# Neurorobotics

## Module 2: Neurorobot Design Principles

## Lecture 4: Design Principle 2 – Adaptive Behaviour
Value and Prediction

David Vernon
Carnegie Mellon University Africa

www.vernon.eu

# TransAIR Workshop on Cognitive Architectures for Robot Agents


https://transair-bridge.org/workshop-2021/

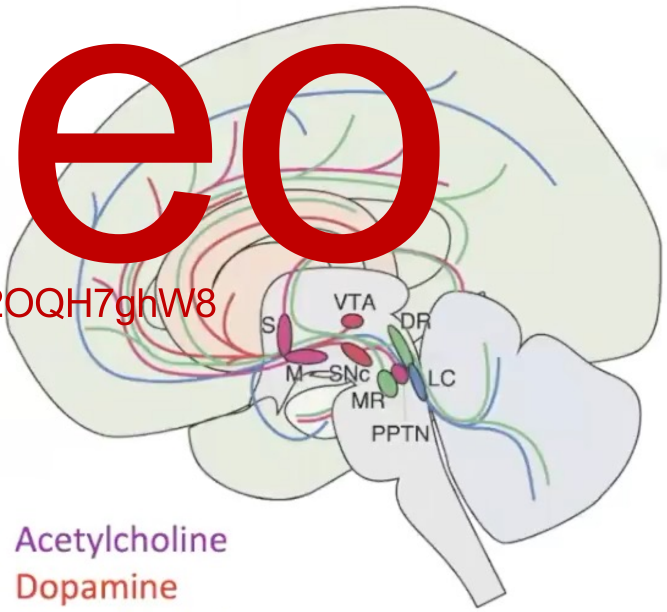
# Neurorobotic Design Principles II
# - Adaptive Behavior, a Change for the Better

- Value – Signals of what is good, bad or interesting shape behavior.

Video

https://youtu.be/rb2OQH7ghW8

K. Doya / Neural Networks 15 (2002) 495–506




Acetylcholine
Dopamine
Norepinephrine
Serotonin

# Value

- A value system captures what is good and what is bad for an agent
- In the brain, value systems are often associated with
  - Neuromodulators
  - Neurohormones
- A value system increases the likelihood of selecting appropriate responses to external phenomena
- "Value can be thought of as a measure of the effort one is willing to expend to obtain reward or to avoid punishment"

# Value

Two types of value system

- Extrinsic: external rewards and punishment
- Intrinsic: internal motivation
    - Intrinsic motivation,

      e.g. curiosity, seeking novelty

# Value

## Neuromodulators

- Chemicals that signal important environmental or internal events
- Cause organisms to adapt behavior
- Through long-lasting signals to broad areas of the nervous systems
- Influence synaptic change … learning and memory … to satisfy global needs according to value

# Value

## Neuromodulators

- Dopamine: dopaminergic neuromodulator system
  - Prediction of reward
- Seratonin: seratonergic neuromodulator system
  - Aversion to harm

# Value

## Neuromodulators

- Noradrenaline: noradrenergic neuromodulator systems
  - Unexpected events
- Acetylcholine: cholinergic neuromodulator system
  - Attention to important features

Signal intrinsic value by allocating attention and triggering learning

# Value

Neuromodulatory systems

- Drive an organism to be decisive when action is needed
- Allow an organism to explore when the is nothing urgent to attend to
- Exploitation vs. exploration

More on neuromodulators in NR02-05 Design Principle 3: Behavioral Tradeoffs

# Prediction

"Predicting outcomes and planning for the future is a hallmark of cognitive behavior"

Much of the cortex is devoted to predicting

- What we will sense
- The outcome of a movement or action
- The need for action (selecting the ones that have bigger payoffs)

Neurorobots should have these predictive abilities

# Prediction

"Organisms minimize surprises
by predicting future outcomes
so that they minimize the energy expenditures
required to deal with unanticipated events"

# Prediction

"Minimizing free energy has close ties to many existing brain theories, such as
Bayesian brain,
predictive coding,
cell assemblies,
Infomax, as well as
Neural Darwinism or neuronal group selection"

Very deep statement

## Free Energy Principle

"… according to which perceptual inference and action emerge as a consequence of a more fundamental imperative towards the avoidance of "surprising" events"

(Seth 2013)

"Organisms must minimize the long-run average surprise of sensory states, since surprising sensory states are likely to reflect conditions incompatible with continued existence"

