

Proof of Metropolis's

i) Does the algorithm give detailed balance, i.e.

$$\pi_i P_{ij} = \pi_j P_{ji}$$

Proof Let $X(i) = \vec{\theta}^i$ be a Markov chain.

Recall for Metropolis's

$$\rho(\vec{\theta}^i, \vec{\theta}^j) = \min \left(1, \frac{\pi(\vec{\theta}^j | \vec{y})}{\pi(\vec{\theta}^i | \vec{y})} \right)$$

For
non-sym.
 \mathcal{J}

$$\rho(\vec{\theta}^i, \vec{\theta}^j) = \min \left(1, \frac{p(\vec{y} | \vec{\theta}^j) \pi_0(\vec{\theta}^j) \mathcal{J}(\vec{\theta}^i | \vec{\theta}^j)}{p(\vec{y} | \vec{\theta}^i) \pi_0(\vec{\theta}^i) \mathcal{J}(\vec{\theta}^j | \vec{\theta}^i)} \right)$$

- So for Metropolis's

$$P_{ij} = \rho(\vec{\theta}^i, \vec{\theta}^j) \mathcal{J}(\vec{\theta}^j | \vec{\theta}^i), \quad i \neq j$$

$$P_{ii} = 1 - \sum_{i \neq j}^{N_S} P_{ij}$$

- Note: If \mathcal{J} is symmetric (\mathcal{J} is Gaussian)

$$P_{ji} = \rho(\vec{\theta}^j, \vec{\theta}^i) \mathcal{J}(\vec{\theta}^i | \vec{\theta}^j) = \rho(\vec{\theta}^i, \vec{\theta}^j) \mathcal{J}(\vec{\theta}^j | \vec{\theta}^i)$$

- Then

$$\pi_i P_{ij} = \pi_j P_{ji}$$

$$s \quad \sim (\sigma_i \sigma_j) \sim (\sigma_i \sigma_j)$$

ii) i) π_i

$$\Rightarrow \pi_i p(\vec{\theta}^i, \vec{\theta}^i) J(\vec{\theta}^i | \vec{\theta}^i) = \pi_j p(\vec{\theta}^i, \vec{\theta}^i) J(\vec{\theta}^i | \vec{\theta}^i)$$

$$\Rightarrow \pi_i p(\vec{\theta}^i, \vec{\theta}^i) = \pi_j p(\vec{\theta}^i, \vec{\theta}^i)$$

$$\Rightarrow \pi_i \min\left(1, \frac{\pi(\vec{\theta}^i | \vec{y})}{\pi(\vec{\theta}^i | \vec{y})}\right) = \pi_j \min\left(1, \frac{\pi(\vec{\theta}^i | \vec{y})}{\pi(\vec{\theta}^i | \vec{y})}\right)$$

- If $\pi(\vec{\theta}^i | \vec{y}) < \pi(\vec{\theta}^j | \vec{y})$

$$\Rightarrow \pi_i \cdot 1 = \pi_j \frac{\pi(\vec{\theta}^i | \vec{y})}{\pi(\vec{\theta}^i | \vec{y})}$$

- If $\pi_i = \pi(\vec{\theta}^i | \vec{y}) + \pi_j = \pi(\vec{\theta}^i | \vec{y})$

$$\Rightarrow \pi(\vec{\theta}^i | \vec{y}) \cdot 1 = \pi(\vec{\theta}^i | \vec{y}) \cdot \frac{\pi(\vec{\theta}^i | \vec{y})}{\pi(\vec{\theta}^i | \vec{y})}$$

$$\Rightarrow \pi(\vec{\theta}^i | \vec{y}) = \pi(\vec{\theta}^i | \vec{y}) \quad \checkmark$$

ii) Is the stationary distribution the posterior?

