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

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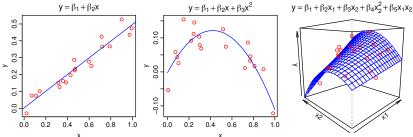
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#### **OUTLINE**

- Why Non-Linear Least Squares regression / fitting?
- The NLLS fitting method
- NLLS in R
- Practicals overview

#### LINEAR MODELS

• Which of these are Linear Models (fitted to data)?



- These are all good Linear Models (really?!)
- The data can be modelled (aka "fitted to a mathematical model") as a *linear combination* of *variables* and *coefficients*
- Easily fitted using Ordinary Least Squares (OLS) regression
- 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  $\beta$ 's)
- Are these models linear in their *parameters*?
  - $y_i = \beta_0 + \beta_1 x_i^{\beta_2} + \varepsilon_i$
  - $y_i = \beta_0 e^{\beta_2 x_i} + \varepsilon_i$
  - $y_i = \frac{\beta_0 x_i}{\beta_1 + x_i} + \varepsilon_i$

NO: at least one parameter ( $\beta$ ) is non-linear (e.g.  $x_i^{\beta_2}$ ,  $e^{\beta_2 x_i}$ , etc.)

## WHY IS INTRINSIC NON-LINEARITY A PROBLEM FOR MDOEL FITTING?

#### 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:  $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$
- The objective of any *least squares* method is to find estimates of values of the parameters ( $\beta_j$ ) that minimize the sum (S) of squared residuals ( $r_i$ ) (AKA RSS):

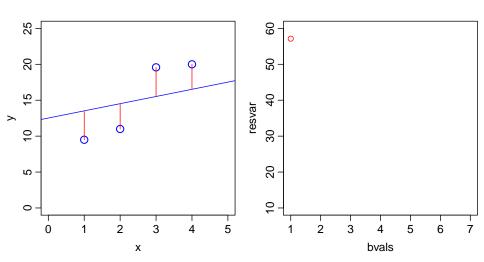
RSS = 
$$S = \sum_{i=1}^{n} [y_i - f(x_i, \beta)]^2 = \sum_{i=1}^{n} r_i^2$$

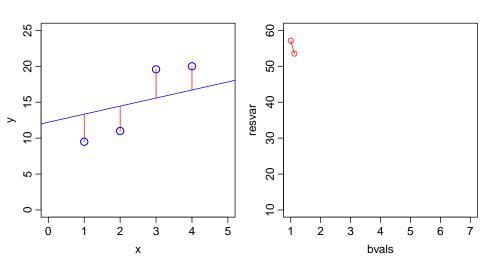
### THE LEAST-SQUARES SOLUTION

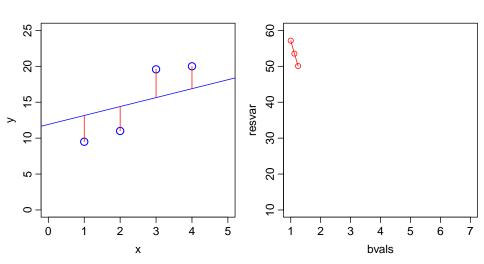
• The objective of any *least squares* method is to find estimates of values of the parameters  $(\hat{\beta}_j)$  that minimize the sum (S) of squared residuals  $(r_i)$  (AKA RSS):

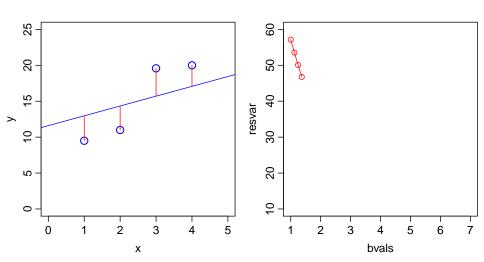
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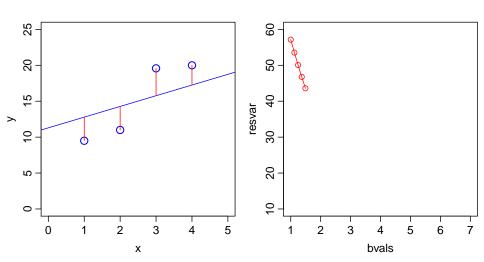
• Let's picture this using a simple (OLS) example; fitting the model  $y_1 = \beta_1 x_1 + \varepsilon_1 \dots$ 

