

Linear Regression

19.11.2014

Introduction - Why Statistics?

- There is a **fast growing amount of data** these days, in nearly all research (and applied) areas.
- We want to **extract useful information** from data or **check our hypotheses**.
- E.g., among a large set of variables (temperature, pressure, . . .): which have an effect on the yield of a process and how do the relationships look like?
- We need to be able to **quantify uncertainty**, because “the data could have been different”.

- Instead of simply determining a plain numerical estimate for a model parameter, we typically have the following goals:
 - ▶ Determine **other plausible values** of the parameter.
 - ▶ **Test** whether a specific parameter value is **compatible** with the data.
- Moreover, we want to be able to **understand** and **challenge** the statistical methodology that is applied in current research papers.

Outline of the content

- Linear Regression
- Nonlinear Regression
- Design of Experiments
- Multivariate Statistics

Comments

- Due to time-constraints we will not be able to do “all the details” but you should get the **main idea** of the different topics.
- The lecture notes contain more material than we will be able to discuss in class!
- The relevant parts are those that we discuss in class.

Goals of Today's Lecture

- Get (again) familiar with the statistical concepts:
 - ▶ tests
 - ▶ confidence intervals
 - ▶ p-values
- Understand the difference between a standard numerical analysis of the least squares problem and the statistical approach.
- Be able to interpret a simple or a multiple regression model (e.g., meaning of parameters). Understand the most important model outputs (tests, coefficient of determination, ...).

Simple Linear Regression

Introduction

Linear regression is a “nice” statistical modeling approach in the sense that:

- It is a good example to **illustrate statistical concepts** and to learn about the **3 basic questions of statistical inference**:
 - ▶ Estimation
 - ▶ Tests
 - ▶ Confidence intervals
- It is simple, powerful and used very often.
- It is the basis of many other approaches.

Goal

Model the relationship between a **response variable** Y and **one predictor variable** x .

- E.g. height of tree (Y) vs. pH-value of soil (x).
- Simplest relation one can think of is

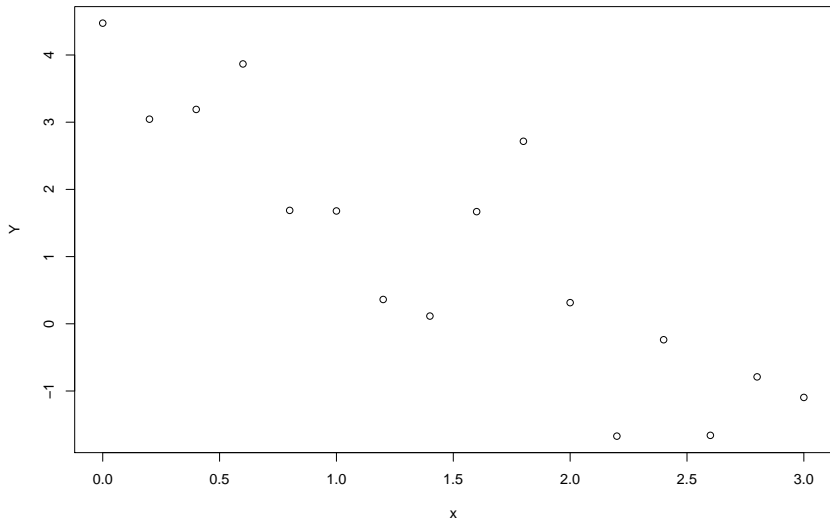
$$Y = \beta_0 + \beta_1 x + \text{Error.}$$

This is called the **simple linear regression model**. It consists of

- an intercept β_0 ,
- a slope β_1 ,
- and an error term (e.g., measurement error).

The error term accounts for the fact that the model does **not** give an exact fit to the data.

