Course introduction

Michael Noonan

December 29, 2020

Biol 520C: Statistical modelling for biological data

Table of contents

Course Overview

About Me

Name: Michael Noonan

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Email: michael.noonan [at] ubc.ca (use subject heading BIOL520C in all email communication)

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Course Website: https://noonanm.github.io/Biol520C/index.html

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- Emphasis on statistical best practices.
- How to use open source software (R) to apply these analyses.

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- Methods for handling *ad hoc*, corner cases.

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- The practicals use structured tutorials to guide you on the use of the open-source software program `R` for applying the methods learned in the lectures to data. The lectures and practicals are designed to be *complementary* and not all the material in the practicals will be covered in the lectures and vice versa.

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Participation from practicals	10%	Exact sched. in course outline

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Presentation #1	10%	Week 7

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Paper #2	25%	Week 14
Presentation #1	10%	Weeks 13 & 14

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The course web page on github will host the practicals, and the various datasets associated with each practical. Lectures will be given on Mondays and Tuesdays. After the Tuesday lecture, we will have covered all of the material that is needed to complete the week's practical assignment material which is due before the start of the following Tuesday lecture (to be submitted online).

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Grading: Each practical assignment is worth a total of 3% of your total grade. Of this, 1% is given for submitting the tutorial on time, irrespective of whether or not the answers are correct (participation). The remaining 2% comes from the answers provided. Late practicals will be accepted, but will only be worth a maximum of 2%.

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- **Appendix:** The appendix material should include an R markdown document that details every step of the analyses. **(30%)**

Papers 1 and 2 cont.

Datasets: To complete these assignments, you will have access to a number of pre-selected datasets. You can opt to use your own data to complete these assignments if you prefer, and are encouraged to do so, but you must seek instructor approval. If you intend on using your own data, it is recommended that you discuss this with me as early as possible.

Papers 1 and 2 cont.

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Late Assignments: You are to submit Paper 1 by the end of the day on Feb. 27th, and paper 2 by the end of the day on Apr 17th. Late papers will have 10% deducted per day that they are overdue, and will receive a grade of zero if more than 10 days late without a valid excuse.

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Prior to submitting their papers to the instructor, students will be required to give a 10-minute presentation to the class.

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The presentation should include all of the sections that are included in the paper, however the appendix detailing the `R` code that was used should be integrated into the methods section of the presentation.

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The presentation should include all of the sections that are included in the paper, however the appendix detailing the `R` code that was used should be integrated into the methods section of the presentation.

Grading: Grading will based on a rubric provided in advance.

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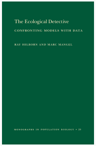

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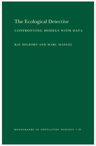

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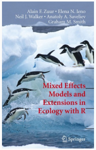

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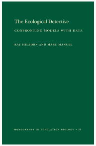

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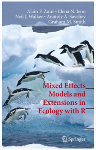
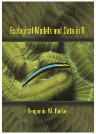


- Bolker, B. M. (2008). Ecological models and data in R. Princeton University Press. $\sim$ \$50



Lecture outline

Week/Dates	Lecture Topics
1 – Jan 10-16	Course introduction; Regression refresher
2 – Jan 17-23	Probability theory; Likelihood; Maximum likelihood
3 – Jan 24-30	Mult. linear regression; Param inter.; Interpreting residuals
4 – Jan 31-Feb 6	Mixed effects models; Model Selection; Information criterion
5 – Feb 7-13	Model Selection; Model averaging; Independent Project Work
6 – Feb 14-20	Mid-term break, no lectures
7 – Feb 21-27	Student presentations (**10%**) & Term paper 1 due (**25%**)
8 – Feb 28-Mar 6	Heteroskedasticity; Temporal autocorrelation
9 – Mar 7-13	Spatial Autocorrelation; Phylogenetic inertia
10 – Mar 14-20	Logistic and Poisson regression
11 – Mar 21-27	Non-linear modelling; Deterministic functions; Stochastic simulation and power analysis
12 – Mar 28-Apr3	Course Overview; Independent Project Work
13 – Apr 4-10	No lecture on Monday; Student presentations (10%)
14 – Apr 11-17	Student presentations (**10%**) & Term paper 1 due (**25%**)

