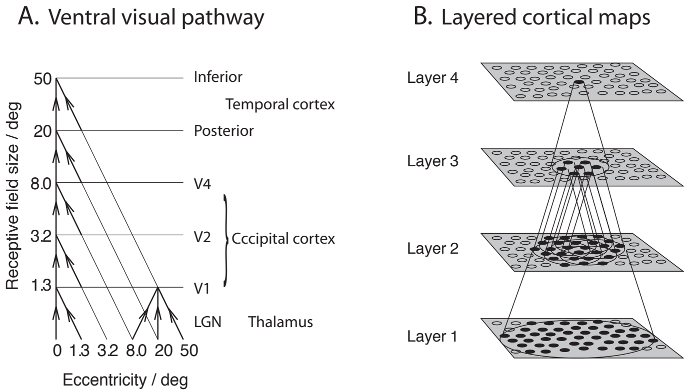
Fundamentals of Computational Neuroscience 2e

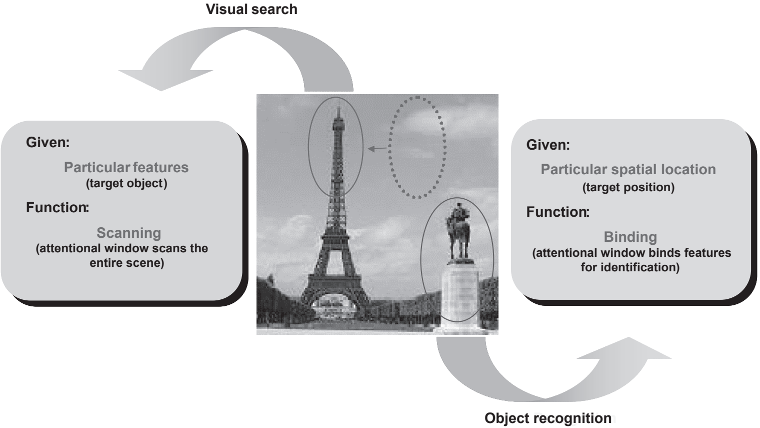
January 1, 2010

Chapter 10: The cognitive brain

Hierarchical maps and attentive vision

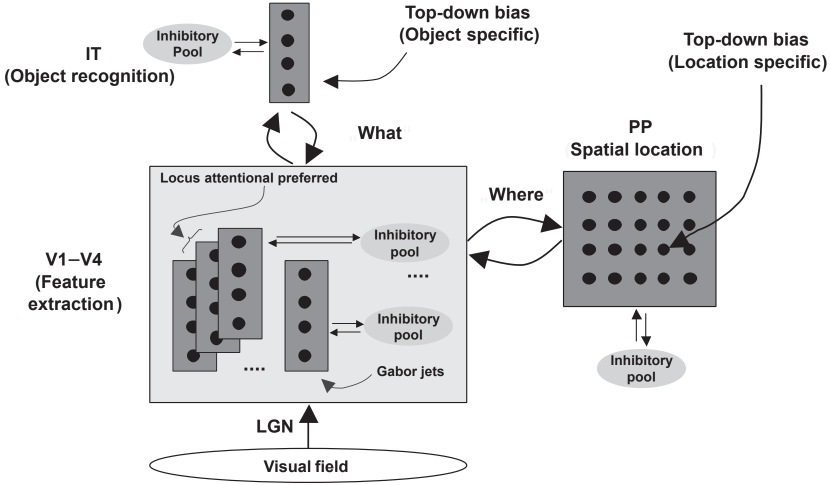


Attention in visual search and object recognition



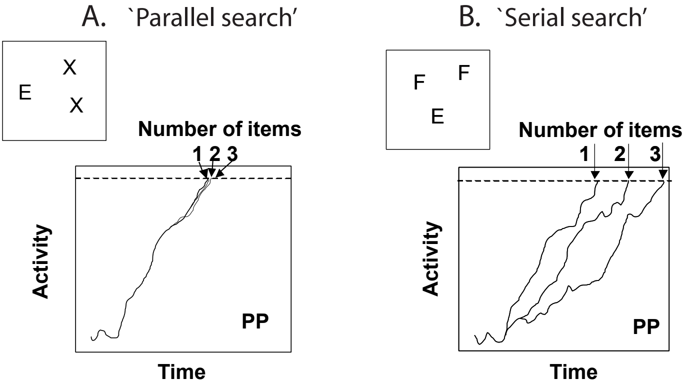
Gustavo Deco

Model

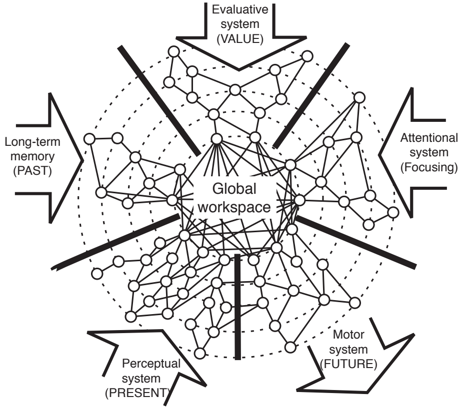


Top-down bias
(Object specific)
Top-down bias
(Location specific)
Inhibitory
Pool
IT
(Object recognition)
„What"
PP
(Spatial location)
Locus attentional preferred
„Where"
Inhibitory
pool
....
V1–V4
(Feature
extraction)
Inhibitory
pool
Inhibitory
pool
....
