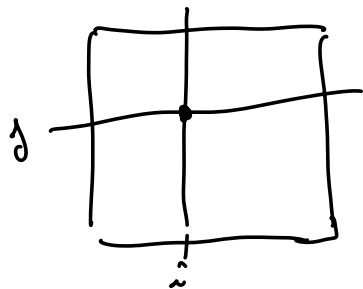


Cours 11/09/2023



$$Z_{ij} = V_{ij} + b_{ij}$$

$V \in \{0, \dots, 255\}$

application probabilité

Expérience aléatoire :  $(\Omega, \mathcal{G}, P)$

ensemble de résultats  
d'expérience  
jet de dé  $\Omega = \{1, \dots, 6\}$

ensemble de événements  
 $\mathcal{G} = \{ \{1\}, \dots, \{6\} \}$   
 $\{1,2\}, \dots, \{5,6\}$

Équiprobabilité

$\Omega, \emptyset$   
 $\Omega$  fini  
 tous les événements élémentaires, i.e., les singletons  $\{a\}$   
 ont la même importance

$$P(A) = \frac{\text{Card } A}{\text{Card } \Omega}$$

Loi Binomiale : n expériences de type {succès, échec}

$$P(k \text{ succès sur } n \text{ expériences}) = \binom{n}{k} p^k (1-p)^{n-k}$$

$k \in \{0, \dots, n\}$

$\frac{n!}{k!(n-k)!}$

$\binom{k}{n}$

$p$  = probabilité de succès sur 1 expérience

Jet de dé : 10 jets  $n=10$        $P(3 \text{ fois } 2) = \binom{10}{3} \left(\frac{1}{6}\right)^3 \left(\frac{5}{6}\right)^7$   
 $k=3$

Proba conditionnelle

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

↑  
sachant

équiprobabilité

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

A et B indépendants  $\Leftrightarrow$   
 $P(A) > 0$   
 $P(B) > 0$

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

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

BAYES

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

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

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

Somme de

Variations aléatoires

NOTATION

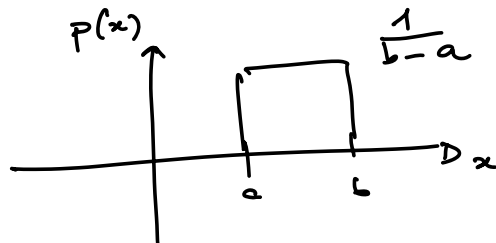
X : somme des résultats des 2 ds

x = 4 réalisation de X

$P[X = 4]$  probabilité que X prenne la valeur x = 4

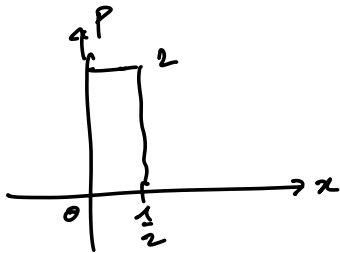
"  $P[\{\omega / \sum_{i=1}^n X_i = 4\}]$

Loi uniforme sur ]a, b[





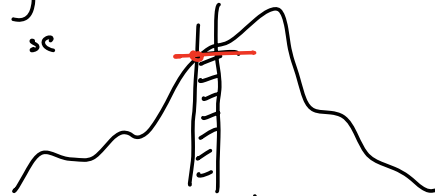
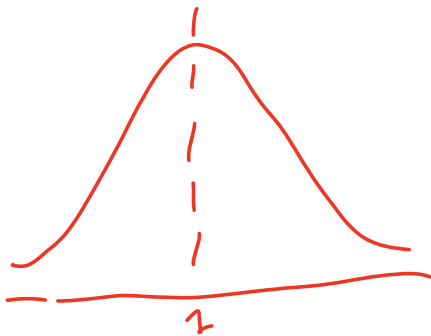
$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$



on peut avoir  $p(x) > 1$  donc  $p(x)$  n'est pas une probabilité

Que représente  $p(x)$ ?

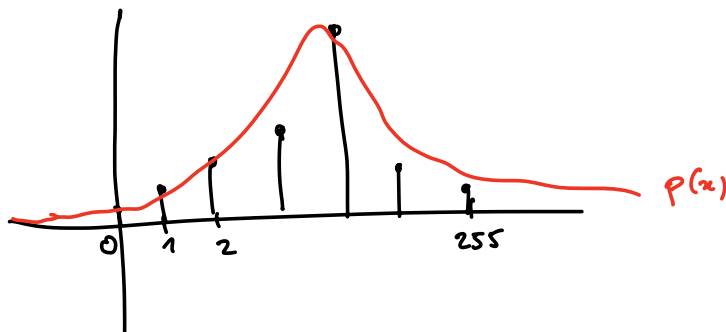
$$P[X \in \underbrace{x, x+dx}_{\Delta}] = \int_x^{x+dx} p(u) du$$

