

HOÀN THÀNH BẢNG SAU VỀ ƯỚC LƯỢNG KHOẢNG

Parameter	Conditions (if any)	The formula of Confidence interval		
		2 sided	Upper	Lower
Mean	known	$\varphi\left(\frac{z_{\alpha}}{2}\right) = \frac{1-\alpha}{2} \rightarrow z_{\alpha/2} \Rightarrow \varepsilon = z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} \Rightarrow (\bar{x} - \varepsilon; \bar{x} + \varepsilon)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{\sigma}{\sqrt{n}} \Rightarrow (\bar{x} - \varepsilon; +\infty)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{\sigma}{\sqrt{n}} \Rightarrow (-\infty; \bar{x} + \varepsilon)$
Mean	σ unknown; $n \geq 30$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = \frac{1-\alpha}{2} \rightarrow z_{\alpha/2} \Rightarrow \varepsilon = z_{\alpha/2} \cdot \frac{s}{\sqrt{n}} \Rightarrow (\bar{x} - \varepsilon; \bar{x} + \varepsilon)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{s}{\sqrt{n}} \Rightarrow (\bar{x} - \varepsilon; +\infty)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{s}{\sqrt{n}} \Rightarrow (-\infty; \bar{x} + \varepsilon)$
Proportion		$\varphi\left(\frac{z_{\alpha}}{2}\right) = \frac{1-\alpha}{2} \rightarrow z_{\alpha/2} \Rightarrow \varepsilon = z_{\alpha/2} \cdot \frac{\sqrt{f(1-f)}}{\sqrt{n}} \Rightarrow (f - \varepsilon; f + \varepsilon)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{\sqrt{f(1-f)}}{\sqrt{n}} \Rightarrow (f - \varepsilon; 0)$	$\varphi\left(\frac{z_{\alpha}}{2}\right) = 0,5 - \alpha \rightarrow z_{\alpha} \Rightarrow \varepsilon = z_{\alpha} \cdot \frac{\sqrt{f(1-f)}}{\sqrt{n}} \Rightarrow (0; f + \varepsilon)$
Variance	μ Unknown	$\alpha \rightarrow \chi^2 = \chi^2_{(n-1, 1-\frac{\alpha}{2})}; \chi^2 = \chi^2_{(n-1, \frac{\alpha}{2})} \Rightarrow \left(\frac{(n-1)s^2}{\chi^2_{(n-1, 1-\frac{\alpha}{2})}}; \frac{(n-1)s^2}{\chi^2_{(n-1, \frac{\alpha}{2})}}\right)$	$\alpha \rightarrow \chi^2 = \chi^2_{(n-1, \alpha)} \Rightarrow \left(\frac{(n-1)s^2}{\chi^2_{(n-1, \alpha)}}; +\infty\right)$	$\alpha \rightarrow \chi^2 = \chi^2_{(n-1, 1-\alpha)} \Rightarrow \left(0; \frac{(n-1)s^2}{\chi^2_{(n-1, 1-\alpha)}}\right)$
2 MEANS	known	$(\bar{x}_1 - \bar{x}_2) \pm z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$		
2 MEANS	σ unknown	$(\bar{x}_1 - \bar{x}_2) \pm t_{\frac{\alpha}{2}, n_1+n_2-2} \sqrt{\frac{s_p^2}{n_1} + \frac{s_p^2}{n_2}}$		
2 PROPORTIONS	$\hat{p}_1 - \hat{p}_2 \neq 0; 1$	$(\hat{p}_1 - \hat{p}_2) \pm z_{\alpha/2} \sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}$		
2 VARIANCE	σ unknown $n \geq 30$	$s_p^2 = \frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}$	$s + z_{\alpha/2} \frac{s}{\sqrt{2n}}$	$s - z_{\alpha/2} \frac{s}{\sqrt{2n}}$

HOÀN THÀNH BẢNG SAU VỀ KIỂM ĐỊNH

Parameter	Conditions (if any)	Test statistic	Critical values		
			2 Tails	Right Tail	Left Tail
Mean	σ known	$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0,1)$	$\pm z_{\alpha/2}$	z_{α}	$-z_{\alpha}$
Mean	σ unknown	$T = \frac{\bar{X} - \mu}{s/\sqrt{n}} \sim t_{(n-1)}$	$\pm t_{\alpha/2}$	t_{α}	$-t_{\alpha}$
Proportion		$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$	$\pm z_{\alpha/2}$	z_{α}	$-z_{\alpha}$
Variance		$\chi^2 = \frac{(n-1)s^2}{\sigma^2}$	$\pm \chi^2_{\alpha/2}$	χ^2_{α}	$-\chi^2_{\alpha}$
2 MEANS	σ known	$Z = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim N(0,1)$	$\pm z_{\alpha/2}$	z_{α}	$-z_{\alpha}$
2 MEANS	σ unknown	$T = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim t_{(n_1+n_2-2)}$	$\pm t_{\alpha/2}$	t_{α}	$-t_{\alpha}$
2 PROPORTIONS		$Z = \frac{(\hat{p}_1 - \hat{p}_2) - (p_1 - p_2)}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}} \sim N(0,1)$	$\pm z_{\alpha/2}$	z_{α}	$-z_{\alpha}$
2 VARIANCE	Giả sử $\sigma_1^2 = \sigma_2^2$	$F = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{s_p^2 \left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \sim t_{(n_1+n_2-2)}$	$\pm t_{\alpha/2}$	t_{α}	$-t_{\alpha}$

