

HW 8, Lab 5 due tonight
Friday: little bit of R

Snapshot of grades on moodle (through HW 6 / quiz 2)

11: HYPOTHESIS TESTING II

Larsen & Marx 6.4, 6.5
Prof Amanda Luby

Last time, we laid the groundwork for a more theoretical treatment of hypothesis testing. Today, we're going to continue that thread by talking about *power functions* and *testing errors* in a more theoretical framework. We'll end by introducing the *likelihood ratio test*, a method for deriving hypothesis test procedures.

1 Power Function

In order to generalize hypothesis testing procedures, it is useful to define the *power function* of a test (sometimes called a *power curve*).

Power Function

Let δ be a test procedure and denote $\pi(\theta|\delta)$ as the power function of the test. If δ is defined in terms of T and rejection region R , then:

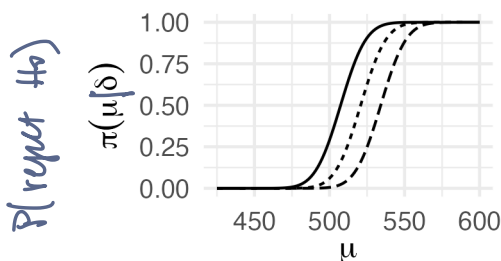
$$\pi(\theta|\delta) = P(T \in R | \theta) \text{ for } \theta \in \Omega$$

π is a function of θ and gives $P(\text{reject } H_0)$

Note: Ideal Power Function?

- ① $\theta \in \Omega_0 \rightarrow \pi(\theta|\delta) = 0$
 - ② $\theta \in \Omega_1 \rightarrow \pi(\theta|\delta) = 1$
- } correct decision w/ probability 1
in practice, want $\pi(\theta|\delta)$ close to 0 when $\theta \in \Omega_0$ and close to 1 when $\theta \in \Omega_1$

Example: Math curriculum example from last time: In the year of the study, 86 sophomores were randomly selected to participate in a special set of classes that integrated geometry and algebra. Those students averaged 502 on the SAT-I math exam; the nationwide average was 494 with a standard deviation of 124. Find the power function $\pi(\theta|\delta)$ for the test δ defined last time.



c
— 1
- - - 2
- · - 3

$$H_0: \mu = 494$$

$$H_1: \mu > 494$$

$$\mu_0 = 494$$

$$\sigma = 124$$

$$n = 86$$

true pop. param

Decision rule δ : reject H_0 when

$$Z = \frac{\bar{Y} - 494}{124/\sqrt{86}} > 1.64$$

T

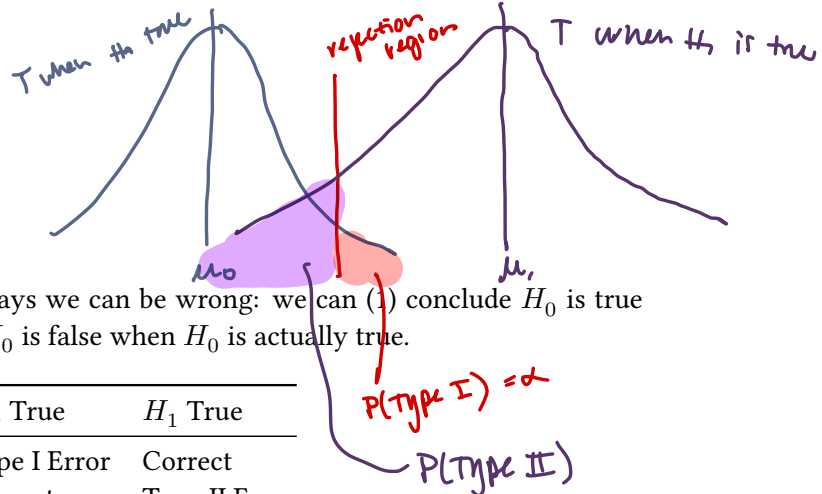
rejection region
 $R = [c, \infty)$
1.64

