Fundamentals of Computational Neuroscience 2e

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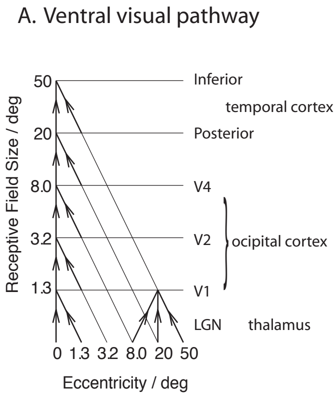
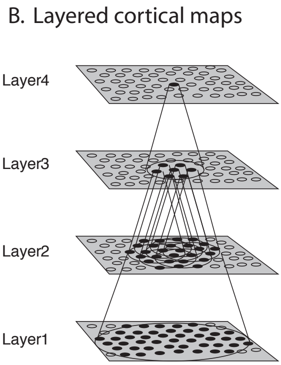
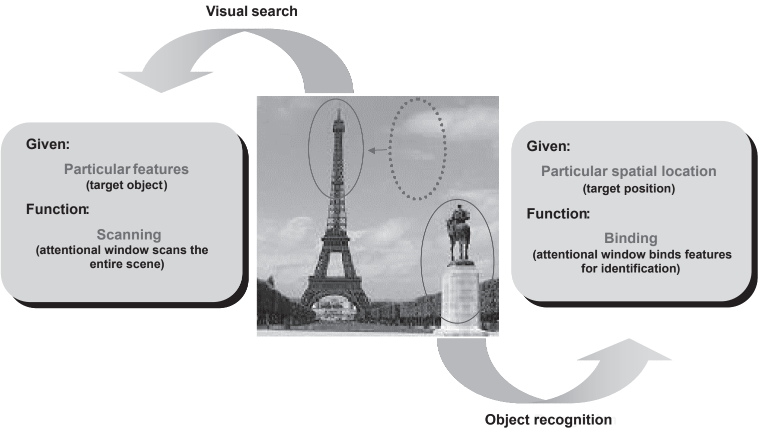
Chapter 10: The cognitive brain

Hierarchical maps and attentive vision



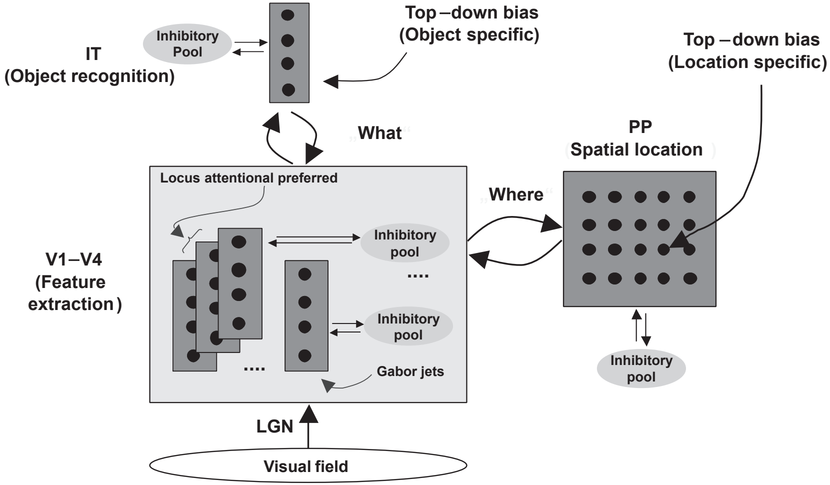


Attention in visual search and object recognition

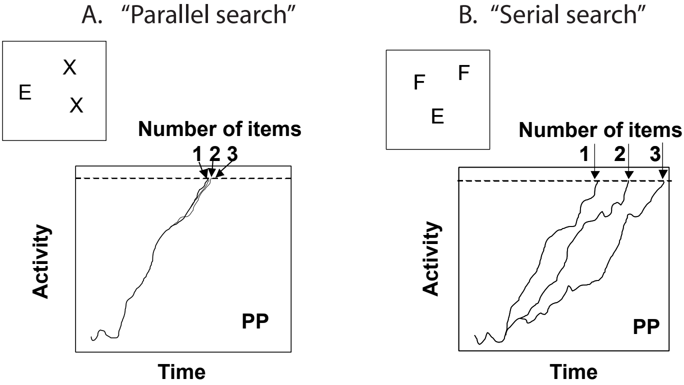


Gustavo Deco

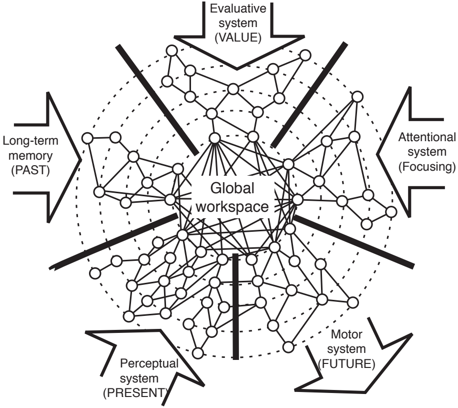
Model


Top–down bias
(Object specific)
Inhibitory
Pool
IT
(Object recognition)
Top–down bias
(Location specific)
„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

