Fitting Mathematical Models to Biological Data using Non-Linear Least-Squares (NLLS)

Samraat Pawar

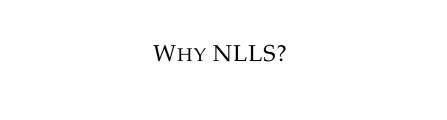
Department of Life Sciences (Silwood Park)

Imperial College London

December 7, 2020

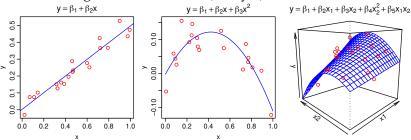
OUTLINE

- Why NLLS?
- The NLLS fitting method
- Practicals (in R) overview



LINEAR MODELS

• These are *all* good *Linear Models* (really?!):



- The data can be modelled (aka "a mathematical model fitted to them") as a *linear combination* of *variables* and *coefficients*
- Easily fitted using Ordinary Least Squares (OLS)
- Linear models can include curved responses (e.g. Polynomial regression)

WHAT MAKES A MODEL NON-LINEAR?

- OLS can be used to fit (model) equations that are *intrinsically linear*, e.g.,
 - Straight line: $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$
 - Polynomial (quadratic): $y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i$
 - Another quadratic: $y_i = e^{\beta_0} + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i$
- What is *intrinsic linearity*? the equation of the model to be fitted should be *linear in the parameters* (the β 's)
- Some non-linear models:
 - $\bullet \ y_i = \beta_0 x_i^{\beta_1} + \varepsilon_i$
 - $y_i = \beta_0 + \beta_1 x_i^{\beta_2} + \varepsilon_i$
 - $y_i = \beta_0 e^{\beta_2 x_i} + \varepsilon_i$
 - $y_i = \frac{\beta_0 x_i}{\beta_1 + x_i} + \varepsilon_i$

In all of these, at least one parameter (a β) is non-linear (e.g., $x_i^{\beta_2}$, $e^{\beta_2 x_i}$, etc.)

THE LEAST-SQUARES SOLUTION

Recall what the Least Squares method does:

- Consider data on a response variable *y*, a predictor (independent) variable *x*, and *n* observations.
- Say we want to fit a model to these data: $f(x_i, \beta) + \varepsilon_i$ $(\beta = (\beta_0, \beta_1, \dots, \beta_k))$ are the model's k + 1 parameters)
- An example of $f(x_i, \beta) + \varepsilon_i$ could be: $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$ (linear regression)
- The objective of any *least squares* method is to find estimates of values of the parameters $(\hat{\beta}_j)$ that *minimize* the sum (S) of squared residuals (r_i) (AKA RSS):

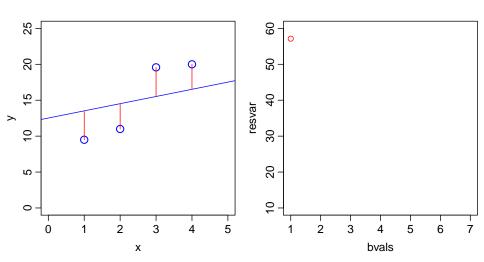
RSS =
$$S = \sum_{i=1}^{n} [y_i - f(x_i, \beta)]^2 = \sum_{i=1}^{n} r_i^2$$

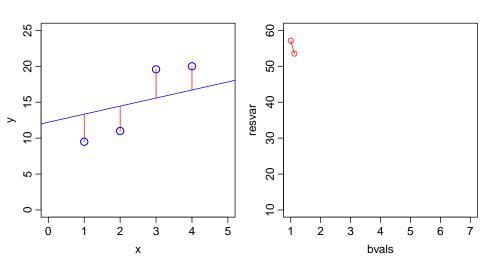
THE LEAST-SQUARES SOLUTION

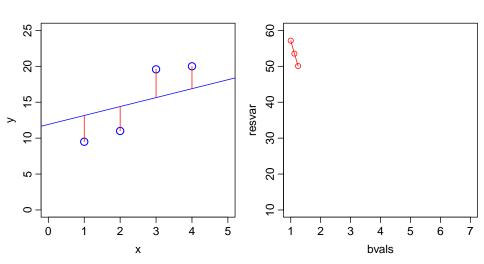
• The objective of any *least squares* method is to find estimates of values of the parameters ($\hat{\beta}_j$) that minimize the sum (S) of squared residuals (r_i) (AKA RSS):

