Neuroinformatics

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Week 11: The cognitive brain (textbook chapter 10)

Outline

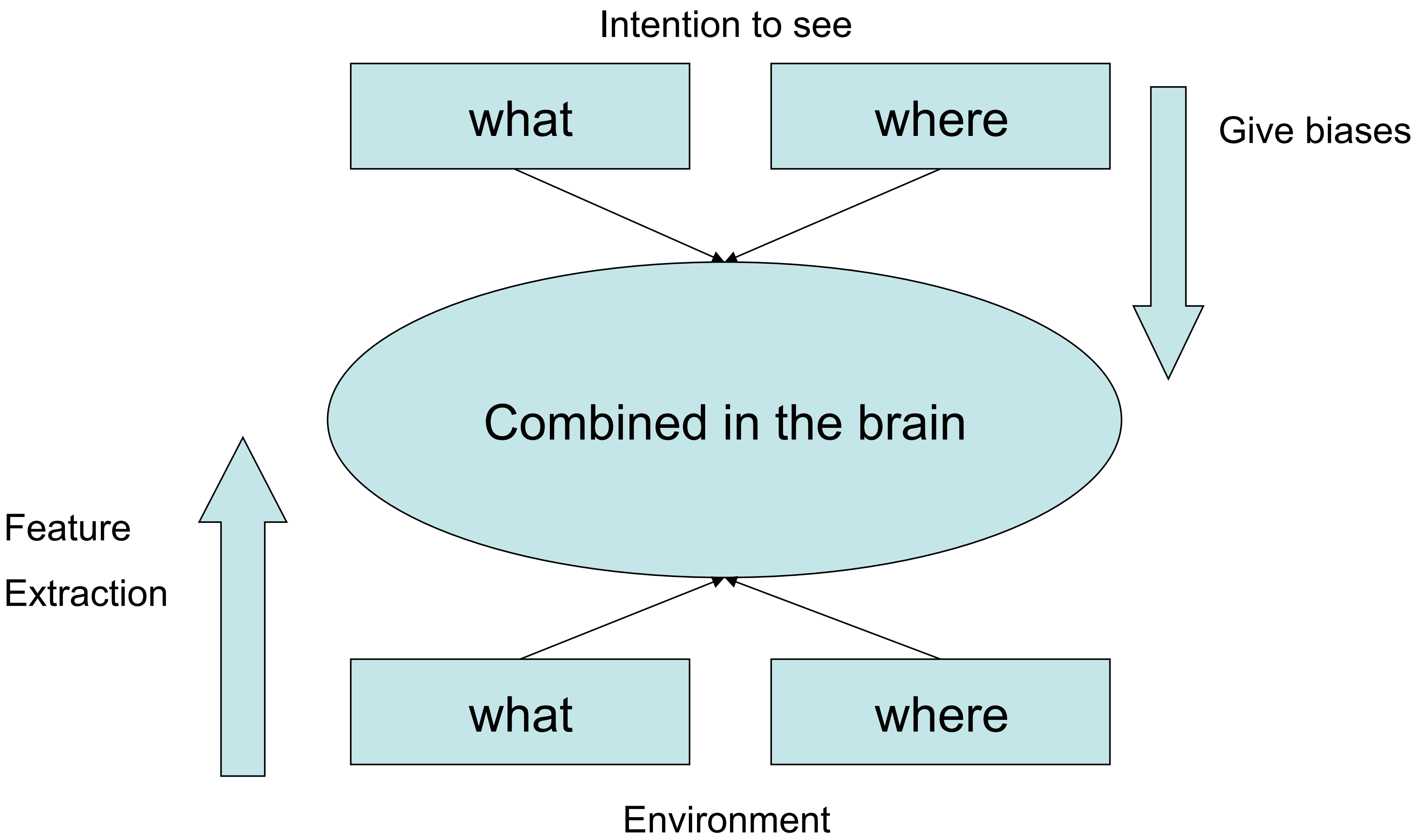
- Hierarchies
  - Top-down vs. bottom-up
  - Hierarchical maps
- Interacting components

  - attention and visual search
  - global workspace model
- Predictive Brain

  - generative and recognition mode

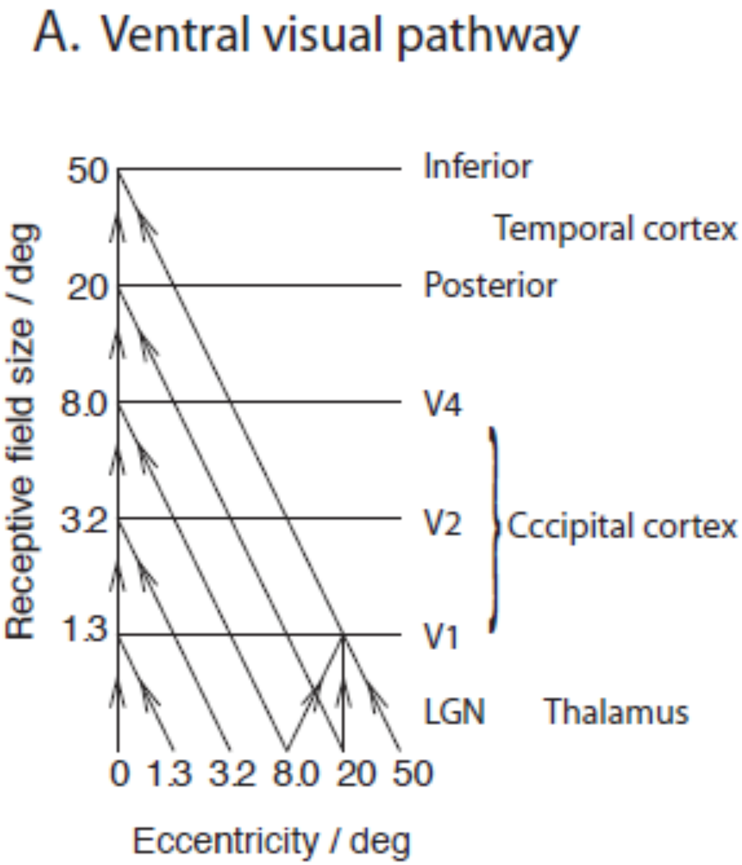
  - active learning
- Adaptive Resonance Theory
- Models and problems of Comp. neuroscience

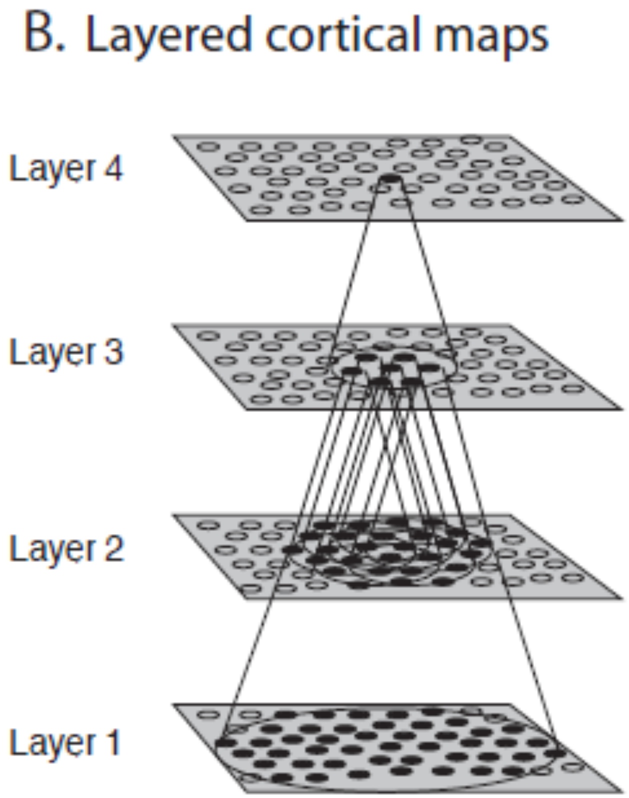
Top-down vs. Bottom-up (in vision)



How does the brain can combine them?

