

Conjugate Distributions for Bayesian Inference

Beta, Bernoulli and Related Distributions

Beta	$Y \sim \text{Beta}(a, b)$
pdf	$p(y) = \frac{1}{B(a,b)} y^{a-1} (1-y)^{b-1}, 0 \leq y \leq 1, a > 0, b > 0$
nc	$\int_0^1 y^{a-1} (1-y)^{b-1} dy \equiv B(a, b)$
mean	$E[Y] = \frac{a}{a+b}$
variance	$\text{Var}[Y] = \frac{ab}{(a+b)^2(a+b+1)}$
R> <code>help(Beta)</code>	<code>rbeta(k, a, b)</code> # generate k Beta rv's
Bernoulli	$Y \sim \text{Ber}(\theta)$
pmf	$p(Y = y \theta) = \theta^y (1-\theta)^{1-y}; y = 0, 1; 0 \leq \theta \leq 1$
mean	$E[Y] = \theta = P(Y = 1)$
variance	$\text{Var}[Y] = \theta(1-\theta)$
R> <code>help(Binomial)</code>	<code>rbinom(k, size=1, p=.5)</code> # generate k <code>Ber(.5)</code> rv's
Updating	
Data Model	$Y_i \theta \stackrel{\text{iid}}{\sim} \text{Ber}(\theta) \text{ for } i = 1, \dots, n, \mathbf{Y} \equiv (Y_1, \dots, Y_n)$
Prior $p(\theta)$	$\theta \sim \text{Beta}(a_0, b_0)$
Likelihood	$L(\theta; y_1, y_n) = \theta^{\sum y_i} (1-\theta)^{n-\sum y_i}$
Posterior $p(\theta \mathbf{Y})$	$\theta \mathbf{Y} \sim \text{Beta}(a_n, b_n), \quad a_n = a_0 + \sum y_i, \quad b_n = b_0 + n - \sum y_i$
Marginal of \mathbf{Y}	$p(y_1, \dots, y_n) = \frac{B(a_n, b_n)}{B(a_0, b_0)}$
Notes	Reference prior Beta (1/2, 1/2)

Binomial	$Y \sim \text{Bin}(n, \theta)$
pmf	$p(Y = y \theta) = \binom{n}{y}\theta^y(1 - \theta)^{n-y}; y = 0, 1, \dots, n; 0 \leq \theta \leq 1$
mean	$E[Y] = n\theta$
variance	$\text{Var}[Y] = n\theta(1 - \theta)$
R> <code>help(Binomial)</code>	<code>rbinom(k, size=n, p=.5)</code> # generate k $\text{Bin}(n, .5)$ rv's
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Updating	
Data Model	$Y \theta \sim \text{Bin}(n, \theta)$
Prior $p(\theta)$	$\theta \sim \text{Beta}(a_0, b_0)$
Likelihood	$L(\theta; y, n) = \binom{n}{y}\theta^y(1 - \theta)^{n-y}$
Posterior $p(\theta y)$	$\theta y \sim \text{Beta}(a_n, b_n), \quad a_n = a_0 + y, \quad b_n = b_0 + n - y$
Marginal of Y	$p(y) = \frac{\binom{n}{y} B(a_n, b_n)}{B(a_0, b_0)}$
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Negative Binomial	$Y \sim \text{NegBin}(r, \theta)$
pmf	$p(Y = y \theta) = \binom{r+y-1}{y}\theta^r(1 - \theta)^y; r = 0, 1, \dots; 0 \leq \theta \leq 1$
mean	$E[Y] = \frac{r(1-\theta)}{\theta}$
variance	$\text{Var}[Y] = \frac{r(1-\theta)}{\theta^2}$
R> <code>help(NegBinomial)</code>	<code>rnbinom(k, r, p=.5)</code> # generate k $\text{NegBin}(r, .5)$ rv's
Notes	Y = Number of Bernoulli failures before the r th success
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Updating	
Data Model	$X \theta \sim \text{NegBin}(y, \theta) \quad n \equiv X + y$
Prior $p(\theta)$	$\theta \sim \text{Beta}(a_0, b_0)$
Likelihood	$L(\theta; x, y) \propto \theta^y(1 - \theta)^x$
Posterior $p(\theta x, y)$	$\theta x \sim \text{Beta}(a_n, b_n), \quad a_n = a_0 + y, \quad b_n = b_0 + x$
Notes	Same posterior for θ as with Binomial sampling $x = n - y$

