

Infomax Control:
*A model of the real-time
organization of behavior*

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In search of a theory of behavior

Aims for the Behavioral Sciences:

- Understand behavior
- Predict behavior
- Design interventions



Actual baby, not a robot

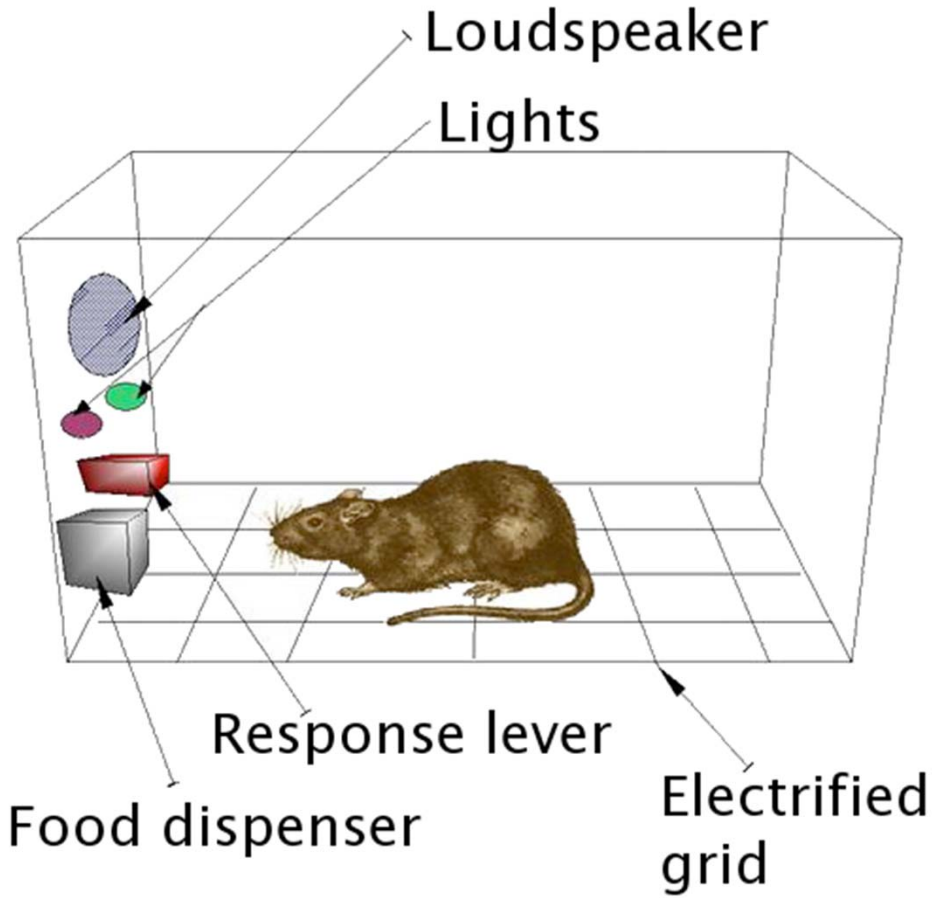
Aims for Robotics:

- Synthesize intelligent behavior for complex, unpredictable, and dynamic environments



