


$$\#1 \text{ (a) } \log l(k) = \log \prod_{i=1}^n k (1+x_i)^{-k-1} = \underline{\underline{n \log k - (k+1) \sum_{i=1}^n \log(1+x_i)}}$$

$$\text{(b) } \frac{\partial}{\partial k} \log l(k) = \frac{n}{k} - \sum_{i=1}^n \log(1+x_i)$$

$$\frac{\partial^2}{\partial k^2} \log l(k) = -\frac{n}{k^2}$$

$$I(k) = -E\left(-\frac{n}{k^2}\right) = \underline{\underline{\frac{n}{k^2}}}$$

$$\text{(c) } \frac{\partial}{\partial k} \log l(k) = 0 \Rightarrow \text{MLE } \hat{k} = \underline{\underline{\frac{n}{\sum_{i=1}^n \log(1+x_i)}}}}$$

$$\underline{\underline{\hat{k} \stackrel{\text{D}}{\sim} N\left(k, \frac{k^2}{n}\right)}}$$

#2.

See Exam_sol_2017_2.pdf.

$$\#3 \quad (a) \quad D = -2 \log L(\hat{\theta}) + 2 \log L(\text{full})$$

$$AIC = -2 \log L(\hat{\theta}) + 2 \cdot p$$

$$\begin{aligned} -2 \log L(\hat{\theta}) &= AIC - 2 \cdot p = 754.49 - 2 \times (48 - 43) \\ &= 744.49 \end{aligned}$$

$$\log L(\hat{\theta}) = -372.245$$

$$\begin{aligned} \log L(\text{full}) &= \frac{1}{2} (D + 2 \log L(\hat{\theta})) = \frac{1}{2} (513.75 - 744.49) \\ &= -115.37 \end{aligned}$$

(b) Model B: (1) AIC is smaller and (2) chisq test rejects hypothesis that model A is correct.

$$(c) \exp(2.88947 - 0.52878 + 1.21614) \\ = 36.1194$$

(d) Deviance is large and $\phi_{\text{hat}} \gg 1$.

(e) Poisson model assumes $\text{Var}(Y_i) = \text{Exp}(Y_i)$, but quasi-Poisson model assumes $\text{Var}(Y_i) = \phi \text{Exp}(Y_i)$ for some ϕ .

$$(f) 0.05279 \times \sqrt{13.93209} = 0.1970424$$

(g) Model C: F test fails to reject the hypothesis that model C is correct.

$$(h) F = \frac{(p_c - p_b) / (df_c - df_b)}{\hat{\phi}} = \frac{7.2729 / 1}{13.93209} = 0.522$$

$df_5 \quad 1 \times 42$

#4

#5 For $y \geq 2$,

$$(a) \quad P(Y=y) = 1 - \frac{1}{y} - \left(1 - \frac{1}{y-1}\right) = \frac{1}{y-1} - \frac{1}{y} = \frac{\cancel{y} - \cancel{y} + 1}{(y-1)y} = \frac{1}{(y-1)y}$$

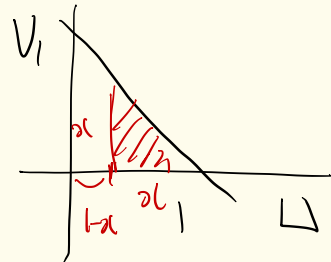
$$(b) \quad f(x) = F_x'(x)$$

$$F_x(x) = P(X \leq x) = P(1-U \leq x \mid U+V < 1)$$

$$= P(1-x \leq U \mid U+V < 1)$$

$$= \frac{P(1-x \leq U, U+V < 1)}{P(U+V < 1)}$$

$$= \frac{\int_0^x \int_{1-x}^v 1 \, du \, dv}{\int_0^1 \int_0^{1-u} 1 \, du \, dv} = \frac{\frac{1}{2}x^2}{\frac{1}{2}} = x^2$$



$$\text{So } \underline{\underline{f(x) = 2x}}$$

$$\#6 (a) \quad f(x|\theta) = \theta^x (1-\theta)^{1-x} \quad p(\theta) = 1 \quad 0 < \theta < 1$$

$$\theta|x \propto p(x|\theta) p(\theta)$$

$$= \theta^x (1-\theta)^{1-x} \cdot 1 \quad 0 < \theta < 1$$

$$\text{Beta}(x+1, 2-x)$$

$$(b) \quad E(\theta|x) = \frac{x+1}{x+1+2-x} = \frac{x+1}{3} = \hat{\theta}$$

$$(c) \quad E_x \left(\left(\frac{x+1}{3} - \theta \right)^2 \right) = E_x \left(\left(\frac{x+1-3\theta}{3} \right)^2 \right)$$

