Signal Processing and Computations in the Brain

Lecture by Professor E T Rolls, Dept Computer Science.

- Is the brain a digital signal processor?
- Digital vs continuous signals
- Digital signals involve streams of binary encoded numbers
- The brain uses digital, all or none, action potentials or spikes for information transmission in its neuronal axons over distances of 1 mm to several metres to avoid the uncertain decay of an analog signal in a long non-uniform cable.
- But the spikes are then converted into analog signals within a neuron, which has a threshold for the summed depolarization produced by many small synaptic currents to elicit an action potential, which is binary.
- The brain does not work by logical operations as in digital computers, but instead by the similarity of an input vector of firing rates with a synaptic weight vector to produce a post-synaptic potential.
- The spikes in the brain have Poisson timing, i.e. are random in time for a given mean firing rate. This leads to stochastic processing in the brain, related to the timing of the digital inputs to a neuron.

Rolls,E.T. (2023) Brain Computations and Connectivity. Oxford University Press: Open Access from www.oxcns.org.

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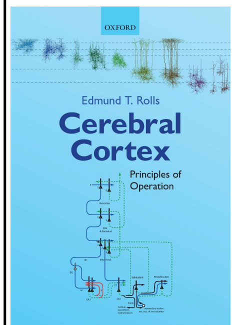
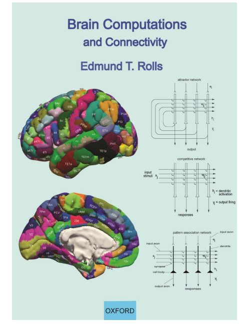
Recommended reading. See also www.oxcns.org/publications



Oxford University Press 2016
Whole book available at www.oxcns.org/ publications



Oxford University Press 2023
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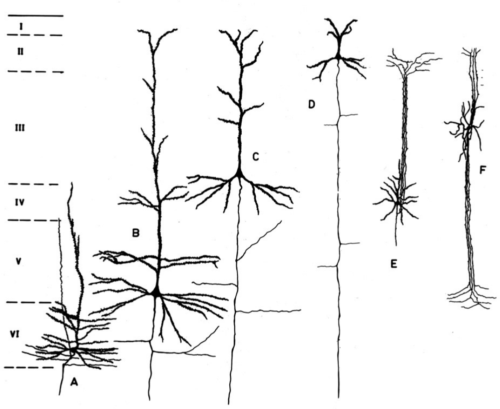
(e.g. Chapter 19.1-19.4)

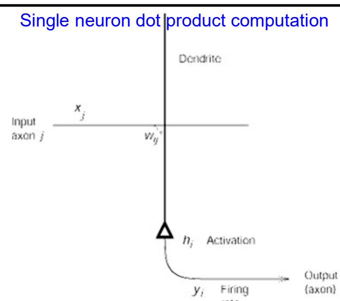
Single neurons in the cerebral cortex



Brain computation vs Digital computer computation

1. Dot product similarity followed by a threshold	vs logical functions e.g. AND, NAND, OR
2. 10,000 inputs per neuron	vs several inputs to a logic gate
3. Content-addressable memory	vs data accessed by address
4. Fault tolerant: dot product	vs no inherent fault tolerance
5. Generalization and completion	vs only exact match in the hardware
6. Fast: inherently parallel update of a neuron, and of neurons in a network	vs serial processing with fast components
7. Approximate, low precision	vs high precision 64 bit
8. Stochastic spiking noise: probabilistic computation helps originality, creativity	vs noise free because of non-linearities
9. Dynamics are parallel – an attractor network retrieves in 1 - 2 time constants of the synapses.	vs inherently serial
10. Heuristics, e.g. Invariant object recognition uses temporo-spatial constraints, analyses only part of a scene.	vs attempt to understand a whole scene
11. Syntax: none inherent	vs syntactical operations on data at an address
12. The architecture adapts to implement different computations.	vs fixed architecture with different software
13. Sparse distributed representation	vs binary encoding in a computer word, e.g. 64 bits
14. Mind vs brain	vs software vs hardware

