

Econ 2148, fall 2019
Reinforcement learning

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Agenda

- ▶ Markov decision problems: Goal oriented interactions with an environment.
- ▶ Expected updates – dynamic programming.
Familiar from economics. Requires complete of knowledge transition probabilities.
- ▶ Sample updates: Transition probabilities are unknown.
 - ▶ On policy: Sarsa.
 - ▶ Off policy: Q-learning.
- ▶ Approximation: When state and action spaces are complex.
 - ▶ On policy: Semi-gradient Sarsa.
 - ▶ Off policy: Semi-gradient Q-learning.
 - ▶ Deep reinforcement learning.
 - ▶ Eligibility traces and $TD(\lambda)$.

Takeaways for this part of class

- ▶ Markov decision problems provide a general model of goal-oriented interaction with an environment.
- ▶ Reinforcement learning considers Markov decision problems where transition probabilities are unknown.
- ▶ A leading approach is based on estimating action-value functions.
- ▶ If state and action spaces are small, this can be done in tabular form, otherwise approximation (e.g., using neural nets) is required.
- ▶ We will distinguish between on-policy and off-policy learning.

Introduction

- ▶ Many interesting problems can be modeled as Markov decision problems.
- ▶ Biggest successes in game play (Backgammon, Chess, Go, Atari games,...), where lots of data can be generated by self-play.
- ▶ Basic framework is familiar from macro / structural micro, where it is solved using dynamic programming / value function iteration.
- ▶ Big difference in reinforcement learning:
Transition probabilities are not known, and need to be learned from data.
- ▶ This makes the setting similar to bandit problems, with the addition of changing states.
- ▶ We will discuss several approaches based on estimating action-value functions.

Markov decision problems

- ▶ Time periods $t = 1, 2, \dots$
- ▶ States $S_t \in \mathcal{S}$ (This is the part that's new relative to bandits!)
- ▶ Actions $A_t \in \mathcal{A}(S_t)$
- ▶ Rewards R_{t+1}
- ▶ Dynamics (transition probabilities):

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

- ▶ The distribution depends only on the current state and action.
- ▶ It is constant over time.
- ▶ We will allow for continuous states and actions later.

Policy function, value function, action value function

- ▶ Objective: Discounted stream of rewards, $\sum_{t \geq 0} \gamma^t R_t$.
- ▶ Expected future discounted reward at time t , given the state $S_t = s$:
Value function,

$$V_t(s) = E \left[\sum_{t' \geq t} \gamma^{t'-t} R_{t'} \mid S_t = s \right].$$

- ▶ Expected future discounted reward at time t , given the state $S_t = s$ **and** action $A_t = a$:
Action value function,

$$Q_t(a, s) = E \left[\sum_{t' \geq t} \gamma^{t'-t} R_{t'} \mid S_t = s, A_t = a \right].$$

Bellman equation

- ▶ Consider a policy $\pi(a|s)$, giving the probability of choosing a in state s . This gives us all transition probabilities, and we can write expected discounted returns recursively

$$Q_{\pi}(a, s) = (\mathcal{B}_{\pi} Q_{\pi})(a, s) = \sum_{s', r} p(s', r | s, a) \left(r + \gamma \cdot \sum_{a'} \pi(a' | s') Q_{\pi}(a', s') \right).$$

- ▶ Suppose alternatively that future actions are chosen optimally. We can again write expected discounted returns recursively

$$Q_{*}(a, s) = (\mathcal{B}_{*} Q_{*})(a, s) = \sum_{s', r} p(s', r | s, a) \left(r + \gamma \cdot \max_{a'} Q_{*}(a', s') \right).$$

Existence and uniqueness of solutions

- ▶ The operators \mathcal{B}_π and \mathcal{B}_* define contraction mappings on the space of action value functions. (As long as $\gamma < 1$.)
- ▶ By Banach's fixed point theorem, unique solutions exist.
- ▶ The difference between assuming a given policy π , or considering optimal actions $\operatorname{argmax}_a Q(a, s)$, is the dividing line between **on policy** and **off policy** methods in reinforcement learning.