Normal/Gamma Models

Normal	$Y \sim N(\mu, 1/\phi)$
pdf	$p(y) = \sqrt{\frac{\phi}{2\pi}} \exp\{-\frac{1}{2}\phi(Y - \mu)^2\}, y \in \mathbb{R}, \mu \in \mathbb{R}, \phi > 0$
mean	$E[Y] = \mu$
variance	$\text{Var}[Y] = 1/\phi$
R> <code>help(Normal)</code>	<code>rnorm(k, 0, 10)</code> # generate k $N(0, 10^2)$ rv's
Notes	ϕ is the precision
Gamma	$Y \sim \text{Gamma}(\alpha, \beta)$
pdf	$p(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{\alpha-1} \exp\{-y\beta\}, y > 0, \alpha > 0, \beta > 0$
mean	$E[Y] = \alpha/\beta$
variance	$\text{Var}[Y] = \alpha/\beta^2$
R> <code>help(rgamma)</code>	<code>rgamma(k, 2, rate=3)</code> # generate k $\text{Gamma}(2, 3)$ rv's
Notes:	Special cases: Exponential $\alpha = 1$ and Chi-Squared with d degrees of freedom $\alpha = d/2, \beta = 1/2$
Student-t	$Y \sim \text{St}(d, m, s), \text{ for } d > 0, m \in \mathbb{R}, s > 0$
pdf	$p(y) = \frac{\Gamma((d+1)/2)}{\Gamma(d/2)\Gamma(1/2)} (ds)^{-1/2} \left[1 + \frac{(y-m)^2}{ds}\right]^{-(d+1)/2}$
mean	$E[Y] = m, \text{ if } d > 1$
variance	$\text{Var}[Y] = sd/(d-2), \text{ if } d > 2$
R> <code>help(rt)</code>	<code>rt(k, 1, rate=3)</code> # generate k $\text{St}(1, 0, 1)$ rv's
Notes:	Special cases: Cauchy $d = 1$ if $\mu \sim \text{St}(d, m, s)$ then $(\mu - m)/\sqrt{s} \sim \text{St}(1, 0, 1)$ if $\mu \phi \sim N(m, s/\phi), \phi \sim \text{Gamma}(d/2, 1/2)$ then $\mu \sim \text{St}(d, m, s)$

Congugate Updating	$\mathbf{Y} \equiv (Y_1, \dots, Y_n), \bar{Y} = \frac{1}{n} \sum_i^n Y_i, S^2 = \sum_i^n (Y_i - \bar{Y})^2 / (n - 1)$
Data	$Y_i \mu, \phi \stackrel{\text{iid}}{\sim} \mathbf{N}(\mu, 1/\phi)$
Prior	$\mu \phi \sim \mathbf{N}(m_0, 1/(n_0\phi))$ $\phi \sim \mathbf{Gamma}(v_0/2, v_0 S_0^2/2)$
Likelihood	$L(\mu, \phi) = (2\pi)^{-n/2} \phi^{n/2} \exp(-\frac{\phi}{2} \{n(\bar{Y} - \mu)^2 + S^2(n - 1)\})$
Posterior	$n_n = n + n_0, \quad m_n = (n\bar{Y} + n_0 m_0) / n_n,$ $v_n = n + v_0, \quad S_n^2 = (v_0 S_0^2 + (n - 1)S^2 + \frac{nn_0}{n_n} (\bar{Y} - m_0)^2) / v_n$ $\mu \phi, \mathbf{Y} \sim N(m_n, \frac{1}{\phi n_n}),$ $\phi \mathbf{Y} \sim \mathbf{Gamma}(v_n/2, v_n S_n^2/2),$ $\mu \mathbf{Y} \sim \mathbf{St}(v_n, m_n, S_n^2/n_n)$
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Reference Analysis	
Prior	$p(\mu, \phi) \propto 1/\phi$
Posterior	$\mu \phi, \mathbf{Y} \sim N(\bar{Y}, \frac{1}{\phi n}),$ $\phi \mathbf{Y} \sim \mathbf{Gamma}((n - 1)/2, (n - 1)S^2/2),$ $\mu \mathbf{Y} \sim \mathbf{St}(n - 1, \bar{Y}, S^2/n)$
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