Machine Learning

NLP: Jordan Boyd-Graber

University of Maryland

Reinforcement Learning

Slides adapted from Tom Mitchell and Peter Abeel

Steve Gorton and Tim Ridley, Alexander Hafemann/Getty Images

From iScoop

Control Learning

Consider learning to choose actions, e.g.,

- Roomba learning to dock on battery charger
- Learning to choose actions to optimize factory output
- Learning to play Backgammon

Problem characteristics:

- Delayed reward
- Opportunity for active exploration
- Possibility that state only partially observable
- Possible need to learn multiple tasks with same sensors/effectors

Early Example: TD-Gammon

Learn to play Backgammon
[Tesauro, 1995]

- +100 if win
- -100 if lose
- 0 for all other states

Trained by playing 1.5 million games against itself
Approximately equal to best human player

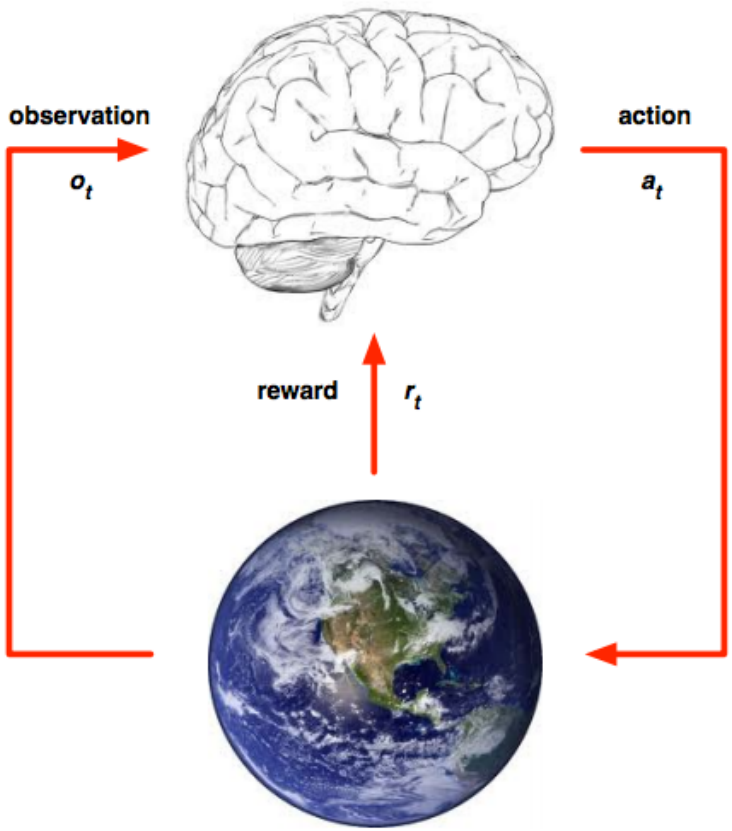
Where RL is Now

- Language Model Alignment
- Machine Translation
- Question answering
- Starcraft
- Go
- Atari
- Robotics

The Problem of Delayed Reward

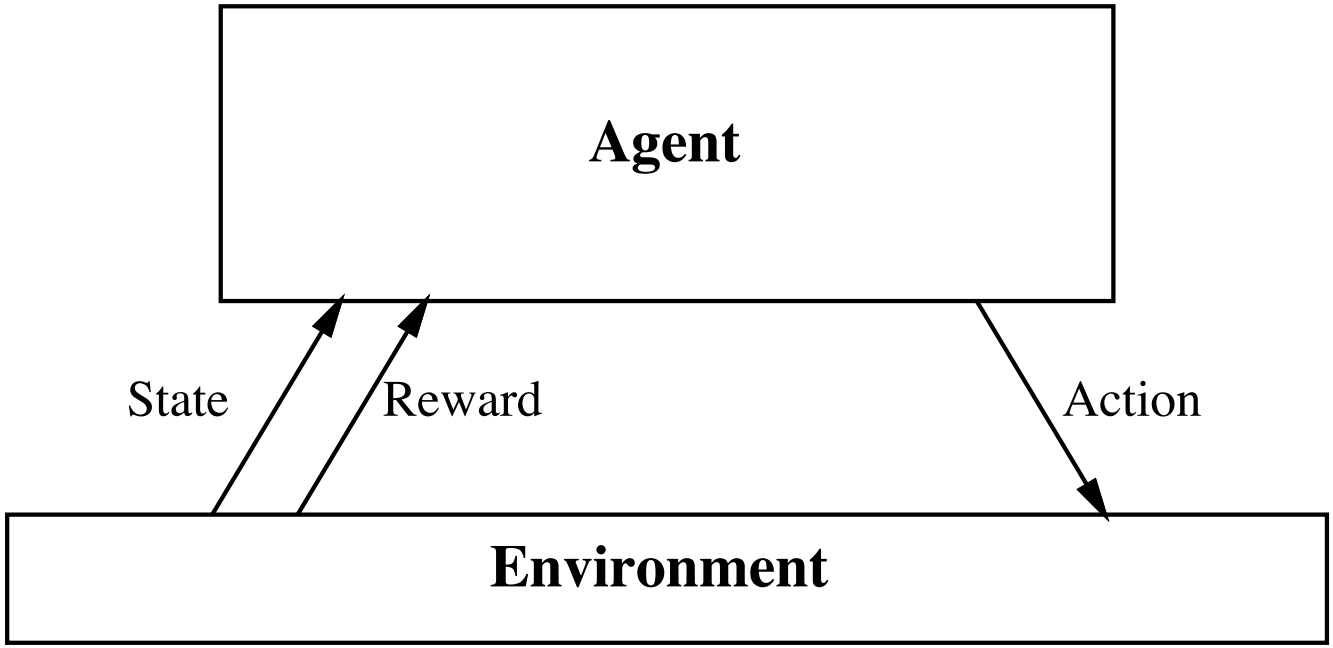
- Mistakes now could have a big cost in the future
- You need to set up an opportunity now for a payoff in the future
- Hard to know which is which

