Computational Cognitive Neuroscience
Introduction

Marcel van Gerven

DONDERS INSTITUTE

Radboud University Radboudumc

Outline

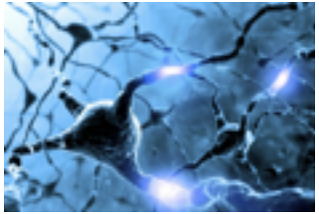
- What is Computational Cognitive Neuroscience?
- Course organisation
- Computational theories and brain function

Additional information like literature, references, etc.

What is Computational Cognitive Neuroscience (CCN)?

Artificial intelligence, computational neuroscience

Cognitive neuroscience, cognitive science



Better artificial agents

New models of brain function

Computational Cognitive Neuroscience

What is Computational Cognitive Neuroscience?

- The brain is an organ which generates adaptive behaviour
- We can gain a better understanding of brain function via new developments in **theory**, **modeling** and **data analysis**
- To this end, we may use advanced approaches that have their roots in artificial intelligence, cognitive science and mathematical psychology.
- In this course you will encounter some of these approaches (Bayesian modeling, neural networks, reinforcement learning, optimal control)
- You will learn about mathematical underpinnings and neural implementation

Course organisation

- Introduction
- Guest lectures
- Student project (research proposal or implementation)
- Pitch presentations
- Exam

Introduction

General overview

Mathematical background for three important pillars:

- Bayesian statistics
- Neural networks
- Reinforcement learning

Three practicals: implement basic models in Python

Lectures

Selection of topics:

- Bayesian connectomics (Max)
- Neuromodulation (Andrew)
- Memory (Sander)
- Neural representations (Umut)
- Optimal feedback control (Lonneke)
- Predictive processing (Silvan)
- Reinforcement learning (Hanneke)
- SurfSara special lecture (Vali)

Student project

Choose one of:

- Implement a computational model in Python and write technical report
- Write a motivated research proposal which probes cognitive function using a computational approach

Pitch presentations

- Students present their project in 3-minute pitch presentations
- Upload one pdf slide to blackboard containing:
  - **The problem** your assignment was aimed at
  - **How** you have/proposed to solved it
  - Your main **conclusions**
  - The scientific/societal **relevance** of your project

Exam

Exam material:

- Lecture slides + required reading

Prerequisites:

- Pass the practical assignments (each assignment ≥ 5.5)
- Hand in of final assignment
- Pitch presentation

Grading

- Exam (50% of the grade)
- Final assignment (50% of the grade)

Metaphors of the human brain

The clockwork metaphor

The switchboard metaphor

The computer metaphor

The computer metaphor is NOT a metaphor: Minds literally *consist* of computations!

The human brain according to Marr's three levels of analysis

Computational level: what problem is the brain trying to solve?

Algorithmic level: how does the brain solve these problems?

Implementational level: How are these solutions implemented in wetware?

What problem is the brain trying to solve?

The generation of goal-oriented behaviors and visceral responses that ensure survival of the individual along with the species as a whole.

Motivated behaviour:

- ingestion (eating and drinking)
- defense (fight or flight)
- reproduction (sexual and parental)

Visceral responses:

- autonomic and neuroendocrine responses that help maintain homeostasis.

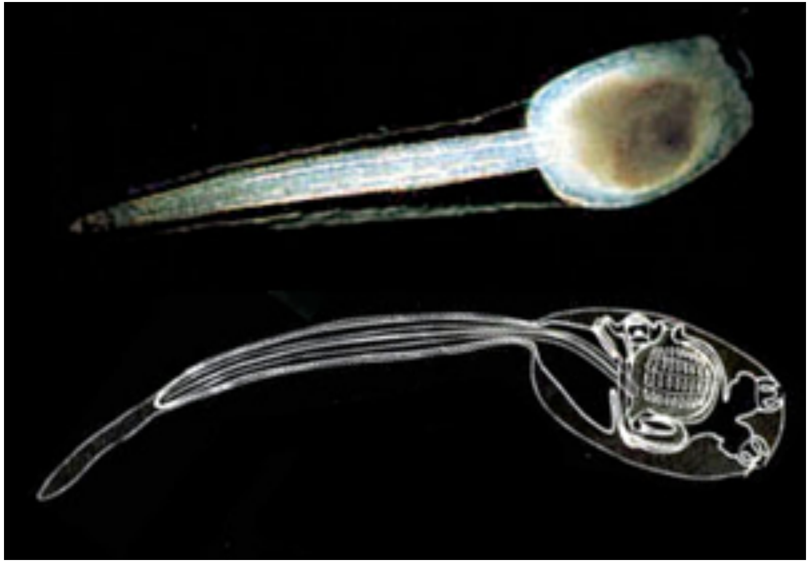
Tinbergen, 1951

What problem is the brain trying to solve?

The [brain’s] rostral segment helps control ingestive, defensive, and reproductive motivated behaviors, whereas its caudal segment helps control foraging or exploratory behavior to obtain or avoid specific goal objects associated with all classes of motivated behavior.

Tinbergen, 1951

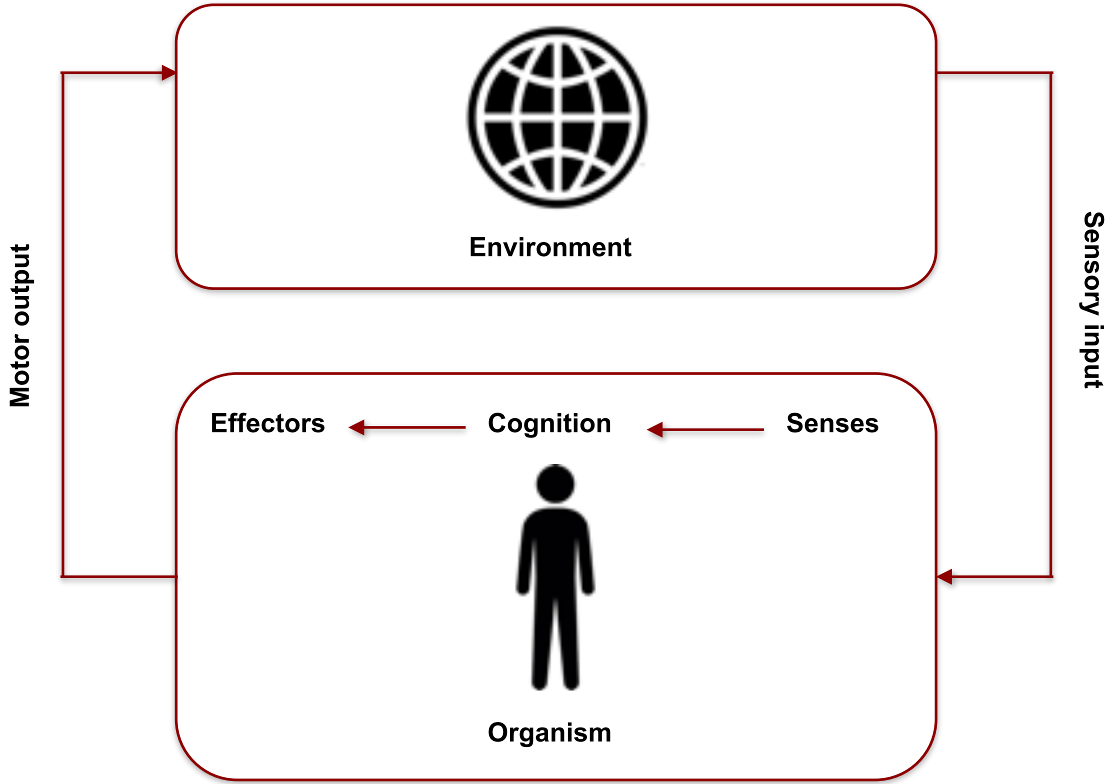
An action-oriented view



Sea squirt larval stage

Sea squirt adult stage

Generating behaviour: The perception-action cycle



Generating behaviour: The perception-action cycle

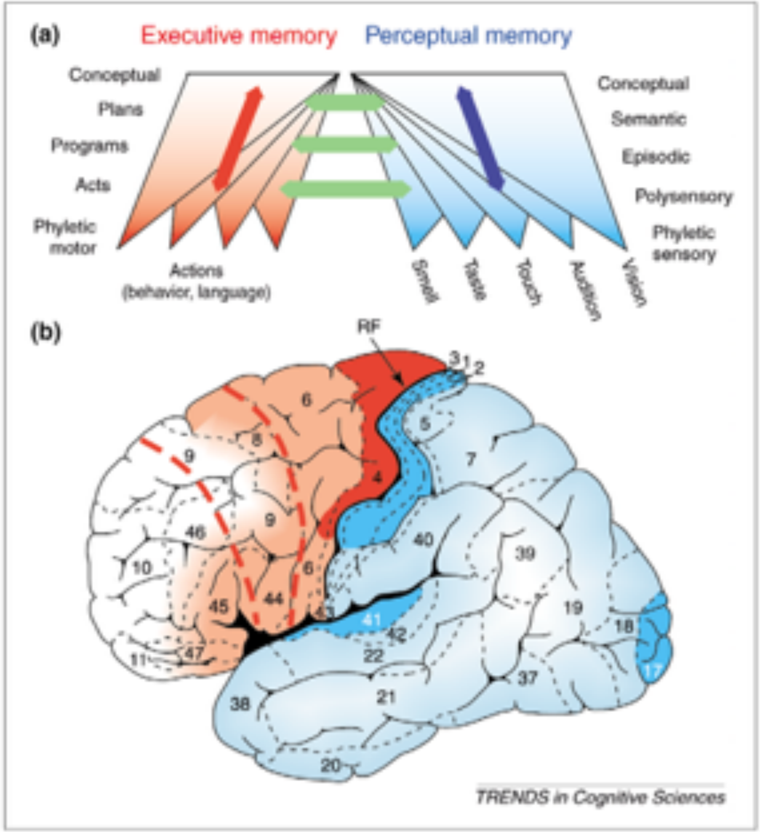
"What we have is a circuit, not an arc or broken segment of a circle. [...] The motor response determines the stimulus, just as truly as sensory stimulus determines movement. Indeed, the movement is only for the sake of determining the stimulus, of fixing what kind of a stimulus it is, of interpreting it."

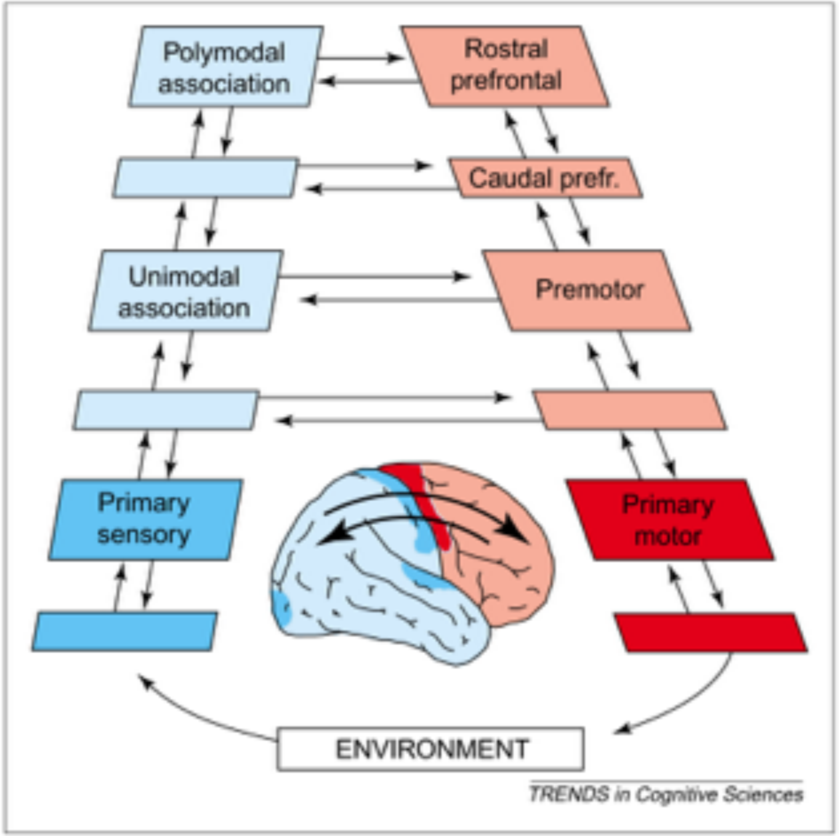
John Dewey (1896) The Reflex Arc Concept in Psychology Psychological Review, 3, 357-370

"The structural unit of the nervous system is in fact a triad, neither of whose elements has any independent existence. The sensory impression exists only for the sake of awaking the central process of reflection, and the central process of reflection exists only for the sake of calling forth the final act."

