What's Missing from Deep Learning?

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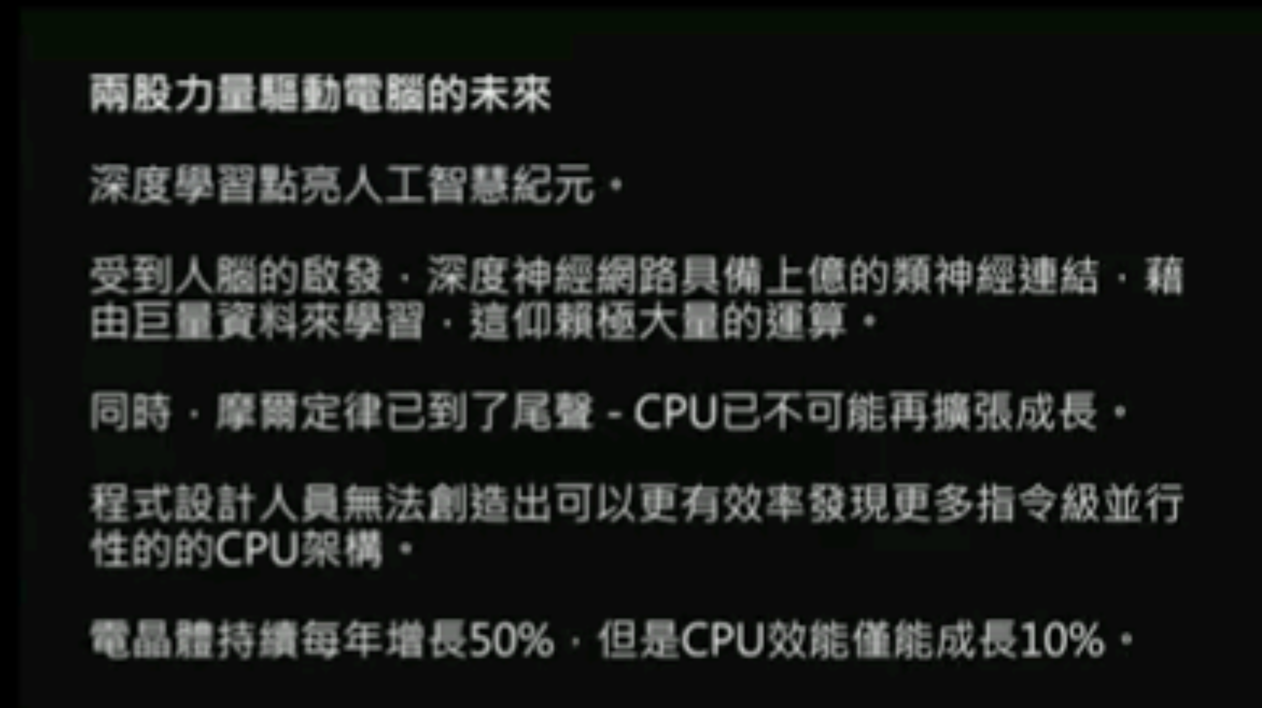
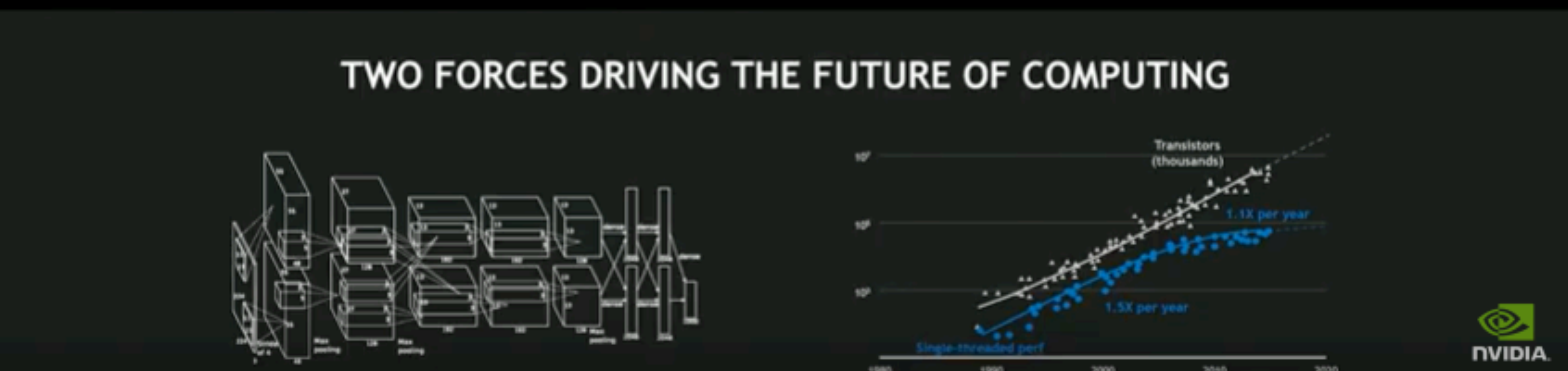
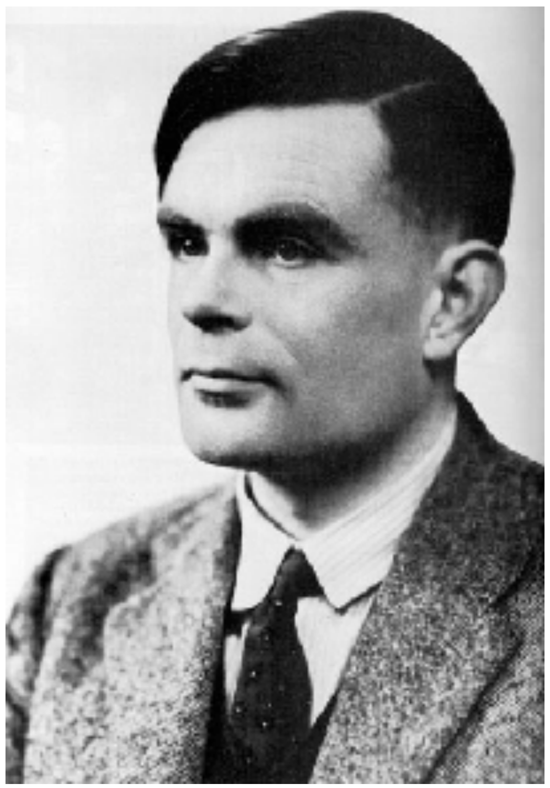
REDWOOD CENTER
for Theoretical Neuroscience

"We're at the beginning of a new day…
This is the beginning of the AI revolution."
— Jensen Huang, GTC Taiwan 2017



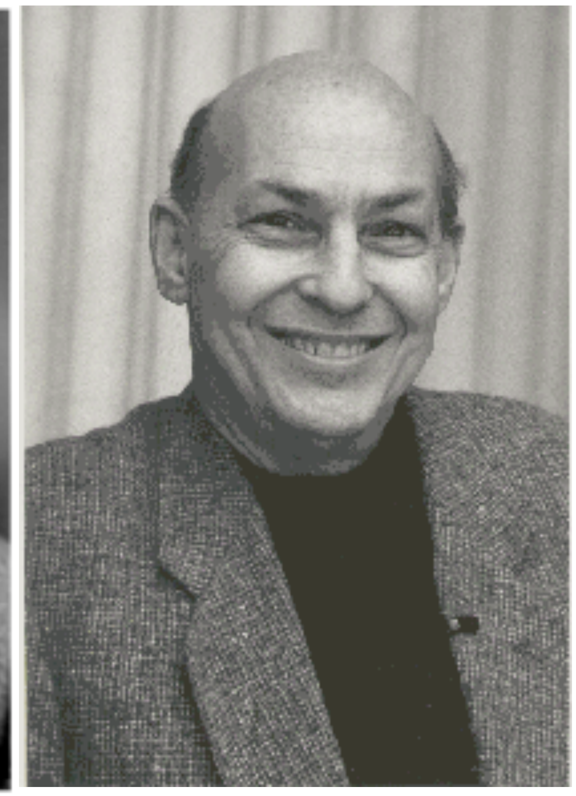


Artificial Intelligence



Alan Turing

John von Neumann

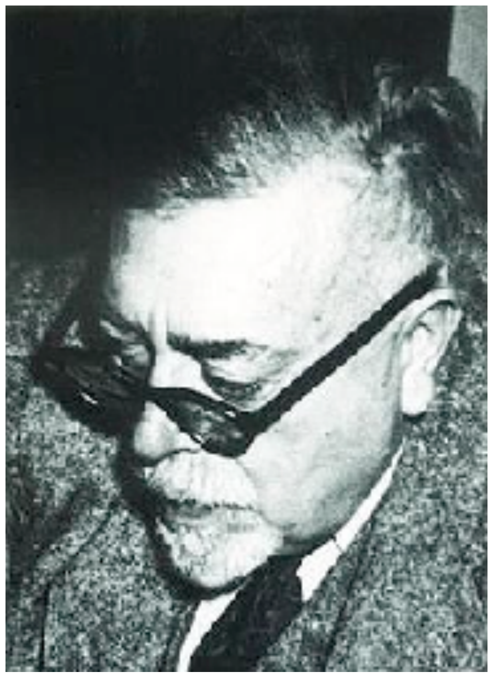


Marvin Minsky

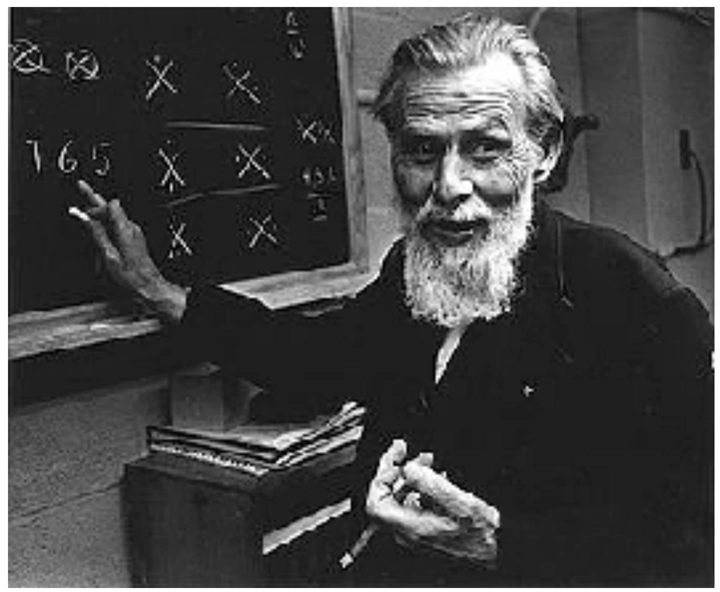
John McCarthy

Among the most challenging scientific questions of our time are the corresponding analytic and synthetic problems: How does the brain function? Can we design a machine which will simulate a brain?
-- *Automata Studies*, 1956

Cybernetics/neural networks



Norbert Wiener



Warren McCulloch & Walter Pitts

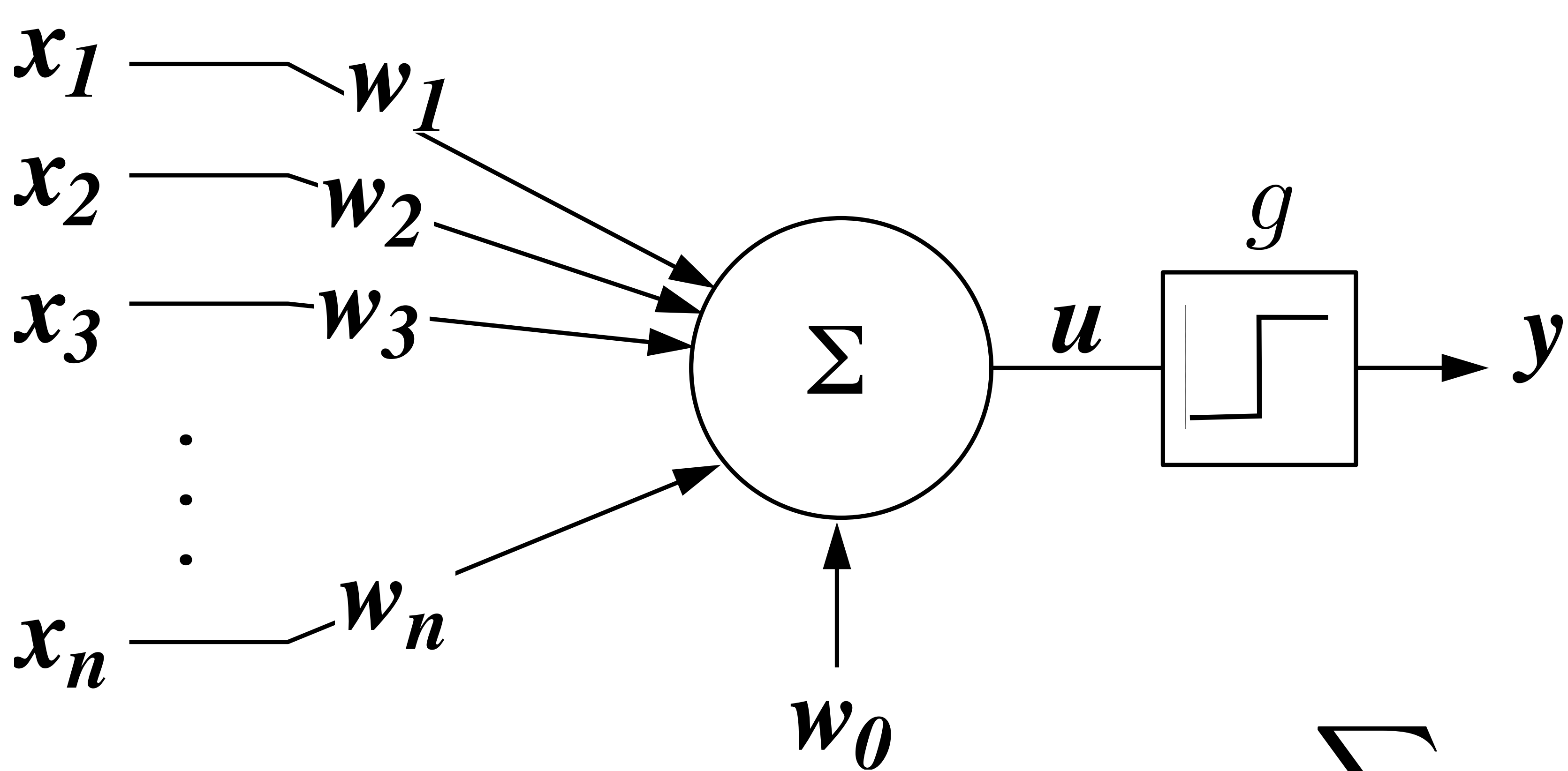
Frank Rosenblatt

“The theory reported here clearly demonstrates the feasibility and fruitfulness of a quantitative statistical approach to the organization of cognitive systems. By the study of systems such as the perceptron, it is hoped that those fundamental laws of organization which are common to all information handling systems, machines and men included, may eventually be understood.” -- Frank Rosenblatt

The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain. In, *Psychological Review*, Vol. 65, No. 6, pp. 386-408, November, 1958.

