# Biophysics & Computation

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Fueling Discovery

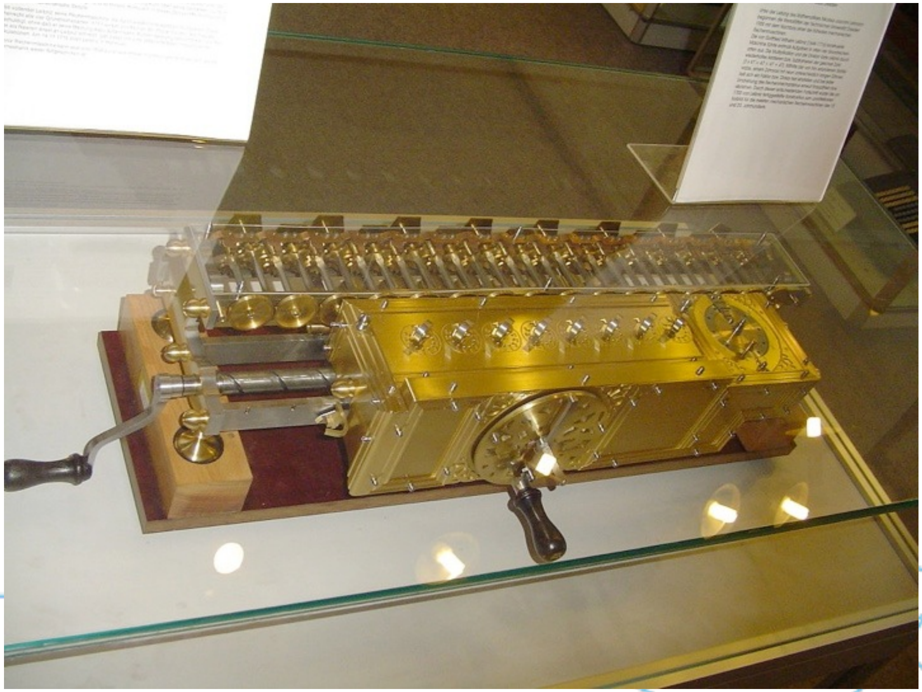
# Themes

- What do we mean by computation?
- Is there an universal computation?
- Does the brain compute and, if so, how?

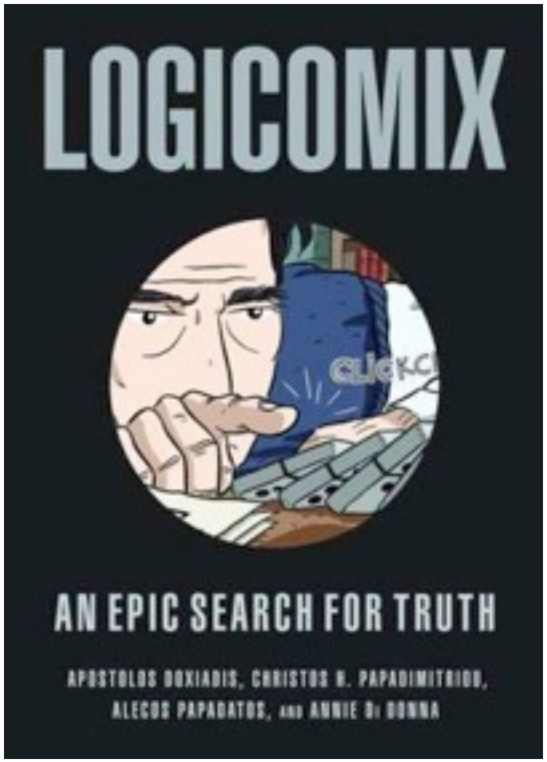
# Leibniz’s Dream

**Calculus ratiocinator** - a mechanization of mathematical logic and human thought in the form of a **machina ratiocinator**, a reasoning machine

Gottfried Wilhelm Leibniz
1646 - 1716
Binary numbers
Mechanical calculators
Co-invented infinitesimal calculus
Rationalism and optimism
Monads and consciousness



# Gödel’s Incompleteness Theorem - 1931




# Gödel's Incompleteness Theorem - 1931

# Turing's Machine

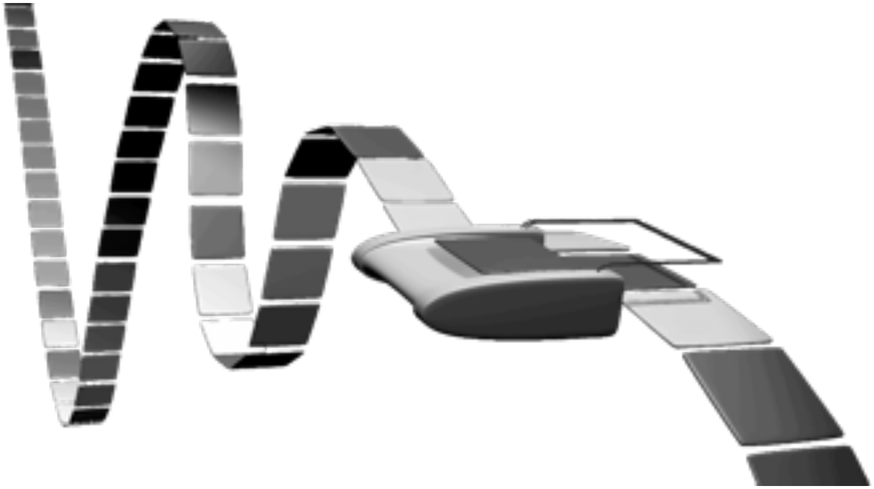
Alan Turing
1912 - 1954
Turing Machines
Decryption
Turing Test
Mathematical Biology

- Turing proved that there is no general procedure for ascertaining the truth or not of any mathematical statement (**decision problem**)

- He showed that there is no general procedure for deciding whether or not an arbitrary program will perform a particular task (**halting problem**)

===> The end of an ancient dream with theological ancestry, a dream whose credo was written in Athens, 2400 years ago

# A Turing Machine



Schadel 2005

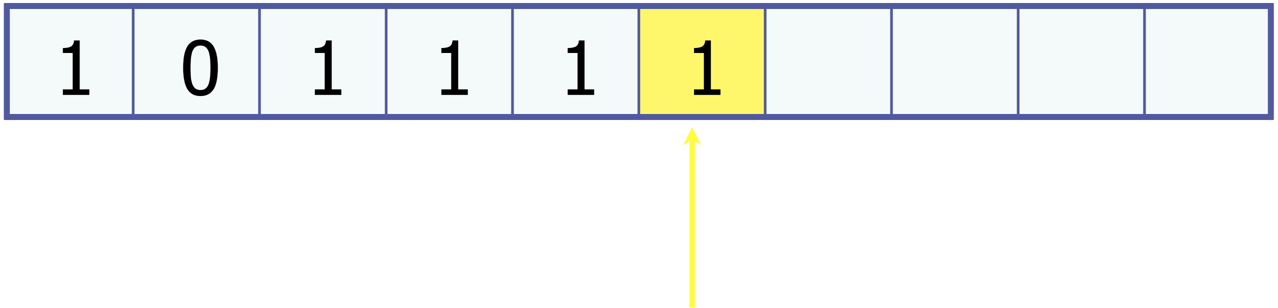
- A finite set of internal states and a transition table
- The ability to read 0/1
- The ability to (over)write 0/1
- An infinite tape with discrete states (cells)

===> Such an idealized machine is capable of any computation. Indeed, it defines our modern notion of 'computable' (Church-Turing thesis)

A simple example - add +1 to the input using the rule

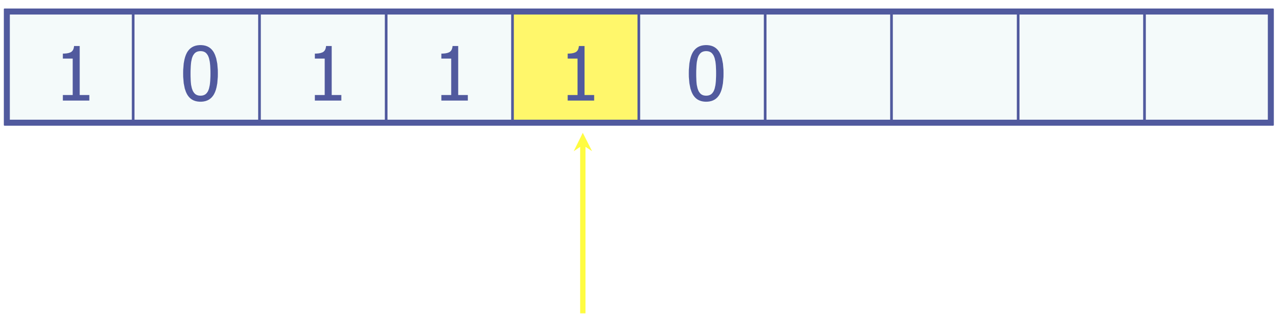
If read ‘1’, write ‘0’, go left & repeat
If read ‘0’, write ‘1’, stop

47 = 32 + 0 8 + 4 + 2 + 1




Start here

If read ‘1’, write ‘0’, go left & repeat
If read ‘0’,  write ‘1’, stop



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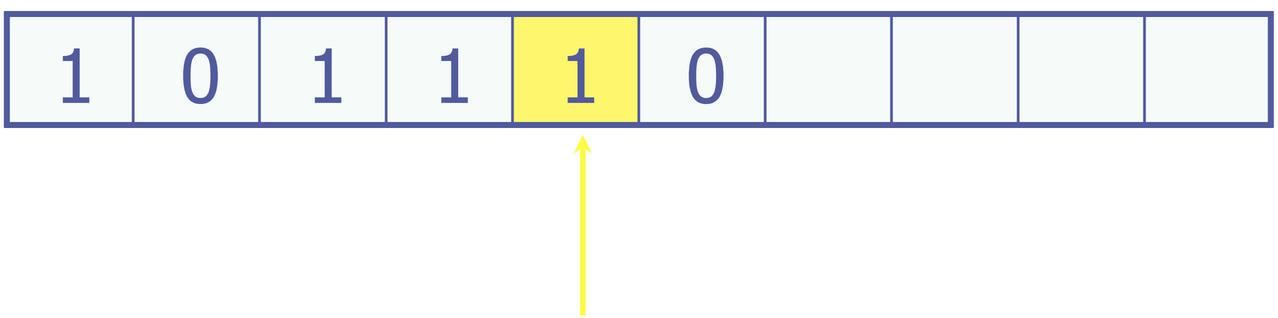

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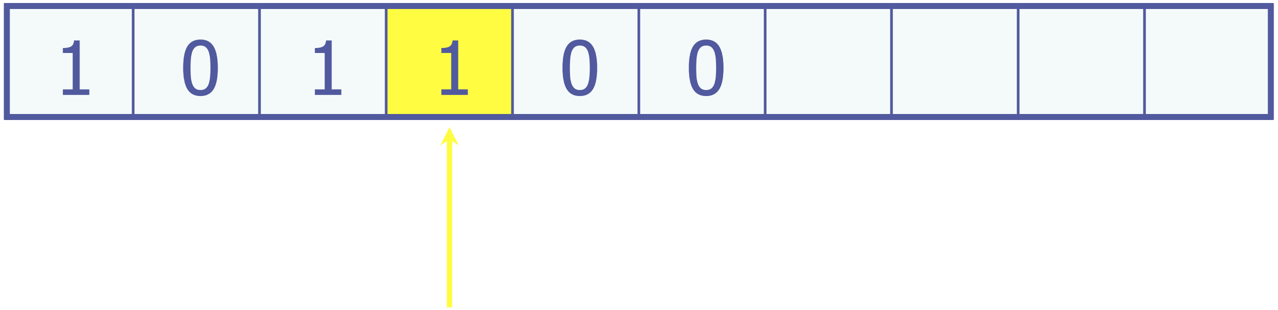

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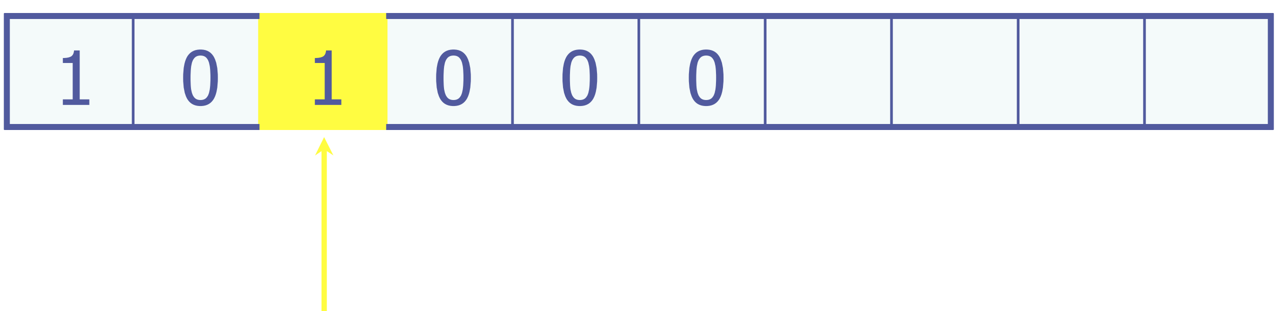


If read ‘1’, write ‘0’, go left & repeat
If read ‘0’,  write ‘1’, stop

48 =  32  +  16  + 0  +  0  +  0  +  0

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 0 | 0 | | | | |

Stop

# Personal Computers


- Out of Turing's proof that there exists no algorithm for deciding the truth of any arbitrary statement arose a definition of computation and algorithm

===> birth of the Age of Computers

Seattle Post-Intelligencer 1981

# McCulloch & Pitts Calculus

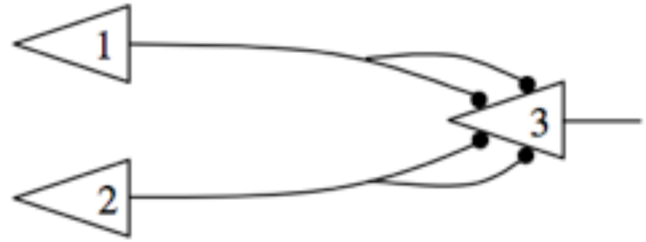
- *A logical calculus of the ideas immanent in nervous activity* (1943)

- Neurons have all or none activity
- A minimum number of excitatory synapses must be active for the neuron to fire
- Propagation delays can be neglected (activity propagates in discrete steps)
- Inhibition prevents excitation
- The structure of the net remains constant

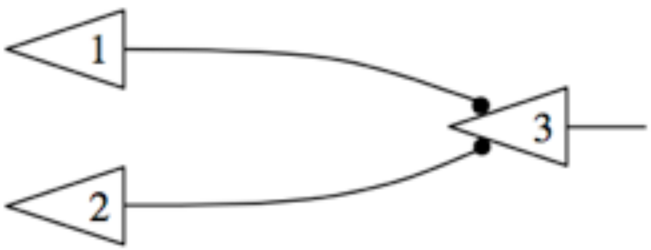
- Using these formal rules, McCulloch & Pitts established an one-to-one relationship between logical propositions (e.g., "Jennifer Aniston is in the room") and neural nets built out of such neurons (logic gates)

- They suggest that brains made out of such nets compute and, together with an infinite tape (memory) are Turing universal