— William James (1911)

The perception-action cycle





Fuster, J. M. (2004). Upper processing stages of the perception–action cycle. Trends in Cognitive Sciences, 8(4), 143–145.

The stimulus-response fallacy

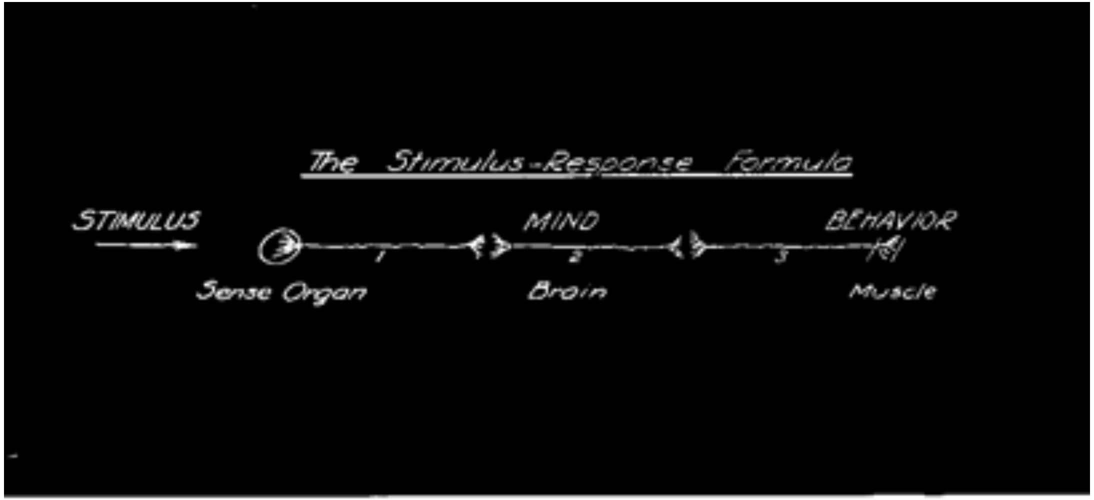


Fig. 1.

To relegate habitually our mental life into the unmental stimulus-response categories is a procedure which carries the appearance of science in its terminology, but which is not infrequently indicative of a superficial and unsympathetic understanding of mental life.

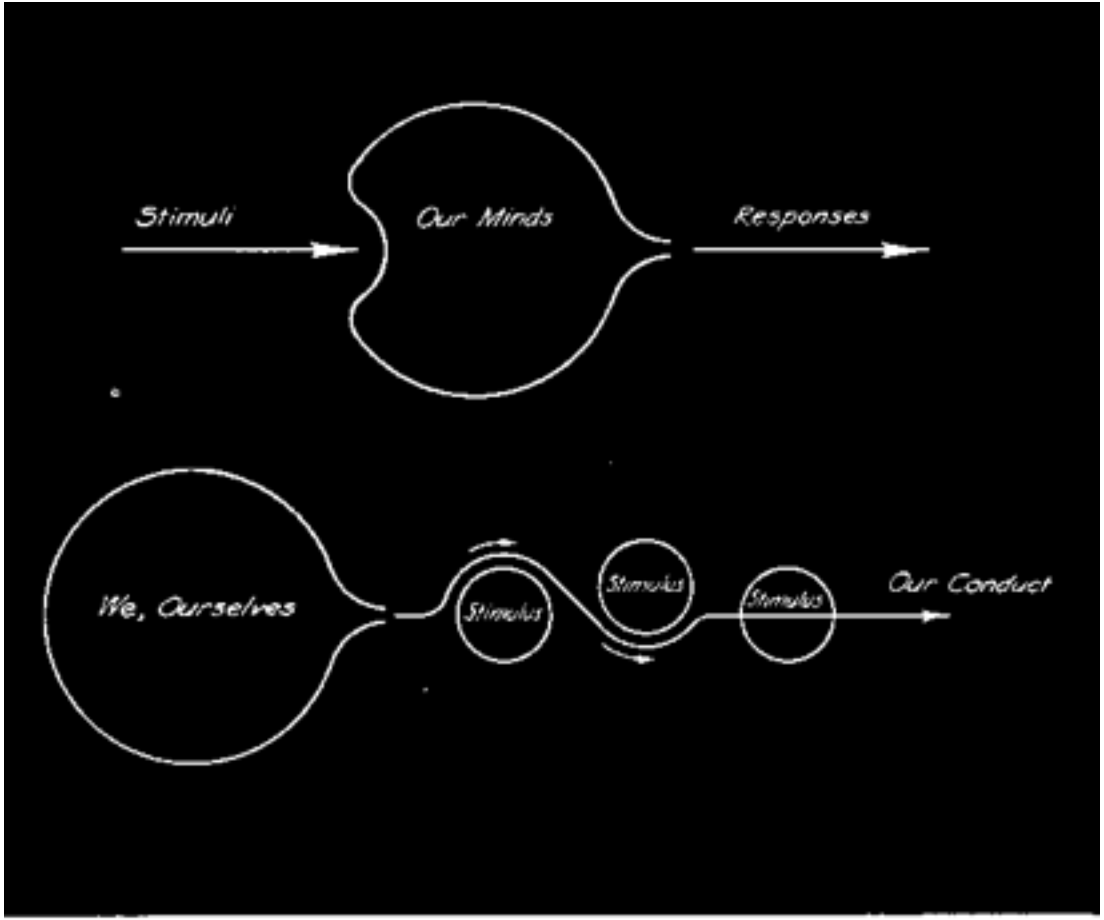
L. L. Thurstone (1923)

The stimulus-response fallacy

"My main thesis is that conduct originates in the organism itself and not in the environment in the form of a stimulus. [...] All mental life may be looked upon as incomplete behavior which is in the process of being formed. [...] Perception is the discovery of the suitable stimulus which is often anticipated imaginally. The appearance of the stimulus is one of the last events in the expression of impulses in conduct. The stimulus is not the starting point for behavior."

L. L. Thurstone (1923)
The Stimulus Response Fallacy in Psychology
Psychological Review, 30, 354-369

Environment-centric vs Organism-centric view



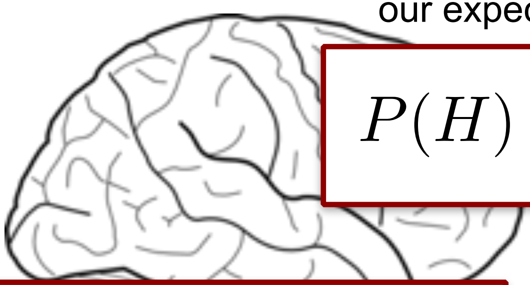
The brain as an inference machine

Perception depends on "inference and judgment" that has become habitual, rapid, and unnoticed (Ibn al-Haytham - Alhazen in Europe; 965-1040)

Perception as unconscious inductive inference (Helmholtz; 1821-1894)

The brain as an inference machine

Central in recent work on the Bayesian brain hypothesis



our expectations

$$P(H)$$

our (noisy) sensations

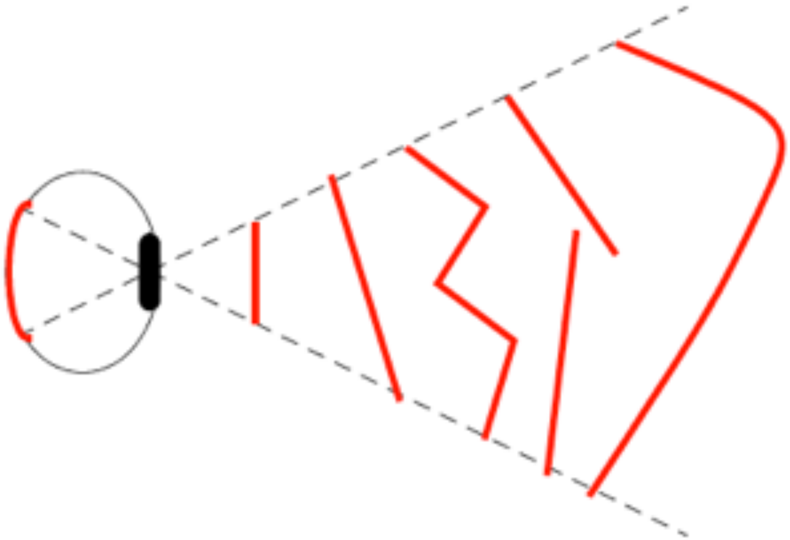
$$P(D \mid H)$$

$$P(H \mid D) = \frac{P(D \mid H)P(H)}{P(D)}$$

our percepts

How perception is shaped by prior knowledge

One-to-many mapping of a retinal image to objects in the world

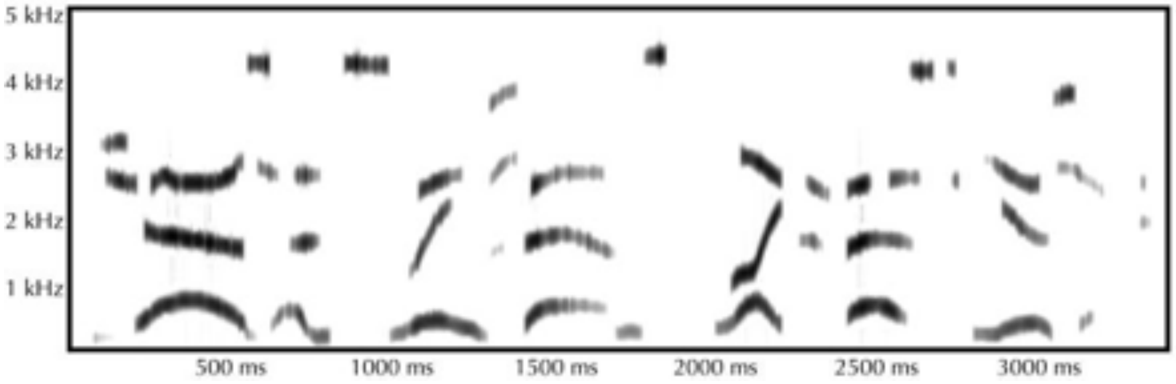


How perception is driven by prior knowledge

How perception is shaped by prior knowledge

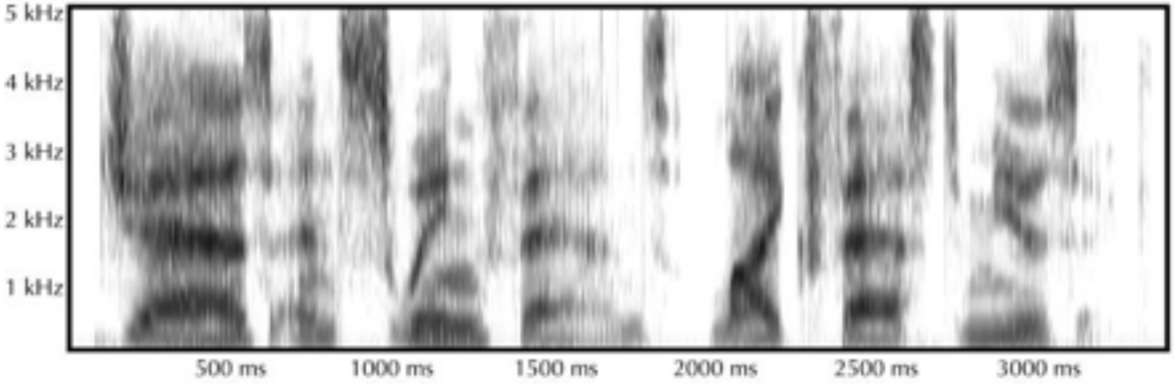
http://www.cam.ac.uk/research/news/how-hallucinations-emerge-from-trying-to-make-sense-of-an-ambiguous-world

