

Testing of Hypothesis

- 2) Hypotheses - Null hyp & Alternative hyp.
- Simple & composite hyp
- One-sided & two-sided hypo

- 2) Test of a hypothesis - test function

- Acceptance, Rejection, Critical region

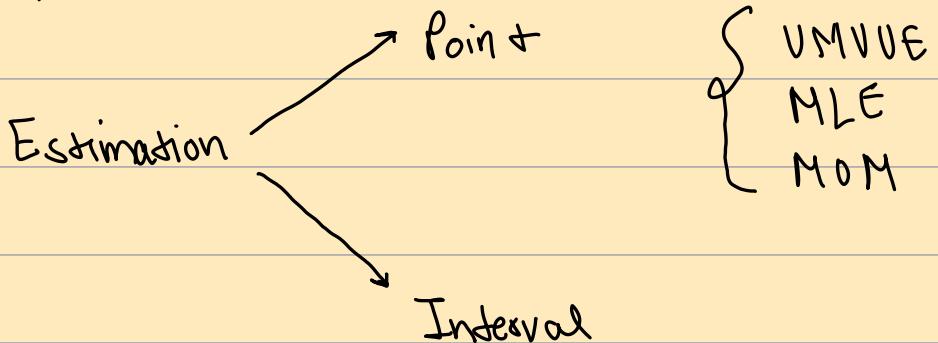
- 3) Types of error - level of significance

- size of a test

- power fn

- power

1) UMP / MP test.



Statistical Hypothesis means a statement about a parameter

Ex: $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$

$$H_0: \mu = 0$$

vs

$$\begin{aligned} H_{11}: \mu > 0 \\ H_{12}: \mu < 0 \end{aligned} \quad \left. \begin{array}{l} \text{one} \\ \text{sided} \end{array} \right\}$$

a) Null Hypothesis (H_0)

$H_{13}: \mu \neq 0$ - two sided

Alternative hypothesis (H_1 / H_A)

Ex: Q: If a coin is fair or not,

$$X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(\theta)$$

$$H_0: \theta = \frac{1}{2}$$

vs

$$H_1: \theta \neq \frac{1}{2}$$

Q: If a new medicine is better than the traditional one.

$$X_i = \begin{cases} 1 & \text{if a person taking the medicine is cured} \\ 0 & \text{ow.} \end{cases}$$

$$X_i \stackrel{iid}{\sim} \text{Bern}(\theta) \quad i = 1, \dots, n$$

$$H_0: \theta = \theta_0 \quad \text{vs} \quad H_1: \theta > \theta_0.$$

→ Test of Hypothesis is about accepting or rejecting the null hypothesis (H_0) only in light of the alternative (H_1)

Simple and composite hypothesis →

- When a hypothesis entirely specifies the population then it is called a 'simple hypothesis'.
- Composite hypothesis: A hypothesis which is not 'simple'.

$$X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(\theta) \quad H_0: \theta = \frac{1}{2} \quad [\text{simple}]$$

$$H_1: \theta \neq \frac{1}{2} \quad [\text{composite}]$$

$$H_1: \theta = \frac{3}{4} \quad [\text{simple}]$$

$$X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2) \quad H_0: \mu = 0, \quad [\text{composite}]$$

Test of Hypothesis →

Q: How to test?

$$X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(\theta) \quad n = 10$$

$$H_0: \theta = \frac{1}{2}$$

$$H_1: \theta > \frac{1}{2}$$

$$\{0, \dots, 0\}$$

Reject if $\{x_1, \dots, x_n\}$ is such that $\sum_{i=1}^n x_i > 5$

Testing rule: For any realisation $\{x_1, \dots, x_n\}$ we should have an unique answer, whether we should accept or reject H_0 .

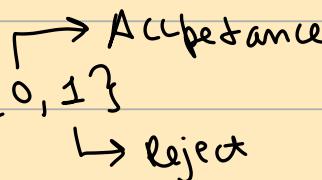
Test f. r. ϕ :

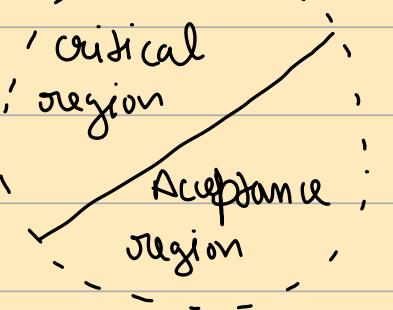
$\{\text{set of all realizations}\} \xrightarrow{\phi} \{\text{Accept}, \text{Reject}\}$

$x =$

[sample space]

$\phi: x \rightarrow \{0, 1\}$



$x =$ 'critical region'


$\phi(\{x_1, \dots, x_n\}) = 1 \Leftrightarrow$ for the realization $\{x_1, \dots, x_n\}$ we reject H_0 .

$$\phi(x) = \begin{cases} 1 & \text{if } \sum_{i=1}^{10} x_i > 5 \Leftrightarrow \bar{x}_n > \frac{1}{5} \\ 0 & \text{otherwise} \end{cases}$$

Critical region: The points in \bar{x} for which the test
(accept)
 ϕ rejects the null hypothesis is called the critical region 'C'.
 (Acceptance region, A).

Errors \rightarrow	Decision \ True state	H_0 is true	H_0 is false
		Accept H_0	Type II error
Reject H_0	Type I error		✓

$$\sum_{i=1}^{10} X_i > 5$$

$$\theta = \frac{1}{2}$$

$$P(\text{Type I error}) = P(\text{Reject } H_0 \mid H_0 \text{ is true})$$

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bern}(\theta)$$

$$\phi(\bar{x}) = \mathbb{I}\left(\sum_{i=1}^{10} x_i > 5\right)$$

$$H_0: \theta = \frac{1}{2} \quad \text{vs} \quad H_1: \theta > \frac{1}{2}$$

$$\begin{aligned} P(\text{Type I error}) &= P(\sum x_i > 5 \mid \theta = \frac{1}{2}) \\ &= \sum_{j=6}^{10} \binom{10}{j} \left(\frac{1}{2}\right)^{10} = 0.376 \end{aligned}$$

$$[\text{Reject if } \sum x_i = 10] \quad P(\text{Type I error}) = \frac{1}{2^{10}}$$

$$H_0: \theta = \frac{1}{2} \quad \text{vs} \quad H_1: \theta = \frac{3}{4}$$

$$\begin{aligned}
 P(\text{Type II error}) &= P(\text{Accept } H_0 \mid H_0 \text{ is false}) \\
 &= P(\sum x_i = 10 \mid \theta = \frac{3}{5}) \\
 &= \left(\frac{3}{5}\right)^{10}
 \end{aligned}$$