A brief history of neural networks

1960's

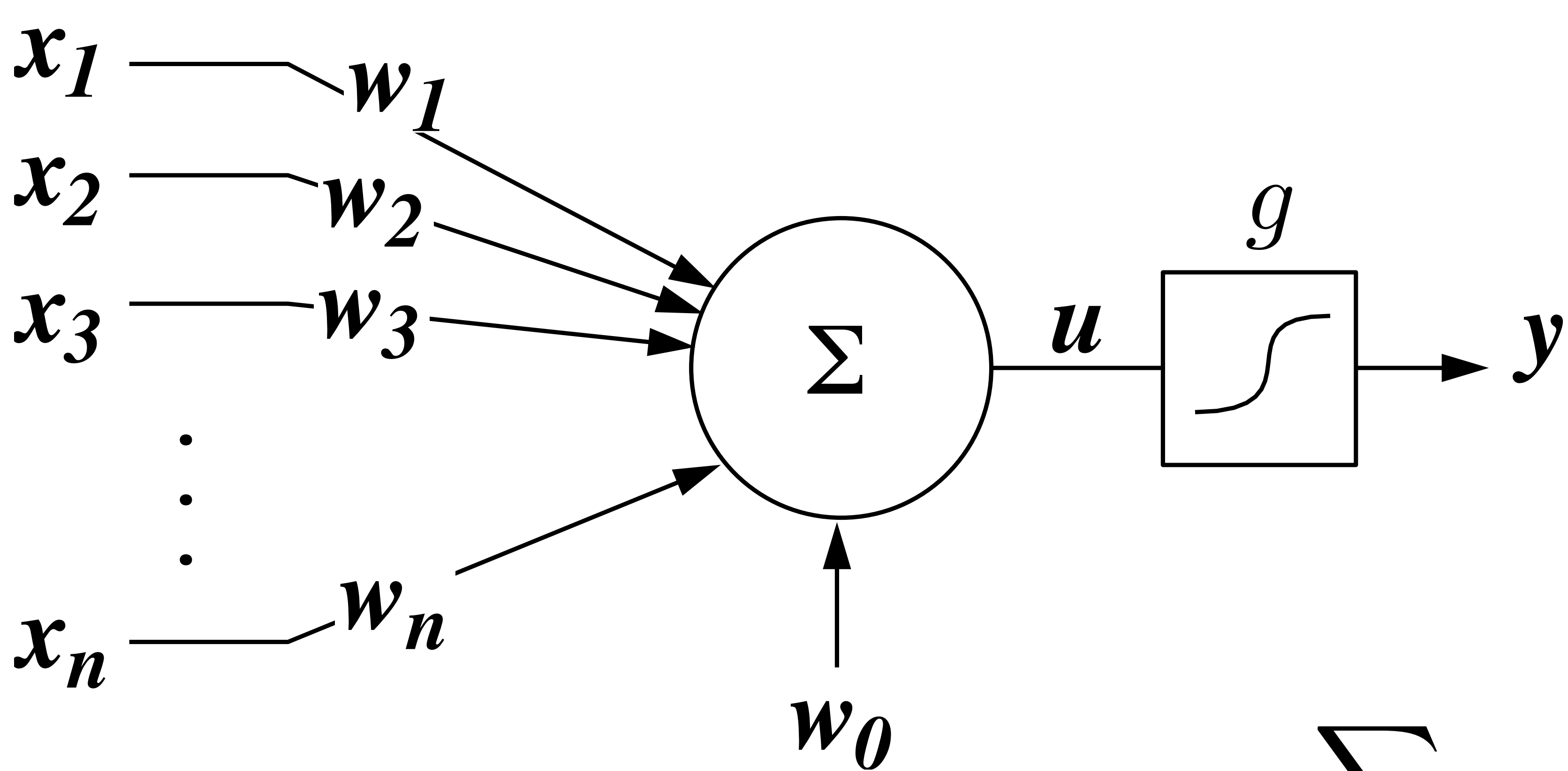


$$u = \sum_i w_i \, x_i$$

$$y = g(u)$$

A brief history of neural networks

1980's

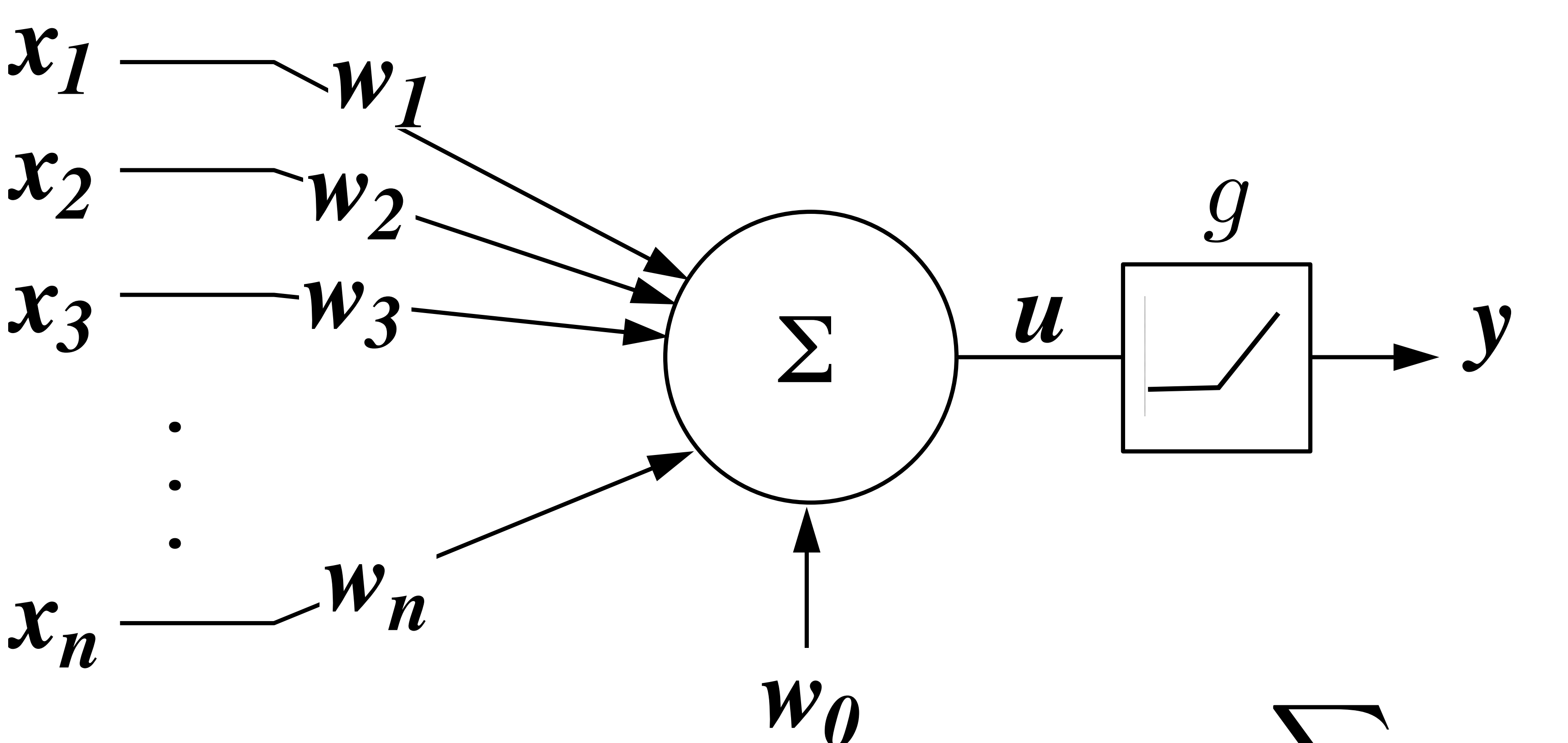


$$u = \sum_i w_i \, x_i$$

$$y = g(u)$$

A brief history of neural networks

2000's



$$u = \sum_i w_i \, x_i$$

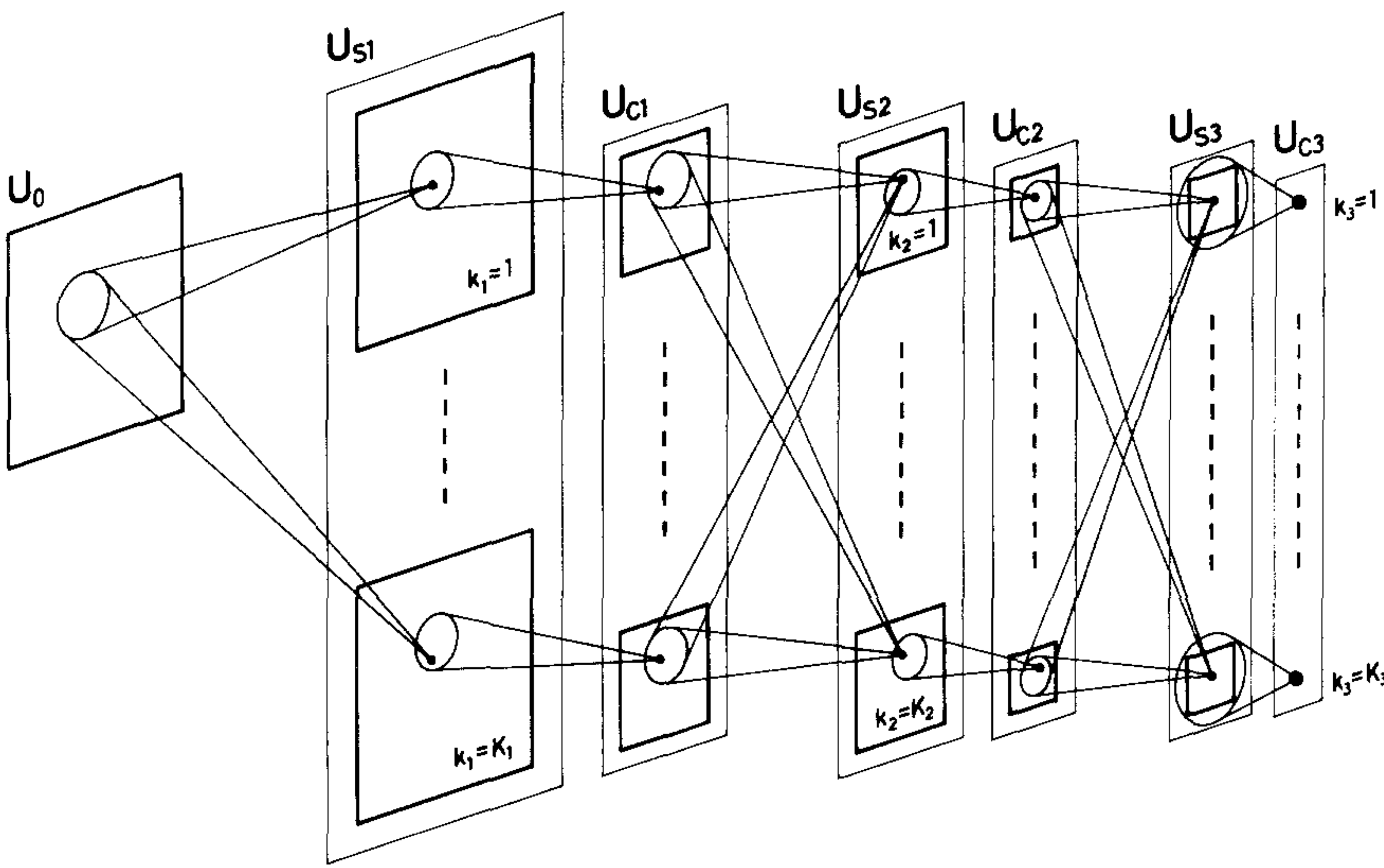
$$y = g(u)$$

Biol. Cybernetics 36, 193–202 (1980)

Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan



Neocognitron: rationale

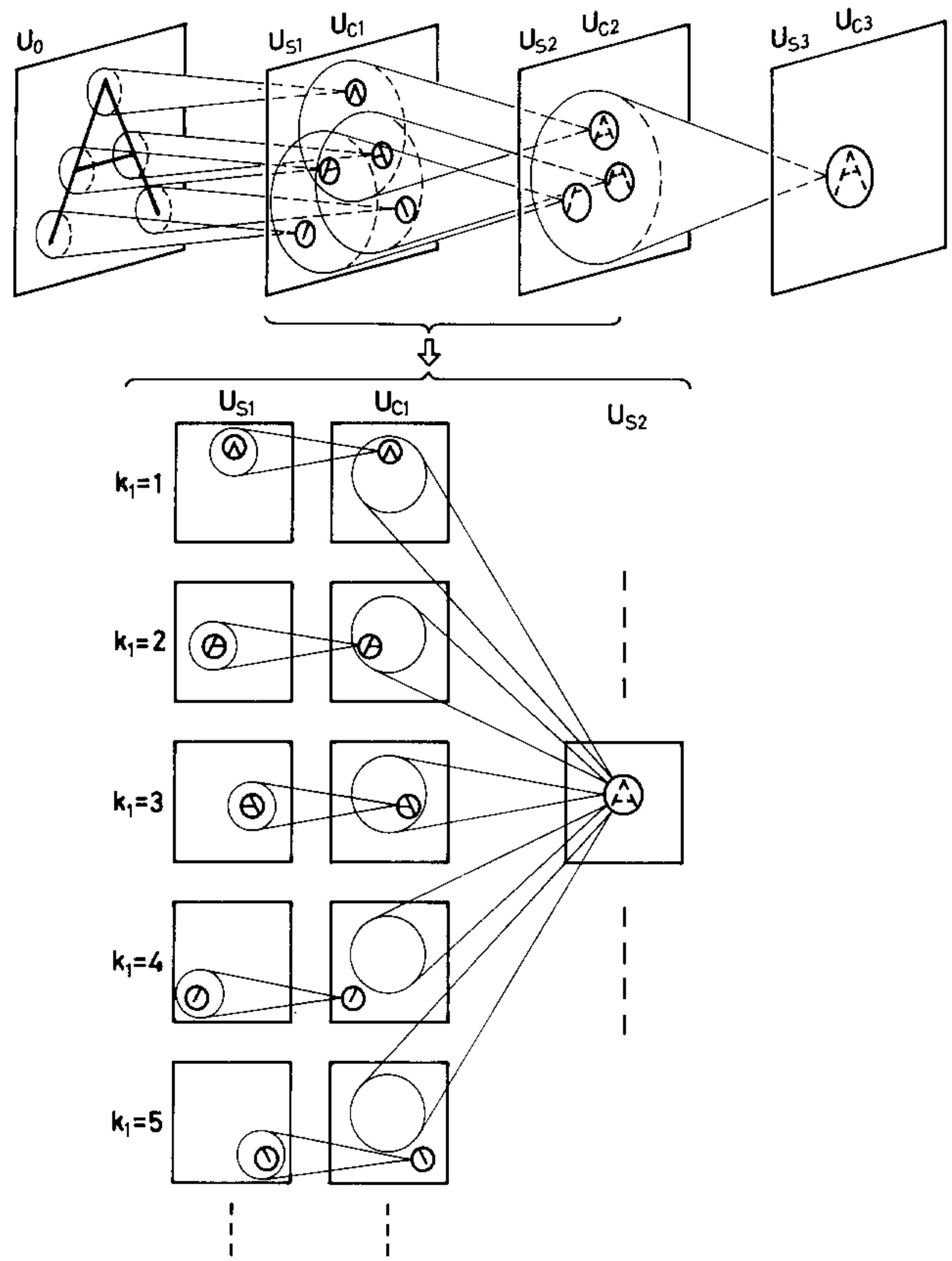


Fig. 5. An example of the interconnections between cells and the response of the cells after completion of self-organization

Neocognitron: activation rule

convolution

$$u_{Sl}(k_l, \mathbf{n}) = r_l \cdot \varphi\left[\frac{1 + \sum_{k_{l-1}=1}^{K_{l-1}} \sum_{\mathbf{v}\in S_l} a_l(k_{l-1}, \mathbf{v}, k_l)\cdot u_{Cl-1}(k_{l-1}, \mathbf{n}+\mathbf{v})}{1 + \frac{2r_l}{1+r_l}\cdot b_l(k_l)\cdot v_{Cl-1}(\mathbf{n})} - 1\right]$$

where

$$\varphi[x] = \begin{cases} x & x \geqq 0 \\ 0 & x < 0\,. \end{cases}$$

divisive normalization

$$v_{Cl-1}(\mathbf{n}) = \sqrt{\sum_{k_{l-1}=1}^{K_{l-1}} \sum_{\mathbf{v}\in S_l} c_{l-1}(\mathbf{v})\cdot u_{Cl-1}^2(k_{l-1}, \mathbf{n}+\mathbf{v})}\,,$$

Relu

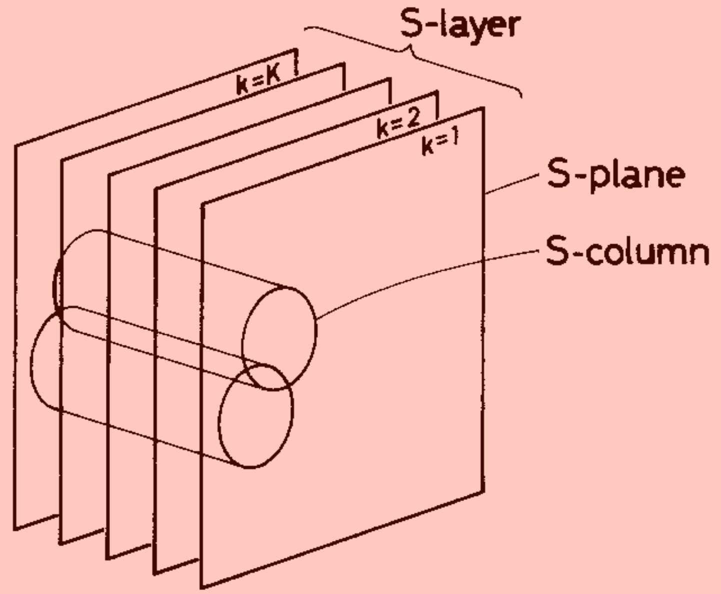
Neocognitron: learning rule

Let cell $u_{Sl}(\hat{k}_l, \hat{\mathbf{n}})$ be selected as a representative.

$$\Delta a_l(k_{l-1}, \mathbf{v}, \hat{k}_l) = q_l \cdot c_{l-1}(\mathbf{v}) \cdot u_{Cl-1}(k_{l-1}, \hat{\mathbf{n}} + \mathbf{v}),$$

Hebbian learning

From each S-column, every time when a stimulus pattern is presented, the S-cell which is yielding the largest output is chosen as a candidate for the representatives. Hence, there is a possibility that a number of candidates appear in a single S-plane. If two or more candidates appear in a single S-plane, only the one which is yielding the largest output among them is selected as the representative from that S-plane. In



Local WTA

Neocognitron: performance

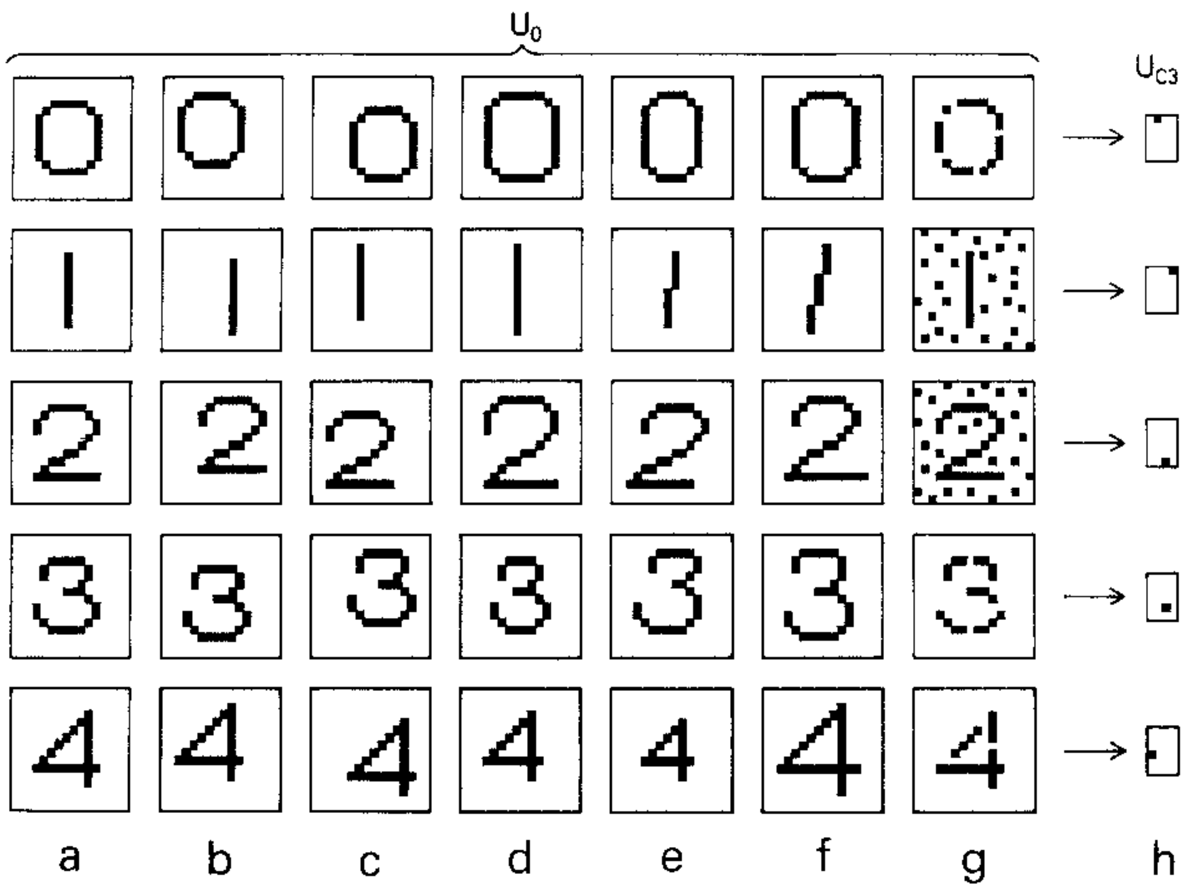


Fig. 6. Some examples of distorted stimulus patterns which the neocognitron has correctly recognized, and the response of the final layer of the network