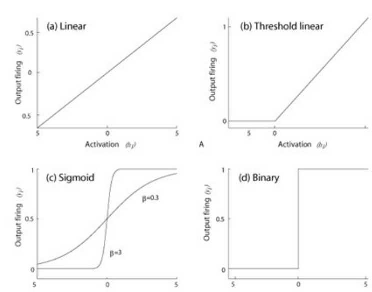
Single neuron dot product computation



Each neuron has approximately 10,000 inputs though synapses. The neuron sums the currents produced by each input firing rate x_j injected through each synapse w_ij to produce an activation h_i.

$$h_i = \Sigma_j\, x_j \,.\, w_{ij}$$

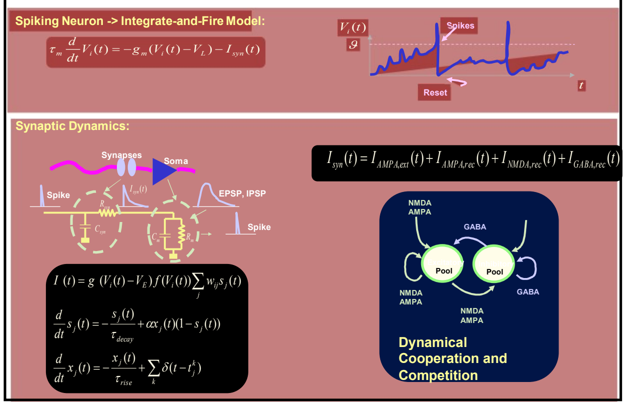
Single neuron activation functions

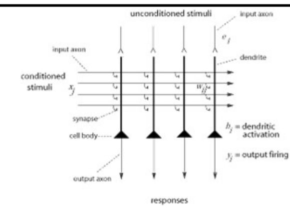


The activations are converted into spikes when the neurons reaches a threshold for firing. This is a non-linear operation and produces digital spikes, with a firing rate that depends on the strength of the activation. The output firing y_i is a function of the activation

$y_i = \mathrm{f}\,(h_i)$

Neurodynamical Modeling:
Neurons, Synapses & Cortical Architecture





Pattern Association Memory

Learning Rule:
Where x_i approximates e_i (which is the unconditioned or external or forcing input)

$$\delta w_{ij} = k \cdot y_i \cdot x_j$$

Recall: The activation,

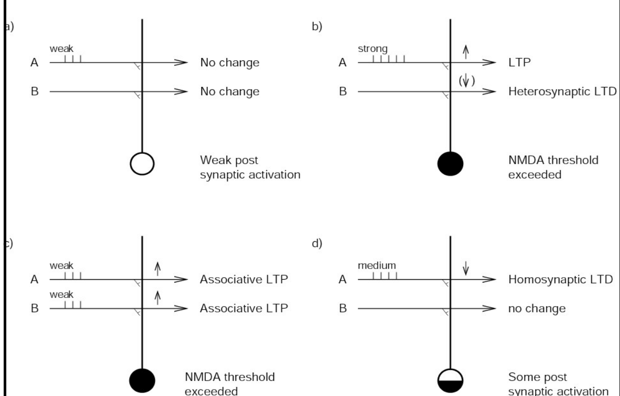
$$h_i = \Sigma_j \, x_j \cdot w_{ij}$$

where the sum is over the C input axons, x_j
The output firing y_i is a function of the activation

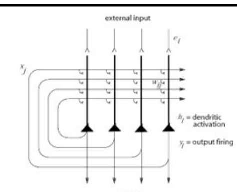
$$y_i = \text{f}\,(h_i)$$

This activation function f may be linear, sigmoid, binary threshold, etc.

Learning: Long Term Potentiation and Long Term Depression of synapses



Auto-association Memory



Learning Rule:
Where y_i approximates e_i (which is the external input)

$$\delta w_{ij} = k \cdot y_i \cdot x_j \qquad \text{(Hebb rule)}$$

and y_i is the firing of the output neuron (post-synaptic term)
x_j is the firing of input axon j (presynaptic term)
w_{ij} is the synapse to output neuron i from input axon j.