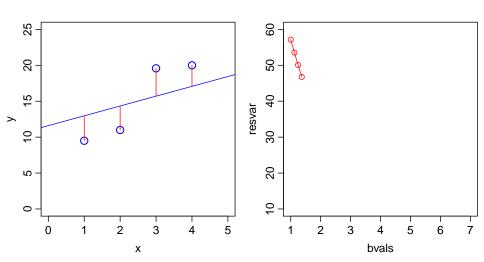
RSS =
$$S = \sum_{i=1}^{n} [y_i - f(x_i, \beta)]^2 = \sum_{i=1}^{n} r_i^2$$

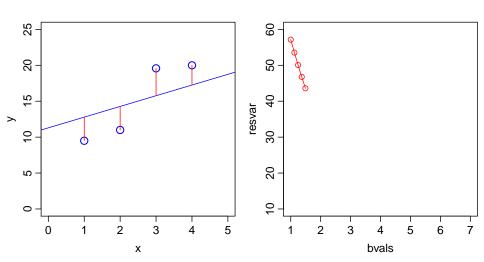
• Let's picture this using a simple (OLS) example; fitting the model $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$...

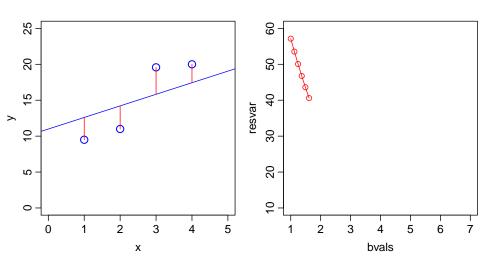


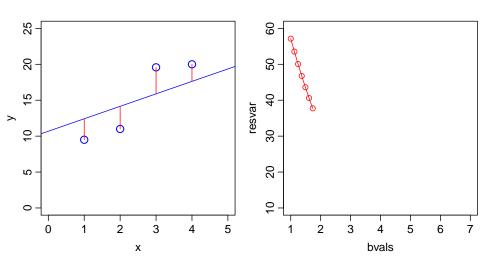


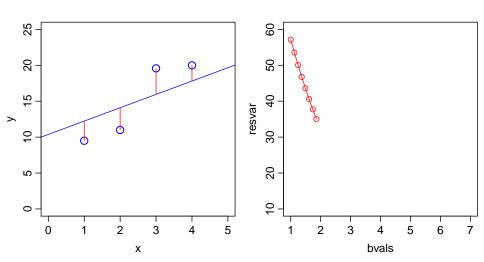


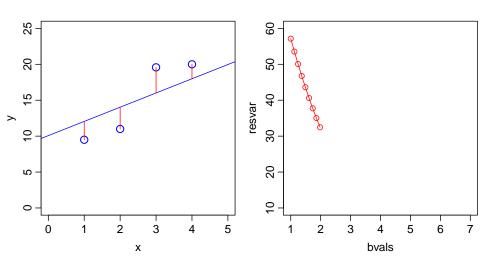


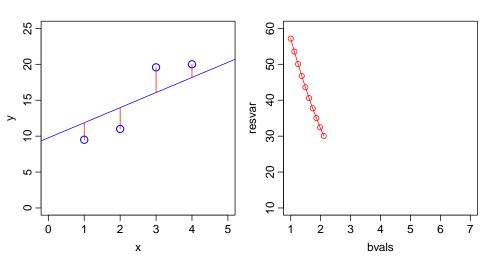


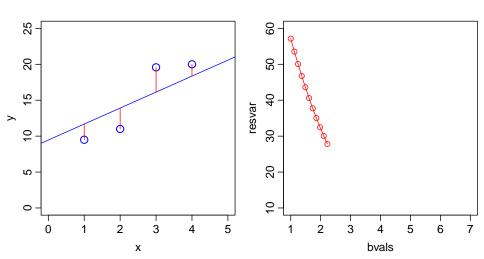


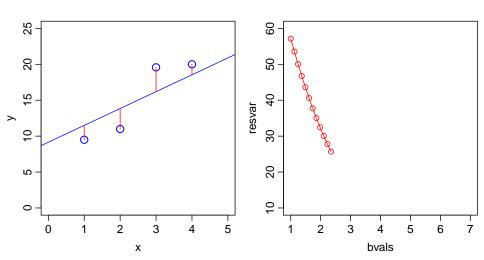


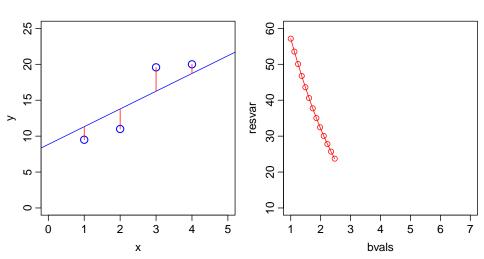


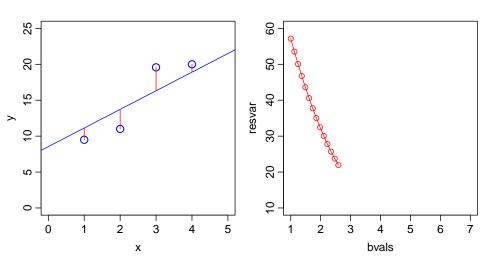


