

Reparameterization Trick дд 14.12.18

$$\mathbb{E}_{q(z|\lambda)} f(z) \rightarrow \max_{\lambda}$$

$$p(x, z | \theta)$$

$$\log p(x | \theta) \geq \text{ELBO}(\theta, \lambda) = \mathbb{E}_{q(z|\lambda)} (\log p(x, z | \theta) - \log q(z | \lambda)) \rightarrow \max_{\theta, \lambda}$$

VAE, Policy Gradient, Actor-Critic

$$\mathbb{E}_{p(\tau|\theta)} R(\tau) \rightarrow \max_{\theta}, \quad \mathbb{E}_{p(s)} \mathbb{E}_{\pi(a|s, \theta)} Q(a, s | w) \rightarrow \max_{\theta}$$

RT $z \sim q(z | \lambda) \Leftrightarrow \begin{aligned} s(z | \lambda) &= \varepsilon, \quad \varepsilon \sim q(\varepsilon) \\ z &= s^{-1}(\varepsilon | \lambda) \end{aligned}$
 стандартное распределение

$$\begin{aligned} \nabla_{\lambda} \mathbb{E}_{q(z|\lambda)} f(z) &= \nabla_{\lambda} \mathbb{E}_{q(\varepsilon)} f(s^{-1}(\varepsilon | \lambda)) = \mathbb{E}_{q(\varepsilon)} \nabla_{\lambda} f(s^{-1}(\varepsilon | \lambda)) = \\ &= \mathbb{E}_{q(\varepsilon)} \nabla_z f(z) \Big|_{z=s^{-1}(\varepsilon | \lambda)} \nabla_{\lambda} s^{-1}(\varepsilon | \lambda) \approx \mathbb{E}_{q(\varepsilon)} \nabla_z f(z) \nabla_{\lambda} s^{-1}(\varepsilon | \lambda) \end{aligned}$$

\uparrow $1 \times d, d = \dim z$ \uparrow $d \times m$ \nwarrow $1 \times m$
 m $m = \dim \lambda$
 MC-sampling

$$\approx \frac{1}{M} \sum_{j=1}^M \nabla_z f(z_j) \nabla_{\lambda} s^{-1}(\varepsilon_j | \lambda), \quad \varepsilon_j \sim q(\varepsilon), z_j = s^{-1}(\varepsilon_j | \lambda)$$

$$z \in \mathbb{R}, F(z | \lambda) = \varepsilon, \quad \varepsilon \sim \mathbb{R}[0, 1]$$

$$z \in \mathbb{R}^d, [F(z_1 | \lambda), F(z_2 | z_1, \lambda), \dots, F(z_d | z_{d-1}, \dots, z_1, \lambda)] =$$

$$= [\varepsilon_1, \dots, \varepsilon_d], \quad \varepsilon_j \sim \mathbb{R}[0, 1] \quad \text{стандартное распределение}$$

можно оформить оп-иш?

Implicit RT

$$\nabla_{\lambda} \mathbb{E}_{q(z|\lambda)} f(z) = \mathbb{E}_{q(\varepsilon)} \nabla_z f(z) \Big|_{z = \tilde{s}^{-2}(\varepsilon|\lambda)} \quad \nabla_{\lambda} \tilde{s}^{-2}(\varepsilon|\lambda) =$$

$$= \mathbb{E}_{q(z|\lambda)} \nabla_z f(z) \nabla_{\lambda} z \Big\{ \nabla_{\lambda} z = \nabla_{\lambda} \tilde{s}^{-2}(\varepsilon|\lambda) \Big|_{\varepsilon = s(z|\lambda)} \Big\}$$

$$s(z|\lambda) = \varepsilon \mid \nabla_{\lambda} \{ z = z(\lambda) \}$$

$$\nabla_z s(z|\lambda) \nabla_{\lambda} z + \nabla_{\lambda} s(z|\lambda) = 0 \quad \text{Решение CNAУ}$$

$$\nabla_{\lambda} z = - \left(\nabla_z s(z|\lambda) \right)^{-2} \nabla_{\lambda} s(z|\lambda)$$

