Course introduction

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August 11, 2020

Biol 520C: Statistical modelling for biological data

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Housekeeping

Slide title

Stuff

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What this course is about

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- How to use open source software (R) to apply these anaylses

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- Math... but you should be familiar with basic calculus (derivatives and integrals) and linear algebra (operations on vectors and matrices)
- Computer programming (we will be using `R`, but the course is not focused on high level coding)
- Methods for handling *ad hoc*, corner cases

Design- vs. Model-based Inference

The Scientific Method

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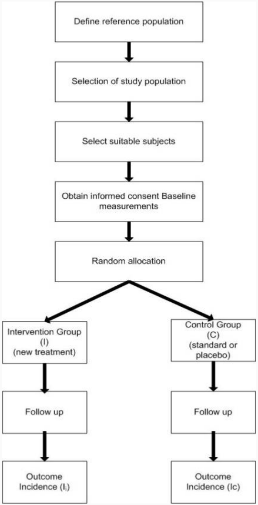
Design-based inference


Define reference population

Selection of study population

Select suitable subjects

Obtain informed consent Baseline measurements

Random allocation

Intervention Group (I) (new treatment)

Control Group (C) (standard or placebo)

Follow up

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Outcome Incidence (I_I)

Outcome Incidence (Ic)

Design-based inference

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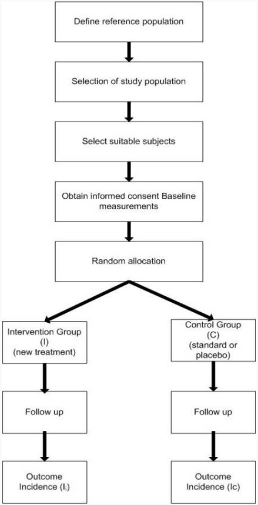

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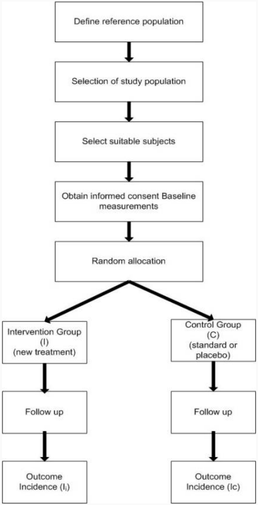

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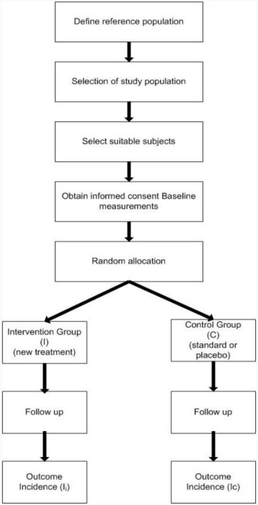
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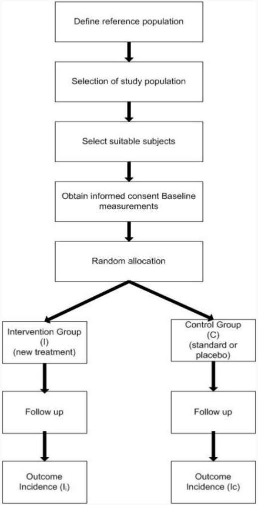

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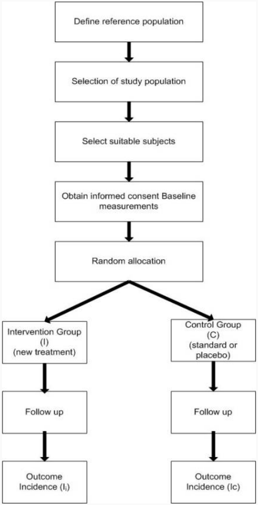
- Data are typically analysed by comparing means and variances across groups (e.g., ANOVAs, *t*-tests, etc...)



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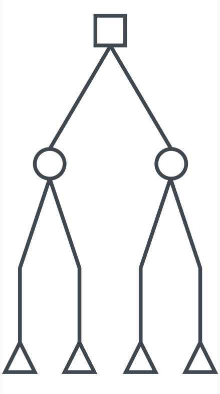

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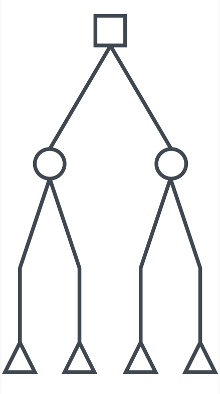

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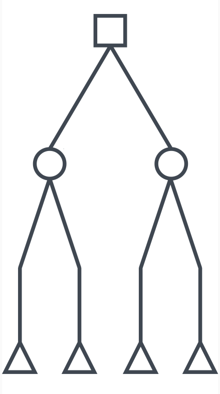

