

# Confidence intervals

# Definition 1.7

If  $Y_1, Y_2, \dots, Y_n \sim \text{iid } N(\mu, \sigma^2)$  with  $\sigma^2$  known, then

$$\bar{y} \pm 1.96 \frac{\sigma}{\sqrt{n}}$$

is the 95% confidence interval for  $\mu$ .

A random interval  $(L, U)$  is called a  $100(1 - \alpha)\%$  confidence interval for the parameter  $\theta$  if it satisfies:

$$P(L < \theta < U) = 1 - \alpha.$$

Diagram illustrating the components of the confidence interval formula:

- $L$ : lower confidence limit
- $U$ : upper confidence limit
- $1 - \alpha$ : coverage probability or confidence coefficient

# Remarks

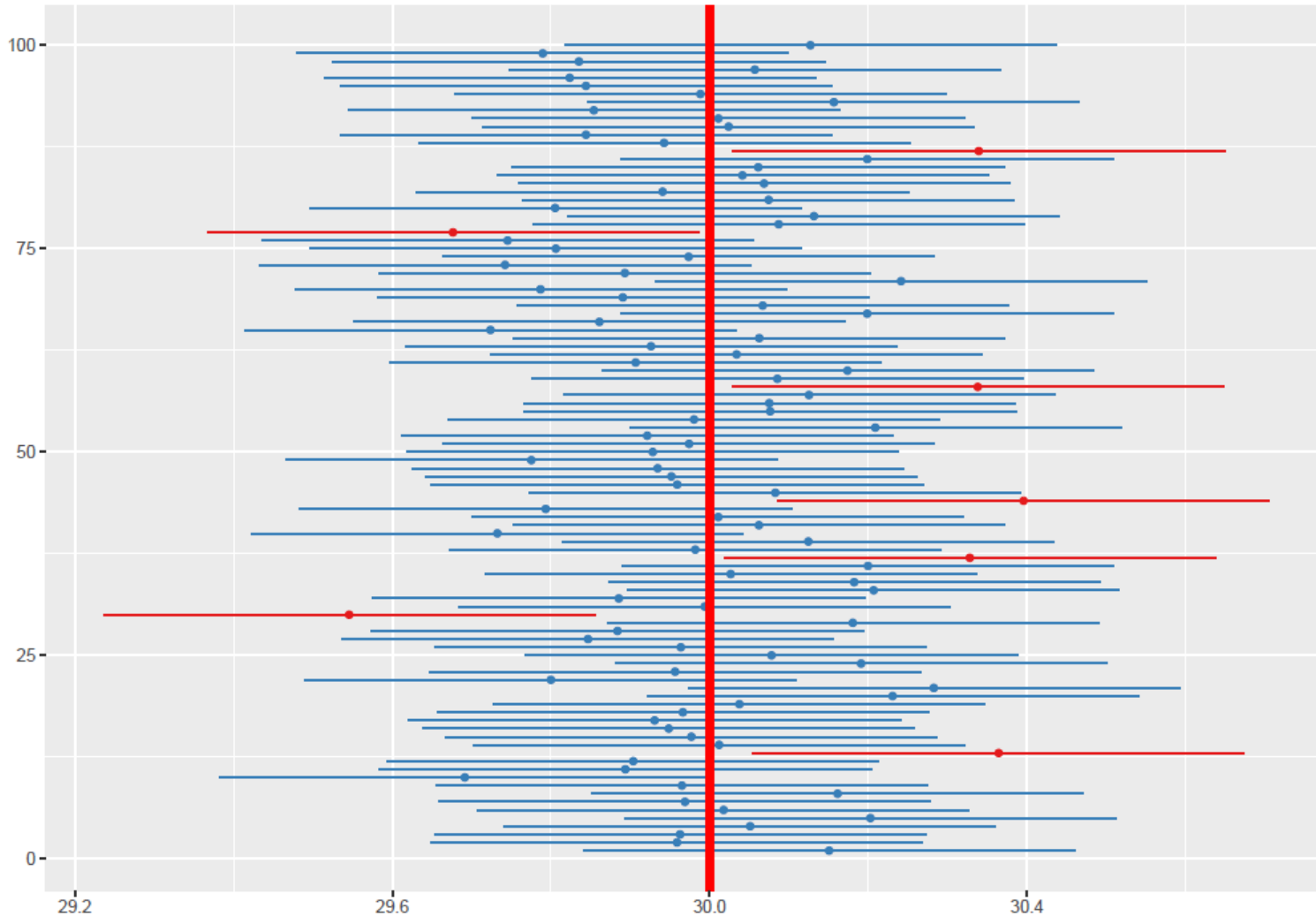
- Note that the endpoints  $L$  and  $U$  are random: not  $\theta$ .  
e.g.  $Y_1, Y_2, \dots, Y_n \sim \text{iid } N(\mu, \sigma^2)$  with  $\sigma^2$  known,  
then the confidence limits  $L = \bar{Y} - 1.96 \frac{\sigma}{\sqrt{n}}$  and  $U = \bar{Y} + 1.96 \frac{\sigma}{\sqrt{n}}$  are random variables.
- The quantity  $(1 - \alpha)$  is called the coverage probability. It lies between 0 and 1.
- A confidence interval gives the range of *plausible* values for  $\theta$ . To be useful, it should
  - be narrow
  - have high coverage probability  $(1 - \alpha)$
- To resolving these two conflicting requirements, the useful approach is to prescribe a small value for  $\alpha$ , and then obtain the narrowest possible confidence interval.

