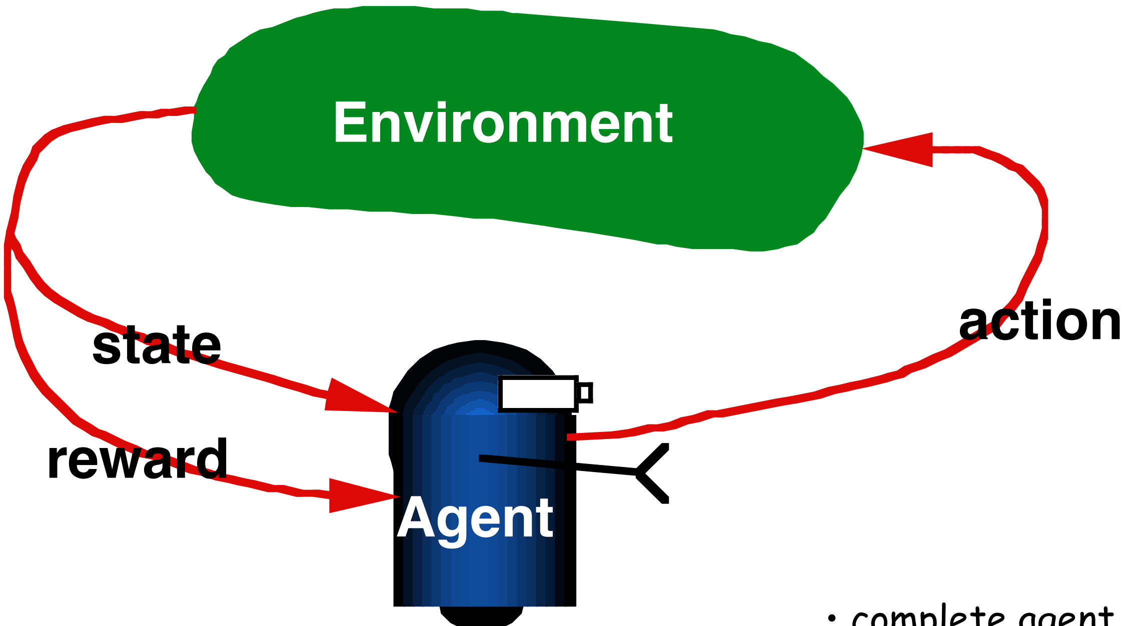
Examples and Videos of Markov Decision Processes (MDPs) and Reinforcement Learning

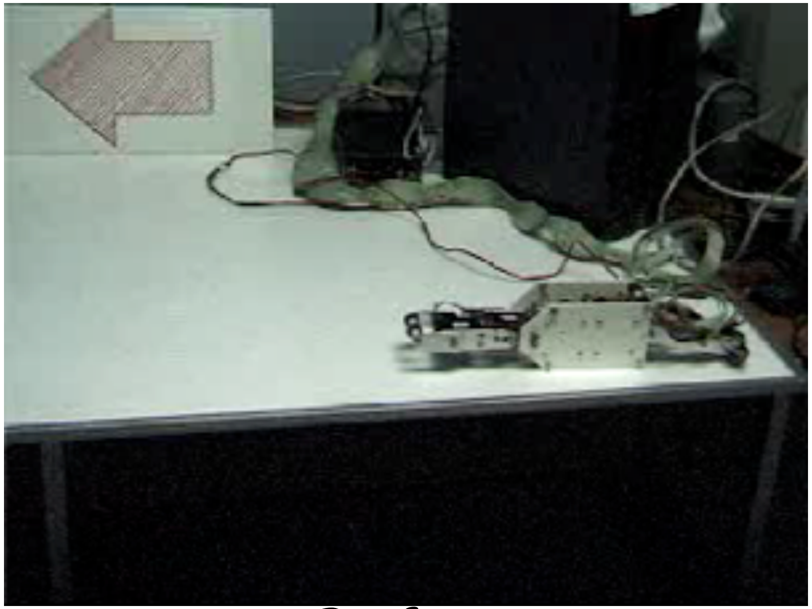
Artificial Intelligence is interaction to achieve a goal



- complete agent
- temporally situated
- continual learning & planning
- object is to affect environment
- environment stochastic & uncertain

