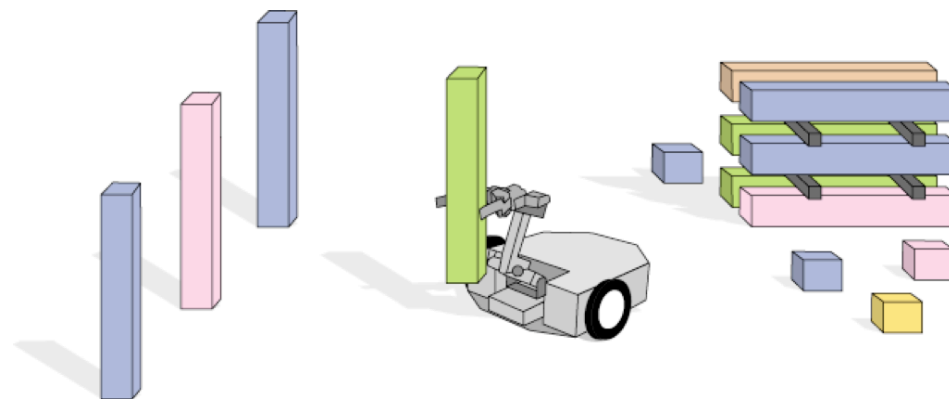


Goal-Leaders

Goal-directed, Adaptive Builder Robots



GIOVANNI PEZZULO
NATIONAL RESEARCH COUNCIL, ROME, ITALY



Goal-Leaders Consortium

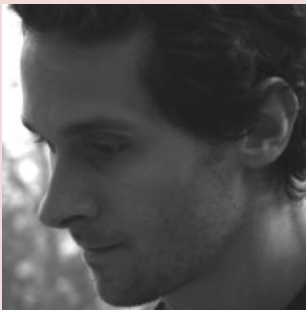


**National
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Pompeu Fabra,
Spain (UPF)**

**Universiteit van
Amsterdam, the
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(UVA)**

**Lund University,
Sweden
(ULUND)**



Giovanni Pezzulo

Paul Verschure

Cyriel Pennartz

Christian Balkenius

**Computational
modeling of
anticipation and
goal-directedness**

**Computational
neuroscience, bio-
constrained robot
models, DAC**

**Neuroscience of
spatial navigation,
prediction and
goal-directedness**

**Epigenetic
robotics, attention
control, navigation
and motivation**

Goal-Leaders: enhancing robots' goal-directedness and proactivity

Brains, goal-directedness and autonomy

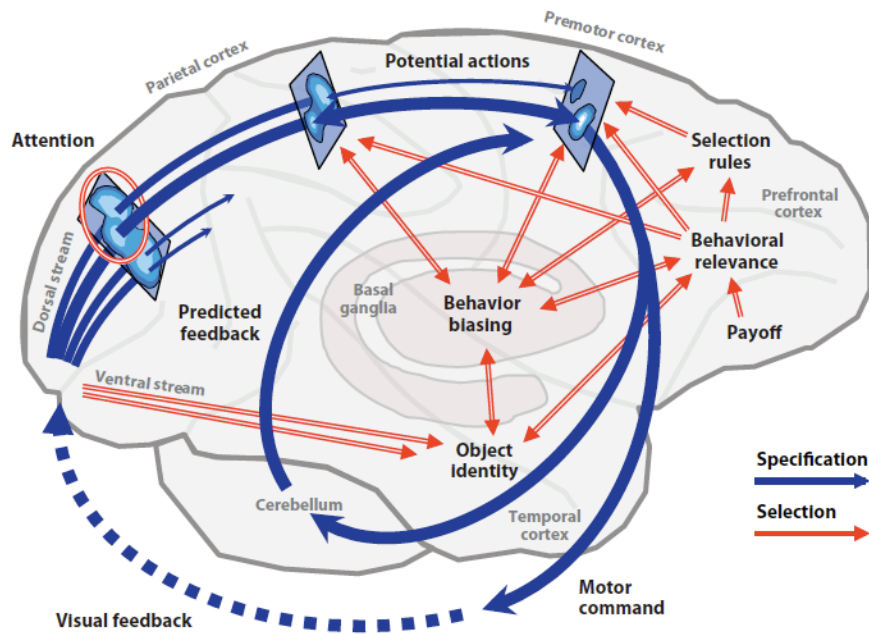


- Brain “information processing” is dominated by endogenously determined motivations, predictions and goals, and processes that prepare to action
 - Cascading effects on perception, memory, attention, monitoring, behavior, etc.
 - In turn, this sensorimotor loop affects internal processing (drive and goal setting, action selection, prediction, etc.)

