

Example: Coin flip example

$$X|\theta \sim \text{Binom}(n, \theta)$$

$$\theta \sim \text{Beta}(\alpha, \beta)$$

$$\begin{aligned} P(\theta) &\propto \theta^{\alpha-1} (1-\theta)^{\beta-1} \\ P(X|\theta) &\propto \theta^x (1-\theta)^{n-x} \end{aligned} \left. \vphantom{\begin{aligned} P(\theta) &\propto \theta^{\alpha-1} (1-\theta)^{\beta-1} \\ P(X|\theta) &\propto \theta^x (1-\theta)^{n-x} \end{aligned}} \right\} \begin{array}{l} \text{Similar} \\ \text{Shapes} \end{array}$$

$$P(\theta|X) \propto P(X|\theta) P(\theta)$$

$$\propto \theta^{x+\alpha-1} (1-\theta)^{n-x+\beta-1}$$

$$\theta|X \sim \text{Beta}(x+\alpha, n-x+\beta)$$

So we see that **Beta** is
in the conjugate family of **Binom**

That is, if $\theta \sim \text{Beta}(\alpha, \beta)$ and $X \sim \text{Binom}(n, \theta)$, then $\theta|X \sim \text{Beta}(\alpha + X, \beta + n - X)$.

Independent Chain MCMC

$$Q(\theta) \sim P(\theta)$$

$$R(\theta, \theta^*) = \frac{P(x|\theta^*)}{P(x|\theta)}$$

$$= \frac{(\theta^*)^x (1-\theta^*)^{n-x}}{(\theta^{(t)})^x (1-\theta^{(t)})^{n-x}}$$

Random Walk

$$\theta^* = \theta^{(t)} + \int \quad \int \sim \text{Unif}(-s, s)$$

$$R(\theta^*, \theta^{(t)}) = \frac{P(\theta^* | x)}{P(\theta^{(t)} | x)}$$

$$= \frac{(\theta^*)^{x+a-1} (1-\theta^*)^{n-x+b-1}}{(\theta^{(t)})^{x+a-1} (1-\theta^{(t)})^{n-x+b-1}}$$

Example:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \sim N\left(\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma\right)$$

RW: $x^* = x^{(t)} + \delta, \quad \delta \sim N(0, \sigma_{rw}^2 I_2)$

$$\begin{aligned} R(x^*, x^{(t)}) &= \frac{P(x^*)}{P(x^{(t)})} \\ &= \frac{\exp\left\{-\frac{1}{2}(x^* - \mu)^T \Sigma^{-1}(x^* - \mu)\right\}}{\exp\left\{-\frac{1}{2}(x^{(t)} - \mu)^T \Sigma^{-1}(x^{(t)} - \mu)\right\}} \end{aligned}$$

Gibbs Sampling

$$x_1 | x_2 \sim N\left(\mu_1 + \frac{\sigma_{12}}{\sigma_2^2} (x_2 - \mu_2), \sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)$$

$$\dots \quad \dots \quad \dots \quad \dots \quad \dots$$

$$X_2 | X_1 \sim N\left(\mu_2 + \frac{\sigma_{12}}{\sigma_1^2} (x_1 - \mu_1), \sigma_2^2 - \frac{\sigma_{12}^2}{\sigma_1^2}\right)$$

update $(\hat{\mu}_1, \hat{\mu}_2)$ iteratively.

Obs: Independent only works all
when $Q \subseteq P$.

Ex: "Capture Recapture Models"

fixed population N .

Census	1	2	...	i	...	k
Captured	c_1	c_2	...	c_i	...	c_k
Marked	0	m_2	...	m_i	...	m_k
newly marked	c_1	$c_2 - m_2$...	$c_i - m_i$...	$c_k - m_k$

... R ... N \

$$c_i | N, \alpha_i \sim \text{Binom}(N, \alpha_i)$$

$$m_i | c_i, M_i, N \sim \text{HG}(N, M_i, c_i)$$

Use Bayes to get posteriors for N .

$$P(N) \propto 1, \quad \alpha_i \text{ iid } \text{Unif}(0, 1)$$

$$P(M, C | N, \alpha) \propto \prod_i \cancel{\binom{N}{c_i}} \alpha_i^{c_i} (1 - \alpha_i)^{N - c_i} \frac{\binom{M_i}{m_i} \binom{N - m_i}{c_i - m_i}}{\cancel{\binom{N}{c_i}}}$$

$$\propto \prod_i \alpha_i^{c_i} (1 - \alpha_i)^{N - c_i} \binom{N - m_i}{c_i - m_i}$$

So

$$P(N, M) \sim P(M) \prod_i P(N | M_i, c_i)$$

$$P(m, c) \propto \Pi (m, c | N, \alpha) P(N) / \Pi(\alpha)$$

$$\propto P(m, c | N, \alpha)$$

$$\propto \prod_i x_i^{c_i} (1-x_i)^{N-c_i} \binom{N-m_i}{c_i-m_i}$$

Exercise: Try to simplify

$$\prod_i \binom{N-m_i}{c_i-m_i} = \frac{N!}{\prod_i n_i! (N-m_i-n_i)!}$$