# Natural scenes, spatial context, salience and eye movements

Computational neuroscience class
Odelia Schwartz, 2019

# 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:
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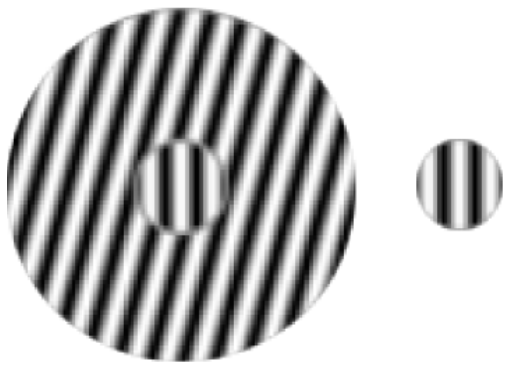
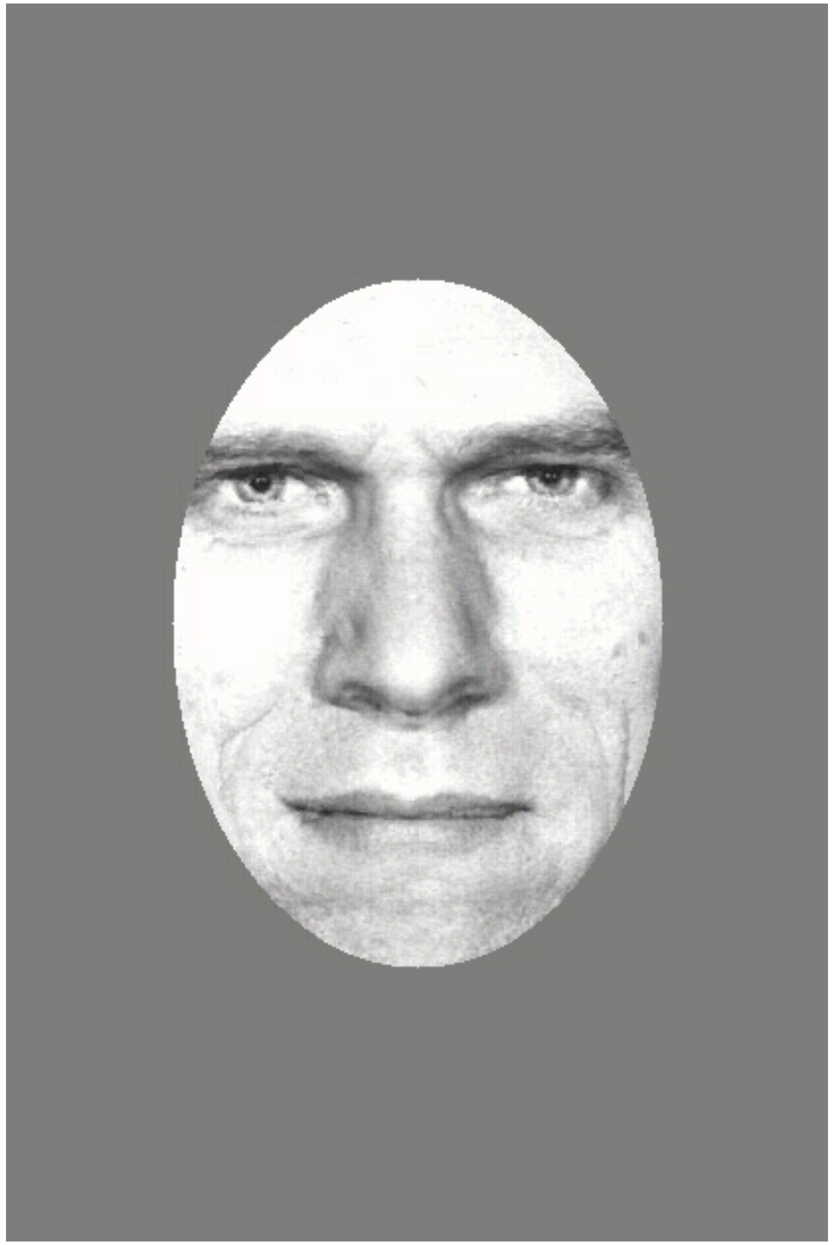
# Contextual influences

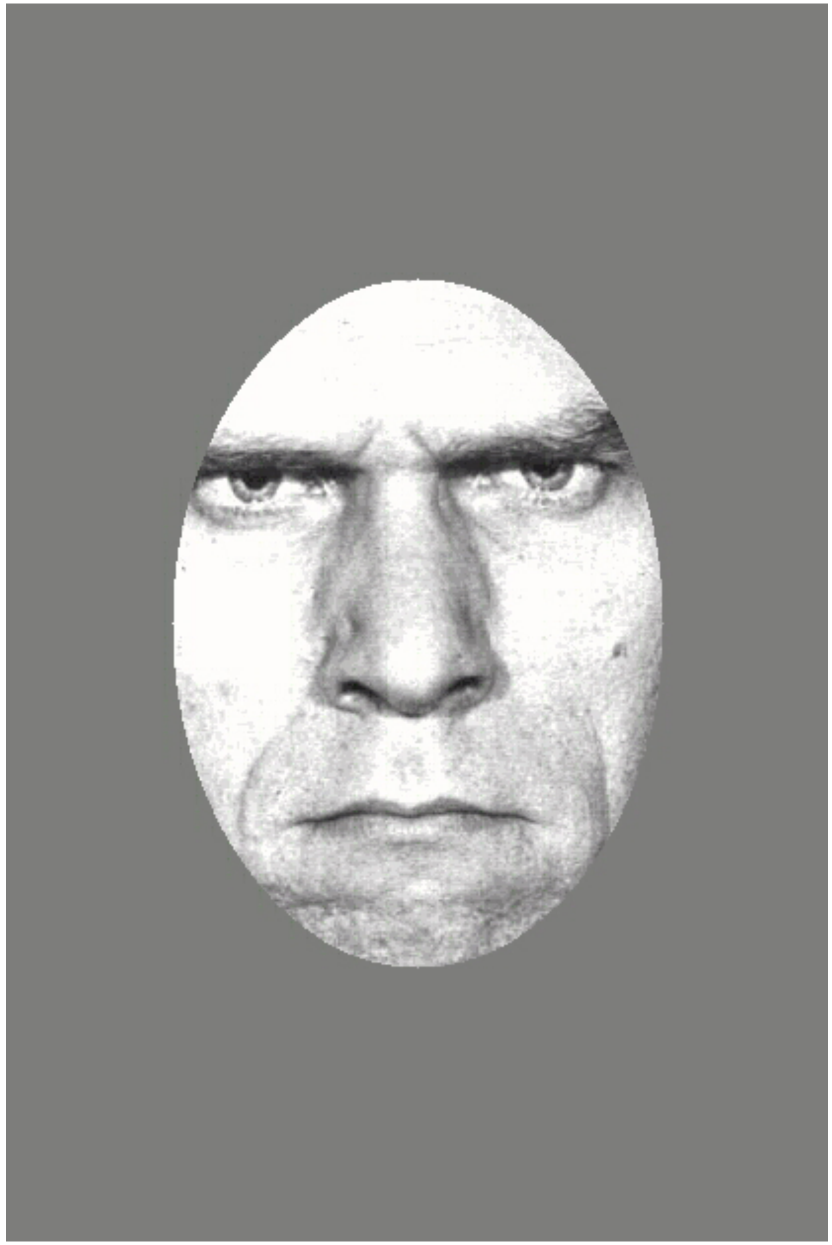
- Perceptual illusions



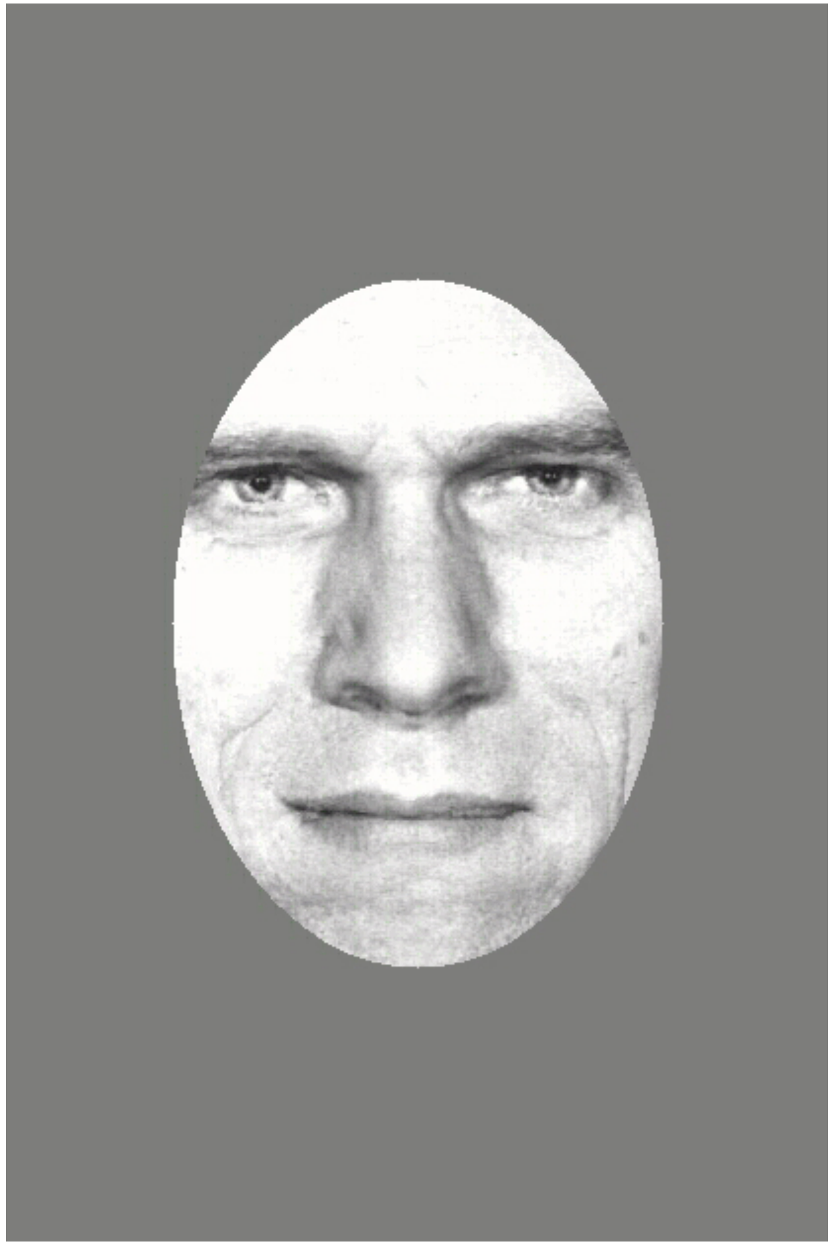
Contextual effects in time...



