

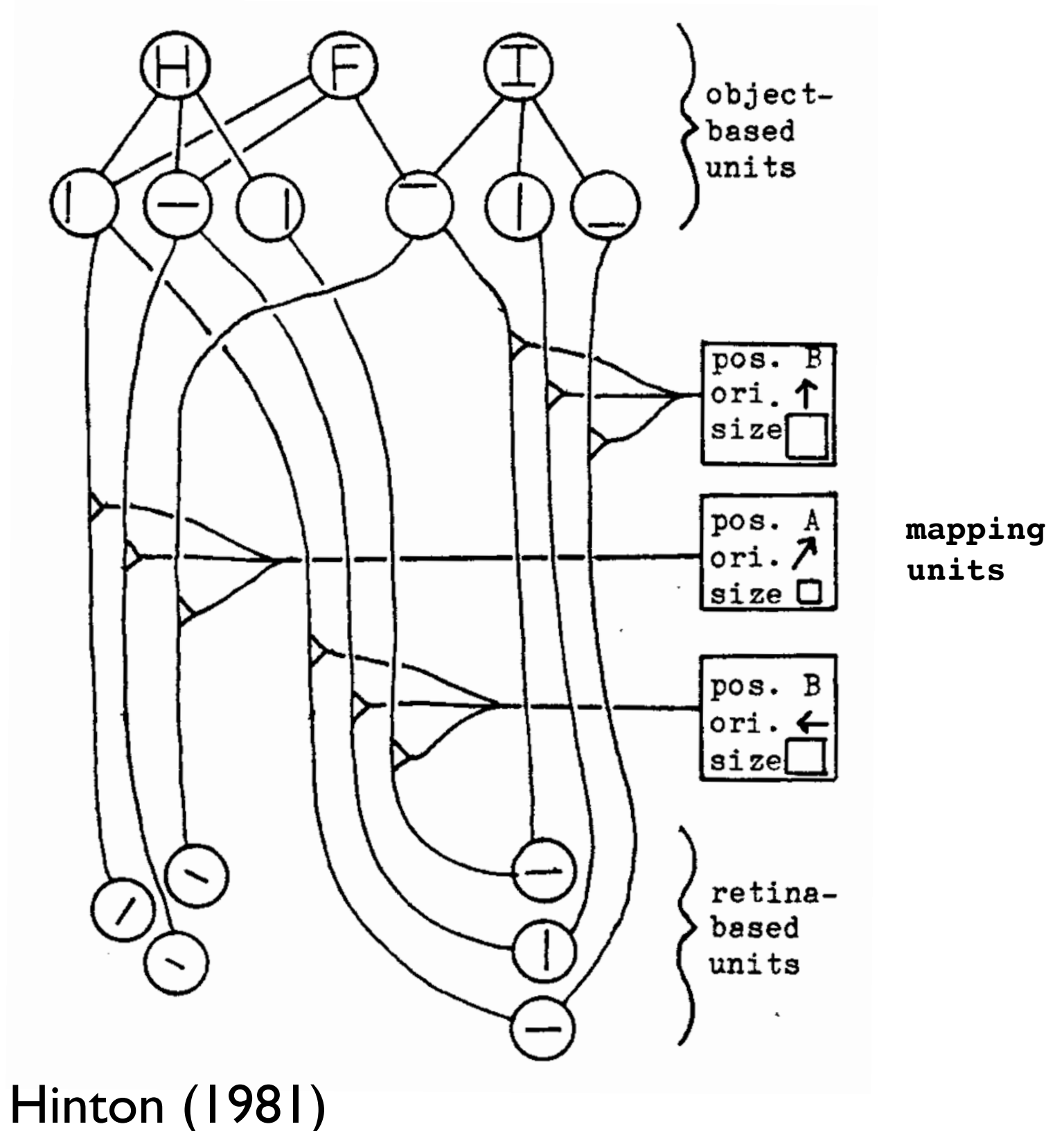
Three-way connections
and 'dynamic routing'

Reference frames require *structured representations*

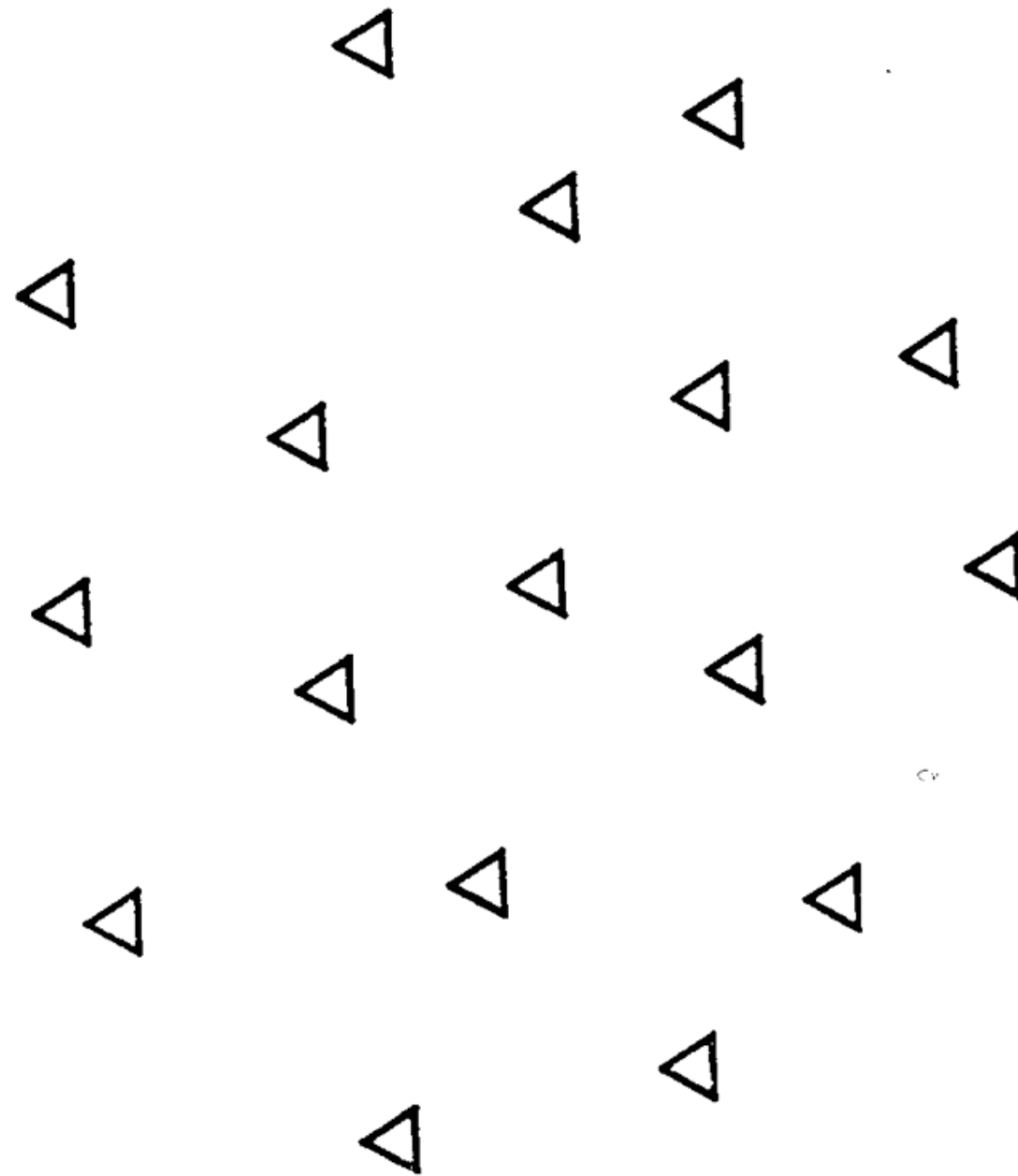
The meaning of the triangular symbol in fig. 1 is quite complex. It stands for two rules:

1. Multiply the activity level in the retina-based unit by the activity level in the mapping unit and send the product to the object-based unit.

2. Multiply the activity level in the retina-based unit by the activity level in the object-based unit and send the product to the mapping unit.



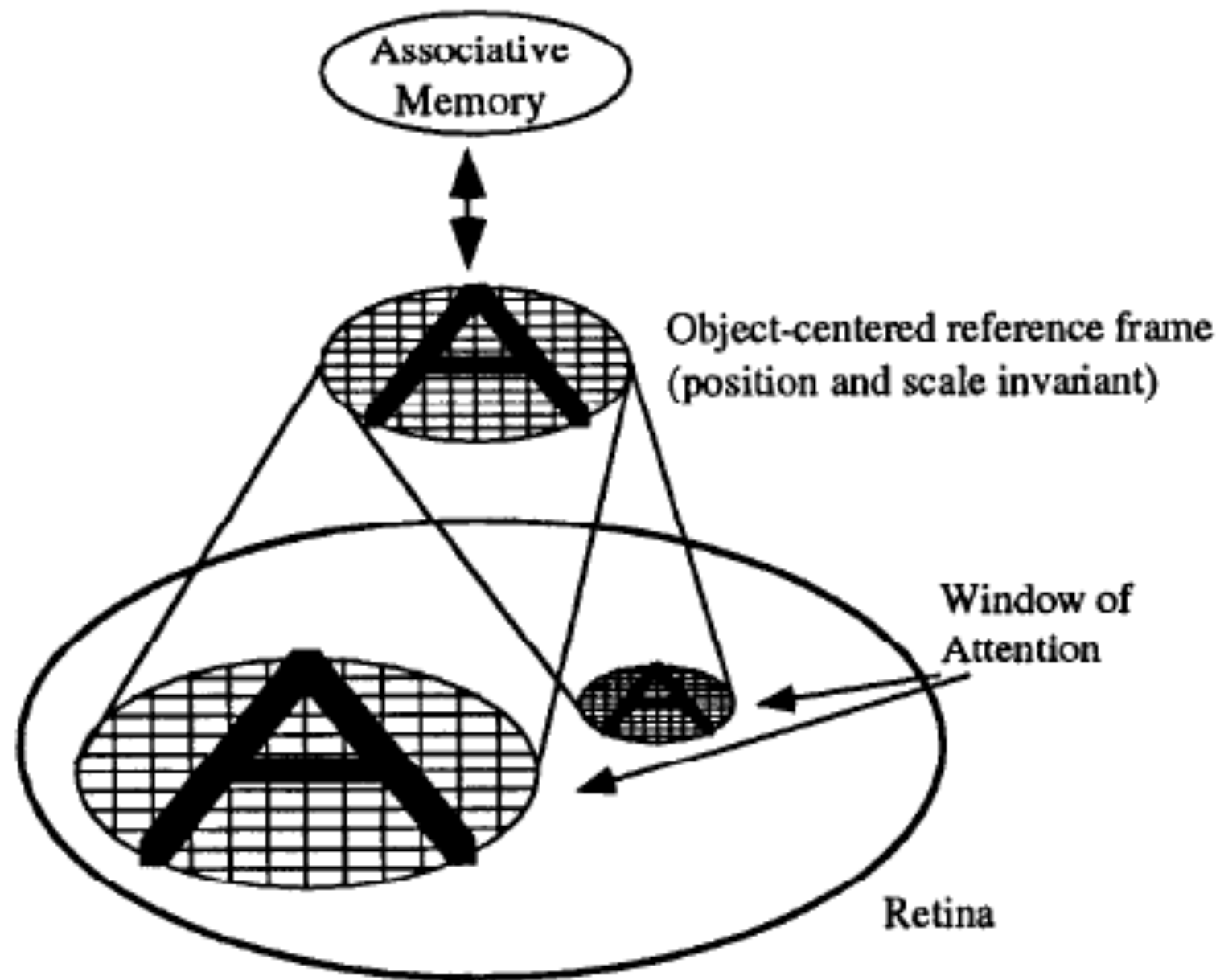
Which way are the triangles pointing?



