Of Rats and Robots

Professor Janet Wiles
University of Queensland

Overview: models, space, and time

Models

Models are fundamental to science and engineering

What makes an effective model of a complex system like the brain?

In theory there is no difference between theory and practice. In practice there is.

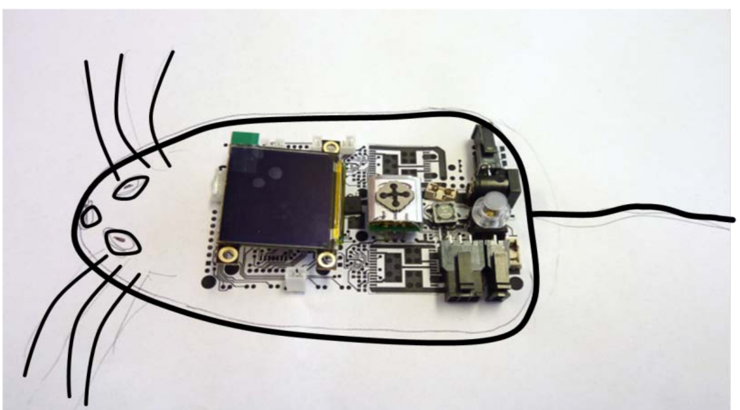
Attributed variously to baseball player Yogi Berra, computer scientist Jan L. A. van de Snepscheut and physicist Albert Einstein.

c2.com/cgi/wiki?DifferenceBetweenTheoryAndPractice

Robots as model organisms

A computational model is a way of integrating a variety of constraints known or suspected about a system:

1. structure – cell types and connectivity;
2. dynamics – molecular, cellular, and systems levels;
3. function – a computational task that it performs.



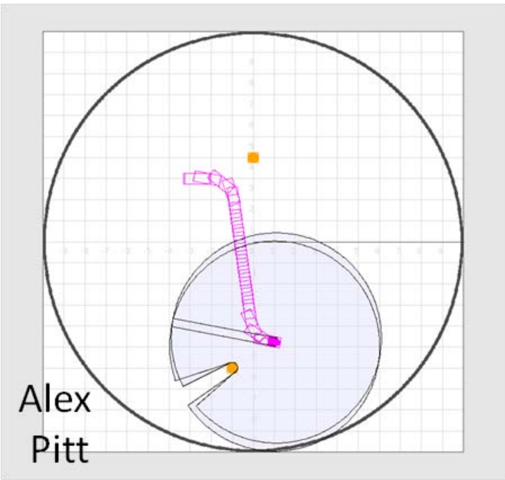
An autonomous robot is a computational model with a physical body.

4. Environment - It needs to solve tasks in an environment.

Robots in model worlds

artificial worlds; simulation worlds; fully embodied

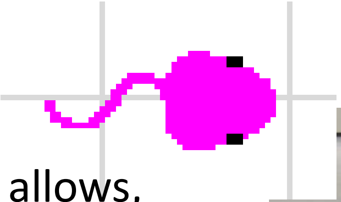
Artificial world



Simulation world

Real world

Artificial worlds: fully flexible design

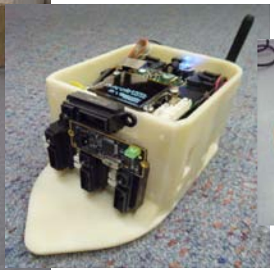


Simulation worlds: as real as theory allows, typically no noise

Real world robots need to deal with physics using a fully functional sensory-motor system, energy and noise.

Pioneer

iRat V1



iRat V2

Michael Milford

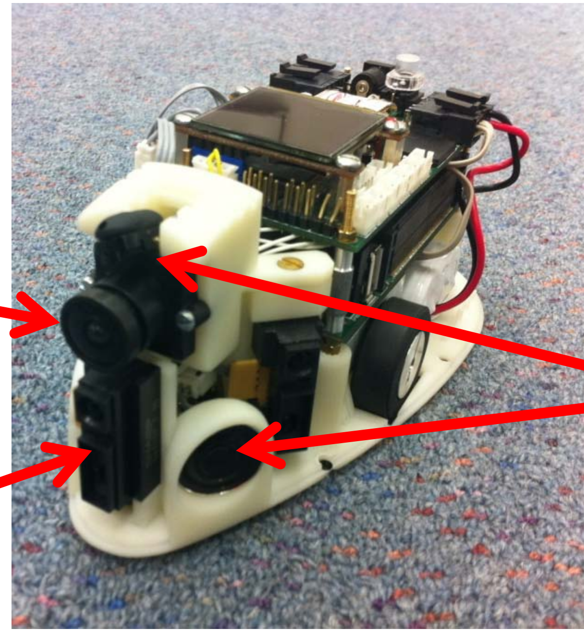
David Ball, Scott Heath

iRat: a platform for research in neuroscience, robotics and embodied cognition

Video by UQ School of Journalism and Communication
John Harrison, Matti Crocker, Bruce Redman, Carmel Rooney

iRat

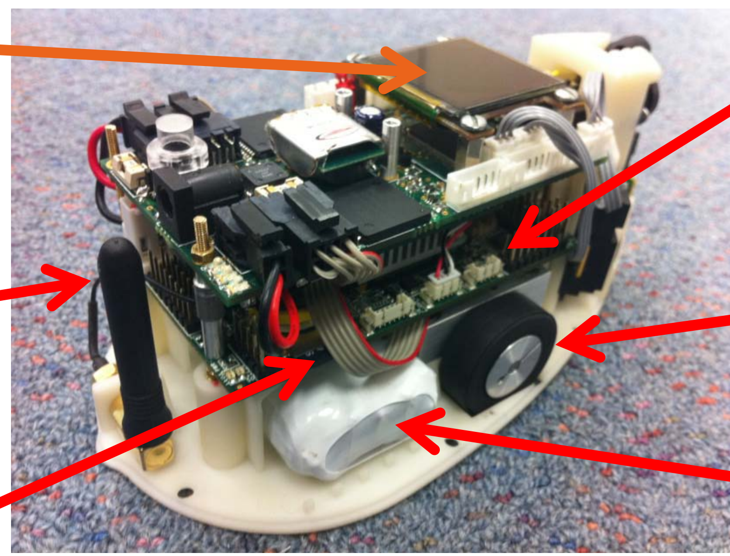
Mass 0.6kg
Size 170mm long



Vision via webcam

Local Communication via speakers and microphone

Avoidance via IR sensors



Local control via LCD and navpad

Brain via x86 PC 1GHz CPU (RoBoard)

Distributed intelligence via WLAN antenna

Mobility via wheels (over 1.5m/s)

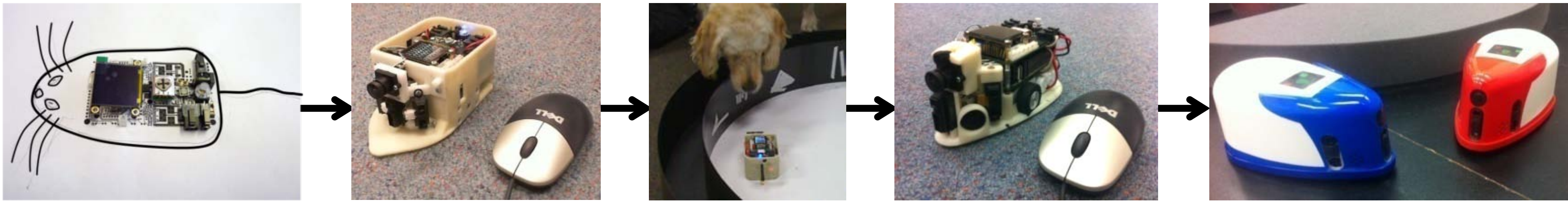
Robot Operating System (ROS) (Windows or Linux)

Energy via Battery (2 hours continuous use)

Ball, Heath, Milford, Wyeth and Wiles (2010) A Navigating Rat Animat, Alife XII

Rat meets iRat

2 key issues:
safety and engagement



iRat
(intelligent rat animat technology)

PC on wheels

Size is the key challenge for the design of a robot that interacts with a rat

Rat

Excellent navigator, flexible, curious, will
chew exposed wires,
easily frightened,
can be aggressive

David Ball, Scott Heath, in collaboration with Andrea Chiba and Laleh Quinn, UCSD
ARC Thinking Systems; Temporal Dynamics of Learning Center

Rat meets iRat

2 key issues:
safety and engagement

David Ball, Scott Heath, in collaboration with Andrea Chiba and Laleh Quinn, UCSD
ARC Thinking Systems; Temporal Dynamics of Learning Center

iRats as model organisms

iRat strengths

- PC on wheels, flexible
- wifi for web, cloud, GPUs
- virtual reality, real world
- open source
- Safe around real rats

Platform for

- systems neuroscience
- bio-inspired robotics
- social interaction
- embodied cognition
- cognitive architecture grounded in space

monitors it own battery and recharges autonomously

iRats with different sensors and mapping systems in conversation

Left iRat: laser scanner and occupancy grid;
Right iRat: forward facing camera and bio-inspired topological map.

(Heath et al, ICRA 2013)

Ball, Heath, Milford, Wyeth and Wiles (2010) A Navigating Rat Animat, Alife XII

Space

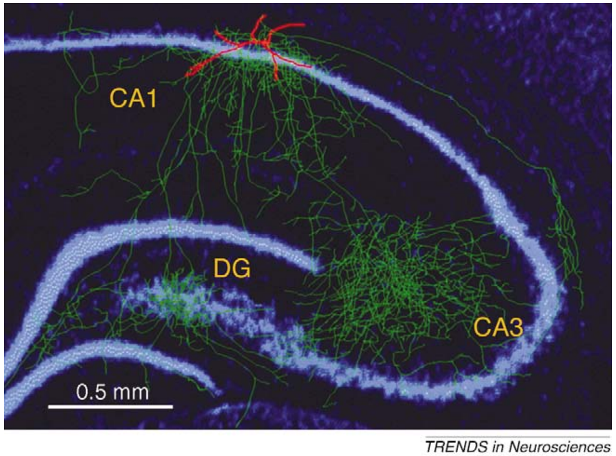
Space is all around us, but you can't see it, hear it or touch it.

How do brains represent something that doesn't change when senses change?