How perception is shaped by prior knowledge



http://www.scholarpedia.org/article/Sine-wave_speech

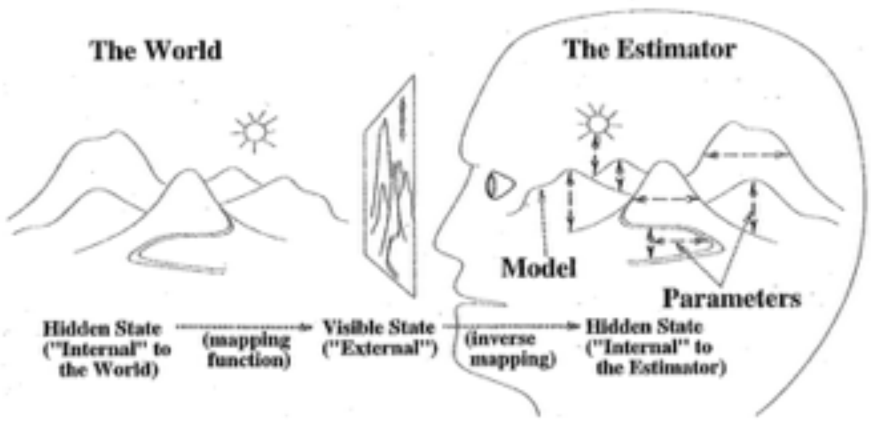
How perception is shaped by prior knowledge



http://www.scholarpedia.org/article/Sine-wave_speech

The Bayesian brain hypothesis

The **Bayesian brain hypothesis** refers to the ability of the nervous system to operate in situations of uncertainty in a fashion that is close to the optimal prescribed by Bayesian statistics.



Presupposes that the brain learns an internal model that infers the causes of its sensations and predicts the consequences of it's actions.

Rao RPN, Sejnowski TJ, Rao RPN, Olshausen BA, Lewicki MS. Predictive coding, cortical feedback, and spike-timing dependent plasticity. In: Probabilistic Models of the Brain. 2002

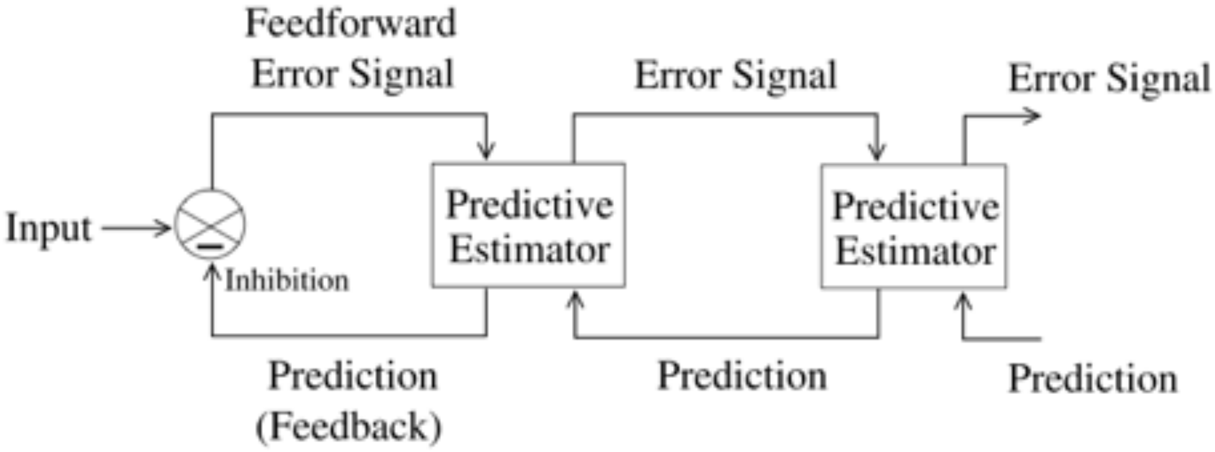
The Bayesian brain hypothesis

A wide range of approaches exist that link Bayesian ideas to the function of the brain:

- **Psychophysics**: Many aspects of human perceptual or motor behavior are modeled with Bayesian statistics (e.g. Knill, Wolpert).
- **Principles of neural coding**: Many theoretical studies ask how the nervous system could implement Bayesian algorithms (e.g. Pouget, Ma, Ballard, Mumford, Fiser, Lengyel).
- **Neural correlates of probabilistic inference**: Various recent electrophysiological and neuroimaging studies focus on the representation of probabilities in the nervous system (e.g. Shadlen, Behrens).
- **Probabilistic cognition**: Bayesian models as explanatory models for human behaviour (e.g. Tenenbaum, Griffith).
- **Free-energy principle:** Bayesian brain emerging from the general principle of free-energy minimisation (e.g. Friston, Kiebel).

Predictive coding

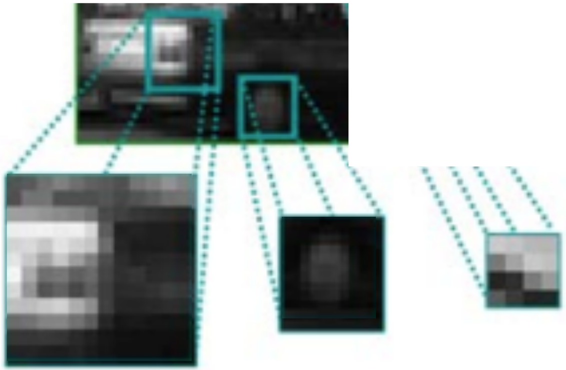
- In predictive coding, the brain is viewed as a hierarchical generative model
- Top-down predictions are combined with bottom-up sensory evidence
- Only prediction errors are propagated upwards



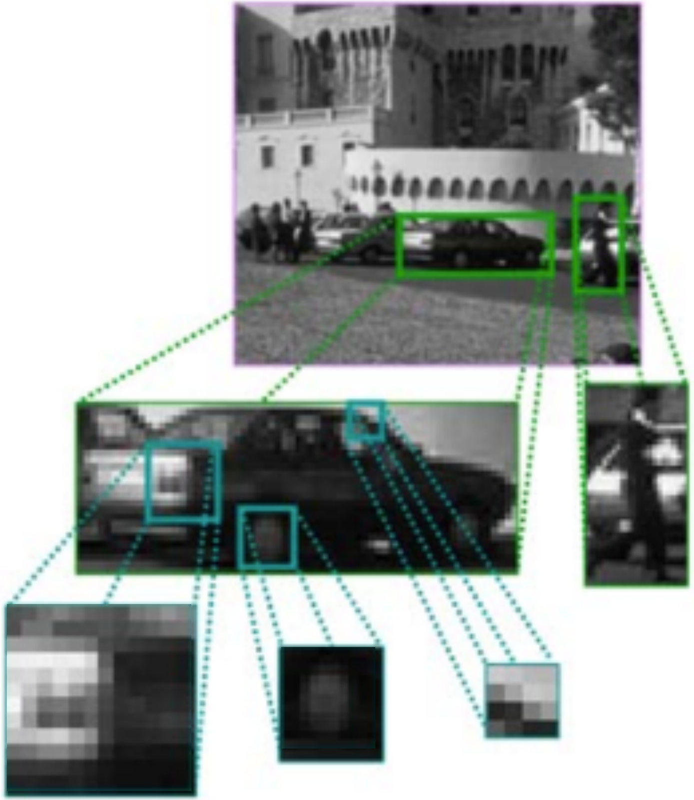
Rao RP, Ballard DH. Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. Nat. Neurosci. 1999 Jan;2(1):79–87.

