

## LECTURE 14

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

**Example 17.6.(See Example 11.)** Using a random sample of size 2, estimate the proportion  $p$  of defectives produced by a machine when we assume our prior density of  $p$  is

$$p(\theta) = \begin{cases} k, & \text{if } 1/2 < \theta < 1 \\ 0, & \text{otherwise} \end{cases}$$

**Solution:** Since for any density function (therefore also and in this example)

$$\int p(\theta) d\theta = 1$$

Hence  $k = 2$ .

As before, we find that

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

Now

$$\begin{aligned} f(x, p) &= f(x|p) f(p) = \\ &= 2(1-p)^2, \quad x = 0, \quad \frac{1}{2} < p < 1 \\ &= 4p(1-p), \quad x = 1, \quad \frac{1}{2} < p < 1 \\ &= 2p^2, \quad x = 2, \quad \frac{1}{2} < p < 1 \end{aligned}$$

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

$$\begin{aligned} g(x) &= \int_{1/2}^1 2(1-p)^2 dp = \frac{1}{12}, \quad \text{for } x = 0 \\ &= \int_{1/2}^1 4p(1-p) dp = \frac{1}{3}, \quad \text{if } x = 1 \\ &= \int_{1/2}^1 2p^2 dp = \frac{7}{12}, \quad \text{if } x = 2. \end{aligned}$$

The posterior distribution is then

$$\begin{aligned}
 f(p|x) &= \frac{f(x,p)}{g(x)} = \\
 &= 24(1-p)^2, \quad x=0, \quad \frac{1}{2} < p < 1 \\
 &= 12p(1-p), \quad x=1, \quad \frac{1}{2} < p < 1 \\
 &= \frac{24}{7}p^2, \quad x=2, \quad \frac{1}{2} < p < 1
 \end{aligned}$$

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

$$\begin{aligned}
 p^* &= 24 \int_{1/2}^1 p(1-p)^2 dp = \frac{5}{8} = 0.625, \quad \text{if } x=0 \\
 &= 12 \int_{1/2}^1 p^2(1-p) dp = \frac{11}{16} = 0.6875, \quad \text{if } x=1 \\
 &= \frac{24}{7} \int_{1/2}^1 p^3 dp = \frac{45}{56}, \quad \text{if } x=2.
 \end{aligned}$$

**Example 17.7 (see Example 14).** An electrical firm manufactures light bulbs that have a length of life that is approximately normally distributed with a standard deviation of 100 hours and mean  $\mu$ . The firm believes, that  $\mu$  is surely between 770 and 830 hours and it is felt that a more realistic Bayesian approach would be to assume the prior distribution

$$f(\mu) = \begin{cases} \frac{1}{60}, & \text{if } 770 < \mu < 830 \\ 0, & \text{otherwise.} \end{cases}$$

If a random sample of 25 bulbs gives an average life of 780 hours, find the posterior distribution

$$p(\mu|x_1, x_2, \dots, x_{25}).$$

**Solution:** Multiplying the density of our sample

$$f(x_1, x_2, \dots, x_{25}|\mu) = \frac{1}{(2\pi)^{25/2} \cdot 100^{25}} \exp \left[ -\frac{1}{2} \sum_{i=1}^{25} \left( \frac{x_i - \mu}{100} \right)^2 \right], \quad -\infty < x_i < \infty, \quad i = 1, 2, \dots, 25$$

by our prior

$$f(\mu) = \begin{cases} \frac{1}{60}, & \text{if } 770 < \mu < 830 \\ 0, & \text{otherwise.} \end{cases}$$

we obtain the joint density of the random sample and  $\mu$ . That is,

$$f(x_1, x_2, \dots, x_{25}, \mu) = \begin{cases} \frac{1}{60} \left( \frac{1}{\sqrt{2\pi}100} \right)^{25} \exp \left[ -\frac{1}{2} \left\{ \sum_{i=1}^{25} \left( \frac{x_i - \mu}{100} \right)^2 \right\} \right] & \text{if } 770 < \mu < 830 \\ 0, & \text{otherwise.} \end{cases}$$

