

Kurs Bio144:

Datenanalyse in der Biologie

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Lecture 3: Multiple linear regression

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Overview

- Checking the assumptions of linear regression: the QQ-plot
- Multiple predictors x_1, x_2, \dots, x_m
- R^2 in multiple linear regression
- t -tests, F -tests and p -values
- Binary and factor covariates

Course material covered today

The lecture material of today is based on the following literature:

- Chapters 3.1, 3.2a-q of *Lineare Regression*
- Chapters 4.1 4.2f, 4.3a-e of *Lineare Regression*
- Chapter 11.2 in the Stahel book *Statistische Datenanalyse*

Recap of last week I

- The linear regression model for the data $\mathbf{y} = (y_1, \dots, y_n)$ given $\mathbf{x} = (x_1, \dots, x_n)$ is

$$y_i = \alpha + \beta x_i + e_i, \quad e_i \sim N(0, \sigma_e^2) \text{ independent.}$$

- Estimate the parameters α , β and σ_e^2 by least squares.
- The estimated parameters $\hat{\alpha}$, $\hat{\beta}$ contain **uncertainty** and are normally distributed around the true values.
- Use the knowledge about the distribution to formulate **statistical tests**, such as: Is $\beta = 0$?
→ **T-test** with $n - 2$ degrees of freedom.
- All this is done automatically by R:

```
> summary(r.bodyfat)$coef
```

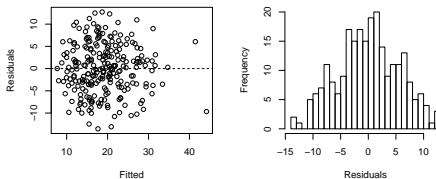
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-26.984368	2.7689004	-9.745518	3.921511e-19
bmi	1.818778	0.1083411	16.787522	2.063854e-42

Recap of last week II

Remember: The assumption in linear regression is that the residuals follow a $N(0, \sigma_e^2)$ distribution, implying that :

- a) The expected value of e_i is 0: $E(e_i) = 0$.
- b) All e_i have the same variance: $\text{Var}(e_i) = \sigma_e^2$.
- c) The e_i are normally distributed.
- d) The e_i are independent of each other.

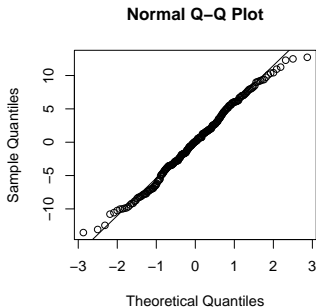
We started to do some residual analysis using the **Tukey-Anscombe plot** and the **Histogram** of the residuals R_i .



Another useful diagnostic plot: The QQ-plot

Usually, not the histogram of the residuals is plotted, but the so-called **quantile-quantile** (QQ) plot. The quantiles of the observed distribution are plotted against the quantiles of the respective theoretical (normal) distribution:

```
> qqnorm(residuals(r.bodyfat))  
> qqline(residuals(r.bodyfat))
```

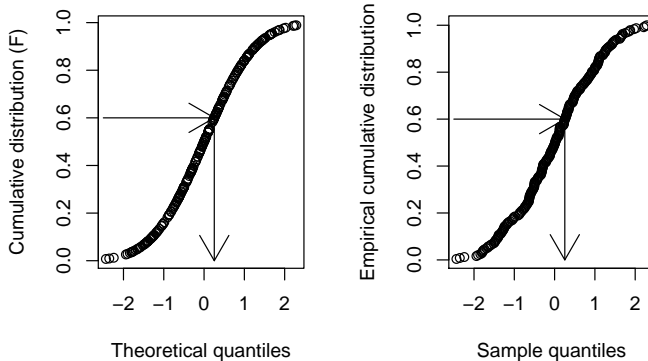


If the points lie approximately on a straight line, the data is fairly normally distributed.

This is often “tested” by eye, and needs some experience.

Please read “Quantil-Quantil-Diagramme”, Chapter 11.2., p.258-261, in “Statistische Datenanalyse” by W. Stahel (Mat183 literature).

It gives a very nice and intuitive description of QQ diagrams!



The idea is that, for each observed point, theoretical quantiles are plotted against the sample quantiles.

