

FORMULÁRIO de EACE, 1a PARTE	$SS_{XY} = \sum_1^n (X_i - \bar{X})(Y_i - \bar{Y}) = \sum_1^n X_i Y_i - n.\bar{X} \bar{Y}$ $SS_{XX} = \sum_1^n (X_i - \bar{X})^2 = \sum_1^n X_i^2 - n.\bar{X}^2$ $SS_{YY} = \sum_1^n (Y_i - \bar{Y})^2 = \sum_1^n Y_i^2 - n.\bar{Y}^2$
Variância	$S_X^2 = \frac{1}{n-1} \sum_1^n (X_i - \bar{X})^2 = \frac{1}{n-1} (\sum_1^n X_i^2 - n.\bar{X}^2)$
CORRELAÇÃO	
Corr. Pearson	$r = \frac{Cov(X,Y)}{S_x.S_Y} = \frac{SS_{XY}}{\sqrt{SS_{XX}.SS_{YY}}}$ Sob $H_0 : \rho = 0, T = r \sqrt{\frac{n-2}{1-r^2}} \sim t_{n-2}$ $Z_r \sim N(Z_\rho, \frac{1}{n-3})$ onde $Z_r = \frac{1}{2} \ln \frac{1+r}{1-r}$ $Z^* = \frac{Z_r^* - Z_\rho^*}{1/\sqrt{n-1}} \sim N(0, 1)$ onde $Z_r^* = Z_r - \frac{3Z_r + r}{4n}$
Corr. Spearman no caso de independência,	$r_S = 1 - \frac{6 \sum_{i=1}^n (R_i - Q_i)^2}{n(n^2 - 1)}$ (sem empates) se $n > 30$: $\sqrt{n-1} r_S \sim N(0, 1)$
Corr. pesada	$r_W = 1 - \frac{6 \sum_{i=1}^n (R_i - Q_i)^2 (2n+2-R_i-Q_i)}{n^4 + n^3 - n^2 - n}$ $r_{W2} = 1 - \frac{90 \sum_{i=1}^n (R_i - Q_i)^2 (2n+2-R_i-Q_i)^2}{n(n-1)(n+1)(2n+1)(8n+11)}$ (Nota: $R'_i = R_i(2n+2-R_i)$)
REGRESSÃO LINEAR SIMPLES	
Modelo: $Y_i = \alpha + \beta x_i + \epsilon_i$, com $\epsilon_i \sim N(0, \sigma^2)$	$\hat{\alpha} = \bar{y} - \hat{\beta} \bar{x}$; $\hat{\beta} = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{SS_{xy}}{SS_{xx}}$; $S^2(\hat{\alpha}, \hat{\beta}) = SS_{yy} - \hat{\beta} SS_{xy}$
	$\frac{S^2(\hat{\alpha}, \hat{\beta})}{\sigma^2} \sim \chi_{n-2}^2$, e ind. de $\hat{\alpha}, \hat{\beta}$; $\hat{\sigma}^2 = \frac{S^2(\hat{\alpha}, \hat{\beta})}{n-2}$ $\frac{(\hat{\alpha} - \alpha)}{s.e.(\hat{\alpha})} = \frac{(\hat{\alpha} - \alpha)}{\hat{\sigma}} \sqrt{\frac{n \sum (x_i - \bar{x})^2}{\sum x_i^2}} \sim t_{n-2}$ $\frac{(\hat{\beta} - \beta)}{s.e.(\hat{\beta})} = \frac{(\hat{\beta} - \beta)}{\hat{\sigma}} \sqrt{\sum (x_i - \bar{x})^2} \sim t_{n-2}$
Intervalo de confiança para $\alpha + \beta x^*$	$(\hat{\alpha} + \hat{\beta} x^*) \pm t_{(n-2, 1-\frac{\alpha}{2})} \sqrt{\hat{\sigma}^2 \left(\frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right)}$
Intervalo de predição para Y em x^*	$(\hat{\alpha} + \hat{\beta} x^*) \pm t_{(n-2, 1-\frac{\alpha}{2})} \sqrt{\hat{\sigma}^2 \left(1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right)}$