Brains, goal-directedness and autonomy

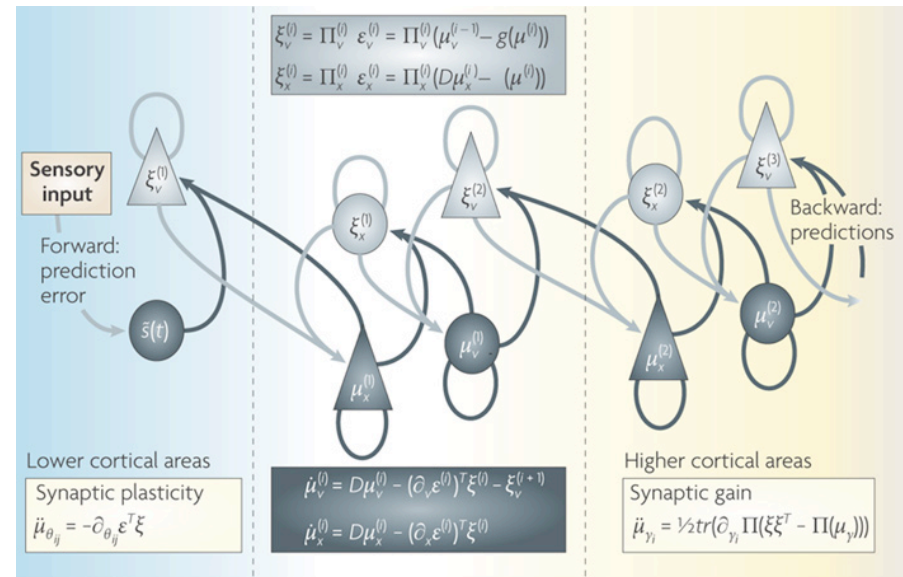


Affordance competition hypothesis



Cisek and Kalaska, 2010

Free energy principle and predictive coding

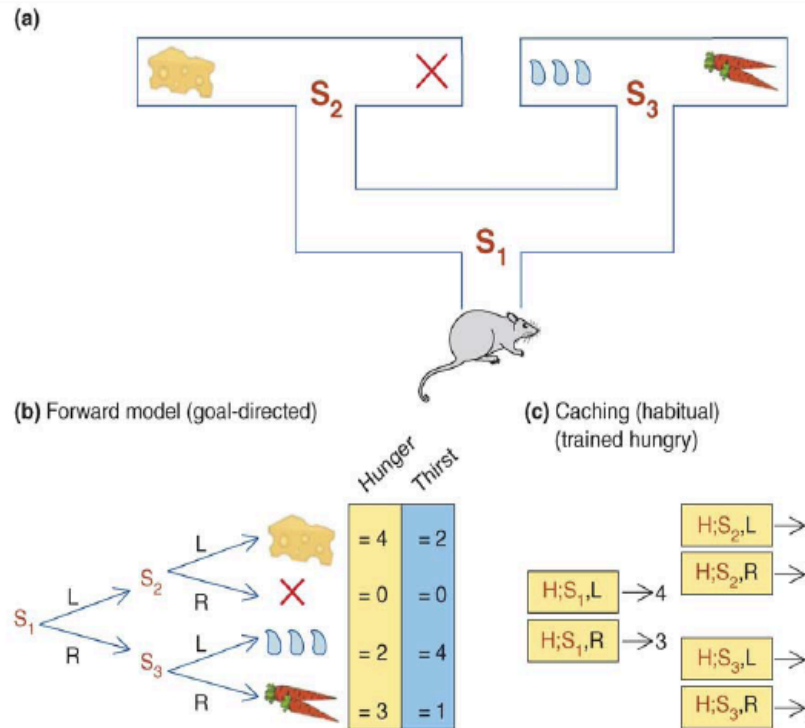


Nature Reviews | Neuroscience

Friston, 2010

Many others: predictive brain, Bayesian brain, ideomotor principle, sensorimotor theories, model-based reinforcement learning in neuroeconomics, etc.

Goal-directed vs. habitual behavior

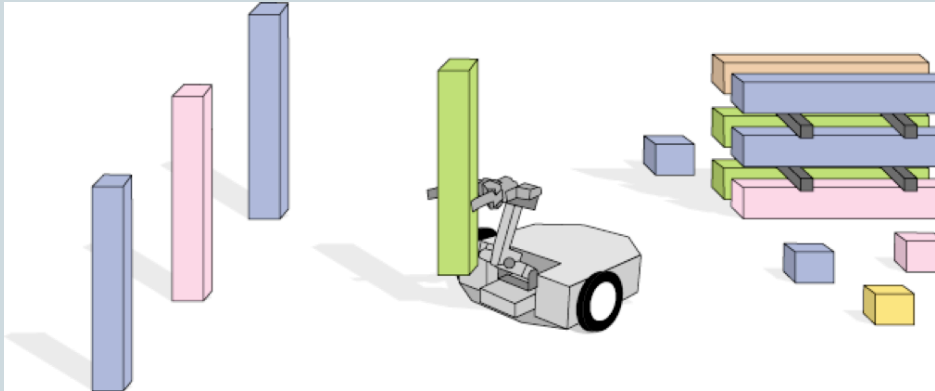


Model-based RL Model-free RL

Dickinson, Balleine (1998); Daw et al., (2005)

**Project Objective:
Adaptive Builder Robots**

Adaptive Builder Robots



The robot is required to assemble a construction by selecting, reaching and assembling materials having different size and colour.