From Attneave

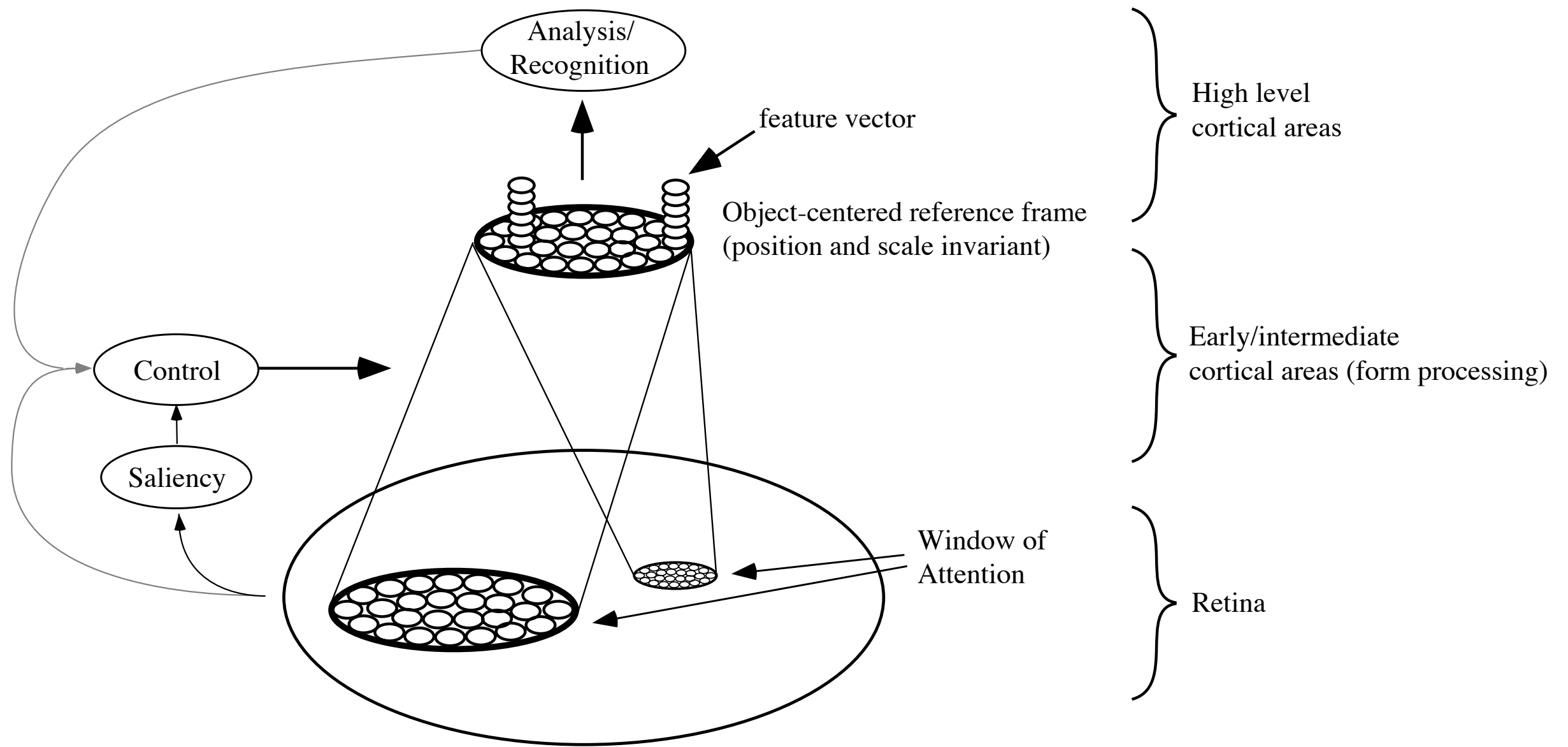
Dynamic routing circuits

(Olshausen, Anderson & Van Essen, 1993)

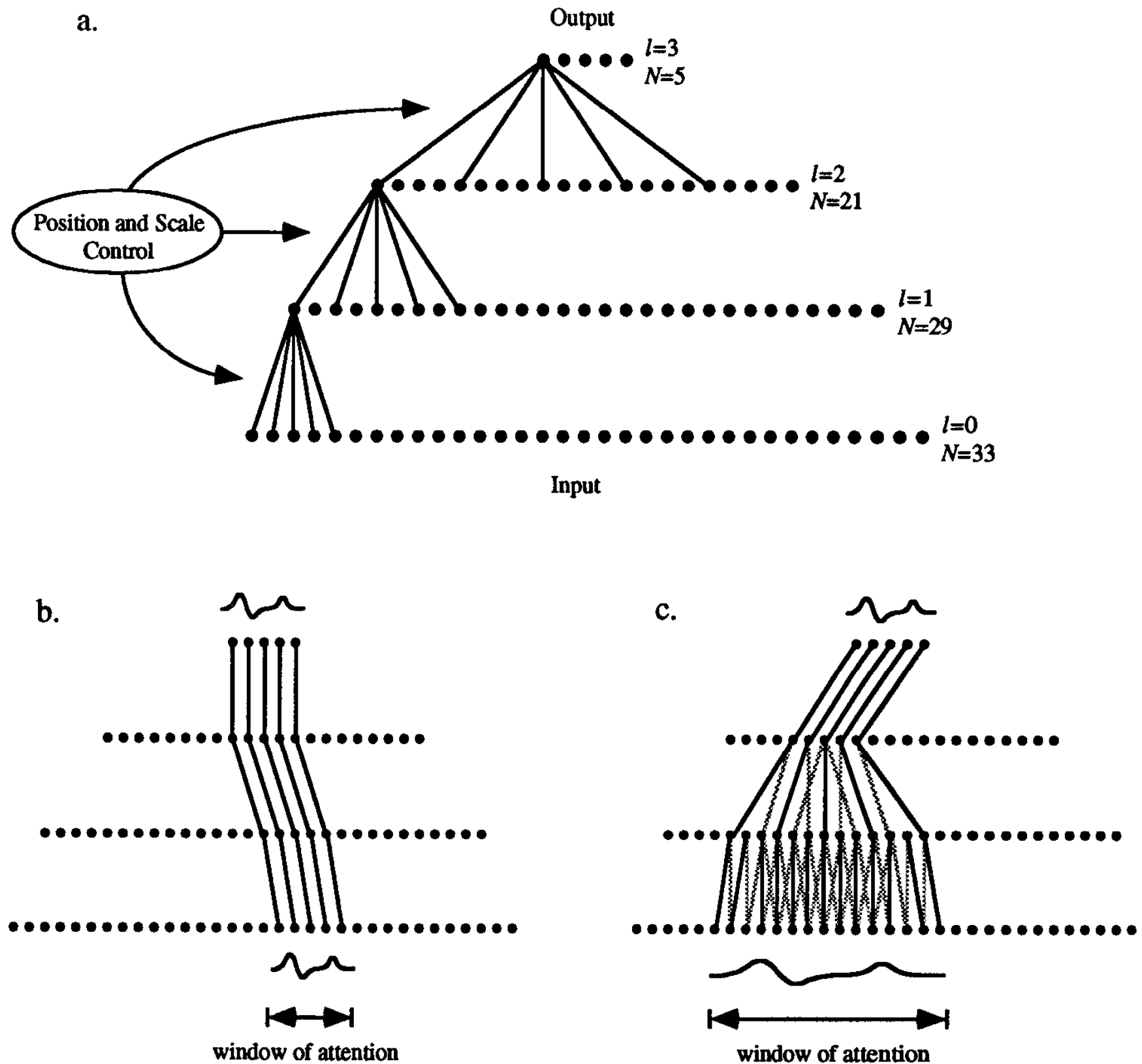


Dynamic routing

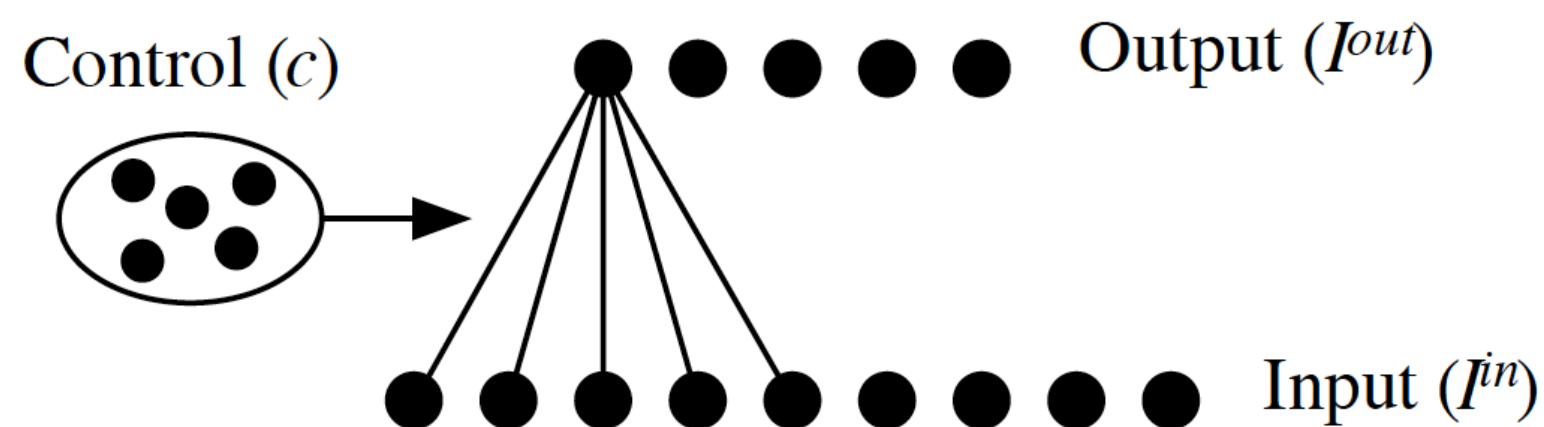
(Olshausen, Anderson, Van Essen 1993)



