Reinforcement Learning

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Overview

- Formalizing the reinforcement learning problem: **Markov Decision Processes** (MDPs)
- **Dynamic programming** techniques for policy evaluation and policy optimization
- **Sampling-based techniques**: Monte-Carlo methods, Temporal-Difference learning, Q-learning
- **Policy-gradient methods**: Score function gradient estimators, actor-critic methods
- **Seq2seq reinforcement learning**: Bandit structured prediction, actor-critic neural seq2seq learning
- **Off-policy/counterfactual** seq2seq reinforcement learning
- **Seq2seq reinforcment learning** from **human feedback**

Textbooks

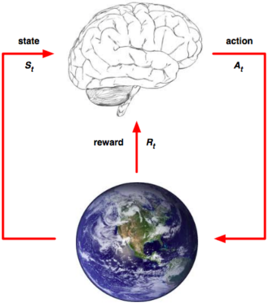
- Richard S. Sutton and Andrew G. Barto (2018, 2nd edition): Reinforcement Learning: An Introduction. MIT Press.
  - `http://incompleteideas.net/sutton/book/the-book-2nd.html`
- Csaba Szepesvári (2010). Algorithms for Reinforcement Learning. Morgan & Claypool.
  - `https://sites.ualberta.ca/~szepesva/RLBook.html`
- Dimitri Bertsekas and John Tsitsiklis (1996). Neuro-Dynamic Programming. Athena Scientific.
  - = another name for deep reinforcement learning, contains a lot of proofs, analog version can be ordered at `http://www.athenasc.com/ndpbook.html`

Reinforcement Learning (RL) Philosopy

- *Hedoninistic* learning system that *wants* something, and adapts its behavior in order to maximize a special signal or *reward* from its environment.
- *Interactive* learning by trial and error, using consequences of own actions in uncharted territory to learn to maximize expected reward.
- *Weak supervision signal* since no gold standard examples from expert are available.

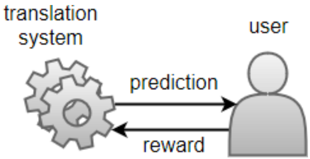
Reinforcement Learning Schema

- RL as Google DeepMind would like to see it (image from David Silver):



Reinforcement Learning Schema

- A real-world example: Interactive Machine Translation



  - action = predicting a target word
  - reward = per-sentence translation quality
  - state = source sentence and target history

Reinforcement Learning Schema

Agent/system and environment/user interact

- at each of a sequence of time steps $t = 0, 1, 2, \ldots$,
- where agent receives a state representation S_t,
- on which basis it selects an action A_t,
- and as a consequence, it receives a reward R_{t+1},
- and finds itself in a new state S_{t+1}.

Goal of RL: Maximize the total amount of reward an agent receives in such interactions in the long run.

Formalizing User/Environment: Markov Decision Processes (MDPs)

A **Markov decision process** is a tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} \rangle$ where

- $\mathcal{S}$ is a set of states,
- $\mathcal{A}$ is a finite set of actions,
- $\mathcal{P}$ is a state transition probability matrix s.t. $\mathcal{P}^a_{ss'} = P[S_{t+1} = s' | S_t = s, A_t = a]$,
- $\mathcal{R}$ is a reward function s.t. $\mathcal{R}^a_s = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$.

Dynamics of MDPs

One-step dynamics of the environment under the Markov property is completely specified by probability distribution over pairs of next state and reward s', r, given state and action s, a:

- $p(s', r|s, a) = P[S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a]$.

Exercise: Specify $\mathcal{P}^a_{ss'}$ and $\mathcal{R}^a_s$ in terms of $p(s', r|s, a)$.
$\mathcal{P}^a_{ss'} = p(s'|s, a) = \sum_{r \in \mathcal{R}} p(s', r|s, a)$,
$\mathcal{R}^a_s = \sum_{r \in \mathcal{R}} r \sum_{s' \in \mathcal{S}} p(s', r|s, a)$.

Formalizing Agent/System: Policies

A **stochastic policy** is a distribution over actions given states s.t.

- $\pi(a|s) = P[A_t = a|S_t = s]$.
- A policy completely specifies the behavior of an agent/system.
- Policies are parameterized π_θ, e.g. by a linear model or a neural nework - we use π to denote π_θ if unambiguous.
- Deterministic policies $a = \pi(s)$ also possible.

Policy Evaluation and Policy Optimization

Two central tasks in RL:

- **Policy evaluation (a.k.a. prediction):** Evaluate the expected reward for a given policy.
- **Policy optimization (a.k.a. learning/control):** Find the optimal policy / optimize a parametric policy under the expected reward criterion.

