

# 01:XXX:XXX - Homework n

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November 5, 2024

## 1 Chapter 11: Confidence Intervals

Given a  $\alpha$  such that  $0 < \alpha < 1$ , an Interval Estimation strategy provides two statistics (r.v)  $L$  and  $R$  s.t  $P(L < \theta < R) = 1 - \alpha$ . The interval  $[L, R]$  is called a  $(1 - \alpha)\%$  confidence interval for  $\theta$ .

We can say that if you repeat the experiment  $N$  times and get  $N$  intervals, then  $(1 - \alpha)\%$  of the intervals will contain the true value of  $\theta$ .

**Definition** (Confidence Interval). A confidence interval with  $(1-\alpha)$  confidence level are two statistics  $L$  and  $R$  such that  $P(L < \theta < R) = 1 - \alpha$ .

**Remark.** If someone says after an experiment that  $2 < \lambda < 2.1$  with 90% confidence, it means that on average that 90% of the intervals will contain the true value of  $\lambda$ .

We want CI to be symmetric about  $\bar{X}$

CI so far:  $N(\mu, \sigma^2)$  population

$$1. \sigma^2 \text{ known: } \bar{X} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$

$$2. \sigma^2 \text{ unknown: } \bar{X} \pm t_{\alpha/2, n-1} \frac{S}{\sqrt{n}}$$

We can think of  $z_{\alpha/2}$  in the normal curve as the shaded area in the tails.

**New Context:** Two pops  $N(\mu_1, \sigma_1^2)$  and  $N(\mu_2, \sigma_2^2)$  and sample from both  $n_1$  and  $n_2$  from each

$$X_{11} \dots X_{1n_1} \sim N(\mu_1, \sigma_1^2)$$

$$X_{21} \dots X_{2n_2} \sim N(\mu_2, \sigma_2^2)$$

These are independent but not necessarily identically distributed.

Let  $\bar{X}_1$  and  $\bar{X}_2$  be the sample means and  $S_1^2$  and  $S_2^2$  be the sample variances.

Want CI for  $\mu_1 - \mu_2$

**Case 1:**  $\sigma_1^2$  and  $\sigma_2^2$  are known.

We can use point estimators:

$$\bar{X}_1 - \bar{X}_2 \sim N(\mu_1 - \mu_2, \frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2})$$

$$\bar{X}_1 - \bar{X}_2 \pm z_{\alpha/2} \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$$

**Case 2:**  $\sigma_1^2$  and  $\sigma_2^2$  are unknown. but  $\sigma_1^2 = \sigma_2^2$

we can define a pooled sample variance:

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

**Remark.** This is a weighted average of the sample variances. with weights  $n_1 - 1$  and  $n_2 - 1$

**Remark.**

$$S_p^2 := \frac{\sum^{n_1} (X_{1i} - \bar{X}_1)^2 + \sum^{n_2} (X_{2i} - \bar{X}_2)^2}{n_1 + n_2 - 2}$$

$$\sim \chi_{n_1 + n_2 - 2}^2$$