Possible (artificial) data set



Simple Linear Regression: Parameter Estimation

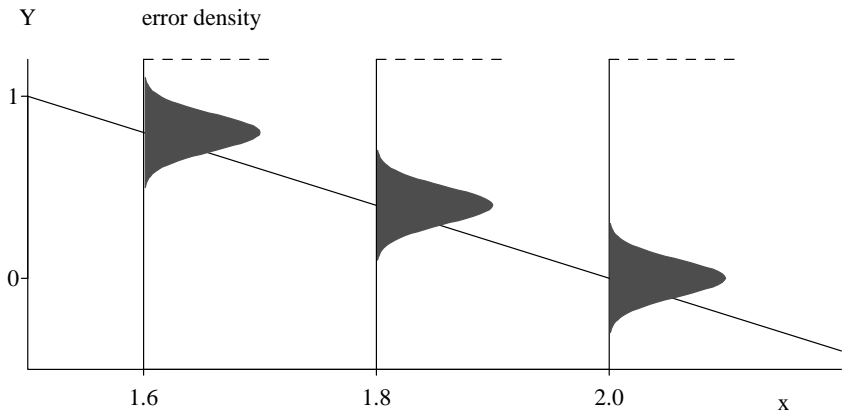
- We have a data set of n points $(x_i, Y_i), i = 1, \dots, n$ and want to **estimate** the unknown parameters.
- We can write the model as

$$Y_i = \beta_0 + \beta_1 x_i + E_i, \quad i = 1, \dots, n,$$

where E_i are the errors (that cannot be observed).

- Usual assumptions are $E_i \sim \mathcal{N}(0, \sigma^2)$, independent.
- Hence, in total we have the following **unknown parameters**
 - ▶ intercept β_0
 - ▶ slope β_1
 - ▶ error variance σ^2 (nuisance parameter).

Visualization of data generating process



- The (unknown) parameters β_0 and β_1 are **estimated** using the principle of **least squares**.
- The idea is to minimize the sum of the squared distances of the observed data-points from the regression line

$$\sum_{i=1}^n (Y_i - \beta_0 - \beta_1 x_i)^2,$$

the so called **sum of squares**.

- This leads to parameter estimates

$$\begin{aligned}\hat{\beta}_1 &= \frac{\sum_{i=1}^n (x_i - \bar{x})(Y_i - \bar{Y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \\ \hat{\beta}_0 &= \bar{Y} - \hat{\beta}_1 \bar{x}.\end{aligned}$$

- This is what you have learned in numerical analysis.
- Moreover

$$\hat{\sigma}^2 = \frac{1}{n-2} \sum_{i=1}^n R_i^2,$$

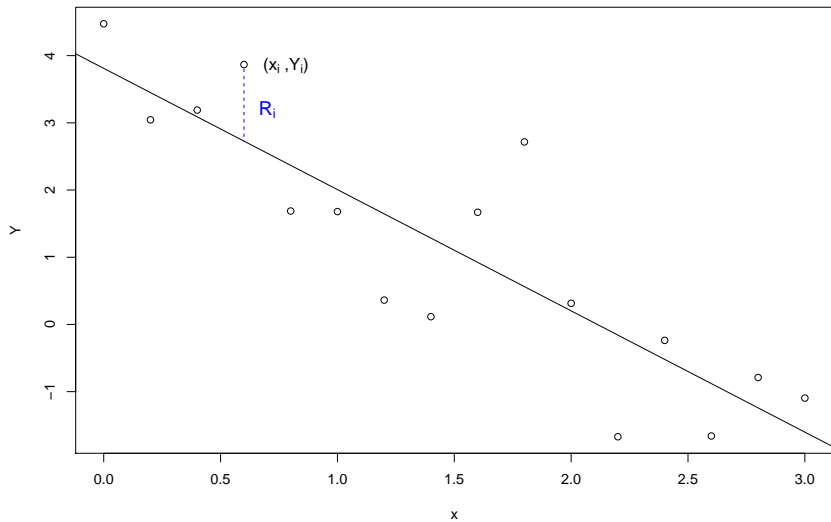
where

$$R_i = Y_i - \hat{y}_i = Y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i$$

are the (observable) **residuals**.

- However, we have made some assumptions about the stochastic behavior of the error term.
- Can we get some extra information based on these assumptions?

