

UNIVERSITY OF OSLO

Faculty of mathematics and natural sciences

Exam in: STK4021 — Applied Bayesian statistics - Home exam

Day of examination: 2013

Examination hours: 15.00 – 19.00.

This problem set consists of 5 pages.

Appendices: None

Permitted aids: Calculator, plus one single sheet of paper with the candidate's

Please make sure that your copy of the problem set is complete before you attempt to answer anything.

Problem 1

(a) $y \sim N(\theta_0, \sigma_0^2 + 1)$

(b) We have

$$\begin{pmatrix} \theta \\ y \end{pmatrix} \sim N \left(\begin{pmatrix} \theta_0 \\ \theta_0 \end{pmatrix}, \begin{pmatrix} \sigma_0^2 & \sigma_0^2 \\ \sigma_0^2 & \sigma_0^2 + 1 \end{pmatrix} \right)$$

giving that $\theta|y$ is Gaussian with

$$\begin{aligned} E[\theta|y] &= \theta_0 + \frac{\sigma_0^2}{\sigma_0^2 + 1}(y - \theta_0) \\ &= \frac{\theta_0 + \sigma_0^2 y}{\sigma_0^2 + 1} \end{aligned}$$

$$\text{Var}[\theta|y] = \sigma_0^2 - \frac{\sigma_0^4}{\sigma_0^2 + 1} = \frac{\sigma_0^2}{\sigma_0^2 + 1}$$

(c) We have

$$\frac{\theta - \frac{\theta_0 + \sigma_0^2 y}{\sigma_0^2 + 1}}{\frac{\sigma_0}{\sqrt{\sigma_0^2 + 1}}} \sim N(0, 1)$$

which gives

$$\Pr(\theta \leq 0) = \Pr \left(Z \leq -\frac{\frac{\theta_0 + \sigma_0^2 y}{\sigma_0^2 + 1}}{\frac{\sigma_0}{\sqrt{\sigma_0^2 + 1}}} \right)$$

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to make this probability equal to 0.1, we need

$$-\frac{\frac{\theta_0 + \sigma_0^2 y}{\sigma_0^2 + 1}}{\frac{\sigma_0}{\sqrt{\sigma_0^2 + 1}}} = -1.282$$

or

$$\frac{\theta_0 + \sigma_0^2 y}{\sigma_0^2 + 1} = 1.282 \frac{\sigma_0}{\sqrt{\sigma_0^2 + 1}}$$

or

$$y = \frac{1.282\sigma_0\sqrt{\sigma_0^2 + 1} - \theta_0}{\sigma_0^2} = 3.728$$

Problem 2

(a) We have

$$\begin{aligned}\ell(\theta) &= \sum_{i=1}^n \left[-\frac{1}{2}\theta y_i^2 + \log(\theta) + \log(y_i) \right] \\ \frac{\partial}{\partial \theta} \ell(\theta) &= \sum_{i=1}^n \left[-\frac{1}{2}y_i^2 + \frac{1}{\theta} \right] = -\frac{1}{2} \sum_{i=1}^n y_i^2 + \frac{n}{\theta} \\ \frac{\partial^2}{\partial \theta^2} \ell(\theta) &= -\frac{n}{\theta^2}\end{aligned}$$

so the function is unimodal and we obtain

$$\hat{\theta}_{ML} = \frac{2n}{\sum_{i=1}^n y_i^2} = 2w_n^{-1}$$

(b) We have

$$\begin{aligned}p(\theta|\mathbf{y}) &\propto \theta^{a-1} e^{-b\theta} \prod_{i=1}^n e^{-0.5\theta y_i^2} \theta y_i \propto \theta^{a+n-1} e^{[b+0.5\sum_{i=1}^n y_i^2]\theta} \\ &\propto \text{Gamma}(a_n, b_n)\end{aligned}$$

with

$$a_n = a + n \quad , \quad b_n = b + 0.5 \sum_{i=1}^n y_i^2$$

(c) Under square root loss, the Bayes rule is the posterior expectation, that is

$$\hat{\theta}_B = \frac{a + n}{b + 0.5 \sum_{i=1}^n y_i^2} = \frac{2a + 2n}{2b + \sum_{i=1}^n y_i^2}$$

90% credibility intervals can be found by taking the 0.05 and 0.95 quantiles in the Gamma distribution about.

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(d) We have

$$\begin{aligned}
 p(y_{n+1}|\mathbf{y}) &= \int_{\theta} p(y_{n+1}|\theta)p(\theta|\mathbf{y})d\theta \\
 &= \int_{\theta} e^{-0.5\theta y_{n+1}^2} \theta y_{n+1} \frac{b_n^{a_n}}{\Gamma(a_n)} \theta^{a_n-1} e^{-b_n\theta} d\theta \\
 &= a_n y_{n+1} \frac{b_n^{a_n}}{[b_n + 0.5y_{n+1}^2]^{a_n+1}} \times \\
 &\quad \int_{\theta} \frac{[b_n + 0.5y_{n+1}^2]^{a_n+1}}{\Gamma(a_n + 1)} \theta^{a_n+1-1} e^{-[b_n+0.5y_{n+1}^2]\theta} d\theta \\
 &= a_n y_{n+1} \frac{b_n^{a_n}}{[b_n + 0.5y_{n+1}^2]^{a_n+1}}
 \end{aligned}$$