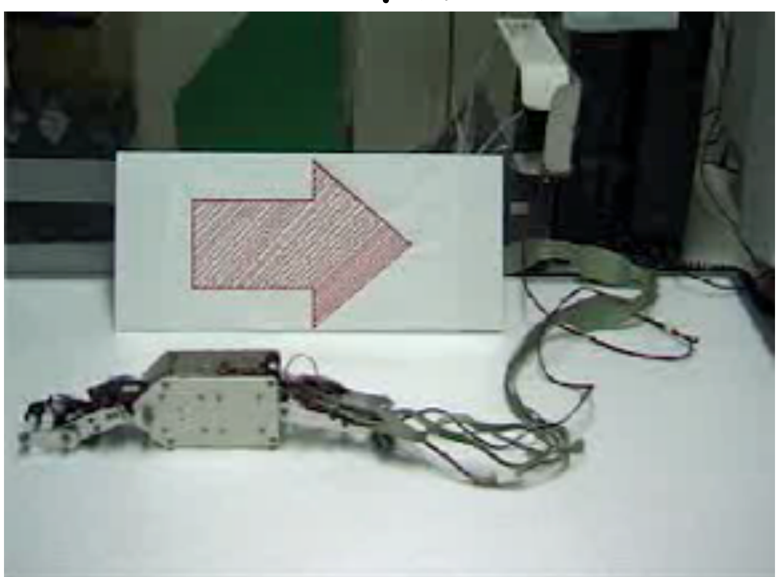
States, Actions, and Rewards

Hajime Kimura's RL Robots

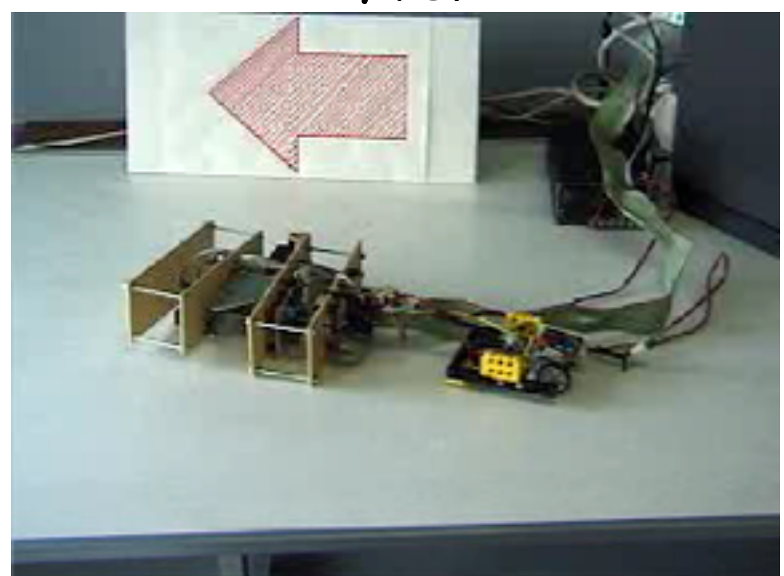


Before

After

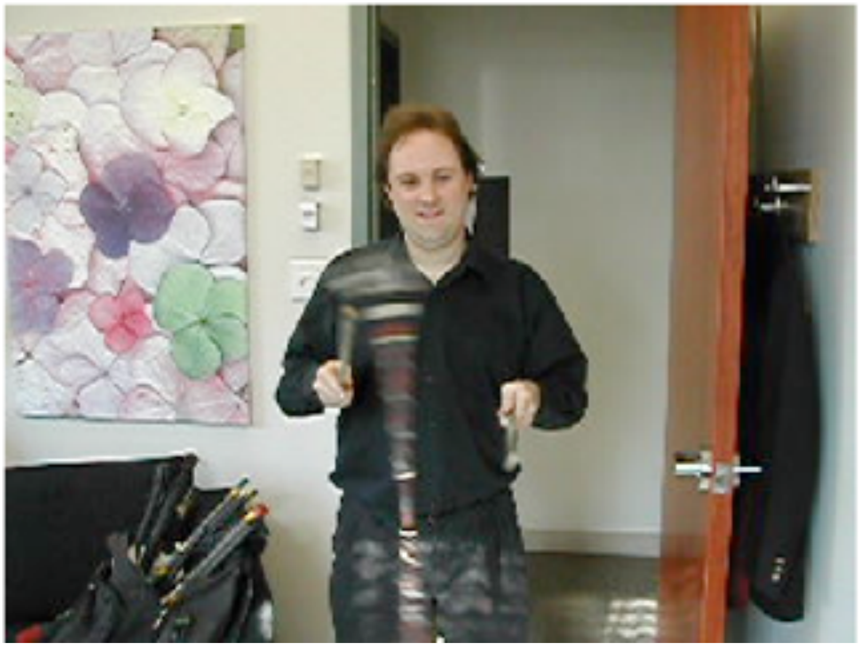


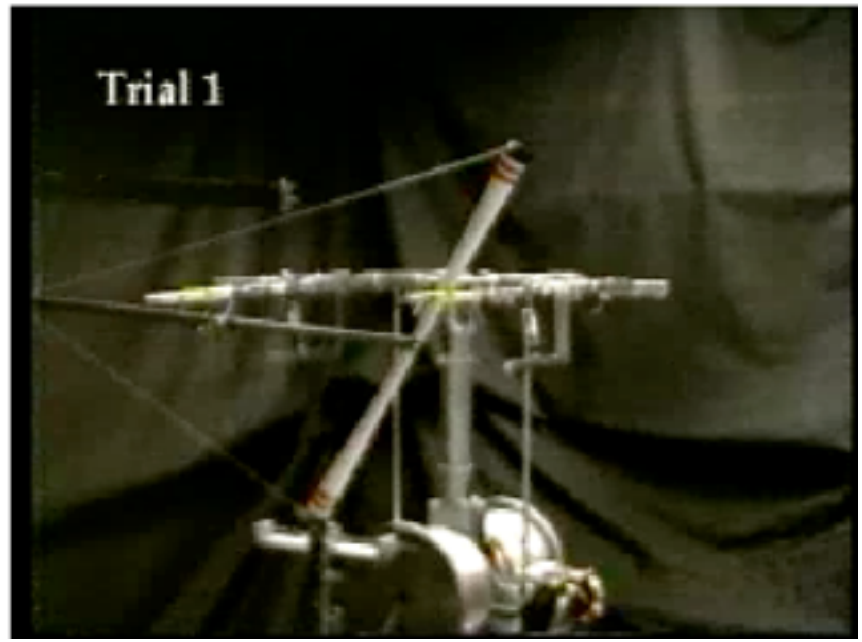
Backward



New Robot, Same algorithm

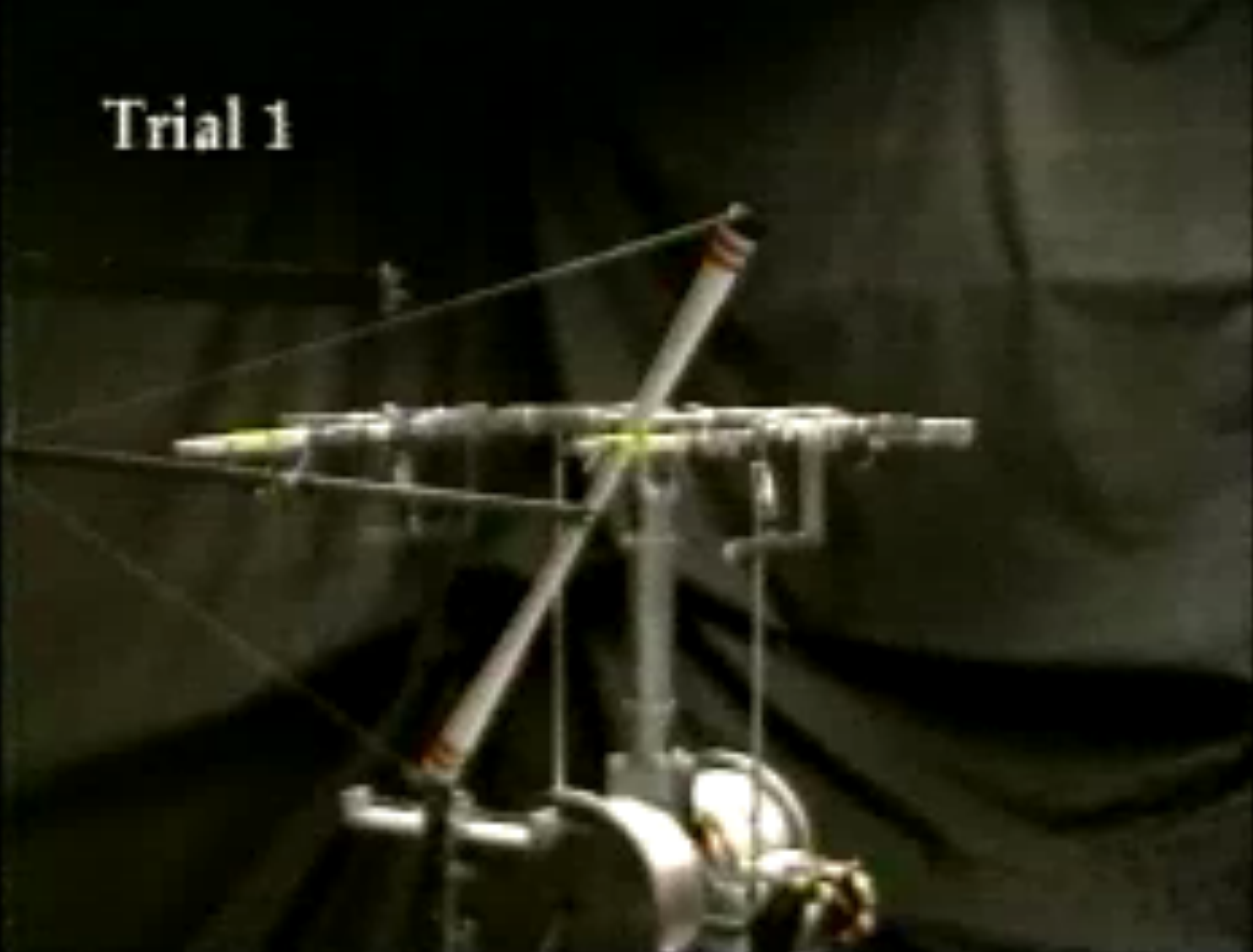
Devilsticking





Finnegan Southey
University of Alberta

Stefan Schaal & Chris Atkeson
Univ. of Southern California
"Model-based Reinforcement
Learning of Devilsticking"


