Reinforcement Learning Algorithms

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In This Lecture

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- **How do we solve an MDP online?**

$\Rightarrow$ *RL Algorithms*

In This Lecture

- Dynamic programming algorithms require an *explicit* definition of
  - transition probabilities $p(\cdot|x, a)$
  - reward function $r(x, a)$

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  - transition probabilities $p(\cdot|x, a)$
  - reward function $r(x, a)$
- This knowledge is often *unavailable* (i.e., wind intensity, human-computer-interaction).
- *Can we relax this assumption?*

In This Lecture

- *Learning with generative model.* A *black-box simulator f* of the environment is available. Given (x, a),

$$f(x, a) = \{y, r\} \text{ with } y \sim p(\cdot|x, a), r = r(x, a).$$

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- *Episodic learning.* Multiple *trajectories* can be repeatedly generated from the same state x and terminating when a *reset* condition is achieved:

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- *Online learning.* At each time t the agent is at state x_t, it takes action a_t, it observes a transition to state x_{t+1}, and it receives a reward r_t. We *assume* that $x_{t+1} \sim p(\cdot|x_t, a_t)$ and $r_t = r(x_t, a_t)$ (i.e., MDP assumption).

Outline

Concentration Inequalities

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$$\lim_{n\to\infty} \mathbb{E}[f(X_n)] = \mathbb{E}[f(X)].$$

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Remark: $X_n \xrightarrow{a.s.} X \implies X_n \xrightarrow{P} X \implies X_n \xrightarrow{D} X.$

Concentration Inequalities

Proposition (Markov Inequality)

Let X be a *positive* random variable. Then for any $a > 0$,

$$\mathbb{P}(X \geq a) \leq \frac{\mathbb{E}X}{a}.$$

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Proof.

$$\mathbb{P}(X \geq a) = \mathbb{E}[\mathbb{I}\{X \geq a\}] = \mathbb{E}[\mathbb{I}\{X/a \geq 1\}] \leq \mathbb{E}[X/a]$$

■

Concentration Inequalities

Proposition (Hoeffding Inequality)

Let X be a *centered* random variable bounded in $[a, b]$. Then for any $s \in \mathbb{R}$,

$$\mathbb{E}[e^{sX}] \leq e^{s^2(b-a)^2/8}.$$

Concentration Inequalities

Proof.

From *convexity* of the exponential function, for any $a \leq x \leq b$,

$$e^{sx} \leq \frac{x-a}{b-a} e^{sb} + \frac{b-x}{b-a} e^{sa}.$$

Let $p = -a/(b-a)$ then (recall that $\mathbb{E}[X] = 0$)

$$\begin{aligned} \mathbb{E}[e^{sx}] &\leq \frac{b}{b-a} e^{sa} - \frac{a}{b-a} e^{sb} \\ &= (1 - p + p e^{s(b-a)}) e^{-ps(b-a)} = e^{\phi(u)} \end{aligned}$$

with $u = s(b-a)$ and $\phi(u) = -pu + \log(1 - p + pe^{u})$ whose derivative is

$$\phi'(u) = -p + \frac{p}{p + (1-p)e^{-u}},$$

and $\phi(0) = \phi'(0) = 0$ and $\phi''(u) = \frac{p(1-p)e^{-u}}{(p+(1-p)e^{-u})^2} \leq 1/4$.

Thus from *Taylor's theorem*, the exists a $\theta \in [0, u]$ such that

$$\phi(\theta) = \phi(0) + \theta\phi'(0) + \frac{u^2}{2}\phi''(\theta) \leq \frac{u^2}{8} = \frac{s^2(b-a)^2}{8}.$$

Concentration Inequalities

Proposition (Chernoff-Hoeffding Inequality)

Let $X_i \in [a_i, b_i]$ be n *independent* r.v. with mean $\mu_i = \mathbb{E}X_i$. Then

$$\mathbb{P}\Big[\Big|\sum_{i=1}^{n}(X_i - \mu_i)\Big| \geq \epsilon\Big] \leq 2\exp\Big(-\frac{2\epsilon^2}{\sum_{i=1}^{n}(b_i - a_i)^2}\Big).$$

Concentration Inequalities

Proof.

$$
\begin{aligned}
\mathbb{P}\Big(\sum_{i=1}^{n} X_i - \mu_i \geq \epsilon\Big) &= \mathbb{P}(e^{s\sum_{i=1}^{n} X_i - \mu_i} \geq e^{s\epsilon}) \\
&\leq e^{-s\epsilon}\mathbb{E}[e^{s\sum_{i=1}^{n} X_i - \mu_i}], \quad \text{Markov inequality} \\
&= e^{-s\epsilon}\prod_{i=1}^{n}\mathbb{E}[e^{s(X_i-\mu_i)}], \quad \text{independent random variables} \\
&\leq e^{-s\epsilon}\prod_{i=1}^{n} e^{s^2(b_i-a_i)^2/8}, \quad \text{Hoeffding inequality} \\
&= e^{-s\epsilon+s^2\sum_{i=1}^{n}(b_i-a_i)^2/8}
\end{aligned}
$$

If we choose $s = 4\epsilon/\sum_{i=1}^{n}(b_i - a_i)^2$, the result follows.
Similar arguments hold for $\mathbb{P}\big(\sum_{i=1}^{n} X_i - \mu_i \leq -\epsilon\big)$.