$d \times m \qquad \qquad d \times d \qquad \qquad d \times m$

Пример I

$$q(z|\lambda) = \mathcal{N}(z|\mu, \sigma^2), \quad z \in \mathbb{R}$$

$$s(z|\mu, \sigma) = \frac{z - \mu}{\sigma} = \varepsilon \sim \mathcal{N}(\varepsilon|0, 1)$$

$$\text{RT: } \tilde{s}^{-2}(\varepsilon|\mu, \sigma) = \mu + \sigma \varepsilon$$

$$\nabla_{\mu} \tilde{s}^{-2}(\varepsilon|\mu, \sigma) = 1, \quad \nabla_{\sigma} \tilde{s}^{-2}(\varepsilon|\mu, \sigma^2) = \varepsilon = \frac{z - \mu}{\sigma}$$

$$\text{IRT: } \nabla_{\mu} z = - \frac{\nabla_{\mu} s(z|\mu, \sigma)}{\nabla_z s(z|\mu, \sigma)} = - \frac{-1/\sigma}{1/\sigma} = 1$$

$$\nabla_{\sigma} z = - \frac{\nabla_{\sigma} s(z|\mu, \sigma)}{\nabla_z s(z|\mu, \sigma)} = - \frac{-\frac{z - \mu}{\sigma^2}}{1/\sigma} = \frac{z - \mu}{\sigma}$$

Пример II

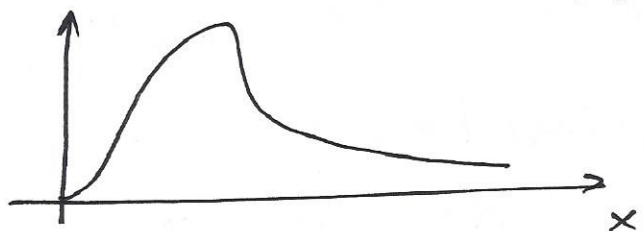
$$z \in \mathbb{R}, \quad s(z|\lambda) = F(z|\lambda) = \varepsilon \sim \mathcal{R}(\gamma, 1)$$

$$\nabla_{\lambda} z = - \frac{\nabla_{\lambda} F(z|\lambda)}{q(z|\lambda)}$$

	$\mathcal{I} \ R \ T$	$I \ R \ T$
Примеры вперёд	$\varepsilon \sim q(\varepsilon)$ $z = s^{-1}(\varepsilon \lambda)$ $f(z)$	$z \sim q(z \lambda)$ $f(z)$
Примеры назад	$\nabla_\lambda z = \nabla_\lambda s^{-1}(\varepsilon \lambda)$ $\nabla_\lambda f = \nabla_z f(z) \nabla_\lambda z$	$\nabla_\lambda z = - (\nabla_z s(z \lambda))^{-1} \nabla_\lambda s(z \lambda)$ $\nabla_\lambda f = \nabla_z f(z) \nabla_\lambda z$

Пример: гамма-распределение

$$\text{Gamma}(x | a, b) = \frac{b^a}{\Gamma(a)} x^{a-1} \exp(-bx), \quad x > 0, \quad a, b > 0$$



$$y \sim \text{Gamma}(y | a, 1)$$

$$x = \frac{y}{b} \sim \text{Gamma}(y | a, b)$$

$$F(y | a) = \int_0^y \frac{1}{\Gamma(a)} t^{a-1} \exp(-t) dt$$

def f(x):

$$y = \text{np.exp}(x)$$

$$z = y + x \rightarrow$$

return z

def f(x):

$$dx = 1$$

$$y = \text{np.exp}(x)$$

$$dy = y \cdot dx$$

$$z = y + x$$

$$dz = dy + dx$$

return z, dz

расчёт производной
при помощи вперёд

LDA

$$\Theta \sim \text{Dir}(\Theta | \alpha) \propto \prod_{j=1}^k \Theta_j^{\alpha_j - 1}$$

$$\Uparrow \sum_{j=1}^k \Theta_j = 1, \Theta_j > 0, \alpha_j > 0$$

$$c_j \sim \text{Gamma}(c_j | \alpha_j, 1), j = 1 \dots k$$

$$\Theta_j = \frac{c_j}{\sum_{i=1}^k c_i} \quad \left\{ \begin{array}{l} g \sim \alpha \quad d = 1 \dots D \\ \Theta_d \sim \text{Dir}(\Theta | \alpha) \\ g \sim \alpha \quad n = 1 \dots N_d \\ z_{d,n} \sim \text{cat}(z | \Theta_d) \\ w_{d,n} \sim \text{cat}(w | \beta_{z_{d,n}}) \end{array} \right.$$

