

Lecture 23: p-values / Bayesian Inference

Often we report the outcome of a HT using a p-value.

Defn: P-value

A p-value is a test statistic $p(\underline{x})$ where

$$0 \leq p(\underline{x}) \leq 1 \quad \forall \underline{x}$$

idea: small $p(\underline{x})$ gives evidence of H_a
large $p(\underline{x})$ gives evidence of H_0

Recall, a HT is just a partition of \mathcal{X} into A and R , and we can use p-val's to defn R as

$$R = \{ \underline{x} : p(\underline{x}) \leq \alpha \}$$

i.e. rej. H_0 when p-val is suff.-small.

We say a p-value is valid if
 $\forall 0 \leq \alpha \leq 1$ and $\theta \in \underline{\Theta}_0$

$$P_{\theta}(p(\underline{X}) \leq \alpha) \leq \alpha$$



↑ stochastically bounded
by a $U(0,1)$ RV

$$F_p(\alpha) \leq \alpha$$

↑ CDF of $U(0,1)$

Allowable (typical) $P(\underline{X}) \sim U(0,1)$ for $\theta \in \underline{\Theta}_0$

$$\text{so } F_p(\alpha) = \alpha.$$

If P is valid and I set up a test

$$R = \{ \underline{X} : p(\underline{X}) \leq \alpha \}$$

then this test is level α .

Reason: under null $\theta \in \underline{\Theta}_0$

$$P_{\theta}(\text{reject})$$

$$= P_{\theta}(p(\underline{X}) \leq \alpha)$$

$$= F_p(\alpha) \leq \alpha \quad \text{by defn that } P \text{ is valid.}$$

Ex. Consider $H_0: \theta = \theta_0$ v. $H_a: \theta \neq \theta_0$

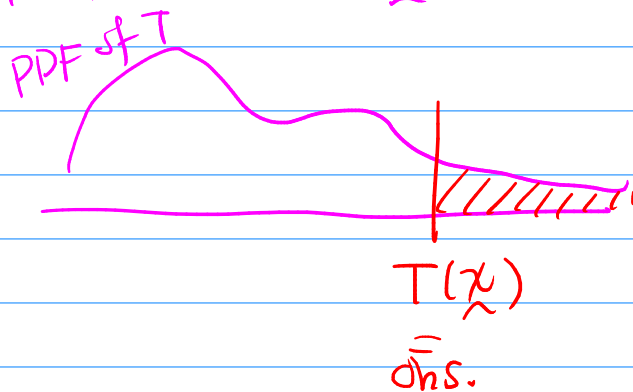
and I get a test stat T and

$$\mathcal{R} = \{ \underline{x} : T(\underline{x}) \text{ is large} \}$$

Let

$$p(\underline{x}) = P_{\theta_0}(\underbrace{T(\underline{x})}_{\text{rad}} \geq \underbrace{T(\underline{x})}_{\text{obs}}) = 1 - F_T(T(\underline{x}))$$

= prob. under H_0 that I obs.
a test stat T as big or
larger than my observed
test stat $T(\underline{x})$.



Claim: P is a valid p-value
i.e. under H_0 $P \sim U(0,1)$

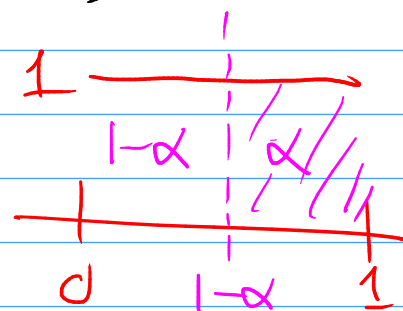
$$F_p(\alpha) = P_{\theta_0}(P(\underline{x}) \leq \alpha)$$

$$= P_{\theta_0}(1 - F_T(T(\underline{x})) \leq \alpha)$$

$$= P_{\theta_0} \left(\underbrace{F_T(T(X))}_{U \sim U(0,1)} \geq 1 - \alpha \right)$$