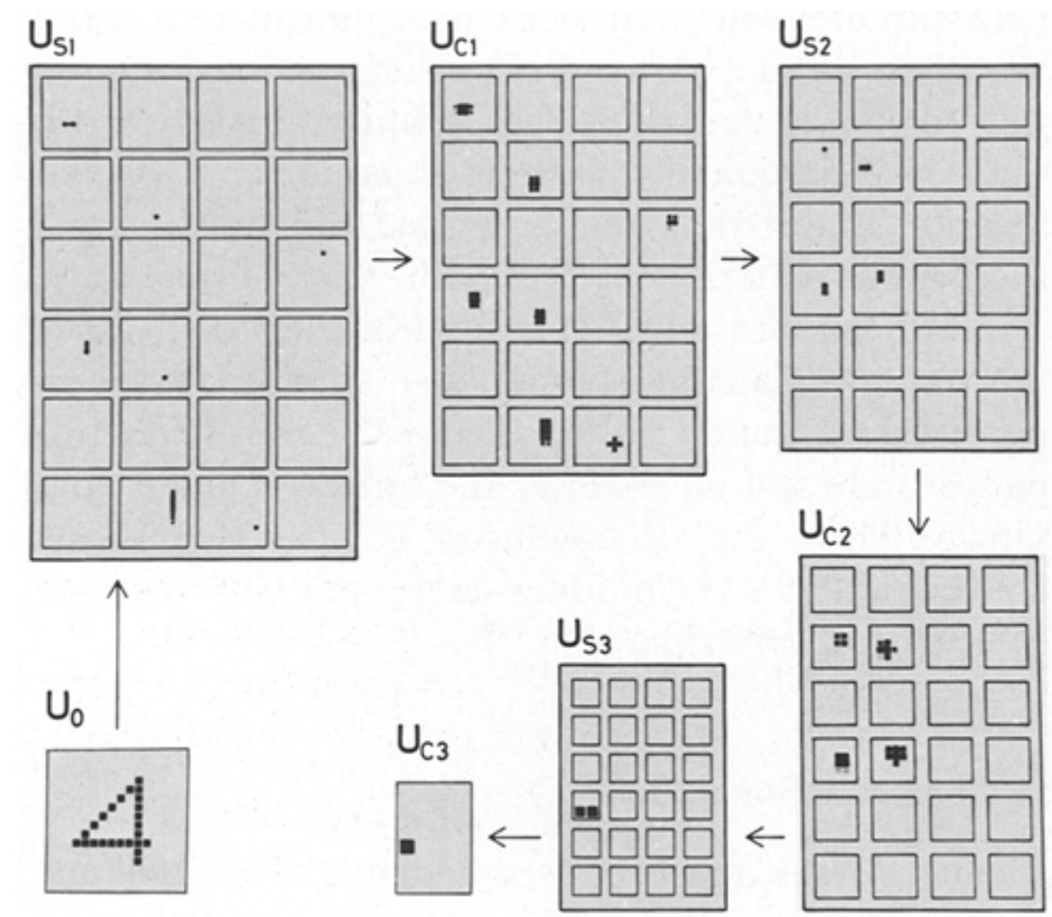
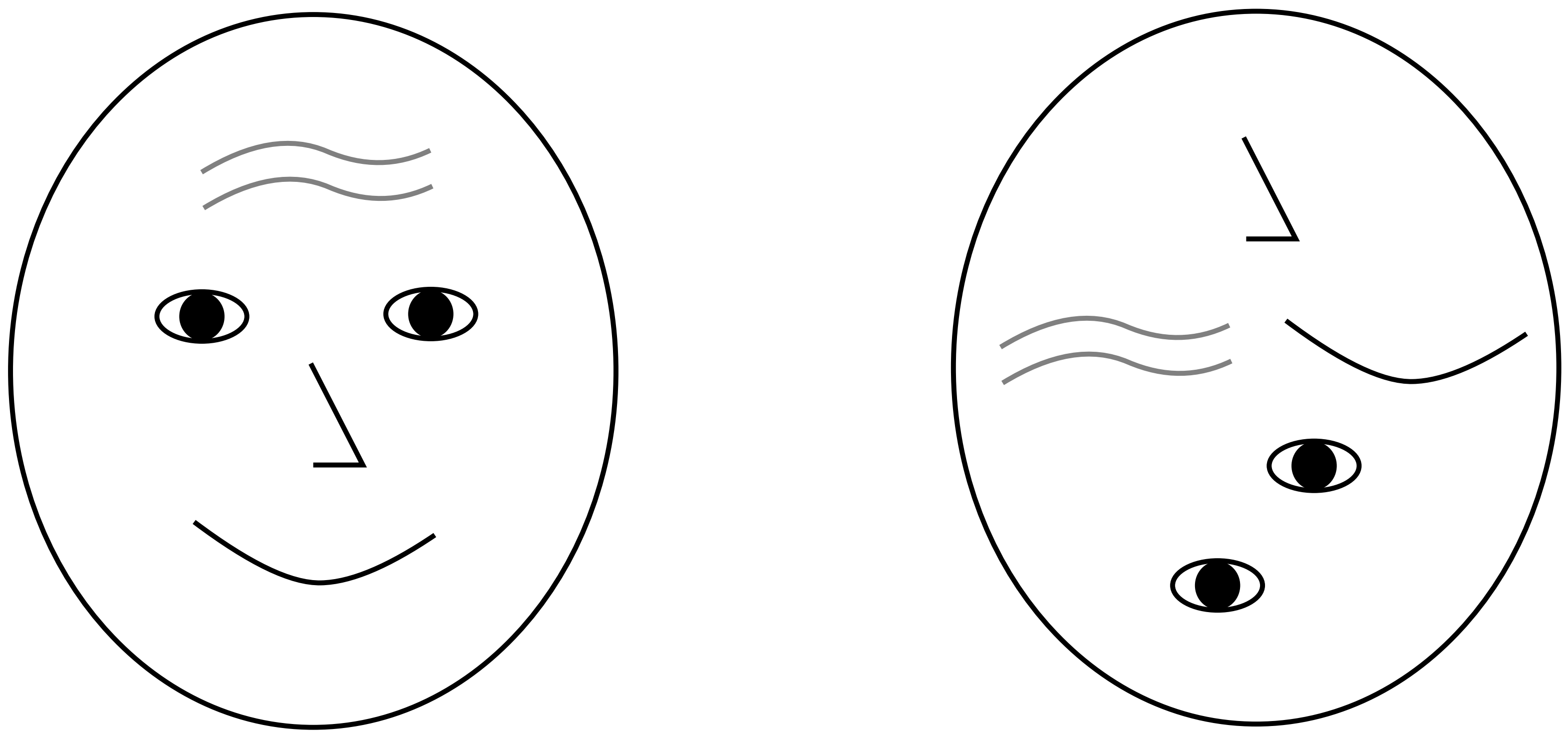


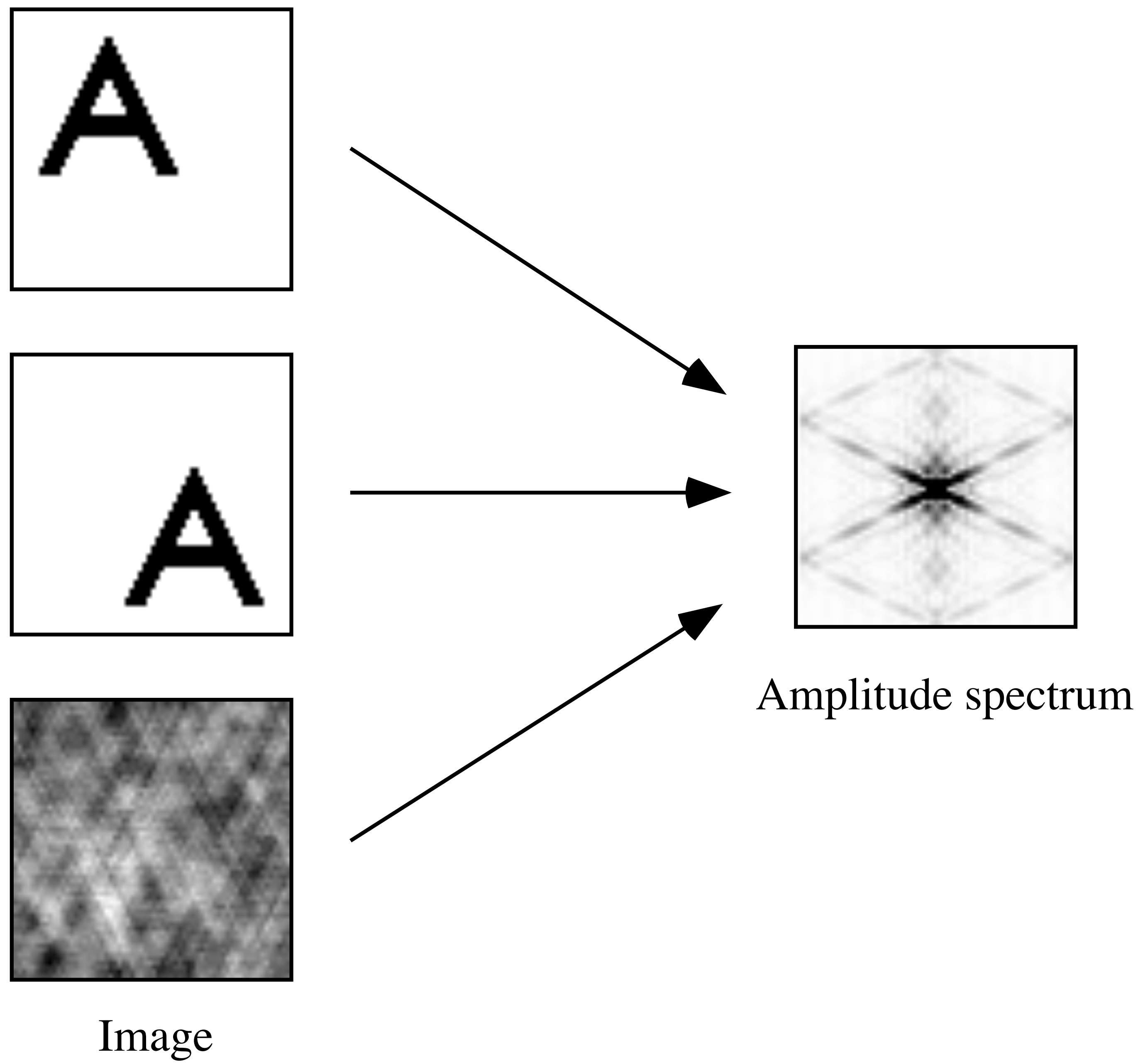
Fig. 7. A display of an example of the response of all the individual cells in the neocognitron

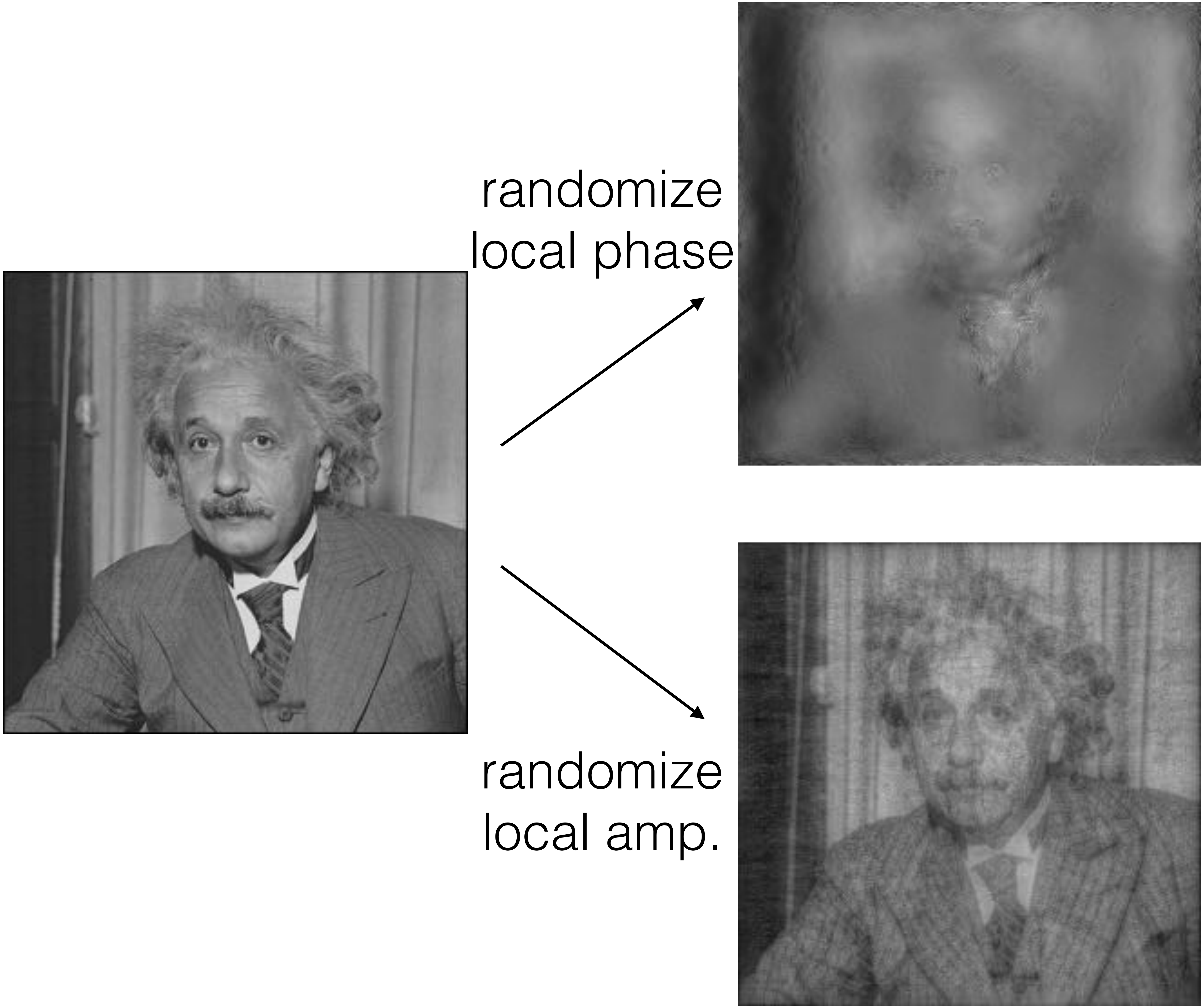
This isn’t a good model of perception

Relative spatial relationships are important



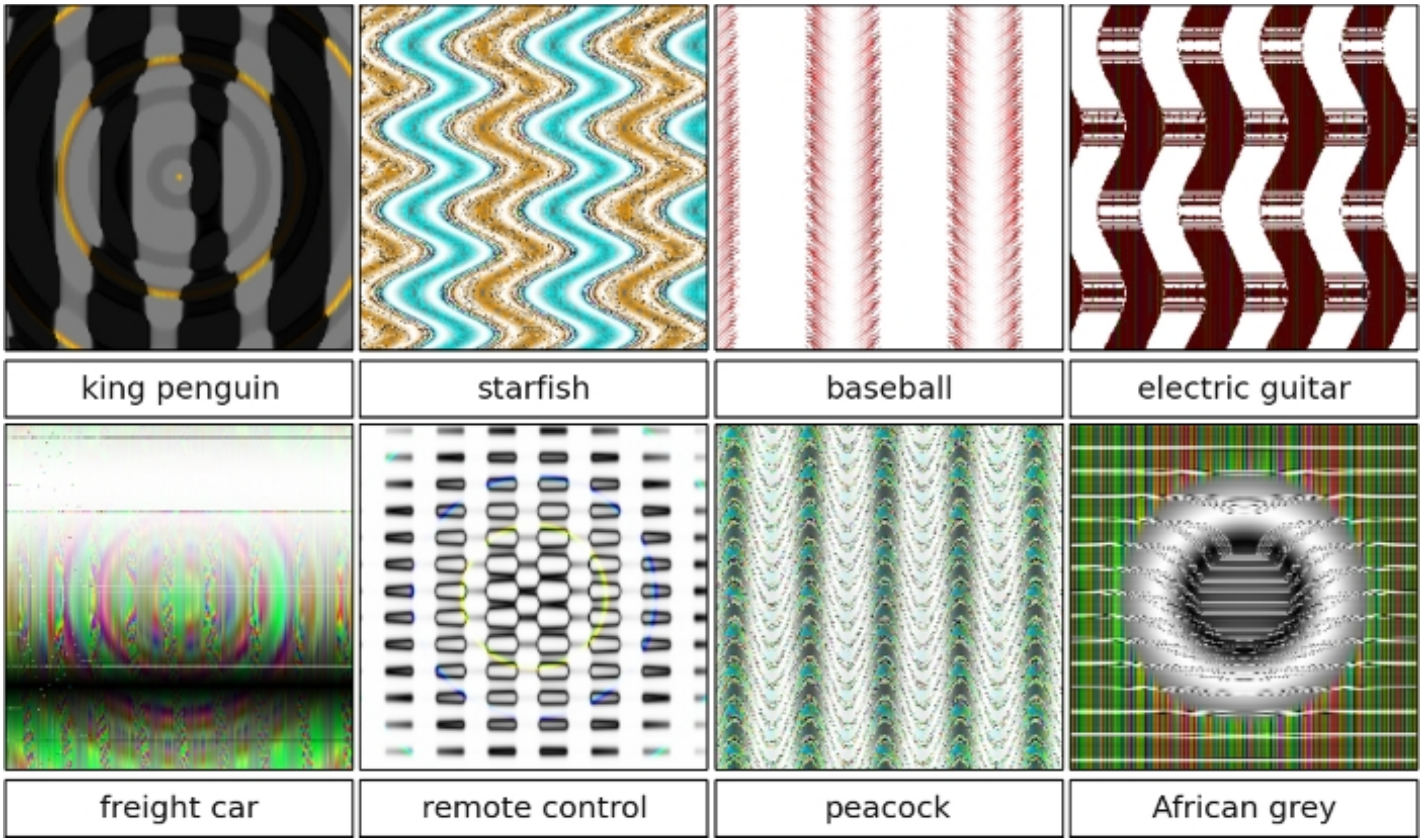
Spatial phase, not amplitude, determines shape




randomize
local phase
randomize
local amp.