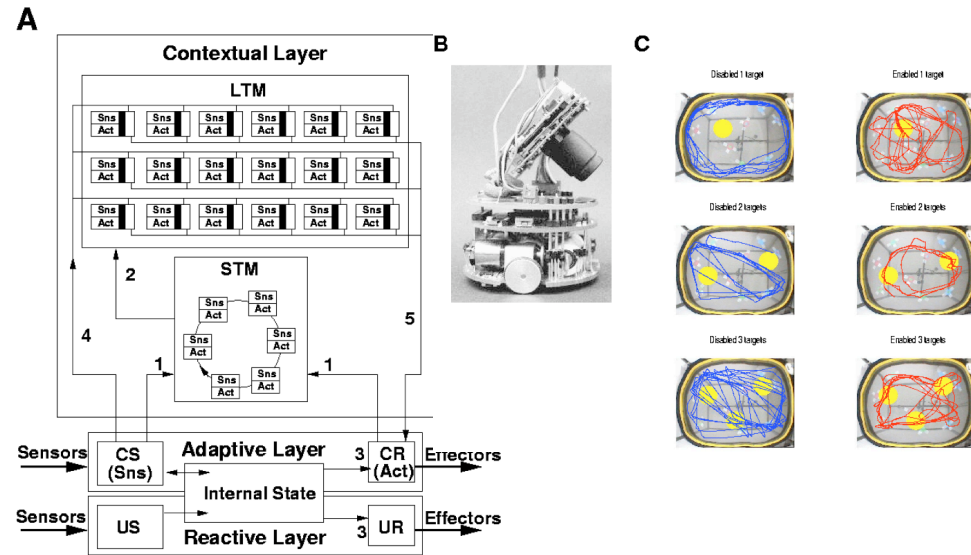
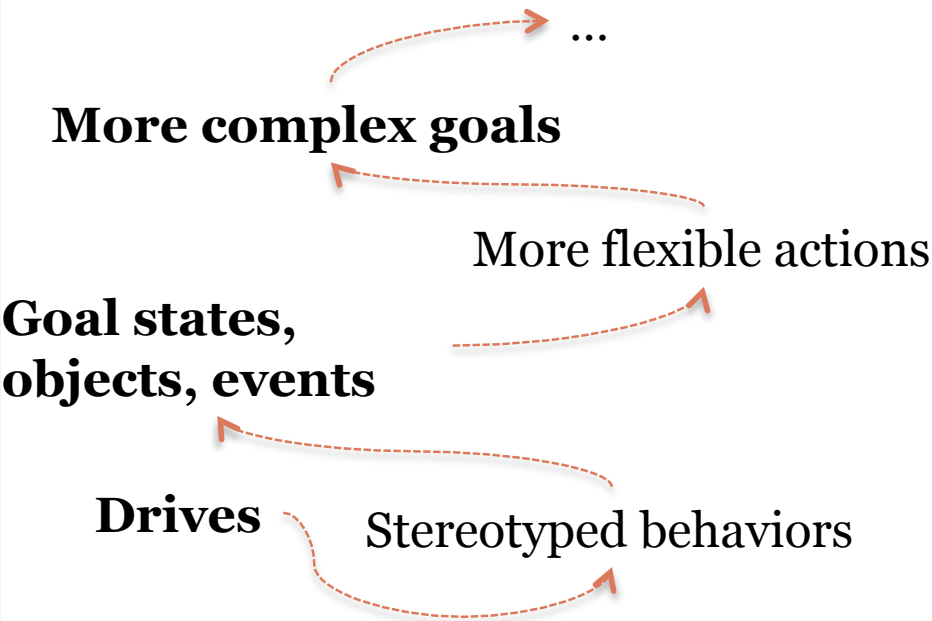
- Realize a set of externally assigned tasks (e.g., fetching objects, clearing an area, composing building parts)
- Maintain homeostatic drives in safe range (e.g., never remain without energy, not get hurt)
- Combinatorial tasks, subgoaling, cognitive control (e.g., finding and stacking objects to compose a given construction)
- Proactivity (e.g., store useful building parts, predict loss of energy and recharge before starting a long task)

**We need breakthroughs in robots'
goal-directedness and proactivity**

1. Enhancing robots' goal-directedness

Learning increasingly sophisticated goals and goal-achieving strategies

Our starting point:
Distributed adaptive control (DAC)



Verschure, Kröser et al.(1993); Verschure, Voegtlin et al. (2003)

Reactive	Adaptive	Contextual
Drive: having stable structure, tall structure	Represents objects in terms of how much they support other objects (cubes vs. sphere; big objects down, small objects on top). Objects / place value	Goal states: "Towers", "bridges"
Reactive behavior: stacking		Strategies for efficient assembling of constructions, storing of useful objects, subgoaling

2. Enhancing robots' proactivity

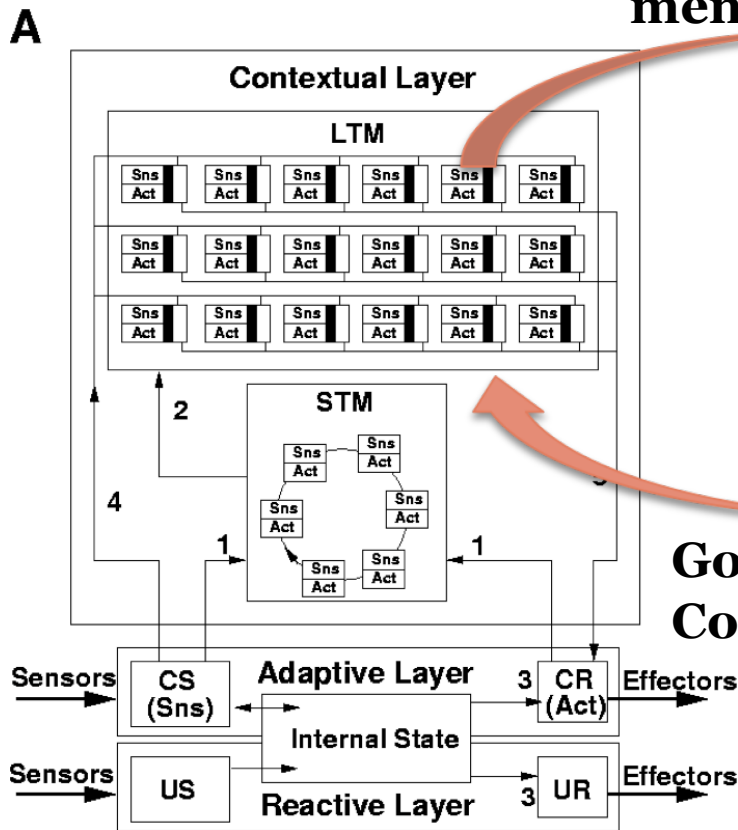


From Marc Jeannerod's Lab

**Prediction,
mental simulation**

**Evaluate outcomes
Predict dangers
Set distal goals**

**Goal-directedness,
Cognitive control**



A few achievements so far

Hippocampal-striatal loops for mental simulation

Prospective coding in the rat hippocampus (CA3): forward sweeps at decision points



