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DSA 8301 – Statistical Inference in Big Data

CAT 1

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Show that  $\frac{63}{512}$  is the probability that the fifth head is observed on the tenth independent flip of a fair coin.

#### Solution

Step 1: Understand the setting. This is a classic negative binomial problem where we are looking for the probability that the 5th success (head) occurs on the 10th trial.

Step 2: Count favorable arrangements. This means we must get exactly 4 heads in the first 9 flips, and the 10th flip must be a head.

$$P(5\text{th head on 10th flip}) = \binom{9}{4}(0.5)^9 \times 0.5 = \binom{9}{4}(0.5)^{10}$$

Step 3: Evaluate.

$$\binom{9}{4} = 126, \quad (0.5)^{10} = \frac{1}{1024}, \quad \Rightarrow \frac{126}{1024} = \frac{63}{512}$$

Answer:  $\frac{63}{512}$ 

This is a good example of how combinatories and probability work together. It's crucial to correctly count the number of sequences with 4 heads in the first 9 tosses using the binomial coefficient.

Let  $X \sim \Gamma(\alpha, \beta)$ . Find:

- 1. Method of moment estimators of  $\alpha$  and  $\beta$ .
- 2. Point estimates based on the dataset:

 $Data:\ 6.9,\ 7.3,\ 6.7,\ 6.4,\ 6.3,\ 5.9,\ 7.0,\ 7.1,\ 6.5,\ 7.6,\ 7.2,\ 7.1,\ 6.1,\ 7.3,\ 7.6,\ 7.6,\ 6.7,\ 6.3,\ 5.7,\ 6.7,\ 7.5,\ 5.3,\ 5.4,\ 7.4,\ 6.9$ 

#### Solution

Step 1: Write the moment equations.

$$E[X] = \alpha \beta, \quad Var(X) = \alpha \beta^2$$

Step 2: Replace with sample moments.

$$\bar{X} = 6.74, \quad S^2 = 0.4432$$

Step 3: Solve for parameters.

$$\hat{\beta} = \frac{S^2}{\bar{X}} = \frac{0.4432}{6.74} \approx 0.0658, \quad \hat{\alpha} = \frac{\bar{X}^2}{S^2} = \frac{6.74^2}{0.4432} \approx 102.5$$

**Answer:**  $\hat{\alpha} \approx 102.5, \ \hat{\beta} \approx 0.066$ 

The method of moments is used, which offers a straightforward estimation technique. It may not always be as efficient as maximum likelihood, but it is computationally simpler and intuitive.

Let  $X_1, \ldots, X_{10}$  and  $Y_1, \ldots, Y_{10}$  be two independent samples with:

$$E[X_i] = E[Y_i] = \mu$$
,  $Var(X_i) = \sigma^2$ ,  $Var(Y_i) = 4\sigma^2$ 

- 1. Show  $\hat{\mu} = \alpha \bar{X} + (1 \alpha) \bar{Y}$  is unbiased.
- 2. Derive MSE of  $\hat{\mu}$ .
- 3. Compare  $\bar{X}$  with  $0.5\bar{X} + 0.5\bar{Y}$ .

#### Solution

(a) Step 1: Show unbiasedness.

$$E[\hat{\mu}] = \alpha E[\bar{X}] + (1 - \alpha)E[\bar{Y}] = \alpha \mu + (1 - \alpha)\mu = \mu$$

Conclusion: The estimator is unbiased.

(b) Step 2: Compute variance.

$$Var(\hat{\mu}) = \alpha^2 \cdot \frac{\sigma^2}{10} + (1 - \alpha)^2 \cdot \frac{4\sigma^2}{10} = \frac{\sigma^2}{10} (\alpha^2 + 4(1 - \alpha)^2)$$

This is the MSE because the estimator is unbiased.

- (c) Step 3: Plug in values.
- For  $\bar{X}$ :  $\alpha = 1 \Rightarrow \text{MSE} = \frac{\sigma^2}{10}$
- For  $0.5\bar{X} + 0.5\bar{Y}$ : MSE =  $\frac{\sigma^2}{10}(0.25 + 1) = \frac{1.25\sigma^2}{10}$

Conclusion:  $\bar{X}$  is more efficient. Assigning equal weights to estimators from data sources

with unequal variances results in increased error. Weighting in proportion to variance is better.

