

$$t0 := \text{time}(1)$$

1. Define two vectors.

$$x := \begin{bmatrix} 0.132 \\ 0.322 \\ 0.511 \\ 0.701 \\ 0.891 \\ 1.082 \\ 1.27 \\ 1.46 \\ 1.65 \\ 1.839 \\ 2.029 \\ 2.219 \end{bmatrix} \quad y := \begin{bmatrix} 0.1 \\ 0.258 \\ 0.543 \\ 0.506 \\ 0.606 \\ 0.622 \\ 0.569 \\ 0.453 \\ 0.438 \\ 0.316 \\ 0.29 \\ 0.195 \end{bmatrix} \quad \beta := \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$$

$$n := \text{length}(\beta) \quad m := \text{length}(x)$$

2. Define a fitting function (Weibull density with unknown parameters).

FUNCTION

$$ft(x) := \beta_1 \cdot \beta_2 \cdot x^{\beta_2 - 1} \cdot \exp\left(-\beta_1 \cdot x^{\beta_2}\right)$$

Jacobian matrix for finite differences

$$\text{derfh}(\beta) := \begin{array}{|l} \text{for } i \in [1..m] \\ \quad \text{for } j \in [1..n] \\ \quad \quad \beta_j := \beta_j + h \\ \quad \quad \text{jjh1} := ft(x)_i \\ \quad \quad \beta_j := \beta_j - 2 \cdot h \\ \quad \quad \text{jjh2} := ft(x)_i \\ \quad \quad \text{jjh0}_{ij} := \frac{\text{jjh1} - \text{jjh2}}{2 \cdot h} \\ \quad \quad \beta_j := \beta_j + h \\ \text{jjh0} \end{array}$$

3. Define initial guess values for the two parameters.

Initial Assumption Values Vector

$$\beta := [0.8 \ 1]^T$$

4. Use an equation to minimize inside a solve block.

Function adjusted to the data

$$fx(\beta) := \begin{array}{|l} \text{for } i \in [1..m] \\ \quad f_i := ft(x_i) - \text{eval}(y_i) \\ f \end{array}$$

Example: Using minerr for Nonlinear

The **minerr** function is similar to the **find** function, except that it returns an array of residuals.

1. Define two vectors.

$$x := \begin{bmatrix} 0.132 \\ 0.322 \\ 0.511 \\ 0.701 \\ 0.891 \\ 1.081 \\ 1.27 \\ 1.46 \\ 1.65 \\ 1.839 \\ 2.029 \\ 2.219 \end{bmatrix}$$

$$n := \text{length}(y) - 1$$

2. Define a fitting function (Weibull density with unknown parameters).

$$Wb(x, \alpha, \beta) := \alpha \cdot \beta \cdot x^{\beta - 1} \cdot \exp(-\alpha \cdot x^\beta)$$

3. Define initial guess values for the two parameters.

$$\alpha := 0.8$$

$$\beta := 1$$

4. Use an equation to minimize inside a solve block.

$$\text{resid}(\alpha, \beta) := y - \overline{Wb(x, \alpha, \beta)}$$

5. Add a solve block and use **minerr** to solve the problem. The **minerr** function returns the minimum of the summing and squaring of the residuals.

$$0 = \text{resid}(\alpha, \beta)$$

$$\begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} := \text{minerr}(\alpha, \beta)$$

5. Use the Levenberg-Marquardt method to minimize this problem.

LEVENBERG MARQUARDT METHOD

$$\left[\begin{array}{l} \text{Eps} := 1.110 \cdot 10^{-16} \quad \text{eta1} := \sqrt{\text{Eps}} \quad \text{eta2} := \text{eta1} \quad \text{h} := \text{eta1} \quad \text{tol} := \sqrt{\text{Eps}} \cdot \text{normi}(\beta) \end{array} \right]$$

$$f := f_x(\beta) \quad J := \text{derfh}(\beta)$$

$$A := J^T \cdot J \quad g := J^T \cdot f \quad ng := \text{normi}(g)$$

$$F := \frac{f^T \cdot f}{2} \quad \mu := \text{eta1} \cdot \max(\text{Diag}(A)) \quad \text{nu} := 2 \quad \text{stop} := 0$$

while $\neg \text{stop}$

 if $ng \leq \text{eta2}$

$\text{stop} := 1$

 else

 try

$p := (A + \mu \cdot \text{identity}(n))^{-1} \cdot (-g)$

 on error

 break

$np := \text{normi}(\beta)$

$nx := \text{eta2} + \text{normi}(\beta)$

 if $np \leq \text{eta2} \cdot nx$

$\text{stop} := 2$

 else

 ""

