Terminal Estimation

willer

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In general cases:

$$Q(s,a) = \sum_{s' \neq \widetilde{s}} p(s'|s,a) V(s') + p(\widetilde{s} \mid s,a) V(\widetilde{s})$$

where \tilde{s} means terminal state so we can set:

$$\hat{Q}(s_t, a_t) = \sum_{s' \neq \widetilde{s}} p(s'|s, a) V(s')$$

$$f(s_t, a_t) = p(\widetilde{s}|s, a) V(\widetilde{s})$$

$$V(s_t) = \sum_{a} \pi(a_t|s_t) Q(s_t, a_t)$$

$$Q(s_t, a_t) = \hat{Q}(s_t, a_t) + f(s_t, a_t)$$

In Network, all output is random and doesn't equal zero. for some cases: if p(s'|s,a) = 0, f(s,a) should be zero always and if p(s'|s,a) = 1, $\hat{Q}(s,a)$ should be zero always, too.

so for all cases

$$\hat{Q}(s_t, a_t) = \alpha * \hat{Q}(s_t, a_t) + (1 - \alpha) * (R_{t+1} - \gamma Q(s_{t+1}, a_{t+1}))$$

$$f(s_t, a_t) = \beta * f(s_t, a_t) + (1 - \beta) * \tilde{R}_{t+1}$$

It has a shrinking effect in network and correct the former bias. And it works well in experiment. The terminal-estimation are more robust in choose of hyperparameters, especially in weight decay coefficient.

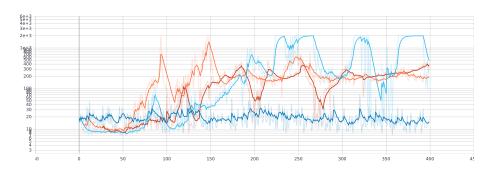


Figure 1: Performance at task CartPole-v0, All of these has the same hyperparameters except weight decay. Bottom deep blue line is baseline with weight decay 1e-3, light blue line is TE AC with weight decay 1e-2, orange line with weight decay 1e-3 and red line with weight decay 1e-4. It shows that TE AC are more rubust with hyperparameters