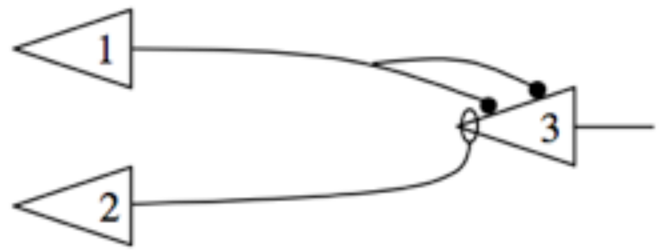

$N_2(t) = N_1(t-1)$




$N_3(t) = N_1(t-1)$ OR $N_2(t-1)$




$N_3(t) = N_1(t-1)$ AND $N_2(t-1)$



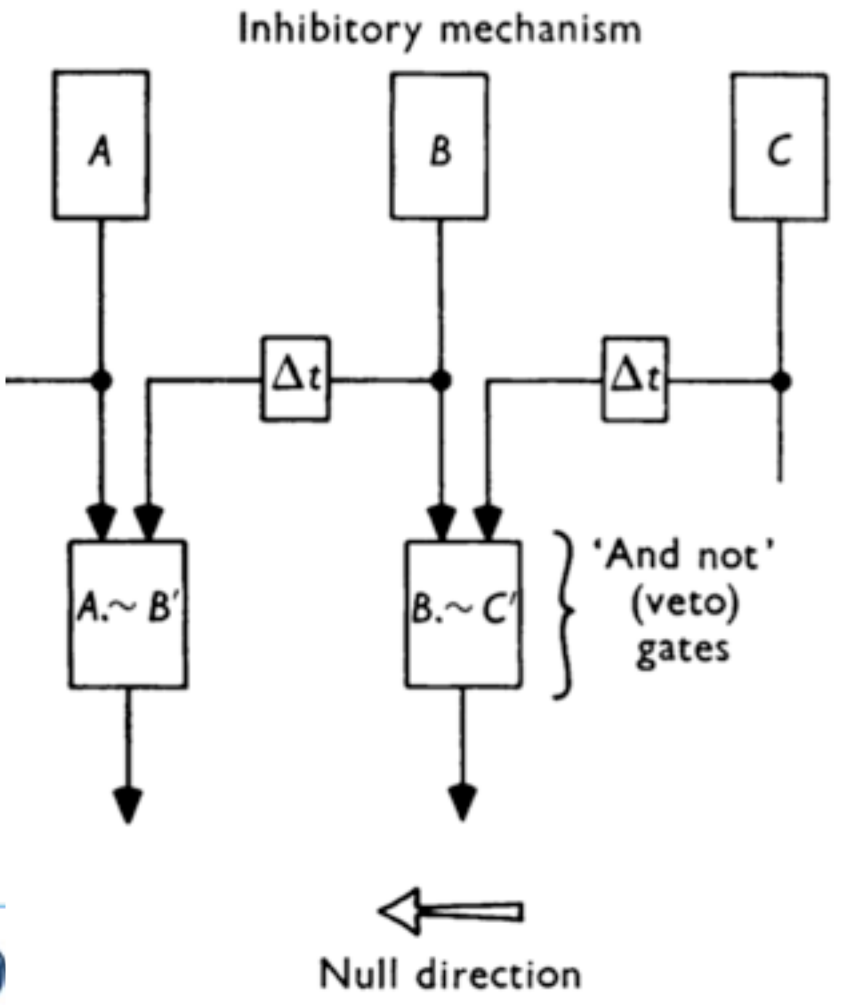

$N_3(t) = N_1(t-1)$ ANDNOT $N_2(t-1)$

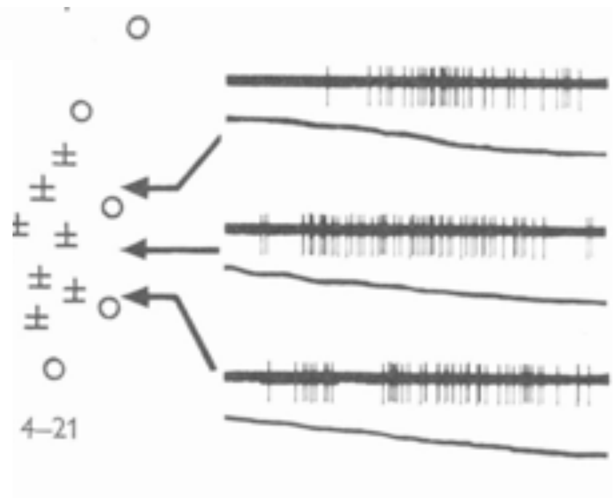
These ideas were taken up by John von Neumann's

*The Computer and the Brain* (1957)

# Feature Detectors

Direction selectivity in the frog retina




AND NOT computation in the retina

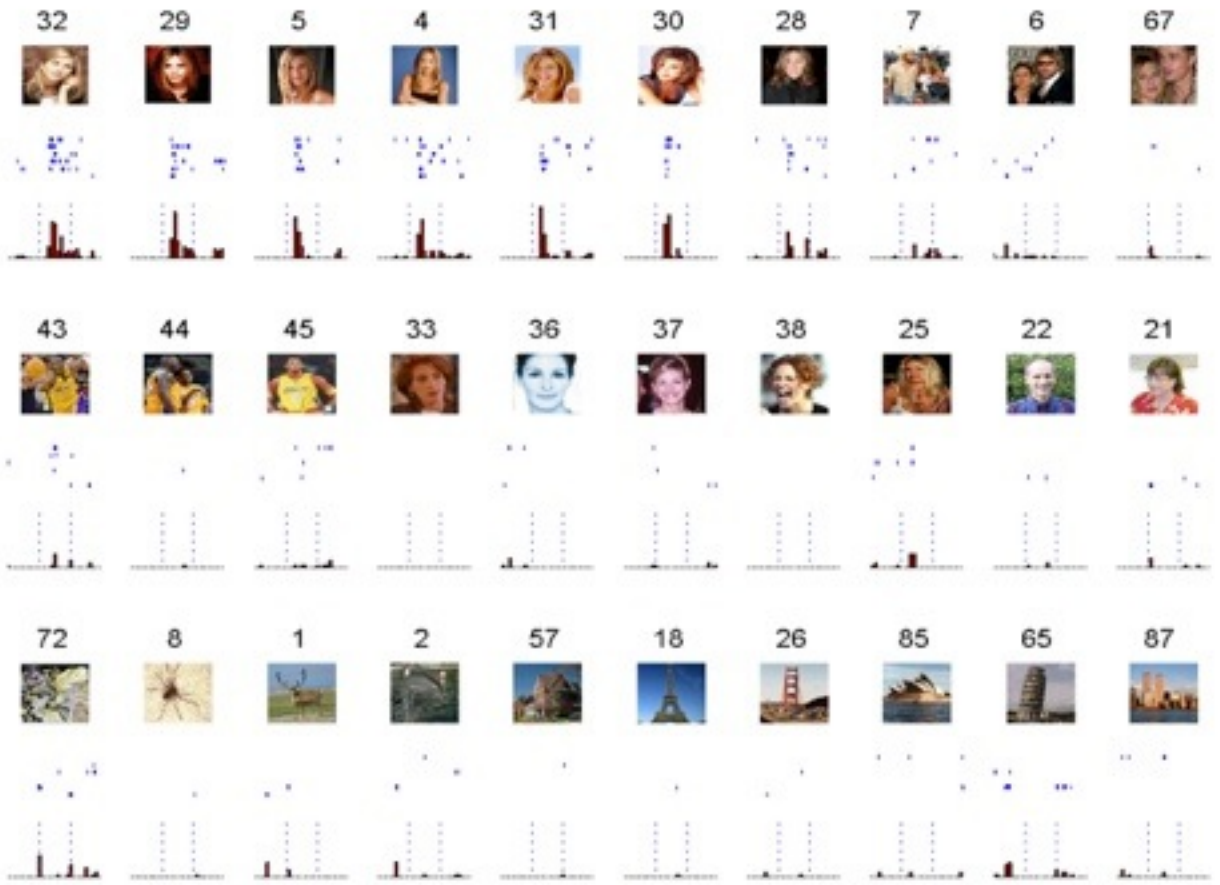
The direction of motion is *encoded* in a population of such cells and can, in principle, be derived (*decoded*)

Barlow & Levick 1965

# Feature Detectors

- Bug detectors in the frog retina - Lettvin, Maturana, McCulloch & Pitts (1959)
- Orientation detectors in cat visual cortex - Hubel & Wiesel (1962)
- Face cells in the monkey cortex - Gross *et al.* (1971)
- Concepts cells in the human medial temporal lobe (Quian-Quiroga, Fried & Koch 2014)

# Jennifer Aniston Cell



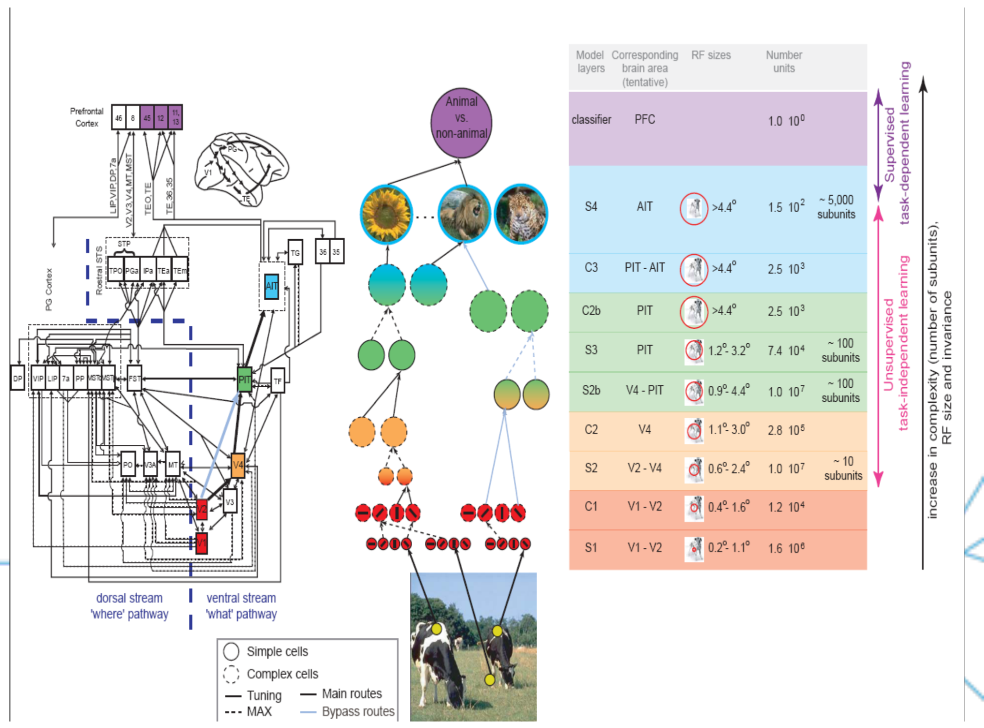

Quian Quiroga *et al.* 2005

# A Caveat

- It makes sense to talk about de- and en-coding information in the brain from an engineering point of view (e.g. brain-machine interfaces)
- However, coding and related information-theoretical ideas (e.g., channel) imply a receiver who decodes the messages and provides the meaning (semantics)
- There is no homunculus!

# Feature Detectors

- These are all examples of the brain encoding particular features by computing on the sensory information
- It is difficult to make sense of these neurons in terms of signal flow but they are much more meaningful in terms of hierarchies of concepts that are used to represent the external world
- We'll return to this in a bit




Serre, Poggio *et al.* 2007

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# Hopfield Networks

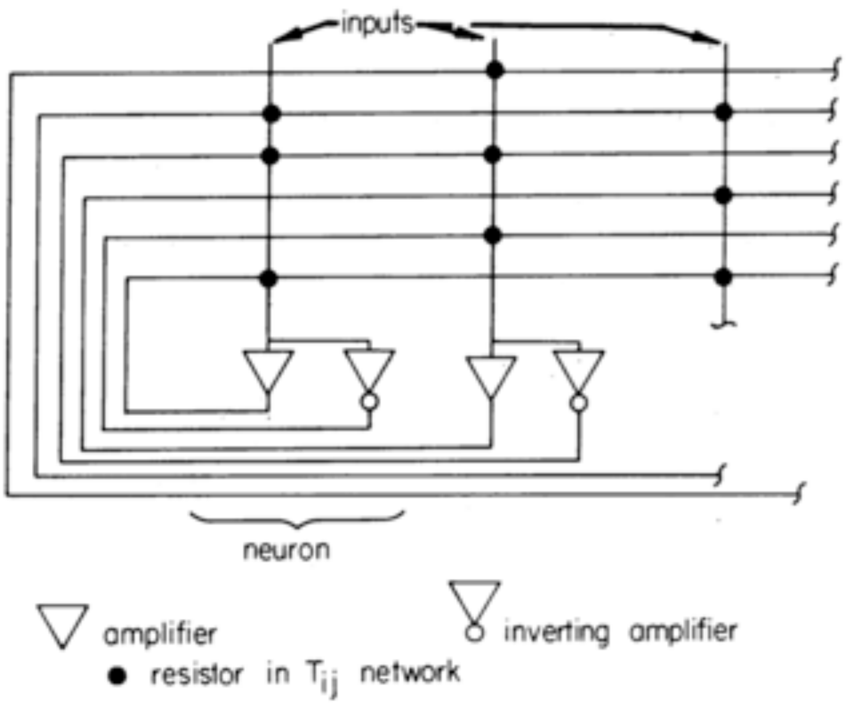
- Consider the dynamics of interconnected networks

- In general, such networks can settle down to a steady state, oscillate or show chaotic behavior

- The Caltech physicist John Hopfield realized in 1982 that if the synaptic weight matrix, $w_{ij}$, (the network's connectome) is symmetric ($w_{ij} = w_{ji}$), the network will converge to a local minimum

- Enormous influential (>14,000 citations)

# Hopfield Networks

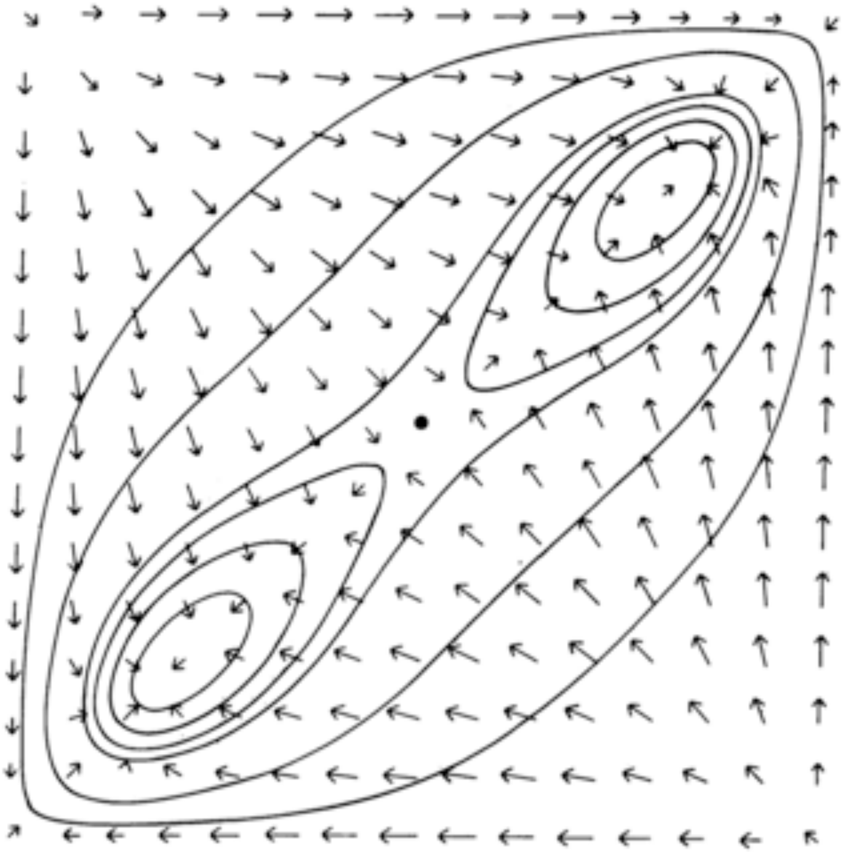



$$C_i \frac{dU_i}{dt} = \sum_j w_{ij} V_j - \frac{U_i}{R_i} + I_i$$

$$V_i = f(U_i)$$

Hopfield 1982 & 1984

# Hopfield Networks



- Such a network acts as a associative memory or can solve optimization problems
- Example of a two neuron network with two stable *attractors*. The two axis correspond to the firing rates of the two neurons
- Cortex may implement such *attractor computations*

