

# Take home 2

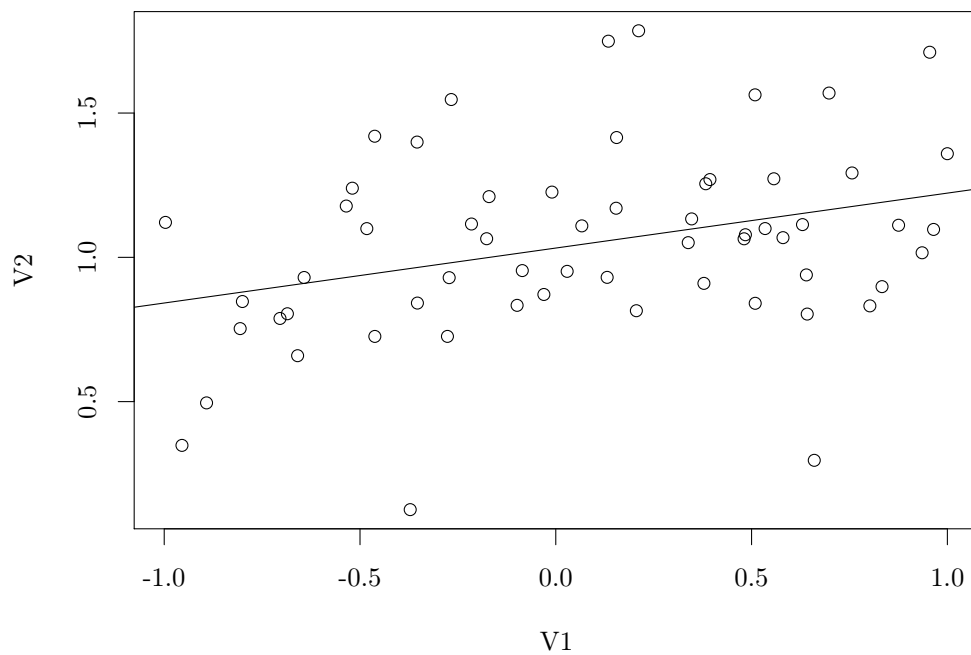
Pieter Luyten

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## Question 1

(a)

The value for the intercept of the fit is 1.0321764 and for the slope of the fit is 0.1904323



Figuur 1: line fit through the data in Ex1.txt

(b)

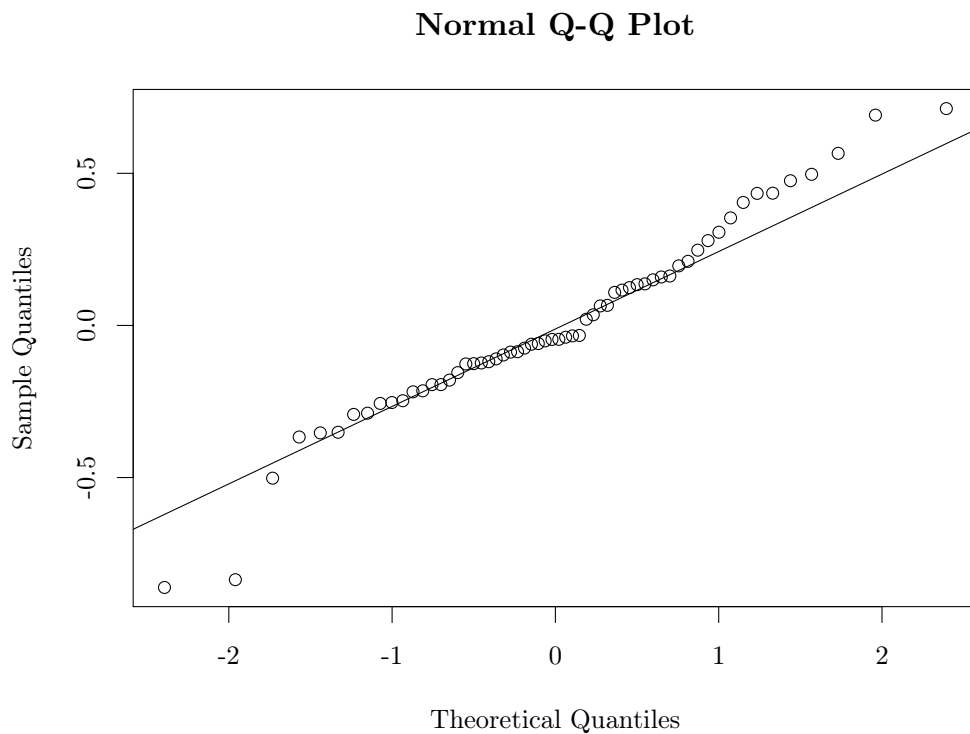
Using the result from section 7.4.1 in <REFERENCE cursus> we know that the random variable