Visualization of residuals



- The parameter estimates $\hat{\beta}_0, \hat{\beta}_1$ are **random variables!**
- Why? Because they depend on the Y_i 's that have a random error component.
- Or in other words: **“The data could have been different”**.
- For other realizations of the error term we get slightly different parameter estimates (\rightsquigarrow see animation!).

- The **stochastic model** allows us to quantify uncertainties. It can be shown that

$$\begin{aligned}\hat{\beta}_1 &\sim \mathcal{N}(\beta_1, \sigma^2/SS_X) \\ \hat{\beta}_0 &\sim \mathcal{N}\left(\beta_0, \sigma^2\left(\frac{1}{n} + \frac{\bar{x}^2}{SS_X}\right)\right),\end{aligned}$$

where $SS_X = \sum_{i=1}^n (x_i - \bar{x})^2$.

- See animation for illustration of empirical distribution.
- This information can now be used to perform **tests** and to derive **confidence intervals**.

Statistical Tests: General Concepts

- First we recall the basics about statistical testing (restricting ourselves to two-sided tests).
- We have to specify a **null-hypothesis** H_0 and an **alternative** H_A about a model parameter.
- H_0 is typically of the form “no effect”, “no difference”, “status quo” etc.
- It is the position of a critic who doesn't believe you.
- H_A is the complement of H_0 (what you want to show).
- We want to **reject** H_0 in favor of H_A .
- In order to judge about H_0 and H_A we need some quantity that is based on our data. We call it a **test statistic** and denote it by T .

- As T is stochastic there is a chance to do wrong decisions:
 - ▶ Reject H_0 even though it is true (**type I error**)
 - ▶ Do not reject H_0 even though H_A holds (**type II error**).
- How can we convince a critic? We assume that he is right, i.e. we assume that H_0 really holds.
- Assume that we know the distribution of T under H_0 . We are nice and allow the critic to control the type I error-rate.
- This means that we choose a rejection region such that T falls in that region only with probability (e.g.) 5% (**significance level**) if H_0 holds.

- We reject H_0 in favor of H_A if T falls in the **rejection region**.
- If we can reject H_0 we have “statistically proven” H_A .
- If we **cannot** reject H_0 we can basically say **nothing**, because **absence of evidence is not evidence of absence**.
- Of course we try to use a test statistic T that falls in the rejection region with high probability if H_0 does not hold (**power of the test**).

- Assume that we want to test whether $\beta_1 = 0$. Or in words: “The predictor x has no influence on the response Y ”
- This means we have the null hypothesis $H_0 : \beta_1 = 0$ vs. the alternative $H_A : \beta_1 \neq 0$.
- Intuitively we should reject H_0 if we observe a large absolute value of $\hat{\beta}_1$. But what does large mean here? Use distribution under H_0 to quantify!

Distribution of $\hat{\beta}_1$

For the true (but unknown) β_1 it holds that

$$T = \frac{\hat{\beta}_1 - \beta_1}{\hat{\sigma}/\sqrt{SS_X}} \sim t_{n-2}.$$

Hence, under H_0 : $\frac{\hat{\beta}_1}{\hat{\sigma}/\sqrt{SS_X}} \sim t_{n-2}$ (null-distribution).

Remarks

- $\hat{\sigma}/\sqrt{SS_X}$ is also called the **estimated standard error** of $\hat{\beta}_1$.
- We have a t -distribution because we use $\hat{\sigma}$ instead of σ .
- We reject H_0 if the test statistic T lies in the “extreme regions” of the t_{n-2} distribution.
- If we test at the 5% significance level we reject H_0 if

