

# Committer function-report 1

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## 1 Thread

Let us consider a Markov process  $\{x_t\}$  with transition density  $p(x, y) = \mathbb{P}(x_{t+\tau} = y \mid x_t = x)$ . For two sets  $A, B$ , the committor function  $q(x)$  is defined as the probability of hitting region  $B$  before region  $A$  with the process starting at  $x$ . By considering the timescale  $\tau$ ,  $q(x)$  satisfies

$$q(x) = \begin{cases} 0, & x \in A \\ 1, & x \in B \\ \tilde{q}(x), & \text{otherwise} \end{cases}$$

where  $\tilde{q}(x) = \int p(x, y)q(y)dy$

$$\begin{aligned} A, B &\subset \Omega, A \cap B = \emptyset \\ \tau_A(x) &= \inf\{t \geq 0 : X_t \in A, X_0 = x\} \\ \tau_B(x) &= \inf\{t \geq 0 : X_t \in B, X_0 = x\} \\ q(x) &= \mathbb{P}\{\tau_B(x) < \tau_A(x)\}, \Omega \rightarrow [0, 1] \\ q(x) &= 0, x \in \partial A \cup A, \quad q(x) = 1, x \in \partial B \cup B \end{aligned}$$

Aim: Find an algorithm of Computing  $q(x)$ .  
Consider

$$\begin{aligned} q(x) &= \int p(x, y)q(y)dy, \quad x \in \Omega \setminus (A \cup B), y \in \Omega \setminus (A \cup B) \\ \rho_0(x)q(x) &= \int \rho_0(x)p(x, y)q(y)dy \\ \rho_0(x) &> 0, x \in \Omega, x \sim \rho_0(x) \end{aligned}$$

### 1.1 Sampling

$$\rho_0(x)q(x) = \int \rho_0(x)p(x, y)q(y)dy \tag{1}$$

Assume that there are  $N$  transition pairs  $\{(x_n, y_n)\}_{n=1}^N$  drawn from  $\rho_0(x)p(x, y)$  and  $\rho_0(x) = 0$  for  $x \in A \cup B$  without lack of generality<sup>1</sup>

## 1.2 WGAN

Here we introduce an instrumental variable  $z \in [0, 1]$ , and define

$$\begin{aligned}\mathbb{Q}(x, z) &= 2\rho_0(x)(z \cdot q(x) + (1 - z) \cdot (1 - q(x))) \\ \tilde{\mathbb{Q}}(x, z) &= 2\rho_0(x)(z \cdot \tilde{q}(x) + (1 - z) \cdot (1 - \tilde{q}(x)))\end{aligned}$$

It can be seen that  $\mathbb{Q}(x, z) = \tilde{\mathbb{Q}}(x, z)$  if  $q(x)$  is exactly the committor function and

$$\iint \mathbb{Q}(x, z) dx dz = \iint \tilde{\mathbb{Q}}(x, z) dx dz = 1$$

Hence, we can optimize the parametric model of  $q$  by minimizing the Wasserstein distance

$$W(\mathbb{Q}, \tilde{\mathbb{Q}}) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{\mathbb{Q}}[f(x, z)] - \mathbb{E}_{\tilde{\mathbb{Q}}}[f(x, z)]$$

where

$$\begin{aligned}\mathbb{E}_{\mathbb{Q}}[f(x, z)] &= \mathbb{E}_{x \sim \rho_0(x), z \sim \mathcal{U}_{[0,1]}}[2(z \cdot q(x) + (1 - z) \cdot (1 - q(x)))f(x, z)] \\ &\approx \frac{1}{N} \sum_n \mathbb{E}_{z \sim \mathcal{U}_{[0,1]}}[2(z \cdot q(x_n) + (1 - z) \cdot (1 - q(x_n)))f(x_n, z)] \\ \mathbb{E}_{\tilde{\mathbb{Q}}}[f(x, z)] &= \mathbb{E}_{x \sim \rho_0(x), z \sim \mathcal{U}_{[0,1]}}[2(z \cdot \tilde{q}(x) + (1 - z) \cdot (1 - \tilde{q}(x)))f(x, z)] \\ &= \iiint 2\rho_0(x)p(x, y)(z \cdot q(y) + (1 - z) \cdot (1 - q(y)))f(x, z) dx dy dz \\ &\approx \frac{1}{N} \sum_n \mathbb{E}_{z \sim \mathcal{U}_{[0,1]}}[2(z \cdot q(y_n) + (1 - z) \cdot (1 - q(y_n)))f(x_n, z)]\end{aligned}$$

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<sup>1</sup>In applications, the latter assumption can be satisfied by simply removing all transition pairs  $(x_n, y_n)$  with  $x_n \in A \cup B$  from the data set.

