, 32, 33, 34, 35, 36

Stat 231 - Statistics

0017

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Lecture 31, 32, 33, 34, 35, 36: July 12 - July 24, 2017

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# 31.1 Estimated Residuals

 $\hat{r_i} = \text{actual}$  - predicted.

## Standardized Estimated Residual

$$\hat{r_i} = \frac{\hat{r_i}}{s} \sim Z$$

where s is the standard error

# 31.2 Tests For The Regression Assumtion

The tests are graphical (and subjective) comes with experience

- Scatter Plot: We draw a scatter plot and check whether a linear relationship is appropriate
- Residual Plots
  - $\hat{r_i}$  's should be in a "small" band around zero
  - Variability in the  $\hat{r}_i$ 's should be more or less constant
  - Absence of any obvious patterns
- The QQ-plot. : If the assumptions are right, the q-q plot should be a 45 degree line

# 31.3 Two Population Problems

# Equality of means

- Matched pair populations
- Unmatched data : equal variance populations
- Unmatched data : unequal variances and large sample sizes

# Matched Pair

Consider the following:

$$B_1, \dots, B_n \sim N(\gamma_1, \sigma_1^2)$$
  
 $A_1, \dots, A_n \sim N(\gamma_2, \sigma_2^2)$ 

**Definition 31.1**  $(B_i, A_i) \rightarrow is$  a matched pair in the population, Given this this the units are the same or there is a natural match between the two populations

In this case the NULL hypothesis and Challenging view are

$$H_0: \gamma_1 = \gamma_2$$

$$H_1: \gamma_1 \neq \gamma_2$$

Define  $Y_i = A_i - B_i$ , so

$$Y_i \sim N(\gamma_2 - \gamma_1, \sigma_1^2 + \sigma_2^2)$$

Using this we find

$$\begin{split} D = \mid \frac{\bar{Y}}{S/\sqrt{n}} \mid \\ d = \mid \frac{\bar{y}}{S/\sqrt{n}} \mid \\ S = \frac{1}{n-1} \sum_{i} (Y_i - \bar{y}) \\ p - value = P(D \ge d) = P(\mid T_{n-1} \mid \ge d) \end{split}$$

## Unmatched Data

There is no natural pairing between the two populations.

Model

$$Y_{1i} \sim N(\gamma_1, \sigma^2)$$

$$Y_{2j} \sim N(\gamma_2, \sigma^2)$$

## First Method for Equal Variance

In this case, we're assuming two populations have the same variability.

From 1 
$$\hat{Y}_1 \sim N(\gamma_1, \sigma^2/n_1)$$

From 2 
$$\hat{Y}_1 \sim N(\gamma_2, \sigma^2/n_2)$$

Thus,

$$\hat{Y}_1 - \hat{Y}_2 \sim N(\gamma_1 - \gamma_2, \sigma^2(\frac{1}{n_1} + \frac{1}{n_1}))$$

So,

$$\begin{split} D = & | \frac{\hat{Y}_1 - \hat{Y}_2 - 0}{S\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} | \sim T_{n_1 + n_2 - 2} \\ S^2 = & \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2} \\ p - value = & P(D \ge d) = P(|T_{n_1 + n_2 - 2}| \ge d) \end{split}$$

### Second Method for Equal Variance

Define 
$$X = \begin{cases} 0 \text{ if population} = 1\\ 1 \text{ if population} = 2 \end{cases}$$

Using this you can draw a linear graph where  $\alpha = E(Y)$  and B = change in 1 unit, As a result the p-value can be found easily.

$$\begin{split} D = \mid \frac{\tilde{\beta} - 0}{S/\sqrt{S_{XX}}} \mid \\ d = \mid \frac{\hat{\beta} - 0}{S/\sqrt{S_{XX}}} \mid \\ p - value = P(D \ge d) = P(\mid T_{n_1 + n_2 - 2} \mid \ge d) \end{split}$$