 if $\neg \text{stop}$

$x_{\text{new}} := \beta + p$

$f_n := f_x(x_{\text{new}})$

$J_n := \text{derfh}(x_{\text{new}})$

$F_n := \frac{f_n^T \cdot f_n}{2}$

$dL := \frac{p^T \cdot (\mu \cdot p - g)}{2}$

$dF := F - F_n$

 if $(dL_1 > 0) \wedge (dF_1 > 0)$

$\beta := x_{\text{new}}$

$F := F_n$

$J := J_n$

$f := f_n$

$A := J^T \cdot J$

$g := J^T \cdot f$

$ng := \text{normi}(g)$

$\mu := \mu \cdot \text{Max} \left(\frac{1}{3}, 1 - \left(2 \cdot \frac{dF_1}{dL_1} - 1 \right)^3 \right)$

$\text{nu} := 2$

 else

$\mu := \mu \cdot \text{nu}$

$\text{nu} := 2 \cdot \text{nu}$

 else

 ""

The parameters for best fit are the calculated values:

SOLUTION

$$\beta = \begin{bmatrix} 0.502 \\ 2.00 \end{bmatrix}$$

6. Calculate the sum of squares implicitly minimized by this method (By JEAN).

$$f(x, \beta) := \beta_1 \cdot \beta_2 \cdot x^{\beta_2 - 1} \cdot \exp\left(-\beta_1 \cdot x^{\beta_2}\right)$$

$$t := x$$

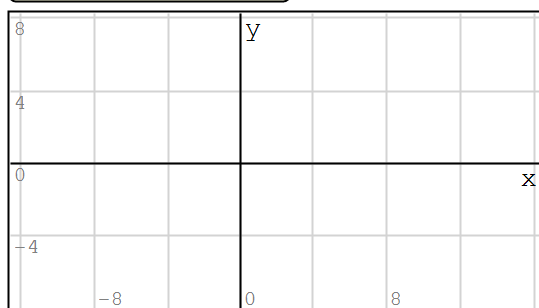
Relative residuals

```
Residuals:=for i∈[1..rows(t)]
              Δi:=eval(1 -  $\frac{y_i}{f(t_i, \beta)}$ )
              augment(t, Δ)
```

SSD = "Sum Square Differences"

$$SSD := \sum_{i=1}^m \left(y_i - f(t_i, \beta) \right)^2 = 0.0186$$

Relative residuals



{BarSize(Residuals, 0.0394)}

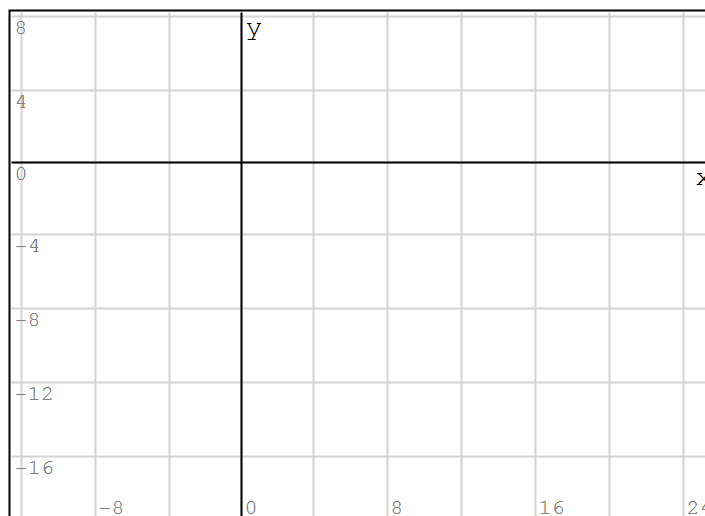
RMS difference

$$\sqrt{\frac{SSD}{m}} = 0.0394$$

7. Plot the best Weibull fit versus the x-y data.

data:=plotG(x, y, ".", 12, "blue")

```
FIT:= "range, populate"
      U:=[0, 0.01..4]
      for i∈[1..rows(U)]
        vyi:=eval(f(Ui, β))
      augment(U, vy)
```



{data
FIT}

$$\text{time}(1) - t_0 = 2.688 \text{ s}$$

The parame

$$\begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} = \begin{bmatrix} 0. \\ 2 \end{bmatrix}$$

The **find** f

0=resi

$$\begin{bmatrix} \alpha_2 \\ \beta_2 \end{bmatrix} :=$$

6. Calculate

$$SSE(\alpha, \beta)$$

7. Plot the b

$$z := 0, 0.1, \dots$$

$$Wb(z)$$

$$y_i$$

8. Evaluate t

$$SSE(\alpha_1, \beta_1)$$