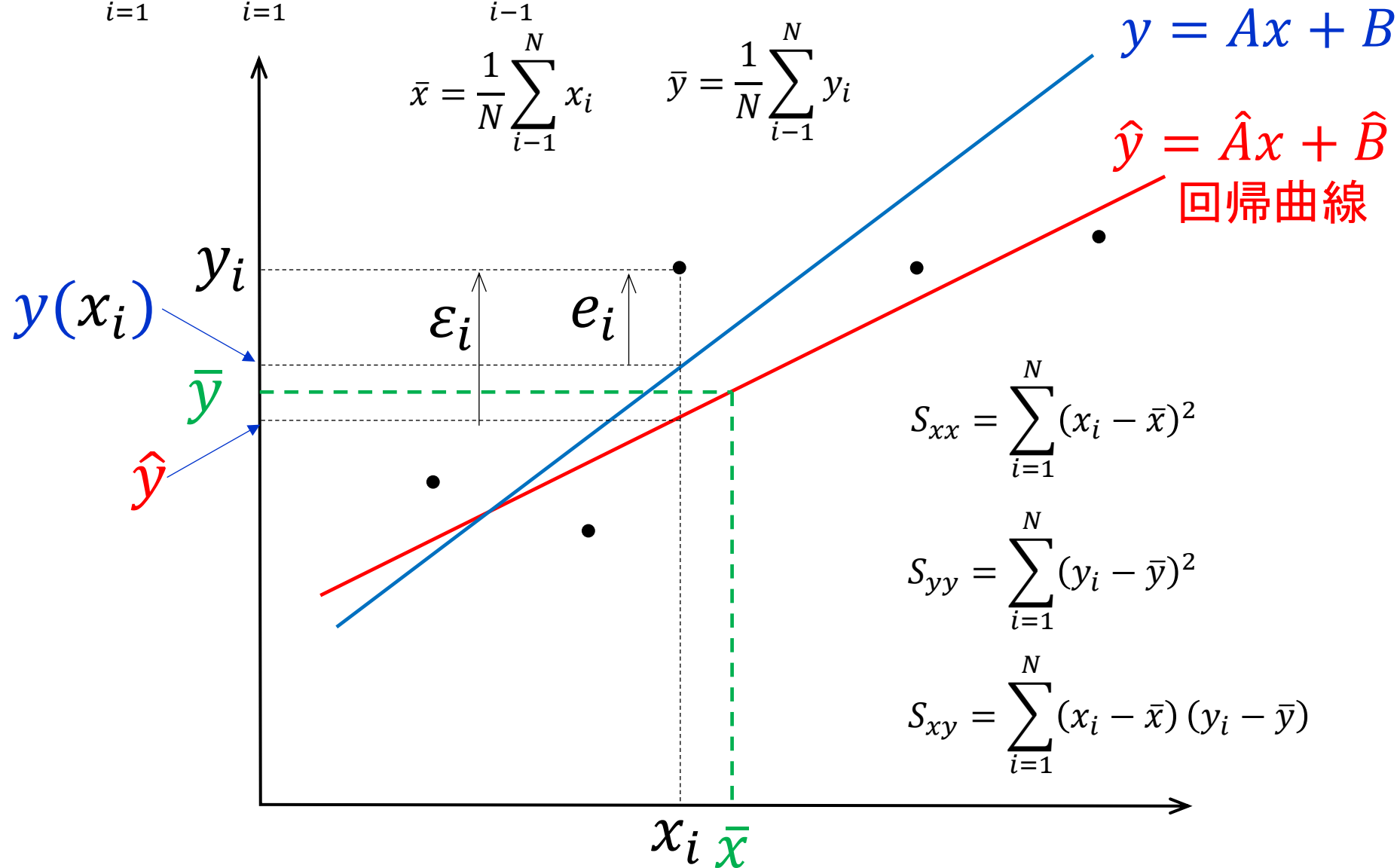


回帰曲線の信頼・予測区間を算出

$$S_{\varepsilon\varepsilon} = \sum_{i=1}^N \varepsilon_i^2 = \sum_{i=1}^N (y_i - \hat{y}_i)^2 = \sum_{i=1}^N (y_i - \hat{B} - \hat{A}x_i)^2$$

