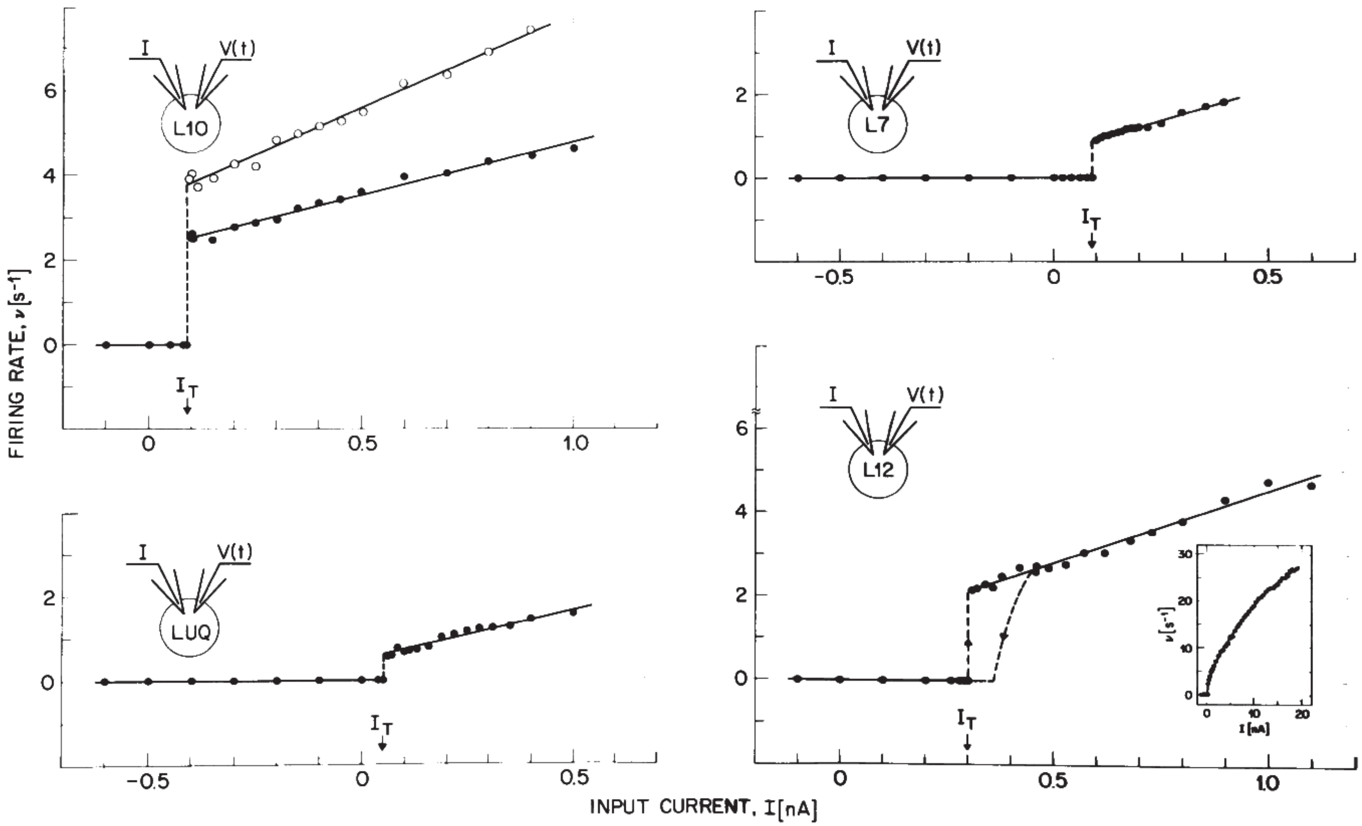
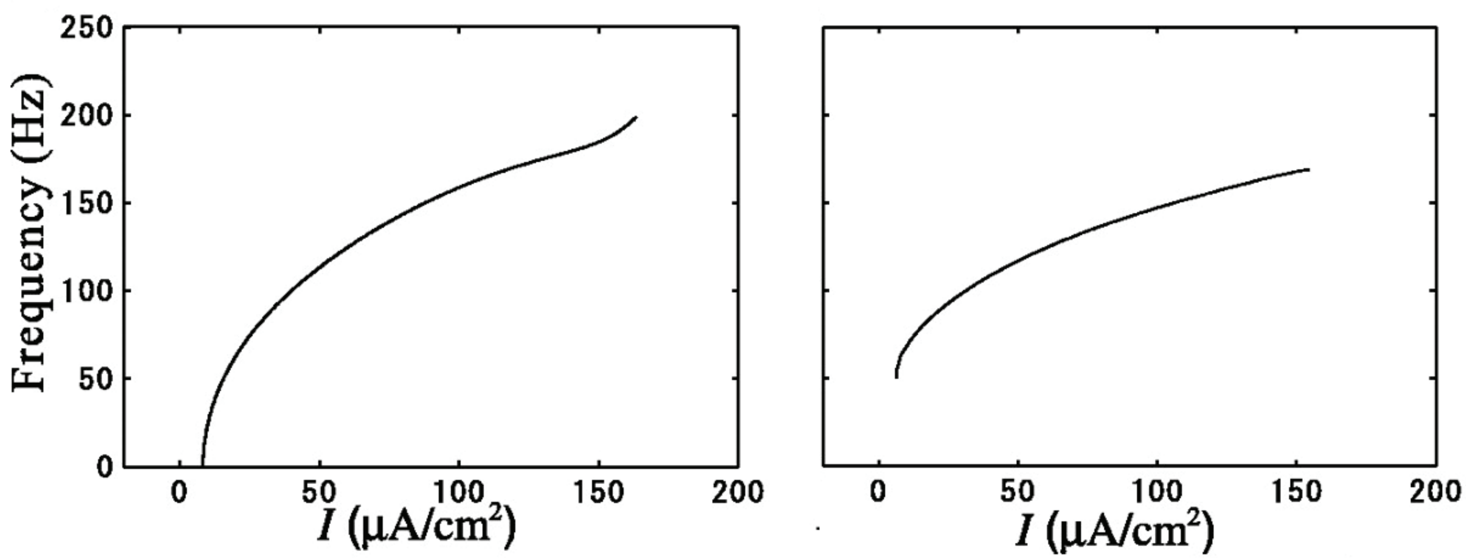

FIRING RATE, ν[s⁻¹]
INPUT CURRENT, I[nA]
L10
L7
LUQ
L12
I
V(t)
I_T
ν[s⁻¹]
I[nA]


Frequency (Hz)
I (μA/cm²)
I (μA/cm²)

Bulletin of Mathematical Biophysics, Vol. 5, pp. 115–133 (1943).
Printed in Great Britain.