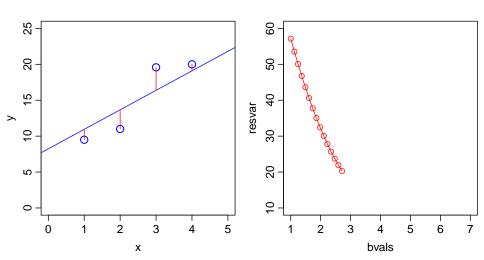


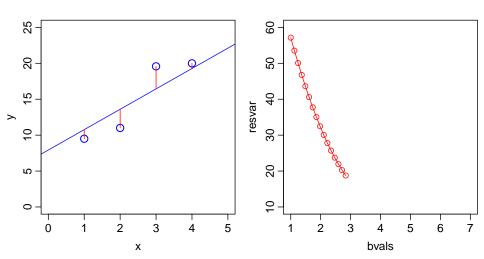


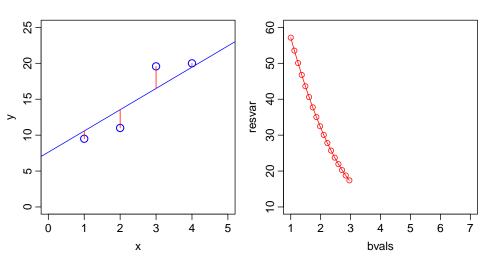


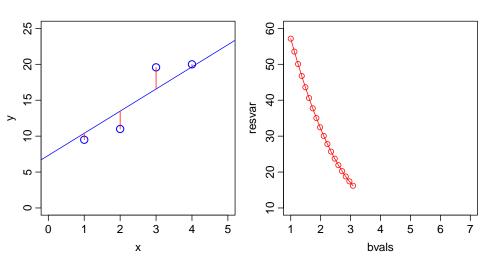


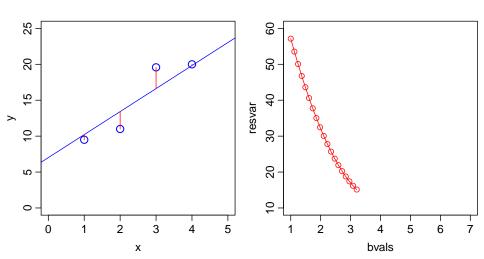


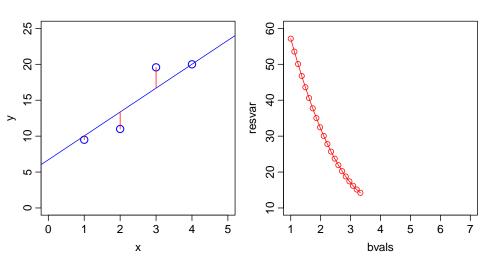


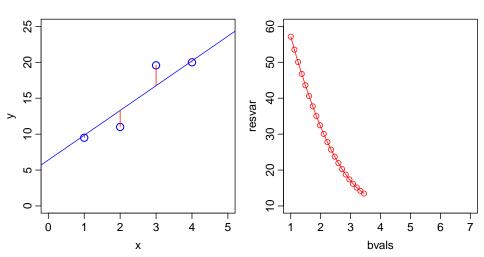


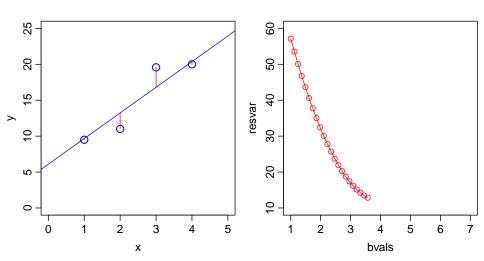


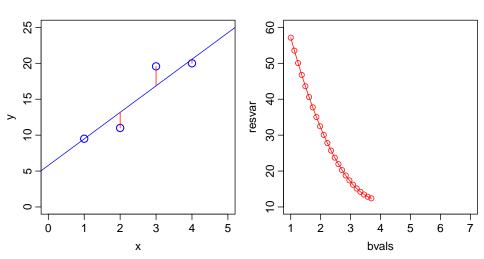


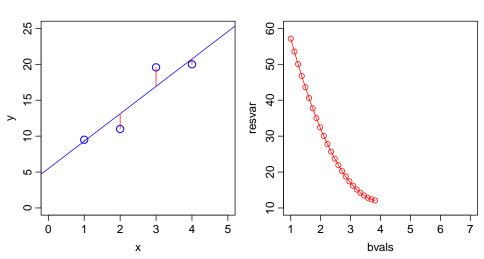


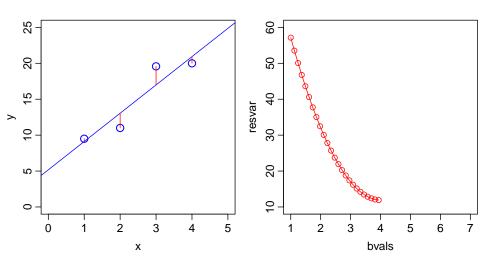


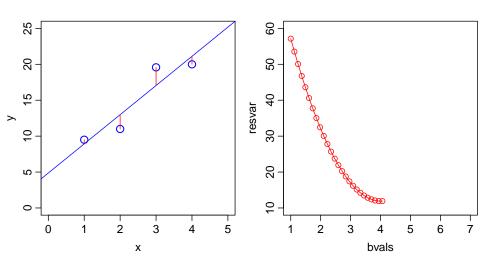


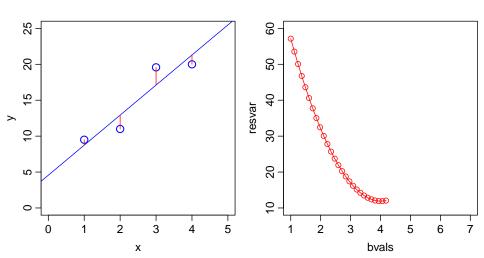


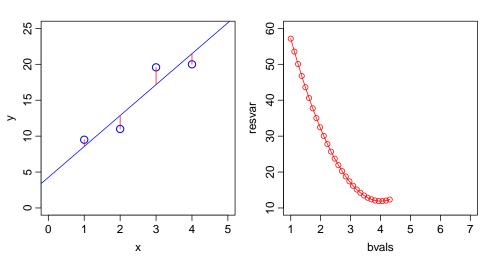


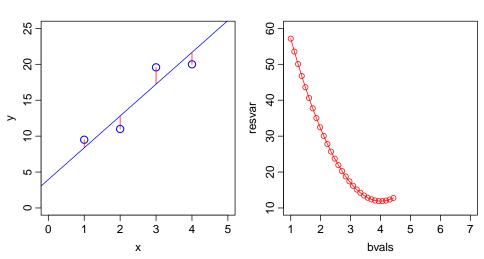


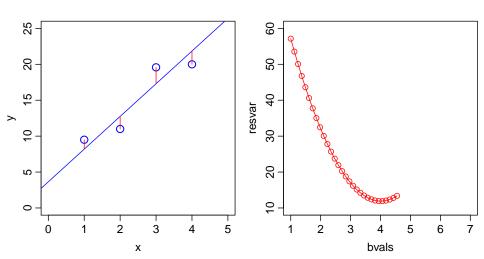


