

• Recall: last time we defined what is hypothesis testing.

• parameter $\theta \in \Theta$: controls how to generate data.

• Random Variable, $X \in \mathcal{X}$: data.

• Hypothesis: H_0 : a subset $\Theta_0 \subset \Theta$. (null hypothesis).

• Test: \mathcal{R} : rejection ~~reg~~ region. $\mathcal{R} \subset \mathcal{X}$.

(we reject H_0 if $X \in \mathcal{R}$)

test say accept

test say "reject"

	$X \notin \mathcal{R}$	$X \in \mathcal{R}$
$\theta \in \Theta$	✓	type I error
$\theta \notin \Theta_0$	type II error	✓

too cautious.
or reject too often.

test too loose.

• (power function of a test):

$$\beta(\theta) = \mathbb{P}_\theta(X \in \mathcal{R})$$

the probability to trigger rejection under θ .

(size of a test):

$$\underline{\alpha} = \sup_{\theta \in \Theta_0} \beta(\theta).$$

the worst case scenario: what is the largest probability to reject H_0 when H_0 is actually true.

$\downarrow H_0$ is true.

Ideally: we want $\beta(\theta)$ to be low when $\theta \in \Theta_0$.

and high when $\theta \notin \Theta_0$.

• Example of test =

- Say $X_1, X_2, \dots, X_n \sim N(\mu, \sigma)$, we want to ask: is $\mu \leq 0$?

Hypothesis:

$$H_0 = \{ \mu \leq 0 \}$$

null hypothesis

$$H_1 = \{ \mu > 0 \}$$

alternative hypothesis

Test :

$\subset \mathbb{R}^n$

$$R = \{ (X_1, \dots, X_n) : T(X_1, \dots, X_n) > c \}$$

\bar{X} to be decided later.

$$T(X_1, \dots, X_n) = \frac{1}{n} (X_1 + \dots + X_n)$$

c : critical threshold.

power function:

$$\beta(\mu) \equiv \mathbb{P}_\mu (\text{do rejection}) \quad \bar{X}$$

$$\equiv \mathbb{P}_\mu \left(\frac{1}{n} (X_1 + \dots + X_n) > c \right)$$

$X_i \sim N(\mu, \sigma)$

CDF

make a Gaussian R.V. standard.

$$= \mathbb{P}_\mu (\bar{X} > c)$$

$$\rightarrow \mathbb{P}_\mu \left(\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} > \frac{c - \mu}{\sigma/\sqrt{n}} \right)$$

number.

$$\bar{X} \sim N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$$

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \sim N(0, 1)$$

$$\boxed{\beta(\mu) = 1 - \Phi\left(\frac{c - \mu}{\sigma/\sqrt{n}}\right)}$$

$$\Phi(x) = \mathbb{P}(Z < x)$$

↑
std normal

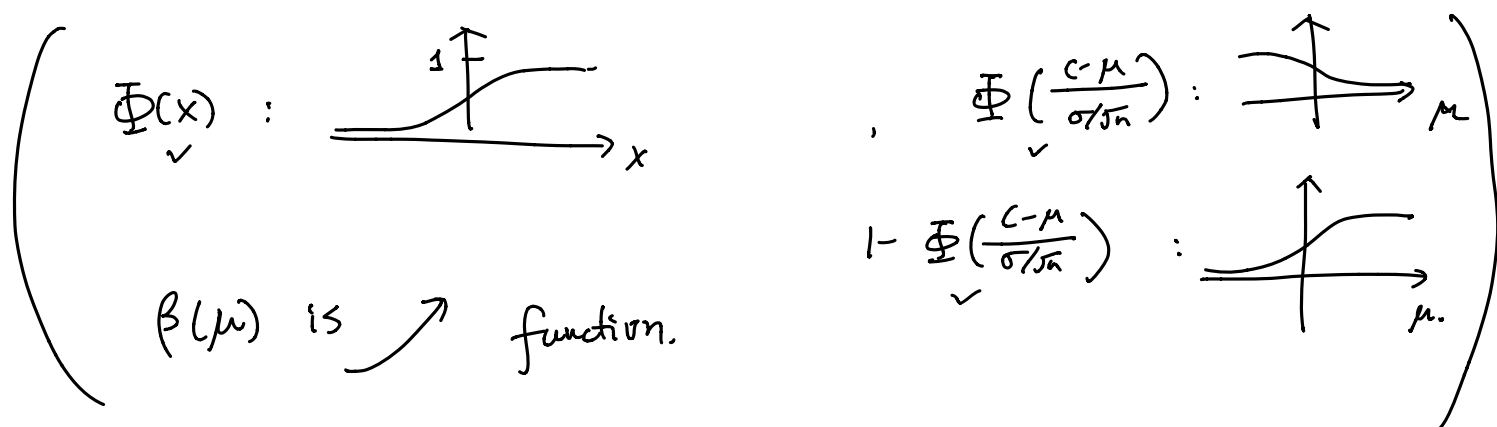
$$\bar{X} > c \iff \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} > \frac{c - \mu}{\sigma/\sqrt{n}}$$

