Introduction to Reinforcement Learning

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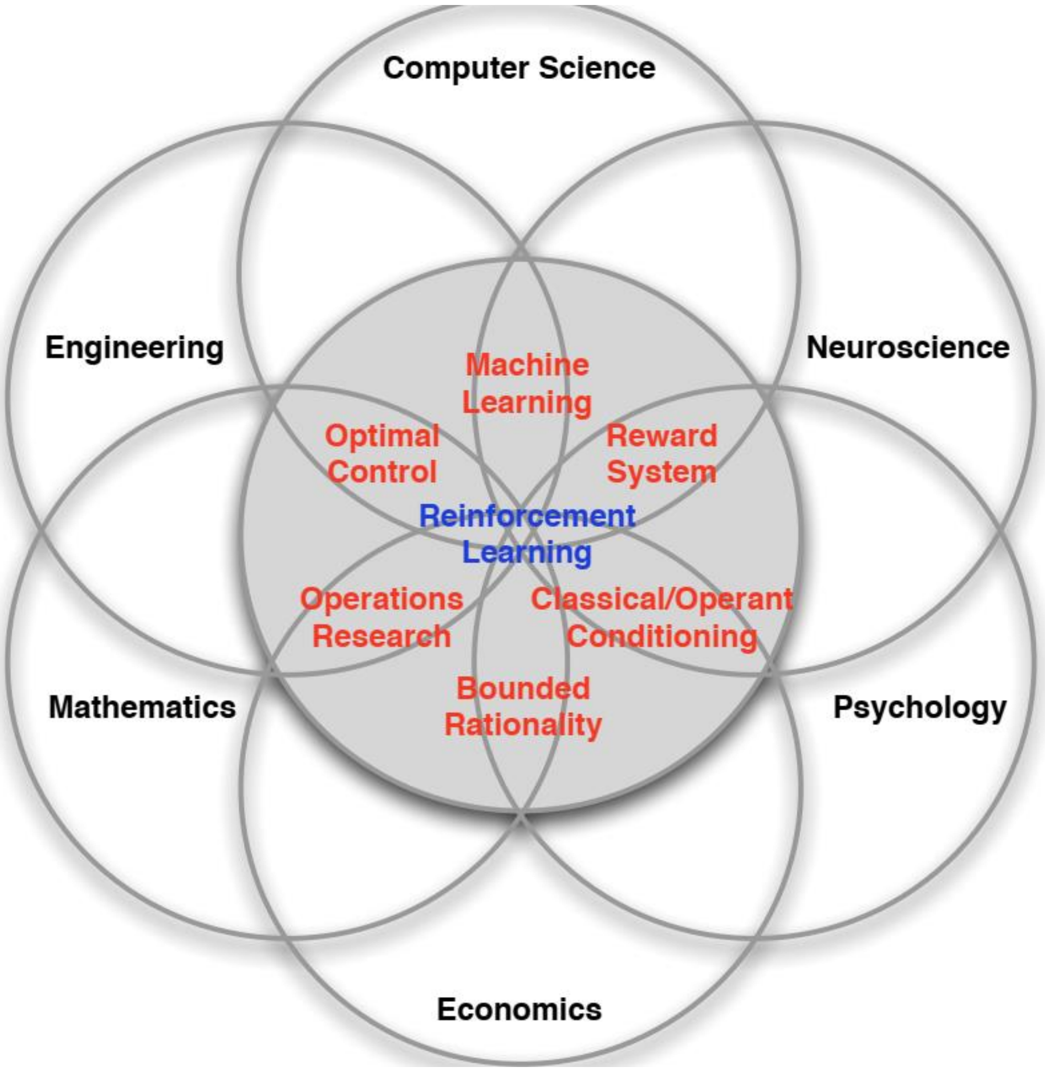
A Note

Much of the content of this course and its slides are heavily based on the classical course by David Silver

https://www.davidsilver.uk/teaching/

Introduction



Positioning Reinforcement Learning

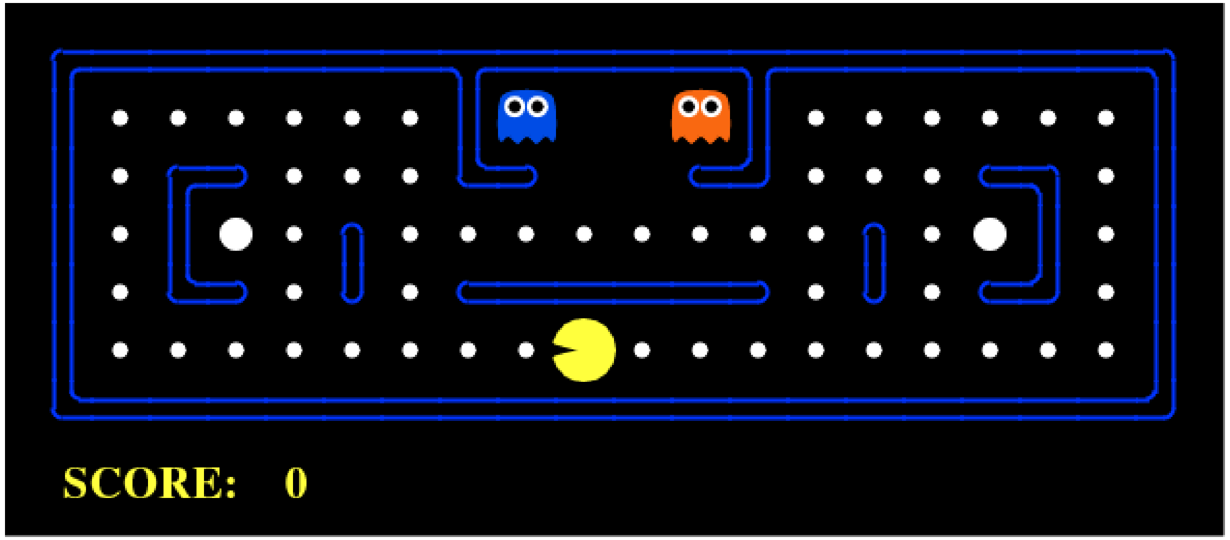
What characterizes Reinforcement Learning (vs other ML tasks)?

- ✓ No supervisor: only a *reward* signal
- ✓ Delayed asynchronous feedback
- ✓ Time matters (sequential data, continual learning)
- ✓ Agent's actions affect the subsequent data it receives (inherent non-stationarity)