We established the identity

$$\sum_{i=1}^n (x_i - \mu)^2 = \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2,$$

which enables us to write

$$f(x_1, x_2, \dots, x_{25}, \mu) = \begin{cases} A \exp \left[ -\frac{1}{2} \left( \frac{\mu - 780}{20} \right)^2 \right] & \text{if } 770 < \mu < 830 \\ 0, & \text{otherwise.} \end{cases}$$

where  $A$  is a function of the sample values. The marginal distribution of the sample is then

$$\begin{aligned} g(x_1, x_2, \dots, x_{25}) &= A \sqrt{2\pi} 20 \int_{770}^{830} \frac{1}{\sqrt{2\pi}20} e^{-(1/2)[(\mu-780)/20]^2} d\mu = \\ &= 20 A \sqrt{2\pi} \left[ \Phi \left( \frac{830 - 780}{20} \right) - \Phi \left( \frac{770 - 780}{20} \right) \right] = \\ &= 20 A \sqrt{2\pi} [\Phi(2.5) - \Phi(-0.5)] = 20 A \sqrt{2\pi} [\Phi(2.5) + \Phi(0.5) - 1] = \\ &= 20 A \sqrt{2\pi} [0.9938 + 0.6915 - 1] = 20 A \sqrt{2\pi} 0.6853 = 13.706 A \sqrt{2\pi}. \end{aligned}$$

and the posterior distribution is

$$\begin{aligned} f(\mu|x_1, x_2, \dots, x_{25}) &= \frac{f(x_1, x_2, \dots, x_{25}, \mu)}{g(x_1, x_2, \dots, x_{25})} = \\ &= \begin{cases} \frac{1}{13.706 \sqrt{2\pi}} \exp \left[ -\frac{1}{2} \left( \frac{\mu - 780}{20} \right)^2 \right] & \text{if } 770 < \mu < 830 \\ 0, & \text{otherwise.} \end{cases} \end{aligned}$$

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

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

## Appendix. Mode of a probability distribution.

A mode of a continuous probability distribution is a value at which the probability density function attains its maximum value.

The mode of the set of data values is the value that appears most often. If  $\eta(\omega)$  is a discrete random variable, the mode is the value  $x$  (that is,  $\eta = x$ ) at which the probability mass function takes its maximum value. In other words, it is the value that is most likely to be sampled.

The mode is not necessary unique to a given discrete distribution, since the probability mass function make take the same maximum value at several points  $x_1, x_2$ , etc.

When the probability density function of a continuous distribution has multiple local maxima it is common to refer to all the local maxima as modes of the distribution. Such a continuous distribution is called multimodal (as opposite to unimodal). A mode of a continuous probability distribution is often considered to be any value  $x$  at which its probability density function has a locally maximal value, so any peak is a mode.

**Example 17.8.** Sample  $(1, 2, 2, 3, 4, 7, 9)$  has sample mean  $\hat{X} = \frac{\sum_{i=1}^7 X_i}{7} = 4$ , sample median  $\tilde{X} = 3$  and sample mode equal 2.

**Example 17.9.**  $\eta$  has the following discrete distribution:

$\eta :$	1	2	3	4
$p :$	0.15	0.3	0.25	0.3

Then we see that the mode is not unique. In fact, we have two modes 2 and 4.

**Example 17.10.** Let  $\eta$  have a density function:

$$f(x) = \begin{cases} \frac{3}{4}x^2(2-x) & \text{if } 0 \leq x \leq 2 \\ 0 & \text{otherwise} \end{cases}$$

Calculate the mode.

Proof: We have to find the first derivative of  $f(x)$ :

$$f'(x) = 2x(2-x) - x^2 = -3x^2 + 4x.$$

To calculate the pick of  $f(x)$  we have to solve the equation  $f'(x) = 0$ . We obtain  $-3x^2 + 4x = 0$ . Thus the roots are  $x_1 = \frac{4}{3}$  and  $x_2 = 0$ . The second root  $x = 0$  does not belong to the interval  $[0, 2]$ . The second derivative  $f''(x) = -6x + 4$  and  $f''(4/3) = -4 < 0$ . Therefore mode is  $\frac{4}{3}$