

STA 302 F17 Assignment 2

$$\begin{aligned} (1) (a) 1-\alpha &= P\left\{-t_{\alpha/2} < \frac{\sqrt{n}(\bar{y}-\mu)}{s} < t_{\alpha/2}\right\} \\ &= P\left\{-t_{\alpha/2} \frac{s}{\sqrt{n}} < \bar{y}-\mu < t_{\alpha/2} \frac{s}{\sqrt{n}}\right\} \\ &= P\left\{-\bar{y}-t_{\alpha/2} \frac{s}{\sqrt{n}} < -\mu < -\bar{y}+t_{\alpha/2} \frac{s}{\sqrt{n}}\right\} \\ &= P\left\{\bar{y}+t_{\alpha/2} \frac{s}{\sqrt{n}} > \mu > \bar{y}-t_{\alpha/2} \frac{s}{\sqrt{n}}\right\} \\ &= P\left\{\bar{y}-t_{\alpha/2} \frac{s}{\sqrt{n}} < \mu < \bar{y}+t_{\alpha/2} \frac{s}{\sqrt{n}}\right\} \end{aligned}$$

$$\begin{aligned} (b) \bar{y}-t_{\alpha/2} \frac{s}{\sqrt{n}} &= 2.57 - (2.07) \sqrt{\frac{5.85}{23}} \\ &= 2.57 - 1.04 = 1.53 \end{aligned}$$

$$\bar{y}+t_{\alpha/2} \frac{s}{\sqrt{n}} = 2.57 + 1.04 = 4.61$$

So the 95% CI is (1.53, 4.61)

$$\begin{aligned} (c) (i) T &= \frac{\bar{y}-\mu_0}{s/\sqrt{n}} = \frac{2.57-3}{0.5043} = \frac{-0.43}{0.5043} \\ &= -0.853 \end{aligned}$$

(ii) No, don't reject H_0

(iii) No

(iv) NA

$$\begin{aligned} \textcircled{2} \text{ (a) } E(y_i) &= E(\beta_0 + \beta_1 x_i + \varepsilon) = E(\beta_0 + \beta_1 x_i) + E(\varepsilon_i) \\ &= \beta_0 + \beta_1 x_i + 0 = \beta_0 + \beta_1 x_i \end{aligned}$$

$$\begin{aligned} \text{(b) } \frac{\partial S}{\partial \beta_0} &= \frac{\partial}{\partial \beta_0} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \\ &= \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(-1) \stackrel{\text{set}}{=} 0 \end{aligned}$$

$$\Rightarrow \sum_{i=1}^n y_i - n\beta_0 - \beta_1 \sum_{i=1}^n x_i = 0$$

$$\Rightarrow n\beta_0 = \sum_{i=1}^n y_i - \beta_1 \sum_{i=1}^n x_i \Rightarrow \beta_0 = \bar{y} - \beta_1 \bar{x} \quad (*)$$

$$\frac{\partial S}{\partial \beta_1} = \frac{\partial}{\partial \beta_1} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

$$= \sum_{i=1}^n 2(y_i - \beta_0 - \beta_1 x_i)(-x_i)$$

$$= -2 \sum_{i=1}^n (x_i y_i - x_i \beta_0 - \beta_1 x_i^2)$$

$$= -2 \left(\sum_{i=1}^n x_i y_i - \beta_0 \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 \right) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - \beta_0 \sum_{i=1}^n x_i - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

Substituting for β_0 using the first equation,

$$\sum_{i=1}^n x_i y_i - (\bar{y} - \beta_1 \bar{x}) n \bar{x} - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

$$\Rightarrow \sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} + \beta_1 n \bar{x}^2 - \beta_1 \sum_{i=1}^n x_i^2 = 0$$

(2b continued)

$$\Rightarrow \sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} - \beta_1 \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right) = 0$$

$$\Rightarrow \beta_1 \left(\sum_{i=1}^n x_i^2 - n \bar{x}^2 \right) = \sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}$$

$$\Rightarrow \beta_1 = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2}$$

Denoting this solution by b_1 , gives (1.13)

