

# STAT 231 - Statistics

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# Chapter 1

## Lectures

### 1.1 2020-03-02

Roadmap:

- (i) 5 min recap
- (ii) Confidence for Normal with unknown variance
- (iii) Prediction Intervals
- (iv) Relationship between likelihood intervals and confidence intervals

$$W \sim \chi_n^2 \iff W = Z_1^2 + Z_2^2 + \cdots + Z_n^2$$

where each  $Z_i \sim N(0, 1)$  and  $Z_i$ 's independent. We know  $E(W) = n$  and  $Var(W) = 2n$ .

Let  $W_1 \sim \chi_{n_1}^2$  and  $W_2 \sim \chi_{n_2}^2$  be independent, then

$$W_1 + W_2 \sim \chi_{n_1+n_2}^2$$

#### Student's T-distribution

We say  $T \sim T_n$  if

$$T = \frac{Z}{\sqrt{W/n}}$$

where  $Z \sim N(0, 1)$  and  $W \sim \chi_n^2$  are independent. Note that  $E(T) = 0$  and  $T$  is symmetric. Also, as  $n \rightarrow \infty$ , then  $T \rightarrow Z \sim N(0, 1)$ .

**THEOREM 1.1.1.** Let  $Y_1, \dots, Y_n$  be iid  $N(\mu, \sigma^2)$  where  $\mu$  and  $\sigma$  are unknown. Let

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$$

and

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2$$

Then,

(i) The pivotal quantity for  $\mu$  is:

$$\frac{\bar{Y} - \mu}{\frac{S}{\sqrt{n}}} \sim T_{n-1}$$

(ii) The pivotal quantity for  $\sigma^2$  is:

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

**REMARK 1.1.2.** (i) Shows that if we replace  $\sigma$  by its estimator  $S$ , then it follows a  $T$ -distribution with  $(n-1)$  degrees of freedom.

**EXAMPLE 1.1.3.** An independent sample of 25 students are taken and STAT 231 scores are recorded.

- $\bar{y} = 75$
- $s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2 = 64$

- (a) Find the 99% confidence interval for  $\mu$ .
- (b) Find the 95% confidence interval for  $\sigma^2$ .
- (c) Find the 99% prediction interval for  $Y_{26}$ .

**Solution.** We know  $Y_1, \dots, Y_{25} \sim N(\mu, \sigma^2)$  where  $Y_i$  = STAT 231 score of the  $i^{\text{th}}$  student.

(a) We know

$$\frac{\bar{Y} - \mu}{\frac{S}{\sqrt{n}}} \sim T_{24}$$

We want a  $t^*$  such that

$$P(|T_{24}| \leq t^*) = 0.99 \iff 2F(t^*) - 1 = 0.99 \iff p = 0.995 = F(t^*)$$

Using the table we see that  $t^* = 2.80$ . Now,

$$\begin{aligned} P(-2.8 \leq T_{24} \leq 2.8) &= 0.99 \\ \implies P\left(-2.8 \leq \frac{\bar{Y} - \mu}{\frac{S}{\sqrt{n}}} \leq 2.8\right) &= 0.99 \\ \implies P\left(\bar{Y} - 2.8 \frac{S}{\sqrt{n}} \leq \mu \leq \bar{Y} + 2.8 \frac{S}{\sqrt{n}}\right) &= 0.99 \end{aligned}$$

Thus, the 99% confidence interval for  $\mu$  is:

$$\bar{y} \pm 2.8 \frac{s}{\sqrt{n}} \implies [62.2, 87.8]$$

(b) We know

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{24}^2$$

We want any value  $a$  and  $b$  such that

$$P(a \leq \chi_{24}^2 \leq b) = 0.95$$

We choose the symmetric solution with  $a = 0.025 \rightarrow 13.120$  and  $b = 0.975 \rightarrow 40.646$ . Now,

$$\begin{aligned} P(13.120 \leq \chi_{24}^2 \leq 40.646) &= 0.95 \\ \Rightarrow P\left(13.120 \leq \frac{(n-1)S^2}{\sigma^2} \leq 40.646\right) &= 0.95 \\ \Rightarrow P\left(\frac{(n-1)S^2}{40.646} \leq \sigma^2 \leq \frac{(n-1)S^2}{13.120}\right) &= 0.95 \end{aligned}$$

Thus, the 95% confidence interval for  $\sigma^2$  is:

$$\left[ \frac{(n-1)s^2}{40.646}, \frac{(n-1)s^2}{13.120} \right] \Rightarrow [37.79, 117.07]$$

(c) Prediction interval.

$$\begin{aligned} Y_{26} &\sim N(\mu, \sigma^2) \\ \bar{Y} &\sim N(\mu, \sigma^2/n) \\ \Rightarrow Y_{26} - \bar{Y} &\sim N\left(0, \sigma^2 \left(1 + \frac{1}{n}\right)\right) \end{aligned}$$

Therefore, the pivotal quantity is:

$$\frac{Y_{26} - \bar{Y}}{\sigma \sqrt{1 + \frac{1}{n}}} = Z \sim N(0, 1)$$

we replace  $\sigma$  by its estimator and get

$$\frac{Y_{26} - \bar{Y}}{S \sqrt{1 + \frac{1}{n}}} \sim T_{24}$$

Thus,

$$P(|T_{24}| \leq 2.8) = 0.99$$

yields the general 99% prediction interval:

$$\bar{y} \pm t^* s \sqrt{1 + \frac{1}{n}}$$

We make the following remark:

**REMARK 1.1.4.** Let  $Y_1, \dots, Y_n$  be iid  $N(\mu, \sigma^2)$ . Then,

(i) The general confidence interval for  $\mu$  is:

$$\begin{aligned} \bar{y} \pm z^* \frac{\sigma}{\sqrt{n}} &\quad \text{if } \sigma \text{ is known} \\ \bar{y} \pm t^* \frac{s}{\sqrt{n}} &\quad \text{if } \sigma \text{ is unknown} \end{aligned}$$

(ii) The general confidence interval for  $\sigma^2$  is:

$$\left[ \frac{(n-1)s^2}{b}, \frac{(n-1)s^2}{a} \right]$$

where  $a$  and  $b$  come from the  $\chi_{n-1}^2$  table and  $b - a = \text{RHS}$ .

(iii) The general prediction interval for  $Y_{n+1}$  is:

$$\bar{y} \pm t^* s \sqrt{1 + \frac{1}{n}}$$

**THEOREM 1.1.5.** As  $n \rightarrow \infty$ ,

$$\Lambda(\theta) = -2 \ln \left[ \frac{L(\theta)}{L(\hat{\theta})} \right] \sim \chi_1^2$$

where  $\hat{\theta}$  is the maximum likelihood estimator. We call the random variable  $\Lambda(\theta)$  the likelihood ratio statistic.

**EXAMPLE 1.1.6.** Suppose  $n$  is large, and we have a 10% likelihood interval. What is the corresponding coverage probability?

**Solution.** 10% likelihood interval  $\implies R(\theta) \geq 0.1$

$$\implies \frac{L(\theta)}{L(\hat{\theta})} \geq 0.1$$

$$\implies -2 \ln \left[ \frac{L(\theta)}{L(\hat{\theta})} \right] \leq -2 \ln(0.1)$$

$$\implies \lambda(\theta) \leq -2 \ln(0.1)$$

Thus, the corresponding coverage:

$$\begin{aligned} P(\Lambda(\theta) \leq -2 \ln(0.1)) &= P(Z^2 \leq -2 \ln(0.1)) \\ &= P(|Z| \leq \sqrt{-2 \ln(0.1)}) \\ &\approx 97\% \end{aligned}$$

## 1.2 2020-03-04

**DEFINITION 1.2.1.** An estimator  $\tilde{\theta}$  is called **unbiased** for  $\theta$  if

$$E(\tilde{\theta}) = \theta$$

**EXAMPLE 1.2.2.** Let  $W = \frac{(n-1)S^2}{\sigma^2}$ . Find  $E(S^2)$ .

**Solution.**

$$\begin{aligned} E(W) &= n - 1 \\ \implies E\left(\frac{(n-1)S^2}{\sigma^2}\right) &= n - 1 \\ \implies \frac{n-1}{\sigma^2} E(S^2) &= n - 1 \\ \implies E(S^2) &= \sigma^2 \end{aligned}$$

Therefore  $S^2$  is an unbiased estimator for  $\sigma^2$ , and this is why we divide by  $(n-1)$ .

