Statisztikus tanulás az idegrendszerben

ORBÁN GERGŐ

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Introduction

Knowledge representation

Probabilistic models

Bayesian behaviour

Approximate inference I (computer lab)

Vision I

Approximate inference II: Sampling

Measuring priors

Neural representation of probabilities

Structure learning

Vision II

Decision making and reinforcement learning elméleti

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elméleti

kognitív

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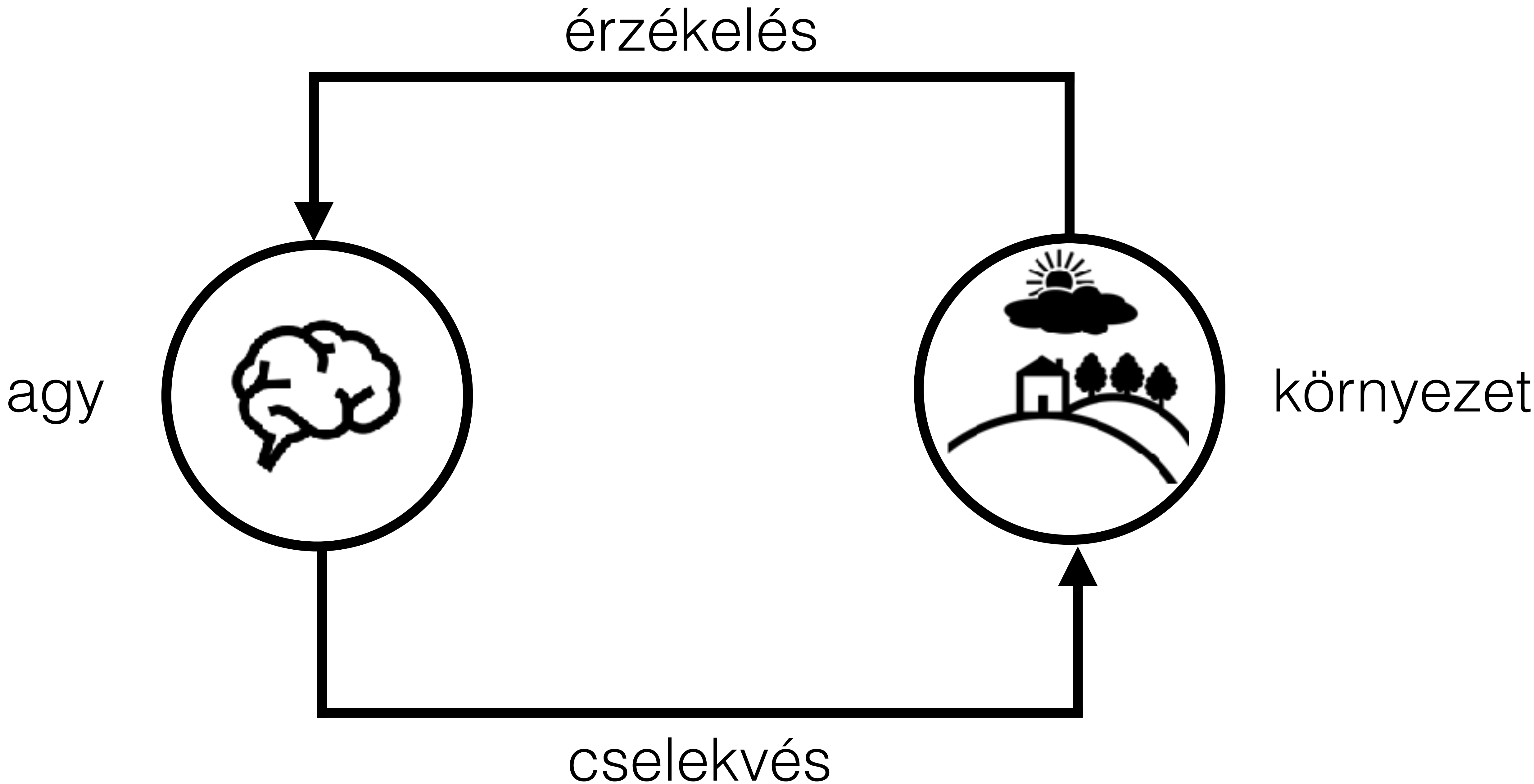
neurális



érzékelés
agy
környezet
cselekvés

Generatív/rekogniciós modell

Generatív/rekogniciós modell

Generatív/rekogniciós modell

objektumok

objektum elhelyezkedése | méret, hely, helyzet, világítás

Generatív/rekogniciós modell

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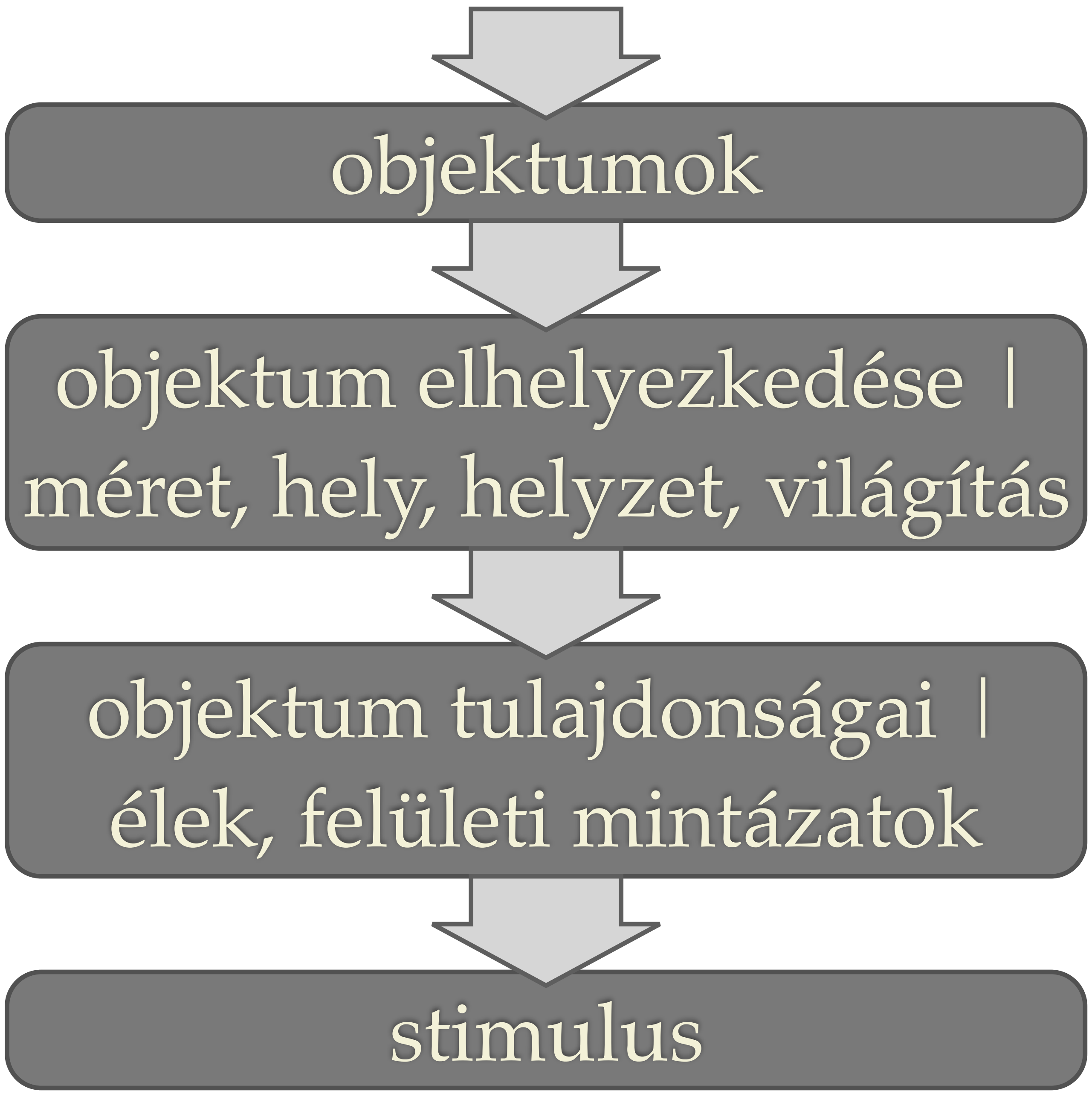
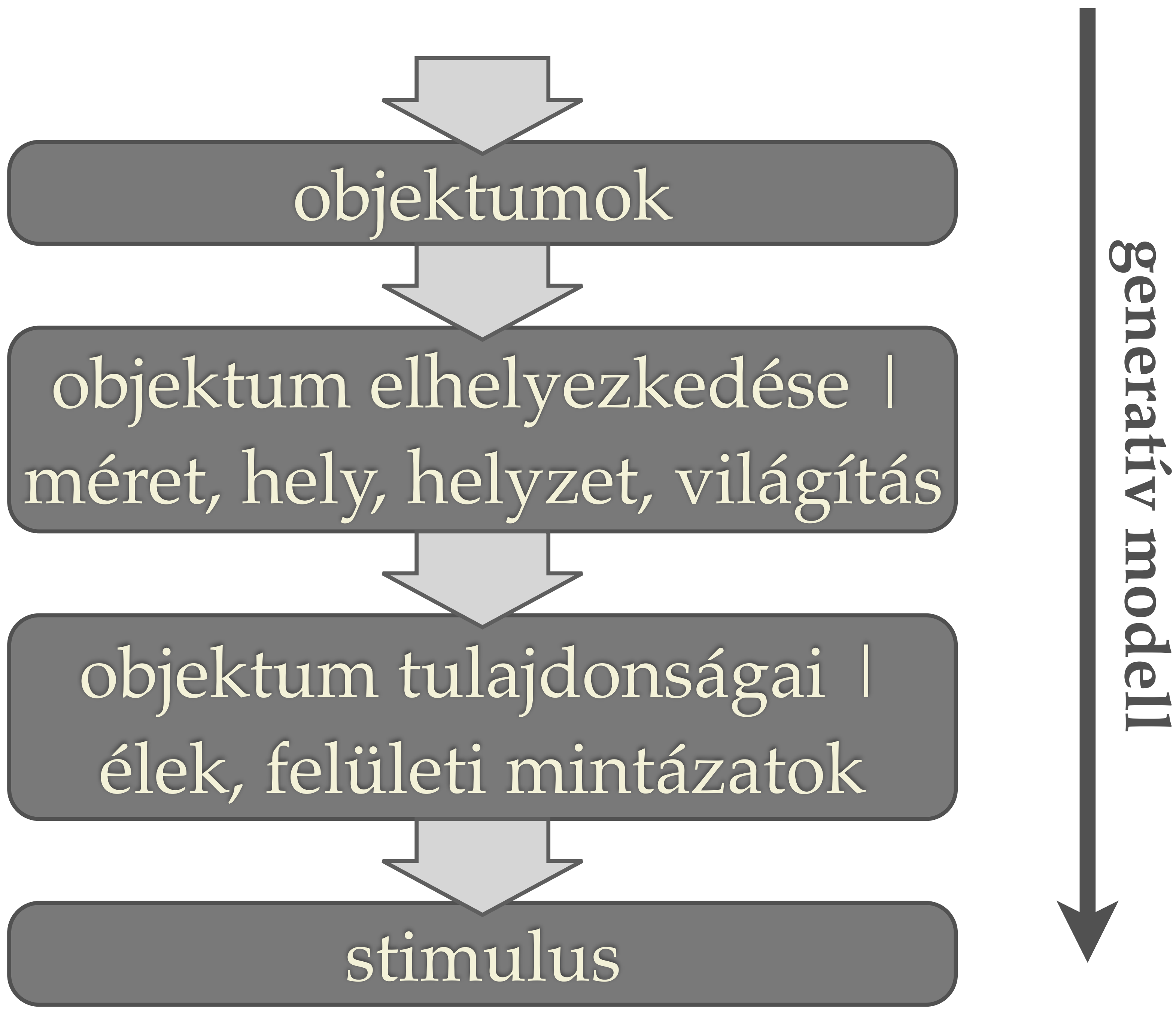
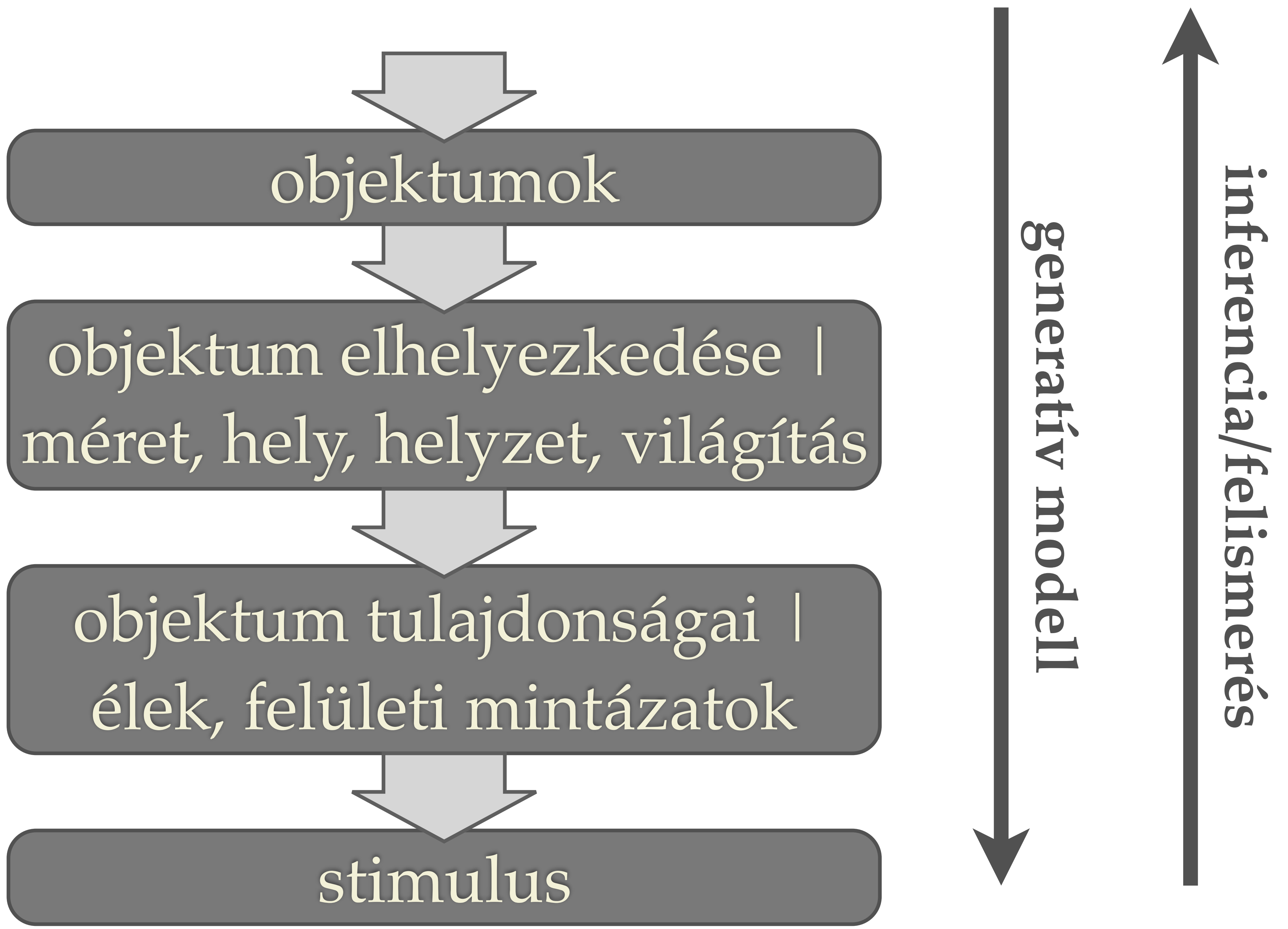


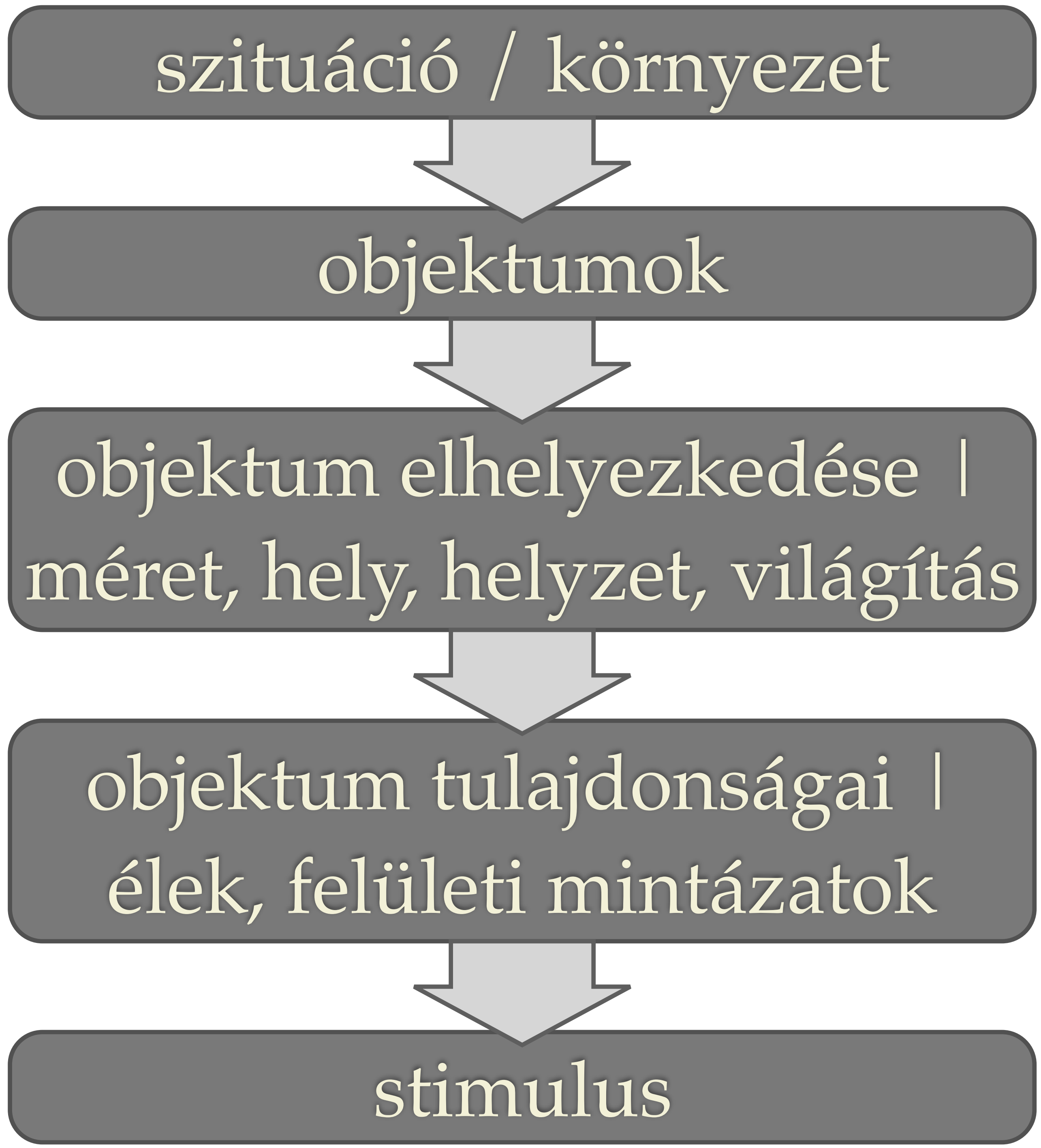
Generatív/rekogniciós modell



Generatív/rekogniciós modell



Generatív/rekogniciós modell



Generatív/rekogniciós modell

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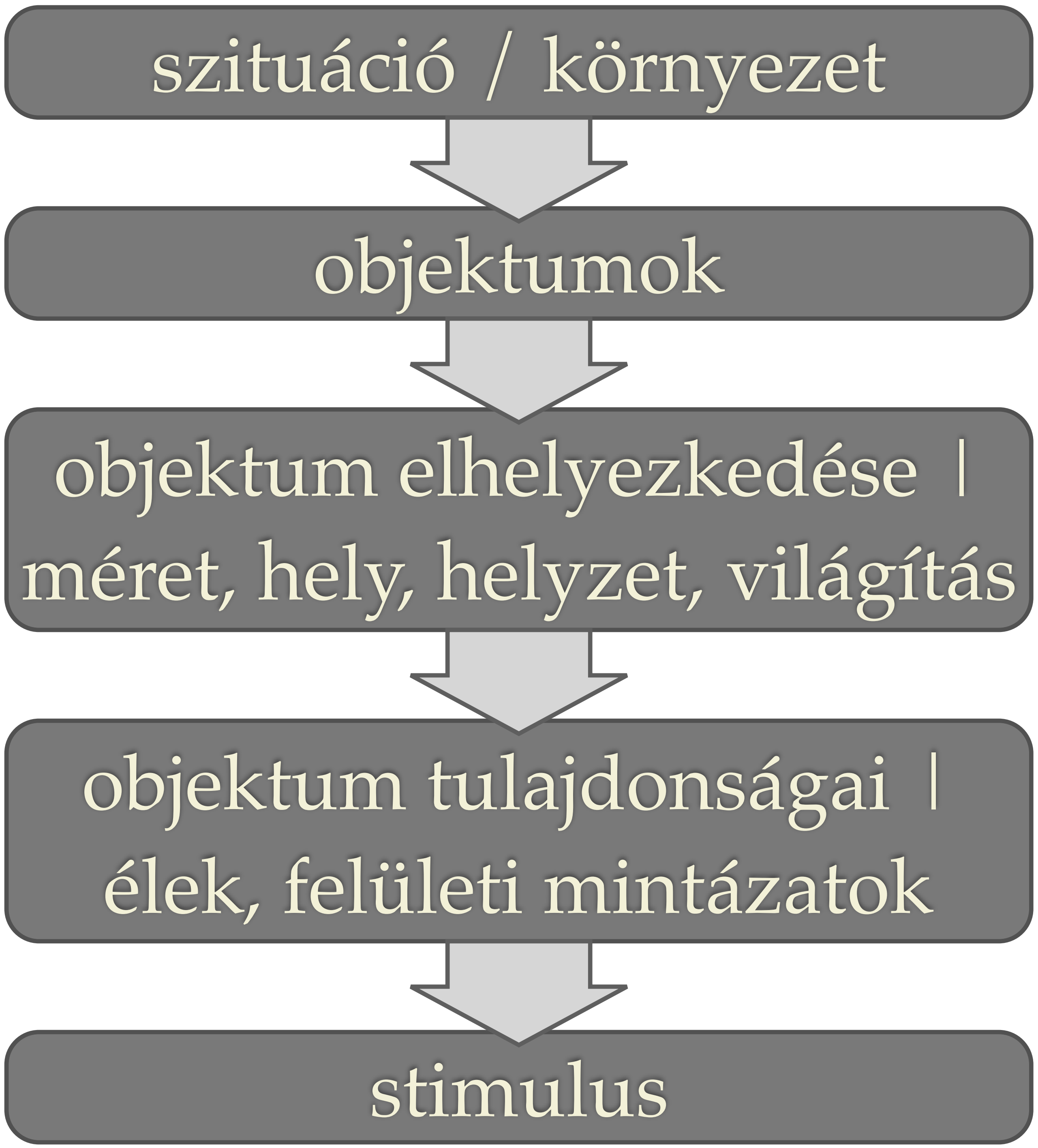
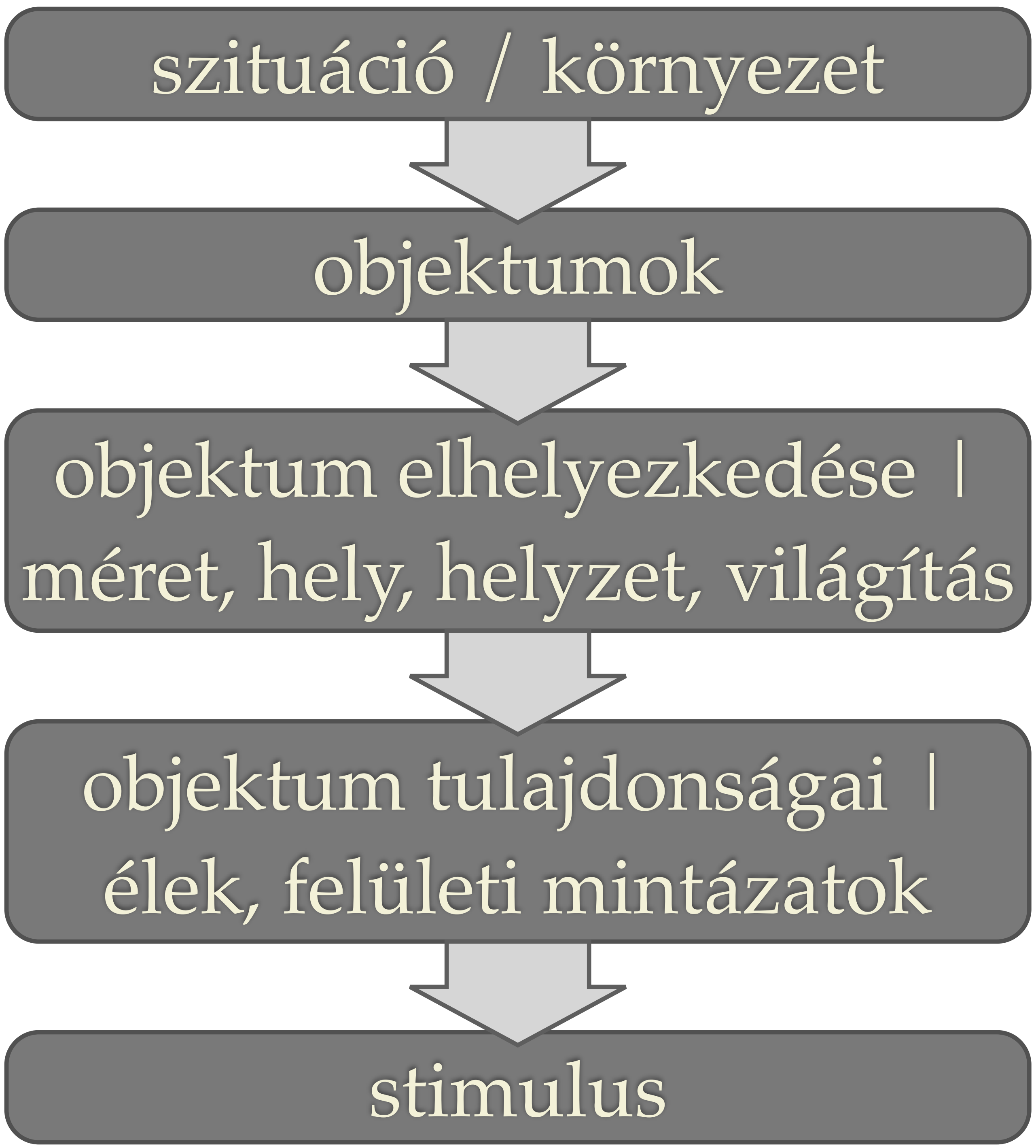


Modell definició -> generáció:
$P(x \mid z)$

Generatív/rekogniciós modell



Modell definició -> generáció:
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Inferencia igénye -> rekogníció:
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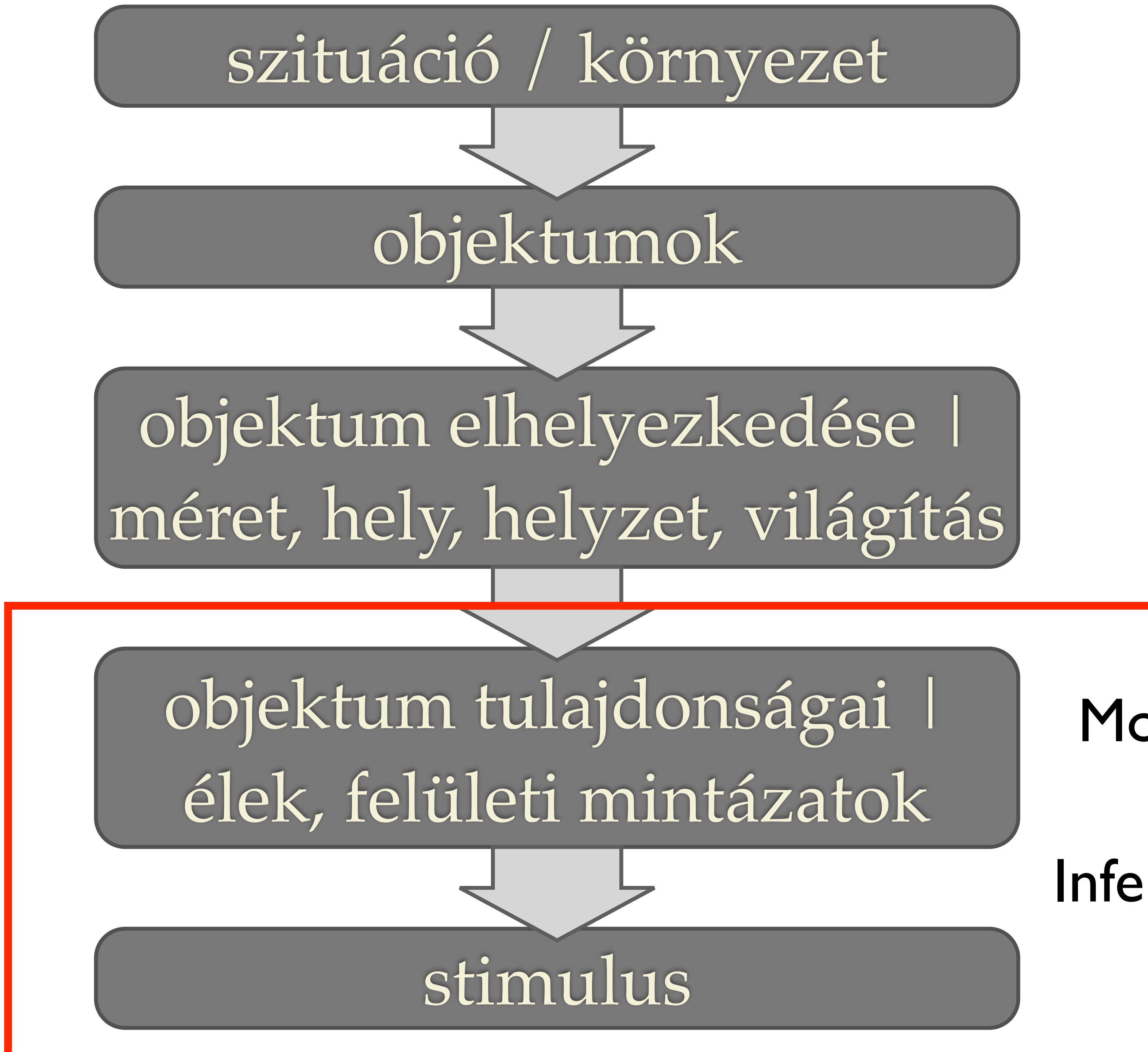
Generatív/rekogniciós modell



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Természetes képek generatív modelljei

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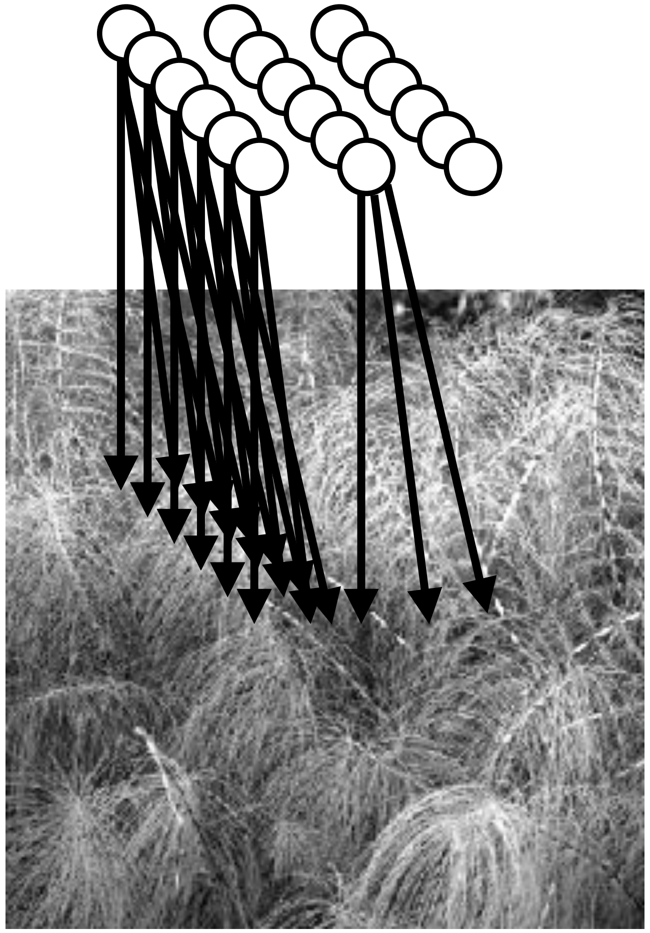
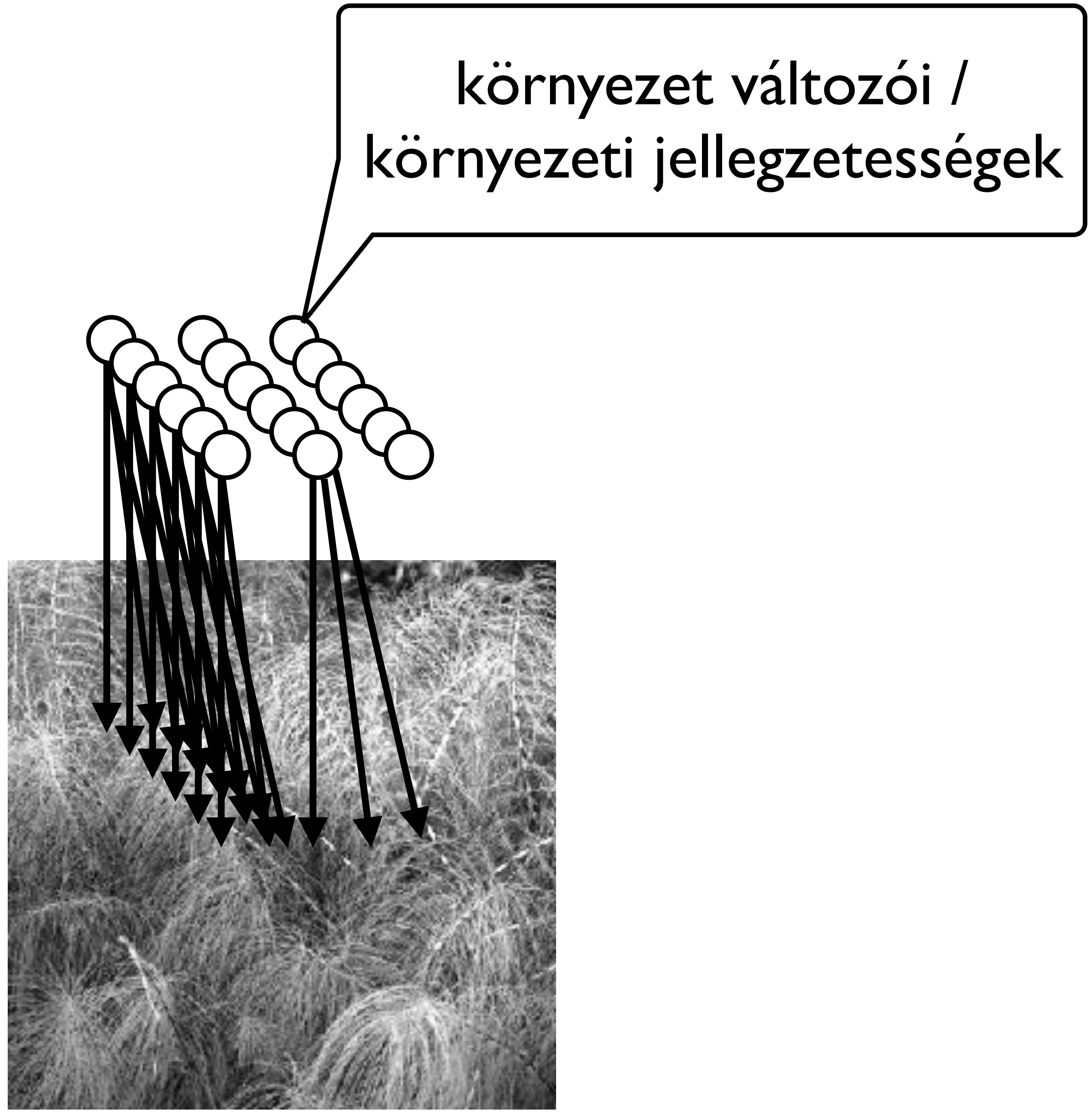
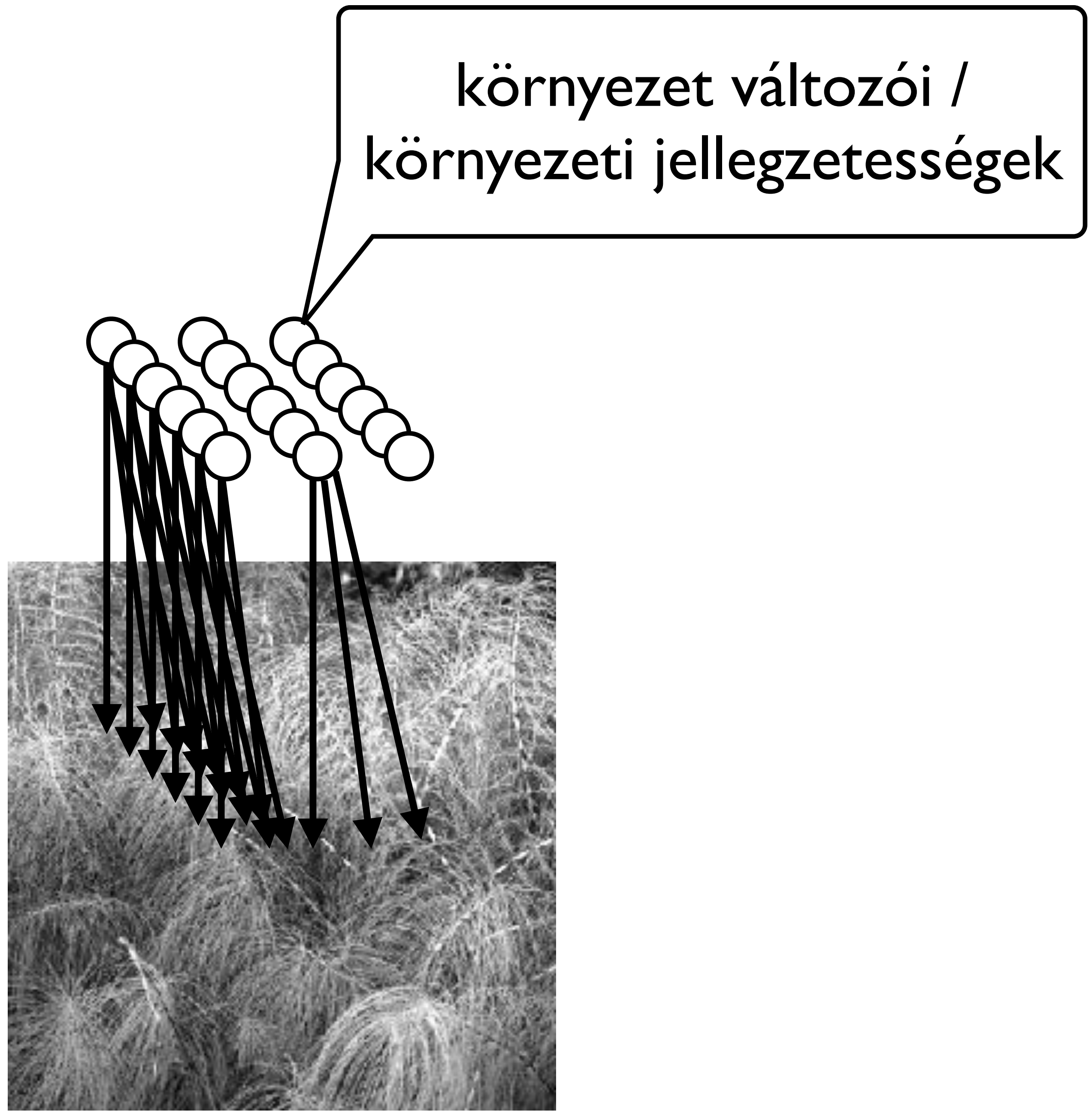


Természetes képek generatív modelljei



Természetes képek generatív modelljei



- Mit mondhatunk az agy által használt modellről?

Principla component analysis

Principla component analysis

$$x = \mathbf{A} \cdot z + \epsilon$$

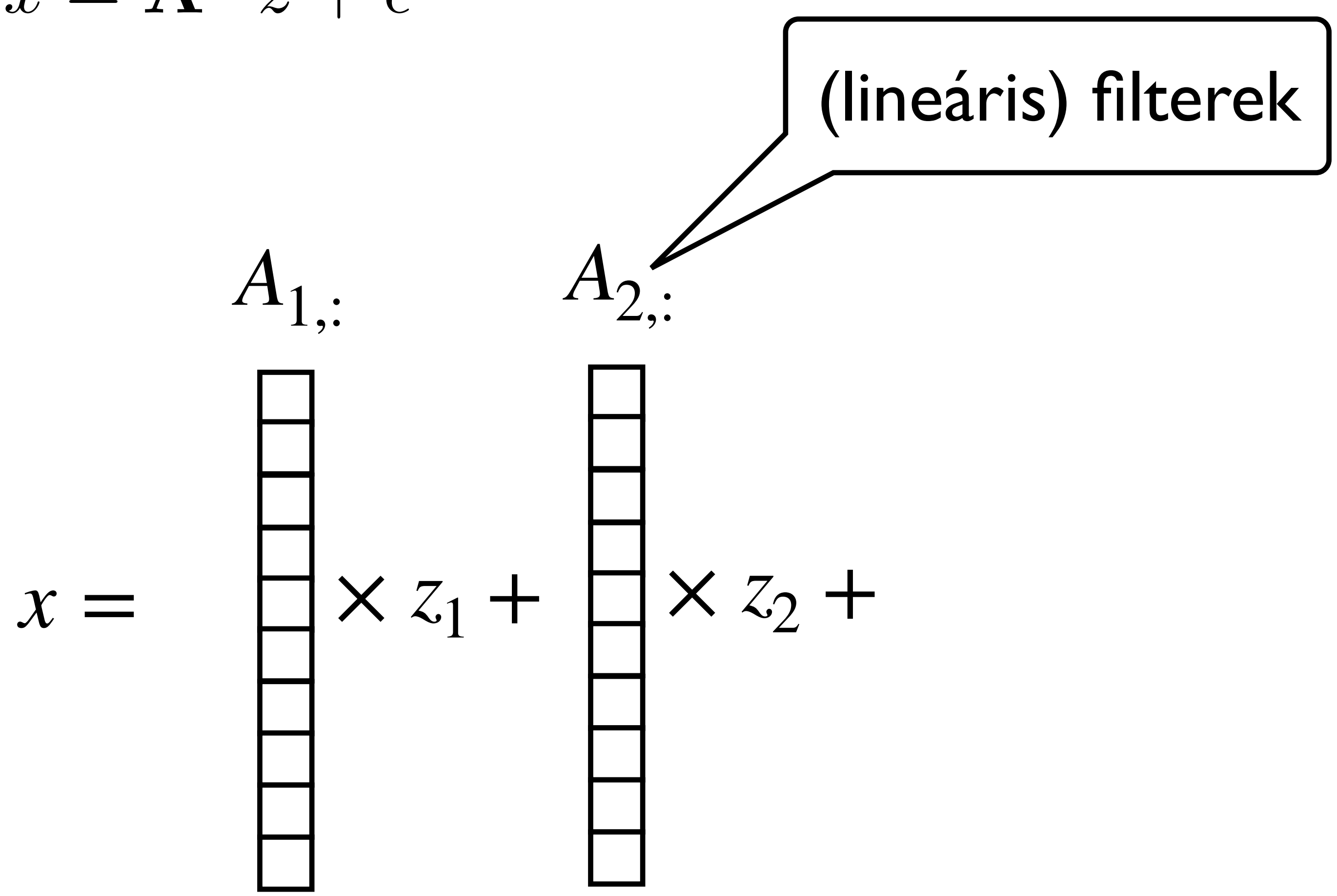
Principla component analysis

$$x = \mathbf{A} \cdot z + \epsilon$$

$$x = \underset{A_{1,:}}{\square} \times z_1 + \underset{A_{2,:}}{\square} \times z_2 +$$

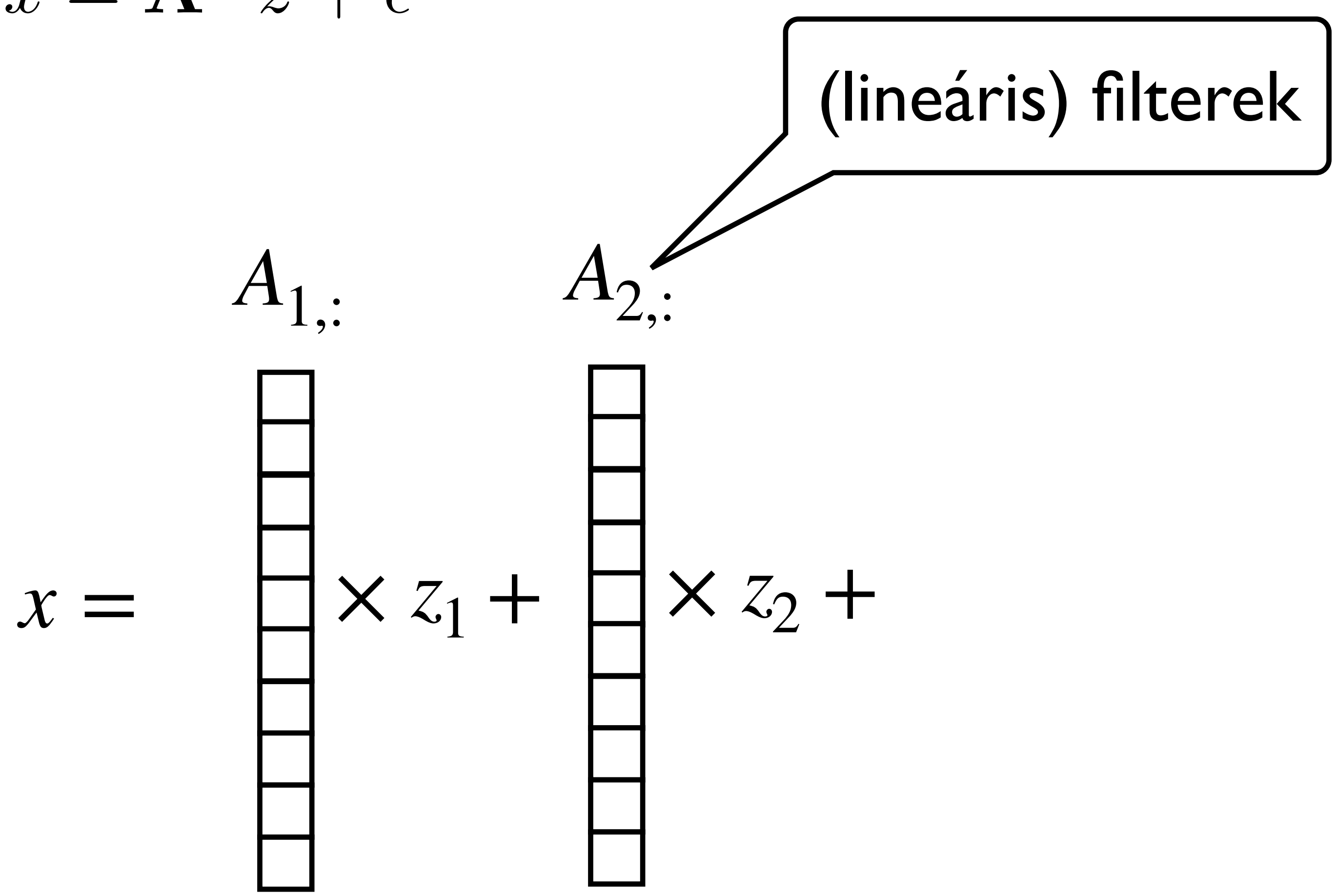
Principla component analysis

$$x = \mathbf{A} \cdot z + \epsilon$$



Principla component analysis

$$x = \mathbf{A} \cdot z + \epsilon$$

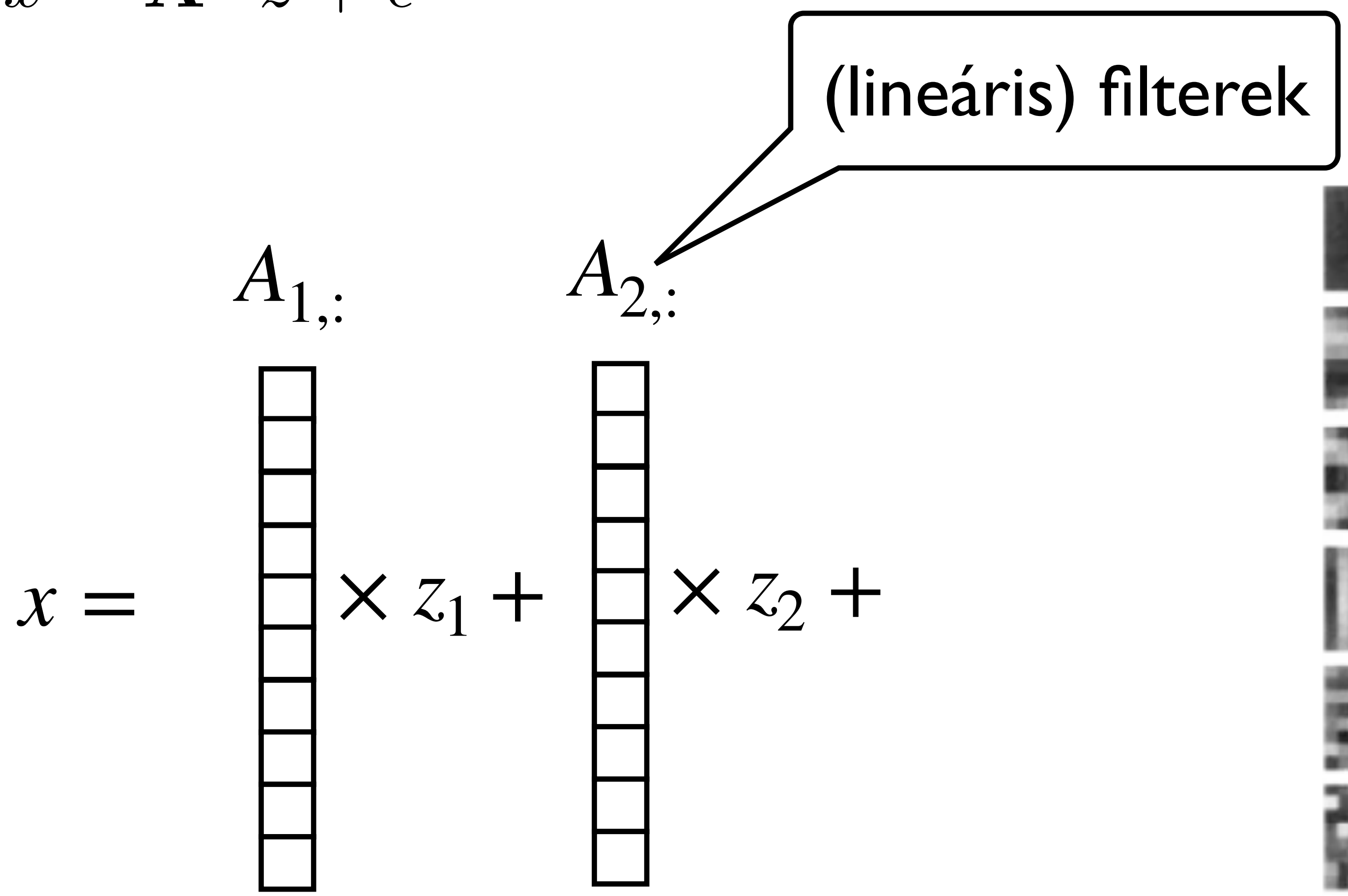


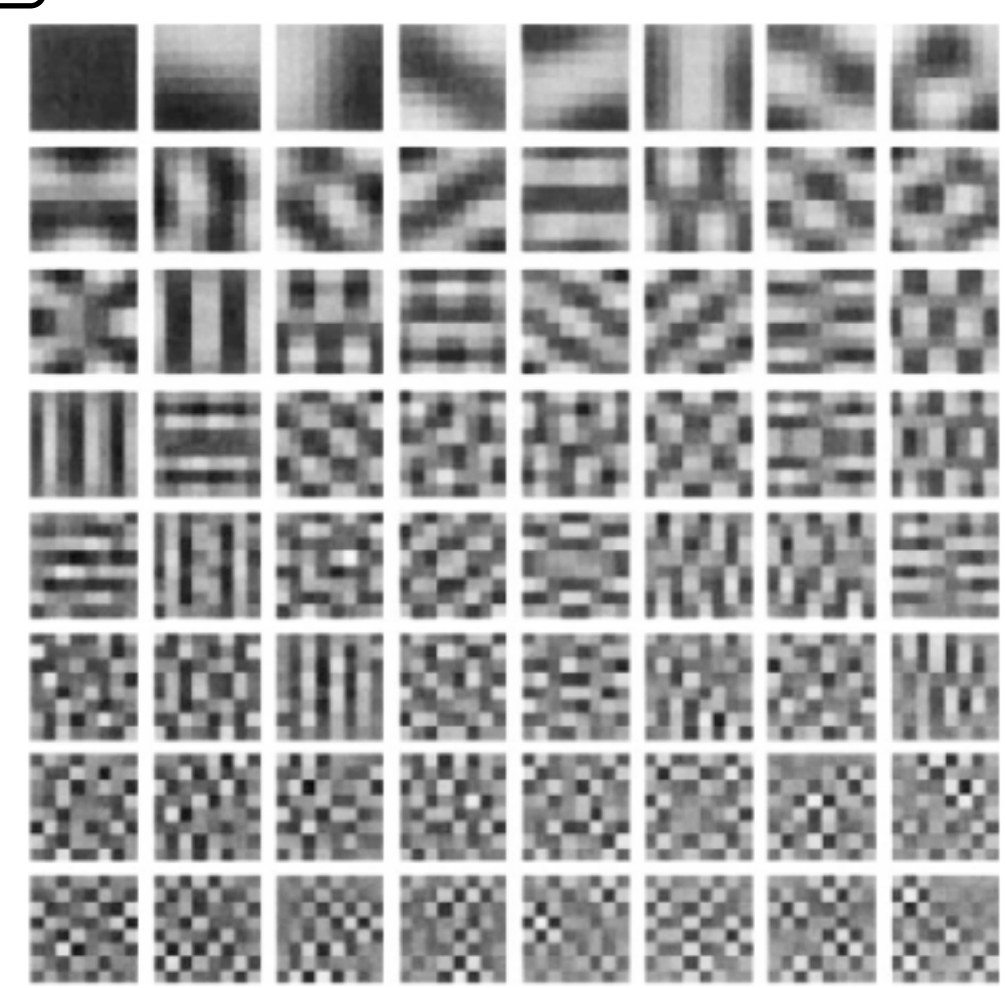
PCA

- $\epsilon \to 0$
- A oszlopvektorai ortogonalisak
- D(x) = D(z)

Principla component analysis

$$x = \mathbf{A} \cdot z + \epsilon$$

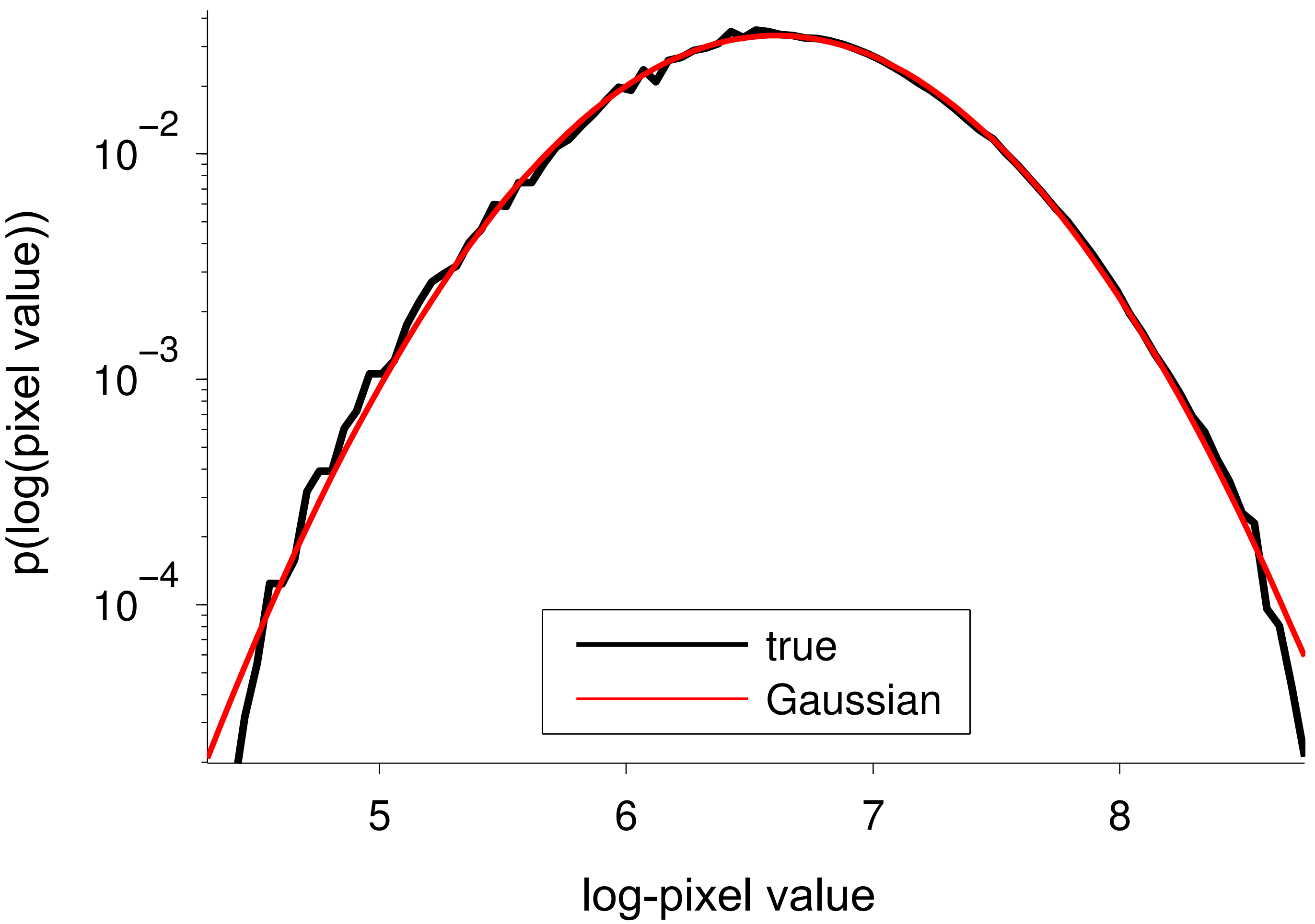




PCA

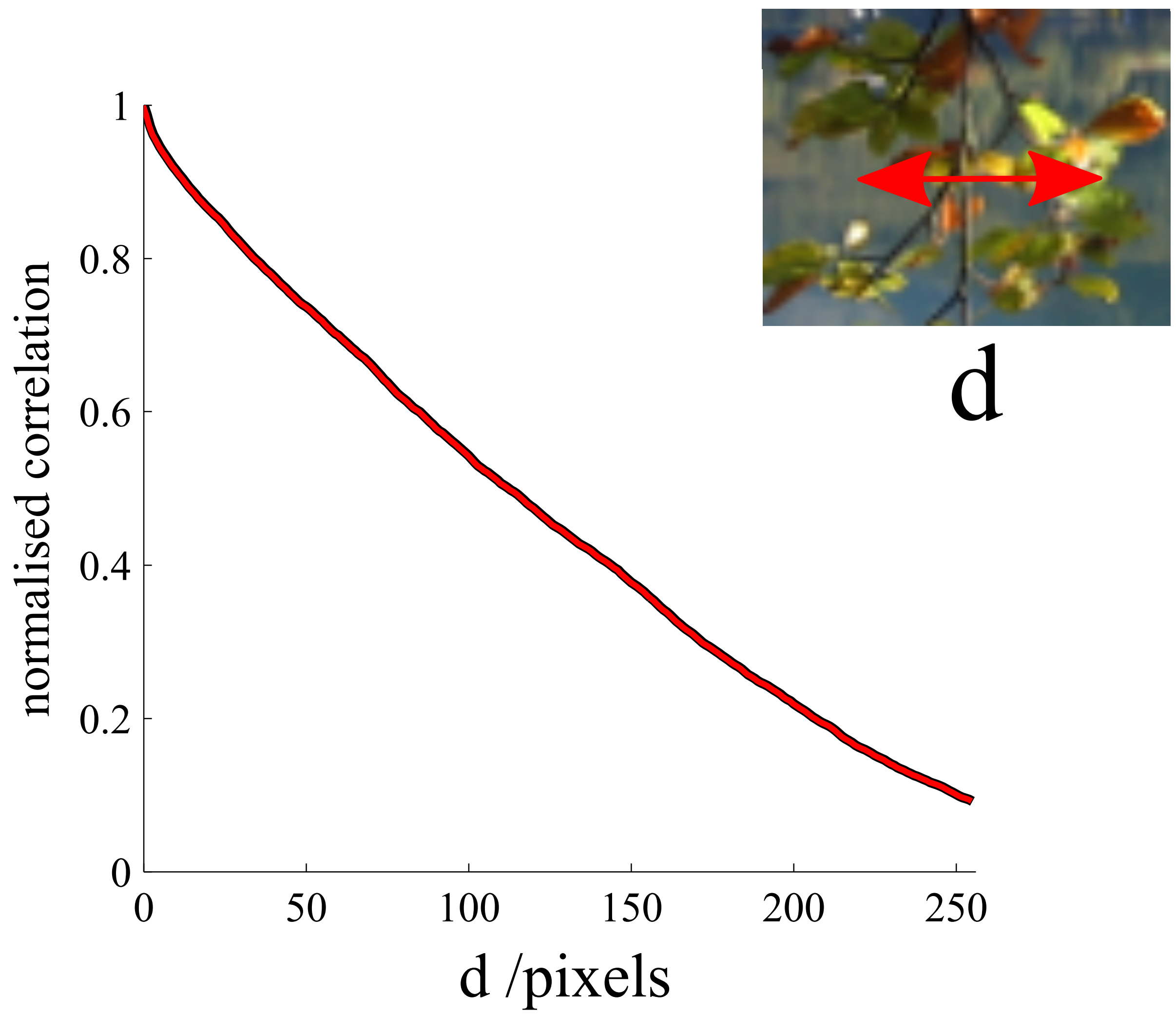
- $\epsilon \to 0$
- A oszlopvektorai ortogonalisak
- D(x) = D(z)

