# Lab notes for Statistics for Social Sciences II: Multivariate Techniques

BSc in International Studies, BSc in International Studies & Political Science, Carlos III University of Madrid

Eduardo García Portugués 2016-09-06

# Contents

In	oduction	5			
	Course logistics	5			
	Vhat are these notes?	5			
	Description of the software required	5			
	.1 How to install it in your own laptop	6			
	.2 Why R? We want this very	6			
1	Simple linear regression	7			
	.1 Motivation; model formulation; examples; applications; assumptions	7			
	.2 Estimation of model parameters; least squares; inference for model parameters; forecasting	13			
	tionships.	13			
<b>2</b>	Multiple linear regression	17			
	.1 Motivation; model formulation; examples; applications; assumptions	17			
	.2 Estimation of model parameters; least squares; inference for model parameters; forecasting	17			
	.3 Assessing model fit; ANOVA; model validation	17			
	.4 Multicollinearity; model diagnostics	17			
3	Binomial logistic regression	19			
	.1 Motivation; model formulation; examples; applications; assumptions	19			
	.2 Parameter estimation; assessing model fit; significance testing; interpreting coefficients	19			
4 Factor analysis and principal component analysis					
	.1 Motivation; formulations; examples; applications; assumptions	21			
	.2 Principal components analysis; choosing the number of factors; analysis and interpretation	21			
	.3 Exploratory factor analysis; design, analysis and interpretation; rotation of factors	21			
5	Cluster analysis				
	.1 Motivation; examples; applications; hierarchical agglomerative clustering; dendrogram	23			
	.2 Choosing the number of clusters; assessing fit; interpretation of clusters	23			

4 CONTENTS

### Introduction

#### Course logistics

- Lessons. Lab INF-15.S.06.
- Office hours. Tuesdays from 15:00 to 18:00 at office 10.0.10 (access through 10.0.7 in *Camponanes* building). If they are incompatible with your schedule, you are welcome to send me an email to get an alternative appointment (preferable) or to drop by my office (but will remove this option if I get overwhelmed with queries...).
- Grading. Continuous evaluation accounts for 60% of the final grade (2 partials and a group project, each accounts for 20%). Final exam is 40%.
- Partials. Based on theory and practise. The first will (likely) cover Topics 1-2, and the second Topics 3-5
- Group project. Students must team up in groups of  $4 (\pm 1)$  and apply the statistical analyses seen to a dataset. As a rule of thumb, all students in a group will be graded evenly, so choose wisely your group! You will have time to. Specific details to be disclosed by the end of the course.

#### What are these notes?

These notes are a compact description of the key points and insights of the methods presented in the lessons throught the help of computer, providing at the same time an effective way of delivering statistical analysis.

These notes are neither an exhaustive, rigorous nor comprehensive treatment of the broad statiscal branch know as Multivariate Analysis. They are designed to be

#### Description of the software required

Available in all computer labs, not only INF-15.S.06. We will employ

- R, a free software environment for statistical computing and graphics. Install instructions available here.
- Deducer, a free easy to use alternative to proprietary data analysis software that provides an intuitive graphical user interface (GUI) for R, encouraging non-technical users to learn and perform analyses without programming getting in their way.

If you plan to use your personal laptop, you are responsible for the right setup of the software (follow the installation links).

6 CONTENTS

- 0.1 How to install it in your own laptop
- 0.2 Why R? We want this very

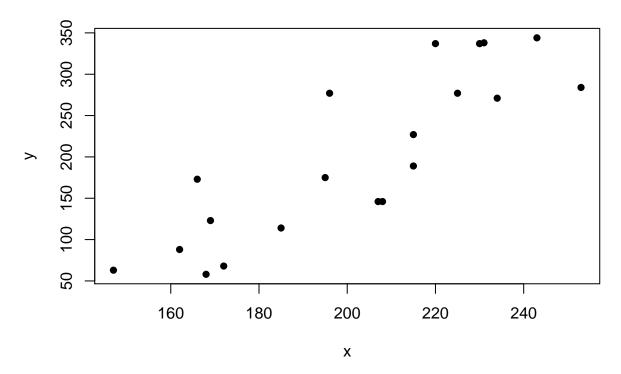
## Simple linear regression

1.1 Motivation; model formulation; examples; applications; assumptions

#### 1.1.1 Motivating example

Suppose we have a production line where we measured the time (in minutes) required to produce a number of solicited items. There are two random variables: y = "time required to produce an order" and x = "number of items in the order". We want to explain/predict y from x from a linear model.