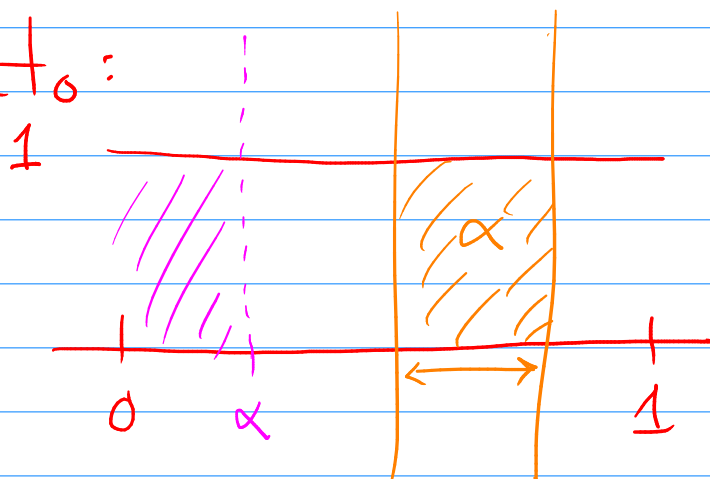
$$= P_{\theta_0} (U \geq 1 - \alpha)$$

$$= \alpha$$



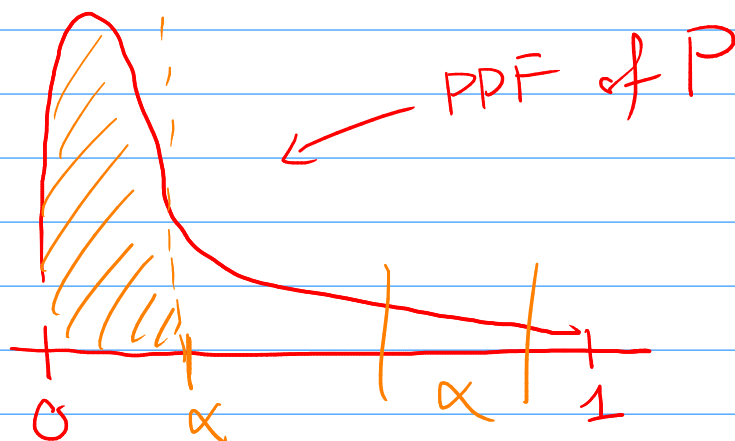
Punchline: under H_0 $P \sim U(0,1)$.

Under H_0 :



Typically higher power when we rej. when P is small.

C_X



Bayesian Inference

this course

Frequentist (classical) Inference

θ fixed but unknown.

Bayesian Inference

θ random

Bayesian approach:

(1) prior dist.

$$\theta \sim \pi$$

← PMF or PDF of θ

(2) get data

← $\pi(\theta)$

$$\underline{x} | \theta = \theta \sim f(\underline{x} | \theta)$$

← sampling dist
likelihood

(3) update / combine prior / likelihood to get posterior

$$\pi(\theta | \underline{x}) = \frac{f(\underline{x} | \theta) \pi(\theta)}{f(\underline{x})} \propto f(\underline{x} | \theta) \pi(\theta)$$

← Bayes' theorem

posterior \propto likelihood \times prior

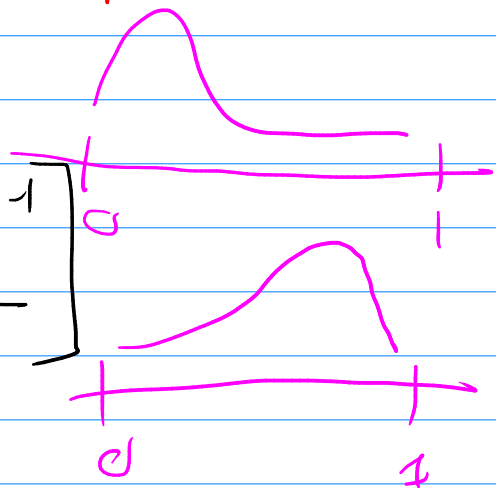
$$f(\underline{x}) = \int f(\underline{x} | \theta) \pi(\theta) d\theta$$

often estimate $\hat{\theta}$ as

$$E[\theta | \underline{x}] \text{ or } \text{mode}(\theta | \underline{x})$$

Ex. $P \sim \text{Beta}(\alpha, \beta)$ prior

$X_n | P=p \stackrel{\text{iid}}{\sim} \text{Bern}(p)$ likelihood

$$\begin{aligned} \pi(p | \underline{x}) &\propto f(\underline{x} | p) \pi(p) \\ &= \left[\prod_n p^{x_n} (1-p)^{1-x_n} \right] \left[\frac{p^{\alpha-1} (1-p)^{\beta-1}}{B(\alpha, \beta)} \right] \end{aligned}$$


$$\propto p^{N\bar{x}} (1-p)^{N-N\bar{x}} p^{\alpha-1} (1-p)^{\beta-1}$$

$$\propto p^{N\bar{x} + \alpha - 1} (1-p)^{N - N\bar{x} + \beta - 1}$$

basically a $\text{Beta}(\underline{N\bar{x} + \alpha}, \underline{N - N\bar{x} + \beta})$

i.e. $P | \underline{x} \sim \text{Beta}(\quad)$



$$\hat{p} = E[P|X] = \frac{N\bar{x} + \alpha}{N\bar{x} + \alpha + N - N\bar{x} + \beta}$$

$$= w\bar{x} + (1-w)\frac{\alpha}{\alpha+\beta}$$

\uparrow freq. \uparrow $E[P]$

$$w = \frac{N}{\alpha + \beta + N}$$

$$w \rightarrow 1 \text{ as } N \rightarrow \infty$$
