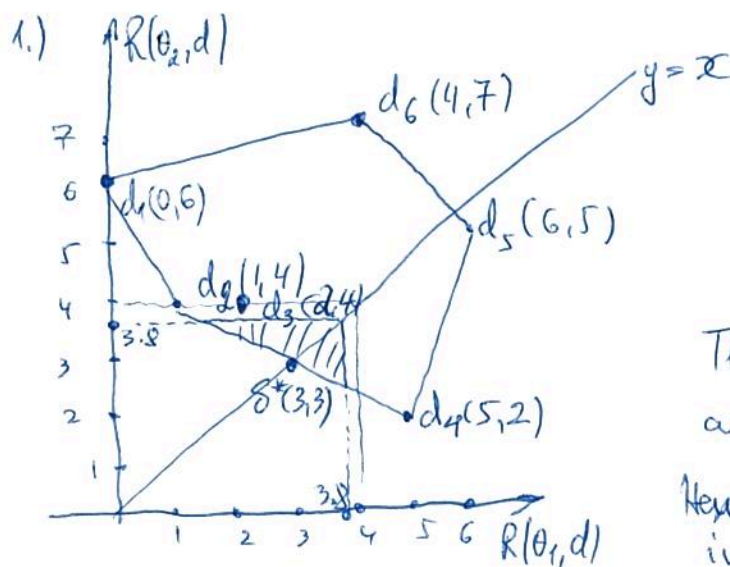


Solutions to Assignment 1, 2014

MATH5905

(1)



a) $d_{\min_{\theta_1, \theta_2} x}$ delivers

$$\min_{d \in D} \max_{\theta_1, \theta_2} \{R(\theta_1, d), R(\theta_2, d)\}$$

The minimax risks of the 6 rules are $(6, 4, 4, 5, 6, 7)$, respectively. Hence there are two minimax rules in D : namely, d_2 and d_3 .

b) See the convex hull plotted above

c) We need to find the intersection of the line $y=x$ with the line $y-4 = \frac{4-2}{1-5}(x-1)$, i.e. solve

$$\begin{cases} y=x \\ y-4 = \frac{1}{2}(x-1) \end{cases} \Rightarrow y=x=3$$

The solution gives $\delta^*(3, 3)$ as the minimax rule in D , with a minimax risk of 3.

d) Apparently $\delta^* = \begin{cases} \text{choose } d_2 \text{ with probability } \alpha \\ \text{choose } d_4 \text{ with probability } 1-\alpha \end{cases}$

$$\text{But } R(\theta_1, \delta^*) = \alpha R(\theta_1, d_2) + (1-\alpha) R(\theta_1, d_4)$$

$$3 = \alpha * 1 + (1-\alpha) * 5 \Rightarrow \alpha = \frac{1}{2}$$

that is: δ^* chooses d_2 with probability $\frac{1}{2}$ and d_4 with probability $\frac{1}{2}$.

e) The line $\overline{d_2 d_4}$ has a slope of $-\frac{1}{2}$. The Bayes risk w.r. to any prior $(p, 1-p)$ is calculated as $px + (1-p)y$ for a risk point (x, y) .

(2)

All rules with risk points (x, y) satisfying $px + (1-p)y = c$, are equivalent w.r. to the Bayes criterion and have the same Bayes risk of c .

We want δ^* to be Bayes $\rightarrow c = 3$

So $px + (1-p)y = 3$ and the slope

$-\frac{p}{1-p}$ must match the slope of $d_2 d_4$ (which is $-\frac{1}{2}$)

$$\text{Hence } -\frac{p}{1-p} = -\frac{1}{2} \Rightarrow p = \frac{1}{3}$$


Hence δ^* turns out to be minimax and Bayes w.r. to the prior $(1/3, 2/3) = (p^*, 1-p^*)$. (This is also the best favourable prior)

f) All rules with risk points (x, y) satisfying

$$\frac{4}{5}x + \frac{1}{5}y = \text{const} \text{ are equivalent w.r. to their Bayes risk.}$$

The slope of this line is -4 . We want to minimize the Bayes risk when looking for the Bayes rule. Hence we "move" the lines with slopes of (-4) south-west while still keeping intersected with the risk set. The extreme point is $(0, 6)$. Hence d_1 is the Bayes rule w.r. to the prior $(\frac{4}{5}, \frac{1}{5})$. Its Bayes risk is:

$$0 \times \frac{4}{5} + 6 \times \frac{1}{5} = \underline{1.2}$$

g) See the shaded area  on the graph of the risk set. It extends north-east up to the point $(3, 8, 3.8)$.