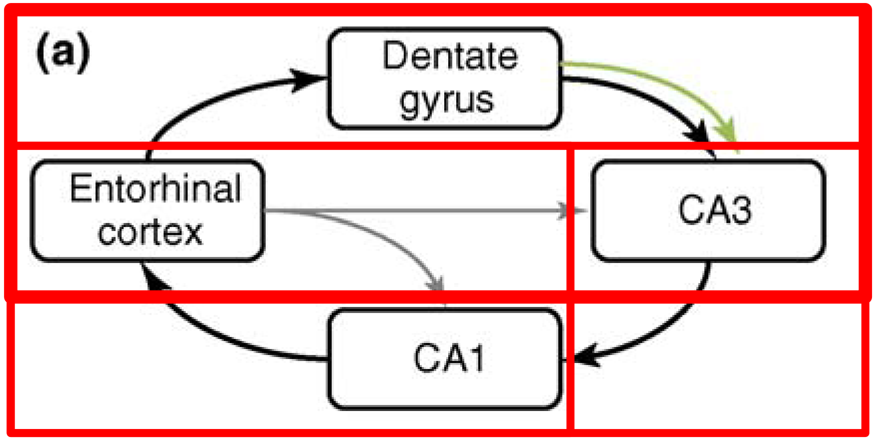
From robot navigation to hippocampal function

Robots	Biology
Pose Cells / Grid Cells Encoding of XYθ input	Entorhinal Cortex EC2 -> CA3 EC3 -> CA1
Experience Map DG – tag for new experience CA3 – recurrent connection, old experience recall	Dentate Gyrus CA1,CA2,CA3 Subiculum
View Cells provide the landmarks	Parietal Cortex

Major regions in hippocampus



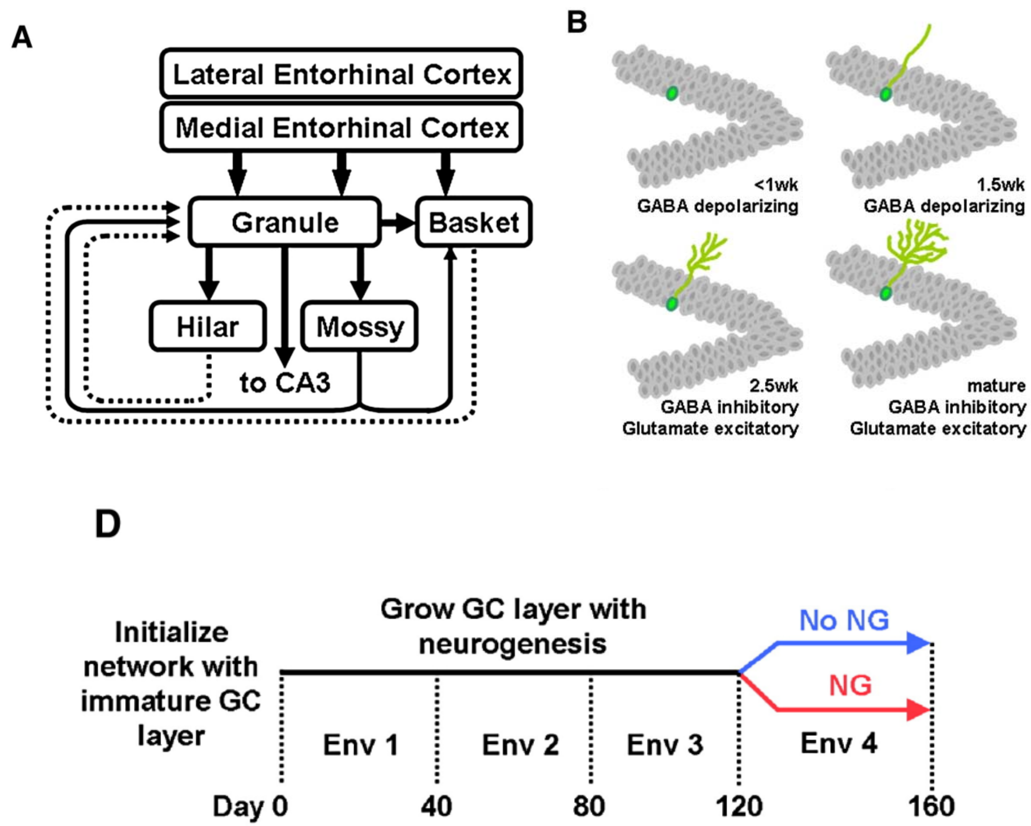
Interneuron diversity series, Buzsaki, et al.



Aimone Deng Gage TICS 2010

Computational Model of Dentate Gyrus with Neurogenesis

- Multi-layer simulation of dentate gyrus circuit
  - 50-1000 neurons per layer
  - Biologically-defined physiology and connectivity
  - Input layers (entorhinal cortex) represent spatial and contextual information
- Continuous neurogenesis
  - Gradual process
  - Based on biological maturation profile
- Model initialized by “growing” in series of four distinct environments
  - Last environment with or without neurogenesis

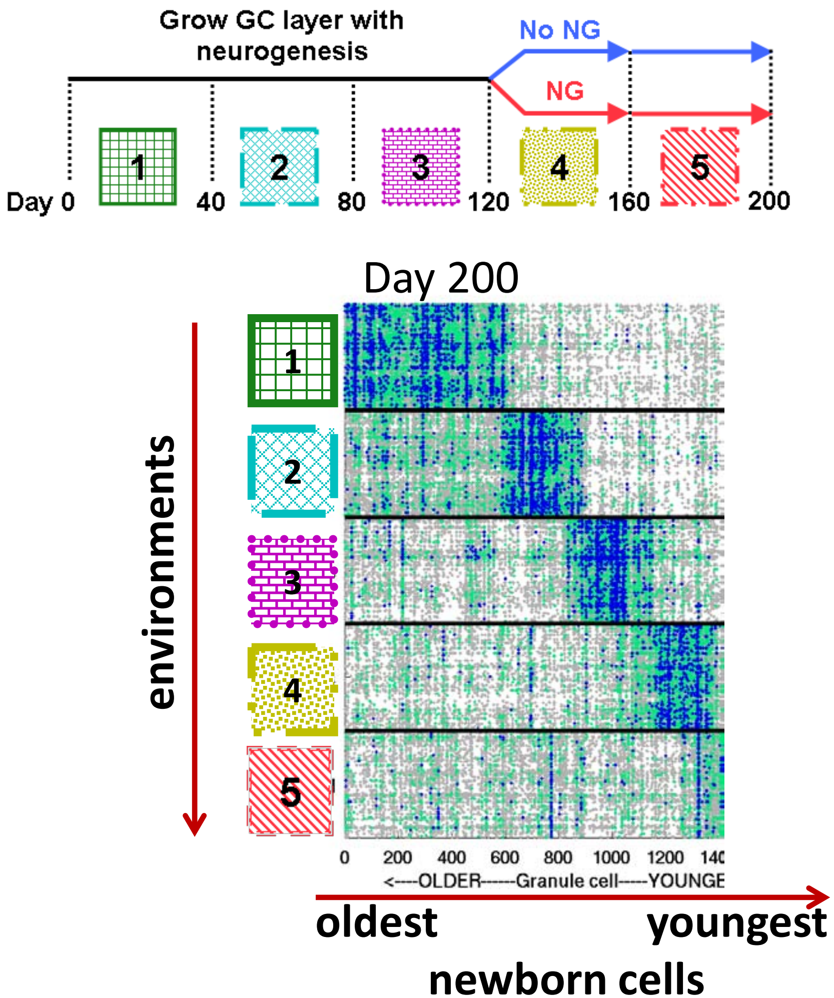


Aimone Wiles Gage *Nature Neuroscience* 2006; Aimone Wiles Gage *Neuron* 2009

Environmental Commitment of Adult-born Neurons

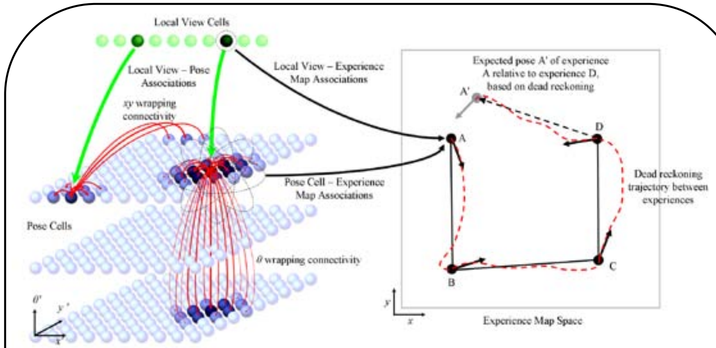
- Neurons learn to represent environment present during maturation
- Prolonged exposure to environment will result in a population of DG granule cells that are "specialized" to that environment

Hypothesis: The specialization of young neurons to the environments present during maturation allows improved encoding of new memories that relate to previously experienced contexts.