Gabor jets
LGN
Visual field

Example results

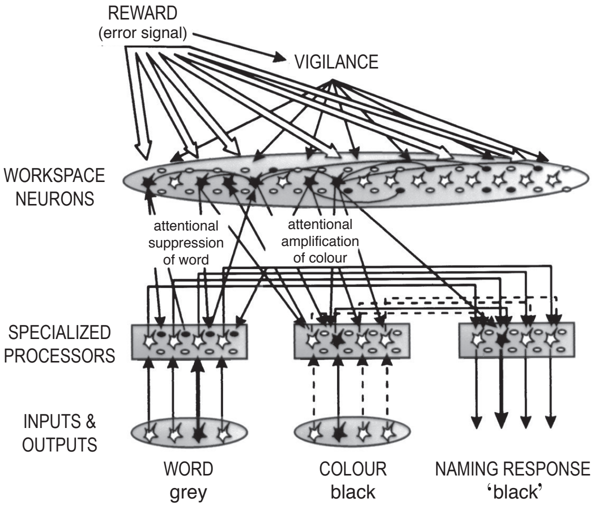


The interconnecting workspace hypothesis



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

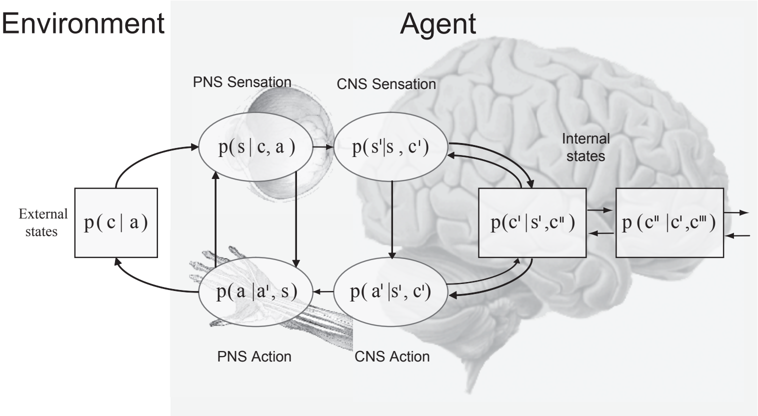
Stroop task modelling



The anticipating brain

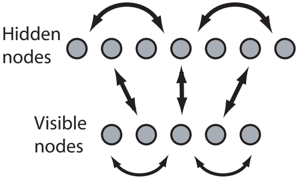
1. The brain can develop a model of the world, which can be used to anticipate or predict the environment.
2. The inverse of the model can be used to recognize causes by evoking internal concepts.
3. Hierarchical representations are essential to capture the richness of the world.
4. Internal concepts 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.

