Tests of reconstructions and Bayes

Test of transfer functions:

- Mainly transfer function
- ▶ TF and reconstruction
- mainly reconstruction

Test of transfer functions:

- Mainly transfer function
 - significance tests
 - spatial autocorrelation
- ▶ TF and reconstruction
 - Analogue quality
 - Passively add fossil samples to ordination of training set samples
- mainly reconstruction
 - randomTF
 - ObsCor

Reconstructability of a variable at a certain site

Telford and Birks (2011)

Some reconstructions are more problematic,[...]

- because the reconstructed changes are small relative to the RMSEP
- the site is of questionable sensitivity [...]
- the environmental variable being reconstructed is of uncertain ecological significance

Reconstructability:

- reconstructed changes are small relative to the RMSEP
 - NAPD: Arizona Alaska (massive temperature change)
 - temporal changes at a site seem minor compared to changes in space
- the site is of questionable sensitivity
 - principle of limiting factors
 - other environemntal variable than variable reconstructed is more limiting

Reconstructability:

- the site is of questionable sensitivity
 - Diatom pH transfer function
- importance in space caused by different bedrock types
- in time:
 - human influence
 - soil formation
 - otherwise pH reconstruction probably spurious

Random TF and Obs Cor

Goal: assess reconstructibility of an environmental variable at a site

A novel method for assessing the statistical significance of quantitative reconstructions inferred from biotic assemblages

R.J. Telford a,b,*, H.J.B. Birks a,b,c,d

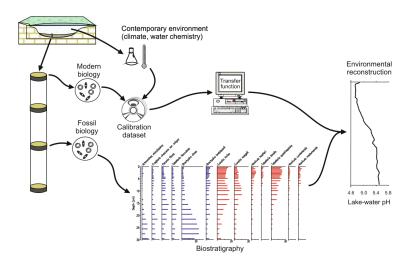
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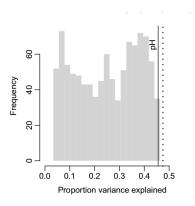
d Environmental Change Research Centre, University College London, UK

Transfer function



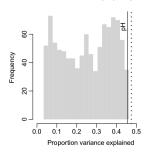
Juggins and Birks (2012)

Random TF:



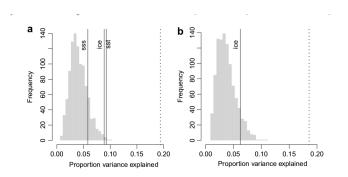
- reconstruct an environmental variable at a site using a (any)
 transfer function and fossil data
- use reconstructed env. variable in constrained ordination of fossil data determine variance explained

Random TF:



- train transfer function on random environmental data and reconstruct random environmental variable using fossil data
- use reconstructed random env. variable in constrained ordination of fossil data determine variance explained
- repeat random procedure 999 times
- compare distribution of variances explained by random data to variance explained by real data

Random TF: partialling

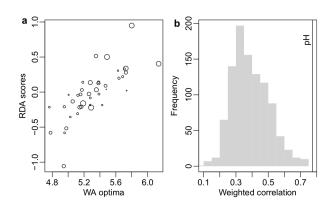


remove effect of most significant env. variable

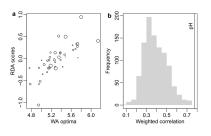
Obs Cor: Comparison of optima

Example: temperature reconstruction

Taxa indicative of warm conditions in training set should be indicative of warm conditions in downcore data



Obs Cor: Comparison of optima



Same idea as Random TF

(Weighted) Correlation WA optima of TF to CCA/RDA species scores of fossil species assemblage $\,$

Equivalent to considering reconstructed env as observed env and re-running transfer function

Only for WA family of TF methods

Obs Cor: Comparison of optima

Different weightings of correlations

Species abundances:

- 1. modern
- 2. fossil
- 3. joint

Effective number of species

$$N_2 = \frac{1}{(\rho_1^2 + \rho_2^2 + \rho_3^2 + ... + \rho_n^2)}$$

- 1. modern
- 2. fossil
- 3. joint

Recommendations

- Compare reconstructions using different methods
 - strong signal should be found in all reconstructions
 - with weak signal rec might differ
- Compare to other proxies (if possible for the same site):
 - chironomids to pollen
 - consider proxy specific issues
- Compare to other sites
 - ▶ issues with age-depth models
 - spatial domain of variable reconstructed
 - temperature is spatially persistent
 - nutrients might differ between sites

Recommendations:

- Think critically about your reconstructions
- How many variables can we reconstruct from a single microfossil assemblage
- ▶ Is a specific variable reconstructable

Transfer function: Training set design:

Maximize gradient of interest

Minimize secondary gradients

Caveat: Training set design will not change plant physiology

Pollen: strong temperature change with about constant precipitation:

- improved estimation of WA optima for temperature
- if precipitation has an influence on taxon composition and changed in the past, this will influence species assemblages even though precipitation does not seem to be an important variable in training set

Conclusions:

- Training sets now exist for a range of organisms and environmental variables for directly and indirectly inferring past environment and climate from biological remains
- A range of numerical methods exists for developing transfer functions
- Methods have advantages and disadvantages
- Producing a reconstruction is easy
- Identifying confounding effects and what can and can't be reconstructed is extremely difficult

Bayesian inference: Probability

What is probability?

