

Tues. Jan. 21st

①

## Confidence Intervals Part 2

---

$X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$  Both unknown.

Estimate  $\mu$  with  $\bar{X}_n$ , want confidence interval

Have  $\bar{X}_n \pm z_{1-\frac{\alpha}{2}} \frac{S_n}{\sqrt{n}}$  for large  $n$

Based on  $Z_n = \frac{\sqrt{n}(\bar{X}_n - \mu)}{S_n} \xrightarrow{d} Z \sim N(0, 1)$

What is the exact (small-sample) distribution of

$$T = \frac{\sqrt{n}(\bar{X} - \mu)}{S}$$

The  $t$  distribution, William Gosset (1908)  
"Student"

Let  $Z \sim N(0,1)$  &  $Y \sim \chi^2(\nu)$  be independent (2)

$$T = \frac{Z}{\sqrt{Y/\nu}} \sim t(\nu)$$

Density of  $T$ : Jacobian problem

$$X_1 \sim N(0,1), X_2 \sim \chi^2(\nu)$$

$$Y_1 = \frac{X_1}{\sqrt{X_2/\nu}}, Y_2 = X_2 \quad \text{get}$$

$$f_T(t|\nu) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi\nu} \Gamma\left(\frac{\nu}{2}\right)} \left(1 + \frac{t^2}{\nu}\right)^{-\frac{\nu+1}{2}}$$

for  $-\infty < t < \infty$

$$T = \frac{Z}{\sqrt{Y/\nu}}$$

Lots of work, directed  
towards obtaining  $Z$ ,  $t$   
 $Y$  from a normal  
random sample

# Background

- Functions of independent RVs are independent
- For normally distributed RVs, zero covariance implies independence. (STA302)
- • If  $X \sim \mathcal{N}(\mu, \sigma^2)$ ,  $Z = \frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$
- If  $Z \sim \mathcal{N}(0, 1)$ ,  $Z^2 \sim \chi^2(\nu=1)$
- Linear combinations of normals are normal (STA302)
- If  $Y_1, \dots, Y_n$  i.i.d.,  $Y_i \sim \chi^2(\nu_i)$ ,  

$$\sum_{i=1}^n Y_i \sim \chi^2\left(\sum_{i=1}^n \nu_i\right)$$
- $\bar{X}_n \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$
- So  $\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \sim \mathcal{N}(0, 1)$

## Recall

$$\text{cov}(X, X) = \text{Var}(X)$$

$$\text{cov}(aX, bY) = ab \text{Cov}(X, Y)$$

$$\text{cov}(X, Y+Z) = \text{cov}(X, Y) + \text{cov}(X, Z)$$

## Preparing for $\chi^2$ part

(4)

We know that if  $Y_1 \sim \chi^2(\gamma_1)$ ,  $Y_2 \sim \chi^2(\gamma_2)$  are independent, then  $Y = Y_1 + Y_2 \sim \chi^2(\gamma_1 + \gamma_2)$  using MGFs

Thm Let  $Y_1, Y_2$  be independent RVs,

$$Y = Y_1 + Y_2, Y \sim \chi^2(\gamma_1 + \gamma_2), Y_2 \sim \chi^2(\gamma_2)$$

$$\text{Then } Y_1 \sim \chi^2(\gamma_1)$$

$$\text{If } X \sim \chi^2(\gamma), M_X(t) = (1 - 2t)^{-\gamma/2}$$

Proof By independence

$$M_Y(t) = M_{Y_1}(t) M_{Y_2}(t)$$

$$\Rightarrow (1 - 2t)^{-\frac{\gamma_1 + \gamma_2}{2}} = M_{Y_1}(t) (1 - 2t)^{-\gamma_2/2}$$

$$\Rightarrow \frac{(1 - 2t)^{-\frac{\gamma_1}{2}} \cancel{(1 - 2t)^{-\frac{\gamma_2}{2}}}}{\cancel{(1 - 2t)^{-\gamma_2/2}}} = (1 - 2t)^{-\gamma_1/2}$$

