

ORIGIN = 0

## Multiple Regression

**Multiple Regression** is an extension of the technique of linear regression to describe the relationship between a single dependent (response) variable ( $Y$ ) and **multiple** independent (predictor) variables ( $X_1, X_2, X_3, \dots$ ). Typically, multiple regression involves specifying one, or sometimes several, linear models, constructing the multiple regression, and then testing hypotheses often involving several regression coefficients ( $\beta_1, \beta_2, \beta_3, \dots$ ) corresponding to each of the  $X$  variables.

```

ZAR := READPRN("c:/DATA/Biostatistics/ZarEX20.1aR.txt" )
Y := ZAR(5)      < dependent variable Y
X1 := ZAR(1)     < independent variables X1-X4
X2 := ZAR(2)     X3 := ZAR(3)     X4 := ZAR(4)
n := length(Y)      n = 33
k := 5               < number of independent variables +1
i := 0..n - 1        < range variables i, ii for n observations
ii := 0..n - 1
j := 0..k - 1        < range variable j for columns of X

```

	0	1	2	3	4	5
0	1	6	9.9	5.7	1.6	2.12
1	2	1	9.3	6.4	3	3.39
2	3	-2	9.4	5.7	3.4	3.61
3	4	11	9.1	6.1	3.4	1.72
4	5	-1	6.9	6	3	1.8
5	6	2	9.3	5.7	4.4	3.21
6	7	5	7.9	5.9	2.2	2.59
7	8	1	7.4	6.2	2.2	3.25
8	9	1	7.3	5.5	1.9	2.86
9	10	3	8.8	5.2	0.2	2.32
10	11	11	9.8	5.7	4.2	1.57
11	12	9	10.5	6.1	2.4	1.5
12	13	5	9.1	6.4	3.4	2.69
13	14	-3	10.1	5.5	3	4.06
14	15	1	7.2	5.5	0.2	1.98

### Assumptions:

- Multiple Linear Regression depends on specifying in advance which variable is considered 'dependent' and which others 'independent'. This decision matters as changing roles for  $Y$  versus  $X$ 's usually produces a different result.
- $Y_1, Y_2, Y_3, \dots, Y_n$  (dependent variable) is a random sample  $\sim N(\mu, \sigma^2)$ .

- $k$  Vectors of *fixed* Independent Variables:

- $X_{1,1}, X_{1,2}, X_{1,3}, \dots, X_{1,n}$  (independent variable) with each value of  $X_{1,i}$  matched to  $Y_i$
- $X_{2,1}, X_{2,2}, X_{2,3}, \dots, X_{2,n}$  (independent variable) with each value of  $X_{2,i}$  matched to  $Y_i$
- ...
- $X_{k,1}, X_{k,2}, X_{k,3}, \dots, X_{k,n}$  (independent variable) with each value of  $X_{k,i}$  matched to  $Y_i$

### Model:

$$Y_i = \alpha + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \beta_3 X_{3,i} + \dots + \beta_k X_{k,i} + \varepsilon_i \quad \text{for } i = 1 \text{ to } n$$

where:  $\alpha$  is the y intercept of the regression line (translation).

$\beta_i$ 's are the regression coefficient (i.e., "slope") for each  $X_i$  of the regression line.

$\varepsilon_i$ 's are the residuals (i.e. "error") in prediction of  $Y$  given that it is a random variable with  $N(0, \sigma^2)$

Note that this is one of many possible linear models involving  $X_i$ 's that may be Squared or higher order functions of an original variable (i.e.,  $X^2, X^3$ , etc.) or cross products of two original variables (i.e.,  $X_{a,i}X_{b,i}$ , etc.). This is the wonderful and extremely powerful world of **Linear Modeling**.

## Least Squares Estimation of the Regression Line:

Calculations in Multiple Regression are extensive, and best visualized using matrix algebra where sums of squares and cross products are implicit in matrix manipulations:

**X:** becomes a ( $n \times k+1$ ) Matrix of fixed X values with first column of 1's and each of  $k$  vectors above comprising subsequent columns.

**$X^{-1}$ :** is the Inverse Matrix of X, such that  $X^{-1}X = I$  (the identity matrix).

**$X^T$ :** is the transpose matrix of X where rows and columns are reversed.

**Y**: is the vector of  $Y_i$ 's arrayed as a column of numbers.

**b**: is the vector of regression coefficients including  $\alpha$  plus all  $\beta_i$ 's arrayed as a single column of numbers.

**$Y_{\text{hat}}$** : is the vector of fitted values for  $Y_i$  arrayed as a column of numbers.

**e**: is the vector of residuals  $e_i (Y_{\text{hat},i} - Y_i)$  arrayed as a column of numbers.

1	6	9.9	5.7	1.6
1	1	9.3	6.4	3
1	-2	9.4	5.7	3.4
1	11	9.1	6.1	3.4
1	-1	6.9	6	3
1	2	9.3	5.7	4.4
1	5	7.9	5.9	2.2
1	1	7.4	6.2	2.2
1	1	7.3	5.5	1.9

1	3	8.8	5.2	0.2
1	11	9.8	5.7	4.2
1	9	10.5	6.1	2.4
1	5	9.1	6.4	3.4
1	-3	10.1	5.5	3
1	1	7.2	5.5	0.2
1	8	11.7	6	3.9
1	-2	8.7	5.5	2.2
1	3	7.6	6.2	4.4
1	6	8.6	5.9	0.2
1	10	10.9	5.6	2.4

## Constructing Design Matrix X of Independent Variables:

$X_{0,i} := 1$  < vector of 1's for constructing matrix X below

$X := \text{augment}(X_0, X_1, X_2, X_3, X_4)$

## Estimated Regression Coefficients (b):

$$b := (X^T X)^{-1} \cdot (X^T Y)$$

<sup>^ Note: all calculations here involve MathCad's matrix algebra functions!</sup>

$$b = \begin{pmatrix} 2.958283 \\ -0.129319 \\ -0.018785 \\ -0.046215 \\ 0.208755 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix}$$

$$X = \begin{pmatrix} 1 & 6 & 9.9 & 5.7 & 1.6 \\ 1 & 1 & 9.3 & 6.4 & 3 \\ 1 & -2 & 9.4 & 5.7 & 3.4 \\ 1 & 11 & 9.1 & 6.1 & 3.4 \\ 1 & -1 & 6.9 & 6 & 3 \\ 1 & 2 & 9.3 & 5.7 & 4.4 \\ 1 & 5 & 7.9 & 5.9 & 2.2 \\ 1 & 1 & 7.4 & 6.2 & 2.2 \\ 1 & 1 & 7.3 & 5.5 & 1.9 \\ 1 & 3 & 8.8 & 5.2 & 0.2 \\ 1 & 11 & 9.8 & 5.7 & 4.2 \\ 1 & 9 & 10.5 & 6.1 & 2.4 \\ 1 & 5 & 9.1 & 6.4 & 3.4 \\ 1 & -3 & 10.1 & 5.5 & 3 \\ 1 & 1 & 7.2 & 5.5 & 0.2 \\ 1 & 8 & 11.7 & 6 & 3.9 \\ 1 & -2 & 8.7 & 5.5 & 2.2 \\ 1 & 3 & 7.6 & 6.2 & 4.4 \\ 1 & 6 & 8.6 & 5.9 & 0.2 \\ 1 & 10 & 10.9 & 5.6 & 2.4 \\ 1 & 4 & 7.6 & 5.8 & 2.4 \\ 1 & 5 & 7.3 & 5.8 & 4.4 \\ 1 & 5 & 9.2 & 5.2 & 1.6 \\ 1 & 3 & 7 & 6 & 1.9 \\ 1 & 8 & 7.2 & 5.5 & 1.6 \\ 1 & 8 & 7 & 6.4 & 4.1 \\ 1 & 6 & 8.8 & 6.2 & 1.9 \\ 1 & 6 & 10.1 & 5.4 & 2.2 \\ 1 & 3 & 12.1 & 5.4 & 4.1 \\ 1 & 5 & 7.7 & 6.2 & 1.6 \\ 1 & 1 & 7.8 & 6.8 & 2.4 \\ 1 & 8 & 11.5 & 6.2 & 1.9 \\ 1 & 10 & 10.4 & 6.4 & 2.2 \end{pmatrix}$$

## Estimated values of Y ( $Y_{\text{hat}}$ ):

$$Y_{\text{hat}} := X \cdot b \quad \text{see next page for } Y_{\text{hat}}$$

$$X^T X = \begin{pmatrix} 33 & 147 & 293.2 & 194.1 & 83.9 \\ 147 & 1127 & 1366.1 & 872.7 & 381.3 \\ 293.2 & 1366.1 & 2675.66 & 1721.84 & 755.6 \\ 194.1 & 872.7 & 1721.84 & 1146.57 & 497.07 \\ 83.9 & 381.3 & 755.6 & 497.07 & 258.27 \end{pmatrix}$$

## Residuals ( $\epsilon$ ):

$$\epsilon := Y - Y_{\text{hat}} \quad \text{see next page for } \epsilon$$

$$X^T Y = \begin{pmatrix} 81.65 \\ 302.73 \\ 718.605 \\ 479.779 \\ 215.64 \end{pmatrix} \quad \text{<sup>^ Sums of XY cross Products Matrix of Lxy</sup>}$$

<sup>^ Sums of Squares and Cross-Products of X's Matrix analog of Lxx</sup>

$$(X^T X)^{-1} = \begin{pmatrix} 10.351 & 0.0441 & -0.2354 & -1.4788 & 0.1072 \\ 0.0441 & 0.0025 & -0.0025 & -0.0059 & 0.0006 \\ -0.2354 & -0.0025 & 0.0176 & 0.0174 & -0.005 \\ -1.4788 & -0.0059 & 0.0174 & 0.2392 & -0.022 \\ 0.1072 & 0.0006 & -0.005 & -0.022 & 0.025 \end{pmatrix}$$

<sup>< Inverse of Matrix  $X^T X$ : Multiplication by this matrix is the matrix algebra analog of dividing by  $X^T X$ .</sup>

**Sums of Squares as Quadratic Forms:**

$$H := X \cdot (X^T \cdot X)^{-1} \cdot X^T \quad < \text{called the "Hat Matrix" often reported in software}$$

$$J_{i,ii} := 1 \quad < n \times n \text{ matrix of 1's useful in calculations}$$

$$I := \text{identity}(n) \quad < \text{identity matrix of length } n$$

$$SSR := Y^T \cdot \left[ H - \left( \frac{1}{n} \right) \cdot J \right] \cdot Y \quad SSR = (9.7174)$$

$$SSE := Y^T \cdot (I - H) \cdot Y \quad SSE = (5.0299)$$

$$SSTO := Y^T \cdot \left[ I - \left( \frac{1}{n} \right) \cdot J \right] \cdot Y \quad SSTO = (14.747206)$$

**Degrees of Freedom:**

$$df_R := k - 1 \quad df_R = 4$$

$$df_E := n - k \quad df_E = 28$$

$$df_T := n - 1 \quad df_T = 32$$

**ANOVA Table:**

SS	df	MS	
SSR = (9.7174)	df_R = 4	MSR := $\frac{SSR}{df_R}$	MSR = (2.4293)
SSE = (5.0299)	df_E = 28	MSE := $\frac{SSE}{df_E}$	MSE = (0.1796)
SSTO = (14.7472)	df_T = 32	MSTO := $\frac{SSTO}{df_T}$	MSTO = (0.4609)

**Standard error of the Regression Parameters:**

$$MS_E := MSE_0 \quad MS_E = 0.1796 \quad < \text{converting } 1 \times 1 \text{ matrix into scalar}$$

$$sb_{sq} := MS_E \cdot (X^T \cdot X)^{-1} \quad < \text{matrix of variances/covariances among regression coefficients:}$$

$$sb_j := \sqrt{sb_{sq,j,j}}$$

$$sb = \begin{pmatrix} 1.363608 \\ 0.021287 \\ 0.056278 \\ 0.20727 \\ 0.067035 \end{pmatrix} \quad < \text{standard error of regression parameters } b$$

2.067	2.067	0.053
2.9848	2.9848	0.4052
3.4867	3.4867	0.1233
1.7927	1.7927	-0.0727
3.307	3.307	-1.507
3.18	3.18	0.03
2.3499	2.3499	0.2401
2.8627	2.8627	0.3873
2.8343	2.8343	0.0257
2.2065	2.2065	0.1135
1.965	1.965	-0.395
1.8163	1.8163	-0.3163
2.5547	2.5547	0.1353
3.5286	3.5286	0.5314
2.4813	2.4813	-0.5013
2.2408	2.2408	0.0492
3.2586	Y <sub>hat</sub> = 3.2586	$\varepsilon = 0.2914$
3.0596	3.0596	0.2504
1.7899	1.7899	0.0401
1.7025	1.7025	-0.0125
2.5312	2.5312	-0.1112
2.825	2.825	0.155
2.2326	2.2326	-0.3926
2.5582	2.5582	-0.0782
1.8683	1.8683	0.9617
2.3524	2.3524	0.0576
2.1272	2.1272	-0.3472
2.2023	2.2023	0.0177
2.9494	2.9494	-0.2294
2.2145	2.2145	0.1455
2.8692	2.8692	-0.0592
1.8178	1.8178	-0.1778
(1.6332)	(1.6332)	0.1868

1.8594	0.0079	-0.0423	-0.2656	0.0193
0.0079	0.0005	-0.0004	-0.0011	0.0001
-0.0423	-0.0004	0.0032	0.0031	-0.0009
-0.2656	-0.0011	0.0031	0.043	-0.004
0.0193	0.0001	-0.0009	-0.004	0.0045

## Coefficient of Multiple Determination ( $R^2$ ):

$$R_{\text{sq}} := 1 - \frac{\text{SSE}_0}{\text{SSTO}_0} \quad R_{\text{sq}} = 0.65893$$

## Coefficient of Multiple Correlation (R):

$$R := \sqrt{R_{\text{sq}}} \quad R = 0.8117$$

## Adjusted Coefficient of Multiple Determination:

$$R_{\text{sqa}} := 1 - \frac{\text{MSE}_0}{\text{MSTO}_0} \quad R_{\text{sqa}} = 0.6102$$

## Overall F Test of the Multiple Regression:

### Hypotheses:

$H_0$ : all slope  $\beta$ 's = 0 < i.e., only  $\alpha$  is left in regression model

$H_1$ : at least some slope  $\beta$ 's not zero

### Test Statistic:

$$F := \frac{\text{MSR}_0}{\text{MSE}_0} \quad F = 13.5235$$

### Sampling Distribution:

If Assumptions hold and  $H_0$  is true, then  $F \sim F_{(k-1)/(n-k)}$

### Critical Value of the Test:

$\alpha := 0.05$  < Probability of Type I error must be explicitly set

$$C := qF(1 - \alpha, k - 1, n - k) \quad C = 2.7141$$

### Decision Rule:

IF  $F > C$ , THEN REJECT  $H_0$  OTHERWISE ACCEPT  $H_0$

$$F = 13.5235 \quad C = 2.7141$$

### Probability Value:

$$P := 1 - pF(F, k - 1, n - k) \quad P = 2.94784 \times 10^{-6}$$

**Partial t/F-Tests of single coefficients:**

Note: this is a "marginal" test, so the order of entry into regression does not matter.

**Hypotheses:**

- $H_0: \beta = 0$  < typically this is the marginal independent variable, but also intercept  $\alpha$   
 $H_1: \beta_j \neq 0$  < test set each taking a turn ( $\alpha$  first, then all  $\beta$ 's in turn)

**Test Statistic:**

$$t_j := \frac{b_j}{s_{b_j}}$$

$$F_j := (t_j)^2$$

$$t = \begin{pmatrix} 2.1695 \\ -6.0751 \\ -0.3338 \\ -0.223 \\ 3.1141 \end{pmatrix} \quad F = \begin{pmatrix} 4.7065 \\ 36.9063 \\ 0.1114 \\ 0.0497 \\ 9.6979 \end{pmatrix} \quad t^2 = \begin{pmatrix} 4.7065 \\ 36.9063 \\ 0.1114 \\ 0.0497 \\ 9.6979 \end{pmatrix}$$

**Sampling Distributions:**

- If Assumptions hold and  $H_0$  is true, then  $t \sim t_{(n-k)}$   $k = 5$   
If Assumptions hold and  $H_0$  is true, then  $F \sim F_{(1, n-k)}$

**Critical Values of the Test:**

$\alpha := 0.05$  < Probability of Type I error must be explicitly set

$$CV_t := qt\left(1 - \frac{\alpha}{2}, n - k\right) \quad CV_t = 2.0484$$

$$CV_F := qF\left(1 - \frac{\alpha}{2}, 1, n - k\right) \quad CV_F = 5.6096$$

**Decision Rules:**

IF  $|t| > CV_t$ , THEN REJECT  $H_0$  OTHERWISE ACCEPT  $H_0$   $CV_t = 2.0484$  < t-test version

IF  $F > CV_F$ , THEN REJECT  $H_0$  OTHERWISE ACCEPT  $H_0$   $CV_F = 5.6096$  < F-test version