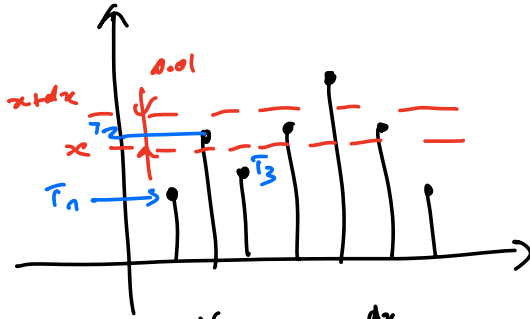
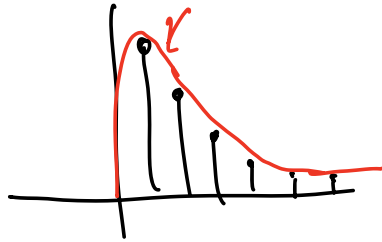


$$dx \text{ "petit"} \approx \int_x^{x+dx} p(u) du = p(x) dx$$

Conclusion

$$p(x) \approx_{dx \text{ petit}} \frac{P[X \in x, x+dx]}{dx}$$

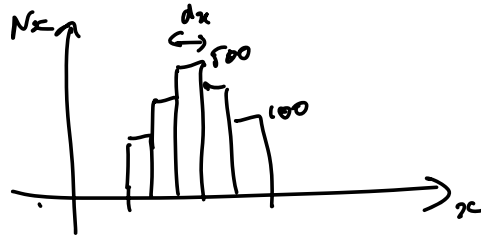




$$p(x) dx \approx P[X \in ]x, x+dx[$$

$$p(x) \approx \frac{P[X \in ]x, x+dx[)}{dx}$$

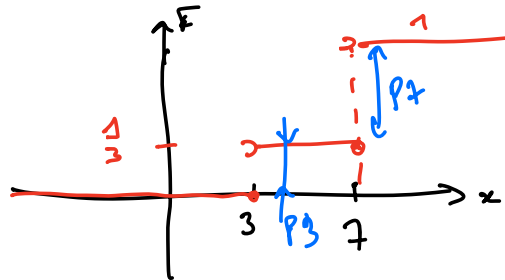
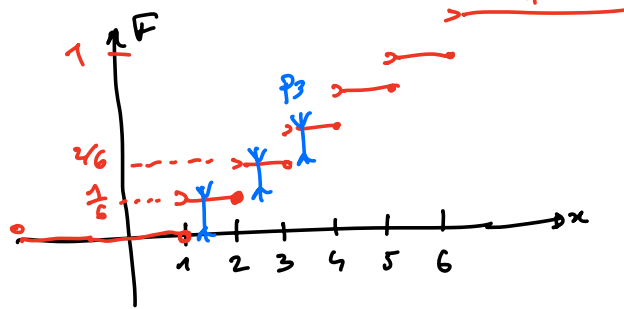
$\approx \frac{N_x}{dx}$  Histogramme des données.



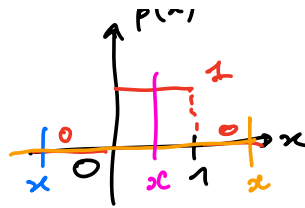
Fonctions de répartition

$$F(x) = P[X < x]$$

Ex 1 : jet de dé  $\Omega = \{1, \dots, 6\}$

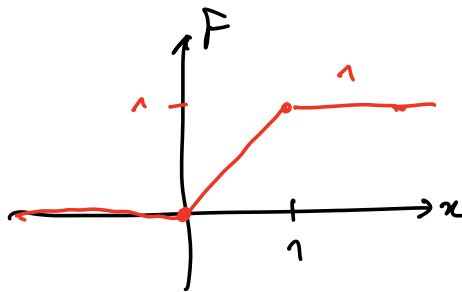


Loi uniforme sur ]0,1[



$$F(x) = P[X < x] = P[X \in ]-\infty, x[$$

$$= \int_{-\infty}^x p(u) du = \begin{cases} 0 & \text{si } x \leq 0 \\ 1 & \text{si } x \geq 1 \\ \int_0^x 1 du = x & \text{si } x \in ]0,1[ \end{cases}$$



$$R_2 : F(x) = \int_{-\infty}^x p(u) du \Rightarrow$$

$$p(x) = F'(x)$$

MOYENNE  $E[X] = \sum_i x_i p_i$

① Jet de dé

$$E(X) = 1 \times \frac{1}{6} + 2 \times \frac{1}{6} + \dots + 6 \times \frac{1}{6} \\ = \frac{1}{6} (1+2+\dots+6) = \frac{1}{6} \frac{6 \times 7}{2} = \boxed{3.5}$$