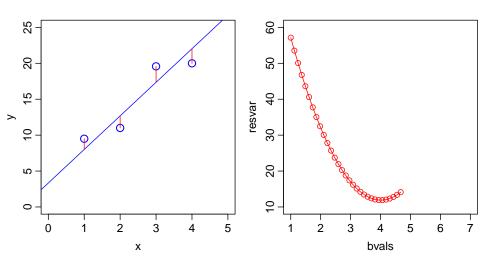


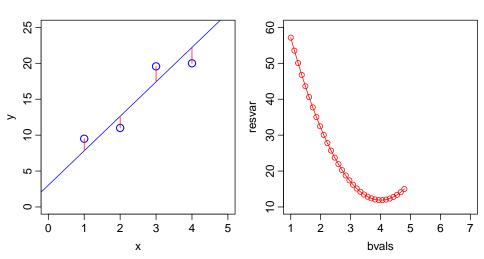


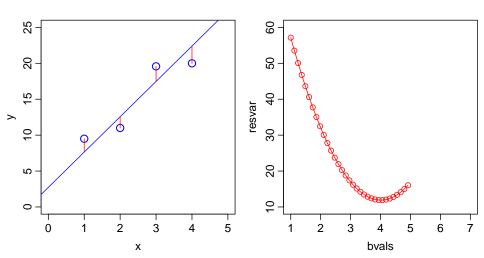


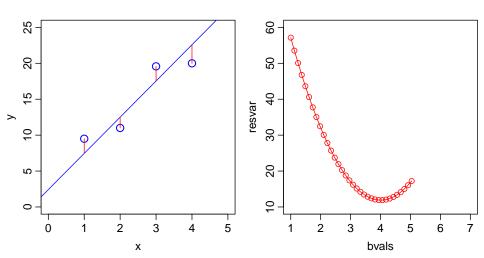


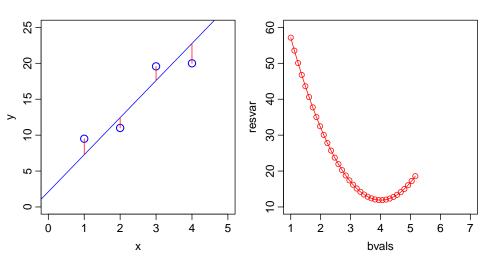


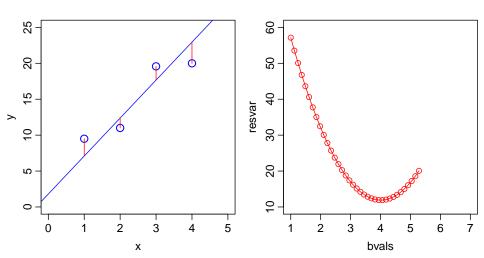


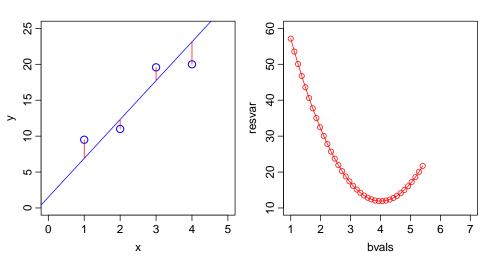


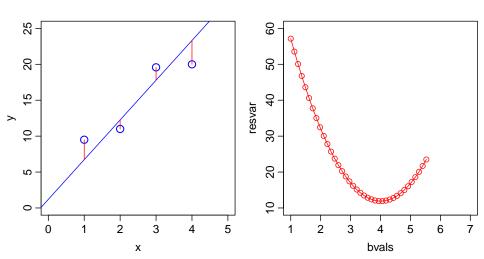


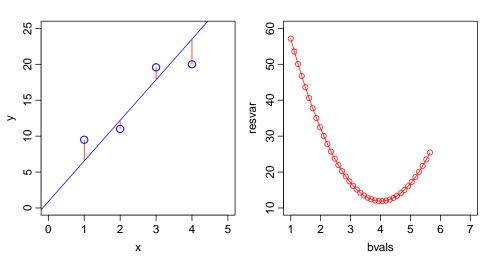


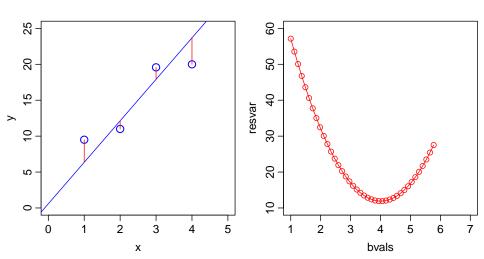


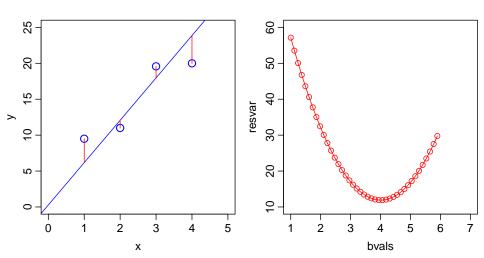


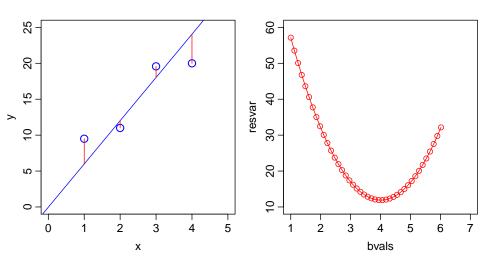


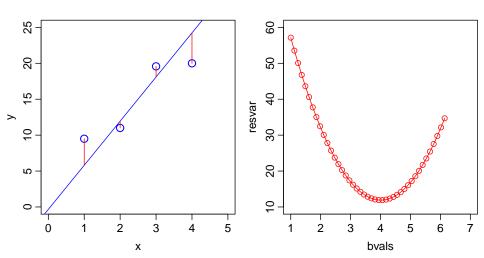


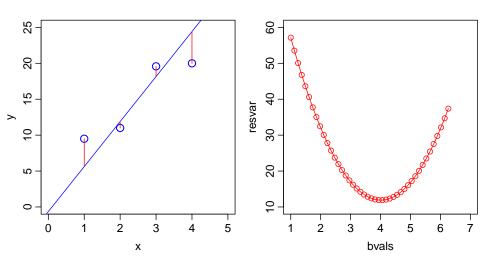


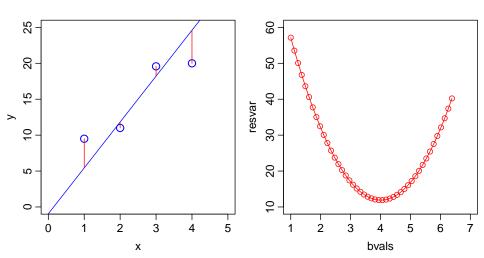


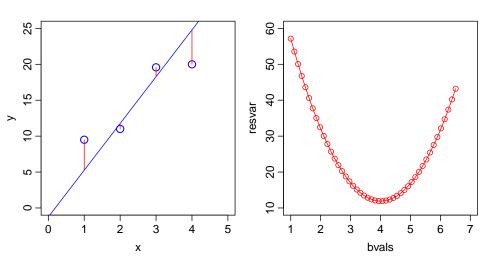


