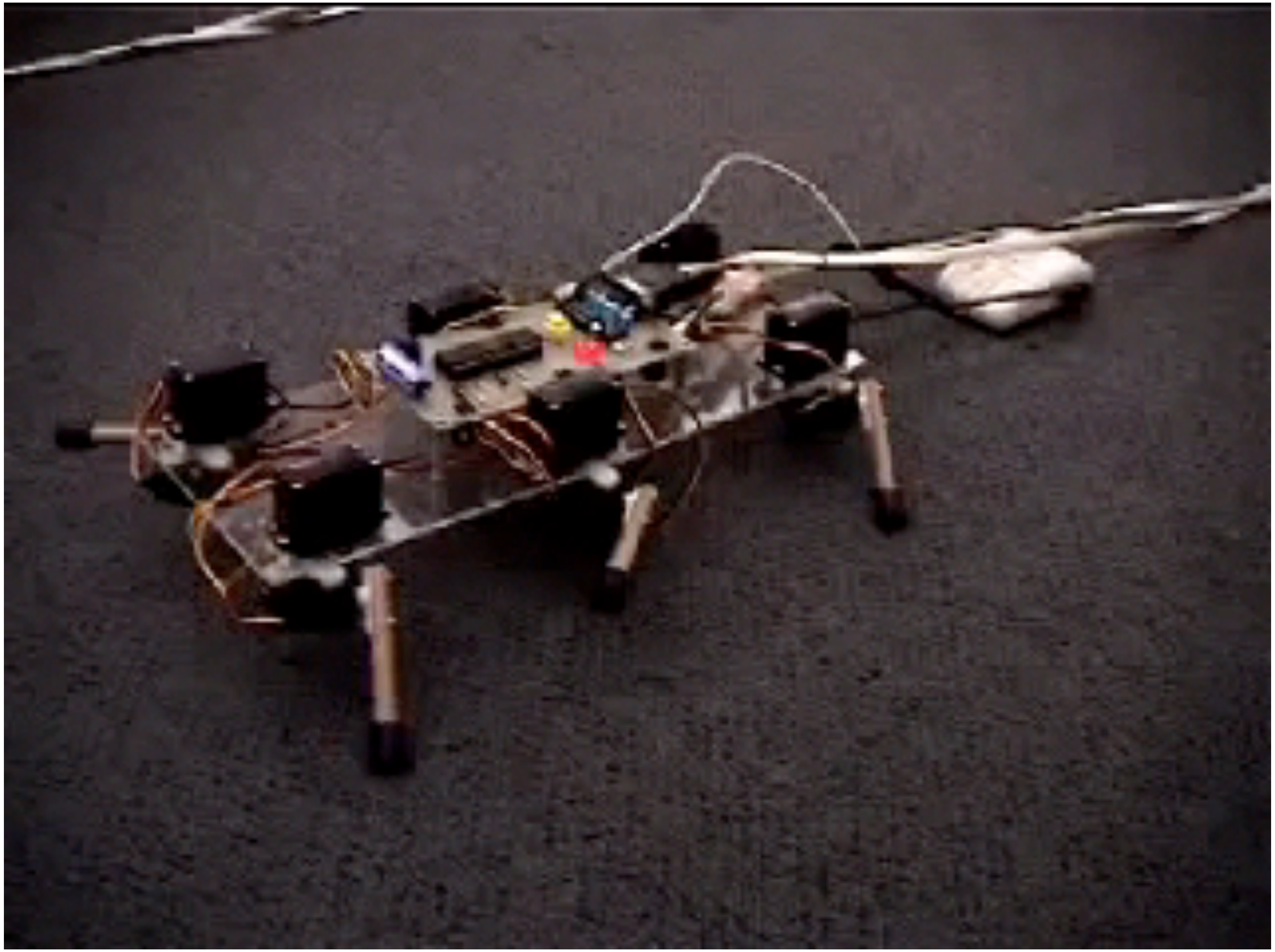
Reinforcement Learning

COMP3431 Robot Software Architectures

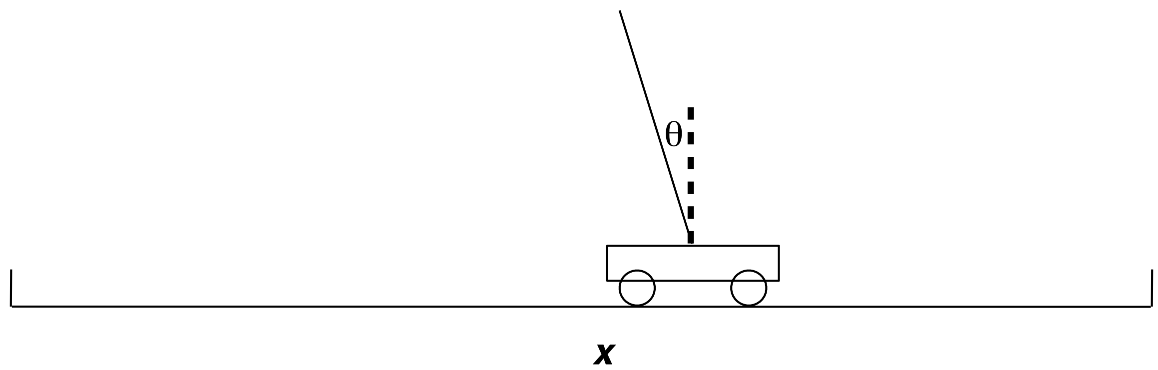
A Simple Learning Robot



Reinforcement Learning

- “Stumpy” receives a *reward* after each action
  - Did it move forward or not?
