

## The role of top-down processing in segmentation & recognition

Object recognition, given real images

- clutter, occlusion, noise
- role of cortical architecture

# 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

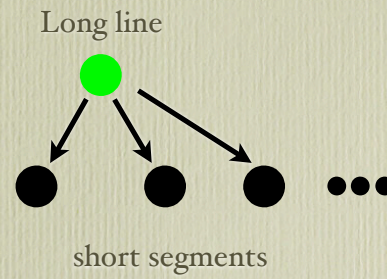
- local ambiguity, noise
- need for generic priors, e.g. smoothness, contour and region-based grouping

Resolving competing explanations

- occlusion, clutter
- need for domain-specific priors

# Simple influence graphs

## Cue integration

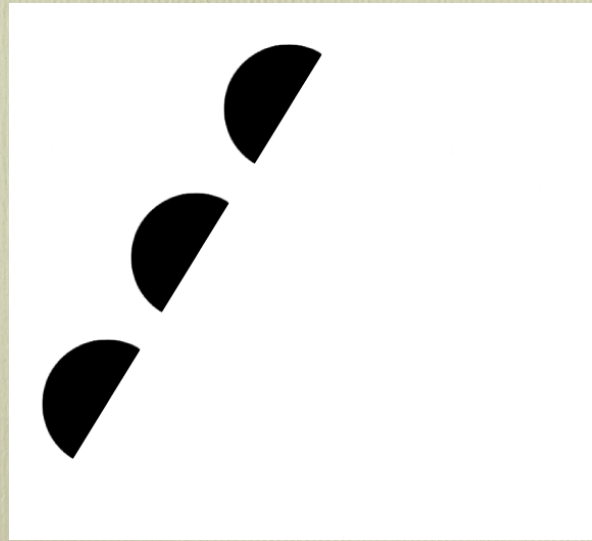


Parent P, Zucker SW (1989) Trace inference, curvature consistency, and curve detection. IEEE Transactions on Pattern Analysis & Machine Intelligence 11:823-839.

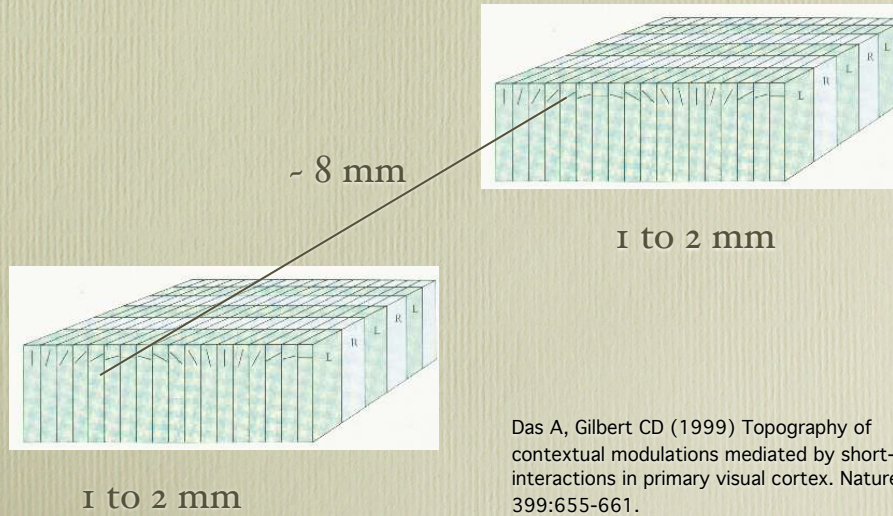
Yuille AL, Fang F, Schrater P, Kersten D (2004) Human and Ideal Observers for Detecting Image Curves. In: Advances in Neural Information Processing Systems 16 (Thrun S, Saul L, Schoelkopf B, eds). Cambridge, MA: MIT Press.



Cortical basis?

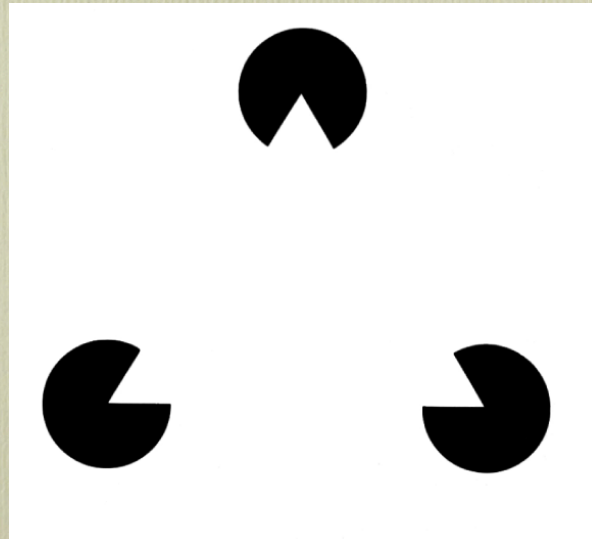


# Short segments to long lines? Within-area linkage?

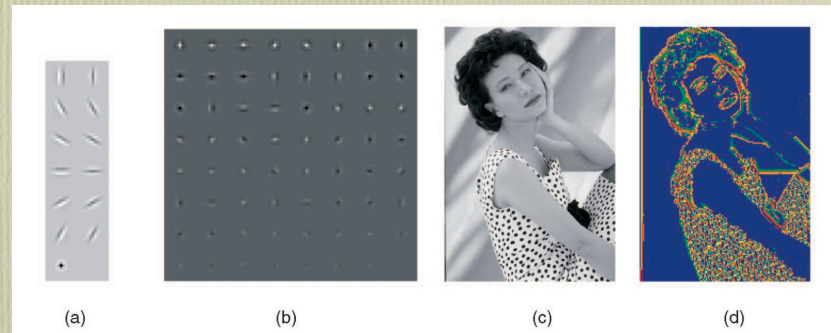


Das A, Gilbert CD (1999) Topography of contextual modulations mediated by short-range interactions in primary visual cortex. *Nature* 399:655-661.