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY*

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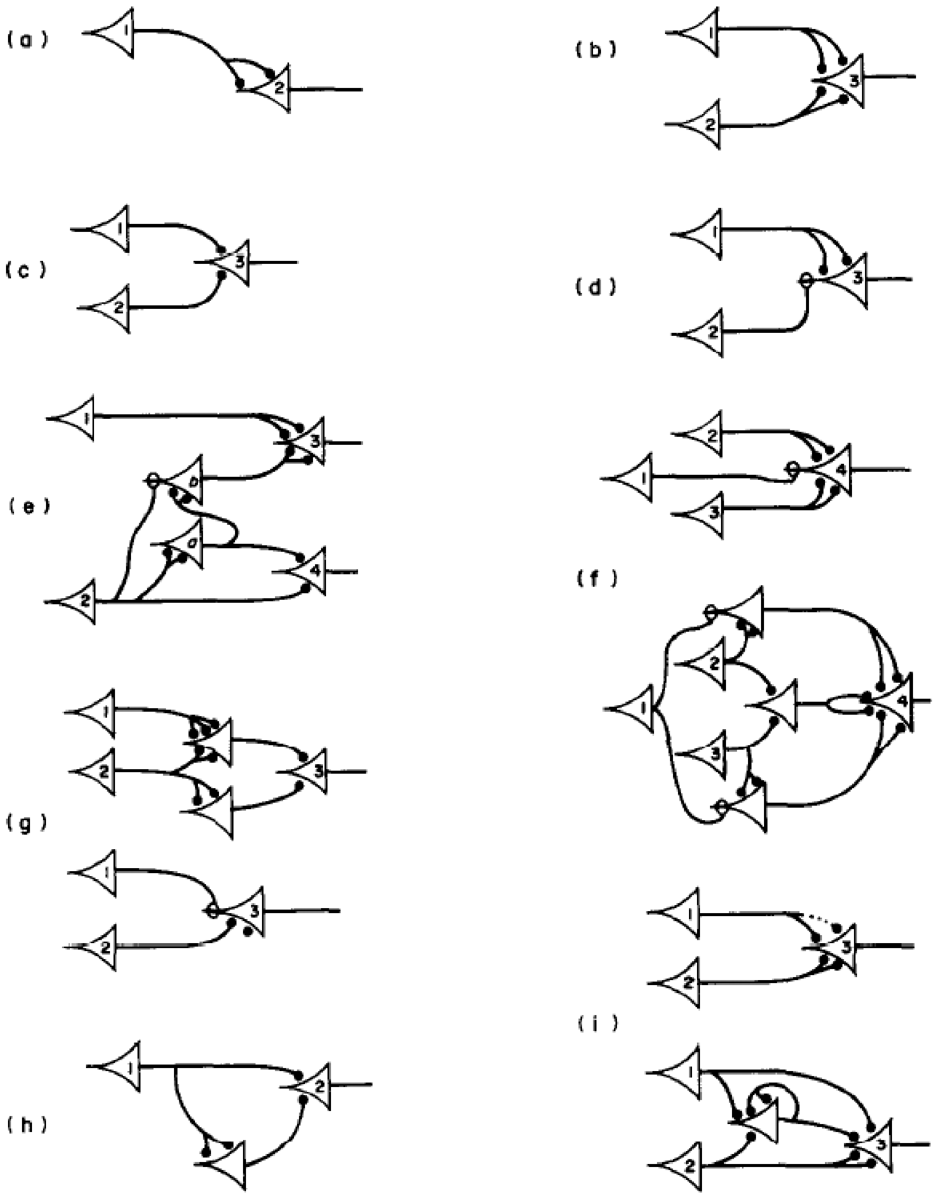
Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

Figure 1. The neuron c_i is always marked with the numeral i upon the body of the cell, and the corresponding action is denoted by "N" with is subscript, as in the text:



(a) $N_2(t) . \equiv . N_1(t-1);$

(b) $N_3(t) . \equiv . N_1(t-1) \vee N_2(t-1);$

(c) $N_3(t) . \equiv . N_1(t-1) . N_2(t-1);$

(d) $N_3(t) . \equiv N_1(t-1) . \sim N_2(t-1);$

(e) $N_3(t) : \equiv : N_1(t-1) . \vee . N_2(t-3) . \sim N_2(t-2);$

$N_4(t) . \equiv . N_2(t-2) . N_2(t-1);$

(f) $N_4(t) : \equiv : \sim N_1(t-1) . N_2(t-1) \vee N_3(t-1) . \vee . N_1(t-1).$
$N_2(t-1) . N_3(t-1)$

$N_4(t) : \equiv : \sim N_1(t-2) . N_2(t-2) \vee N_3(t-2) . \vee . N_1(t-2).$
$N_2(t-2) . N_3(t-2);$

(g) $N_3(t) . \equiv . N_2(t-2) . \sim N_1(t-3);$

(h) $N_2(t) . \equiv . N_1(t-1) . N_1(t-2);$

(i) $N_3(t) : \equiv : N_2(t-1) . \vee . N_1(t-1) . (Ex)t-1 . N_1(x) . N_2(x).$

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Circuits constructed from identified *Aplysia* neurons exhibit multiple patterns of persistent activity