Reinforcement Learning Problem



- 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}

Reinforcement Learning Problem



$$s_0 \xrightarrow[r_0]{a_0} s_1 \xrightarrow[r_1]{a_1} s_2 \xrightarrow[r_2]{a_2} \ldots$$

Goal: Learn to choose actions that maximize

$r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$, where $0 < \gamma < 1$

Markov Decision Processes

Assume

- finite set of states S
- set of actions A
- at each discrete time agent observes state $s_t \in S$ and chooses action $a_t \in A$
- then receives immediate reward r_t
- and state changes to s_{t+1}
- Markov assumption: $s_{t+1} = \delta(s_t, a_t)$ and $r_t = r(s_t, a_t)$
  - i.e., r_t and s_{t+1} depend only on current state and action
  - functions δ and r may be nondeterministic
  - functions δ and r not necessarily known to agent

State

- Experience is a sequence of observations, actions, rewards

$$o_1, r_1, a_1, \ldots, a_{t-1}, o_t, r_t \tag{1}$$

- The state is a summary of experience

$$s_t = f(o_1, r_1, a_1, \ldots, a_{t-1}, o_t, r_t) \tag{2}$$

- In a fully observed environment

$$s_t = f(o_t) \tag{3}$$

Agent's Learning Task

Execute actions in environment, observe results, and

- learn action policy $\pi : S \rightarrow A$ that maximizes

$$\mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots\right]$$

  from any starting state in S
- here $0 \leq \gamma < 1$ is the discount factor for future rewards

Note something new:

- Target function is $\pi : S \rightarrow A$
- but we have no training examples of form $\langle s, a \rangle$
- training examples are of form $\langle \langle s, a \rangle, r \rangle$

What makes 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

Policy

- A policy is the agent's behavior
  - It is a map from state to action:
  - Deterministic policy: $a = \pi(s)$
  - Stochastic policy: $\pi(a \mid s) = p(a \mid s)$

Value Function

To begin, consider deterministic worlds . . .
For each possible policy π the agent might adopt, we can define an evaluation function over states

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

where $r_t, r_{t+1}, \ldots$ are from following policy π starting at state s

Example: Imitation Learning

- Take examples of experts $\{(s_1, a_1)\ldots\}$
- Learn a classifier mapping $s \rightarrow a$
- Create loss as the negative reward

Example: Imitation Learning

- Take examples of experts $\{(s_1, a_1)\ldots\}$
- Learn a classifier mapping $s \rightarrow a$
- Create loss as the negative reward
- What if we diverge?

Likelihood Ratio Policy Gradient

Let τ be state-action $s_0, u_0, \ldots, s_H, u_H$. Utility of policy π parametrized by θ is

$$U(\theta) = \mathbb{E}_{\pi_\theta, U}\left[\sum_t^H R(s_t, u_t); \pi_\theta\right] = \sum_\tau P(\tau; \theta) R(\tau). \tag{4}$$

Our goal is to find θ:

$$\max_\theta U(\theta) = \max_\theta \sum_\tau p(\tau; \theta) R(\tau) \tag{5}$$

Approaches to RL

Value-based RL

- Estimate the optimal value function $Q^\star(s, a)$
- This is the maximum value achievable under any policy

Policy-based RL

- Search directly for the optimal policy $\pi^\star$
- This is the policy achieving maximum future reward

Model-based RL

- Build a model of the environment
- Plan (e.g. by lookahead) using model