

Crash Course in Statistics

ZNZ 2026

V

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Based on Script by Daniel J. Stekhoven

Tests and linear models

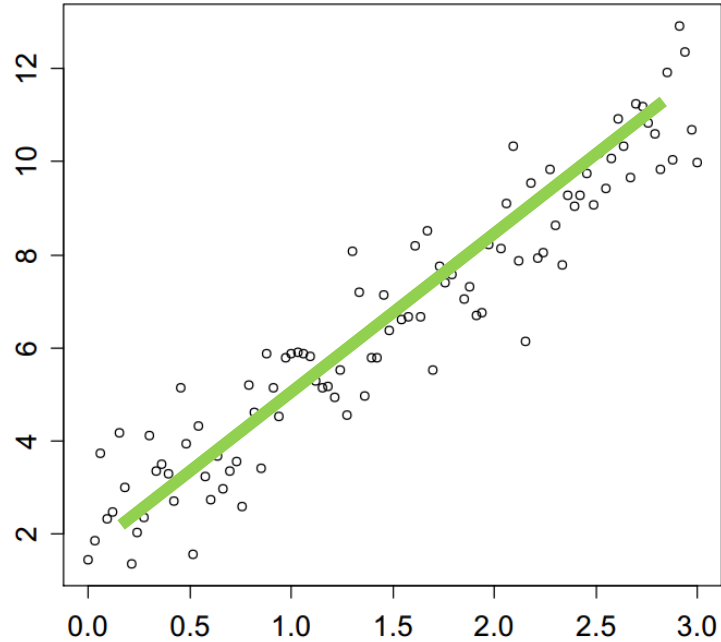
- Regression
- Diagnostics of regression
- R output of regression
- Multiple testing

Requirements for linear regression

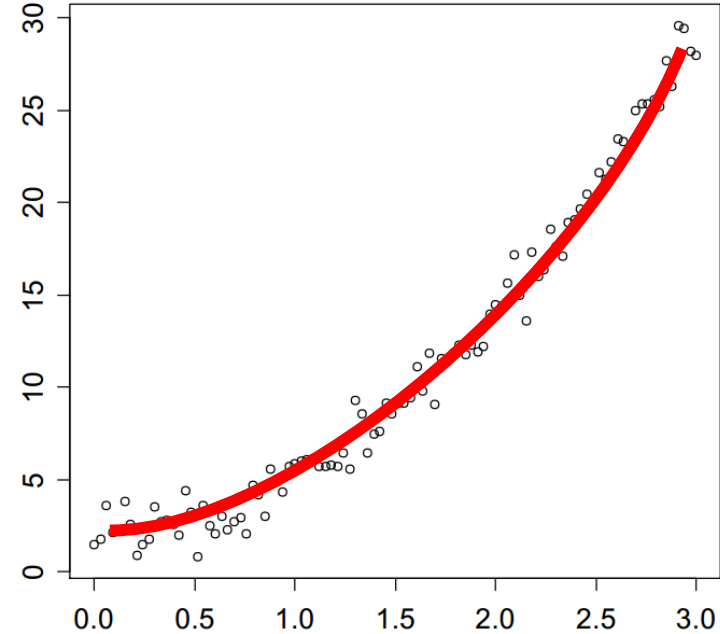
- 1. Linearity** – Y can be explained using a linear combination, e.g., $Y = \beta_0 + \beta_1 \cdot X + \varepsilon$
- 2. Constant variance** – error has constant variance (independent of X)
- 3. Normality** – error ε needs to be normally distributed