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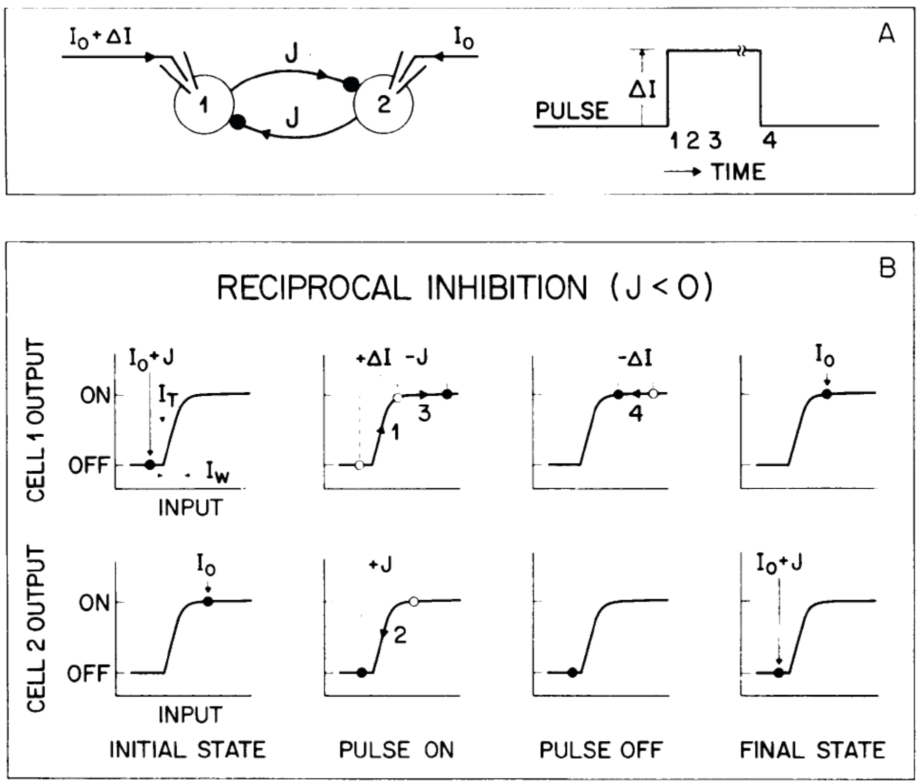
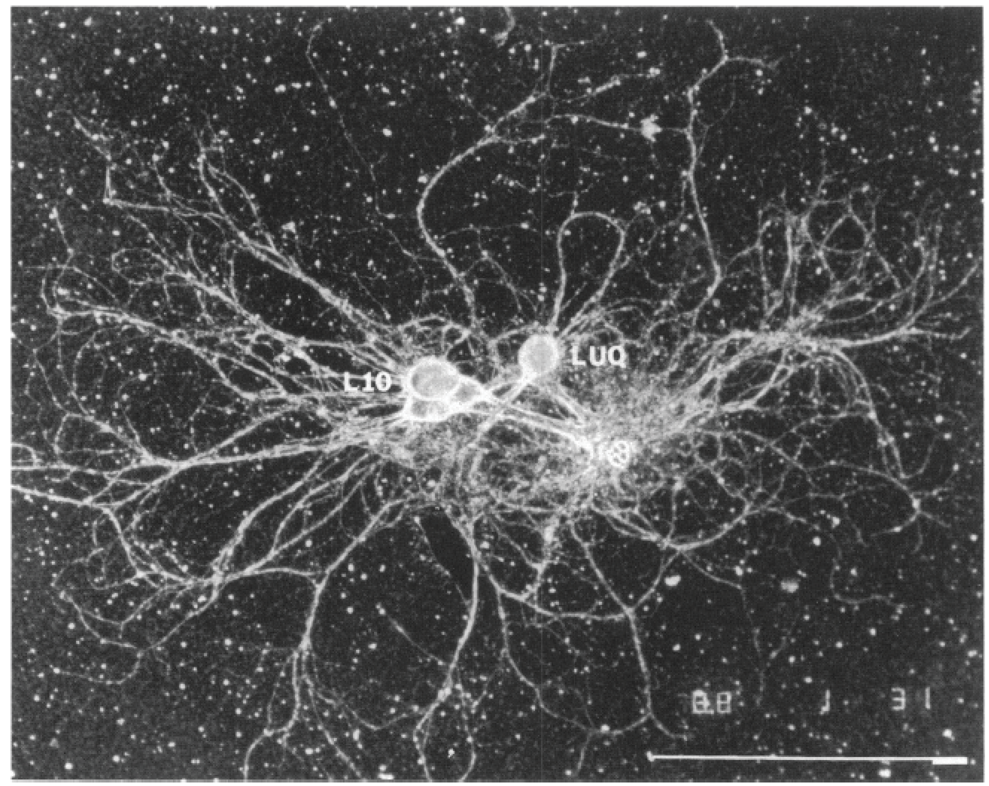
[‡]Department of Biology, Case Western Reserve University, Cleveland, Ohio 44106





