

ECON 6190 Section 5

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1. [Hong 6.8] Establish the following recursion relations for sample means and sample variances. Let  $\bar{X}_n$  and  $s_n^2$  be the sample mean and sample variances based on random sample  $\{X_1, X_2, \dots, X_n\}$ . Then suppose another observation,  $X_{n+1}$ , becomes available. Show:

(a)  $\bar{X}_{n+1} = \frac{X_{n+1} + n\bar{X}_n}{n+1}$ .

(b)  $ns_{n+1}^2 = (n-1)s_n^2 + \frac{n}{n+1}(X_{n+1} - \bar{X}_n)^2$ .

(a) check solution

(b) Method 1 start with LHS

$$\begin{aligned}
 ns_{n+1}^2 &\stackrel{\text{def}}{=} \frac{1}{n+1} \sum_{i=1}^{n+1} (X_i - \bar{X}_{n+1})^2 \\
 &= \sum_{i=1}^{n+1} (X_i - \bar{X}_n + \bar{X}_n - \bar{X}_{n+1})^2 \\
 &= \sum_{i=1}^{n+1} (X_i - \bar{X}_n)^2 + 2 \sum_{i=1}^{n+1} (X_i - \bar{X}_n)(\bar{X}_n - \bar{X}_{n+1}) + \sum_{i=1}^{n+1} (\bar{X}_n - \bar{X}_{n+1})^2 \\
 &\quad \text{only term indexed by } i \qquad \text{not indexed by } i \\
 &= 2(\bar{X}_n - \bar{X}_{n+1}) \sum_{i=1}^{n+1} (X_i - \bar{X}_n) + (n+1)(\bar{X}_n - \bar{X}_{n+1})^2 \\
 &= 2(\bar{X}_n - \bar{X}_{n+1}) \left( \sum_{i=1}^{n+1} X_i - (n+1)\bar{X}_n \right) \\
 &= (n+1) \left( \frac{1}{n+1} \sum_{i=1}^{n+1} X_i - \bar{X}_n \right) \\
 &\quad \bar{X}_{n+1} \\
 &= (n+1)(\bar{X}_{n+1} - \bar{X}_n) \\
 &= -2(n+1)(\bar{X}_n - \bar{X}_{n+1})^2 \qquad \text{side note:} \\
 &= \sum_{i=1}^{n+1} (X_i - \bar{X}_n)^2 - (n+1)(\bar{X}_n - \bar{X}_{n+1})^2 \qquad \text{on a high level, when} \\
 &= \underbrace{\sum_{i=1}^n (X_i - \bar{X}_n)^2}_{(n-1)s_n^2} + \underbrace{(X_{n+1} - \bar{X}_n)^2 - (n+1)(\bar{X}_n - \bar{X}_{n+1})^2}_{\text{WTS: } \frac{n}{n+1}(X_{n+1} - \bar{X}_n)^2} \\
 &\quad \text{typically get forms like } (\square)^2 + 2(\square)(\Delta) + (\Delta)^2 \\
 &\quad \quad \quad = -2(\Delta)^2 \\
 &\quad \quad \quad = (\ )^2 - (\ )^2
 \end{aligned}$$

Recall from (a):  $\bar{X}_{n+1} = \frac{X_{n+1} + n\bar{X}_n}{n+1}$

$$\begin{aligned}
 \Rightarrow (\bar{X}_n - \bar{X}_{n+1})^2 &= \left( \bar{X}_n - \frac{X_{n+1} + n\bar{X}_n}{n+1} \right)^2 \\
 &= \left( \frac{X_{n+1}}{n+1} - \frac{(n+1-n)\bar{X}_n}{n+1} \right)^2 \\
 &= \left( \frac{1}{n+1} \right)^2 (X_{n+1} - \bar{X}_n)^2
 \end{aligned}$$

$$\begin{aligned}
 &= (n-1)S_n^2 + (x_{n+1} - \bar{x}_n)^2 - \cancel{(n+1)} \left(\frac{1}{n+1}\right)^2 (x_{n+1} - \bar{x}_n)^2 \\
 &= (n-1)S_n^2 + \frac{n}{n+1} (x_{n+1} - \bar{x}_n)^2
 \end{aligned}$$