exp) $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} f_0$ $\begin{cases} \text{Bern}(\theta) \\ \text{N}(\theta, 10) \end{cases}$

$$\begin{aligned}
 H_0: \theta &= \theta_0 \quad \text{against} \quad H_1: \theta = \theta_1 \quad (\theta_1 > \theta_0) \\
 \begin{matrix} \text{I} \\ \text{II} \end{matrix} &= [0.5, 0] \quad \begin{matrix} \text{I} \\ \text{II} \end{matrix} = [0.4, 1]
 \end{aligned}$$

$$\phi: \mathbb{R} \rightarrow \{0, 1\}$$

$$⑤ \mathbb{R}^n = \left\{ \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{pmatrix}, \dots, \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \right\}$$

$$⑥ \mathbb{R}^n = \mathbb{R}^n = \left\{ \begin{pmatrix} x_1 \\ \vdots \\ x_{10} \end{pmatrix}; x_i \in \mathbb{R} \right\}$$

$$\phi^*: \mathbb{R} \rightarrow \{0, 1\}; \quad \phi^*(\bar{x}_n) = \begin{cases} 1 & \text{if } \bar{x}_n \geq R \\ 0 & \text{otherwise} \end{cases}$$

Type I error : Rejection of a true H_0

Type II error : Acceptance of a false H_0

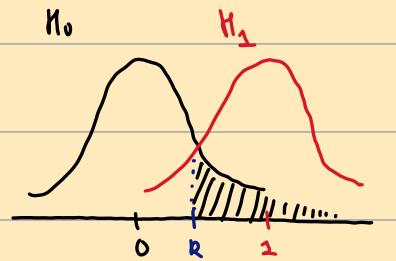
$$P(\text{Type I error}) = P(\text{Reject } H_0 \mid H_0 \text{ is true})$$

→ Distribution of \bar{X}_n under

$$P[\bar{X}_n \geq k \mid X_i \sim N(0, 1)]$$

$$= P[\bar{X}_n \geq k \mid \bar{X}_n \sim N(0, 1)] \quad ; n = 10$$

$$= 1 - \Phi(k) = \Phi(-k)$$



$$P(\text{Type II error}) = P(\text{Accept } H_0 \mid H_0 \text{ false})$$

$$= P(\bar{X}_n < k \mid \bar{X}_n \sim N(1, 1)) \Rightarrow P(\bar{X}_{n-1} < k-1 \mid \bar{X}_{n-1} \sim N(0, 1))$$

$$= \Phi(k-1)$$

$P(\text{Type I error})$	$P(\text{Type II error})$
$k = 1 \quad \Phi(-k) = c$	$\Phi(k-1) = k$
$k = 2 \quad c' < c$	$k' > k$

(decreases)

Remark: If one increases k then the $P(\text{Type I error})$ is reduced and $P(\text{Type II error})$ is increased.

(increased)

(reduced)

Usually one puts a threshold to the maximum prob

of type I error, which is called the 'level-of-significance'

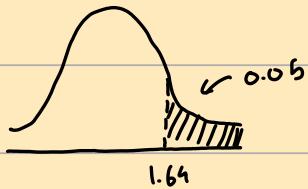
denoted by α

expt: $\alpha = 0.05$

Q: What will be the 'best value' of R in the above test if $\alpha = 0.05$?

→ Any test with R s.t. $P(-R) \leq 0.05$ is permitted

→ However, for maximum reduction of $P(\text{Type II error})$, one should choose R s.t $P(-R) = 0.05 \Leftrightarrow R = 1.64$



$$\text{power} = 1 - P(\text{Type II error})$$

= $P(\text{Rejecting } H_0 \text{ when } H_0 \text{ is false})$

- All test with $R \geq 1.64$ obeys the level- α condition
- But we choose the test with $R = 1.64$ because it is the most powerful test.

$$\text{Size of test} = P(\text{Type I error})$$

expt $X_1, \dots, X_n \sim \text{Bin}(n, \theta)$ $n = 10$

$$H_0: \theta = \frac{1}{2} \quad \text{vs} \quad H_1: \theta = \frac{3}{4}$$

$$\phi^*(S_n) = \begin{cases} 1 & \text{if } S_n \geq R \\ 0 & \text{ow} \end{cases} \quad S_n = x_1 + \dots + x_n$$

$\alpha = 0.05$

$$\text{size} = P(\text{Type I error}) = P(S_n \geq R \mid S_n \sim \text{Bin}(10, \frac{1}{2}))$$

R	Size
10	0.001
9	0.0107
8	0.0547
:	:

$R = 9$

if we take $R = 9$ then size = 0.0107

power = 0.244

To increase the power, we can Randomize the test.

$$\phi^{**}(S_n) = \begin{cases} 1 & \text{if } S_n \geq a \\ 0.89 & \text{if } S_n = 8 \\ 0 & \text{if } S_n < 8 \end{cases}$$

$$\text{size} = P(\text{Type I error of } \phi^{**})$$

$$= P(\text{Reject } H_0 \mid S_n \sim \text{Bin}(10, \frac{1}{2}))$$

$$= P(S_n \geq 9 \mid S_n \sim \text{Bin}(10, \frac{1}{2})) + 0.89 P(S_n = 8 \mid S_n \sim \text{Bin}(10, \frac{1}{2}))$$

$$= 0.0107 + 0.89 \cdot (0.0547 - 0.0107) = 0.05$$

$$\gamma = 0.89$$

$$\phi^{**} : \mathbb{R} \rightarrow [0, 1]$$

$$X_1, \dots, X_n \sim f_{\theta}$$

$$H_0: \theta \in H_0$$

\curvearrowleft

$$\theta = \theta_0$$

$$\theta \leq \theta_0$$

$$\theta = \theta_0$$

vs

$$H_1: \theta \in H_1$$

\curvearrowleft

$$\theta = \theta_1$$

$$\theta > \theta_0$$

$$\theta \neq \theta_0$$

$$H_0 = \{\theta_0\}$$

$$H_1 = \{\theta_1\}$$

$$H_0 = (-\infty, \theta_0]$$

$$H_1 = (\theta_0, \infty)$$

$$H_0 = \{\theta_0\}$$

$$H_1 = R - \{\theta_0\}$$

$$\phi: \tilde{x} \rightarrow [0, 1]$$

↓ sample space

$$\text{eg } \phi(\tilde{x}) = \begin{cases} 1 & \text{if } \bar{x}_n > k \\ 0 & \text{ow} \end{cases}$$

ϕ : probability of rejecting H_0 given \tilde{x} .