Dynamic routing circuit



Dynamic routing: control

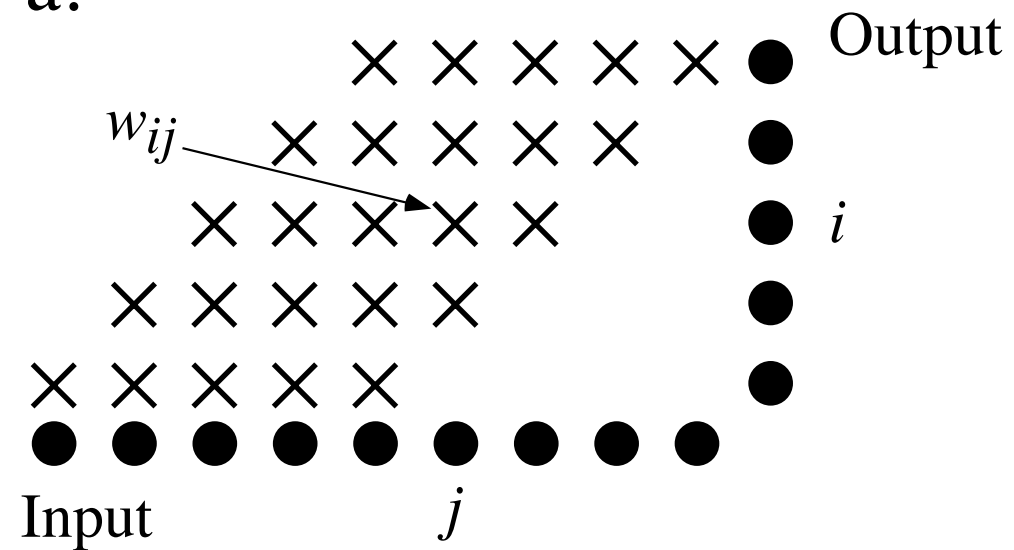


$$I_i^{out} = \sum_j w_{ij} I_j^{in}$$

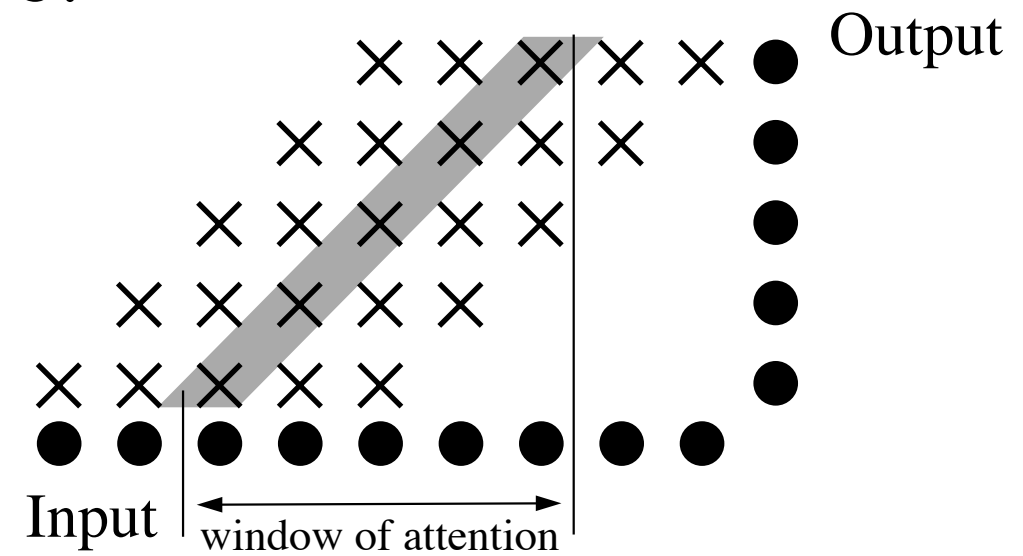
$$w_{ij} = \sum_k c_k \Gamma_{ijk}$$

Dynamic routing: control

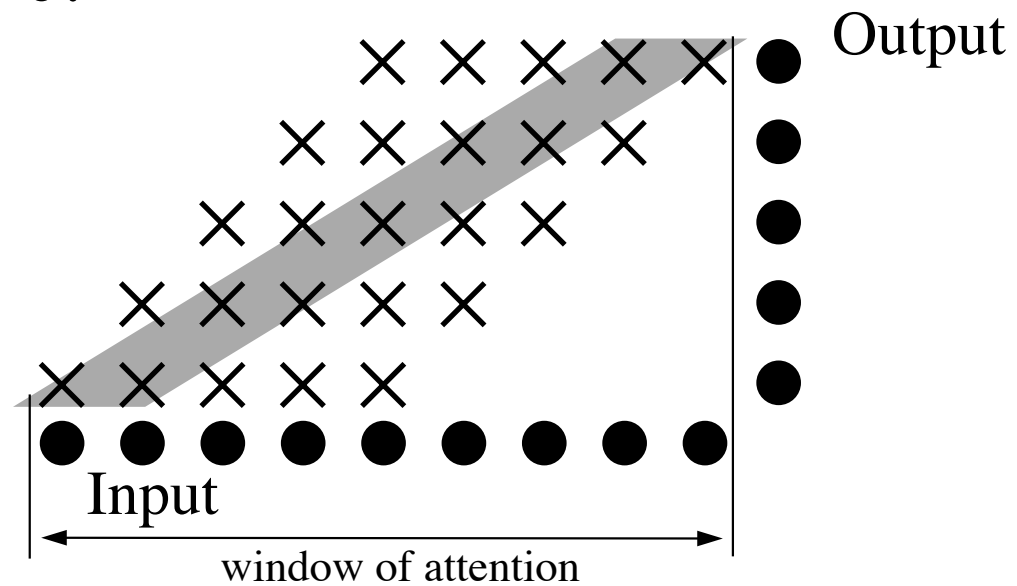
a.



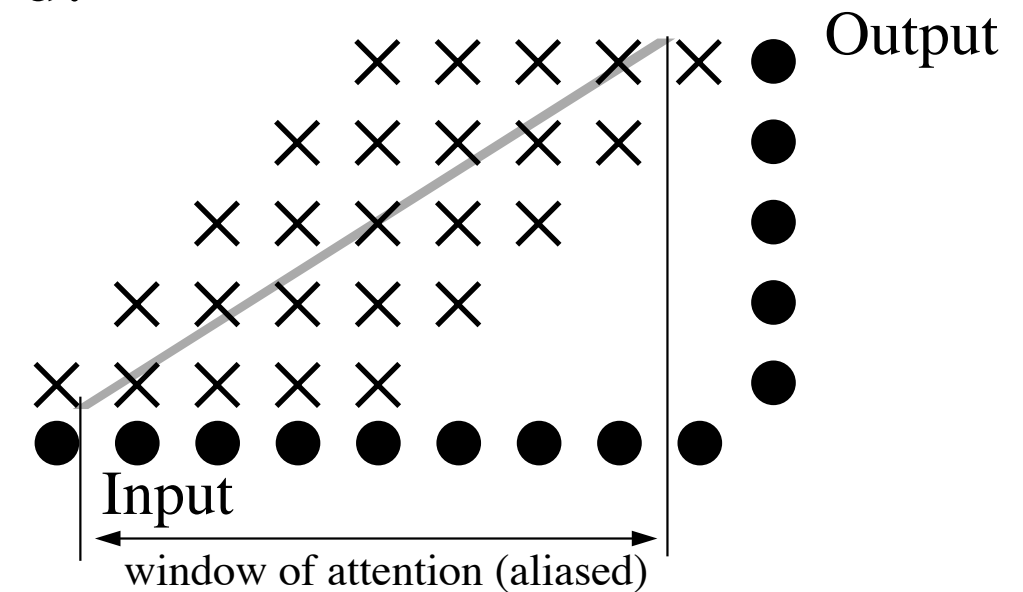
b.