MGF of  $\chi^2(\gamma_1)$

Working toward  $Y = Y_1 + Y_2$   $X_1, \dots, X_n$  iid  $N(\mu, \sigma^2)$  (5)

$$\begin{aligned} \sum_{i=1}^n (X_i - \mu)^2 &= \sum_{i=1}^n (X_i - \bar{X} + \bar{X} - \mu)^2 \\ &= \sum_{i=1}^n (X_i - \bar{X})^2 + 2(\bar{X} - \mu) \sum_{i=1}^n (X_i - \bar{X}) + \sum_{i=1}^n (\bar{X} - \mu)^2 \\ &= \sum_{i=1}^n (X_i - \bar{X})^2 + 2(\bar{X} - \mu) \left[ \underbrace{\sum_{i=1}^n X_i - n\bar{X}}_{=0} \right] + n(\bar{X} - \mu)^2 \\ &= \sum_{i=1}^n (X_i - \bar{X})^2 + n(\bar{X} - \mu)^2 \end{aligned}$$

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

$$\Rightarrow \sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2 = \frac{(n-1)S^2}{\sigma^2} + \left( \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \right)^2$$

$$Y_1 \sim \chi^2(n) = Y_1 + Y_2 \sim \chi^2(1)$$

$Y_1, Y_2$  ind bec  $S^2 \neq \bar{X}$  are ind.

$$Z_i = \frac{X_i - \mu}{\sigma} \sim N(0, 1)$$

$$Z_i^2 \sim \chi^2(1)$$

$$\sum_{i=1}^n Z_i^2 \sim \chi^2(n)$$

$$\bar{X} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$$

$$Z^2 \sim \chi^2(1)$$

$$Z^2 \sim \chi^2(1)$$

So  $Y_1 \sim \chi^2(n-1)$

$$\text{Have } V_{\sigma} = \frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$$

(6)

Again if  $Z \sim N(0,1)$ ,  $Y \sim \chi^2(\nu)$  ind

$$T = \frac{Z}{\sqrt{Y/\nu}} \sim t(\nu)$$

$$\text{Set } Z = \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \sim N(0,1)$$

$$T = \frac{\frac{\sqrt{n}(\bar{X} - \mu)}{\sigma}}{\sqrt{\frac{(n-1)S^2}{\sigma^2} / (n-1)}} = \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t(n-1)$$

$$\bullet T_n = \frac{\sqrt{n}(\bar{X}_n - \mu)}{S_n}$$

Special case of  $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma}$

$$\xrightarrow{d} \text{~~scribble~~ } Z \sim N(0,1)$$

• Can't integrate  $f_T(t/\nu)$ , but good numerical approximations are available

Filling a hole: Why are  $S^2$  &  $\bar{X}$  independent? (7)

$$\text{Cov}(\bar{X}_n, X_j - \bar{X}_n) = \text{Cov}(\bar{X}, X_j) - \text{Cov}(\bar{X}_n, \bar{X}_n)$$

$$= \text{Cov}\left(X_j, \frac{1}{n} \sum_{i=1}^n X_i\right) - \text{Var}(\bar{X}_n)$$

$$= \frac{1}{n} \sum_{i=1}^n \text{Cov}(X_i, X_j) - \frac{\sigma^2}{n}$$


$$= \frac{1}{n} \left( \text{Cov}(X_j, X_j) + \sum_{i \neq j} \underbrace{\text{Cov}(X_i, X_j)}_0 \right) - \frac{\sigma^2}{n}$$

$$= \frac{1}{n} (\sigma^2 + 0) - \frac{\sigma^2}{n} = 0 \quad \text{Any random sample}$$

~~Q~~ <sup>If</sup> normal random sample  
bec linear combos of normals are normal  
 $\bar{X}_n$  &  $X_j - \bar{X}$  are independent, for  $j=1, \dots, n$