But what about whole shapes?



# Region-based grouping



From: Martin, D. R., Fowlkes, C. C., & Malik, J. (2004). Learning to detect natural image boundaries using local brightness, color, and texture cues. *IEEE Trans Pattern Anal Mach Intell*, 26(5), 530-549.



# Object recognition given occlusion, clutter

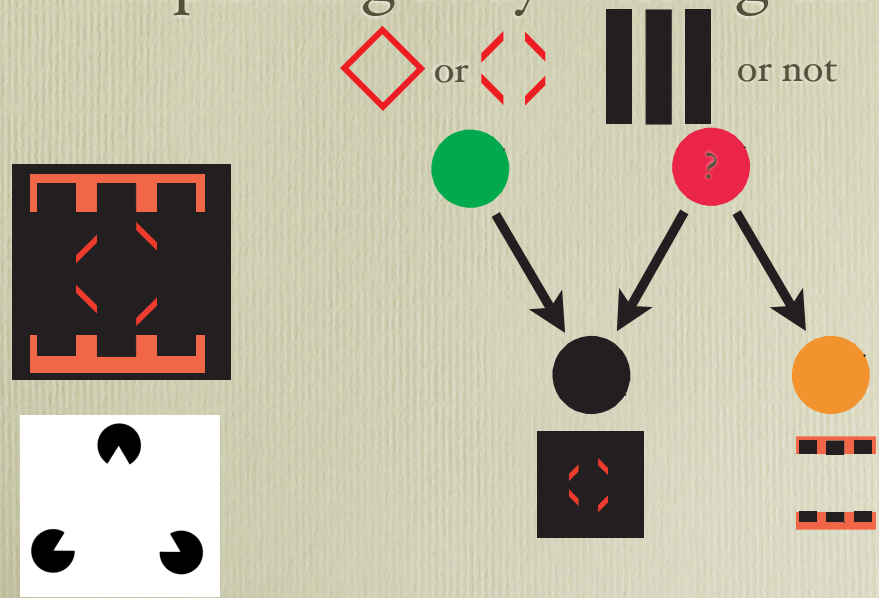
Linking local information (features) likely to belong to the same object or pattern

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

Resolving competing explanations

- occlusion, clutter
- need for domain-specific priors

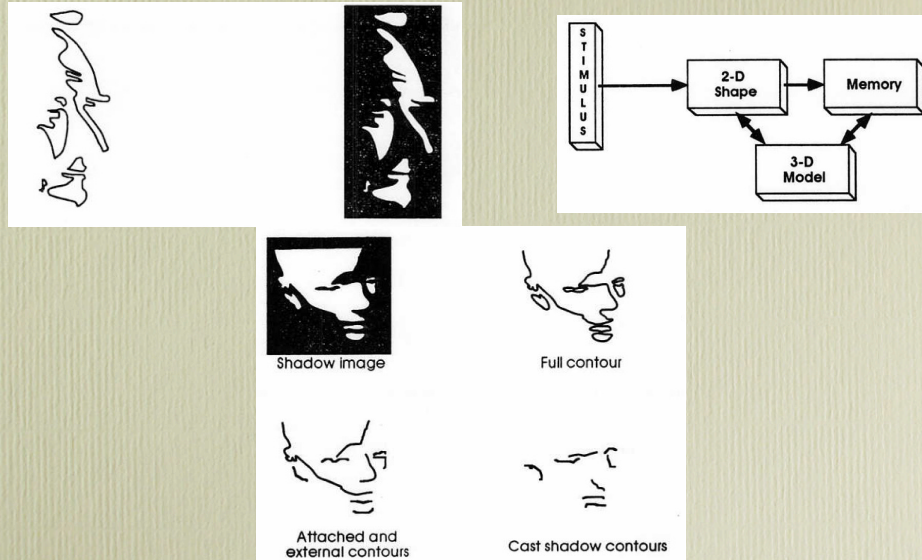
# Competing explanations: Explaining away missing data



# Auxiliary evidence for occlusion

QuickTime™ and a  
MPEG-4 Video decompressor  
are needed to see this picture.

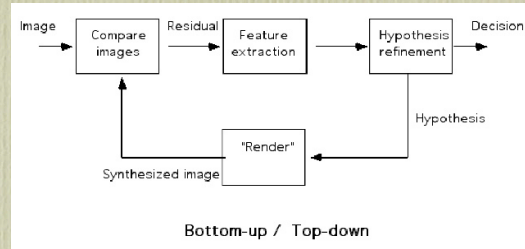
# Recognition despite cast shadows



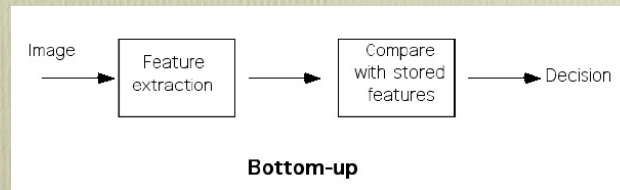
Cavanagh P (1991) What's up in top-down processing? In: Representations of Vision: Trends and tacit assumptions in vision research (Gore A, ed), pp 295-304. Cambridge, UK: Cambridge University Press.