If these assumptions are strongly violated
the model is not valid

1. Linearity: Scatter plot for simple linear regression



OK

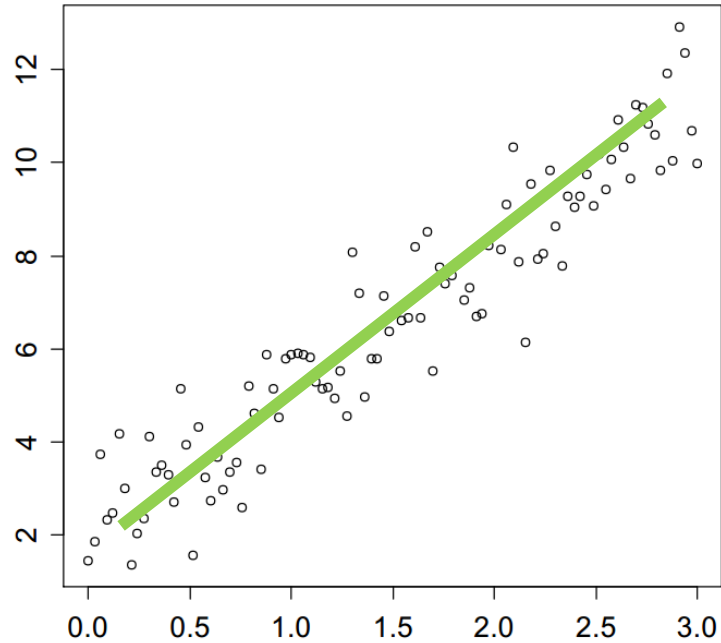


Systematic error

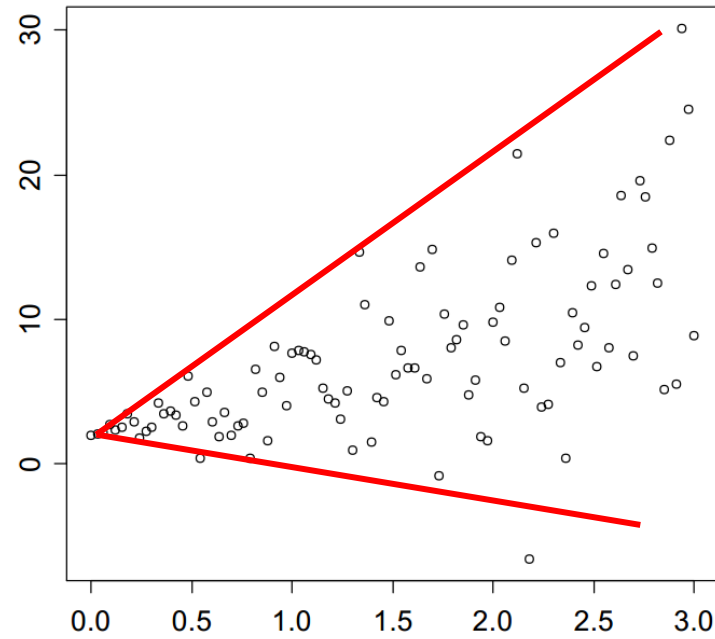
Curvature:

$$y = b_0 + b_1x + b_2x^2$$

2. Constant Variance? Scatter plot for simple linear regression

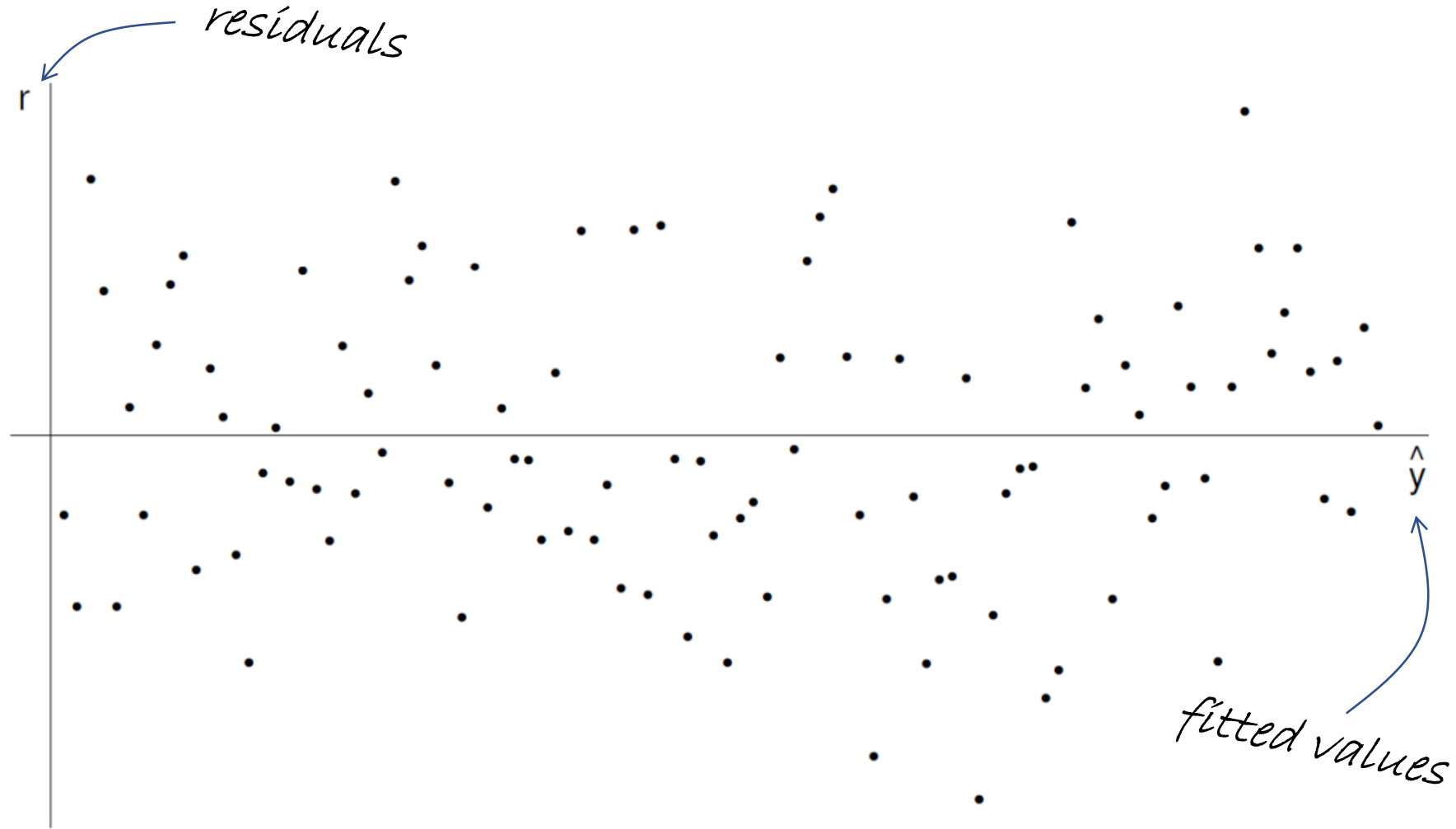


OK

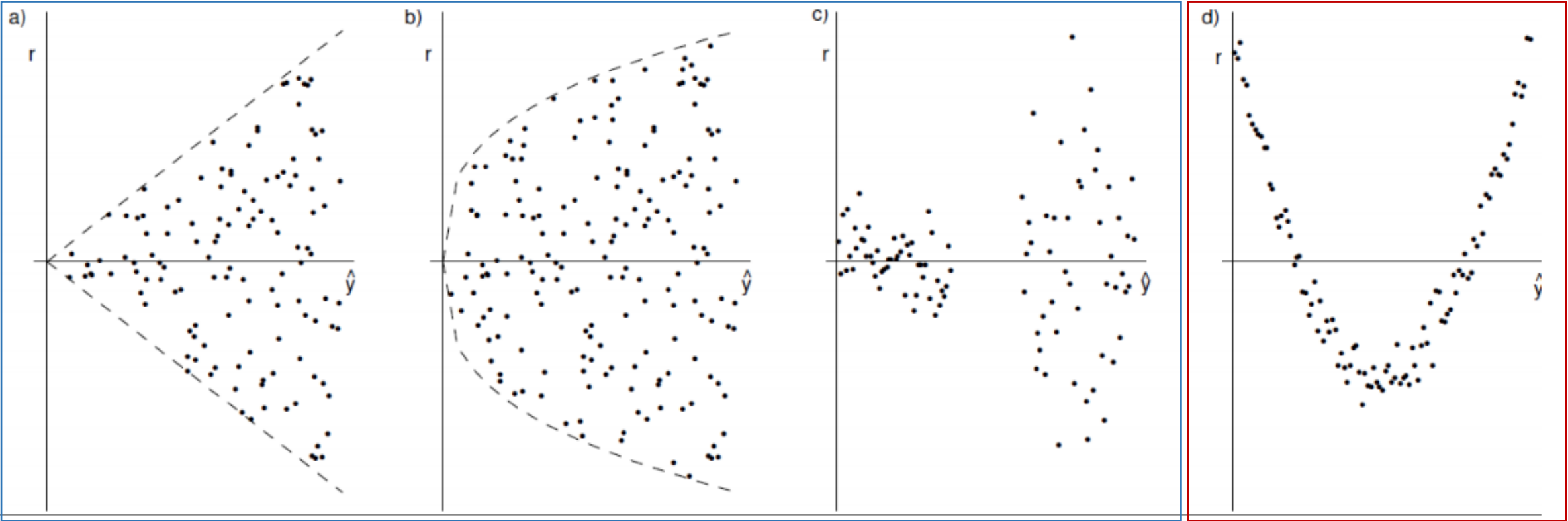


Error variance is not constant

Constant variance: Example for a good TA-plot (Tukey-Anscombe-Plot)



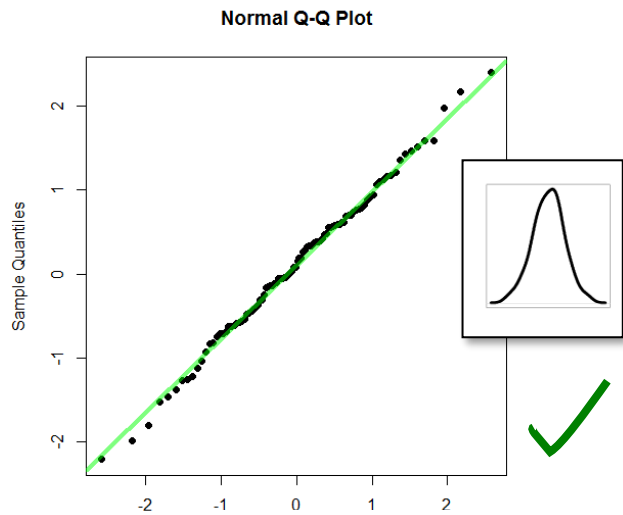
Constant variance: Examples for bad TA-plots



