



# Presentation 7.3b: Multiple linear regression

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### 0.1. Preparations

#### 0.1.1. Packages

```
library(ggplot2)
library(car)
library(GGally)
library(rstan)
library(brms)
library(coda)
library(dplyr)
library(gridExtra)
```

#### 0.1.2. Data

[www.flutterbys.com.au/stats/downloads/data/loyn.csv](http://www.flutterbys.com.au/stats/downloads/data/loyn.csv)

[www.flutterbys.com.au/stats/downloads/data/paruelo.csv](http://www.flutterbys.com.au/stats/downloads/data/paruelo.csv)

## 1. Theory

### 1.1. Multiple Linear Regression

#### 1.1.1. Additive model

$$\text{growth} = \text{intercept} + \text{temperature} + \text{nitrogen}$$

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_j x_{ij} + \epsilon_i$$

OR

$$y_i = \beta_0 + \sum_{j=1:n}^N \beta_j x_{ji} + \epsilon_i$$

### 1.2. Multiple Linear Regression

#### 1.2.1. Additive model

$$\text{growth} = \text{intercept} + \text{temperature} + \text{nitrogen}$$



$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_j x_{ij} + \epsilon_i$$

- effect of one predictor holding the other(s) constant

### 1.3. Multiple Linear Regression

#### 1.3.1. Additive model

$$\text{growth} = \text{intercept} + \text{temperature} + \text{nitrogen}$$

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_j x_{ij} + \epsilon_i$$

Y	X1	X2
3	22.7	0.9
2.5	23.7	0.5
6	25.7	0.6
5.5	29.1	0.7
9	22	0.8
8.6	29	1.3
12	29.4	1

### 1.4. Multiple Linear Regression

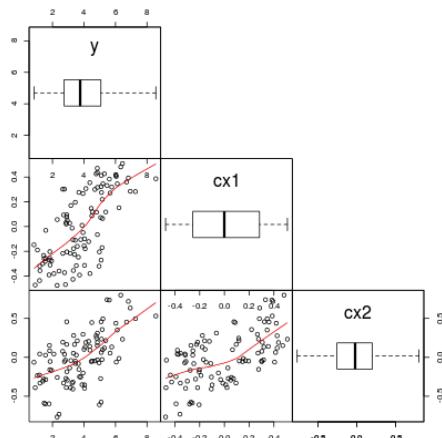
#### 1.4.1. Multiplicative model

$$\text{growth} = \text{intercept} + \text{temp} + \text{nitro} + \text{temp} \times \text{nitro}$$

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i1} x_{i2} + \dots + \epsilon_i$$

### 1.5. Assumptions

- normality, homogeneity of variance, linearity
- (multi)collinearity



## 1.6. Multiple Linear Regression

### 1.6.1. Variance inflation

$$\text{var.inf} = \frac{1}{1 - R^2}$$

Collinear when  $\text{var.inf} \geq 5$

Some prefer  $> 3$

## 2. Worked Examples

### 2.1. Worked examples

```
loyn <- read.csv('~/data/loyn.csv', strip.white=T)
head(loyn)
```

	ABUND	AREA	YR.ISOL	DIST	LDIST	GRAZE	ALT
1	5.3	0.1	1968	39	39	2	160
2	2.0	0.5	1920	234	234	5	60
3	1.5	0.5	1900	104	311	5	140
4	17.1	1.0	1966	66	66	3	160
5	13.8	1.0	1918	246	246	5	140
6	14.1	1.0	1965	234	285	3	130

### 2.2. Worked Examples

Question: what effects do fragmentation variables have on the abundance of forest birds

Linear model:

$$\begin{aligned} \text{Abund}_i &\sim \mathcal{N}(\mu, \sigma^2) \\ \mu &= \beta_0 + \sum_{j=1:n}^N \beta_j X_{ji} \\ \beta_0, \beta_j &\sim \mathcal{N}(0, 1000) \\ \sigma &\sim \text{Cauchy}(0, 5) \end{aligned}$$



## 2.3. Worked Examples

```
paruelo <- read.csv('..../data/paruelo.csv', strip.white=T)
head(paruelo)
```

	C3	LAT	LONG	MAP	MAT	JJAMAP	DJFMAP
1	0.65	46.40	119.55	199	12.4	0.12	0.45
2	0.65	47.32	114.27	469	7.5	0.24	0.29
3	0.76	45.78	110.78	536	7.2	0.24	0.20
4	0.75	43.95	101.87	476	8.2	0.35	0.15
5	0.33	46.90	102.82	484	4.8	0.40	0.14
6	0.03	38.87	99.38	623	12.0	0.40	0.11

## 2.4. Worked Examples

Question: what effects do fragmentation geographical variables have on the abundance of C3 grasses

Linear model:

$$\begin{aligned}\sqrt{C3_i} &\sim \mathcal{N}(\mu, \sigma^2) \\ \mu &= \beta_0 + \sum_{j=1:n}^N \beta_j X_{ji} \\ \beta_0, \beta_j &\sim \mathcal{N}(0, 1000) \\ \sigma &\sim \text{Cauchy}(0, 5)\end{aligned}$$