$$\mathbb{P}(Z > c) = 1 - \mathbb{P}(Z < c) = 1 - \Phi(c)$$

$Z \sim N(0, 1)$

$N(0, 1)$

$$\text{size} = \sup_{\mu \in \mathcal{H}_0} \beta(\mu) = \sup_{\mu \leq 0} \beta(\mu) = \beta(0) = 1 - \Phi\left(\frac{c}{\sigma/\sqrt{n}}\right)$$



For a size α test, we want.

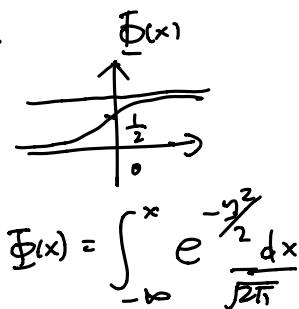
$$1 - \Phi\left(\frac{c}{\sigma/\sqrt{n}}\right) = \alpha$$

$$1 - \alpha = \Phi\left(\frac{c}{\sigma/\sqrt{n}}\right)$$

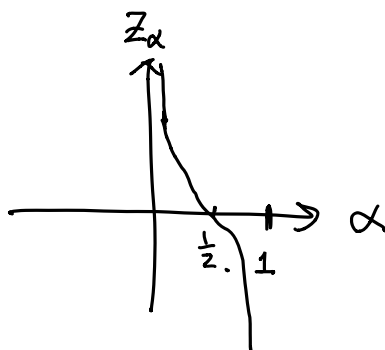
$$\Phi^{-1}(1 - \alpha) = \frac{c}{\sigma/\sqrt{n}}$$

$$c = \frac{\sigma}{\sqrt{n}} \cdot \Phi^{-1}(1 - \alpha)$$

say, $\alpha = 0.5$, then $\Phi^{-1}(1 - \frac{1}{2}) = \Phi^{-1}(\frac{1}{2}) = 0$
 then $c = 0$.



$$Z_\alpha = \Phi^{-1}(1 - \alpha)$$



$$c = \frac{\sigma}{\sqrt{n}} \cdot Z_\alpha$$

to have smaller α , we need to have bigger c .

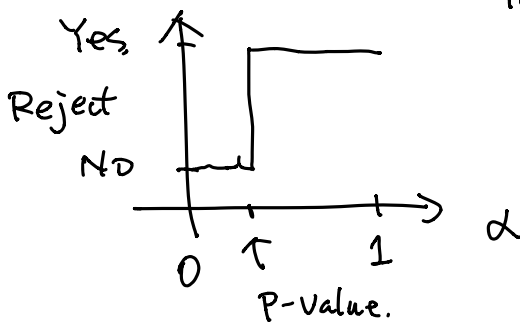
Remark: this is an example where we can adjust the test R_α , depending on the desired size of the test (α -value).

Definition (p-value): (assume we have a rejection region) R_α dep. on α
 Given the data X , what is the smallest α that we reject H_0 .

$$p\text{-value} = \inf \{ \alpha : X \in R_\alpha \}.$$

↑ infimum.

$$\begin{aligned} \inf &= \min \\ \sup &= \max \end{aligned}$$



e.g. $\inf \left(\left(\frac{1}{2}, \frac{2}{3} \right) \right) = \frac{1}{2}$

- $p\text{-value} < 0.01$: strong evidence against H_0 .
- $p\text{-value} > 0.1$: little or no evidence against H_0 .

warning: large p-value means either H_0 is true; or the test is too weak.

Reading Further:

- Wassermann : All of statistics. (prob + stat)
- Dobrow : intro to stochastic process in \underline{R} . (lots of examples)
- (math) • Rick Durrett : Introduction to probability.

Final :

- vector space, linear alg 30%
 - differential eq. special fun. 50%
 - probability (only things in Boas) 20%
- Zoom channel: math 121B.