Willow Garage's PR2 Robot

Skinnerian Behaviorism and Operant Conditioning



A (Slightly) More Complex Organism

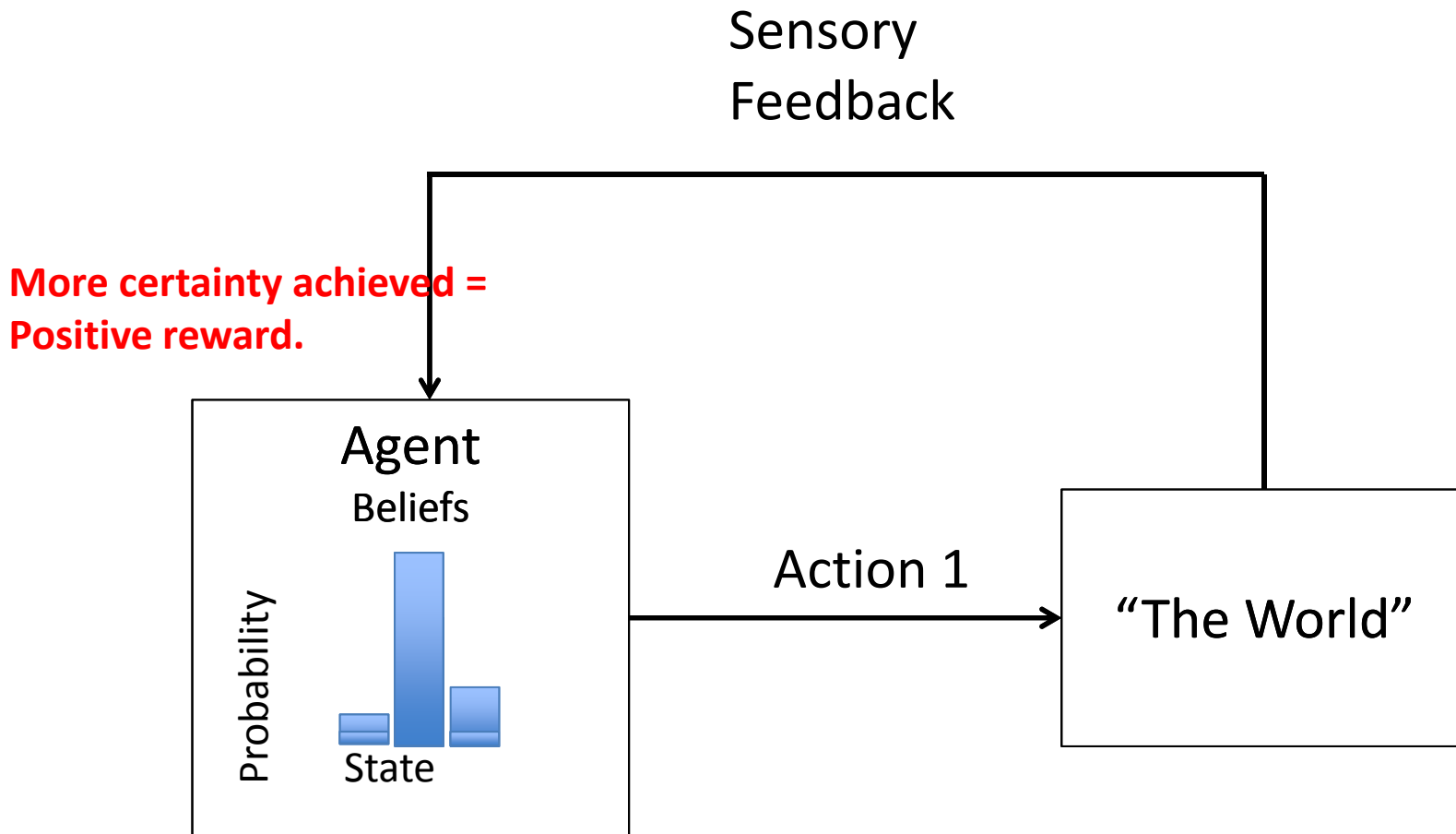


Rewards and punishments are seldom unambiguous (“every cloud has its silver lining”)

Decisions must be made in the face of highly uncertain and delayed rewards.

In order to be successful, organisms (and robots) must evaluate the efficacy of their own behavior.

Information is its Own Reward: Schematic of an InfoMax Agent



Information is its Own Reward: Schematic of an InfoMax Agent

The agent's reward signal is generated internally, rather than given externally by world.

No change in certainty =
no reward

Agent

InfoMax agents choose actions that minimize uncertainty about the world.

Probability



State

POMDPs

POMDP: Partially Observable Markov Decision Process

Objective: choose actions to control a stochastic system optimally

$$\text{optimal behavior} = \arg \max_{\text{behavior}} E \left[\sum_{t=0}^{\infty} \gamma^t r(X_t) \mid \text{behavior} \right]$$

System's state, X_t , governed by stochastic dynamics

$$p(X_t | X_{t-1}, A_{t-1}) \longleftarrow \text{e.g. Newtonian Physics}$$

Information about the system's state must be inferred using noisy observations

$$p(O_t | X_t) \longleftarrow \text{e.g. Sensory System}$$

POMDPs for InfoMax Control

All **the information needed** to make optimal decisions is **given by the belief state**