**Probability Values:**

$$P_{t_j} := \min[2 \cdot pt(t_j, n - k), 2 \cdot (1 - pt(t_j, n - k))]$$

^ takes the minimum of the two-tailed P calculations

$$P_{F_j} := 1 - pF(F_j, 1, n - k)$$

$$P_t = \begin{pmatrix} 0.038691 \\ 0.000001 \\ 0.741024 \\ 0.825178 \\ 0.004227 \end{pmatrix} \quad \text{for: } \begin{array}{ll} \alpha & 0.038691 \\ \beta_1 & 0.000001 \\ \beta_2 & 0.741024 \\ \beta_3 & 0.825178 \\ \beta_4 & 0.004227 \end{array} \quad P_F = \begin{pmatrix} 0.038691 \\ 0.000001 \\ 0.741024 \\ 0.825178 \\ 0.004227 \end{pmatrix}$$

## Confidence Intervals for single coefficients $\alpha$ & $\beta$ :

$CI_b := \text{augment}(b - C \cdot sb, b + C \cdot sb)$  < augment function puts them into a matrix for display

$$CI_b = \begin{pmatrix} -0.7427 & 6.6592 \\ -0.1871 & -0.0715 \\ -0.1715 & 0.134 \\ -0.6088 & 0.5163 \\ 0.0268 & 0.3907 \end{pmatrix} \quad b = \begin{pmatrix} 2.9583 \\ -0.1293 \\ -0.0188 \\ -0.0462 \\ 0.2088 \end{pmatrix} \quad \text{for:}$$

$\alpha$   
 $\beta_1$   
 $\beta_2$   
 $\beta_3$   
 $\beta_4$

## Prototype in R:

```
#MULTIPLE REGRESSION > LM
#ZAR EXAMPLE 20.1a
ZAR=read.table("ZarEX20.1aR.txt")
ZAR
attach(ZAR)
Y=var5
X1=var1
X2=var2
X3=var3
X4=var4
LM=lm(Y~X1+X2+X3+X4)
LM
summary(LM)
anova(LM)

Partial t-tests of individual coefficients >
Call:
lm(formula = Y ~ X1 + X2 + X3 + X4)
Residuals:
    Min      1Q  Median      3Q     Max 
-1.5070 -0.1112  0.0401  0.1550  0.9617 
Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.95828   1.36361   2.169  0.03869 *  
X1          -0.12932   0.02129  -6.075 1.50e-06 *** 
X2          -0.01878   0.05628  -0.334  0.74102    
X3          -0.04621   0.20727  -0.223  0.82518    
X4          0.20876   0.06703   3.114  0.00423 ** 
---
Signif. codes:  0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1 

Residual standard error: 0.4238 on 28 degrees of freedom
Multiple R-squared:  0.6589,    Adjusted R-squared:  0.6102 
F-statistic: 13.52 on 4 and 28 DF,  p-value: 2.948e-06
```

Overall F-test >

Coefficient of Multiple Determination  $R^2$  ^

Adjusted Coefficient of Multiple Determination  $R_a^2$  ^

$$b = \begin{pmatrix} 2.9583 \\ -0.1293 \\ -0.0188 \\ -0.0462 \\ 0.2088 \end{pmatrix} \quad sb = \begin{pmatrix} 1.36361 \\ 0.02129 \\ 0.05628 \\ 0.20727 \\ 0.06703 \end{pmatrix} \quad t = \begin{pmatrix} 2.1695 \\ -6.0751 \\ -0.3338 \\ -0.223 \\ 3.1141 \end{pmatrix} \quad P_t = \begin{pmatrix} 0.0387 \\ 1.4958 \times 10^{-6} \\ 0.741 \\ 0.8252 \\ 0.0042 \end{pmatrix} < \text{equivalent to summary() report of partial t-tests of individual coefficients}$$

**Note: Sums of Squares for X1-X4 in R's  
ANOVA table sum to SSR above, and SS for  
'Residuals' in R equals SSE above.**

> **anova(LM)**

Analysis of Variance Table

	Response:	Y	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
X1			1	7.8762	7.8762	43.8450	3.496e-07	***
X2			1	0.0131	0.0131	0.0732	0.788785	
X3			1	0.0859	0.0859	0.4781	0.494963	
X4			1	1.7421	1.7421	9.6979	0.004227	**
Residuals			28	5.0299	0.1796			
			---					
				Signif. codes:	0	'***'	0.001	'**'
					0.01	'*'	0.05	'.'
					0.1	' '	1	

**Sums of Squares for X1-X4 in the ANOVA chart, also known as "Partial" or "Extra" Sums of Squares are not calculated in this worksheet. To understand how to interpret them, see *Biostatistics Worksheet 400*.**