



Tutorial Letter 201/1/2016

Applied Statistics II

STA2601

Semester 1

Department of Statistics

Solutions to Assignment 1

BAR CODE



QUESTION 1

(a) The *mean* value of X is calculated as:

$$\begin{aligned}\mu &= E(x) = \sum_x x f_X(x) \\ &= 0\left(\frac{1}{10}\right) + 1\left(\frac{3}{10}\right) + 2\left(\frac{2}{5}\right) + 3\left(\frac{1}{5}\right) \\ &= 0 + \frac{3}{10} + \frac{4}{5} + \frac{3}{5} \\ &= 1.7\end{aligned}$$

(3)

(b) The *variance* of X is calculated as:

$$\begin{aligned}\sigma^2 &= \sum_{x \in A} (x - \mu)^2 f_X(x) \\ &= (0 - 1.7)^2 \frac{1}{10} + (1 - 1.7)^2 \frac{3}{10} + (2 - 1.7)^2 \frac{2}{5} + (3 - 1.7)^2 \frac{1}{5} \\ &= (-1.7)^2 \frac{1}{10} + (-0.7)^2 \frac{3}{10} + (0.3)^2 \frac{2}{5} + (1.3)^2 \frac{1}{5} \\ &= 0.289 + 0.147 + 0.036 + 0.338 \\ &= 0.81\end{aligned}$$

OR

$$\begin{aligned}\sigma^2 &= E(X^2) - (E(X))^2 \\ &= \sum_x x^2 f_X(x) - \mu^2 \\ &= \left(0^2 \times \frac{1}{10}\right) + \left(1^2 \times \frac{3}{10}\right) + \left(2^2 \times \frac{2}{5}\right) + \left(3^2 \times \frac{1}{5}\right) - 1.7^2 \\ &= 0 + \frac{3}{10} + \frac{8}{5} + \frac{9}{5} - 2.89 \\ &= 3.7 - 2.89 \\ &= 0.81\end{aligned}$$

(4)

(c) The *third central moment* of X is calculated as:

$$\begin{aligned}
 \mu_3 &= \sum_{x \in A} (x - \mu)^3 f_X(x) \\
 &= (0 - 1.7)^3 \frac{1}{10} + (1 - 1.7)^3 \frac{3}{10} + (2 - 1.7)^3 \frac{2}{5} + (3 - 1.7)^3 \frac{1}{5} \\
 &= (-1.7)^3 \frac{1}{10} + (-0.7)^3 \frac{3}{10} + (0.3)^3 \frac{2}{5} + (1.3)^3 \frac{1}{5} \\
 &= -0.4913 - 0.1029 + 0.0108 + 0.4394 \\
 &= -0.144
 \end{aligned}$$

The coefficient of skewness of X is calculated as $\beta_1 = \frac{\mu_3}{\sigma^3} = \frac{-0.144}{(\sqrt{0.81})^3} = -\frac{16}{81} \approx -0.1975$

No. The data is negatively skewed.

(8)

[15]

QUESTION 2

(a) Yes. $f_{X_5}(x_5) = f_{X_6}(x_6)$ (2)

(b)

$$\begin{aligned}
 f_{X_6}(x_6) &= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2} \frac{(x_i - \mu)^2}{\sigma^2}} \\
 &= \frac{1}{5\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x_6 - 9}{25} \right)^2} \quad -\infty < x_6 < \infty
 \end{aligned}$$

(2)

(c)

$$\begin{aligned}
 P(X_1 < 8) \text{ or } P(X_1 > 10) &= P(X_1 < 8) + P(X_1 > 10) \\
 &= P\left(\frac{X_1 - \mu}{\sigma} < \frac{8 - 9}{5}\right) + P\left(\frac{X_1 - \mu}{\sigma} > \frac{10 - 9}{5}\right) \\
 &= P\left(Z < -\frac{1}{5}\right) + P\left(Z > \frac{1}{5}\right)
 \end{aligned}$$

$$\begin{aligned}
P(X_1 < 8) \text{ or } P(X_1 > 10) &= P(Z < -0.2) + P(Z > 0.2) \\
&= 2P(Z > 0.2) \\
&= 2(1 - P(Z < 0.2)) \\
&= 2(1 - 0.5793) \\
&= 0.8414
\end{aligned}$$