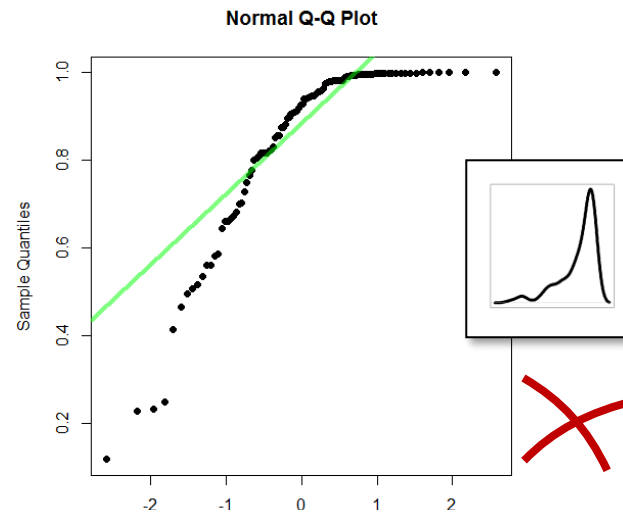
Error variance not constant

**Systematic
error**

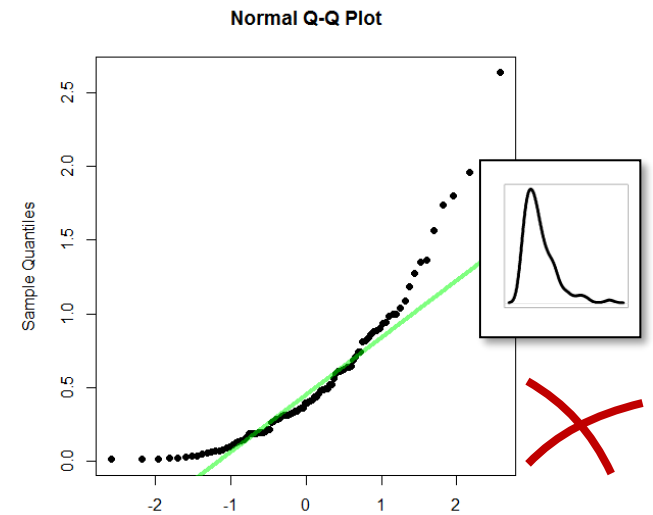
3. Normality: QQ-Plot



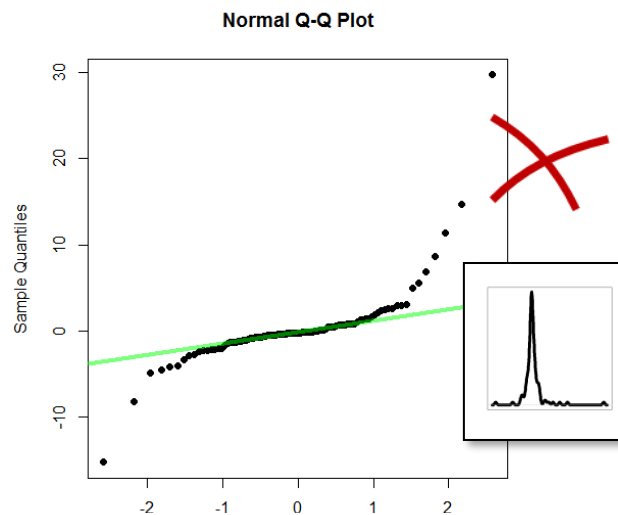
normal



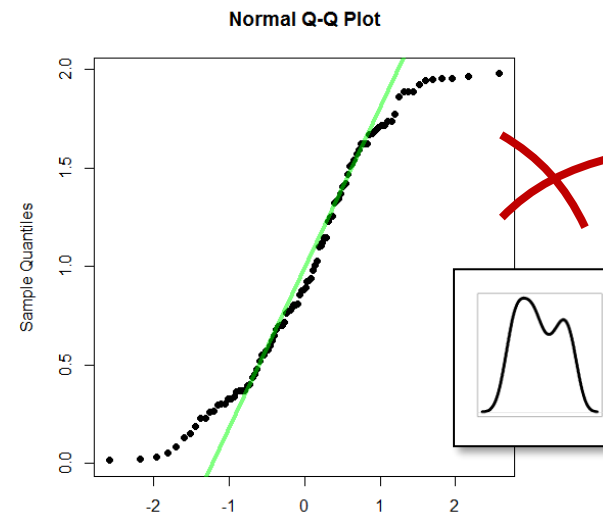
left skewed



right skewed

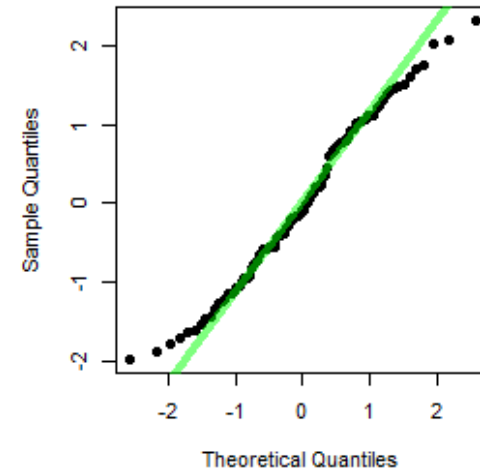