## Free Energy Principle

"… according to which perceptual inference and action emerge as a consequence of a more fundamental imperative towards the avoidance of "surprising" events"

(Seth 2013)

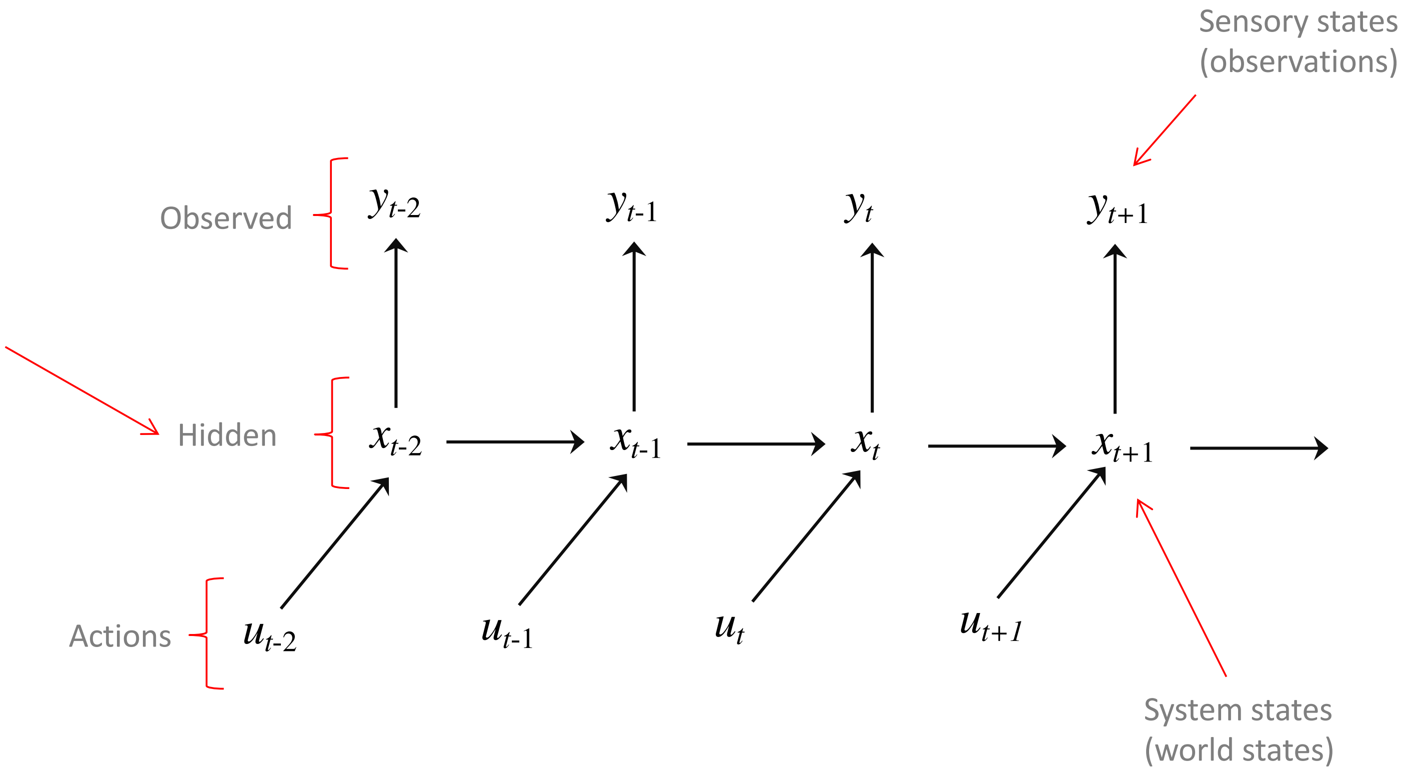
"Surprising" in an information-theoretic sense:
surprisal, a measure of uncertainty of an event
(or "unlikeliness of the occurrence of an event")

$$u_i = -\log_2(P_i) \quad [= \log_2(1/P_i)]$$

The average surprisal is entropy $H = -\sum_{i=1}^{M} P_i \log_2 P_i$

Cannot evaluate surprisal of world state
or average long-run surprisal, i.e. entropy

World states are hidden &
entropy requires averaging over all
possible occurrences of events



# Free Energy Principle

Instead, the agent maintains a lower limit on surprisal by minimizing

the difference between actual sensory signals and the signals produced by a predictive model