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i \quad \bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$$



$$\overline{x^2} = \frac{1}{N} \sum_{i=1}^N x_i^2$$

$$\begin{aligned} S_{xx} &= \sum_{i=1}^N (x_i - \bar{x})^2 = \sum_{i=1}^N x_i^2 - 2 \sum_{i=1}^N x_i \bar{x} + \sum_{i=1}^N \bar{x}^2 = N \overline{x^2} - 2N\bar{x}^2 + N\bar{x}^2 \\ &= N(\overline{x^2} - \bar{x}^2) \end{aligned}$$

$$\overline{y^2} = \frac{1}{N} \sum_{i=1}^N y_i^2$$

$$\begin{aligned} S_{yy} &= \sum_{i=1}^N (y_i - \bar{y})^2 = \sum_{i=1}^N y_i^2 - 2 \sum_{i=1}^N y_i \bar{y} + \sum_{i=1}^N \bar{y}^2 = N \overline{y^2} - 2N\bar{y}^2 + N\bar{y}^2 \\ &= N(\overline{y^2} - \bar{y}^2) \end{aligned}$$

$$\begin{aligned} S_{xy} &= \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}) = \sum_{i=1}^N (x_i y_i - \bar{x} y_i - x_i \bar{y} + \bar{x} \bar{y}) \\ &= N\overline{xy} - 2N\bar{x}\bar{y} + N\bar{x}\bar{y} \\ &= N(\overline{xy} - \bar{x}\bar{y}) \end{aligned}$$

回帰曲線 $\hat{y} = \hat{A}x + \hat{B}$ の係数 $\hat{A}$ 及び $\hat{B}$ を最小二乗法で算出する

$$S_{\varepsilon\varepsilon} = \sum_{i=1}^N \varepsilon_i^2 = \sum_{i=1}^N (y_i - \hat{y}_i)^2 = \sum_{i=1}^N (y_i - \hat{B} - \hat{A}x_i)^2$$

$$\frac{\partial S_{\varepsilon\varepsilon}}{\partial \hat{B}} = -2 \sum_{i=1}^N (y_i - \hat{B} - \hat{A}x_i) = 0 \quad \longrightarrow \quad \hat{B} + \hat{A}\bar{x} = \bar{y}$$

$$\frac{\partial S_{\varepsilon\varepsilon}}{\partial \hat{A}} = -2 \sum_{i=1}^N (y_i - \hat{B} - \hat{A}x_i) x_i = 0$$

$$\sum_{i=1}^N (y_i - \hat{B} - \hat{A}x_i) x_i = \sum_{i=1}^N (x_i y_i - \hat{B} x_i - \hat{A} x_i^2) = N\bar{x}\bar{y} - N\hat{B}\bar{x} - N\hat{A}\bar{x}^2$$

$$= 0$$

$$S_{xx} = N(\bar{x}^2 - \bar{x}^2) \quad S_{yy} = N(\bar{y}^2 - \bar{y}^2) \quad S_{xy} = N(\bar{x}\bar{y} - \bar{x}\bar{y})$$

$$N\hat{B}\bar{x} + (S_{xx} + N\bar{x}^2)\hat{A} = S_{xy} + N\bar{x}\bar{y}$$

$$\hat{B} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

$$\hat{A} = \frac{S_{xy}}{S_{xx}}$$

$$\hat{A} = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} \sqrt{\frac{S_{yy}}{S_{xx}}} = r \sqrt{\frac{S_{yy}}{S_{xx}}}$$

$$\hat{A} = \frac{S_{xy}}{S_{xx}} = \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}) \frac{1}{S_{xx}} = \sum_{i=1}^N \frac{(x_i - \bar{x})}{S_{xx}} (y_i - \bar{y})$$