Remarque : si  $x_1^*, x_2^*, \dots, x_n^*$  sont des réalisations d'une même variable aléatoire  $X$ , alors sous certaines hypothèses

Loi des grands nombres

$$\underbrace{\frac{x_1^* + x_2^* + \dots + x_n^*}{n}}_{\text{moyenne arithmétique}} \xrightarrow[n \rightarrow \infty]{} E[X]$$

② Loi normale

$$\boxed{X \sim N(\mu, \sigma^2)} \quad \text{NOTATION}$$

↑  
suit la loi

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

$$E[X] = \int_{\mathbb{R}} x P(x) dx$$

$$= \int_{\mathbb{R}} x \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] dx$$

$u = \frac{x-\mu}{\sigma}$   
on centre et on réduit

$$x = \sigma u + \mu$$

$$\int_{\mathbb{R}} (\sigma u + \mu) \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{u^2}{2}\right) \frac{\sigma du}{dx}$$

$\frac{1}{\sqrt{2\pi}} e^{-u^2/2}$

$$= \int_{\mathbb{R}} (\sigma u + \mu) \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

$$= \sigma \int_{\mathbb{R}} u \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du + \mu \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

fonction impaire = 0      1

$$\boxed{E[X] = \mu}$$

Moments non centrés :  $E[X], E[X^2], E[X^3], \dots$

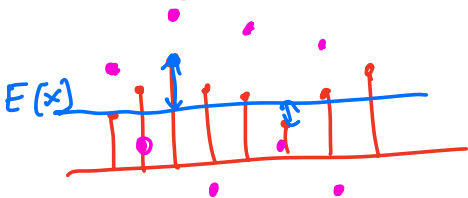
Moments centrés

$$: \boxed{E[(X - E[X])^k]}, E[(X - E[X])^2], \dots$$

$$E[X] - \underbrace{E[E[X]]}_{E[X]} = 0$$

$(X - E[X])^2$   
écart quadratique  
entre  $x$  et sa moyenne

$$\boxed{\text{VARIANCE}}$$



Calcul de variance

$$\sqrt{\text{Variance}} = \text{écart type}$$

Définition

$$E[(X - E(X))^2] = E[X^2 - 2XE(X) + E^2(X)]$$

$$= E(X^2) - 2E(X)E(X) + E^2(X)$$

$$\boxed{\text{Var } X = E(X^2) - E^2(X)}$$
 utilisé pour le calcul

Exemple de calcul  $X \sim N(m, \sigma^2)$   
 $\uparrow$   
 $E(X)$

$$\text{Var } X = E(X^2) - E^2(X) \quad E(X) = m$$

$$E(X^2) = \int x^2 \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left[-\frac{(x-m)^2}{2\sigma^2}\right] dx$$

$$= \int (\sigma u + m)^2 \frac{1}{\sqrt{2\pi}\sigma^2} e^{-u^2/2} du$$

$$u = \frac{x-m}{\sigma}$$
  
 $x = \sigma u + m$

$$= \sigma^2 \int_{\mathbb{R}} u^2 \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du + 2m\sigma \int_{\mathbb{R}} u \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

intégration par parties

$$\left. \begin{aligned} v' &= u e^{-u^2/2} du & v &= -e^{-u^2/2} \\ w &= \frac{1}{\sqrt{2\pi}} & w' &= \frac{1}{\sqrt{2\pi}} \end{aligned} \right\}$$

$$\int_{\mathbb{R}} u^2 p(u) du = \left[ -\frac{u}{\sqrt{2\pi}} e^{-u^2/2} \right]_{-\infty}^{+\infty} + \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

$$\begin{cases} E(x^2) = \sigma^2 + m^2 \\ E(x) = m \end{cases} \Rightarrow \text{Var } X = E(x^2) - E(x)^2 = \sigma^2 + m^2 - m^2 = \sigma^2$$

$$\boxed{\text{Var } X = \sigma^2}$$

$$X \sim N(m, \sigma^2)$$

$\uparrow$   $\uparrow$   
 $E(X)$   $\text{Var } X$

On centre et on réduit

$$E\left[\frac{x-m}{\sigma}\right] = \frac{1}{\sigma} E(x-m) = \frac{1}{\sigma} (E(x) - m) = \boxed{0}$$

$$\begin{aligned} \text{Var}\left(\frac{x-m}{\sigma}\right) &= \boxed{1} \\ &= \text{Var}\left[\frac{x}{\sigma} - \frac{m}{\sigma}\right] \\ &= \text{Var}\left[\frac{x}{\sigma}\right] \\ &= \frac{1}{\sigma^2} \underbrace{\text{Var } X}_{\sigma^2} = \boxed{1} \end{aligned}$$

