

EXPLOITING STRUCTURE AND UNCERTAINTY OF BELLMAN UPDATES IN MARKOV DECISION PROCESSES

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MILANO 1863

PROBLEM

- Learning is difficult in highly stochastic environments
- Uncertainty in action-value function estimates propagates
- Some algorithms face this problem focusing on the bias of the estimate
- Despite empirical evidence, there is **no proof** that focusing on the bias is the solution

CONTRIBUTIONS

- 1. Split the action-value function estimate **two components**:
 - The expected reward $\widetilde{R}(x, u)$
 - The expected next state value function Q(x, u)
- 2. Use different learning rates for the two components
- 3. We provide **empirical results** showing the effectiveness of our approach

RQ-LEARNING ALGORITHM

IDEA

Improve accuracy of the estimate exploiting:

Structure of the Bellman update

Uncertainty of the estimation

APPROACH

Split the action-value function in two components

Compute the update as follows

$$\widetilde{R}(x,u) = \mathbb{E}\left[r(x,u,x')\right] \qquad \widetilde{Q}(x,u) = \mathbb{E}\left[\max_{x' \sim \mathcal{P}(x'|x,u')} Q^*(x',u')\right] \qquad \widetilde{R}_{t+1}(x,u) \leftarrow \widetilde{R}_t(x,u) + \alpha_t(R(x,u,x') - \widetilde{R}_t(x,u))$$

$$Q^*(x,u) = \widetilde{R}(x,u) + \gamma \widetilde{Q}(x,u) \qquad \widetilde{Q}_{t+1}(x,u) \leftarrow \widetilde{Q}_t(x,u) + \beta_t(\max_{x' \sim \mathcal{P}(x',u')} Q^*(x,u))$$

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$$\widetilde{Q}_{t+1}(x,u) \leftarrow \widetilde{Q}_t(x,u) + \beta_t(\max_{u'} Q_t(x',u') - \widetilde{Q}_t(x,u))$$

Q-Learning: $\beta_t = \alpha_t$ RQ-Learning: $\beta_t \neq \alpha_t$ RQ_{δ}-Learning: $\beta_t = \alpha_t \delta_t$

Exploit the variance of estimation to set the learning rate

1. Estimate the variance of the estimator Q, using the sample variance of the target:

$$\operatorname{Var}\left[\widetilde{Q}\right] \approx S_t^2 \omega_t$$

$$\operatorname{Var}\left[\widetilde{Q}\right] \approx S_t^2 \omega_t \qquad \qquad \omega_{t+1} = (1 - \beta_t)^2 \omega_t + \beta_t^2$$

2. Compute the learning rate according to the precision of the estimate:

Noisy Gridworld

 $\max Q(s, a)$

10000

• Inversely proportional β :

-0.5

10000

$$\beta_t = \frac{\sigma_e^2(t)}{\sigma_e^2(t) + \eta}$$

Thirtheath interpretations in

5000

5000

steps

steps

10000

10000

20

• Directly proportional δ :

The charge appropriate and anded

5000

— RQDelta

--- RQWin

5000

steps

steps

RQBeta

— RQAlphaBeta

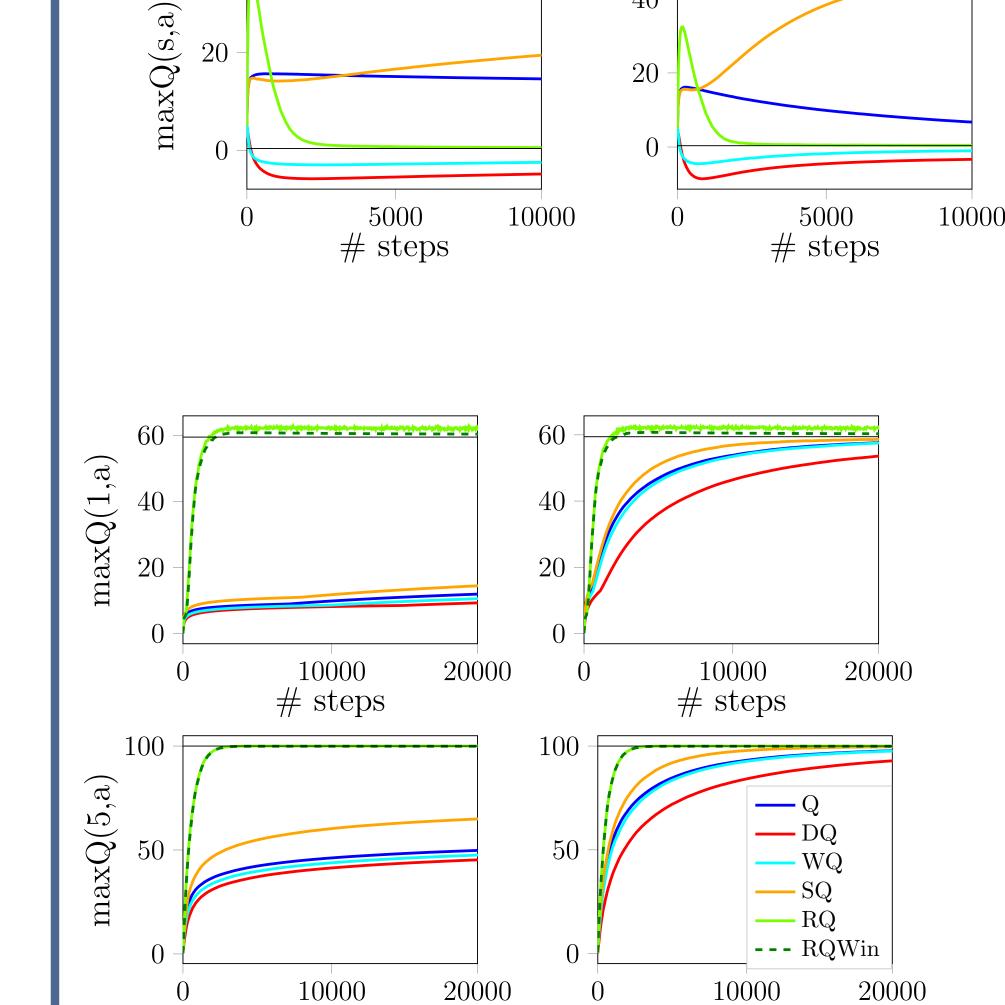
--- RQWinAlpha

10000

10000

EMPIRICAL RESULTS

5000



steps

steps

