**MAS 6003** 



### **SCHOOL OF MATHEMATICS AND STATISTICS**

Spring Semester 2010–2011

Linear Models 3 hours

RESTRICTED OPEN BOOK EXAMINATION.

Candidates may bring to the examination lecture notes and associated lecture material (but no textbooks) plus a calculator that conforms to University regulations.

All answers will be marked but credit will be given only for the best **FIVE** answers. All questions are worth 20 marks. Total marks 100.

Corner point constraints (treatment contrasts) are used in all R output.

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MAS 6003 1 Turn Over

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An experiment is conducted to investigate the effect of vitamin C intake (0.5, 1, and 2 mg) and delivery method (orange juice or vitamin C supplement) on the tooth length of guinea pigs. 10 guinea pigs are used at each of the levels of vitamin C and delivery method so that there are 60 guinea pigs in the experiment. Figure 1 shows a plot of tooth length versus dose by delivery method. Consider the following linear model:

$$y_i = \beta_0 + \beta_1 dose_i + \beta_2 OJ_i + \epsilon_i$$

where  $y_i$  is tooth length of guinea pig i,  $dose_i$  is the vitamin C dose of guinea pig i,  $OJ_i$  is an indicator variable for guinea pig i taking the value 1 if the dose was administered by orange juice and zero otherwise and  $\epsilon_i$  has a  $N(0, \sigma^2)$  distribution. The following R output is available:

```
> tooth.lm<-lm(len~dose+0J)</pre>
```

```
> summary(tooth.lm)
```

Call:

lm(formula = len ~ dose + OJ)

#### Coefficients:

Estimate	Std. Error	t value	Pr(> t )
9.2725	1.2824	7.231	1.31e-09
9.7636	0.8768	11.135	6.31e-16
-3.7000	1.0936	-3.383	0.0013
	9.2725 9.7636	9.27251.28249.76360.8768	9.7636 0.8768 11.135

\_ \_ -

Residual standard error: 4.236 on 57 degrees of freedom Multiple R-squared: 0.7038, Adjusted R-squared: 0.6934 F-statistic: 67.72 on 2 and 57 DF, p-value: 8.716e-16

> vcov(tooth.lm)

	(Intercept)	dose	OJ
(Intercept)	1.644	-0.897	-0.598
dose	-0.897	0.769	0
OJ	-0.598	0	1.196

> influence(tooth.lm) \$hat

```
2
                  3
                        4
                                            7
                                                               10
                               5
                                      6
                                                   8
                                                                     11
0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.052
                      15
                                   17
                                                       20
                                                              21
                                                                    22
         13
                14
                             16
                                          18
                                                 19
0.035 0.035 0.035 0.035 0.035 0.035 0.035 0.035 0.035 0.063 0.063
   23
         24
                25
                      26
                             27
                                   28
                                          29
                                                 30
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                                                              32
0.063 0.063 0.063 0.063 0.063 0.063 0.063 0.063 0.052 0.052 0.052
   34
                36
                      37
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                                          40
                                                 41
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                                                              43
                                                                    44
0.052 0.052 0.052 0.052 0.052 0.052 0.052 0.035 0.035 0.035 0.035
         46
                47
                      48
                             49
                                   50
                                          51
                                                 52
                                                       53
                                                              54
0.035 0.035 0.035 0.035 0.035 0.035 0.063 0.063 0.063 0.063 0.063
         57
                58
                      59
0.063 0.063 0.063 0.063 0.063
```

- (i) For the tooth.lm linear model fitted above, the residual for observation 6 is -0.454; provide an R command that would give the residual for observation 6. (1 mark)
- (ii) Calculate the 6th scaled residual. (2 marks)
- (iii) Calculate the 6th standardized residual. (2 marks)
- (iv) Calculate the 6th standardized deletion residual. (2 marks)
- (v) Fig 2 shows some diagnostic plots for the model fitted. Comment on whether the plots indicate that the assumptions of the linear model are met.