# What do we mean by confidence?

Suppose  $\alpha = 0.05$ .

- ✗ There is a 95% chance that the true value of  $\theta$  falls within our confidence interval.
- ✗ The true value of  $\theta$  will fall within our confidence interval 95% of the time.
- ✓ If samples of the same size are drawn repeatedly from the same population, and a confidence interval is calculated for each sample (using the same method), then it is expected that 95% of these intervals to contain the true value of  $\theta$ .

# What do we mean by confidence?



# Lemma 3

Suppose  $Y_1, Y_2, \dots, Y_n$  are i.i.d.  $N(\mu, \sigma^2)$ , and let

$$Z = \frac{\bar{Y} - \mu}{\sigma/\sqrt{n}},$$

then

$$Z \sim N(0, 1).$$

Proof

Take  $a_i = \frac{1}{n}$ , then by Lemma 1,  $\bar{Y} \sim N(\mu, \frac{\sigma^2}{n})$ .

Standardizing  $\bar{Y}$  gives  $Z = \frac{\bar{Y} - E(\bar{Y})}{sd(\bar{Y})} = \frac{\bar{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1)$ .

(See next slide regarding standardising a normal random variable.)

## Standardising a normal random variable

If  $Y \sim N(\mu, \sigma^2)$ , then  $Z = \frac{Y - \mu}{\sigma} \sim N(0, 1)$ .

Proof:

We will use the method of transformation.

The density of  $Y$  is  $f_Y(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}(y-\mu)^2}$

The transformation  $Z = h(Y) = \frac{Y - \mu}{\sigma}$  is a one-to-one function of  $Y$ .

The inverse function is  $Y = h^{-1}(Z) = \sigma Z + \mu$ .

Observe that  $\left| \frac{dh^{-1}(z)}{dz} \right| = \sigma$ .

$$\begin{aligned} \text{Then } f_Z(z) &= f_Y(h^{-1}(z)) \left| \frac{dh^{-1}(z)}{dz} \right| \\ &= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2\sigma^2}(\sigma z + \mu - \mu)^2} |\sigma| \\ &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} \quad \text{which is the standard normal distribution.} \end{aligned}$$

So  $Z \sim N(0, 1)$ .