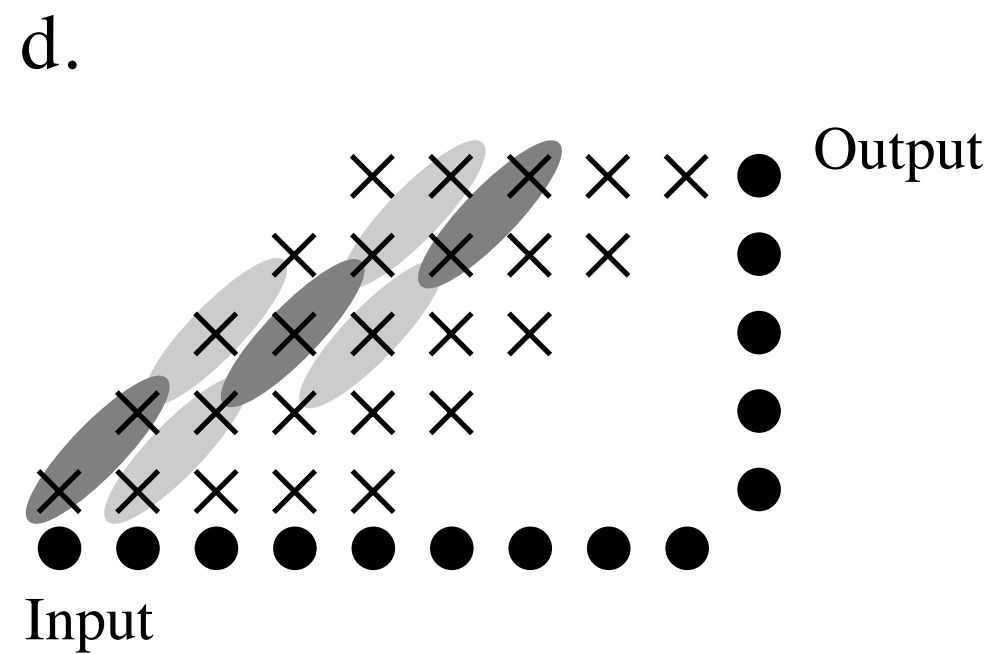
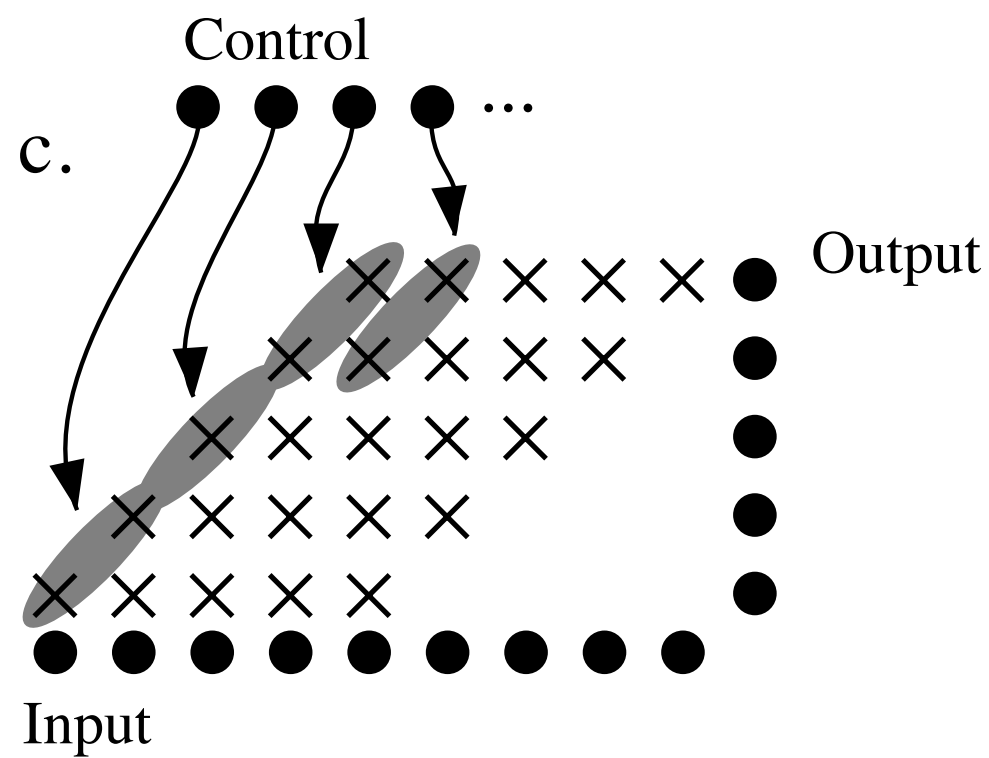
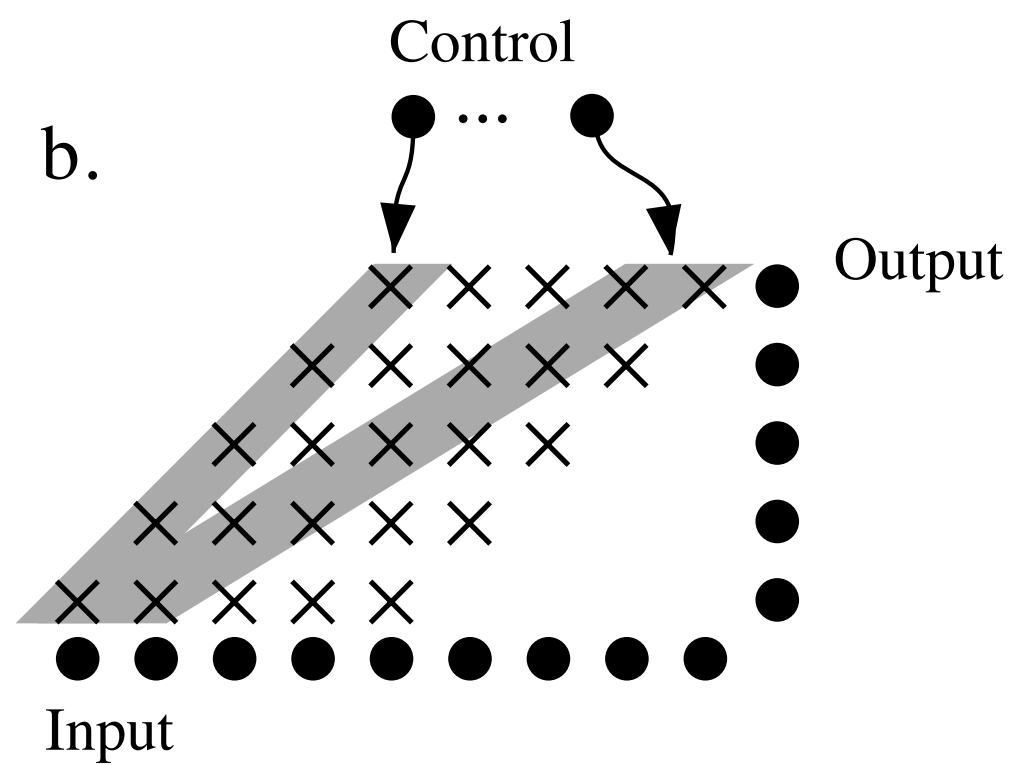
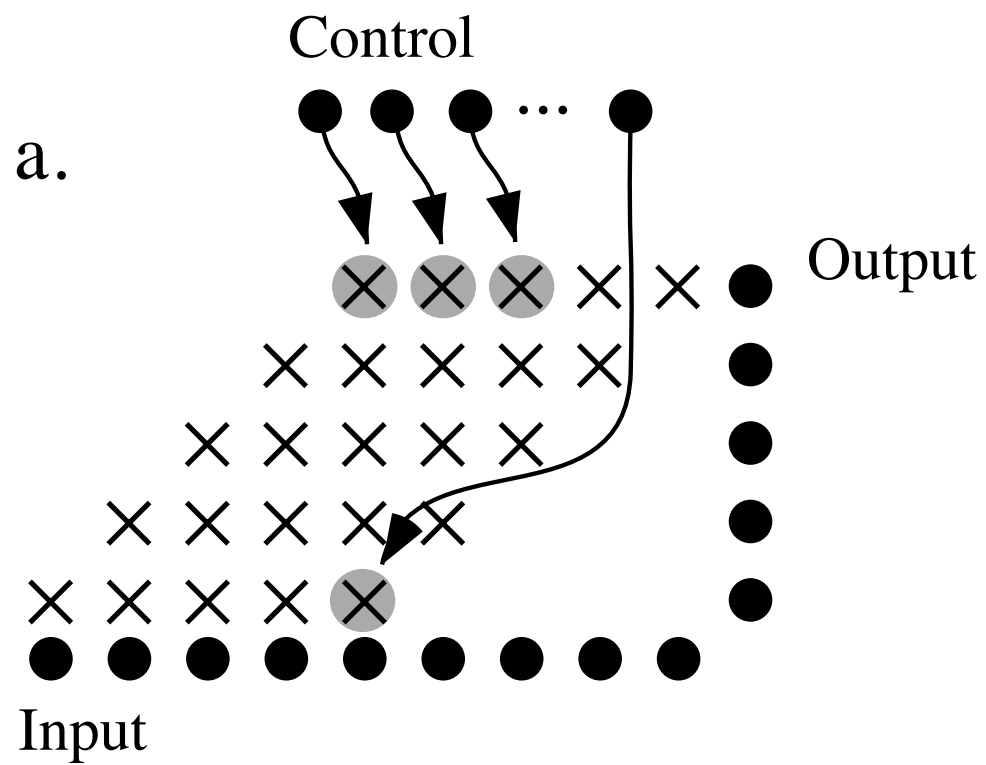


c.



