

V. Statistical analysis in R (exercises)

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Introduction

Most of this exercise is about analysis with so-called *Gaussian linear models*. This is the class of models where data are assumed to be independent, Gaussian and with the same variance. All such models are fitted with the `lm()` function in R. The term *regression* is usually used for models where all explanatory variables are numerical, whereas the term *analysis of variance* (ANOVA) is usually used for models where all explanatory variables are categorical (factors). However, predictors of both types can be included in the same Gaussian linear model.

In the last two sections, we consider a logistic regression model (for binary outcomes) and a linear mixed model (for data with a block structure).

The purpose of the exercise is to show how to fit and work with statistical models in R. This means that the analyses are not necessarily those that should be used in a real-life analysis of the data.

Start with the **Data** part. The later parts are *almost* independent of each other, so you can choose the parts that are most appropriate for you. However, not all statistical concepts are studied in all parts.

Data

The used dataset is about risk factors for low infant birth weight. This dataset is available in the R-package **MASS** (part of base R, so it is installed automatically) as a data frame called **birthwt**. If nothing else is mentioned, then use the infants' birth weight, **bwt**, as outcome (response).

1. Use the commands below to load the MASS package and get the help page for the data frame. The help page will appear in the lower right window of RStudio. Read about the data; in particular about the variables **age**, **lwt**, **ftv**, **smoke**, and **bwt**.

```
library(MASS)
?birthwt
```

2. **birthwt** is not a tibble (the modern way to organize data), but we can make it one:

```
library(tidyverse)
birthData <- as_tibble(birthwt)
birthData
```

3. Mother's smoking habits (**smoke**) is coded as numerical variable. Make it a factor (categorical variable).
4. The **ftv** is a numerical variable, but we would also like a categorical version of it, with groups corresponding to zero visits, one visit, and two or more visits, respectively. Try the following commands, and check the results:

```
table(birthData$ftv)
birthData <- mutate(birthData, ftvFac = factor(ftv))
birthData <- mutate(birthData, visits = fct_collapse(ftvFac, Never="0", Once="1", other_
birthData %>% group_by(ftvFac, visits) %>% count()
table(birthData$visits, birthData$ftvFac)
```

5. Make groupwise boxplots of **bwt** by **visits**, i.e., boxplots of birthweight for those women who did not see their doctor, those who saw their doctor once, and those who saw their doctor more than once during first trimester - with all boxplots in one graph. Do the same thing for **smoke** (instead of **visits**). You may also make groupwise boxplots for each combination of **smoke** and **visits**. What is your initial impression about potential associations?
6. Make a scatter plot with **lwt** on the *x*-axis and **bwt** on the *y*-axis. Modify the plot such that points are coloured according to **visits**, and modify it further such that the symbol type are different for smokers and non-smokers.

Regression

The term *regression* is usually used for models where all explanatory variables are numerical.

7. Fit a linear regression model with `bwt` as response and `lwt` as covariate, and identify the estimates for the intercept and for the slope. Find the 95% confidence interval for the slope parameter.
8. Carry out model validation for the regression model. Does the model seem appropriate for the data?
9. Fit the multiple linear regression model where you include `lwt` as well as `age` and `ftv` (numerical variable) as covariates. Identify the parameter estimates, and consider what their interpretation is.
10. Try the following commands, and see if you can figure out what the outcome means. You should replace `reg2` with the name of the model object from the previous question.

```
newData <- data.frame(lwt=100, age=25, ftv=0)
newData
predict(reg2, newData)
predict(reg2, newData, interval="prediction")
```

11. Fit the multiple linear regression model again, but now only using data from mothers with a weight less than 160 pounds (`lwt < 160`). *Hint:* Use the `filter` function and change the `data` argument in the `lm` command.

ANOVA

The term *analysis of variance* (ANOVA) is usually used for models where all explanatory variables are categorical (factors). It is important that you have coded `smoke` as a factor, cf. question 3.