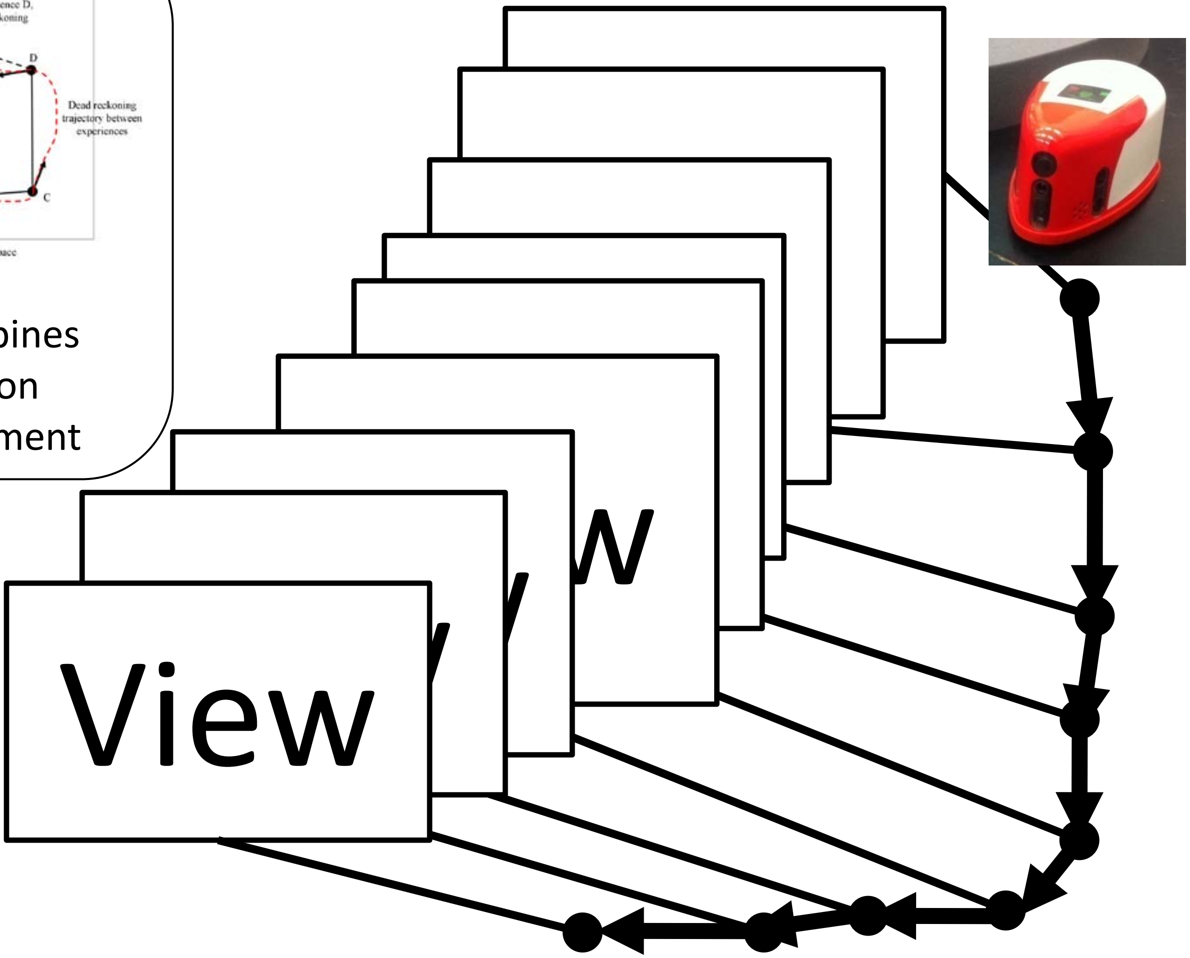


Aimone Wiles Gage *Nature Neuroscience* 2006; Aimone Wiles Gage *Neuron* 2009

RatSLAM: Micro-experiences create a network of sense impressions (views) linked by motor actions (odometry)

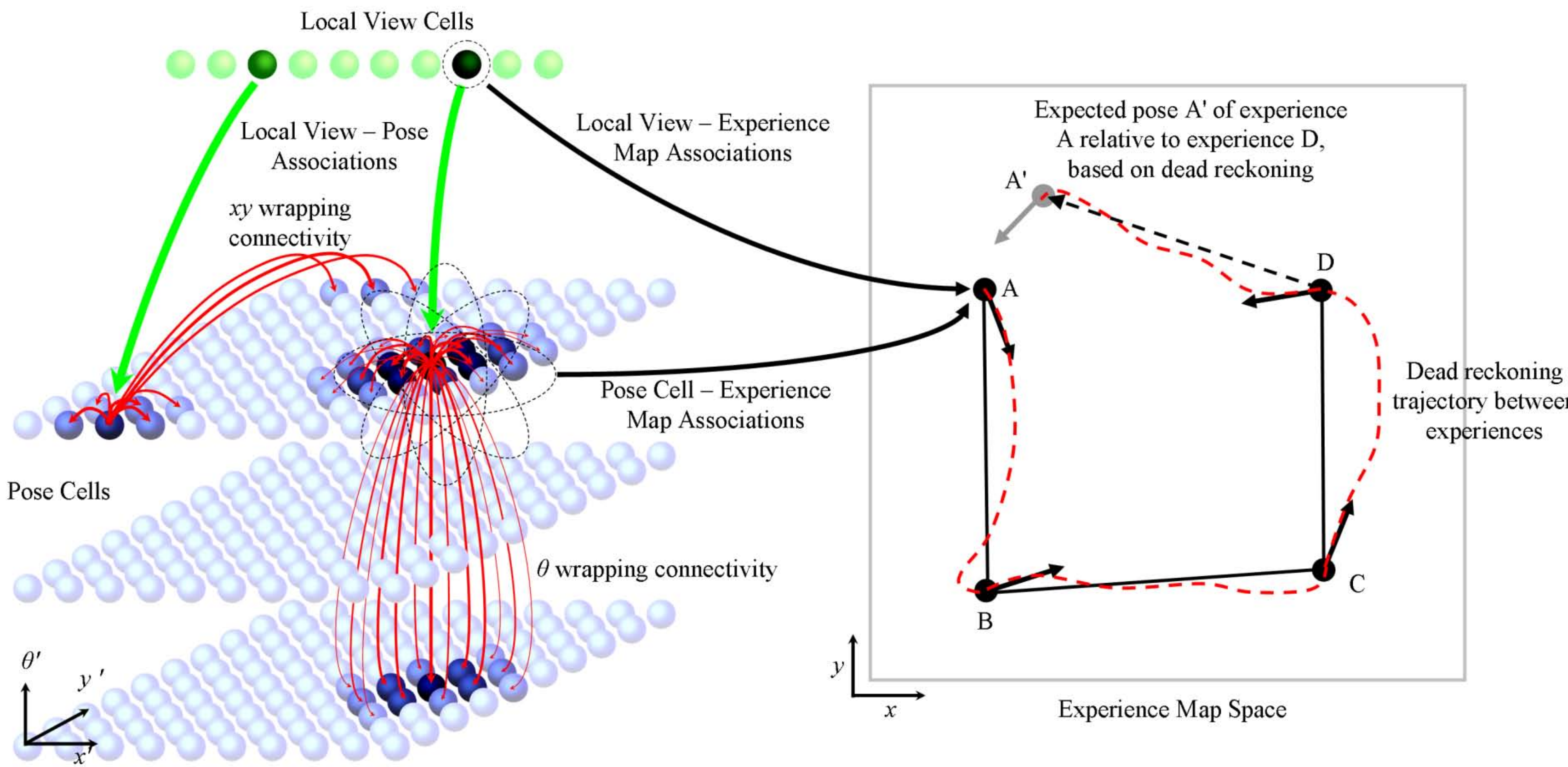


The pose cell network combines position and head direction relative to the previous moment



Milford and Wyeth, RatSLAM, 2010; Ball et al 2013 open source RatSLAM

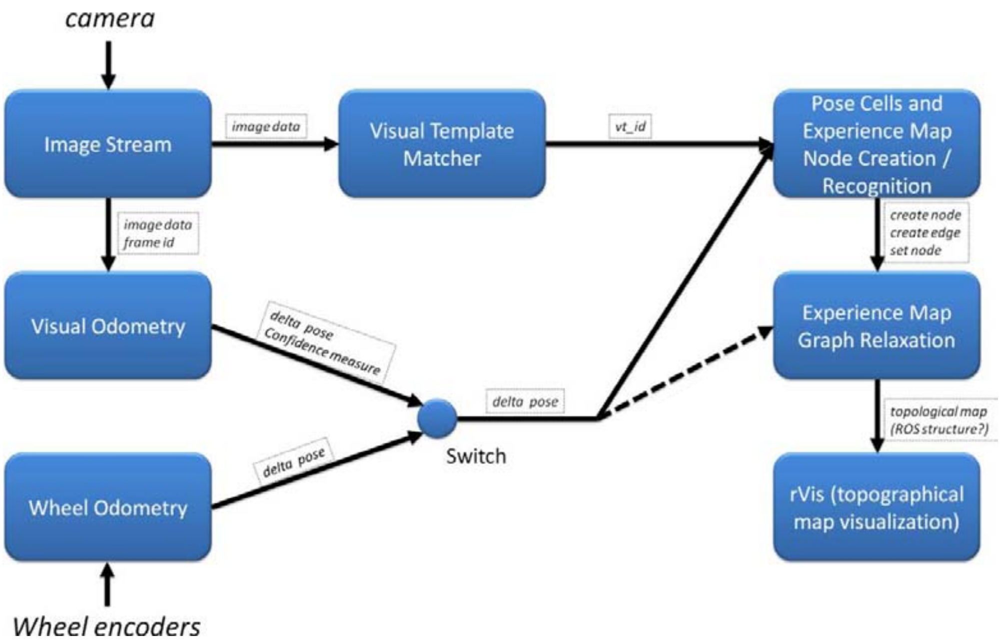
Closing the loop is the heart of spatial cognition: The iRat's algorithm is RatSLAM (Milford&Wyeth)



The pose cell network combines position and head direction relative to where you were a moment ago

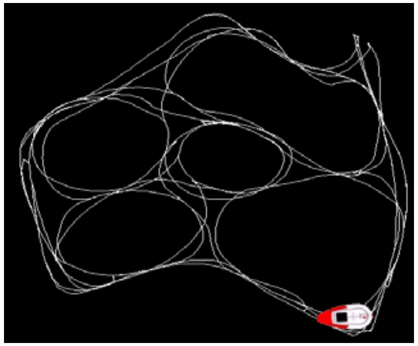
Open RatSLAM
Simultaneous localisation and mapping

