

# Spatial context, salience and eye movements



Computational neuroscience class  
Odelia Schwartz, 2021

- Midterm assignments (graded)
- Final Projects / assignments
- Other questions

# Final projects / assignments

## Initial discussion

Choosing one of the following options:

1. You can work in a group on a project (if you are comfortable doing so remotely), or individually on a project. Projects can be done in any programming language. Ideally, group projects include multiple disciplines. Please discuss with me.
2. In lieu of a project, you can hand in an individual assignment, in which you either extend one lab as a project (please discuss with me); or choose two of the upcoming labs, explain the labs and answer the questions at the end.
3. Students who do not have a CS or Engineering background can hand in a discussion about a computational neuroscience paper. You can choose one of the papers that we discuss in class (I will make this more explicit, providing a choice of papers). Please discuss with me.

# Spatial context



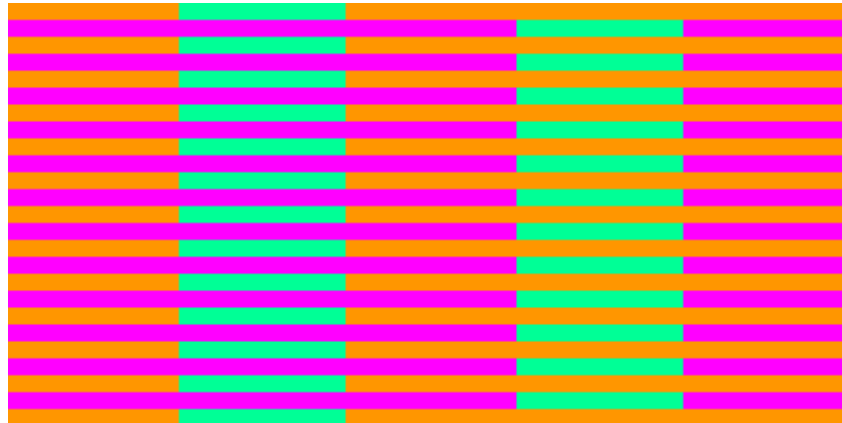


# Spatial context



# Contextual influences

- Perceptual illusions: “no man is an island..”



Review paper on context:

Schwartz, Hsu, Dayan, Nature Reviews Neuroscience 2007

# Contextual influences

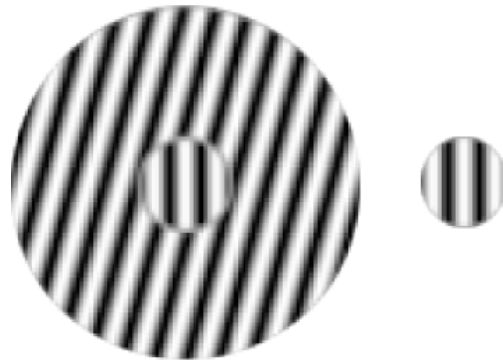
- Perceptual illusions: “no man is an island..”



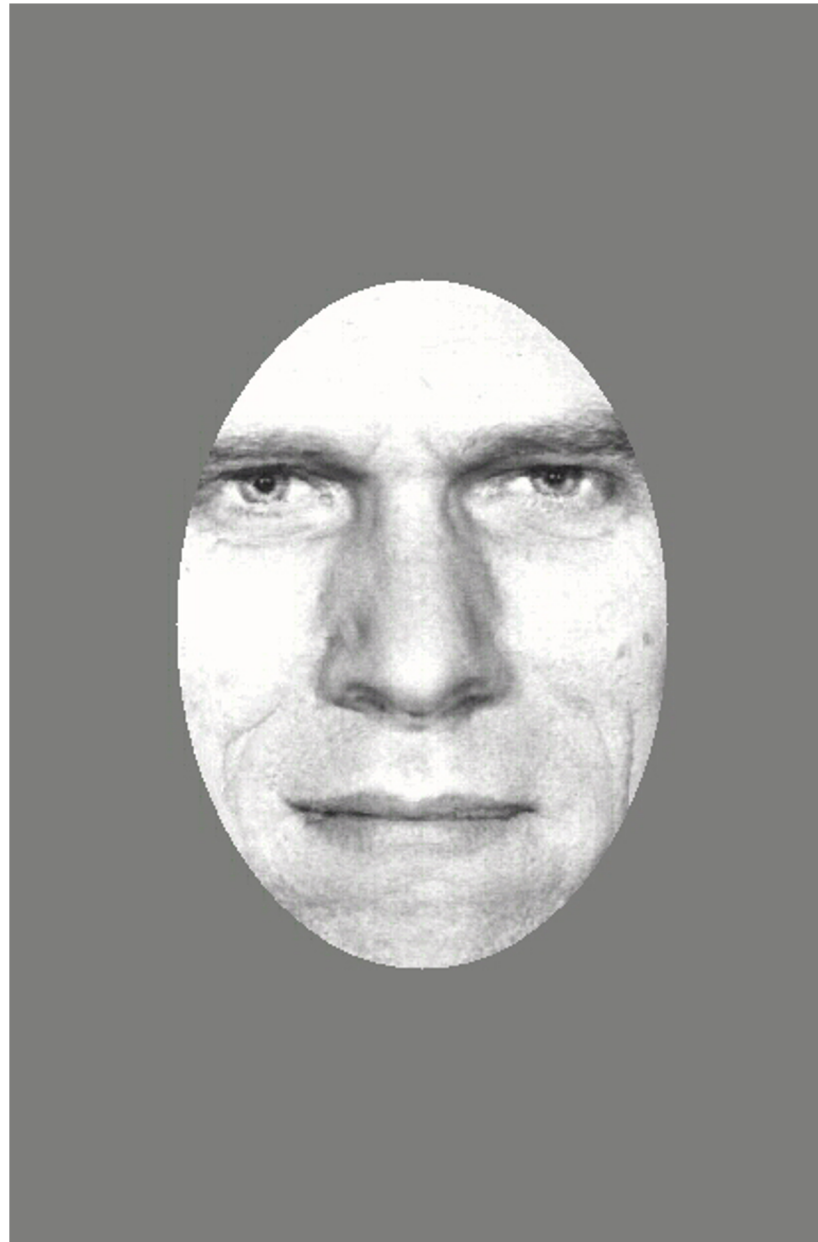
Review paper on context:  
Schwartz, Hsu, Dayan, Nature Reviews Neuroscience 2007

# Contextual influences

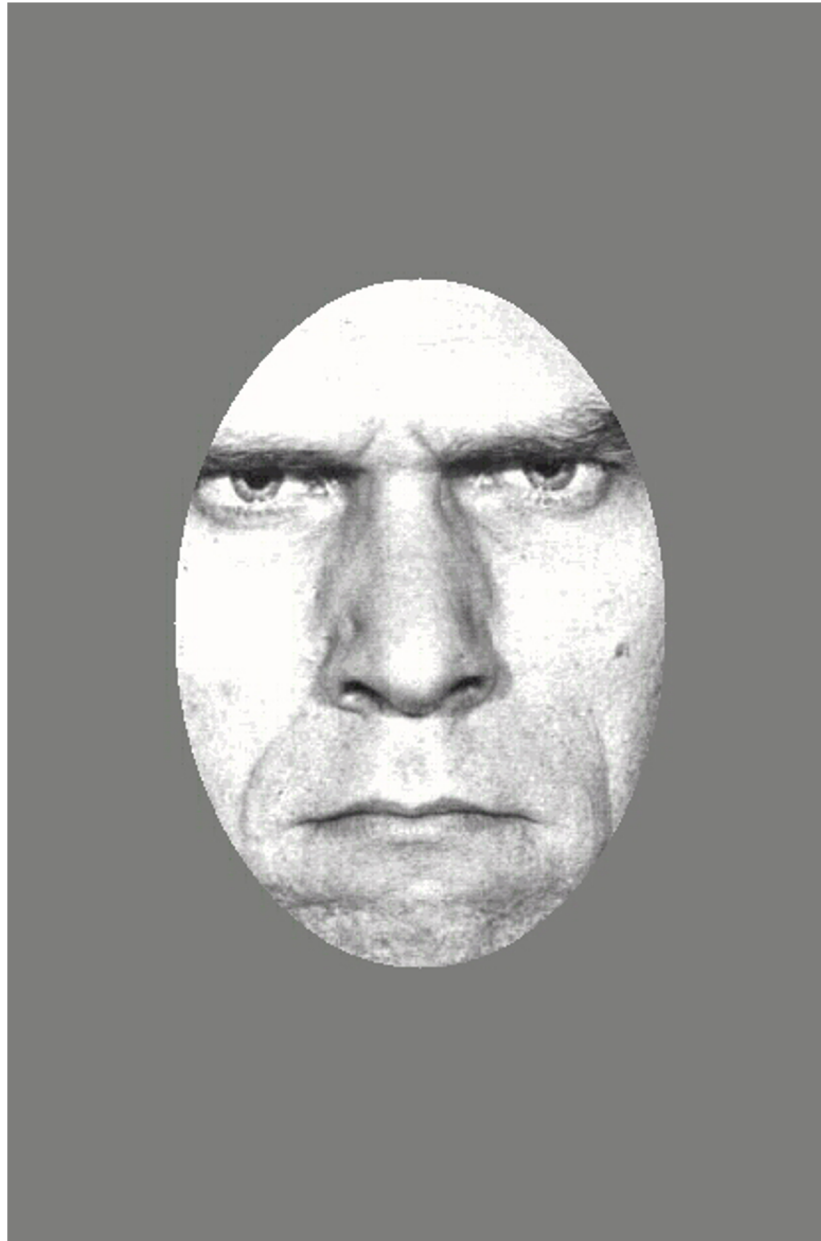
- Perceptual illusions



Contextual effects in time...



Adaptation to expression: pre-adapt (from Michael Webster)