Substituting b_1 for β_1 in (*) gives

$$b_0 = \bar{y} - b_1 \bar{x}, \text{ which is (1.11)}$$

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(1.15)

$$b_1 \text{ (1.14) says } b_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \frac{\sum_{i=1}^n (x_i y_i - x_i \bar{y} - \bar{x} y_i + \bar{x} \bar{y})}{\sum_{i=1}^n (x_i^2 - 2x_i \bar{x} + \bar{x}^2)}$$

$$= \frac{\sum_{i=1}^n x_i y_i - \bar{y} \sum_{i=1}^n x_i - \bar{x} \sum_{i=1}^n y_i + n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - 2\bar{x} \sum_{i=1}^n x_i + n \bar{x}^2}$$

$$= \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y} - n \bar{x} \bar{y} + n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - 2n \bar{x} \bar{x} + n \bar{x}^2}$$

$$= \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2} \quad \text{which is (1.13)}$$

$$\begin{aligned}
 (d) \quad \sum_{i=1}^n (x_i - \bar{x}) &= \sum_{i=1}^n x_i - \sum_{i=1}^n \bar{x} = \sum_{i=1}^n x_i - n\bar{x} \\
 &= \sum_{i=1}^n x_i - n \frac{\sum_{i=1}^n x_i}{n} = 0
 \end{aligned}$$

$$\begin{aligned}
 (e) \quad \frac{d}{d\gamma_0} \sum_{i=1}^n (\gamma_i - \gamma_0 - \beta_1 (x_i - \bar{x}))^2 \\
 &= 2 \sum_{i=1}^n (\gamma_i - \gamma_0 - \beta_1 (x_i - \bar{x})) (-1) \stackrel{d}{=} 0 \\
 \Rightarrow \sum_{i=1}^n \gamma_i - n\gamma_0 - \beta_1 \underbrace{\sum_{i=1}^n (x_i - \bar{x})}_{=0 \text{ by (d)}} &= 0
 \end{aligned}$$

$$\Rightarrow \sum_{i=1}^n \gamma_i = n\gamma_0 \Rightarrow \gamma_0 = \frac{\sum_{i=1}^n \gamma_i}{n} = \bar{\gamma}$$

And the least squares estimate of γ_0 is $\bar{\gamma}$ for any β_1

(2 e continued)

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^n (y_i - \gamma_0 - \beta_1 (x_i - \bar{x}))^2$$

$$= 2 \sum_{i=1}^n (y_i - \gamma_0 - \beta_1 (x_i - \bar{x})) (-1) (x_i - \bar{x}) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \sum_{i=1}^n (y_i - \gamma_0 - \beta_1 (x_i - \bar{x})) (x_i - \bar{x}) = 0$$

$$\Rightarrow \sum_{i=1}^n (y_i - \gamma_0) (x_i - \bar{x}) - \beta_1 \sum_{i=1}^n (x_i - \bar{x})^2 = 0$$

Substituting $\gamma_0 = \bar{y}$ from the first equation,

$$\sum_{i=1}^n (x_i - \bar{x}) (y_i - \bar{y}) = \beta_1 \sum_{i=1}^n (x_i - \bar{x})^2$$

$$\Rightarrow \beta_1 = \frac{\sum_{i=1}^n (x_i - \bar{x}) (y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{which is (1.14)}$$

And the least squares estimate of the slope b_1 is unaffected by centering

$$(f) \sum_{i=1}^n e_i = \sum_{i=1}^n (y_i - \hat{y}_i) = \sum_{i=1}^n (y_i - (b_0 + b_1 x_i))$$

$$= \sum_{i=1}^n (y_i - (\bar{y} - b_1 \bar{x}) - b_1 x_i)$$

$$= \sum_{i=1}^n (y_i - \bar{y} - b_1 (x_i - \bar{x})) =$$

$$= \underbrace{\sum_{i=1}^n (y_i - \bar{y})}_0 - b_1 \underbrace{\sum_{i=1}^n (x_i - \bar{x})}_0 = 0$$

Zg Exerciso 1.6, p. 23

$y_i = \mu + \varepsilon_i$, $E(\varepsilon_i) = 0$, $\text{Var}(\varepsilon_i) = \sigma^2$, ε_i independent

$$E(y_i) = \mu, \text{ minimize } S = \sum_{i=1}^n (y_i - \mu)^2$$

$$\frac{dS}{d\mu} = \frac{d}{d\mu} \sum_{i=1}^n (y_i - \mu)^2 = \sum_{i=1}^n 2(y_i - \mu)(-1) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \sum_{i=1}^n (y_i - \mu) = 0 \Rightarrow \sum_{i=1}^n y_i - \sum_{i=1}^n \mu = \sum_{i=1}^n y_i - n\mu = 0$$

$$\Rightarrow \sum_{i=1}^n y_i = n\mu \Rightarrow \mu = \bar{y}$$

$$\begin{aligned} \text{Var}(\bar{y}) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n y_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n y_i\right) \\ &\stackrel{\text{ind}}{=} \frac{1}{n^2} \sum_{i=1}^n \text{Var}(y_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 = \frac{1}{n^2} n \sigma^2 \\ &= \frac{\sigma^2}{n} \end{aligned}$$