- Let $\pi_x = \pi(\vec{\theta}^x | \vec{y})$ + let

$$P_{x-1, x} = P(X_x = \vec{\theta}^x | X_{x-1} = \vec{\theta}^{x-1})$$

- Note: $\min(x, z) = x \min\left(1, \frac{z}{x}\right) = z \min\left(1, \frac{x}{z}\right)$

- If detailed balance holds

$$\pi(\vec{\theta}^{z+1} | \vec{y}) P_{z, z+1} = \pi(\vec{\theta}^{z+1} | \vec{y}) J(\vec{\theta}^z | \vec{\theta}^{z+1}) P(\vec{\theta}^z, \vec{\theta}^{z+1})$$

note: $J(\vec{\theta}^{z+1} | \vec{\theta}^z) = J(\vec{\theta}^z | \vec{\theta}^{z+1})$

also

$$\begin{aligned} & \pi(\vec{\theta}^{z+1} | \vec{y}) J(\vec{\theta}^z | \vec{\theta}^{z+1}) \min \left(1, \frac{\pi(\vec{\theta}^z | \vec{y})}{J(\vec{\theta}^z | \vec{\theta}^{z+1})} \cdot \frac{J(\vec{\theta}^{z+1} | \vec{y})}{J(\vec{\theta}^{z+1} | \vec{\theta}^z)} \right) \\ \rightarrow & = \underbrace{\pi(\vec{\theta}^{z+1} | \vec{y}) J(\vec{\theta}^z | \vec{\theta}^{z+1})}_{= \chi} \min \left(1, \frac{\overbrace{\pi(\vec{\theta}^z | \vec{y}) \cdot J(\vec{\theta}^{z+1} | \vec{\theta}^z)}^{\chi}}{\underbrace{\pi(\vec{\theta}^{z+1} | \vec{y}) \cdot J(\vec{\theta}^z | \vec{\theta}^{z+1})}_{\chi}} \right) \end{aligned}$$

$$= \pi(\vec{\theta}^z | \vec{y}) J(\vec{\theta}^{z+1} | \vec{\theta}^z) \min \left(1, \frac{\pi(\vec{\theta}^{z+1} | \vec{y}) J(\vec{\theta}^z | \vec{\theta}^{z+1})}{\pi(\vec{\theta}^z | \vec{y}) J(\vec{\theta}^{z+1} | \vec{\theta}^z)} \right)$$

$$= \pi(\vec{\theta}^z | \vec{y}) J(\vec{\theta}^{z+1} | \vec{\theta}^z) P(\vec{\theta}^{z+1}, \vec{\theta}^z)$$

$$= \pi(\vec{\theta}^z | \vec{y}) P_{z, z+1}$$

□

$$\Rightarrow \boxed{\pi(\vec{\theta}^{z+1} | \vec{y}) P_{z, z+1} = \pi(\vec{\theta}^z | \vec{y}) P_{z, z+1}}$$

Adaptive Metropolis' (AM)

- The proposal, J , has a large effect on sampling

- AM adapts the covariance for J by:

• for every k steps

$$\mathbf{V}_k = S_p \text{Cov}(\vec{\theta}^0, \vec{\theta}^1, \dots, \vec{\theta}^{k-1}) + \eta \mathbf{I}_P, \quad 0 < \eta < 1$$

• η is a "fitter" term

• S_p is a scaling factor (we will use $S_p = 2.38^2 / P$)

- In practice, we cannot generate \mathbf{V}_k at every step explicitly.

- Instead, we sequentially update:

$$\mathbf{V}_{k+1} = \frac{k}{k+1} \mathbf{V}_k + \frac{S_p}{k+1} \left[k \vec{\theta}^{k-1} \vec{\theta}^{k-1T} - (k+1) \vec{\theta}^k \vec{\theta}^{kT} + \vec{\theta}^k \vec{\theta}^{kT} + \eta \mathbf{I}_P \right]$$

where

$$\vec{\theta}^k = \frac{k}{k+1} \vec{\theta}^{k-1} + \frac{1}{k+1} \vec{\theta}^k$$

- In practice, we only update every k_0 steps