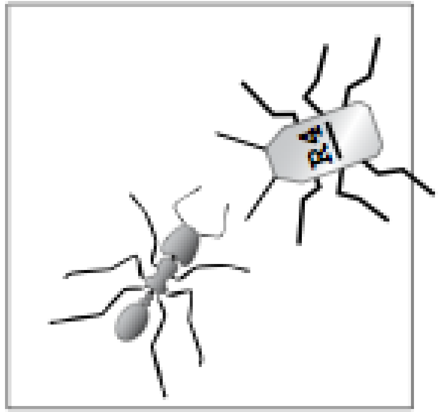
Evolution and Learning



What you will learn in this class

- Advantages and costs of learning in evolution
- How learning can help and guide evolution
- How evolution can help learning
- Darwinian vs Lamarckian evolution
- The Baldwin effect
- Evolution of learning rules
- Evolution of reward-based learning with neuro-modulation

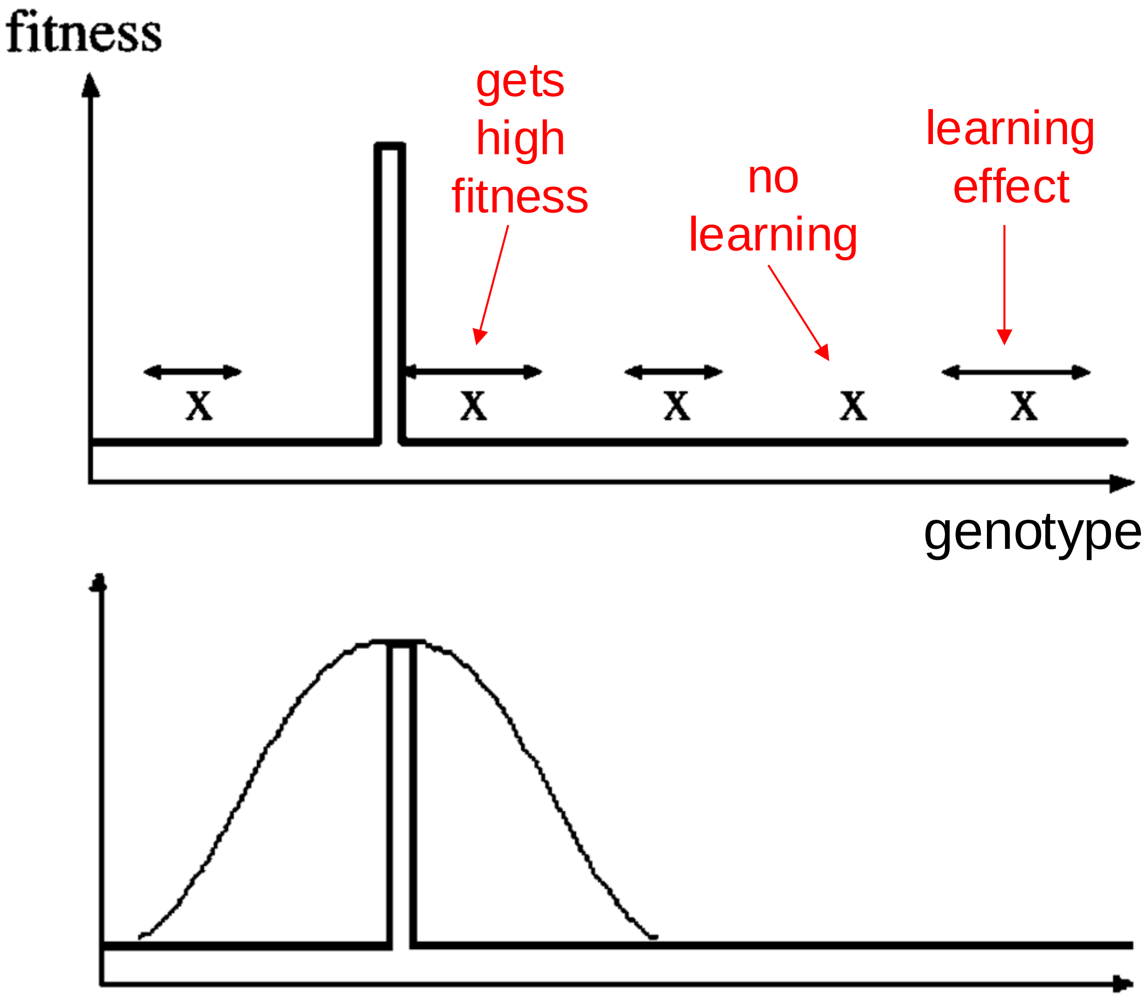
Evolutionary advantages and costs of learning

Evolution and learning are both adaptive mechanisms, but have important differences:

- They take place at different time scales
- They use different processes
- Evolution operates on the genotype, learning operates on the phenotype

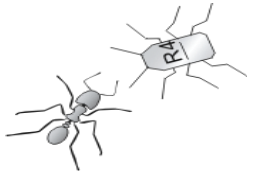
ADVANTAGES of learning	**COSTS of learning**
It can capture environmental change that occurs faster than generation time	It implies a delay in the ability of improving fitness
It can help and guide evolution	It can learn things that are wrong or delay fitness improvement
It can enable shorter genotypes	It requires tutoring, energy, may imply physical damage

How learning can help and guide evolution *(Hinton and Nowlan, 1987)*



Learning process explores the surroundings in the fitness landscape (individuals who learn may obtain high fitness even if their genes are in low fitness region)

As a consequence, the fitness landscape becomes smoother and displays a “gradient” towards peaks of high fitness, resulting in faster and better evolution



How evolution can help learning

Find initial network weights for better and faster learning

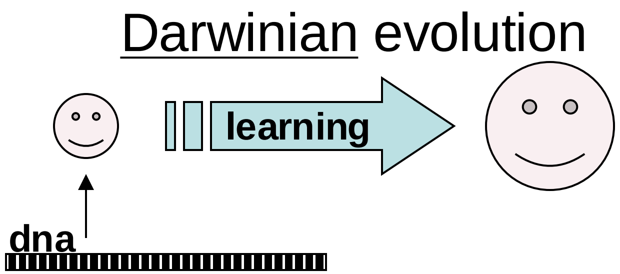
Find good set of learning hyperparameters (initialization range, learning rate, momentum, etc.)

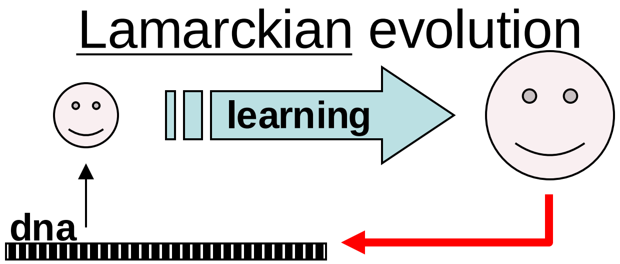
Find suitable learning algorithms

Find network morphology for better and faster learning

Simplify learning problem by co-evolving suitable sensors and bodies

Darwinian vs. Lamarckian evolution



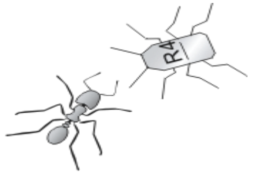


Phenotypic changes cannot be transmitted to the DNA.
Learned abilities cannot be inherited by offsping

Phenotypic changes can be transmitted to the DNA.
Learned abilities can be inherited by offspring.
(No biological evidence for Lamarckian evolution)

In static environments, Lamarckian evolution can produce better and faster results [Lund, 1999].

In dynamic environments, Lamarckian evolution can get stuck in local minima [Sasaki & Tokoro, 1997, 1999].



The Baldwin effect

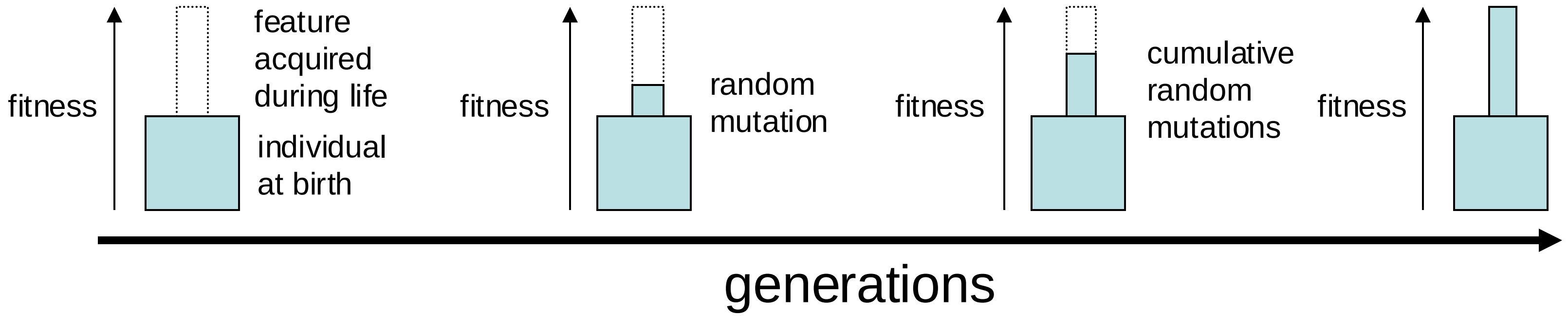
The Baldwin effect [Baldwin, 1896; Morgan, 1896; Waddington, 1942] describes a phenomenon whereby learned features can *indirectly* transfer to the DNA. It has been reported also in evolution of artificial systems [Mayley, 1997; Ackley and Littman, 1991]. Here is how it works:

1- Learning is good for survival and thus is selected and maintained by evolution

2- But learning has evolutionary costs

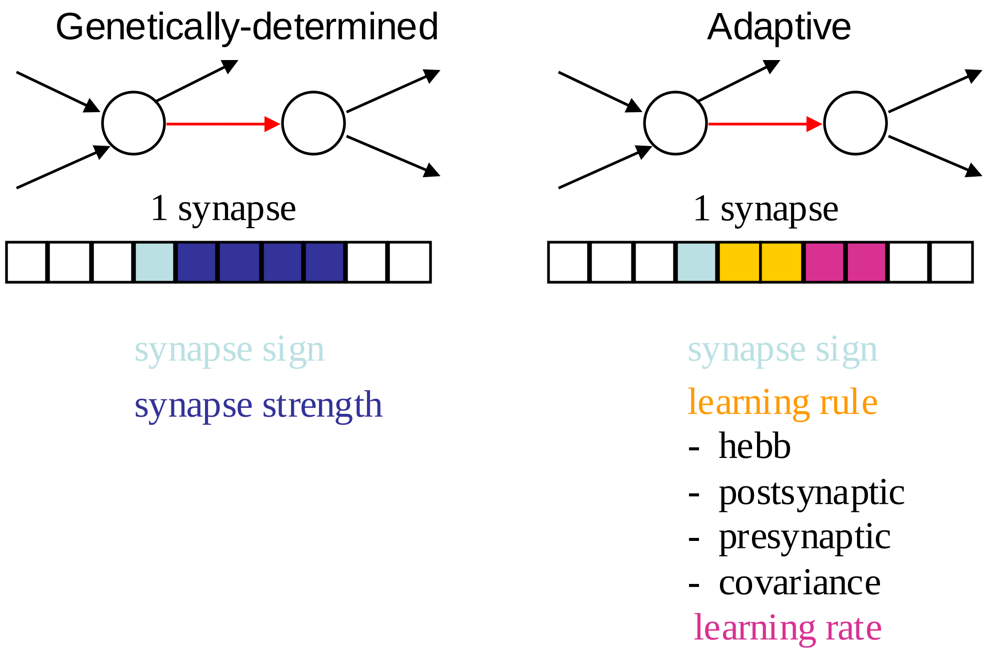
3- Therefore, individuals with mutations that are primitive sketch of abilities that would normally be learned, have a selective advantage with respect to those that must learn them.

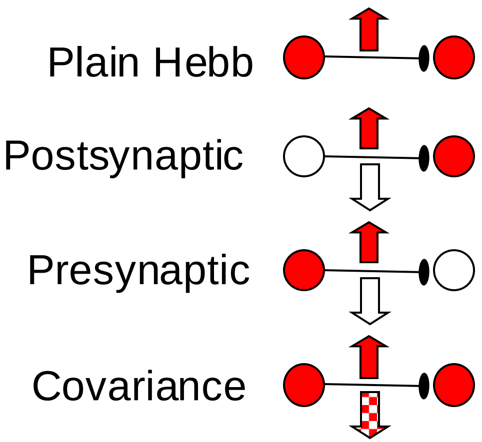
4- Gradually, individuals are born with fully-fledged abilities that had to be learned in early generations



Evolution of Learning Algorithms

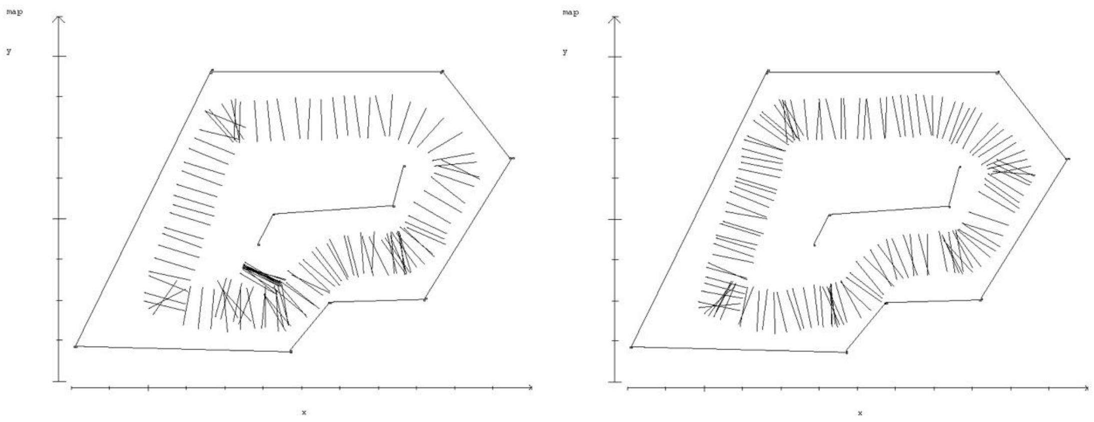
Genotype encodes variations of Hebbian learning rules for each connection or each neuron
Connection weights of newborn individuals are always initialized to random values (no Baldwin effect)
Neural network learns during life time using learning rules described in its genotype





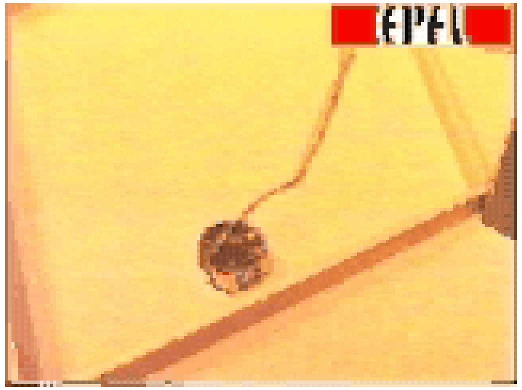
- A neural network can use different learning rules in different parts
- There is no need of teacher or reinforcement learning, no gradient descent and local minima
- Individuals are selected for their ability to learn, not simply to solve a specific problem

Online Adaptation

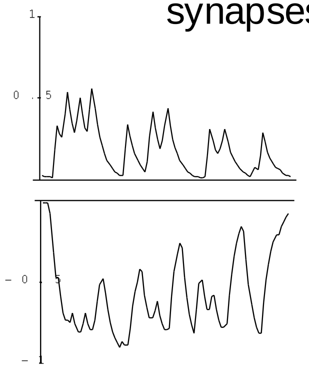


In addition, they perform well in different environments by developing suitable strategies. Contrary to conventional models, several synapses continue to change, but the overal pattern of change is dynamically stable.

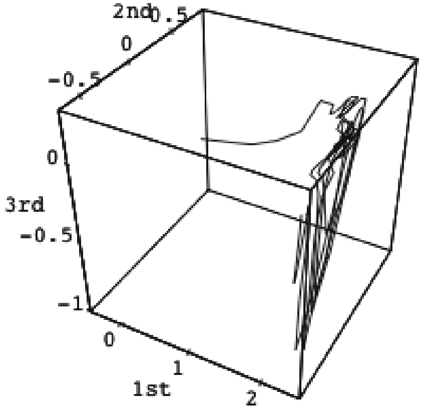
Test in new environment



Continuously changing synapses



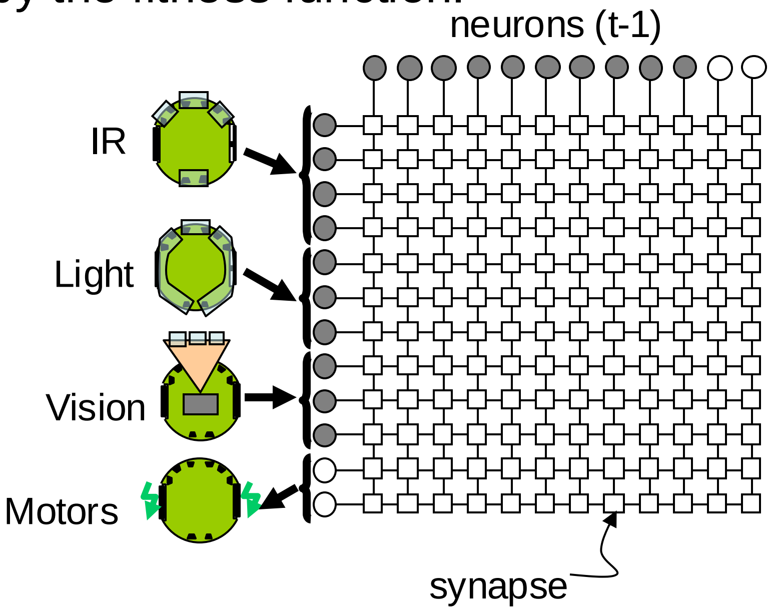
Dynamic stability



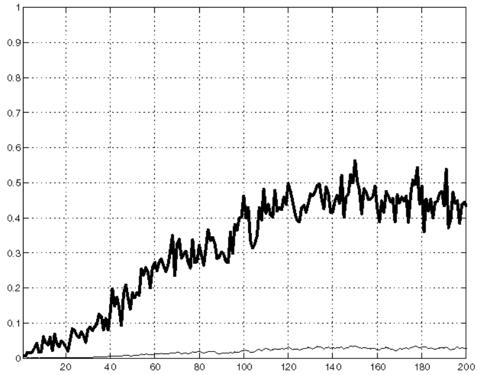
A Sequential Task

A Khepera robot is evolved to switch on a light and go under the light, but this sequence of actions is not directly rewarded by the fitness function.

