

Tutorial 4, Feb 9, 2024

Hypothesis Testing

Definition

Hypothesis Testing: Let X be an RV with distribution $f_X(x; H_0)$ or $f_X(x; H_1)$, and we observe x ; we would like to infer whether H_0 or H_1 is true by designing a decision rule $g(x)$.

- Generally we partition S into regions A_0, A_1 , so $g(x) = \begin{cases} H_0 & x \in A_0 \\ H_1 & x \in A_1 \end{cases}$
- A good decision rule minimizes both the probability of type I errors α (false rejection of H_0 /false acceptance of H_1) and type II errors β (false acceptance of H_0 /false rejection of H_1)
 - $\alpha = P[X \notin A_0; H_0] = \int_{A_0^c} f(x; H_0) dx$
 - $\beta = P[X \in A_0; H_1] = \int_{A_0} f(x; H_1) dx$

Definition

Neyman-Pearson Lemma: For a given target α , the minimum β is achieved by a decision rule of the form

$$\frac{f(x; H_0)}{f(x; H_1)} \underset{H_1}{\overset{H_0}{\geq}} \zeta$$

- Setting ζ to 1 gives MLE, but in general we can set this to anything
- If we have priors $\pi_0 = P[H_0], \pi_1 = P[H_1]$ then $\frac{\pi_0 f(x; H_0)}{\pi_1 f(x; H_1)} \underset{H_1}{\overset{H_0}{\geq}} \zeta$
- Example: Let X be the number of coin tosses until the first heads
 - H_0 : fair coin with $P[H] = \frac{1}{2}$
 - H_1 : biased coin with $P[H] = \frac{1}{8}$
 - The number of tosses until first heads is given by a geometric distribution
 - With ML:
 - * $p(x; H_0) = \left(\frac{1}{2}\right)^x$
 - * $p(x; H_1) = \left(1 - \frac{1}{8}\right)^{x-1} \left(\frac{1}{8}\right)$
 - * Test: $\left(\frac{1}{2}\right)^x \underset{H_1}{\overset{H_0}{\geq}} \left(1 - \frac{1}{8}\right)^{x-1} \left(\frac{1}{8}\right)$
 - * Log both sides: $-x \underset{H_1}{\overset{H_0}{\geq}} (x-1) \log\left(1 - \frac{1}{8}\right) + \log\left(\frac{1}{8}\right)$
 - * $x \underset{H_0}{\overset{H_1}{\geq}} \frac{3 + \log(7/8)}{1 + \log(7/8)} \approx 3.5$
 - * Type I error: $\alpha = P[X \geq 4; H_0] = \sum_{x=4}^{\infty} \left(\frac{1}{2}\right)^x = \frac{1}{8}$
 - * Type I error: $\beta = P[X \leq 3; H_1] = \sum_{x=1}^3 \left(1 - \frac{1}{8}\right)^{x-1} \left(\frac{1}{8}\right)$
- Example: $f(x; H_0)$ is uniform on $[0, 1]$; $f(x; H_1)$ is uniform on $[-a, a]$
 - With ML:
 - * If $a < \frac{1}{2}$ then select H_1 if $x \in [-a, a]$ and H_0 otherwise

- This is because with $a < \frac{1}{2}$ the likelihood of H_1 is always greater, as long as x falls within the interval
- * If $a \geq \frac{1}{2}$ then select H_0 if $x \in [0, 1]$ and H_1 otherwise
 - Again with $a \geq \frac{1}{2}$ the likelihood of H_1 is always less, as long as x falls within the interval of H_0
- * Note this assumes we never see an x outside these distributions