

1. (40 points) Consider the Galapagos islands data with different geological variables measured from 30 islands. For example, the row for the island Baltra is as follows:

#	Species	Area	Elevation	Nearest	Scruz	Adjacent
# Baltra	58	25.09	346	0.6	0.6	1.84

Consider the relationship between the number of species (counts) and these geological variables. The Poisson regression with the log link yields the following output.

Call:

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glm(formula = Species ~ ., family = poisson, data = gala)
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Deviance Residuals:

Min	1Q	Median	3Q	Max
-8.2752	-4.4966	-0.9443	1.9168	10.1849

Coefficients:

Estimate	Std. Error	z value	Pr(> z)
(Intercept)	3.155e+00	5.175e-02	60.963 < 2e-16 ***
Area	-5.799e-04	2.627e-05	-22.074 < 2e-16 ***
Elevation	3.541e-03	8.741e-05	40.507 < 2e-16 ***
Nearest	8.826e-03	1.821e-03	4.846 1.26e-06 ***
Scruz	-5.709e-03	6.256e-04	-9.126 < 2e-16 ***
Adjacent	-6.630e-04	2.933e-05	-22.608 < 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

,
(Dispersion parameter for poisson family taken to be 1)

Null deviance: 3510.73 on 29 degrees of freedom

Residual deviance: 716.85 on 24 degrees of freedom

AIC: 889.68

Number of Fisher Scoring iterations: 5

Based on the output, answer the following questions.

- What is the interpretation of the slope for “Area”?
- What is the fitted value $\hat{\mu}_{Baltra}$ for the island Baltra?
- What are the Pearson residual and deviance residual for the island Baltra?
- What is the sum of all response residuals? Why?

2. (28 points) A random vector $\mathbf{Y}_{J \times 1} = (Y_1, \dots, Y_J)$ is said to follow a multinomial distribution, denoted by $Multinomial(n, \boldsymbol{\pi})$, where $\boldsymbol{\pi} = (\pi_1, \dots, \pi_J)$ with $\sum_{j=1}^J \pi_j = 1$, if

$$f(\mathbf{y}) = \frac{n!}{\prod_{j=1}^J y_j!} \prod_{j=1}^J \pi_j^{y_j}.$$

Show the following properties of $Multinomial(n, \boldsymbol{\pi})$.

- $Multinomial(n, \boldsymbol{\pi})$ is a $(J - 1)$ -dimensional exponential family.
- $\forall j \neq k, Cov(Y_j, Y_k) = -n\pi_j\pi_k$.
- $\forall j, (Y_1, \dots, Y_{j-1}, Y_{j+1}, \dots, Y_J) | Y_j = y_j \sim Multinomial(n - y_j, (\frac{\pi_1}{1 - \pi_j}, \dots, \frac{\pi_J}{1 - \pi_j}))$.
- Suppose W_1, \dots, W_J are independent with $W_j \sim Poisson(\lambda_j)$, where $\lambda_j > 0$ and $j = 1, \dots, J$. Then

$$(W_1, \dots, W_J) | \sum_{j=1}^J W_j \sim Multinomial(\sum_{j=1}^J W_j, (\frac{\lambda_1}{\sum_{j=1}^J \lambda_j}, \dots, \frac{\lambda_J}{\sum_{j=1}^J \lambda_j})).$$

3. (32 points) Consider the linear mixed model $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{\alpha} + \boldsymbol{\epsilon}$ where $\mathbf{y} \in \mathbb{R}^n$, $\mathbf{X} \in \mathbb{R}^{n \times p}$ with $rank(\mathbf{X}) = p < n$, $\mathbf{Z} \in \mathbb{R}^{n \times q}$, $\boldsymbol{\beta} \in \mathbb{R}^p$, $\boldsymbol{\alpha} \sim \mathcal{N}_q(\mathbf{0}, \sigma_\alpha^2 \mathbf{I})$ is a random vector of i.i.d. coefficients, and $\boldsymbol{\epsilon} \sim \mathcal{N}_n(\mathbf{0}, \sigma_\epsilon^2 \mathbf{I})$ is a vector of i.i.d. random errors and is independent of $\boldsymbol{\alpha}$.

Consider the REML with $\mathbf{K}_{(n-p) \times n}$ matrix s.t. $rank(\mathbf{K}) = n - p$ and $\mathbf{K}\mathbf{X} = \mathbf{0}_{(n-p) \times p}$. We mentioned in class that the choice of \mathbf{K} is not unique, and different choices of \mathbf{K} lead to the same estimate. Let's work out why here.

- Show that for any positive definite matrix \mathbf{V} ,

$$\mathbf{K}^T(\mathbf{K}\mathbf{V}\mathbf{K}^T)^{-1}\mathbf{K} = \mathbf{V}^{-1} - \mathbf{V}^{-1}\mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}.$$

(Hint: Note that $\mathbf{K}\mathbf{X} = \mathbf{K}\mathbf{V}^{1/2}\mathbf{V}^{-1/2}\mathbf{X} = \mathbf{0}_{(n-p) \times p}$.)

- Write the likelihood $\mathcal{L}(\boldsymbol{\beta}, \sigma_\epsilon^2, \sigma_\alpha^2 | \mathbf{K}\mathbf{y})$ in terms of \mathbf{X} , \mathbf{Z} , and \mathbf{y} (but without \mathbf{K} !). (Hint: You may assume (a) here. Also use Sylvester's determinant theorem: For matrices $\mathbf{A}_{s \times t}$ and $\mathbf{B}_{t \times s}$, $det(\mathbf{I}_s + \mathbf{A}\mathbf{B}) = det(\mathbf{I}_t + \mathbf{B}\mathbf{A})$)