The OpenRatSLAM module structure



Overhead view of environment

OpenRatSLAM map

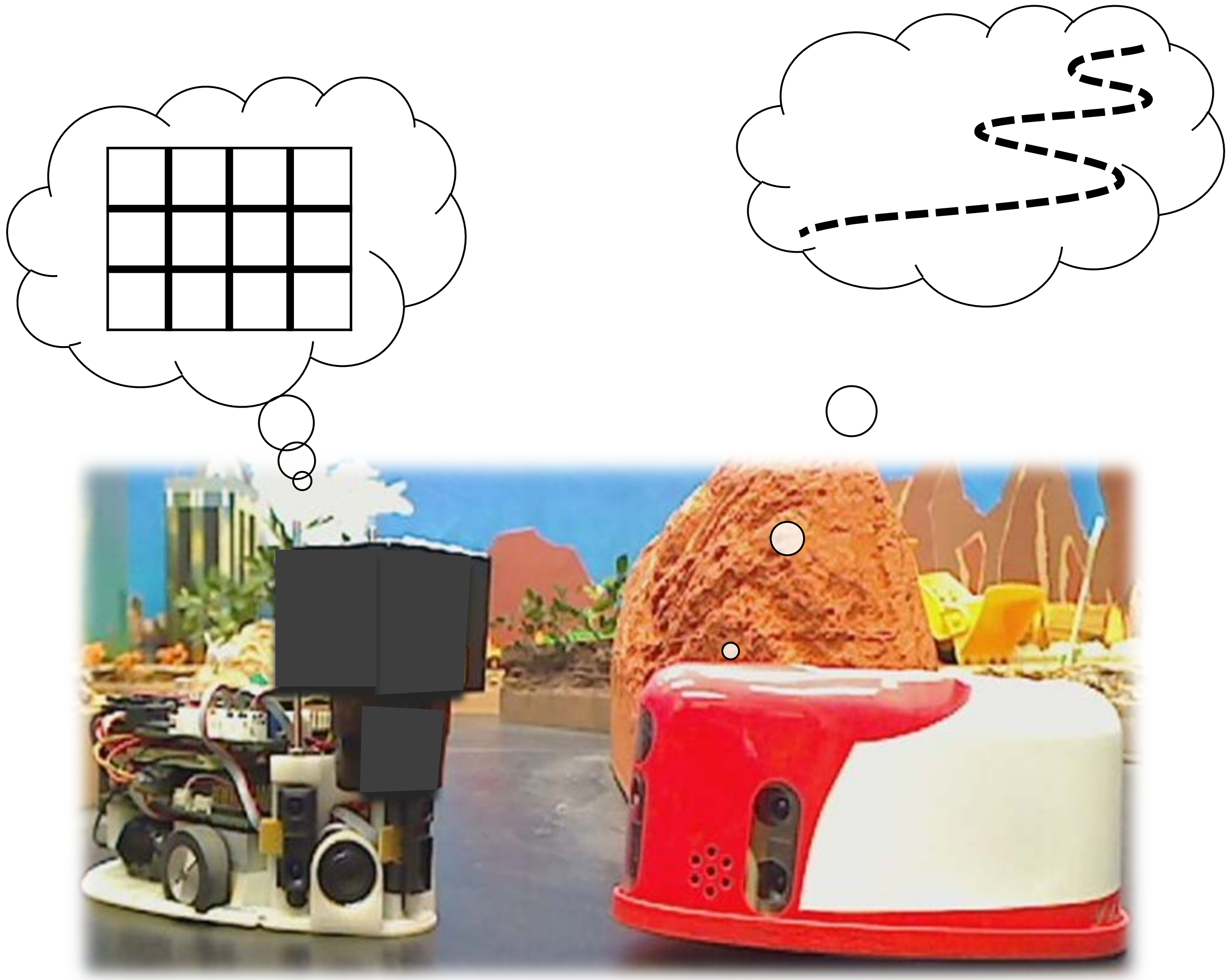


OpenRatSLAM: An Open Source Brain-Based Robotic SLAM System
Ball, Heath, Wiles, Wyeth, Corke, Milford (2013), in press.

Bio-inspired navigation

Mapping by David Ball, Scott Heath and Michael Milford
OpenRatSLAM: An Open Source Brain-Based Robotic SLAM System

Robots (and different neural regions) can model space as occupancy grids or paths

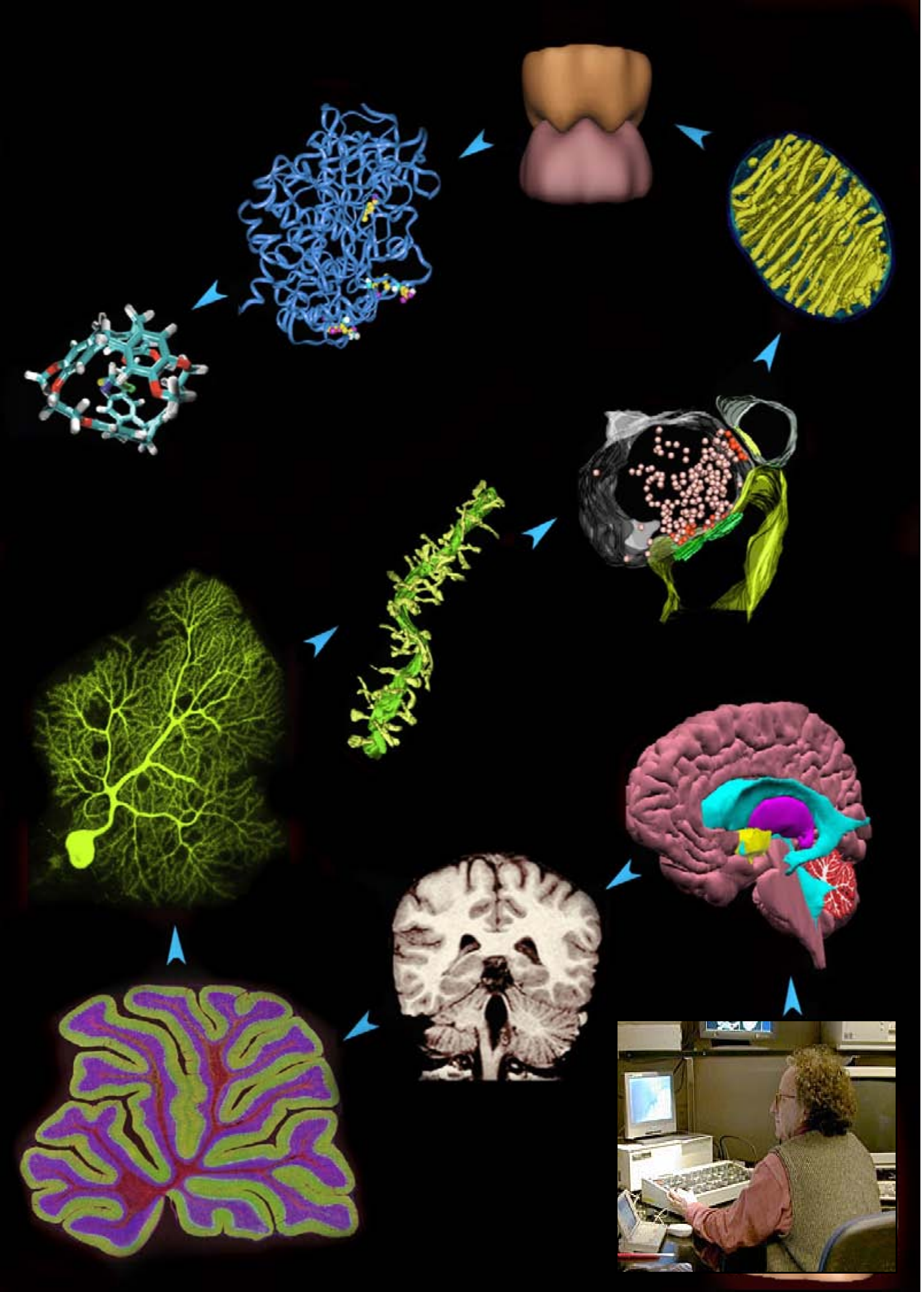


Heath et al, ICRA 2013

Time

Time has an explicit role in <u>dynamical</u> systems.

What is time in neural <u>computation</u>
(biological and modeled systems)?



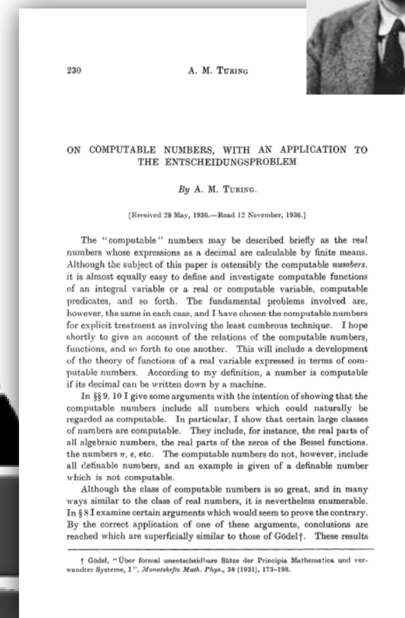
Q. What is the "right" abstraction?

A. modelling biology;
modelling physics;
modelling chemistry;
real computation

Dynamics occurs at multiple scales.
Does computation?

Forms of computation

A Turing machine can compute any computable function



230 A. M. Turing

ON COMPUTABLE NUMBERS, WITH AN APPLICATION TO THE ENTSCHEIDUNGSPROBLEM

By A. M. Turing.

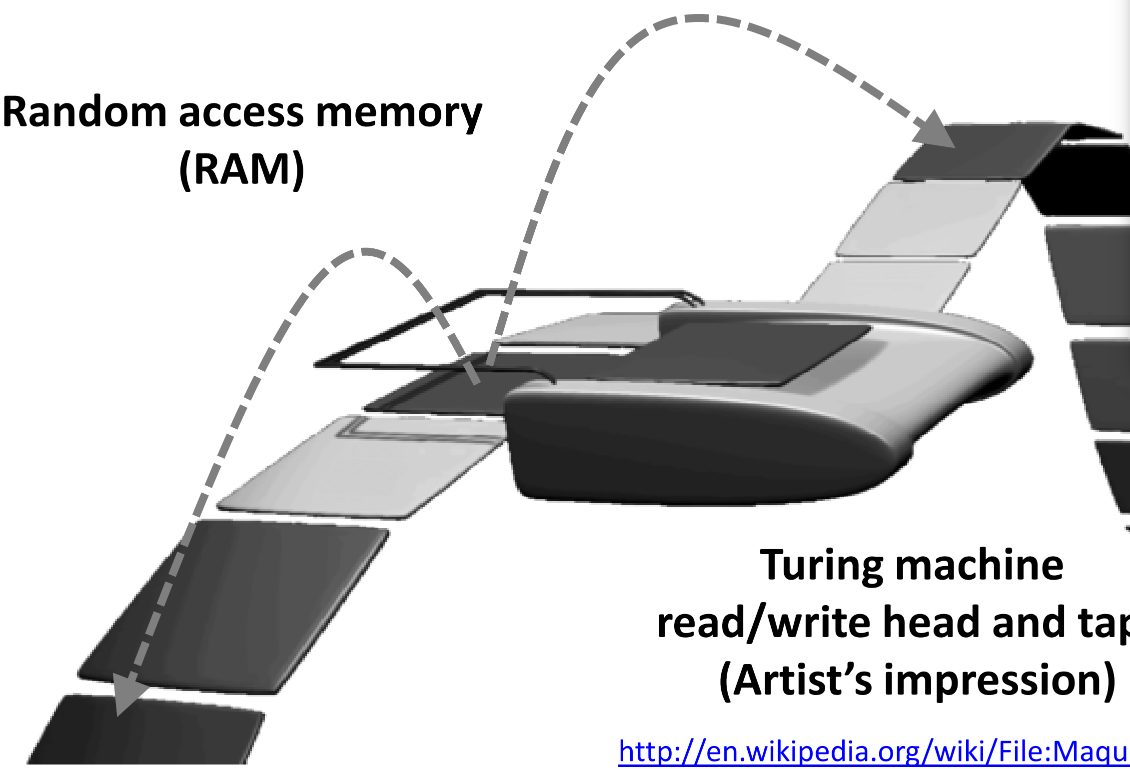
[Received 28 May, 1936.—Read 12 November, 1936.]

