

One-sample

$$X_1, \dots, X_n \sim N(\mu, \sigma^2) \text{ indpt}$$

$$\bar{X} = \frac{1}{n} \sum_i X_i$$

$$- E(\bar{X}) = \mu$$

$$- \text{Var}(\bar{X}) = \sigma^2/n$$

-  $\bar{X} \sim \text{normal}$ .

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

if  $\sigma^2$  known, done.

But : if  $\sigma^2$  not known,  
estimate  $\sigma^2$  by  $S^2 = \frac{\sum (X_i - \bar{X})^2}{n-1}$

$$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} \sim ?$$

- def: if  $z_1, \dots, z_k \sim N(0, 1)$   
 then  $\sum_{j=1}^k z_j^2 \sim \chi_k^2$

- def: if  $z \sim N(0, 1)$   
 $u \sim \chi_k^2$

then  $\frac{z}{\sqrt{u/k}} \sim t_k$

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

$$t = \frac{\bar{X} - \mu}{S/\sqrt{n}} = \frac{(\bar{X} - \mu) / (\sigma/\sqrt{n})}{S/\sqrt{n} / (\sigma/\sqrt{n})}$$

$$= \frac{z}{S/\sigma} = \frac{z}{\sqrt{S^2/\sigma^2}} = \frac{z}{\sqrt{\frac{(n-1)S^2}{\sigma^2} \cdot \frac{1}{n-1}}}$$

$$= \frac{z}{\sqrt{u/(n-1)}} \sim t_{n-1}$$

- if  $X_i$  not normal, this fails
- but if  $n$  large, CLT  
and approx normality of  $Z$   
hence  $s^2 \simeq \sigma^2 \Rightarrow$  approx  
normality of  $T$
- if  $n$  not large, ???

Two-sample

$$\begin{matrix} X_1, \dots, X_{n_1} \sim N(\mu_1, \sigma_1^2) \\ Y_1, \dots, Y_{n_2} \sim N(\mu_2, \sigma_2^2) \end{matrix} \text{ indpt}$$

$$E(\bar{X}) = \mu_1 \quad \text{Var}(\bar{X}) = \sigma_1^2 / n_1$$

$$E(\bar{Y}) = \mu_2 \quad \text{Var}(\bar{Y}) = \sigma_2^2 / n_2$$

$$E(\bar{X} - \bar{Y}) = \mu_1 - \mu_2$$

$$\text{Var}(\bar{X} - \bar{Y}) = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$$

$$Z = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim N(0, 1)$$

if  $\sigma_i^2$  unknown, estimate by  $s_i^2$

$$T = \frac{\bar{X} - \bar{Y} - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim ?$$

\- assume  $\sigma_1^2 = \sigma_2^2 = \sigma^2$

$$\frac{(n_1 - 1)s_1^2}{\sigma^2} + \frac{(n_2 - 1)s_2^2}{\sigma^2} \sim \chi^2_{n_1 + n_2 - 2}$$

$T \sim t_{n_1 + n_2 - 2}$   
pooled t

$$\frac{(n_i-1)S_i^2}{\sigma_i^2} \sim \chi^2_{n_i-1}$$

So its mean  
is  $n_i-1$   
and variance  
is  $2(n_i-1)$

$$\Rightarrow E(S_i^2) = \sigma_i^2$$

$$\text{Var}(S_i^2) = \frac{2\sigma_i^4}{n_i-1}$$

$$E\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right) = \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}$$

$$\text{Var}\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right) = \frac{2\sigma_1^4}{n_1-1} + \frac{2\sigma_2^4}{n_2-1}$$

if  $\sigma_1^2 \neq \sigma_2^2$ ,  $\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2} \not\sim \chi^2$

Not exactly  $\chi^2$  but  $W = a\chi_b^2$

$$E(W) = ab \quad \text{Var}(W) = 2a^2b$$

$$a\phi = \frac{\sigma_1^2}{\lambda_1} + \frac{\sigma_2^2}{\lambda_2}$$

$$2a^2b = \frac{2\sigma_1^4}{\lambda_1 - 1} + \frac{2\sigma_2^4}{\lambda_2 - 1}$$

$$a = \frac{\frac{2\sigma_1^4}{\lambda_1 - 1} + \frac{2\sigma_2^4}{\lambda_2 - 1}}{1}$$

$$b = \frac{\left[ \frac{\sigma_1^2}{\lambda_1} + \frac{\sigma_2^2}{\lambda_2} \right]^2}{\frac{2\sigma_1^4}{\lambda_1 - 1} + \frac{2\sigma_2^4}{\lambda_2 - 1}}$$

pretend that

$$\frac{S_1^2}{\lambda_1} + \frac{S_2^2}{\lambda_2} \sim \chi_f^2$$

pretend that

$T \sim t_b$  even though  $\sigma_1^2 \neq \sigma_2^2$

finally in formula for  $t$ ,  
est.  $\sigma^2$  by  $S_i^2$

Welch-Satterthwaite  $t$

use when don't assume

$$\sigma_1^2 = \sigma_2^2$$

in practice, lose little by using  
even if  $\sigma_1^2 = \sigma_2^2$