

	Simple LR	Multiple LR (full model)	Centered Form Regression	Reduced Model	General Linear
Formula	$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$	$y_i = \beta_0 j_n + \beta_1 x_i + \dots + \beta_k x_k + \epsilon_i$ $= (X_1, X_2) \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} + \epsilon$ $= X_1 \beta_1 + X_2 \beta_2 + \epsilon$	$y_i = \beta_0 j_n + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \epsilon_i$ $= \alpha + \beta_1 (x_{i1} - \bar{x}_1) + \dots + \beta_k (x_{ik} - \bar{x}_k) + \epsilon_i$ $y = (j, X_c) \begin{pmatrix} \alpha \\ \beta_1 \end{pmatrix} + \epsilon$ , where $X_c = \left(I - \frac{1}{n}J\right)X_1$	$y = X_1 \beta_1^* + \epsilon^*, \text{var}(\epsilon^*) = \sigma^2 I$	
Least-Squares Estimator $\beta$	$\beta_0 = \bar{y} - \hat{\beta}_1 \bar{x}$ $\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$	$\hat{\beta} = (X'X)^{-1}X'y$	$\hat{\alpha} = \bar{y}$ $\hat{\beta}_1 = (X_c'X_c)^{-1}X_c'y = S_{xx}^{-1}S_{yx}$ $\hat{\beta}_0 = \hat{\alpha} - \hat{\beta}_1 \bar{x}_1 - \dots - \hat{\beta}_k \bar{x}_k$ $= \bar{y} - \hat{\beta}_1' \bar{x} = \bar{y} - S_{yx}' S_{xx}^{-1} \bar{x}$ $S_{xx} = \frac{X_c'X_c}{n-1} = \widehat{cov(x, x)},$ $S_{yx} = \frac{X_c'y}{n-1} = \widehat{cov(x, y)}$	$\hat{\beta}_1^* = (X_1'X_1)^{-1}X_1'y$	$\hat{\beta}_c = \hat{\beta} - (X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}C\beta$
Estimator for $\sigma^2$	$s_2 = SSE/(n-2)$	$s_2 = SSE/(n-k-1)$ $\sigma^2 = \frac{1}{n}(y - X\hat{\beta})'(y - X\hat{\beta})$			
Mean, Variance	$E(\hat{\beta}_0) = \beta_0, E(\hat{\beta}_1) = \beta_1$ $var(\hat{\beta}_0) = \sigma^2 \left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum (x_i - \bar{x})^2} \right]$ $var(\hat{\beta}_1) = \frac{\sigma^2}{\sum (x_i - \bar{x})^2}$	$E(\hat{\beta}) = \beta$ $E(s^2) = \sigma^2$ $cov(\hat{\beta}) = var(\hat{\beta})$ $= \sigma^2(X'X)^{-1}$ $c\hat{o}v(\hat{\beta}) = s^2(X'X)^{-1}$		$E(\hat{\beta}_1^*) = \beta_1 + A\beta_2$ , where $A = (X'X)^{-1}X_1'X_2$ $E(\hat{\beta}_1^*) = \beta * _1$ $cov(\hat{\beta}_1^*) = \sigma^2(X_1'X_1)^{-1}$	$E(\hat{\beta}_c) = \beta - (X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}C\beta$ $cov(\hat{\beta}_c) = \sigma^2(X'X)^{-1} - \sigma^2(X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}C(X'X)^{-1}$
Hypothesis $H_0: \beta_1 = 0$		If true, $F = \frac{SSR/k}{SSE/(n-k-1)} \sim F(k, n-k-1)$ , where $SSR/\sigma^2 \sim \chi^2(k, \lambda_1)$ , $SSE/\sigma^2 \sim \chi^2(n-k-1)$ If not, $F \sim F(k, n-k-1, \lambda_1)$ , $\lambda_1 = \hat{\beta}_1' X_c' X_c \hat{\beta}_1 / 2\sigma^2$			
Hypothesis $H_0: \beta_2 = 0$	-	If true, $F = \frac{SS(\beta_2 \beta_1)/h}{SSE/(n-k-1)} = \frac{(R^2 - R_1^2)/h}{(1-R^2)/(n-k-1)} \sim F(h, n-k-1)$ , where $SS(\beta_2 \beta_1)/\sigma^2 \sim \chi^2(n-k-1)$ , $SSE/\sigma^2 \sim \chi^2(h, \lambda_1)$ , $R_1^2 = \frac{\hat{\beta}_1' X_1' y - n\bar{y}^2}{y'y - n\bar{y}^2}$ , $R^2 = \frac{SSR}{SST}$ If not, $F \sim F(h, n-k-1, \lambda_1)$ , $\lambda_1 = \  (P_{C(X)} - P_{C(X_1)})\mu \ ^2 = \ \mu - \mu_0\ ^2 / 2\sigma^2 = \beta_2' [X_2' X_2 - X_2' X_1 (X_1' X_1)^{-1} X_1' X_2] \beta_2 / 2\sigma^2$			$E\left(\frac{SSE}{SST}\right) = \frac{n-k-1}{n-1}$ $E(R_a^2) = 0$ $E(R^2) = 1 - \frac{n-k-1}{n-1} = \frac{k}{n-1}$
Hypothesis $H_0: C\beta = 0$		If true, $F = \frac{SSH/q}{SSE/(n-k-1)} \sim F(q, n-k-1)$ , where $SSH/\sigma^2 \sim \chi^2(q, \lambda)$ , $SSE/\sigma^2 \sim \chi^2(n-k-1)$ If not, $F \sim F(q, n-k-1, \lambda)$ , where $\lambda = (C\hat{\beta})'[C(X'X)^{-1}C']C\hat{\beta} / 2\sigma^2$			
Hypothesis $H_0: C\beta = t$		If true, $F = \frac{SSH/q}{SSE/(n-k-1)} \sim F(q, n-k-1)$ , where $SSH/\sigma^2 \sim \chi^2(q, \lambda)$ , $SSE/\sigma^2 \sim \chi^2(n-k-1)$ If not, $F \sim F(q, n-k-1, \lambda)$ , where $\lambda = (C\beta - t)'[C(X'X)^{-1}C'](C\beta - t) / 2\sigma^2$			
Hypothesis $H_0: a'\beta = 0$		If true, $F = \frac{SSH/q}{SSE/(n-k-1)} = \frac{(a'\hat{\beta})^2}{s^2 a'(X'X)^{-1}a} \sim F(1, n-k-1)$ or $t = \frac{a'\hat{\beta}}{s\sqrt{a'(X'X)^{-1}a}} \sim t(n-k-1)$			
Hypothesis $H_0: \beta_j = 0$	for j=1, $t = \frac{\hat{\beta}_1}{s/\sqrt{\sum (x_i - \bar{x})^2}}$	If true, $F = \frac{\hat{\beta}_j^2}{s^2 g_{jj}} \sim F(1, n-k-1)$ or $t_i = \frac{\hat{\beta}_j}{s\sqrt{g_{jj}}} \sim t(n-k-1)$ , where $g_{jj} = diag((X'X)^{-1})$			
CI	$\hat{\beta}_1 \pm t_{\alpha/2, n-2} \frac{s}{\sqrt{\sum (x_i - \bar{x})^2}}$	$\hat{\beta}_j \pm t_{1-\alpha/2, n-k-1} s \sqrt{g_{jj}}, s = \sqrt{SSE/(n-k-1)}$ (for $\beta_j$ ) $a'\hat{\beta} \pm t_{1-\alpha/2, n-k-1} s \sqrt{a'(X'X)^{-1}a}$ (for $a'\beta$ ) $x_0'\hat{\beta} \pm t_{1-\alpha/2, n-k-1} s \sqrt{x_0'(X'X)^{-1}x_0}$ (for $E(y)$ ) $x_0'\hat{\beta} \pm t_{1-\alpha/2, n-k-1} s \sqrt{1 + x_0'(X'X)^{-1}x_0}$ (for prediction)			

- $$\mathbf{SST} = \sum_{i=1}^n (y_i - \bar{y})^2 = \|(I - P_{j_n}y)y\|^2 = \|(y - \bar{y}j_n)\|^2 = y'y - n\bar{y}^2 = (\hat{\beta}'X'y - n\bar{y}^2) + (y'y - n\bar{y}^2) = y'(I - \frac{1}{n}J)y = y'(I - H)y + y'(H - H_1)y + y'(H_1 - \frac{1}{n}J)y = y'H_cy + y'(I - \frac{1}{n}J - H_c)y = SSR + SSE, \text{ where } y'(I - H)y \sim \chi^2(n - k - 1), y'(H - H_1)y \sim \chi^2(h, \lambda_1), \lambda_1 = \beta_2' \left[ X_2'X_2 - X_2'X_1(X_1'X_1)^{-1}X_1'X_2 \right] \beta_2 / 2\sigma^2$$
- $$\mathbf{SSR} = \hat{\beta}_1'X_c'X_c\hat{\beta}_1 = \hat{\beta}'X'y - n\bar{y}^2 = (P_{C(X)}y)'y - y'P_{\mathcal{L}(j_n)}'P_{\mathcal{L}(j_n)}y = \hat{\beta}_1'X_c'y = y'X_c(X_c'X_c)^{-1}X_c'y = \|P_{X_c}y\|^2 = y'H_cy$$
- $$\mathbf{SSE} = \varepsilon'\varepsilon = \sum_{i=1}^n (y_i - x_i'\hat{\beta}) = (y - X\hat{\beta})'(y - X\hat{\beta}) = y'[I - P_{C(X)}]y = y'[I - X(X'X)^{-1}X']y = y'y - \hat{\beta}'X'y = \sum_{i=1}^n (y_i - \bar{y})^2 - \hat{\beta}_1'X_c'y = \sum_{i=1}^n (y_i - \bar{y})^2 - \|P_{X_c}y\|^2 = y'(I - \frac{1}{n}J - H_c)y = \|(I - H)y\|^2 = \|P_{C(X)^\perp}y\|^2$$
- $$\mathbf{SS}(\beta_2|\beta_1) = SSR(full) - SSR(reduced) = SSE(reduced) - SSE(full) = \|\hat{y} - \hat{y}_0\|^2 = \|y - \hat{y}_0\|^2 - \|y - \hat{y}\|^2 = y'(H - H_1)y = \hat{\beta}'X'y - \hat{\beta}_1^{*'}X'y = \hat{\beta}_1'X_c'X_c\hat{\beta}_1 - \hat{\beta}_1^{*'}X_c'X_c\hat{\beta}_1$$
- $$\mathbf{SSH} = y'(P_{C(X)} - P_{C(X_1)})y = \|(P_{C(X)} - P_{C(X_1)})y\|^2 = (C\hat{\beta})'[C(X'X)^{-1}C']^{-1}C\hat{\beta} = (C\hat{\beta} - t)'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - t)$$
- $$R^2 = \frac{SSR}{SST}$$
- $$R_a^2 = \frac{(n-1)R^2 - k}{n - k - 1}$$

$$< y \sim N_n(X\beta, \sigma^2 I) >$$

$H_0: \beta_1 = 0$  (ANOVA table)

variation	df	Sum of Squares	Mean Squares	E(Mean Squares)
$\beta_1$	k	$SSR = \hat{\beta}_1' X_c' y = \hat{\beta}' X' y - n\bar{y}^2$	SSR/k	$\sigma^2 + \frac{1}{k} \hat{\beta}_1' X_c' X_c \hat{\beta}_1$
Error	n-k-1	$SSE = y'y - \hat{\beta}' X' y$	SSE/(n-k-1)	$\sigma^2$
Total	n-1	$SST = \sum_{i=1}^n (y_i - \bar{y})^2$		

$H_0: \beta_2 = 0$  (ANOVA table)

variation	df	Sum of Squares	Mean Squares	E(Mean Squares)
$\beta_2$ adjusted for $\beta_1$	h	$S(\beta_2   \beta_1) = \hat{\beta}' X' y - \hat{\beta}_1' X' y$ $= y'(P_{C(X)} - P_{C(X_1)})y$	$SS(\beta_2   \beta_1)/h$	$\sigma^2 + \frac{1}{h} \beta_2' \left[ X_2' X_2 - X_2' X_1 (X_1' X_1)^{-1} X_1' X_2 \right] \beta_2$ $= \sigma^2 + \frac{1}{h}   \mu - \mu_0  $
Error	n-k-1	$SSE = y'y - \hat{\beta}' X' y$ $= y'(I - P_{C(X)})y$	SSE/(n-k-1)	$\sigma^2$
Total	n-1	$SST = y'y - n\bar{y}^2$		

$H_0: C\beta = 0$  (ANOVA table),  $C\hat{\beta} \sim N_q(C\beta, \sigma^2 C(X'X)^{-1}C')$

variation	df	Sum of Squares	Mean Squares	E(Mean Squares)
General Linear	q	$SSH = \hat{\beta}' X' y - \hat{\beta}_c' X' y = (C\hat{\beta})' [C(X'X)^{-1}C']^{-1} (C\hat{\beta})$	SSH/q	$\sigma^2 + \frac{1}{q} (C\beta)' [C(X'X)^{-1}C']^{-1} (C\beta)$
Error	n-k-1	$SSE = y'[I - X(X'X)^{-1}X']y$	SSE/(n-k-1)	$\sigma^2$
Total	n-1	$SST = \sum_{i=1}^n (y_i - \bar{y})^2$		

$H_0: C\beta = t$  (ANOVA table),  $C\hat{\beta} - t \sim N_q(C\beta - t, \sigma^2 C(X'X)^{-1}C')$

variation	df	Sum of Squares	Mean Squares	E(Mean Squares)
General Linear	q	$SSH = (C\hat{\beta} - t)' [C(X'X)^{-1}C']^{-1} (C\hat{\beta} - t)$	SSH/q	$\sigma^2 + \frac{1}{q} (C\beta - t)' [C(X'X)^{-1}C']^{-1} (C\beta - t)$
Error	n-k-1	$SSE = y'[I - X(X'X)^{-1}X']y$	SSE/(n-k-1)	$\sigma^2$
Total	n-1	$SST = \sum_{i=1}^n (y_i - \bar{y})^2$		