Recall, size = P(Type I error)

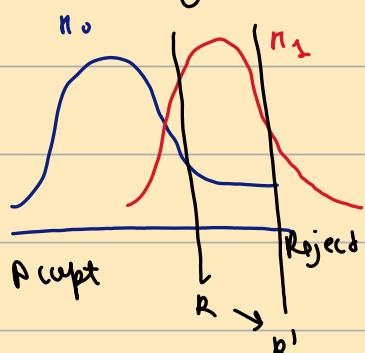
= prob of rejection when H_0 is true

power = prob of rejection when H_0 is false

Fix a lvl-of-significance α

if size of a test $\phi \leq \alpha$,

then ϕ is called a level- α test



- Among the level- α test, one must look at the most powerful test.

Power function : $\beta_\phi(\theta) = E_\theta [\phi(x)]$
 $= P(\text{Rejecting } H_0 | \theta)$

Ex1 $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, 1)$

$$H_0: \theta = \theta_0 \quad \text{vs} \quad H_1: \theta = \theta_1 \quad (\theta_1 > \theta_0)$$

$$\theta \neq \theta_0$$

$$\theta > \theta_0$$

$$\phi(x) = \begin{cases} 1 & \text{if } \bar{x}_n \geq R \\ 0 & \text{ow} \end{cases}$$

$$\beta_\phi(\theta) = E_\theta [\phi(x)] = P(\phi(x) = 1) = P_\theta (\bar{x}_n \geq R)$$

Ex2 $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bern}(\theta)$

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

$$\beta_\phi(\theta) = E_\theta [\phi(x)]$$

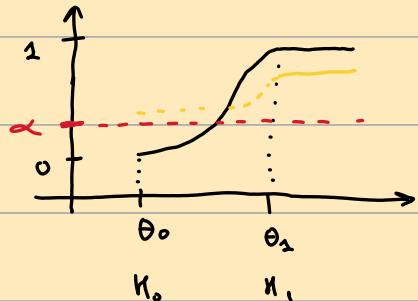
$$0 \quad \text{if } \sum x_i < R$$

$$= P_\theta (\sum x_i > R) + \gamma P_\theta (\sum x_i = R)$$

= prob of rejection

For $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$

$$\beta_\phi(\theta_0) = \text{size of } \phi \quad \beta_\phi(\theta_1) = \text{power}$$



Most powerful level- α -test \rightarrow

Consider the testing problem

$$H_0: \theta \in H_0 \quad \text{vs} \quad H_1: \theta \in H_1$$

$$H_0: \theta_{01} \leq \theta \leq \theta_{02}$$

A test ϕ is called a level- α test if

$$\sup_{\theta \in H_0} \beta_\phi(\theta) \leq \alpha$$

$$\text{size} = \sup_{\theta \in [0, \theta_{01}, \theta_{02}]} \beta_\phi(\theta)$$

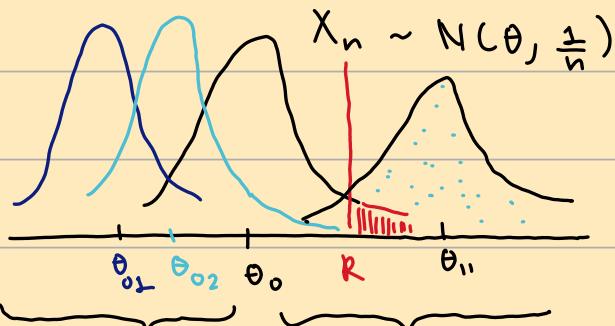
$$\theta \in [\theta_{01}, \theta_{02}]$$

Eg $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\theta, 1)$

$$H_0: \theta \leq \theta_0 \quad \text{vs} \quad H_1: \theta > \theta_0$$

$$\phi(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq R \\ 0 & \text{ow} \end{cases}$$

$$\beta_\phi(\theta) = P_\theta(\bar{X}_n > R)$$



$$\text{size} = \alpha$$

H_0 H_1

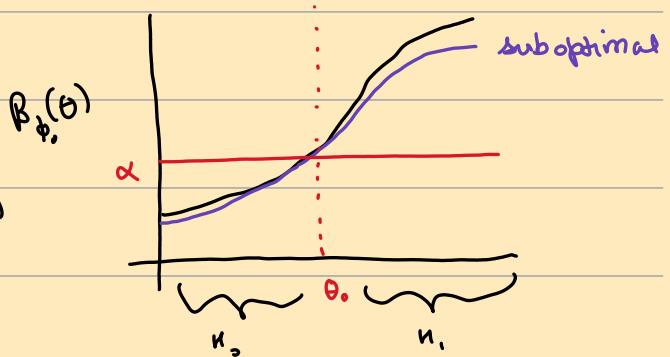
$$\sup_{\theta \leq \theta_0} \beta_{\phi}(\theta) = P(\bar{X}_n \geq R \mid \theta_0) = \text{size}$$

$$\theta \leq \theta_0$$

A test is called a uniformly most powerful test (UMP test)

if for any ϕ satisfying (*)
[for any level- α test ϕ]

$$\beta_{\phi_0}(\theta) \geq \beta_{\phi}(\theta) \quad \forall \theta \in \mathbb{R}$$



when $\theta = \theta_0$ } simpler vs simpler
vs $n_1: \theta = \theta_1$ }

then UMP \equiv MP test

$$(*) \equiv \beta_{\phi}(\theta_0) \leq \alpha$$

$$(**) \equiv \beta_{\phi_0}(\theta_1) \geq \beta_{\phi}(\theta_1)$$

Neyman Pearson's lemma: [Provides the MP test for simple vs simple hypothesis]

$$X_1, \dots, X_n \stackrel{iid}{\sim} f_0$$

Suppose we want to test

$$H_0: \theta = \theta_0 \quad \text{against}$$

$$H_1: \theta = \theta_1$$

$$(\text{equiv}, X_i \stackrel{iid}{\sim} f_0)$$

$$(\text{equiv}, X_i \stackrel{iid}{\sim} f_1)$$

NP lemma says that a most powerful test ϕ_0
will be of the form

$$(*) \quad \phi_0(\underline{x}) = \begin{cases} 1 & \text{if } \frac{f_1(\underline{x})}{f_0(\underline{x})} > R \\ 0 & \text{if } \frac{f_1(\underline{x})}{f_0(\underline{x})} < R \end{cases}$$

and satisfies $\phi_{\phi_0}(0_0) = \alpha \quad \text{--- } (**)$

exp) $X_1, X_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$

$H_0: \mu = \mu_0 \quad \text{vs} \quad H_1: \mu = \mu_1 \quad (\mu_1 > \mu_0)$

when, $\mu_0 \Rightarrow N(\mu_0, \sigma_0^2)$

, $\mu_1 \Rightarrow N(\mu_1, \sigma_0^2)$

$\lambda(\underline{x}_n)$

$$\phi(\underline{x}) = \begin{cases} 1 & \text{if } \frac{f_1(\underline{x})}{f_0(\underline{x})} > R \\ 0 & \text{if } \lambda(\underline{x}) < R \end{cases}$$