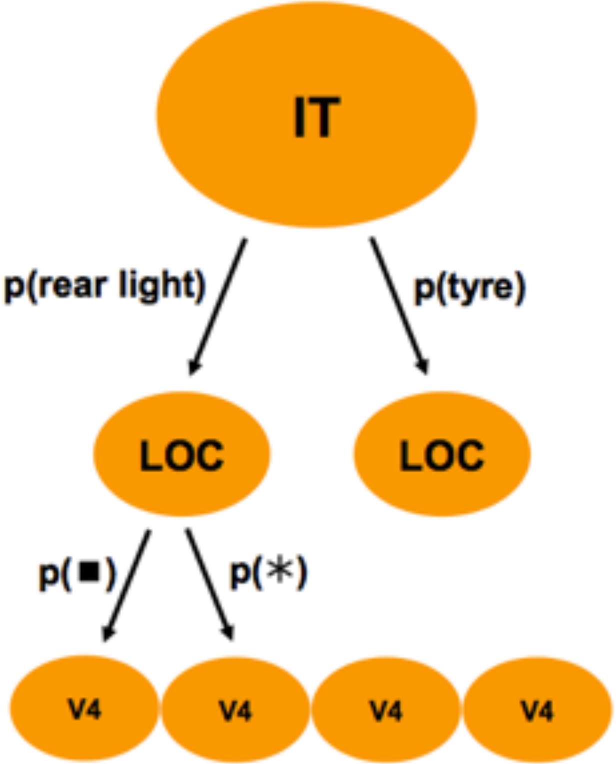
Example of predictive processing

Example of predictive processing



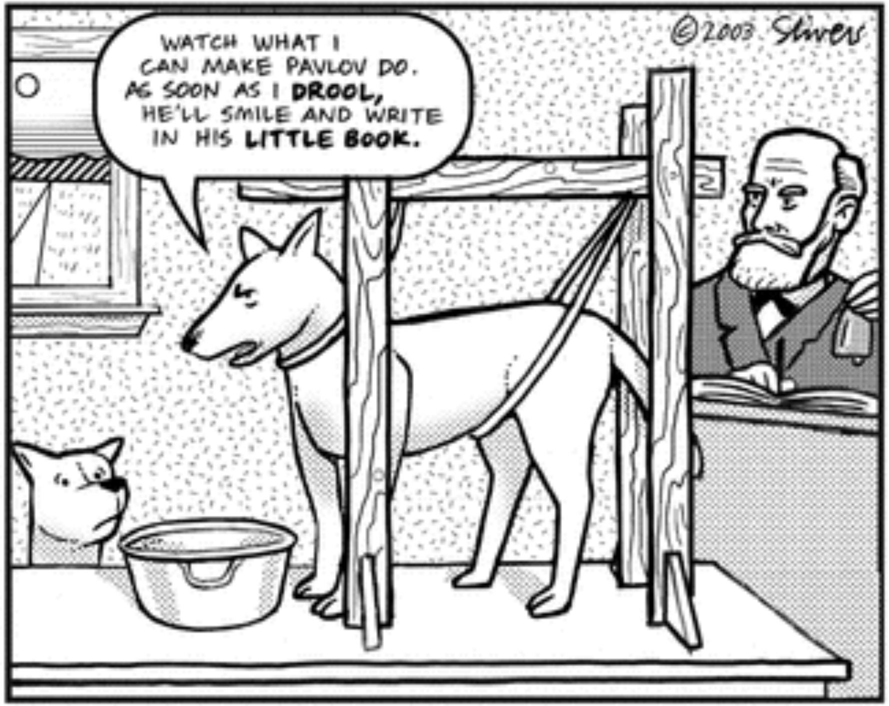
Example of predictive processing





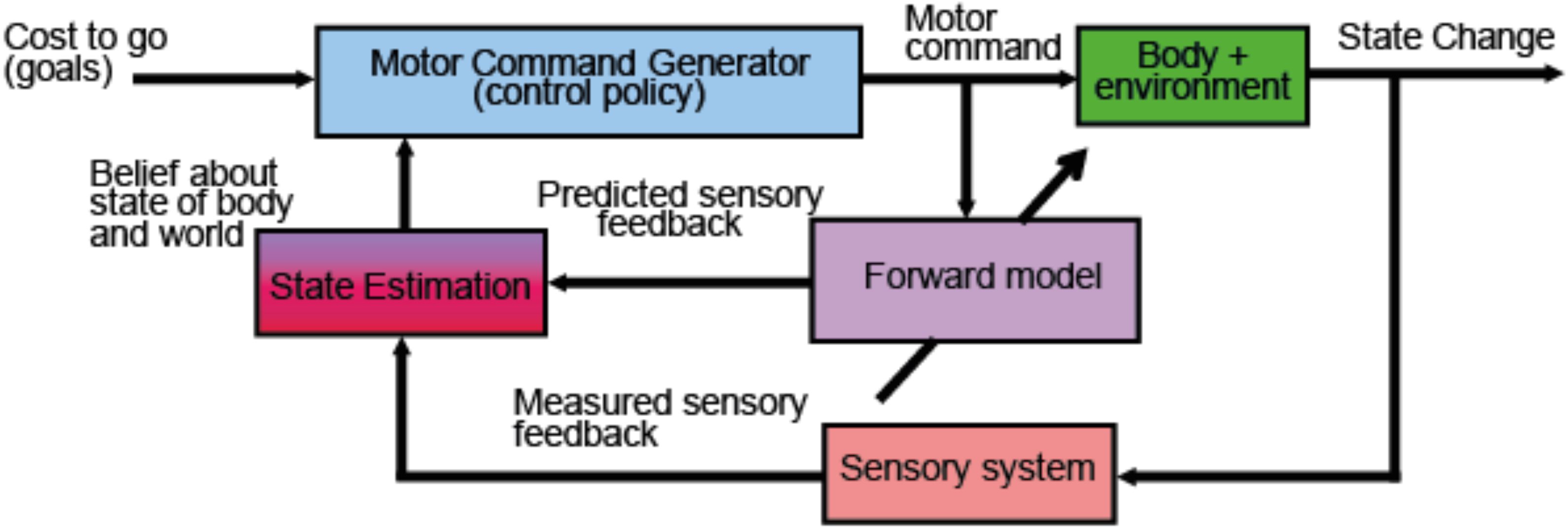
Reinforcement learning

- Inference alone does not produce appropriate actions
- Reinforcement learning implements reward-based learning of appropriate actions

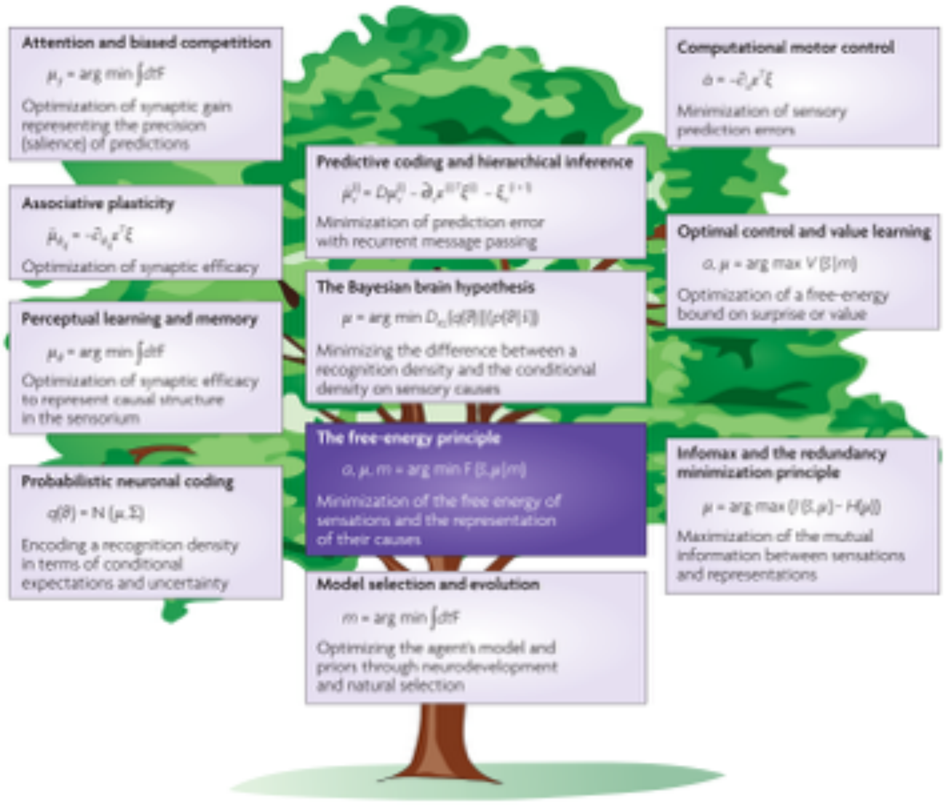


Optimal control theory

How can we generate the motor commands that are required to attain our goals?



The free energy principle



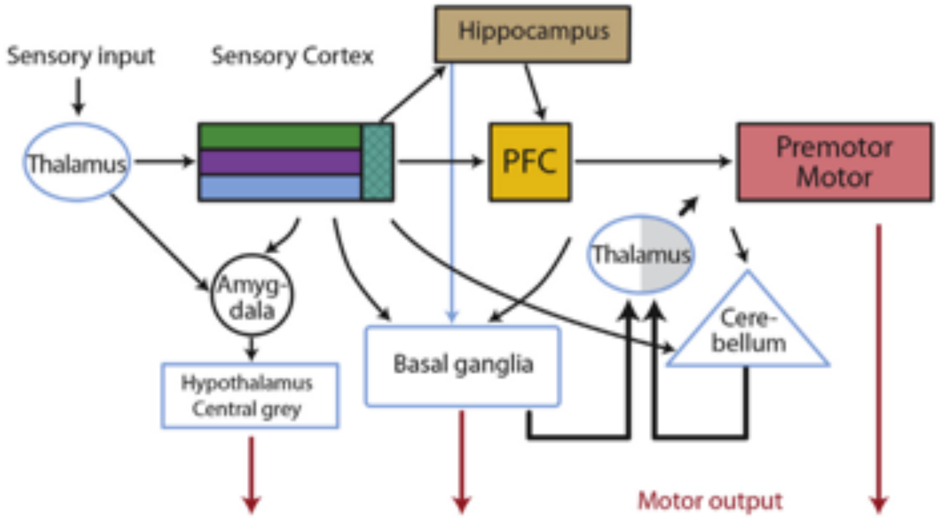
Friston, K. J. (2010). The free-energy principle: a unified brain theory? Nature Reviews. Neuroscience, 11(2), 127–138

Unifying theories

- The free-energy framework aims to tie together different computational models, placing perception and action within one framework.
- Strongly linked to the Bayesian brain hypothesis and the predictive processing account (Clark, 2016)
- In this framework, actions are set to come about such as to realize expectations on interoceptive, exteroceptive and proprioceptive states
- The verdict is still out

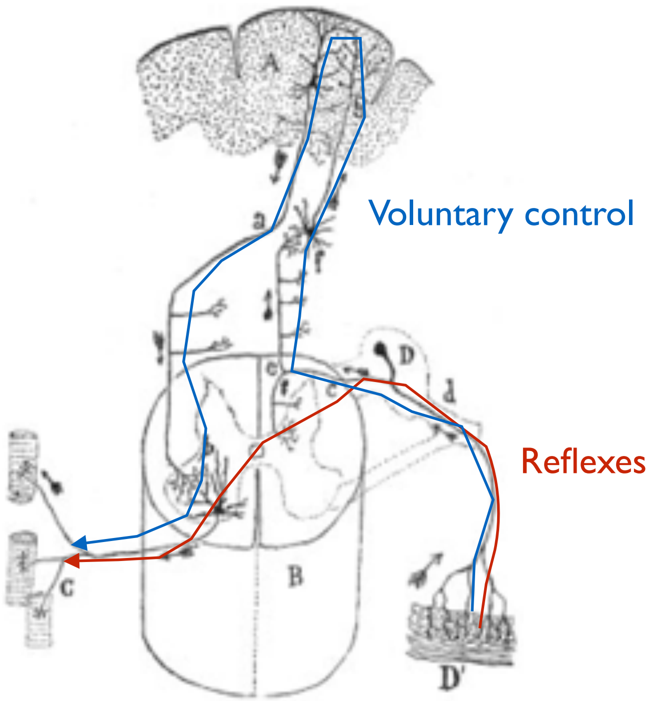
Neural implementation of computational models

- From normative models towards implementation-level descriptions
- Can we understand how cognitive processes can be an emergent property of neurons and their connections

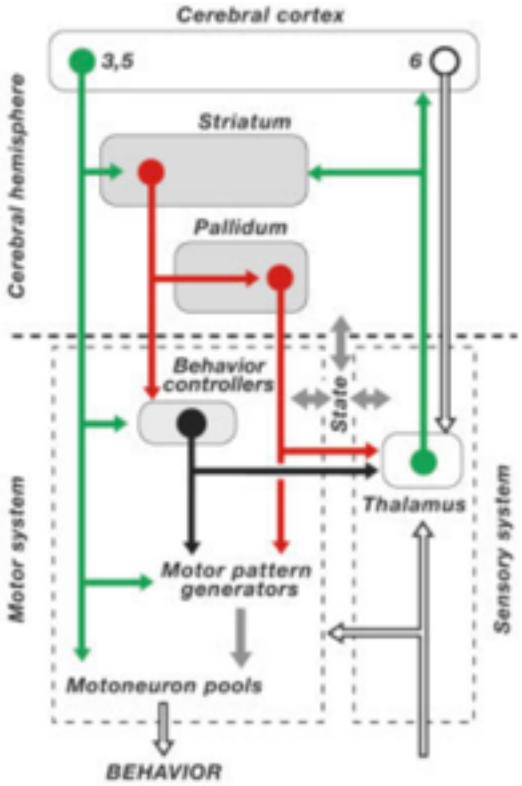


Lisman, J. (2015). The Challenge of Understanding the Brain: Where We Stand in 2015. Neuron, 86(4), 864–882. doi:10.1016/j.neuron.2015.03.032

