

Lecture 22

W: 2:30 - 3:30

Thurs: 3:30 - 5:00

M: 10 am - 12:00 pm

} Extra office hours

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

Defn: p-value

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

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

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

Recall that a HT is just a partition of \mathcal{X} into A and R

Can use $p(\underline{x})$ to define R

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

We say a p-value is valid if
 $\forall \alpha \in [0, 1]$ and $\theta \in \Theta_0$

$$P_{\theta}(P(X) \leq \alpha) \leq \alpha$$

$$F_P(\alpha) \leq \alpha \leftarrow \text{CDF of } U(0,1)$$

P is stochastically bounded
by $U(0,1)$

Typically we actually have that

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

$F_P(\alpha)$

i.e. $P(X) \sim U(0,1)$ for $\theta \in \Theta_0$

If P is valid then test that rejects when
 $P(X) \leq \alpha$ is an α -level test.

reason!

$$P_{\theta}(\text{reject}) = P_{\theta}(P(X) \leq \alpha) \leq \alpha \quad \forall \theta \in \Theta_0$$

Ex. Consider

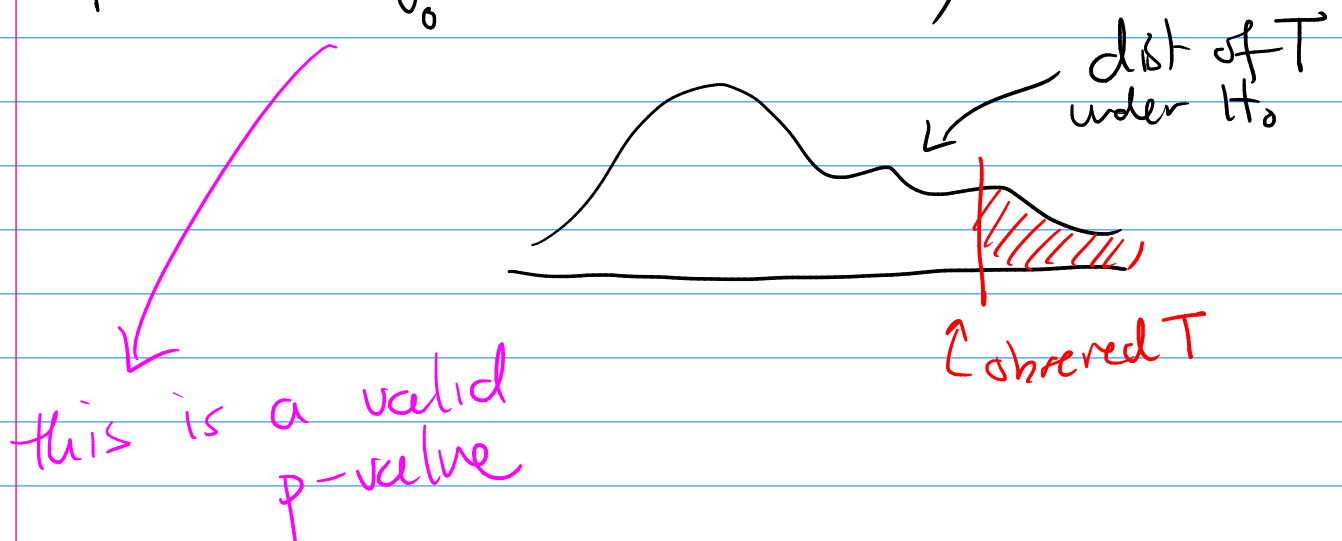
$$H_0: \theta = \theta_0 \quad \text{v.} \quad H_a: \theta \neq \theta_0$$

I get a test stat T and my test rejs when

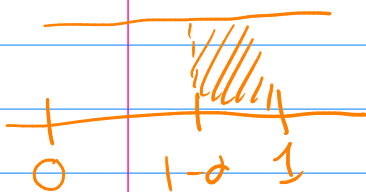
$$R = \{ \underline{x} : T(\underline{x}) \text{ is large} \}$$