  (2 marks)
- (vi) Calculate a 95% confidence interval for  $\beta_1$ . (4 marks)
- (vii) Let X be the design matrix in which the first column has a one in every position, the second column contains the vitamin C dose and the third column contains the indicator variable values for delivery method as described earlier in the question. Given that the variance-covariance matrix of  $\hat{\beta}$  given in the R output above is  $\hat{\sigma}^2(X^TX)^{-1}$ , perform a single hypothesis test to test whether both  $\beta_0 = 2\beta_1$  and  $\beta_2 = 0$ . You may find the following helpful:

$$\left( \left( \begin{array}{ccc} 1 & -2 & 0 \\ 0 & 0 & 1 \end{array} \right) \left( \begin{array}{ccc} 1.64 & -0.90 & -0.60 \\ -0.90 & 0.77 & 0 \\ -0.60 & 0 & 1.20 \end{array} \right) \left( \begin{array}{ccc} 1 & 0 \\ -2 & 0 \\ 0 & 1 \end{array} \right) \right)^{-1} = \left( \begin{array}{ccc} 0.12 & 0.06 \\ 0.06 & 0.87 \end{array} \right)$$

(7 marks)

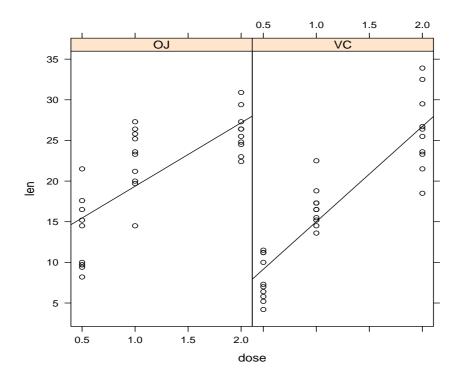


Figure 1: Tooth length against vitamin C dose by delivery method

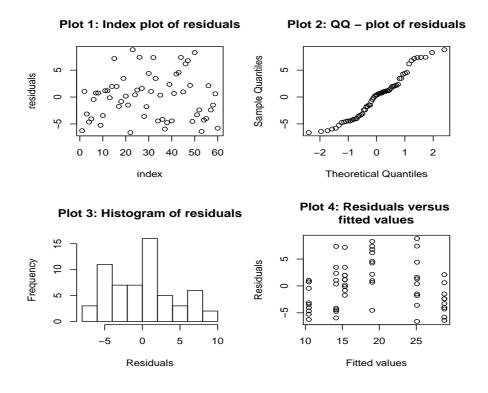


Figure 2: Residual plots for the guinea pig data

- The linear model  $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$  is to be fitted by the least squares method using n observations;  $\boldsymbol{\beta}$  is a  $p \times 1$  vector of unknown parameters and it is assumed that  $\mathbf{X}$  is of full rank p. The errors  $\boldsymbol{\varepsilon}$  are assumed to be independent and normally distributed and to have zero mean vector and covariance matrix  $\sigma^2 I_n$ , where  $\sigma^2 > 0$ . Let  $\widehat{\boldsymbol{\beta}}$  be the LS estimate of  $\boldsymbol{\beta}$ .
  - (i) Given that  $\hat{\boldsymbol{\beta}} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{y}$  show that  $\boldsymbol{X}^T (\boldsymbol{y} \boldsymbol{X} \hat{\boldsymbol{\beta}}) = \boldsymbol{0}$ . (2 marks)
  - (ii) Let  $Q = (\boldsymbol{y} \boldsymbol{X}\boldsymbol{\beta})^T(\boldsymbol{y} \boldsymbol{X}\boldsymbol{\beta})$ . By noting that

$$Q = \{ \boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}} + \boldsymbol{X}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \}^T \{ \boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}} + \boldsymbol{X}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \}$$

show that

$$Q = (\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}})^T (\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}) + (\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta})^T \boldsymbol{X}^T \boldsymbol{X} (\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}).$$

(3 marks)

(iii) Use Q to derive the distributions of  $Q/\sigma^2$ ,  $(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}})^T(\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}})/\sigma^2$  and  $(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta})\boldsymbol{X}^T\boldsymbol{X}(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta})/\sigma^2$ , stating any general results to which you appeal. (5 marks)

The data for the rest of this question relate to how protein concentration (conc) can be predicted from the optical density of an experimental assay. Output from an R session is given below. Some of the numerical values have been replaced by letters.

#### > DNase

	conc	density
1	0.04882812	0.017
2	0.04882812	0.018
3	0.19531250	0.121
4	0.19531250	0.124
5	0.39062500	0.206
6	0.39062500	0.215
7	0.78125000	0.377
8	0.78125000	0.374
9	1.56250000	0.614
10	1.56250000	0.609
11	3.12500000	1.019
12	3.12500000	1.001
13	6.25000000	1.334
14	6.25000000	1.364
15	12.50000000	1.730
16	12.50000000	1.710

