Hypothesis Testing

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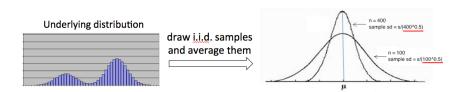
Galvanize

Morning Lecture Objectives

- The general steps of a statistical hypothesis test
- One-tail vs. Two-tailed tests
- Type-I and Type-II Error
- One-sample and Two-sample tests of mean
- One-sample and Two-sample tests of proportion

Central Limit Theorem

The CLT states that given certain conditions, the mean of a sufficiently large number of *i.i.d* random variables will be approximately normal, regardless of the underlying distribution



Central Limit Theorem

Not only is the sample mean normally distributed, but the variance of the sample mean is smaller

$$ar{X} \sim \textit{Normal}\left(\mu, rac{\sigma^2}{n}
ight)$$

 As with any normal variable, we can derive a standard normal Z-score

$$Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}}$$

Hypothesis Testing

Estimation

- Parameter value is unknown
- Goal is to find a point estimate and a confidence interval for likely values

Hypothesis Testing

- Parameter value is stated
- Goal is to see if the parameter has changed

General Steps of Hypothesis Testing

- I State the null hypothesis (H_0) and alternative hypothesis (H_A)
- **2** Choose the significance level, α
- 3 Compute the appropriate test statistic
- 4 Compute the p-value under the assumption that H_0 is true
 - If p-value $\leq \alpha \longrightarrow \text{Reject } H_0$ in favor of H_A
 - if p-value $> \alpha \longrightarrow \text{Fail}$ to Reject H_0

Null Hypothesis vs. Alternative Hypothesis

- Null Hypothesis (*H*₀)
 - Typically a measure of the status quo such as no effect
 - In terms of the parameter: H_0 : $\mu = 0$
- Alternative Hypothesis (H_A)
 - Usually states the effect the researcher hopes to detect
 - Example: Advertising causes 1% lift
 - In terms of the parameter: H_A : $\mu \neq 0$

Two-sided vs One-sided tests

- By default, we should compute a two-sided test which is more conservative:
 - For example: $H_0: \mu = \mu_0$ vs $H_A: \mu \neq \mu_0$
 - Reject if test statistic in upper or lower tail
 - One half of p-value in each tail
- However, if we expect the effect to be in a specific direction, we can use a one-sided test:
 - Example: $H_0: \mu \leq \mu_0$ vs $H_A: \mu > \mu_0$
 - Reject H_0 if test statistic in tail designated by H_A
 - \blacksquare P-value calculated based on direction specified in H_A

Two-sided vs One-sided tests

Direction	H_0	H_A	P-value
2-sided	=	#	One half of P-value
Test			in each tail
Left-Tail	>	<	All of P-value
			in left tail
Right-Tail	<	>	All of P-value
			in right tail

Type I and Type II Errors

- Type I error: Rejecting H_0 when it is true
- Type II error: Failing to reject H_0 when it is false

	H_0 is True	H_0 is False
Fail to	Correct Decision	Type II Error
Reject H ₀	$(1-\alpha)$	(β)
	Type I Error	Correct Decision
Reject H ₀	(α)	(1-eta)

Type I Error is also the Level of Significance

Multiple Comparisons

- If a researcher wants to conduct multiple tests (i.e. make multiple comparisons), we need to adjust the individual α_I rate so that the overall experimental α_E rate remains at the desired level.
- Bonferroni correction to the individual rate is straightforward, easy to apply, but overly conservative

$$\alpha_I = \frac{\alpha_E}{m}$$
 where *m* is number of comparisons

Multiple Comparisons Example:

■ Lets say you have 5 categories and you want to make all possible pairwise comparisons of the mean

$$\mu_i = \mu_j \quad \forall i \neq j$$

■ This gives us 10 possible comparisons. If we use $\alpha_I = 0.05$ then the overall error rate would be

$$\alpha_E = 1 - (1 - \alpha_I)^{10} = (1 - 0.95^{10}) = 0.401$$

So we would have a 40% chance of falsely rejecting at least one of the null hypotheses

One Sample Test of Population Mean

Z-test used when σ^2 is known or $n \ge 30$

- **1** Default choice should be a two-sided test: $H_0: \mu = \mu_0$ vs. $H_A: \mu \neq \mu_0$
- **2** Level of significance, α
- 3 Calculating standardized test statistic:

$$X_1, X_2, \dots, X_n \stackrel{iid}{\sim} N(\mu_0, \sigma^2) \stackrel{CLT}{\longrightarrow} \bar{X} \sim N\left(\mu_0, \frac{\sigma^2}{n}\right)$$

$$z_{ts} = \frac{\bar{x} - \mu_0}{\frac{\sigma}{\sqrt{p}}}$$

4 P-value for a 2-sided test:

P-value =
$$2P(Z > |z_{ts}|)$$

One Sample Test of Population Mean

T-test used when σ^2 is unknown and n < 30

- **1** Example of a right-tail test: $H_0: \mu \leq \mu_0$ vs. $H_A: \mu > \mu_0$
- **2** Level of significance, α
- Calculating standardized test statistic:

$$X_1, X_2, \dots, X_n \overset{iid}{\sim} N(\mu_0, \sigma^2) \overset{CLT}{\longrightarrow} \bar{X} \sim N\left(\mu_0, \frac{\sigma^2}{n}\right)$$
 $t_{ts} = \frac{\bar{x} - \mu_0}{\frac{s}{\sqrt{c}}} \sim t_{df} \text{ where } df = n - 1$

