Reinforcement Learning Exercise 8 - Solution

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1 n-step TD compared to planing

- a) Improve TD(0) with n-step TD The difference of the n-step temporal difference to the Dyna-Q planning, is that only the reward of the path which was taken can be accounted for. Therefore, unlike the image it is not possible after one episode to have a policy for all tiles, but instead only for the taken path. In contrast, Dyna-Q planning revisits arbitrary a virtual tile, which allows a richer interpretation.
- b) Recursive lambda-return The λ -return is defined as

$$G_t^{\lambda} = (1 - \lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_{t:t+n}$$

$$\tag{1}$$

with

$$G_{t:t+n} = R_{t+1} + \gamma R_{t+2} + \dots + \gamma^{n-1} R_{t+n} + \gamma^n V(S_{t+n})$$
 (2)

To define it recursively, we want to reframe the problem involving G_t^{λ}

$$G_{t+1}^{\lambda} = (1 - \lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_{t+1:t+n+1}$$
(3)

Here we can note that

$$G_{t+1:t+n+1} = R_{t+2} + \gamma R_{t+3} + \ldots + \gamma^{n-1} R_{t+n+1} + \gamma^n V(S_{t+n+1})$$
 (4)

We can rewrite $G_{t+1:t+n+1}$ as

$$G_{t+1:t+n+1} = \frac{1}{\gamma} \left(G_{t:t+n} - R_{t+1} + \gamma^n R_{t+n+1} - \gamma^n V(S_{t+n}) \right) + \gamma^n V(S_{t+n+1})$$
 (5)

Then we can rewrite the λ -return as

$$\begin{split} G_{t+1}^{\lambda} &= (1-\lambda) \sum_{n=1}^{\infty} \lambda^{n-1} \left[\frac{1}{\gamma} \left(G_{t:t+n} - R_{t+1} + \gamma^n R_{t+n+1} - \gamma^n V(S_{t+n}) \right) + \gamma^n V(S_{t+n+1}) \right] \\ G_{t+1}^{\lambda} &= \frac{1}{\gamma} (1-\lambda) \sum_{n=1}^{\infty} \lambda^{n-1} G_{t:t+n} \\ &+ (1-\lambda) \sum_{n=1}^{\infty} \lambda^{n-1} \left[\frac{1}{\gamma} \left(-R_{t+1} + \gamma^n R_{t+n+1} - \gamma^n V(S_{t+n}) \right) + \gamma^n V(S_{t+n+1}) \right] \\ G_{t+1}^{\lambda} &= \frac{1}{\gamma} G_t^{\lambda} + (1-\lambda) \sum_{n=1}^{\infty} \lambda^{n-1} \left[-\frac{R_{t+1}}{\gamma} + \gamma^{n-1} R_{t+n+1} - \gamma^{n-1} V(S_{t+n}) + \gamma^n V(S_{t+n+1}) \right] \end{split}$$

Could be extended further, but this should be sufficient for today.