## Example 1.6

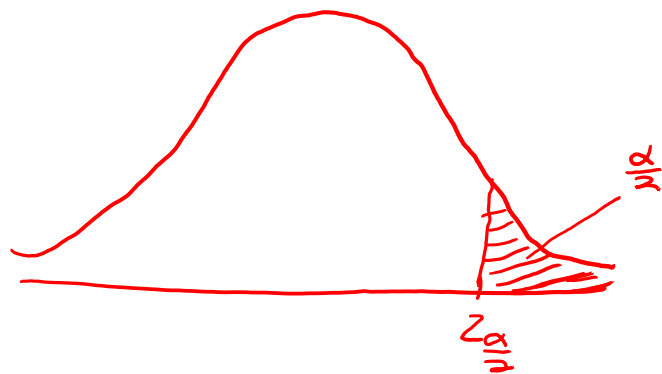
Suppose that  $Y_1, Y_2, \dots, Y_n$  are i.i.d.  $N(\mu, \sigma^2)$  with  $\sigma^2$  known, then

$$\left( \bar{y} - z_{\alpha/2} \frac{\sigma}{\sqrt{n}}, \bar{y} + z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \right),$$

where

$$P(Z > z_{\alpha/2}) = \frac{\alpha}{2}, \text{ for } Z \sim N(0, 1),$$

is a  $100(1 - \alpha)\%$  confidence interval for  $\mu$ .





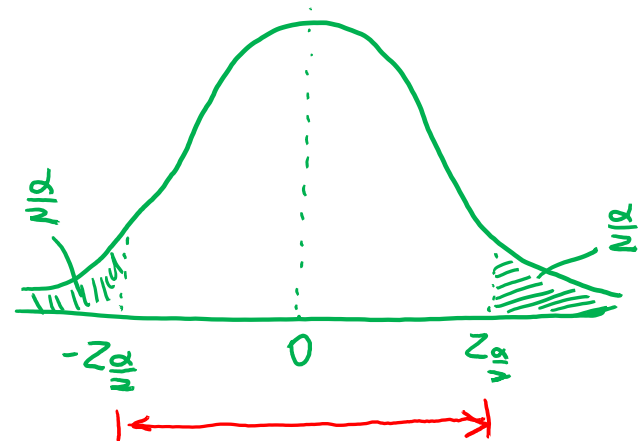
# Example 1.6 Proof

Show that  $P(\bar{Y} - Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} < \mu < \bar{Y} + Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}) = 1 - \alpha$ .

$$\begin{aligned} & P(\bar{Y} - Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} < \mu < \bar{Y} + Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}) \\ &= P(-Z_{\frac{\alpha}{2}} < \frac{\mu - \bar{Y}}{\frac{\sigma}{\sqrt{n}}} < Z_{\frac{\alpha}{2}}) \\ &= P(-Z_{\frac{\alpha}{2}} < \frac{\bar{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} < Z_{\frac{\alpha}{2}}) \\ &= P(-Z_{\frac{\alpha}{2}} < Z < Z_{\frac{\alpha}{2}}) \quad \text{where } Z \sim N(0,1). \\ &= 1 - \frac{\alpha}{2} - \frac{\alpha}{2} \\ &= 1 - \alpha \end{aligned}$$

$\therefore$  This interval estimator has the correct coverage probability.

Hence  $\bar{Y} \pm Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}$  is the  $100(1-\alpha)\%$  confidence interval for  $\mu$ , as required.



# Definition 1.8

The random interval  $(L, U)$  in Definition 1.7, where

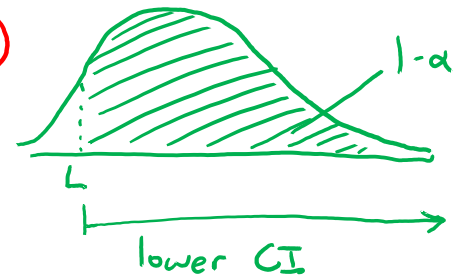
$$P(L < \theta < U) = 1 - \alpha$$

is a two-sided confidence interval.