This difference is **free energy**

Under some general assumptions, this is the long-run sum of prediction error

This links the free energy principle with predictive processing

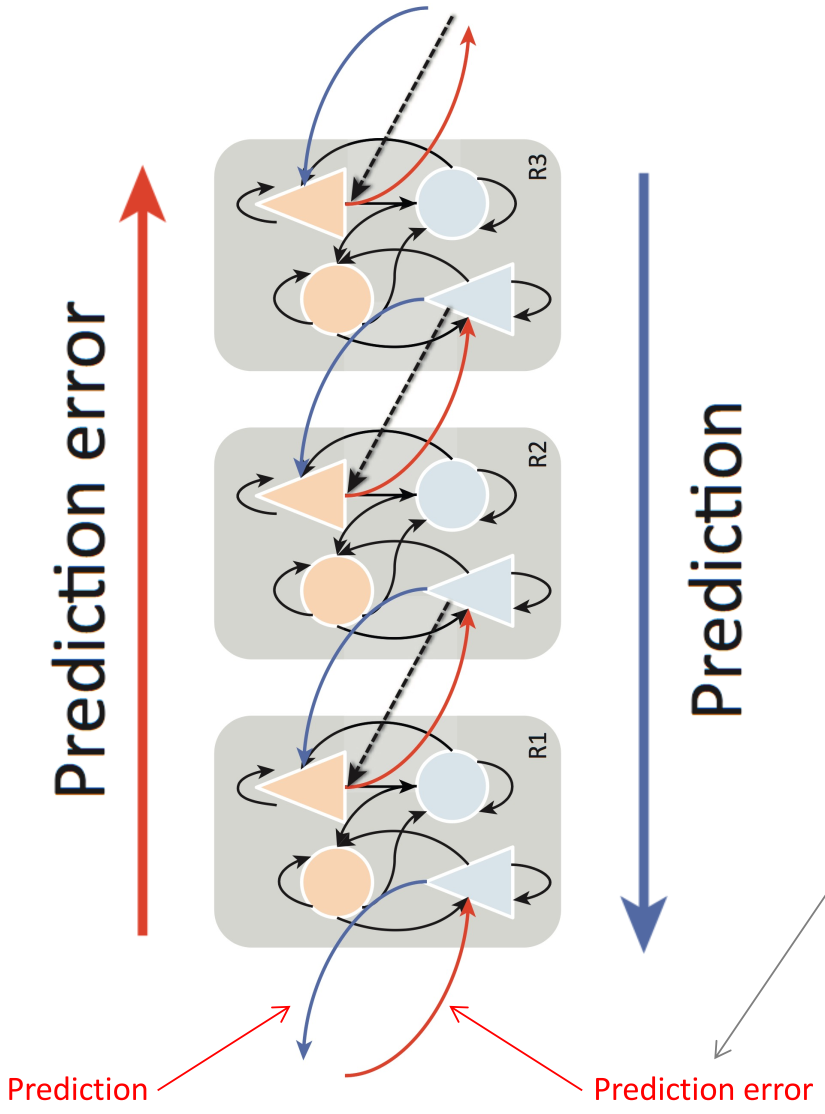
Free Energy Principle

Entropy is the average surprisal $H = -\sum_{i=1}^{M} P_i \log_2 P_i$

"Organisms minimize an upper bound on the entropy of sensory signals (the free energy).

Under specific assumptions, free energy translates to prediction error."

(Seth 2013)



