

Stochastic Approximation

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Convergence with pseudo gradient

$$v_{t+1} = v_t + \alpha_t g_t$$

Assumption: There exists a $f : \mathbb{R}^n \rightarrow \mathbb{R}$ such that

1. $f(v) \geq 0$
2. ∇f is Lipschitz continuous
3. $\exists c > 0$ such that

$$c \|\nabla f(v_t)\|^2 \leq -\nabla f(v_t)^\top \mathbb{E}[g_t | \mathcal{F}_t]$$

4. $\exists K_1 > 0, K_2 > 0$ such that

$$\mathbb{E}[\|g_t\|^2 | \mathcal{F}_t] \leq K_1 + K_2 \|\nabla f(v_t)\|^2$$

5. $\sum \alpha_t = \infty, \sum \alpha_t^2 < \infty$

Convergence with pseudo gradient

Results:

1. $\{f(v_t)\}$ converges
2. $\lim_{t \rightarrow \infty} \nabla f(v_t) = 0$
3. Every limit point of $\{v_t\}$ is a stationary point of f

Convergence with pseudo contraction

$$v_{t+1}(i) = (1 - \alpha_t(i))v_t(i) + \alpha_t(i)((\mathcal{T}_t v_t)(i) + \epsilon_t(i) + \xi_t(i))$$

Assumption:

1. $\sum_t \alpha_t(i) = \infty, \sum_t \alpha_t^2(i) < \infty$
2. $\mathbb{E}[\epsilon_t(i)|\mathcal{F}_t] = 0, \mathbb{E}[\epsilon_t^2(i)|\mathcal{F}_t] \leq A + B\|v_t\|^2$
3. $\exists v_*, \gamma > 0$ such that

$$\|\mathcal{T}_t v_t - v_*\|_\infty \leq \gamma \|v_t - v_*\|_\infty$$

4. $\exists \{\theta_t\}$ satisfying $\lim_{t \rightarrow \infty} \theta_t = 0$ such that w.p. 1

$$|\xi(i)| \leq \theta_t (\|v_t\| + 1)$$

Results:

$$\lim_{t \rightarrow \infty} v_t = v_* \quad \text{w.p. 1}$$

Convergence of TD(0)

$$V_{t+1}(s) = \begin{cases} V_t(s) + \alpha_t(s) (R_{t+1} + \gamma V_t(S_{t+1}) - V_t(s)), & s = S_t, \\ 0, & s \neq S_t \end{cases}$$

$$V_{t+1}(s) = (1 - \alpha_t(s)) V_t(s) + \alpha_t(s) ((\mathcal{T}_\pi V_t)(s) + R_{t+1} + \gamma V_t(S_{t+1}) - (\mathcal{T}_\pi V_t)(s))$$

Convergence of Q-learning

$$\delta_t \doteq R_{t+1} + \gamma \max_{a'} Q_t(S_{t+1}, a') - Q_t(S_t, A_t)$$

$$Q_{t+1}(s, a) = \begin{cases} Q_t(s, a) + \alpha_t(s, a)\delta_t, & (s, a) = (S_t, A_t), \\ Q_t(s, a), & (s, a) \neq (S_t, A_t) \end{cases}$$

References

- Neuro-Dynamic Programming by Dimitri Bertsekas and John Tsitsiklis