Other Confidence Intervals

Poisson Suppose  $Y_1, \dots, Y_n \sim \text{Poi}(\mu)$  are independent and  $n$  is large. Find the 95% confidence interval.

$$\bar{Y} \sim N(\mu, \sigma^2 = \mu/n)$$

Find the pivotal quantity now.

Exponential Suppose  $Y_1, \dots, Y_n \sim \exp(\theta)$  are independent and  $n$  is small.

**THEOREM 1.2.3.** If  $Y \sim \exp(\theta)$ , then

$$\frac{2Y}{\theta} \sim \exp(2)$$

If  $W_i = 2Y_i/\theta$ , then

$$\sum_{i=1}^n W_i \sim \chi_{2n}^2$$

*Proof.* Let  $F_W(w)$  be the cumulative distribution function of  $W$ . Then,

$$\begin{aligned} F_W(w) &= P(W \leq w) \\ &= P\left(\frac{2Y}{\theta} \leq w\right) \\ &= P\left(Y \leq \frac{w\theta}{2}\right) \\ &= 1 - e^{-\frac{w\theta}{2}/\theta} \\ &= 1 - e^{-w/2} \end{aligned}$$

Therefore,

$$f(w) = \frac{1}{2}e^{-w/2}$$

□

Using this theorem, we can find the confidence interval for  $\theta$ .

$$\begin{aligned} P(a \leq \chi_{2n}^2 \leq b) &= 0.95 \\ \implies P\left(a \leq \sum_{i=1}^n W_i \leq b\right) &= 0.95 \\ \implies P\left(a \leq \sum_{i=1}^n \frac{2Y_i}{\theta} \leq b\right) &= 0.95 \\ \implies P\left(a \leq \frac{2}{\theta} \sum_{i=1}^n Y_i \leq b\right) &= 0.95 \end{aligned}$$

yields

$$\left[ \frac{2 \sum_{i=1}^n Y_i}{b}, \frac{2 \sum_{i=1}^n Y_i}{a} \right]$$

where  $a$  and  $b$  are from the  $\chi^2$  table.

**THEOREM 1.2.4.** If we have a  $p\%$  coverage interval with  $Z$  as a pivot, and  $n$  is large, then the corresponding likelihood is given by

$$e^{-(z^*)^2/2}$$

**EXAMPLE 1.2.5.** If  $p = 0.95$  and  $z^* = 1.96$ , then the corresponding likelihood is:

$$e^{-(1.96)^2/2} \approx 0.15$$

## 1.3 2020-03-06

Roadmap:

- (i) Recap (excluded from these notes)
- (ii) Testing of hypotheses (Null vs Alternate) and (Two-sided vs One-sided tests)
- (iii) Clicker

Hypothesis Testing

**DEFINITION 1.3.1.** A hypothesis is a statement about the (parameters of) population. There are two (competing) hypotheses.

Null Hypothesis  $H_0$ : current belief, conventional wisdom

Alternate Hypothesis  $H_1$ : challenger to the conventional wisdom

**EXAMPLE 1.3.2.** Suppose we want to test whether a coin is biased. We flip the coin 100 times and get 52 heads. Let  $\theta = P(H)$

- $H_0: \theta = \frac{1}{2}$
- $H_1: \theta \neq \frac{1}{2}$

Approach  $p$ -value approach.

**DEFINITION 1.3.3.** The  $p$ -value: is the probability of observing my evidence (or worse) under the assumption that  $H_0$  is true. The lower the  $p$ -value, the strong is the evidence against  $H_0$ .

Notes:

- $H_0$  and  $H_1$  are not treated symmetrically.
- Unless there is overwhelming evidence (“beyond a reasonable doubt”) against  $H_0$ , we stick with it. The burden is on the challenger.

	$H_0$ is true	$H_1$ is true
Reject $H_0$ (convict)	$X_1$	✓
Do not reject $H_0$	✓	$X_2$

where  $X_1$  is a Type I error and  $X_2$  is a Type II error.

Two-sided vs One-sided tests:

- $H_0: \theta = \frac{1}{6}$
- $H_1: \theta < \frac{1}{6}$

Clicker Question The  $p$ -value =  $P(H_0 \text{ is true})$ .



- (a) True
- (b) **False**

## 1.4 2020-03-09

Roadmap:

- (i) Binomial testing
- (ii) Review for the midterm (excluded from these notes)

**DEFINITION 1.4.1.**  $p$ -value: Probability of observing as extreme an observation of your data, given the null hypothesis is true.

**DEFINITION 1.4.2.** A test statistic (discrepancy measure) is a random variable that measures the level of disagreement of your data with the null hypothesis. Typically, it satisfies the following properties:

- (i)  $D \geq 0$
- (ii)  $D = 0 \implies$  best news for  $H_0$
- (iii) High values of  $D \implies$  bad news for  $H_0$
- (iv) Probabilities can be calculated if  $H_0$  is true

Steps for a Statistical test

Step 1: Construct the test-statistic  $D$

**EXAMPLE 1.4.3.** Test whether a coin is fair (against the two sided alternative). Let  $n = 100$  and  $y = 52$  heads.

- $H_0: \theta = \frac{1}{2}$
- $H_1: \theta \neq \frac{1}{2}$

where  $\theta = P(H)$ .

Model:  $Y \sim \text{Bin}(100, \theta)$ .

$$D = |Y - 50|$$

as it satisfies (i)-(iv).

Step 2: Find  $d$  from your data set.

$$p\text{-value} = P(D \geq d; H_0 \text{ is true})$$

Step 3: Make conclusions based on your p-value

For our Binomial problem,

$$D = |Y - 50| \implies d = |52 - 50| = 2$$

Thus,

$$p\text{-value} = P(|Y - 50| \geq 2)$$

but this is difficult to calculate. For  $n$  large enough, we can use

$$D = \left| \frac{Y - n\theta}{\sqrt{n\theta(1-\theta)}} \right|$$

as a possible test statistic.

## 1.5 2020-03-11

Roadmap:

- (i) Testing for normal problems
- (ii) How to test for a “bias” of a scale
- (iii) One-sided tests
- (iv) Relationship between C.I and H.T
- (v) Other distributions

Problem:  $Y_1, \dots, Y_n \sim N(\mu, \sigma^2)$  iid.

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

Steps involved:

- (i) Construct the Discrepancy measure  $D$  (satisfying the properties), this measures how much the data disagrees with  $H_0$
- (ii) Calculate the value of  $D$  from your sample ( $d$ )
- (iii)  $p\text{-value} = P(D \geq d; H_0 \text{ is true})$
- (iv) Draw appropriate conclusions based on your  $p\text{-value}$

**EXAMPLE 1.5.1.** The STAT 231 scores are normally distributed with mean  $\mu$  and variance  $\sigma^2 = 49$ .

- $H_0: \mu = 75$
- $H_1: \mu \neq 75$

A random sample of 25 students are taken  $\bar{y} = 72$ . Find the  $p\text{-value}$ .