Marginális statisztika

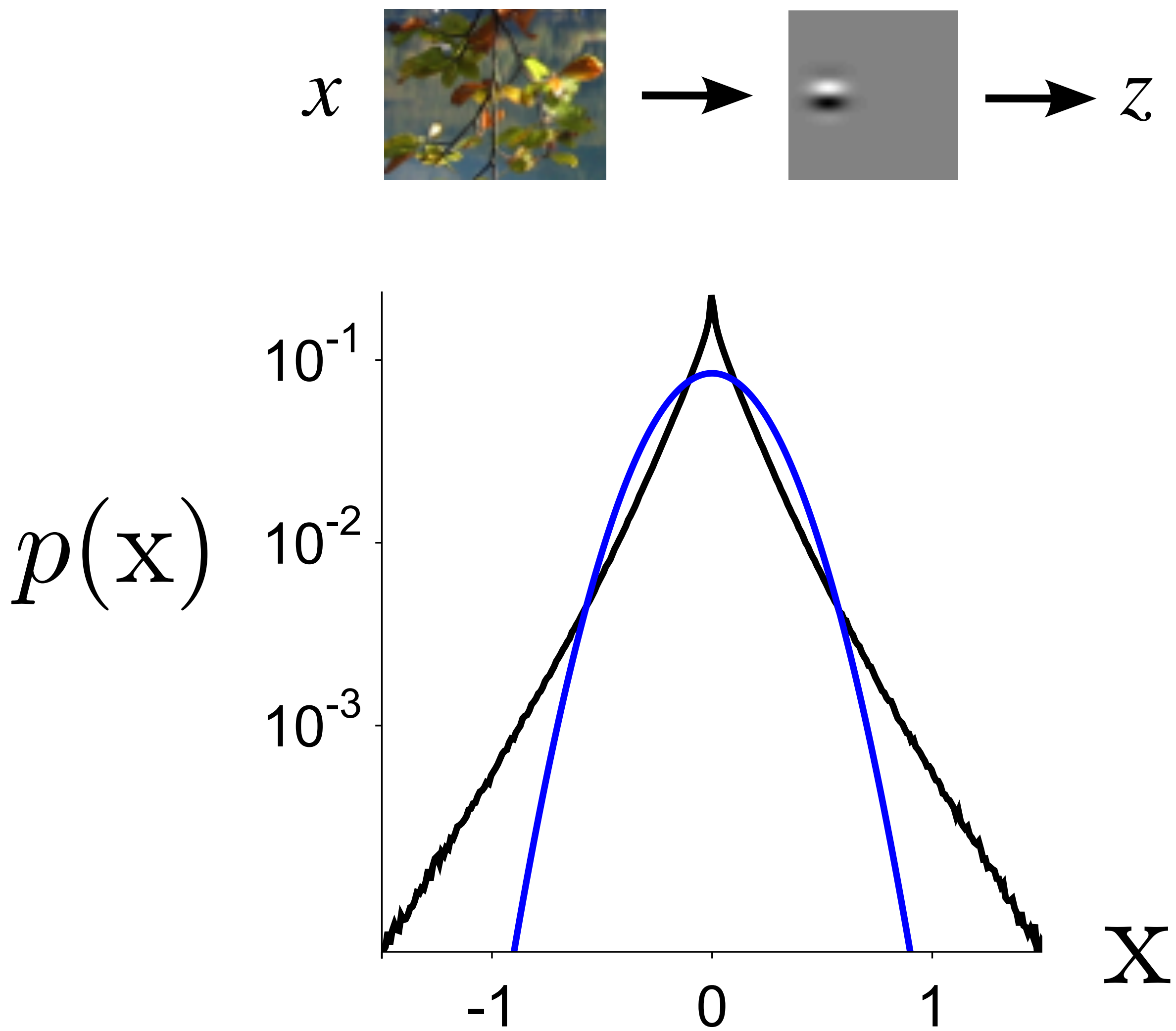


Ruderman, 1994

Pixel korrelációk



Magasabb rendű statisztika: ritkaság



Independent component analysis

- “z”-k függetlenek
- y priorja “ritka”(P(z))

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Independent component analysis

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- “z”-k függetlenek
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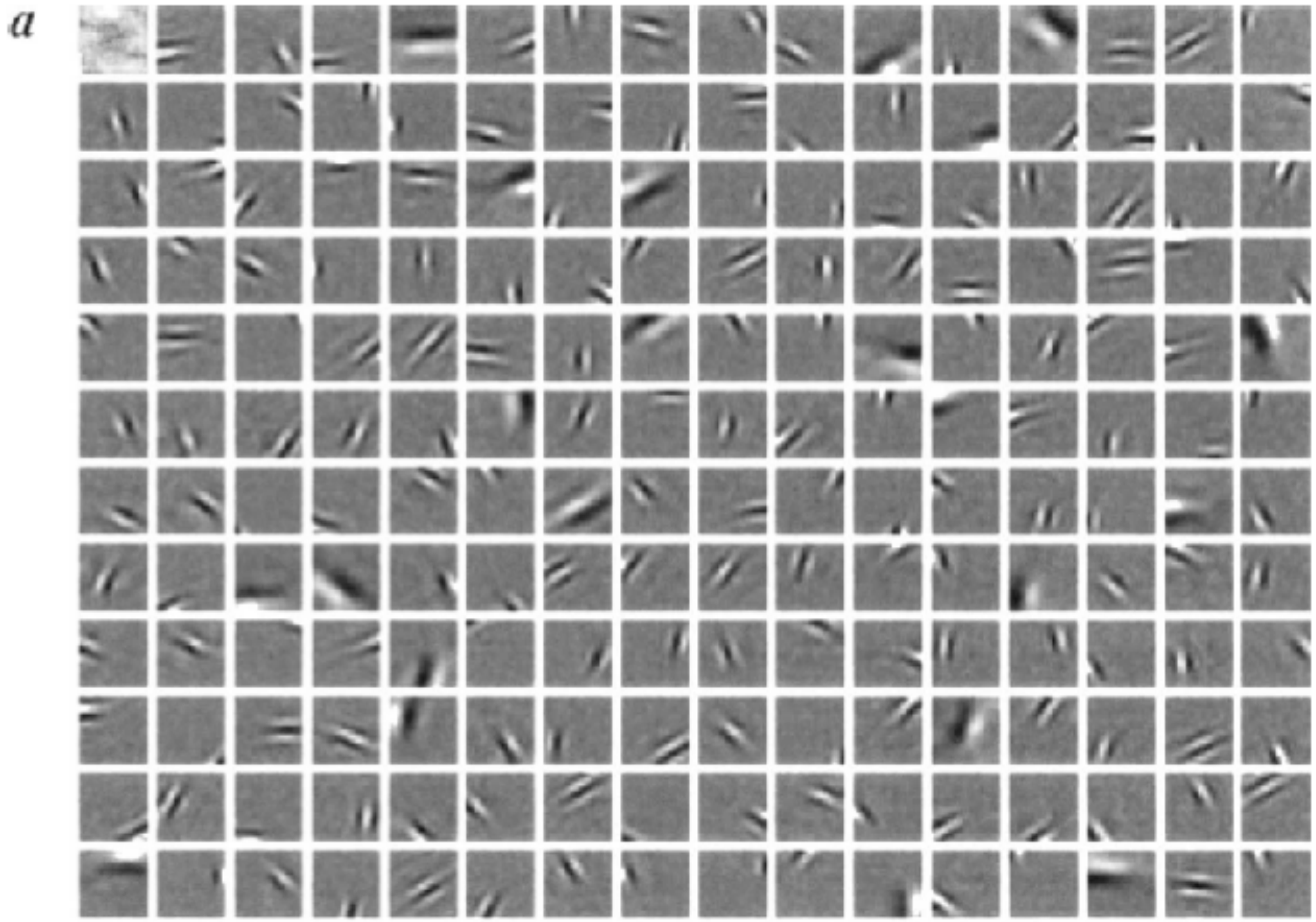
Komputációs kritériumok:

- Hiteles rekonstrukció
  költség egy adatpontra (képre):
  $$\mathrm{cost}_1 = \left(x - \sum_i A'_i \cdot z_i \right)^2$$
- Kis “energiafelhasználás (kevés szimultán aktiv neuron)
  további költség a kód “ritkasága”:
  $$\mathrm{cost}_2 = -\sum_i S\left(\frac{z_i}{\sigma}\right)$$
  S a Gauss-nál nagyobb kurtózissal bíró eloszlás
- teljes költség (~energia):
  $$E = -\mathrm{cost}_1 - \lambda \mathrm{cost}_2$$

Sparse kódolás: eredmény

tréningezés természetes képekkel

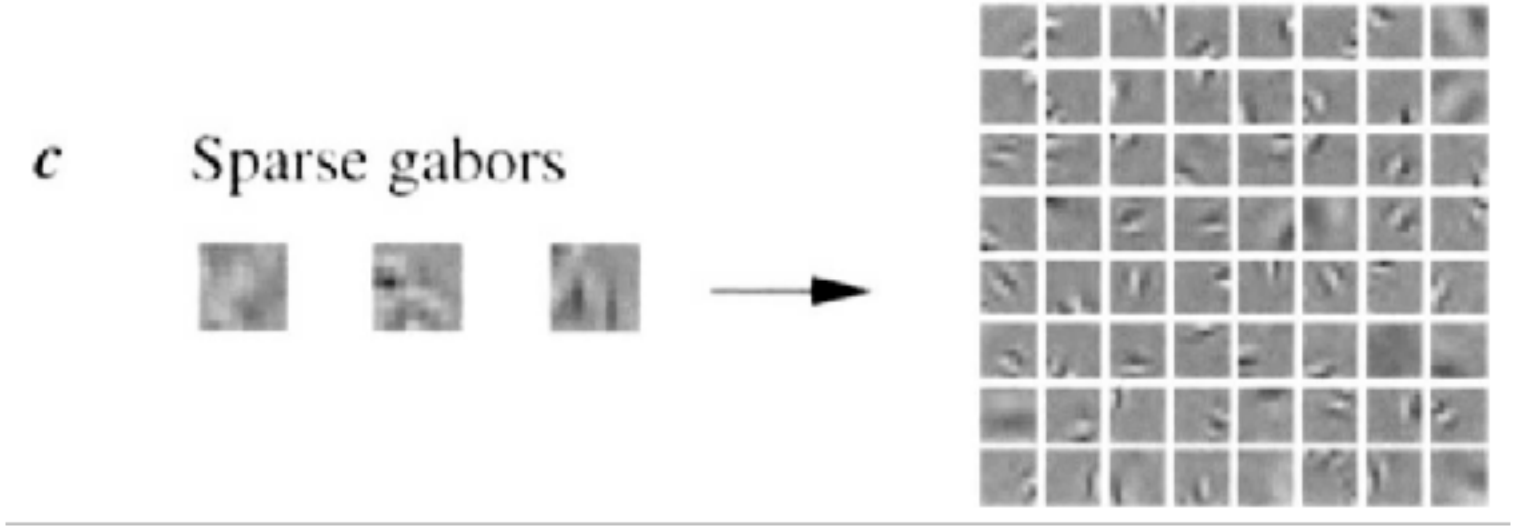


Olshausen & Field '96

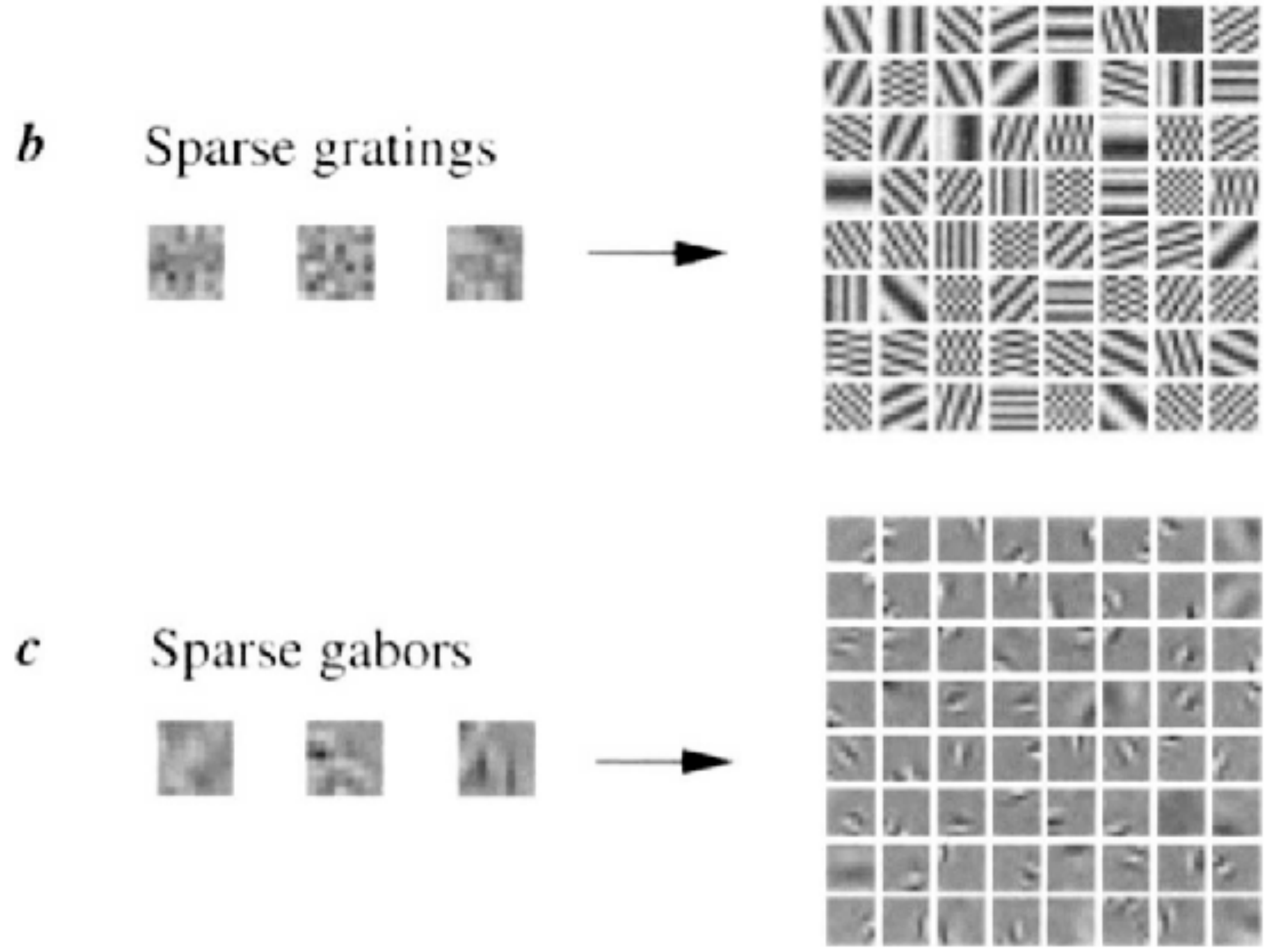
A kialakult bázis:

- irányított
- térbeli sávszűrést valósít meg
- lokalizált

Tanulás és stimulus statisztika



Tanulás és stimulus statisztika



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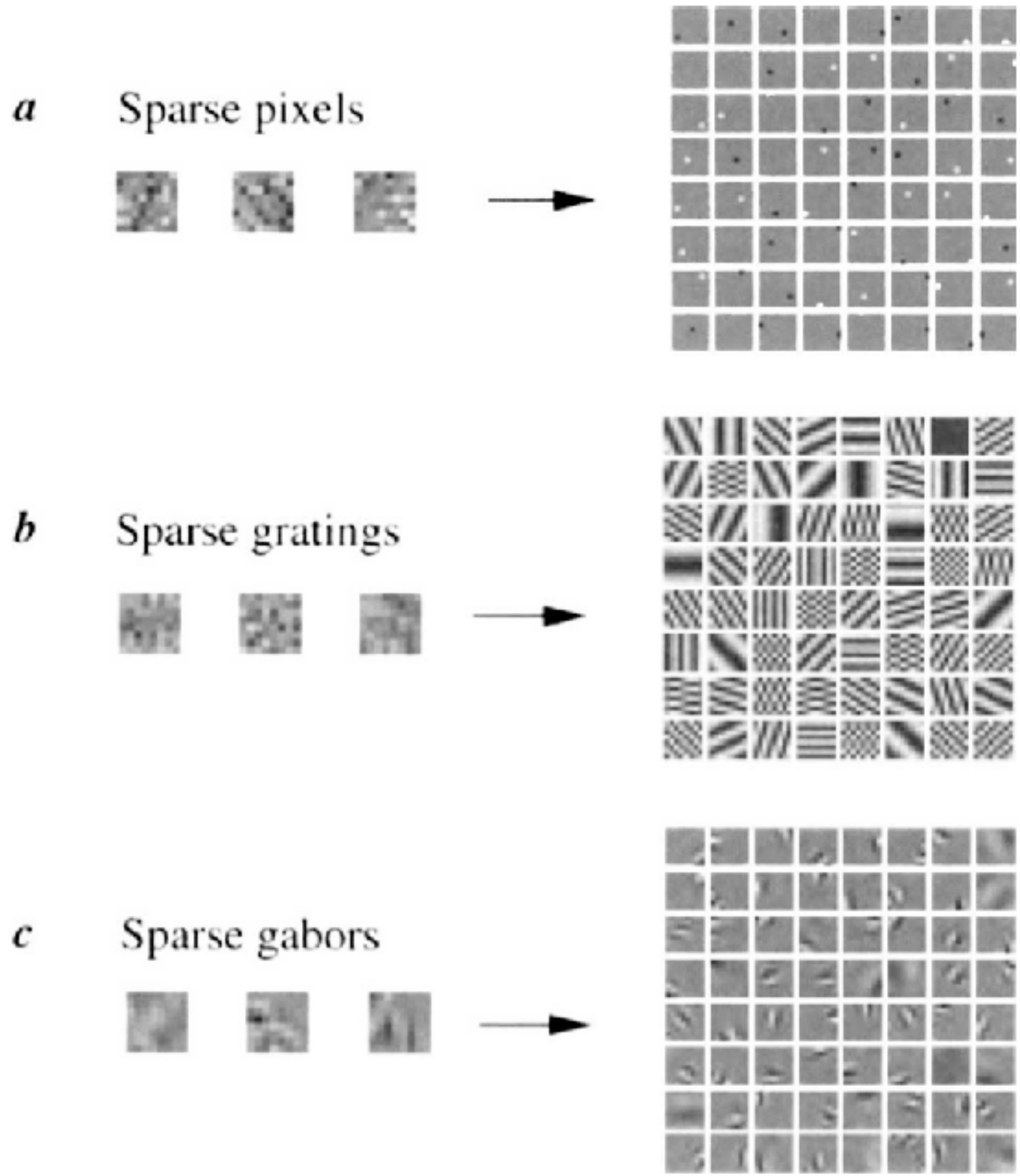
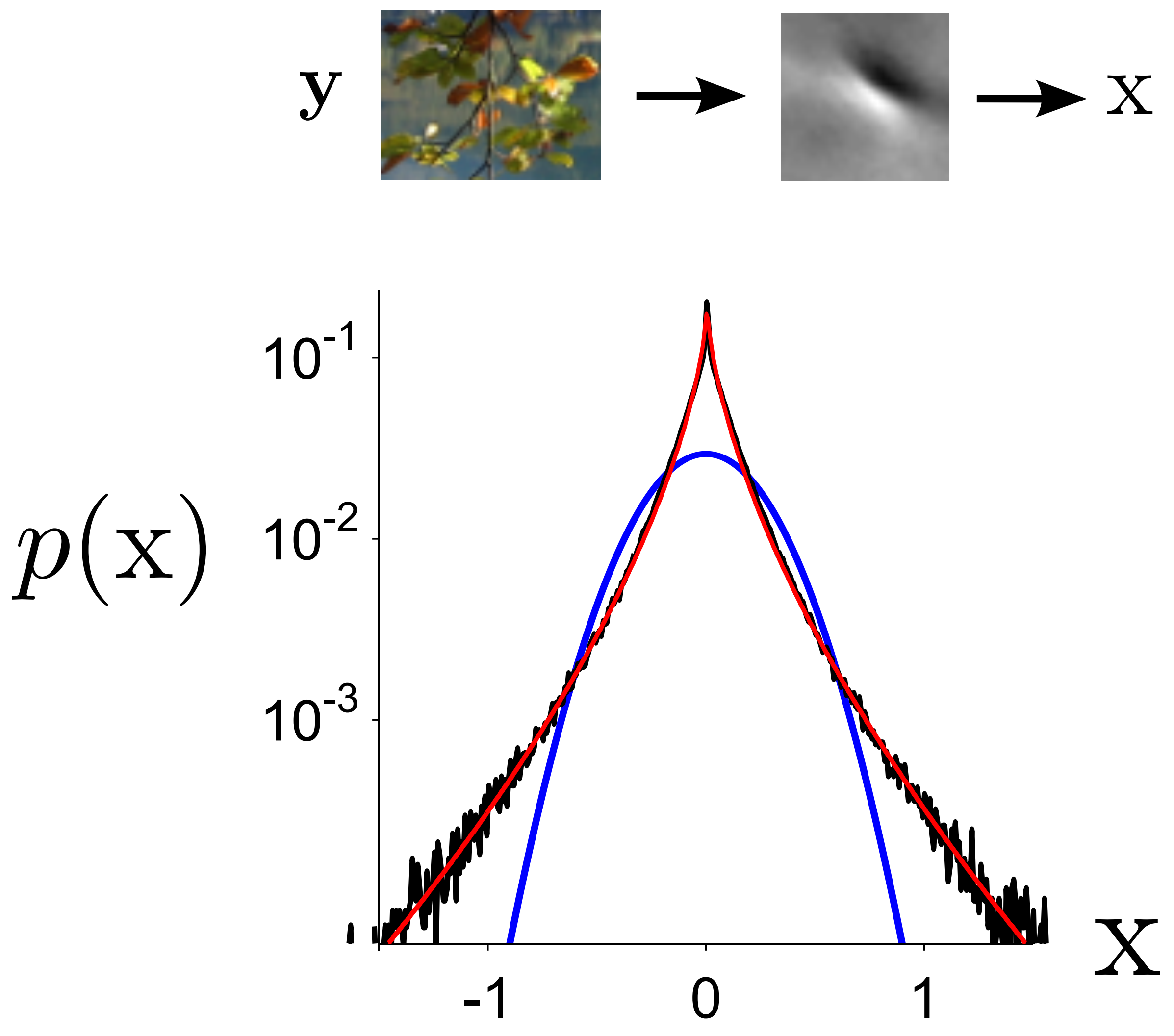
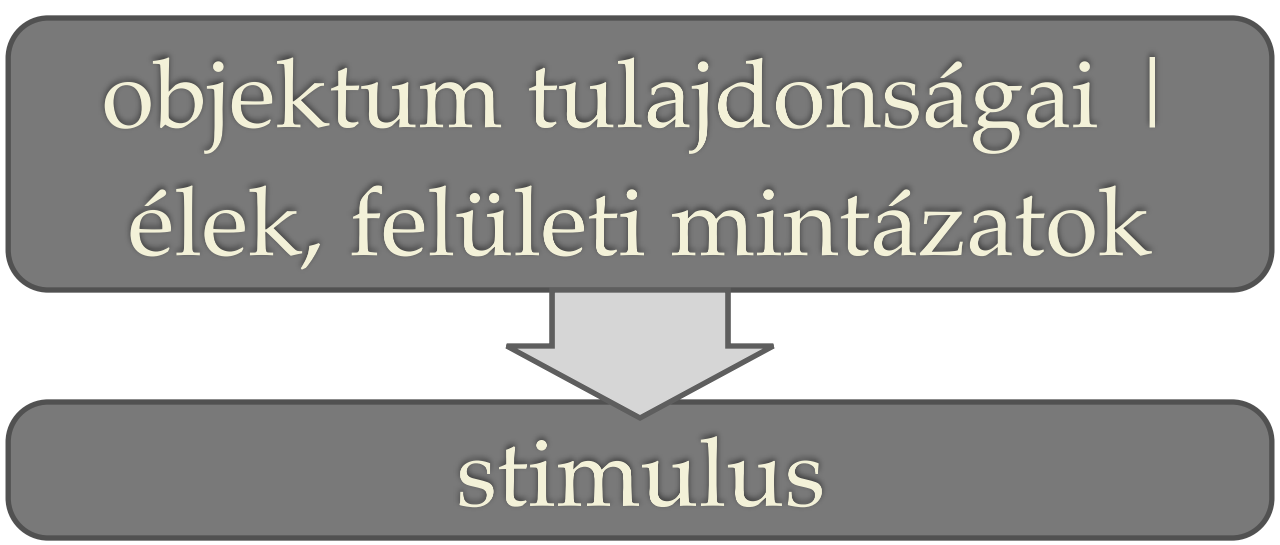


Magasabb rendű korrelációk: ritkaság



Lineáris modellek



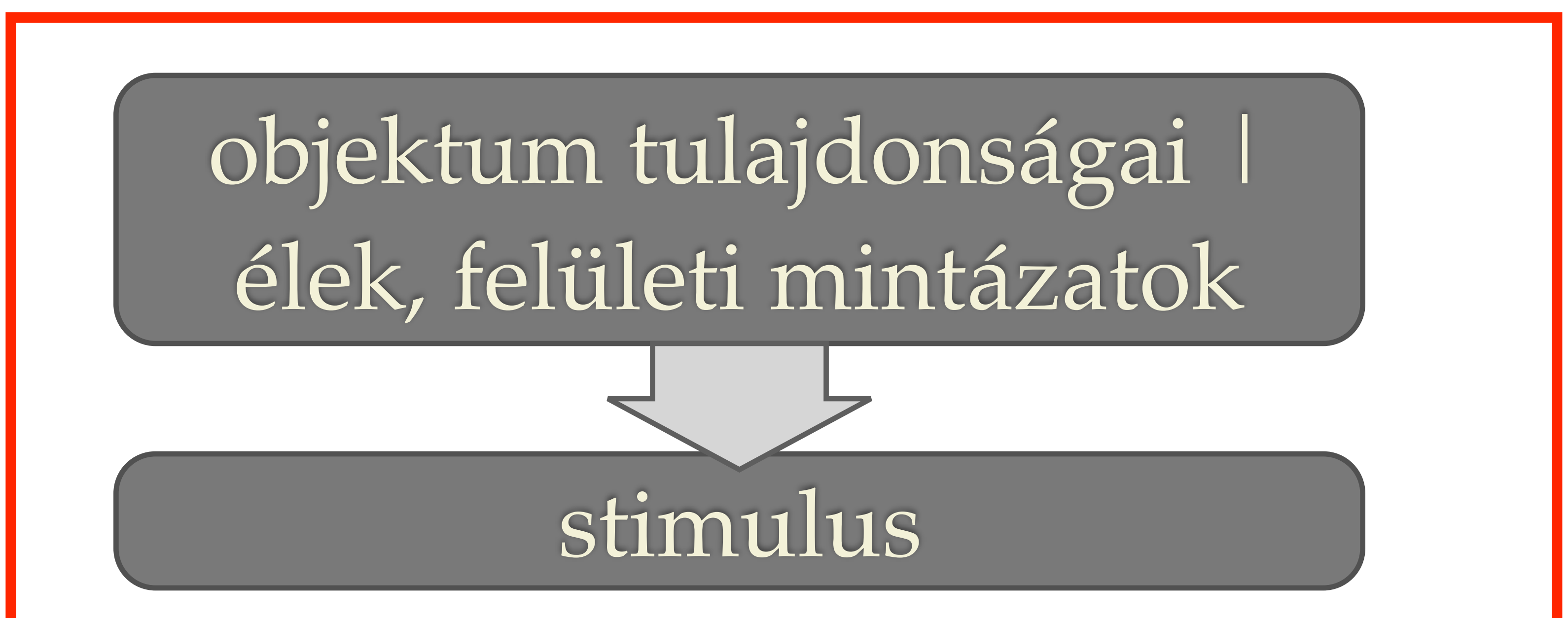
Lineáris modellek

$x = A\ z + eps$

Lineáris modellek

V1 receptive mezők:
- orientált
- sáváteresztő
- lokalizált

x = A z + eps



Indepedens komponensek

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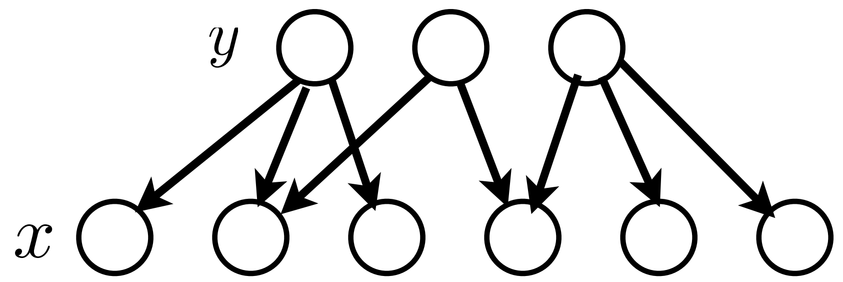
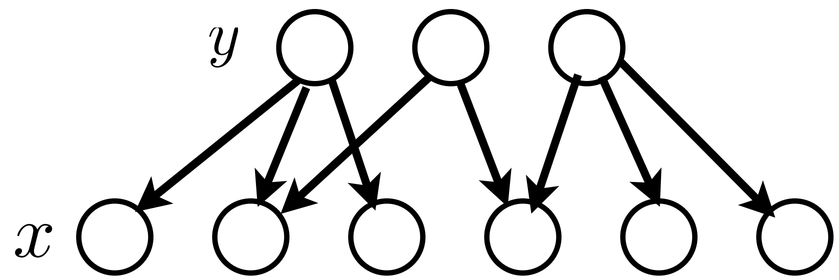
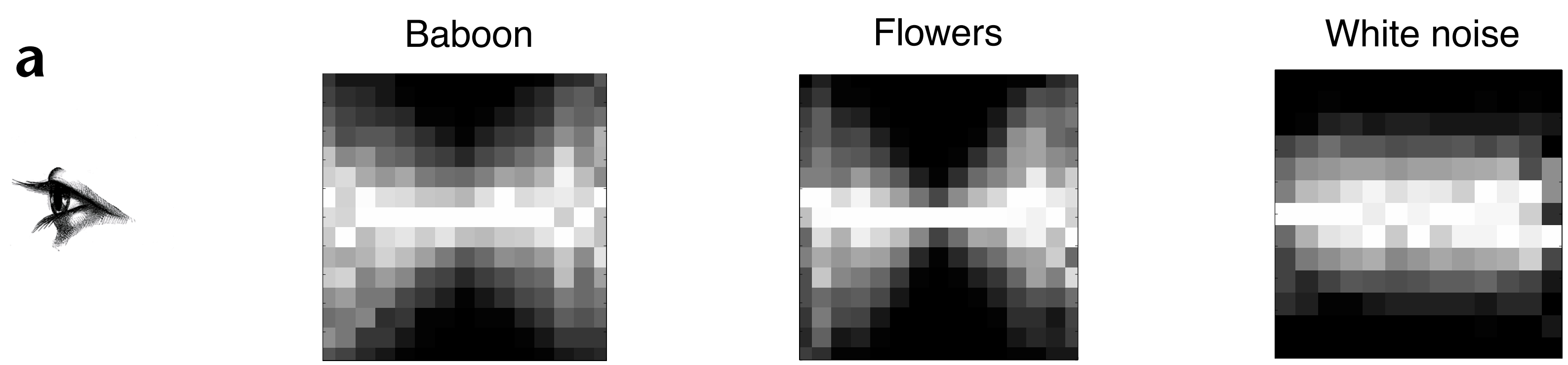


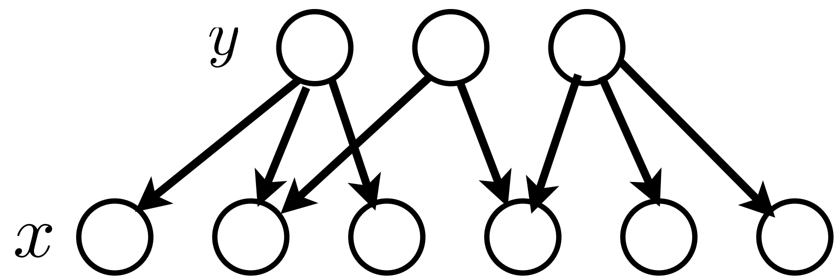
Independens komponensek

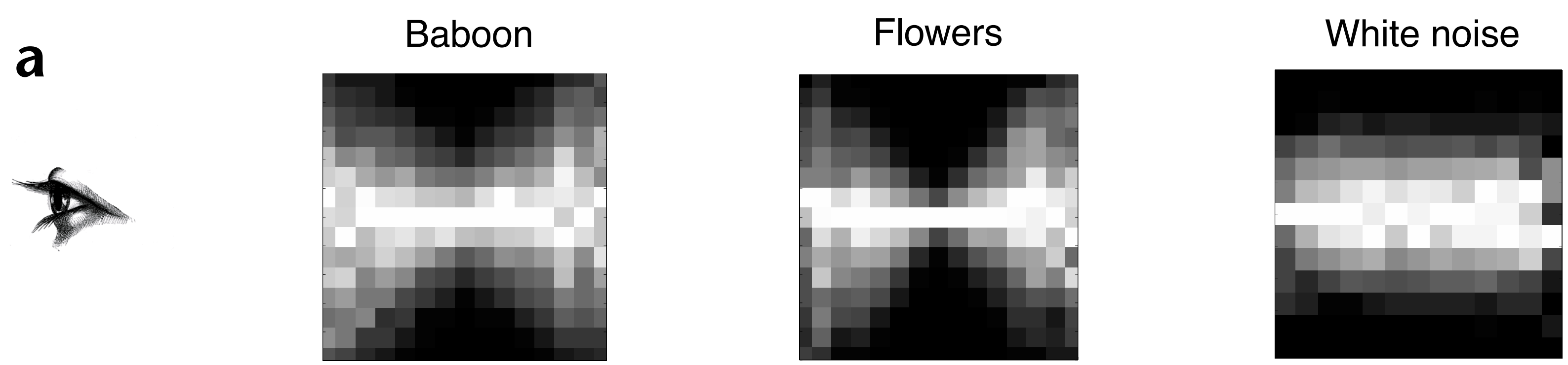




Schwartz & Simoncelli, 2001

Independens komponensek

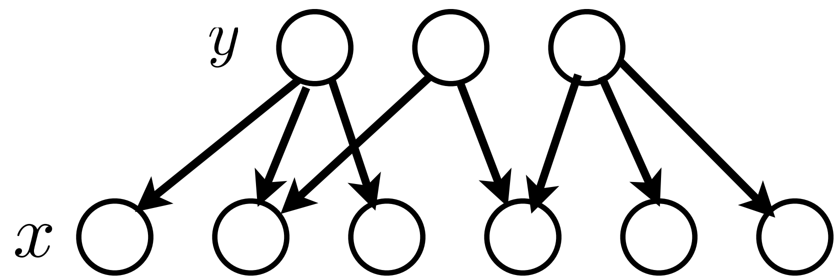


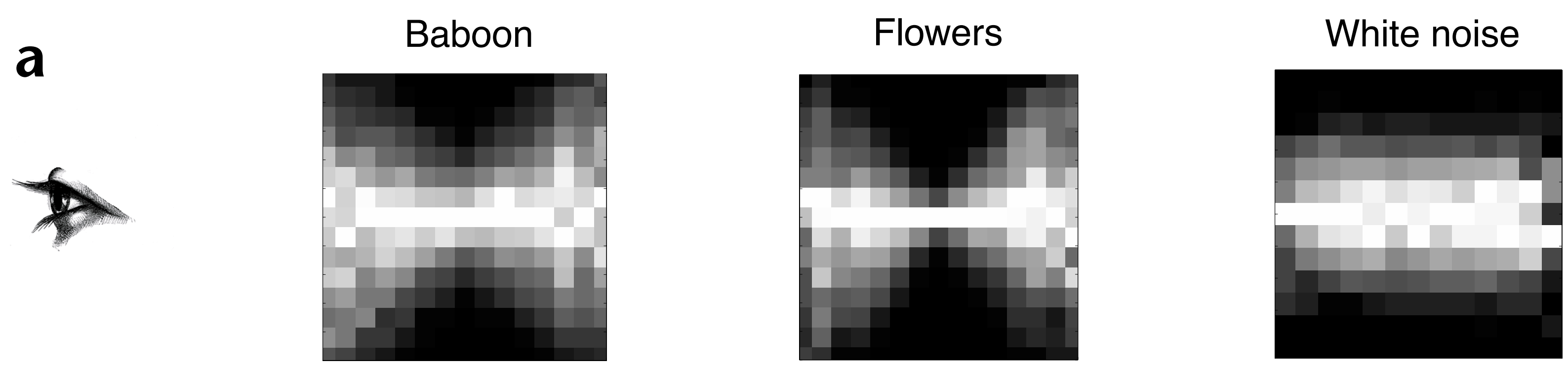


Schwartz & Simoncelli, 2001

$$\mathrm{var}(y_1 | y_2) = w y_2^2 + \sigma^2$$

Independens komponensek





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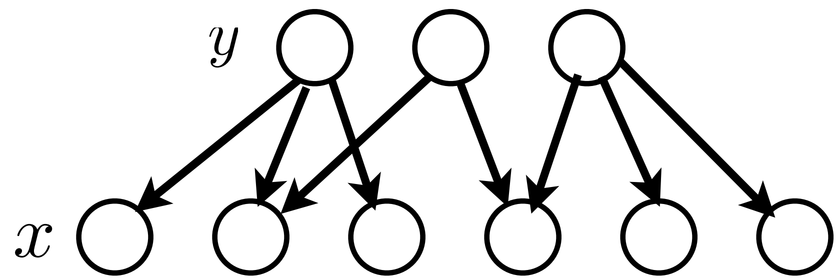
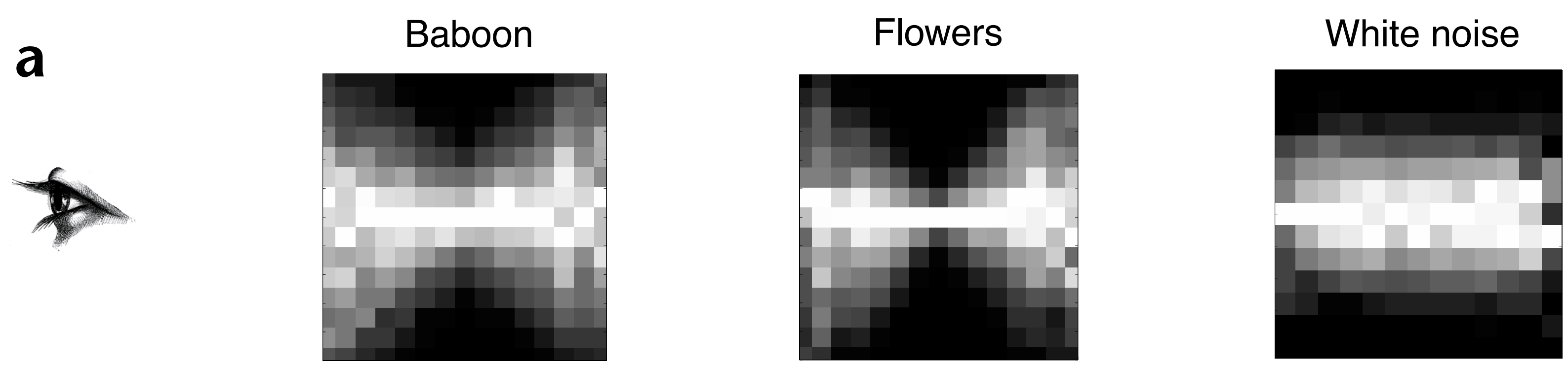
amennyiben y_1 aktivitását normalizáljuk

$$R_1 = \frac{y_1^2}{w y_2^2 + \sigma^2}$$

akkor a függés eliminálható

Independens komponensek





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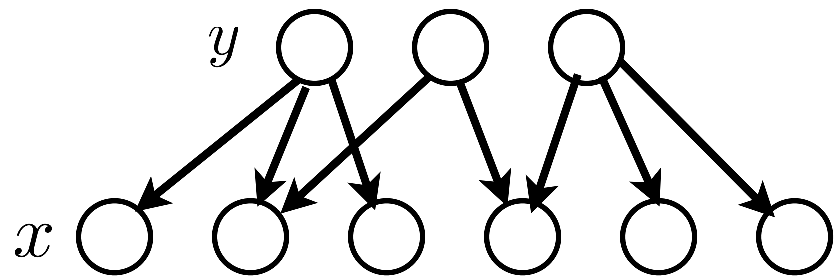
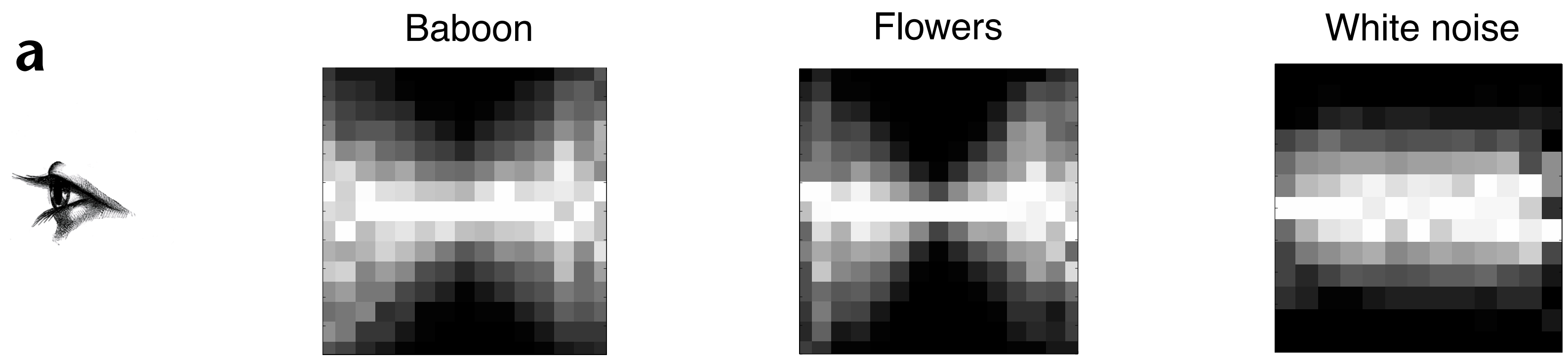
feltételezés: analóg módon több másik sejtre: $R_i = \dfrac{y_i^2}{\sum_j w_{ji} y_j^2 + \sigma^2}$

Independens komponensek





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amennyiben y_1 aktivitását normalizáljuk

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akkor a függés eliminálható

divizív nomarlizáció

feltételezés: analóg módon több másik sejtre: $R_i = \dfrac{y_i^2}{\sum_j w_{ji} y_j^2 + \sigma^2}$

Scale Mixtures of Gaussians and the Statistics of Natural Images

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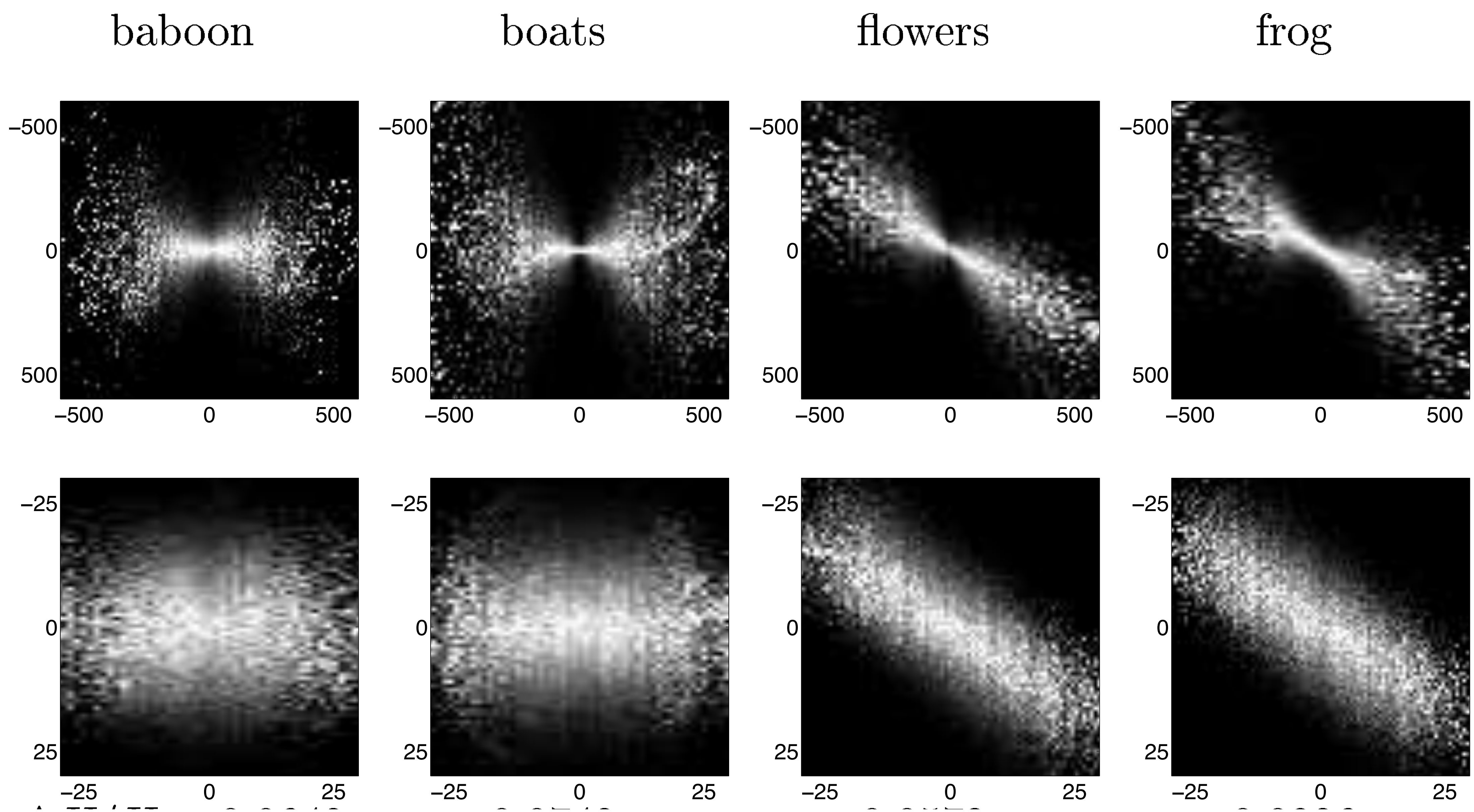
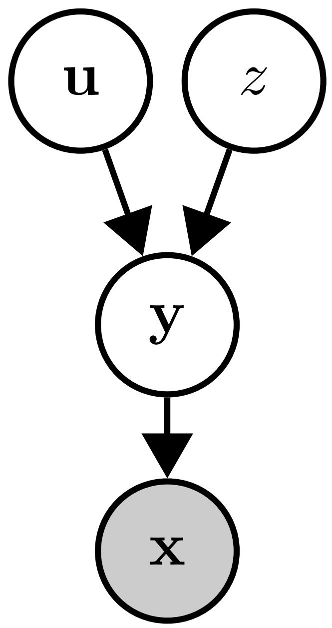
Abstract

The statistics of photographic images, when represented using multiscale (wavelet) bases, exhibit two striking types of non-Gaussian behavior. First, the marginal densities of the coefficients have extended heavy tails. Second, the joint densities exhibit variance dependencies not captured by second-order models. We examine properties of the class of Gaussian scale mixtures, and show that these densities can accurately characterize both the marginal and joint distributions of natural image wavelet coefficients. This class of model suggests a Markov structure, in which wavelet coefficients are linked by hidden scaling variables corresponding to local image structure. We derive an estimator for these hidden variables, and show that a nonlinear "normalization" procedure can be used to Gaussianize the coefficients.


baboon
boats
flowers
frog
−500
0
500
−25
25

Gaussian Scale Mixtures



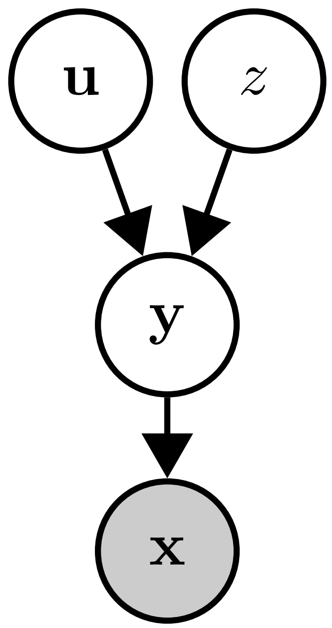
$$
\begin{aligned}
\mathrm{P}(\mathbf{x}|\mathbf{y}) &= \mathcal{N}\big(\mathbf{x}; \mathbf{A}\mathbf{y}, \sigma_{\mathrm{x}}^2 \mathbf{I}\big)
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{y} &= z\,\mathbf{u} \\
\mathrm{P}(\mathbf{u}) &= \mathcal{N}(\mathbf{u}; \mathbf{0}, \mathbf{C}) \\
\mathrm{P}(z) &= \mathrm{Gamma}(z; k, \theta)
\end{aligned}
$$

1

image

Gaussian Scale Mixtures



$$\mathrm{P}(\mathbf{x}|\mathbf{y}) = \mathcal{N}\big(\mathbf{x}; \mathbf{A}\mathbf{y}, \sigma_{\mathrm{x}}^2 \mathbf{I}\big)$$

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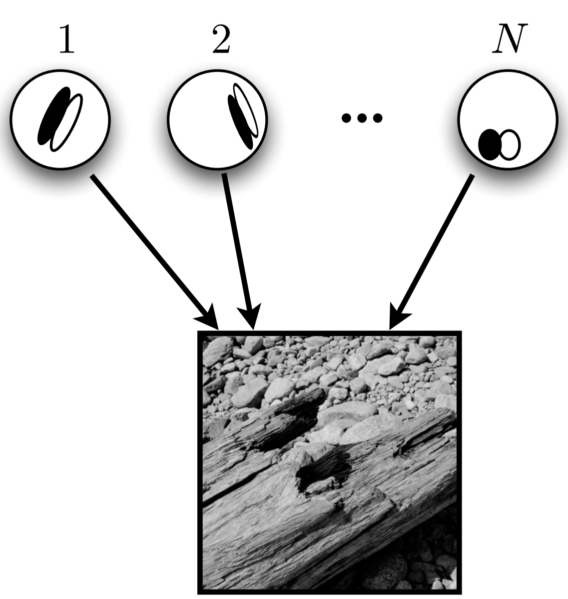
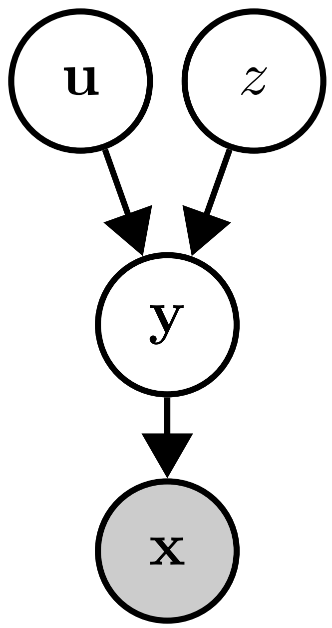
linear features



image

Gaussian Scale Mixtures



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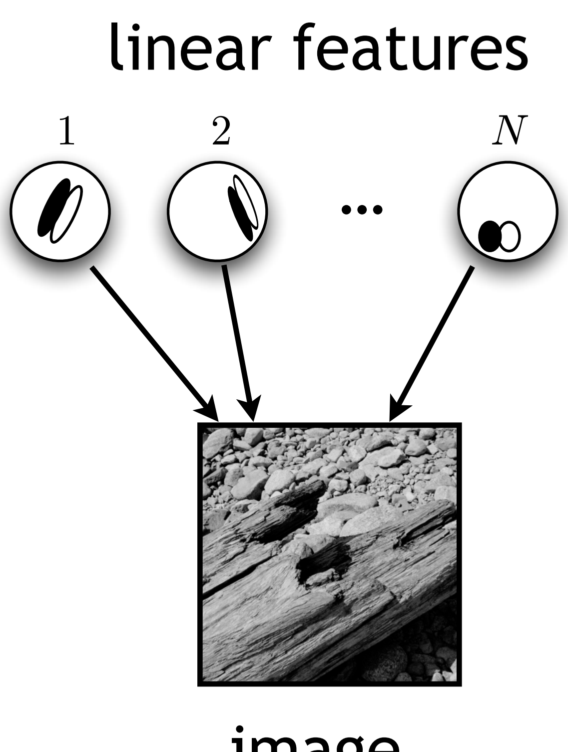
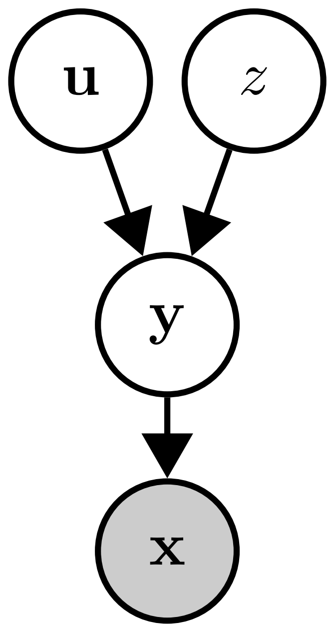
\end{aligned}
$$

$$
\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}
$$



Gaussian Scale Mixtures



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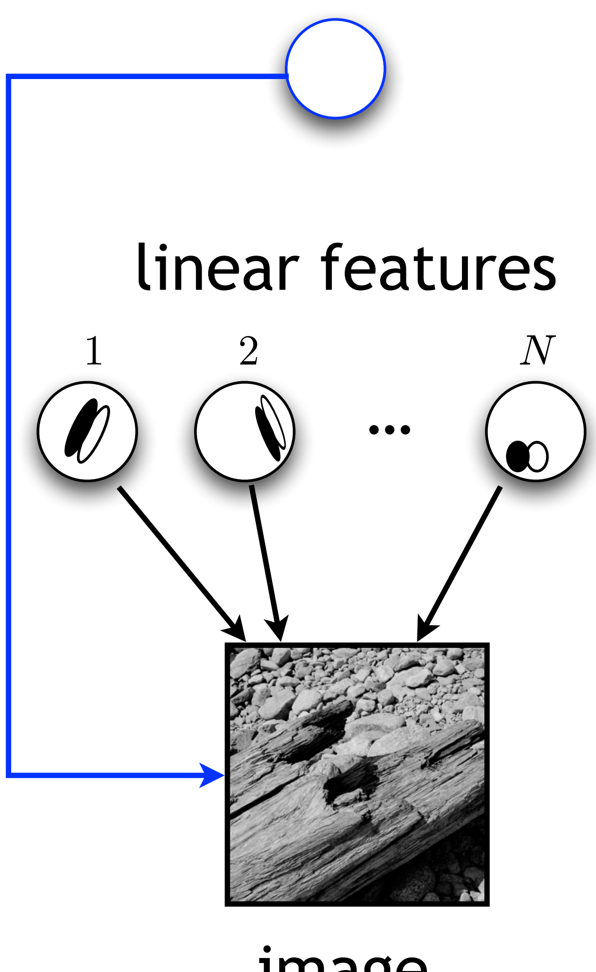
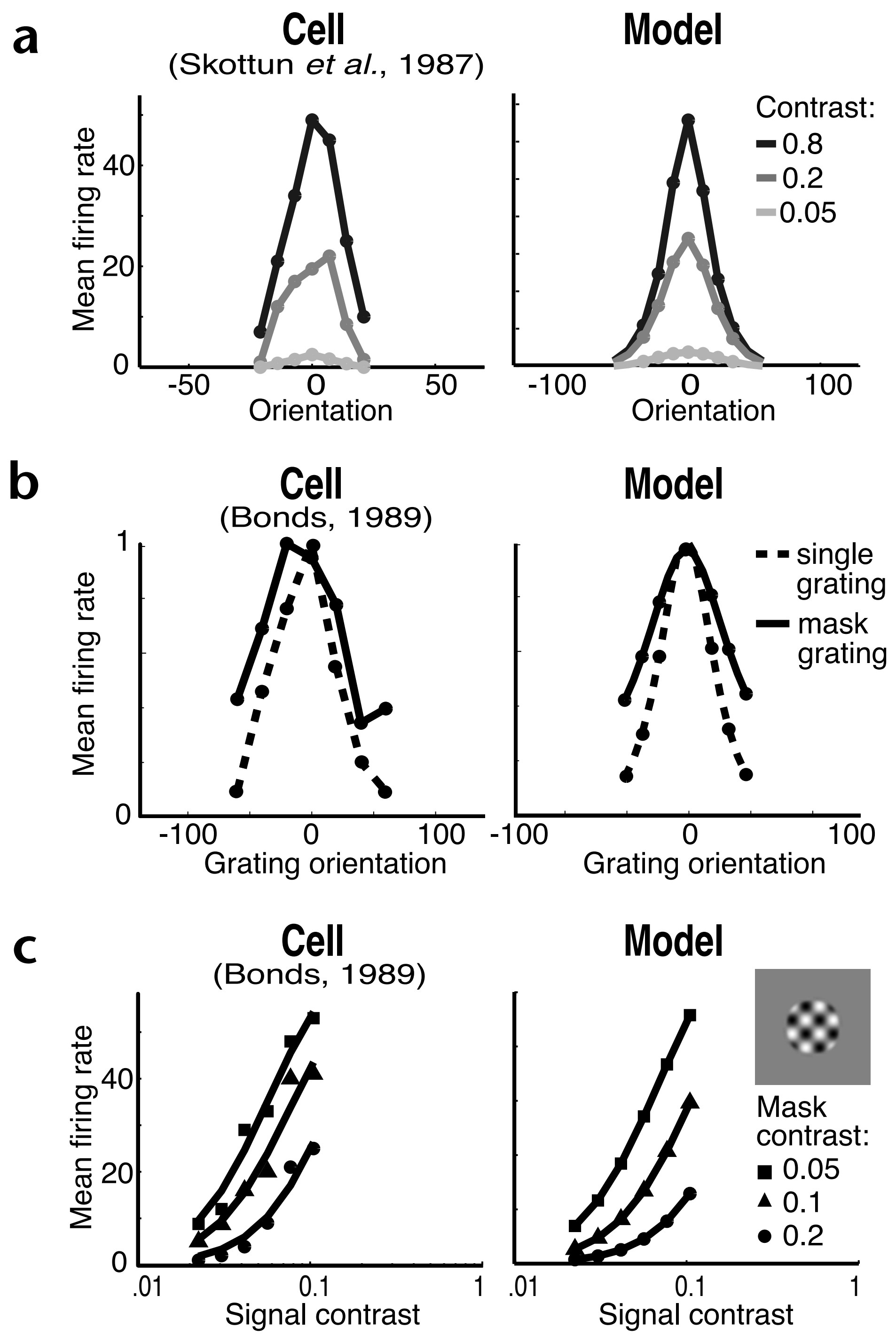
\mathbf{y} &= z\,\mathbf{u} \\
\mathrm{P}(\mathbf{u}) &= \mathcal{N}(\mathbf{u}; \mathbf{0}, \mathbf{C}) \\
\mathrm{P}(z) &= \mathrm{Gamma}(z; k, \theta)
\end{aligned}
$$

