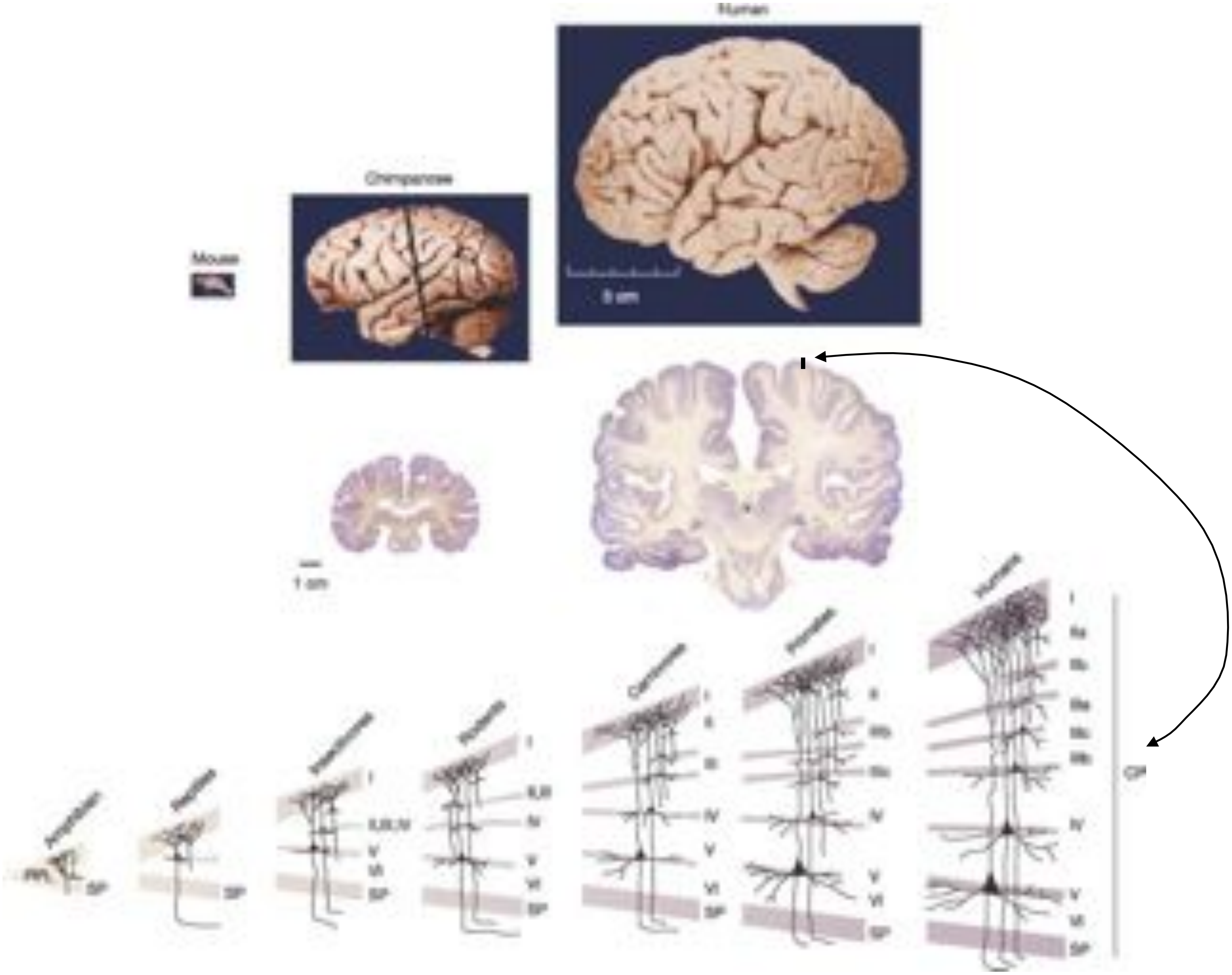
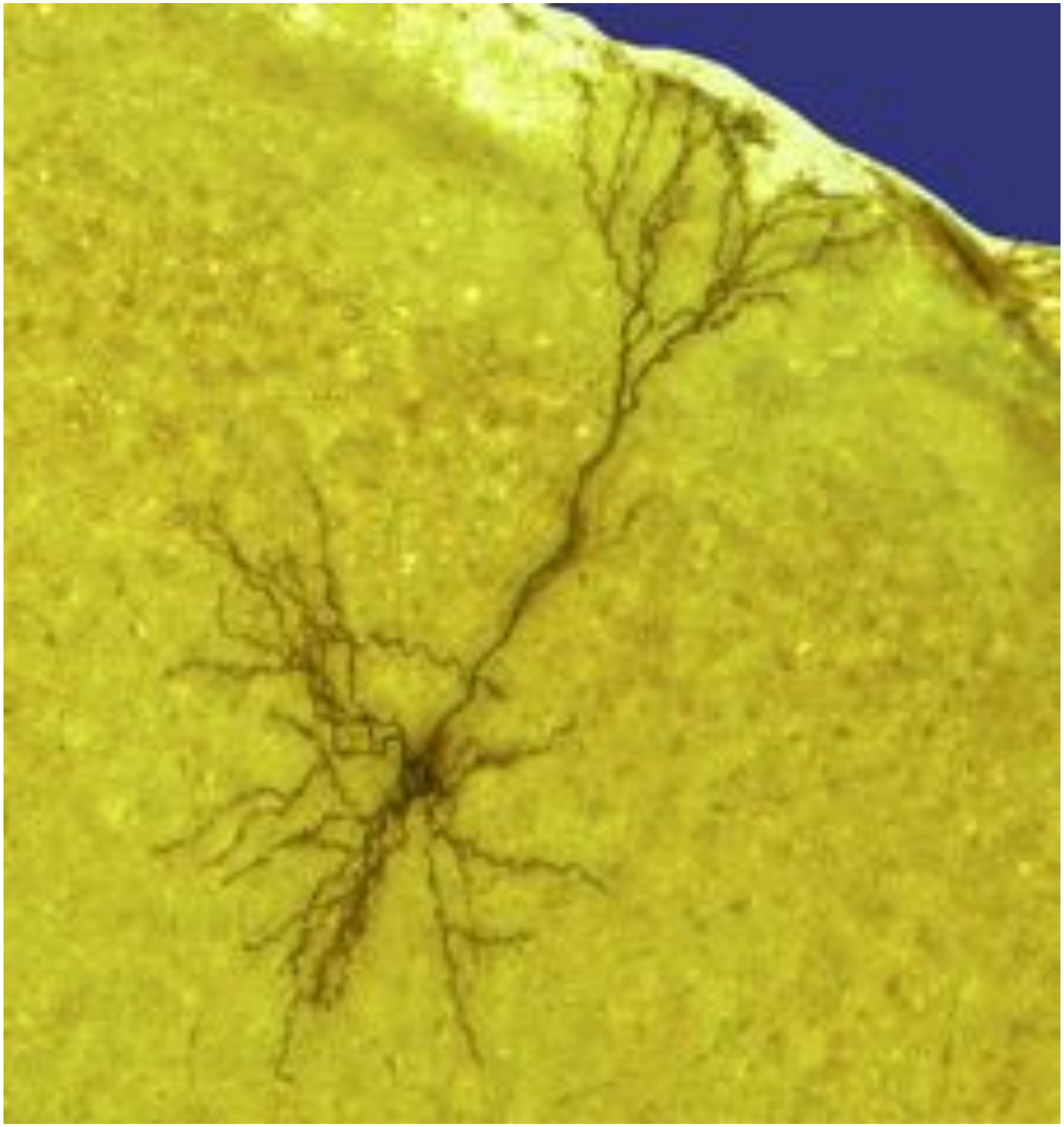
Figure 5. Horizontal section of the brain showing the line of Gennari in the striate cortex. From Polyak (1957).

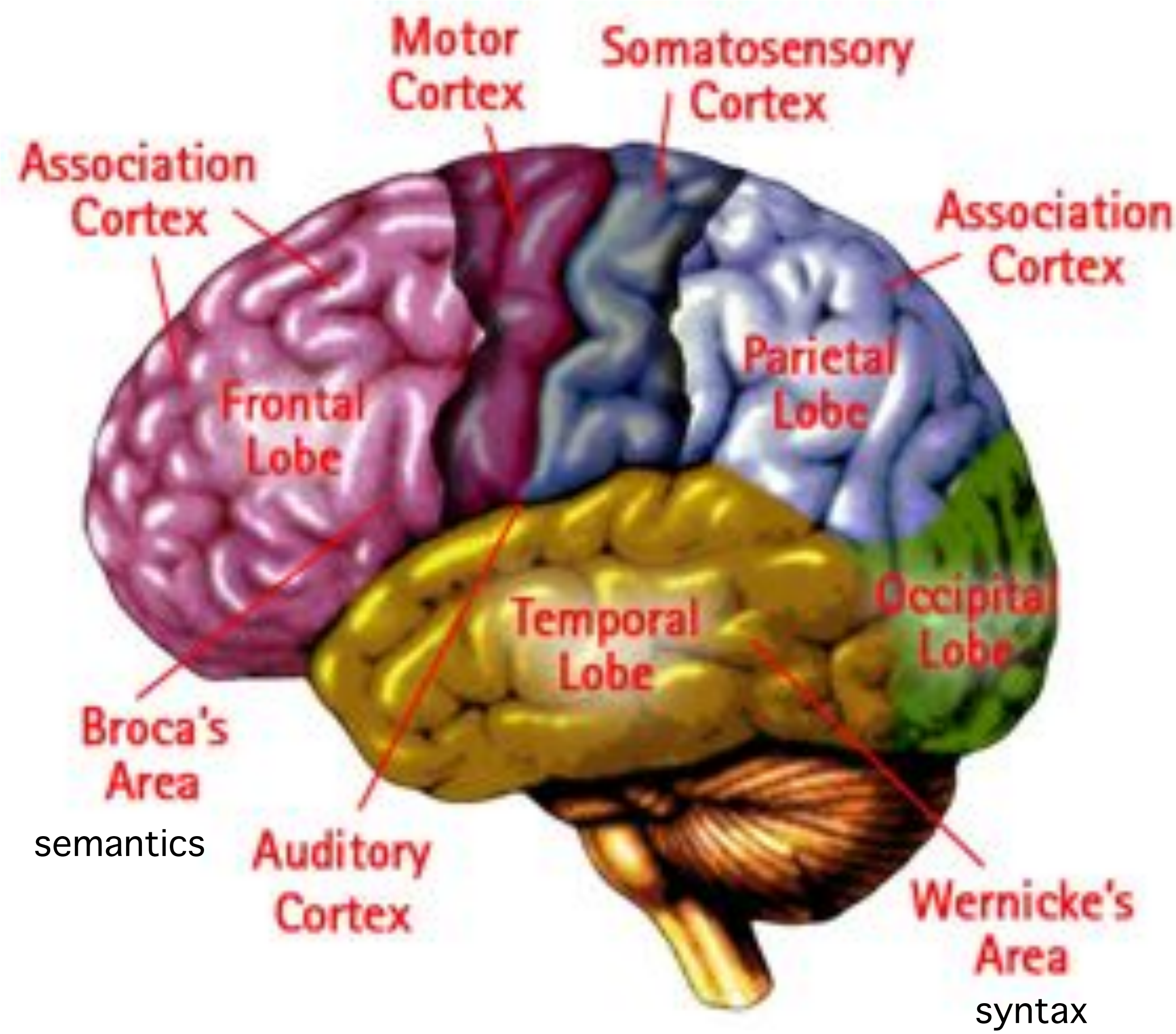
White matter: Axons

Gray matter: Local circuitry


Human
Chimpanzee
Mouse
5 cm
1 cm
Carnivores
I
II
III
IV
V
VI
SP
II,III
II,III,IV
IIa
IIb
IIIa
IIIb
IIIc
CP

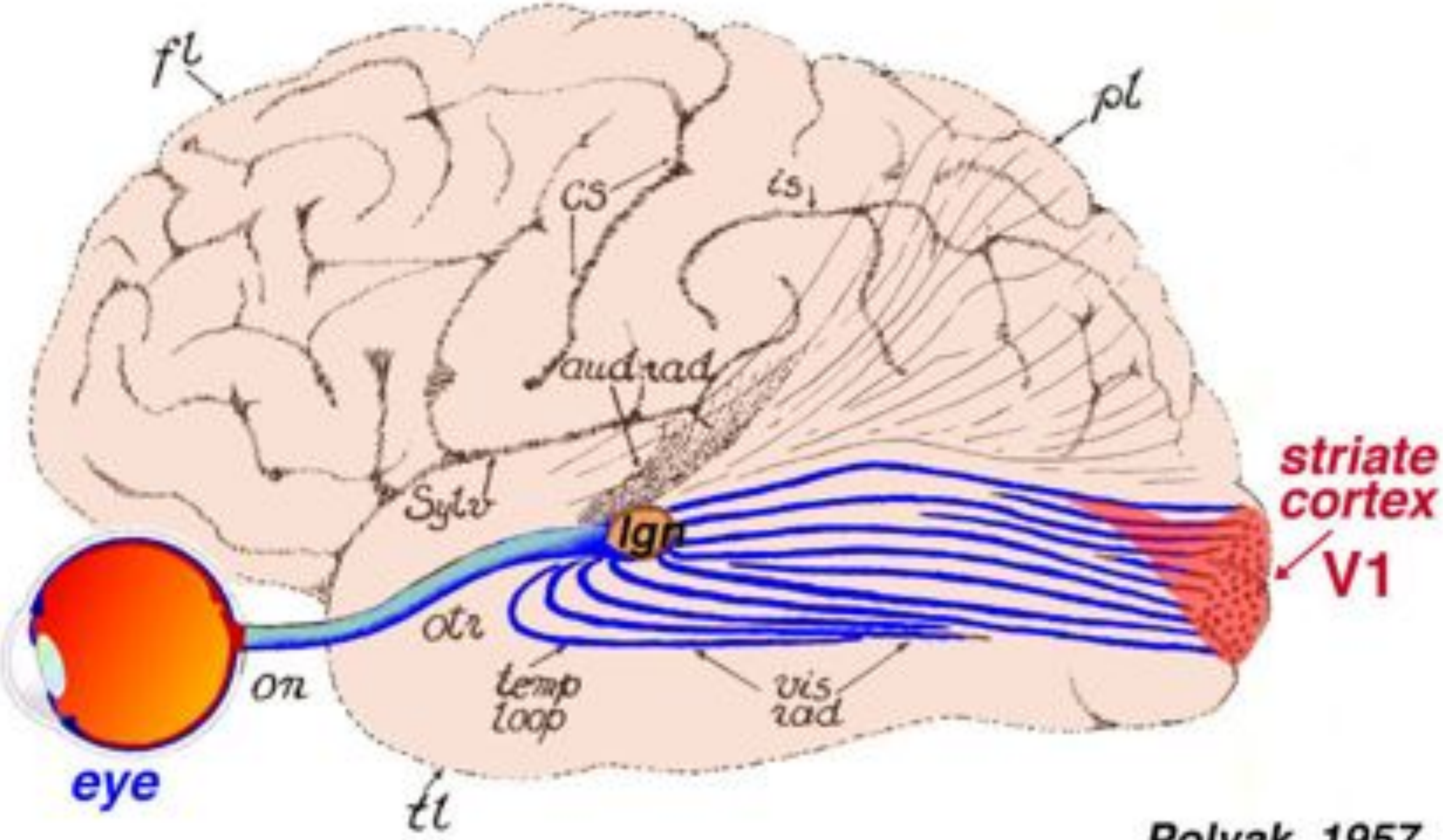


Cortex: Basic divisions

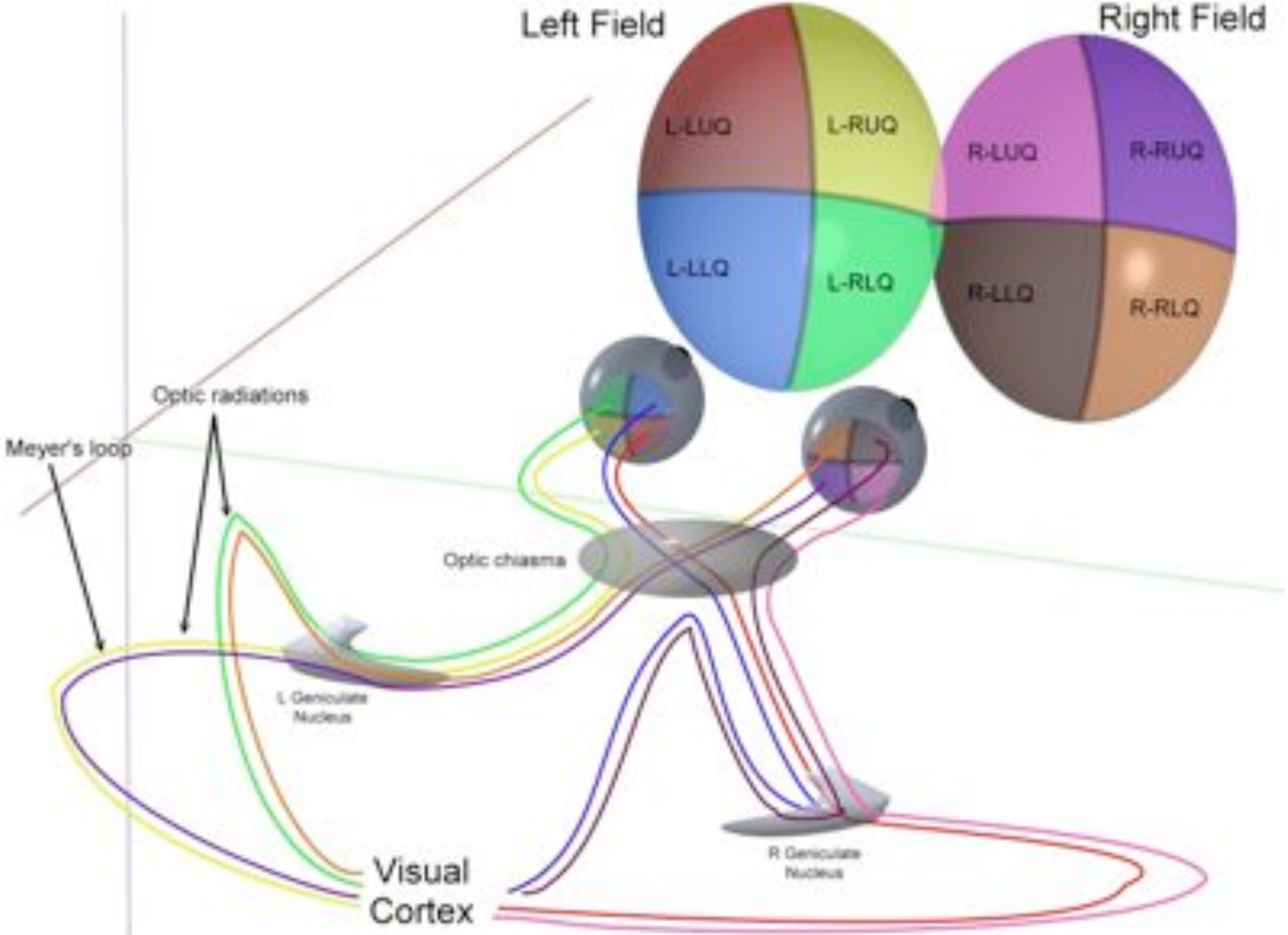


semantics

syntax


fl
pl
cs
is
aud rad
Sylv
lgn
striate cortex
V1
otr
on
temp loop
vis rad
eye
tl

Polyak, 1957


Left Field
Right Field
L-LUQ
L-RUQ
R-LUQ
R-RUQ
L-LLQ
L-RLQ
R-LLQ
R-RLQ
Optic radiations
Meyer's loop
Optic chiasma
L Geniculate Nucleus
R Geniculate Nucleus
Visual Cortex