HOÀN THÀNH BẢNG SAU VỀ REG.

Parameter	Conditions (if any)	The formula of confident interval		
		2 slides	upper	lower
Beta_0		$\hat{\beta}_1 - t_{\alpha/2, n-2} \sqrt{\frac{\hat{\sigma}^2}{S_{xx}}} \leq \beta_1 \leq \hat{\beta}_1 + t_{\alpha/2, n-2} \sqrt{\frac{\hat{\sigma}^2}{S_{xx}}}$		
Beta_1		$\hat{\beta}_0 - t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}} \right]} \leq \beta_0 \leq \hat{\beta}_0 + t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}} \right]}$		
Mean reponse		$\hat{\mu}_{Y x_0} - t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right]} \leq \mu_{Y x_0} \leq \hat{\mu}_{Y x_0} + t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[\frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right]}$		
Future observation		$\hat{y}_0 - t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right]} \leq Y_0 \leq \hat{y}_0 + t_{\alpha/2, n-2} \sqrt{\hat{\sigma}^2 \left[1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{S_{xx}} \right]}$		

Parameter	Condition (if any)	The formula of CI		
		2 sided	Upper	Lower
Mean	σ unknown	$(\bar{x} - E, \bar{x} + E)$ $E = Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}}$	$(-\infty, \bar{x} + E)$ $E = Z_{\alpha} \cdot \frac{s}{\sqrt{n}}$	$(\bar{x} - E, +\infty)$ $E = Z_{\alpha} \cdot \frac{s}{\sqrt{n}}$
Mean	σ unknown	$(\bar{x} - E, \bar{x} + E)$ $E = t_{\alpha/2, n-1} \cdot \frac{s}{\sqrt{n}}$	$(-\infty, \bar{x} + E)$ $E = t_{\alpha, n-1} \cdot \frac{s}{\sqrt{n}}$	$(\bar{x} - E, +\infty)$ $E = t_{\alpha, n-1} \cdot \frac{s}{\sqrt{n}}$
Proportion	n - large $n\hat{p} > 5$ $n(1-\hat{p}) > 5$	$(\hat{p} - E, \hat{p} + E)$ $E = Z_{\alpha/2} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$		
Variance		$\frac{(n-1)s^2}{\chi_{\alpha/2, n-1}^2} \leq \sigma^2 \leq \frac{(n-1)s^2}{\chi_{1-\alpha/2, n-1}^2}$	$\sigma^2 \leq \frac{(n-1)s^2}{\chi_{1-\alpha, n-1}^2}$	$\sigma^2 \geq \frac{(n-1)s^2}{\chi_{\alpha, n-1}^2}$

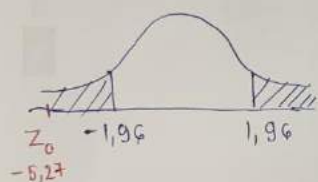
BÀI TẬP B

9.92

9.92 a)
$$\begin{cases} H_0: p = 0.9 \\ H_1: p \neq 0.9 \end{cases} \quad (\alpha = 0.05)$$

$$\hat{p} = \frac{850}{1000} = 0.85$$

$$Z_{\text{calc}} = \frac{\hat{p} - p_0}{\sqrt{p_0(1-p_0)}} = \frac{0.85 - 0.9}{\sqrt{0.9 \cdot 0.1}} = -5.27$$