**Solution.** From Chapter 4 we know that

$$\frac{\bar{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} = Z \sim N(0, 1)$$

$$D = \left| \frac{\bar{Y} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \right|$$

where we can see that  $D$  is a legitimate test statistic as it satisfies all the required properties since:

1.  $D \geq 0$  for all  $d$
2.  $D = 0 \implies$  best news for  $H_0$
3. High values of  $D \implies$  bad news for  $H_0$
4. Probabilities can be calculated if  $H_0$  is true

Thus, we have

$$d = \left| \frac{\bar{y} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \right| = \left| \frac{72 - 75}{\frac{7}{\sqrt{5}}} \right| = \frac{15}{7} = 2.14$$

$$\begin{aligned} p\text{-value} &= P(D \geq d) \\ &= P(|Z| \geq 2.14) \\ &< 0.05 \end{aligned}$$

Evidence against  $H_0$ .

**EXAMPLE 1.5.2.** UW brochure claims that the average starting salary of UW graduates is \$60000/year. We assume normality. We want to test this claim. Let  $\bar{y} = 58000$  and  $s = 5000$ . What should you conclude?

**Solution.**

- $H_0: \mu = 60000$
- $H_1: \mu \neq 60000$

$$D = \left| \frac{\bar{Y} - \mu_0}{\frac{S}{\sqrt{n}}} \right|$$

where all the properties of  $D$  are satisfied.

$$d = \left| \frac{\bar{y} - 60000}{\frac{5000}{\sqrt{25}}} \right| = 2$$

$$\begin{aligned} p\text{-value} &= P(D \geq d) \\ &= P(|T_{24}| \geq 2) \end{aligned}$$

The  $p$ -value for this test is between 5% and 10%. Weak evidence against  $H_0$ .

## 1.6 2020-03-13

Roadmap:

- Recap and the relationship between Confidence and Hypothesis
- Example: Bias Testing
- Testing for variance (Normal)
- What if we don't know how to construct a Test-Statistic?

**EXAMPLE 1.6.1.**  $Y_1, \dots, Y_n$  iid  $N(\mu, \sigma^2)$

- $\sigma^2 = \text{known}$
- $\mu = \text{unknown}$
- Sample:  $\{y_1, \dots, y_n\}$
- $\bar{y} = \text{sample mean}$
- $H_0: \mu = \mu_0$  where  $\mu_0$  is given
- $H_1: \mu \neq \mu_0$

$$D = \left| \frac{\bar{Y} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \right| \quad \rightarrow \quad \text{Test-Statistic (r.v.)}$$

$$d = \left| \frac{\bar{y} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \right| \quad \rightarrow \quad \text{Value of the Test-Statistic}$$

$$\begin{aligned} p\text{-value} &= P(D \geq d) \quad \text{assuming } H_0 \text{ is true} \\ &= P(|Z| \geq d) \quad Z \sim N(0, 1) \end{aligned}$$

Question: Suppose the  $p$ -value for the test  $> 0.05$  if and only if  $\mu_0$  belongs in the 95% confidence interval for  $\mu$ ?

YES.

Suppose  $\mu_0$  is in the 95% confidence interval for  $\mu$ , i.e.

$$\begin{aligned}\bar{y} \pm 1.96 \frac{\sigma}{\sqrt{n}} \\ \mu_0 \leq \bar{y} + 1.96 \frac{\sigma}{\sqrt{n}} \\ \mu_0 \geq \bar{y} - 1.96 \frac{\sigma}{\sqrt{n}}\end{aligned}$$

These two equations yield

$$d = \left| \frac{\bar{y} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \right| \leq 1.96$$

$$p\text{-value} = P(|Z| \geq d) > 0.05$$

General result (assuming same pivot)

$p$ -value of a test  $H_0: \theta = \theta_0$  vs  $H_1: \theta \neq \theta_0$  is more than  $q\%$ , then  $\theta_0$  belongs to the  $100(1 - q)\%$  confidence interval and vice versa.

**EXAMPLE 1.6.2** (Bias). A 10 kg weight is weighed 20 times  $(y_1, \dots, y_n)$ .

- $\bar{y} = 10.5$
- $s = 0.4$
- $H_0$ : The scale is unbiased
- $H_1$ : The scale is biased

If the scale was unbiased,

$$Y_1, \dots, Y_n \sim N(10, \sigma^2)$$

If the scale was biased,

$$Y_1, \dots, Y_n \sim N(10 + \delta, \sigma^2)$$

- $H_0: \delta = 0$  (unbiased)
- $H_1: \delta \neq 0$  (biased)

is equivalent to

- $H_0: \mu = 10$
- $H_1: \mu \neq 10$

Test-statistic:

$$D = \left| \frac{\bar{Y} - 10}{\frac{S}{\sqrt{n}}} \right|$$

Compute  $d$ .

$$d = \left| \frac{\bar{y} - 10}{\frac{s}{\sqrt{n}}} \right| = \left| \frac{10.5 - 10}{\frac{0.4}{\sqrt{20}}} \right| = 5.59017$$

$$\begin{aligned}p\text{-value} &= P(D \geq d) \\ &= P(|T_{19}| \geq 5.59) \\ &= 1 - P(|T_{19}| \leq 5.59) \\ &= 1 - [2P(T_{19} \leq 5.59) - 1] \\ &\approx 1 - (2 - 1) \\ &= 0\end{aligned}$$

Very strong evidence against  $H_0$ .

**EXAMPLE 1.6.3** (Draw Conclusions).  $Y_1, \dots, Y_n = \text{co-op salaries}$ .  $Y_1, \dots, Y_n \sim N(\mu, \sigma^2)$

- $H_0: \mu = 3000$
- $H_1: \mu < 3000$  ( $\mu \neq 3000$ )

$$D = \left| \frac{\bar{Y} - \mu_0}{\frac{S}{\sqrt{n}}} \right|$$

$$D = \begin{cases} 0 & \bar{Y} > \mu_0 \\ \frac{\bar{Y} - \mu_0}{\frac{S}{\sqrt{n}}} & \bar{Y} < \mu_0 \end{cases}$$

If  $n$  is large, then

$$Y_1, \dots, Y_n \sim f(y_i; \theta)$$

- $H_0: \theta = \theta_0$
- $H_1: \theta \neq \theta_0$

$$\Lambda(\theta) = -2 \ln \left[ \frac{L(\theta_0)}{L(\hat{\theta})} \right]$$

where  $\Lambda$  satisfies all the properties of  $D$ . Also,

$$\lambda(\theta) = -2 \ln \left[ \frac{L(\theta_0)}{L(\hat{\theta})} \right] = -2 \ln [R(\theta_0)]$$

and

$$p\text{-value} = P(\Lambda \geq \lambda) = P(Z^2 \geq \lambda)$$

# Chapter 2

## Online Lectures

### 2.1 2020-03-16: Testing for Variances

Roadmap:

- (i) General info
- (ii) Testing for variance for Normal
- (iii) An example

The general problem:

- $Y_1, \dots, Y_n \sim N(\mu, \sigma^2)$  iid where  $\mu$  and  $\sigma$  are both unknown.
- Sample:  $\{y_1, \dots, y_n\}$
- $H_0: \sigma^2 = \sigma_0^2$  vs two sided alternative.

- (i) Test statistic? Problem
- (ii) Convention?

The pivot is:

$$U = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi_{n-1}^2$$

can we use this as our test statistic? We will calculate

$$u = \frac{(n-1)s^2}{\sigma_0^2}$$

We want to compare  $u$  to the median of  $\chi_{n-1}^2$ :

- If  $u > \text{median}$ , then  $p\text{-value} = 2P(U \geq u)$ .
- If  $u < \text{median}$ , then  $p\text{-value} = 2P(U \leq u)$ .