Changement de variables

loi de Poisson  $\left\{ \begin{array}{l} X \sim P(\lambda) \quad P(X=k) = \frac{\lambda^k}{k!} e^{-\lambda} \quad k \in \mathbb{N} \\ \text{quelle est la loi de } Y = (X-2)^2? \end{array} \right.$

X	Y
0	4
1	1
2	0

• Y prend ses valeurs dans  $\{k^2, k \in \mathbb{N}\}$  (carré des entiers)



3	1
4	4
5	9
6	

•  $P[Y = k^2] ?$

$$P(Y = k^2) = P[(X-2)^2 = k^2]$$

$$= P[X-2 = k \text{ ou } X-2 = -k]$$

$$= P[X = 2+k \text{ ou } X = 2-k]$$

Case 1  $2+k = 2-k \Leftrightarrow \boxed{k=0}$

$$P(Y = k^2) = P(Y = 0) = P(X = 2)$$

$$= \boxed{\frac{1}{2} e^{-1}}$$

Case 2  $\boxed{k \neq 0}$   $P(Y = k^2) = P(X = \underbrace{2+k}_{\in \mathbb{N}}) + P(X = 2-k)$

$$= \frac{1}{(2+k)!} e^{-1} + P(X = 2-k)$$

$2-k \geq 0 \Leftrightarrow \boxed{k \leq 2}$        $0 \leq k < 3$

$$P(X = 2-k) = \begin{cases} P(X=0) & k=2 \\ P(X=1) & k=1 \\ P(X=2) & k=0 \end{cases} \text{ d'après traitée}$$

Conclusion

$$P(Y = k^2) = \begin{cases} \frac{1}{2} e^{-1} & k=0 \\ \frac{1}{6} e^{-1} + e^{-1} & k=1 \\ \frac{1}{2k} e^{-1} + e^{-1} & k=2 \\ \frac{1}{(2+k)!} e^{-1} & k \geq 3, k \in \mathbb{N} \end{cases}$$

Exemple  $X \sim \Sigma(1)$   
 Loi exponentielle de paramètre  $\lambda=1$

$$P(x) = \begin{cases} e^{-x} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

Quelle est la loi de  $Y = \frac{1}{X}$  ?

Loi de  $Y$

$$P(x) = \begin{cases} e^{-x} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$\pi(y) = \begin{cases} e^{-\frac{1}{y}} \times \left| \frac{dx}{dy} \right| & y \in \Delta \\ 0 & \text{sinon} \end{cases}$$

$y = \frac{1}{x} \Leftrightarrow x = \frac{1}{y}$

Jacobien  
 $\frac{dx}{dy} = -\frac{1}{y^2}$

$$\pi(y) = \begin{cases} e^{-\frac{1}{y}} \frac{1}{y^2} & y \in \Delta \\ 0 & \text{sinon} \end{cases}$$

Recherche de  $\Delta$  : on connaît le domaine de  $X$

$$x > 0 \Leftrightarrow \frac{1}{y} > 0 \Leftrightarrow y > 0$$

$\Delta = ]0, +\infty[$

Idee de preuve

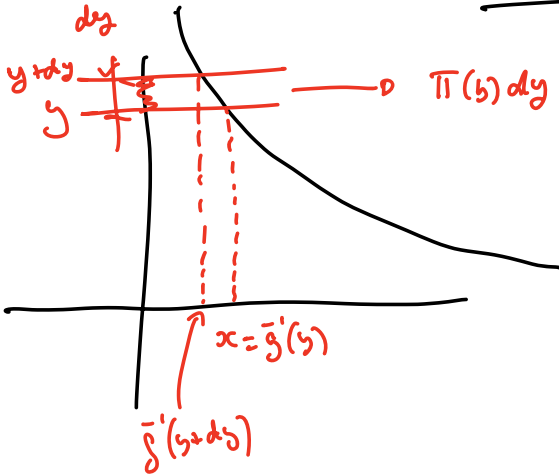
$y = g(x) \Leftrightarrow x = \bar{g}(y)$

Densité de  $Y$  :  $P(Y \in ]y, y+dy[) \approx \pi(y) dy$

//

$$P[Y \in ]y, y+dy[) = P[\bar{g}'(y)] dx$$

$$\text{donc } \boxed{\pi(y) = P[\bar{g}'(y)] \frac{dx}{dy}}$$



$= \left| \frac{dx}{dy} \right|$  car  $x \rightarrow y$   
 est une fonction  
 croissante

