# Lecture 1: Introduction to Reinforcement Learning

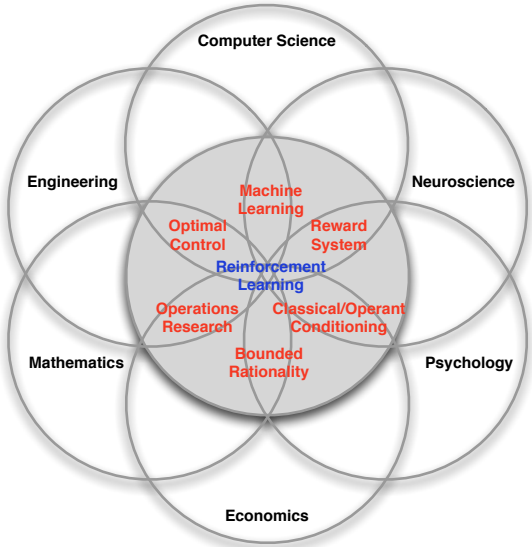
David Silver

# Outline

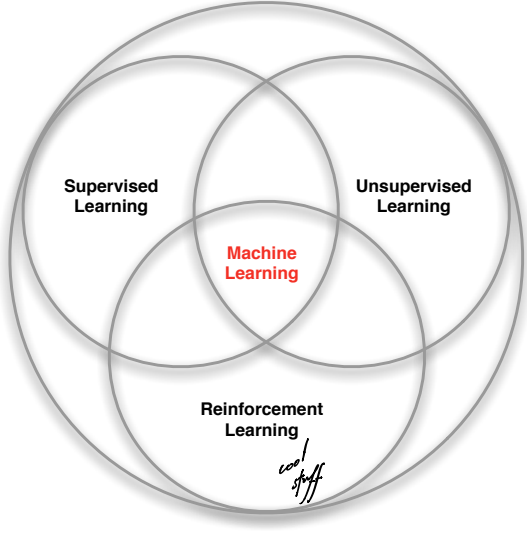
# Textbooks

- An Introduction to Reinforcement Learning, Sutton and Barto, 1998
  - MIT Press, 1998
  - $\sim$ 40 pounds
  - Available free online!
  - http://webdocs.cs.ualberta.ca/∼sutton/book/the-book.html
- Algorithms for Reinforcement Learning, Szepesvari
  - Morgan and Claypool, 2010
  - $\sim$ 20 pounds
  - Available free online!
  - http://www.ualberta.ca/∼szepesva/papers/RLAlgsInMDPs.pdf

# Many Faces of Reinforcement Learning



# Branches of Machine Learning



# Characteristics of Reinforcement Learning

What makes reinforcement learning different from other machine learning paradigms?

- There is no supervisor, only a *reward* signal → we don't know what specifically we did right or wrong
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non i.i.d data)
- Agent's actions affect the subsequent data it receives

# Examples of Reinforcement Learning

- Fly stunt manoeuvres in a helicopter
- Defeat the world champion at Backgammon
- Manage an investment portfolio
- Control a power station
- Make a humanoid robot walk
- Play many different Atari games better than humans

# Helicopter Manoeuvres

# Bipedal Robots

# Atari

# 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

**Definition (Reward Hypothesis)**

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

Do you agree with this statement?