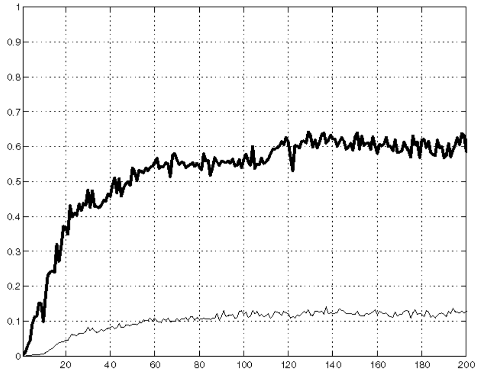
Fitness= time_gray_light / total_time



evolution of weights

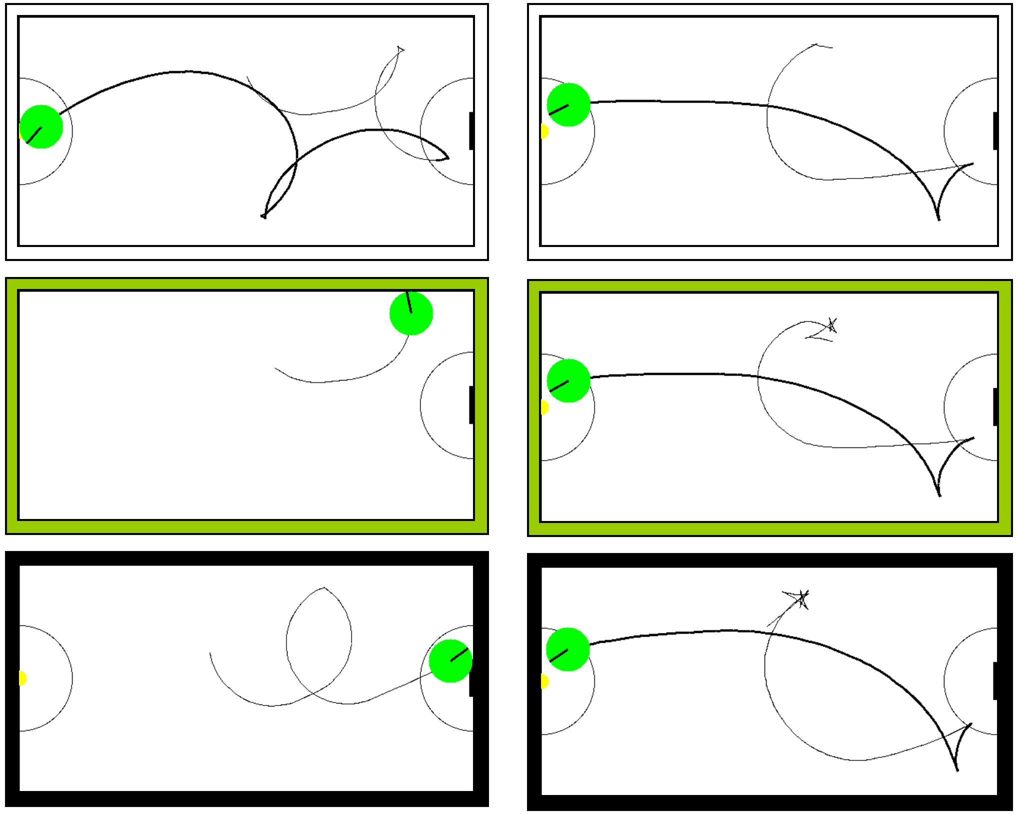


evolution of rules



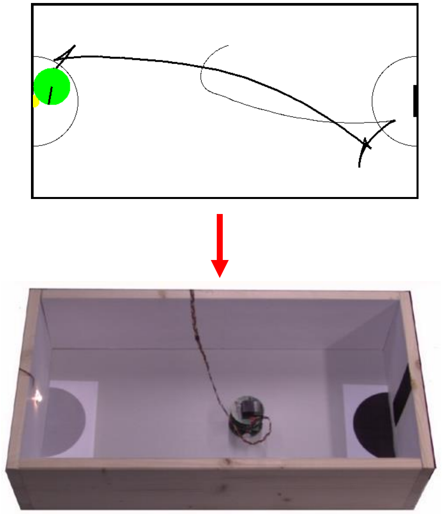
Robustness to Color Change

Evolved adaptive individuals can cope with new colours of the walls whereas genetically-determined individuals fail.



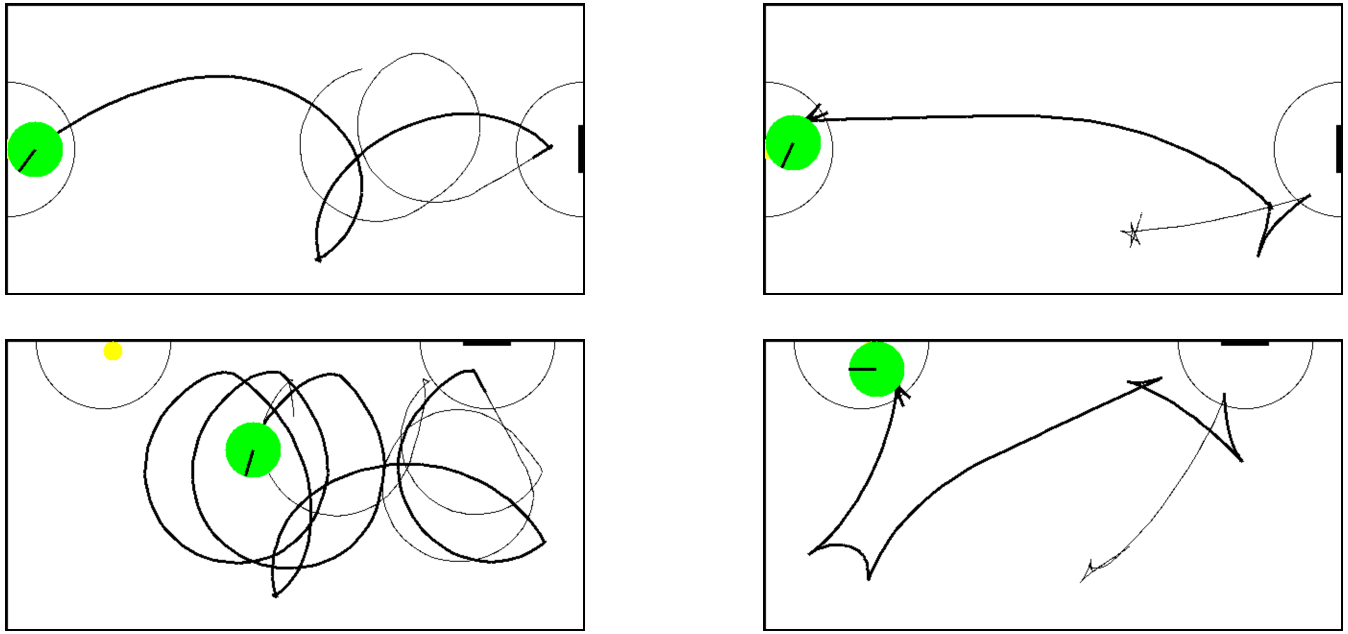
Genetically-determined Adaptive

Similarly, evolved adaptive individuals transfer smoothly from simulated to real world.



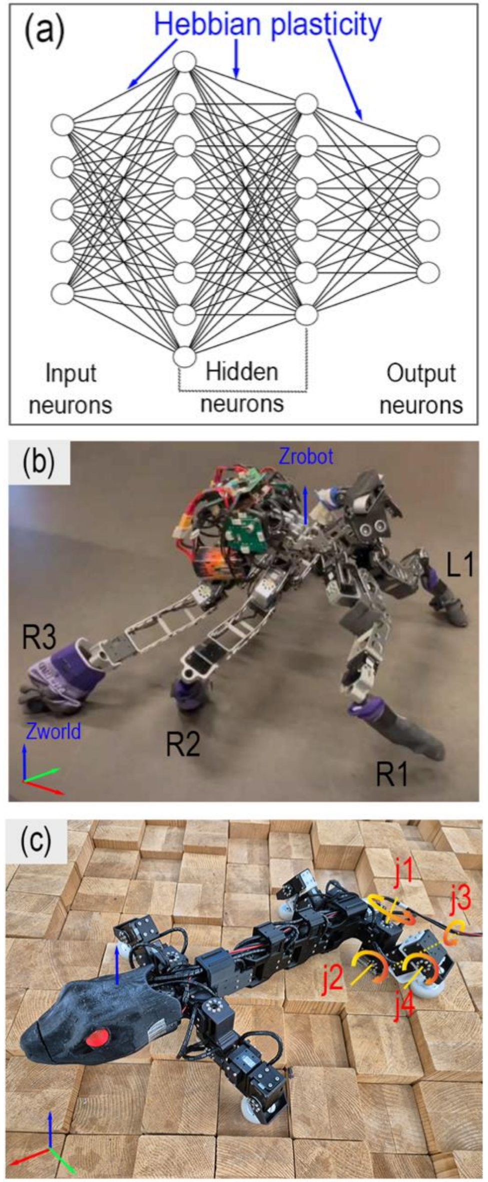
Robustness to Layout Modification

Evolved adaptive individuals can cope with new positions of the two landmarks whereas genetically-determined inviduals cannot.