#### EXAMPLE 2.1.1.

- Normal population:  $\{y_1, \dots, y_n\}$
- $n = 20$
- $\sum_{i=1}^n y_i = 888.1$
- $\sum_{i=1}^n y_i^2 = 39545.03$

- $H_0: \sigma = \sigma_0 = 2 \iff \sigma^2 = \sigma_0^2 = 4$
- $H_1: \sigma \neq \sigma_0 = 2 \iff \sigma^2 \neq \sigma_0^2 = 4$

What is the  $p$ -value? We know

$$s^2 = \frac{1}{n-1} \left[ \sum_{i=1}^n y_i^2 - n\bar{y}^2 \right] = \frac{1}{19} \left[ (39545.03) - (20) \left( \frac{888.1}{20} \right)^2 \right] = 5.7342$$

Compute  $u$ :

$$u = \frac{(n-1)s^2}{\sigma_0^2} = \frac{(19)(5.7342)}{4} = 27.24$$

We need to determine if  $u$  is to the right or left of the median  $\chi_{19}^2$ . We know it will be to the right since the mean of  $\chi_{19}^2$  is 19.  $\chi^2$  is right-skewed, so the mean must be bigger than the median, thus the median must be less than 19. Therefore,  $u > \text{median}$ . Alternatively, we can use the table and look at  $p = 0.5$ ,  $df = 19 \rightarrow 18.338 < u$ .

$$\begin{aligned} p\text{-value} &= 2P(U \geq u) \\ &= 2P(U \geq 27.24) \\ &= 2P(\chi_{19}^2 \geq 27.24) \end{aligned}$$

We see that 27.24 falls between  $p = 0.9$  and  $p = 0.95$ . The area to the right of  $p = 0.9$  is 10% and the area to the right of  $p = 0.95$  is 5%. Thus,  $2P(5\% \text{ and } 10\%) = 10\% \text{ and } 20\%$ , which implies  $p > 0.1$  and we conclude there is no evidence against null-hypothesis.

## 2.2 2020-03-18: Likelihood Ratio Test Statistic Example

Roadmap:

- (i) 5 min recap
- (ii) LTRS for large  $n$
- (iii) An example
- (i) 5 min recap

$Y_1, \dots, Y_n \text{ iid } \sim N(\mu, \sigma^2)$

- $H_0: \sigma^2 = \sigma_0^2$
- $U = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi_{n-1}^2$

We calculated the  $p$ -value:

$$u = \frac{(n-1)s^2}{\sigma_0^2}$$

- If  $u > \text{median } \chi_{n-1}^2 \implies p\text{-value} = 2P(U \geq u)$  (twice right tail)
- If  $u < \text{median } \chi_{n-1}^2 \implies p\text{-value} = 2P(U \leq u)$  (twice left tail)

Exercise For 2.1.1,

- Construct the 95% confidence interval for  $\sigma^2$ .
- Check if  $\sigma_0^2(4) \in 95\% \text{ confidence interval}$ .

We already know that  $H_0: \sigma^2 = 4$  yields a  $p\text{-value} > 0.1$ , so it should be in the 90% confidence interval  $\implies$  it's in the 95% confidence interval.

(ii) LTRS for large  $n$ 

$Y_1, \dots, Y_n$  iid  $f(y_i; \theta)$  with  $n$  large.

- Sample:  $\{y_1, \dots, y_n\}$
- $\theta$  = unknown parameter
- $H_0: \theta = \theta_0$
- $H_1: \theta \neq \theta_0$

Step 1: Test statistic:

$$\Lambda(\theta) = -2 \ln \left[ \frac{L(\theta)}{L(\hat{\theta})} \right]$$

If  $H_0$  is true:

$$\Lambda(\theta_0) = -2 \ln \left[ \frac{L(\theta_0)}{L(\hat{\theta})} \right] \sim \chi_1^2$$

Step 2: Calculate  $\lambda(\theta_0)$

$$\lambda(\theta_0) = -2 \ln \left[ \frac{L(\theta_0)}{L(\hat{\theta})} \right] = -2 \ln [R(\theta_0)]$$

$$\begin{aligned} p\text{-value} &= P(\Lambda \geq \lambda) \\ &= P(Z^2 \geq \lambda) \\ &= 1 - P(|Z| \leq \sqrt{\lambda}) \end{aligned}$$

(iii) An example

**EXAMPLE 2.2.1.** Suppose  $Y_1, \dots, Y_n \sim f(y_i; \theta)$  iid where

$$f(y, \theta) = \frac{2y}{\theta} e^{-y^2/\theta}$$

- $n = 20$
- $\sum_{i=1}^n y_i^2 = 72$

We want to test  $H_0: \theta = 5$  (two sided alternative).

- $\hat{\theta} = \frac{1}{n} \sum_{i=1}^n y_i = \frac{1}{20}(72) = 3.6$
- $R(\theta_0) = \left( \frac{\hat{\theta}}{\theta_0} \right)^n e^{\left(1 - \frac{\hat{\theta}}{\theta_0}\right)n} = 0.379052$
- $\lambda(\theta_0) = -2 \ln [R(\theta_0)] = 1.94016$

$$\begin{aligned} p\text{-value} &= P(\Lambda \geq \lambda) \\ &= P(Z^2 \geq 1.94016) \\ &= 1 - \left[ 2P(Z \leq \sqrt{1.94016}) - 1 \right] \\ &= 1 - [2(0.97381) - 1] \\ &= 0.16452 \\ &\approx 16.5\% \end{aligned}$$

Thus, no evidence against null-hypothesis ( $H_0$ ).

A few final points:



(i) Careful about the previous example:

$n = 20$  is not large

(ii)  $\lambda$  and the relationship with  $R$ :

high values of  $\lambda \implies$  low values of  $R(\theta_0)$

(iii) Next video

## 2.3 2020-03-20: Intro to Gaussian Response Models

Roadmap:

(i) Housekeeping

Modified Syllabus + Incentives

Extra materials

Dropbox link + MathSoc

(ii) Gaussian Response Model: An introduction

Gaussian Response Models

Assumption:  $Y_1, \dots, Y_n \sim \text{Normal}$

Before:  $Y_1, \dots, Y_n \sim N(\mu, \sigma^2)$  iid with  $\mu, \sigma^2 = \text{unknown}$ . Equivalently,

$$Y_i = \mu + R_i$$

where  $R_i \sim N(0, \sigma^2)$  and  $R_i$ 's independent for each  $i \in [1, n]$ . We call:

- $Y_i$  **response** variate (dependent variable)
- $\mu$  **systematic part**
- $R$  **random part**

Now:

- $x$  = (independent) explanatory variable
- $\mu = \mu(x)$
- $\sigma^2 = \sigma^2(x)$

The general gaussian response model is:

$$Y_i \sim N(\mu(x_i), \sigma^2(x_i))$$

Simple Linear Regression:  $\mu = \alpha + \beta x$  and  $\sigma^2 = \text{constant}$ .

### EXAMPLE 2.3.1.

- Response variable:  $Y_i = \text{STAT 231 score of student } i$
- Explanatory variable:  $x_i = \text{STAT 230 score of student } i \text{ (given)}$

Can  $Y$  be explained by  $x$ ?

Simple Linear Regression Model

$$Y_i \sim N(\alpha + \beta x_i, \sigma^2)$$

for each  $i \in [1, n]$  independent.

Our assumptions are:

- $E(Y) = \mu(x) = \alpha + \beta x$
- $Y \sim \text{Normal}$

- $\sigma^2 = \text{constant}$  (independent of  $x$ )
- Independent

Goal: We want to estimate  $\alpha$  and  $\beta$ .

## 2.4 2020-03-23: MLE Regression

Roadmap:

- (i) 5 min recap
- (ii) MLE for  $\alpha, \beta, \sigma$
- (iii) Least Squares
- (iv) Example

Recap:

General:  $Y \sim N(\mu(x), r(x))$

Assumptions for the Simple Linear Regression Model (Gauss Markov Assumptions)

- (i) One covariate (for the time being)
- (ii) Normality:  $Y_i$ 's are Normal
- (iii) Linearity:  $E(Y) = \alpha + \beta x$
- (iv) Independence:  $Y_i$ 's are all independent
- (v) Homoscedasticity:  $\sigma^2 = \sigma^2(x) = \sigma^2$  for all  $x$

We call it a Simple since  $x$  is the only explanatory variate. If we used more than one explanatory variate, we call it a multi-variable regression (not covered in this course).

