CS 747, Autumn 2022: Lecture 14

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Autumn 2022

Reinforcement Learning

1. Prediction with Monte Carlo methods

2. On-line implementation

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- Here are the first 5 episodes.

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Episode 2: $s_2, 2, s_3, 1, s_3, 1, s_3, 2, s_2, 1, s_\top$.
Episode 3: $s_1, 2, s_2, 2, s_1, 5, s_1, 1, s_\top$.
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- What is your estimate of V^π (call it $\hat{V}^5$)?
  Monte Carlo (MC) methods estimate based on sample averages.

Defining Relevant Quantities

- For $s \in S$, $i \geq 1, j \geq 1$, let
  - $\mathbf{1}(s, i, j)$ be 1 if s is visited at least j times on episode i (else $\mathbf{1}(s, i, j) = 0$), and
  - $G(s, i, j)$ be the discounted long-term reward starting from the j-th visit of s on episode i,
  - Taking $G(s, i, j) = 0$ if $\mathbf{1}(s, i, j) = 0$; also $0/0 = 0$.

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- $\mathbf{1}(s_1, 1, 1) = 1$, $G(s_1, 1, 1) = 5 + \gamma \cdot 2 + \gamma^2 \cdot 3 + \gamma^3 \cdot 1 = 11$.
- $\mathbf{1}(s_1, 1, 3) = 0$.
- $\mathbf{1}(s_2, 5, 1) = 1$, $G(s_2, 5, 1) = 3 + \gamma \cdot 3 + \gamma^2 \cdot 1 = 7$.
- $\mathbf{1}(s_2, 5, 2) = 1$, $G(s_2, 5, 2) = 3 + \gamma \cdot 1 = 4$.

Some Standard Estimates of $V^{\pi}(s)$

Episode 1: $s_1, 5, s_1, 2, s_2, 3, s_2, 1, s_\top$.
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Let $\hat{V}^N$ denote estimate after N *episodes*.

First-visit MC: Average the G's of every first occurrence of s in an episode.

$$\hat{V}^N_{\text{First-visit}}(s) = \frac{\sum_{i=1}^{N} G(s, i, 1)}{\sum_{i=1}^{N} \mathbf{1}(s, i, 1)}.$$

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$$\text{Hence } \hat{V}^5_{\text{First-visit}}(s_2) = \frac{4 + 7 + 8 + 7}{4} = 6.5.$$

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$$\text{Hence } \hat{V}^5_{\text{Every-visit}}(s_2) = \frac{(4+1)+(7+1)+8+(7+4)}{7} \approx 4.57.$$

Some Not-so-standard Estimates of $V^{\pi}(s)$

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Second-visit MC: Average the G's of every second occurrence of s in an episode.

$$\hat{V}^N_{\text{Second-visit}}(s) = \frac{\sum_{i=1}^{N} G(s, i, 2)}{\sum_{i=1}^{N} \mathbf{1}(s, i, 2)}.$$

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Last-visit MC: Average the G's of every last occurrence of s in episode i (assume *times*(s, i) visits).

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$$\text{Hence } \hat{V}^5_{\text{Last-visit}}(s_2) = \frac{1 + 1 + 8 + 4}{4} = 3.5.$$

Question

- Recall that we generate N episodes.
- Which claims below are true?

$$\lim_{N \to \infty} \hat{V}^N_{\text{First-visit}} = V^\pi.$$
$$\lim_{N \to \infty} \hat{V}^N_{\text{Every-visit}} = V^\pi.$$
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- Assume episodic task with S = $\{s_1, s_2, s_3\}$; following π.
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- $\hat{V}^1 = G(s_2, 1, 1) = 4$.
- $\hat{V}^2 = \frac{1}{2}\{G(s_2, 1, 1) + G(s_2, 2, 1)\} = 5.5$.

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- $\hat{V}^1 = G(s_2, 1, 1) = 4$.
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- $\hat{V}^3 = \frac{1}{3}\{G(s_2, 1, 1) + G(s_2, 2, 1) + G(s_2, 3, 1)\} \approx 6.33$.
- In general, for $t \geq 1$:

$$\hat{V}^t(s) = \frac{1}{t}\sum_{i=1}^{t} G(s, i, 1).$$

An On-line Implementation

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- We already know that $\lim_{t\to\infty} \hat{V}^t(s) = V^\pi(s)$.
- Will we get convergence to $V^\pi(s)$ for other choices for α_t, $\hat{V}^0(s)$?

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- $(\alpha_t)_{t \geq 1}$ is the "learning rate" or "step size".
- Must be large enough, as well as small enough!
- No need to store all previous episodes; t and $\hat{V}^t$ suffice.

Reinforcement Learning

1. Prediction with Monte Carlo methods

2. On-line implementation

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Next class: Bootstrapping.