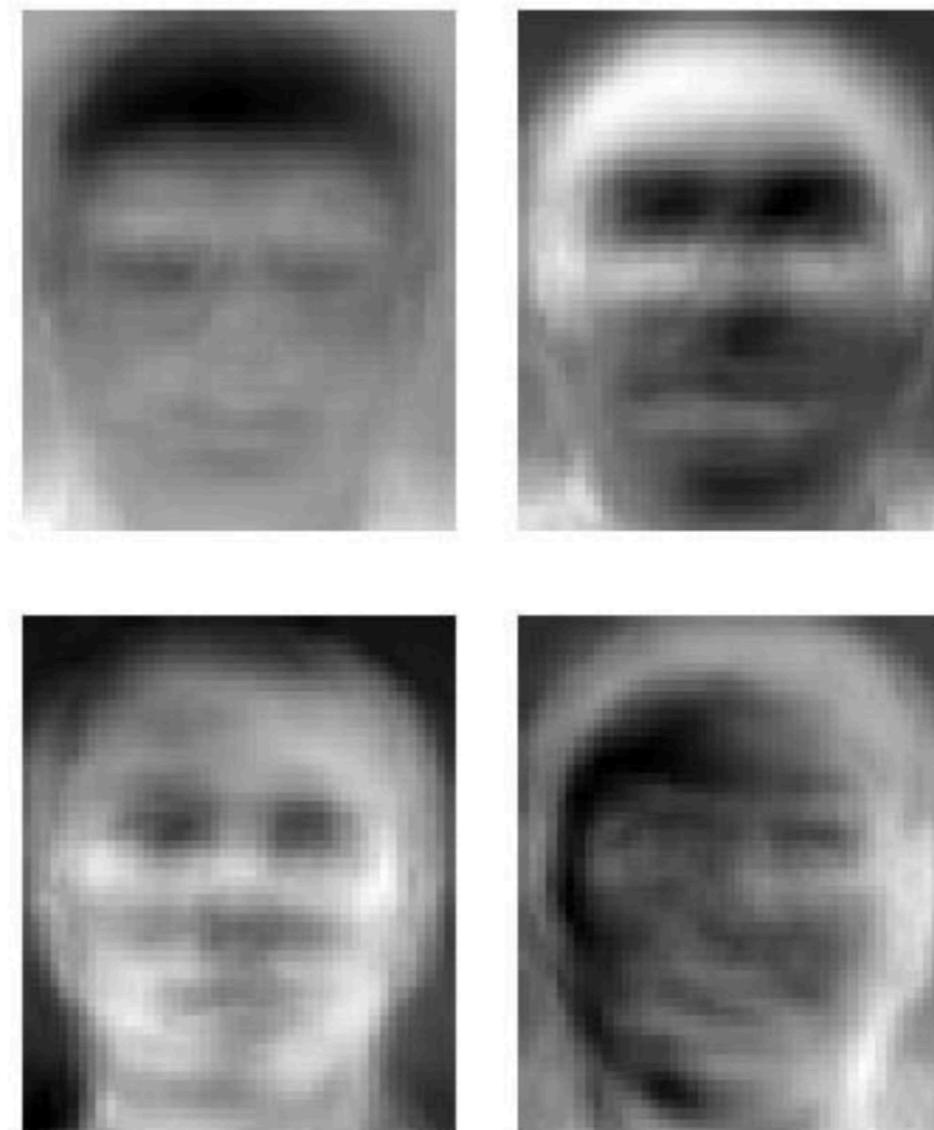
Grewe et al., 2017

# Unsupervised Clustering via PCA

## PCA: Principal Component Analysis



# PCA Example: The Eigenfaces.



**From Pixels (high-dim.) to 7-8 Eigenfaces.**

# Short Recap QUIZ.

**If we discretize a stimulus waveform in time, we can represent it as a vector in some vector space. What is the dimensionality of this vector space?**

1. The standard deviation of the stimulus.
2. The number of presentations of the stimulus.
3. The length of the stimulus (in seconds).
4. The number of points used in the discretization.

**When we plot  $P(\text{spike} \mid s_1)$  as a function of  $s_1$ , why does  $P(\text{spike})$  only act as a scaling factor, rather than as something that changes the general shape of the function?**

1. This is not correct.  $P(\text{spike})$  has a large effect on the shape of the conditional distribution plotted as a function of  $s_1$ .
2.  $P(\text{spike})$  influences the spike-triggered average.
3.  $P(\text{spike})$  is the first moment of the spike-conditional distribution.
4.  $P(\text{spike})$  is not a function of  $s_1$ .

# Short Recap QUIZ.

**Principal component analysis (PCA) gives us a method to:**

1. Find a representation of our data which has lower dimensionality, giving us a computationally easier problem to work with.
2. Find the vectors along which the variation of our data is maximal in our feature space.
3. Neither of these
4. Both of these

# Thank you for your Attention!