MLE Calculation

$$Y_i \sim N(\alpha + \beta x_i, \sigma^2)$$

for each  $i \in [1, n]$  independent. We can also write

$$Y_i = (\alpha + \beta x_i) + R_i$$

where  $R_i \sim N(0, \sigma^2)$  and  $R_i$ 's independent. We say  $\alpha + \beta x_i$  is the systematic part, and  $R_i$  is the random part.

$$f(y_i) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(y_i - (\alpha + \beta x_i))^2}$$

$$L(\alpha, \beta, \sigma) = \frac{1}{(2\pi)^{n/2}\sigma^n} e^{-\frac{1}{2\sigma^2} \sum [y_i - (\alpha + \beta x_i)]^2}$$

so,

$$\ell(\alpha, \beta, \sigma) = -\frac{n}{2} \ln(2\pi) - n \ln(\sigma) - \frac{1}{2\sigma^2} \sum [y_i - (\alpha + \beta x_i)]^2$$

$$\frac{\partial \ell}{\partial \alpha} = 0 \implies \hat{\alpha} = \bar{y} - \hat{\beta} \bar{x}$$

$$\frac{\partial \ell}{\partial \beta} = 0 \implies \hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$\frac{\partial \ell}{\partial \sigma} = 0 \implies \hat{\sigma}^2 = \frac{1}{n} \sum [y_i - (\hat{\alpha} + \hat{\beta} x_i)]^2$$

**EXAMPLE 2.4.1** (Numerical Example).

$x$	$y$	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(y - \bar{y})^2$	$(x - \bar{x})(y - \bar{y})$
1	2	-4	-4	16	16	16
3	3	-2	-3	4	9	6
5	7	0	1	0	1	0
7	9	2	3	4	9	6
9	9	4	3	16	16	12
		0	0	$S_{xx} = 40$	$S_{yy}$	$S_{xy} = 40$

- $\bar{x} = 5$
- $\bar{y} = 6$

Find the regression equation.

**Solution.**

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}} = 40/40 = 1$$

$$\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x} = 6 - (1)(5) = 1$$

Thus, the regression equation is:

$$y = \hat{\alpha} + \hat{\beta}x = 1 + x$$

Method of Least Squares

$$\text{minimize} \quad \sum_{i=1}^n \left[ y_i - (\hat{\alpha} + \hat{\beta}x_i) \right]^2$$

This is exactly the same as what we did previously. Sometimes we call  $\hat{\alpha}$  and  $\hat{\beta}$  least square estimates.

**2.5 2020-03-23: Beta Properties and a Look Ahead**Roadmap:

- (i) Interpretation of SLRM and Recap
- (ii) An example
- (iii) Possible Questions

What we know so far:

- $Y_i$  = response variate = random variable where  $i = 1, \dots, n$
- $x_i$  = explanatory variable = given (known numbers)

Examples:

- $Y_i$  = STAT 231,  $x$  = STAT 230
- $Y_i$  = stock price in month  $i$ ,  $x = P/E$
- $Y_i$  = wage of UW graduate,  $x$  = major

Model:  $Y_i \sim N(\alpha + \beta x_i, \sigma^2)$   $i \in [1, n]$  independent.

$$Y_i = \alpha + \beta x_i + R_i$$

$R_i$  = residuals and  $R_i \sim N(0, \sigma^2)$ .

Goal: Extract the relationship between  $x$  and  $Y$ .

Interpretation:

$$E(Y_i) = \alpha + \beta x_i + 0$$

$\beta$  = change in  $E(Y)$  if  $x$  changes by 1 unit

Suppose  $x = 0$ , then  $Y_i = \alpha + R_i$ . So  $E(Y_i) = \alpha$ .

### EXAMPLE 2.5.1.

- $n = 30$
- $\bar{x} = 76.733$
- $\bar{y} = 72.233$
- $S_{yy} = 7585.3667$
- $S_{xx} = 5135.8667$
- $S_{xy} = 5106.8667$

Find the regression equation.

**Solution.**

- $\hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{5106.8667}{5135.8667} = 0.9944$
- $\hat{\alpha} = \bar{y} - \hat{\beta}\bar{x} = 72.233 - (0.9944)(76.733) = -4.0677$

Thus, the regression equation is:

$$y = -4.0677 + 0.9944x$$

Note: Suppose we have the data set  $\{(x_1, y_1), \dots, (x_{30}, y_{30})\}$ . If  $x_{15} = 75$ , we can predict  $y_{15}$  using the regression equation. However, it may or may not lie on the line.

Given  $y = -4.0677 + 0.9944x$ , suppose  $\beta = 0$ , this means that  $x$  has no effect on  $Y_i$  since

$$Y_i \sim N(\alpha, \sigma^2)$$

Exercise:  $\hat{\beta} = 0 \iff r_{xy} = 0$ ?

We could also figure out the following (next lecture):

- Confidence interval for  $\beta$
- $H_0: \beta = 0$  ( $x$  is uncorrelated to  $Y$ )
- $H_1: \beta \neq 0$

## 2.6 2020-03-25: Interval Estimation and Hypothesis for Beta

Roadmap:

- Confidence Interval for  $\beta$
- Testing for  $H_0: \beta = 0$  (Test for correlation for  $x$  and  $Y$ )

**EXAMPLE 2.6.1.** Last class we found the least square equation using the following data.

- $n = 30$
- $\bar{x} = 76.733$
- $\bar{y} = 72.233$
- $S_{yy} = 7585.3667$
- $S_{xx} = 5135.8667$
- $S_{xy} = 5106.8667$
- $\hat{\alpha} = -4.0677$
- $\hat{\beta} = 0.9944$

$$y = -4.0677 + 0.9944x$$

- $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \left[ y_i - (\hat{\alpha} + \hat{\beta}x_i) \right]^2$

We now introduce the standard error, denoted  $s_e$ , where we divide by  $(n - 2)$  instead of  $(n - 1)$  in our sample standard variance.

$$s_e^2 = \frac{1}{n-2} \sum_{i=1}^n \left[ y_i - (\hat{\alpha} + \hat{\beta}x_i) \right]^2$$

In our example,  $s_e = 9.4630$ . Don't forget to square root  $s_e^2$ !

A look ahead:  $s_e^2$  is an unbiased estimator for  $\sigma^2$ .

### Some Algebra

$$\begin{aligned} S_{xy} &= \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) = \sum_{i=1}^n (x_i - \bar{x})y_i \\ &= \sum_{i=1}^n x_i(y_i - \bar{y}) = \sum_{i=1}^n (x_i y_i) - n\bar{x}\bar{y} \\ S_{xx} &= \sum_{i=1}^n (x_i - \bar{x})^2 = \sum_{i=1}^n (x_i - \bar{x})x_i \end{aligned}$$

Thus,

$$\hat{\beta} = \frac{S_{xy}}{S_{xx}} = \frac{\sum_{i=1}^n (x_i - \bar{x})y_i}{S_{xx}} = \sum_{i=1}^n a_i y_i$$

where  $a_i = \frac{x_i - \bar{x}}{S_{xx}}$ . Also,

$$\tilde{\beta} = \sum_{i=1}^n a_i Y_i$$

Result:

$$\tilde{\beta} \sim N\left(\beta, \frac{\sigma^2}{S_{xx}}\right)$$

Therefore,

$$\frac{\tilde{\beta} - \beta}{\frac{\sigma}{\sqrt{S_{xx}}}} \sim N(0, 1)$$

but,  $\sigma$  is unknown, so

$$\frac{\tilde{\beta} - \beta}{\frac{s_e}{\sqrt{S_{xx}}}} \sim T_{n-2}$$

**THEOREM 2.6.2.** We can use

$$\frac{\tilde{\beta} - \beta}{\frac{s_e}{\sqrt{S_{xx}}}} \sim T_{n-2}$$

as a pivotal quantity for  $\beta$ . We can use

$$\frac{(n-2)S_e^2}{\sigma^2} \sim \chi_{n-2}^2$$

as a pivotal quantity for  $\sigma^2$ .