Trial 1

The RoboCup Soccer Competition

Autonomous Learning of Efficient Gait

Kohl & Stone (UTexas) 2004

Policies

- A policy maps each state to an action to take
  - Like a stimulus–response rule
- We seek a policy that maximizes cumulative reward
- The policy is a subgoal to achieving reward

The Reward Hypothesis

The goal of intelligence is to maximize the cumulative sum of a single received number:
"reward" = pleasure - pain

Artificial Intelligence = reward maximization

Value

Value systems are hedonism with foresight

We value situations according to how much reward we expect will follow them

All efficient methods for solving sequential decision problems determine (learn or compute) "value functions" as an intermediate step

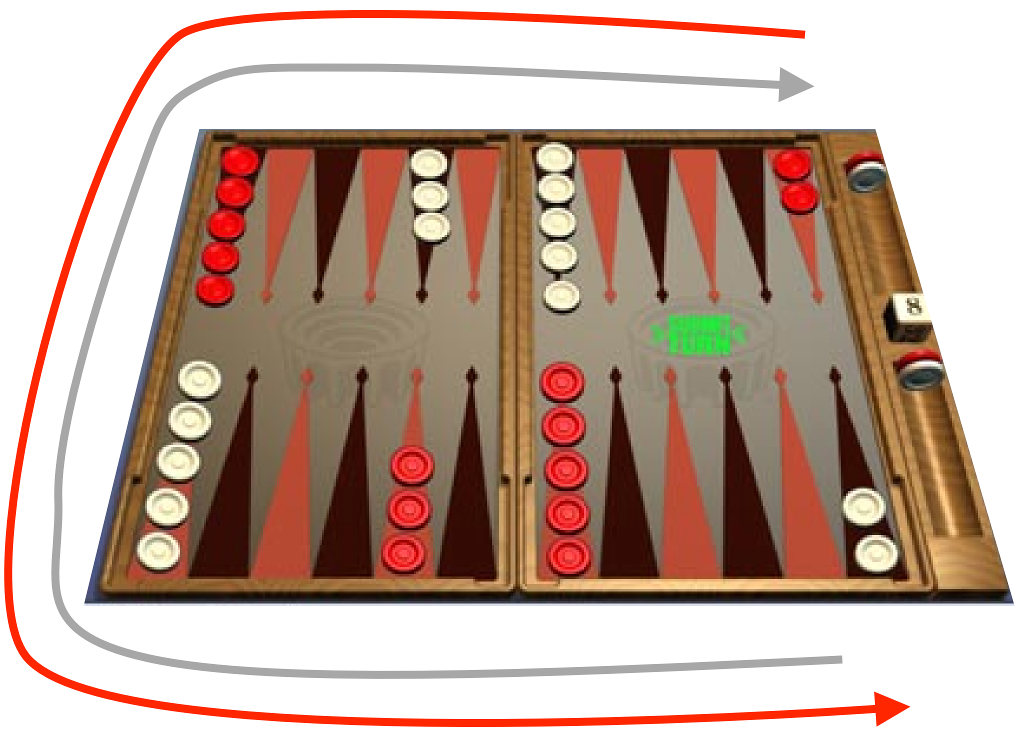
Value systems are a *means* to reward, yet we *care more* about values than rewards

Pleasure = Immediate Reward $\neq$ good = Long-term Reward

"Even enjoying yourself you call evil whenever it leads to the loss of a pleasure greater than its own, or lays up pains that outweigh its pleasures. ... Isn't it the same when we turn back to pain? To suffer pain you call good when it either rids us of greater pains than its own or leads to pleasures that outweigh them."

–Plato, Protagoras

Backgammon



STATES: configurations of the playing board ($\approx 10^{20}$)