Monte-Carlo Approximation of a Mean

Definition

Let X be a random variable with mean $\mu = \mathbb{E}[X]$ and variance $\sigma^2 = \mathbb{V}[X]$ and $x_n \sim X$ be n i.i.d. realizations of X. The Monte-Carlo approximation of the mean (i.e., the empirical mean) built on n i.i.d. realizations is defined as

$$\mu_n = \frac{1}{n} \sum_{i=1}^{n} x_i .$$

Monte-Carlo Approximation of a Mean

- *Unbiased estimator*: Then $\mathbb{E}[\mu_n] = \mu$ (and $\mathbb{V}[\mu_n] = \frac{\mathbb{V}[X]}{n}$)

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- *Central limit theorem (CLT)*: $\sqrt{n}(\mu_n - \mu) \xrightarrow{D} \mathcal{N}(0, \mathbb{V}[X])$.

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- *Finite sample guarantee*:

$$\mathbb{P}\Bigg[\underbrace{\Big|\frac{1}{n}\sum_{t=1}^{n} X_t - \mathbb{E}[X_1]\Big|}_{deviation} > \underbrace{\epsilon}_{accuracy}\Bigg] \leq \underbrace{2\exp\Big(-\frac{2n\epsilon^2}{(b-a)^2}\Big)}_{confidence}$$

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$$\mathbb{P}\left[\left|\frac{1}{n}\sum_{t=1}^{n} X_t - \mathbb{E}[X_1]\right| > (b-a)\sqrt{\frac{\log 2/\delta}{2n}}\right] \leq \delta$$

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$$\mathbb{P}\left[\left|\frac{1}{n}\sum_{t=1}^{n} X_t - \mathbb{E}[X_1]\right| > \epsilon\right] \leq \delta$$

if $n \geq \frac{(b-a)^2 \log 2/\delta}{2\epsilon^2}$.

Exercise

Simulate n Bernoulli of probability p and verify the correctness and the accuracy of the C-H bounds.

Stochastic Approximation of a Mean

Definition

Let X a random variable bounded in $[0,1]$ with mean $\mu = \mathbb{E}[X]$ and $x_n \sim X$ be n i.i.d. realizations of X. The stochastic approximation of the mean is,

$$\mu_n = (1-\eta_n)\mu_{n-1} + \eta_n x_n$$

with $\mu_1 = x_1$ and where (η_n) is a sequence of learning steps.

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Remark: When $\eta_n = \frac{1}{n}$ this is the *recursive* definition of empirical mean.

Stochastic Approximation of a Mean

Proposition (Borel-Cantelli)

Let $(E_n)_{n\geq 1}$ be a *sequence* of events such that $\sum_{n\geq 1}\mathbb{P}(E_n) < \infty$, then the probability of the *intersection of an infinite subset* is 0. More formally,

$$\mathbb{P}\Big(\limsup_{n\to\infty} E_n\Big) = \mathbb{P}\Big(\bigcap_{n=1}^{\infty}\bigcup_{k=n}^{\infty} E_k\Big) = 0.$$

Stochastic Approximation of a Mean

Proposition

If for any n, $\eta_n \geq 0$ and are such that

$$\sum_{n \geq 0} \eta_n = \infty; \qquad \sum_{n \geq 0} \eta_n^2 < \infty,$$

then

$$\mu_n \xrightarrow{a.s.} \mu,$$

and we say that μ_n is a *consistent* estimator.

Stochastic Approximation of a Mean

Proof. We focus on the case $\eta_n = n^{-\alpha}$.
In order to satisfy the two conditions we need $1/2 < \alpha \leq 1$. In fact, for instance

$$\alpha = 2 \Rightarrow \sum_{n \geq 0} \frac{1}{n^2} = \frac{\pi^2}{6} < \infty \quad \text{(see the Basel problem)}$$

$$\alpha = 1/2 \Rightarrow \sum_{n \geq 0} \left(\frac{1}{\sqrt{n}}\right)^2 = \sum_{n \geq 0} \frac{1}{n} = \infty \quad \text{(harmonic series).}$$

Stochastic Approximation of a Mean

Proof (cont'd).

Case $\alpha = 1$

Let $(\epsilon_k)_k$ a sequence such that $\epsilon_k \to 0$, *almost sure* convergence corresponds to

$$\mathbb{P}\Big(\lim_{n\to\infty} \mu_n = \mu\Big) = \mathbb{P}(\forall k, \exists n_k, \forall n \geq n_k, \big|\mu_n - \mu\big| \leq \epsilon_k) = 1.$$

From Chernoff-Hoeffding inequality for any ***fixed*** n

$$\mathbb{P}\big(\big|\mu_n - \mu\big| \geq \epsilon\big) \leq 2e^{-2n\epsilon^2}. \quad (1)$$

Let $\{E_n\}$ be a sequence of events $E_n = \{\big|\mu_n - \mu\big| \geq \epsilon\}$. From C-H

$$\sum_{n\geq 1} \mathbb{P}(E_n) < \infty,$$

and from Borel-Cantelli lemma we obtain that with probability 1 there exist only a *finite* number of n values such that $\big|\mu_n - \mu\big| \geq \epsilon$.

Stochastic Approximation of a Mean

Proof (cont'd).

Case $\alpha = 1$

Then for any ϵ_k there exist only a finite number of instants were $\big|\mu_n - \mu\big| \geq \epsilon_k$, which corresponds to have $\exists n_k$ such that

$$\mathbb{P}(\forall n \geq n_k, \big|\mu_n - \mu\big| \leq \epsilon_k) = 1$$

Repeating for all ϵ_k in the sequence leads to the statement.