# Suggests...



is a more complete picture than this



Doesn't mean that bottom-up segmentation can't work, but that achieving high-performance requires a combination of good bottom-up processing with top-down verification.

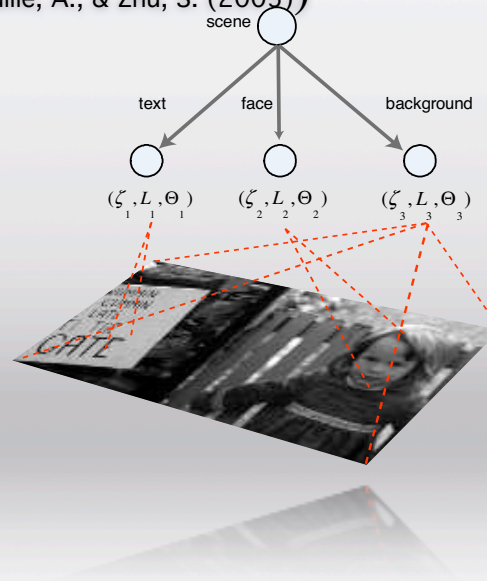
Neural evidence for top-down role in perceptual organization?

# 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 three types of models (text, faces, background/texture) models
- Verification through top-down synthesis
- If bottom-up proposals are good, synthesis is not needed to find most probable scene
- Flexible graph

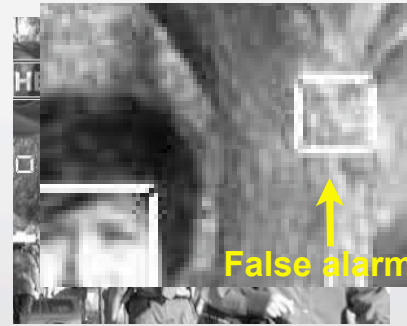


# Image parsing & “Explaining away”



**Input**

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

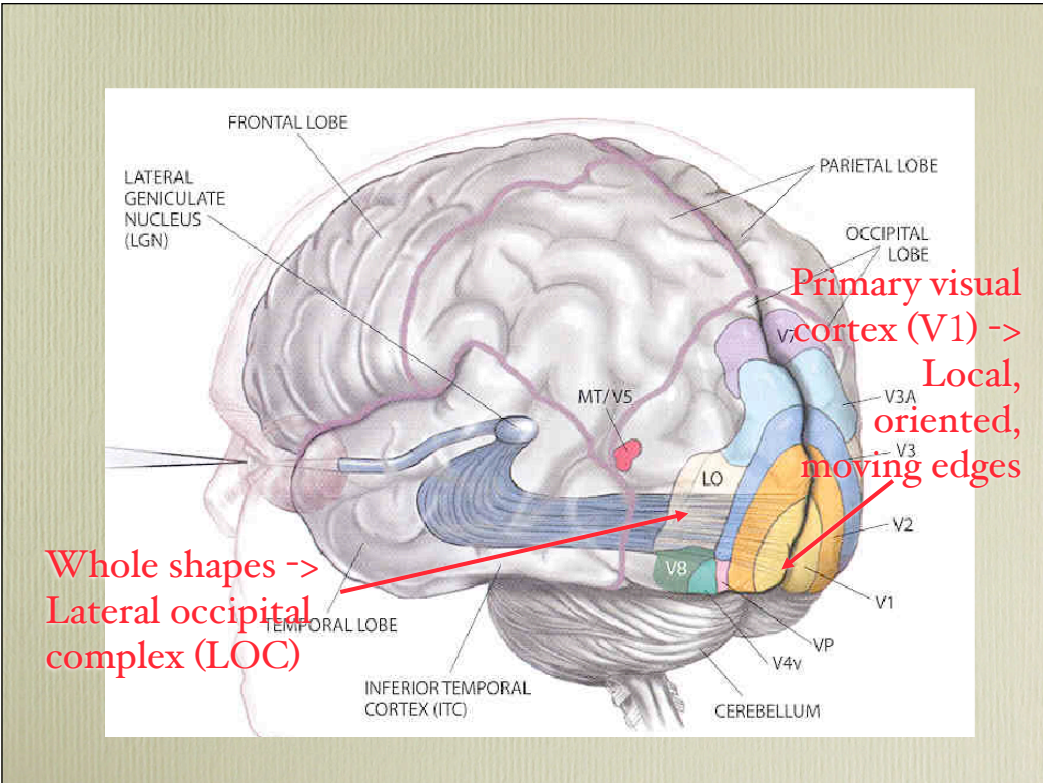


**Bottom-up result**

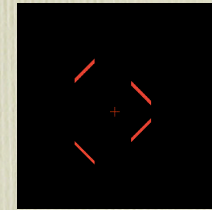
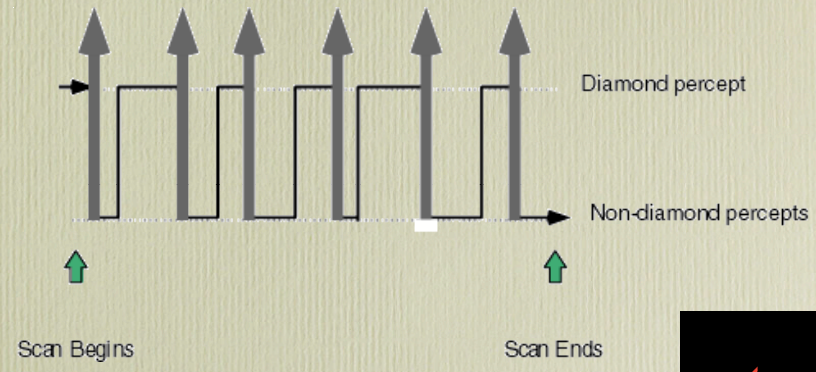