Method #2 Start with RHS

$$\begin{aligned}
 &(n-1)S_n^2 + \frac{n}{n+1} (x_{n+1} - \bar{x}_n)^2 \\
 \stackrel{\text{DEF}}{=} & \cancel{(n+1)} \left(\frac{1}{n+1} \sum_{i=1}^n (x_i - \bar{x}_n)^2\right) + \frac{n}{n+1} (x_{n+1} - \bar{x}_n)^2 \\
 &= \sum_{i=1}^n (x_i - \bar{x}_n)^2 + (x_{n+1} - \bar{x}_n)^2 - \frac{1}{n+1} (x_{n+1} - \bar{x}_n)^2 \\
 &= \sum_{i=1}^{n+1} (x_i - \bar{x}_n)^2 - \frac{1}{n+1} (x_{n+1} - \bar{x}_n)^2 \\
 & \quad \text{combine} \\
 &= \sum_{i=1}^{n+1} (x_i - \bar{x}_n)^2 - \frac{1}{n+1} \left( (n+1)\bar{x}_{n+1} - n\bar{x}_n \right)^2 \\
 & \quad \text{b/c } (n+1)\frac{1}{n+1}\sum_{i=1}^{n+1} x_i - n\frac{1}{n}\sum_{i=1}^n x_i = x_{n+1} \\
 &= \sum_{i=1}^{n+1} (x_i - \bar{x}_n)^2 - \frac{1}{n+1} \left( (n+1)\bar{x}_{n+1} - (n+1)\bar{x}_n \right)^2 \\
 &= \sum_{i=1}^{n+1} (x_i - \bar{x}_n)^2 - (n+1) (\bar{x}_{n+1} - \bar{x}_n)^2 \\
 & \quad = \sum_{i=1}^{n+1} (\bar{x}_{n+1} - \bar{x}_n)^2 \\
 & \quad \text{constant, not indexed by } i \\
 &= \sum_{i=1}^{n+1} \underbrace{(x_i - \bar{x}_n)}_a^2 - \underbrace{(x_{n+1} - \bar{x}_n)}_b^2 \quad \text{Recall: } a^2 - b^2 = (a+b)(a-b) \\
 &= \sum_{i=1}^{n+1} (x_i - \bar{x}_n + x_{n+1} - \bar{x}_n)(x_i - \bar{x}_n - x_{n+1} + \bar{x}_n) \\
 &= \sum_{i=1}^{n+1} \left( \underbrace{x_i - x_{n+1}}_a + 2(\bar{x}_{n+1} - \bar{x}_n) \right) (x_i - x_{n+1}) \\
 &= \underbrace{\sum_{i=1}^{n+1} (x_i - x_{n+1})^2}_{= n \left(\frac{1}{n} \sum_{i=1}^{n+1} (x_i - \bar{x}_{n+1})^2\right)} + 2 \sum_{i=1}^{n+1} (\bar{x}_{n+1} - \bar{x}_n)(x_i - x_{n+1}) \\
 & \quad \text{WTS: } \otimes = 0 \\
 &= nS_{n+1}^2
 \end{aligned}$$

Consider  $\otimes$  : 
$$2 \sum_{i=1}^{n+1} (\bar{X}_{n+1} X_i - (\bar{X}_{n+1})^2 - X_i \bar{X}_n + \bar{X}_n \bar{X}_{n+1})$$

$$= 2 \left( \underbrace{\bar{X}_{n+1} \sum_{i=1}^{n+1} X_i}_{=(n+1)\bar{X}_{n+1}} - \underbrace{(n+1)(\bar{X}_{n+1})^2}_{(n+1)(\bar{X}_{n+1})^2} - \bar{X}_n \sum_{i=1}^{n+1} X_i + (n+1)(\bar{X}_n \bar{X}_{n+1}) \right)$$