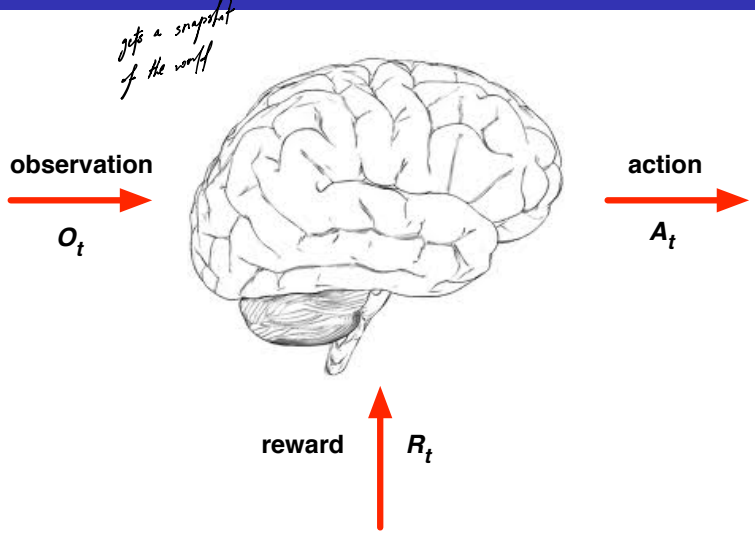
# Examples of Rewards

- Fly stunt manoeuvres in a helicopter
  - +ve reward for following desired trajectory
  - −ve reward for crashing
- Defeat the world champion at Backgammon
  - +/−ve reward for winning/losing a game
- Manage an investment portfolio
  - +ve reward for each $ in bank
- Control a power station
  - +ve reward for producing power
  - −ve reward for exceeding safety thresholds
- Make a humanoid robot walk
  - +ve reward for forward motion
  - −ve reward for falling over
- Play many different Atari games better than humans
  - +/−ve reward for increasing/decreasing score

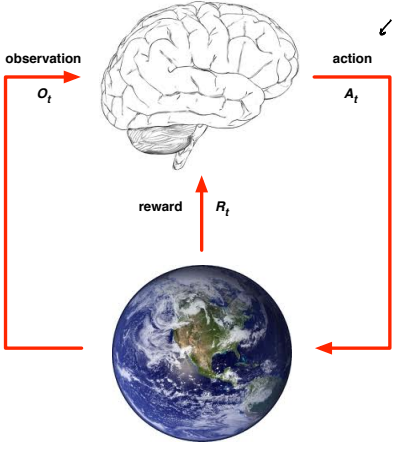
# Sequential Decision Making

- 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



# Agent and Environment




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

# History and State

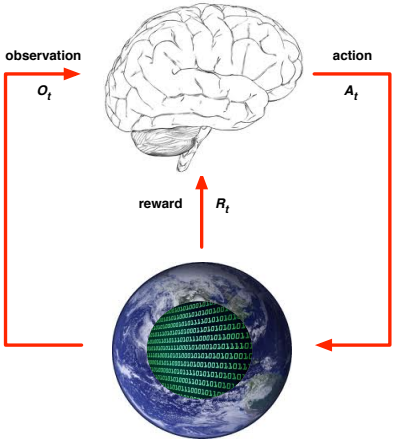
- The history is the sequence of observations, actions, rewards

$$H_t = O_1, R_1, A_1, ..., A_{t-1}, O_t, R_t$$

- 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 is the information used to determine what happens next
- Formally, state is a function of the history:

$$S_t = f(H_t)$$

# Environment State

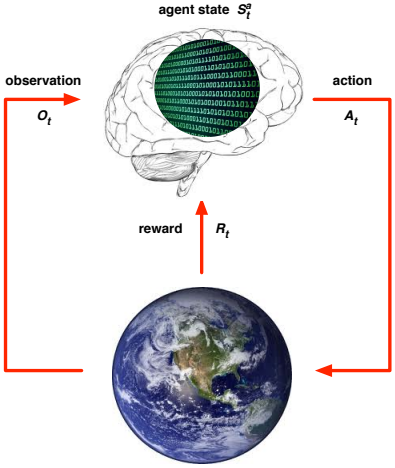



- The environment state $S_t^e$ is the environment's private representation
- i.e. whatever data the environment uses to pick the next observation/reward
- The environment state is not usually visible to the agent
- Even if $S_t^e$ is visible, it may contain irrelevant information

→ not usually visible. we don't have that luxury

↳ the fact that there are can be opponent in env. doesn't change our approach. what happens in env. is not our concern.