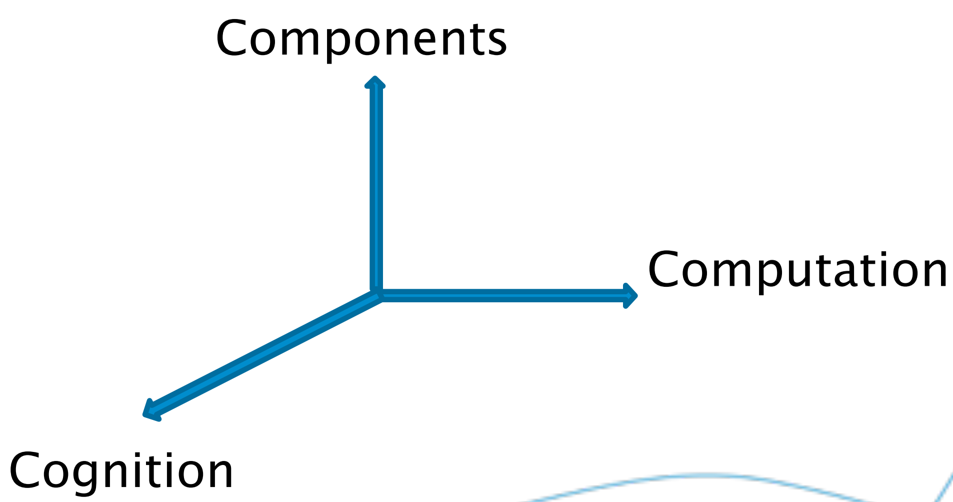
Hopfield 1984

# Multiple Levels of Understanding

- Careful to distinguish computational modeling - which uses the computer as a tool - from computational explanations

- Computational explanations versus bio-physical explanations

- Marr & Poggio’s multiple level of analysis - computational, algorithmic and (bio)-physical levels (see also Herb Simon)

# Differences between the Brain and the Liver

- Very complicated bio-physical and chemical reactions are taking place in the liver and in other organs (and at the molecular, sub-cellular level) that are flexible and adaptive
- These can also be mapped onto **computations**
- Yet we do not think of these as computations, as metabolic functions do not directly underpin cognition
- Thus, we think of the human brain - and by inference, the brain of other animals - as **computing** because of the widespread influence of logic and programmable computers (i.e. mechanized thought, the ancient dream of Leibniz)

# An Example of a Computation

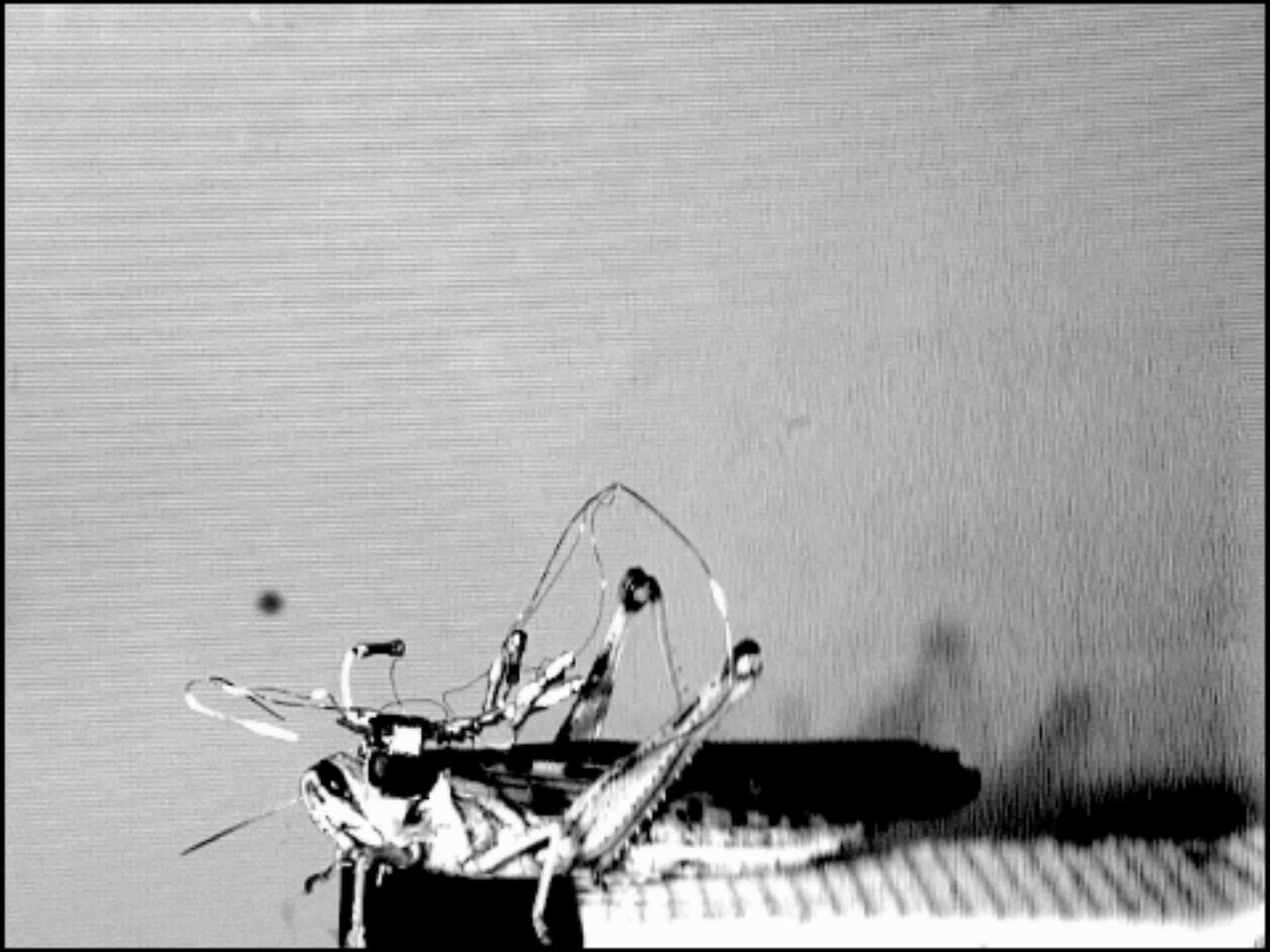
- Computation - To compute motion, compute the correlation of the image in different directions and pick the maximum. This involves computing the product of I(x,t) and I(x+delta x,t+delta d t)

- Algorithm - $I(x,t) \cdot I(x+\delta x, t+\delta t) = e^{\log I(x,t) + \log I(x+\delta x, t+\delta t)}$

- Hardware - Digital computer with binary representation, long hand multiplication, analog VLSI or neurons

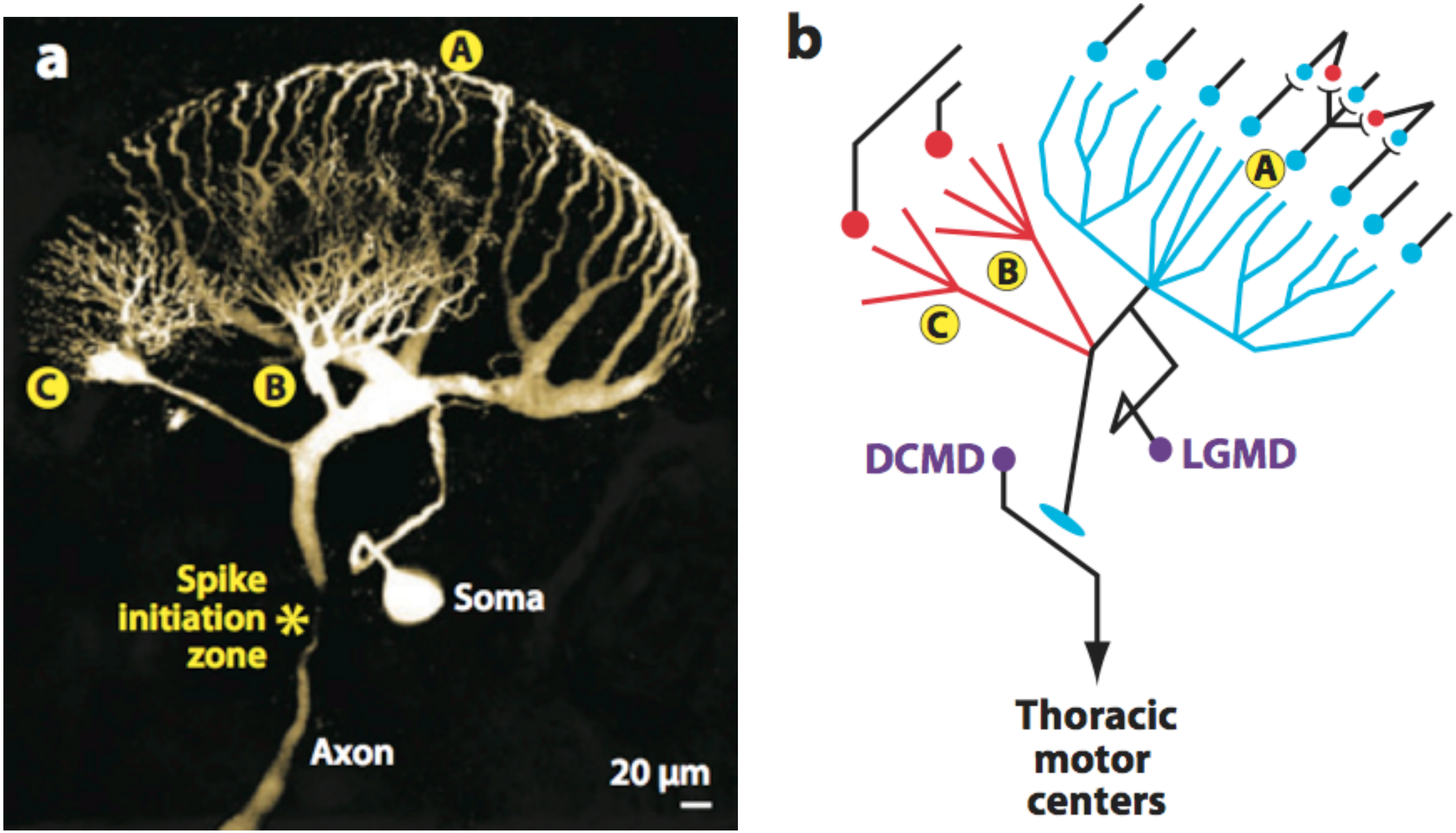
# Locust: A Model System for Visually-Guided Collision Avoidance

# Locust Jump Escape Behavior



Fotowat, Harrison & Gabbiani (2011)

# LGMD Anatomy and Circuitry

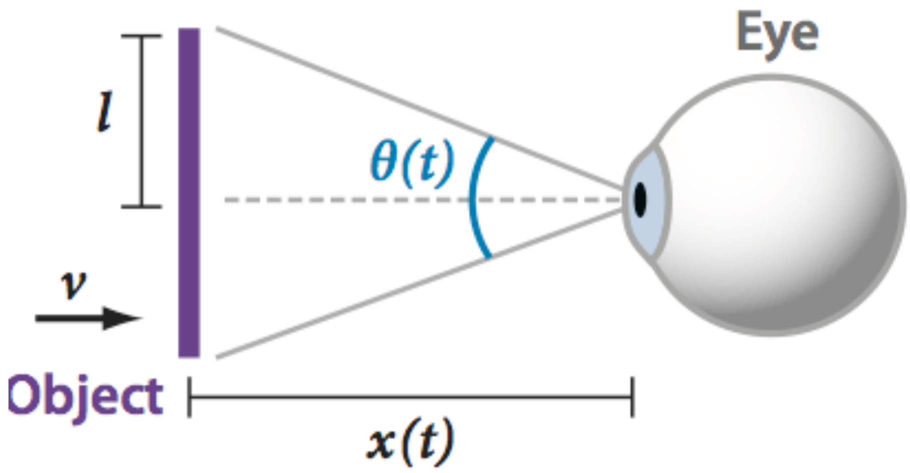



es
out
ry

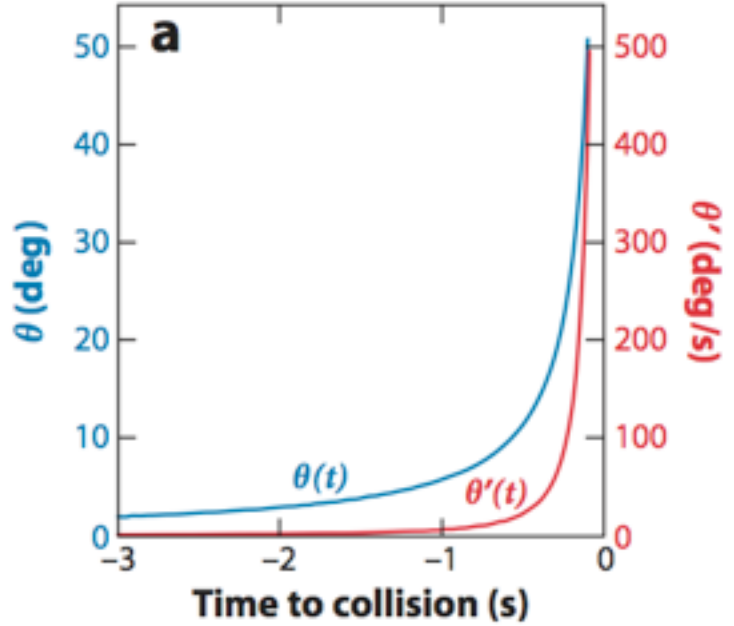


Gabbiani, Krapp, Koch & Laurent (2002)