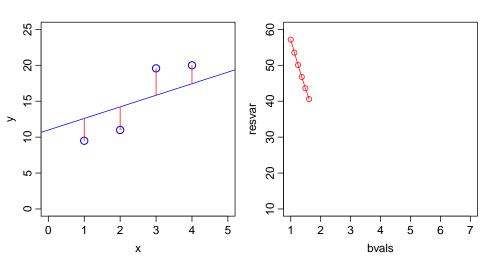


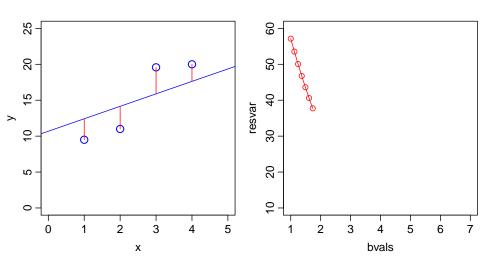


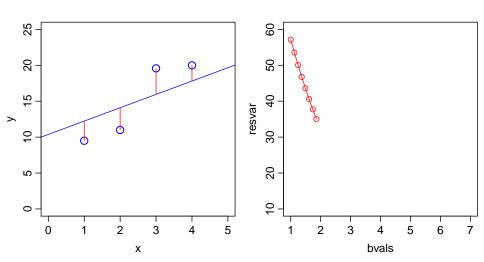


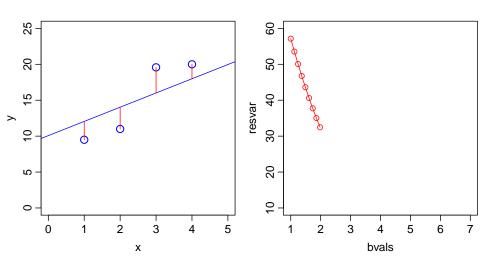


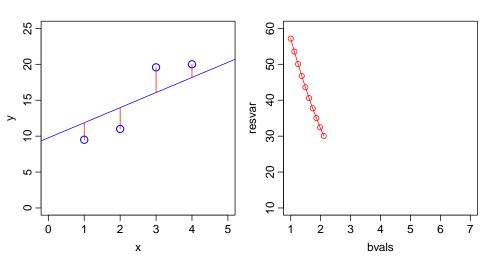


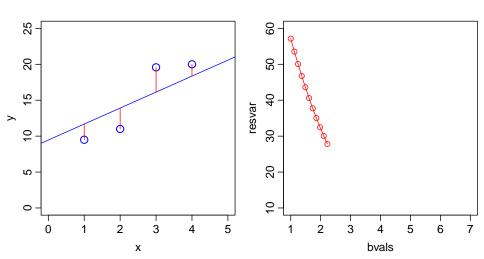


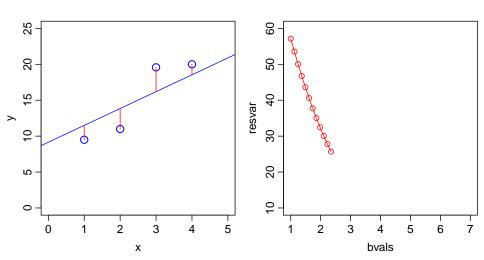


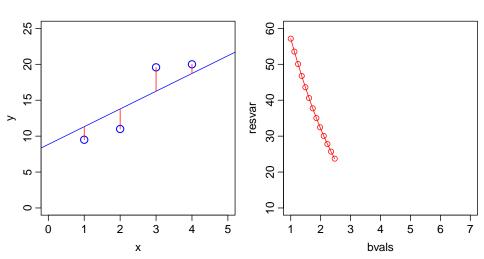


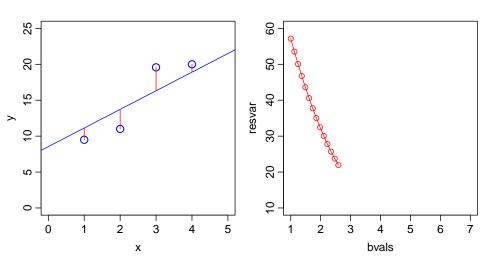


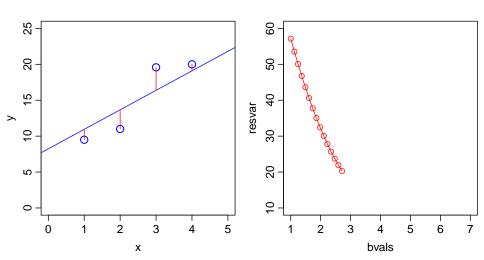


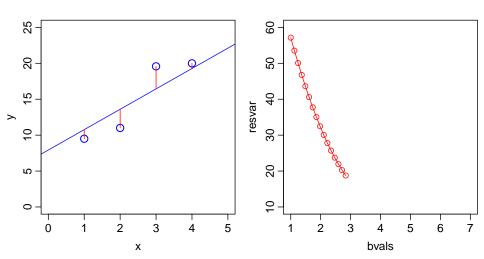


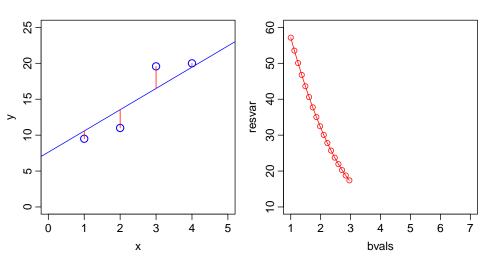


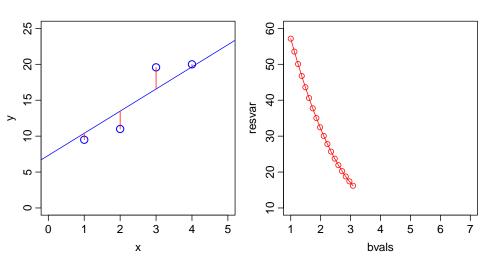


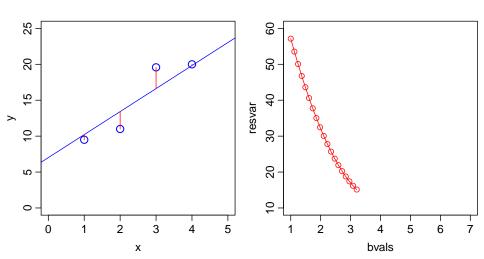


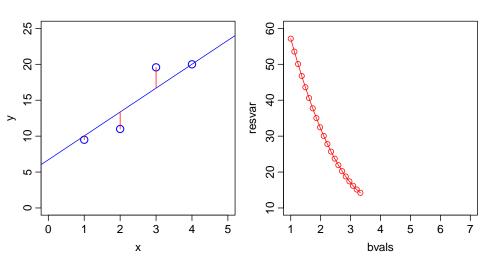


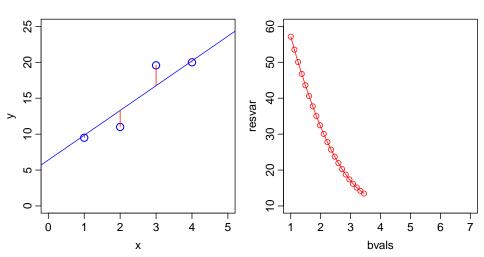


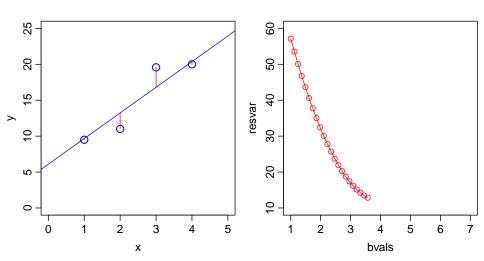


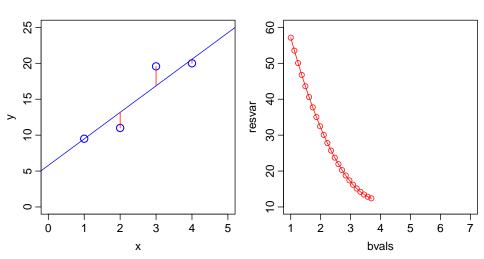


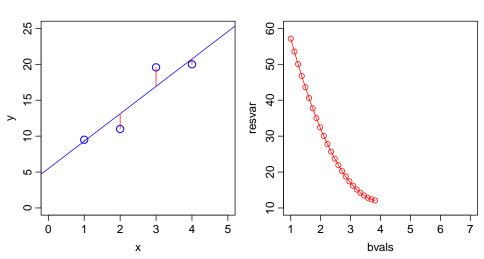


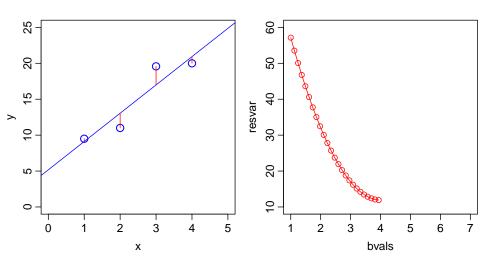