Genetically-determined Adaptive

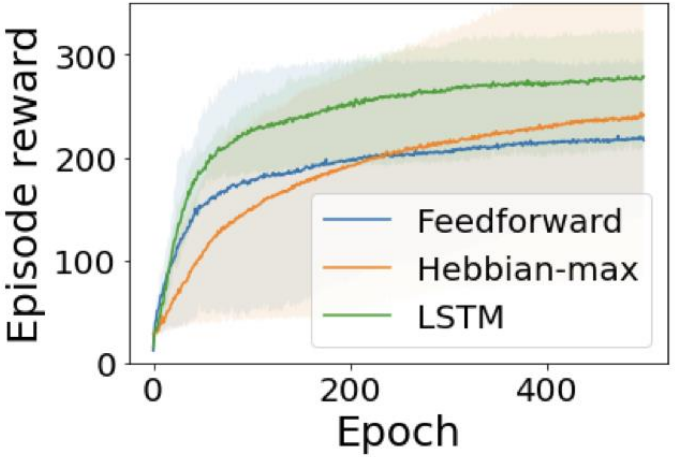
Polynomial Representation of Plastic Hebbian Rules



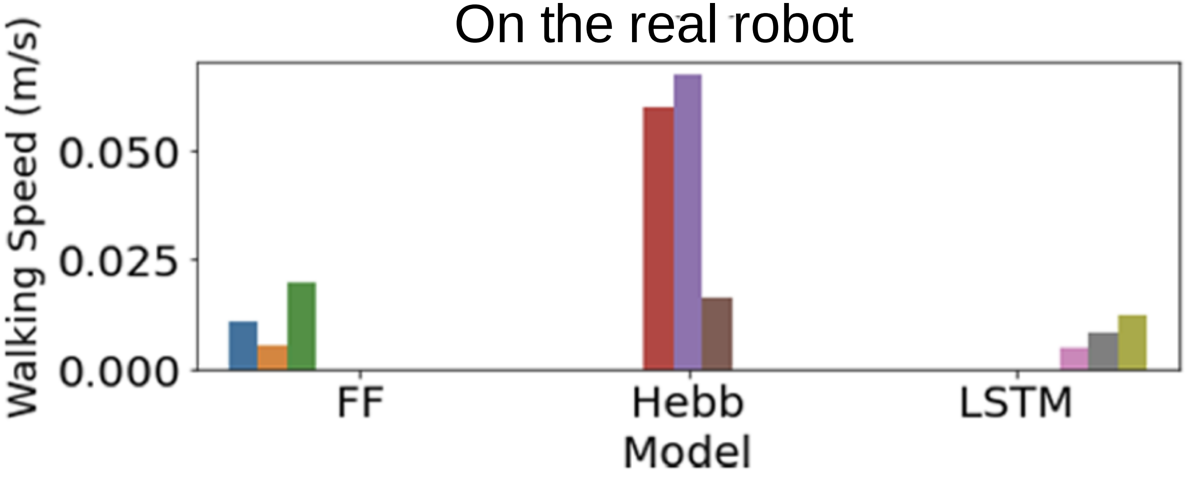
$$\Delta w_{ij}^{k} = \eta \cdot (A o_i o_j + B o_i + C o_j + D)$$