$$= \frac{1}{9} \left[E_x(x^2) + 2(1-3\theta) \underbrace{E_x(x)}_{\theta} + (1-3\theta)^2 \right]$$

$$= \frac{1}{9} \left[\frac{\theta(1-\theta) + \theta^2}{\cancel{\theta-\theta^2}} + \cancel{2\theta} - \cancel{6\theta^2} + 1 - \cancel{6\theta} + \cancel{9\theta^2} \right]$$

$$= \frac{1}{9} \left[3\theta^2 - 3\theta + 1 \right] = \frac{1}{3} \theta^2 - \frac{1}{3} \theta + \frac{1}{9}$$

$$(d) \int_0^1 \left[\frac{1}{3} \theta^2 - \frac{1}{3} \theta + \frac{1}{9} \right] d\theta = \frac{1}{9} - \frac{1}{6} + \frac{1}{9}$$

$$= \frac{2-3+2}{18} = \frac{1}{18}$$

7 (a) μ_1, μ_2, τ

$$(b) p(\mu_1, \mu_2, \tau, x, y) \propto p(x | \mu_1, \tau) p(y | \mu_2, \tau) p(\mu_1) p(\mu_2) p(\tau)$$

$$= \tau^{\frac{n_1}{2}} \exp\left(-\frac{\tau}{2} \underbrace{\sum_{i=1}^{n_1} (x_i - \mu_1)^2}_{[n_1 \mu_1^2 - 2\mu_1 n_1 \bar{x} + \sum x_i^2]}\right) \times \tau^{\frac{n_2}{2}} \exp\left(-\frac{\tau}{2} \sum_{i=1}^{n_2} (y_i - \mu_2)^2\right)$$

$$\times \frac{1}{\tau}$$

$$p(\mu_1 | \mu_2, \tau, x, y) \propto \exp\left(-\frac{\tau n_1}{2} (\mu_1 - \bar{x})^2\right)$$

$$\sim N\left(\bar{x}, \frac{1}{\tau n_1}\right)$$

$$p(\mu_2 | \mu_1, x, y, \tau) \propto \exp\left(-\frac{\tau}{2} n^2 (\mu_2 - \bar{y})^2\right)$$

$$\sim N(\bar{y}, \frac{1}{\tau n^2})$$

$$p(\tau | \mu_1, \mu_2, x, y) \propto \tau^{\frac{1}{2}(n_1+n_2)-1} \exp\left(-\frac{\tau}{2} \left[\sum_{i=1}^{n_1} (x_i - \mu_1)^2 + \sum_{j=1}^{n_2} (y_j - \mu_2)^2 \right]\right)$$

$$\sim \Gamma\left(\frac{1}{2}(n_1+n_2), \frac{1}{2} \left[\sum_{i=1}^{n_1} (x_i - \mu_1)^2 + \sum_{j=1}^{n_2} (y_j - \mu_2)^2 \right]\right)$$

(c)

Start with $\tau(0), \mu_1(0), \mu_2(0)$. Given $\tau(n), \mu_1(n), \mu_2(n)$, generate $\tau(n+1)$ from $\tau | \mu_1(n), \mu_2(n), \mu_1(n+1) \sim \mu_1 | \tau(n+1), \mu_2(n), \mu_2(n+1) \sim \mu_2 | \tau(n+1), \mu_1(n+1)$: do this step for $n = 0$ to M .

(d)

Run multiple chains with widely separated initial values. Informal check - make a trace plot and see whether multiple chains come together and start to behave similarly. Formal method - compute BGR statistic which compare within-chain variability to between-chain variability. If BGR statistic < 1.05 , it's good.

#8 for $l = 1, \dots, L$

- ① Simulate $\theta^{(l)} \sim p(\theta | y)$
- ② Simulate $\tilde{y}^{(l)} \sim p(\tilde{y} | \theta^{(l)})$

Then, $\tilde{y}^{(1)}, \tilde{y}^{(2)}, \dots, \tilde{y}^{(L)}$ are samples from $p(\tilde{y} | y)$.

$\frac{1}{L} \sum_{l=1}^L \tilde{y}^{(l)} \Rightarrow$ estimator for the mean of the
posterior predictive distribution.