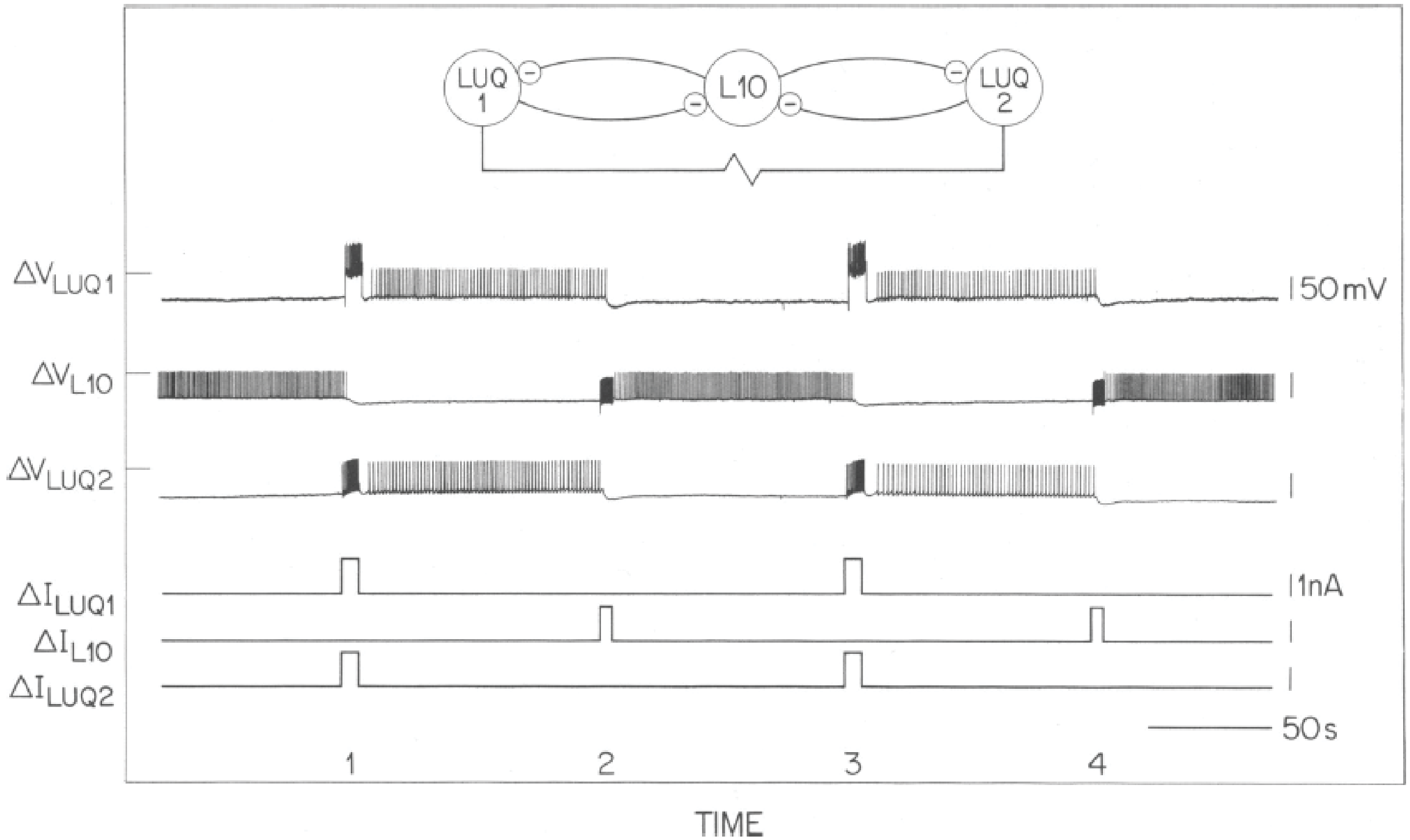


FIGURE 8 The basic dynamic behavior of the inhibitory circuit. This particular circuit consisted of L10 co-cultured with two LUQs. The L10 formed reciprocal connections with each LUQ; the LUQs were coupled by a strong electrotonic connection and thus functioned essentially as a single cell. The bias currents were $I_0 = 0.15$, 0.55, and 0.15 nA for LUQ1, L10, and LUQ2, respectively. The circuit was initially in the state OFF/ON, with the LUQs quiescent and L10 active. At time 1 a brief pulse of current was injected into the LUQs, causing a transition to the state ON/OFF. Subsequent transitions were induced at times 2, 3, and 4.

Proc. Natl. Acad. Sci. USA
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Biophysics

Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

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Contributed by John J. Hopfield, January 15, 1982

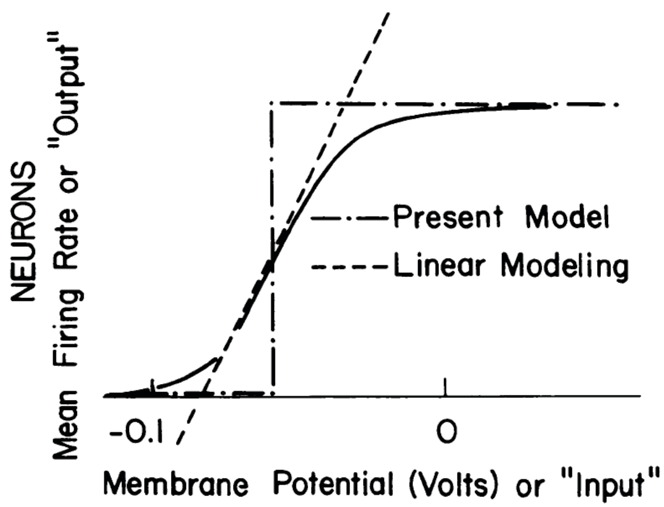


FIG. 1. Firing rate versus membrane voltage for a typical neuron (solid line), dropping to 0 for large negative potentials and saturating for positive potentials. The broken lines show approximations used in modeling.

