Top-down

Object recognition, given real images

- clutter, occlusion, noise
- role of cortical architecture

- Learning object categories
    - Amazing ability to learn from a small number of examples

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Object recognition in real images

Background clutter and occlusion

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Object recognition in real images

Background clutter and occlusion

Object recognition given occlusion, clutter

Linking local information (features) likely to belong to the same object or pattern

- local ambiguity, noise
- need for generic priors, e.g. smoothness

Resolving competing explanations

- occlusion, clutter
- need for domain-specific priors

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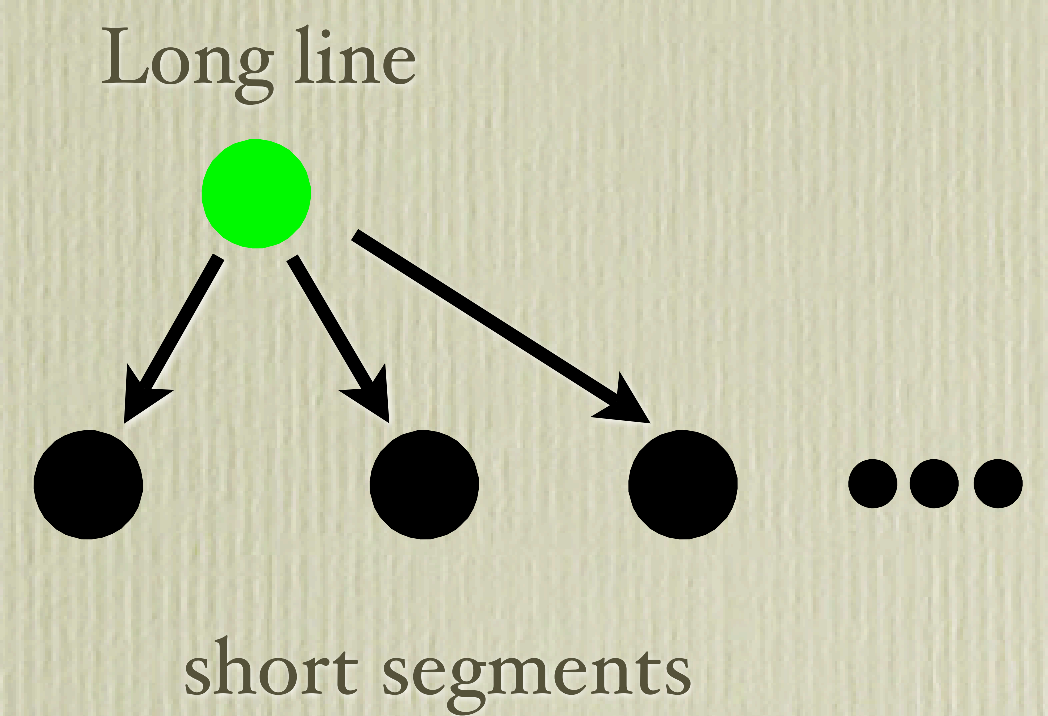
Simple influence graphs

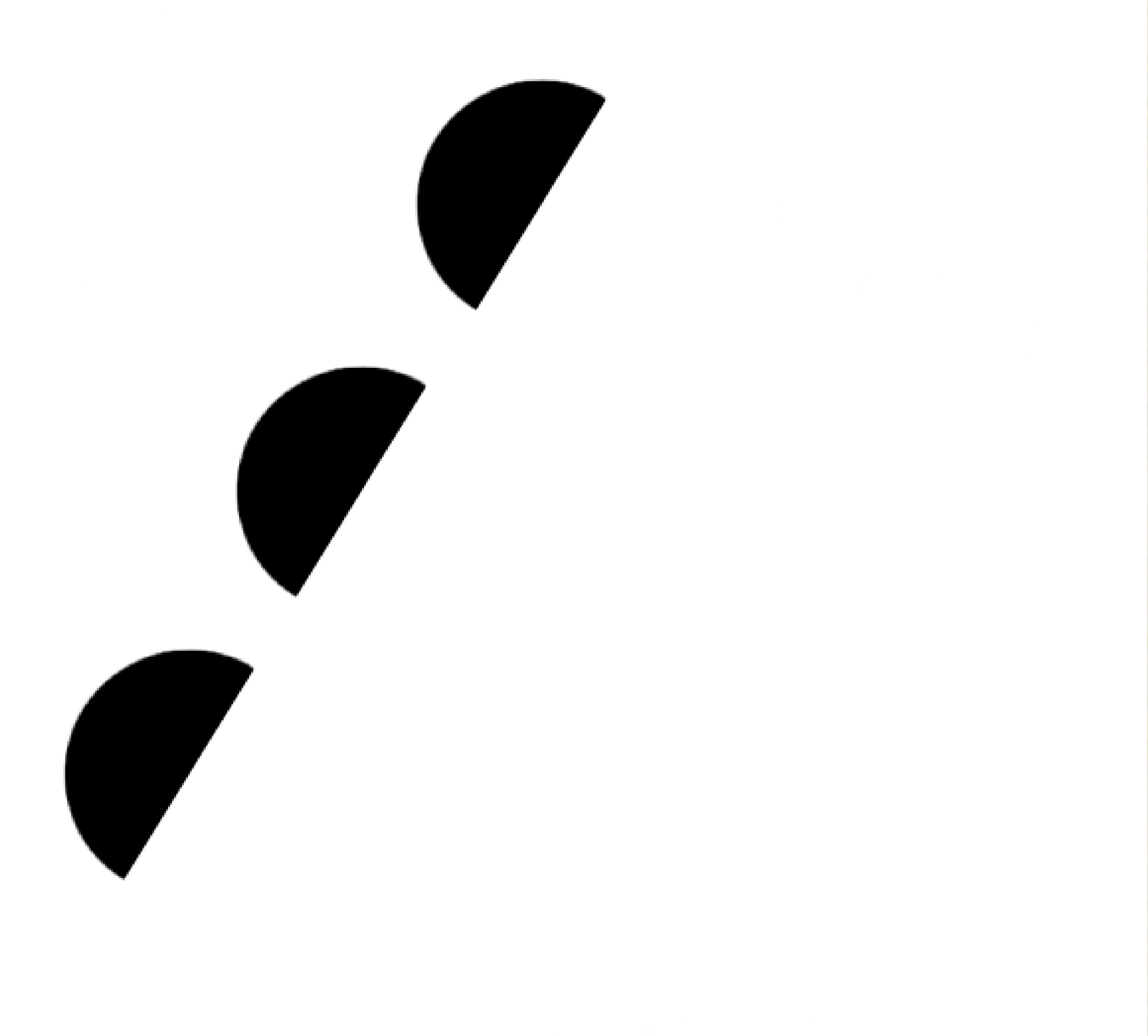
Cue integration



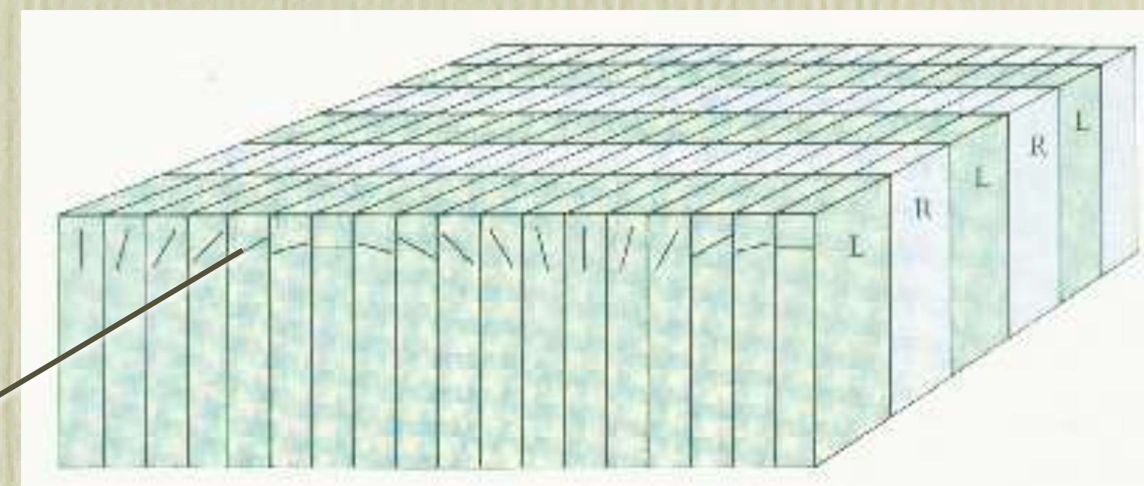
Parent P, Zucker SW (1989) Trace inference, curvature consistency, and curve detection. IEEE Transactions on Pattern Analysis & Machine Intelligence 11:823-839.

Yuille AL, Fang F, Schrater P, Kersten D (2004) Human and Ideal Observers for Detecting Image Curves. In: Advances in Neural Information Processing Systems 16 (Thrun S, Saul L, Schoelkopf B, eds). Cambridge, MA: MIT Press.

Cortical basis?

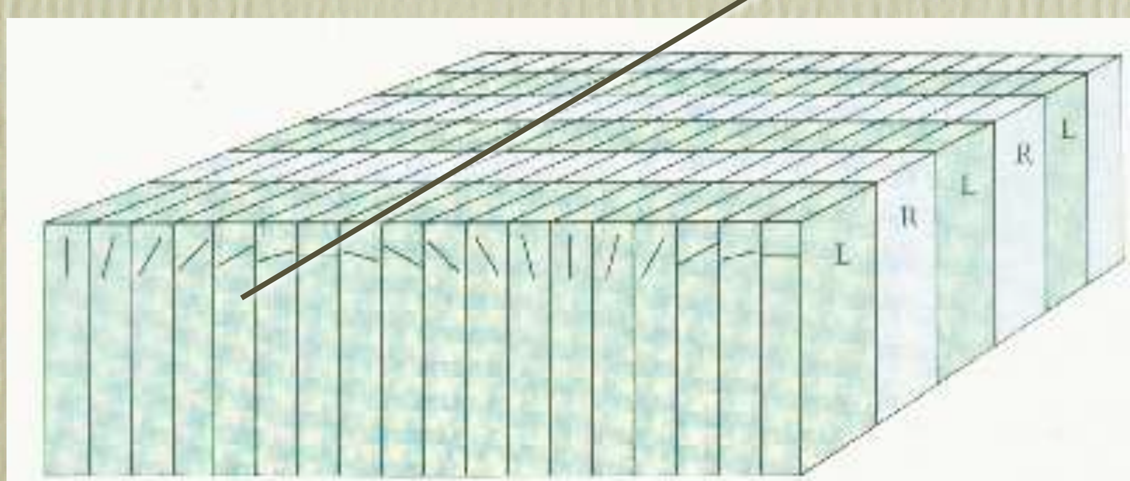


Short segments to long lines? Within-area linkage?



~ 8 mm

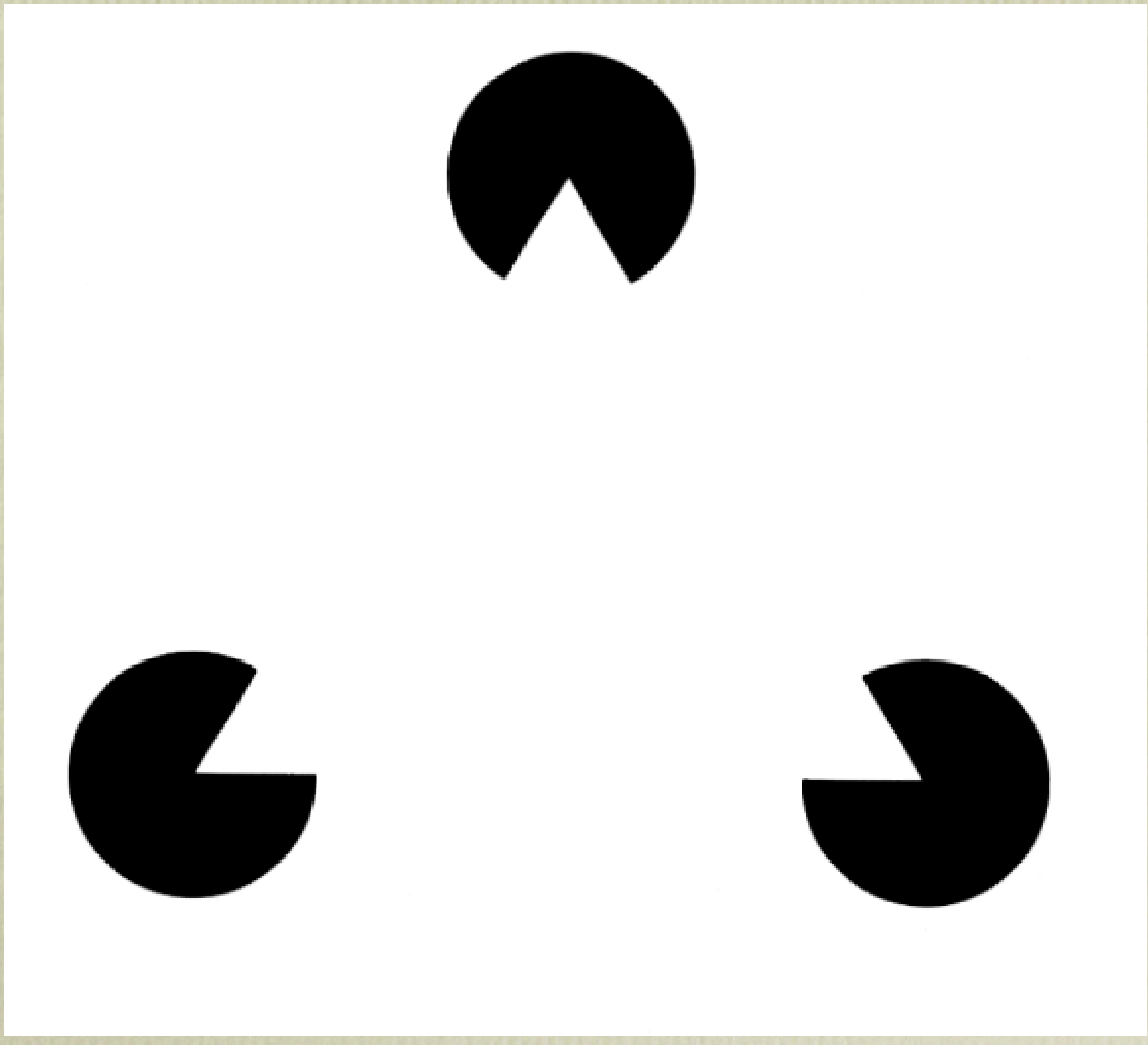
1 to 2 mm



1 to 2 mm

Das A, Gilbert CD (1999) Topography of contextual modulations mediated by short-range interactions in primary visual cortex. Nature 399:655-661.

But what about whole shapes?



Object recognition given occlusion, clutter

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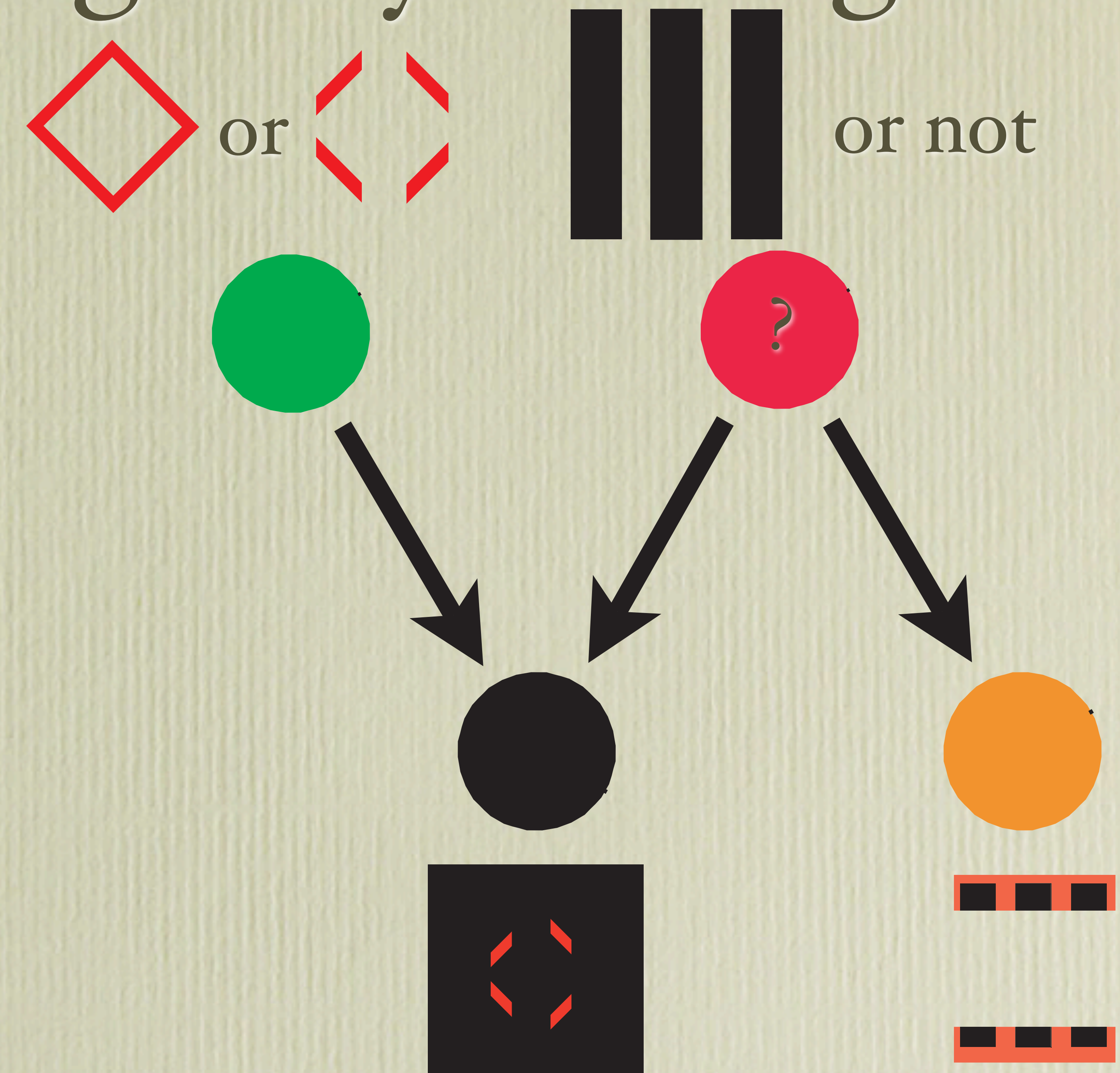
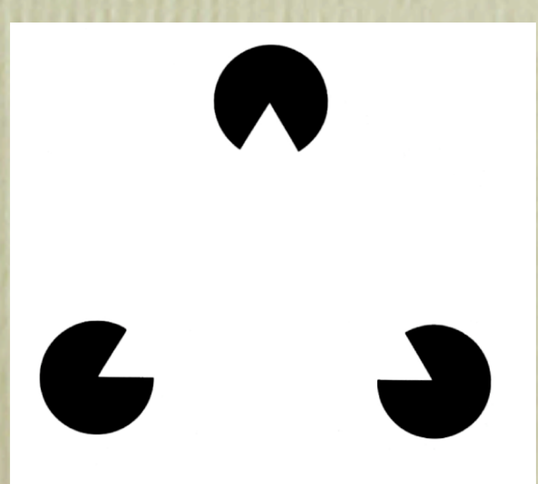
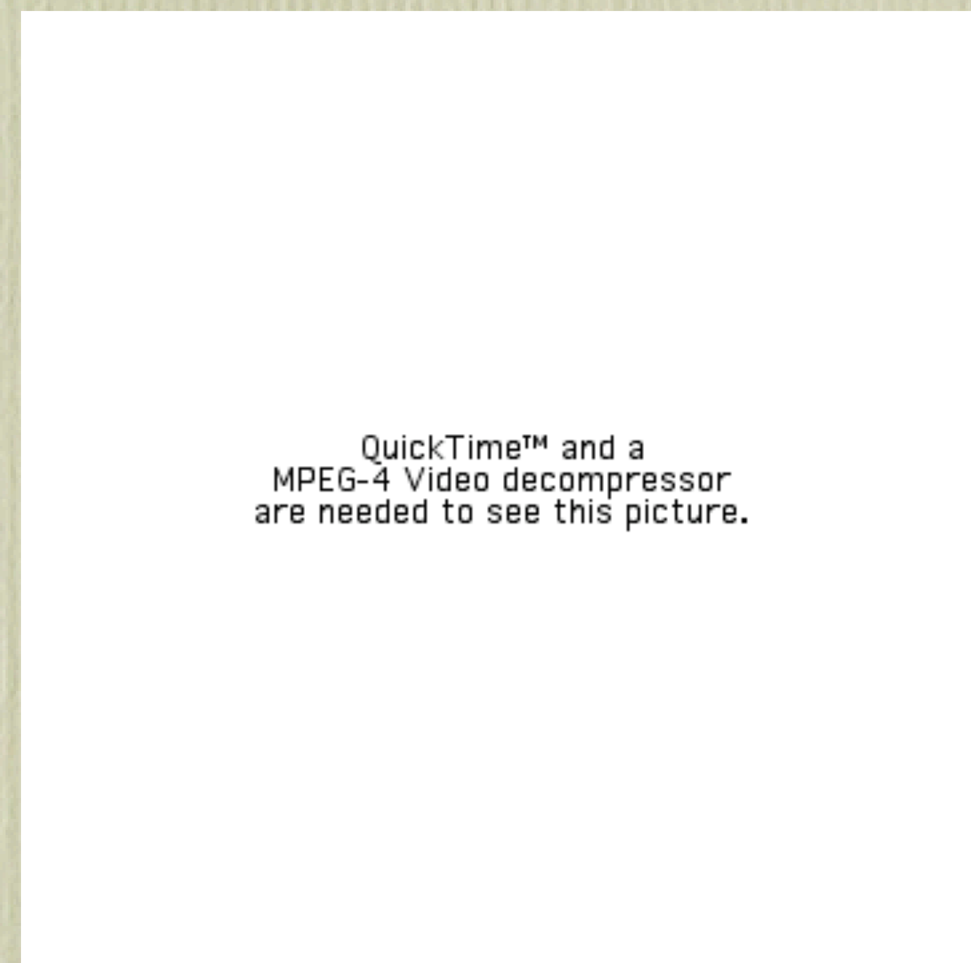
Competing explanations: Explaining away missing data