Hierarchical maps

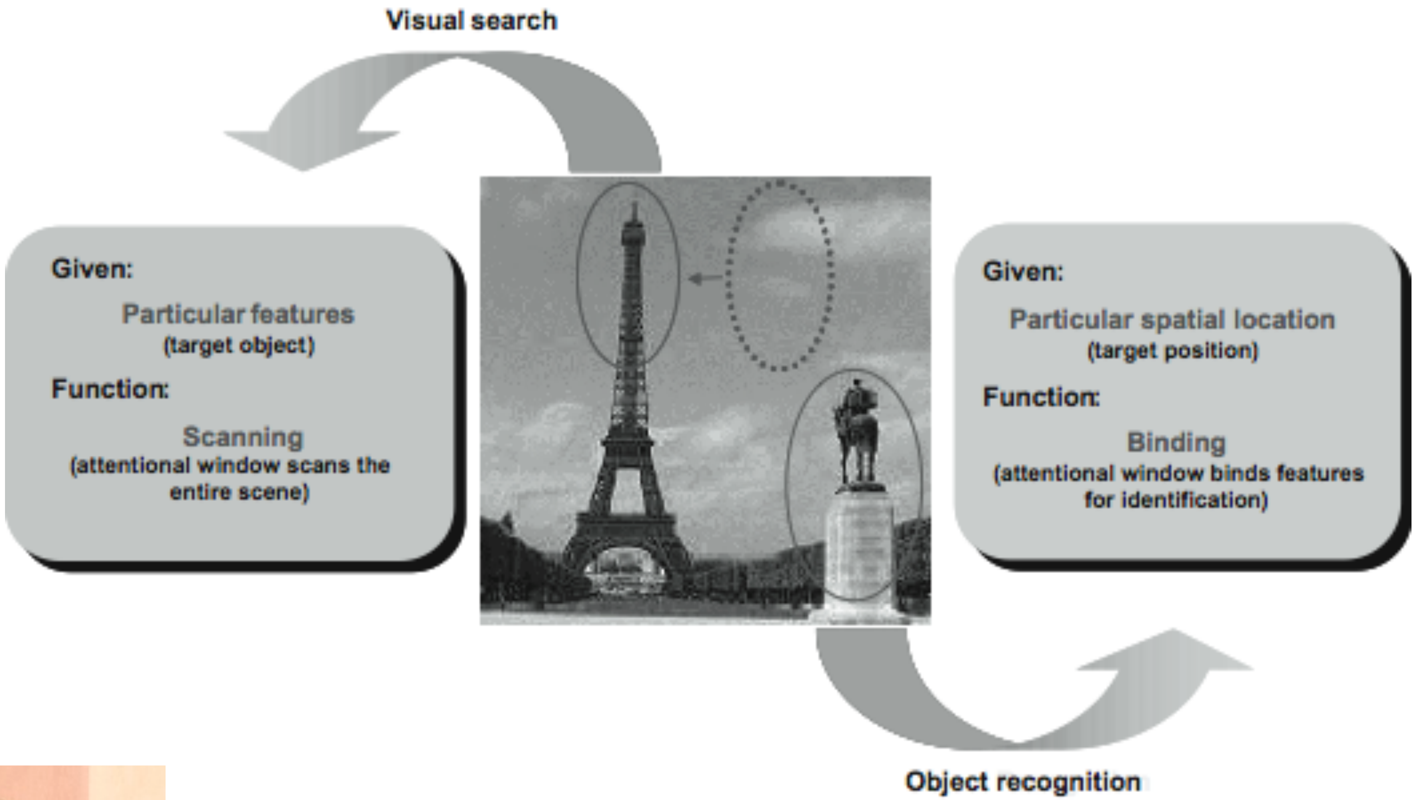




A model: each node is connected to a spatially restricted area in the layer below -> receptive field increases

Attention in visual search and object recognition

Top-down Intention: want to see “the tower”