adapt

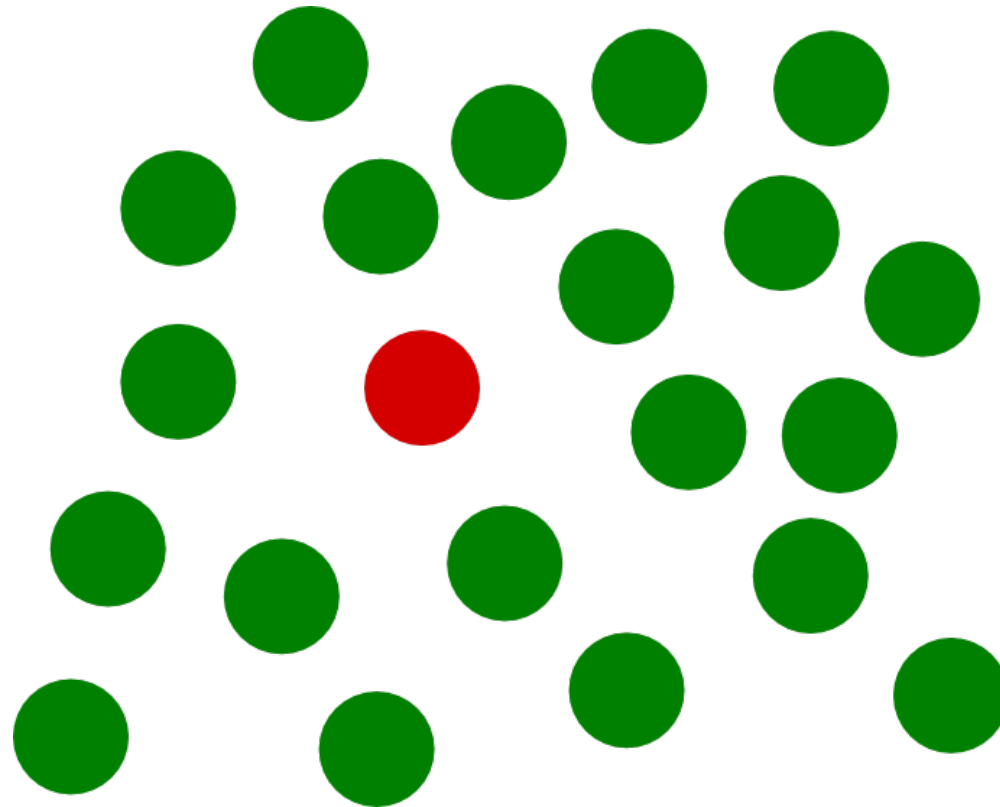




post-adapt

# Contextual influences

- Visual salience

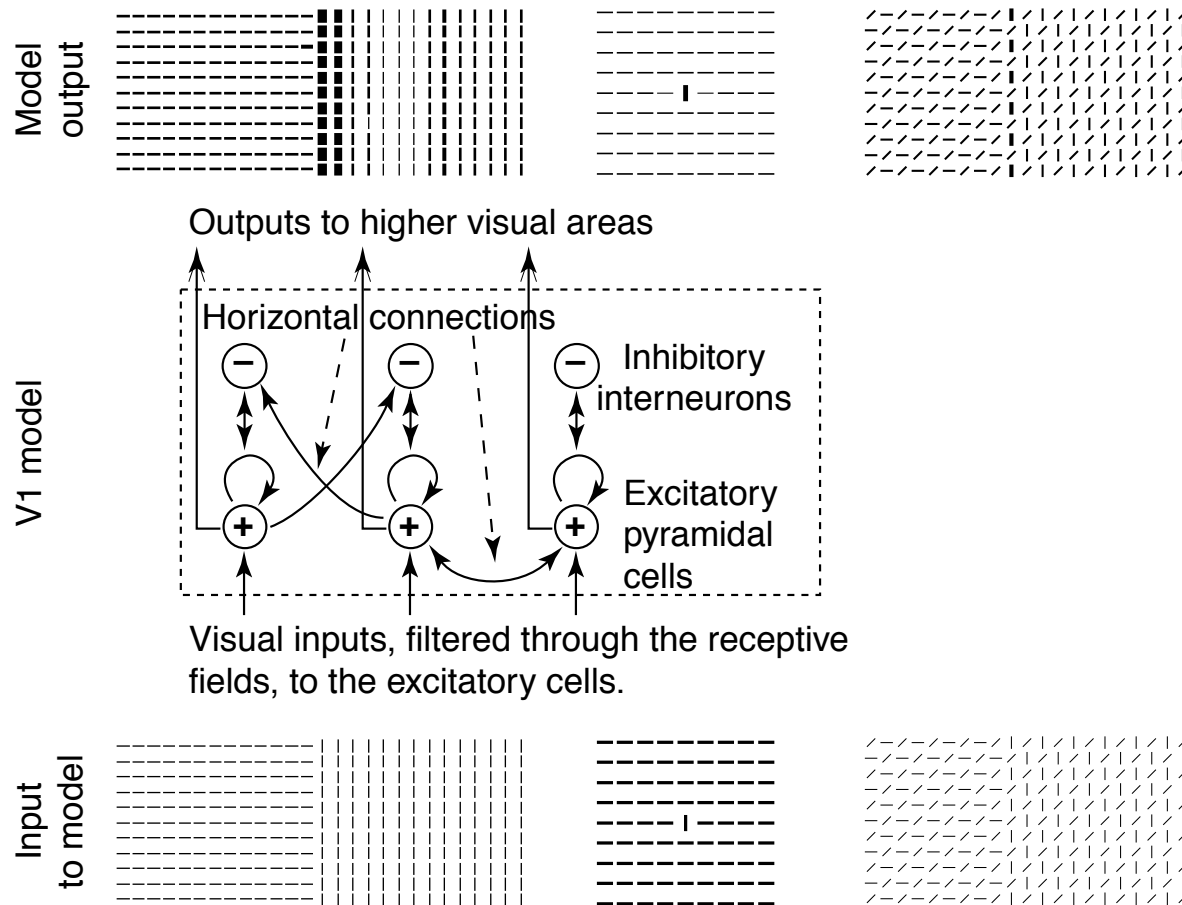


# Contextual influences

- Visual salience



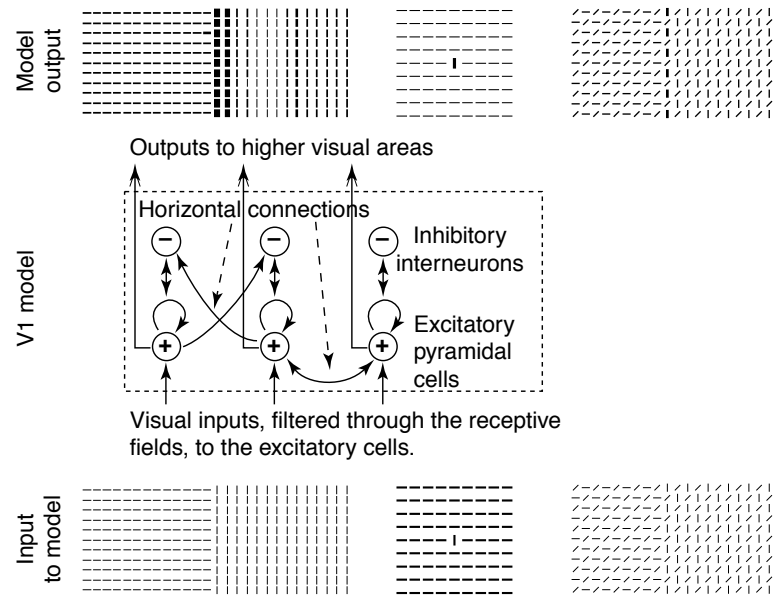
# Saliency model of V1 (Zhaoping)



*TRENDS in Cognitive Sciences*

Li Zhaoping, Trends in Cognitive Sciences, 2002.

# Saliency model of V1 (Zhaoping)



*TRENDS in Cognitive Sciences*

- Dynamical circuit model
- V1 saliency map
- Saliency as breakdown of statistical homogeneity

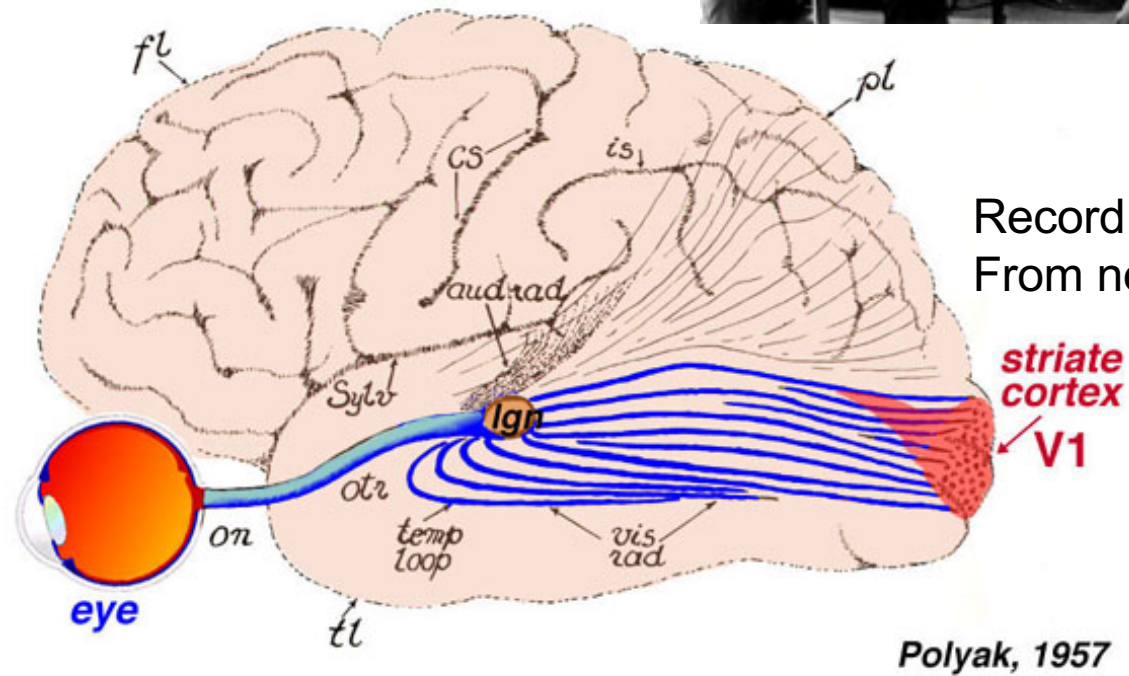
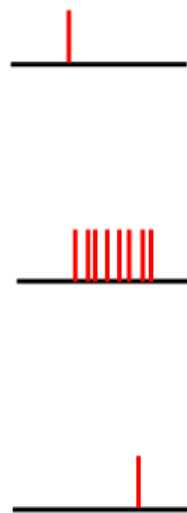
Li Zhaoping, Trends in Cognitive Sciences, 2002.

**Surround context (non classical  
receptive field) effects in visual  
neurons**



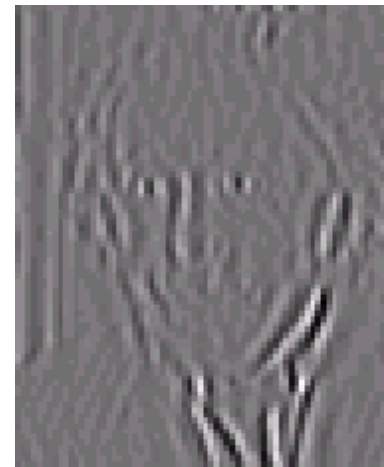
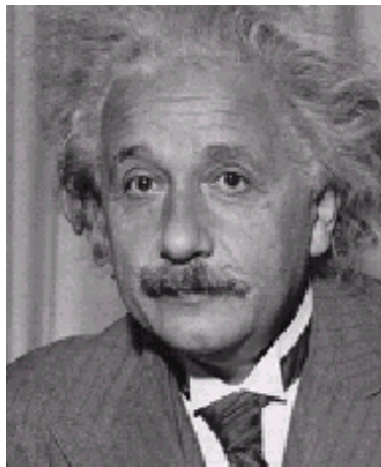
# What about neurons?

- Cortical neural processing

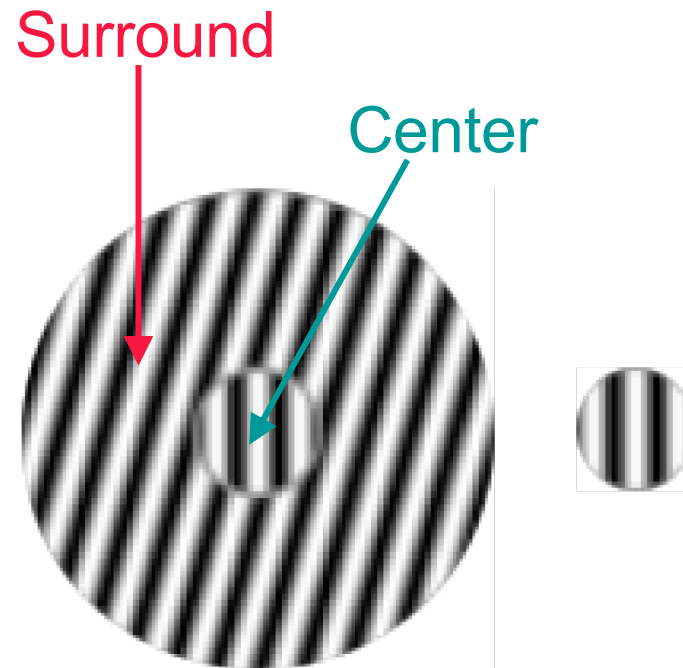


# What about neurons?

- Computer science / Engineering:  
visual receptive field or filter

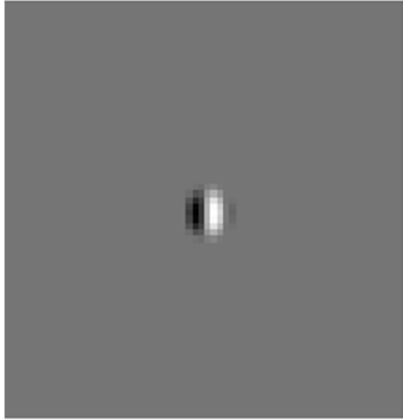


# Focus: spatial surround context



# Visual cortex: non classical RF

Center  
(classical RF)



Large response

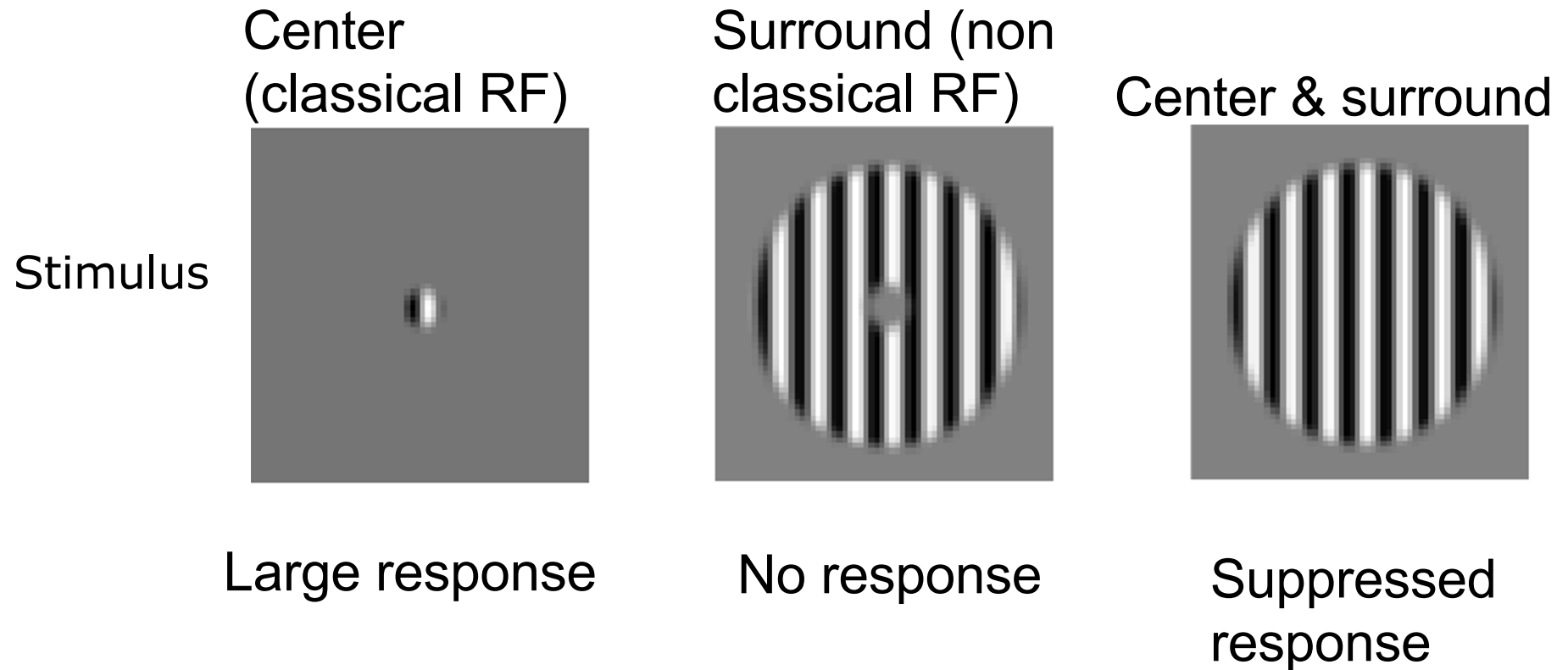
Surround (non  
classical RF)



