

Problem 6.2 of Shuler. How to find model parameters in μ via regression.
Instructor: Nam Sun Wang

Specific growth rate is a function of s and pH

$$\mu = \frac{1}{x} \cdot \frac{dx}{dt} = \frac{\mu_m \cdot s}{K_s \cdot \left(1 + 10^{-\text{pH} + \text{pK}_1}\right) + s} = \frac{\mu_m \cdot s}{K_s \cdot \left(1 + \frac{H}{K_1}\right) + s} = \frac{\mu_m \cdot s}{K_{s,\text{app}} + s}$$

Linear Regression. Given experimental data (t, x, s) at several pH values, find μ_m , K_s , and K_1 .

Step 1. calculate μ $\mu = \frac{1}{x} \cdot \frac{dx}{dt}$

Step 2. for each pH value, find μ_m and $K_{s,\text{app}}$ via linear regression.

Regress $1/\mu$ versus $1/s$ (double reciprocal, Lineweaver-Burk, or Eadie-Hofstee, or Hanes-Woolf)

$$\frac{1}{\mu} = \frac{1}{\mu_m} + \frac{K_{s,\text{app}}}{\mu_m} \cdot \frac{1}{s} \quad \mu_m = \frac{1}{\text{intercept}} \quad K_{s,\text{app}} = \frac{\text{slope}}{\text{intercept}}$$

Decreasing pH (increasing H) increases $K_{s,\text{app}}$; thus, increases the slope, while the intercept remains unchanged.

Step 3. From $K_{s,\text{app}}$ and pH, find K_s and K_1 via linear regression.

Regress $K_{s,\text{app}}$ versus H

$$K_{s,\text{app}} = K_s + \frac{K_s}{K_1} \cdot H \quad K_s = \text{intercept} \quad K_1 = \frac{\text{intercept}}{\text{slope}}$$

Or we can combine Step 2 & Step 3. find μ_m , K_s , & K_1 via linear regression.

Regress $1/\mu$ versus $1/s$, and H/s .

$$\frac{1}{\mu} = \frac{1}{\mu_m} + \frac{K_{s,\text{app}}}{\mu_m} \cdot \frac{1}{s} = \frac{1}{\mu_m} + \frac{K_s}{\mu_m} \cdot \frac{1}{s} + \frac{K_s}{\mu_m \cdot K_1} \cdot \frac{H}{s} = a_0 \cdot 1 + a_1 \cdot \frac{1}{s} + a_2 \cdot \frac{H}{s} = \begin{pmatrix} 1 & \frac{1}{s} & \frac{H}{s} \end{pmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = X \cdot a$$

$$a = (X^T \cdot X)^{-1} \cdot X^T \cdot \frac{1}{\mu} \quad \longrightarrow \quad \mu_m = \frac{1}{a_0} \quad K_s = \frac{a_1}{a_0} \quad K_1 = \frac{K_s}{\mu_m \cdot a_2} = \frac{a_1}{a_2}$$

Nonlinear Regression. However, because this is inherently a nonlinear problem, it is far more reliable to estimate model parameters via nonlinear regression in practice. Furthermore, μ values calculated through dx/dt amplify the experimental error in x . Steps in nonlinear regression.

Step 1. Integrate with Euler's method to generate predicted values of x based on the given μ_m , K_s , K_1 .

$$\mu(s, H, \mu_m, K_s, K_1) = \frac{\mu_m \cdot s}{K_s \cdot \left(1 + \frac{H}{K_1}\right) + s}$$

Start with $x_{\text{pred}_0} = x_0$

for $i=0 \dots n-1$ $x_{\text{pred}_{i+1}} = x_{\text{pred}_i} + \mu(s_i, H_i, \mu_m, K_s, K_1) \cdot x_{\text{pred}_i} \cdot (t_{i+1} - t_i)$

Step 2. Define an error function that returns the sum of squared error.

$$\text{sse}(\mu_m, K_s, K_1) = \sum_i (x_{\text{pred}_i} - x_i)^2$$

Step 3. Minimize sse by changing μ_m , K_s , K_1 .

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For $\text{pH} < (\text{p}K_1 + \text{p}K_2)/2$, decreasing pH increases $K_{s,\text{app}}$; for $(\text{p}K_1 + \text{p}K_2)/2 < \text{pH}$, increasing pH increases $K_{s,\text{app}}$ thus, increases the slope, while the intercept remains unchanged.

Step 3. From $K_{s,\text{app}}$ and pH , find K_s , K_1 & K_2 via linear regression.

Regress $K_{s,\text{app}}$ versus $1, H, \& 1/H$

$$K_{s,\text{app}} = K_s \cdot 1 + \frac{K_s}{K_1} \cdot H + K_s \cdot K_2 \cdot \frac{1}{H} = a_0 \cdot 1 + a_1 \cdot H + a_2 \cdot \frac{1}{H} = \begin{pmatrix} 1 & H & \frac{1}{H} \end{pmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = X \cdot a$$

$$a = (X^T \cdot X)^{-1} \cdot X^T \cdot K_{s,\text{app}} \quad \longrightarrow \quad K_s = a_0 \quad K_1 = \frac{a_0}{a_1} \quad K_2 = \frac{a_2}{a_0}$$

Or we can combine Step 2 & Step 3. find μ_m , K_s , K_1 & K_2 via linear regression.

Regress $1/\mu$ versus $1, 1/s, \& H/s, 1/(H \cdot s)$.

$$\frac{1}{\mu} = \frac{1}{\mu_m} + \frac{K_{s,\text{app}}}{\mu_m} \cdot \frac{1}{s} = \frac{1}{\mu_m} + \frac{K_s}{\mu_m} \cdot \frac{1}{s} + \frac{K_s}{\mu_m \cdot K_1} \cdot \frac{H}{s} + \frac{K_s \cdot K_2}{\mu_m} \cdot \frac{1}{H \cdot s} = a_0 \cdot 1 + a_1 \cdot \frac{1}{s} + a_2 \cdot \frac{H}{s} + a_3 \cdot \frac{1}{H \cdot s} = \begin{pmatrix} 1 & \frac{1}{s} & \frac{H}{s} & \frac{1}{H \cdot s} \end{pmatrix} \cdot \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{bmatrix} = X \cdot a$$

$$a = (X^T \cdot X)^{-1} \cdot X^T \cdot \frac{1}{\mu} \quad \longrightarrow \quad \mu_m = \frac{1}{a_0} \quad K_s = \frac{a_1}{a_0} \quad K_1 = \frac{K_s}{\mu_m \cdot a_2} = \frac{a_1}{a_2} \quad K_2 = \frac{\mu_m}{K_s} \cdot a_3 = \frac{a_3}{a_1}$$

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