Reward-predictive cues modulate firing patterns of hippocampal and striatal neurons



Johnson and Redish (2007)



MISSING

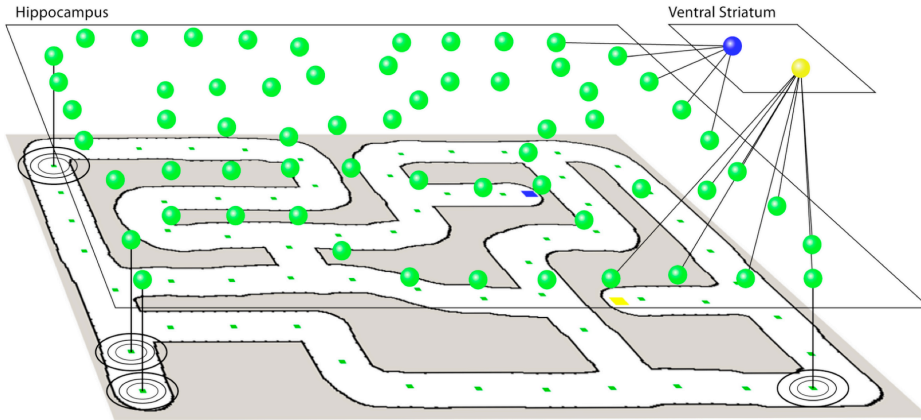
Lansink et al. (in prep)

The rat's position is indicated by the white circle. The reddish areas indicate the firing rate of hippocampal neurons with place fields at that particular point of the maze.

Goal-directed decision-making: hippocampal replay for accessing reward info in the striatum



Neural circuit for the affective labeling of spatial representations

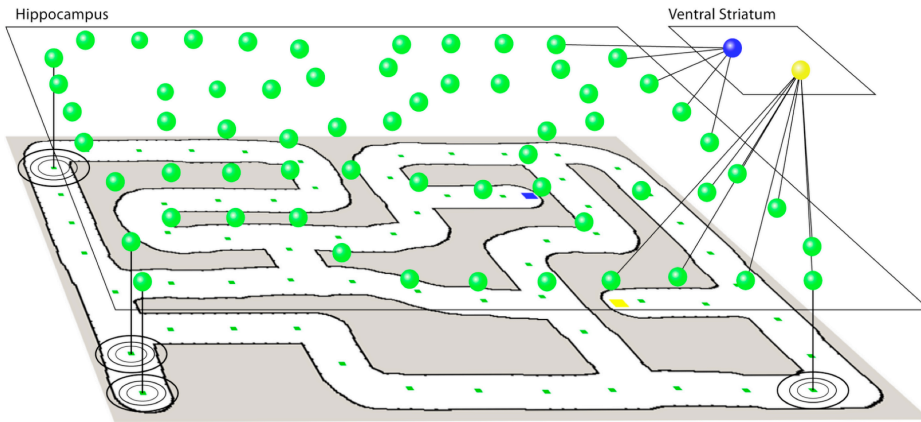


Chersi, Pezzulo (in prep.)

Goal-directed decision-making: hippocampal replay for accessing reward info in the striatum

