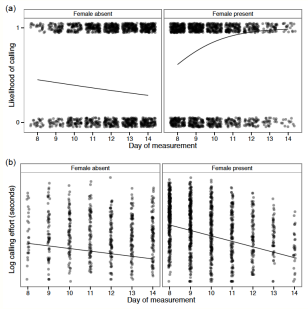
Advancing in R combining approaches



Outline

- How to advance even further
- More complex analyses
  - glmm
  - nlme
  - ZAP
- Suggested workflow

So far…

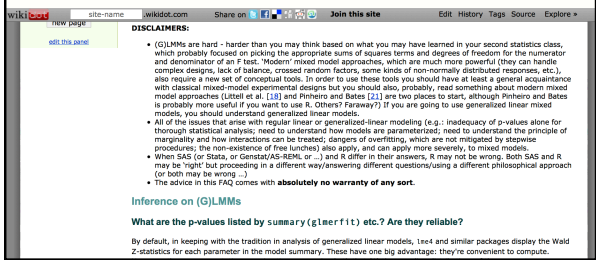
- Data manipulation
- Data visualization
- Univariate regression
- Multiple regression
- ANCOVA
- Generalized models
- Mixed models
- Nonlinear models

What is left?

- For example, in linear models universe:
  - Generalized linear mixed models
  - Nonlinear mixed effects models
  - Survival models
  - Zero-altered models
- Other techniques unrelated to lm()
  - Canonical analyses (data reduction)

glmms

- http://glmm.wikidot.com/faq
- You will need to do a lot of reading, and be able to cope with uncertainty



wikidot site-name .wikidot.com Share on Join this site Edit History Tags Source Explore »

new page

edit this panel

DISCLAIMERS:

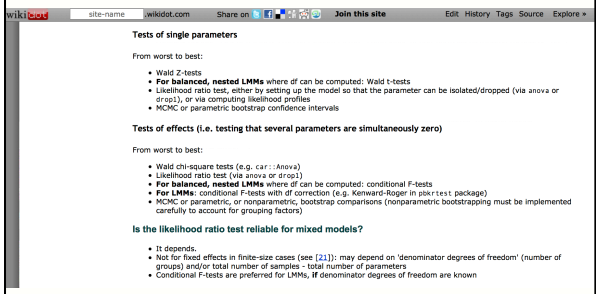
- (G)LMMs are hard - harder than you may think based on what you may have learned in your second statistics class, which probably focused on picking the appropriate sums of squares terms and degrees of freedom for the numerator and denominator of an F test. 'Modern' mixed model approaches, which are much more powerful (they can handle complex designs, lack of balance, crossed random factors, some kinds of non-normally distributed responses, etc.), also require a new set of conceptual tools. In order to use these tools you should have at least a general acquaintance with classical mixed-model experimental designs but you should also, probably, read something about modern mixed model approaches (Littell et al. [18] and Pinheiro and Bates [21] are two places to start, although Pinheiro and Bates is probably more useful if you want to use R. Others? Faraway?) If you are going to use generalized linear mixed models, you should understand generalized linear models.
- All of the issues that arise with regular linear or generalized-linear modeling (e.g.: inadequacy of p-values alone for thorough statistical analysis; need to understand how models are parameterized; need to understand the principle of marginality and how interactions can be treated; dangers of overfitting, which are not mitigated by stepwise procedures; the non-existence of free lunches) also apply, and can apply more severely, to mixed models.
- When SAS (or Stata, or Genstat/AS-REML or ...) and R differ in their answers, R may not be wrong. Both SAS and R may be 'right' but proceeding in a different way/answering different questions/using a different philosophical approach (or both may be wrong ...)
- The advice in this FAQ comes with **absolutely no warranty of any sort**.

Inference on (G)LMMs

What are the p-values listed by `summary(glmerfit)` etc.? Are they reliable?

By default, in keeping with the tradition in analysis of generalized linear models, `lme4` and similar packages display the Wald Z-statistics for each parameter in the model summary. These have one big advantage: they're convenient to compute.

Example: how to generate p-values for glmms?



wikidot site-name .wikidot.com Share on Join this site Edit History Tags Source Explore »

Tests of single parameters

From worst to best:

- Wald Z-tests
- **For balanced, nested LMMs** where df can be computed: Wald t-tests
- Likelihood ratio test, either by setting up the model so that the parameter can be isolated/dropped (via `anova` or `drop1`), or via computing likelihood profiles
- MCMC or parametric bootstrap confidence intervals

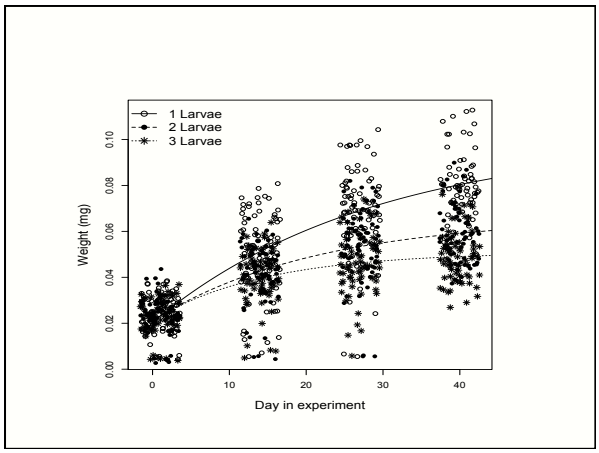
Tests of effects (i.e. testing that several parameters are simultaneously zero)

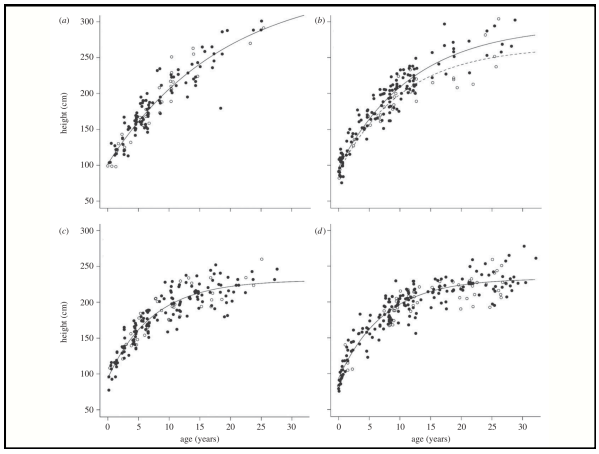
From worst to best:

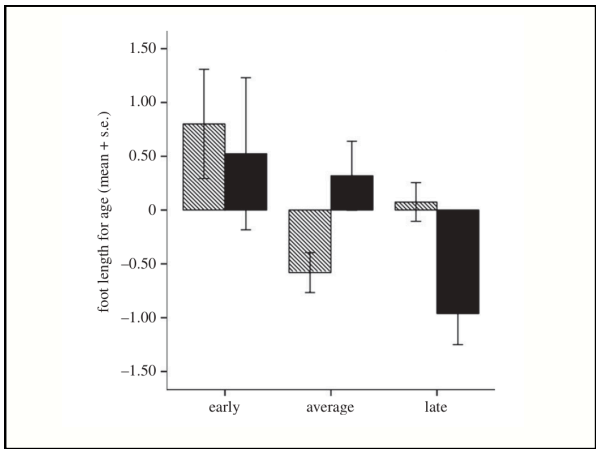
- Wald chi-square tests (e.g. `car::Anova`)
- Likelihood ratio test (via `anova` or `drop1`)
- **For balanced, nested LMMs** where df can be computed: conditional F-tests
- **For LMMs**: conditional F-tests with df correction (e.g. Kenward-Roger in `pbkrtest` package)
- MCMC or parametric, or nonparametric, bootstrap comparisons (nonparametric bootstrapping must be implemented carefully to account for grouping factors)

Is the likelihood ratio test reliable for mixed models?

- It depends.
- Not for fixed effects in finite-size cases (see [21]): may depend on 'denominator degrees of freedom' (number of groups) and/or total number of samples - total number of parameters
- Conditional F-tests are preferred for LMMs, **if** denominator degrees of freedom are known

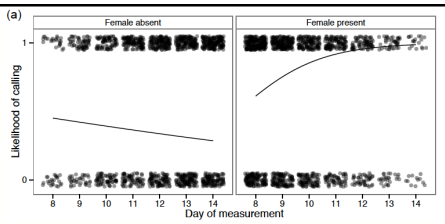


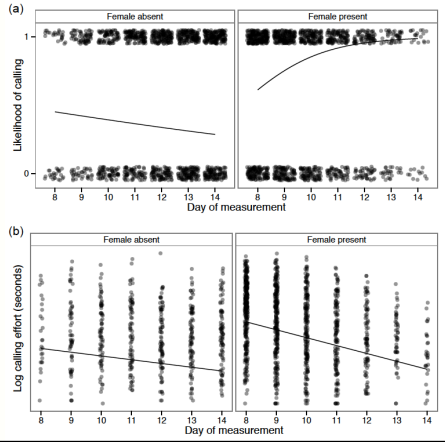

(a)
(b)
(c)
(d)
height (cm)
age (years)