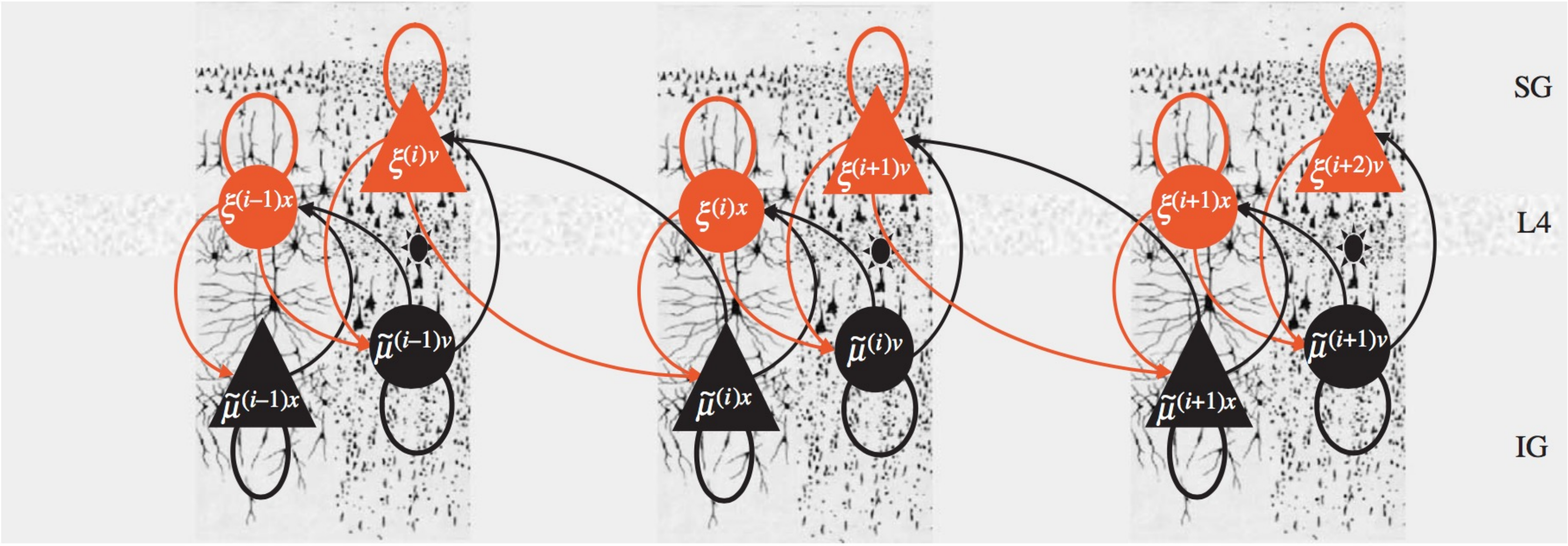

Free energy principle
Minimize the long-run prediction error

A. K. Seth. Interoceptive inference, emotion, and the embodied self. Trends in Cognitive Sciences, 17(11):565–573, November 2013.

$$\xi^{(i)v} = \tilde{\mu}^{(i-1)v} - \tilde{g}(\tilde{\mu}^{(i)}) - \Lambda^{(i)z}\, \xi^{(i)v}$$

$$\xi^{(i)x} = D\tilde{\mu}^{(i)x} - \tilde{f}(\tilde{\mu}^{(i)}) - \Lambda^{(i)w}\, \xi^{(i)x}$$

forward prediction error




backward predictions

$$\dot{\tilde{\mu}}^{(i)v} = D\tilde{\mu}^{(i)v} - \tilde{\varepsilon}_v^{(i)T}\, \xi^{(i)} - \xi^{(i+1)v}$$

$$\dot{\tilde{\mu}}^{(i)x} = D\tilde{\mu}^{(i)x} - \tilde{\varepsilon}_x^{(i)T}\, \xi^{(i)}$$

K. Friston and S. Kiebel. Predictive coding under the free-energy principle. Philosophical Transactions of the Royal Society of London, Series B, Biological Sciences, 364(1521)):1211–1221, 2009

# Prediction

Prediction is a fundamental computation in cortical systems

- Uncertainty due to sensor noise and environmental change leads to surprise
- The brain constructs an internal model to make predictions about
  - Sensory input
  - Action outcomes
- Adapt when the predictions are in error

# Prediction

Biological organisms and neurorobots use a policy that minimized surprise

- By minimizing the difference between likely and desired outcomes

This involves

- Pursuing the goal-state that has the highest expected utility: exploitation
- Visiting a number of goal-states : exploration

Novelty seeking behavior and curiosity reduces surprises in the long run

# Prediction

Prediction and internal models facilitate mental simulation

Heslow's simulation hypothesis: three elements

1. Simulation of behavior
   - The frontal cortex is activated when simulating movement
     - But the movement isn't executed: covert action

# Prediction

Prediction and internal models facilitate mental simulation

Heslow's simulation hypothesis: three elements

2. Simulation of perception
   - This simulated movement activates the sensory cortex
     - Covert perception

# Prediction

Prediction and internal models facilitate mental simulation

Heslow's simulation hypothesis: three elements

3. Anticipation

   – This enables a sensory-motor activity that would have been active if the action had been carried out

     - Prediction of outcome of the action
     - Allows for the generation of a prediction error