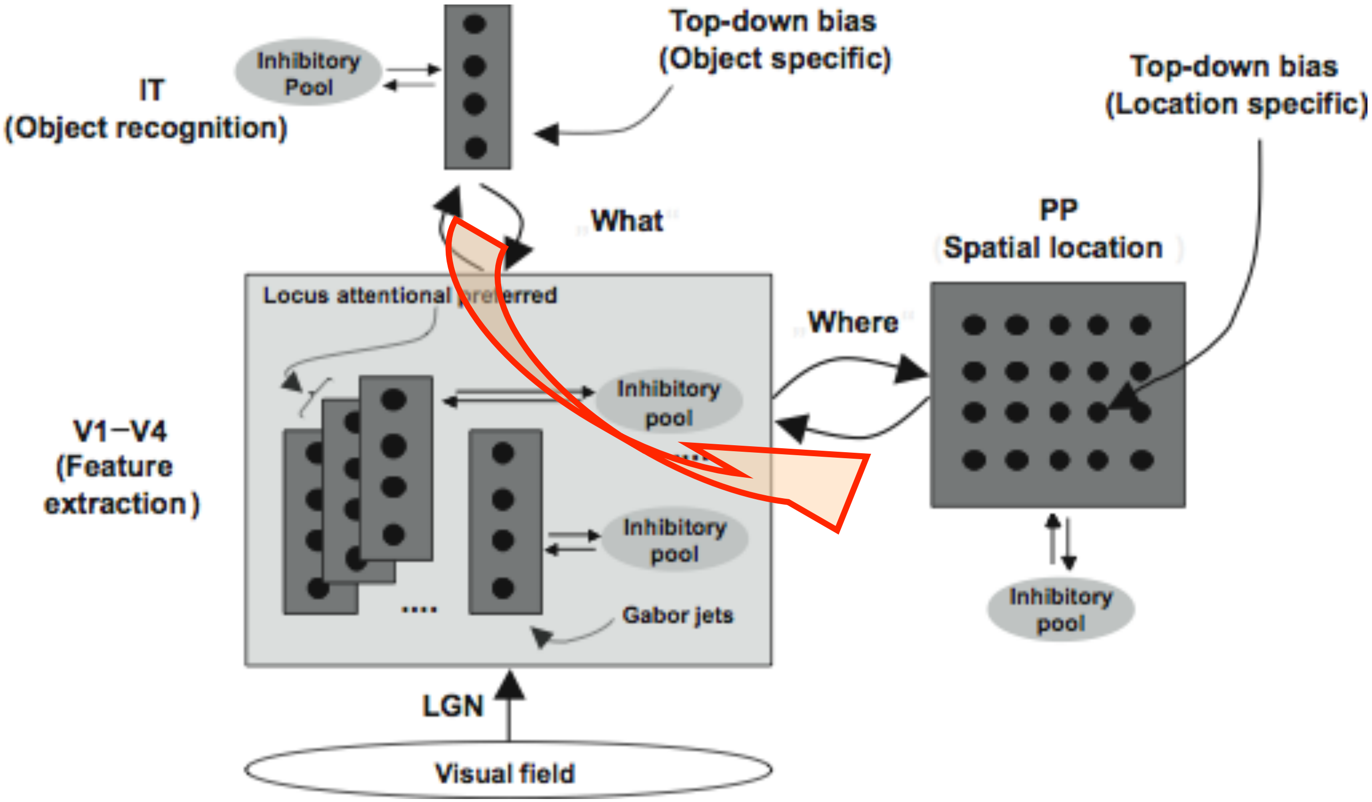
Bottom-up

Environment: what am I seeing?

Gustavo Deco
Barcelona, Spain

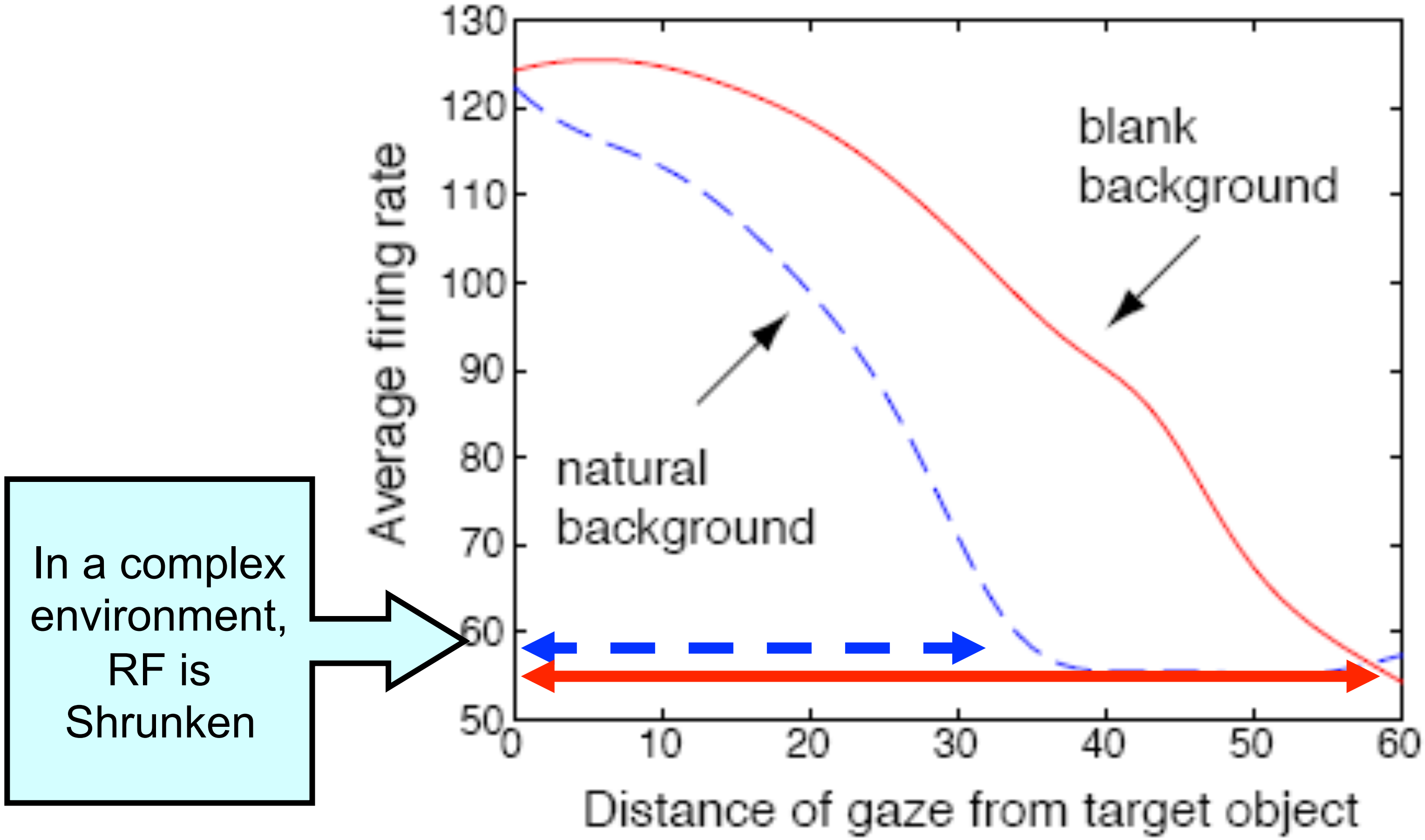
Model by Gustavo Deco

Object specific bias affects where to see through the system.



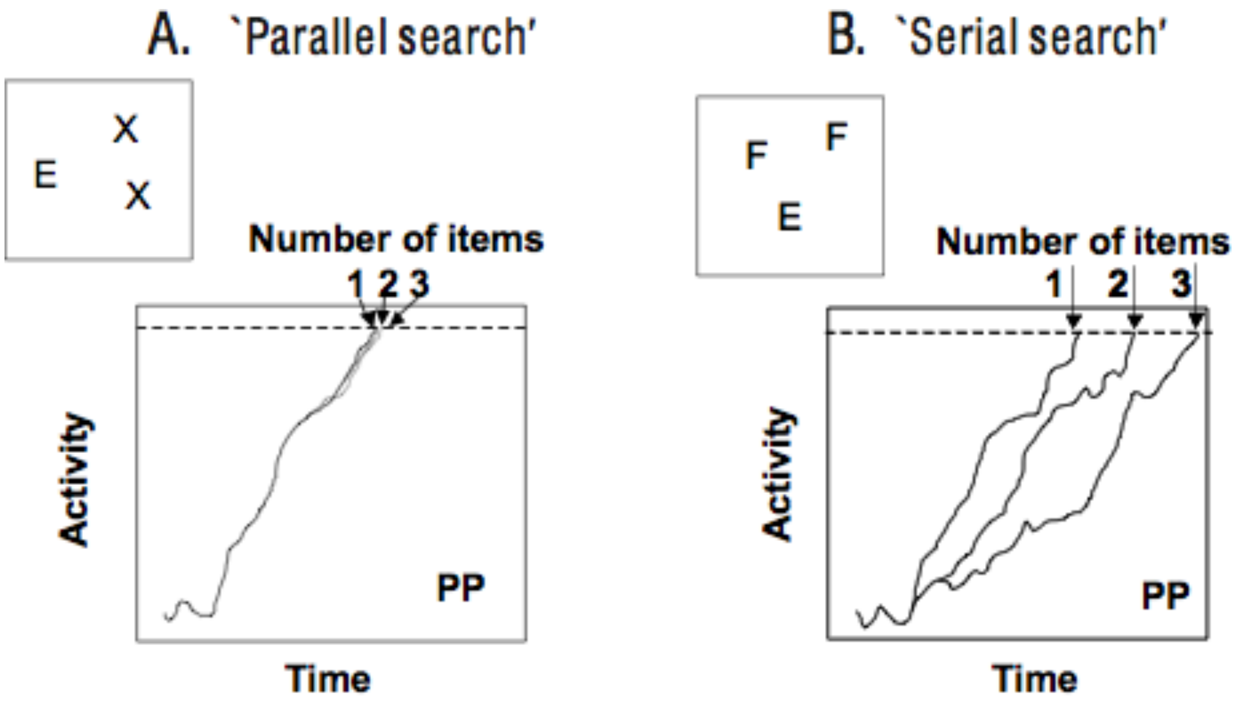
Cf. Indeed, a spatial location for visual search is also based on the visual field: we saw a part of scene in order of saliency. (Visual Attention: http://ilab.usc.edu/bu/movie/index.html)