$$|T| \geq q_{0.975}^{t_{n-2}},$$

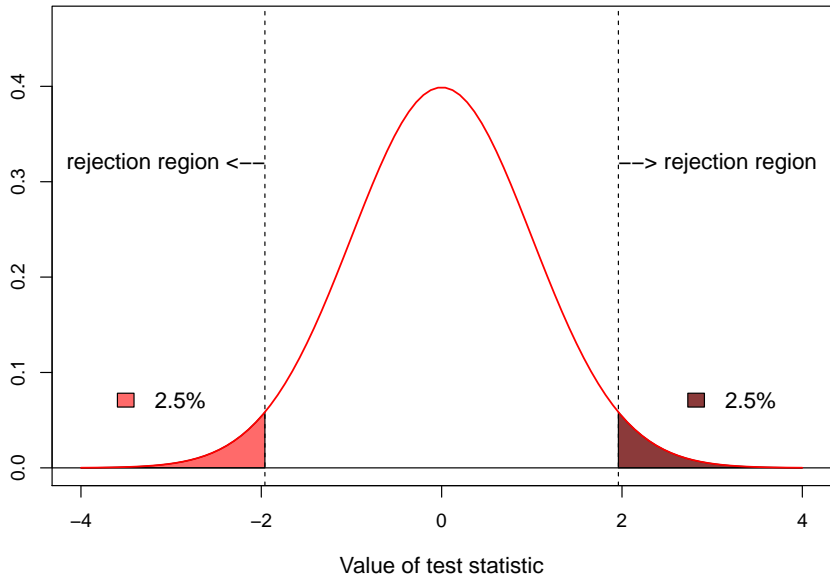
where $q_{0.975}^{t_{n-2}}$ is the 97.5%-quantile of the t_{n-2} distribution.

- Or in other words:

“We reject H_0 if T falls either in the region of the 2.5% extreme cases on the left side or the 2.5% extreme cases on the right side of the distribution under H_0 ” (see picture on next slide).

- Remember: $q_{0.975}^{t_{n-2}} \approx 1.96$ for large n .

Null Distribution

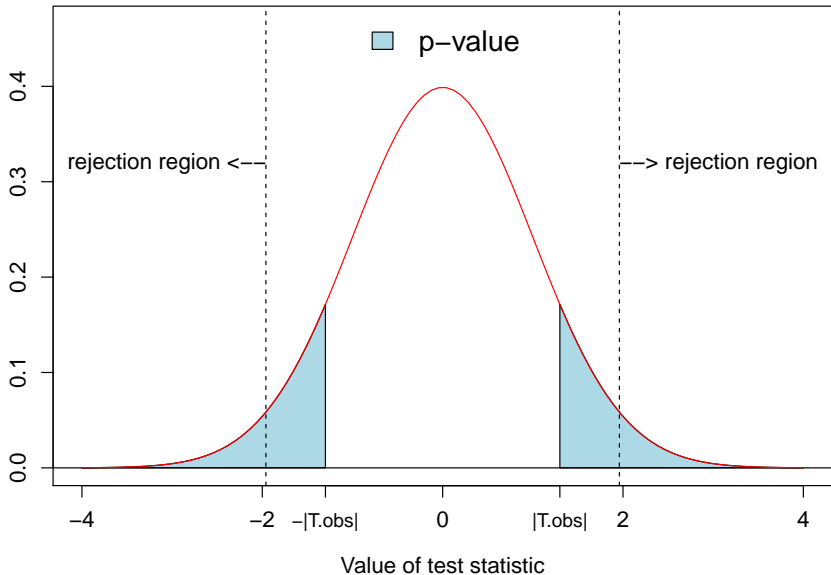


- The p-value is the probability of observing an at least as extreme event if the null-hypothesis is true.

$$p = P_{H_0}(|T| \geq |T_{\text{observed}}|).$$

- Here: “Given that x has no effect on Y , what is the probability of observing a test-statistic T at least as extreme as the observed one?”
- The p-value tells us how extreme our observed T is with respect to the null-distribution.
- If the p-value is less than the significance-level (5%), we reject H_0 .
- The p-value contains more information than the test decision alone.