**Synthesized image**

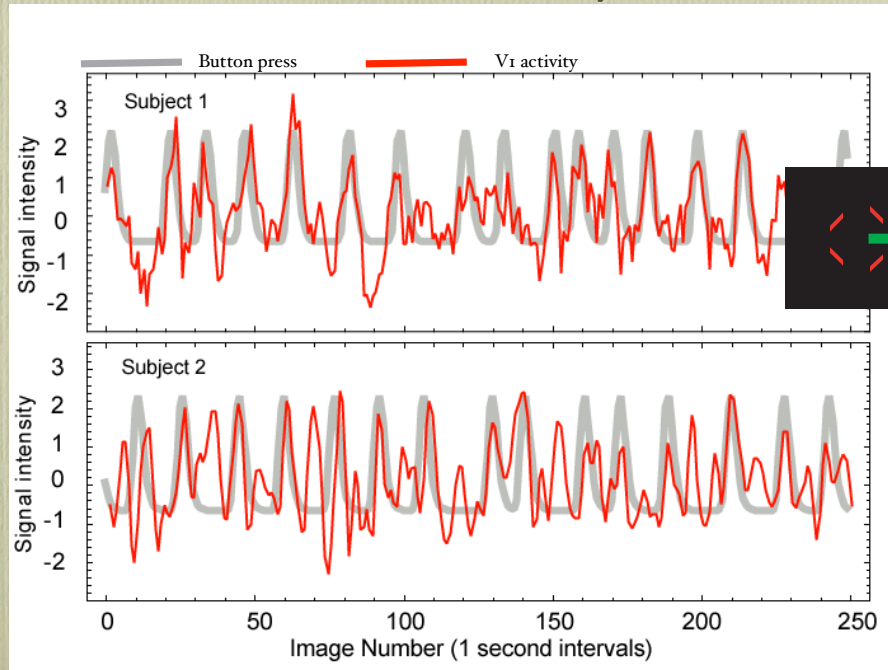




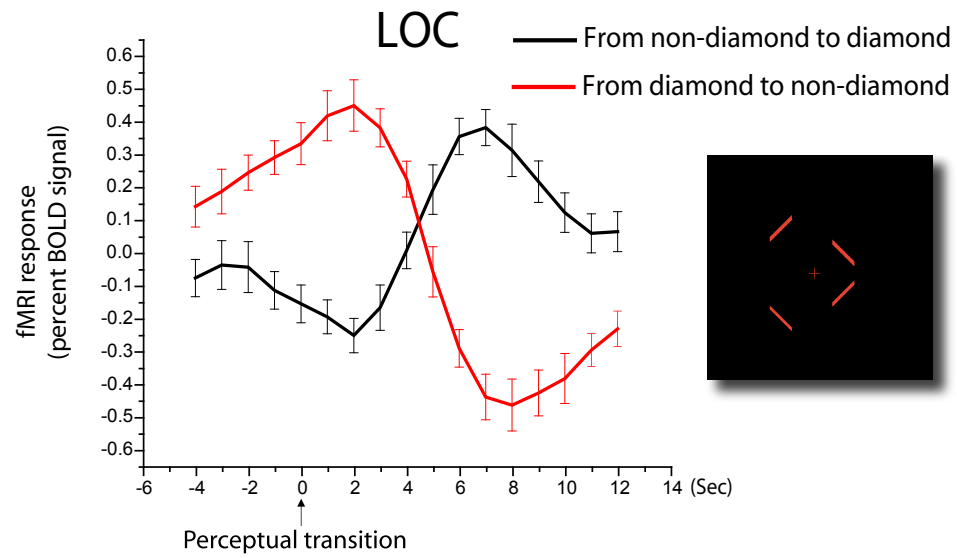
# Button presses



# Perceptual organization correlates with reduced VI activity



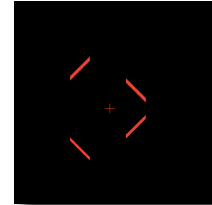
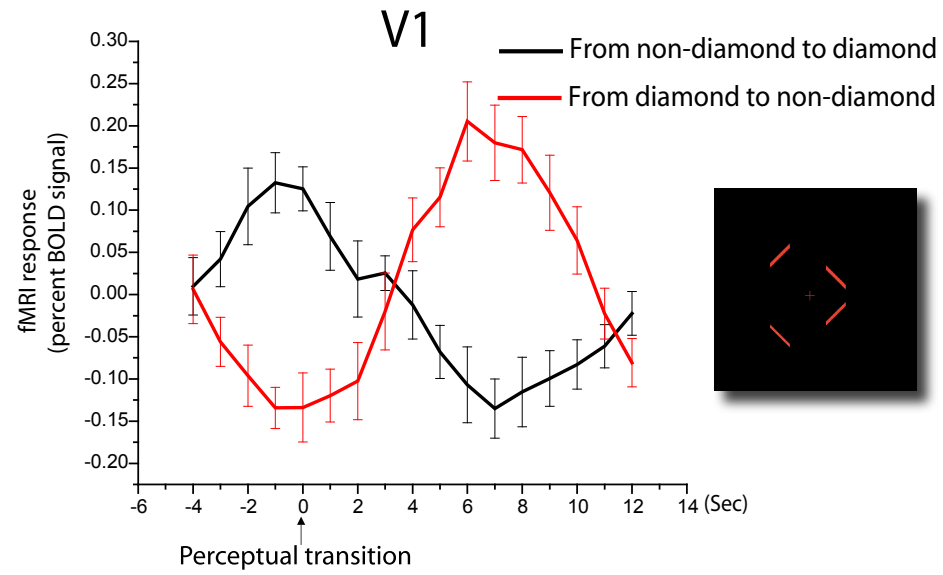
# Perceptual organization is correlated with *increased LOC activity*



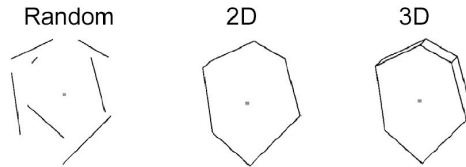
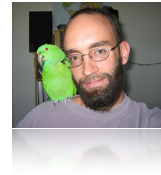
From: Fang, Murray, He & Kersten, 2004, International Congress of Psychology, Beijing