These parameters are genetically encoded and evolved for every weight

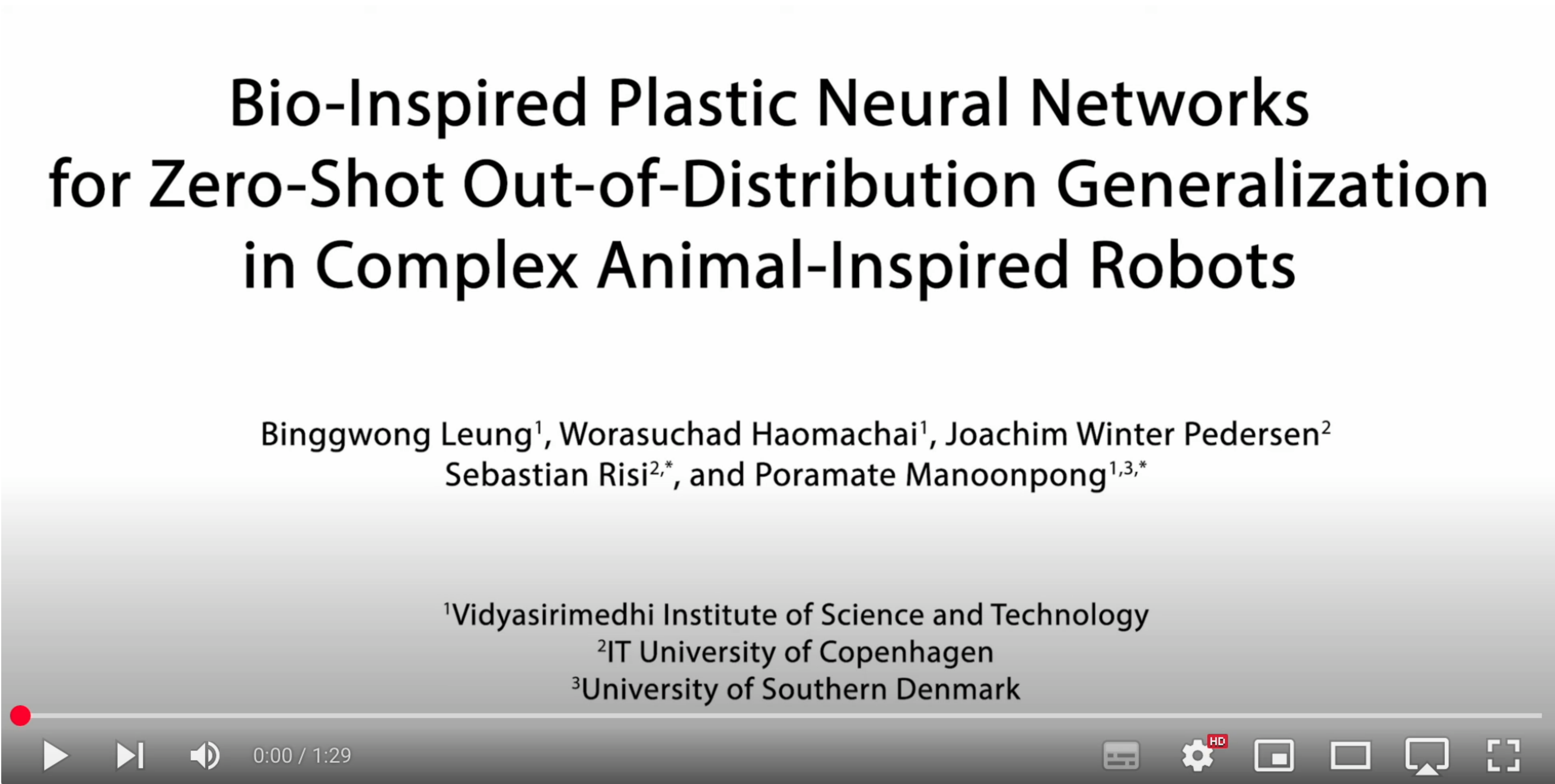
Evolution in simulation



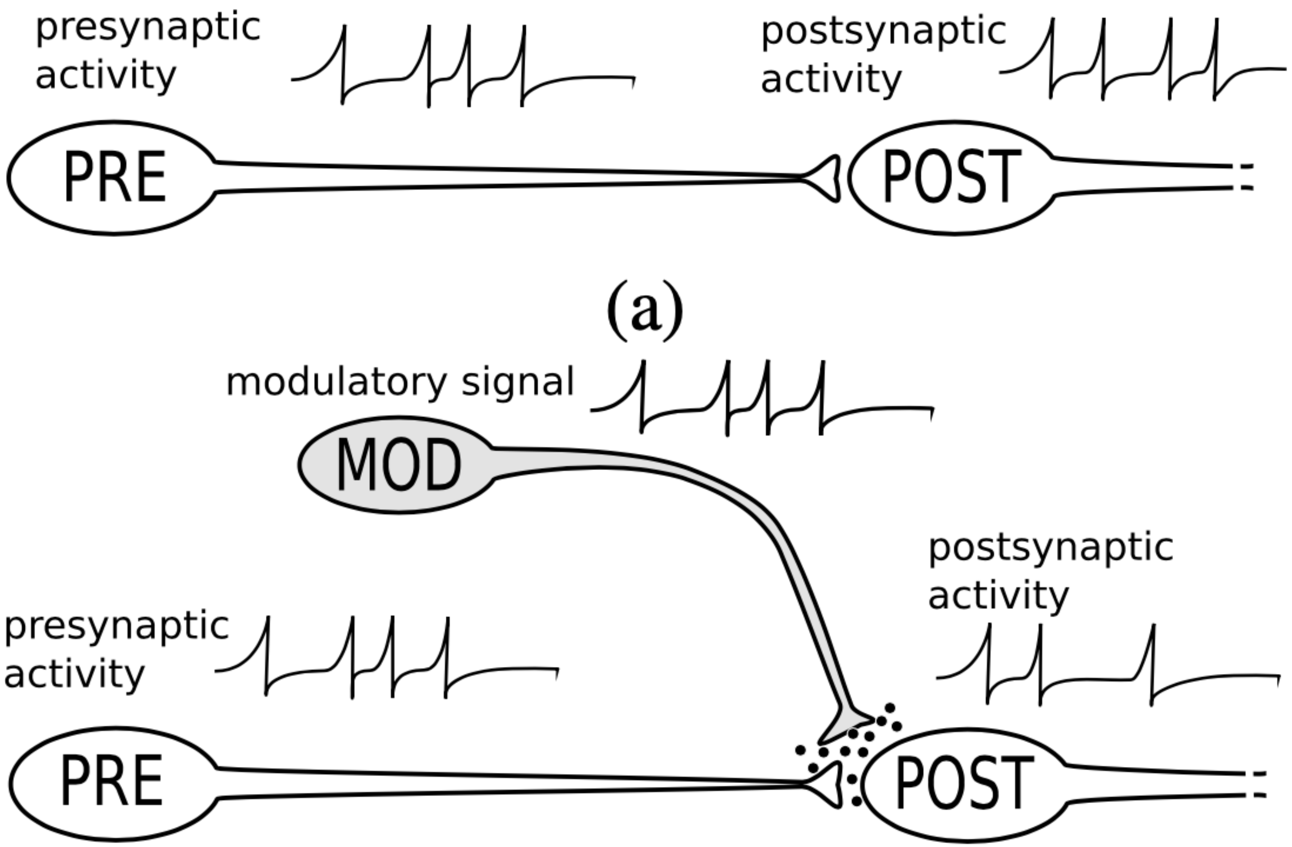
On the real robot



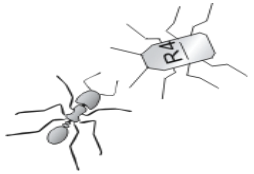
Leung et al (2025) *Bio-Inspired Plastic Neural Networks for Zero-Shot Out-of-Distribution Generalization in Complex Animal-Inspired Robots*, https://arxiv.org/pdf/2503.12406 https://haomachai.com/2025/03/02/bio-inspired-plastic-neural-networks-for-zero-shot-out-of-distribution-generalization-in-complex-animal-inspired-robots/



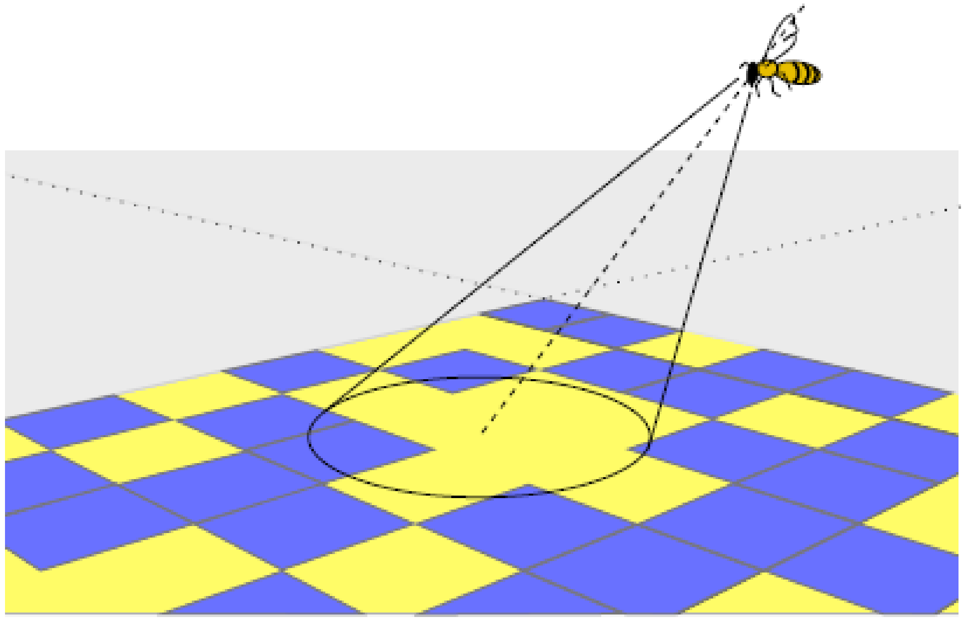
Neuromodulation of synaptic plasticity



Bailey, M. Giustetto, Y.-Y. Huang, R. D. Hawkins, and E. R. Kandel. (2000) Is heterosynaptic modulation essential for stabilizing Hebbian plasticity and memory? *Nature Reviews Neuroscience*, 1(1):11–20



Reward-based behavioural choice



Scenario	Nectar of the high rewarding flower	Nectar of the low rewarding flower
1	$0.8\mu l$	$0.3\mu l$
2	$0.7\mu l$	$1.0\mu l$ with P=0.2 $0.0\mu l$ with P=0.8
3	$1.6\mu l$ with P=0.75 $0.0\mu l$ with P=0.25	$0.8\mu l$ with P=0.75 $0.0\mu l$ with P=0.25
4	$0.8\mu l$ with P=0.75 $0.0\mu l$ with P=0.25	$0.8\mu l$ with P=0.25 $0.0\mu l$ with P=0.75

G% — Percentage of GREY colour under the cone-view

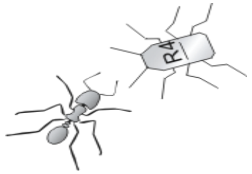
B% — Percentage of BLUE colour under the cone-view