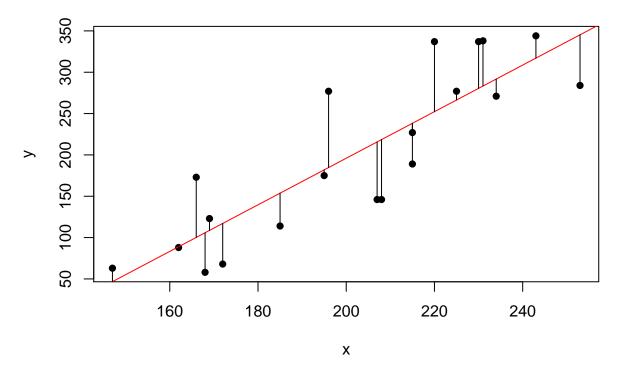
```
# Production time
y <- c(175, 189, 344, 88, 114, 338, 271, 173, 284, 277, 337, 58, 146, 277, 123, 227, 63, 337, 146, 68)
# Number of units in the order
x <- c(195, 215, 243, 162, 185, 231, 234, 166, 253, 196, 220, 168, 207, 225, 169, 215, 147, 230, 208, 1
# Data scatterplot (pch = 16 for filled points)
plot(y ~ x, pch = 16)</pre>
```



#### 1.1.2 The lm function

The linear fit in R is done by the lm function and the formula  $y \sim x$ , used to denote that we are interested in regressing y over x.

```
\# Fit a linear model y = beta0 + beta1 * x
reg \leftarrow lm(y \sim x)
# The result is a list with several objects
names(reg)
##
    [1] "coefficients" "residuals"
                                          "effects"
                                                           "rank"
    [5] "fitted.values" "assign"
                                          "qr"
                                                           "df.residual"
##
   [9] "xlevels"
                         "call"
                                          "terms"
# The fitted coefficients beta0 (intercept) and beta1 (slope)
reg$coefficients
## (Intercept)
## -367.360643
                  2.816682
# The regression line with the minimized distances
plot(y \sim x, pch = 16)
abline(reg, col = 2)
segments(x0 = x, y0 = y, x1 = x, y1 = reg$fitted.values)
```



#### 1.1.3 The least squares estimate

We can check and visualize that reg\$coefficients indeed contains the least squares estimates and that they minimize the Residual Sum of Squares (RSS).

```
# Create the design matrix
X <- cbind(1, x)

# The analytical solution
betahat <- solve(t(X) %*% X) %*% t(X) %*% y
betahat

## [,1]
## -367.360643
## x 2.816682

# Minimal RSS
sum((y - X %*% betahat)^2)

## [1] 51658.57</pre>
```

#### 1.1.4 Summary of the model

You can try to get a better RSS. Good luck! :)

The summary function applied to a 1m object gives the fitted coefficients and its significances ("Pr(>|t|)"), the  $R^2$  ("Multiple R-squared") and the fitted error variance ("Residual standard error").

```
# Summary of the fit
summary(reg)
##
## Call:
```

```
## lm(formula = y \sim x)
##
## Residuals:
               1Q Median
##
      Min
                               3Q
                                      Max
## -72.509 -48.159 -3.917 33.857
                                   92.291
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -367.3606
                          82.4122 -4.458 0.000304 ***
## x
                 2.8167
                            0.4035 6.980 1.61e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 53.57 on 18 degrees of freedom
## Multiple R-squared: 0.7302, Adjusted R-squared: 0.7152
## F-statistic: 48.72 on 1 and 18 DF, p-value: 1.615e-06
```

#### 1.1.5 Prediction

Prediction of a new observation can be done via the function predict, which also provides conficence intervals. The newdata argument of predict needs a data.frame.

```
# Point in which we want a prediction for y
newx <- data.frame(x = 200)

# Prediction with 95% confidence interval
predict(reg, newdata = newx, interval = "prediction", level = 0.95)

## fit lwr upr
## 1 195.9758 80.63344 311.3182

# The same prediction
reg$coefficients %*% c(1, 200)

## [,1]
## [1,] 195.9758</pre>
```

#### 1.1.6 Some words of caution with $R^2$

 $R^2$  does not measure the correctness of a linear model but the **usefulness assuming the model is correct**.