(5)

(d) Yes, $Z = \frac{X_5 - 9}{5} \sim n(0; 1)$. If we subtract 9 from X_5 and divide by $\sqrt{25}$, we obtain the standard normal distribution. (3)

(e) $W = \sum_{i=1}^7 \frac{(X_i - 9)^2}{25}$ is defined as the sum of 7 independent squared $n(0; 1)$ variates. Using **result 1.2 in our study guide (page 29)**, $W \sim \chi_n^2 \implies W \sim \chi_7^2$. Since $W \sim \chi_7^2$, it follows from the properties of the chi-square distribution that $E(W) = 14$ using **result 1.1 in our study guide (page 28)**. (2)

(f) If $T = \frac{\sqrt{7}(\bar{X} - \mu)}{\sqrt{\frac{\sum(X_i - \bar{X})^2}{6}}} \sim t_6$ $P(T \geq 2.447) = 0.025$ from Table III (Stoker) with $\nu = 6$ and $p = 0.025$. (2)

(g) Since $V_1 \sim \chi_3^2$ and $V_2 \sim \chi_4^2$, then $U = \frac{V_1/3}{V_2/4} \sim F_{3;4}$ using definition 1.21. (2)

(h) The table gives $P(U > a) = \alpha$. $P(U < a) = 1 - P(U > a) = 1 - \alpha$.

Since $U \sim F_{3;4} \implies P(U < a) = 1 - P(U > a) = 1 - 0.05$

and from Table 4 (Stoker) we find that $F_{0.05;3;4} = 6.59$ and $P(U > 6.59) = 0.05$.

Hence $P(U < 6.59) = 0.95$ and thus $a = 6.59$ (2)

[20]

QUESTION 3

(a)

$$\begin{aligned}
 A_1 &= \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2 \\
 &= \frac{\sigma^2}{n} \left[\sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2 \right] \quad (\text{multiplying both sides by } \sigma^2) \\
 \implies E(A_1) &= \frac{\sigma^2}{n} E \left[\sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2 \right]
 \end{aligned}$$

From **result 1.2** in the study guide we know $\sum_{i=1}^n \left[\frac{X_i - \mu}{\sigma} \right]^2 \sim \chi_n^2$.

This also means (from **result 1.1**) that $E \left(\sum_{i=1}^n \left[\frac{X_i - \mu}{\sigma} \right]^2 \right) = n$ and

$$\text{var} \left(\sum_{i=1}^n \left[\frac{X_i - \mu}{\sigma} \right]^2 \right) = 2n$$

$$\begin{aligned}
 \implies E(A_1) &= \frac{\sigma^2}{n} E \left[\sum_{i=1}^n \left(\frac{X_i - \mu}{\sigma} \right)^2 \right] \\
 &= \frac{\sigma^2}{n} \times n \\
 &= \sigma^2
 \end{aligned}$$

Now

$$\begin{aligned}
 A_2 &= \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \\
 &= \frac{\sigma^2}{n-1} \left[\sum_{i=1}^n \left(\frac{X_i - \bar{X}}{\sigma} \right)^2 \right] \quad (\text{multiplying both sides by } \sigma^2) \\
 \implies E(A_2) &= \frac{\sigma^2}{n-1} E \left[\sum_{i=1}^n \left(\frac{X_i - \bar{X}}{\sigma} \right)^2 \right]
 \end{aligned}$$

From **result 1.3** in the study guide we know $\sum_{i=1}^n \left[\frac{X_i - \bar{X}}{\sigma} \right]^2 \sim \chi_{n-1}^2$.