Deep neural networks are easily fooled

(Nguyen, Yosinki & Clune 2014)



International Journal of Computer Vision 42(3), 145–175, 2001

Modeling the Shape of the Scene: A Holistic Representation of the Spatial Envelope*

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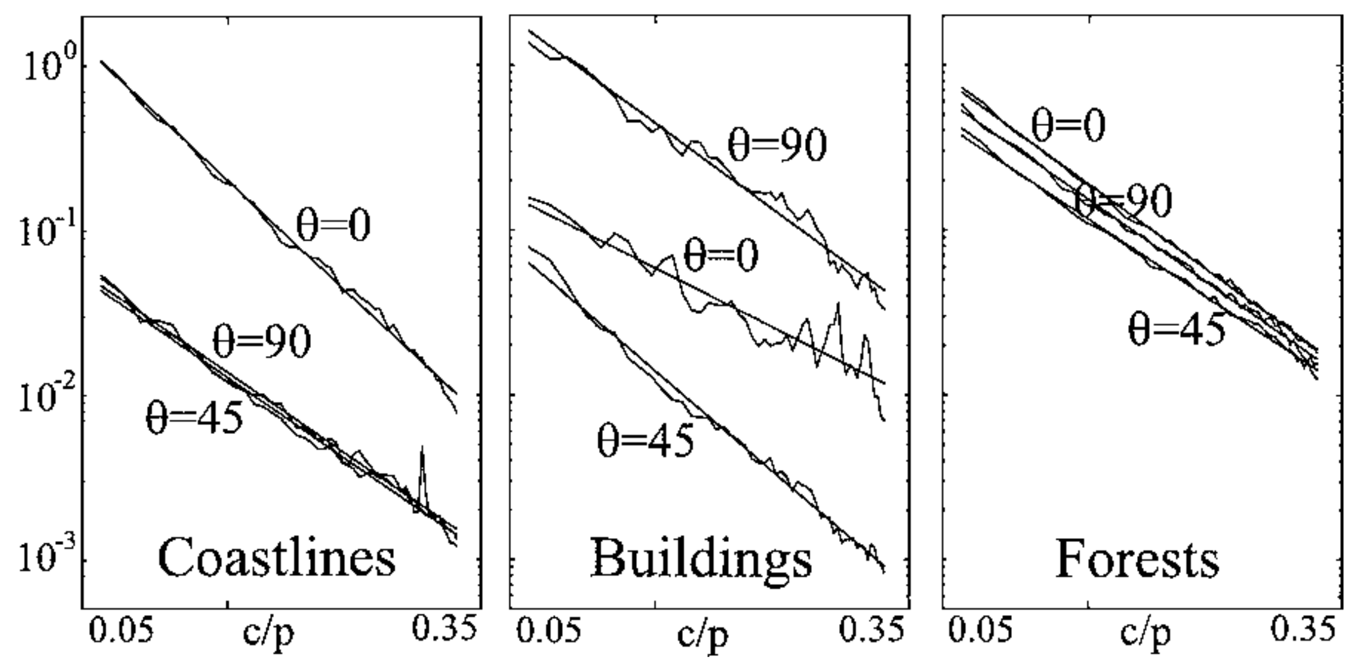
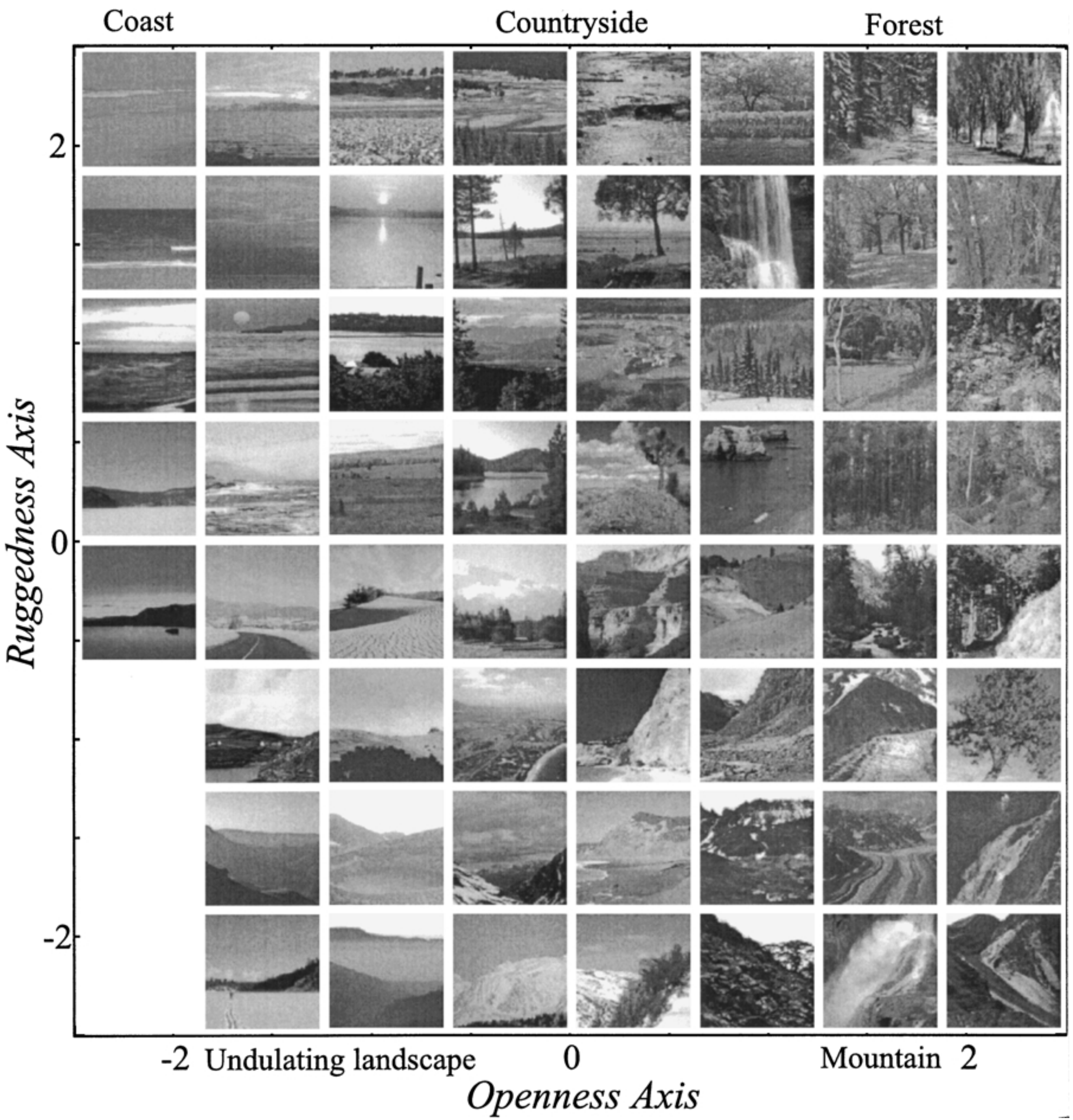
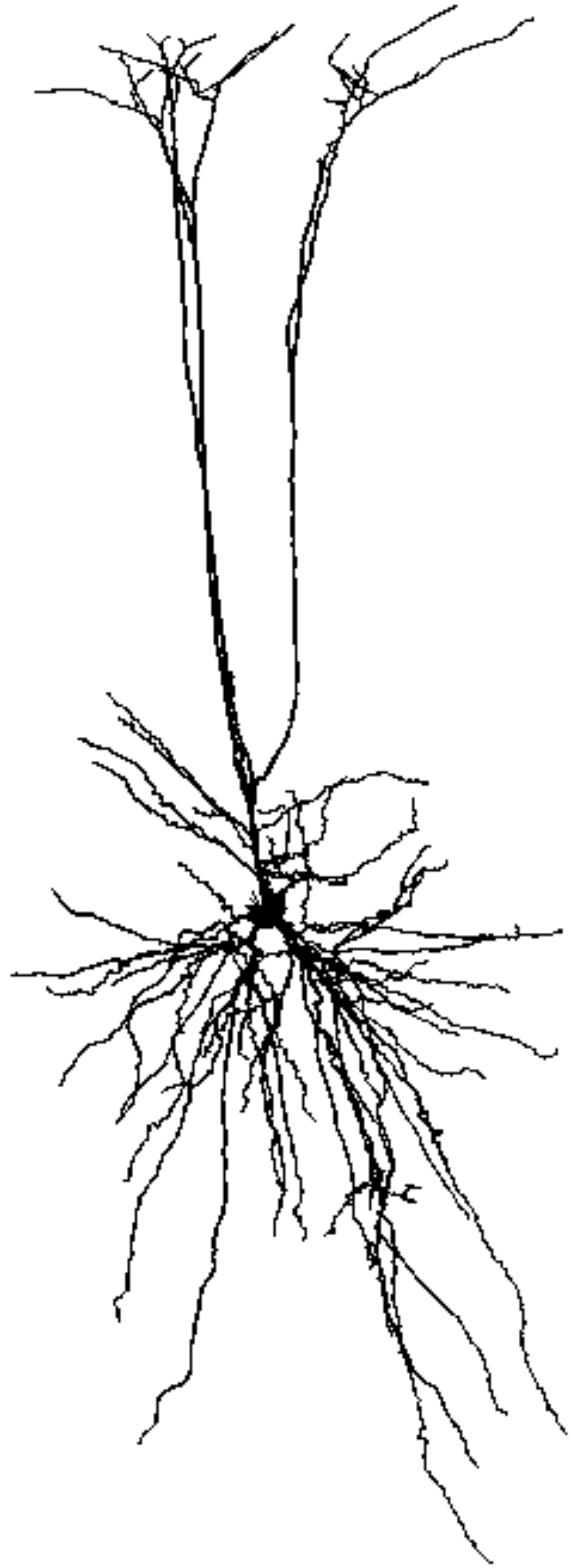
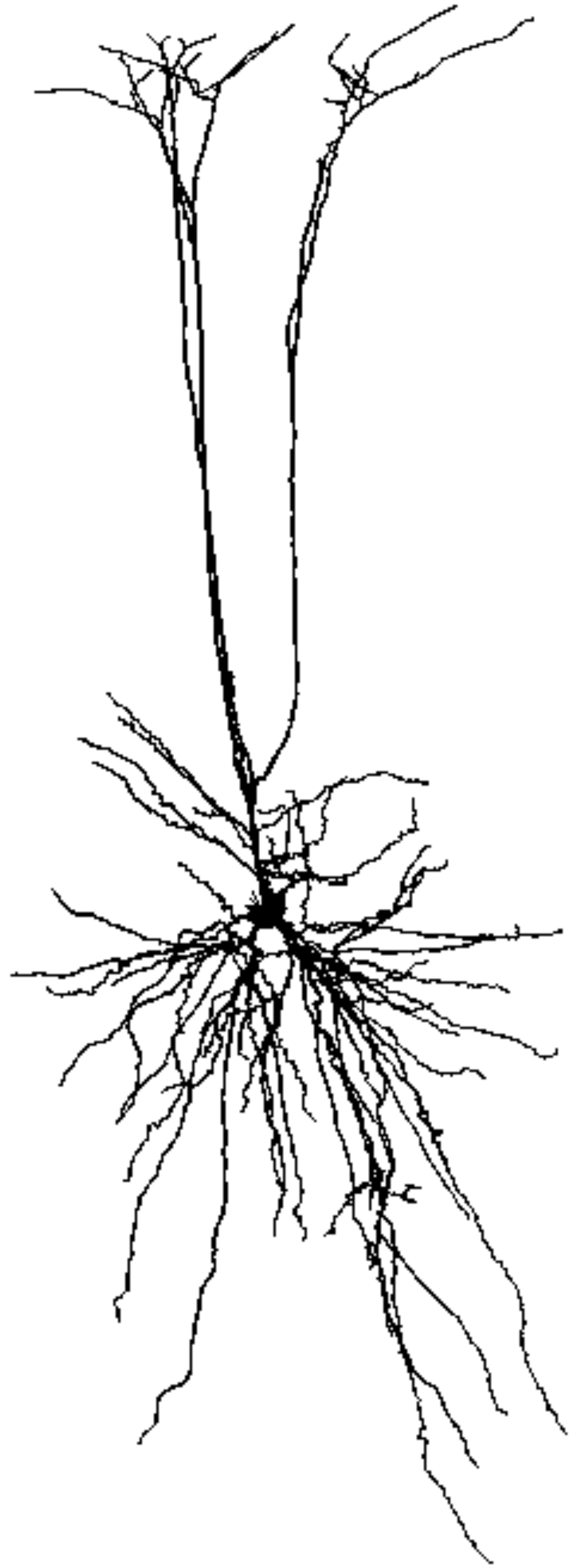



Coast
Countryside
Forest
Ruggedness Axis
2
0
-2
-2
Undulating landscape
0
Mountain
2
Openness Axis

What’s missing?



$$\neq \quad g\Big(\sum_i w_i\, x_i\Big)$$



$$\sim \quad g\left(\sum_i w_i \, \Pi_{j \in G_i} \, x_j\right)$$

Single neuron recording ⇒ Single neuron thinking

1940 PROCEEDINGS OF THE IRE November

What the Frog's Eye Tells the Frog's Brain*

J. Y. LETTVIN†, H. R. MATURANA‡, W. S. McCULLOCH||, SENIOR MEMBER, IRE, AND W. H. PITTS||

Summary—**In this paper, we analyze the activity of single fibers in the optic nerve of a frog. Our method is to find what sort of stimulus causes the largest activity in one nerve fiber and then what is the exciting aspect of that stimulus such that variations in everything else cause little change in the response. It has been known for the past 20 years that each fiber is connected not to a few rods and cones in the retina but to very many over a fair area. Our results show that for**

factor. There are four types of fibers, each type concerned with a different sort of pattern. Each type is uniformly distributed over the

visual image in terms of local pattern independent of average illumination. We describe the patterns and show the functional and anatomical separation of the channels. This work has been done on the frog, and our interpretation applies only to the frog.

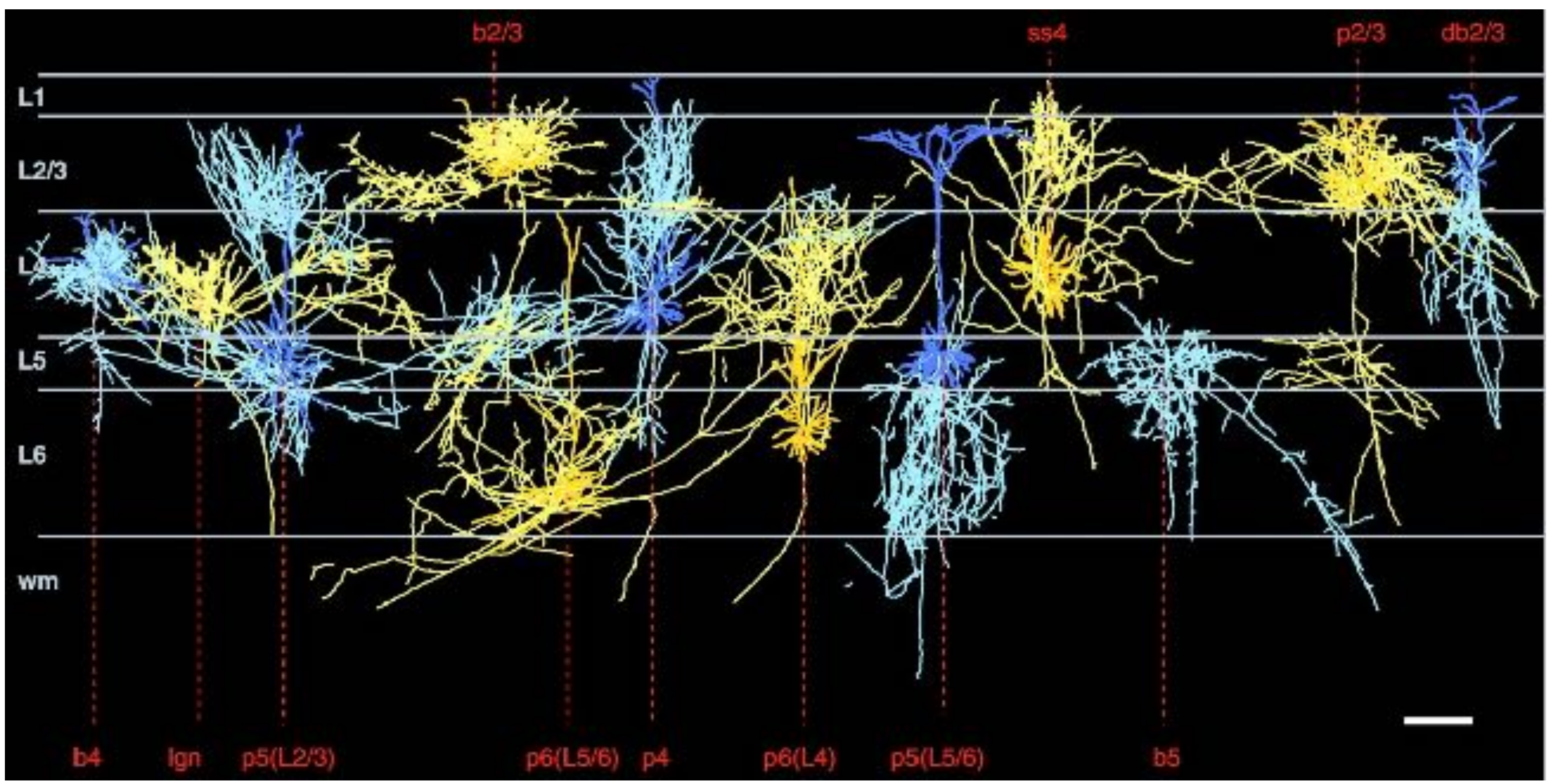
it moves like one. He can be fooled easily not only by a bit of dangled meat but by any moving small object. His sex life is conducted by sound and touch. His choice of paths in escaping enemies does not seem to be governed by anything more devious than leaping to where it is darker. Since he is equally at home in water and on