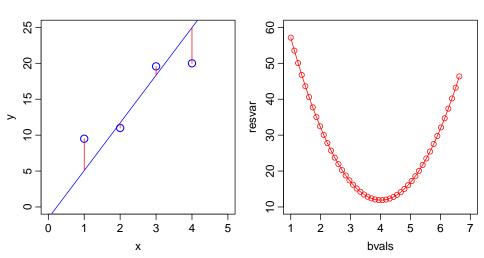


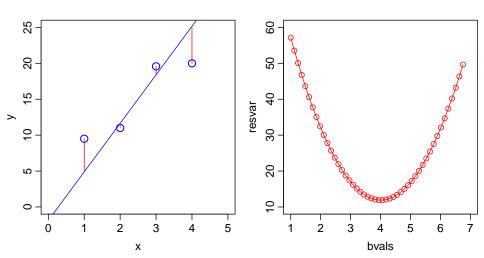


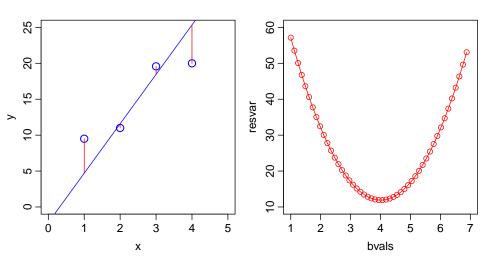


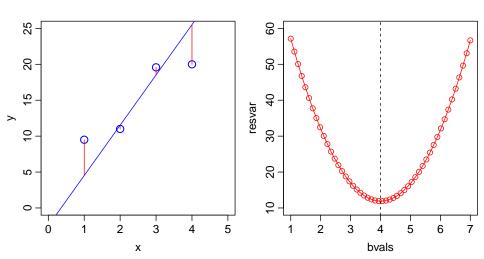




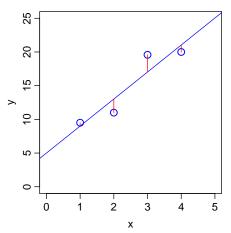








IF THE MODEL IS LINEAR, THE LEAST-SQUARE SOLUTION IS EXACT



$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

$$9.50 = 5 + 4 \times 1 + 0.50$$

$$11.00 = 5 + 4 \times 2 - 2.00$$

$$19.58 = 5 + 4 \times 3 + 2.58$$

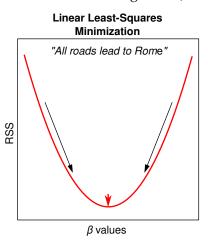
$$20.00 = 5 + 4 \times 4 - 1.00$$

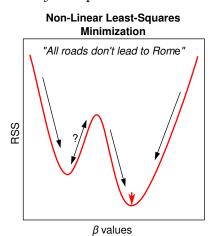
The least squares solution here is: $\beta_0 = 5$: $\beta_1 = 4$