The "computable" numbers may be described briefly as the real numbers whose expressions as a decimal are calculable by finite means. Although the subject of this paper is ostensibly the computable *numbers*, it is almost equally easy to define and investigate computable functions of an integral variable or a real or computable variable, computable predicates, and so forth. The fundamental problems involved are, however, the same in each case, and I have chosen the computable numbers for explicit treatment as involving the least cumbrous technique. I hope shortly to give an account of the relations of the computable numbers, functions, and so forth to one another. This will include a development of the theory of functions of a real variable expressed in terms of computable numbers. According to my definition, a number is computable if its decimal can be written down by a machine.

In §§ 9, 10 I give some arguments with the intention of showing that the computable numbers include all numbers which could naturally be regarded as computable. In particular, I show that certain large classes of numbers are computable. They include, for instance, the real parts of all algebraic numbers, the real parts of the zeros of the Bessel functions, the numbers π, e, etc. The computable numbers do not, however, include all definable numbers, and an example is given of a definable number which is not computable.

Although the class of computable numbers is so great, and in many ways similar to the class of real numbers, it is nevertheless enumerable. In § 8 I examine certain arguments which would seem to prove the contrary. By the correct application of one of these arguments, conclusions are reached which are superficially similar to those of Gödel†. These results

† Gödel, "Über formal unentscheidbare Sätze der Principia Mathematica und verwandter Systeme, I", *Monatshefte Math. Phys.*, 38 (1931), 173–198.



Random access memory (RAM)

Turing machine read/write head and tape (Artist's impression)

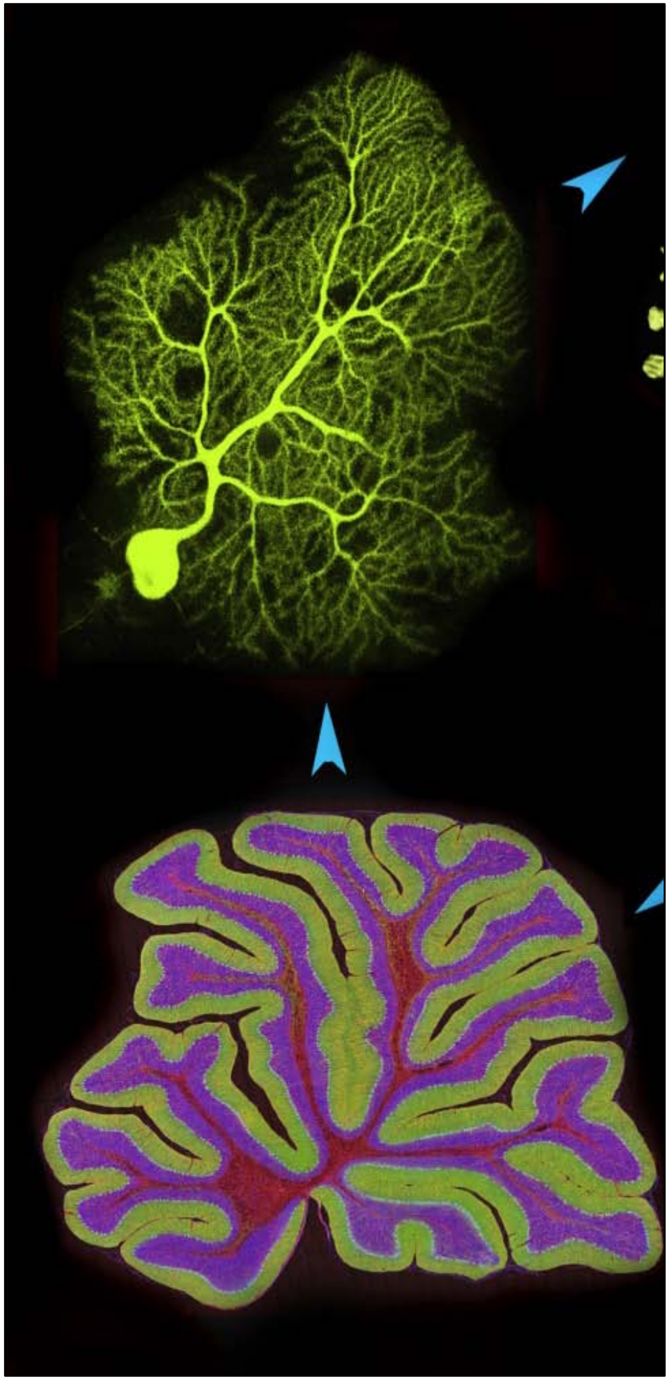
http://en.wikipedia.org/wiki/File:Maquina.png

O(N)

Theoretical computer science distinguishes between the computability of a function and its complexity (in terms of the resources that it uses).

Main resources used by algorithms are
time and space.

Spiking network models have more powerful resource usage than rate coded neural networks (but they are still not the preferred model for engineers and machine learning).



What is computation in a neural system and how does it differ from dynamics?

The dominant model in computational neuroscience is that the neuron is <u>the</u> computing element of the brain.

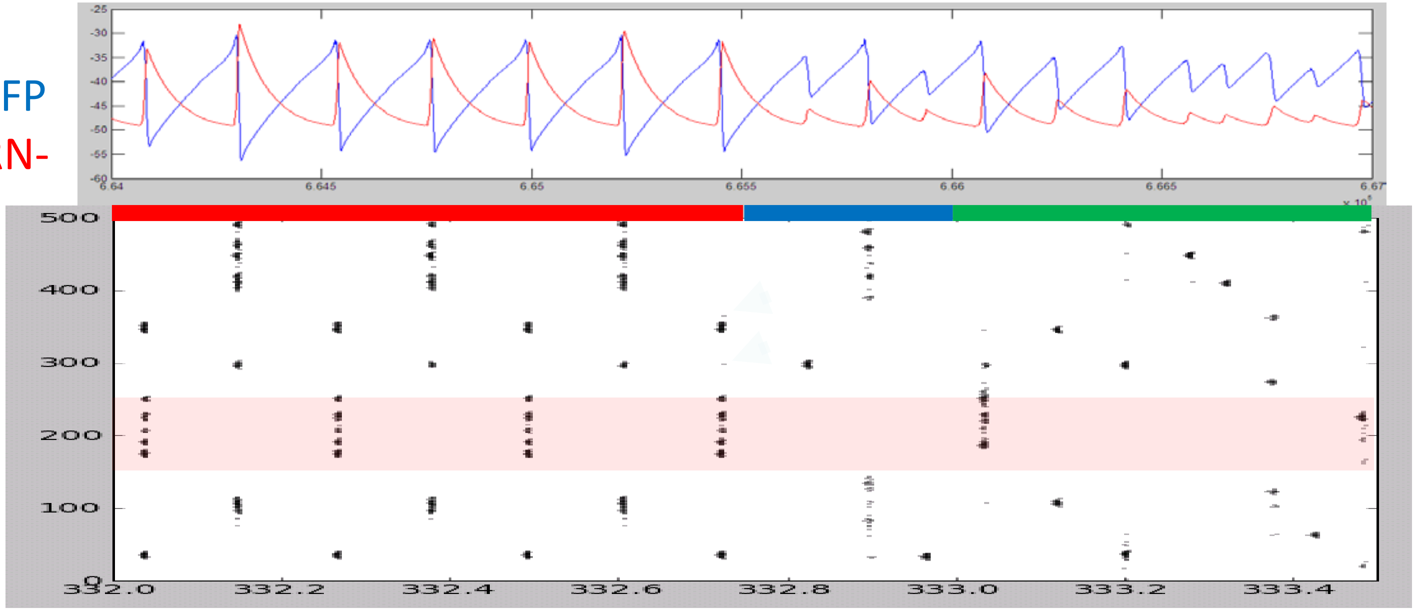
What else performs computation?

Spikes are used in many different coding schemes

Spiking networks are more frequently studied as complex dynamical systems than as computational devices.