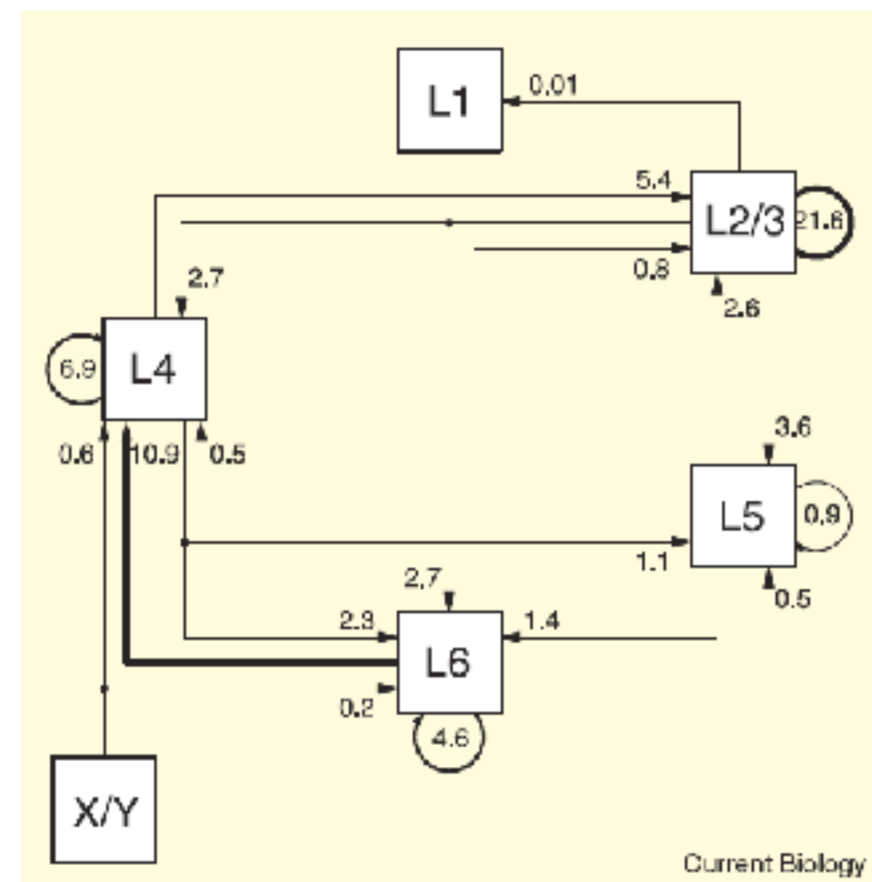
Anatomy of Frog Visual Apparatus

The retina of a frog is shown in Fig. 1(a). Between the rods and cones of the retina and the ganglion cells, whose axons form the optic nerve, lies a layer of con-

Cortical circuits

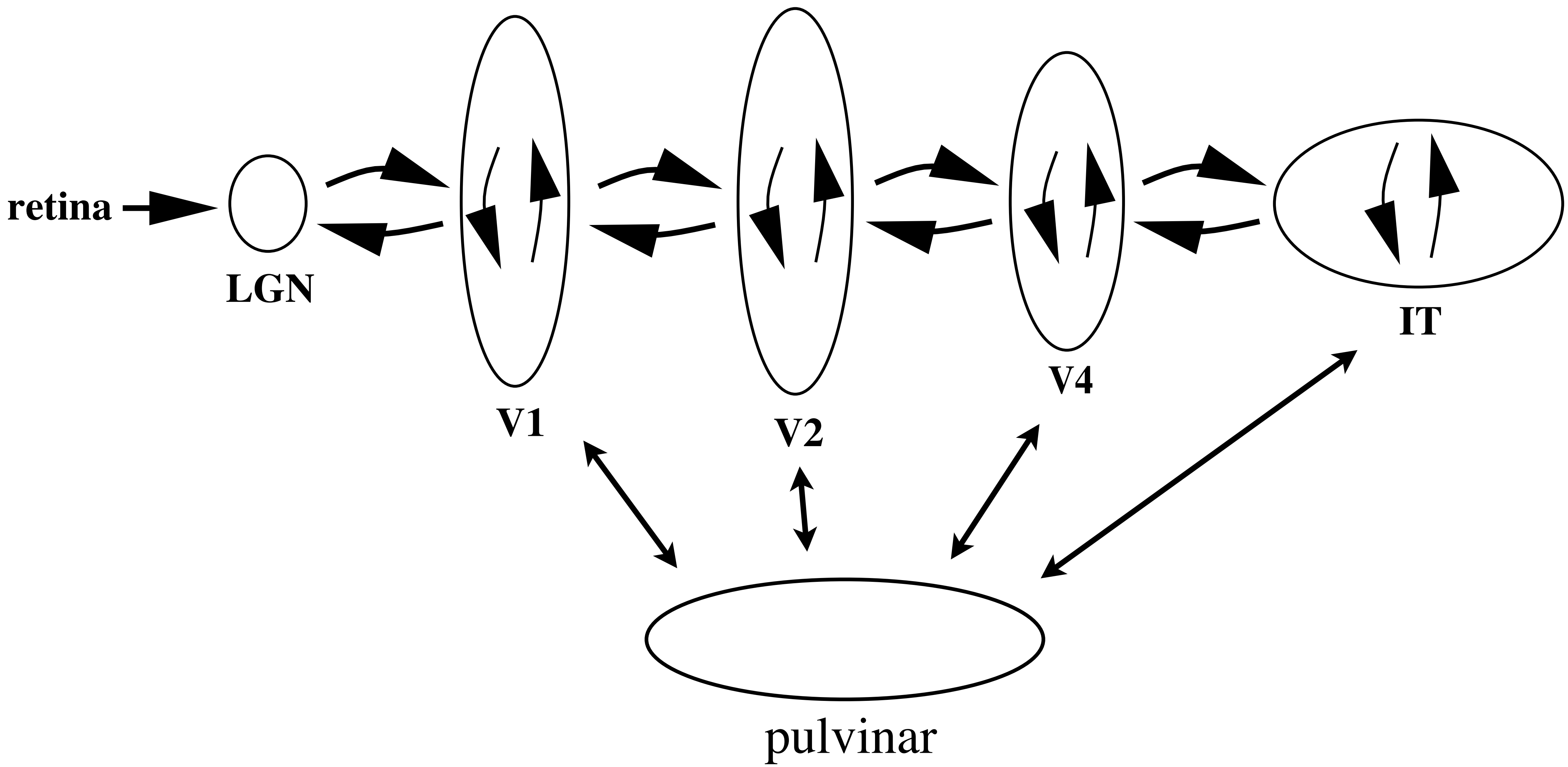
- highly organized by layer
- layers are interconnected in a 'canonical microcircuit'
- signals are strongly intermixed within layers 2/3





(Douglas and Martin, 2007)

Feedback is pervasive throughout the thalamo-cortical system



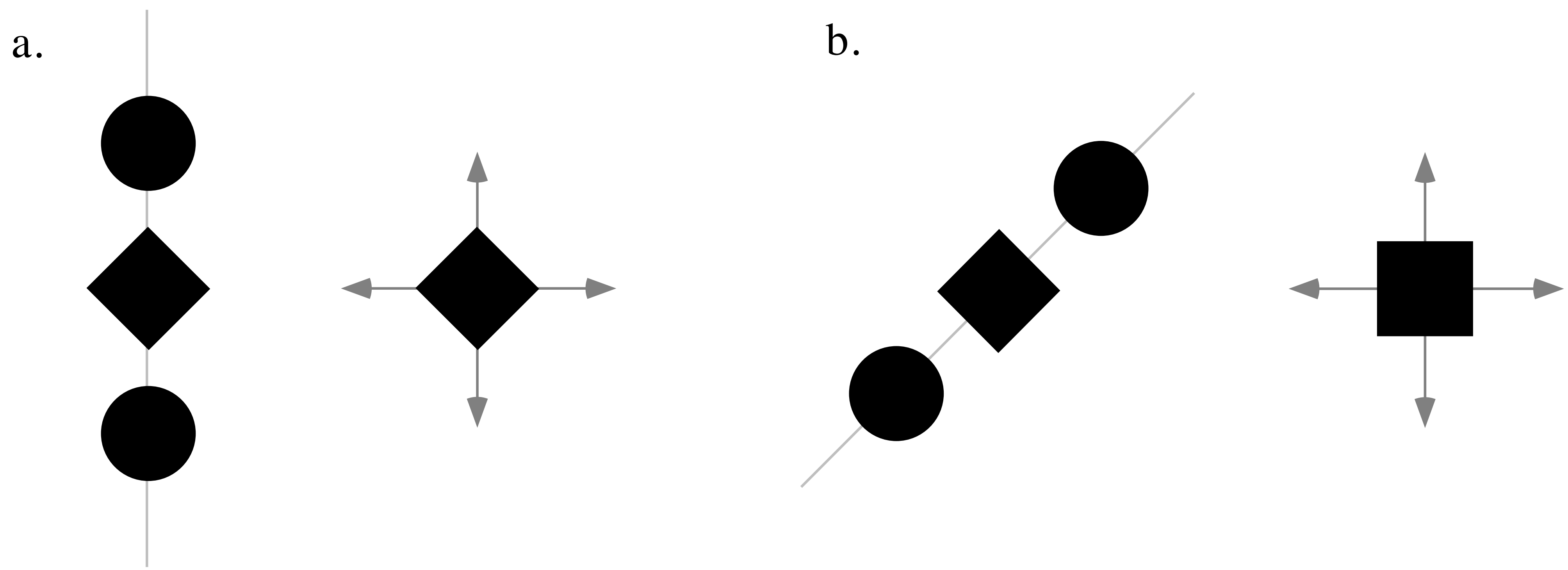
Two specific proposals

1. Dynamic routing

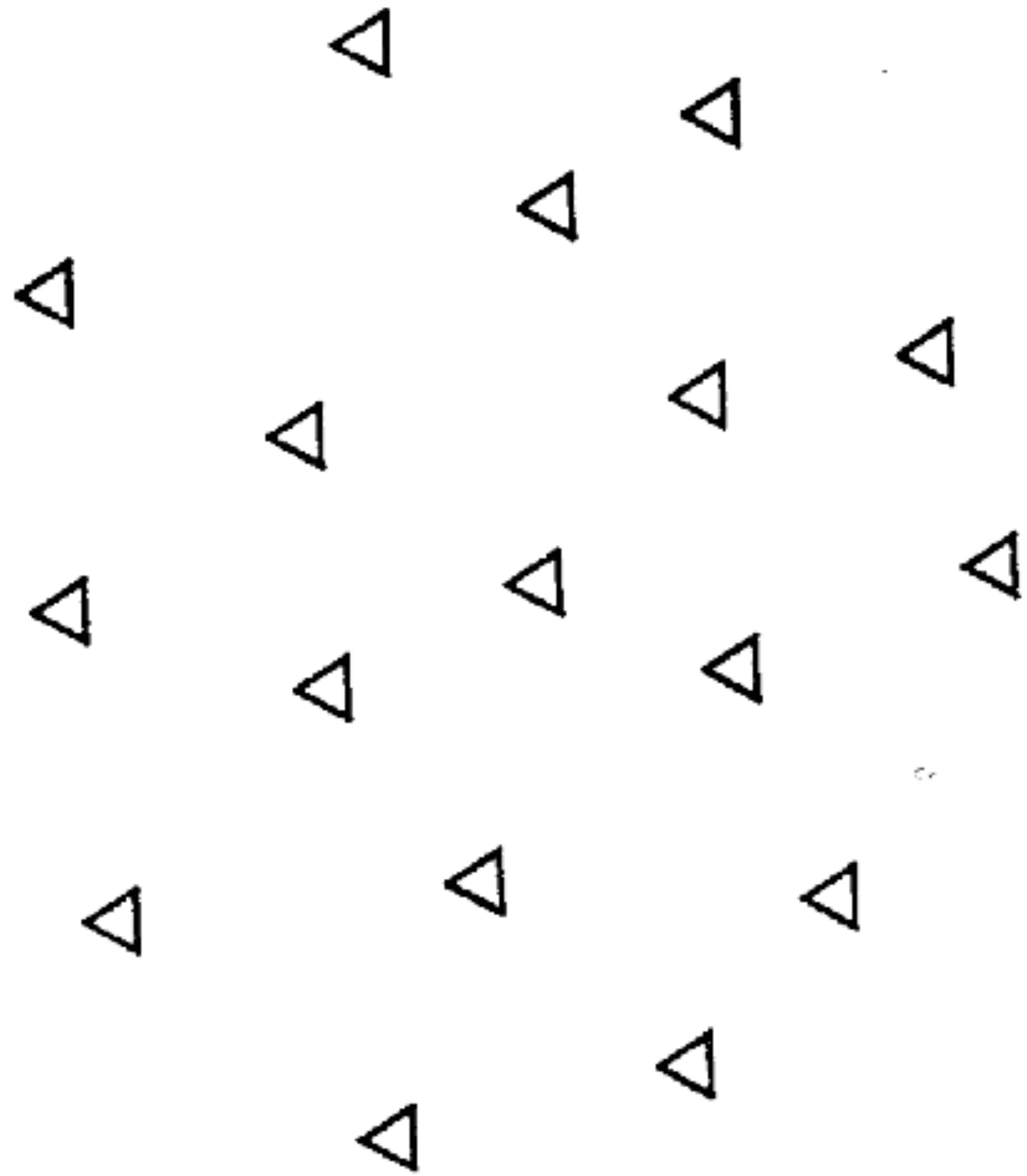
2. Hierarchical Bayesian inference

Reference frame effects in perception

Diamond or square?

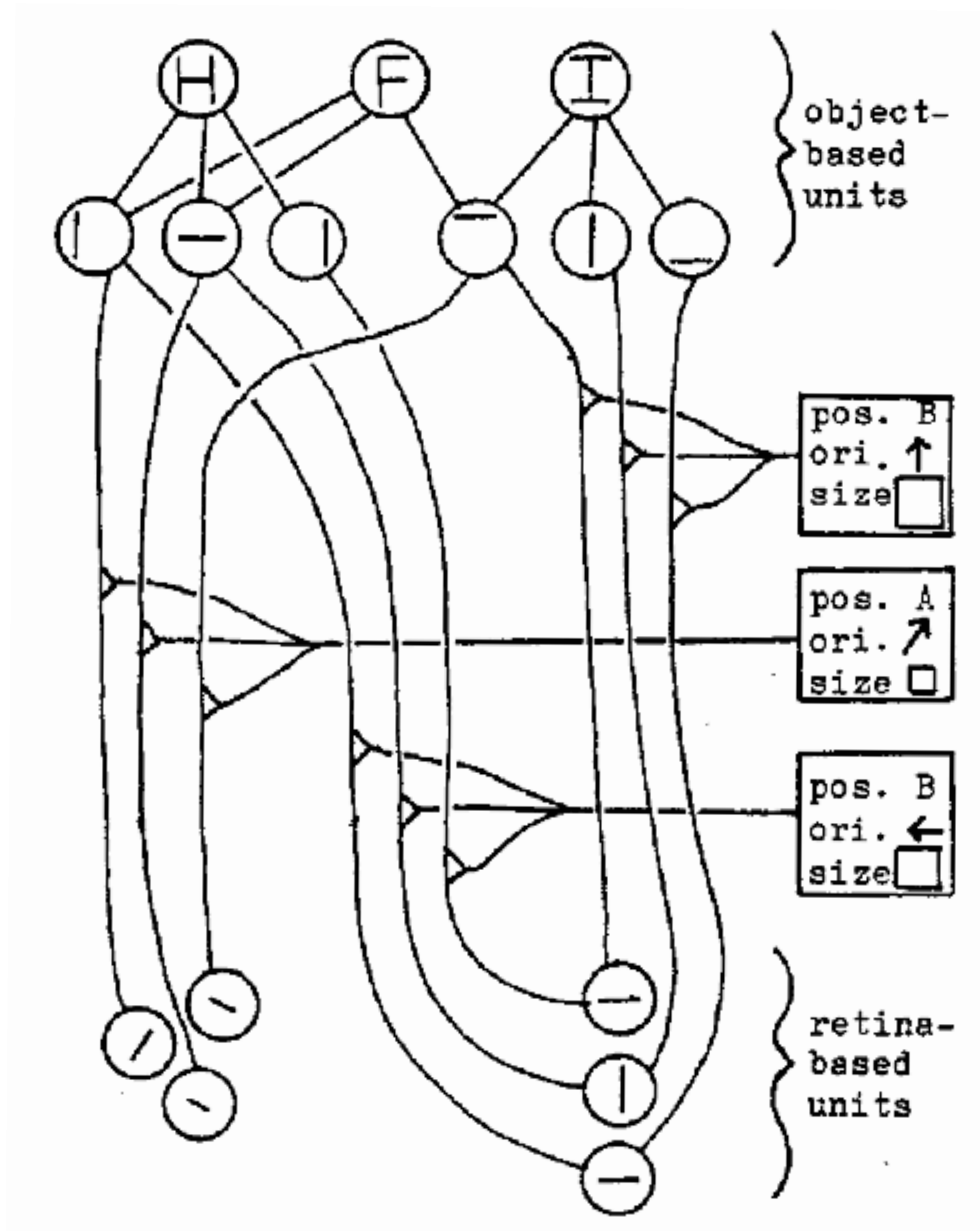


Which way are the triangles pointing?