**PREUVE**

$$P[Y \in \Delta] = \int_{\Delta} \boxed{\pi(y)} dy \quad \text{d\u00e9finition de } \pi$$

$$P[Y \in \Delta] = P[g(x) \in \Delta] \\ = P[x \in \bar{g}'(\Delta)]$$

$$= \int_{\bar{g}'(\Delta)} P(x) dx$$

$$= \int_{\Delta} \boxed{P[\bar{g}'(y)] \left| \frac{dx}{dy} \right|} dy$$

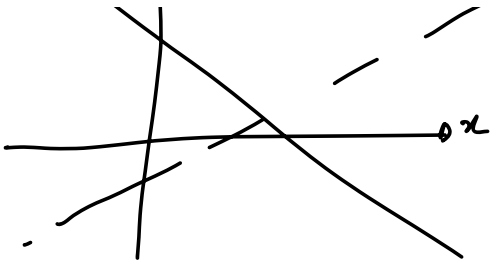
$e \bar{g}'(a)$   
 $x = \bar{g}'(y)$   
 $y = g(x)$

$\forall \Delta$   
 $\equiv$

Exemple 2

$$\boxed{\begin{array}{ll} X \sim N(m, \sigma^2) & \text{Ln de } Y? \\ Y = aX + b & a \neq 0 \end{array}}$$





$$y = ax + b \Leftrightarrow x = \frac{y-b}{a}$$

bijection de  $\mathbb{R}$  dans  $\mathbb{R}^2$

Densité de  $Y$

$$\pi(y) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left[-\frac{\left(\frac{y-b}{a} - m\right)^2}{2\sigma^2}\right] \left|\frac{dx}{dy}\right|$$

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left[-\frac{(x-m)^2}{2\sigma^2}\right]$$

$x \in \mathbb{R}$

$$\frac{dx}{dy} = \frac{1}{a}$$

$$\begin{aligned} \text{donc } \pi(y) &= \frac{1}{\sqrt{2\pi}\sigma^2} \frac{1}{|a|} \exp\left[-\frac{(y-b-am)^2}{2a^2\sigma^2}\right] \\ &= \frac{1}{\sqrt{2\pi}a^2\sigma^2} \exp\left[-\frac{\left[y - (b+am)\right]^2}{2a^2\sigma^2}\right] \end{aligned}$$

$$y = ax + b \Rightarrow E(y) = aE(x) + b = am + b$$

$$\text{Var } y = a^2 \text{Var } x = a^2\sigma^2$$

$$Y \sim N(am + b, a^2\sigma^2)$$

Cours du 18/09/2023

Exemple d'application où on utilise  $F(x) = P(X < x)$

$$X = \max\{X_1, X_2\}$$

$$\begin{aligned} P(X < x) &= P(X_1 < x, X_2 < x) \\ &\quad \text{et} \\ &= P(X_1 < x) P(X_2 < x) \end{aligned}$$



$$F(x) = F_1(x) F_2(x)$$

$X_1 \sim N(m_1, \sigma_1^2)$   
 $X_2 \sim N(m_2, \sigma_2^2)$   
 $X_1$  et  $X_2$  ind

quelle est la loi de  $X = X_1 + X_2$ ?

$$\begin{aligned}
 \varphi_X(t) &= E[e^{itX}] = E[e^{it(X_1 + X_2)}] \\
 &= E[e^{itX_1} e^{itX_2}] \\
 &= E[e^{itX_1}] E[e^{itX_2}] \\
 &= \varphi_{X_1}(t) \varphi_{X_2}(t)
 \end{aligned}$$

$$\varphi_X(t) = \varphi_{X_1}(t) \varphi_{X_2}(t)$$

Take

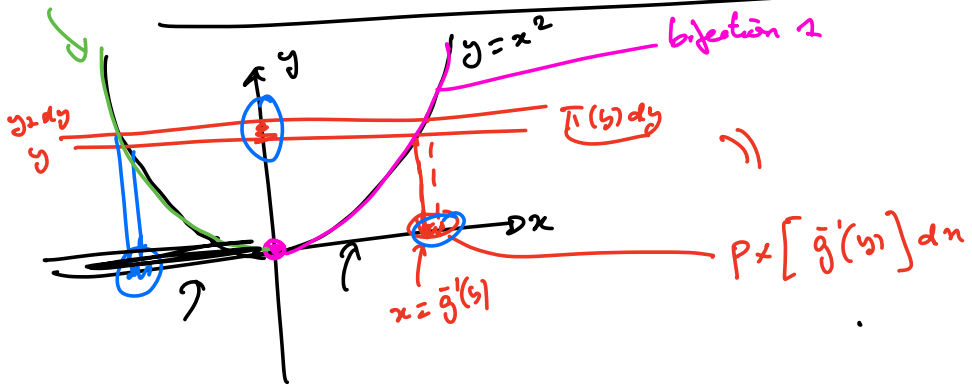
$$e^{im_1 t - \frac{\sigma_1^2}{2} t^2} \quad e^{im_2 t - \frac{\sigma_2^2}{2} t^2}$$

donc  $\varphi_X(t) = \exp\left[ i(m_1 + m_2)t - \frac{1}{2}(\sigma_1^2 + \sigma_2^2)t^2 \right]$

donc  $X \sim N(m_1 + m_2, \sigma_1^2 + \sigma_2^2)$

$X \sim N(0,1)$   $p(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$   $x \in \mathbb{R}$   
 loi de  $Y = X^2$ ?