(This needs to change for dynamics to be used for computational purposes)

GFP
50.RN-50

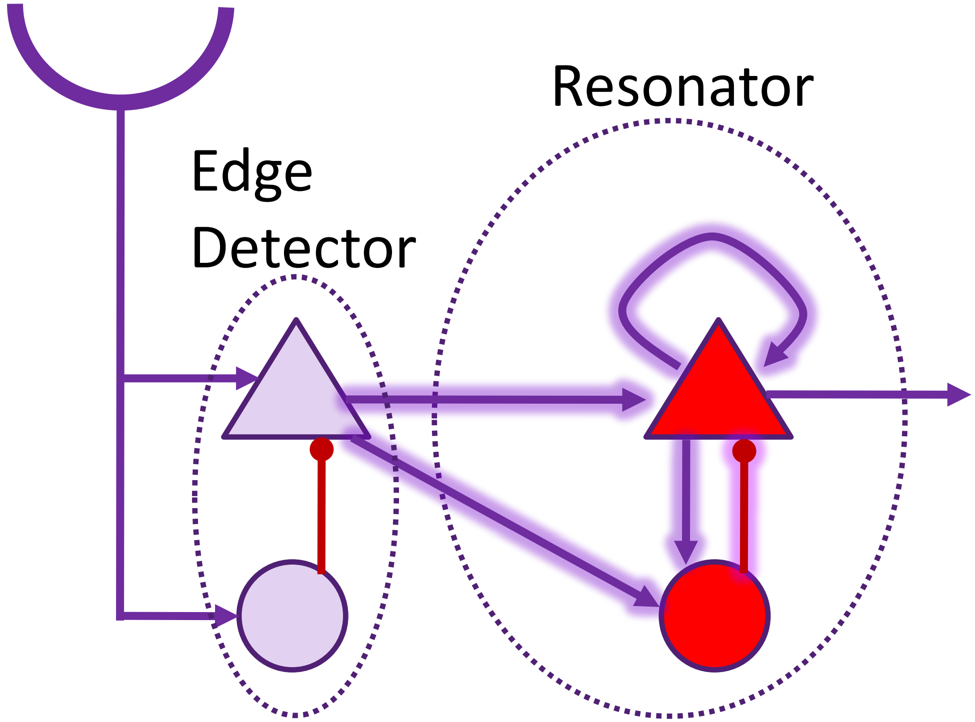


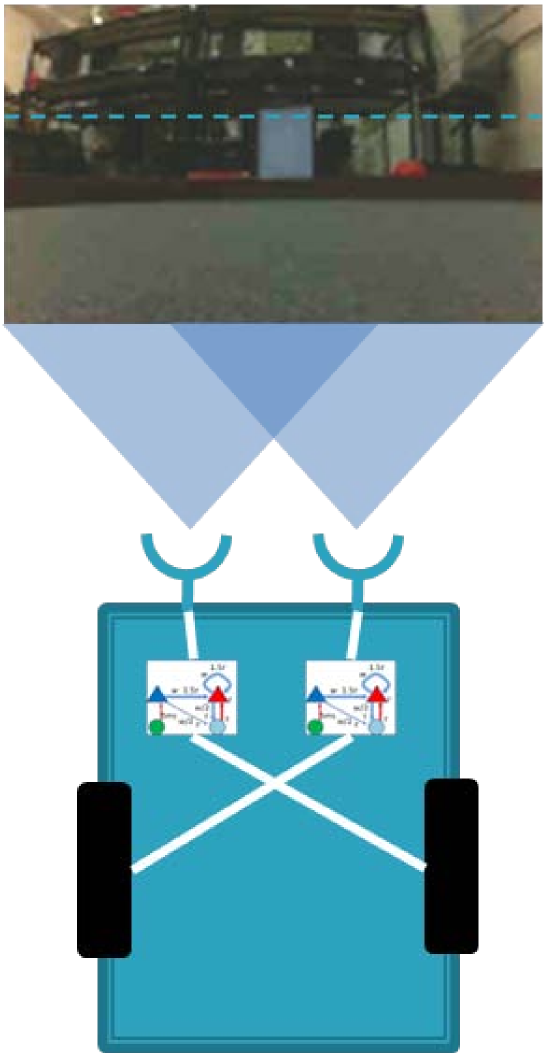
Complex Spiking Network (CSN)

Spontaneous entry and exit from seizure [Pete Stratton]

Resonators: Spike time robotics

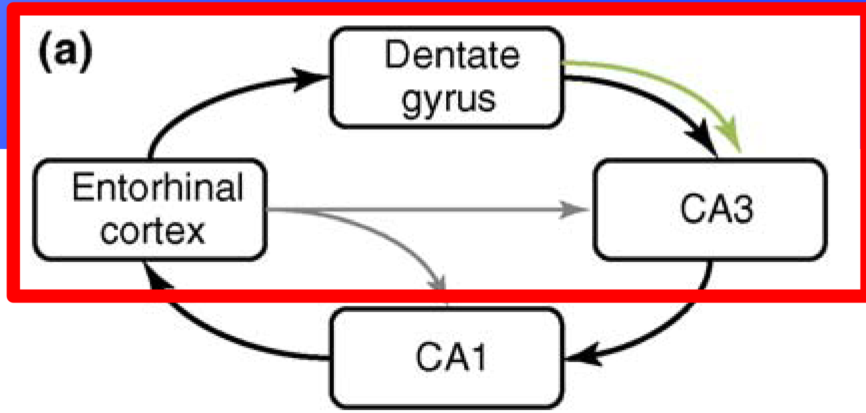
Spiking neural circuit to direct the iRat's movement towards a temporal code of an appropriate frequency





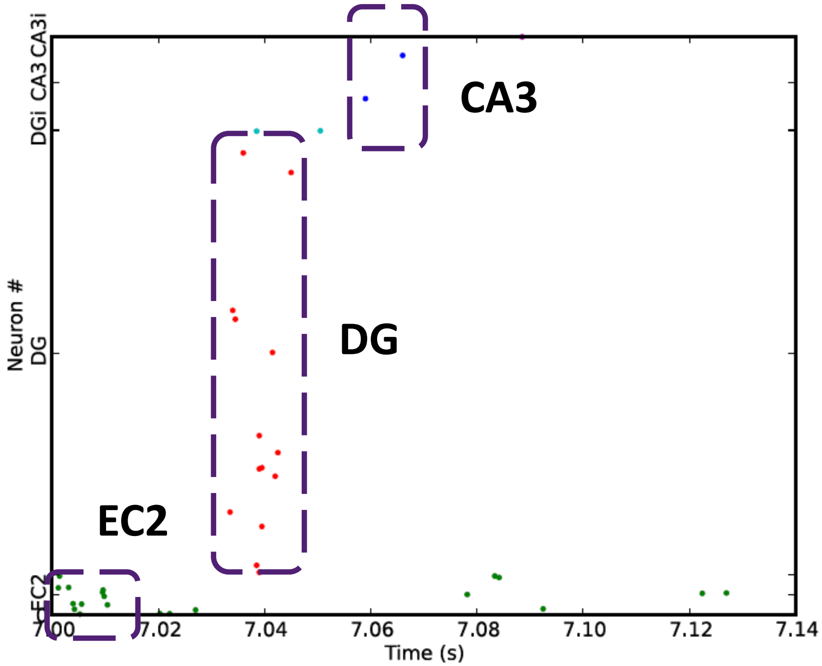
Janet Wiles, David Ball, Scott Heath, Chris Nolan and Peter Stratton (2010) Spike-Time Robotics: A Rapid Response Circuit for a Robot that Seeks Temporally Varying Stimuli, 17th International Conference on Neural Information Processing (ICONIP)

A race with a computational function

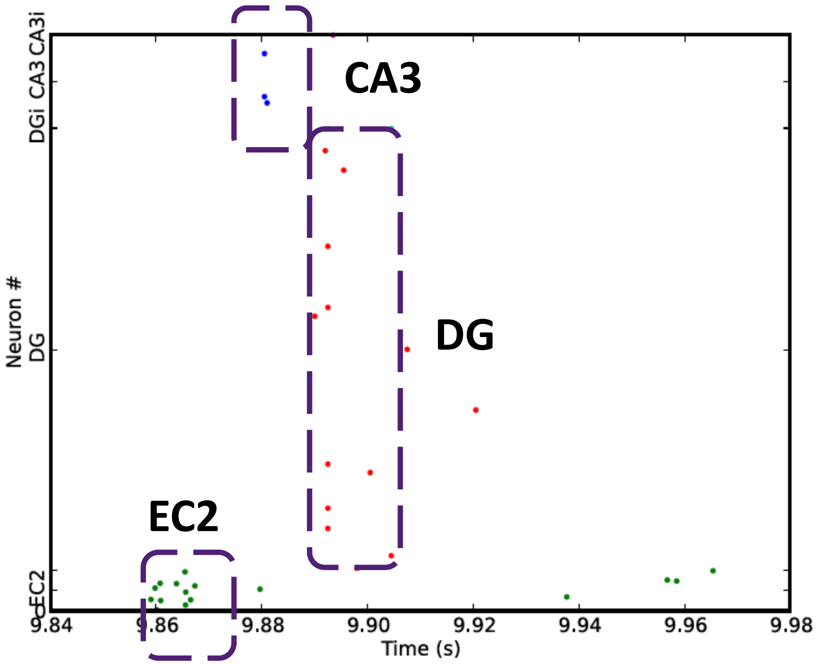


Fast spike response times in CA3 signal familiarity

Novel pattern (before learning)



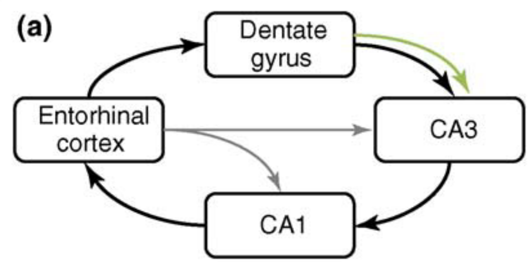
Familiar pattern (after learning)



Nolan Wyeth Milford & Wiles Hippocampus 2010

Message of the Race model:

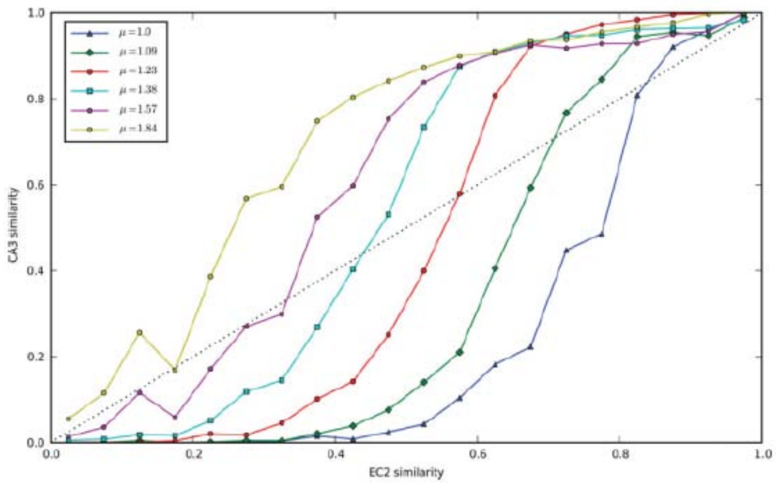
a pattern signals its own novelty by its microtiming



How does the race influence the circuit dynamics?