ACTIONS: moves

REWARDS: win: +1

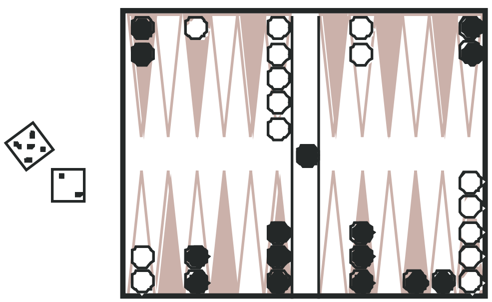
lose: –1

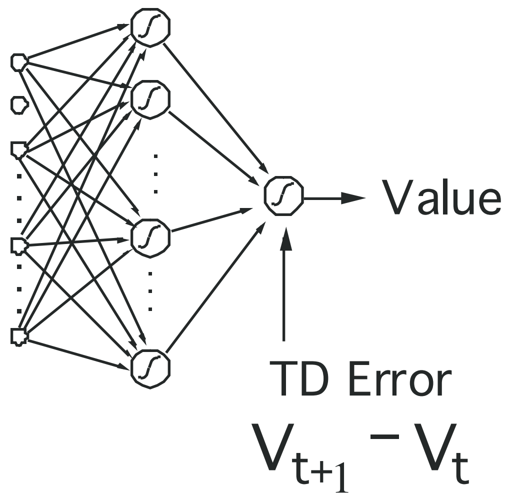
else: 0

a “big” game

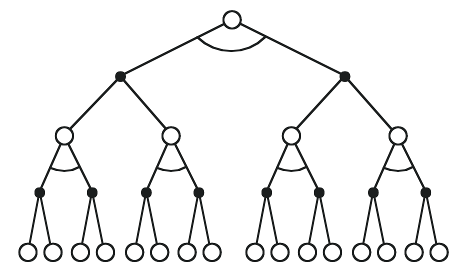
TD-Gammon

Tesauro, 1992-1995





Action selection
by 2-3 ply search



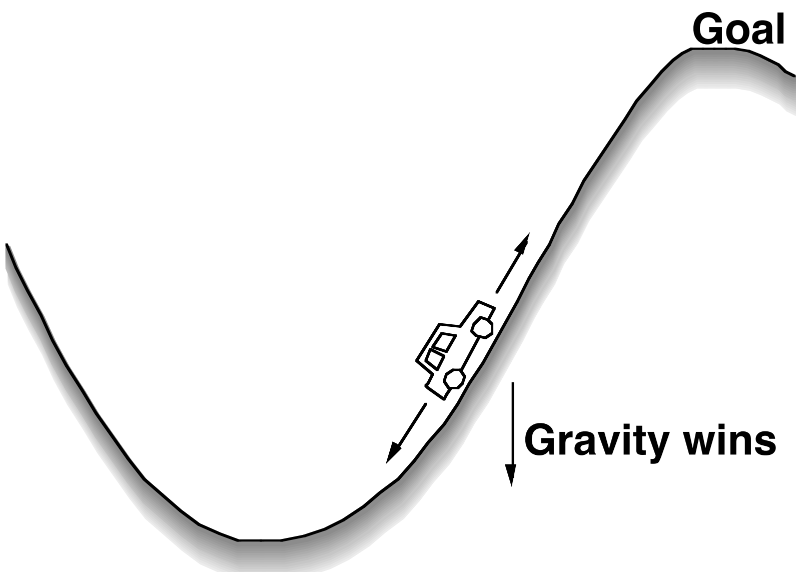
Start with a random Network

Play millions of games against itself

Learn a value function from this simulated experience

Six weeks later it’s the best player of backgammon in the world

The Mountain Car Problem



Minimum-Time-to-Goal Problem

SITUATIONS: car's position and velocity

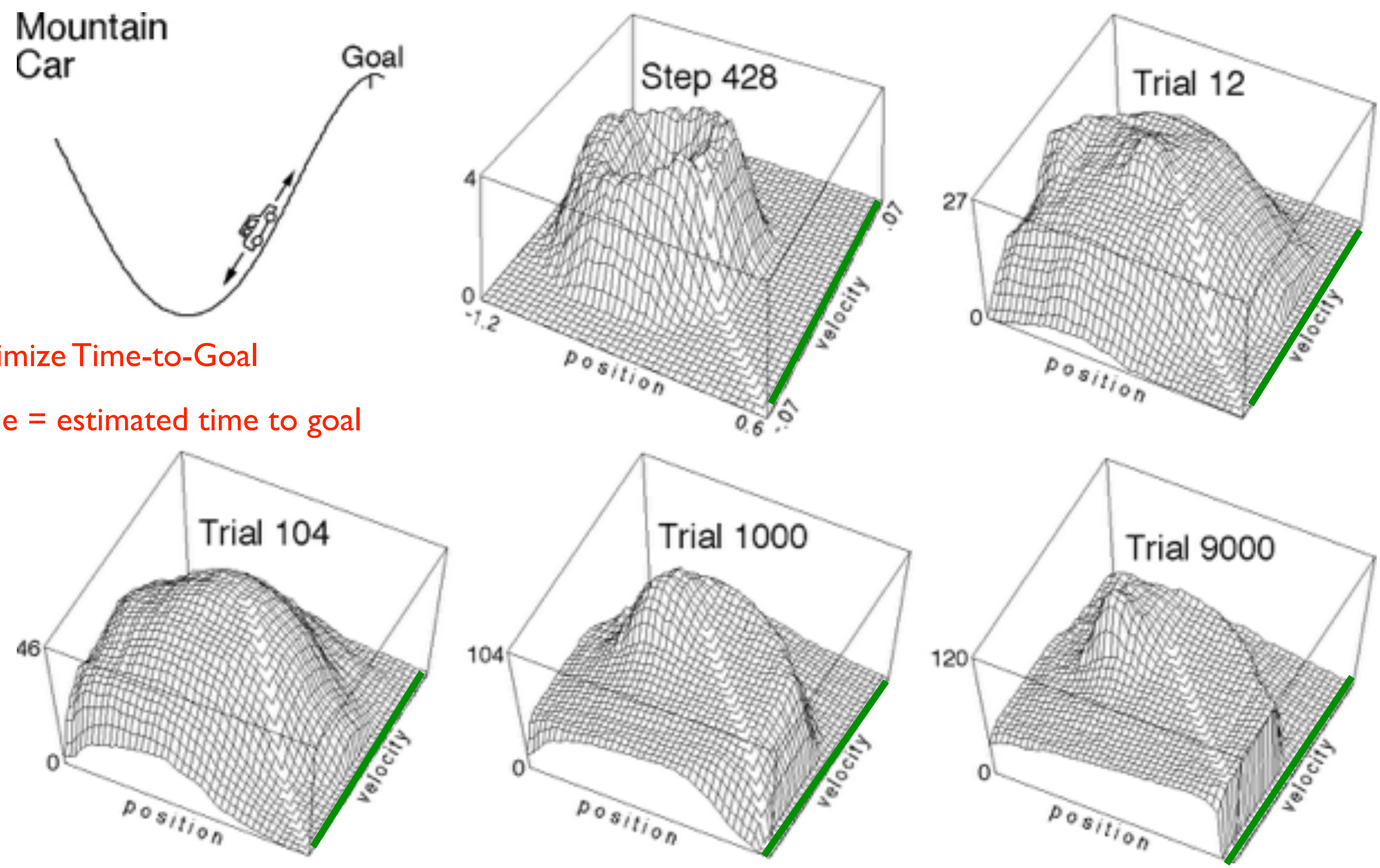
ACTIONS: three thrusts: forward, reverse, none

REWARDS: always –1 until car reaches the goal

No Discounting

Moore, 1990

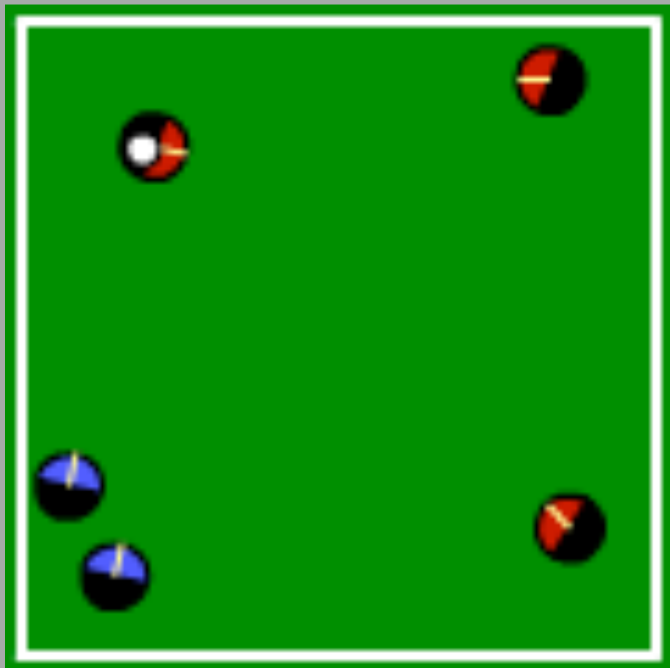
Value Functions Learned while solving the Mountain Car problem