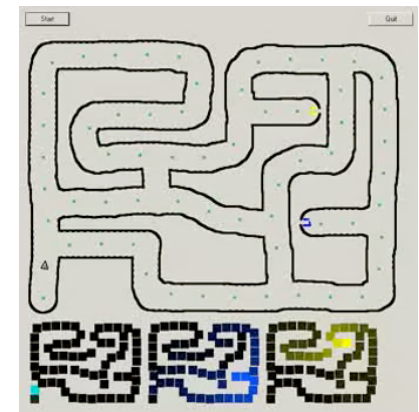


Neural circuit for the affective labeling
of spatial representations

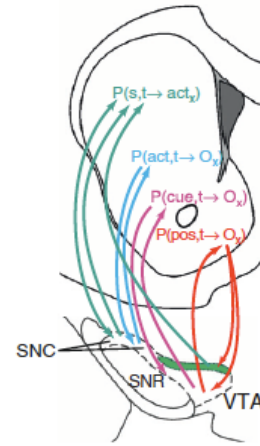
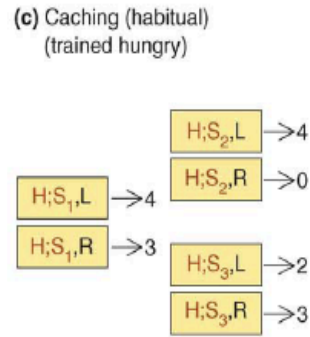
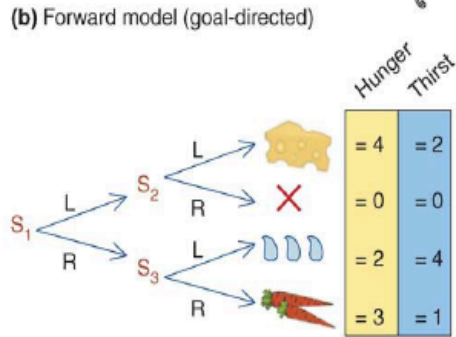
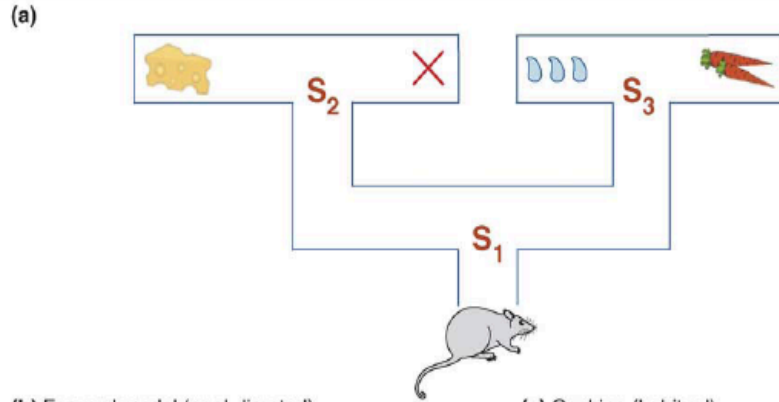


Chersi, Pezzulo (in prep.)

The neural circuit at work

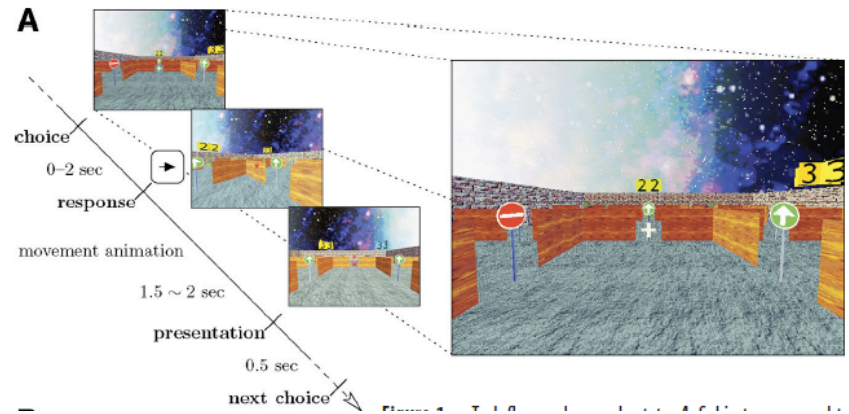


Balance between goal-directed vs. habitual choice



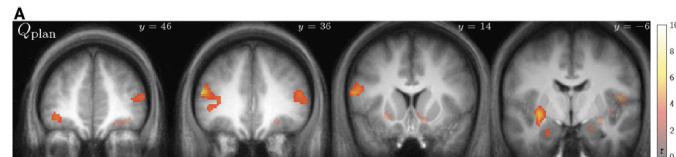
Different types of predictive learning associated with striatal sectors in rat brain.

Pennartz et al., 2011



Model-based RL Model-free RL

Dickinson, Balleine (1998); Daw et al., (2005)

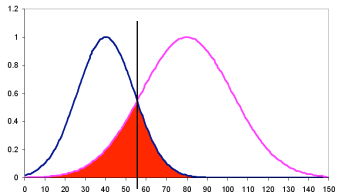


Simon and Daw., 2011

Balance between goal-directed vs. habitual choice

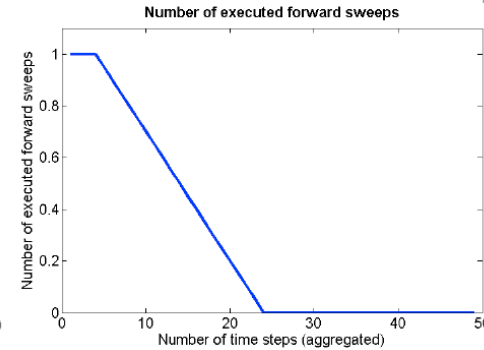


A mixed instrumental controller that solves an **exploration-exploitation dilemma**, trading off the costs of mental simulations with the value of information it produces

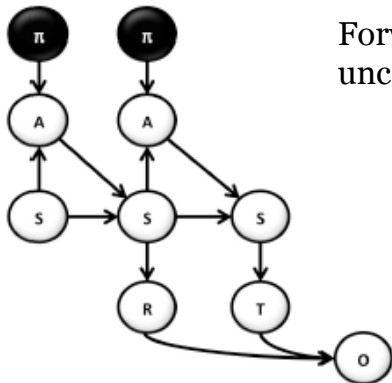
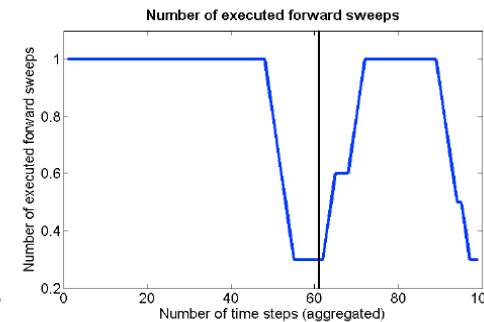


