

Regression and the General Linear Model

Multivariate Statistic

Made by:

**Lasse Gøransson, Marc Evald,
Anne-Charlotte Poulsen & Aske
Møller**

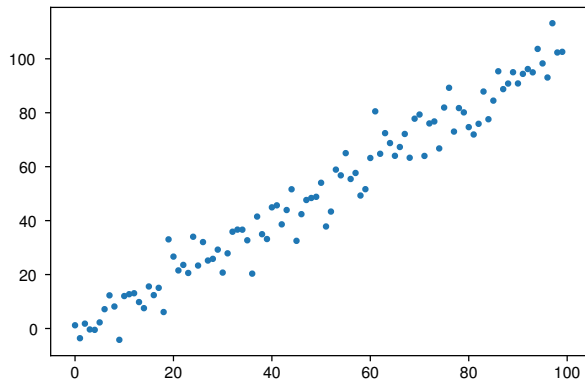
SDU Robotics
The Maersk Mc-Kinney Møller Institute
University of Southern Denmark

Agenda



- ▶ Motivation
- ▶ UMLR
 - ▶ Model
 - ▶ Estimation
 - ▶ Model Check
 - ▶ Inference on β
 - ▶ Model reduction
- ▶ MMLR

Motivation



Assumptions



$$Y = z\beta + \epsilon$$



$$E[\epsilon] = 0$$



$$V[\epsilon] = \sigma^2$$

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & z_{11} & z_{12} & \cdots & z_{1r} \\ 1 & z_{21} & z_{22} & & \vdots \\ \vdots & & & \ddots & \\ 1 & z_{n1} & \cdots & & z_{nr} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_r \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

Estimation of Coefficients



$$(z^T z)^{-1} \quad z^T Y = \hat{\beta}_{LS}$$

$$(z^T z)^+ \quad z^T Y = \hat{\beta}_{LS}$$

Model check



$$\sum_{j=1}^n (Y_j - \bar{Y}) (Y_j - \bar{Y})^T = \sum_{j=1}^n (Y_j - \hat{Y}_j) (Y_j - \hat{Y}_j)^T + \sum_{j=1}^n (\hat{Y}_j - \bar{Y}) (\hat{Y}_j - \bar{Y})^T$$

Model check



$$\sum_{j=1}^n (Y_j - \bar{Y}) (Y_j - \bar{Y})^T = \sum_{j=1}^n (Y_j - \hat{Y}_j) (Y_j - \hat{Y}_j)^T + \sum_{j=1}^n (\hat{Y}_j - \bar{Y}) (\hat{Y}_j - \bar{Y})^T$$

$SST = SSE \qquad \qquad \qquad + SSR$

$$R^2 = \frac{SSR}{SST}$$

Model check



$$\sum_{j=1}^n (Y_j - \bar{Y}) (Y_j - \bar{Y})^T = \sum_{j=1}^n (Y_j - \hat{Y}_j) (Y_j - \hat{Y}_j)^T + \sum_{j=1}^n (\hat{Y}_j - \bar{Y}) (\hat{Y}_j - \bar{Y})^T$$

$SST = SSE \qquad \qquad \qquad + SSR$

$$R^2 = \frac{SSR}{SST}$$

$$R_{adj}^2 = 1 - \frac{(n-1) SSE}{(n-r-1) SST}$$



New assumption.

$$\left(\hat{\beta} - \beta^*\right)^T \left(\frac{Z^T Z}{(r+1)\sigma^2} \right) \left(\hat{\beta} - \beta^*\right) \sim F_{r+1, n-(r+1)}$$



New assumption.

$$\left(\hat{\beta} - \beta^*\right)^T \left(\frac{Z^T Z}{(r+1)\sigma^2} \right) \left(\hat{\beta} - \beta^*\right) \sim F_{r+1, n-(r+1)}$$

- ▶ Hypothesis Test
- ▶ Confidence Region

Model reduction



$$\beta = \begin{bmatrix} \beta_{(1)} \\ \beta_{(2)} \end{bmatrix} \begin{pmatrix} q+1 \\ r-q \end{pmatrix}$$



$$\beta = \begin{bmatrix} \beta_{(1)} \\ \beta_{(2)} \end{bmatrix} \begin{matrix} (q+1) \\ (r-q) \end{matrix}$$

$$ESS = \Delta SSR = SSR_{\beta} - SSR_{\beta_{(1)}}$$

$$\frac{1}{\sigma^2} \cdot \frac{ESS}{r-q} \sim F_{r-q, n-(r+1)}$$



$$\begin{bmatrix} y_{11} & \cdots & y_{1p} \\ \vdots & & \vdots \\ y_{n1} & \cdots & y_{np} \end{bmatrix} = \begin{bmatrix} 1 & z_{11} & z_{12} & \cdots & z_{1r} \\ 1 & z_{21} & z_{22} & & \vdots \\ \vdots & & & \ddots & \\ 1 & z_{n1} & \cdots & & z_{nr} \end{bmatrix} \begin{bmatrix} \beta_{01} & \cdots & \beta_{0p} \\ \vdots & & \vdots \\ \beta_{0r} & \cdots & \beta_{rp} \end{bmatrix} + \begin{bmatrix} \epsilon_{11} & \cdots & \epsilon_{1p} \\ \vdots & & \vdots \\ \epsilon_{n1} & \cdots & \epsilon_{np} \end{bmatrix}$$



$$\Lambda = \frac{\max L(\beta_{(1)}, \Sigma)}{\max L(\beta, \Sigma)} = \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right)^{\frac{n}{2}}$$



$$\Lambda = \frac{\max L(\beta_{(1)}, \Sigma)}{\max L(\beta, \Sigma)} = \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right)^{\frac{n}{2}}$$

$$\hat{\Sigma} = \hat{\epsilon}^T \hat{\epsilon}$$



$$\Lambda = \frac{\max L(\beta_{(1)}, \Sigma)}{\max L(\beta, \Sigma)} = \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right)^{\frac{n}{2}}$$

$$\hat{\Sigma} = \hat{\epsilon}^T \hat{\epsilon}$$

$$-2 \log(\Lambda) = -n \log \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right) \underset{approx}{\sim} \chi^2_{(r-q)p}$$



$$\Lambda = \frac{\max L(\beta_{(1)}, \Sigma)}{\max L(\beta, \Sigma)} = \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right)^{\frac{n}{2}}$$

$$\hat{\Sigma} = \hat{\epsilon}^T \hat{\epsilon}$$

$$-2 \log(\Lambda) = - \left(n - (r+1) - \frac{p-r+q+1}{2} \right) \log \left(\frac{|\hat{\Sigma}|}{|\hat{\Sigma}_{(1)}|} \right) \underset{approx}{\sim} \chi^2_{(r-q)p}$$