No response

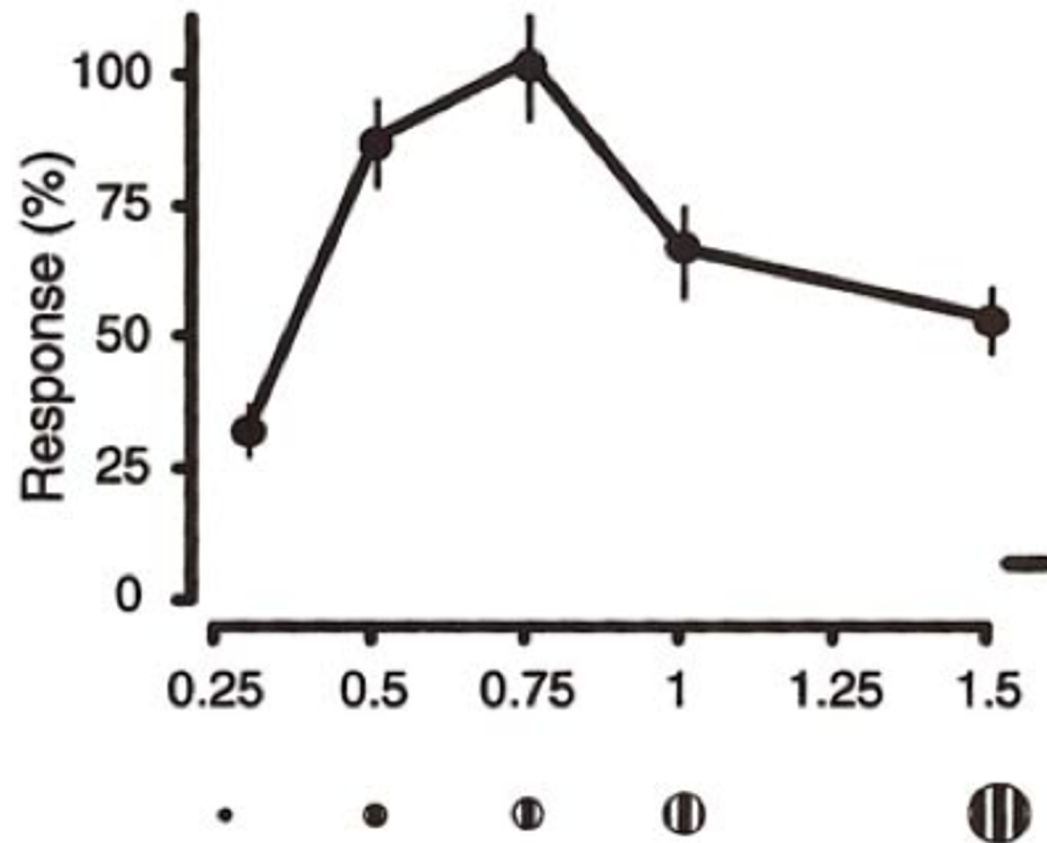
Surround stimulus defined such that by itself there is no response in the neuron

# Visual cortex: spatial surround



But surround stimulus can modulate response to center. Cortical neurons are affected by spatial context (often reduced response, as illustrated by spiking cartoon).

# Visual cortex: spatial surround

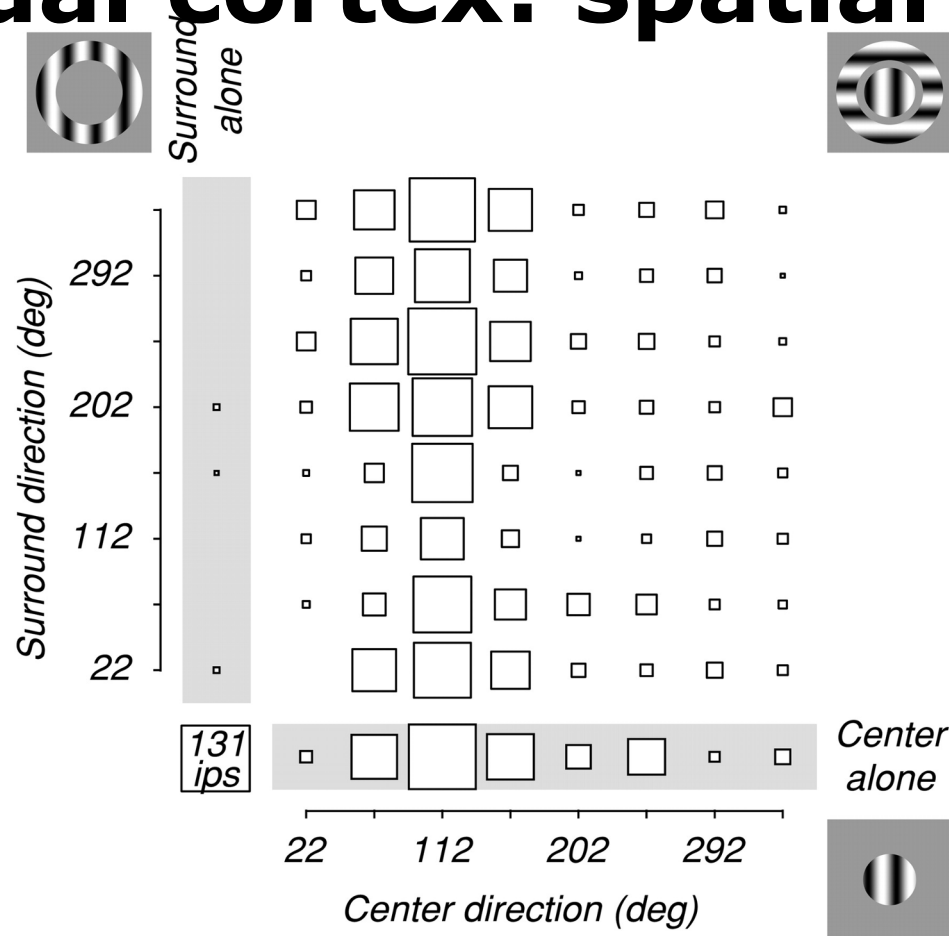


Jones and Sillito, 2001

Response reduced as stimulus size (spatial context) made larger

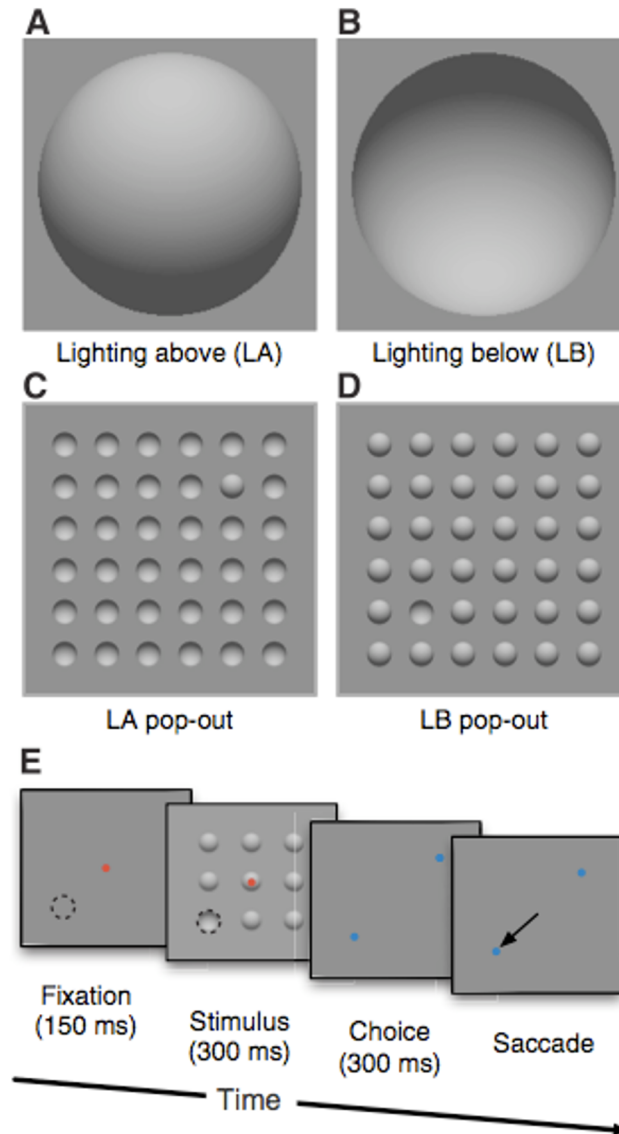


# Visual cortex: spatial surround



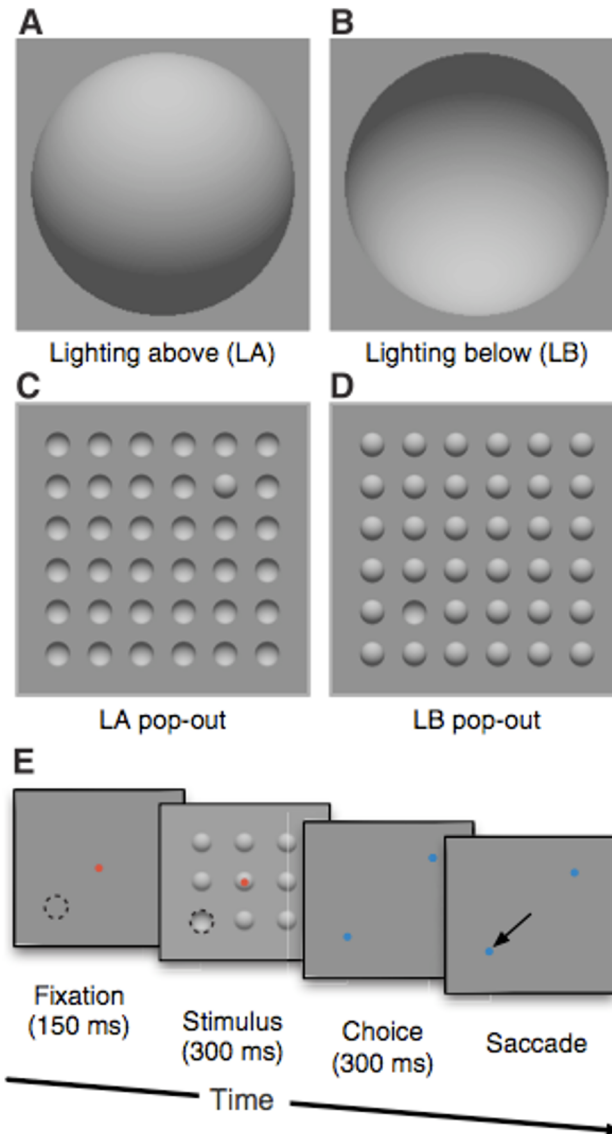
Response reduced most when the center and surround stimuli have the same orientation

# Context by other visual cues?



Smith et al. 2007

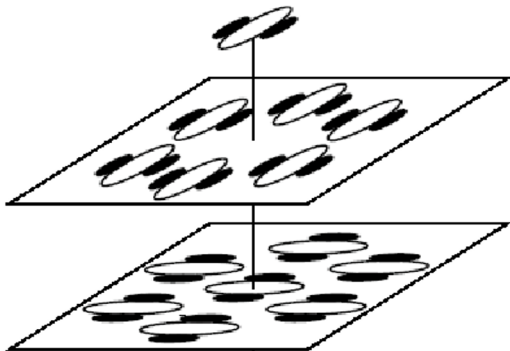
# Context by other visual cues?



Which one  
pops out more?