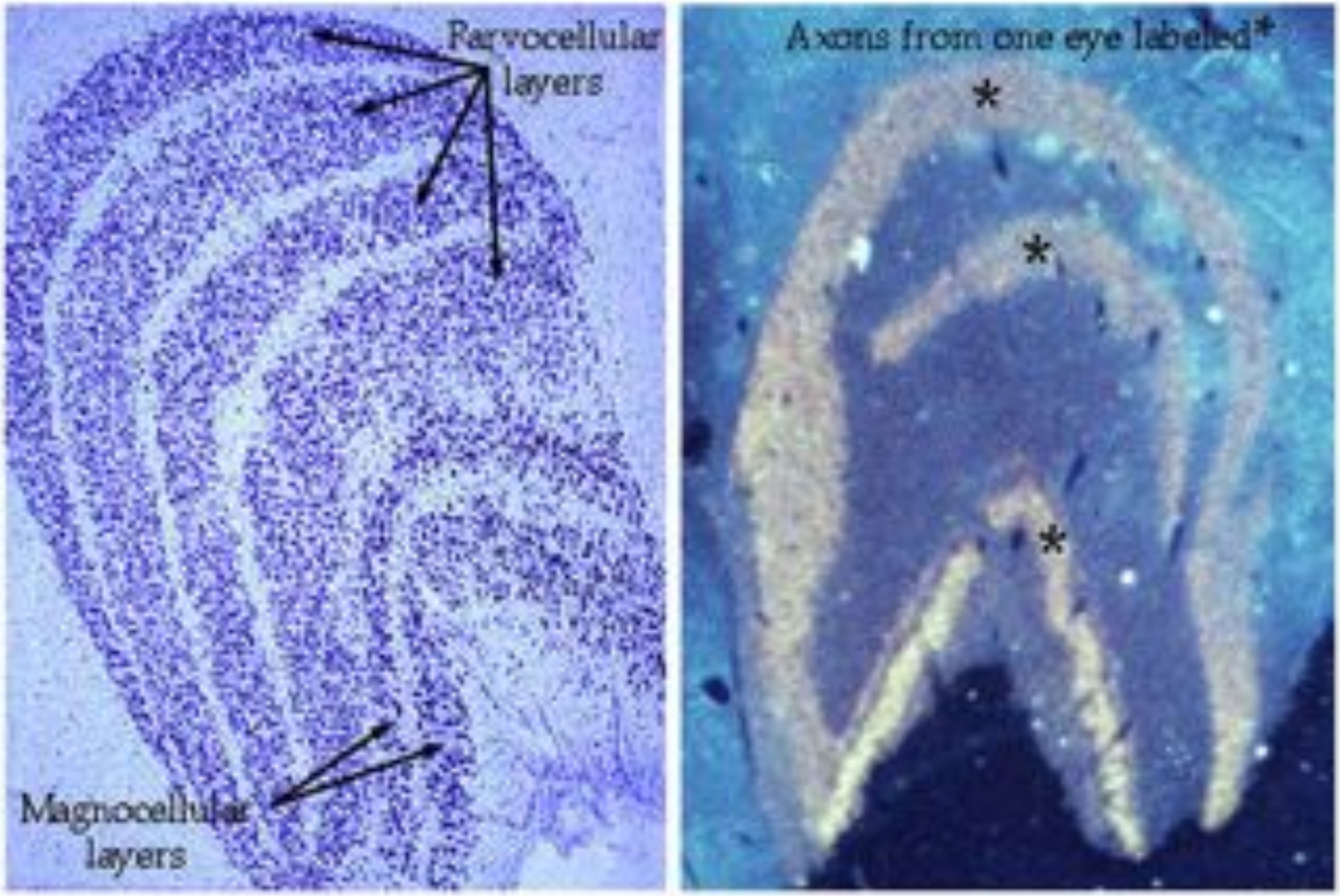
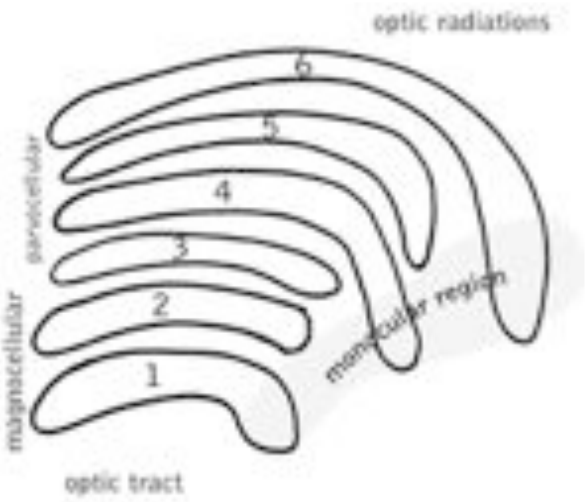
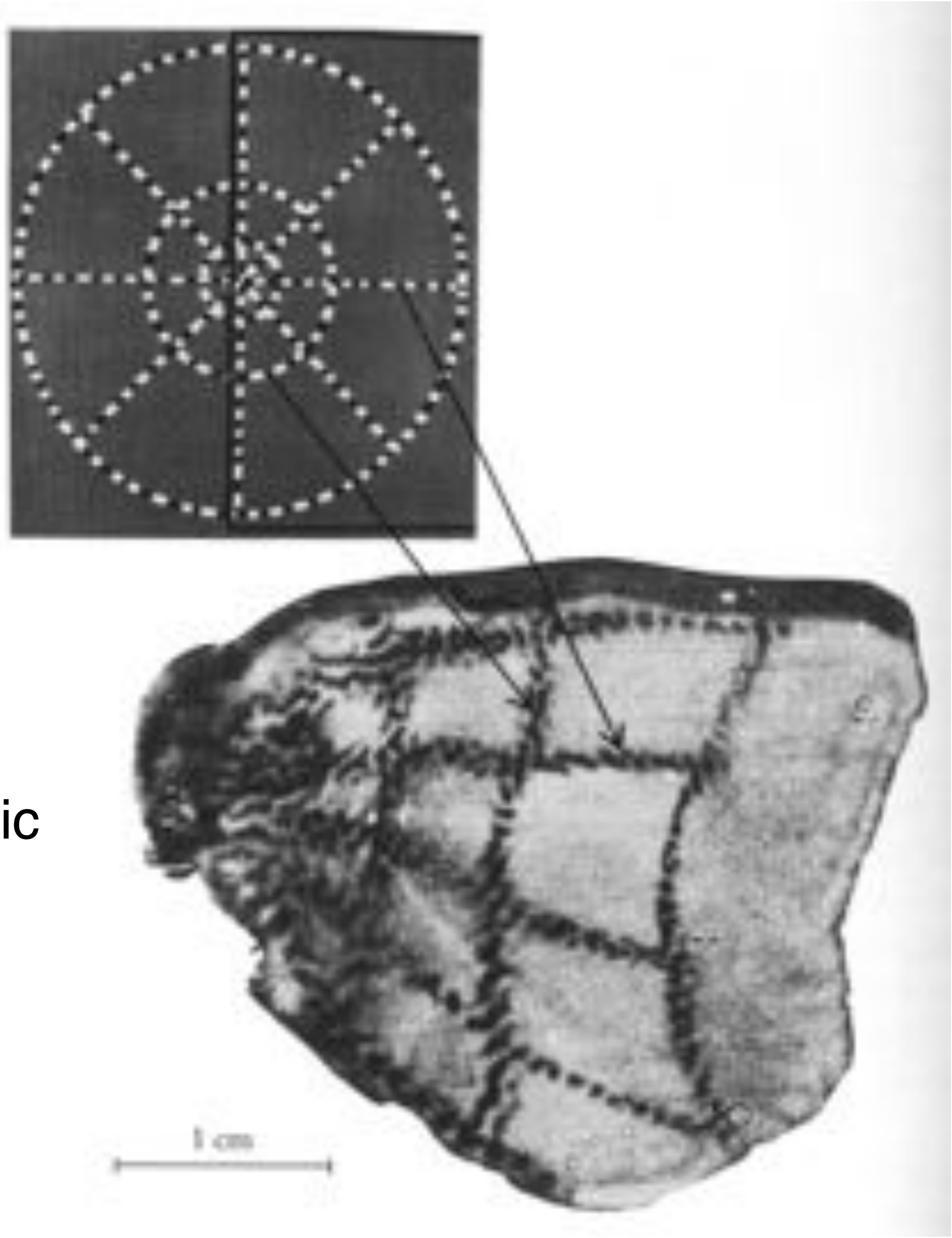


Figure 11. The projections of the small (P cells), and large (M cells) ganglion cells from the two eyes to parvocellular and magnocellular layers of the LGN respectively. Each eye projects to alternating layers as seen in the autoradiogram (right).

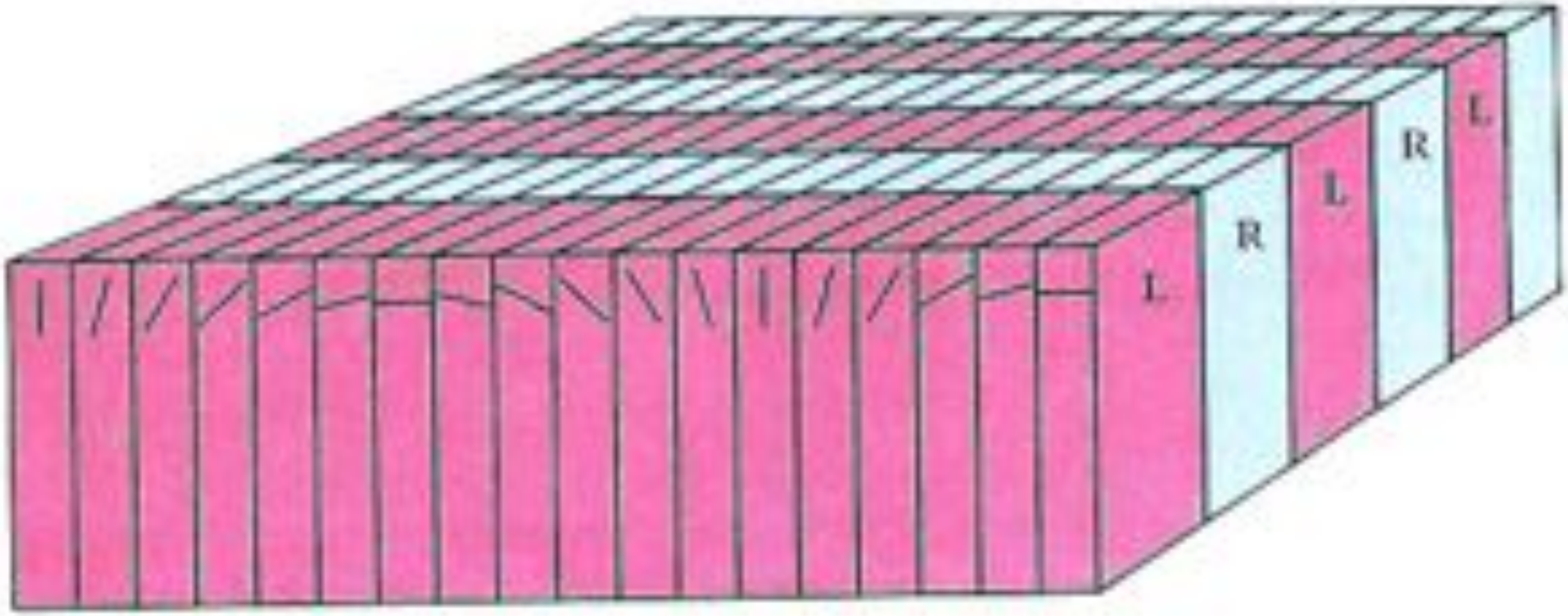
LGN

Cell Type	Size	Source/info	Location	Number
M	Large	Rods/motion	Layers 1-2	95%
P	Small	R-G cones/ form	Layers 4-6	5%
K	Small	Blue cones/ form	In between layers	?