Neural circuits underlying voluntary control of motivated behaviors

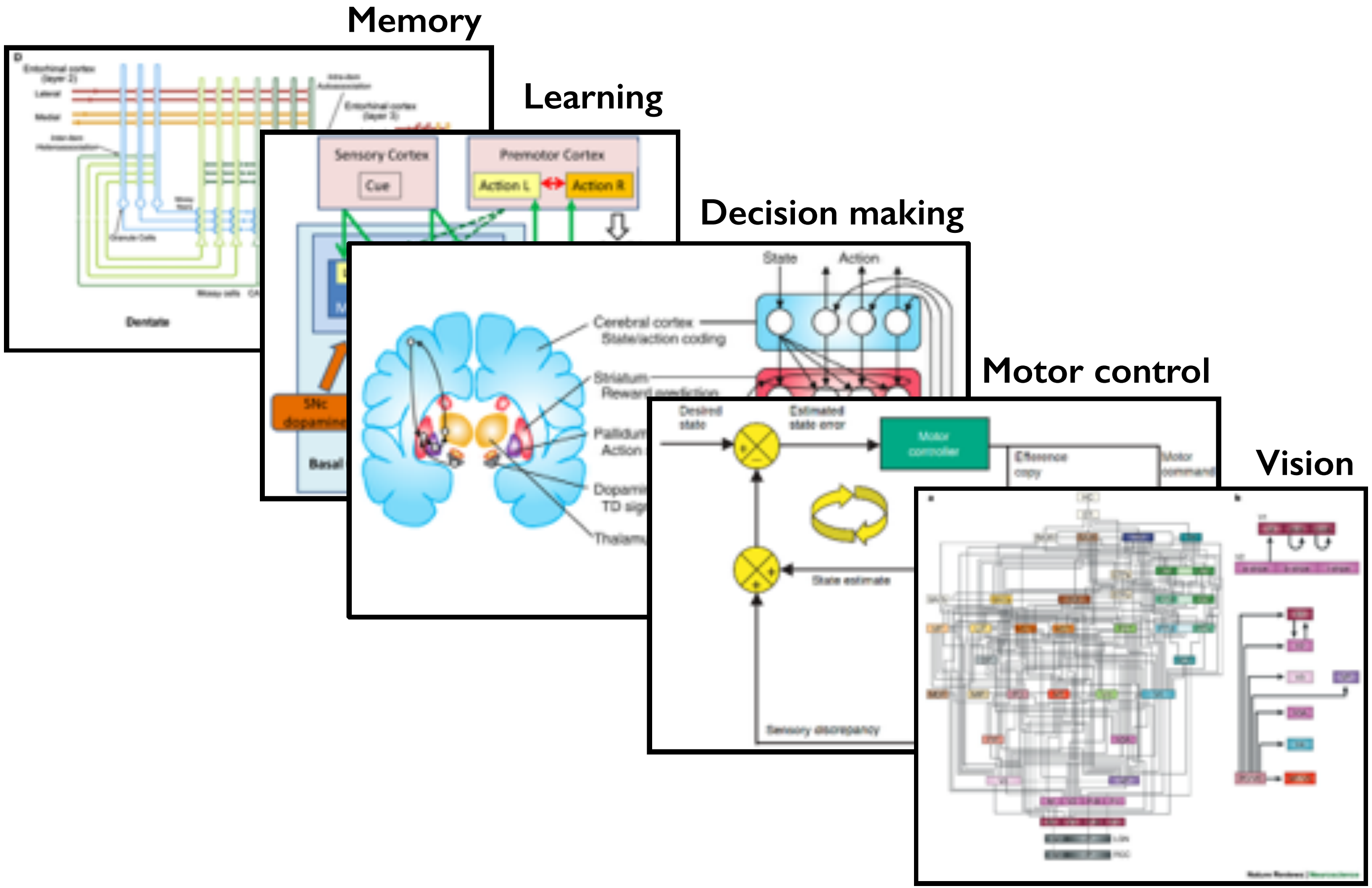


Cajal, 1894

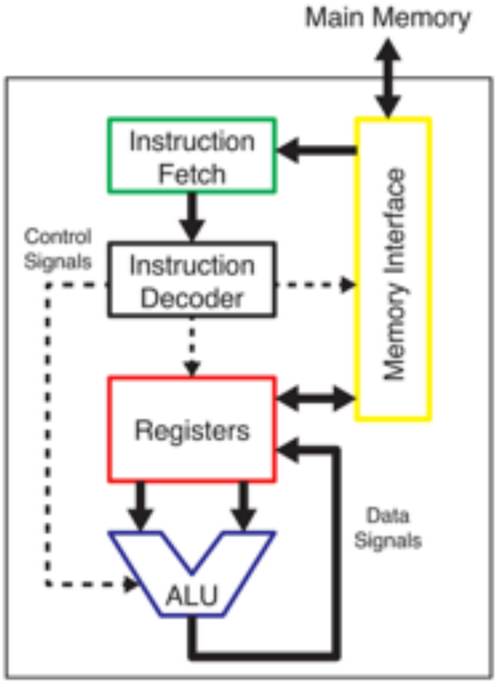


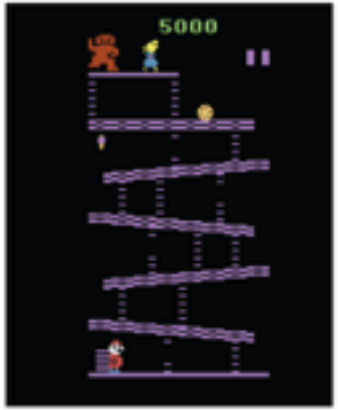
Swanson, 2000

The brain as a collection of special-purpose devices



Could a neuroscientist understand a microprocessor?





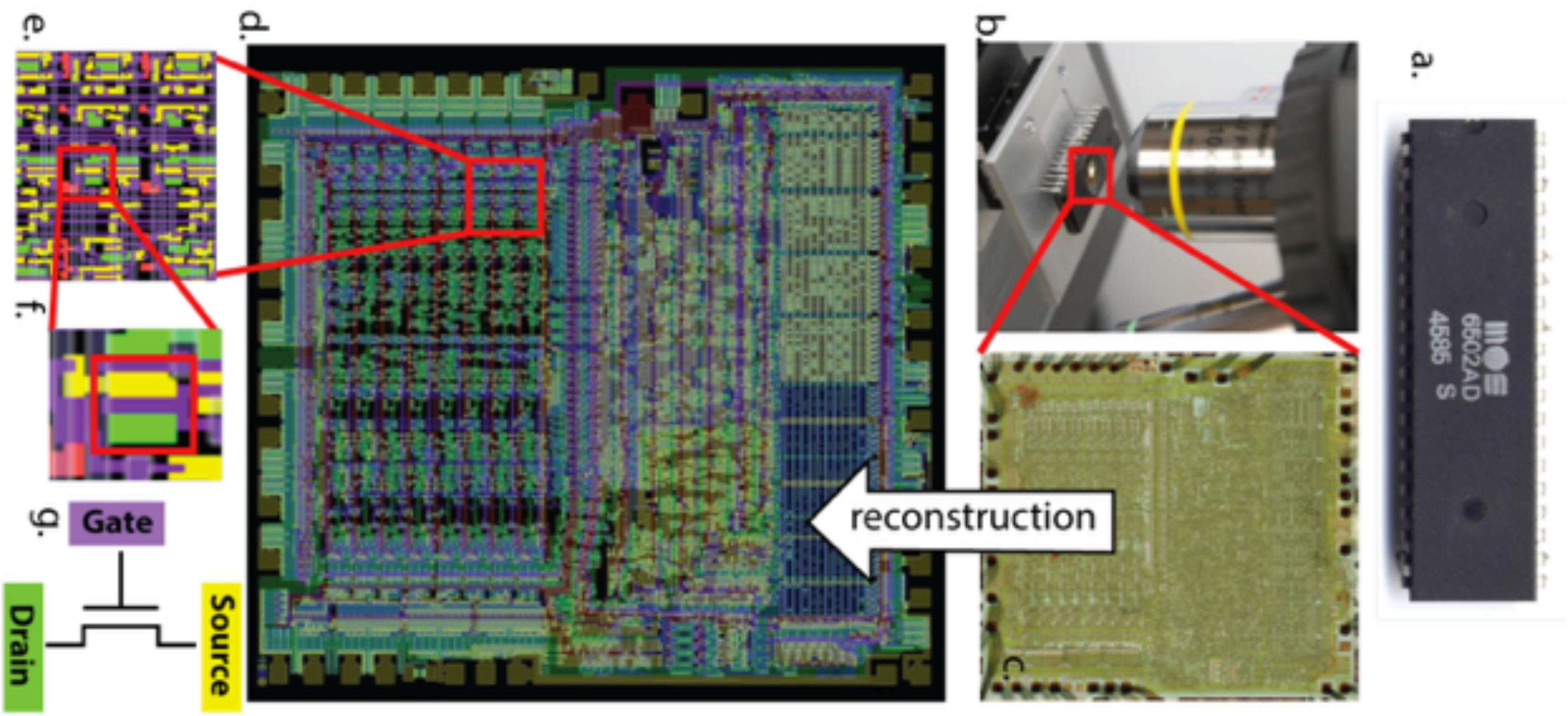
a. Donkey Kong (DK)

b. Space Invaders (SI)

c. Pitfall (PF)

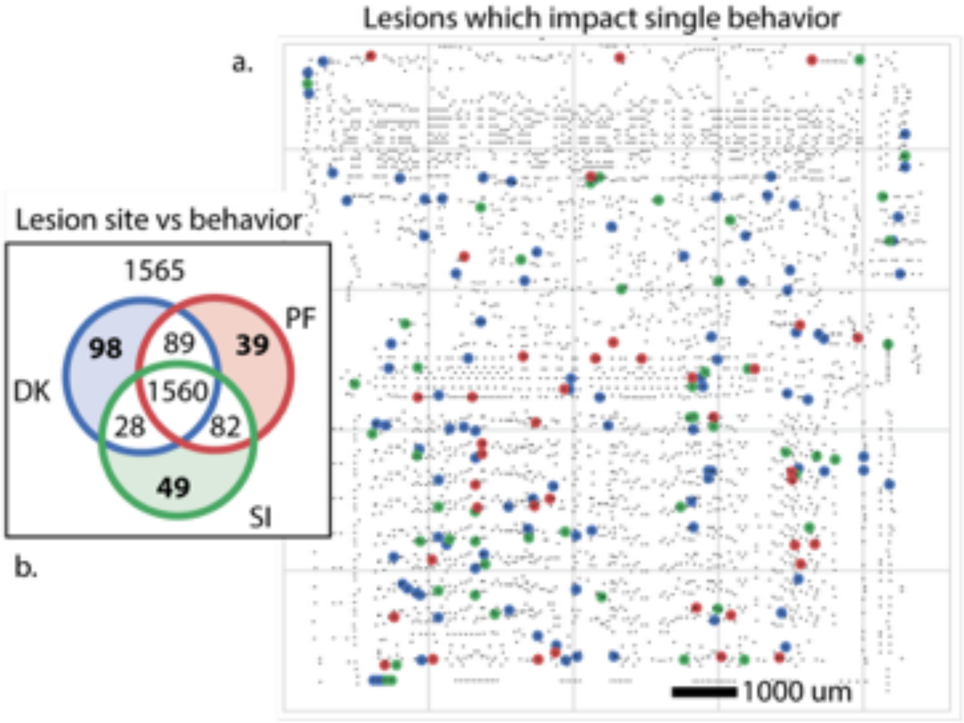
Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Connectomics: Reverse engineering the chip



Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

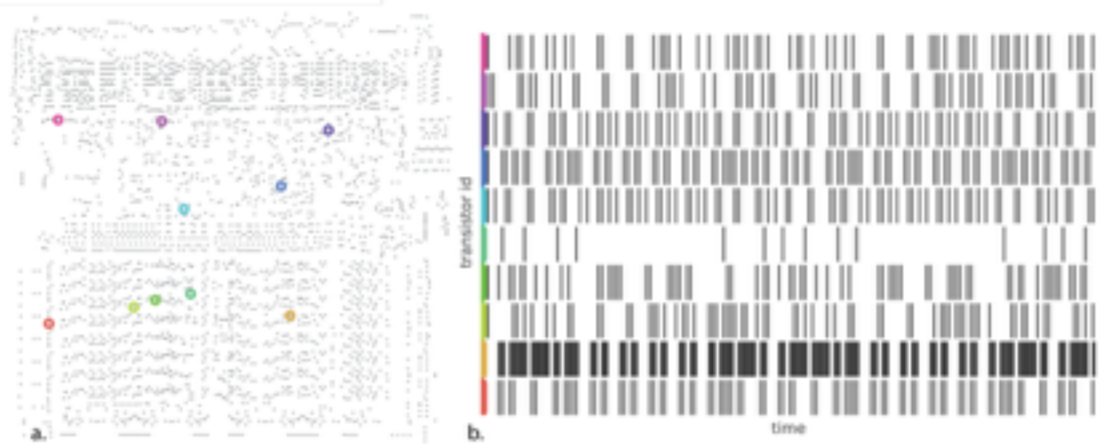
Lesioning study

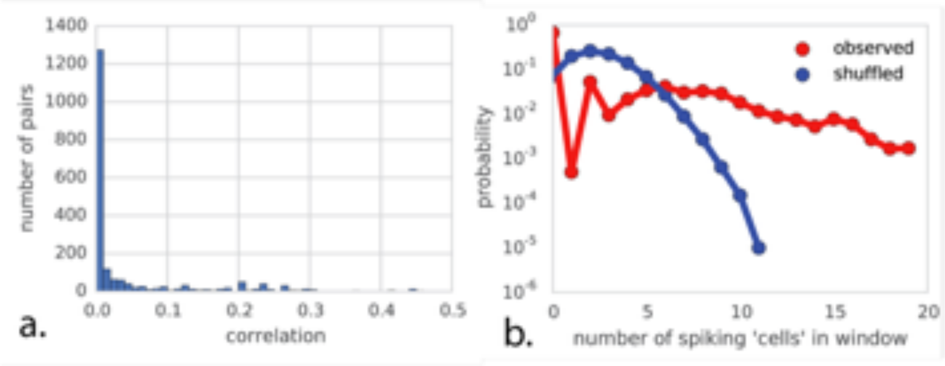


A given transistor is obviously not “responsible” for Donkey Kong or Space Invaders.

Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

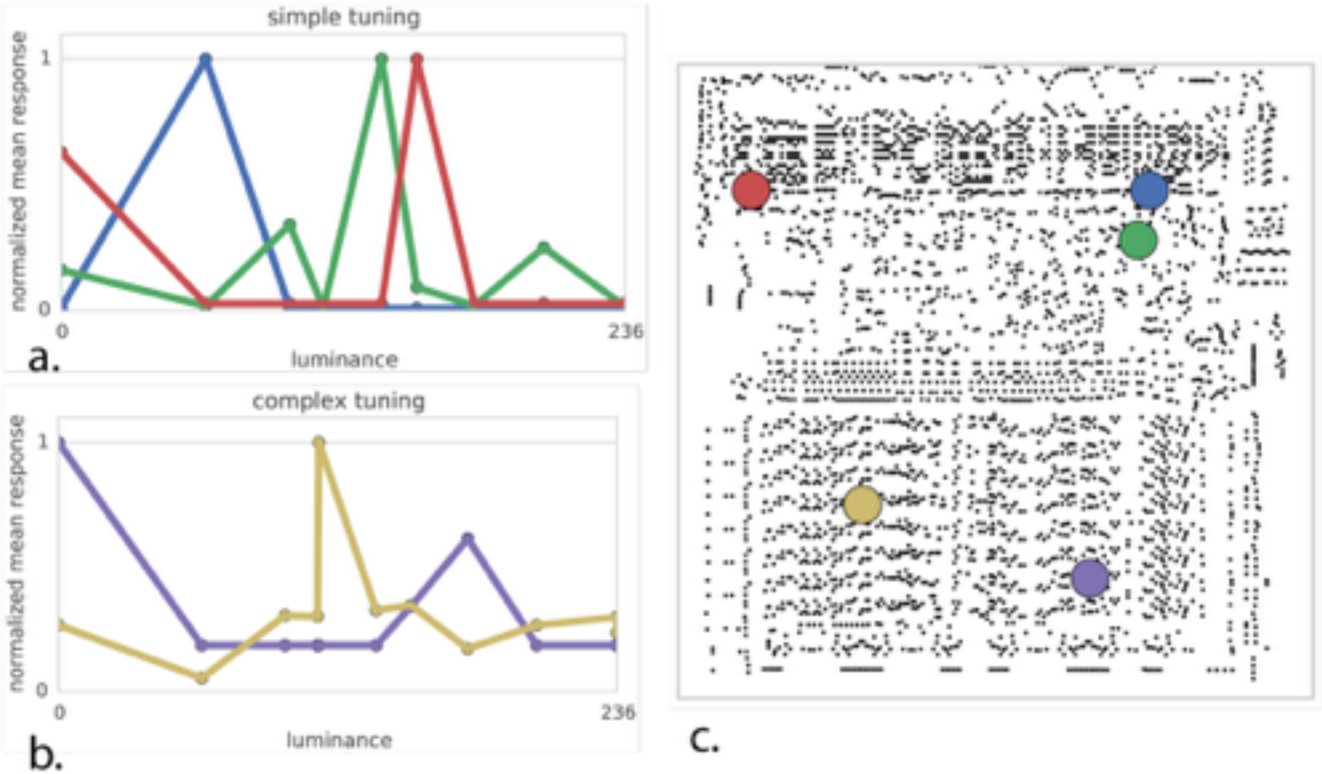
Spike analysis





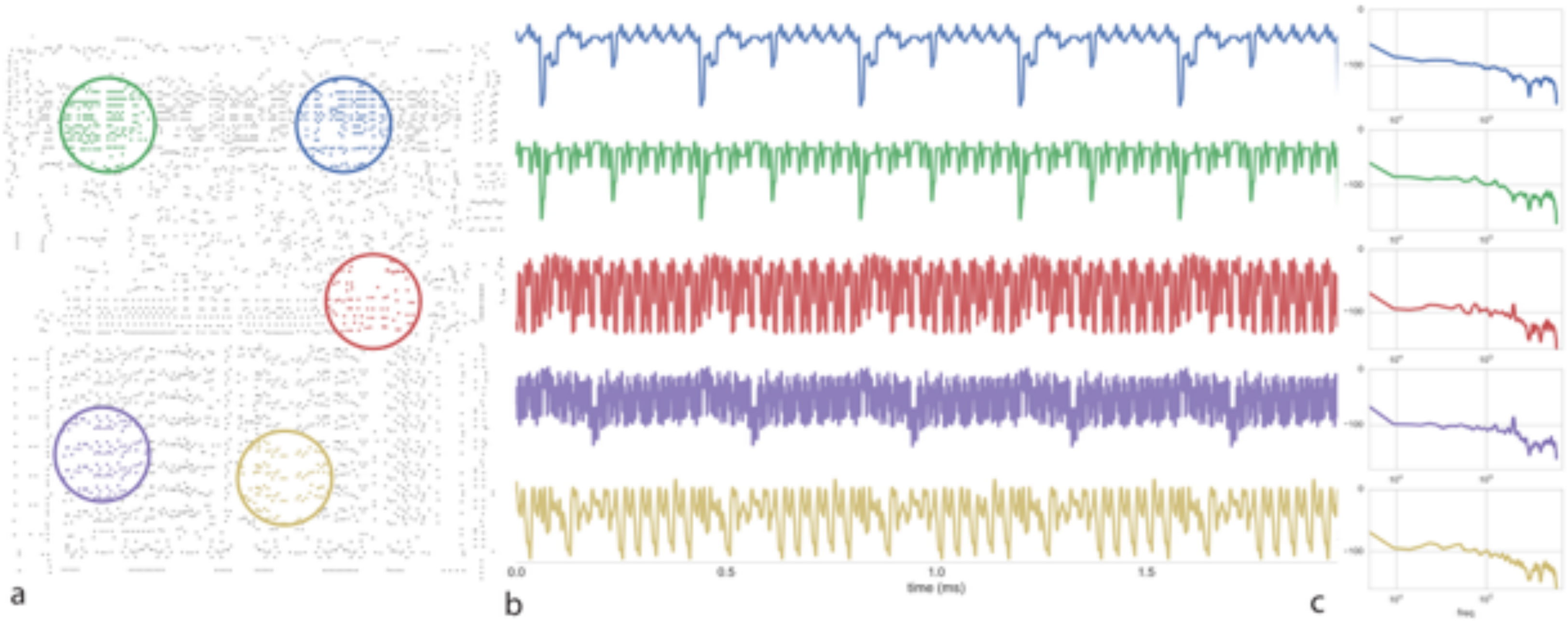
Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624
Elad Schneidman et al. “Weak pairwise cor- relations imply strongly correlated network states in a neural population.” In: Nature 440.April (2006), pp. 1007–1012.

Tuning curves



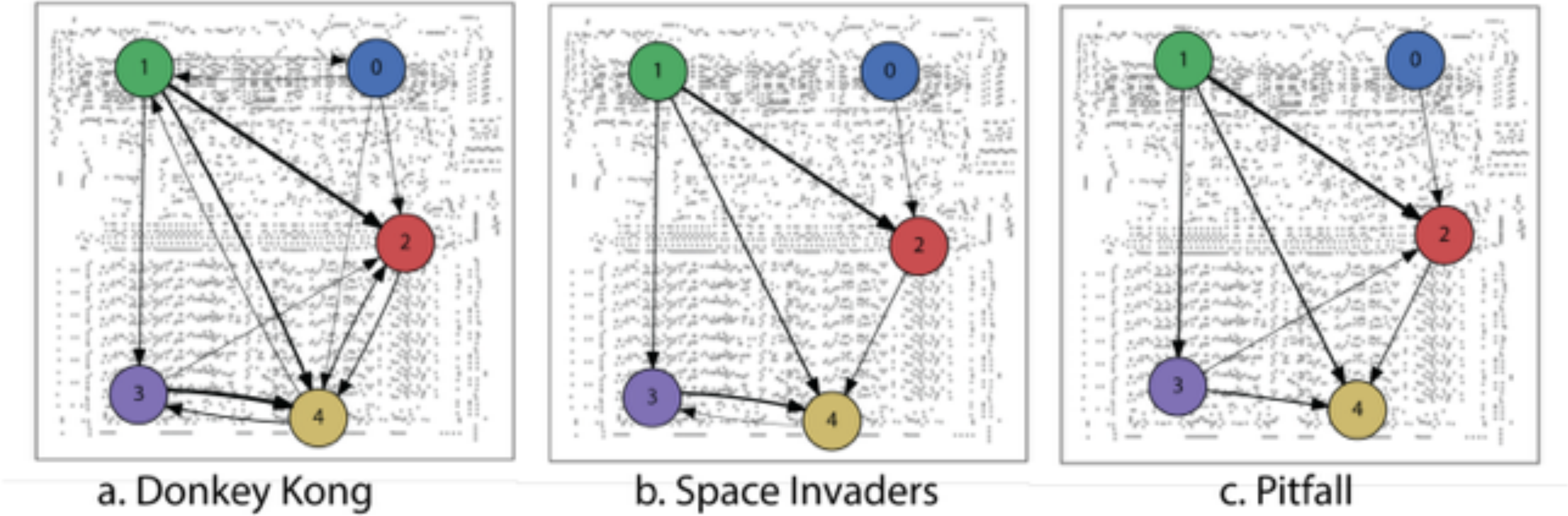
Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Local field potentials