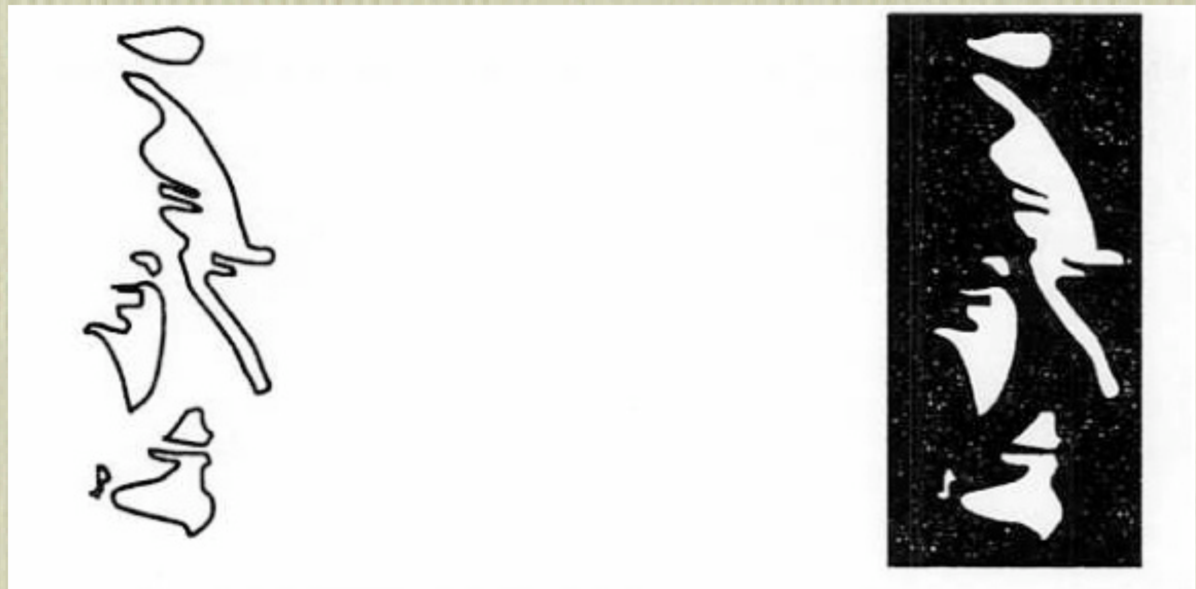


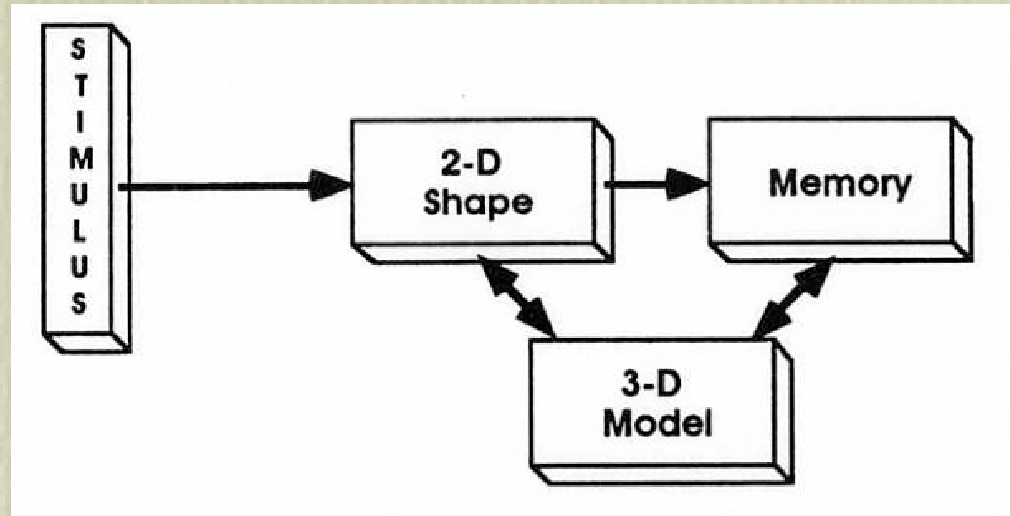
Auxiliary evidence for occlusion

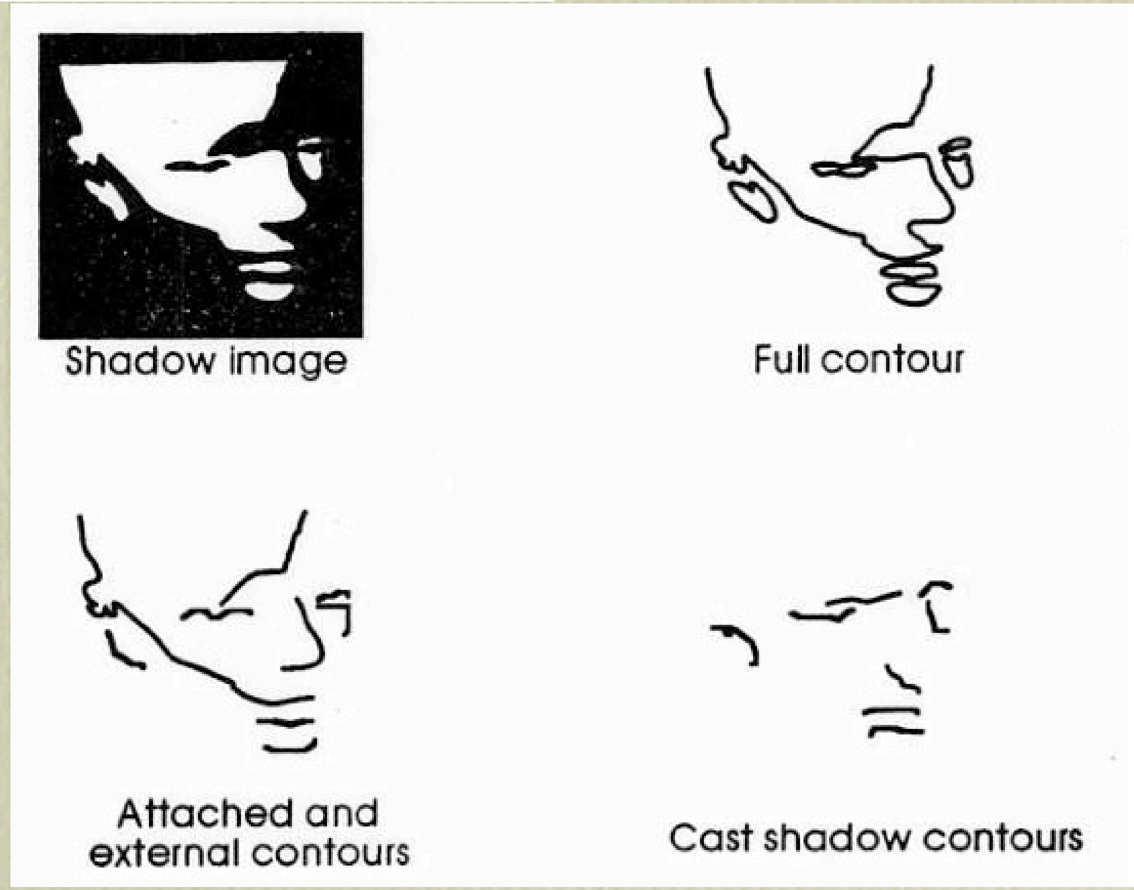
Auxiliary evidence for occlusion



Recognition despite cast shadows

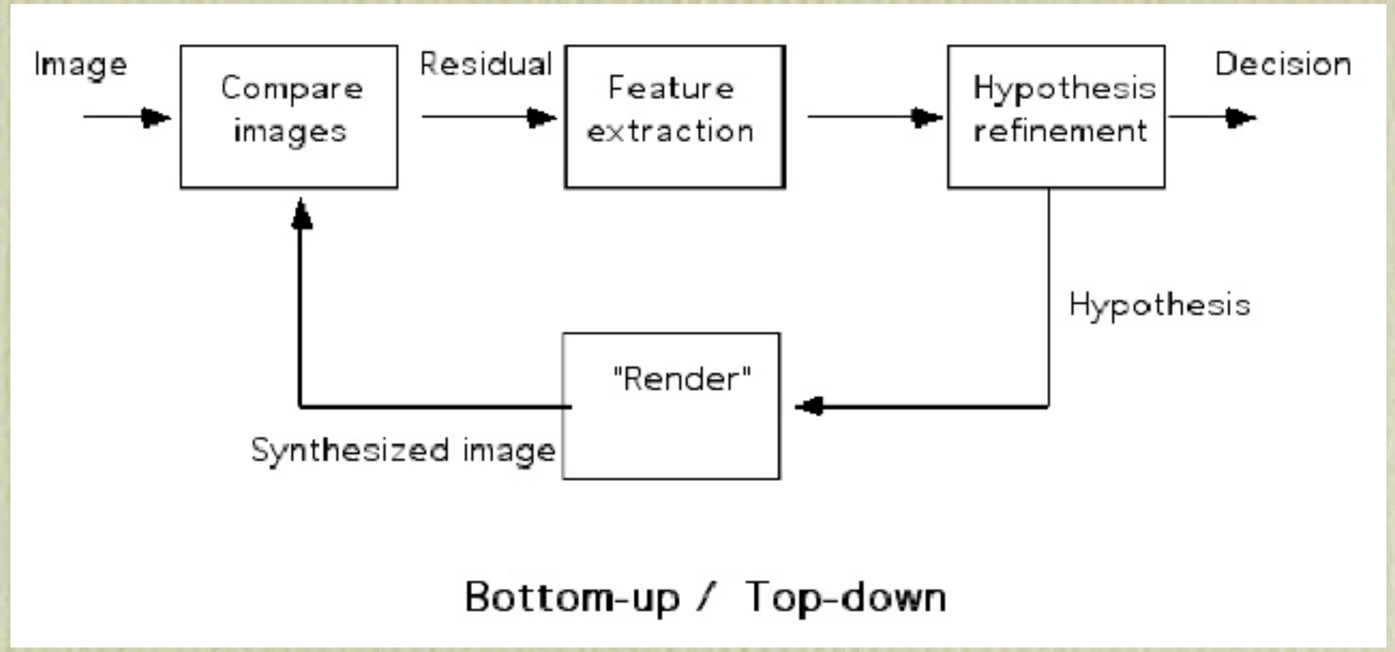




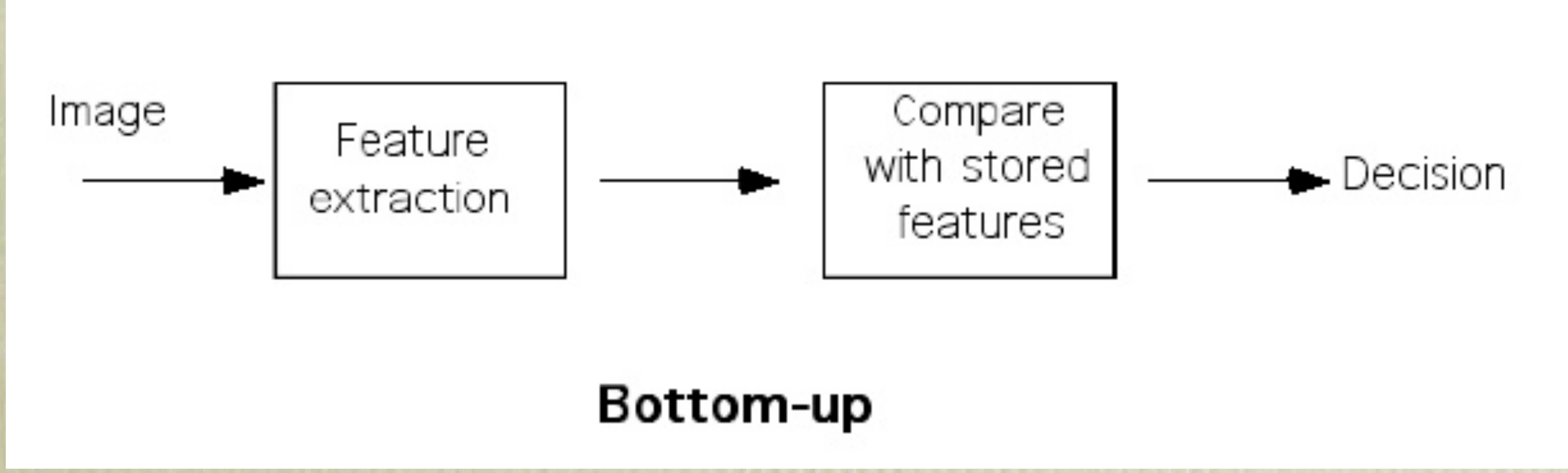


Cavanagh P (1991) What's up in top-down processing? In: Representations of Vision: Trends and tacit assumptions in vision research (Gorea A, ed), pp 295-304. Cambridge, UK: Cambridge University Press.

Suggests...



Rather than this



Computer vision
Image parsing: analysis by synthesis
(Tu, Z., Chen, X., Yuille, A., & Zhu, S. (2005))

- Find most probable scene description
- Bottom-up “proposals” (cues) to access low- (shading) and high-level (faces, letters) models
- Verification through top-down synthesis
- If bottom-up proposals are good, synthesis is not needed to find most probable scene
- Flexible graph

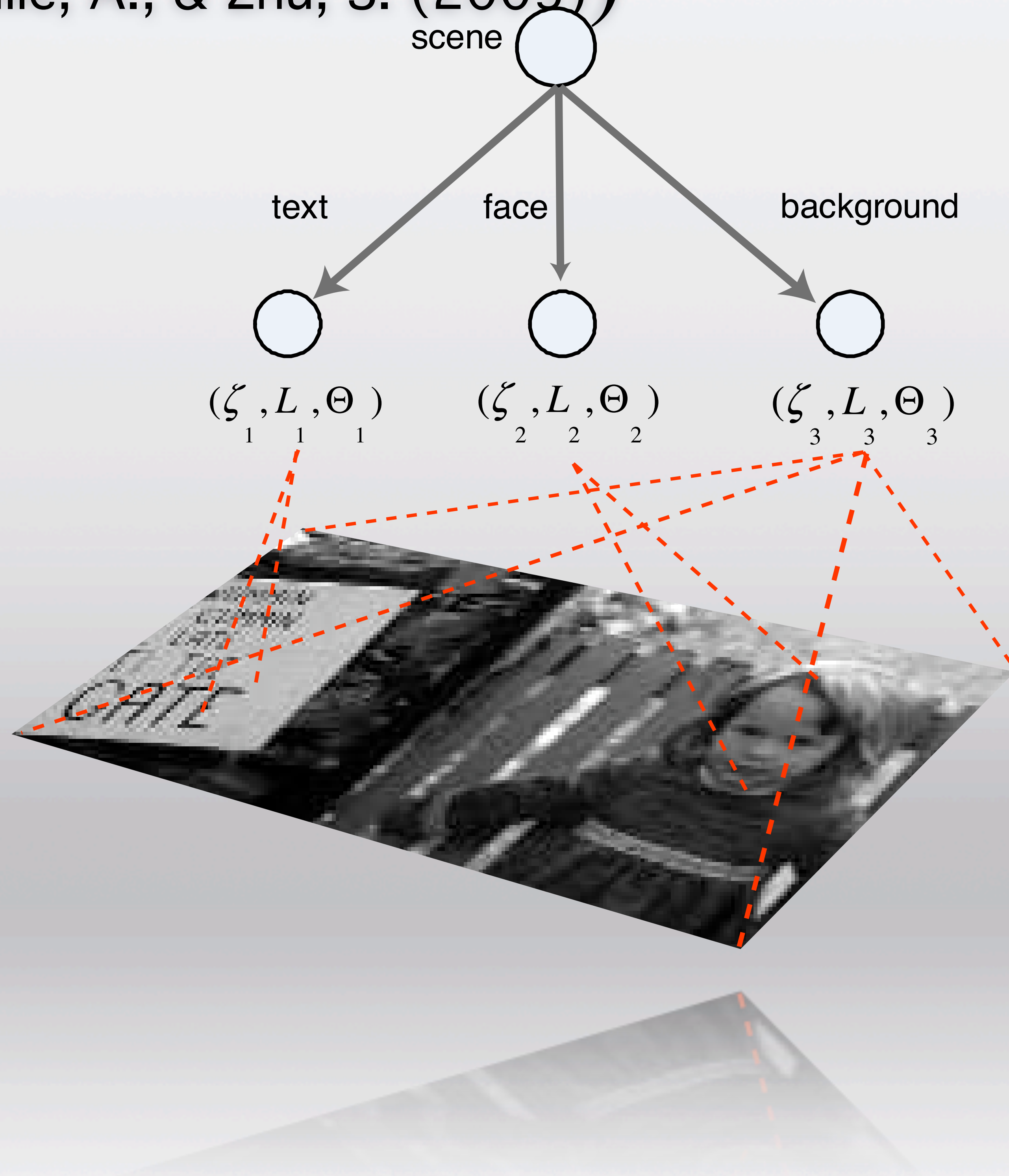


Image parsing & "Explaining away"

Input

Tu, Z., Chen, X., Yuille, A., & Zhu, S. (2005). Image Parsing: Unifying Segmentation, Detection and Recognition. IJCV, 63(2).

Image parsing & "Explaining away"

Bottom-up result

Input

Tu, Z., Chen, X., Yuille, A., & Zhu, S. (2005). Image Parsing: Unifying Segmentation, Detection and Recognition. IJCV, 63(2).

Image parsing & "Explaining away"

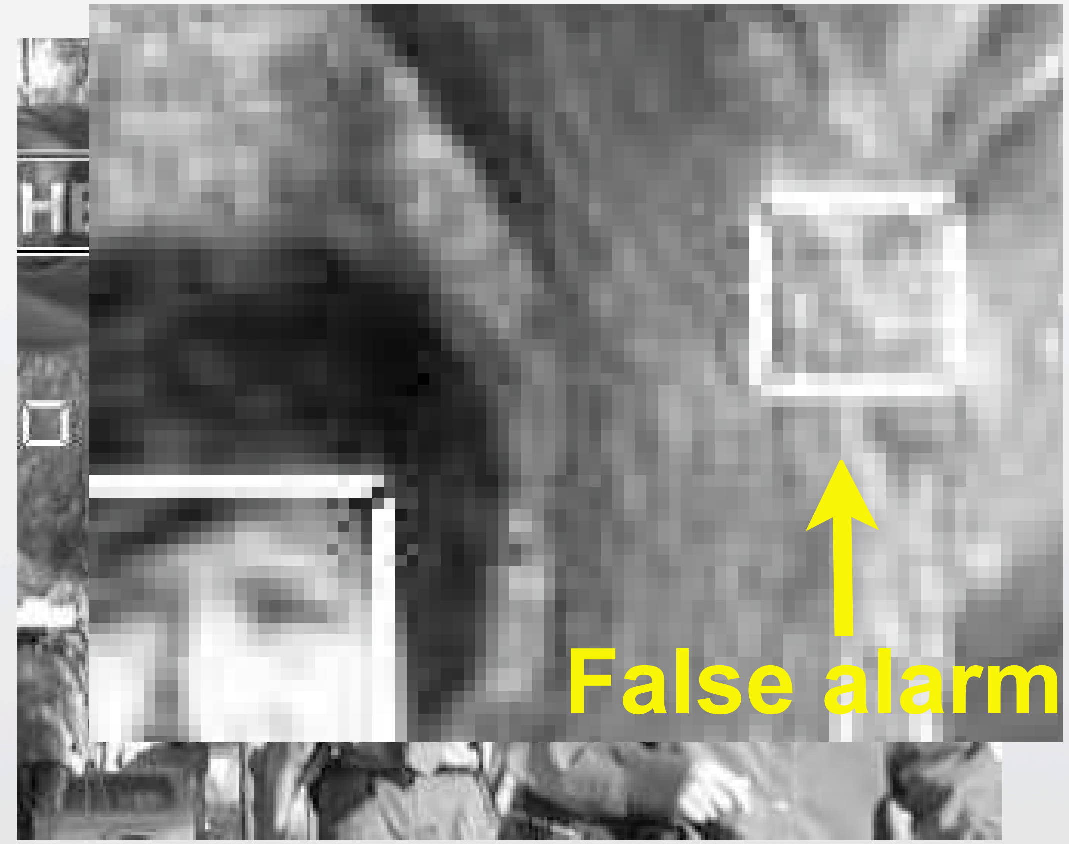


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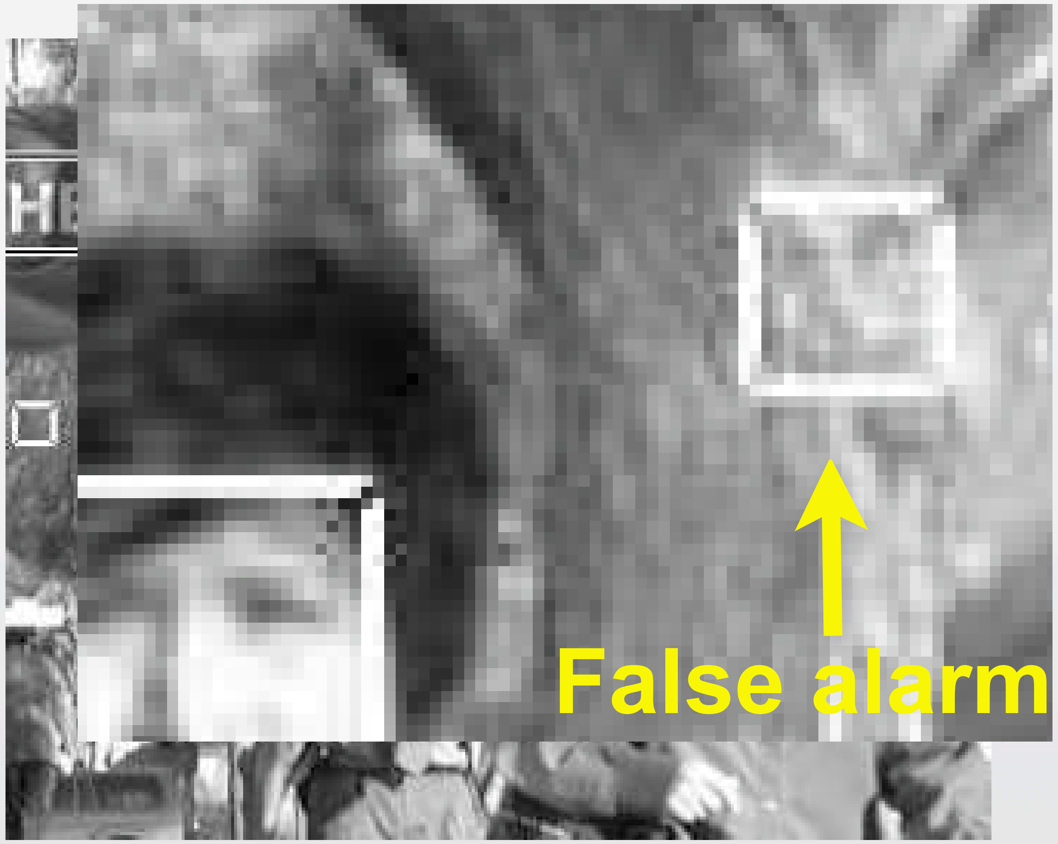
Image parsing & “Explaining away”

Input



Bottom-up result

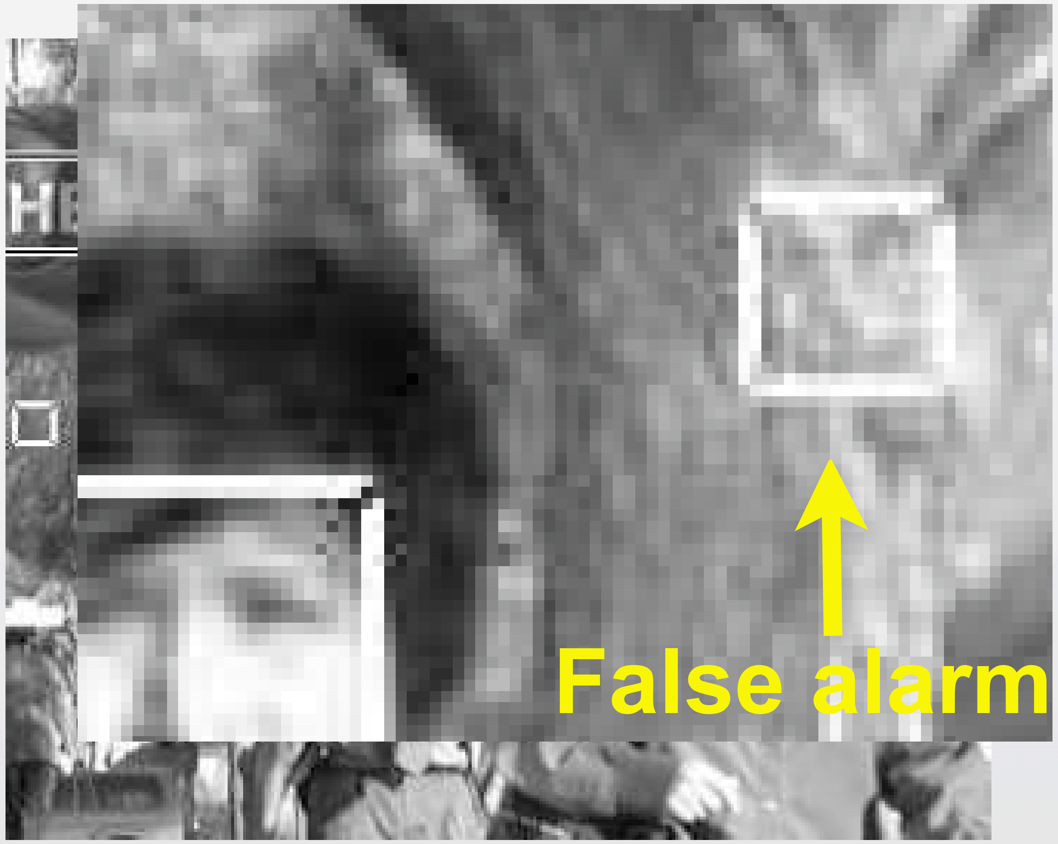
Synthesized image

Tu, Z., Chen, X., Yuille, A., & Zhu, S. (2005). Image Parsing: Unifying Segmentation, Detection and Recognition. IJCV, 63(2).