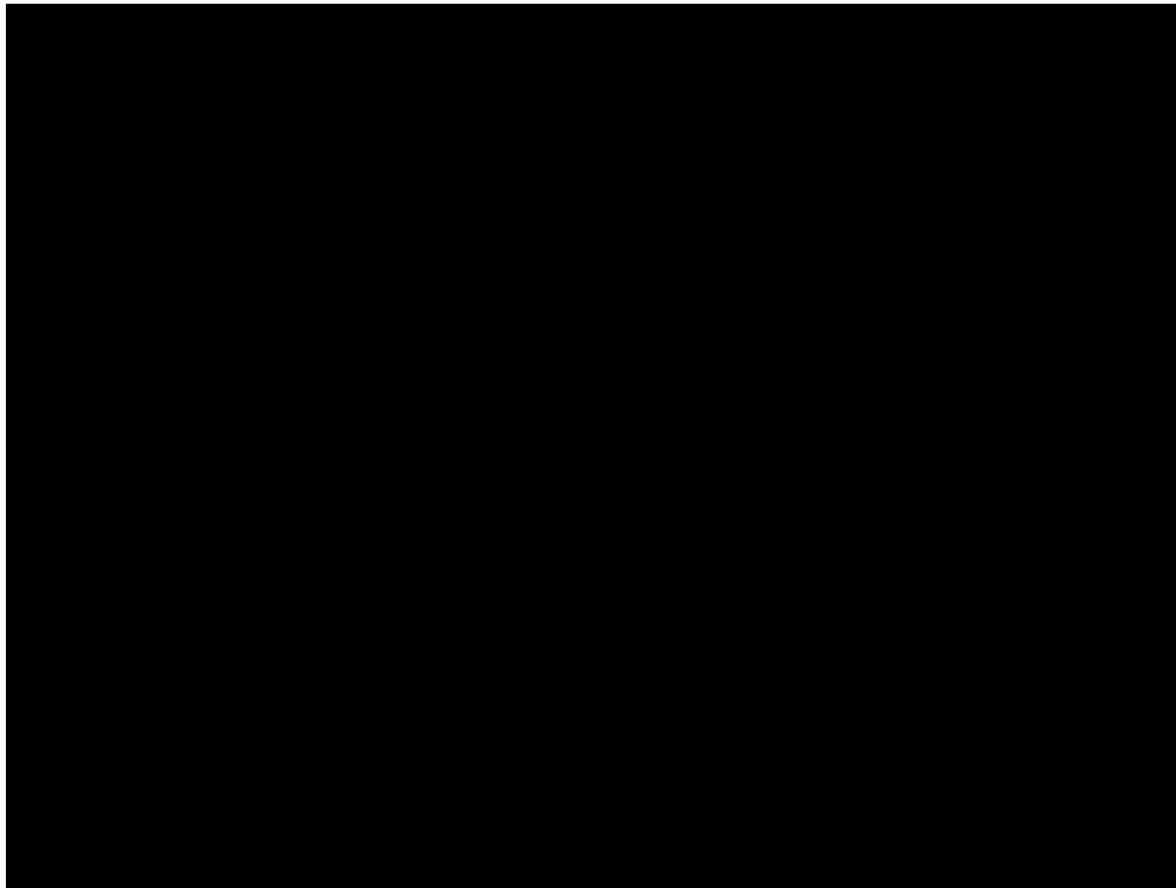
For discrete systems, beliefs written as:

$$b_{t,i} = p(X_t = i | o_1 \dots o_t, a_1 \dots a_t)$$

Reward value is the certainty of the belief state

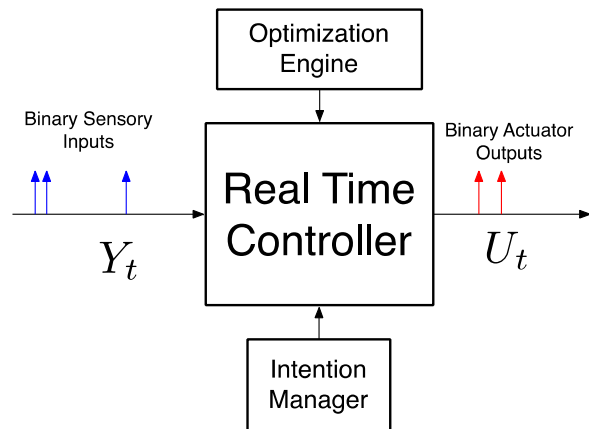
$$r(b_t) = -H[b_t] = \sum_{i=1}^n b_{t,i} \log b_{t,i}$$

Example 1: Contingency Detection



Movellan and Watson (1985)

Computational Model



How should an infant probe the environment in an optimal fashion?