- If signals into CA3 arrive faster on the direct route from EC2 than from DG, it can indicate a familiar memory.
- Otherwise it can indicate a new memory and create a new CA3 attractor.

Memory can also be intentionally directed to recall or learning by synaptic modulation of CA3.

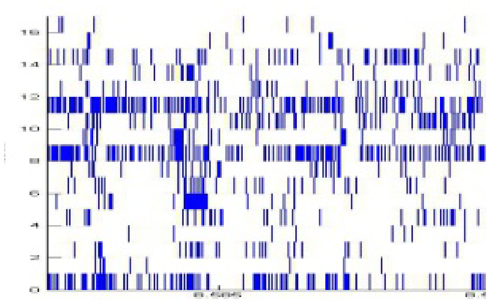


An algorithm for sequence learning based on spike transmission delays

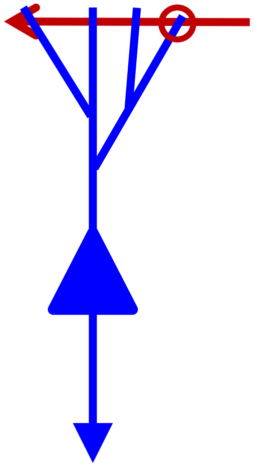
In neural systems, timing is critical
at the millisecond level.

Real neural systems:

- learn temporal order in perceptual input, motor control, coordination and memory tasks
- become faster with increased experience
- can change if the stimuli changes
- don’t need explicit reward to learn
- can learn sequences in one or a few trials



Spike delay variance learning (SDVL)
An algorithm for sequence learning



Gaussian Synapse Model

$$I = pe^{\frac{-(t_0-\mu)^2}{2v}}$$

- where:
  - p is the peak postsynaptic current
  - t_0 is the time since a presynaptic spike in ms ($t_0 \geq 0$)
  - μ is the mean
  - v is the variance

- The ‘weight’ of a synapse is the integral of the curve, so p is varied to match a given integral
- Hence each synapse has 3 parameters (μ, v and integral)

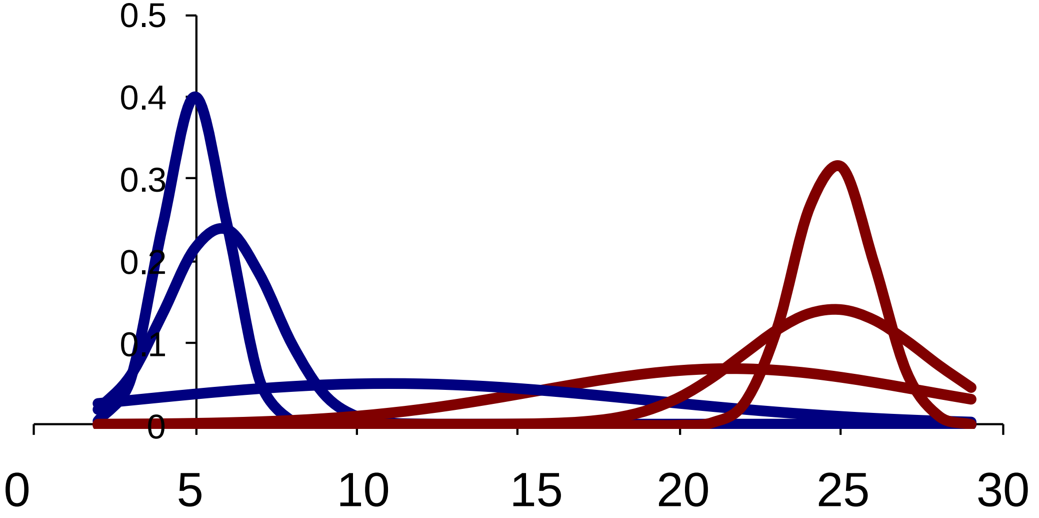
Wright and Wiles, IJCNN (2012)

Post synaptic release profile adapting delay mean μ, and variance v

Low variance (v < 0.1):
current is delivered as a single burst at delay μ

High variances (v >5):
current is slowly released, peaking at delay μ

Single synapse adapting both μ and v (1+1 EA, 50 updates)



Initial
$\mu = 5; v = 1$

Target
$\mu = 25$

Wright and Wiles (2012)

Spike Delay-Variance Learning (SDVL) Algorithm

The change of mean, Δμ, is determined by:

$$\Delta\mu = \begin{cases} sgn(t_0 - \mu)k\eta_\mu, & if \quad |t_0 - \mu| \geq \alpha_1 \\ -k\eta_\mu, & if \quad t_0 \geq \alpha_2 \\ 0, & otherwise \end{cases}$$

where:
t_0 is the time difference between the presynaptic and postsynaptic spike (ms)
μ is the mean of the synapse in milliseconds [min 0, max 15]
v is the variance of the synapse [min 0.1, max 10]
k(v) is the learning accelerator, here $k = (v + 0.9)^2$
η_μ is the mean learning rate
α_1, α_2 are constants

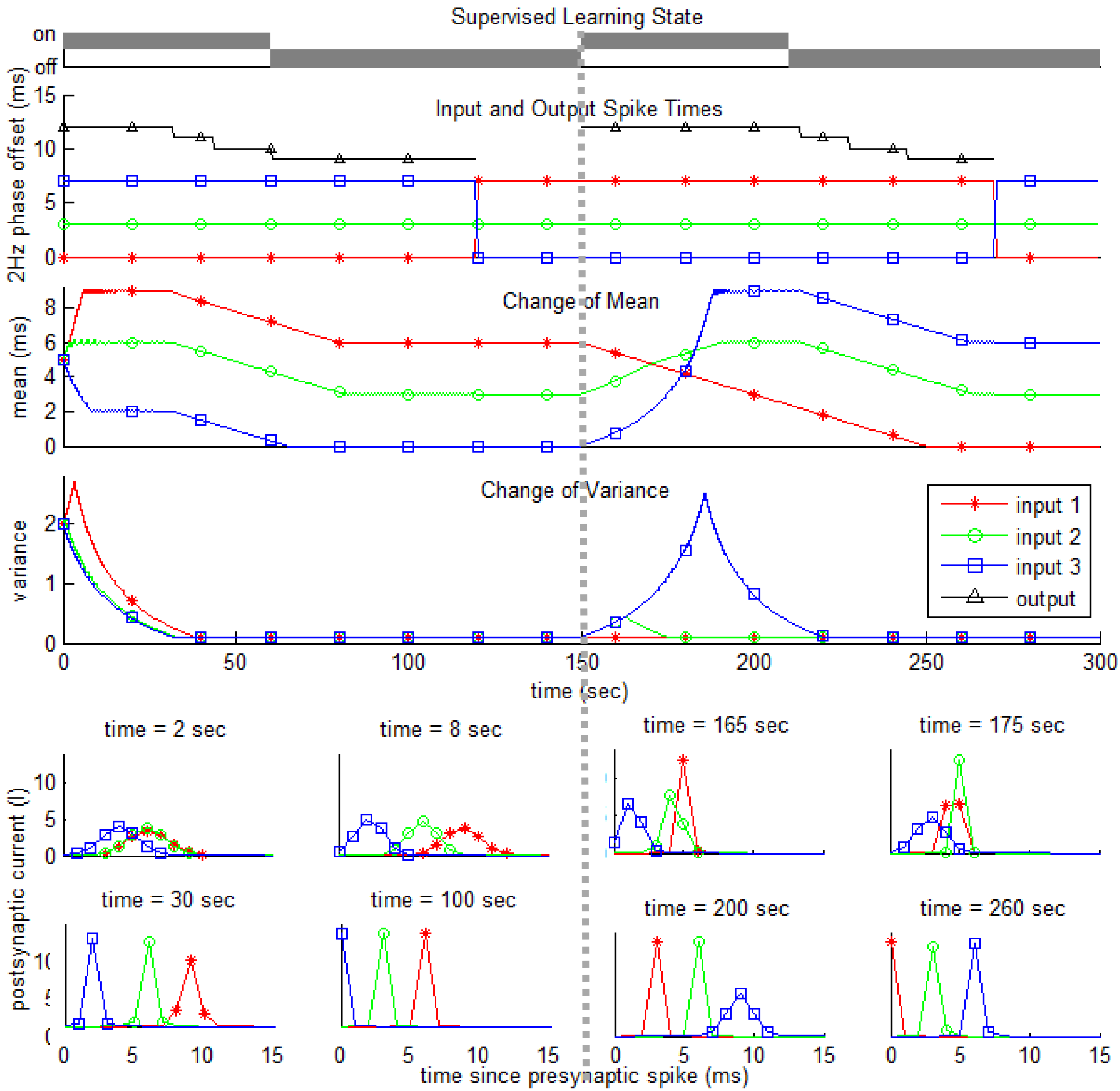
The change of variance, Δv, is determined by:

$$\Delta v = \begin{cases} k\eta_v, & if \quad |t_0 - \mu| \geq \beta_1 \\ -k\eta_v, & if \quad |t_0 - \mu| < \beta_2 \\ 0, & otherwise \end{cases}$$

where:
η_v is the variance learning rate
β_1, β_2 are constants

Wright and Wiles (2012)

Sequence recognition task results



A Task phases

B Spike arrival times

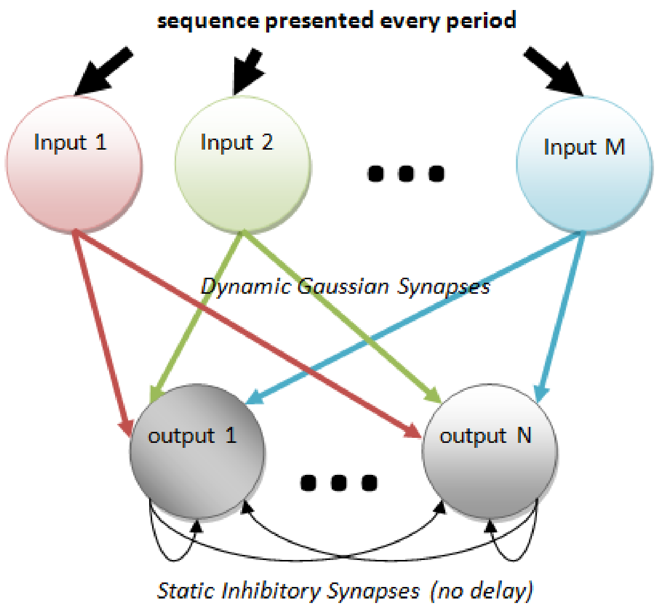
C Synapse traces

D Variance traces

E Gaussian postsynaptic release profiles

Wright and Wiles (2012)

