

UNIVERSITY OF TECHNOLOGY SYDNEY

SCHOOL OF MATHEMATICAL AND PHYSICAL SCIENCES

37457 Advanced Bayesian Methods

Practice Final Examination

SOLUTIONS

1. (a) The maximal cliques are  $x_1 - x_2$ ,  
 $x_6 - x_7$  and  $x_{12} - x_{16}$ , for example  
 and each contain 2 nodes.

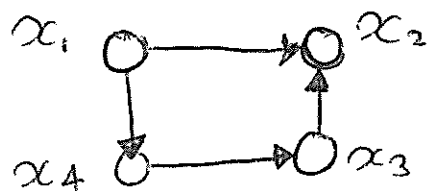
(b) 
$$p(x_i | \text{rest}) = p(x_i | \text{Markov blanket of } x_i)$$

$$= p(x_i | x_2, x_5)$$

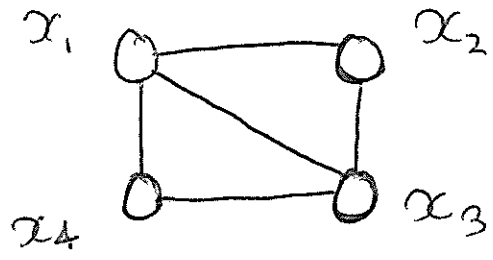
(c) Via the same argument used for (b),

- i.  $p(x_8 | \text{rest}) = p(x_8 | x_4, x_7, x_{12})$
- ii.  $p(x_{11} | \text{rest}) = p(x_{11} | x_7, x_{10}, x_{15}, x_{16})$
- iii.  $p(x_3 | \text{rest}) = p(x_3 | x_9, x_{14})$

(d) i. The smallest ancestral sub-graph containing  $\{x_1, x_2, x_3, x_4\}$  is, trivially, the full DAG:



Moralising this DAG we get



Since  $\{x_1, x_3\}$  separates  $\{x_2\}$  and  $\{x_4\}$  in this moral graph we can conclude that

$$x_2 \perp\!\!\!\perp x_4 \mid \{x_1, x_3\}$$

ii. The smallest ancestral sub-graph containing  $\{x_1, x_3\}$  is  $x_1, \emptyset$

Moralising this DAG we get (trivially)



which is such that  $\{x_1\}$  and  $\{x_3\}$  are separated. Hence

$$x_1 \perp\!\!\!\perp x_3 \mid \emptyset \quad (\emptyset \text{ is the empty set})$$

which simply means

$$x_1 \perp\!\!\!\perp x_3 .$$

(e)

$$\begin{aligned}
 p(x_1, x_2, x_3) &\propto \Psi_{12}(x_1, x_2) \Psi_3(x_3) \\
 &= (x_1 + x_2 + 1) 6^{x_3}, \quad x_1, x_2, x_3 \in \{0, 1\}.
 \end{aligned}$$

The normalising factor is:

$$\begin{aligned}
 &\sum_{x_1=0}^1 \sum_{x_2=0}^1 \sum_{x_3=0}^1 (x_1 + x_2 + 1) 6^{x_3} \\
 &= \left\{ \sum_{x_1=0}^1 \sum_{x_2=0}^1 (x_1 + x_2 + 1) \right\} \left\{ \sum_{x_3=0}^1 6^{x_3} \right\} \\
 &= \left\{ (0+0+1) + (0+1+1) + (1+0+1) + (1+1+1) \right\} \{6^0 + 6^1\} \\
 &= (1 + 2 + 2 + 3)(1 + 6) \\
 &= 56
 \end{aligned}$$

$$\Rightarrow p(x_1, x_2, x_3) = \begin{cases} \frac{(x_1 + x_2 + 1) 6^{x_3}}{56}, & x_1, x_2, x_3 \in \{0, 1\} \\ 0, & \text{otherwise} \end{cases}$$

2.