Smith et al. 2007

# Simple descriptive model of cortical surround effects



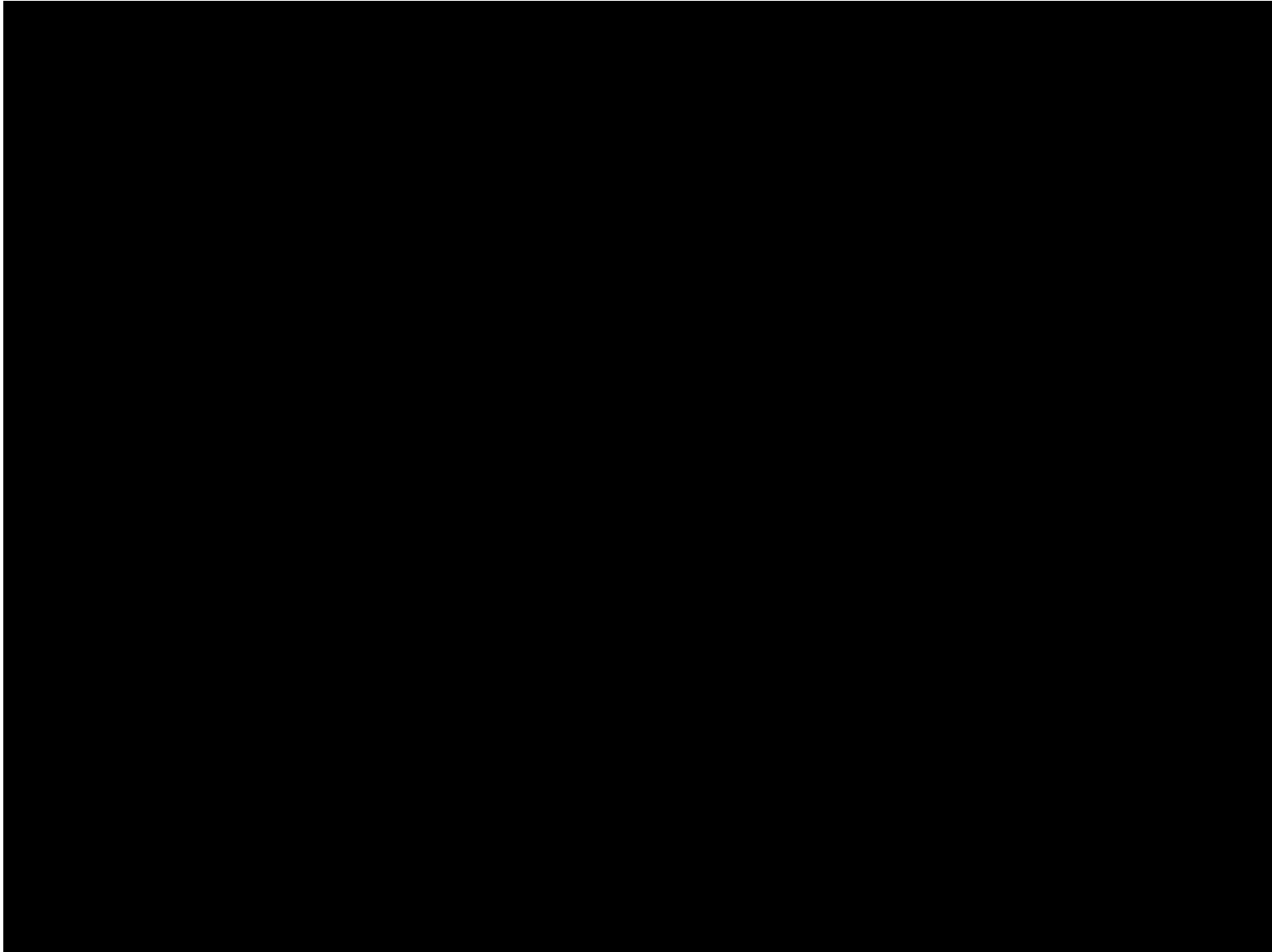
$$R_i = \frac{L_i^2}{\sum_j w_{ji} L_j^2 + \sigma^2}$$

Linear filters followed by  
nonlinearity (divide by surround  
responses)

After Heeger 1992

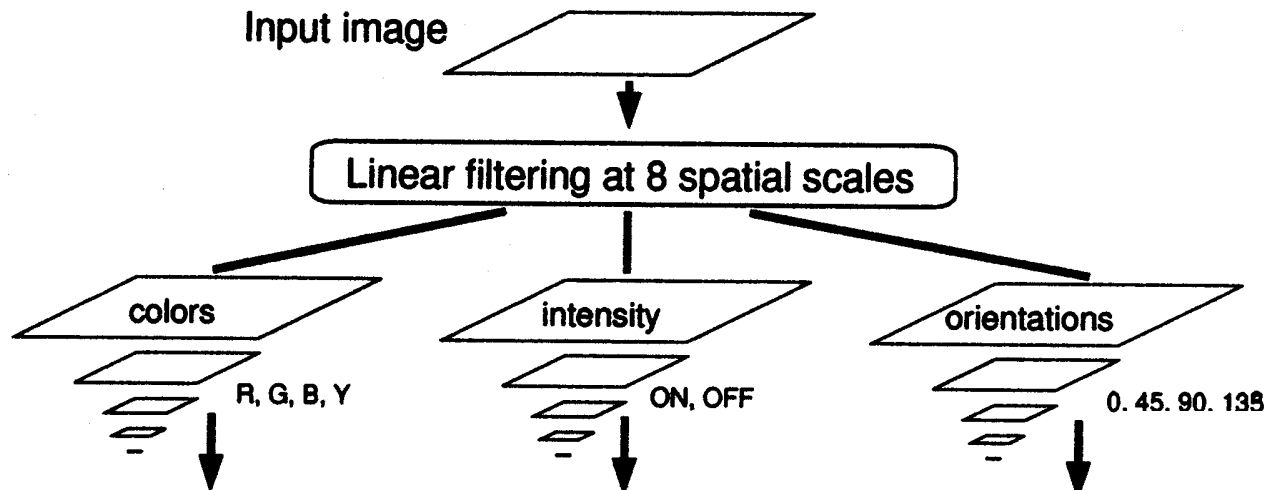
## **Eye movements and salience**

## **Example 1: Eye movements and salience (Laurent Itti, University of Southern California)**



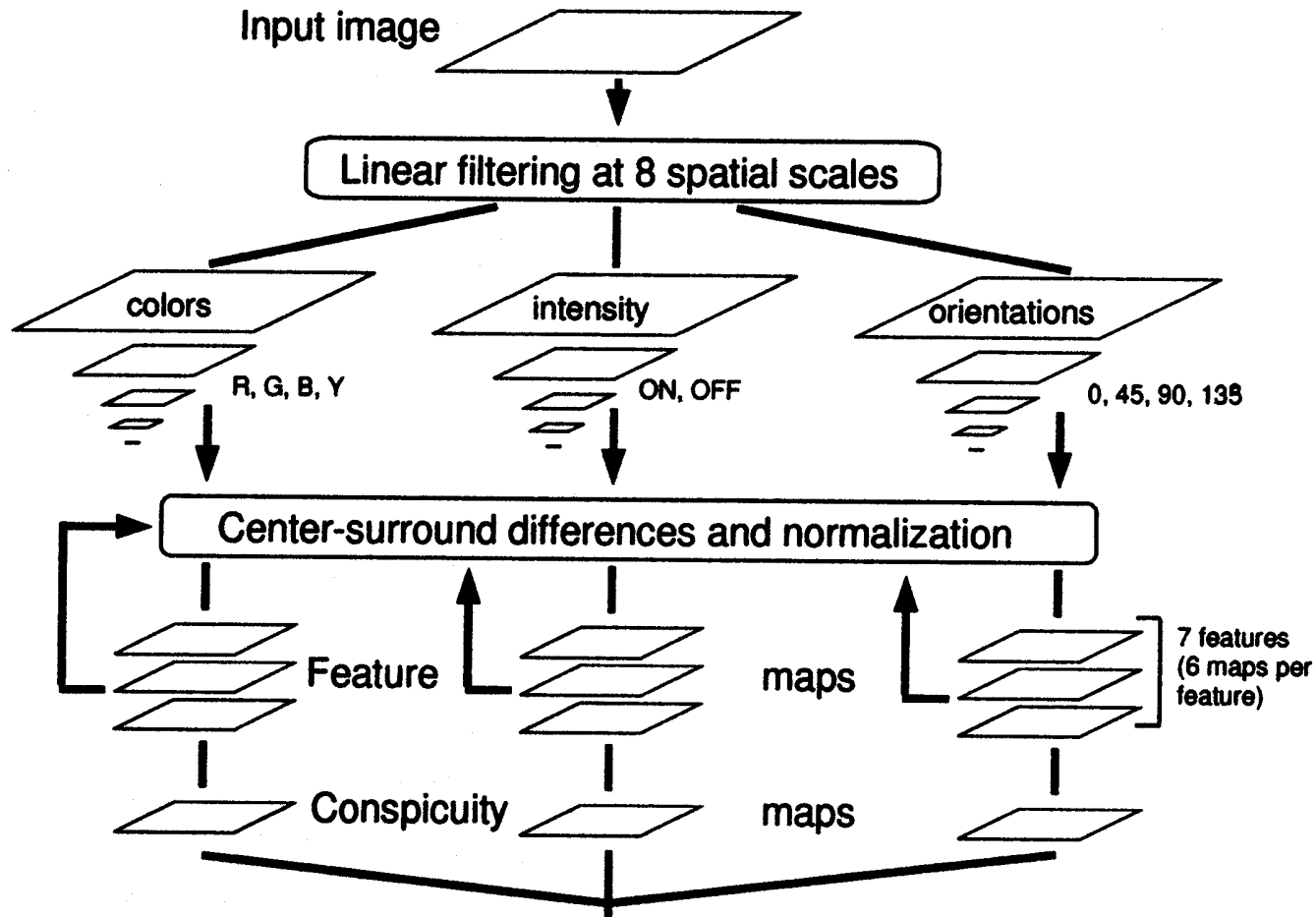


# Eye movements and salience (Itti and Koch, 2000)



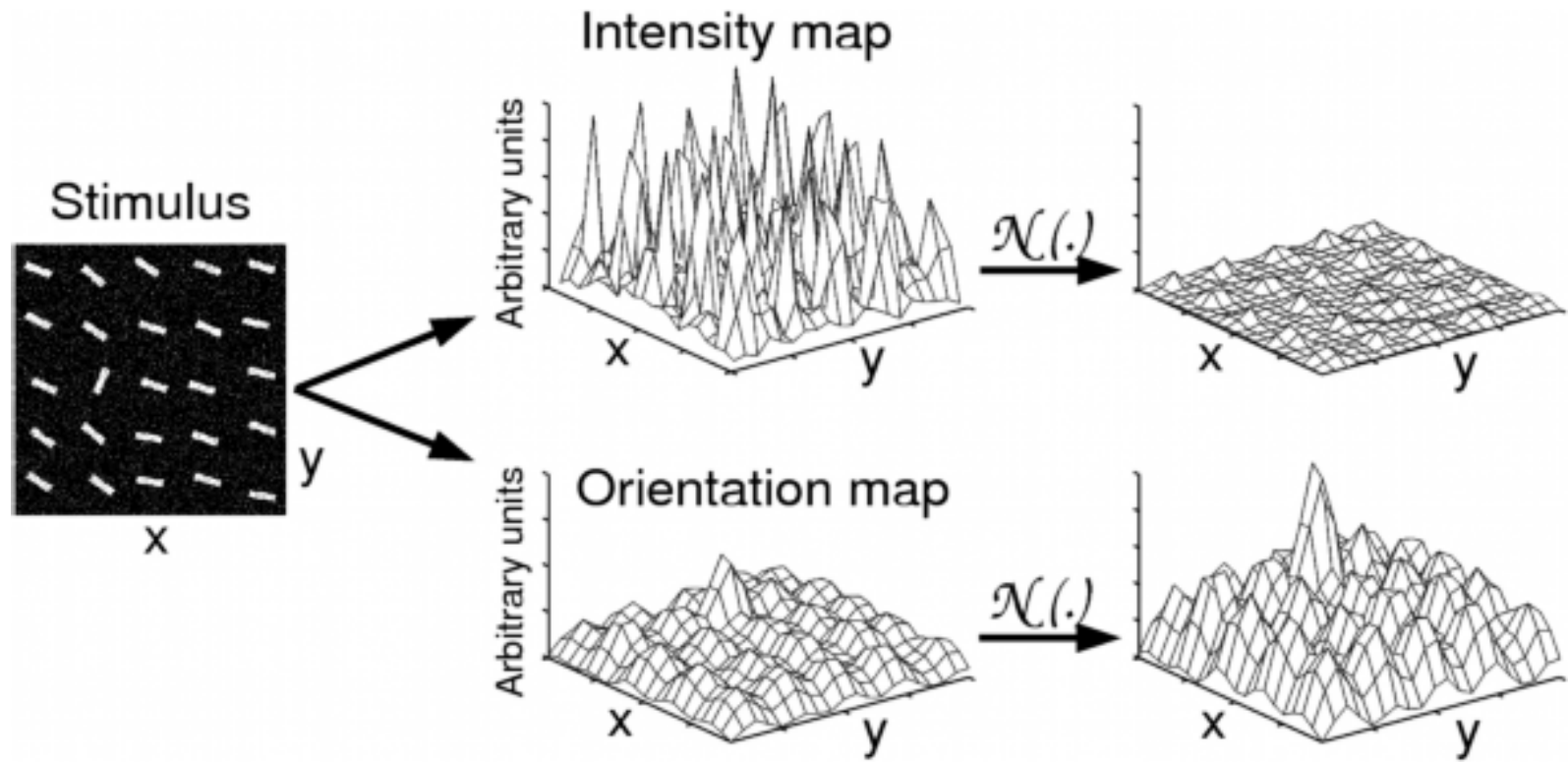
Analyze salience for different features:  
Colors, intensity, orientations ....

# Eye movements and saliency (Itti and Koch, 2000)



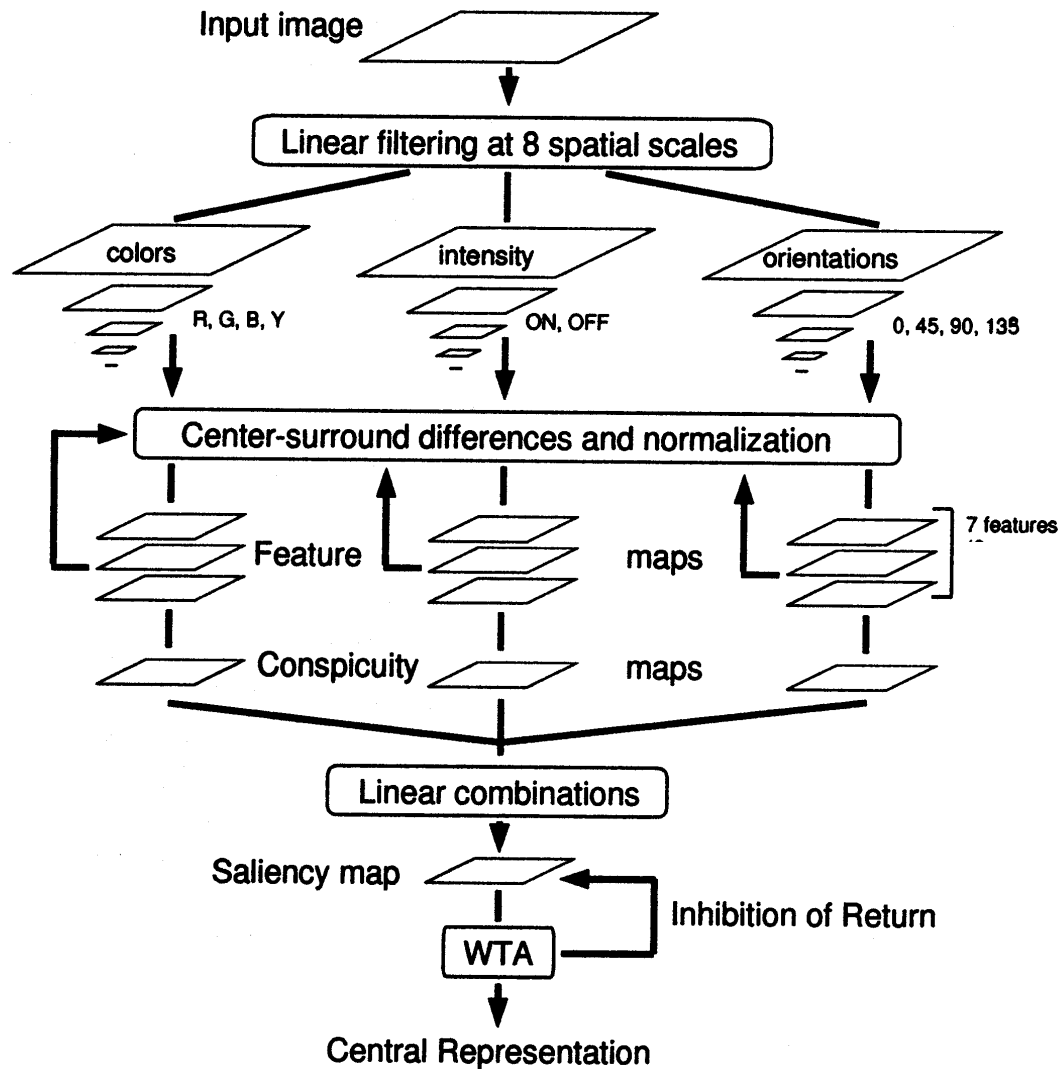
Analyze saliency for different feature maps:  
Colors, intensity, orientations ....

# Eye movements and salience (Itti and Koch, 2000)



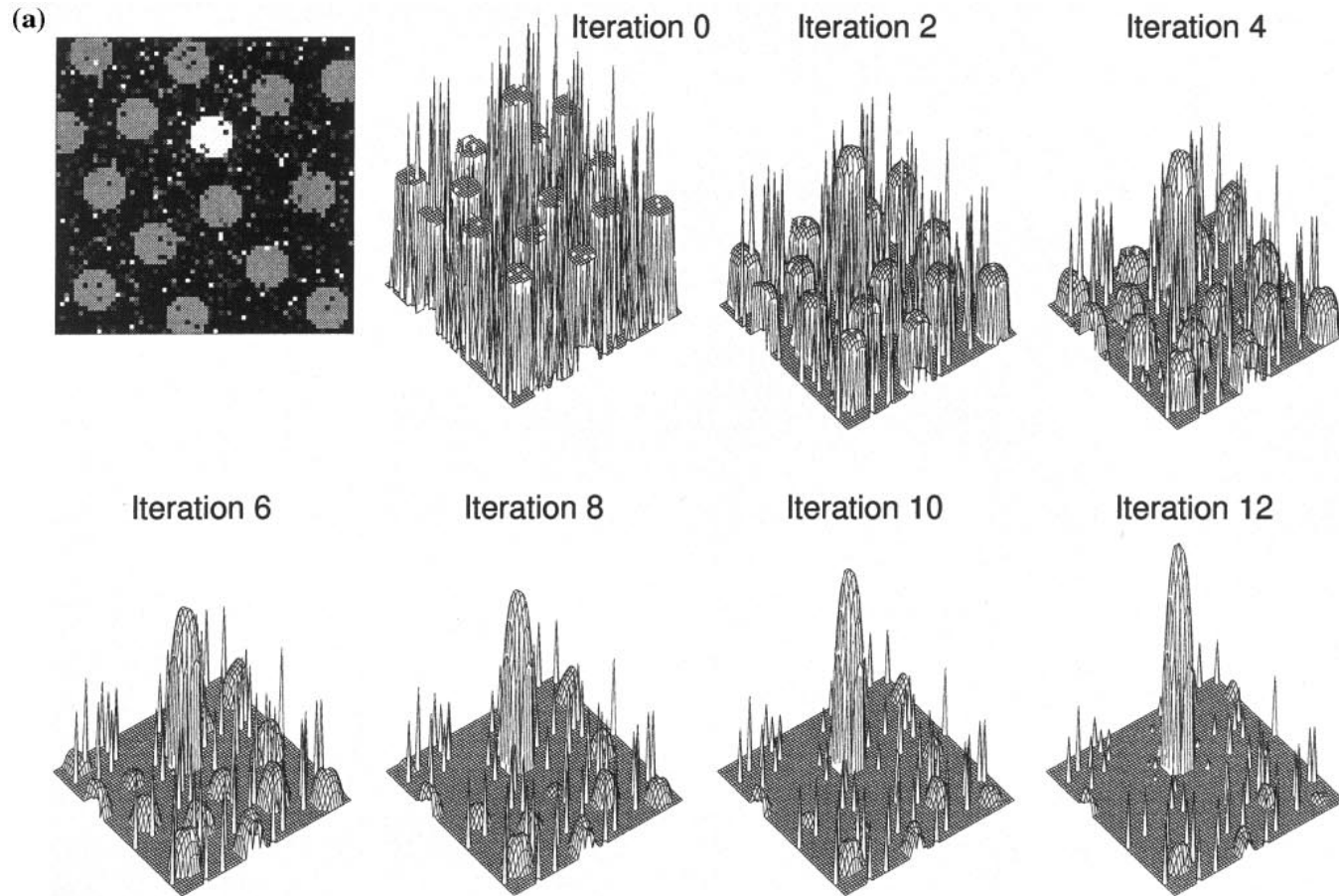
From Wikipedia page

# Eye movements and saliency (Itti and Koch, 2000)



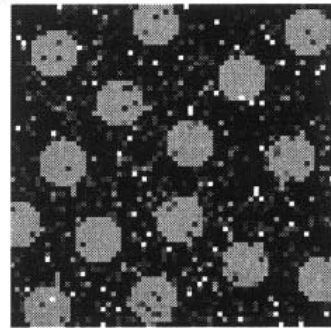
Linearly combine the saliency maps of different features

# Eye movements and saliency (Itti and Koch, 2000)

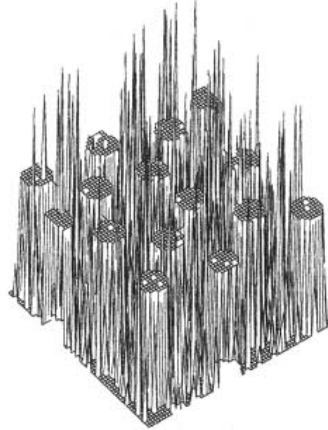


# Eye movements and saliency (Itti and Koch, 2000)

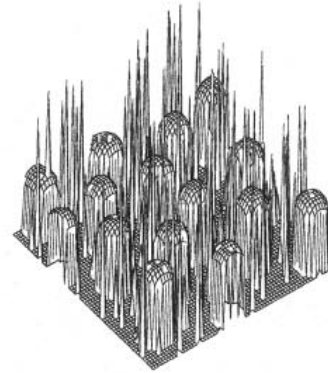
(b)