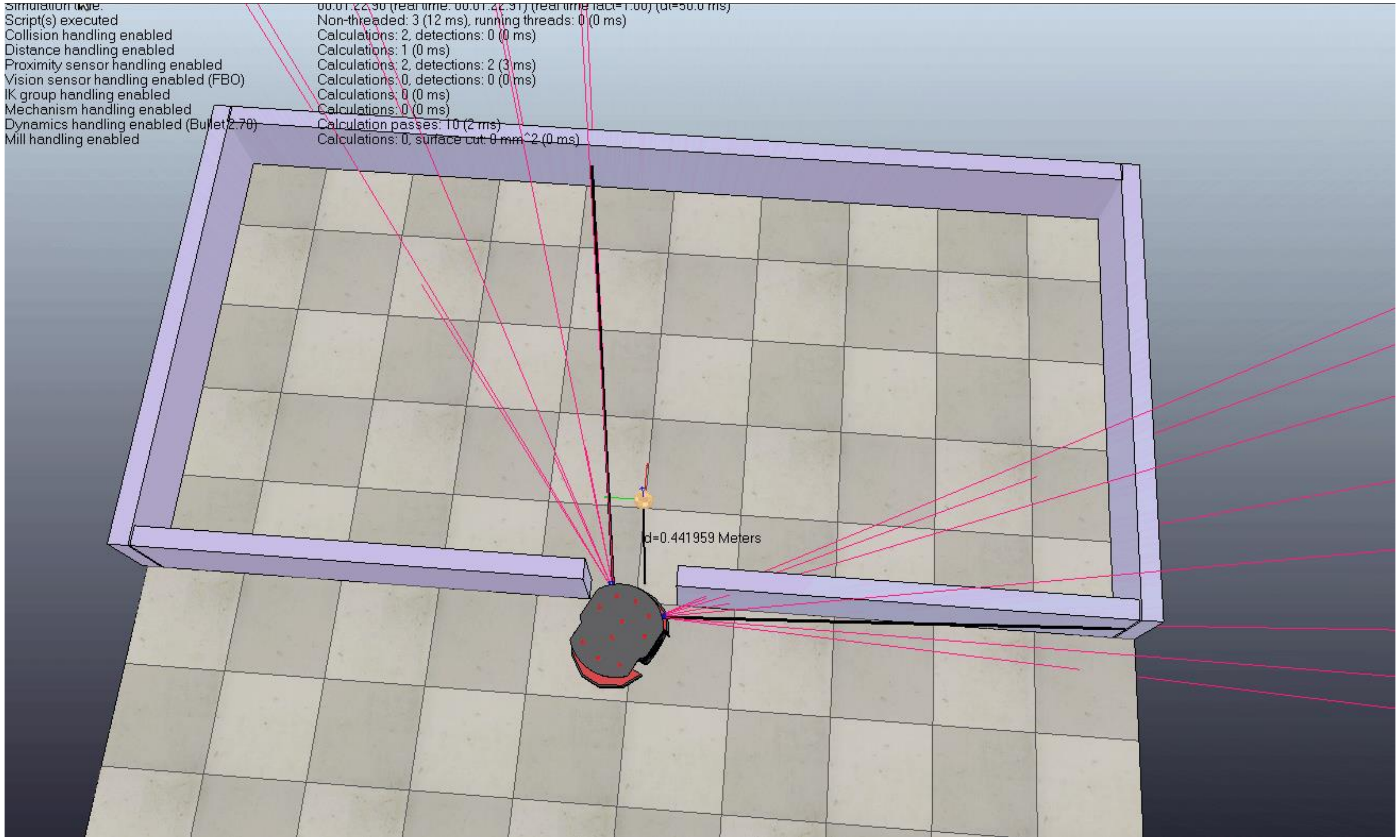
Using Reinforcement Learning

- ✓ Learning to maneuver vehicles
- ✓ Learn to control robots (walking, navigation, manipulation)
- ✓ Manage portfolios
- ✓ Play games
- ✓ Discover new molecules
- ✓ End-to-end learning with discrete structures

Game Playing



Navigation


Script(s) executed
Collision handling enabled
Distance handling enabled
Proximity sensor handling enabled
Vision sensor handling enabled (FBO)
IK group handling enabled
Mechanism handling enabled
Dynamics handling enabled (Bullet 2.78)
Mill handling enabled
Non-threaded: 3 (12 ms), running threads: 0 (0 ms)
Calculations: 2, detections: 0 (0 ms)
Calculations: 1 (0 ms)
Calculations: 2, detections: 2 (3 ms)
Calculations: 0, detections: 0 (0 ms)
Calculations: 0 (0 ms)
Calculations: 0 (0 ms)
Calculation passes: 10 (2 ms)
Calculations: 0, surface cut: 0 mm^2 (0 ms)
d=0.441959 Meters

Manipulation

https://www.youtube.com/watch?v=jwSbzNHGflM

Formalizing Reinforcement Learning

Rewards

- ✓ A reward R_t is a scalar feedback signal
- ✓ Indicates how well agent is doing at step t
- ✓ The agent's job is to maximise cumulative reward

Reinforcement learning is based on the reward hypothesis

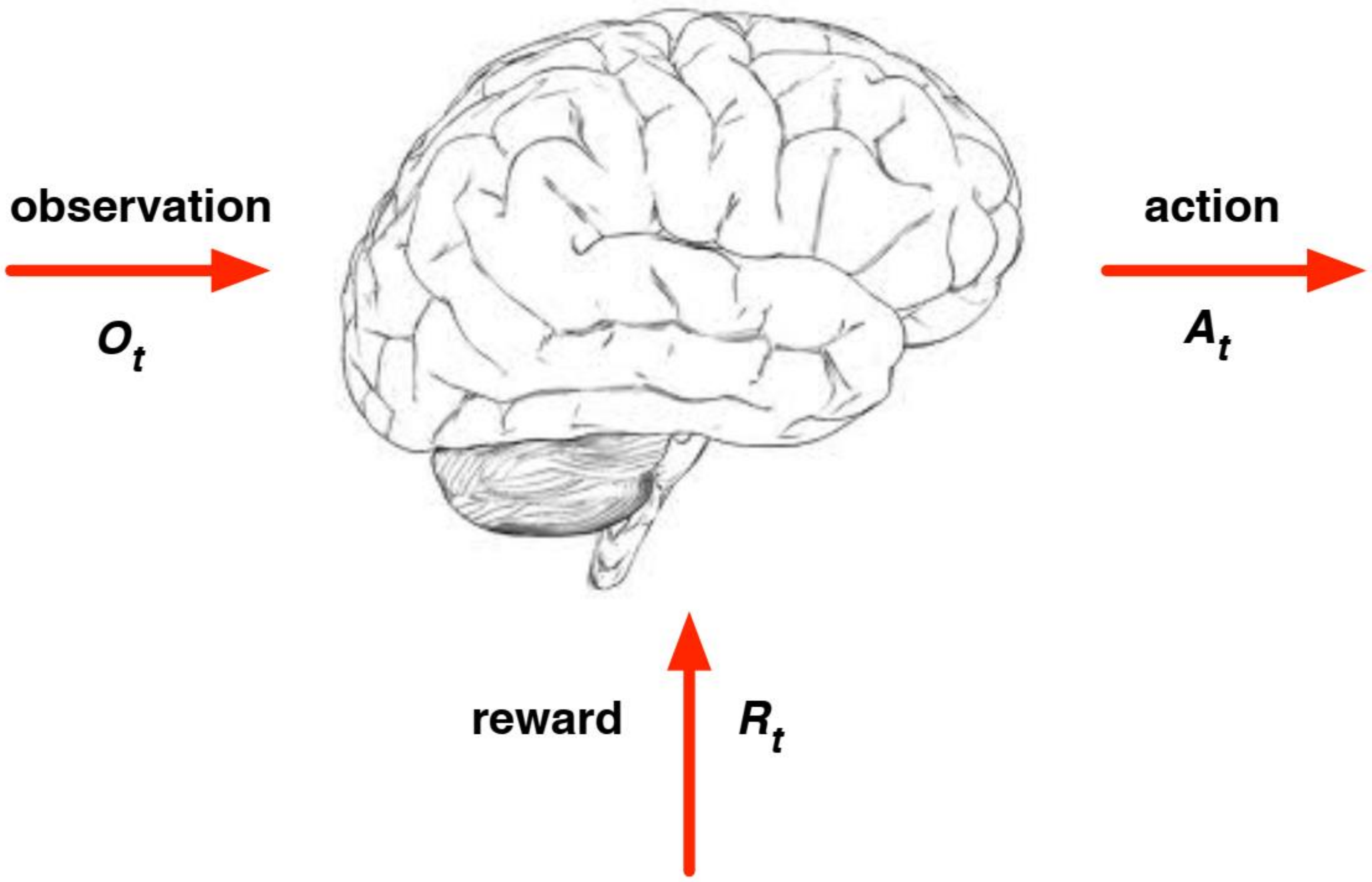
- ✓ All goals can be described by the maximisation of expected cumulative reward

What is a Reward?

