

Previously on ECE 645 ...

Bayesian Composite Binary Test where Costs are Constant over H_0 and H_1 :

- Random parameter $\Theta = \theta \in \Delta = \Delta_0 \cup \Delta_1$; $\Delta_0 \cap \Delta_1 = \phi$
- $H_0: \Theta \in \Delta_0$ vs. $H_1: \Theta \in \Delta_1$
- When $\Theta = \theta$ is drawn (i.e., H_0 vs. H_1 determined) an observation is made according to

$$Y \sim P_\theta$$

$$Y = y \in \Gamma$$

P_θ is conditional distribution of Y given $\Theta = \theta$

- Cost function: $C(i, \theta)$ $i = 0, 1$ $\theta \in \Delta$

Assume $C(i, \theta) = c_{ij}$ if $\theta \in \Delta_j$

- Find $\delta(y)$ a 0,1 function of $y \in \Gamma$ st.

$$\delta(y) = E\{C(\delta(Y), \Theta)\}$$

is minimized.

Equivalent Formulations of Bayes Rule

$$d_B(y) = \begin{cases} 1 \\ 0 \text{ or } 1 \\ 0 \end{cases} \quad \text{if } E\{C(1, \Theta) | Y=y\} < E\{C(0, \Theta) | Y=y\}$$

$$= \begin{cases} 1 \\ 0 \text{ or } 1 \\ 0 \end{cases} \quad \text{if } \frac{P(\Theta \in \Delta_1 | Y=y)}{P(\Theta \in \Delta_0 | Y=y)} > \frac{c_{10} - c_{00}}{c_{01} - c_{11}}$$

Assume
 $c_{00} < c_{10}$
 $c_{11} < c_{01}$

$$= \begin{cases} 1 \\ 0 \text{ or } 1 \\ 0 \end{cases} \quad \text{if } \frac{f_Y(y | \Theta \in \Delta_1)}{f_Y(y | \Theta \in \Delta_0)} > \frac{\pi_0 (c_{10} - c_{00})}{\pi_1 (c_{01} - c_{11})}$$

define as $L(y)$

$\pi_0 = P(\Theta \in \Delta_0)$
 $\pi_1 = P(\Theta \in \Delta_1)$

Note: To go from δ_B version #2 to δ_B version #3 use Bayes Formula

$$P(\Theta \in \Delta_1 | Y=y) = \frac{f_Y(y | \Theta \in \Delta_1) P(\Theta \in \Delta_1)}{f_Y(y | \Theta \in \Delta_0) P(\Theta \in \Delta_0) + f_Y(y | \Theta \in \Delta_1) P(\Theta \in \Delta_1)}$$

⋮

Similarly for

$$P(\Theta \in \Delta_0 | Y=y) = \dots$$

too: $P(A|B) = \frac{P(A \cap B)}{P(B)}$

~~$P(\Theta \in \Delta_1)$~~

Re: Testing on Radius of Point in \mathbb{R}^2

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} \in \mathbb{R}^2$$

$$H_0: Y_1 = \varepsilon_1, Y_2 = \varepsilon_2$$

vs.

$$H_1: Y_1 = A \cos \Psi + \varepsilon_1, Y_2 = A \sin \Psi + \varepsilon_2$$

$$\varepsilon_1, \varepsilon_2 \sim N(0, \sigma^2)$$

$$A > 0$$

$$\Psi \text{ unif. } [0, 2\pi)$$

$$\varepsilon_1 \perp \varepsilon_2 \perp \Psi \perp \text{ hypoth.}$$

Setting up the Bayesian Model more carefully:

$$\Theta = \begin{pmatrix} A \\ \Psi \end{pmatrix}$$

where this is a mixed discrete-continuous random vector made up of

$$A \perp \Psi$$

discrete rv.
taking values
 $0, a$ with

$$P(A=a) = p$$

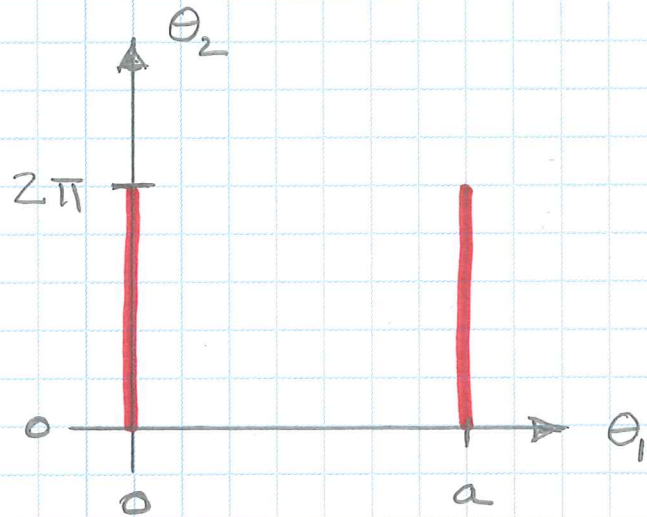
$$P(A=0) = q$$

$$p+q=1$$

cont. rv. unif
on $[0, 2\pi)$ i.e.

$$f_{\Psi}(\varphi) = \begin{cases} \frac{1}{2\pi} & 0 \leq \varphi < 2\pi \\ 0 & \text{else} \end{cases}$$

Then the r.vec. Θ takes its values in the following subset of \mathbb{R}^2 :



There is no continuous pdf on \mathbb{R}^2 that can model the r.vec. Θ .

