

Lecture 27

We now construct a confidence interval for the unknown p in the model $X \sim \text{Binomial}(n, p)$. We require $np \geq 5$ and $n(1 - p) \geq 5$ (ie. n large and p moderate) so that we can use the approximation $X \sim \text{Normal}(np, np(1 - p))$. We denote $\hat{p} = X/n$ and $\hat{p}_{\text{obs}} = X_{\text{obs}}/n$. A $(1 - \alpha)\%$ confidence interval for p is obtained via:

$$\begin{aligned} & \text{P} \left(-z_{\frac{\alpha}{2}} < \frac{X - np}{\sqrt{np(1 - p)}} < z_{\frac{\alpha}{2}} \right) = 1 - \alpha \\ \Leftrightarrow & \text{P} \left(-z_{\frac{\alpha}{2}} < \frac{\hat{p} - p}{\sqrt{p(1 - p)/n}} < z_{\frac{\alpha}{2}} \right) = 1 - \alpha \\ \Leftrightarrow & \text{P} \left(-z_{\frac{\alpha}{2}} \sqrt{p(1 - p)/n} - \hat{p} < -p < z_{\frac{\alpha}{2}} \sqrt{p(1 - p)/n} - \hat{p} \right) = 1 - \alpha \\ \Leftrightarrow & \text{P} \left(\hat{p} - z_{\frac{\alpha}{2}} \sqrt{p(1 - p)/n} < p < \hat{p} + z_{\frac{\alpha}{2}} \sqrt{p(1 - p)/n} \right) = 1 - \alpha \end{aligned}$$

Therefore,

$$\hat{p}_{\text{obs}} \pm z_{\frac{\alpha}{2}} \sqrt{\hat{p}_{\text{obs}}(1 - \hat{p}_{\text{obs}})/n} \quad (1)$$

is an approximate $(1 - \alpha)100\%$ CI for p . The CI (1) is based on two approximations:

1. approximating the Binomial with the Normal
2. replacing p with \hat{p}

Example: From a sample of 1250 BC voters, 420 indicate that they support the NDP. Obtain an approximate 95% CI for the proportion of BC voters who support the NDP.

CI's based on the Student distribution: Suppose X_1, \dots, X_n are iid Normal(μ, σ^2) where σ is unknown (the realistic case). It can be shown that

$$\frac{\bar{X} - \mu}{s/\sqrt{n}} \sim t_{n-1}$$

where t_{n-1} denotes the t distribution with $n - 1$ degrees of freedom. The pdf of $Y \sim t_{n-1}$ is

$$f(y) = \frac{\Gamma(n/2)}{\Gamma((n-1)/2)\Gamma(1/2)} \left(1 + \frac{y^2}{n-1}\right)^{-n/2}$$

Here, the $(1 - \alpha)100\%$ confidence interval for μ is

$$\bar{X} \pm t_{\frac{\alpha}{2}, n-1} \frac{s}{\sqrt{n}}$$

Discussion points:

- the t_{n-1} distribution is symmetric on \mathcal{R}
- the t_{n-1} has longer tails than the normal
- as $n \rightarrow \infty$, $t_{n-1} \rightarrow Z \sim \text{Normal}(0, 1)$
- for $n \geq 30$, you can replace t_{n-1} with Z
- the t distribution is intractable; no need to memorize pdf
- Table B.1 in the text gives points $t_{\frac{\alpha}{2}, n-1}$

The logic of hypothesis testing: We view the testing of hypotheses as consisting of three steps. We discuss the three steps in some detail.

1. The experimenter forms a *null hypothesis* H_0 to test against an *alternative hypothesis* H_1 .
2. The experimenter collects data.
3. In the inference step, the question is asked “Are the data compatible wrt H_0 ?” If yes, H_0 is not rejected. If no, H_0 is rejected.

Example: In this informal example, we go over the three steps of hypothesis testing. Imagine a court of law where a defendant is accused of a crime.

Example: In this informal example, we go over the three steps of hypothesis testing. Imagine that you are playing cards and that your friend has obtained a royal flush three hands in a row.

In the inference step, if we answer “yes” to the key question (Are the data compatible wrt H_0 ?), we conclude using the curious language, “ H_0 is not rejected”. We discuss why this does not mean the same thing as “ H_0 is accepted”.