Somas de quadrados, total: regressão: residual:	$SST = SS_{yy} = \sum (y_i - \bar{y})^2 = \sum y_i^2 - (\sum y_i)^2 / n$ $SSR = \sum (\hat{y}_i - \bar{y})^2 = \hat{\beta}^2 [\sum x_i^2 - (\sum x_i)^2 / n] = \hat{\beta}^2 SS_{xx}$ $SSE = S^2(\hat{\alpha}, \hat{\beta}) = \sum (y_i - \hat{y}_i)^2 = SS_{yy} - SSR$ $SST = SSR + SSE$
Coefficiente de determinação:	$R^2 = [Cor(Y, \hat{Y})]^2 = [Cor(Y, X)]^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2} = r^2$
REGRESSÃO LINEAR MÚLTIPLA	
X matriz de dados com $p + 1$ colunas Y vetor resposta	$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$ $\hat{\sigma}^2 = \frac{1}{n-p-1} \sum_{i=1}^n (\mathbf{y}_i - \hat{\mathbf{y}}_i)^2 = \frac{1}{n-p-1} SSE$
Modelo: $\mathbf{Y} = \beta_0 + \sum \mathbf{X}_j \beta_j + \epsilon$, em que $\epsilon \sim \mathbf{N}(\mathbf{0}, \sigma^2)$	$\hat{\beta} \sim \mathbf{N}(\beta, (\mathbf{X}^T \mathbf{X})^{-1} \sigma^2)$ $\frac{(n-p-1)\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-p-1}^2$; $\hat{\beta}$ e $\hat{\sigma}^2$ são independentes Sob $\mathbf{H}_0 : \beta_j = \mathbf{0}, \frac{\hat{\beta}_j}{\hat{\sigma} \sqrt{\nu_j}} \sim t_{n-p-1}$ (ν_j é o j-ésimo elemento da diagonal de $(\mathbf{X}^T \mathbf{X})^{-1}$)
IC para β_j IC para média de Y em $x^* = (x_1^*, \dots, x_p^*)$ Int. de predição para Y em x^*	$\hat{\beta}_j \pm t_{(1-\alpha/2)} s.e.(\hat{\beta}_j) = \hat{\beta}_j \pm t_{(1-\alpha/2)} \hat{\sigma} \sqrt{\nu_j}$ $\hat{\mu}^* \pm t_{(n-p-1, 1-\frac{\alpha}{2})} s.e.(\hat{\mu}^*) = \hat{\mu}^* \pm t_{(n-p-1, 1-\frac{\alpha}{2})} \hat{\sigma} \sqrt{x^{*T} (X^T X)^{-1} x^*}$ $\hat{Y}^* \pm t_{(n-p-1, 1-\frac{\alpha}{2})} s.e.(\hat{Y}^*) = \hat{Y}^* \pm t_{(n-p-1, 1-\frac{\alpha}{2})} \hat{\sigma} \sqrt{1 + x^{*T} (X^T X)^{-1} x^*}$
Seja $\mathbf{H}_0 : \beta_1 = \beta_2 = \dots = \beta_k = \mathbf{0}$	Sob $\mathbf{H}_0, \mathbf{F} = \frac{(SSE_0 - SSE_1) / (p_1 - p_0)}{SSE_1 / (n - p_1)} \sim \mathbf{F}_{p_1 - p_0, n - p_1} \rightarrow \chi_{p_1 - p_0}^2$ $\mathbf{p}_1 = \mathbf{p} + \mathbf{1}$ e $\mathbf{p}_0 = \mathbf{p} + \mathbf{1} - \mathbf{k}$. Rejeita-se H_0 se $F > F_{p_1 - p_0, n - p_1, 1 - \alpha}$ dem: Graybill (1976), Rao(1973), Searle(1971) ou Seber & Lee (2003)
Coefficiente de correlação múltipla	$Cor(Y, \hat{Y})$
Coefficiente de determinação	$R^2 = [Cor(Y, \hat{Y})]^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$
Coefficiente de determinação ajustado	$R_a^2 = 1 - \frac{SSE/(n-p-1)}{SST/(n-1)} = 1 - \frac{n-1}{n-p-1} (1 - R^2)$ (\neq prop. var. exp. reg.)