# Kinematics of Object Approach

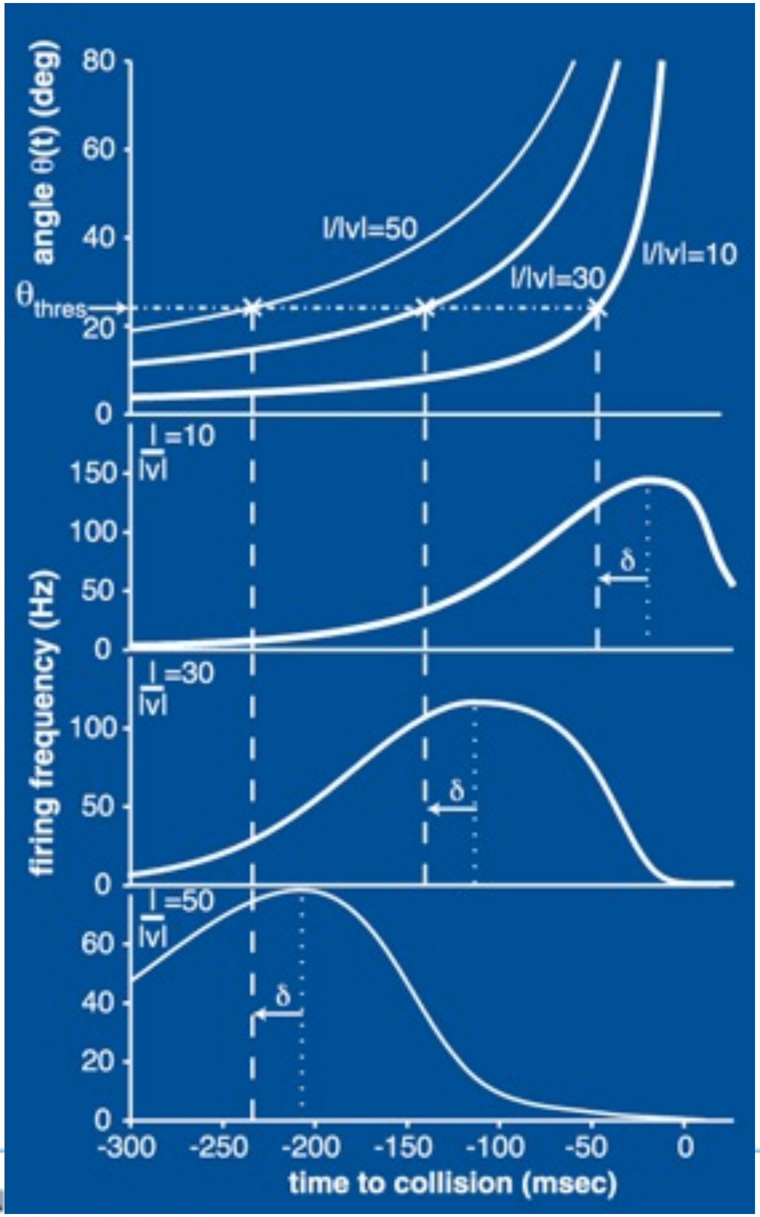


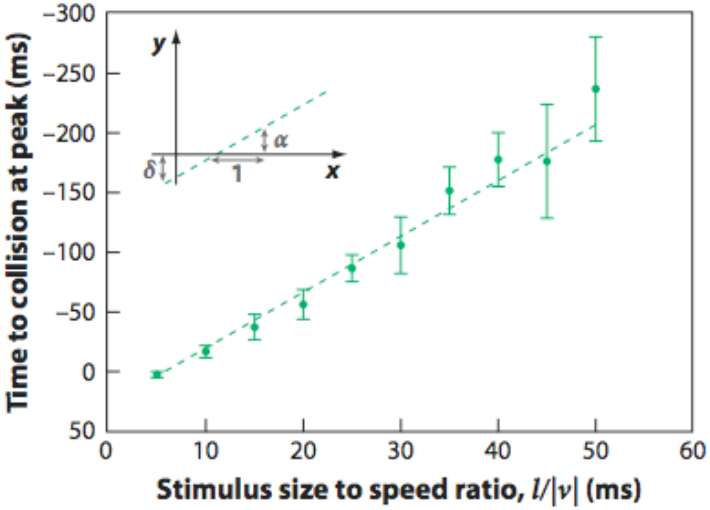

$\theta(t) = 2\tan^{-1}(l/vt)$




Fotowat & Gabbiani (2011)

# Angular Threshold Computation




Peak firing rate always occurs a fixed delay after a threshold angular size has been reached

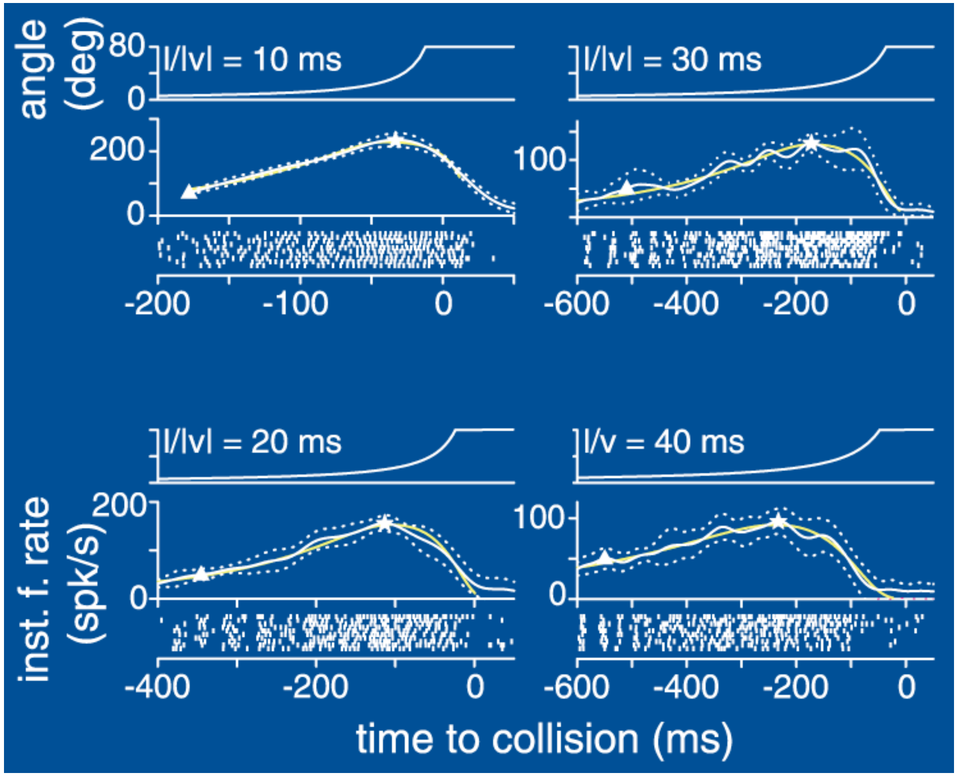
Gabbiani, Krapp & Laurent (1999)

# Firing Rate can be Derived

Assuming that the firing rate *f* is solely a function of the angular size and angular velocity at time *t-delta*, and that the peak firing rate always occurs *delta* after a threshold angular size is reached leads to

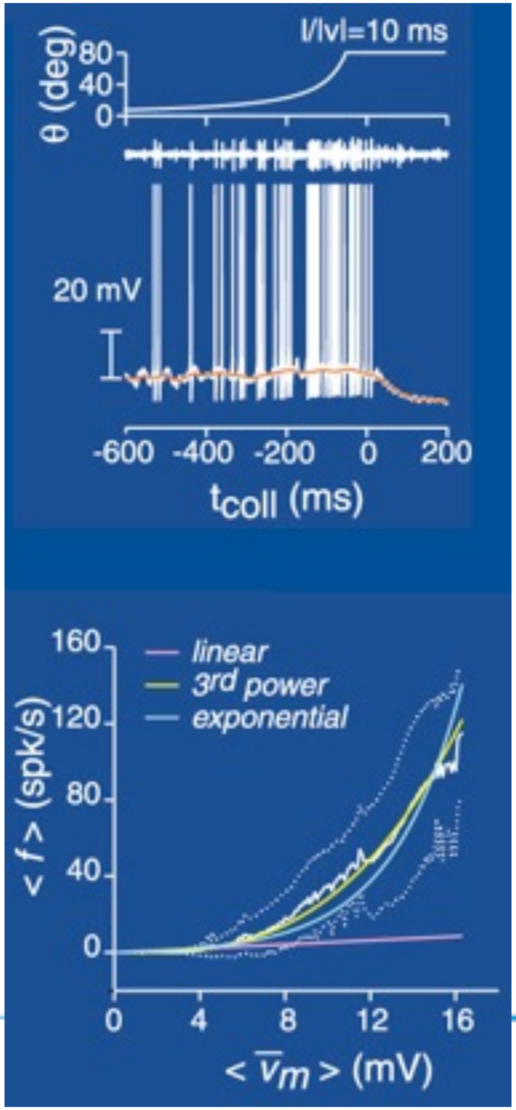
$$f(t) = \dot{\theta}(t-\delta) \cdot e^{-\alpha\theta(t-\delta)}$$

# LGMD Firing Rate is the Product of Angular Speed and the Exponential of the negative Size



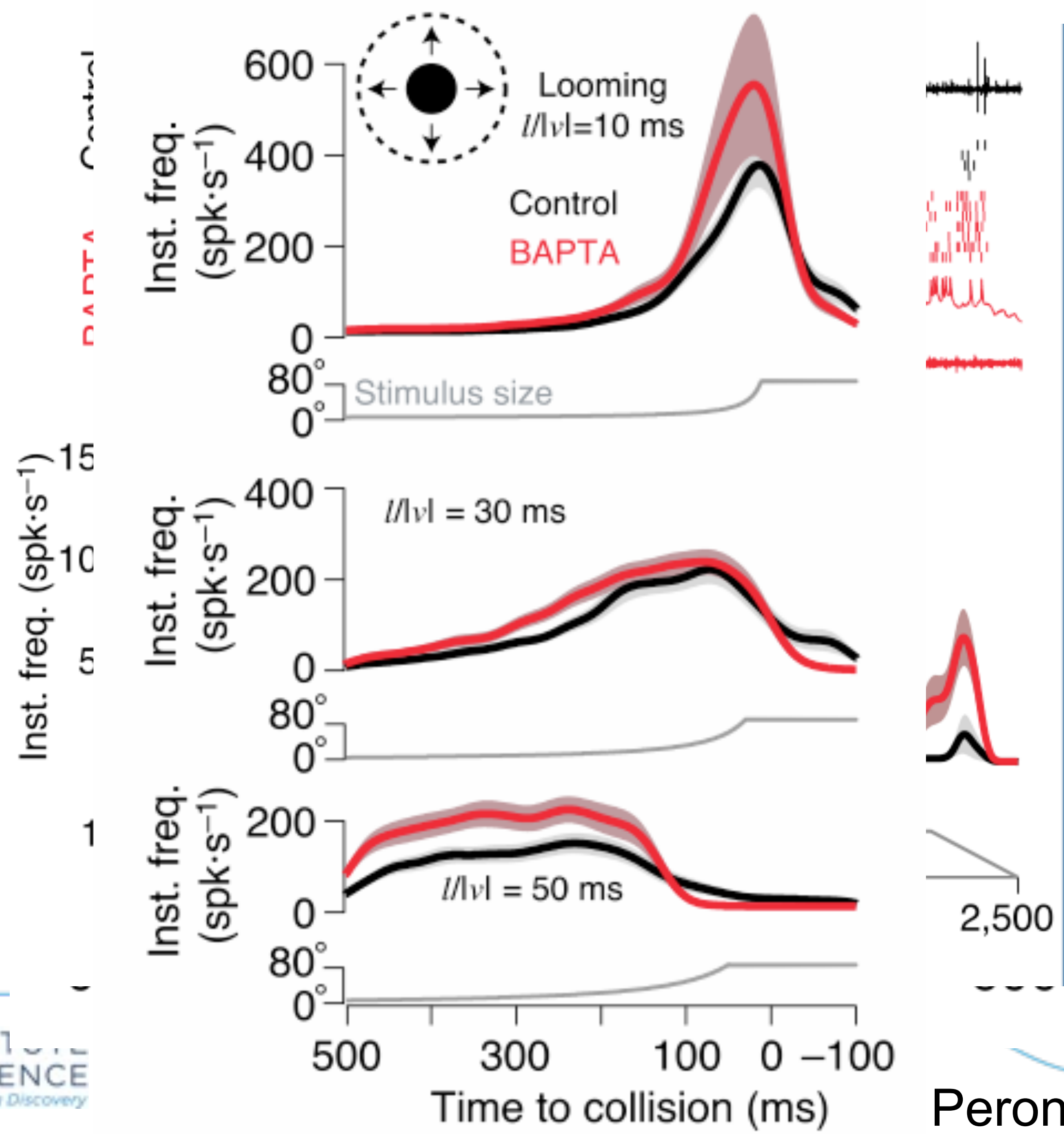

Gabbiani, Krapp, Koch & Laurent (2002)

# Transformation between Membrane Potential and Firing Rate



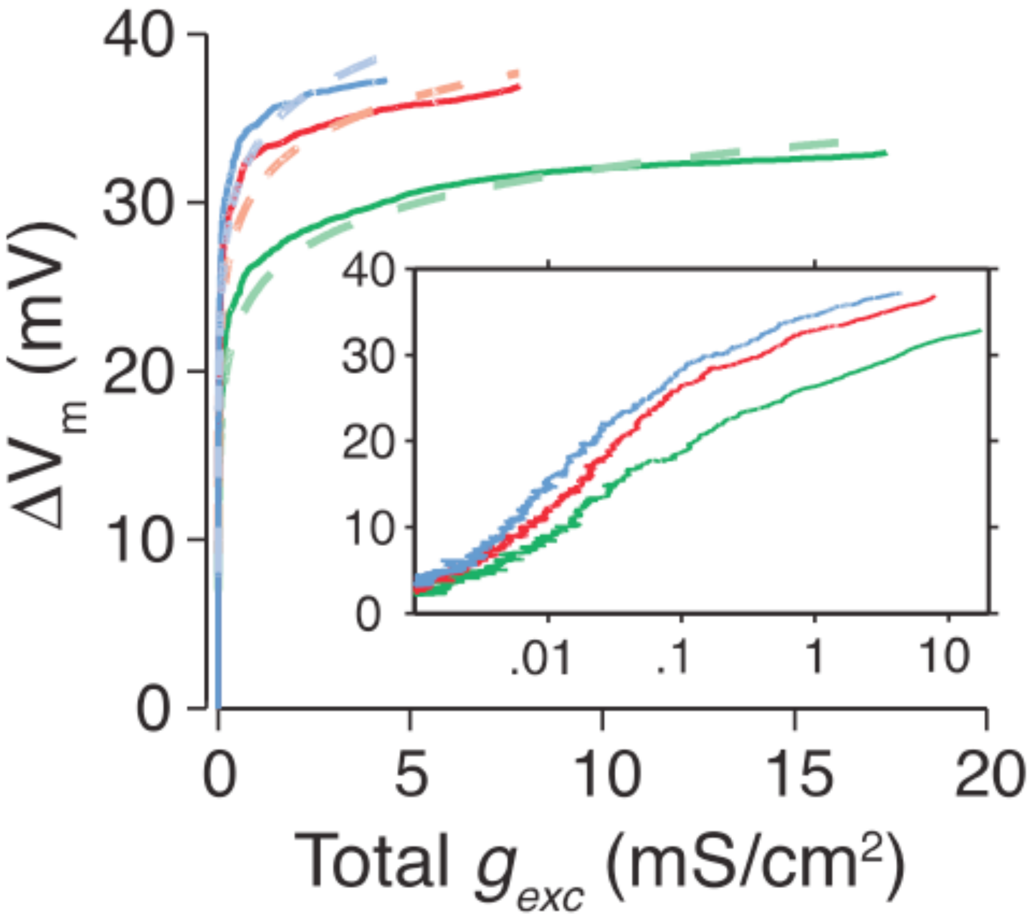

Gabbiani *et al.* (2002)

# Calcium Mediates Spike Frequency Adaptation Through a Calcium-Dependent Potassium Conductance, $K_{Ca}$



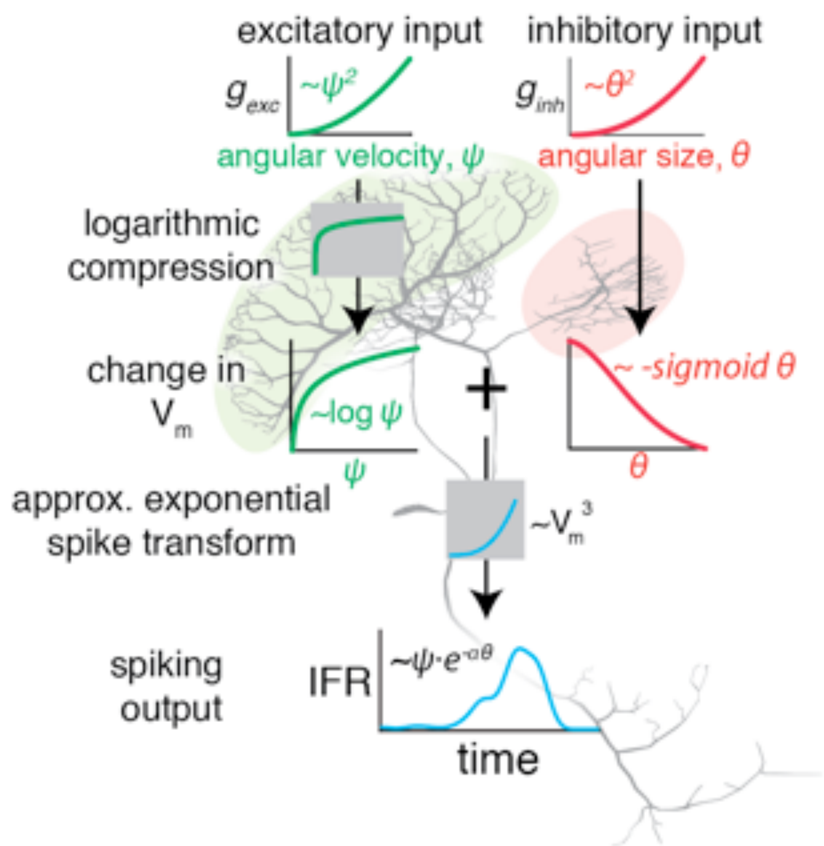

Peron & Gabbiani (2009)