Outline


Environment
Agent
PNS Sensation
CNS Sensation
p(s | c, a)
p(s'|s , c')
Internal
states
External
states
p(c | a)
p(c' | s' ,c'')
p (c'' |c' ,c''')
p(a |a', s)
p(a' |s', c')
PNS Action
CNS Action

Recurrent networks with hidden nodes

The Boltzmann machine:



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

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

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

Training Boltzmann machine

Kulbach-Leibler divergence

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

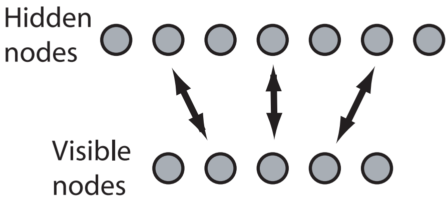
Minimizing KL is equivalent to maximizing the average log-likelihood function

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

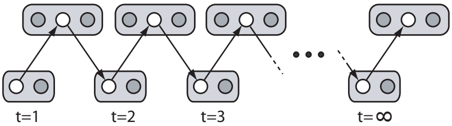
Gradient decent $\rightarrow$ Boltzmann Learning

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

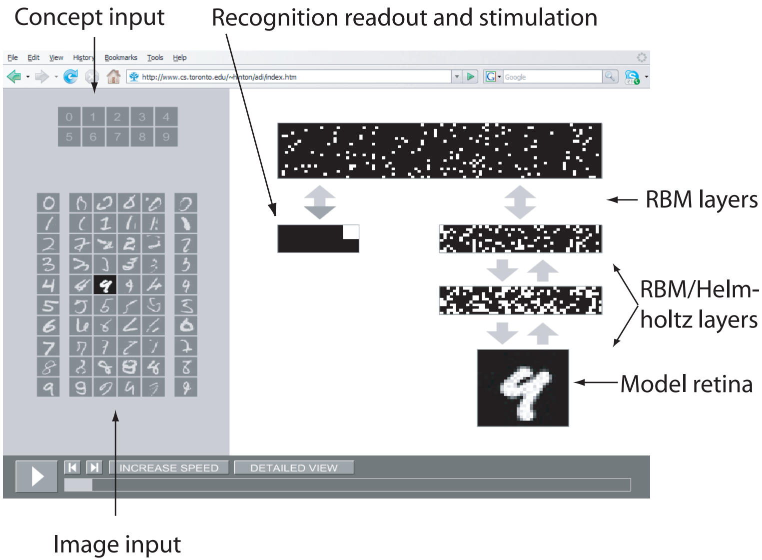
The restricted Boltzmann machine



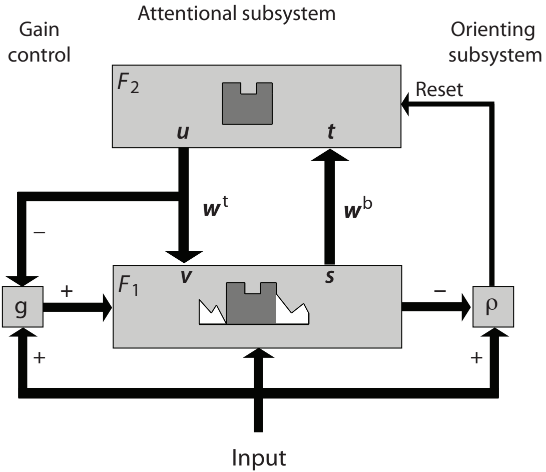
Contrastive Hebbian learning: Alternating Gibbs sampling



Deep generative models



Adaptive Resonance Theory (ART)



Further Readings

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