Model selection in practice

(or 'Which variables should I keep in my model?')

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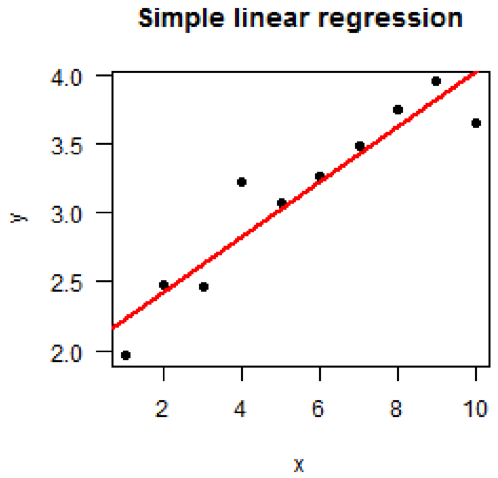
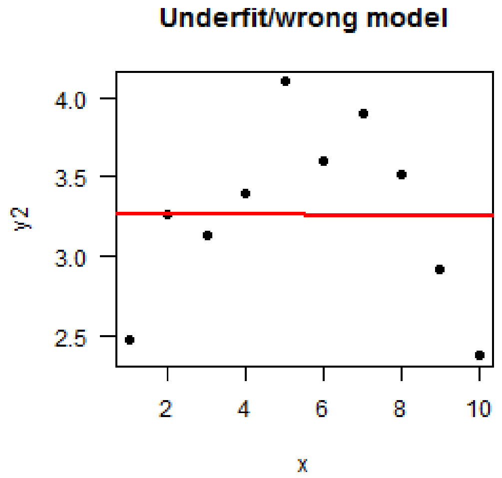
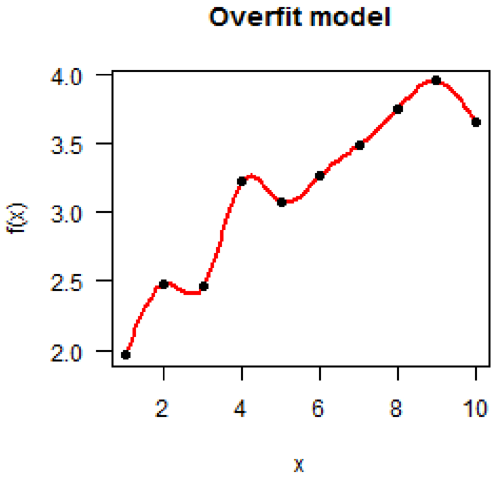
Why model selection?

- Nested models: how much complexity is necessary to fit the data?
- Non-nested models: compare fit of different models (e.g. alternative hypotheses)
  - Note that building a larger model may be better than choosing any one of them!
- Important facts:
  - Larger models usually fit data better
  - Models usually perform much worse with independent data than with observed (calibration) data
  - Need to account for model complexity (overfitting)

Overfitting and balanced model complexity



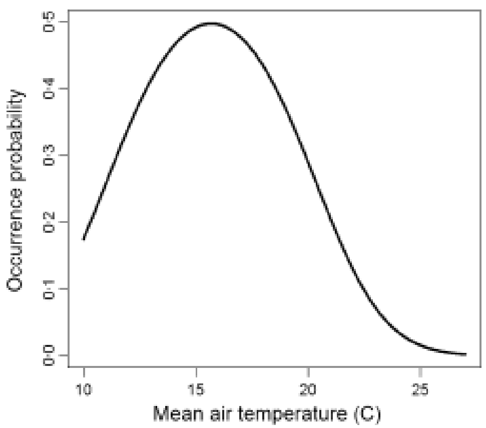




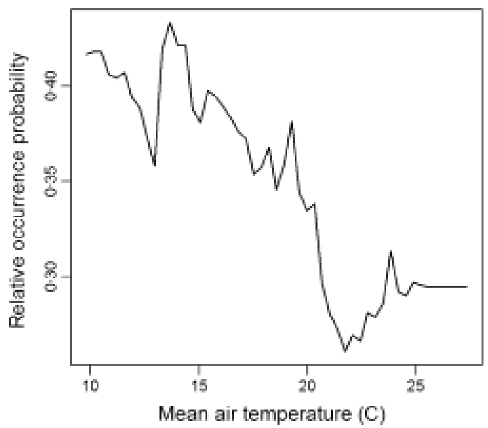
Overfitting: an example with niche modelling

Wenger & Olden (2012) Assessing transferability of ecological models: an underappreciated aspect of statistical validation. Methods Ecol Evol.

GLMM



Random forests (overfit)



So, two important aspects of model selection

- On one hand, we want to maximise fit.
- On the other hand, we want to avoid overfitting and overly complex models.

Evaluating models' predictive accuracy

- Cross-validation (k fold, leave one out...)
- Alternatives:
  - AIC
  - BIC
  - DIC
  - WAIC
- All these attempt an impossible task:
  - estimating out-of-sample prediction error without external data or further model fits!
- All these methods have flaws!