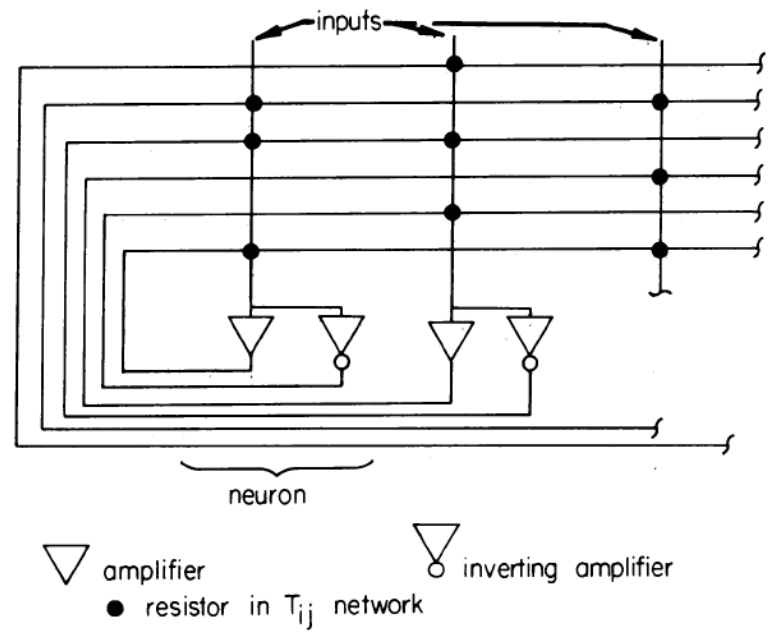


FIG. 2. An electrical circuit that corresponds to Eq. **5** when the amplifiers are fast. The input capacitance and resistances are not drawn. A particularly simple special case can have all positive T_{ij} of the same strength and no negative T_{ij} and replaces the array of negative wires with a single negative feedback amplifier sending a common output to each "neuron."

Using goal-driven deep learning models to understand sensory cortex

Daniel L K Yamins[1,2] & James J DiCarlo[1,2]

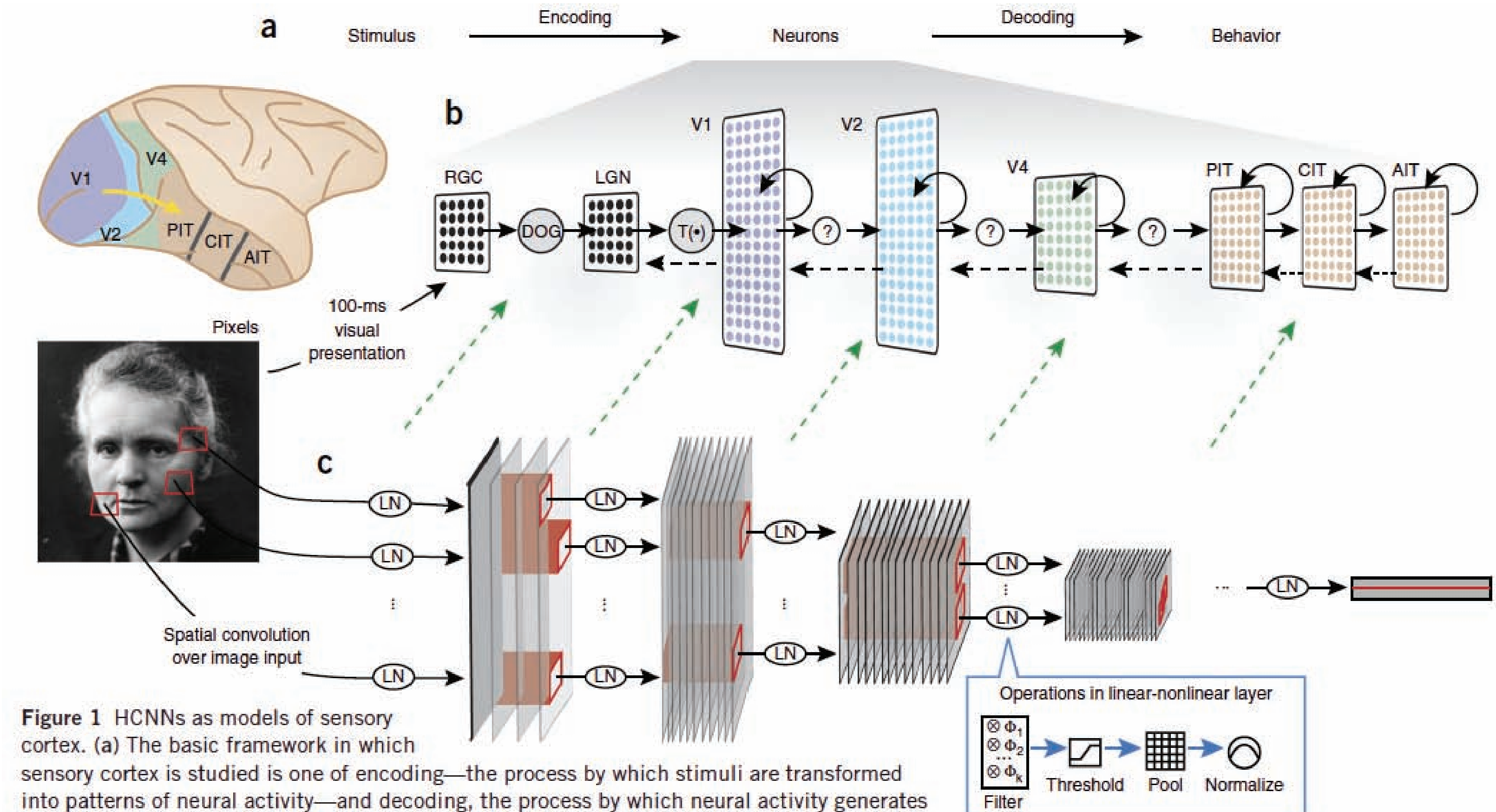
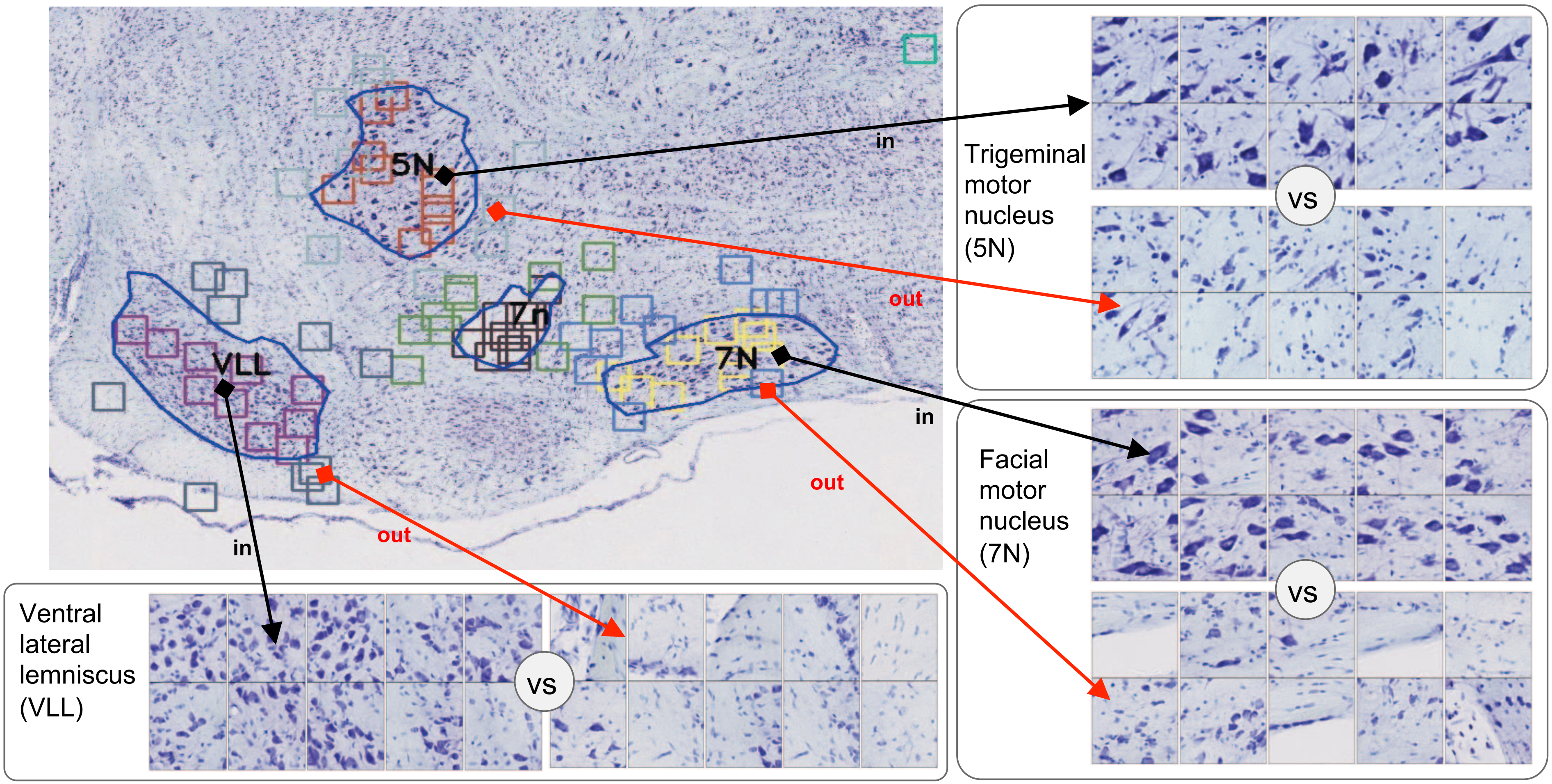