Multiple linear regression

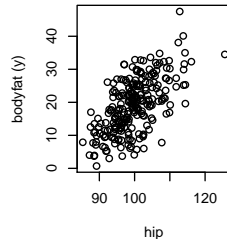
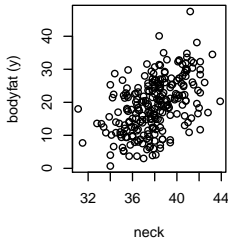
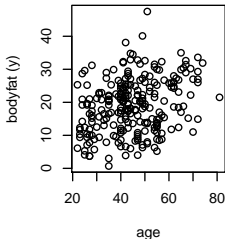
Bodyfat example

We have so far modelled bodyfat in dependence of bmi, that is:

$$(bodyfat)_i = \alpha + \beta \cdot bmi_i + e_i.$$

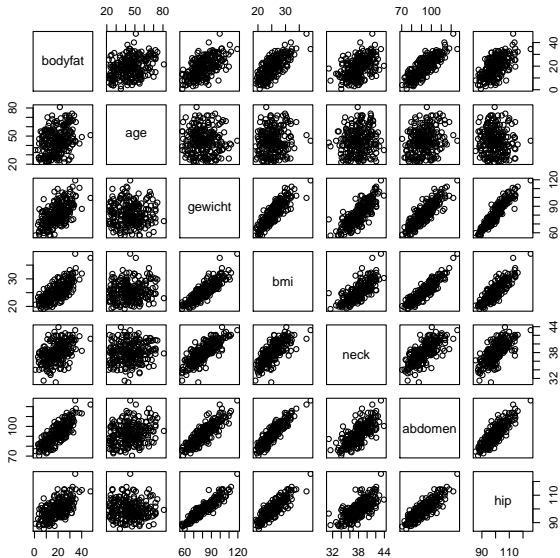
However, other predictors might also be relevant for an accurate prediction of bodyfat.

Examples: Age, neck fat (Nackenfalte), hip circumference, abdomen circumference etc.



Or again the pairs plot:

```
> pairs(d.bodyfat)
```



Multiple linear regression model

The idea is simple: Just **extend the linear model by additional predictors**.

- Given several influence factors $x_i^{(1)}, \dots, x_i^{(m)}$, the straightforward extension of the simple linear model is

$$y_i = \beta_0 + \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \dots + \beta_m x_i^{(m)} + e_i$$

with $e_i \sim N(0, \sigma_e^2)$.

- The parameters of this model are $\beta = (\beta_0, \beta_1, \dots, \beta_m)$ and σ_e^2 .

The components of β are again estimated using the **least squares** method. Basically, the idea is (again) to minimize

$$\sum_{i=1}^n r_i^2$$

with

$$r_i = y_i - (\beta_0 + \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \dots + \beta_m x_i^{(m)})$$

It is a bit more complicated than for simple linear regression, see Section 3.4 of the Stahel script.

Some **linear algebra** is needed to understand these sections, but we do not look into this for the moment. (It will come later in week 6.)

Multiple linear regression for bodyfat

Let us regress the proportion (%) of bodyfat (from last week) on the predictors **bmi** and **age** simultaneously. The model is thus given as

$$\begin{aligned}(bodyfat)_i &= \beta_0 + \beta_1 \cdot bmi_i + \beta_2 \cdot age_i + e_i , \\ \text{with } e_i &\sim N(0, \sigma_e^2) .\end{aligned}$$

Before we estimate the parameters, let us ask the questions that we intend to answer:

- 1 Does the **ensemble** of all covariates have an effect on the response?
- 2 If yes, which influence variables are relevant predictors of bodyfat?
- 3 Which proportion of response variability is explained by the model?