Design- vs. Model-based Inference

The Scientific Method

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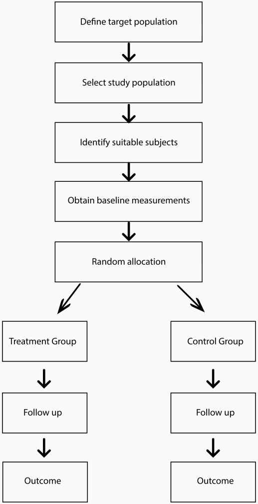
Design-based inference



Design-based inference

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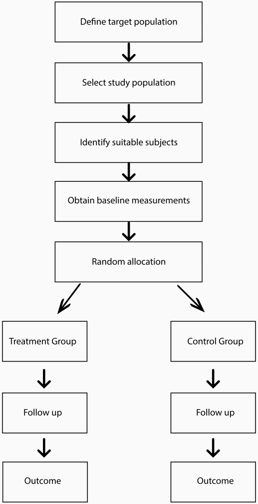

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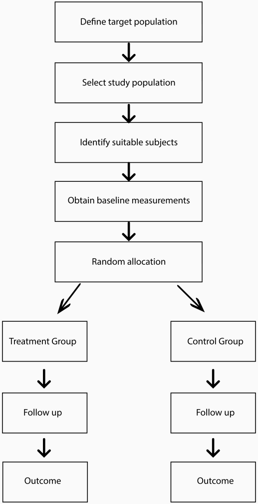

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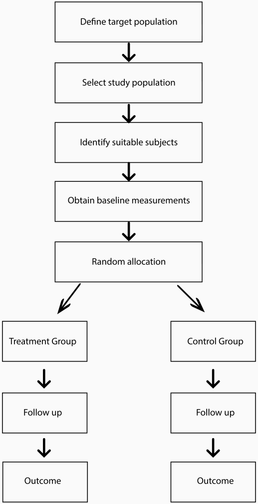

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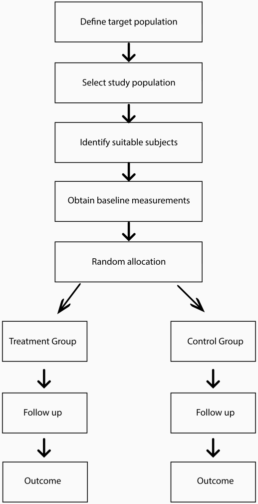

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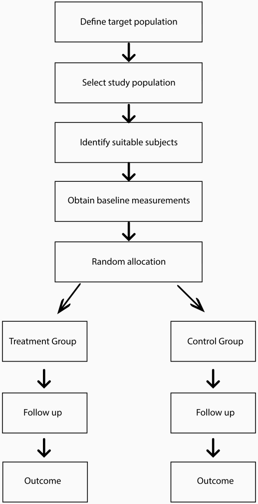
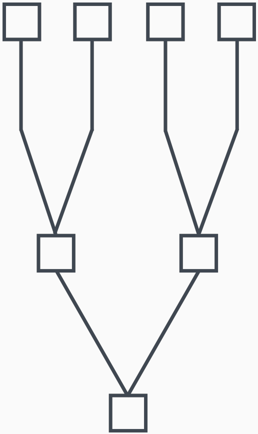
- Data are typically analysed by comparing means and variances across groups (e.g., ANOVAs, t-tests, etc...)