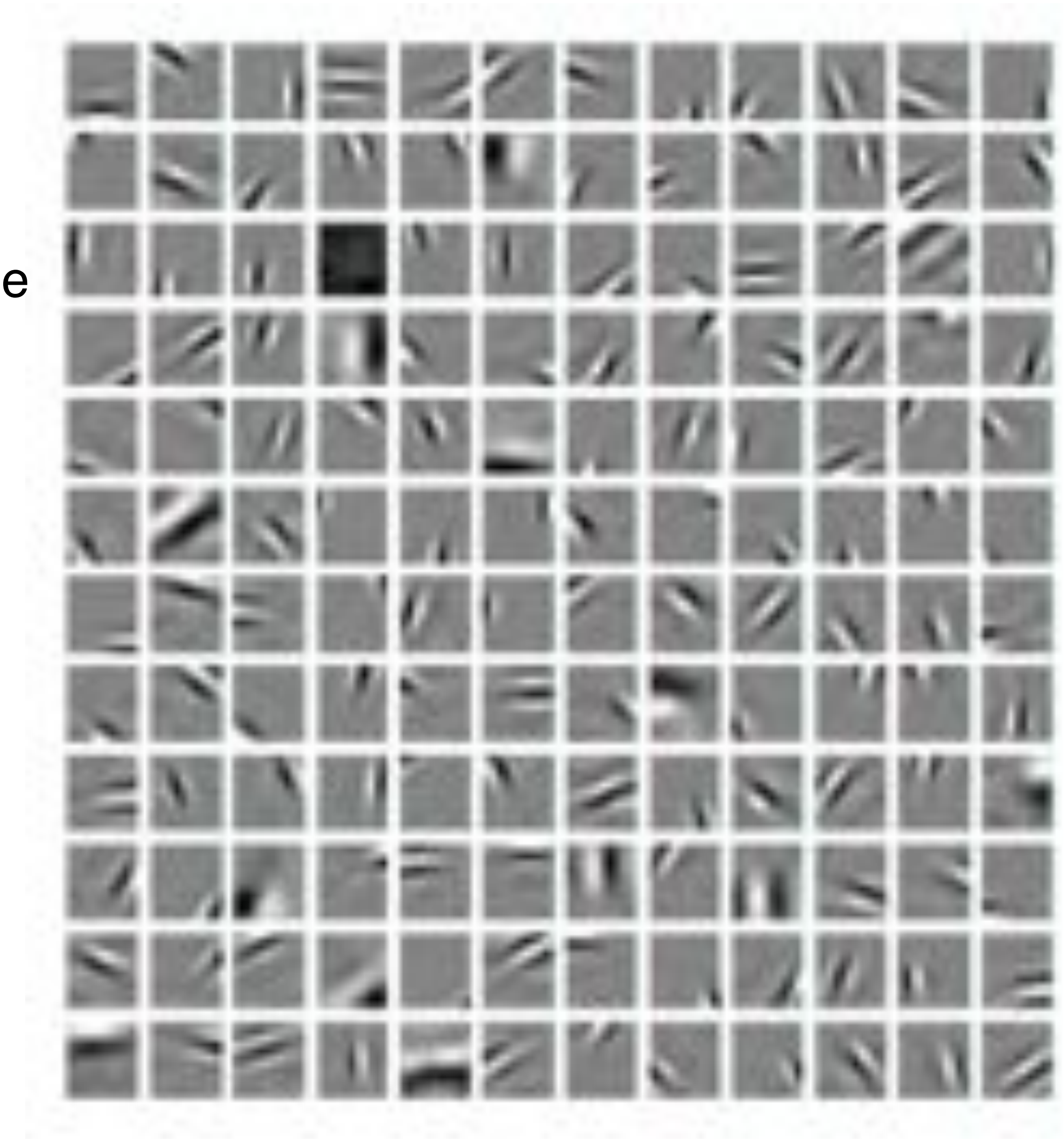
Retinotopic Map



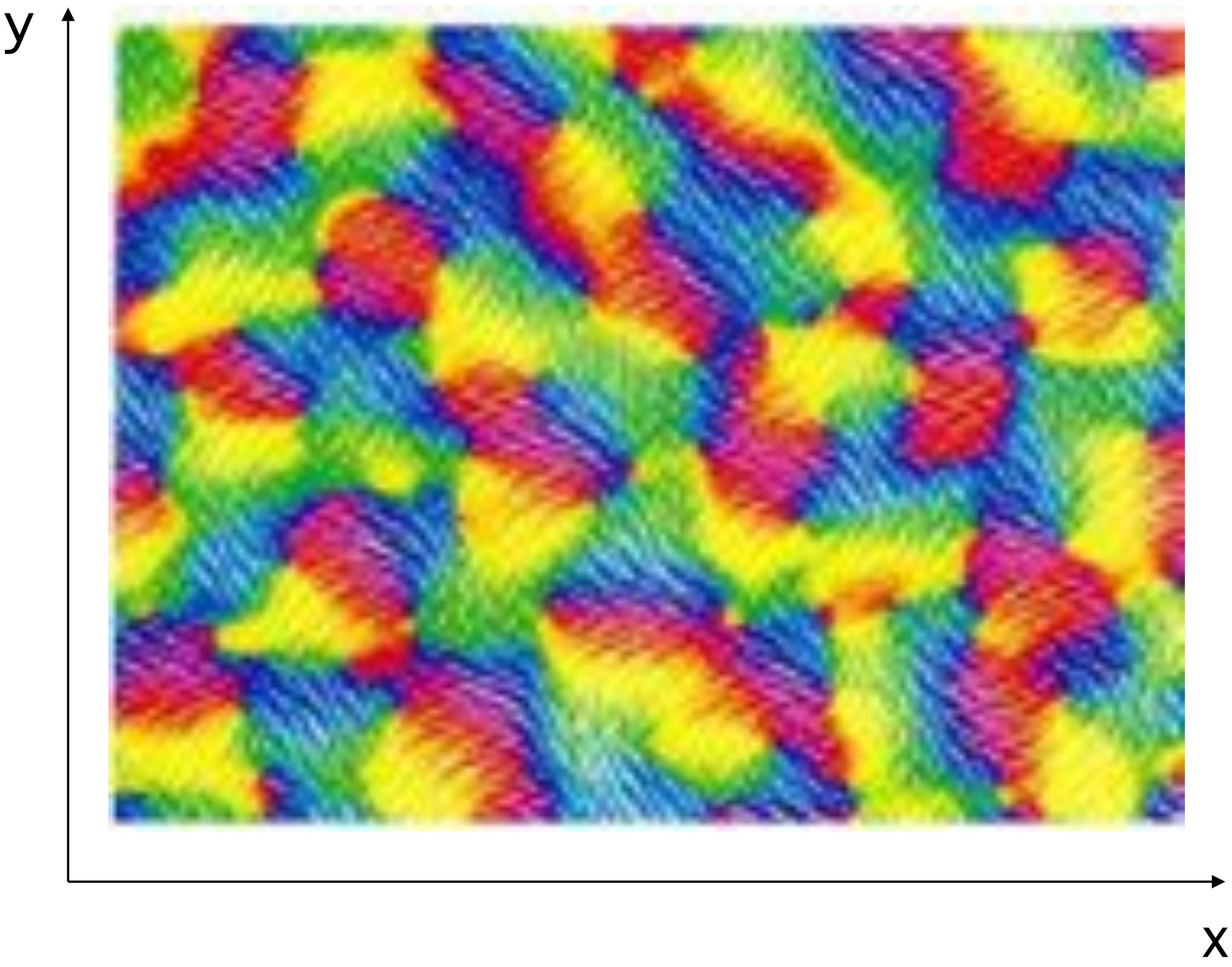
Orientation and ocular dominance columns

Figure 23. The ice-cube model of the cortex. It illustrates how the cortex is divided, at the same time, into two kinds of slabs, one set of ocular dominance (left and right) and one set for orientation. The model should not be taken literally: Neither set is as regular as this, and the orientation slabs especially are far from parallel or straight.

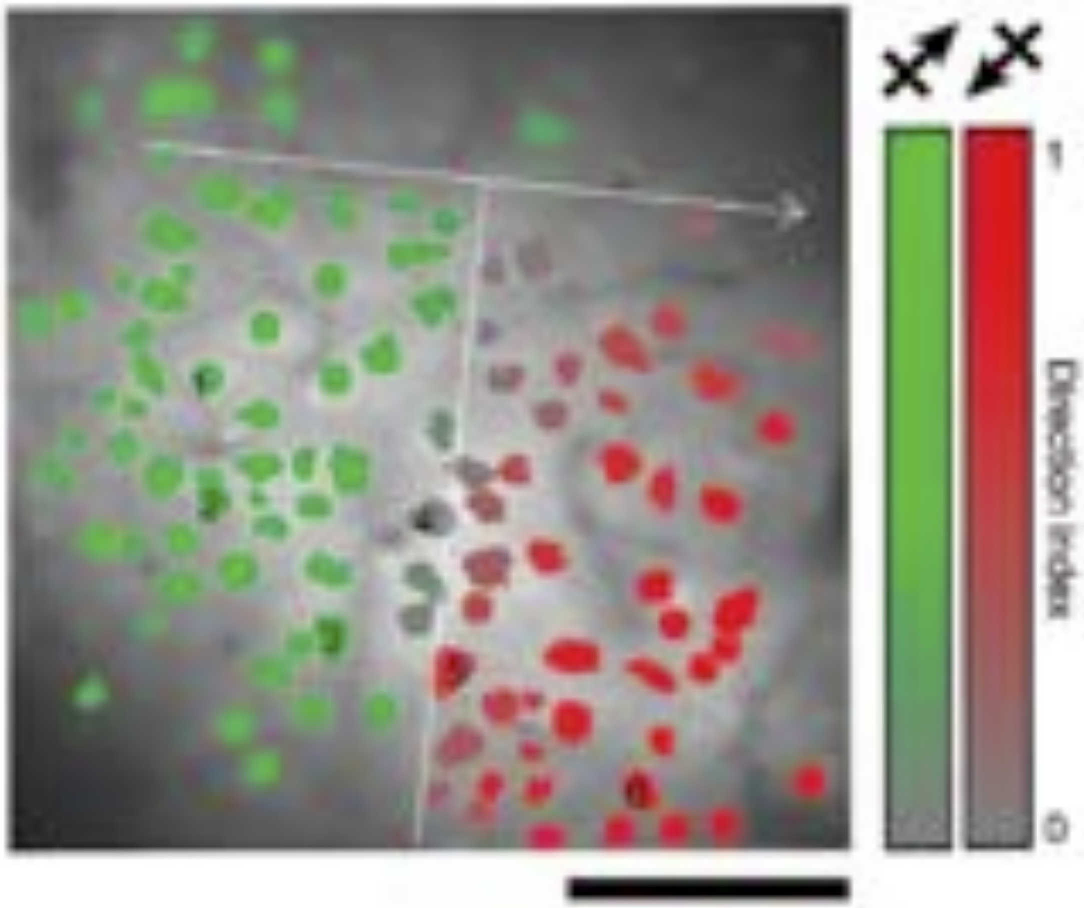
Mathematical models of simple cell cortical receptive fields



Orientation Maps in Striate Cortex



Direction selectivity (another property) revealed at high magnification with calcium imaging



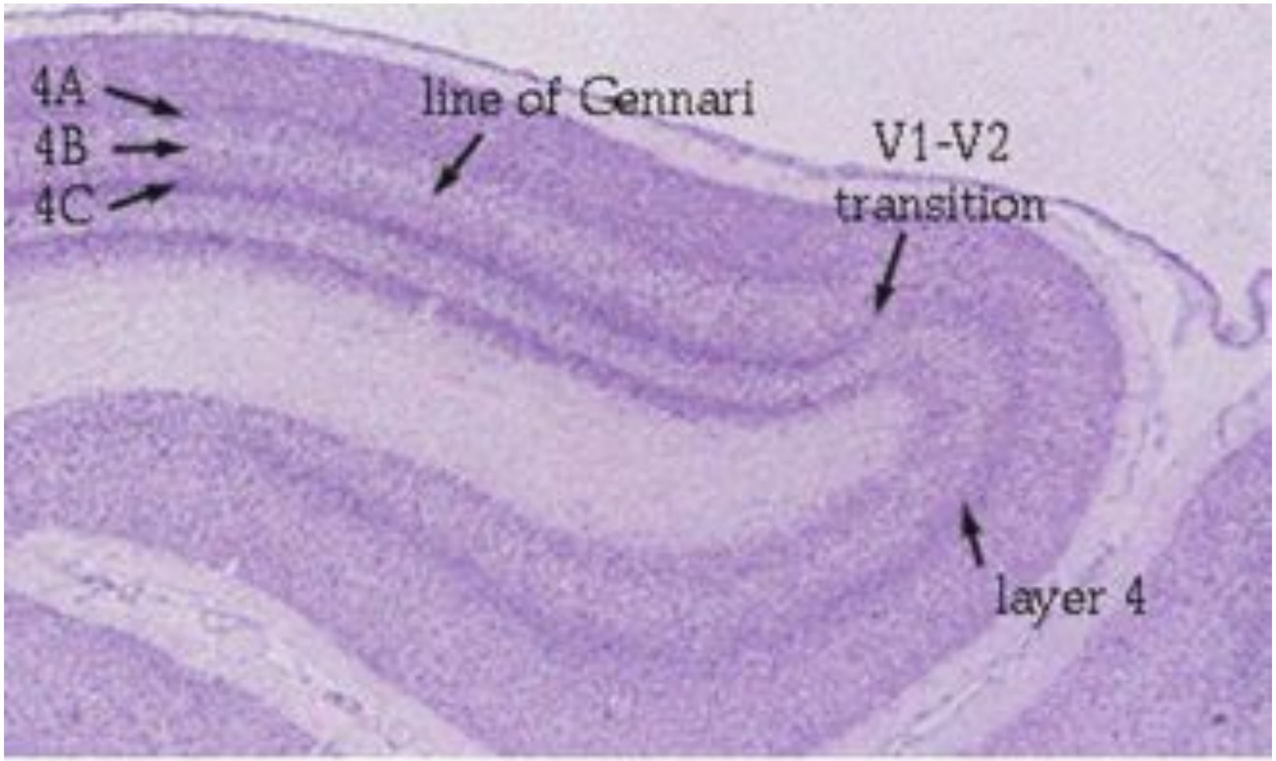
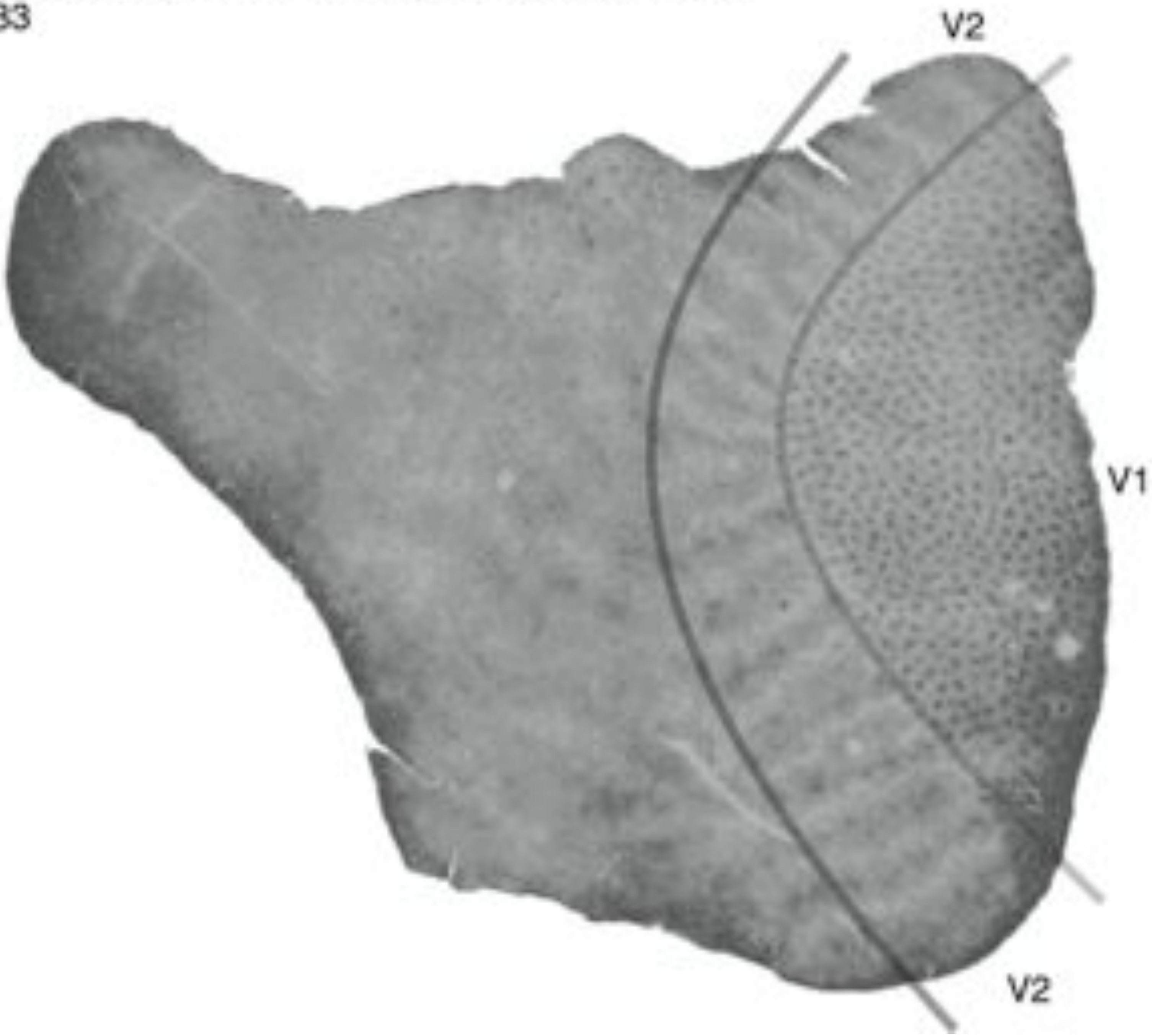


Figure 9. Nissl stained section of the visual cortex to show the border between area 17 (V1) and area 18 (V2).

