1 Symbol

1.1 Constant

$$\alpha, \beta, \gamma, \delta, \epsilon(\varepsilon), \zeta, \eta, \theta(\vartheta), \iota, \kappa, \lambda, \mu, \nu, \xi, o, \pi, \rho(\varrho), \sigma, \tau, \upsilon, \pi(\varphi), \chi, \psi, \omega$$

$$\mathbb{1}, \mathcal{N}, \mathcal{R}$$

1.2 Scalar

$$a, b, c, d, e, f, g, h, i, j, k, l, m, n, o, p, q, r, s, t, u, v, w, x, y, z$$

1.3 Vector

$$\mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}, \mathbf{e}, \mathbf{f}, \mathbf{g}, \mathbf{h}, \mathbf{i}, \mathbf{j}, \mathbf{k}, \mathbf{l}, \mathbf{m}, \mathbf{n}, \mathbf{o}, \mathbf{p}, \mathbf{q}, \mathbf{r}, \mathbf{s}, \mathbf{t}, \mathbf{u}, \mathbf{v}, \mathbf{w}, \mathbf{x}, \mathbf{y}, \mathbf{z}$$

1.4 Matrix

$$A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, V, W, X, Y, Z$$

1.5 Tensor

1.6 Set

$$\mathcal{A}, \mathcal{B}, \mathcal{C}, \mathcal{D}, \mathcal{E}, \mathcal{F}, \mathcal{G}, \mathcal{H}, \mathcal{I}, \mathcal{J}, \mathcal{K}, \mathcal{L}, \mathcal{M}, \mathcal{N}, \mathcal{O}, \mathcal{P}, \mathcal{Q}, \mathcal{R}, \mathcal{S}, \mathcal{T}, \mathcal{U}, \mathcal{V}, \mathcal{W}, \mathcal{X}, \mathcal{Y}, \mathcal{Z}$$

- 2 Statistics
- 2.1 Probability

$$x \sim \mathcal{X}$$
 (sample)
 $x \doteq \mathcal{X}$ (define)
 $x \leftarrow \mathcal{X}$ (generate)
 $x \leftrightarrow \mathcal{X}$ (shuffle)

$$p(\alpha), p(a), p(\mathbf{a}), p(\mathbf{A}), p(\mathbf{A}), p(\mathbf{A})$$

$$p(\alpha \mid \beta), p(a \mid b), p(\mathbf{a} \mid \mathbf{b}), p(\mathbf{A} \mid \mathbf{B}), p(\mathbf{A} \mid \mathbf{B}), p(\mathbf{A} \mid \mathbf{B})$$

3 Indexing

$$\underset{a \in \mathcal{A}}{\operatorname{argmax}} \ p(a)$$
$$\underset{x \in \mathcal{X}}{\operatorname{argmin}} \ p(x \mid y)$$

4 Distribution

$$\sigma(x)$$

$$\frac{\exp(p(x))}{\sum_{x'\in\mathcal{X}}\exp(p(x'))}$$

5 Neural Networks

5.1 Activation

$$\max(\mathbf{0},\mathbf{x})$$

 $tanh(\mathbf{x})$

$$\{0,1\}$$

$$\{a,\dots,z\}$$

$$\mathbf{x} \oplus \mathbf{y}$$
 (26.85016pt)

 $\mathbf{x} \ominus \mathbf{y}$
 (26.85016pt)

 $\mathbf{x} \odot \mathbf{y}$
 (26.85016pt)

 $\mathbf{x} \oslash \mathbf{y}$
 (26.85016pt)

$$x \overline{*} y$$
 (1)

 $\mathbf{A}^{\!\top}$

 $\mathbf{A}^{\text{-}1}$

 $\mathbf{A}^{\text{-}\!\top}$

$$\mathbb{1}\left[x\right]$$

$$\mathbf{i}_{t} = \sigma(\mathbf{W}_{i} \cdot \mathbf{x}_{t} + \mathbf{b}_{i})$$

$$\mathbf{f}_{t} = \sigma(\mathbf{W}_{f} \cdot \mathbf{x}_{t} + \mathbf{b}_{f})$$

$$\mathbf{o}_{t} = \sigma(\mathbf{W}_{o} \cdot \mathbf{x}_{t} + \mathbf{b}_{o})$$