• This system of (linear) equations can be compactly represented (and solved using matrix algebra) as
$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

INTRINSIC NON-LINEARITY MAKES LEAST-AQUARES MODEL FITTING DIFFICULT

• In an intrinsically non-linear model such as $y_i = \beta_0 e^{\beta_2 x_i} + \varepsilon_i$, the nice trick of solving $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ exactly is impossible



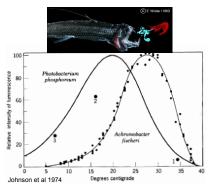


Samraat

OK, FINE, WHY WOULD I EVER NEED NLLS?

- Many observations in biology are just not well-fitted by a linear model
- That is, the underlying biological phenomena/phenomenon are not well-described by a linear equation
- Examples:
 - Michaelis-Menten biochemical (reaction) kinetics
 - Allometric growth
 - Responses of metabolic rates to changing temperature
 - Consumer-Resource (e.g., predator-prey) functional responses
 - Individual growth
 - Population growth
 - Time-series data (e.g., fitting a sinusoidal function)
- Can you think of some examples?

NON-LINEAR MODEL EXAMPLE: TEMPERATURE AND METABOLISM



$$B = B_0 e^{-\frac{E}{kT}} f(T, T_{pk}, E_D)$$

T = temperature (K)

 $k = \text{Boltzmann constant (eV K}^{-1})$

E = Activation energy (eV)

 T_{pk} = Temperature of peak performance

 E_D = Deactivation energy (eV)

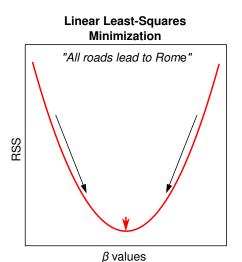
(J H van't Hoff 1884, S Arrhenius 1889)