①

$$(a) \quad \{ \gamma_1, \gamma_2, \gamma_3 \}$$

$$(b) \quad \{ \beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, y \}$$

$$(c) \quad p(\sigma^2 | \text{rest}) = p(\sigma^2 | \text{Markov blanket of } \sigma^2)$$

$$= p(\sigma^2 | \beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, y)$$

$$\propto p(y, \beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, \sigma^2)$$

$$\propto p(y | \beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, \sigma^2) p(\sigma^2).$$

We are given  $p(y | \beta_0, \beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2, \gamma_3, \sigma^2)$  and

$$\sigma^2 \sim \text{Inverse-Gamma}(\sigma^2)$$

$$\Rightarrow p(\sigma^2) = \frac{(0.01)^{0.01}}{\Gamma(0.01)} (\sigma^2)^{-0.01-1} e^{-0.01/\sigma^2}, \quad \sigma^2 > 0$$

Ignoring multiplicative factors that don't involve  $\sigma^2$ :

$$p(\sigma^2 | \text{rest}) \propto \prod_{i=1}^n \left[ (\sigma^2)^{-\frac{1}{2}} \exp \left\{ \frac{-(y_i - \beta_0 - \beta_1 \gamma_{1i} - \beta_2 \gamma_{2i} - \beta_3 \gamma_{3i})^2}{2\sigma^2} \right\} \right]$$

$$\times (\sigma^2)^{-0.01-1} e^{-0.01/\sigma^2}, \quad \sigma^2 > 0$$

$$\Rightarrow p(\sigma^2 | \text{rest}) \propto (\sigma^2)^{-(\frac{n}{2} + 0.01) - 1} \\ \times e^{-\frac{0.01 + \frac{1}{2} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_{1i} - \beta_2 x_{2i} - \beta_3 x_{3i})^2}{\sigma^2}}$$

which is proportional to the

Inverse Gamma density function with  
shape parameter  $A = \frac{n}{2} + 0.01$

and scale parameter  $B = 0.01 + \frac{1}{2} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_{1i} - \beta_2 x_{2i} - \beta_3 x_{3i})^2$

Hence

$$\sigma^2 | \text{rest} \sim \text{Inverse-Gamma} \left( 0.01 + \frac{n}{2}, 0.01 + \frac{1}{2} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_{1i} - \beta_2 x_{2i} - \beta_3 x_{3i})^2 \right)$$

$$(d) p(\rho | \text{rest}) = p(\rho | \gamma_1, \gamma_2, \gamma_3)$$

$$\propto p(\gamma_1, \gamma_2, \gamma_3 | \rho) p(\rho)$$

$$\propto \rho^{\gamma_1 + \gamma_2 + \gamma_3} (1 - \rho)^{3 - (\gamma_1 + \gamma_2 + \gamma_3)}$$

$$\times \rho^{24} (1 - \rho)^{39}$$

$\Rightarrow$ 

$$p(p|\text{rest}) \propto p^{(25 + \gamma_1 + \gamma_2 + \gamma_3) - 1} (1-p)^{43 - (\gamma_1 + \gamma_2 + \gamma_3) - 1}$$

$$\Rightarrow p|\text{rest} \sim \text{Beta}\left(25 + \sum_{j=1}^3 \gamma_j, 43 - \sum_{j=1}^3 \gamma_j\right)$$

# 3.

Ⓞ

(a)

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

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

$$\propto \prod_{i=1}^{10} (\theta e^{-\theta x_i}) \cdot \theta^{39} e^{-5\theta}$$

$$= \theta^{49} e^{-\theta(5 + \sum_{i=1}^{10} x_i)}$$

$$= \theta^{50-1} e^{-(5 + \sum_{i=1}^{10} x_i)\theta}, \quad \theta > 0$$

$\Rightarrow p(\theta|x)$  is the Gamma(50,  $5 + \sum_{i=1}^{10} x_i$ ) density function

$$\Rightarrow p(\theta|x) = \frac{(5 + \sum_{i=1}^{10} x_i)^{50}}{\Gamma(50)} \theta^{49} e^{-(5 + \sum_{i=1}^{10} x_i)\theta}, \quad \theta > 0$$

(b) Using the result for the mean of the Gamma distribution given in the POSSIBLY USEFUL INFORMATION sheet:



(H)

$$\hat{\theta}_{\text{Bayes}} = E(\theta|x) = \frac{50}{5 + \sum_{i=1}^{10} x_i}$$

$$(c) \quad \bar{x} = 9.96 \Rightarrow \sum_{i=1}^{10} x_i = 10 \times 9.96 = 99.6$$