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



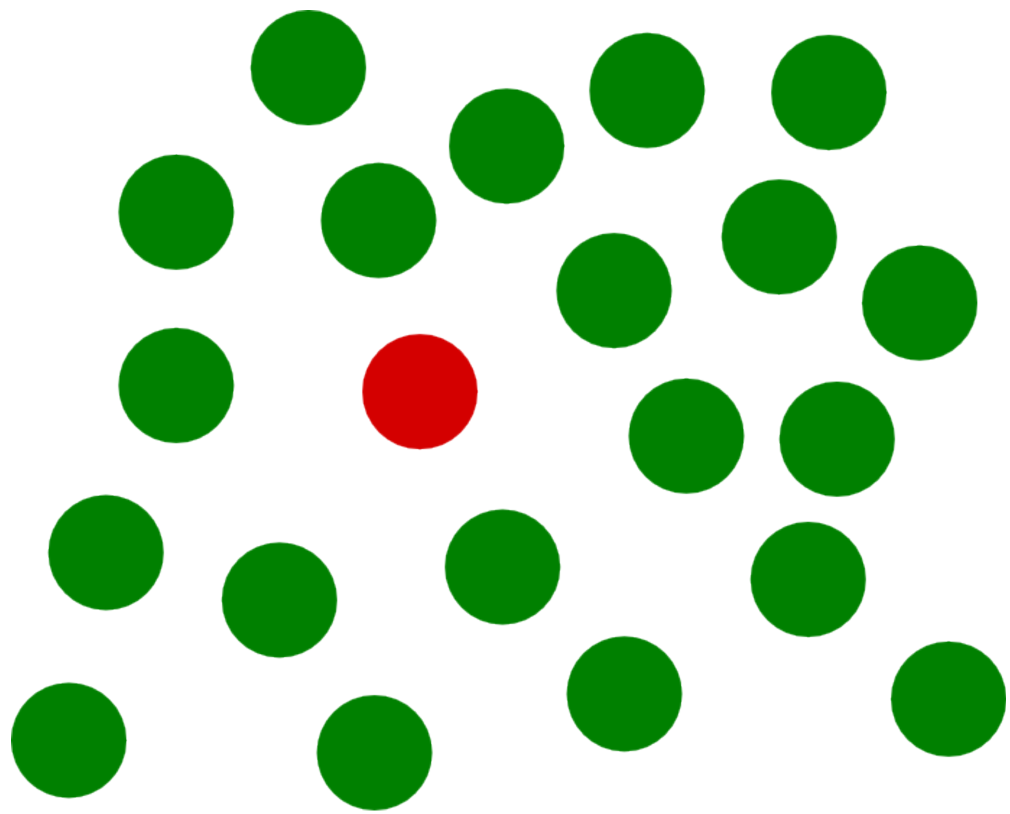
adapt



post-adapt

# Contextual influences

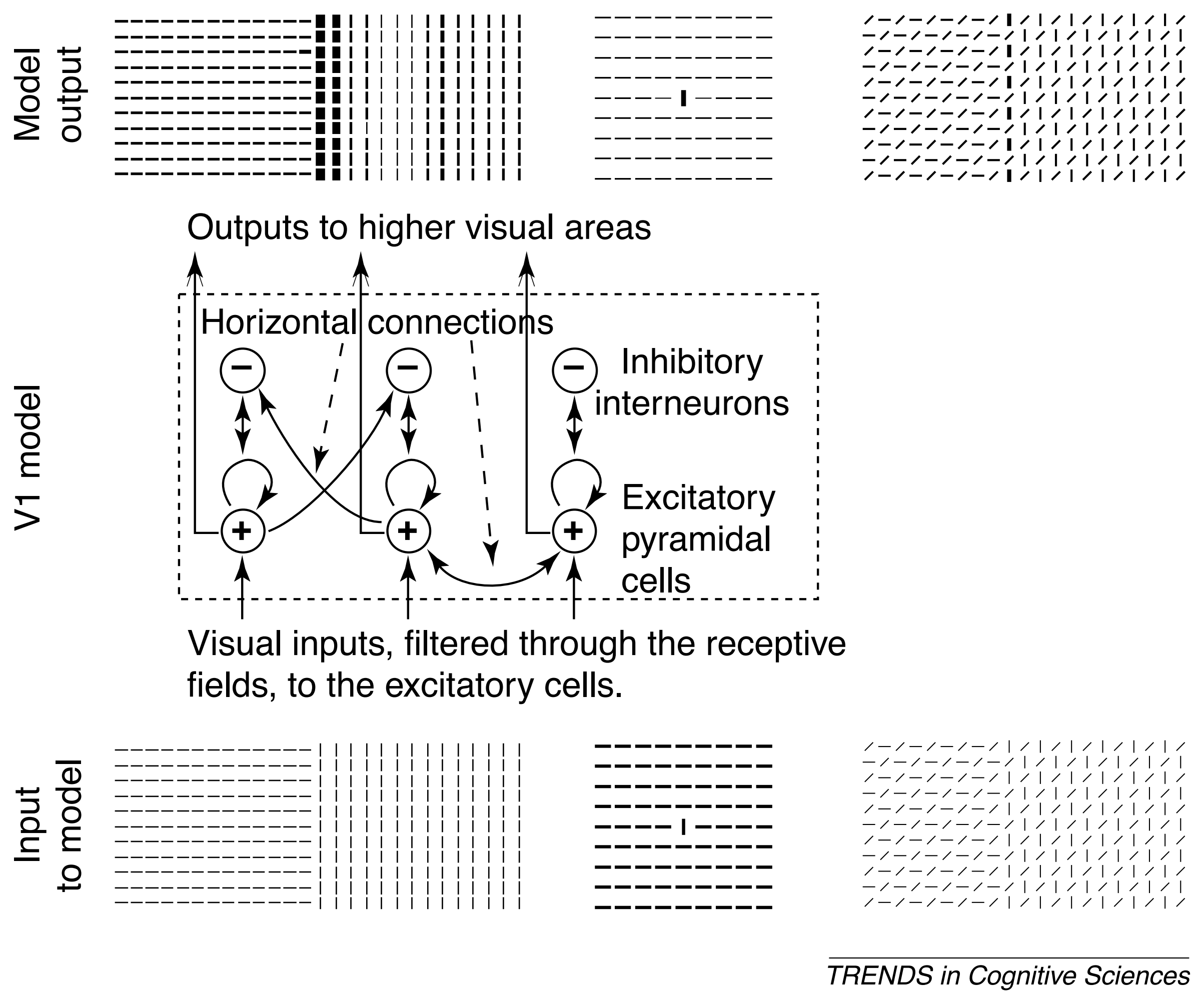
- Visual salience



# Contextual influences

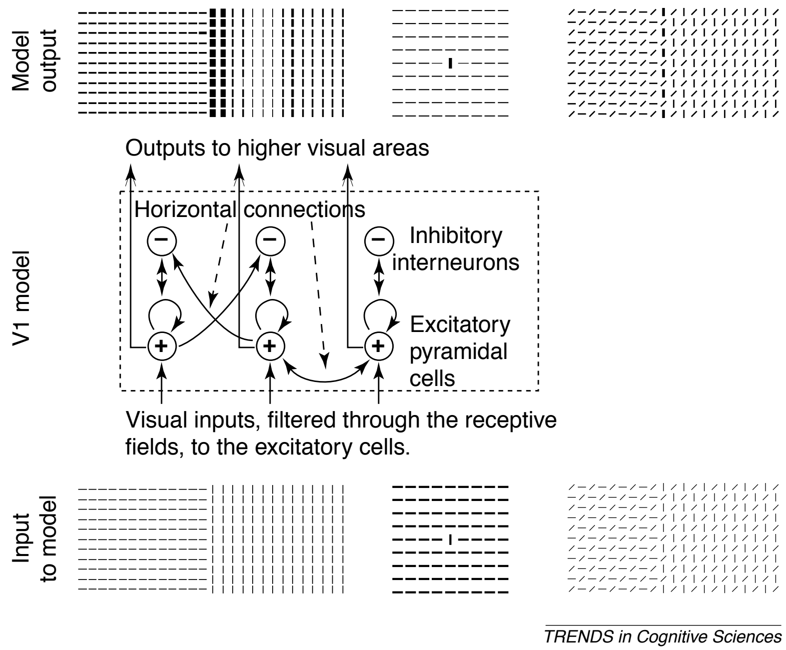
- Visual salience

# Salience model of V1 (Zhaoping)




Li Zhaoping, Trends in Cognitive Sciences, 2002.

# Salience model of V1 (Zhaoping)



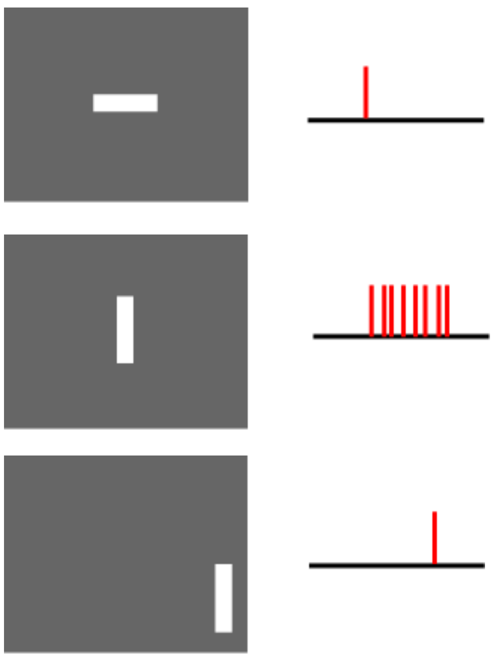

- Dynamical model
- V1 salience map
- Salience as breakdown of statistical homogeneity

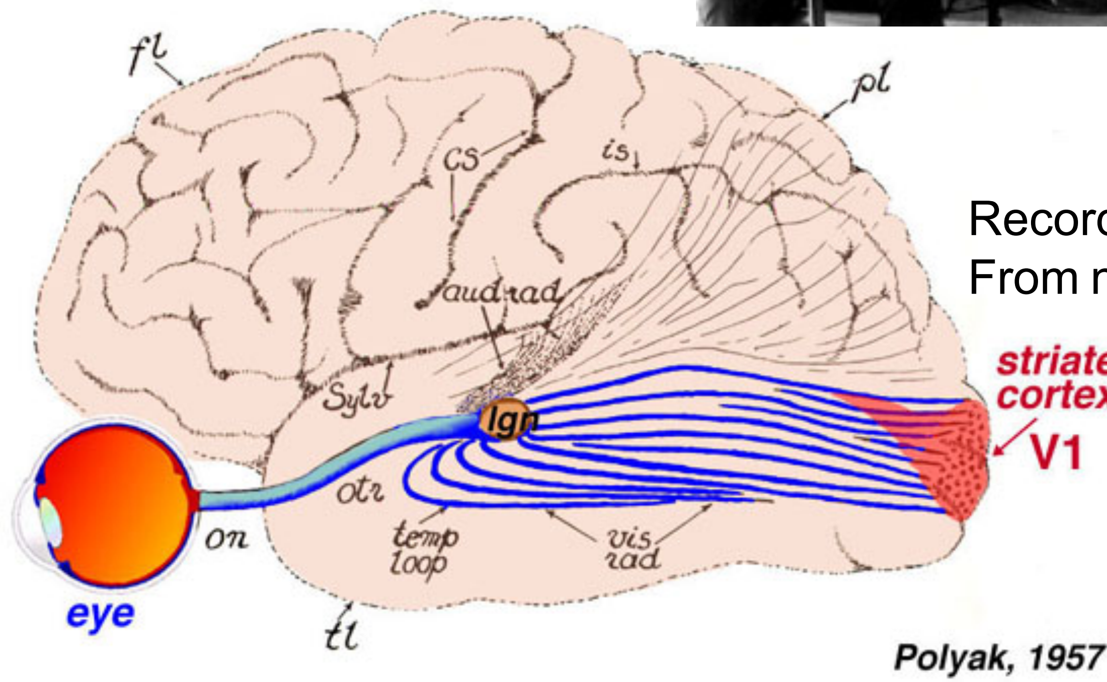
Li Zhaoping, Trends in Cognitive Sciences, 2002.

# Surround (non classical receptive field) effects in visual physiology

# What about neurons?

- Cortical neural processing

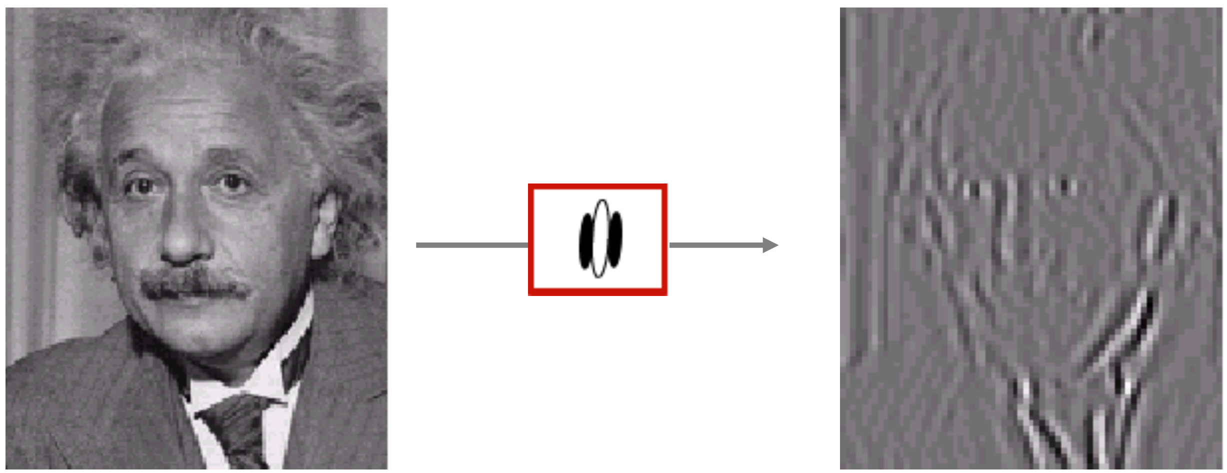




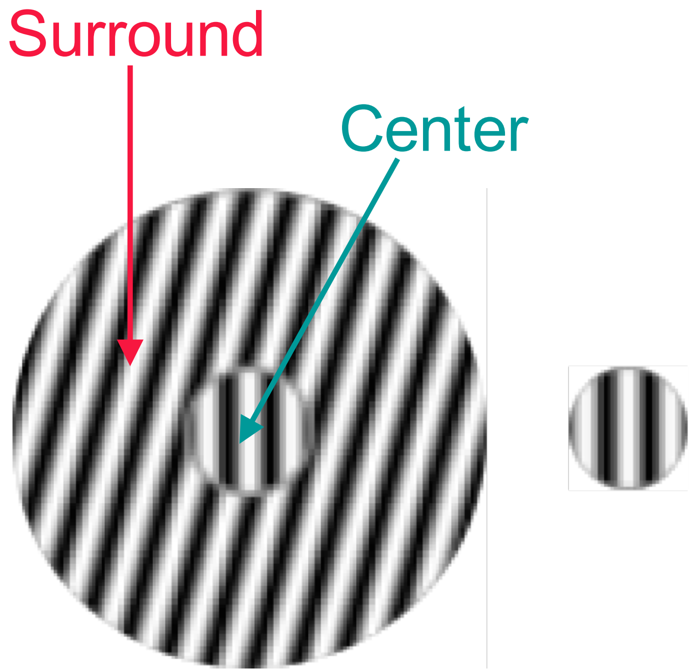

Record
From neuron

# What about neurons?

- Computer science / Engineering: visual receptive field or filter



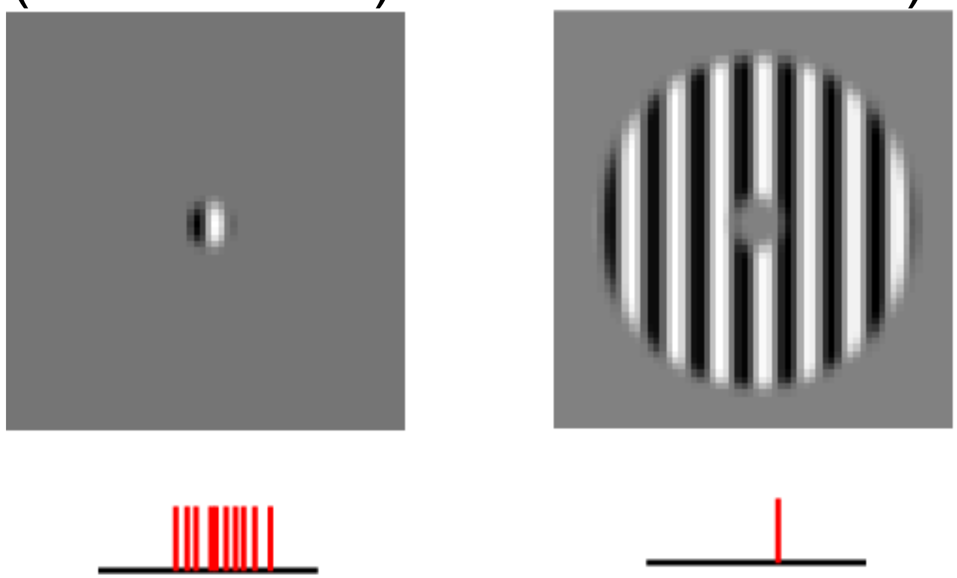
# Focus: spatial surround context



# Visual cortex: non classical RF

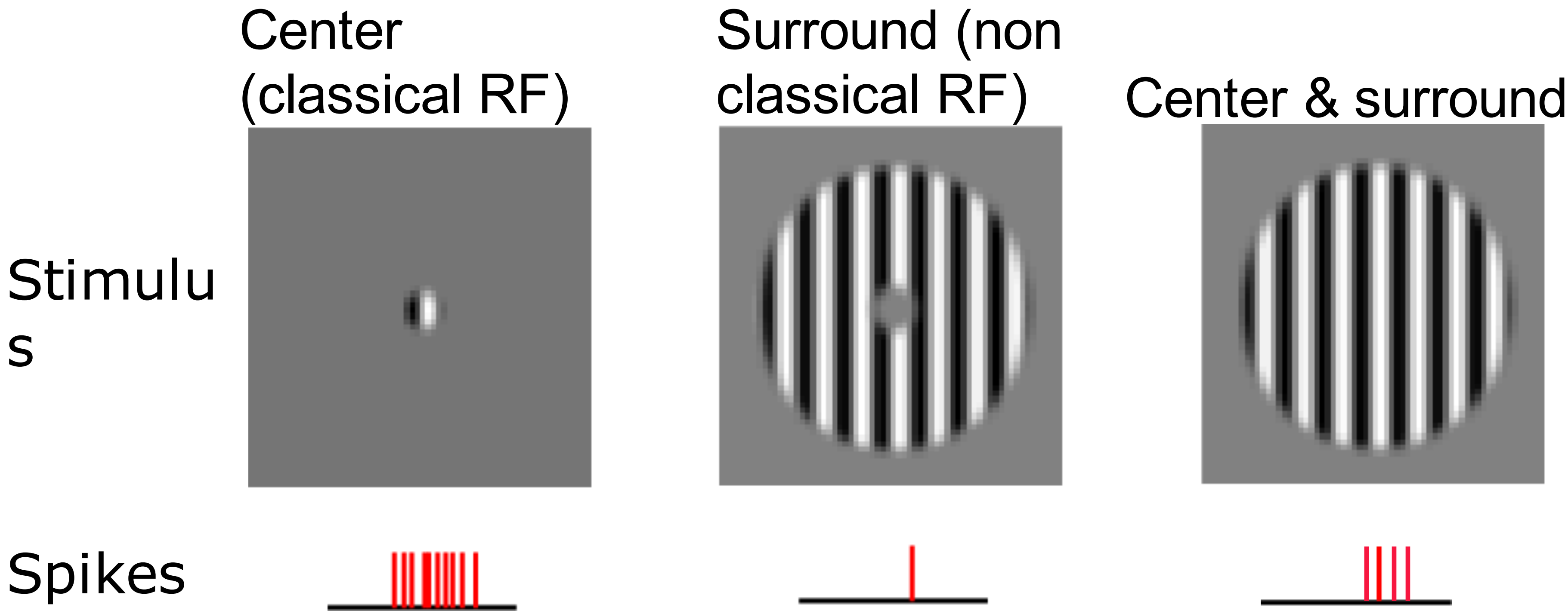
Center (classical RF)

Surround (non classical RF)



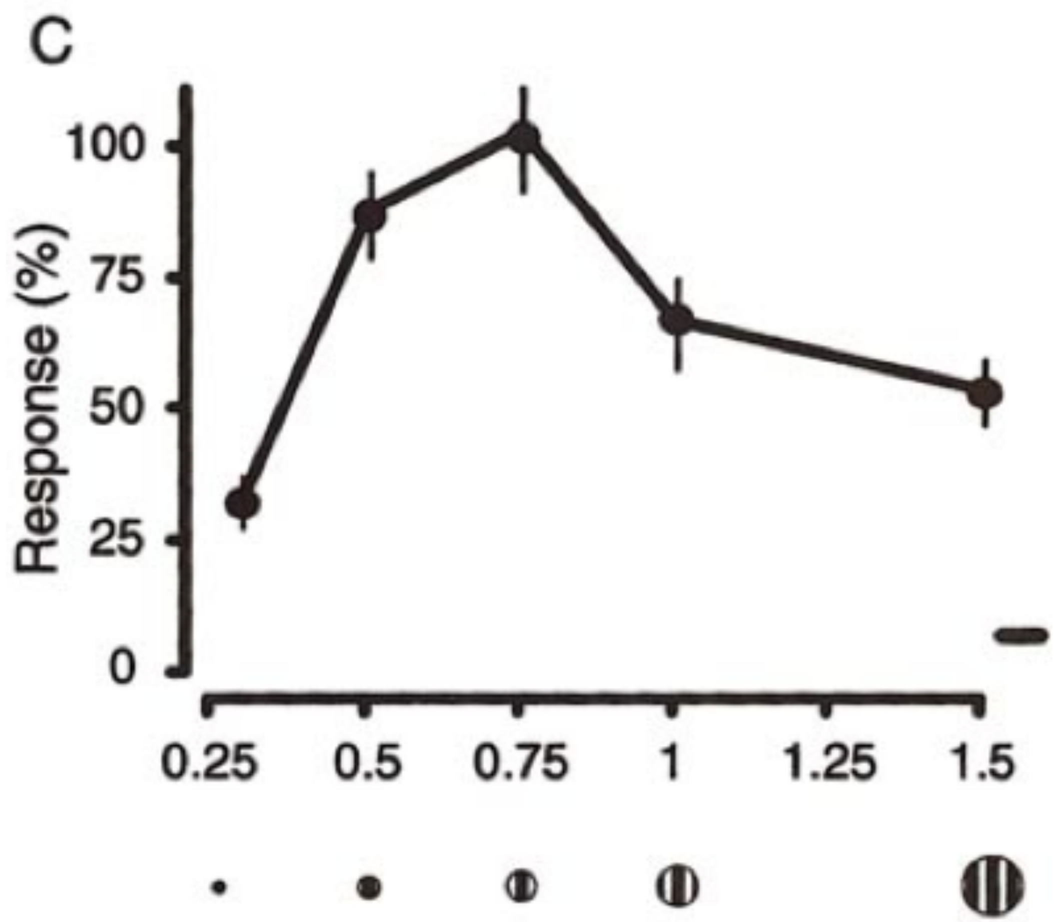
Surround stimulus is defined such that by itself elicits no response