$$\lambda(x) = \frac{(1/\sqrt{2\pi}\sigma_0)^n \exp(-\frac{1}{2\sigma_0^2} \sum_{i=1}^n (x_i - \mu_1)^2)}{(1/\sqrt{2\pi}\sigma_0)^n \exp(-\frac{1}{2\sigma_0^2} \sum_{i=1}^n (x_i - \bar{x}_n)^2 + n((\bar{x}_n) - \mu_0)^2)}$$

$$(1/\sqrt{2\pi}\sigma_0)^n \exp(-\frac{1}{2\sigma_0^2} \sum_{i=1}^n (x_i - \bar{x}_n)^2 + n((\bar{x}_n) - \mu_0)^2))$$

$$\Rightarrow \lambda(\underline{x}) = \exp\left(-\frac{n}{2\sigma_0^2} (2\bar{x}_n - \mu_0 - \mu_1)(\mu_0 - \mu_1)\right)$$

We need $\lambda(\tilde{x}) > R$

$$\Rightarrow \log \lambda(\tilde{x}) > \log R$$

$$\Rightarrow \frac{-n}{2\sigma_0^2} (2\bar{x}_n - \mu_0 - \mu_1)(\mu_0 - \mu_1) > \log R$$

$$\Rightarrow \bar{x}_n > \left(\frac{\sigma_0^2 \log R}{n(\mu_1 - \mu_0)} + \frac{\mu_0 + \mu_1}{2} \right) = k_0$$

except k everything is known

$$\Rightarrow \bar{x}_n > k_0$$

(**)

$$\beta_{\phi_0}(\mu_0) = \alpha = 0.05$$

$$\text{from } \phi_0(\tilde{x}) = \begin{cases} 1 & \text{if } \bar{x}_n > k_0 \\ 0 & \text{if } \bar{x}_n < k_0. \end{cases}$$

$$P(\bar{x}_n > R \mid \bar{x}_n \sim N(\mu_0, \frac{\sigma_0^2}{n})) = \alpha$$

$$P\left(\frac{\bar{x}_n - \mu_0}{\frac{\sigma_0}{\sqrt{n}}} > \frac{k_0 - \mu_0}{\frac{\sigma_0}{\sqrt{n}}}\right) = 0.05$$

$$1 - \Phi\left(\frac{R_0 - \mu_0}{\frac{\sigma_0}{\sqrt{n}}}\right) = 0.05$$

$$\frac{R_0 - \mu_0}{\sigma_0 / \sqrt{n}} = 1.64$$

$$\phi_0(\bar{x}_n) = \begin{cases} 1 & \text{if } \bar{x}_n \geq \mu_0 + \frac{\sigma_0}{\sqrt{n}} (1.64) \\ 0 & \text{if } \bar{x}_n < \mu_0 + \frac{\sigma_0}{\sqrt{n}} (1.64) \end{cases}$$

Exp) $x_1, \dots, x_n \stackrel{iid}{\sim} \text{Ber}(\theta)$

$$H_0: \theta = \theta_0 \quad H_1: \theta = \theta_1$$

$$\lambda(\tilde{x}) = \frac{\theta_1^{\sum_{i=1}^n x_i} (1-\theta_1)^{n-\sum_{i=1}^n x_i}}{\theta_0^{\sum_{i=1}^n \tilde{x}_i} (1-\theta_0)^{n-\sum_{i=1}^n \tilde{x}_i}}$$

$$= \frac{\theta_1^{n\bar{x}_n} (1-\theta_1)^{n(1-\bar{x}_n)}}{\theta_0^{n\bar{x}_n} (1-\theta_0)^{n(1-\bar{x}_n)}}$$

$$\log \lambda(\tilde{x}) > \log k$$

$$\Rightarrow n\bar{x}_n > -\frac{n \log(1-\theta_1) + n \log(1-\theta_0) + \log k}{\log(\theta_1(1-\theta_0)) - \log(\theta_0(1-\theta_1))} = k_0.$$

$$(*) \quad \phi_0(\tilde{x}) = \begin{cases} 1 & \text{if } n\bar{x}_n > k_0 \\ \gamma & \text{if } n\bar{x}_n = k_0 \\ 0 & \text{if } n\bar{x}_n < k_0 \end{cases}$$

$$(**) \quad \beta_{\phi_0}(\theta_0) = \alpha$$

$$\Rightarrow P(n\bar{x}_n > k_0) + \gamma P(n\bar{x}_n = k_0) = \alpha$$

$$\text{if } n = 20$$

k_0	$P(\sum x_i \geq k_0)$
10	0.001
9	0.0107
8	0.0517

Generalization \rightarrow

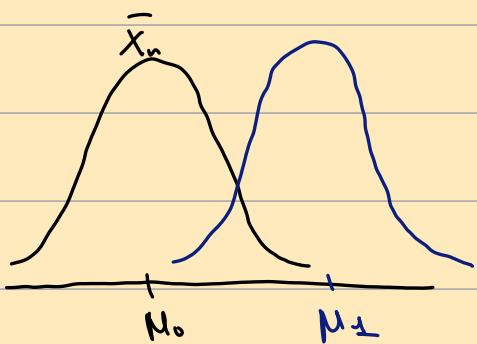
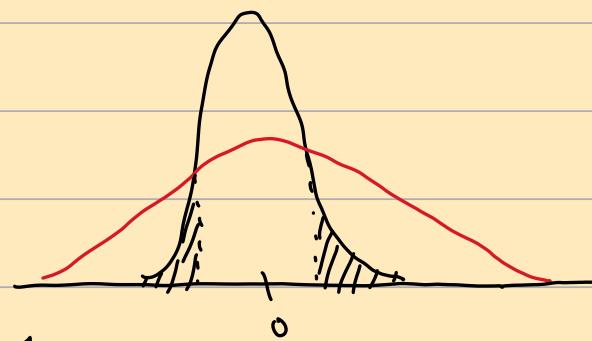
Ex. $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$

$H_0: \mu = \mu_0$ vs $H_1: \mu = \mu_1$ ($\mu_1 > \mu_0$)

$$\phi_0(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq \mu_0 + \frac{\sigma_0}{\sqrt{n}} 1.64 \\ 0 & \text{ow} \end{cases}$$