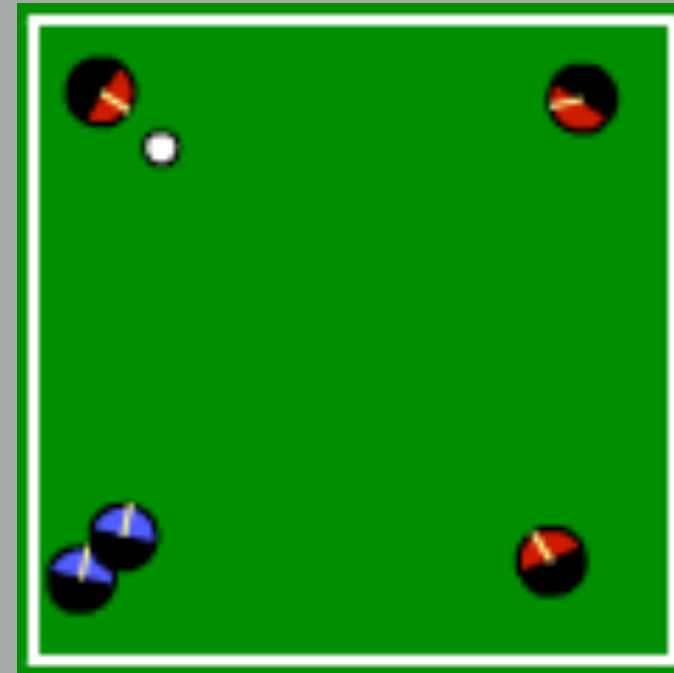
Minimize Time-to-Goal

Value = estimated time to goal

Goal region

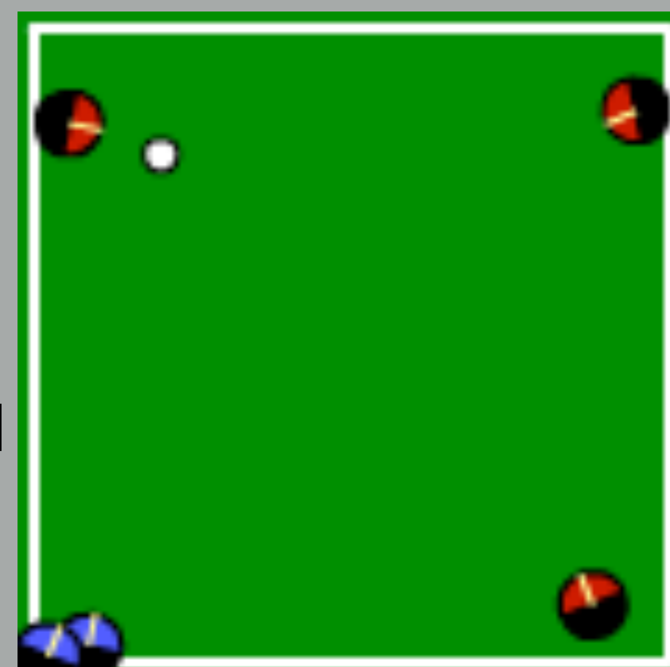


Random

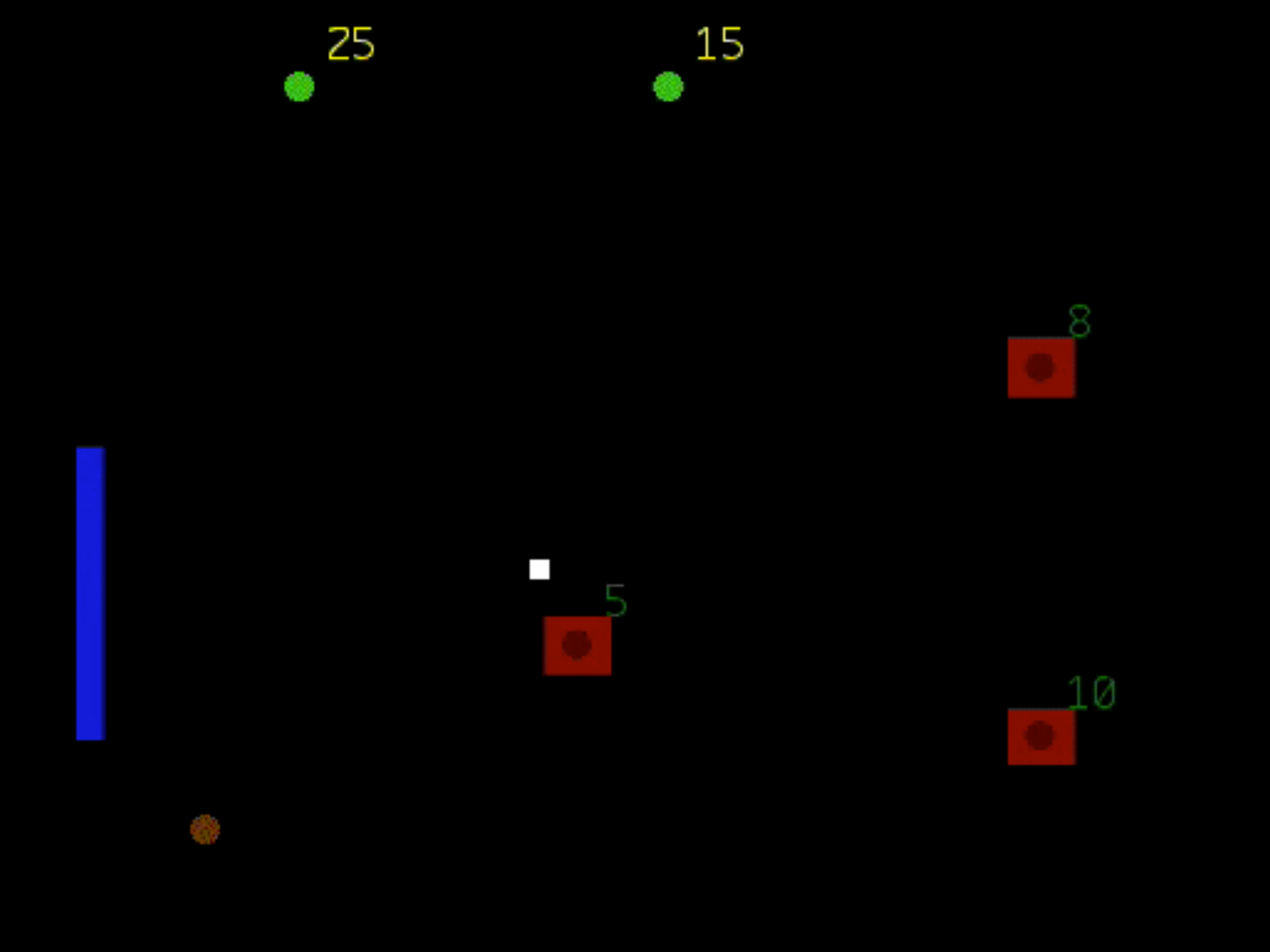


Learned

Hand-coded