Image parsing & "Explaining away"

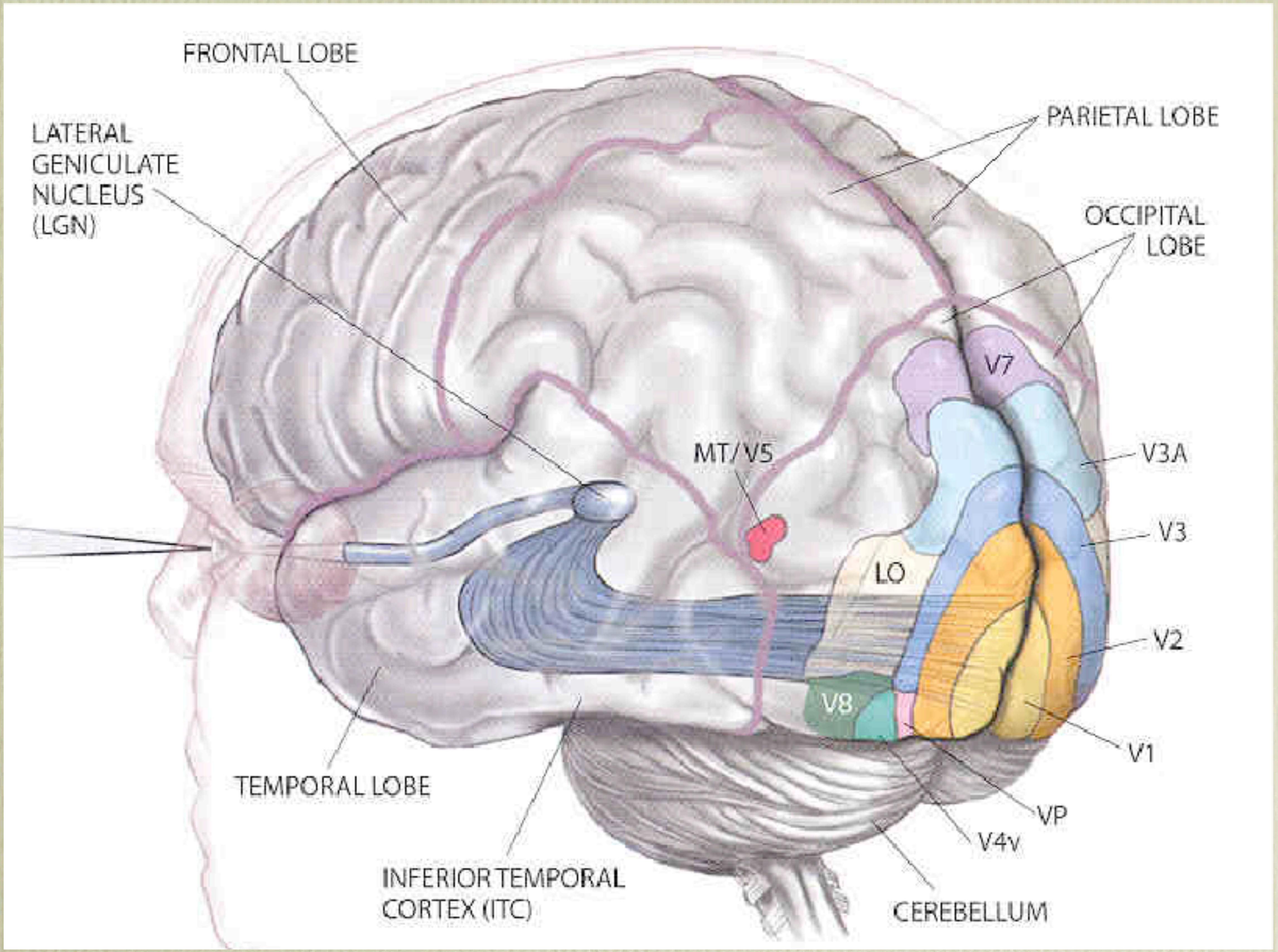
Input

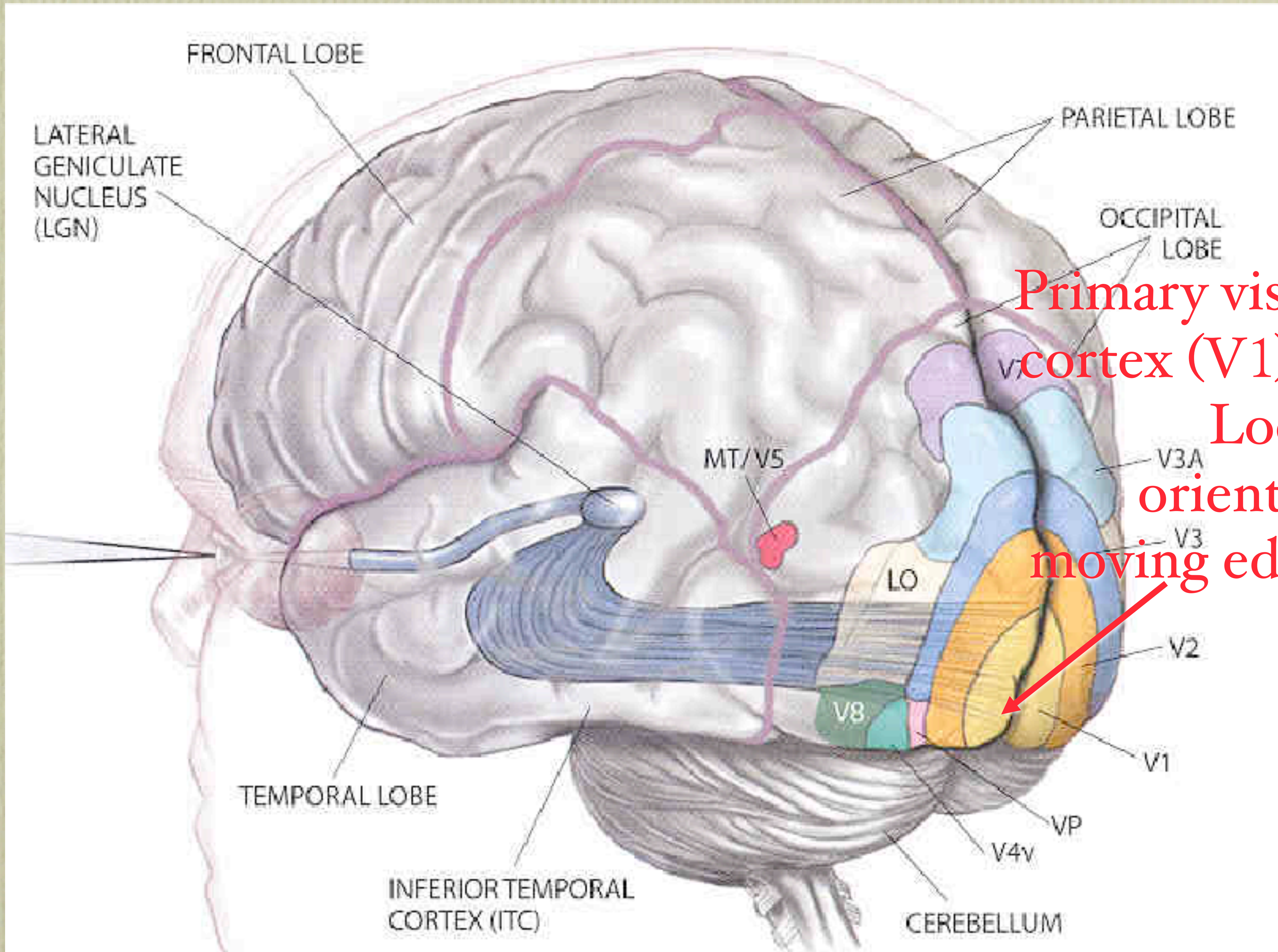
Tu, Z., Chen, X., Yuille, A., & Zhu, S. (2005). Image Parsing: Unifying Segmentation, Detection and Recognition. IJCV, 63(2).



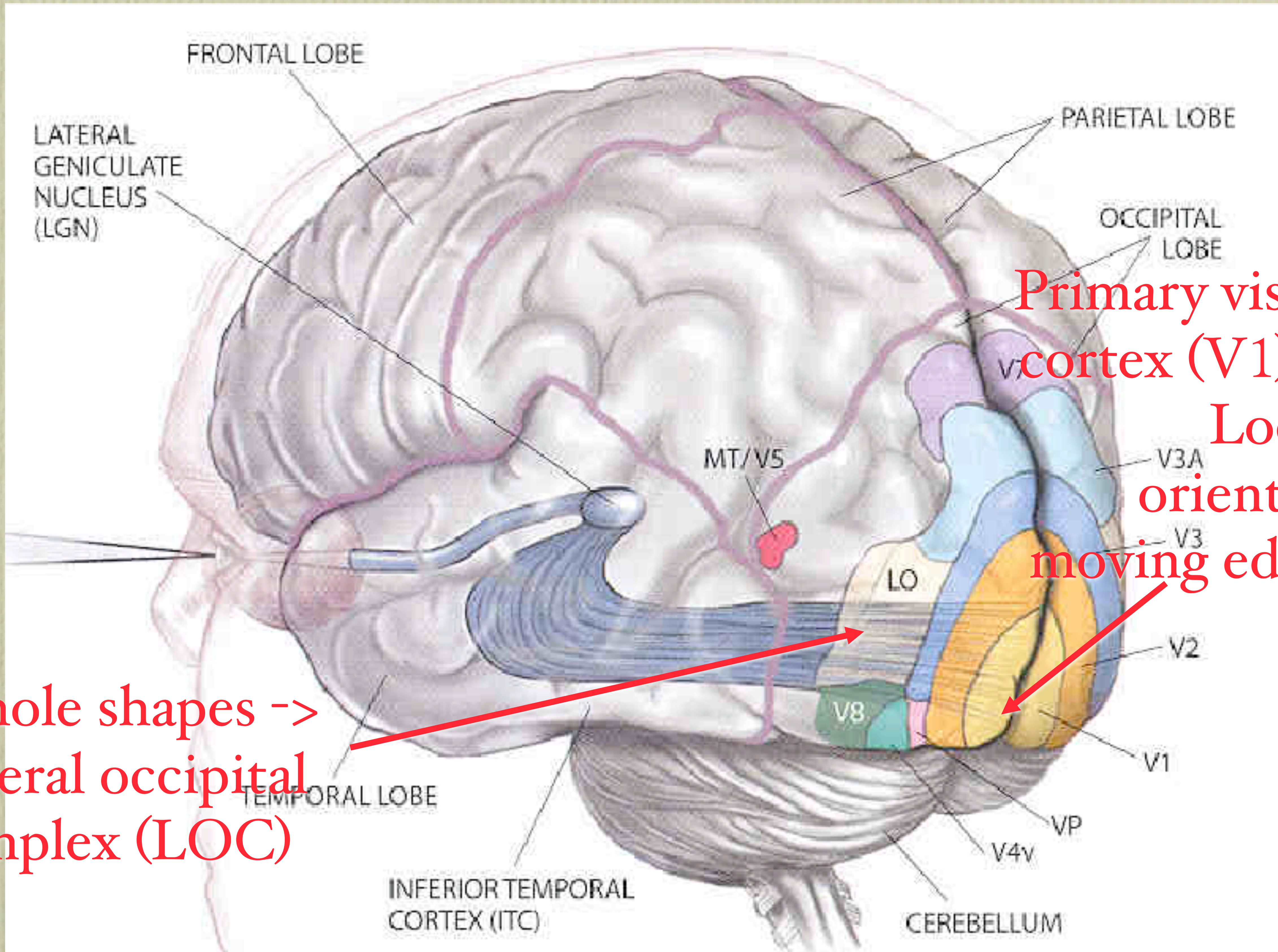
Bottom-up result

Synthesized image


FRONTAL LOBE
LATERAL GENICULATE NUCLEUS (LGN)
PARIETAL LOBE
OCCIPITAL LOBE
V7
MT/V5
V3A
V3
LO
V2
V8
V1
TEMPORAL LOBE
VP
V4v
INFERIOR TEMPORAL CORTEX (ITC)
CEREBELLUM



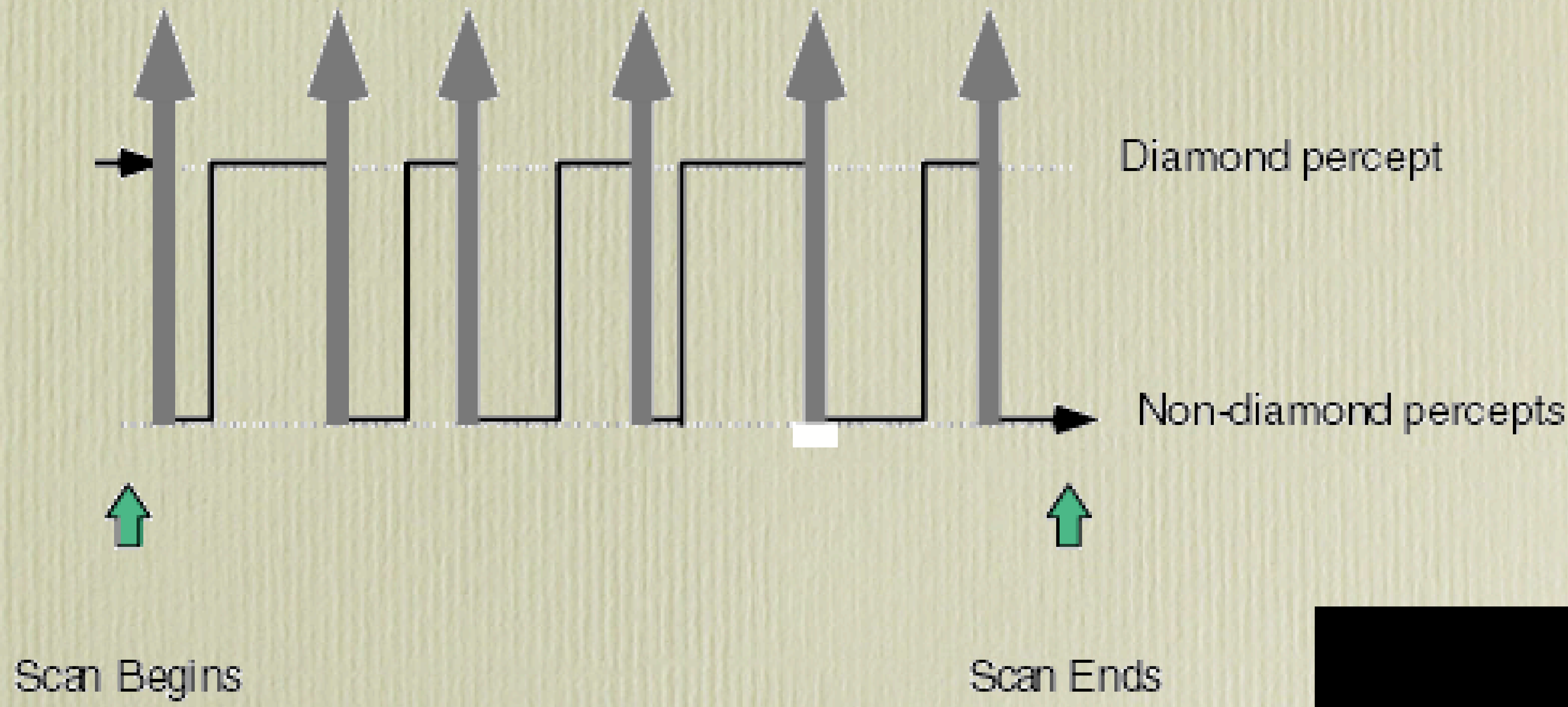
Primary visual cortex (V1) -> Local, oriented, moving edges

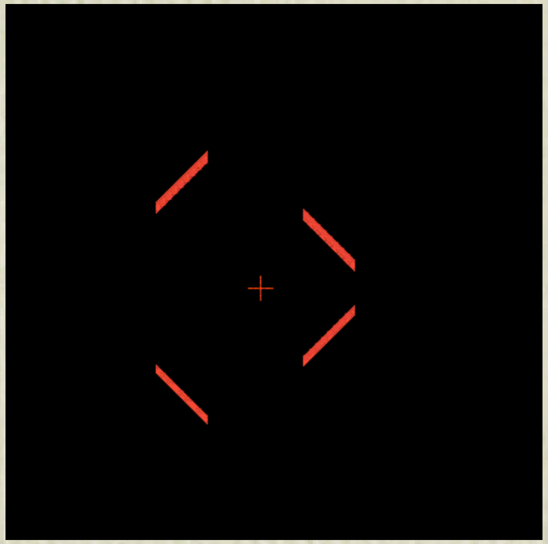


Primary visual cortex (V1) -> Local, oriented, moving edges

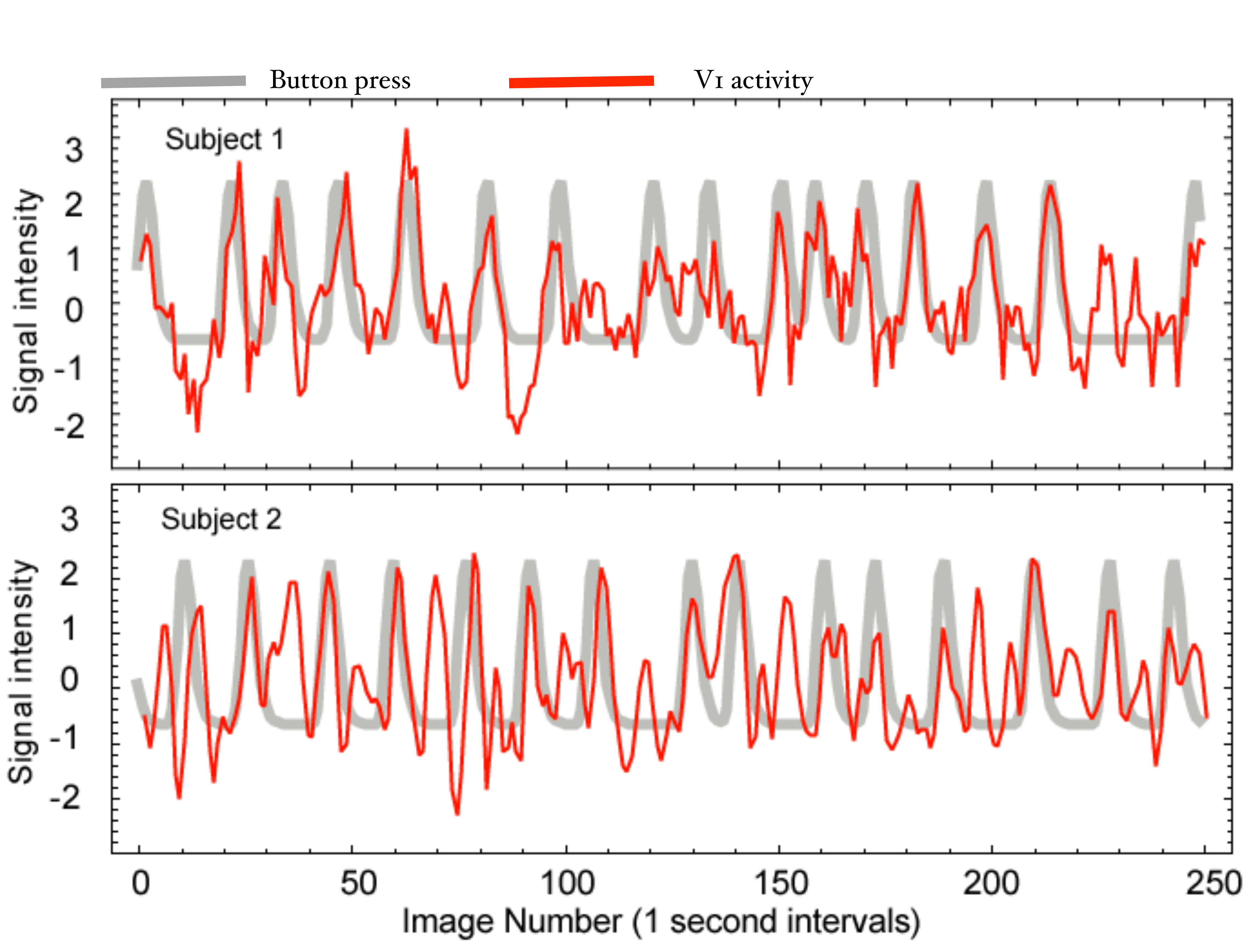
Whole shapes -> Lateral occipital complex (LOC)

Button presses





Perceptual organization correlates with reduced V1 activity



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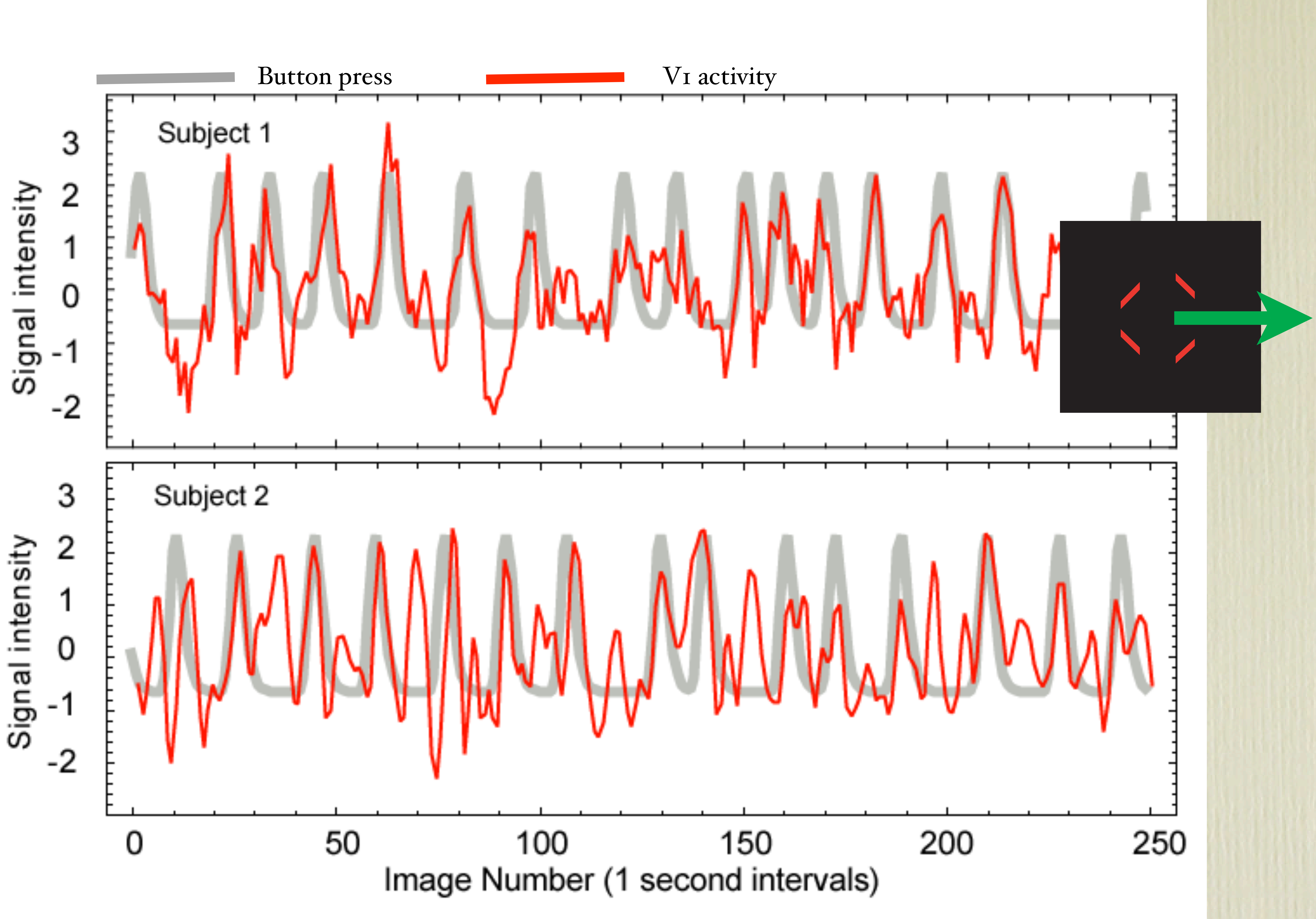
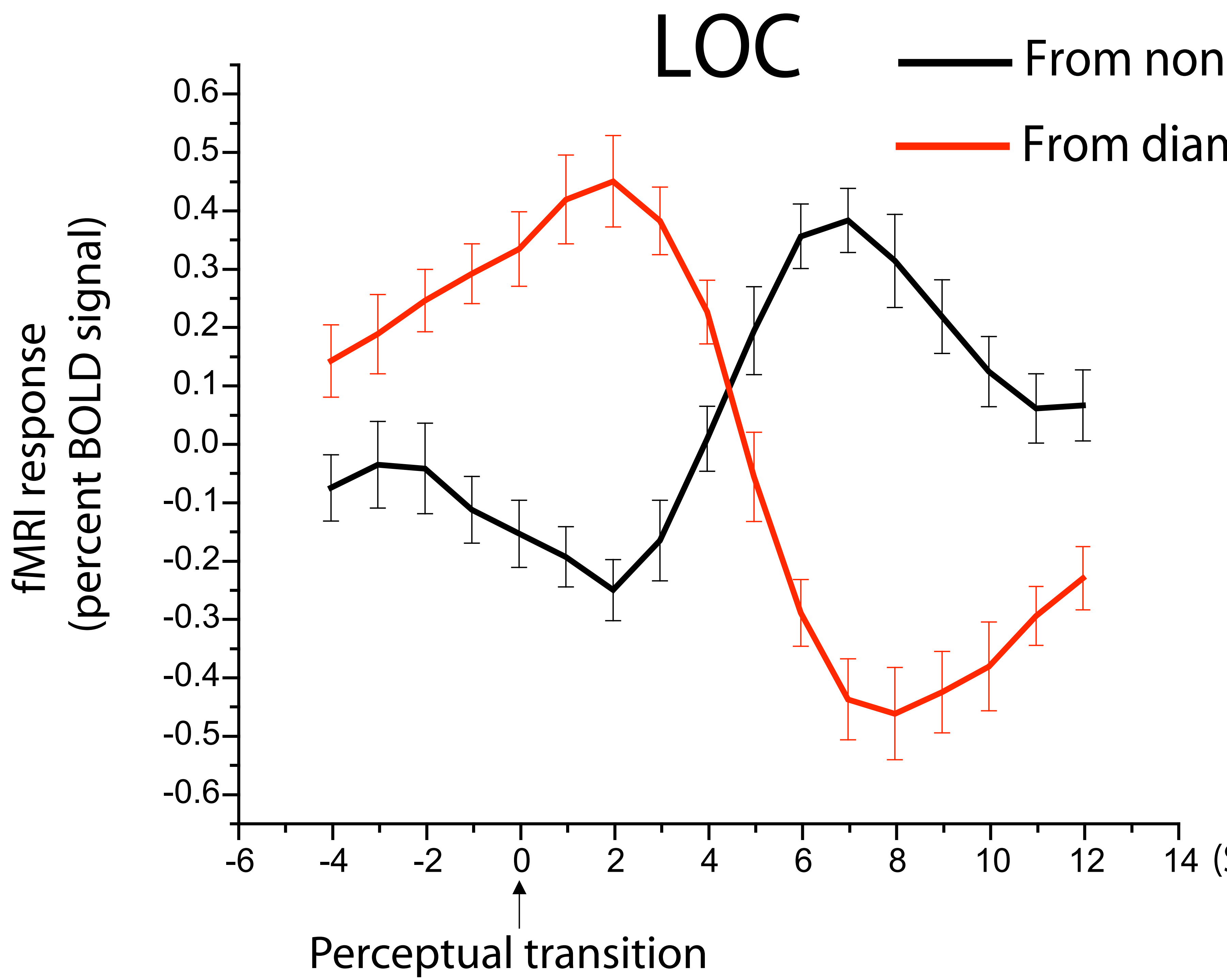
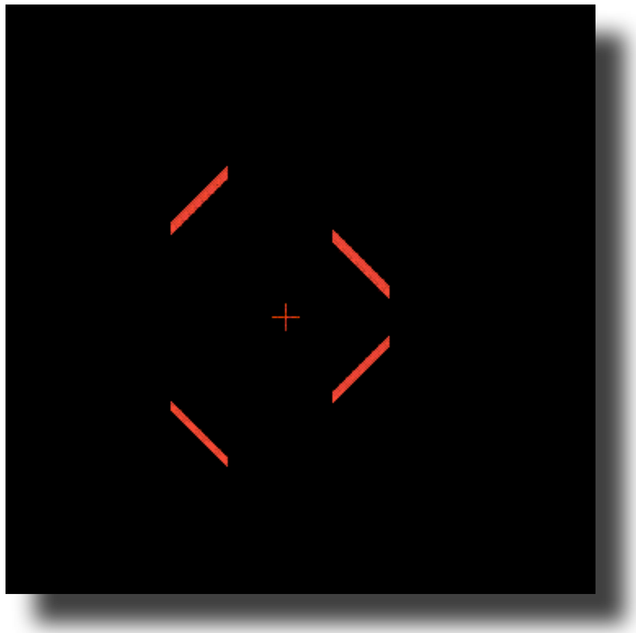