2.) It is given that $f(x|\lambda) = \frac{e^{-\lambda} \lambda^x}{x!}$, $x=0,1,2,\dots$

and the prior is $\tau(\lambda) = \frac{\lambda^{a-1} e^{-\lambda/b}}{\Gamma(a)b^a}$, $\lambda > 0$

a) For $\mathbf{X} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{pmatrix}$ we get $f(\mathbf{X}|\lambda) = \frac{e^{-T\lambda} \lambda^{\sum_{i=1}^T x_i}}{\prod_{i=1}^T (x_i!)}$

Then

$$h(\lambda|\mathbf{X}) \propto e^{-T\lambda - \frac{\lambda}{b}} \lambda^{\sum_{i=1}^T x_i + a - 1} = e^{-\lambda(T + \frac{1}{b})} \lambda^{\sum_{i=1}^T x_i + a - 1}$$

Hence $h(\lambda|\mathbf{X})$ must be the Gamma density with parameters $\sum_{i=1}^T x_i + a$ and $\frac{b}{Tb+1}$, i.e.

$$h(\lambda|\mathbf{X}) \sim \text{Gamma}\left(\sum_{i=1}^T x_i + a, \frac{b}{Tb+1}\right)$$

The Bayes estimator of λ w.r. to quadratic loss is the expected value of this (conditional) density. This is known to be the product of the parameters: $\hat{\lambda}_{\text{Bayes}} = \frac{(\sum_{i=1}^T x_i + a)b}{Tb+1}$

b) Given the data, we have $T=6$, $b=2$, $a=2$
 $\mathbf{X} = (0, 2, 3, 3, 2, 2)$ so $\sum_{i=1}^T x_i = 12$

and $\hat{\lambda}_{\text{Bayes}} = 2 \frac{2}{13}$ (which is just a bit higher than the hypothetical borderline value of 2 so the role of the prior in testing $H_0: \lambda \leq 2$ vs $H_1: \lambda > 2$ becomes very important. To test in Bayesian setting we need

$P(\lambda \leq 2|\mathbf{X})$ and the posterior is $\text{Gamma}(14, \frac{2}{13})$

$$\text{Now } P(\lambda \leq 2|\mathbf{X}) = \int_0^2 \frac{e^{-\frac{13\lambda}{2}} \lambda^{13}}{\Gamma(14)(\frac{2}{13})^{14}} d\lambda = \frac{1}{\Gamma(14)(\frac{2}{13})^{14}} \int_0^2 e^{-\frac{13\lambda}{2}} \lambda^{13} d\lambda$$

$= 0.427$ (using integration programme for example). The posterior being $< \frac{1}{2}$ implies to reject the Bank's claim that $\lambda < 2$.

Q3/

X_1, X_2, \dots, X_n are i.i.d. uniform in $(0, \theta)$
 $\Rightarrow f(x_i|\theta) = \frac{1}{\theta} I_{(x_i, \infty)}(\theta)$

$$\text{Hence } \prod_{i=1}^n f(x_i|\theta) = \frac{1}{\theta^n} I_{(x_{(n)}, \infty)}(\theta)$$

The prior $\pi(\theta) = \begin{cases} \beta \alpha^\beta \theta^{-(\beta+1)} & \theta > \alpha > 0 \\ 0 & \text{otherwise} \end{cases}$ can also be written
 via indicators on "one line" as $\beta \alpha^\beta \theta^{-(\beta+1)} I_{(\alpha, \infty)}(\theta)$

The joint is a product; the product of indicators is an indicator
 so we end up with

$$\begin{aligned} \prod_{i=1}^n f(x_i|\theta) \pi(\theta) &= \frac{\beta \alpha^\beta \theta^{-(\beta+1)}}{\theta^n} I_{(\max(x_{(n)}, \alpha), \infty)}(\theta) = \\ &= \beta \alpha^\beta \theta^{-(n+\beta+1)} I_{(\max(x_{(n)}, \alpha), \infty)}(\theta) \end{aligned}$$