# Agent State




- The agent state $S_t^a$ is the agent's internal representation
- i.e. whatever information the agent uses to pick the next action
- i.e. it is the information used by reinforcement learning algorithms
- It can be any function of history:

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

# Information State

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

**Definition**

A state $S_t$ is Markov if and only if

$$\mathbb{P}[S_{t+1} \mid S_t] = \mathbb{P}[S_{t+1} \mid S_1, ..., S_t]$$

(1) (2)

It's saying (1) & (2) are same. This $S_t$ has enough info about all history. We can throw away the $S_1, \ldots, S_{t-1}$ history.

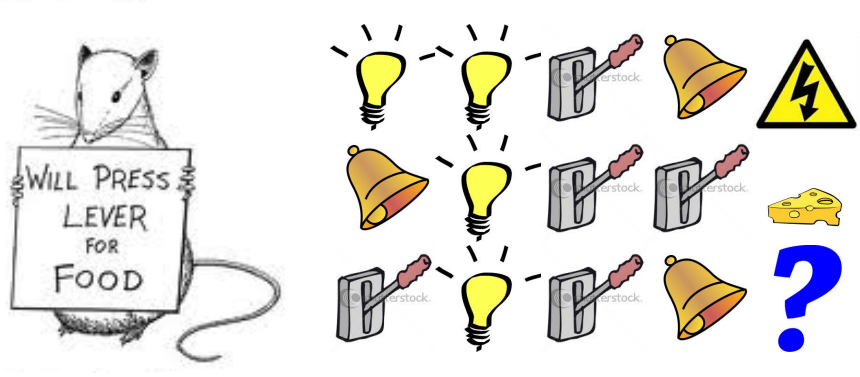
- "The future is independent of the past given the present"

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

- Once the state is known, the history may be thrown away
- i.e. The state is a sufficient statistic of the future
- The environment state $S_t^e$ is Markov
- The history $H_t$ is Markov → just not as useful.

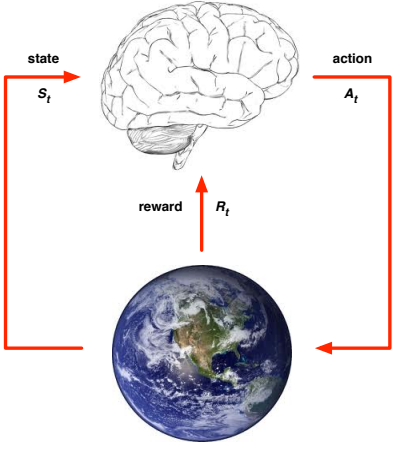
There's always a markov state. In worst case we store $H_t$ as markov state

# Rat Example




- What if agent state = last 3 items in sequence?
- What if agent state = counts for lights, bells and levers?
- What if agent state = complete sequence?

# Fully Observable Environments




Full observability: agent directly observes environment state

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

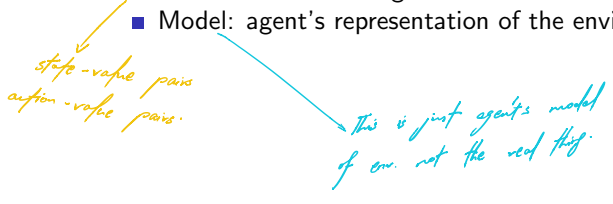
- Agent state = environment state = information state
- Formally, this is a Markov decision process (MDP)
- (Next lecture and the majority of this course)

# Partially Observable Environments

- Partial observability: agent indirectly observes environment:
  - A robot with camera vision isn't told its absolute location
  - A trading agent only observes current prices
  - A poker playing agent only observes public cards
- Now agent state $\neq$ environment state
- Formally this is a partially observable Markov decision process (POMDP)
- Agent must construct its own state representation $S_t^a$, e.g.
  - Complete history: $S_t^a = H_t$
  - Beliefs of environment state: $S_t^a = (\mathbb{P}[S_t^e = s^1], ..., \mathbb{P}[S_t^e = s^n])$
  - Recurrent neural network: $S_t^a = \sigma(S_{t-1}^a W_s + O_t W_o)$