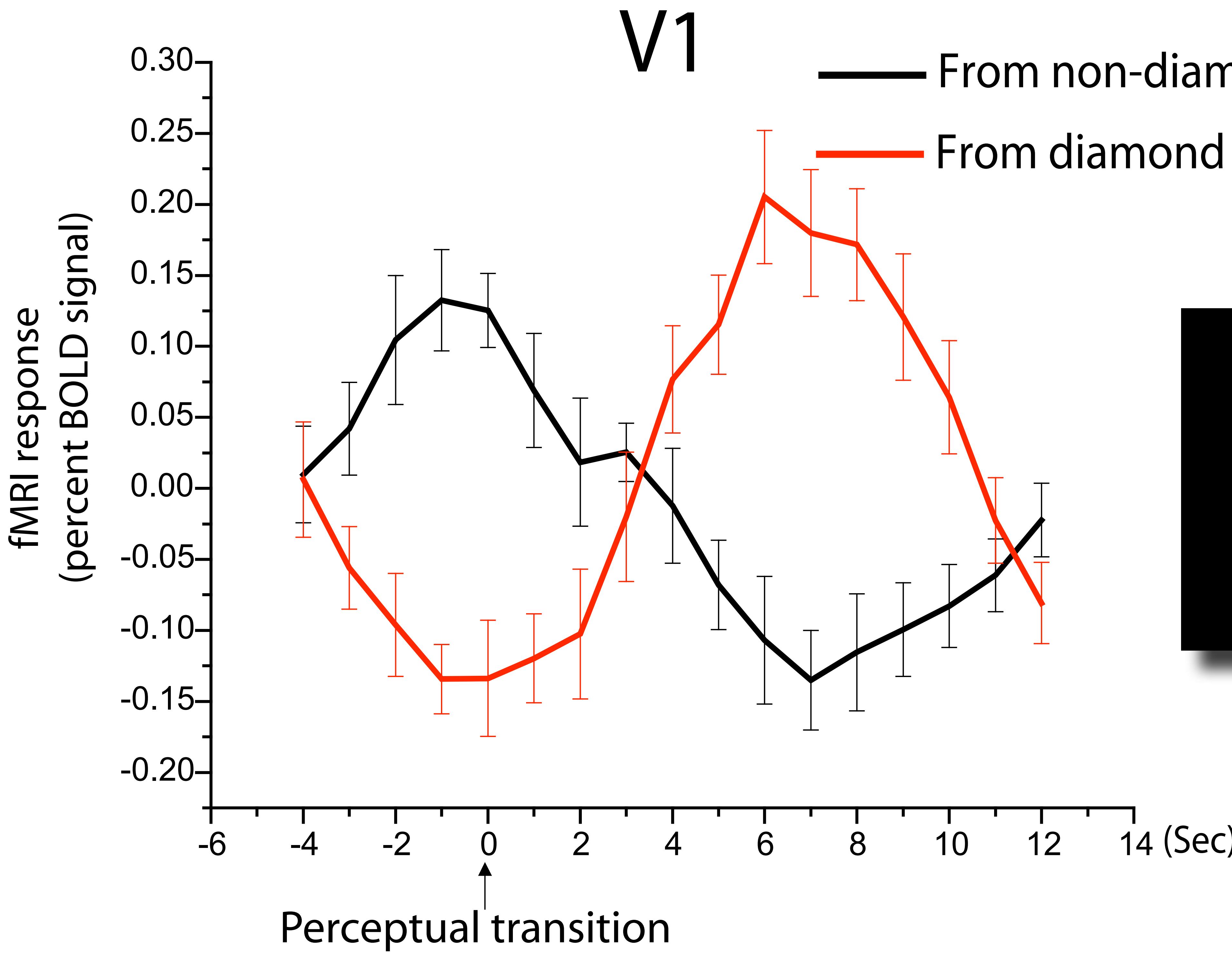
Perceptual organization is correlated with *increased* LOC activity

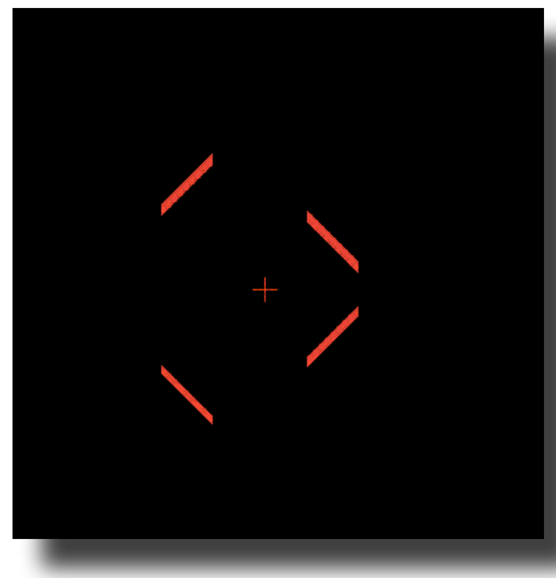




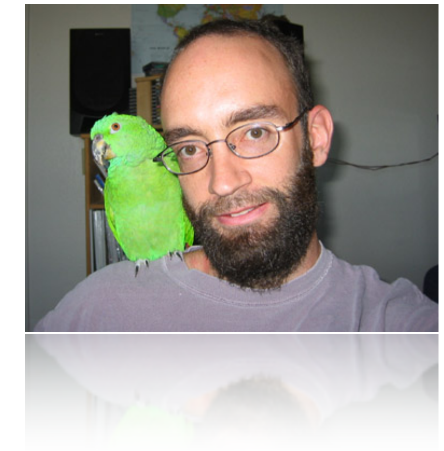
From: Fang, Murray, He & Kersten, 2004, International Congress of Psychology, Beijing

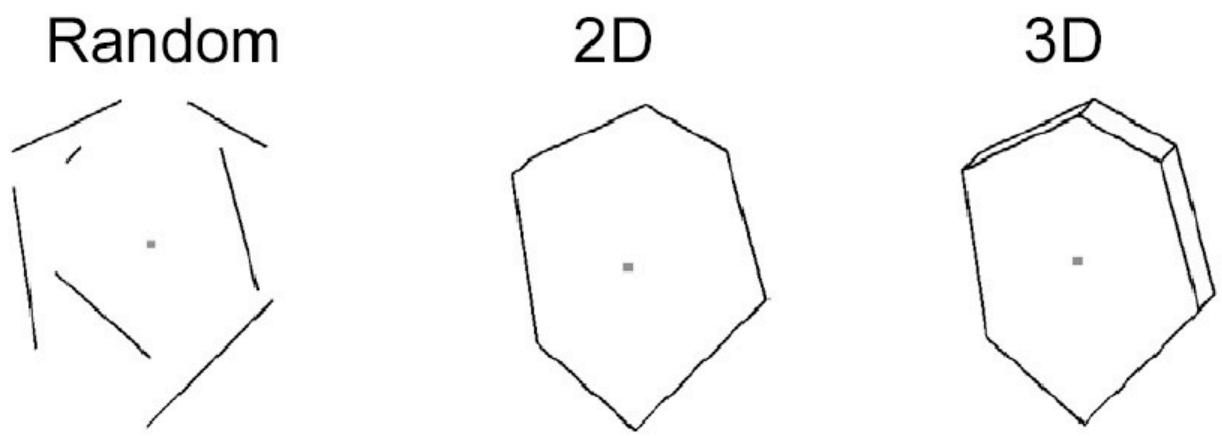
Perceptual organization is correlated with *decreased* V1 activity

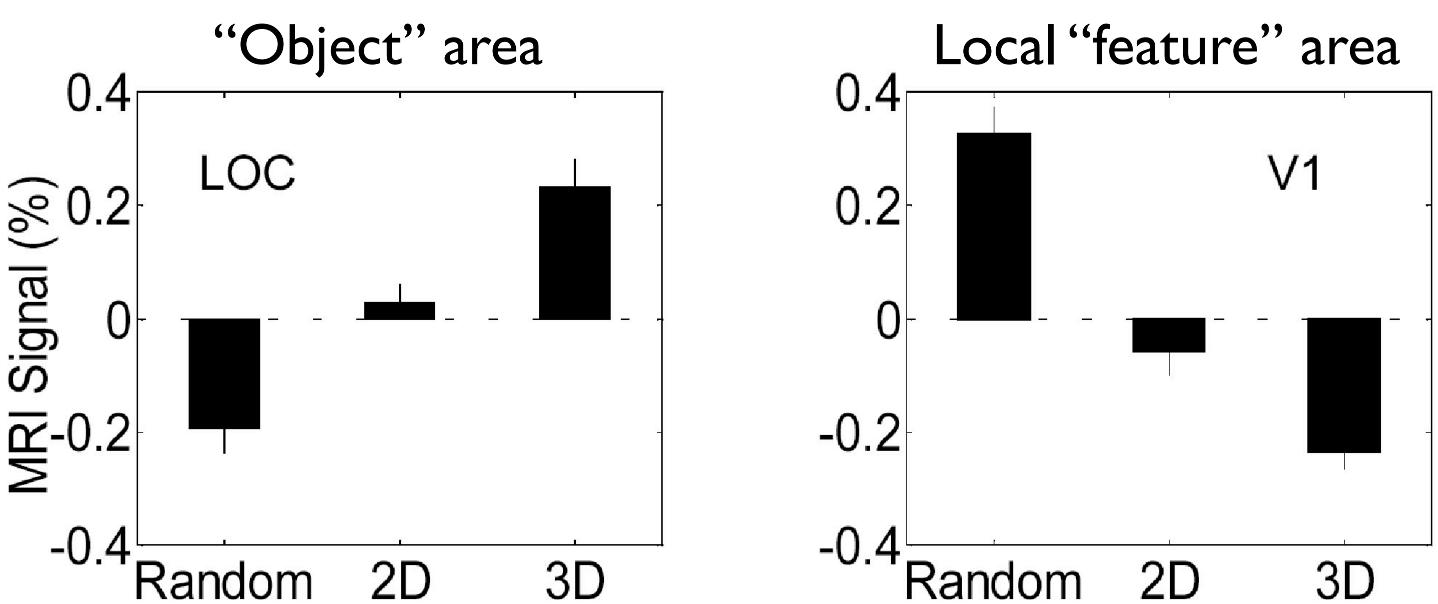




Shape perception can reduce V1 activity

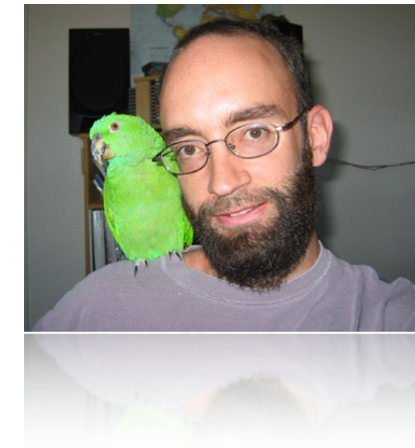


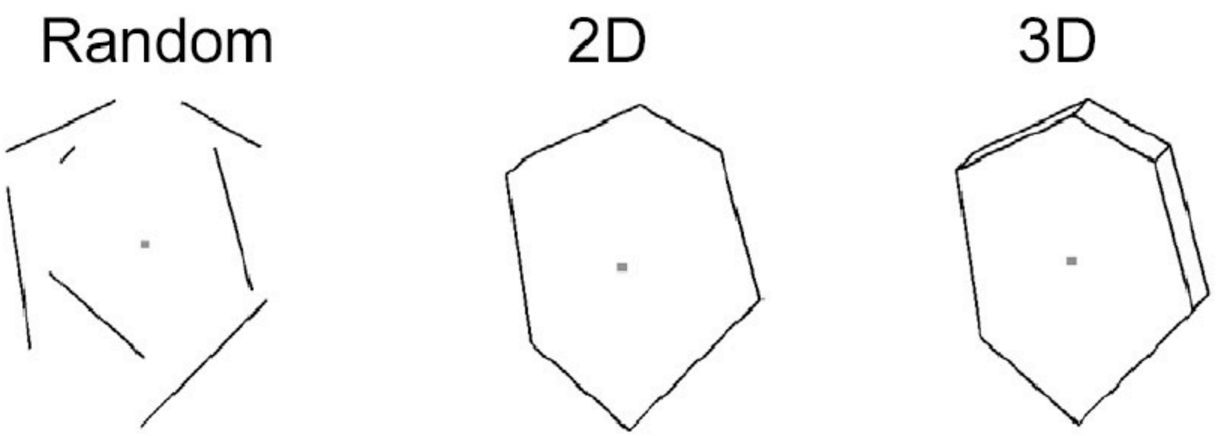


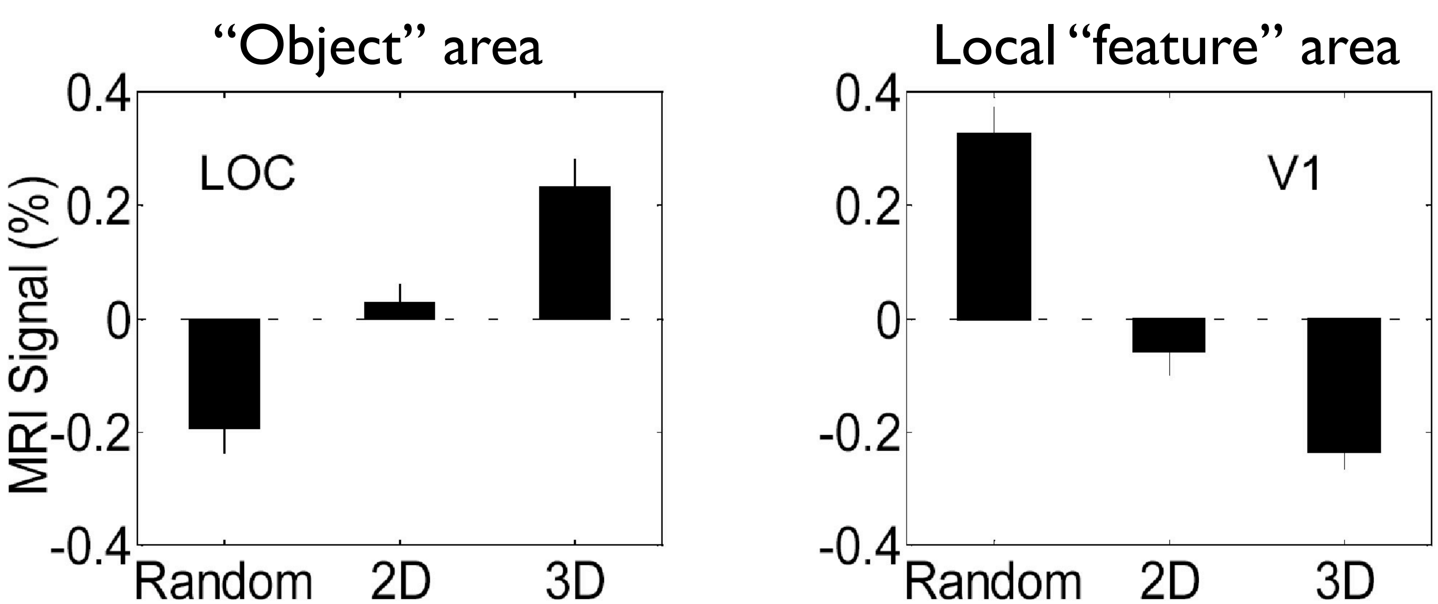


Murray, S. O., Kersten, D., Olshausen, B. A., Schrater, P., & Woods, D. L. (2002). Shape perception reduces activity in human primary visual cortex. Proc Natl Acad Sci U S A, 99, 15164-15169.

Shape perception can reduce V1 activity







Explanation?

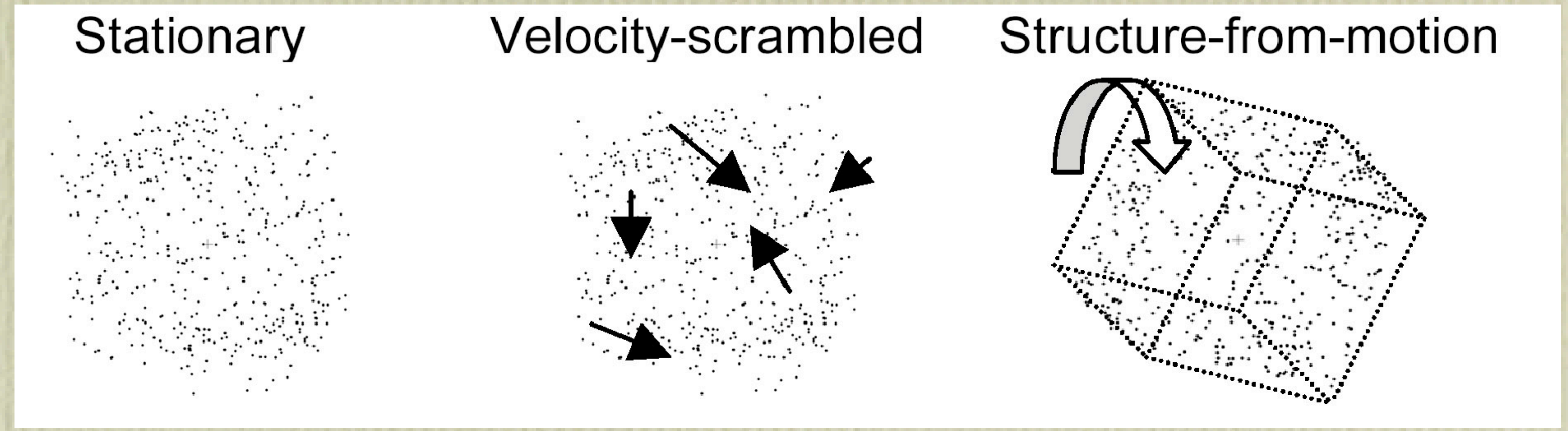
Many...

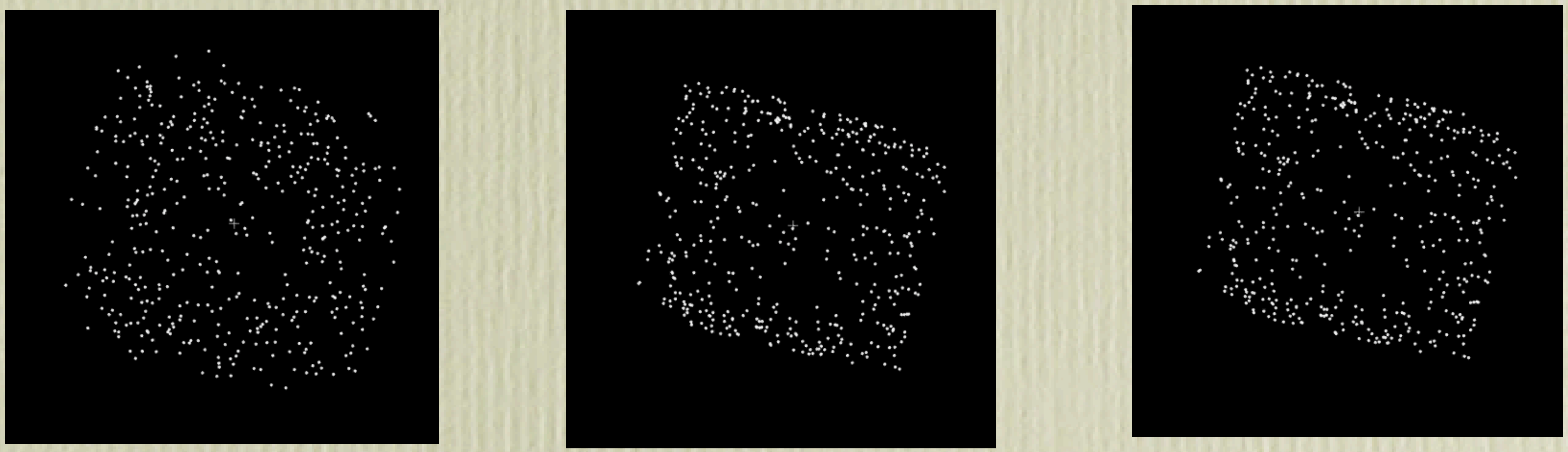
"Explaining away" through predictive coding

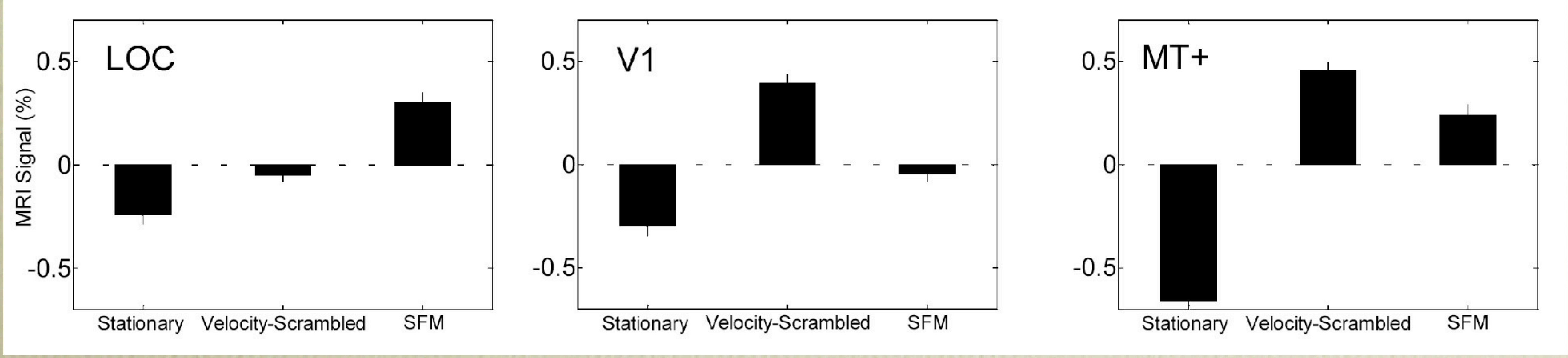
Sparse coding

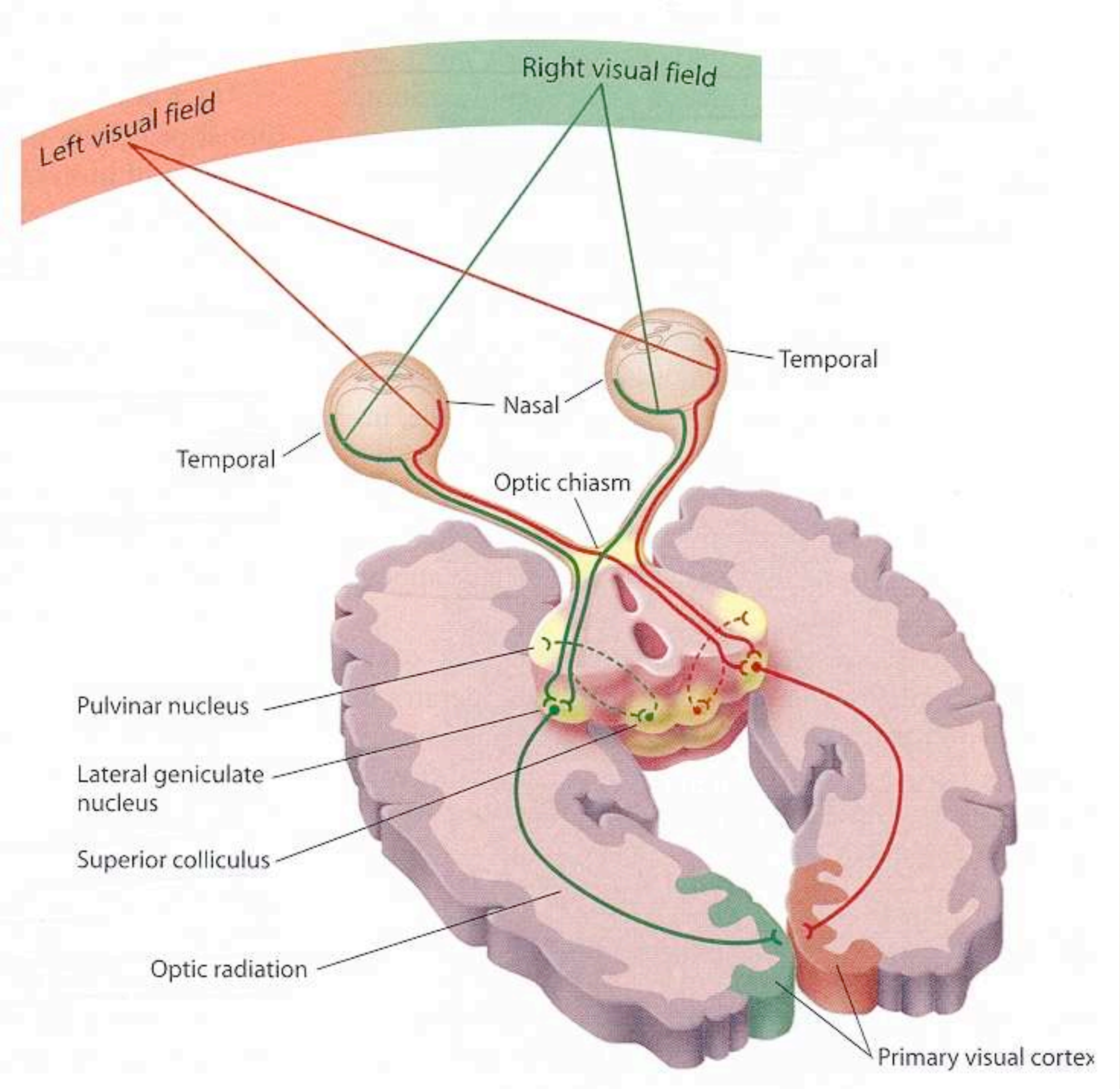
Murray, S. O., Kersten, D., Olshausen, B. A., Schrater, P., & Woods, D. L. (2002). Shape perception reduces activity in human primary visual cortex. Proc Natl Acad Sci U S A, 99, 15164-15169.