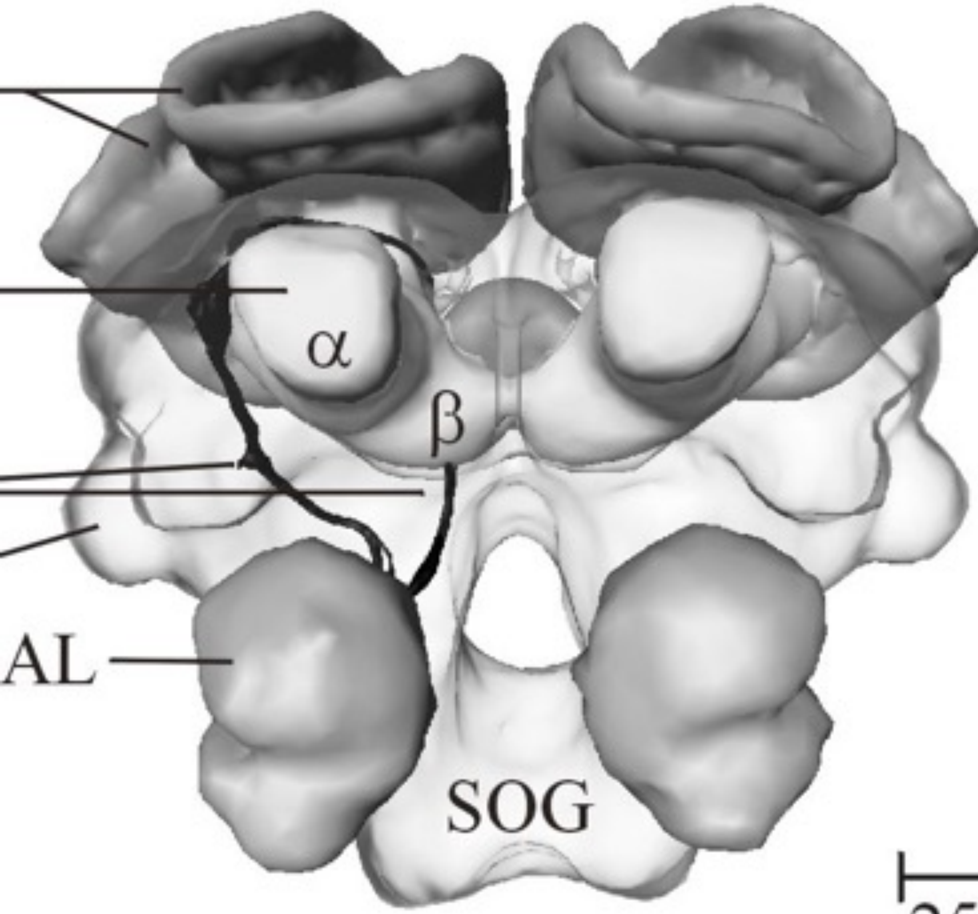
Hold

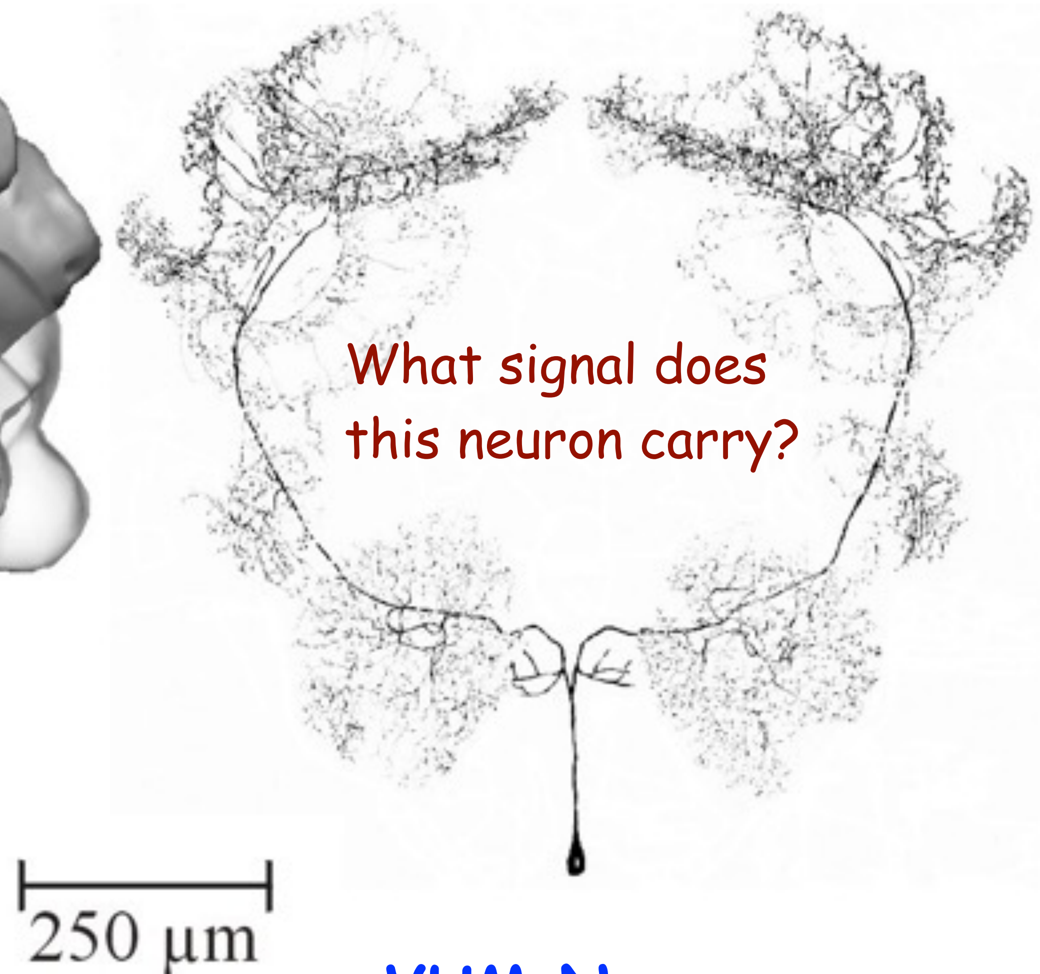

25
15
8
5
10

Temporal-difference (TD) error

Do things seem to be getting better or worse,
in terms of long-term reward,
at this instant in time?