Multiple linear regression with R

Let's now fit the model with R, and quickly glance at the output:

```
> r.bodyfatM <- lm(bodyfat ~ bmi + age ,d.bodyfat)
> summary(r.bodyfatM)
```

Call:

```
lm(formula = bodyfat ~ bmi + age, data = d.bodyfat)
```

Residuals:

Min	1Q	Median	3Q	Max
-12.0415	-3.8725	-0.1237	3.9193	12.6599

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-31.25451	2.78973	-11.203	< 2e-16 ***
bmi	1.75257	0.10449	16.773	< 2e-16 ***
age	0.13268	0.02732	4.857	2.15e-06 ***

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

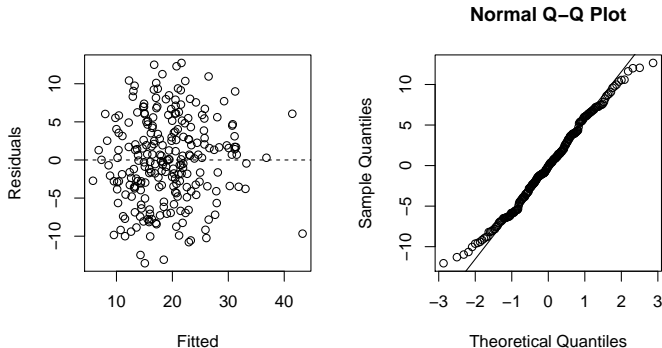
Residual standard error: 5.329 on 240 degrees of freedom

Multiple R-squared: 0.5803, Adjusted R-squared: 0.5768

F-statistic: 165.9 on 2 and 240 DF, p-value: < 2.2e-16

Model checking

Before we look at the results, we have to check if the modelling assumptions are fulfilled:



This seems ok, so continue with answering questions 1-3.

Question 1: Do the covariates have an effect on the response?

To answer question 1, we need to perform a so-called **F-test**. The results of the test are displayed in the final line of the regression summary. Here, it says:

```
F-statistic: 165.9 on 2 and 240 DF, p-value: < 2.2e-16
```

So apparently (and we already suspected that) the model has some explanatory power.

*The F -statistic and -test is briefly recaptured in 3.1.f) of the Stahel script, but see also Mat183 chapter 6.2.5. It uses the fact that

$$\frac{SSQ^{(R)}/m}{SSQ^{(E)}/(n-p)} \sim F_{m,n-p}$$

follows an F -distribution (`df()` in R) with m and $(n-p)$ degrees of freedom, where m are the number of variables, n the number of data points, p the number of β -parameters (typically $m+1$). $SSQ^{(E)} = \sum_{i=1}^n R_i^2$ is the squared sum of the residuals, and $SSQ^{(R)} = SSQ^{(Y)} - SSQ^{(E)}$ with $SSQ^{(Y)} = \sum_{i=1}^n (y_i - \bar{y})^2$.

Question 2: Which variables influence the response?

```
> summary(r.bodyfatM)$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-31.2545057	2.78973238	-11.203406	1.039096e-23
bmi	1.7525705	0.10448723	16.773060	2.600646e-42
age	0.1326767	0.02731582	4.857137	2.149482e-06

To answer this question, again look at the ***t*-tests**, for which the *p*-values are given in the final column. Each *p*-value refers to the test for the null hypothesis $\beta_0^{(j)} = 0$ for covariate $x^{(j)}$.

As in simple linear regression, the *T*-statistic for the *j*-th covariate is calculated as

$$T_j = \frac{\hat{\beta}_j - \beta_{j0}}{se^{(\beta_j)}} \underbrace{=}_{\text{if } \beta_{j0}=0} \frac{\hat{\beta}_j}{se^{(\beta_j)}}, \quad (1)$$

with $se^{(\beta_j)}$ given in the second column of the regression output.

The distribution of this statistic is $T_j \sim t_{n-p}$.

Therefore: A “small” p -value indicates that the variable is relevant in the model.

Here, we have

- $p < 0.001$ for bmi
- $p < 0.001$ for age

Thus both, bmi and age seem to have some predictive power for bodyfat.

Again, a 95% CI for β_j can be calculated with $[\hat{\beta} - c \cdot \sigma^{(\beta)}; \hat{\beta} + c \cdot \sigma^{(\beta)}]$, where c is the 97.5% quantile of the t -distribution with $n - p$ degrees of freedom (compare to slides 38-40 of last week). With R:

```
> confint(r.bodyfatM)

              2.5 %      97.5 %
(Intercept) -36.7499929 -25.7590185
bmi          1.5467413   1.9583996
age          0.0788673   0.1864861
```

!However!:

The p -value and T -statistics should only be used as a **rough guide** for the “significance” of the coefficients.

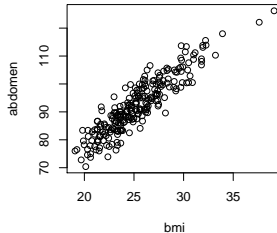
For illustration, let us extend the model a bit more, including also neck, hip and abdomen:

	Coefficient	95%-confidence interval	p -value
Intercept	-7.75	from -22.13 to 6.63	0.29
bmi	0.43	from -0.03 to 0.88	0.066
age	0.015	from -0.04 to 0.07	0.60
neck	-0.80	from -1.18 to -0.43	< 0.0001
hip	-0.32	from -0.53 to -0.11	0.003
abdomen	0.84	from 0.67 to 1.00	< 0.0001

It is now much less clear what the influences of age ($p = 0.60$) and bmi ($p = 0.06$) are.

Basically, the problem is that the **variables in the model are correlated** and therefore explain similar aspects of % bodyfat.

Example: Abdomen (Bauchumfang) seems to be a relevant predictor and it is obvious that abdomen and BMI are correlated:



This problem of **collinearity** is at the heart of many confusions of regression analysis, and we will talk about such issues later in the course (lectures 7 and 8).

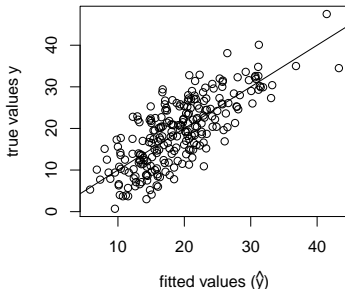
Please see also IC: practical 3 (week 4) for an example and more thoughts.

Question 3: Which proportion of variability is explained?

To answer this question, we can look at the **multiple R^2** (see Stahel 3.1.h). It is a generalized version of R^2 for simple linear regression:

R^2 for multiple linear regression is defined as the squared correlation between (y_1, \dots, y_n) and $(\hat{y}_1, \dots, \hat{y}_n)$, where the \hat{y} are the fitted values

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x^{(1)} + \dots + \hat{\beta}_m x^{(m)}$$



R^2 is also called the *coefficient of determination* or “Bestimmtheitsmass”, because it measures the proportion of the response's variability that is explained by the ensemble of all covariates:

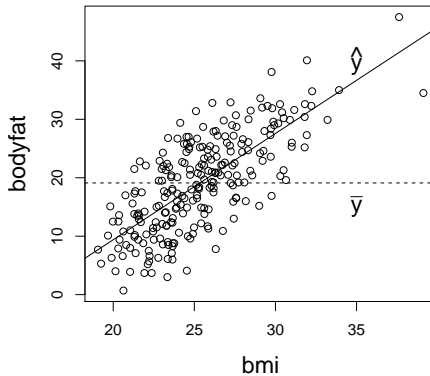
$$R^2 = SSQ^{(R)} / SSQ^{(Y)} = 1 - SSQ^{(E)} / SSQ^{(Y)}$$

Remembering that

total variability = explained variability + residual variability

$$\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 + \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$SSQ^{(Y)} = SSQ^{(R)} + SSQ^{(E)}$$



Let us look at the R^2 s from the three bodyfat models

(model 1: $y \sim bmi$

model 2: $y \sim bmi + age$

model 3: $y \sim bmi + age + neck + hip + abdomen$):

[1] 0.5390391

[1] 0.5802956

[1] 0.718497

The models thus explain 54 %, 58 % and 72 % of the total variability of y .

It thus *seems* that larger models are “better”. However, R^2 does always increase when new variables are included, but this does not mean that the model is more reasonable.

Model selection is a topic that will be treated in more detail later in this course (week 7).

Adjusted R^2

When the sample size n is small with respect to the number of variables m included in the model, an **adjusted** R^2 gives a better (or “fairer”, i.e. unbiased) estimation of the actual variability that is explained by the covariates:

$$R_a^2 = 1 - (1 - R^2) \frac{n - 1}{n - m - 1}$$

Why R_a^2 ?

Penalization for adding more independent variables that do not fit the model!

Note: R_a may decrease when a new variable is added.

Interpretation of the coefficients

Apart from model checking and thinking about questions 1-3, it is probably even **more important to understand what you see**. Look at the output and ask yourself:

What does the regression output actually mean?

	Coefficient	95%-confidence interval	<i>p</i> -value
Intercept	-31.25	from -36.75 to -25.76	< 0.0001
bmi	1.75	from 1.55 to 1.96	< 0.0001
age	0.13	from 0.08 to 0.19	< 0.0001

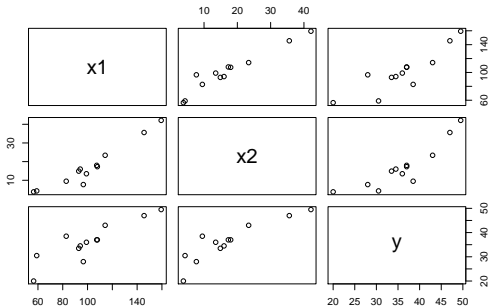
Table: Parameter estimates of model 3.

Task in teams: Interpret the coefficients, 95% CIs and *p*-values.

Example: Catheter Data

Catheter length (y) for heart surgeries depending on two characteristic variables $x^{(1)}$ and $x^{(2)}$ of the patients. Aim: estimate y from $x^{(1)}$ and $x^{(2)}$ ($n = 12$). Again look at the data first:

```
> pairs(d.cath)
```

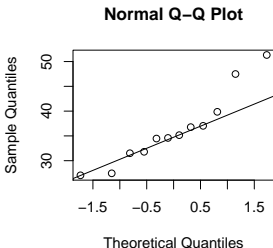
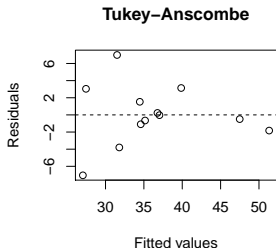


Note that $x^{(1)}$ and $x^{(2)}$ are highly correlated!

Regression results:

	Coefficient	95%-confidence interval	<i>p</i> -value
Intercept	21.09	from 1.25 to 40.93	0.04
x1	0.077	from -0.25 to 0.40	0.61
x2	0.43	from -0.41 to 1.26	0.28

with $R^2 = 0.81$, $R_a^2 = 0.76$, *p*-value of the *F*-test $p = 0.0006$, and diagnostic residual plots:



- ① Are the modelling assumptions met?
- ② Do the covariates improve the model (compared to a model without covariates)?
- ③ Which variable(s) influence(s) the response?
- ④ Which proportion of variability is explained?
- ⑤ Interpretation of the results?

To understand what is going on, the regression results of y on $x^{(1)}$ and $x^{(2)}$ alone may be useful:

	Coefficient	95%-confidence interval	p -value
Intercept	12.13	from 2.66 to 21.59	0.017
x_1	0.24	from 0.15 to 0.33	0.0002

$$R^2 = 0.78, R_a^2 = 0.75$$

	Coefficient	95%-confidence interval	p -value
Intercept	25.63	from 21.16 to 30.09	< 0.0001
x_2	0.62	from 0.40 to 0.83	< 0.0001

$$R^2 = 0.80, R_a^2 = 0.78$$

Binary covariates

So far, the covariates x were always continuous.

However, in our regression models there are **no restrictions assumed with respect to the x variables**.

One very frequent data type of covariates are **binary** variables, that is, variables that can only attain values 0 or 1.

See section 3.2c of the Stahel script:

If the binary variable x is the only variable in the model $y_i = \beta_0 + \beta_1 x_i + e_i$, the model has only two predicted outcomes (plus error):

$$y_i = \begin{cases} \beta_0 + e_i & \text{if } x_i = 0 \\ \beta_0 + \beta_1 + e_i & \text{if } x_i = 1 \end{cases}$$

Example: Smoking variable in Hg Study

For the 59 mothers in the Hg study, check if their smoking status (0=no,1=yes) influences the Hg-concentration in their urine.

We fit the following linear regression model:

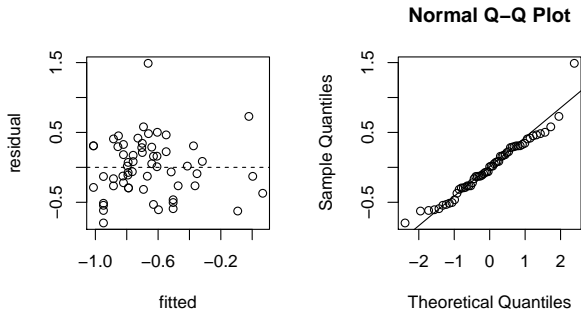
$$\log(Hg_{urin})_i = \beta_0 + \beta_1 \cdot x_i^{(1)} + \beta_2 \cdot x_i^{(2)} + \beta_3 \cdot x_i^{(3)} + e_i ,$$

Where

- $\log(Hg_{urin})_i$ is the urine mercury concentration.
- $x^{(1)}$ is the binary smoking indicator (0/1), denoted as **dummy variable**.
- $x^{(2)}$ the number of amalgam fillings.
- $x^{(3)}$ the monthly number of marine fish meals.

(Remember from week 1 that the log of Hg concentrations is needed to obtain useful distributions.)

First check the modelling assumptions:



It seems ok, apart from one point that could be categorized as an outlier. We ignore it for the moment.

The results table is given as follows:

	Coefficient	95%-confidence interval	<i>p</i> -value
Intercept	-1.01	from -1.22 to -0.80	< 0.0001
smoking	0.22	from -0.06 to 0.50	0.12
amalgam	0.092	from 0.05 to 0.14	0.0001
fish	0.032	from 0.01 to 0.06	0.015

There is some weak ($p = 0.12$) indication that smokers have an increased Hg concentration in their body. Their $\log(Hg_{urin})$ is in average by 0.22 higher than for nonsmokers.

In principle, we have now – at the same time – fitted **two models**: one for smokers and one for non-smokers, assuming that the slopes of the other covariates are the same for both groups.

Smokers: $y_i = -1.01 + 0.22 \cdot \text{smoking}_i + 0.092 \cdot \text{amalgam}_i + 0.032 \cdot \text{fish}_i + e_i$

Non-smokers: $y_i = -1.01 + 0.092 \cdot \text{amalgam}_i + 0.032 \cdot \text{fish}_i + e_i$

Factor covariates

Some covariates indicate a **category**, for instance the species of an animal or a plant. This type of covariate is called a **factor**. The trick is to convert a factor with k levels (for instance 3 species) into k dummy variables $x_i^{(j)}$ with

$$x_i^{(j)} = \begin{cases} 1, & \text{if the } i\text{th observation belongs to group } j. \\ 0, & \text{otherwise.} \end{cases}$$

Each of the covariates $x^{(1)}, \dots, x^{(k)}$ can then be included as a binary variable in the model

$$y_i = \beta_0 + \beta_1 x^{(1)} + \dots + \beta_k x^{(k)} + e_i .$$

However: this model is **not identifiable**. I could add a constant to $\beta_1, \beta_2, \dots, \beta_k$ and subtract it from β_0 , and the model would fit as good to the data.

Solution: One of the k categories must be selected as a *reference category* and is *not included in the model*. Typically: the first category is the reference, thus $\beta_1 = 0$.

The model thus discriminates between the factor levels, such that (assuming $\beta_1 = 0$)

$$\hat{y}_i = \begin{cases} \beta_0, & \text{if } x_i^{(1)} = 1 \\ \beta_0 + \beta_2, & \text{if } x_i^{(2)} = 1 \\ \dots \\ \beta_0 + \beta_k, & \text{if } x_i^{(k)} = 1 \end{cases} .$$

Please also consult Stahel 3.2e and g.

!!Important to remember!!

(Common aspect that leads to confusion!)

Please note that a factor covariate with k factor levels requires $k - 1$ parameters!

→ The degrees of freedom are also reduced by $k - 1$.

Example: Earthworm study

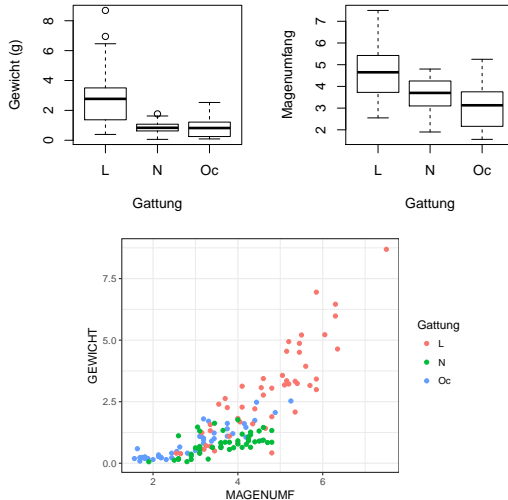
(Angelika von Förster und Burgi Liebst)

Die Dachse im Sihlwald ernähren sich zu einem grossen Prozentsatz von Regenwürmern. Ein Teil des Muskelmagens der Regenwürmer wird während der Passage durch den Dachsdarm nicht verdaut und mit dem Kot ausgeschieden. Wenn man aus der Grösse des Muskelmagenteilchens auf das Gewicht des Regenwurms schliessen kann, ist die Energiemenge berechenbar, die der Dachs aufgenommen hat.

Frage: Besteht eine Beziehung zwischen dem Umfang des Muskelmagenteilchens und dem Gewicht des Regenwurms?

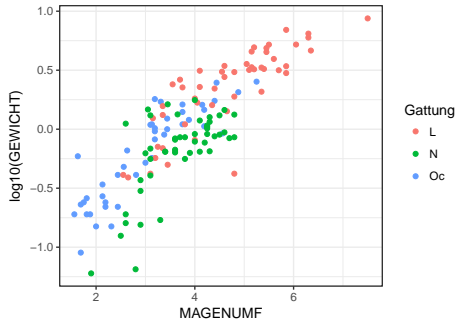
Data set of $n = 143$ worms with three species (Lumbricus, Nicodrilus, Octolasion), weight, stomachic circumference (Magenumfang).

Data inspection suggests that the three species have different weight and stomach sizes:



However, data inspection also suggests that there is not really a linear relationship between weight and stomach size – rather it looks **exponential!**

Therefore, **log-transform** the response (weight), and it looks much better:

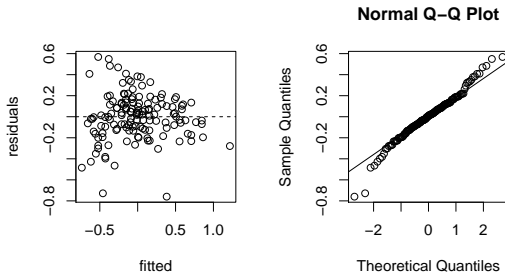


Formulate a model with $\log_{10}(\text{Gewicht})$ as response and Magenumfang and Gattung as covariates. This is imple in R:

(But make sure that Gattung is stored as a factor in R (check by `str(d.wurm)`!))

```
> r.lm <- lm(log10(GEWICHT) ~ MAGENUMF + Gattung,d.wurm)
```

Before doing anything else, check the modelling assumptions:



→ This seems ok.

Results:

	Coefficient	95%-confidence interval	p-value
Intercept	-1.10	from -1.29 to -0.91	< 0.0001
MAGENUMF	0.31	from 0.27 to 0.35	< 0.0001
GattungN	-0.22	from -0.32 to -0.13	< 0.0001
GattungOc	-0.039	from -0.15 to 0.07	0.48

$$R^2 = 0.76, R_a^2 = 0.75.$$

- Question: Why is Gattung Lumbricus (L) not in the results table?
- Answer: L was chosen as the “reference category”, thus $\beta_L = 0$.

Degrees of freedom: We had 143 data points. How many degrees of freedom are left for the residual error?

Answer: We estimated 4 parameters, thus $143 - 4 = 139$.

Interpreting the results I

- $\beta_0 = -1.10$ is the intercept.
- $\beta_1 = 0.31$ is the slope for MAGENUMF.
- $\beta_2 = -0.22$ is the coefficient for Gattung=Nicodrilus.
- $\beta_3 = -0.039$ is the coefficient for Gattung =Octolasion.
- No coefficient is needed for Gattung Lumbricus, because $\beta_L = 0$.

We have now actually fitted **three** models, one model for each species:

Lumbricus: $\hat{y}_i = -1.10 + 0.31 \cdot \text{MAGENUMF}$

Nicodrilus: $\hat{y}_i = -1.10 + (-0.22) + 0.31 \cdot \text{MAGENUMF}$

Octolasion: $\hat{y}_i = -1.10 + (-0.039) + 0.31 \cdot \text{MAGENUMF}$

Interpreting the results II

Main question: Is there a relation between stomach size and body mass?

Results: MAGENUMF is a positive coefficient with $p < 0.0001$, thus very strong evidence that the relation exists. Increasing MAGENUMF by 1 unit increases $\log_{10}(\text{GEWICHT})$ by $+0.31$.

Moreover, the $R^2 = 0.76$ is relatively high and almost identical to R_a^2 .

Interpreting the results III

Question: Is the “Gattung” covariate relevant in the model, that is, do the model intercepts differ for the three species?

Problem: The p -values of the worm species are not very meaningful. They belong to tests that compare the actual level with the reference level. However, the question is whether the variable Gattung has an effect in total.

Solution: When a factor covariate with k levels is in the model, it occupies $k - 1$ parameters. Therefore, the t -test needs to be replaced by the F -test.

F-test to compare models

F-Test zum Vergleich von Modellen. Die Frage sei, ob die q Koeffizienten $\beta_{j_1}, \beta_{j_2}, \dots, \beta_{j_q}$ in einem linearen Regressionsmodell gleich null sein könnten.

- Nullhypothese: $\beta_{j_1} = 0$ und $\beta_{j_2} = 0$ und ... und $\beta_{j_q} = 0$
- Teststatistik:

$$T = \frac{(\text{SSQ}^{(E)*} - \text{SSQ}^{(E)})/q}{\text{SSQ}^{(E)}/(n-p)};$$

$\text{SSQ}^{(E)*}$ ist die Quadratsumme des Fehlers im „kleinen“ Modell, die man aus einer Regression mit den verbleibenden $m - q$ X -Variablen erhält, und p die Anzahl Koeffizienten im „grossen“ Modell ($= m + 1$, falls das Modell einen Achsenabschnitt enthält, $= m$ sonst).

- Verteilung von T unter der Nullhypothese: $T \sim \mathcal{F}_{q, n-p}$, F-Verteilung mit q und $n - p$ Freiheitsgraden.

Der Test heisst F-Test zum Vergleich von Modellen. Allerdings kann nur ein kleineres Modell mit einem grösseren verglichen werden, in dem alle X -Variablen des kleinen wieder vorkommen, also mit einem „umfassenderen“ Modell. Der früher besprochene F-Test für das gesamte Modell (3.1.e) ist ein Spezialfall: das „kleine“ Modell besteht dort nur aus dem Achsenabschnitt β_0 .

Remember: $F_{1, n-p} = t_{n-p}^2$

F-test for the earthworms

There exists a function (ANOVA) in R that does the F -test for categorical variables.

