

### Cramer-Rao lower bound: an example

Suppose that  $\underline{X} = (X)$ , a single observation from  $Bin(m, p)$ , where  $m$  is *known*. The pmf is given by

$$f(x; p) = \binom{m}{x} p^x (1-p)^{m-x} \quad \text{where } x = 0, 1, \dots, m.$$

Note that the *range* of  $X$  depends on  $m$ , but *not* on the unknown parameter  $p$ . Also, the sample size is  $n = 1$ .

### Cramer-Rao lower bound

Since the range of  $X$  does not depend on the unknown parameter  $p$  which we wish to estimate, we can proceed to compute and use the Cramer-Rao lower bound for unbiased estimators:

$$\begin{aligned} \log f(x; p) &= \log \binom{m}{x} + x \log p + (m-x) \log(1-p) \\ \frac{\partial}{\partial p} \log f(x; p) &= \frac{x}{p} - \frac{m-x}{1-p} = \frac{x-mp}{p(1-p)} \\ \left( \frac{\partial}{\partial p} \log f(x; p) \right)^2 &= \frac{(x-mp)^2}{p^2(1-p)^2}. \end{aligned}$$

Thus,

$$E \left( \left( \frac{\partial}{\partial p} \log f(X; p) \right)^2 \right) = \frac{E(X-mp)^2}{p^2(1-p)^2} = \frac{Var(X)}{p^2(1-p)^2} = \frac{m}{p(1-p)}.$$

It follows that for any *unbiased* estimator,  $g(\underline{X})$ , for  $p$ , we have

$$Var(g(\underline{X})) \geq \frac{1}{1 \cdot \frac{m}{p(1-p)}} = \frac{p(1-p)}{m}.$$

**Alternatively**, we can compute the Cramer-Rao lower bound as follows:

$$\frac{\partial^2}{\partial p^2} \log f(x; p) = \frac{\partial}{\partial p} \left( \frac{\partial}{\partial p} \log f(x; p) \right) = \frac{\partial}{\partial p} \left( \frac{x}{p} - \frac{m-x}{1-p} \right) = \frac{-x}{p^2} - \frac{(m-x)}{(1-p)^2}.$$

Thus,

$$E \left( \frac{\partial^2}{\partial p^2} \log f(X; p) \right) = \frac{-E(X)}{p^2} - \frac{(m-E(X))}{(1-p)^2} = \frac{-mp}{p^2} - \frac{(m-mp)}{(1-p)^2} = \frac{-m}{p(1-p)}.$$

It follows that the Cramer-Rao lower bound is given by

$$\frac{1}{-nE \left( \frac{\partial^2}{\partial p^2} \log f(X; p) \right)} = \frac{1}{-1 \cdot \frac{-m}{p(1-p)}} = \frac{p(1-p)}{m}$$

as above.

**Comparing estimators**

Consider the estimator  $g_1(\underline{X}) = \frac{X}{m}$ .

$$E(g_1(\underline{X})) = \frac{E(X)}{m} = \frac{mp}{m} = p$$

so  $g_1(\underline{X})$  is an *unbiased* estimator of  $p$ . Is it the most efficient unbiased estimator for  $p$ ? To answer this question, we compute the variance of  $g_1$  and compare it to the Cramer-Rao lower bound which we calculated above.

$$\text{Var}(g_1(\underline{X})) = \text{Var}\left(\frac{X}{m}\right) = \frac{\text{Var}(X)}{m^2} = \frac{mp(1-p)}{m^2} = \frac{p(1-p)}{m}.$$

Since  $\text{Var}(g_1)$  equals the Cramer-Rao lower bound, we can conclude that  $g_1(\underline{X})$  is the most efficient *unbiased* estimator for  $p$ .

Now consider the estimator  $g_2(\underline{X}) = \frac{X+1}{m+2}$ .

$$E(g_2(\underline{X})) = \frac{E(X) + 1}{m + 2} = \frac{mp + 1}{m + 2} \neq p \quad (\text{except when } p = 1/2).$$

So  $g_2$  is a biased estimator with

$$\text{bias}(g_2) = E(g_2(\underline{X})) - p = \frac{mp + 1}{m + 2} - p = \frac{1 - 2p}{m + 2}.$$

To compare the performance of  $g_2$  with the performance of  $g_1$ , we must first compute the mean square error of  $g_2$ :

$$\text{Var}(g_2(\underline{X})) = \text{Var}\left(\frac{X + 1}{m + 2}\right) = \frac{\text{Var}(X + 1)}{(m + 2)^2} = \frac{mp(1-p)}{(m + 2)^2}.$$

Thus,

$$MSE(g_2) = \text{Var}(g_2) + (\text{bias}(g_2))^2 = \frac{mp(1-p)}{(m+2)^2} + \frac{(1-2p)^2}{(m+2)^2} = \frac{1}{(m+2)^2} (1 + (m-4)p - (m-4)p^2).$$

We can compare the (relative) efficiency of  $g_1$  and  $g_2$  by comparing the *graphs* of  $MSE(g_1)$  (which is just the variance of  $g_1$ ) and  $MSE(g_2)$  as *functions* of  $p$ .

**Exercise:** Fix  $m = 10$  and sketch the graphs of  $MSE(g_1)$  and  $MSE(g_2)$  as *functions* of  $p$ . Also, determine the values of  $p$  for which  $g_2$  is more efficient than  $g_1$ .