Null Distribution



Confidence Intervals

- A confidence interval (CI) for the parameter β_1 contains all **“plausible values”** for β_1 .
- Construction: A 95%-CI consists of all parameter values β_1 that cannot be rejected using the 5%-test above.

$$\begin{aligned} CI &= \{\text{all parameter values that are not rejected}\} \\ &= \{\beta_1; |T| \leq q_{0.975}^{t_{n-2}}\} \\ &= \hat{\beta}_1 \pm \hat{\sigma} / \sqrt{SS_X} \cdot q_{0.975}^{t_{n-2}} \\ &\approx \hat{\beta}_1 \pm 2 \cdot \hat{\sigma} / \sqrt{SS_X} \text{ (for large } n\text{)} \\ &= \text{estimate} \pm 2 \cdot \text{estimated standard error (for large } n\text{)}. \end{aligned}$$

- Alternative interpretation:

A 95%-confidence interval covers the true parameter value with probability 0.95.

Simple Linear Regression: Computer Output

Example

Model the lead content of tree barks ($\mu\text{g}/\text{g}$) using the traffic amount (in 1000 cars per day). Data was collected at different streets.

Computer Output

Coefficients:

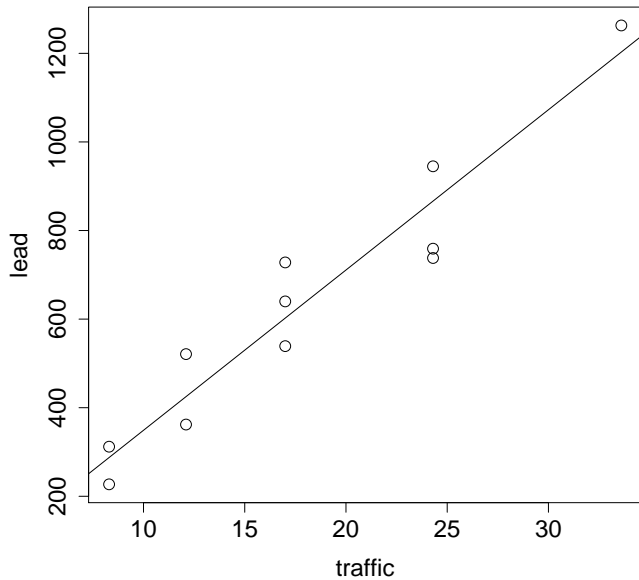
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-12.842	72.143	-0.178	0.863
traffic	36.184	3.693	9.798	4.24e-06 ***

Residual standard error: 92.19 on 9 degrees of freedom

Multiple R-squared: 0.9143, Adjusted R-squared: 0.9048

F-statistic: 96.01 on 1 and 9 DF, p-value: 4.239e-06

Data and fitted model



Multiple Linear Regression

- Now we have **more than one predictor**.

- **Model**

$$Y_i = \beta_0 + \beta_1 x_i^{(1)} + \beta_2 x_i^{(2)} + \dots + \beta_m x_i^{(m)} + E_i, \quad i = 1, \dots, n$$

$$E_i \sim \mathcal{N}(0, \sigma^2), \text{ independent.}$$

- Unknown parameters: $\beta_0, \beta_1, \dots, \beta_m, \sigma^2$.
- The model is called **linear** because it is **linear in the parameters**.
- Note: There are **no assumptions regarding the predictors!**
- **Interpretation of Coefficients**

β_j measures the effect of $x^{(j)}$ on Y **after** having subtracted all other effects from $x^{(k)}$ on Y , $k \neq j$.

- In matrix form we have

$$Y = X\beta + E,$$

where

$$X = \begin{pmatrix} 1 & x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(m)} \\ 1 & x_2^{(1)} & x_2^{(2)} & \dots & x_2^{(m)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_n^{(1)} & x_n^{(2)} & \dots & x_n^{(m)} \end{pmatrix}, \quad Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix},$$

$$\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_m \end{pmatrix}, \quad E = \begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_n \end{pmatrix}.$$

- The matrix X is called the **design matrix**. It consists of n rows (the different observations) and $p = m + 1$ columns (the different predictors).