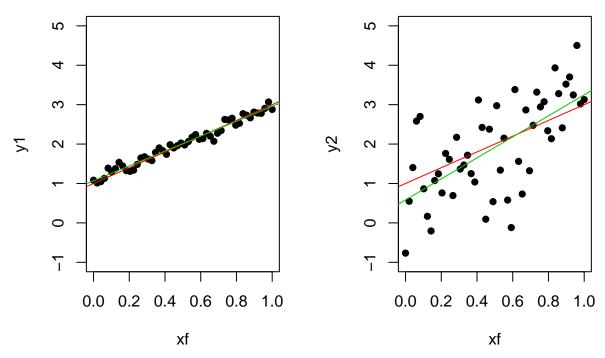
```
# Fixed design
xf <- seq(0, 1, 1 = 50)

# Errors with different variance
set.seed(123456)
eps1 <- rnorm(50, sd = 0.1)
eps2 <- rnorm(50, sd = 1)

# Responses generated following a linear model
y1 <- 1 + 2 * xf + eps1
y2 <- 1 + 2 * xf + eps2

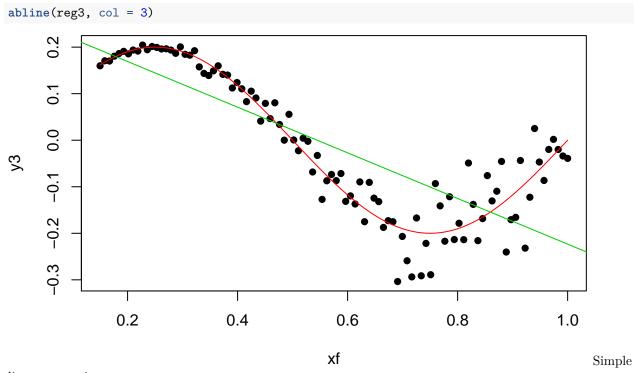
# Fits
reg1 <- lm(y1 ~ xf)</pre>
```

```
reg2 \leftarrow lm(y2 \sim xf)
# R^2 depends on the
summary(reg1)
##
## Call:
## lm(formula = y1 ~ xf)
## Residuals:
                1Q Median
       Min
                                   3Q
                                           Max
## -0.26738 -0.08220 -0.00143 0.06930 0.19892
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.06719
                          0.02781
                                  38.37
                                            <2e-16 ***
                                          <2e-16 ***
                          0.04793
## xf
              1.88910
                                    39.42
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.09981 on 48 degrees of freedom
## Multiple R-squared: 0.97, Adjusted R-squared: 0.9694
## F-statistic: 1554 on 1 and 48 DF, p-value: < 2.2e-16
summary(reg2)
##
## Call:
## lm(formula = y2 ~ xf)
##
## Residuals:
##
       Min
              1Q Median
                               30
## -2.27986 -0.59235 0.03505 0.57115 1.89983
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
                        0.2595 2.247 0.0293 *
## (Intercept) 0.5830
                2.6665
                           0.4472 5.963 2.86e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.9313 on 48 degrees of freedom
## Multiple R-squared: 0.4255, Adjusted R-squared: 0.4136
## F-statistic: 35.55 on 1 and 48 DF, p-value: 2.858e-07
# Plot
par(mfrow = c(1, 2))
plot(y1 \sim xf, pch = 16, ylim = c(-1, 5))
abline(a = 1, b = 2, col = 2)
abline(a = reg1$coefficients[1], b = reg1$coefficients[2], col = 3)
plot(y2 \sim xf, pch = 16, ylim = c(-1, 5))
abline(a = 1, b = 2, col = 2)
abline(a = reg2$coefficients[1], b = reg2$coefficients[2], col = 3)
```



A large  $R^2$  means nothing if the assumptions of the model do not hold.

```
# Create data that:
# 1) does NOT follow a linear model
# 2) the error is heteroskedastic
xf \leftarrow seq(0.15, 1, 1 = 100)
y3 \leftarrow 0.2 * \sin(2 * pi * xf) + rnorm(n = 100, sd = 0.1 * xf^2)
# Great R^2!?
reg3 \leftarrow lm(y3 \sim xf)
summary(reg3)
##
## Call:
## lm(formula = y3 ~ xf)
##
## Residuals:
##
                           Median
         Min
                    1Q
                                         3Q
                                                   Max
  -0.231885 -0.070384 0.006934 0.056374 0.218962
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
                            0.02343
                                      11.40
## (Intercept) 0.26718
                                               <2e-16 ***
                            0.03742 -13.11
               -0.49051
                                               <2e-16 ***
## xf
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.09274 on 98 degrees of freedom
## Multiple R-squared: 0.6368, Adjusted R-squared: 0.6331
## F-statistic: 171.8 on 1 and 98 DF, p-value: < 2.2e-16
# But predicting is obviously problematic
plot(y3 \sim xf, pch = 16)
lines(0.2 * sin(2 * pi * xf) ~ xf, col = 2)
```



linear regression

$$Y_i = a + bX_i + \varepsilon, \quad i = 1, \dots, n.$$

- 1.2 Estimation of model parameters; least squares; inference for model parameters; forecasting.
- 1.3 Assessing model fit; ANOVA; model validation; model diagnostics; handling nonlinear relationships.