# Logarithmic Compression of Excitatory Input within LGMD's Dendrites




Jones & Gabbiani (2012)

# Information Processing at a Single Neuron

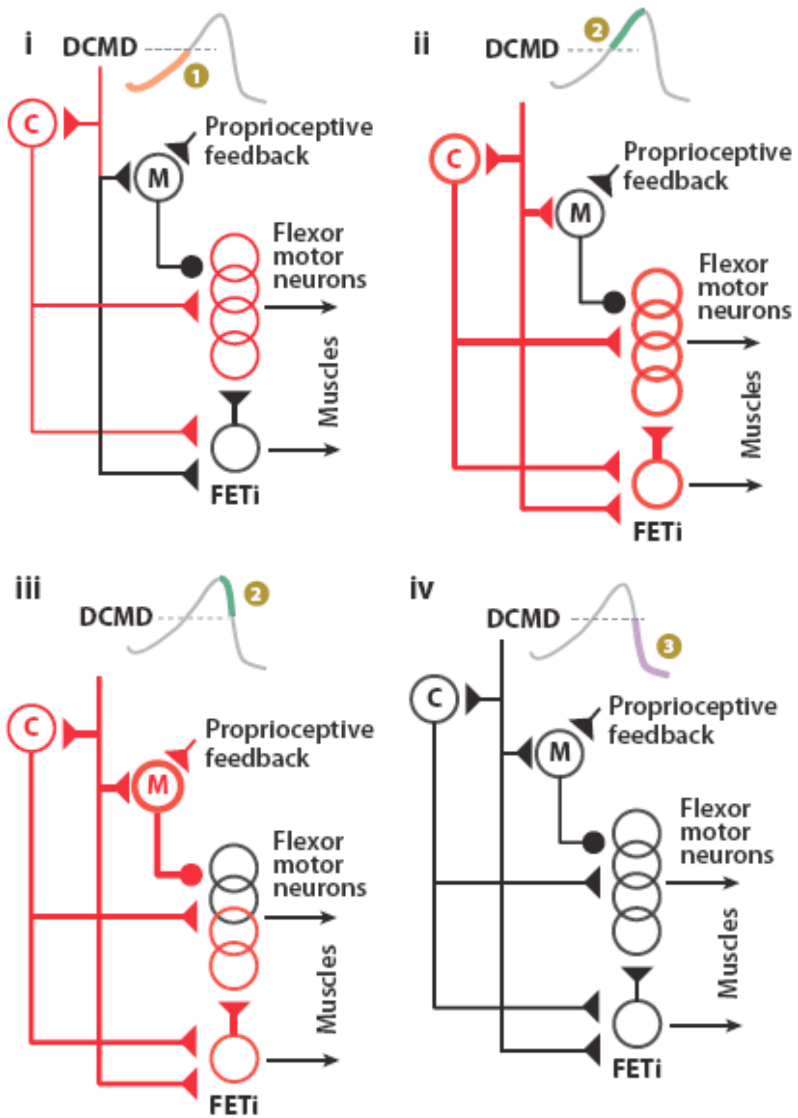



Feedforward Processing



Fotowat & Gabbiani (2011)

# Subsequent Processing to Initiate Movement

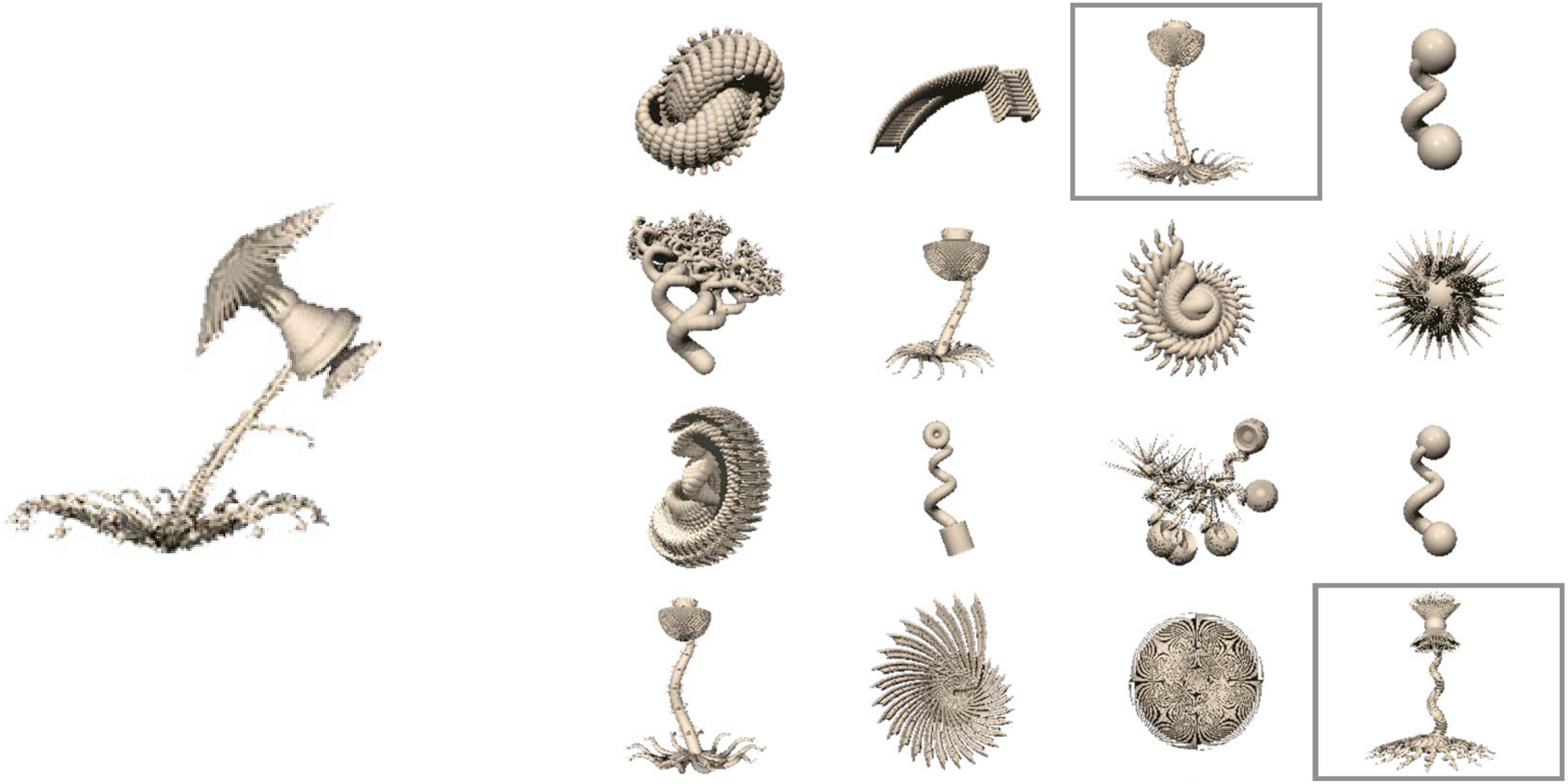



Fotowat & Gabbiani (2011)

# Human Visual Recognition is Powerful

~30,000 object categories (Biederman,1987)

# Human Visual Recognition is Powerful



Tenenbaum

Humans know 10,000 - 30,000 categories and can learn new ones from one or a few examples

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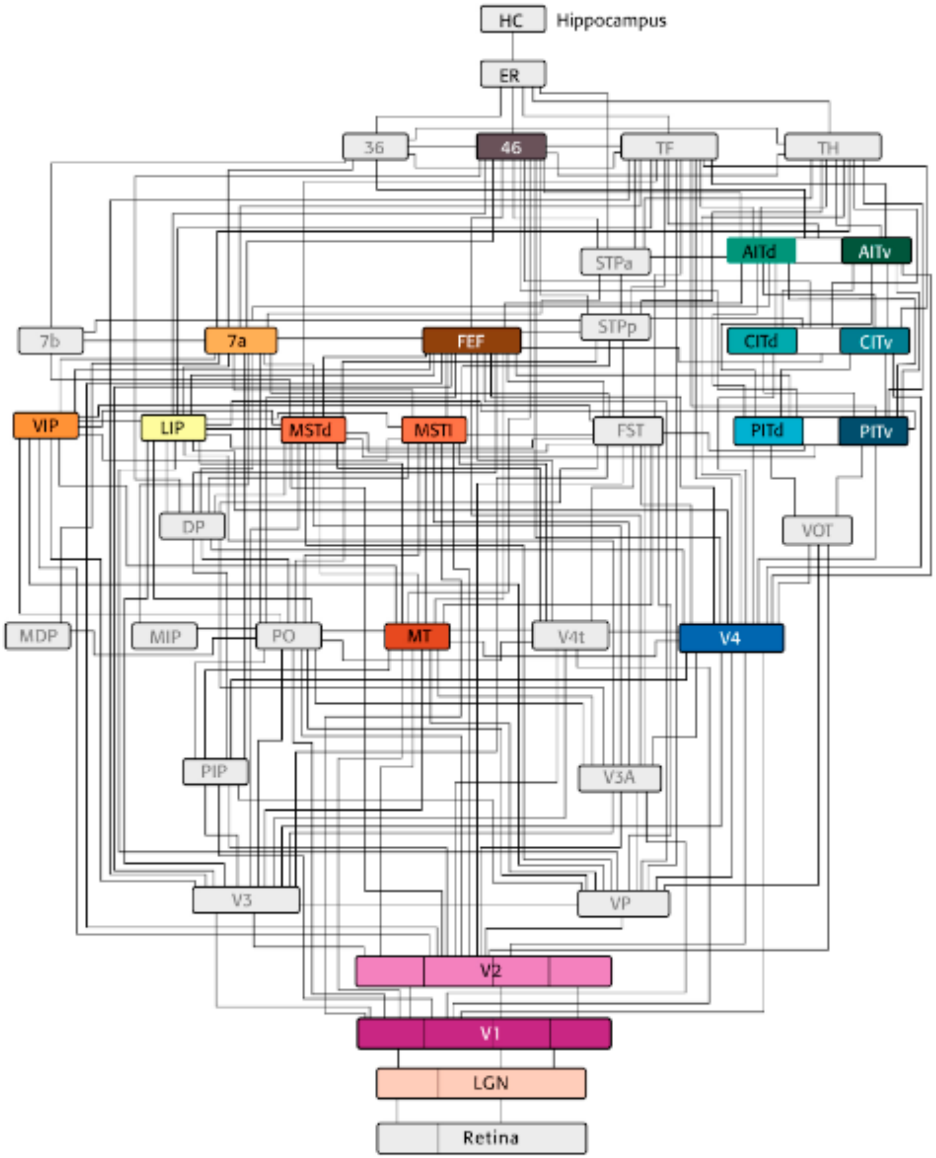
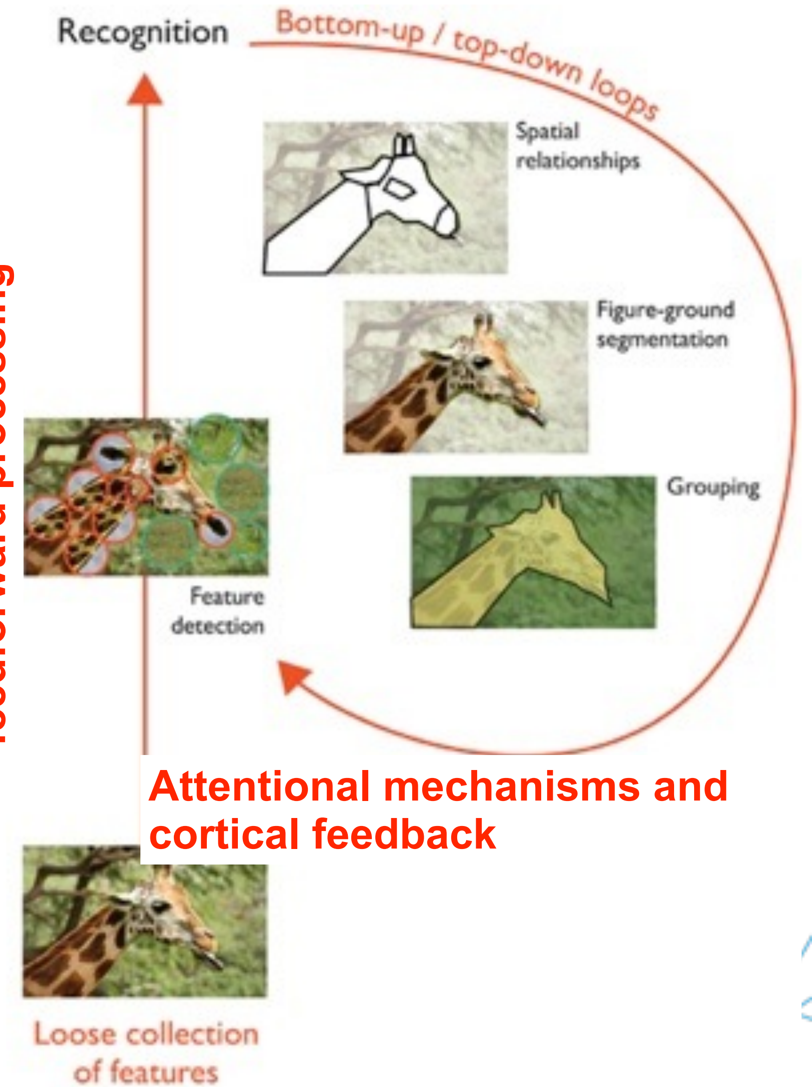
# Feedforward Visual Processing




Felleman & Van Essen (1991)