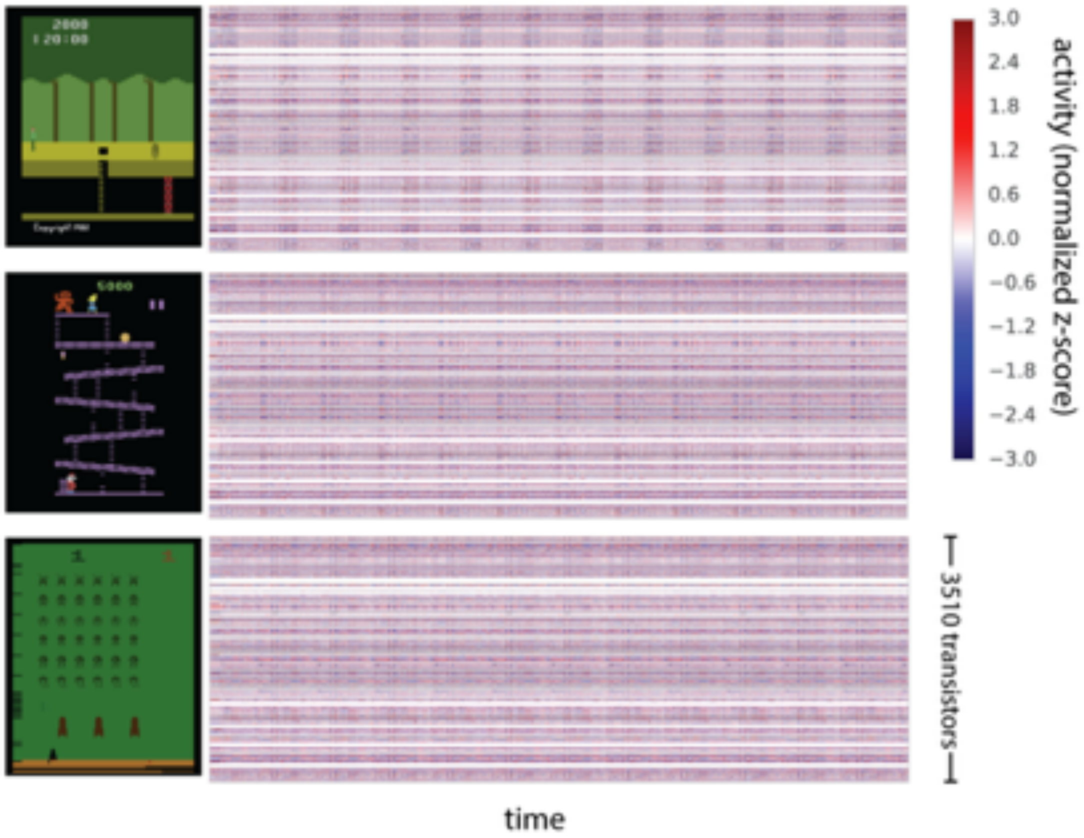
Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Granger causality



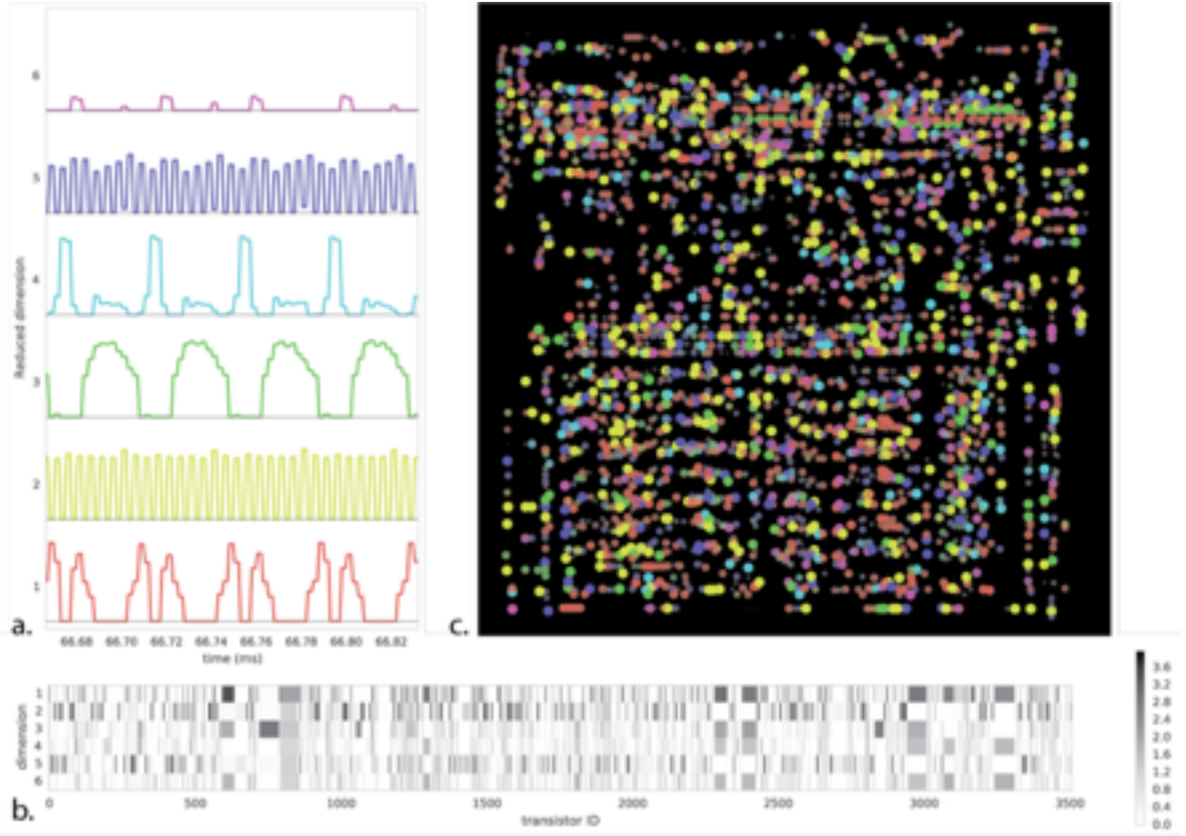
Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Whole brain recordings



Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Dimensionality reduction



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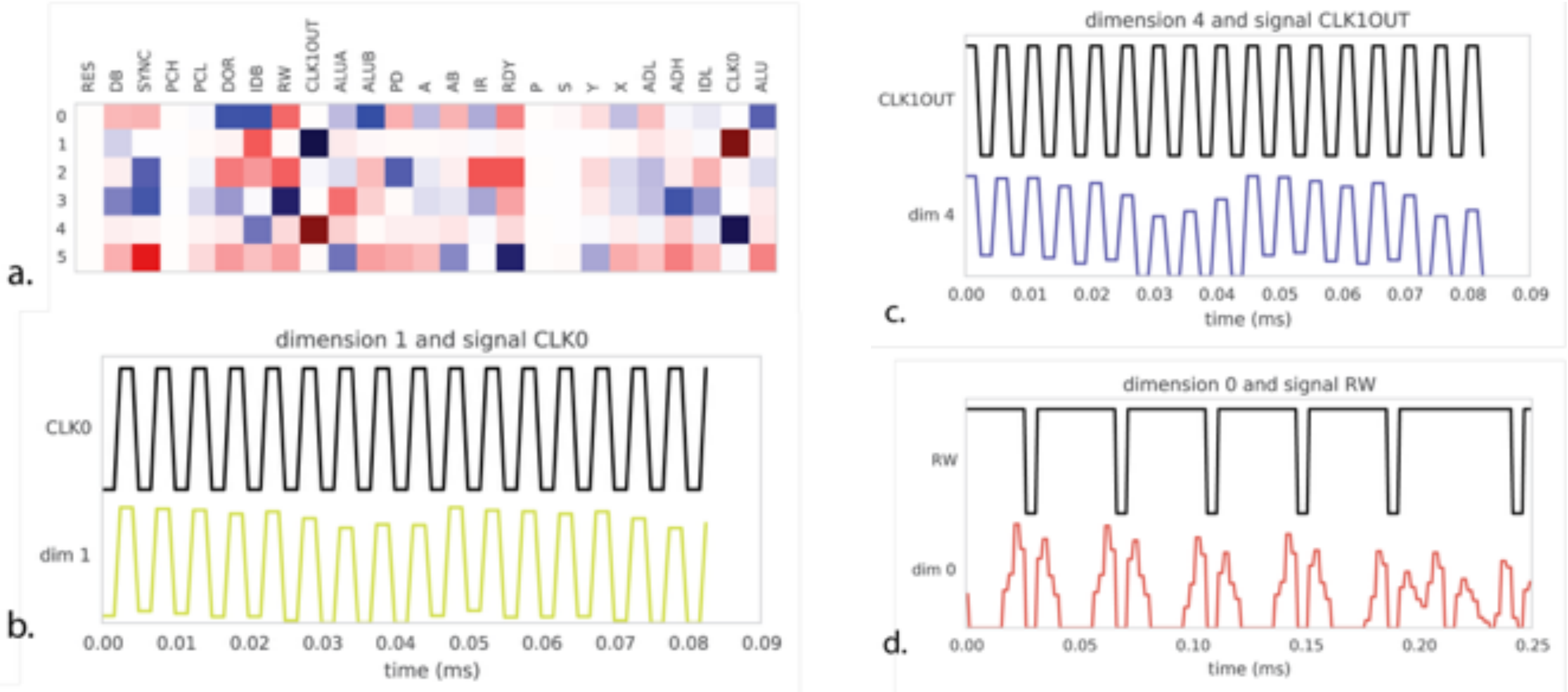
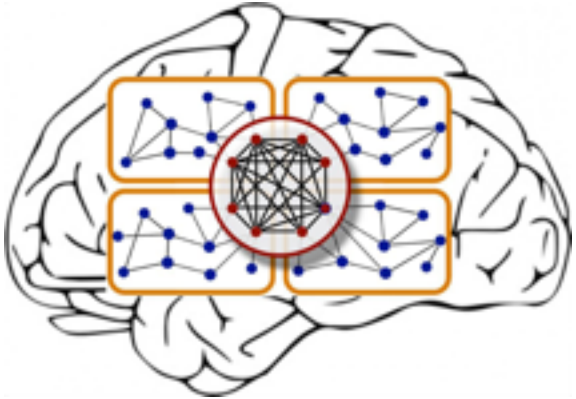
Dimensionality reduction



Jonas, E., Kording, K.P., 2016. Could a neuroscientist understand a microprocessor ? XXI, 1–5. doi:10.1101/055624

Artificial neural networks



Previously described computational models focus on normative (computational and algorithmic) principles

Artificial neural networks provide a framework for implementing cognitive processes using locally interacting artificial neurons

These ANNs may or may not embed Bayesian inference, reinforcement learning, and optimal control principles