Cytochrome Oxidase in Monkey Visual Cortex

Tootell et al 1983



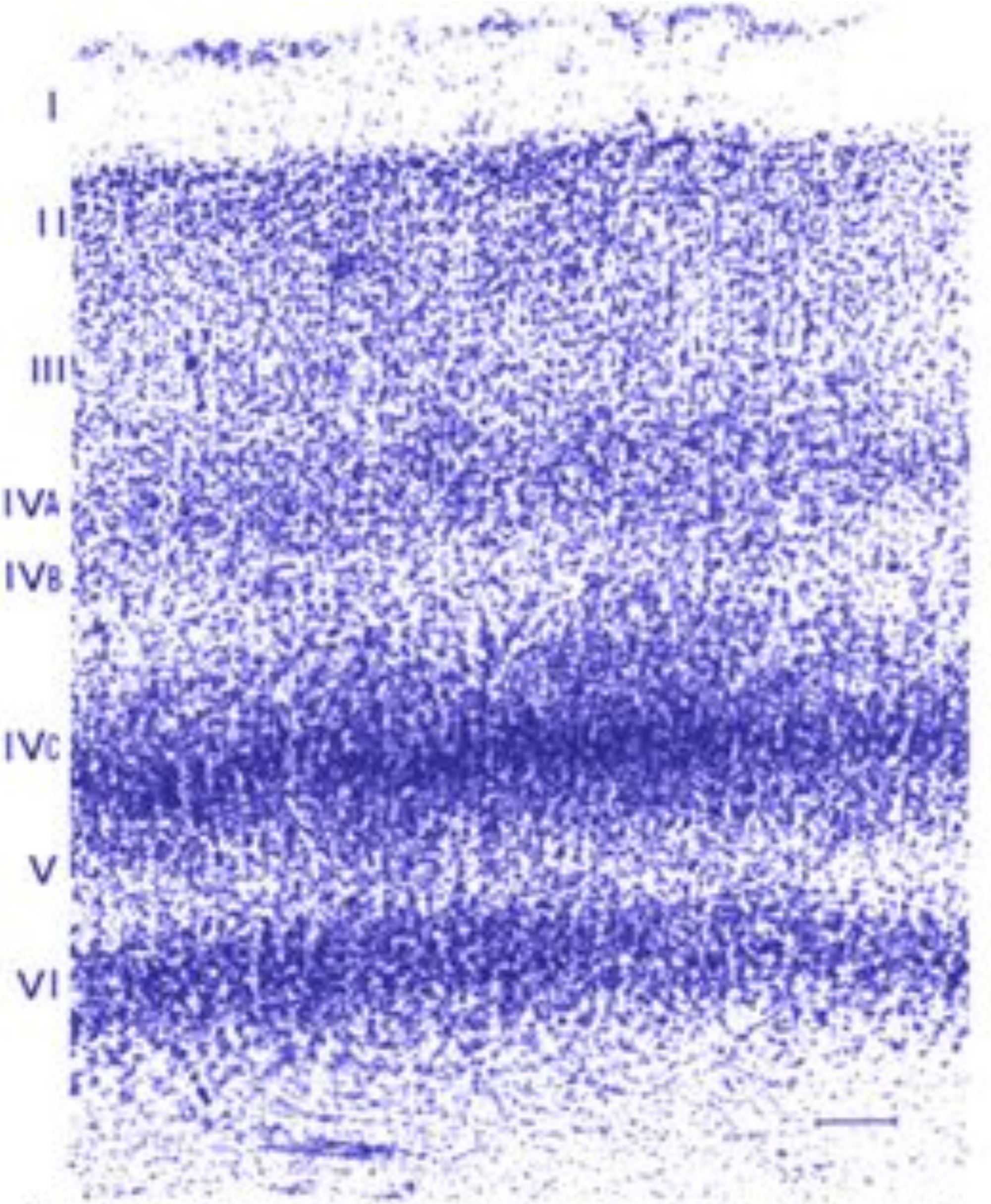


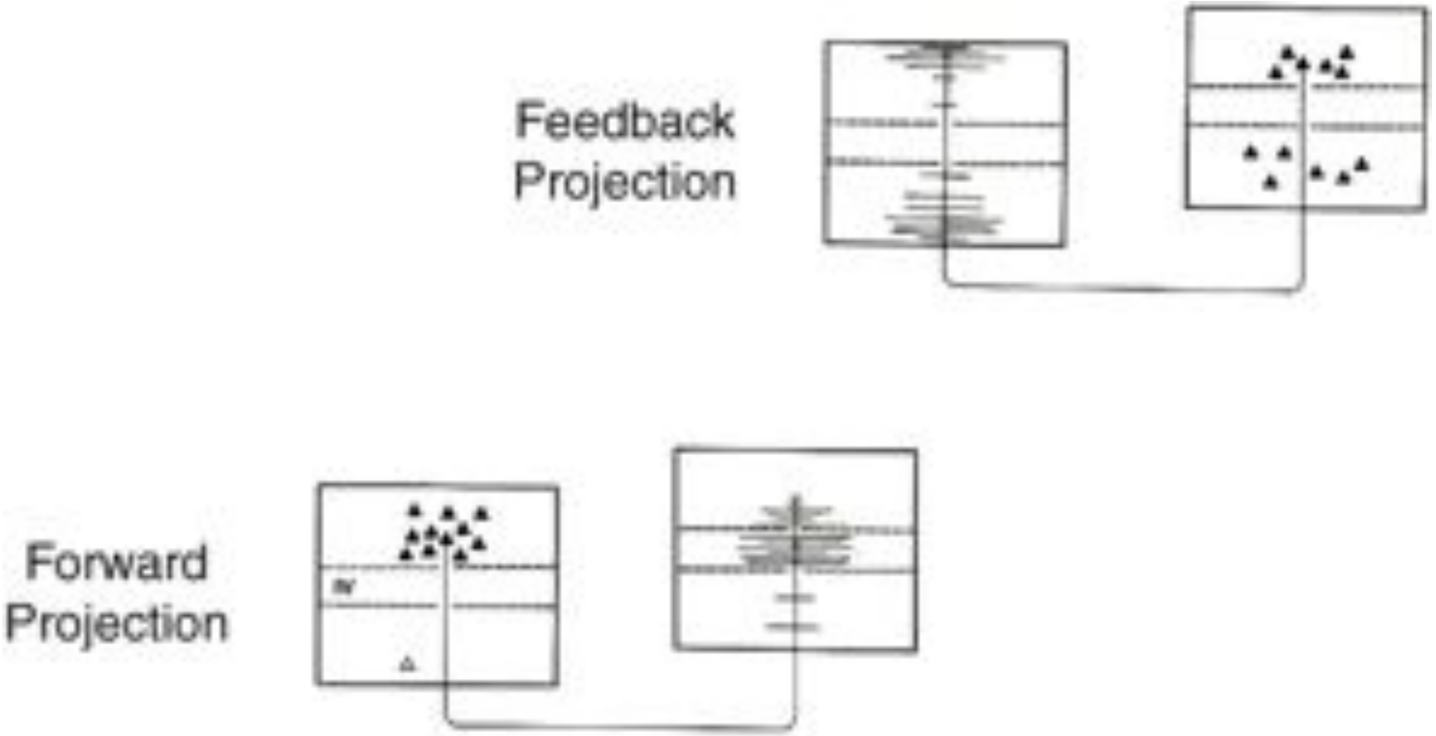
Figure 13. Nissl stain of the visual cortex reveals the different layers I through VI quite clearly.