Cross-validation

Preferred method, but

- Requires splitting data (difficult for structured data: space, time)
- Data may not be independent (e.g. due to spatial or temporal autocorrelation)
- Computationally expensive (requires fitting many models)

AIC

$$\text{AIC} = -2\log p(y|\hat{\theta}_{\text{mle}}) + 2k$$

- First term: model fit (deviance, log likelihood)
- k: number of estimated parameters (penalisation for model complexity)
- AIC biased towards complex models.
- AICc recommended with 'small' sample sizes (n/p < 40). But see Richards 2005 Ecology.
- Doesn't work with hierarchical models or informative priors!

DIC

$$\mathrm{DIC} = -2\log p(y|\hat{\theta}_{\mathrm{Bayes}}) + 2p_{\mathrm{DIC}}$$

- First term: posterior deviance (Bayesian)
- p_{DIC} effective number of parameters
  - (influenced by priors and the amount of pooling in hierarchical models)

What about BIC?

$$\mathrm{BIC} = -2\log p(y|\hat{\theta}) + k\,\log n$$

- Larger penalty with large datasets (favouring simpler models)
- Not intended for assessing out-of-sample model performance
- Problematic (e.g. Burnham et al. 2011, or Gelman et al. 2013 do not recommend it; but see Link & Barker 2006).

Problems of IC

- No information criteria is panacea: all have problems (see refs at the end).
- They give average out-of-sample prediction error, but prediction errors can differ substantially within the same dataset (e.g. populations, species).
- Sometimes better models rank poorly (Gelman et al. 2013). So, combine with thorough model checks.

So which variables should enter my model?

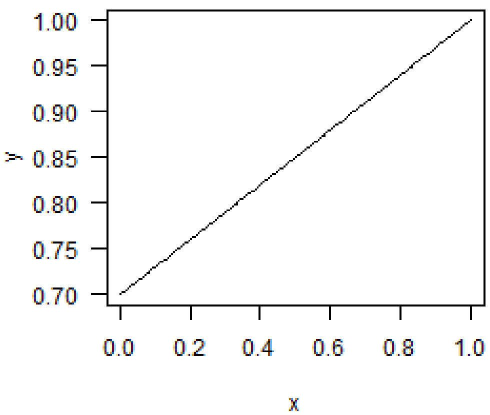
- Choose variables based on **ecological understanding**, rather than throwing plenty of them in a fishing expedition.
- Propose single global model or small set (< 10 - 20) of **reasonable** candidate models.
- Number of variables balanced with sample size (at least 10 - 30 obs per param)
- Assess collinearity between predictors (Dormann et al 2013)
  - pairs() or similar
  - If |r| > 0.5 - 0.7, consider leaving one variable out, but keep it in mind when interpreting model results.
  - Or combine 2 or more in a synthetic variable (e.g. water deficit ~ Temp + Precip).
  - Many methods available, e.g. sequential, ridge regression… (see Dormann et al)
  - Measurement error can seriously complicate things (Biggs et al 2009; Freckleton 2011)
- For predictors with large effects, consider interactions.
- See also Zuur et al 2010.

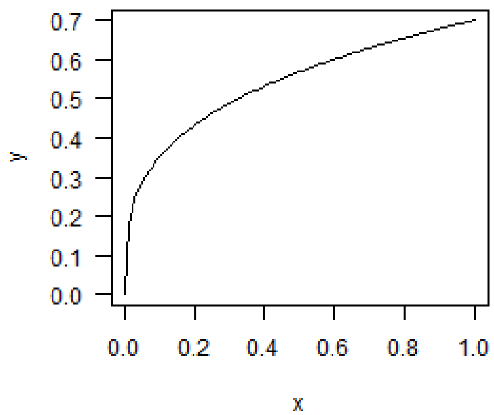
Think about the shape of relationships

y ~ x + z

Really? Not everything has to be linear! Actually, it often is not.

Think about shape of relationship. See chapter 3 in Bolker's book.





Sample size is important

http://vimeo.com/57127001

Especially if you want to include interactions!

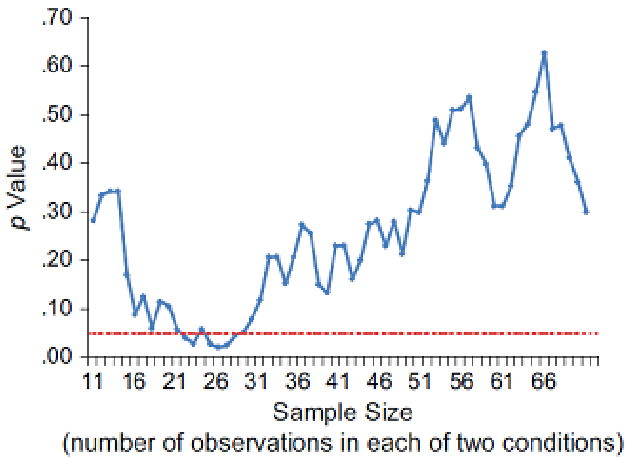


Fig. 2. Illustrative simulation of p values obtained by a researcher who continuously adds an observation to each of two conditions, conducting a t test after each addition. The dotted line highlights the conventional significance criterion of $p \leq .05$.