# Visual cortex: spatial surround



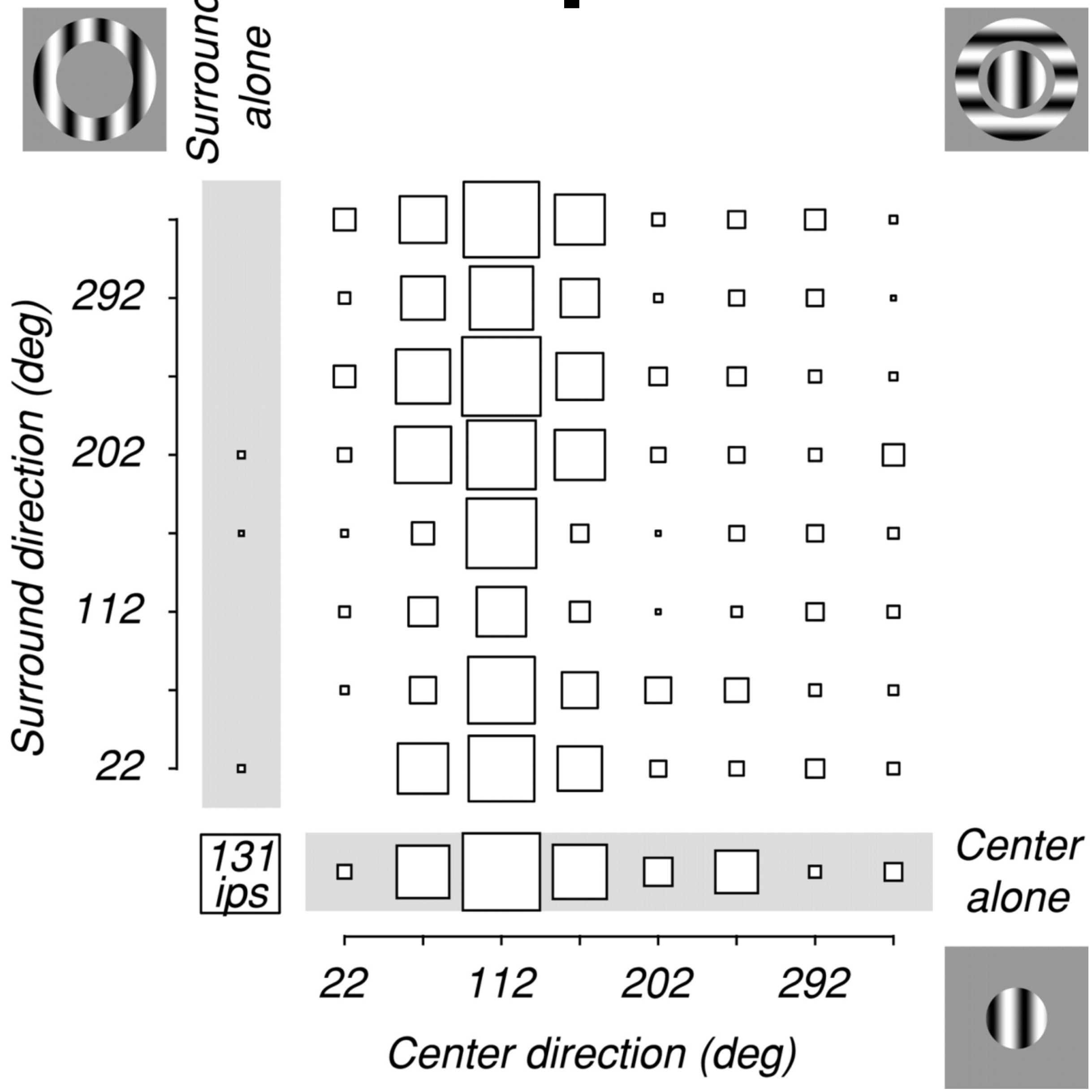

But surround stimulus can modulate response to center. Cortical neurons are affected by spatial context.

# Visual cortex: spatial surround



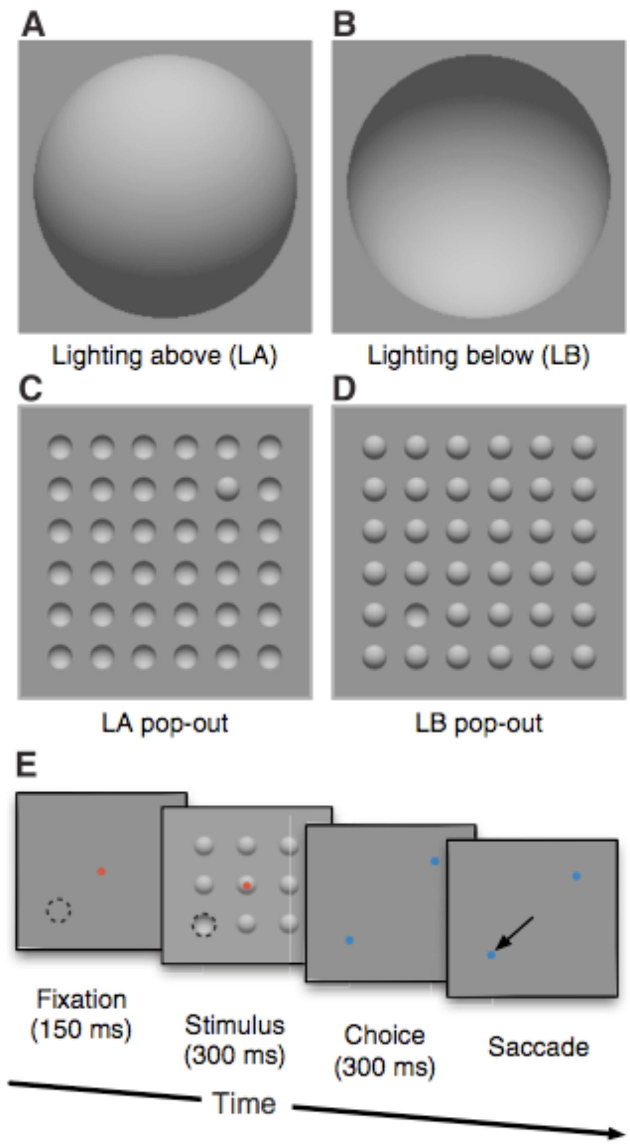

Jones and Silito, 2001

# Visual cortex: spatial surround



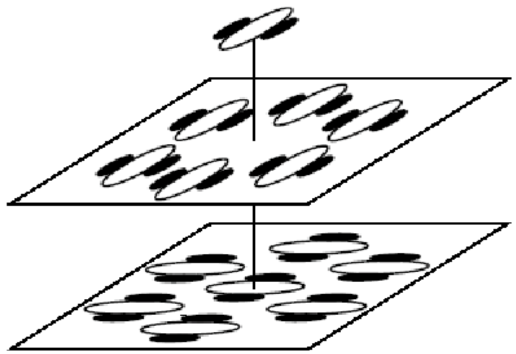

Cavanaugh et al. 2002

# Context by other visual cues?




Smith et al. 2007

# Simple descriptive model of cortical surround nonlinearity



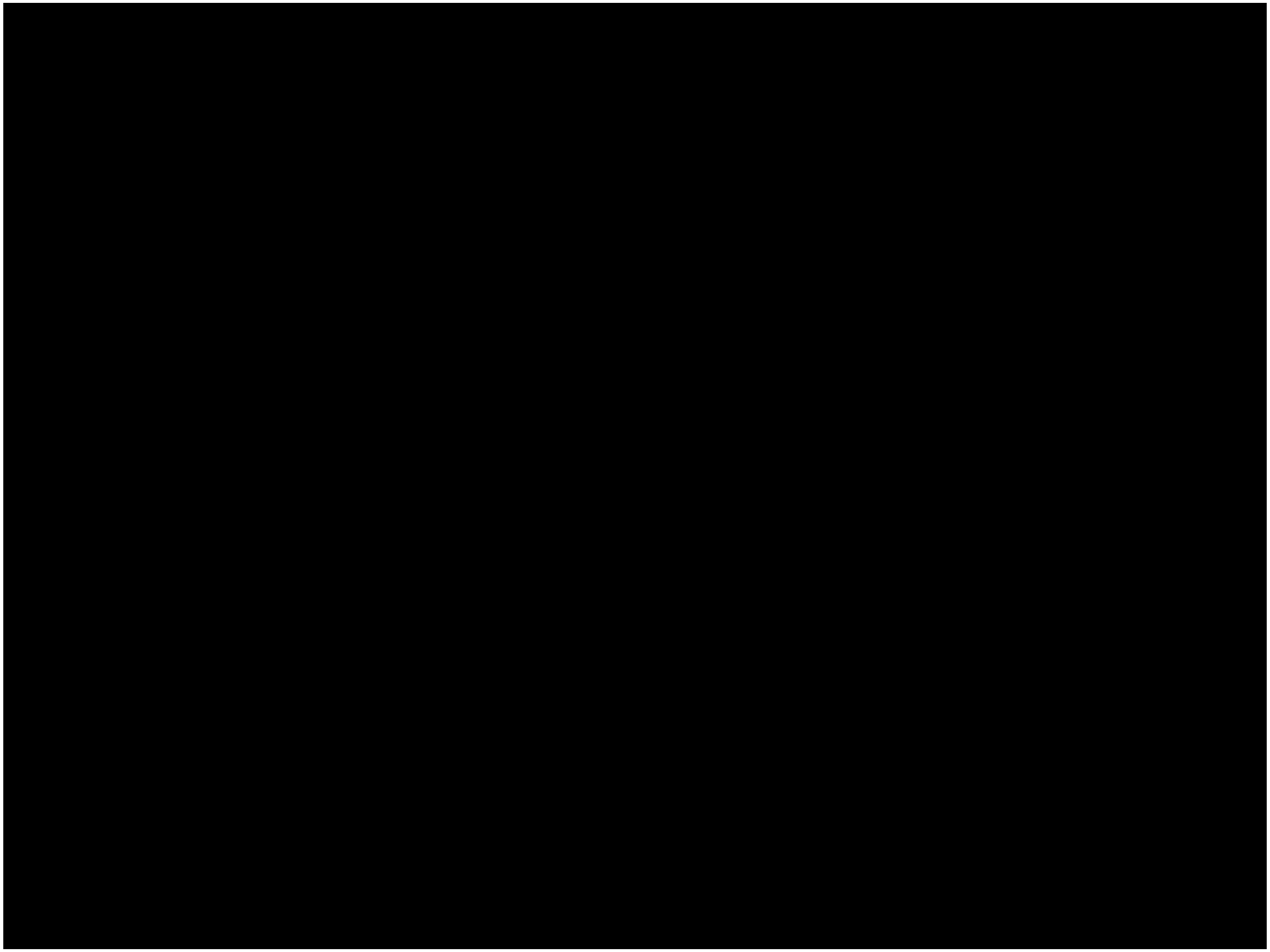
$$R_i = \frac{L_i^2}{\sum_j w_{ji} L_j^2 + \sigma^2}$$