$$\mathbf{g}_{t} = \tanh(\mathbf{W}_{g} \cdot \mathbf{x}_{t} + \mathbf{b}_{g})$$

$$\mathbf{c}_{t} = \mathbf{i}_{t} \odot \mathbf{f}_{t}$$

$$-\log(p(y_{t} \mid \mathbf{h}_{t-1}, y_{t-1}; \theta))$$

$$\epsilon \sim \mathcal{U}(a, b)$$

$$\epsilon \sim \mathcal{V}(0, (\sigma/t)^{2})$$

$$\epsilon \sim \mathcal{B}(1, p)$$

$$\epsilon \sim \mathcal{B}(1, p)$$

$$\max_{x \in \mathcal{X}} f(x)$$

$$\min_{x \in \mathcal{X}} f(x)$$

$$\sum_{x \in \mathcal{X}} f(x)$$

$$\frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} f(x)$$

$$\big\{f(x)\mid x\,\in\,\mathcal{X}\big\}$$

$$\frac{\partial f(x)}{\partial x}$$
$$\frac{\partial^2 f(x)}{\partial x^2}$$
$$\frac{\partial^2 f(x)}{\partial x \partial y}$$

$$\mathbb{E}_{s_t \sim E, a_i \sim \pi} \left[R(s_t, a_t) \right] \tag{2}$$

$$\mathbf{y} = \mathbf{W}_l^{[1,3]} * \mathbf{x} + \mathbf{b}_l \tag{3}$$

6 Reinforcement Learning

$$\nabla_{\mathbf{x}} f(\mathbf{x})$$
$$\nabla_{\mathbf{x}}^2 f(\mathbf{x})$$

$$\mathbb{E}\left[\frac{\partial f(x)}{\partial x}\right], y^*, y' \tag{4}$$

$$\tilde{\mathbf{y}}$$
 (5)

$$(x), [x], \{x\} \tag{6}$$

7 Decoding

$$\hat{y}_t = \underset{y' \in \mathcal{V}}{\operatorname{argmax}} \ p(\mathbf{h}_{t-1}, y_{t-1})$$
(7)

$$\hat{y}_t = \underset{y' \in \mathcal{V}}{\operatorname{argmax}} \ p(\mathbf{h}_{t-1}, \hat{y}_{t-1})$$
(8)

$$\hat{y}_t = \underset{y' \in \mathcal{V}}{\operatorname{argmax}} \ p(\mathbf{h}_{t-1} + \epsilon, y_{t-1})$$
(9)

$$\epsilon \sim \mathcal{N}(0,1)$$
 (10)

$$\hat{y}_t = \underset{y' \in \mathcal{V}}{\operatorname{argmax}} \ p(\mathbf{h}_{t-1} + \mathbf{a}, y_{t-1})$$
(11)

$$\mathbf{a} = \pi(\mathbf{a} \mid \mathbf{x}; \theta_{\pi}) \tag{actor}$$

$$S_t \mapsto G_t$$
 (Monte Carlo)

$$S_t \mapsto \mathbb{E}\left[R_{t+1} + \gamma \hat{v}(S_{t+1})\right]$$
 (Dynamic Programming)

$$S_t \mapsto R_{t+1} + \gamma \hat{v}(S_{t+1}) \tag{TD(0)}$$

$$S_t \mapsto R_{t+1} + \gamma R_{t+2} + \dots \gamma^n \hat{v}(S_{t+n})$$
 (n-step TD(0))

$$\overline{\mathrm{VE}}(\theta_v) \doteq \mathbb{E}_{s \sim \mu} \left[v_{\pi}(s) - \hat{v}_{\pi}(s; \theta_v) \right]$$
 (mean squared value error)

$$a'a'$$
 (12)

$$^{\epsilon}\mathcal{C}(\mathbf{x})$$
 (13)

$$\ell_{\pi} = \mathbb{E}_{\mathbf{s}_{t} \sim \mu(s), a_{t} \sim \pi} \left[-\left(r_{t} - \hat{v}(\mathbf{s}_{t}; \theta_{\hat{v}})\right) \cdot \log\left(\pi\left(a_{t} \mid \mathbf{s}_{t}; \theta_{\pi}\right)\right) \right]$$

$$\ell_{\hat{v}} = \mathbb{E}_{\mathbf{s}_{t} \sim \mu(s), a_{t} \sim \pi} \left[\left(r_{t} - \hat{v}(\mathbf{s}_{t}; \theta_{\hat{v}})\right)^{2} \right]$$