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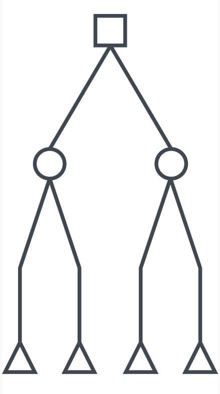

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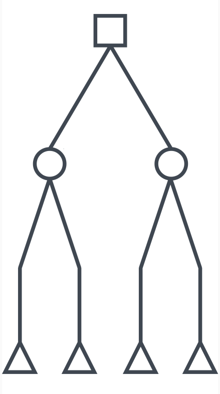

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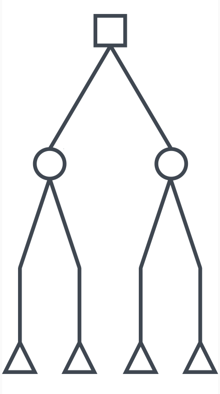
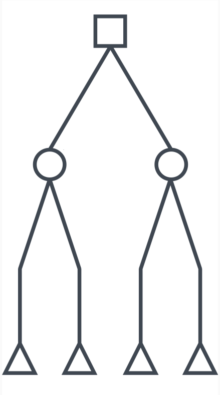


Core of design-based inference is confronting single hypotheses with data

Limitations of design-based inference

Platt's decision tree is based on:



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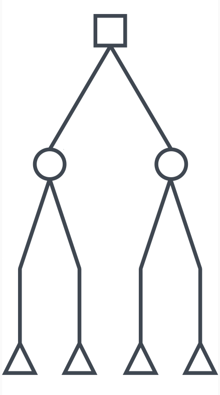
Platt's decision tree is based on:

i) Clear, distinct hypotheses



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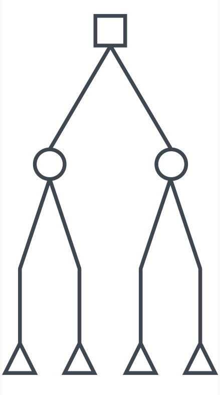

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Platt's decision tree is based on:

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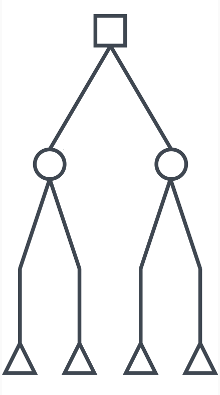
iii) A relationship between statistical significance and biological relevance



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Bristlecone pines (*Pinus longaeva*) live for thousands of years

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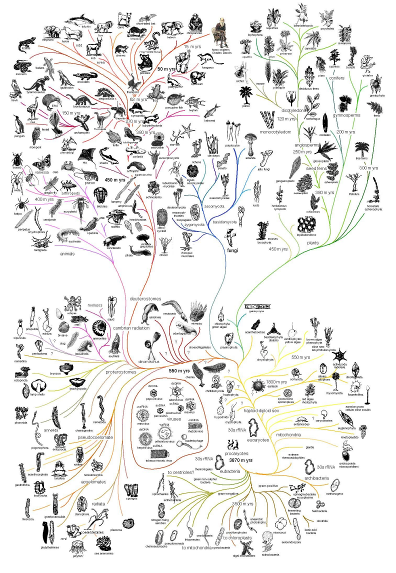

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How can you design a controlled experiment in a wild population?

Limitations of design-based inference

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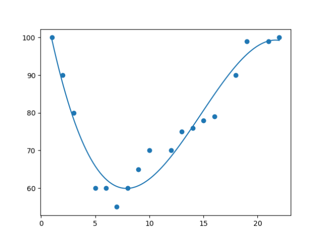
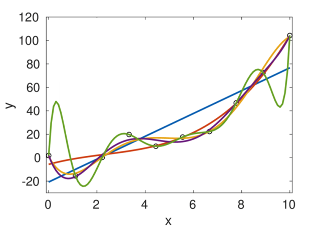
What do you do if a power analysis says you need 20 animals?

Model-based inference





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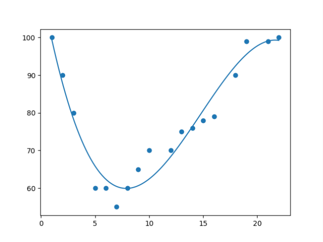

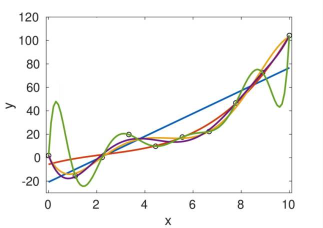

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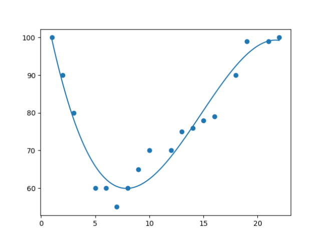