- Linear filters followed by nonlinearity

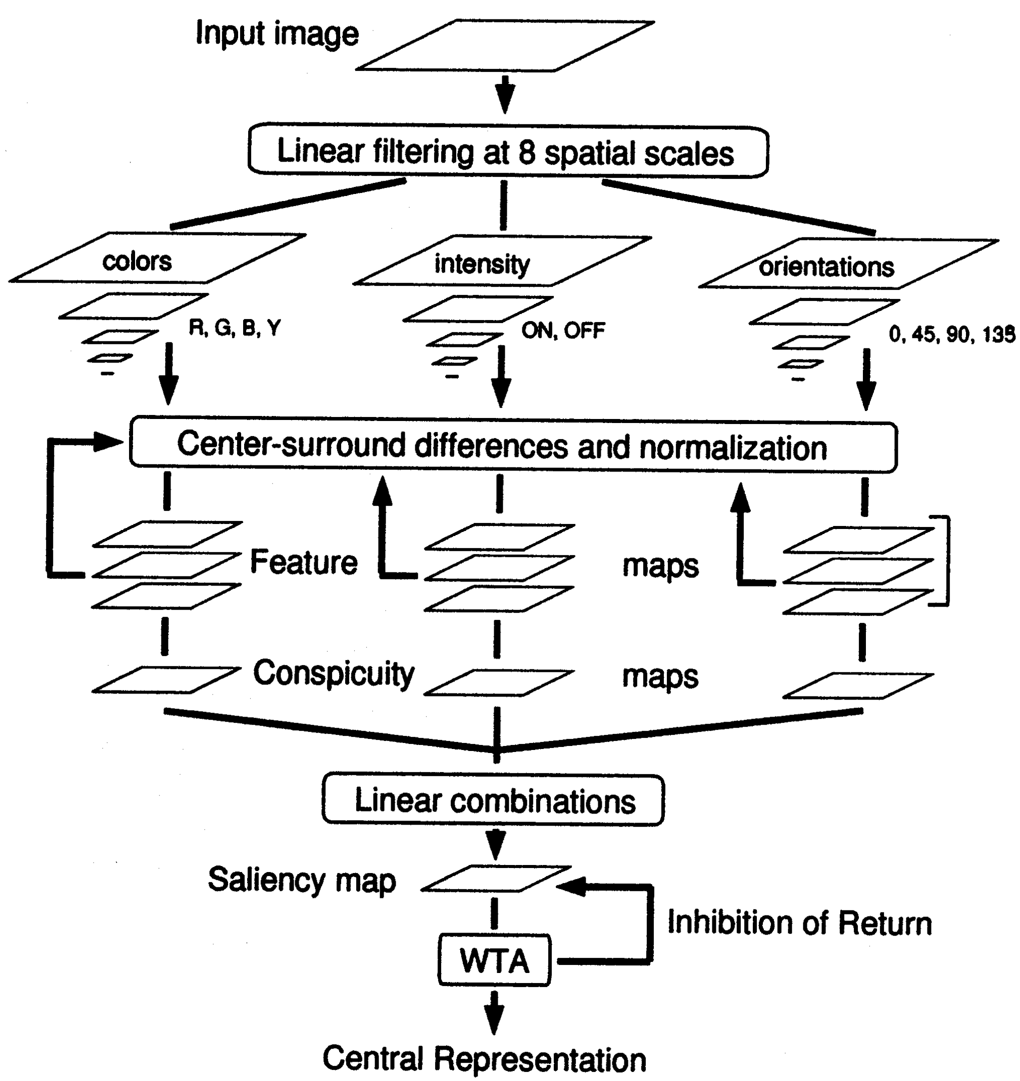
After Heeger 1992

# Eye movements and salience

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

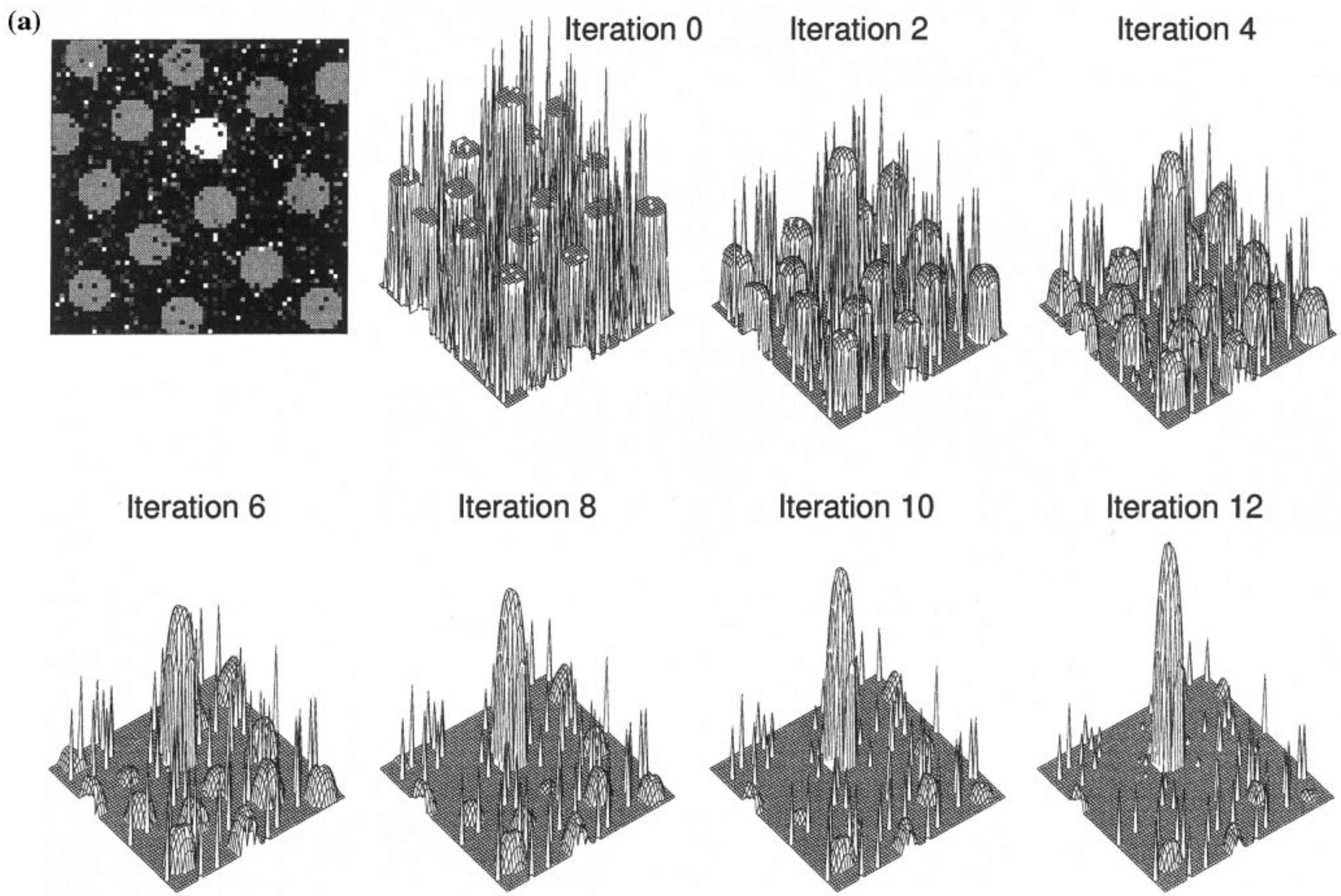


# Eye movements and salience (Itti and Koch, 2000)

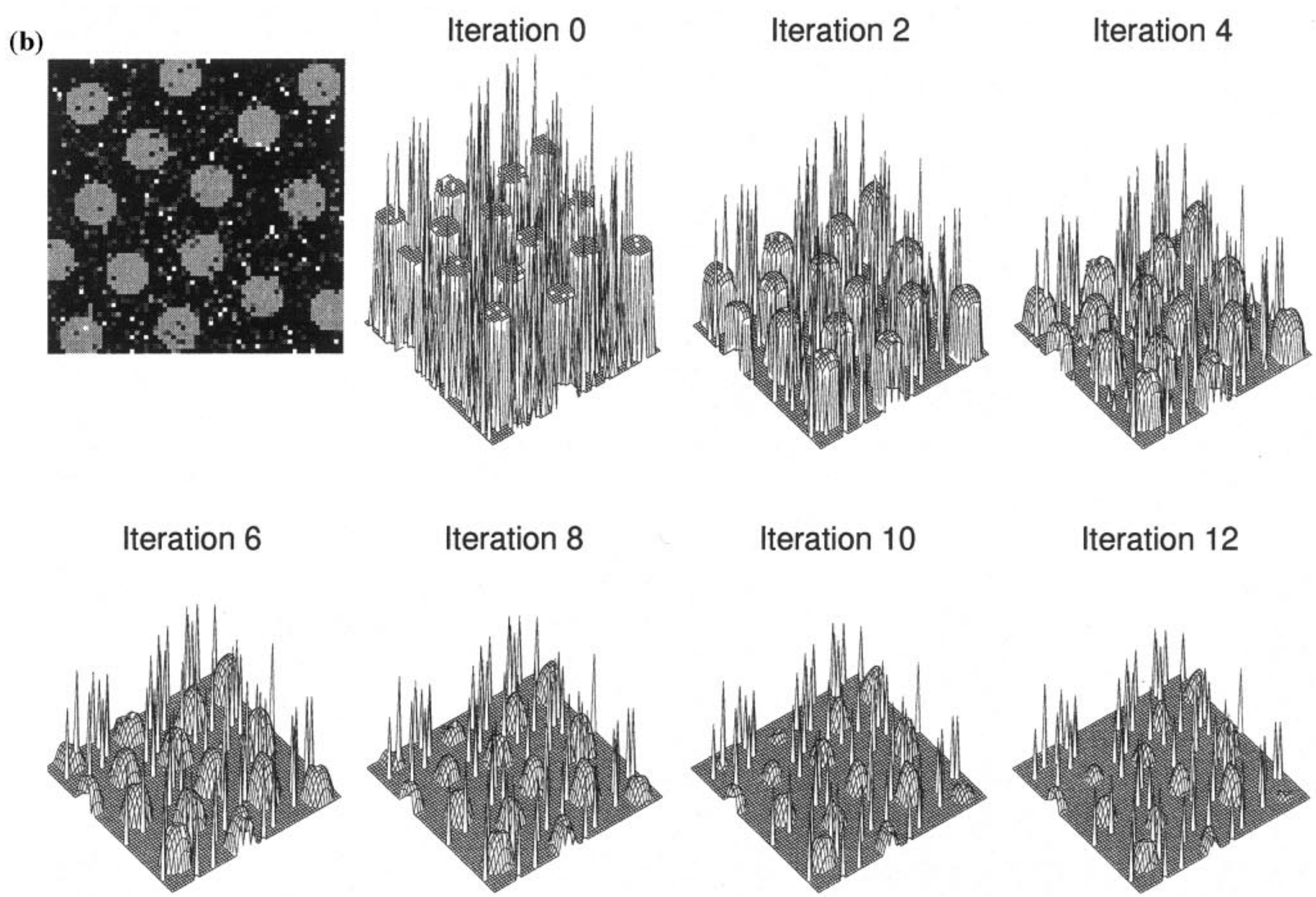


(b)

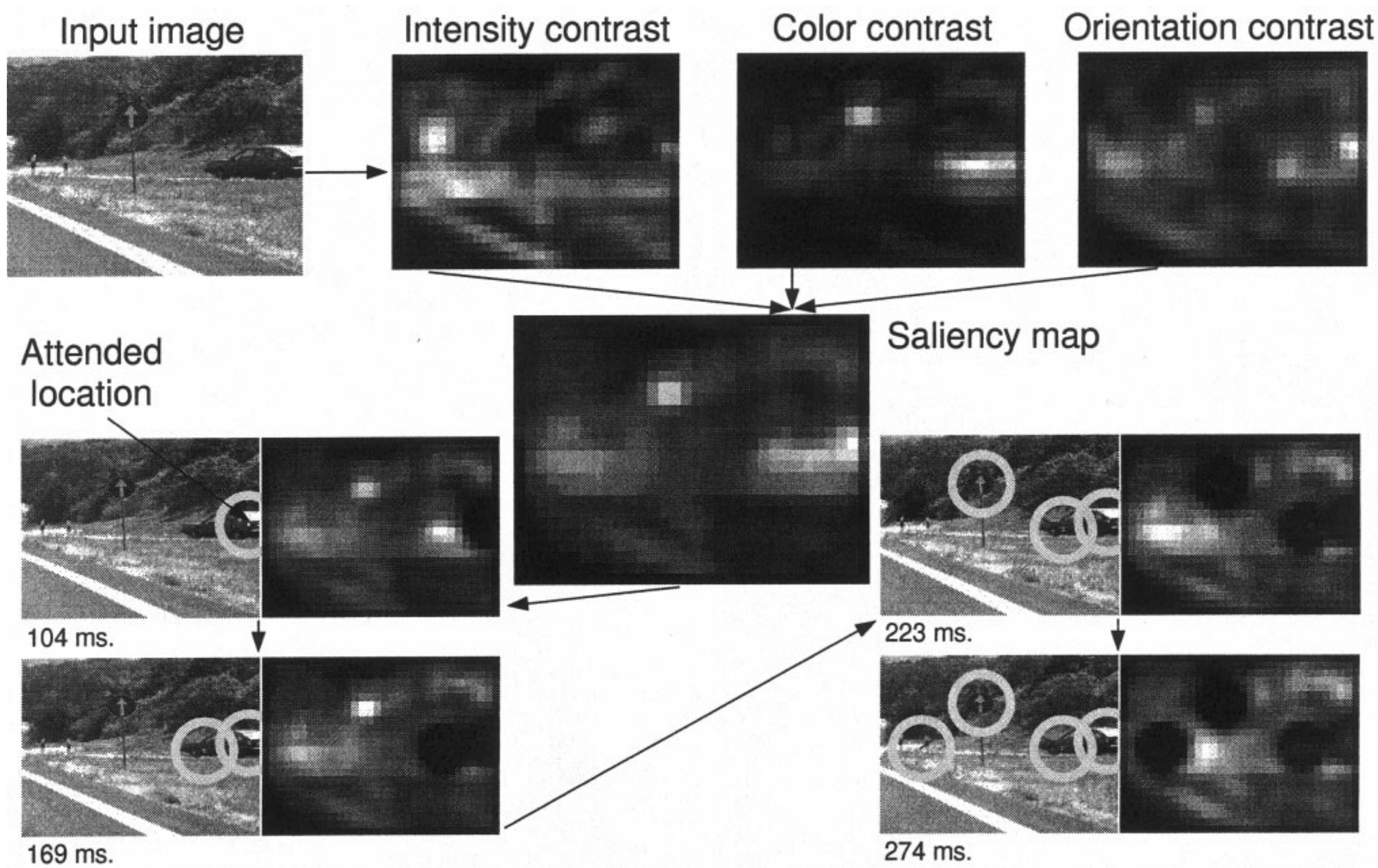
Eye movements and salience (Itti and Koch, 2000)



Eye movements and salience (Itti and Koch, 2000)



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



# Eye movements: not only salience (Yarbus 1967)

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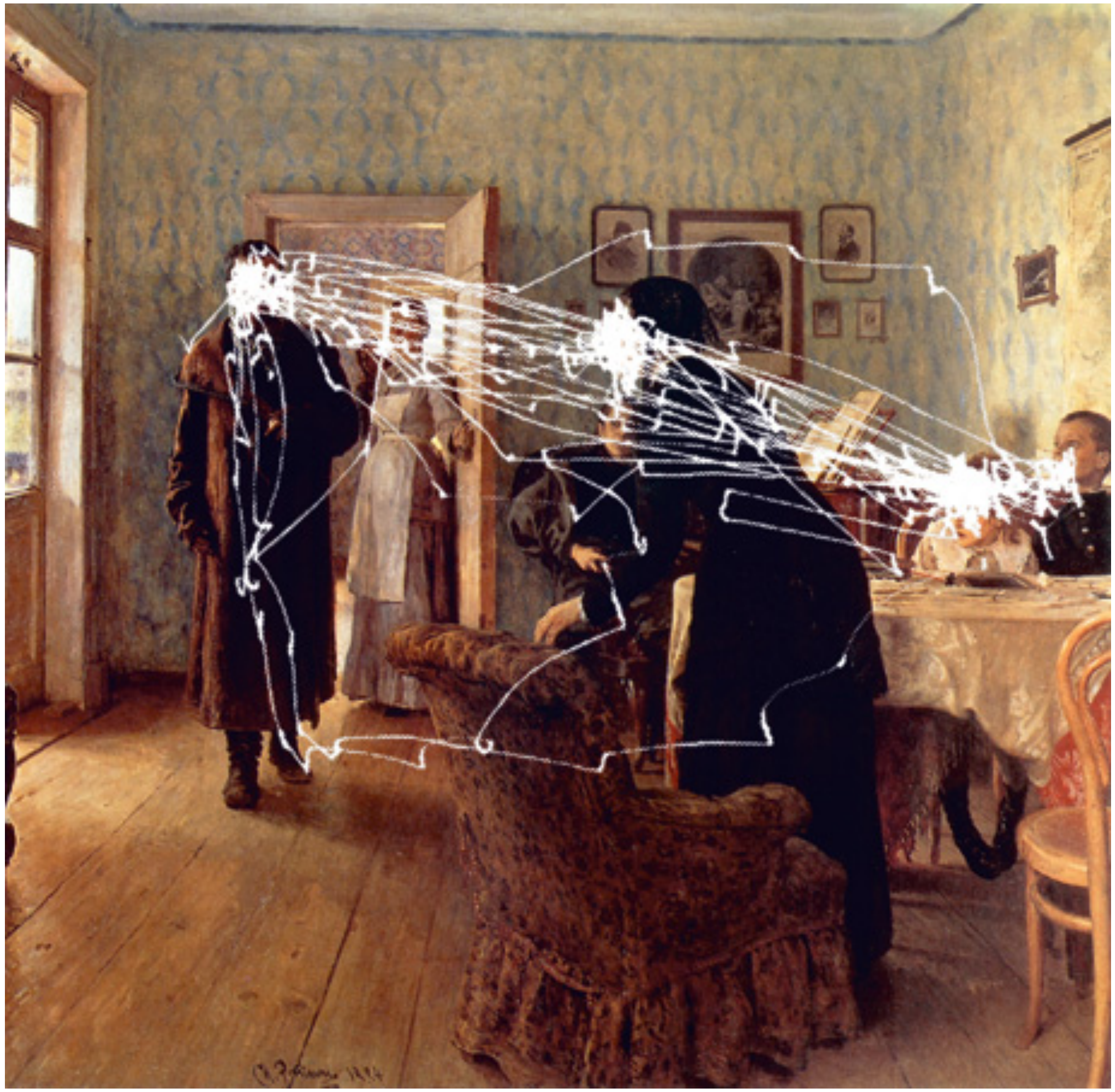
Free examination