Processing

Input

Output

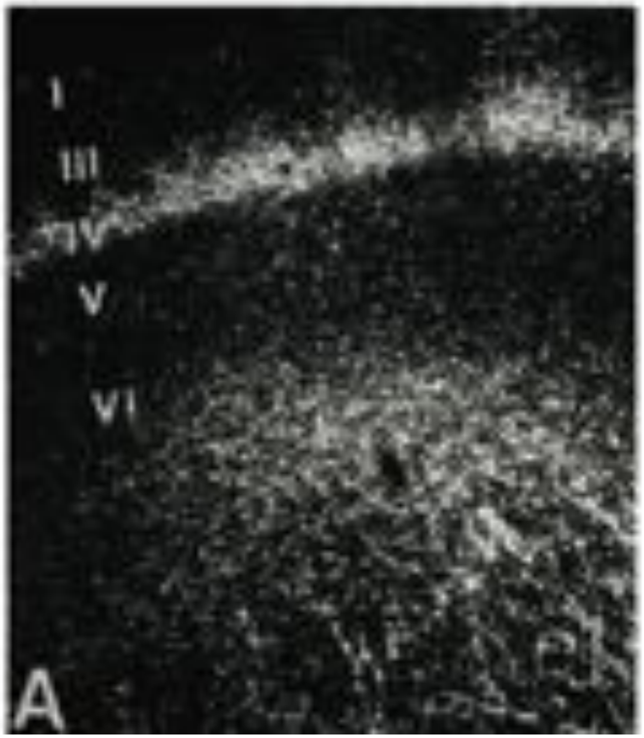
Characteristic connections between maps



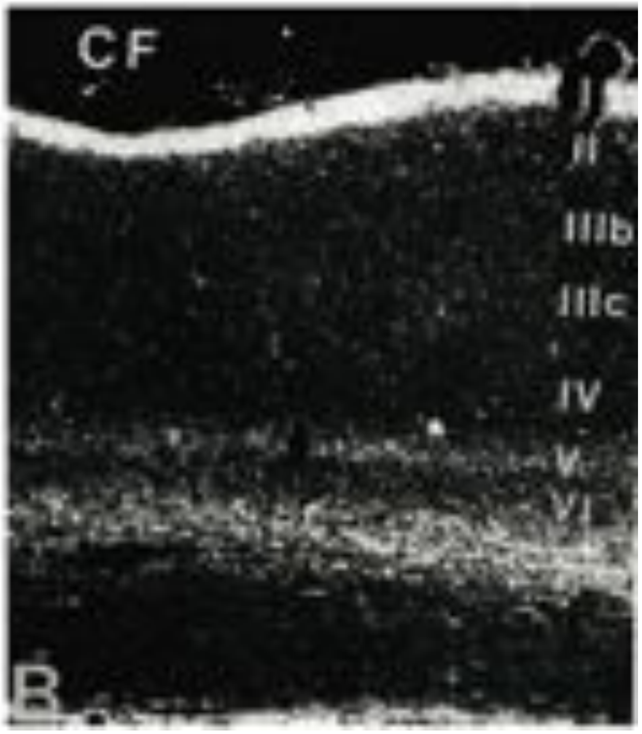
Forward and Feedback Projections

Rockland and Pandya 1979

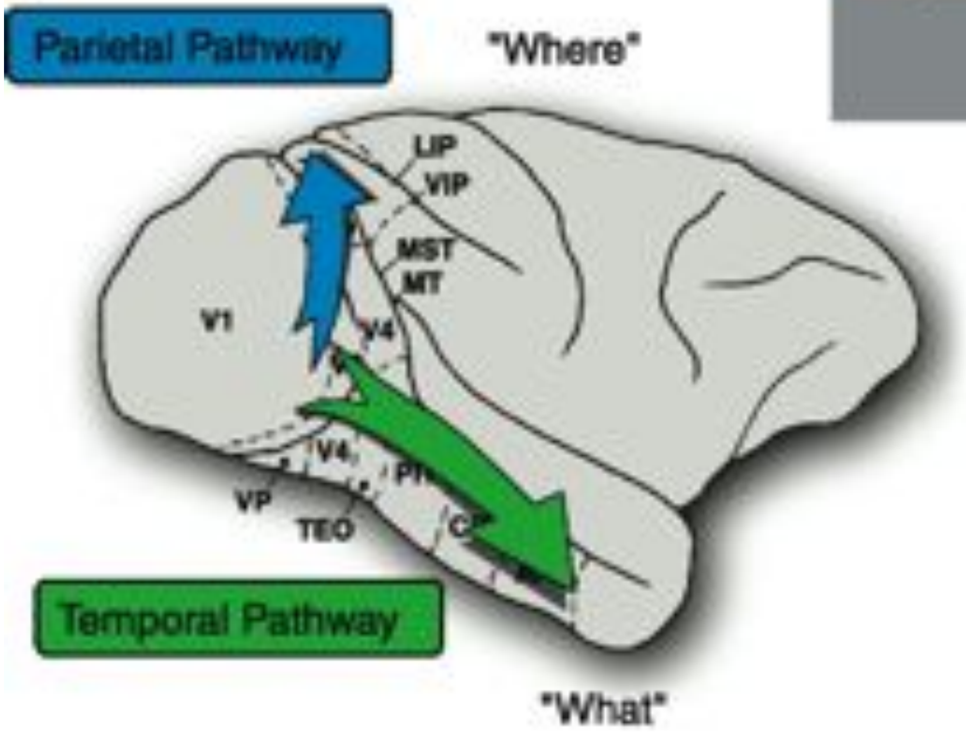
V2: Forward Projection
From V1

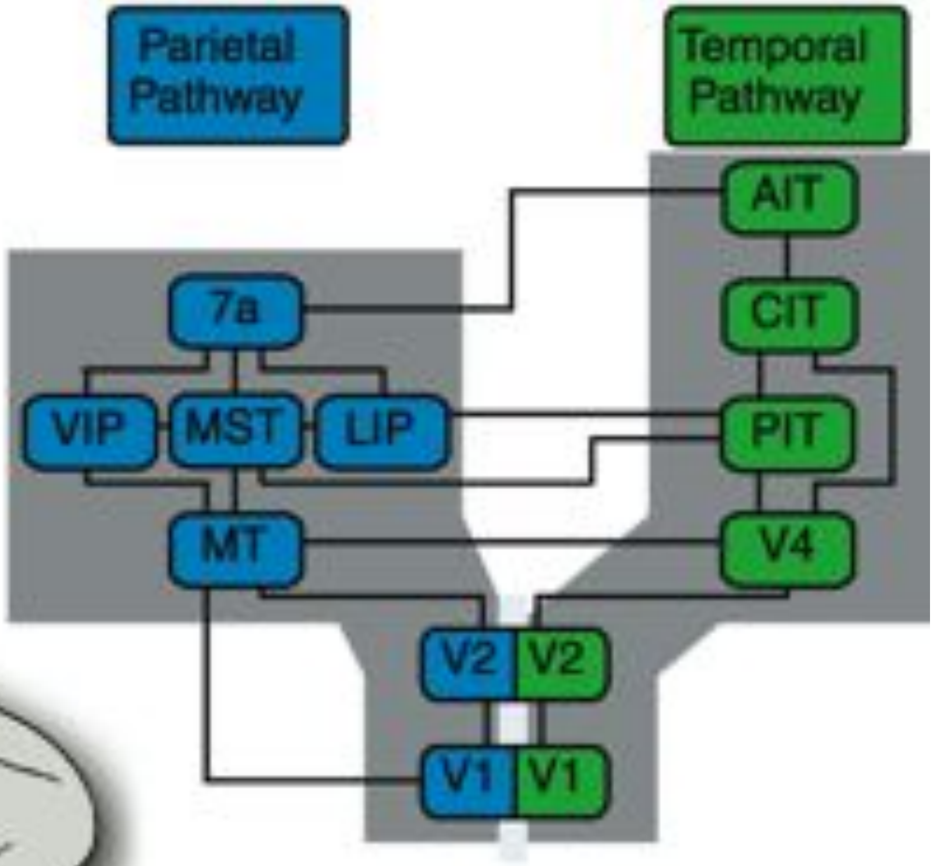


V1: Feedback Projection
From V2

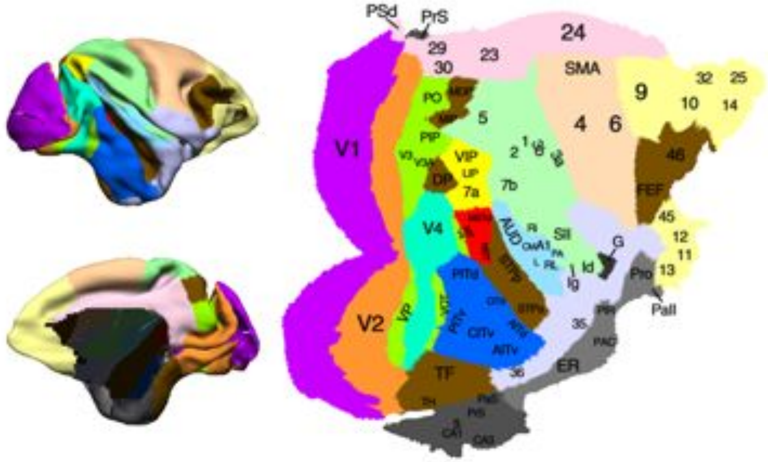


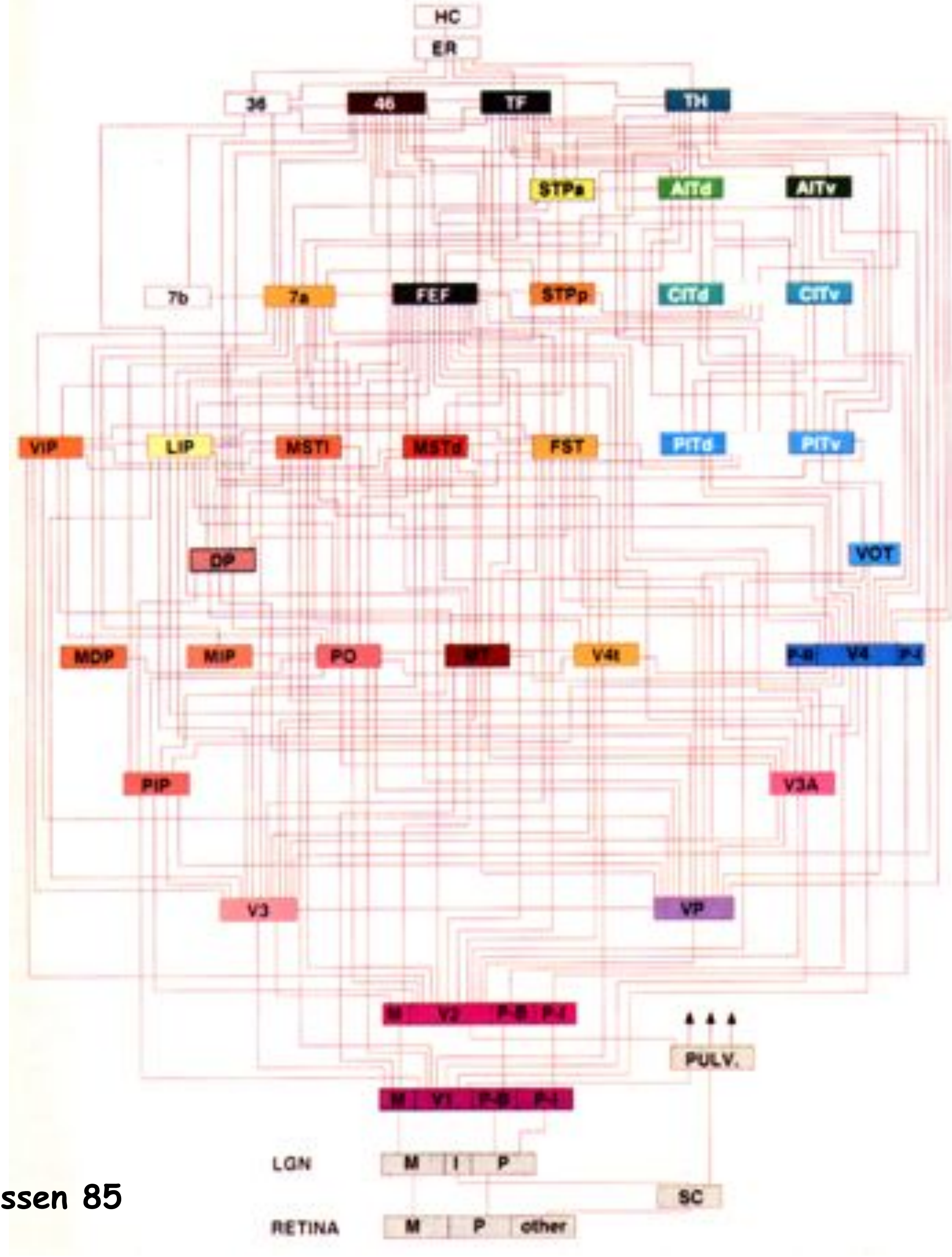
Parallel Pathways in Visual Cortex



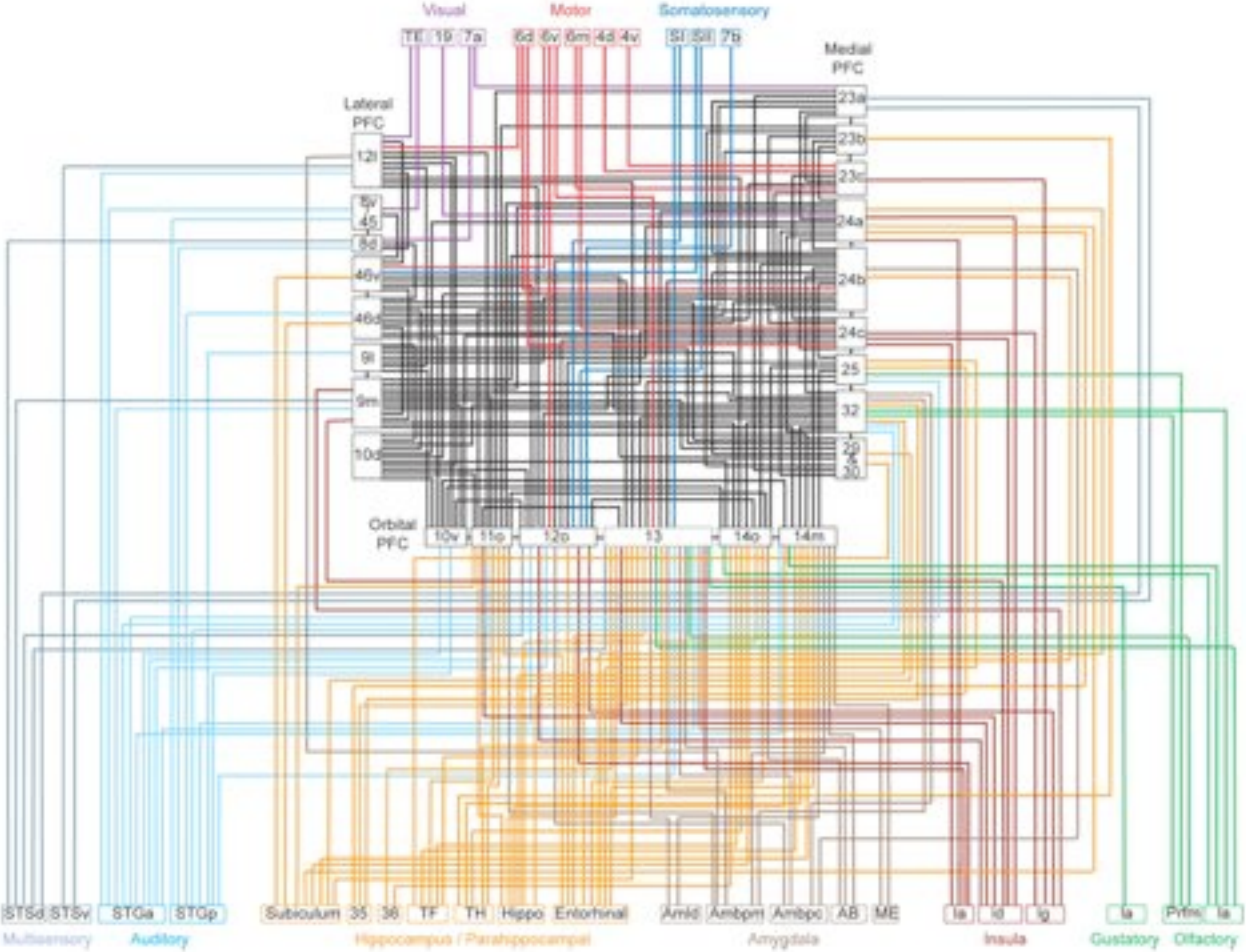


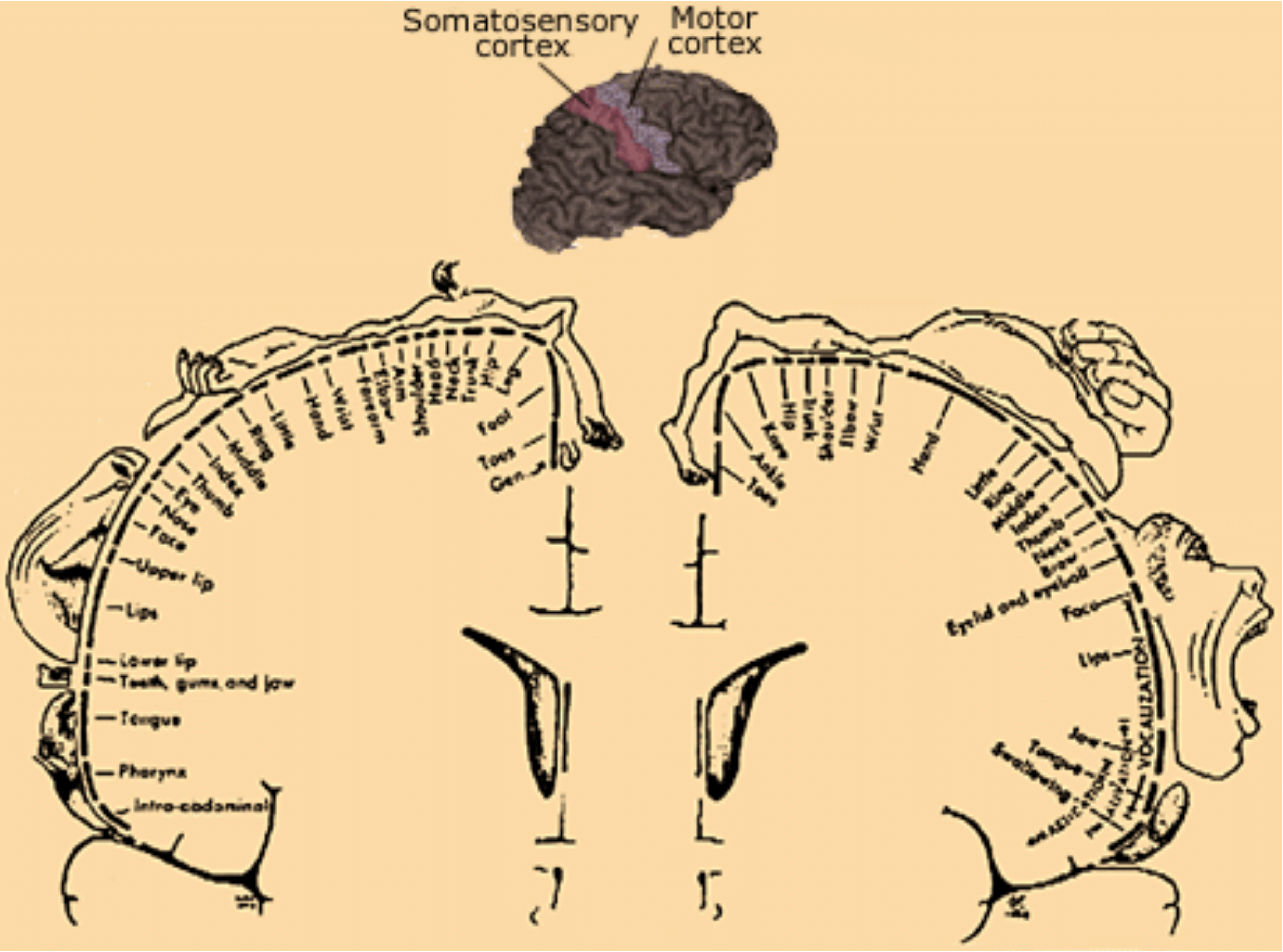
Flattened Representation of Monkey Cerebral Cortex
Van Essen and Drury 1998





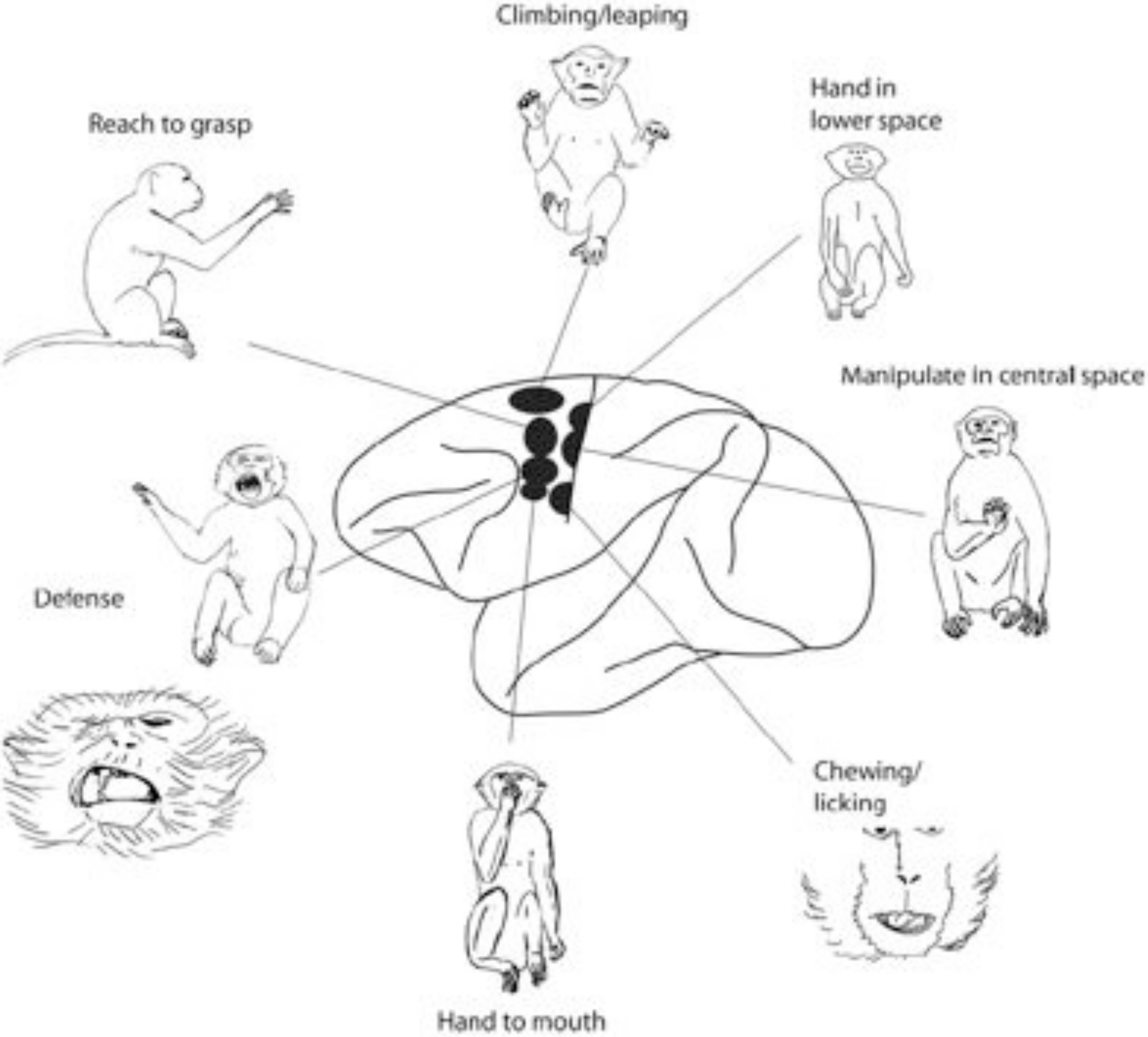
Fellerman and Van Essen 85

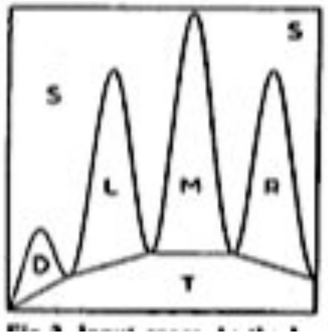

Visual
Motor
Somatosensory
TE
19
7a
6d
6v
6m
4d
4v
SI
SII
7b
Medial PFC
23a
23b
23c
24a
24b
24c
25
32
29 & 30
Lateral PFC
12l
8v
45
8d
46v
46d
9l
9m
10d
Orbital PFC
10v
11o
12o
13
14o
14m
STSd
STSv
STGa
STGp
Subiculum
35
36
TF
TH
Hippo
Entorhinal
Amld
Ambpm
Ambpc
AB
ME
Ia
Id
Ig
Ia
Prfm
Ia
Multisensory
Auditory
Hippocampus / Parahippocampal
Amygdala
Insula
Gustatory
Olfactory


Somatosensory cortex
Motor cortex
Genitals
Toes
Foot
Leg
Hip
Trunk
Neck
Head
Shoulder
Arm
Elbow
Forearm
Wrist
Hand
Little
Ring
Middle
Index
Thumb
Eye
Nose
Face
Upper lip
Lips
Lower lip
Teeth, gums, and jaw
Tongue
Pharynx
Intra-abdominal
Toes
Ankle
Knee
Hip
Trunk
Shoulder
Elbow
Wrist
Hand
Little
Ring
Middle
Index
Thumb
Neck
Brow
Eyelid and eyeball
Face
Lips
VOCALIZATION
Jaw
Tongue
Swallowing
MASTICATION
SALIVATION

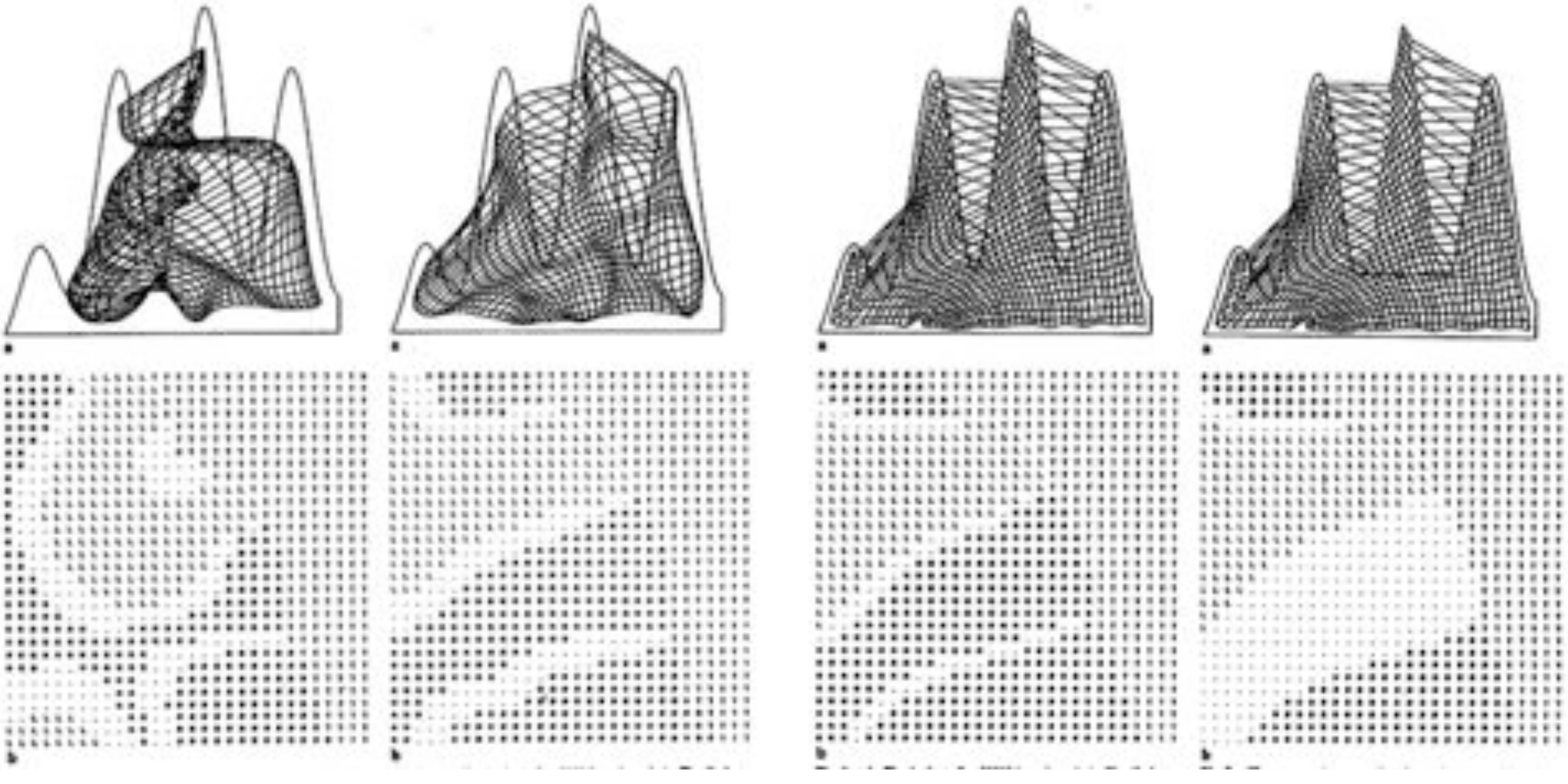
Abstract motor maps?

Three views of a schematized monkey showing the distribution of hand locations allowed for hand-to-mouth movements (light blue), reaching (dark blue), defense (red), central space/ manipulation (green), and climbing (pink with black border).