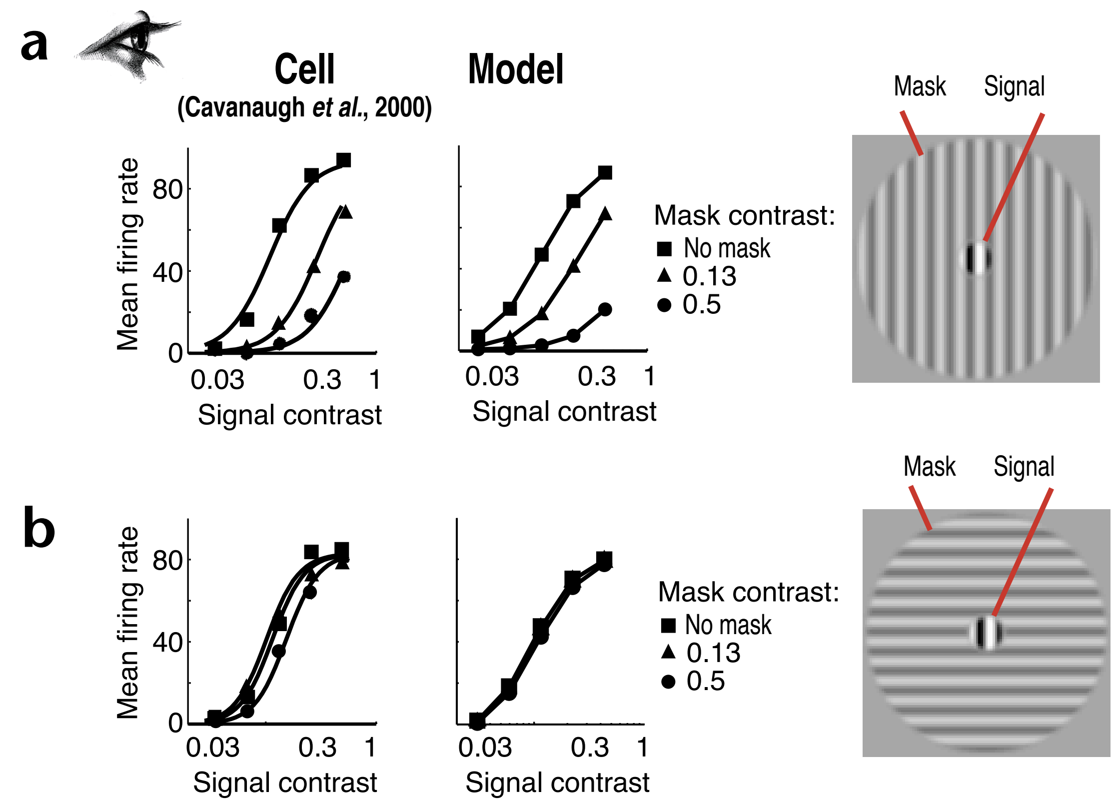


$$\text{image} = \text{contrast} \times \left(a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}\right)$$

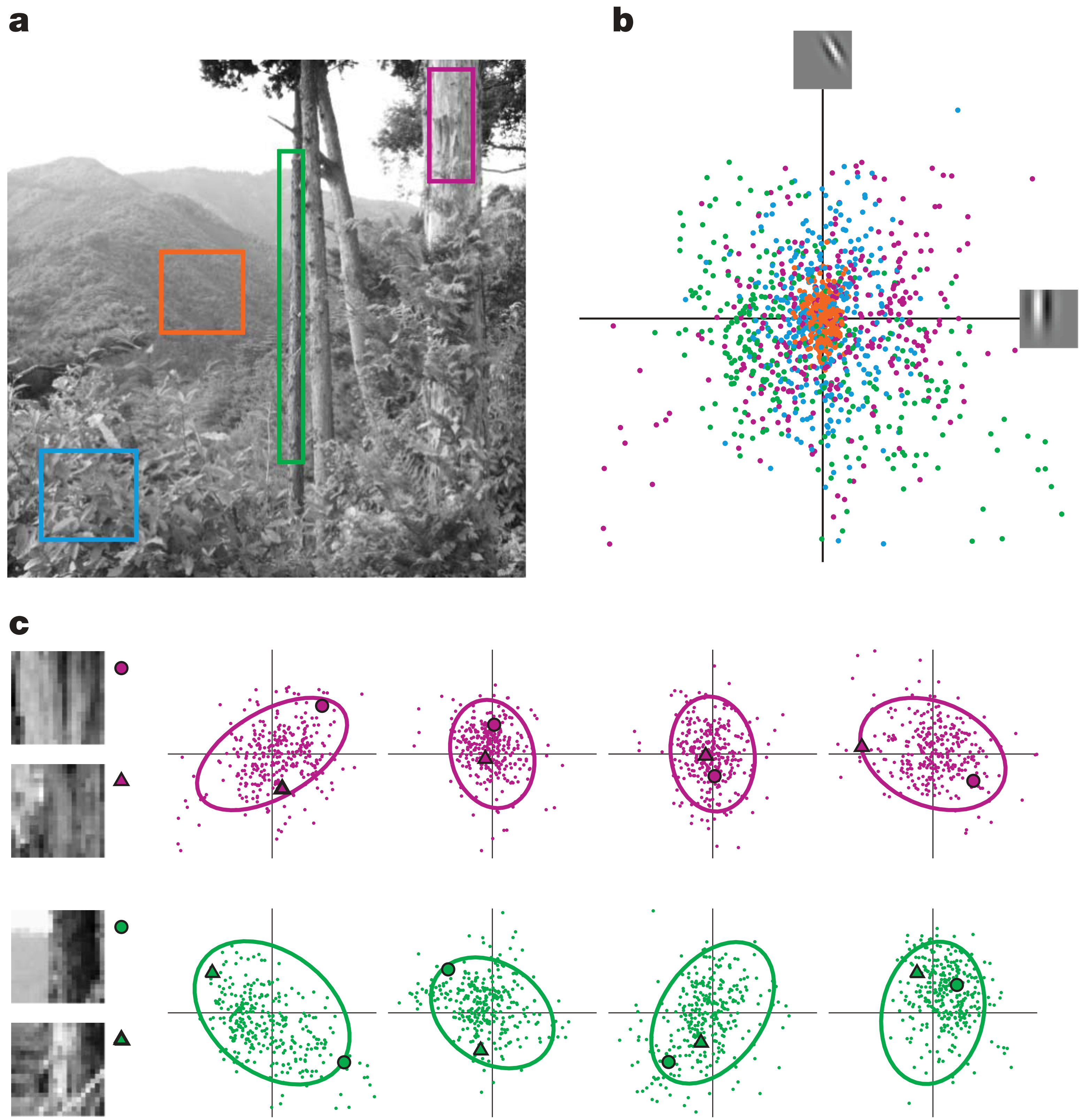
Neurális adatok és GSM



Schwartz & Simoncelli, 2001

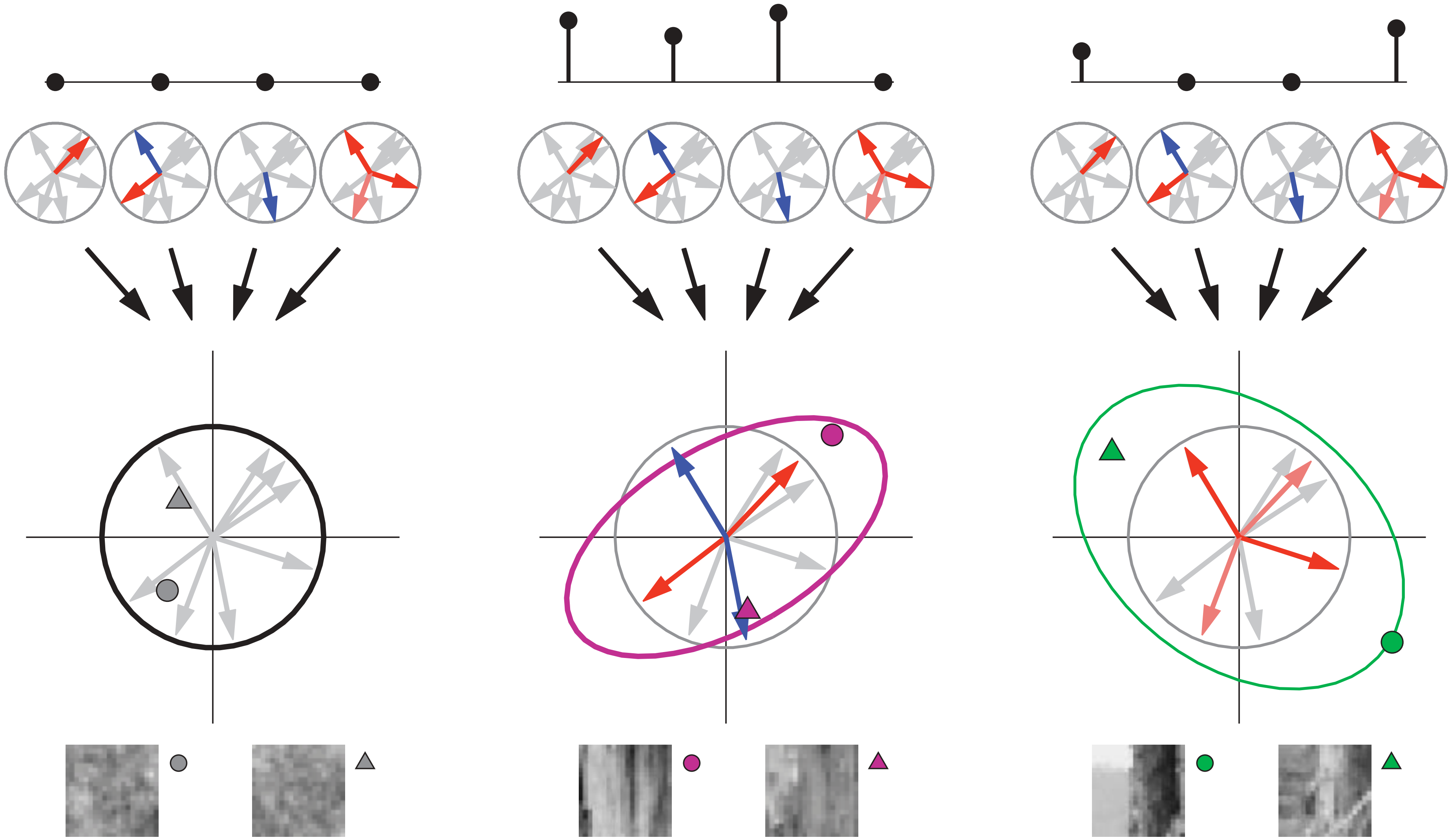


Egyrétegű modellek: filter korrelációk

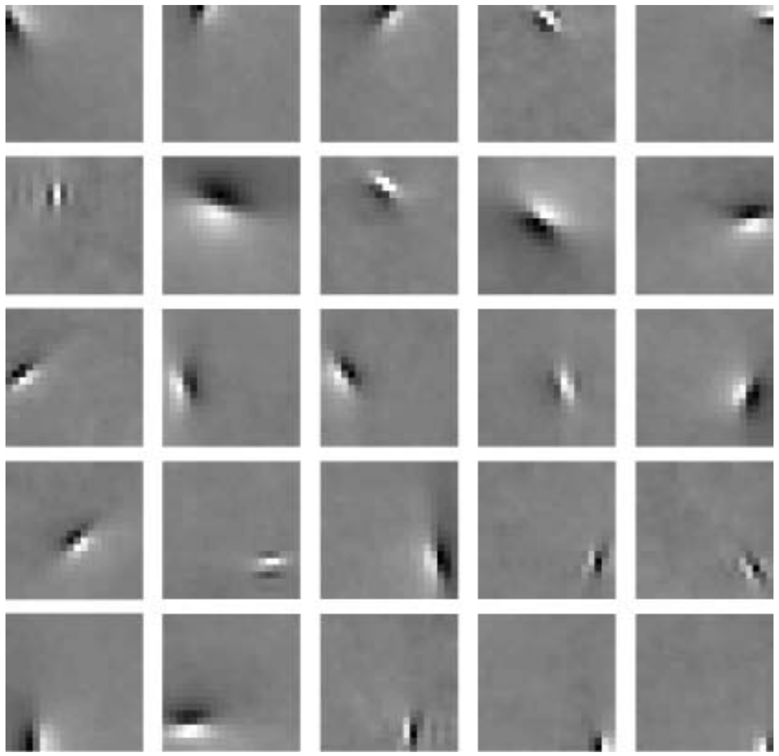


Egyrétegű modellek: filter korrelációk

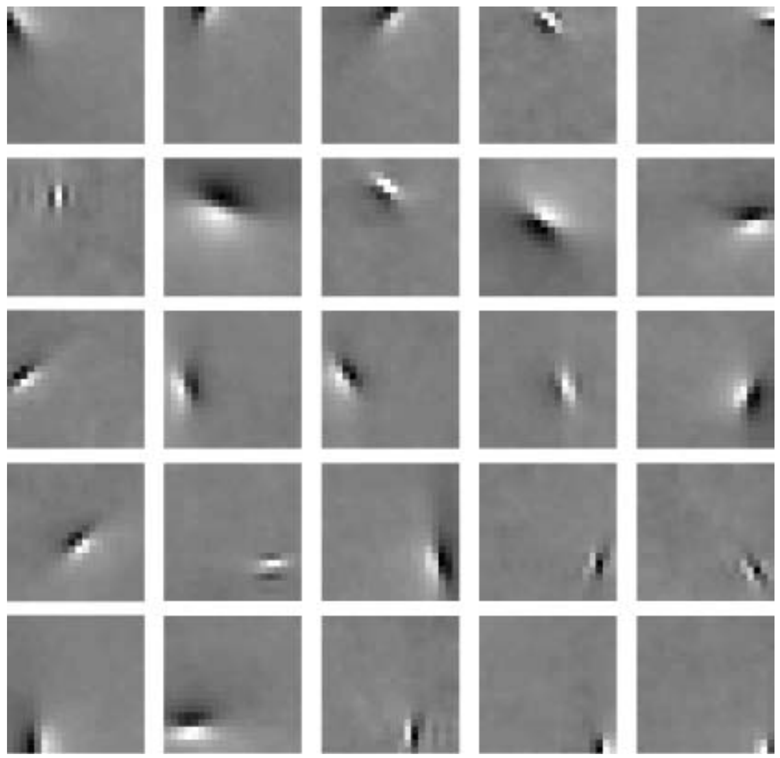
Változók a korrelációs struktúrát kódolják

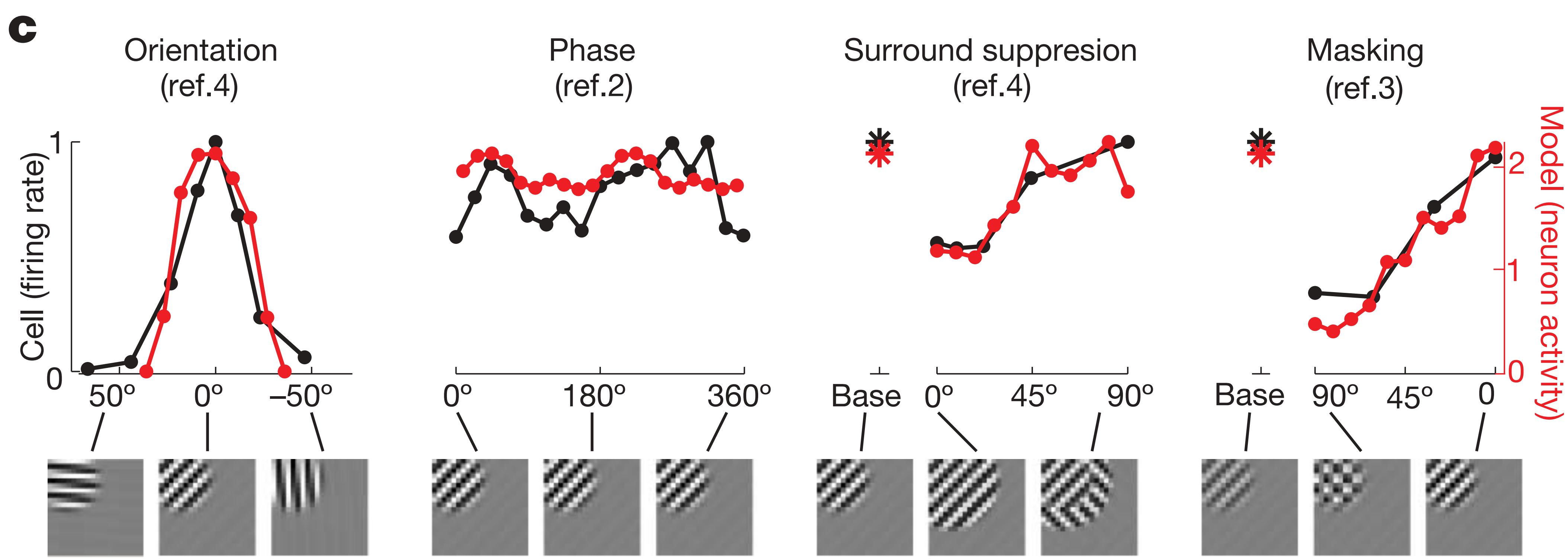


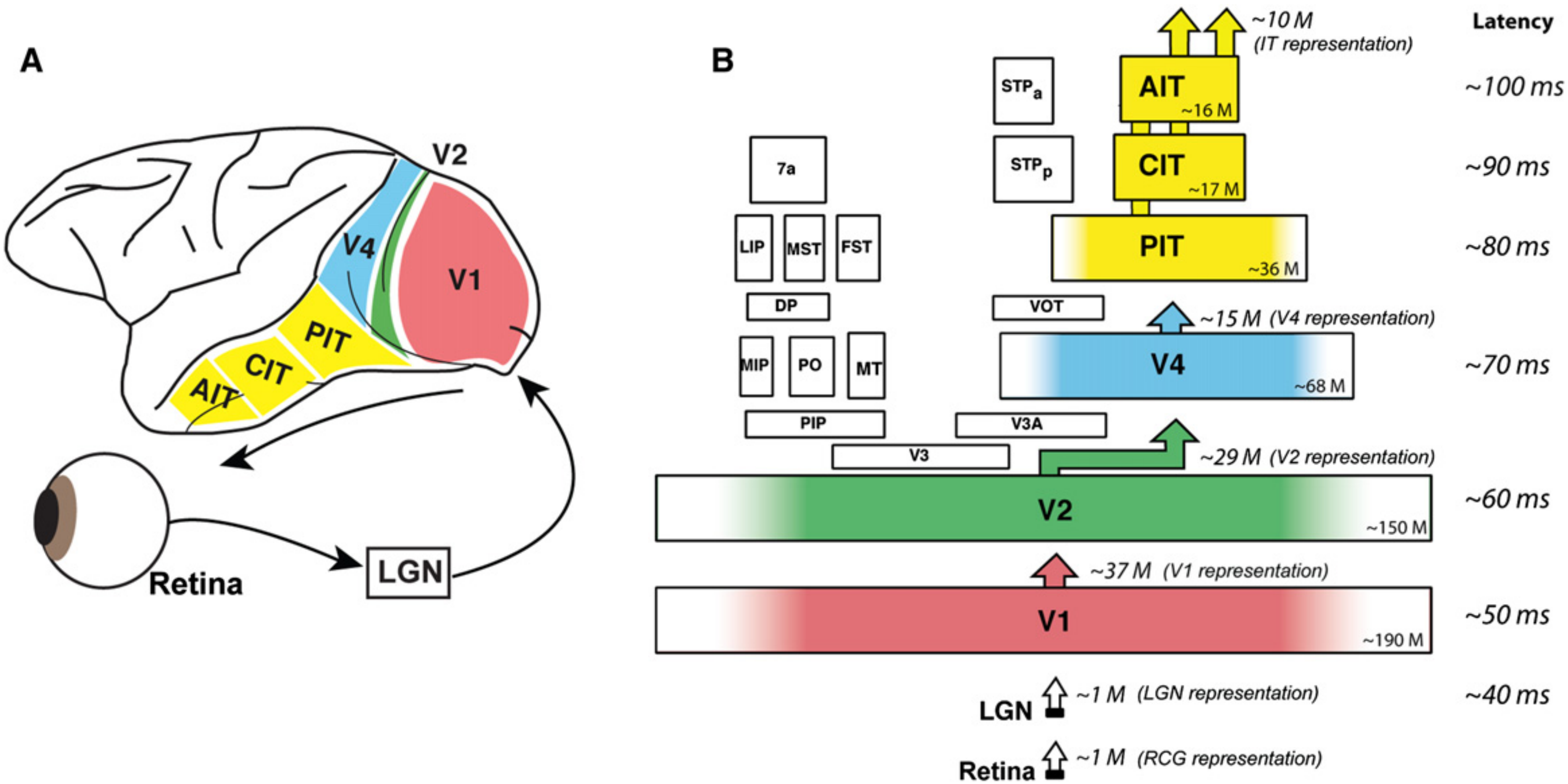
Egyrétegű modellek: filter korrelációk



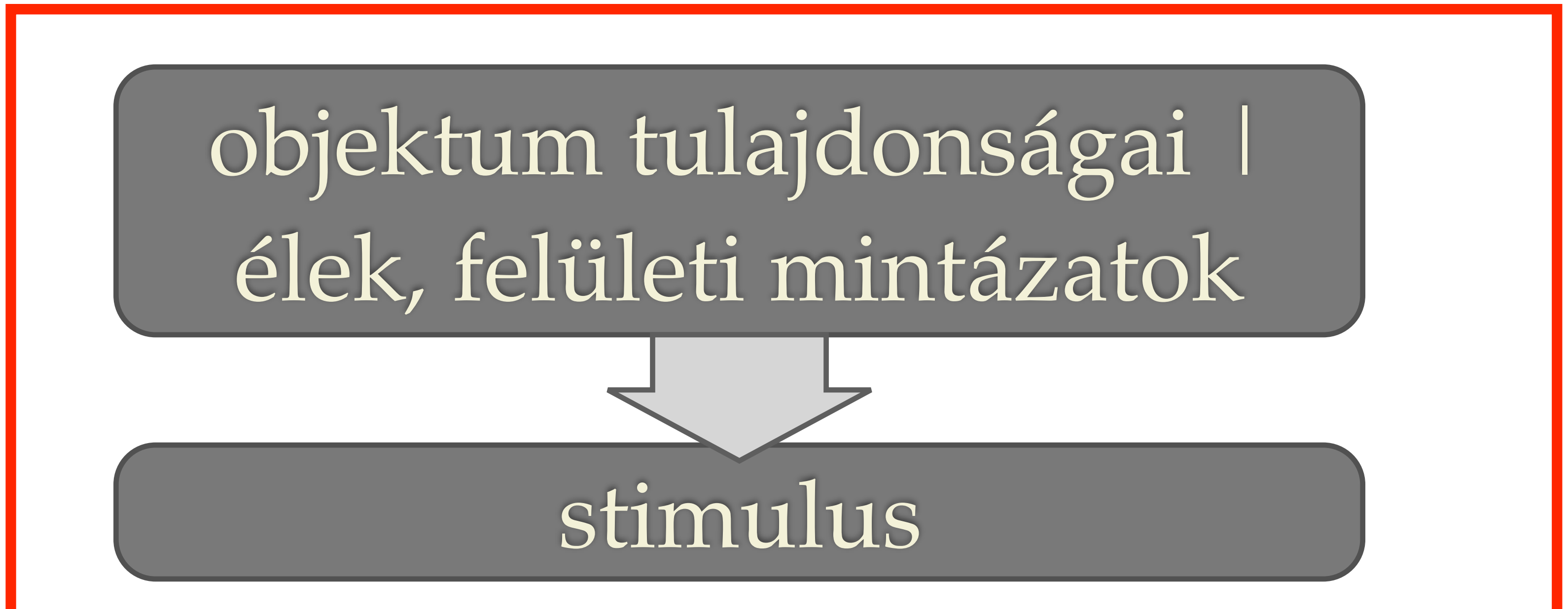
Egyrétegű modellek: filter korrelációk





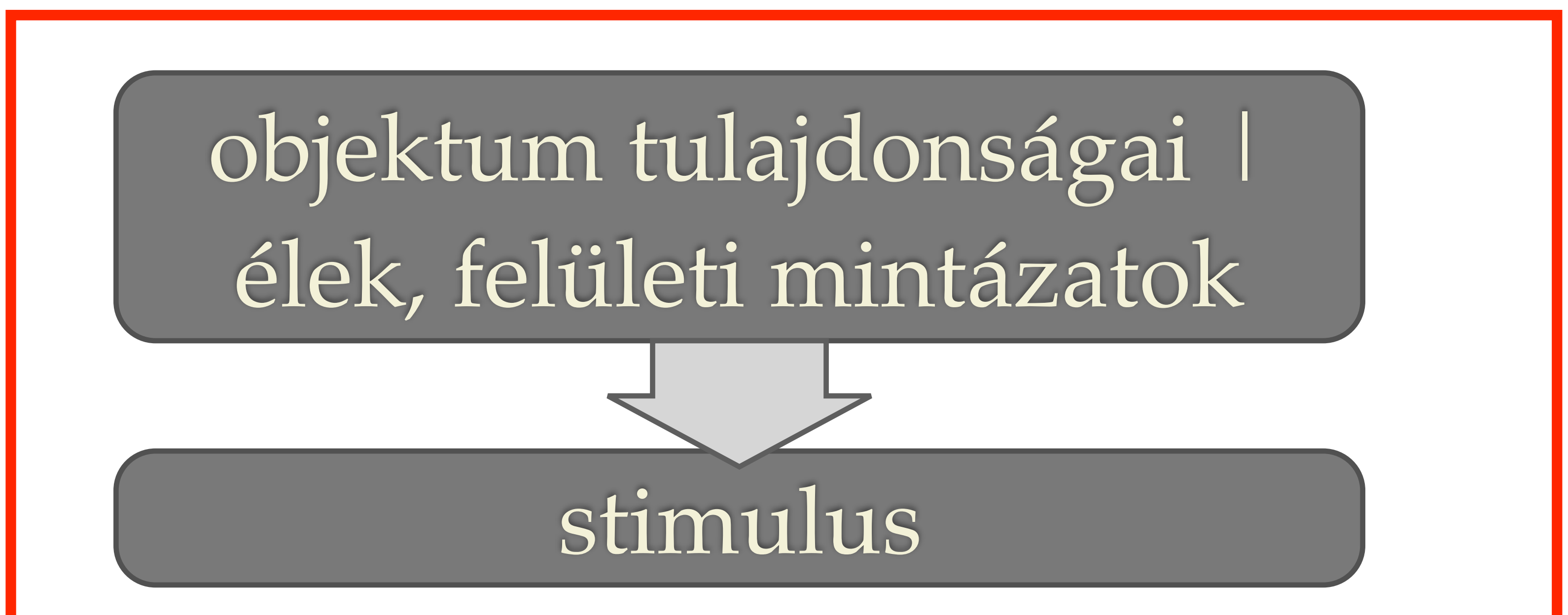

A
V2
V4
V1
PIT
CIT
AIT
Retina
LGN
B
~10 M
(IT representation)
Latency
STP_a
AIT
~16 M
~100 ms
7a
STP_p
CIT
~17 M
~90 ms
LIP
MST
FST
PIT
~36 M
~80 ms
DP
VOT
~15 M (V4 representation)
MIP
PO
MT
V4
~68 M
~70 ms
PIP
V3A
V3
~29 M (V2 representation)
V2
~150 M
~60 ms
~37 M (V1 representation)
V1
~190 M
~50 ms
LGN
~1 M (LGN representation)
~40 ms
Retina
~1 M (RCG representation)

Lineáris modellek



Lineáris modellek

x = A z + eps



Lineáris modellek

V1 receptive mezők:

- orientált
- sáváteresztő
- lokalizált

x = A z + eps

objektum tulajdonságai |
élek, felületi mintázatok

↓

stimulus

Lineáris modellek

V1 receptive mezők:

- orientált
- sáváteresztő
- lokalizált

x = A z + eps

objektum tulajdonságai |
élek, felületi mintázatok

↓

stimulus

x = c (A z) + eps

Lineáris modellek

V1 receptive mezők:

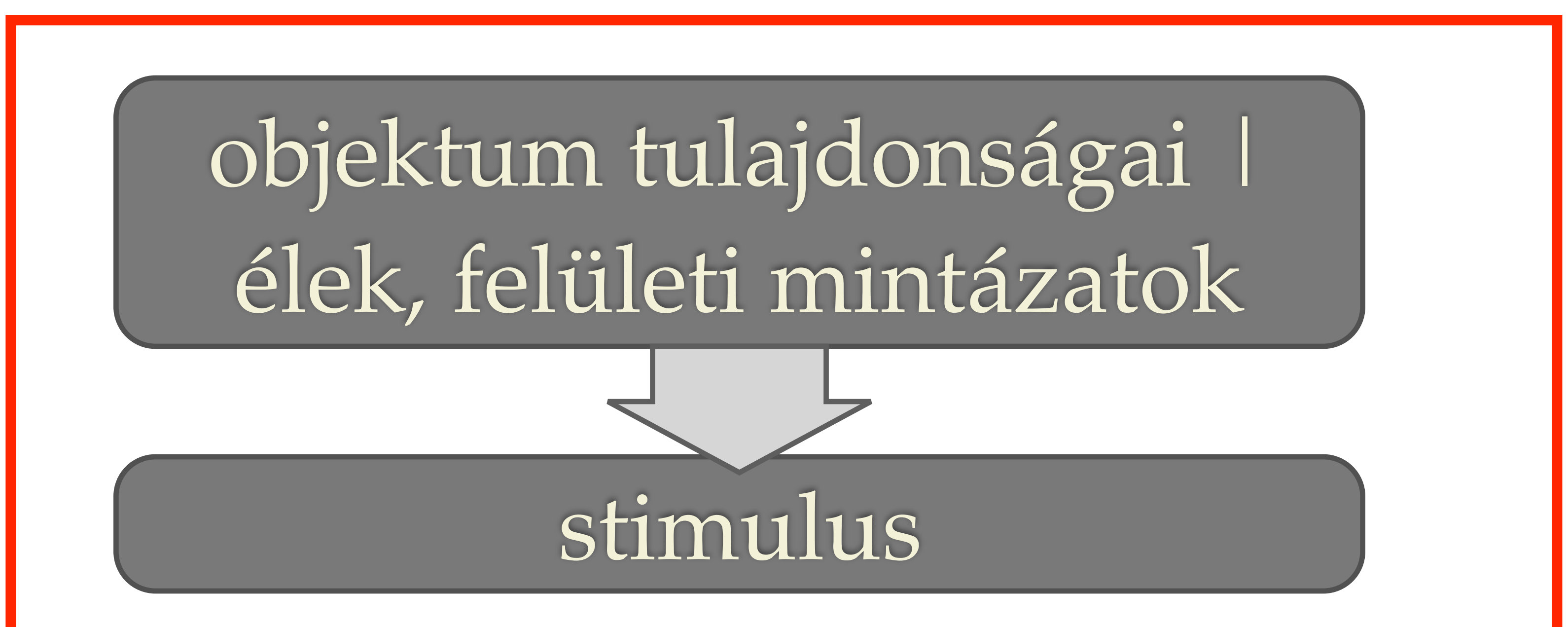
- orientált
- sáváteresztő
- lokalizált

$$x = A\,z + eps$$

V1 stimulus-függés

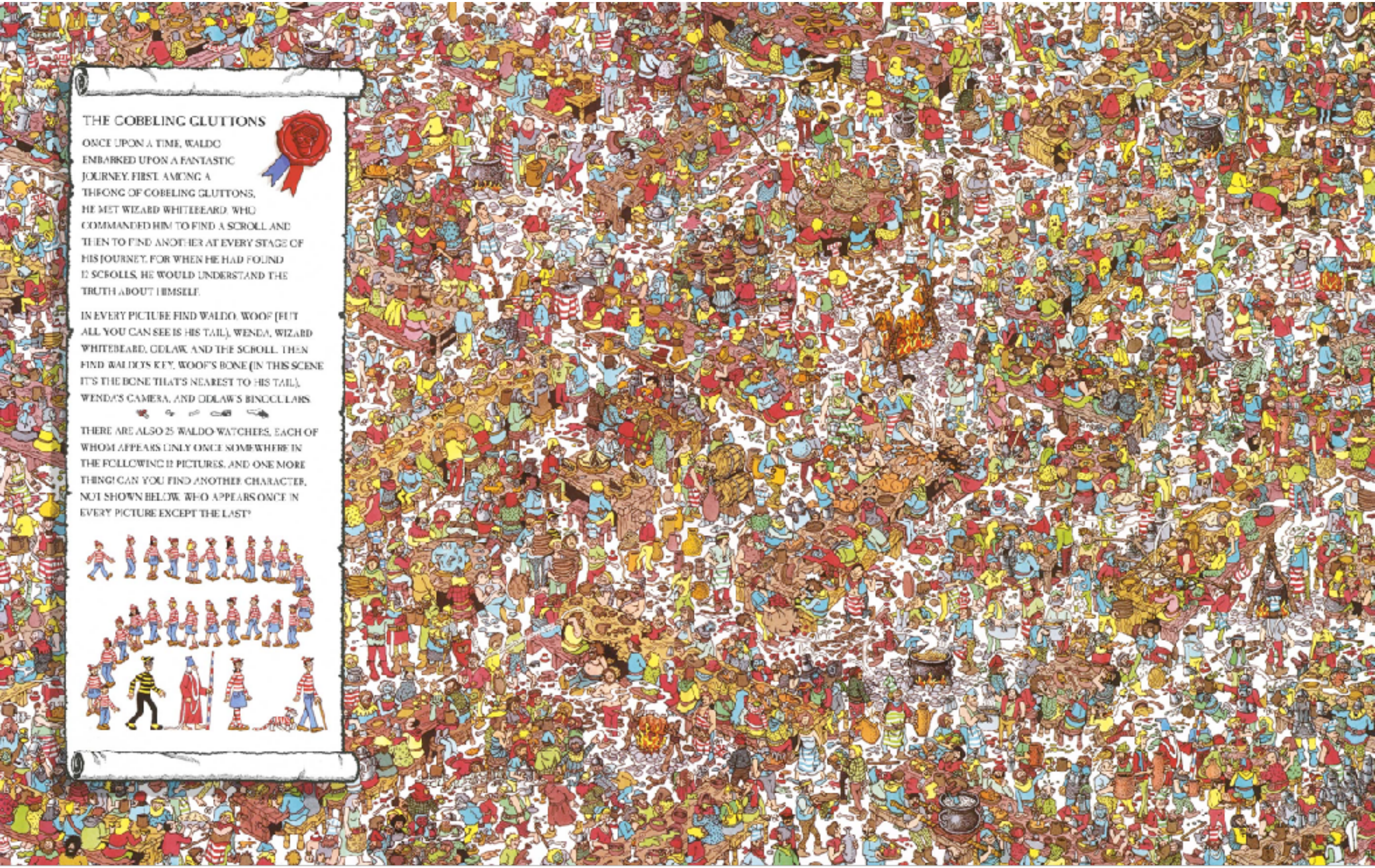
- kontraszt invariancia
- extra-klasszikus receptív mezők

$$x = c\,(A\,z) + eps$$



Gauging V2 responses so far

- gratings
- contours
- angles
- other forms of second order stats
- border ownership


THE GOBBLING GLUTTONS
ONCE UPON A TIME, WALDO EMBARKED UPON A FANTASTIC JOURNEY. FIRST, AMONG A THRONG OF GOBBLING GLUTTONS, HE MET WIZARD WHITEBEARD, WHO COMMANDED HIM TO FIND A SCROLL AND THEN TO FIND ANOTHER AT EVERY STAGE OF HIS JOURNEY. FOR WHEN HE HAD FOUND 12 SCROLLS, HE WOULD UNDERSTAND THE TRUTH ABOUT HIMSELF.
IN EVERY PICTURE FIND WALDO, WOOF (BUT ALL YOU CAN SEE IS HIS TAIL), WENDA, WIZARD WHITEBEARD, ODLAW, AND THE SCROLL. THEN FIND WALDO'S KEY, WOOF'S BONE (IN THIS SCENE IT'S THE BONE THAT'S NEAREST TO HIS TAIL), WENDA'S CAMERA, AND ODLAW'S BINOCULARS.
THERE ARE ALSO 25 WALDO-WATCHERS, EACH OF WHOM APPEARS ONLY ONCE SOMEWHERE IN THE FOLLOWING 12 PICTURES. AND ONE MORE THING! CAN YOU FIND ANOTHER CHARACTER, NOT SHOWN BELOW, WHO APPEARS ONCE IN EVERY PICTURE EXCEPT THE LAST?

International Journal of Computer Vision 40(1), 49–71, 2000

A Parametric Texture Model Based on Joint Statistics of Complex Wavelet Coefficients

JAVIER PORTILLA AND EERO P. SIMONCELLI
Center for Neural Science, and Courant Institute of Mathematical Sciences, New York University, New York, NY 10003, USA

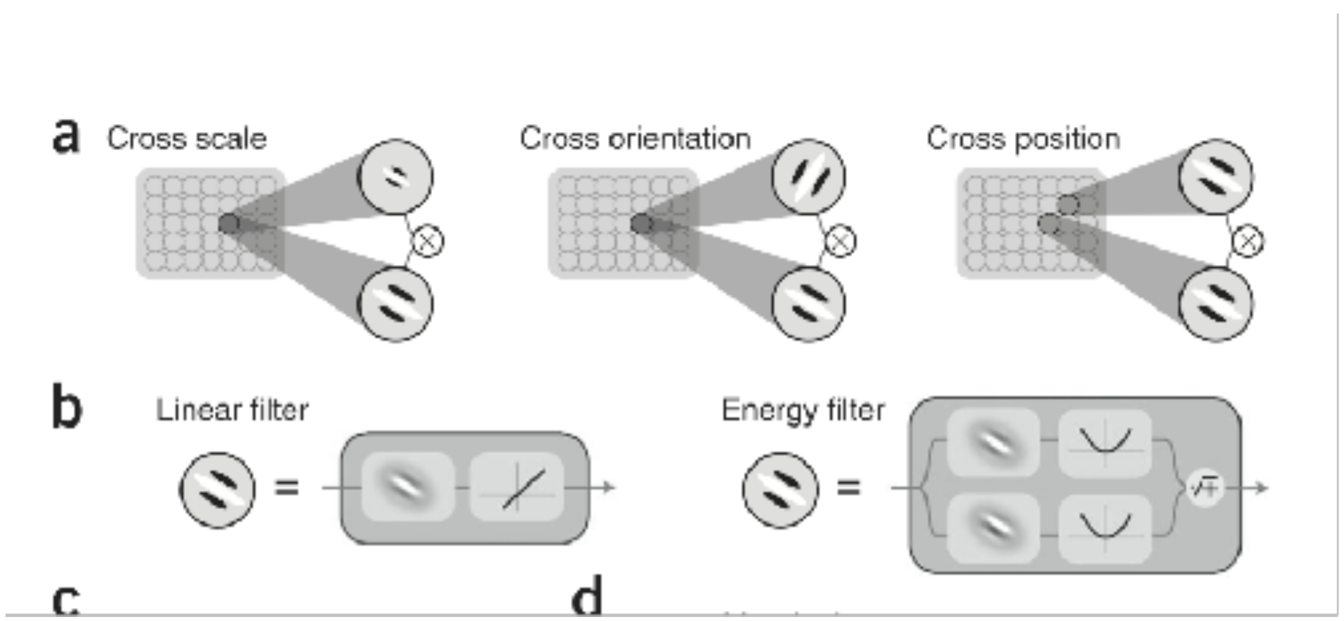
Learning about the stats of an image

- Registering the responses of linear filters (simple cells)
- Registering the responses of energy filters (complex cells)
- Marginal statistics: variance, kurtosis, skewness

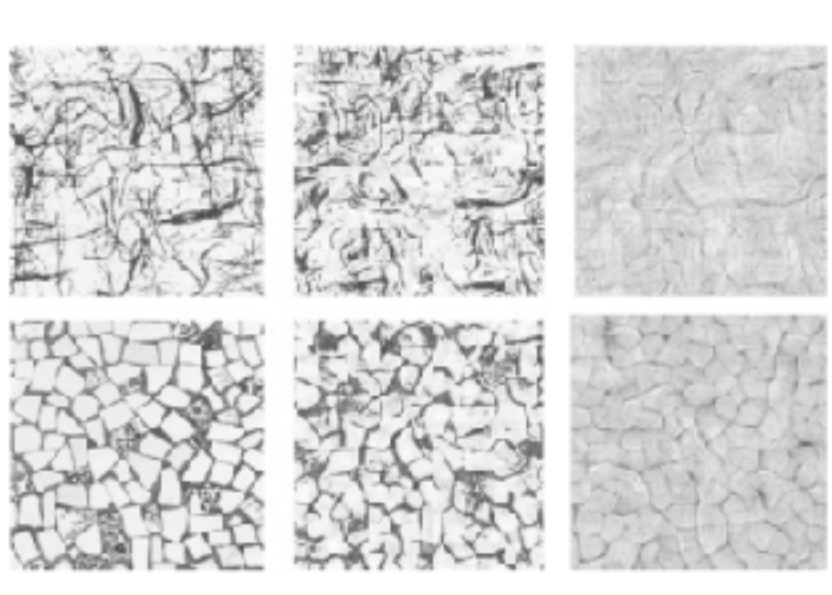
Learning about the stats of an image

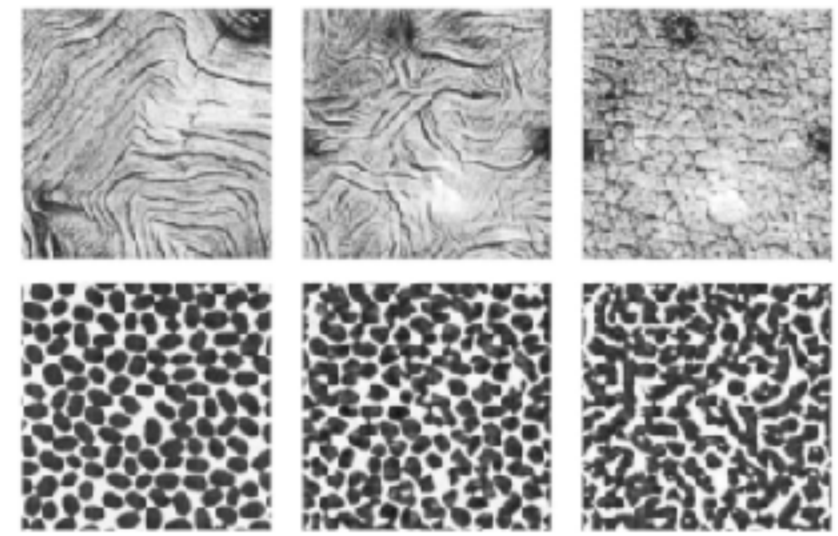
- Registering the responses of linear filters (simple cells)
- Registering the responses of energy filters (complex cells)
- Marginal statistics: variance, kurtosis, skewness

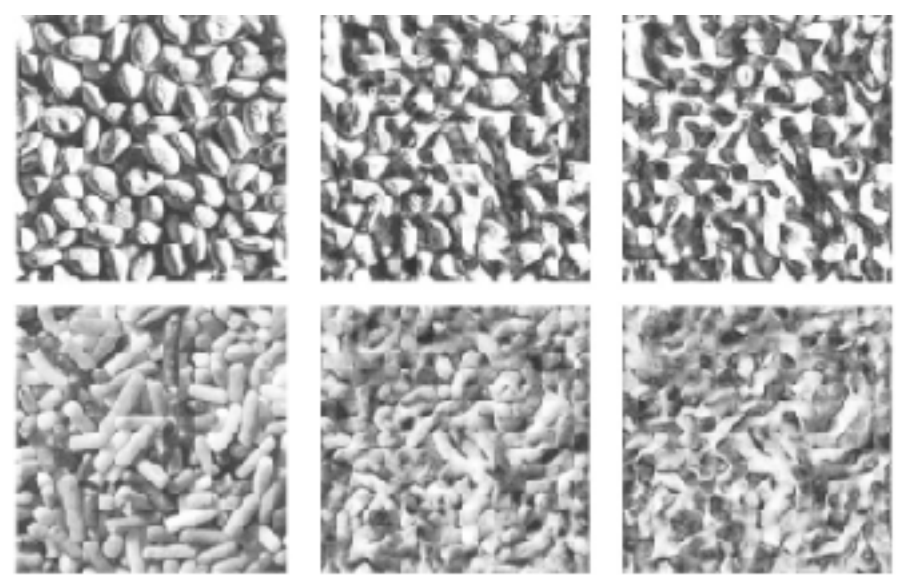
- Registering correlations between orientations
- Registering correlations between spatial frequencies
- Registering correlations across positions



Synthetic textures





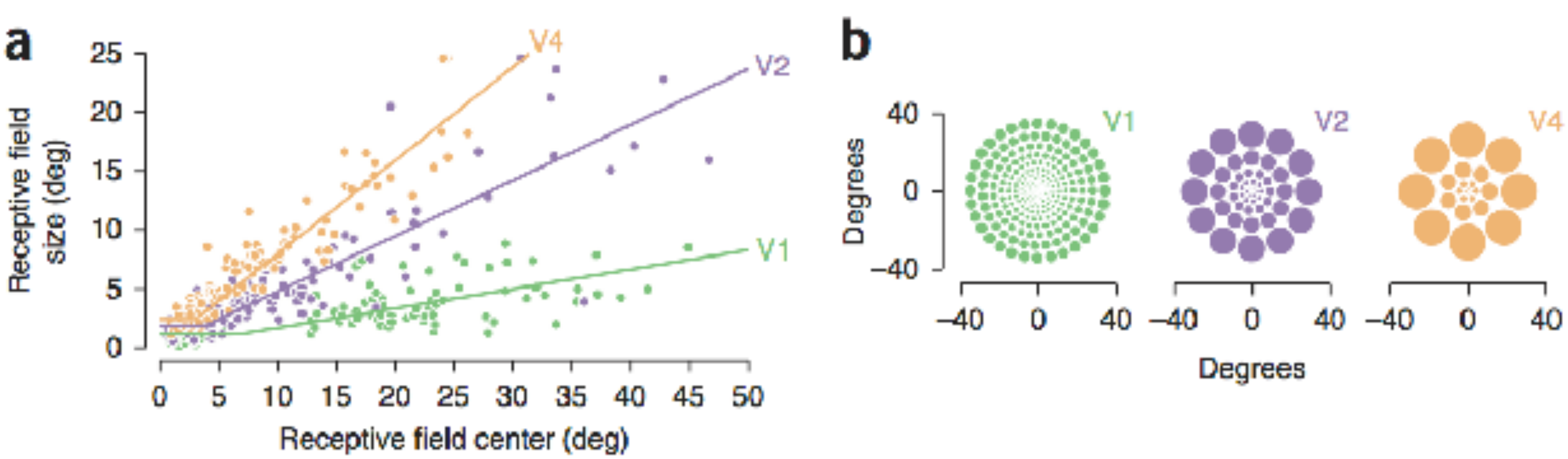


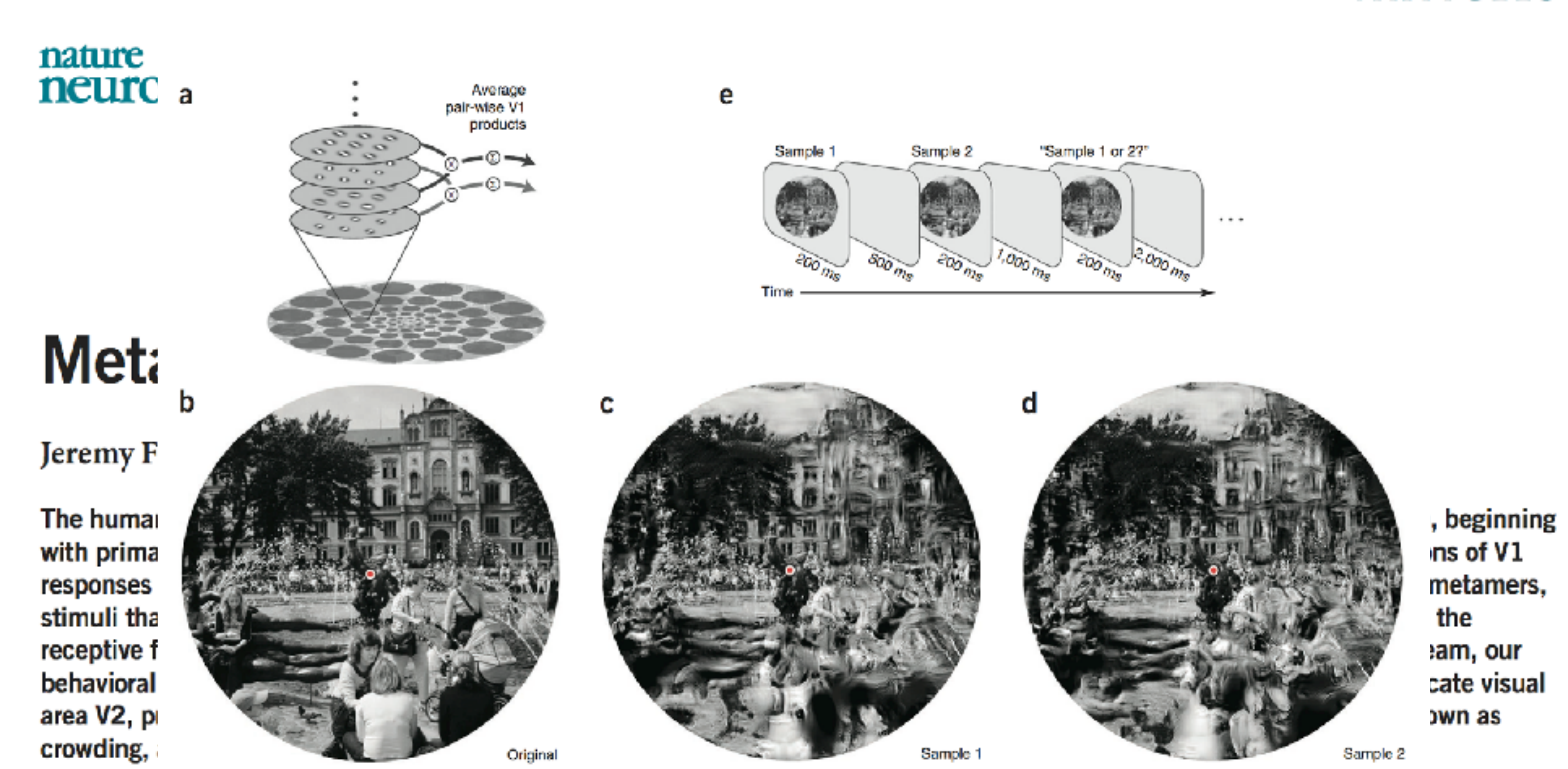
nature neuroscience

Metamers of the ventral stream

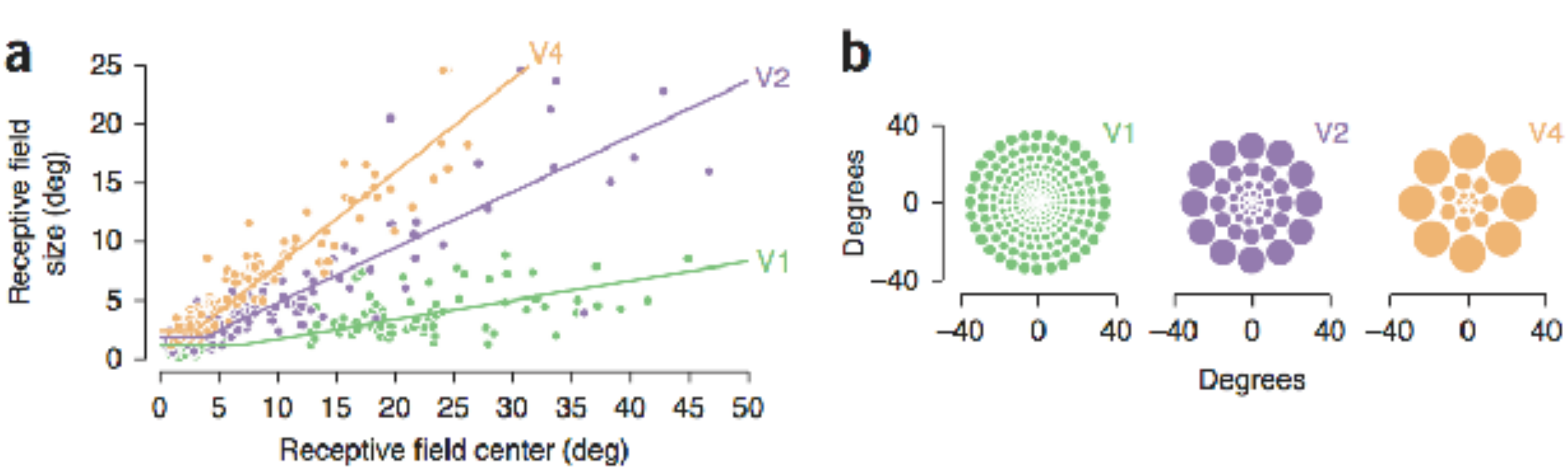
Jeremy Freeman[1] & Eero P Simoncelli[1–3]

The human capacity to recognize complex visual patterns emerges in a sequence of brain areas known as the ventral stream, beginning with primary visual cortex (V1). We developed a population model for mid-ventral processing, in which nonlinear combinations of V1 responses are averaged in receptive fields that grow with eccentricity. To test the model, we generated novel forms of visual metamers, stimuli that differ physically but look the same. We developed a behavioral protocol that uses metameric stimuli to estimate the receptive field sizes in which the model features are represented. Because receptive field sizes change along the ventral stream, our behavioral results can identify the visual area corresponding to the representation. Measurements in human observers implicate visual area V2, providing a new functional account of neurons in this area. The model also explains deficits of peripheral vision known as crowding, and provides a quantitative framework for assessing the capabilities and limitations of everyday vision.