bijection 1



Bijection 1

$$\mathbb{R}^{+*} \rightarrow \mathbb{R}^{+*}$$

$$x \rightarrow y = x^2 \Leftrightarrow x = \sqrt{y}$$

$$\pi_1(y) = \frac{1}{\sqrt{2\pi}} e^{-y/2} \left| \frac{1}{2\sqrt{y}} \right| = \frac{1}{2\sqrt{2\pi y}} e^{-y/2}$$

$$P(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \quad x \in \mathbb{R}$$

Bijection 2

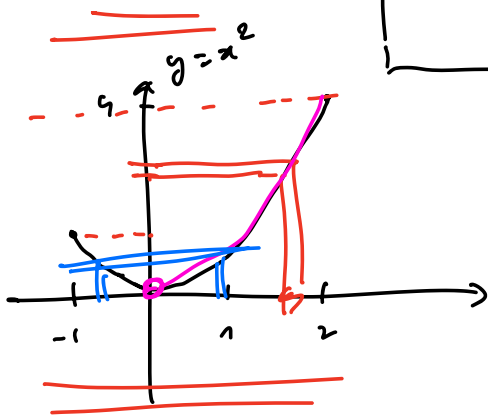
$$\mathbb{R}^{-*} \rightarrow \mathbb{R}^{+*}$$

$$x \rightarrow y = x^2 \Leftrightarrow x = -\sqrt{y}$$

$$\pi_2(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y}{2}} \left| -\frac{1}{2\sqrt{y}} \right| = \frac{1}{2\sqrt{2\pi y}} e^{-y/2}$$

La densité de Y est  $\pi(y) = \pi_1(y) + \pi_2(y)$  soit

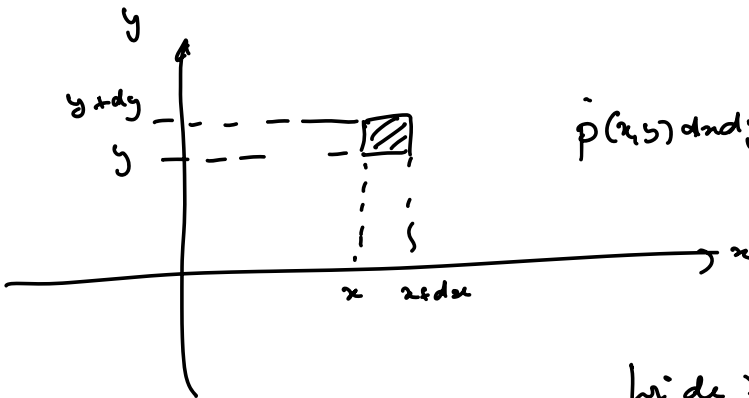
$$\pi(y) = \begin{cases} \frac{1}{\sqrt{2\pi y}} e^{-y/2} & y \in ]0, +\infty[ \\ 0 & \text{sinon} \end{cases}$$



$$(X \sim \mathcal{U}[-1, 2])$$

si  $y \in ]1, 4[$  alors  $\pi(y) = \pi_1(y)$

si  $y \in ]0, 1[$  alors  $\pi(y) = \pi_1(y) + \pi_2(y)$



$$p(x, y) dx dy \approx P[X \in ]x, x+dx[, Y \in ]y, y+dy[)$$

dx petit  
dy petit

largeur de X

$$X \begin{cases} 0 \\ 1 \end{cases}$$

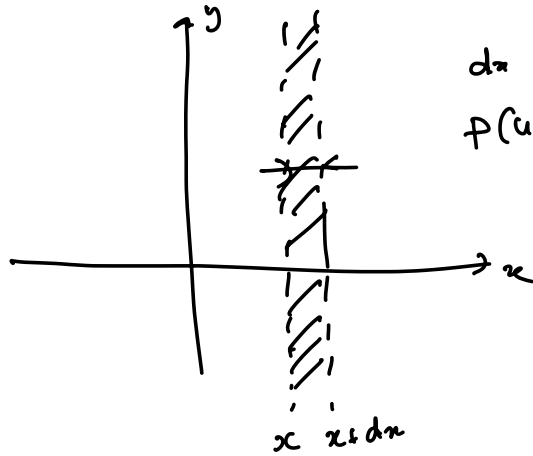
$$P(X=0) = \frac{1}{2} + \frac{1}{6} = \frac{2}{3}$$