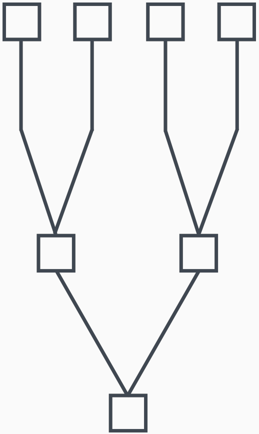


Worklow of design-based inference



Worklow of design-based inference

- Devise a hypotheses



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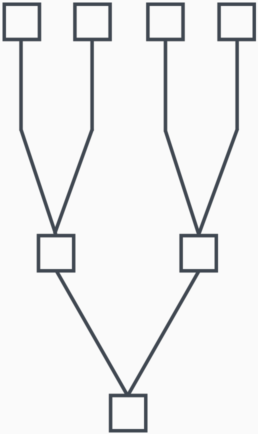
- Devise an experiment with outcomes that will clearly accept or reject the hypothesis



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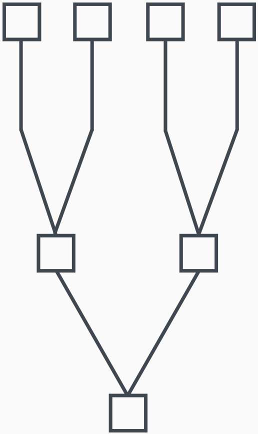

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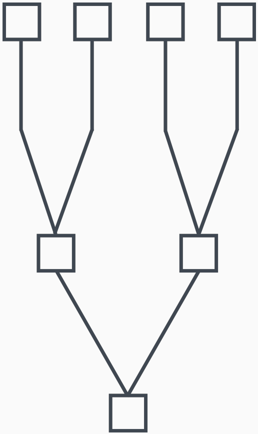

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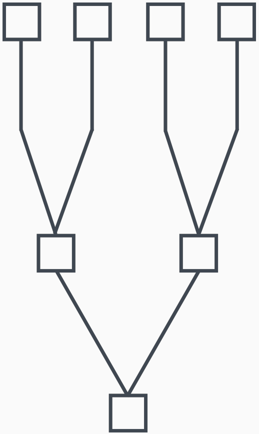
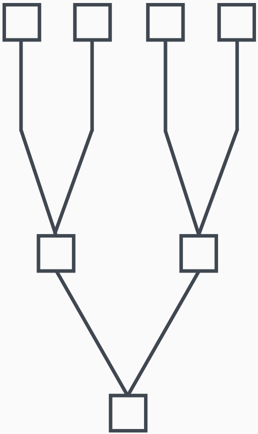


Core of design-based inference is confronting single hypotheses with data

Limitations of design-based inference

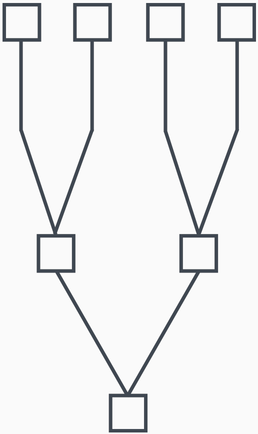
Platt's decision tree is based on:



Limitations of design-based inference

Platt's decision tree is based on:

i) Clear, distinct hypotheses



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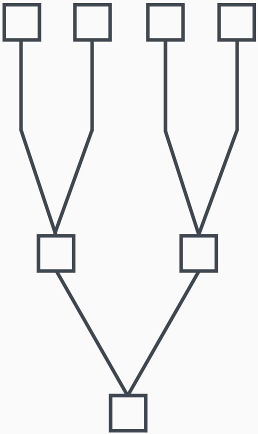
ii) Unambiguous outcomes



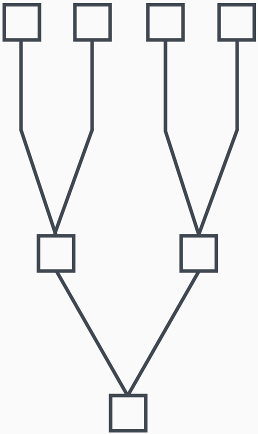
Limitations of design-based inference

Platt's decision tree is based on:

i) Clear, distinct hypotheses

ii) Unambiguous outcomes

iii) A relationship between statistical significance and biological relevance



Limitations of design-based inference

Many biological processes have long time-scales.