- ✓Learning to drive a car (+ve reward for getting places safely - -ve reward for crashing)
- ✓Make a humanoid robot walk (+ve reward for forward motion, -ve reward for tripping over)
- ✓Make a robot arm manipulate objects (+ve reward for goal achievement, -ve reward for object falling)
- ✓Manage an investment portfolio (+ve reward for each $ in bank)
- ✓Play games (+=-ve reward for increasing/decreasing score)
- ✓Discover new molecules (+ve reward for synthesizable molecule, -ve reward for toxic molecule)

Sequential Decision Making

- ✓Goal: *select actions to maximise total future reward*
- ✓Actions may have long term consequences
- ✓Reward may be delayed
- ✓It may be better to sacrifice immediate reward to gain more long-term reward
- ✓Examples:
  - ✓A financial investment (may take months to mature)
  - ✓Refuelling a helicopter (might prevent a crash in several hours)
  - ✓Blocking opponent moves (might help winning chances many moves from now)



Agent and Environment

- At each step t the agent:
  - Executes action at
  - Receives observation $\boldsymbol{O_t}$
  - Receives scalar reward $\boldsymbol{R_t}$
- The Environment:
  - Receives action at
  - Emits observation $\boldsymbol{O_{t+1}}$
  - Emits scalar reward $\boldsymbol{R_{t+1}}$
- t increments at environment step

History and State

The history is the sequence of observations, actions, rewards

$$H_t = O_1; R_1; A_1 \ldots A_{t-1}; O_r; R_t$$

- ✓i.e. all observable variables up to time t
- ✓i.e. the sensorimotor stream of a robot or embodied agent

What happens next depends on the history:

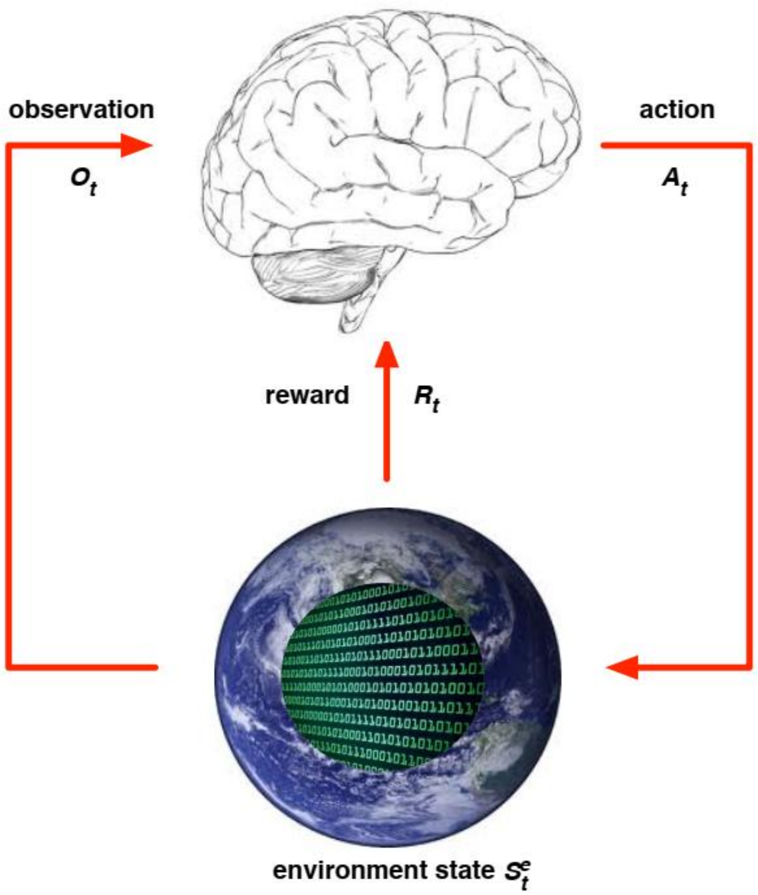
- ✓The agent selects actions
- ✓The environment selects observations/rewards

State S_t is the information used to determine what happens next and is a function of history

$$S_t = f(H_t)$$

Environment State

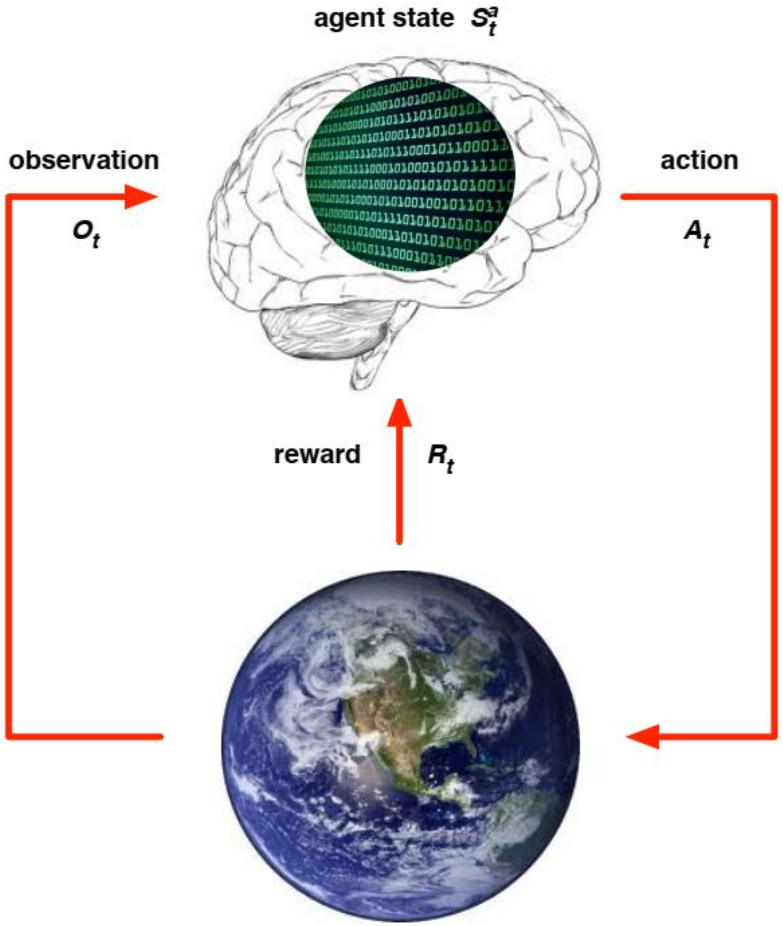
- ✓The environment state S_t^e is the environment e private representation at time t
  - ✓Whatever information the environment uses to generate the next observation/reward
- ✓The environment state is not usually visible to the agent (unobservable environment)
- ✓ Even if S_t^e is visible, it may contain irrelevant information



Agent State

- ✓The agent state S_t^a the internal representation owned by agent a
  - ✓Whatever information the agent uses to select next action
- ✓The agent state is the information used by reinforcement learning algorithms
- ✓Generally speaking a function of history

$$S_t^a = f(H_t)$$



Information (Markov) State

An information state (Markov state) contains all useful information from the history

Definition (Markov State)
A state S_t is Markov if and only if $$P(S_{t+1} \mid S_1, \ldots, S_t) = P(S_{t+1} \mid S_t)$$

✓The future is independent of the past given present (d-separation)

