

Introductory Statistics with R:
Linear models for continuous response (Chapters 6, 7, and 11)
Statistical Packages

STAT 1301 / 2300, Fall 2014

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① Simple linear regression

② Multiple Regression

③ Analysis of Variance

Section 1

Simple linear regression

Fitting simple linear regression

lm (Linear Model) function

A model for thuesen data:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2),$$
$$\text{short.velocity}_i = \text{intercept} + \text{slope} \times \text{blood.glucose}_i + \text{error}_i.$$

```
library(ISwR)
plot( thuesen$blood.glucose, thuesen$short.velocity)
lm(short.velocity ~ blood.glucose, data = thuesen)
> attach(thuesen)
> lm(short.velocity ~ blood.glucose)
```

Call:

```
lm(formula = short.velocity ~ blood.glucose)
```

Coefficients:

(Intercept)	blood.glucose
1.09781	0.02196

Saving and extracting the result of analysis

Model object

- The result of `lm` is a *model object*. Whereas other statistical systems focus on generating printed output that can be controlled by setting options, you get instead the result of a model fit encapsulated in an object.
- The model object is a sort of list.
- From the model object the desired quantities can be obtained using extractor functions.

```
fit<-lm(short.velocity ~ blood.glucose)
summary(fit)
str(fit)
fit$coefficients
fit$fitted.values
plot(short.velocity ~ blood.glucose)
abline(fit)
```

Model Diagnostics

All further analysis is based on the model object (`fit` in this example).

Fitted values \hat{y}_i

```
fitted(fit)
fit$fitted.values
```

Residuals $r_i = y_i - \hat{y}_i$

```
resid(fit)
fit$residuals
```

Exercise: Produce a scatterplot of `short.velocity` versus `blood.glucose` with fitted line and residual line segments.

Model Diagnostics

Leverage, Cook's distance and studentized residuals

```
leverages <- hatvalues(fit)
cooks.distance(fit)
rstudent(fit)
```

Residual vs fitted values plot

```
plot(fitted(fit), rstudent(fit))
```

Checking Normality

```
qqnorm(resid(fit))
qqline(resid(fit))
```

Just want everything?

```
plot(fit)
```

Prediction and confidence intervals

predict function

Obtain the fitted values with upper and lower bounds on confidence intervals (`interval="confidence"`) or prediction interval (`interval="prediction"`).

The arguments can be abbreviated:

```
predict(fit, int = "c")  
predict(fit, int = "p")
```


Prediction and confidence intervals

Prediction for new data points

New data points (here `newpts`) arranged as a data frame containing suitable x values (here `blood.glucose`).

```
newpts <- data.frame(blood.glucose = 1:30)
pp <- predict(fit, int="p", newdata=newpts)
pc <- predict(fit, int="c", newdata=newpts)
plot(blood.glucose, short.velocity,
     ylim=range(short.velocity, pp, na.rm=T),
     xlim=range(blood.glucose, newdata, na.rm=T))
matlines(newpts$blood.glucose, pp, lty=c(1,3,3), col="black")
matlines(newpts$blood.glucose, pc, lty=c(1,3,3), col="blue")
```

- `range` function returns a vector of length 2 containing the minimum and maximum values of *all* of its arguments.
- `matlines` function plots the columns of one matrix against the columns of another.

Section 2

Multiple Regression

Scatterplot matrix

```
data(cystfibr)
par(mex = 0.5)
pairs(cystfibr, gap = 0, cex.labels= 0.9)
```

Fitting multiple regression model by `lm` function

```
lm(pemax~age+sex+height+weight+bmp+fev1+rv+frc+tlc,
   data = cystfibr)
a<-lm(pemax~., data = cystfibr)
summary(a)
```

Here, the model formula `pemax~.` stands for `pemax` explained by *all* variables in the data frame.

Model formulas

Suppose we have either continuous (numeric) or categorical (factor) variables as follows.

- Y : response variable
- X, Z, W : predictor variables.

Basic formulas

- $Y \sim X$: $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$.
- $Y \sim X+W$: $Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + \epsilon_i$.

Examples:

```
lm(pemax ~ age, data = cystfibr)
lm(pemax ~ age + sex, data = cystfibr)
```

Importantly, the use of the “+” symbol in this context is different than its usual meaning.