The size of the receptive fields of IT neurons depends on the content of the visual field and the task



Average firing rates of a neuron in the inferior temporal cortex of a macaque in visual search task (Arrows indicate the size of their receptive fields)

Reaction time in visual search tasks: activity of PP neurons

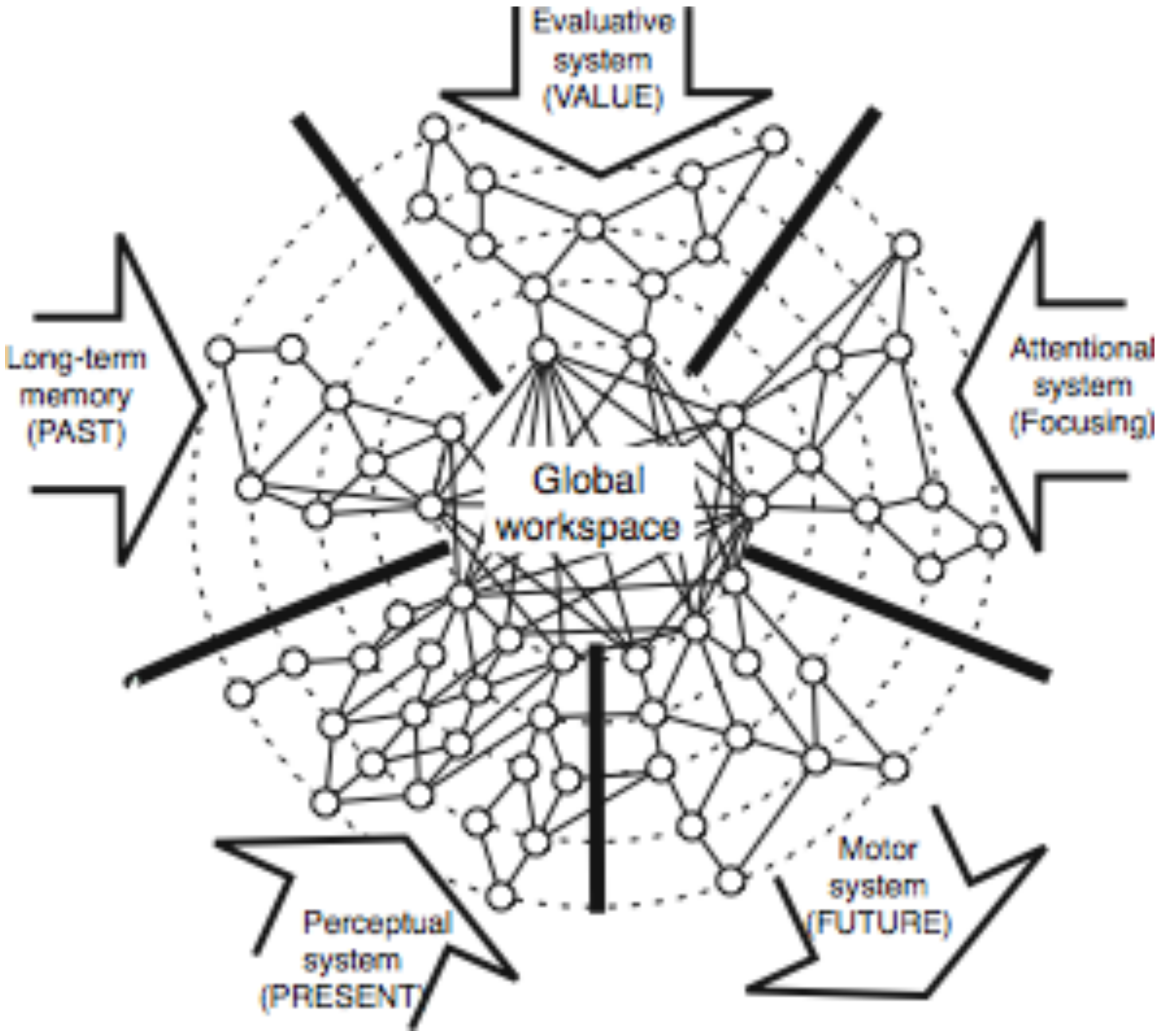


How much time is required to gaze a target object (E).

Gaze location is encoded in PP.

Environments affects reaction time also: the model behaves both

The interconnecting workspace hypothesis



5 Basic (essential) systems

(for each function)

&

Global workspace

(to combine them)

Lots of cortico-cortical connections on Layer II&III may contain the global workspace network.

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

Stroop task

Tell the color of word.