You can label chapter and section titles using {#label} after them, e.g., we can reference Chapter ??. If you do not manually label them, there will be automatic labels anyway, e.g., Chapter ??.

Figures and tables with captions will be placed in figure and table environments, respectively.

```
par(mar = c(4, 4, .1, .1))
plot(pressure, type = 'b', pch = 19)
```

Reference a figure by its code chunk label with the fig: prefix, e.g., see Figure 1.1. Similarly, you can reference tables generated from knitr::kable(), e.g., see Table 1.1.

```
knitr::kable(
  head(iris, 20), caption = 'Here is a nice table!',
  booktabs = TRUE
)
```

You can write citations, too. For example, we are using the **bookdown** package (Xie, 2016) in this sample book, which was built on top of R Markdown and **knitr** (Xie, 2015).

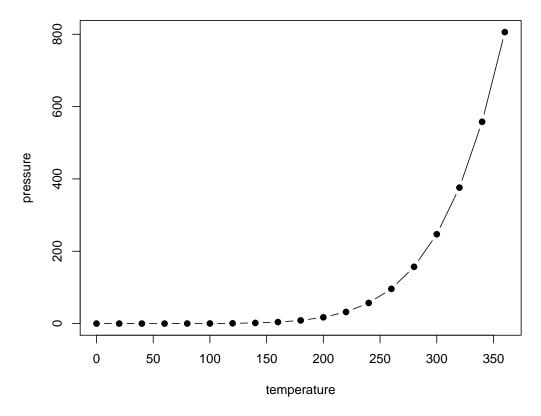


Figure 1.1: Here is a nice figure!

Table 1.1: Here is a nice table!

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa
4.6	3.4	1.4	0.3	setosa
5.0	3.4	1.5	0.2	setosa
4.4	2.9	1.4	0.2	setosa
4.9	3.1	1.5	0.1	setosa
5.4	3.7	1.5	0.2	setosa
4.8	3.4	1.6	0.2	setosa
4.8	3.0	1.4	0.1	setosa
4.3	3.0	1.1	0.1	setosa
5.8	4.0	1.2	0.2	setosa
5.7	4.4	1.5	0.4	setosa
5.4	3.9	1.3	0.4	setosa
5.1	3.5	1.4	0.3	setosa
5.7	3.8	1.7	0.3	setosa
5.1	3.8	1.5	0.3	setosa

#### $1.3.\ ASSESSING\ MODEL\ FIT;\ ANOVA;\ MODEL\ VALIDATION;\ MODEL\ DIAGNOSTICS;\ HANDLING\ NONLINEAR\ RECEIVED AND ANOVA;\ MODEL\ VALIDATION;\ MODEL\ DIAGNOSTICS;\ HANDLING\ NONLINEAR\ RECEIVED ANOVA;\ MODEL\ NONLINEAR\ RECEIVED ANOVA;\ MODE$

This is a sample book written in **Markdown**. You can use anything that Pandoc's Markdown supports, e.g., a math equation  $a^2 + b^2 = c^2$ .

For now, you have to install the development versions of **bookdown** from Github:

devtools::install\_github("rstudio/bookdown")

Remember each Rmd file contains one and only one chapter, and a chapter is defined by the first-level heading #.

To compile this example to PDF, you need to install XeLaTeX.

# Multiple linear regression

- 2.1 Motivation; model formulation; examples; applications; assumptions.
- 2.2 Estimation of model parameters; least squares; inference for model parameters; forecasting.
- 2.3 Assessing model fit; ANOVA; model validation.
- 2.4 Multicollinearity; model diagnostics.

# Binomial logistic regression

- 3.1 Motivation; model formulation; examples; applications; assumptions.
- 3.2 Parameter estimation; assessing model fit; significance testing; interpreting coefficients.

# Factor analysis and principal component analysis

- 4.1 Motivation; formulations; examples; applications; assumptions.
- 4.2 Principal components analysis; choosing the number of factors; analysis and interpretation.
- 4.3 Exploratory factor analysis; design, analysis and interpretation; rotation of factors.

## Cluster analysis

- 5.1 Motivation; examples; applications; hierarchical agglomerative clustering; dendrogram.
- 5.2 Choosing the number of clusters; assessing fit; interpretation of clusters.

# Bibliography

Xie, Y. (2015). Dynamic Documents with R and knitr. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.

Xie, Y. (2016). bookdown: Authoring Books with R Markdown. R package version 0.1.6.