Stochastic Approximation of a Mean

Proof (cont'd).
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Repeating for all ϵ_k in the sequence leads to the statement.

Remark: when $\alpha = 1$, μ_n is the Monte-Carlo estimate and this corresponds to the strong law of large numbers. A more precise and accurate proof is here:
http://terrytao.wordpress.com/2008/06/18/the-strong-law-of-large-numbers/

Stochastic Approximation of a Mean

Proof (cont'd).
Case $1/2 < \alpha < 1$. The stochastic approximation μ_n is

$$\mu_1 = x_1$$
$$\mu_2 = (1-\eta_2)\mu_1 + \eta_2 x_2 = (1-\eta_2)x_1 + \eta_2 x_2$$
$$\mu_3 = (1-\eta_3)\mu_2 + \eta_3 x_3 = (1-\eta_2)(1-\eta_3)x_1 + \eta_2(1-\eta_3)x_2 + \eta_3 x_3$$
$$\ldots$$
$$\mu_n = \sum_{i=1}^{n} \lambda_i x_i,$$

with $\lambda_i = \eta_i \prod_{j=i+1}^{n}(1-\eta_j)$ such that $\sum_{i=1}^{n} \lambda_i = 1$.
By C-H inequality

$$\mathbb{P}\Big(\Big|\sum_{i=1}^{n} \lambda_i x_i - \sum_{i=1}^{n} \lambda_i \mathbb{E}[x_i]\Big| \geq \epsilon\Big) = \mathbb{P}\big(\big|\mu_n - \mu\big| \geq \epsilon\big) \leq e^{-\frac{2\epsilon^2}{\sum_{i=1}^{n} \lambda_i^2}}.$$

Stochastic Approximation of a Mean

Proof (cont'd).

Case $1/2 < \alpha < 1$**.**

From the definition of λ_i

$$\log \lambda_i = \log \eta_i + \sum_{j=i+1}^{n} \log(1-\eta_j) \leq \log \eta_i - \sum_{j=i+1}^{n} \eta_j$$

since $\log(1-x) < -x$. Thus $\lambda_i \leq \eta_i e^{-\sum_{j=i+1}^{n} \eta_j}$ and for any $1 \leq m \leq n$,

$$\begin{aligned}\sum_{i=1}^{n} \lambda_i^2 &\leq \sum_{i=1}^{n} \eta_i^2 e^{-2\sum_{j=i+1}^{n} \eta_j} \\ &\overset{(a)}{\leq} \sum_{i=1}^{m} e^{-2\sum_{j=i+1}^{n} \eta_j} + \sum_{i=m+1}^{n} \eta_i^2 \\ &\overset{(b)}{\leq} m e^{-2(n-m)\eta_n} + (n-m)\eta_m^2 \\ &\overset{(c)}{=} m e^{-2(n-m)n^{-\alpha}} + (n-m)m^{-2\alpha}.\end{aligned}$$

Stochastic Approximation of a Mean

Proof (cont'd).

Case $1/2 < \alpha < 1$.

Let $m = n^{\beta}$ with $\beta = (1 + \alpha/2)/2$ (i.e. $1 - 2\alpha\beta = 1/2 - \alpha$):

$$\sum_{i=1}^{n} \lambda_i^2 \leq n e^{-2(1-n^{-1/4})n^{1-\alpha}} + n^{1/2-\alpha} \leq 2n^{1/2-\alpha}$$

for *n big enough*, which leads to

$$\mathbb{P}\big(|\mu_n - \mu| \geq \epsilon\big) \leq e^{-\frac{\epsilon^2}{n^{1/2-\alpha}}}.$$

From this point we follow the same steps as for $\alpha = 1$ (application of the Borel-Cantelli lemma) and obtain the convergence result for μ_n.

Stochastic Approximation of a Fixed Point

Definition

Let $\mathcal{T} : \mathbb{R}^N \to \mathbb{R}^N$ be a contraction in some norm $||\cdot||$ with fixed point V. For any function W and state x, a noisy observation $\widehat{\mathcal{T}}W(x) = \mathcal{T}W(x) + b(x)$ is available.
For any $x \in X = \{1, \ldots, N\}$, we defined the stochastic approximation

$$
\begin{aligned}
V_{n+1}(x) &= (1 - \eta_n(x))V_n(x) + \eta_n(x)(\hat{\mathcal{T}}V_n(x)) \\
&= (1 - \eta_n(x))V_n(x) + \eta_n(x)(\mathcal{T}V_n(x) + b_n),
\end{aligned}
$$

where η_n is a sequence of learning steps.