It is possible to form a one-sided confidence interval such that

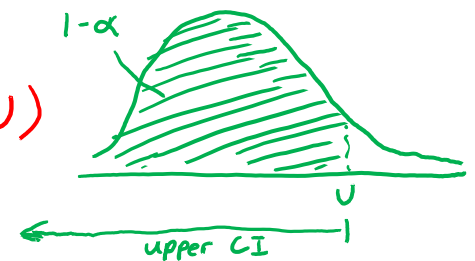
$$\underline{P(L < \theta) = 1 - \alpha.} \quad (L, \infty)$$

This is the **lower** one-sided confidence interval.



Similarly, the **upper** one-sided confidence interval can be formed such that

$$\underline{P(\theta < U) = 1 - \alpha.} \quad (-\infty, U)$$



# Example 1.7

Suppose that  $Y_1, Y_2, \dots, Y_n$  are i.i.d.  $N(\mu, \sigma^2)$  with  $\sigma^2$  known.  
What is the  $100(1 - \alpha)\%$  upper and lower one-sided confidence interval for  $\mu$ ?

$$\begin{aligned} 1 - \alpha &= \mathcal{P}(\mu > L) \\ &= \mathcal{P}\left(\frac{\mu - \bar{Y}}{\frac{\sigma}{\sqrt{n}}} > \frac{L - \bar{Y}}{\frac{\sigma}{\sqrt{n}}}\right) \\ &= \mathcal{P}\left(\frac{\bar{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} < \frac{\bar{Y} - L}{\frac{\sigma}{\sqrt{n}}}\right) \\ &= \mathcal{P}\left(Z < \frac{\bar{Y} - L}{\frac{\sigma}{\sqrt{n}}}\right) \text{ where } Z \sim N(0, 1) \\ &= \mathcal{P}(Z < Z_\alpha) \\ \Rightarrow Z_\alpha &= \frac{\bar{Y} - L}{\frac{\sigma}{\sqrt{n}}} \\ L &= \bar{Y} - Z_\alpha \frac{\sigma}{\sqrt{n}} \end{aligned}$$

$$\begin{aligned} 1 - \alpha &= \mathcal{P}(\mu < U) \\ &= \mathcal{P}\left(\frac{\mu - \bar{Y}}{\frac{\sigma}{\sqrt{n}}} < \frac{U - \bar{Y}}{\frac{\sigma}{\sqrt{n}}}\right) \\ &= \mathcal{P}\left(\frac{\bar{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} > \frac{\bar{Y} - U}{\frac{\sigma}{\sqrt{n}}}\right) \\ &= \mathcal{P}\left(Z > \frac{\bar{Y} - U}{\frac{\sigma}{\sqrt{n}}}\right) \\ &= \mathcal{P}(Z > -Z_\alpha) \\ \Rightarrow -Z_\alpha &= \frac{\bar{Y} - U}{\frac{\sigma}{\sqrt{n}}} \\ U &= \bar{Y} + Z_\alpha \frac{\sigma}{\sqrt{n}} \end{aligned}$$

$\therefore$  lower  $(1 - \alpha)100\%$  one-sided confidence interval for  $\mu$  is  $(\bar{Y} - Z_\alpha \frac{\sigma}{\sqrt{n}}, \infty)$   
upper  $(1 - \alpha)100\%$  one-sided confidence interval for  $\mu$  is  $(-\infty, \bar{Y} + Z_\alpha \frac{\sigma}{\sqrt{n}})$

# Example 1.8



The shopping times of  $n = 64$  randomly selected customer at a supermarket were recorded. The mean shopping time of this sample is 33 minutes. Suppose that the variance of shopping time is 256 minutes, what is the 90% two-sided confidence interval for the true average shopping time per customer?

