

To call in the statistician after the experiment is done may be no more than asking him to perform a post-mortem examination: he may be able to say what the experiment died of.

Sir Ronald Fisher

Presidential Address to the First Indian Statistical Congress, 1938. Sankhya 4, 14-17

(BUT maybe you don't need to call in a statistician if you know some principles)

When assumptions are not met

Timothée Bonnet

Biological Data Science Institute

May 2, 2019

If you haven't enough R in your life

<https://www.meetup.com/rladies-canberra/events/dvrjwqyzhbjb/>

6
MAY

Monday, May 6, 2019

Tidying and plotting in R



Hosted by [Petra K.](#) and 2 others

From [R-Ladies Canberra](#)

Public group

Are you going? 18 people going



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Details

R is primarily known as a tool for statistics and data analysis, but it is also great for "simpler" data wrangling and plotting purposes. As R is becoming more accessible and useful in this regards, it is becoming a more viable alternative to Microsoft Excel and other spreadsheet-based applications for wrangling,



Monday, May 6, 2019

1:00 PM to 2:30 PM

Every week on Monday until May 12, 2019

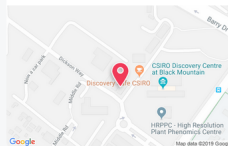


CSIRO - Synergy Building

N Science Rd · Acton

How to find us

Stringybark, Building 801, Cnr of
Dickson Way and, N Science Rd,
Acton ACT 2601



Take-home messages

- 1 Assumptions are about math properties, but also about scientific logic

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- ➎ All models are wrong, a few are useful

- 1 Why we need assumptions
- 2 What can go wrong; e.g. Linear models

Statistical inference: General approach

1. Scientific question

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2. Model and Statistical question

Statistical inference: General approach

1. Scientific question



2. Model and Statistical question



3. Data collection

Statistical inference: General approach

1. Scientific question



2. Model and Statistical question



4.a Estimation

4.b Uncertainty and statistical significance

3. Data collection



Statistical inference: General approach

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2. Model and Statistical question



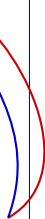
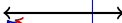
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5. Prediction, diagnostic, check assumptions

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Until "good enough"

Statistical inference: General approach

1. Scientific question



2. Model and Statistical question



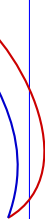
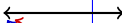
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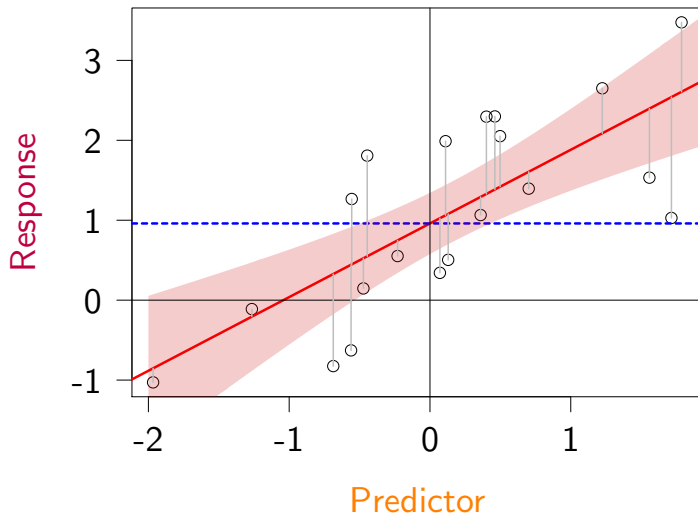


Until "good enough"
to trust 4.a and 4.b

- 1 Why we need assumptions
- 2 What can go wrong; e.g. Linear models

Simple linear model

$$\text{Response} = \text{Intercept} + \text{Slope} \times \text{Predictor} + \text{Error}$$



What are linear model assumptions?

Linear model assumptions

Assumptions do NOT include:

- Relationship is a straight line ("Linear" means a line on some scale, not any scale)
- Data normality (Only error normality)
- Collinearity (Changes parameter meaning, not the validity)

Linear model assumptions

- Linear combination of parameters (including transformation, polynoms, interactions. . .)
Risk: biologically meaningless
- Predictor not **perfectly** correlated
Risk: Model won't run, unstable convergence, or huge SE
- Little error in predictors
Risk: bias estimates (underestimate with Gaussian error)
- Gaussian **error** distribution
Risk: Poor predictions, wrong uncertainty
- **Homoscedasticity** (constant error variance)
Risk: Poor predictions, wrong uncertainty
- **Independence of error**
Risk: Bias and over-optimistic uncertainty

Exercise 1

Exercise 1

Exercise 2

Exercise 3

Exercise 3

Exercise 4

Let's think about more complex issues

- Non-Linear relationships / Thinking

Solution: do you really need that? / non-linear models

Problems / Detection / Typical solutions:

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Solution: Transformation / GLM
- Correlated errors Thinking (/plot)
Solution: Experimental design / control variables / mixed models

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