(Q1) $H_{12}: \mu = \mu_1 + \delta$ $\delta > 0$

$$f_2 > f_0$$



$$H_0: \sigma^2 = 1$$

$$H_1: \sigma^2 = 9$$

$$\Rightarrow R_0 \neq \delta \cdot \sigma \quad P(|X| > R_0) = \alpha$$

Q: $H_0: \mu \leq \mu_0$ vs $H_1: \mu = \mu_1$ ($\mu_1 > \mu_0$)

$$\text{size} = \beta_\phi(\theta_0) = \alpha$$

$$\text{size} = \sup_{\mu \leq \mu_0} \beta_\phi(\mu)$$

$$\beta_\phi(\mu) = 1 - \Phi\left(\frac{R_0 - \mu}{\sigma_0 / \sqrt{n}}\right) \quad \phi(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n > R_0 \\ 0 & \text{ow} \end{cases}$$

observe, $\beta_\phi(\mu)$ is an increasing fn. of μ

$\frac{f_{\theta_1}(\underline{x})}{f_{\theta_0}(\underline{x})} = \lambda(\underline{x})$, for $\theta_1 > \theta_0$, is a
monotone fn. of $T(\underline{x}) (= \bar{X}_n)$



Some statistic

Testing of hypothesis

- Unbiased test
- p-value

From NP lemma, the MP test

for testing $H_0: \theta = \theta_0$ vs $H_1: \theta = \theta_1$, given
a random sample X_1, \dots, X_n is of the form

$$\phi(\underline{x}) = \begin{cases} 1 & \text{if } \lambda(\underline{x}) = \frac{f_{\theta_1}(\underline{x})}{f_{\theta_0}(\underline{x})} > k \\ \gamma & \text{if } \lambda(\underline{x}) = k \\ 0 & \text{if } \lambda(\underline{x}) < k \end{cases}$$

and satisfying $E_{\theta_0}(\phi(\underline{x})) = \beta_\phi(\theta_0) = \alpha - (\star)$

$\text{Ex}) \quad X_1, \dots, X_n \sim \text{Poisson}(\lambda)$

$H_0: \lambda = \lambda_0 \quad \text{vs} \quad H_1: \lambda = \lambda_1 \quad (\lambda_1 > \lambda_0)$

$$\lambda(\underline{x}) = e^{-n(\lambda - \lambda_0)} \left(\frac{\lambda_1}{\lambda_0} \right)^{\sum x_i} > k$$

$$\Rightarrow \sum x_i > \frac{\log k + n(\lambda_1 - \lambda_0)}{\log \lambda_1 - \log \lambda_0} = R_0$$

$$\phi(\underline{x}) = \begin{cases} 1 & \text{if } \sum x_i > R_0 \\ \gamma & \sum x_i = R_0 \\ 0 & \sum x_i < R_0 \end{cases}$$

and (R_0, γ) is such that

$$E_{\lambda_0} [\phi(\underline{x})] = \alpha$$

$$\begin{aligned} \beta_\alpha(\lambda) &= P_\lambda(\text{Rejecting } H_0) = P_\lambda(\text{Reject } H_0 \cap \sum x_i > R_0) \\ &\quad + P_\lambda(\text{Reject } H_0 \cap \sum x_i = R_0) \\ &\quad + P_\lambda(\text{Reject } H_0 \cap \sum_{i=1}^n x_i < R_0) \end{aligned}$$

$\left[\{A, B, C\} \text{ are mutually exclusive and exhaustive} \right]$

$$P(D) = P(D \cap A) + P(D \cap B) + P(D \cap C)$$

$$= P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C)$$

$$= P(\text{reject } H_0 | \sum X_i > R_0) P(\sum X_i > R_0)$$

$$+ P(\text{reject } H_0 | \sum X_i = R_0) P(\sum X_i = R_0)$$

$$+ P(\text{reject } H_0 | \sum X_i < R_0) P(\sum X_i < R_0)$$

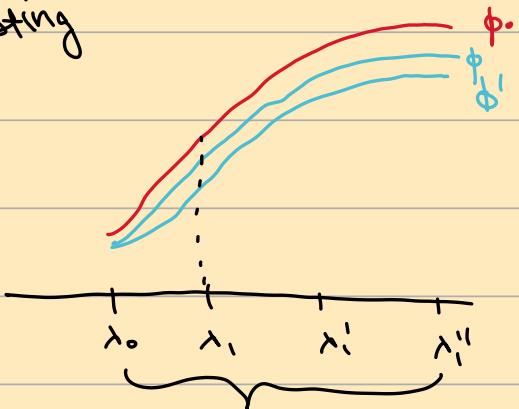
$$= 1 \cdot \underset{\lambda}{P}(\sum X_i > R_0) + r P_{\lambda}(\sum X_i = R_0)$$

Q. Can we generalize to $H_0: \lambda = \lambda_0$ vs $H_1: \lambda > \lambda_0$

Same test follows

So, ϕ is UMP for testing

H_0 vs H_1

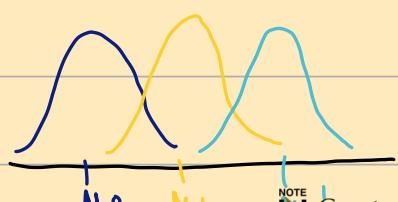


Q: Can we generalize to

$H_0: \lambda \leq \lambda_0$ vs $H_1: \lambda > \lambda_0$

size = α

$$\sup_{\lambda \leq \lambda_0} \beta_{\phi}(\lambda) = \sup_{\lambda \leq \lambda_0} [P_{\lambda}(\sum X_i > R_0) + r P_{\lambda}(\sum X_i = R_0)]$$



Verify that, $\beta_\phi(\lambda)$ is an ↑ fcn of λ

$$\text{size} = \sup_{\lambda \leq \lambda_0} \beta_\phi(\lambda) = \beta_\phi(\lambda_0) = \alpha$$

Again, in order to solve the
size = α condition

we need to solve $\beta_\phi(\lambda_0) = \alpha$ for (R_0, δ)

So, some soln will appear

The MP test for testing $H_0: \lambda = \lambda_0$ vs $H_1: \lambda = \lambda_1$
turns out to be the UMP test $(\lambda_1 > \lambda_0)$