You don't have to show quite this much work.

h

~~$b_0 = -1.6384$~~

~~$b_1 = 0.3264$~~

-1.60384

0.03264

$$\begin{aligned} (3) (a) E(y_i) &= E(\beta_1 x_i + \varepsilon_i) = E(\beta_1 x_i) + E(\varepsilon_i) \\ &= \beta_1 x_i + 0 = \beta_1 x_i \end{aligned}$$

$$(b) \frac{d}{d\beta_1} \sum_{i=1}^n (y_i - \beta_1 x_i)^2 = 2 \sum_{i=1}^n (y_i - \beta_1 x_i)(-x_i)$$

$$= -2 \sum_{i=1}^n (x_i y_i - \beta_1 x_i^2) = -2 \left(\sum_{i=1}^n x_i y_i - \beta_1 \sum_{i=1}^n x_i^2 \right)$$

$$\underline{\text{set}} \ 0 \Rightarrow \sum_{i=1}^n x_i y_i = \beta_1 \sum_{i=1}^n x_i^2$$

$$\Rightarrow \beta_1 = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} \quad \text{call this solution } b_1$$

2nd Derivative test

$$\frac{d}{d\beta_1} -2 \left(\sum_{i=1}^n x_i y_i - \beta_1 \sum_{i=1}^n x_i^2 \right)$$

$$= (-2) \left(-\sum_{i=1}^n x_i^2 \right) = 2 \sum_{i=1}^n x_i^2 > 0$$

Concave up, minimum

$$(c) (\text{Exercise 1.1}) E(b_1) = E \left\{ \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} \right\}$$

$$= \frac{\sum_{i=1}^n x_i E(y_i)}{\sum_{i=1}^n x_i^2} = \frac{\sum_{i=1}^n x_i (x_i \beta_1)}{\sum_{i=1}^n x_i^2} = \beta_1 \frac{\sum x_i^2}{\sum x_i^2} = \beta_1$$

$$\textcircled{3d} \quad \sum_{i=1}^n e_i = \sum_{i=1}^n (y_i - \hat{y}_i) = \sum_{i=1}^n b_i - \sum_{i=1}^n b_i x_i$$

$$= \sum_{i=1}^n b_i - \frac{\left(\sum_{i=1}^n x_i b_i\right) \left(\sum_{i=1}^n x_i\right)}{\sum_{i=1}^n x_i^2}$$

No, no particular reason it should be zero

$$\textcircled{e} \quad E(e_i) = E(y_i - \hat{y}_i) = E(y_i) - E(b_i x_i)$$

$$= x_i \beta - x_i E(b_i) = x_i \beta - x_i \beta = 0$$

$$E\left(\sum_{i=1}^n e_i\right) = \sum_{i=1}^n E(e_i) = \sum_{i=1}^n 0 = 0$$

That's the easy way, but also taking the expected value of the messy expression in (3d) yields zero.

$$(4) (a) M_{ax}(t) = E(e^{(ax)t}) = E(e^{x(at)}) \\ = M_x(at)$$

$$(b) M_{x+a}(t) = E(e^{(x+a)t}) = E(e^{xt+at}) \\ = E(e^{xt} e^{at}) = e^{at} E(e^{xt}) \\ = e^{at} M_x(t)$$

$$(c) M_{\sum_{i=1}^n x_i}(t) = E(e^{(\sum_{i=1}^n x_i)t}) = E(e^{\sum_{i=1}^n (x_i)t})$$

$$= E\left(\prod_{i=1}^n e^{x_i t}\right)$$

$$= \int \dots \int e^{x_1 t} e^{x_2 t} \dots e^{x_n t} f_{\underline{x}}(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n$$

$$\stackrel{\text{ind}}{\downarrow} = \int \dots \int e^{x_1 t} \dots e^{x_n t} f_{x_1}(x_1) \dots f_{x_n}(x_n) dx_1 \dots dx_n$$

$$= \int \dots \int e^{x_2 t} \left(\int e^{x_1 t} f_{x_1}(x_1) dx_1 \right) f_{x_2}(x_2) dx_2 \dots f_{x_n}(x_n) dx_n$$

$$= M_{x_1}(t) \int \dots \int e^{x_3 t} \left(\int e^{x_2 t} f_{x_2}(x_2) dx_2 \right) f_{x_3}(x_3) dx_3 \dots f_{x_n}(x_n) dx_n$$

4c continued

$= M_{x_1}(t) M_{x_2}(t) \dots M_{x_n}(t)$ as claimed.