Winner Takes All Spiking Network with spike delay variance learning (SDVL)



2-layer spiking network
gaussian synapses + SDVL
winner-take-all output layer

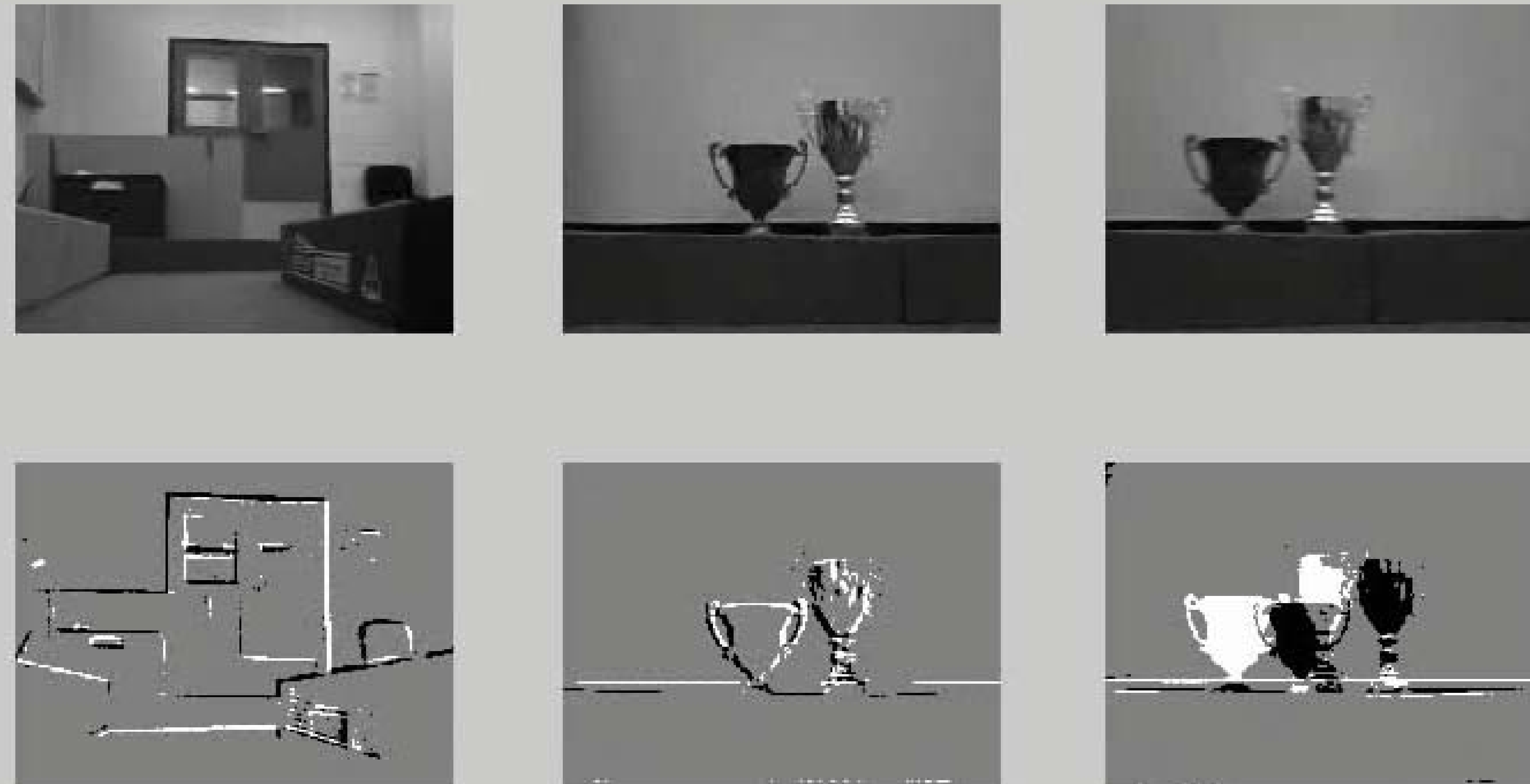
Implementation notes

Learning multiple sequences works best when:

- neurons return to baseline before each presentation (period < 5-10Hz)
- the integral of all the synapses is a constant
- the same number of input neurons fire within 15ms at each presentation (at least 3-5)

Wright and Wiles (2012)

Onset-offset responses from differences between video frames



Moving forwards | Moving forwards | Turning right

Dynamic Vision Sensor (DVS128) asynchronous temporal contrast silicon retina www.inilabs.com

x .03

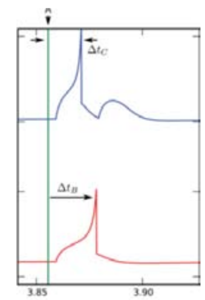
- No video frames: address-event representation (AER) only transmits local pixel-level changes
- Output is a stream of events at *micro*second time resolution
- Power, data storage and computational requirements are drastically reduced, and dynamic sensor range is increased by orders of magnitude.

Summary: Neural codes for time and space

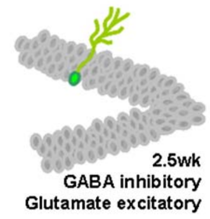
Neural computing is not just about information carried by spikes.

An embodied organism is a multi-scale dynamical system that gives rise to and interprets spikes.

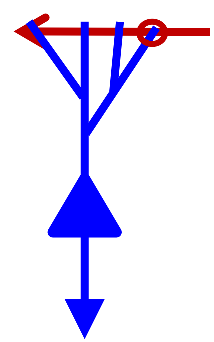
Every level in a biological system has rich dynamics and signals about those dynamics.



Micro-timing enables a pattern to signal its own novelty



Maturation processes can enhance capacity for specific environments



Dendritic computation enables direct learning of delays in sequences

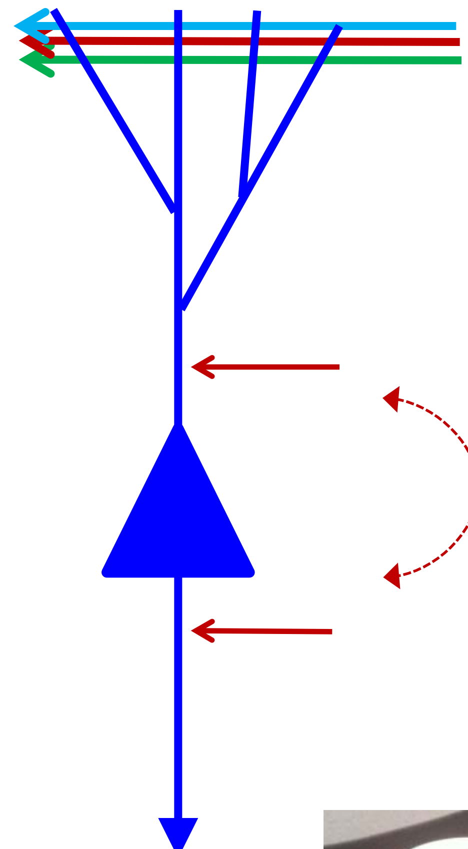
Future directions in Bio-inspired computation
Rethinking the role of time in processing

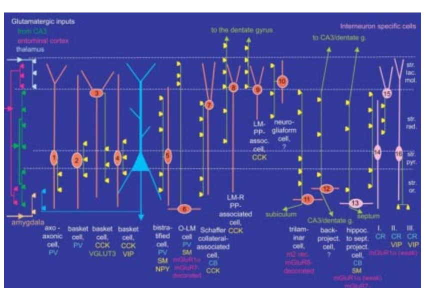
Clock-free: spiking neuron as an asynchronous micro-pipeline

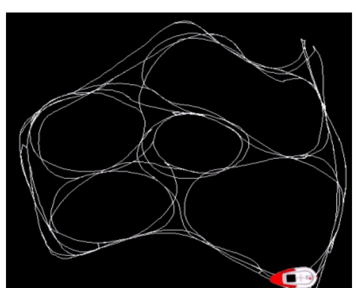
Grid-free: topological graphs with local metric structure and global regularization

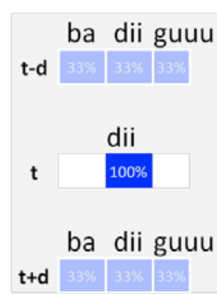
Scale-free and symbol-free: multi-scale recurrent networks

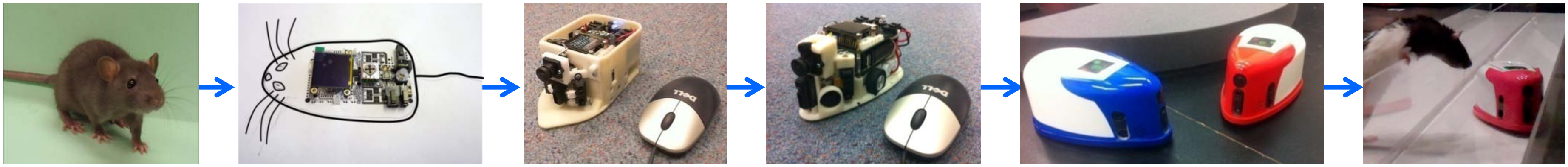
iRat: Neurorobotic platform to address all 4 challenges











Collaborators

UQ: Scott Heath, Peter Stratton, Chris Nolan, Allen Cheung, Amy Gibson; James Henderson; UQ School of Journalism;

QUT: David Ball, Michael Milford, Gordon Wyeth
UCSD: Andrea Chiba, Laleh Quinn, Doug Nitz, Andy Alexander,
Salk: James (Brad) Aimone and Fred (Rusty) Gage

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