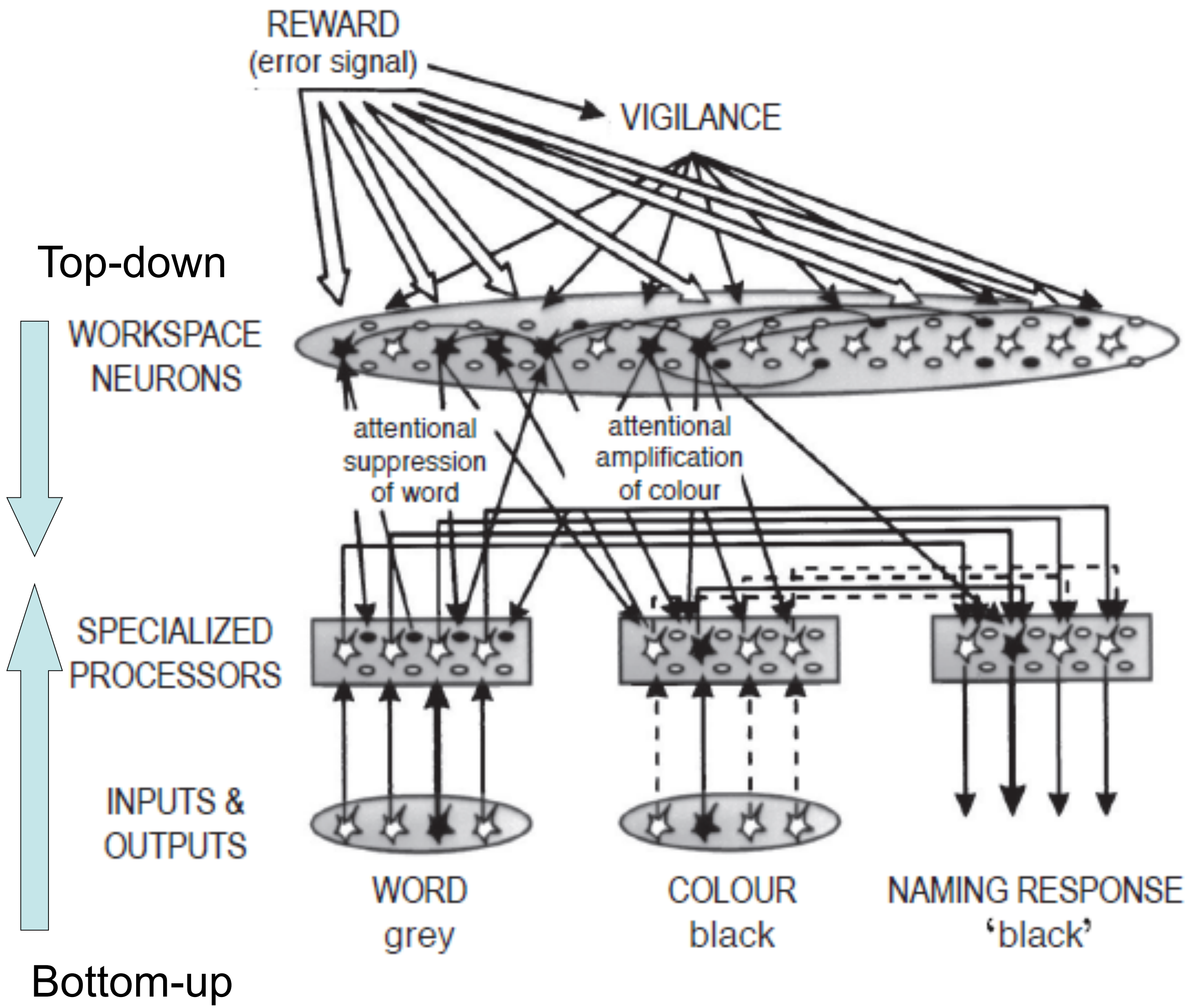
Is it easy to do?

An example of global workspace hypothesis: Stroop task modeling

GREY

What's the color of the word?

Both "meaning" and "color" is determined, then workspace neurons affect selection among them.

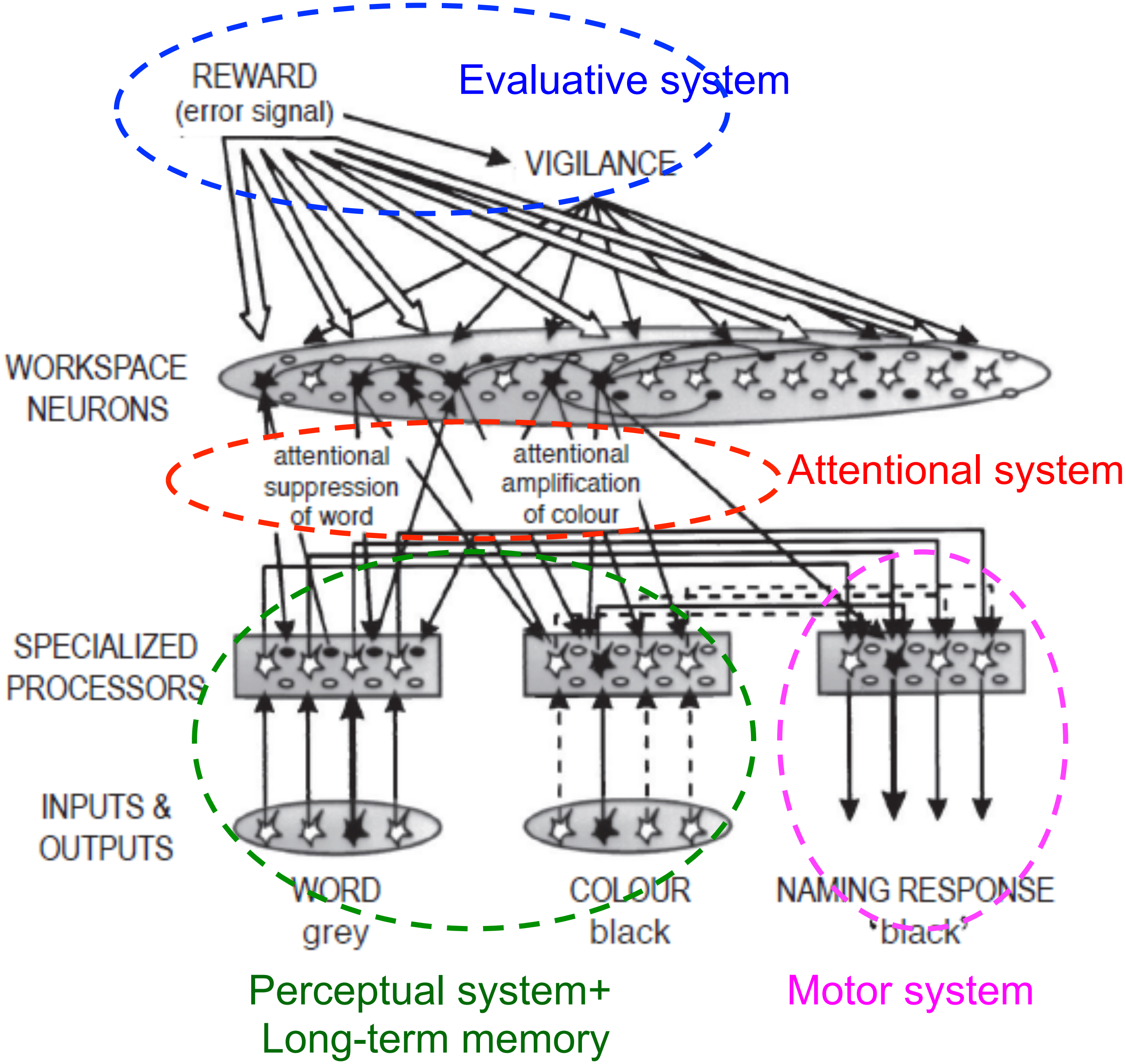


An example of global workspace hypothesis: Stroop task modeling

GREY

In this model, the correct answer is given through reward, and this implies task purpose.

When the answer is wrong, small reward is given and "vigilance" increases. Which enable reconfiguration of workspace neurons



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.