$H_0: \lambda \leq \lambda_0$ vs $H_1: \lambda > \lambda_0$

Two-side testing

Let X_1, \dots, X_n be iid from $N(\mu, 1)$

$H_0: \mu = \mu_0$ vs $H_1: \mu \neq \mu_0$

$$N \in \mathbb{U} = \mathbb{R} - \{\mu_0\}$$

$$\mathbb{U}_1 = \mathbb{U}_{11} \cup \mathbb{U}_{12}$$

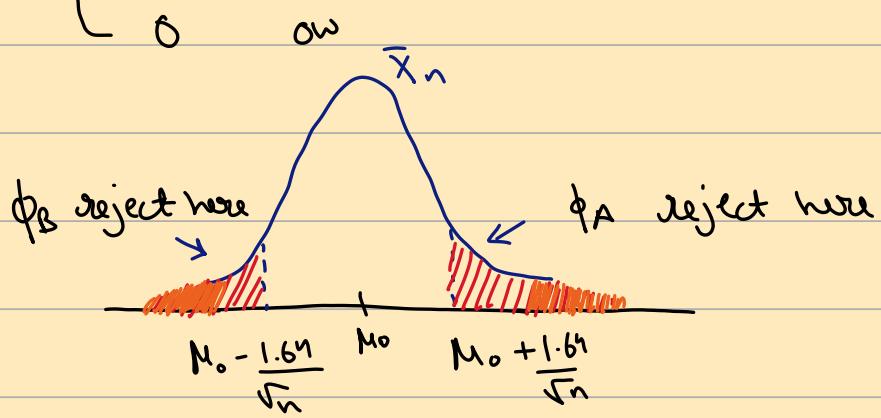
$$\mathbb{U}_{11} = (\mu_0, \infty)$$

$$\mathbb{U}_{12} = (-\infty, \mu_0)$$

$$\alpha = 0.05$$

$$\phi_A(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq \mu_0 + \frac{1.64}{\sqrt{n}} \\ 0 & \text{ow} \end{cases}$$

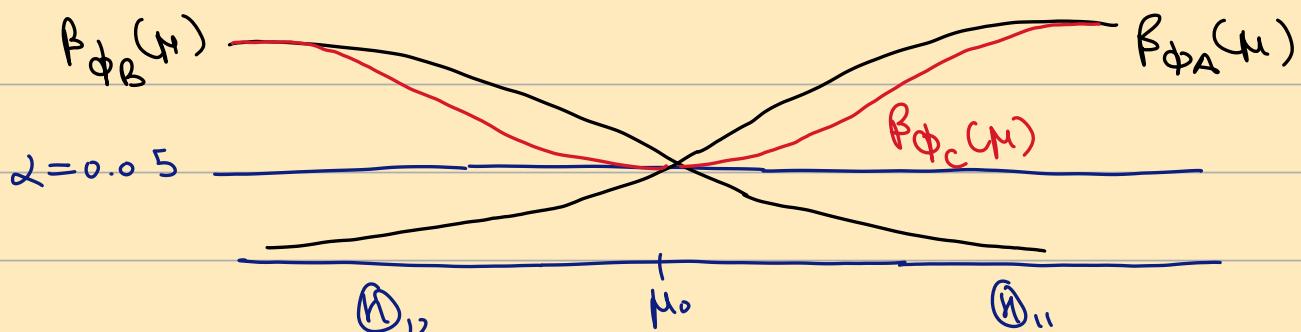
$$\phi_B(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \leq \mu_0 - \frac{1.64}{\sqrt{n}} \\ 0 & \text{ow} \end{cases}$$



$$\phi_C(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq \mu_0 + \frac{1.97}{\sqrt{n}} \text{ or } \bar{x}_n \leq \mu_0 - \frac{1.97}{\sqrt{n}} \\ 0 & \text{ow} \end{cases}$$

$$\phi_C(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq R_0 \text{ or } \bar{x}_n \leq c_0 \\ 0 & \text{ow} \end{cases}$$

and solve (R_0, c_0) by size = α condition



ϕ_A is the UMP test for $H_0: \mu \leq \mu_0$ vs $H_1: \mu > \mu_0$

ϕ_B " " " " " " $H_0: \mu \geq \mu_0$ vs $H_1: \mu < \mu_0$

So, \nexists a UMP level- α test for testing

$H_0: \mu = \mu_0$ vs $H_1: \mu \neq \mu_0$

\exists some $\mu' \in \mathbb{N}_1$ for which

$$\begin{aligned} R(\text{Rejecting } H_0 | \mu') &< R(\text{Rejecting } H_0 | \mu_0) \\ \beta_{\phi_A}(\mu') &\quad \downarrow \text{power} \\ &= \beta_{\phi_A}(\mu_0) \\ &\quad \uparrow \text{size} \end{aligned}$$

Unbiasedness: A test ϕ is called unbiased for testing

$H_0: \theta \in \mathbb{N}_0$ vs $H_1: \theta \in \mathbb{N}_1$ if

for any $\theta' \in \mathbb{N}_0$ and $\theta'' \in \mathbb{N}_1$,

$$\begin{aligned} \beta_{\phi}(\theta') &= P(\text{Rejecting } H_0 | \theta') \\ \left(\text{Power of Type I error under } \theta' \right) &< P(\text{Rejecting } H_0 | \theta'') \\ &= \beta_{\phi}(\theta'') = \text{power at } \theta'' \end{aligned}$$

$$\sup_{\theta \in \mathbb{N}_0} \beta_{\phi}(\theta) \leq \inf_{\theta \in \mathbb{N}_1} \beta_{\phi}(\theta)$$

UMPU test: Uniformly most powerful unbiased test

$x_1, \dots, x_n \stackrel{iid}{\sim} N(\mu, 1)$

P-value: $H_0: \mu = 0$ vs $H_1: \mu > 0$

$$\phi_A = \begin{cases} 1 & \text{if } \bar{x}_n \geq 1.64/\sqrt{n} \\ 0 & \text{ow} \end{cases}$$

Realization 1: $\sqrt{n}\bar{x}_n = 1.8$ (Reject H_0)

Realization 2: $\sqrt{n}\bar{y}_n = 3$ (Reject H_0)

P-value: Let $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$

$$H_0: \mu = 0 \quad \text{vs} \quad H_1: \mu > 0$$

The MP test at level $\alpha = 0.025$ is

$$\phi_0(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq 1.96 \\ 0 & \text{ow} \end{cases}$$

Consider two realization $\underline{y}_n = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$ and $\underline{z}_n = \begin{pmatrix} z_1 \\ \vdots \\ z_n \end{pmatrix}$

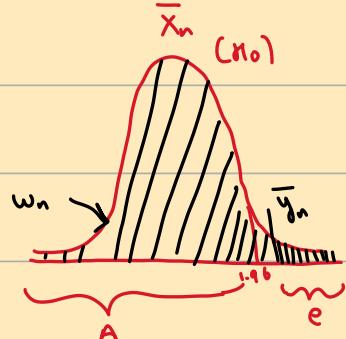
such that $\bar{y}_n = \frac{1}{n} (y_1 + \dots + y_n) = 2$ and $\bar{z}_n = 3.5$