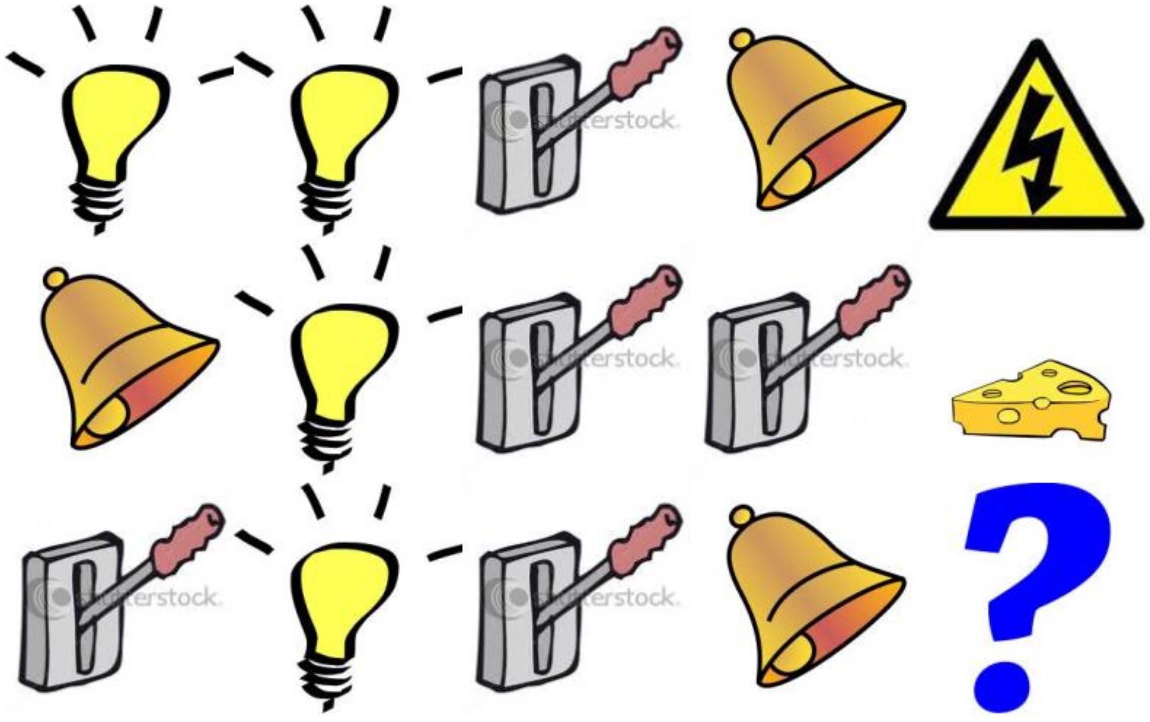
$$H_{1:t} \rightarrow S_t \rightarrow H_{t+1:\infty}$$

✓The state is a sufficient statistics for the future

✓The environment state S_t^e is Markov

✓The history H_t is Markov

What’s the best (agent) state model?

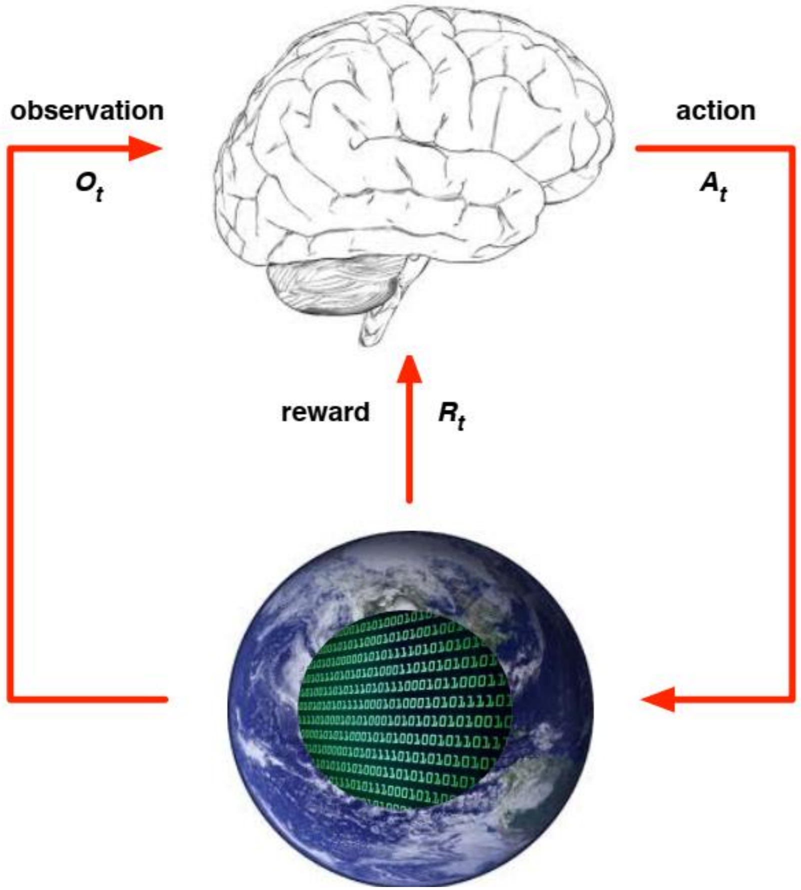


Fully Observable Environment

- ✓Full observability ⟹ Agent directly observes the environment state

$$O_t = S_t^a = S_t^e$$

- ✓Formally this is a Markov Decision Process (MDP)
- ✓Next lecture (and much of the RL literature)



Partially Observable Environment

- ✓Partial observability $\Longrightarrow$ Agent indirectly observes the environment
  - ✓A robot with camera vision only may not know absolute location
  - ✓A trading agent only observes current prices
  - ✓A poker player only observes public cards
- ✓Formally $S_t^a \neq S_t^e$ and the problem is a Partially Observable Markov Decision Process (POMDP)
- ✓The agent needs to build its own state representation S_t^a
  - ✓History: $S_t^a = H_t$
  - ✓Beliefs on environment state: $S_a^t = [P(S_t^e = s^1) \ldots P(S_t^e = s^N)]$
  - ✓A dynamic memory (RNN): $S_a^t = \sigma(W_s S_a^{t-1} + W_o O^t)$

Components of a Reinforcement Learning Agent

Key Components of an RL Agent

- ✓ Policy: agent's behaviour function
- ✓ Value function: how good is each state and/or action
- ✓ Model: agent's representation of the environment

An RL agent may include one or more of the above

Policy

- ✓ A policy π is the agent's behaviour
- ✓ It is a map from state s to action a
  - ✓ Deterministic policy: a $= \pi(s)$
  - ✓ Stochastic policy: $\pi(a|s) = P(A_t = a|S_t = s)$

Value Function

How “good” is a specific state/action for an agent?