Stochastic Approximation of a Fixed Point

Proposition

Let $\mathcal{F}_n = \{V_0, \ldots, V_n, b_0, \ldots, b_{n-1}, \eta_0, \ldots, \eta_n\}$ the filtration of the algorithm and assume that

$$\mathbb{E}[b_n(x)|\mathcal{F}_n] = 0 \quad \text{and} \quad \mathbb{E}[b_n^2(x)|\mathcal{F}_n] \leq c(1 + ||V_n||^2)$$

for a constant c.
If the learning rates $\eta_n(x)$ are positive and satisfy the stochastic approximation conditions

$$\sum_{n \geq 0} \eta_n = \infty, \qquad \sum_{n \geq 0} \eta_n^2 < \infty,$$

then for any $x \in X$

$$V_n(x) \xrightarrow{a.s.} V(x).$$

Stochastic Approximation of a Zero

Robbins-Monro (1951) algorithm. Given a noisy function f, find x^* such that $f(x^*) = 0$.
In each x_n, observe $y_n = f(x_n) + b_n$ (with b_n a zero-mean independent noise) and compute

$$x_{n+1} = x_n - \eta_n y_n.$$

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$$x_{n+1} = x_n - \eta_n y_n.$$

If f is an *increasing* function, then under the same assumptions on the learning step

$$x_n \xrightarrow{a.s.} x^*$$

Stochastic Approximation of a Minimum

Kiefer-Wolfowitz (1952) algorithm. Given a function f and noisy observations of its gradient, find $x^* = \arg\min f(x)$.
In each x_n, observe $g_n = \nabla f(x_n) + b_n$ (with b_n a zero-mean independent noise) and compute

$$x_{n+1} = x_n - \eta_n g_n.$$

Stochastic Approximation of a Minimum

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$$x_{n+1} = x_n - \eta_n g_n.$$

If the Hessian $\nabla^2 f$ is *positive*, then under the same assumptions on the learning step

$$x_n \xrightarrow{a.s.} x^*$$

Remark: this is often referred to as the **stochastic gradient** algorithm.

Outline

Policy Evaluation

We consider the the problem of evaluating the performance of a policy π in the *undiscounted infinite horizon* setting.

Policy Evaluation

We consider the the problem of evaluating the performance of a policy π in the *undiscounted infinite horizon* setting.
For any (*proper*) policy π the value function is

$$V^\pi(x) = \mathbb{E}\Big[\sum_{t=0}^{T-1} r^\pi(x_t) \,|\, x_0 = x; \pi \Big],$$

where $r^\pi(x_t) = r(x_t, \pi(x_t))$ and T is the *random* time when the *terminal state* is achieved.

Question

How can we estimate the value function if an episodic interaction with the environment is possible?

$\Rightarrow$ *Monte-Carlo approximation of a mean!*

The Monte-Carlo Algorithm

Algorithm Definition (Monte-Carlo)

Let $(x_0^i = x, x_1^i, \dots, x_{T_i}^i = 0)_{i \leq n}$ be a set of n *independent trajectories* starting from x and terminating after T_i steps. For any $t < T_i$, we denote by

$$\widehat{R}^i(x_t^i) = \big[r^\pi(x_t^i) + r^\pi(x_{t+1}^i) + \cdots + r^\pi(x_{T_i-1}^i)\big]$$

the *return* of the i-th trajectory at state x_t^i.

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the *return* of the i-th trajectory at state x_t^i.
Then the *Monte-Carlo* estimator of $V^\pi(x)$ is

$$V_n(x) = \frac{1}{n}\sum_{i=1}^{n}\big[r^\pi(x_0^i) + r^\pi(x_1^i) + \dots + r^\pi(x_{T_i-1}^i)\big] = \frac{1}{n}\sum_{i=1}^{n}\widehat{R}^i(x)$$

The Monte-Carlo Algorithm

All the returns are unbiased estimators of $V^\pi(x)$ since

$$\mathbb{E}[\widehat{R}^i(x)] = \mathbb{E}\big[r^\pi(x_t^i) + r^\pi(x_{t+1}^i) + \cdots + r^\pi(x_{T_i-1}^i)\big] = V^\pi(x)$$

then

$$V_n(x) \xrightarrow{a.s.} V^\pi(x).$$

First-visit and Every-Visit Monte-Carlo

Remark: any trajectory $(x_0, x_1, x_2, \ldots, x_T)$ contains also the sub-trajectory $(x_t, x_{t+1}, \ldots, x_T)$ whose return $\widehat{R}(x_t) = r^\pi(x_t) + \cdots + r^\pi(x_{T-1})$ could be used to build an estimator of $V^\pi(x_t)$.

First-visit and Every-Visit Monte-Carlo

Remark: any trajectory $(x_0, x_1, x_2, \dots, x_T)$ contains also the sub-trajectory $(x_t, x_{t+1}, \dots, x_T)$ whose return $\widehat{R}(x_t) = r^\pi(x_t) + \cdots + r^\pi(x_{T-1})$ could be used to build an estimator of $V^\pi(x_t)$.

- *First-visit MC.* For each state x we only consider the sub-trajectory when x is first achieved. *Unbiased estimator*, *only one sample per trajectory*.

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- *First-visit MC.* For each state x we only consider the sub-trajectory when x is first achieved. *Unbiased estimator*, *only one sample per trajectory*.
- *Every-visit MC.* Given a trajectory $(x_0 = x, x_1, x_2, \ldots, x_T)$, we list all the m sub-trajectories starting from x up to x_T and we average them all to obtain an estimate. *More than one sample per trajectory*, *biased estimator*.

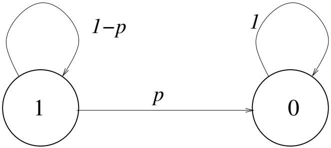
Question

More samples or no bias?