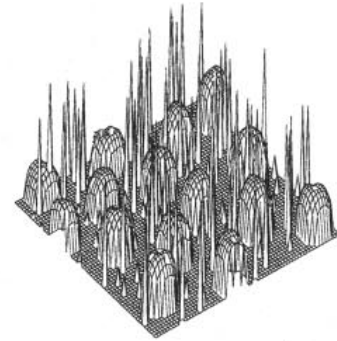
Iteration 0



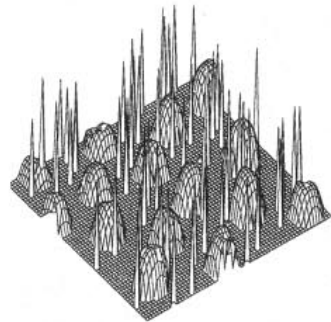
Iteration 2



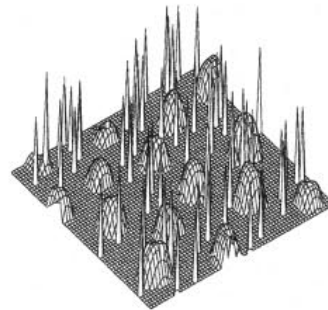
Iteration 4



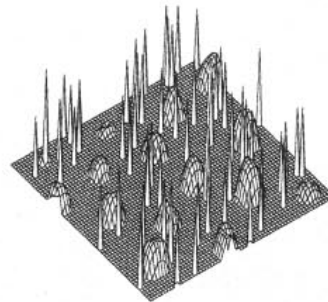
Iteration 6



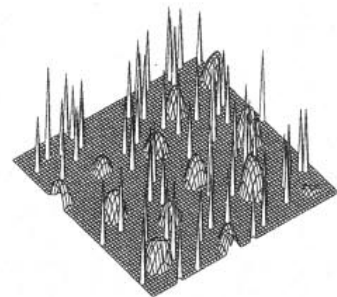
Iteration 8



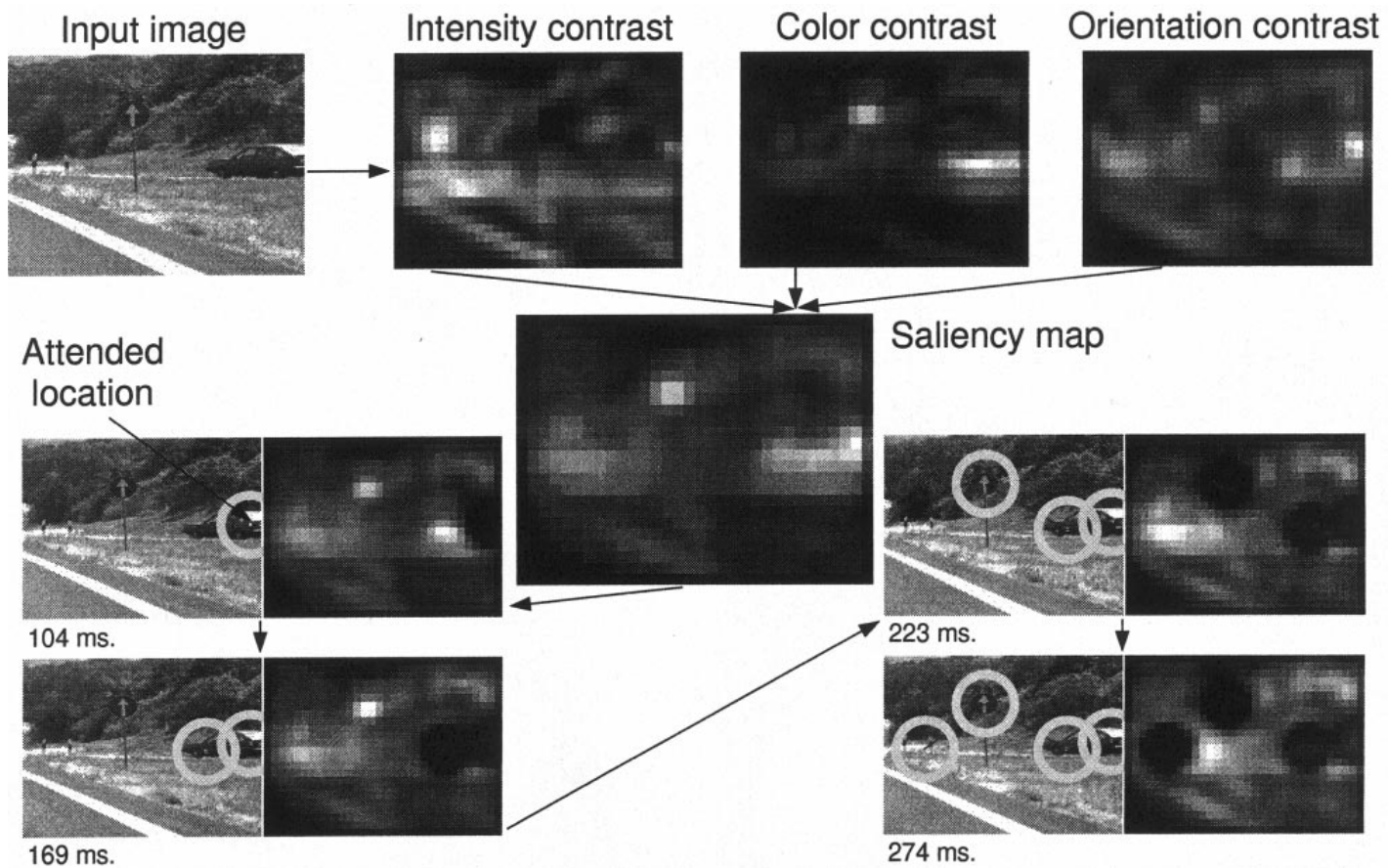
Iteration 10



Iteration 12



# Eye movements and saliency (Itti and Koch, 2000)



# Eye movements: not only salience (Yarbus 1967)





# Eye movements: not only salience (Yarbus 1967)



Free examination

# Eye movements: not only salience (Yarbus 1967)





# Eye movements: not only salience (Yarbus 1967)



Remember the clothes worn by people

# Eye movements: not only salience (Yarbus 1967)





# Eye movements: not only salience (Yarbus 1967)



Give the ages of the people

# Eye movements: not only salience



Free examination.

1



Estimate material circumstances of the family

2



Give the ages of the people.

3



Surmise what the family had been doing before the arrival of the unexpected visitor.

4



Remember the clothes worn by the people.

5



Remember positions of people and objects in the room.

6



Estimate how long the visitor had been away from the family.

7

3 min. recordings of the same subject

# **Surround spatial context and cortical neural processing of visual scenes**

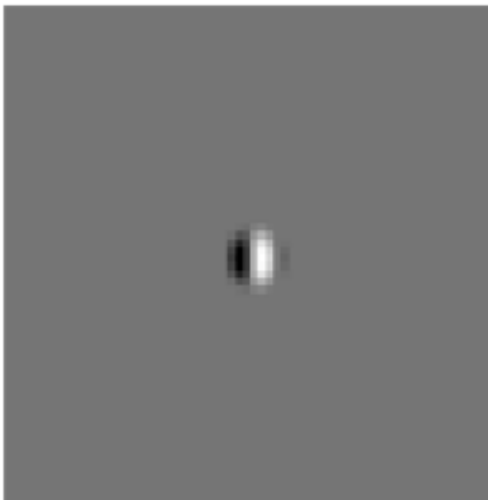
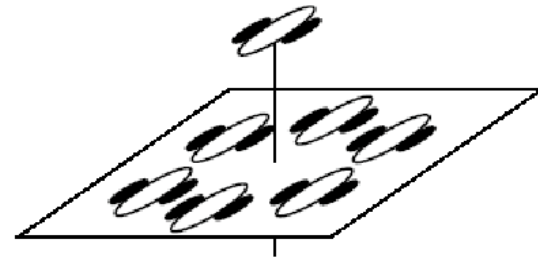
# Motivation

- Spatial context plays critical role in object *grouping* and recognition, and in *segmentation*. It is key to everyday behavior; deficits have been implicated in neurological and developmental disorders and aging
- Poor understanding for how we (and our cortical neurons) process complex, natural images



# Contextual influences

- Cortical visual neurons (V1)



Large response



Suppressed response



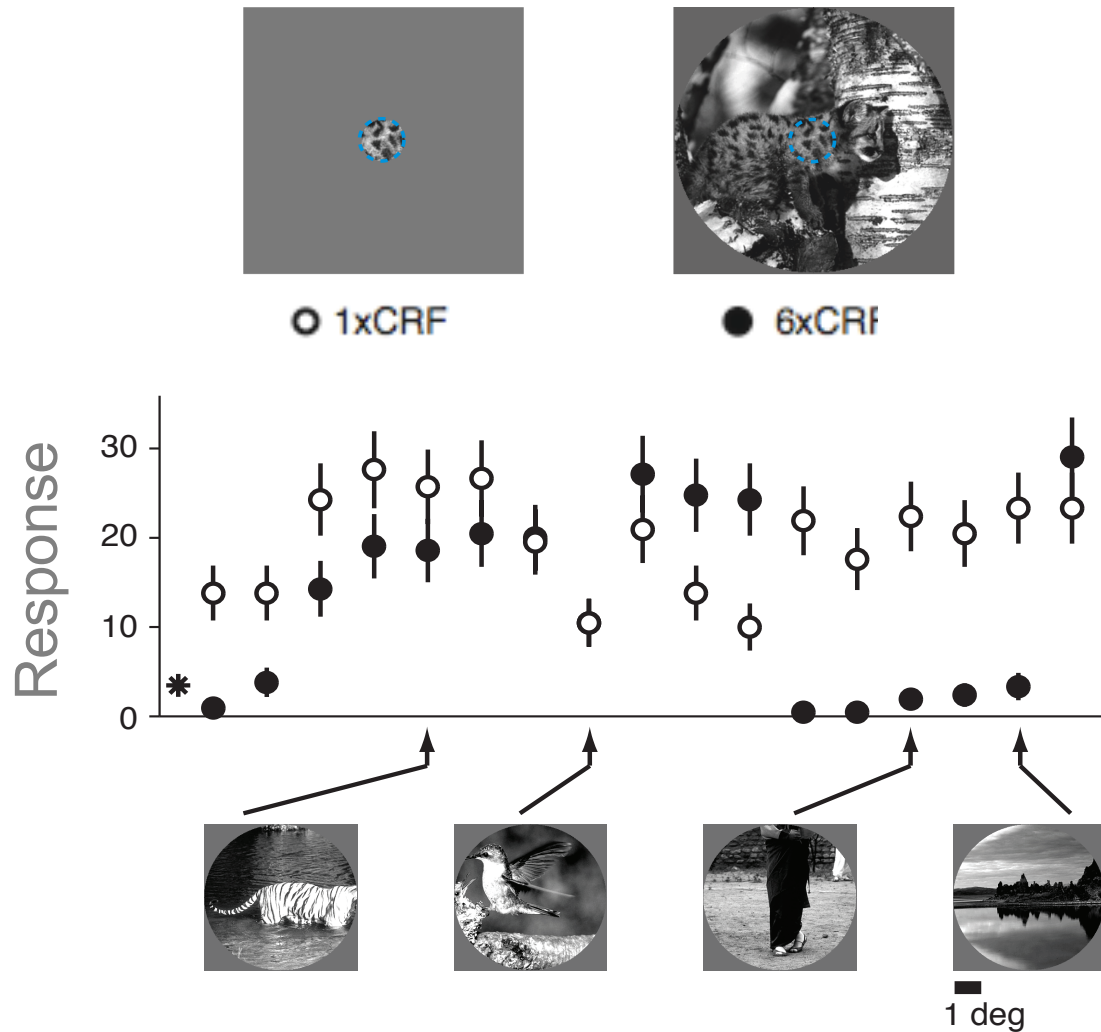
??

Simple oriented stimuli

Image

# Cortical Neurons

- Spatial context and natural scenes



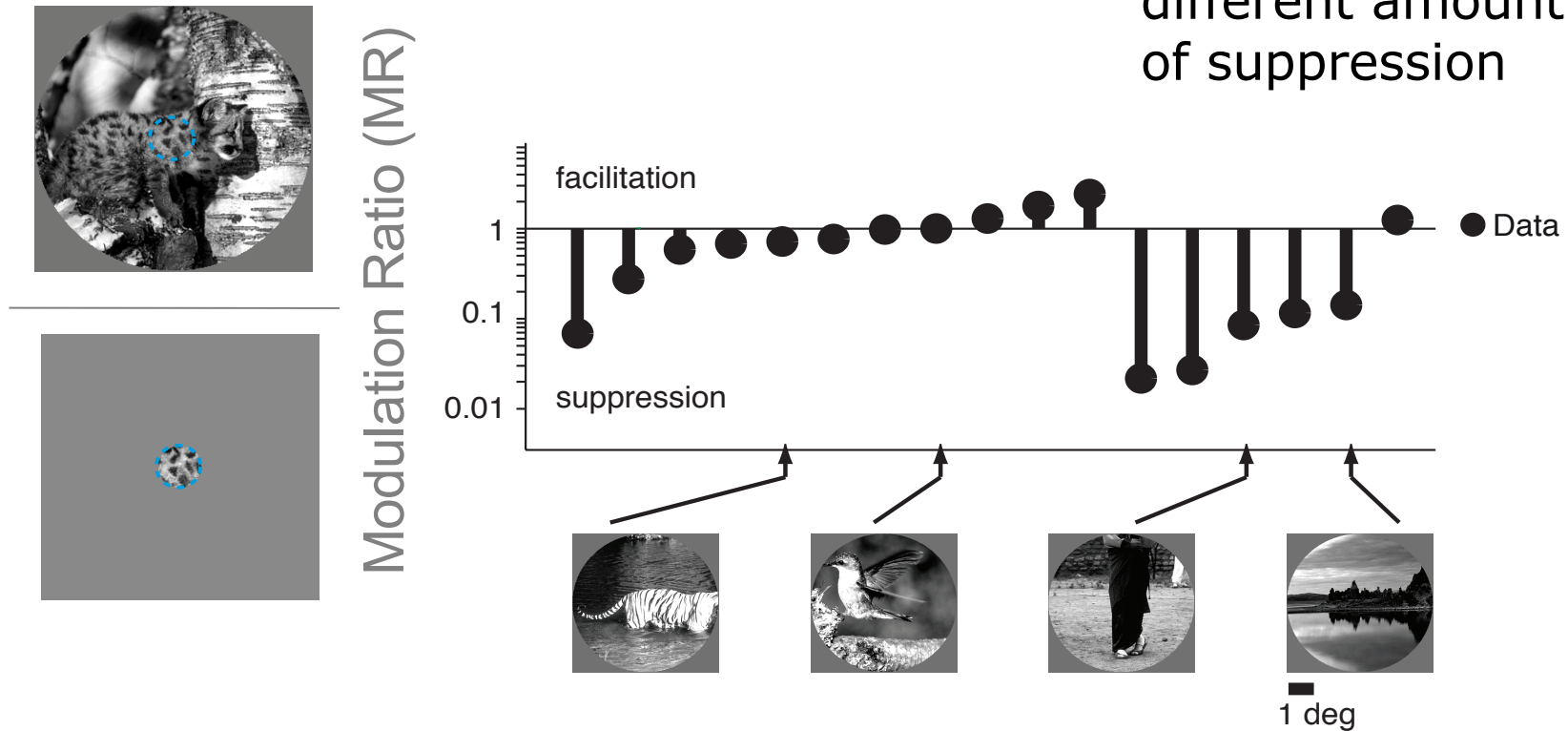
One neuron,  
different images,  
different amount  
of suppression  
by large stimuli

Data: Adam Kohn lab  
(Coen-Cagli, Kohn,  
Schwartz, 2015)

# Cortical Neurons

- Spatial context and natural scenes

One neuron,  
different images,  
different amount  
of suppression



Data: Adam Kohn lab (Coen-Cagli, Kohn, Schwartz, 2015)