Return and Value Functions

- The **total discounted return** from time-step t for discount $\gamma \in [0, 1]$ is
  - $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$.
- The **action-value function** $q_\pi(s, a)$ on an MDP is the expected return starting from state s, taking action a, and following policy π s.t.
  - $q_\pi(s, a) = \mathbb{E}_\pi[G_t | S_t = s, A_t = a]$.
- The **state-value function** $v_\pi(s)$ on an MDP is the expected return starting from state s and following policy π s.t.
  - $v_\pi(s) = \mathbb{E}_\pi[G_t | S_t = s] = \mathbb{E}_{a \sim \pi}[q_\pi(s, a)]$.

Bellman Expectation Equation

The state-value function can be decomposed into immediate reward plus discounted value of successor state s.t.

$$\begin{aligned} v_\pi(s) &= \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) | S_t = s] \\ &= \sum_{a \in \mathcal{A}} \pi(a|s) \left(\mathcal{R}_s^a + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}_{ss'}^a v_\pi(s') \right). \end{aligned}$$

In matrix notation:

$$\mathbf{v}_\pi = \boldsymbol{\mathcal{R}}^\pi + \gamma \boldsymbol{\mathcal{P}}^\pi \mathbf{v}_\pi.$$

$$\begin{bmatrix} v(1) \\ \vdots \\ v(n) \end{bmatrix} = \begin{bmatrix} \mathcal{R}_1 \\ \vdots \\ \mathcal{R}_n \end{bmatrix} + \gamma \begin{bmatrix} \mathcal{P}_{11} & \dots & \mathcal{P}_{1n} \\ \vdots & & \\ \mathcal{P}_{n1} & \dots & \mathcal{P}_{nn} \end{bmatrix} \begin{bmatrix} v(1) \\ \vdots \\ v(n) \end{bmatrix}$$

Policy Evaluation by Linear Programming

The value of $\mathbf{v}_\pi$ can be found directly by solving the linear equations of the Bellman Expectation Equation:

- **Solving linear equations:**

$$\mathbf{v}_\pi = (\mathbf{I} - \gamma \mathcal{P}^\pi)^{-1} \mathcal{R}^\pi$$

  - Only applicable to small MDPs.

Exercise: Derive $\mathbf{v}_\pi$ from the Bellman Expectation Equaition.

$$\begin{aligned} \mathbf{v}_\pi &= \mathcal{R}^\pi + \gamma \mathcal{P}^\pi \mathbf{v}_\pi \\ (\mathbf{I} - \gamma \mathcal{P}^\pi) \mathbf{v}_\pi &= \mathcal{R}^\pi \\ \mathbf{v}_\pi &= (\mathbf{I} - \gamma \mathcal{P}^\pi)^{-1} \mathcal{R}^\pi \end{aligned}$$

Policy Evaluation by Dynamic Programming (DP)

Value of $\mathbf{v}_\pi$ can also be found by iterative application of Bellman Expectation Equation:

- **Iterative policy evaluation:**

$$\mathbf{v}_{k+1} = \mathcal{R}^\pi + \gamma \mathcal{P}^\pi \mathbf{v}_k.$$

  - Performs **dynamic programming** by recursive decomposition of Bellman equation.
  - Can be parallelized (or backed up asynchronously), thus applicable to large MDPs.
  - Converges to $\mathbf{v}_\pi$.

Policy Optimization using Bellman Optimality Equation

An optimal policy π_* can be found by maximizing over the optimal action-value function $q_*(s,a) = \max_\pi q_\pi(s,a)$ s.t.

$$\pi_*(s) = \operatorname*{argmax}_a q_*(s,a).$$

The optimal value functions are recursively related by the Bellman Optimality Equation:

$$\begin{aligned} q_*(s,a) &= \mathbb{E}_{\pi_*}[R_{t+1} + \gamma \max_{a'} q_*(S_{t+1}, a') | S_t = s, A_t = a] \\ &= \mathcal{R}_s^a + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}_{ss'}^a \max_{a'} q_*(s', a'). \end{aligned}$$

Policy Optimization by Value Iteration

The Bellman Optimality Equation is non-linear and requires iterative solutions such as value iteration by dynamic programming:

- **Value iteration for q-function:**

$$q_{k+1}(s,a) = \mathcal{R}_s^a + \gamma \sum_{s' \in \mathcal{S}} \mathcal{P}_{ss'}^a \max_{a'} q_k(s',a').$$

  - Converges to $q_*(s,a)$.

Summary: Dynamic Programming

- Earliest RL algorithms with well-defined convergence properties.
- Bellman equation gives recursive decomposition for iterative solution to various problems in policy evaluation and policy optimization.
- Can be trivially parallelized or even run asynchronously.
- We **need to know a full MDP model** with all transitions and rewards, and touch all of them in learning!