Y% — Percentage of YELLOW colour under the cone-view

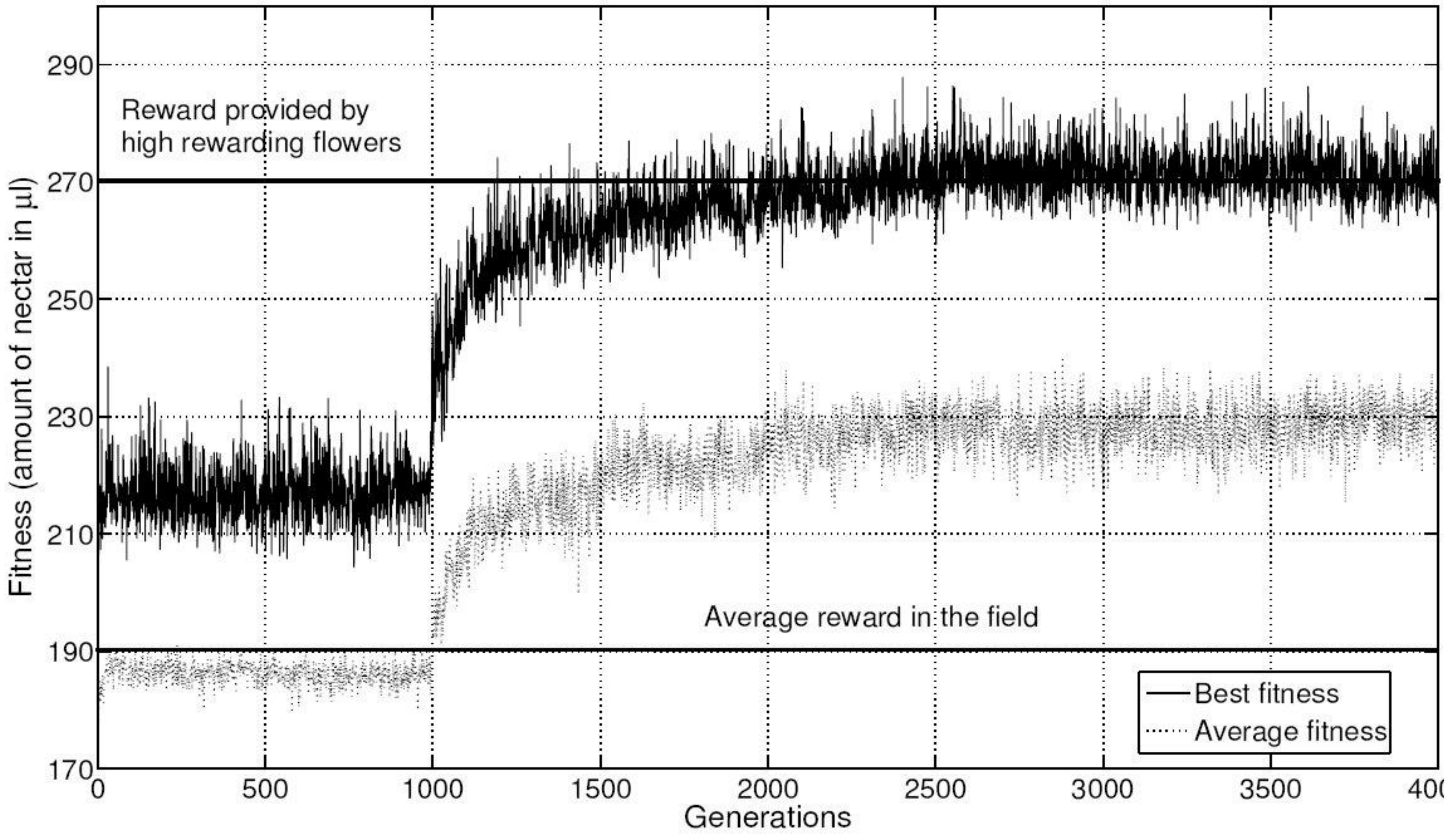
R — Reward received upon landing

L — Landing signal

$$fitness = \sum rewards$$

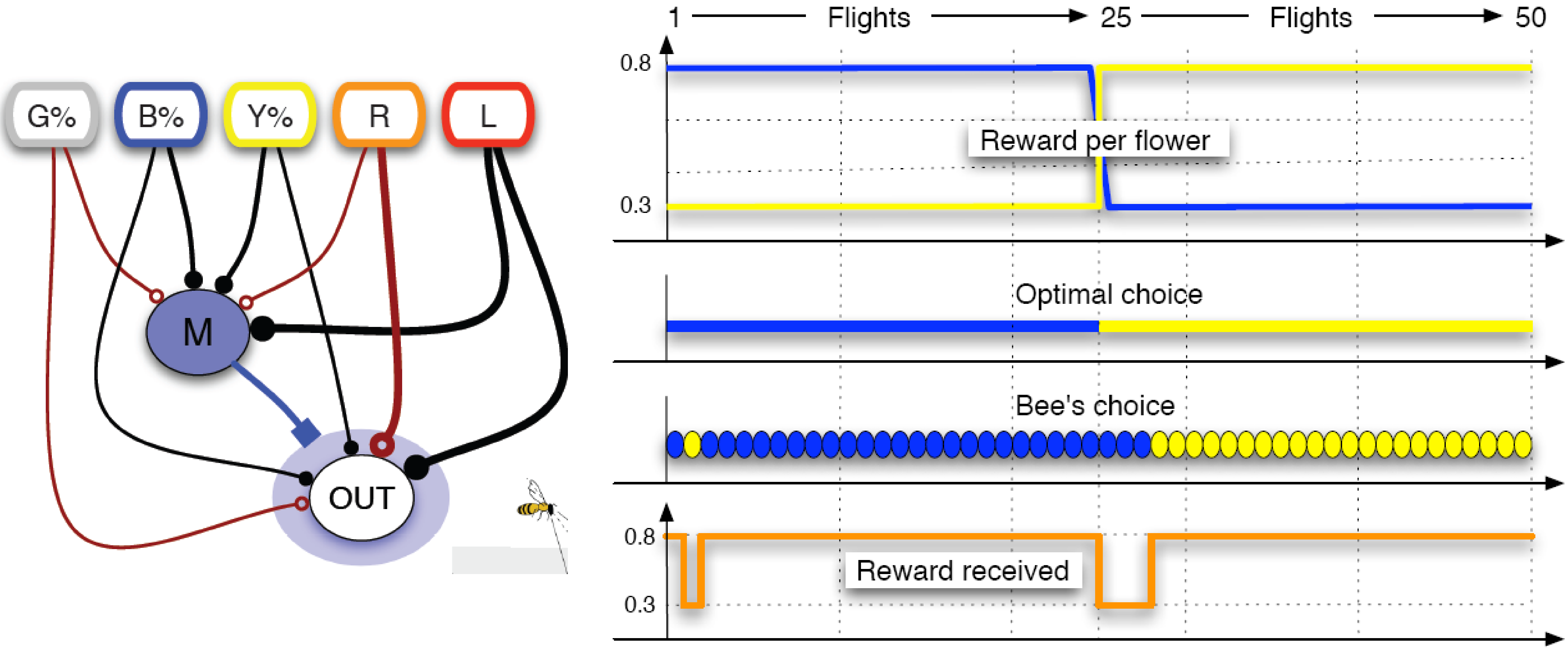


Evolutionary discovery of modulated plasticity



A. Soltoggio, P. Durr, C. Mattiussi and D. Floreano (2007) Evolving neuromodulatory topologies for reinforcement learning-like problems, *IEEE Congress on Evolutionary Computation*, 2471-2478

Best evolved individual



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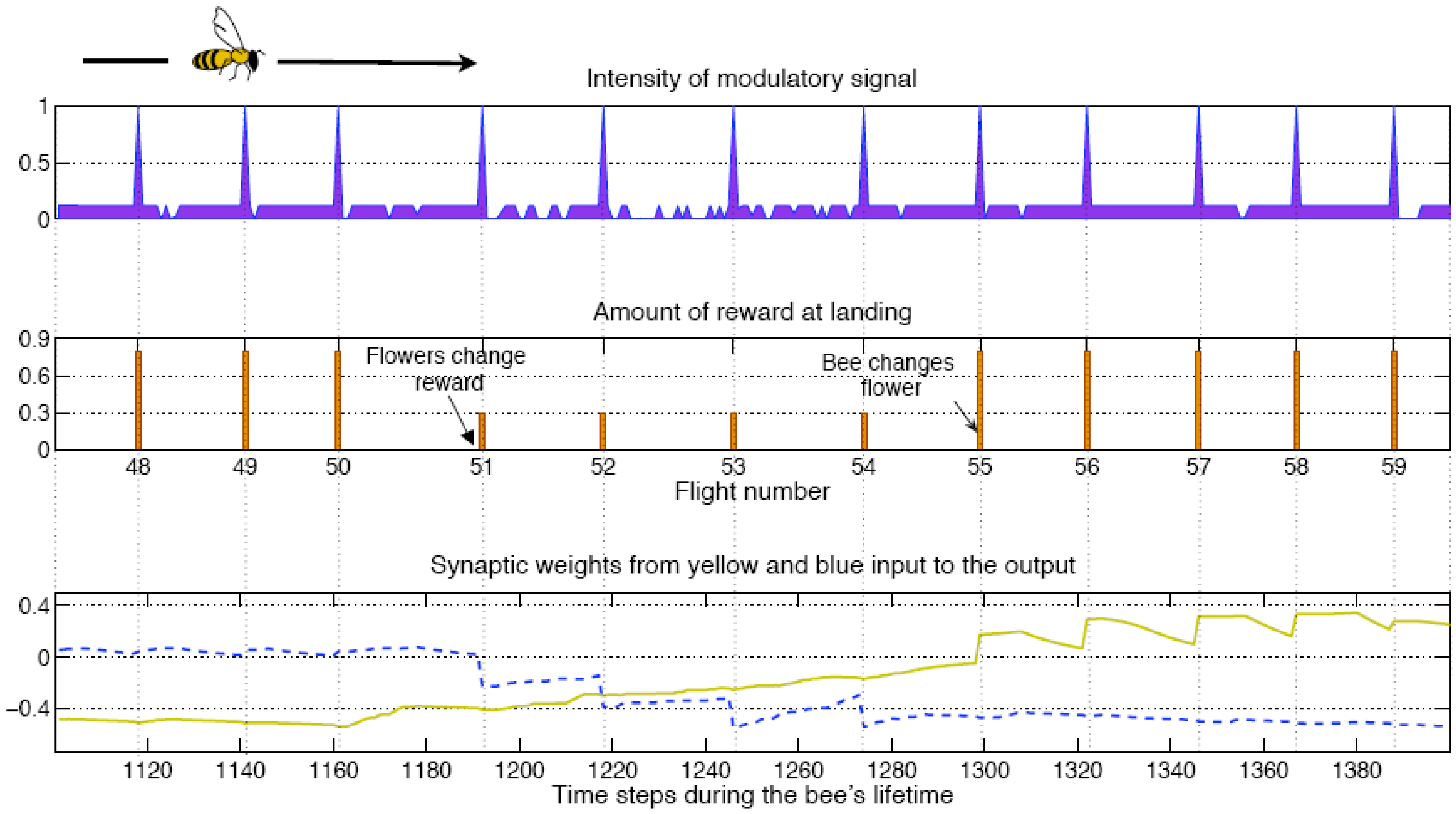
Learning dynamics



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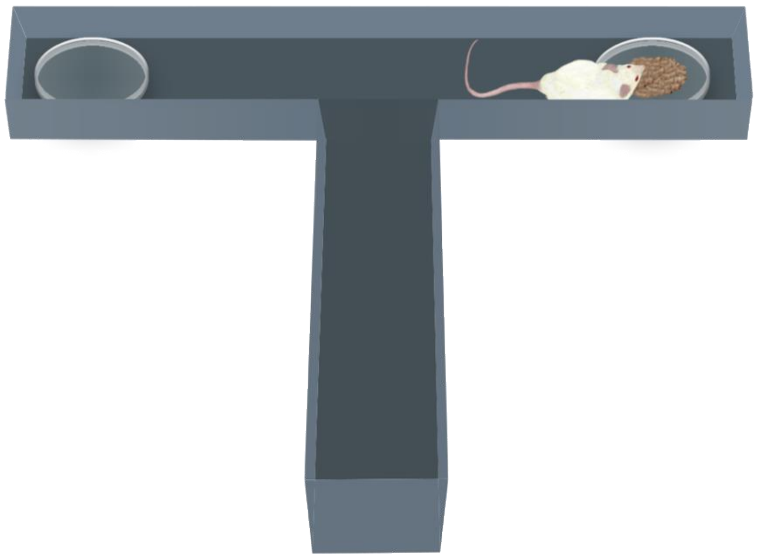
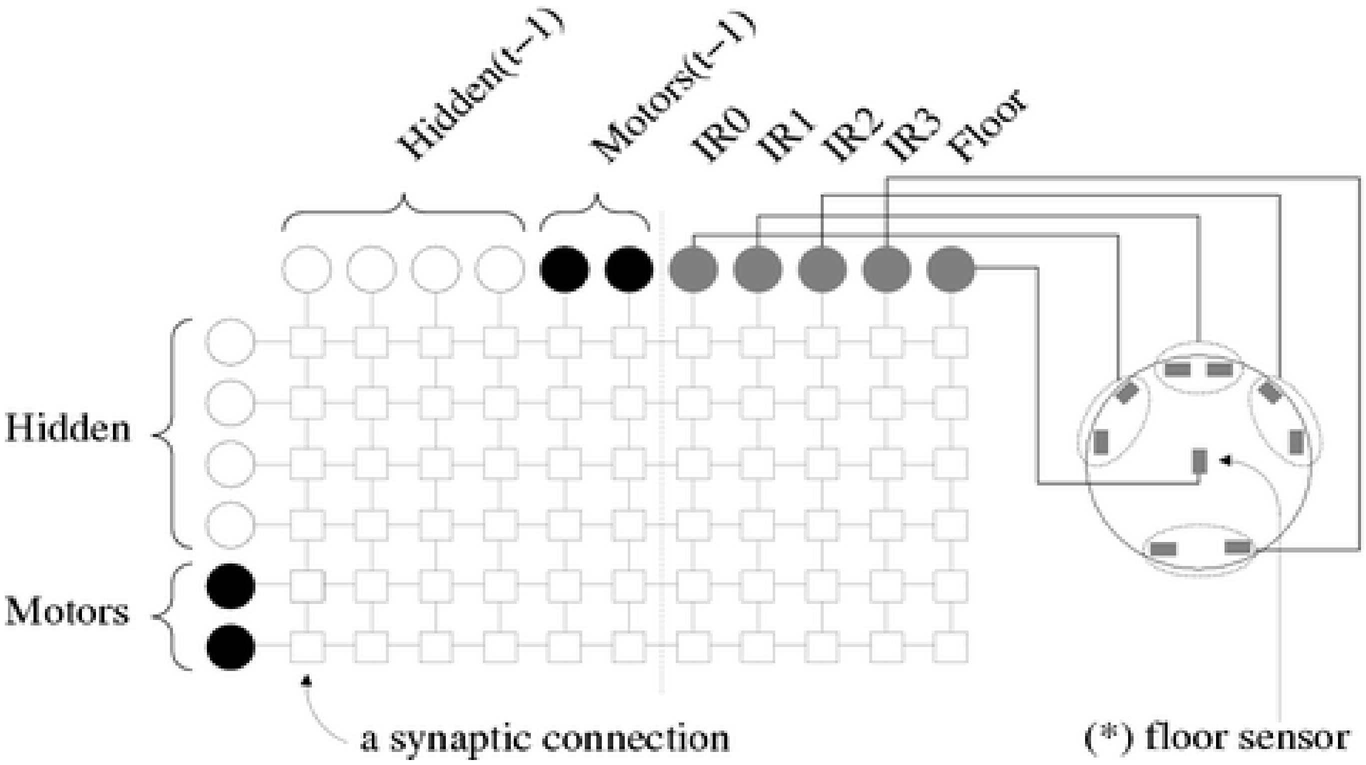
Reinforcement learning in the T-maze