7.1 Q Learning

$$A \leftarrow \pi(\cdot \mid S) \tag{14}$$

$$S', R \leftarrow \mathcal{E}(A) \tag{15}$$

$$A' \leftarrow \underset{A' \in \mathcal{A}}{\operatorname{argmax}} \ \pi\Big(\cdot \mid S'\Big) \tag{16}$$

$$S \to R + \gamma Q(S', A')$$
 (17)

$$\ell = \mathbb{E}_{A \sim \pi(\cdot|S), S', R \leftarrow \mathcal{I}(A)},\tag{18}$$

7.2 Sarsa

$$A \leftarrow \pi(\cdot \mid S) \tag{19}$$

$$S', R \leftarrow \mathcal{E}(A)$$
 (20)

$$A' \leftarrow \pi\Big(\cdot \mid S'\Big) \tag{21}$$

$$S \to R + \gamma Q(S', A')$$
 (22)

7.3 $TD(\lambda)$

$$A \leftarrow \pi(\cdot \mid S)$$

$$S', R \leftarrow \mathcal{E}(A)$$

$$\mathbf{z} \leftarrow \gamma \lambda \mathbf{z} + \nabla_{\mathbf{w}} \hat{v}(S; \mathbf{w})$$

$$S \rightarrow R + \gamma Q(S; \mathbf{w})$$

7.4 Expected Sarsa

$$V(S_t) \leftarrow V(S_t) + \alpha \left[G_t - V(S_t) \right] \tag{23}$$

$$V(S_t) \leftarrow V(S_t) + \alpha \mathbb{E}_{\pi} \left[R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \right]$$
(24)

$$G_t = R_t + \gamma G_{t+1}$$

$$= R_t + \gamma R_{t+1} + \gamma^2 G_{t+2}$$

$$= \sum_{k=t}^{T} \gamma^{k-t} R_k$$

$$V(S_t) \leftarrow V(S_t) + \alpha \left[R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \right]$$
(25)

8 Exercise 6.1

$$V_{t+1}(S_t) \leftarrow V_t(S_t) + \sigma \left[R_{t+1} + \gamma V_t(S_{t+1}) - V_t(S_t) \right]$$
$$\delta_t \doteq R_{t+1} + \gamma V_t(S_{t+1}) - V_t(S_t)$$
$$\psi_{t+1} \doteq V_{t+1}(S_{t+1}) - V_t(S_{t+1})$$

$$G_{t} - V_{t}(S_{t}) = R_{t+1} + \gamma G_{t+1} - V_{t}(S_{t}) + \gamma V_{t+1}(S_{t+1}) - \gamma V_{t+1}(S_{t+1}) + \gamma V_{t}(S_{t+1}) - \gamma V_{t}(S_{t+1})$$

$$= \delta_{t} + \gamma \left(G_{t+1} - V_{t+1}(S_{t+1})\right) + \gamma \psi_{t+1}$$

$$= \delta_{t} + \gamma \delta_{t+1} + \gamma^{2} \left(G_{t+2} - V_{t+2}(S_{t+2})\right) + \gamma \psi_{t+1} + \gamma^{2} \psi_{t+2}$$

$$= \delta_{t} + \gamma \delta_{t+1} + \dots + \gamma^{T-t-1} \delta_{T-1} + \gamma^{T-t} \left(G_{T} - V_{T}(S_{T})\right) + \gamma \psi_{t+1} + \gamma^{2} \psi_{t+2} + \dots + \gamma^{T-t} \psi_{T}$$

$$= \delta_{t} + \gamma \delta_{t+1} + \dots + \gamma^{T-t-1} \delta_{T-1} + \gamma^{T-t} \left(0 - 0\right) + \gamma \psi_{t+1} + \gamma^{2} \psi_{t+2} + \dots + \gamma^{T-t} \psi_{T}$$

$$= \sum_{k=t}^{T-1} \gamma^{k-t} \delta_{k} + \sum_{k=t}^{T-1} \gamma^{k-t+1} \psi_{k+1}$$

$$= \sum_{k=t}^{T-1} \gamma^{k-t} \delta_{k} + \sum_{k=t}^{T-1} \gamma^{k-t+1} \left(V_{k+1}(S_{k+1}) - V_{k}(S_{k+1})\right)$$

$$= \sum_{k=t}^{T-1} \gamma^{k-t} \left(\delta_{k} + \gamma \left(V_{k+1}(S_{k+1}) - V_{k}(S_{k+1})\right)\right)$$

(26)

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