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Let  $X_1, \ldots, X_n \sim N(\mu, \sigma^2)$ .

- 1. Show  $Y = (X_1 + X_2)/2$  is unbiased.
- 2. Find Cramer-Rao lower bound (CRLB).
- 3. Find efficiency of Y.

#### Solution

(a) Step 1: Unbiasedness

$$E[Y] = \frac{1}{2}(E[X_1] + E[X_2]) = \mu$$

(b) Step 2: Compute Fisher Information

$$I(\mu) = \frac{n}{\sigma^2}, \quad \text{CRLB} = \frac{\sigma^2}{n}$$

(c) Step 3: Compute efficiency

$$\operatorname{Var}(Y) = \frac{\sigma^2}{2}$$
, Efficiency  $= \frac{\sigma^2/n}{\sigma^2/2} = \frac{2}{n}$ 

Efficiency reflects how well an estimator uses data. Using only part of the sample reduces efficiency unless there's a strong reason to restrict the sample.

Given  $f(x; \theta) = \theta x^{\theta-1}$  on (0, 1). Test:

$$H_0: \theta = 1$$
 vs.  $H_a: \theta = 2$ 

Show best critical region is:

$$C = \{(x_1, ..., x_n) : \prod x_i \ge c\}$$

#### Solution

Step 1: Write likelihood ratio.

$$\Lambda = \frac{L(\theta = 2)}{L(\theta = 1)} = 2^n \prod x_i$$

Step 2: Apply Neyman-Pearson Lemma.

We reject  $H_0$  for large values of the likelihood ratio  $\Rightarrow$  large  $\prod x_i$ .

Critical Region:

$$C = \left\{ \prod_{i=1}^{n} x_i \ge c \right\}$$

A large product of  $x_i$  values favors  $\theta=2$  over  $\theta=1$ . Hence this is a powerful test statistic.

Test:

$$H_0: \theta_2 = \theta_2'$$
 vs.  $H_a: \theta_2 \neq \theta_2'$  (mean  $\theta_1$  unspecified)

Show rejection region:

$$\sum (x_i - \bar{x})^2 \le c_1 \quad \text{or} \quad \sum (x_i - \bar{x})^2 \ge c_2$$

#### Solution

Step 1: Construct likelihood ratio. The statistic depends on the sample variance:

$$T = \sum (x_i - \bar{x})^2$$

Step 2: Determine behavior under  $H_0$ . If T is far from expected under  $H_0$ , reject. Rejection Region:

$$T \le c_1$$
 or  $T \ge c_2$ 

A two-tailed test is suitable here since both smaller and larger sample variances contradict the null hypothesis.

Let  $X_i \sim \text{Bern}(\theta)$ . Test:

$$H_0: \theta = 0.5$$
 vs.  $H_a: \theta < 0.5$ 

Reject if  $Y = \sum X_i \le c$ .

- 1. Show this is UMP.
- 2. Find  $\alpha$  when c = 1.
- 3. Find  $\alpha$  when c = 0.

#### Solution

- (a) Step 1: Use monotone likelihood ratio. Binomial distribution has MLR in Y. Hence, Karlin-Rubin theorem implies test is UMP.
  - (b) Step 2: Calculate significance level.

$$\alpha = P(Y \le 1) = \frac{1+5}{32} = \frac{3}{16} = 0.1875$$

(c) Step 3: Calculate when c = 0.

$$\alpha = P(Y = 0) = \frac{1}{32} = 0.03125$$

This example demonstrates the use of discrete probabilities in hypothesis testing. Using a lower c leads to a more conservative test.

Observed: 124, 30, 43, 11 Expected ratio: 9:3:3:1  $\alpha = 0.05$ 

#### Solution

Step 1: Calculate expected frequencies.

$$E_1 = 117, E_2 = 39, E_3 = 39, E_4 = 13$$

Step 2: Compute test statistic.

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} = \frac{49}{117} + \frac{81}{39} + \frac{16}{39} + \frac{4}{13} \approx 3.214$$

Step 3: Compare with critical value.

$$\chi^2_{0.95.3} = 7.815 \Rightarrow 3.214 < 7.815 \Rightarrow \text{Fail to reject}$$

Conclusion: The data supports Mendel's theoretical prediction.

Chi-square is sensitive to count discrepancies. Here, observed values are close enough to expected ones to attribute the difference to chance.