

Recap \rightarrow Intro to tests of Significance

8th Feb '2024

Section 4.2 \rightarrow Likelihood Ratio Tests (LRTs) for Simple Hypothesis

Determining test statistics (and their distributions under H_0) can be tricky, sometimes. The likelihood Ratio Statistic (LRS) in these cases, has an intuitive appeal.

Simple Hypothesis \rightarrow Hypothesis that specifies numerical values for all model parameters

Exact Equality.
(No inequalities here!)

1-parameter case

LRS for testing $H_0: \theta = \theta_0$ is

$$D \equiv -2[\ln(\theta_0)] = \underset{\substack{\uparrow \\ \text{"defined"}}}{-2} [\ln(\hat{\theta}) - \ln(\theta_0)]$$

Where, $\hat{\theta}$ is the MLE of θ and $D \geq 0$ b/c $\ln(\theta) \leq 0$ for all θ .

"Intuition" behind D :

- ① D is big $\Rightarrow \ln(\theta_0)$ is "far" from $\ln(\hat{\theta}) \Rightarrow \theta_0$ is not very plausible.
- ② D is small $\Rightarrow \ln(\theta_0)$ is pretty close to maximised likelihood $\Rightarrow \theta_0$ is more plausible.

Under the assumption that $H_0: \theta = \theta_0$ is true,

$$D \approx \chi^2_{(1)}$$

"Approx. distributed", implies
"Asymptotically distributed"

Let, d_{obs} be our observed value of D .

$$D \approx \chi^2_{(1)} \Rightarrow \text{P-value} = \mathbb{P}(D \geq d_{obs})$$

$$\Rightarrow \text{P-value} \approx \mathbb{P}(\chi^2_{(1)} \geq d_{obs})$$

"approx. equal to"

Now, let's look at an Example;

Example 4.2.1 from the Complete Lecture Notes

Here, X = Measurement error of a scale.

$$X \sim \mathcal{N}(\mu, \sigma = 1.3)$$

Need LRS, \Rightarrow Need $L(\mu) \Rightarrow$ joint pdf.

$$f(x_1, x_2, \dots, x_{10}; \mu) = \prod_{i=1}^{10} \left[\frac{1}{\sqrt{2\pi} \sigma} \right] \exp\left[-\frac{1}{2\sigma^2} (x_i - \mu)^2\right], \mu \in \mathbb{R}, \sigma > 0$$

σ treated as constant,
so, we don't need this!

$$L(\mu) = \prod_{i=1}^{10} \exp\left[-\frac{1}{2\sigma^2} (x_i - \mu)^2\right]$$

$$= \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{10} (x_i - \mu)^2\right]$$

$$\ell(\mu) = -\frac{1}{2\sigma^2} \sum_{i=1}^{10} (x_i - \mu)^2; \mu \in \mathbb{R}$$

$$\Rightarrow \hat{\mu} = \frac{\sum_{i=1}^{10} x_i}{10} = \bar{x}$$

(refer to 30th Jan, note)

$$\begin{aligned} D = -2\mathfrak{H}(\mu_0) &= 2[\ell(\hat{\mu}) - \ell(\mu_0)] \xrightarrow{\hat{\mu} = \bar{x}} \\ &= 2\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{10} (x_i - \bar{x})^2 - \frac{-1}{2\sigma^2} \sum_{i=1}^{10} (x_i - \mu_0)^2\right] \xrightarrow{\mu_0 = 226} \\ &= \frac{1}{\sigma^2} \left[\sum_{i=1}^{10} (x_i - \mu_0)^2 - \sum_{i=1}^{10} (x_i - \bar{x})^2 \right] \end{aligned}$$

$$\begin{aligned}
 \sum_{i=1}^{10} (x_i - \mu_0)^2 &= \sum_{i=1}^{10} (x_i - \bar{x} + \bar{x} - \mu_0)^2 \\
 &= \sum_{i=1}^{10} [(x_i - \bar{x}) + (\bar{x} - \mu_0)]^2 \\
 &= \underbrace{\sum_{i=1}^{10} (x_i - \bar{x})^2}_{\text{Ex: Show this cross-product is equal to zero.}} + \underbrace{\sum_{i=1}^{10} 2[(x_i - \bar{x})(\bar{x} - \mu_0)]}_{\text{Ex: Show this cross-product is equal to zero.}} + \sum_{i=1}^{10} (\bar{x} - \mu_0)^2
 \end{aligned}$$

$$\begin{aligned}
 &= \frac{1}{8^2} \left[\sum_{i=1}^{10} (x_i - \mu_0)^2 - \sum_{i=1}^{10} (x_i - \bar{x})^2 \right] \\
 &= \frac{1}{8^2} \left[\sum_{i=1}^{10} \cancel{(x_i - \bar{x})^2} + \sum_{i=1}^{10} (\bar{x} - \mu_0)^2 - \sum_{i=1}^{10} \cancel{(x_i - \bar{x})^2} \right] \\
 &= \frac{1}{8^2} \sum_{i=1}^{10} (\bar{x} - \mu_0)^2 \quad \left. \begin{array}{l} \text{No Subscripts} \\ \text{here!} \end{array} \right\} \\
 &= \frac{10 (\bar{x} - \mu_0)^2}{8^2} = \underbrace{(\bar{x} - \mu_0)^2 / 8^2 / 10}_{\text{Look familiar?}}
 \end{aligned}$$

Recall from Stat 260:-

If, $X \sim \mathcal{N}(\mu, \sigma^2)$, then $\bar{X} \sim \mathcal{N}(\mu, \sigma^2/n)$; n is sample size.

Then, $Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim \mathcal{N}(0, 1)$

So, $Z^2 = \frac{(\bar{X} - \mu)^2}{\sigma^2/n} \sim \chi^2_{(1)}$, from Section 3.2.

Hence, in this case, $D \sim \chi^2_{(1)}$. Exact equality!
 even though in LRS defn above,
 $D \approx \chi^2_{(1)}$

Then calculating our p -value is also exact,

$$\begin{aligned} p\text{-value} &= P(D \geq d_{\text{obs}}) = P[\chi^2_{(1)} \geq d_{\text{obs}}] \\ &= 2P[Z \geq \sqrt{d_{\text{obs}}}] \end{aligned} \quad \left. \vphantom{\begin{aligned} p\text{-value} &= P(D \geq d_{\text{obs}}) = P[\chi^2_{(1)} \geq d_{\text{obs}}] \\ &= 2P[Z \geq \sqrt{d_{\text{obs}}}] \end{aligned}} \right\} \begin{array}{l} \text{2-tailed} \\ \text{test.} \end{array}$$

We use our Data to Calculate our d_{obs} :

$$d_{\text{obs}} = \frac{(227.49 - 226)^2}{1.3^2/10} = 13.14 \quad ; \quad \bar{x} = 227.49$$

$$p\text{-value} = P[\chi^2_{(1)} \geq 13.14] = 0.00029 < 0.01$$

Checklist for Conclusion \rightarrow

- Estimated parameter values of interval estimate (i)
- p -value (ii)
- In words, what is the result of the Data. (iii)

Our estimated mean weight is 227.49g, with a 10%.

L.I of 226.61 - 228.37 grams. (i) The p -value of our test was 2.9×10^{-4} , showing very strong evidence against H_0 . (ii)

The Data are not consistent with the hypothesis that the mean weight of the item is 226 grams. (iii)