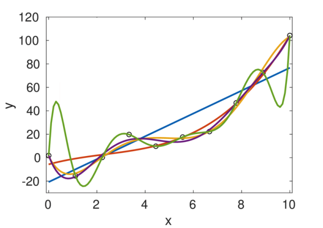

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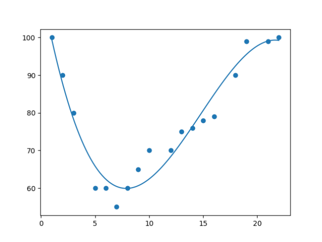

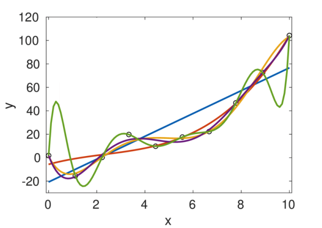

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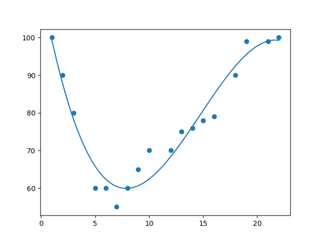

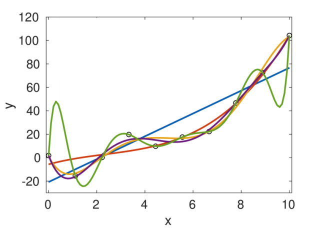

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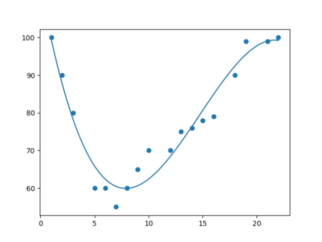
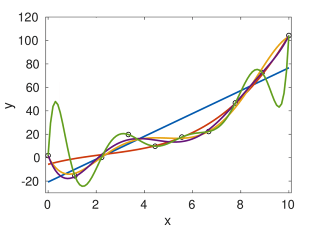
- Data are typically analysed by fitting a model to data and interpreting the parameter estimates





What is modelling?

Hypothesis vs. model

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

One hypothesis, many models

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Hypothesis: Body mass M increases with age L

One hypothesis, many models

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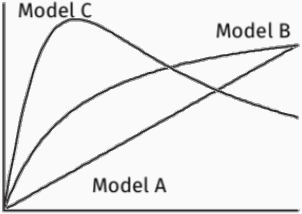
Hypothesis: Body mass M increases with age L

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



General points about modelling

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

Model complexity

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Short answer: Let the data tell you.

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Simple models risk leaving out important parameters, complex models need lots of data for good parameter estimation

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Short answer: Let the data tell you.

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

Components of a model

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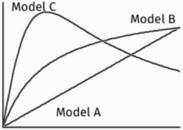

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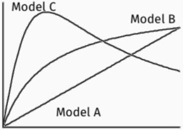

Stochastic part: Describes the randomness of the process (i.e., captures the noise in a system).

Deterministic vs. Stochastic

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Deterministic models

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Deterministic models

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Deterministic vs. Stochastic

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Deterministic vs. Stochastic

Deterministic models

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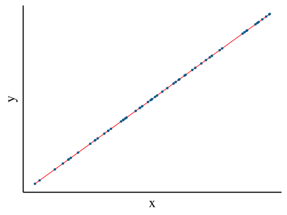
- Outcome is always the same
- $y_i = \beta_0 + \beta_1 x_i$



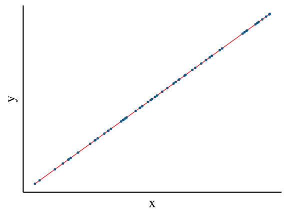
Deterministic vs. Stochastic

Deterministic models

- No components are uncertain

- Outcome is always the same

- $y_i = \beta_0 + \beta_1 x_i$



Stochastic models

Deterministic vs. Stochastic

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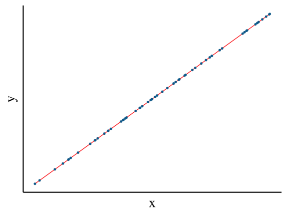

Stochastic models

- Some components are uncertain and characterised by probability distributions

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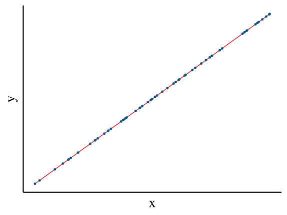

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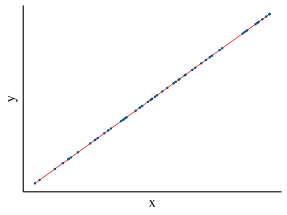
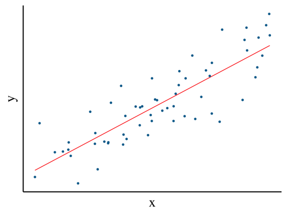


Stochastic models

- Some components are uncertain and characterised by probability distributions
- Outcome is variable
- $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$



References

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