

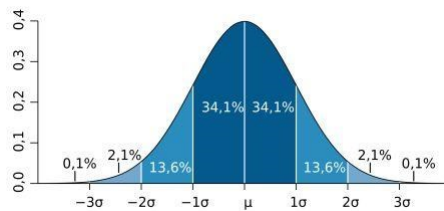
Statistics and Probability Dictionary

Select a term from the dropdown text box. The online statistics glossary will display a definition, plus links to other related web pages.

Select term: Central Limit Theorem

Central Limit Theorem

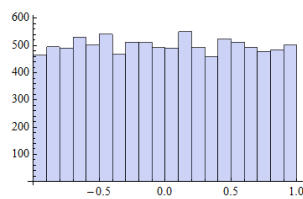
The **central limit theorem** states that the sampling distribution of the mean of any **independent, random variable** will be normal or nearly normal, if the sample size is large enough.



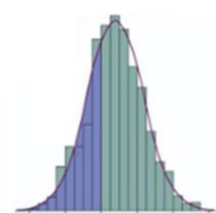
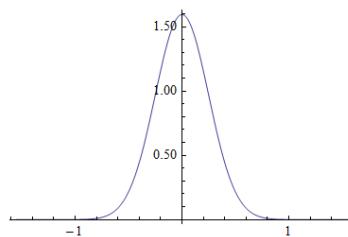
$$f(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Distribució Gaussian

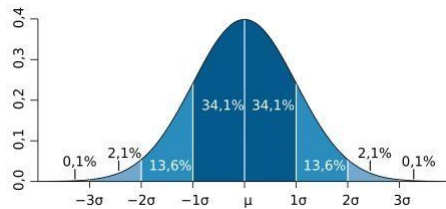
Histogram[RandomReal[{-1, 1}, 10 000]]



```
n = 1000;
data = Table[0, {i, 1, n}];
For[i = 1, i ≤ n, i++,
  data[[i]] = Mean[RandomReal[{-1, 1}, 10 000]];
SmoothHistogram[data, 0.25]
```



Distribució Gaussiana



$$\mu = \bar{x} \pm 2 \sigma$$

Mesures indirectes $y = f(x)$

$$\bar{y} = \frac{1}{N} \sum_i f(x_i) = \frac{1}{N} \sum_i f(\bar{x} + \delta_i) \cong \frac{1}{N} \sum_i \left[f(\bar{x}) + \delta_i \left(\frac{df}{dx} \right) \right] = f(\bar{x}) + \frac{1}{N} \sum_i f(\delta_i) = f(\bar{x})$$

Propagació de la imprecisió

$$y = f(x) \rightarrow dy = \left(\frac{df}{dx} \right) dx \rightarrow (y - y_i)^2 = \left(\frac{df}{dx} \right)^2 (x - x_i)^2$$

$$\sum_i (y - y_i)^2 = \left(\frac{df}{dx} \right)^2 \sum_i (x - x_i)^2 \rightarrow \boxed{S_y^2 = \left(\frac{df}{dx} \right)^2 S_x^2}$$

Propagació de la imprecisió: dos variables

$$z = f(x, y) \rightarrow dz = \left(\frac{\partial f}{\partial x} \right) dx + \left(\frac{\partial f}{\partial y} \right) dy$$

$$\rightarrow (z - z_{ij}) = \left(\frac{\partial f}{\partial x} \right) (x - x_i) + \left(\frac{\partial f}{\partial y} \right) (y - y_j)$$