# Perceptual organization is correlated with *decreased* V1 activity



# Shape perception can reduce V1 activity

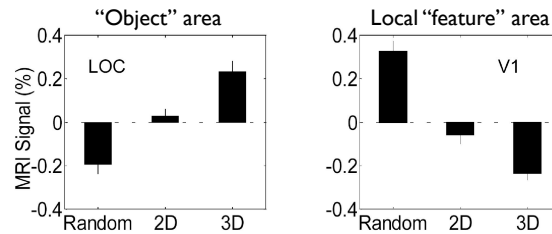


Explanation?

Many...

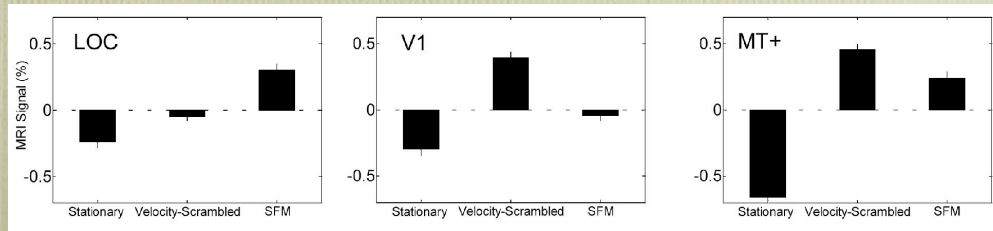
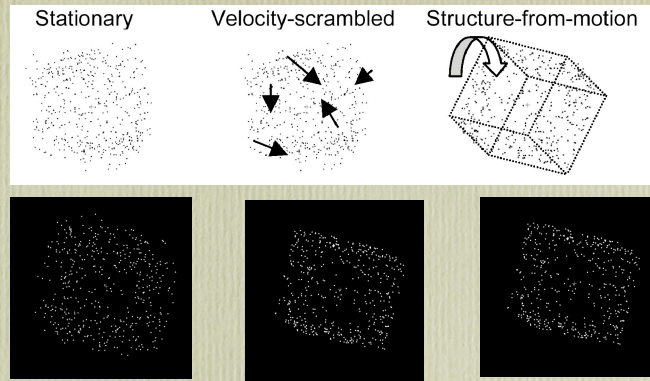
“Explaining away” through predictive coding

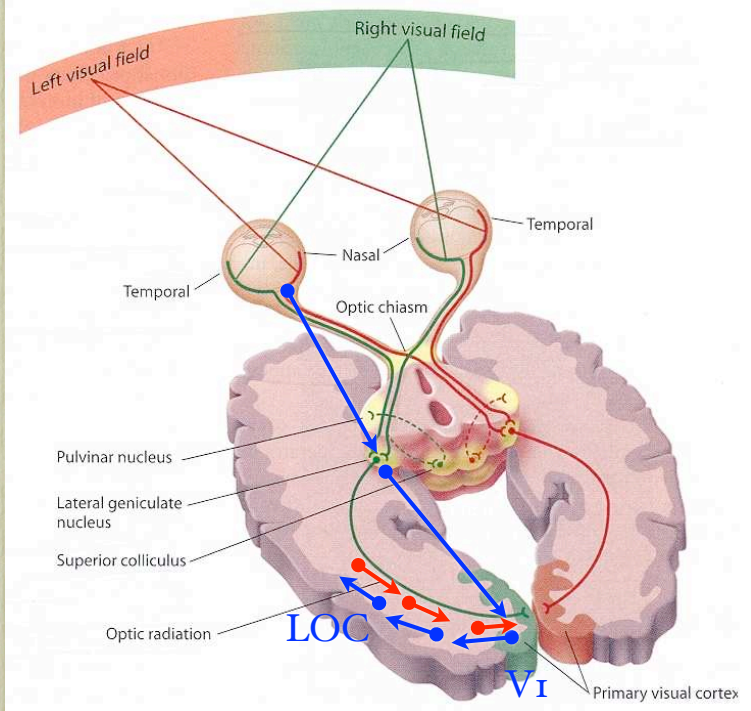
Sparse coding



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





# Cortical Mechanism? ...some speculation

1. Feedforward: local features to objects

2. Feedback models

a. Feedforward + attention:

competitive selection of features

b. Predictive coding

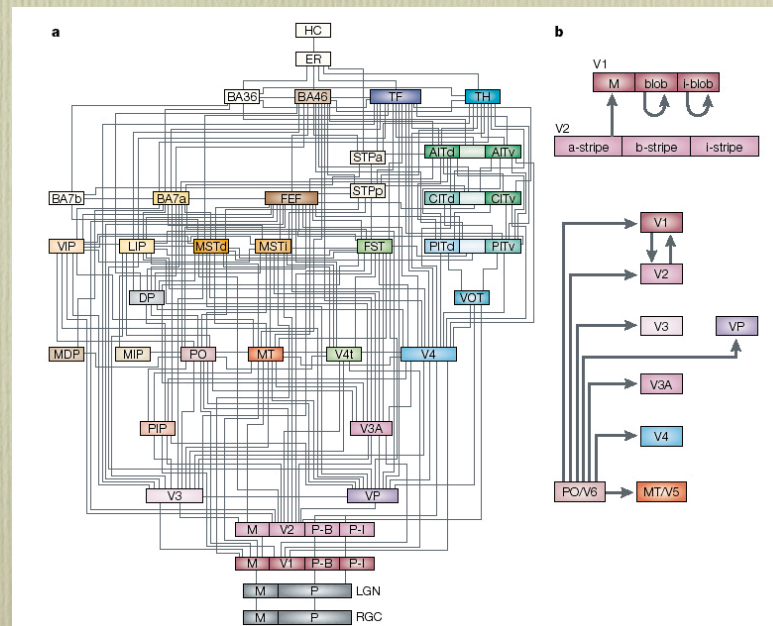
Internal  
generative  
models

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.