This also means (from **result 1.1**) that $E \left(\sum_{i=1}^n \left[\frac{X_i - \bar{X}}{\sigma} \right]^2 \right) = n - 1$ and

$$\text{var} \left(\sum_{i=1}^n \left[\frac{X_i - \bar{X}}{\sigma} \right]^2 \right) = 2(n-1)$$

$$\begin{aligned} \implies E(A_2) &= \frac{\sigma^2}{n} E \left[\sum_{i=1}^n \left(\frac{X_i - \bar{X}}{\sigma} \right)^2 \right] \\ &= \frac{\sigma^2}{n-1} \times n-1 \\ &= \sigma^2 \end{aligned}$$

Thus A_1 and A_2 are both unbiased estimators for σ^2 . (10)

(b) The *most efficient* estimator is the one with the smallest variance (see definition 2.4).

$$\begin{aligned} \text{Now } \text{var}(A_1) &= \left[\frac{\sigma^2}{n} \right]^2 \cdot \text{var} \left[\sum_{i=1}^n \left[\frac{X_i - \mu}{\sigma} \right]^2 \right] \\ &= \frac{\sigma^4}{n^2} \times 2n \\ &= \frac{2\sigma^4}{n} \end{aligned}$$

$$\begin{aligned} \text{Now } \text{var}(A_2) &= \left[\frac{\sigma^2}{n-1} \right]^2 \cdot \text{var} \left[\sum_{i=1}^n \left[\frac{X_i - \bar{X}}{\sigma} \right]^2 \right] \\ &= \frac{\sigma^4}{(n-1)^2} \times 2(n-1) \\ &= \frac{2\sigma^4}{(n-1)} \end{aligned}$$

It follows that

$$\text{var}(A_1) < \text{var}(A_2) \text{ because } \frac{2\sigma^4}{n} < \frac{2\sigma^4}{n-1}$$

$\implies A_1$ is the *most efficient* estimator.

(10)

[20]

QUESTION 4

$E(X_i) = c_i\theta_1 + w_i\theta_2$ for $i = 1, 2, 3 \dots, n$

$$\begin{aligned} Q(\theta_1, \dots, \theta_k) &= \sum_{i=1}^n (X_i - E(X_i))^2 \\ &= \sum_{i=1}^n (X_i - (c_i\theta_1 + w_i\theta_2))^2 \\ &= \sum_{i=1}^n (X_i - c_i\theta_1 - w_i\theta_2)^2 \end{aligned}$$

Differentiating with respect to θ_1 gives

$$\begin{aligned} \frac{dQ}{d\theta_1} &= 2 \times \sum_{i=1}^n (X_i - c_i\theta_1 - w_i\theta_2) \times -c_i \\ &= -2c_i \sum_{i=1}^n (X_i - c_i\theta_1 - w_i\theta_2) \\ &= -2 \left(\sum_{i=1}^n (c_i X_i - c_i^2 \theta_1 - c_i w_i \theta_2) \right) \end{aligned}$$

Equating to zero gives

$$\begin{aligned} 0 &= -2 \left(\sum_{i=1}^n (c_i X_i - c_i^2 \theta_1 - c_i w_i \theta_2) \right) \\ &= \sum_{i=1}^n (c_i X_i - c_i^2 \theta_1 - c_i w_i \theta_2) \\ &= \sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i^2 - \theta_2 \sum_{i=1}^n c_i w_i \end{aligned}$$

Making θ_1 subject of the formula gives

$$\begin{aligned} \theta_1 \sum_{i=1}^n c_i^2 &= \sum_{i=1}^n c_i X_i - \theta_2 \sum_{i=1}^n c_i w_i \\ \theta_1 &= \frac{\sum_{i=1}^n c_i X_i - \theta_2 \sum_{i=1}^n c_i w_i}{\sum_{i=1}^n c_i^2} \dots\dots\dots(1) \end{aligned}$$