Structure from motion

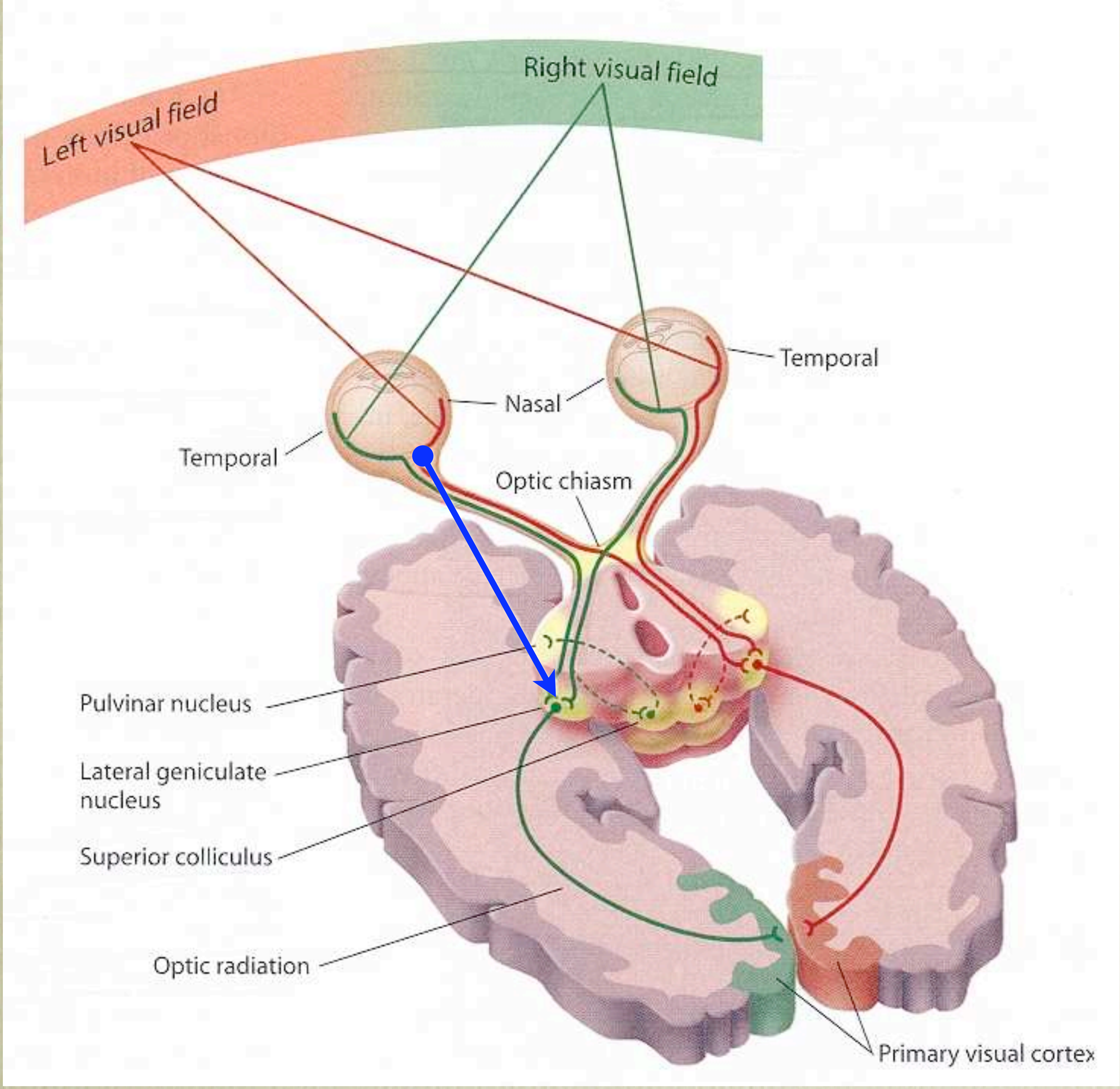








Left visual field
Right visual field
Temporal
Nasal
Temporal
Optic chiasm
Pulvinar nucleus
Lateral geniculate nucleus
Superior colliculus
Optic radiation
Primary visual cortex


Left visual field
Right visual field
Temporal
Nasal
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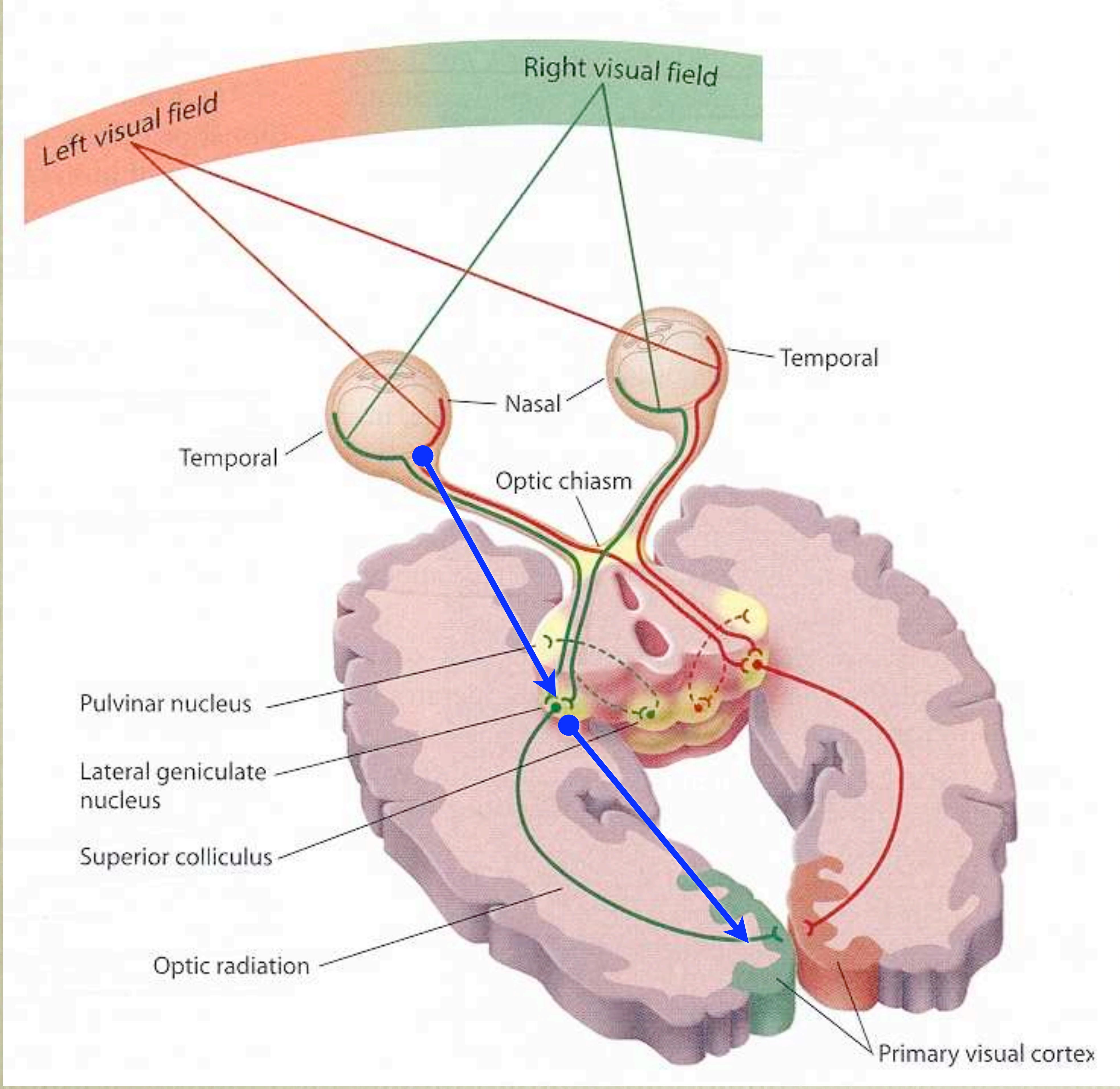
Lateral geniculate nucleus
Superior colliculus
Optic radiation
Primary visual cortex


Left visual field
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Temporal
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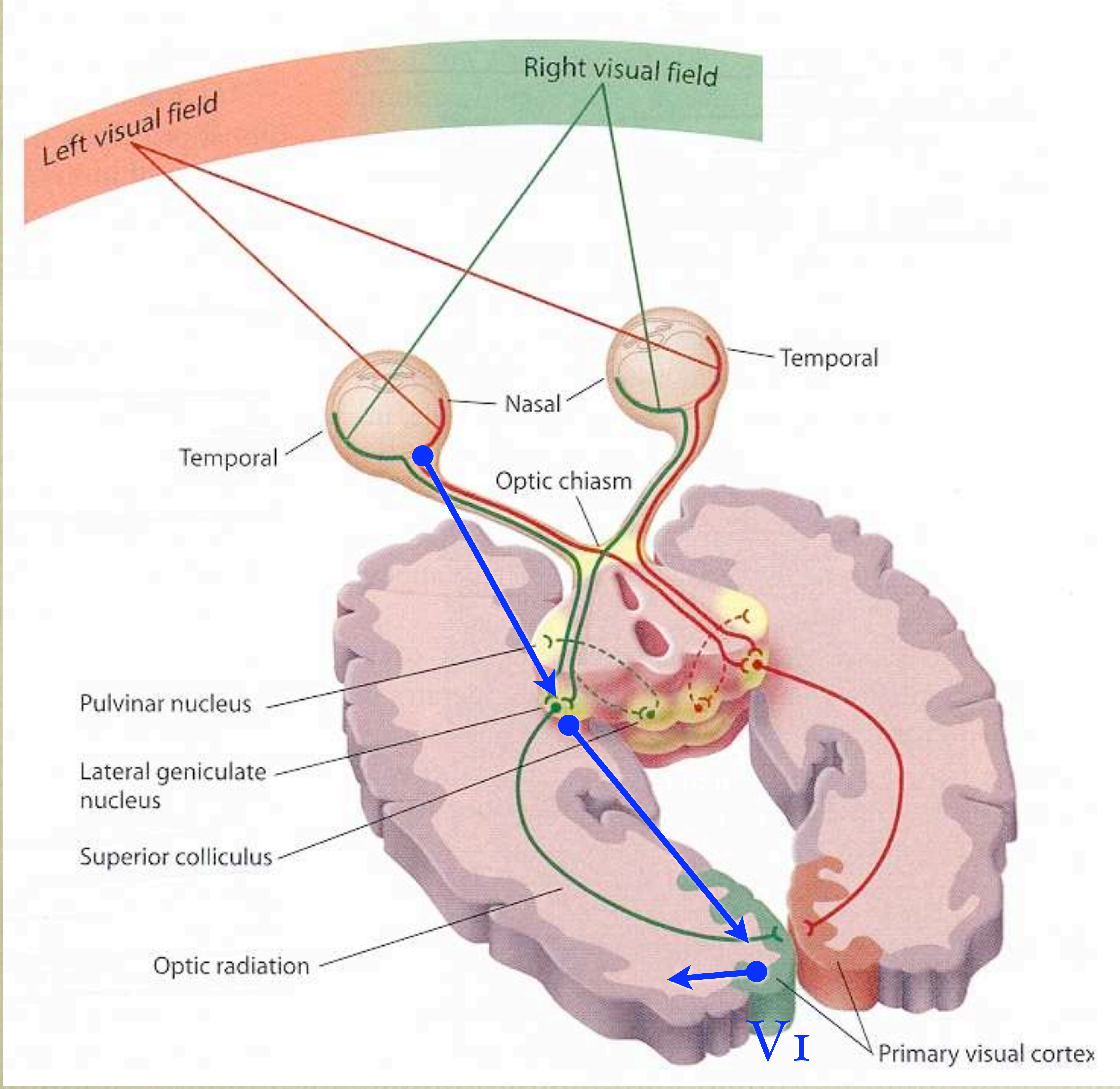
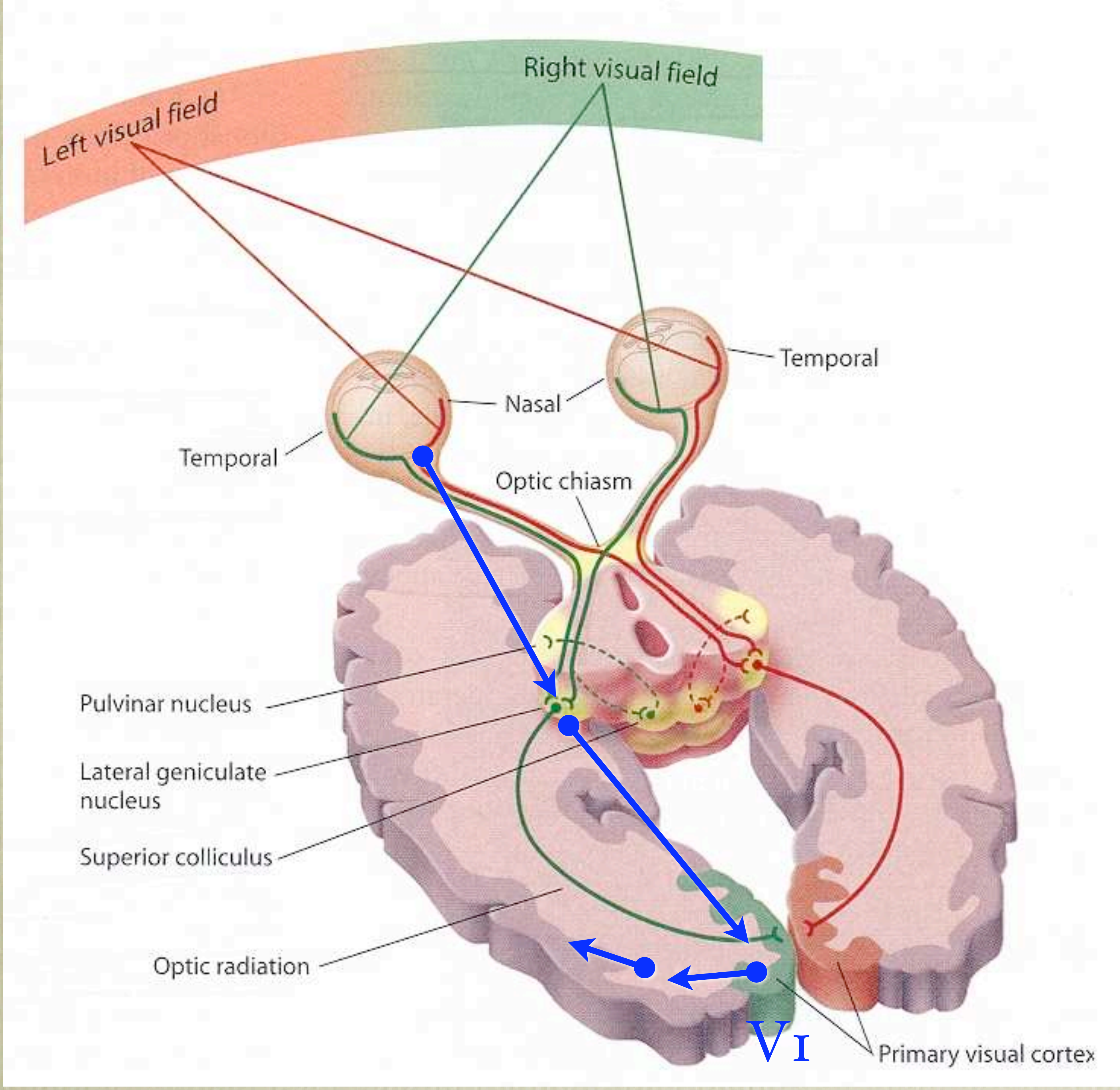
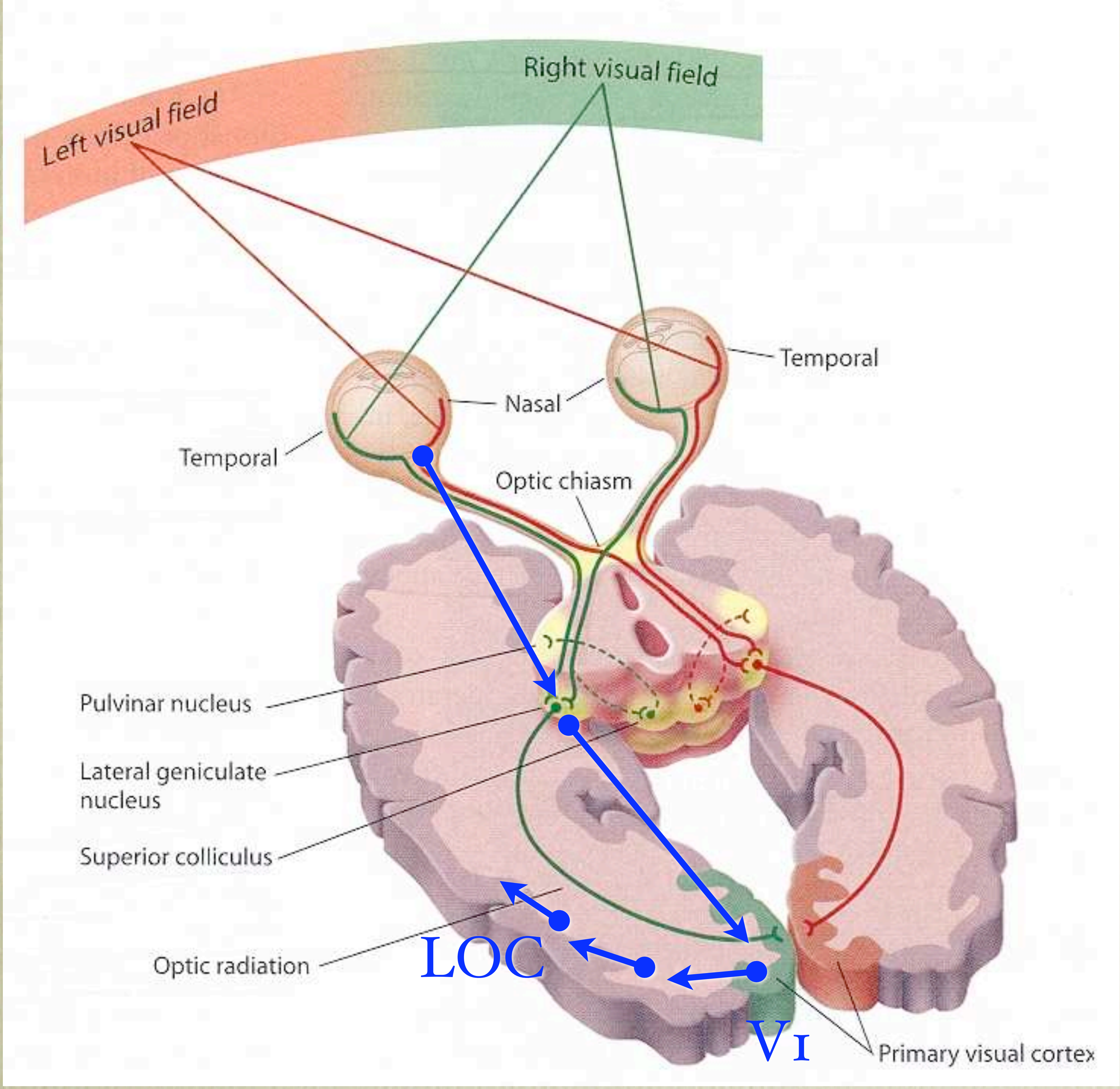
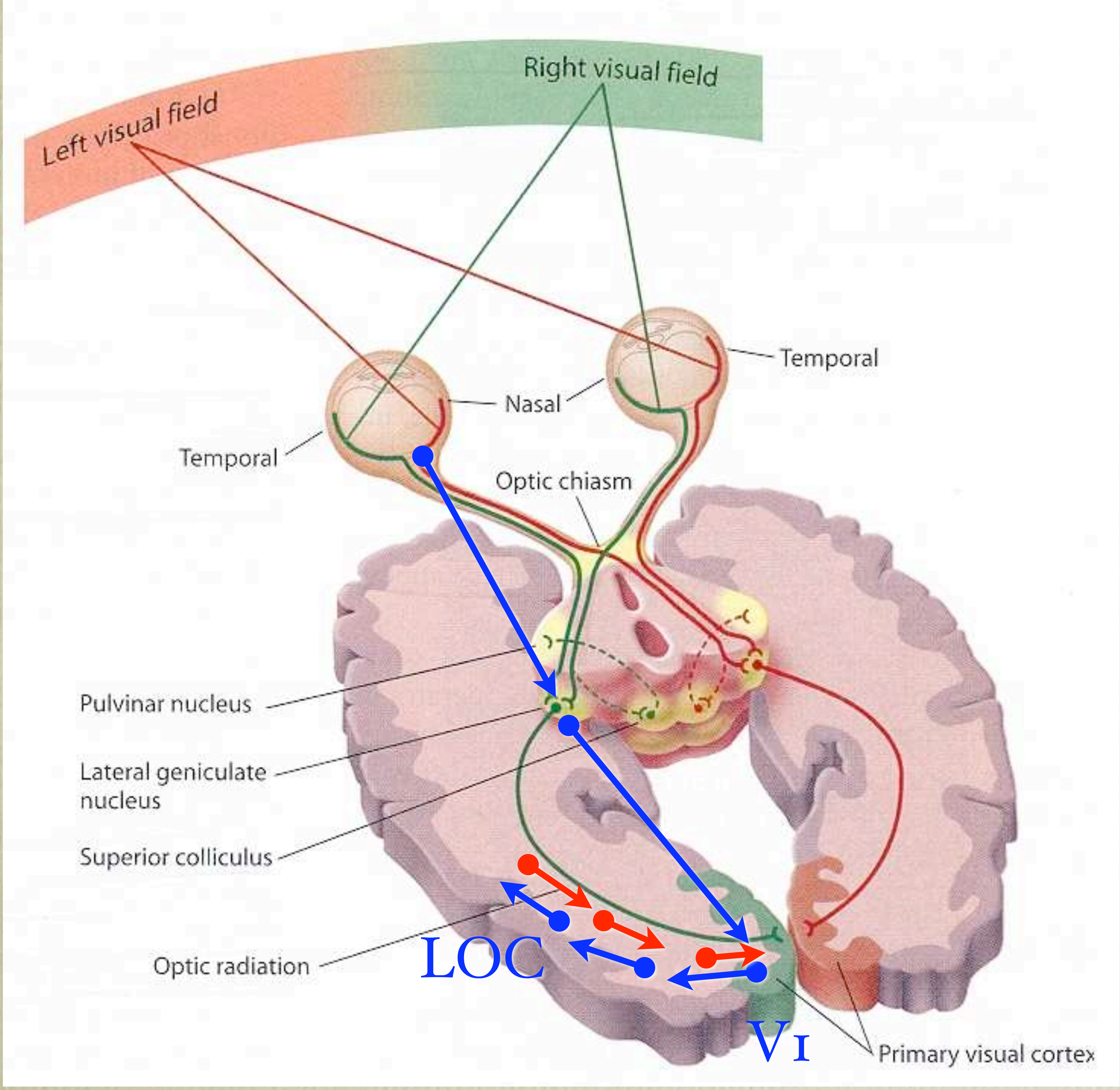


Left visual field
Right visual field
Temporal
Nasal
Temporal
Optic chiasm
Pulvinar nucleus
Lateral geniculate nucleus
Superior colliculus
Optic radiation
V1
Primary visual cortex



Left visual field
Right visual field
Temporal
Nasal
Temporal
Optic chiasm
Pulvinar nucleus
Lateral geniculate nucleus
Superior colliculus
Optic radiation
V1
Primary visual cortex


Left visual field
Right visual field
Temporal
Nasal
Temporal
Optic chiasm
Pulvinar nucleus
Lateral geniculate nucleus
Superior colliculus
Optic radiation
LOC
V1
Primary visual cortex



Left visual field
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Optic chiasm
Pulvinar nucleus
Lateral geniculate nucleus
Superior colliculus
Optic radiation
LOC
V1
Primary visual cortex

Cortical Mechanism?
...some speculation

MacKay DM (1956) The epistemological problem for automata. In: Automata Studies (Shannon CE, McCarthy J, eds), pp 235-250. Princeton: Princeton University Press.