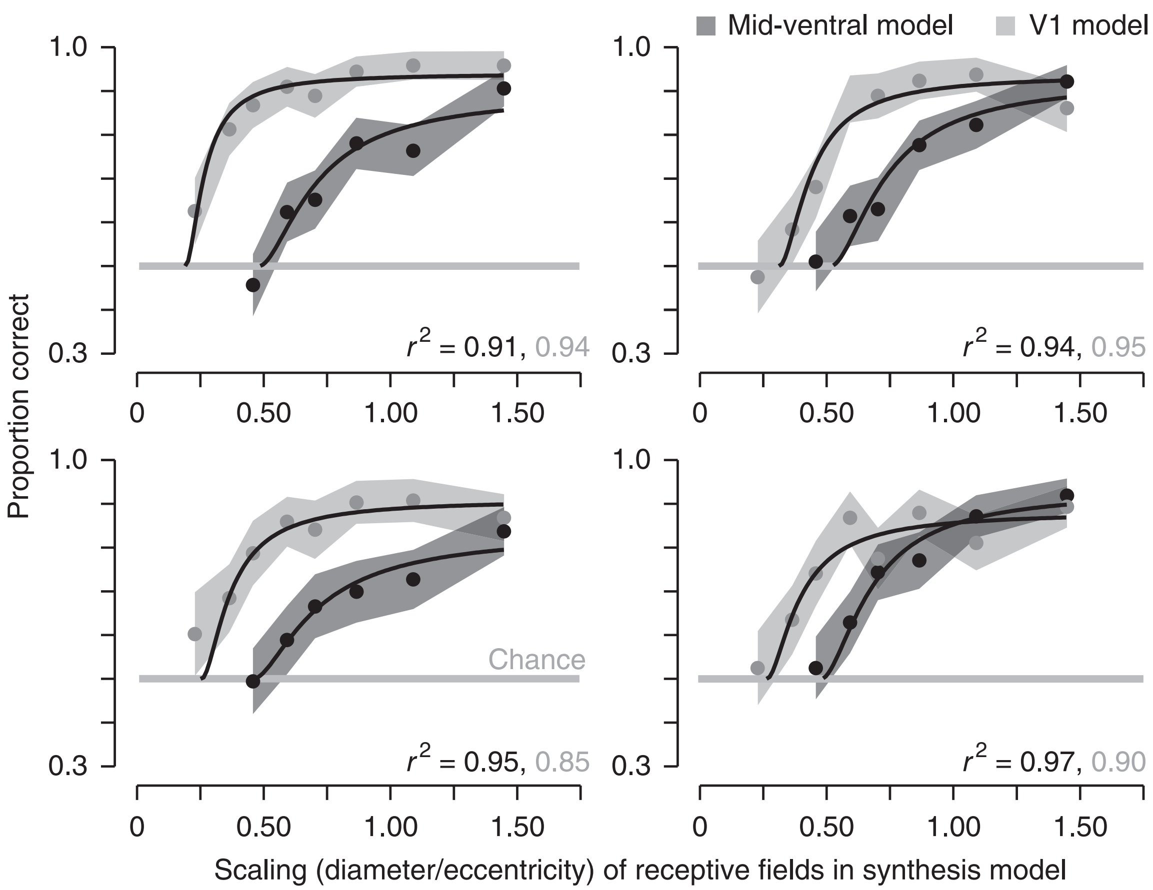




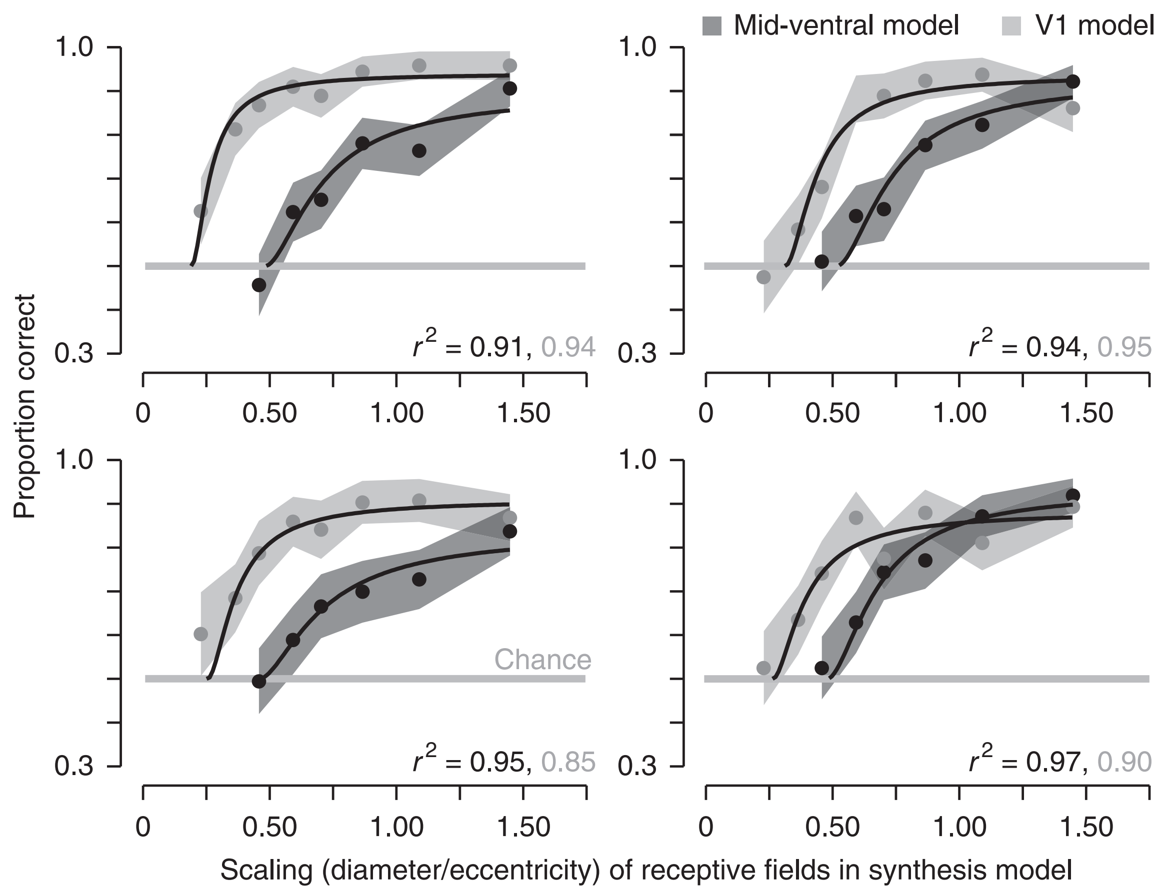
nature
neuro
Meta
Jeremy F
The huma
with prima
responses
stimuli tha
receptive f
behavioral
area V2, p
crowding,
, beginning
ns of V1
metamers,
the
eam, our
cate visual
own as
a
Average
pair-wise V1
products
e
Sample 1
Sample 2
"Sample 1 or 2?"
200 ms
800 ms
200 ms
1,000 ms
200 ms
2,000 ms
Time
b
c
d
Original
Sample 1
Sample 2



a
Receptive field size (deg)
Receptive field center (deg)
V4
V2
V1
b
Degrees
Degrees
V1
V2
V4



Mid-ventral model
V1 model
1.0
0.3
Proportion correct
r^2 = 0.91, 0.94
r^2 = 0.94, 0.95
r^2 = 0.95, 0.85
r^2 = 0.97, 0.90
Chance
0
0.50
1.00
1.50
Scaling (diameter/eccentricity) of receptive fields in synthesis model



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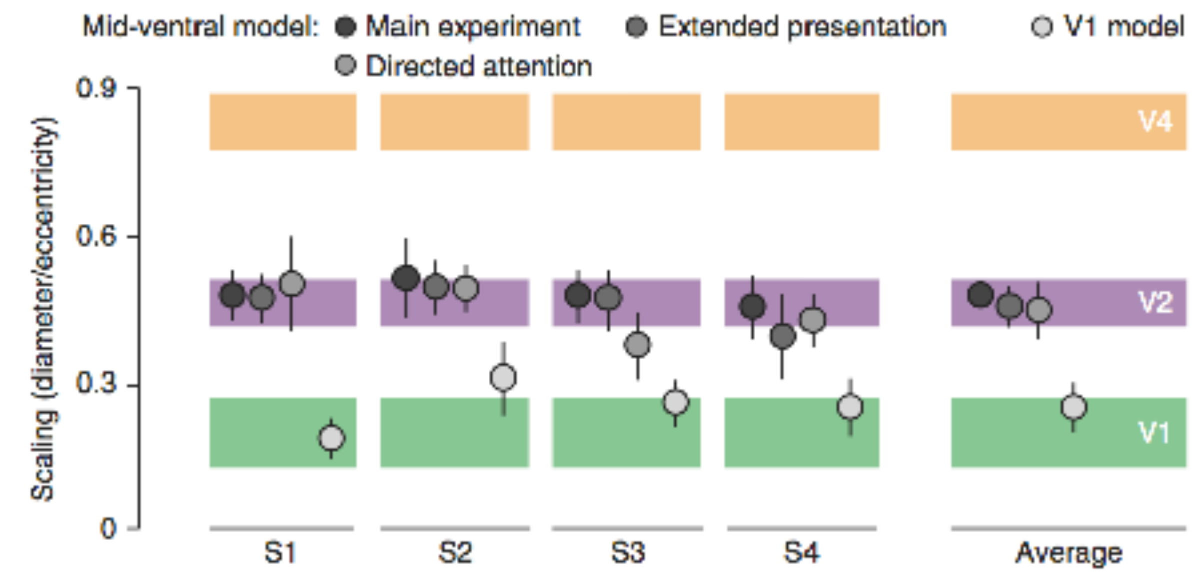
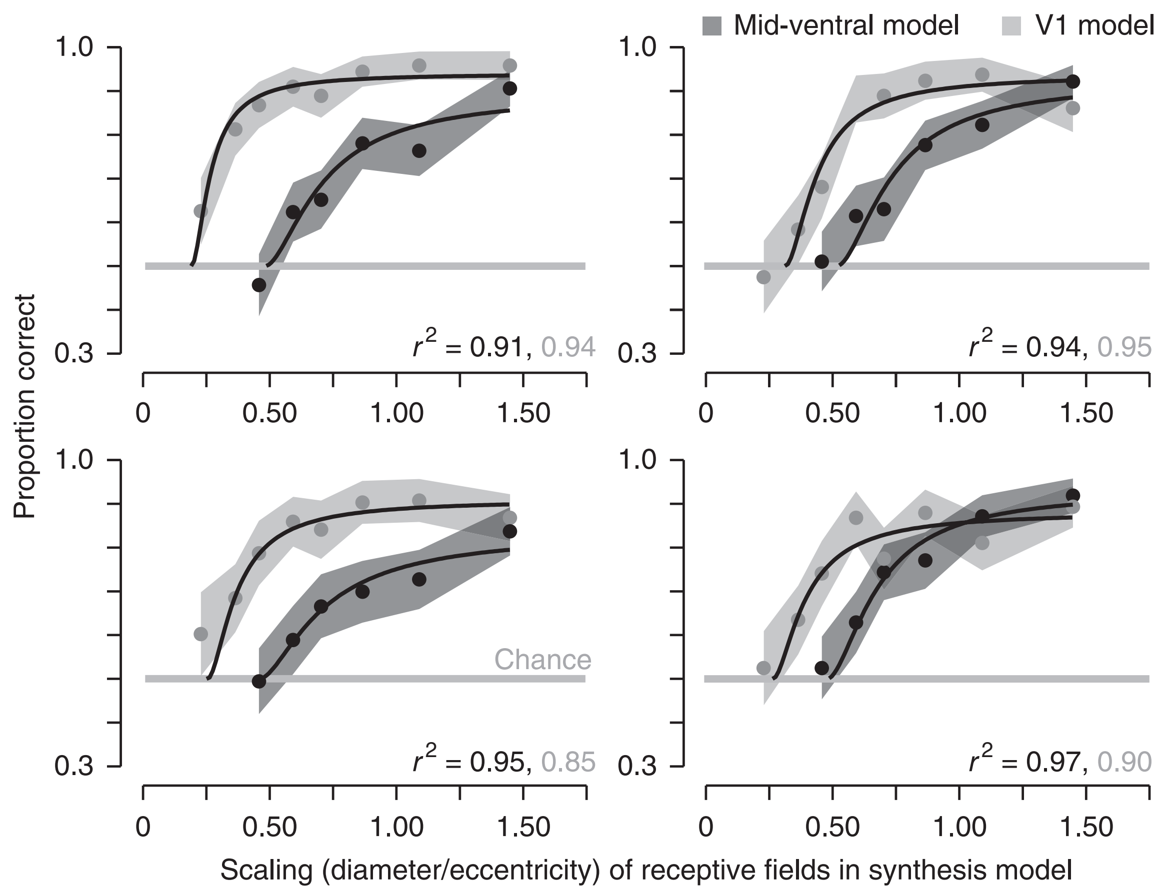


Mid-ventral model: Main experiment
Extended presentation
V1 model
Directed attention
Scaling (diameter/eccentricity)
0.9
0.6
0.3
0
V4
V2
V1
S1
S2
S3
S4
Average



Mid-ventral model
V1 model
Proportion correct
1.0
0.3
r^2 = 0.91, 0.94
r^2 = 0.94, 0.95
r^2 = 0.95, 0.85
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Chance
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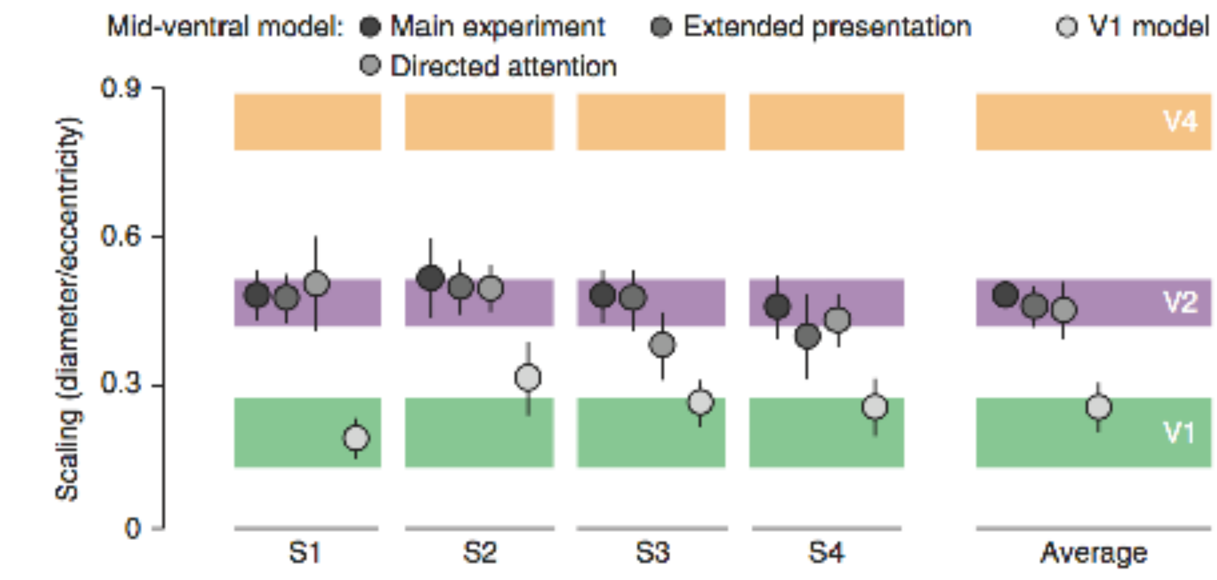
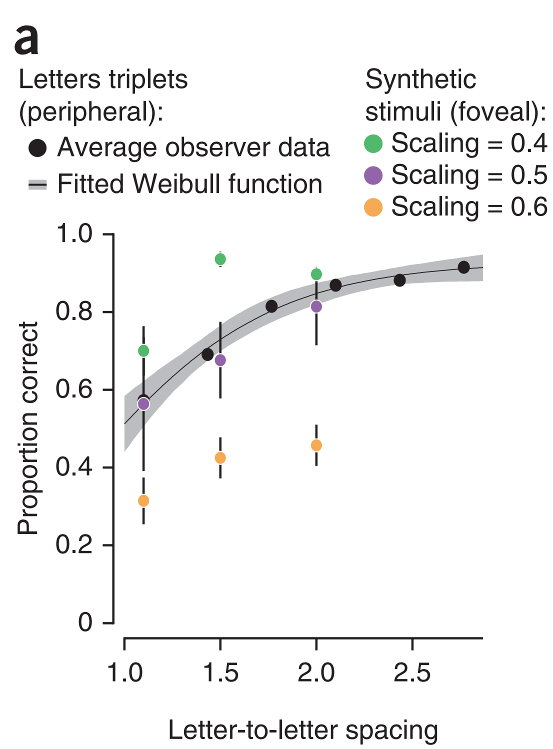
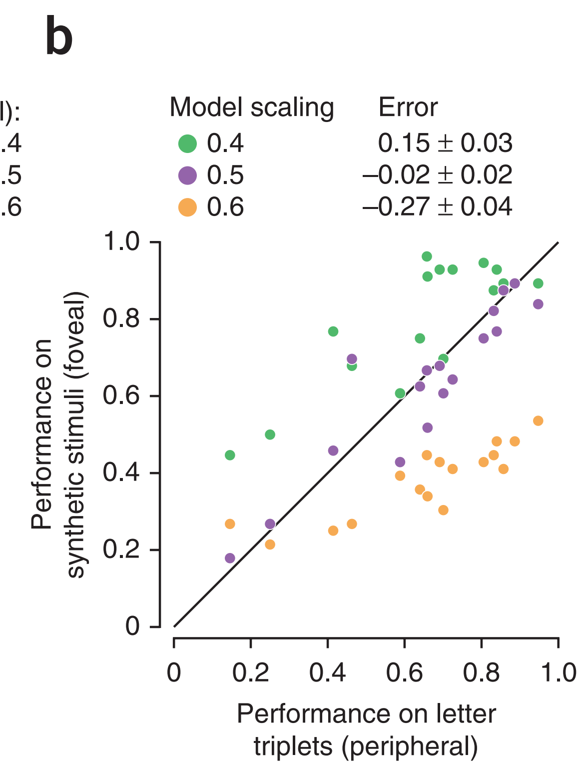
0.50
1.00
1.50
Scaling (diameter/eccentricity) of receptive fields in synthesis model



Mid-ventral model: Main experiment
Extended presentation
V1 model
Directed attention
Scaling (diameter/eccentricity)
0.9
0.6
0.3
0
V4
V2
V1
S1
S2
S3
S4
Average



a
Letters triplets (peripheral):
Average observer data
Fitted Weibull function
Synthetic stimuli (foveal):
Scaling = 0.4
Scaling = 0.5
Scaling = 0.6
Proportion correct
1.0
0.8
0.6
0.4
0.2
0
1.0
1.5
2.0
2.5
Letter-to-letter spacing



b
Model scaling
Error
0.4
0.15 ± 0.03
0.5
–0.02 ± 0.02
0.6
–0.27 ± 0.04
Performance on synthetic stimuli (foveal)
1.0
0.8
0.6
0.4
0.2
0
Performance on letter triplets (peripheral)

ARTICLES

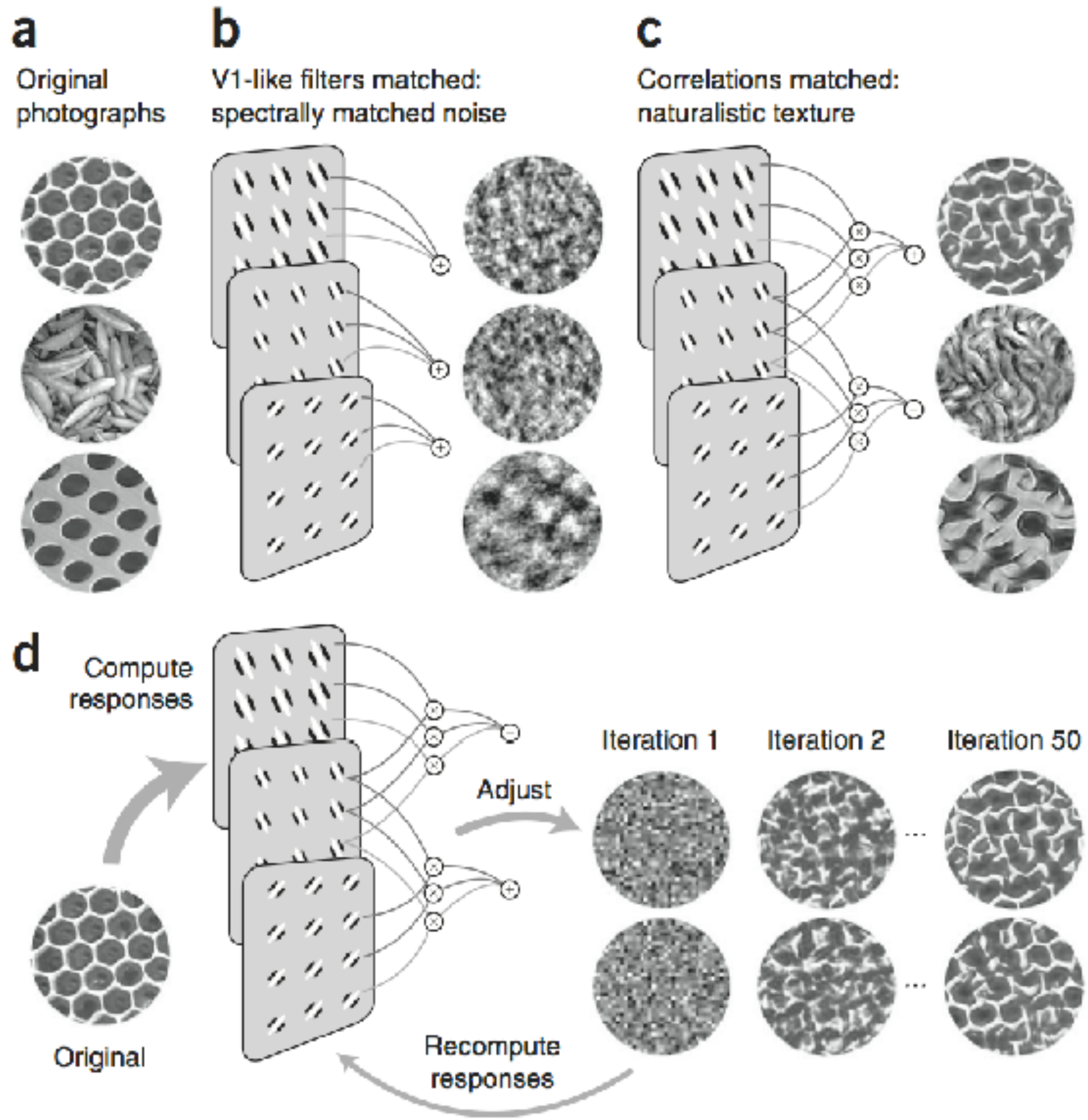
nature neuroscience

A functional and perceptual signature of the second visual area in primates

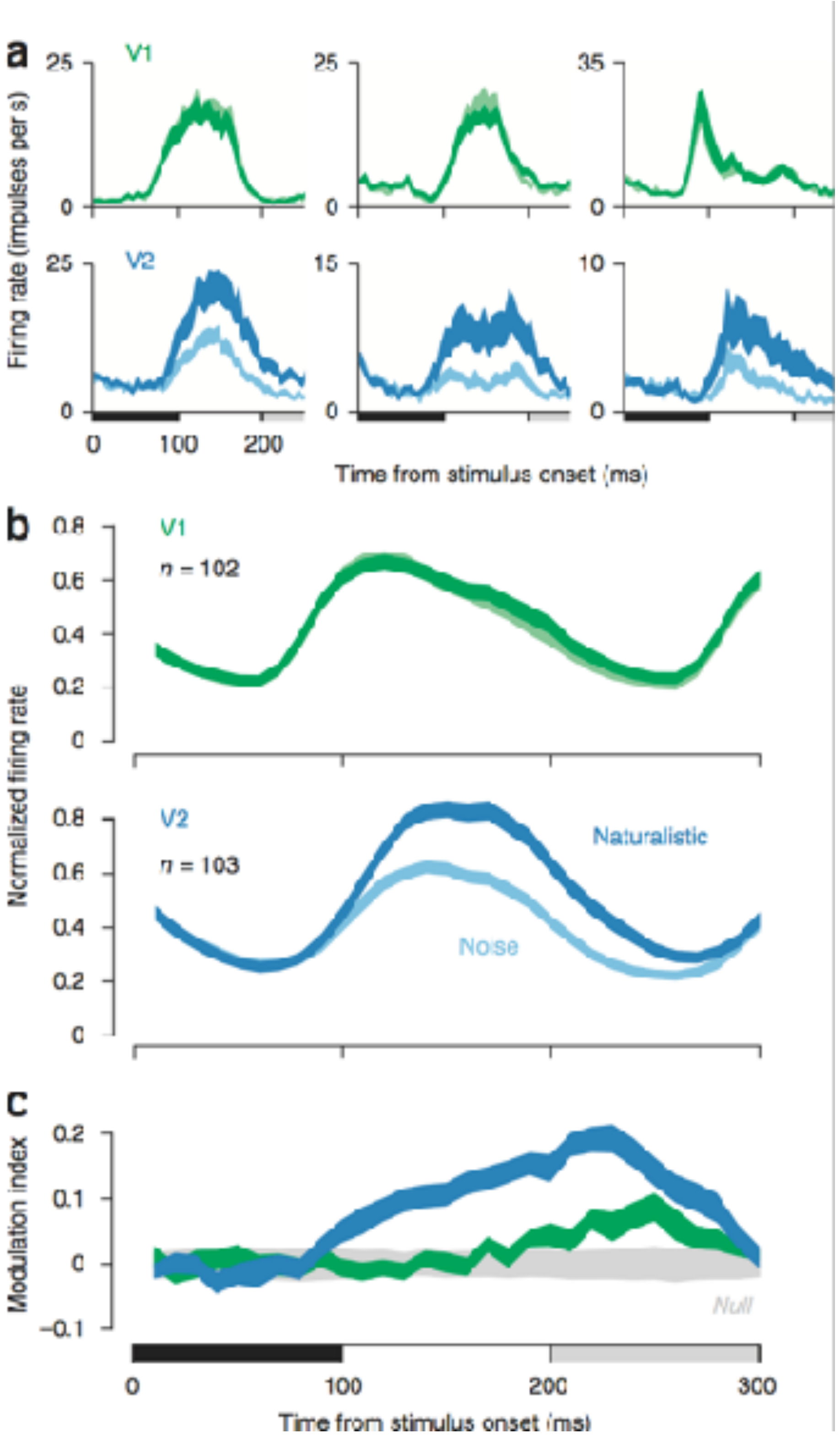
Jeremy Freeman[1,5,7], Corey M Ziemba[1,5], David J Heeger[1,2], Eero P Simoncelli[1–4,6] & J Anthony Movshon[1,2,6]

There is no generally accepted account of the function of the second visual cortical area (V2), partly because no simple response properties robustly distinguish V2 neurons from those in primary visual cortex (V1). We constructed synthetic stimuli replicating the higher-order statistical dependencies found in natural texture images and used them to stimulate macaque V1 and V2 neurons. Most V2 cells responded more vigorously to these textures than to control stimuli lacking naturalistic structure; V1 cells did not. Functional magnetic resonance imaging (fMRI) measurements in humans revealed differences between V1 and V2 that paralleled the neuronal measurements. The ability of human observers to detect naturalistic structure in different types of texture was well predicted by the strength of neuronal and fMRI responses in V2 but not in V1. Together, these results reveal a particular functional role for V2 in the representation of natural image structure.

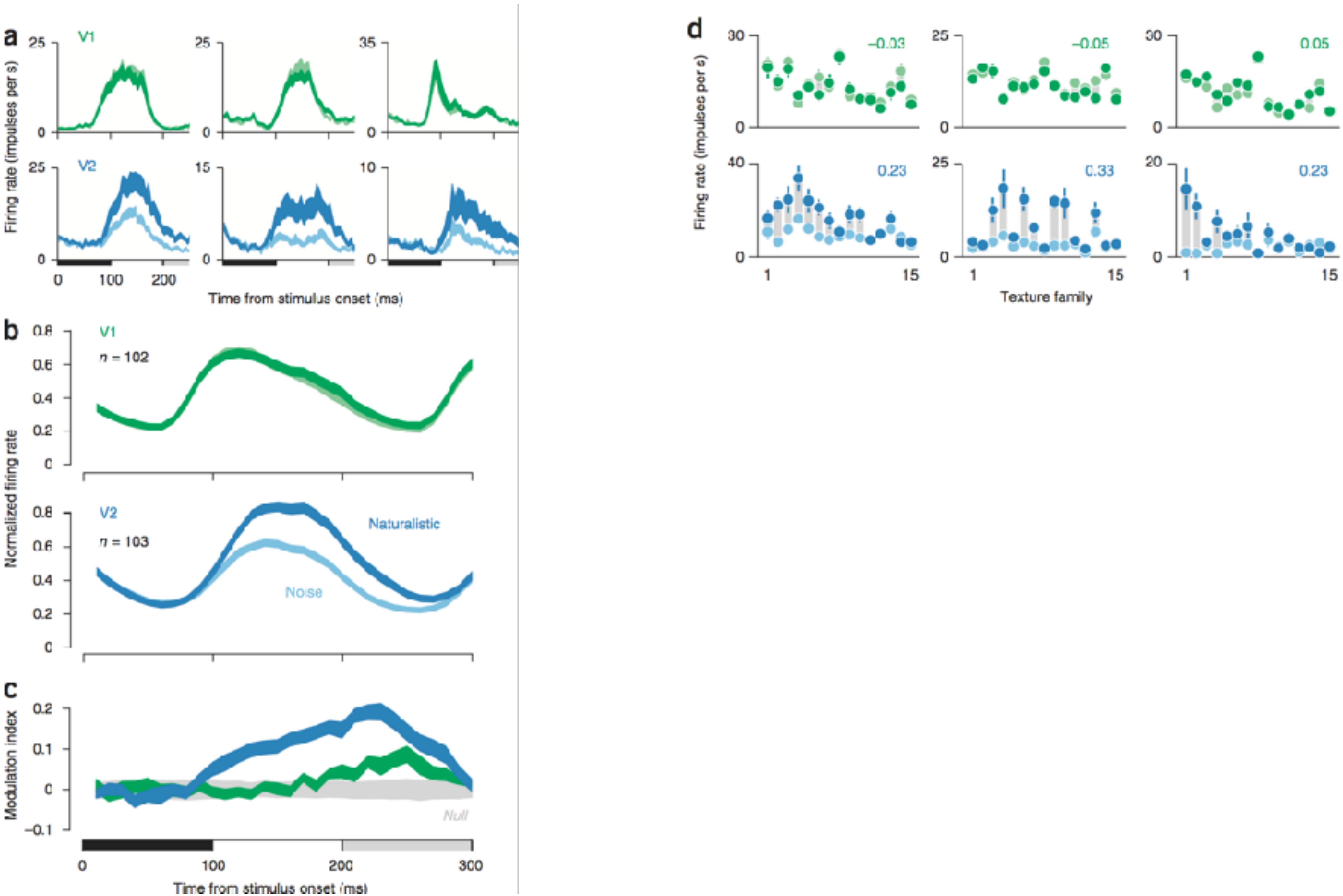
Synthetising images



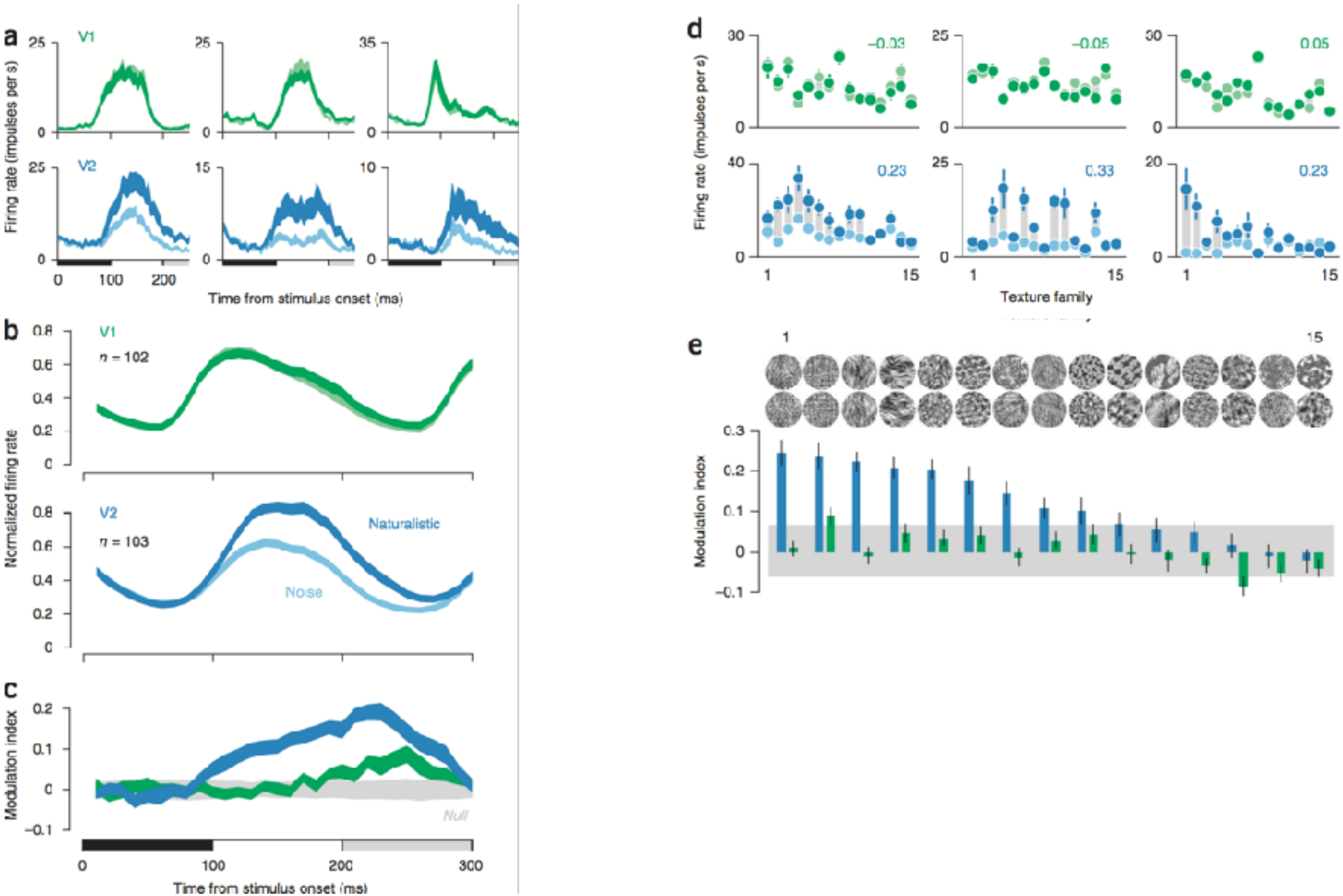
V2 responses to Portilla textures



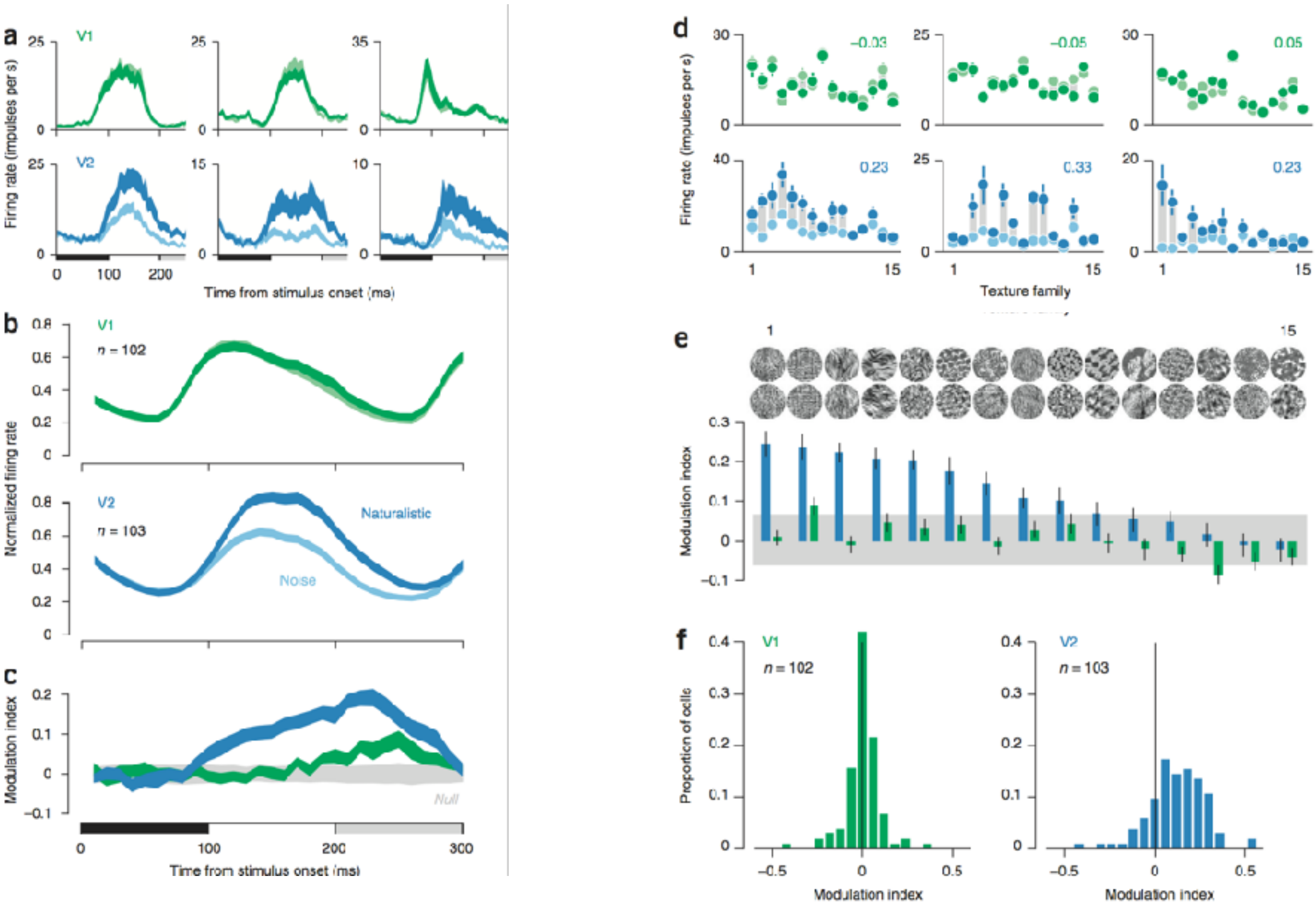
V2 responses to Portilla textures



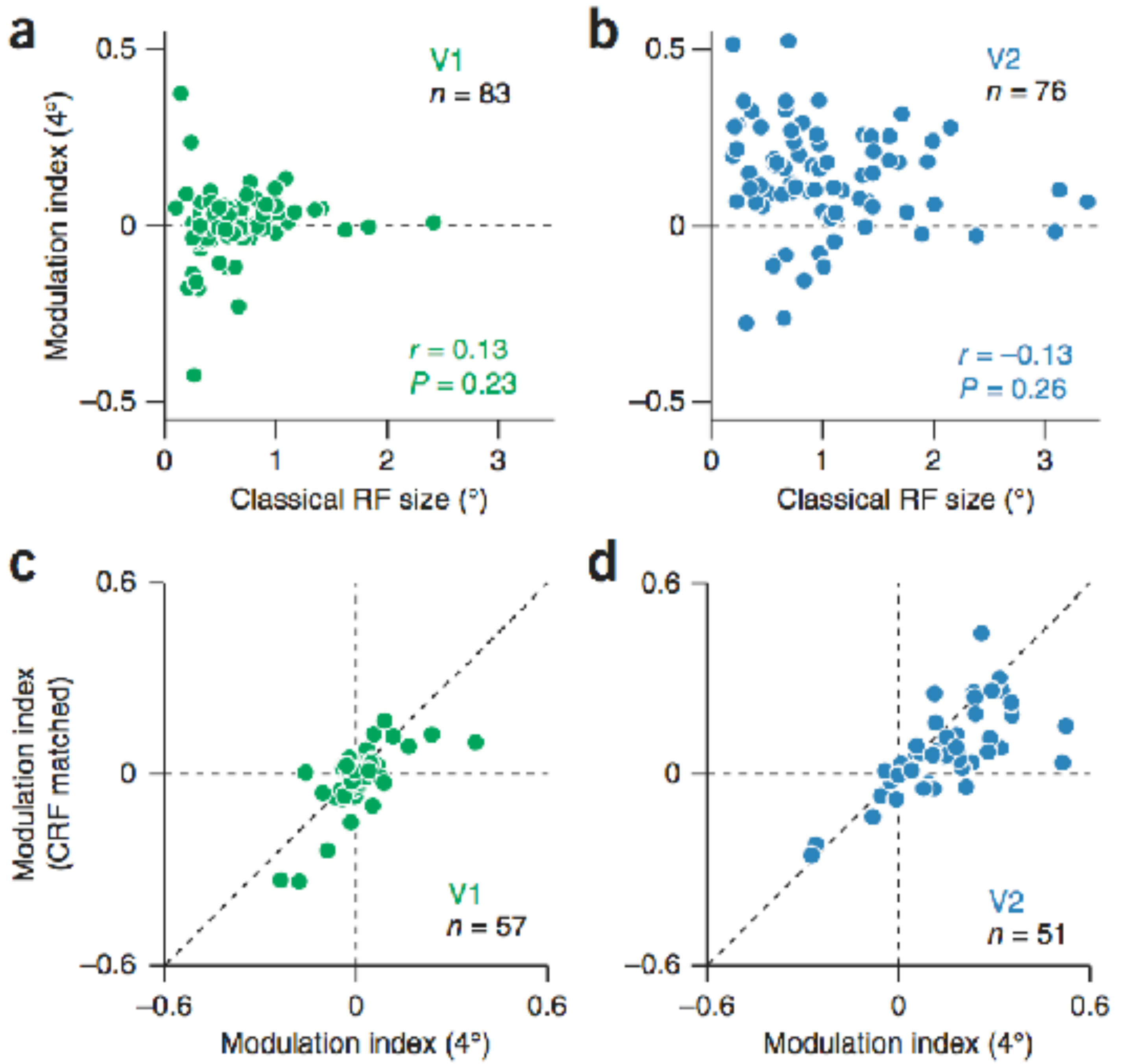
V2 responses to Portilla textures



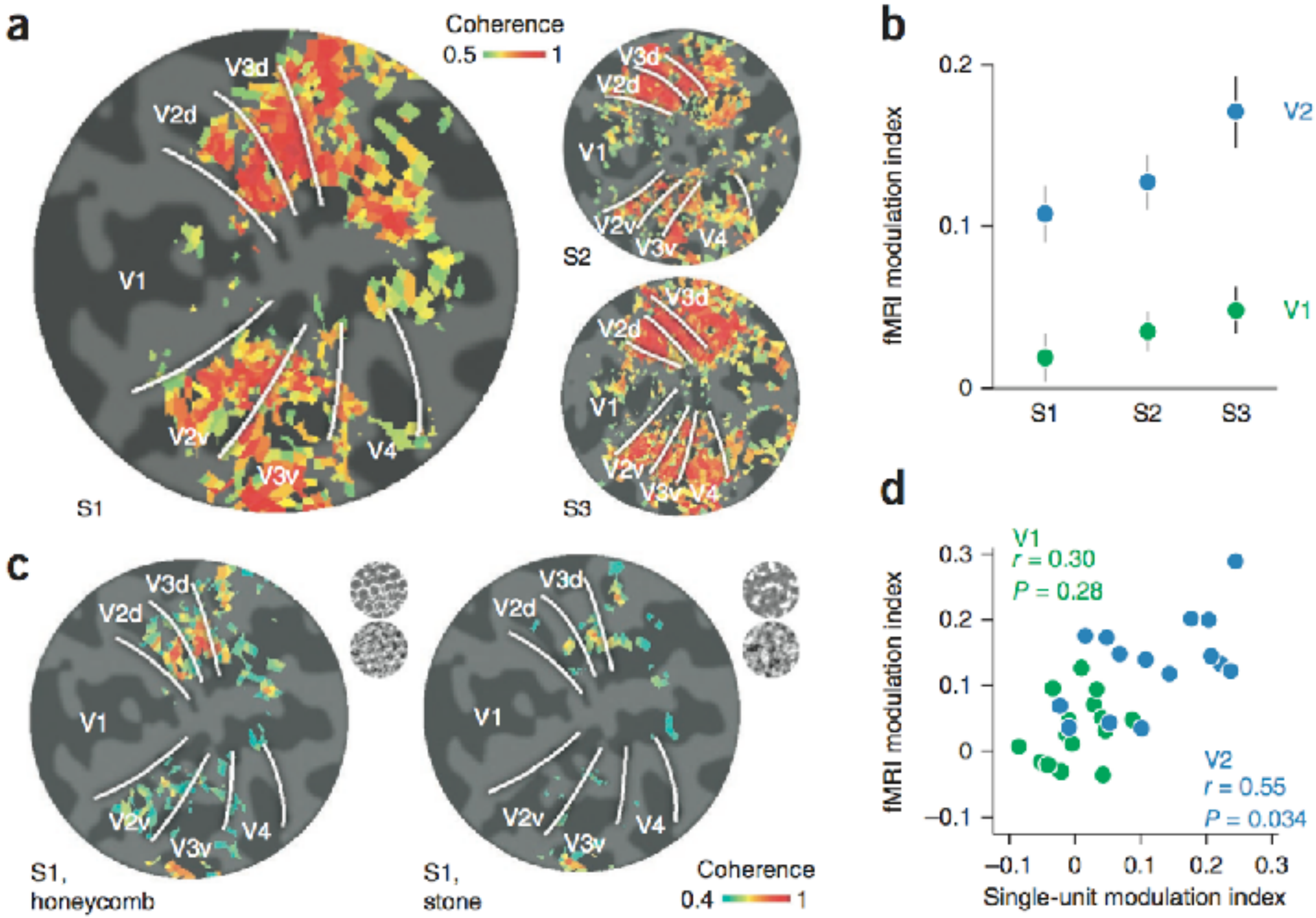
V2 responses to Portilla textures



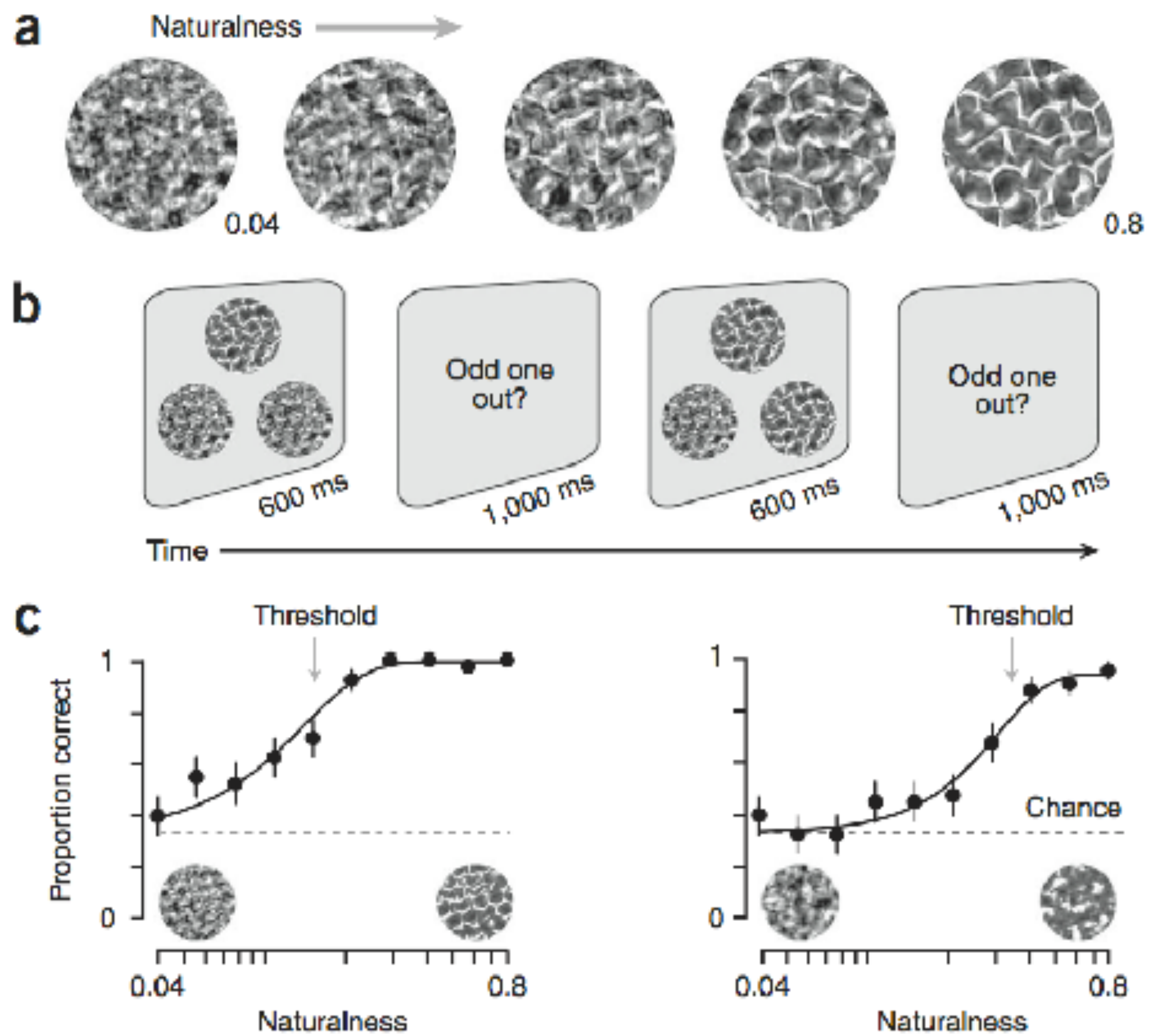
V2 responses to Portilla textures



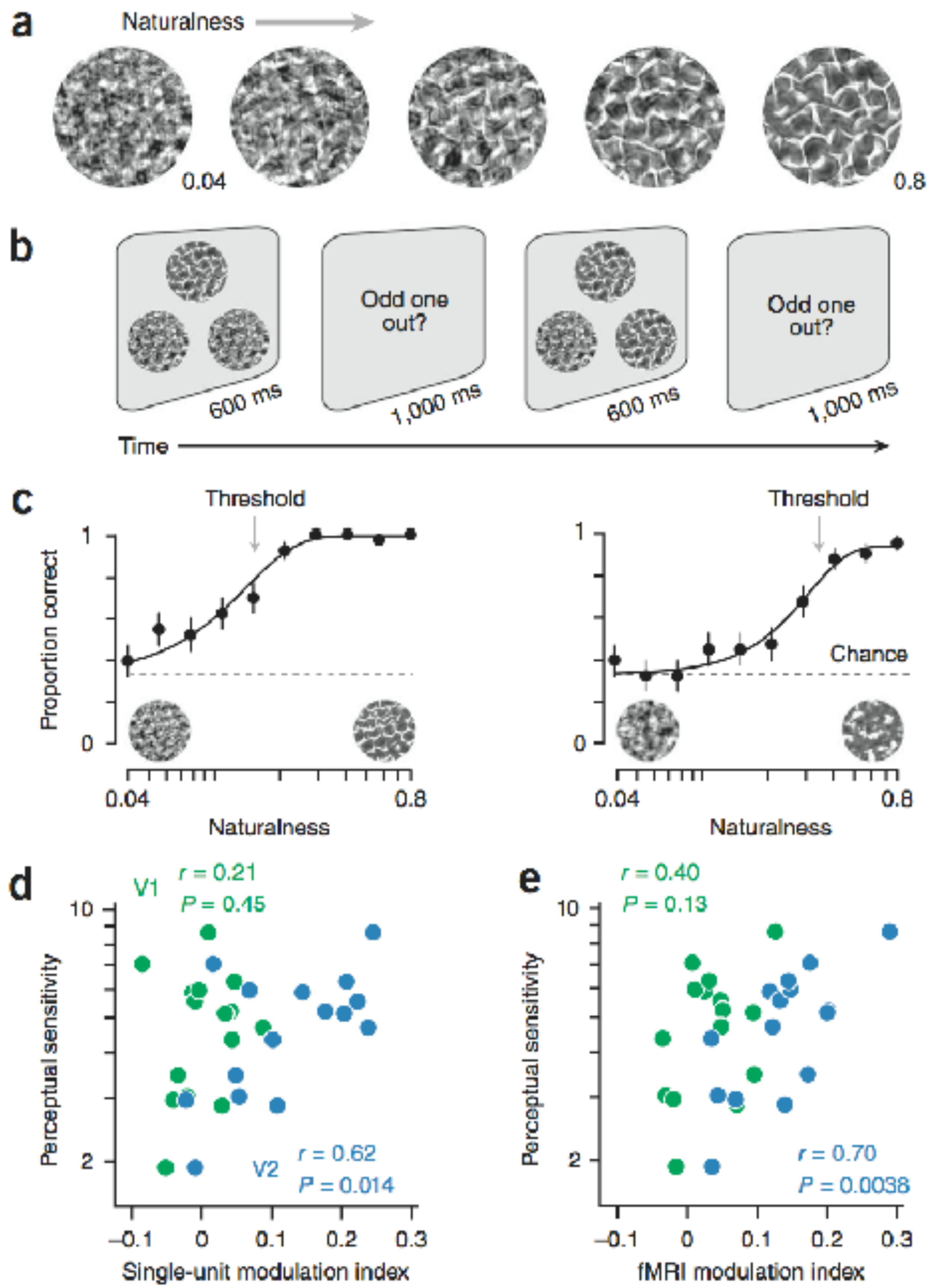
fMRI responses to Portilla textures



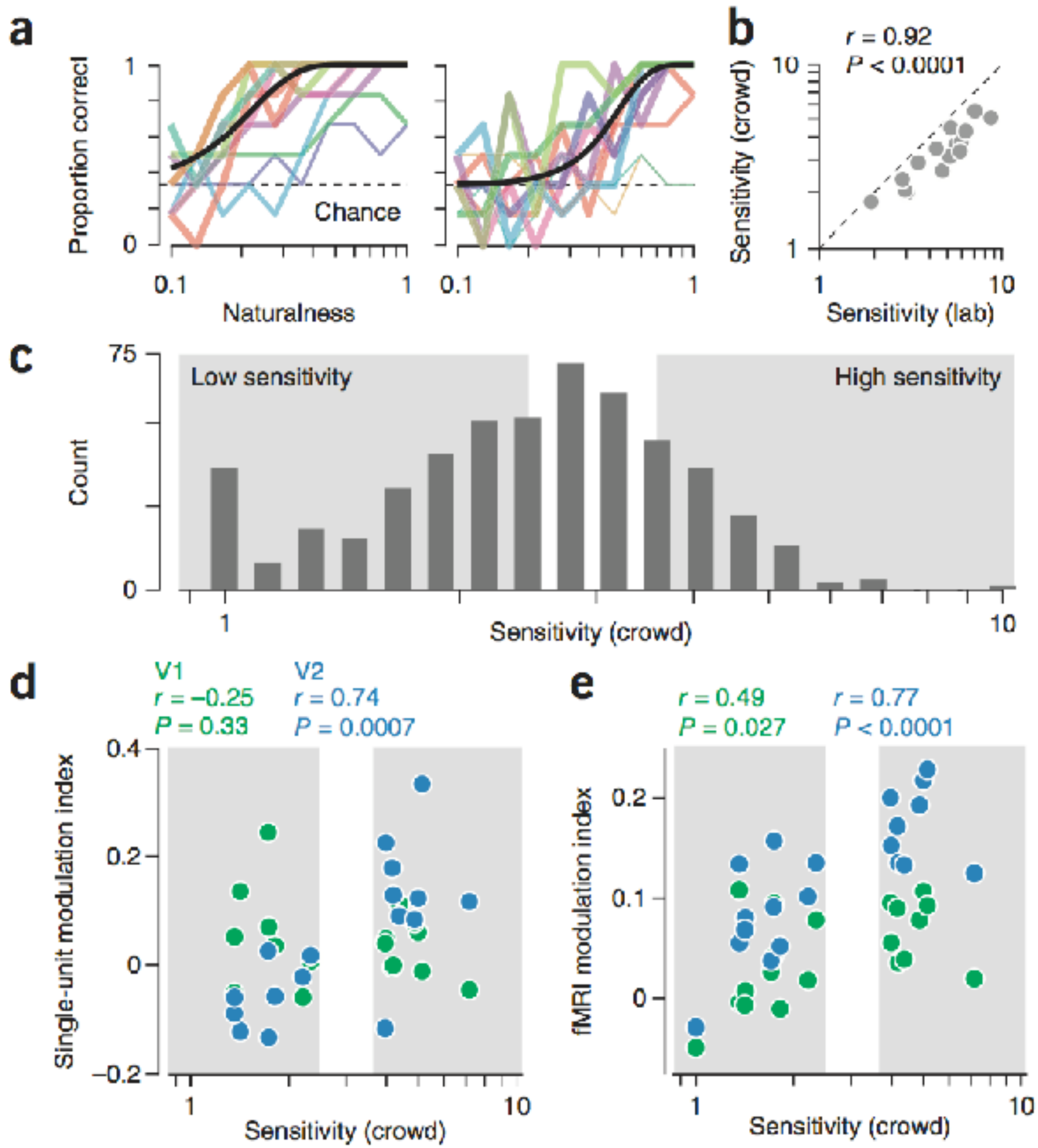
Perceptual correlates



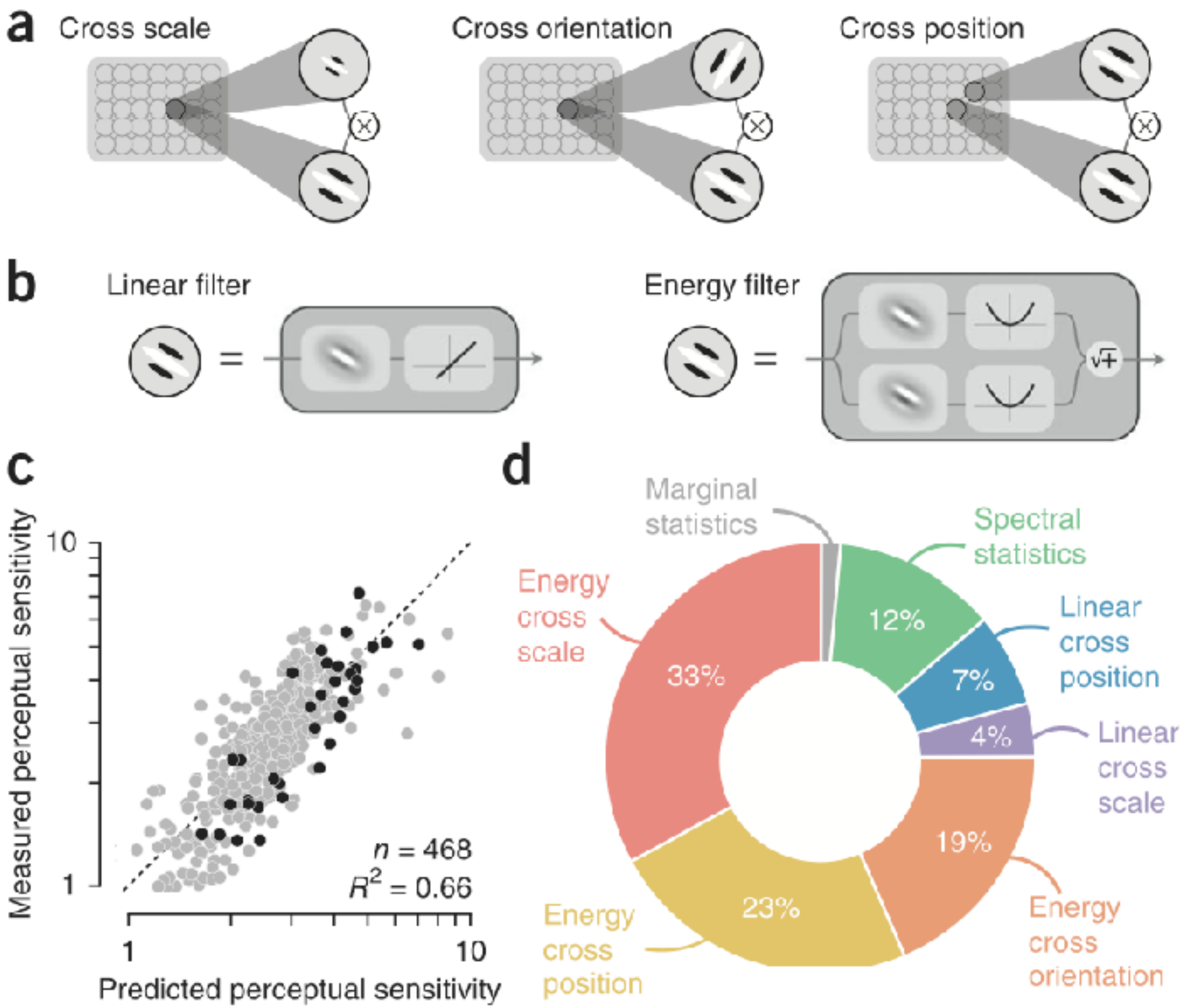
Perceptual correlates



The mechanical Turk challenge



The mechanical Turk challenge



Representational untangling

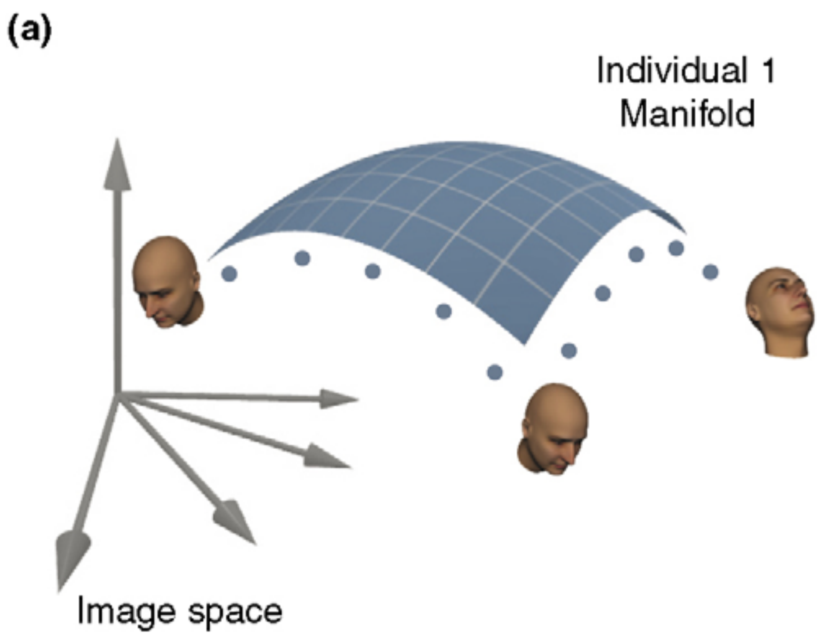
Opinion
TRENDS in Cognitive Sciences Vol.11 No.8
Full text provided by www.sciencedirect.com
ScienceDirect
ELSEVIER

Untangling invariant object recognition

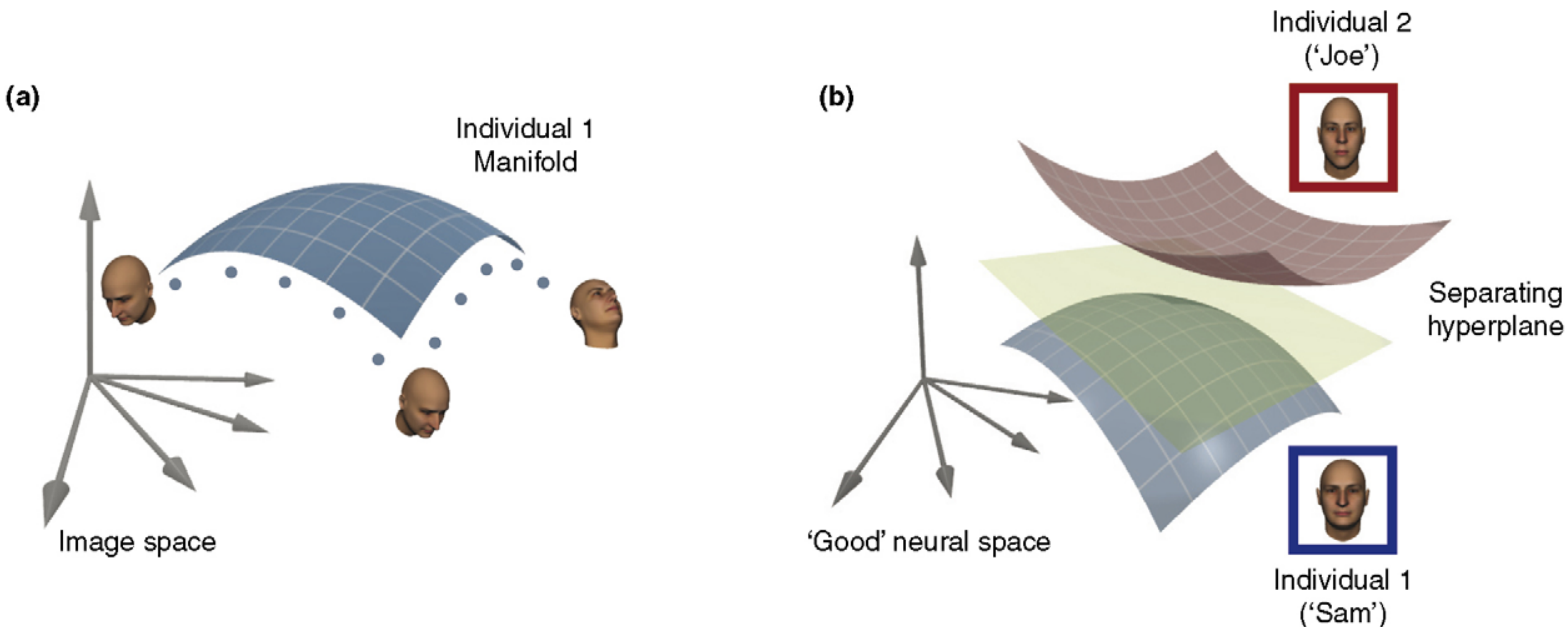
James J. DiCarlo and David D. Cox

Representational untangling

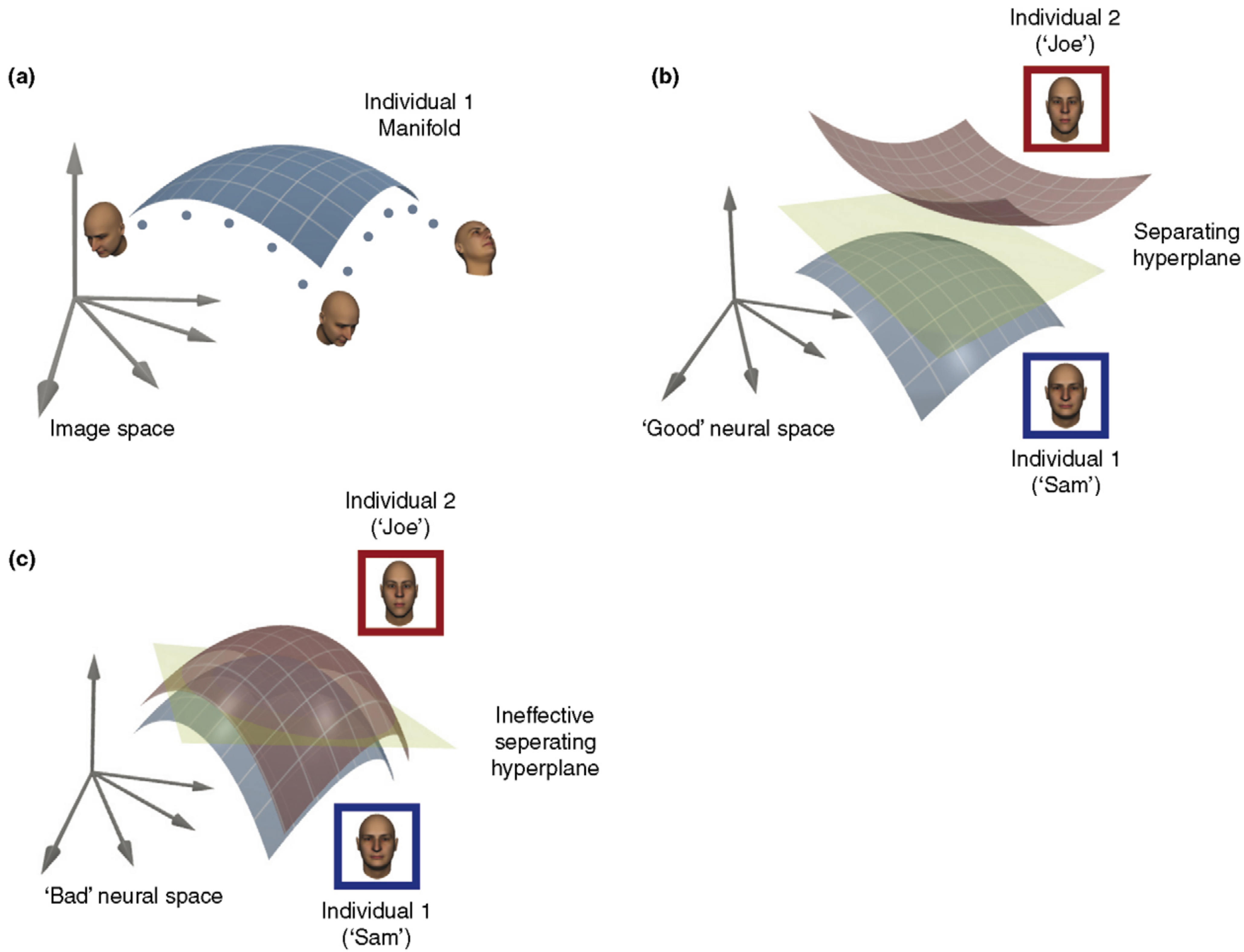
Representational untangling



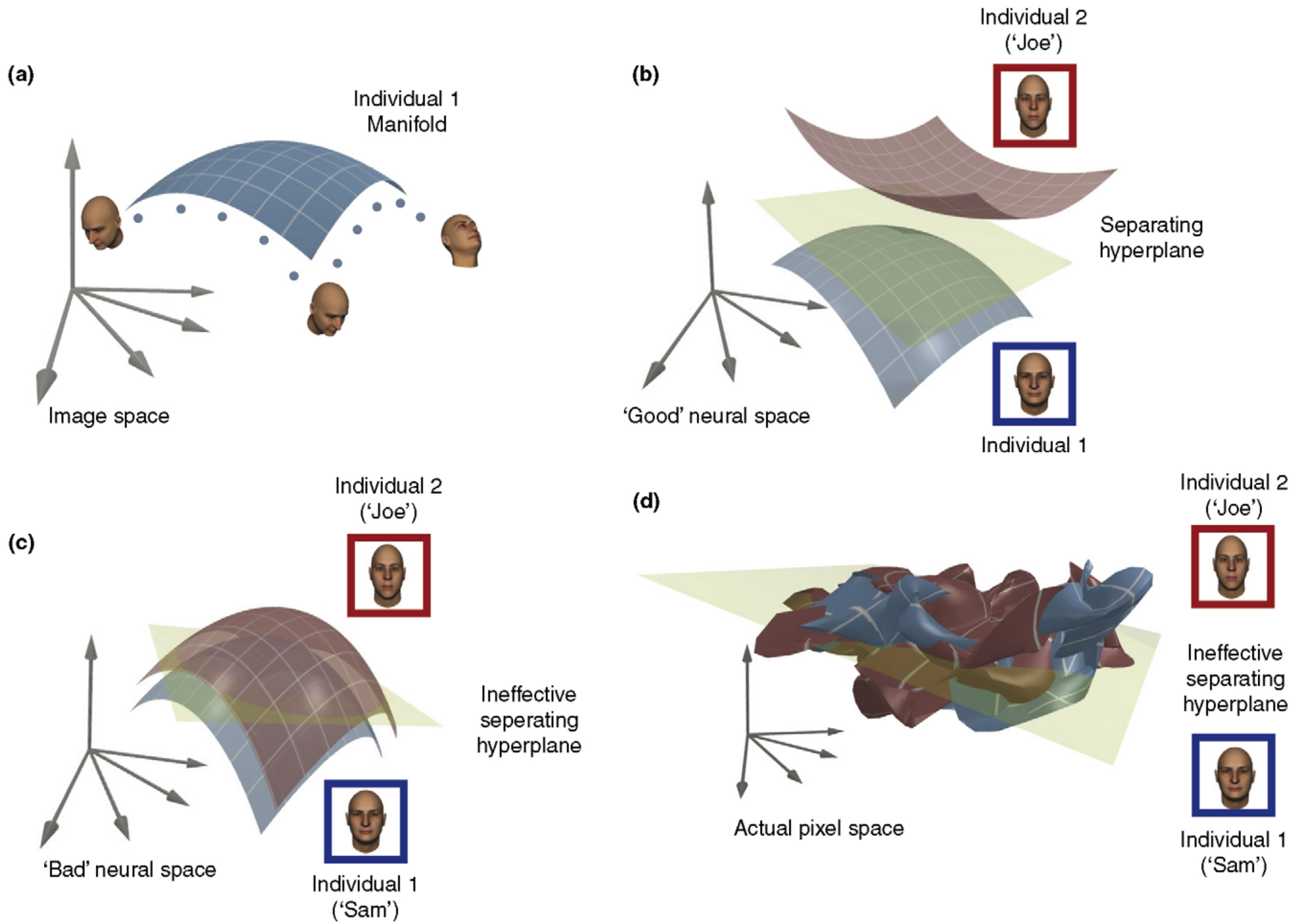
Representational untangling



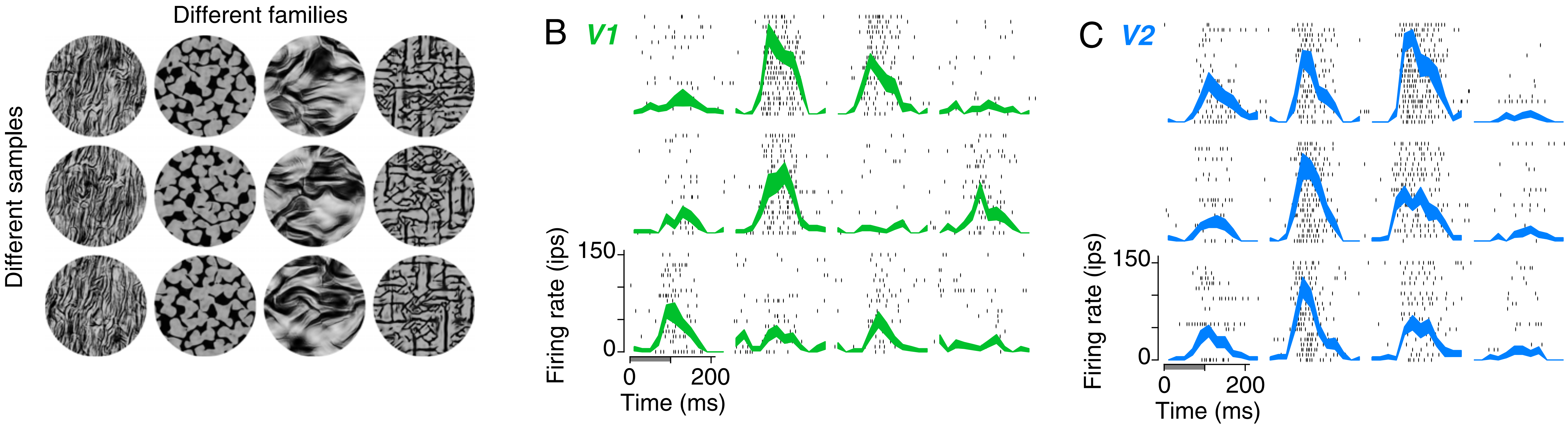
Representational untangling



Representational untangling

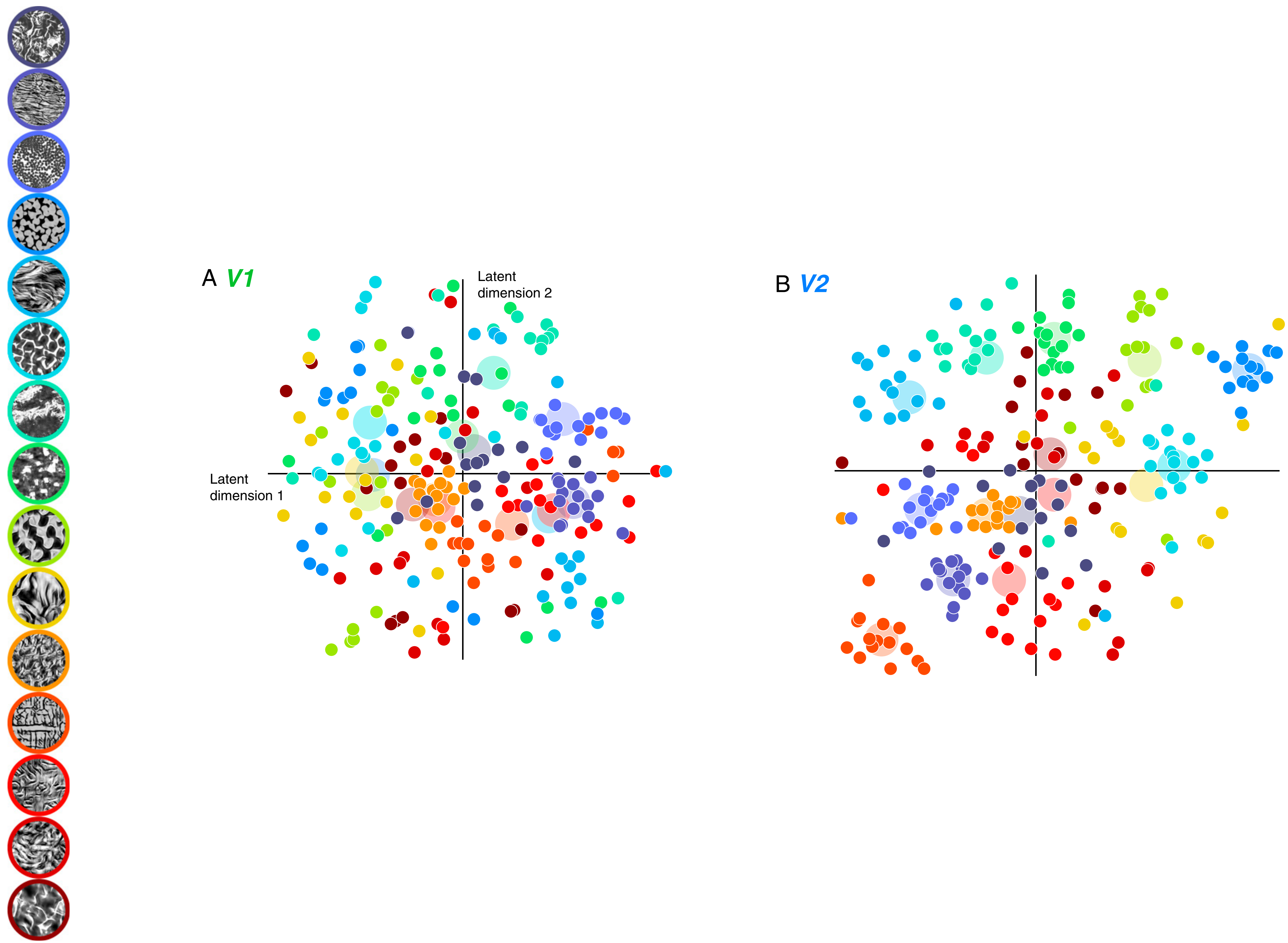


Invariance properties of V1/V2 neurons

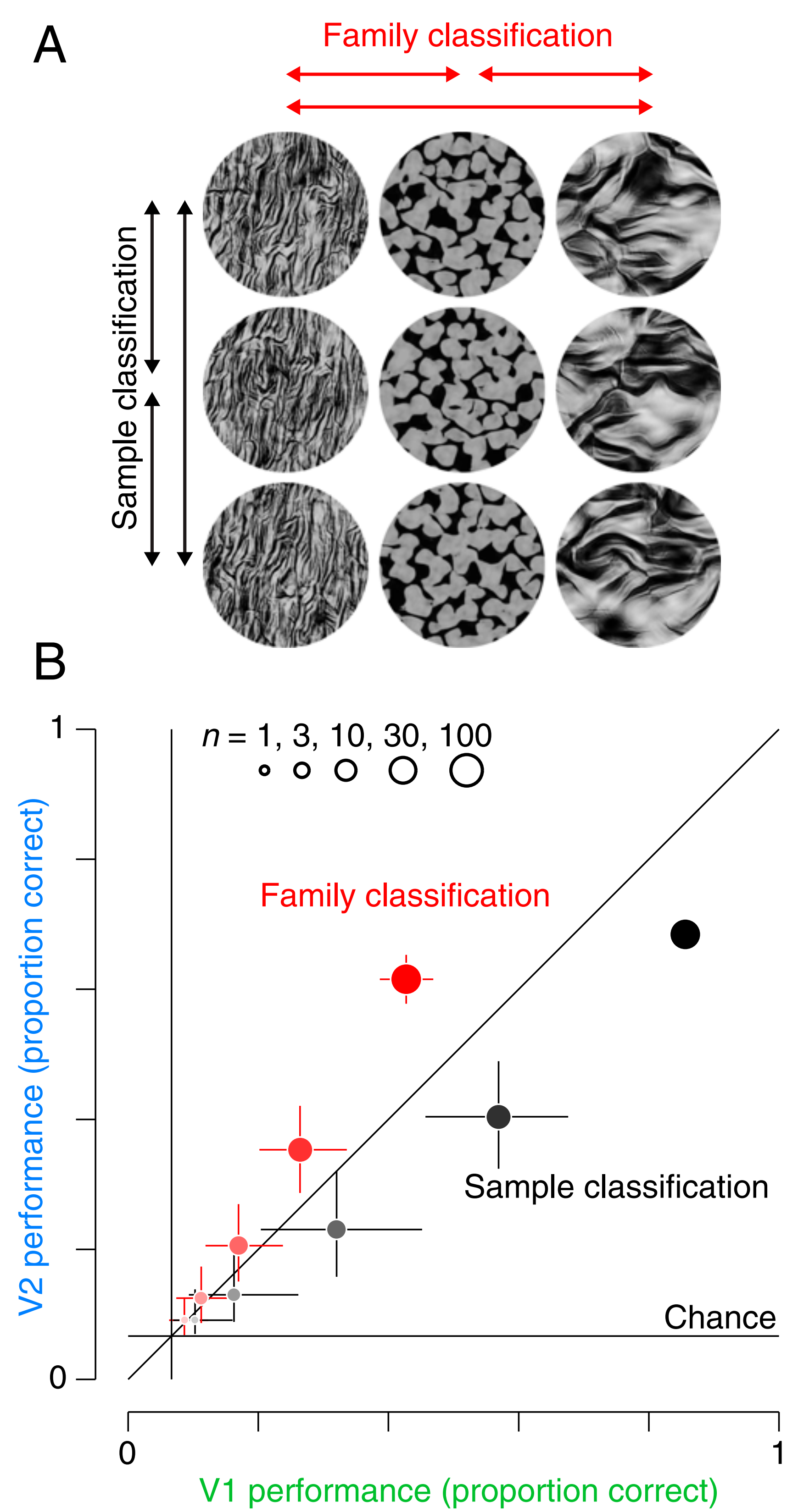


Representational untangling in the visual system

Texture family



Decoding of stimulus information

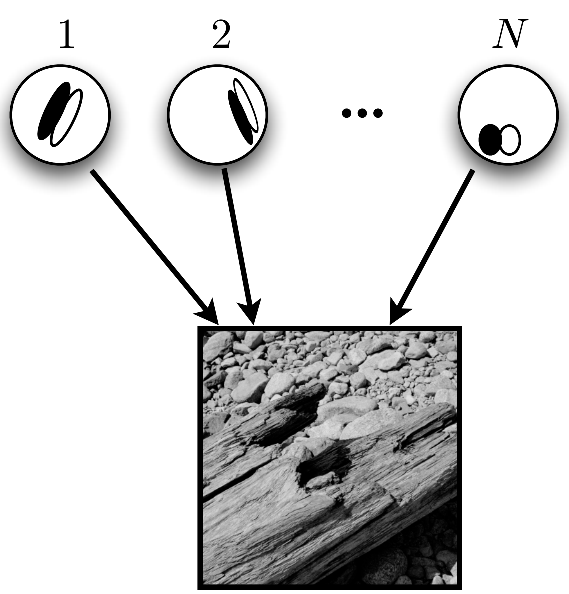


Bayesian inference

image

Bayesian inference

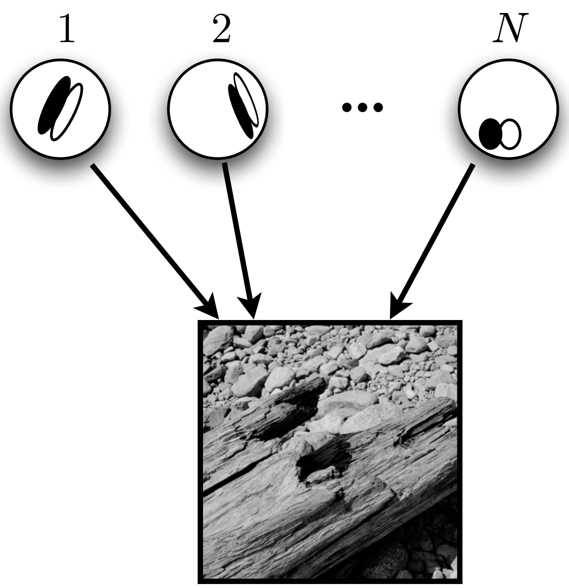
linear features



image

Bayesian inference

linear features

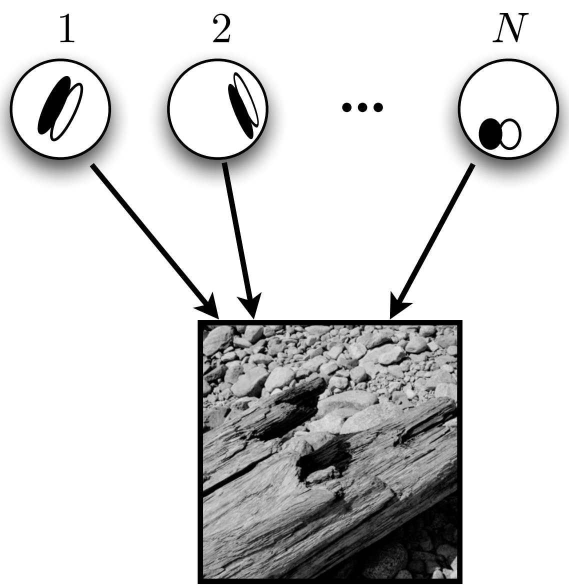


image

$$\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}$$

Bayesian inference

linear features

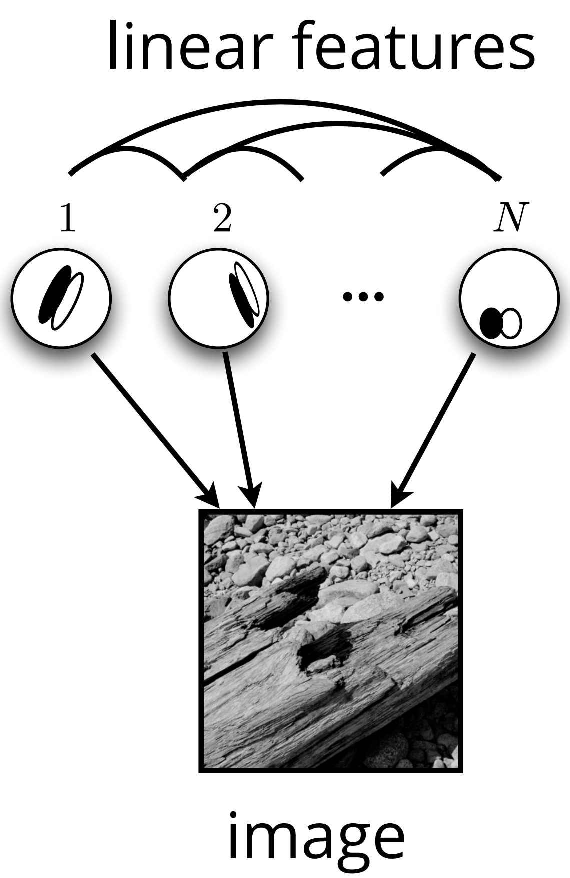


image

neural activities
[a_1, a_2, …, a_N]

$$\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}$$

Bayesian inference

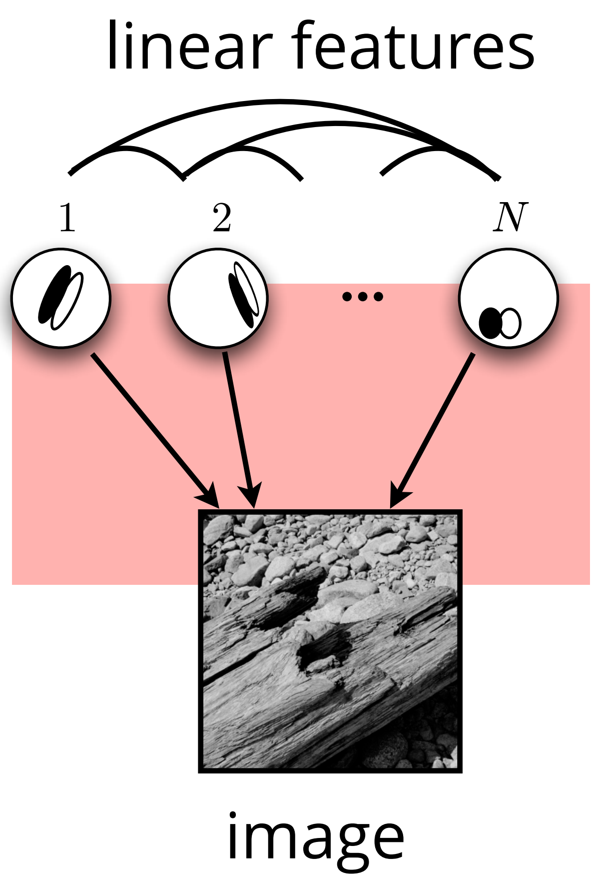


neural activities

[a_1, a_2, …, a_N]

$$\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}$$

Bayesian inference



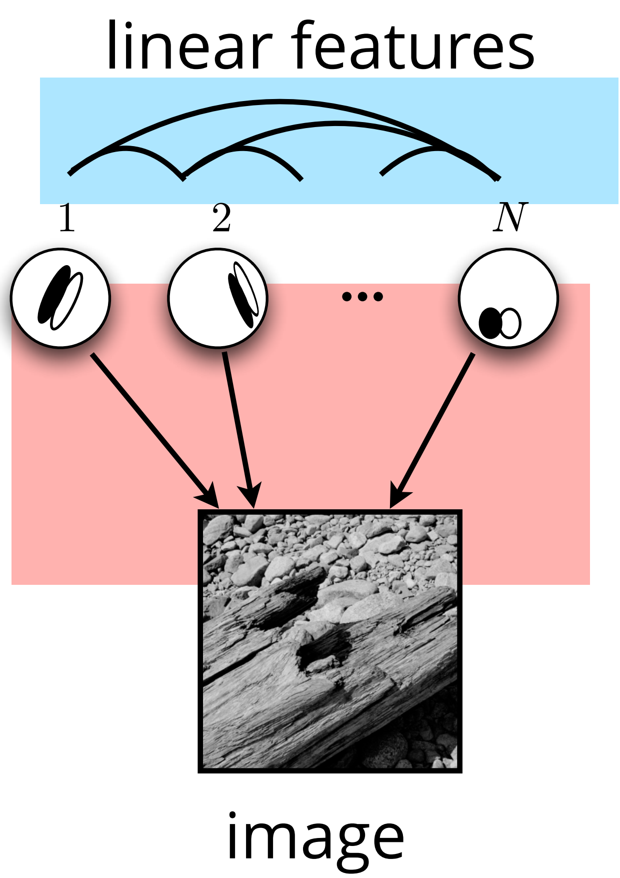
neural activities

[a_1, a_2, …, a_N]

evidence

$$\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}$$

Bayesian inference



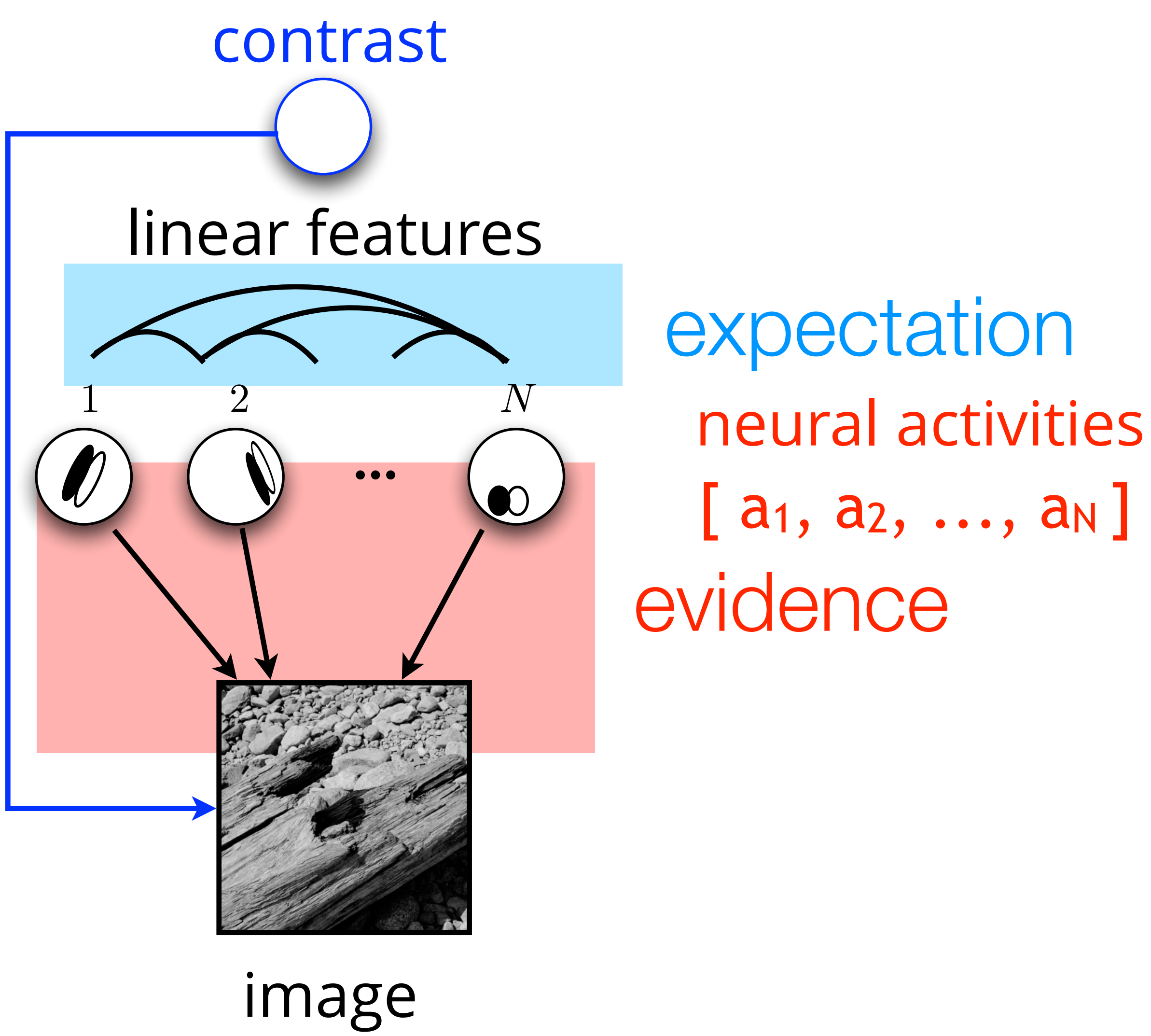
expectation

neural activities

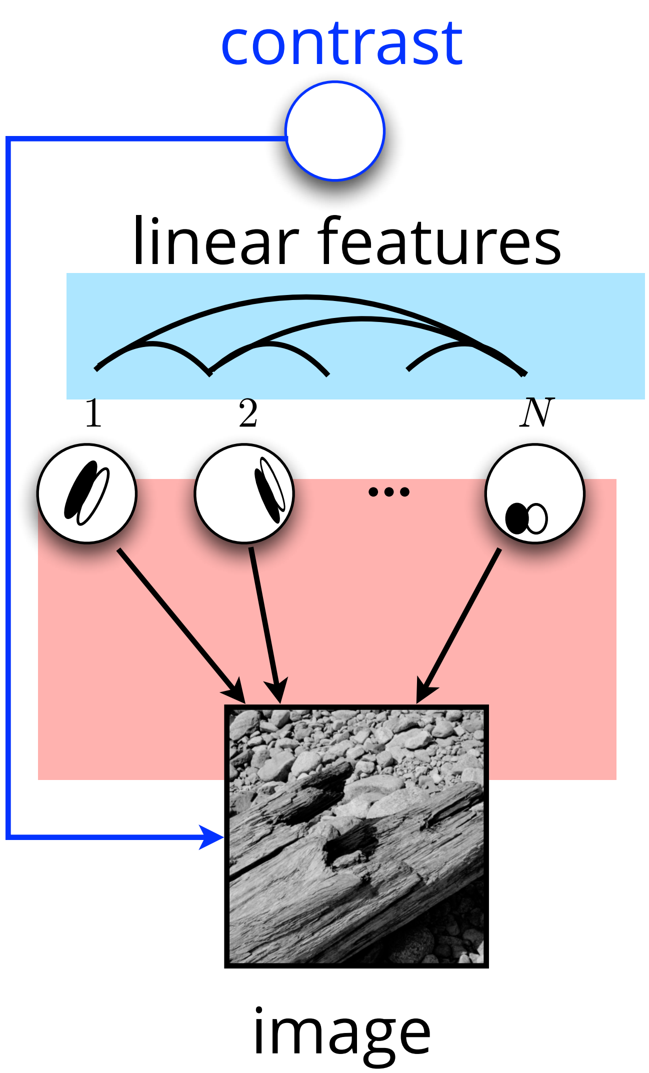
[a_1, a_2, …, a_N]

evidence

$$\text{image} = \quad a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N \quad + \text{noise}$$



$$\text{image} = \text{contrast} \times \left(a_1 \,\text{feature}_1 + a_2 \,\text{feature}_2 + \ldots + a_N \,\text{feature}_N \right) + \text{noise}$$



expectation

neural activities

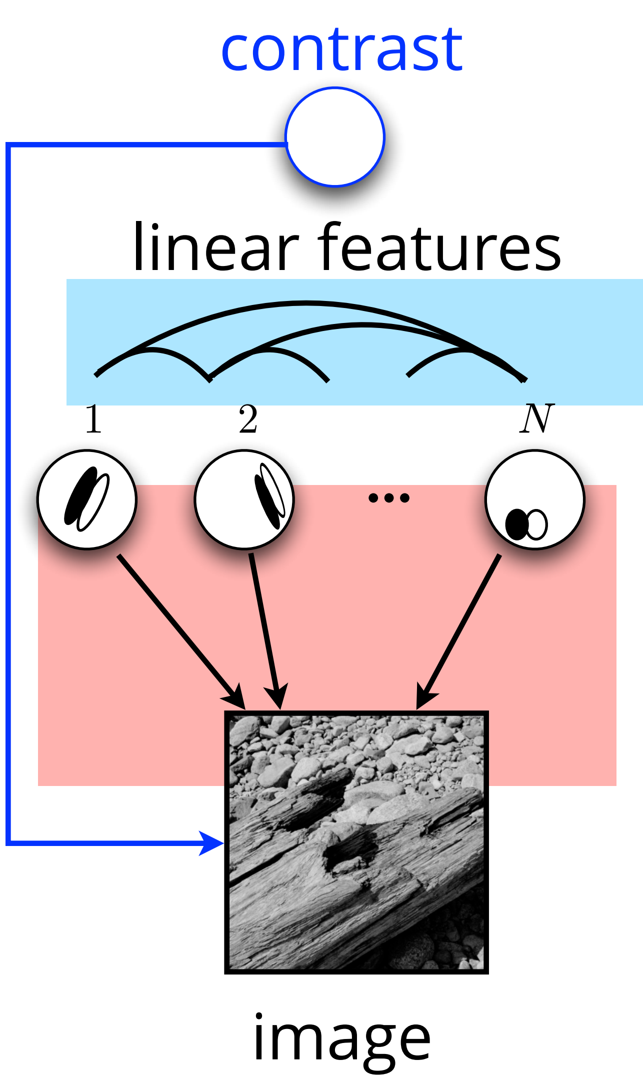
[a_1, a_2, …, a_N]

evidence

$$\underbrace{\text{image} = \text{contrast} \times \left(a_1\ \text{feature}_1 + a_2\ \text{feature}_2 + \ldots + a_N\ \text{feature}_N\right) + \text{noise}}$$

$$\underbrace{\mathrm{P}(\text{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$

Bayesian inference



expectation

neural activities

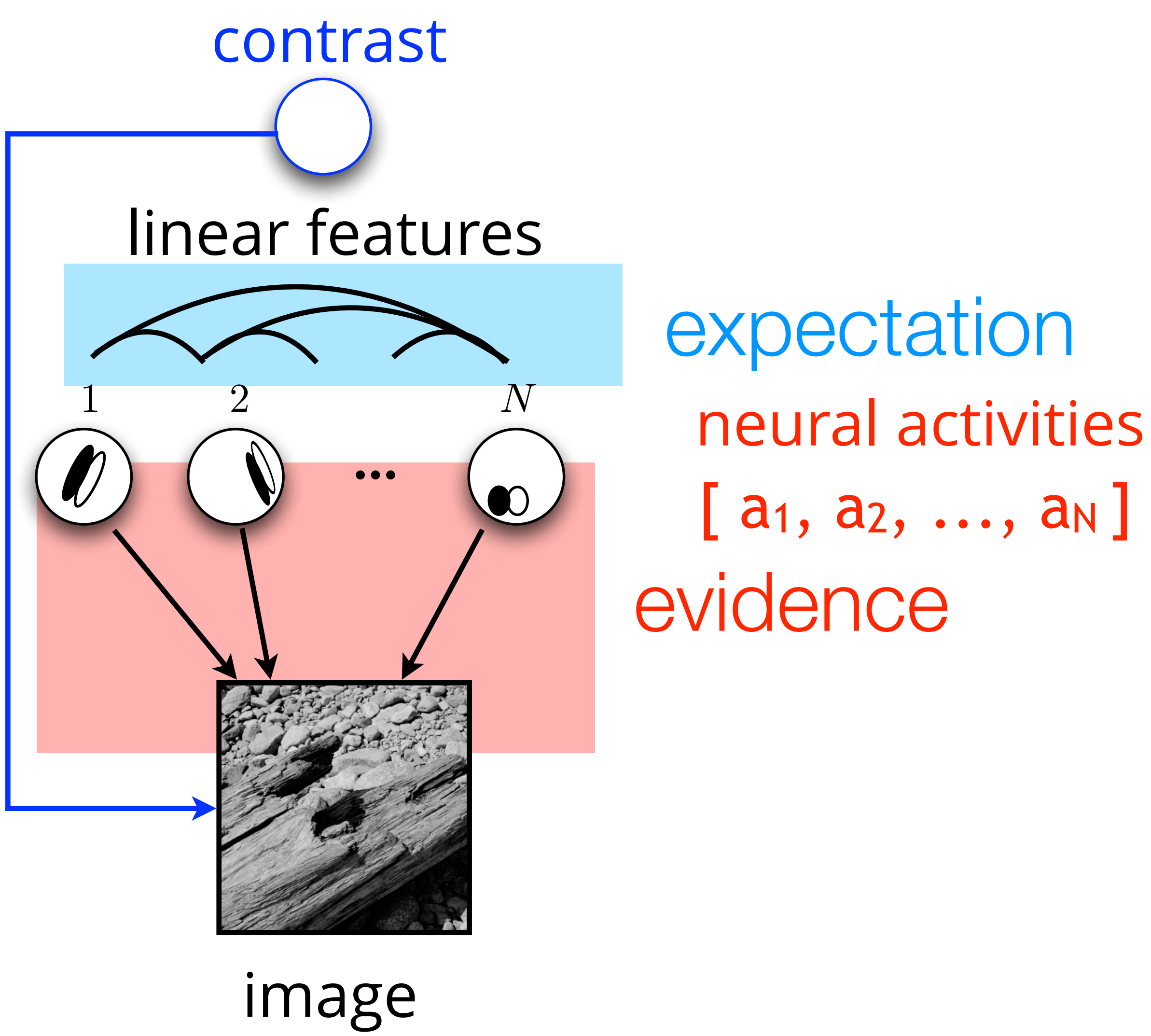
[a_1, a_2, …, a_N]

evidence

$$\text{image} = \text{contrast} \times \left(a_1\,\text{feature}_1 + a_2\,\text{feature}_2 + \ldots + a_N\,\text{feature}_N\right) + \text{noise}$$

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid \text{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\text{image} \mid a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$

Bayesian inference



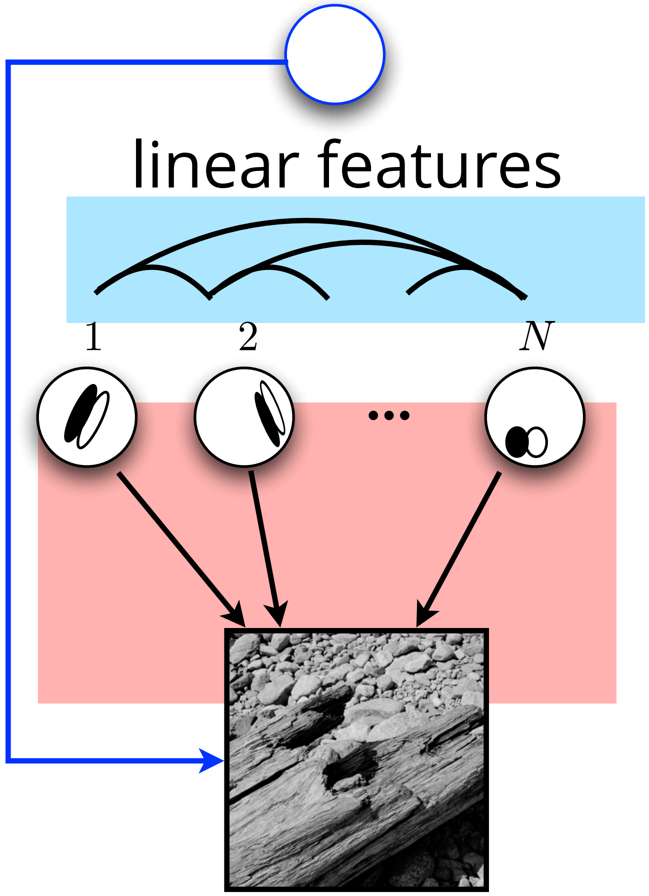
Demonstrated efficiency in:

- ★ pattern-completion
- ★ compression
- ★ denoising

$$\text{image} = \text{contrast} \times \left(a_1 \, \text{feature}_1 + a_2 \, \text{feature}_2 + \ldots + a_N \, \text{feature}_N \right) + \text{noise}$$

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid \text{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\text{image} \mid a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$

Bayesian inference



expectation

neural activities

[a_1, a_2, …, a_N]

evidence

Demonstrated efficiency in:

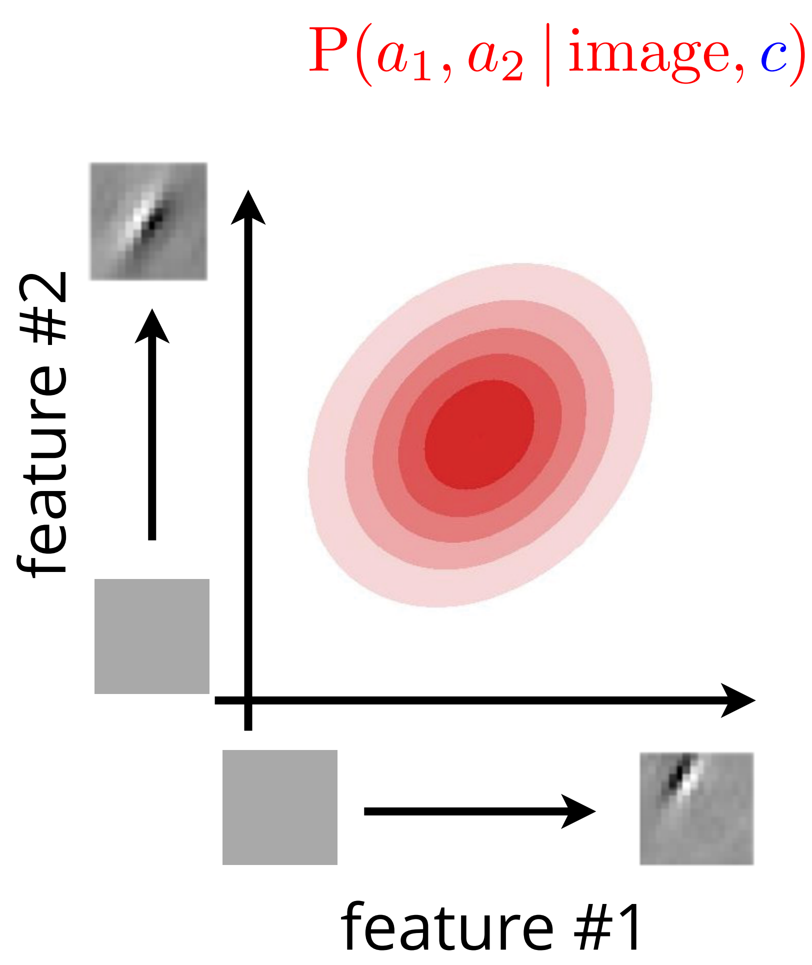
- ★ pattern-completion
- ★ compression
- ★ denoising

the parametric form of both
evidence and expectation is determined by
natural image statistics

mean responses

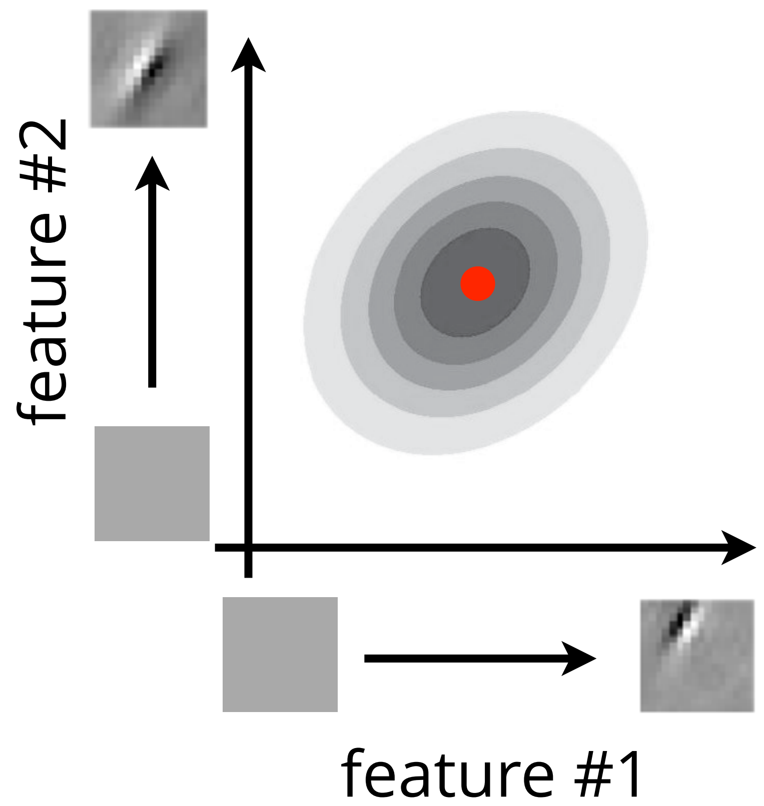
$$\mathrm{P}(a_1, a_2 \,|\, \mathrm{image}, c)$$

mean responses

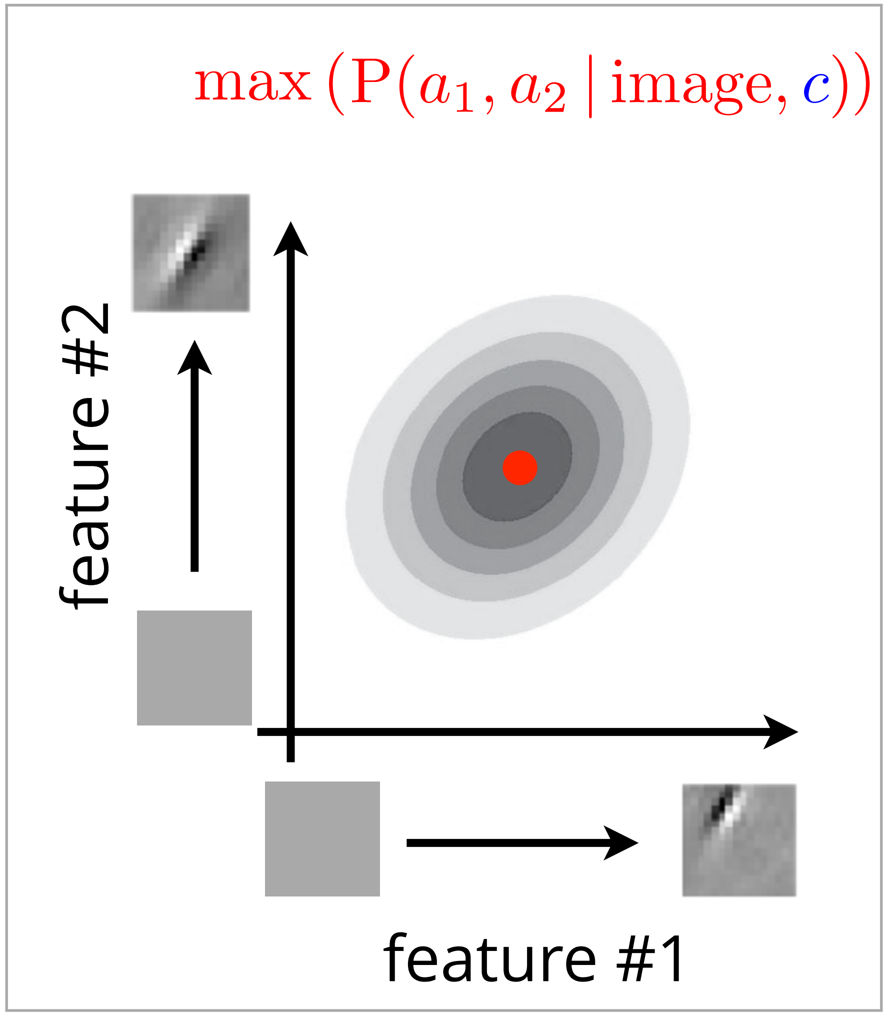


mean responses

$$\max\left(\mathrm{P}(a_1, a_2 \mid \text{image}, c)\right)$$



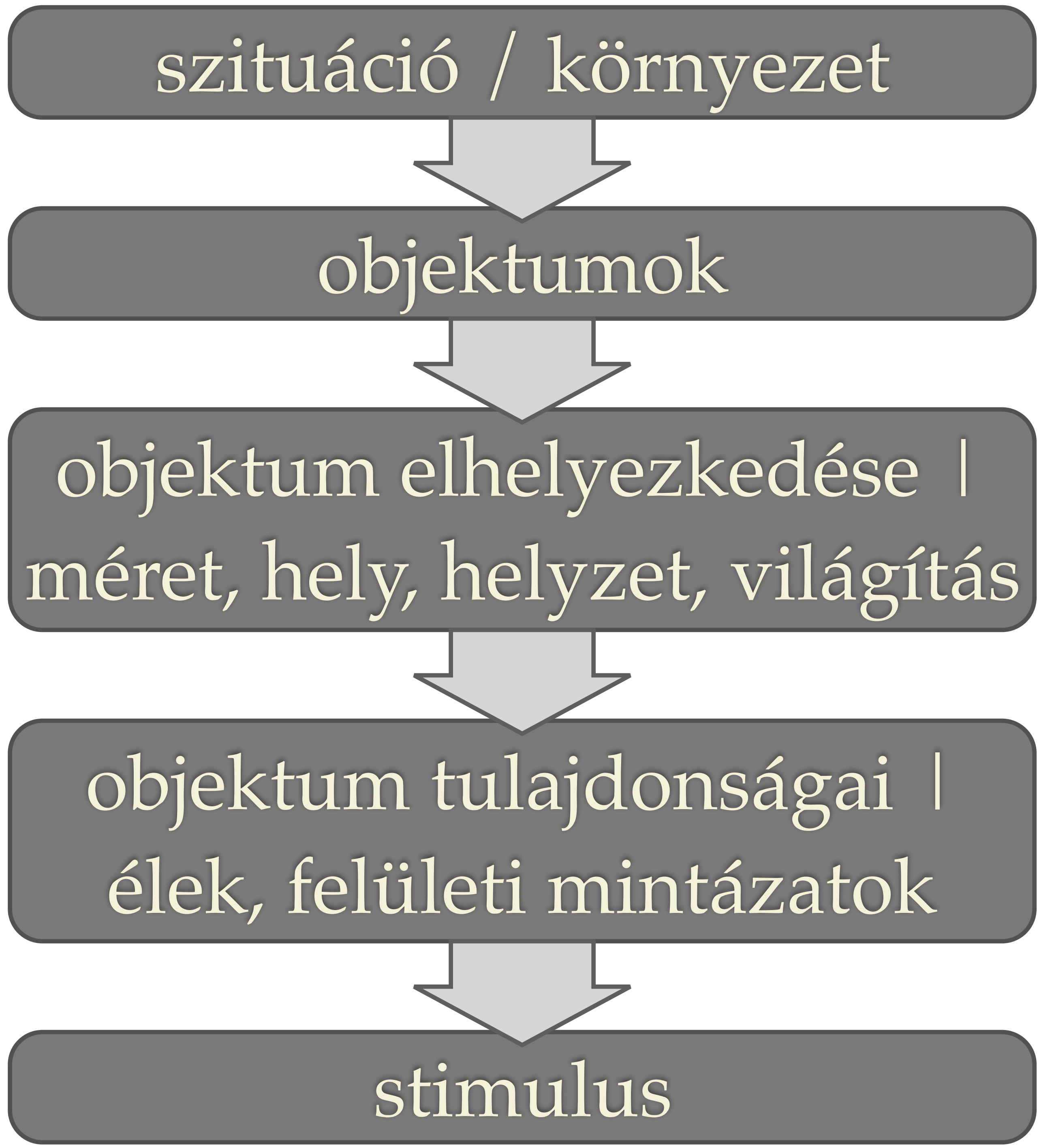
mean responses



traditional theories
e.g. Olshausen & Field, Nature 1996,
Schwartz & Simoncelli, Nat Neurosci
2001

mean response $\rightsquigarrow$ maximum a posteriori inference

Generatív/rekogniciós modell



Generatív/rekogniciós modell

szituáció / környezet

↓

objektumok

↓

objektum elhelyezkedése | méret, hely, helyzet, világítás

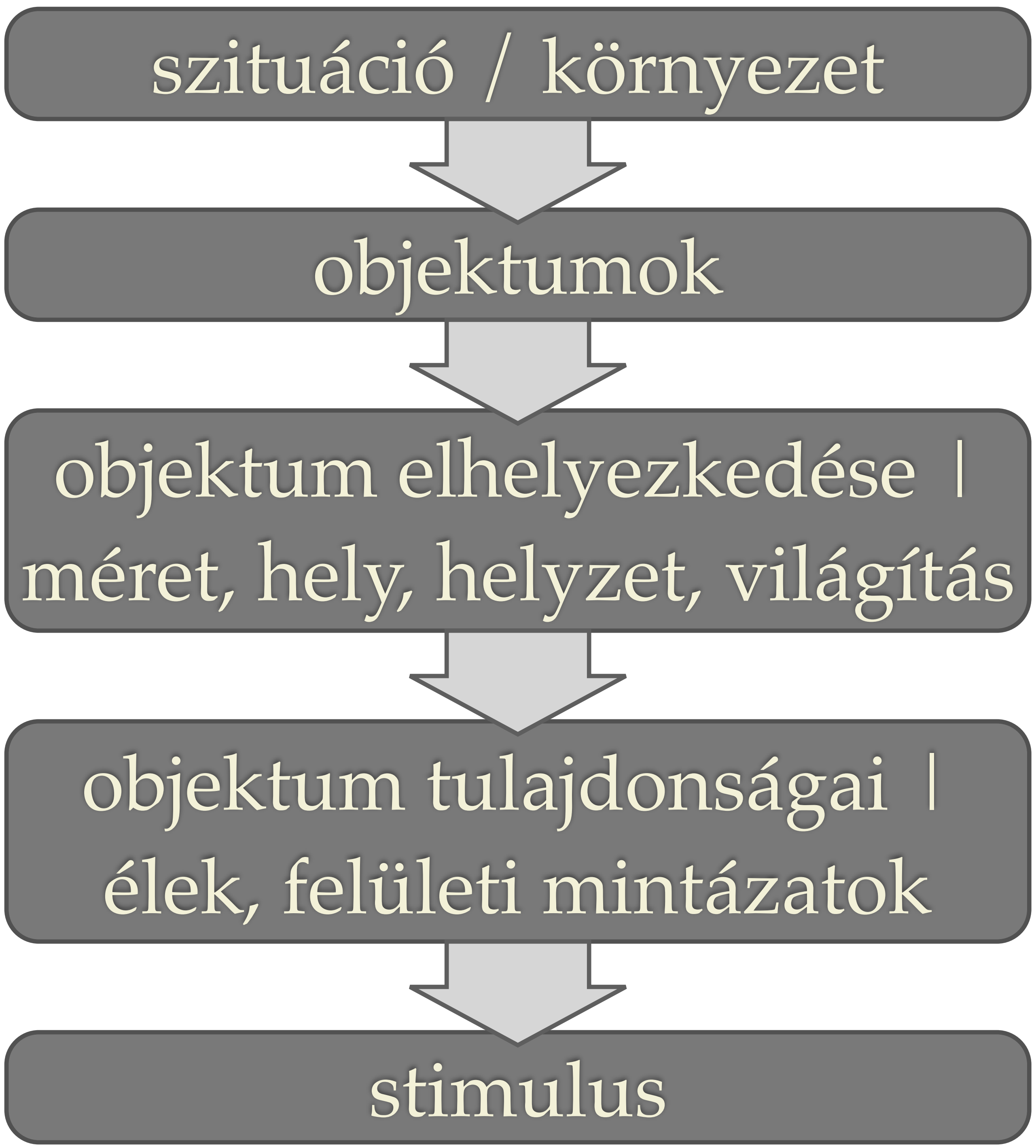
↓

objektum tulajdonságai | élek, felületi mintázatok

↓

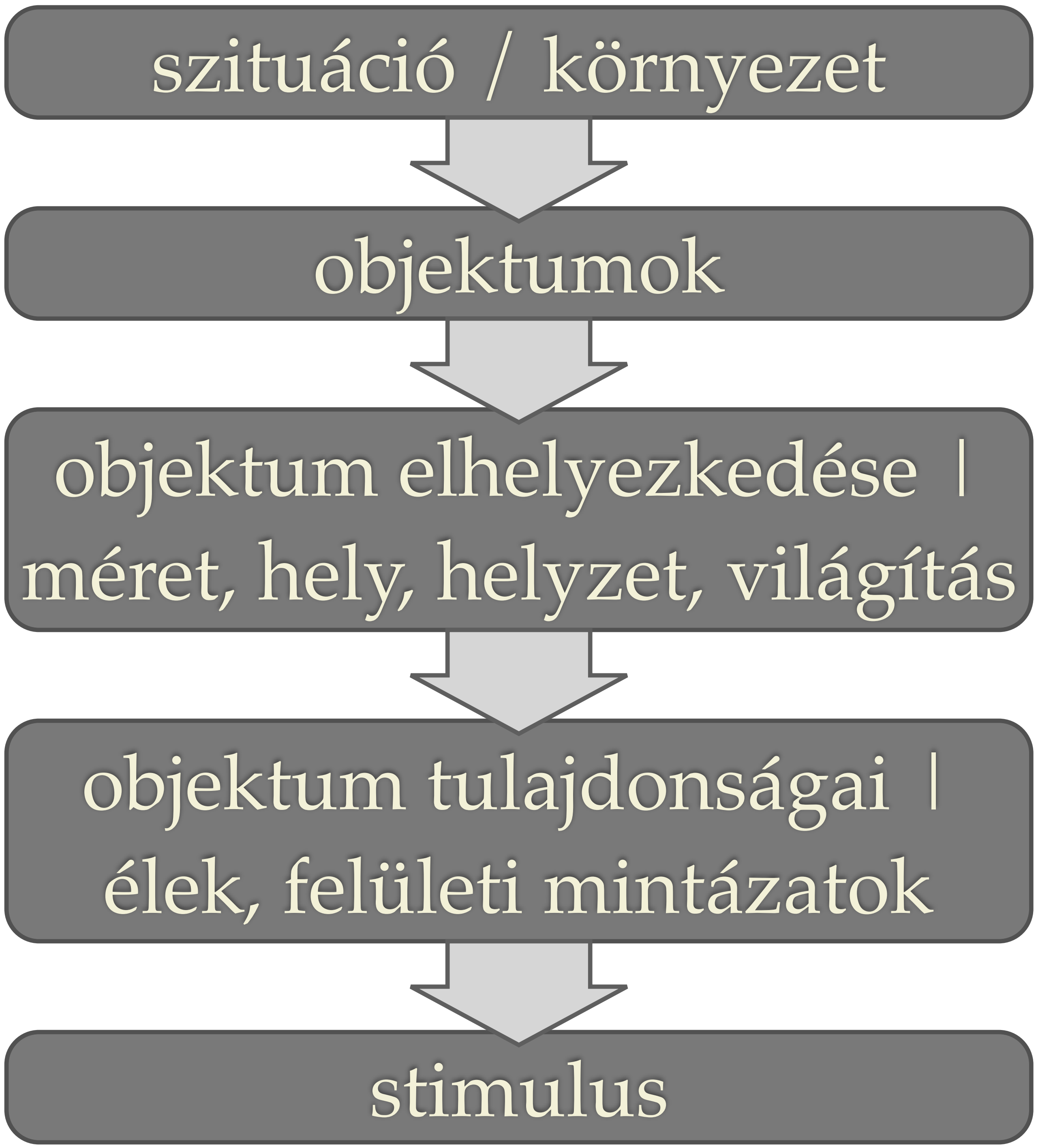
stimulus

Generatív/rekogniciós modell



Modell definició -> generáció:
P(x | z)