Long time-scales

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Humpback whales (*Megaptera novaeangliae*) can live for 50+ years. Source: David Valencia

Long time-scales


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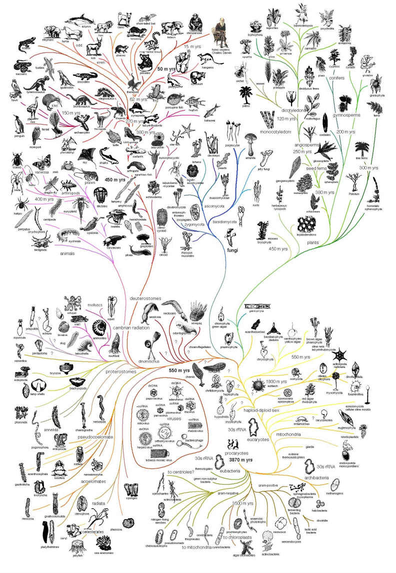
Bristlecone pines (*Pinus longaeva*) live for thousands of years. Source: wired.com

Long time-scales



Source: Chris King

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Limitations of design-based inference

Many biological processes have long time-scales.

Many biological systems have very poor reproducibility.

Poor reproducibility

Source: Tom and Pat Leeson

Limitations of design-based inference

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Many biological systems have very poor reproducibility.

How can you design a controlled experiment in a wild population?

Limitations of design-based inference

What if you're interested in species conservation?

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Source: Wikipedia

In 1988 the wild pop. of black footed ferrets (*Mustela nigripes*) was down to 18 ind.

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What do you do if a power analysis says you need 20 animals?

Model-based inference

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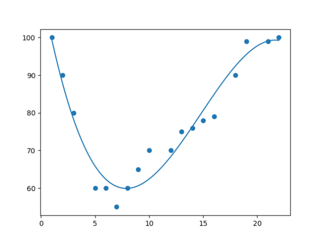
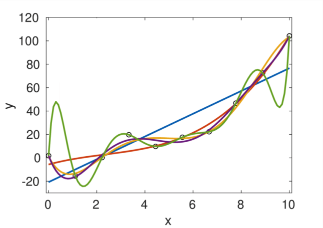
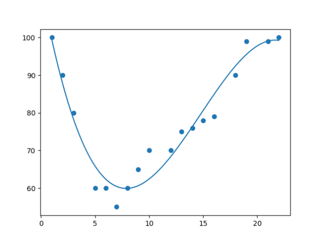
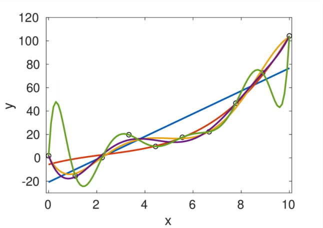




Model-based inference

- In model-based inference, most of the focus is on identifying an unknown deterministic model





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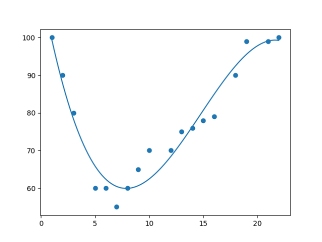

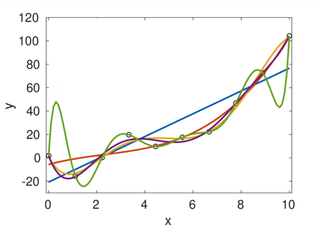

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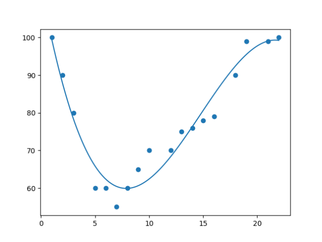