Figure 1 HCNNs as models of sensory cortex. (**a**) The basic framework in which sensory cortex is studied is one of encoding—the process by which stimuli are transformed into patterns of neural activity—and decoding, the process by which neural activity generates behavior. HCNNs have been used to make models of the encoding step; that is, they describe the mapping of stimuli to neural responses as measured in brain. (**b**) The ventral visual pathway is the most comprehensively studied sensory cascade. It consists of a series of connected cortical brain areas (macaque brain shown). PIT, posterior inferior temporal cortex; CIT, central; AIT, anterior; RGC, retinal ganglion cell; LGN, lateral geniculate nucleus. DoG, difference of Gaussians model; T(•), transformation. (**c**) HCNNs are multilayer neural networks, each of whose layers are made up of a linear-nonlinear (LN) combination of simple operations such as filtering, thresholding, pooling and normalization. The filter bank in each layer consists of a set of weights analogous to synaptic strengths. Each filter in the filter bank corresponds to a distinct template, analogous to Gabor wavelets with different frequencies and orientations; the image shows a model with four filters in layer 1, eight in layer 2, and so on. The operations within a layer are applied locally to spatial patches within the input, corresponding to simple, limited-size receptive fields (red boxes). The composition of multiple layers leads to a complex nonlinear transform of the original input stimulus. At each layer, retinopy decreases and effective receptive field size increases. HCNNs are good candidates for models of the ventral visual pathway. By definition, they are image computable, meaning that they generate responses for arbitrary input images; they are also mappable, meaning that they can be naturally identified in a component-wise fashion with observable structures in the ventral pathway; and, when their parameters are chosen correctly, they are predictive, meaning that layers within the network describe the neural response patterns to large classes of stimuli outside the domain on which the models were built.

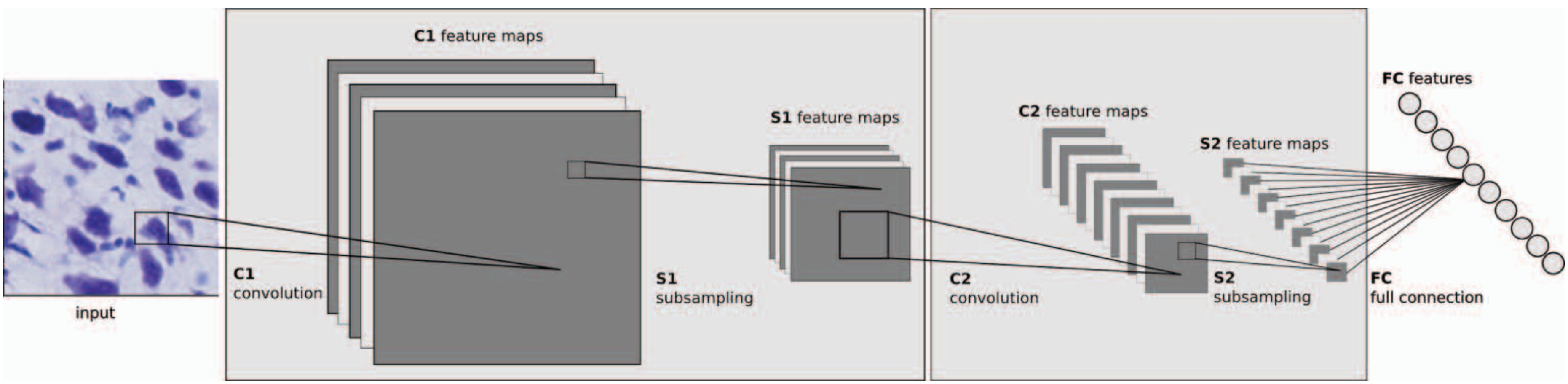
Train binary classifiers to recognize patches inside vs. outside each structure