From Attneave

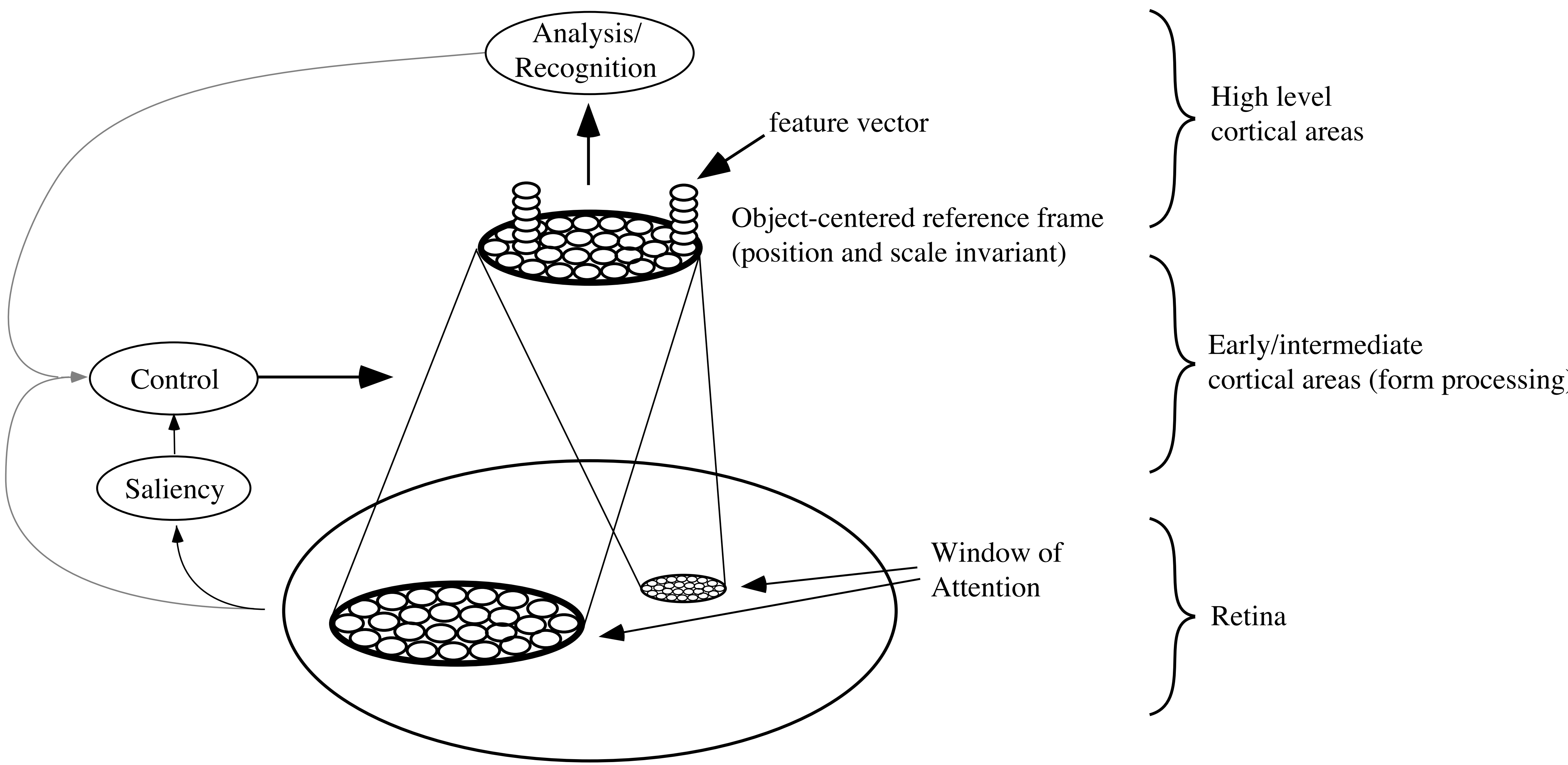
Reference frames require *structured representations*



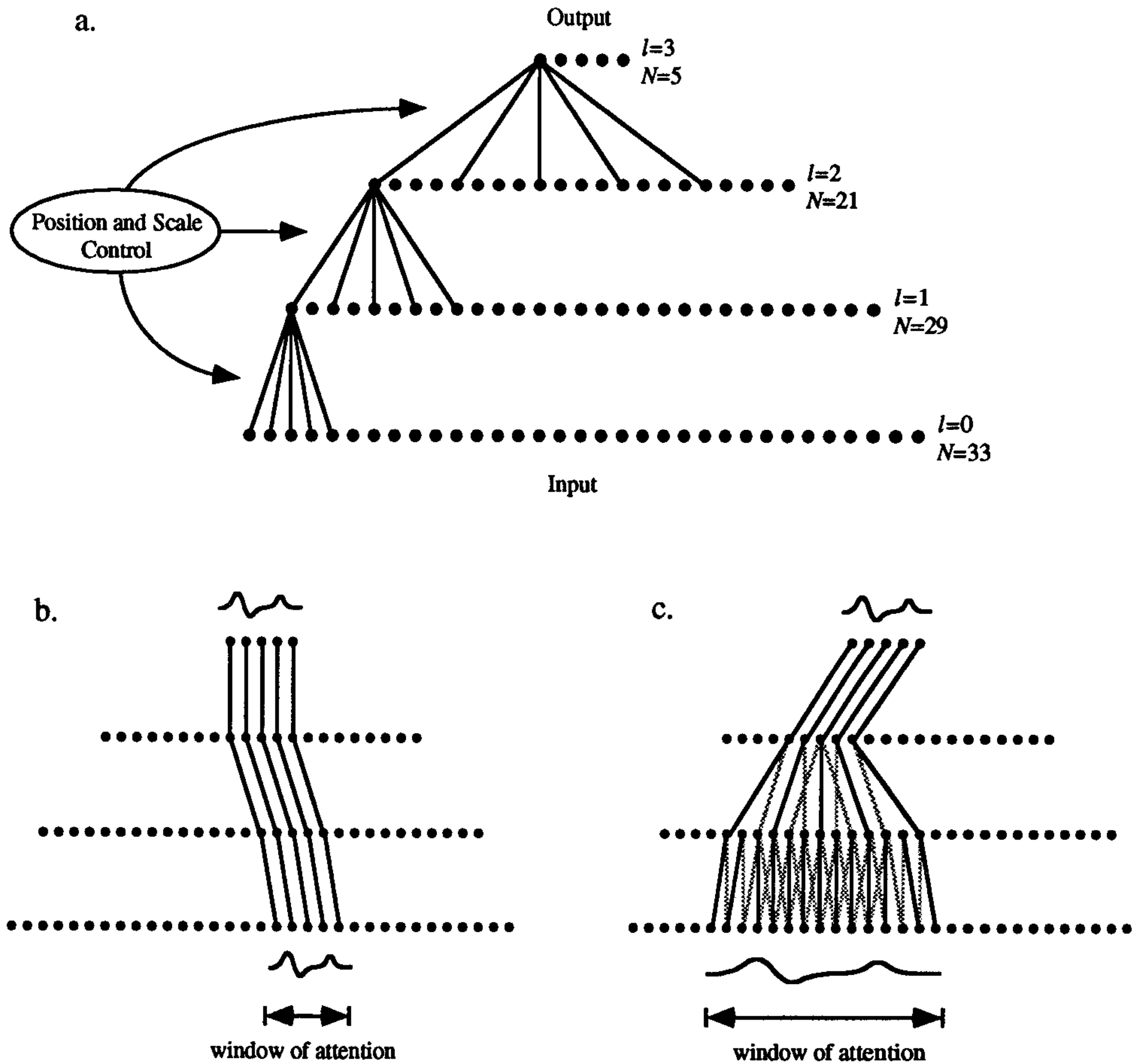
mapping
units

Hinton (1981)

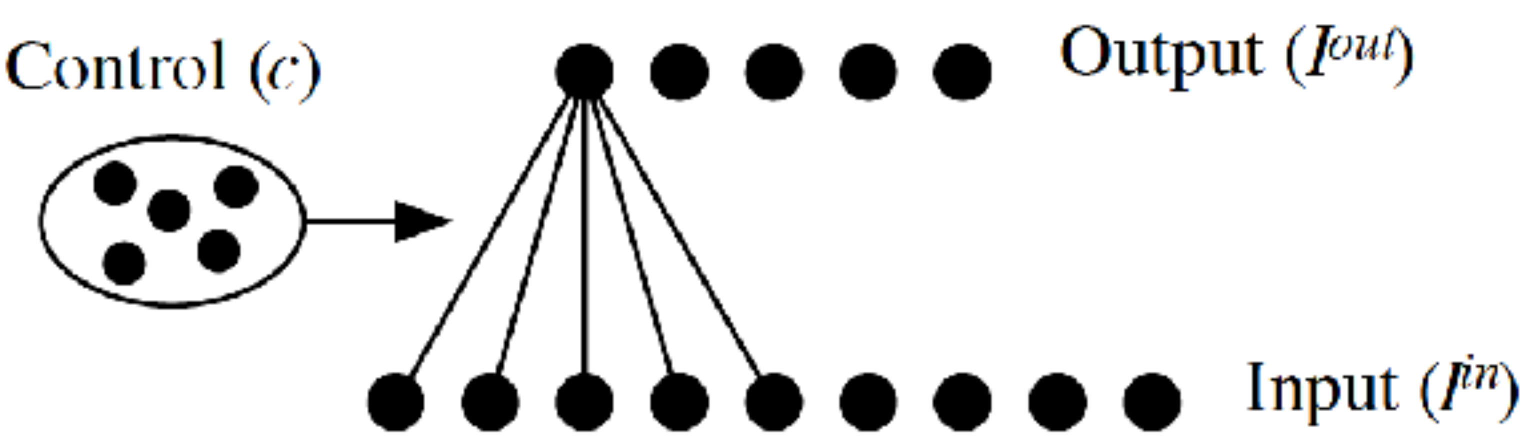
Dynamic routing
(Olshausen, Anderson, Van Essen 1993)



Dynamic routing circuit

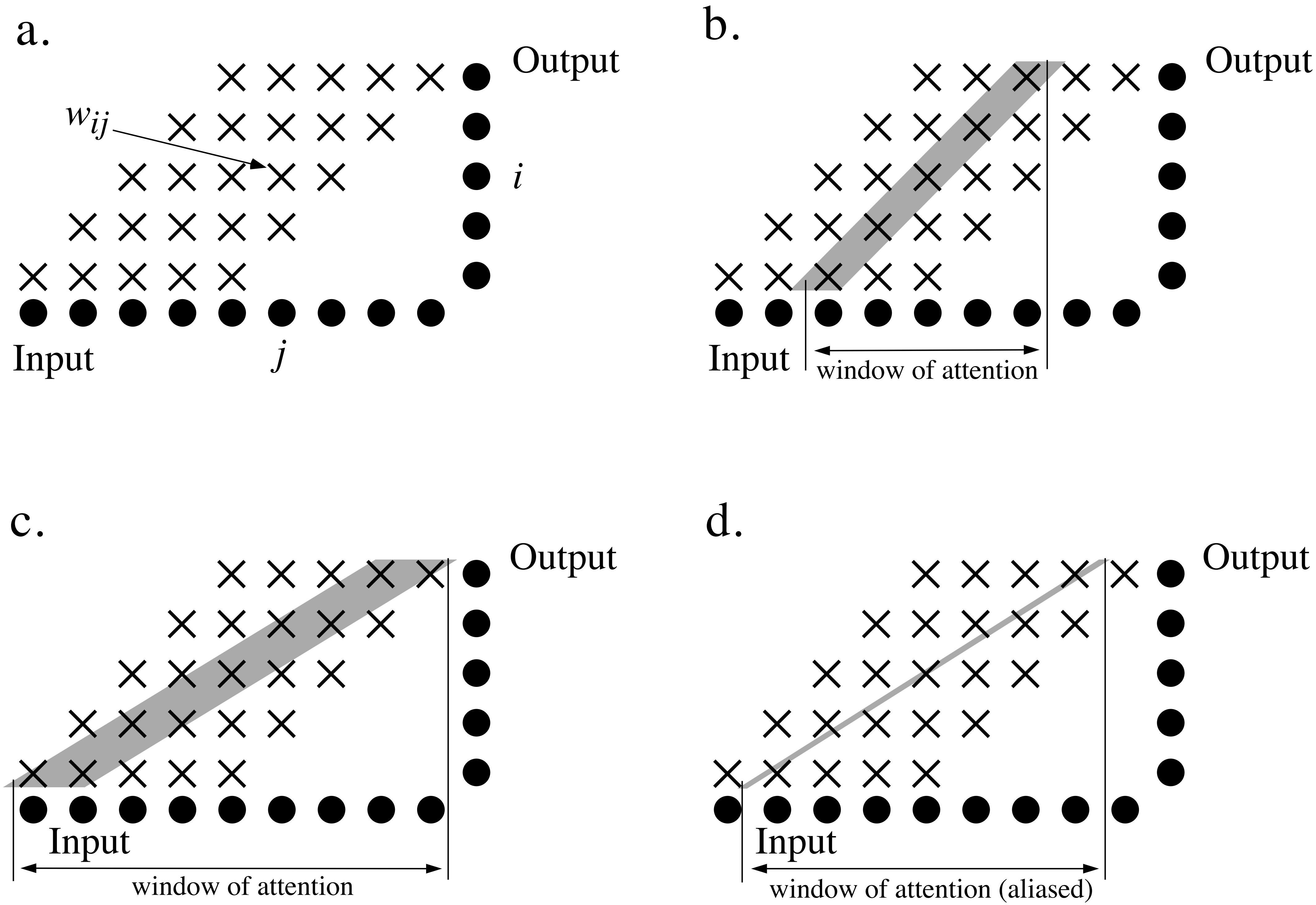


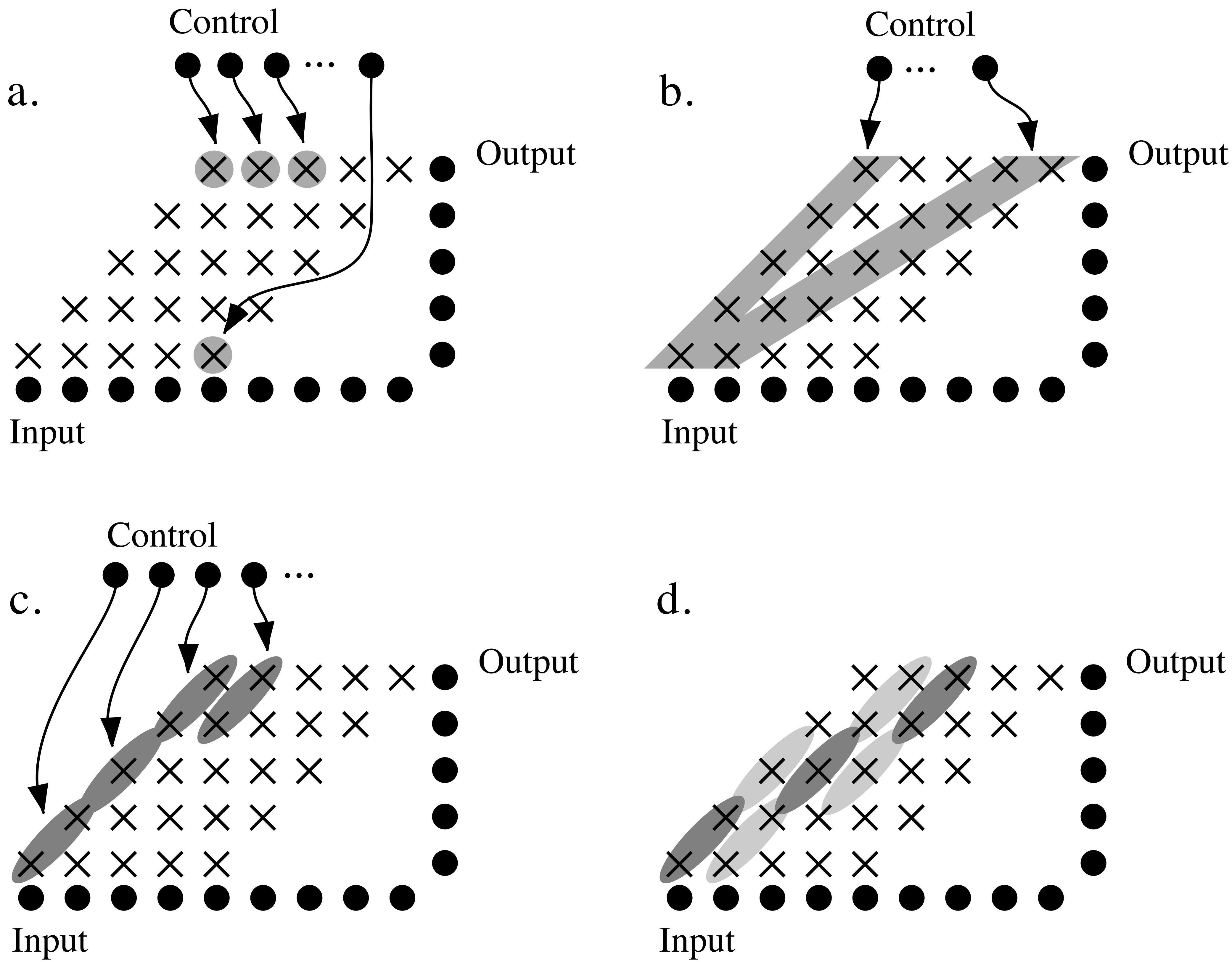
Dynamic routing: control



$$
\begin{aligned}
I_i^{out} &= \sum_j w_{ij} I_j^{in} \\
w_{ij} &= \sum_k c_k \Gamma_{ijk}
\end{aligned}
$$