$$y_i - \bar{y} \text{の分散が}\sigma^2\text{とする} \quad V_{\hat{A}} = \sum_{i=1}^N \left(\frac{x_i - \bar{x}}{S_{xx}} \right)^2 \sigma^2 = \frac{\sigma^2}{S_{xx}}$$

$$\hat{B} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x} \quad \text{の分散は}$$

$$V_{\hat{B}} = V_{\bar{y}} + \bar{x}^2 V_{\hat{A}} = \left(\frac{\sigma}{\sqrt{N}} \right)^2 + \bar{x}^2 \frac{\sigma^2}{S_{xx}} = \left(\frac{1}{N} + \frac{\bar{x}^2}{S_{xx}} \right) \sigma^2$$

↑ 標本平均の分散

$$\hat{y} = \hat{A}(x - \bar{x}) + \bar{y}$$

$$V_{\hat{y}} = V_{\hat{A}}(x - \bar{x})^2 + \left(\frac{1}{N} \right) \sigma^2 = \frac{\sigma^2}{S_{xx}} (x - \bar{x})^2 + \left(\frac{1}{N} \right) \sigma^2 = \left(\frac{1}{N} + \frac{(x - \bar{x})^2}{S_{xx}} \right) \sigma^2$$

σ^2 を自由度N-2の不偏分散 $\hat{V}_E = S_{\varepsilon\varepsilon}/(N-2)$ に置き換えて

$$V_{\hat{y}} = V_{\hat{A}}(x - \bar{x})^2 + \left(\frac{1}{N} \right) \sigma^2 = \frac{\sigma^2}{S_{xx}} (x - \bar{x})^2 + \left(\frac{1}{N} \right) \sigma^2 = \left(\frac{1}{N} + \frac{(x - \bar{x})^2}{S_{xx}} \right) \hat{V}_e$$

回帰曲線 $\hat{y} = \hat{A}x + \hat{B}$ の信頼度 $1 - \alpha$ の信頼区間は、

$$\hat{A}x + \hat{B} \pm t(N-2, \alpha) \sqrt{\left(\frac{1}{N} + \frac{(x - \bar{x})^2}{S_{xx}} \right) \hat{V}_e}$$