4 P-value for a right-sided test:

P-value =
$$P(T > t_{ts})$$

One Sample Test of Population Proportion

- **1** Example of a left-sided test: $H_0: p \ge p_0$ vs. $H_A: p < p_0$
- 2 Level of significance, α
- 3 Calculating standardized test statistic:

$$X \sim Bin(n, p_0) \stackrel{CLT}{\longrightarrow} \hat{p} = \frac{x}{n} \sim N\left(p_0, \frac{p_0(1-p_0)}{n}\right)$$
 $z_{ts} = \frac{\hat{p} - p_0}{\sqrt{rac{\hat{p}(1-\hat{p})}{n}}}$

4 P-value for a left-sided test:

P-value =
$$P(Z < z_{ts})$$

Two Sample Test of Difference in Population Means

- 1 $H_0: \mu_1 \mu_2 = 0$ vs. $H_A: \mu_1 \mu_2 \neq 0$
- 2 Level of significance, α
- 3 Calculating standardized test statistic:

$$egin{aligned} ar{X}_1 &\sim \mathcal{N}\left(\mu_1, rac{\sigma_1^2}{n_1}
ight) \ ext{and} \ ar{X}_2 &\sim \mathcal{N}\left(\mu_2, rac{\sigma_2^2}{n_2}
ight) \ &\longrightarrow ar{X}_1 - ar{X}_2 &\sim \mathcal{N}\left(\mu_1 - \mu_2, rac{\sigma_1^2}{n_1} + rac{\sigma_2^2}{n_2}
ight) \ &t_{ts} = rac{ar{x}_1 - ar{x}_2 - 0}{\sqrt{rac{s_1^2}{n_1} + rac{s_2^2}{n_2}}} \sim t_{df} \end{aligned}$$

4 P-value for a 2-sided test:

P-value =
$$2P(T > |t_{ts}|)$$

Two Sample Test of Difference in Population Means

With no assumptions about the population variances we utilize the formula on the previous slide with

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{1}{n_1 - 1} \left(\frac{s_1^2}{n_1}\right)^2 + \frac{1}{n_2 - 1} \left(\frac{s_2^2}{n_2}\right)^2}$$

For simplicity, you can always choose the more conservative

$$df = min(n_1 - 1, n_2 - 1)$$

Assumption of equal variance $(\sigma_1^2 = \sigma_2^2)$, use the pooled variance estimator in the test statistic:

$$s^{2} = \frac{(n_{1} - 1)s_{1}^{2} + (n_{2} - 1)s_{2}^{2}}{n_{1} + n_{2} - 2}$$

$$t_{ts}=rac{ar{x}_1-ar{x}_2-0}{\sqrt{s^2\left(rac{1}{n_1}+rac{1}{n_2}
ight)}}\sim t_{df}$$
 where $df=n_1+n_2-2$

Two Sample Test of Difference in Population Proportions

- 1 $H_0: p_1 p_2 = 0$ vs. $H_A: p_1 p_2 \neq 0$
- 2 Level of significance, α
- 3 Calculating standardized test statistic:

$$\begin{split} \hat{\rho}_1 &= \frac{x_1}{n_1} \sim N\left(p_1, \frac{p_1(1-p_1)}{n_1}\right) \quad \hat{p}_2 = \frac{x_2}{n_2} \sim N\left(p_2, \frac{p_2(1-p_2)}{n_2}\right) \\ \hat{p}_1 &- \hat{p}_2 \sim N\left(p_1 - p_2, \frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}\right) \\ z_{ts} &= \frac{\hat{p}_1 - \hat{p}_2 - 0}{\hat{p}(1-\hat{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)} \text{ where } \hat{p} = \frac{x_1 + x_2}{n_1 + n_2} \end{split}$$

4 P-value for a two-sided test:

P-value =
$$2P(Z > |z_{ts}|)$$

Two Sample Test of Difference in Population Proportions

- 1 $H_0: p_1 p_2 = D$ vs. $H_A: p_1 p_2 \neq D$
- 2 Level of significance, α
- 3 Calculating standardized test statistic:

$$\hat{p}_1 \sim N\left(p_1, \frac{p_1(1-p_1)}{n_1}\right) \text{ and } \hat{p}_2 \sim N\left(p_2, \frac{p_2(1-p_2)}{n_2}\right)$$

$$\hat{p}_1 - \hat{p}_2 \sim N\left(p_1 - p_2, \frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}\right)$$

$$z_{ts} = \frac{\hat{p}_1 - \hat{p}_2 - D}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}}$$

4 P-value for a two-sided test:

P-value =
$$2P(Z > |z_{ts}|)$$