

LECTURE 4

§10. EXAMPLES (continuation)

Definition 2. The mean of the posterior distribution $f(\theta|x_1, x_2, \dots, x_n)$ denoted by θ^* , is called Bayes estimate for θ .

Example 10. Using a random sample of size 2, estimate the proportion p of defectives produced by a machine when we assume our prior distribution to be

p	0.1	0.2
$f(p)$	0.6	0.4

Solution: Let X be the number of defectives in our sample. Then the probability distribution for our sample is

$$f(x|p) = \binom{2}{x} p^x (1-p)^{2-x}, \quad x = 0, 1, 2.$$

From the fact that

$$f(x, p) = f(x|p) f(p),$$

we can set up the following table:

$f(x, p)$	0	1	2
0.1	0.486	0.108	0.006
0.2	0.256	0.128	0.016

The marginal distribution for X is then

x	0	1	2
$g(x)$	0.742	0.236	0.022

We obtain the posterior distribution from the formula $f(p|x) = f(x, p)/g(x)$. Hence we have

p	0.1	0.2
$f(p x=0)$	0.655	0.345
p	0.1	0.2
$f(p x=1)$	0.458	0.542
p	0.1	0.2
$f(p x=2)$	0.273	0.727

from which we get

$$\begin{aligned}
p^* &= (0.1)(0.655) + (0.2)(0.345) = 0.1345, \quad \text{if } x = 0 \\
&= (0.1)(0.458) + (0.2)(0.542) = 0.1542, \quad \text{if } x = 1 \\
&= (0.1)(0.273) + (0.2)(0.727) = 0.1727, \quad \text{if } x = 2.
\end{aligned}$$

Example 11. Repeat the previous example using the uniform prior distribution $f(p) = 1$, $0 < p < 1$.

Solution: As before, we find that

$$f(x|p) = \binom{2}{x} p^x (1-p)^{2-x}, \quad x = 0, 1, 2.$$

Now

$$\begin{aligned}
f(x, p) &= f(x|p) f(p) = \binom{2}{x} p^x (1-p)^{2-x} = \\
&= (1-p)^2, \quad x = 0, \quad 0 < p < 1 \\
&= 2p(1-p), \quad x = 1, \quad 0 < p < 1 \\
&= p^2, \quad x = 2, \quad 0 < p < 1
\end{aligned}$$

and the marginal distribution for X is obtained by evaluating the integral

$$g(x) = \int_0^1 (1-p)^2 dp = \frac{1}{3}, \quad \text{for } x = 0$$

$$\begin{aligned}
&= \int_0^1 2p(1-p) dp = \frac{1}{3}, & \text{if } x = 1 \\
&= \int_0^1 p^2 dp = \frac{1}{3}, & \text{if } x = 2.
\end{aligned}$$

The posterior distribution is then

$$\begin{aligned}
f(p|x) &= \frac{f(x,p)}{g(x)} = 3 \binom{2}{x} p^x (1-p)^{2-x} = \\
&= 3(1-p)^2, & x = 0, \quad 0 < p < 1 \\
&= 6p(1-p), & x = 1, \quad 0 < p < 1 \\
&= 3p^2, & x = 2, \quad 0 < p < 1
\end{aligned}$$

from which we evaluate the point estimate of our parameter to be

$$\begin{aligned}
p^* &= 3 \int_0^1 p(1-p)^2 dp = \frac{1}{4}, & \text{if } x = 0 \\
&= 6 \int_0^1 p^2(1-p) dp = \frac{1}{2}, & \text{if } x = 1 \\
&= 3 \int_0^1 p^3 dp = \frac{3}{4}, & \text{if } x = 2.
\end{aligned}$$

Comparing these estimates with the values obtained by classical procedures, we see that p^* and \hat{p} are equivalent if $x = 1$, but that $\hat{p} = 0$ for $x = 0$ and $\hat{p} = 1$ for $x = 2$.

A $(1 - \alpha)100\%$ Bayesian interval for the parameter θ can be constructed by finding an interval centered at the posterior mean that contains $(1 - \alpha)100\%$ of the posterior probability.

Definition 3. The interval $a < \theta < b$ will be called a $(1 - \alpha)100\%$ Bayes interval for θ if

$$\int_{\theta^*}^b f(\theta|x_1, x_2, \dots, x_n) d\theta = \int_a^{\theta^*} f(\theta|x_1, x_2, \dots, x_n) d\theta = \frac{1 - \alpha}{2}.$$