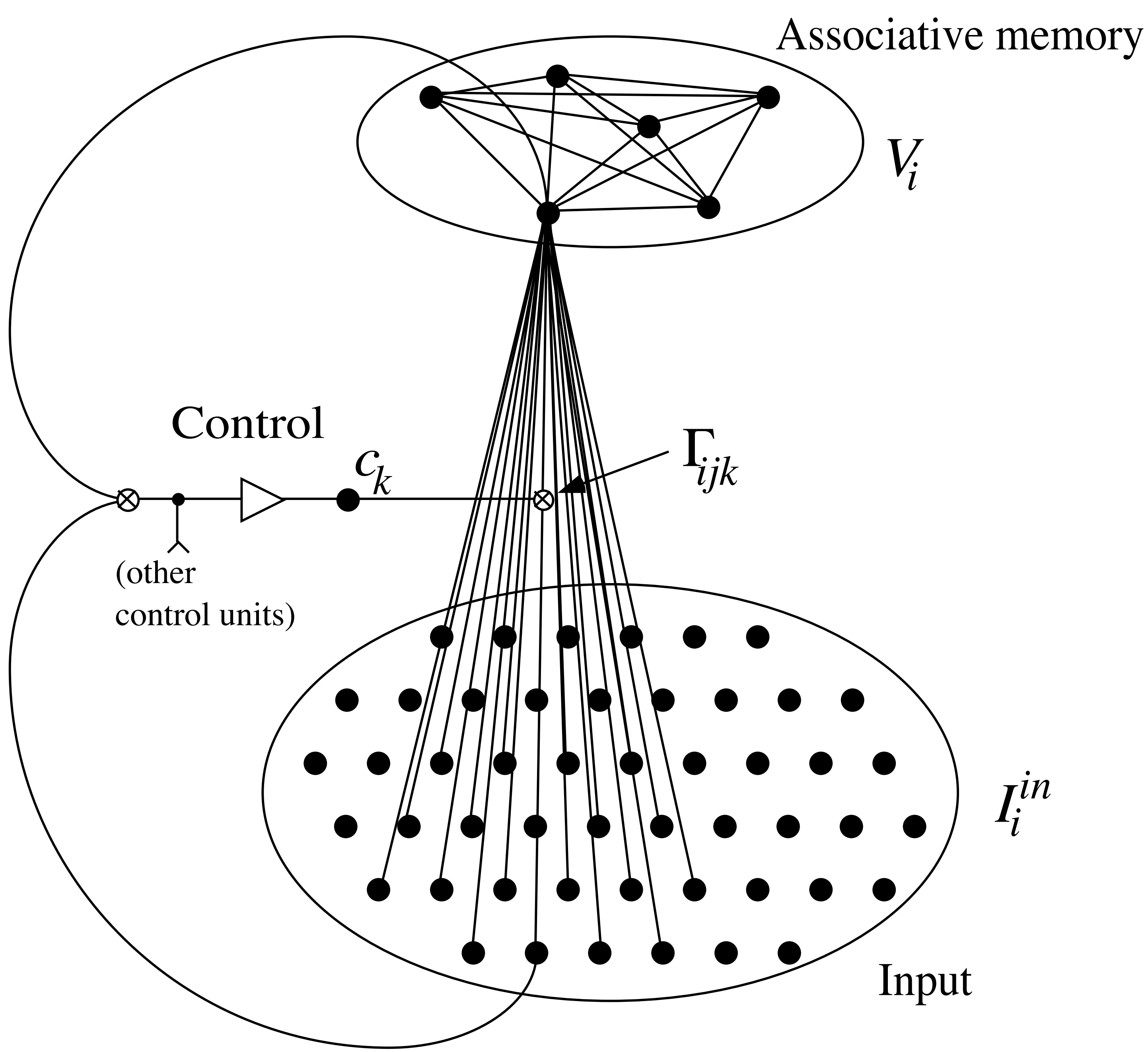
Dynamic routing: control



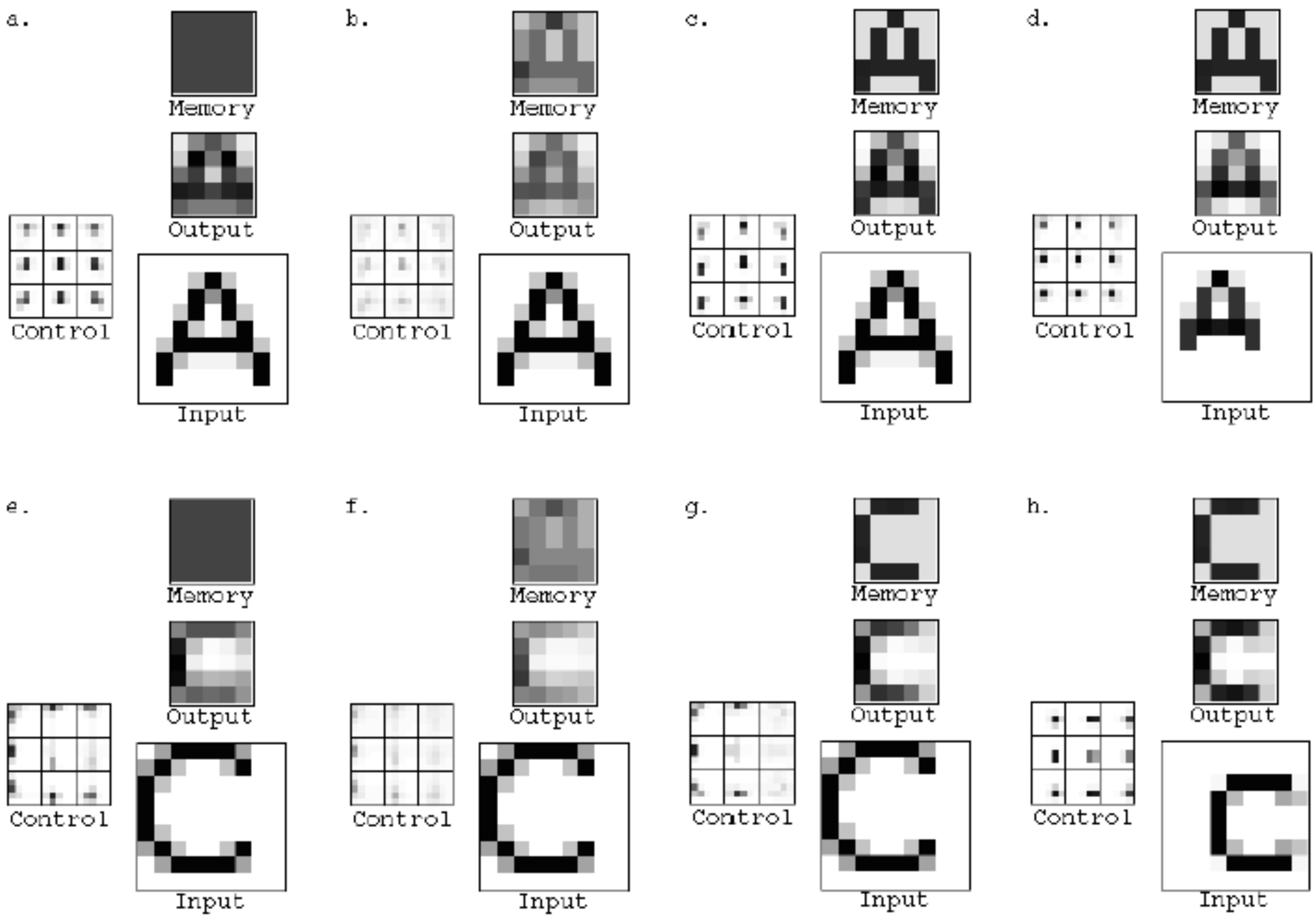


a.
Control
...
Output
Input
b.
Control
...
Output
Input
c.
Control
...
Output
Input
d.
Output
Input

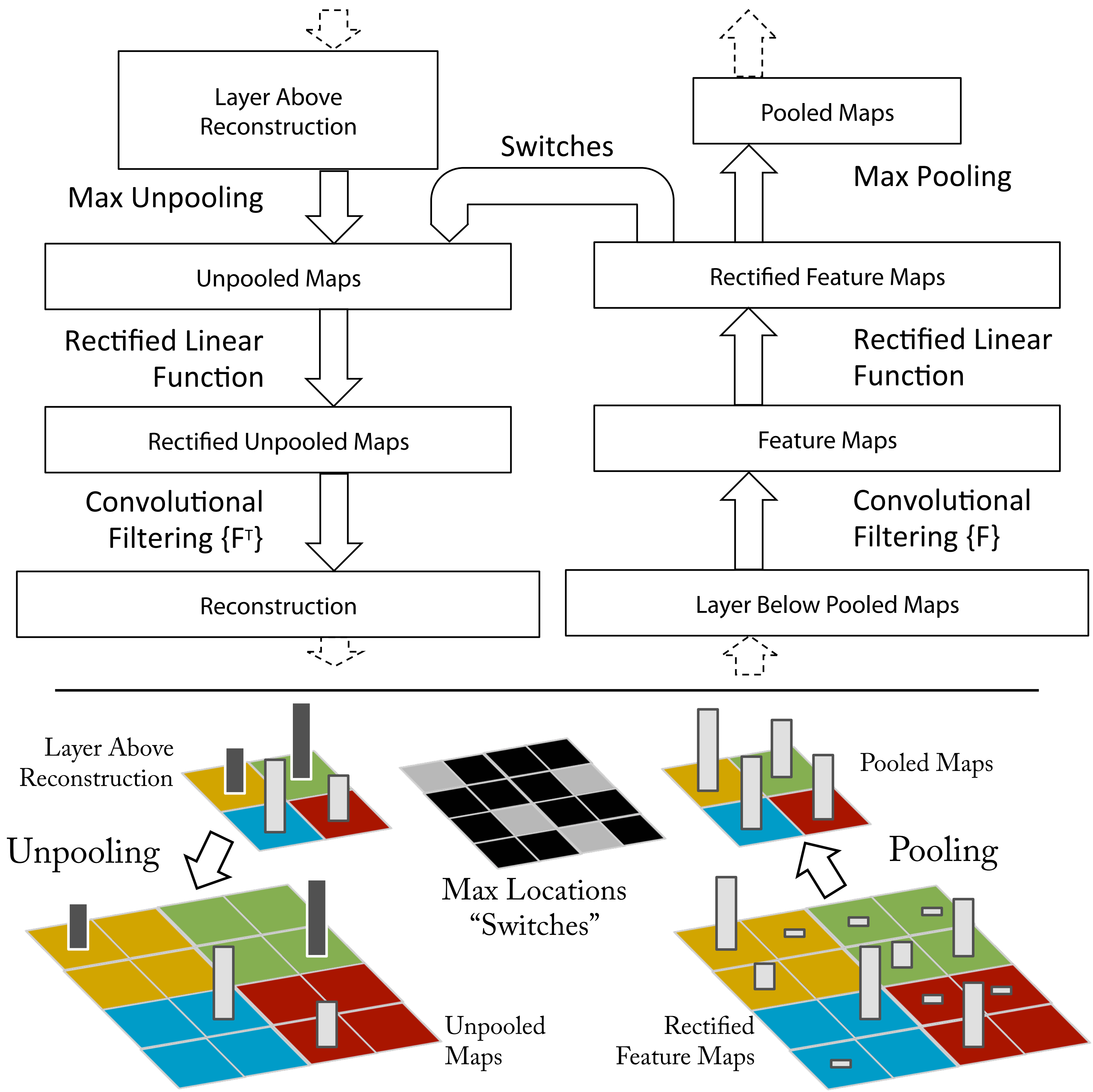
Pattern matching via dynamic routing



Pattern matching via dynamic routing



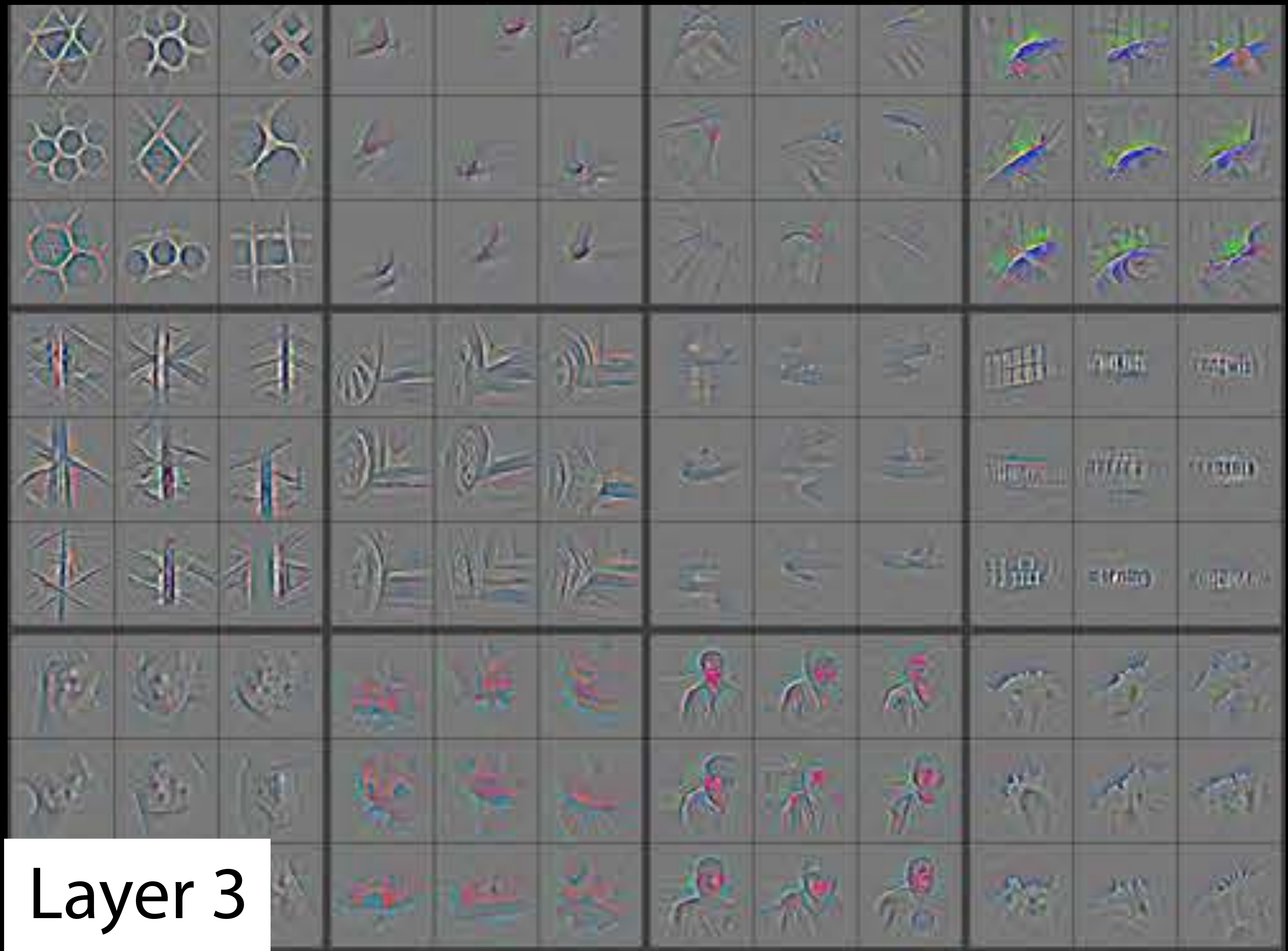
Dynamic routing in deep networks



(Zeiler & Fergus, 2013)

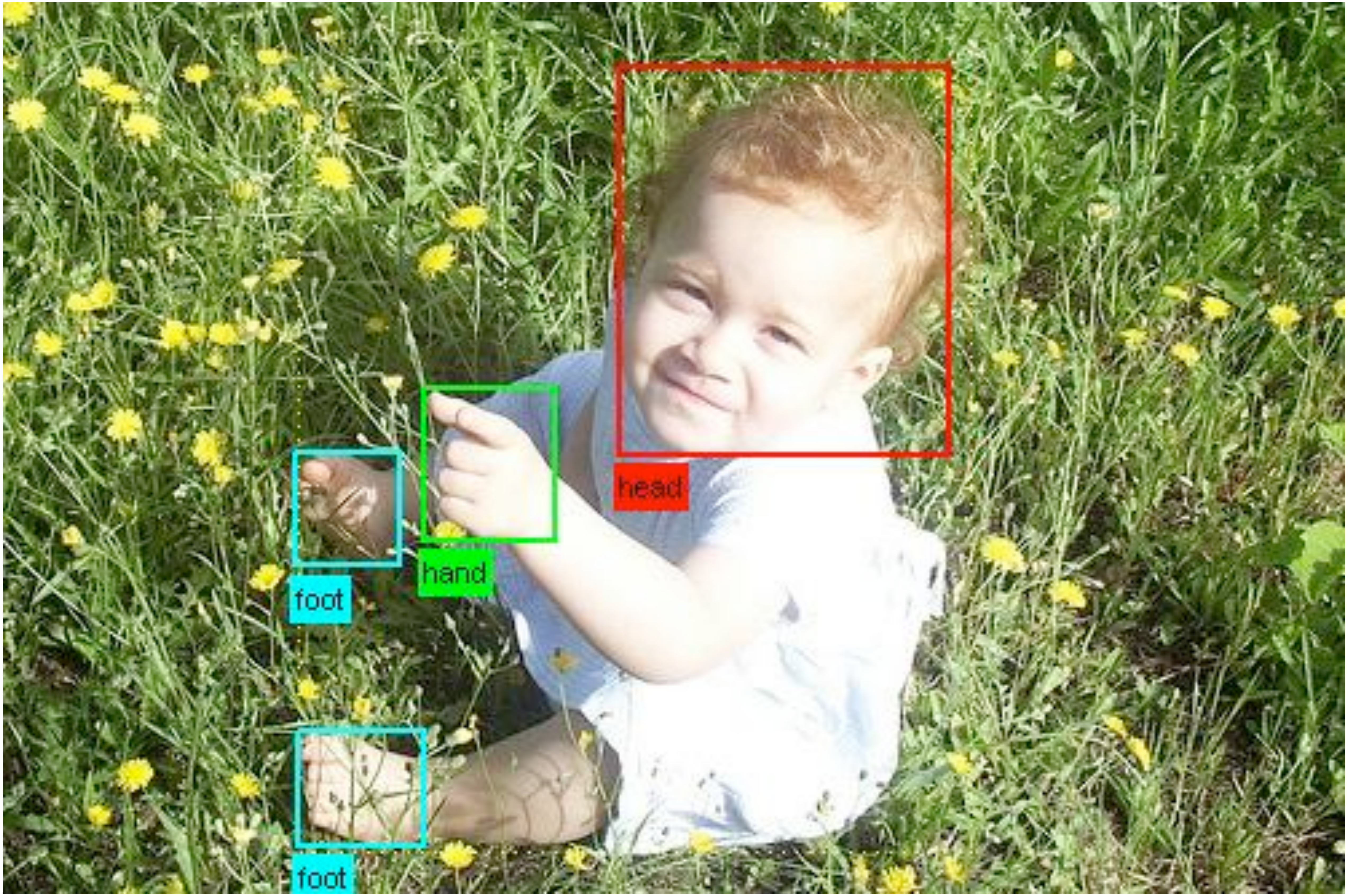
Visualization of filters learned at intermediate layers

(Zeiler & Fergus 2013)

