Beyond inspiration:
Three lessons from biology on building intelligent machines

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Inspiration is a good start
...but not enough

Real progress will require gaining a more solid understanding of the principles of information processing at work in nervous systems.

This is both engineering *and* biology.
The evolution of eyes
Land & Fernald (1992)
Three lessons from biology

• Tiny brains
• Nonlinear processing in dendritic trees
• Feedback
1. Tiny brains
<1 million neurons
< 1 mW

86 billion neurons
20 Watts
The results of lens eyes as a jellyfish moves about in the mangrove lagoon. We were able to simulate the retinal image formed in the upper retinal locations. Applying these point-spread functions to still images of Snell's window in the mangrove swamp, different retinal locations. Applying these point-spread functions to still images of Snell's window in the mangrove swamp, different retinal locations.

The eye to calculate the point-spread function of the optics at different retinal locations. Applying these point-spread functions to still images of Snell's window in the mangrove swamp, different retinal locations.

With their upper lens eyes, we used the optical model to calculate the point-spread function of the optics at different retinal locations. Applying these point-spread functions to still images of Snell's window in the mangrove swamp, different retinal locations.

These results thus predict that if...
Jumping spider visual system
Jumping spider retina

Horizontal section

Photoreceptor array

Layer 1

Layer 2

Layer 3

Layer 4
Jumping spiders do object recognition

Text-fig. 12. Stimuli found by Drees to evoke courtship (a) and prey capture (b) in male jumping spiders (Epiblenum scenicum). The numbers beneath each figure in (a) are the percentage of trials on which courtship was evoked. After Drees (1952).
Spider mimicry in flies
Prey capture

- attention
- orienting
- tracking
Navigation

(Tarsitano & Jackson 1997)
One-day old jumping spider
(filmed in the Bower lab, Caltech)
One-day old jumping spider
(filmed in the Bower lab, Caltech)
One-day old jumping spider
(filmed in the Bower lab, Caltech)
…problem solving behavior, language, expert knowledge and application, and reason, are all pretty simple once the essence of being and reacting are available. That essence is the ability to move around in a dynamic environment, sensing the surroundings to a degree sufficient to achieve the necessary maintenance of life and reproduction. This part of intelligence is where evolution has concentrated its time—it is much harder.

2. Nonlinear processing in dendritic trees
A brief history of neural networks

1960’s

\[
x_1 \quad w_1 \\
x_2 \quad w_2 \\
x_3 \quad w_3 \\
\vdots \\
x_n \quad w_n
\]

\[
\sum w_0
\]

\[
u = \sum_i w_i x_i
\]

\[
y = g(u)
\]
A brief history of neural networks

1980’s

\[
\begin{align*}
    u &= \sum_{i} w_i x_i \\
    y &= g(u)
\end{align*}
\]
A brief history of neural networks

2000's

\[ u = \sum_{i} w_i x_i \]

\[ y = g(u) \]
\[ g(\sum_{i} w_i \prod_{j \in G_i} x_j) \]
be difficult to achieve ([71]; see also Figure 7 in [72]). The precise lower limit on compartment size in the thin dendrites of pyramidal cells remains to be determined, perhaps through the use of voltage-sensitive dyes ([73]) and highly focal uncaging techniques ([74]).

Getting at the inner neuron

What are the implications of these findings for single-neuron computation? Could there be an underlying principle that permits the full complexity of a dendritic tree to be represented in highly simplified terms? The available data suggest that the thin terminal branches of the apical and basal trees of pyramidal cells provide a set of independent non-linear 'subunits' that sum up their synaptic inputs and then apply a sigmoidal thresholding non-linearity to the output. In this scenario, how should the outputs of multiple subunits be combined to influence the cell's overall response? In the few experimental studies that have addressed the question of location dependent synaptic summation, so far only involving simple spatial integration scenarios, the data are most consistent with a linear or sublinear summation rule for signals that originate in different dendritic branches ([30,75–78]). Building on these findings, one can formulate a working model in which the thin branches are the integrative subunits of pyramidal neurons. According to this model, each thin-branch subunit sums up its synaptic drive and then applies a sigmoidal thresholding non-linearity to the result, and the subunit outputs are summed linearly within the main trunks and cell body before output spike generation. This hypothesis is interesting, in that it states that an individual pyramidal neuron functions something like a conventional two-layer abstract 'neural network' ([12]), in which the thin dendritic branches themselves act like classical point neurons (Figure 3b).

Poirazi and co-workers ([79]–[81]) used a detailed CA1 pyramidal cell model ([80]) to test the two-layer neural network hypothesis. The authors used a complex set of

\[ \text{A single neuron may be better approximated as a multilayer neural network} \]


3. Feedback
Feedback is pervasive throughout the thalamo-cortical system
VI contains a highly recurrent microcircuit

from Douglas and Martin (2004)
Hierarchical Bayesian inference in visual cortex

(Lee & Mumford, 2003)

The feedforward input drives the generation of the hypothesis particle, which is a distribution of hypotheses particles. In particular, at each point in time, a distribution of hypothesis particles is generated, each of which is influenced by the bottom-up feedforward data. The system as a whole includes multiple layers of hierarchical inference, where each layer uses belief propagation to refine the hypothesis particles conditioned on the context that has been incorporated by the bottom-up and top-down belief propagation. The top-down beliefs are the responses conditioned on the context that has been incorporated by the bottom-up and top-down beliefs, respectively. They are sets of probabilities that represent the belief in the existence of certain objects or features at different levels of the visual hierarchy. The bottom-up beliefs are the activities of the responses of the superficial layer pyramidal cells that project to the higher areas. The top-down and bottom-up beliefs are combined using particle filtering and belief propagation.
Discriminative models vs. Generative models

- **Output**
  - Image

- **Underlying causes**
  - Analysis
  - Synthesis
20 years of learning about vision: Questions answered, questions unanswered, and questions not yet asked. In: 20 Years of Computational Neuroscience. J.M. Bower, Ed. (Symposium of the CNS2010 annual meeting)


http://redwood.berkeley.edu/bruno