$$T = \frac{\beta_1}{\sqrt{\frac{S^2}{\sum_{i=1}^n (x_i - \bar{x}^2)}}} \quad (1)$$

has a Student distribution with  $n - 2$  degrees of freedom. The test value is 2.603. Using a student-t distribution with  $60 - 2 = 58$  degrees of freedom we find a p-value of 0.0117. At the confidence level  $\alpha = 0.01$ , the null hypothesis that  $\beta_1 = 0$  holds. The 99% confidence region for the test value is  $[-2.663, 2.663]$ .

(c)

A q-q plot is a plot where the quantiles of the assumed distribution are plotted against the quantiles from the sample. So in a sample of  $n$  points where we label the observation  $x_i, i \in \{1, 2, \dots, n\}$  from lowest to highest, the  $i$ th point will be plotted at the  $(Q(i/n), x_i)$ . Here  $Q(x)$  is the quantile function of the assumed distribution. This is a function such that  $P(X < Q(p)) = p$ . If the assumed distribution is a good model for the observed sample, the points will well fitted by a linear function.



Figuur 2: qq plot for the errors on the fit

(d)

We use the formula from section 7.5.4 in the book to find a confidence region for  $\beta$ . This region is of the form:

$$\left\{ \beta \left| \frac{(\hat{\beta} - \beta)^T (X^T X) (\hat{\beta} - \beta)}{p S^2} \leq F_{p, n-p}(1 - \alpha) \right. \right\} \quad (2)$$

Because the matrix  $X^T X$  is positive definite, this is an ellips with center  $\beta$  and axes along the eigenvectors of  $X^T X$ . The upper bound for this expression is in this case:  $F_{2, 58}(0.99) = 4.9910$ . Filling in the values for  $X, p = 2, n = 60$  and  $S^2$  we get the following result (obtained using the cAS system sympy):

$$\{\beta | 5.2596\alpha^2 + 0.8222\alpha\beta - 0.4950\alpha + 1.6711\beta^2 - 0.6629\beta + 0.0711 \leq 4.9910\}$$

## Question 2

(a)

The value for  $\hat{\beta}_{OLS}$  obtained using ordinary least squares with the correlated errors is:

$$\hat{\beta}_{OLS} = (3.923161, 1.214355)^T \quad (3)$$

(b)

we know that the variance is the same for all  $\epsilon_i$  and that they obey the recursive relation:

$$\epsilon_i = \rho\epsilon_{i-1} + \eta_i$$

with  $\eta_i$  standard normaly distributed. Using  $Var(\epsilon_i) = Var(\epsilon_j)$  for all  $i, j \in \{1, 2, \dots, 80\}$  we find:

$$\begin{aligned} Var(\epsilon_i) &= \rho^2 Var(\epsilon_{i-1}) + Var(\eta_i) \\ \Leftrightarrow Var(\epsilon_i) &= \rho^2 Var(\epsilon_i) + 1 \\ \Leftrightarrow Var(\epsilon_i) &= \frac{1}{1 - \rho^2} \\ &= \frac{25}{9} \\ &= 2.777\dots \end{aligned}$$

We conclude that the variance of  $\epsilon$  is  $\frac{25}{9}$ .