THE NLLS FITTING METHOD

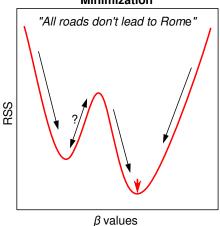
THE NLLS METHOD: OVERVIEW

- OK, so we cannot find an exact, simple solution to the least-squares problem for non-linear models
- But we can use a computer to find a *approximate but close-to-optimal* least-squares solution as follows:
 - Choose starting (initial values for the parameters we want to estimate (β_i 's)
 - Then, adjust the parameters iteratively (using a specific "algorithm" that is better than searching randomly) such that the RSS is gradually decreased
 - Eventually, if it all goes well, a combination of β_j 's that is *very close* to the desired solution (where the RSS is *approximately* minimized) can be found

THE NLLS FITTING / OPTIMIZATION PROCESS



Non-Linear Least-Squares Minimization



THE NLLS FITTING / OPTIMIZATION PROCESS

The general procedure / algorithm is:

- Start with an initial value for each parameter in the model
- Generate the curve defined by the initial values
- Calculate the residual sum-of-squares (RSS)
- Adjust the parameters to make the curve come closer to the data points. *This the tricky part more on this in the next slide*
- Adjust the parameters again so that the curve comes even closer to the points (RSS decreases)
- **6** Repeat 4–5
- Stop simulations when the adjustments make virtually no difference to the RSS

NLLS FITTING / OPTIMIZATION ALGORITHMS

The tricky part — adjust parameters to make curve come closer to the data points (step 4) — has two main algorithms that are generally used:

- The Gauss-Newton algorithm is often used, but doesn't work very well if the model to be fitted is mathematically complicated (the parameter search "landscape" is difficult) and the *starting* values for parameters are far-off-optimal
- The Levenberg-Marquardt algorithm switches between Gauss-Newton and "gradient descent" and is more robust against starting values that are far-off-optimal and is more reliable in most scenarios.

NLLS FITS – ASSESSMENT AND REPORTING

- Once the NLLS fitting is done, you need to get the goodness of fit measures
- First, of course, examine the fits visually
- Report the goodness-fit results:
 - Sums of deviations of the data points from the final model fit (final RSS)
 - Estimated coefficients
 - For each coefficient, standard error (can be used for CI's), t-statistic and corresponding (two-tailed) p-value
- You will learn to calculate all these in the practicals
- You may also want to compare and select between multiple competing models
- Unlike Linear Models, R² values *should not* be used to interpret the quality of the fit of NLLS fit (more on this in the practicals).

NLLS ASSUMPTIONS

NLLS-regression has all the assumptions of OLS-regression:

- No (in practice, minimal) measurement error in explanatory variable (*x*-axis variable)
- Data have constant normal variance errors in the *y*-axis are homogeneously distributed over the *x*-axis range
- The measurement/observation errors are Normally distributed (Gaussian)
- What if the errors are not normal? Interpret results cautiously, and use Maximum Likelihood or Bayesian fitting methods instead

PRACTICALS OVERVIEW

NLLS FITTING PRACTICALS

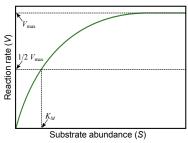
- We will use R
- For fitting simple non-linear models, the nls function in R is sufficient
 - It uses the Gauss-Newton algorithm by default
 - The command is nls()
 - It is part of the stats base package (so no extra installation and loading of package necessary)
- For fitting complex non-linear models the Levenberg-Marquardt (LM) algorithm is better
 - The command is nlsLM()
 - It is available through the minpack.lm package
 http://cran.r-project.org/web/packages/minpack.lm
 - It offers additional features like the ability to "bound" parameters to realistic values

NLLS FITTING PRACTICALS

 We will start with NLLS fitting of the Michaelis-Menten model of biochemical reaction kinetics:

$$V = \frac{V_{\max}[S]}{K_m + [S]}$$

- S = Substrate density
- V_{max} = Maximum reaction rate (at saturating substrate concentration)
- K_M = Half-saturation constant; the S at which reaction rate reaches half of possible maximum (= ½V_{max})



- ullet You will use NLLS fitting to obtain estimates of $V_{\rm max}$ and K_M
- Note that $V_{\text{max}} \le 0$ and $K_M \le 0$ are physically impossible (useful fir picking starting values)

READINGS

 Motulsky, Harvey, and Arthur Christopoulos. Fitting models to biological data using linear and nonlinear regression: a practical guide to curve fitting. OUP USA, 2004.