(5) (a) $M_{ax+b}(t) = M_{ax+b}(t) \stackrel{4a \neq b}{=} e^{bt} M_x(at)$
 $= e^{bt} e^{\mu(at) + \frac{1}{2} \sigma^2 (at)^2}$
 $= e^{(a\mu+b)t + \frac{1}{2} (a^2 \sigma^2) t^2}$

MGF of $N(a\mu+b, a^2 \sigma^2)$

(b) $z = \frac{x-\mu}{\sigma}$. This is (5a) with $a = \frac{1}{\sigma}$, $b = -\frac{\mu}{\sigma}$

So $z \sim N\left(\frac{1}{\sigma} \mu - \frac{\mu}{\sigma}, \frac{1}{\sigma^2} \sigma^2\right) = N(0, 1)$

(c) $M_{\sum x_i}(t) = M_{\sum x_i}(t) \stackrel{4c}{=} \prod_{i=1}^n M_{x_i}(t)$
 $= \prod_{i=1}^n e^{\mu t + \frac{1}{2} \sigma^2 t^2} = e^{(n\mu)t + \frac{1}{2} (n\sigma^2) t^2}$

MGF of $N(n\mu, n\sigma^2)$

(d) $M_{\bar{x}}(t) = M_{\frac{1}{n} \sum x_i}(t) \stackrel{4a}{=} M_{\sum x_i}\left(\frac{t}{n}\right)$
 $= M_{\sum x_i}\left(\frac{t}{n}\right)$ where $\sum x_i$ as in 5c
 $= e^{n\mu \cdot \frac{t}{n} + \frac{1}{2} n\sigma^2 \cdot \frac{t^2}{n^2}} = e^{\mu t + \frac{1}{2} \left(\frac{\sigma^2}{n}\right) t^2}$
MGF of $N\left(\mu, \frac{\sigma^2}{n}\right)$

5e) By 5d, $\bar{x} \sim N(\mu, \frac{\sigma^2}{n})$, and then
 by 5b $z = \frac{\sqrt{n}(\bar{x} - \mu)}{\sigma} = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}}$
 $= \frac{\bar{x} - E(\bar{x})}{\sqrt{\text{Var}(\bar{x})}} \sim N(0, 1)$

(f) By (5a), $a_i x_i \sim N(a_i \mu_i, a_i^2 \sigma_i^2)$, and
 then by (4c),

$$M_{\sum a_i x_i}(t) = \prod_{i=1}^n M_{a_i x_i}(t) = \prod_{i=1}^n e^{a_i \mu_i t + \frac{1}{2} (a_i^2 \sigma_i^2) t^2}$$

$$= e^{(\sum_{i=1}^n a_i \mu_i) t + \frac{1}{2} (\sum_{i=1}^n a_i^2 \sigma_i^2) t^2}$$

MGF of $N(\sum_{i=1}^n a_i \mu_i, \sum_{i=1}^n a_i^2 \sigma_i^2)$

6) Model (1.20) is $y_i = \beta_1 x_i + \varepsilon_i$
 If $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$, $y_i \sim N(\beta_1 x_i, \sigma^2)$

$b_1 = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}$ is a linear combination of
 y_i values as in (5f), so

it's normal. $E(b_1) = \beta_1$ by 3c, and

6 continued

$$\text{Var}(b_1) = \text{Var}\left(\frac{\sum_{i=1}^n x_i y_i}{\sum x_i^2}\right)$$

$$\stackrel{\text{ind}}{=} \frac{1}{(\sum x_i^2)^2} \sum_{i=1}^n x_i^2 \text{Var}(y_i)$$

$$= \frac{\sigma^2 \sum x_i^2}{(\sum x_i^2)^2} = \frac{\sigma^2}{\sum x_i^2}, \text{ so}$$