$$= 2 \left( \underbrace{(n+1)\bar{X}_{n+1}}_{(n+1)\bar{X}_{n+1}} - \underbrace{(n+1)(\bar{X}_{n+1})^2}_{(n+1)(\bar{X}_{n+1})^2} - \underbrace{(n+1)\bar{X}_n \bar{X}_{n+1}}_{(n+1)\bar{X}_n \bar{X}_{n+1}} + \underbrace{(n+1)\bar{X}_n \bar{X}_{n+1}}_{(n+1)\bar{X}_n \bar{X}_{n+1}} \right)$$

$$= 0$$

$$\Rightarrow \text{RHS} = n S_{n+1}^2 \quad \square$$

2. [Hong 6.6] Suppose  $\underline{X}^n = (X_1, \dots, X_n)$  is an iid  $N(\mu, \sigma^2)$  random sample,  $\underline{Y}^n = (Y_1, \dots, Y_n)$  is an iid  $N(\mu, \sigma^2)$  random sample, and the two random samples are mutually independent. Let  $\bar{X}_n$  and  $\bar{Y}_n$  be the sample means of the first and second random samples, respectively, and let  $s_X^2$  and  $s_Y^2$  be the sample variances of the first and second random samples respectively. Find:

(a) the distribution of  $(\bar{X}_n - \bar{Y}_n) / \sqrt{2\sigma^2/n}$ ;

Theorem If  $X_i, i = 1, \dots, n$  are iid  $\mathcal{N}(\mu, \sigma^2)$ , then

①  $\bar{X}_n$  and  $S^2$  are independent

②  $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$

DEF Let  $\{Z_1, Z_2, \dots, Z_r\}$  be iid  $\mathcal{N}(0,1)$ , then  $\sum_{i=1}^r Z_i^2 \sim \chi_r^2$

DEF Let  $Z \sim \mathcal{N}(0,1)$  and  $Q \sim \chi_r^2$  be independent. Then  $T = \frac{Z}{\sqrt{Q/r}} \sim t_r$

(a) (b) (c) see solution

(d) the distribution of  $(\bar{X}_n - \bar{Y}_n) / \sqrt{(s_X^2 + s_Y^2)/n}$ ;

$$\frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{2\sigma^2}{n}}} \sim \mathcal{N}(0,1)$$

$$\frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{s_X^2 + s_Y^2}{n}}} = \frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{2\sigma^2}{n}}} \cdot \frac{\sqrt{\frac{2\sigma^2}{n}}}{\sqrt{\frac{s_X^2 + s_Y^2}{n}}} = \frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{s_X^2 + s_Y^2}{2\sigma^2}}} \sim \mathcal{N}(0,1)$$

$$= \sqrt{\frac{(n-1)(s_X^2 + s_Y^2)}{2(n-1)\sigma^2}} = \sqrt{\frac{(n-1)s_X^2}{2(n-1)\sigma^2} + \frac{(n-1)s_Y^2}{2(n-1)\sigma^2}}$$

(loose notation)  $\sqrt{\frac{1}{2(n-1)} \sum_{i=1}^{n-1} Z_i^2 + \frac{1}{2(n-1)} \sum_{i=1}^{n-1} W_i^2} = \sqrt{\frac{1}{2(n-1)} \sum_{i=1}^{2(n-1)} Z_i^2} \sim \chi_{2(n-1)}^2$

Since  $\bar{X}_n$  and  $S_x^2$  independent,  $\bar{Y}_n$  and  $S_y^2$  are independent,

$\left(\frac{\bar{X} - \bar{Y}}{\sqrt{\frac{2\sigma^2}{n}}}\right)$  and  $\left(\frac{S_x^2 + S_y^2}{2\sigma^2}\right)$  are also independent.

$$\Rightarrow \frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{S_x^2 + S_y^2}{n}}} \sim t_{2(n-1)}$$

(e) the distribution of  $(\bar{X}_n - \bar{Y}_n) / \sqrt{s_n^2/n}$ , where  $s_n^2$  is the sample variance of the difference sample  $Z^n = (Z_1, Z_2, \dots, Z_n)$ , where  $Z_i = X_i - Y_i, i = 1, 2, \dots, n$ .

