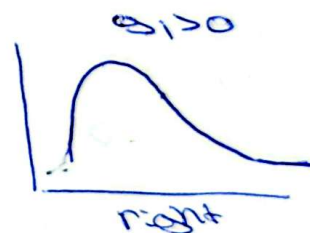
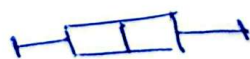
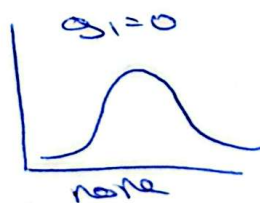


• Expansion de la variancia

$$\begin{aligned}
 \sigma^2 &= \frac{1}{N} \sum (x_i - \bar{x})^2 n_i = \frac{1}{N} \sum (x_i^2 + \bar{x}^2 - 2x_i\bar{x}) n_i \\
 &= \frac{1}{N} \left[\sum x_i^2 n_i + \bar{x}^2 \sum n_i - 2\bar{x} \sum x_i n_i \right] = \\
 &= \frac{1}{N} \left[\sum x_i^2 n_i + \bar{x}^2 N - 2\bar{x} \sum x_i n_i \right] = \\
 &= \frac{1}{N} \sum x_i^2 n_i + \bar{x}^2 - 2\bar{x}^2 = \boxed{\frac{1}{N} \sum x_i^2 n_i - \bar{x}^2}
 \end{aligned}$$

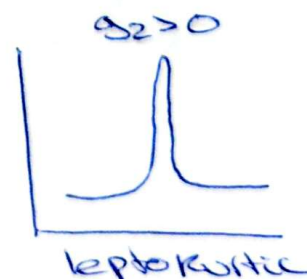
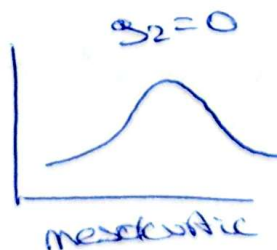
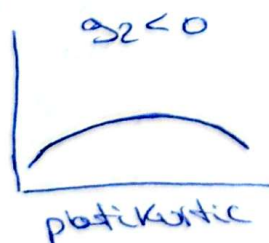
• Coeficientes de gamma

→ Fisher (asimetría) : $g_1 = \frac{1}{N\sigma^3} \sum (x_i - \bar{x})^3$
skewness



→ Kurtosis :

$$g_2 = \frac{1}{N\sigma^4} \sum (x_i - \bar{x})^4 - 3$$



→ we consider gaussian rand is

$$-2 < g_1 < 2$$

$$-2 < g_2 < 2$$

• Transformación de variables

→ Transformación afín: cambiar variables

$$z = a x + b$$

\uparrow transformación lineal \nwarrow traslación

• ejemplo: medida en metros con zapatos → convertidos sin zapatos

→ Tipificación / estandarización: comparación relativa

$$z = \frac{x - \bar{x}}{s}$$

• ejemplo: que es relativamente más alto un doguete o una hormiga dentro de su grupo

→ cambio de variable sobre los medidos antes

media $\bar{x} = \frac{1}{N} \sum x_i \rightarrow \boxed{\bar{z}} = \frac{1}{N} \sum (a x_i + b) =$

$$= a \left(\frac{1}{N} \sum x_i \right) + \frac{1}{N} b N$$

$$\boxed{= a \bar{x} + b}$$

Varianza

$$s_x^2 = \frac{1}{N} \sum (x_i - \bar{x})^2 \rightarrow \boxed{s_z^2} = \frac{1}{N} \sum [a x_i + b - (a \bar{x} + b)]^2$$