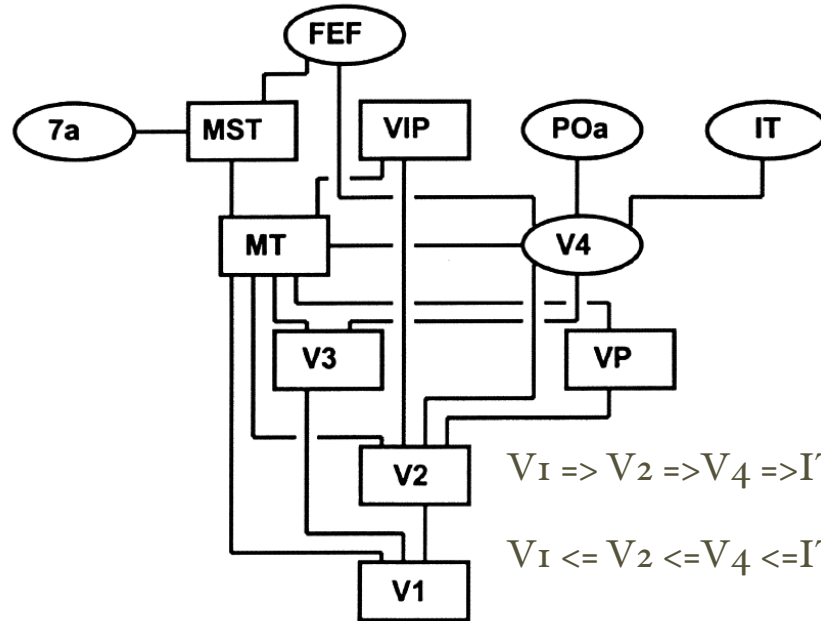
# Cortical organization



# 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?



# 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.



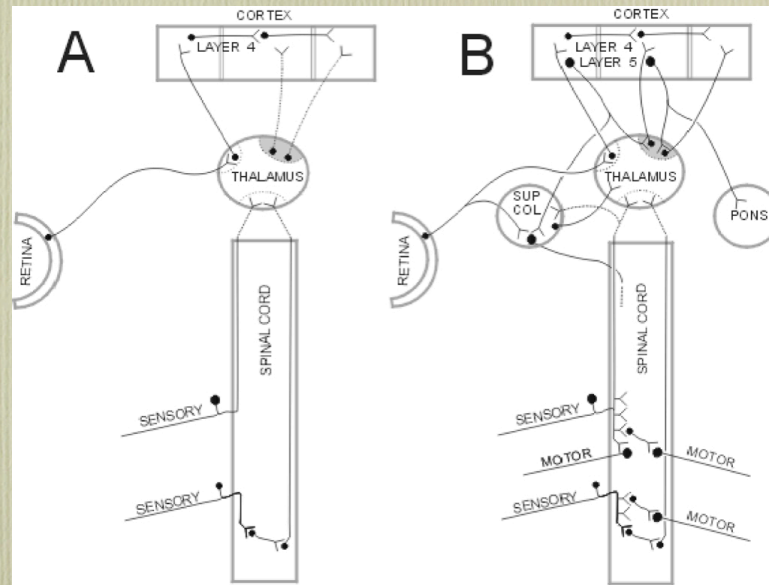


Figure courtesy of Ray Guillery

# Internal generative models

## Analysis-by-synthesis

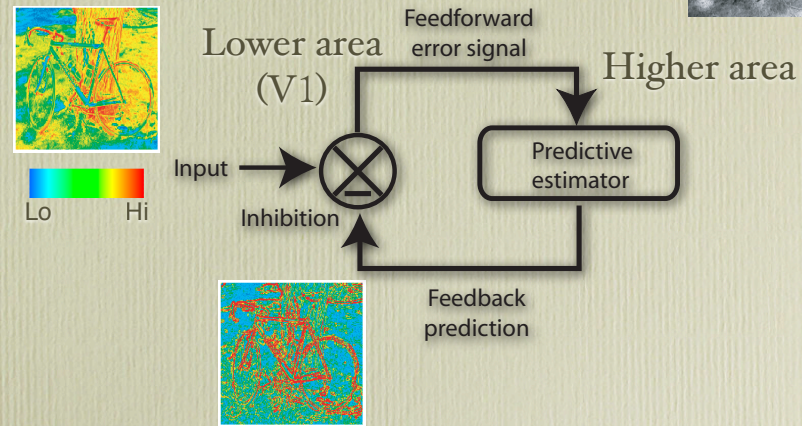
### Predictive coding

- High-level object models project back predictions of the incoming data  
Poor fit, high residual => high activity

### Sparsification

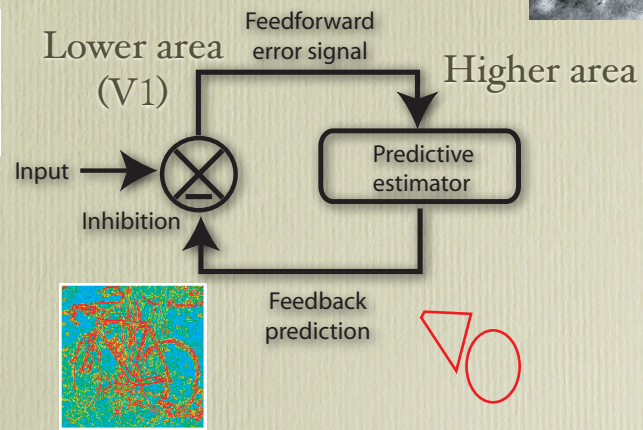
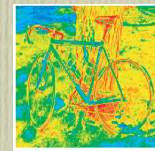
- A good high-level fit tells earlier areas to “stop gossiping”  
Amplify the activity for early features that belong to object, suppress the rest

# Predictive (top-down) processes in the brain?



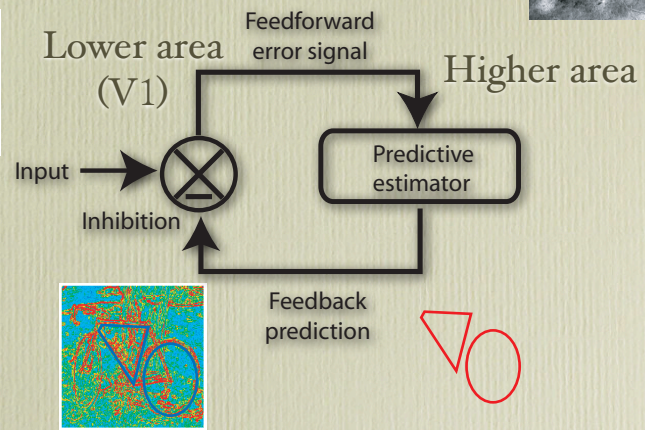
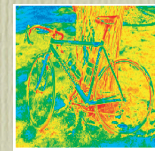
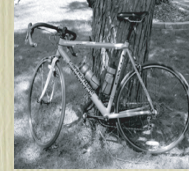
e.g. Rao, R. P., & Ballard, D. H. (1997). Dynamic model of visual recognition predicts neural response properties in the visual cortex. *Neural Comput*, 9(4), 721-763.

# Predictive coding



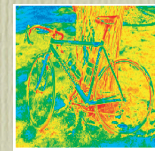
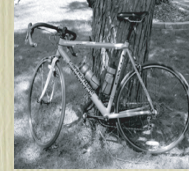


# Predictive coding

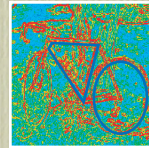
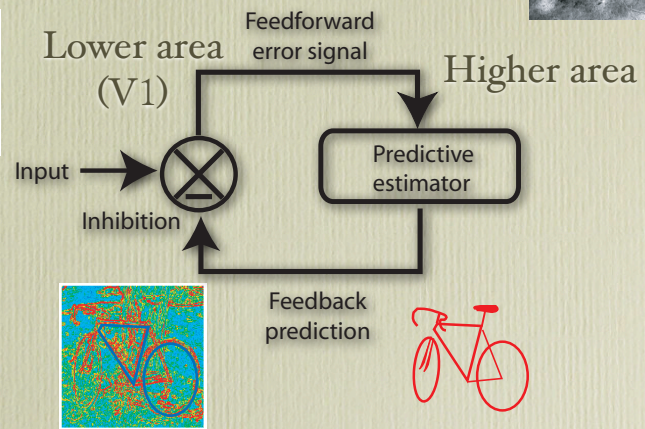