Mapping to POMDP:

State: contingent caregiver present or not present

Actions: vocalize or do not vocalize

Observations: sound volume level

Observation model: fit to data

Optimal behavior “emerges” from this problem description

Movellan (2005)

Contingency Detecting Robot



Example 2: Visual Search

We move our eyes 100,000 times a day. What is driving our choice of where to move them?

Theory: in part we move our eyes to maximize information about the state of the world

Mapping to POMDP:

State: location of some target of interest

Actions: fixation position

Observations: visual feedback

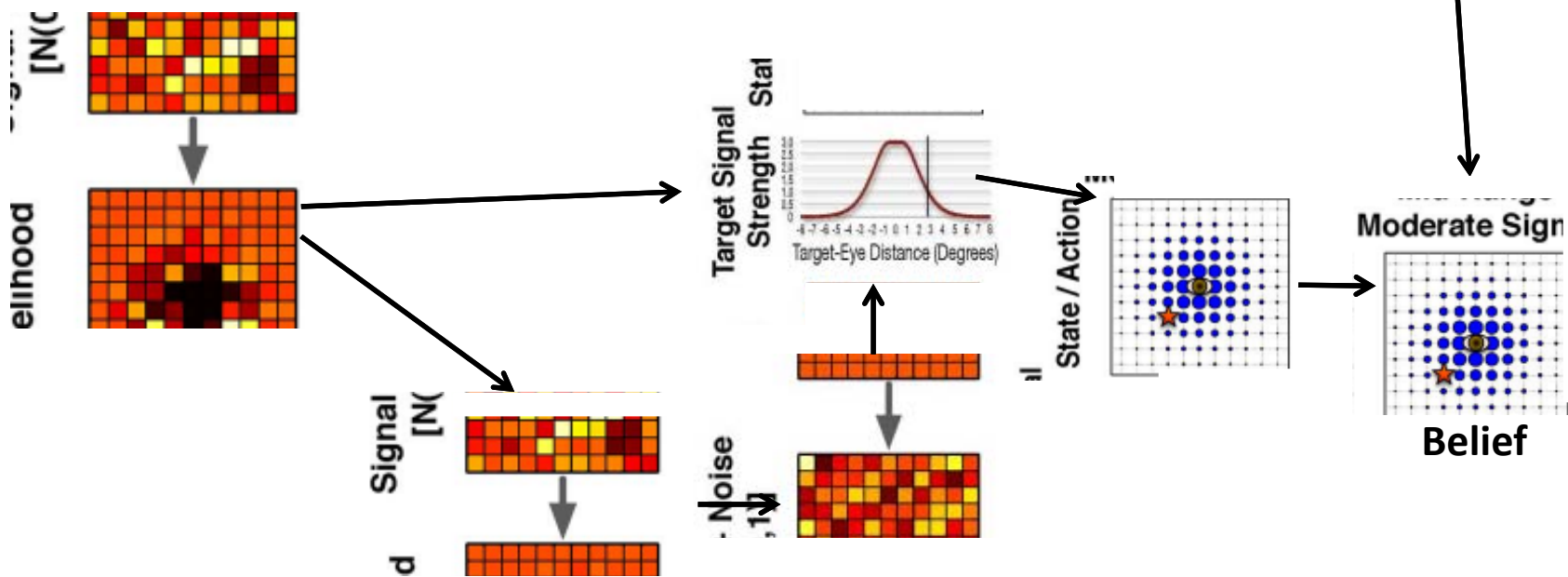
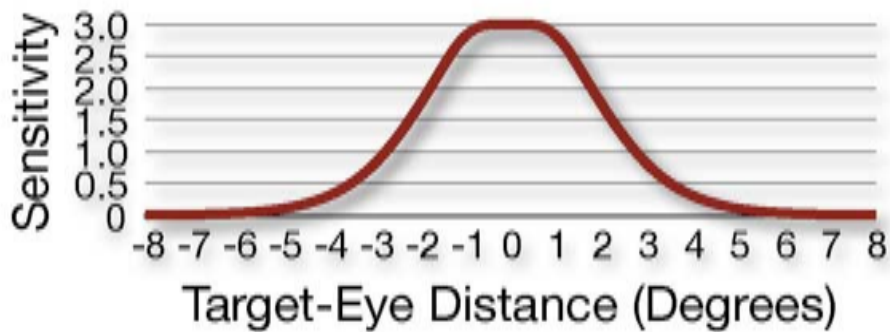
Observation model: derived from psychophysical experiments