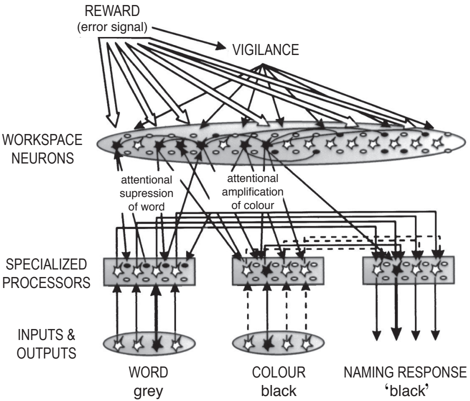


Stroop task modelling

A. Stroop task

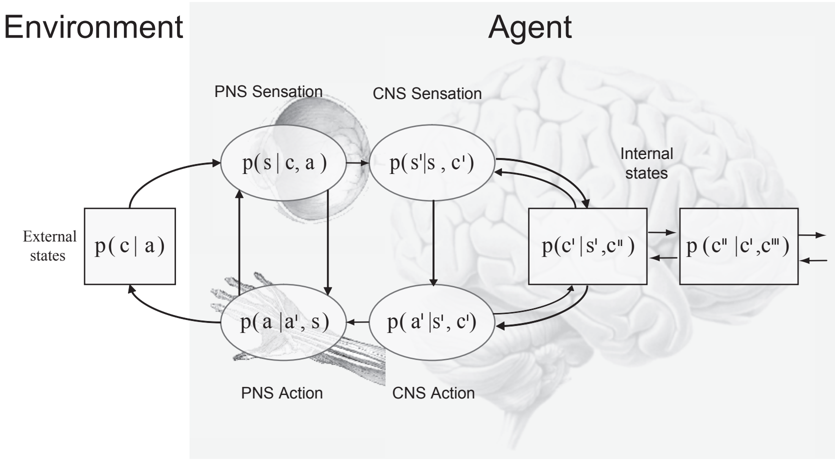
task / image	word naming	colour naming
grey	grey	black
black	black	grey

B. Workspace model for stroop task



The anticipating brain

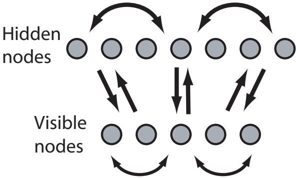
1. The brain can develop a model of the world, which can be used to anticipate or predict the environment.
2. The inverse of the model can be used to recognize causes by evoking internal concepts.
3. Hierarchical representations are essential to capture the richness of the world.
4. Internal concepts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



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

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

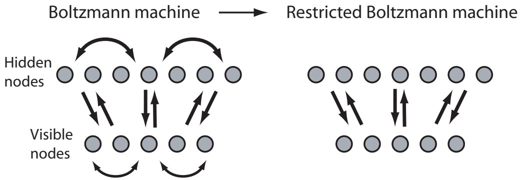
Minimizing KL is equivalent to maximizing the average log-likelihood function

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

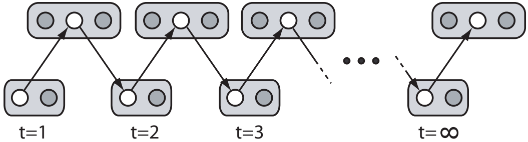
Gradient decent $\rightarrow$ Boltzmann Learning

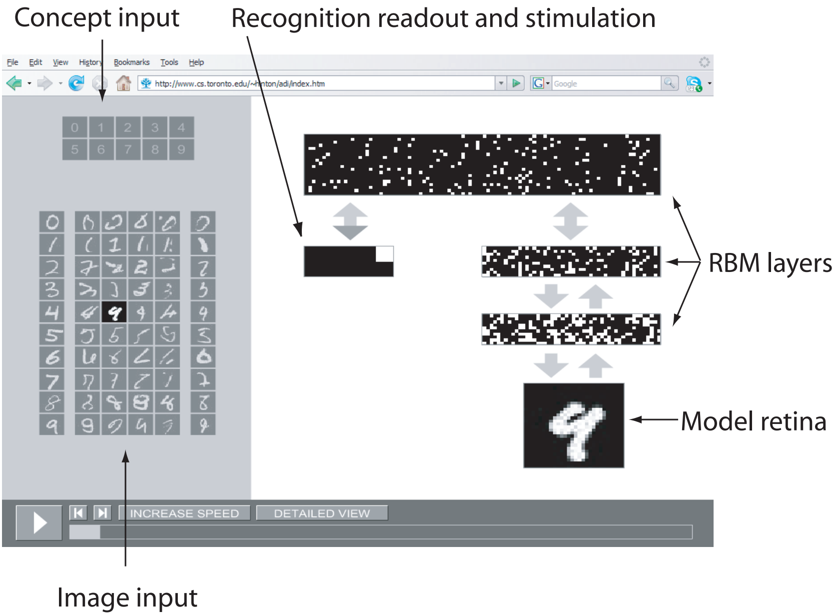
$\Delta w_{ij} = \eta \frac{\partial l}{\partial w_{ij}} = \eta \frac{\beta}{2} \left(\langle s_i s_j \rangle_{\mathrm{clamped}} - \langle s_i s_j \rangle_{\mathrm{free}} \right) .$

The restricted Boltzmann machine



Contrastive Hebbian learning: Alternating Gibbs sampling





Concept input
Recognition readout and stimulation
File Edit View History Bookmarks Tools Help
http://www.cs.toronto.edu/~hinton/adi/index.htm
Google
0 1 2 3 4
5 6 7 8 9
RBM layers
Model retina
INCREASE SPEED
DETAILED VIEW
Image input