Brain reward systems



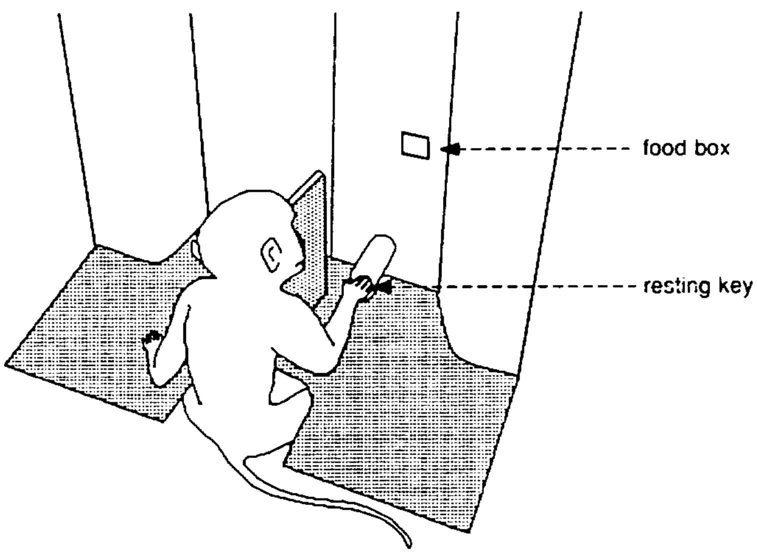


Honeybee Brain

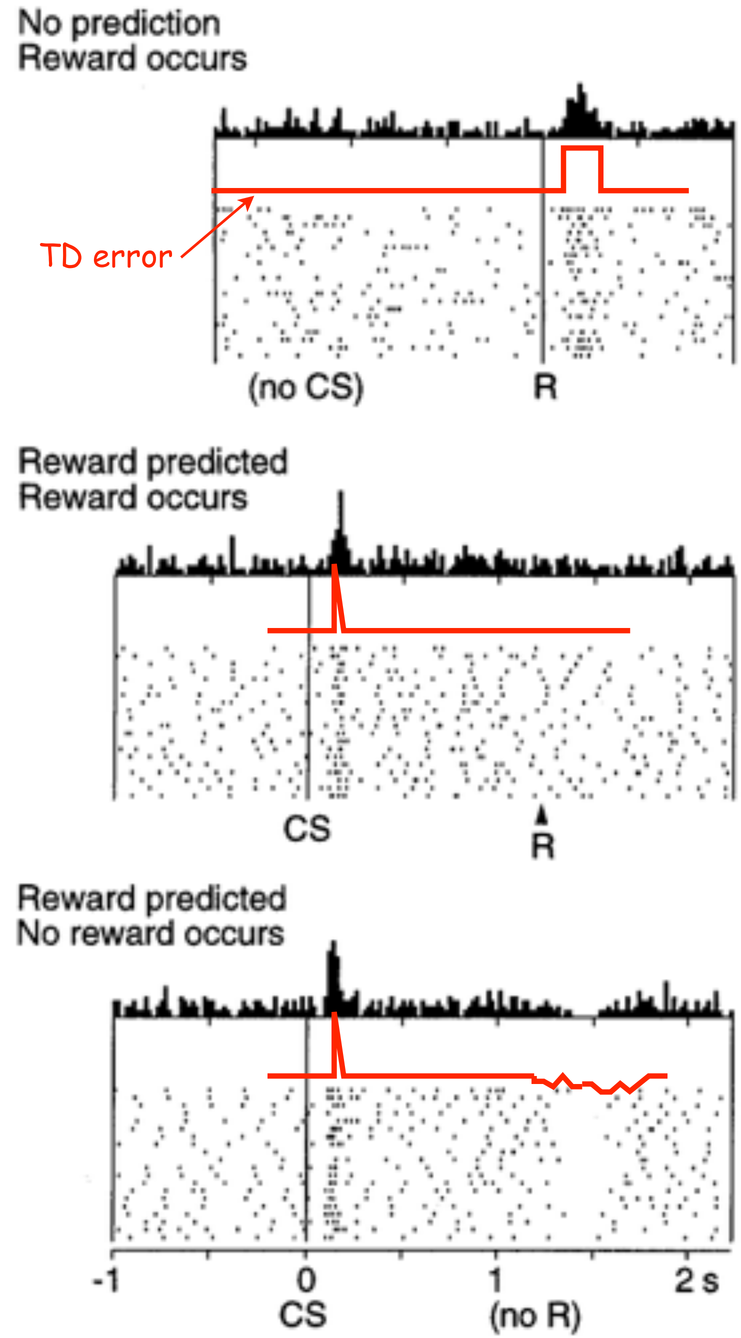
VUM Neuron

Hammer, Menzel

Brain reward systems seem to signal TD error

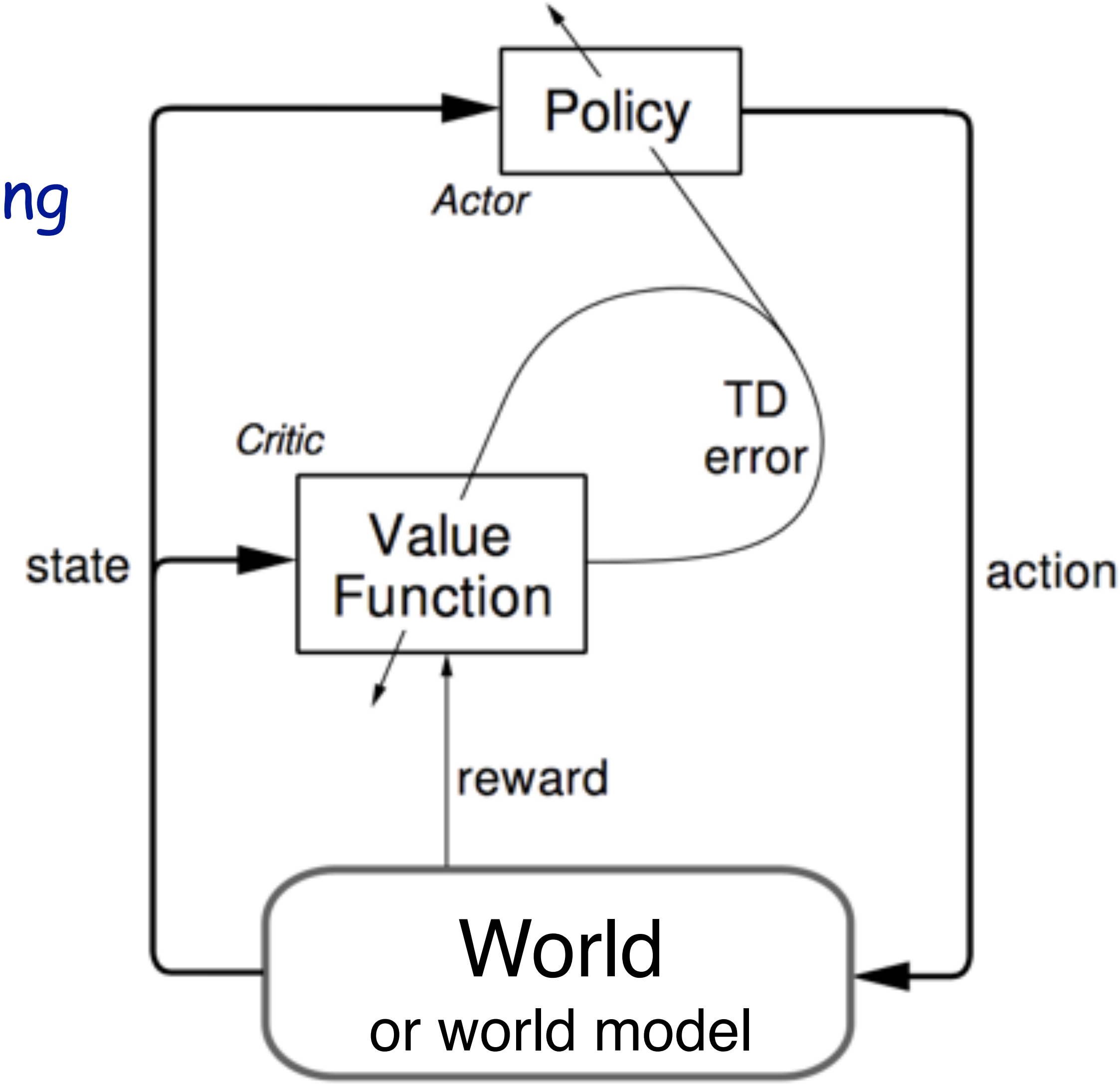


Wolfram Schultz, et al.



World models

the actor-critic reinforcement learning architecture



"Autonomous helicopter flight via Reinforcement Learning"

Ng (Stanford), Kim, Jordan, & Sastry (UC Berkeley) 2004

Reason as RL over Imagined Experience

1. Learn a predictive model of the world's dynamics

   transition probabilities, expected immediate rewards

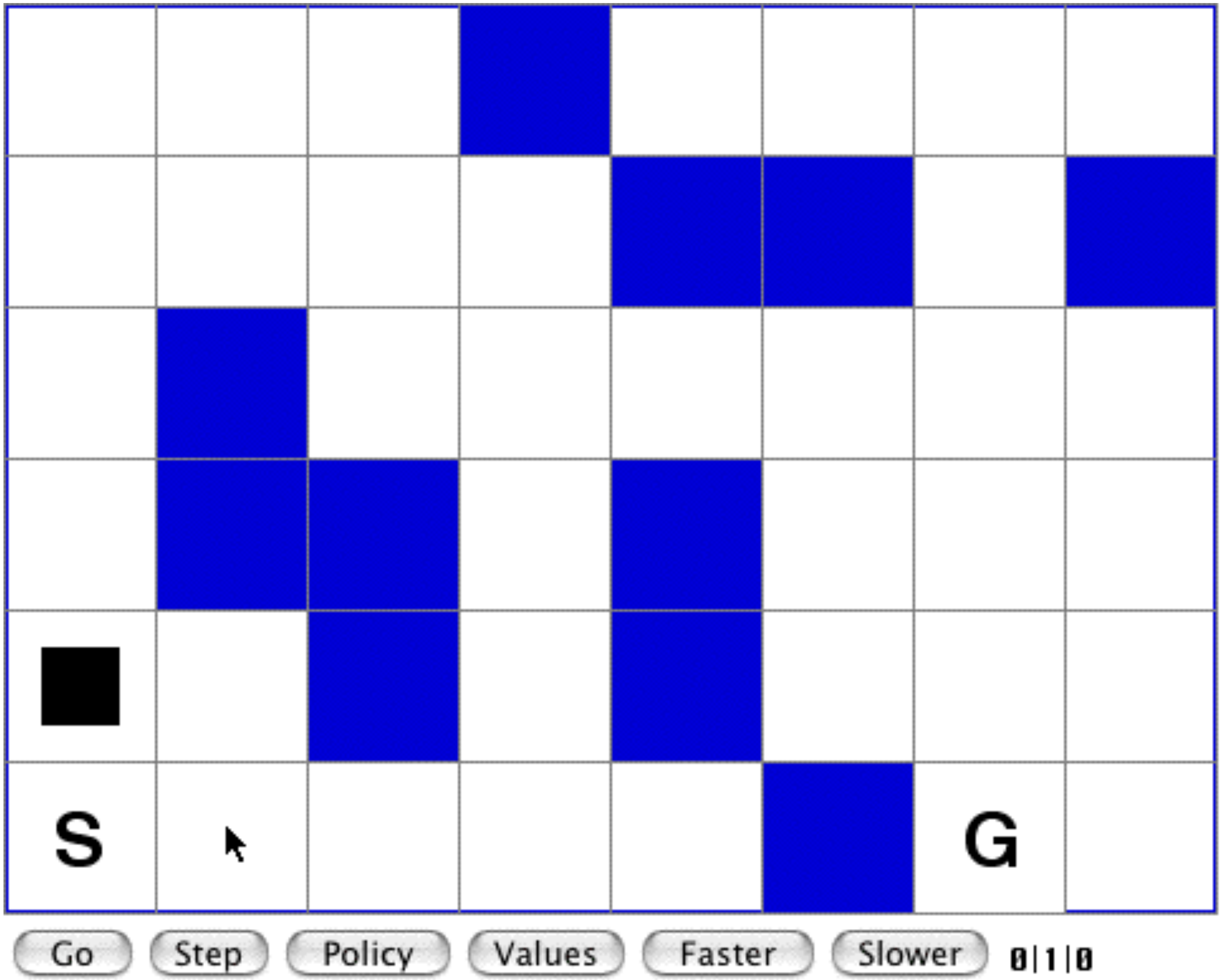
2. Use model to generate imaginary experiences