# Major Components of an RL Agent

- An RL agent may include one or more of these components:
  - Policy: agent's behaviour function
  - Value function: how good is each state and/or action
  - Model: agent's representation of the environment



# Policy

- A policy is the agent's behaviour
- It is a map from state to action, e.g.
- Deterministic policy: $a = \pi(s)$
- Stochastic policy: $\pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$

given a state, give an action.

what's prob of taking action a

give state s

# Value Function

- Value function is a prediction of future reward
- Used to evaluate the goodness/badness of states
- And therefore to select between actions, e.g.

$$v_\pi(s) = \mathbb{E}_\pi \left[ R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + ... \mid S_t = s \right]$$

if we're in state $s$, and we go ahead with this policy $\pi$, what's the value we get out of it.

# Example: Value Function in Atari

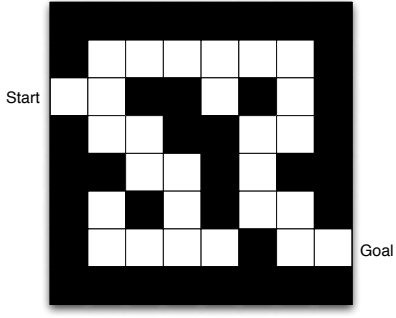
# Model

- A model predicts what the environment will do next
- $\mathcal{P}$ predicts the next state
- $\mathcal{R}$ predicts the next (immediate) reward, e.g.

$$\mathcal{P}^a_{ss'} = \mathbb{P}[S_{t+1} = s' \mid S_t = s, A_t = a]$$
$$\mathcal{R}^a_s = \mathbb{E}[R_{t+1} \mid S_t = s, A_t = a]$$

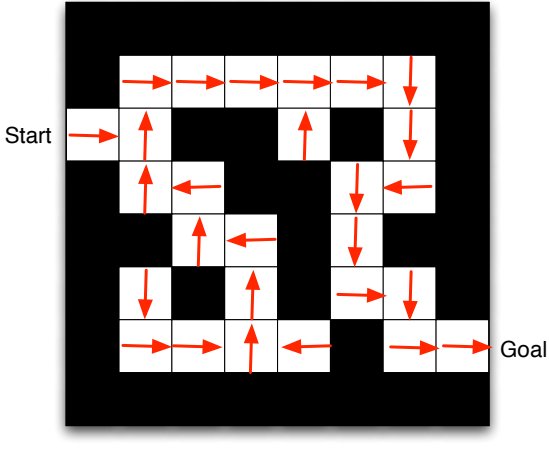
→ this is optional. most of the course will focus on model-free agents.