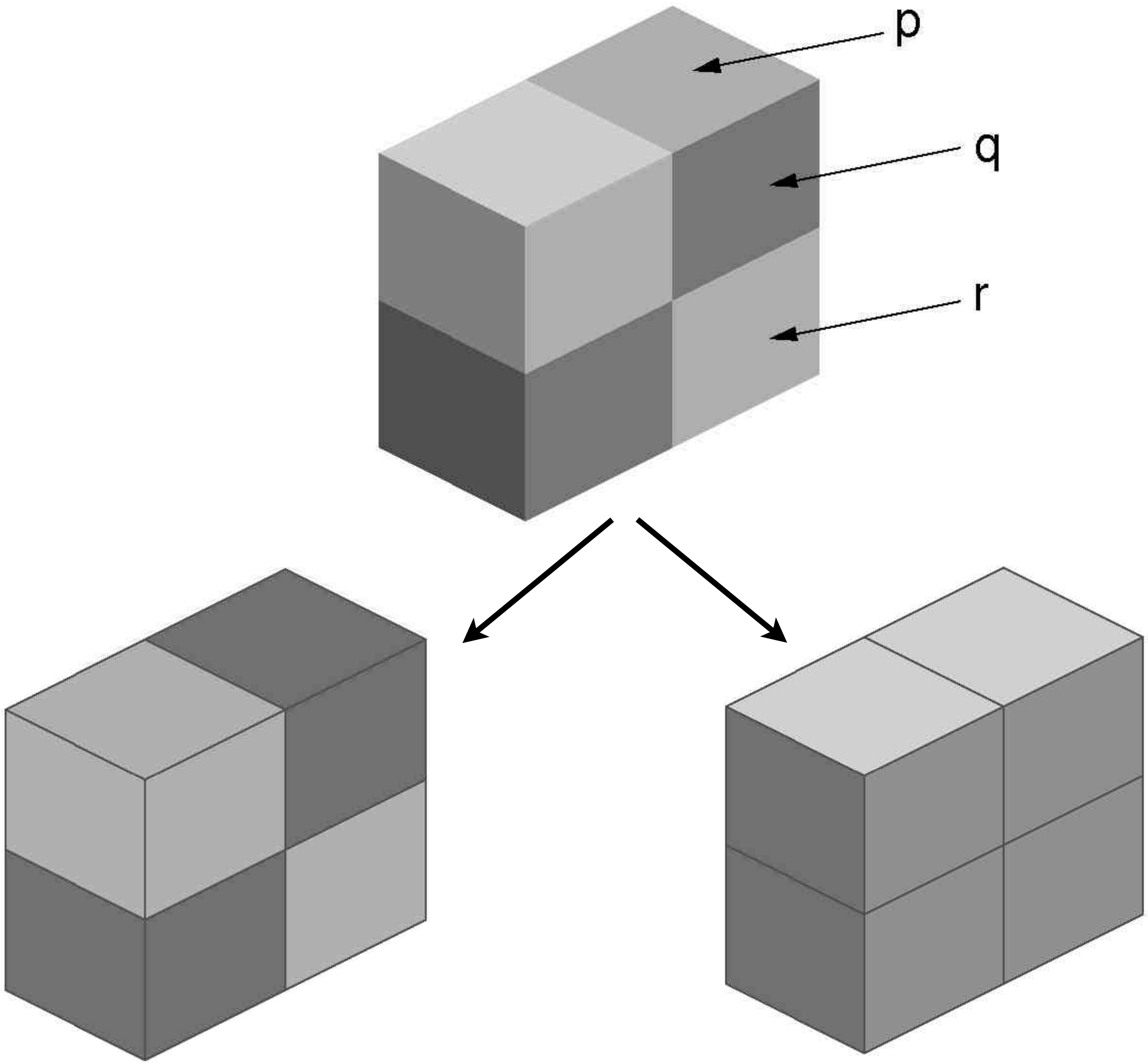


Perception as inference

Is this the goal of perception?



What do these edges mean?

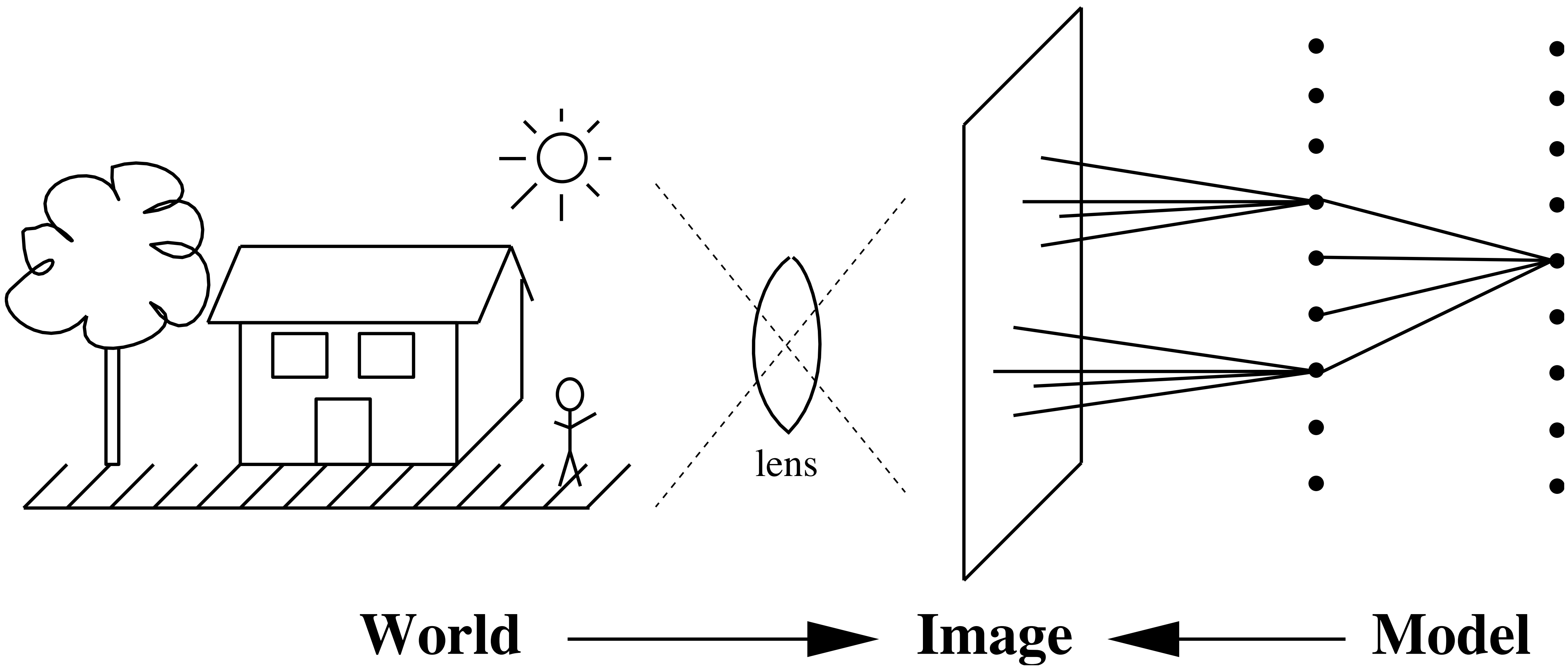


reflectance

shading

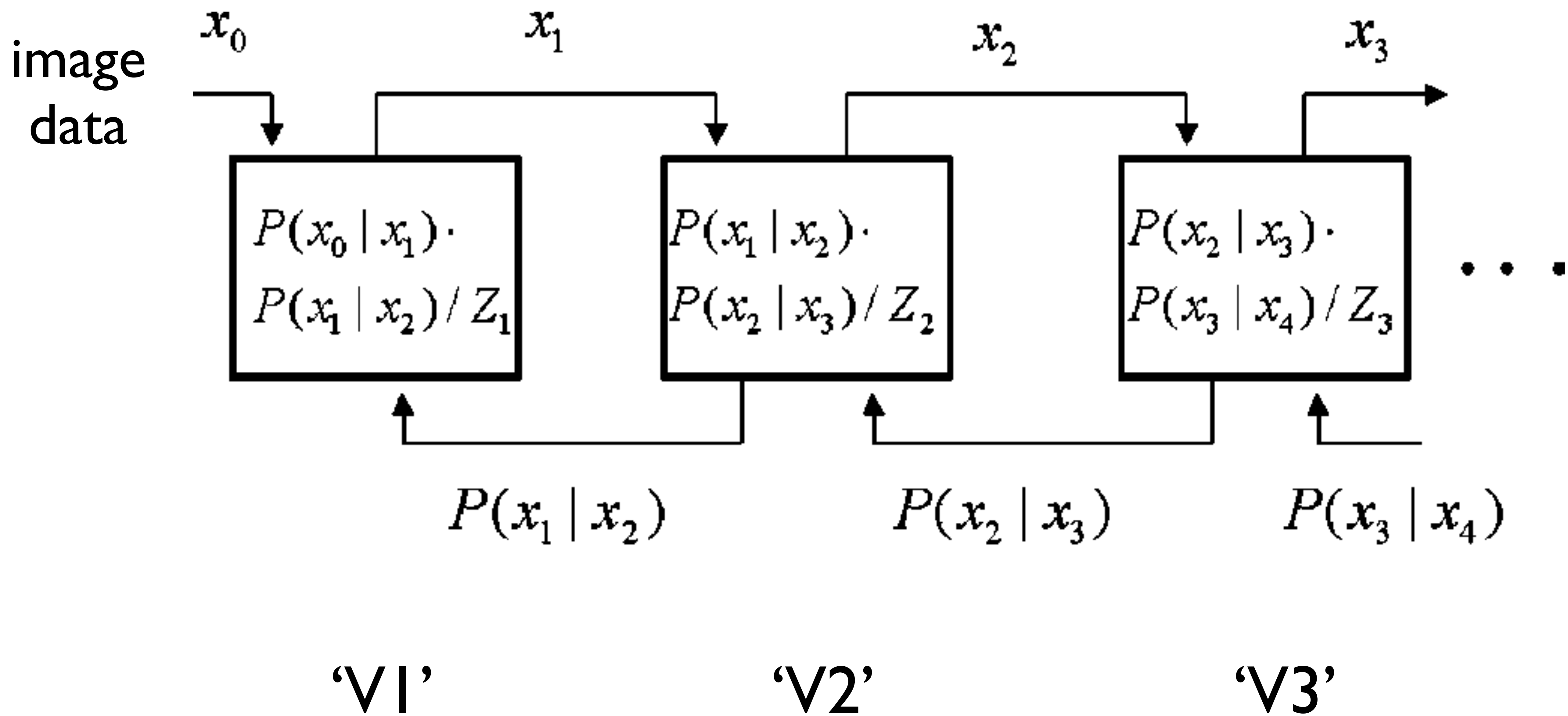
(Adelson, 2000)

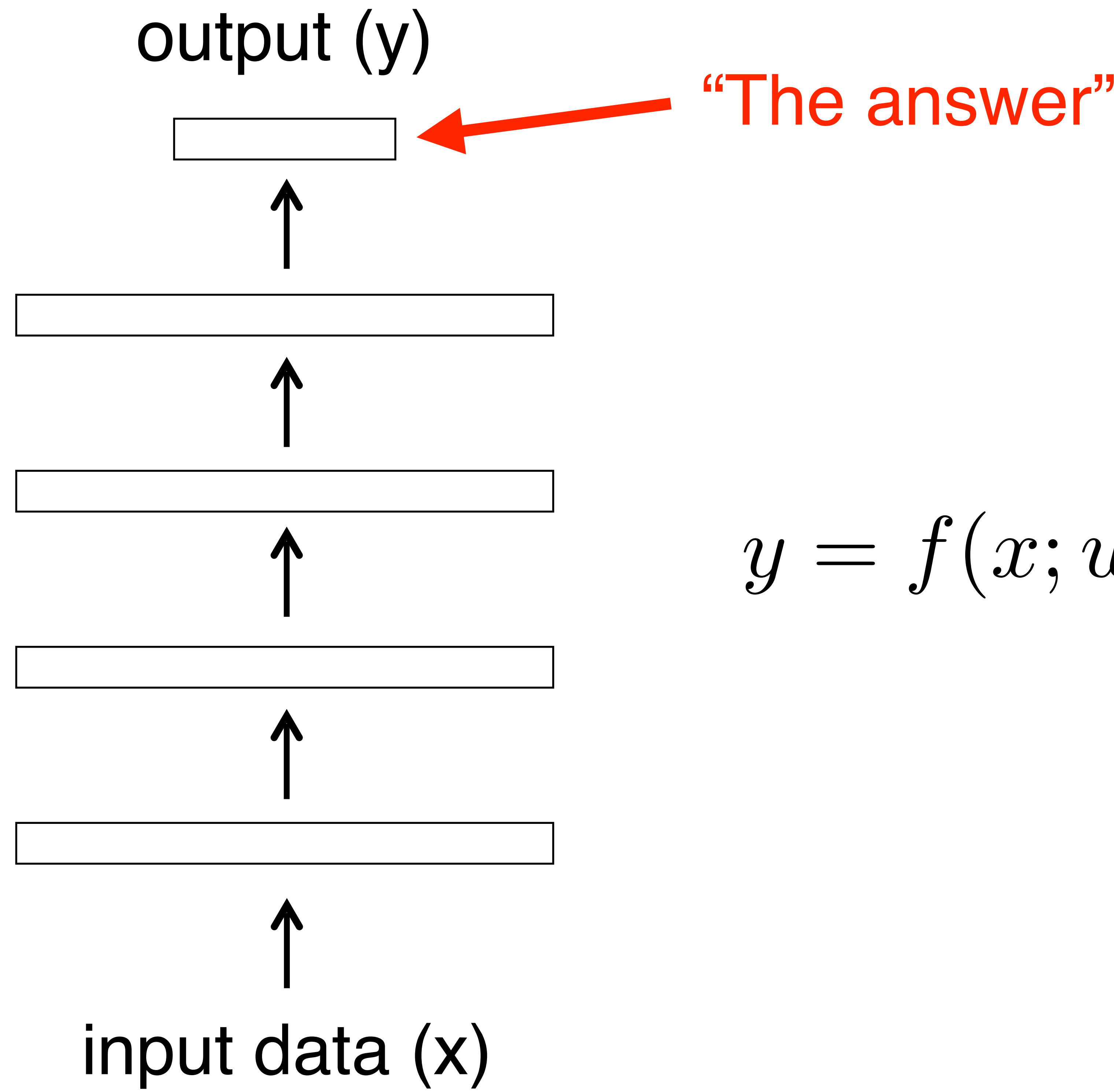
Vision as inference



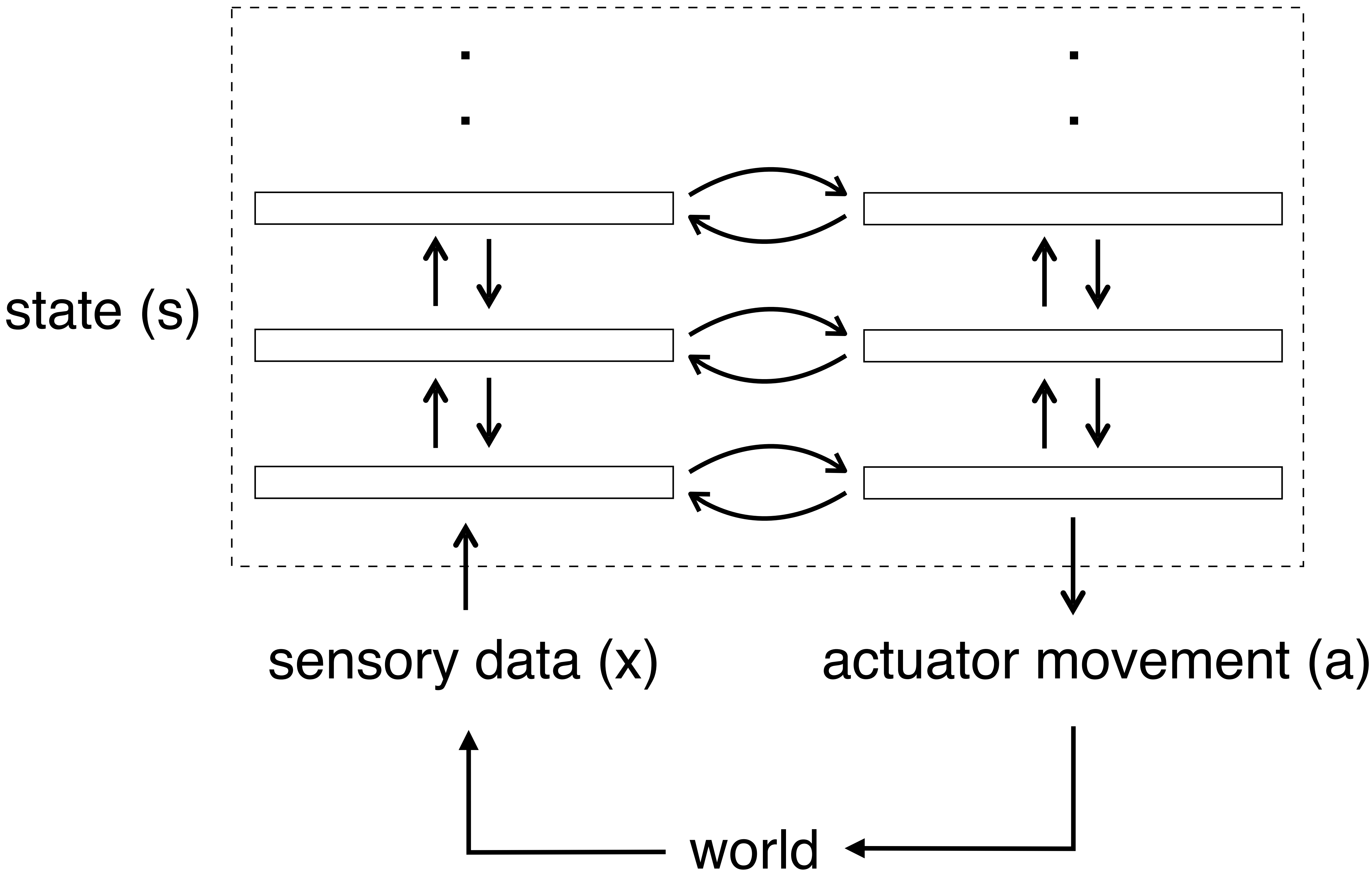
Hierarchical Bayesian inference in visual cortex

(Lee & Mumford, 2003)





$$y = f(x; w)$$


state (s)
sensory data (x)
actuator movement (a)
world

Main points

- Multilayer perceptrons were a good idea in 1960's

- Neocognitron was a good idea in 1980's

- The way forward:
  - identify the right problems to be solved
  - exploit the computational richness offered by real neurons and cortical circuits

- Two examples:
  - Dynamic routing
  - Hierarchical Bayesian inference