- After each move, updates its *policy*
- Continues trying to maximise its reward

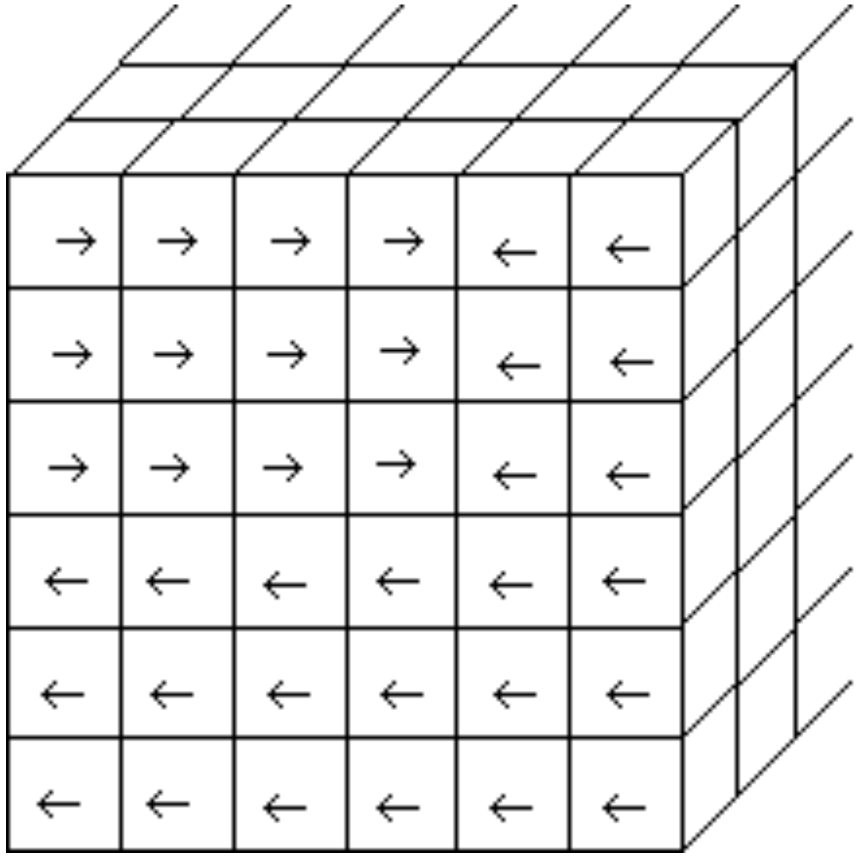
Pole Balancing



- Pole balancing can be learned the same way except that reward is only received at the end
  - after falling or hitting the end of the track

