

## MCMC: Metropolis-Hastings and Gibbs

Note (MCMC for continuous distributions):

Instead of  $P(y|x)$ , we will write

$$p(\theta, \phi) = \begin{cases} q(\theta, \phi) \alpha(\theta, \phi), & \theta \neq \phi, \\ \left(1 - \int_{-\infty}^{\infty} q(\theta, \phi) \alpha(\theta, \phi) d\phi\right), & \theta = \phi. \end{cases}$$

For  $A \subseteq S$ ,

$$P(\theta, A) = \int_A q(\theta, \phi) \alpha(\theta, \phi) d\phi + \mathbb{I}\{\theta \in A\} \left[1 - \int_{-\infty}^{\infty} q(\theta, \phi) \alpha(\theta, \phi) d\phi\right]$$

$$\alpha(\theta, \phi) = \min\left\{1, \frac{\pi(\phi) q(\phi, \theta)}{\pi(\theta) q(\theta, \phi)}\right\}.$$

Gibbs Sampling (acceptance rate = 1) :

$$Q(y^j | x_{i-1}^j, \vec{x}_{i-1}^{-j}) = \pi(y^j | \vec{x}_{i-1})$$

$$\alpha(\vec{y} | \vec{x}_{i-1}) = \min \left\{ \frac{\pi(\vec{y})}{\pi(\vec{x}_{i-1})} \cdot \frac{Q(x_{i-1}^j | \vec{y}^{-j})}{Q(y^j | \vec{x}_{i-1}^{-j})}, 1 \right\}$$

$$= \min \left\{ \frac{\cancel{\pi(y^j | \vec{y}^{-j})} \cancel{\pi(\vec{y}^{-j})}}{\cancel{\pi(x_{i-1}^j | \vec{x}_{i-1}^{-j})} \cancel{\pi(\vec{x}_{i-1}^{-j})}} \cdot \frac{\pi(x_{i-1}^j | \vec{y}^{-j})}{\cancel{\pi(y^j | \vec{x}_{i-1}^{-j})}}, 1 \right\}$$

$$(\vec{y}^{-j} = \vec{x}_{i-1}^{-j})$$

$$= 1$$