

Stat 543

3-9-05

"Simple vs Simple" Testing (+ The N-P Lemma)

Suppose  $\Theta = \{\theta_0, \theta_1\}$   $\Theta_0 = \{\theta_0\}$   $\Theta_1 = \{\theta_1\}$

$f(x|\theta_0)$  vs  $f(x|\theta_1)$

Bayes look at this problem:  $g(\theta_0) + g(\theta_1) = 1$

$$f(x, \theta) = f(x|\theta)g(\theta)$$

$$g(\theta|x) = \frac{f(x|\theta)g(\theta)}{f(x|\theta_0)g(\theta_0) + f(x|\theta_1)g(\theta_1)}$$

Bayes rule is "minimize posterior expected loss"

If  $a = 0$  posterior expected loss is

$$1 \cdot g(\theta_1 | x)$$

If  $a = 1$  posterior expected loss is

$$1 \cdot g(\theta_0 | x)$$

So "obviously" choose between  $a = 0$  and  $a = 1$  depending upon how  $g(\theta_1 | x)$  compares to  $g(\theta_0 | x)$  i.e. we choose action corresponding to the  $\theta$  with largest posterior probability

So a Bayes test for this simple vs simple problem is of the form

$$\phi(x) = \begin{cases} 1 & \text{if } g(\theta_1|x) > g(\theta_0|x) \\ 0 & < \end{cases}$$

$$= \begin{cases} 1 & \text{if } f(x|\theta_1)g(\theta_1) > f(x|\theta_0)g(\theta_0) \\ 0 & < \end{cases}$$

$$= \begin{cases} 1 & \frac{f(x|\theta_1)}{f(x|\theta_0)} > \frac{g(\theta_0)}{g(\theta_1)} \\ 0 & < \end{cases}$$

ie. good (Bayes) tests reject  $H_0$  (decide  $a=1$ ) for large values of the "likelihood ratio"

$$R(x) = \frac{L_x(\theta_1)}{L_x(\theta_0)}$$

Example  $X \sim N(\mu, 1)$   $\mu_0 < \mu_1$

$$R(x) = \frac{\frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-\mu_1)^2\right]}{\frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2}(x-\mu_0)^2\right]}$$

$$= \exp\left[x(\mu_1 - \mu_0)\right] \exp\left[\mu_1^2 - \mu_0^2\right]$$

$H_0$  (decide  $a=1$ )  $\nearrow$  in  $x$  so Bayes tests reject for large  $x$

## Example Simple discrete

$x$	0	1	2	3	4	5
$f(x \theta_1)$	.2	.1	.4	.2	.05	.05
$f(x \theta_0)$	.2	.1	.2	.05	.3	.15
$R(x)$	1	1	2	4	$\frac{1}{6}$	$\frac{1}{3}$

So "good" tests look like

$$\phi_1(x) = \begin{cases} 1 & \text{if } x=3 \\ 0 & \text{otherwise} \end{cases}$$

or

$$\phi_2(x) = \begin{cases} 1 & \text{if } x=3 \text{ or } 2 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{or } \phi_3(x) = \begin{cases} 1 \\ 0 \end{cases} \quad x = 3 \text{ or } 2 \text{ or } 1$$

$$\text{or } \phi_4(x) = \begin{cases} 1 \\ 0 \end{cases} \quad x = 3 \text{ or } 2 \text{ or } 0$$

$$\text{or } \phi_5(x) = \begin{cases} 1 \\ 0 \end{cases} \quad x = 3 \text{ or } 2 \text{ or } 0 \text{ or } 1$$

$$\text{or } \phi_6(x) = \begin{cases} 1 \\ 0 \end{cases} \quad \begin{array}{l} x = 3 \text{ or } 2 \text{ or } 0 \text{ or } 1 \text{ or } 5 \\ x = 4 \end{array}$$

Notice that this prescription (reject  $H_0$ /decide  $a=1$  when  $R(x)$  is big) adds points to

rejection regions by reducing what is "large" and this is in some sense buying "power" ( $f(x|\theta_1)$ ) as cheaply (for smallest possible  $f(x|\theta_0)$ ) as possible - that story makes plausible the fundamental result of testing  $H_0$  (Neyman-Pearson Lemma) -

A bit more notation/terminology:

In a simple vs simple problem for a test  $\phi$  it's common to call

$$\begin{aligned}\pi_{\phi}(\theta_0) &= P_{\theta_0}[\phi(X) = 1] \\ &= \text{Type I error probability}\end{aligned}$$

$$\begin{aligned}
 &= \alpha \\
 &= \text{"The 'size' of the test } \phi \text{"} \\
 \pi_{\phi}(\theta_1) &= 1 - \underbrace{\text{Type II error probability}}_{\beta} \\
 &= \text{"The 'power' of the test } \phi \text{"}
 \end{aligned}$$

Theorem Neyman - Pearson Lemma (Part I)

If

$$\phi(x) = \begin{cases} 1 & \text{if } R(x) > k \\ 0 & \text{if } R(x) < k \end{cases}$$

then  $\phi$  is "most powerful of its size"

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Conclusion: If  $\phi'$  is another test with

$$\underbrace{\overline{\pi}_{\phi'}(\theta_0)}_{\text{size of } \phi'} \leq \underbrace{\overline{\pi}_{\phi}(\theta_0)}_{\text{size of } \phi}$$

Then

$$\underbrace{\overline{\pi}_{\phi}(\theta_1)}_{\text{"power" of } \phi} \geq \underbrace{\overline{\pi}_{\phi'}(\theta_1)}_{\text{"power" of } \phi'}$$