Uncertainty and variance of action value estimates

Stable environment: habituation



Changing reward contingencies



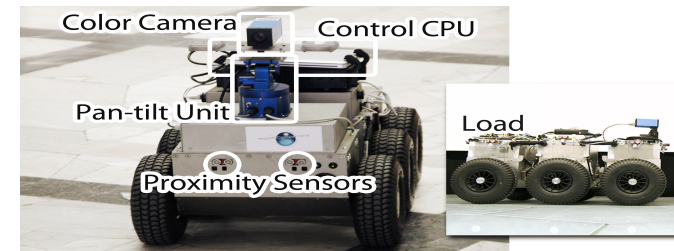
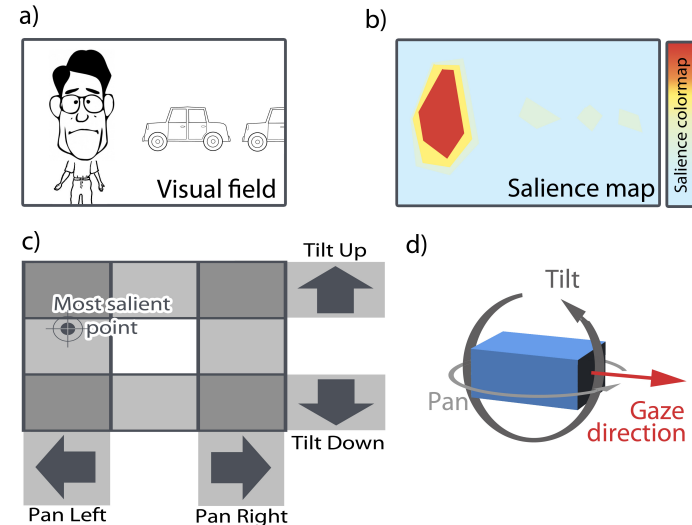
Forward sweeps to reduce uncertainty when necessary

Pezzulo et al. (sub)

Multifunctionality: Internal drive regulation of sensorimotor reflexes

Demo @ FET '11, Warsaw:
a catering assistant autonomous robot

Integration of two loops:
goal-directed navigation and
face detection



Renno-Costa, Verschure

Hippocampal place fields modeling



Emerging single place field without plasticity using a spiking model

César Rennó-Costa¹, John E. Lisman², Paul F.M.J Verschure^{1,3}

SPECS, Universitat Pompeu Fabra, Barcelona, Spain; 2. Brandeis University, Boston, USA; 3. ICREA, Barcelona, Spain

Introduction

- Mean-field model emerges place fields instantaneously - and without plasticity - from the input of grid cells, found upstream in the medial entorhinal cortex.
- Model based on two mechanisms: the integration of massive convergent input and feedback inhibition, which is translated to the E%-MAX-WTA competition rule.
- Hierarchical topology can explain the formation of multiple place fields in the dentate gyrus and single place fields in the downstream region CA3.
- Can explain how place fields are affected by environmental changes in the rate remapping phenomena when non-spatial information is considered.
- To extend the applicability of this model to more complex dynamics, including time-dependence, we've developed an implementation of its principles with spiking neurons using integrate-and-fire units.

The Model

- Three layered network based on the hippocampal anatomy: the entorhinal cortex, the dentate gyrus and CA3.
- Each layer comprises a set of standard integrate-and-fire neurons.
- The forward connections are convergent and random, with the weights set according to a Gaussian distribution, and are elicited by spikes.
- At the dentate gyrus and CA3 levels there are set associated inhibition networks capable of global inhibition. These interneurons are triggered after a specific interval from the first spike detected in the population during a cycle. This kind of circuitry generates overall population oscillation as observed in these brain regions.

Results

- The activity of the entorhinal cortex neurons at a certain time is set accordingly to the position of the virtual rat in a pre-defined trajectory. The activity of each cell mimics a grid cell with specific scale and spatial and angular offset. Though the model, the activity of the DG and CA3 neurons is computed.
- Spike activity is confronted with the position to obtain standard place cell analysis.
- Rate map analysis shows that the entorhinal cells exhibit grid cell formation. Place cells can be observed in both dentate gyrus and CA3 populations.
- A higher number of place fields per cell have been observed on the dentate gyrus.

Conclusion

- Results show that the spike model produces similar results to the mean-field model.
- This establishes a checkpoint for further studies that might depend on spiking data such as well-timed features of the spatial code like phase precession and spike coincidence and to include other physiological facts such as the auto-associative connections in the CA3.

Acknowledgement

Supported by GoalLeaders project (FP7-ICT-97732)



Figure 1: model hierarchy: from grid cells to place cells

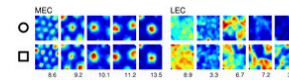


Figure 2: rate maps from grid cells and non-spatial cells

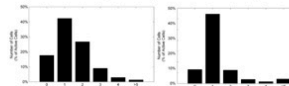


Figure 3: multiple place fields in the DG and single in the CA3

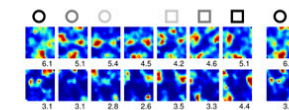


Figure 4: rate remapping in two DG cells

Reference

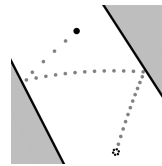
L. de Almeida, M. Ištart, and J. E. Lisman, "A second function of gamma frequency oscillations: an E%-max winner-take-all mechanism selects which cells fire," *The Journal of Neuroscience*, 29(23), pp.7497-503, 2009.
L. de Almeida, M. Ištart, and J. E. Lisman, "The input-output transformation of the hippocampal granule cells: from grid cells to place fields," *The Journal of Neuroscience*, 29(23), pp.7504-13, 2009.
L. de Almeida, M. Ištart, and J. E. Lisman, "The single place fields of CA3 cells: A two-stage transformation from grid cells," *Hippocampus*, 21(12), pp.200-8, 2010.
C. Rennó-Costa, J. E. Lisman, and P. F. M. J. Verschure, "The mechanism of rate remapping in the dentate gyrus," *Neuron*, 68(6), pp. 1051-8, 2010.

