

# STAT2371 Assignment

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## Question 1

Suppose that two independent binomial random variables  $X_1$  and  $X_2$  are observed where  $X_1$  has a  $\text{Binomial}(n, p)$  distribution and  $X_2$  has a  $\text{Binomial}(2n, p)$  distribution. You may assume that  $n$  is known, whereas  $p$  is an unknown parameter. Define two possible estimators of  $p$

$$\hat{p}_1 = \frac{1}{3n}(X_1 + X_2) \quad \text{and} \quad \hat{p}_2 = \frac{1}{2n}(X_1 + 0.5X_2).$$

(a) Show that both of the estimators  $\hat{p}_1$  and  $\hat{p}_2$  are unbiased estimators of  $p$ .

$$\begin{aligned} E(\hat{p}_1) &= \frac{1}{3n}(E(X_1) + E(X_2)) \quad \text{applying expected value linearity} \\ &= \frac{1}{3n}(n \cdot p + 2n \cdot p) \quad \text{applying the binomial expectation formula} \\ &= p \\ \text{bias}(\hat{p}_1, p) &= E(\hat{p}_1) - p = 0. \end{aligned}$$

Similarly,

$$\begin{aligned} E(\hat{p}_2) &= \frac{1}{2n}(E(X_1) + 0.5E(X_2)) \\ &= \frac{1}{2n}(n \cdot p + 0.5 \cdot 2n \cdot p) \\ &= p \\ \text{bias}(\hat{p}_2, p) &= E(\hat{p}_2) - p = 0. \end{aligned}$$

Hence  $\hat{p}_1$  and  $\hat{p}_2$  are unbiased estimators of  $p$ .

(b) Find  $\text{Var}(\hat{p}_1)$  and  $\text{Var}(\hat{p}_2)$ .

$$\begin{aligned} \text{Var}(\hat{p}_1) &= \frac{1}{9n^2}(\text{Var}(X_1) + \text{Var}(X_2)) \quad \text{applying the formula for independent case} \\ &= \frac{1}{9n^2}(np(1-p) + 2np(1-p)) \quad \text{applying the binomial variance formula} \end{aligned}$$

$$= \frac{p(1-p)}{3n}.$$

Similarly,

$$\begin{aligned} \text{Var}(\hat{p}_2) &= \frac{1}{4n^2} (\text{Var}(X_1) + 0.5^2 \text{Var}(X_2)) \\ &= \frac{1}{4n^2} (np(1-p) + 0.25 \cdot 2np(1-p)) \\ &= \frac{3p(1-p)}{8n}. \end{aligned}$$

**(c) Show that both estimators are consistent estimators of  $p$ .**

Let  $\varepsilon > 0$ .

$$\begin{aligned} \lim_{n \rightarrow \infty} P(|\hat{p}_1 - p| > \varepsilon) &\leq \lim_{n \rightarrow \infty} \frac{E((\hat{p}_1 - p)^2)}{\varepsilon^2} \quad \text{applying Markov's inequality} \\ &= \lim_{n \rightarrow \infty} \frac{\text{Var}(\hat{p}_1)}{\varepsilon^2} \quad \text{since } \hat{p}_1 \text{ is unbiased} \\ &= \lim_{n \rightarrow \infty} \frac{p(1-p)}{3n\varepsilon^2} \\ &= 0 \quad \text{for all } p \in [0, 1]. \end{aligned}$$

Applying the squeeze theorem,  $\lim_{n \rightarrow \infty} P(|\hat{p}_1 - p| > \varepsilon) = 0$ . Similarly,

$$\begin{aligned} \lim_{n \rightarrow \infty} P(|\hat{p}_2 - p| > \varepsilon) &\leq \lim_{n \rightarrow \infty} \frac{E((\hat{p}_2 - p)^2)}{\varepsilon^2} \\ &= \lim_{n \rightarrow \infty} \frac{\text{Var}(\hat{p}_2)}{\varepsilon^2} \\ &= \lim_{n \rightarrow \infty} \frac{3p(1-p)}{8n\varepsilon^2} \\ &= 0 \quad \text{for all } p \in [0, 1]. \end{aligned}$$

So  $\lim_{n \rightarrow \infty} P(|\hat{p}_2 - p| > \varepsilon) = 0$ . Hence  $\hat{p}_1$  and  $\hat{p}_2$  are weakly consistent estimators of  $p$ .

**(d) Show that  $\hat{p}_1$  is the most efficient estimator among all unbiased estimators.**

$$\underset{\sim}{X} \equiv \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}, \underset{\sim}{x} \equiv \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}.$$

$$\begin{aligned} f_{\underset{\sim}{X}}(\underset{\sim}{x}, p) &= f_{X_1}(x_1, p) \cdot f_{X_2}(x_2, p) \quad \text{applying the r.v. independence definition} \\ &= \begin{cases} \binom{n}{x_1} p^{x_1} (1-p)^{n-x_1} \cdot \binom{2n}{x_2} p^{x_2} (1-p)^{2n-x_2} & \text{if } x_1 \in [0, n] \cap \mathbb{N} \text{ and } x_2 \in [0, 2n] \cap \mathbb{N} \\ 0 & \text{if otherwise} \end{cases} \end{aligned}$$

$$\begin{aligned}
&= \begin{cases} \binom{n}{x_1} \binom{2n}{x_2} p^{x_1+x_2} (1-p)^{3n-(x_1+x_2)} & \text{if } x_1 \in [0, n] \cap \mathbb{N} \text{ and } x_2 \in [0, 2n] \cap \mathbb{N} \\ 0 & \text{if otherwise} \end{cases} \\
&= \begin{cases} \binom{n}{x_1} \binom{2n}{x_2} \exp \left( \begin{bmatrix} \ln(p) \\ \ln(1-p) \end{bmatrix}^T \begin{bmatrix} x_1 + x_2 \\ 3n - (x_1 + x_2) \end{bmatrix} \right) & \text{if } x_1 \in [0, n] \cap \mathbb{N} \text{ and } x_2 \in [0, 2n] \cap \mathbb{N} \\ 0 & \text{if otherwise} \end{cases}
\end{aligned}$$

Since  $n$  is known and fixed,  $\tilde{X}$  has a pdf in the exponential family, and any sufficient static is also complete.  $X_1 + X_2$  is thus sufficient and complete by the sufficient statistic factorisation theorem. By the Lehmann-Scheffé theorem,  $E(\hat{p}_1 | X_1 + X_2) = \hat{p}_1$  is the unique MVUE, i.e. it is the most efficient estimator among all unbiased estimators.

(e) Derive the efficiency of the estimator  $\hat{p}_1$  relative to  $\hat{p}_2$ .

$$\begin{aligned}
\text{eff}(\hat{p}_2, \hat{p}_1, p) &= \frac{\text{MSE}(\hat{p}_2, p)}{\text{MSE}(\hat{p}_1, p)} = \frac{\text{Var}(\hat{p}_2) + (\text{bias}(\hat{p}_2, p))^2}{\text{Var}(\hat{p}_1) + (\text{bias}(\hat{p}_1, p))^2} = \frac{\frac{3p(1-p)}{8n}}{\frac{p(1-p)}{3n}} \\
&= \frac{9}{8}
\end{aligned}$$

## Question 2

The random variables  $X_1, X_2, \dots, X_{2n}$  are independent and normally distributed with common variance  $\sigma^2$ . However,  $X_1, X_2, \dots, X_n$  have mean 0 while  $X_{n+1}, X_{n+2}, \dots, X_{2n}$  have mean  $\mu$ .