Hence

$$\hat{\theta}_{\text{Bayes}} = \frac{50}{104.6} = \frac{500}{1046}$$

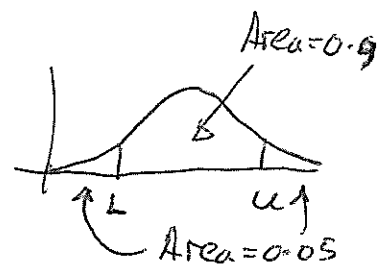
(d) Based on Corla's observed data

 $p(\theta|x)$  is the

Gamma(50, 104.6) density function.

A 90% credible interval for  $\theta$  is $(L, u)$ 

where



$$0.05 = P(G \leq L) \quad \text{and} \quad 0.95 = P(G \leq u)$$

where  $G \sim \text{Gamma}(50, 104.6)$

(I)

ie.  $0.05 = F(L)$  and  $0.95 = F(u)$

where  $F$  is the cumulative dist<sup>n</sup> function of  $G$

$$\Leftrightarrow L = Q(0.05) \text{ and } u = Q(0.95).$$

Carla should obtain

quantile-gamma(0.05, 50, 104.6)

and quantile-gamma(0.95, 50, 104.6)

using SASQWATCH. These answers are the lower and upper limits, respectively, of the required 90% credible interval.

(e) Since, according to the density  $f^n$   $p(\theta|x)$ ,

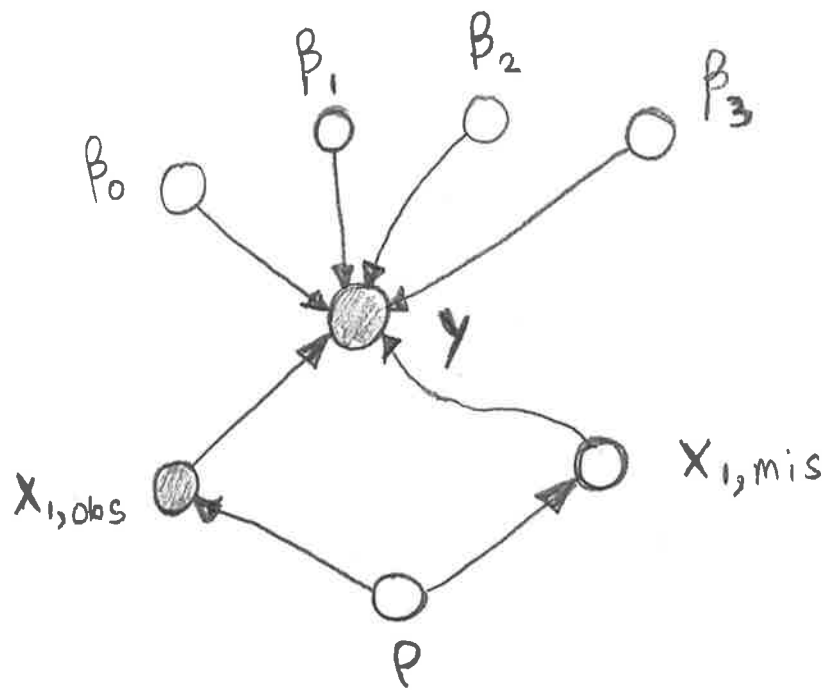
$$0.9 = P(L < \theta < u)$$

$$= P\left(\frac{1}{u} < \frac{1}{\theta} < \frac{1}{L}\right)$$

the interval  $\left(\frac{1}{u}, \frac{1}{L}\right)$  is a 90% credible interval for  $\frac{1}{\theta}$ .

4.

(a)



(b)

### MEMORANDUM

From: Annika Chadwick

To: Leroy Meng

Re: Bayesian analysis of your  
lung disease study data

The Bayesian Poisson regression model (which accounted for missingness in the smoking data) revealed

that smoking and dietary saturated fat have statistically significant positive impacts on the mean

response (number of carcinogen-DNA complexes in the lungs). There was no gender effect.

(c)