Predicting objects dynamics



Learning to Simulate the Behavior of a Dynamical Object

Stefan Winberg and Christian Balkenius
Lund University Cognitive Science
Lund, Sweden

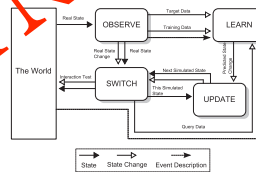


An example of prediction in a two dimensional environment. The large black circle is the ball being tracked. The gray dots are the predictions and the black dots are a graphical representation of how future obstacles will be placed.

The model predicts how a ball will fall down while bouncing on some obstacles.

Hesslow (2002) suggested that the brain simulates the future by first learning the expected outcome of an action or event and then uses this as input for a new prediction. As the process is repeated multiple times, the brain is able to simulate future consequences of an action. Here we apply this idea to the understanding of dynamical scenes where a system for prediction is converted into one for simulation.

To investigate how a system for prediction can be used for simulation we implemented the framework illustrated in the figure below. This framework consists of four modules that interact with each other and with the world in order to anticipate the temporal unfolding of an observed dynamic.



The model was implemented using the Ikaros system (Balkenius et al. 2010) where each of the components of the model were implemented as a separate module. A module reads data from its input connections in discrete time and generates new output at discrete intervals, usually referred to as ticks. These ticks can be locked to real-time when the system is used to control a robot and thus supports a seamless transition from simulation to a real robot.

We tested the accuracy of the predictions in a computer simulation using the open source physics engine Box2d (www.box2d.org). The simulated world was a two dimensional environment observed from the horizontal perspective, meaning that gravity pulled any objects down. A ball was launched from one of the edges of the world and as soon as the ball moved outside the boundaries of the world it was placed at a new starting position.

C. Balkenius, J. Morén, B. Johansson, and M. Johnsson, Ikaros: Building cognitive models for robots, *Advanced Engineering Informatics*, 24, 1, 40-48, 2010.
G. Hesslow, Conscious thought as simulation of behaviour and perception, *Trends in Cognitive Sciences*, 6, 6, 242-247, 2002.



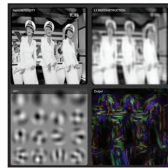
Winberg, Balkenius

Vision hierarchies modulated by value



Hierarchical Models of Vision and Attention

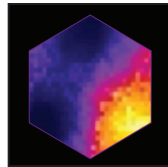
Christian Balkenius and Birger Johansson
Lund University Cognitive Science
Lund, Sweden



Top Left: Input image. Top Right: Reconstructed input from top-down attention signals. Bottom Left: Learned receptive fields. Bottom Right: Activity pattern in the first layer of the hierarchy. The color indicates the most active feature and the intensity represents the level of activation.



Image reconstructed from top-down expectations from the third hierarchical layer through layer 2 and 1.

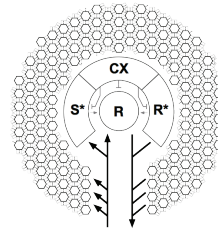


Activity pattern in one of the cortical modules.

We present a system-level computational model of visual learning and attention. The hexagons represent different cortical regions that are controlled by a central system consisting of subsystems for stimulus evaluation (S^*), response evaluation (R^*) as well as contextual modulation of learning and processing (CX). The central system R is responsible for the production of 'innate' responses to visual stimuli.

The cortical part of the model learns on line to code for visual stimuli using hierarchical principal component analysis (HPCA). By combining features of self-organizing maps, convolutional networks and principal components analysis, a hierarchical network with an arbitrary number of layers can be organized from input data consisting of natural images. The hierarchical system is capable of both bottom-up analysis and top-down reconstruction of the visual input. The processing in the hierarchical system can also be modulated by value as coded by the S^* system.

The S^* system uses a form of classical conditioning while the R^* system uses reinforcement learning. Finally, the CX system learns both to integrate stimuli over time to form a context and to modulate processing in the S^* , R and R^* systems.



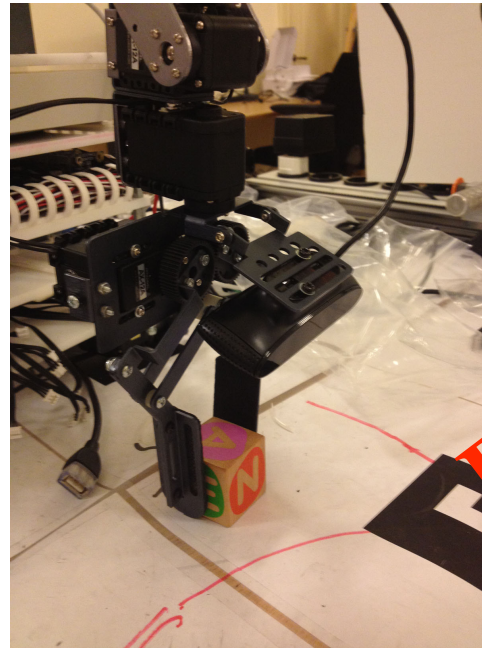
The model has been implemented within the Ikaros framework and exploits the duality between multiple self-organizing maps with weight-sharing and multiple parallel convolution operations to obtain real-time processing through the efficient utilization of multiple processor cores and hardware accelerated convolution operations.