Hence the Bayes estimator w.r. quadratic loss is

$$E(\theta|X) = \frac{\beta \alpha^\beta \int_{\max(x_{(n)}, \alpha)}^{\infty} \theta^{-(n+\beta)} d\theta}{\beta \alpha^\beta \int_{\max(x_{(n)}, \alpha)}^{\infty} \theta^{-(n+\beta+1)} d\theta} =$$

$$= \frac{(n+\beta)}{(n+\beta-1)} \max(x_{(n)}, \alpha)$$

(5)

(Q4) The observation scheme: we have $n=1$ observation only from a geometric distribution with

$$f(x|\theta) = (1-\theta)^{x-1}\theta$$

where $\theta \in (0,1)$ is the probability of success in a single trial (since our data expresses the total number of trials until the first success).

The two priors are $\tau_1(\theta) = 6\theta(1-\theta)$ of the aviation minister and $\tau_2(\theta) = 4\theta^3$ of the prime minister.

The two corresponding posteriors are:

$$h_1(\theta|x) \propto \theta^2(1-\theta)^x \quad \text{and} \quad h_2(\theta|x) \propto \theta^4(1-\theta)^{x-1}$$

These can easily be identified as

$$h_1(\theta|x) \sim \text{Beta}(3, x+1)$$

$$h_2(\theta|x) \sim \text{Beta}(5, x)$$

We have 2 actions available: $a_0 \equiv \text{continue}$
 $a_1 \equiv \text{abandon}$

The losses related to these actions are:-

$$L(\theta, a_0) = \begin{cases} \frac{1}{2} - \theta & \text{if } \theta < \frac{1}{2} \\ 0 & \text{if } \theta \geq \frac{1}{2} \end{cases} \quad \text{and}$$

$$L(\theta, a_1) = \begin{cases} 0 & \text{if } \theta < \frac{1}{2} \\ \theta - \frac{1}{2} & \text{if } \theta \geq \frac{1}{2} \end{cases}$$

6

For an optimal Bayes decision we need to

compare: $Q(x, a_0) = \int_{\frac{1}{2}}^1 (\frac{1}{2} - \theta) h(\theta|x) d\theta = \frac{1}{2} \int_0^1 h(\theta|x) d\theta - \int_0^{\frac{1}{2}} \theta h(\theta|x) d\theta$ with

$$Q(x, a_1) = \int_{\frac{1}{2}}^1 (\theta - \frac{1}{2}) h(\theta|x) d\theta = \int_{\frac{1}{2}}^1 \theta h(\theta|x) d\theta - \frac{1}{2} \int_{\frac{1}{2}}^1 h(\theta|x) d\theta.$$

Then a_0 would be preferred to a_1 if $Q(x, a_0) < Q(x, a_1)$ (alternatively if $Q(x, a_0) > Q(x, a_1)$ then a_1 would be preferred (and there is hesitation if $Q(x, a_0) = Q(x, a_1)$)

From the inequality

$$\frac{1}{2} \int_{\frac{1}{2}}^1 h(\theta|x) d\theta - \int_0^{\frac{1}{2}} \theta h(\theta|x) d\theta < \int_{\frac{1}{2}}^1 \theta h(\theta|x) d\theta - \frac{1}{2} \int_{\frac{1}{2}}^1 h(\theta|x) d\theta$$

we see that adding $\pm \frac{1}{2} \int_0^1 h(\theta|x) d\theta$, noting that $\frac{1}{2} \int_0^1 h(\theta|x) d\theta = \frac{1}{2}$ and re-arranging we get

$$\frac{1}{2} \int_0^1 h(\theta|x) d\theta - \int_0^{\frac{1}{2}} \theta h(\theta|x) d\theta < \int_{\frac{1}{2}}^1 \theta h(\theta|x) d\theta - \frac{1}{2} + \frac{1}{2} \int_0^1 h(\theta|x) d\theta$$

Hence $\frac{1}{2} < \int_0^1 \theta h(\theta|x) d\theta = E(\theta|x)$

In other words, we choose $a_0 \equiv$ continue if $E(\theta|x) > \frac{1}{2}$ (and, of course, this decision is also intuitively appealing).