Cortical Mechanism? ...some speculation

1. Feedforward: local features to objects

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Cortical Mechanism? ...some speculation

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    a. Feedforward + attention:

MacKay DM (1956) The epistemological problem for automata. In: Automata Studies (Shannon CE, McCarthy J, eds), pp 235-250. Princeton: Princeton University Press.

Cortical Mechanism? ...some speculation

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   a. Feedforward + attention:

      competitive selection of features

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Cortical Mechanism? ...some speculation

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Cortical Mechanism? ...some speculation

1. Feedforward: local features to objects
2. Feedback models
    a. Feedforward + attention:

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    b. Predictive coding
    c. Sparsification

MacKay DM (1956) The epistemological problem for automata. In: Automata Studies (Shannon CE, McCarthy J, eds), pp 235-250. Princeton: Princeton University Press.

Cortical Mechanism? ...some speculation

1. Feedforward: local features to objects

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   a. Feedforward + attention:

      competitive selection of features

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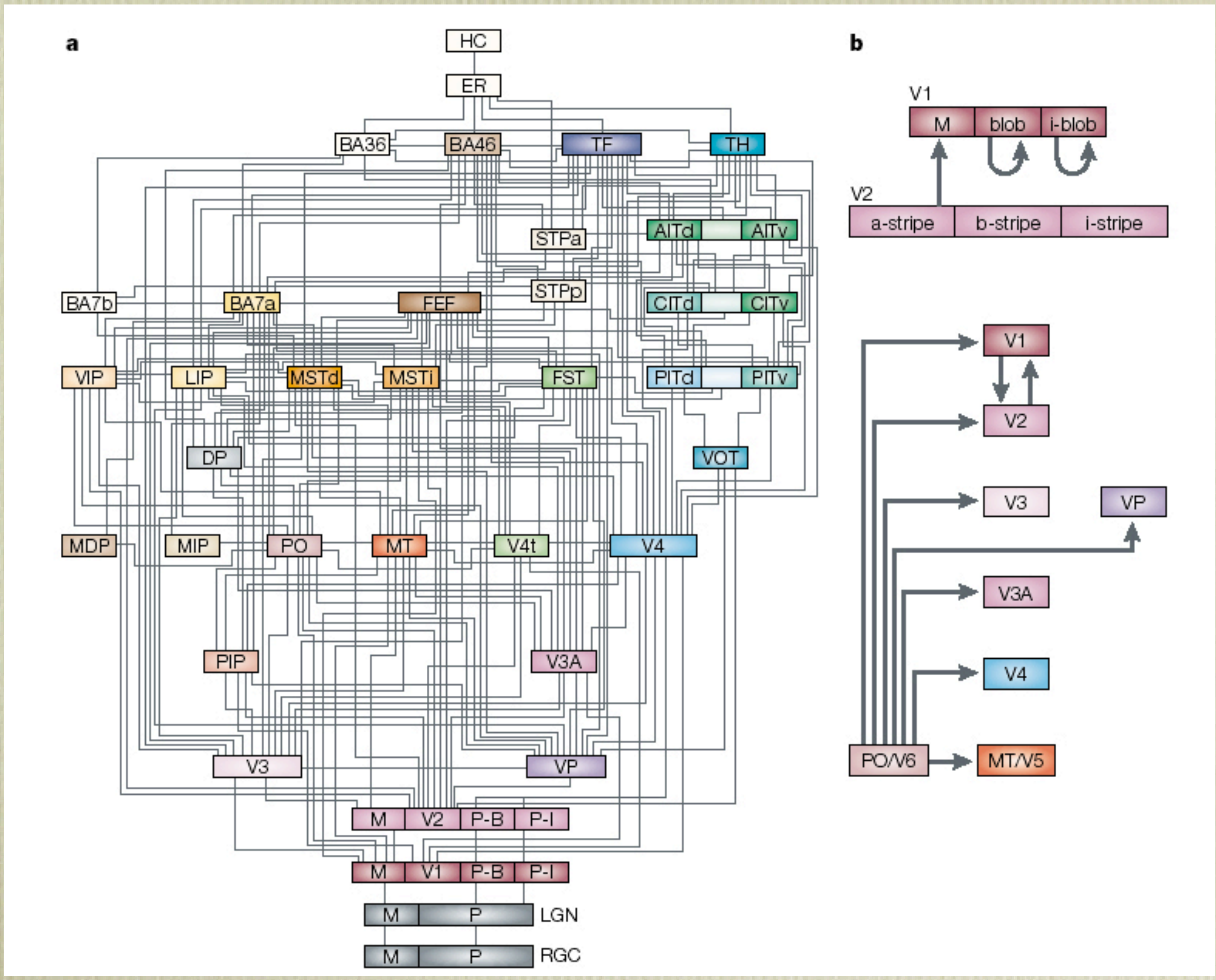
Internal generative models

MacKay DM (1956) The epistemological problem for automata. In: Automata Studies (Shannon CE, McCarthy J, eds), pp 235-250. Princeton: Princeton University Press.

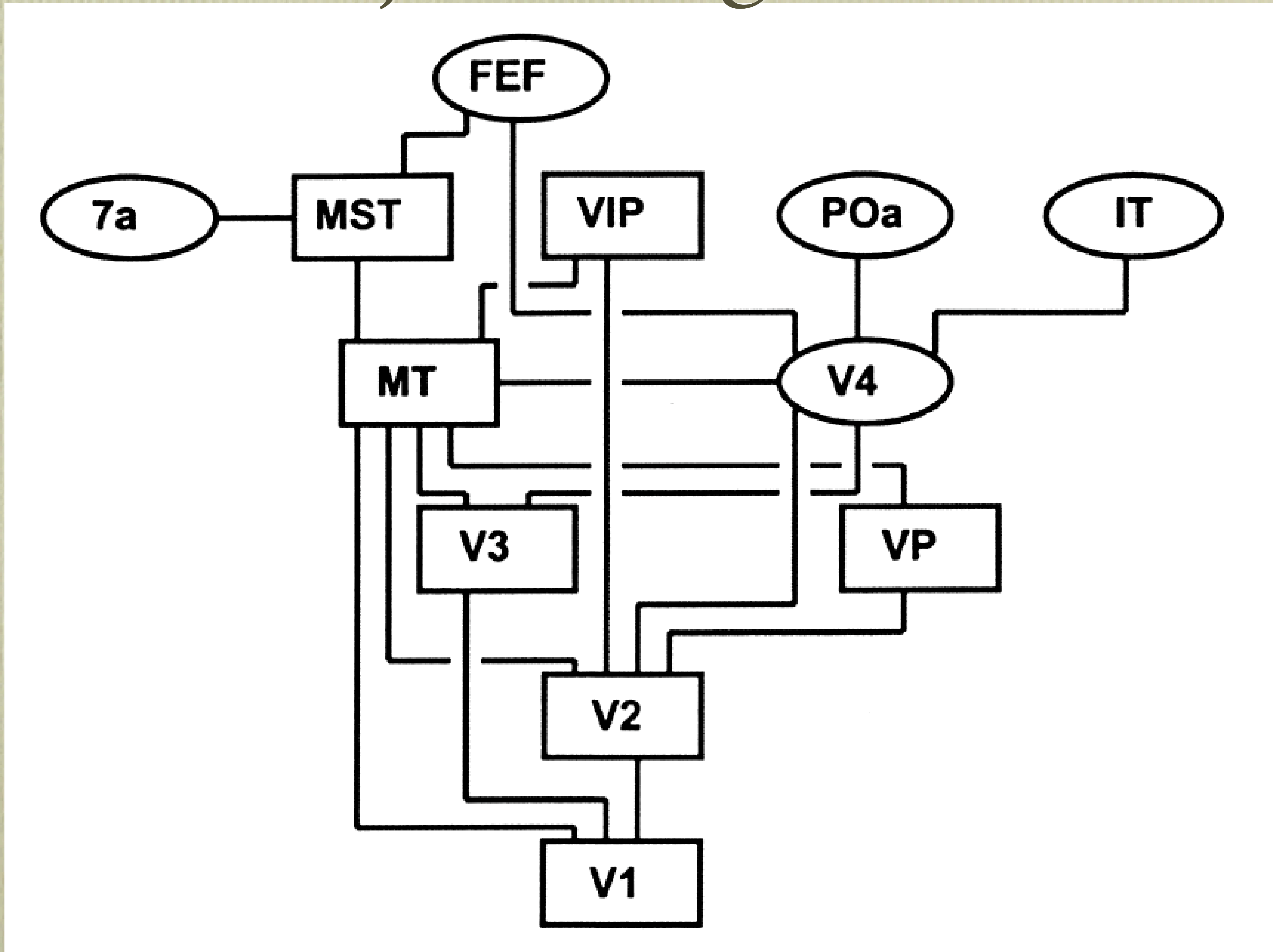
Cortical organization



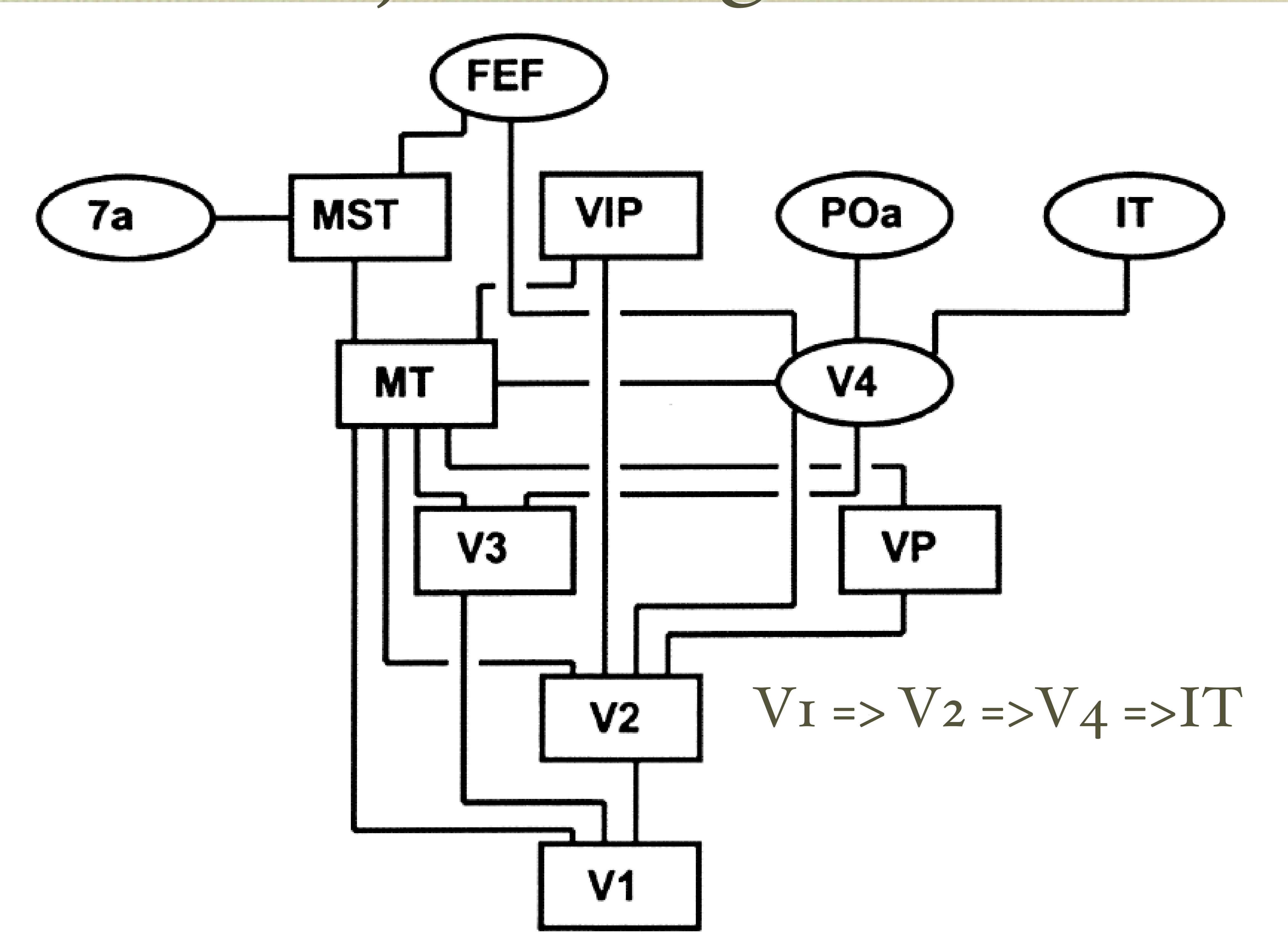
Cortical organization

- Organization of visual cortices is a hierarchy
- Depends on distinct feedforward/feedback pathways
- Different laminar specificity
- More backward connections
- Backward connections more diffuse

Object recognition?

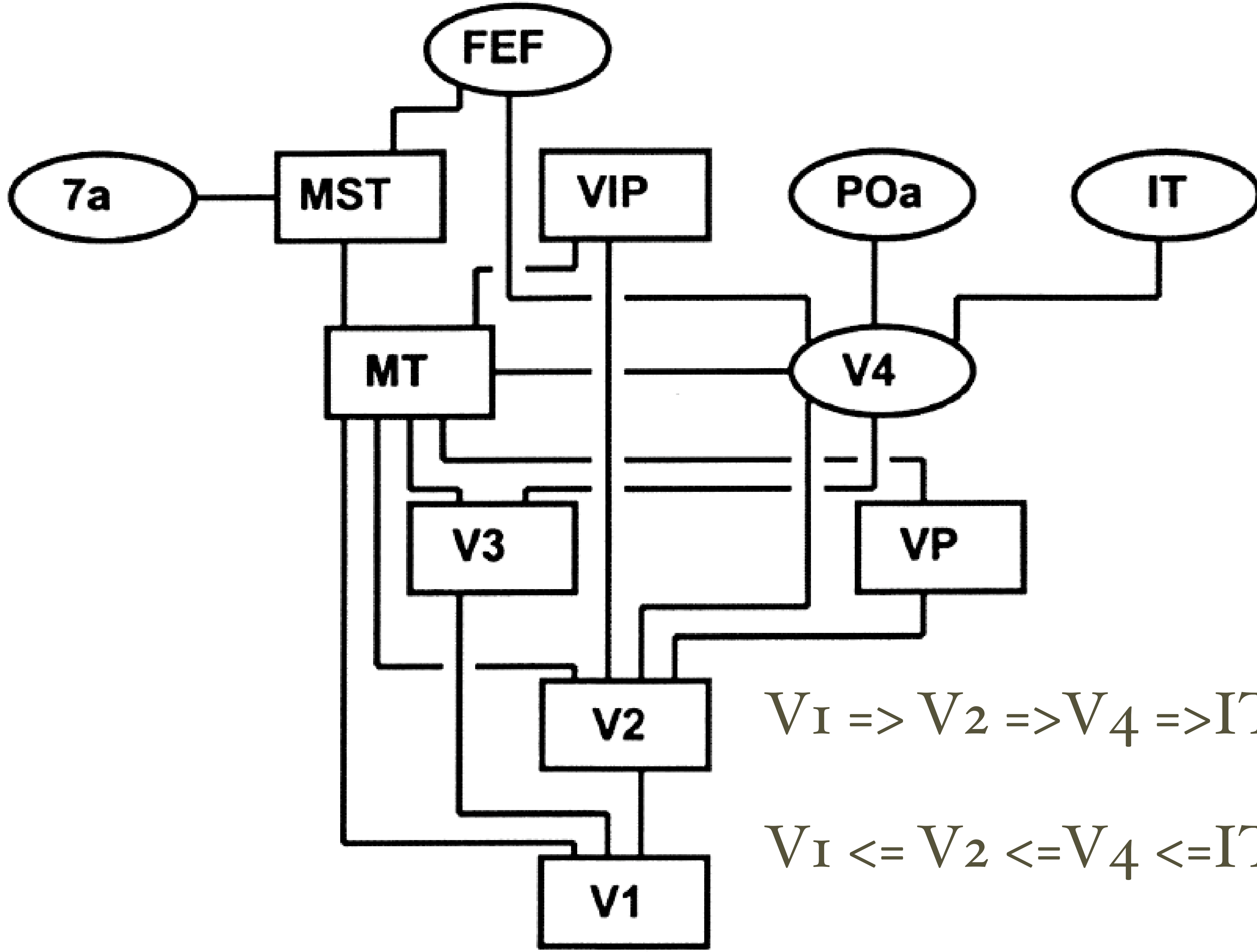


Object recognition?



V1 => V2 =>V4 =>IT

Object recognition?



V1 => V2 =>V4 =>IT

V1 <= V2 <=V4 <=IT

Forward connections

- Sparse axonal bifurcations
- Topographically organized
- Originate in supragranular layers (I,II,III)
  - III => adjacent columns
  - II => other cortical areas
- Terminate in layer IV

Friston K (2003) Learning and inference in the brain. Neural Netw 16:1325-1352.

Feedback connections

- Lots of axonal bifurcation
- Diffuse topography
- Originate in infragranular (V, VI) layers
- Mainly terminate in supragranular layers (I,II,III)

Friston K (2003) Learning and inference in the brain. Neural Netw 16:1325-1352.

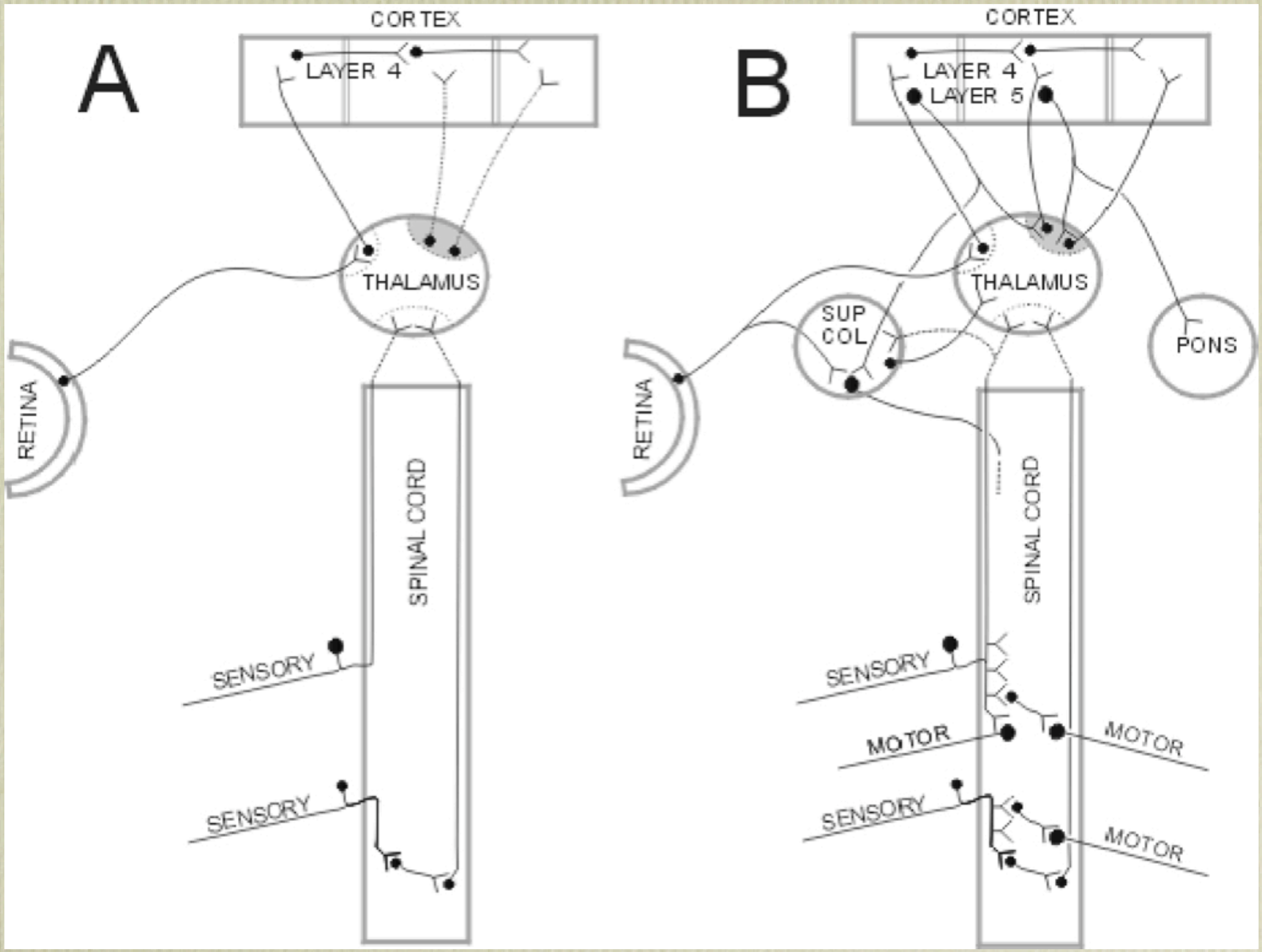


Figure courtesy of Ray Guillery

Internal generative models

Analysis-by-synthesis

Internal generative models

Analysis-by-synthesis

Predictive coding

Internal generative models
Analysis-by-synthesis

Predictive coding

- High-level object models project back predictions of the incoming data

Internal generative models
Analysis-by-synthesis

Predictive coding

- High-level object models project back predictions of the incoming data

  Poor fit, high residual => high activity

Internal generative models

Analysis-by-synthesis

Predictive coding

- High-level object models project back predictions of the incoming data

  Poor fit, high residual => high activity

Sparsification

Internal generative models

Analysis-by-synthesis

Predictive coding

- High-level object models project back predictions of the incoming data

  Poor fit, high residual => high activity

Sparsification

- A good high-level fit tells earlier areas to "stop gossiping"