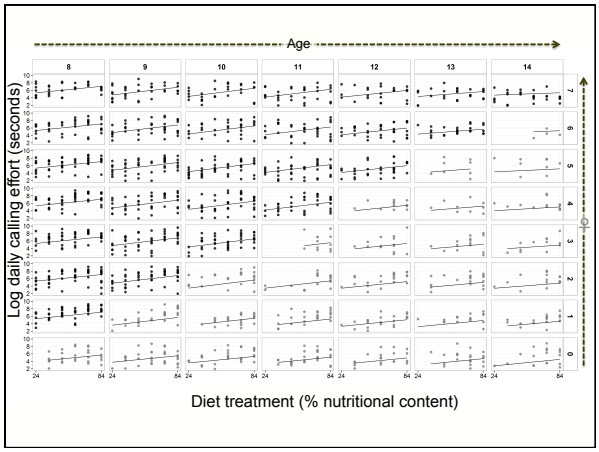

foot length for age (mean + s.e.)
1.50
1.00
0.50
0
–0.50
–1.00
–1.50
early
average
late

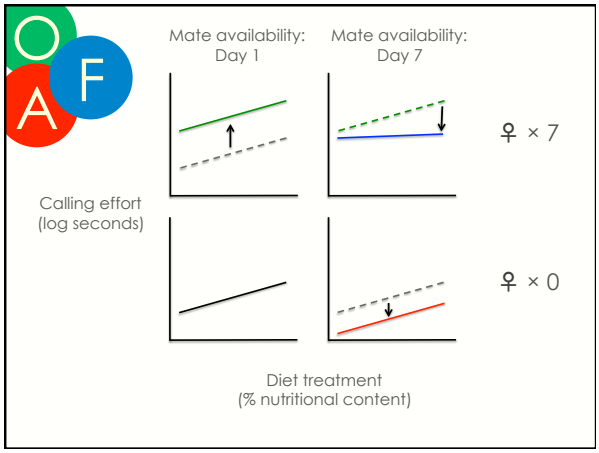
Fixed effect	Estimate	95% CI (lower, upper)	*P*	
Zero-altered				
(Intercept)	-4.621	(-5.026, -4.195)	<0.001	***
Female presence	2.981	(2.523, 3.477)	<0.001	***
Diet	0.019	(-0.139, 0.173)	0.818	
Day	-0.120	(-0.237, -0.005)	0.036	*
Body condition (beginning week 2)	0.364	(0.010, 0.751)	0.062	.
Mate availability history	-0.640	(-0.865, -0.439)	<0.001	***
Female presence × day	0.776	(0.577, 0.993)	<0.001	***
Mate availability history × diet	0.053	(-0.025, 0.134)	0.188	
Mate availability history × day	0.012	(-0.038, 0.067)	0.600	
Mate availability history × diet × day	0.018	(-0.011, 0.045)	0.210	
Poisson				
(Intercept)	4.066	(3.758, 4.400)	<0.001	***
Female presence	0.736	(0.471, 0.961)	<0.001	***
Diet	0.348	(0.251, 0.461)	<0.001	***
Day	-0.195	(-0.265, -0.133)	<0.001	***
Body condition (beginning week 2)	0.825	(0.563, 1.153)	<0.001	***
Mate availability history	-0.075	(-0.203, 0.070)	0.296	
Female presence × day	-0.215	(-0.339, -0.094)	<0.001	***
Mate availability history × diet	0.023	(-0.014, 0.060)	0.204	
Mate availability history × day	0.053	(0.025, 0.076)	<0.001	***
Mate availability history × diet × day	-0.020	(-0.033, -0.007)	<0.001	***

Variance component	Estimate	95% CI (lower, upper)
Zero-altered		
ID	4.969	(3.844, 6.105)
Poisson		
ID	1.819	(1.557, 2.331)
Residual	1.273	(1.181, 1.391)









Suggested workflow

1) Assess structure & quality control
2) Visualize
   a) Distributions of response & predictor(s)?
   b) Collinearity?
   c) Effects? (ADF & predict coefficients)
   d) Possible alternative explanations?
3) Analyses
   a) Model quality (assumptions & fit)
   b) Simplification & selection
4) Better plots