Removing predictors

Do not use stepwise regression

- Whittingham et al. (2006) Why do we still use stepwise modelling in ecology and behaviour? J. Animal Ecology.
- Mundry & Nunn (2009) Stepwise Model Fitting and Statistical Inference: Turning Noise into Signal Pollution. Am Nat.
- This includes stepAIC (e.g. Dahlgren 2010; Burnham et al 2011; Hegyi & Garamszegi 2011).

Gelman's criteria for removing predictors

(assuming only potentially relevant predictors have been selected a priori)

- NOT significant + expected sign = let it be.
- NOT significant + NOT expected sign = remove it.
- Significant + NOT expected sign = check… confounding variables?
- Significant + expected sign = keep it!

How to make your results significant

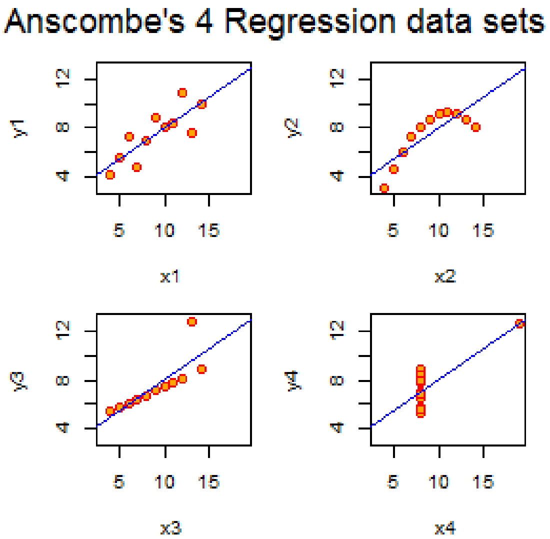
1. Test multiple variables, then report the ones that are significant.
2. Artificially choose when to end your experiment.
3. Add covariates until effects are significant.
4. Test different conditions (e.g. different levels of a factor) and report the ones you like.
5. Read Simmons et al 2011
6. Let's substitute 'statistical significance' by something more informative and less misleading

Statistical Errors: type I-II versus M-S

- Type I: incorrect rejection of null hypothesis.
- Type II: failure to reject false null hypothesis.
- In ecology, everything is different. Finding a significant difference will mostly depend on your sample size (and researchers' degrees of freedom; Simmons et al 2011).
- Type S (Sign): estimating effect in opposite direction.
- Type M (Magnitude): Misestimating magnitude of the effect (under or overestimating).
- Avoid also Type III error (Dangles & Casas 2012): finding right answer to the wrong question!

Plot everything

These 4 datasets give identical linear regressions. But differences are obvious. So models' summary statistics are not enough: plot everything!



Summary

1. Choose meaningful variables
   - Beware collinearity
   - Keep good n/p ratio
2. Generate global model or (small) set of candidate models
   - Avoid stepwise and all-subsets
   - Don't assume linear effects: think about appropriate functional relationships
   - Consider interactions for strong main effects
3. If > 1 model have similar support, consider model averaging.
4. Always check thoroughly fitted models
   - Residuals, goodness of fit...
   - Plot. Check models. Plot. Check assumptions. Plot. (Lavine 2014).
5. Move away of statistical significance -> effect sizes, type M and S errors...

To read more

- Olden & Jackson (2000) Torturing data for the sake of generality: How valid are our regression models? Ecoscience.
- Burnham & Anderson book (2002). Anderson 2008 book.
- Johnson & Omland (2004) Model selection in ecology and evolution. TREE
- Anderson & Burnham (2002) Avoiding pitfalls when using information-theoretic methods. J. Wildlife Management.
- Richards (2005) Testing ecological theory using the information-theoretic approach: Examples and cautionary results. Ecology.
- Link & Barker (2006) MODEL WEIGHTS AND THE FOUNDATIONS OF MULTIMODEL INFERENCE. Ecology.
- Murray & Conner (2009) Methods to quantify variable importance: implications for the analysis of noisy ecological data. Ecology.

To read more

- Murtaugh (2009) Performance of several variable-selection methods applied to real ecological data. Ecology Letters.
- Dahlgren (2010) Alternative regression methods are not considered in Murtaugh (2009) or by ecologists in general. Ecology Letters.
- Model selection, multimodel inference and information-theoretic approaches in behavioural ecology. Special Issue of Behav Ecol & Sociobiol.
- Grueber et al (2011) Multimodel inference in ecology and evolution: challenges and solutions. J. Evol Biol.
- Gelman et al (2013) Understanding predictive information criteria for Bayesian models.

END

Hope it was useful!