Lesson 6 - More Random Effects

MLE Software Online Course

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Topics

- Overdispersion via random effects
- What about REML?
- Residuals
- So is the Laplace approximation working?

Overdispersion via random effects

- For distributions where variance cannot be controlled separately from mean (e.g., Poisson, multinomial)
  - Treat parameters of these distributions as random
- New probability distributions have been defined this way.
  - E.g., the NB (Poisson, gamma rate parameter), Dirichlet-multinomial (multinomial, p vector Dirichlet)
  - Compound pdf found by integrating the joint likelihood
- Alternatively could specify observation-specific random effects. E.g., Poisson with log of rate normal (this is GLMM, with log link function) - Easy to generalize using RTMB.

REML

- ML variance estimates are known to be biased
- REML variance estimates are unbiased in linear normal models and generally less biased than ML estimates
- REML estimates can be obtained by declaring all the fixed effects other than the variances as random (don't add anything to the function you minimize)
- Pretty much ignored and not studied/evaluated in stock assessment

Demonstration of REML for “known” bias case

- In standard regression (with normal errors) the maximum likelihood estimate for residual error variance is (residual SS)/n.
- The minimum variance unbiased estimate for linear regression is (residual SS)/(n-2).
- This is approximately unbiased for nonlinear regression.
- The RTMB reml procedure will produce the approximatley unbiased estimates (see musky_vonb_reml.R)
- This is just to demo of what REML is doing for a known answer case!

Residuals

- standard Pearson residuals
- Problems with standard Pearson residuals
- One step ahead (osa) aka recursive quantile residuals

Pearson residuals

- defined as (obs-pred)/sd
- sd is what the standard deviation for (obs-pred) should be given your model and model estimates
- Idea is that if raw residuals are approximately normal and independent then Pearson residuals will be approximately normal, independent, with equal (1) variance.
  - So all the residuals can be looked at together

Problems with Pearson residuals

- Actual residuals typically:
  - Not normal
  - Not independent
- In addition, we really want to look at residuals in some sense integrated over random effects, rather than at the best estimates of random effects

Solutions: OSA = Recursive quantile residuals:

- The capability is built into RTMB and in theory can be applied almost automatically: oneStepPredict(obj) - with data set up using OBS
- Numerically intensive and can be numerically tricky.
- The theory underlying this is pretty intense. See:

Thygesen et al. Environ Ecol Stat 24(2): 317–339.

- I have not gotten this working for multinomial.
- Near automatic approach relies on TMB/RTMB understanding the density functions you are using.

Checking on the Laplace approximation

- Approximation depends on approximate normality of the combined vector or parameter estimates and random estimates.
- This is why we generally don't specify non-normal distributions for random effects.
- RTMB includes a helper function that checks the Laplace approximation

RTMB function checkConsistency to check on Laplace approximation

- Call as checkConsistency(obj) or as checkConsistency(obj,estimate=TRUE). Run summary on result.
- Requires you have set up your function for simulation (using OBS) (and the simulations work!).
- Usually want estimate=TRUE optional argument. This conducts a full simulation and evaluates parameter bias and whether simulated data are constent with assumed distributions.of simulation.
  - Without this it evaluates the approximation in an approximate way (but faster)