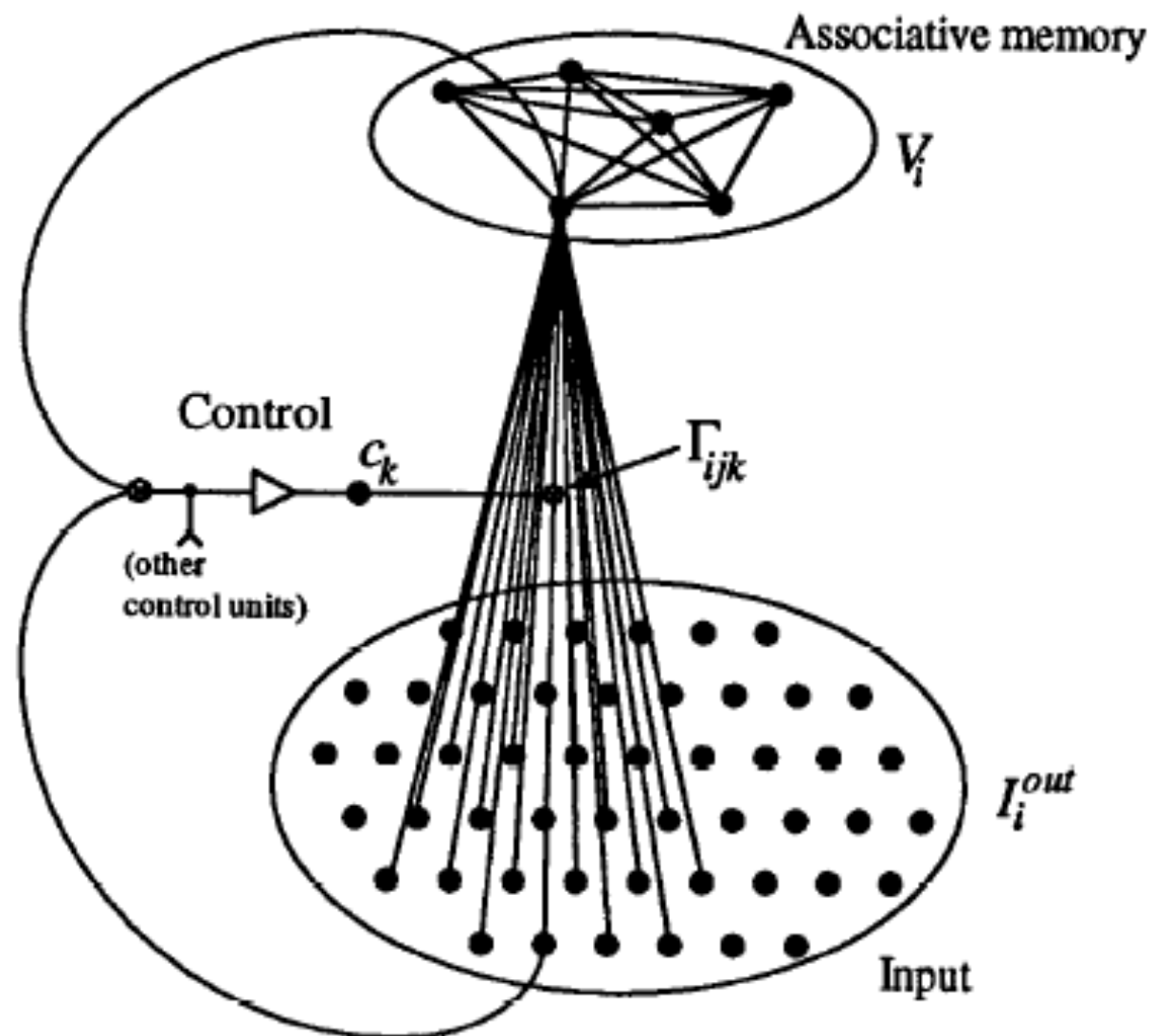
d.



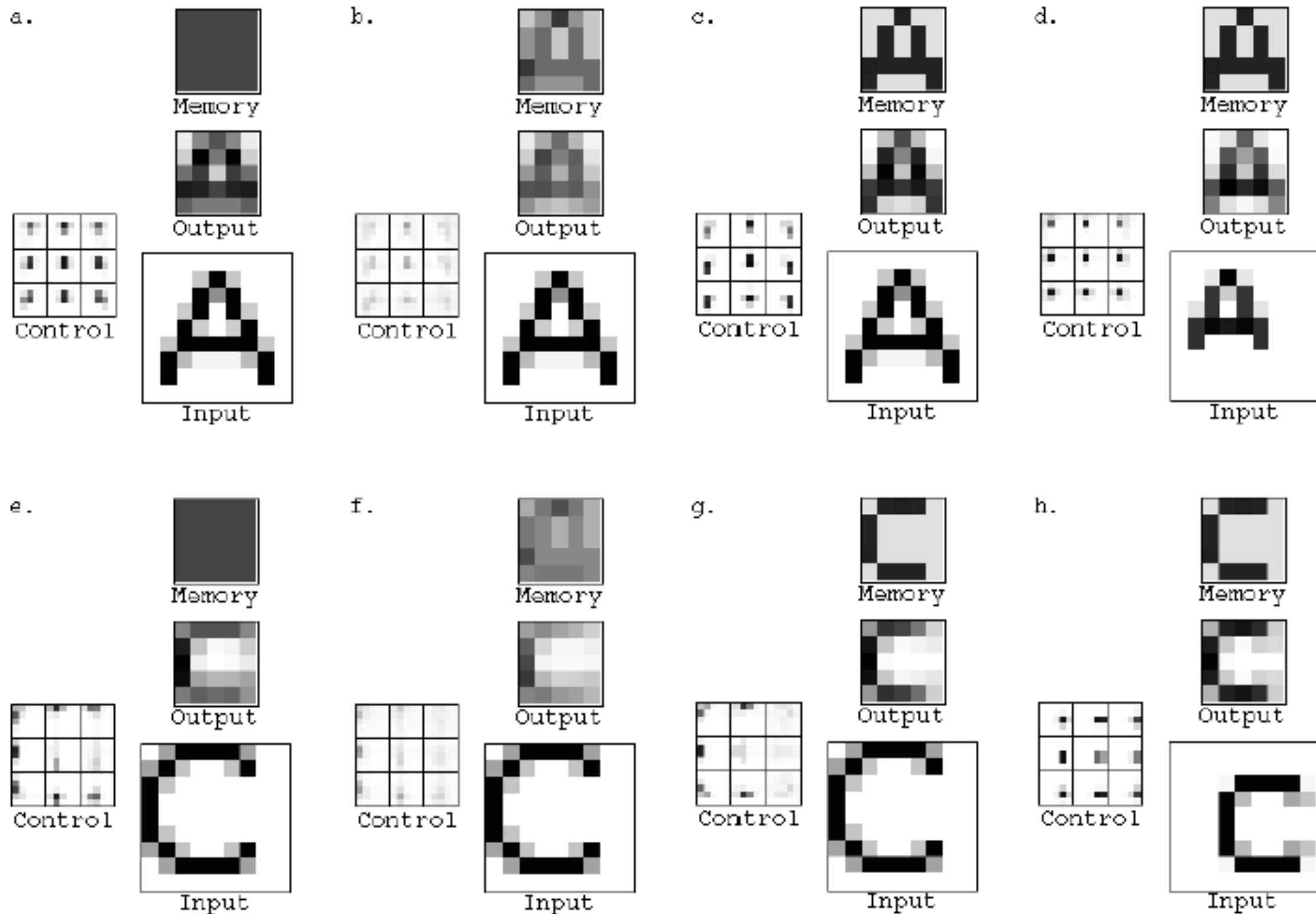


Energy function

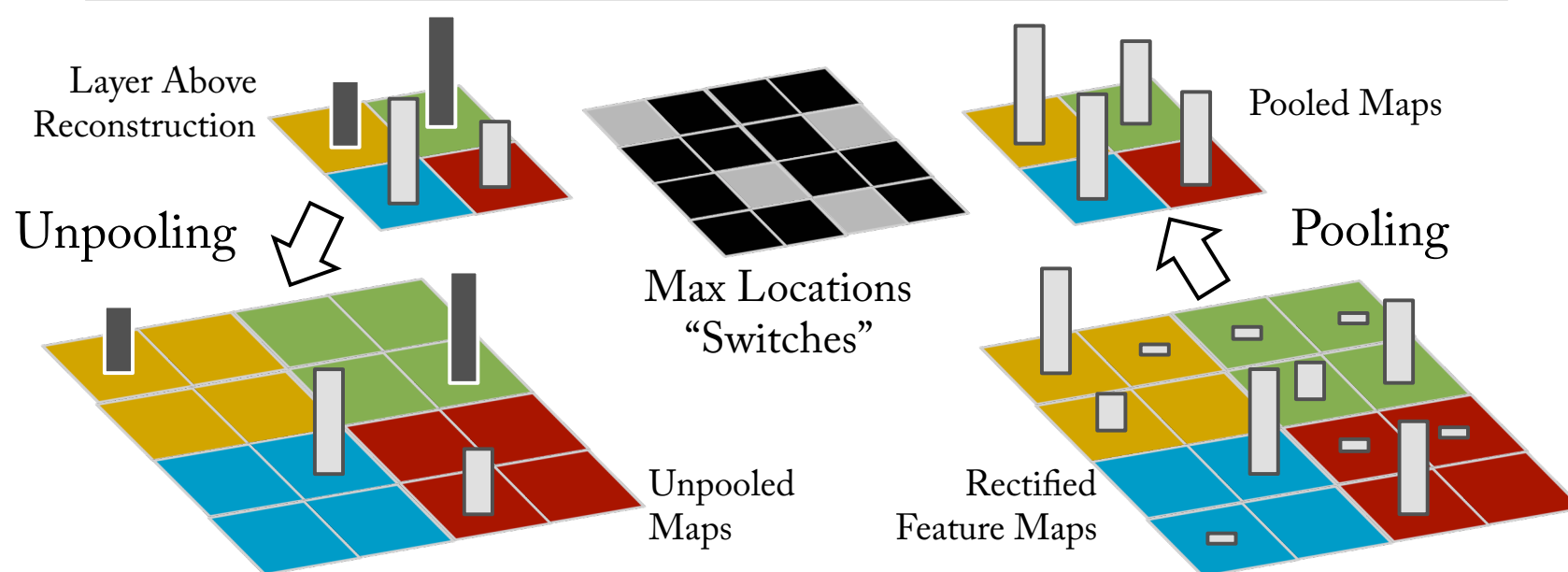
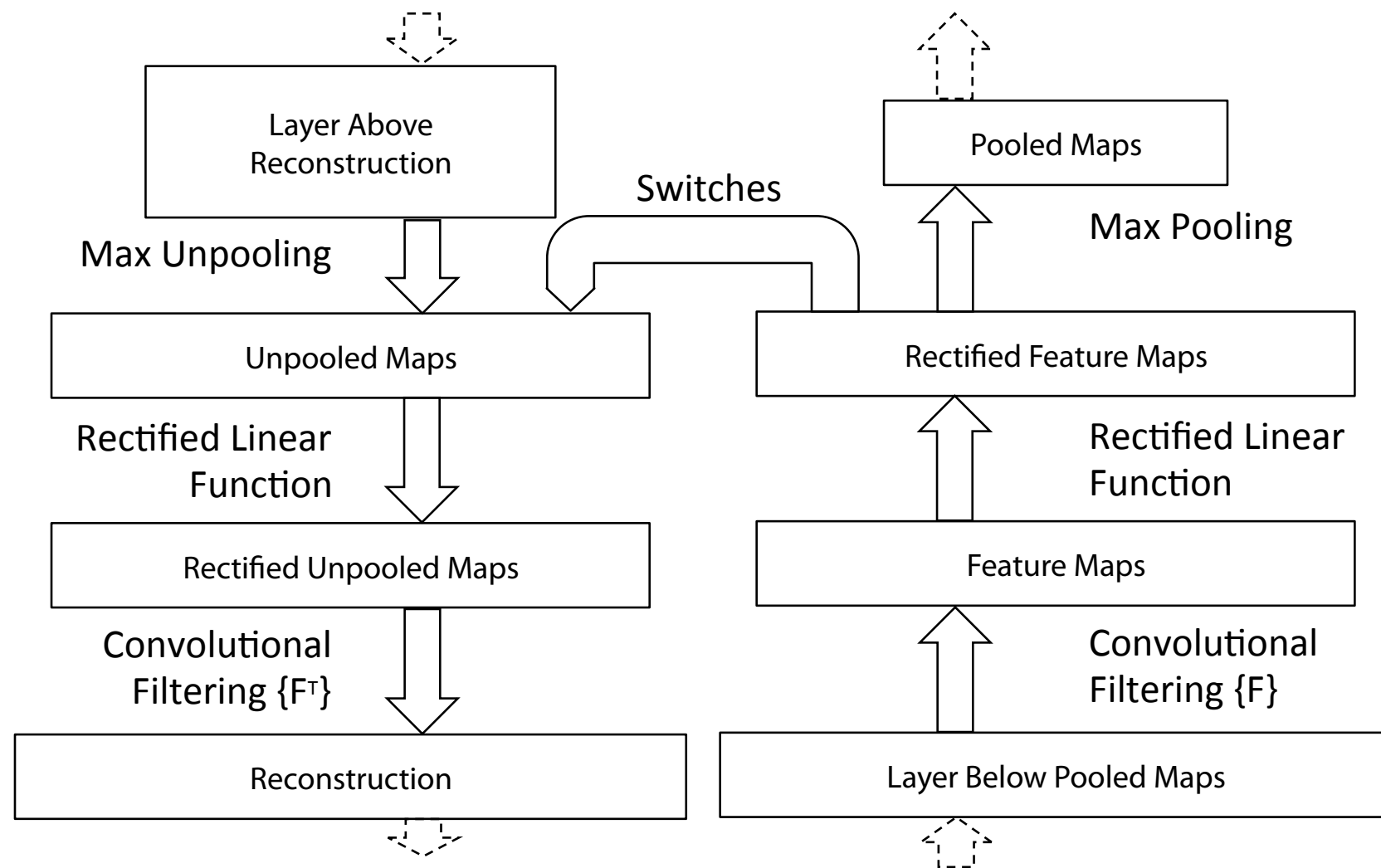
$$E = \sum_{ijk} V_i \Gamma_{ijk} c_k I_j + \sum_{ij} T_{ij}^V V_i V_j + \sum_{kl} T_{kl}^c c_k c_l$$