Model formulas

Symbol	Example	Meaning
+	+X	include this variable
-	-X	delete this variable
:	X:Z	include the interaction between these variables
*	X*Y	include these variables and the interactions between them
	X Z	conditioning: include x given z
^	(X + Z + W) ^ 3	include these variables and all interactions up to three way
I	I (X*Z)	as is: include a new variable consisting of these variables multiplied
1	X - 1	intercept: delete the intercept (regress through the origin)

In addition, the dot symbol (".") can only be used when the data frame is specified, and means "all variables except the response".

Examples

```
Y ~ X + Z + W + X:Z + X:W + Z:W
```

```
Y ~ X * Z * W - X:Z:W
```

```
Y ~ (X + Z + W)^2
```

```
Y ~ X + Y - 1
```

```
Y ~ . - X , data = adataframe # used within lm()
```

Exercises

- Fit a quadratic regression to `thuesen` data

- Fit a Quartic regression to `thuesen` data without the intercept.

- Merge weight and height to create $BMI = wt/ht^2$ and fit a linear regression model `pemax ~ BMI` to `cystfibr` data

AIC and BIC for each model

```
fit1 <- lm(pemax~rv+bmp, data = cystfibr)
AIC(fit1)
extractAIC(fit1)
BIC(fit1)
```

Comparing two models

H0: Model 1: $pemax \sim rv + bmp$ is true. (or the weight coefficient = 0))
H1: Model 2: $pemax \sim rv + bmp + weight$ is true. (coefficient $\neq 0$)

To request an F-test for significance of the more complex model, use `anova` function.

```
fit1 <- lm(pemax~rv+bmp, data = cystfibr)
fit2 <- lm(pemax~rv+bmp+weight, data = cystfibr)
anova(fit1,fit2)
```

Model Selection

add1 function: try adding one more predictor to the current model

```
>fit1 <- lm(pemax~age, data = cystfibr)
>add1(fit1, pemax~age+sex+height+weight+bmp+fev1+rv+frc+tlc,
      data = cystfibr, test = 'F')
```

Unfortunately, using `pemax~.` in the second argument of `add1` function does not provide all variables in the data frame, but provides all variables in the current model.

drop1: try removing one predictor from the current model

```
> fit1 <- lm(pemax~., data = cystfibr)
> drop1(fit1, test = 'F')
```

Exercise: do forward and backward variable selections by i) F-tests and ii) AIC values.

Model Selection

Automated variable selection by step function

```
step(model.object, scope, direction = "backward", test = "F", ...))
```

- model.object the model object representing the initial model in the stepwise search.
- scope a model formula for full model (as used in add1)
- Options for direction include "both", "backward", "forward".
- Optional argument test = "F" is passed to add1 and drop1.

Example:

```
fit.null <- lm(pemax~1, data =cystfibr)
step(fit.null, pemax~age+sex+height+weight+bmp+fev1+rv+frc+tlc,
      data= cystfibr, direction="both")
fit.full <- lm(pemax~., data =cystfibr)
step(fit.full, direction="backward", test = "F")
```

Section 3

Analysis of Variance

One-way and two-way ANOVA Models

red cell folate data

```
> summary(red.cell.folate)
      folate      ventilation
Min.   :206.0   N20+02,24h:8
1st Qu.:249.5   N20+02,op  :9
Median :274.0   02,24h      :5
Mean   :283.2
3rd Qu.:305.5
Max.   :392.0
```

juul data

```
> summary(juul[,3:5])
      sex      igf1      tanner
Min.   :1.000   Min.   : 25.0   Min.   :1.00
1st Qu.:1.000   1st Qu.:202.2   1st Qu.:1.00
Median :2.000   Median :313.5   Median :2.00
Mean   :1.534   Mean   :340.2   Mean   :2.64
3rd Qu.:2.000   3rd Qu.:462.8   3rd Qu.:5.00
Max.   :2.000   Max.   :915.0   Max.   :5.00
NA's   :5      NA's   :321   NA's   :240
```

Exercise: Treat variables `sex` and `tanner` as categorical variables.

ANOVA model fit and ANOVA table

aov for balanced data

```
> table(red.cell.folate$ventilation)

N20+02,24h  N20+02,op    02,24h
           8           9           5
> aov(folate~ventilation, data = red.cell.folate)
Call:
  aov(formula = folate ~ ventilation, data = red.cell.folate)

Terms:
              ventilation Residuals
Sum of Squares      15515.77  39716.10
Deg. of Freedom           2         19

Residual standard error: 45.72003
Estimated effects may be unbalanced
> summary(aov(folate~ventilation, data = red.cell.folate))
              Df Sum Sq Mean Sq F value Pr(>F)
ventilation   2  15516    7758   3.711 0.0436 *
Residuals    19  39716    2090
---
```

ANOVA model fit and ANOVA table

An ANOVA model is a linear regression model with multiple (binary) predictors.