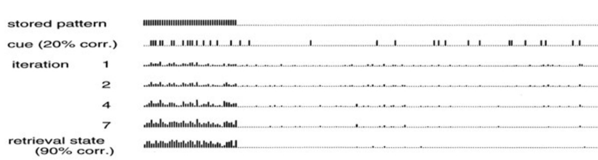
Recall: The (internal) activation produced by the recurrent collateral effect (after the first iteration) is

$$h_i = \Sigma_j \, x_j \cdot w_{ij} \qquad \text{where the sum is over the } C \text{ axons indexed by } j.$$

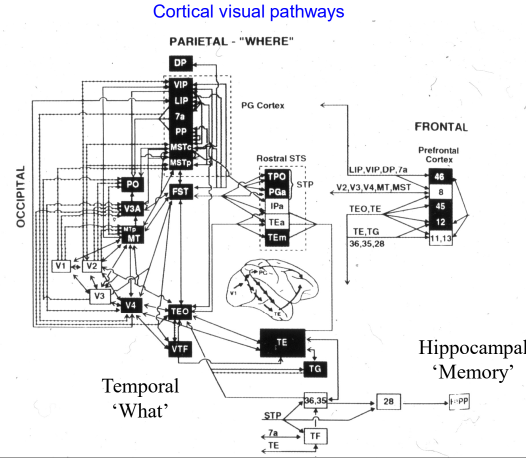
The output firing y_i is a function of the activation produced by the recurrent collateral effect and by the external input (e_i):

$$y_i = \text{f}\,(h_i + e_i)$$

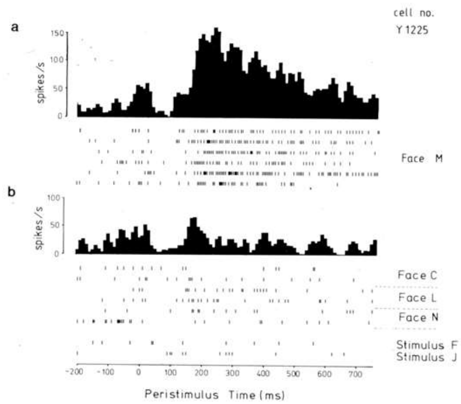
The activation function f may be binary threshold, linear threshold, sigmoid, etc.
See Rolls (2023) Brain Computations and Connectivity. Oxford. Appendix B.3.



Cortical visual pathways



Single neuron selectivity: in this case to a face

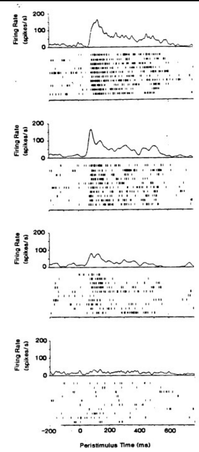


Stimulus 1

Stimulus 2

Stimulus 3

Stimulus 4

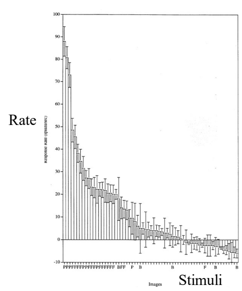


How is information encoded by the inferior temporal visual cortex?

<u>Rate Code</u>

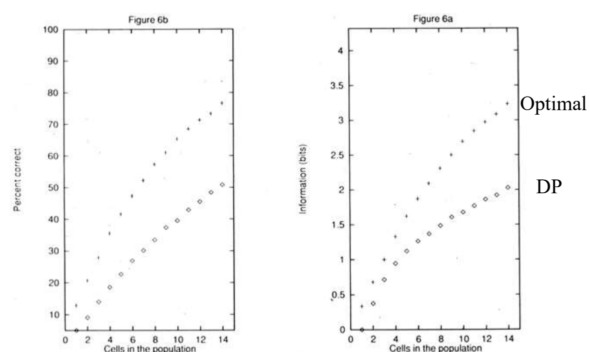
Local (Grandmother), Distributed and Sparse Distributed Coding

- Local (Grandmother): One cell codes for one stimulus and fires only in response to this one.
- Fully Distributed: Almost every cell participates in encoding all stimuli. (With binary firing rates half the cells respond to any stimulus)
- Sparse Distributed: The cell responds to a certain number of stimuli. Intermediate between Grandmother and Fully distributed.