$$\bar{Y} \sim N(\mu, \frac{\sigma^2}{n})$$

$$\begin{aligned} \pi(\theta|\delta) &= P(T \in R | \mu) = P\left(\frac{\bar{Y} - \mu_0}{\sigma/\sqrt{n}} > c \mid \mu\right) = P(\bar{Y} > c \cdot \sigma/\sqrt{n} + \mu_0 \mid \mu) \\ &= P\left(\frac{\bar{Y} - \mu}{\sigma/\sqrt{n}} > \frac{c \cdot \sigma/\sqrt{n} + \mu_0 - \mu}{\sigma/\sqrt{n}}\right) \\ &= P\left(Z > c + \frac{\mu_0 - \mu}{\sigma/\sqrt{n}}\right) \\ &= 1 - \Phi\left(c + \frac{\mu_0 - \mu}{\sigma/\sqrt{n}}\right) \end{aligned}$$

$P(Z \leq z) = \Phi(z)$
norm.cdf

2 Types of Errors



In any hypothesis test procedure, there are two ways we can be wrong: we can (1) conclude H_0 is true when H_1 is actually true, or we can (2) conclude H_0 is false when H_0 is actually true.

	H_0 True	H_1 True
Reject H_0	Type I Error	Correct
Fail to reject H_0	Correct	Type II Error

- If $\theta \in \Omega_0$: $\pi(\theta|\delta) = P(\text{Type I error})$
- If $\theta \in \Omega_1$: $1 - \pi(\theta|\delta) = P(\text{Type II error})$

→ Only 1 possible error for any θ , but we never know whether $\theta \in \Omega_0$ or $\theta \in \Omega_1$.

Solution:

Choose $\alpha_0 \in (0,1)$ such that $\pi(\theta|\delta) \leq \alpha_0$ for all $\theta \in \Omega_0$.

If simple H_0 : Set α_0 such that $\pi(\theta|\delta) \leq \alpha_0$ for $\theta = \theta_0$.

Level- α_0 Test

A test that satisfies the above is called a *level α_0 test* and we say it has *significance level α_0* . In addition, the *size $\alpha(\delta)$* of a test is defined as:

$$\max_{\theta \in \Omega_0} \pi(\theta|\delta) \leftarrow \max(\text{Type I error}) \text{ over all possible } \theta \in \Omega_0$$

A test is a level α_0 test if and only if its size is at most α_0 . If H_0 is simple, $\alpha(\delta) = \pi(\theta|\delta)$.

Example: Suppose that a random sample X_1, \dots, X_n is taken from the uniform distribution on the interval $[0, \theta]$, where θ is unknown but positive, and suppose we wish to test the following hypotheses. Find the power function and size of the test.

$$H_0 : 3 \leq \theta \leq 4$$

$$H_1 : \theta < 3 \text{ or } \theta > 4$$

3 Likelihood Ratio Test

Many of the most popular hypothesis tests used in practice have the same conceptual heritage - a fundamental notion known as the *Generalized likelihood ratio* or GLR.

Example: Suppose $X_1, \dots, X_n \sim \text{Unif}(0, \theta)$ and we wish to test $H_0 : \theta = \theta_0$ against $H_1 : \theta < \theta_0$.

Generalized likelihood ratio

Let y_1, \dots, y_n be iid from $f_y(y; \theta)$. The generalized likelihood ratio is defined as:

Generalized likelihood ratio test

A generalized likelihood ratio test (GLRT) is one that rejects H_0 when

Let f_Λ denote the PDF of the GLR under H_0 . If we knew what the pdf was, we could find λ^* and δ by solving:

Generally, however, we can't find f_Λ . Instead, we find a quantity W that we *do* know the distribution of,

and show that Λ is a monotone function of W . Then, a test based on W is equivalent to one based on Λ .

Back to example: