

# Data modeling: CSCI E-106

Applied Linear Statistical Models

Chapter 2

# Summary

The linear regression function with one predictor variable:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i, \quad i = 1, \dots, n$$

- $Y_i$ : the value of response variable in the  $i$ th trial
- $\beta_0, \beta_1$ : parameters
- $X_i$ : a known constant; the value of the predictor variable in the  $i$ th trial
- $\varepsilon_i$ : random error term;  $E\{\varepsilon_i\} = 0$ ;  $\sigma^2(\varepsilon_i) = \sigma^2$ ; uncorrelated ( $\sigma\{\varepsilon_i, \varepsilon_j\} = 0, i \neq j$ )

How to obtain the estimators  $b_0, b_1$  ?

$$Q = \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2 \quad \Rightarrow \quad \begin{aligned} b_1 &= \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2} \\ b_0 &= \frac{1}{n} \left( \sum Y_i - b_1 \sum X_i \right) = \bar{Y} - b_1 \bar{X} \end{aligned}$$

1. The sum of the residuals is zero:

$$\sum_{i=1}^n e_i = 0 \quad (1.17)$$

Table 1.2, column 4, illustrates this property for the Toluca Company example. Rounding errors may, of course, be present in any particular case, resulting in a sum of the residuals that does not equal zero exactly.

2. The sum of the squared residuals,  $\sum e_i^2$ , is a minimum. This was the requirement to be satisfied in deriving the least squares estimators of the regression parameters since the criterion  $Q$  in (1.8) to be minimized equals  $\sum e_i^2$  when the least squares estimators  $b_0$  and  $b_1$  are used for estimating  $\beta_0$  and  $\beta_1$ .

3. The sum of the observed values  $Y_i$  equals the sum of the fitted values  $\hat{Y}_i$ :

$$\sum_{i=1}^n Y_i = \sum_{i=1}^n \hat{Y}_i \quad (1.18)$$

This property is illustrated in Table 1.2, columns 2 and 3, for the Toluca Company example. It follows that the mean of the fitted values  $\hat{Y}_i$  is the same as the mean of the observed values  $Y_i$ , namely,  $\bar{Y}$ .

4. The sum of the weighted residuals is zero when the residual in the  $i$ th trial is weighted by the level of the predictor variable in the  $i$ th trial:

$$\sum_{i=1}^n X_i e_i = 0 \quad (1.19)$$

5. A consequence of properties (1.17) and (1.19) is that the sum of the weighted residuals is zero when the residual in the  $i$ th trial is weighted by the fitted value of the response variable for the  $i$ th trial:

$$\sum_{i=1}^n \hat{Y}_i e_i = 0 \quad (1.20)$$

6. The regression line always goes through the point  $(\bar{X}, \bar{Y})$ .

## Chapter 2: Inferences in Regression and Correlation Analysis

Inferences concerning:

- the regression parameters  $\beta_0$  and  $\beta_1$
- interval estimation of  $\beta_0$  and  $\beta_1$  tests about them
- interval estimation of  $E(Y)$  of the probability distribution of  $Y$  for given  $X$
- prediction intervals of a new observation  $Y$
- confidence bands for the regression line

# Normal Error Regression Model

Assume that the normal error regression model is applicable:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

- $\beta_0$  and  $\beta_1$  are parameters
- $X_i$  are known constants
- $\varepsilon_i \sim N(0, \sigma^2)$ : are independent
- $Y_i$ : independently, normally distributed
- A linear combination of independent normal random variables is normally distributed

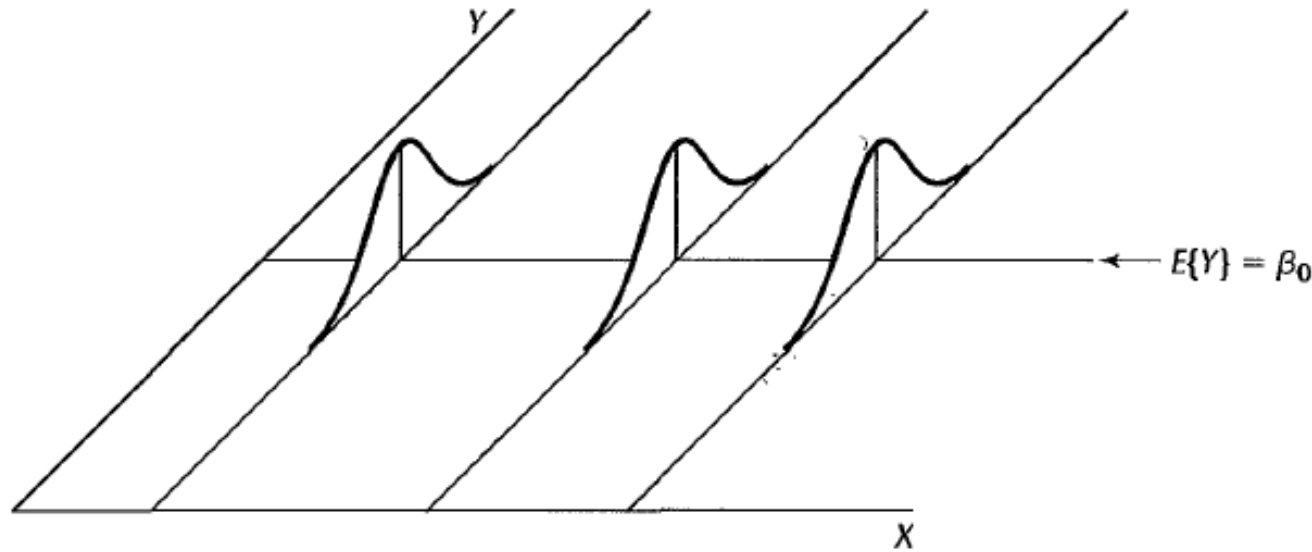
# Inferences about the slope $\beta_1$ of the regression line

- Market research analyst studying the relation between sales ( $Y$ ) and advertising expenditures ( $X$ ) may wish to obtain an interval estimate of  $\beta_1$ , because it will provide information as to how many additional sales dollars, on the average, are generated by an additional dollar of advertising expenditure.
- At times, tests concerning  $\beta_1$  are of interest, particularly one of the form:

$$H_0 : \beta_1 = 0;$$

$$H_a : \beta_1 \neq 0.$$

# Inferences about the slope $\beta_1$ of the regression line, cont'd



- $\beta_1 = 0 \Rightarrow$  no linear association between  $Y$  and  $X$
- The regression line is horizontal. The means of  $Y$ :  $E\{Y\} = \beta_0$ .
- The probability distribution of  $Y$  are identical at all levels of  $X$

# Sampling Distribution of $b_1$

- The sample distribution of  $b_1$  refers to the different values of  $b_1$  that would be obtained with repeated sampling when the levels of the predictor variable  $X$  are held constant from sample to sample.

$$b_1 = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}$$

- For normal error regression model, the sampling distribution of  $b_1$  is normal, with mean and variance

$$E\{b_1\} = \beta_1$$
$$\sigma^2\{b_1\} = \frac{\sigma^2}{\sum (X_i - \bar{X})^2}$$

# Sampling Distribution of $b_1$ , *cont'd*

- $b_1$  as Linear Combination of the  $Y_i$  • It can be shown that  $b_1$  can be expressed as follows:

$$b_1 = \sum k_i Y_i$$

where:

$$k_i = \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2}$$

The coefficients  $k_i$  have a number of **interesting properties** that will be used later:

$$\sum k_i = 0 \quad (2.5)$$

$$\sum k_i X_i = 1 \quad (2.6)$$

$$\sum k_i^2 = \frac{1}{\sum (X_i - \bar{X})^2} \quad (2.7)$$



## Sampling Distribution of $b_1$ , *cont'd*

- **Mean.** The unbiasedness of the point estimator  $b_1$  stated earlier in the Gauss-Markov theorem (1.11), is easy to show:

$$\begin{aligned} E\{b_1\} &= E\left\{\sum k_i Y_i\right\} = \sum k_i E\{Y_i\} = \sum k_i (\beta_0 + \beta_1 X_i) \\ &= \beta_0 \sum k_i + \beta_1 \sum k_i X_i \end{aligned}$$

By the equations 2.5 and 2.6 in the previous slide, we then obtain  $E\{b_1\} = \beta_1$ .

- **Variance.** The variance of  $b_1$  can be derived readily. We need to remember that the  $Y_i$  are independent random variables, each with variance  $\sigma^2$ , and that the  $k_i$  are constants. Hence, we obtain:

$$\begin{aligned} \sigma^2\{b_1\} &= \sigma^2\left\{\sum k_i Y_i\right\} = \sum k_i^2 \sigma^2\{Y_i\} \\ &= \sum k_i^2 \sigma^2 = \sigma^2 \sum k_i^2 \\ &= \sigma^2 \frac{1}{\sum (X_i - \bar{X})^2} \end{aligned}$$

## Sampling Distribution of $b_1$ , *cont'd*

- Estimated Variance. We can estimate the variance of the sampling distribution of  $b_1$  :

$$\sigma^2\{b_1\} = \frac{\sigma^2}{\sum (X_i - \bar{X})^2}$$

- by replacing the parameter  $\sigma^2$  with  $MSE$ , the unbiased estimator of  $\sigma^2$ :

$$s^2\{b_1\} = \frac{MSE}{\sum (X_i - \bar{X})^2}$$

- The point estimator  $s^2\{b_1\}$  is an unbiased estimator of  $\sigma^2\{b_1\}$ . Taking the positive square root, we obtain  $s\{b_1\}$ , the point estimator of  $\sigma\{b_1\}$ .

## Theorem 1:

- The estimator  $b_1$  has minimum variance among all unbiased linear estimators of:

$$\widehat{\beta}_1 = \sum c_i Y_i$$

Where  $c_i$  are arbitrary constants which holds  $\sum c_i = 0$ ;  $\sum c_i X_i = 1$

We now prove this. Since  $b_1$  is required to be unbiased, the following must hold:

$$\begin{aligned} E\{\widehat{\beta}_1\} &= E\{\sum c_i Y_i\} = \sum c_i E(Y_i) = \beta_1 \text{ then} \\ \sum c_i E(Y_i) &= \sum c_i E(\beta_0 + \beta_1 X_i) = \beta_0 \sum c_i + \beta_1 \sum c_i X_i \end{aligned}$$

By using conditions above  $\sum c_i = 0$ ;  $\sum c_i X_i = 1$ , it follows that

$$E\{\widehat{\beta}_1\} = \beta_1$$

$$\sigma^2\{\widehat{\beta}_1\} = \sum c_i^2 \sigma^2\{Y_i\} = \sigma^2 \sum c_i^2$$

## Theorem 1, cont'd

- We now prove that  $b_1$  has minimum variance among all unbiased linear estimators of:

$$\widehat{\beta}_1 = \sum c_i Y_i$$

under the conditions that  $\sum c_i = 0$ ;  $\sum c_i X_i = 1$

$$\begin{aligned}\sigma^2\{\hat{\beta}_1\} &= \sigma^2\{\sum c_i Y_i\} = \sum c_i^2 \sigma^2(Y_i) \\ &= \sum c_i^2 \sigma^2(Y_i) = \sum c_i^2 \sigma^2 = \sigma^2 \sum c_i^2\end{aligned}$$

Let us define  $c_i = d_i + k_i$ , where  $k_i$  are the least squares constants (remember from slide 8 that  $\sigma^2\{b_1\} = \sigma^2 \sum k_i^2$ ), now we can write that



$$\begin{aligned}\sigma^2\{\hat{\beta}_1\} &= \sigma^2 \sum c_i^2 = \sigma^2 \sum (d_i + k_i)^2 = \sigma^2 (\sum d_i^2 + \sum k_i^2 + \sum d_i k_i) = \sigma^2 \sum d_i^2 + \sigma^2 \sum k_i^2 + \sum d_i k_i \\ &= \sigma^2 \sum d_i^2 + \sigma^2\{b_1\} + \sum d_i k_i\end{aligned}$$

## Theorem 1, cont'd

- We will show that  $\sum d_i k_i = 0$

$$\begin{aligned}\sum k_i d_i &= \sum k_i (c_i - k_i) \\ &= \sum c_i k_i - \sum k_i^2 \\ &= \sum c_i \left[ \frac{X_i - \bar{X}}{\sum (X_i - \bar{X})^2} \right] - \frac{1}{\sum (X_i - \bar{X})^2} \\ &= \frac{\sum c_i X_i - \bar{X} \sum c_i}{\sum (X_i - \bar{X})^2} - \frac{1}{\sum (X_i - \bar{X})^2} = 0\end{aligned}$$

- $\sigma^2\{\hat{\beta}_1\} = \sigma^2 \sum d_i^2 + \sigma^2\{b_1\} + \sum d_i k_i = \sigma^2 \sum d_i^2 + \sigma^2\{b_1\}$
- Note that the smallest values of  $\sum d_i^2$  is 0, it occurs if all  $d_i = 0$ , which implies that  $c_i = k_i$ . Thus, this proves the theorem.

# Sampling Distribution of $(b_1 - \beta_1)/s\{b_1\}$

- Since  $b_1$ , is normally distributed, we know that the standardized statistic  $\frac{b_1 - \beta_1}{\sigma(b_1)}$  is a standard normal variable.
- $\sigma(b_1)$  is estimated by  $s(b_1)$ .

$\frac{b_1 - \beta_1}{s(b_1)}$  is distributed as  $t(n-2)$ , t distribution with  $n-2$  degree of freedom.

Proof:

Reminder:

$Z_i$  are independent identical distributed (iid) with  $\sim N(0,1)$ :

- $\sum_{i=1}^n Z_i \sim N(0,n)$
- $Z_i^2 \sim \chi^2(1)$  and  $\sum_{i=1}^n Z_i^2 \sim \chi^2(n)$

The pdf of a Normal distribution  $N(\mu, \sigma^2)$

$$f(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/2\sigma^2}$$

The pdf of a Normal distribution  $N(0,1)$

$$f_Z(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$$

## Sampling Distribution of $(b_1 - \beta_1)/s\{b_1\}$ , cont'd

### Chi-square Distribution

$$f(x|p) = \frac{1}{\Gamma(p/2)2^{p/2}} x^{(p/2)-1} e^{-x/2}, \quad 0 < x < \infty,$$

Where  $\Gamma$  is the gamma function.

$t(v) = \frac{Z}{\sqrt{\frac{\chi^2(v)}{v}}}$  is the t-distribution with  $v$  degree of freedom, where  $Z$  is the

standard normal distribution and  $\chi^2(v)$  is the chi square distribution with  $v$  degree of freedom.

## Sampling Distribution of $(b_1 - \beta_1)/s\{b_1\}$ , cont'd

- First we need to *rewrite*  $\frac{b_1 - \beta_1}{s(b_1)}$
- $\frac{b_1 - \beta_1}{s(b_1)} * \frac{\sigma(b_1)}{\sigma(b_1)} = \frac{b_1 - \beta_1}{\sigma(b_1)} * \frac{\sigma(b_1)}{s(b_1)} = \frac{b_1 - \beta_1}{\sigma(b_1)} \div \frac{s(b_1)}{\sigma(b_1)} = Z \div \frac{s(b_1)}{\sigma(b_1)}$

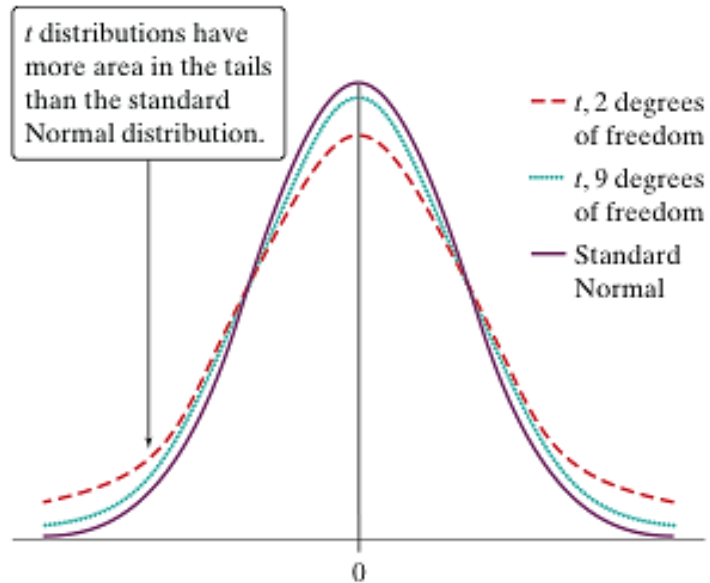
$$\frac{s^2\{b_1\}}{\sigma^2\{b_1\}} = \frac{\frac{MSE}{\sum(X_i - \bar{X})^2}}{\sigma^2} = \frac{MSE}{\sigma^2} = \frac{SSE}{\sigma^2}$$
$$= \frac{SSE}{\sigma^2(n-2)} \sim \frac{\chi^2(n-2)}{n-2}$$

- Then,  $\frac{b_1 - \beta_1}{s\{b_1\}} \sim \frac{z}{\sqrt{\frac{\chi^2(n-2)}{n-2}}}$  is distributed with *t distribution with n-2 degree of freedom*



# The $t$ Distributions

When comparing the density curves of the standard Normal distribution and  $t$  distributions, several facts are apparent:



- ✓ The density curves of the  $t$  distributions are similar in shape to the standard Normal curve.
- ✓ The spread of the  $t$  distributions is a bit larger than that of the standard Normal distribution.
- ✓ The  $t$  distributions have more probability in the tails and less in the center than does the standard Normal.
- ✓ As the degrees of freedom increase, the  $t$  density curve becomes ever closer to the standard Normal curve.

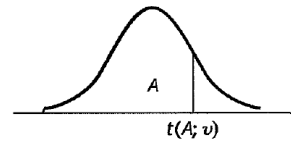
We can use Table B.2 in the Appendix of the book to determine critical values  $t^*$  for  $t$  distributions with different degrees of freedom.

# T TABLE

Appendix B Tables 1317

**TABLE B.2**  
Percentiles  
of the  $t$   
Distribution.

Entry is  $t(A; \nu)$  where  $P\{t(\nu) \leq t(A; \nu)\} = A$



$\nu$	A						
	.60	.70	.80	.85	.90	.95	.975
1	0.325	0.727	1.376	1.963	3.078	6.314	12.706
2	0.289	0.617	1.061	1.386	1.886	2.920	4.303
3	0.277	0.584	0.978	1.250	1.638	2.353	3.182
4	0.271	0.569	0.941	1.190	1.533	2.132	2.776
5	0.267	0.559	0.920	1.156	1.476	2.015	2.571
6	0.265	0.553	0.906	1.134	1.440	1.943	2.447
7	0.263	0.549	0.896	1.119	1.415	1.895	2.365
8	0.262	0.546	0.889	1.108	1.397	1.860	2.306
9	0.261	0.543	0.883	1.100	1.383	1.833	2.262
10	0.260	0.542	0.879	1.093	1.372	1.812	2.228
11	0.260	0.540	0.876	1.088	1.363	1.796	2.201
12	0.259	0.539	0.873	1.083	1.356	1.782	2.179
13	0.259	0.537	0.870	1.079	1.350	1.771	2.160
14	0.258	0.537	0.868	1.076	1.345	1.761	2.145
15	0.258	0.536	0.866	1.074	1.341	1.753	2.131
16	0.258	0.535	0.865	1.071	1.337	1.746	2.120
17	0.257	0.534	0.863	1.069	1.333	1.740	2.110
18	0.257	0.534	0.862	1.067	1.330	1.734	2.101
19	0.257	0.533	0.861	1.066	1.328	1.729	2.093
20	0.257	0.533	0.860	1.064	1.325	1.725	2.086
21	0.257	0.532	0.859	1.063	1.323	1.721	2.080
22	0.256	0.532	0.858	1.061	1.321	1.717	2.074
23	0.256	0.532	0.858	1.060	1.319	1.714	2.069
24	0.256	0.531	0.857	1.059	1.318	1.711	2.064
25	0.256	0.531	0.856	1.058	1.316	1.708	2.060
26	0.256	0.531	0.856	1.058	1.315	1.706	2.056
27	0.256	0.531	0.855	1.057	1.314	1.703	2.052
28	0.256	0.530	0.855	1.056	1.313	1.701	2.048
29	0.256	0.530	0.854	1.055	1.311	1.699	2.045
30	0.256	0.530	0.854	1.055	1.310	1.697	2.042
40	0.255	0.529	0.851	1.050	1.303	1.684	2.021
60	0.254	0.527	0.848	1.045	1.296	1.671	2.000
120	0.254	0.526	0.845	1.041	1.289	1.658	1.980
$\infty$	0.253	0.524	0.842	1.036	1.282	1.645	1.960

**TABLE B.2**  
(concluded)  
Percentiles  
of the  $t$   
Distribution.

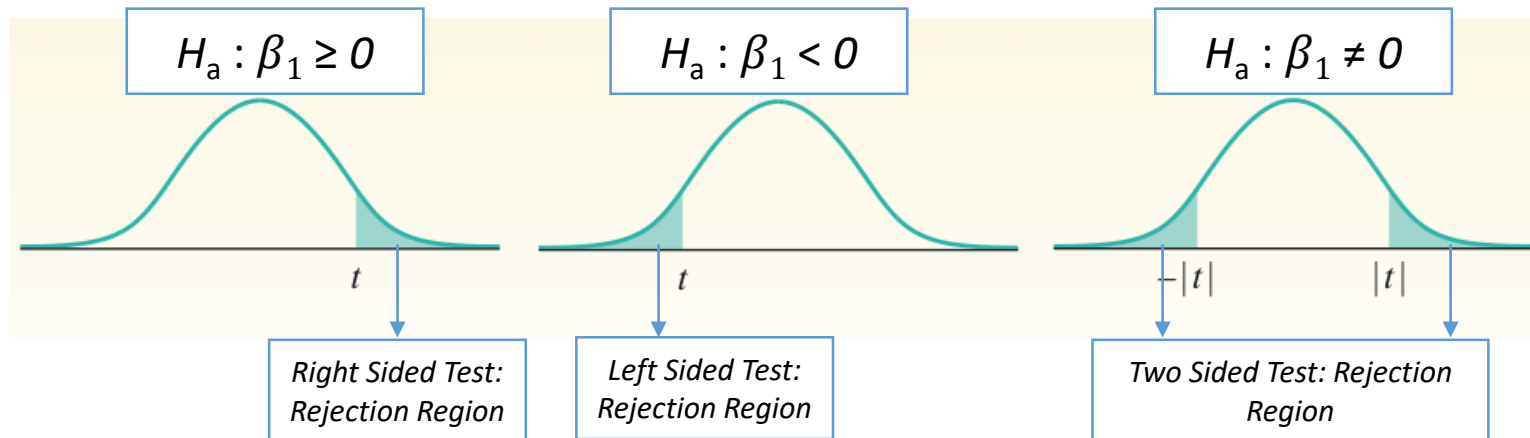
$\nu$	A						
	.98	.985	.99	.9925	.995	.9975	.9995
1	15.895	21.205	31.821	42.434	63.657	127.322	636.590
2	4.849	5.643	6.965	8.073	9.925	14.089	31.598
3	3.482	3.896	4.541	5.047	5.841	7.453	12.924
4	2.999	3.298	3.747	4.088	4.604	5.598	8.610
5	2.757	3.003	3.365	3.634	4.032	4.773	6.869
6	2.612	2.829	3.143	3.372	3.707	4.317	5.959
7	2.517	2.715	2.998	3.203	3.499	4.029	5.408
8	2.449	2.634	2.896	3.085	3.355	3.833	5.041
9	2.398	2.574	2.821	2.998	3.250	3.690	4.781
10	2.359	2.527	2.764	2.932	3.169	3.581	4.587
11	2.328	2.491	2.718	2.879	3.106	3.497	4.437
12	2.303	2.461	2.681	2.836	3.055	3.428	4.318
13	2.282	2.436	2.650	2.801	3.012	3.372	4.221
14	2.264	2.415	2.624	2.771	2.977	3.326	4.140
15	2.249	2.397	2.602	2.746	2.947	3.286	4.073
16	2.235	2.382	2.583	2.724	2.921	3.252	4.015
17	2.224	2.368	2.567	2.706	2.898	3.222	3.965
18	2.214	2.356	2.552	2.689	2.878	3.197	3.922
19	2.205	2.346	2.539	2.674	2.861	3.174	3.883
20	2.197	2.336	2.528	2.661	2.845	3.153	3.849
21	2.189	2.328	2.518	2.649	2.831	3.135	3.819
22	2.183	2.320	2.508	2.639	2.819	3.119	3.792
23	2.177	2.313	2.500	2.629	2.807	3.104	3.768
24	2.172	2.307	2.492	2.620	2.797	3.091	3.745
25	2.167	2.301	2.485	2.612	2.787	3.078	3.725
26	2.162	2.296	2.479	2.605	2.779	3.067	3.707
27	2.158	2.291	2.473	2.598	2.771	3.057	3.690
28	2.154	2.286	2.467	2.592	2.763	3.047	3.674
29	2.150	2.282	2.462	2.586	2.756	3.038	3.659
30	2.147	2.278	2.457	2.581	2.750	3.030	3.646
40	2.123	2.250	2.423	2.542	2.704	2.971	3.551
60	2.099	2.223	2.390	2.504	2.660	2.915	3.460
120	2.076	2.196	2.358	2.468	2.617	2.860	3.373
$\infty$	2.054	2.170	2.326	2.432	2.576	2.807	3.291

# The One-Sample $t$ Test

To test the hypothesis  $H_0 : \beta_1 = 0$ , compute the one-sample  $t$  statistic:

$$t = \frac{b_1}{s(b_1)}$$

Find the  $P$ -value by calculating the probability (at degree of freedom =  $n - 2$ ) of getting a  $t$  statistic this large or larger *in the direction specified by the alternative hypothesis  $H_a$* .



# Hypothesis testing for $\beta_1$

$(1-\alpha/2)\%$  confidence interval for  $\beta_1$  is

$$b_1 \pm t(1 - \alpha/2; n - 2)s(b_1) = [b_1 - t(1 - \alpha/2; n - 2)s(b_1), b_1 + t(1 - \alpha/2; n - 2)s(b_1)]$$

Example: Consider the Toluca Company example of Chapter 1.

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$n = 25$	$\bar{X} = 70.00$
$b_0 = 62.37$	$b_1 = 3.5702$
$\hat{Y} = 62.37 + 3.5702X$	$SSE = 54,825$
$\sum(X_i - \bar{X})^2 = 19,800$	$MSE = 2,384$
$\sum(Y_i - \hat{Y})^2 = 307,203$	

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The regression equation is  
 $Y = 62.4 + 3.57 X$

Predictor	Coef	Stdev	t-ratio	p
Constant	62.37	26.18	2.38	0.026
X	3.5702	0.3470	10.29	0.000

$s = 48.82$        $R\text{-sq} = 82.2\%$        $R\text{-sq(adj)} = 81.4\%$

Analysis of Variance

SOURCE	DF	SS	MS	F	p
Regression	1	252378	252378	105.88	0.000
Error	23	54825	2384		
Total	24	307203			

## Inferences about the slope $\beta_0$ of the regression line

- There are only infrequent occasions when we wish to make inferences concerning  $\beta_0$ , the intercept of the regression line. These occur when the scope of the model includes  $X = 0$  times.
- The point estimator  $b_0$  was shown in Chapter as follow:

$$b_0 = \bar{Y} - b_1 \bar{X}$$

- The sampling distribution of  $b_0$  is normal, with mean and variance:

$$E\{b_0\} = \beta_0$$
$$\sigma^2\{b_0\} = \sigma^2 \left[ \frac{1}{n} + \frac{\bar{X}^2}{\sum (X_i - \bar{X})^2} \right]$$

## Inferences about the slope $\beta_0$ of the regression line, cont'd

- The normality of the sampling distribution of  $b_0$  follows because  $b_0$ , like  $b_1$ , is a linear combination of the observations  $Y_i$
- The results for the mean and variance of the sampling distribution of  $b_0$  can be obtained in similar fashion as those for  $b_1$
- An estimator of a  $\sigma^2(b_0)$  is obtained by replacing a  $\sigma^2$  by its point estimator MSE:

$$s^2\{b_0\} = MSE \left[ \frac{1}{n} + \frac{\bar{X}^2}{\sum (X_i - \bar{X})^2} \right]$$

- The positive square root,  $s(b_0)$ , is an estimator of  $\sigma(b_0)$

# Sampling Distribution of $(b_o - \beta_o)/s(b_o)$

- Similar to  $b_1$ , the sampling distributions follows a t distribution with  $n-2$  degree of freedom.

$$\frac{b_o - \beta_o}{s(b_o)} \sim t(n-2)$$

- $(1-\alpha/2)\%$  confidence interval for  $\beta_o$  is

$$b_o \pm t(1 - \alpha/2; n - 2)s(b_o) = [b_o - t(1 - \alpha/2; n - 2)s(b_o) , b_o + t(1 - \alpha/2; n - 2)s(b_o)]$$

# Example: Toluca Example

## Long Way

- `n<-length(lotsize)`
- `alpha<-0.05`
- `tdf<-qt(1-alpha/2,n-2)`
- `Sxx<-sum((lotsize-mean(lotsize))^2)`
- `b1<-sum((lotsize-mean(lotsize))*(workhrs-mean(workhrs)))/Sxx`
- `b0<-mean(workhrs)-b1*mean(lotsize)`
- `SSE<-sum((workhrs-(b0+b1*lotsize))^2)`
- `MSE<-SSE/(n-2)`
- `sb1<-sqrt(MSE/sum((lotsize-mean(lotsize))^2)) #s{b1}`
- `conf_b1<-c(b1-tdf*sb1,b1+tdf*sb1)`
- `conf_b1`
- `sb0<-sqrt(MSE*(1/n+mean(lotsize)^2/sum((lotsize-mean(lotsize))^2)))`
- `conf_bo<-c(b0-tdf*sb0,b0+tdf*sb0)`
- `conf_bo`

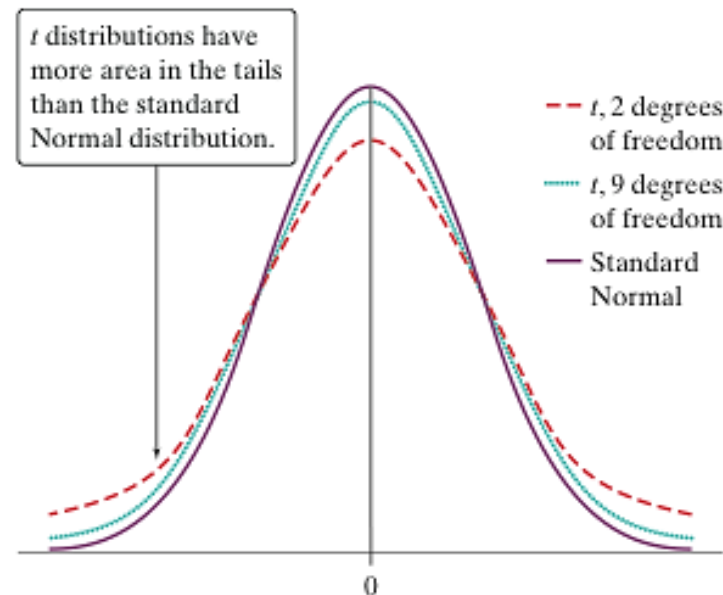
## Using build in Function

- `toluca.reg<-lm(workhrs~ lotsize)`
- `summary(toluca.reg)`
- `confint(toluca.reg)`



# Departures from Normality

- Even if the distribution of  $Y$  are far from normal, the estimators  $b_0$  and  $b_1$  generally have the property of asymptotic normality-their distributions approach normality under very general conditions as the sample size increases. Thus, with sufficiently large samples, the confidence intervals and decision rules given earlier still apply even if the probability distributions of  $Y$  depart far from normality. For large samples, the  $t$  value is, of course, replaced by the  $z$  value for the standard normal distribution.



# Power of the test

When we draw a conclusion from a significance test, we hope our conclusion will be correct. But sometimes it will be wrong. There are two types of mistakes we can make.

If we reject  $H_0$  when  $H_0$  is true, we have committed a **Type I error**.  
If we fail to reject  $H_0$  when  $H_0$  is false, we have committed a **Type II error**.

		Truth about the population	
		$H_0$ true	$H_0$ false ( $H_a$ true)
Conclusion based on sample	Reject $H_0$	Type I error	Correct conclusion
	Fail to reject $H_0$	Correct conclusion	Type II error

# Power of the test, cont'd

## Type I Error

The probability of a Type I error is the probability of rejecting  $H_0$  when it is really true. This is exactly the significance level of the test.

The significance level  $\alpha$  of any fixed-level test is the probability of a Type I error. That is,  $\alpha$  is the probability that the test will reject the null hypothesis  $H_0$  when  $H_0$  is in fact true. Consider the consequences of a Type I error before choosing a significance level.

## Type II Error and Power

A significance test makes a Type II error when it fails to reject a null hypothesis that really is false. There are many values of the parameter satisfying the alternative hypothesis. We can calculate the probability that a test *does* reject  $H_0$  when any *specific* alternative is true. This probability is called the **power** of the test against that specific alternative.

The power of a test against any alternative is 1 minus the probability of a Type II error for that alternative; that is, **power =  $1 - \beta$** .

# The One-Sample $t$ Test

To test the hypothesis

$$H_0 : \beta_1 = \beta_{10}$$

$$H_0 : \beta_1 \neq \beta_{10}$$

The test statistics becomes

$$t = \frac{b_1 - \beta_{10}}{s(b_1)} \sim \text{non-central } t\text{-distribution with } \delta = \left| \frac{b_1 - \beta_{10}}{\sigma(b_1)} \right| \text{ and } n-2 \text{ degree of freedom (df)}$$

Where  $\delta$  is the non-central measure i.e., a measure of how far the true value of  $b_1$  is from  $\beta_{10}$

Table B.5 (on page 1327 ) presents the power of the two-sided  $t$  test for  $\alpha = .05$  and  $\alpha = .01$ , for various df

# Power Values

**TABLE B.5**  
Power Values  
for Two-Sided  
 $t$  Test.

df	$\alpha = .05$								
	$\delta$								
	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0
1	.07	.13	.19	.25	.31	.36	.42	.47	.52
2	.10	.22	.39	.56	.72	.84	.91	.96	.98
3	.11	.29	.53	.75	.90	.97	.99	1.00	1.00
4	.12	.34	.62	.84	.95	.99	1.00	1.00	1.00
5	.13	.37	.67	.89	.98	1.00	1.00	1.00	1.00
6	.14	.39	.71	.91	.98	1.00	1.00	1.00	1.00
7	.14	.41	.73	.93	.99	1.00	1.00	1.00	1.00
8	.14	.42	.75	.94	.99	1.00	1.00	1.00	1.00
9	.15	.43	.76	.94	.99	1.00	1.00	1.00	1.00
10	.15	.44	.77	.95	.99	1.00	1.00	1.00	1.00
11	.15	.45	.78	.95	.99	1.00	1.00	1.00	1.00
12	.15	.45	.79	.96	1.00	1.00	1.00	1.00	1.00
13	.15	.46	.79	.96	1.00	1.00	1.00	1.00	1.00
14	.15	.46	.80	.96	1.00	1.00	1.00	1.00	1.00
15	.16	.46	.80	.96	1.00	1.00	1.00	1.00	1.00
16	.16	.47	.80	.96	1.00	1.00	1.00	1.00	1.00
17	.16	.47	.81	.96	1.00	1.00	1.00	1.00	1.00
18	.16	.47	.81	.97	1.00	1.00	1.00	1.00	1.00
19	.16	.48	.81	.97	1.00	1.00	1.00	1.00	1.00
20	.16	.48	.81	.97	1.00	1.00	1.00	1.00	1.00
21	.16	.48	.82	.97	1.00	1.00	1.00	1.00	1.00
22	.16	.48	.82	.97	1.00	1.00	1.00	1.00	1.00
23	.16	.48	.82	.97	1.00	1.00	1.00	1.00	1.00
24	.16	.48	.82	.97	1.00	1.00	1.00	1.00	1.00
25	.16	.49	.82	.97	1.00	1.00	1.00	1.00	1.00
26	.16	.49	.82	.97	1.00	1.00	1.00	1.00	1.00
27	.16	.49	.82	.97	1.00	1.00	1.00	1.00	1.00
28	.16	.49	.83	.97	1.00	1.00	1.00	1.00	1.00
29	.16	.49	.83	.97	1.00	1.00	1.00	1.00	1.00
30	.16	.49	.83	.97	1.00	1.00	1.00	1.00	1.00
40	.16	.50	.83	.97	1.00	1.00	1.00	1.00	1.00
50	.17	.50	.84	.98	1.00	1.00	1.00	1.00	1.00
60	.17	.50	.84	.98	1.00	1.00	1.00	1.00	1.00
100	.17	.51	.84	.98	1.00	1.00	1.00	1.00	1.00
120	.17	.51	.85	.98	1.00	1.00	1.00	1.00	1.00
$\infty$	.17	.52	.85	.98	1.00	1.00	1.00	1.00	1.00

# Example –Toluca Company

Suppose we want to calculate the power of the test for  $\beta_1=1.5$

$$H_0 : \beta_1 = \beta_{10} = 0$$

$$H_a : \beta_1 \neq \beta_{10} \neq 0$$

From the previous slides,  $\sigma^2(b_1) = \frac{\sigma^2}{\sum(X_i - \bar{X})^2} = \frac{2,500}{19,800} = 0.1263$  and  $\sigma(b_1) = 0.3553$

$$\text{Then, } \delta = \left| \frac{b_1 - \beta_{10}}{\sigma(b_1)} \right| = \frac{|1.5 - 0|}{0.3553} = 4.22$$

From the table by using  $\alpha = .05$  and 23 df and interpolate linearly between

$\delta = 4$  and  $\delta = 5$ , we obtain

$$.97 + \frac{4.22 - 4.00}{5.00 - 4.00} (1.00 - .97) = .9766$$

- Thus, if  $\beta_1 = 1.5$ , the probability would be about .98 that we would be led to conclude  $H_a (\beta_1 \neq 0)$ . In other words, if  $\beta_1 = 1.5$ , we would be almost certain to conclude that there is a linear relation between work hours and lot size.

# Interval Estimation of $E\{Y_h\}$

- Let  $X_h$  denote the level of  $X$  for which we wish to estimate the mean response.
- $X_h$  may be a value which occurred in the sample, or it may be some other value of the predictor variable within the scope of the model.
- The mean response when  $X = X_h$  is denoted by  $E\{Y_h\}$ .
- Formula gives us the point estimator  $Y_h$  of  $E\{Y_h\}$ :
  - $Y_h = b_0 + b_1 X_h$
- What is the sampling distribution of  $Y_h$ ?

# Sampling Distribution of $\hat{Y}_h$

- For normal error regression model, the sampling distribution of  $\hat{Y}_h$  is normal, with mean and variance:

$$E\{\hat{Y}_h\} = E\{Y_h\}$$

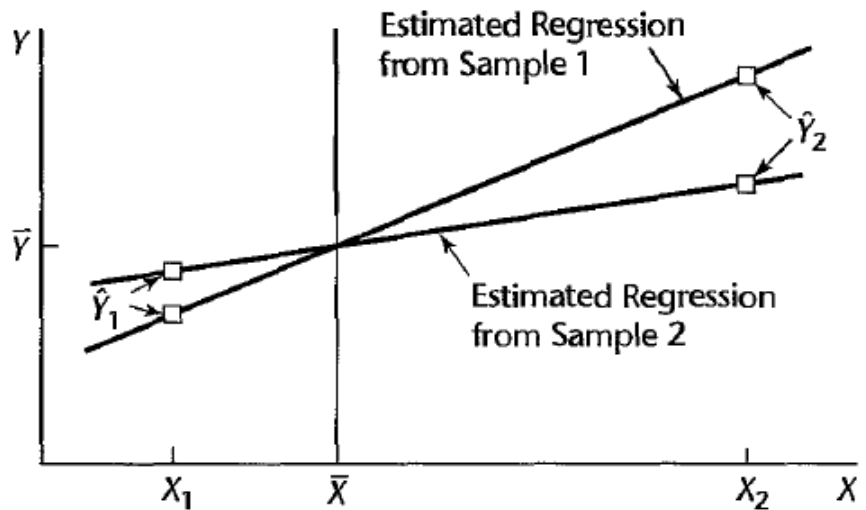
$$\sigma^2\{\hat{Y}_h\} = \sigma^2 \left[ \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]$$

- Normality:** The normality of the sampling distribution of  $\hat{Y}_h$  follows directly from the fact that  $\hat{Y}_h$ , like  $b_0$  and  $b_1$ , is a linear combination of the observations  $Y_i$
- Mean.** Note from that  $Y_h$  is an unbiased estimator of  $E\{Y_h\}$ . To prove this, we proceed as follows:

$$E\{\hat{Y}_h\} = E\{b_0 + b_1 X_h\} = E\{b_0\} + X_h E\{b_1\} = \beta_0 + \beta_1 X_h$$



# Sampling Distribution of $\hat{Y}_h$ , cont'd



- The two regression lines are assumed to go through the same  $(\bar{X}, \bar{Y})$  point to isolate the effect of interest, namely, the effect of variation in the estimated slope  $b_1$  from sample to sample.
- Note that at  $X_1$  near  $\bar{X}$ , the fitted values  $\hat{Y}_1$  for the two sample regression lines are close to each other.
- At  $X_2$  which is far from  $\bar{X}$ , the fitted values  $\hat{Y}_2$  differ substantially

- Thus, variation in the slope  $b_1$  from sample to sample has a much more pronounced effect on  $\hat{Y}_h$  for  $X$  levels far from the mean  $X$  than for  $X$  levels near  $X$ .
- Hence, the variation in the  $\hat{Y}_h$  values from sample to sample will be greater when  $X_h$  is far from the mean than when  $X_h$  is near the mean.

# Sampling Distribution of $\hat{Y}_h$ , cont'd

- When  $MSE$  is substituted for  $\sigma^2$ , we obtain  $s^2\{\hat{Y}_h\}$ , the estimated variance of  $\hat{Y}_h$ :

$$s^2\{\hat{Y}_h\} = MSE \left[ \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]$$

- The estimated standard deviation of  $\hat{Y}_h$  is then  $s\{\hat{Y}_h\}$ , the positive square root of  $s^2\{\hat{Y}_h\}$ .

# Sampling Distribution of $\hat{Y}_h$ , cont'd

## Derivation of $s^2\{\hat{Y}_h\}$

–  $Y_h = b_0 + b_1 X_h$  and  $b_0 = \bar{Y} - b_1 \bar{X}$  and then

–  $Y_h = \bar{Y} - b_1 \bar{X} + b_1 X_h = \bar{Y} + b_1(X_h - \bar{X})$

–  $\sigma^2(Y_h) = \sigma^2(\bar{Y} + b_1(X_h - \bar{X})) = \sigma^2(\bar{Y}) + \sigma^2(b_1)(X_h - \bar{X})^2 + 2(X_h - \bar{X})^2 \sigma^2(\bar{Y}, b_1)$

–  $= \frac{\sigma^2}{n} + (X_h - \bar{X})^2 \frac{\sigma^2}{\sum (X_i - \bar{X})^2} + 0$

–  $= \sigma^2 \left( \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right)$

# Sampling Distribution of $(\hat{Y}_h - E(\hat{Y}_h))/s(\hat{Y}_h)$ ,

$$\frac{\hat{Y}_h - E(\hat{Y}_h)}{s(\hat{Y}_h)} \sim \text{t distribution with } n-2 \text{ df}$$

**$(1-\alpha/2)\%$  Confidence Interval for  $E\{\hat{Y}_h\}$**

$$\hat{Y}_h \pm t(1 - \alpha/2; n - 2)s(\hat{Y}_h) = [\hat{Y}_h - t(1 - \alpha/2; n - 2)s(\hat{Y}_h), \hat{Y}_h + t(1 - \alpha/2; n - 2)s(\hat{Y}_h)]$$

# Example

- Returning to the Toluca Company example, let us find a 90 percent confidence interval for  $E\{Y_h\}$  when the lot size is  $X_h = 65$  units.

$$\hat{Y}_h = 62.37 + 3.5702(65) = 294.4$$

$$s^2\{\hat{Y}_h\} = 2,384 \left[ \frac{1}{25} + \frac{(65 - 70.00)^2}{19,800} \right] = 98.37$$

$$s\{\hat{Y}_h\} = 9.918$$

- For a 90 percent confidence coefficient, we require  $t(.95; 23) = 1.714$ . Hence, our confidence interval with confidence coefficient .90 is

$$294.4 - 1.714(9.918) \leq E\{Y_h\} \leq 294.4 + 1.714(9.918)$$

$$277.4 \leq E\{Y_h\} \leq 311.4$$

- We conclude with confidence coefficient .90 that the mean number of work hours required when lots of 65 units are produced is somewhere between 277.4 and 311.4 hours.

# Example

- Let us find a 90 percent confidence interval for  $E\{Y_h\}$  when the lot size is  $X_h = 100$  units.

$$\hat{Y}_h = 62.37 + 3.5702(100) = 419.4$$

$$s^2\{\hat{Y}_h\} = 2,384 \left[ \frac{1}{25} + \frac{(100 - 70.00)^2}{19,800} \right] = 203.72$$

$$s\{\hat{Y}_h\} = 14.27$$

$$t(.95; 23) = 1.714$$

- our confidence interval with confidence coefficient .90 is

$$419.4 - 1.714(14.27) \leq E\{Y_h\} \leq 419.4 + 1.714(14.27)$$

$$394.9 \leq E\{Y_h\} \leq 443.9$$

- Note that this confidence interval is somewhat wider than that from the previous example, since the  $X_h$  level here ( $X_h = 100$ ) is substantially farther from the mean  $\bar{X} = 70.0$  than the  $X_h$  level from the previous example ( $X_h = 65$ ).

# Prediction of New Observation

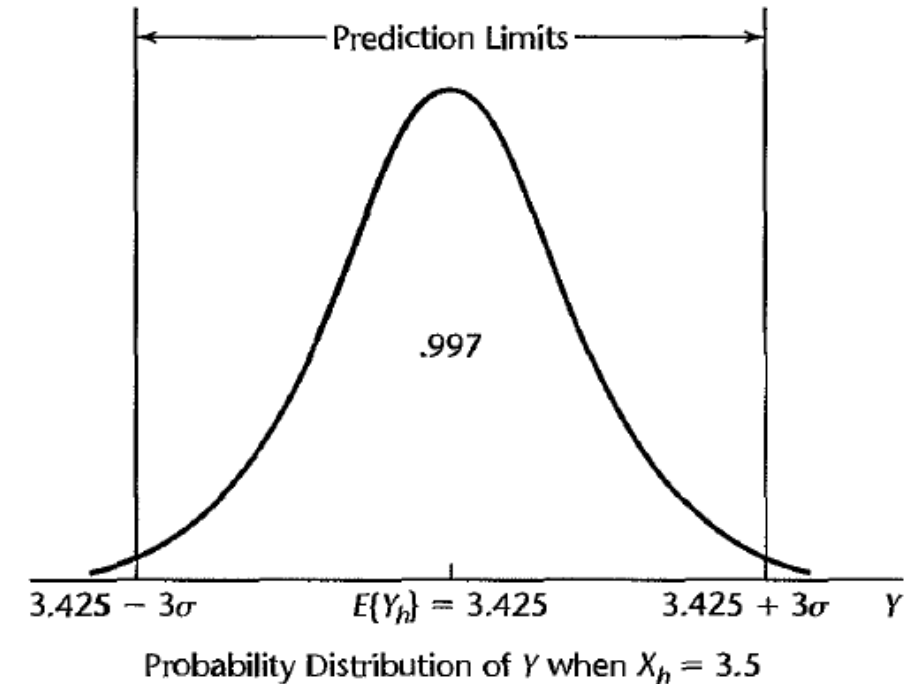
- The new observation on  $Y$  to be predicted is viewed as the result of a new trial, independent of the trials on which the regression analysis is based.
- We denote the level of  $X$  for the new trial as  $X_h$  and the new observation on  $Y$  as  $Y_{h(\text{new})}$ .
- **It is assumed that the underlying regression model applicable for the basic sample data continues to be appropriate for the new observation !**
- We predict an individual outcome drawn from the distribution of  $Y$ .

# Example: College Admissions

- Suppose that in the college admissions example the relevant parameters of the regression model are known to be

$$\begin{aligned}\beta_0 &= .10 & \beta_1 &= .95 \\ E\{Y\} &= .10 + .95X \\ \sigma &= .12\end{aligned}$$

- The admissions officer is considering an applicant whose high school GPA is  $X_h = 3.5$ .
- The mean college GPA for students whose high school average is 3.5 is:
- $E\{Y_h\} = .10 + .95(3.5) = 3.425$
- $E\{Y_h\} \pm 3\sigma$ :
  - $3.425 \pm 3(0.12) \Rightarrow 3.065 \leq Y_{h(new)} \leq 3.785$



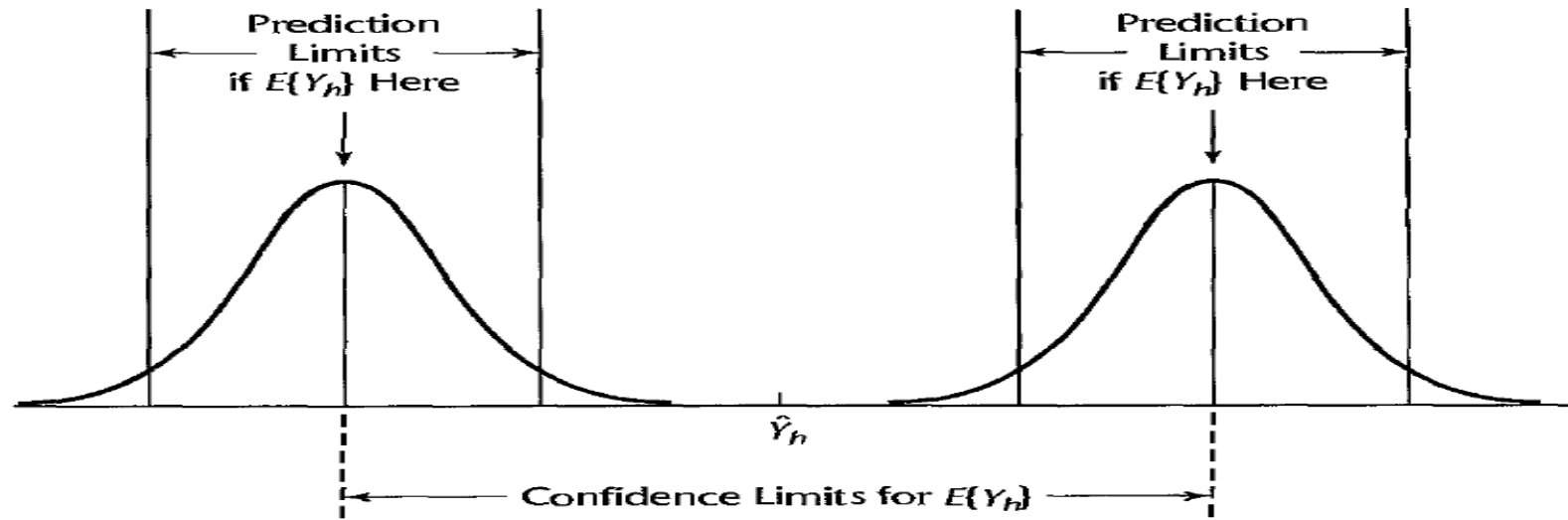


# Prediction of New Observation, cont'd

- The basic idea of a prediction interval is to choose a range in the distribution of  $Y$  wherein most of the observations will fall, and then to declare that the next observation will fall in this range.
- When the regression parameters of normal error regression model are known, the  $1 - \alpha$  prediction limits for  $Y_{h(new)}$  are:

$$E\{Y_h\} \pm z(1 - \alpha/2)\sigma$$

# Prediction Interval for $Y_{h(new)}$ when Parameters Unknown



- Figure shows the prediction limits for each of the two probability distributions of  $Y$  presented there. Since we cannot be certain of the location of the distribution of  $Y$ , prediction limits for  $Y_{h(new)}$  must take account of two elements
  1. Variation in possible location of the distribution of  $Y$ .
  2. Variation within the probability distribution of  $Y$ .

## Prediction Interval for $Y_{h(new)}$ when Parameters Unknown, cont'd

- Prediction limits for a new observation  $Y_{h(new)}$  at a given level  $X_h$  are obtained by means of the following theorem:
- $\frac{Y_{h(new)} - \hat{Y}_h}{s(pred)} \sim t(n-2)$  distribution
- The  $1 - \alpha$  prediction limits for  $Y_{h(new)}$ :
  - $\hat{Y}_h \pm t(1 - \alpha/2; n - 2)s\{pred\}$
- The difference may be viewed as the prediction error, with  $\hat{Y}_h$  serving as the best point estimate of the value of the new observation  $Y_{h(new)}$
- $\sigma^2\{pred\}$ : the variance of the prediction error
  - $\sigma^2\{pred\} = \sigma^2\{Y_{h(new)} - \hat{Y}_h\} = \sigma^2 + \sigma^2\{\hat{Y}_h\}$

## Prediction Interval for $Y_{h(new)}$ when Parameters Unknown, cont'd

- $\sigma^2\{\text{pred}\}$  has two components:
  - The variance of the distribution of  $Y$  at  $X = X_h$ ;  $\sigma^2$
  - The variance of the sampling distribution of  $\hat{Y}_h$ ;  $\sigma^2\{\hat{Y}_h\}$
- An unbiased estimator of  $\sigma^2\{\text{pred}\}$

$$\begin{aligned} s^2(\text{pred}) &= MSE + s^2(\hat{Y}_h) = MSE + MSE \left( \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right) \\ &= MSE \left[ 1 + \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right] \end{aligned}$$

# Example: Toluca Company

- Toluca Company:  $X_h = 100$
- 90 percent prediction interval:  $t(0.95; 23) = 1.714$ 
  - $\hat{Y}_h = 419.4$        $s^2\{\hat{Y}_h\} = 203.72$        $MSE = 2,384$
  - $\Rightarrow s^2(\text{pred}) = 2,384 + 203.72 = 2,587.72$
  - $s(\text{pred}) = 50.87$
- The 90 percent prediction interval for  $Y_{h(\text{new})}$ :
  - $332.2 \leq Y_{h(\text{new})} \leq 506.6$



# Example: Toluca Company - Rcode

- `toluca.reg <- lm(workhrs ~ lotsize , data= toluca_data)`
- `Xh<-data.frame(lotsize=100)`
- `fitnew<-predict(toluca.reg,Xh,se.fit=T, interval="prediction", level=0.9)`
- `s2pred<-fitnew$se.fit^2+fitnew$residual.scale^2`
- `c(s2pred,sqrt(s2pred))`

OR

- `predict(toluca.reg,Xh,interval="prediction",level=0.90)`

# Example: Toluca Company, cont'd

- This prediction interval is rather wide and may not be useful for planning worker requirements for the next lot.
- The interval can still be useful for control purposes.
  - If the actual work hours fall outside the prediction limits  $\Rightarrow$  some alerts may have occurred a change in the production process
- Toluca Company: The C.I. for  $Y_{h(\text{new})}$  is wider than the C.I. for  $E\{Y_h\}$ :
- predicting the work hours required for a new lot
- encounter the variability in  $\hat{Y}_h$  from sample to sample as well as the lot-to-lot variation within the probability distribution of  $Y$
- The prediction interval is wider the further  $X_h$  is from  $\bar{X}$

# Prediction of Mean of m New Observations for Given $X_h$

- Predict the mean of  $m$  new observations on  $Y$  for a given  $X_h$
- $\bar{Y}$ : the mean of the new observations to be predicted as  $\bar{Y}_{h(new)}$
- The new  $Y$  observations are **independent**
- The appropriate  $1 - \alpha$  prediction limits:

$$- \hat{Y}_h \pm t(1 - \alpha/2; n - 2)s\{\text{predmean}\}$$

$$s^2(\text{predmean}) = \frac{MSE}{m} + s^2(\hat{Y}_h) = MSE \left[ \frac{1}{m} + \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2} \right]$$

1. The variance of the mean of m observations from the probability distribution of  $Y$  at  $x = X_h$
2. The variance of the sampling distribution of  $Y_h$



## Example: Toluca Example

- Toluca Company:  $X_h = 100$
- %90 prediction interval for the mean number of work hours  $\bar{Y}_{h(new)}$  in three new production runs
- Previous results:
  - $\hat{Y}_h = 419.4$ ;  $s^2\{Y_h\} = 203.72$
  - $MSE = 2,384$ ;  $t(0.95; 23) = 1.714$
- $s^2\{\text{predmean}\} = \frac{2384}{3} + 203.72 = 998.4$
- $s\{\text{predmean}\} = 31.60$
- $419.4 - 1.714(31.60) \leq \bar{Y}_{h(new)} \leq 419.4 + 1.714(31.60)$
- $365.2 \leq \bar{Y}_{h(new)} \leq 473.6$
- The prediction interval for the total number of work hours for the three lots by multiplying the prediction limits for  $\bar{Y}_{h(new)}$  by 3:
  - $3(365.2) = 1,095.6 \leq \text{Total work hours} \leq 3(473.6) = 1,420.8$
- Thus, it can be predicted with 90% confidence that between 1,096 and 1,421 work hours will be needed to fill the contract for three lots of 100 units each.

# Confidence-Band for Regression Line

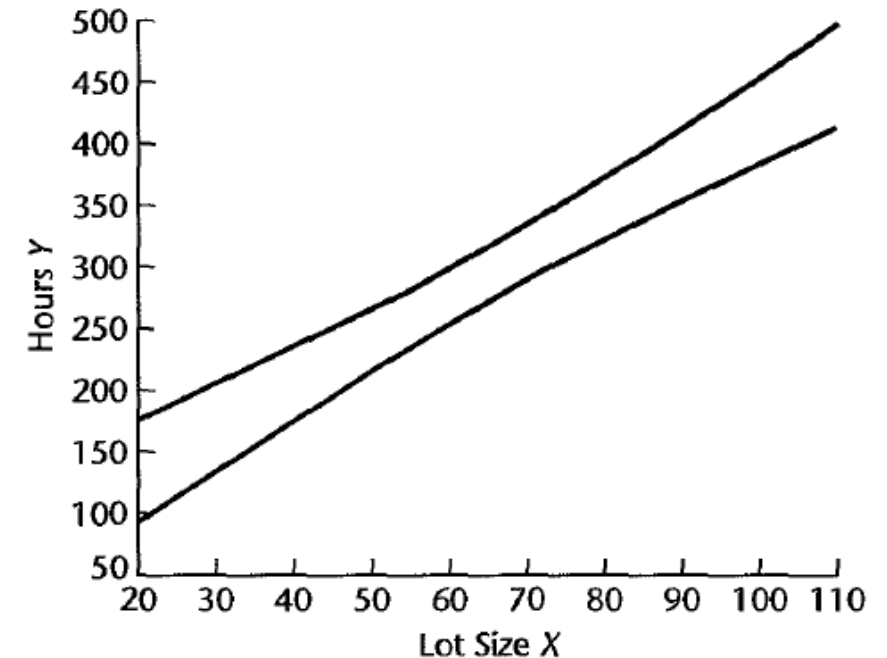
- At times we would like to obtain a confidence band for the entire regression line  $E\{Y\} = \beta_0 + \beta_1 X$
- This band enables us to see the region in which the entire regression line lies.
- The Working-Hotelling  $1 - \alpha$  confidence band for the regression line for regression model has the following two boundary values at any level  $X_h$  :

$$\hat{Y}_h \pm W s(\hat{Y}_h)$$

- Where  $W^2 = 2F(1 - \alpha; 2, n - 2)$  and F is the F distribution with 2 and n-2 degree of freedom.

# Example: Toluca Data

- Toluca Company:  $X_h = 100$
- $\hat{Y}_h = 419.4$ ;  $s^2\{Y_h\} = 203.72$ ;  $MSE = 2,384$ ;
- $W^2 = 2F(1 - \alpha; 2, n - 2) = 2F(.90; 2, 23) = 2(2.549) = 5.098$
- $W = 2.258$
- Hence, the boundary values of the confidence band for the regression line at  $X_h = 100$  are
- $419.4 \pm 2.258(14.27)$ , and the confidence band is:
- $387.2 \leq \beta_0 + \beta_1 X_h \leq 451.6$  for  $X_h = 100$



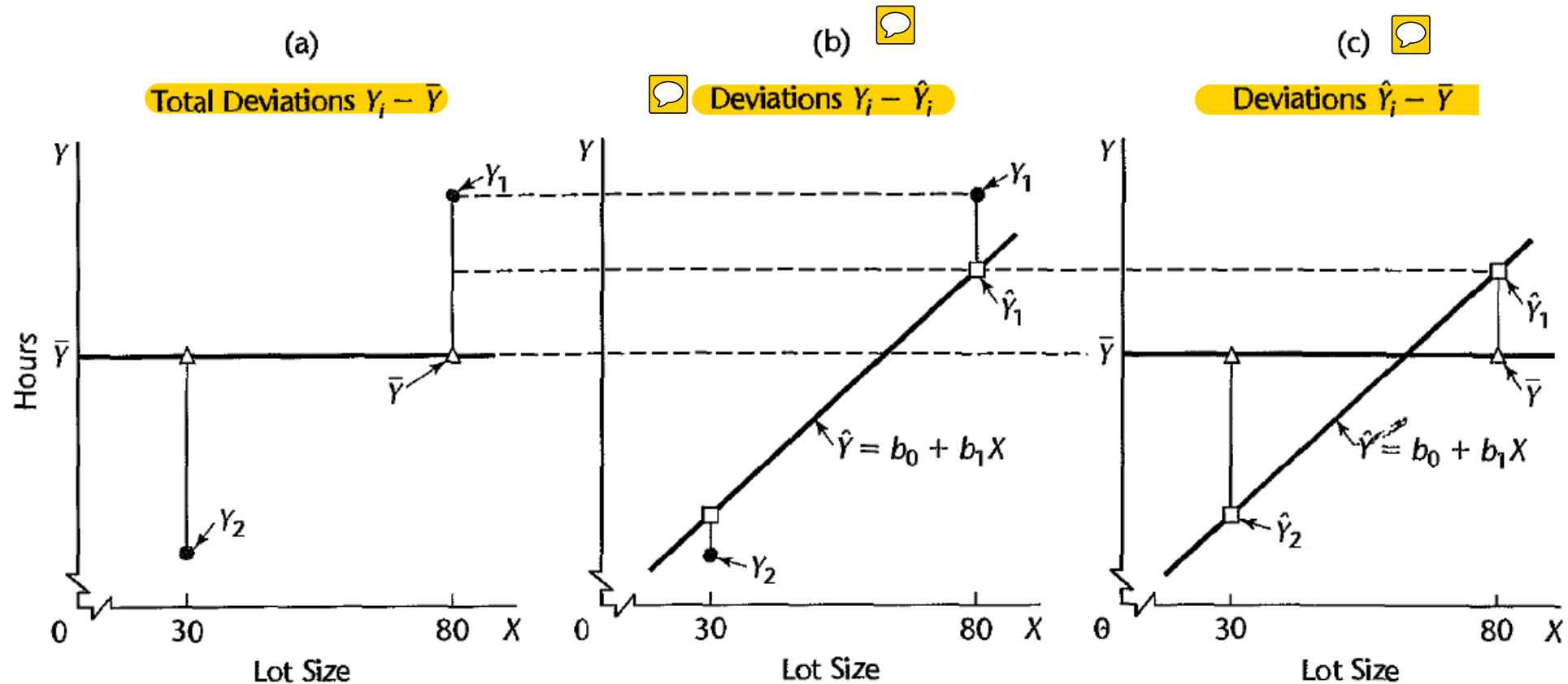
Confidence Band for the regression line

# Partition of Total Sum of Squares

- The analysis of variance approach is based on the partitioning of sums of squares and degrees of freedom associated with  $Y$ .
- The variation is measured: the deviations of the  $Y_i$  around their mean  $\bar{Y}$ :

$$Y_i - \bar{Y}$$

# Partition of Total Sum of Squares, cont'd



## Partition of Total Sum of Squares, cont'd

- Total variation: (SSTO or SST: total sum of squares)

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

- $Y_i$  are the same  $\Rightarrow SST = 0$
- The greater the variation among the  $Y_i$ , the larger is SST.

- Total Error: (SSE: Sum of Squares of Error)

$$SSE = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

- $Y_i$  fall on the fitted regression line  $\Rightarrow SSE = 0$
- The greater the variation of the  $Y_i$  around the fitted regression line, the larger is SSE.

## Partition of Total Sum of Squares, cont'd

- Total Regression: (**SSR: Regression Sum of Squares**)

$$SSR = \sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2$$

- The regression line is horizontal  $\Rightarrow SSR = 0$ , otherwise  $SSR > 0$
- a measure associated with the regression line
- The larger SSR is in relation to SST, the greater is the effect of the regression relation in accounting for the total variation in the  $Y_i$  observations.

# Partition of Total Sum of Squares, cont'd

- The total deviation:

$$\underbrace{Y_i - \bar{Y}}_{\text{Total deviation}} = \underbrace{\hat{Y}_i - \bar{Y}}_{\substack{\text{Deviation of fitted} \\ \text{regression value} \\ \text{around mean}}} + \underbrace{Y_i - \hat{Y}_i}_{\substack{\text{Deviation} \\ \text{around} \\ \text{fitted} \\ \text{regression} \\ \text{line}}}$$

- Two components:
  1. The deviation of the fitted value  $\hat{Y}_i$  around the mean  $\bar{Y}$ .
  2. The deviation of the observation  $Y_i$  around the fitted regression line.



# Partition of Total Sum of Squares, cont'd

$$\underbrace{\sum (Y_i - \bar{Y})^2}_{SSTO} = \underbrace{\sum (\hat{Y}_i - \bar{Y})^2}_{SSR} + \underbrace{\sum (Y_i - \hat{Y})^2}_{SSE}$$



$$2 \sum (\hat{Y}_i - \bar{Y})(Y_i - \hat{Y}_i) = 0$$

$$SSR = b_1^2 \sum (X_i - \bar{X})^2$$

Source of Variation	Degree of Freedom (df)	Explanation
SSR	1	$\beta_0$ and $\beta_1$ are estimated, due to constraint we lose 1 df.
SSE	n - 2	$\beta_0$ and $\beta_1$ are estimated, as such we lose 2 df
SST	n - 1	$\sum_{i=1}^n (Y_i - \bar{Y}) = 0$ , as such we lose 1 df

## MEAN SQUARES

- Mean Square (MS) is Sum of Square (SS) divided by the degree of freedom (df)

SS	df	MS
$SSR$	1	$MSR = \frac{SSR}{1}$ (regression mean square)
$SSE$	$n - 2$	$MSE = \frac{SSE}{n-2}$ (error mean square)

# Analysis of Variance (ANOVA) Table

Source of Variation	$SS$	$df$	$MS$	$E\{MS\}$
Regression	$SSR = \sum(\hat{Y}_i - \bar{Y})^2$	1	$MSR = \frac{SSR}{1}$	$\sigma^2 + \beta_1^2 \sum(X_i - \bar{X})^2$
Error	$SSE = \sum(Y_i - \hat{Y}_i)^2$	$n - 2$	$MSE = \frac{SSE}{n-2}$	$\sigma^2$
Total	$SSTO = \sum(Y_i - \bar{Y})^2$	$n - 1$		

## ANOVA TABLE, cont'd

$$SST = \sum (Y_i - \bar{Y})^2 = \sum Y_i^2 - n\bar{Y}^2$$

- In the modified ANOVA table, the total uncorrected sum of squares, denoted by SSTOU, is defined as:

$$SSTOU = \sum Y_i^2$$

- $SS(\text{correction for mean}) = n\bar{Y}^2$

# Modified ANOVA Table

Source of Variation	$SS$	$df$	$MS$
Regression	$SSR = \sum (\hat{Y}_i - \bar{Y})^2$	1	$MSR = \frac{SSR}{1}$
Error	$SSE = \sum (Y_i - \hat{Y}_i)^2$	$n - 2$	$MSE = \frac{SSE}{n-2}$
Total	$SSTO = \sum (Y_i - \bar{Y})^2$	$n - 1$	
Correction for mean	$SS(\text{correction for mean}) = n \bar{Y}^2$	1	
Total, uncorrected	$SSTOU = \sum Y_i^2$	$n$	

## Expected Mean Squares

$$E\{MSE\} = \sigma^2$$

$$E\{MSR\} = \sigma^2 + \beta_1^2 \sum (X_i - \bar{X})^2$$

- MSE is an unbiased estimator of  $\sigma^2$ . Implication:
  - The mean of the sampling distribution of MSE is  $\sigma^2$ ;
  - when  $\beta_1 = 0$ , the mean of the sampling distribution of MSR is  $\sigma^2$ ;
  - when  $\beta_1 \neq 0$ ,  $E\{MSR\} > E\{MSE\}$

## F test of $\beta_1 = 0$ vs. $\beta_1 \neq 0$

- The analysis of variance approach provides us with a battery highly useful tests for regression models.
- For the simple linear regression case, the ANOVA provides us with a test:

$$H_0 : \beta_1 = 0$$

$$H_a : \beta_1 \neq 0$$

- Test Statistics

$$F^* = \frac{MSR}{MSE}$$

- large values of  $F^* \Rightarrow H_a$ ;
- values of  $F^*$  near 1  $\Rightarrow H_0$ ;

# F test of $\beta_1 = 0$ vs. $\beta_1 \neq 0$ , cont'd

## Cochran's theorem

If all  $n$  observations  $Y_i$  come from the same normal distribution with mean  $\mu$  and variance  $\sigma^2$ , and  $SSTO$  is decomposed into  $k$  sums of squares  $SS_r$ , each with degrees of freedom  $df_r$ , then the  $SS_r/\sigma^2$  terms are independent  $\chi^2$  variables with  $df_r$  degrees of freedom if

$$\sum_{r=1}^k df_r = n - 1$$



# F test of $\beta_1 = 0$ vs. $\beta_1 \neq 0$

## Property

If  $\beta_1 = 0$  so that all  $Y_i$  have the same mean  $\mu = \beta_0$  and the same variance  $\sigma^2$ ,  $SSE/\sigma^2$  and  $SSR/\sigma^2$  are independent  $\chi^2$  variables.

- When  $H_0$  holds:

$$F^* = \frac{\frac{SSR}{\sigma^2}}{1} \div \frac{\frac{SSE}{\sigma^2}}{n-2} = \frac{MSR}{MSE} \sim \frac{\chi^2(1)}{1} \div \frac{\chi^2(n-2)}{n-2} \sim F(1, n-2)$$

- When  $H_a$  holds,  $F^*$  follows the **noncentral**  $F$  distribution.

# F test of $\beta_1 = 0$ vs. $\beta_1 \neq 0$ , cont'd

$$F^* \sim F(1, n - 2)$$

The decision rule:  $\alpha$ =Type I error

## Decision

If  $F^* \leq F(1 - \alpha; 1, n - 2)$ , conclude  $H_0$ ;

If  $F^* > F(1 - \alpha; 1, n - 2)$ , conclude  $H_a$ ;

where  $F(1 - \alpha; 1, n - 2)$  is the  $(1 - \alpha)100$  percentile of the approximate  $F$  distribution.

# Example: Toluca Data

## Two-Sided Test

$$H_0 : \beta_1 = \beta_{10}$$

$$\text{If } |t^*| = \frac{b_1 - \beta_{10}}{s\{b_1\}} \leq t(1 - \alpha/2; n - 2), \text{ conclude } H_0$$

$$\text{If } |t^*| \frac{b_1 - \beta_{10}}{s\{b_1\}} > t(1 - \alpha/2; n - 2), \text{ conclude } H_a$$

# Example: Toluca Data, cont'd

Using the  $F$  test

$$H_0 : \beta_1 = \beta_{10} = 0$$

$$H_a : \beta_1 \neq \beta_{10} = 0$$

$$\alpha = 0.05; n = 26; F(0.95; 1, 23) = 4.28$$

If  $F^* \leq 4.28$ , conclude  $H_0$

We have

$$F^* = \frac{MSR}{MSE} = \frac{252,378}{2,384} = 105.9$$

What is the conclusion?

# Equivalence of $F$ test and $t$ Test

For a given  $\alpha$  level, the  $F$  test of

$$H_0 : \beta_1 = 0 \quad H_a : \beta_1 \neq 0$$

is equivalence algebraically to the two-tailed  $t$  test.

Decision

$$F^* = \frac{b_1^2}{s^2\{b_1\}} = \left( \frac{b_1}{s\{b_1\}} \right)^2 = (t^*)^2$$

$$[t(1 - \alpha/2; n - 2)]^2 = F(1 - \alpha; 1, n - 2)$$

$t$  test: two-tailed;       $F$  test: one-tailed;

# General Linear Test Approach

1. Fit the full model and  $SSE(F)$
2. Fit the reduced model under  $H_0$  and  $SSE(R)$
3. Use test statistic and decision rule



## Full Model

The *full* or *unrestricted* model:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

$SSE(F)$ :

$$SSE(F) = \sum \left[ Y_i - (b_0 + b_1 X_i) \right]^2 = \sum (Y_i - \hat{Y}_i)^2 = SSE$$

# Reduced Model

Hypothesis:

$$H_0 : \beta_1 = 0 \quad H_a : \beta_1 \neq 0$$

The *reduced* or *restricted model* when  $H_0$  holds:

$$Y_i = \beta_0 + \varepsilon_i$$

$SSE(R)$ :

$$SSE(R) = \sum \left[ Y_i - (b_0) \right]^2 = \sum (Y_i - \bar{Y})^2 = SSTO$$



# Test Statistics

$$SSE(F) \leq SSE(R)$$


- The more parameters are in the model, the better one can fit the data and the smaller are the deviations around the fitted regression function.

# Test Statistics, cont'd

- When  $SSE(F)$  is not much less than  $SSE(R)$ , using the full model does not account for much more of the variability of the  $Y_i$  than does the reduced model.
- $\Rightarrow$  Suggest that the reduced model is adequate i.e.,  $H_0$  holds.
- When  $SSE(F)$  is close to  $SSE(R)$ , the variation of the observations around the fitted regression function for the full model is almost as great as the variation around the fitted regression function for the reduced model.

# Test Statistics, cont'd

- A small difference  $SSE(R) - SSE(F)$  suggests that  $H_0$  holds.
- $\Leftrightarrow$  A large difference suggests that  $H_a$  holds.
- Test Statistic: a function of  $SSE(R) - SSE(F)$ :


$$F^* = \frac{SSE(R) - SSE(F)}{df_R - df_F} \div \frac{SSE(F)}{df_F} \sim F\text{distribution}$$

- when  $H_0$  holds. Decision rule:
  - If  $F^* \leq F(1 - \alpha; df_R - df_F, df_F)$ , conclude  $H_0$
  - If  $F^* > F(1 - \alpha; df_R - df_F, df_F)$ , conclude  $H_a$

## Test Statistics, cont'd

For testing whether or not  $\beta_1 = 0$ , we have

$$SSE(R) = SSTO$$

$$df_R = n - 1$$

$$SSE(F) = SSE$$

$$df_F = n - 2$$

$$\Rightarrow F^* = \frac{MSR}{MSE}$$

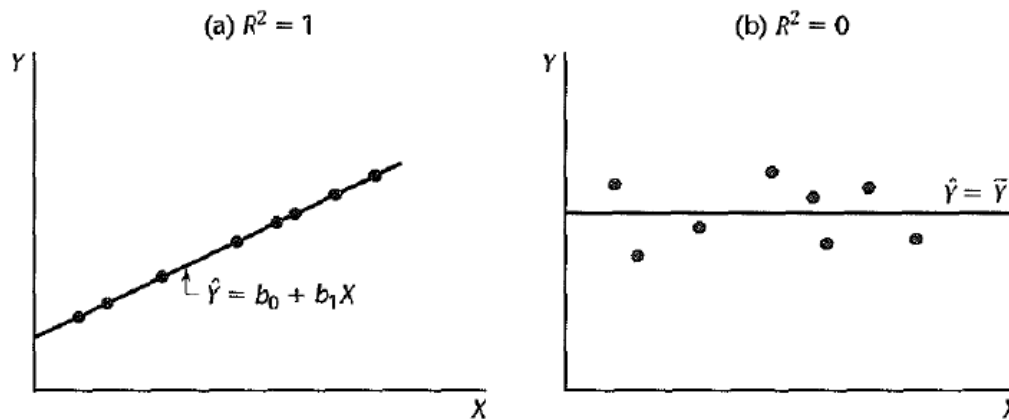
# Coefficient of Determination

- SST (or SSTO) is a measure of the uncertainty in predicting Y when X is not considered.
- SSE measures the variation in the  $Y_i$  when a regression model utilizing the predictor variable X is employed.
- A natural measure of the effect of X in reducing the variation in Y is to express the reduction in variation ( $SST - SSE = SSR$ ) as a proportion of the total variation:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$

# Coefficient of Determination, cont'd

- $R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$  and given  $SST \geq SSR \Rightarrow 0 \leq R^2 \leq 1$



**$R^2 = 0$ :** There is no linear association between  $X$  and  $Y$  in the sample data, and the predictor variable  $X$  is of no help in reducing the variation in  $Y_i$  with linear regression.

**$R^2 = 1$ :** The closer it is to 1, the greater is said to be the degree of linear association between  $X$  and  $Y$ .

## Example: Toluca Company, cont'd

- `fitreg<-lm(Hrs~Size,data=toluca)`
- `anova(fitreg)`
- `summary(fitreg)`

```
> anova(fitreg)
```

```
Analysis of Variance Table
```

```
Response: Hrs
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Size	1	252378	252378	105.88	4.449e-10 ***
Residuals	23	54825	2384		

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

# Example: Toluca Company, cont'd

```
> summary(fitreg)
```

```
Call:
```

```
lm(formula = Hrs ~ Size, data = toluca)
```

```
Residuals:
```

Min	1Q	Median	3Q	Max
-83.876	-34.088	-5.982	38.826	103.528

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	62.366	26.177	2.382	0.0259 *
Size	3.570	0.347	10.290	4.45e-10 ***

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 48.82 on 23 degrees of freedom
```

```
Multiple R-squared: 0.8215,    Adjusted R-squared: 0.8138
```

```
F-statistic: 105.9 on 1 and 23 DF,  p-value: 4.449e-10
```

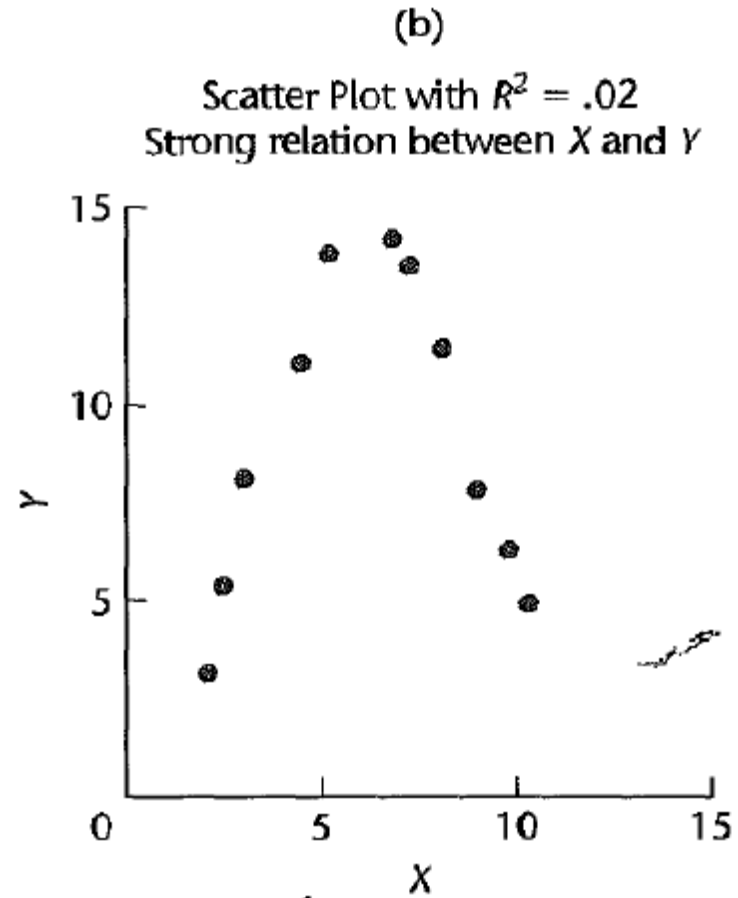
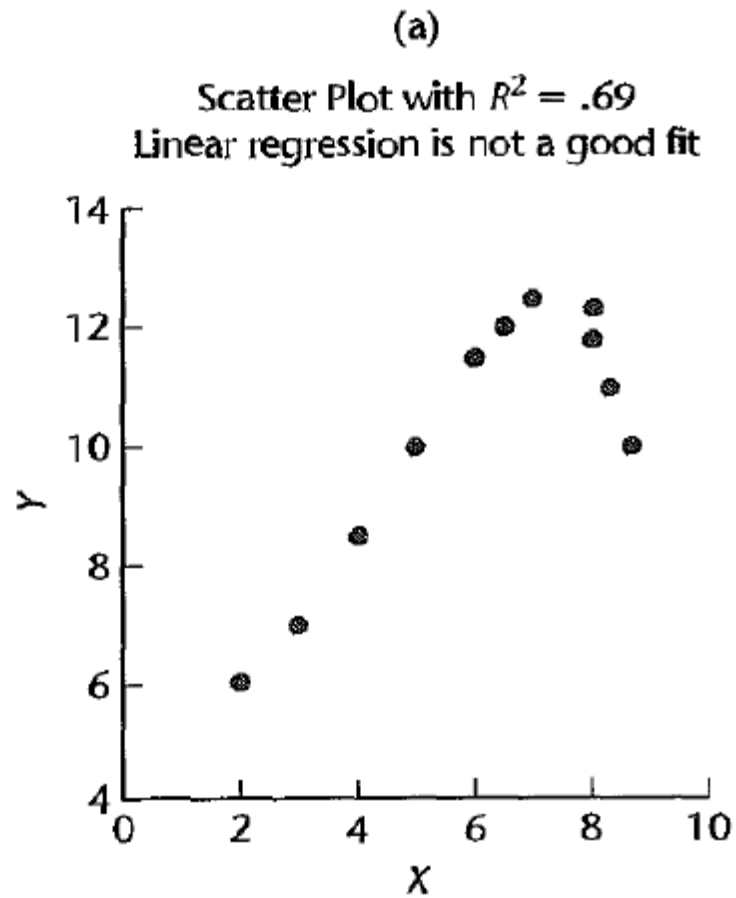
- The variation in work hours is reduced by 82.2% when lot size is considered.



# Coefficient of Determination, cont'd

- $R^2$  is widely used for describing the usefulness of a regression model.
- **Serious misunderstanding:**
  - A high  $R^2$  indicates that useful predictions can be made. (Not necessarily correct. Ex:  $X_h = 100$ )
  - A high  $R^2$  indicated that the estimated regression line is a good fit. (Not necessarily correct. **Curvilinear**)
  - A  $R^2$  near 0 indicated that  $X$  and  $Y$  are not related. (Not necessarily correct. **Curvilinear**)

# Coefficient of Determination, cont'd



# Coefficient of Correlation

- Measure of linear association between Y and X when both Y and X are random is the coefficient of correlation. This measure is the signed square root of  $R^2$ :

$$r = \pm\sqrt{R^2}$$

- A plus or minus sign is attached to this measure according to whether the slope of the fitted regression line is positive or negative. Thus, the range of  $r$  is:  $-1 \leq r \leq 1$ .

# Example:

- For the Toluca Company example, we obtained  $R^2 = .822$ .
- Treating X as a random variable, the correlation coefficient here is:
- $r = \pm\sqrt{.822} = .907$
- The plus sign is affixed since  $b_1$  is positive.

## Normal Correlation Models

Assume that the  $X$  values are known constants?

The confidence coefficients and risks of errors refer to repeated sampling when  $X$  values are kept the same from sample to sample.

Frequently, it may not be appropriate to consider the  $X$  values as known constants.

- cannot control daily temperatures
- “height of person” vs. “weight of person”: using correlation model

the normal correlation model

# Bivariate Normal Distribution

Two variables  $Y_1, Y_2$ : bivariate normal distribution.

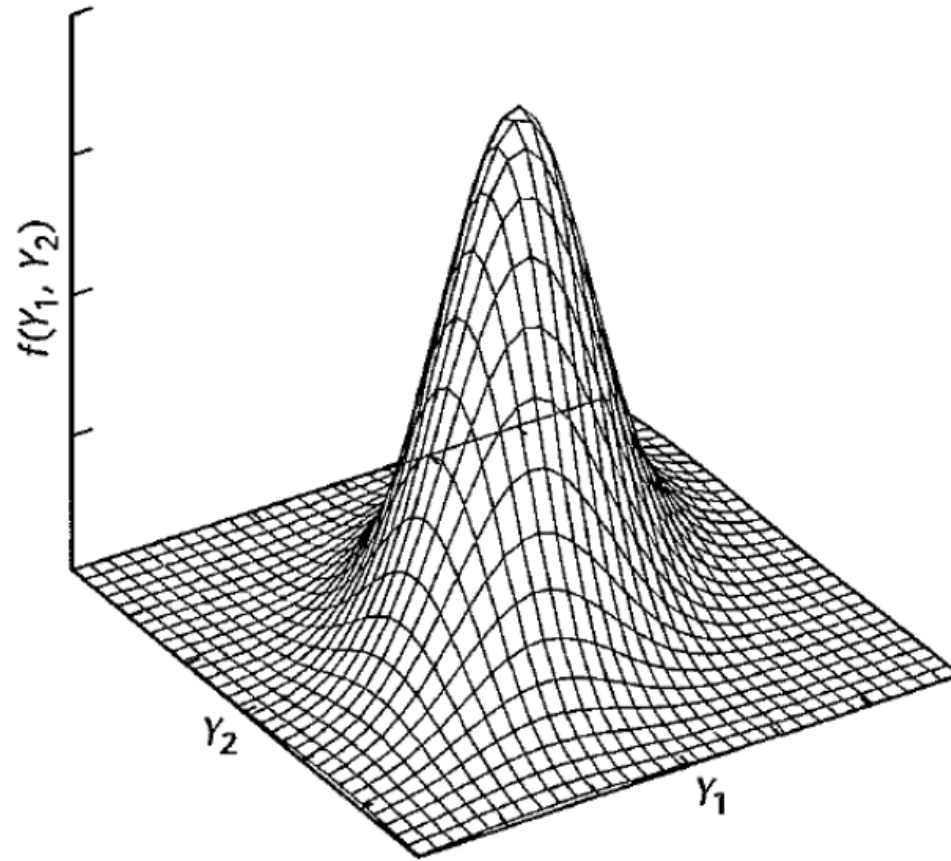
## Density Function

The density function of the bivariate normal distribution:

$$f(Y_1, Y_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho_{12}^2}} \exp \left\{ -\frac{1}{2(1-\rho_{12}^2)} \left[ \left( \frac{Y_1 - \mu_1}{\sigma_1} \right)^2 - 2\rho_{12} \left( \frac{Y_1 - \mu_1}{\sigma_1} \right) \left( \frac{Y_2 - \mu_2}{\sigma_2} \right) + \left( \frac{Y_2 - \mu_2}{\sigma_2} \right)^2 \right] \right\}$$

Five parameters:  $\mu_1, \mu_2, \sigma_1, \sigma_2, \rho_{12}$

## Bivariate Normal Distribution, cont'd



# Bivariate Normal Distribution, cont'd

## Marginal Distribution

$Y_1, Y_2 \sim N_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho_{12})$ :

$$Y_1 \sim N(\mu_1, \sigma_1^2) \Rightarrow f_1(Y_1) = \frac{1}{\sqrt{2\pi}\sigma_1} \exp \left[ -\frac{1}{2} \left( \frac{Y_1 - \mu_1}{\sigma_1} \right)^2 \right]$$

$$Y_2 \sim N(\mu_2, \sigma_2^2) \Rightarrow f_2(Y_2) = \frac{1}{\sqrt{2\pi}\sigma_2} \exp \left[ -\frac{1}{2} \left( \frac{Y_2 - \mu_2}{\sigma_2} \right)^2 \right]$$

- When  $Y_1, Y_2 \sim N_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho_{12}) \Rightarrow Y_1 \sim N(\mu_1, \sigma_1^2); Y_2 \sim N(\mu_2, \sigma_2^2)$
- The converse is not generally true.



## Bivariate Normal Distribution, cont'd

$\rho_{12}$ : the coefficient of correlation between  $Y_1, Y_2$

$$\rho_{12} = \frac{\sigma\{Y_1, Y_2\}}{\sigma\{Y_1\}\sigma\{Y_2\}} = \frac{\sigma_{12}}{\sigma_1\sigma_2}$$

$$Y_1 \perp Y_2 \Rightarrow \sigma_{12} = 0 \Rightarrow \rho_{12} = 0$$

If  $Y_1$  and  $Y_2$  are positively related  $\Rightarrow \sigma_{12}$  and  $\rho_{12}$  are positive.

$$-1 \leq \rho_{12} \leq 1$$

# Conditional Probability Distribution of $Y_1$

$Y_1, Y_2 \sim N_2(\mu_1, \mu_2, \sigma_1, \sigma_2, \rho_{12})$ ; and

$Y_1 \sim N(\mu_1, \sigma_1^2)$ ;  $Y_2 \sim N(\mu_2, \sigma_2^2)$ ;

The density function of the conditional probability of  $Y_1$  for given value of  $Y_2$ : ( $Y_1|Y_2 \sim N(\alpha_{1|2} + \beta_{12} Y_2, \sigma_{1|2})$ )

$$f(Y_1|Y_2) = \frac{f(Y_1, Y_2)}{f_2(Y_2)} = \frac{1}{\sqrt{2\pi}\sigma_{1|2}} \exp \left[ -\frac{1}{2} \left( \frac{Y_1 - \alpha_{1|2} - \beta_{12} Y_2}{\sigma_{1|2}} \right)^2 \right]$$

$$\alpha_{1|2} = \mu_1 - \mu_2 \rho_{12} \frac{\sigma_1}{\sigma_2}$$

$$\beta_{12} = \rho_{12} \frac{\sigma_1}{\sigma_2}$$

$$\sigma_{1|2}^2 = \sigma_1^2 (1 - \rho_{12}^2)$$

# Conditional Probability Distribution of $Y_1$ , cont'd

$\alpha_{1|2}$ : the intercept of the line of regression of  $Y_1$  and  $Y_2$

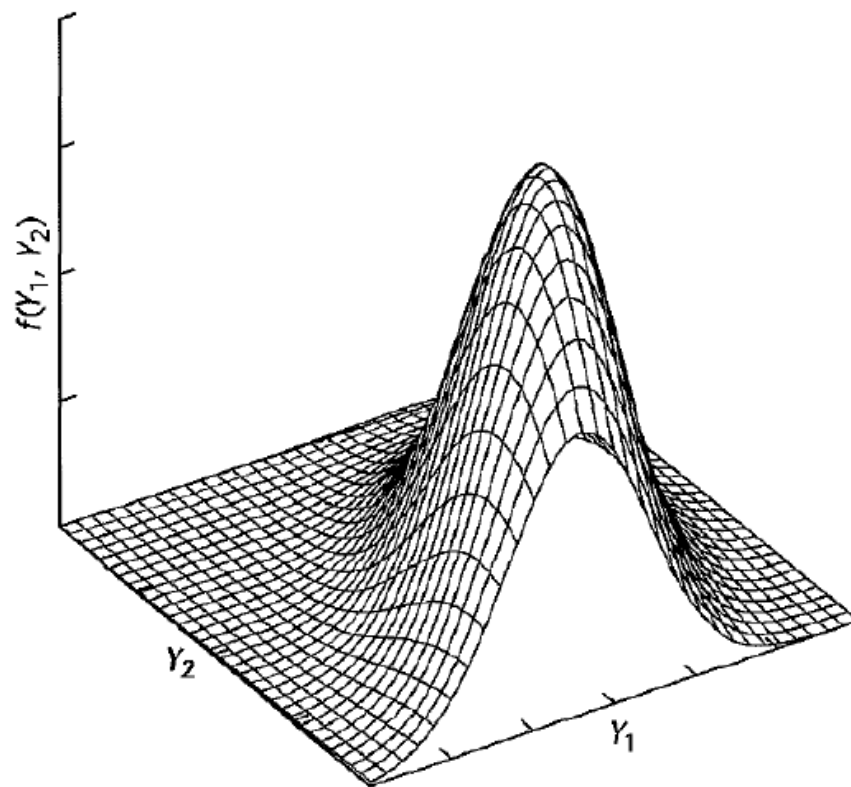
$\beta_{12}$ : the slope of this line

The conditional distribution of  $Y_1$ , given  $Y_2$ , is equivalent to the normal error regression model (1.24).

# Conditional Probability Distribution of $Y_1$ , cont'd

Three important characteristics of the conditional distributions of  $Y_1$ :

- ① normal: slice a bivariate normal distribution vertically; scaled its area;



# Conditional Probability Distribution of $Y_1$ , cont'd

- ② The means of the conditional probability distributions of  $Y_1$  fall on a straight line:

$$E\{Y_1|Y_2\} = \alpha_{1|2} + \beta_{12}Y_2$$

- ③ All conditional probability distribution have the same standard deviation  $\sigma_{1|2}$ .

Equivalence to Normal Error Regression Model.

## Inferences on Correlation Coefficients

To study the relationship between two variables:  $\rho_{12}$

MLE of  $\rho_{12}$ :

$$r_{12} = \frac{\sum (Y_{i1} - \bar{Y}_1)(Y_{i2} - \bar{Y}_2)}{[\sum (Y_{i1} - \bar{Y}_1)^2 \sum (Y_{i2} - \bar{Y}_2)^2]^{1/2}}$$

$r_{12}$  is a biased estimator of  $\rho_{12}$ .

$$-1 \leq r_{12} \leq 1$$

# Inferences on Correlation Coefficients, cont'd

## Test

The population is bivariate normal

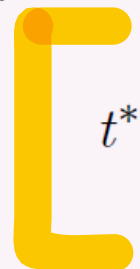
$$H_0 : \rho_{12} = 0 \quad \text{vs.} \quad H_a : \rho_{12} \neq 0$$

$$(\rho_{12} = 0 \Rightarrow Y_1 \perp Y_2)$$

$$\iff H_0 : \beta_{12} = 0 \quad \text{vs.} \quad H_a : \beta_{12} \neq 0$$

$$\iff H_0 : \beta_{21} = 0 \quad \text{vs.} \quad H_a : \beta_{21} \neq 0$$

Test statistics:


$$t^* = \frac{r_{12}\sqrt{n-2}}{\sqrt{1-r_{12}^2}} \sim t(n-2)$$

## Inferences on Correlation Coefficients, cont'd

This test statistics is identical to the regression  $t^*$  test statistics  $\frac{b_1}{s\{b_1\}}$ . ( $\because r = \sqrt{\frac{SSR}{SSTO}} = b_1 \left( \frac{\sum (X_i - \bar{X})^2}{SSTO} \right)^{1/2}$ )

The appropriate decision rule to control the Type I error  $\alpha$ :

If  $|t^*| \leq t(1 - \alpha/2; n - 2)$ , conclude  $H_0$

If  $|t^*| > t(1 - \alpha/2; n - 2)$ , conclude  $H_a$



# Inferences on Correlation Coefficients, cont'd

- A national oil company: service station gasoline sales vs. sales of auxiliary product
- 23 of its service stations
- average monthly sales data:  $Y_1$  =gasoline sales vs.  $Y_2$  =auxiliary products and services
- $r_{12} = 0.52$ ;  $\alpha = 0.05$
- To test whether or not the association was positive

$$H_0: \rho_{12} \leq 0$$

$$H_a: \rho_{12} > 0$$

- $t(.95; 21) = 1.721$

$$t^* = \frac{.52\sqrt{21}}{\sqrt{1 - (.52)^2}} = 2.79$$

- We would conclude  $H_a$ , that  $\rho_{12} > 0$ . The P-value for this test is .006

# Interval Estimation of $\rho_{12}$

- Fisher's transformation, is as follows:

$$z' = \frac{1}{2} \log_e \left( \frac{1 + r_{12}}{1 - r_{12}} \right)$$

- When  $n$  is large (25 or more is a useful rule of thumb), the distribution of  $z'$  is approximately normal with approximate mean and variance:

$$E\{z'\} = \zeta = \frac{1}{2} \log_e \left( \frac{1 + \rho_{12}}{1 - \rho_{12}} \right)$$
$$\sigma^2\{z'\} = \frac{1}{n - 3}$$

- $(Z', \xi)$ : Table B.8 (on page 1332 shows the transformation correlation coefficient

# Interval Estimation of $\rho_{12}$ , *con't*

Interval estimate: ( $n \geq 25$ )

$$\frac{z' - \varsigma}{\sigma\{z'\}} \sim N(0, 1)$$
$$\Rightarrow z' \pm z(1 - \alpha/2)\sigma\{z'\}$$

A C.I. for  $\rho_{12}$  can be employed to test whether or not  $\rho_{12}$  has a specified value. (ex. 0.5)

$0 \leq \rho_{12}^2 \leq 1$ : measures the **relative reduction** in the variability of  $Y_2$  associated with the use of variable  $Y_1$ .

$$\rho_{12}^2 = \frac{\sigma_1^2 - \sigma_{1|2}^2}{\sigma_1^2}$$
$$\rho_{12}^2 = \frac{\sigma_2^2 - \sigma_{2|1}^2}{\sigma_2^2}$$

## Example:

- An economist investigated food purchasing patterns by households in a midwestern city. Two hundred households with family incomes between \$40,000 and \$60,000 were selected to ascertain, among other things, the proportions of the food budget expended for beef and poultry, respectively. The economist expected these to be negatively related, and wished to estimate the coefficient of correlation with a 95 percent confidence interval.
- The point estimate of  $\rho_{12}$  was  $r_{12} = -.61$ . From table B.8,  $Z' = -0.7089$  when  $r_{12} = -.61$

$$\sigma\{z'\} = \frac{1}{\sqrt{200 - 3}} = .07125$$
$$z(.975) = 1.960$$

- Hence, the confidence limits for  $\xi$  are  $-.7089 \pm 1.960(.07125)$ , and the approximate 95 percent confidence interval is
  - $-.849 \leq \xi \leq -.569$
- Using Table B.8 to transform back to  $\rho_{12}$ , we obtain:
  - $-.69 \leq \rho_{12} \leq -.51$
- This confidence interval was sufficiently precise to be useful to the economist, confirming the negative relation and indicating that the degree of linear association is moderately high.

# Spearman Rank Correlation Coefficient

- When no appropriate transformations can be found, a nonparametric *rank correlation* procedure may be useful for making inferences about the association between  $Y_1$  and  $Y_2$ .
- The ordinal Pearson product-moment correlation coefficient:

$$r_s = \frac{\sum (R_{i1} - \bar{R}_1)(R_{i2} - \bar{R}_2)}{[\sum (R_{i1} - \bar{R}_1)^2 \sum (R_{i2} - \bar{R}_2)^2]^{1/2}}$$

- Test: (two-sided)

$H_0$  : There is no association between  $Y_1$  and  $Y_2$

$H_a$  : There is an association between  $Y_1$  and  $Y_2$

$$\Rightarrow t^* = \frac{r_s \sqrt{n-2}}{1 - r_s^2} \sim t(n-2)$$

Example:

- A market researcher wished to examine whether an association exists between population size ( $Y_1$ ) and per capita expenditures for a new food product ( $Y_2$ ).
- The data for a random sample of 12 test markets are given below. Because the distributions of the variables do not appear to be approximately normal, a nonparametric test of association is desired.

	(1)	(2)	(3)	(4)
Test Market	Population (in thousands)	Per Capita Expenditure (dollars)		
$i$	$Y_{i1}$	$Y_{i2}$	$R_{i1}$	$R_{i2}$
1	29	127	1	2
2	435	214	8	11
3	86	133	3	4
4	1,090	208	11	10
5	219	153	7	6
6	503	184	9	8
7	47	130	2	3
8	3,524	217	12	12
9	185	141	6	5
10	98	154	5	7
11	952	194	10	9
12	89	103	4	1

- $r_s$  is 0.985

$$t^* = \frac{.895\sqrt{12-2}}{\sqrt{1-(.895)^2}} = 6.34$$

- $t(.995; 10) = 3.169$ . Since  $|t^*| = 6.34 > 3.169$ , we conclude  $H_a$ , that there is an association between population size and per capita expenditures for the food product.

## Example:

	(1)	(2)	(3)	(4)
Test Market	Population	Per Capita		
<i>i</i>	(in thousands)	Expenditure		
	$Y_{i1}$	(dollars)	$R_{i1}$	$R_{i2}$
1	29	127	1	2
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- $r_s$  is 0.895
- $t(.995; 10) = 3.169$ . Since  $|t^*| = 6.34 > 3.169$ , we conclude  $H_a$ , that there is an association between population size and per capita expenditures for the food product.

$$t^* = \frac{.895\sqrt{12-2}}{\sqrt{1-(.895)^2}} = 6.34$$

- `cor(expenditures$Y1,expenditures$Y2,method="spearman")`
- `cor.test(expenditures$Y1,expenditures$Y2,method="spearman")`