Let  $Y$  = shopping time per customer

$\mu$  = true average shopping time per customer

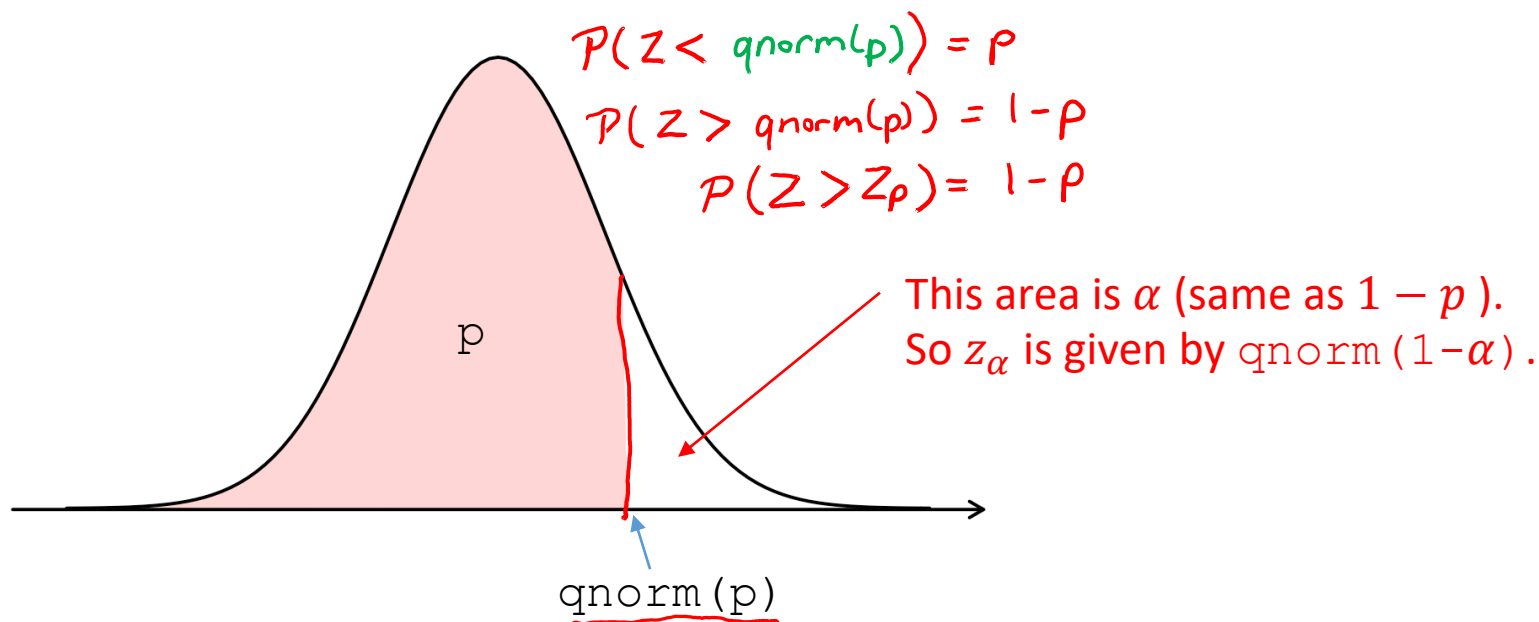
$n = 64$ ,  $\sigma^2 = 256$ ,  $\bar{y} = 33$ ,  $1 - \alpha = 0.90$

The two-sided CI for  $\mu$  is  $(\bar{y} - Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}, \bar{y} + Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}})$   
 $= (33 - Z_{\frac{\alpha}{2}} \sqrt{\frac{256}{33}}, 33 + Z_{\frac{\alpha}{2}} \sqrt{\frac{256}{33}})$   
 $= (33 - Z_{0.05} 2, 33 + Z_{0.05} 2)$   
 $\approx (29.71, 36.29)$

```
> qnorm(1-0.05)  
[1] 1.644854
```

# Some notes about using R to compute $z_\alpha$

The R command `qnorm(p)` computes the  $p$ th percentile (i.e. the inverse of the cdf) of the normal distribution.



In Example 1.8, we had  $1 - \alpha = 0.90$ , implying  $\alpha = 0.10$  and  $\alpha/2 = 0.05$ . Hence, our  $z_{\alpha/2}$  can be computed using `qnorm(0.95)`.

Alternatively, use `qnorm(0.05, lower.tail=FALSE)`.