- Again, the model is fitted using **least squares**, leading to

$$\hat{\beta} = (X^T X)^{-1} X^T Y,$$

i.e., we have a **closed form solution**.

- Moreover

$$\hat{\sigma}^2 = \frac{1}{n - p} \sum_{i=1}^n (Y_i - \hat{y}_i)^2.$$

Multiple Linear Regression: Inference

- Again, it can be shown that

$$\widehat{\beta}_j \sim \mathcal{N}\left(\beta_j, \sigma^2 \left((X^T X)^{-1}\right)_{jj}\right).$$

- Again, the estimator $\widehat{\beta}_j$ fluctuates around the true value β_j .
- The standard error is given by

$$\sigma \sqrt{\left((X^T X)^{-1}\right)_{jj}}$$

- This leads to the test statistic

$$T_j = \frac{\widehat{\beta}_j - \beta_j}{\widehat{\sigma} \sqrt{\left((X^T X)^{-1}\right)_{jj}}} \sim t_{n-p}.$$

- This is very similar to simple linear regression, with the exception that we now have a t_{n-p} instead of a t_{n-2} distribution.

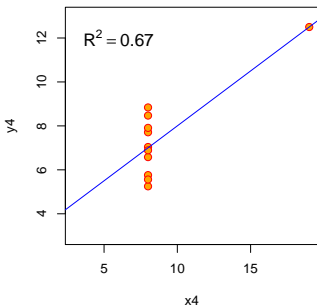
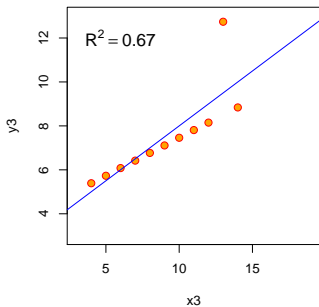
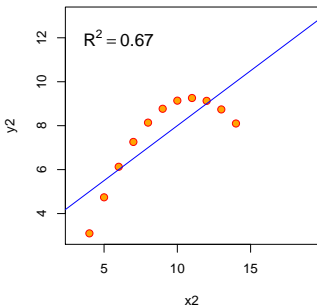
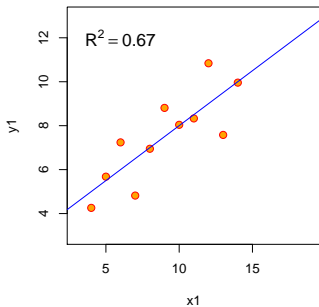
- Tests and CI for individual parameters are constructed as in the simple linear regression case.
- Here we can also do **simultaneous tests**.
 $H_0 : \beta_1 = \beta_2 = \dots = \beta_m = 0$ (no effect from any of the predictors).
 $H_A : \text{at least one } \beta_j \neq 0$.
- This can be tested using an F -test (see computer output).

Coefficient of Determination R^2

$$R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

- R^2 is the proportion of the variance that can be explained by the regression model.
- $R^2 = 1$ is equivalent to a perfect fit (all residuals equal 0).
- Simple linear regression: $R^2 = \text{Corr}(x, y)^2$.
- Multiple linear regression: $R^2 = \text{Corr}(\hat{y}, y)^2$.
- R^2 **does not tell you how well your model fits the data** (see next slide). E.g, it does not tell you whether the relationships are really linear or not.

Anscombe's 4 Regression data sets



Multiple Linear Regression: Computer Output

Example

Model the “monthly steam demand” of a factory using the predictors “operating days” and “average outside temperature”.

Computer Output

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	9.126885	1.102801	8.276	3.35e-08	***
Operating.Days	0.202815	0.045768	4.431	0.00021	***
Temperature	-0.072393	0.007999	-9.050	7.19e-09	***

Residual standard error: 0.6616 on 22 degrees of freedom

Multiple R-squared: 0.8491, Adjusted R-squared: 0.8354

F-statistic: 61.9 on 2 and 22 DF, p-value: 9.226e-10

Residual Analysis

- We made assumptions about the error term in the model. We assumed that the errors
 - ▶ have expectation 0 (i.e. the regression model is correct),
 - ▶ have constant variance,
 - ▶ are normally distributed,
 - ▶ are independent.
- Tests and confidence intervals are based on these assumptions. They can be (substantially) wrong if they are not fulfilled!
- Results can be “worthless” if assumptions are not met!
- **Residual Analysis** is the visual inspection of the model fit to verify assumptions.
- Among the most popular tools are the **Tukey-Anscombe plot** and **QQ-plots** (and many more...).