 $(\mathbf{v})$ 

```
> DNase.lm<-lm(conc~density)</pre>
     > summary(DNase.lm)
     Coefficients:
                 Estimate Std. Error t value
                                              Pr(>|t|)
     (Intercept) -1.3010
                            0.5878 -2.213
                                                  0.044
     density
                   6.5100
                              0.6586 9.885
                                               1.08e-07
     ____
     Residual standard error: A on 14 degrees of freedom
     Multiple R-squared: 0.875,
                                Adjusted R-squared: 0.866
     F-statistic: 97.71 on 1 and 14 DF, p-value: 1.078e-07
     > anova(DNase.lm)
     Analysis of Variance Table
     Response: conc
               Df Sum Sq Mean Sq F-value
                                               Pr(>F)
               1 229.360 229.360
                                   97.712 1.078e-07
     density
     Residuals 14 32.862 2.347
     > DNase.lm$resid[1:8]
                             4
                                           6 7
                                  5
      1.239 1.233
                      B 0.689 0.351 0.292 -0.372 -0.353
     > vcov(DNase.lm)
                 (Intercept)
                                density
                   0.3455301 -0.2936573
     (Intercept)
                  -0.2936573 0.4337225
     density
     > influence(DNase.lm)$hat[2]
             2
             C
(iv)
     Calculate the value of A.
                                                         (3 marks)
     Calculate the value of B.
                                                         (3 marks)
     Calculate the value of C.
                                                         (4 marks)
(vi)
```

- 3 An investigator collects data on 200 crabs. The following variables are measured:
  - sex the gender of the crab
  - sp the species (blue or orange)
  - FL frontal lobe size (mm)
  - RW rear width (mm)
  - CL shell length (mm)
  - CW carapace width (mm)
  - BD body depth (mm)

The interest is in how the frontal lobe size depends on the other variables collected. The investigator uses R to help choose a statistical model.

(i) In the following output, explain what the 'regsubsets' command does and which of the various sized subsets you would select based on the outputs of the three 'summary' commands.

```
> a<-regsubsets(FL~factor(sex)+factor(sp)+RW+CL+CW+BD)</pre>
> summary(a)
Subset selection object
Call:regsubsets.formula(FL~factor(sex)+factor(sp)+RW+CL+CW+BD)
6 Variables (and intercept)
1 subsets of each size up to 6
Selection Algorithm: exhaustive
        factor(sex)M factor(sp)O RW CL CW
                   11 11
                             (1)""
  (1)""
                   "*"
                              "*"
                              3 (1) "*"
                              11 * 11
4 (1) "*"
                              "*"
5 (1) "*"
6 (1) "*"
                   "*"
                              ||*|| ||*|| ||*|| ||*||
> summary(a)$rsq
[1] 0.975407 0.986325 0.987568 0.988003 0.988074 0.988087
> summary(a)$cp
[1] 202.433 27.548
                   9.404
                          4.354
                                 5.213
                                        7.000
> summary(a)$bic
[1] -730.466 -842.548 -856.314 -858.142 -854.021 -848.944
                                              (5 marks)
```

```
(ii) Describe what is being done at each stage of the R output below.
```

```
> crabs.lm<-lm(FL~1,data=crabs)</pre>
```

- > step(crabs.lm,scope=list(upper=FL~factor(sex)+CW+BD+RW,
- + data=crabs),direction="both")

Start: AIC=501.57

FL ~ 1

	Df	Sum of Sq	RSS	AIC
+ BD	1	2371.45	59.79	-237.49
+ CM	1	2263.83	167.42	-31.57
+ RW	1	2000.00	431.24	157.67
<none></none>			2431.24	501.57
+ factor(sex)	1	4.56	2426.68	503.19

Step: AIC=-237.49

FL ~ BD

	Df	Sum	of	Sq	RSS	AIC
+ RW	1		9.	62	50.17	-270.59
+ factor(sex)	1		5.	03	54.76	-253.07
+ CW	1		3.	19	56.60	-246.47
<none></none>					59.79	-237.49
- BD	1	23	71.	45	2431.24	501.57

Step: AIC=-270.59 FL  $\sim$  BD + RW

	Df	Sum of Sq	RSS	AIC
+ CM	1	0.58	49.59	-270.91
<none></none>			50.17	-270.59
+ factor(sex)	1	0.24	49.92	-269.56
- RW	1	9.62	59.79	-237.50
- BD	1	381.07	431.24	157.67

Step: AIC=-270.91

 $FL \sim BD + RW + CW$ 

	Df	$\operatorname{\mathtt{Sum}}$	of Sq	RSS	AIC
<none></none>				49.588	-270.913
- CW	1		0.579	50.167	-270.593
+ factor(sex)	1		0.034	49.554	-269.052
- RW	1		7.011	56.599	-246.466
- BD	1	9	99.143	148.732	-53.235

#### Call:

lm(formula = FL ~ BD + RW + CW, data = crabs)

#### Coefficients:

(Intercept)	BD	RW	CW
0.71812	0.82993	0.16991	0.02901

(5 marks)

- (iii) The AIC for the chosen model using the 'steps' command above is -270.91; show how to calculate this value based on the 'RSS' values in the output.