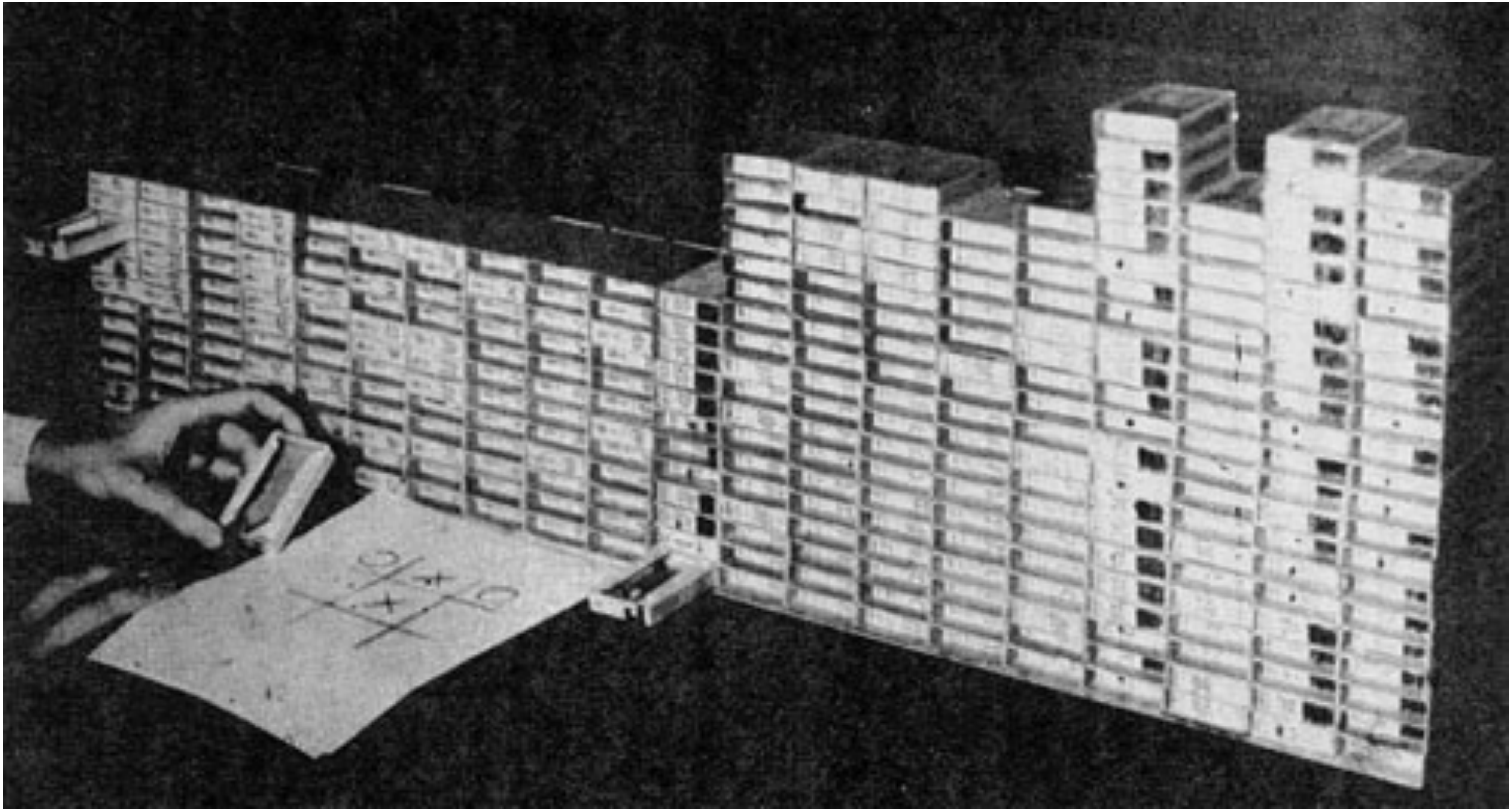
Boxes

- State space is discretised
- Each “box” represents a subset of state space
- When system lands in a box, execute action specified
    - left push
    - right push



MENACE

(Machine Educable Noughts and Crosses Engine – D.Michie, 1961)



Simulation

$$
\begin{aligned}
x_{t+1} &= x_t + \tau \dot{x}_t \\
\dot{x}_{t+1} &= \dot{x}_t + \tau \ddot{x}_t \\
\theta_{t+1} &= \theta_t + \tau \dot{\theta}_t \\
\dot{\theta}_{t+1} &= \dot{\theta}_t + \tau \ddot{\theta}_t
\end{aligned}
$$

$$
\ddot{x}_t = \frac{F_t + m_p l \left[\dot{\theta}^2 \sin \theta_t - \ddot{\theta}_t \cos \theta_t\right]}{m_c + m_p}
$$

$$
\ddot{\theta}_t = \frac{g \sin \theta_t + \cos \theta_t \left[\dfrac{-F_t - m_p l \dot{\theta}_t^2 \sin \theta_t}{m_c + m_p}\right]}{l \left[\dfrac{4}{3} - \dfrac{m_p \cos^2 \theta_t}{m_c + m_p}\right]}
$$

Parameters

$m_c = 1.0$ kg	*mass of cart*
$m_p = 1.0$ kg	*mass of pole*
$l = 0.5$ m	*distance of centre of mass of pole from the pivot*
$g = 9.8$ ms^{-2}	*acceleration due to gravity*
$F_t = \pm\ 10$ N	*force applied to cart*
$t = 0.02$ s	*time interval of simulation*

The BOXES Algorithm

- Each box contains statistics on performance of controller, which are updated after each failure
  - How many times each action has been performed (*usage*)
  - The sum of lengths of time the system has survived after taking a particular action (*LifeTime*)
- Each sum is weighted by a number less than one which places a discount on earlier experience.

Update Rule

if an action has not been tested

choose that action

else if $\frac{LeftLife}{LeftUsage^k} > \frac{RightLife}{RightUsage^k}$

choose left

else

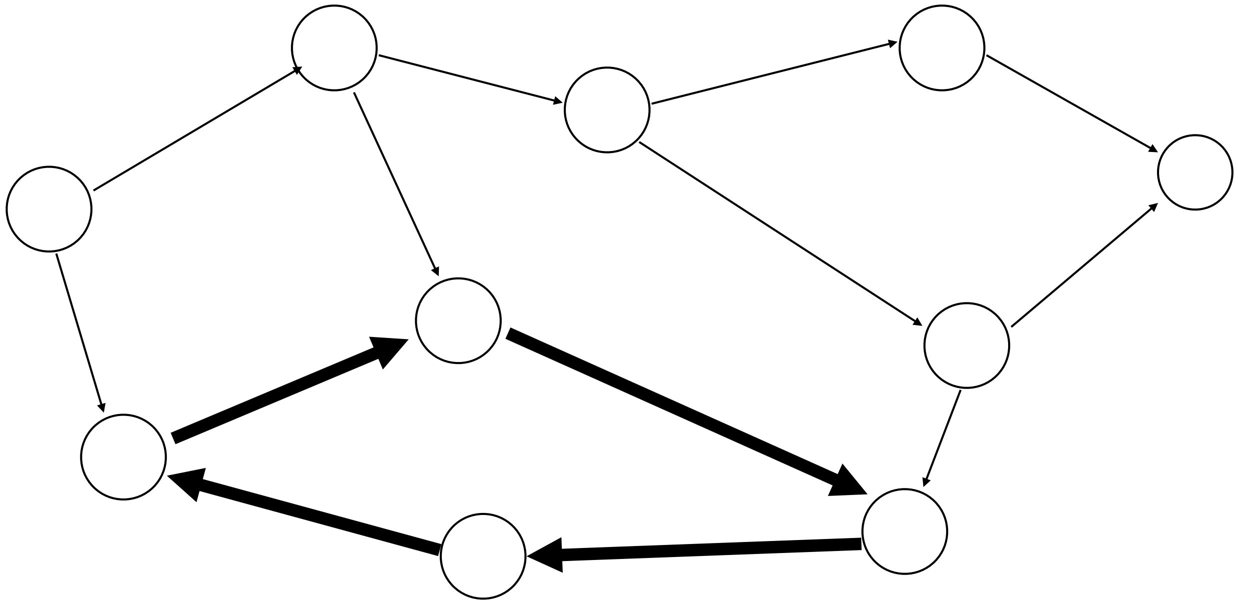
choose right

k is a bias to force exploration
e.g. k = 1.4

Performance

- BOXES is *much* faster than genetic algorithm
  - Only 75 trials, on average, to reach 10,000 time steps
- But only works for *episodic* problems
  - i.e. has a specific termination
- Doesn’t work for continuous problems like Stumpy

State Transition Graph



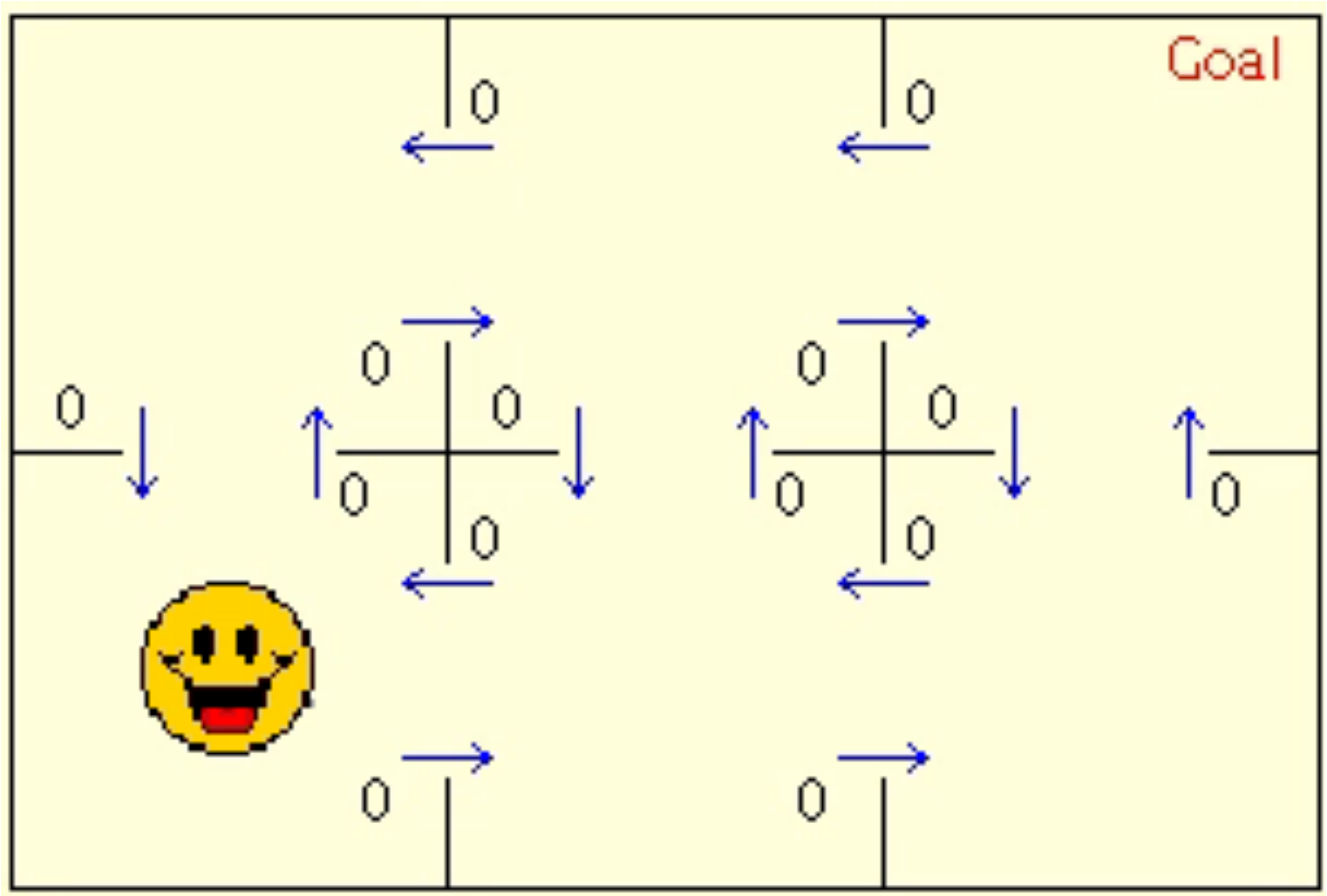
States and Actions

- Each node is a *state*
- *Actions* cause transitions from one state to another
- A *policy* is the set of transition rules
  - i.e. which action to apply in a given state
- Agent receives a *reward* after each action
- Actions may be non-deterministic
  - Same action may not always produce same state

Markov Decision Process (MDP)

- Assume that current state has all the information needed to decide which action to take

Grid World Example



Expected Reward

- Try to maximise expected future reward:

$$
\begin{aligned}
V^{\pi}(s_t) &= r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \\
&= \sum_{i=0}^{\infty} \gamma^i r_{t+i}
\end{aligned}
$$

- V is the value of state S under policy $\boldsymbol{\pi}$
- $\boldsymbol{\gamma}$ is a discount factor (0..1)

Q Function

- How to choose an action in a state?

$$Q(s,a) = r(s,a) + \gamma V^*(\delta(s,a))$$

- The Q value for an action, a, in a state, s, is the immediate reward for the action plus the discounted value of following the optimal policy after that

- V^* is value obtained by following the optimal policy

- $\delta(s,a)$ is the succeeding state, assuming the optimal policy

Q Learning

initialise $Q(s,a) = 0$ for all s and a

observe current state s

repeat

select an action a and execute it

observe immediate reward r and next state s'

$$Q(s,a) \leftarrow r + \max_{a'} Q(s',a')$$

$$s \leftarrow s'$$

Exploration vs Exploitation

- How do you choose an action?
  - Random
  - Pick the current “best” action
  - Combination:
    - most of the time pick the best action
    - occasionally throw in random action

Background

- Reinforcement learning is based in earlier work in optimisation: dynamic programming
- Text book: Sutton & Barto

Reinforcement Learning Variants

- There are *many* variations on reinforcement learning to improve search.

- RL was one of the components of alphaGo, which recently beat a Go master

- Used to learn helicopter aerobatics