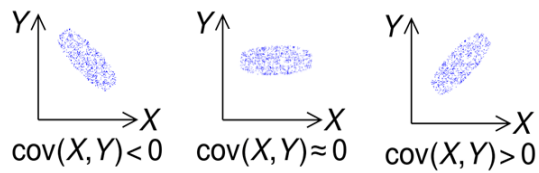
$$\rightarrow \frac{1}{N^2} \sum_{i,j} (z - z_{ij})^2 = \frac{1}{N^2} \left(\frac{\partial f}{\partial x} \right)^2 N \sum_i (x - x_i)^2 + \frac{1}{N^2} \left(\frac{\partial f}{\partial y} \right)^2 N \sum_j (y - y_j)^2 + \frac{2}{N^2} \left(\frac{\partial f}{\partial x} \right) \left(\frac{\partial f}{\partial y} \right) \sum_i (x - x_i) \sum_j (y - y_j)$$

$$\boxed{S_z^2 = \left(\frac{df}{dx} \right)^2 S_x^2 + \left(\frac{df}{dy} \right)^2 S_y^2 + 2 \left(\frac{\partial f}{\partial x} \right) \left(\frac{\partial f}{\partial y} \right) S_{xy}^2}$$

$$x, y \text{ indep.} \rightarrow S_{xy}^2 = 0$$

$$\boxed{S_f^2 = \sum_i \left(\frac{\partial f}{\partial x_i} \right)^2 S_{x_i}^2}$$

$$\frac{1}{N^2} \sum_{ij} (\bar{x} - x_i)(\bar{y} - y_j) = \frac{1}{N^2} \sum_{ij} x_i y_j - \frac{1}{N} \bar{y} \sum_i x_i - \frac{1}{N} \bar{x} \sum_j y_j + \bar{x} \bar{y} = (\overline{xy} - \bar{x} \bar{y})$$

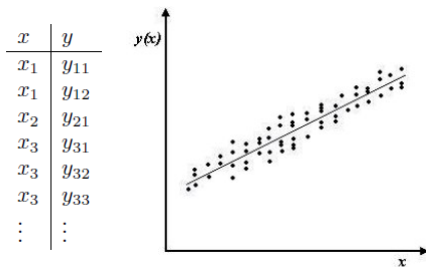


Imprecisió de la mitjana

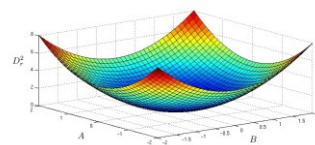
$$\bar{x} = \frac{1}{N} \sum_i x_i \quad \rightarrow \quad \bar{x} = f(x_1, x_2, \dots, x_N)$$

$$\frac{\partial \bar{x}}{\partial x_i} = \frac{1}{N} \quad \rightarrow \quad S_{\bar{x}}^2 = \frac{1}{N^2} \sum_i S_x^2 = \frac{1}{N^2} N S_x^2 \quad \rightarrow \quad S_{\bar{x}}^2 = \frac{S_x^2}{N}$$

Ajust Lineal $y = A + Bx$



$$D_r^2 = \sum_{ij} (y_{ij} - y_i^c)^2 = \sum_{ij} (y_{ij} - A - Bx_i)^2$$



$$\left. \begin{aligned} \frac{\partial D_r^2}{\partial A} &= 0 = -2 \sum_{ij} (y_{ij} - A - Bx_i) \rightarrow \bar{y} = A + B\bar{x} \\ \frac{\partial D_r^2}{\partial B} &= 0 = -2 \sum_{ij} (y_{ij} - A - Bx_i)x_i \rightarrow \overline{xy} = A\bar{x} + B\overline{x^2} \end{aligned} \right\} \quad \overline{xy} = (\bar{y} - B\bar{x})\bar{x} + B\overline{x^2}$$

$$B = \frac{\overline{xy} - \bar{x}\bar{y}}{\overline{x^2} - \bar{x}^2}$$

$$A = \bar{y} - B\bar{x}$$

$$S_y^2 = \sum_i \left(\frac{df}{dx_i} \right)^2 S_{x_i}^2$$

Càlcul S_B^2

$$B = \frac{\overline{xy} - \bar{x}\bar{y}}{\overline{x^2} - \bar{x}^2} = \frac{1}{N} \frac{\sum_{ij} y_{ij} x_i - \bar{x} \sum_{ij} y_{ij}}{\overline{x^2} - \bar{x}^2} \rightarrow \frac{\partial B}{\partial y_{ij}} = \frac{1}{N} \frac{x_i - \bar{x}}{\overline{x^2} - \bar{x}^2}$$

$$S_B^2 = \frac{1}{N} \frac{1}{(\overline{x^2} - \bar{x}^2)^2} \left(\frac{1}{N} \sum_{ij} (x_i - \bar{x})^2 \right) S_r^2 \rightarrow S_B^2 = \frac{1}{N} \frac{1}{\overline{x^2} - \bar{x}^2} S_r^2$$