Internal generative models

Analysis-by-synthesis

Predictive coding

- High-level object models project back predictions of the incoming data

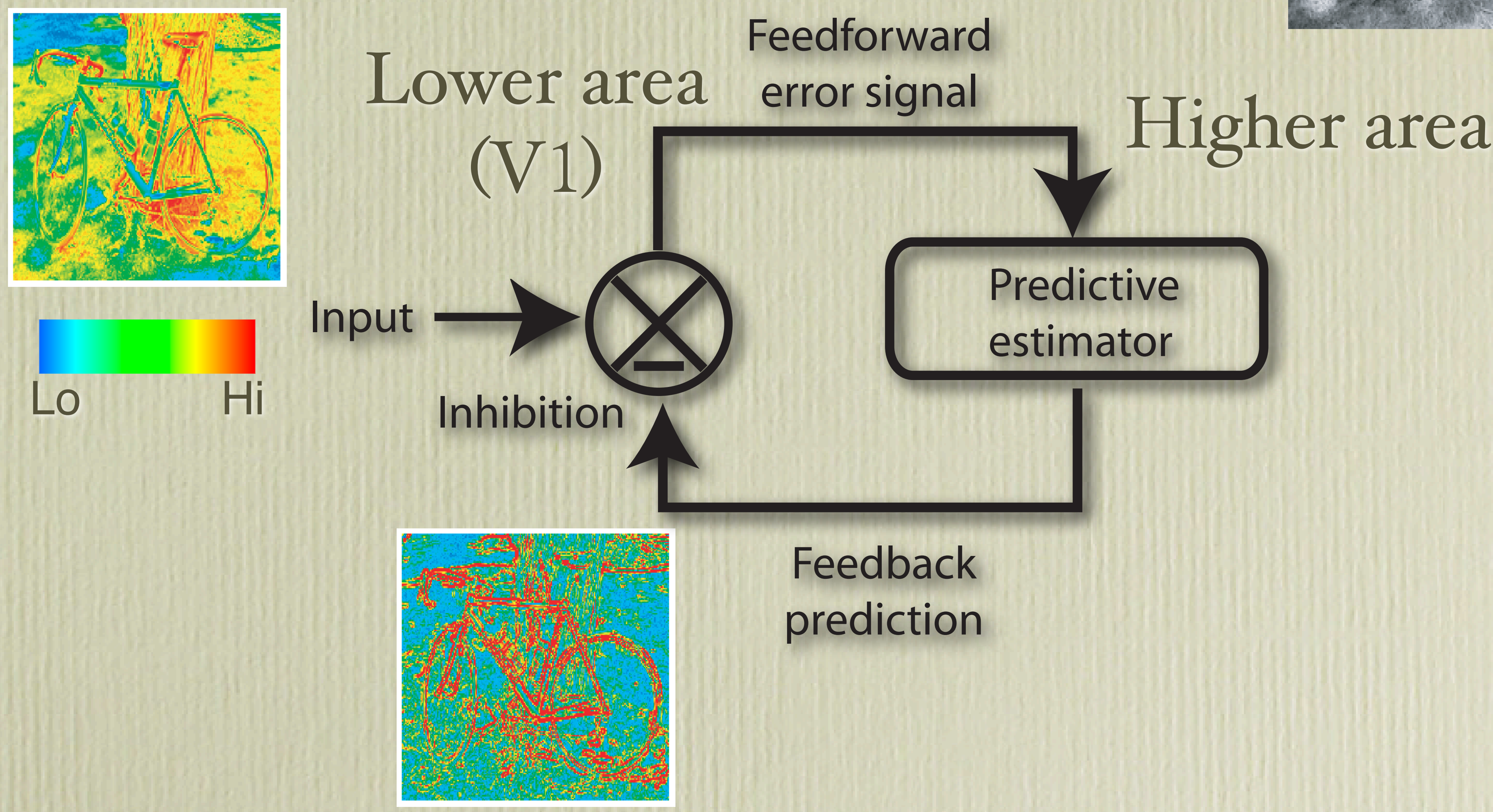
  Poor fit, high residual => high activity

Sparsification

- A good high-level fit tells earlier areas to "stop gossiping"

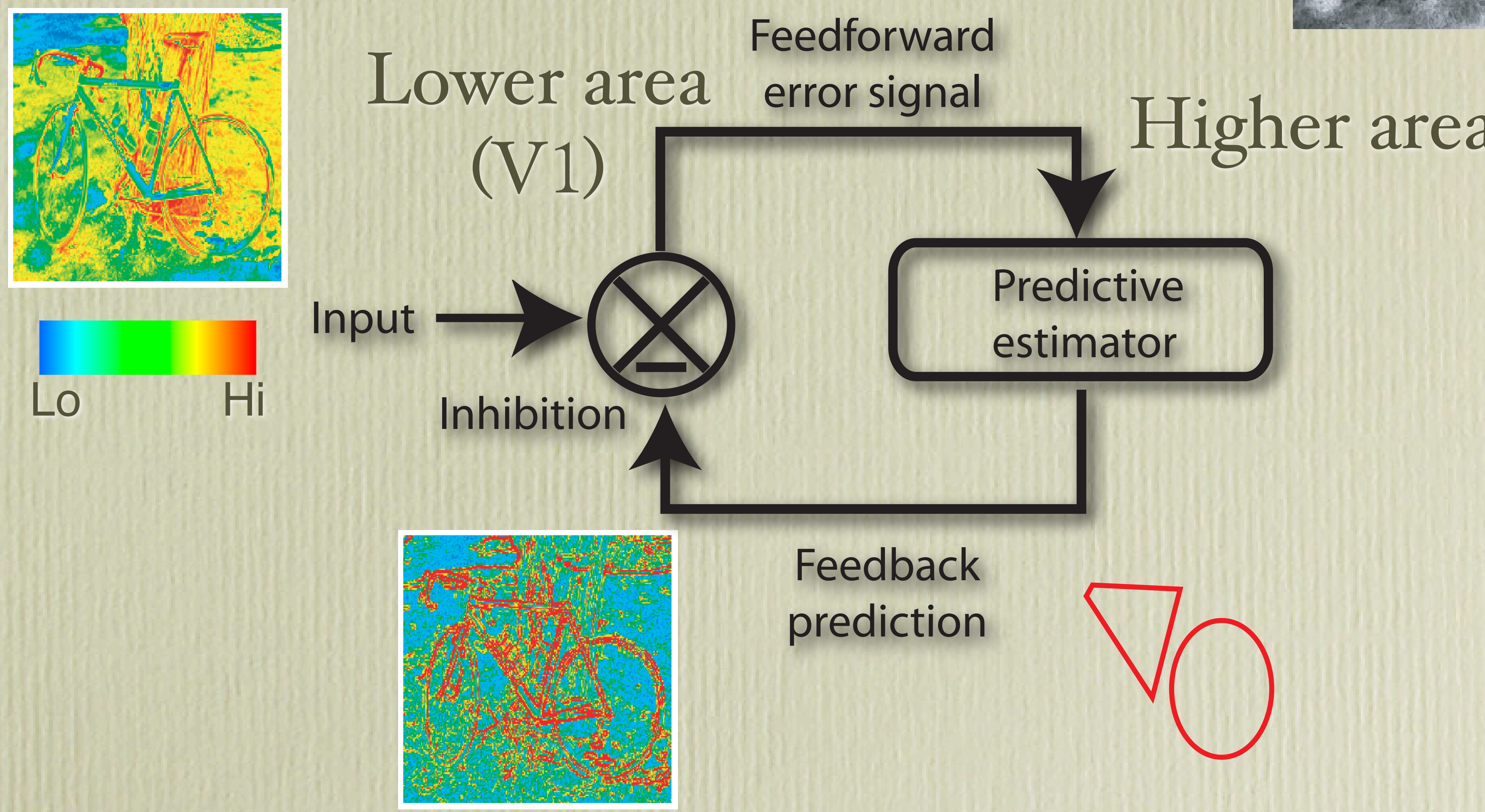
  Amplify the activity for early features that belong to object, suppress the rest

Predictive (top-down) processes in the brain?

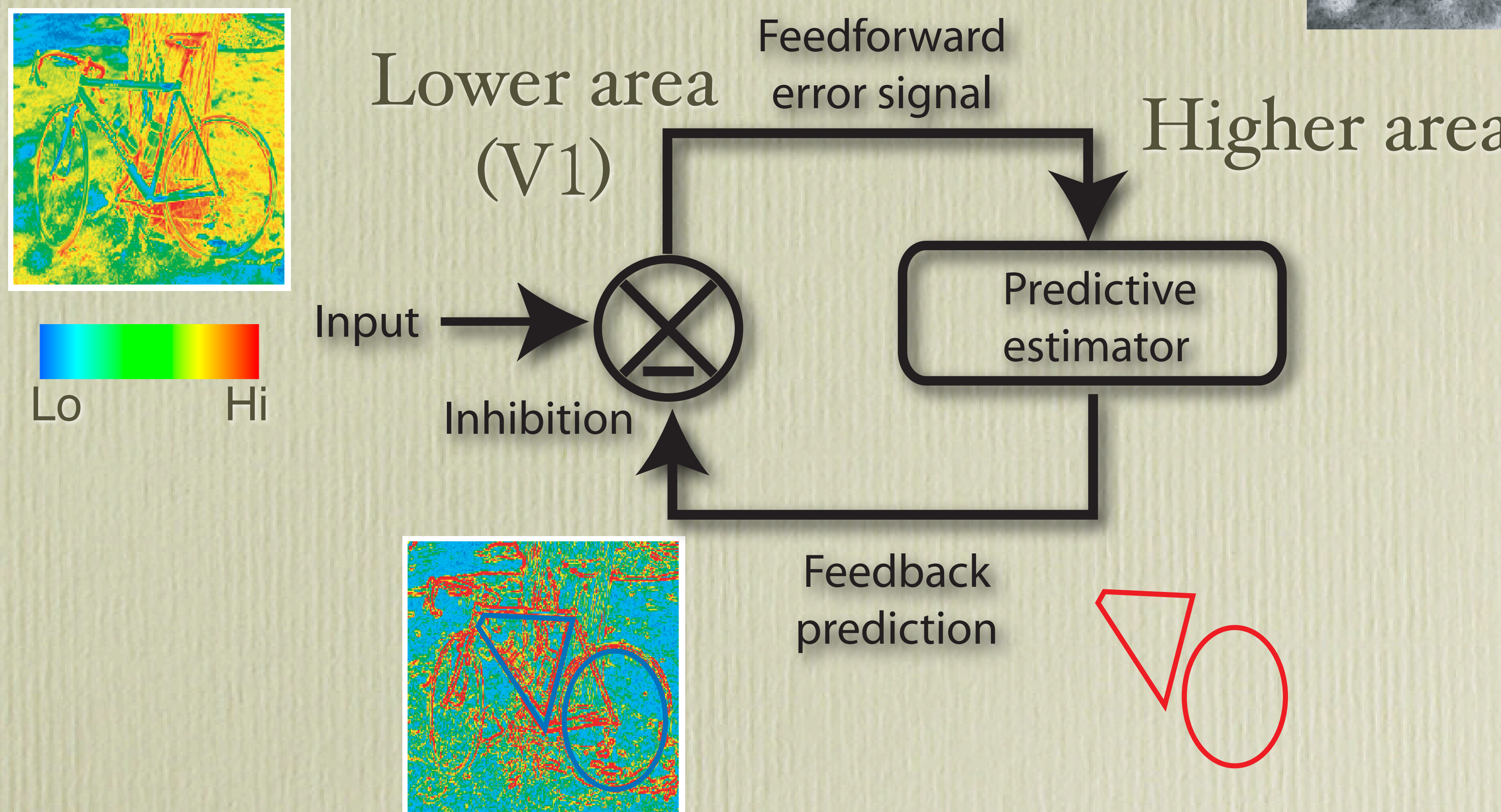


e.g. Rao, R. P., & Ballard, D. H. (1997). Dynamic model of visual recognition predicts neural response properties in the visual cortex. Neural Comput, 9(4), 721-763.

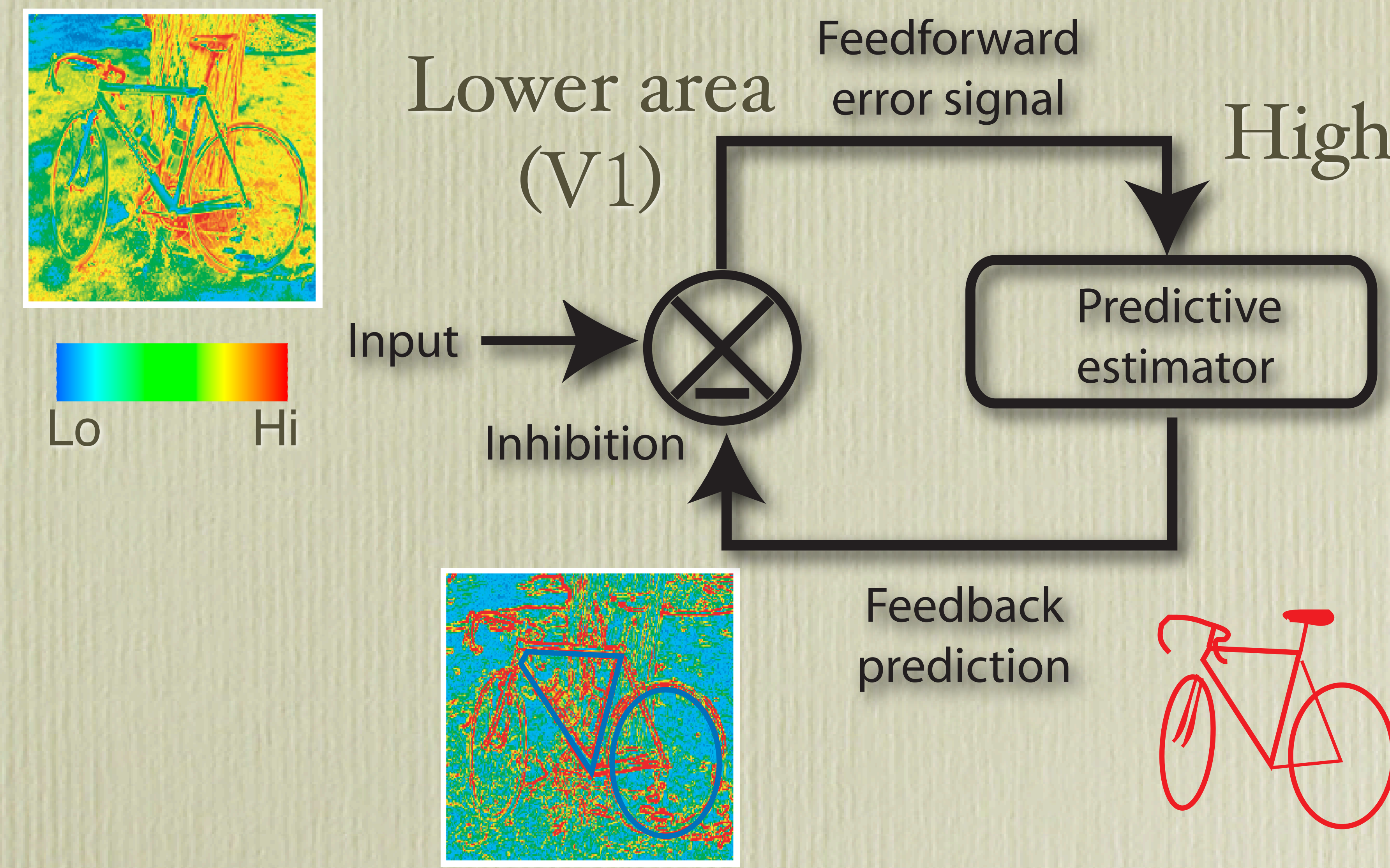
Predictive coding



Predictive coding



Predictive coding



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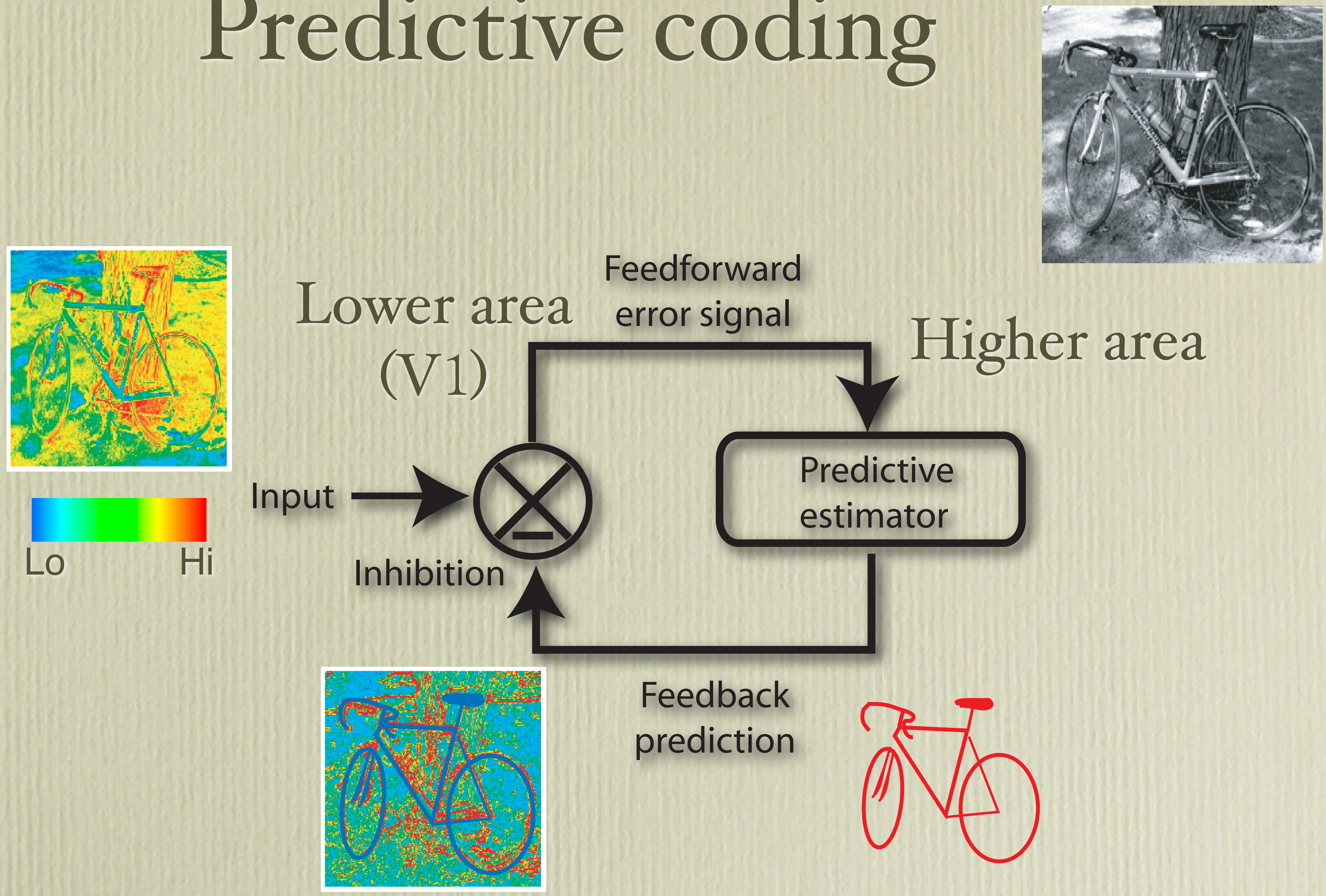
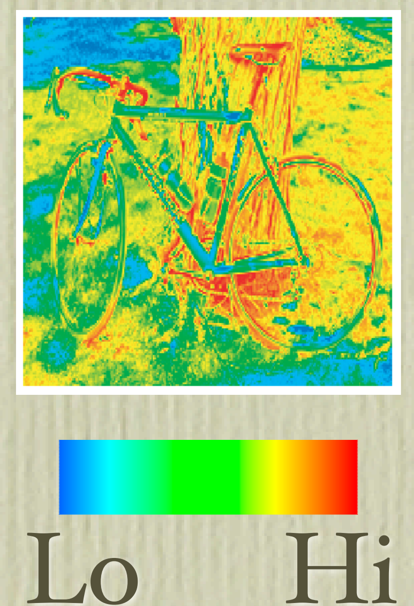
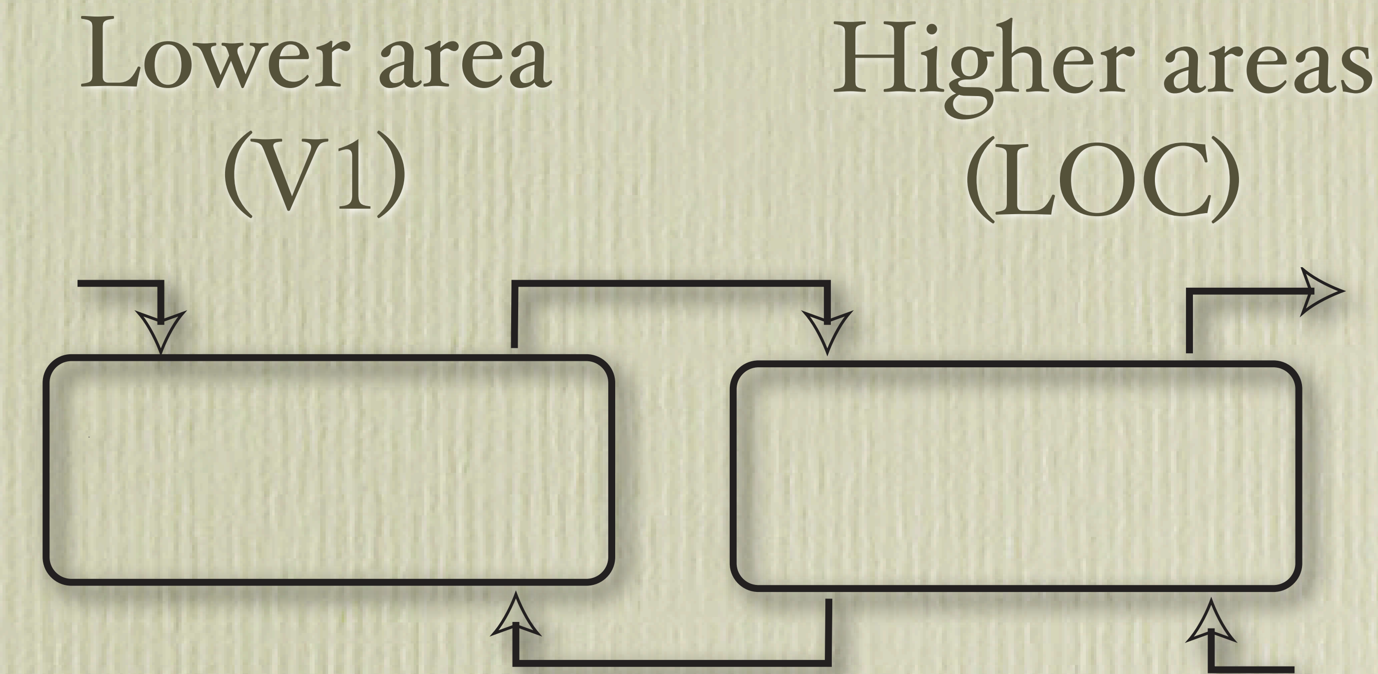
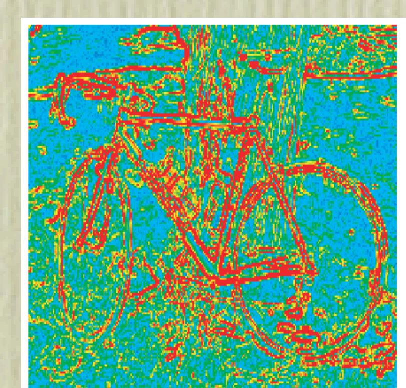


Sparsification

"Stop gossiping"







Grossberg S (1994) 3-D vision and figure-ground separation by visual cortex. Percept Psychophys 55:48-121.