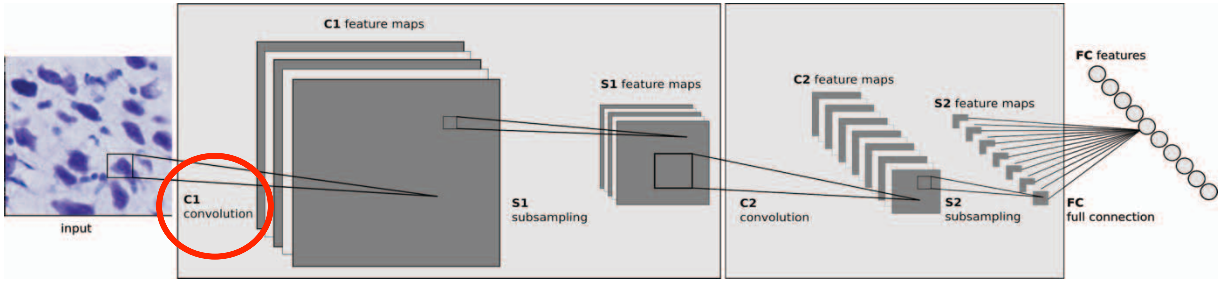


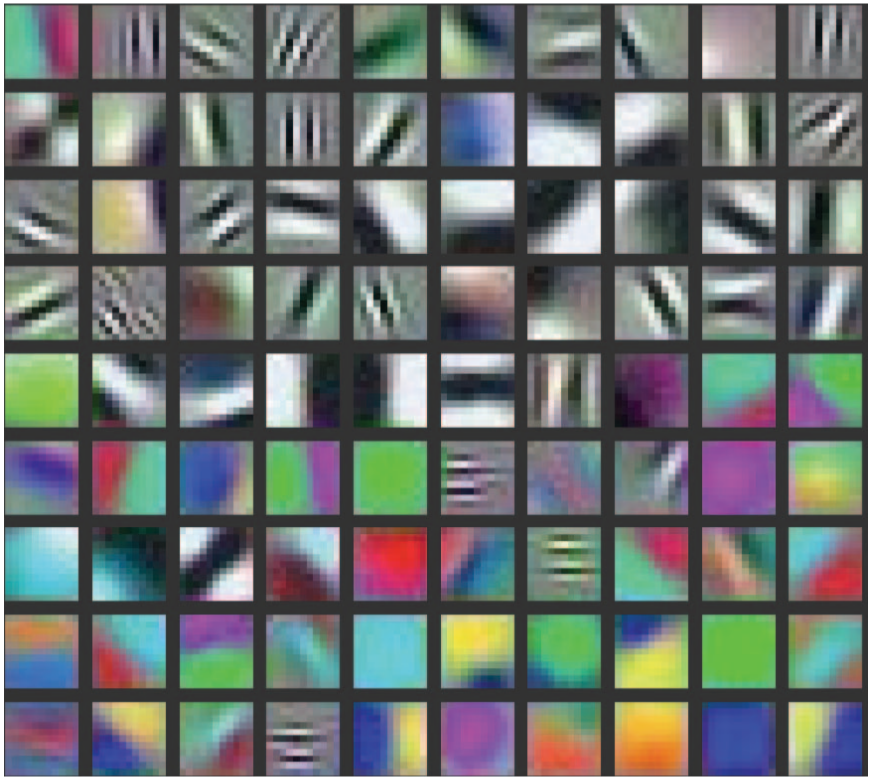
Textures (currently) represented with convolutional neural networks

- Encode an image patch into a feature vector.

- Alternating **convolution layers** and **subsampling layers** of various sizes.
- Output of each layer modulated by nonlinear function.
- Several **fully connected layers** at the end.
- Pre-trained on natural images, also applicable to histology images.