The Robot Builder



The Ikaros framework



The Ikaros Project: System Level Cognitive Modeling
Björger Johansson, Rasmus Bååth, Stefan Winberg, Magnus Johansson, Christian Balkenius
Lund University Cognitive Science
Lund, Sweden

Summary
The goal of the project is to develop an open infrastructure for system level modeling of the brain including large amounts of experimental data, computational models and functional brain data. The system makes heavy use of the emerging standards for internet based information and will make all information available through an open web-based interface. In addition, Ikaros can be used as a control architecture for robots which in the extension will lead to the development of a brain inspired robot architecture.

System Level
The Ikaros kernel starts a number of threads where a number of modules are executed. The modules communicate through a set of standard interfaces that correspond to outputs from the modules. The kernel can be configured to communicate with other Ikaros processes running on the same or on a different processor or computer. In addition, the kernel communicates with an optional graphical user interface client running in a web browser.

We have consequently strived to comply with the relevant standards as much as possible. These include ANSI C++, POSIX and BSD sockets. A related choice was to depend on as few external libraries as possible.

Examples

How can I try it?
Go to www.ikaros-project.org to download the latest version of Ikaros.

References

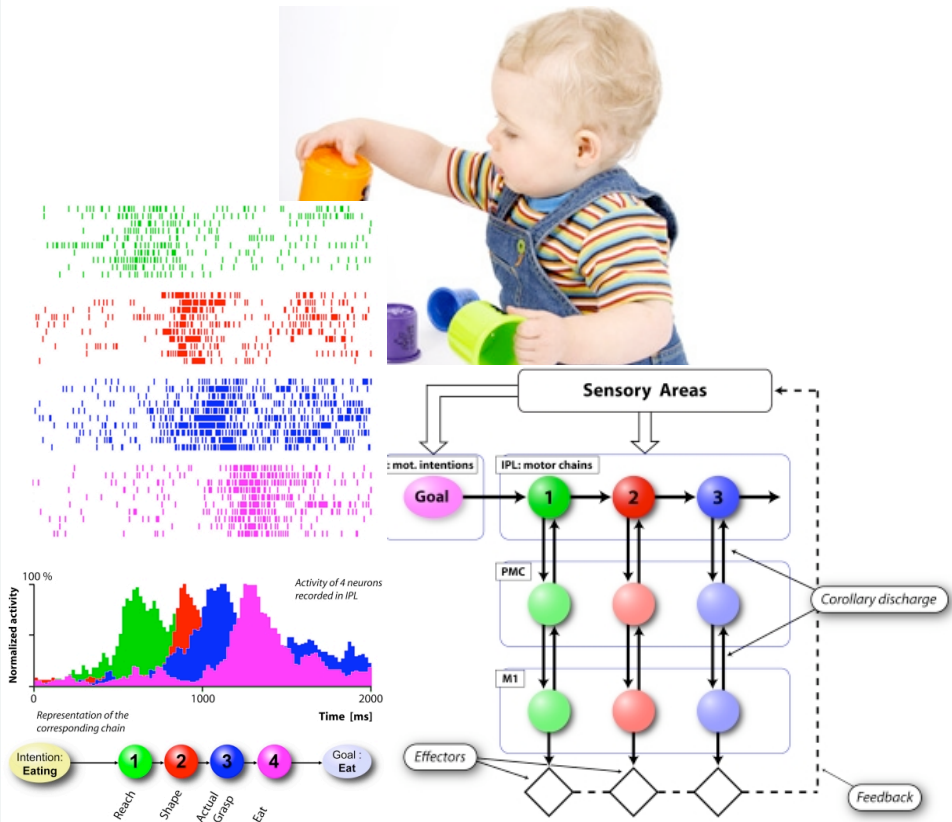
Björger Johansson, C. Balkenius, R. Bååth, and M. Johansson. 2010. Brain Building/Cognitive Models for Robots. Advanced Engineering Informatics 24, 1: 66-80. doi:10.1016/j.aei.2009.08.002. doi:10.1016/j.aei.2009.08.002. doi:10.1016/j.aei.2009.08.002. doi:10.1016/j.aei.2009.08.002.

Check out www.ikaros-project.org

GOAL
LUND
UNIVERSITY

A few planned achievements:

Action sequences, distal goals, subgoals, cognitive control



Fogassi et al., 2005

Chersi et al., 2011

Mental simulation Embodied problem solving



Thanks!

Our Advisory Board: Matthew Botvinick, Neil Burgess, Martin Butz, Michael Hasselmo, Bjorn Merker, Tony Prescott, Peter Redgrave

For these and other results, check:
www.goal-leaders.eu



The screenshot shows the homepage of the GOAL LEADERS project website. It includes a navigation menu, a login form, and several news items. The main content area features a 'Welcome to Goal-Leaders' section with the project's aims and a 'Robot Builder Scenario' section with a small image of a robot.

Advertisement: Open PhD Position

PhD subject: Visual perception and motor anticipation in biological and artificial systems. Keywords: eye tracking, attention, prediction, neural networks. Driving fields: robotics, psychology, computational neuroscience

Starting date: position already available,

Affiliation: LAPSCO, Pascal Institute (Clermont-Ferrand, Fr)
 Contact me or j-charles.quinton@univ.bpclermont.fr