Now, for a Beta (α, β) distribution, the expected value is $\frac{\alpha}{\alpha+\beta}$ which implies in our case:

$E(\theta|x) = 3/(x+4)$ for aviation minister

$E(\theta|x) = 5/(x+5)$ for prime minister

Hence the aviation minister wants the project to continue when $x=1$, hesitates when $x=2$ and wants to stop when $x=3, 4, 5, \dots$. The prime minister wants to continue when $x=1, 2, 3, 4$; hesitates when $x=5$ and wants to stop when $x=6, 7, 8, \dots$. Obviously, for $x=3$ and $x=4$ we have the most serious disagreement

Q5] a) Let $Z_i = \frac{X_i}{\sigma}$, $i=1,2,\dots,n$, $\sigma > 0$

$$P(Z_i < z) = P\left(X_i < \sigma z\right) = F_{\sigma}(\sigma z) = F\left(\frac{\sigma z}{\sigma}\right) = F(z)$$

i.e. the distribution of Z_i does not depend on σ .

$$F_{X_1/X_n, X_2/X_n, \dots, X_{n-1}/X_n}(y_1, y_2, \dots, y_{n-1}) = P\left(\frac{X_1}{X_n} \leq y_1, \dots, \frac{X_{n-1}}{X_n} \leq y_{n-1}\right)$$

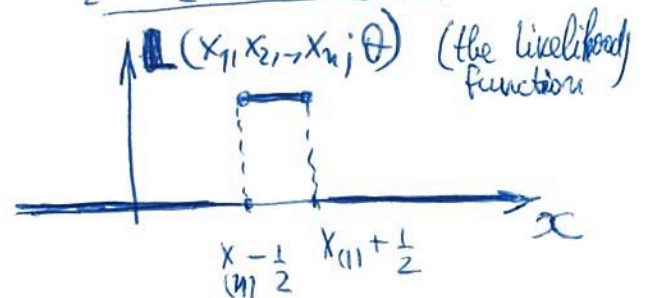
$$= P\left(\frac{X_1/\sigma}{X_n/\sigma} \leq y_1, \dots, \frac{X_{n-1}/\sigma}{X_n/\sigma} \leq y_{n-1}\right) = P\left(\frac{Z_1}{Z_n} \leq y_1, \dots, \frac{Z_{n-1}}{Z_n} \leq y_{n-1}\right)$$

which also does not depend on σ . Then for any statistic $T = g\left(\frac{X_1}{X_n}, \dots, \frac{X_{n-1}}{X_n}\right)$, we arrive at the conclusion, that its distribution would not depend on σ .

b) Since X_1, \dots, X_n are i.i.d. uniform in $[\theta - \frac{1}{2}, \theta + \frac{1}{2}]$

their density is $f(x_i, \theta) = 1 * I_{[\theta - \frac{1}{2}, \theta + \frac{1}{2}]}(x_i) = f(x_i - \theta)$

$$\begin{aligned} \text{Then } L(X_1, X_2, \dots, X_n; \theta) &= \prod_{i=1}^n I_{[\theta - \frac{1}{2}, \theta + \frac{1}{2}]}(x_i) = \prod_{i=1}^n f(x_i - \theta) \\ &= I_{[\theta - \frac{1}{2}, \infty)}(x_{(1)}) I_{(-\infty, \theta + \frac{1}{2})}(x_{(n)}) \\ &= I_{(-\infty, x_{(1)} + \frac{1}{2})}(\theta) I_{(x_{(n)} - \frac{1}{2}, \infty)}(\theta) \end{aligned}$$



Hence the Pitman estimator is

$$\begin{aligned} \hat{\theta}_P &= \frac{\int_{-\infty}^{\infty} \theta \prod_{i=1}^n f(x_i - \theta) d\theta}{\int_{-\infty}^{\infty} \prod_{i=1}^n f(x_i - \theta) d\theta} = \frac{\int_{x_{(1)} - \frac{1}{2}}^{x_{(n)} + \frac{1}{2}} \theta d\theta}{\int_{x_{(1)} - \frac{1}{2}}^{x_{(n)} + \frac{1}{2}} 1 * d\theta} = \frac{\frac{1}{2} \left[(x_{(n)} + \frac{1}{2})^2 - (x_{(1)} - \frac{1}{2})^2 \right]}{x_{(n)} + \frac{1}{2} - x_{(1)} + \frac{1}{2}} \end{aligned}$$

$$= \boxed{\frac{x_{(1)} + x_{(n)}}{2}}$$