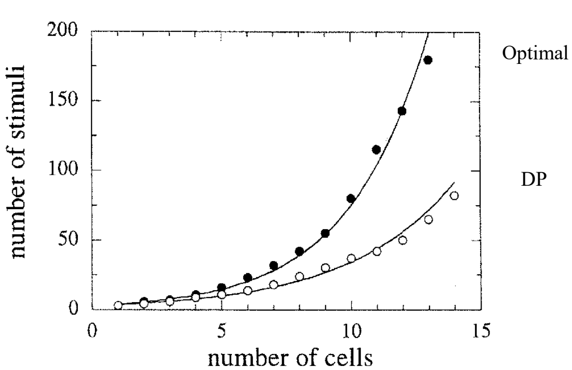
Inferior Temporal Visual Cortex neuron firing rate response to a set of 68 visual stimuli

How does the information scale with the number of neurons ?

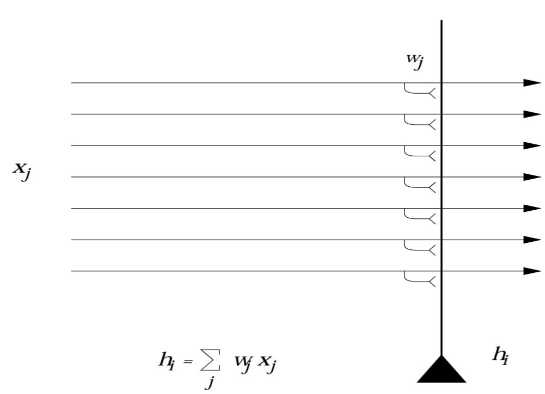


Approximately linearly.
Optimal vs Dot Product decoding.

How does the number of stimuli encoded scale with the number of neurons ? (Information uses a log scale.)



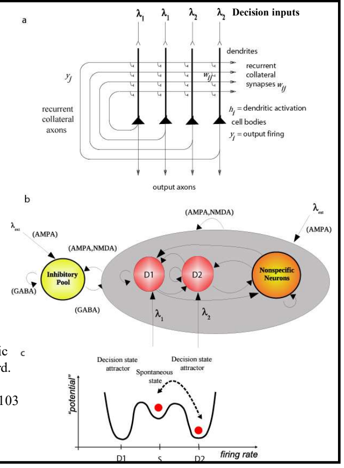
Dot Product Multiple Cell Decoding



$$h_i = \sum_j w_j x_j$$

An attractor network for probabilistic decision-making, with lambda 1 and 2 inputs, and noise from the neuronal spiking influencing which decision attractor, D1 or D2, wins.

This is also a model for short-term memory.

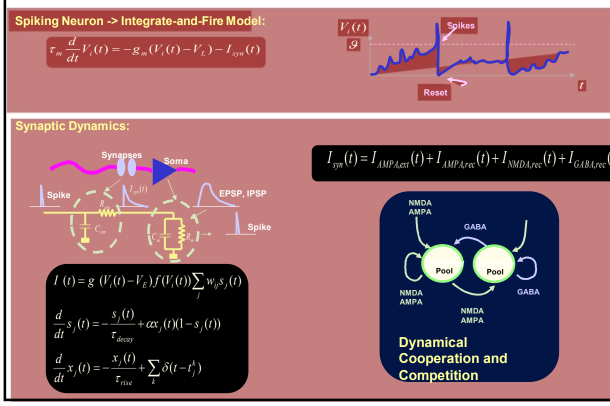


Rolls and Deco 2010 The Noisy Brain: Stochastic Dynamics as a Principle of Brain Function. Oxford.