   internal thought trials, mental simulation (Craik, 1943)

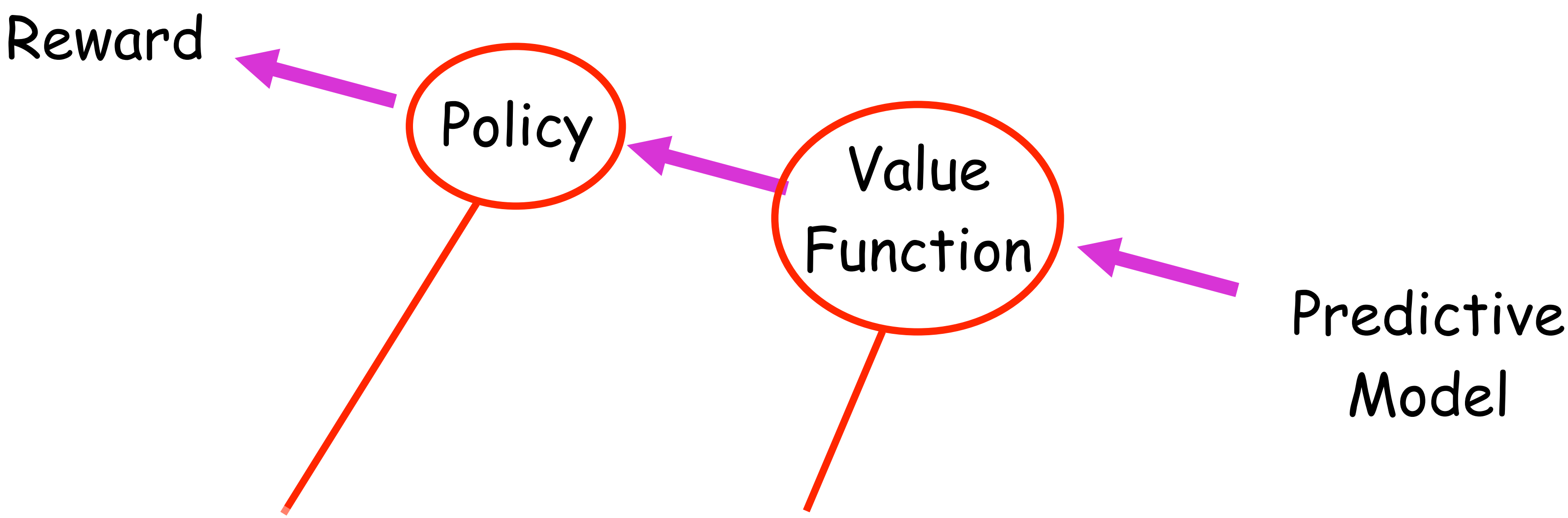
3. Apply RL as if experience had really happened

   vicarious trial and error (Tolman, 1932)

GridWorld Example



Summary:
RL's Computational Theory of Mind



A learned, time-varying prediction of imminent reward
Key to all efficient methods for finding optimal policies

This has nothing to do with either biology or computers

Summary:
RL's Computational Theory of Mind

Reward $\leftarrow$ Policy $\leftarrow$ Value Function $\leftarrow$ Predictive Model

It's all created from
the scalar reward signal

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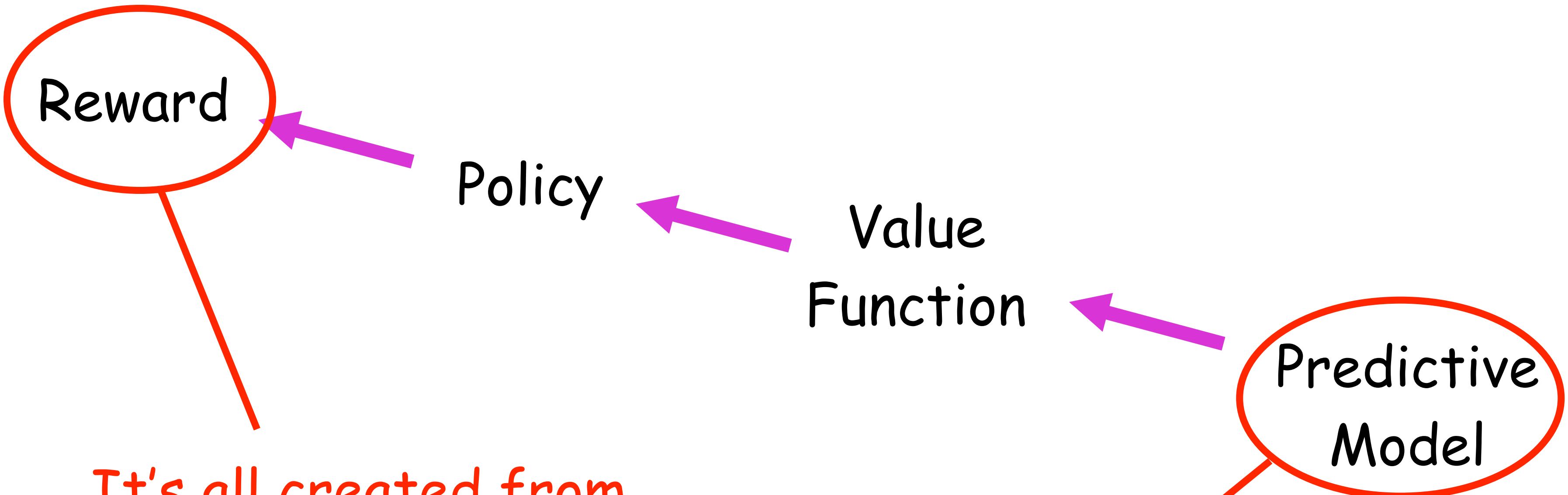
RL's Computational Theory of Mind



It's all created from
the scalar reward signal

together with the causal structure of the world