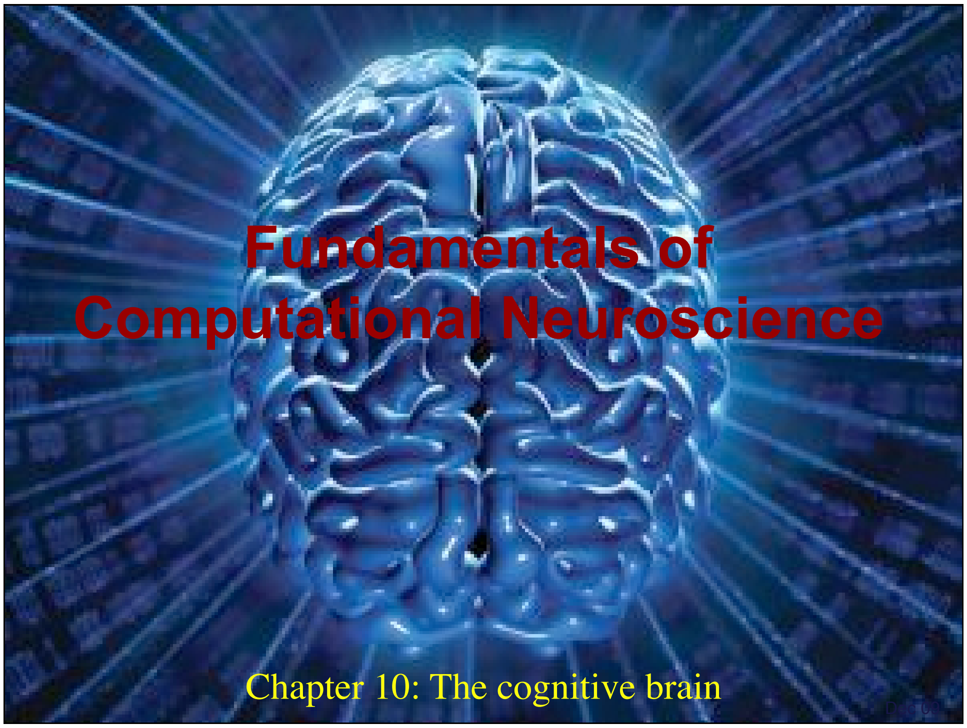
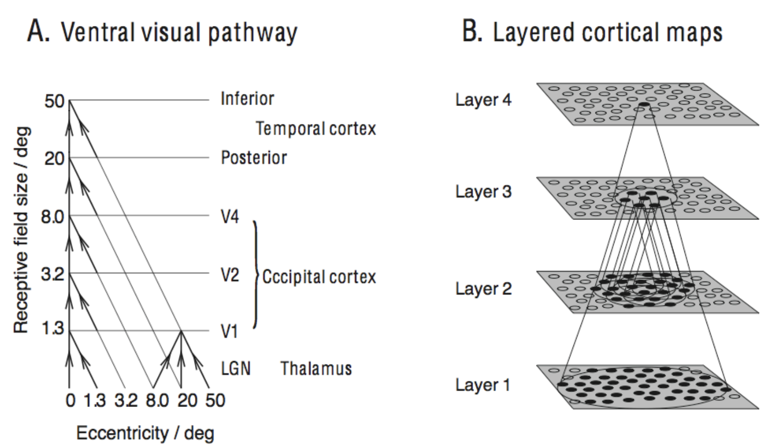