Similarly making θ_2 subject of the formula gives

$$\begin{aligned}\theta_2 \sum_{i=1}^n c_i w_i &= \sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i^2 \\ \theta_2 &= \frac{\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i^2}{\sum_{i=1}^n c_i w_i} \dots\dots\dots(2)\end{aligned}$$

Differentiating with respect to θ_2 gives

$$\begin{aligned}\frac{dQ}{d\theta_2} &= 2 \sum_{i=1}^n (X_i - c_i \theta_1 - w_i \theta_2) \times -w_i \\ &= -2w_i \sum_{i=1}^n (X_i - c_i \theta_1 - w_i \theta_2) \\ &= -2 \sum_{i=1}^n (w_i X_i - w_i c_i \theta_1 - w_i^2 \theta_2)\end{aligned}$$

Equating to zero gives

$$\begin{aligned}0 &= -2 \sum_{i=1}^n (w_i X_i - c_i w_i \theta_1 - w_i^2 \theta_2) \\ &= \sum_{i=1}^n (w_i X_i - c_i w_i \theta_1 - w_i^2 \theta_2) \\ &= \sum_{i=1}^n w_i X_i - \theta_1 \sum_{i=1}^n c_i w_i - \theta_2 \sum_{i=1}^n w_i^2\end{aligned}$$

Making θ_1 subject of the formula gives

$$\begin{aligned}\theta_1 \sum_{i=1}^n c_i w_i &= \sum_{i=1}^n w_i X_i - \theta_2 \sum_{i=1}^n w_i^2 \\ \theta_1 &= \frac{\sum_{i=1}^n w_i X_i - \theta_2 \sum_{i=1}^n w_i^2}{\sum_{i=1}^n c_i w_i} \dots\dots\dots(3)\end{aligned}$$

Similarly making θ_2 subject of the formula gives

$$\begin{aligned} \theta_2 \sum_{i=1}^n w_i^2 &= \sum_{i=1}^n w_i X_i - \theta_1 \sum_{i=1}^n c_i w_i \\ \theta_2 &= \frac{\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i w_i}{\sum_{i=1}^n w_i^2} \dots\dots\dots(4) \end{aligned}$$

Equating equations 1 and 3 gives

$$\begin{aligned} \frac{\sum_{i=1}^n c_i X_i - \theta_2 \sum_{i=1}^n c_i w_i}{\sum_{i=1}^n c_i^2} &= \frac{\sum_{i=1}^n w_i X_i - \theta_2 \sum_{i=1}^n w_i^2}{\sum_{i=1}^n c_i w_i} \\ \sum_{i=1}^n c_i w_i \left(\sum_{i=1}^n c_i X_i - \theta_2 \sum_{i=1}^n c_i w_i \right) &= \sum_{i=1}^n c_i^2 \left(\sum_{i=1}^n w_i X_i - \theta_2 \sum_{i=1}^n w_i^2 \right) \\ \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i - \theta_2 \left(\sum_{i=1}^n c_i w_i \right)^2 &= \sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i X_i - \theta_2 \sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i^2 \\ \theta_2 \sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i^2 - \theta_2 \left(\sum_{i=1}^n c_i w_i \right)^2 &= \sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i X_i - \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i \\ \theta_2 \left(\sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i^2 - \left(\sum_{i=1}^n c_i w_i \right)^2 \right) &= \sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i X_i - \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i \\ \hat{\theta}_2 &= \frac{\sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i X_i - \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i}{\sum_{i=1}^n c_i^2 \sum_{i=1}^n w_i^2 - \left(\sum_{i=1}^n c_i w_i \right)^2} \end{aligned}$$