Let

$$P(\underline{x}) = P_{\theta_0}(\overset{\text{random}}{T(\underline{x})} \geq \overset{\text{observed}}{T(\underline{x})}) = 1 - F_T(T(\underline{x}))$$



$$\begin{aligned} P_{\theta_0}(P(\underline{x}) \leq \alpha) &= P_{\theta_0}(1 - F_T(T(\underline{x})) \leq \alpha) \\ &= P_{\theta_0}(\underbrace{F_T(T(\underline{x}))}_{U(0,1)} \geq 1 - \alpha) = \alpha \end{aligned}$$



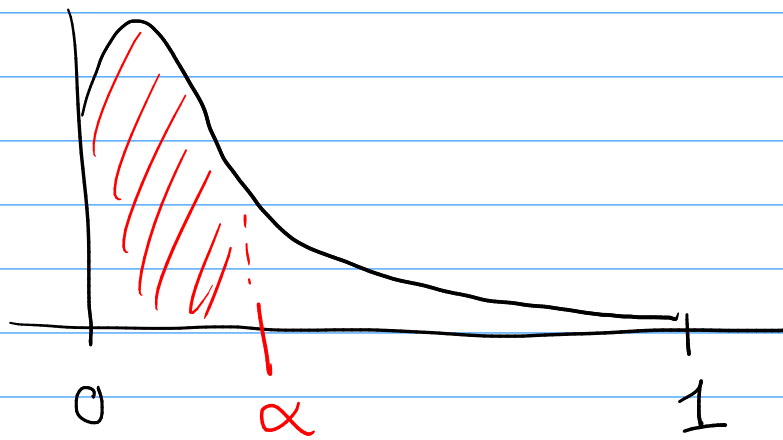
so this is valid.

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

Under H_0 :



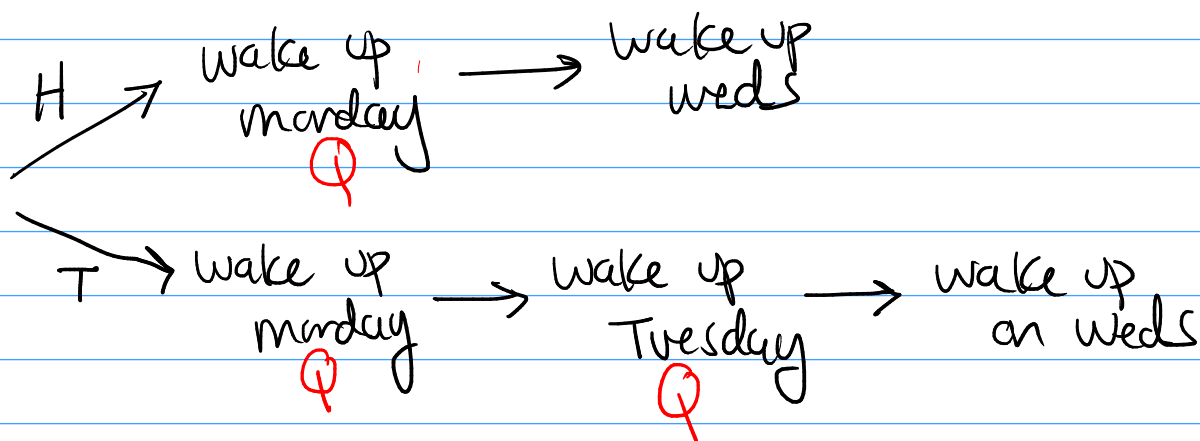
Under H_a : typically, p-value is small



Frequentists: prob = long run freq of events

Bayesians: prob = degree of belief/information

Sleeping Beauty



Practical!

Frequentist: θ fixed but unknown

Bayesian: θ is random

Bayesian approach:

(1) prior dist $\theta \sim \pi$

(2) get data

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

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

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

Then use $\pi(\theta|\underline{x})$ for whatever, e.g.

estimate $\hat{\theta}$ as

$$E[\theta|\underline{x}].$$

Ex. $X_n | P=p \sim \text{Bern}(p)$

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



$$\pi(p|\underline{x}) \propto f(\underline{x}|p)\pi(p)$$

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

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

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

freq. est.
of \hat{p}

$$= w\bar{x} + (1-w) \underbrace{\frac{\alpha}{\alpha+\beta}}_{\text{mean of prior}}$$