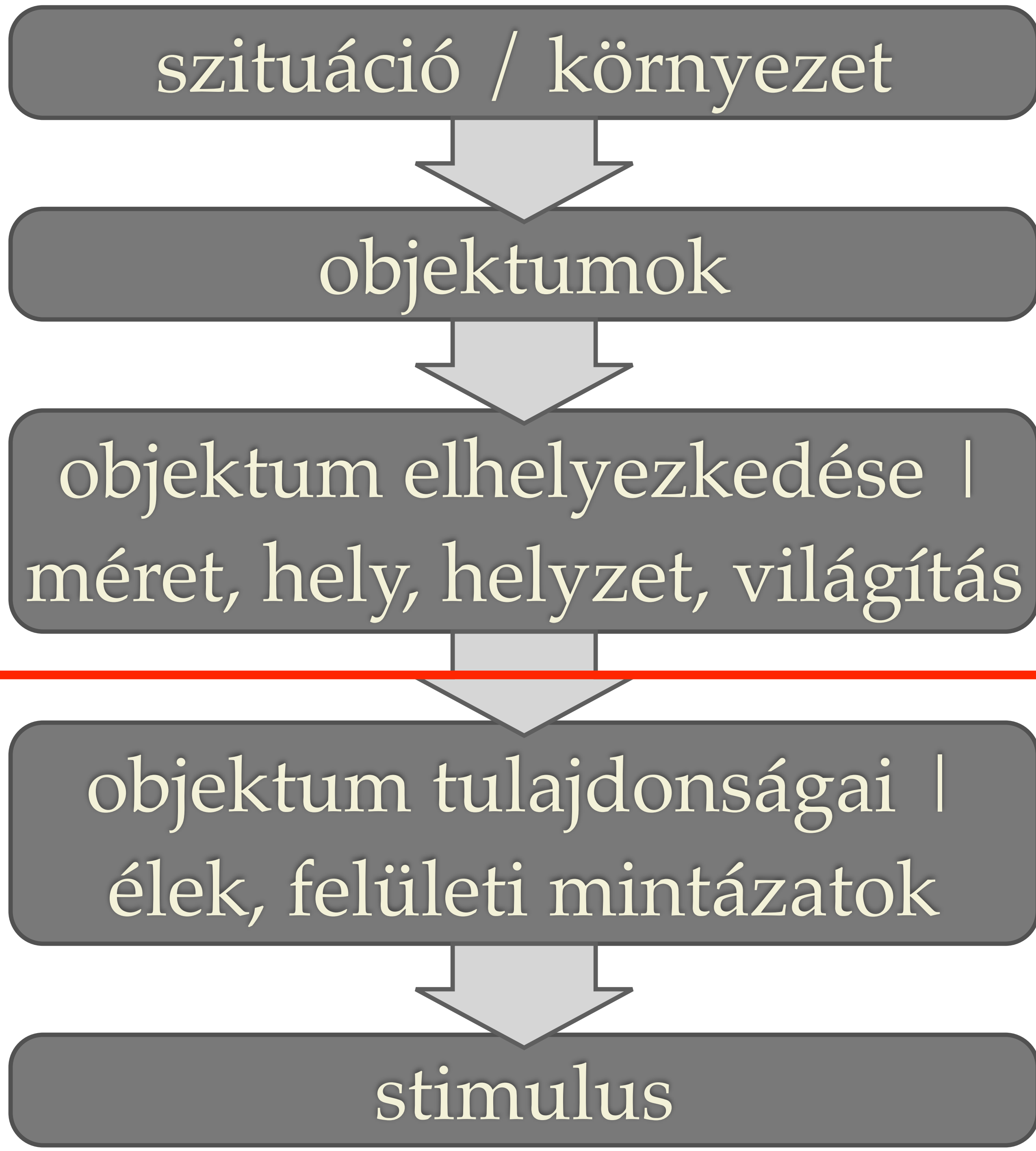
Generatív/rekogniciós modell



Modell definició -> generáció: $P(x \mid z)$

Inferencia igénye -> rekogníció: $P(z \mid x)$

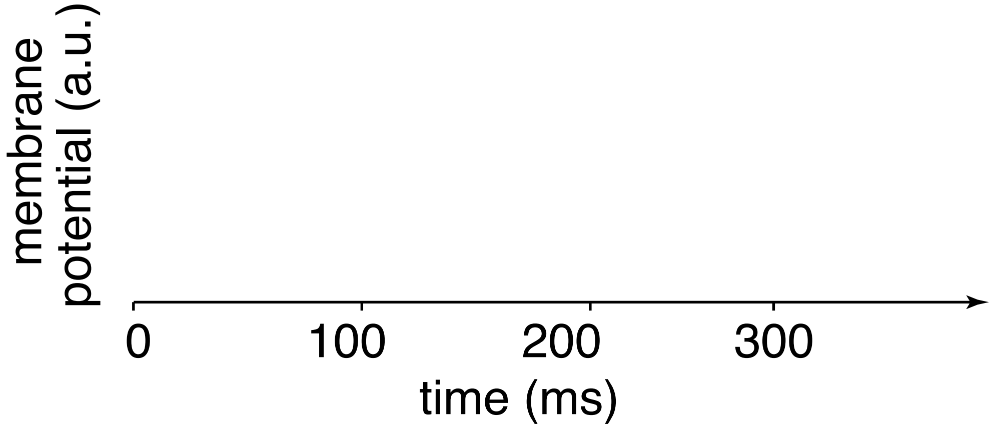
Generatív/rekogniciós modell



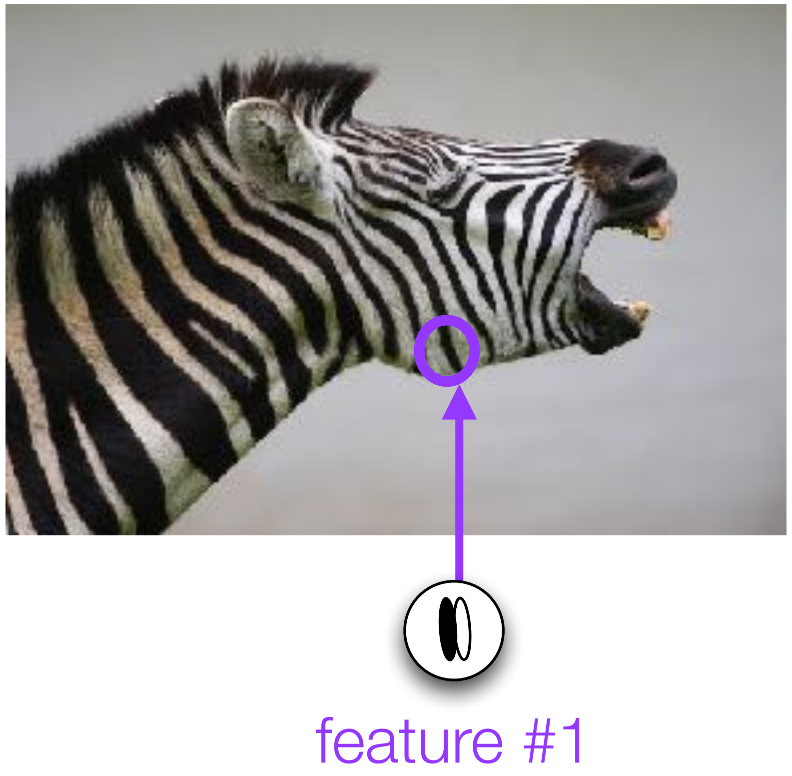
Modell definició -> generáció:
$P(x \mid z)$

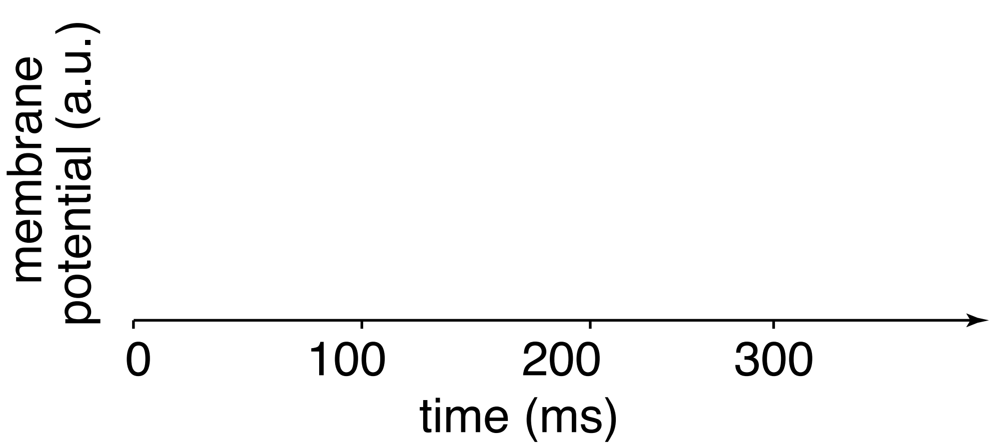
Inferencia igénye -> rekogníció:
$P(z \mid x)$

stochastic sampling

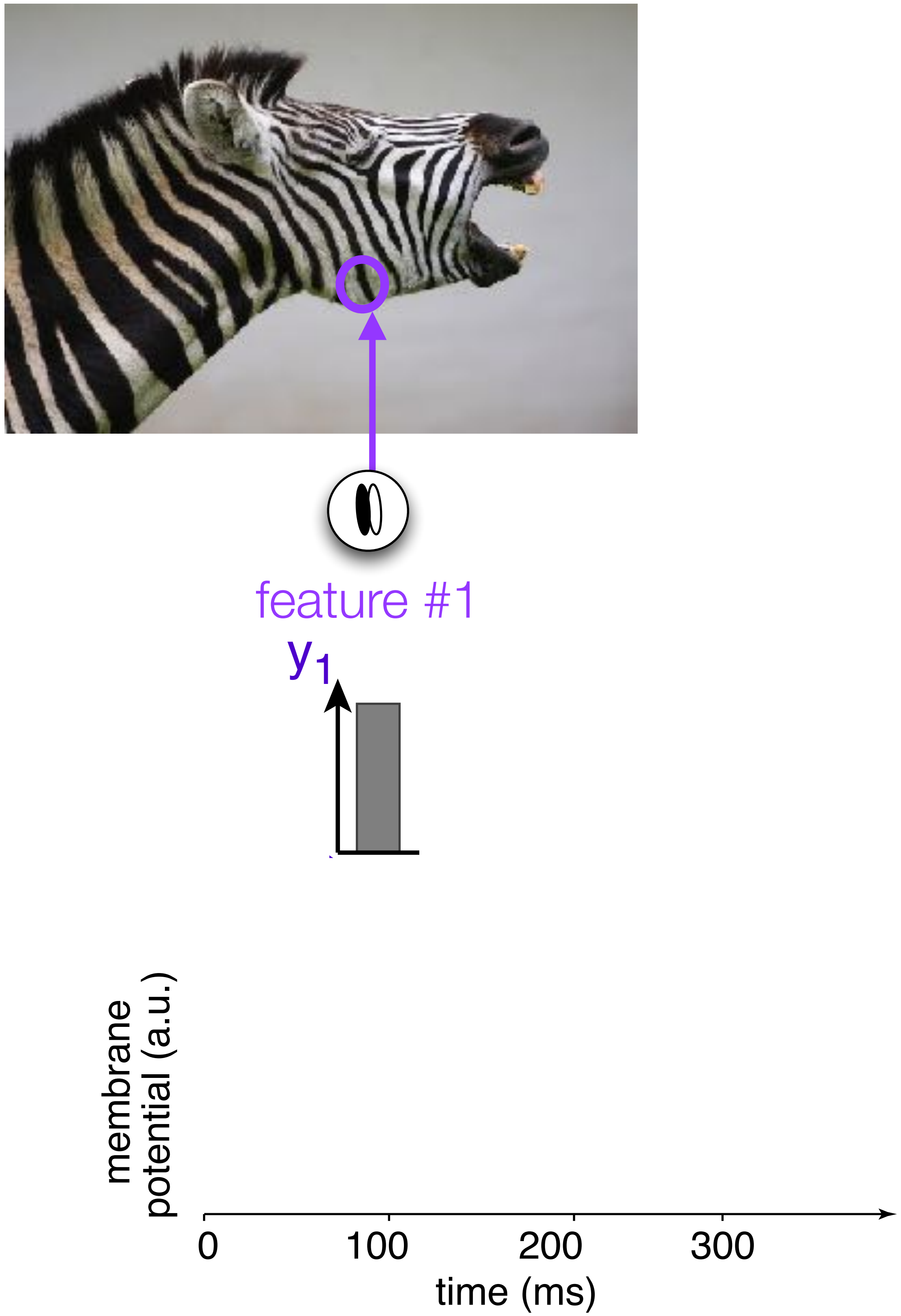


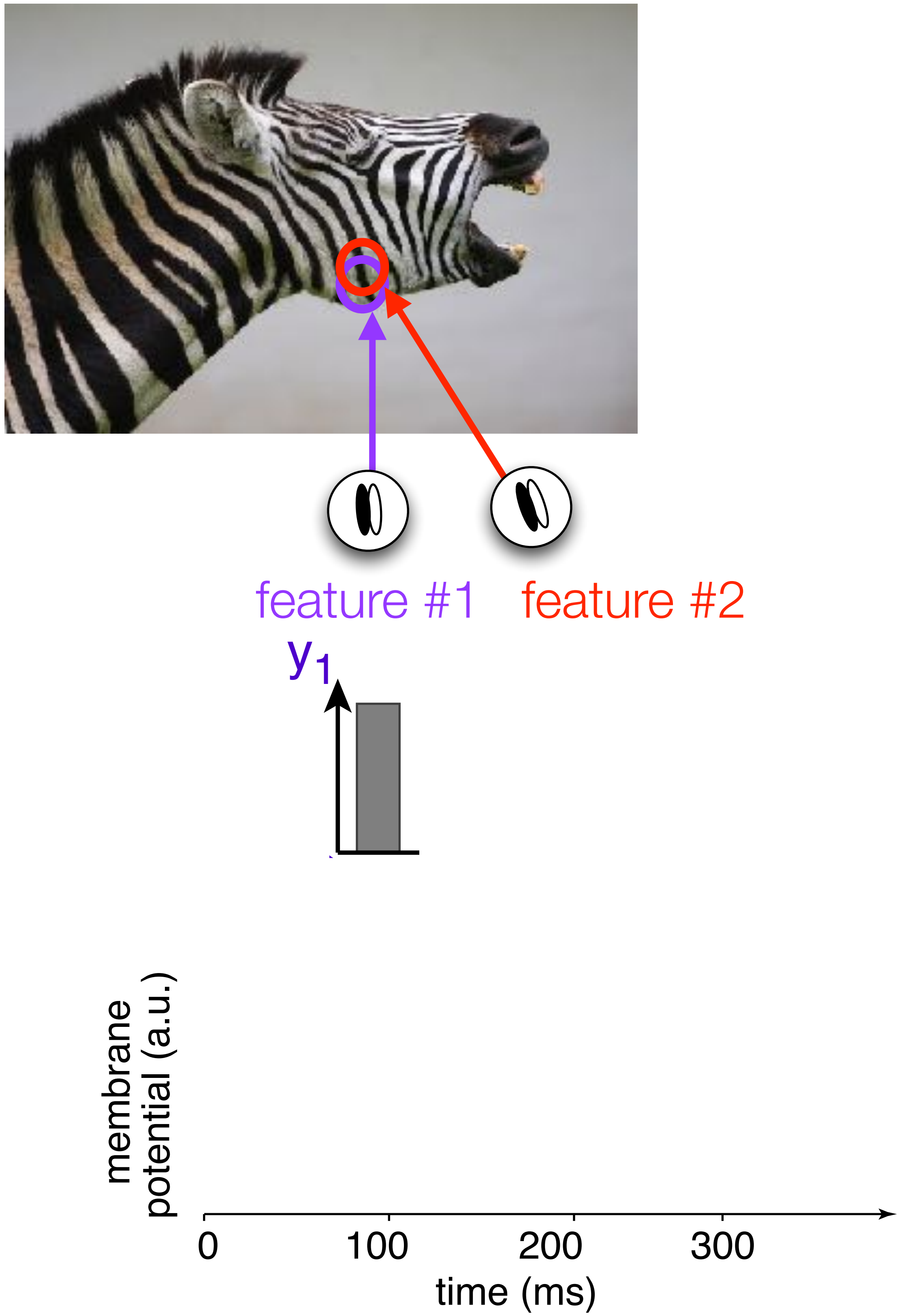
stochastic sampling

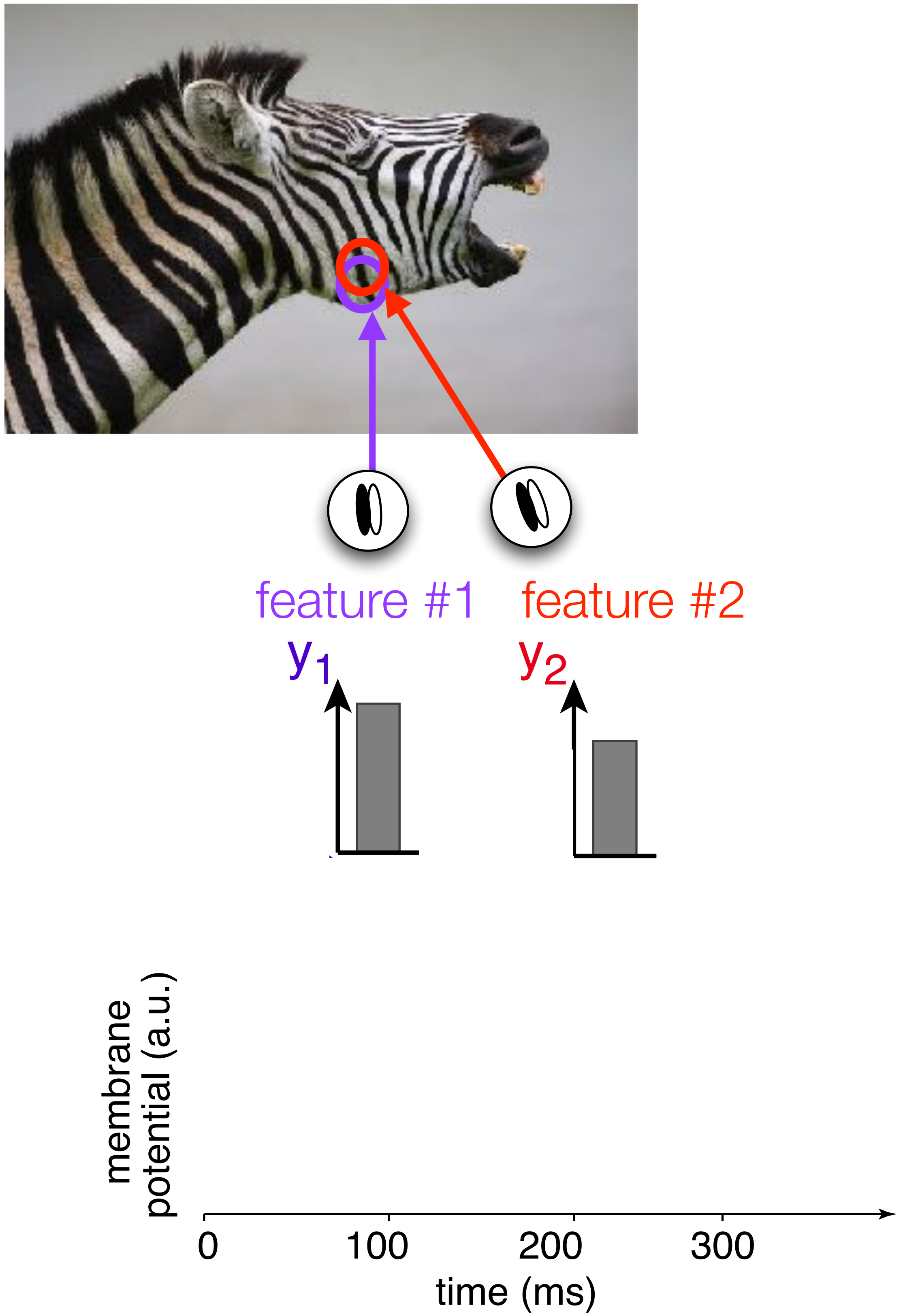




stochastic sampling

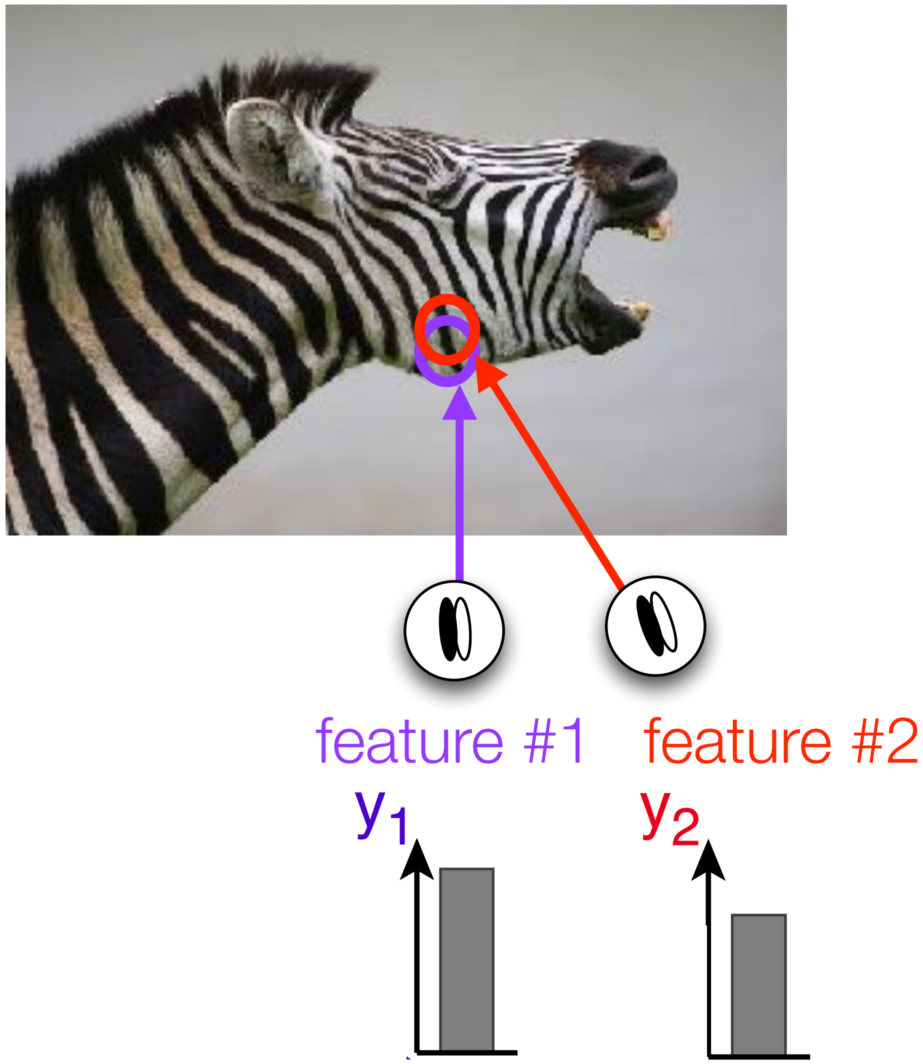


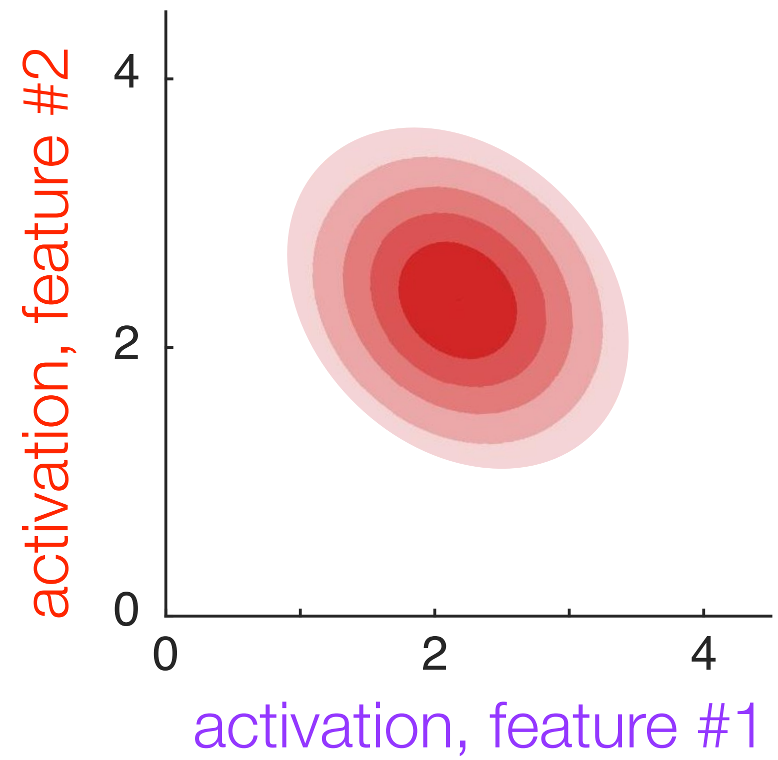

feature #1
feature #2
y_1
membrane potential (a.u.)
0
100
200
300
time (ms)

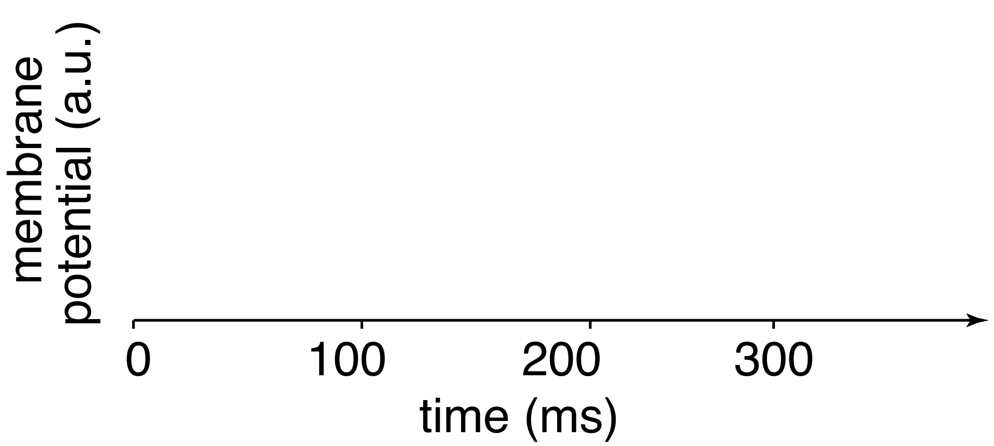


feature #1
feature #2
y_1
y_2
membrane potential (a.u.)
0
100
200
300
time (ms)

