

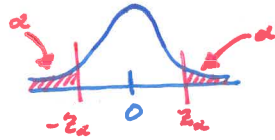
§7.2: Large Sample Confidence Intervals

Recall: $z_\alpha = \text{qnorm}(\alpha, 0, 1)$

is "# std deviations away from mean for Prob = α "

→ Textbook doesn't like z_α to be negative so it uses $z_\alpha = -\text{qnorm}(\alpha, 0, 1)$

$$\hat{P}(Z > z_\alpha) = \alpha$$



Basic plan for confidence intervals for θ :

$$\theta = \hat{\theta} \pm z_{\alpha/2} \cdot \sigma_{\hat{\theta}}$$

Point estimate
for θ

standard error
of $\hat{\theta}$

(Pretending that $\hat{\theta}$ is Normal)

Previously: If we know $\sigma^2 = \text{Var}[X]$ then
 $\text{Var}[\bar{X}] = \frac{\sigma^2}{n}$ so

$$\mu = \bar{x} \pm z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}}$$

Now: What if we don't know $\text{Var}[X]$?

$\text{Var}[X]$ unknown \Rightarrow Must use point estimate for it too...

Plan: Replace σ^2 by S^2

Thm: If n big (like... $n > 40$) then

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \approx \text{Normal}(0, 1)$$

So confidence interval is

$$\mu = \bar{x} \pm z_{\alpha/2} \cdot \frac{S}{\sqrt{n}}$$

!!!

(Seriously... at some point you've got to start worrying that the world is too nice...)

We can apply this to the Binomial distribution.

Recall: (§4.3, p166)

Binomial $(n, p) \approx \text{Normal}(np, \sqrt{npq})$

if n big & $np \geq 10$

$nq \geq 10$

$q = 1 - p$

X = #occurrences in population of size n

$\hookrightarrow X \sim \text{Binomial}$

Also $\hat{p} = \frac{X}{n}$ is point estimator for p .

Confidence Interval for \hat{p} ?

$$E[\hat{p}] = E\left[\frac{X}{n}\right]$$

$$= \frac{nP}{n}$$

$$= P \quad (\text{unbiased})$$

$$\text{Var}[\hat{p}] = \text{Var}\left[\frac{X}{n}\right]$$

$$= \frac{1}{n^2} (npq)$$

$$= \frac{Pq}{n} \quad \rightarrow \text{std. error} \quad \sigma_{\hat{p}} = \sqrt{\frac{Pq}{n}}$$

$$\hat{p} - 2\hat{p}P + P^2 = z_{\alpha/2}^2 \frac{P(1-P)}{n}$$

$$\left[\left(1 + \frac{z_{\alpha/2}^2}{n}\right)P - \left(\frac{\hat{p} + z_{\alpha/2}^2/2n}{1 + z_{\alpha/2}^2/n}\right) \right]^2 = z_{\alpha/2}^2 \left[\frac{\hat{p}(1-\hat{p})}{n} + \frac{z_{\alpha/2}^2}{4n} \right]$$

$$P = \underbrace{\frac{\hat{p} + \frac{z_{\alpha/2}^2}{2n}}{1 + \frac{z_{\alpha/2}^2}{n}}}_{\hat{p}} \pm z_{\alpha/2} \underbrace{\frac{\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z_{\alpha/2}^2}{4n}}}{1 + \frac{z_{\alpha/2}^2}{n}}}_{\sqrt{\frac{\hat{p}\hat{q}}{n}}}$$

please don't try to memorize this...

(So this can get ugly if you insist on things being precise...)

Rough confidence interval:

$$P = \hat{p} \pm z_{\alpha/2} \cdot \sigma_{\hat{p}}$$

$$= \frac{X}{n} \pm z_{\alpha/2} \sqrt{\frac{\hat{p}\hat{q}}{n}}$$

$\hat{p} = \frac{X}{n}$
 $\hat{q} = 1 - \hat{p} = \frac{n-X}{n}$

Note: Textbook computes a more precise interval which works for all values of p (not just $np \geq 10$)

$$P\left(\frac{|\hat{p} - P|}{\sqrt{\frac{Pq}{n}}} < z_{\alpha/2}\right) \approx 1 - \alpha$$

\downarrow roots

$$(\hat{p} - P)^2 = \left(z_{\alpha/2} \cdot \sqrt{\frac{Pq}{n}}\right)^2$$

(Want to solve for P...)

One-Sided Intervals

If you only want to compute intervals on a single side of $\hat{\theta}$ then you can:

