

A.2.3 Frequency weighting in ADMB-RE

Model description Let X_i be binomially distributed with parameters $N = 2$ and p_i , and assume that

$$p_i = \frac{\exp(\mu + u_i)}{1 + \exp(\mu + u_i)}, \quad (\text{A.3})$$

where μ is a parameter and $u_i \sim N(0, \sigma^2)$ is a random effect. Assuming independence, the loglikelihood function for the parameter $\theta = (\mu, \sigma)$ can be written:

$$l(\theta) = \sum_{i=1}^n \log [p(x_i; \theta)]. \quad (\text{A.4})$$

In ADMB-RE $p(x_i; \theta)$ is approximated using the Laplace approximation. However, since x_i only can take the values 0, 1 and 2, we can re-write the loglikelihood as

$$l(\theta) = \sum_{j=0}^2 n_j \log [p(j; \theta)], \quad (\text{A.5})$$

where n_j is the number x_i being equal to j . Still the Laplace approximation must be used to approximate $p(j; \theta)$, but now only for $j = 0, 1, 2$, as opposed to n times above. For large n this can give large savings.

To implement the loglikelihood (A.5) in ADMB-RE you must organize your code into a SEPARABLE_FUNCTION (see the section "Nested models" in the ADMB-RE manual). Then you should do the following

- Formulate the objective function in the weighted form (A.5).
- Include the statement `!! set_multinomial_weights(w)` in the PARAMETER_SECTION, where `w` is a vector (with indexes starting at 1) containing the weights, so in our case $w = (n_0, n_1, n_2)$.

Files <http://otter-rsch.com/admbre/examples/weights/weights.html>

Bibliography

ADMB Development Core Team (2009), *An Introduction to AD Model Builder*, ADMB project.

ADMB Foundation (2009), ‘ADMB-IDE: Easy and efficient user interface’, *ADMB Foundation Newsletter* **1**, 1–2.

Eilers, P. & Marx, B. (1996), ‘Flexible smoothing with B-splines and penalties’, *Statistical Science* **89**, 89–121.

Harvey, A., Ruiz, E. & Shephard, N. (1994), ‘Multivariate stochastic variance models’, *Review of Economic Studies* **61**, 247–264.

Hastie, T. & Tibshirani, R. (1990), *Generalized Additive Models*, Vol. 43 of *Monographs on Statistics and Applied Probability*, Chapman & Hall, London.

Kuk, A. Y. C. & Cheng, Y. W. (1999), ‘Pointwise and functional approximations in Monte Carlo maximum likelihood estimation’, *Statistics and Computing* **9**, 91–99.

Lin, X. & Zhang, D. (1999), ‘Inference in generalized additive mixed models by using smoothing splines’, *J. Roy. Statist. Soc. Ser. B* **61**(2), 381–400.

Pinheiro, J. C. & Bates, D. M. (2000), *Mixed-Effects Models in S and S-PLUS*, Statistics and Computing, Springer.

Rue, H. & Held, L. (2005), *Gaussian Markov random fields: theory and applications*, Chapman & Hall/CRC.

Ruppert, D., Wand, M. & Carroll, R. (2003), *Semiparametric Regression*, Cambridge University Press.

- Skaug, H. & Fournier, D. (2006), ‘Automatic approximation of the marginal likelihood in non-gaussian hierarchical models’, *Computational Statistics & Data Analysis* **56**, 699–709.
- Zeger, S. L. (1988), ‘A regression-model for time-series of counts’, *Biometrika* **75**, 621–629.