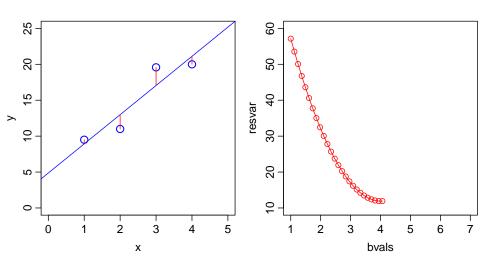


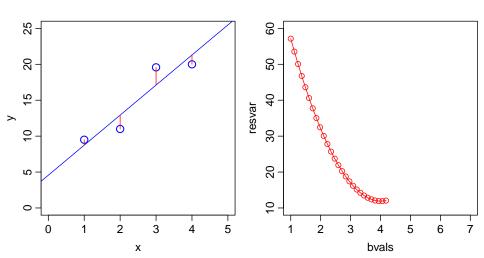


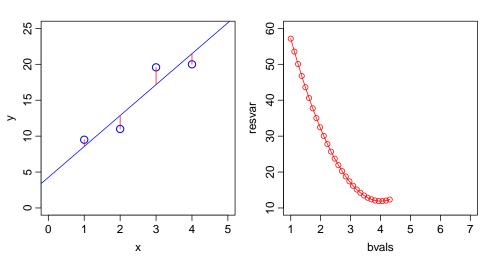


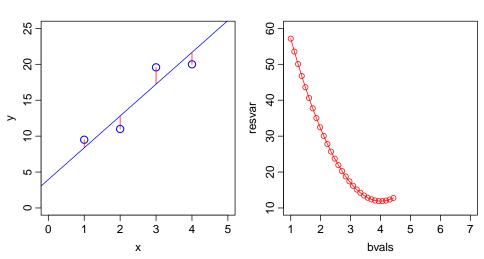


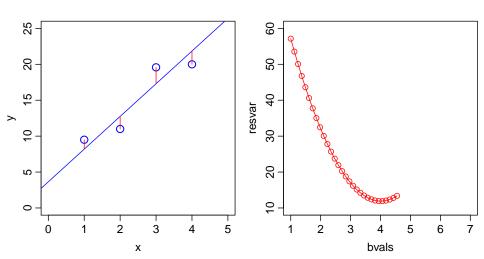


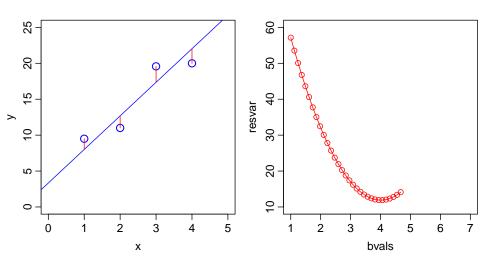


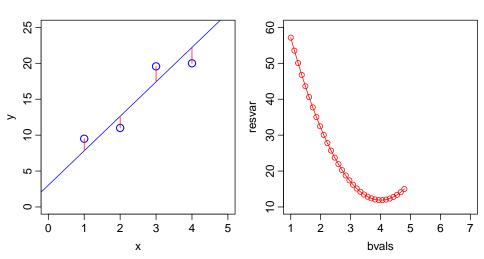


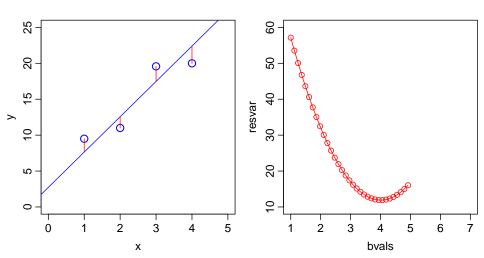


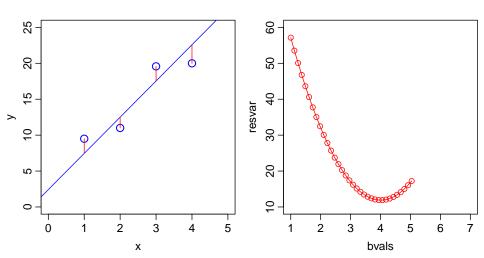


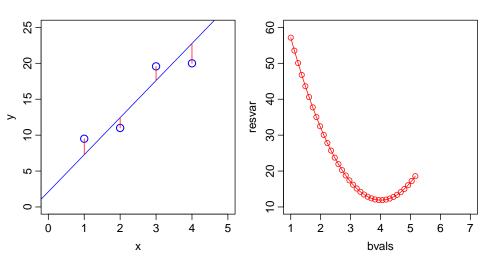


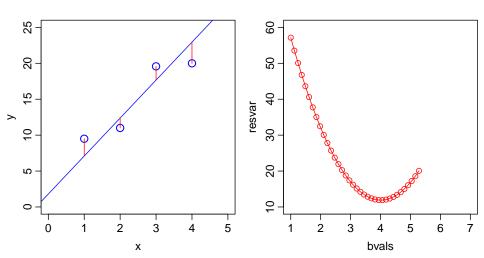


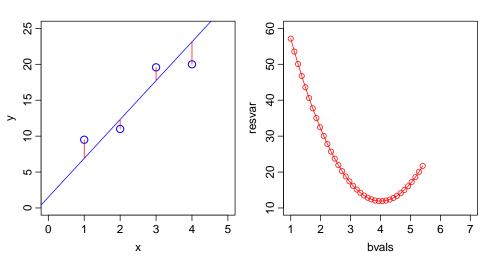


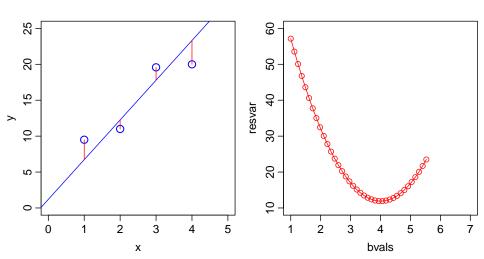


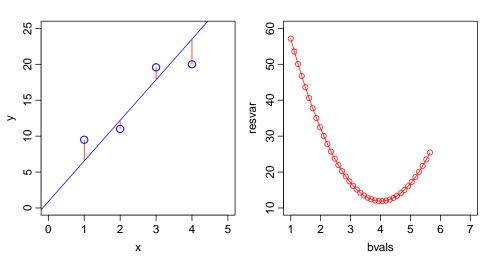


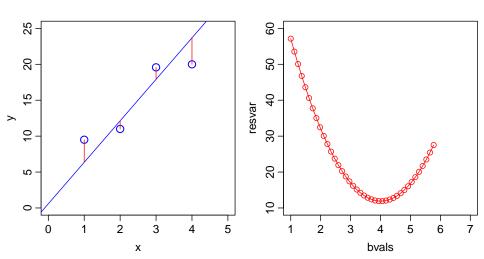


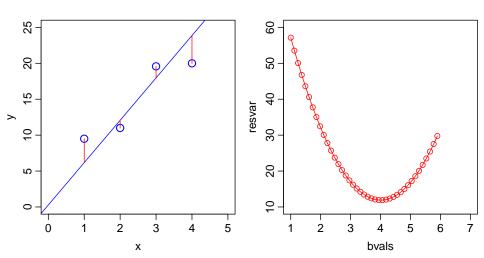


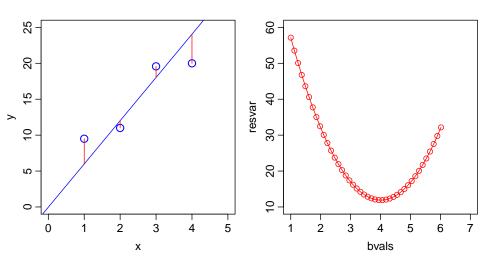


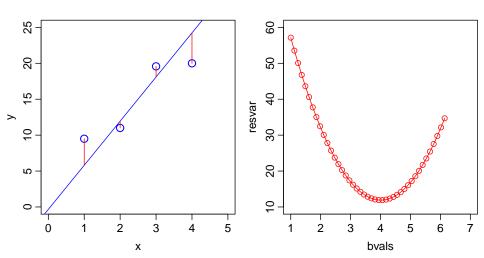


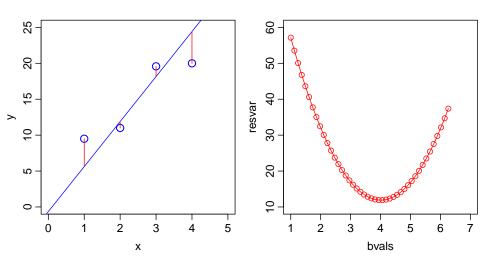


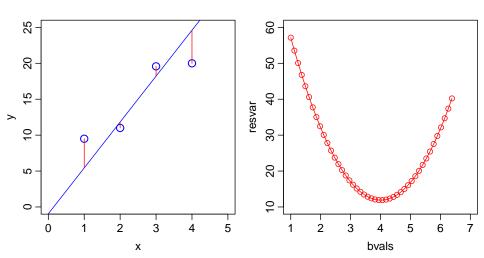