Similarly equating equations 2 and 4 gives

$$\begin{aligned} \frac{\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i^2}{\sum_{i=1}^n c_i w_i} &= \frac{\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i w_i}{\sum_{i=1}^n w_i^2} \\ \sum_{i=1}^n w_i^2 \left(\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i^2 \right) &= \sum_{i=1}^n c_i w_i \left(\sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n c_i w_i \right) \end{aligned}$$

$$\begin{aligned}
\sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i X_i - \theta_1 \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i^2 &= \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i - \theta_1 \left(\sum_{i=1}^n c_i w_i \right)^2 \\
\theta_1 \left(\sum_{i=1}^n c_i w_i \right)^2 - \theta_1 \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i^2 &= \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i - \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i X_i \\
\theta_1 \left(\left(\sum_{i=1}^n c_i w_i \right)^2 - \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i^2 \right) &= \sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i - \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i X_i \\
\hat{\theta}_1 &= \frac{\sum_{i=1}^n c_i w_i \sum_{i=1}^n c_i X_i - \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i X_i}{\left(\sum_{i=1}^n c_i w_i \right)^2 - \sum_{i=1}^n w_i^2 \sum_{i=1}^n c_i^2}
\end{aligned}$$

[20]

QUESTION 5

(a)

$$\begin{aligned}
L(\theta) &= \prod_{i=1}^n f_X(x_i; \theta) \\
&= \prod_{i=1}^n \frac{1}{\theta} e^{-x_i/\theta} \\
&= \frac{1}{\theta} e^{-x_1/\theta} \times \frac{1}{\theta} e^{-x_2/\theta} \times \dots \times \frac{1}{\theta} e^{-x_n/\theta} \\
&= \frac{1}{\theta^n} e^{-(x_1/\theta + x_2/\theta + \dots + x_n/\theta)} \\
&= \theta^{-n} e^{-\sum x_i/\theta} \quad (\text{see definition 2.5})
\end{aligned}$$

$$\implies \ln L(\theta) = -n \ln \theta - \sum x_i \theta^{-1}$$

$$\implies \frac{\partial \ln L(\theta)}{\partial \theta} = \frac{-n}{\theta} - \frac{\sum x_i}{\theta^2} (-1)$$

If we set $\frac{\partial \ln L(\theta)}{\partial \theta} = 0$ we get

$$\frac{\sum x_i}{\theta^2} = \frac{n}{\theta}$$

$$\begin{aligned}
\implies \hat{\theta} &= \frac{\sum X_i}{n} \\
&= \bar{X}
\end{aligned}$$

Thus $\hat{\theta} = \bar{X}$ (the maximum likelihood estimator(m.l.e.) of θ)

(6)

(b) To show that the m.l.e. is an unbiased estimator, we have to show that $E(\hat{\theta}) = \theta$.

$$E(\hat{\theta}) = E\left[\frac{1}{n} \sum X_i\right] = \frac{1}{n} \sum E(X_i) = \frac{1}{n} n\theta = \theta \text{ (q.e.d.)}.$$
 (4)

$$(c) \text{Var}(\hat{\theta}) = \text{var}\left[\frac{1}{n} \sum X_i\right] = \left(\frac{1}{n}\right)^2 \sum \text{var}(X_i) = \left(\frac{1}{n}\right)^2 \sum \theta^2 = \frac{1}{n^2} n\theta^2 = \frac{\theta^2}{n}$$
 (3)

[13]**QUESTION 6**

(a) It follows from snapshot 1 that we have a data table with the name "Untitled 2". (2)

(b) From snapshot 1 it follows that we have activated the first column with the name "Column 1" and selected the Formula option under the menu of Column Properties. (2)

(c) From snapshot 2 it follows that we have selected the random function to create simulated data form a normal population. (2)

(d) From snapshot 2 it follows that we have edited the random function to create simulated data form a **normal population** with $\mu = 73$ and $\sigma^2 = 8$. (2)

(e) From snapshot 3 it follows that we have a data table with the name "**STA2601Sem1Ass12016Q6**". (2)

(f) From snapshot 3 it follows that we will have a first column with the name "normal(73, 8)" which will contain 20 rows if the OK button is pressed. (2)

[12]**[100]**