## Unequal variance

$$Y_{1i} \sim G(\gamma_1, \sigma^2)$$
  
 $Y_{2i} \sim G(\gamma_2, \sigma^2)$ 

Assume  $n_1, n_2$  are large

$$D = \frac{(\bar{y}_1 - \bar{y} - 2) - (y_1 - y_2)}{\sqrt{(S_1^2/n_1) + (S_2^2/n_2)}}$$

# 31.4 Test For Goodness Of Fit

In so,e situations, the unknown parameter of interest is a vector

$$\varrho = (\theta_1, \dots, \theta_m)$$

$$H_0 = \varrho = \varrho(\alpha)$$

Recall:

$$\triangle(\theta) = -2\log\frac{L(\theta)}{L(\hat{\theta})} \sim X_1^2$$

**Theorem 31.2** If  $\theta$  is a vector then

$$\triangle(\theta) = -2\log\frac{L(\theta)}{L(\hat{\theta})} \sim X_n^2$$

Where n = the number of independent unrestricted parameters of  $\theta + the$  number of parameters estimated under  $H_0$ 

### For a Multinomial Problem

$$\triangle = 2\sum Y_i \cdot \ln \frac{Y_i}{E_i} \sim X^2 + n - 1 - 1$$

where

- $Y_i$  = observation frequency of category i
- $E_i$  = expected frequency of category i if  $H_0$  is true

Given this we can determine that

- $E_i = n \times p_i$
- $p_i$  = expected probabilities of category i under H
- n = sample size

### Poisson Problem

Divide the sata into categories and compute the observed frequency of each category

$$\hat{p_i} = \frac{e^{\bar{x}}\bar{x}^i}{i!}$$

$$E_i = nxp_i$$

### **Exponential Problem**

Produce a table consisting of the frequency associated with the interval, then use the following to determine the expected values

$$\hat{\theta} = \bar{x}$$

$$\hat{p_i} = \int_{interval_{min}}^{interval_{max}} \frac{1}{\bar{x}} e^{-\frac{2}{\bar{x}}} dx$$

### **Restrictions:**

- n needs to be large
- $n_i \geq 5 \forall i$

# Two Categorical Variables

$$e_{ij} = \frac{\text{ith Row Total} \times \text{jth Column Total}}{\text{Total sample size}}$$
 
$$\lambda = 2 \sum_i \sum_j y_{ij} \ln \frac{y_{ij}}{e_{ij}}$$

### Normal Problem

$$H_0: X_i \sim G(\gamma, \sigma^2)$$

1. Divide the data into mutually exclusive and exhaustive categories and calculate the frequencies of each category.

We need atleast 3 categories

2. Assume the null hypothesis is true Estimate  $\hat{p}_i$  = estimate probability of each category.

$$\gamma = x$$

$$p_i = P(\frac{interval_{min} - \bar{x}}{\text{number of elements}} \le x \le \frac{interval_{max} - \bar{x}}{\text{number of elements}}$$

3. Calculate  $e_i$ 

$$e_i = n \times \hat{p_i}$$

4. Compute  $\lambda$ 

$$\lambda = 2\sum_{i} y_i \ln \frac{y_i}{e_i}$$

5. Compute the p-value

$$p-value = P(X_{\text{number of categories}}^2 \ge \lambda)$$

#### General Problem

$$f(y_i; \theta) = \frac{2y}{\theta} e^{-y^2/\theta} y \ge 0$$
  
$$H_0: Y_i \sim f(y_i; \theta);$$

• Compute  $\theta = MLE$  for  $\theta$  from your data and use that to compute  $\hat{p_i}$  and thus  $e_i$ 

# Pearson's Chi-Squared Statistic:

$$k = \sum_{i=1}^{n} \frac{(Y_i - E_i)^2}{E_i}$$

This also follows  $X^2$  with the same degree of freedom, but is less powerful than the LRTS.

# 31.5 Design of Experiments

We have to design the experiments in such as way that confounding variables are taken into account.

- Blocking: we collect data holding the value if confounding variable constant, the problem is identifying all variables.
- Randomization : we divide the data into two groups with the expectation that confounding factors cancel each other.