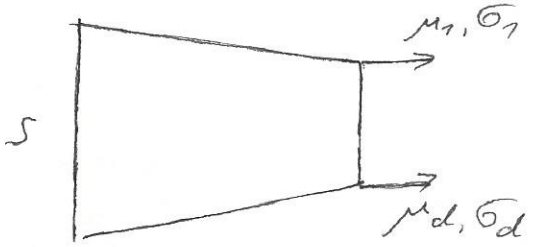
07.12.18 dl

Policy gradients methods, $\pi(a|s) = \pi(a|s,\theta)$, $a \in \mathbb{R}^d$



$$\pi(a|s,\theta) = \prod_{j=1}^{d} \mathcal{N}(a_j | \mu_j(s,\theta), \sigma_j^2(s,\theta))$$

$a \in \{1,\dots,k\}$, $\pi(a|s,\theta) = sm(output(s,\theta))$

$$F(\theta) = \mathbb{E}_{p(s)} \mathbb{E}_{\pi(a|s,\theta)} Q^{\pi_\theta}(s,a) \to \max_\theta$$

$$p(\tau|\theta) = p(s_0) \prod_{j=0}^{\infty} p(s_{j+1}|s_j,a_j)\pi(a_j|s_j,\theta)$$

$$\nabla_\theta F(\theta) = \nabla_\theta \mathbb{E}_{p(\tau|\theta)} f(\tau), \quad \text{log-der-trick}$$

$$\nabla_\theta F(\theta) = \nabla_\theta \int p(\tau|\theta) f(\tau) d\tau = \int \nabla_\theta p(\tau|\theta) f(\tau) d\tau =$$

$$= \int \nabla_\theta \log p(\tau|\theta) = \frac{1}{p(\tau|\theta)} \nabla_\theta p(\tau|\theta) \Big) = \int p(\tau|\theta) \nabla_\theta \log p(\tau|\theta) f(\tau) d\tau =$$

$$= \mathbb{E}_{p(\tau|\theta)} \nabla_\theta \log p(\tau|\theta) f(\tau)$$

? $\pi(s_t,\theta)$ ← gen. случ.

$$\nabla_\theta \log p(\tau|\theta) = \nabla_\theta \log \left(p(s_0) \prod_{t=0}^{\infty \to T} p(s_{t+1}|s_t,a_t)\pi(a_t|s_t,\theta) \right) =$$

$$= \sum_{t=0}^{\infty \to T} \nabla_\theta \log \pi(a_t|s_t,\theta)$$

REINFORCE

Алгоритм

Инициализировать θ

повторять

$\tau = \{s_0, a_0, s_1, a_1, \dots, s_T\}$

$$\nabla F(\theta) = \left(\sum_{t=0}^{T} \nabla_\theta \log \pi(a_t, s_t|\theta) \right) \left(\sum_{t=0}^{T} \gamma^t r(s_t,a_t) \right)$$

$\theta \leftarrow \theta + \alpha \nabla_\theta F(\theta)$

ограничая дисперсия из-за log-der-trick

$$\mathop{\mathbb{E}}_{p(\tau|\theta)} \nabla_\theta \log p(\tau|\theta) = \int p(\tau|\theta) \frac{1}{p(\tau|\theta)} \nabla_\theta p(\tau|\theta) d\tau = 0$$

Baseline B

RL

- Value-based
- Policy Gradient
- Actor-Critic

Actor: $\pi(a|s,\theta)$

Critic: $Q(s,a|w) \approx Q^\pi(s,a)$

$$F(\theta) = \mathop{\mathbb{E}}_{p(s)} \mathop{\mathbb{E}}_{\pi(a|s,\theta)} Q(s,a|w) \to \max_\theta$$

$$Q^\pi(s,a) = r(s,a) + \gamma \mathop{\mathbb{E}}_{p(s'|s,a)} \mathop{\mathbb{E}}_{\pi(a'|s')} Q^\pi(s',a')$$

$$G(w) = \frac{1}{|S||A|} \sum_{s,a} \left(Q(s,a|w) - \left[r(s,a) + \gamma \mathop{\mathbb{E}}_{p(s'|s,a)} \mathop{\mathbb{E}}_{\pi(a'|s',\theta)} Q(s',a'|w) \right] \right)^2 \to \min_w$$

Алгоритм QAC

Инициализация θ, w

повторять

сэмплировать (s,a,r,s') ← 1) memory replay 2) parallel learning

$a' \sim \pi(a'|s',\theta)$

$y = r(s,a) + \gamma Q(s',a'|w)$

$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi(a|s,\theta) Q(s,a|w)$

$w \leftarrow w - \beta \cdot 2 (Q(s,a|w) - y) \nabla_w Q(s,a|w)$

Baseline: $\nabla_\theta F(\theta) = \nabla_\theta \mathop{\mathbb{E}}_{p(s)} \mathop{\mathbb{E}}_{\pi(a|s,\theta)} (Q(a,s|w) - B(s))$

$$\nabla_\theta \mathop{\mathbb{E}}_{p(s)} \mathop{\mathbb{E}}_{\pi(a|s,\theta)} B(s) = \nabla_\theta \int p(s) \int \pi(a|s,\theta) B(s) da\, ds =$$

$$= \int p(s) B(s) \left(\nabla_\theta \underbrace{\int \pi(a|s,\theta) da}_{1} \right) ds = 0$$

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - \underbrace{V^{\pi}(s)}_{B(s)}$$

advantage

$$Q^{\pi}(s,a) = r(s,a) + \gamma \mathbb{E}_{p(s'|s,a)} V^{\pi}(s'')$$

Схема A2C

Инициализация Θ, w

повторять

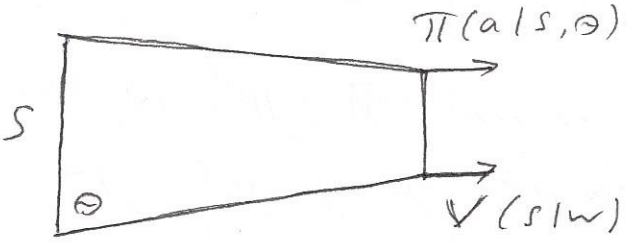
сэмплим (s, a, r, s')

$y = r(s,a) + \gamma V(s'|w)$

$A(s,a) = y - V(s|w)$

$\Theta \leftarrow \Theta - \alpha \nabla_{\Theta} \log \pi(a|s,\Theta) A(s,a)$

$w \leftarrow w - \beta 2 (V(s|w) - y) \nabla_w V(s|w)$



Процесс Дирихле

$$\begin{cases} f(x) \sim GP(0, k(\cdot,\cdot)) \\ y_i | f(x_i) \sim p(y|f) \end{cases} \Rightarrow p(f|y,x)$$

$$p(y_{test}|x_{test}) = \int p(y_{test}|f(x_{test})) \cdot p(f|y,x)\, df$$

непараметрическая модель, зависит от числа объектов

$$\begin{cases} \pi \sim Dir(\pi|\alpha) \\ \Theta_1, \dots \Theta_K \sim p(\Theta) \\ z_1, \dots z_N \sim Discrete(z|\pi) \\ x_i | z_i, \Theta \sim p(x|\Theta_{z_i}) \end{cases}$$

$$p(x, z, \Theta, \pi) = \underbrace{p(\Theta)p(\pi)}\, p(z|\pi)p(x|z,\Theta)$$

непараметрическая модель ?

(здесь нет, но нужно сделать)