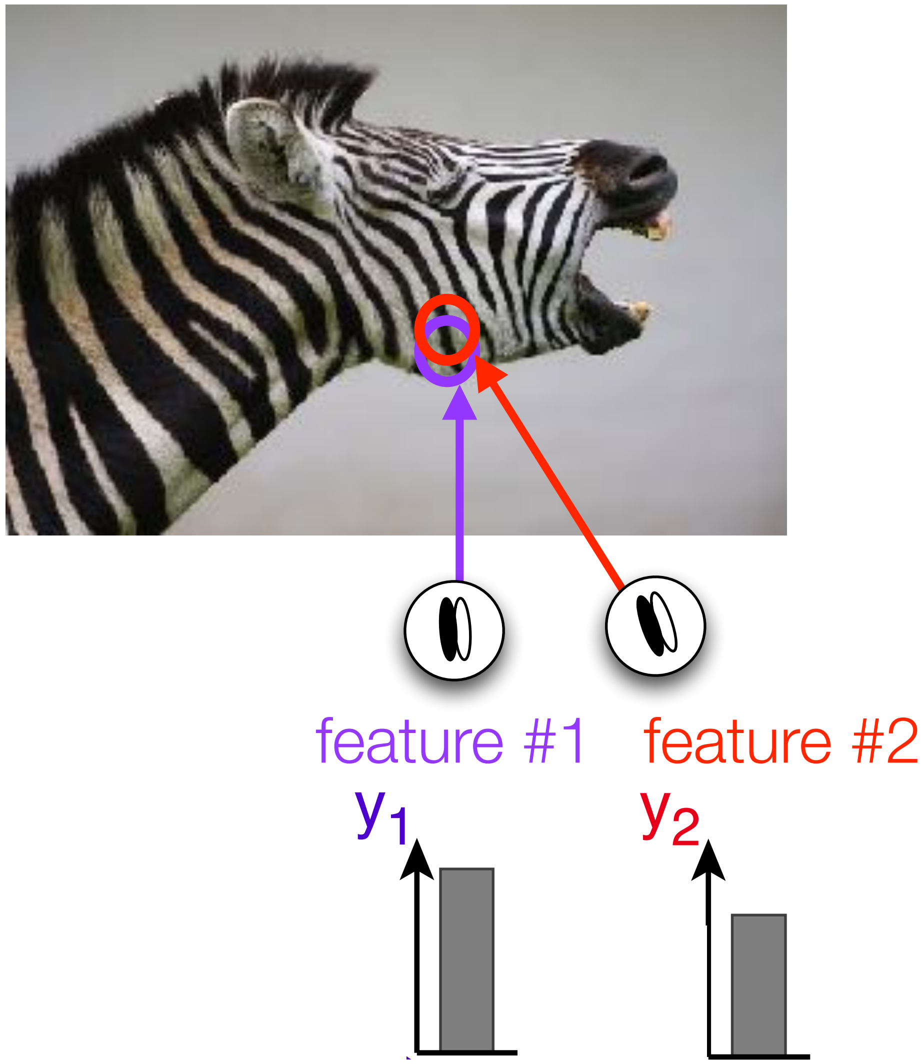
stochastic sampling

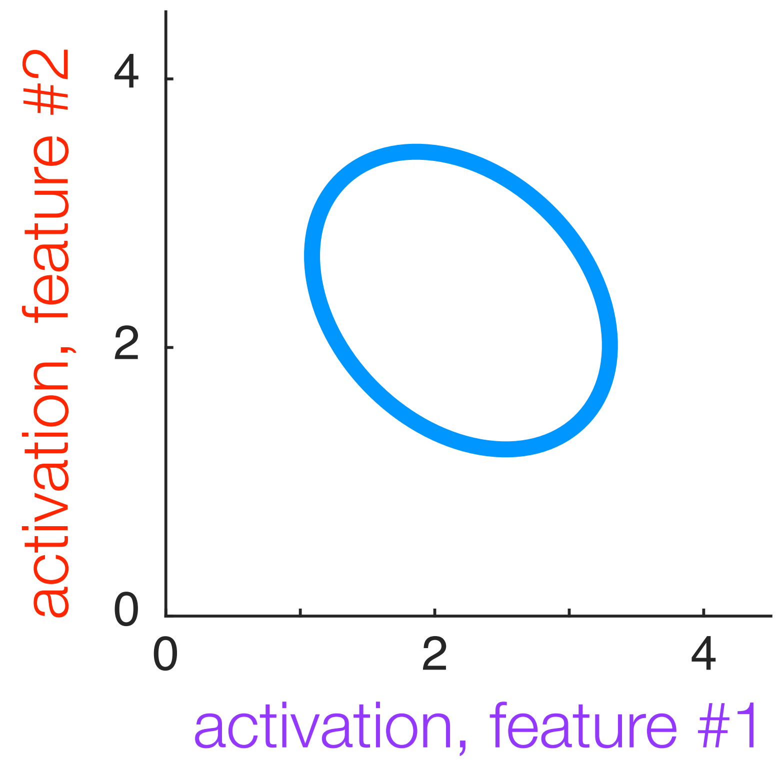


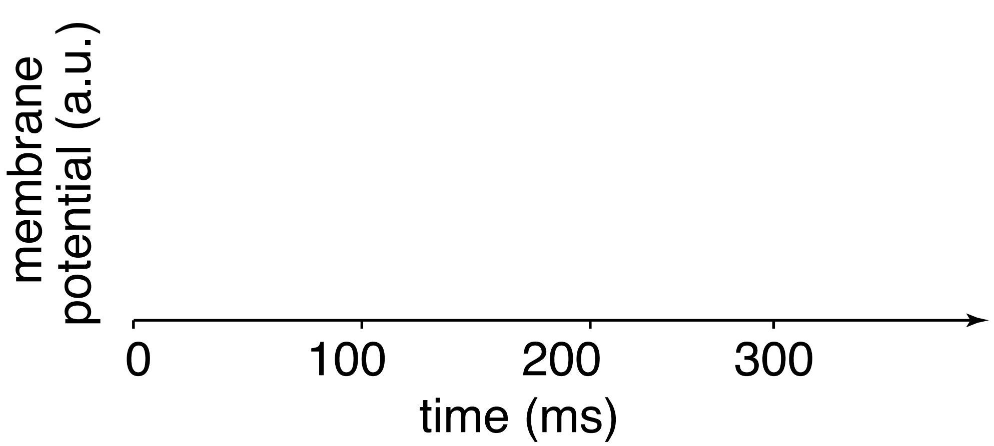




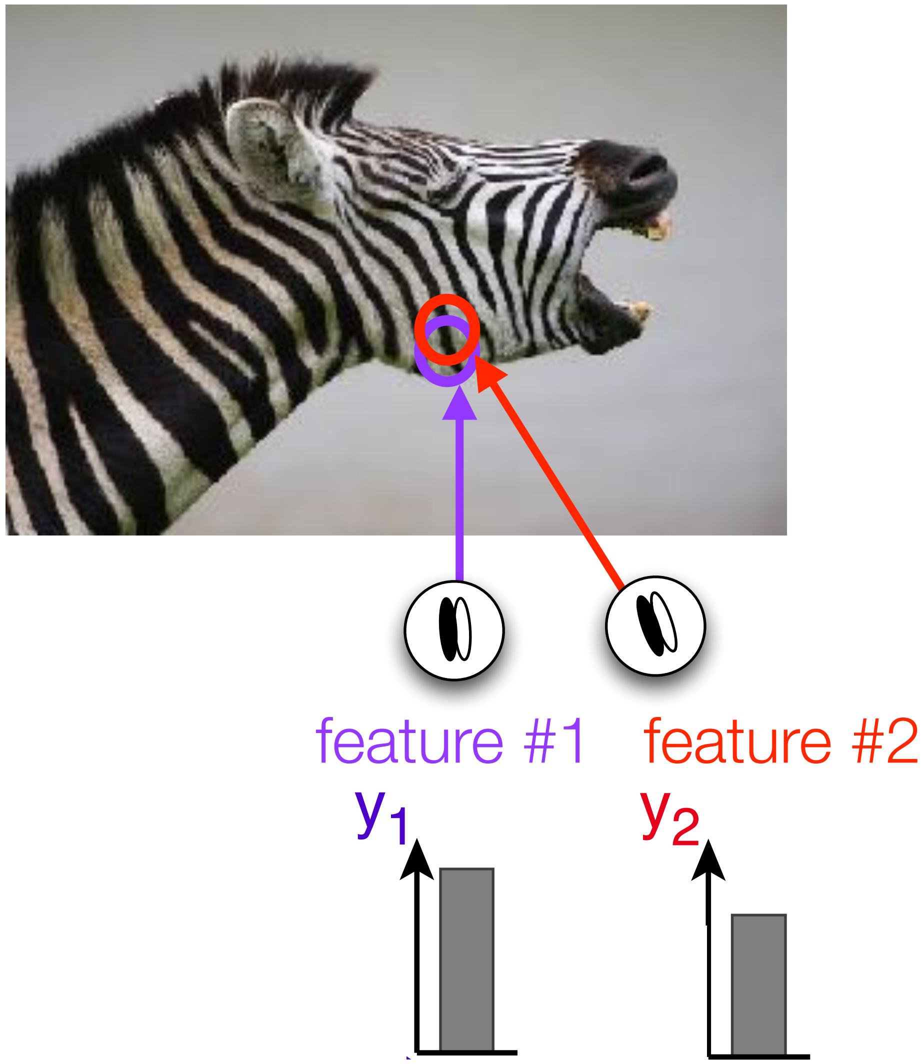
stochastic sampling

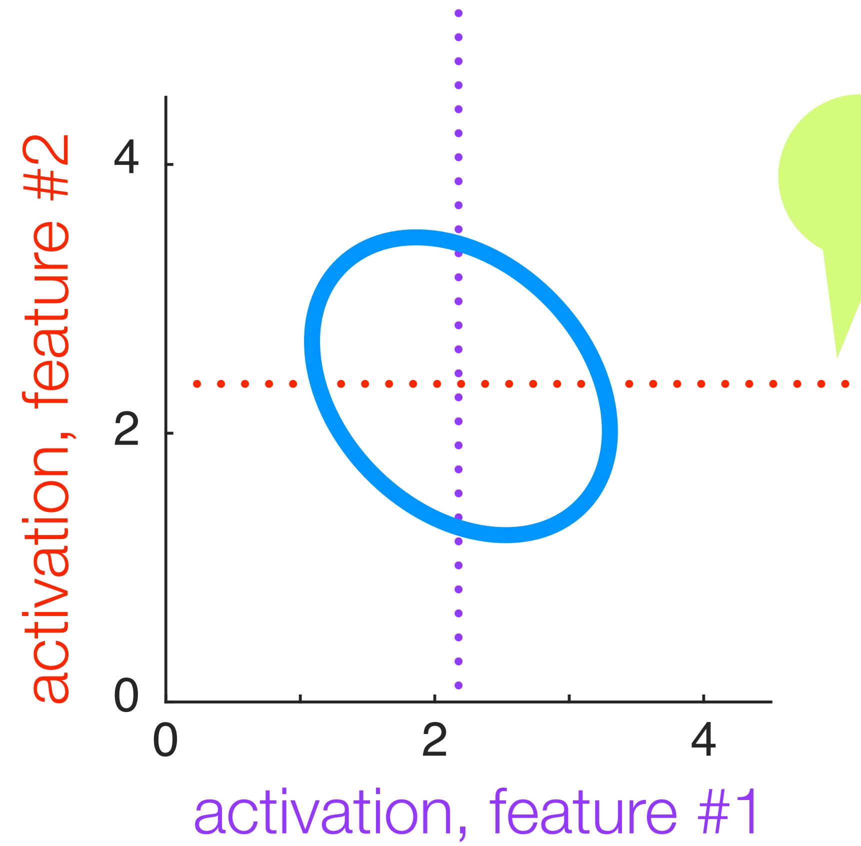




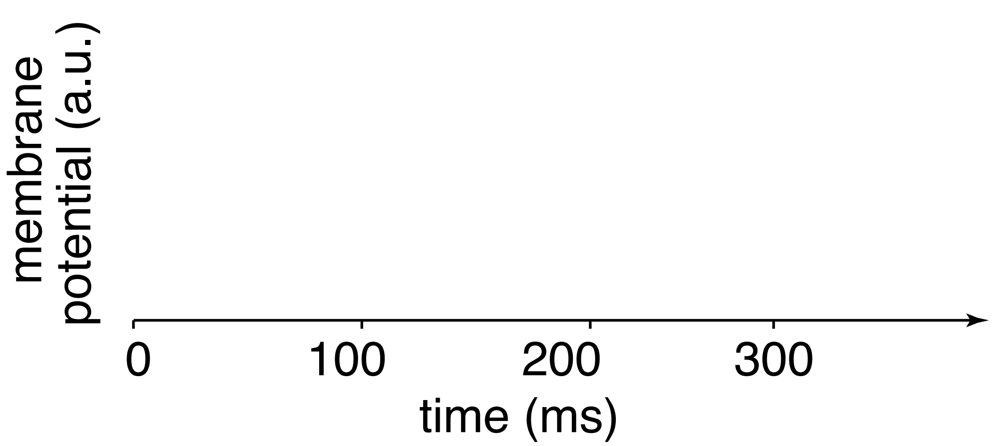


stochastic sampling

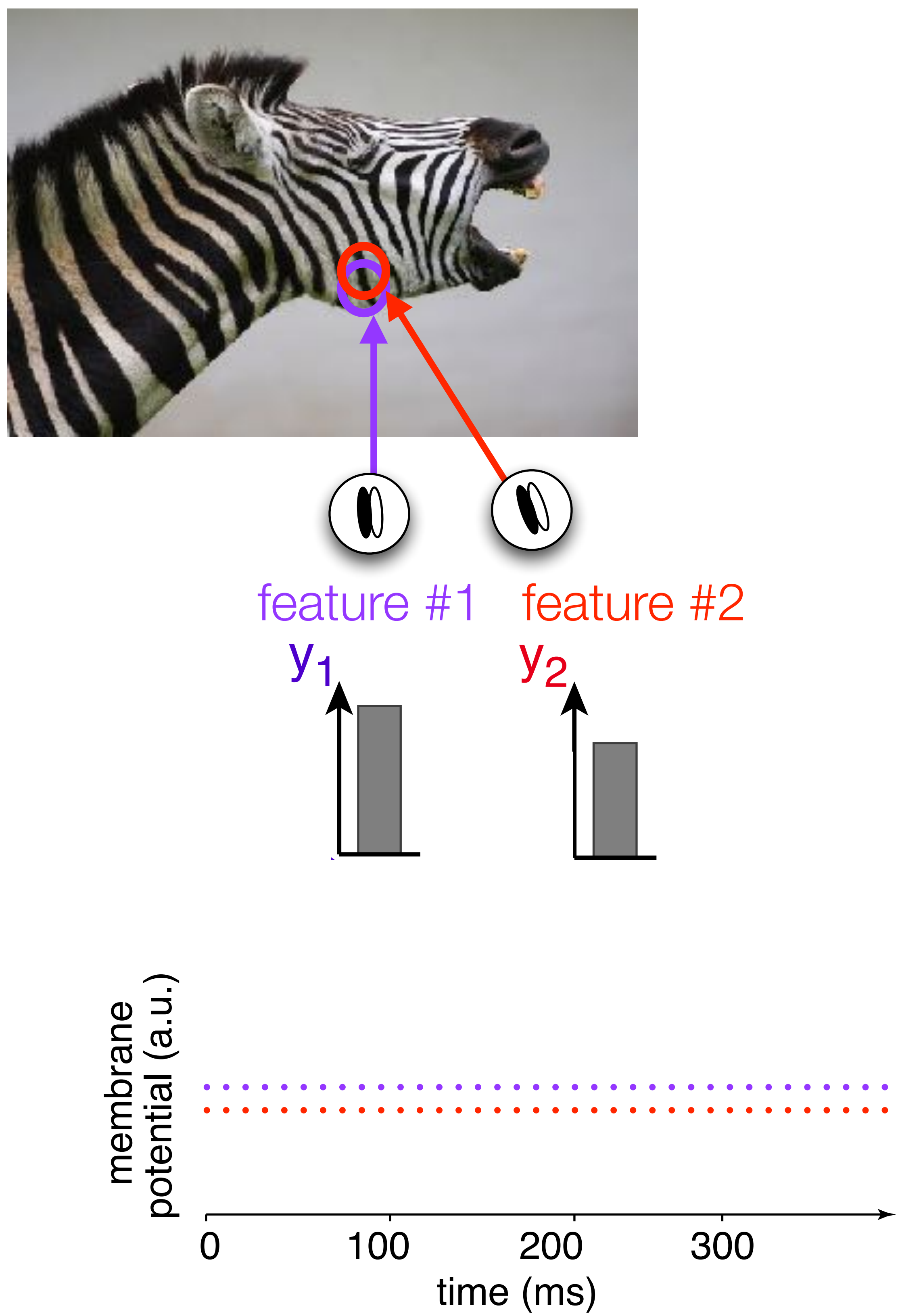


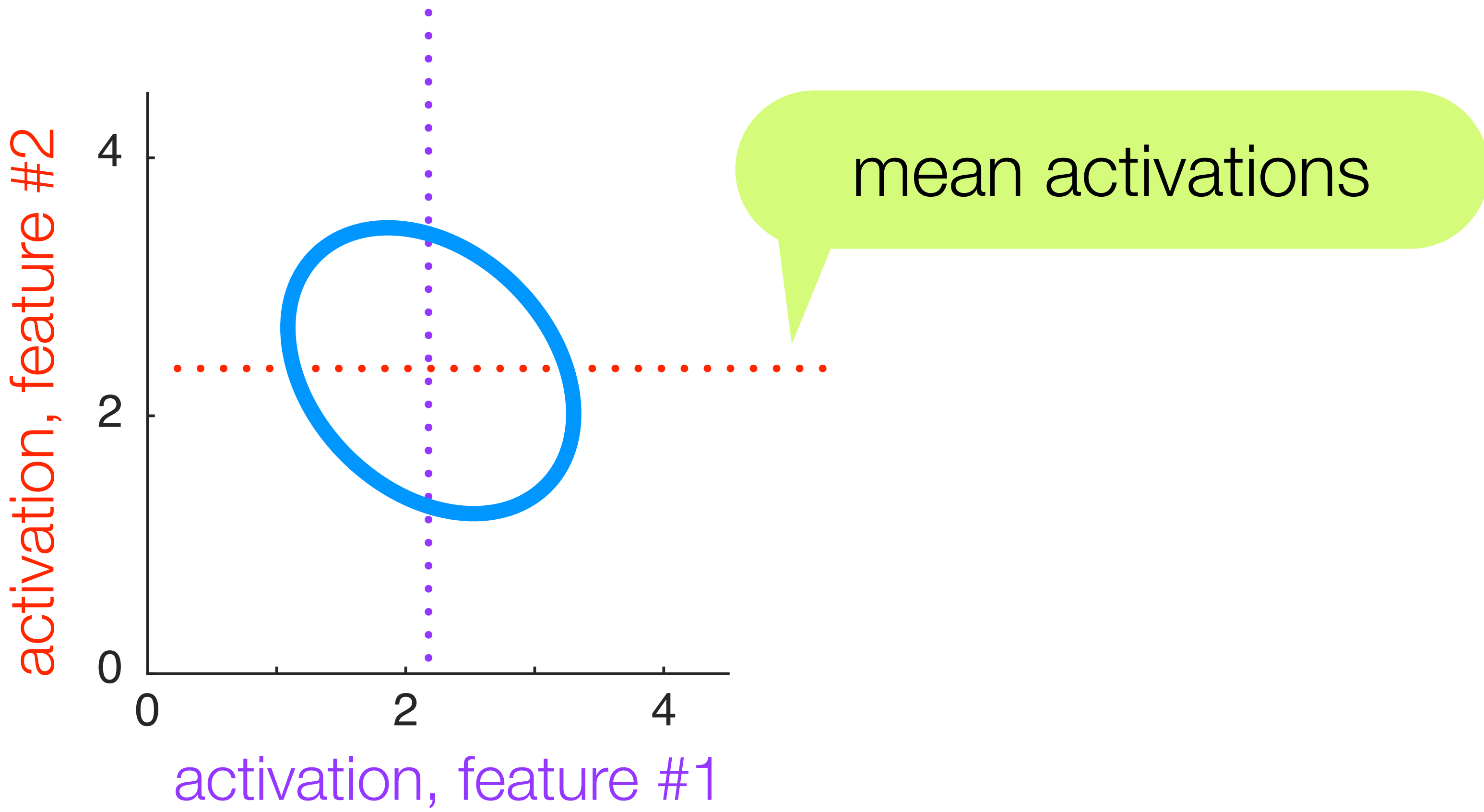


mean activations

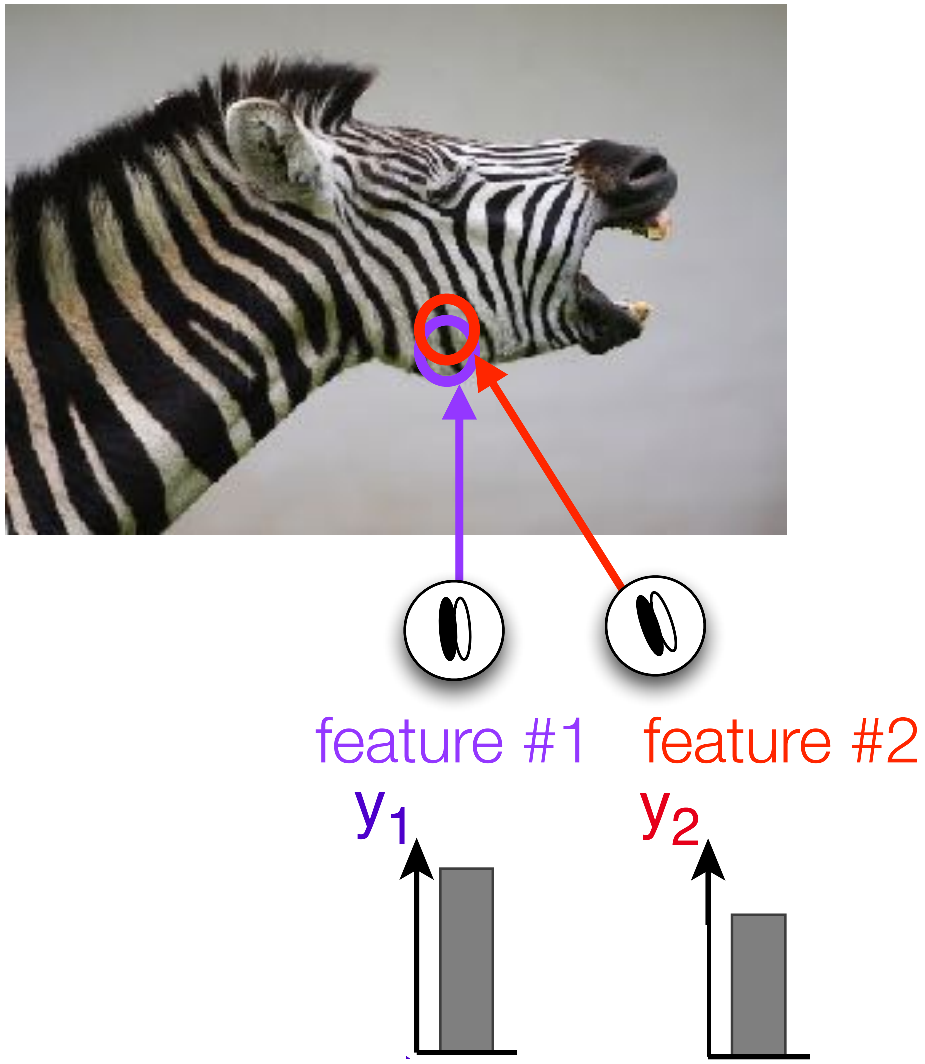


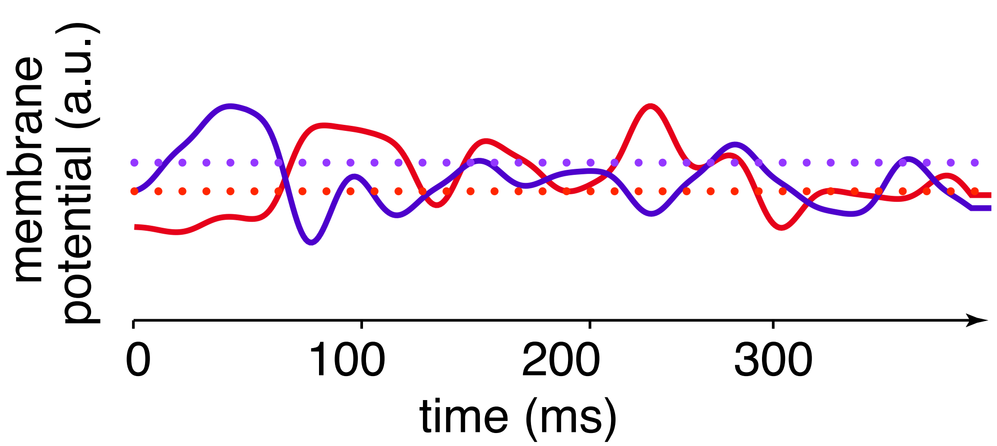
stochastic sampling

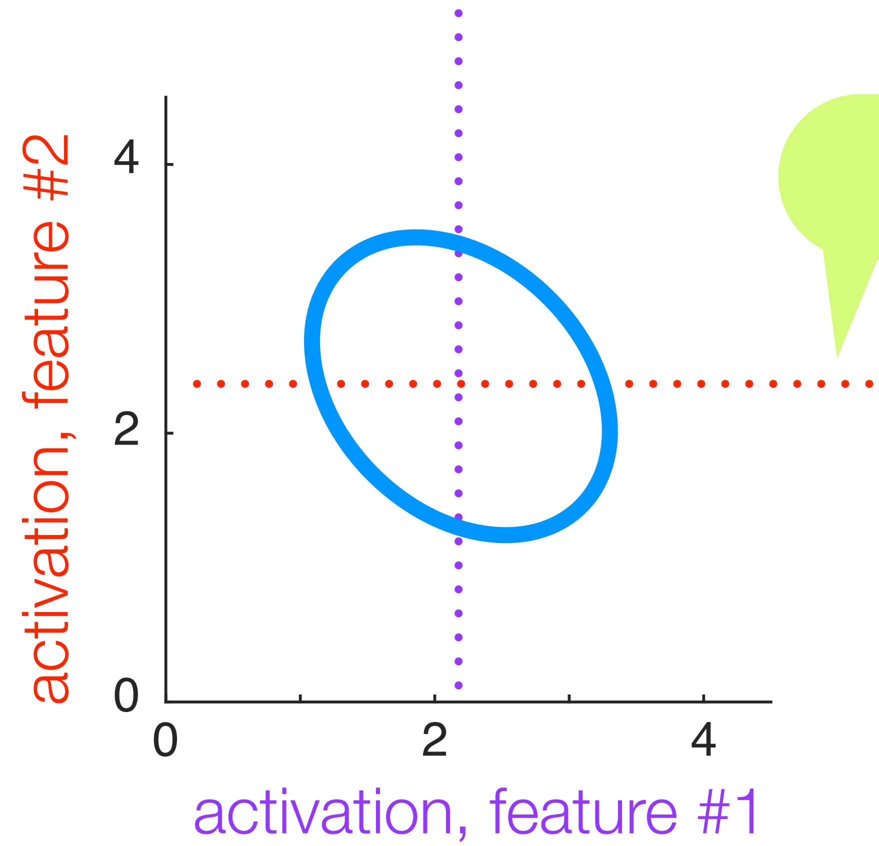




stochastic sampling

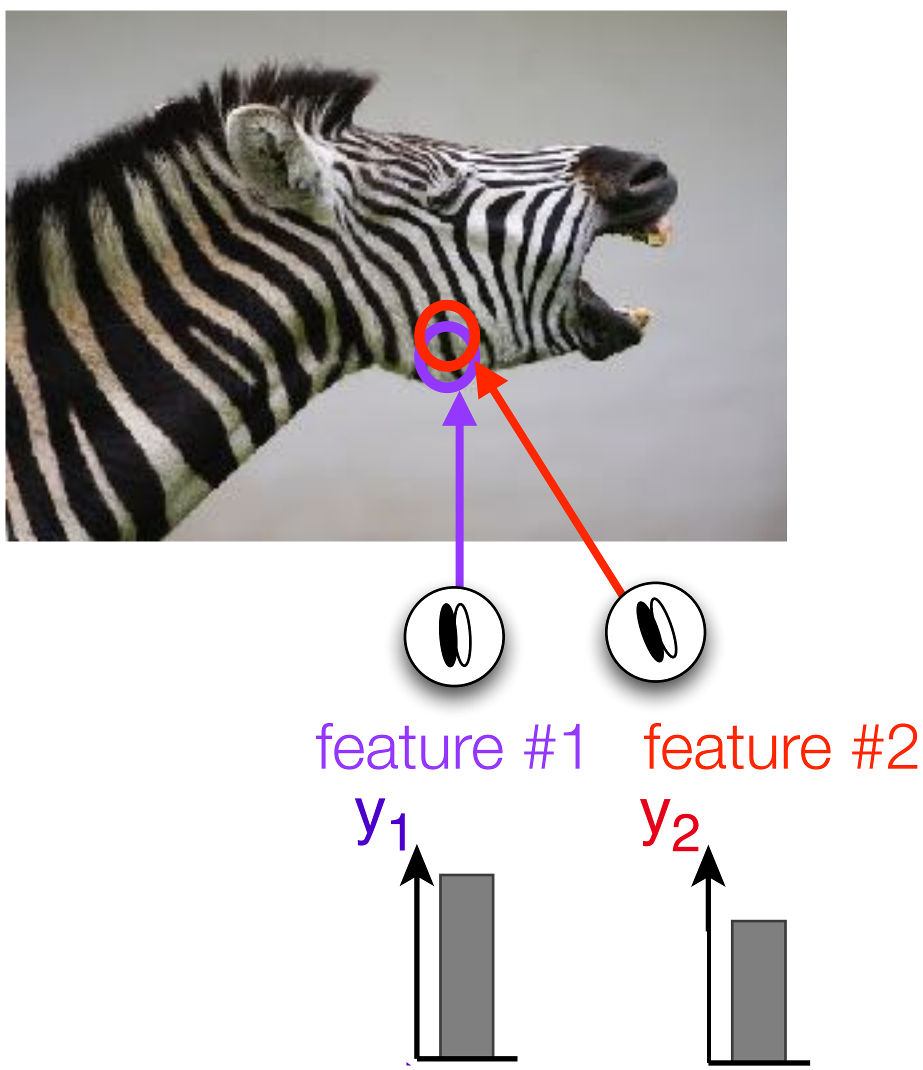


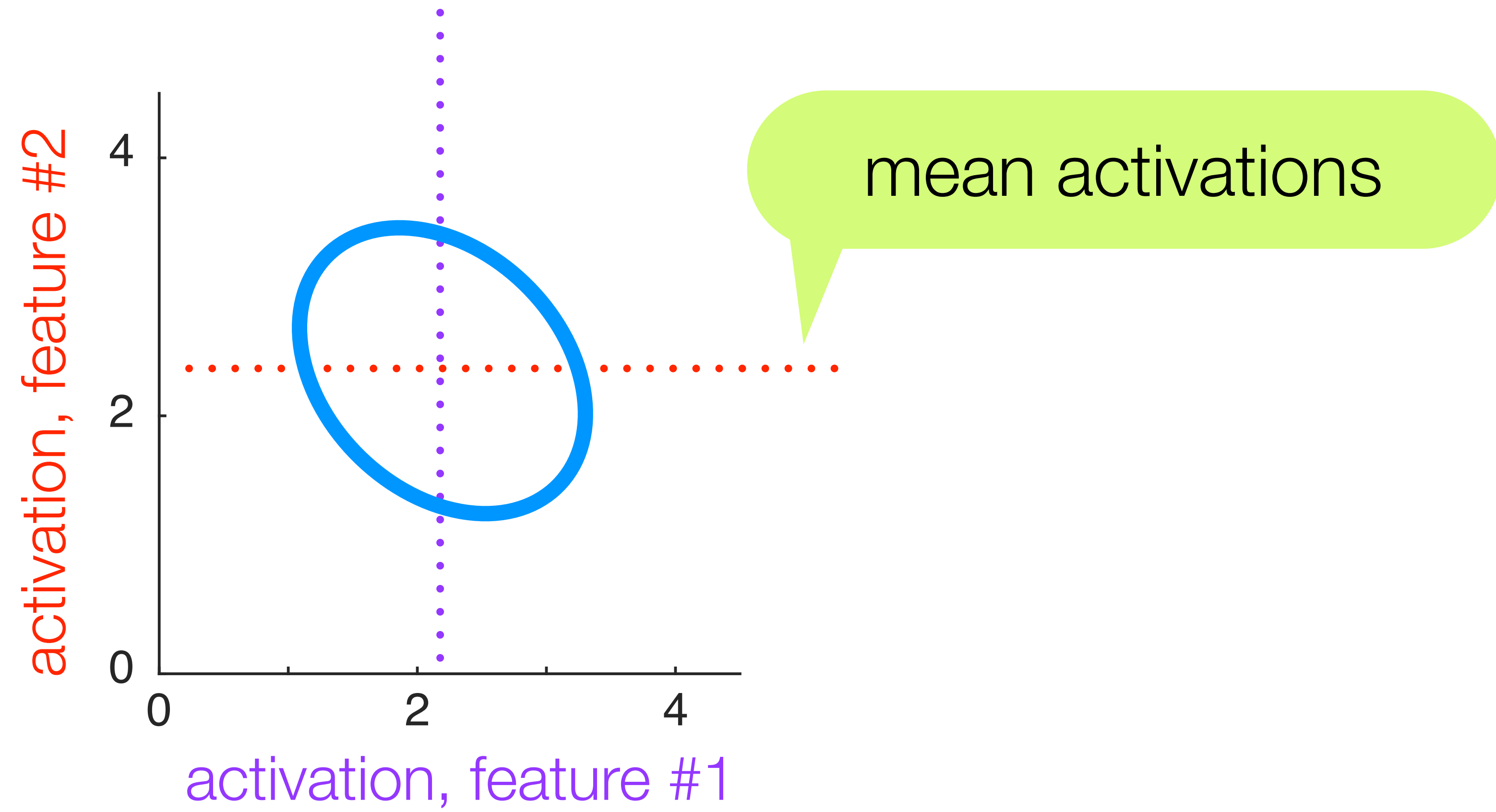


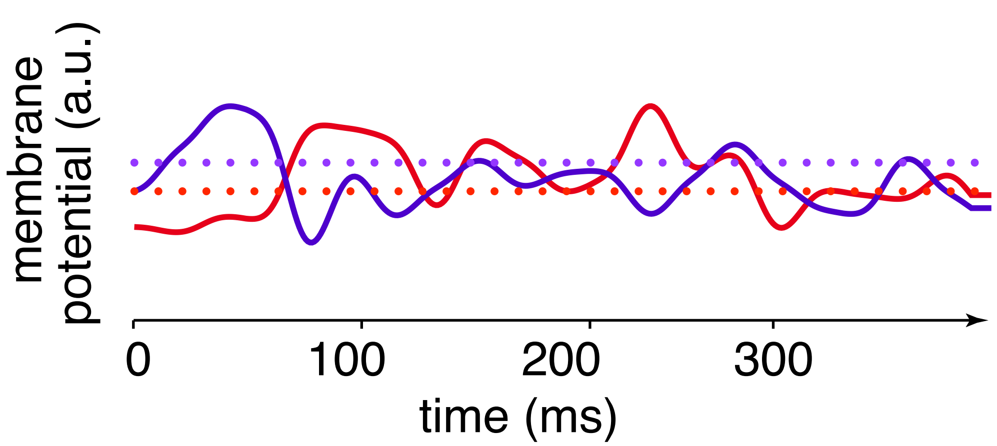


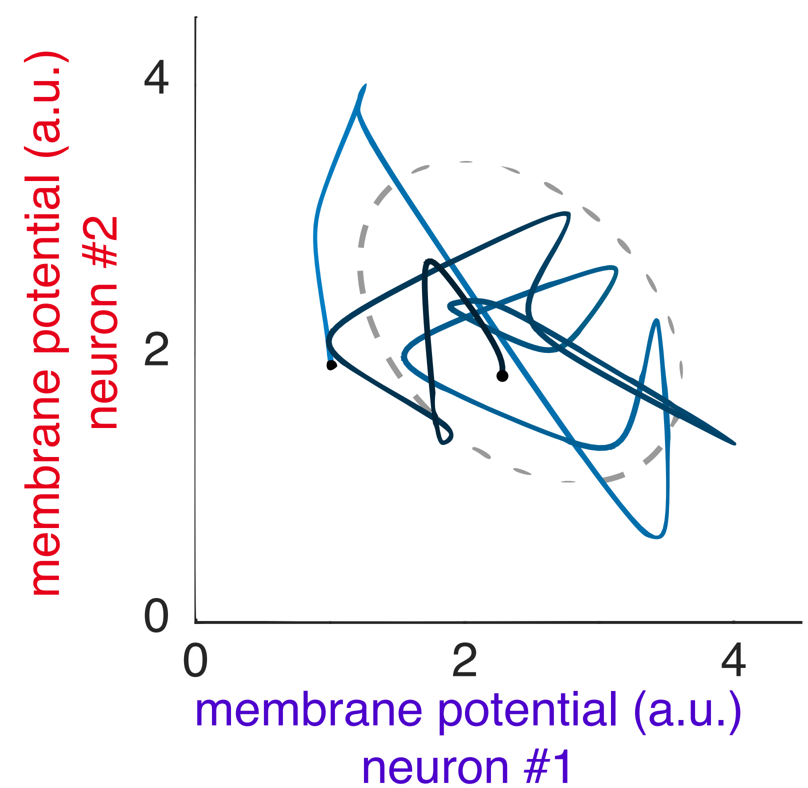
mean activations

stochastic sampling

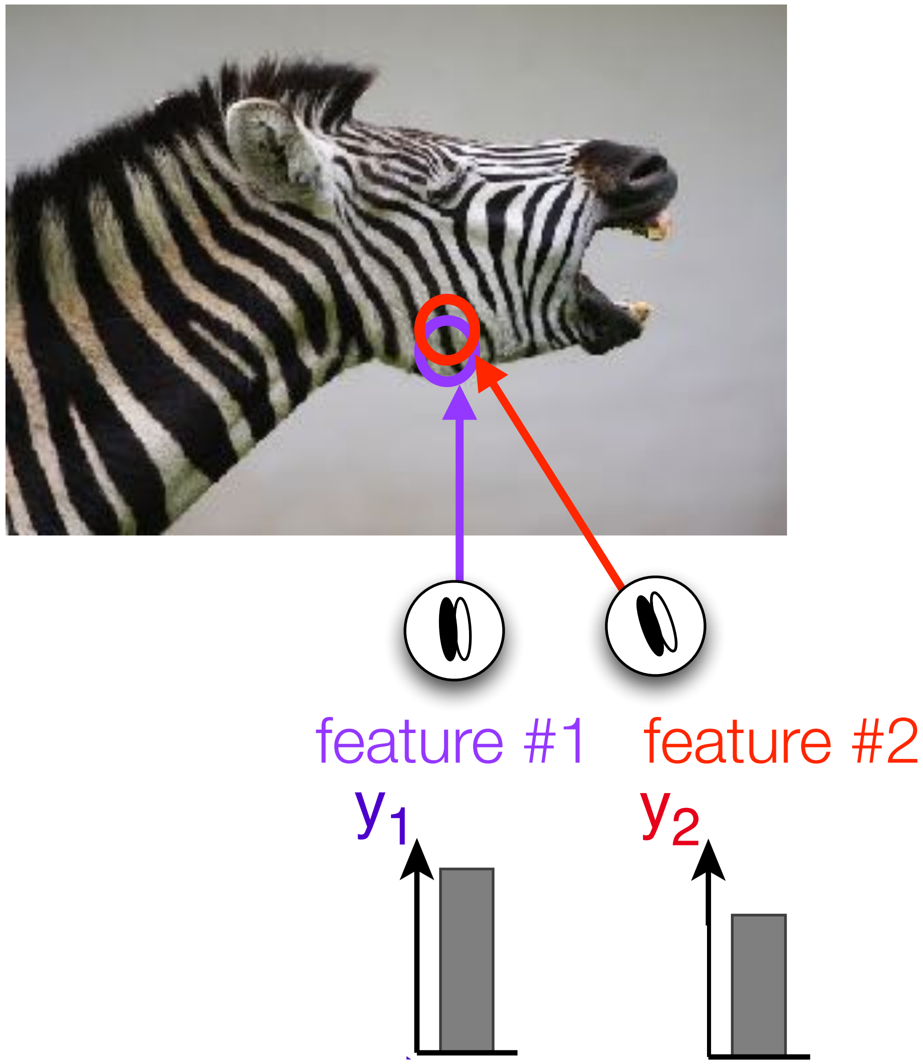


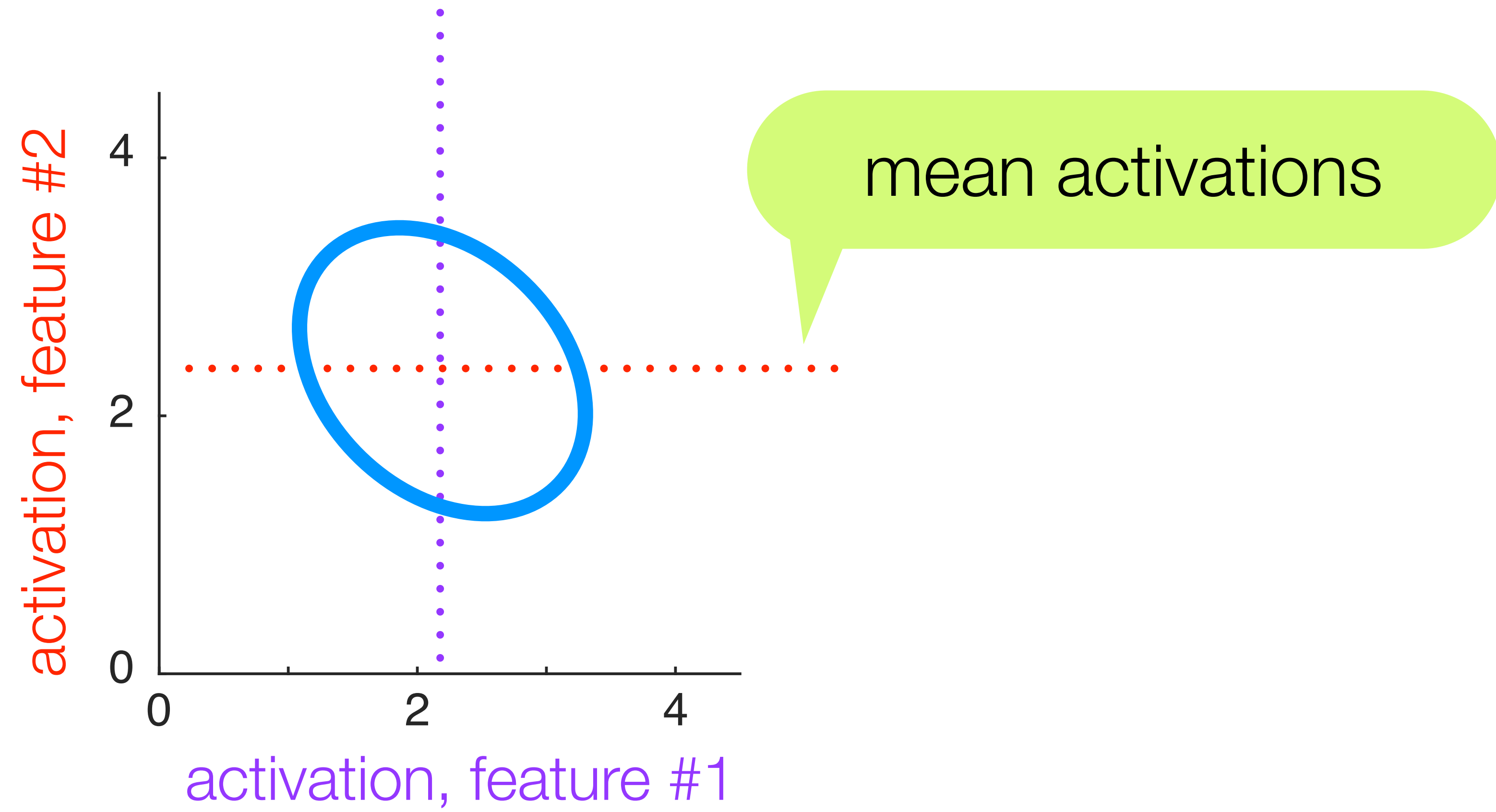


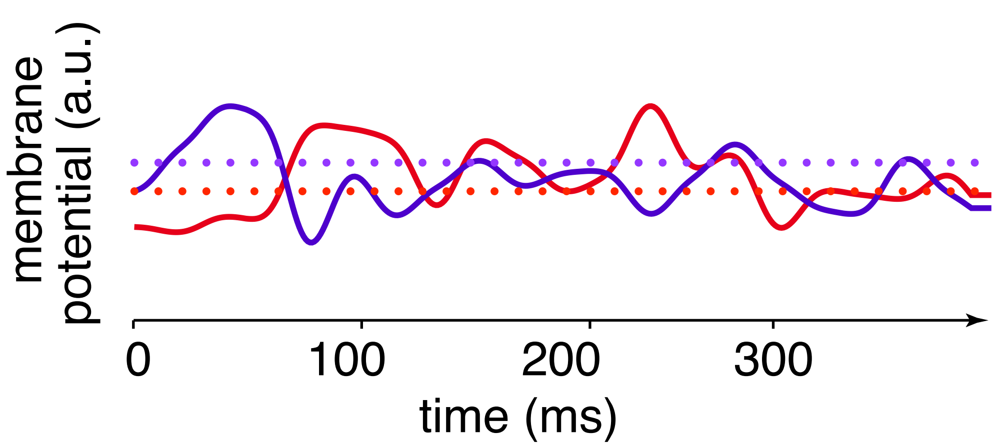


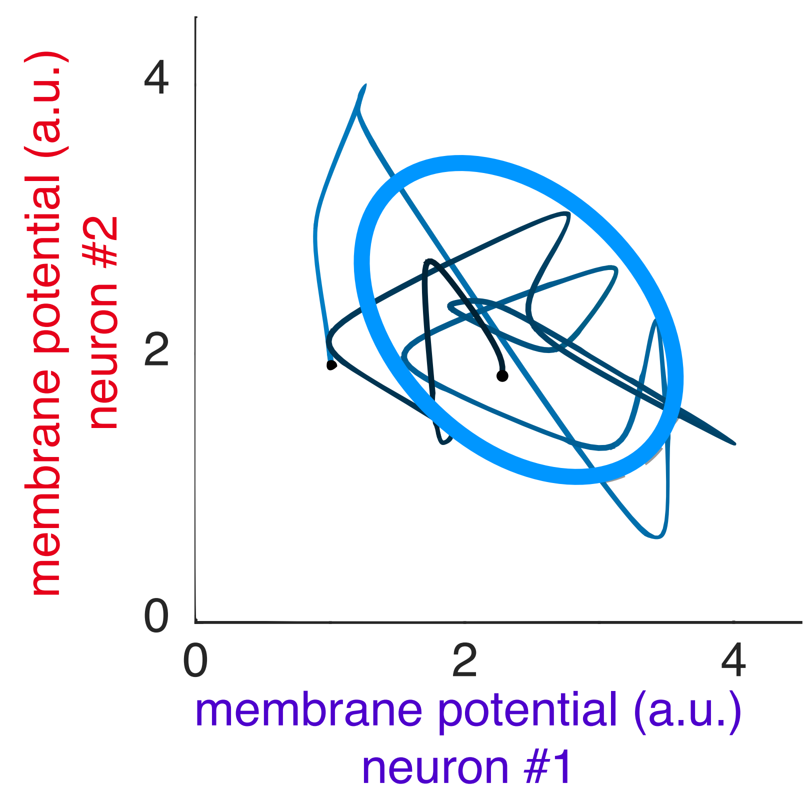


stochastic sampling

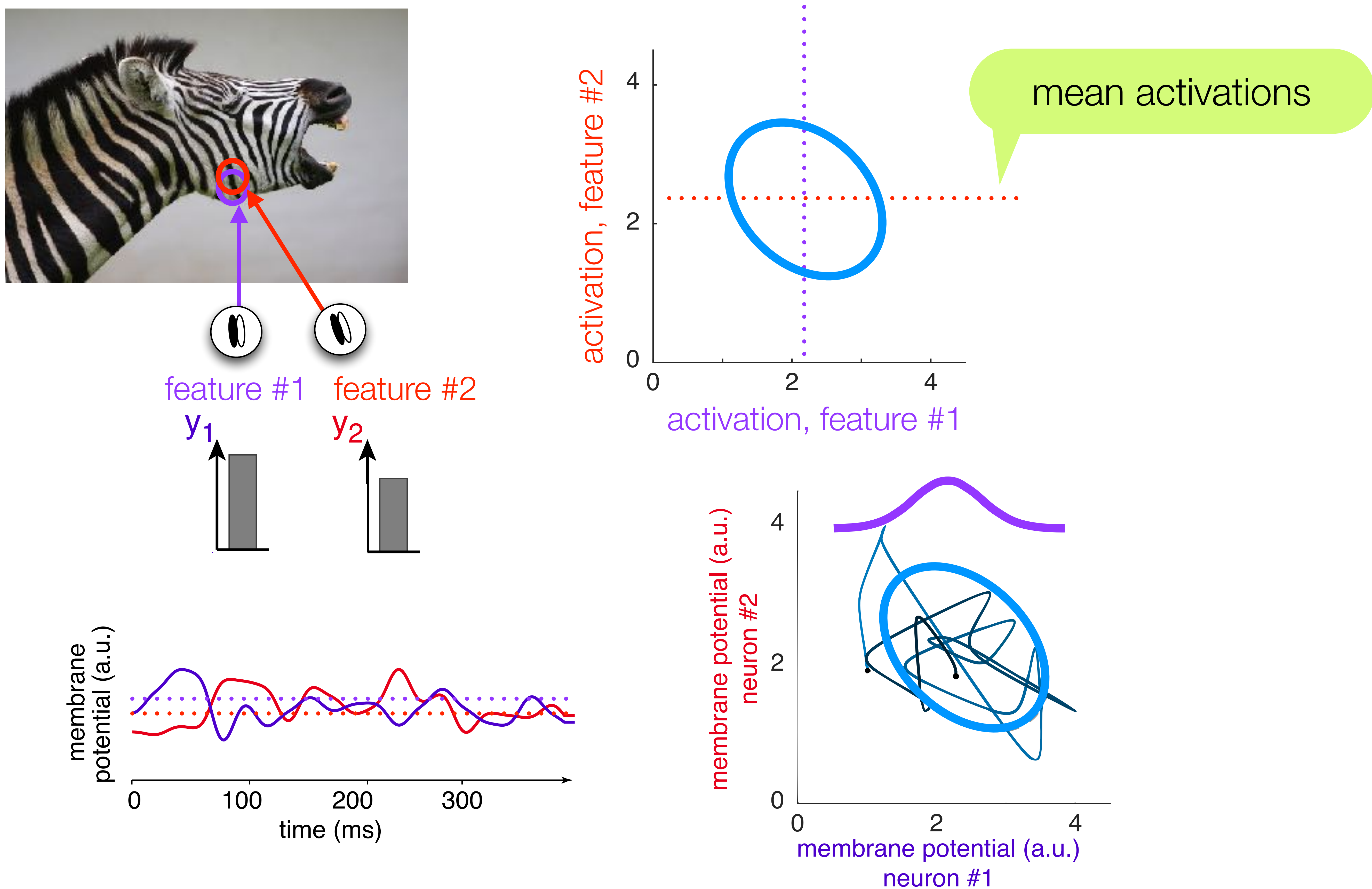




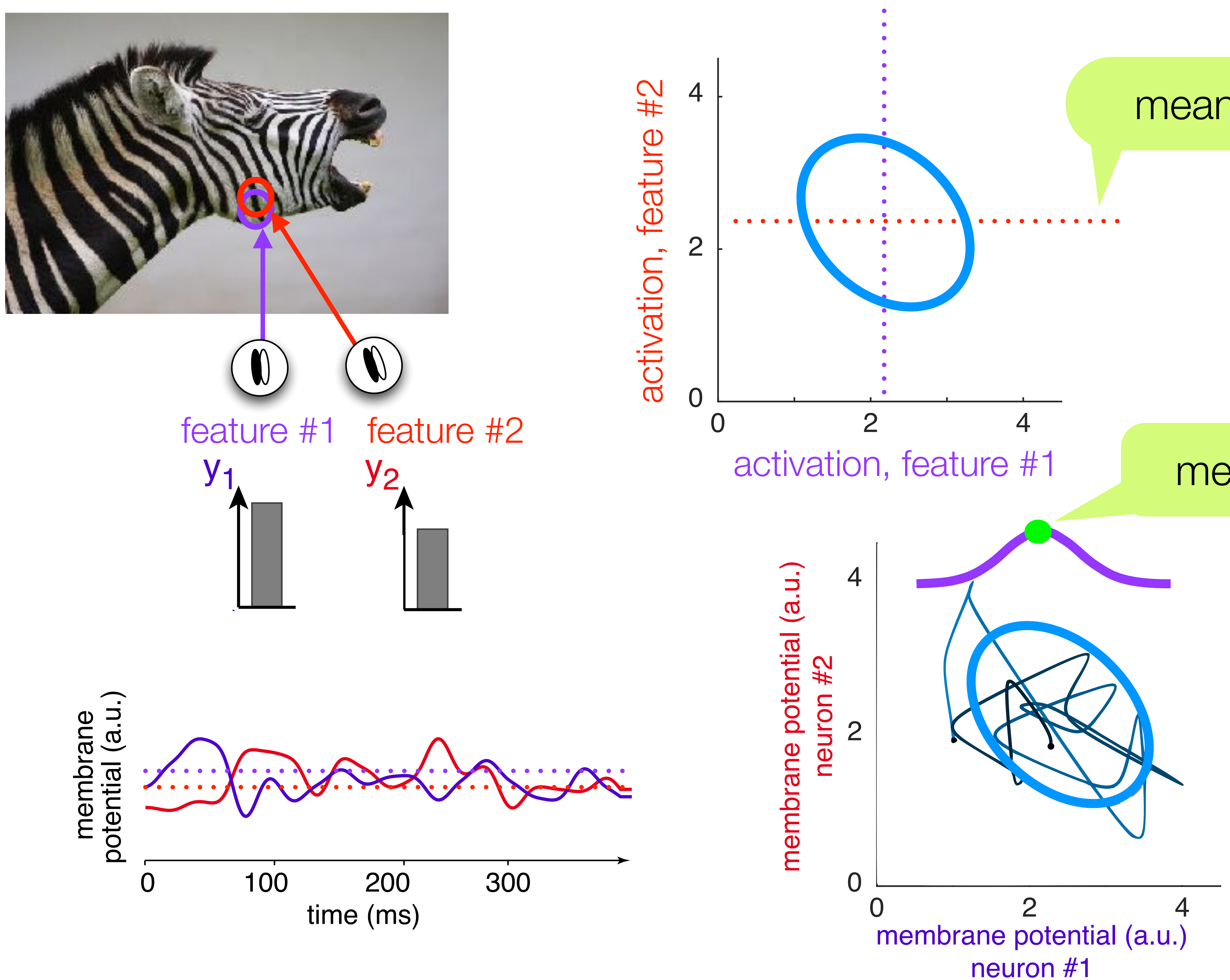




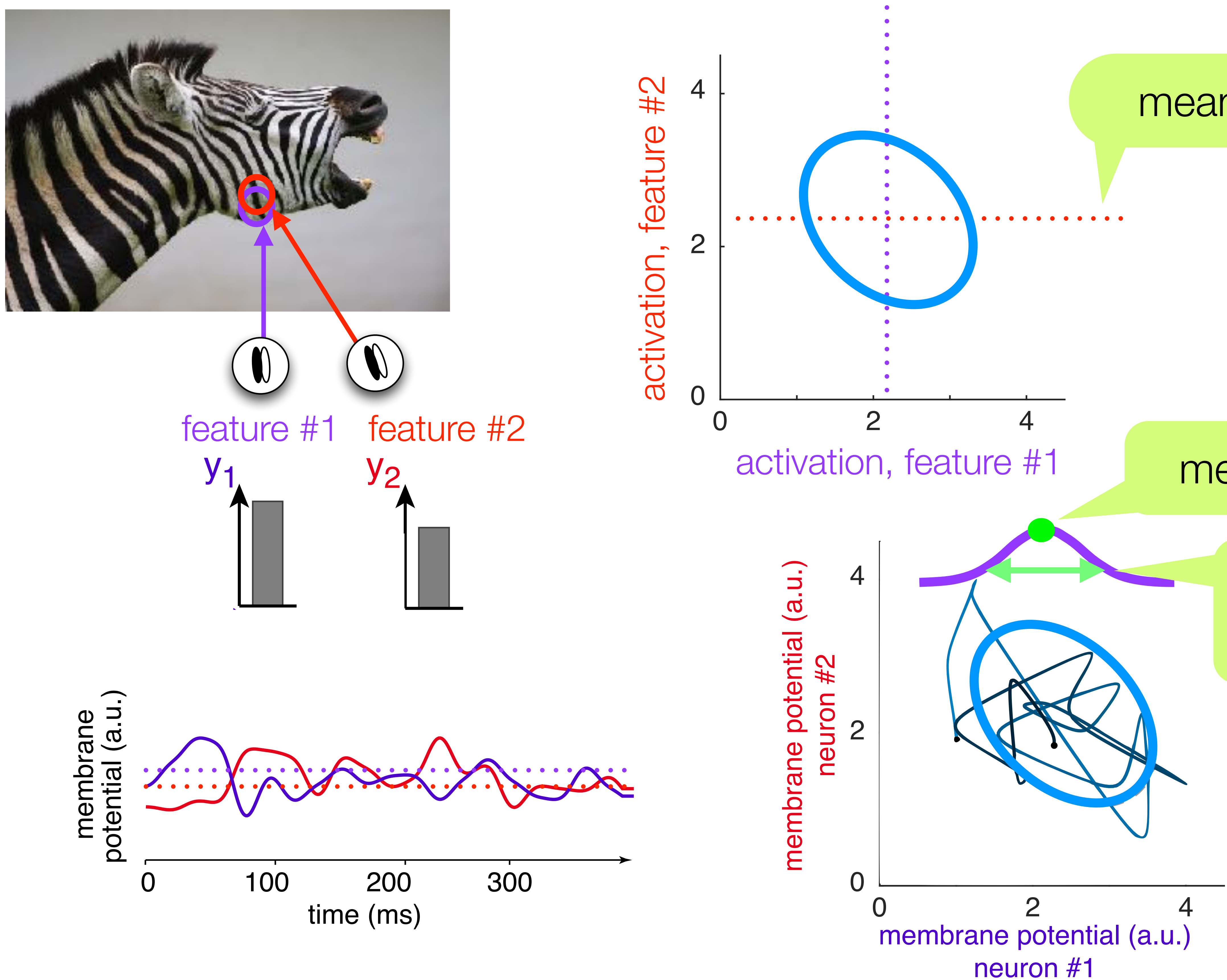
stochastic sampling



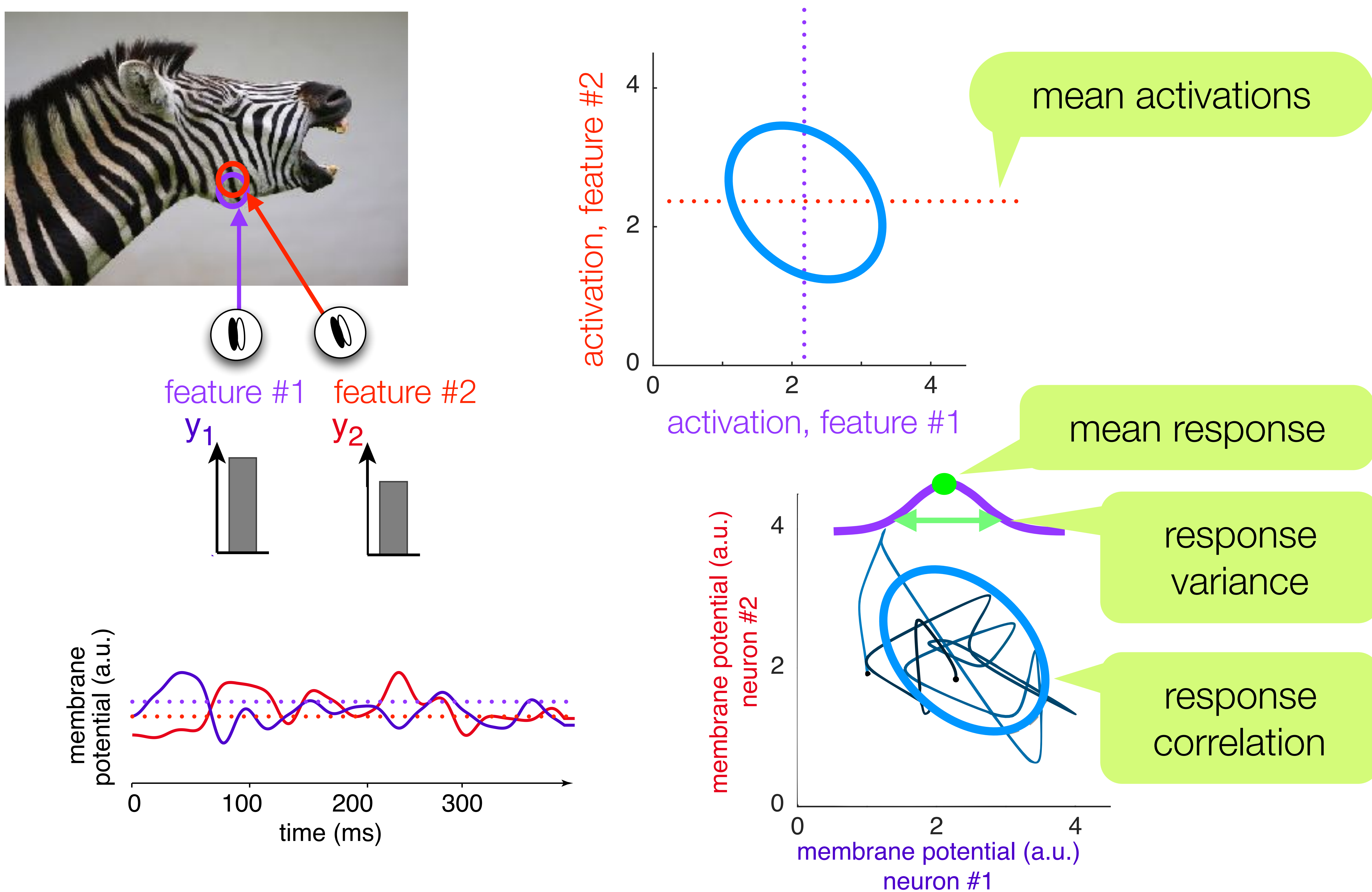
stochastic sampling

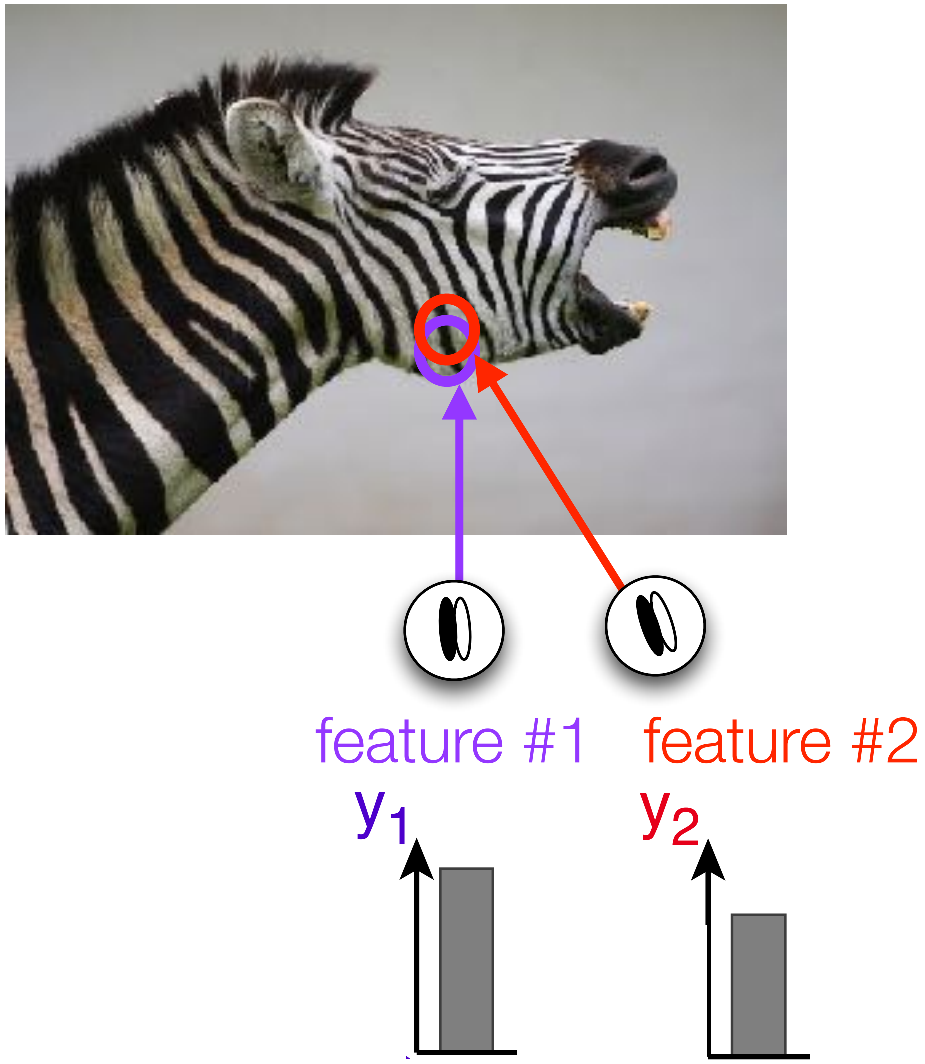


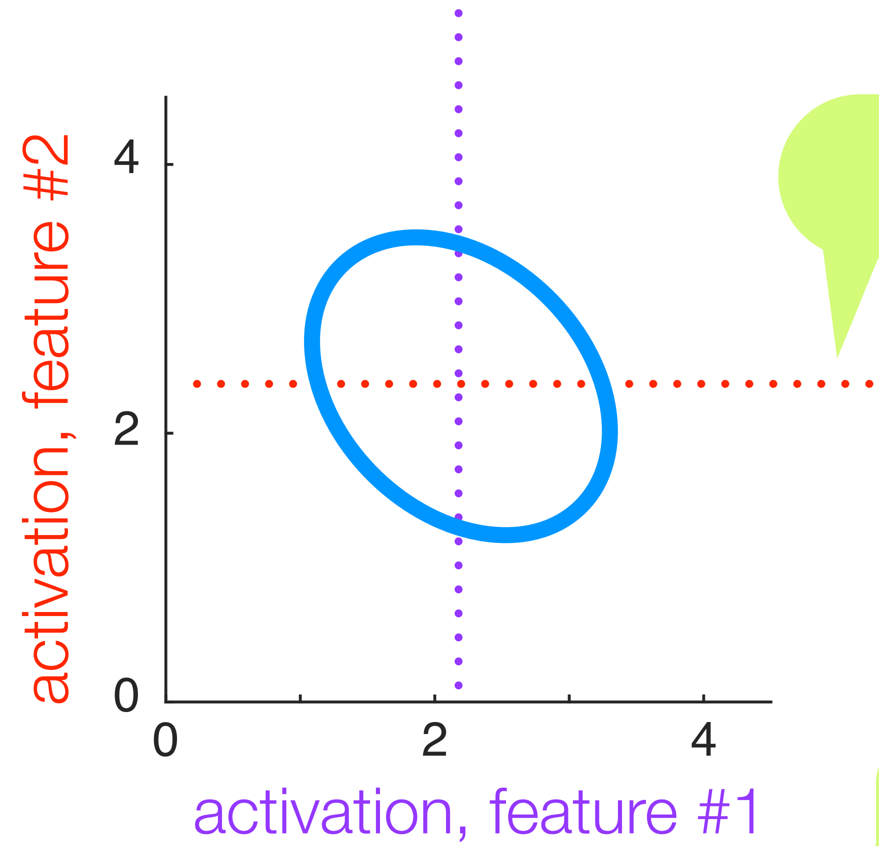
stochastic sampling



stochastic sampling





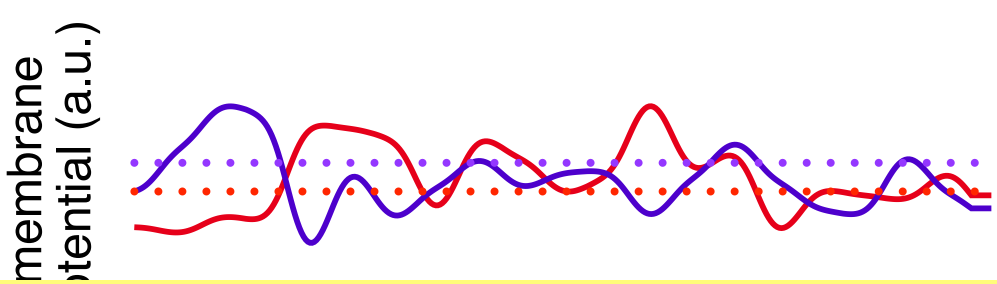


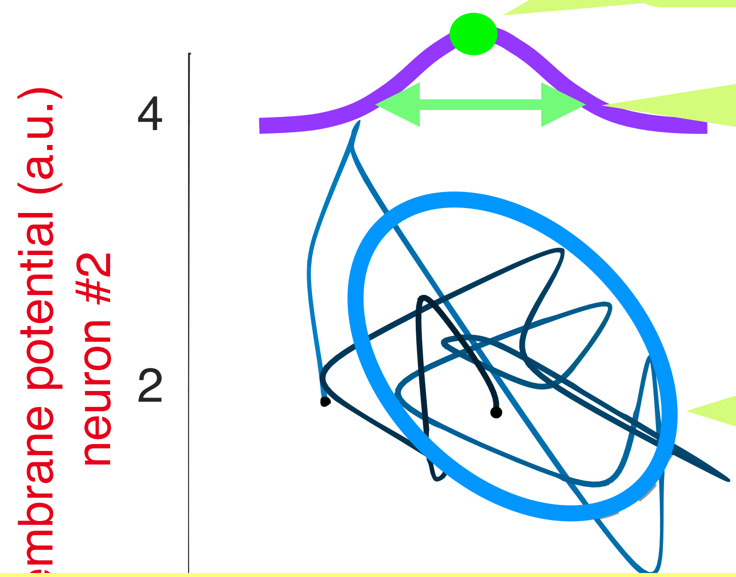
mean activations

mean response

response variance

response correlation





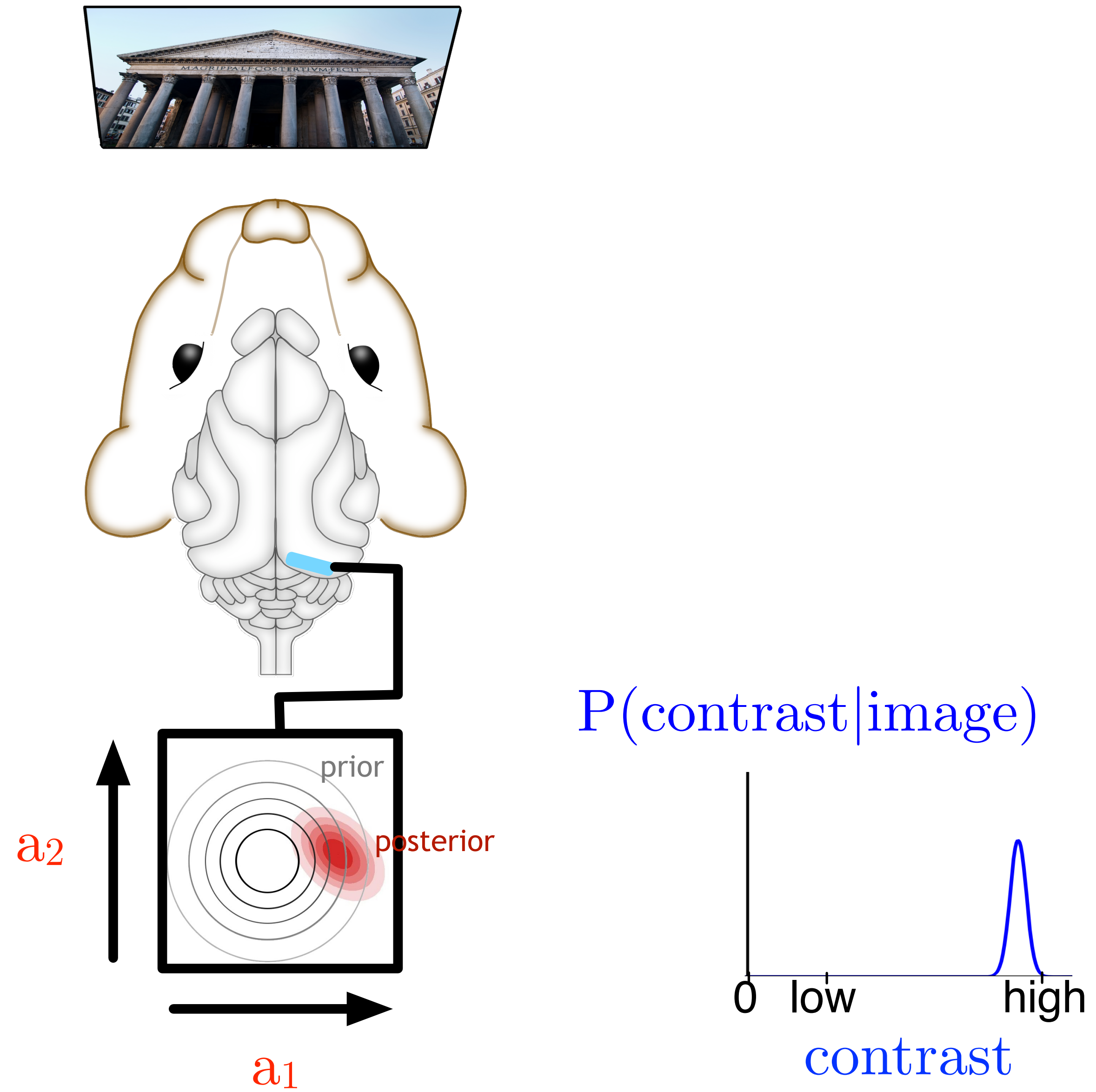
changes in inferences need to be reflected in the response statistics

inference and uncertainty

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image} | a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$

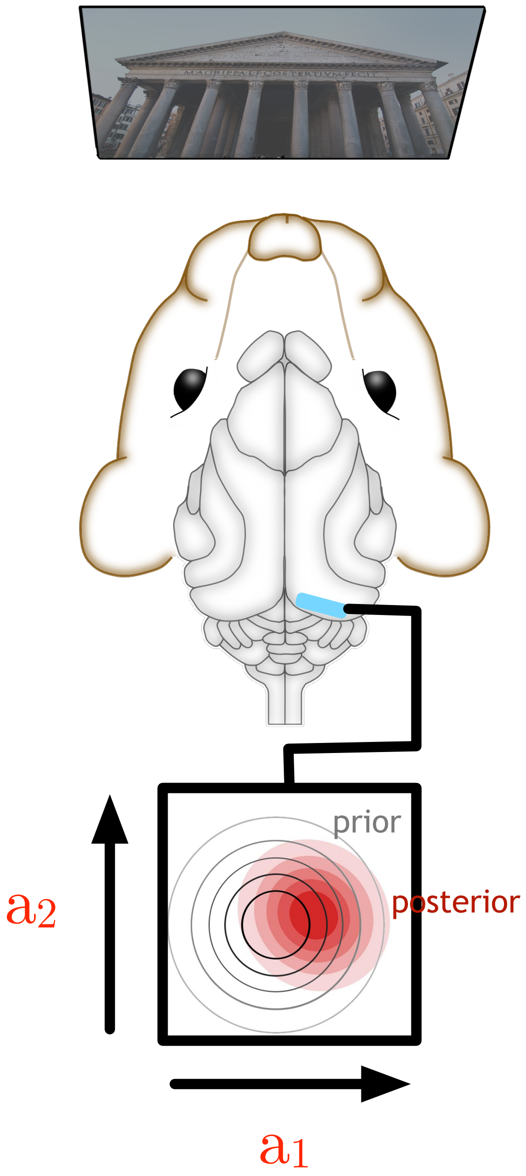
inference and uncertainty

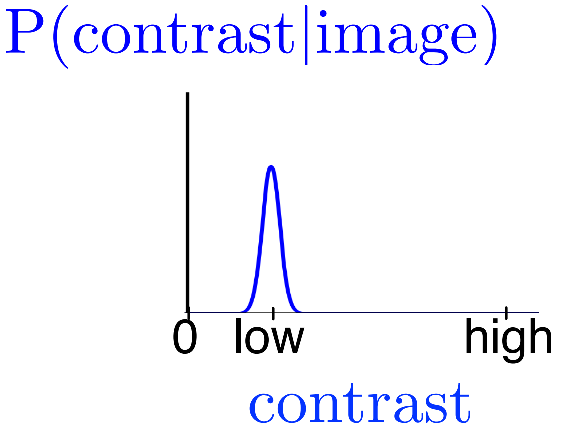
$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid \text{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\text{image} \mid a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$



inference and uncertainty

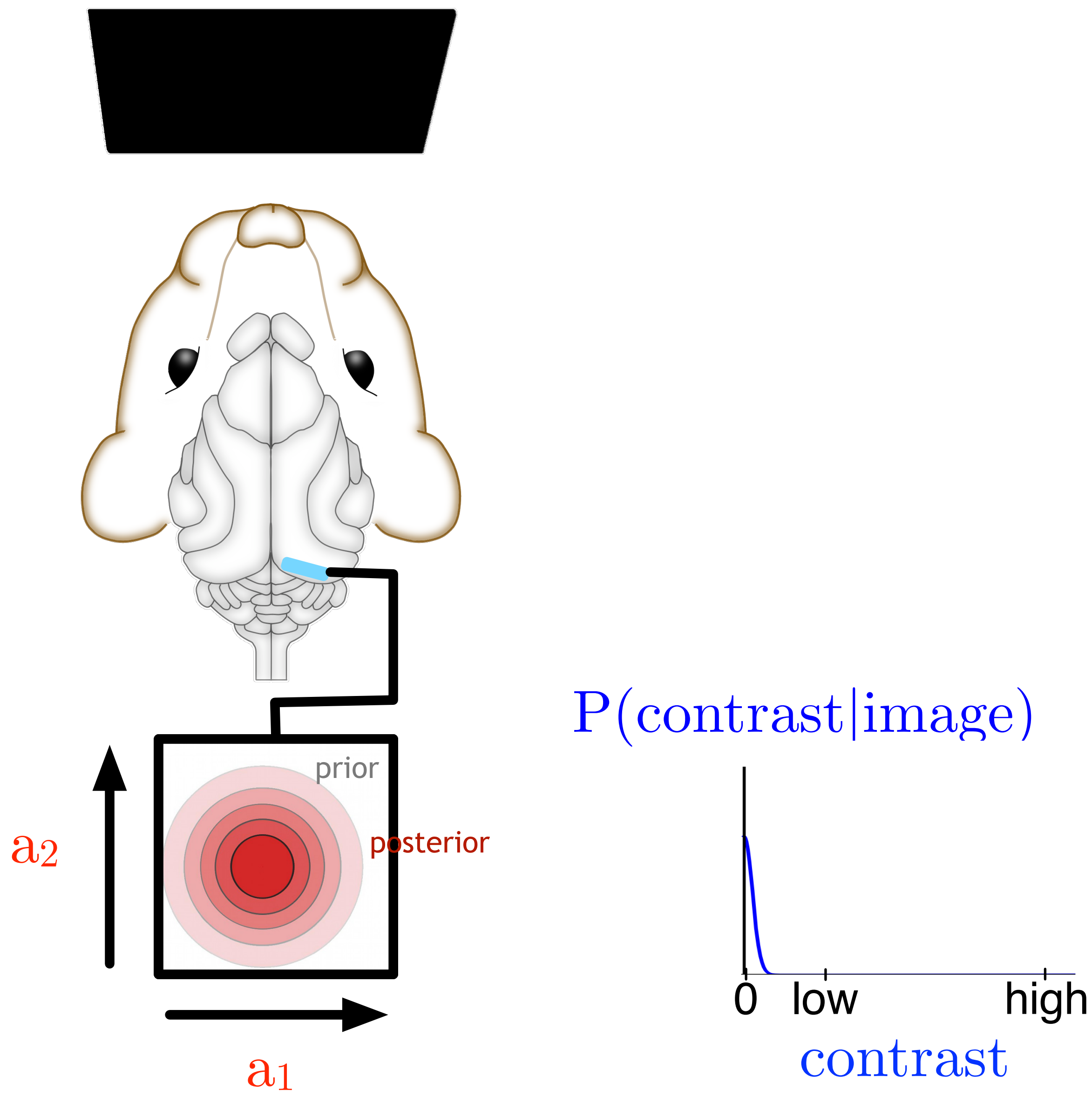
$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$





inference and uncertainty

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$



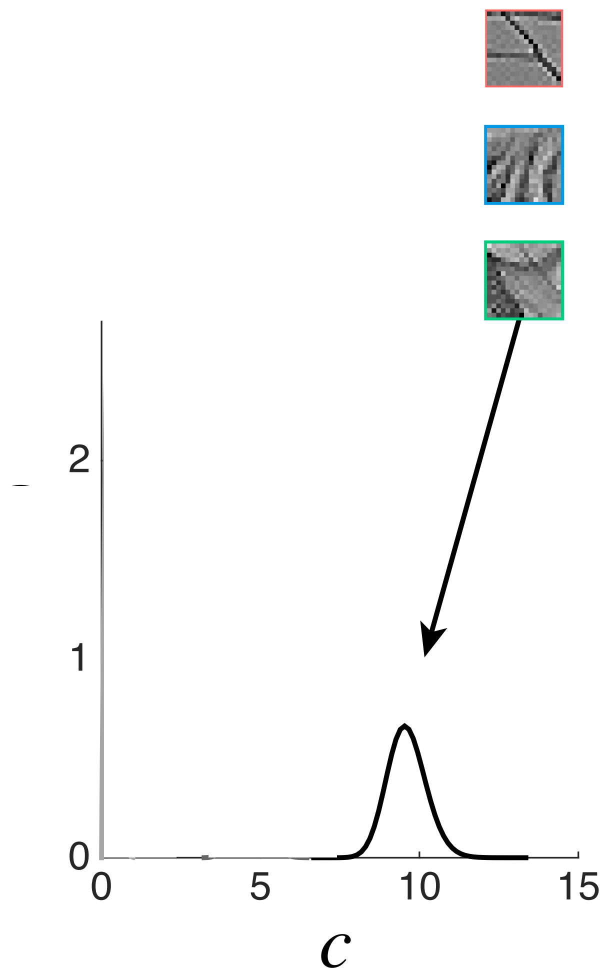
Stimulus-dependence of variance

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$

Orbán et al (2016) Neuron

Stimulus-dependence of variance

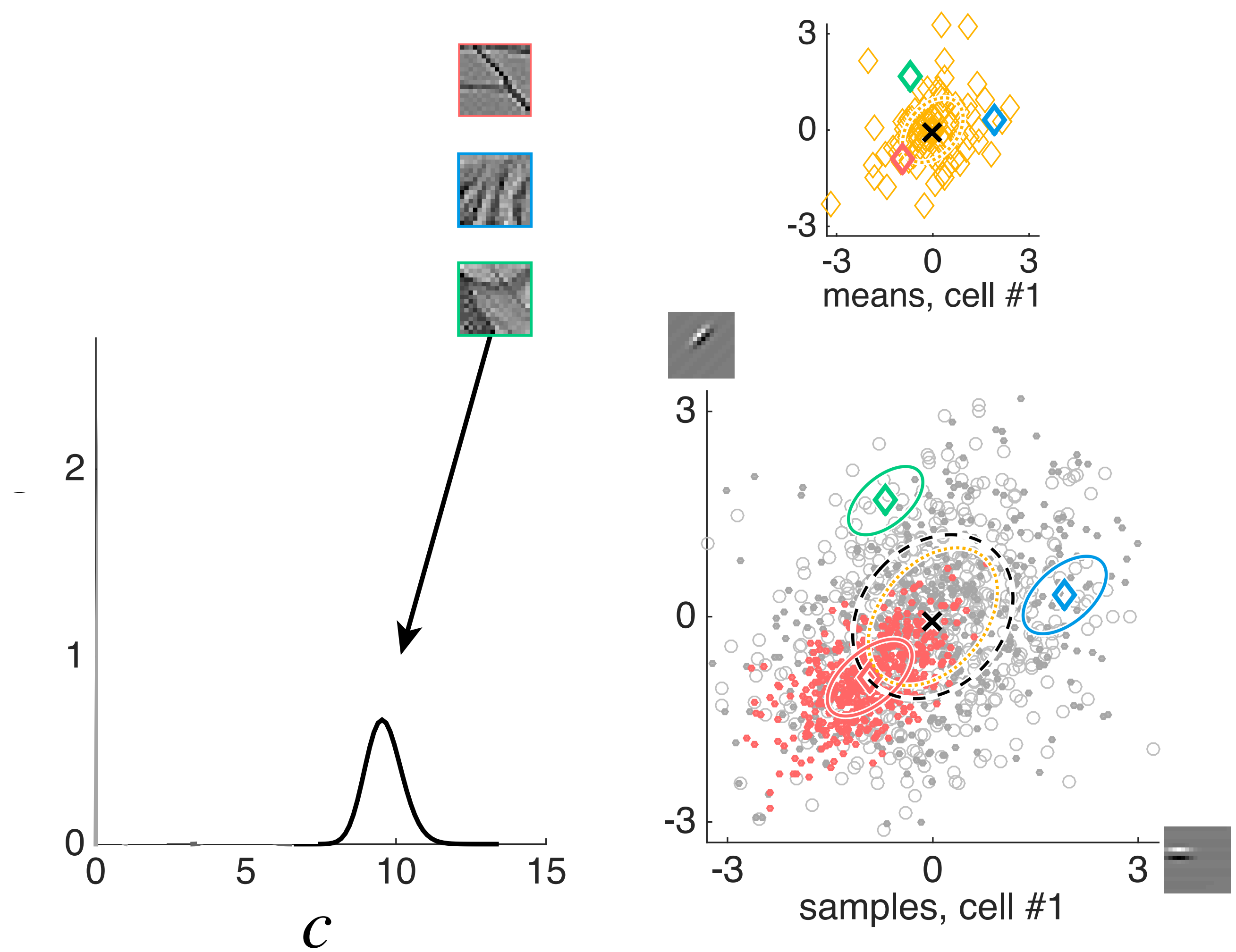
$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$



