

University of Technology Sydney
School of Mathematical and Physical Sciences

Mathematical Statistics (37262) –
Class 8 Preparation Work
SOLUTIONS

1.

i)
$$\bar{y} = \frac{1}{10} \sum_{i=1}^{10} y_i = \frac{36.9}{10} = 3.69$$

ii) The sample mean is an unbiased estimator of the population mean hence $\hat{\mu} = 3.69$.

iii) The 95% confidence interval for μ is given by $\bar{y} \pm 1.96 \sqrt{\frac{\sigma^2}{n}}$ (since, for $Z \sim N(0,1)$, $P(-1.96 < Z < 1.96) \approx 0.95$)

This gives an interval of $3.69 \pm \frac{3.92}{\sqrt{10}}$ i.e. (2.45, 4.93).

iv) Given that we know the variance is $\sigma^2 = 2^2$, our new observation $Y_{new} \sim N(\mu, 2^2)$. The distribution of the sample mean is $\bar{Y} \sim N\left(\mu, \frac{2^2}{10}\right)$

hence we have that $Y_{new} - \bar{Y} \sim N\left(0, \left(2^2 + \frac{2^2}{10}\right)\right)$

Our 95% prediction interval for Y_{new} is then given by $\bar{y} \pm 1.96 \sqrt{\sigma^2 + \frac{\sigma^2}{10}}$.

This is approximately (-0.42, 7.80)

v)
$$s^2 = \frac{1}{10} \sum_{i=1}^{10} (y_i - \bar{y})^2 = 6.7729.$$

vi)

$$\begin{aligned}
 E(s^2) &= E\left(\frac{1}{10} \sum_{i=1}^{10} (y_i - \bar{y})^2\right) \\
 &= \frac{E\left(\sum_{i=1}^{10} (y_i - \mu)^2\right)}{10} + \frac{E\left(\sum_{i=1}^{10} (\bar{y} - \mu)^2\right)}{10} - \frac{2E\left(\sum_{i=1}^{10} (y_i - \mu)(\bar{y} - \mu)\right)}{10} \\
 &= \frac{E\left(\sum_{i=1}^{10} (y_i - \mu)^2\right)}{10} - E((\bar{y} - \mu)^2) \\
 &= \sigma^2 - \frac{\sigma^2}{n} \\
 E(s^2) &= \sigma^2 - \frac{\sigma^2}{n} \text{ hence } bias(s^2, \sigma^2) = \sigma^2 - \frac{\sigma^2}{n} - \sigma^2 = -\frac{\sigma^2}{n} \neq 0.
 \end{aligned}$$

vii) The confidence intervals for the population mean μ would be wider when assuming $Y \sim N(\mu, \sigma^2)$ rather than $Y \sim N(\mu, 2^2)$ since our uncertainty is greater when the variance is not known.

vii) The 95% confidence interval for μ is given by $\bar{y} \pm 2.62 \sqrt{\frac{\hat{\sigma}^2}{n}}$ where

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^{10} (y_i - \bar{y})^2}{10 - 1}, \text{ since for } T \sim t_9, P(-2.262 < Z < 2.262) \approx 0.95.$$

This gives an interval of $3.69 \pm \frac{2.262}{\sqrt{10}} \sqrt{\frac{67.729}{9}}$ i.e. (1.99, 5.39).

2.

$$f(x) = \begin{cases} (2\theta)^{-1} & x \in [0, 2\theta] \\ 0 & \text{otherwise} \end{cases}.$$

i) Calculate $E(X) = \int_0^{2\theta} x(2\theta)^{-1} dx = \left[\frac{x^2}{4\theta} \right]_0^{2\theta} = \theta$.

ii) $L(\{x_1, x_2, \dots, x_n\} | \theta) = (2\theta)^{-n}$. hence $\ell(\{x_1, x_2, \dots, x_n\} | \theta) = -n \ln(2\theta)$.

$$\frac{\partial}{\partial \theta} \ell(\{x_1, x_2, \dots, x_n\} | \theta) = -\frac{n}{\theta}.$$

This is never zero. The likelihood is

maximised when θ is as small as possible.

$$x \in [0, 2\theta] \text{ so we set } 2\hat{\theta}_{MLE} = \max\{x_1, x_2, \dots, x_n\}$$

$$\text{i.e. } \hat{\theta}_{MLE} = \frac{\max\{x_1, x_2, \dots, x_n\}}{2}.$$

iii) $E(X) = \theta$ so, by matching first moments, we obtain $\hat{\theta}_{MM} = \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$.

iv) Consider $\{x_1, x_2, \dots, x_5\} = \{1, 2, 3, 4, 90\}$.

$$\text{The sample mean is } \bar{x} = \frac{1}{5}(1 + 2 + 3 + 4 + 90) = 20.$$

This would give $\hat{\theta}_{MM} = 20$ implying that $x \in [0, 40]$ which we know is not true, as we have an observation $x_5 = 90$.