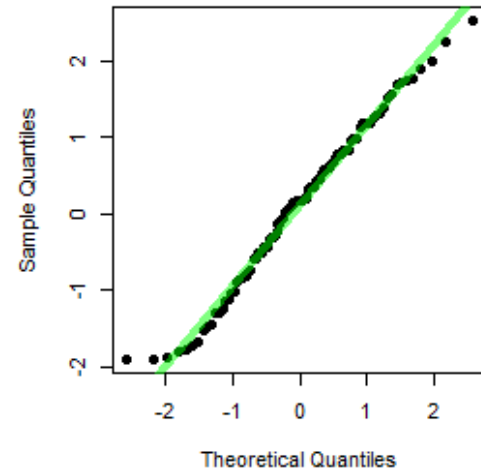
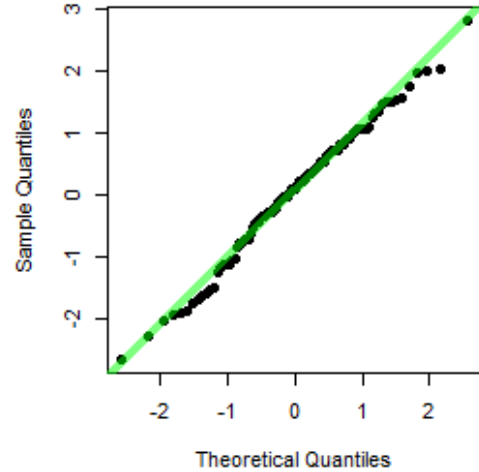
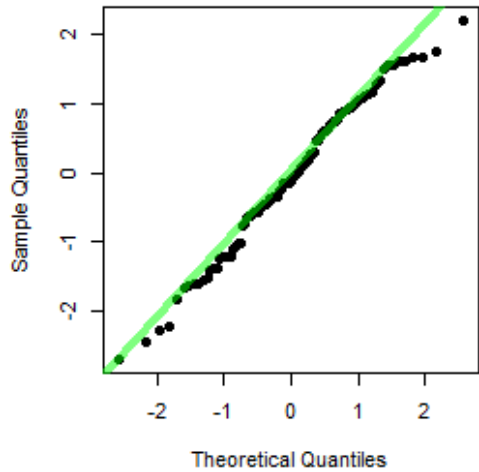
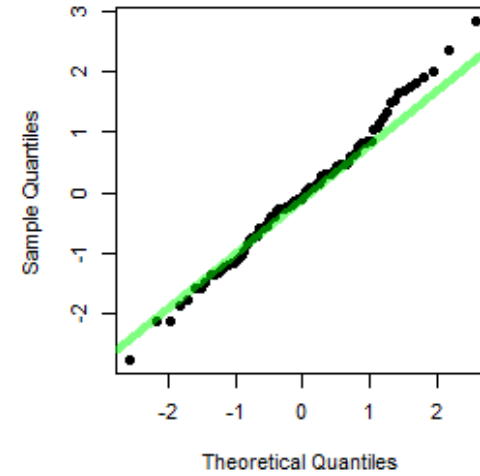
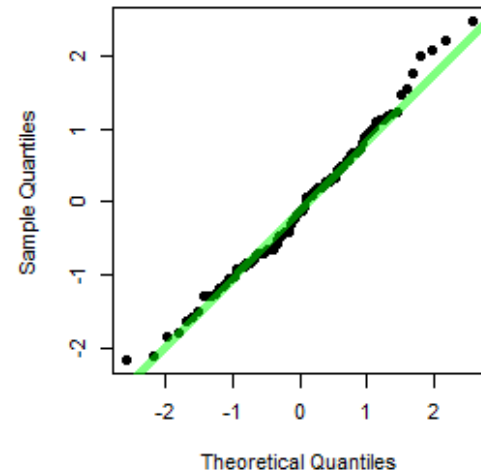
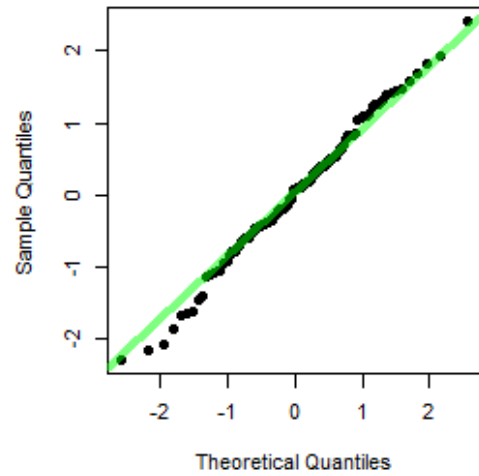
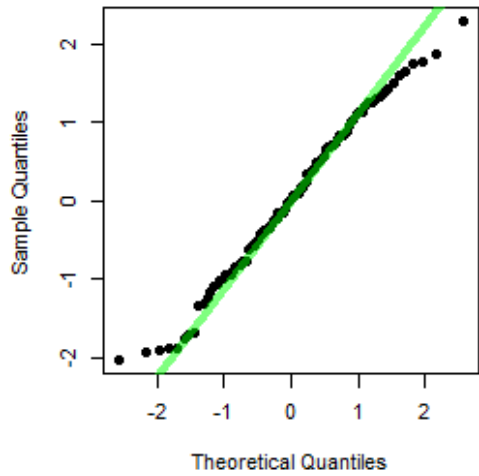


heavy tailed



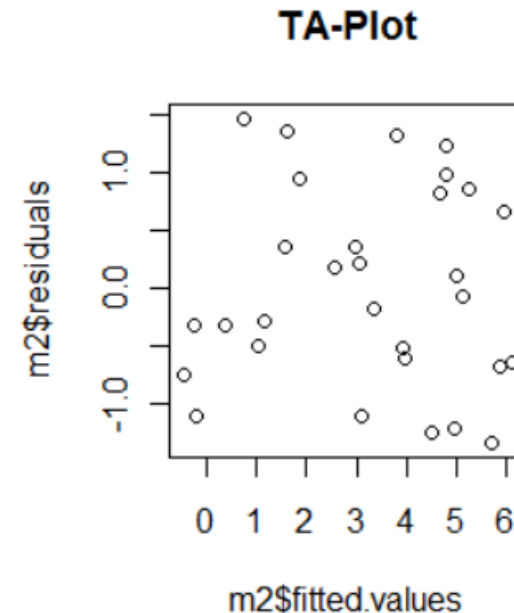
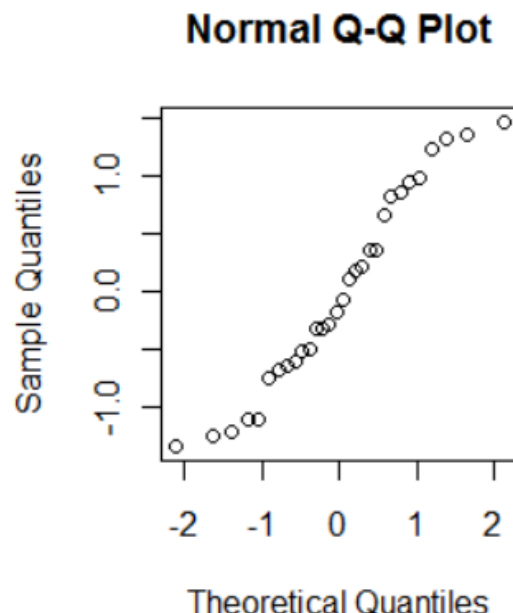
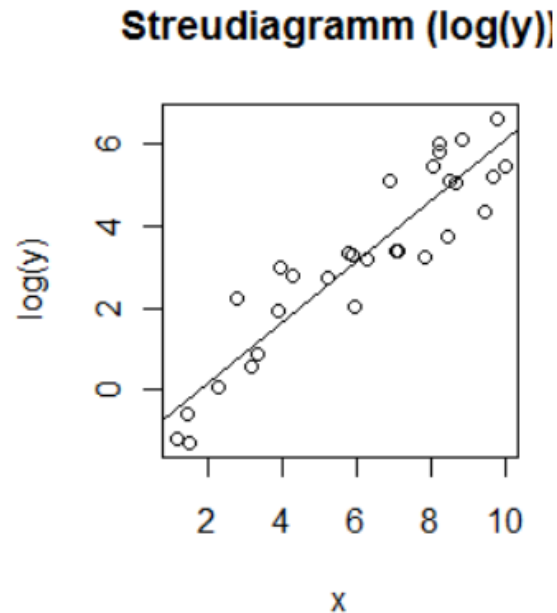
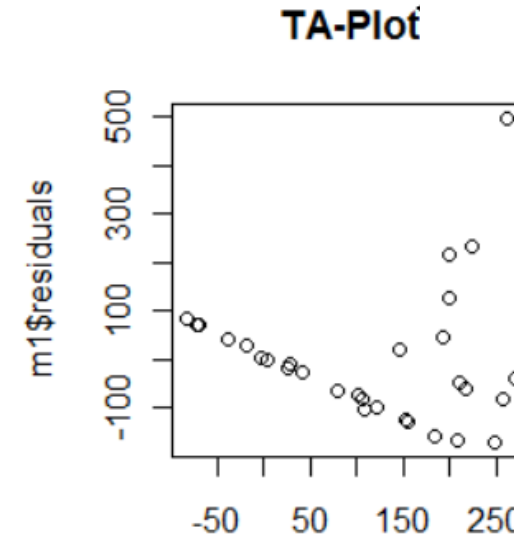
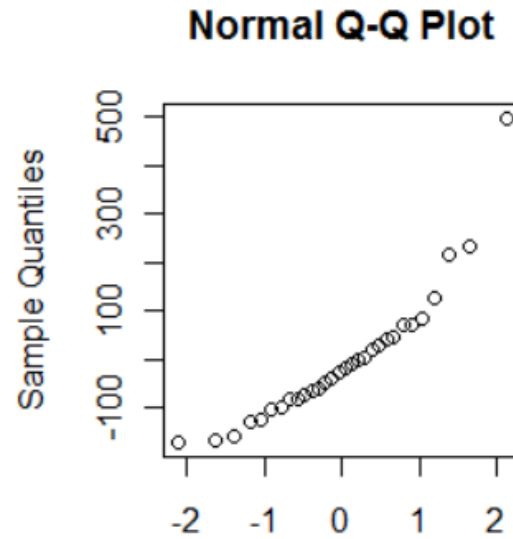
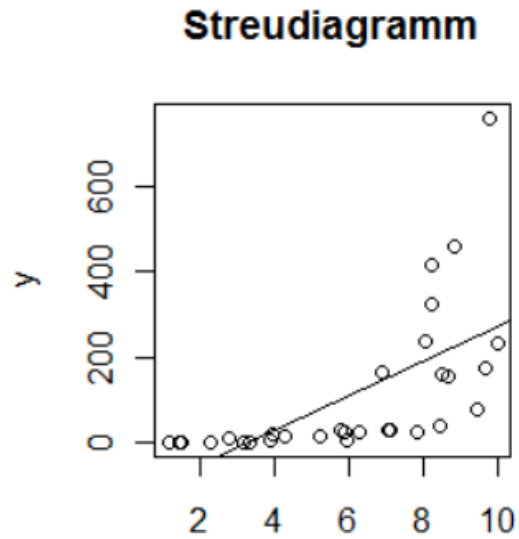
short tailed

QQ-Plots: what are «good» QQ-Plots



• $n = 100, R_i \sim \mathcal{N}(0, 1)$

...what if residual analysis is haywire (drunter & drüber)



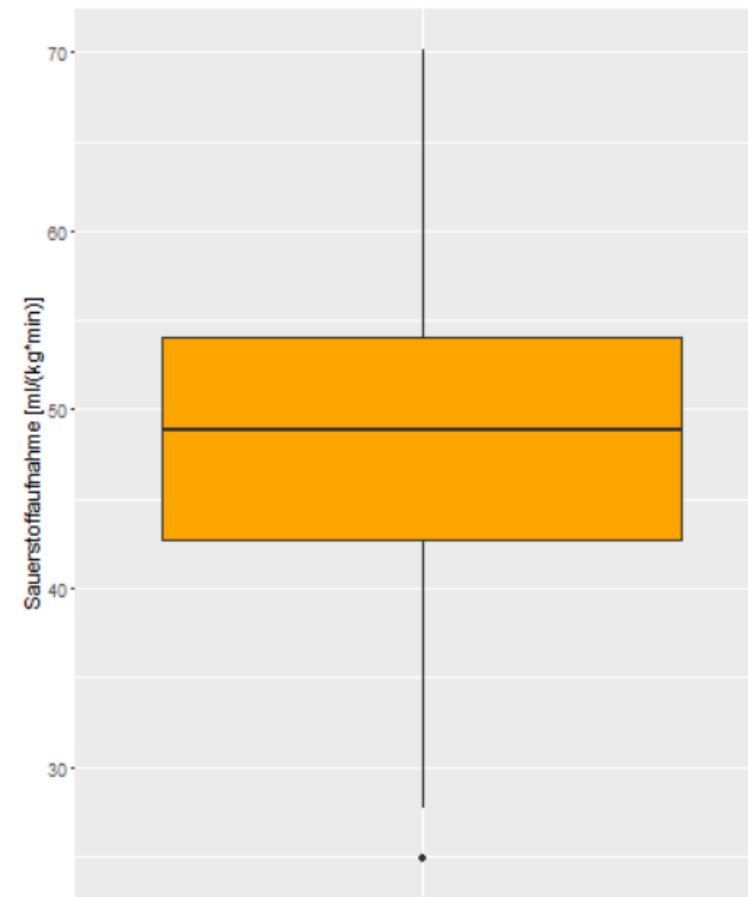
Aerobic performance

- VO_2max : amount of oxygen, the body can absorb per kg mass and minute
- Test is **expensive** and **effortful**
- **Not** meant for the broad community
- Alternative?