# Internal Simulation and Action

- Several simulation theories, but perhaps the most influential is known as the Simulation Hypothesis (Hesslow 2002, Hesslow 2012)

- Three core assumptions

Covert action / covert behaviour

1. The regions in the brain that are responsible for motor control can be activated **without** causing bodily movement

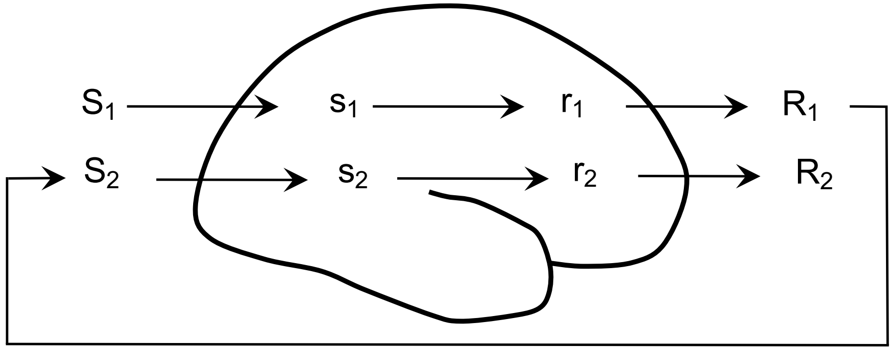
Simulation of perceptions

2. Perceptions can be caused by internal brain activity and not just by external stimuli

3. The brain has associative mechanisms that allow motor behaviour or perceptual activity to evoke other perceptual activity

Simulated action elicit perceptions

# Internal Simulation and Action

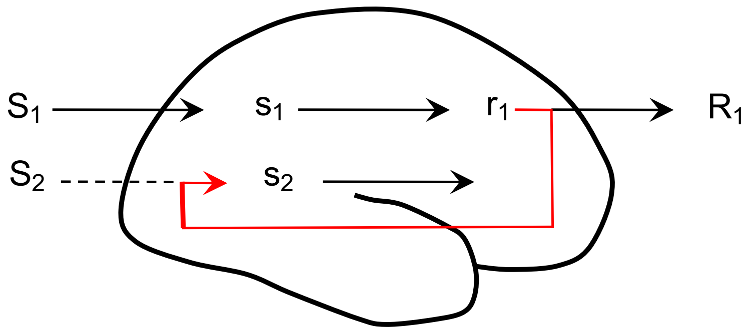



No internal simulation

**Internal Simulation Hypothesis**

(Hesslow 2002, 2012)

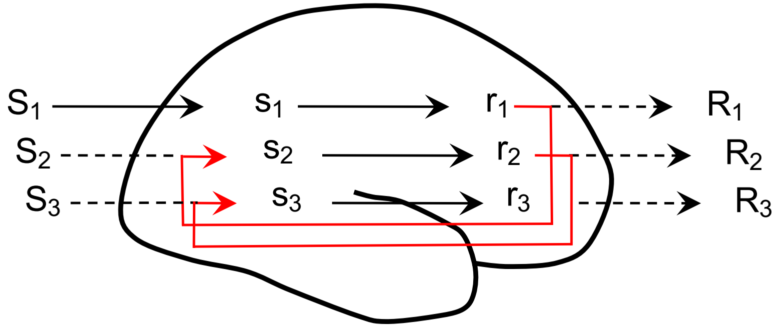
# Internal Simulation and Action




A motor response
to an input stimulus
causes the internal simulation
of an associated perception …

**Internal Simulation Hypothesis**
(Hesslow 2002, 2012)

# Internal Simulation and Action




This elicits a covert action which in turn elicits a simulated perception and a consequent covert action

**Internal Simulation Hypothesis**
(Hesslow 2002, 2012)

# Internal Simulation and Action

There is an increasing amount of neurophysiological evidence in support of all three assumptions

For example, see (Svensson et al., 2013)

# Reading

Hwu, T. and Krichmar, J. (2022). Neurorobotics: Connecting the Brain, Body and Environment, MIT Press.

Chapter 6, Sections 6.3 - 6.4, pp. 111 - 119

# References


A. K. Seth (2013). Interoceptive inference, emotion, and the embodied self. Trends in Cognitive Sciences, 17(11):565–573, November 2013.

H. Svensson, S. Thill, and T. Ziemke (2013). Dreaming of electric sheep? Exploring the functions of dream-like mechanisms in the development of mental imagery simulations. *Adaptive Behavior*, 21:222–238.