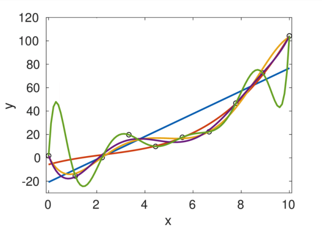

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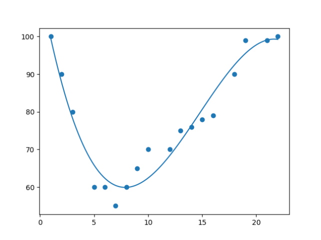

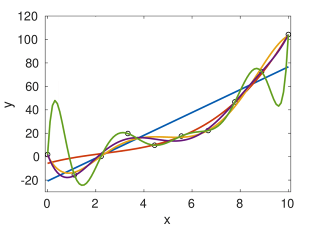

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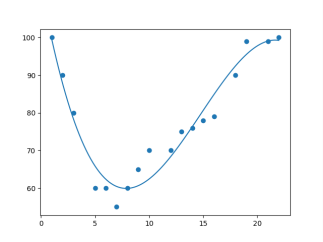
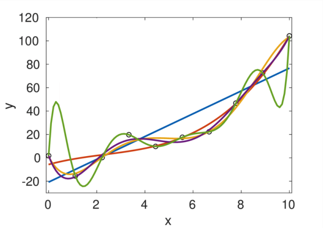
- Data are typically analysed by fitting a model to data and interpreting the parameter estimates





What is modelling?

Hypothesis vs. model

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$$\text{Model} \neq \text{Hypothesis}$$

One hypothesis, many models

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A single hypothesis can be represented by multiple models.

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Hypothesis: Body mass M increases with age L

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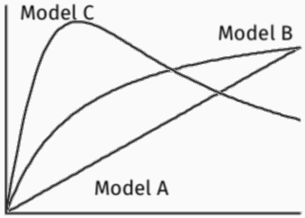
Hypothesis: Body mass M increases with age L

Models:

- $M = aL$ Model A: Body mass is proportional to age
- $M = \frac{AL}{1+bL}$ Model B: Body mass saturates as age increases
- $M = aLe^{-bL}$ Model C: Body mass increases and then decreases as age increases



Source: Hillborn and Mangel 1997

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Don't fall in love with a model, the important thing is the system

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Long answer: There are methods for this that we'll cover in later lectures.

Components of a model

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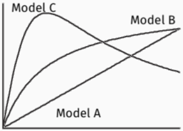

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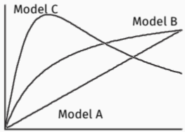

Stochastic part: Describes the randomness of the process (i.e., captures the noise in a system).

Deterministic vs. Stochastic

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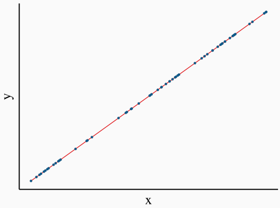

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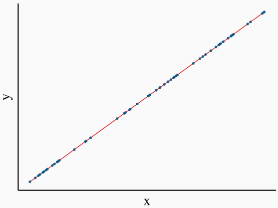

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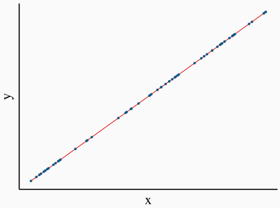

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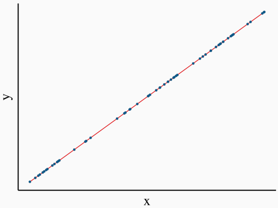

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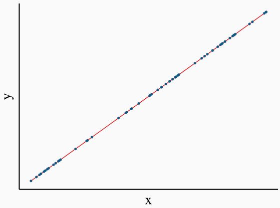

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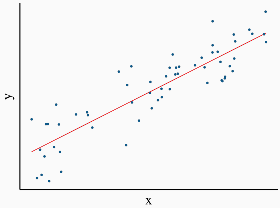
- Outcome is variable
- $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$



References

Platt, J.R. (1964). Strong inference. *science*, 146, 347–353.