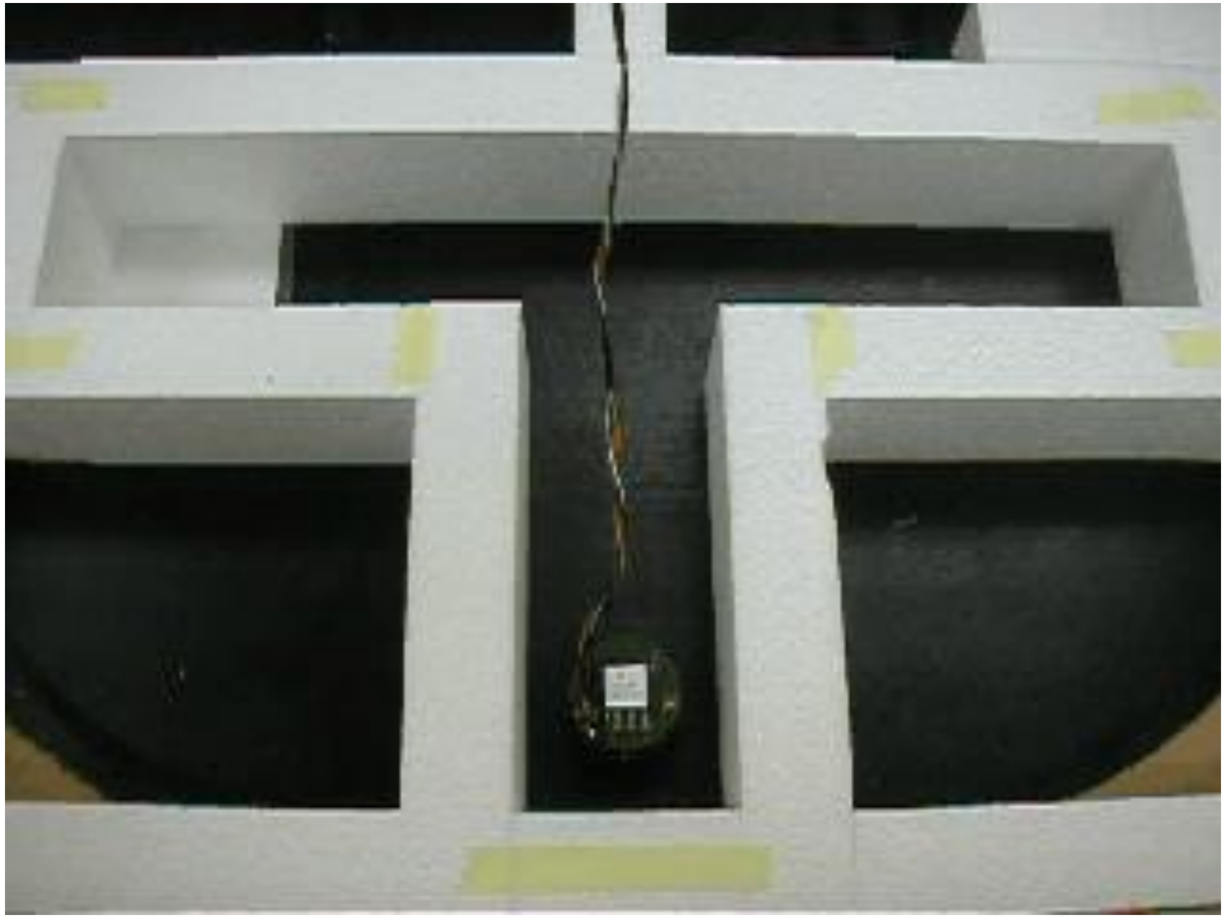


The T-maze (Tolman, 1925)

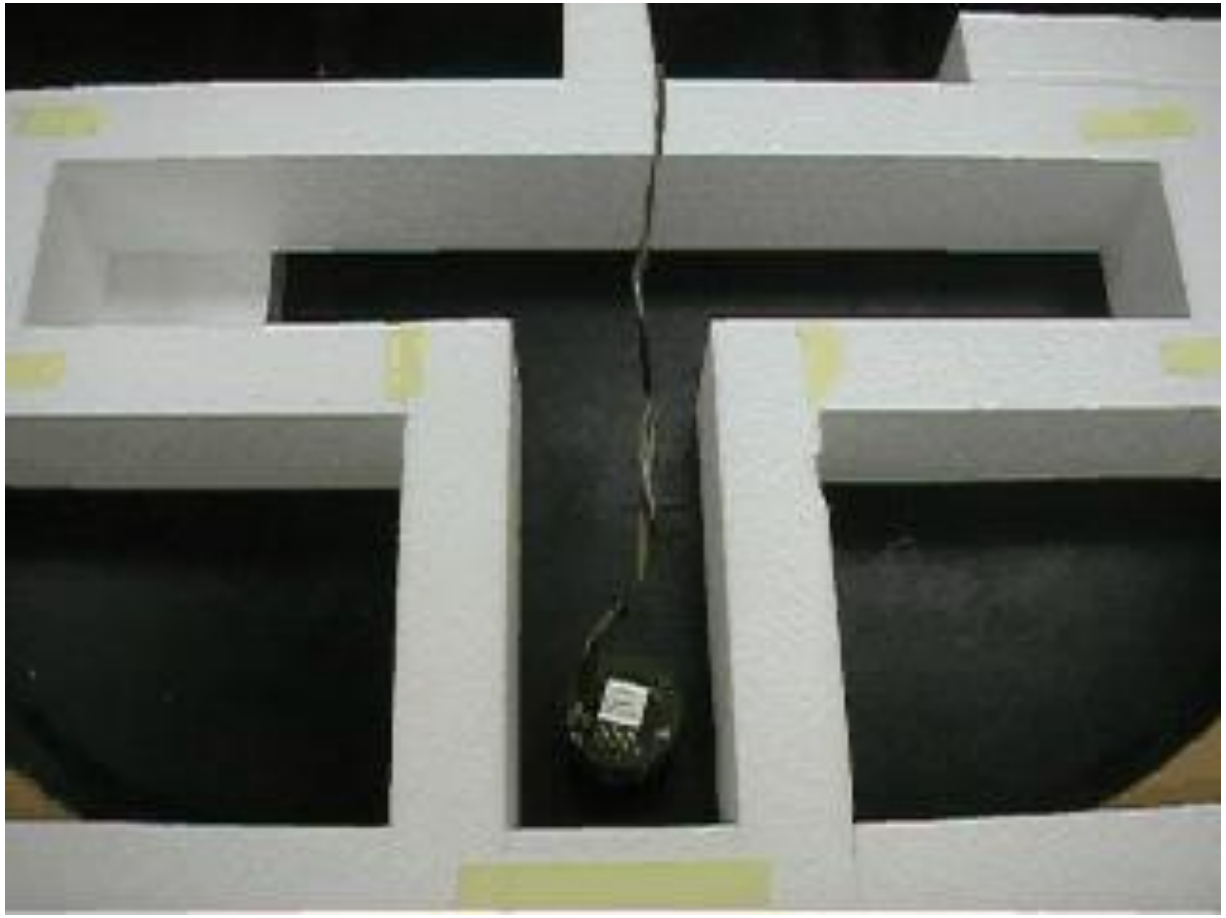


Blynel and Floreano, 2003

Look ma, no learning!