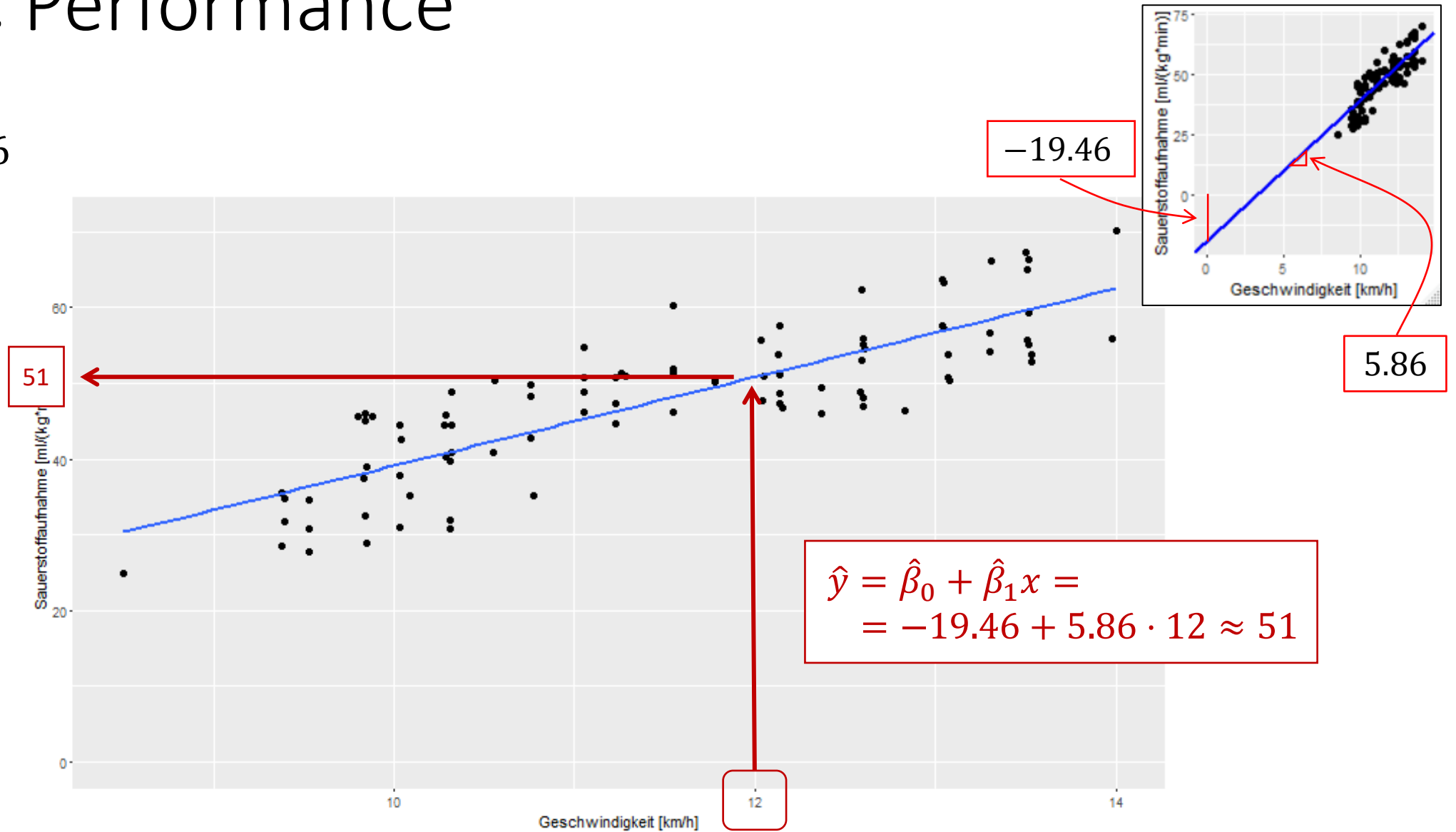
Léger et al., 1983

- 91 subjects, 20m-shuttle-test and VO_2max measurement



Aerobic Performance

- $\hat{\beta}_0 = -19.46$
- $\hat{\beta}_1 = 5.86$
- $\hat{\sigma} = 5.4$



Linear regression in R

- Model: $Y_i = \beta_0 + \beta_1 x_i + E_i, E_i \sim \mathcal{N}(0, \sigma^2)$ i.i.d.
- Model: $Y_i = -19.46 + 5.86 \cdot x_i + E_i, E_i \sim \mathcal{N}(0, 5.43^2)$ i.i.d.

```

> fit <- lm(vo2max ~ vmax, data = dat)
> summary(fit)

Call:
lm(formula = vo2max ~ vmax, data = dat)

Residuals:
    Min       1Q   Median       3Q      Max
-10.2230  -4.3976  -0.2016   4.7026  12.0348

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -19.4582     4.7239  -4.119  8.5e-05 ***
vmax         5.8566     0.4082  14.347 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.433 on 89 degrees of freedom
Multiple R-squared:  0.6981, Adjusted R-squared:  0.6948
F-statistic: 205.8 on 1 and 89 DF,  p-value: < 2.2e-16
    
```

Degrees of freedom:
 $n - k = 91 - 2 = 89$

Standard error of $\hat{\beta}_1$
 approx. 95%-CI:
 $5.86 \pm 2 \cdot 0.41$
 exact 95%-CI:
 $5.86 \pm 1.99 \cdot 0.41$

$t_{89}; 0.975$

Observed Test statistic t
 in the test:
 $\mathcal{H}_0: \beta_1 = 0$ vs $\mathcal{H}_A: \beta_1 \neq 0$

P-value:
 Assume $\beta_1 = 0$; what is the probability of t or an even more extreme value?