However, allowing delta functions we can model this mixed situation as ...

$$f_{\Theta}(\theta_1, \theta_2) = \begin{cases} q \frac{1}{2\pi} \delta(\theta_1) + p \frac{1}{2\pi} \delta(\theta_1 - a) & 0 \leq \theta_2 < 2\pi \\ 0 & \text{else} \end{cases}$$

Then

$$H_0: A = 0$$

vs.

$$H_1: A = a$$

$$\text{with } Y = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = A \begin{pmatrix} \cos \Psi \\ \sin \Psi \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix}$$

To compute $L(y)$ need $f(y | \Theta \in \Delta_j)$ $y \in \mathbb{R}^2$ $j=0,1$

What is $f(y | \Theta \in \Delta_j)$ ^{← "lambda"}

$$\frac{P(Y=y, \Theta \in \Delta_j)}{P(\Theta \in \Delta_j)} \quad ??$$

$$F_{Y|\{\Theta \in \Delta_j\}}(y_1, y_2)$$

$$P(y_1 \leq Y_1 \leq y_2)$$

$$= P(Y_1 \leq y_1, Y_2 \leq y_2 | \Theta \in \Delta_j)$$

$$= P(Y_1 \leq y_1, Y_2 \leq y_2, \Theta \in \Delta_j)$$

$$P(\Theta \in \Delta_j)$$

$$\int_{-\infty}^{y_2} \int_{-\infty}^{y_1} \int_{\Delta_j} f_{Y_1, Y_2, \Theta_1, \Theta_2}(y_1, y_2, \theta_1, \theta_2) dy_1 dy_2 d\theta_1 d\theta_2$$

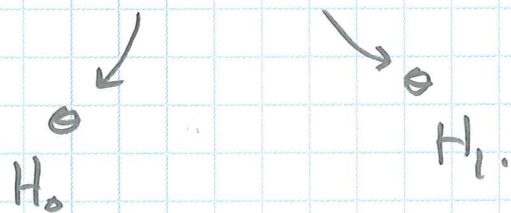
$$f_{Y_1, Y_2 | \Theta_1, \Theta_2}(y_1, y_2 | \theta_1, \theta_2) f_{\Theta}(\theta_1, \theta_2)$$

$$\rightarrow \frac{1}{2\pi} \delta(\theta_1) + \frac{1}{2\pi} \delta(\theta_1 - a)$$

Uniformly Most Powerful Tests

θ is modeled as deterministic, but unknown.

$$\Delta = \Delta_0 \cup \Delta_1, \quad \Delta_0 \cap \Delta_1 = \emptyset$$



$\delta(y)$ the dec. rule is a number between 0 and 1

$$\delta: \Gamma \rightarrow [0, 1]$$

False alarm: $P_F(\delta; \theta) = E_{\theta} \{ \delta(Y) \}$ for $\theta \in \Delta_0$

Det. Prob. $P_D(\delta; \theta) = E_{\theta} \{ \delta(Y) \}$ for $\theta \in \Delta_1$

A UMP test of level α is one that maximizes

$$P_D(\delta; \theta)$$

for every $\theta \in \Delta_1$ subject to

$$P_F(\delta; \theta) \leq \alpha \quad \text{for all } \theta \in \Delta_0.$$

But UMP Test Don't Always Exist

$\Lambda = \Lambda_0 \cup \Lambda_1$ Say H_0 is simple i.e. $\Lambda_0 = \{\theta_0\}$

Say P_θ has a density $f_\theta(\cdot)$ for each $\theta \in \Lambda$.

$$H_0: Y \sim P_{\theta_0}$$

vs

$$H_1: Y \sim P_\theta$$

for some fixed $\theta \in \Lambda_1$.

↳ a simple H.T.

Know from NPL that \exists a most powerful test for θ vs. θ_0 α -level

$$\Gamma_\theta = \{y \in \Gamma: f_\theta(y) > \tau f_{\theta_0}(y)\}$$

where τ and a poss. randomization are chosen to give size α .

Say have two distinct params $\theta', \theta'' \in \Lambda_1$

\swarrow \searrow
 $\Pi_{\theta'}$ $\Pi_{\theta''}$

Test with $\Pi_{\theta'}$ will have $P_D(\delta'; \theta'') < P_D(\delta''; \theta'')$ unless $\Pi_{\theta'}$ and $\Pi_{\theta''}$ are the same.

Fact A UMP test for H_{θ_0} vs $H_{\theta}: Y \sim P_{\theta}, \theta \in \Lambda_1$ exists \Leftrightarrow the critical region Π_{θ} is same for all θ .

\Rightarrow