Value Function

- ✓The value function v is a predictor of future reward
- ✓Used to evaluate the goodness/badness of states
- ✓And therefore to select between actions, e.g

$$v_\pi(s) = \mathbb{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+2} + \cdots | S_t = s]$$

Expected (discounted) future reward following policy π from state s

Model

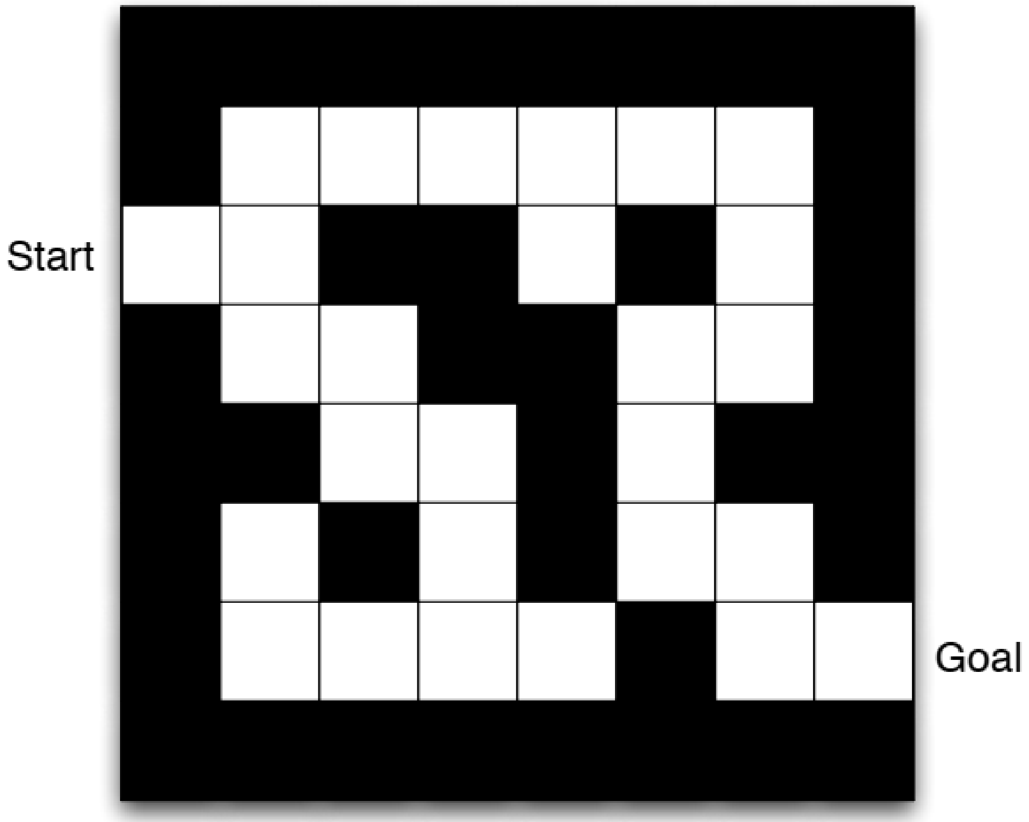
- ✓A model predicts what the environment will do next
- ✓Predict next state s' following an action a

$$\mathcal{P}^a_{ss'} = P(S_{t+1} = s' | S_t = s, A_t = a)$$

- ✓Predict next reward

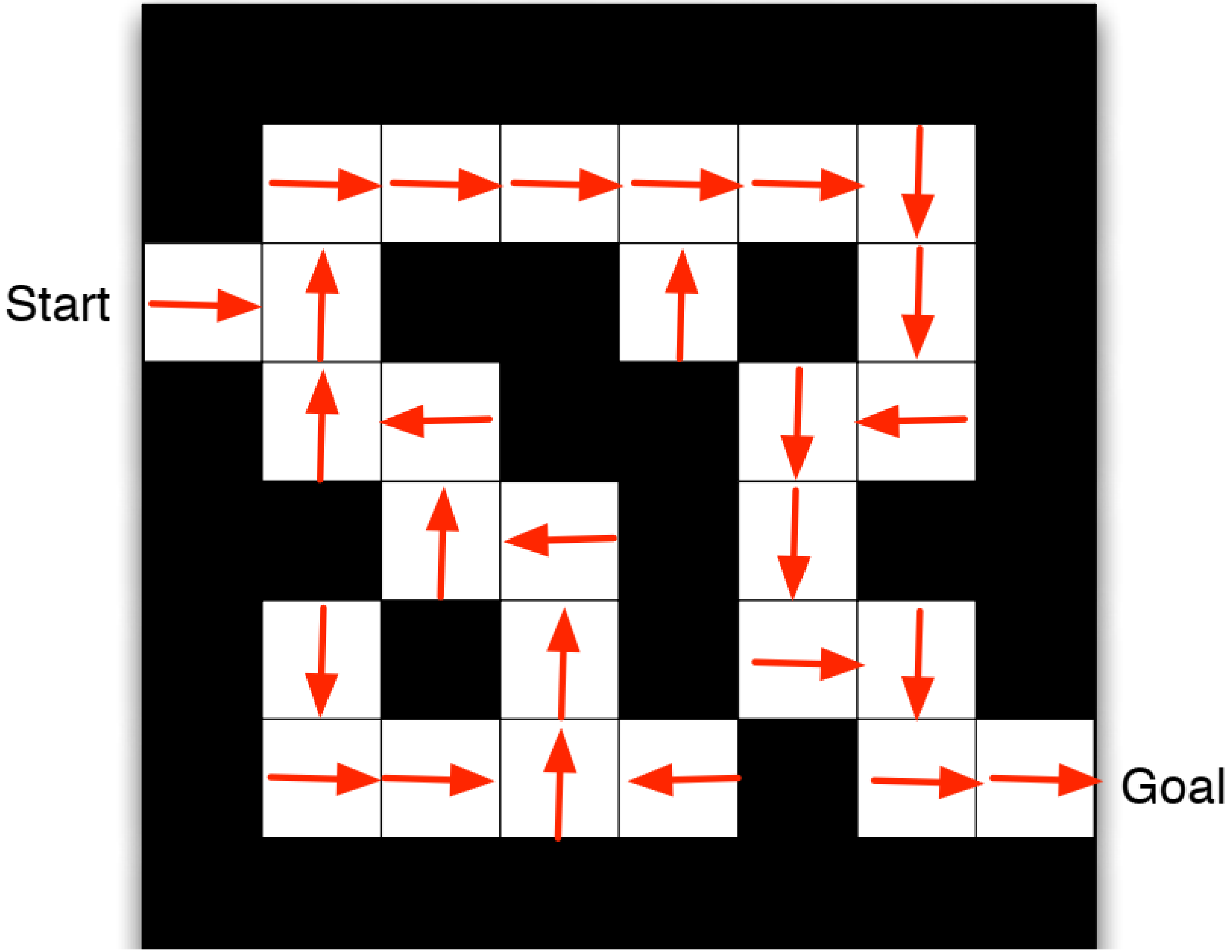
$$\mathcal{R}^a_s = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$$