Deco, Rolls et al 2013 Progress in Neurobiology 103

Rolls 2023 Brain Computations and Connectivity. 11.5.1 and 11.5.2

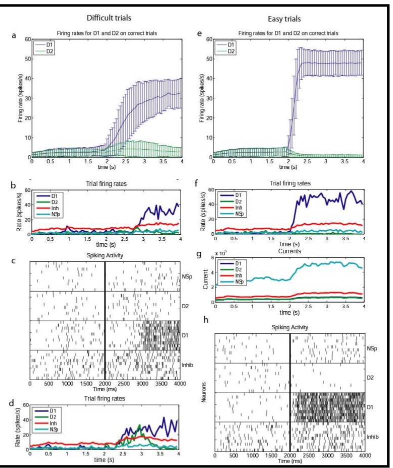
Neurodynamical Modeling: Neurons, Synapses & Cortical Architecture



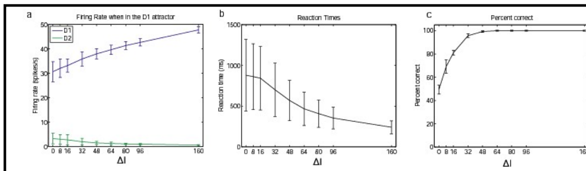
Integrate-and-fire simulations predict earlier and higher neuronal responses on easy vs difficult trials.

Confidence is reflected in the higher firing on easy trials.

The decision stimuli start at t=2 s



Rolls, Grabenhorst and Deco 2010 Neuroimage



- The theoretical framework based in statistical mechanics predicts higher and faster neuronal responses as Delta I, the difference between the two stimuli, increases.
- Delta I is a measure of the easiness of the decision, and subjective confidence ratings correlate with this.

Rolls, Grabenhorst and Deco 2010a Neuroimage

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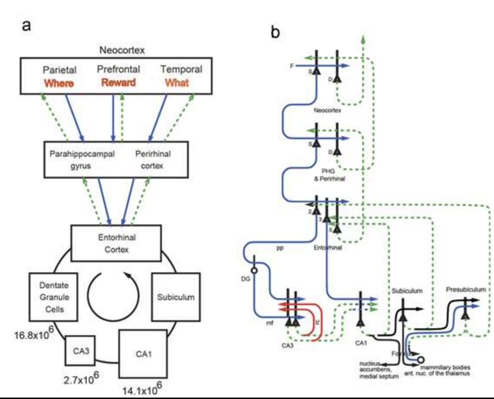
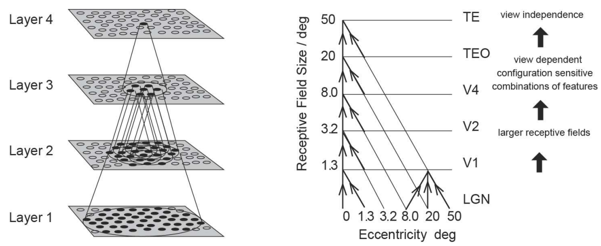
The hippocampal episodic memory system



Invariant visual object recognition in the brain



Right – convergence in the ventral stream cortical hierarchy for object recognition. LGN, lateral geniculate nucleus; V1, visual cortex area V1; TEO, posterior inferior temporal cortex; TE, anterior inferior temporal cortex (IT).

Left – convergence as implemented in VisNet, the model of invariant visual object recognition described here. Convergence through the hierarchical feedforward network is designed to provide Layer 4 neurons with information from across the entire input retina, by providing an increase of receptive field size of 2.5 times at each stage. Layer 1 of the VisNet model corresponds to V2 in the brain, and Layer 4 to the anterior inferior temporal visual cortex (TE).

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Signal Processing and the Brain.

Further reading:

On differences between signal processing in the brain and in digital computers:
On the signal processing performed by neuronal networks in the brain:
On the representation of information in the brain:

Rolls, E. T. (2023) Brain Computations and Connectivity. Oxford University Press: Open Access from www.oxcns.org. (e.g. **Chapter 19.1-19.4 on signal processing in the brain**)
Appendix B.2-B.4 are on biologically plausible networks.
Section 9.2 is on hippocampal computations for memory.
Section 2.8 is on a biologically plausible approach to visual object recognition.
Appendix C.3 is on neuronal encoding in the brain.

Rolls, E. T. (2021) Learning invariant object and spatial view representations in the brain using slow unsupervised learning. Frontiers in Computational Neuroscience 15: 686239. doi: 10.3389/fncom.2021.686239.

Rolls,E.T. and Treves.A. (2011) The neuronal encoding of information in the brain. Progress in Neurobiology 95: 448-490. http://www.oxcns.org/papers/508

Papers, books, and contact information:

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