Problem 3

(a) We have

$$\begin{aligned}
 \Pr(M_1|y) &\propto \Pr(M_1)p(y|M_1) = \pi_1 f_1(y) \\
 \Pr(M_2|y) &\propto \Pr(M_2)p(y|M_2) = \pi_2 f_2(y)
 \end{aligned}$$

Since these probabilities needs to sum to one, we obtain

$$\Pr(M_1|y) = \frac{\pi_1 f_1(y)}{\pi_1 f_1(y) + \pi_2 f_2(y)} = \frac{\pi_1}{\pi_1 + \pi_2 f_2(y)/f_1(y)}$$

(b) We have

$$\begin{aligned}
 E[L(M, 2)|y] &= 1 \cdot \Pr(M = 1|y) + 0 \cdot \Pr(M = 2|y) = 1 - \Pr(M_2|y) \\
 E[L(M, 1)|y] &= 1 \cdot \Pr(M = 2|y) + 0 \cdot \Pr(M = 1|y) = 1 - \Pr(M_1|y)
 \end{aligned}$$

We then make decision 1 if $1 - \Pr(M_1|y) < 1 - \Pr(M_2|y)$ or $\Pr(M_1|y) > \Pr(M_2|y)$.

(c) We classify to normal if $f_1(y) > f_2(y)$, that is

$$\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}y^2) > \frac{1}{\sqrt{2}} \exp(-\sqrt{2}|y|)$$

or

$$-\frac{1}{2}y^2 - \frac{1}{2} \log(\pi) > -\sqrt{2}|y|$$

or

$$y^2 < 2\sqrt{2}|y| - \log(\pi)$$

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(d) Now

$$\Pr(M_1|y_1, \dots, y_n) \propto \pi_1 \prod_{i=1}^n f_1(y_i)$$

$$\Pr(M_2|y_1, \dots, y_n) \propto \pi_2 \prod_{i=1}^n f_2(y_i)$$

(e) (Tricky!!) We have that

$$\frac{\Pr(M_1|\mathbf{y})}{\Pr(M_2|\mathbf{y})} = \exp\left(n \frac{1}{n} \sum_{i=1}^n \log f_1(y_i) - n \frac{1}{n} \sum_{i=1}^n \log f_2(y_i)\right)$$

$$\approx \exp(n[E[\log f_1(y_i)] - E[\log f_2(y_i)]])$$

for large n

For $y_i \sim f_1$, we have

$$E[\log f_1(y_i)] - E[\log f_2(y_i)] = \int_y f_1(y) \log \frac{f_1(y)}{f_2(y)} dy$$

which is the Kullback-Leibler distance between f_1 and f_2 . This distance is always positive, making the fraction above increase exponentially and making $\Pr(M_1|y)$ convergence towards 1.

For $y_i \sim f_2$, we have

$$E[\log f_1(y_i)] - E[\log f_2(y_i)] = \int_y f_2(y) \log \frac{f_1(y)}{f_2(y)} dy = - \int_y f_2(y) \log \frac{f_2(y)}{f_1(y)} dy$$

which is the minus Kullback-Leibler distance between f_2 and f_1 . This distance is again always positive, making the fraction above decrease exponentially and making $\Pr(M_1|y)$ convergence towards 0.

Problem 4

(a) We have

$$p(y|\theta) = \prod_{i=1}^n p(y_i|\theta) = \prod_{i=1}^n \frac{1}{\theta} I(0 \leq y_i \leq \theta) = \theta^{-n} I(0 \leq \min(y_i) \leq \max(y_i) \leq \theta)$$

Now since the maximum is larger than 1 and θ^{-n} will decrease with increasing values of $\theta > 1$, we find that the maximum likelihood estimate is $\max(y_i) = 4.294$.

(b) We now have

$$p(\theta|y) \propto p(\theta)p(y|\theta) \propto \theta^{-(n+1)} I(\theta \geq 4.294)$$

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Now

$$\int_{4.294}^{\infty} \theta^{-11} d\theta = \left[-\frac{1}{10}\theta^{-10}\right]_{4.294}^{\infty} = \frac{1}{10}4.294^{-10}$$

giving

$$p(\theta|\mathbf{y}) = 10 * 4.294^{10}\theta^{-11}I(\theta \geq 4.294)$$

For the absolute loss, we have that the Bayes estimate is the median.

Now

$$\begin{aligned} \Pr(\theta \leq u|\mathbf{y}) &= \int_{4.294}^u [10 * 4.294^{10}\theta^{-11}]dy \\ &= 10 * 4.294^{10} \left[-\frac{1}{10}\theta^{-10}\right]_{4.294}^u \\ &= 10 * 4.294^{10} \left[\frac{1}{10}4.294^{-10} - \frac{1}{10}u^{-10}\right] \\ &= 1 - 4.294^{10}u^{-10} \end{aligned}$$

and putting this to 0.5, we obtain $\hat{\theta} = 4.294 * 2^{1/10} = 4.602$