`lm` to fit, `anova` for table

```
> lm(folate~ventilation, data =red.cell.folate)
```

Call:

```
lm(formula = folate ~ ventilation, data = red.cell.folate)
```

Coefficients:

(Intercept)	ventilationN20+02,op	ventilation02,24h
316.62	-60.18	-38.62

```
> anova(lm(folate~ventilation, data =red.cell.folate))
```

Analysis of Variance Table

Response: folate

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
ventilation	2	15516	7757.9	3.7113	0.04359 *
Residuals	19	39716	2090.3		

Pairwise comparisons

The p-value in the ANOVA table is used for testing $H_0 : \alpha_1 = \dots = \alpha_I = 0$. In case where H_0 is rejected (i.e., we have enough evidence for the alternative: there is at least one pair (i, j) such that $\alpha_i \neq \alpha_j$), one often performs the pairwise comparison for all pairs of levels.

`pairwise.t.test` function

```
> attach(red.cell.folate)
> pairwise.t.test(folate, ventilation)
```

Pairwise comparisons using t tests with pooled SD

```
data: folate and ventilation
```

```
                N20+02,24h N20+02,op
N20+02,op  0.042          -
02,24h     0.310          0.408
```

```
P value adjustment method: holm
```

Other methods for p-value adjustment can be used:

```
pairwise.t.test(folate, ventilation, p.adj= "bonferroni" )
# try none, holm, fdr for option p.adj
TukeyHSD(aov(folate~ventilation, data =red.cell.folate))
```

Miscellaneous functions for one-way ANOVA

`bartlett.test` for homogeneity of variances

The traditional one-way ANOVA requires an assumption of equal variances for all groups. To check whether this assumption is true:

```
bartlett.test(folate~ventilation)
```

`oneway.test` for unequal variances

There is, however, an alternative procedure that does not require that assumption. It is due to Welch and similar to the unequal-variances t test.

```
oneway.test(folate~ventilation)
```

Kruskal-Wallis test

A nonparametric counterpart of a one-way analysis of variance:

```
kruskal.test(folate~ventilation)
```

Diagnostics

```
plot(model.object)
```

Graphical representation for comparing levels

```
xbar <- tapply(folate, ventilation, mean)
s <- tapply(folate, ventilation, sd)
n <- tapply(folate, ventilation, length)
sem <- s/sqrt(n)
stripchart(folate~ventilation, method="jitter",
           jitter=0.05, pch=16, vert=T)
arrows(1:3, xbar+sem, 1:3, xbar-sem, angle=90, code=3, length=.1)
lines(1:3, xbar, pch=4, type="b", cex=2)

boxplot(folate~ventilation)
```


Two-way ANOVA models

juul data: Preparation

```
detach(juul)
juul$sex <- factor(juul$sex, labels=c("M", "F"))
juul$menarche <- factor(juul$menarche, labels=c("No", "Yes"))
juul$tanner <- factor(juul$tanner,
                      labels=c("I", "II", "III", "IV", "V"))
attach(juul)
```

Main effect model

```
TF <- complete.cases(juul[,2:5])
juul2 <- subset(juul, TF)
a <- lm(igf1 ~ menarche + tanner, data = juul2)
anova(a)
```

Full model with interaction

```
a <- lm(igf1 ~ menarche + tanner + menarche:tanner, data = juul2)
a2 <- lm(igf1 ~ menarche*tanner, data = juul2)
anova(a)
table(menarche, tanner)
```

Two-way ANOVA models

ToothGrowth data

The response is the length of odontoblasts (teeth) in each of 10 guinea pigs at each of three dose levels of Vitamin C (0.5, 1, and 2 mg) with each of two delivery methods (orange juice or ascorbic acid).

```
TG2<-transform(ToothGrowth, dose = factor(dose))
attach(TG2)
table(supp,dose)
summary(aov(len~ supp*dose))
```

Two-way Interaction plot

```
#interaction.plot(x.factor, trace.factor, response)
interaction.plot(supp,dose,len)
interaction.plot(dose,supp,len)
```