Càlcul S_A^2 $A = \bar{y} - B\bar{x} = \sum_{ij} \left(\frac{1}{N} - \frac{\bar{x}(x_i - \bar{x})}{D_x^2} \right) y_{ij} \rightarrow S_A^2 = \left(\frac{1}{N} + \frac{\bar{x}^2}{D_x^2} \right) S_{reg}^2 = \frac{\overline{x^2}}{D_x^2} S_{reg}^2$

Càlcul $S_{y_c}^2$ $y_i^c = \bar{y} - B(x_i - \bar{x}) = \frac{1}{N} \sum_{ij} \left(1 - \frac{1}{\overline{x^2} - \bar{x}^2} (x_i - \bar{x}) \right) y_{ij}$

$$\rightarrow S_{y_i^c}^2 = \frac{S_{reg}^2}{N} \left[1 + \frac{N(x_i - \bar{x})^2}{D_x^2} \right]$$

Altres ajustos lineals

$$y = A_0 + Bx$$

$$D_r^2 = \sum_{ij} (y_{ij} - y_i^c)^2 = \sum_{ij} (y_{ij} - A_0 - Bx_i)^2$$

$$\frac{dD_r^2}{dB} = 0 = -2 \sum_{ij} (y_{ij} - A_0 - Bx_i) x_i \rightarrow \overline{xy} - A_0 \bar{x} - B \overline{x^2} = 0$$

$$B = \frac{\overline{xy} - A_0 \bar{x}}{\overline{x^2}}$$

Càlcul S_B^2

recordem que:

$$S_y^2 = \sum_i \left(\frac{df}{dx_i} \right)^2 S_{x_i}^2$$

$$\frac{\partial B}{\partial y_{ij}} = \frac{1}{N} \frac{x_i}{\overline{x^2}} \rightarrow S_B^2 = \frac{1}{N} \frac{1}{\overline{x^2}} S_r^2 \quad \text{etc.}$$

En forma matricial

$$y_i^c = a + bx_i \quad [y_i^c] = [1 \ x_i] \cdot \begin{bmatrix} a \\ b \end{bmatrix} \quad \begin{bmatrix} y_1^c \\ \vdots \\ y_n^c \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$\begin{matrix} Y = X \cdot A \\ n \times 1 \quad n \times 2 \quad 2 \times 1 \end{matrix}$$

$$Y = X A \longrightarrow X^T Y = X^T X A \longrightarrow (X^T X)^{-1} X^T Y = (X^T X)^{-1} (X^T X) A = A$$

$$A = (X^T X)^{-1} X^T Y$$

En forma matricial: imprecisions

$$S_z^2 = \left(\frac{\partial f}{\partial x} \right)_y^2 S_x^2 + \left(\frac{\partial f}{\partial y} \right)_x^2 S_y^2 + 2 \left(\frac{\partial f}{\partial x} \right)_y \left(\frac{\partial f}{\partial y} \right)_x S_{xy} = \begin{bmatrix} \left(\frac{\partial f}{\partial x} \right)_y & \left(\frac{\partial f}{\partial y} \right)_x \end{bmatrix} \begin{pmatrix} S_x^2 & S_{xy} \\ S_{yx} & S_y^2 \end{pmatrix} \begin{bmatrix} \left(\frac{\partial f}{\partial x} \right)_y \\ \left(\frac{\partial f}{\partial y} \right)_x \end{bmatrix} = Z^T \cdot cov \cdot Z$$

