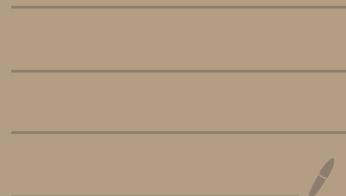


# 8 Hypothesis Testing



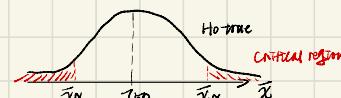
# 8.1 hypothesis testing

- ① formulate null & alternative hypothesis
- ② determine test statistic and its distribution, given  $H_0$
- ③ describe the assumptions
- ④ determine the critical region for the test statistic.

$$H_0: \mu = 750 \quad H_1: \mu \neq 750$$

$X_i$  test statistics  $\bar{X} = \frac{1}{n}(x_1 + x_2 + \dots + x_n)$  assume  $H_0$  is true,  $\bar{X} \sim N(750, \frac{\sigma^2}{n})$ , known to true

Sample is random; ppl is normally distributed,  $\sigma^2 = 400$  known



$$\bar{x}_{\text{crit}} = P(Z < -z_{\alpha}) = 750 - z_{\alpha} \cdot 20 = 743.42$$

$$(-\infty, 743.42)$$

$$\bar{x} = 741.2 \rightarrow \text{reject } H_0; \bar{x} = 748.2 \rightarrow \text{not reject } H_0$$

- ⑤ Compare sample outcome of test statistic with critical region
- ⑥ reject or not reject the null hypothesis.

## D One-sided vs Two-sided HT: 这是根据 $H_1$ 来定的



$$\text{critical region} = (-\infty, \bar{x}_L) \cup (\bar{x}_U, \infty)$$

- ② Composite
- ③ Discrete:

two equivalent test statistics $\bar{X}$ and $Z$	
hypotheses	$H_0: \mu = \mu_0$ $H_1: \mu < \mu_0$
test statistic	$\bar{X} \sim N(\mu_0, \frac{\sigma^2}{n})$ with $\sigma$ known, assuming $H_0$ true
critical region	$\bar{X} < z_{\alpha, \text{crit}}$ $(-\infty, \bar{x}_{\text{crit}}] = (-\infty, \mu_0 - z_{\alpha} \cdot \frac{\sigma}{\sqrt{n}}]$
conclusion	<ul style="list-style-type: none"> <li><math>\bar{x} \in \text{crit} \Rightarrow \text{reject } H_0</math></li> <li><math>\bar{x} \notin \text{crit} \Rightarrow \text{not reject } H_0</math></li> </ul>
	$Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} \sim N(0, 1)$ with $\sigma$ known, assuming $H_0$ true
	$Z < z_{\alpha, \text{crit}}$ $(-\infty, z_{\alpha, \text{crit}}] = (-\infty, -z_{\alpha}]$
	<ul style="list-style-type: none"> <li><math>z_{\alpha, \text{crit}} = \frac{\bar{x}_{\text{crit}} - \mu_0}{\sigma/\sqrt{n}} \leq z_{\alpha, \text{true}} \Rightarrow \text{reject } H_0</math></li> <li><math>z_{\alpha, \text{crit}} = \frac{\bar{x}_{\text{crit}} - \mu_0}{\sigma/\sqrt{n}} &gt; z_{\alpha, \text{true}} \Rightarrow \text{do not reject } H_0</math></li> </ul>

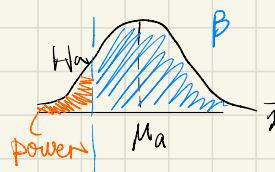
## 8.2 probability of type I error & power

- ① type I error:  $P(\text{reject } H_0 \mid H_0 \text{ is true}) = \alpha$
- ② type II error:  $P(\text{not reject } H_0 \mid H_0 \text{ false}) = \beta$

power of test:  $P(\text{reject } H_0 \mid H_0 \text{ false}) = 1 - \beta$

○  $\alpha$  表示  $\leq \bar{x} - \mu$   
●  $\beta$  表示  $\bar{x} - \mu$

$\mu$  为真实值。



## 8.3 p-value

the probability of obtaining a result equal to or "more extreme" than what was actually observed assuming  $H_0$  is true.

(Theorem):  $p\text{-value} \leq \alpha \Leftrightarrow H_0$  can be rejected with significance level  $\alpha$

## 8.4 hypothesis testing for a single pop.

test for:

$$\textcircled{1} \text{ for } \mu \text{ (}\sigma \text{ known)} \quad Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$$

$$\textcircled{2} \text{ for } \mu \text{ (}\sigma \text{ unknown)} \quad T_{n-1} = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \sim t_{n-1}$$

$$\textcircled{3} \quad \sigma = \sigma_0 \quad \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2(n-1)$$

$$\textcircled{4} \quad \hat{P} = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} \sim N(0, 1) \quad Z = \frac{\bar{X} - \mu_0}{\sqrt{\hat{P}(\hat{P} + 1)}} \sim N(0, 1)$$