Fundamentals of Computational Neuroscience

Chapter 10: The cognitive brain

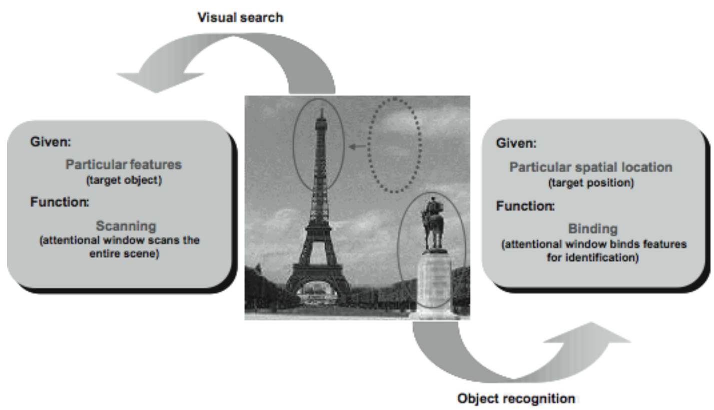
1

Hierarchical maps and attentive vision



2

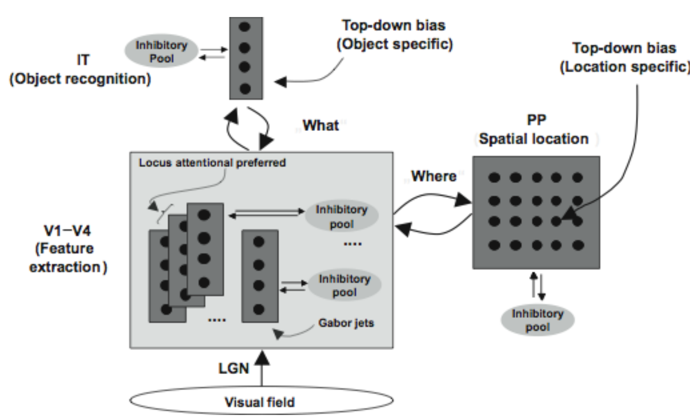
Attention in visual search and object recognition



Gustavo Deco

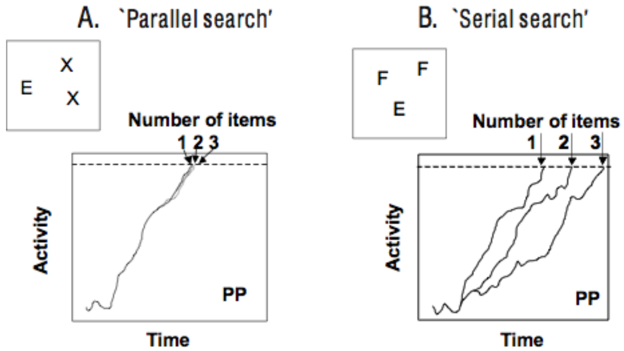
3

Model



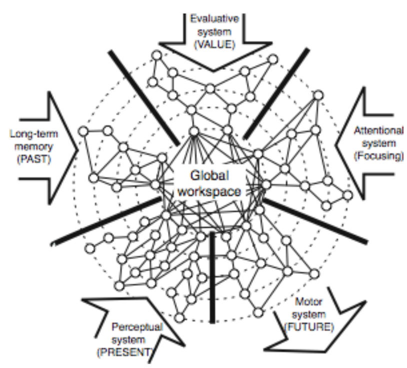
4

Example results



5

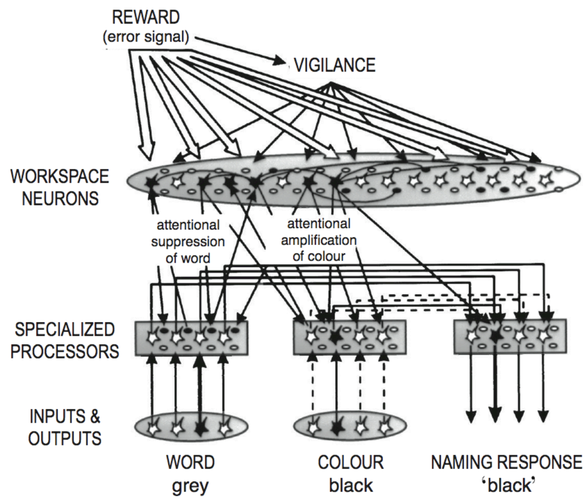
The interconnecting workspace hypothesis



