

Class Notes on Nonlinear Regression (Chapter 5)

Class 1

- Nonlinear models often result from compartmental models (scientific “common sense”), and the parameters are usually very important and interpretable (as compared with linear models)
- Need to give **starting values**, and that often requires understanding the model function and sometimes some ingenuity (p.4)
- Iterate to a solution using e.g. MGN (Modified Gauss Newton) method (p.6); results in parameter estimates, and then interpretation or prediction
- Rival model functions exist for the same dataset – e.g., SE_2 (Simple Exponential), MM_2 (Michaelis-Menton), and Lasky model functions all look very similar (like the figure at the bottom of p.9)
- CI's: two types are: **Wald** (estimate $\pm t \cdot SE$) is based on a parabolic approximation to the SSE or likelihood, and **Likelihood**-based. PLCI's are often asymmetric, which makes more sense since usually our information about a parameter is asymmetric. Best to use PLCI's, but they can be hard to find. The difference between WCI's (Wald) and PLCI's depends upon “curvature”; more on this later
- Better understanding of MM_2 model function parameters, and how to give good starting values
- **Example 5.1 BOD** – pp. 7-13: parameter estimation, WCR for θ , LBCR for θ , PLCI's for individual parameters (graph

pp.11-12), WCI's for individual parameters from a parabolic approximation – summarized in Tables on p.12

- **Example 5.2** – linear model, but nonlinear model is appropriate since we are interested in the intra-class correlation (p.14), which is a nonlinear function of the linear model parameters. Find the PLCI from graph on p.14; $\hat{\phi} = 0.811$ occurs where this plot hits its minimum

Class 2

- **Example 5.3 (Laetisarinic acid)** another linear model 'reparameterized' into a nonlinear one; here too Wald & Likelihood intervals differ: use PLCI's when available
- **Example 5.4** – two treatment groups ("conv" vs. "eshb") fitting a 3-parameter curve to each and testing for common parameters. Compound hypothesis (on p.20) is tested using the Full-and-Reduced F statistic,

$$F_{2,18} = [(0.2465 - 0.1737)/2] / [0.1737/18] = 3.772,$$

Here, p-value = 0.0428. What is the conclusion here?

- **Example 5.5** – downward SE2 doesn't fit (see residuals on p.22), but SE2 with a lag (i.e., a "variable knot") **does** fit: 95% WCI for knot extends from 25.16 minutes to 46.19 minutes; what is the interpretation?
- **Example 5.6** – another lag example
- **Example 5.7** – Fitting one (modified) LL₄ model function for May and one for June; wish to test

$$H_0: \theta_{1M} = \theta_{1J}, \theta_{2M} = \theta_{2J} \text{ and } \theta_{3M} = \theta_{3J}$$

This is tested using Full-and-Reduced F statistic,

$$F_{3,24} = [(0.0206-0.0179)/3] / [0.0179/24] = 1.20,$$

Here, $p = 0.329$. We retain the claim of common upper and lower asymptotes and slopes for May and June.

Class 3

- All our models so far are homoskedastic normal NLINs, but data in **Example 5.8** show non-constant variance. Letting “rhs” denote the (mean) model function, we propose that $\text{VAR} = \sigma^2 * \text{mean}^p$, where p is an additional parameter to be estimated. The case where $p = 0$ is then **constant variances** across the X values. To test $H_0: p = 0$, we use Wald or LR. Wald gives $t_{55} = 1.4707/0.4699 = 3.13$ and $p = 0.0028$. More reliable is the LR test $\chi^2 = 254.0 - 245.3 = 8.7$ and $p = 0.0032$. (That Wald gives a similar p-value means quadratic approx. is good here.) Regardless, we reject the null, and accept **heteroskedasticity**. One of the consequences is that the SE for the LD_{50} drops from 0.3805 to 0.3297 (drops by 13.4%).
- Next, exponential family (generalized) nonlinear models
- **Example 5.10**: return to **Menarche example** but with the $LD_{50} = \gamma$ as a new model parameter; now, SAS gives a 95% WCI for γ in the NLMIXED output. We could also find a PLCI, which would be more reliable
- Return to **Budworms** example in Example 5.11 – we accept common slopes using the $-2\Delta LL \chi^2$ test ($p = 0.1797$ on p.33)

- **Grauer Logistic curve** doesn't fit (see residuals on p.34) when using $x = \text{age at death}$. Output 5.10c indicates that we should use the log-age scale, and new model is Equation (5.25). Then, LD_{50} is estimated as 10.9717 yrs., which is down from 15.7003. Also, note the associated SE drops from 3.9748 to 2.1488, a drop of about 46%.