(c)

To transform the errors to a basis where they are no longer correlated we will use the variance-covariance matrix  $V$  of the errors. The off-diagonal elements, so the covariances, are (suppose  $i < j$ ):

$$\begin{aligned} Cov(\epsilon_i, \epsilon_j) &= E[(\epsilon_i - E(\epsilon_i))(\epsilon_j - E(\epsilon_j))] \\ &= E[\epsilon_i \epsilon_j] \\ &= E[\epsilon_i (\rho \epsilon_{j-1} + \eta_j)] \\ &\vdots \\ &= E[\epsilon_i (\rho^{j-i} \epsilon_i + \rho^{j-i-1} \eta_i + \rho^{j-i-2} \eta_{i-2} + \dots + \eta_j)] \\ &= E[\epsilon_i \rho^{i-j} \epsilon_i] \\ &= \rho^{i-j} Var(\epsilon) \\ &= \rho^{i-j} \frac{25}{9} \end{aligned}$$

So the matrix  $V$  has  $\frac{25}{9}$  on the diagonal,  $\frac{25}{9}\rho$  on the two sub-diagonals next to the diagonal,  $\frac{25}{9}\rho^k$  on the  $k$ th sub-diagonal. the matrix  $V$  can be diagonalized with an orthogonal transformation  $M$ :  $\Lambda = MV M^T$ . When we use the definition of the variance-covariance matrix (where  $\epsilon$  denotes the column vector with the errors) we find:

$$\begin{aligned} V &= E((\epsilon - E(\epsilon))(\epsilon - E(\epsilon))^T) \\ \Leftrightarrow \Lambda &= ME(\epsilon \epsilon^T)M^T \\ \Leftrightarrow \Lambda &= E((M\epsilon)(M\epsilon)^T) \end{aligned}$$

Where we used that  $E(\epsilon) = \mathbf{0}$ . The vector  $M\epsilon$  has variance-covariance matrix  $\Lambda$  so we conclude that it is a vector of uncorrelated stochastic variables.

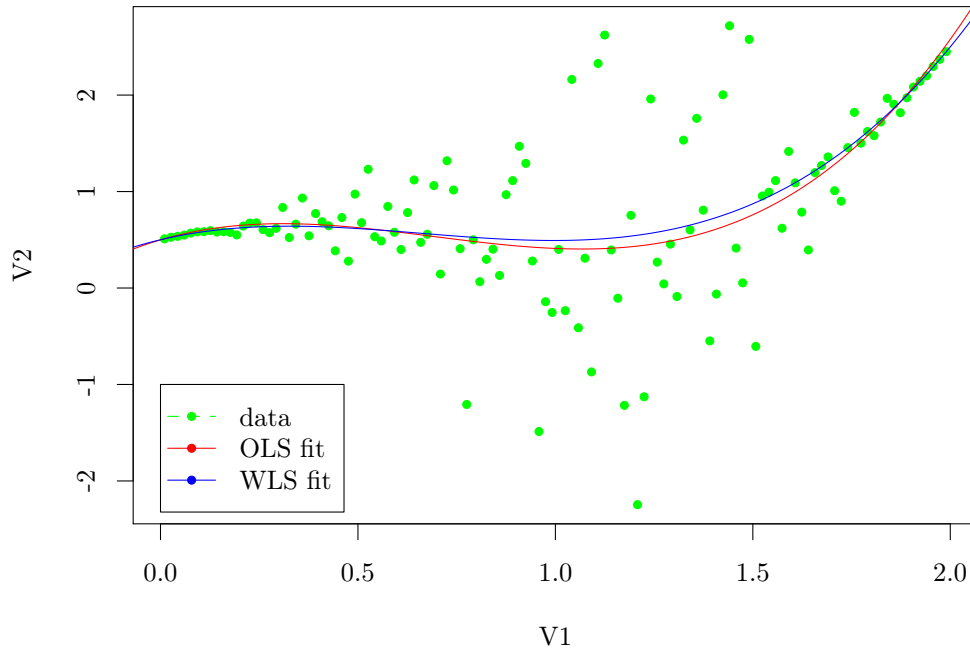


Figure 3: fit of cubic function through the data in ex3.txt using ordinary least squares

### Question 3

(a)

The values for the fitted coefficients with ordinary least squares are:  $[0.4994, 1.1985, -2.4959, 1.2082]$ . In figure 3 the fit is plotted along with the data.