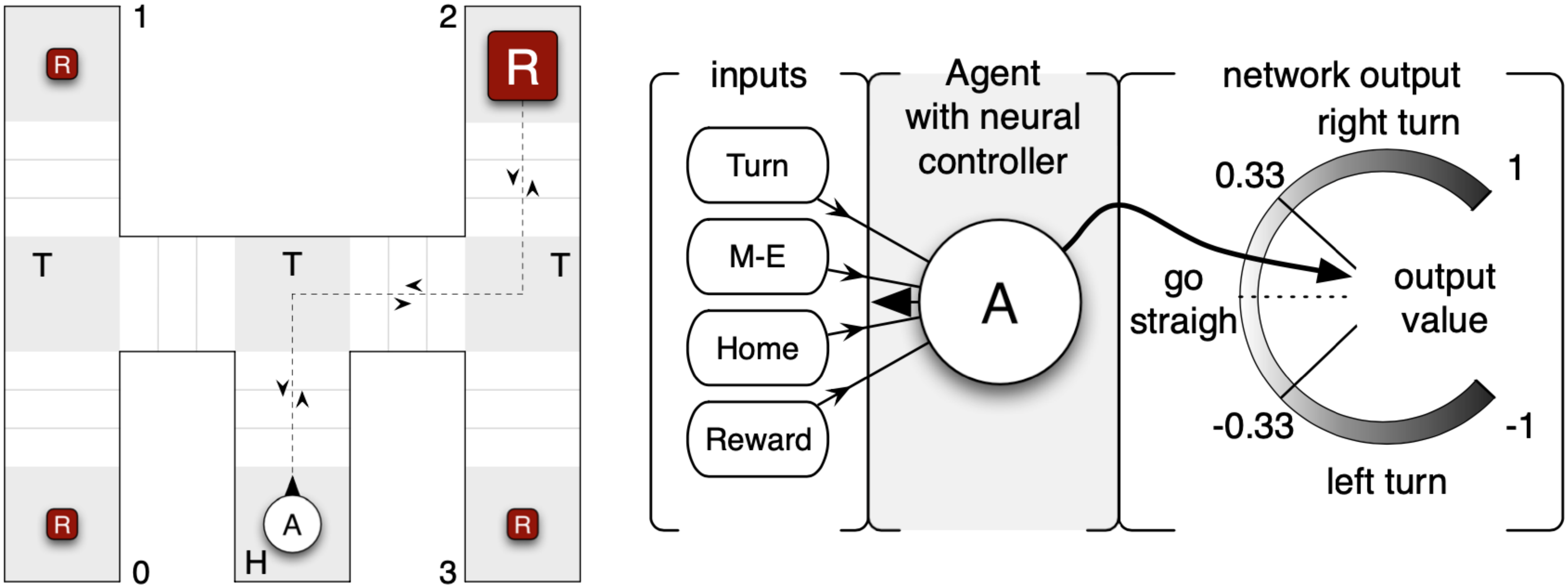


Trial 1



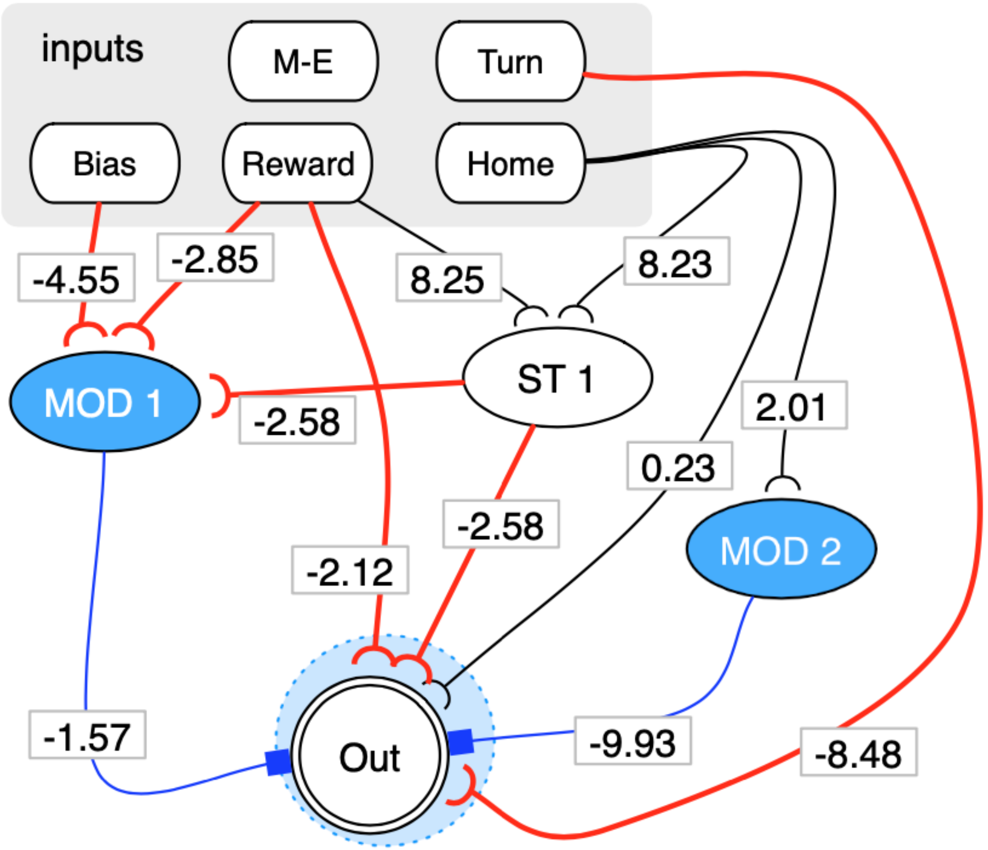
Trial 2

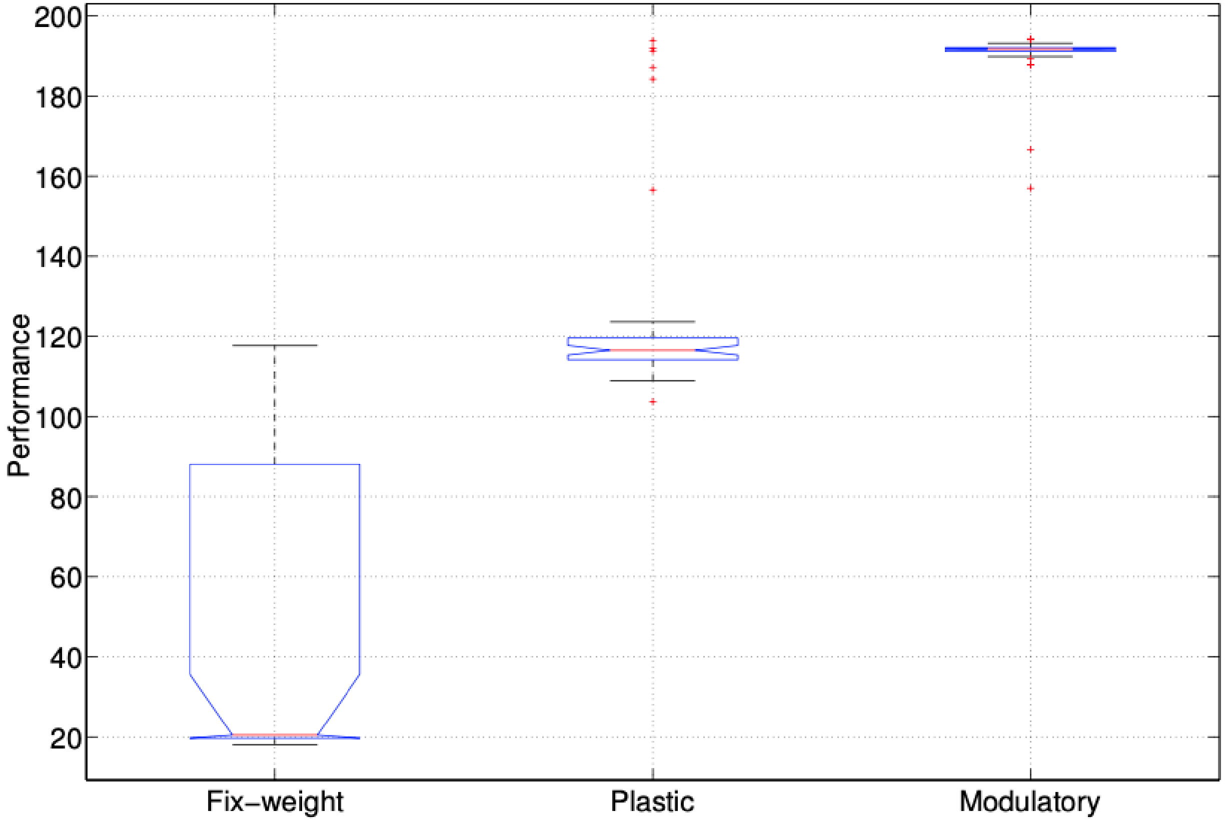
The double T-maze



A. Soltoggio; J. A. Bullinaria; C. Mattiussi; P. Dürr; D. Floreano (2008) Evolutionary Advantages of Neuromodulated Plasticity in Dynamic, Reward- based Scenarios. In *Artificial Life XI*, p. 569–576

Evolution of reward-based learning





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