Expected updates - dynamic programming

- ▶ Suppose we know the transition probabilities $p(s', r | s, a)$.
- ▶ Then we can in principle just solve for the action value functions and optimal policies.
- ▶ This is typically assumed in macro, IO models.
- ▶ Solutions: Dynamic programming.
Iteratively replace
 - ▶ $Q_\pi(a, s)$ by $(\mathcal{B}_\pi Q_\pi)(a, s)$, or
 - ▶ $Q_*(a, s)$ by $(\mathcal{B}_* Q_*)(a, s)$.
- ▶ Decision problems with terminal states: Can solve in one sweep of backward induction.
- ▶ Otherwise: Value function iteration until convergence – replace repeatedly.

Sample updates

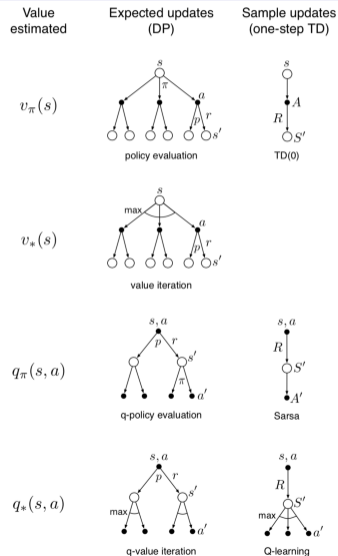
- ▶ In practically interesting settings, agents (human or AI) typically don't know the transition probabilities $p(s', r|s, a)$.
- ▶ This is where reinforcement learning comes in.
Learning from observation while acting in an environment.
- ▶ Observations come in the form of tuples

$$\langle s, a, r, s' \rangle.$$

- ▶ Based on a sequence of such tuples, we want to learn Q_π or Q_* .

Classification of one-step reinforcement learning methods

1. Known vs. unknown transition probabilities.
 2. Value function vs. action value function.
 3. On policy vs. off policy.
- ▶ We will discuss Sarsa and Q-learning.
 - ▶ Both: unknown transition probabilities and action value functions.
 - ▶ First: “tabular” methods, where we keep track off all possible values (a, s) .
 - ▶ Then: “approximate” methods for richer spaces of (a, s) , e.g., deep neural nets.



Sarsa

- ▶ On policy learning of action value functions.
- ▶ Recall Bellman equation

$$Q_{\pi}(a, s) = \sum_{s', r} p(s', r | s, a) \left(r + \gamma \cdot \sum_{a'} \pi(a' | s') Q_{\pi}(a', s') \right).$$

- ▶ Sarsa estimates expectations by sample averages.
- ▶ After each observation $\langle s, a, r, s', a' \rangle$, replace the estimated $Q_{\pi}(a, s)$ by

$$Q_{\pi}(a, s) + \alpha \cdot (r + \gamma \cdot Q_{\pi}(a', s') - Q_{\pi}(a, s)).$$

- ▶ α is the step size / speed of learning / rate of forgetting.

Sarsa as stochastic (semi-)gradient descent

- ▶ Think of $Q_\pi(a, s)$ as prediction for $Y = r + \gamma \cdot Q_\pi(a', s')$.

- ▶ Quadratic prediction error:

$$(Y - Q_\pi(a, s))^2.$$

- ▶ Gradient for minimization of prediction error for current observation w.r.t. $Q_\pi(a, s)$:

$$-(Y - Q_\pi(a, s)).$$

- ▶ Sarsa is thus a variant of stochastic gradient descent.
- ▶ Variant: Data are generated by actions where π is chosen as the optimal policy for the current estimate of Q_π .
- ▶ Reasonable method, but convergence guarantees are tricky.

Q-learning

- ▶ Similar to Sarsa, but **off policy**.
- ▶ Like Sarsa, estimate expectation over $p(s', r|s, a)$ by sample averages.
- ▶ Rather than the observed next action a' consider the optimal action **$\operatorname{argmax}_{a'} Q_*(a', s')$** .
- ▶ After each observation $\langle s, a, r, s' \rangle$, replace the estimated $Q_*(a, s)$ by

$$Q_*(a, s) + \alpha \cdot \left(r + \gamma \cdot \max_{a'} Q_*(a', s') - Q_*(a, s) \right).$$

Approximation

- ▶ So far, we have implicitly assumed that there is a small, finite number of states s and actions a , so that we can store $Q(a, s)$ in tabular form.
- ▶ In practically interesting cases, this is not feasible.
- ▶ Instead assume parametric functional form for $Q(a, s; \theta)$.
- ▶ In particular: Deep neural nets!
- ▶ Assume differentiability with gradient $\nabla_{\theta} Q(a, s; \theta)$.