$$= \frac{1}{N} a^2 \sum (x_i - \bar{x})^2$$

$$\boxed{= a^2 s_x^2}$$

g_1 y g_2

→ son invariantes bajo trasf. afines

CV

→ No es invariante sobre transformaciones afines

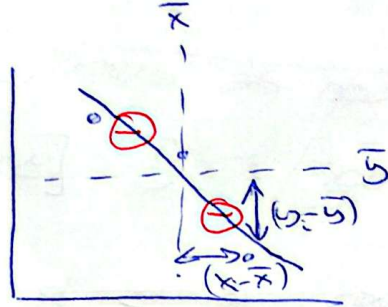
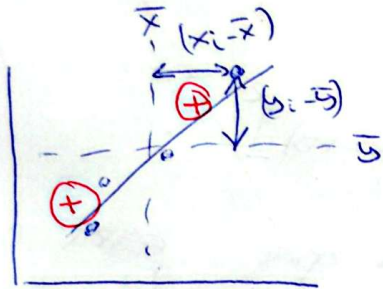
$$CV_x = \frac{s_x}{\bar{x}} \rightarrow CV_z = \frac{s_z}{\bar{z}} = \frac{a s_x}{a \bar{x} + b}$$

pero si sobre transformaciones lineales puros

Regression linear I

$$y - \bar{y} = \frac{\sigma_{xy}}{\sigma_x^2} (x - \bar{x})$$

$$\sigma_{xy} = \frac{1}{N} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) = \frac{1}{N} \sum_{i=1}^n x_i y_i - \bar{x} \bar{y}$$



Pearson correlation coefficient

$$r = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

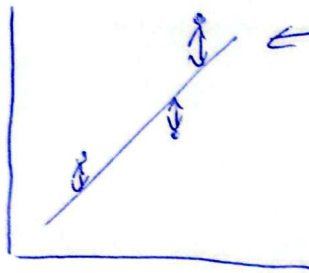
coefficient of determination r^2 :

% of ~~error~~ in the prediction explained by
variances ~~precision~~

Predictions are valid only in the range of study

Tema X

Regression lineal: minimización de la función error



$$g(x) = ax + b$$

$$E(a, b) = \sum [y_i - g(x_i)]^2$$

$$a \text{ y } b$$

ta

$$\frac{\partial E}{\partial a} = 0$$

$$\text{y } \frac{\partial E}{\partial b} = 0$$

$$\frac{\partial E}{\partial a} = 0$$

$$\frac{\partial E}{\partial b} = 0$$

$$\left\{ \begin{array}{l} \sum [y_i - (ax_i + b)] \cdot (-x_i) = 0 \\ \sum [y_i - (ax_i + b)] = 0 \end{array} \right.$$

$$\begin{aligned} -\sum y_i x_i + \sum a x_i^2 + \sum b x_i &= 0 \\ -\sum y_i x_i + a \sum x_i^2 + b \sum x_i &= 0 \\ -\sum y_i x_i + a \sum x_i^2 + b \bar{x} &= 0 \end{aligned}$$

$$\begin{aligned} -\sum y_i x_i + a \sum x_i^2 + (\bar{y} - a \bar{x}) \bar{x} &= 0 \\ \frac{1}{n} [-\sum y_i x_i + \bar{y} \bar{x} + a [\sum x_i^2 - \bar{x}^2]] &= 0 \end{aligned}$$

$$\bar{y} - a \bar{x} - b = 0 \quad \leftarrow \boxed{b = \bar{y} - a \bar{x}}$$

$$\frac{1}{n} [-\sum y_i x_i + \bar{y} \bar{x} + a [\sum x_i^2 - \bar{x}^2]] = 0$$

$$-\sigma_{xy} + a \sigma_x^2 = 0$$

$$\boxed{\begin{aligned} a &= \frac{\sigma_{xy}}{\sigma_x^2} \\ b &= \bar{y} - \frac{\sigma_{xy}}{\sigma_x^2} \bar{x} \end{aligned}}$$

$$g(x) = \hat{y} = \frac{\sigma_{xy}}{\sigma_x^2} x + \bar{y} - \frac{\sigma_{xy}}{\sigma_x^2} \bar{x}$$

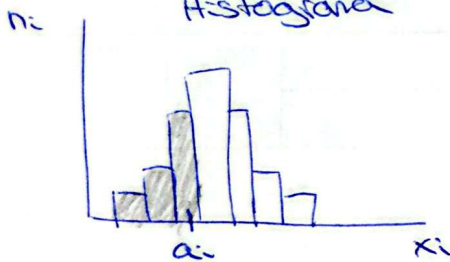
$$\boxed{\hat{y} - \bar{y} = \frac{\sigma_{xy}}{\sigma_x^2} (x - \bar{x})} \quad \text{Cvd}$$