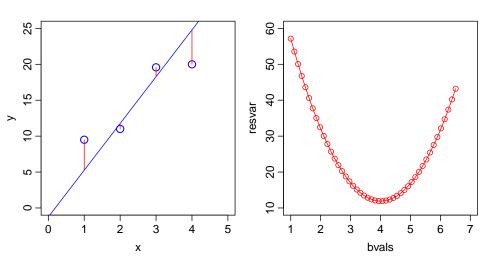


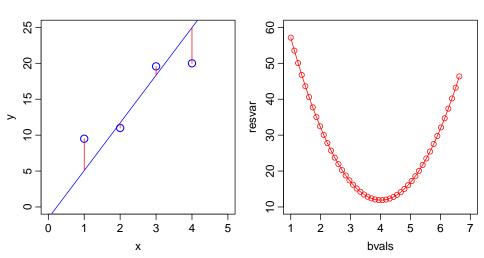


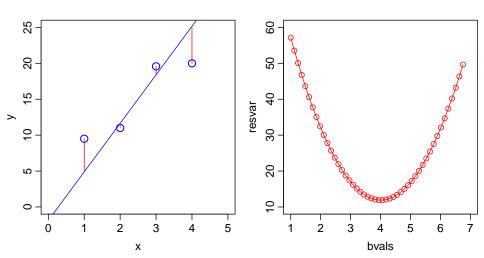


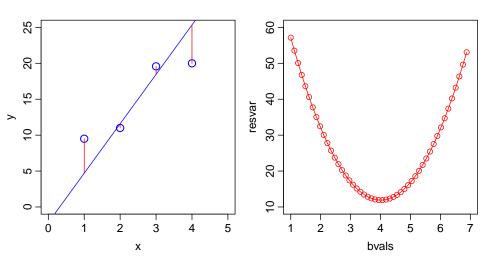


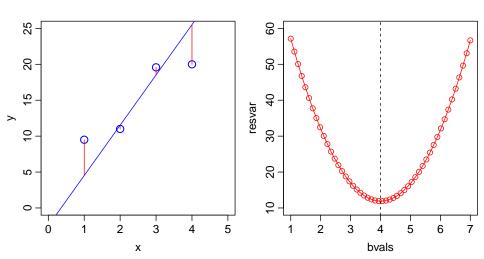




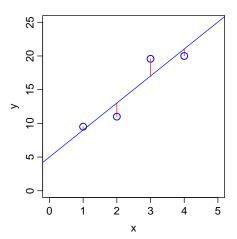








# IF THE MODEL IS LINEAR, THE SOLUTION IS EASY USING ALGEBRA



$$y_1 = \beta_0 + \beta_1 x_1 + \varepsilon_1$$

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

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

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

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

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  $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ 

# WHAT NLLS SOLVES (AND HOW)

• In an intrinsically non-linear model such as

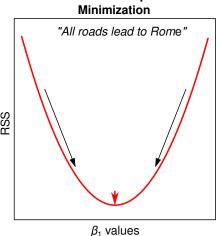
$$y_i = \beta_0 e^{\beta_2 x_i} + \varepsilon_i ,$$