$$y_i^c = a + bx_i \longrightarrow S_{y_i^c}^2 = Z_i^T \cdot cov \cdot Z_i \quad \left\{ \begin{array}{l} Z_i^T = \left[\left(\frac{\partial y_i^c}{\partial a} \right)_b \quad \left(\frac{\partial y_i^c}{\partial b} \right)_a \right] = [1 \ x_i] \\ cov = \begin{pmatrix} S_a^2 & S_{ab} \\ S_{ba} & S_b^2 \end{pmatrix} \end{array} \right.$$

$$S_{y_i^c}^2 = Z_i^T \cdot cov \cdot Z_i$$

$$S_{y_i^c}^2 = Z_i^T \cdot cov \cdot Z_i$$

$$S_{y_i^c}^2 Z_i \cdot Z_i^T = Z_i \cdot Z_i^T \cdot cov \cdot Z_i \cdot Z_i^T$$

$$S_{y_i^c}^2 (Z_i \cdot Z_i^T)^{-1} (Z_i \cdot Z_i^T) = (Z_i \cdot Z_i^T) (Z_i \cdot Z_i^T)^{-1} \cdot cov \cdot Z_i \cdot Z_i^T$$

$$S_{y_i^c}^2 = cov \cdot Z_i \cdot Z_i^T$$

$$\begin{aligned} \sum_i S_{y_i^c}^2 &= cov \cdot \sum_i \begin{bmatrix} 1 \\ x_i \end{bmatrix} \cdot [1 \ x_i] = cov \cdot \sum_i \begin{pmatrix} 1 & x_i \\ x_i & x_i^2 \end{pmatrix} = cov \cdot \begin{pmatrix} n & \Sigma x_i \\ \Sigma x_i & \Sigma x_i^2 \end{pmatrix} \\ &= cov \cdot \begin{bmatrix} 1 & \dots & 1 \\ x_1 & \dots & x_n \end{bmatrix} \cdot \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix} = cov \cdot Z^T \cdot Z \end{aligned}$$

$$\sum_i S_{y_i^c}^2 = cov \cdot Z^T \cdot Z$$

$$\sum_i S_{y_i^c}^2 = cov \cdot Z^T \cdot Z$$

$$\Sigma_i S_{y_i^c}^2 = ? \left\{ \begin{array}{l} S_x^2 = \frac{1}{n} S_x^2 \\ S_{y_i^c}^2 = \frac{1}{n} S_{y_i}^2 \\ \sum_i S_{y_i^c}^2 = \frac{1}{n} \sum_i S_{y_i}^2 = S_r^2 \end{array} \right\} \quad \sum_i S_{y_i^c}^2 = S_r^2$$

$$\rightarrow S_r^2 = cov \cdot (Z^T \cdot Z) \rightarrow cov = (Z^T \cdot Z)^{-1} S_r^2$$

$$S_{y_i^c}^2 = Z_i^T \cdot cov \cdot Z_i = Z_i^T \cdot (Z^T \cdot Z)^{-1} \cdot Z_i \ S_r^2$$

EXCEL

X

	x	y
1	1	2,2
1	2	3,3
1	3	3,8
1	4	5,2
1	5	6,2
1	6	6,8
1	7	8,1
1	8	9,3
1	9	9,9
1	10	10,6

Regressió Lineal

$Y = X A$ $X = \begin{bmatrix} 1 & x_1 \\ \dots & \dots \\ 1 & x_n \end{bmatrix}$ $A = \begin{bmatrix} a \\ b \end{bmatrix} \rightarrow A = (X^T X)^{-1} X^T Y$

$x^T x$	10	55
	55	385

MMULT(TRANSPOSA(B12:C21);B12:C21)

$x^T y$	65,4	
	439	

MMULT(TRANSPOSA(B12:C21);D12:D21)

$(x^T x)^{-1}$	0,466667	-0,06667
	-0,06667	0,012121

MINVERSA(C24:D25)

$(x^T x)^{-1} x^T y =$	a	1,253333
	b	0,961212

MMULT(C28:D29;G24:G25)

y_c	$(y - y_c)^2$
2,214545	0,00021157
3,175758	0,01543618
4,13697	0,113548577
5,098182	0,010366942
6,059394	0,019770064
7,020606	0,048667034
7,981818	0,013966942
8,94303	0,127427365
9,904242	1,79982E-05
10,86545	0,070466116
Sr ²	0,052484848