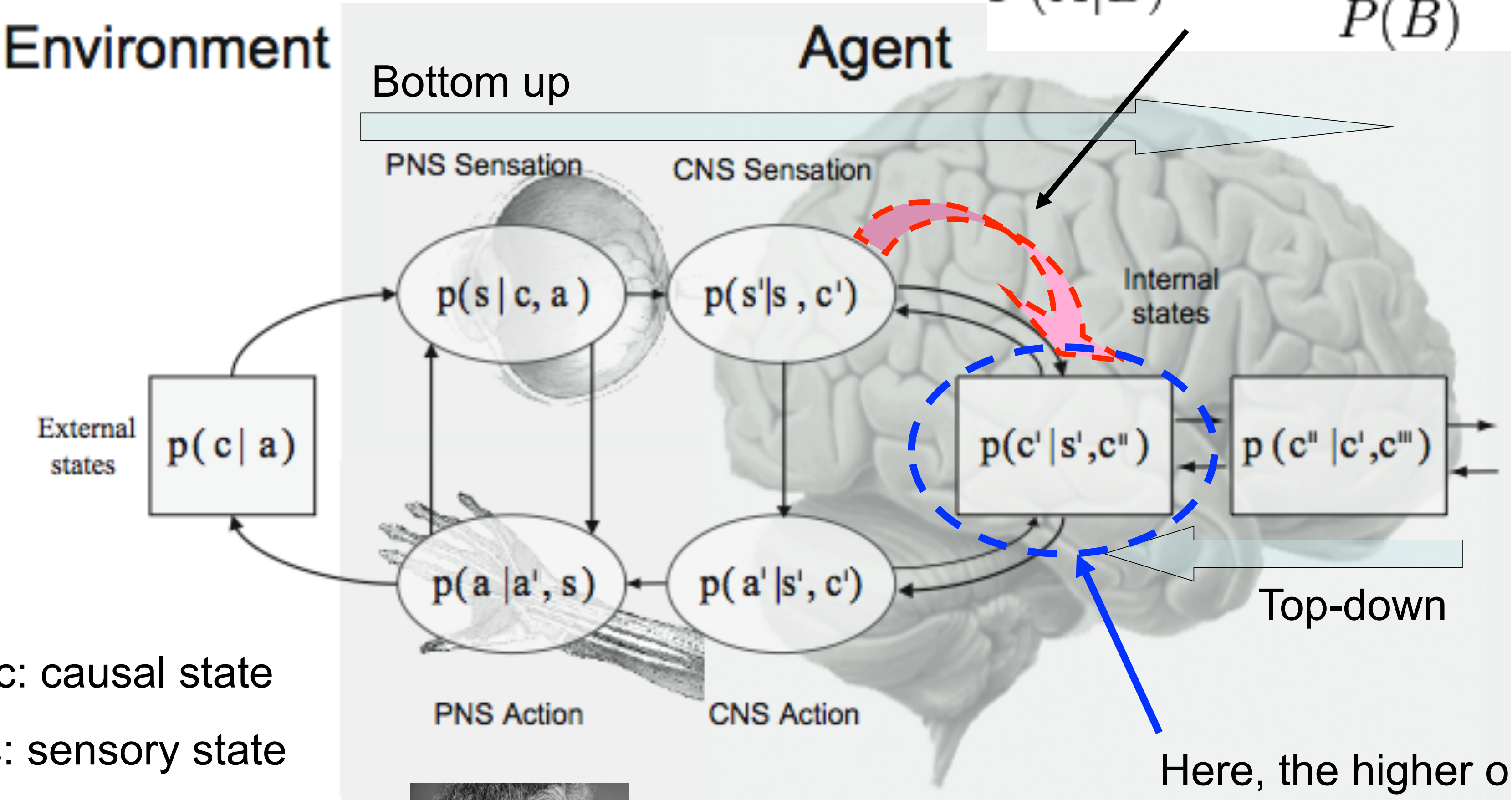
5) An agent can learn actively by testing hypothesis through actions.

6) The temporal domain is an important degree of freedom.

(I) Probabilistic framework

Bayes Theorem

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}.$$



c: causal state

s: sensory state

a: action

‘ represents estimated (internal or cortical)

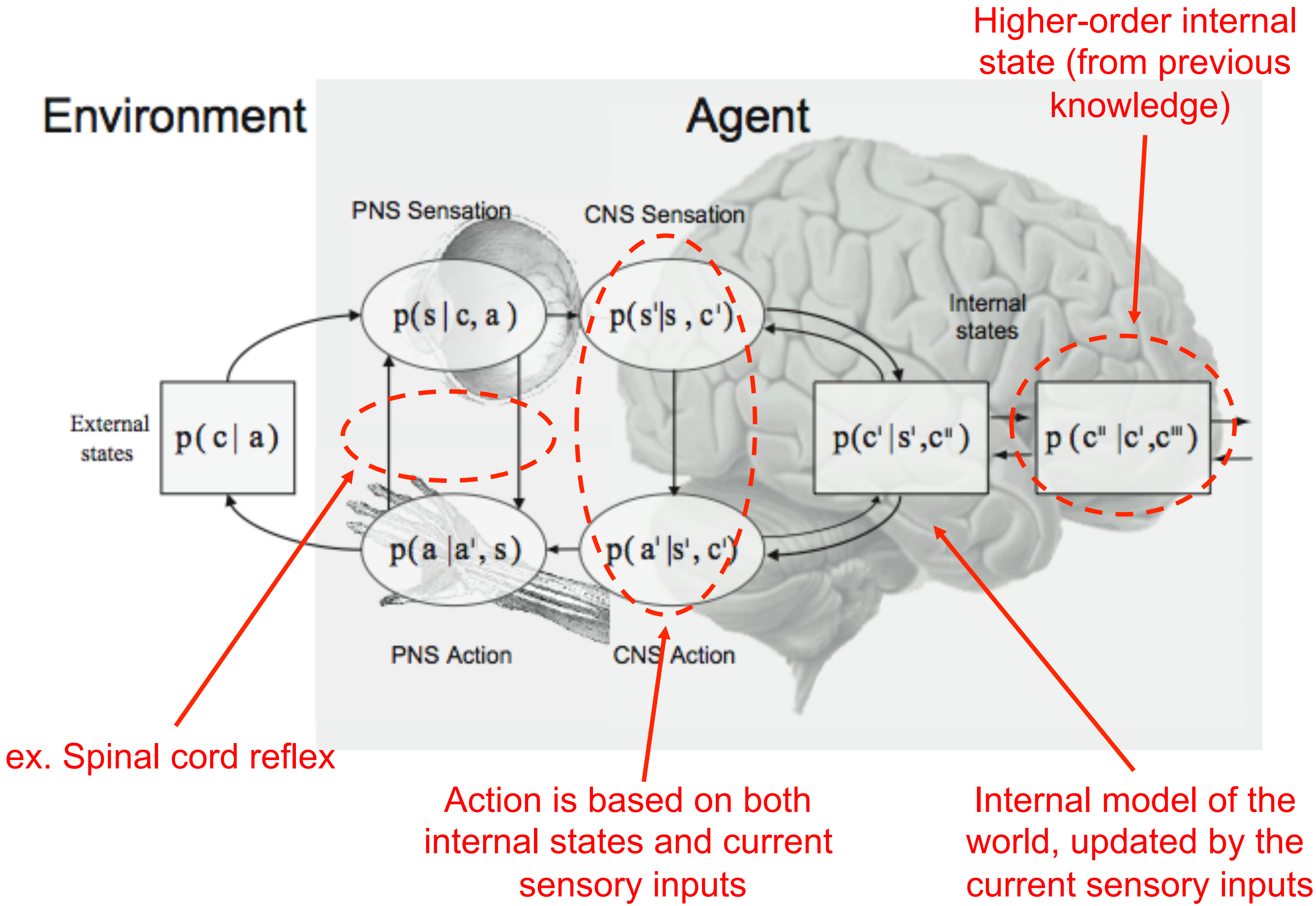
Karl Friston, FRS
University College London, UK