**EXAMPLE 2.6.3.** Continuation of 2.6.1.

- (i) Find the 95% Confidence Interval for  $\beta$ .
- (ii) Test whether  $\beta = 0$

(i) The pivot is:

$$\frac{\tilde{\beta} - \beta}{\frac{S_e}{\sqrt{S_{xx}}}} \sim T_{28}$$

Step 1: Critical points using table with  $p = 0.975$ ,  $df = 28 \rightarrow t^* = 2.05$ .

$$P\left(-2.05 \leq \frac{\tilde{\beta} - \beta}{\frac{S_e}{\sqrt{S_{xx}}}} \leq 2.05\right) = 0.95$$

Coverage interval:

$$\tilde{\beta} \pm t^* \frac{S_e}{\sqrt{S_{xx}}}$$

Confidence interval:

$$\tilde{\beta} \pm t^* \frac{S_e}{\sqrt{S_{xx}}} \\ \Rightarrow [0.72, 1.26]$$

(ii) We know  $\beta = [0.72, 1.26]$ . We want to test  $\beta = 0$  (we can already see it's not within this interval).

- $H_0: \beta = 0$
- $H_1: \beta \neq 0$

$$D = \left| \frac{\tilde{\beta}}{\frac{S_e}{\sqrt{S_{xx}}}} \right|$$

Value of the test:

$$d = \frac{\hat{\beta}}{\frac{s_e}{s_{xx}}} = \frac{0.9944}{\frac{9.4630}{\sqrt{5135.8667}}} = 7.53$$

$$\begin{aligned} p\text{-value} &= P(D \geq d) \\ &= P(|T_{28}| \geq 7.53) \\ &\approx 0 \end{aligned}$$

There is very strong evidence against  $H_0$ . We could also test for any  $\beta = \beta_0 \in \mathbb{R}$ .

## 2.7 2020-03-26: Pivotal Distribution for Beta and Confidence for the Mean

Roadmap:

(i) A look back: Pivot for  $\beta$

(ii) A look ahead: Confidence interval for  $\mu(x)$  = mean response

STAT 230: If  $X \sim N(\mu_1, \sigma^2)$ ,  $Y \sim N(\mu_2, \sigma^2)$ ,  $X$  and  $Y$  independent, then

$$aX + bY \sim N(a\mu_1 + b\mu_2, \sigma^2(a^2 + b^2))$$

General result: If  $X_i \sim N(\mu_i, \sigma^2)$  with  $i = 1, \dots, n$  independent, then

$$\sum_{i=1}^n a_i X_i \sim N\left(\sum_{i=1}^n a_i \mu_i, \sigma^2 \sum_{i=1}^n a_i^2\right)$$

We know

$$\hat{\beta} = \sum_{i=1}^n a_i y_i \quad \tilde{\beta} = \sum_{i=1}^n a_i Y_i \quad Y_i \sim N(\underbrace{\alpha + \beta x_i}_{\mu_i}, \sigma^2)$$

$$\tilde{\beta} \sim \left( \sum_{i=1}^n a_i (\alpha + \beta x_i), \sigma^2 \sum_{i=1}^n a_i^2 \right)$$

Recall:

$$a_i = \frac{x_i - \bar{x}}{S_{xx}}$$

1.  $\sum_{i=1}^n a_i = 0$
2.  $\sum_{i=1}^n a_i x_i = 1$
3.  $\sum_{i=1}^n a_i^2 = \frac{1}{S_{xx}}$

So, the mean is

$$\begin{aligned} &= \sum_{i=1}^n a_i \alpha + \sum_{i=1}^n a_i \beta x_i \\ &= \alpha \sum_{i=1}^n a_i + \beta \sum_{i=1}^n a_i x_i \\ &= \beta \end{aligned}$$

the result now follows.  $\square$

Now, we fix  $x$  were

- $Y = \text{STAT 231}$
- $x = \text{STAT 230}$

Confidence interval for  $\mu(x) = \alpha + \beta x$ .

(Average STAT 231 score for all students with a 75 in STAT 230).

$$\mu(x) = \alpha + \beta 75$$

$$\hat{\mu}(x) = \hat{\alpha} + \hat{\beta} x$$

$$\tilde{\mu}(x) = \tilde{\alpha} + \tilde{\beta} x$$

We know  $\tilde{\beta}$  is normal, and we can show  $\tilde{\alpha}$  is normal. So,

$$\tilde{\mu}(x) \sim N \left( \mu(x), \sigma^2 \left( \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}} \right) \right)$$

(proof beyond the scope of this course) Thus, the corresponding pivot is

$$\frac{\tilde{\mu}(x) - \mu(x)}{S_e \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}} \sim T_{n-2}$$

Therefore, the confidence interval (exercise) for  $\mu(x)$  is:

$$\left[ \hat{\alpha} + \hat{\beta} x \right] \pm t^* s_e \sqrt{\frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}$$

Can we find the confidence interval for  $\alpha$ ? Yes.

Recall,  $\alpha = \mu(0)$ , so we can just plug in 0 and we get the confidence interval for  $\alpha$ .

## 2.8 2020-03-28: Prediction Interval and Intro to Model Checking

Roadmap:

- (i) Prediction Interval for  $Y$  given  $x = x_{\text{new}}$
- (ii) Model Checking

Problem:  $Y_i \sim N(\alpha + \beta x_i, \sigma^2)$   $i = 1, \dots, n$  independent. Find the 95% Prediction Interval for  $Y_{\text{new}}$  when  $x = x_{\text{new}}$ .

Difference:

- $\mu$  was constant (stationary target)
- $Y_{\text{new}}$  is a random variable with mean  $\mu$  (moving target)

**EXAMPLE 2.8.1.**  $x = x_{\text{new}}$

Problem 1: Find the 95% Confidence Interval for  $\mu = \alpha + \beta(75)$ . Done last lecture.

Problem 2: Find the 95% Prediction Interval for  $Y$  when  $x_{\text{new}} = 75$ .

$$Y \sim N(\alpha + \beta(75), \sigma^2) \quad (2.1)$$

$$\tilde{\mu}(75) \sim N\left(\mu(75), \sigma^2 \left(\frac{1}{n} + \frac{(75 - \bar{x})^2}{S_{xx}}\right)\right) \quad (2.2)$$

Subtracting (1) from (2), we get

$$Y - \tilde{\mu}(75) \sim N\left(0, \sigma^2 \left(1 + \frac{1}{n} + \frac{(75 - \bar{x})^2}{S_{xx}}\right)\right)$$

Thus,

$$\frac{Y - \tilde{\mu}(75)}{\sigma \sqrt{1 + \frac{1}{n} + \frac{(75 - \bar{x})^2}{S_{xx}}}} = Z \sim N(0, 1)$$

we replace  $S_e$ , then we get

$$\frac{Y - \tilde{\mu}(75)}{S_e \sqrt{1 + \frac{1}{n} + \frac{(75 - \bar{x})^2}{S_{xx}}}} \sim T_{n-2}$$

Finally, the Prediction Interval is:

$$\hat{\mu}(x_{\text{new}}) \pm t^* s_e \sqrt{1 + \frac{1}{n} + \frac{(x_{\text{new}} - \bar{x})^2}{S_{xx}}}$$

$$\hat{\mu}(x_{\text{new}}) = \hat{\alpha} + \hat{\beta} x_{\text{new}}$$

Checking the assumptions

Main assumptions

- (i) Normality, with constant variance
- (ii) Linearity:  $E(Y) = \alpha + \beta x$
- (iii) Independence



Checking

- (i) Warning
- (ii) The Least Squares line
- (iii) The residual plots

Estimated residuals =  $r_i = y_i - \underbrace{(\hat{\alpha} + \hat{\beta}x_i)}_{\hat{y}_i}$ . The  $r_i$ 's should behave like independent outcomes of  $N(0, \sigma^2)$ .