# Eye movements: not only salience (Yarbus 1967)

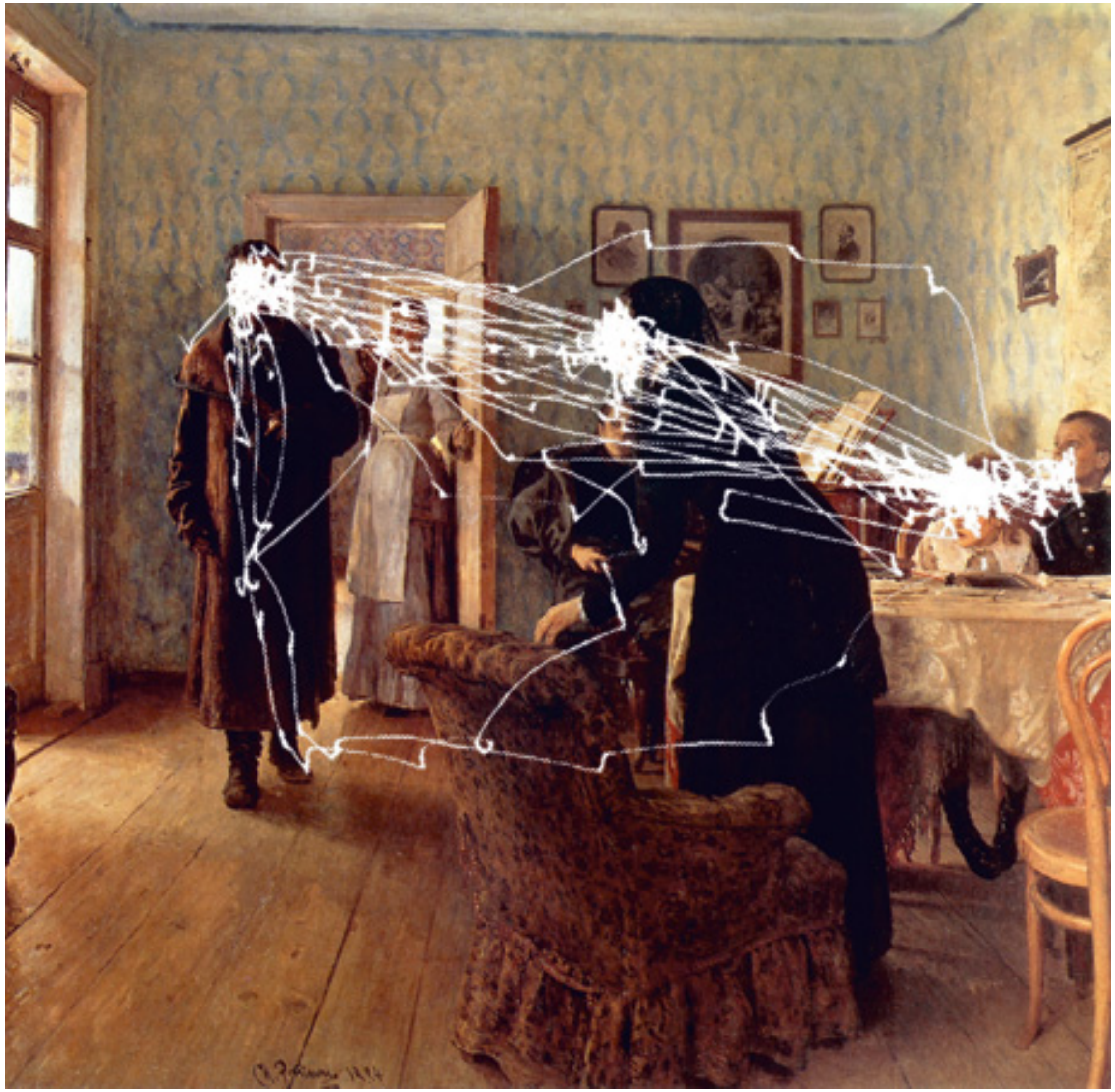
Eye movements: not only salience (Yarbus 1967)

Remember the clothes worn by people

# Eye movements: not only salience (Yarbus 1967)

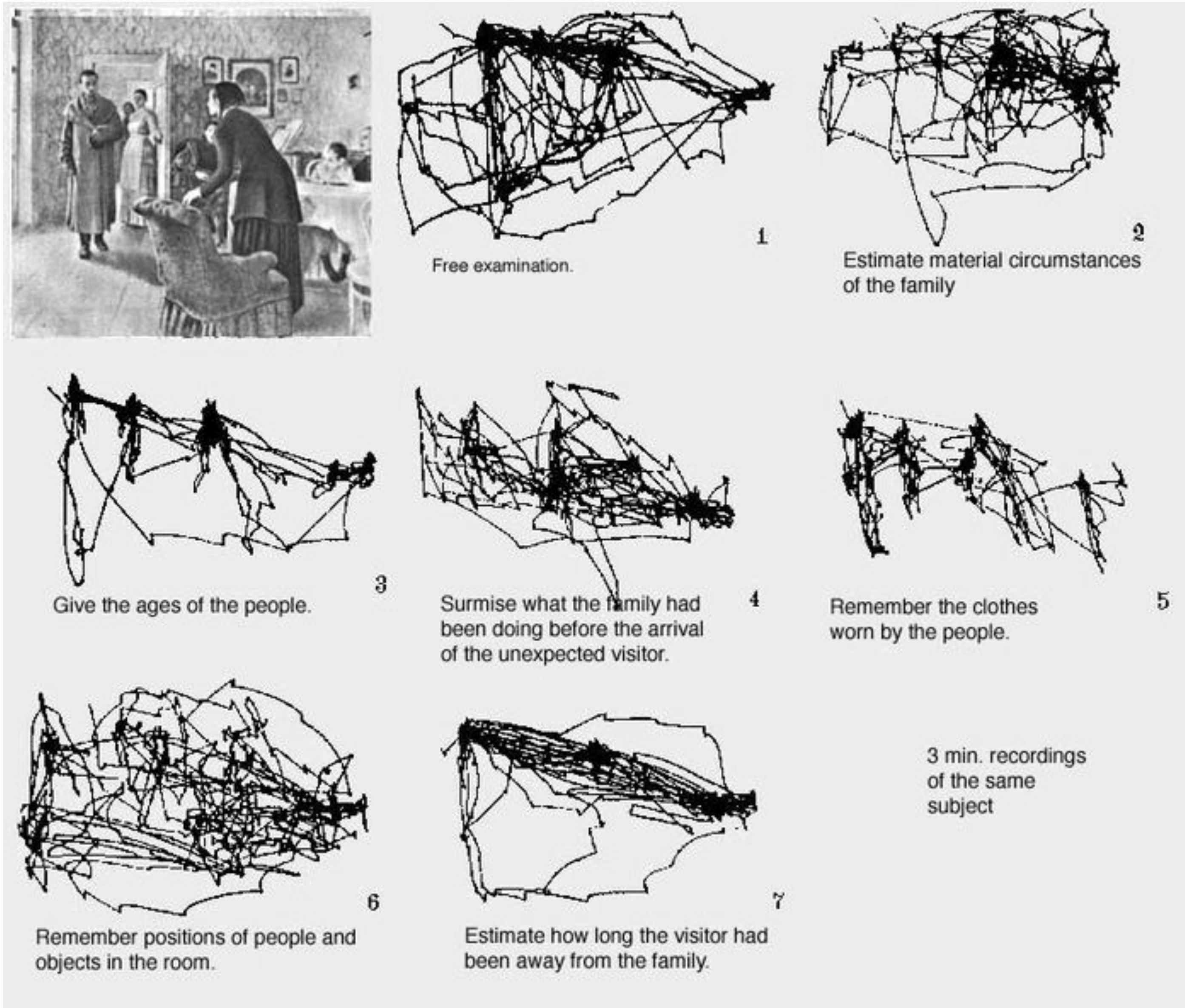


Eye movements: not only salience (Yarbus 1967)



Give the ages of the people

# Eye movements: not only salience



# Surround scene statistics and Divisive normalization

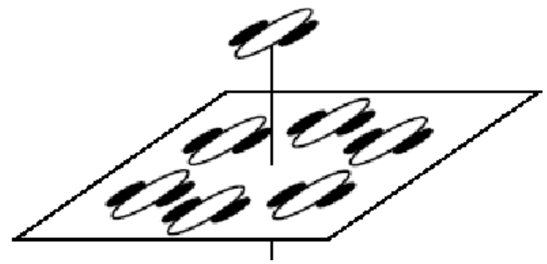
# Motivation

- 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

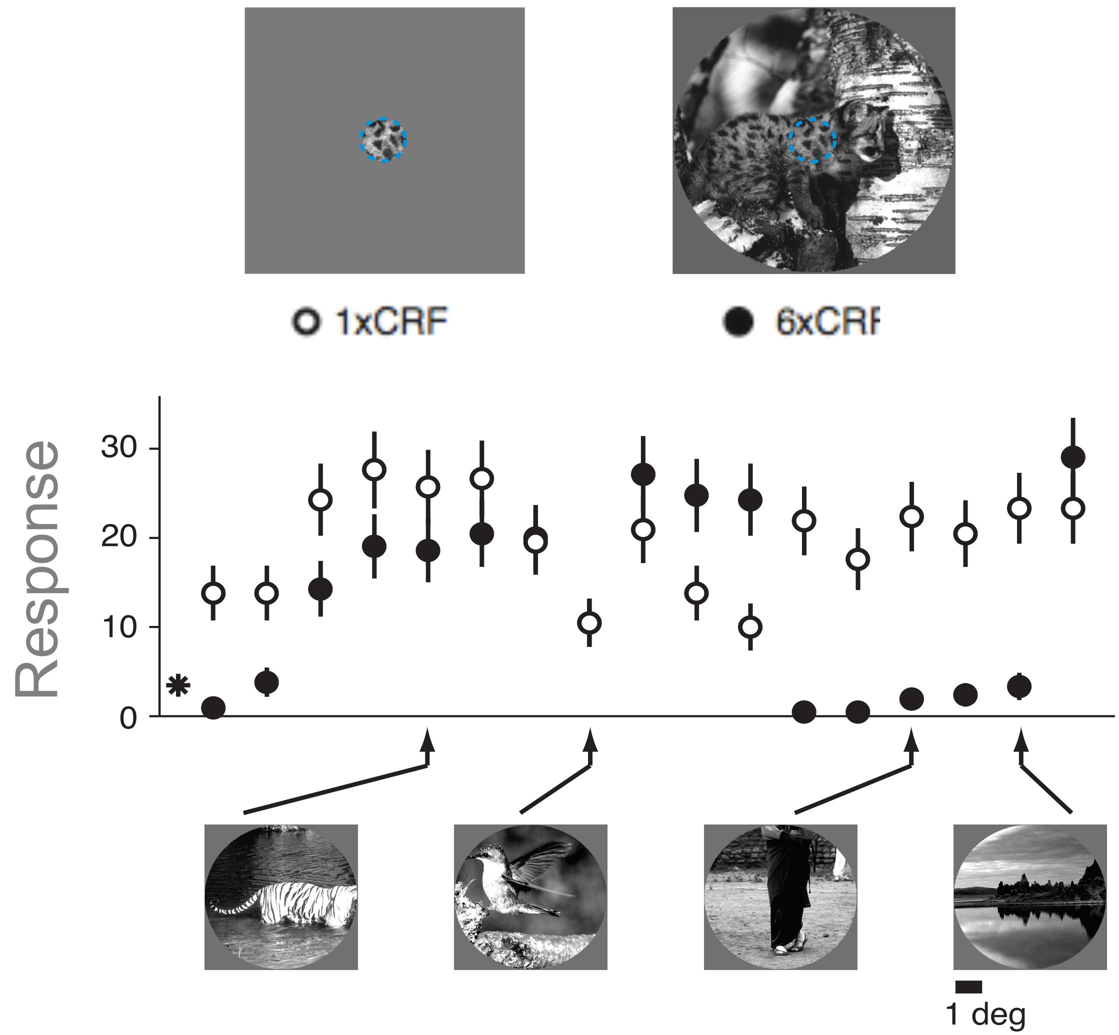
# Contextual influences

- Cortical visual neurons (V1)



# Cortical Neurons

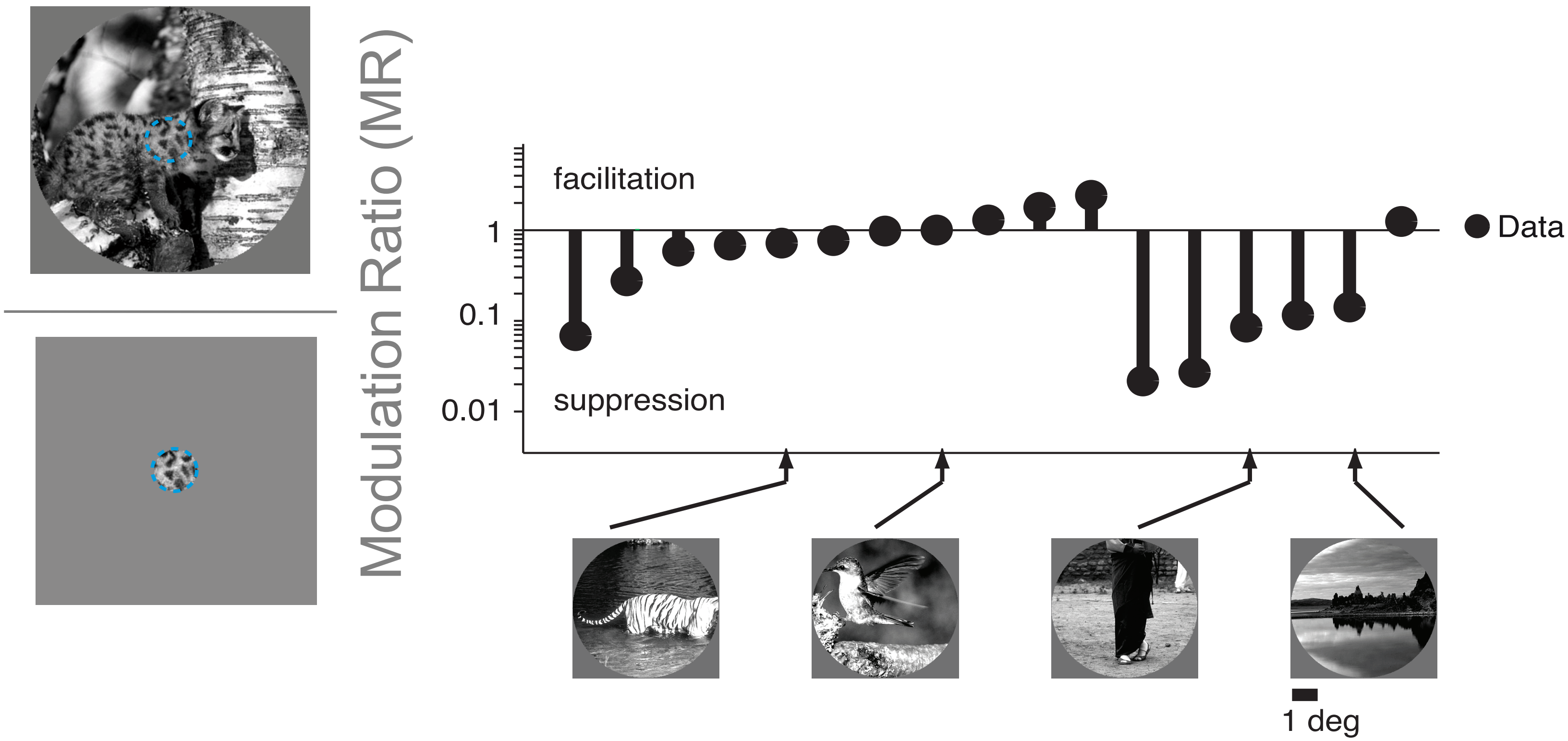
- Spatial context and natural scenes




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

# Cortical Neurons

- Spatial context and natural scenes



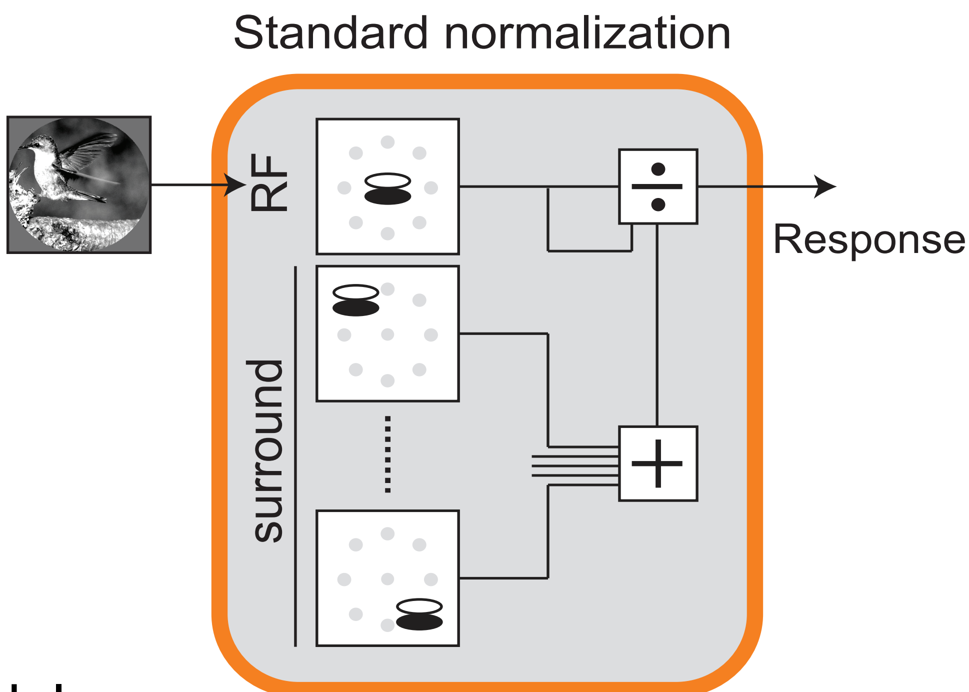

Data: Adam Kohn lab (Coen-Cagli, Kohn, Schwartz, 2015)