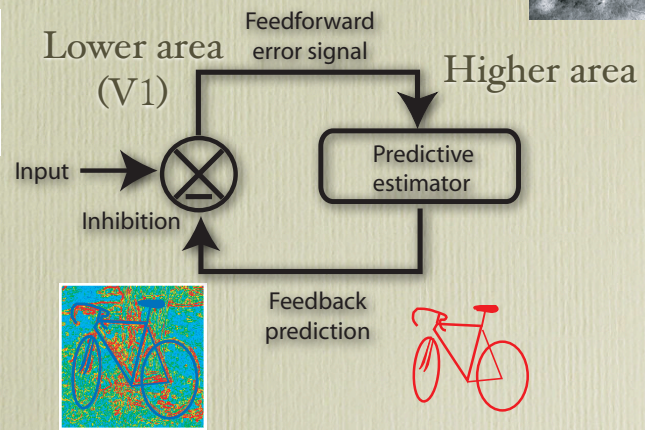
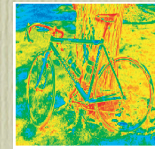
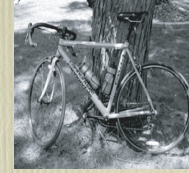
# Predictive coding



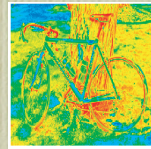
Lo Hi



# Predictive coding

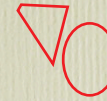
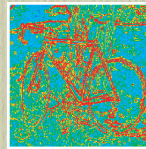
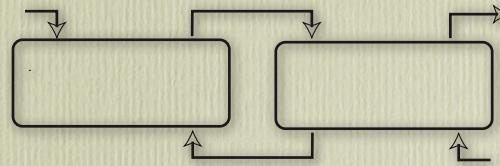


# Sparsification “Stop gossiping”



Lo Hi

Lower area (V1) Higher areas (LOC)

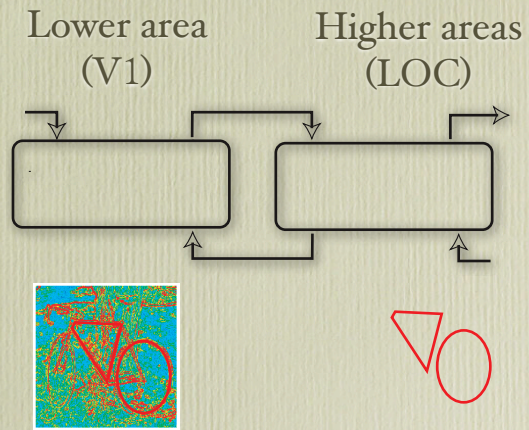
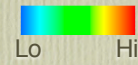
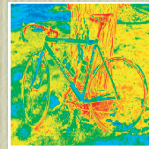


Grossberg S (1994) 3-D vision and figure-ground separation by visual cortex. *Percept Psychophys* 55:48-121.



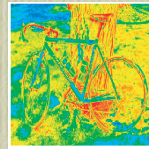
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“Stop gossiping”

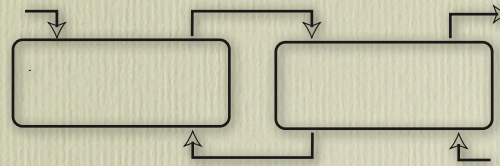


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“Stop gossiping”



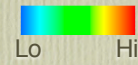
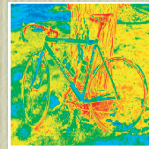
Lower area (V1)      Higher areas (LOC)



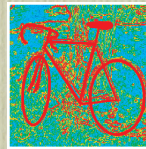
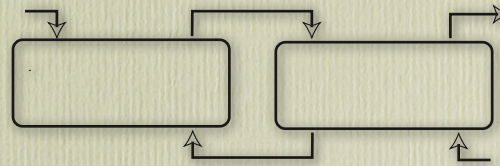


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“Stop gossiping”

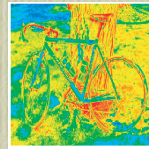


Lower area (V1)      Higher areas (LOC)

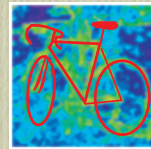
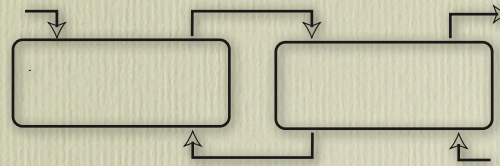


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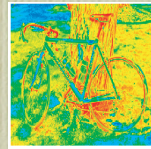
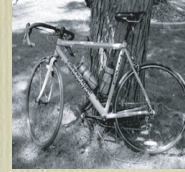
“Stop gossiping”



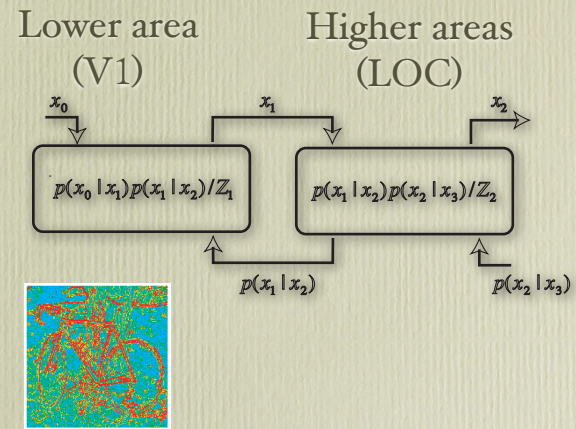
Lower area (V1)      Higher areas (LOC)



# Bayesian Interpretation Sparsification



Lo Hi



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...