Some questions to think about:

- (1)  $(r_i, x_i)$
- (2)  $(r_i, \hat{y}_i)$
- (3) Q-Q plot of  $r_i$ 's

## 2.9 2020-03-29: Model Checking and Final Points

Roadmap:

- (i) Model Checking
- (ii) Final points

SLRM:  $Y_i = \alpha + \beta x_i$ ,  $R_i \sim N(0, \sigma^2)$

Residuals:  $r_i = y_i - \hat{y}_i = y_i - (\hat{\alpha} + \hat{\beta}x_i)$ .

(a) If the model is correct, how should  $r_i$ 's behave?

$$\hat{r}_i = r_i / s_e = \text{standardized residuals} \sim N(0, 1)$$

(b) How should  $\hat{r}_i$ 's behave?

Note:  $\sum_{i=1}^n r_i = 0$  (check)

Graphical methods

- (i) Residual plots

$$(r_i, x_i)$$

$$(r_i, \hat{y}_i)$$

Q-Q plot of  $r_i$ 's

$$\hat{r}_i?$$

- (ii) Warning signs

Final points

- Extensions

Multivariate Linear Regression  $(x_1, x_2, \dots, x_k)$ : STAT 3xx

Time Series  $(Y_{t-1}, Y_{t-2}, \dots, Y_{t-k})$ : STAT 443 (Forecasting)

Non-linearity  $(E(Y) = \text{non-linear})$ : STAT 4xx

## 2.10 2020-03-30: Two Population Case I Equal Variance

Two population problems

Roadmap: Gaussian mean problem with equal variances

Problem:  $Y_{11}, \dots, Y_{1n_1} \sim N(\mu_1, \sigma^2)$  and  $Y_{21}, \dots, Y_{2n_2} \sim N(\mu_2, \sigma^2)$

Question:

- (i) Test  $H_0: \mu_1 = \mu_2$  (Two sided alternative)
- (ii) Equivalently, find the confidence interval for  $(\mu_1 - \mu_2)$

### EXAMPLE 2.10.1.

- CS vs FARM (STAT 231 score)
- Constant variance assumption

Idea:

$$\begin{aligned} Y_{1i} &\sim N(\mu_1, \sigma^2) \implies \bar{Y}_1 \sim N\left(\mu_1, \frac{\sigma^2}{n_1}\right) \\ Y_{2j} &\sim N(\mu_2, \sigma^2) \implies \bar{Y}_2 \sim N\left(\mu_2, \frac{\sigma^2}{n_2}\right) \\ \implies \bar{Y}_1 - \bar{Y}_2 &\sim N\left(\mu_1 - \mu_2, \sigma^2 \left(\frac{1}{n_1} + \frac{1}{n_2}\right)\right) \end{aligned}$$

Therefore,

$$\frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{\sigma \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} = Z$$

But  $\sigma$  is unknown, so we can say

$$\frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim T_{n_1+n_2-2}$$

for some  $S_p$ , we need to find this.

The calculation of the MLE

$$\begin{aligned} \hat{\mu}_1 &= \frac{1}{n_1} \sum_{i=1}^{n_1} y_{1i} \\ \hat{\mu}_2 &= \frac{1}{n_2} \sum_{j=1}^{n_2} y_{2j} \\ \hat{\sigma}^2 &= \frac{1}{n_1 + n_2} \left[ \sum_{i=1}^{n_1} (y_{1i} - \bar{y}_1)^2 + \sum_{j=1}^{n_2} (y_{2j} - \bar{y}_2)^2 \right] = \frac{1}{n_1 + n_2} [(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2] \\ S_p^2 &= \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} \end{aligned}$$

Check  $E(S_p^2) = \sigma^2$ ; that is,  $S_p^2$  is an unbiased estimator for  $\sigma^2$ . Hint: We already know  $E(S_1^2) = E(S_2^2) = \sigma^2$

**EXAMPLE 2.10.2.** Assume equal variances hold.

- $n_1 = 10$
- $n_2 = 10$
- $\bar{y}_1 = 10.4$
- $\bar{y}_2 = 9.0$
- $s_1 = 1.1314$
- $s_2 = 1.8742$

Test whether  $H_0: \mu_1 = \mu_2$  vs the two sided alternative.

Test statistic:

$$D = \left| \frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right| = \left| \frac{(\bar{Y}_1 - \bar{Y}_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \right|$$

$$d = \frac{\bar{y}_1 - \bar{y}_2}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} = \frac{10.4 - 9.0}{1.5480 \sqrt{\frac{1}{10} + \frac{1}{10}}} = 2.0223$$

where

$$s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} = \frac{(10 - 1)(1.1314)^2 + (10 - 1)(1.8742)^2}{10 + 10 - 2} = 2.3963458$$

Thus,  $s_p = 1.5480$  and  $d = 2.0223$ . Look in the table with  $df = 18$ ,  $t = 2.10 \rightarrow p = 0.975$ .

$$p\text{-value} < 5\%$$

reject  $H_0$ .

Final points:

- Relationship with SLRM?
- A look ahead

## 2.11 2020-04-01: Large Samples and Paired Data

Roadmap:

- Independent population, unequal variance
- Paired Data
- Housekeeping: [evaluate.uwaterloo.ca](http://evaluate.uwaterloo.ca)
- Recap

The following are equivalent:

- $H_1: \mu_1 = \mu_2$
- Confidence interval:  $\mu_1 - \mu_2 = 0$

Recap: Equal variances:

$$Y_{1i} \sim N(\mu_1, \sigma^2), Y_{2j} \sim N(\mu_2, \sigma^2)$$

Pivotal Quantity:

$$\frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim T_{n_1 + n_2 - 2} \implies (\bar{y}_1 - \bar{y}_2) \pm t^* s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

where

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

Test statistic is the absolute value of above.

Unequal variances, large samples, independent population

$$Y_{1i} \sim N(\mu, \sigma_1^2), Y_{2j} \sim N(\mu_2, \sigma_2^2)$$

where  $i = 1, \dots, n_1$  and  $j = 1, \dots, n_2$ .

**THEOREM 2.11.1.** *If  $n_1$  and  $n_2$  are large, then*

$$\frac{(\bar{Y}_1 - \bar{Y}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim Z$$

The 95% confidence interval; that is, we solve  $P(-1.96 \leq Z \leq 1.96) = 0.95$  where  $Z$  is defined as in the theorem is:

$$(\bar{y}_1 - \bar{y}_2) \pm z^* \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

where  $z^* = 1.96$ . To test  $H_0: \mu_1 = \mu_2$ , check if 0 is within the interval.

**EXAMPLE 2.11.2.**

- $n_1 = 278$
- $n_2 = 345$
- $\bar{y}_1 = 60.2$
- $\bar{y}_2 = 58.1$
- $s_1 = 10.16$
- $s_2 = 9.02$

Find the 95% confidence interval for  $\mu_1 - \mu_2$ .

**Solution.**

$$(\bar{y}_1 - \bar{y}_2) \pm z^* \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

yields

$$[0.57, 3.63]$$

Suppose we are given  $H_0: \mu_1 = \mu_2 \iff \mu_1 - \mu_2 = 0$  at 5%, is this reasonable? No, since 0 is not within the interval above  $\implies p\text{-value} < 0.05$ .

Paired Data: Natural 1 – 1 map between the units of the population.