$Z_0 = -5.27 < Z_{0.025} = -1.96$
 \Rightarrow Reject H_0

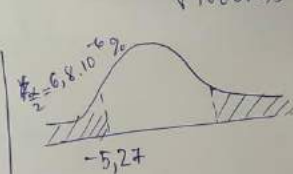
b) 95% CI for 2 sides

$$\hat{p} - Z_{\frac{\alpha}{2}} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \leq p \leq \hat{p} + Z_{\frac{\alpha}{2}} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

$$\Leftrightarrow 0.85 - 1.96 \cdot \sqrt{\frac{0.85(1-0.85)}{1000}} \leq p \leq 0.85 + 1.96 \cdot \sqrt{\frac{0.85(1-0.85)}{1000}}$$

$$\Leftrightarrow 0.828 \leq p \leq 0.872$$

value $p = 0.9 \notin \text{CI}(0.828; 0.872) \Rightarrow$ reject H_0



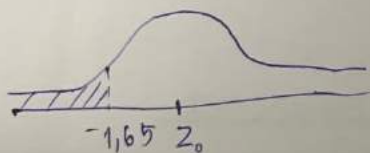
P-value = $\min \alpha = 1.36 \cdot 10^{-5}$

9.93

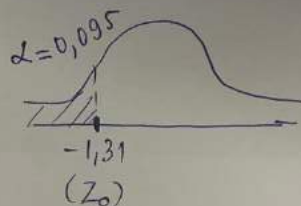
9.93 a) $H_0: p = 0,03$ ($\alpha = 0,05$)
 $H_1: p < 0,03$

$$\hat{p} = \frac{10}{500} = 0,02$$

$$Z_0 = \frac{10 - 500 \cdot 0,03}{\sqrt{500 \cdot 0,03 \cdot (1 - 0,03)}} = -1,31$$



$\bullet Z_0 = -1,31 > Z_{0,05} = -1,65$
 \Rightarrow Fail to reject H_0



P-value = $\min \alpha = 0,095$

b) ~~95%~~ Z_0 for one-side

$$p < \hat{p} + Z_{\alpha} \cdot \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

$$p < 0,02 + 1,65 \cdot \sqrt{\frac{0,02(1-0,02)}{500}}$$

$$p < 0,0303$$

$\bullet p = 0,03 \in (-\infty; 0,0303)$
 \Rightarrow Fail to reject H_0

$\bar{z} \sqrt{n}$

10.32

a. Let X : weight of a paper sheet 1.

Y : weights of a paper sheet 2.

Using Shapiro test we can test the normality of the variables X & Y in R software.

Null & Alternative hypothesis:

H_0 : The data is not normally distributed. Vs.

H_a : The data is normally distributed.

R-code:

```
rm(list = ls())
```

```
x = c(3.481, 3.448, 3.485, 3.475, 3.472, 3.472, 3.464, 3.470, 3.470, 3.477, 3.473, 3.474);
```

```
y = c(3.268, 3.254, 2.56, 3.249, 3.241, 3.254, 3.247, 3.257, 3.239, 3.250, 3.258, 3.239, 3.245, 3.240, 3.254)
```

```
qqnorm(x)
```

```
qqnorm(y)
```

```
shapiro.test(x)
```

```
shapiro.test(y)
```

R-output

```
rm(list = ls())
```


a. Let X : weight of a paper sheet 1.

Y : weights of a paper sheet 2.

Using shapiro. test we can test the normality of the variables X & Y in R software.

Null & Alternative hypothesis:

H_0 : The data is not normally distributed. Vs.

H_a : The data is normally distributed.

R-code:

```
rm (list = ls ())
```

```
x = c(3.481, 3.448, 3.485, 3.475, 3.472, 3.472, 3.464, 3.470, 3.470, 3.477, 3.473, 3.474);
```

```
y = c(3.268, 3.254, 256, 3.249, 3.241, 3.254, 3.247, 3.257, 3.239, 3.250, 3.258, 3.239, 3.245, 3.240, 3.254)
```

```
qqnorm(x)
```

```
qqnorm(y)
```

```
shapiro.test(x)
```

```
shapiro.test(y)
```

R- output

```
rm (list = ls ())
```

```
> x = c(3.481, 3.488, 3.485, 3.475, 3.472, 3.477, 3.472,  
        3.464, 3.472, 3.470, 3.470, 3.477, 3.473,  
        3.474);
```

```
y = c(3.258, 3.254, 3.256, 3.249, 3.241, 3.254,  
      3.247, 3.257, 3.239, 3.250, 3.258, 3.239,  
      3.245, 3.240, 3.254);
```

```
> qqplot(x, y)
```

```
> rm(list = ls())
```

```
> x = c(3.481, 3.488, 3.485, 3.475, 3.472, 3.477, 3.472,  
        3.464, 3.472, 3.470, 3.470, 3.477, 3.473,  
        3.474);
```

```
> y = c(3.258, 3.254, 3.256, 3.249, 3.241, 3.254,  
      3.247, 3.257, 3.239, 3.250, 3.258, 3.239,  
      3.245, 3.240, 3.254);
```

```
> qqnorm(x)
```

```
> qqnorm(y)
```

```
> shapiro.test(x)
```