# Cortical Neurons

- Spatial context and natural scenes

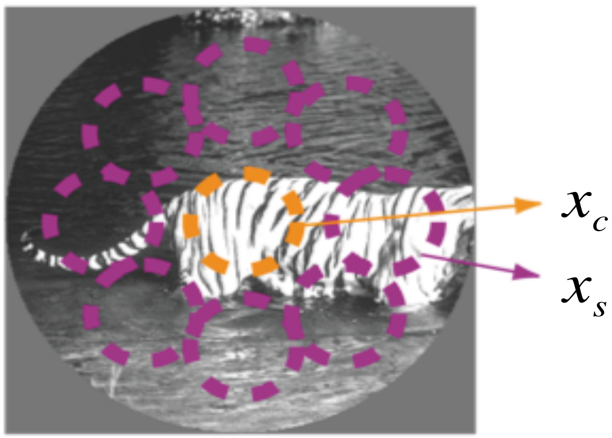
Can we capture data with
canonical divisive normalization?
(descriptive model)

# 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

# Cortical Neurons

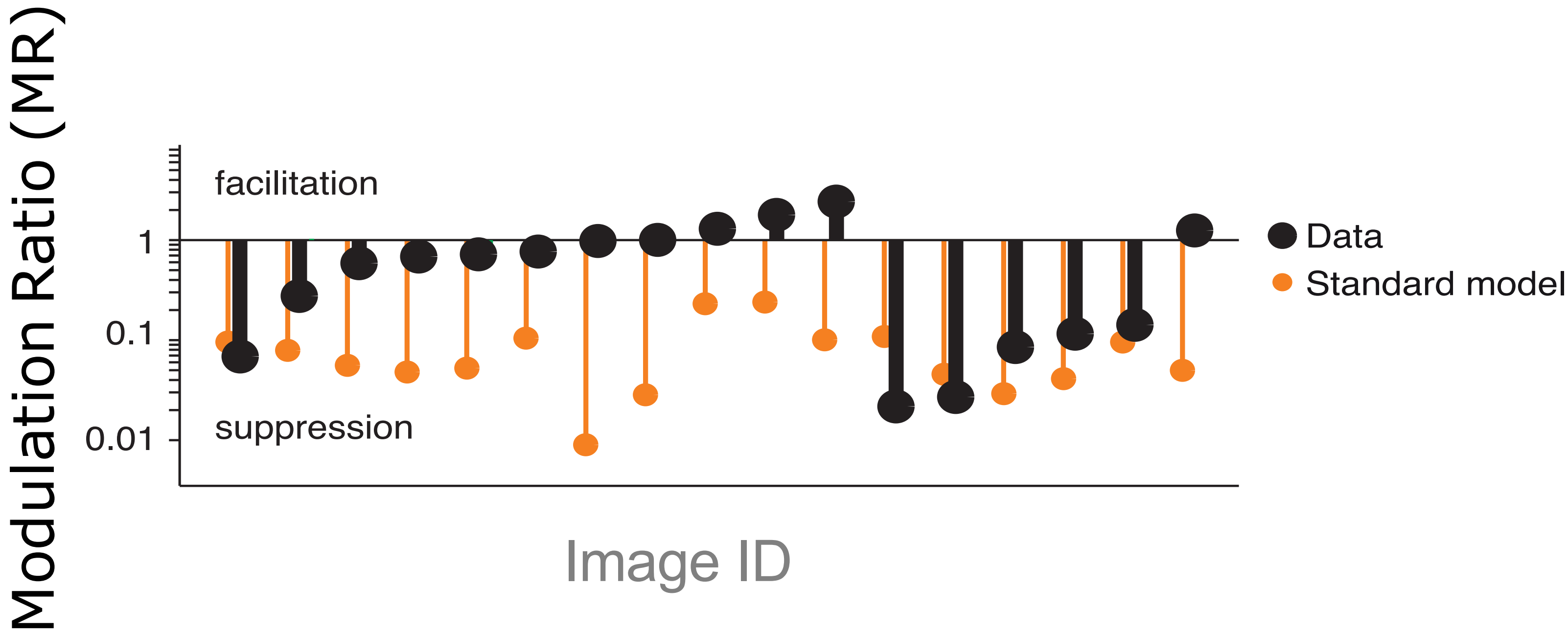



Canonical divisive normalization:

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

V1 Data: Kohn lab

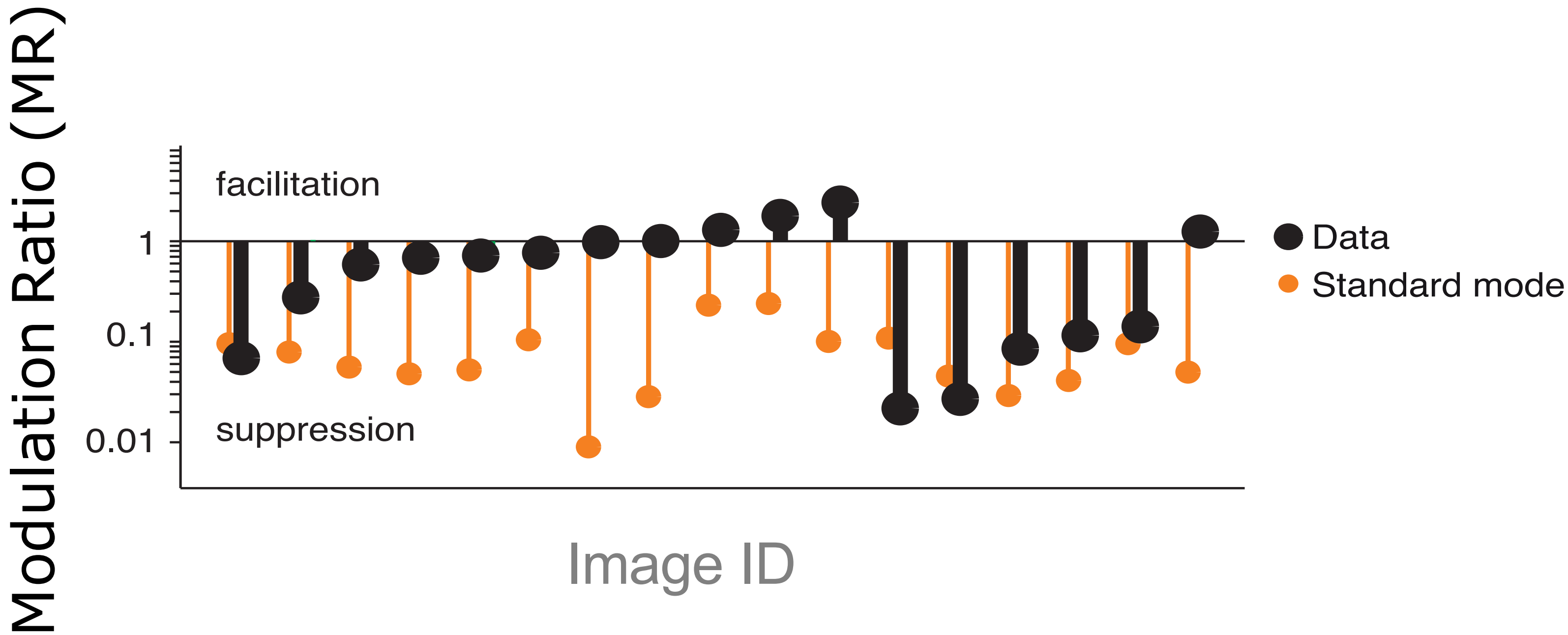
# Cortical responses to natural images




- We fit the standard normalization model to neural data
- Poor prediction quality

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

# Cortical responses to natural images




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

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

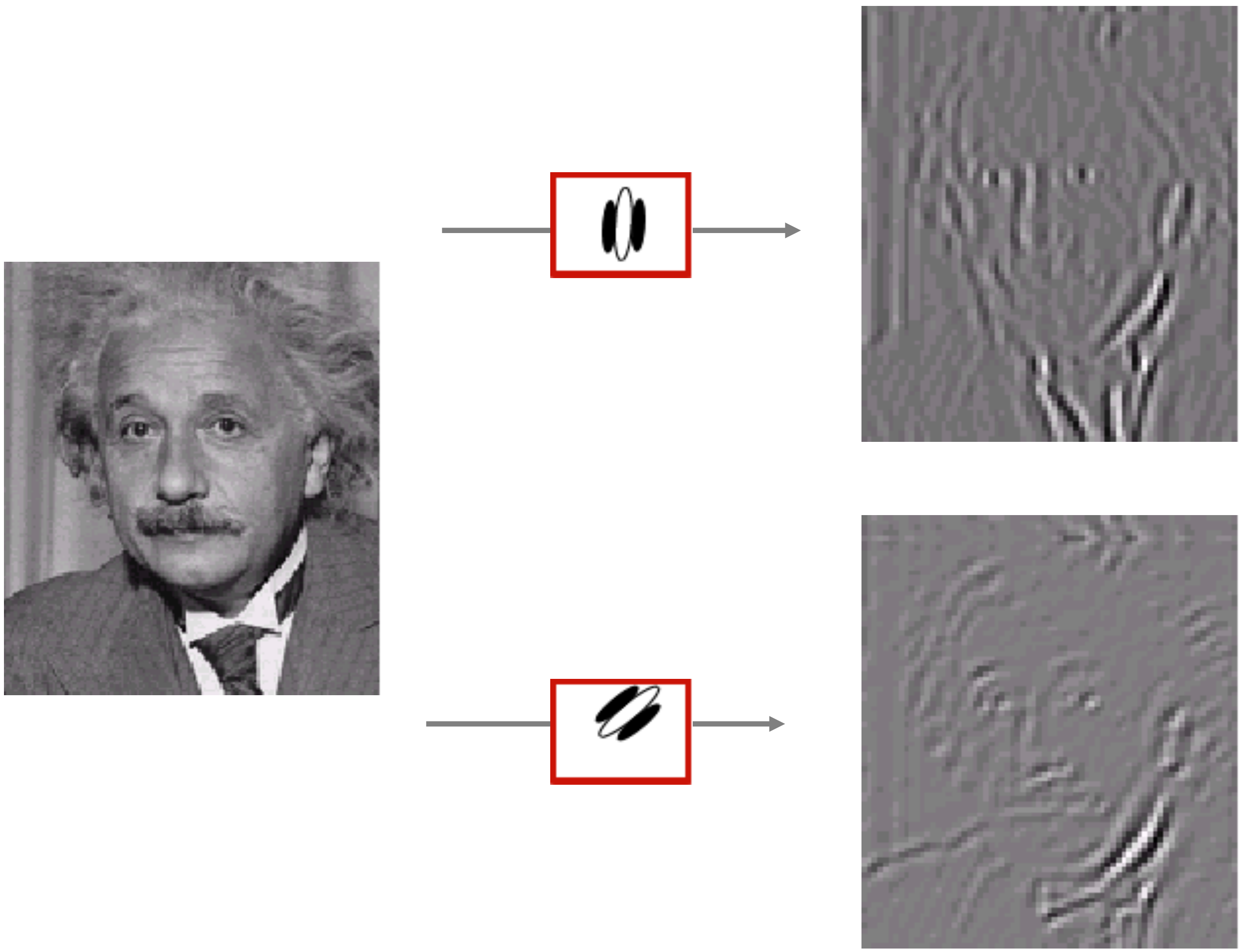
# Outline

- Experimental data on cortical responses to natural images (standard descriptive model can't explain)

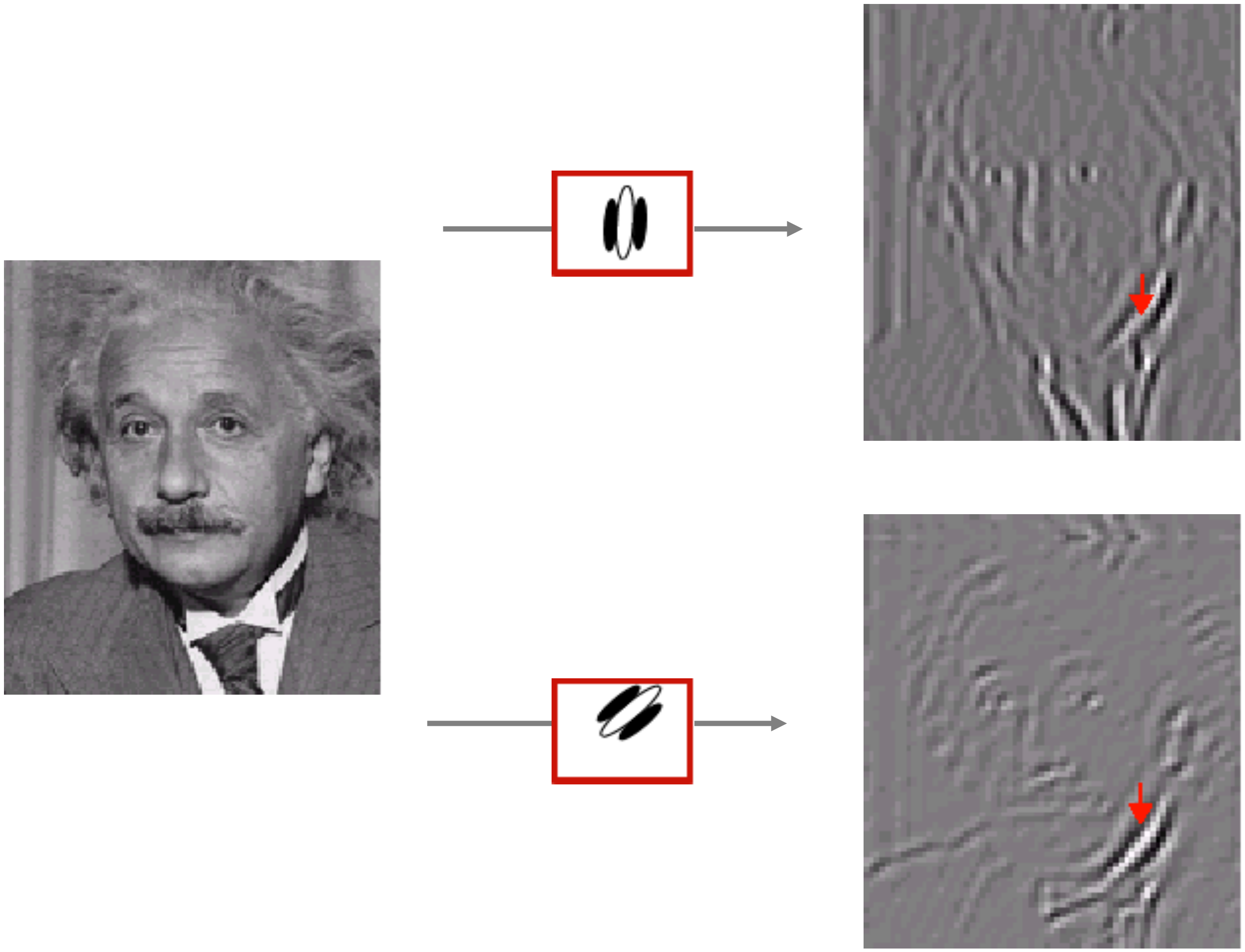
- Computational neural model that captures contextual regularities in natural images

- A Interplay of modeling with biological neural and psychology data (focus on natural images data)