$\beta_1 \dots \beta_T$
вер-мн слов
в меморизах

$$p(w, z, \Theta | \alpha, \beta) = \prod_{d=1}^D p(\Theta_d | \alpha) \cdot \prod_{n=1}^{N_d} p(z_{d,n} | \Theta_d) p(w_{d,n} | z_{d,n}, \beta)$$

$$p(w, \Theta | \alpha, \beta) = \prod_{d=1}^D p(\Theta_d | \alpha) \cdot \prod_{n=1}^{N_d} \left(\sum_{z_{d,n}=1}^T p(z_{d,n} | \Theta_d) p(w_{d,n} | z_{d,n}, \beta) \right) =$$

$$= \prod_{d=1}^D p(\Theta_d | \alpha) \prod_{n=1}^{N_d} p(w_{d,n} | \Theta_d, \beta)$$

$$\log p(w | \alpha, \beta) \geq \sum_{d=1}^D \left[\mathbb{E}_{q(\Theta_d | \lambda)} \log p(w_d | \Theta_d, \beta) - k \mathcal{L}(q(\Theta_d | \lambda) \parallel p(\Theta_d | \alpha)) \right] \rightarrow \max_{d, \beta, \lambda}$$

$$q(\theta_d | \lambda) = \text{Dir}(\theta | \text{NN}(w_d, \lambda))$$

??

$$p(\theta_d | w_d, \beta, d)$$

$$q(\theta, z) = q(\theta) q(z) ?$$

Этап делаем раньше через VI?

Ренормализация дискретных распределений

$$z \sim \text{Cat}(z | \pi) : \quad 1 \dots k \quad \sum_{i=1}^k \pi_i = 1, \pi_i \geq 0$$

\Downarrow

$$c_i \sim \text{Exp}(1) = \exp(-c_i), c_i \geq 0$$

$$z = \underset{1 \leq i \leq k}{\text{argmin}} \frac{c_i}{\pi_i} = \underset{1 \leq i \leq k}{\text{argmax}} (\log \pi_i - \log c_i) \Leftrightarrow$$

$$F(c) = \int_0^c \exp(-t) dt = -\exp(-t) \Big|_0^c = 1 - \exp(-c) = \varepsilon$$

$\text{Exp}(z)$

$$\varepsilon \sim \mathcal{U}[0, 1]$$

$$\Rightarrow c = -\log(1 - \varepsilon)$$

$$c = -\log \varepsilon \quad \varepsilon \sim \mathcal{U}[0, 1]$$

$$\delta_i = -\log c_i = -\log(-\log \varepsilon_i) \sim \text{Gumbel}(\delta | 0, 1)$$

$$\Leftrightarrow \underset{1 \leq i \leq k}{\text{argmax}} (\log \pi_i + \delta_i), \text{ Gumbel-Max trick}$$

Gumbel-Softmax:

$$z = \text{softmax}_{\tau}(\log \pi + \delta) = \left\{ \frac{\exp\left(\frac{\log \pi_i + \delta_i}{\tau}\right)}{\sum_{j=1}^k \exp\left(\frac{\log \pi_j + \delta_j}{\tau}\right)} \right\}_{i=1}^k$$

$$\mathbb{E}_{\pi} \mathbb{E}_{\text{Cat}(z | \pi)} f(z) \approx \mathbb{E}_{\text{Gumbel}(\delta | 0, 1)^k} \left(\mathbb{E}_{\pi} f(\text{softmax}_{\tau}(\log \pi + \delta)) \right)$$

$$\tau = \text{const}, \tau = 1, \tau \rightarrow 0$$