Orbán et al (2016) Neuron

Stimulus-dependence of variance

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid \text{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \mid c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\text{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$



Orbán et al (2016) Neuron

Stimulus-dependence of variance

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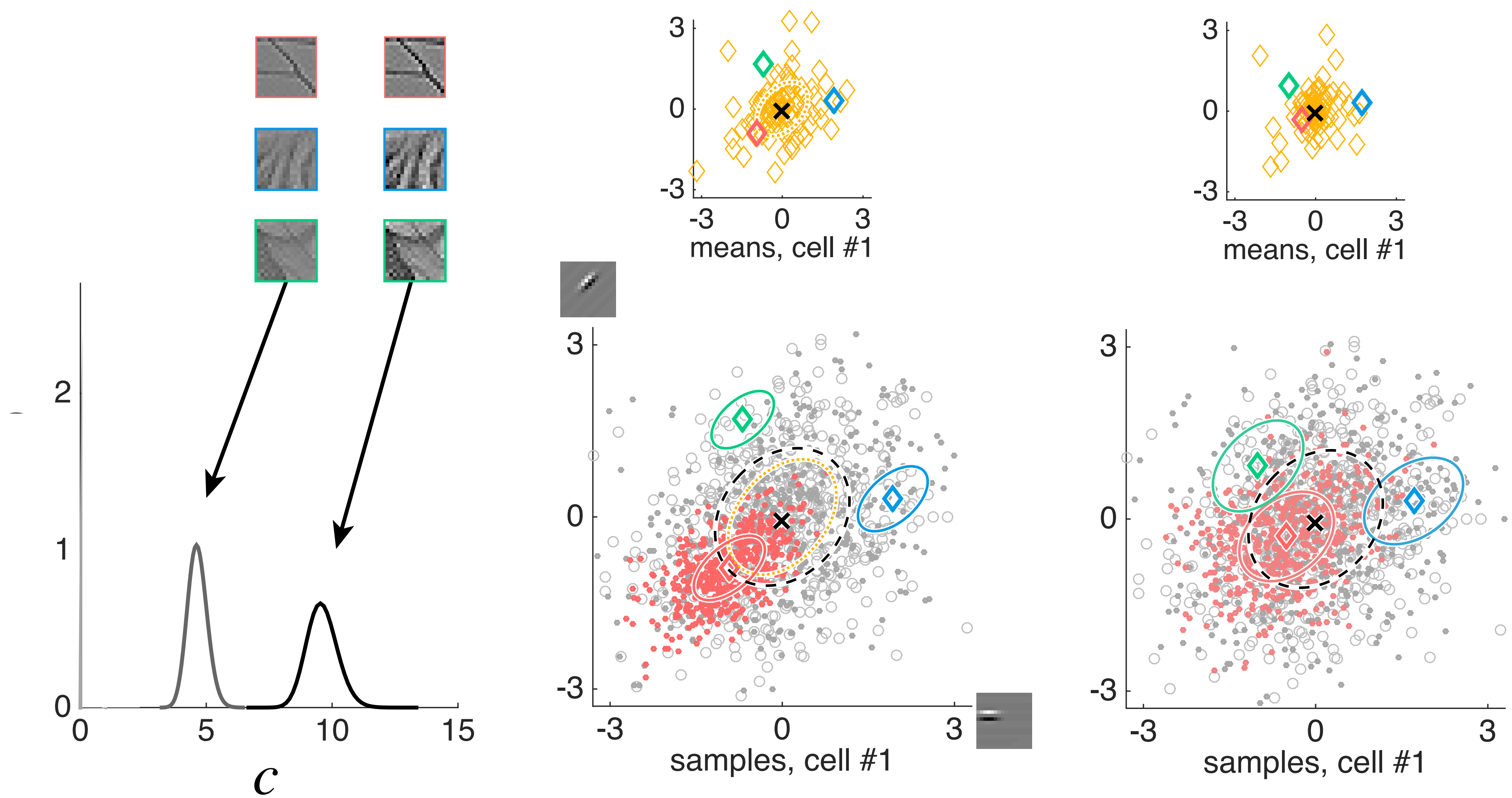
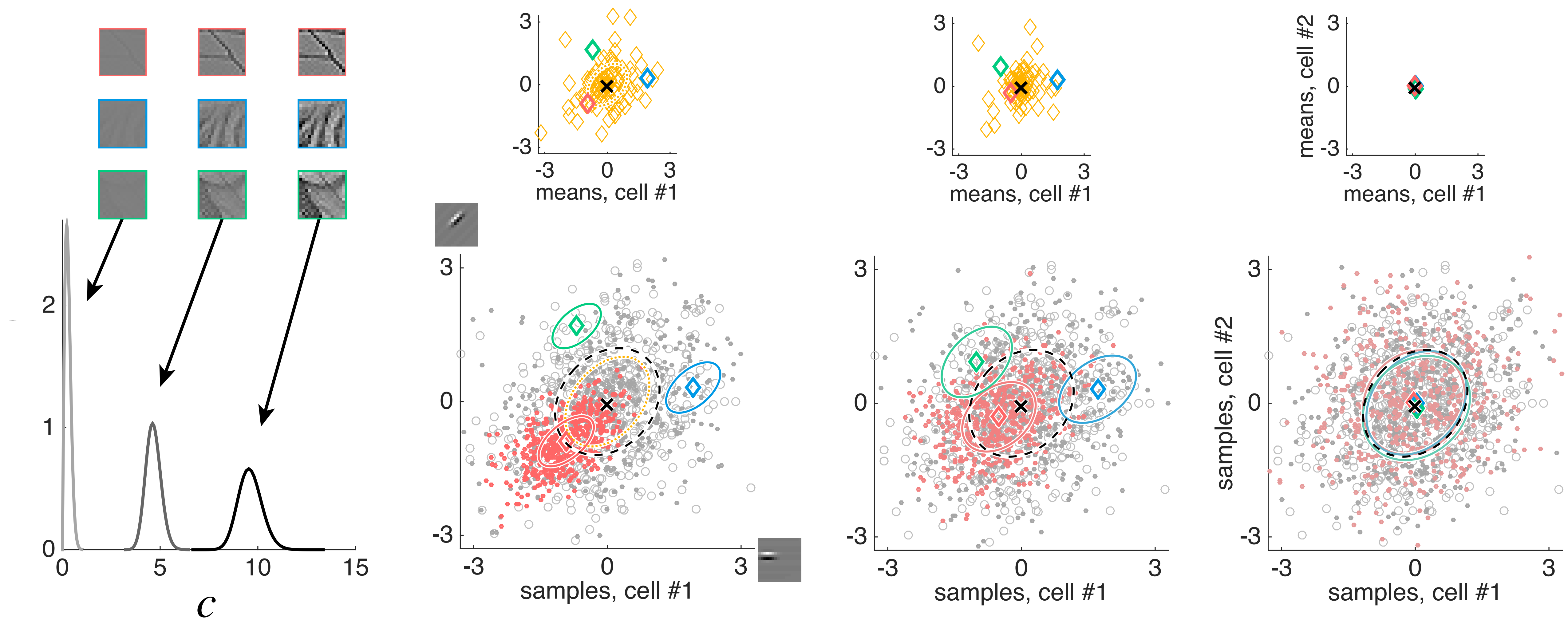


Orbán et al (2016) Neuron

Stimulus-dependence of variance

$$\underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, \mathrm{image}, c)}_{\text{posterior}} \propto \underbrace{\mathrm{P}(a_1, a_2, \ldots, a_N \,|\, c)}_{\text{prior}} \times \underbrace{\mathrm{P}(\mathrm{image}|a_1, a_2, \ldots, a_N, c)}_{\text{sensory evidence}}$$



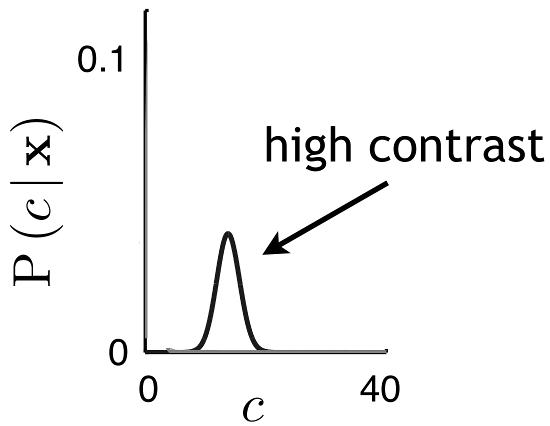
Orbán et al (2016) Neuron

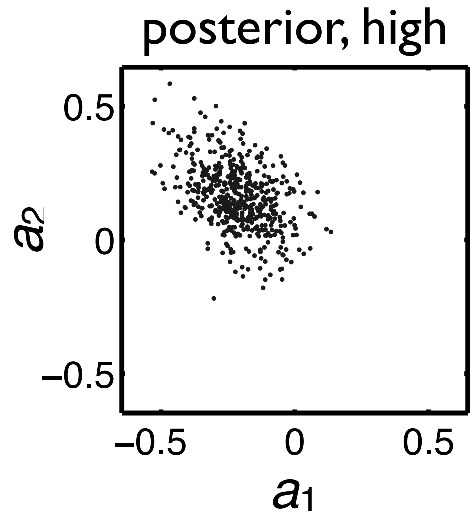
roadmap

- image model
- consequence of the representation of prior
- stimulus-dependence of variability
- stimulus dependence of covariability of multiple neurons

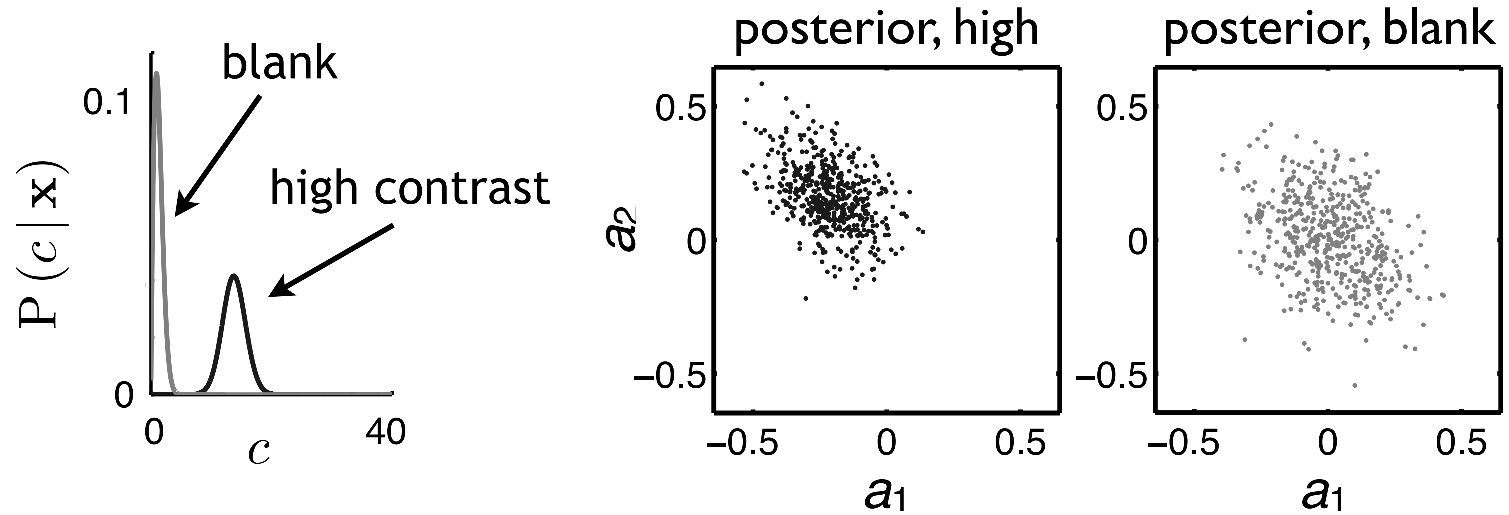
Stimulus onset quenches neural variability

Stimulus onset quenches neural variability

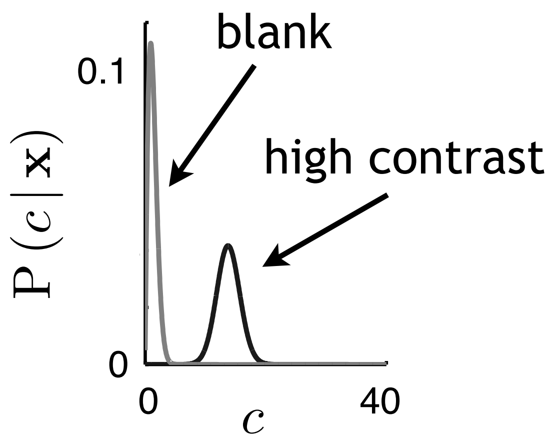


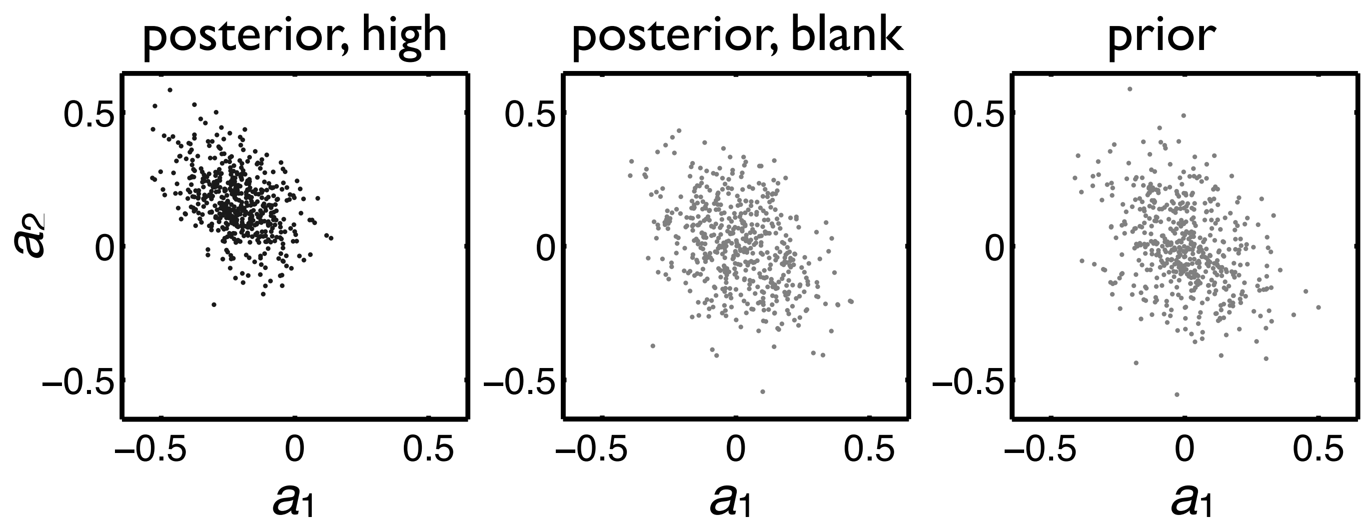


Stimulus onset quenches neural variability

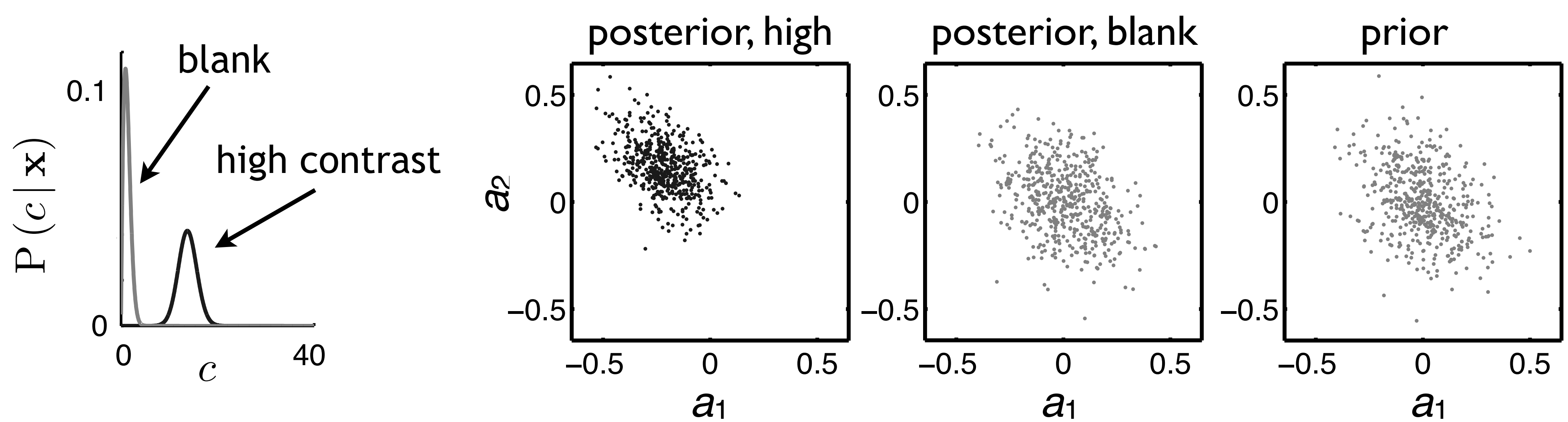


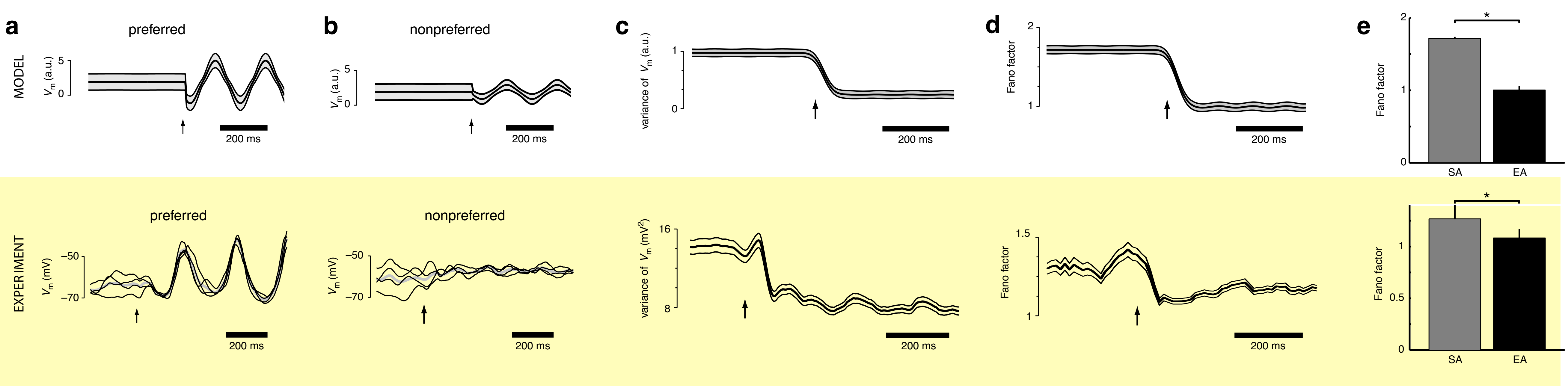
Stimulus onset quenches neural variability



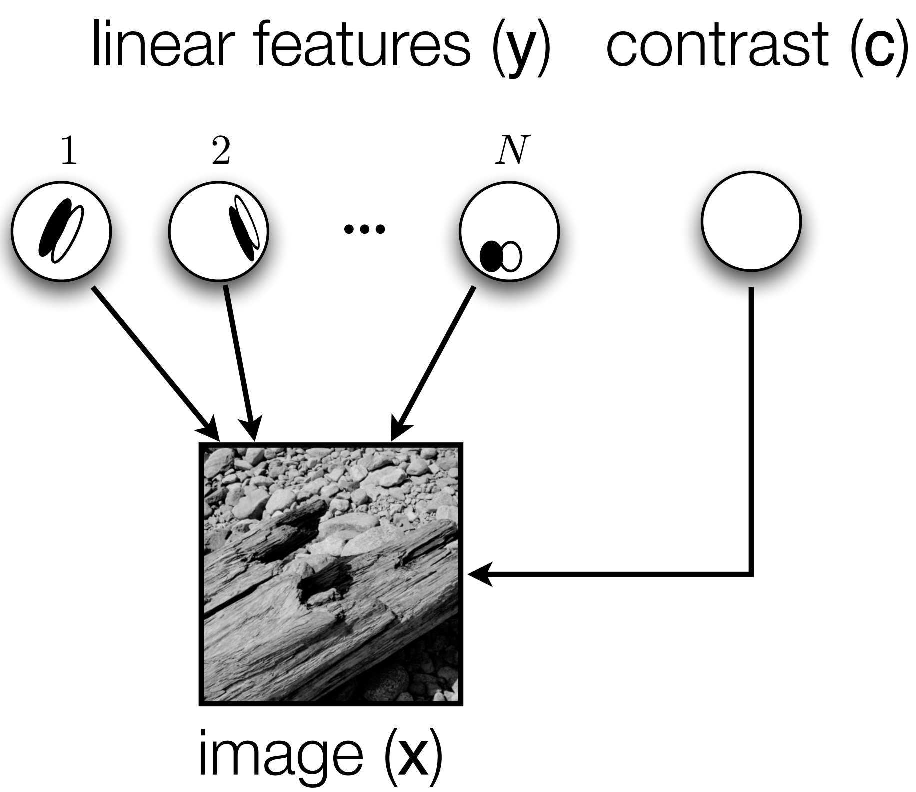


Stimulus onset quenches neural variability

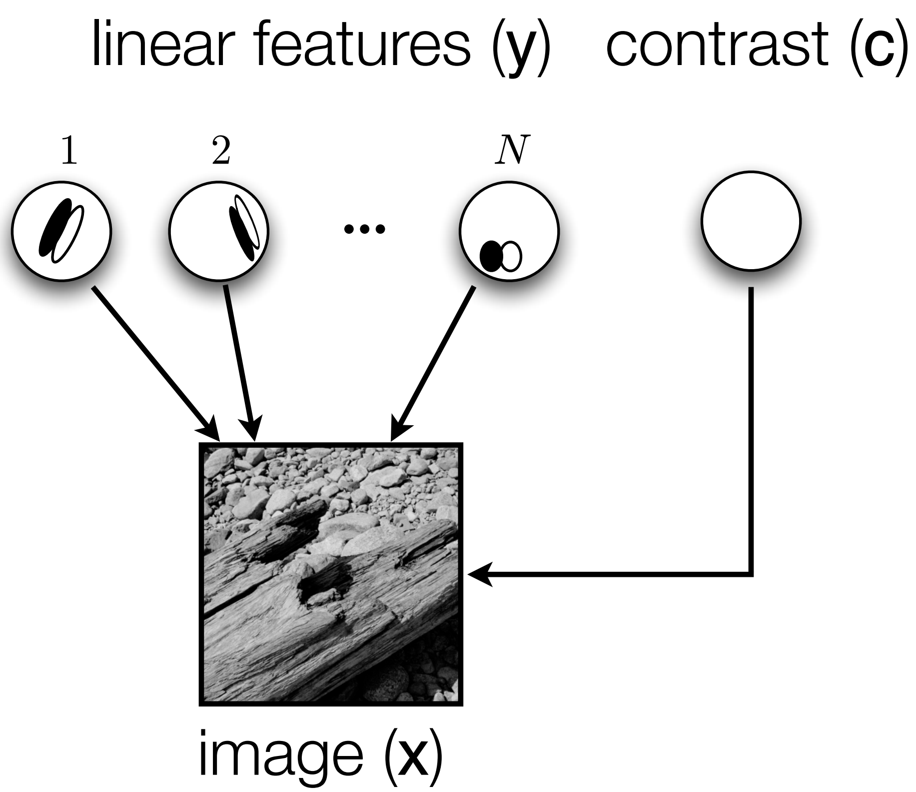




Response statistics in a simple model of natural images



Response statistics in a simple model of natural images



$$P(y \mid x) = \int P(y \mid x, c) P(c \mid x) \, dc$$

Response statistics in a simple model of natural images

linear features (**y**)   contrast (**c**)

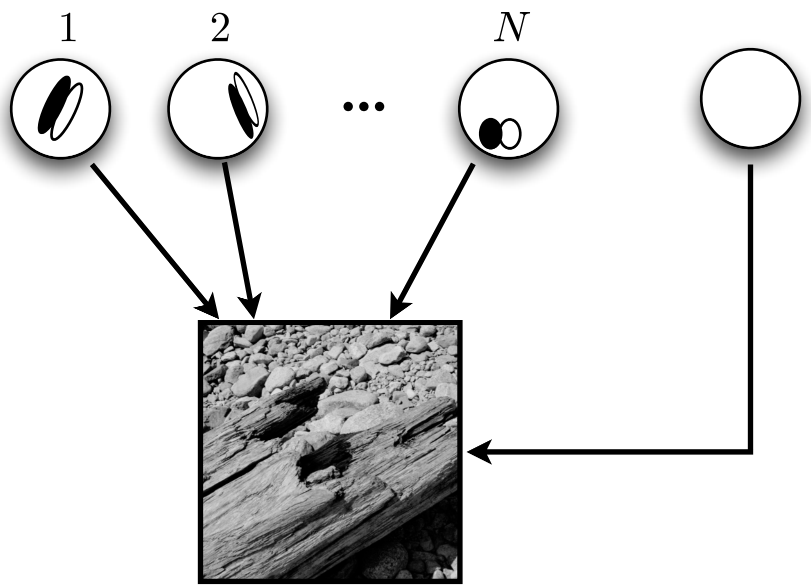
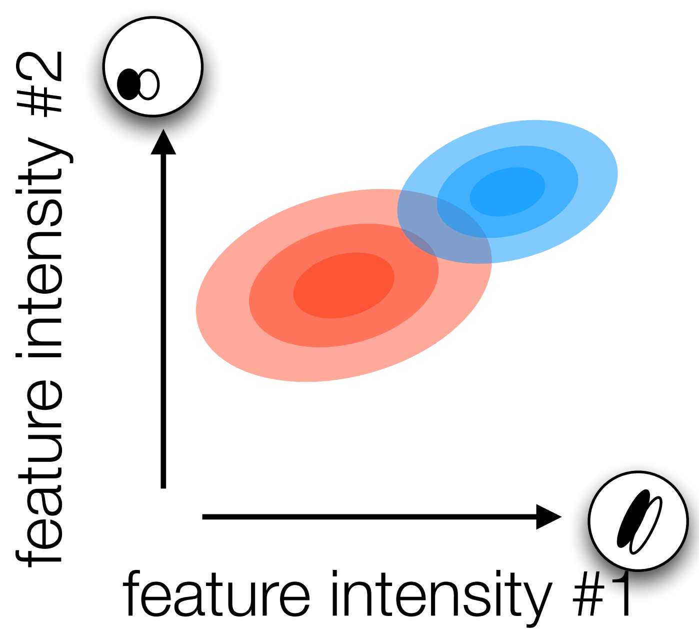
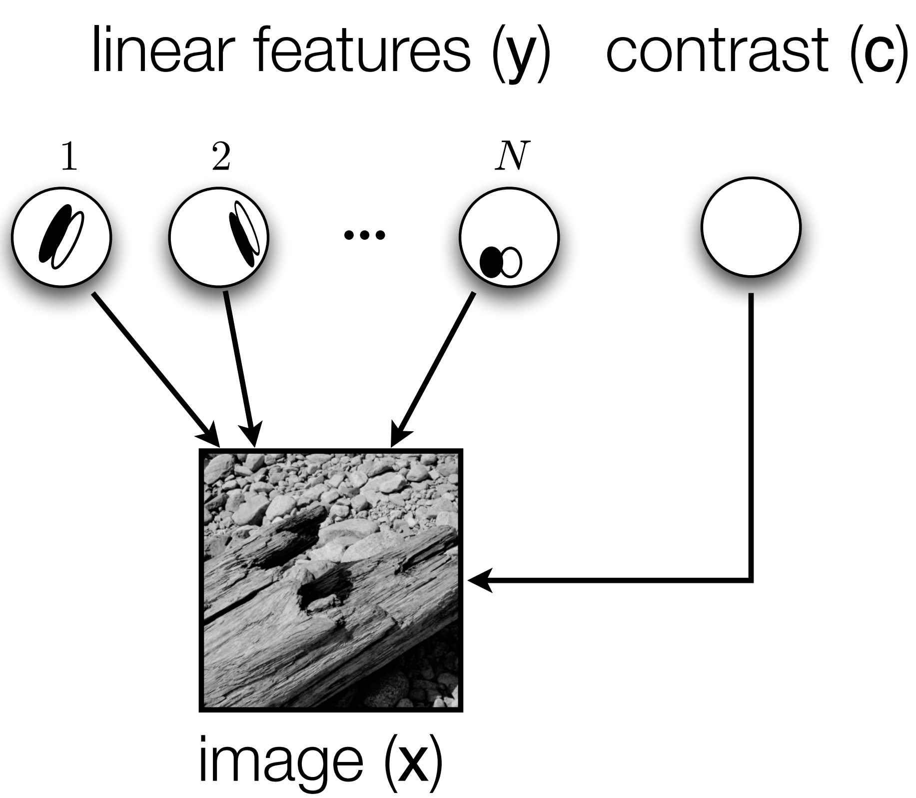


image (**x**)

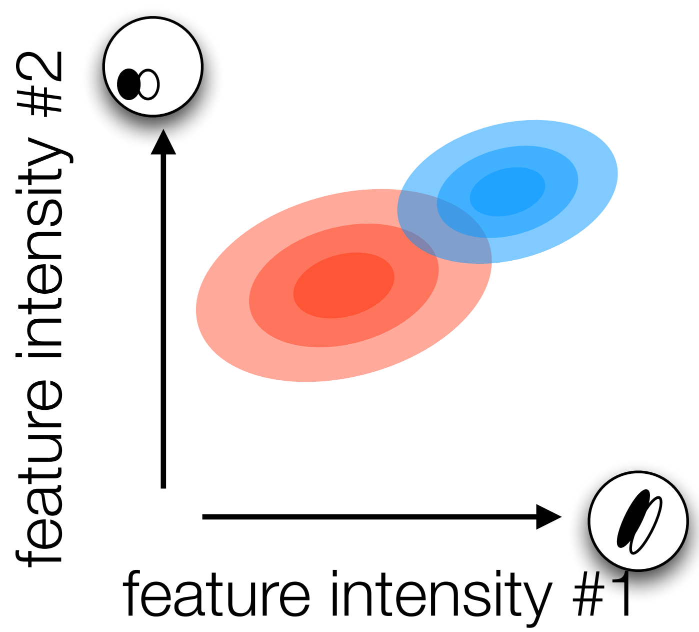
$$P(y \mid x) = \int P(y \mid x, c)P(c \mid x)\, dc$$

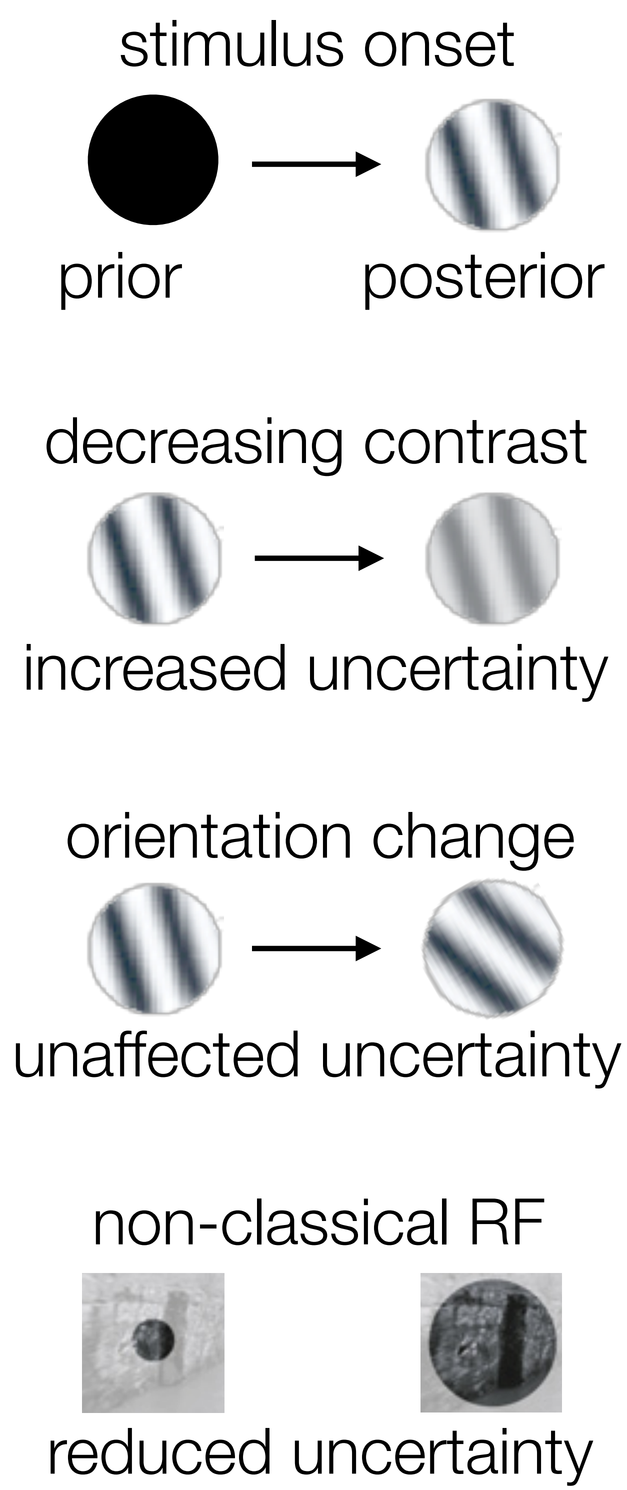


Response statistics in a simple model of natural images

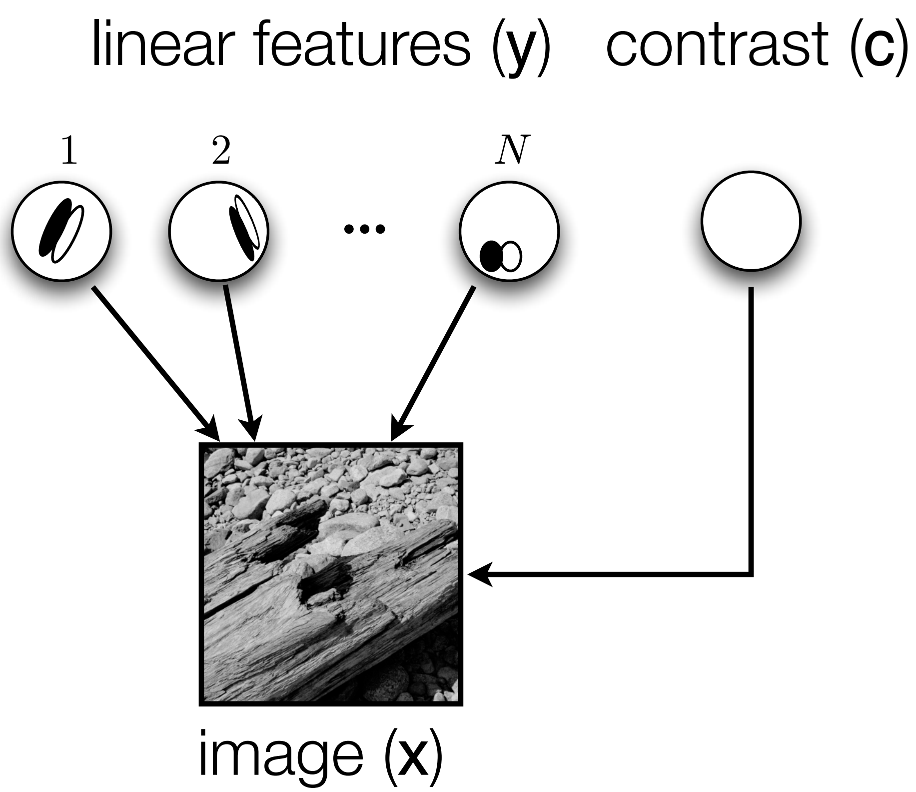


$$P(y \mid x) = \int P(y \mid x, c) P(c \mid x)\, dc$$





Response statistics in a simple model of natural images



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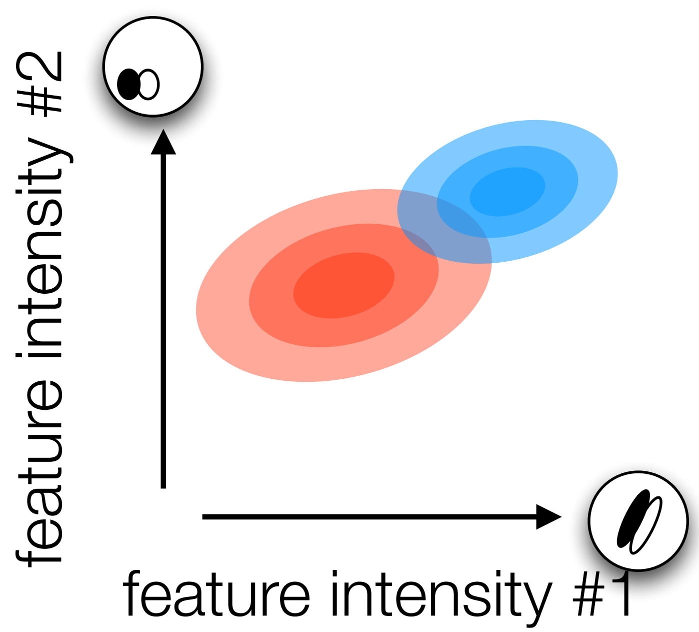
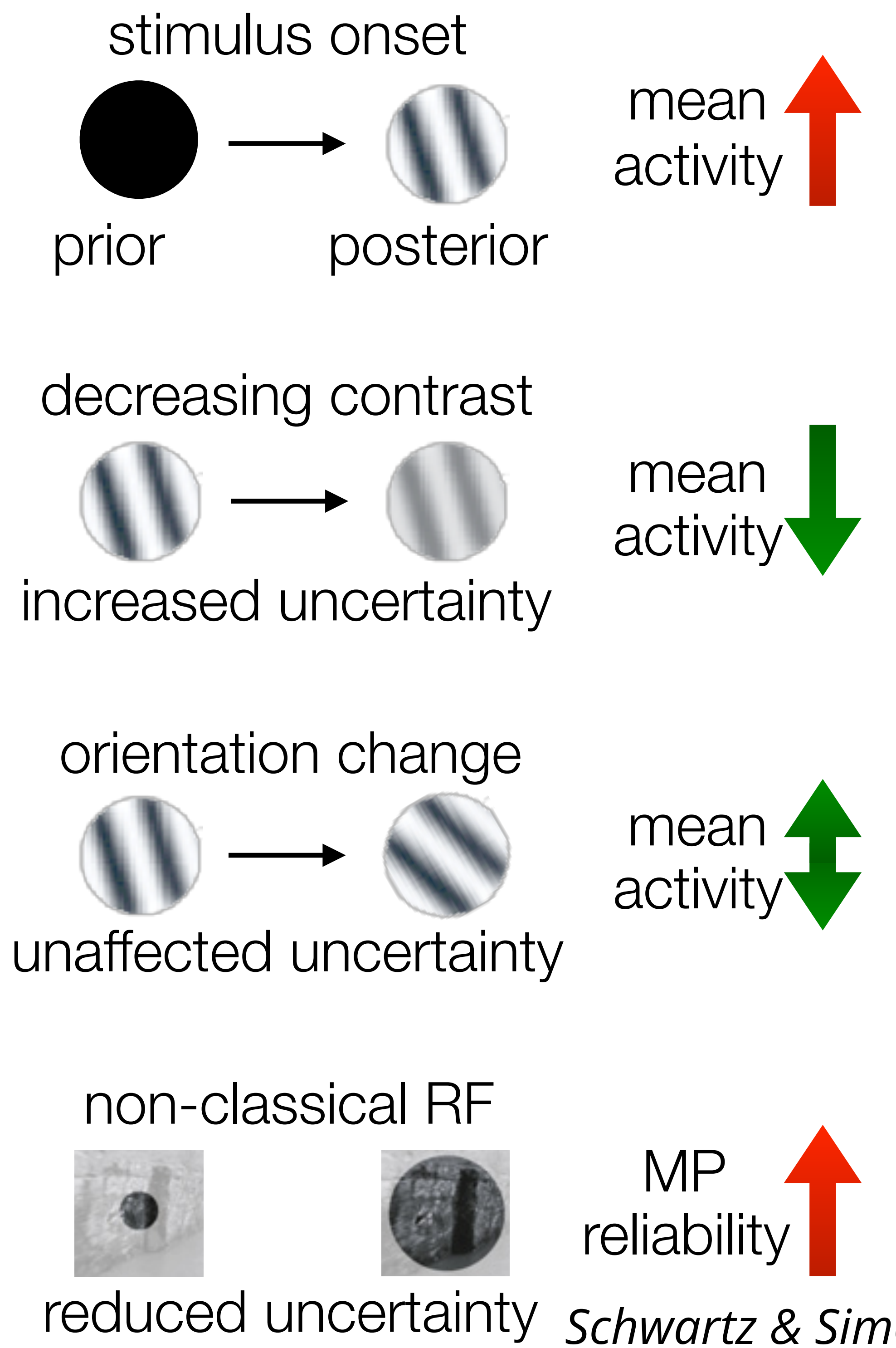
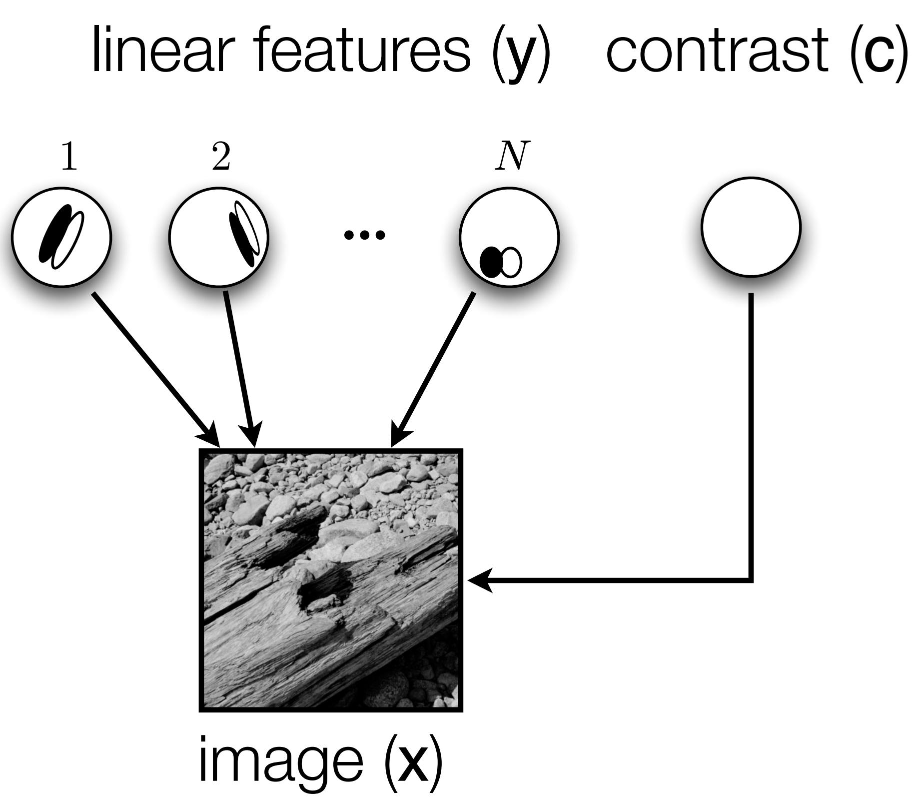


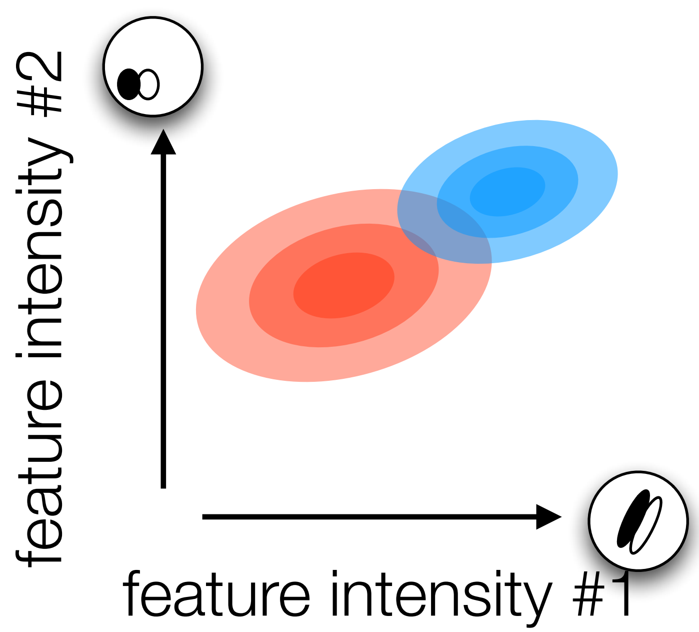


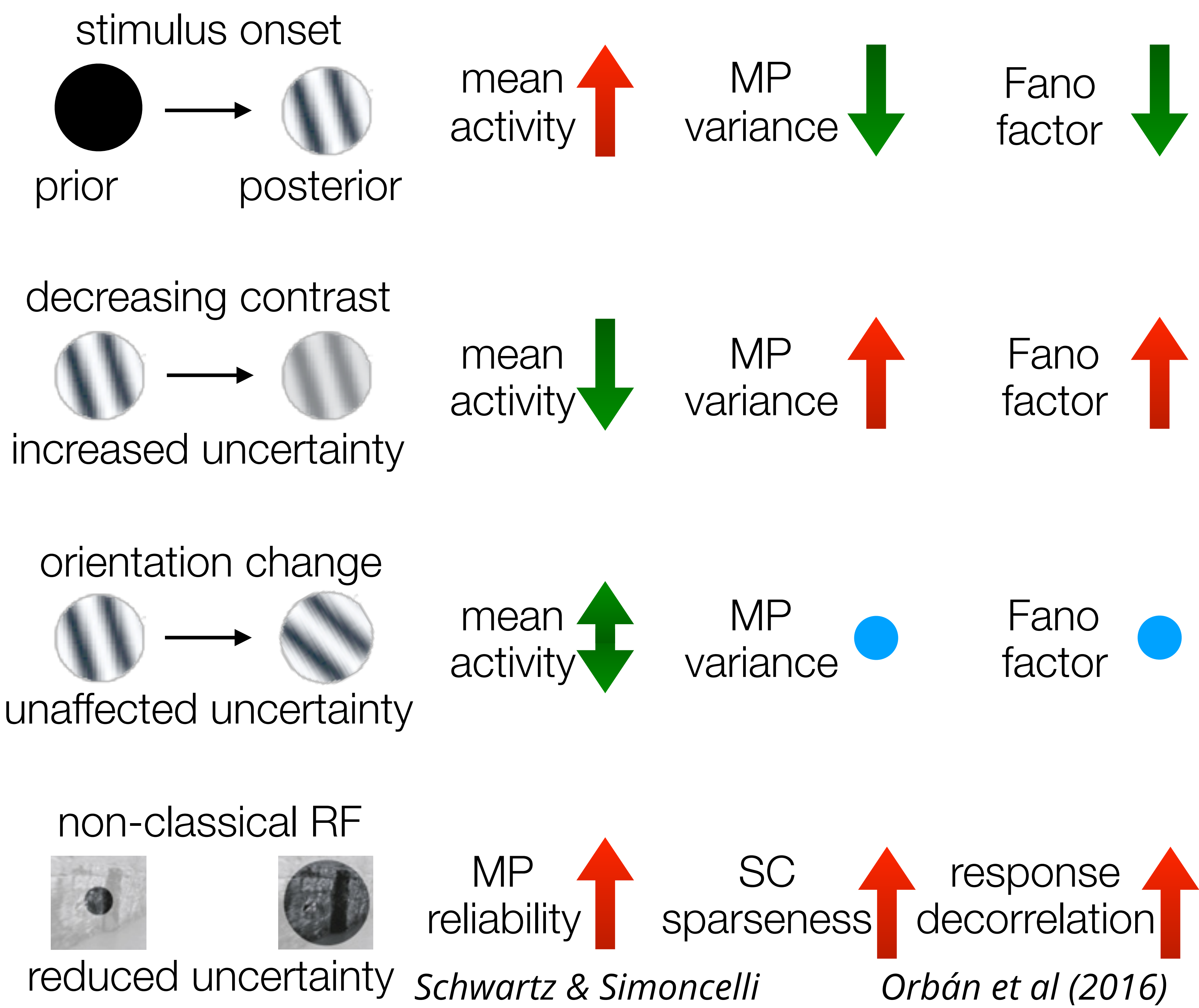
Schwartz & Simoncelli (2001) Nat Neuro

Response statistics in a simple model of natural images



$$P(y \mid x) = \int P(y \mid x, c) P(c \mid x)\, dc$$





Schwartz & Simoncelli (2001) Nat Neuro

Orbán et al (2016) Neuron

Churchland et al (2010) Nat Neurosci; Ecker et al (2010) Science; Finn et al (2007) Neuron; Vinje & Gallant (2001) Science; Haider et al (2007) Neuron

Response statistics in a simple model of natural images

linear features (**y**) contrast (**c**)

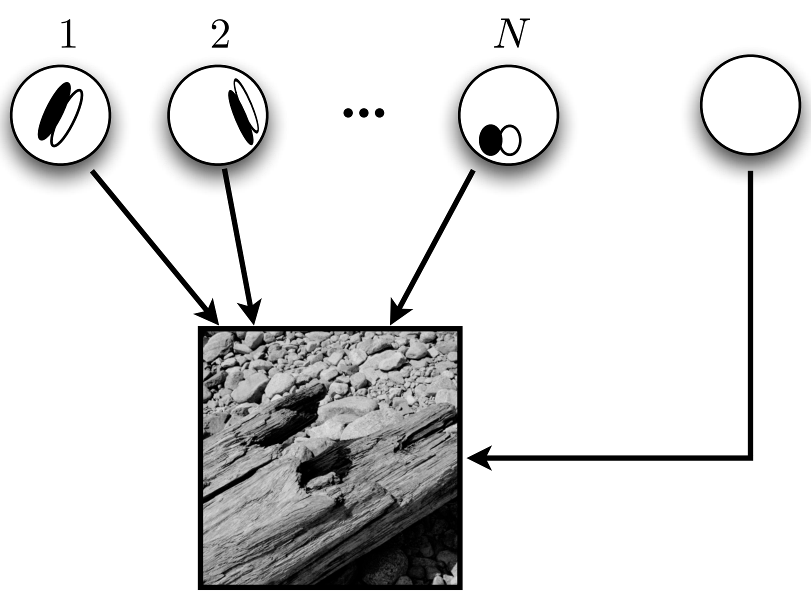
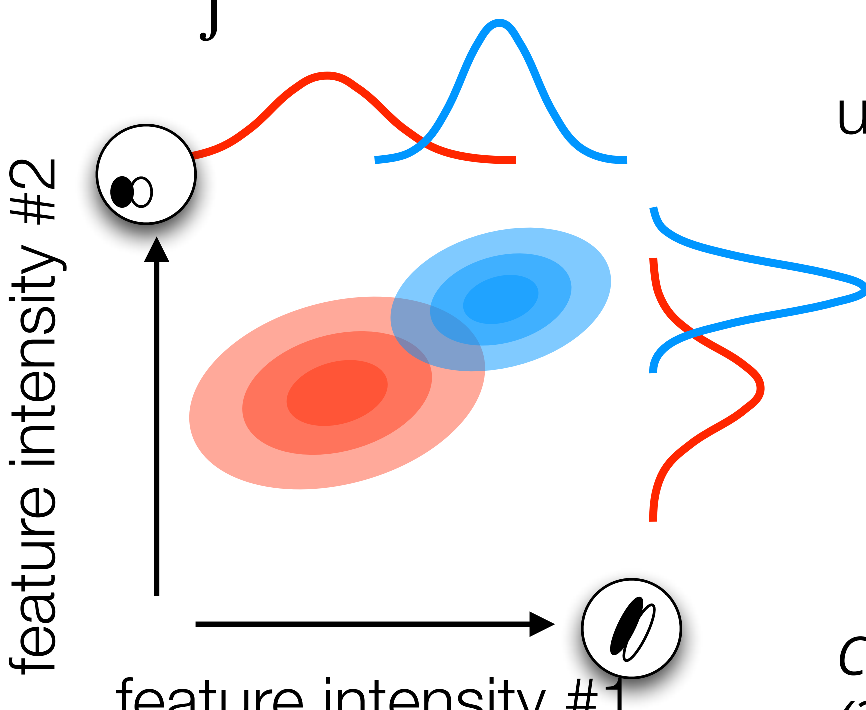
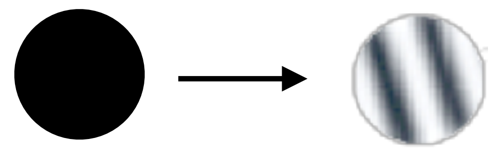


image (**x**)

$$P(y \mid x) = \int P(y \mid x, c)P(c \mid x)\, dc$$



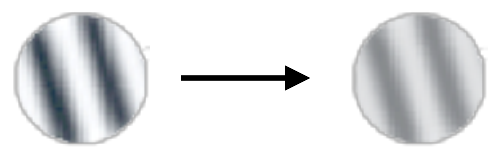
stimulus onset



prior posterior

mean activity | MP variance | Fano factor

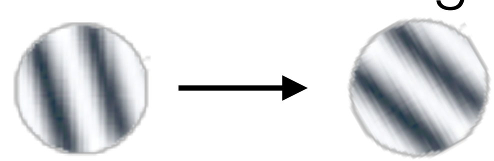
decreasing contrast



increased uncertainty

mean activity | MP variance | Fano factor

orientation change



unaffected uncertainty

mean activity | MP variance | Fano factor

non-classical RF

reduced uncertainty

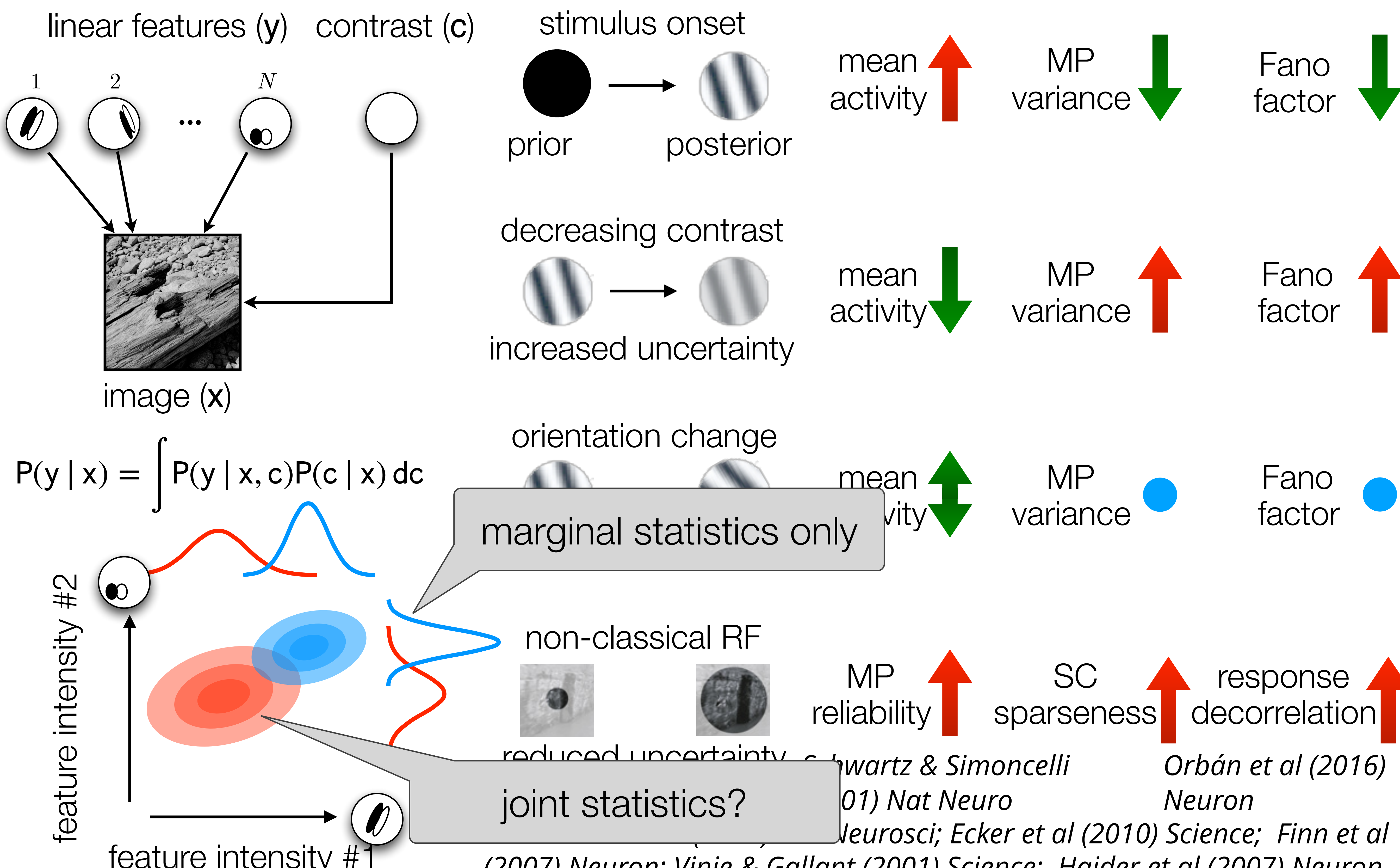
MP reliability | SC sparseness | response decorrelation

Schwartz & Simoncelli (2001) Nat Neuro

Orbán et al (2016) Neuron

Churchland et al (2010) Nat Neurosci; Ecker et al (2010) Science; Finn et al (2007) Neuron; Vinje & Gallant (2001) Science; Haider et al (2007) Neuron

Response statistics in a simple model of natural images



…wartz & Simoncelli (…01) Nat Neuro

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