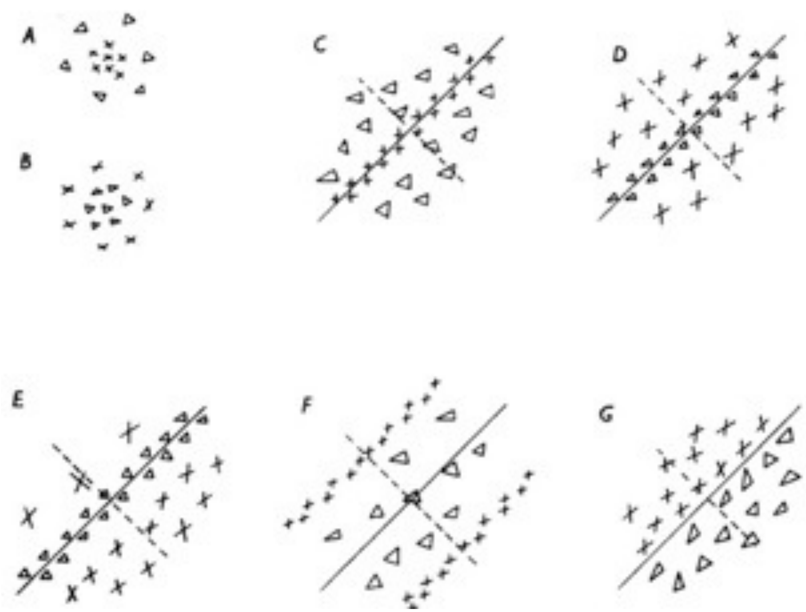



Rapid recognition and feedforward processing

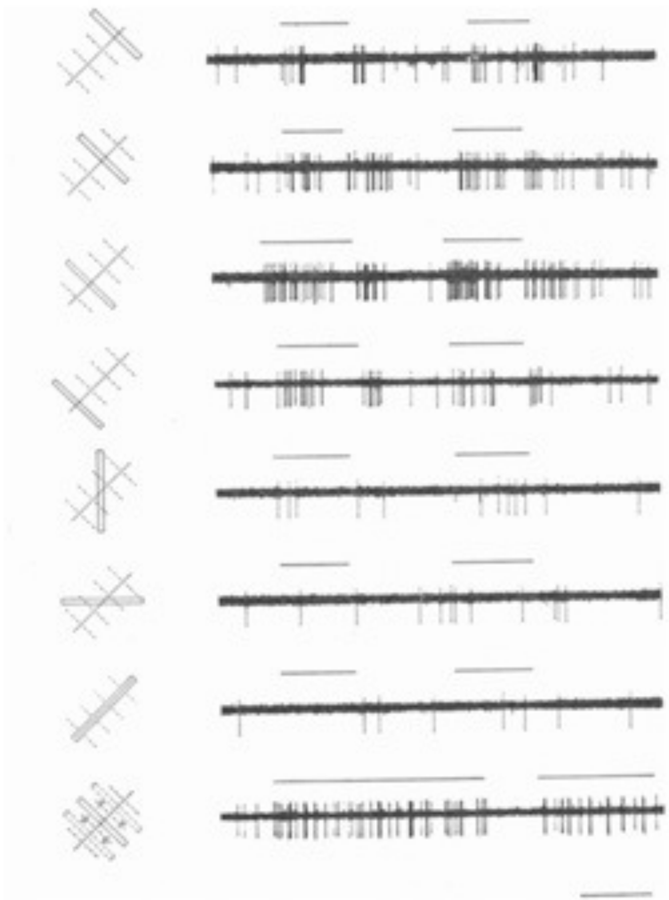
Attentional mechanisms and cortical feedback

Serre & Poggio (2010)

# Receptive Field Organization in V1



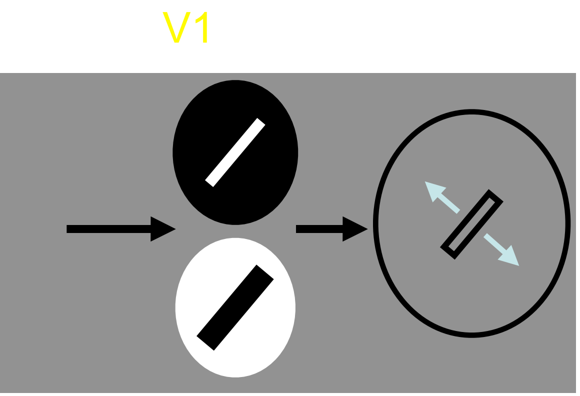

Simple cell



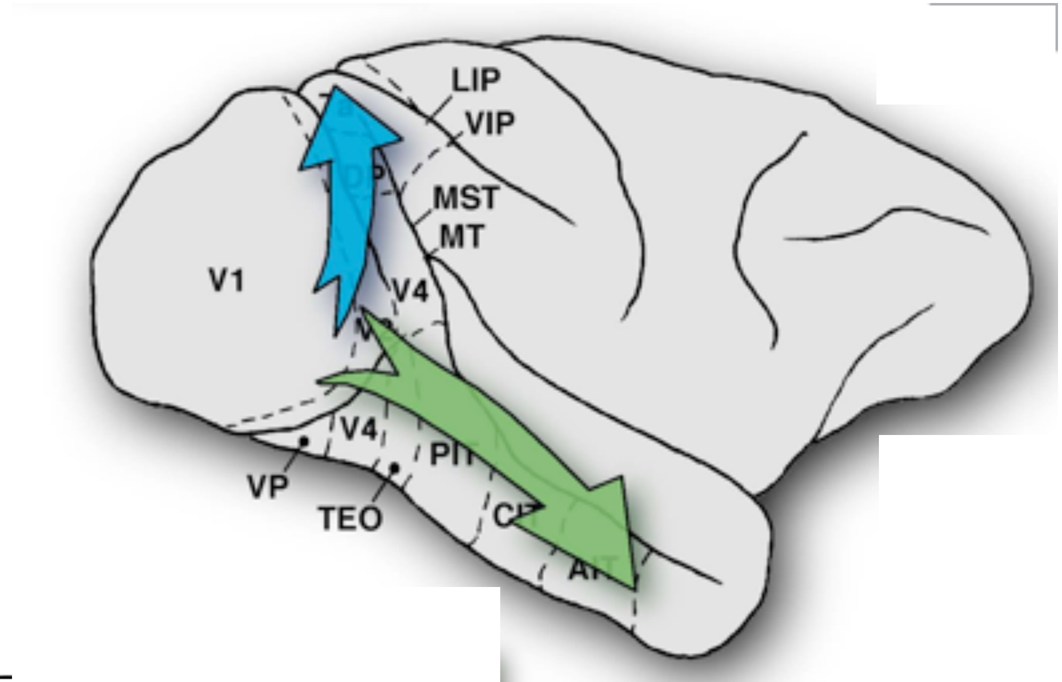
Complex cell

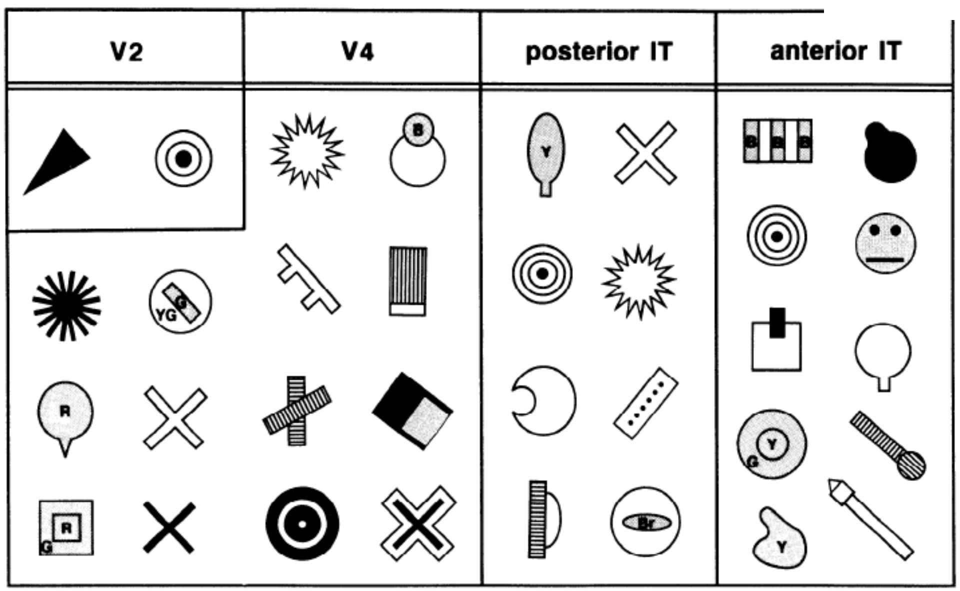
Hubel & Wiesel 1959, 1962, 1968

# Object Recognition in the Ventral Stream




Maunsell

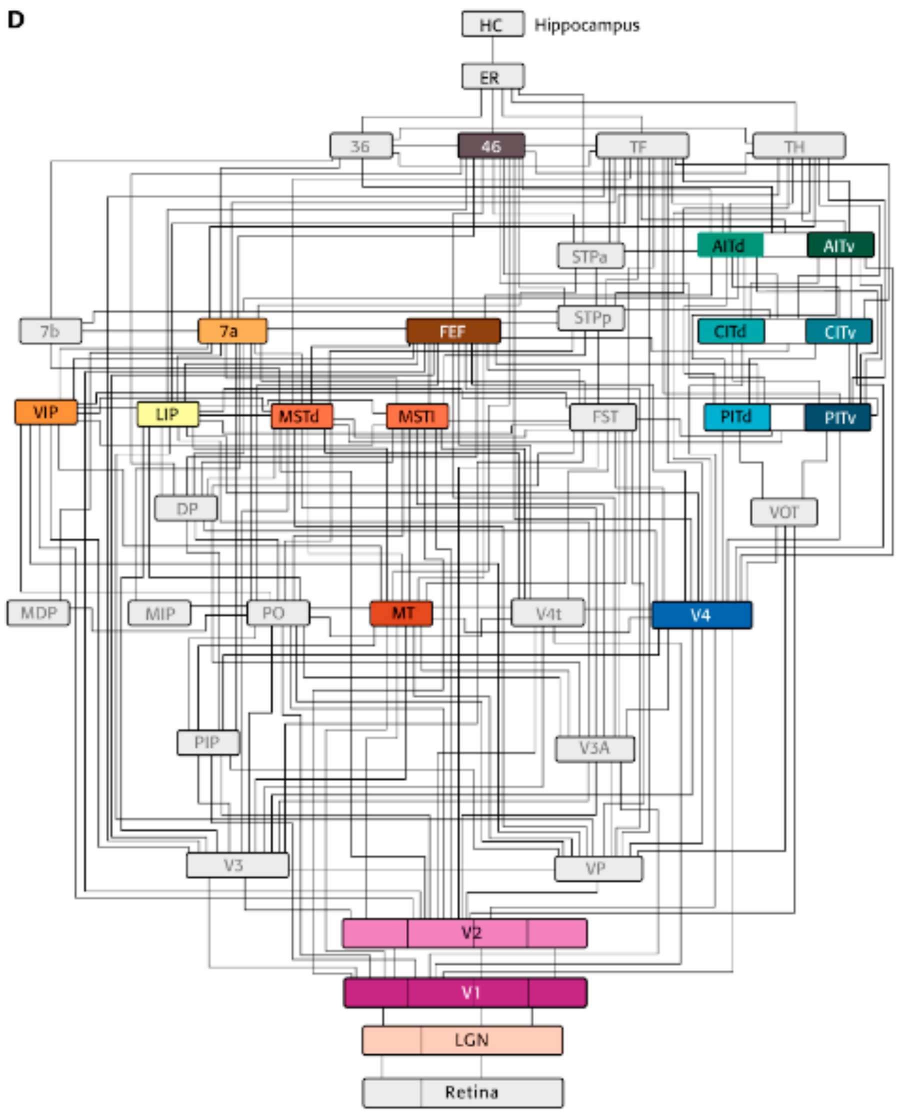


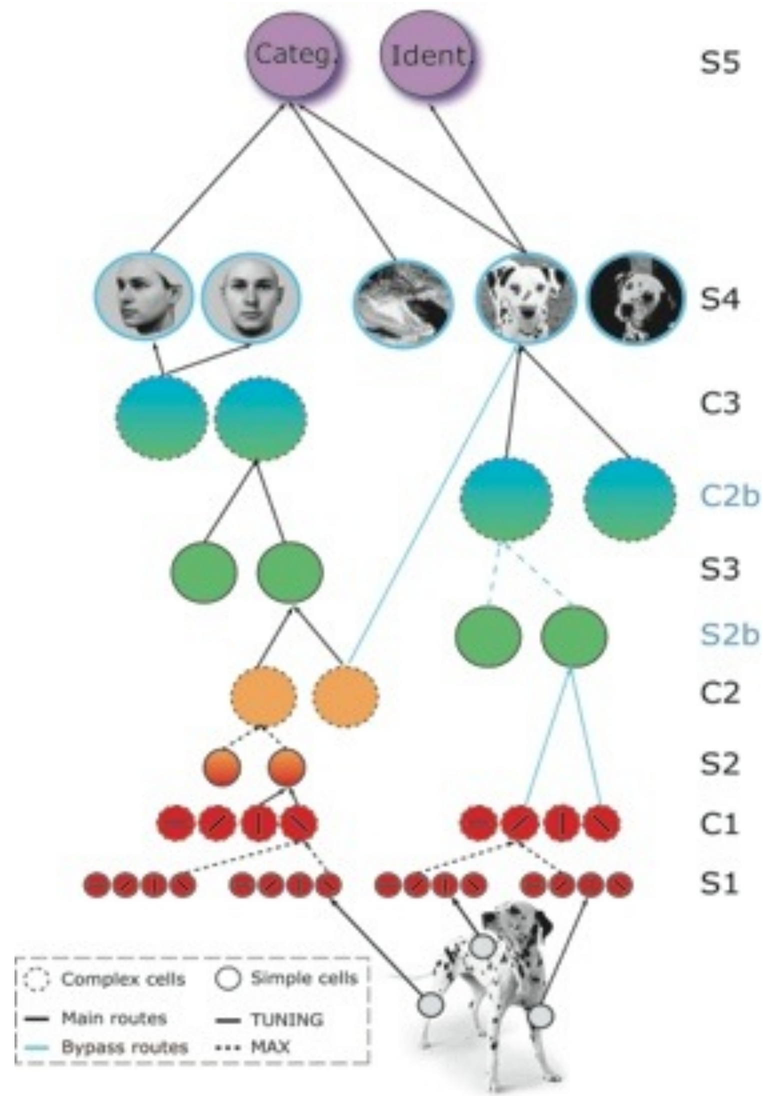

- From V1, V2, V4, to IT and beyond
- A gradual increase in the receptive field size, in the "complexity" of the preferred stimulus, in "invariance" to position and scale changes

Kobatake & Tanaka (1994)

# Object Recognition in the Ventral Stream
# The feedforward model



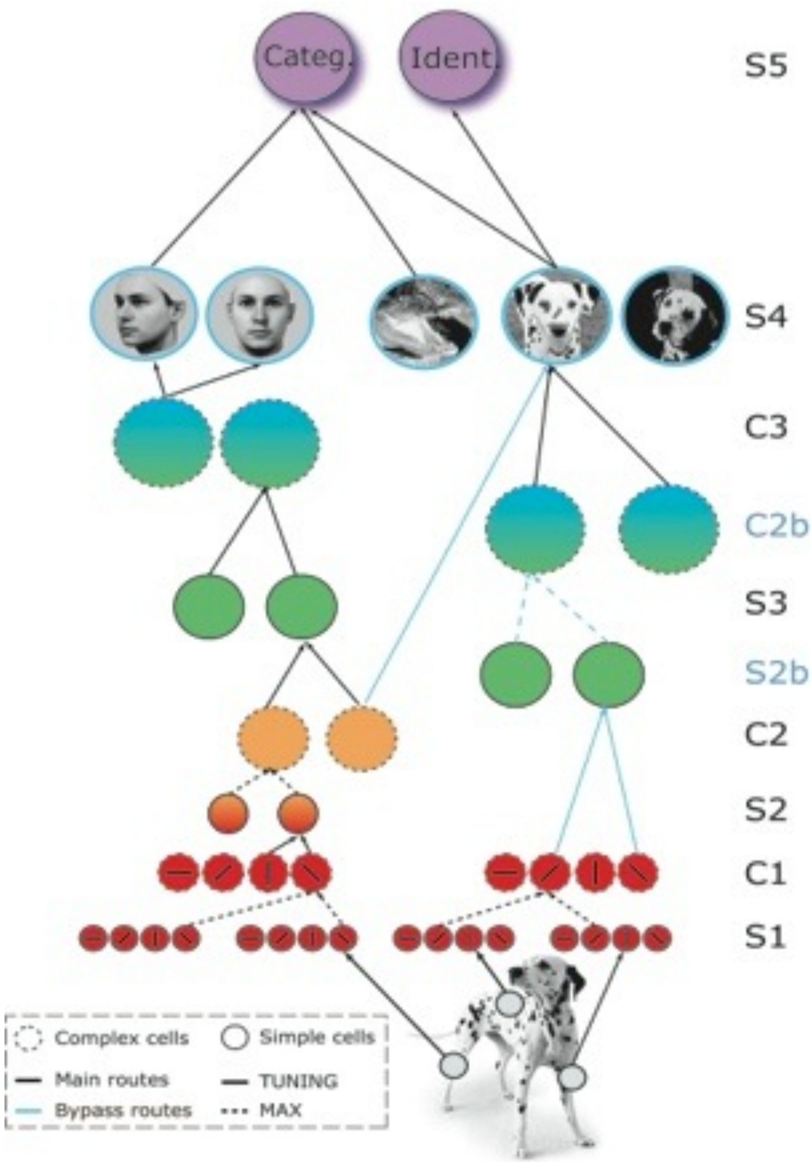

Felleman & Van Essen (1991)