We reject H_0 based on \underline{y}_n as well as \underline{z}_n

P-value offers a quantitative measurement of the strength of the decision -

$$p(\underline{y}_n) = P_{H_0}(\bar{X}_n \geq \bar{y}_n)$$

$$H_1: \mu > 0$$



$$p(\underline{z}_n) = P_{H_0}(\bar{X}_n \geq \bar{z}_n)$$

$$p(\underline{y}_n) > p(\underline{z}_n)$$

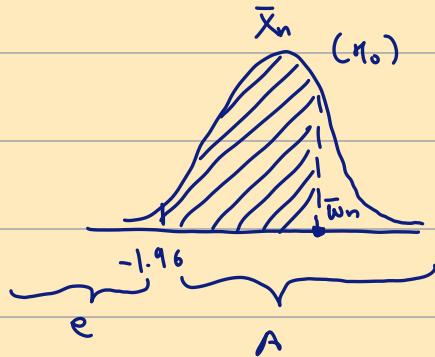
$\Rightarrow \underline{z}_n$ indicates more extreme situation

$H_0: \mu = 0$ vs $H_1: \mu < 0$ at level $\alpha = 0.025$

$$\phi_0(\bar{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \leq -1.96 \\ 0 & \text{ow} \end{cases}$$

$$\tilde{w}_n \text{ s.t. } \bar{w}_n = 0.5$$

$$p(\tilde{w}_n) = P_{H_0}(\bar{X}_n \leq \bar{w}_n)$$



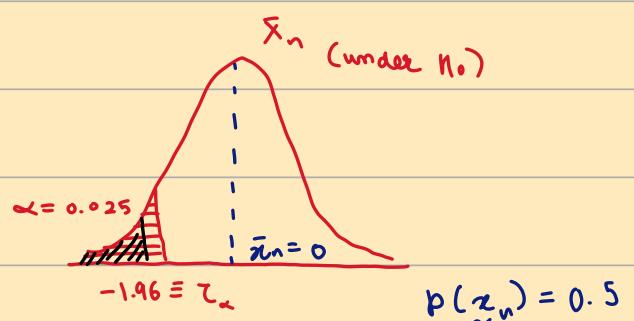
For another realization $\tilde{v}_n = \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix}$,

$$\text{Suppose } p(\tilde{v}_n) = 0.05 = P_{H_0}(\bar{X}_n \leq \bar{v}_n)$$

Q: Should we accept H_0 at level $\alpha = 0.025$ against

H_1 , based on \tilde{v}_n ?

\rightarrow If p -value for some realization, say \tilde{x}_n , is $\leq \alpha$ (reject), then, we accept H_0 at level α .



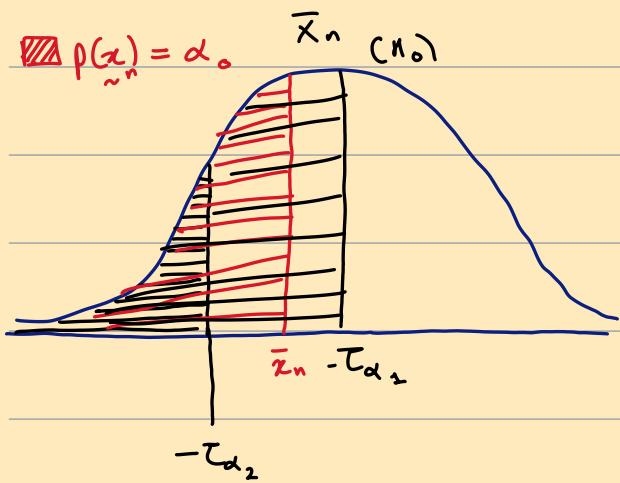
$$P_{H_0}(\bar{X}_n \leq -\tau_\alpha) = 0.025$$

• If I take any $\bar{x}_n > -\tau_\alpha$, then $p(\tilde{x}_n) > 0.025$ and H_0 will be accepted.

• If I take any $\bar{x}_n < -\tau_\alpha$ then $p(\tilde{x}_n) < 0.025$. Also, based on \tilde{x}_n , H_0 is rejected.

Defn - (p-value)

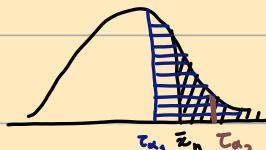
$p(\tilde{x}_n) = \inf \{ \alpha : H_0 \text{ is rejected based on } \tilde{x}_n \text{ against } H_1 \text{ at level } \alpha \}$



$\alpha_1 \geq \alpha_0 : \text{Reject } H_0 \text{ ag. } H_1 \text{ at level } \alpha_1 \text{ based on } \tilde{x}_n$

$\alpha_1 < \alpha_0 : \text{Accept } H_0 \text{ ag. } H_1 \text{ at level } \alpha_1 \text{ based on } \tilde{x}_n$

$$H_0: \mu = 0 \quad \text{vs} \quad H_1: \mu > 0$$



$$p(\tilde{x}_n) = \alpha_0$$

$\alpha_1 > \alpha_0 \Rightarrow \text{reject } H_0 \text{ based on } \tilde{x}_n$

$\alpha_1 < \alpha_0 \Rightarrow \text{Accepting } H_0$
based on \tilde{x}_n

Informal def'n of p-value

$p(\tilde{x}_n) = P_{H_0}(\text{observing at least as extreme obs'n as } \tilde{x}_n)$

$$H_0: \mu = 0 \quad \text{vs} \quad H_1: \mu \neq 0$$

$$\phi(\tilde{x}) = \begin{cases} 1 & \text{if } \bar{x}_n \geq c_1 \text{ or } \bar{x}_n \leq -c_2 \\ 0 & \text{ow} \end{cases}$$

Realization $\tilde{x}_n = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$

$$p(\tilde{x}_n) = \min \left\{ P_{H_0}(\bar{X}_n \geq \bar{x}_n), P_{H_0}(\bar{X}_n \leq \bar{x}_n) \right\}$$

$$H_1: \mu > 0 \quad |P_{H_0}(\bar{X}_n \geq \bar{x}_n)$$

$$H_2: \mu < 0 \quad |P_{H_0}(\bar{X}_n \leq \bar{x}_n)$$

Some important testing - problems

(A) Testing of binomial proportion

$$X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(p)$$

$$H_0: p = p_0 \quad \text{against} \quad H_{11}: p > p_0$$

$$H_{12}: p < p_0$$

$$H_{13}: p \neq p_0$$

The UMP test for H_0 against H_{11}

$$\phi(\underline{x}) = \begin{cases} 1 & \text{if } \sum_{i=1}^n x_i > K_\alpha \\ \gamma & \text{if } \sum_{i=1}^n x_i = K_\alpha \\ 0 & \text{if } \sum_{i=1}^n x_i < K_\alpha \end{cases}$$

$$\text{with } E_{H_0} [\phi(\underline{x})] = \alpha \Rightarrow P_{H_0} \left(\sum_{i=1}^n x_i > K_\alpha \right) + \gamma P_{H_0} \left(\sum_{i=1}^n x_i = K_\alpha \right) = \alpha$$