(b)

The coefficients fitted with the weighted least square algorithm are  $[0.5003, 0.9669, -1.9655, 0.99100]$ .

(c)

The coefficients that are calculated using the least squares method are closer to the real values than the ones calculated using the ordinary least squares. To really say something about the difference and how well they match the given real values of the function we need more information about the distribution of the parameters.

(d)

Using the result from class that the distribution is given by:

$$\hat{\beta}_{WLS} = (X^T W^{-1} X)^{-1} X^T W^{-1} Y \sim N_p(\beta, (X^T W^{-1} X)^{-1})$$

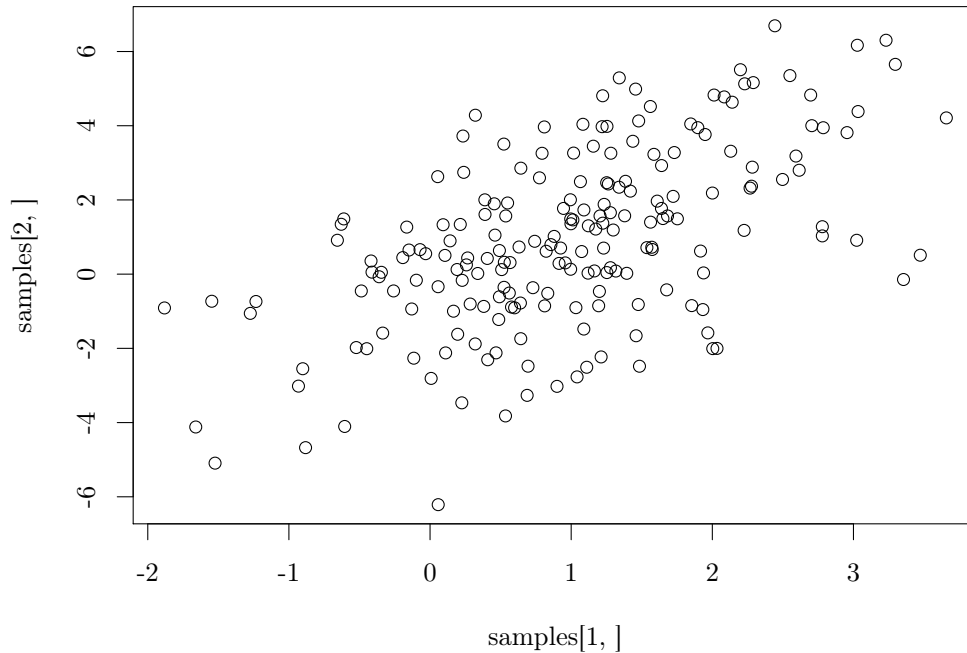


Figure 4: Projection on the  $xy$ -plane of the sample from the multivariate normal distribution

This result can be derived by noting that the vector  $Y$  has a multinormal distribution with mean  $\bar{Y}$  and as variance-covariance matrix  $W$ . Therefore  $\hat{\beta}_{WLS}$  is a linear combination of multinormal distributions and is itself again a multinormal distribution. <REF NAAR FORMULE?>.

## Question 4

(a)

To generate a sample from a multi-normal distribution we work analogues to the derivation in section 6.2 in the course notes, but backwards. We are given the variance-covariance matrix  $\Sigma_X$  of a multivariate normal model. This matrix must be positive definite, so the square root of this matrix exists. Let  $A$  be a matrix such that  $AA^T = \Sigma_X$ . This matrix can be found by diagonalizing  $\Sigma_X$ :  $\Sigma_X = U\Lambda U^T$  and then taking  $A = U\sqrt{\Lambda}$ . We can do this because all eigenvalues of  $\Sigma_X$  are positive. The result from section 6.2 now tells us that  $X = AY + \mu$  where  $Y$  is a vector of standard normal distributions. This observation can be used to draw a sample from  $X$  by drawing  $n$  independent samples from a standard normal distribution, filling them in in a vector  $y$  and then calculating the sample from  $X$  as  $x = Ay + \mu$ . This was implemented in *R*

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