Probabilidad I : variable aleatoria continua

Estadística

Datos 2D (1D)

Histograma



Estadística

$N \rightarrow$ grande

$$\sum_i$$

$$N = \sum_i n_i$$

$$\bar{x} = \frac{1}{N} \sum_i n_i x_i$$

$$\sigma^2 = \frac{1}{N} \sum_i n_i (x_i - \bar{x})^2$$

$$F(x_i < a_i) = \frac{1}{N} \sum_{i=1}^{a_i} n_i x_i$$

Suma con ordenador o a mano

condición de F ~~prob~~ ~~acum~~

~~condición de F~~

$$F(-\infty < x < \infty) = \frac{1}{N} \sum_i n_i = 1$$

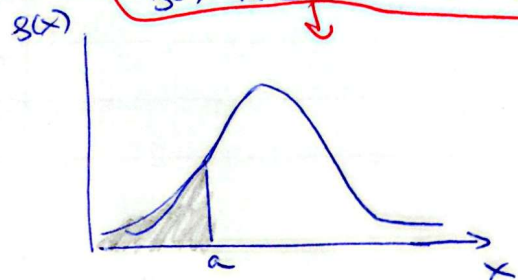


distribución de frecuencias

Probabilidad

función integrable

$$g(x) = A e^{-z^2/2} \quad z = \frac{x-\mu}{\sigma}$$



Probabilidad

$N \rightarrow \infty$

$$\int dx$$

$$Norma = \int_{-\infty}^{\infty} g(x) dx$$

$$\mu = \frac{1}{Norma} \int_{-\infty}^{\infty} g(x) x dx$$

$$\sigma^2 = \frac{1}{Norma} \int_{-\infty}^{\infty} g(x) (x - \mu)^2 dx$$

$$P(x < a) = \frac{1}{Norma} \int_{-\infty}^a g(x) dx$$

Suma con ordenador o tablas

condición de P ~~acum~~ ~~prob~~

$$P(-\infty < x < \infty) = \frac{1}{Norma} \int_{-\infty}^{\infty} g(x) dx = 1$$



distribución de probabilidad

PDF

Continuous random variable

↳ can take any value on a real interval

↳ it make no sense to calculate the prob. of an isolated value and we calculate prob. for intervals

$$\int_{-\infty}^{\infty} g(x) dx = 1 \quad \} \quad P(a \leq x \leq b) = \int_a^b g(x) dx$$

$$\mu = \int_{-\infty}^{\infty} x g(x) dx$$

$$\sigma^2 = \int_{-\infty}^{\infty} x^2 g(x) dx - \mu^2$$

example

$$g(x) = \begin{cases} 0 & x < 0 \\ e^{-x} & x \geq 0 \end{cases}$$

$$\text{Normalization: } \int_{-\infty}^{\infty} g(x) dx = \int_{-\infty}^0 0 dx + \int_0^{\infty} e^{-x} dx = [-e^{-x}]_0^{\infty} = -e^{-\infty} + e^0 = 1$$

$$P(0 \leq x \leq 2) = \int_0^2 e^{-x} dx = [-e^{-x}]_0^2 = 0,8646$$

$$\mu = \int_{-\infty}^{\infty} x g(x) dx = \int_{-\infty}^0 0 dx + \int_0^{\infty} x e^{-x} dx = [-e^{-x}(1+x)]_0^{\infty} = 1$$

$$\sigma^2 = \int_{-\infty}^{\infty} x^2 g(x) dx - \mu^2 = \int_{-\infty}^0 0 dx + \int_0^{\infty} x^2 e^{-x} dx - 1^2 = [-e^{-x}(x^2 + 2x + 2)]_0^{\infty} - 1 = 1$$

Uniform

$$g(x) = \frac{1}{b-a}$$

$$\mu = \frac{a+b}{2}$$

$$\sigma^2 = \frac{(b-a)^2}{12}$$

Normal $N(\mu, \sigma)$

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

μ : mean

σ : standard deviation

to avoid integrating the normal density to compute prob it is common to use tables