Multiple testing correction

- Significance level α
 - Probability to reject H_0 (*alarm goes off*), given it is true (*there is no fire*).

Is there a fire?	
Yes	No
TP There's a fire, the alarm goes off!	FP There's no fire, the alarm goes off!
FN There's a fire, the alarm doesn't go off!	TN There's no fire, the alarm doesn't go off!

- Traditionally set to 0.05 (5%)
- If a test is performed on this level under H_0 , we have a 5% chance that it gives a wrong result...

Multiple testing correction

- Let's test 100 samples versus a reference with $\alpha = 0.05$ each (1 out of 20, 1/20)
- Assume that \mathcal{H}_0 is **always** true \rightarrow there's **never** a difference!
- The chance of observing **at least one** significant result is
$$1 - P[\text{no significant result}]$$
- No significant result means, the test will not reject, given \mathcal{H}_0 is true – the chance for that is $1 - \alpha$
- Doing 100 tests the chance of no significant result becomes
$$(1 - \alpha)^{100} = (0.95)^{100} = 0.0059$$

...and thus the chance to observe at least one significant result is

$$1 - 0.0059 = \mathbf{0.9941}$$

Multiple testing correction

- This is corrected by adjusting the significance levels of the test (or equivalently, the resulting p-values)
- Methods are:
 - Bonferroni Correction (very stringent)
 - Benjamini-Hochberg (less stringent, better for large scale data)
 - ...

Multiple testing correction

- Example from before using Bonferroni:
 - P[at least one significant result] = $1-(1-\alpha)^{100}$
 - Bonferroni: divide α by the number of tests

$$\tilde{\alpha} = \frac{\alpha}{n}$$

- then

$$1-(1-\tilde{\alpha})^{100} = 1-(1-0.0005)^{100} = 0.0488$$

this is quite tough

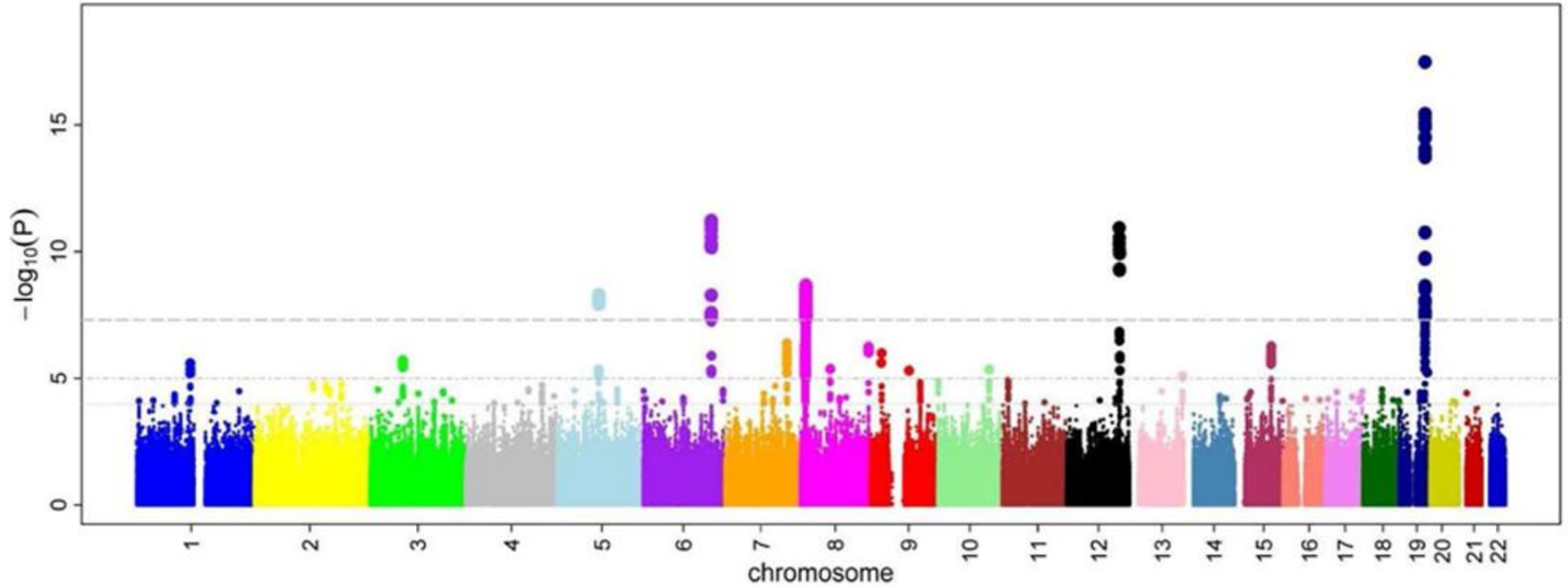


Essay

Why Most Published Research Findings Are False

John P. A. Ioannidis

Manhattan plot



Summary

- Make sure that your model is the right one
- If not either transform data or change the model
- Multiple testing is ruining everyone's day ... but we need to do it

- Now solve exercise 2 and 3, you will need:
- In 2) $qt(0.025, 50) = -2.008559$ and $qt(0.05, 50) = -1.675905$
- In 3) $qt(0.025, 7) = -2.364624$ and $qt(0.05, 7) = -1.894579$