回帰曲線 $\hat{y} = \hat{A}x + \hat{B}$ の信頼度 $1 - \alpha$ の信頼区間は、

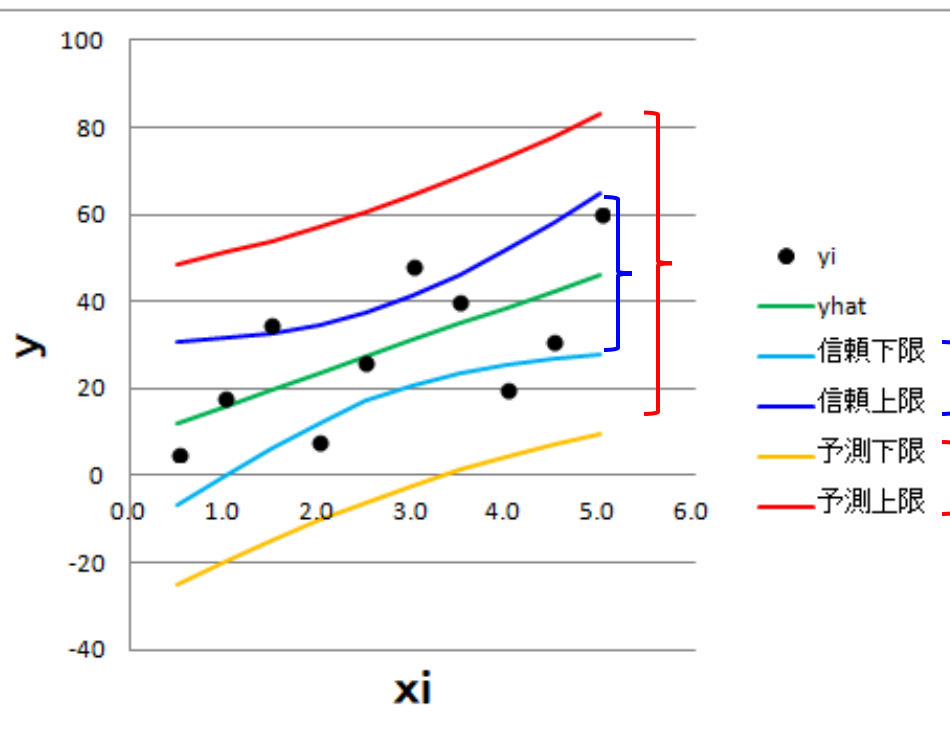
信頼区間

$$\hat{A}x + \hat{B} \pm t(N - 2, \alpha) \sqrt{\left(\frac{1}{N} + \frac{(x - \bar{x})^2}{S_{xx}}\right) \hat{V}_e}$$

回帰曲線 $\hat{y} = \hat{A}x + \hat{B}$ の信頼度 $1 - \alpha$ の予測区間は、

予測区間

$$\hat{A}x + \hat{B} \pm t(N - 2, \alpha) \sqrt{\left(1 + \frac{1}{N} + \frac{(x - \bar{x})^2}{S_{xx}}\right) \hat{V}_e}$$



回帰曲線 $\hat{y} = \hat{A}x + \hat{B}$ は信頼度 $1 - \alpha$ でこの区間に入る

観測値 y_i は信頼度 $1 - \alpha$ でこの区間に入る

Excelで回帰曲線の信頼・予測区間を算出

$$y = \hat{A}x_i + \hat{B} \pm t(n-2, \alpha) \sqrt{\left\{ \frac{1}{N} + \frac{(x_i - \bar{x})^2}{S_{xx}} \right\} \hat{V}_e}$$

$$y = \hat{A}x_i + \hat{B} \pm t(n-2, \alpha) \sqrt{\left\{ 1 + \frac{1}{N} + \frac{(x_i - \bar{x})^2}{S_{xx}} \right\} \hat{V}_e}$$

	xi	yi	xi-xbar	yi-ybar	yhati	ei	信頼下限	信頼上限	予測下限	予測上限
1	0.5	5	-2.3	-24.1	11.9	-6.9	-6.69	30.58	-24.83	48.72
2	1.0	18	-1.8	-11.1	15.8	2.2	-0.05	31.56	-19.67	51.18
3	1.5	35	-1.3	5.9	19.6	15.4	6.28	32.86	-14.81	53.95
4	2.0	8	-0.8	-21.1	23.4	-15.4	12.07	34.69	-10.28	57.04
5	2.5	26	-0.3	-3.1	27.2	-1.2	17.02	37.37	-6.10	60.49
6	3.0	48	0.3	18.9	31.0	17.0	20.83	41.18	-2.29	64.30
7	3.5	40	0.8	10.9	34.8	5.2	23.51	46.13	1.16	68.48
8	4.0	20	1.3	-9.1	38.6	-18.6	25.34	51.92	4.25	73.01
9	4.5	31	1.8	1.9	42.4	-11.4	26.64	58.25	7.02	77.87
10	5.0	60	2.3	30.9	46.3	13.7	27.62	64.89	9.48	83.03

平均値	2.75	29.1
σ	1.44	16.46

=SUMPRODUCT(D2:D11,E2:E11)

$$S_e = \sum_{i=1}^N e_i$$

Ahat	7.62	Sxy	157.25
Bhat	8.13	Sxx	20.63

=SUMSQ(D2:D11)

Se	1511.99	t(n-2,α)	2.31
n	10		
Ve	189.00		

$$\hat{A} = \frac{S_{xy}}{S_{xx}}$$

$$\hat{B} = \bar{y} - \frac{S_{xy}}{S_{xx}} \bar{x}$$

$$V_e = \frac{S_e}{N-2}$$

=TINV(0.05,8)

α5%

N-2 = 10 - 2