Coin flip: probability of head?

Rolling dice: probability of a double six?

Probability:

$$P = \frac{\#Favourable}{\#Possible} \tag{1}$$

Coin flip: probability of head?

Event A: head Event B: tail

Rolling dice: probability of a double six?

Event A: $1 A^{C} = \{2, 3, 4, 5, 6\}$ not A

Probability of two events:

$$P(A \cup B) : A \text{ or } B$$

$$P(A \cap B)$$
: A and B

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

If A and B are independent:

$$P(A \cup B) = P(A) + P(B)$$

Conditional probability

Probability that event A happens if we know that event B happened

$$P(A|B)$$
 Probability of A given B

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(B|A) = \frac{P(B \cap A)}{P(A)}$$

Conditional probability

$$P(A|B) \neq P(B|A)$$

A = Member of Congress

 $\mathsf{B} = \mathsf{US} \mathsf{citizen}$

$$P(A|B) = \frac{535}{250000000} = 0.00000214 = 2.14e^{-6}$$

$$P(B|A)=1$$

Bayes Rule

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(A \cap B) = P(A|B)P(B)$$

$$P(B|A) = \frac{P(B \cap A)}{P(A)}$$

$$P(A \cap B) = P(B|A)P(A)$$

$$P(A|B)P(B) = P(B|A)P(A)$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Bayes Rule

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Total probability:

$$P(B) = P(B \cap A) + P(B \cap A^{C})$$

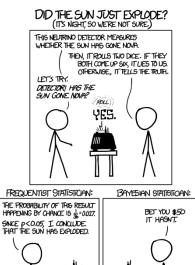
$$P(B) = P(B|A)P(A) + P(B|A^{C})P(A^{C})$$

$$P(B) = \sum_{j=1}^{m} P(B|A_{j})P(A_{j})$$

$$A^{C} : not A$$

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{i=1}^{m} P(B|A_i)P(A_i)} \ i \in \{1, 2, 3, ..., m\}$$

Bayes Rule: Example



Example

A: Sun has gone Nova

B: Detector tells us sun has gone nova

Bayesian

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^{C})P(A^{C})}$$

Prior:
$$P(A) = 10^{-9}$$

Likelihood
$$P(B|A) = \frac{35}{36}$$

Denominator
$$P(A^C) = 1 - P(A) = 1 - 10^{-9}$$

$$P(B|A^C) = \frac{1}{36}$$

Example: Bayesian

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^{C})P(A^{C})} = \frac{\frac{35}{36} \frac{1}{10^{9}}}{\frac{35}{36} \frac{1}{10^{9}} + \frac{1}{36}(1 - \frac{1}{10^{9}})}$$

$$P(A|B) = 3.5 * 10^{-8}$$

Posterior = 35 times prior: probability of saying the truth is 35 times probability of lying

Monty Hall problem:

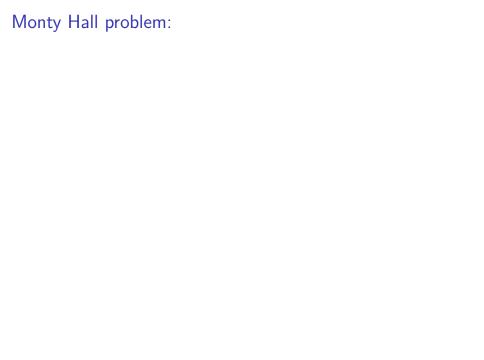
A: Car behind door A

B: Car behind door B

C: Car behind door C

$$P(A) = P(B) = P(C) = \frac{1}{3}$$

D: Candidate stands in front of door A and Monty opens door B



Monty Hall problem:

$$P(A|D) = \frac{P(D|A)P(A)}{P(D|A)P(A) + P(D|B)P(B) + P(D|C)P(C)}$$

$$P(D|A) = \frac{1}{2}$$

$$P(D|B)=0$$

$$P(D|C)=1$$

$$P(A|D) = \frac{\frac{\frac{1}{2}\frac{1}{3}}{\frac{1}{2}\frac{1}{3} + 0\frac{1}{3} + 1\frac{1}{3}}$$

$$P(A|D)=\frac{1}{3}$$

CHANGE!!