Pattern matching via dynamic routing

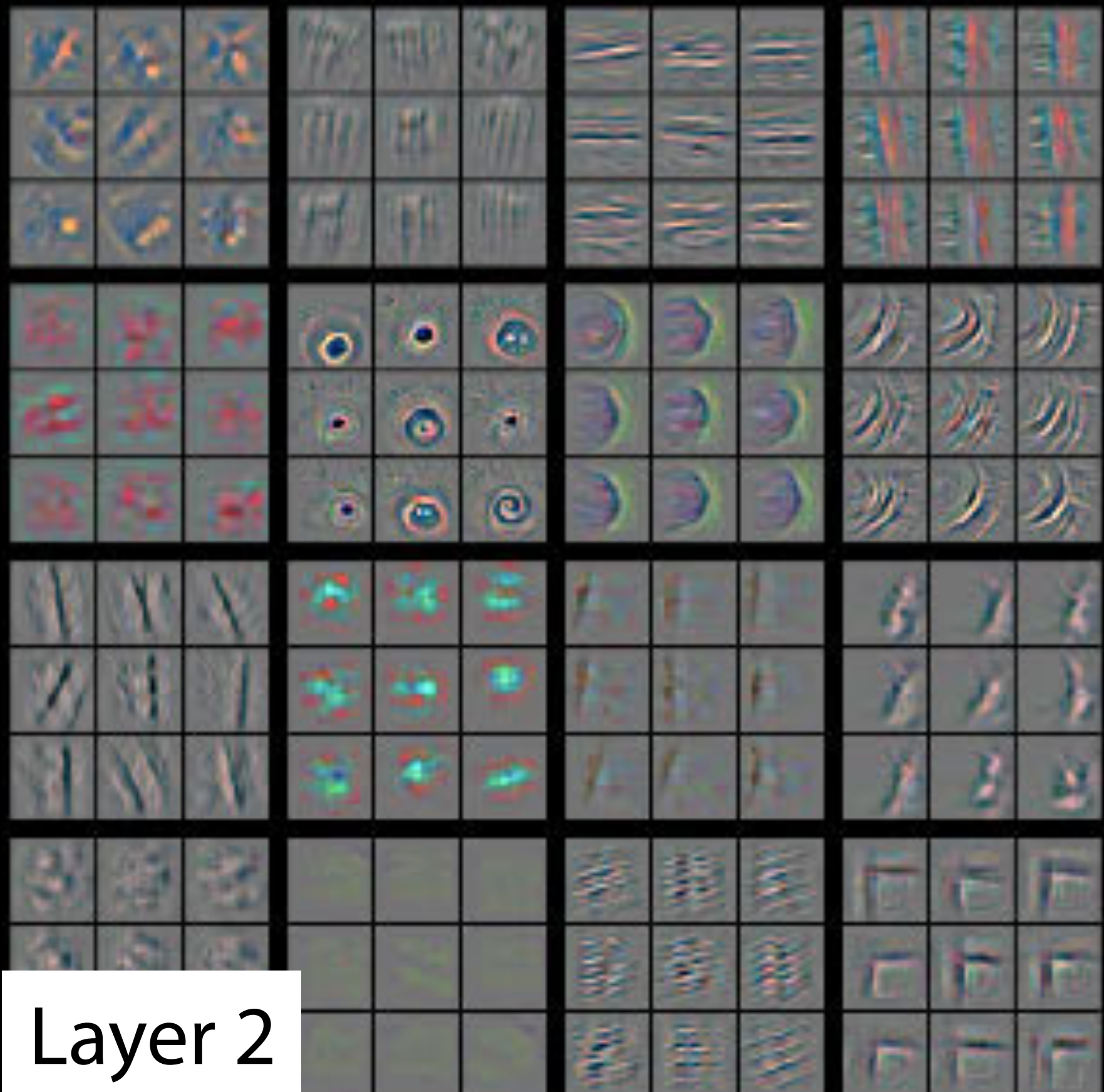


Dynamic routing in deep networks

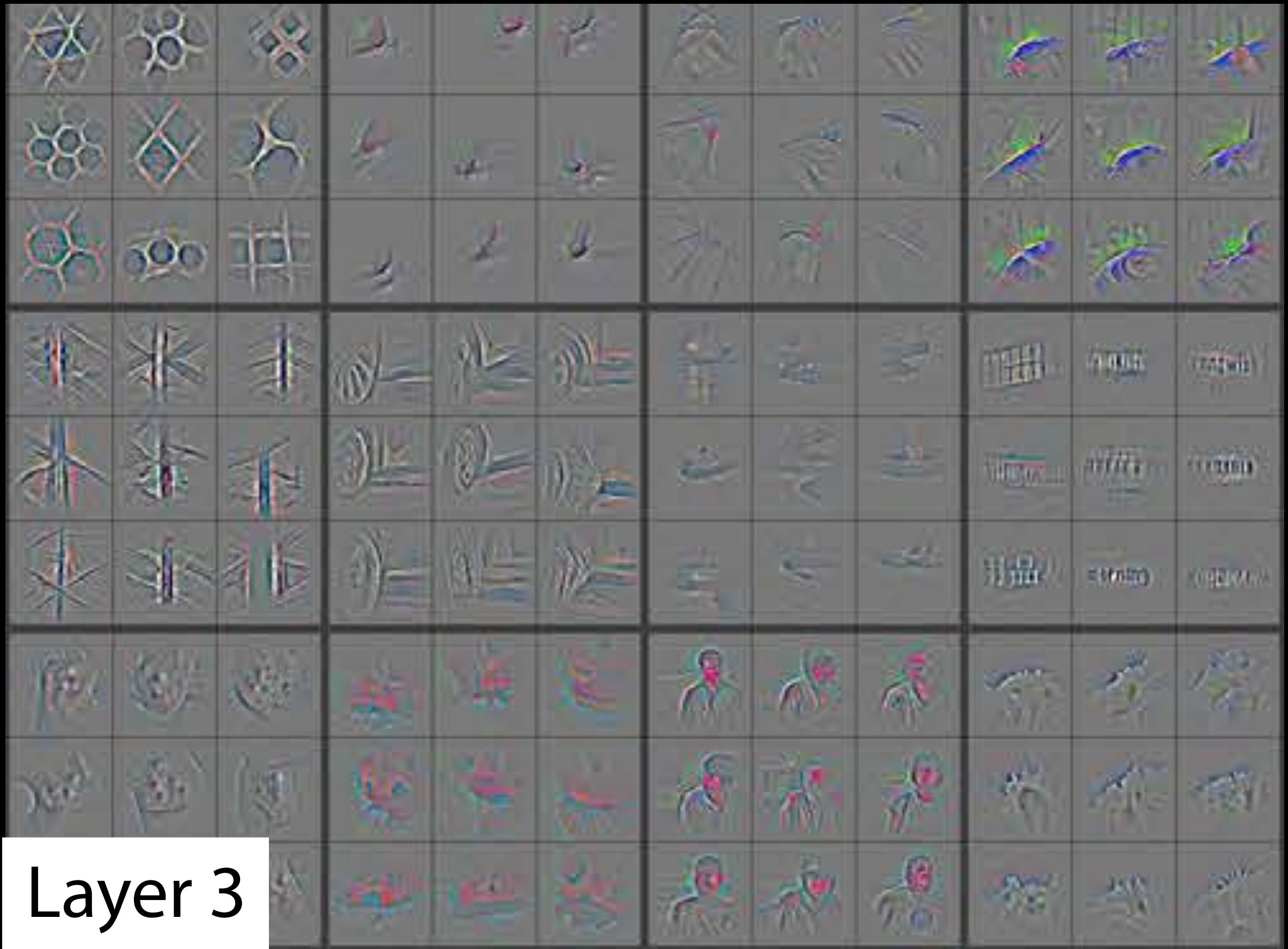


(Zeiler & Fergus, 2013)