↳ z-values

+ standardization

$$z = \frac{x-\mu}{\sigma}$$

$$N(\mu=6, \sigma=1.5) \rightarrow P(X < 5) = P\left(\underbrace{\frac{5-6}{1.5}}_z < \frac{5-6}{1.5}\right) =$$

$$= P(Z < -0.67) = 0.2514$$

↑
table z value
 $(-0.6, 0.07) = 0.2514$

Discrete Random Variables

$g(x)$: probability function
 $= P(X=x)$

$F(x)$: distribution function, cumulative of $g(x)$
 $= P(X \leq x) = g(x_0) + g(x_1) + g(x_2) + \dots + g(x_i)$

$$\mu = \sum_{i=1}^n x_i g(x_i)$$

$$\sigma^2 = \sum_{i=1}^n x_i^2 g(x_i) - \mu^2$$

$$\sigma = \sqrt{\sigma^2}$$

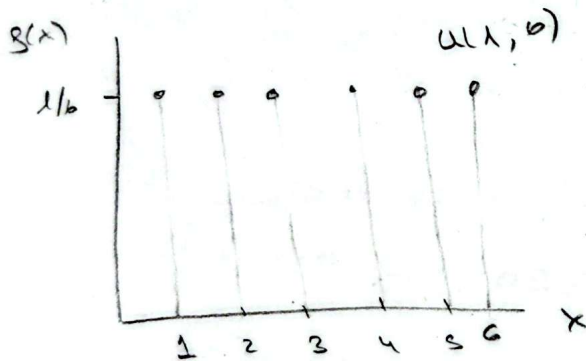
Uniform $U(a, b)$

$\text{Ran}(X) = \{a, a+1, \dots, b\}$

$$g(x) = \frac{1}{b-a+1}$$

$$\mu = \sum_{i=0}^{b-a} \frac{a+i}{b-a+1} = \frac{a+b}{2}$$

$$\sigma^2 = \sum_{i=0}^{b-a} \frac{(a+i-\mu)^2}{b-a+1} = \frac{(b-a+1)^2 - 1}{12}$$



when all the values of a random variable X have equal prob

↓
 (rolling dice)

Binomial

$\text{Ran}(X) = \{0, 1, \dots, n\}$

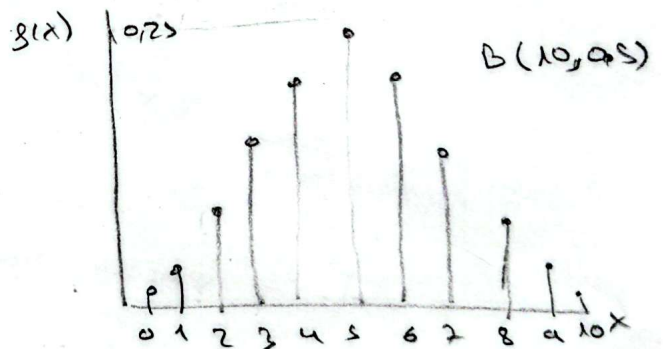
n : num of repetitions

p : prob of success

$$g(x) = \binom{n}{x} p^x (1-p)^{n-x} = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

$$\mu = n \cdot p$$

$$\sigma^2 = n \cdot p \cdot (1-p)$$



$$g(4) = \binom{10}{4} 0.5^4 (1-0.5)^{10-4} = \frac{10!}{4!6!} 0.5^4 \cdot 0.5^6 = 0.2051$$

$$\mu = 10 \cdot 0.5 = 5$$

sequence of n repetitions of same trial with same prob (p)

↳ each trial is identical and produce two possible outcomes

↳ each trial is independent

↳ each trial has same prob

(tossing coins)

