Variable and model selection

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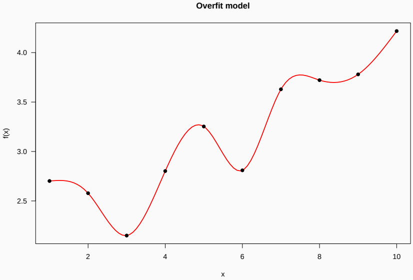
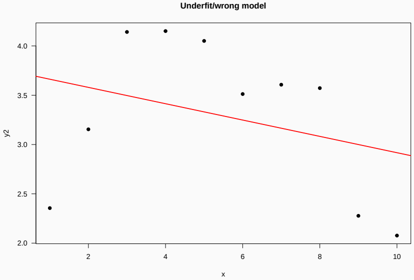
Overfitting and balanced model complexity

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

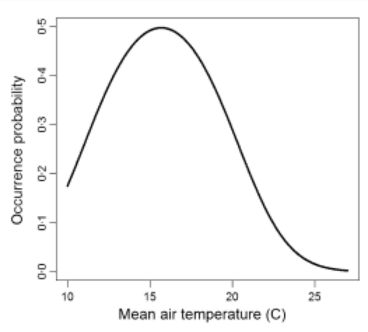
Overfitting and balanced model complexity



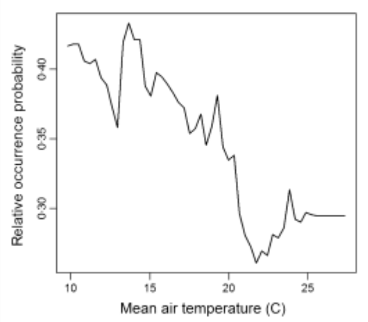


Overfitting and balanced model complexity

GLMM



Random forests



Wenger & Olden (2012)

Overfitted models will work badly on new data

Evaluating models' predictive accuracy

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- All these methods have flaws!

AIC (Akaike Information Criteria)

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- AICc recommended with 'small' sample sizes (n/p < 40). But see Richards 2005

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- They estimate *average* out-of-sample prediction error. But errors can differ substantially within dataset.
- Sometimes better models rank poorly (e.g. see Gelman et al. 2013). Combine with **thorough model checks**.

So which variables should enter my model?

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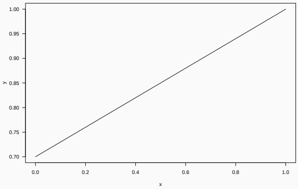
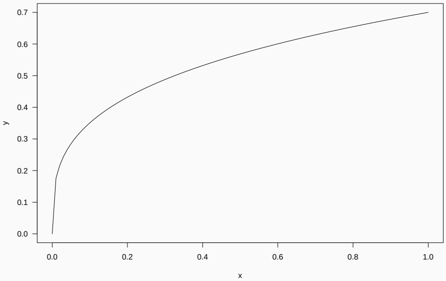
- For predictors with large effects, **consider interactions**.

y ~ x + z

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

Think about shape of relationship.





Removing predictors

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- This includes `stepAIC` (e.g. Dahlgren 2010; Burnham et al 2011; Hegyi & Garamszegi 2011).

Other common bad practices

- Testing bivariate relationships before building multivariable model

Heinze & Dunkler 2016

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- Testing bivariate relationships before building multivariable model
- Removing non-significant predictors

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- Always **keep 'core' predictors** (based on previous knowledge)

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- If performing variable selection, always **assess stability** (bootstrap, etc)

Heinze et al 2018

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3. If > 1 model have similar support, consider model averaging (or blending).
4. Always check fitted models thoroughly
5. Always report effect sizes