Riesenhuber & Poggio (2000)

Serre, Oliva & Poggio (2007)

# Object Recognition in Visual Cortex - Selective and Invariant




- In the family of "Hubel-Wiesel" feed-forward models (Hubel & Wiesel, 1959)
- See also Fukushima, 1980: Oram & Perrett, 1993: qual; Wallis & Rolls, 1997; Thorpe, 2002; Ullman et al., 2002; Mel, 1997; Wersing & Koerner, 2003; LeCun et al 1998: not-bio; Amit & Mascaro, 2003: Hinton, LeCun, Bengio, deep learning in convolutional networks

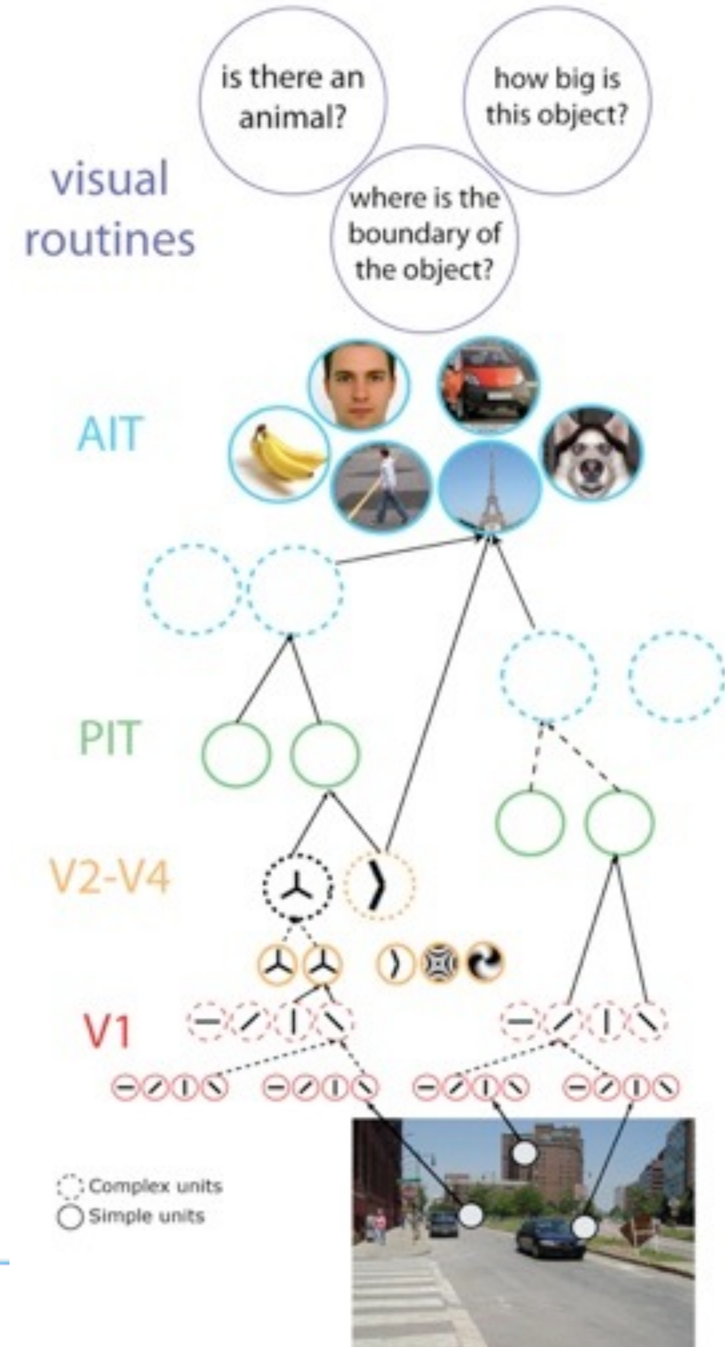
- As a biological model of object recognition in the ventral stream – from V1 to PFC -- it is the most quantitatively faithful to known neuroscience data

Riesenhuber & Poggio (2000)

Serre Oliva & Poggio (2007)

# Feedforward hierarchical model of object recognition

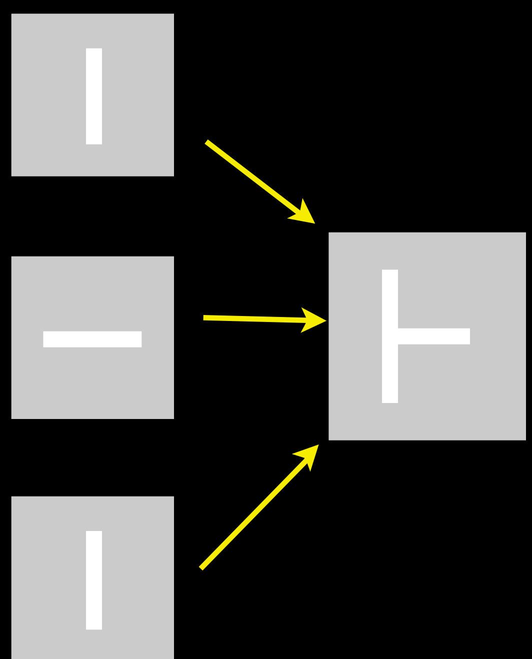
- Consists of a series of simple-complex transformations a la Hubel & Wiesel
- Simple cells - selectivity for orientation, spatial tuning, wave length etc.
- Complex stage - pool over location, orientation, spatial tuning etc for invariance
- Each simple cell stage increases the complexity of the representation
- Each complex cell stages implements tolerance to one or more features and thus leads to generalization




Serre & Poggio (2010)

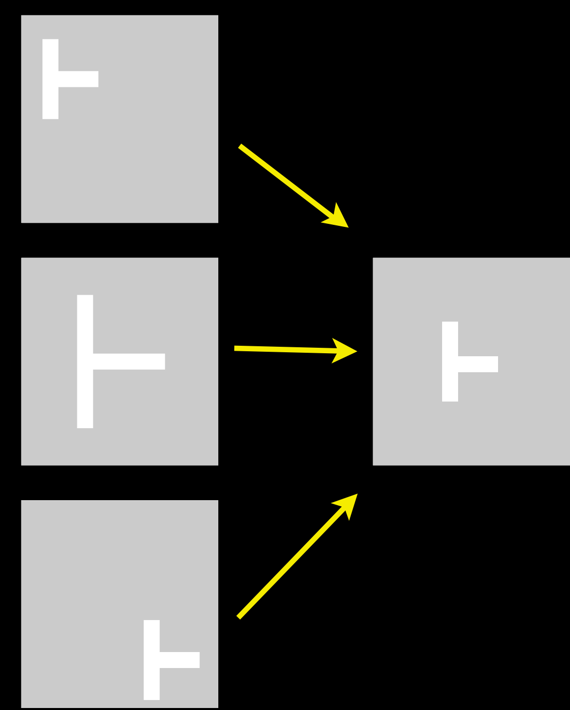
# RF organization in First Layer

## Simple units



Selective & invariant
pooling max-like operation

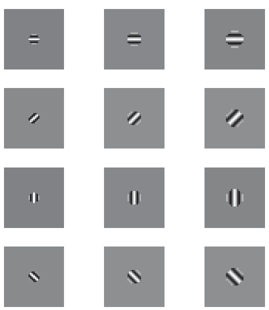
## Complex units

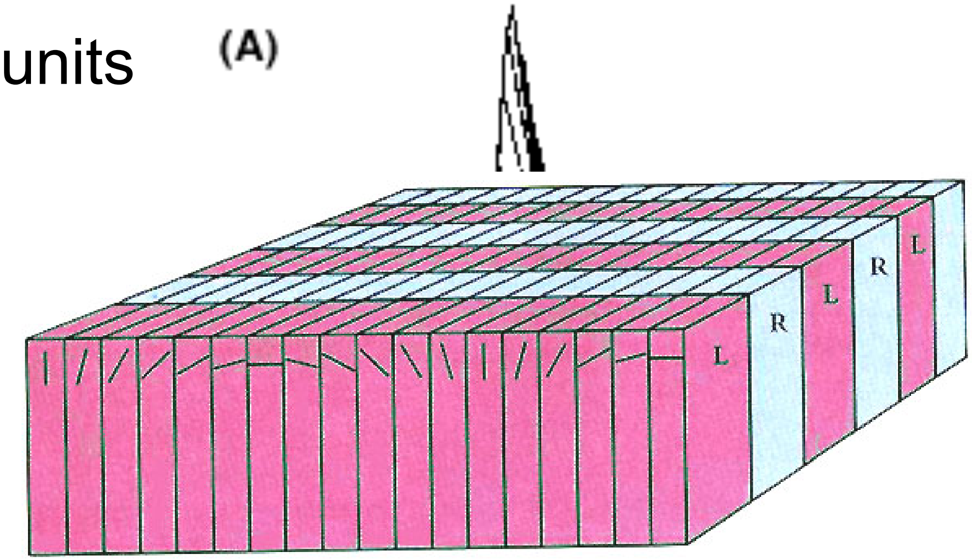


Riesenhuber & Poggio (1999), building on
Fukushima (1980) and Hubel & Wiesel (1962)

# **S1** simple units

(A)



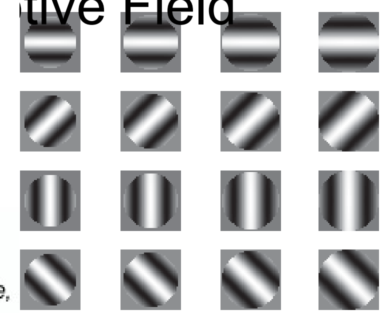



Orientation and ocular dominance columns

*Figure 23. The ice-cube model of the cortex. It illustrates how the cortex is divided, at the same time, into two kinds of slabs, one set of ocular dominance (left and right) and one set for orientation. The model should not be taken literally: Neither set is as regular as this, and the orientation slabs especially are far from parallel or straight.*

Function for

tive Field



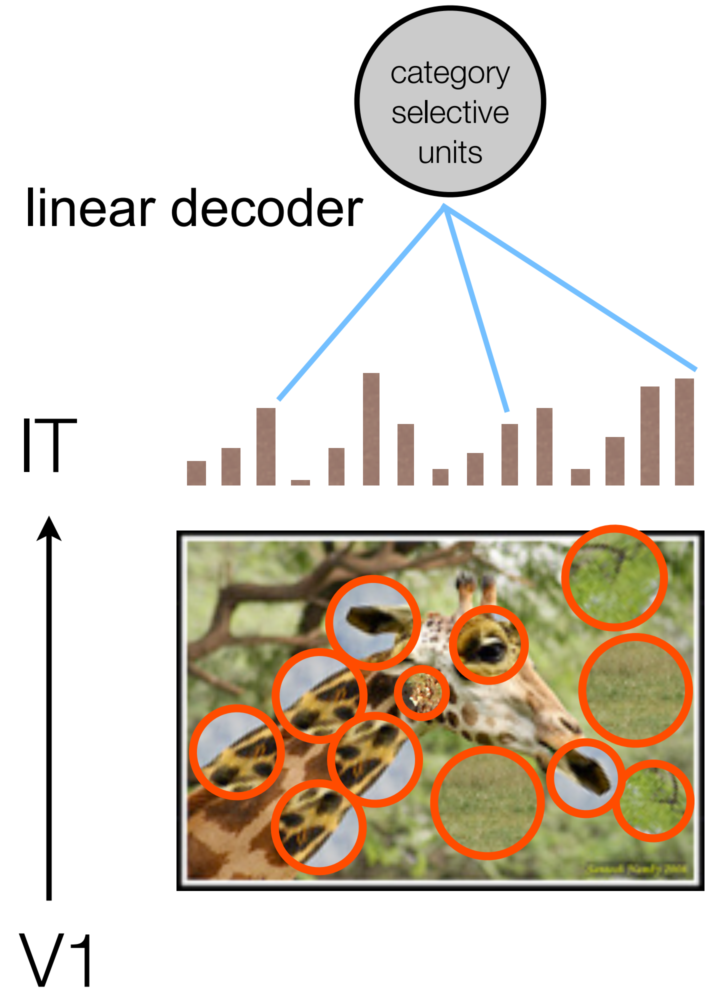
Gabor filters at mult

nd spatial scales

Palmer, Jones & Stepnoski (1991)

# Mechanisms of invariant recognition

- Unit parameters (i.e., RF sizes, pooling ranges, etc) constrained by available experimental data
- Unsupervised learning of (hierarchy) of frequent image fragments during development (in intermediate stages) shared across categories
- Rapid object recognition based on bottom-up activation of hierarchy of image fragments
- This allows category info. to be decoded by higher level categorization processes, up to Jennifer Aniston cells




Serre & Poggio (2010)

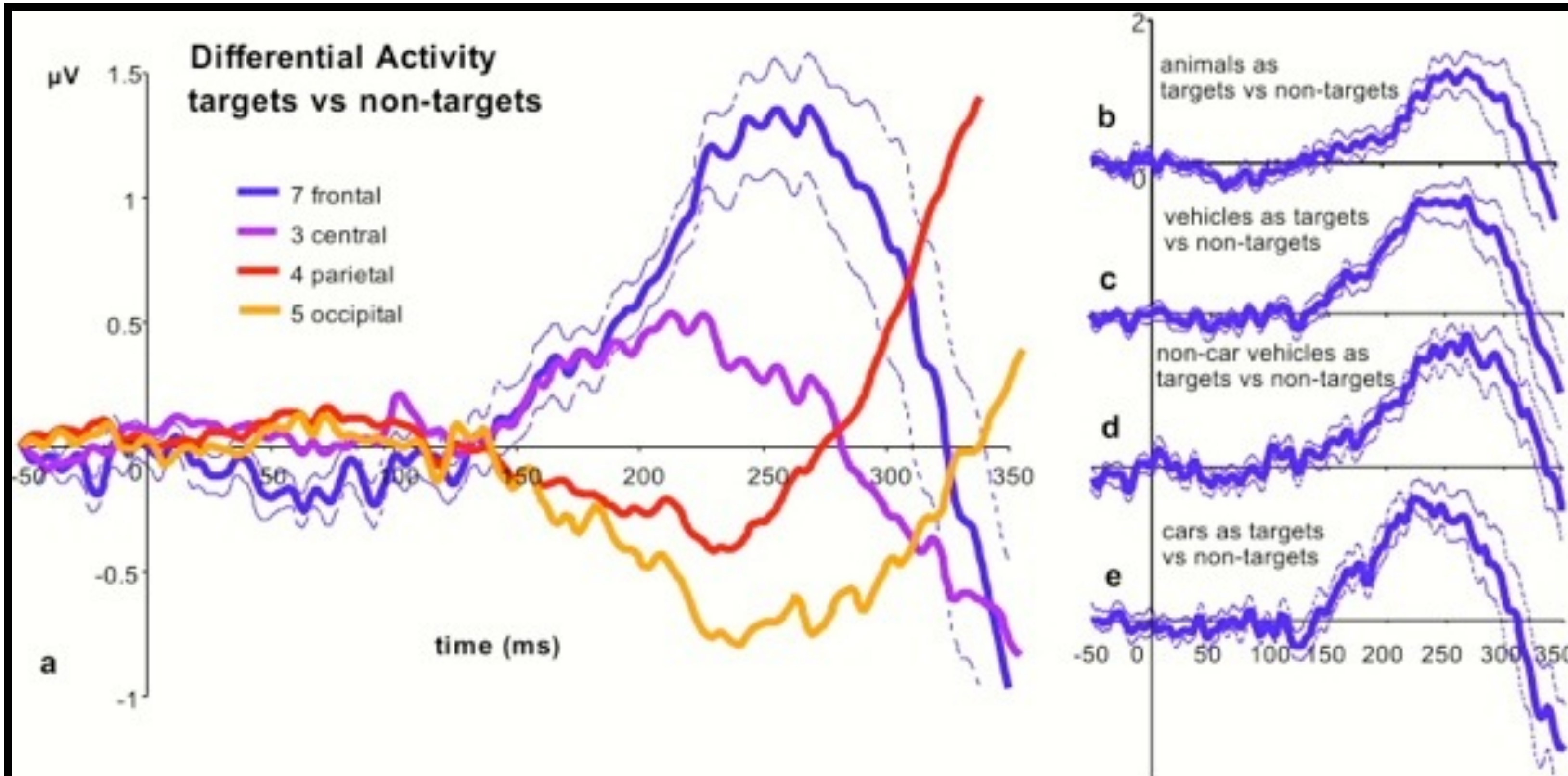
# Visual Behaviors Can be Fast

Binary classification task - animal [Y/N]?