Here, the higher order (top-down) causal state is combined with sensory inputs (bottom-up)

Probabilistic framework

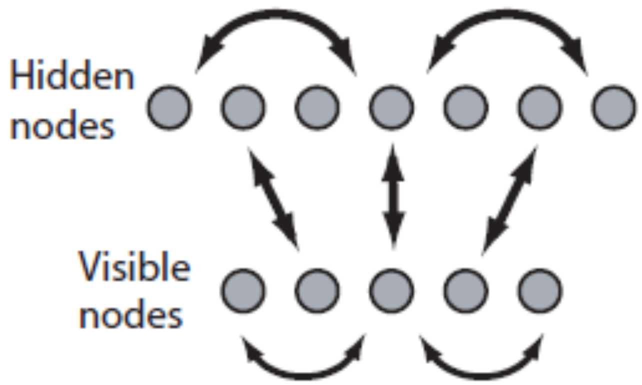
- **Why probability?**
  - The world is uncertain!
  - The sensory system is imperfect (noisy and distorted).
  - The motor system is highly uncertain (the world can respond in a different manner with the same action).
  - The internal state can be wrong (can we sure what we believe? ex. Visual illusion)
- In the brain, there are “estimates” of the world (through sensory inputs), and “expectation” (based on the previous experience).

Probabilistic framework



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

Boltzmann machine may help that brain-generated (top-down) states can be compared to physical evidence (bottom-up) state to guide self-organization of useful representations.

Training Boltzmann machines

Kulbach-Leibler divergence

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

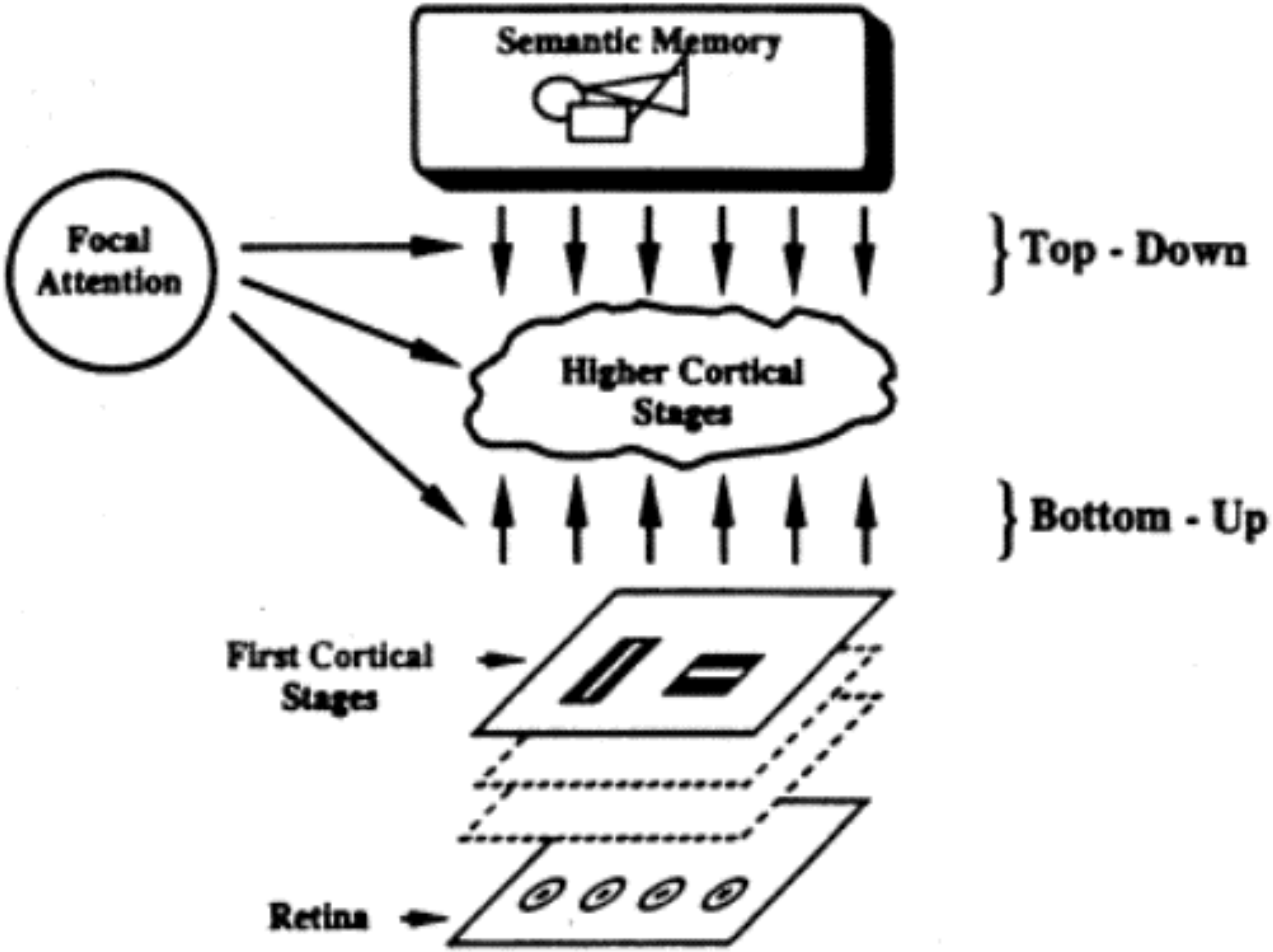
Minimizing KL is equivalent to maximizing the average log-likelihood function