A Forever Classic - The Maze Example

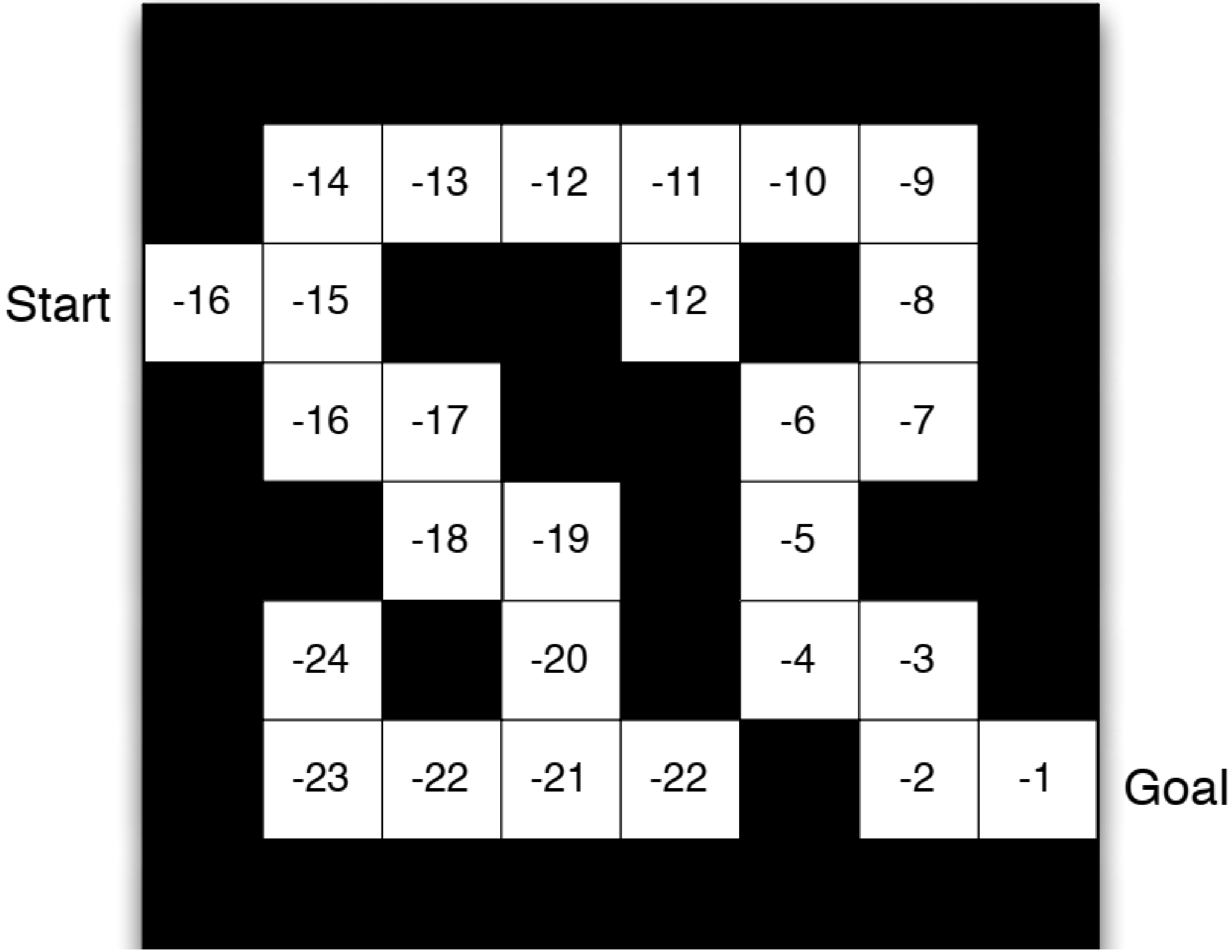


- ✓ **Rewards**: -1 per time-step
- ✓ **Actions**: N, E, S, W
- ✓ **States**: Agent location

Maze Example (Policy)



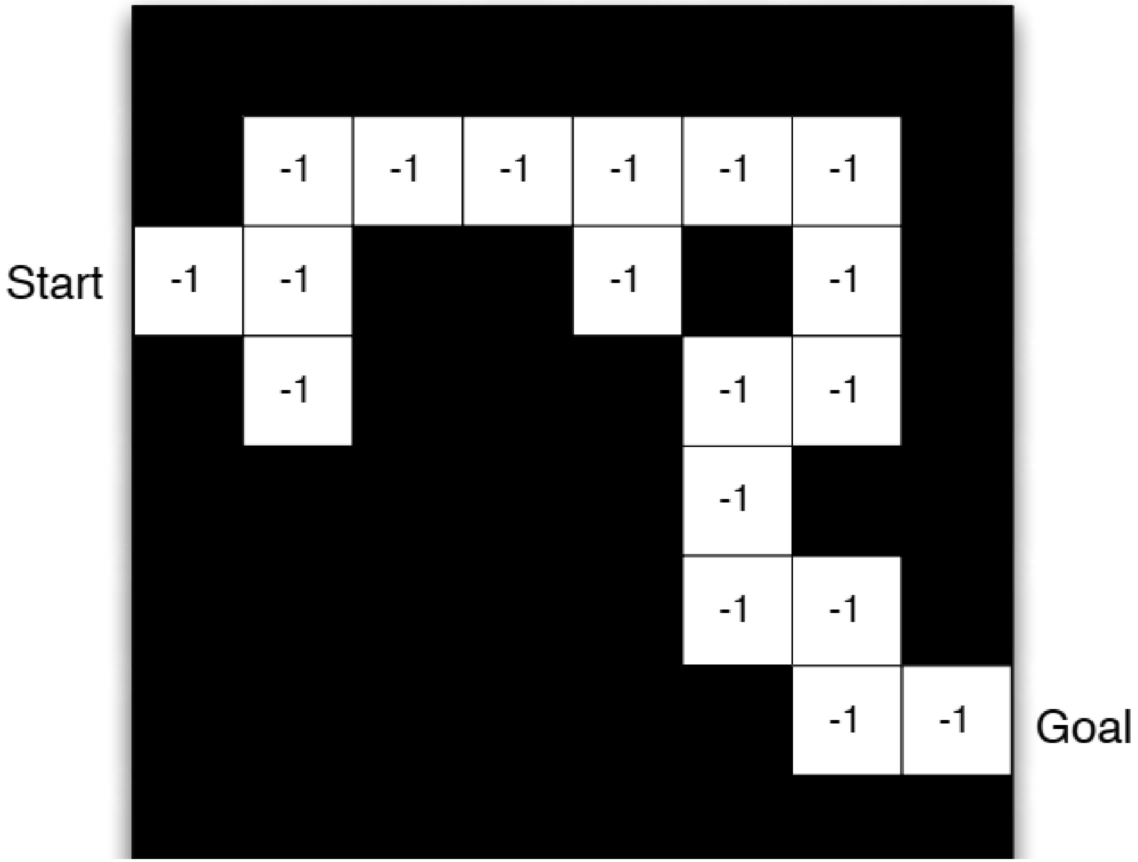
Arrows represent policy $\pi(s)$ for each state s



Maze Example (Value Function)

Numbers denote the value $v_\pi(s)$ for each s

Expected time to reach the goal



Maze Example (Model)