$$P(X=1) = \frac{1}{6} + \frac{1}{6} = \frac{1}{3}$$

$Y \backslash X$	0	1
0	$\frac{1}{2}$	$\frac{1}{6}$
1	$\frac{1}{6}$	$\frac{1}{6}$

$\Delta x$

$$\boxed{p(x) dx} \approx P[X \in ]x, x+dx[$$



$$P[(X,Y) \in \Delta_x]$$

$$\int_x^{x+dx} \int_{\mathbb{R}} p(x,v) dv dx$$

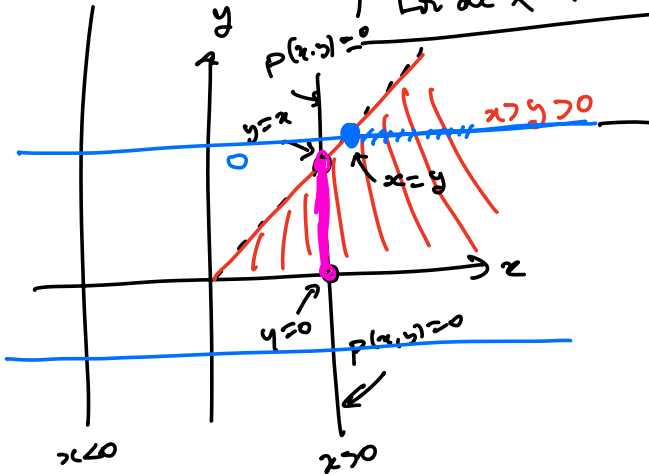
$$\int_x^{x+dx} \left[ \int_{\mathbb{R}} p(u,v) dv \right] dx \approx \int_x^{x+dx} p(x,v) dv dx = p(x) dx$$

$$\int_x^{x+dx} \left( \int_{\mathbb{R}} p(x,v) dv \right) dx = \int_{\mathbb{R}} p(x,v) dv \int_x^{x+dx} dx$$

Exo

$$p(x,y) = \begin{cases} \theta^2 e^{-\theta x} & x > y > 0 \\ 0 & \text{sinon} \end{cases}$$

Loi de X ?



X ne va pas continue de densite

$$p(x,0) = \int_{\mathbb{R}} p(x,y) dy$$

si  $x \leq 0$   $p(x,0) = \int 0 dy = 0$

si  $x > 0$   $p(x,0) = \int_0^x \theta^2 e^{-\theta y} dy$

$$= \theta^2 e^{-\theta x} \int_0^x dy$$

Conclusion

$$p(x, \theta) = \theta^2 x e^{-\theta x} I_{]0, +\infty[}(x)$$

$$\text{avec } I_{]0, +\infty[}(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

donc

$$X \sim G(\theta, 2)$$

Loi de Y

$$p(\cdot, y) = \int_{\mathbb{R}} p(x, y) dx$$

$$= \begin{cases} 0 & y \leq 0 \\ \int_y^{+\infty} \theta^2 e^{-\theta x} dx & y > 0 \end{cases} = -\theta \left[ e^{-\theta x} \right]_y^{+\infty} = \theta e^{-\theta y}$$

$$p(\cdot, y) = \theta e^{-\theta y} I_{]0, +\infty[}(y)$$

TD # 1 du 15/03/2023

$$f(x) = \begin{cases} k x^a & x \in ]0, 1[ \\ 0 & \text{sinon} \end{cases}$$

$$1) \int_{\mathbb{R}} f(x) dx = 1 \Leftrightarrow k \left( \frac{x^{a+1}}{a+1} \right)_0^1 = 1 \Leftrightarrow \boxed{k = a+1}$$

Ré: c'est une loi Beta  $B(a+1, 1)$

$$2) E(X^n) = \int_{\mathbb{R}} x^n f(x) dx = \int_0^1 x^n (a+1) x^a dx$$

$$= (a+1) \left( \frac{x^{a+n+1}}{a+n+1} \right)_0^1 = \boxed{\frac{a+1}{a+n+1}}$$