Shapiro-Wilk normality test

11.12

11-12

b) The least squares estimate of the intercept and slope are

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i - \frac{\sum_{i=1}^n y_i}{n}}{\sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n x_i)^2}{n}} = \frac{309,96 - \frac{306,9(14,51)}{18}}{6727,13 - \frac{(306,9)^2}{18}} = \frac{309,96 - 24,5673}{6727,13 - 5180,925} = \frac{285,3927}{1546,205} \approx 18,46$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = \frac{\sum_{i=1}^n y_i}{n} - \hat{\beta}_1 \frac{\sum_{i=1}^n x_i}{n} = \frac{14,51}{18} - 18,46 \cdot \frac{306,9}{18} \approx 0,4705$$

The least squares regression line then become

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x = 0,4705 + 18,46x$$

Determine the sum of squares error

$$SSE = SST - \hat{\beta}_1 S_{xy}$$

$$= 14,7075 - \frac{14,51^2}{18} - 20,5673 \left(\frac{306,9 \cdot 306,9}{18} - \frac{306,9^2}{18} \right)$$

$$\approx 120,9472$$

$$\sigma^2 \approx \frac{SSE}{n-2} = \frac{120,9472}{18-2} \approx 7,8092$$

c) $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x = 0,4705 + 18,46(1) = 18,9305$

d) $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x = 0,4705 + 18,46(0,1371) = 2,9371$

RESIDUAL = $y - \hat{y} = 4,8 - 2,9371 = 1,8629$

Summary:

- a) Reasonable
- b) $\hat{y} = 0,4705 + 18,46x$
- c) $\sigma^2 \approx 7,8092$
- d) 18,9305, 2,9371, 1,8629

8.40

a)

In the previously described way we construct a normal probability plot based on observations 8.24 8.25 8.20 8.23 8.24 8.21 8.26 8.26 8.20 8.25 8.23 8.23 8.19 8.28 8.24

If \bar{x} and s are the mean and standard deviation of a random sample from a normal distribution with unknown variance σ^2 , $\text{\textbf{a } } 100(1 - \alpha)\%$ confidence interval on μ is given by

$$\bar{x} - t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}} \leq \mu \leq \bar{x} + t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}, \quad (1)$$

where $t_{\frac{\alpha}{2}, n-1}$ is the upper $100\frac{\alpha}{2}\%$ percentage point of the t distribution with $n - 1$ degrees of freedom.

b)

The simple mean is

$$\bar{x} = \frac{1}{15} \sum_{i=1}^{15} x_i = 8.234,$$

and standard deviation is

$$s = \left(\frac{\sum_{i=1}^{15} (x_i - \bar{x})^2}{n - 1} \right)^{\frac{1}{2}} = \left(\frac{\sum_{i=1}^{15} (x_i - 8.234)^2}{14} \right)^{\frac{1}{2}} = 0.0253.$$

Now, we need to find a 95% CI on the population mean, then

$$\frac{\alpha}{2} = \frac{1 - 0.95}{2} = 0.025 \quad \Rightarrow \quad t_{\frac{\alpha}{2}, n-1} = t_{0.025, 14} = 2.145. \quad (2)$$

From Equations (1) and (2) we get

$$\begin{aligned} 8.234 - 2.145 \frac{0.0253}{\sqrt{15}} &\leq \mu \leq 8.234 + 2.145 \frac{0.0253}{\sqrt{15}} \\ 8.234 - 2.145 \times 0.0065 &\leq \mu \leq 8.234 + 2.145 \times 0.0065. \end{aligned}$$

Therefore, a 95% CI on the population mean is

$$\boxed{8.219 \leq \mu \leq 8.248.}$$

c.

If \bar{x} and s are the mean and standard deviation of a random sample from a normal distribution with unknown variance σ^2 , a $\text{100}(1 - \alpha)\%$ upper confidence bound for μ is given by

$$\mu \leq \bar{x} + t_{\alpha, n-1} \frac{s}{\sqrt{n}}. \quad (3)$$

Now, we need to find a 95% upper confidence bound on the population mean, then

$$\alpha = 1 - 0.95 = 0.05 \quad \Rightarrow \quad t_{\alpha, n-1} = t_{0.05, 14} = 1.761. \quad (4)$$

From Equations (1) and (2) we get

$$\begin{aligned} \mu &\leq 8.234 + 1.761 \frac{0.0253}{\sqrt{15}} \\ \mu &\leq 8.234 + 1.761 \times 0.0065. \end{aligned}$$

Therefore, a 95% upper confidence bound on the population mean is

$$\boxed{\mu \leq 8.2455.}$$

From subsection b) and c) we conclude that 95% two-sided confidence interval on the population mean is higher than 95% upper confidence bound on the population mean, because

$$t_{0.05, 14} = 1.761 < 2.145 = t_{0.025, 14}.$$