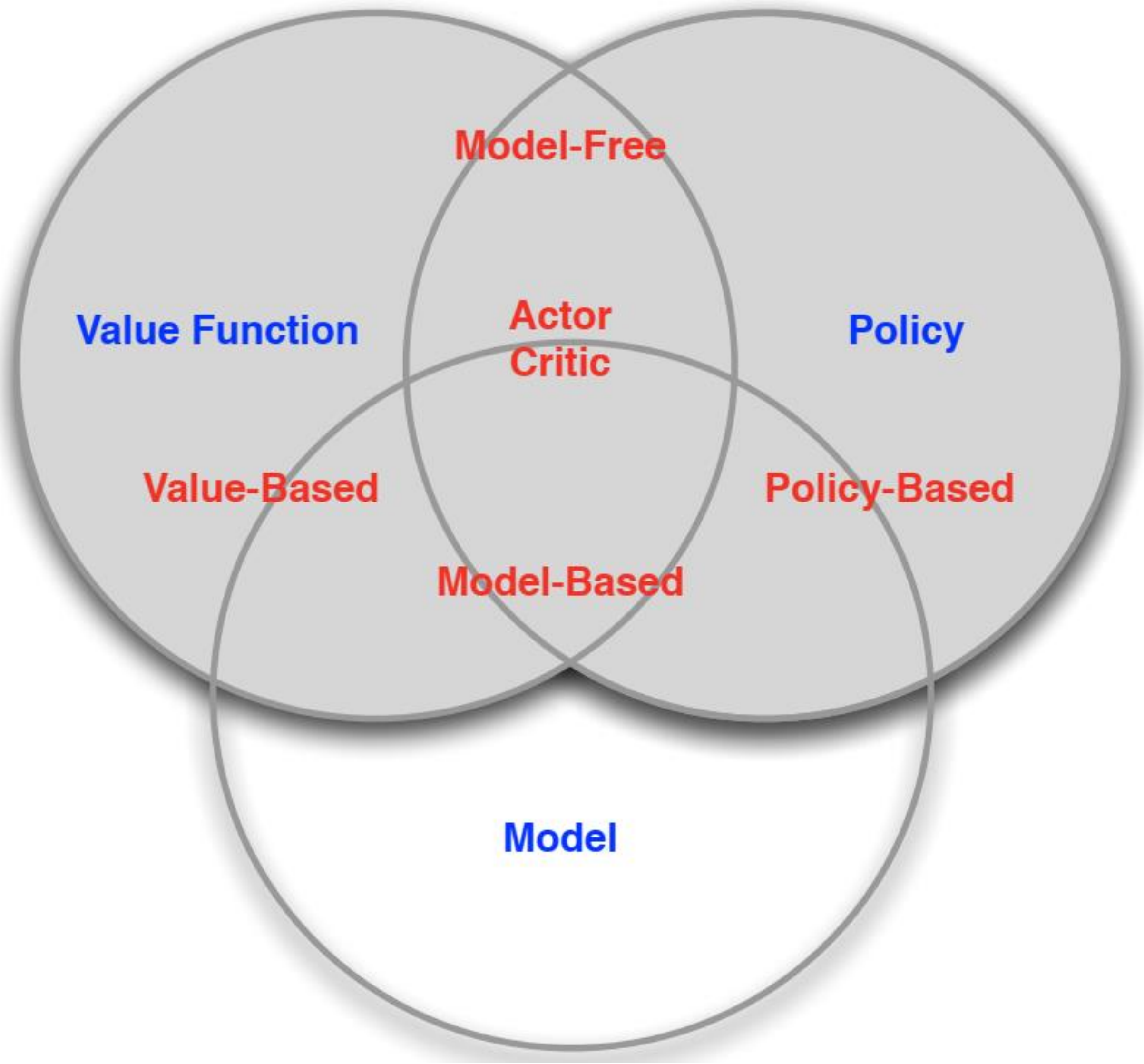
- ✓ Agent may have an internal (imperfect) model of the environment
  - ✓ How actions change the state
  - ✓ How much reward from each state
- ✓ Grid Layout: transition model $\mathcal{P}^a_{ss'}$
- ✓ Numbers: immediate reward model $\mathcal{R}^a_s$

Characterizing RL Agents (I)

- ✓ Value Based
  - ✓ ~~Policy~~ (Implicit)
  - ✓ Value Function
- ✓ Policy Based
  - ✓ Policy
  - ✓ ~~Value Function~~
- ✓ Actor Critic
  - ✓ Policy
  - ✓ Value Function

Characterizing RL Agents (II)

- Model Free
  - ~~Model~~
  - Policy and/or Value Function
- Model Based
  - Model
  - Policy and/or Value Function


Model-Free
Value Function
Actor
Critic
Policy
Value-Based
Policy-Based
Model-Based
Model

A Taxonomy

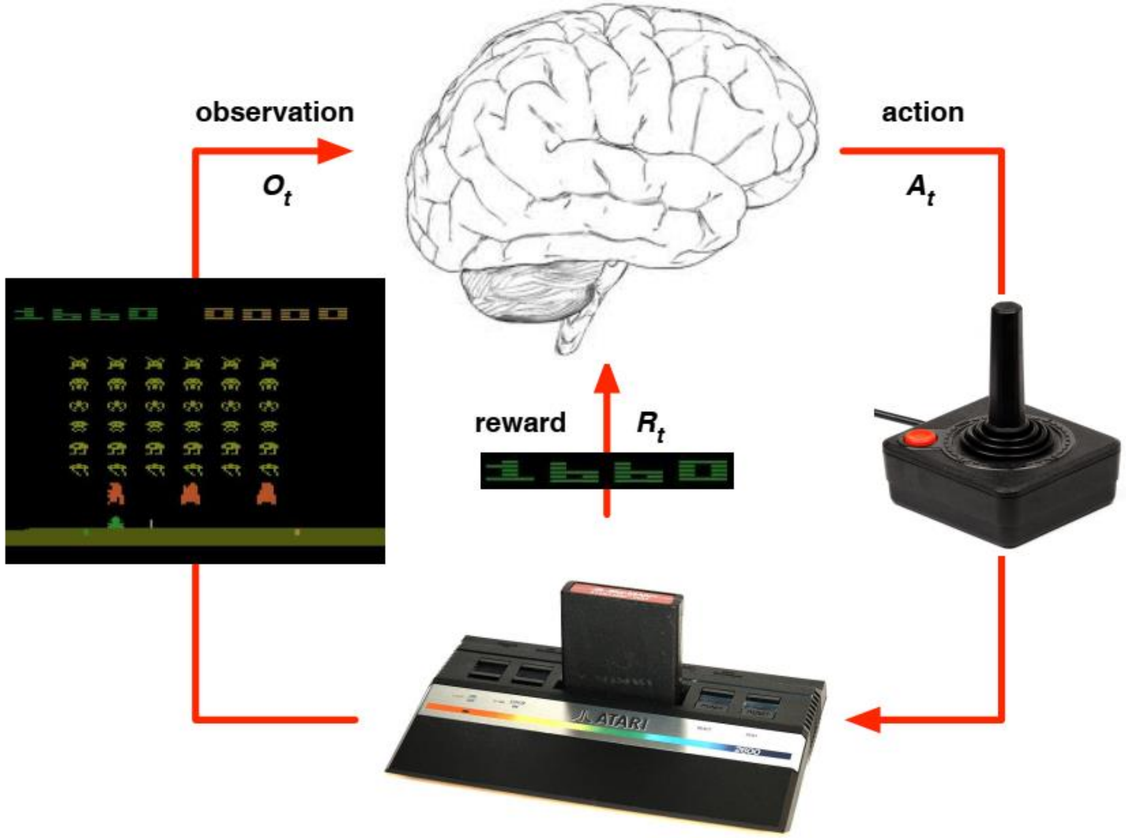
Problems within Reinforcement Learning

Learning and Planning

Two fundamental problems in sequential decision making

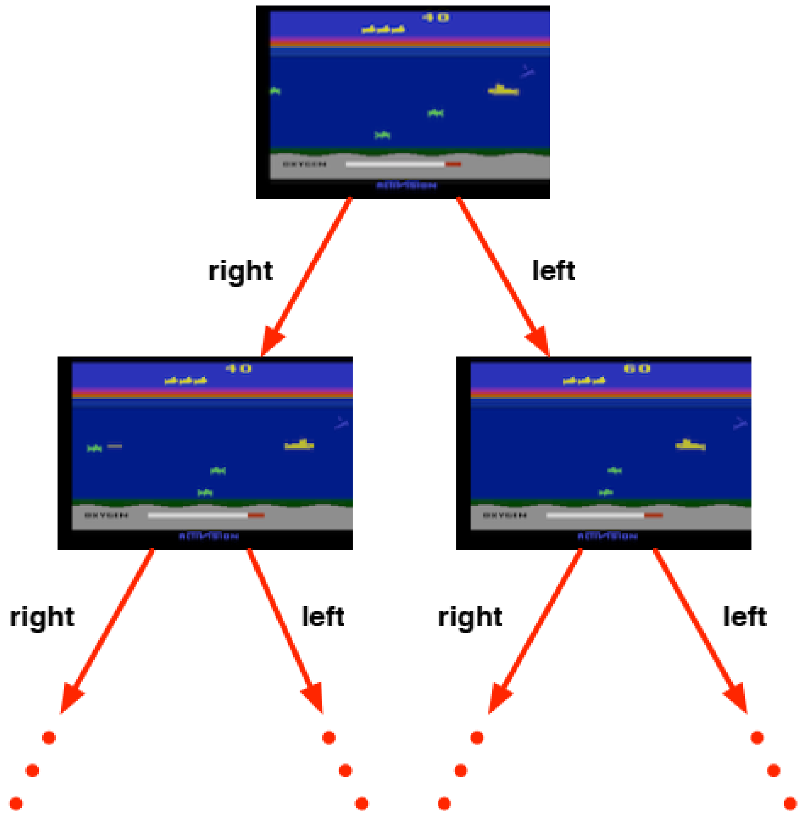
- ✓ Reinforcement Learning
  - ✓ The environment is initially unknown
  - ✓ The agent interacts with the environment
  - ✓ The agent improves its policy
- ✓ Planning (reasoning, introspection, search,…)
  - ✓ A model of the environment is known
  - ✓ The agent performs computations with its model (no external interaction)
  - ✓ The agent improves its policy