```
> anova(r.lm)
```

```
Analysis of Variance Table
```

```
Response: log10(GEWICHT)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
MAGENUMF	1	19.7790	19.7790	409.69	< 2.2e-16 ***
Gattung	2	1.3537	0.6768	14.02	2.842e-06 ***
Residuals	139	6.7106	0.0483		

```
---
```

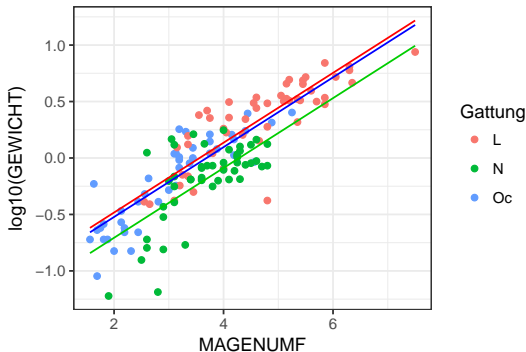
```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note: Here, the F -value for *Gattung* is distributed as $F_{2,139}$ under the Null-Hypothesis.

This gives $p = 2.842e - 06$, thus a clear difference in the regression models for the three species (“*Gattung* is relevant”).

Plotting the earthworms results

All species have the same slope (this is a modelling assumption), but different intercepts:



Summary

To remember:

- Multiple linear regression model

$$y_i = \beta_0 + \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \dots + \beta_m x_i^{(m)} + e_i.$$

- The degrees of freedom are reduced with each slope parameter β_k .
- The F -statistic is used to test whether the ensemble of all covariates has some predictive/explanatory power.
- Collinearity of covariates is a problem.
- Adjusted R_a^2 used to correct for the number of covariates by penalization.
- Binary covariates: Implicitly fit two models.
- Factor covariates with k levels: Implicitly fit $k - 1$ models.
- Use the F -test to test if factor covariates are relevant.