Sparsification

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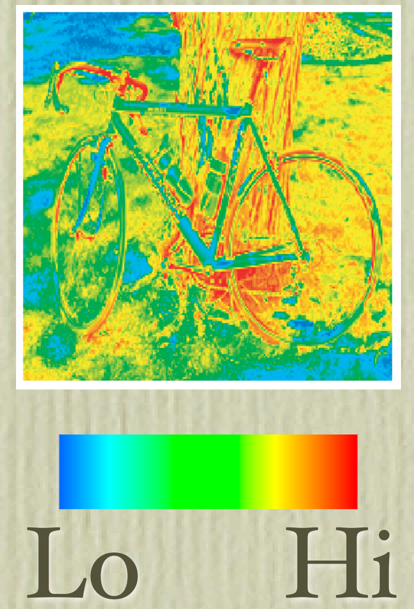

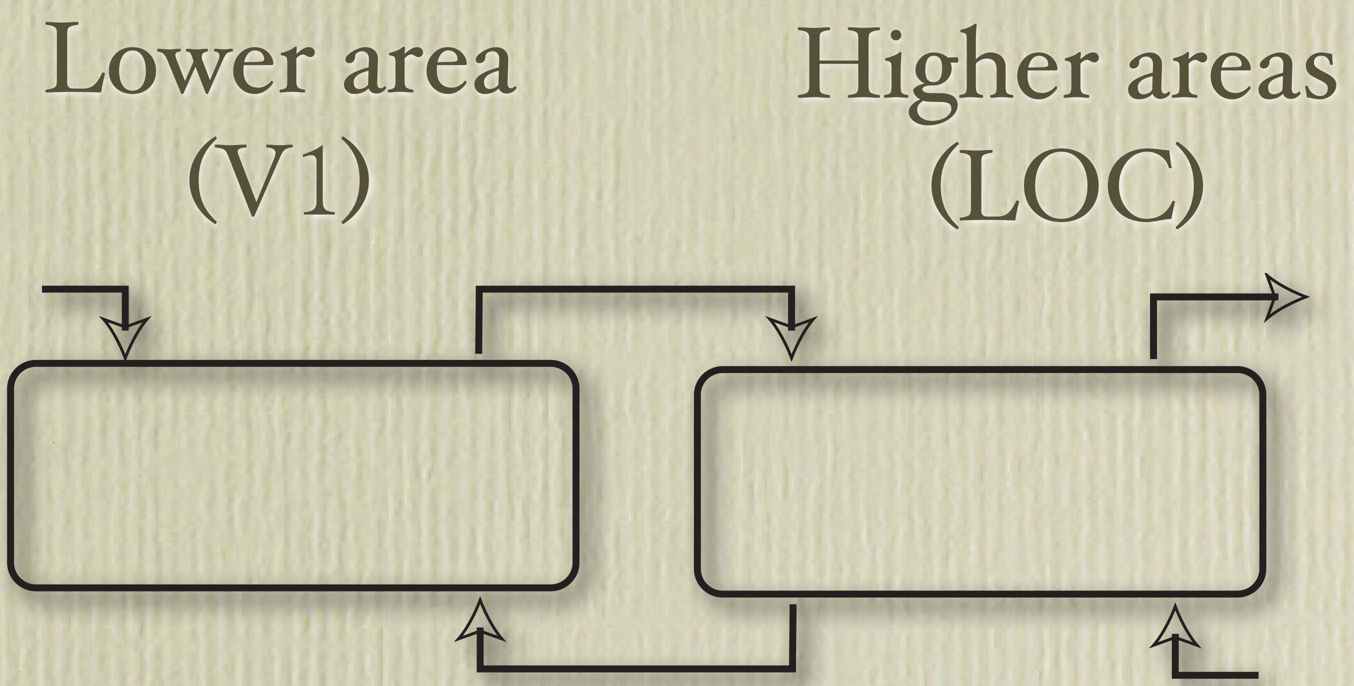

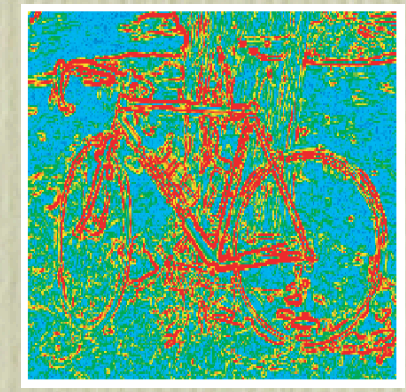

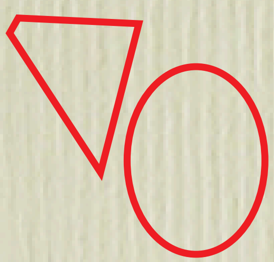

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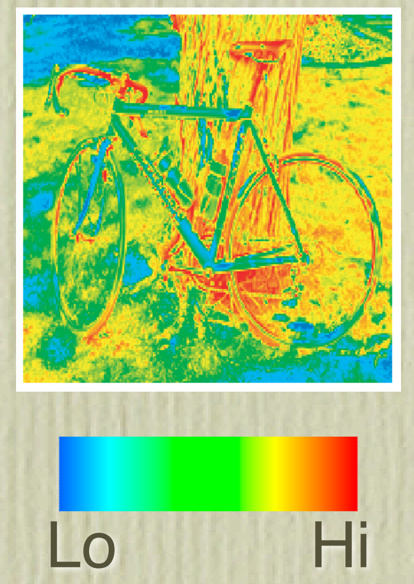
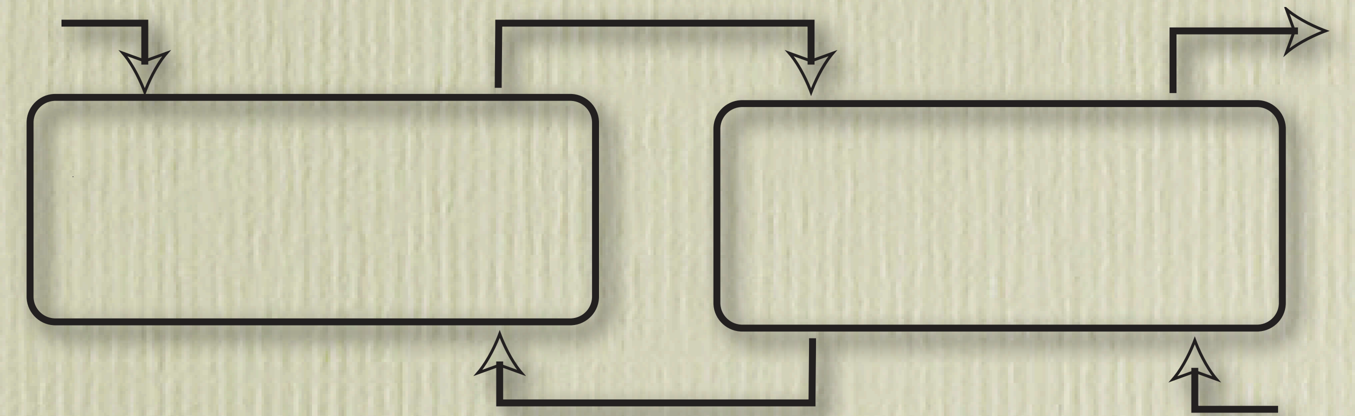
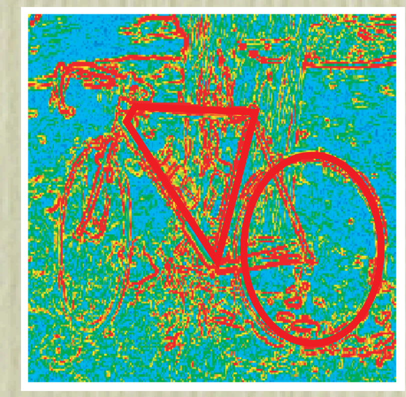
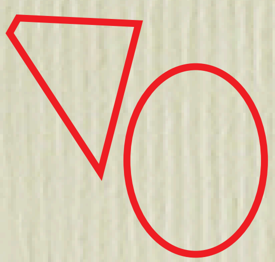


Lower area (V1)

Higher areas (LOC)







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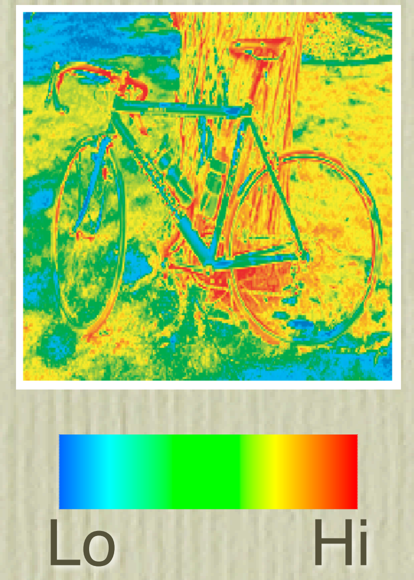

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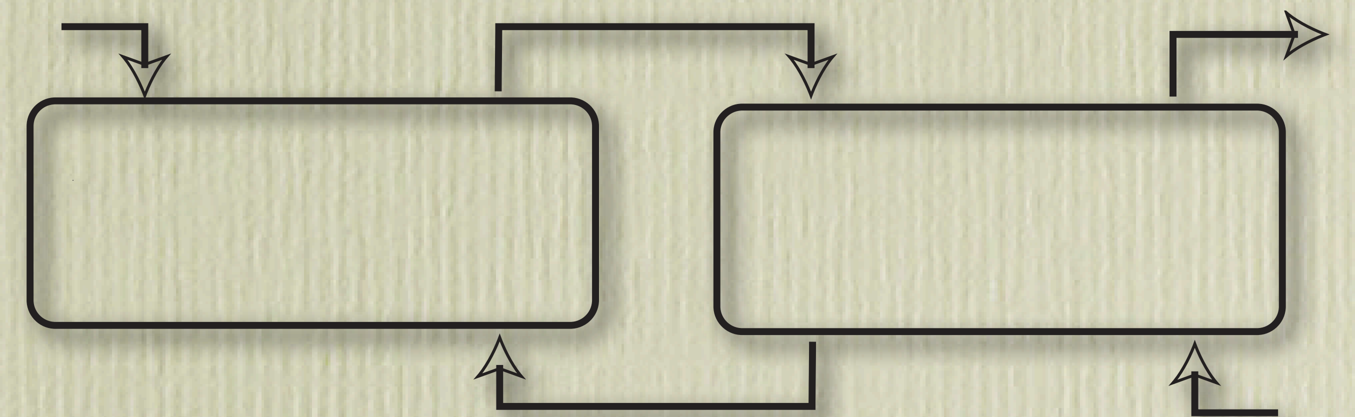

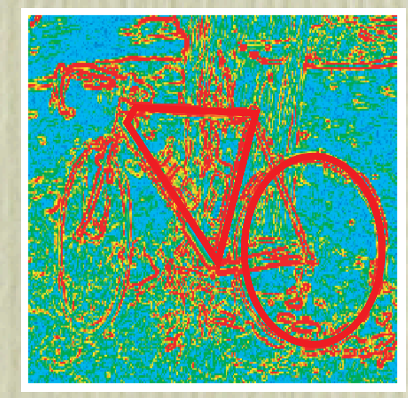

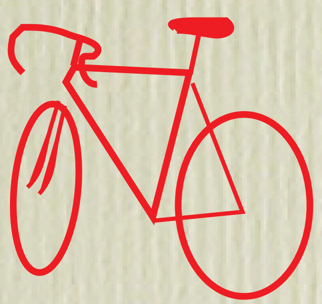

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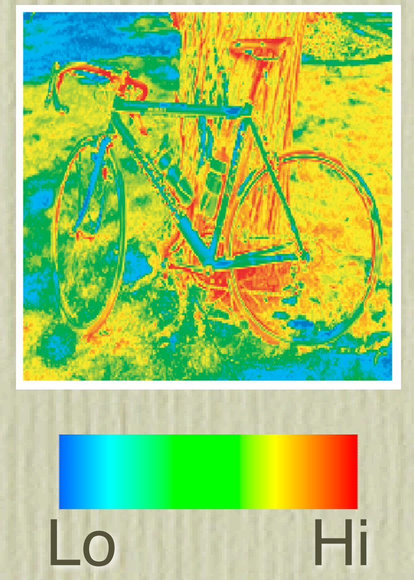

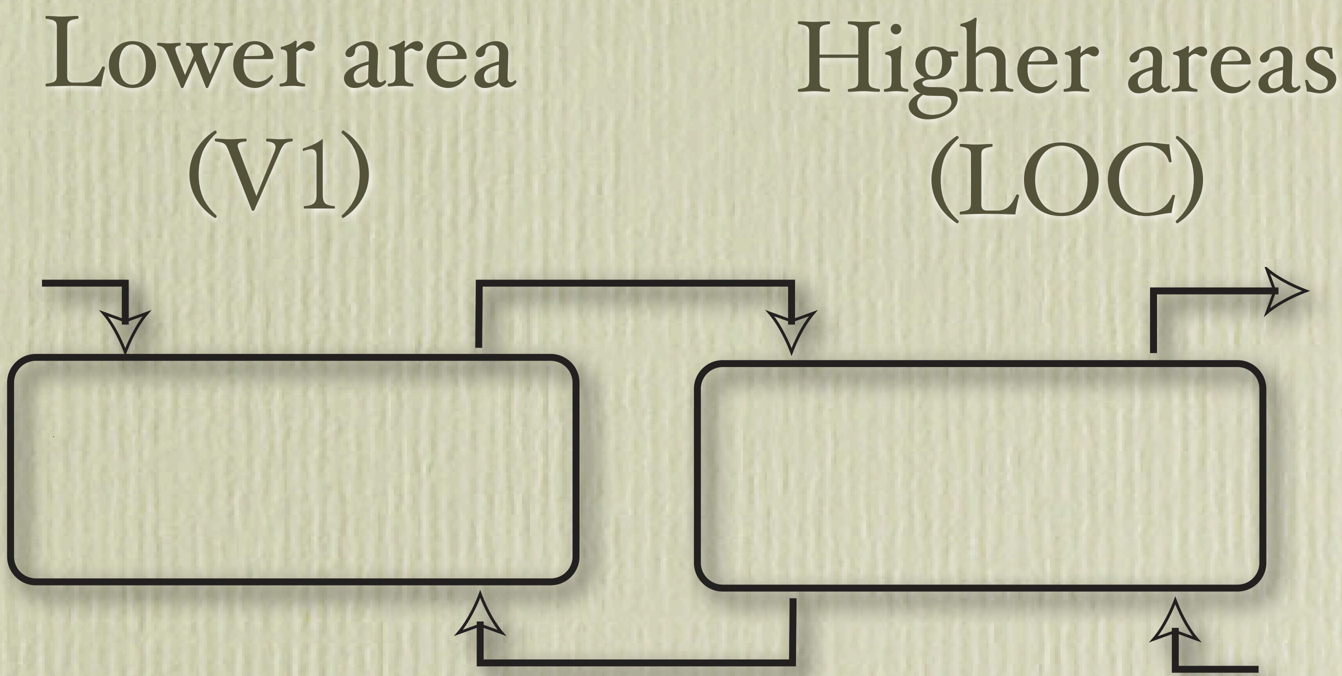

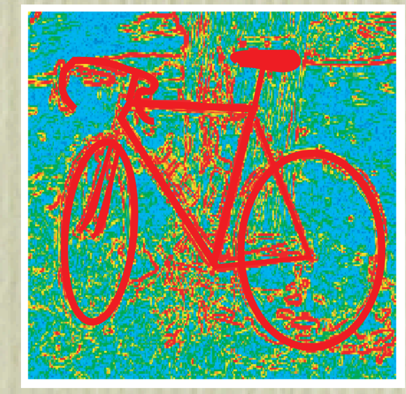

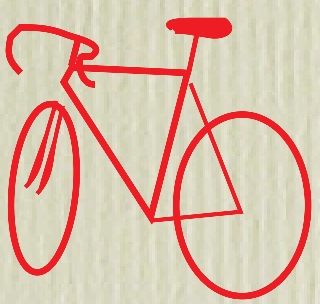

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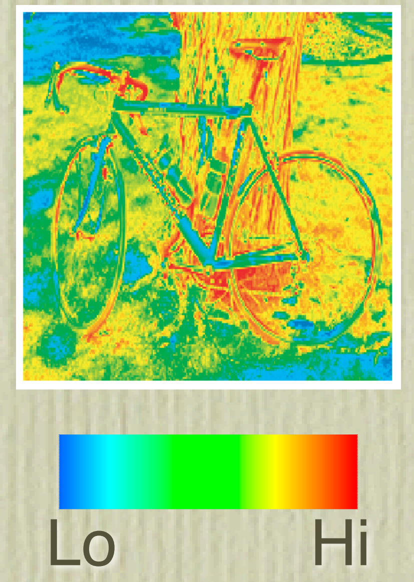

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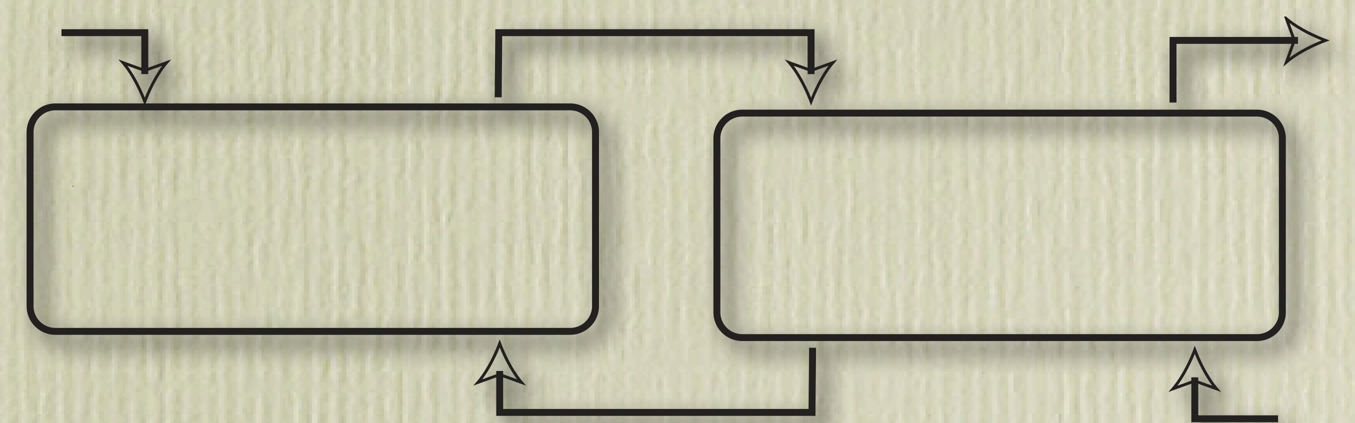

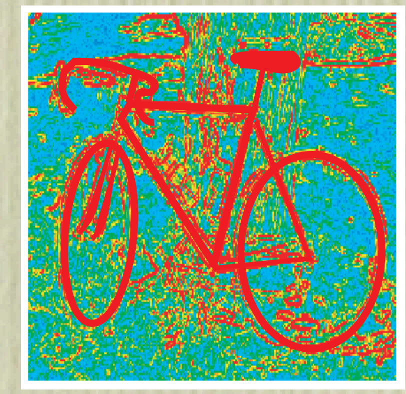

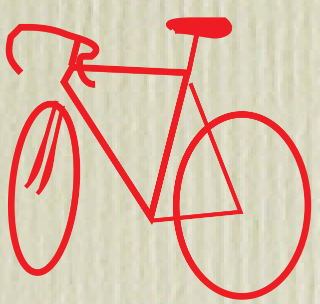

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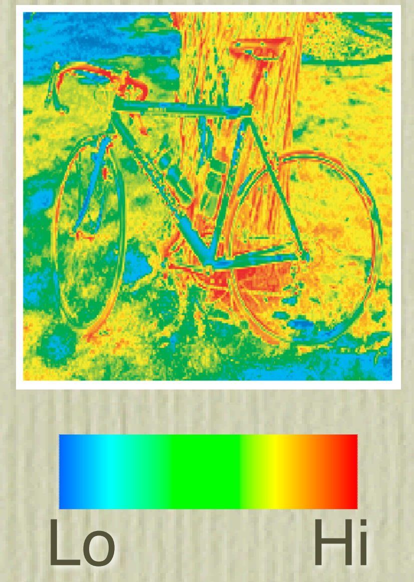

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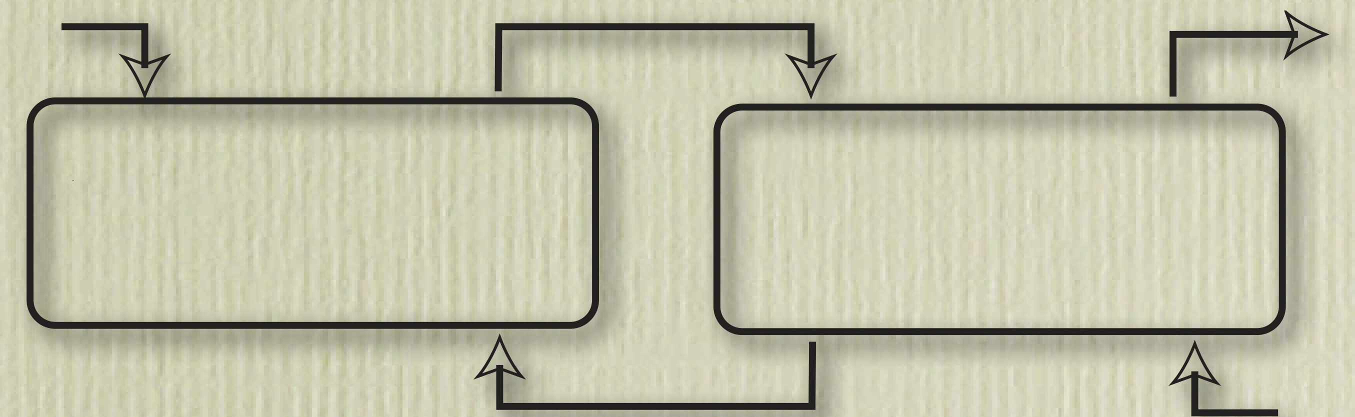
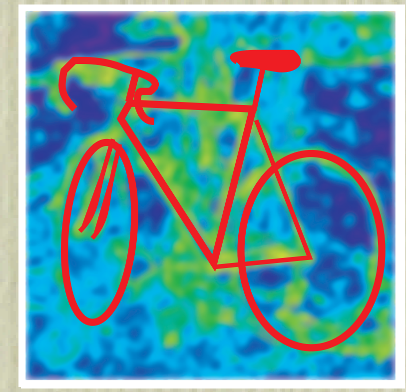
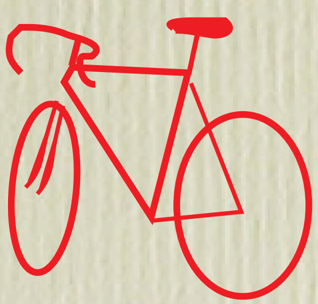
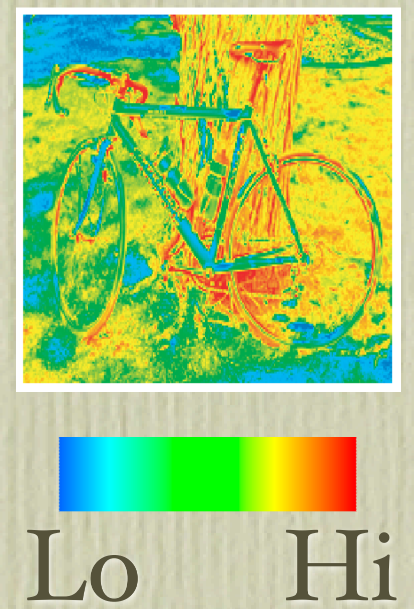






Bayesian Interpretation
Sparsification



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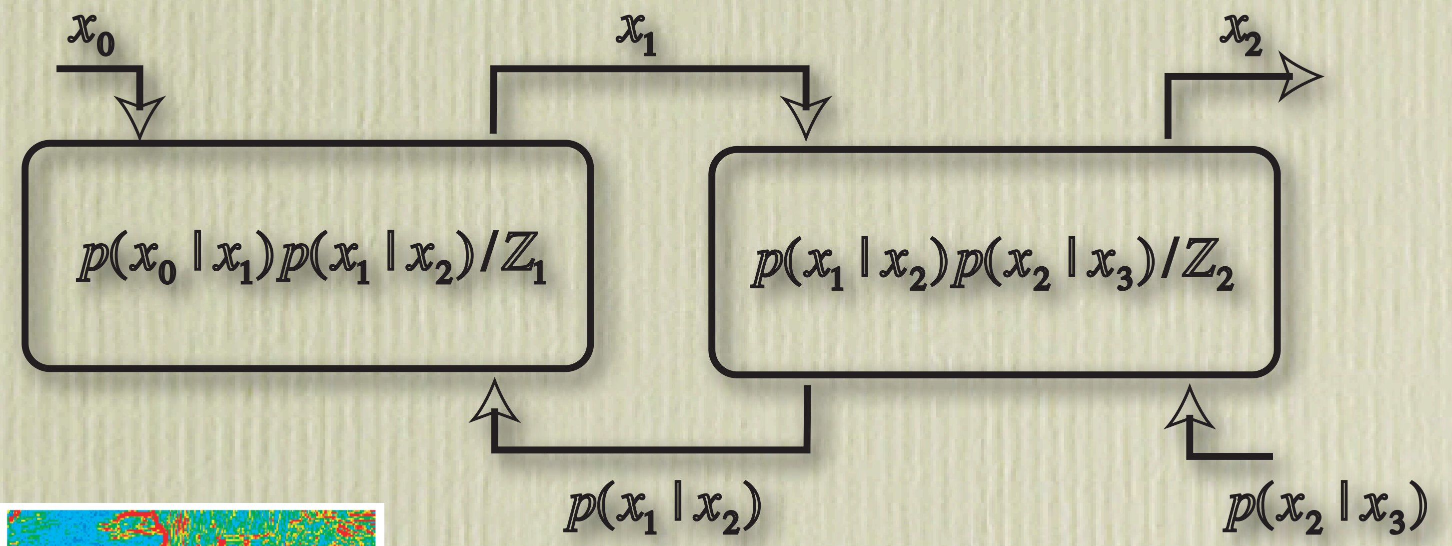

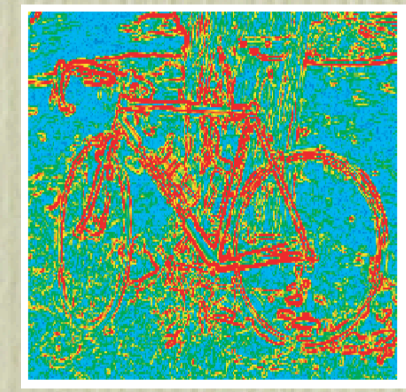

Lee & Mumford, 2003, JOSA

Particle filtering ideas: Isard M, Blake A (1998) Condensation -- conditional density propagation for visual tracking. International Journal of Computer Vision 29:5--28.

Summary

Common patterns of neocortex structure

- Has inspired lots of models of cortical information processing

Key target problem?

- Object perception given occlusion, clutter

fMRI and object grouping given occlusion

- consistent with feedback, but...