Atari Example – Reinforcement learning



- ✓Rules of the game are unknown
- ✓Learn directly from interactive game-play
- ✓Pick actions on joystick, see pixels and scores

Atari Example – Planning



- ✓Rules of the game are known
- ✓Agent contains emulator (model)
- ✓If I take action a from state s:
  - ✓what would the next state be?
  - ✓what would the score be?
- ✓Plan ahead to find optimal policy
  - ✓e.g. tree search

Exploration Vs Exploitation

- ✓ Reinforcement Learning follows a trial-and-error process
- ✓ The agent should discover a good policy
- ✓ From its experiences of the environment
- ✓ Without losing too much reward along the way

- ✓ Exploration finds more information about the environment
- ✓ Exploitation exploits known information to maximise reward

Effective reinforcement learning requires to trade between exploration and exploitation

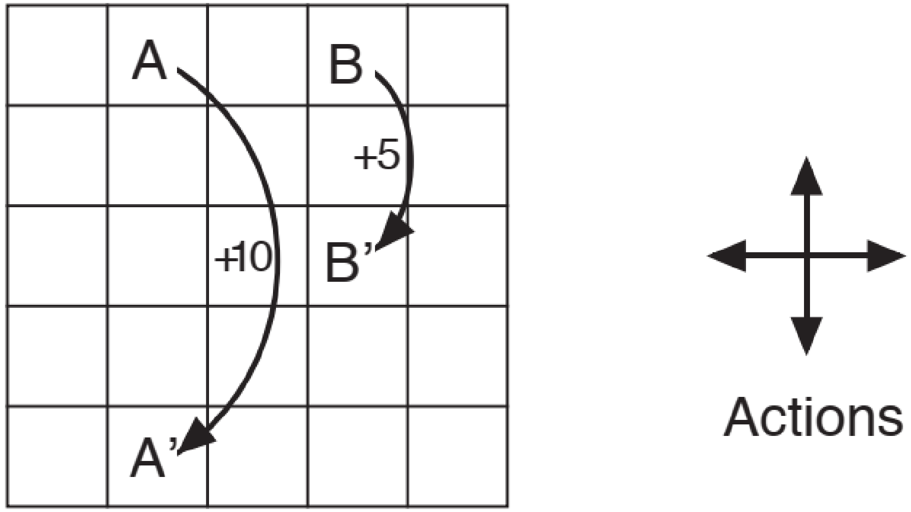
Examples

- ✓ Restaurant Selection
  - ✓ Exploitation - Go to your favourite restaurant
  - ✓ Exploration - Try a new restaurant
- ✓ Holiday planning
  - ✓ Exploitation – The camping site you go to since you are born
  - ✓ Exploration – Hitchhike and follow the flow
- ✓ Game Playing
  - ✓ Exploitation - Play the move you believe is best
  - ✓ Exploration - Play an experimental move

Prediction & Control

- ✓ Prediction: evaluate the future
  - ✓ Given a policy
- ✓ Control: optimise the future
  - ✓ Find the best policy

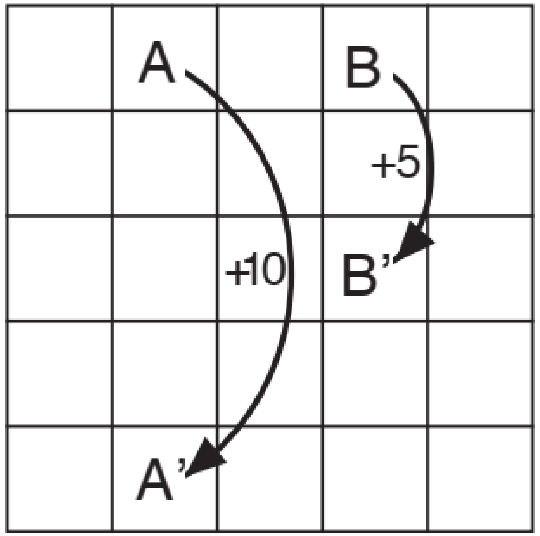
Gridworld Example - Prediction



3.3	8.8	4.4	5.3	1.5
1.5	3.0	2.3	1.9	0.5
0.1	0.7	0.7	0.4	-0.4
-1.0	-0.4	-0.4	-0.6	-1.2
-1.9	-1.3	-1.2	-1.4	-2.0

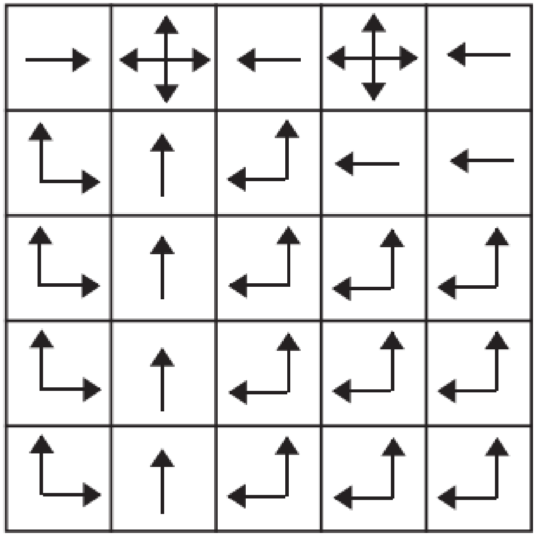
What is the value function for the uniform random policy?

Gridworld Example - Control



22.0	24.4	22.0	19.4	17.5
19.8	22.0	19.8	17.8	16.0
17.8	19.8	17.8	16.0	14.4
16.0	17.8	16.0	14.4	13.0
14.4	16.0	14.4	13.0	11.7

v_*



π_*

What is the optimal value function over all possible policies?

What is the optimal policy?

Wrap-up

Take (stay) home messages

- ✓ Reinforcement learning is a general-purpose framework for decision-making
- ✓ Reinforcement learning is for an agent with the capacity to act and observe
- ✓ The state is the sufficient statistics to characterize the future
  - ✓ Depends on the history of actions and observations
  - ✓ Environment state Vs Agent state
- ✓ Success is measured by a scalar reward signal
  - ✓ The goal is to select actions to maximise future reward (exploit)
  - ✓ In order to be effective we should not forget to explore

Next Lecture

Markov Decision Processes (MDP)

- ✓ A formal model for (observable) environments in reinforcement learning
- ✓ Foundational approach to reinforcement learning
  - ✓ Markov property and processes
  - ✓ Discounted rewards
  - ✓ Bellman expectation
- ✓ Extending to partially-observable environments