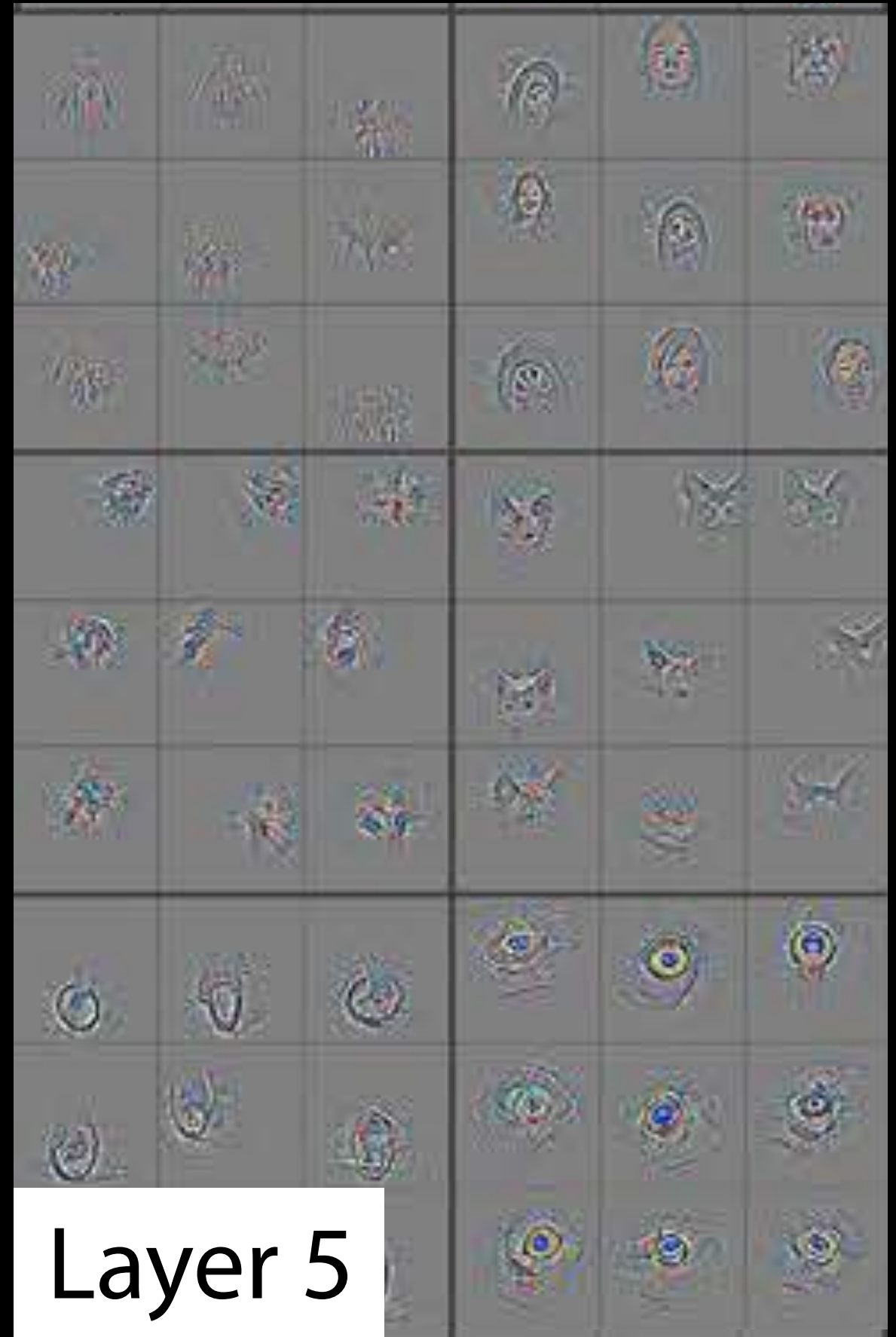
Visualization of filters learned at intermediate layers (Zeiler & Fergus 2013)



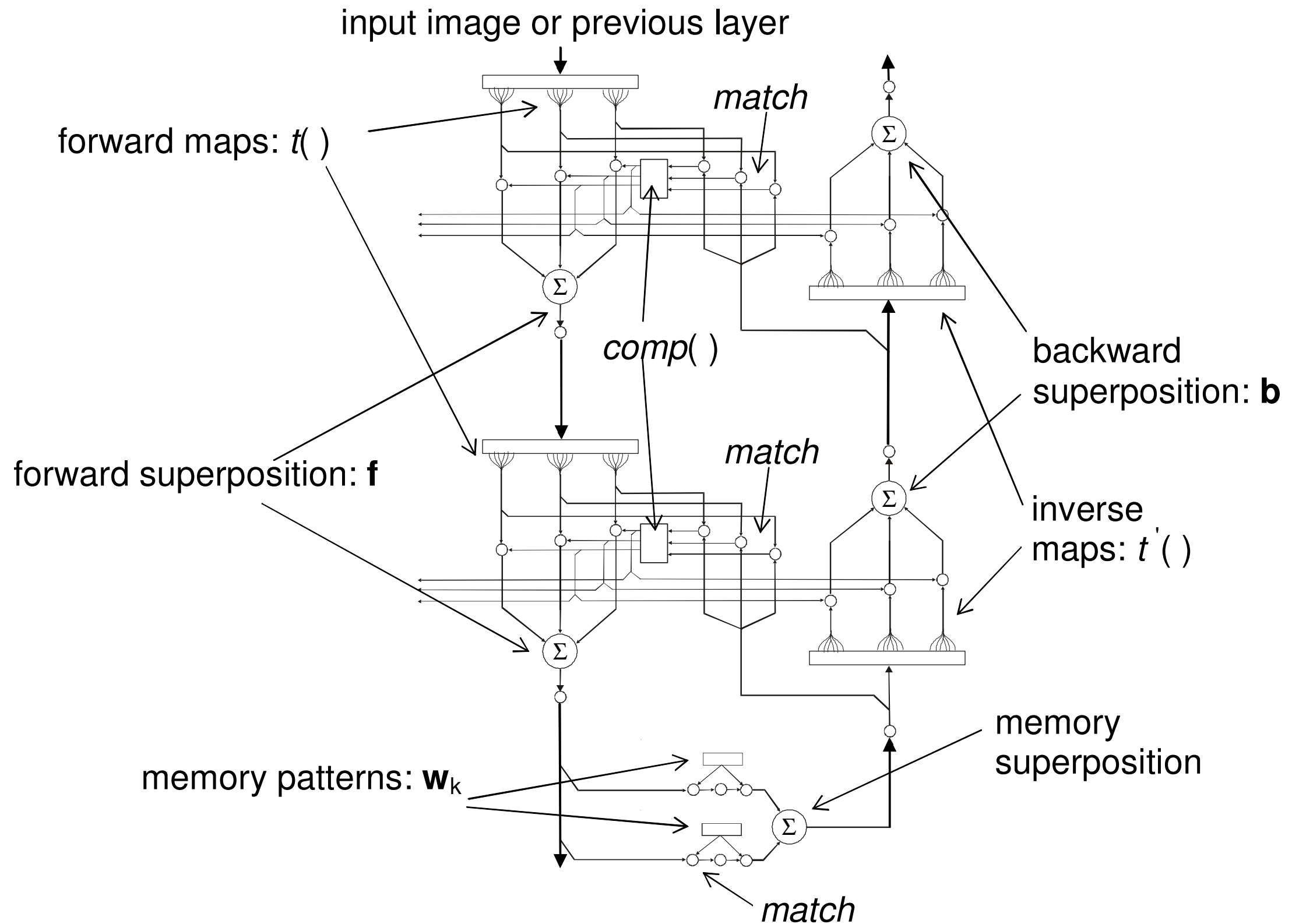
Visualization of filters learned at intermediate layers (Zeiler & Fergus 2013)



Visualization of filters learned at intermediate layers (Zeiler & Fergus 2013)



Map-seeking circuit (Arathorn 2002)



Bilinear models

(Tenenbaum & Freeman 2000)

A

Classification

A	B	C	D	E
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
A	B	C	D	E
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
A	B	C	D	E
B	C	A	E	D

Training

Generalization

B

Extrapolation

A	B	C	D	E
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
A	B	C	D	E
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>
A	B	C	D	E
?	?	C	D	E

$$y_k^{sc} = \sum_{i=1}^I \sum_{j=1}^J w_{ijk} a_i^s b_j^c$$

C

Translation

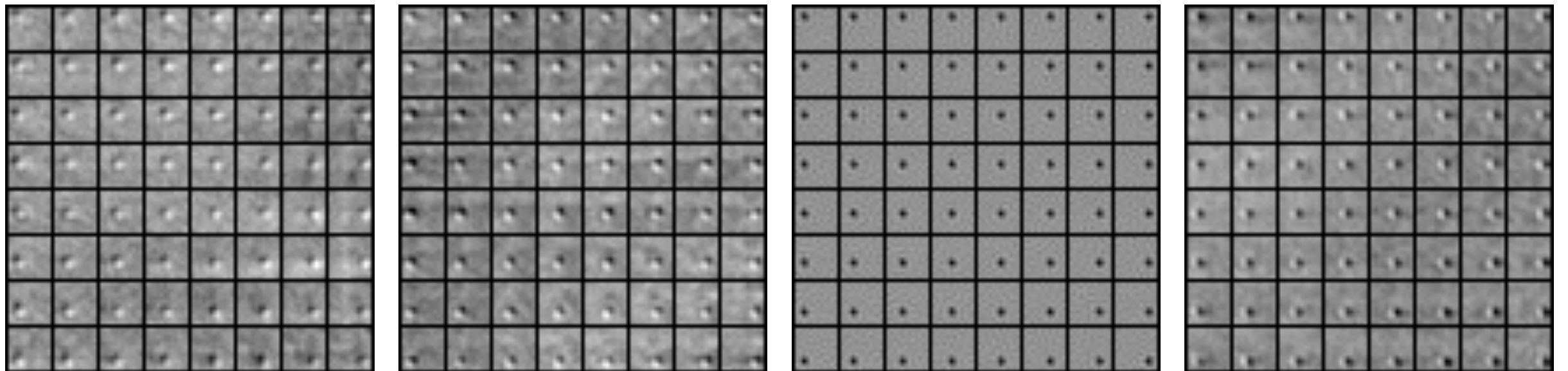
A	B	C	D	E	?	?	?
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>			
A	B	C	D	E			
<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>			
A	B	C	D	E	?	?	?
?	—	—	—	?	F	G	H

