Adjoint Walks

Xiaoyu Chen

1 Adjoint walk on two disjoint spaces

Let Ω_1 and Ω_2 be two disjoint state spaces. Let π_1 and π_2 be two distribution on Ω_1 and Ω_2 , respectively. Let $P_{12} \in \mathbb{R}^{\Omega_1 \times \Omega_2}$ and $P_{21} \in \mathbb{R}^{\Omega_2 \times \Omega_1}$ be two stochastic matrices.

Definition 1. *If for any* $x \in \Omega_1$ *and* $y \in \Omega_2$, we have $\pi_1(x)P_{12}(x,y) = \pi_2(y)P_{21}(y,x)$, then we say P_{12} and P_{21} are adjoint random walk over π_1 and π_2 .

Fact 1. P_{12} and P_{21} are adjoint random walk over π_1 and π_2 iff

$$\forall f: \Omega_1 \to \mathbb{R}, \forall g: \Omega_2 \to \mathbb{R} \ , \ \langle f, P_{12}g \rangle_{\pi_1} = \langle P_{21}f, g \rangle_{\pi_2}.$$

Proof. ⇒:

$$\langle f, P_{12}g\rangle_{\pi_1} = \sum_{x\in\Omega_1} \pi_1(x)f(x)\left[P_{12}g\right](x) = \sum_{x\in\Omega_1} \sum_{y\in\Omega_2} \pi_1(x)P_{12}(x,y)f(x)g(y)$$

$$\langle P_{21}f,g\rangle_{\pi_2} = \sum_{y\in\Omega_2} \pi_2(y) \left[P_{21}f\right](y)g(y) = \sum_{x\in\Omega_1} \sum_{y\in\Omega_2} \pi_2(y)P_{21}(y,x)f(x)g(y)$$

 \Leftarrow : Let $x \in \Omega_1$ and $y \in \Omega_2$ be arbitrary elements in Ω_1 and Ω_2 , respectively. Let $\delta_x : \Omega_1 \to \{0,1\}$ and $\delta_y : \Omega_2 \to \{0,1\}$, be the indicator function of x and y, respectively. Then,

$$\langle \delta_x, P_{12} \delta_y \rangle_{\pi_1} = \langle P_{21} \delta_x, \delta_y \rangle_{\pi_2} \Rightarrow \pi_1(x) P_{12}(x, y) = \pi_2(y) P_{21}(y, x)$$

Fact 2. *If* P_{12} *and* P_{21} *are* adjoint random walk *over* π_1 *and* π_2 , *then*

$$\pi_1 P_{12} = \pi_2$$
 and $\pi_2 P_{21} = \pi_1$

Fact 3. Let P_{12} and P_{21} be adjoint random walk over π_1 and π_2 . Then for any distribution ν_1 over Ω_1 , we have,

$$\frac{\nu_1 P_{12}}{\pi_1 P_{12}} = P_{21} \frac{\nu_1}{\pi_1}.\tag{1}$$

Symmetrically, for any distribution v_2 over Ω_2 , we have,

$$\frac{\nu_2 P_{21}}{\pi_2 P_{21}} = P_{12} \frac{\nu_2}{\pi_2}. (2)$$

Proof. We only proof (1). For any $y \in \Omega_2$, we have

$$\frac{\nu_1 P_{12}}{\pi_1 P_{12}}(y) = \frac{\left[\nu_1 P_{12}\right](y)}{\pi_2(y)}$$

On the other hand, we have

$$\begin{split} P_{21} \frac{\nu_1}{\pi_1}(y) &= \sum_{x \in \Omega_1} P_{21}(y, x) \frac{\nu_1(x)}{\pi_1(x)} \\ &= \sum_{x \in \Omega_1} \pi_2(y) P_{21}(y, x) \frac{\nu_1(x)}{\pi_2(y) \pi_1(x)} \\ &= \sum_{x \in \Omega_1} \pi_1(x) P_{12}(x, y) \frac{\nu_1(x)}{\pi_2(y) \pi_1(x)} \\ &= \sum_{x \in \Omega_1} \pi_1(x) P_{12}(x, y) \frac{\nu_1(x)}{\pi_2(y) \pi_1(x)} \\ &= \frac{\left[\nu_1 P_{12}\right](y)}{\pi_2(y)} \end{split}$$

2 Understand variance and Dirichlet form

For any distribution $\pi: \Omega \to \mathbb{R}$, and any function $f: \Omega \to \mathbb{R}$, the variance is defined as

$$\operatorname{Var}_{\pi}[f] \triangleq \mathbb{E}_{\pi}[f^2] - \mathbb{E}_{\pi}[f]^2.$$

We could represent the variance in a more general way:

$$\operatorname{Var}_{\pi}[f] = \langle f - \pi(f), f - \pi(f) \rangle_{\pi},$$

where, for conveniene, we use $\pi(f)$ to stand for $\pi^T f$, which is equivalent to $\mathbb{E}_{\pi}[f]$. Then, we define the projection operator as follows.

Definition 2. We define $J_{\pi} \triangleq \mathbb{1}\pi^T$, which is a matrix with each row equals to π^T .

Fact 4. For any $f:\Omega\to\mathbb{R}$, it is easy to verify that $J_{\pi}f=\langle f,\mathbb{1}\rangle_{\pi}\mathbb{1}$. So, J_{π} is a projection matrix that maps f to $f^{\mathbb{1}}$.

Then, for the variance, we have

$$\begin{aligned} \operatorname{Var}_{\pi}[f] &= \langle f - J_{\pi}f, f - J_{\pi}f \rangle_{\pi} \\ &= \langle f^{\perp_{\pi}\mathbb{1}}, f^{\perp_{\pi}\mathbb{1}} \rangle_{\pi} \\ &= \langle f, (I - J_{\pi})f \rangle_{\pi} \\ &= \mathcal{E}_{J_{\pi}}(f, f) \end{aligned}$$