  (2 marks)
- (iv) The investigator looks at a plot for a particular statistical model and concludes that it shows evidence of heteroscedasticity.
  - (a) Explain what heteroscedasticity means in a linear model.

(1 mark)

- (b) Justify which plot would allow heteroscedasticity to be observed and what you would expect to see. (2 marks)
- (c) Explain why heteroscedasticity is a problem in linear models.

(1 mark)

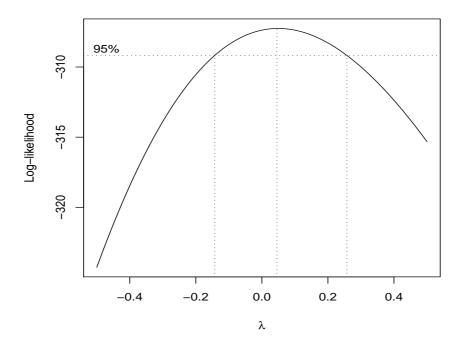


Figure 3: Log-likelihood function for the Box-Cox family of transformations

(v) Figure 3 shows a plot of the log-likelihood as a function of the Box-Cox family parameter  $\lambda$ . Give a point estimate and a 95% confidence interval for  $\lambda$  based on the plot and hence explain whether the investigator's claim of heteroscedasticity is justified. (4 marks)

This question relates to data on the body weights of 5 rats (selected from a large population of rats) measured at various time points over 64 days. The body weights of the rats (in grams) are measured on day 1 and every seven days thereafter until day 64, with an extra measurement on day 44. Several weeks before day 1, the rats were given a drug that was thought to slow the metabolism and hence increase body weight. The interest is in how the weight changes with time in the rat population.

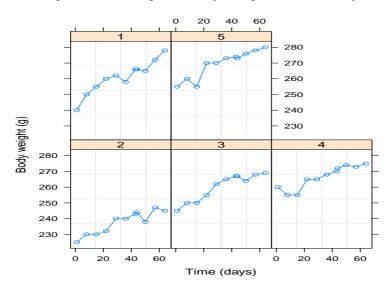


Figure 1: Change in body weight with time by rat

The R commands used to fit two linear mixed effects models to the data are

rats1.lme<-lme(weight~Time,Bodyweight,random=~1|Rat)
rats2.lme<-lme(weight~Time,Bodyweight,random=~Time|Rat)</pre>

- (i) For each of the models rats1.lme and rats2.lme, write down the algebraic specification of the model, defining any terms that you use. (4 marks)
- (ii) Explain why the designation of explanatory variables as fixed and random in the models is reasonable, given the aim of the study. (2 marks)
- (iii) Discuss which of these two models seems the most sensible based on Figure 1. (1 mark)

(iv) Explain what each of the anova commands below does and what conclusions you would draw based on them.

```
> anova(rats1.lme,rats2.lme)
          Model df
                       logLik
                                Test L.Ratio p-value
              1 4 -154.0386
rats1.lme
                   -153.3843 1 vs 2 1.308685 0.5198
              2 6
rats2.lme
> anova(rats1.lme)
            numDF denDF
                          F-value p-value
(Intercept)
                1
                     49 2134.6668 < .0001
Time
                1
                     49 309.1238 <.0001
                                                     (4 marks)
```

- (v) Describe the model checks that you would carry out to check the assumptions of the rats1.lme model. You do not need to provide the R code to do the checks but you should state what values you would assign to the levels option within R where appropriate. (5 marks)
- (vi) For each of the three mixed effects models below, state the algebraic form of the variance-covariance matrix of the within-subject random effects:

The data in this question relate to the occurrence of pain in the chest of patients with heart disease after taking a single deep breath. The response, y, is the occurrence (y = 1) or non-occurrence (y = 0) of pain. The continuous explanatory variables are the volume and rate of air inhaled in a single breath. The only factor explanatory variable is the type of drug each subject was taking (each subject was on one of three different drugs labelled 1,2 and 3). The three explanatory variables are labelled volume, rate and drug.