Bilinear Models of Natural Images

Bruno A. Olshausen^a, Charles Cadieu^b, Jack Culpepper^c, and David K. Warland^d

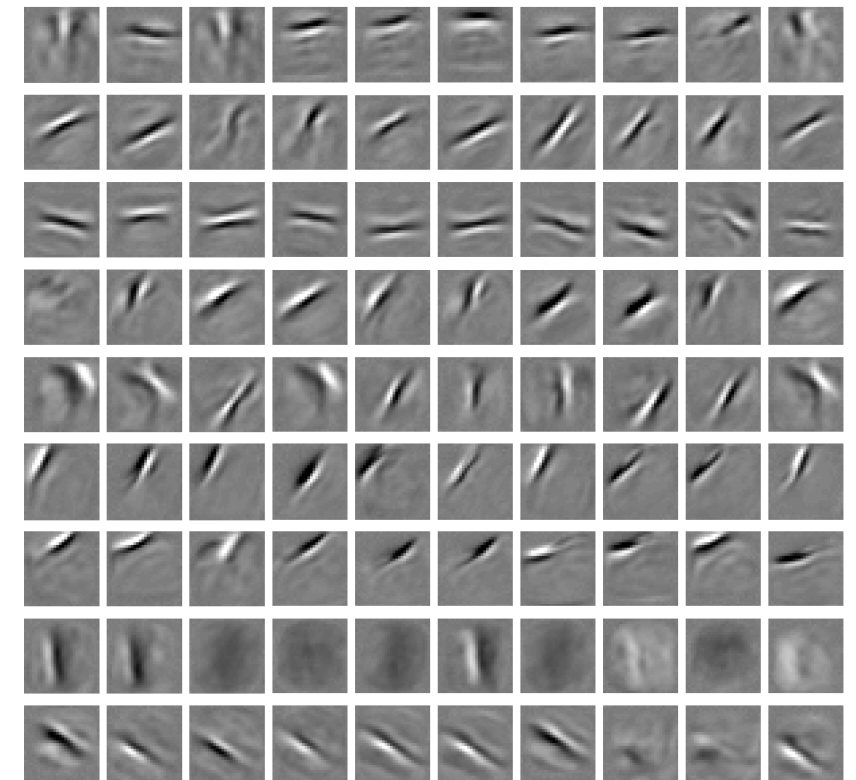
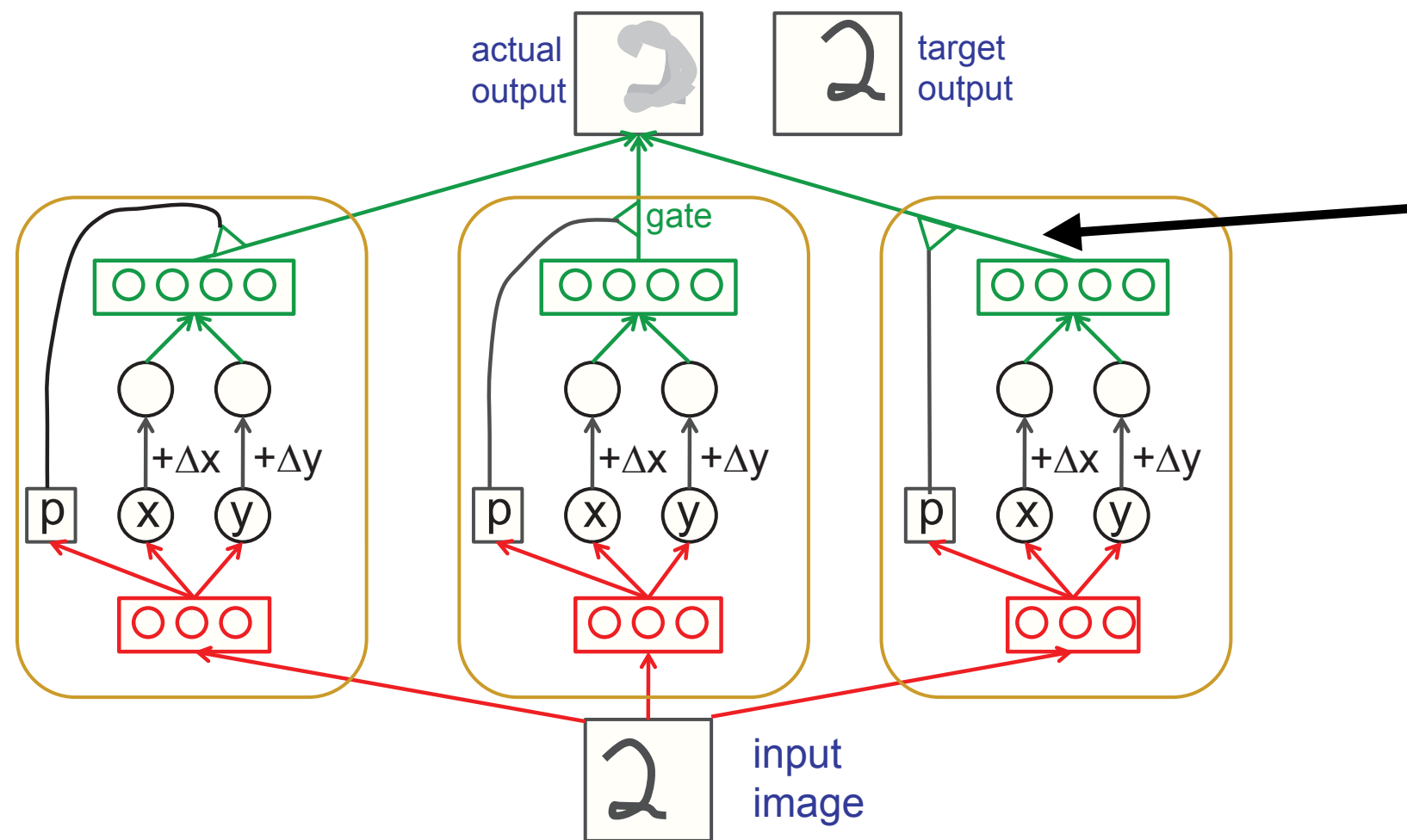
$$I(\mathbf{x}, t + 1) = \sum_{\mathbf{x}'} T(\mathbf{x}, \mathbf{x}', t) I(\mathbf{x}', t) + \nu(\mathbf{x}, t)$$

$$T(\mathbf{x}, \mathbf{x}', t) = \sum_k c_k(t) \psi_k(\mathbf{x}, \mathbf{x}')$$



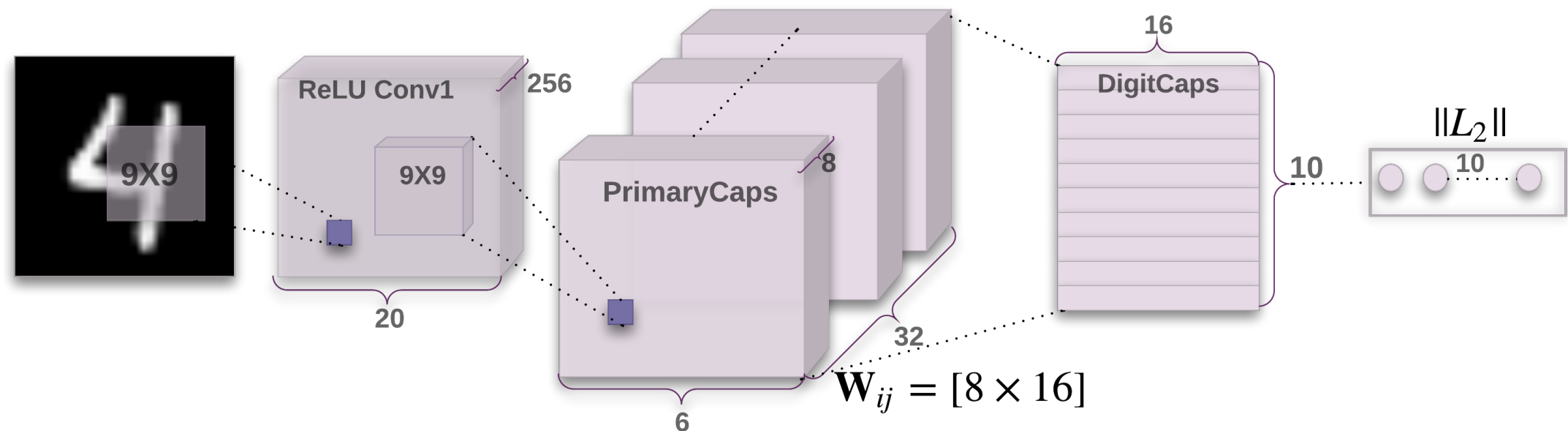
Transforming Auto-encoders

(Hinton, Krizhevsky & Wang 2011)



Dynamic routing between capsules

(Sabour, Frosst & Hinton 2017)



This type of “routing-by-agreement” should be far more effective than the very primitive form of routing implemented by max-pooling, which allows neurons in one layer to ignore all but the most active feature detector in a local pool in the layer below. We demonstrate that our dynamic routing mechanism is an effective way to implement the “explaining away” that is needed for segmenting highly overlapping objects.

For low level capsules, location information is “place-coded” by which capsule is active. As we ascend the hierarchy, more and more of the positional information is “rate-coded” in the real-valued components of the output vector of a capsule.

Dynamic routing between capsules

(Sabour, Frosst & Hinton 2017)