Thorpe *et al.* (1996)

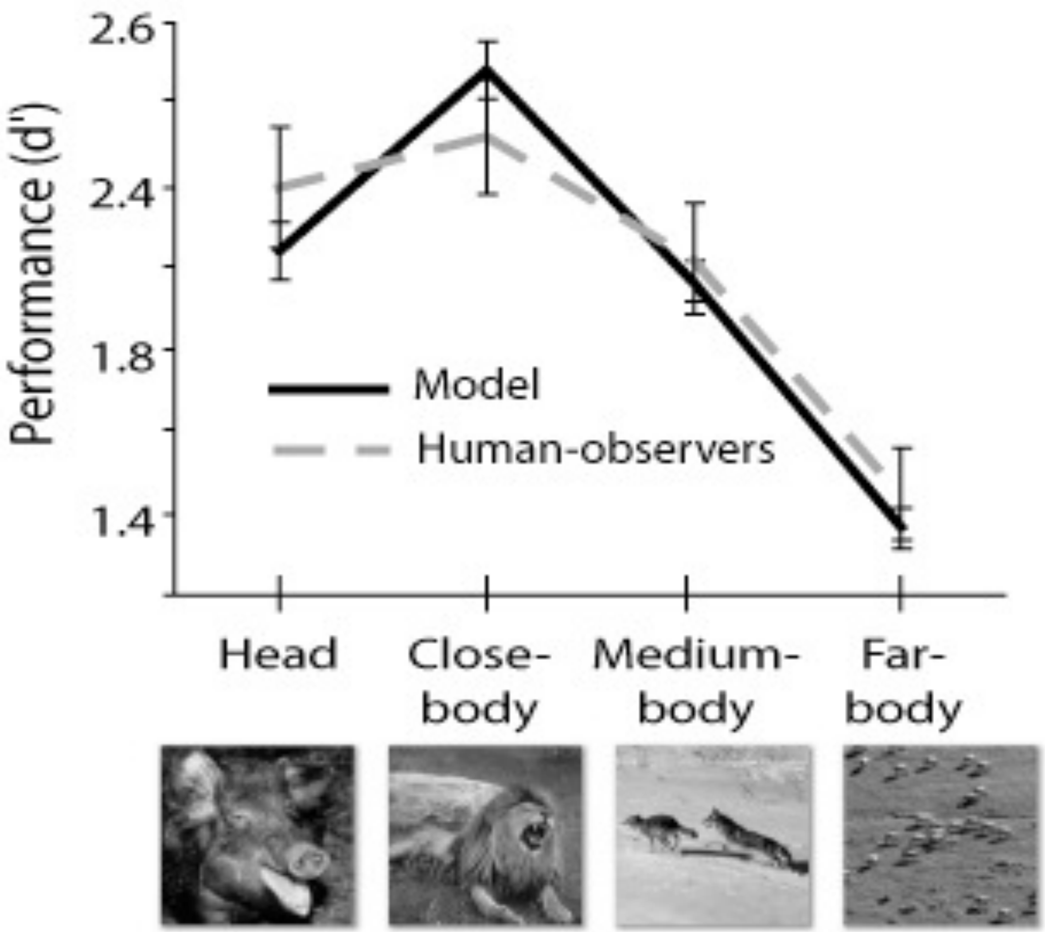
# Feed-Forward Vision is Fast

Comparison of target and non-target trials shows that the brain begins to express the answer at 150 msec




Thorpe *et al.* (1996)

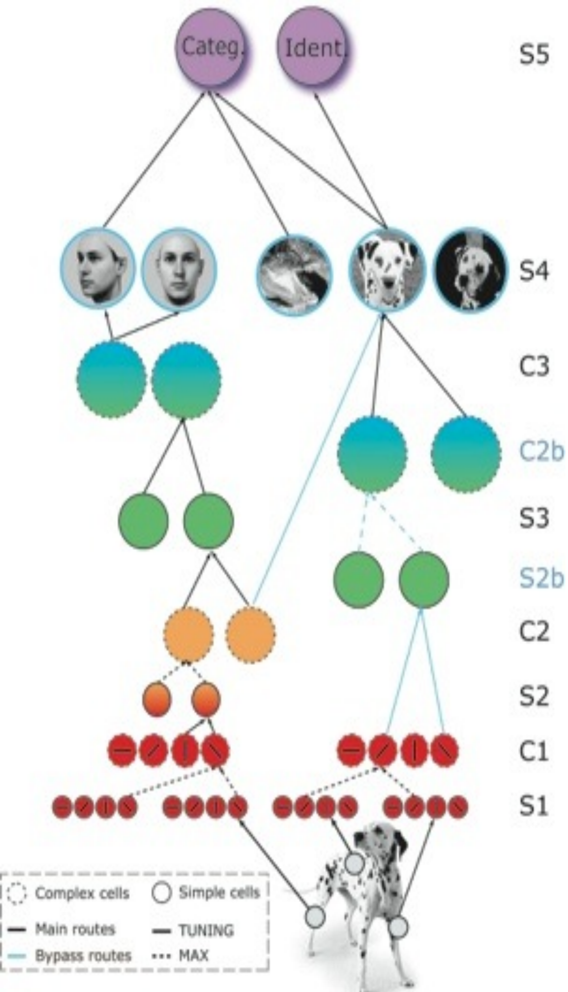
# Feedforward Model Replicates Some Human Behavior



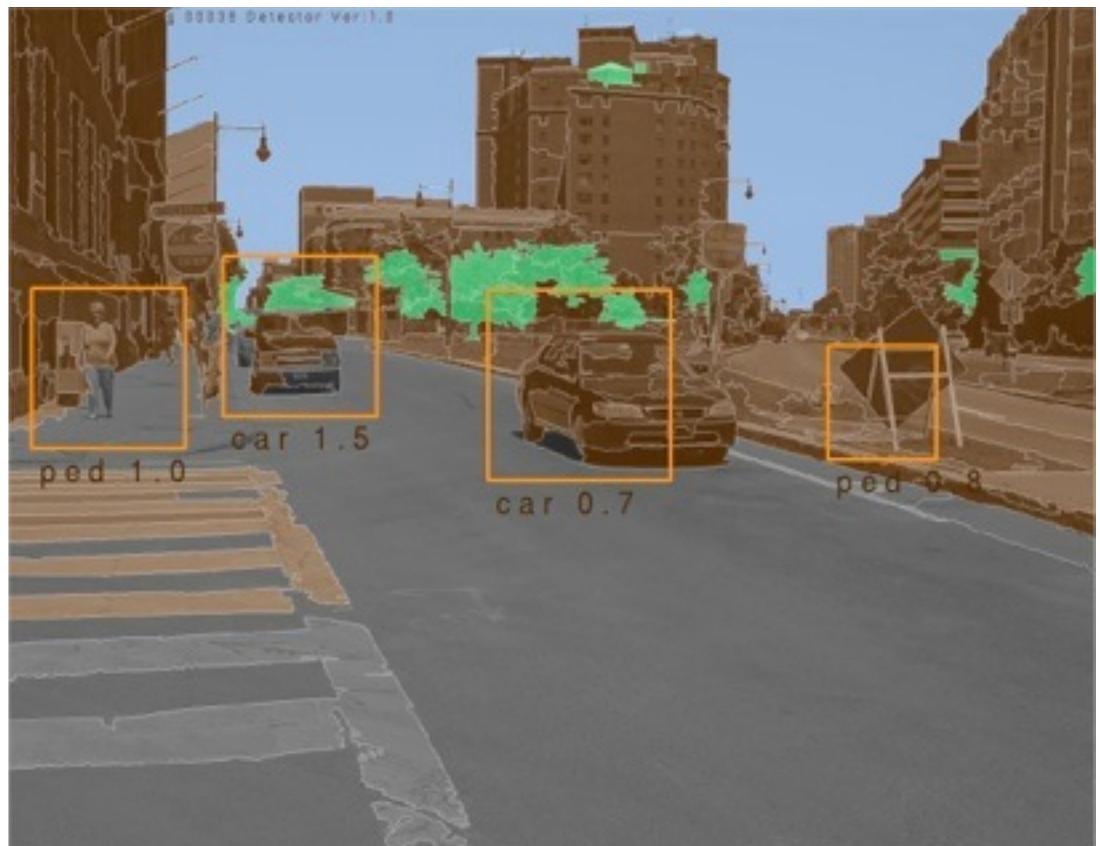

- Feedforward model rapidly categorizes images - 82% model vs. 80% humans
- Image-by-image correlation: around 73% for model vs. humans

Serre, Oliva & Poggio (2007)

# Feedforwad Models Are Powerful Machine Vision Systems



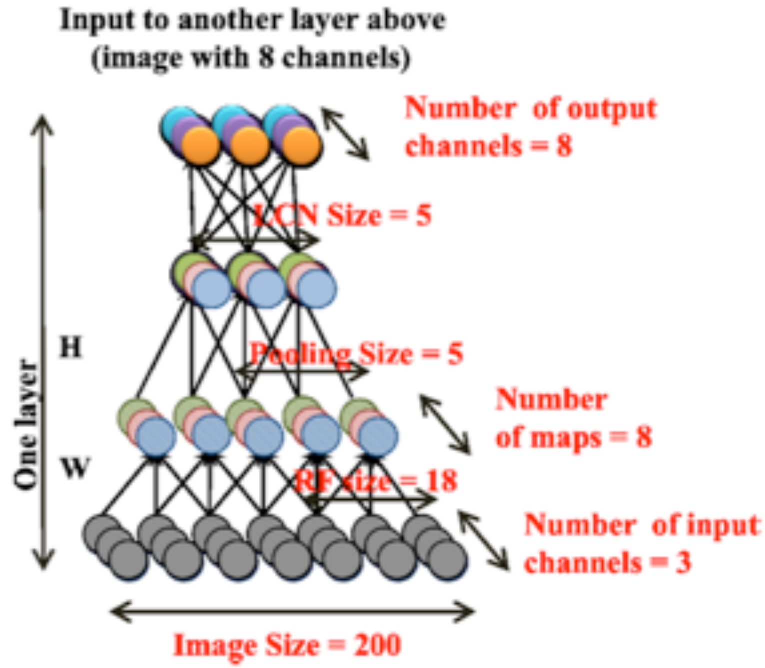

Models of the ventral stream in cortex
perform well compared to
engineered computer vision systems (in 2006)
on several databases




Bileschi, Wolf, Serre & Poggio (2007)

# Feedforward Models Are Powerful Machine Vision Systems

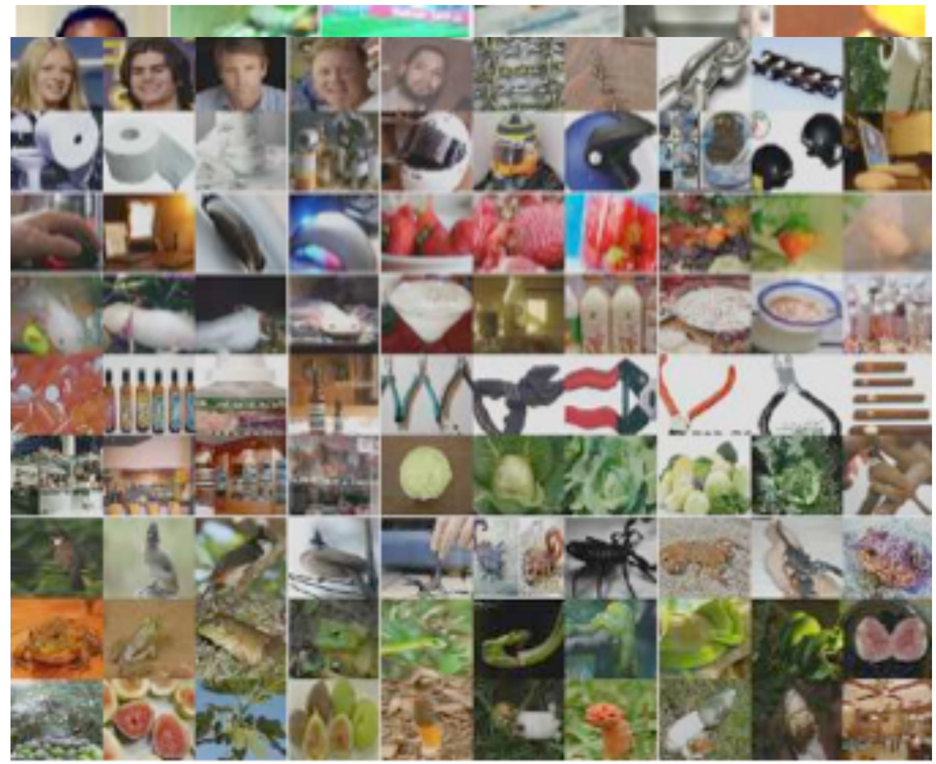
- State of the art computer vision system at Google
- Uses **deep learning** networks (in 3 layers) of feed-forward processing




Le *at al.* (2012)

# Feedforward Models Are
# Powerful Machine Vision Systems

- Unsupervised training on 10 million unlabeled 200x200 pixel images of 16,000 cores for 3 days



Some training images
Some test images

ALLEN INSTITUTE *for* BRAIN SCIENCE
*Fueling Discovery*

Le *at al.* (2012)

# Feedforward Models Are Powerful Machine Vision Systems

• 19.2% recognition on database of 9 million images in 10,000 categories or 15.8% for object recognition on a dataset with 20,000 categories

Most responsive test images for human body ne

Most responsive test images for 'cat' neurons

Le *at al.* (2012)

# Summary

- Feedforward hierarchical learning architectures seem consistent:
  - with anatomy and physiology of visual cortex
  - with human psychophysics during rapid categorization tasks
- But they are incomplete. They
  - suffer from ‘clutter problem’ and cannot parse and interpret visual scenes
  - can’t learn from single examples
  - is this the function of cortical feedback and shifts of attention?