12. Fit the oneway ANOVA where the expected value of `bwt` is allowed to differ between smokers and non-smokers. Find the estimated birth weight for infants from smokers as well as non-smokers. Is there significant difference between smokers and non-smokers when it comes to infants' birthweight? *Hints:* Use `summary` and/or `emmeans`.
13. Fit the oneway ANOVA where you use `visits` as the explanatory variable. Find the estimated birth weight for each group, and make the pairwise comparisons between the groups. Furthermore, carry out the *F*-test for the overall comparison of the three levels. What is the conclusion?
14. Now, consider both `visits` and `smoke` as explanatory variables. Since they are both categorical variables (factors), the relevant model is a *twoway* ANOVA. Fit the twoway ANOVA model *without interaction*, and make sure you understand the estimates:

```
twoway1 <- lm(bwt ~ visits + smoke, data=birthData)
summary(twoway1)
```

15. Fit the twoway ANOVA model *with interaction* (use the command below). Then use `anova` and/or `drop1` to test if the interaction between visits and smoking habits is statistically significant.

```
twoway2 <- lm(bwt ~ visits * smoke, data=birthData)
```

16. You should still use `twoway2` in for this question. Use `emmeans` to compute the expected birthweight of infants from for smokers and non-smokers, respectively, on average over the three levels of `visits`. Explain why the estimates differ (slightly) from those in question 12.

Models with numerical as well as categorical predictors

Predictors of any type can be included in Gaussian linear models, still using `lm()`.

17. Fit a model where `lwt` (numeric) and `smoke` (factor) are included as predictors in an additive way:

```
model1 <- lm(bwt ~ lwt + smoke, data=birthData)
summary(model1)
```

What is the interpretation of the estimates?

18. Fit a model with *interaction* between the two predictors, replacing `+` by a `*`:

```
model2 <- lm(bwt ~ lwt * smoke, data=birthData)
summary(model2)
```

What is the interpretation of the estimates? Is there evidence in the dataset that the effect of mother's weight on infants' weight differs between smokers and non-smokers? *Hint:* What does the last question have to do with interaction? Use `anova` on appropriate models.

19. Fit the model with additive effects of mothers' weight, smoking status, age, and visit status, and carry out model validation. Give an interpretation of the estimate associated to `smoke`. Does smoking affect the weight of infants?

Logistic regression

The variable `low` is 1 if birth weight is smaller than 2500 g, and 0 otherwise, see the plot

```
ggplot(birthData, aes(x=bwt, y=low)) + geom_point()
```

Consider for a moment the situation where the actual birth weight (`bwt`) was not registered, such that `low` was the only information on the child. Hence, the outcome is binary (`low` has two values), and the relevant analysis would be a *logistic regression* where the probability $Pr(low = 1)$ is described in terms of predictors. For example, we may consider a model with mothers weight, smoking status, age, and visit status as predictors, just like in the previous question. In math terms, this corresponds to the assumption that, for observation i ,

$$Pr(low_i = 1) = \frac{\exp(\alpha_{visits_i} + \gamma_{smoke_i} + \beta_1 \cdot lwt_i + \beta_2 \cdot age_i)}{1 + \exp(\alpha_{visits_i} + \gamma_{smoke_i} + \beta_1 \cdot lwt_i + \beta_2 \cdot age_i)}$$

20. Fit the model, and consider the estimates:

```
logreg1 <- glm(low ~ lwt + smoke + age + visits, data=birthData, family="binomial")
summary(logreg1)
```

Does this model give evidence for an effect of smoking on the weight of infants? Compare the signs of the estimates from `model3` (Gaussian model, which was made as solution to Question 18) and `model4` (logistic regression model). Can you explain ‘what happens’?

Linear mixed models

21. Assume for a moment that the 189 births took place at 19 different medical centers with 10 births at each center, except for one center with only nine births. This is not the case, so we have to generate a center variable artificially. You should of course never invent such an artificial structure for a real dataset! Anyway, do it like this:

```
set.seed(123)
center <- sample(rep(1:19, each=10)[1:189])
center
birthData <- mutate(birthData, center=factor(center))
```

The `rep` command repeats the number from 1 to 19, 10 times each. We only need the first 189 numbers. The `sample` changes the order of the 189 numbers at random. The `set.seed` command has the effect that you get a the same sample each time you run the commands. The last line includes the new variable in the original dataset as a categorical variable.

22. The `center` variable would typically be included in the model as a *random effect*. Gaussian models with both fixed and random effects are called *linear mixed models*, and are fitted with the `lmer()` function from the `lme4` package. Run the code below and identify relevant estimates. Remember that `lme4` must be installed before the commands below can be used.

```
library(lme4)
lmm1 <- lmer(bwt ~ lwt + smoke + age + visits + (1|center), data=birthData)
summary(lmm1)
```

End of exercise