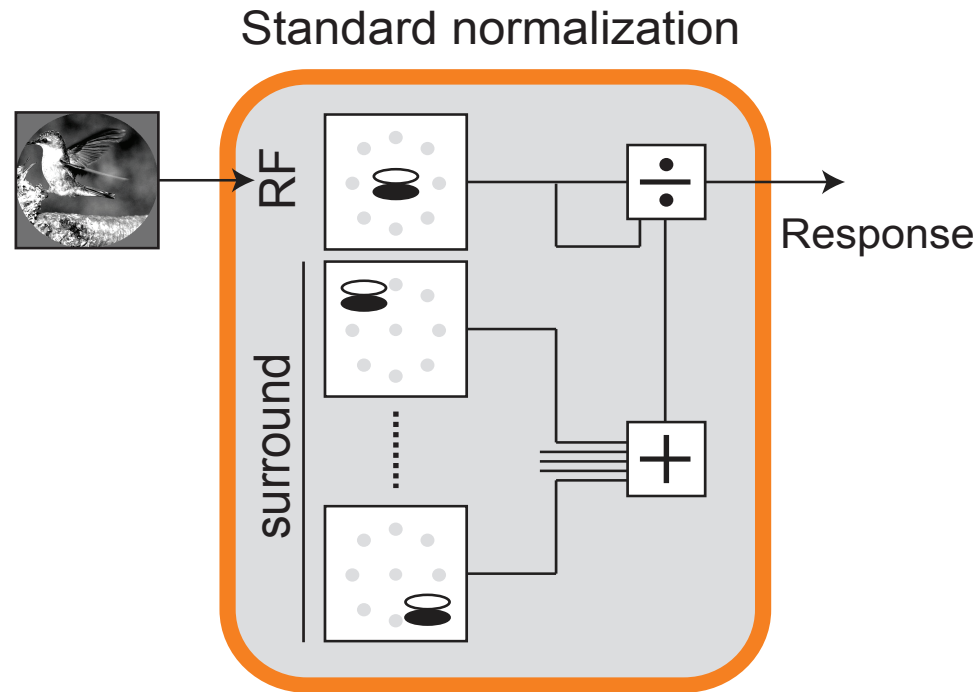
# Cortical Neurons

- Spatial context and natural scenes



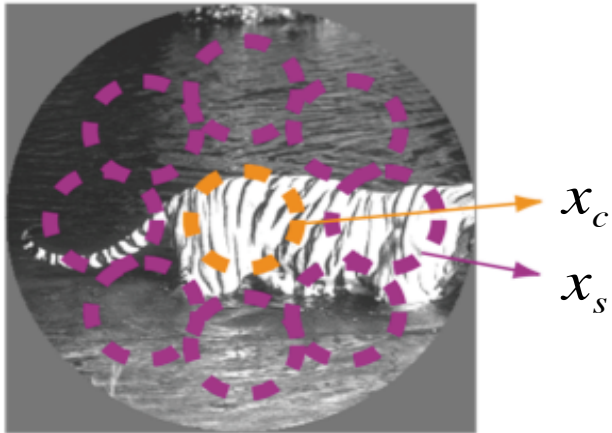
Can we capture data with  
**canonical** divisive normalization?  
(**descriptive model**)

# Divisive normalization



- Descriptive model
- Canonical computation (Carandini, Heeger, Nature Reviews Neuro, 2012)
- Has been applied to visual cortex, as well as other systems and modalities, multimodal processing, value encoding, etc
- Here center responses divided by surround responses

# Cortical Neurons

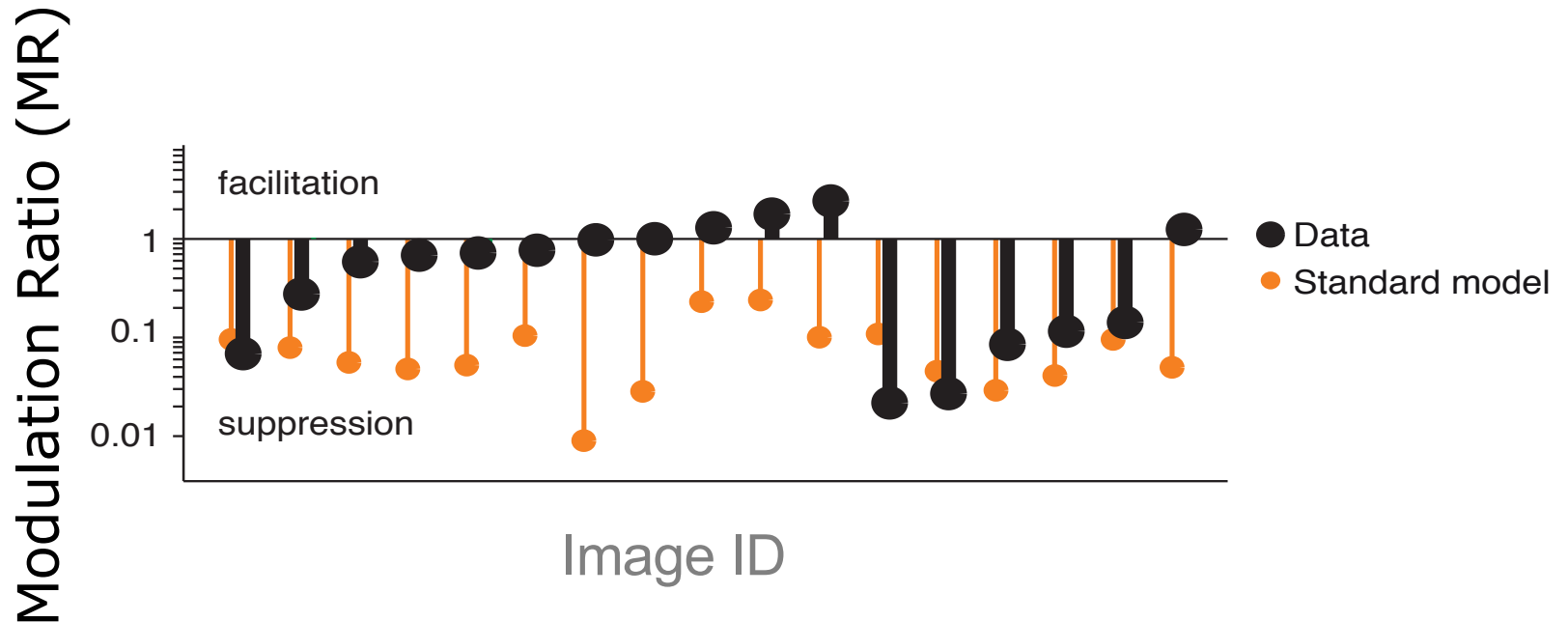


Canonical divisive normalization:

$$R_c \propto \frac{x_c}{\sqrt{x_c^2 + x_s^2}}$$

V1 Data: Adam Kohn lab

# Cortical responses to natural images

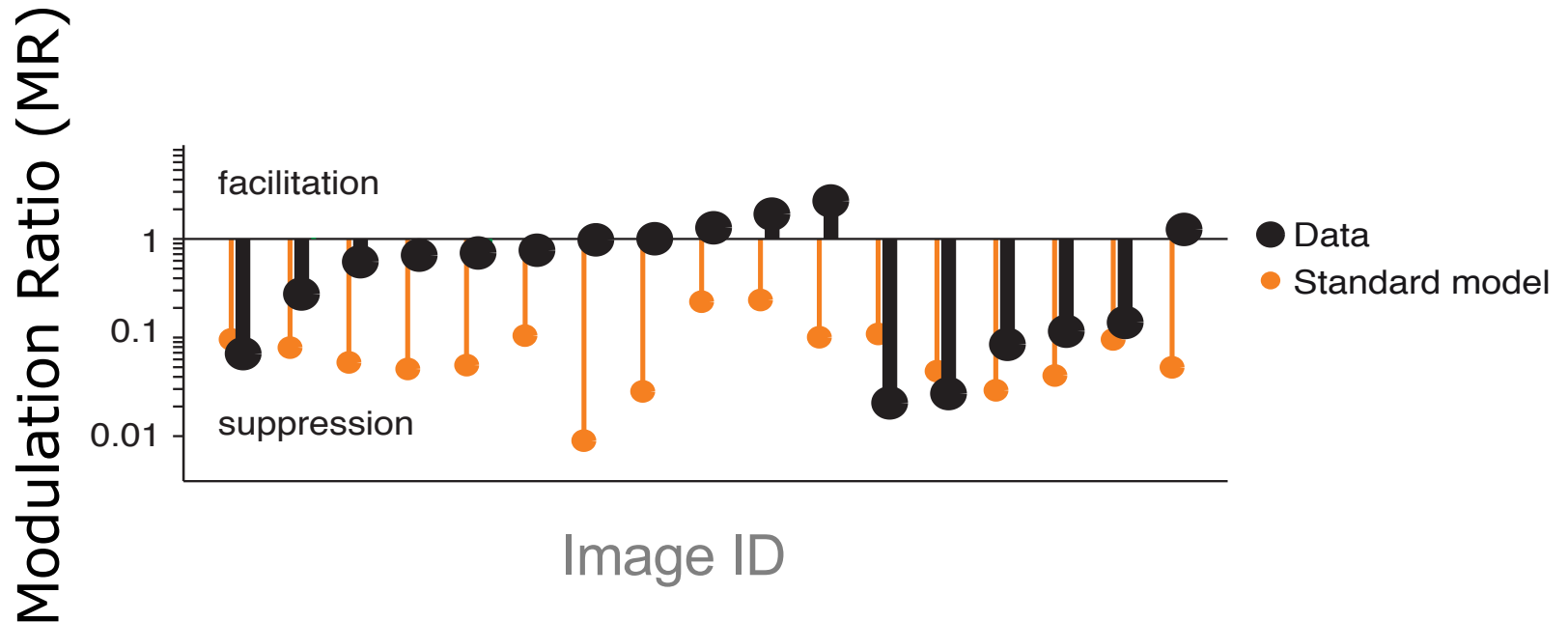


- We fit the standard normalization model to neural data
- Often predicts suppression when there is none in the data
- Poor prediction quality

Data: Adam Kohn lab

Coen-Cagli, Kohn, Schwartz, Nature Neuroscience 2015

# Cortical responses to natural images



- Can we explain as strategy to encode natural images optimally based on expected spatial contextual regularities?