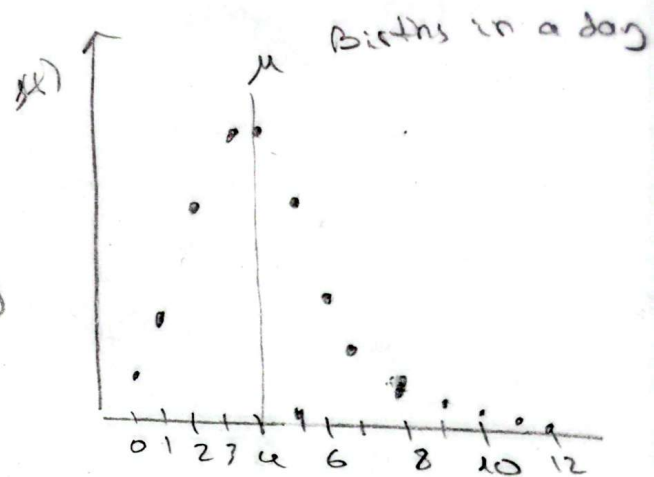
Poisson

$$g(x) = e^{-\lambda} \cdot \frac{\lambda^x}{x!}$$

$$\text{Dom}(x) = \{0, 1, \dots, \infty\}$$

λ : average rate of event per interval unit (change is the interval changes)

$$\mu = \lambda \quad \sigma^2 = \lambda$$



- # of events occurring in a given interval of time/space

↳ Births in a month

↳ emails in one hour

↳ red blood cells in a volume of blood

- events occur independently

- the same average rate of event λ for every interval unit

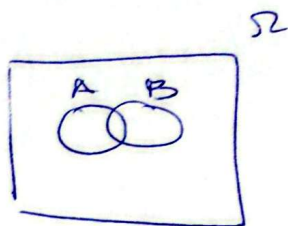
Law of rare events

Poisson = Binomial when $\left\{ \begin{array}{l} \text{number of trials } n \rightarrow \infty \\ \text{prob of success } p \rightarrow 0 \end{array} \right.$

$$\lim_{\substack{n \rightarrow \infty \\ p \rightarrow 0}} \binom{n}{x} p^x (1-p)^{n-x} = e^{-\lambda} \frac{\lambda^x}{x!}$$

\uparrow
 $\lambda = np$

! it works for $n \geq 30$ and $p \leq 0.1$!



Ω : Ω set of all possibilities

A: Ω sub-set of possibilities

B: Ω different sub-set

\bar{A} : complement

$$P(\Omega) = 1$$

$A \cup B$: union

$$P(A) = \frac{N_A}{N_\Omega}$$

$A \cap B$: intersection

$$P(\bar{A}) = 1 - P(A)$$

$$P(\bar{A} \cap \bar{B}) = 1 - P(A \cup B)$$

$$P(A) + P(B) = P(A \cup B) + P(A \cap B)$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(A - B) = P(A) - P(A \cap B)$$

independent: $P(A|B) = P(A)$ or $P(A \cap B) = P(A) \cdot P(B)$

incompatible: $P(A \cap B) = 0$ or $P(A) + P(B) = P(A \cup B)$

Bayes

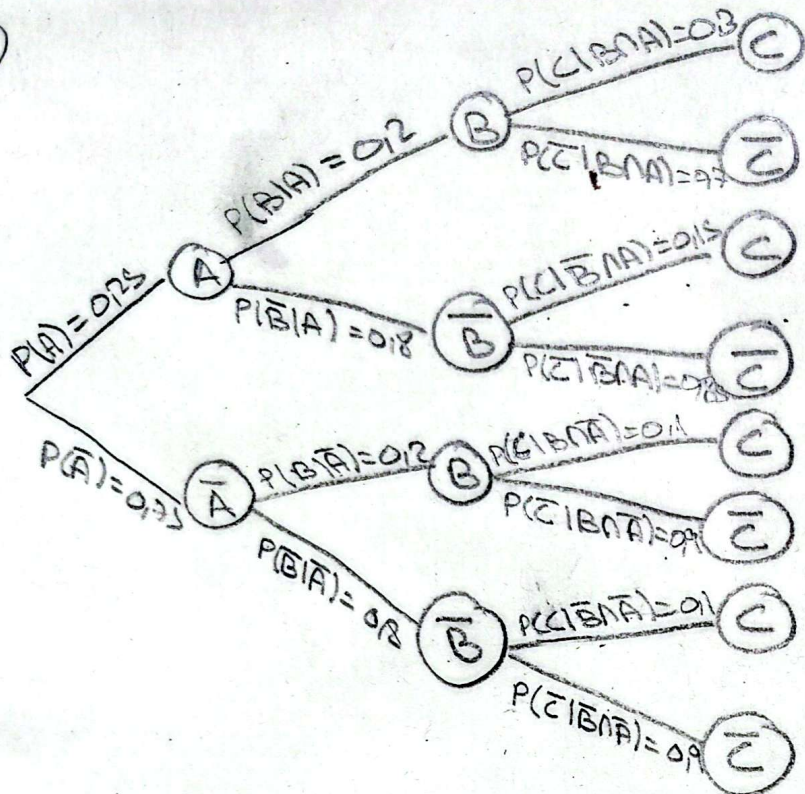
$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