$\Rightarrow$ *Sometimes a biased estimator is preferable if consistent!*

First-visit vs Every-Visit Monte-Carlo

Example: 2-state Markov Chain



The reward is 1 while in state 1 (while is 0 in the terminal state). All trajectories are $(x_0 = 1, x_1 = 1, \ldots, x_T = 0)$. By Bellman equations

$$V(1) = 1 + (1-p)V(1) + 0 \cdot p = \frac{1}{p},$$

since $V(0) = 0$.

First-visit vs Every-Visit Monte-Carlo

We measure the mean squared error (MSE) of $\widehat{V}$ w.r.t. V

$$\mathbb{E}\big[(\widehat{V} - V)^2\big] = \underbrace{\big(\mathbb{E}[\widehat{V}] - V\big)^2}_{\color{red}{Bias^2}} + \underbrace{\mathbb{E}\big[\big(\widehat{V} - \mathbb{E}[\widehat{V}]\big)^2\big]}_{\color{red}{Variance}}$$

First-visit vs Every-Visit Monte-Carlo

First-visit Monte-Carlo. All the trajectories start from state 1, then the return over one single trajectory is exactly T, i.e., $\widehat{V} = T$.
The time-to-end T is a *geometric* r.v. with expectation

$$\mathbb{E}[\widehat{V}] = \mathbb{E}[T] = \frac{1}{p} = V^{\pi}(1) \Rightarrow \textit{unbiased estimator.}$$

Thus the MSE of $\widehat{V}$ coincides with the variance of T, which is

$$\mathbb{E}\Big[\big(T - \frac{1}{p}\big)^2\Big] = \frac{1}{p^2} - \frac{1}{p}.$$

First-visit vs Every-Visit Monte-Carlo

Every-visit Monte-Carlo. Given one trajectory, we can construct $T-1$ sub-trajectories (number of times state 1 is visited), where the t-th trajectory has a return $T-t$.

$$\widehat{V} = \frac{1}{T}\sum_{t=0}^{T-1}(T-t) = \frac{1}{T}\sum_{t'=1}^{T} t' = \frac{T+1}{2}.$$

The corresponding expectation is

$$\mathbb{E}\Big[\frac{T+1}{2}\Big] = \frac{1+p}{2p} \neq V^{\pi}(1) \Rightarrow \textit{ biased estimator}.$$

First-visit vs Every-Visit Monte-Carlo

Let's consider *n independent trajectories*, each of length T_i.
Total number of samples $\sum_{i=1}^n T_i$ and the estimator $\widehat{V}_n$ is

$$\begin{aligned}\widehat{V}_n &= \frac{\sum_{i=1}^n \sum_{t=0}^{T_i-1}(T_i - t)}{\sum_{i=1}^n T_i} = \frac{\sum_{i=1}^n T_i(T_i+1)}{2\sum_{i=1}^n T_i} \\ &= \frac{1/n\sum_{i=1}^n T_i(T_i+1)}{2/n\sum_{i=1}^n T_i} \\ &\xrightarrow{a.s.} \frac{\mathbb{E}[T^2]+\mathbb{E}[T]}{2\mathbb{E}[T]} = \frac{1}{p} = V^\pi(1) \Rightarrow \textit{ consistent estimator}.\end{aligned}$$

The MSE of the estimator

$$\mathbb{E}\Big[\big(\frac{T+1}{2} - \frac{1}{p}\big)^2\Big] = \frac{1}{2p^2} - \frac{3}{4p} + \frac{1}{4} \leq \frac{1}{p^2} - \frac{1}{p}.$$

First-visit vs Every-Visit Monte-Carlo

In general

- *Every-visit MC*: *biased* but *consistent* estimator.
- *First-visit MC*: *unbiased* estimator with potentially *bigger MSE*.

First-visit vs Every-Visit Monte-Carlo

In general

- *Every-visit MC*: *biased* but *consistent* estimator.
- *First-visit MC*: *unbiased* estimator with potentially *bigger MSE*.

Remark: when the state space is large the probability of visiting multiple times the same state is low, then the performance of the two methods tends to be the same.

Outline

Policy Evaluation

We consider the the problem of evaluating the performance of a policy π in the *undiscounted infinite horizon* setting.

Policy Evaluation

We consider the the problem of evaluating the performance of a policy π in the *undiscounted infinite horizon* setting.
For any (*proper*) policy π the value function is

$$V^\pi(x) = \mathbb{E}\Big[\sum_{t=0}^{T-1} r^\pi(x_t) \,|\, x_0 = x; \pi\Big],$$

where $r^\pi(x_t) = r(x_t, \pi(x_t))$ and T is the *random* time when the *terminal state* is achieved.

Question

MC requires all the trajectories to be available at once, can we update the estimator online?

$\Rightarrow$ *TD(1)!*

The TD(1) Algorithm

Algorithm Definition (TD(1))

Let $(x_0^n = x, x_1^n, \ldots, x_{T_n}^n)$ be the n-th trajectory and $\widehat{R}^n$ be the corresponding return. For all x_t with $t \leq T - 1$ observed along the trajectory, we update the value function estimate as

$$V_n(x_t^n) = (1 - \eta_n(x_t^n)) V_{n-1}(x_t^n) + \eta_n(x_t^n) \widehat{R}^n(x_t^n).$$

The TD(1) Algorithm

Each sample is an unbiased estimator of the value function

$$\mathbb{E}\big[r^\pi(x_t) + r^\pi(x_{t+1}) + \cdots + r^\pi(x_{T-1})|x_t\big] = V^\pi(x_t),$$

then the convergence result of stochastic approximation of a mean applies and if *all the states* are visited in an *infinite number of trajectories* and for all $x \in X$

$$\sum_n \eta_n(x) = \infty, \qquad \sum_n \eta_n(x)^2 < \infty,$$

then

$$V_n(x) \stackrel{a.s.}{\rightarrow} V^\pi(x)$$

Outline

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For any (*proper*) policy π the value function is

$$V^\pi(x) = r(x, \pi(x)) + \sum_{y \in X} p(y|x, \pi(x) V^\pi(x) = \mathcal{T}^\pi V^\pi(x).$$

$\Rightarrow$ use *stochastic approximation for fixed point*.