Bukto and Movellan (2008)

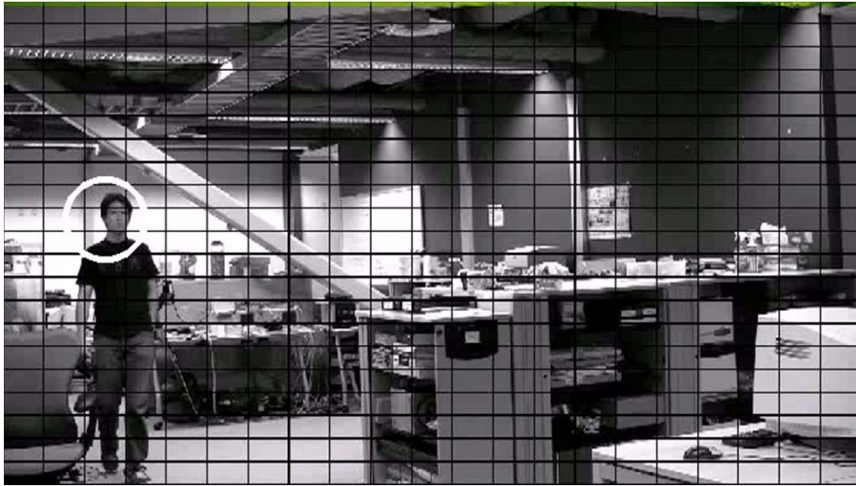
Extension: Fasel, Ruvolo, Wu, and Movellan (2009).

Sensory Model

Foveal-Periphery Operating Characteristic

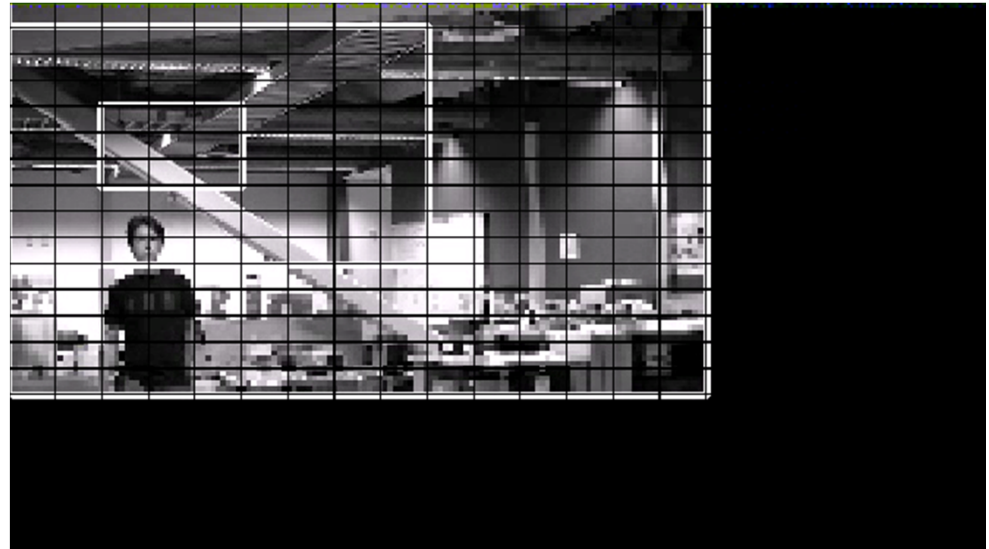


Digital Retina



Exhaustive Search

Foveated Search



Summary

Infomax Control is an example of a computational bridge to phenomena that students may not think of as computational.