Data: Adam Kohn lab

Coen-Cagli, Kohn, Schwartz, Nature Neuroscience 2015

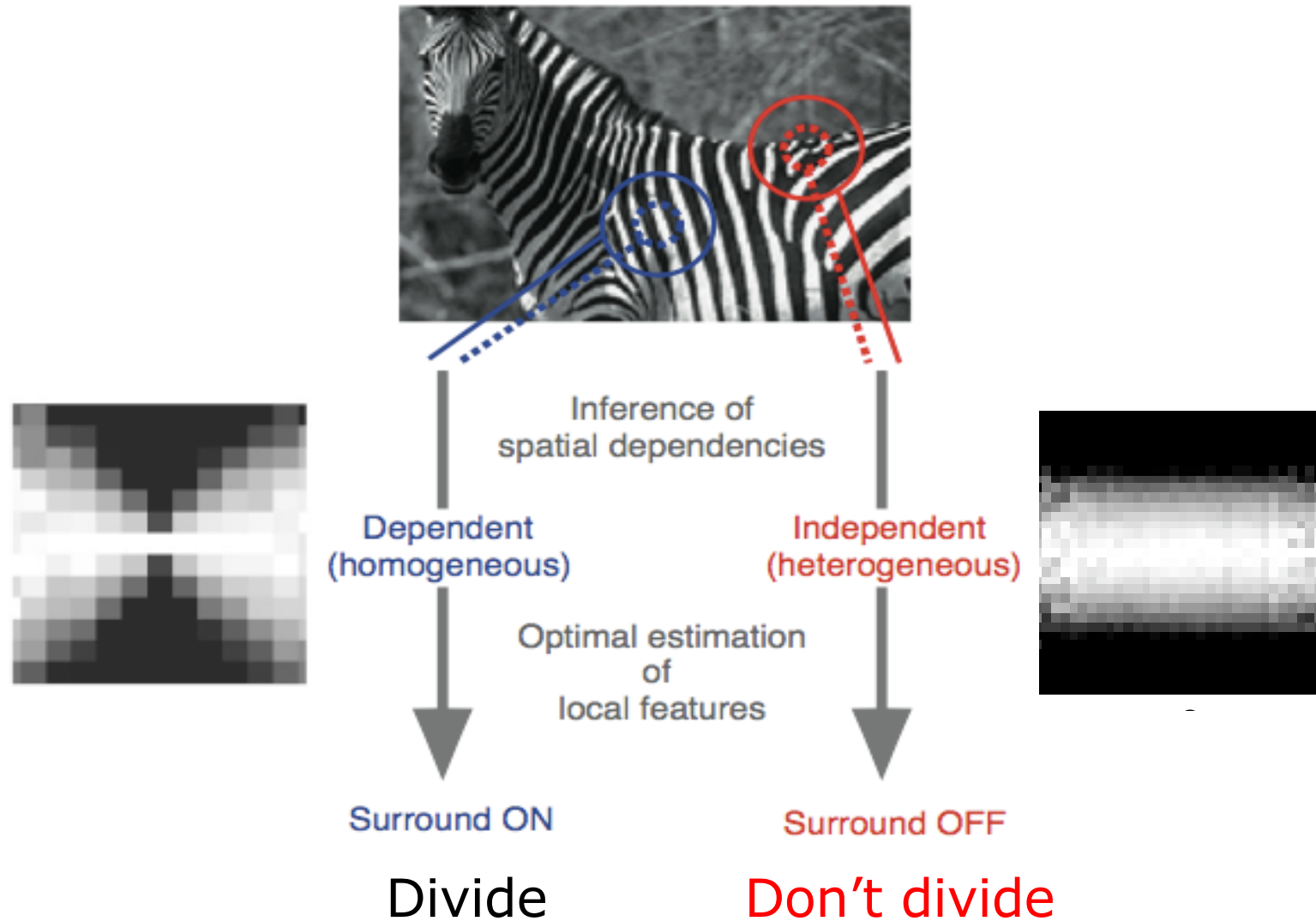


## Divisive normalization: richer model



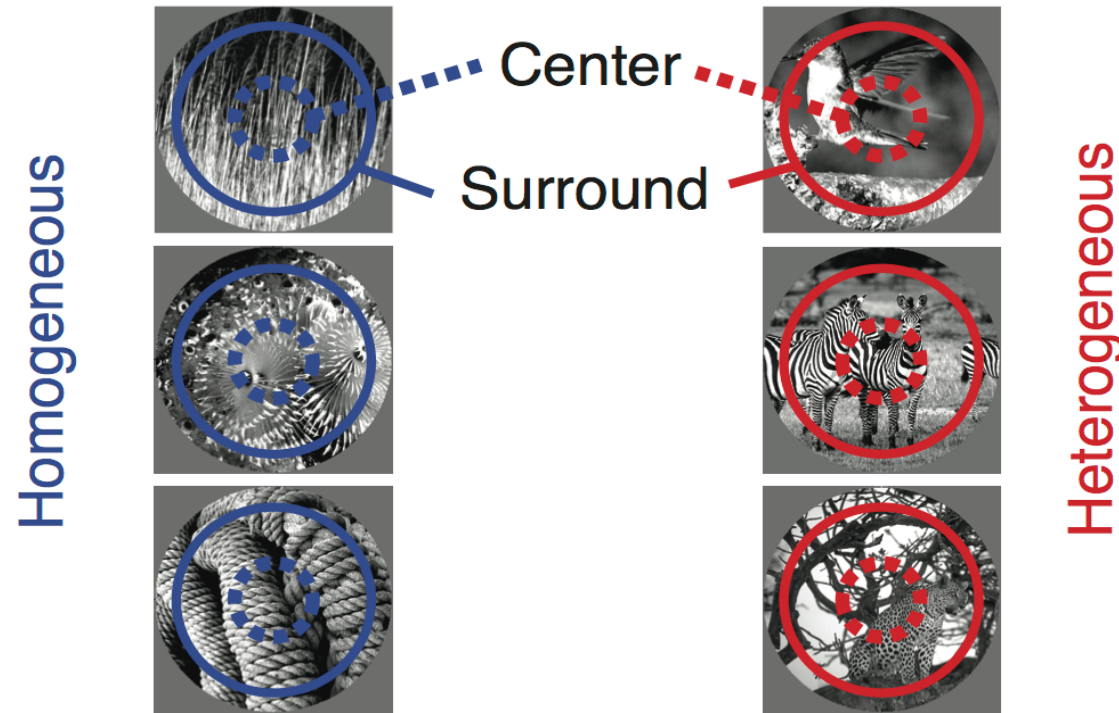
Divisive normalization *descriptive* models have been applied in many neural systems. We sought to develop a **richer model** based on image statistics

# Flexible Divisive Normalization



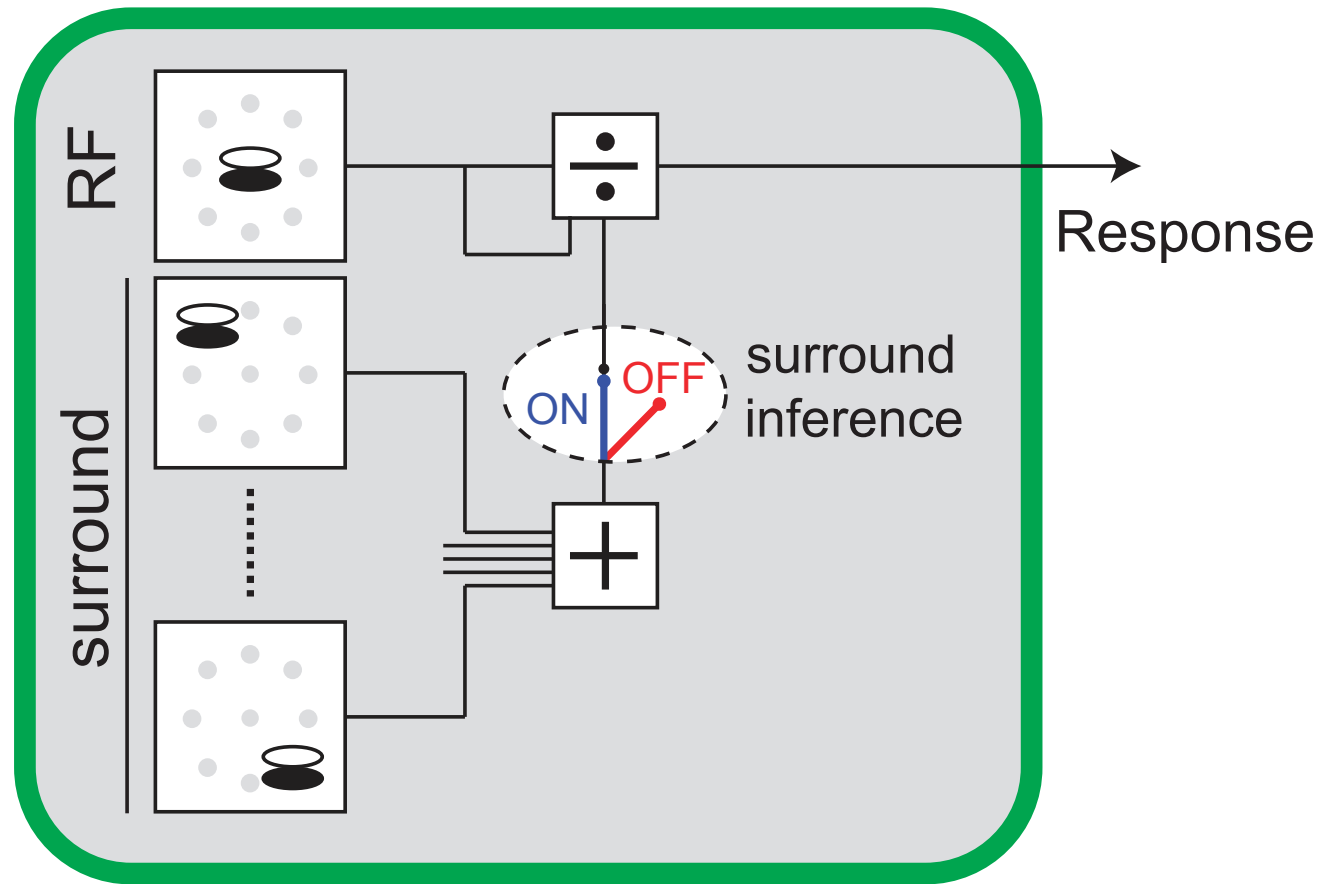
Model and experimental tests: Cagli, Kohn, Schwartz 2015

# Model predictions for natural images



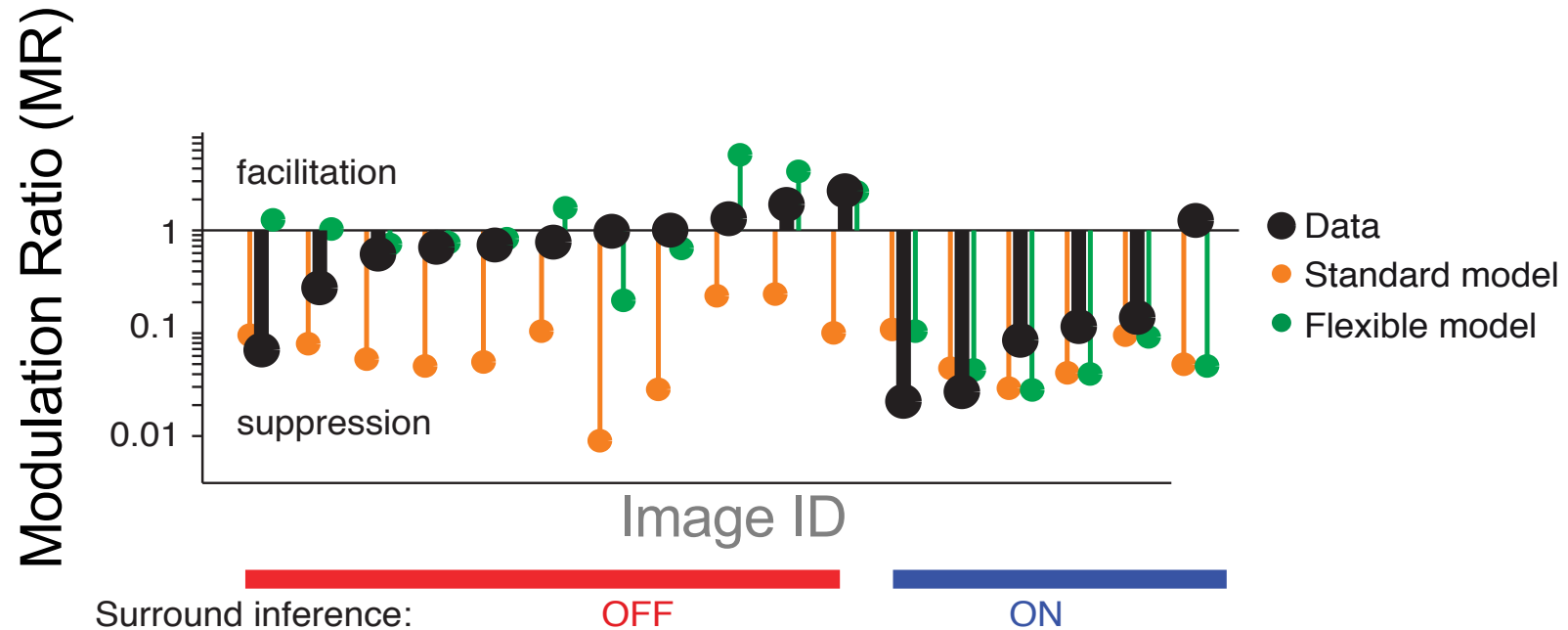
- **Homogeneous** and **heterogeneous** determined by model!
- Expect more suppression in neurons for homogeneous
- Related to salience (eg, Zhaoping Li)

# Model summary



Inference determined by model

# Natural scenes data



- Taking account of image statistics across space, we obtain better fit to neural data with the model

Coen-Cagli, Kohn, Schwartz, Nature Neuroscience, 2015

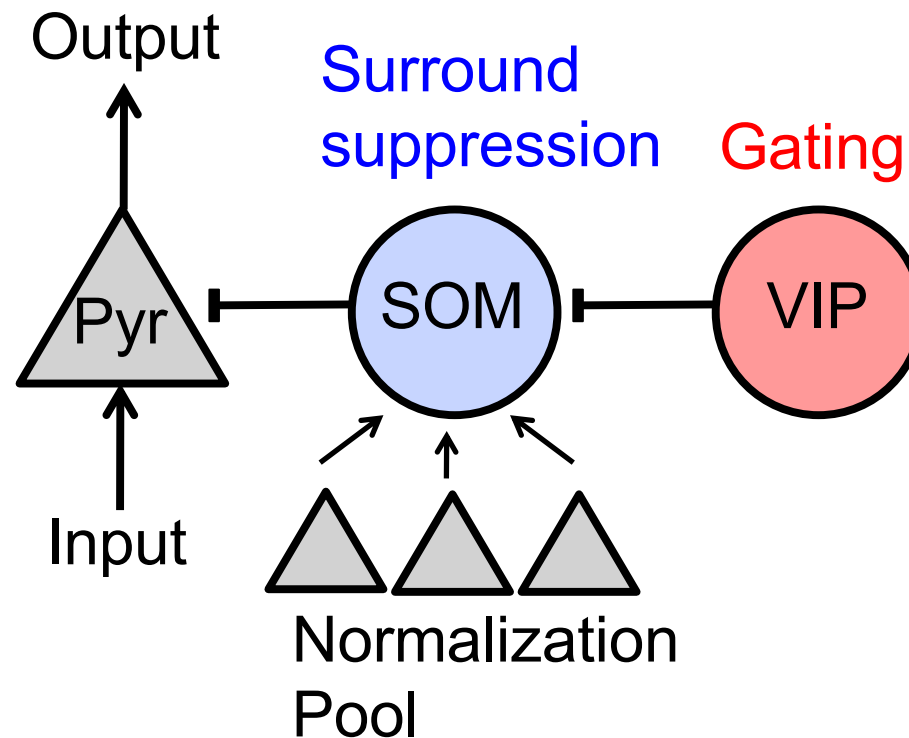
# Model Mechanisms

Divisive normalization:

- Feedback inhibition
- Distal dendrite inhibition
- Depressing synapses
- Internal biochemical adjustments
- Non-Poisson spike generation

# Flexible Normalization Mechanism?

- Adjusting gain by circuit mechanisms?
- Distinct classes of inhibitory interneurons? (eg, Adesnik, Scanziani et al. 2012; Pfeffer, Scanziani et al. 2013; Pi, Kepecs et al. 2013; Lee, Rudy et al. 2013)



# Key take-home points

- New approach to understanding cortical processing of natural images. Rather than fitting more complicated models, use insights from scene statistics
- Connects to neural computations that are ubiquitous, but enriches the “standard” model
- Our results suggest flexibility of contextual influences in natural vision, depending on whether center and surround are deemed statistically homogeneous



# Deep learning: normalization

Normalization has been shown to sometimes improve object recognition in deep neural networks

- Local normalization in Alexnet, 2012
- Other recent normalizations include: batch normalization in Ioffe and Szegedy, 2015; layer normalization in Ba et al., 2016
- More restricted than some of the normalizations used in cortical modeling
- But face some similar questions: How to choose what neural activations to normalize by