$$b_1 \sim \mathcal{N}\left(\beta_1, \frac{\sigma^2}{\sum x_i^2}\right)$$

$$\begin{aligned} \textcircled{7} \text{ (a) } M_{\sum y_i}(t) &= M_{\sum x_i}(t) = \prod_{i=1}^n M_{x_i}(t) \\ &= \prod_{i=1}^n (1-2t)^{-x_i/2} = (1-2t)^{-\left(\sum_{i=1}^n x_i\right)/2} \end{aligned}$$

$$\text{MGF of } \chi^2\left(\sum_{i=1}^n x_i\right)$$

$$\textcircled{7b} \quad M_{Z^2}(t) = E(e^{Z^2 t})$$

$$= \int_{-\infty}^{\infty} e^{z^2 t} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(1-2t)z^2} dz$$

$$= (1-2t)^{-\frac{1}{2}} \int_{-\infty}^{\infty} \frac{1}{(1-2t)^{-\frac{1}{2}} \sqrt{2\pi}} e^{-\frac{1}{2} \frac{z^2}{(1-2t)^{-1}}} dz$$

Density of a normal with expected value zero & variance $(1-2t)^{-1}$, provided $(1-2t)^{-1} = \frac{1}{1-2t} > 0 \Leftrightarrow 1-2t > 0 \Leftrightarrow 1 > 2t \Leftrightarrow t < \frac{1}{2}$. If so the integral converges and = 1

$$= (1-2t)^{-\frac{1}{2}}, \quad \text{MGF of } \chi^2(1)$$

(7c)

$$\begin{aligned} \sigma^2 &= \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 = \sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma} \right)^2 \\ &= \sum_{i=1}^n z_i^2, \text{ where } z_i \text{ are independent,} \end{aligned}$$

because the x_i are independent,

$$z_i \sim \mathcal{N}(0, 1) \text{ by (5b), } z_i^2 \sim \chi^2(1)$$

by (7b), and the sum of independent chi-squares is chi-squared by (7a) with

$$df = \sum_{i=1}^n \nu_i = \sum_{i=1}^n 1 = n, \text{ so}$$

$$\sigma^2 \sim \chi^2(n)$$

$$\begin{aligned} (d) \quad M_{\sigma^2}(t) &= M_{x_1}(t) M_{x_2}(t) \\ \text{"} & \quad \quad \quad \text{"} \\ (1-2t)^{-\frac{\nu_1 + \nu_2}{2}} & \quad \quad \quad (1-2t)^{-\frac{\nu_2}{2}} \end{aligned}$$

$$\Rightarrow (1-2t)^{-\nu_1/2} (1-2t)^{-\nu_2/2} = M_{x_1}(t) (1-2t)^{-\nu_2/2}$$

$$\Rightarrow M_{x_1}(t) = (1-2t)^{-\nu_1/2}, \text{ MGF of } \chi^2(\nu_1)$$

(7e) Following the hint,

$$\begin{aligned} \sum_{i=1}^n (x_i - \mu)^2 &= \sum_{i=1}^n \underbrace{(x_i - \bar{x})}_{a_i} + \underbrace{(\bar{x} - \mu)}_b)^2 \\ &= \sum_{i=1}^n \left((x_i - \bar{x})^2 + 2(\bar{x} - \mu)(x_i - \bar{x}) + (\bar{x} - \mu)^2 \right) \\ &= \sum_{i=1}^n (x_i - \bar{x})^2 + 2(\bar{x} - \mu) \underbrace{\sum_{i=1}^n (x_i - \bar{x})}_{=0 \text{ by } 7d} + n(\bar{x} - \mu)^2 \\ &= \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \mu)^2 \end{aligned}$$

$$\Rightarrow \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \mu)^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{\sigma^2} + \frac{n(\bar{x} - \mu)^2}{\sigma^2}$$

That is

$$\sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma} \right)^2 = \frac{(n-1) s^2}{\sigma^2} + \left(\frac{\sqrt{n}(\bar{x} - \mu)}{\sigma} \right)^2$$

$\chi^2(n)$ by (7c)

Inside is $N(0,1)$
by 5e, Square is
 $\chi^2(1)$ by 7b

The two terms on the right are independent because they are functions of s^2 and \bar{x} , which are independent. Then by (7d),

$$\frac{(n-1)s^2}{\sigma^2} \sim \chi^2(n-1)$$

$$(\gamma_1 + \gamma_2 = n, \gamma_2 = 1)$$