Artificial neural networks

Major research focus in Computational Cognitive Neuroscience lab

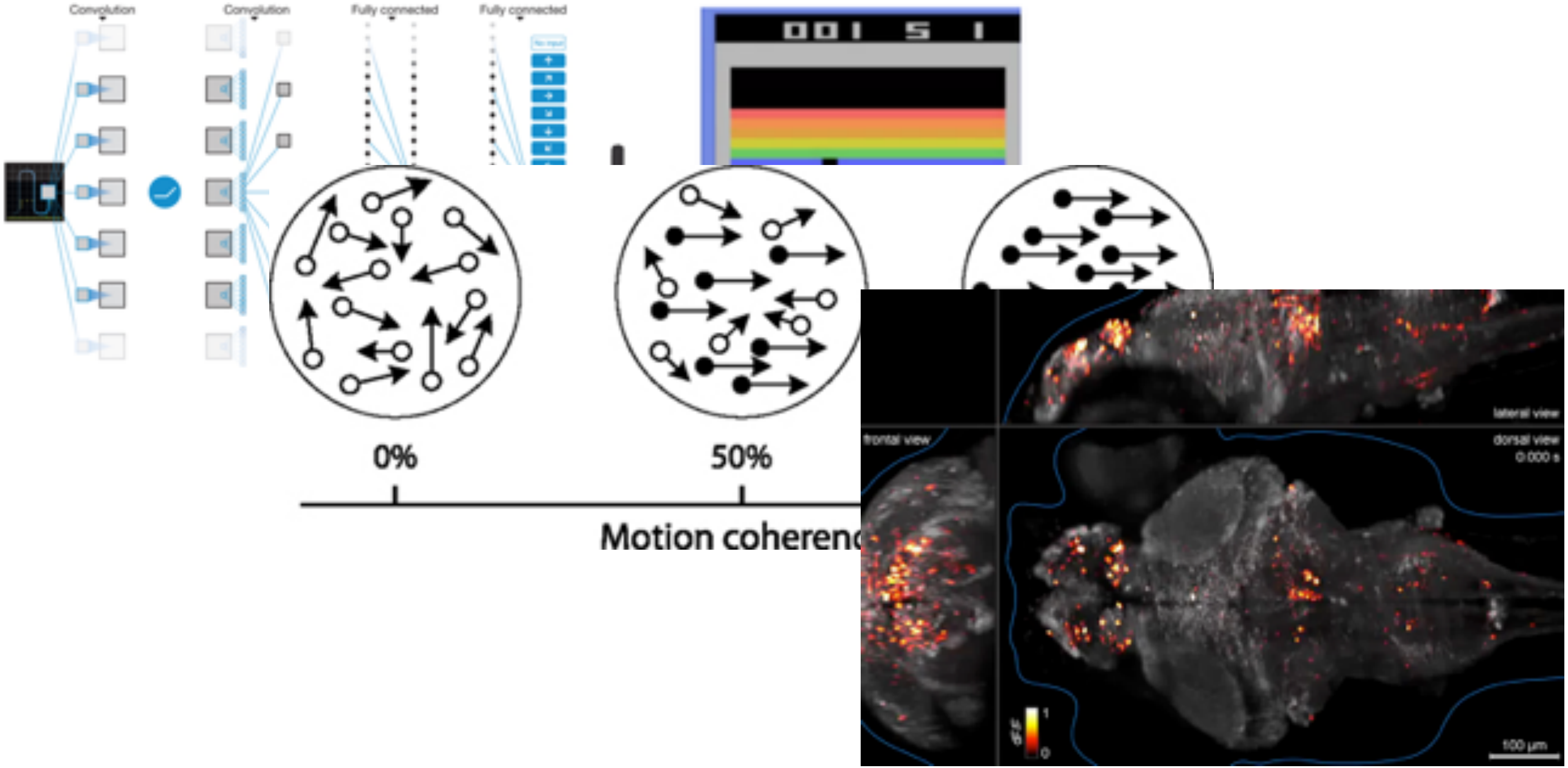
Understanding the nature of representations in our brains

Improving biological realism of existing ANNs

Development of ANNs that model particular cognitive tasks

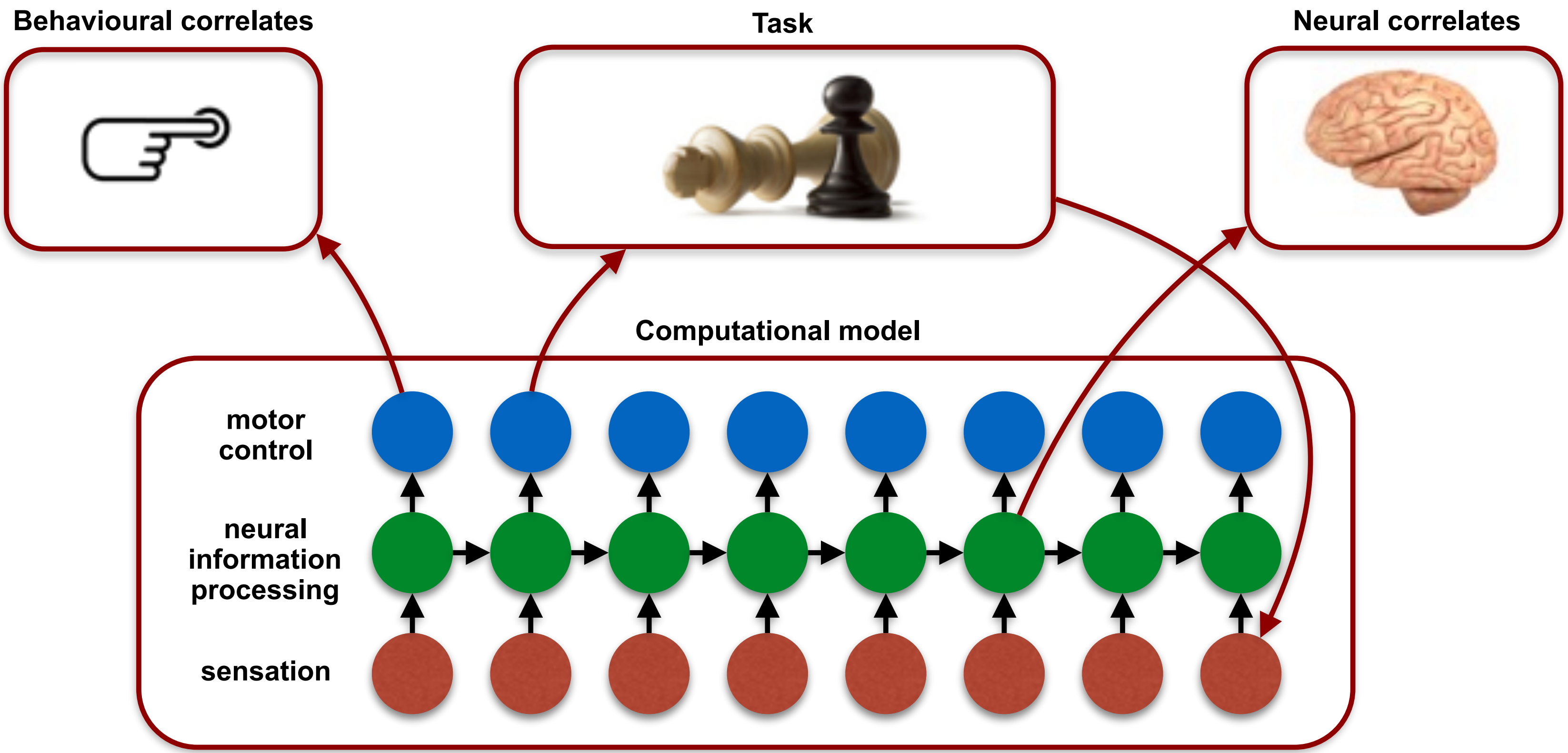
Building computational models of cognitive function might be more fruitful than data analysis methods applied to the system at hand

Examples


Convolution
Convolution
Fully connected
Fully connected
0%
50%
Motion coherenc
lateral view
frontal view
dorsal view
0.000 s
100 µm

Cognitive neuroscience in the 20th century

Cognitive neuroscience in the 21st century



What do artificial neural networks tell us about the human brain?

The great convergence

- New developments in AI and neuroscience start to shed light on how organisms can behave in an adaptive manner
- An example of The Great Convergence
- Still we should mind the reality gap between cognitive processing in artificial and biological agents
- In the following, we identify a number of important topics that are relevant for this discussion

Core ingredients of biologically plausible models

- Developmental start-up software (intuitive physics, intuitive psychology)
- Learning as rapid model building (compositionality, causality, learning-to-learn)
- Thinking fast (approximate inference in structured models)
- Model-free versus model-based reinforcement learning
- Continual learning
- The right objective function(s)

Lake, B.M., Ullman, T.D., Tenenbaum, J.B., Gershman, S.J., 2016. Building Machines That Learn and Think Like People 2, 1–44.

Kumaran, D., Hassabis, D., McClelland, J.L., 2016. What learning systems do intelligent agents need? Complementary Learning Systems Theory Updated. Trends Cogn. Sci. 20, 512–534. doi:10.1016/j.tics.2016.05.004

Marblestone, A.H., Wayne, G., Kording, K.P., 2016. Towards an integration of deep learning and neuroscience 1–61.

Core ingredients (continued)

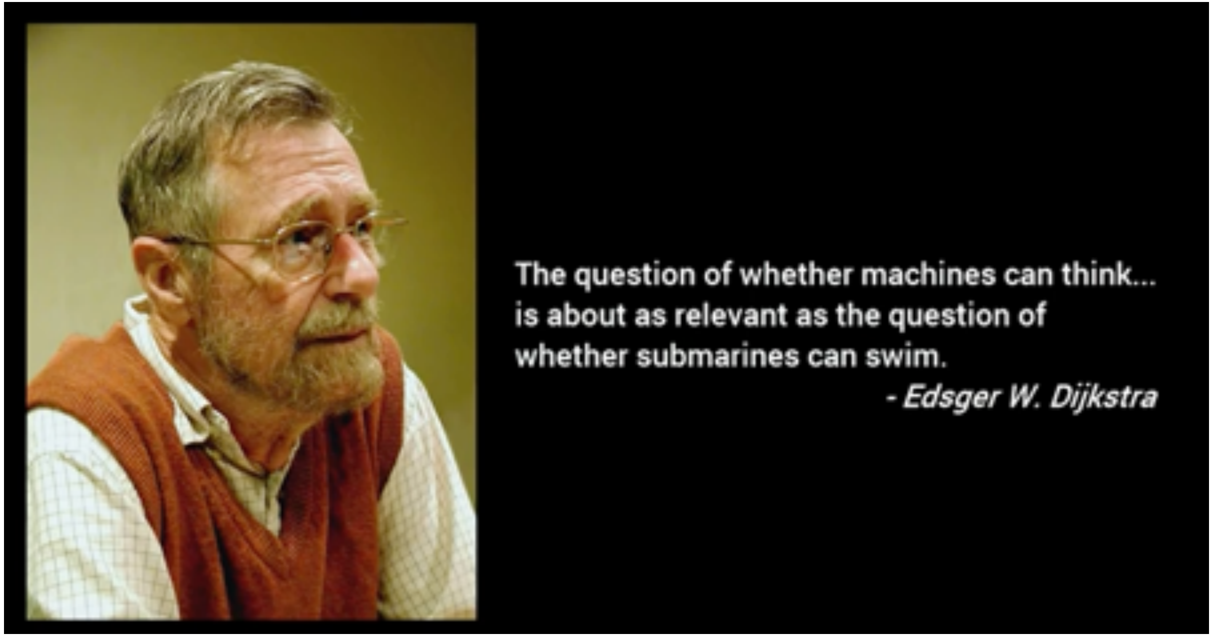
- The right architecture
- Spiking versus rate-based models
- Plausible learning rules
- Operate according to Bayes optimal principles
- Incorporate top-down and bottom-up drive
- Disentanglement
- Online learning
- Incorporate long range dependencies

Lake, B.M., Ullman, T.D., Tenenbaum, J.B., Gershman, S.J., 2016. Building Machines That Learn and Think Like People 2, 1–44.

Kumaran, D., Hassabis, D., McClelland, J.L., 2016. What learning systems do intelligent agents need? Complementary Learning Systems Theory Updated. Trends Cogn. Sci. 20, 512–534. doi:10.1016/j.tics.2016.05.004

Marblestone, A.H., Wayne, G., Kording, K.P., 2016. Towards an integration of deep learning and neuroscience 1–61.

A computer scientist's point of view



But…

- Computational modeling of cognitive processes may lead to better AI as well as fundamental new insights on neural information processing

Goal of this course

- Get acquainted with computational modeling approaches in CNS
- Learn about a cross-section of different topics
- Practice with basic python assignments
- Shape your own thinking about this topic via individual projects
- Present your work via a pitch presentation

Related:

- Computational neuroscience
- Statistical machine learning
- Capita selecta on advances in neural networks
- Potential for master thesis research projects

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www.ccnlab.net

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