### 1.3 WGAN-GP

Consider

$$\begin{aligned}
& \min_q \max_{\|f\|_{Lip} \leq 1} \mathbb{E}_{x,z} [2(z \cdot q(x) + (1-z)(1-q(x)))f(x,z)] - \mathbb{E}_{x,z} [2(z \cdot \tilde{q}(x) + (1-z)(1-\tilde{q}(x)))f(x,z)] + \\
& \lambda \mathbb{E}_{x,z} \left[ (\|\nabla_x f(x,z)\|_2 - 1)^2 \right] \\
& \text{sample} \{x^{(n)}, y^{(n)}\}_1^N \sim p(x,y) \\
& \min_q \max_{\|f\|_{Lip} \leq 1} \frac{1}{N} \sum_n \mathbb{E}_{z \sim U[0,1]} [2(z \cdot q(x_n) + (1-z)(1-q(x_n)))f(x_n,z)] - \\
& \frac{1}{N} \sum_n \mathbb{E}_{z \sim U[0,1]} [2(z \cdot q(y_n) + (1-z)(1-q(y_n)))f(x_n,z)] + \lambda \frac{1}{N} \mathbb{E}_{z \sim U[0,1]} \left[ (\|\nabla_{x_n} f(x_n,z)\|_2 - 1)^2 \right] \\
& \text{sample} \{z^{(m)}\}_1^M \sim U[0,1] \\
& \min_q \max_{\|f\|_{Lip} \leq 1} \frac{2}{MN} \sum_N \sum_M [(2z_m - 1)(q(x_n) - q(y_n))f(x_n, z_m) \\
& \lambda \left[ (\|\nabla_x f(x_n, z_m)\|_2 - 1)^2 \right]
\end{aligned}$$

### 1.4 Algorithm

Aim:  $\theta : q_\theta, w : f_w$

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#### Algorithm 1 Committor Function

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- 1: Input: gradient penalty coefficient  $\lambda$ ; Number of critic iterations per generator iteration  $n_{critic}$ ; batch size  $N$ ; Adam hyperparameters  $\alpha, \beta_1, \beta_2$ ; initial critic parameters  $\omega_0$ ; initial generator parameters  $\theta_0$
  - 2: **while**  $\theta$  has not converged **do**
  - 3:   **for**  $t = 1, \dots, n_{critic}$  **do**
  - 4:     **for**  $n = 1, \dots, N$  **do**
  - 5:       Sample real data  $(x_n, y_n) \sim \rho_0(x) * p(x, y)$
  - 6:       **for**  $m = 1, \dots, M$  **do**
  - 7:          Sample  $z_m \sim U[0, 1]$
  - 8:           $L^{(n,m)} \leftarrow (2z_m - 1)(q(x_n) - q(y_n))f(x_n, z_m) + \lambda(\|\nabla_x f(x, z)\|_2 - 1)^2$
  - 9:       **end for**
  - 10:     **end for**
  - 11:      $\omega \leftarrow Adam(\nabla_\omega \frac{2}{N*M} \sum_n \sum_m L^{(n,m)}, \omega, \alpha, \beta_1, \beta_2)$
  - 12:   **end for**
  - 13:   Sample  $(x_n, y_n) \sim \rho_0(x) * p(x, y), z_m \sim U[0, 1]$
  - 14:    $\theta \leftarrow Adam(\nabla_\theta \frac{2}{N*M} \sum_n \sum_m (2z_m - 1)(q(x_n) - q(y_n))f(x_n, z_m), \omega, \alpha, \beta_1, \beta_2)$
  - 15: **end while**
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