The TD(0) Algorithm

- *Noisy* observation of the operator $\mathcal{T}^\pi$:

$$\widehat{\mathcal{T}}^\pi V(x_t) = r^\pi(x_t) + V(x_{t+1}), \text{ with } x_t = x,$$

- *Unbiased* estimator of $\mathcal{T}^\pi V(x)$ since

$$\begin{aligned}\mathbb{E}[\widehat{\mathcal{T}}^\pi V(x_t)|x_t = x] &= \mathbb{E}[r^\pi(x_t) + V(x_{t+1})|x_t = x] \\ &= r(x,\pi(x)) + \sum_y p(y|x,\pi(x))V(y) = \mathcal{T}^\pi V(x).\end{aligned}$$

- *Bounded* noise since

$$|\widehat{\mathcal{T}}^\pi V(x) - \mathcal{T}^\pi V(x)| \leq ||V||_\infty.$$

The TD(0) Algorithm

Algorithm Definition (TD(0))

Let $(x_0^n = x, x_1^n, \dots, x_{T_n}^n)$ be the n-th trajectory, and $\{\widehat{\mathcal{T}}^\pi V_{n-1}(x_t^n)\}_t$ the noisy observation of the operator $\mathcal{T}^\pi$. For all x_t^n with $t \leq T_n - 1$, we update the value function estimate as

$$\begin{aligned} V_n(x_t^n) &= (1 - \eta_n(x_t^n))V_{n-1}(x_t^n) + \eta_n(x_t^n)\widehat{\mathcal{T}}^\pi V_{n-1}(x_t^n) \\ &= (1 - \eta_n(x_t^n))V_{n-1}(x_t^n) + \eta_n(x_t^n)\big(r^\pi(x_t^n) + V_{n-1}(x_{t+1}^n)\big). \end{aligned}$$

The TD(0) Algorithm

if *all the states* are visited in an *infinite number of trajectories* and for all $x \in X$

$$\sum_n \eta_n(x) = \infty, \qquad \sum_n \eta_n(x)^2 < \infty,$$

then

$$V_n(x) \stackrel{a.s.}{\rightarrow} V^\pi(x)$$

The TD(0) Algorithm

Definition

At iteration n, given the estimator V_{n-1} and a transition from state x_t to state x_{t+1} we define the temporal difference

$$d_t = \big(r^\pi(x_t) + V_{n-1}(x_{t+1})\big) - V_{n-1}(x_t).$$

The TD(0) Algorithm

Definition

At iteration n, given the estimator V_{n-1} and a transition from state x_t to state x_{t+1} we define the temporal difference

$$d_t = \big(r^\pi(x_t) + V_{n-1}(x_{t+1})\big) - V_{n-1}(x_t).$$

Remark: Recalling the definition of Bellman equation for state value function, the temporal difference d_t^n provides a measure of *coherence* of the estimator V_{n-1} w.r.t. the transition $x_t \rightarrow x_{t+1}$.

The TD(0) Algorithm

Algorithm Definition (TD(0))

Let $(x_0^n = x, x_1^n, \ldots, x_{T_n}^n)$ be the n-th trajectory, and $\{d_t^n\}_t$ the temporal differences. For all x_t^n with $t \leq T^n - 1$, we update the value function estimate as

$$V_n(x_t^n) = V_{n-1}(x_t^n) + \eta_n(x_t^n) d_t^n.$$

Outline

Comparison between TD(1) and TD(0)

- TD(1)

$$V_n(x_t) = V_{n-1}(x_t) + \eta_n(x_t)[d_t^n + d_{t+1}^n + \cdots + d_{T-1}^n].$$

- TD(0)

$$V_n(x_t^n) = V_{n-1}(x_t^n) + \eta_n(x_t^n) d_t^n.$$

Question

Is it possible to take the best of both?

$\Rightarrow$ *TD(λ)!*

The $\mathcal{T}_\lambda^\pi$ Bellman operator

Definition

Given $\lambda < 1$, then the Bellman operator $\mathcal{T}_\lambda^\pi$ is

$$\mathcal{T}_\lambda^\pi = (1-\lambda) \sum_{m \geq 0} \lambda^m (\mathcal{T}^\pi)^{m+1}.$$

The $\mathcal{T}^\pi_\lambda$ Bellman operator

Definition

Given $\lambda < 1$, then the Bellman operator $\mathcal{T}^\pi_\lambda$ is

$$\mathcal{T}^\pi_\lambda = (1-\lambda)\sum_{m\geq 0}\lambda^m(\mathcal{T}^\pi)^{m+1}.$$

Remark: convex combination of the m-step Bellman operators $(\mathcal{T}^\pi)^m$ weighted by a sequences of coefficients defined as a function of a λ.