Stochastic gradient descent

- ▶ Denote our prediction target for an observation $\langle s, a, r, s', a' \rangle$ by

$$Y = r + \gamma \cdot Q_{\pi}(a', s'; \theta).$$

- ▶ As before, for the on-policy case, we have the quadratic prediction error

$$(Y - Q_{\pi}(a, s; \theta))^2.$$

- ▶ Semi-gradient: Only take derivative for the $Q_{\pi}(a, s; \theta)$ part, but not for the prediction target Y :

$$-(Y - Q_{\pi}(a, s; \theta)) \cdot \nabla_{\theta} Q(a, s; \theta).$$

- ▶ Stochastic gradient descent updating step: Replace θ by

$$\theta + \alpha \cdot (Y - Q_{\pi}(a, s; \theta)) \cdot \nabla_{\theta} Q(a, s; \theta).$$

Off policy variant

- ▶ As before, can replace a' by the estimated optimal action.
- ▶ Change the prediction target to

$$Y = r + \gamma \cdot \max_{a'} Q_*(a', s'; \theta).$$

- ▶ Updating step as before, replacing θ by

$$\theta + \alpha \cdot (Y - Q_*(a, s; \theta)) \cdot \nabla_{\theta} Q_*(a, s; \theta).$$

Multi-step updates

- ▶ All methods discussed thus far are one-step methods.
- ▶ After observing $\langle s, a, r, s', a' \rangle$, only $Q(a, s)$ is targeted for an update.
- ▶ But we could pass that new information further back in time, since

$$Q(a, s) = E \left[\sum_{t'=t}^{t+k} \gamma^{t'-t} R_{t'} + \gamma^{k+1} Q(A_{t+k+1}, S_{t+k+1}) \mid A_t = a, S_t = s \right].$$

- ▶ One possibility: at time $t + k + 1$, update θ using the prediction target

$$Y_t^k = \sum_{t'=t}^{t+k-1} \gamma^{t'-t} R_{t'} + \gamma^k Q_\pi(A_{t+k}, S_{t+k}).$$

- ▶ k -step Sarsa: At time $t + k$, replace θ by

$$\theta + \alpha \cdot (Y_t^k - Q_\pi(A_t, S_t; \theta)) \cdot \nabla_\theta Q_\pi(A_t, S_t; \theta).$$

$TD(\lambda)$ algorithm

- ▶ Multi-step updates can result in faster learning.
- ▶ We can also weight the prediction targets for different numbers of steps, e.g. using weights λ^k :

$$Y_t^k = \sum_{t'=t}^{t+k} \gamma^{t'-t} R_{t'} + \gamma^{k+1} Q_\pi(A_{t+k+1}, S_{t+k+1}),$$

$$Y_t^\lambda = (1 - \lambda) \sum_{k=1}^{\infty} \lambda^k \cdot Y_t^k.$$

- ▶ But don't we have to wait forever before we can make an update based on Y_t^λ ?
- ▶ Note quite, since we can do the updating piece-wise!
- ▶ This idea leads to the so-called $TD(\lambda)$ algorithm.

Eligibility traces

- ▶ For $TD(\lambda)$, we proceed as for one-step Sarsa, using the prediction target

$$Y_t = R_t + \gamma \cdot Q_\pi(A_{t+1}, S_{t+1}; \theta).$$

- ▶ But we replace the gradient $\nabla_\theta Q_\pi(A_t, S_t; \theta)$ by a weighted average of past gradients, the so-called eligibility trace: Let $Z_0 = 0$ and

$$Z_t = \gamma\lambda \cdot Z_{t-1} + \nabla_\theta Q_\pi(A_t, S_t; \theta).$$

- ▶ Updating step: At time t replace θ by

$$\theta + \alpha \cdot (Y_t - Q_\pi(A_t, S_t; \theta)) \cdot Z_t.$$

- ▶ This exactly implements the updating by Y_t^λ in the long run.
- ▶ This is one of the most popular and practically successful reinforcement learning algorithms.

References

- ▶ *Sutton, R. S. and Barto, A. G. (2018). Reinforcement learning: An introduction. MIT press.*
- ▶ *François-Lavet, V., Henderson, P., Islam, R., Bellemare, M. G., and Pineau, J. (2018). An introduction to deep reinforcement learning. Foundations and Trends® in Machine Learning, 11(3-4):219–354.*