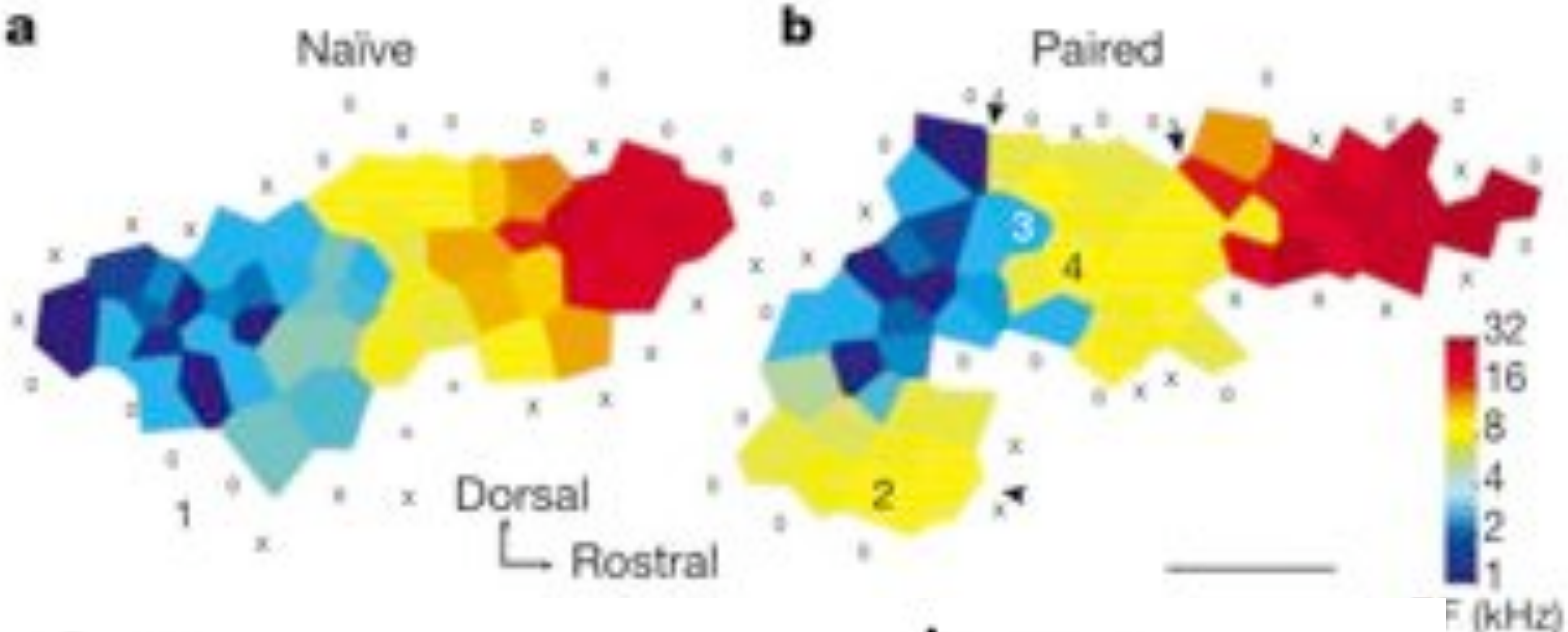

Climbing/leaping
Reach to grasp
Hand in lower space
Manipulate in central space
Defense
Chewing/ licking
Hand to mouth

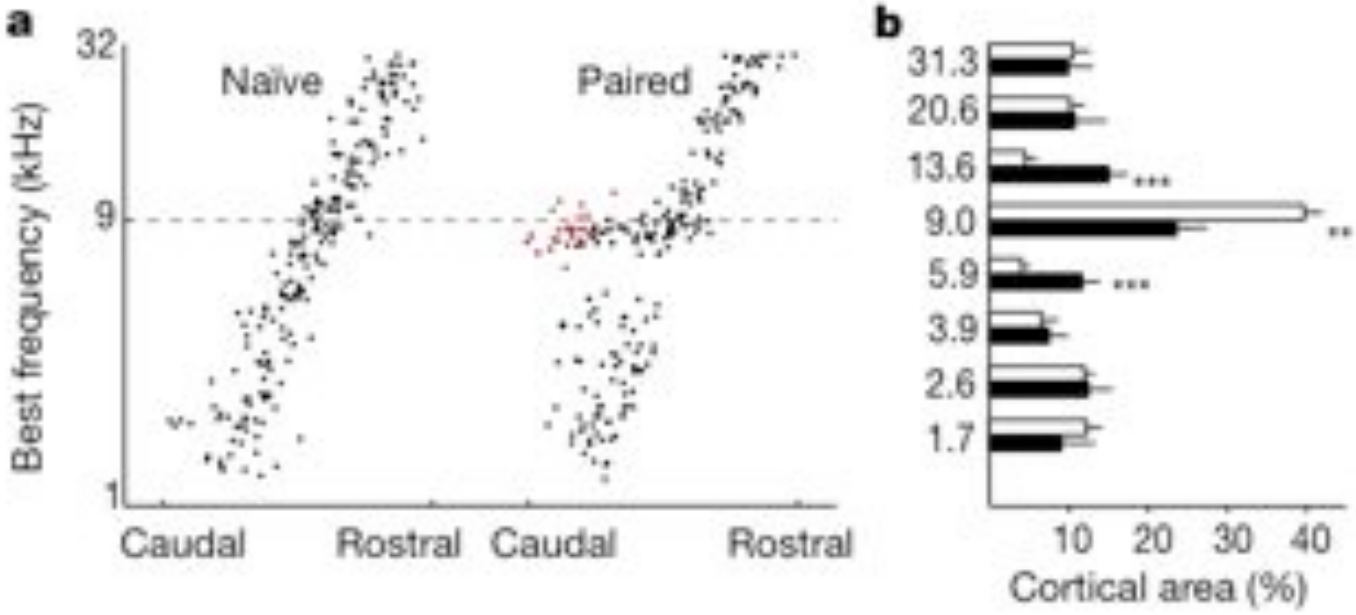


Somatosensory map reorganization after digit amputation

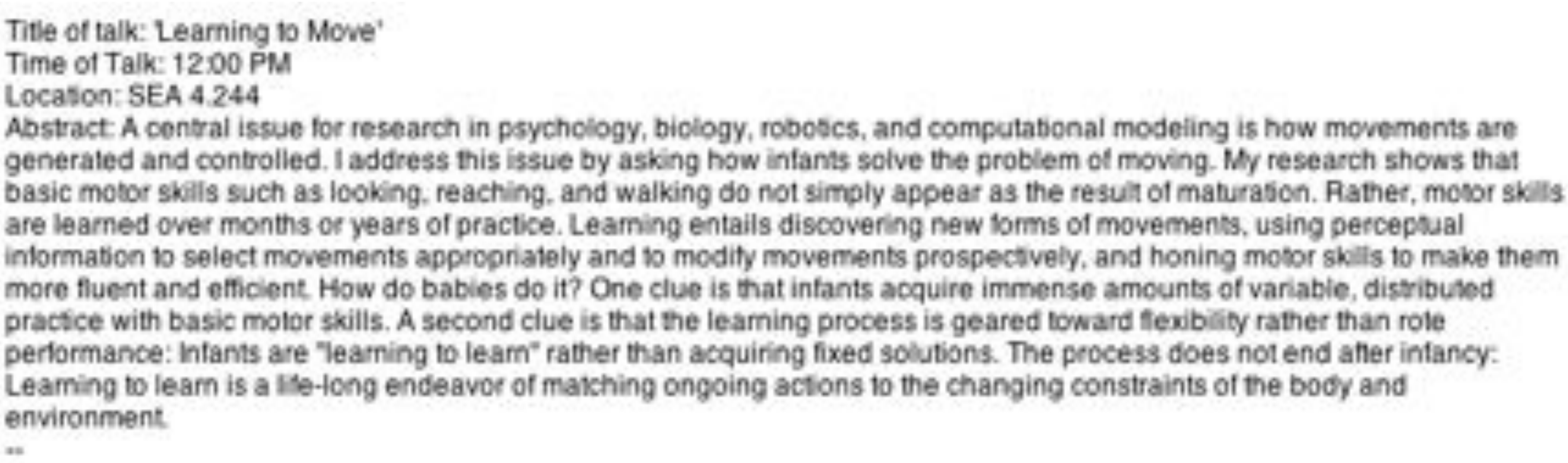


Dopamine reorganizes tonotopic maps





Monday Sep 26



Title of talk: 'Learning to Move'
Time of Talk: 12:00 PM
Location: SEA 4.244
Abstract: A central issue for research in psychology, biology, robotics, and computational modeling is how movements are generated and controlled. I address this issue by asking how infants solve the problem of moving. My research shows that basic motor skills such as looking, reaching, and walking do not simply appear as the result of maturation. Rather, motor skills are learned over months or years of practice. Learning entails discovering new forms of movements, using perceptual information to select movements appropriately and to modify movements prospectively, and honing motor skills to make them more fluent and efficient. How do babies do it? One clue is that infants acquire immense amounts of variable, distributed practice with basic motor skills. A second clue is that the learning process is geared toward flexibility rather than rote performance: Infants are "learning to learn" rather than acquiring fixed solutions. The process does not end after infancy: Learning to learn is a life-long endeavor of matching ongoing actions to the changing constraints of the body and environment.
--

Institute for Neuroscience &
Center for Perceptual Systems

Yoram Burak, Ph.D.
Harvard University
Center for Brain Science

"Visual Inference Amid Fixational Eye Movements."

Monday, September 26th
4:00 pm - MBB 1.210

Hosted by Dr. Ila Fiete

How does the brain infer the structure of the external world from sensory inputs, while remaining insensitive to transformations such as translation and rotation? This is a central question in the study of sensory processing in the brain. In vision, the image projected on the retina is subject not only to a static transformation: it continuously undergoes a dynamic transformation, due to the motion of the eye and head. On the scale of vision at the center of the visual field (the fovea), the amplitude of this motion is large: naively, the motion would smear the image and hinder the brain's ability to infer high-resolution structure. I will present a theoretical analysis of this problem, and ask how the brain might achieve high-acuity perception despite the eye's motion.

I will first consider how the visual system might infer the structure of images drawn from a large, relatively unconstrained ensemble. Due to the combinatorially large number of possible images, it is impossible for the brain to act as an ideal observer that performs optimal inference based on the retinal spikes. I will propose an approximate scheme, which is based on a factorial representation of the multi-dimensional probability distribution, similar to a mean-field approximation. The decoding scheme that emerges from this approximation suggests a neural implementation that involves two neural populations, one that tracks the position of the eye, and another that represents an estimate of the stabilized image.

Monday Sep 26

LAB WEEK

Gabriel Diaz(Racquetball)
<gdiaz@mail.cps.utexas.edu>

James Wyatt Ray(CAR)
<j.wyatt.ray@gmail.com>

Group	Expt
1-3	Racquetball
4-5	Car – Multi-task
6-7 -	Car Interrupts

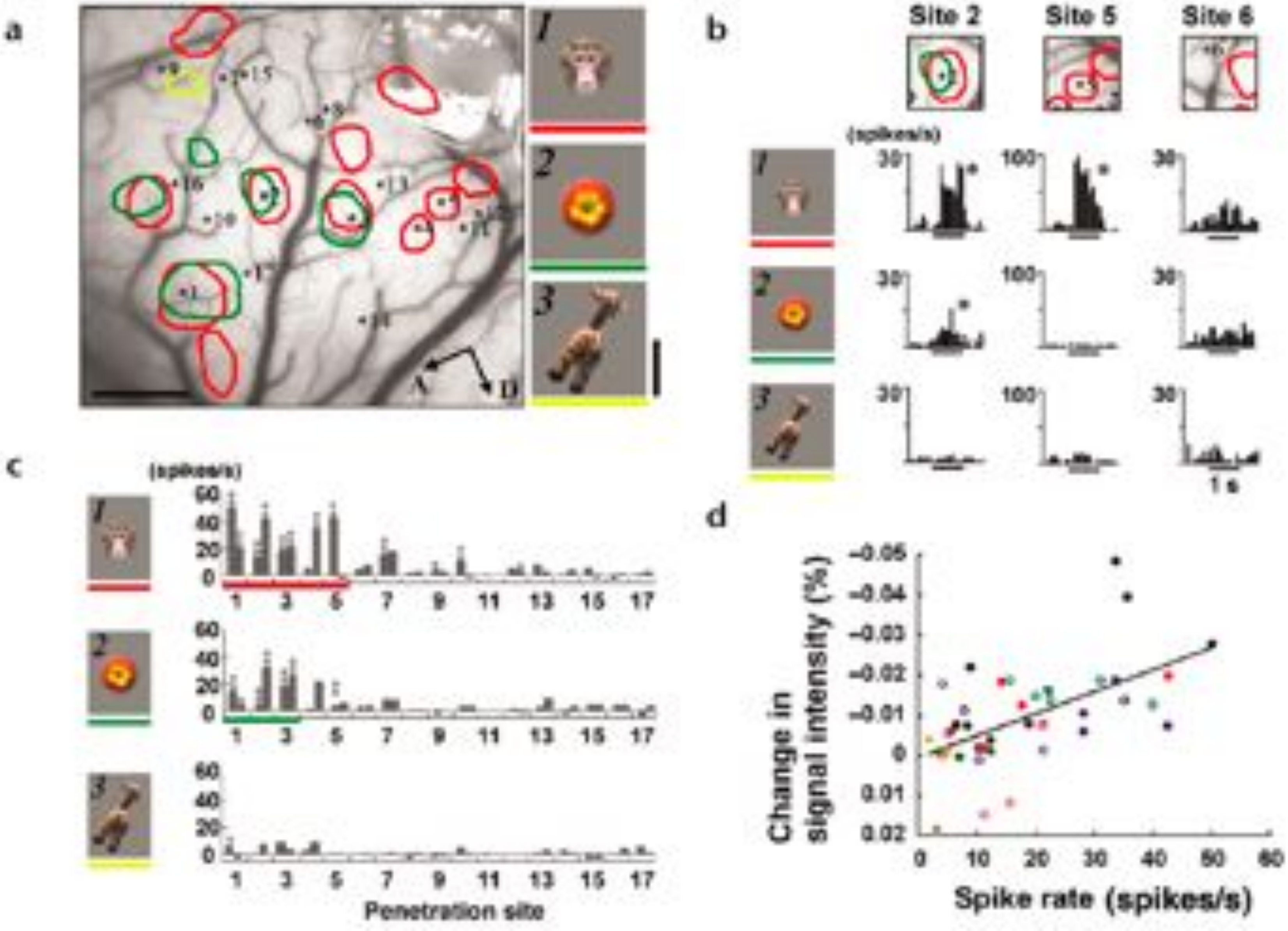
Protocol

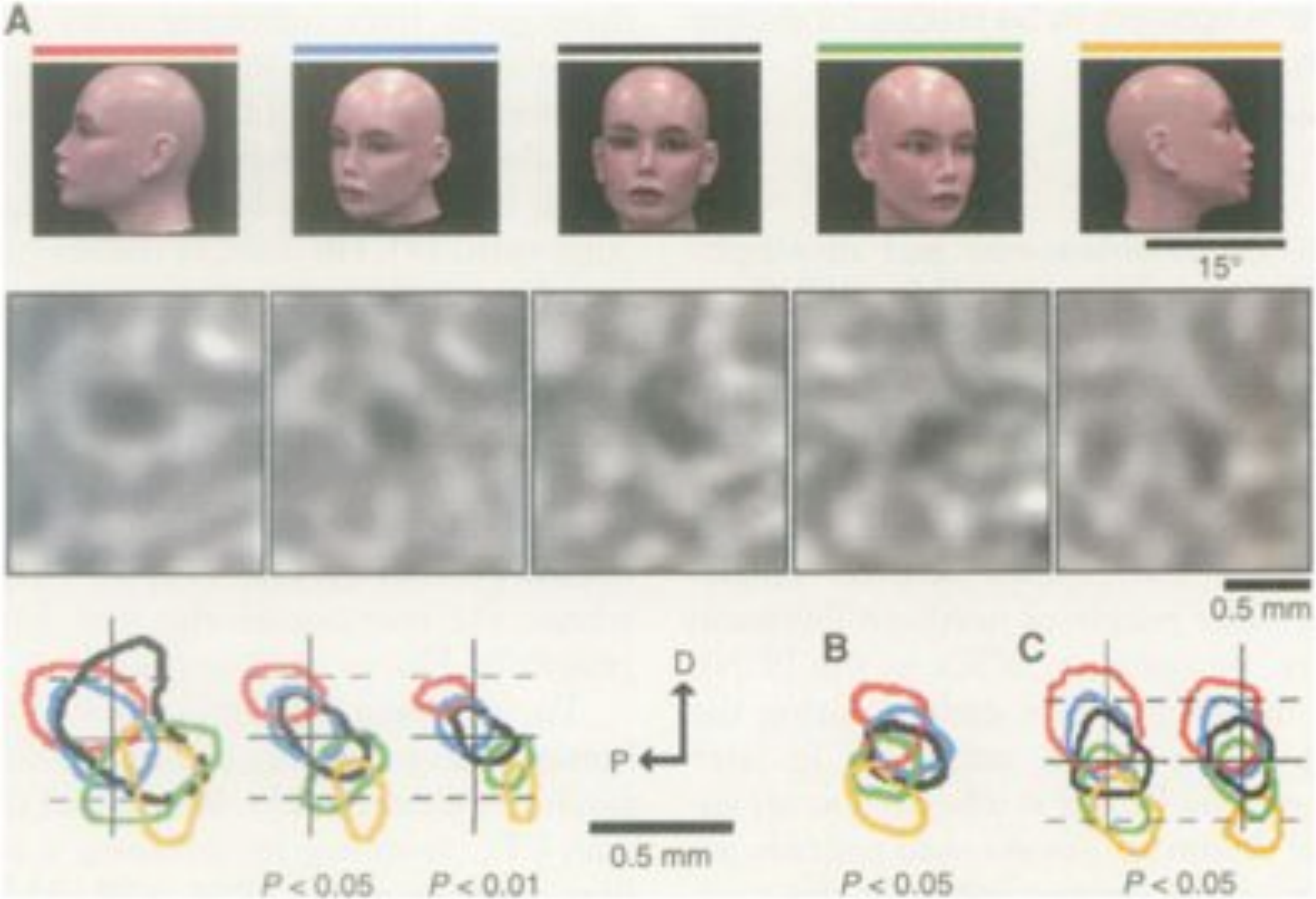
1. Group leader make appt.
2. Group shows up at lab for:
    A. Briefing
    B. Experimental subj simulation
    C. Get link for movie data
    A. Analyze data and write group report & PPT