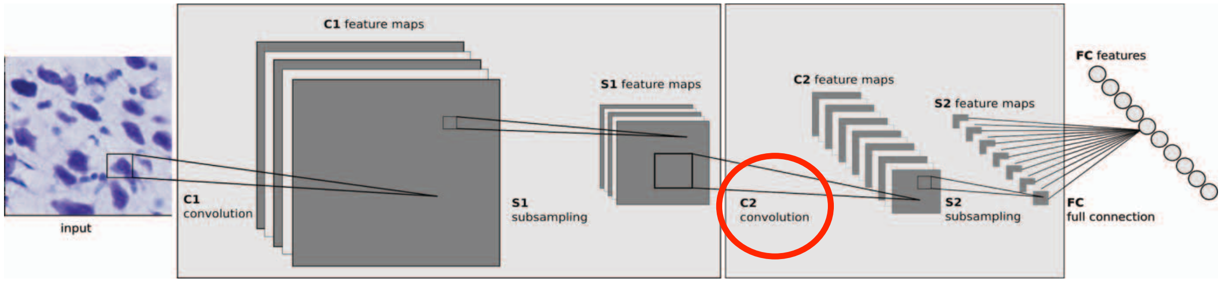






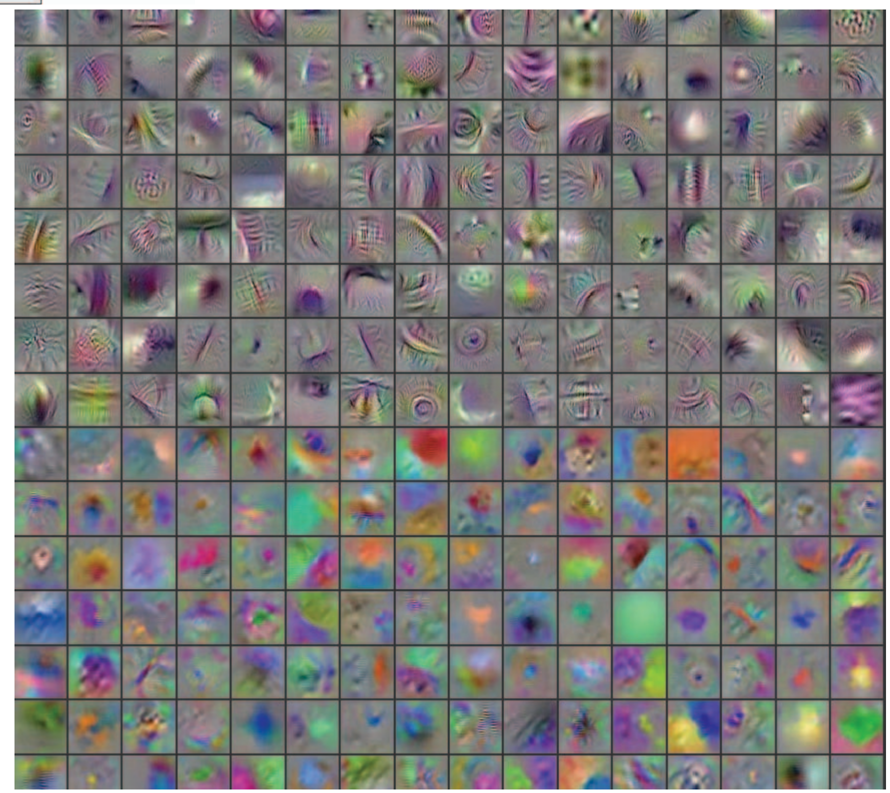
Filters @ convolution layer 1

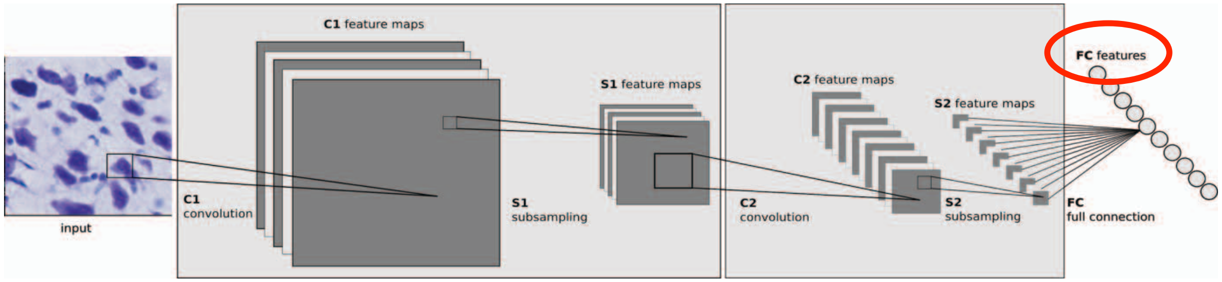
These lowest-level filters resemble Gabor filters
(simple cells in mammalian primary visual cortex).



Filters @ convolution layer 2

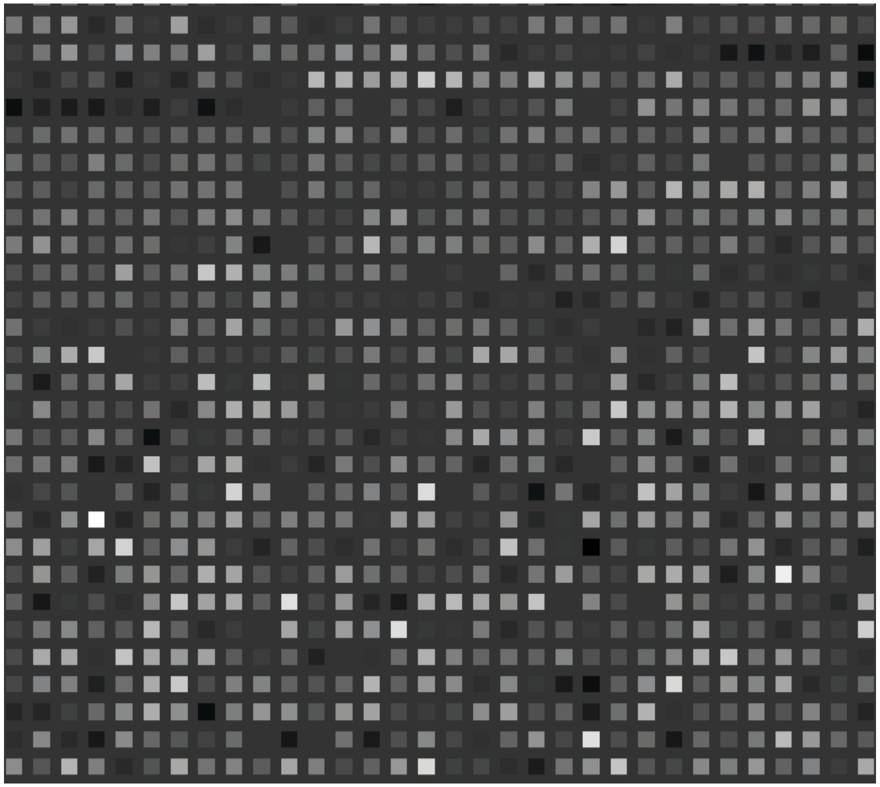
These mid-level filters appear as Surrealist elements





Output @ fully connected layer

Neurons at the output of fully connected layer comprise the feature vector of this patch.



Prediction: Assign each patch a score vector, form score maps