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

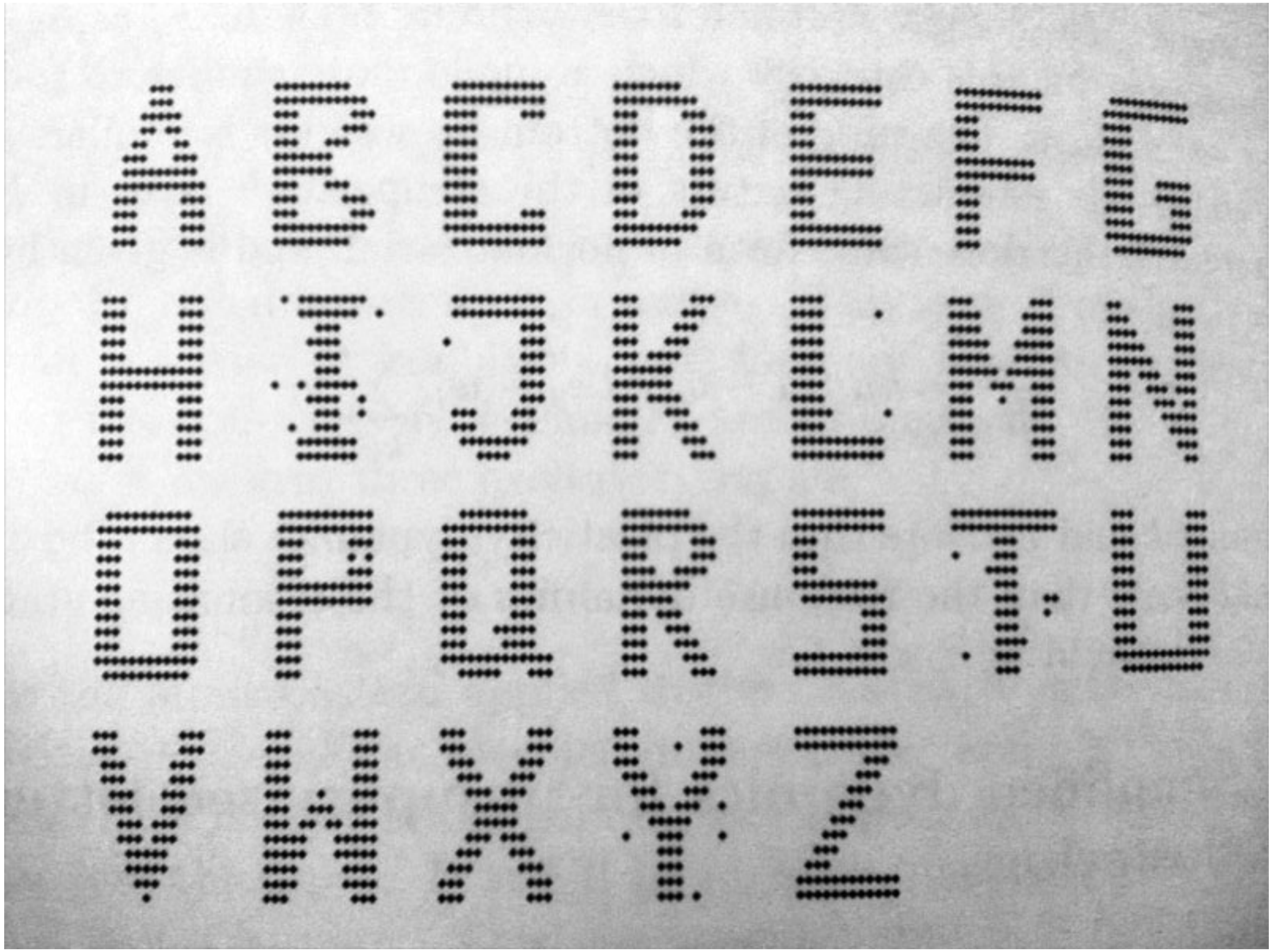
Gradient decent $\rightarrow$ Boltzmann Learning

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

(III) Adaptive resonance theory (ART)



An example of ART: OCR



- After training noisy characters, ART can capture less-noisy characters in its memory.

The big picture

Summary of this module

Challenges of *in silico* models

- Assumptions
  - At what level should a system be modeled?
  - Not all parameters can be measured from biological systems. How can parameters be estimated?
  - Are results robust?

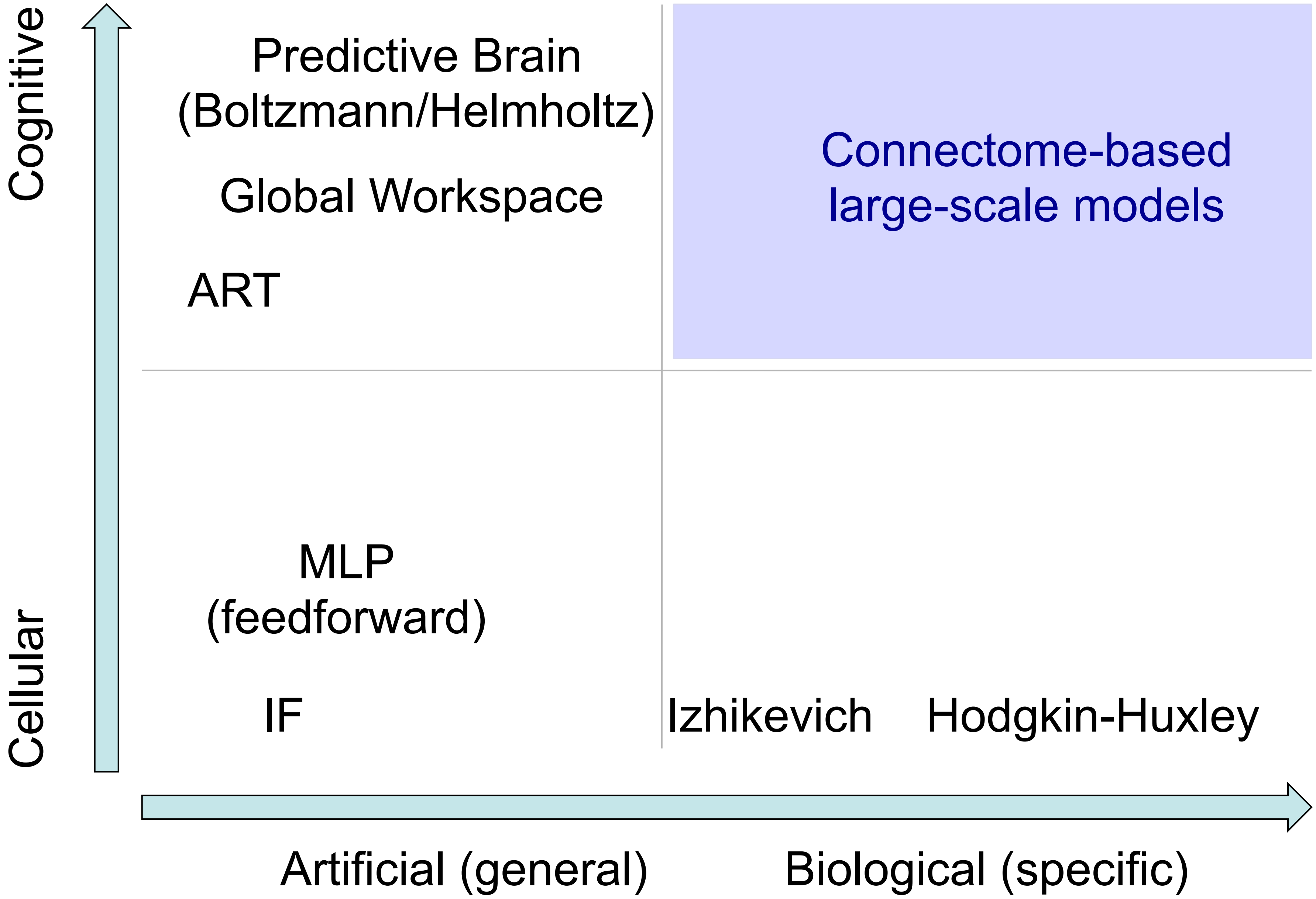
- Validation

  - How can the simulation be compared with the real biological system?
  - Can there be a proof of correctness?

- Insights

  - What can the model tell us about the real biological system? What are the limits?
  - What do the results mean for clinical, industrial, or experimental applications?

Summary of models



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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.

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