Section 8.4 Hypotheses concerning a single population			
	"z-test"	"t-test"	
hypotheses	$H_0: \mu = \mu_0$ vs $H_a: \mu \neq \mu_0$ ( $\sigma$ known)	$H_0: \mu = \mu_0$ vs $H_a: \mu \neq \mu_0$ ( $\sigma$ unknown)	$H_0: \sigma = \sigma_0$ vs $H_a: \sigma \neq \sigma_0$
test statistic (assuming $H_0$ is true)	$\bar{X} \sim N(\mu_0, \frac{\sigma^2}{n})$ $Z = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}} \sim N(0, 1)$	$T_{n-1} = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} \sim t(n-1)$ $\sim t(n-1)$	$(n-1) \sum_{i=1}^n (x_i - \bar{x})^2 \sim \chi^2(n-1)$
critical region	$(-\infty, -Z_{\alpha/2}] \cup [Z_{\alpha/2}, \infty)$ $\dots \cup [Z_{\alpha/2}, \infty)$ or $(-\infty, -Z_{\alpha/2}] \cup [Z_{\alpha/2}, \infty)$	$(-\infty, -t_{\alpha/2}] \cup [t_{\alpha/2}, \infty)$ $\dots \cup [t_{\alpha/2}, \infty)$	$[0, Z_{\alpha/2}] \cup [Z_{\alpha/2}, \infty)$
conditions	Population normal or $n \geq 30$ with CLT	Population normal or $n \geq 30$ with CLT	Population normal

Section 8.4 The hypothesis $p = p_0$ (binomial distribution)		
$p =$ probability of "success" in a Bernoulli		
$H_0: p = p_0$ vs $H_a: p > p_0$		(if $H_0$ true)
$X =$ number of successes in a sample of size $n \Rightarrow X \sim \text{Bin}(n, p)$		
test statistic	critical region/p-value	conditions
$\hat{p} = \frac{X}{n} \text{ approx } N(p_0, \frac{p_0(1-p_0)}{n})$	$[p_0 + z_{\alpha/2} \sqrt{\frac{p_0(1-p_0)}{n}}, \infty)$	$n, p_0 \geq 5$
$Z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \text{ approx } N(0, 1)$	$[z_{\alpha/2}, \infty)$	$n(1-p_0) \geq 5$
		" — "
	$p\text{-value} = P(X \geq x_0   p = p_0)$ $= \sum_{k=x_0}^n \binom{n}{k} p_0^k (1-p_0)^{n-k}$	$n/a$
		$\Rightarrow \text{compare with } \alpha.$

## 8.5 hypothesis testing for differences between 2 populations

① for  $\mu_1, \mu_2$

- a)  $\sigma_1, \sigma_2$  known  $Z$
- b)  $\sigma_1 = \sigma_2$  unknown  $T$
- c)  $\sigma_1 \neq \sigma_2$  unknown no test

Section 8.5 Hypotheses concerning differences between two populations		
$H_0: \mu_1 = \mu_2 + \Delta_0$ vs. $H_a: \mu_1 \neq \mu_2 + \Delta_0$		
test statistic		
$\sigma_1, \sigma_2$ known	$Z = \frac{\bar{X}_1 - \bar{X}_2 - \Delta_0}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$	if population normal or CLT with $n \geq 30$ if $H_0$ true
$\sigma_1 = \sigma_2$ unknown	$T = \frac{\bar{X}_1 - \bar{X}_2 - \Delta_0}{\sqrt{\frac{\hat{\sigma}_p^2}{n_1} + \frac{\hat{\sigma}_p^2}{n_2}}} \sim t(n_1 + n_2 - 2)$	if $H_0$ true if $n_1 = n_2$ pooled sample variance (act 7.5)
$\sigma_1, \sigma_2$ unknown	<ul style="list-style-type: none"> <li>• no test statistic <math>X</math></li> <li>• confidence interval <math>\checkmark</math></li> <li>• p-value <math>\checkmark</math></li> </ul> <p>for <math>\mu_1, \mu_2</math> and check if <math>\Delta_0</math> is inside CI</p>	see section 7.4.4

② for  $\sigma^2$

$$H_0: \sigma_1^2 = \sigma_0^2 \text{ vs. } H_a: \sigma_1^2 \neq \sigma_0^2$$

$$\frac{S_1^2}{\sigma_0^2 S_2^2} \sim F(n_1-1, n_2-1)$$

Variances of two populations		
$H_0: \sigma_1^2 = \sigma_0^2$	$\sigma_1^2$	$\sigma_0^2$
test statistic:	$\frac{S_1^2}{\sigma_0^2 S_2^2} \sim F(n_1-1, n_2-1)$	if $H_0$ true and populations must be normally distributed
critical region:	$[0, f_{n_1-1, n_2-1, 1-\alpha/2}] \cup [f_{n_1-1, n_2-1, \alpha/2}, \infty)$	

③ for  $p_1 = p_2$

$$\frac{p_1 - p_2 - \Delta_0}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}} \text{ approx } N(0, 1)$$

The hypothesis  $p_1 = p_2$

$$( \text{from section 7.4.6} ) \quad \frac{\hat{p}_1 - \hat{p}_2 - (p_1 - p_2)}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}} \text{ approx } N(0, 1)$$

$$H_0: p_1 = p_2 = p$$

$$\frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}} \text{ approx } N(0, 1)$$

is a good test statistic, because it's not a unknown parameter.

$$H_0: p_1 = p_2 + \Delta_0$$

$$\frac{\hat{p}_1 - \hat{p}_2 - \Delta_0}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}} \text{ approx } N(0, 1) \text{ if } H_0 \text{ true.}$$