The TD(λ) Algorithm

Proposition

If π is a *proper* policy and $\mathcal{T}^\pi$ is a *β-contraction* in $L_{\mu,\infty}$-norm, then $\mathcal{T}^\pi_\lambda$ is a *contraction* of factor

$$\frac{(1-\lambda)\beta}{1-\beta\lambda} \in [0,\beta].$$

The TD(λ) Algorithm

Proof. Let P^π be the transition matrix of the Markov chain then

$$\begin{aligned}
\mathcal{T}^\pi_\lambda V &= (1-\lambda)\Big[\sum_{m\geq 0}\lambda^m \sum_{i=0}^{m}(P^\pi)^i\Big] r^\pi + (1-\lambda)\sum_{m\geq 0}\lambda^m (P^\pi)^{m+1} V \\
&= \Big[\sum_{m\geq 0}\lambda^m (P^\pi)^m\Big] r^\pi + (1-\lambda)\sum_{m\geq 0}\lambda^m (P^\pi)^{m+1} V \\
&= (I-\lambda P^\pi)^{-1} r^\pi + (1-\lambda)\sum_{m\geq 0}\lambda^m (P^\pi)^{m+1} V.
\end{aligned}$$

Since $\mathcal{T}^\pi$ is a β-contraction then $||(P^\pi)^m V||_\mu \leq \beta^m ||V||_\mu$. Thus

$$\Big\|(1-\lambda)\sum_{m\geq 0}\lambda^m (P^\pi)^{m+1} V\Big\|_\mu \leq (1-\lambda)\sum_{m\geq 0}\lambda^m ||(P^\pi)^{m+1} V||_\mu \leq \frac{(1-\lambda)\beta}{1-\beta\lambda}||V||_\mu,$$

which implies that $\mathcal{T}^\pi_\lambda$ is a contraction in $L_{\mu,\infty}$ as well.

The TD(λ) Algorithm

Algorithm Definition (Sutton, 1988)

Let $(x_0^n = x, x_1^n, \dots, x_{T_n}^n)$ be the n-th trajectory, and $\{d_t^n\}_t$ the temporal differences. For all x_t with $t \leq T-1$, we update the value function estimate as

$$V_n(x_t^n) = V_{n-1}(x_t^n) + \eta_n(x_t^n) \sum_{s=t}^{T_n-1} \lambda^{s-t} d_s^n.$$

The TD(λ) Algorithm

We need to show that the temporal difference samples are *unbiased* estimators.
For any $s \geq t$

$$\mathbb{E}[d_s|x_t = x] = \mathbb{E}\Big[r^\pi(x_s) + V_{n-1}(x_{s+1}) - V_{n-1}(x_s)\Big|x_t = x\Big]$$

$$= \mathbb{E}\Big[\sum_{i=t}^{s} r^\pi(x_i) + V_{n-1}(x_{s+1})\Big|x_t = x\Big] - \mathbb{E}\Big[\sum_{i=k}^{s-1} r^\pi(x_i) + V_{n-1}(x_s)\Big|x_t = x\Big]$$

$$= (\mathcal{T}^\pi)^{s-t+1} V_{n-1}(x) - (\mathcal{T}^\pi)^{s-t} V_{n-1}(x).$$

The TD(λ) Algorithm

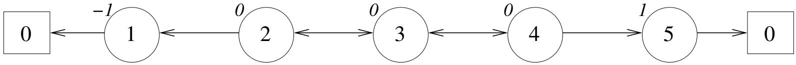
$$
\begin{aligned}
\mathbb{E}\Big[\sum_{s=t}^{T-1}\lambda^{s-t}d_s|x_t=x\Big] &= \sum_{s=t}^{T-1}\lambda^{s-t}\Big[(\mathcal{T}^\pi)^{s-t+1}V_{n-1}(x)-(\mathcal{T}^\pi)^{s-t}V_{n-1}(x)\Big]\\
&=\sum_{m\geq 0}\lambda^m\Big[(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)-(\mathcal{T}^\pi)^{m}V_{n-1}(x)\Big]\\
&=\sum_{m\geq 0}\lambda^m(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)-\Big[V_{n-1}(x)+\sum_{m>0}\lambda^m(\mathcal{T}^\pi)^{m}V_{n-1}(x)\Big]\\
&=\sum_{m\geq 0}\lambda^m(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)-\Big[V_{n-1}(x)+\lambda\sum_{m>0}\lambda^{m-1}(\mathcal{T}^\pi)^{m}V_{n-1}(x)\Big]\\
&=\sum_{m\geq 0}\lambda^m(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)-\Big[V_{n-1}(x)+\lambda\sum_{m\geq 0}\lambda^{m}(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)\Big]\\
&=(1-\lambda)\sum_{m\geq 0}\lambda^m(\mathcal{T}^\pi)^{m+1}V_{n-1}(x)-V_{n-1}(x)=\mathcal{T}^\pi_\lambda V_{n-1}(x)-V_{n-1}(x).
\end{aligned}
$$

Then

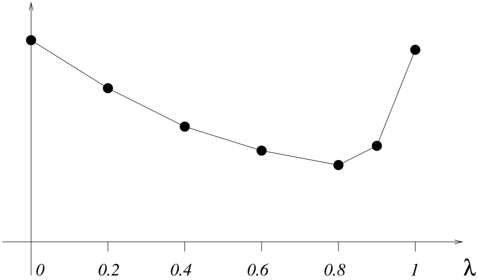
$$V_n \xrightarrow{a.s.} V^\pi$$

Sensitivity to λ

Linear chain example



The MSE of V_n w.r.t. V^π after $n = 100$ trajectories:



Sensitivity to λ

- $\lambda < 1$: *smaller variance* w.r.t. $\lambda = 1$ (MC/TD(1)).
- $\lambda > 0$: *faster propagation* of rewards w.r.t. $\lambda = 0$.