the nice trick of solving  $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$  algebraically is impossible

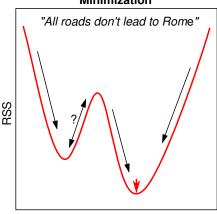
- But we can use brute-force computation to find close-to-optimal least squares minimization:
  - Choose starting (initial values for the parameters we want to estimate (  $\beta_i$ 's)
  - Then, adjust the parameters iteratively (using a specific "algorithm" that is better than searching randomly) such that the RSS is gradually decreased
  - Eventually, if it all goes well, a combination of  $\beta_j$ 's that is *very close* to the desired solution (where the RSS is *approximately* minimized) can be found

#### THE NLLS OPTIMIZATION PROCESS

# **Linear Least-Squares**



#### **Non-Linear Least-Squares** Minimization



# 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?

# **NLLS FITTING**

#### 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)
- Repeat 4–5
- Stop simulations when the adjustments make virtually no difference to the RSS

### **NLLS FITTING**

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 the default in the nls package (part of the stats base package) — good in many cases, but doesn't work very well if the model is mathematically weird (the optimization landscape is difficult) and the starting values for parameters are far-off-optimal
- The Levenberg-Marquardt (LM) algorithm switches switches between Gauss-Newton and "gradient descent" and is more robust against starting values that are far-off-optimal
- the LM algorithm is available in R through the minpack.lm package
   http://cran.r-project.org/web/packages/minpack.lm
- The command is nlsLM

# 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, R<sup>2</sup> values *should not* be used to interpret the quality of the fit of NLLS fit (more on this in the practicals).

# **NLLS ASSUMPTIONS**

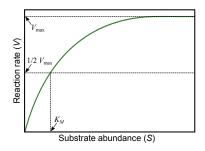
# NLLS-regression has all the assumptions of OLS-regression:

- 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

# PRACTICAL: MICHAELIS-MENTEN BIOCHEMICAL KINETICS

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

- S = Substrate density
- $V_{\max}$  = Maximum reaction rate (at saturating substrate concentration)
- K<sub>M</sub> = Half-saturation constant; the S at which reaction rate reaches half of possible maximum (= ½V<sub>max</sub>)



- ullet You will use NLLS fitting to obtain estimates of  $V_{\rm max}$  and  $K_H$
- Note that  $V_{\text{max}} \le 0$  and  $K_H \le 0$  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.