$cov = (X^T X)^{-1} S_r^2$

cov	0,024493	-0,0035
	-0,0035	0,000636

$cov = J22*sr_2 = K22*sr_2$

$= J23*sr_2 = K23*sr_2$

$S_{y_i}^2 = (1 - x_i) cov \begin{pmatrix} 1 \\ x_i \end{pmatrix}$

Syc

0,1346519

0,1142002

0,0960448

0,0817306

0,0735359

0,0735359

0,0817306

0,0960448

0,1142002

0,1346519

Regressió Lineal

7

Regressió no Lineal

$$y = f(\underline{x}, \underline{\theta}),$$

$$Z_{iu}^0 = \left(\frac{\partial f(\underline{x}_u, \underline{\theta})}{\partial \theta_i} \right)$$

$$cov = (Z_0^T Z_0)^{-1} S_r^2$$

$$S_{y_i^c}^2 = Z_i^T cov Z_i \quad Z_i = (Z_{i1}^0 \quad \dots \quad Z_{ip}^0)$$

EXCEL

Regressió no Lineal

X(mL/min)	Y(mm)
3,4	9,59
7,1	5,29
16,1	3,63
20	3,42
23,1	3,46
34,4	3,06
40	3,25
44,7	3,31
65,9	3,5
78,9	3,86
96,8	4,24

Eq. Teòrica		
Y=A X+ B/X+C		
A		1
B		1
C		1
Solver		
A	0,024808	
B	26,80485	
C	1,548675	

Y teòrica	(Y-Yc)^2
9,52	0,01
5,50	0,04
3,61	0,00
3,39	0,00
3,28	0,03
3,18	0,01
3,21	0,00
3,26	0,00
3,59	0,01
3,85	0,00
4,23	0,00
SUMA	0,110191648
Sr2	0,013773956

$$cov = (Z_0^T Z_0)^{-1} S_r^2 \underbrace{\left(\frac{\partial f(x_u, \theta)}{\partial \theta_i} \right)_{\theta_0}}_{Z_{iu}^0}$$

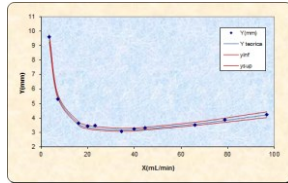
$\partial Y / \partial A = x$	$\partial Y / \partial B = 1/x$	$\partial Y / \partial C = 1$
3,4	0,294117647	1
7,1	0,14084507	1
16,1	0,062111801	1
20	0,05	1
23,1	0,043290043	1
34,4	0,029069767	1
40	0,025	1
44,7	0,022371365	1
65,9	0,015174507	1
78,9	0,012674271	1
96,8	0,010330579	1

Z^T Z	25974,5	11	430,4
	11	0,11704258	0,704985051
	430,4	0,70498505	11

Z_i^T

$$(Z^T Z)^{-1} \times S_r^2 \leftarrow cov$$

parametre	estimació	S ²
A	0,02480846	0,00034171
B	26,8048521	0,36920885
C	1,54867494	0,02133138



Syc
0,11034715
0,05397389
0,05181047
0,05089314
0,04960845
0,04373915
0,04144147
0,04035411
0,04830205
0,06148399
0,08440633

$$S_{y_i}^2 = Z_i^T cov Z_i$$

$$\begin{pmatrix} z1 & z2 & z3 \end{pmatrix} \begin{pmatrix} a11 & a12 & a13 \\ a21 & a22 & a23 \\ a31 & a32 & a33 \end{pmatrix} \begin{pmatrix} z1 \\ z2 \\ z3 \end{pmatrix} = \{ z1 (a11 z1 + a21 z2 + a31 z3) + z2 (a12 z1 + a22 z2 + a32 z3) + z3 (a13 z1 + a23 z2 + a33 z3) \}$$