Question

Is it possible to update the V estimate at each step?

$\Rightarrow$ *Online implementation!*

Online Implementation of TD algorithm: Eligibility Traces

Remark: since the update occurs at each step, now we drop the dependency on n.

- *Eligibility* traces $z \in \mathbb{R}^N$
- For every transition $x_t \to x_{t+1}$

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  1. Compute the temporal difference

$$d_t = r^\pi(x_t) + V(x_{t+1}) - V(x_t)$$

  2. Update the eligibility traces

$$z(x) = \begin{cases} \lambda z(x) & \text{if } x \neq x_t \\ 1 + \lambda z(x) & \text{if } x = x_t \\ 0 & \text{if } x_t = 0 \text{ (reset the traces)} \end{cases}$$

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- For every transition $x_t \to x_{t+1}$
  1. Compute the temporal difference
  $$d_t = r^\pi(x_t) + V(x_{t+1}) - V(x_t)$$
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  3. For all state $x \in X$
  $$V(x) \leftarrow V(x) + \eta_t(x) z(x) d_t.$$

TD(λ) in discounted reward MDPs

The Bellman operator $\mathcal{T}_\lambda^\pi$ is defined as

$$\begin{aligned}
\mathcal{T}_\lambda^\pi V(x_0) &= (1-\lambda)\mathbb{E}\Big[\sum_{t\geq 0}\lambda^t\Big(\sum_{i=0}^{t}\gamma^i r^\pi(x_i) + \gamma^{t+1}V(x_{t+1})\Big)\Big] \\
&= \mathbb{E}\Big[(1-\lambda)\sum_{i\geq 0}\gamma^i r^\pi(x_i)\sum_{t\geq i}\lambda^t + \sum_{t\geq 0}\gamma^{t+1}V(x_{t+1})(\lambda^t - \lambda^{t+1})\Big] \\
&= \mathbb{E}\Big[\sum_{i\geq 0}\lambda^i\big(\gamma^i r^\pi(x_i) + \gamma^{i+1}V(x_{i+1}) - \gamma^i V(x_i)\big)\Big] + V_n(x_0) \\
&= \mathbb{E}\Big[\sum_{i\geq 0}(\gamma\lambda)^i d_i\Big] + V(x_0),
\end{aligned}$$

with the temporal difference $d_i = r^\pi(x_i) + \gamma V(x_{i+1}) - V(x_i)$.
The corresponding TD(λ) algorithm becomes

$$V_{n+1}(x_t) = V_n(x_t) + \eta_n(x_t)\sum_{s\geq t}(\gamma\lambda)^{s-t}d_t.$$

Outline

Question

How do we compute the optimal policy online?

$\Rightarrow$ *Q-learning!*

Q-learning

Remark: if we use TD algorithms to compute $V_n \approx V^{\pi_k}$, then we could compute the *greedy policy* as

$$\pi_{k+1}(x) \in \arg\max_a \Big[r(x,a) + \sum_y p(y|x,a) V_n(y) \Big].$$

Q-learning

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Problem: the transition p is unknown!!

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$$\pi_{k+1}(x) \in \arg\max_a \Big[r(x,a) + \sum_y p(y|x,a) V_n(y) \Big].$$

Problem: the transition p is unknown!!
Solution: use Q-functions and compute

$$\pi_{k+1}(x) \in \arg\max_a Q_n(x,a)$$

Q-learning

Algorithm Definition (Watkins, 1989)

We build a sequence $\{Q_n\}$ in such a way that for every observed transition (x, a, y, r)

$$Q_{n+1}(x, a) = (1 - \eta_n(x, a))Q_n(x, a) + \eta_n(x, a)\Big[r + \max_{b \in A} Q_n(y, b)\Big].$$

Q-learning

Proposition

[Watkins et Dayan, 1992] Let assume that all the policies π are proper and that all the state-action pairs are visited *infinitely often*. If

$$\sum_{n \geq 0} \eta_n(x,a) = \infty, \quad \sum_{n \geq 0} \eta_n^2(x,a) < \infty$$

then for any $x \in X$, $a \in A$,

$$Q_n(x,a) \xrightarrow{a.s.} Q^*(x,a).$$

Q-learning

Proof.

Optimal Bellman operator $\mathcal{T}$

$$\mathcal{T}W(x,a) = r(x,a) + \sum_y p(y|x,a) \max_{b \in A} W(y,b),$$

with unique fixed point Q^*. Since all the policies are proper $\mathcal{T}$ is a contraction in the $L_{\mu,\infty}$-norm.

Q-learning can be written as

$$Q_{n+1}(x,a) = (1 - \eta_n(x,a))Q_n(x,a) + \eta_n[\mathcal{T}Q_n(x,a) + b_n(x,a)],$$

where $b_n(x,a)$ is a zero-mean random variable such that

$$\mathbb{E}[b_n^2(x,a)] \leq c(1 + \max_{y,b} Q_n^2(y,b))$$

The statement follows from convergence of stochastic approximation of fixed point operators.

Bibliography I

Reinforcement Learning

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