Total

$$P(B) = \sum_A P(A) P(B|A)$$

$$\sum_A P(B \cap A)$$

41



$$P(A \cap B \cap C) = 0.25 \cdot 0.2 \cdot 0.3 = 0.015$$

$$P(A \cap B \cap \bar{C}) = 0.25 \cdot 0.2 \cdot 0.7 = 0.035$$

$$P(A \cap \bar{B} \cap C) = 0.25 \cdot 0.8 \cdot 0.15 = 0.03$$

$$P(A \cap \bar{B} \cap \bar{C}) = 0.25 \cdot 0.8 \cdot 0.85 = 0.17$$

$$P(\bar{A} \cap B \cap C) = 0.75 \cdot 0.2 \cdot 0.11 = 0.0165$$

$$P(\bar{A} \cap B \cap \bar{C}) = 0.75 \cdot 0.2 \cdot 0.89 = 0.1335$$

$$P(\bar{A} \cap \bar{B} \cap C) = 0.75 \cdot 0.8 \cdot 0.1 = 0.06$$

$$P(\bar{A} \cap \bar{B} \cap \bar{C}) = 0.75 \cdot 0.8 \cdot 0.9 = 0.54$$

Teorema probabilidad total

$$P(C) = P(A \cap B \cap C) + P(A \cap \bar{B} \cap C) + P(\bar{A} \cap B \cap C) + P(\bar{A} \cap \bar{B} \cap C) =$$

$$= 0.015 + 0.03 + 0.0165 + 0.06 = 0.1215$$

Teorema de Bayes

$$P(B|C) = \frac{\sum \text{all the lines } P(B \cap C)}{P(C)} = *$$

$$\begin{aligned} P(B \cap C) &= \sum \text{all the lines } P(B_i) \cdot P(C|B_i) = \\ &= P(B \cap A) \cdot P(C|B \cap A) + P(B \cap \bar{A}) \cdot P(C|B \cap \bar{A}) = \\ &= P(A) \cdot P(B|A) \cdot P(C|B \cap A) + P(\bar{A}) \cdot P(B|\bar{A}) \cdot P(C|B \cap \bar{A}) = \\ &= 0.25 \cdot 0.2 \cdot 0.3 + 0.75 \cdot 0.2 \cdot 0.11 = 0.0335 \end{aligned}$$

Sum of all the lines that contain B and C

$$* = \frac{0.0335}{0.1215} = 0.2758$$

$$P(\bar{A}|\bar{B}\cap\bar{C}) = \frac{P(\bar{A}\cap\bar{B}\cap\bar{C})}{P(\bar{B}\cap\bar{C})} = \frac{0,14}{0,71}$$

Teorema prob total

$$\begin{aligned} P(\bar{B}\cap\bar{C}) &= \sum_{\text{all even}} P(\bar{B}) \cdot P(\bar{B}|\bar{C}) = \dots \\ &= 0,14 + 0,17 = 0,31 \end{aligned}$$

Sum all the lines that contain $\bar{B}\cap\bar{C}$

e) son B y C independientes?

$$P(B|C) = P(B)$$

↑

0,25

↓

Teorema de la Probabilidad total

$$\begin{aligned} P(B) &= \sum_{\text{even}} P(B_i) = P(A) \cdot P(B|A) + P(\bar{A}) \cdot P(B|\bar{A}) = \\ &= 0,25 \cdot 0,2 + 0,75 \cdot 0,2 = 0,2 \end{aligned}$$

Sum all the lines that contain B

$$0,25 \stackrel{?}{=} 0,2 \quad \text{No}$$

⇓

no son independientes