Under H_0 , $\sum_{i=1}^n x_i \sim \text{Bin}(n, p_0)$

The test function for testing H_0 against $H_{13}: p \neq p_0$

$$\phi_3(\underline{x}) = \begin{cases} 1 & \text{if } \sum x_i > K_\alpha \text{ or } \sum x_i < C_\alpha \\ \gamma_1 & \text{if } \sum x_i = K_\alpha \\ \gamma_2 & \text{if } \sum x_i = C_\alpha \\ 0 & \text{otherwise} \end{cases}$$

Example constraint: $x_1 = x_2$

$$\mathbb{E}_{n_0} [\phi(x)] = \alpha$$

$$c_2, k_2 \in \{0, \dots, n\}$$



Large sample version:

Let $\{T_n\}$ be a seq. of r.v.s, T_1, T_2, \dots

The asymptotic distribution of T_n is defined when

$$\frac{T_n - a_n}{b_n} \xrightarrow{d} G, \text{ where } G \text{ is non-degenerate}$$

What is the asymptotic distn. of $T_n = \sum_{i=1}^n x_i$ under $H_0: p = p_0$?

$$\frac{T_n - a_n}{b_n}$$

$$a_n = np_0$$

$$\frac{T_n - np_0}{\sqrt{np_0(1-p_0)}} \xrightarrow{d} N(0, 1)$$

$$b_n = \sqrt{np_0(1-p_0)}$$

$$G \equiv N(0, 1)$$

The asymptotic distn. of T_n is normal with asymptotic mean np_0 and variance $np_0(1-p_0)$

$$\phi(x) = \begin{cases} 1 & \text{if } T_n > k_2 \\ \gamma & \text{if } T_n = k_2 \\ 0 & \text{ow} \end{cases}$$

$$P(T_n > K_\alpha)$$

$$= P\left(\frac{T_n - np_0}{\sqrt{np_0(1-p_0)}} > \frac{K_\alpha - np_0}{\sqrt{np_0(1-p_0)}}\right)$$

$$\approx 1 - \Phi\left(\frac{K_\alpha - np_0}{\sqrt{np_0(1-p_0)}}\right) \quad \text{when } n \text{ is large}$$

To obtain K_α we need to solve

$$1 - \Phi\left(\frac{K_\alpha - np_0}{\sqrt{np_0(1-p_0)}}\right) = \alpha$$

(B) Testing mean of normal population

Let $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2)$; σ^2 is unknown

$H_0: \mu = \mu_0$ against $H_0: \mu > \mu_0$

$H_{12}: \mu < \mu_0$

$H_{13}: \mu \neq \mu_0$

$$\phi(x) = \begin{cases} 1 & \text{if } \bar{x}_n \geq K_\alpha \\ 0 & \text{ow} \end{cases}$$

$$E_{H_0}(\phi(x)) = P_{H_0}(\bar{X}_n \geq K_\alpha) = \alpha$$

$$\Rightarrow 1 - \Phi\left(\frac{K_\alpha - \mu_0}{\sigma/\sqrt{n}}\right) = \alpha$$

We need a test statistic which depends on \bar{X}_n ,
but its distribution is completely known under H_0 .

$$T_n = \frac{\bar{X}_n - \mu_0}{\hat{\sigma} / \sqrt{n}} \quad \text{where} \quad \hat{\sigma}^2 = \frac{1}{(n-1)} \sum_{i=1}^n (x_i - \bar{x}_n)^2$$

What is the distribution of T_n under H_0 ?

$$\bar{X}_n \stackrel{H_0}{\sim} N(\mu_0, \sigma^2 / n) \quad \begin{matrix} \text{indep} \\ \downarrow \end{matrix} \quad \frac{\sum_{i=1}^n (x_i - \bar{x}_n)^2}{\sigma^2} \sim \chi^2_{(n-1)}$$

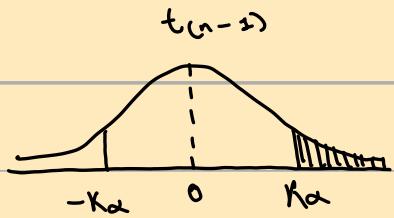
$$\frac{\bar{X}_n - \mu_0}{\sigma / \sqrt{n}} \stackrel{H_0}{\sim} N(0, 1)$$

$$T_n = \frac{\bar{X}_n - \mu_0}{\sigma / \sqrt{n} \sqrt{\frac{\sum (x_i - \bar{x}_n)^2}{\sigma^2 (n-1)}}} \stackrel{H_0}{\sim} t_{(n-1)}$$

$$\phi(\tilde{x}) = \begin{cases} 1 & \text{if } T_n \geq K_\alpha \\ 0 & \text{ow} \end{cases}$$

To find K_α we need to solve size = α

$$\underset{H_0}{P}(T_n \geq K_\alpha | T_n \sim t_{(n-1)}) = \alpha$$



$$\Rightarrow K_\alpha = t_{\alpha/2; n-1}$$

upper α -point
of $t_{(n-1)}$
dist?

Test fr. for H_0 ag. H_1 : $\mu \neq \mu_0$

$$\phi(x) = \begin{cases} 1 & \text{if } T_n > K_\alpha \text{ or } T_n < -K_\alpha; |T_n| \geq K_\alpha \\ 0 & \text{ow} \end{cases}$$

Paired-t test :

$$\begin{pmatrix} x_1 \\ y_1 \end{pmatrix}, \dots, \begin{pmatrix} x_n \\ y_n \end{pmatrix} \sim N_2 \left(\begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \begin{pmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{pmatrix} \right)$$

$$x_1, \dots, x_n \stackrel{iid}{\sim} N(\mu_x, \sigma_x^2)$$

$$y_1, \dots, y_n \stackrel{iid}{\sim} N(\mu_y, \sigma_y^2)$$

x_i, y_i are correlated

$$\text{Cov}(x_i, y_i) = \sigma_{xy}$$

$H_0: \mu_x = \mu_y$ against $H_{11}: \mu_x > \mu_y$

$$H_{12}: \mu_x < \mu_y$$

$$H_{13}: \mu_x \neq \mu_y$$

$$\text{or } \mu_x - \mu_y = 0$$

$$w_i = (x_i - y_i), i = 1, \dots, n$$

$$\mathbb{E}(w_i) = \mu_x - \mu_y$$

$$\text{var}(w_i) = \sigma_x^2 + \sigma_y^2 - 2\sigma_{xy} = \sigma_w^2$$

$w_i \sim N(\mu_w, \sigma_w^2)$ X

$$\left| \begin{array}{l} z_1 \perp\!\!\!\perp z_2 \\ g(z_1) \perp\!\!\!\perp g(z_2) \\ w_1 \perp\!\!\!\perp w_2 \end{array} \right.$$