Stanislas Dehaene, M. Kergsberg, and J.P. Changeux, PNAS 1998

6

Stroop task modelling



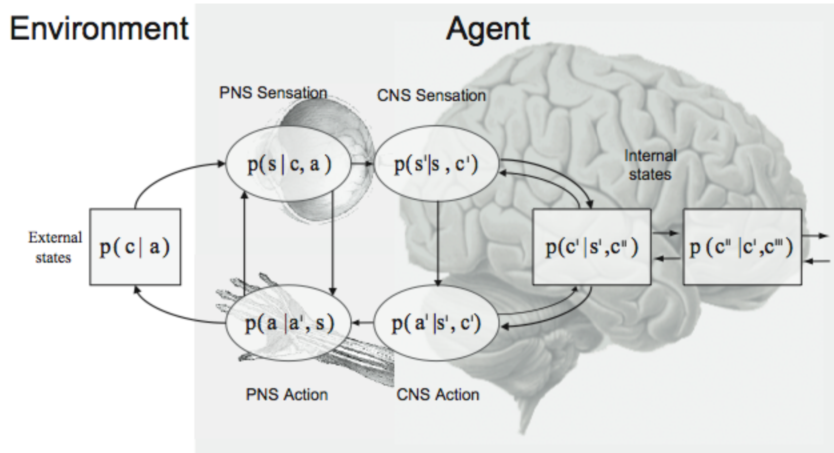
7

The anticipating brain

1) The brain can develop a model of the world, which can be used to anticipate or predict the environment.
2) The inverse of the model can be used to recognize causes by evoking internal concepts.
3) Hierarchical representations are essential to capture the richness of the world.
4) Internal concepts are learned through matching the brain's hypotheses with input from the world.
5) An agent can learn actively by testing hypothesis through actions.
6) The temporal domain is an important degree of freedom.

8

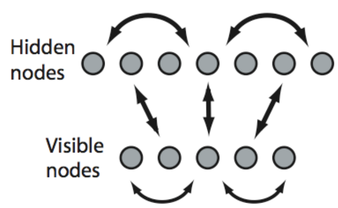
Outline



9

Recurrent networks with hidden nodes

The Boltzmann machine:



Energy: $H^{nm} = \quad \frac{1}{2}\sum_{ij} w_{ij} s_i^n s_j^m$

Probabilistic update: $p(s_i^n = +1) = \frac{1}{1+\exp(-\beta \sum_j w_{ij} s_j^n)}$

Boltzmann-Gibbs distribution: $p(\mathbf{s}^v; \mathbf{w}) = \frac{1}{Z}\sum_{m \in h} \exp(\quad \beta H^{vm})$

10

Training Boltzmann machines

Kulbach-Leibler divergence

$$\begin{aligned}\mathrm{KL}(p(\mathbf{s}^v), p(\mathbf{s}^v;\mathbf{w})) &= \sum_{\mathbf{s}}^{v} p(\mathbf{s}^v)\log\frac{p(\mathbf{s}^v)}{p(\mathbf{s}^v;\mathbf{w})}\\ &= \sum_{\mathbf{s}}^{v} p(\mathbf{s}^v)\log p(\mathbf{s}^v) - \sum_{\mathbf{s}}^{v} p(\mathbf{s}^v)\log p(\mathbf{s}^v;\mathbf{w})\end{aligned}$$

Minimizing KL is equivalent to maximizing the average log-likelihood function

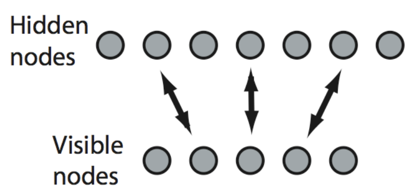
$$l(\mathbf{w}) = \sum_{\mathbf{s}}^{v} p(\mathbf{s}^v)\log p(\mathbf{s}^v;\mathbf{w}) = \langle \log p(\mathbf{s}^v;\mathbf{w})\rangle.$$