$$Z_i = X_i - Y_i, \quad Z \sim \mathcal{N}(\mu - \mu, \sigma^2 + \sigma^2 + 0)$$

$$\Rightarrow Z \sim \mathcal{N}(0, 2\sigma^2)$$

$$\frac{\bar{X}_n - \bar{Y}_n}{\sqrt{\frac{S_n^2}{n}}} = \frac{\bar{Z}_n}{\sqrt{\frac{2\sigma^2}{n}}} \cdot \frac{\sqrt{\frac{2\sigma^2}{n}}}{\sqrt{\frac{S_n^2}{n}}} = \frac{\frac{\bar{Z}_n}{\sqrt{\frac{2\sigma^2}{n}}} \sim \mathcal{N}(0,1)}{\sqrt{\frac{S_n^2}{2\sigma^2}} \sim \frac{\chi_{n-1}^2}{n-1}}$$

Since  $\bar{Z}_n$  and  $S_n^2$  are independent,

$$\frac{\bar{X} - \bar{Y}_n}{\sqrt{\frac{S_n^2}{n}}} \sim t_{n-1}$$

4. [Final exam, 2022] Let  $\{X_1, \dots, X_n\}$  be i.i.d with pdf  $f(x | \theta) = e^{-(x-\theta)} \mathbf{1}\{x \geq \theta\}$ . Show  $Y = \min\{X_1, \dots, X_n\}$  is a sufficient statistic for  $\theta$  without using the Factorization Theorem.

$$\mathbf{1}\{x \geq \theta\} = \begin{cases} 1, & x \geq \theta \\ 0, & \text{o/w} \end{cases}$$

$$f(x|\theta) = e^{-(x-\theta)} \mathbf{1}\{x \geq \theta\} \Leftrightarrow f(x|\theta) = \begin{cases} e^{-(x-\theta)}, & x \geq \theta \\ 0, & \text{o/w} \end{cases}$$

Property of Indicator function:  $E[\mathbf{1}\{x \in A\}] = P(x \in A)$

WTS:  $\frac{P(\mathbf{X} | \theta)}{q(t(\mathbf{X}) | \theta)}$  is not a function of  $\theta$  over the sample space.

1) density of  $\{x_1, \dots, x_n\}$ .

$$P(x_1, \dots, x_n | \theta) \stackrel{\text{iid}}{=} \begin{cases} e^{-\sum_{i=1}^n x_i} e^{-n\theta}, & \min\{x_1, \dots, x_n\} \geq \theta. \\ 0, & \text{o/w} \end{cases}$$

2) To find the density of  $Y$ , start with cdf of  $Y$

$$\begin{aligned} P(Y \leq y) &= P(\min\{x_1, \dots, x_n\} \leq y) \\ &= 1 - P(\min\{x_1, \dots, x_n\} > y) \\ &= 1 - P(x_1 > y, x_2 > y, \dots, x_n > y) \\ &= 1 - \prod_{i=1}^n P(x_i > y) \\ &= \begin{cases} 1 - e^{-n(y-\theta)}, & \text{for } y \geq \theta \\ 0, & \text{o/w} \end{cases} \end{aligned}$$

$\Rightarrow$  pdf of  $Y$   $f(y|\theta) = \begin{cases} n e^{-n(y-\theta)}, & \text{for } y \geq \theta \\ 0, & \text{o/w} \end{cases}$  For  $y < \theta$ ,  $P(x_i > y) = 1$

$$\Rightarrow \frac{P(x_1, \dots, x_n | \theta)}{f(y|\theta)} = \frac{e^{-\sum_{i=1}^n x_i}}{n e^{-n(\min\{x_1, \dots, x_n\})}} \quad \text{for } \min(x_1, \dots, x_n) \geq \theta.$$

$\hookrightarrow$  NOT A function of  $\theta$

$\Rightarrow \min\{x_1, \dots, x_n\}$  is a s.s.