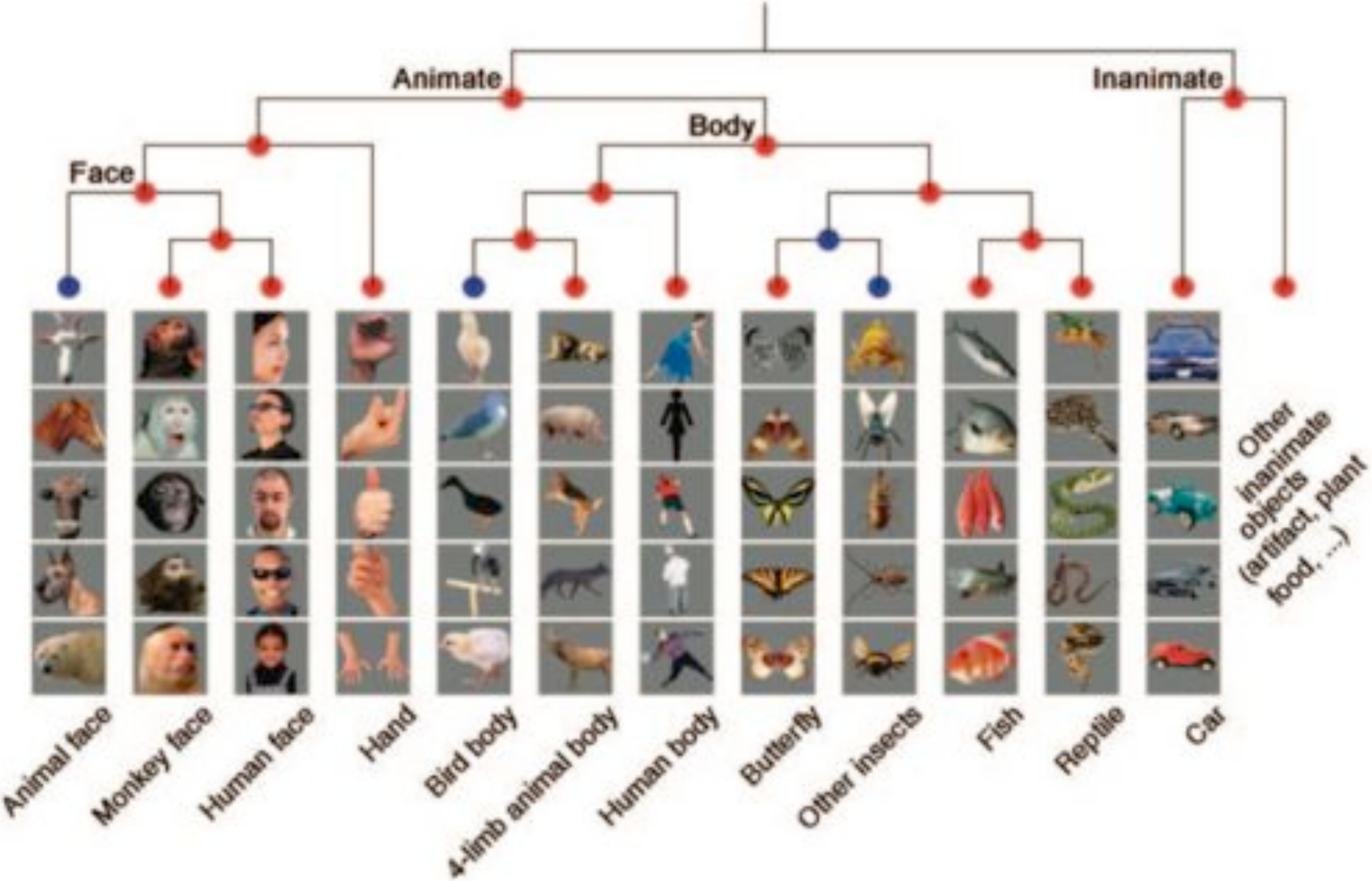
PRESENTATION WEEK

TUESDAY	THURSDAY
GROUPS 1 4 6	GROUPS 2 3 5 7

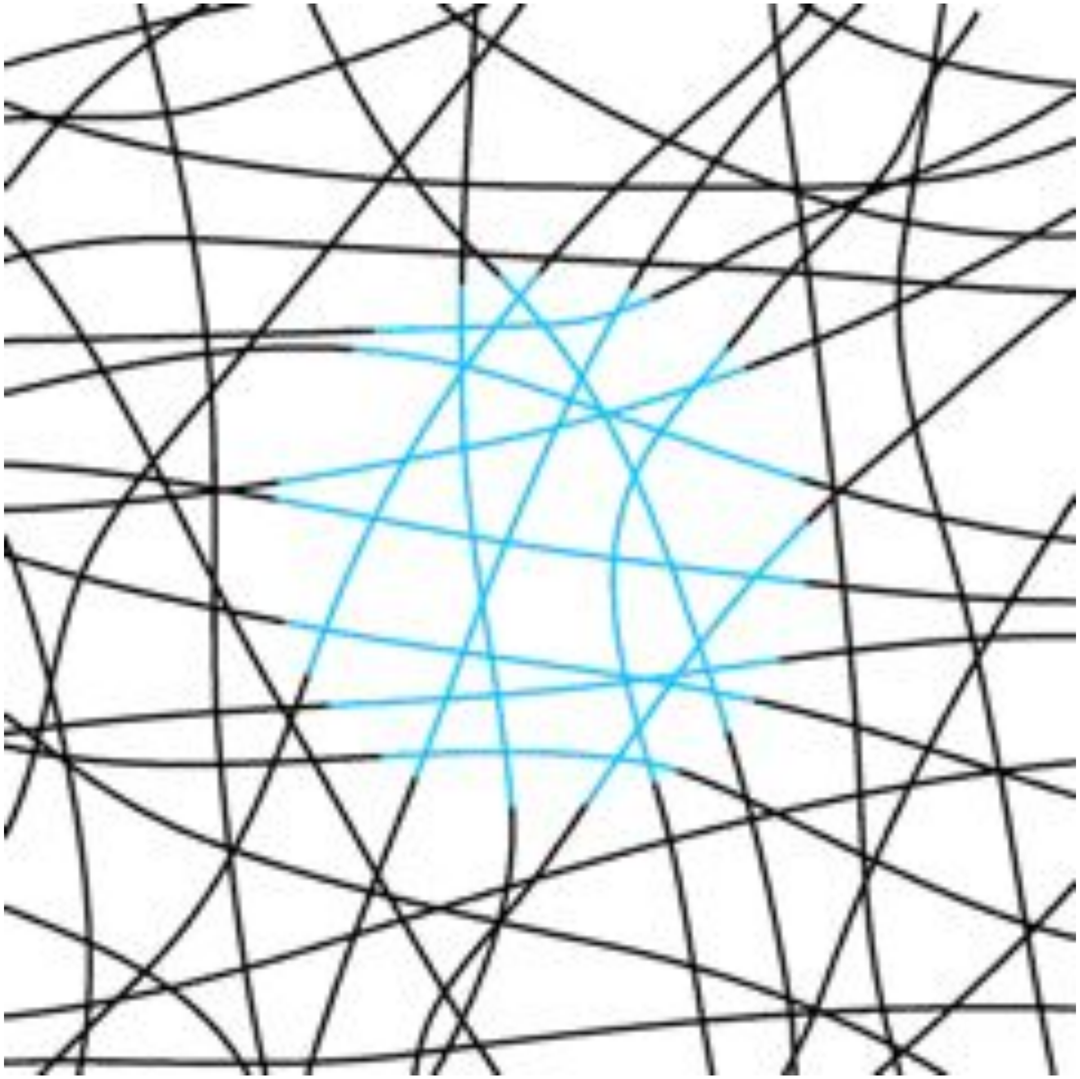
Group	Expt
1-3	Racquetball
4-5	Car – Multi-task
6-7 -	Car Interrupts


a
b
c
d
1
2
3
A
D
Site 2
Site 5
Site 6
(spikes/s)
30
100
1 s
60
40
20
0
1
3
5
7
9
11
13
15
17
Penetration site
Change in signal intensity (%)
−0.05
−0.04
−0.03
−0.02
−0.01
0
0.01
0.02
0
10
20
30
40
50
60
Spike rate (spikes/s)

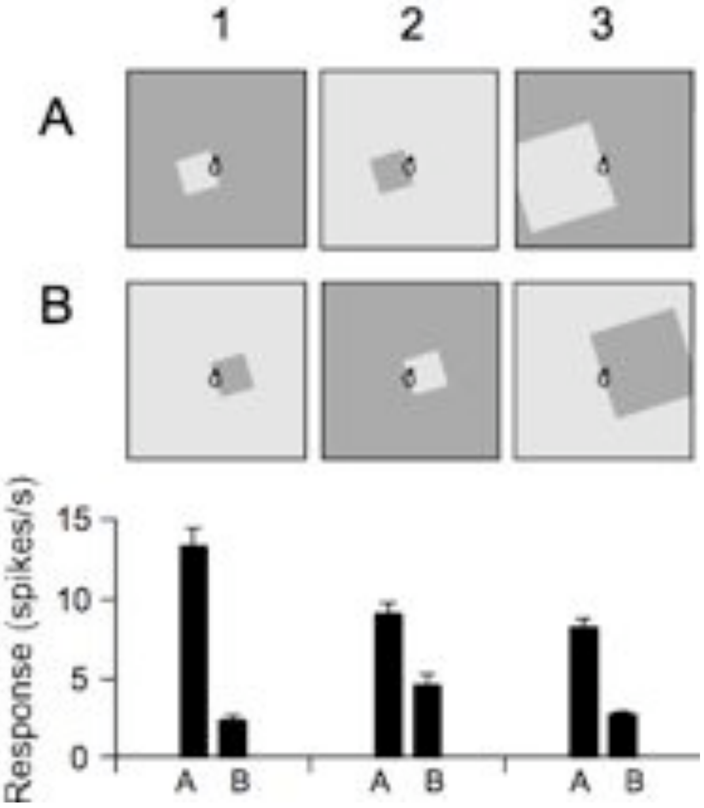

A
15°
0.5 mm
D
P
0.5 mm
P < 0.05
P < 0.01
B
P < 0.05
C
P < 0.05

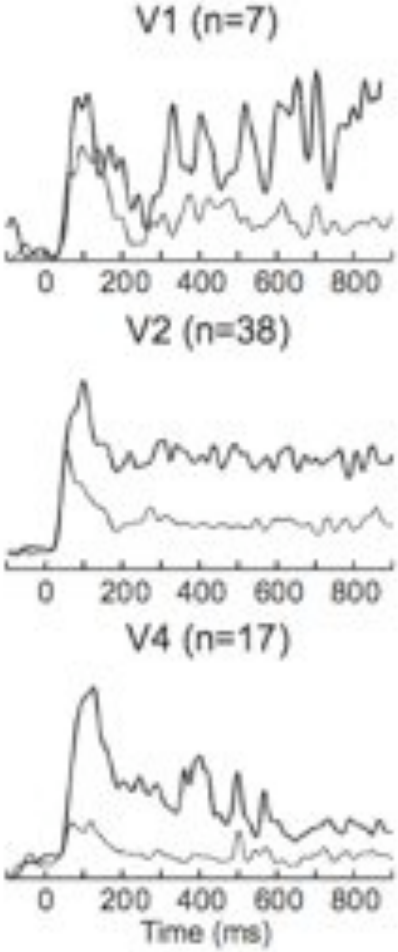

Animate
Inanimate
Body
Face
Animal face
Monkey face
Human face
Hand
Bird body
4-limb animal body
Human body
Butterfly
Other insects
Fish
Reptile
Car
Other inanimate objects (artifact, plant food, ...)

Cortical computation II: neon spreading illusion



Cortical computation II: border ownership





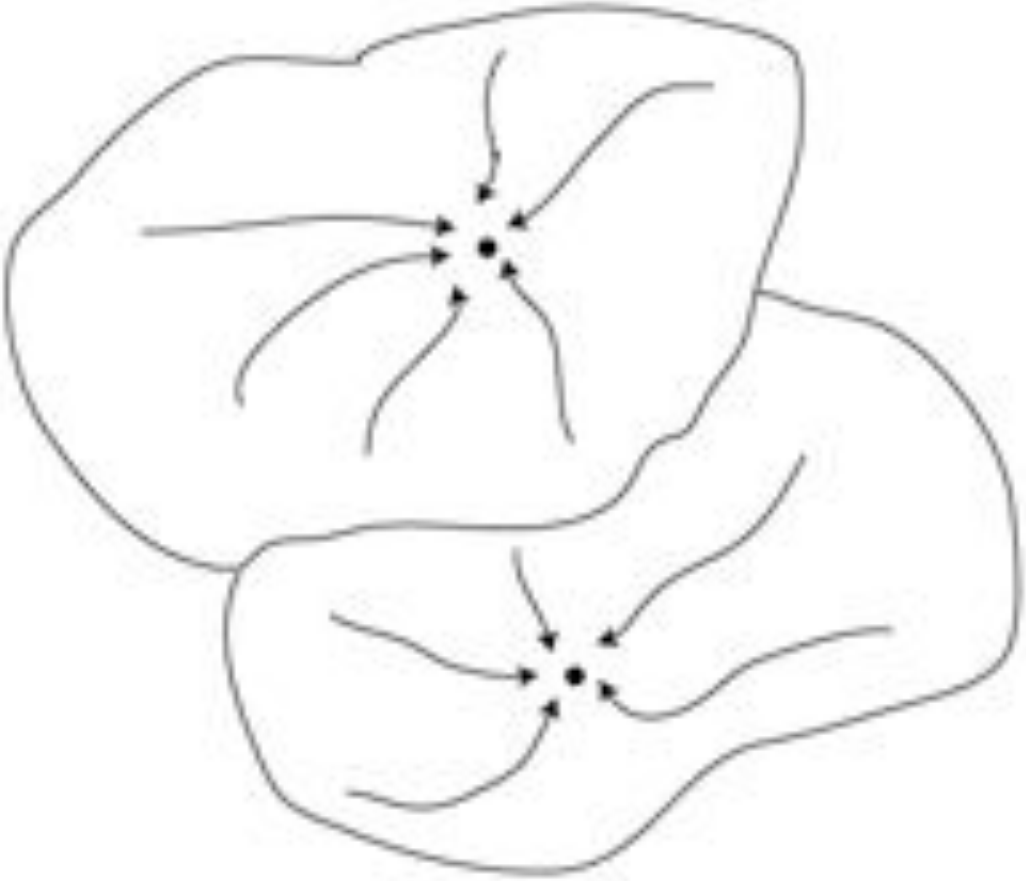
Basic model of cortical computation: CAM

$$w_{ij} = \sum_{p=1}^{P} x_i^p x_j^p$$

In this case $P = 3$ and let
$\boldsymbol{x}^1 = (-1, 1, 1, -1, \dots)^T$
$\boldsymbol{x}^2 = (1, 1, -1, -1, \dots)^T$
$\boldsymbol{x}^3 = (-1, 1, -1, 1, \dots)^T$

Now calculate one of the weights, for example, w_{23}:

$$\begin{aligned} w_{23} &= x_2^1 x_3^1 + x_2^2 x_3^2 + x_2^3 x_3^3 \\ &= (1 \times 1) + (1 \times -1) + (1 \times -1) = -1 \end{aligned}$$



Quick math quiz:

$$x + 3 = 8$$

What is x?