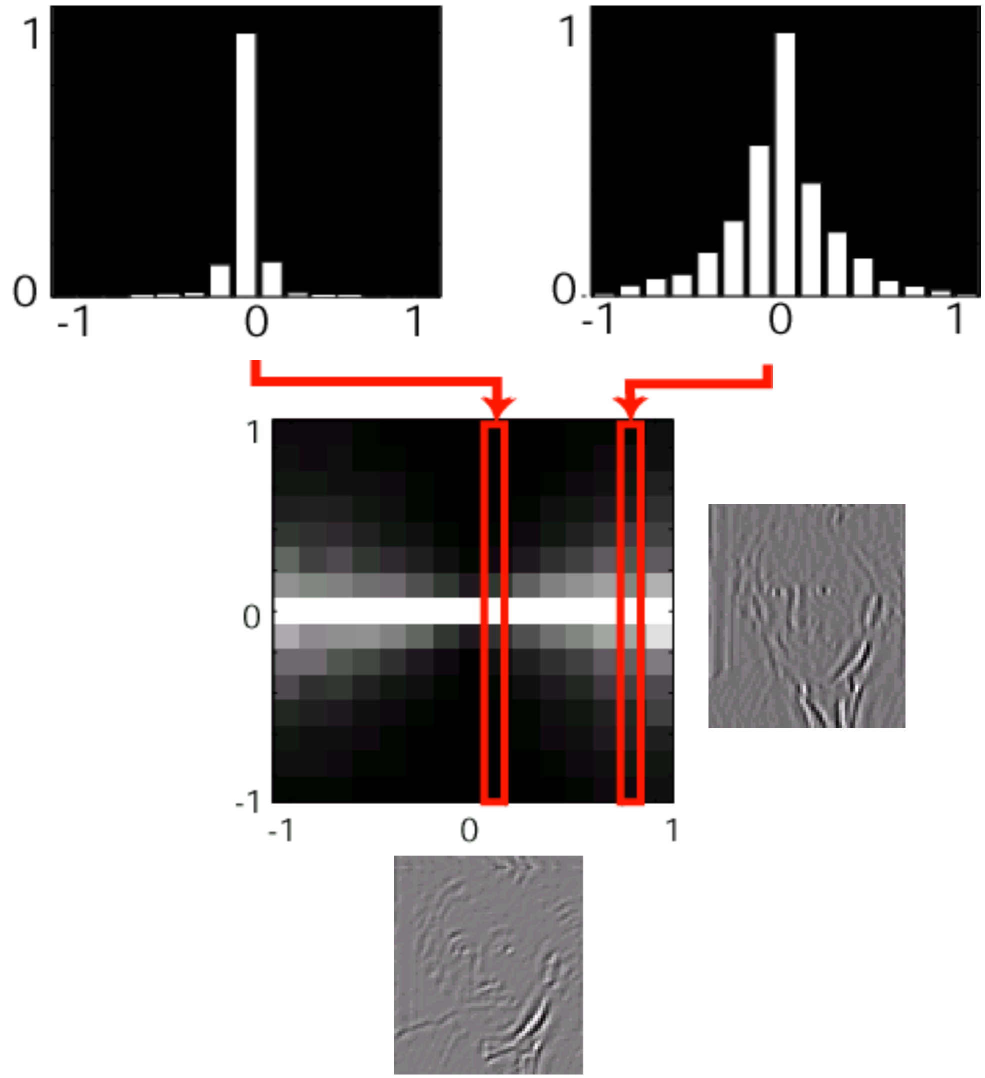
# Contextual dependencies across space



# Contextual dependencies across space

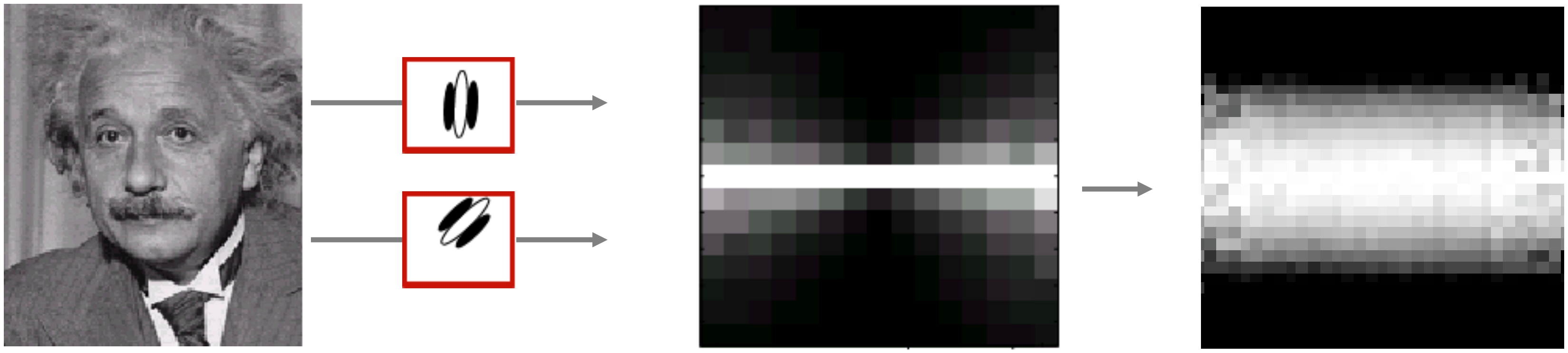


# Contextual dependencies across space




Schwartz, Simoncelli, Nature Neuroscience 2001

# Generative model framework



- Hypothesize that cortical neurons aim to reduce statistical dependencies (so as to highlight what is salient)
  Schwartz, Simoncelli 2001 (for salience: Zhaoping Li, 2002)

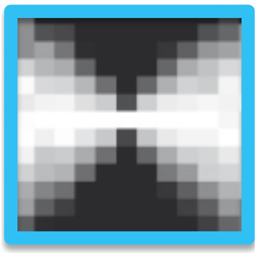
- Formally, we build a generative model of the dependencies and invert the model (Bayesian inference) – richer representation!
  Andrews, Mallows, 1974; Wainwright, Simoncelli, 2000; Schwartz, Sejnowski, Dayan 2006

- Generating the dependencies is a multiplicative process and to undo the dependencies we divide

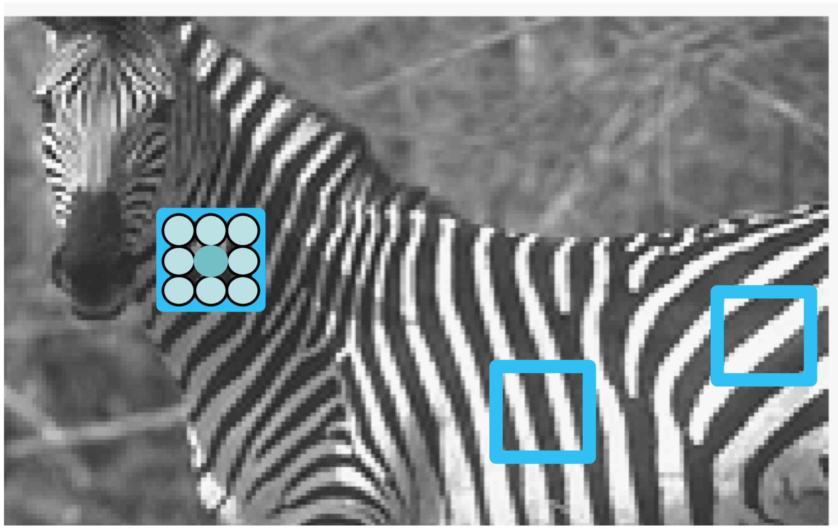
# Divisive normalization: richer model

Divisive normalization *descriptive* models have been applied in many neural systems. Here we provide a *principled explanation.* We will next show that it also leads to a richer model based on image statistics and makes predictions

# Non-homogeneity of images



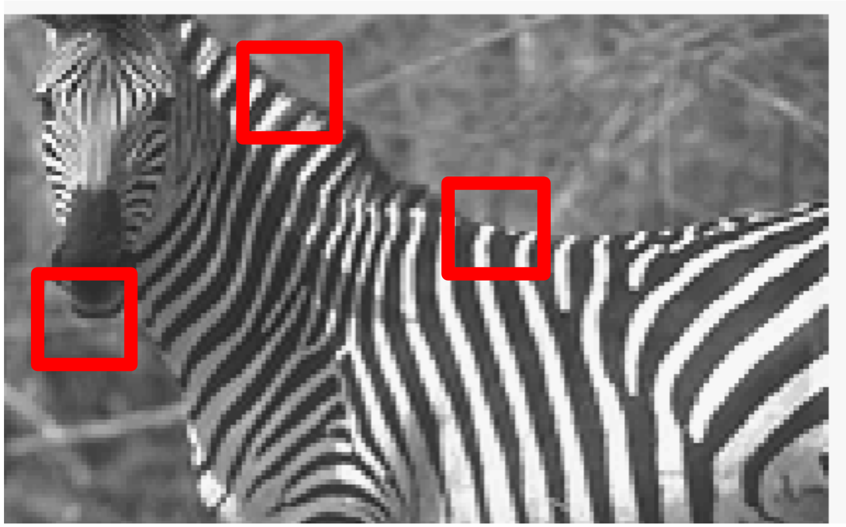
Center and surround dependent

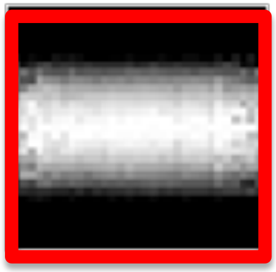


homogenous image patches

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

# Non-homogeneity of images





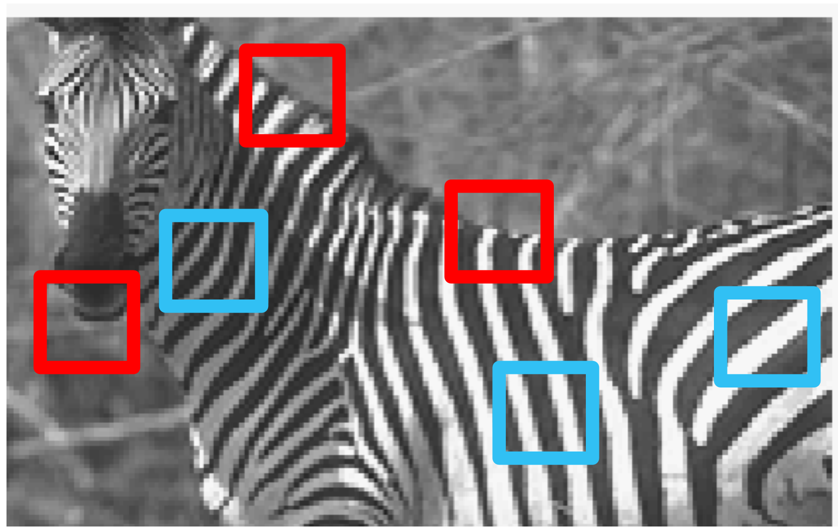
Center and surround independent

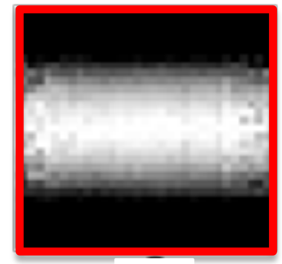
non-homogenous image patches

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

# Non-homogeneity of images

homogenous

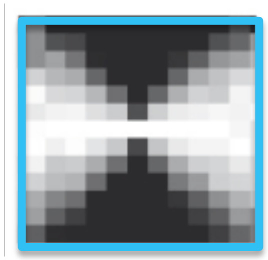




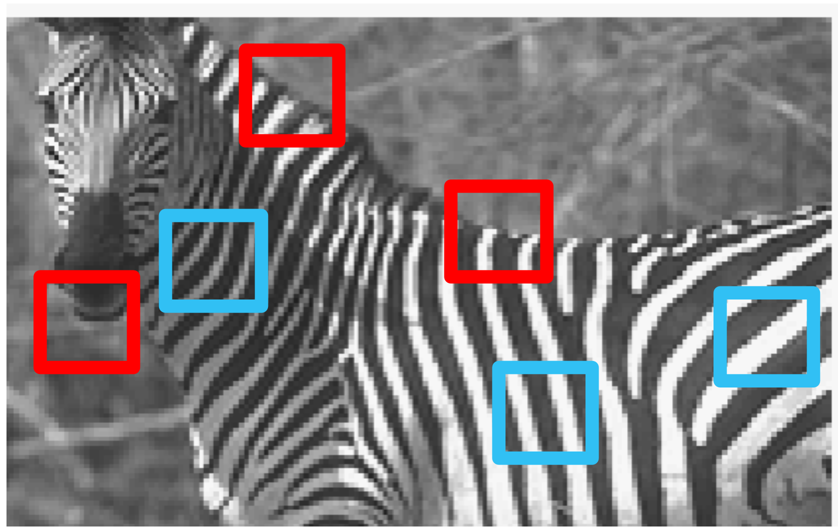
heterogeneous

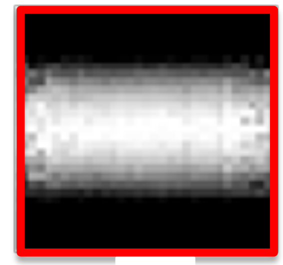
Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

# Non-homogeneity of images



divisive
normalization
ON

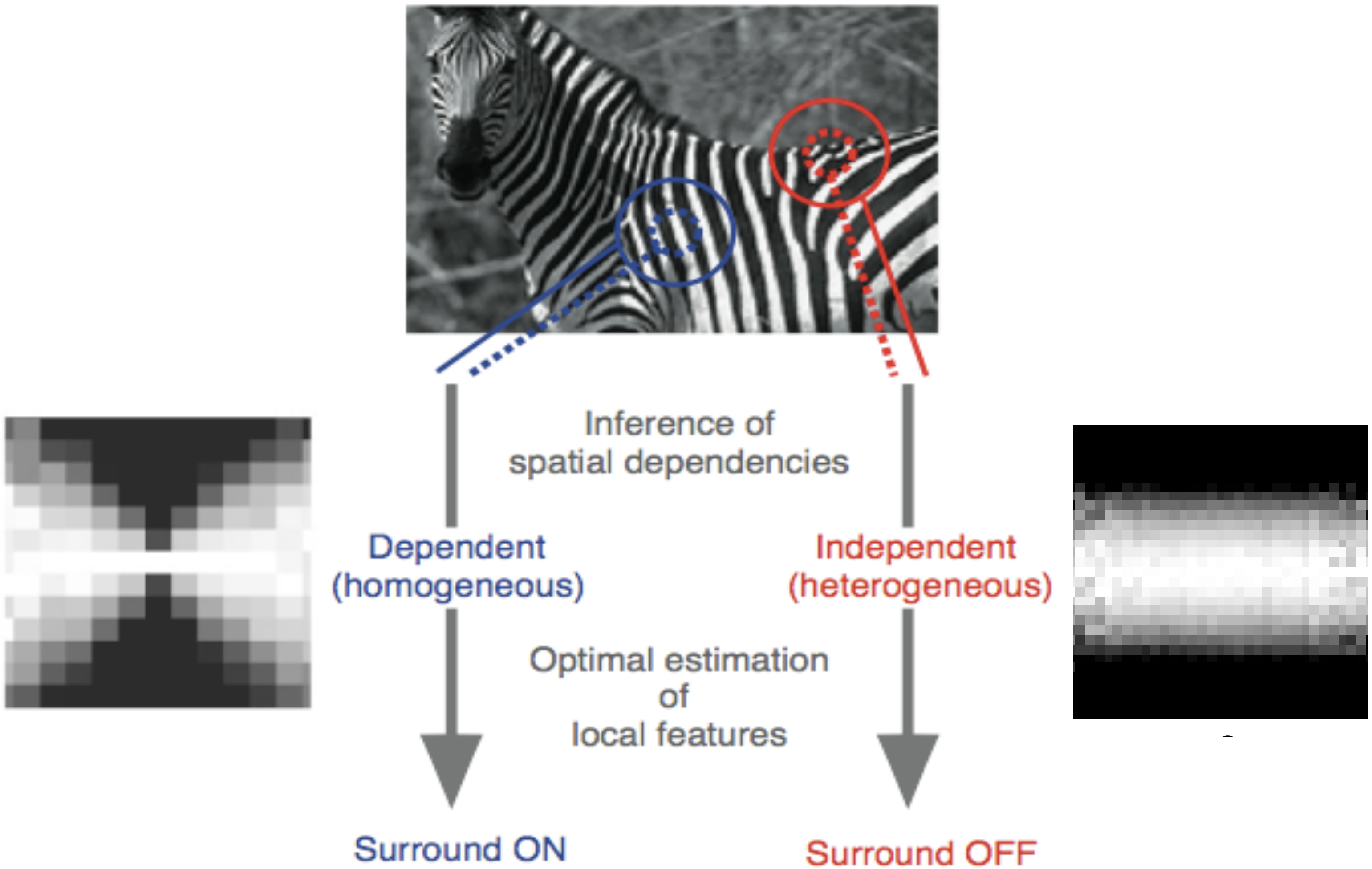




divisive
normalization
OFF

Schwartz, Sejnowski, Dayan, 2009; Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012