Some edited R output is provided below:

```
> model1.glm<-glm(Y~Rate*factor(drug),binomial)</pre>
```

> summary(model1.glm)

#### Call:

```
glm(formula = Y ~ Rate * factor(drug),family = binomial)
```

#### Coefficients:

	Estimate	Std. Error z val	ue $Pr(> z )$
(Intercept)	-1.7027	1.8603 -0.9	15 0.360
Rate	1.6388	1.3751 1.19	92 0.233
factor(drug)2	0.5562	2.4575 0.226	0.821
factor(drug)3	0.1082	2.2615 0.048	0.962
Rate:factor(drug)2	-1.0691	1.5464 -0.691	0.489
Rate:factor(drug)3	-0.7323	1.5752 -0.465	0.642

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 54.040 on 38 degrees of freedom Residual deviance: 47.851 on 33 degrees of freedom AIC: 59.851
```

- (i) Write down an algebraic specification of the linear predictor  $(\eta_i)$  for patient i in the above model. (3 marks)
- (ii) How does  $E(y_i)$ , the expected value of the response for patient i, relate to  $\eta_i$  for the fitted model? (1 mark)
- (iii) Based on the above output, what proportion of patients with heart disease on drug 2 and with an inhalation rate of 1.1 would you expect to feel chest pain?

  (3 marks)
- (iv) Based on the above output, calculate the odds ratio of chest pain for a patient on drug 3 with an inhalation rate of 1.2 compared to a patient on drug 2 with an inhalation rate of 0.7 units.

  (4 marks)
- (v) Assess the model fit of the above model. (2 marks)
- (vi) Describe, in detail, how to use iteratively re-weighted least squares to estimate the parameters in the model fitted in the output above. You should derive the algebraic form of any vectors or matrices that you suggest using.

  (7 marks)

- 6 Data is collected on 189 mothers for a study in which the interest is in how the race and smoking status of mothers affects the birth weight of their babies. The variables recorded in the study are 'race', 'smoke' and 'low'.
  - 'race' is a categorical variable with 3 levels (A,B and C);
  - 'smoke' is a binary variable (1 = smoked in pregnancy, 0 = did not smoke in pregnancy);
  - 'low' is a binary variable that records whether the baby was low weight at birth (1=was low weight, 0=wasn't low weight).

The results are shown in Table 1.

	Race						
	A	A.	В		$\mathbf{C}$		
	$\operatorname{smoke}$		$\operatorname{smoke}$		$\operatorname{smoke}$		
Low	0	1	0	1	0	1	
0	40	33	11	4	35	7	
1	$\mid 4 \mid$	19	5	6	20	5	

Table 1: Birth weight of babies by race and smoking status of the mother.

For notational convenience we use L, R and S to represent the variables low, race and smoke respectively. For this question, assume that L is a response factor and R and S are controlled factors.

Several log-linear models with Poisson errors were fitted giving the following results:

Model fitted	Res. Deviance	df
R*S	45.19	6
R*S+L	17.85	5
R*S+L*R	12.844	
R*S+L*S	12.987	

- (i) Explain why R\*S appears in all the above fitted models. What is the effect of including R\*S on row and column totals in the table of fitted values?

  (3 marks)
- (ii) State, with justification, the 2 missing degrees of freedom in the output above. (4 marks)
- (iii) Assuming appropriate model-checking diagnostics proved satisfactory, what would you conclude about the dependence of birth weight on race and smoking status during pregnancy? Refer to the residual deviances above.

(5 marks)

- (iv) For the R\*S+L\*R model, calculate the expected number of low birth weight babies with mothers having a race code of B that did not smoke during pregnancy.

  (3 marks)
- (v) Calculate the Pearson residual for low birth weight babies with mothers having a race code of B that did not smoke during pregnancy. (2 marks)
- (vi) Some edited R output is given below (where count is the variable recording the number of mothers in each cell):
  - > birth3.glm<-glm(count~race\*smoke+low\*race,family=poisson)
  - > summary(birth3.glm)

#### Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	3.51030	0.16127	21.766	< 2e-16
raceB	-1.28776	0.34163	-3.769	0.000164
raceC	0.03001	0.23038	0.130	0.896361
smoke	0.16705	0.20484	0.816	0.414759
low	-1.15497	0.23912	-4.830	1.36e-06
raceB:smoke	-0.63706	0.45217	-1.409	0.158868
raceC:smoke	-1.68948	0.37878	-4.460	8.18e-06
raceB:low	0.84481	0.46341	1.823	0.068301
raceC:low	0.63617	0.34783	1.829	0.067405

Calculate the expected number of low birth weight babies with mothers having a race code of C that did smoke during pregnancy. (3 marks)

# **End of Question Paper**