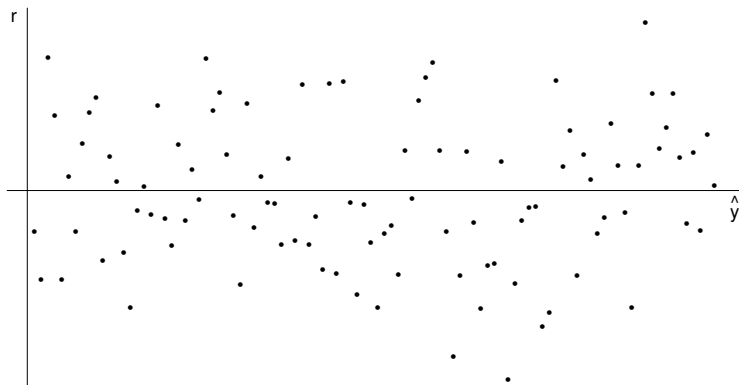
Tukey-Anscombe Plot

Plot (standardized) residuals R_i against fitted values \hat{y}_i .

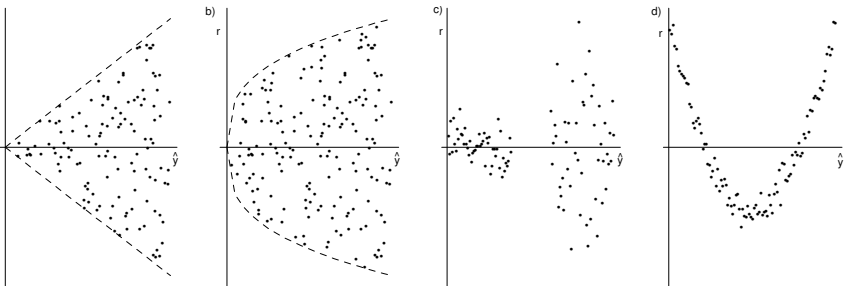
Checks

- $E[E_i] = 0$?
- $\text{Var}(E_i) = \sigma^2$ constant?

TA-plot should show random scatter around the zero line:



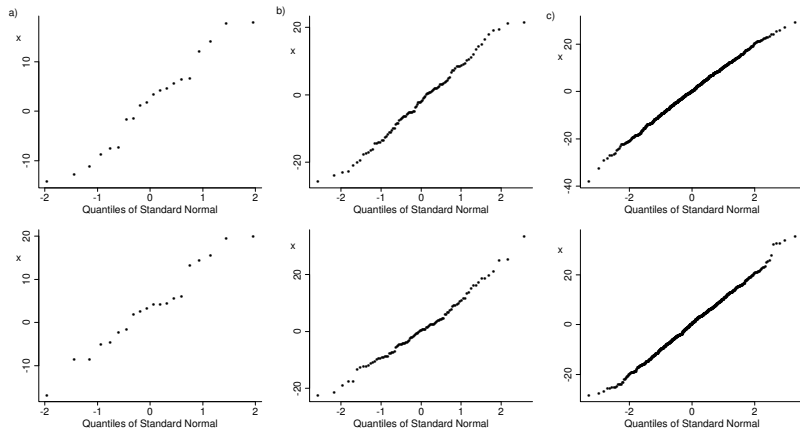
TA-Plots: Regression Assumptions Violated



QQ-Plot

Plot empirical quantiles of residuals against quantiles of standard normal distribution \rightsquigarrow Should show a more or less **straight line**.

Good examples for various sample sizes



QQ-Plots: Non-Normal Distributions