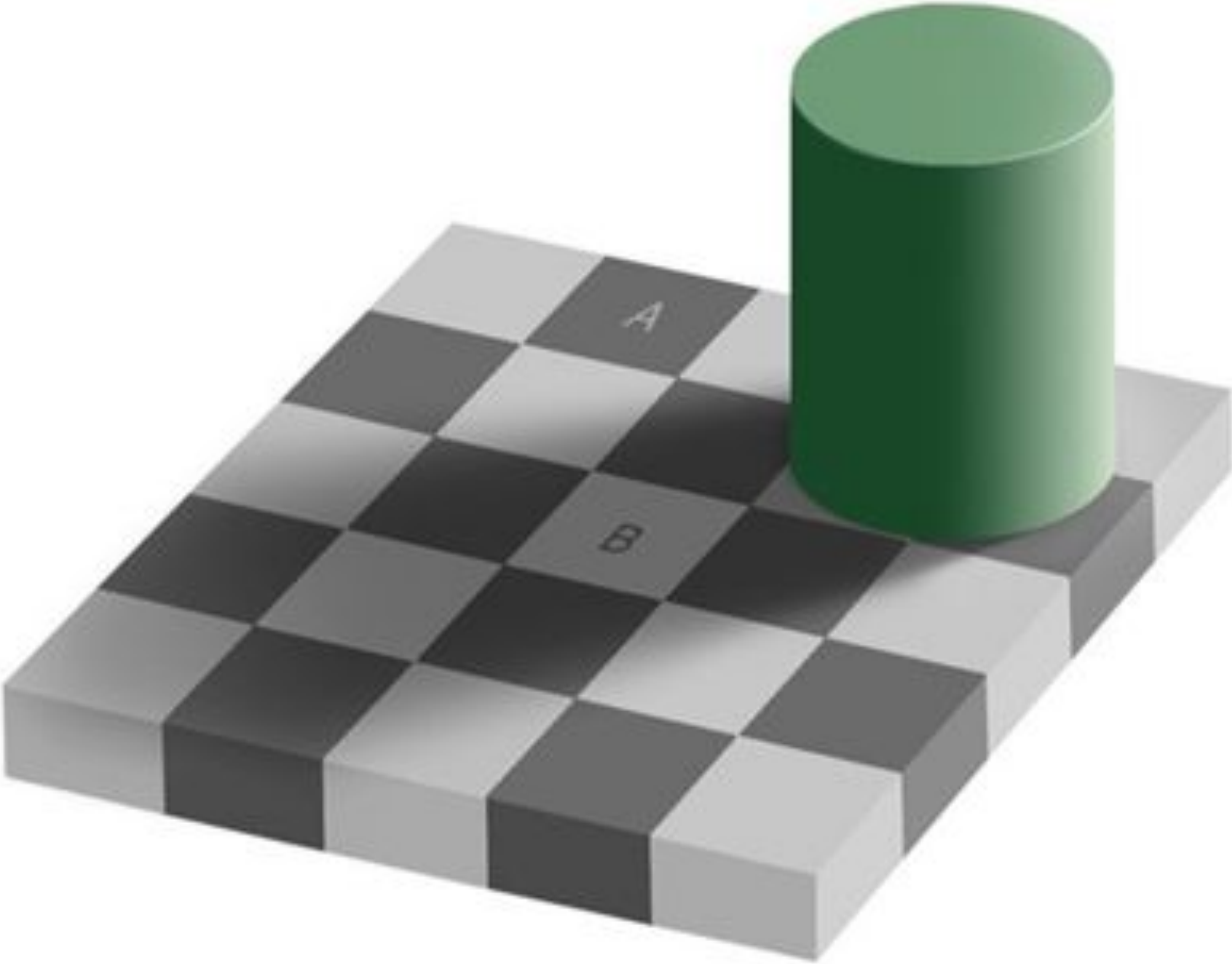
Quick math quiz:

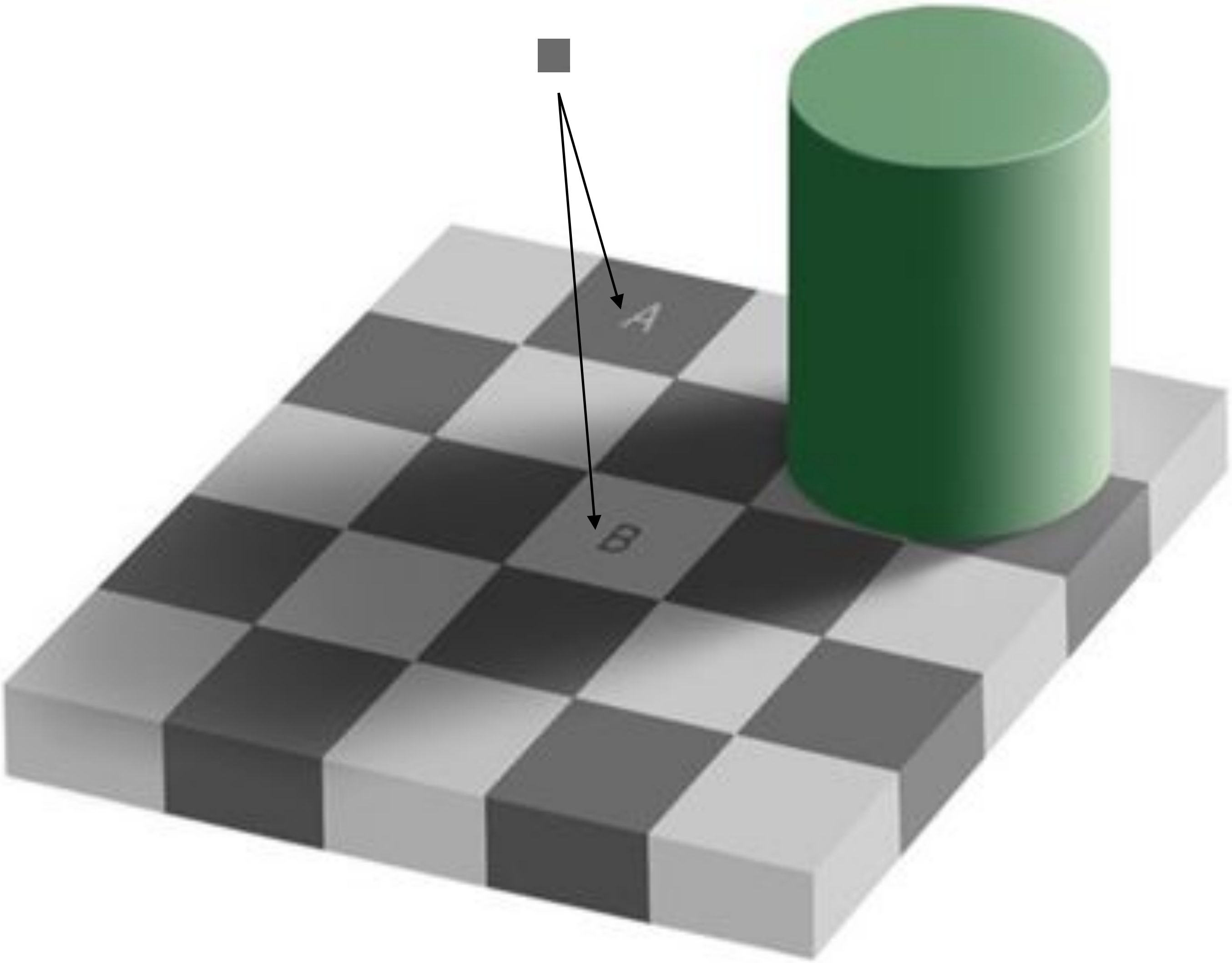
$$x + y = 9$$

What are x and y?

This is an example of an *ill-posed* problem

- problem that has no unique solution

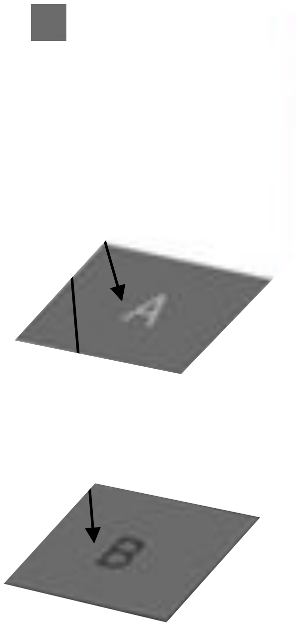

A
B



Comparison patch

Same light hits the eye from both patches

Comparison patch



Same light hits the eye from both patches

Luckily, having some probabilistic information can help:

$$x + y = 9$$

Tables showing past values of y:

y		
7	7	7
7	7	7
5	7	7
7	6	7
7	7	7
8	7	8
7	7	7
7	7	7

Given this information about past values, what would you guess to be the values of x?

How confident are you in your answer?

A little math: Bayes’ rule

- very simple formula for manipulating probabilities

$$P(B \mid A) = \frac{P(A \mid B)\, P(B)}{P(A)}$$

conditional probability
“probability of B given that A occurred”

e.g. You roll a 6-sided die

What is the probability of getting a “3” given that the number rolled was “odd”

A little math: Bayes' rule

- very simple formula for manipulating probabilities

$$P(B \mid A) = \frac{P(A \mid B)\,P(B)}{P(A)}$$

conditional probability
"probability of B given that A occurred"

Formula for computing: P(what's in the world | sensory data)

(This is what our brain wants to know!)

from

P(sensory data | what's in the world) = "likelihood"

(given by laws of physics;
ambiguous because many world states
could give rise to same sense data)

&

P(what's in the world) = "prior"

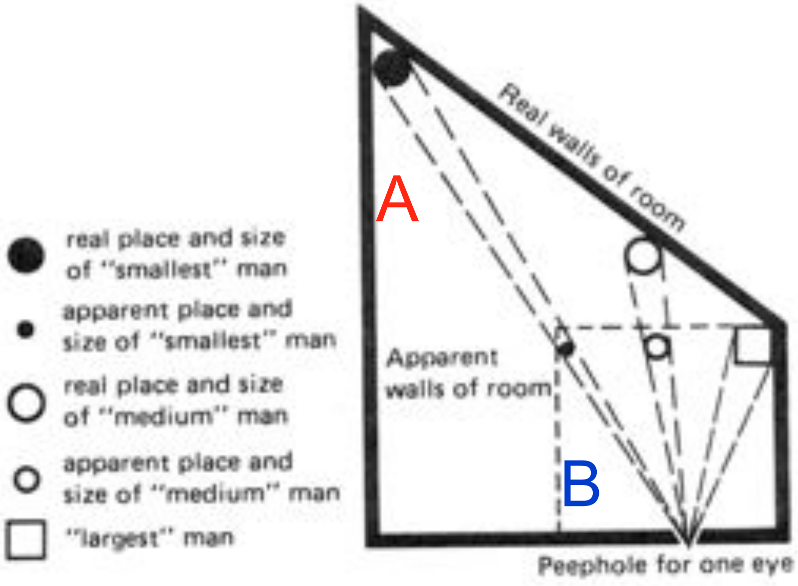
(given by past experience)

Examples:

Using Bayes’ rule to understand how the brain resolves ambiguous stimuli

Many different 3D worlds can give rise to the same 2D retinal image

The Ames Room



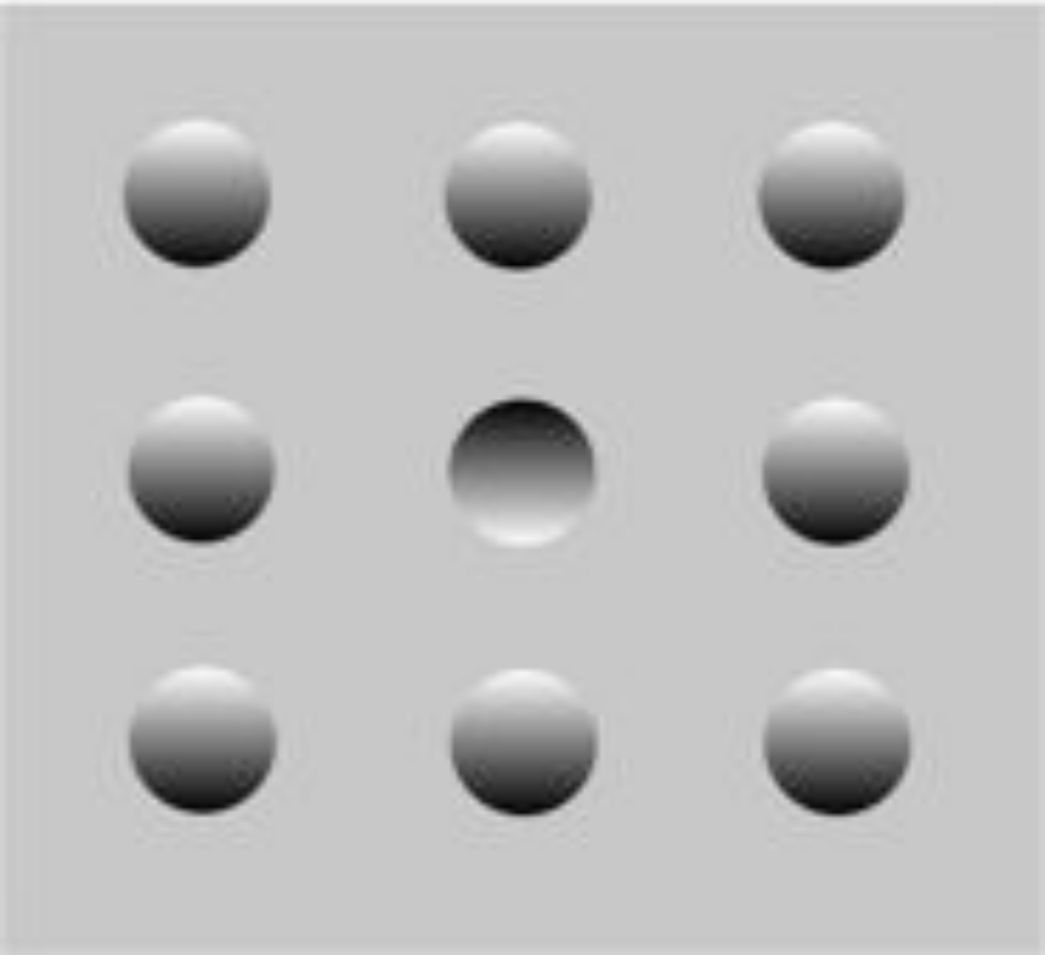
How does our brain go about deciding which interpretation?

P(image | A) and P(image | B) are equal!   (both A and B could have generated this image)

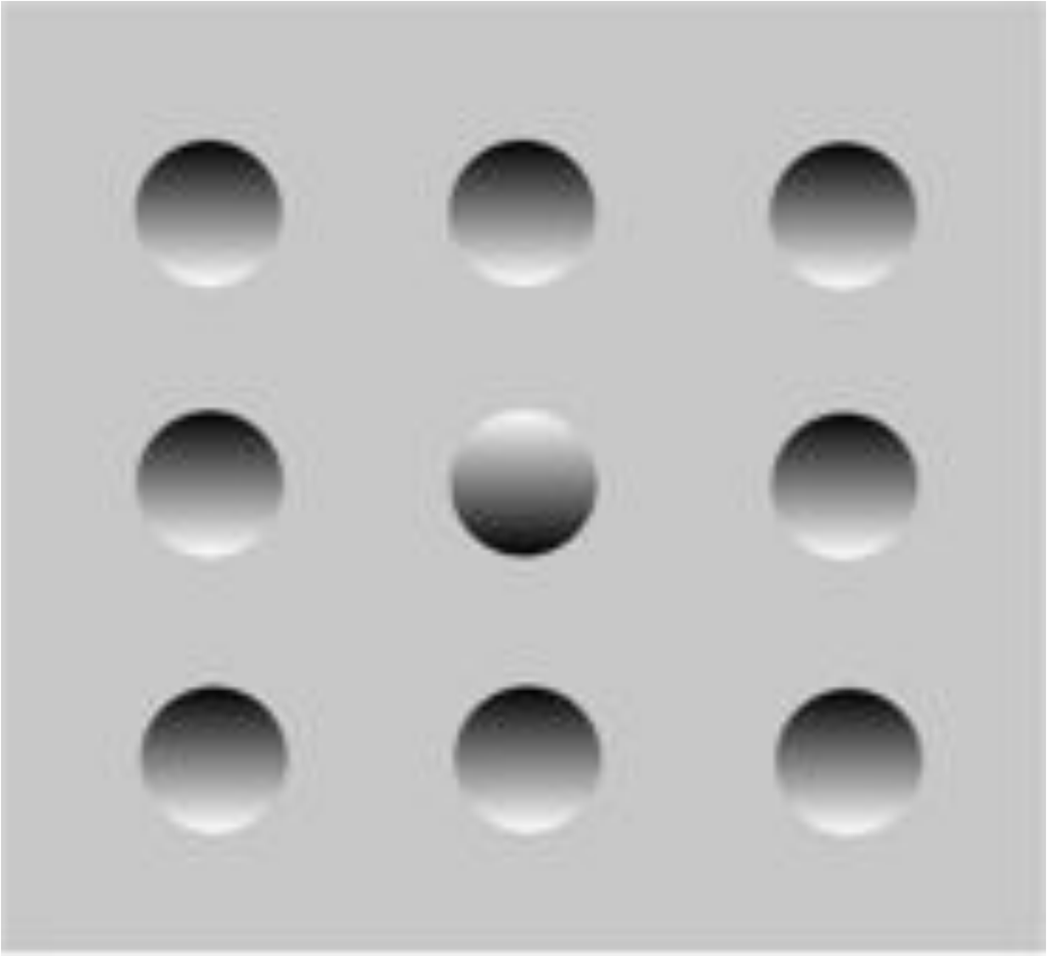
Let's use Bayes' rule:

P(A | image) = P(image | A) P(A)
P(B | image) = P(image | B) P(B)

Which of these is greater?



Which dimples are popping out and which popping in?



Which dimples are popping out and which popping in?

P(image | OUT & light is above) = A
P(image | OUT & light is below) = 0
P(image | IN & Light is above) = 0
P(image | IN & Light is below) = A

- Image equally likely to be OUT or IN given sensory data alone

What we want to know: P(OUT | image) vs. P(IN | image)

Apply Bayes' rule:

$$P(\text{OUT} \mid \text{image}) = P(\text{image} \mid \text{OUT \& light above}) \times \overbrace{P(\text{OUT}) \times P(\text{light above})}^{\text{prior}}$$

$$P(\text{IN} \mid \text{image}) = P(\text{image} \mid \text{IN \& light below }) \times P(\text{IN}) \times P(\text{light below})$$

Which of these is greater?

P(image | OUT & light is above) = A
P(image | OUT & light is below) = 0
P(image | IN & Light is above) = 0
P(image | IN & Light is below) = A

P(OUT | image) = P(image | OUT & light above) × P(OUT) × P(light above)
P(IN | image) = P(image | IN & light below) × P(IN) × P(light below)

P(OUT | image) = A × 0.5 × P(light above)
P(IN | image) = A × 0.5 × P(light below)

Let's say: “Light above” is 10 times more likely than “light below”

P(image | OUT & light is above) = A
P(image | OUT & light is below) = 0
P(image | IN & Light is above) = 0
P(image | IN & Light is below) = A

P(OUT | image) = P(image | OUT & light above) × P(OUT) × P(light above)
P(IN | image) = P(image | IN & light below) × P(IN) × P(light below)

P(OUT | image) = A × 0.5 × P(light above) = 5 × A
P(IN | image) = A × 0.5 × P(light below) = 0.5 × A

Let’s say: “Light above” is 10 times more likely than “light below”

Bayesian account: “Out” is 10 times more likely!