# Maze Example



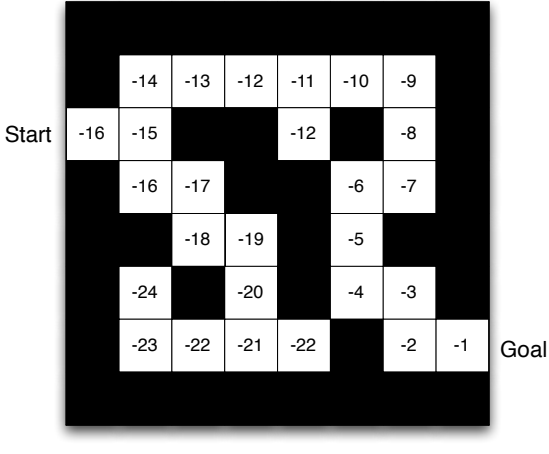

- Rewards: -1 per time-step
- Actions: N, E, S, W
- States: Agent's location

# Maze Example: Policy



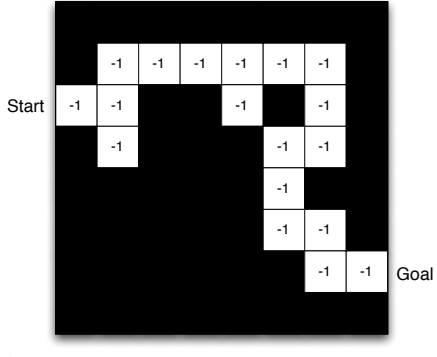

- Arrows represent policy $\pi(s)$ for each state $s$

# Maze Example: Value Function




- Numbers represent value $v_\pi(s)$ of each state $s$

# Maze Example: Model




- Agent may have an internal model of the environment
- Dynamics: how actions change the state
- Rewards: how much reward from each state
- The model may be imperfect

- Grid layout represents transition model $\mathcal{P}^a_{ss'}$
- Numbers represent immediate reward $\mathcal{R}^a_s$ from each state $s$ (same for all $a$)

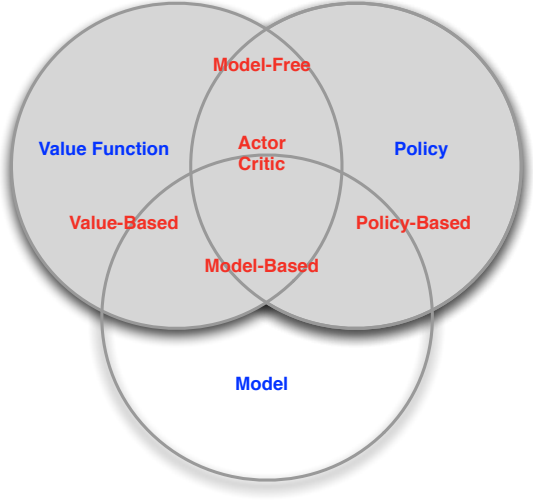
# Categorizing RL agents (1)

- Value Based
  - No Policy (Implicit)
  - Value Function
- Policy Based
  - Policy
  - No Value Function
- Actor Critic
  - Policy
  - Value Function

# Categorizing RL agents (2)

- Model Free
  - Policy and/or Value Function
  - No Model
- Model Based
  - Policy and/or Value Function
  - Model

# RL Agent Taxonomy



# Learning and Planning

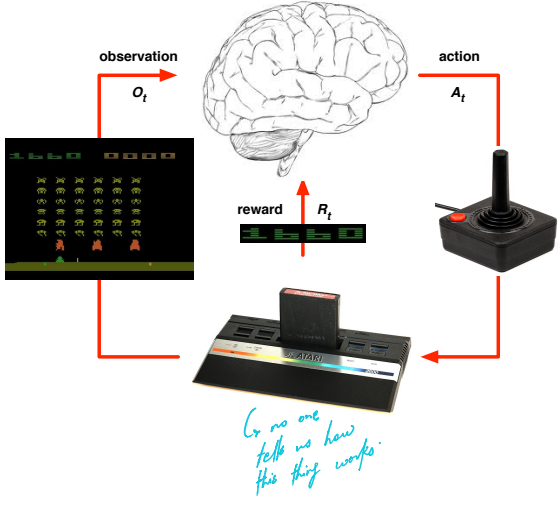
Two fundamental problems in sequential decision making

- Reinforcement Learning:
  - The environment is initially unknown
  - The agent interacts with the environment
  - The agent improves its policy
- Planning:
  - A model of the environment is known
  - The agent performs computations with its model (without any external interaction)
  - The agent improves its policy
  - a.k.a. deliberation, reasoning, introspection, pondering, thought, search

we tell it all the rules of the game.

first learn how env. works ⇒ then plan.