Gradient decent → Boltzmann Learning

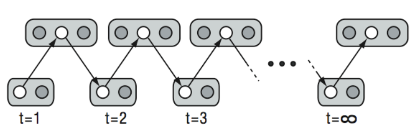
$$\Delta w_{ij} = \eta\frac{\partial l}{\partial w_{ij}} = \eta\frac{\beta}{2}\left(\langle s_i s_j\rangle_{\text{clamped}} - \langle s_i s_j\rangle_{\text{free}}\right).$$

11

The restricted Boltzmann machine

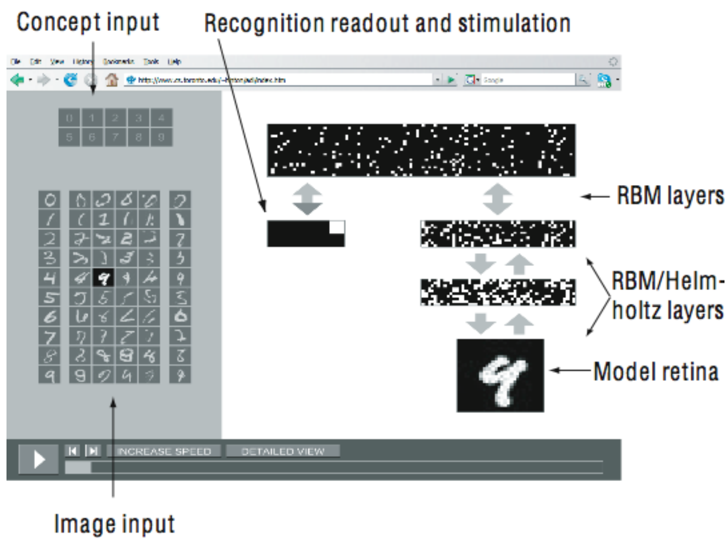


Contrastive Hebbian learning: Alternating Gibbs sampling



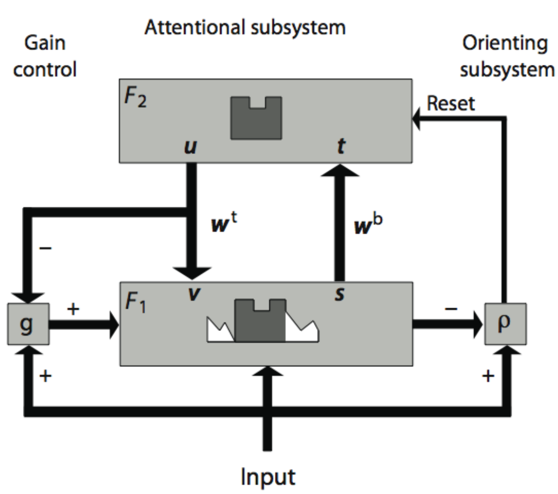
12

Deep generative models



13

Adaptive resonance theory (ART)



14

Further readings

Edmund T. Rolls and Gustavo Deco (2001), **Computational neuroscience of vision**, Oxford University Press.

Karl Friston (2005), **A theory of cortical responses**, in **Philosophical Transactions of the Royal Society** B 360, 815–36.

Jeff Hawkins with Sandra Blakeslee (2004), **On intelligence**, Henry Holt and Company.

Robert Rosen (1985), **Anticipatory systems: Philosophical, mathematical and methodological foundations**, Pergamon Press.

Geoffrey E. Hinton (2007), **Learning Multiple Layers of Representation**, in **Trends in Cognitive Sciences** 11: 428–434.

Stephen Grossberg (1976), **Adaptive pattern classification and universal recoding: Feedback, expectation, olfaction, and illusions**, in **Biological Cybernetics** 23: 187–202.

Gail Carpenter and Stephen Grossberg (1987), **A massively parallel architecture for a self-organizing neural pattern recognition machine** in **Computer Vision, Graphics and Image Processing** 37: 54–115.

Daniel S. Levine (2000), **Introduction to neural and cognitive modeling**, Lawrence Erlbaum, 2nd edition.

James A. Freeman (1994), **Simulating neural networks with Mathematica**, Addison-Wesley.