# Flexible Divisive Normalization

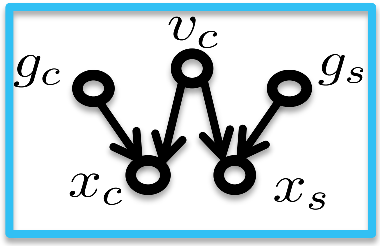


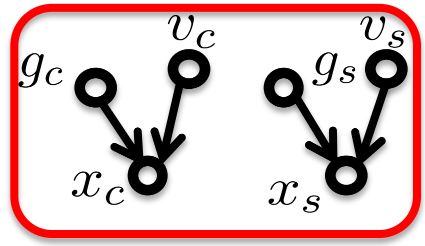

Divide

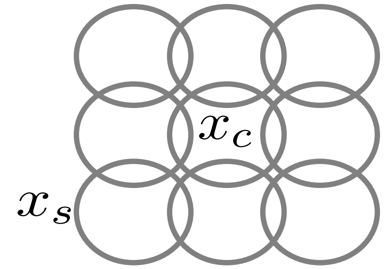
Don't divide

Model and experimental tests: Cagli, Kohn, Schwartz 2015

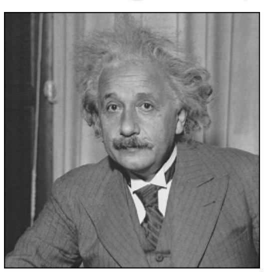
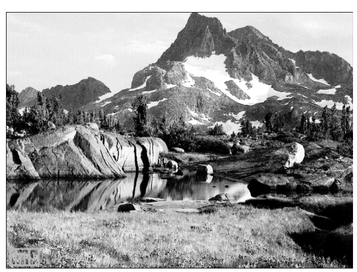
# Model: Optimizing Image Ensemble



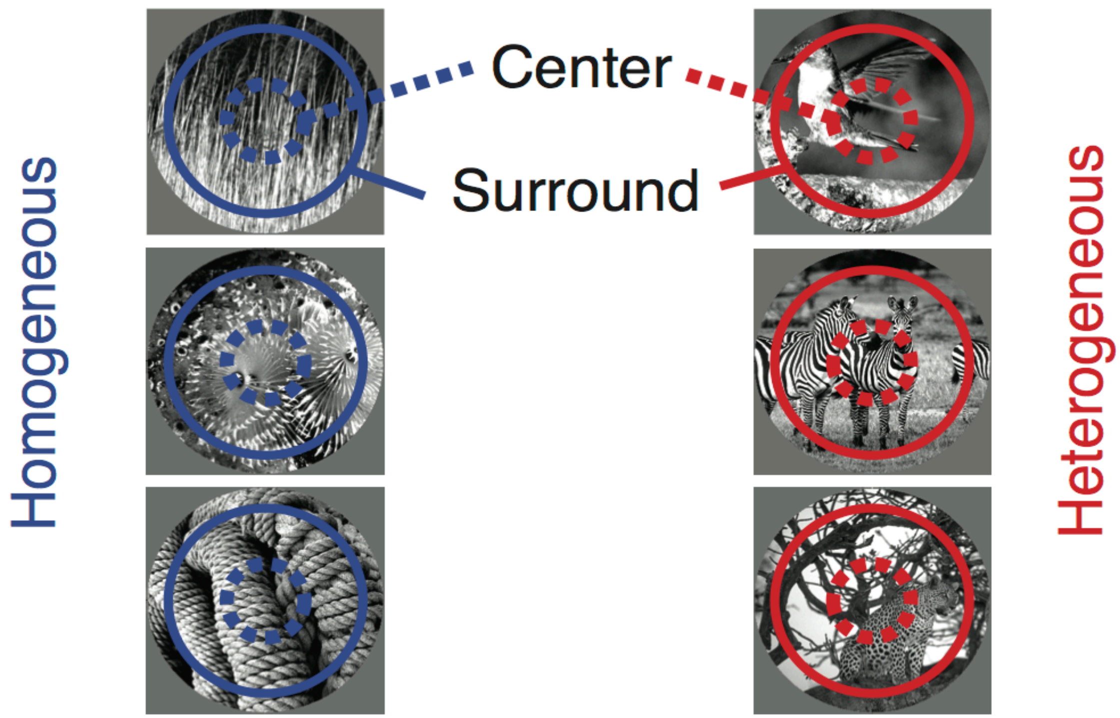




- 3x3 spatial positions, 6px separation
- 4 orientations in the center
- 4 orientations in the surround
- 2 phases (quadrature)
- model parameters (prior probability for dependent, independent and also linear covariance matrices) optimized to maximize the likelihood of a database of natural images using Expectation Maximization

Coen-Cagli, Dayan, Schwartz, PLoS Comp Biology 2012;
Schwartz, Sejnowski, Dayan, 2006

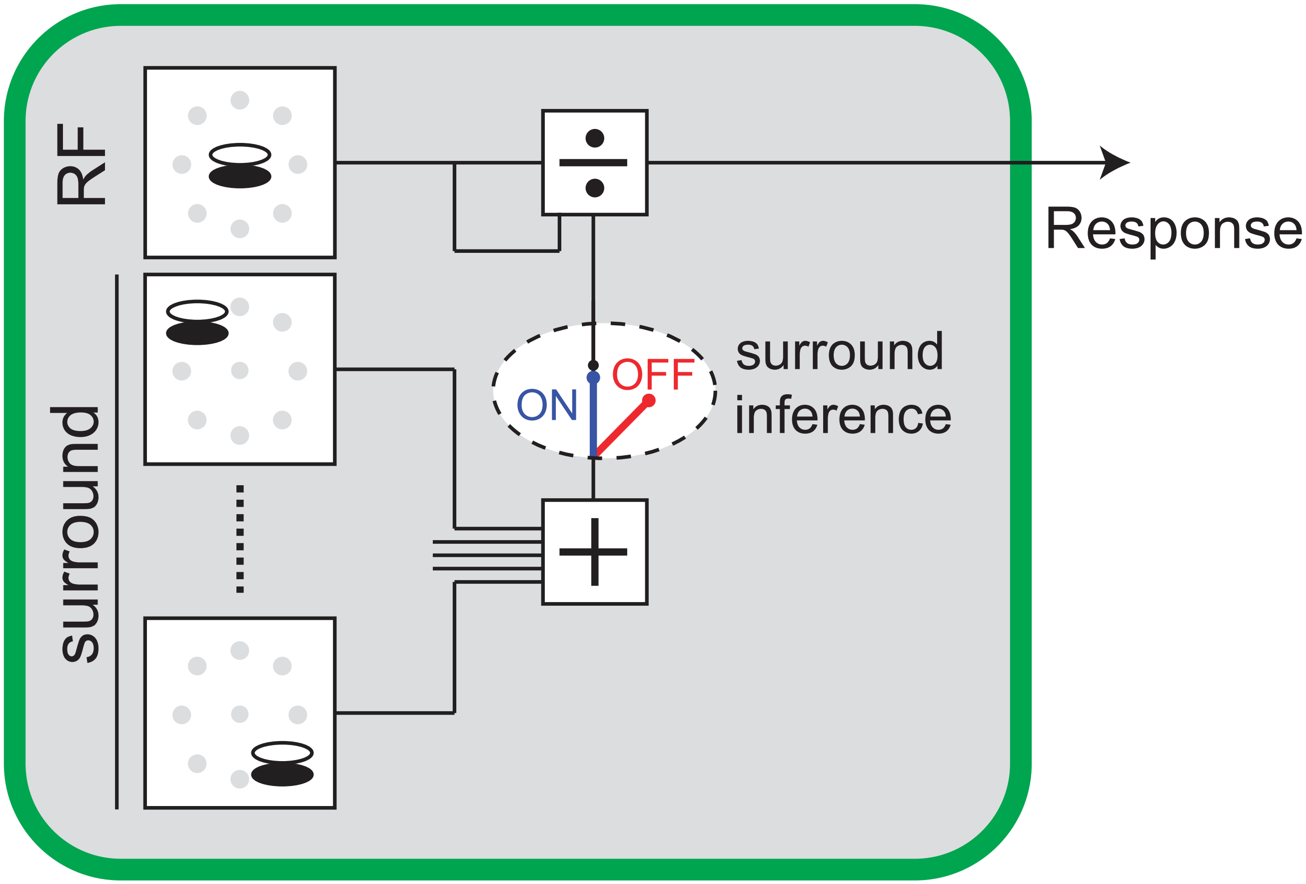
# Model predictions for natural images




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

Coen-Cagli, Kohn, Schwartz, 2015

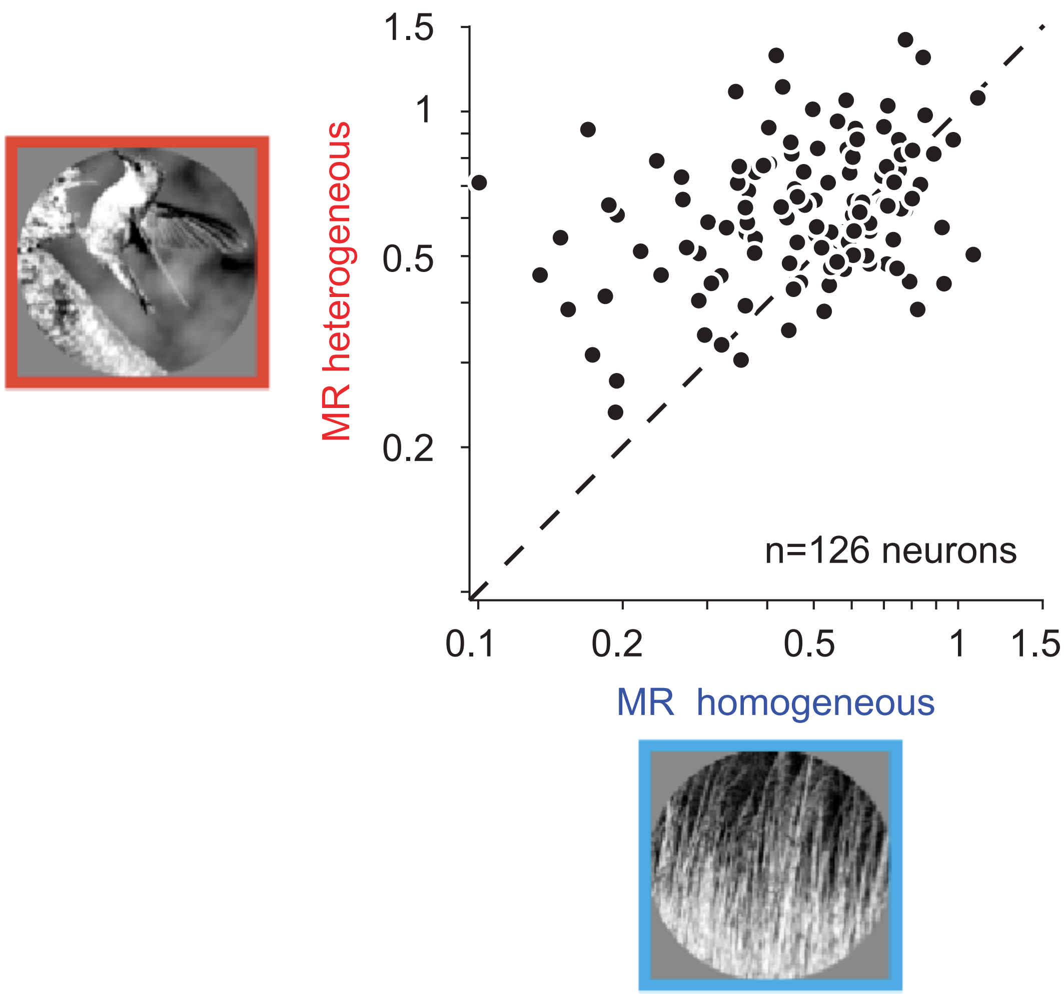
# Model summary




Inference determined by model

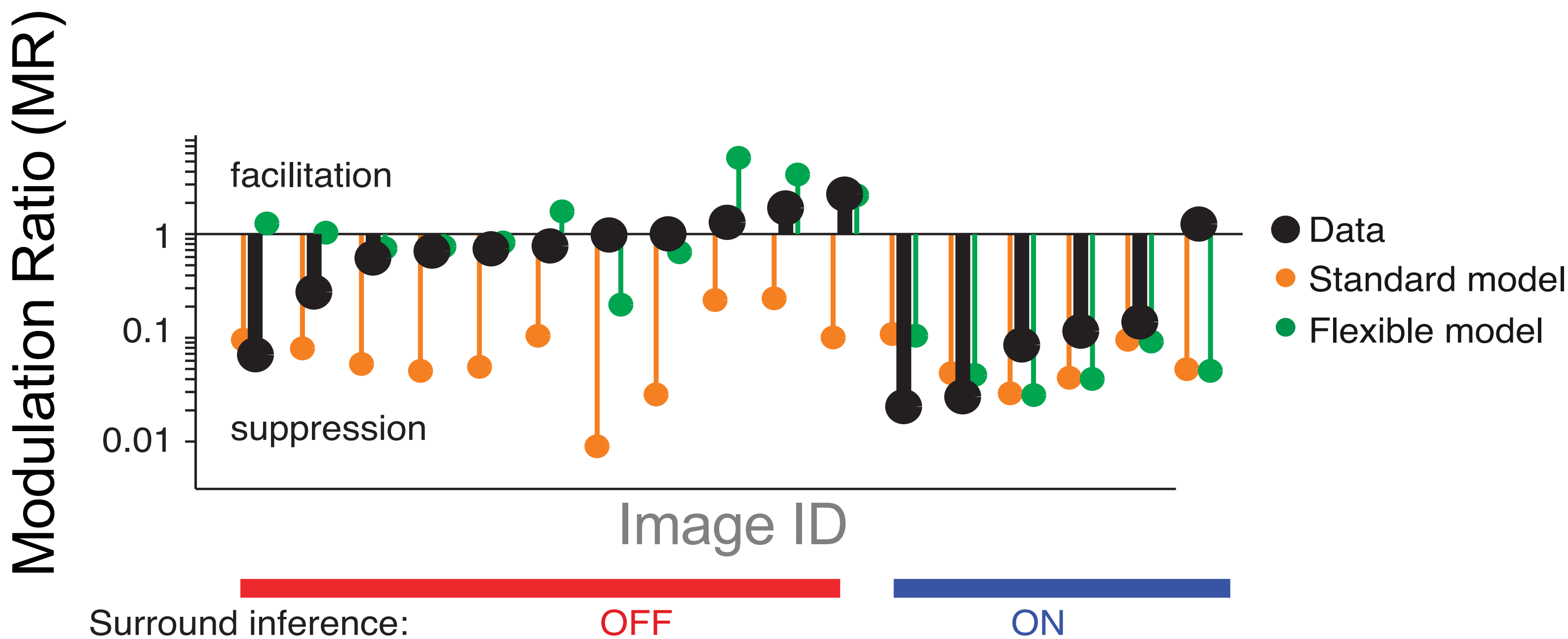
# Model predictions for natural images

Cortical V1 data:




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

# Natural scenes data




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

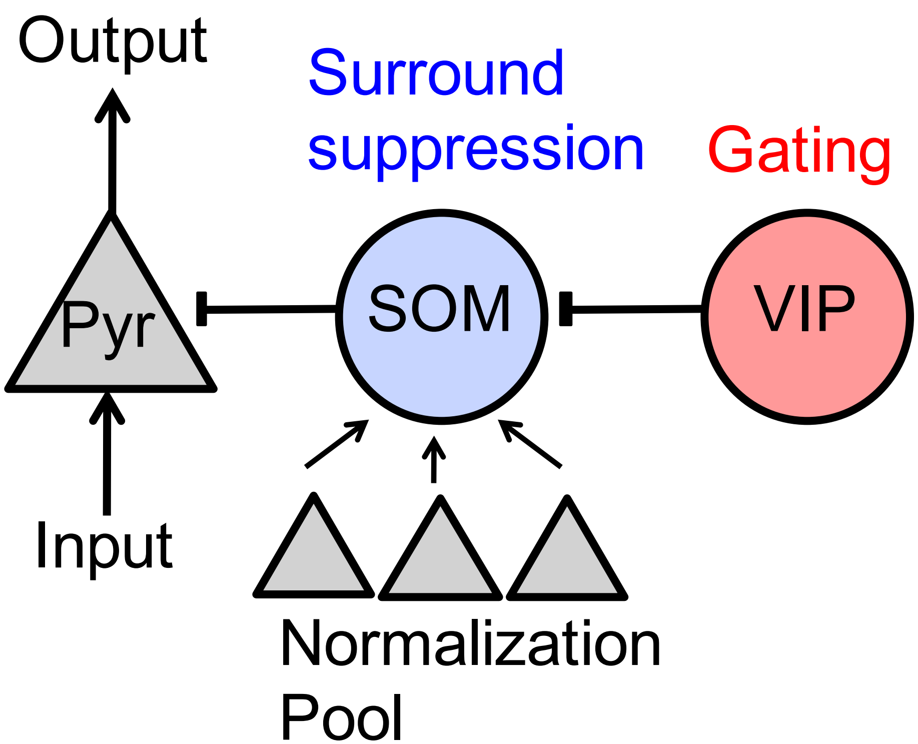
# Model Mechanisms

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 unit activations to normalize by