# Atari Example: Reinforcement Learning

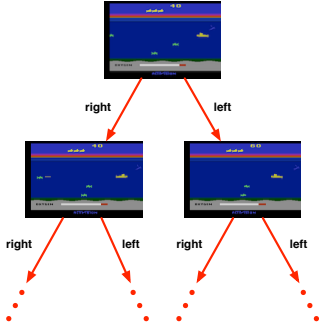



- Rules of the game are unknown
- Learn directly from interactive game-play
- Pick actions on joystick, see pixels and scores

# Atari Example: Planning

- Rules of the game are known
- Can query emulator
  - perfect model inside agent's brain
- 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

look ahead search etc



# Exploration and Exploitation (1)

- Reinforcement learning is like trial-and-error learning
- The agent should discover a good policy
- From its experiences of the environment
- Without losing too much reward along the way

# Exploration and Exploitation (2)

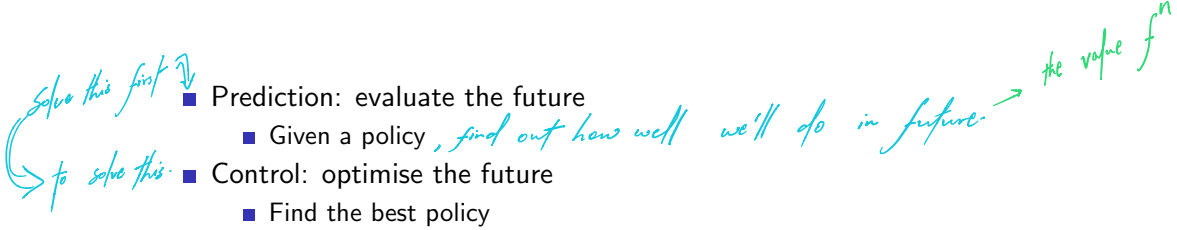
- *Exploration* finds more information about the environment
- *Exploitation* exploits known information to maximise reward
- It is usually important to explore as well as exploit

# Examples

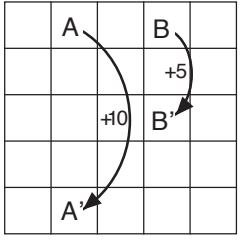
- Restaurant Selection
  - Exploitation Go to your favourite restaurant
  - Exploration Try a new restaurant
- Online Banner Advertisements
  - Exploitation Show the most successful advert
  - Exploration Show a different advert
- Oil Drilling
  - Exploitation Drill at the best known location
  - Exploration Drill at a new location
- Game Playing
  - Exploitation Play the move you believe is best
  - Exploration Play an experimental move

# Prediction and Control

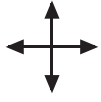
- Prediction: evaluate the future
  - Given a policy
- Control: optimise the future
  - Find the best policy



# Gridworld Example: Prediction




(a)



Actions

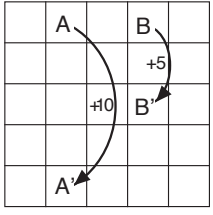
| | | | | |
|---|---|---|---|---|
| 3.3 | 8.8 | 4.4 | 5.3 | 1.5 |
| 1.5 | 3.0 | 2.3 | 1.9 | 0.5 |
| 0.1 | 0.7 | 0.7 | 0.4 | -0.4 |
| -1.0 | -0.4 | -0.4 | -0.6 | -1.2 |
| -1.9 | -1.3 | -1.2 | -1.4 | -2.0 |

(b)

What is the value function for the uniform random policy?

this is a prediction problem.

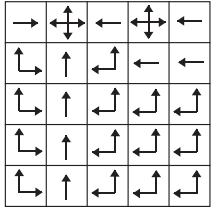
# Gridworld Example: Control




a) gridworld

| | | | | |
|---|---|---|---|---|
| 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 |

b) $v_*$



c) $\pi_*$

What is the optimal value function over all possible policies?
What is the optimal policy?

# Course Outline

- Part I: Elementary Reinforcement Learning
  1. Introduction to RL
  2. Markov Decision Processes
  3. Planning by Dynamic Programming
  4. Model-Free Prediction
  5. Model-Free Control
- Part II: Reinforcement Learning in Practice
  1. Value Function Approximation
  2. Policy Gradient Methods
  3. Integrating Learning and Planning
  4. Exploration and Exploitation
  5. Case study - RL in games