$\bar{X}_n$  is independent of all functions of  
 $(X_1 - \bar{X}), (X_2 - \bar{X}) / \dots (X_n - \bar{X})$ . In particular  
 $S^2 = \frac{\sum_{j=1}^n (X_j - \bar{X})^2}{n-1}$  is ind of  $\bar{X}_n$   $\square$

Have  $T = \frac{\sqrt{n}(\bar{X} - \mu)}{S} \sim t(n-1)$  (8)



a) Derive a  $(1-d)100\%$  confidence interval for  $\mu$ .

$$1-d = P\left(\frac{\sqrt{n}(\bar{X} - \mu)}{S} > t_{d/2} \text{ or } \frac{\sqrt{n}(\bar{X} - \mu)}{S} < -t_{d/2}\right)$$

$$= P(-t_{1-d/2}(n-1) < T < t_{1-d/2}(n-1))$$

Pivotal  
Quantity

$$= P\left(-t_{1-d/2} < \frac{\sqrt{n}(\bar{X} - \mu)}{S} < t_{1-d/2}\right)$$

$$= P\left(-t_{1-d/2} \frac{S}{\sqrt{n}} < \bar{X} - \mu < t_{1-d/2} \frac{S}{\sqrt{n}}\right)$$

$$= P\left(-\bar{X} - t_{1-d/2} \frac{S}{\sqrt{n}} < -\mu < -\bar{X} + t_{1-d/2} \frac{S}{\sqrt{n}}\right)$$

$$= P\left(\bar{X} + t_{1-d/2} \frac{S}{\sqrt{n}} > \mu > \bar{X} - t_{1-d/2} \frac{S}{\sqrt{n}}\right)$$

$$= P\left(\bar{X} - t_{1-d/2}(n-1) \frac{S}{\sqrt{n}} < \mu < \bar{X} + t_{1-d/2}(n-1) \frac{S}{\sqrt{n}}\right)$$

$$= P(L < \mu < U)$$

$$\text{or } \bar{X} \pm t_{1-d/2}(n-1) \frac{S}{\sqrt{n}}$$



b) What is the capacity of the human stomach? (9)

Stomachs from a sample of  $n=12$  cadavers were measured, yielding  $\bar{x} = 994 \text{ ml}$ ,  $s^2 = 407$

Give a 95% CI for  $\mu$ .

$$\begin{aligned}\bar{x} \pm t_{1-\alpha/2} \frac{s}{\sqrt{n}} &= 994 \pm 2.201 \sqrt{\frac{407}{12}} \\ &= 994 \pm 12.82 = (981.18, 1006.82)\end{aligned}$$

c) Derive a  $(1-\alpha)100\%$  CI for  $\sigma^2$

Have  $\chi^2_1 = \frac{(n-1)s^2}{\sigma^2} \sim \chi^2(n-1)$

$$1-\alpha = P(\chi^2_{\alpha/2} < Y < \chi^2_{1-\alpha/2})$$



$$= P\left(\chi^2_{\alpha/2} < \frac{(n-1)s^2}{\sigma^2} < \chi^2_{1-\alpha/2}\right)$$

$$= P\left(\frac{\chi^2_{\alpha/2}}{(n-1)s^2} < \frac{1}{\sigma^2} < \frac{\chi^2_{1-\alpha/2}}{(n-1)s^2}\right)$$

$$= P\left(\frac{(n-1)s^2}{\chi^2_{\alpha/2}} > \sigma^2 > \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}}\right)$$

$$= P\left(\frac{(n-1)s^2}{\chi^2_{1-\alpha/2}} < \sigma^2 < \frac{(n-1)s^2}{\chi^2_{\alpha/2}}\right) = P(L < \sigma^2 < U)$$

Using  $\left( \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}(n-1)} , \frac{(n-1)s^2}{\chi^2_{\alpha/2}(n-1)} \right)$  ,

10

$$= \left( \frac{11 \times 407}{21.92} , \frac{11 \times 407}{3.82} \right)$$

$$= (204.24, 1171.99) \checkmark$$

(Recall  $s^2 = 407$ )