(i) Examples

(ii) Idea of Pivotal Quantity

(iii) Example

(i)

- Before and after
- Same car, same driver, number of miles travelled between fuel A and fuel B (not independent)

$$\begin{pmatrix} b_1 \\ a_1 \end{pmatrix}, \dots, \begin{pmatrix} b_n \\ a_n \end{pmatrix}$$

where each  $b_i$  are before data and each  $a_i$  are after data.

$$B_i \sim N(\mu_1, \sigma_1^2)$$

$$A_i \sim N(\mu_2, \sigma_2^2)$$

these are pairs, so let's subtract them

$$(B_i - A_i) = Y_i \sim N(\mu_1 - \mu_2, \sigma^2)$$

for some  $\sigma^2$  (there will be covariance within there). We are testing  $H_0: \mu = 0$ . Population of differences ( $B_i$ 's vs  $A_i$ 's)

**EXAMPLE 2.11.3.** See Table 6.3 in the course notes for the data. Step 1: Construct  $y_i = b_i - a_i$  for each  $i \in [1, n]$ .

$$Y_i \sim N(\mu, \sigma^2)$$

and test  $H_0: \mu = 0$ .

- $\bar{y} = -0.020$
- $s = 0.411$
- $d = \frac{\bar{y}}{s/\sqrt{n}} \sim T_{n-1}$  where  $n - 1 = 19$
- Confidence interval:  $[-0.212, 0.172]$

$$\bar{y} + t^*s/\sqrt{n}, t^* = \text{column 19, row 0.975.}$$

0 falls within the confidence interval, so the  $p$ -value is less than 5%.

### Final points

- (i) Case I: Equal variance, independent samples
- (ii) Case II: Unequal variance, independent samples, large sample sizes
- (iii) Case III: Paired data

We ignored one case: small sample sizes, unequal variances (we don't worry about it in this course).

Typically, in paired data the two variables are not independent, but positively correlated, however the variance is  $\sigma_1^2 + \sigma_2^2 - 2\text{Cov}(b_i, a_i)$  where  $\text{Cov}(b_i, a_i) > 0$  if the variance is lower, the variances are more accurate. We should always go for the paired method iff the covariance is positively correlated.

## 2.12 2020-03-02: The Big Picture–Take 2

### Roadmap

- (i) The big picture
- (ii) Two examples

Example 1: Check whether a die is fair

- $\theta_i = P(i^{\text{th}} \text{ face})$  where  $i = 1, \dots, 6$
- $H_0: \theta_1 = \theta_2 = \dots = \theta_6 = \frac{1}{6}$
- $\theta = (\theta_1, \dots, \theta_6)$

If  $H_0$  was true, then the expected frequency would be close to the observed frequency.

	Observed Frequency	Expected Frequency
1	48	50
2	72	50
3	60	50
4	40	50
5	40	50
6	40	50

The question we want to answer is how close is close enough?

Example 2:  $W_1, \dots, W_n \sim \text{Poi}(\mu)$ .  $H_0: W_i \sim \text{Poi}(\mu)$ .

	Observed Frequency	Expected Frequency
0	$y_0$	$e_0$
1	$y_1$	$e_1$
2	$y_2$	$e_2$
3	$y_3$	$e_3$
$\geq 4$	$y_4$	$e_4$

where

$$e_i = n \times \frac{e^{-\hat{\mu}} \hat{\mu}^i}{i!}$$

### Multinomial

- Extension to the Binomial
- Distribution function
- Likelihood function
- MLE
- LRTS

Distribution function and likelihood function:

$$\frac{n!}{x_1! \dots x_k!} \theta_1^{x_1} \dots \theta_k^{x_k}$$

where  $x_1 + \dots + x_k = n$ .

The MLE is

$$\hat{\theta}_i = \frac{x_i}{n}$$

for each  $i \in [1, k]$ .

LRTS: If  $n$  is large, we can construct a LRTS to test  $H_0$ .

$$\Lambda(\theta) = -2 \ln \left[ \frac{L(\theta)}{L(\hat{\theta})} \right]$$

The particular form is,

$$\Lambda = 2 \sum_{i=1}^n \left[ Y_i \ln \left( \frac{Y_i}{E_i} \right) \right] \sim \chi_{k-\ell-1}^2$$

where

- $Y_i$  is the observed frequency,
- $E_i$  is the expected frequency if  $H_0$  was true,

- $k$  is the number of categories, and
- $\ell$  is the number of components of  $\theta$  we need to estimate under  $H_0$ .

**EXAMPLE 2.12.1.**  $H_0: \theta_1 = \cdots = \theta_6 = \frac{1}{6}$ .

	Observed Frequency	Expected Frequency
1	48	50
2	72	50
3	60	50
4	40	50
5	40	50
6	40	50

Calculate the  $p$ -value.

**Solution.**

$$\lambda = 2 \sum_{i=1}^6 \left[ y_i \ln \left( \frac{y_i}{e_i} \right) \right]$$

Then, let  $n$  the number of categories and  $k$  be the number of parameters we estimate under  $H_0$ . So the degrees of freedom in our case is  $6 - k - 1 = 5$  where  $k = 0$  since we are given all of the  $\theta_i$ 's.

$$\begin{aligned} p\text{-value} &= P(\Lambda \geq \lambda) \\ &= P(\chi_5^2 \geq \lambda) \end{aligned}$$

**REMARK 2.12.2.** In the example we have different letters for the degrees of freedom compared to our derivation to match the course notes.

## 2.13 2020-03-02: Goodness of Fit

Roadmap:

- Recap
- Goodness of fit

Discrete  $\rightarrow$  Poisson

Continuous  $\rightarrow$  Exponential

These results will only hold for large  $n$ . Also, the observed frequencies should be at least 5.

**EXAMPLE 2.13.1** (Poisson). Let  $W_i$  be the number of service interruptions on the  $i^{\text{th}}$  day over 200 days.

Number of interruptions	0	1	2	3	4	5	$\geq 5$
Observed Frequency ( $y_i$ )	64	71	42	18	4	1	0
Expected Frequency ( $e_j$ )	63.3	72.8	41.8	16.0	4.6	1.3	$\cdots$

Is the Poisson model appropriate?  $H_0: W \sim Poi(\theta)$ . We must calculate the expected frequencies (done above, formula below).

- We estimate:  $\hat{\theta} = \frac{1}{n} \sum_{i=1}^n w_i = 1.15$
- $e_j = n \times \frac{e^{-\hat{\theta}} \hat{\theta}^j}{j!}$

$$\lambda_j = 2 \sum_{i=1}^n \left[ y_i \ln \left( \frac{y_i}{e_i} \right) \right] = 0.43$$

$$\begin{aligned}
 p\text{-value} &= P(\Lambda \geq \lambda) \\
 &= P(\chi_{5-1-1}^2 \geq \lambda) \\
 &= P(\chi_3^2 \geq 0.43) \\
 &\geq 0.9
 \end{aligned}$$

No evidence against  $H_0$ , so Poisson is a good model.

**EXAMPLE 2.13.2 (Exponential).**

Interval	[0, 100]	(100, 200]	(200, 300]	(300, 400]	(400, 600]	(600, 800]	> 800
$y_j$	29	22	12	10	10	9	8
$e_j$	27.6	20	14.4	...			

$H_0: W \sim \exp(\theta)$ .  $\hat{\theta} = \bar{w} = 310$

$$e_1 = n \times P[W \in [100, 200]] = n \times [F(200) - F(100)] = n \times \left(1 - e^{-\frac{200}{310}} - \left(1 - e^{-\frac{100}{310}}\right)\right)$$

$$\Lambda \sim \chi_{7-1-1}^2$$

Final points:

- (a) In all our problems above, we always try to convert to a multinomial.
- (b) Suppose we are given  $W \sim N(\mu, \sigma^2)$  with 5 intervals. Our LRTS will have  $df = 5 - 2 - 1 = 2$  where we subtract by 2 since we estimate  $\mu$  and  $\sigma$ . If we were given  $\sigma$ , we would have  $df = 5 - 1 - 1 = 3$ .
- (c) Final answer ( $p$ -value) will depend on how we divide our data into categories.

## 2.14 2020-03-02: Contingency Tables

Roadmap:

- (i) Independence of categorical variables
- (ii) Equality of proportions