Moyenne

$$\boxed{\frac{a+1}{a+2} = E(X)}$$

$$\text{Variance } \text{Var}(X) = E(X^2) - E(X)^2 = \frac{a+1}{a+3} - \left( \frac{a+1}{a+2} \right)^2$$



$$= \frac{a+1}{(a+3)(a+2)} e^{\left[ \underbrace{(a+2)^2 - (a+1)(a+3)}_1 \right]}$$

$$= \boxed{\frac{a+1}{(a+3)(a+2)^2}}$$

Rq loi Beta(a,b)

$$a \rightarrow a+1$$

$$b \rightarrow 1$$

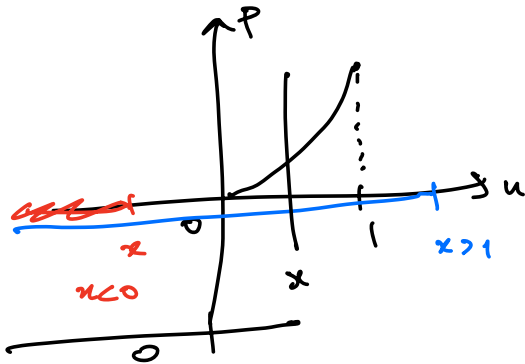
$$\forall x = \frac{ab}{(a+b)^2(a+b+1)}$$

$$\frac{(a+1) \times 1}{(a+2)^2(a+3)}$$

ok

Fonction de répartition

$$F(x) = P[X \leq x] = \int_{-\infty}^x p(u) du$$



$$\int_{-\infty}^x p(u) du = 0 \quad x \leq 0$$

$$\int_{-\infty}^x p(u) du = 1 \quad x \geq 1$$

$$\text{Si } x \in ]0; 1[ \quad F(x) = \int_{-\infty}^0 0 du + \int_0^x (a+1)u^a du$$

$$= x^{a+1} \quad \left[ \frac{u^{a+1}}{a+1} \right]_0^x$$

$$F(x) = \begin{cases} 0 & x \leq 0 \\ 1 & x \geq 1 \\ x^{a+1} & x \in ]0; 1[ \end{cases}$$

Changement de variable

$$Y = -\ln x$$

$$f(x) = \begin{cases} (a+1)x^a & x \in ]0; 1[ \\ 0 & \text{sinon} \end{cases}$$

Densité de Y!

$$Y = -\ln x \text{ donc } x = e^{-Y}$$

donc le changement de variable n'est pas spécifique

Densité de  $Y$  
$$\pi(y) = (a+1) (e^{-y})^a \times \left| -e^{-y} \right| \frac{dx}{dy}$$
$$= (a+1) e^{-ay} e^{-y} \frac{dx}{dy}$$

$$\pi(y) = (a+1) e^{-(a+1)y} \quad y \in \mathbb{R}^+!$$

Domaine de  $Y$

$$x \in ]0, 1[ \Leftrightarrow e^{-y} \in ]0, 1[$$

$$\Leftrightarrow \ln(e^{-y}) = -y \in ]-\infty, 0[$$

$$\Leftrightarrow y \in ]0, +\infty[ \quad y \in \mathbb{R}^+$$

$$\pi(y) = (a+1) e^{-(a+1)y} \mathbb{I}_{]0, +\infty[}(y)$$

$$Y \sim \mathcal{E}_a(a+1, 1)$$

$$E(Y) = \frac{V}{a} = \frac{1}{a+1}$$

$$Var(Y) = \frac{V}{a^2} = \frac{1}{(a+1)^2}$$

$$E(Y^n) = \int_0^{+\infty} y^n (a+1) e^{-(a+1)y} dy$$

$$\int_0^{+\infty} \frac{u^n}{(a+1)^n} (a+1) e^{-u} \frac{du}{(a+1)}$$

$$u = (a+1)y$$

$$y = \frac{u}{a+1}$$

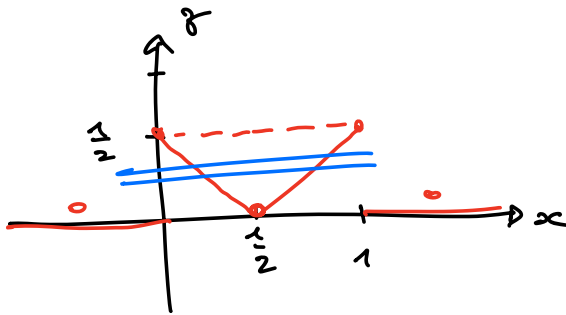
$$= \frac{1}{(a+1)^n} \int_0^{+\infty} u^n e^{-u} du$$

$$\Gamma(n+1) = n!$$

$$= \frac{n!}{(a+1)^n}$$

6)  $Z = \left| x - \frac{1}{2} \right|$

Loi de Z ?



$$f(x) = \begin{cases} (a+1)x^a & x \in ]0, 1[ \\ 0 & \text{sinon} \end{cases}$$

$$\left| x - \frac{1}{2} \right| = \begin{cases} x - \frac{1}{2} & x > \frac{1}{2} \\ \frac{1}{2} - x & x \leq \frac{1}{2} \end{cases}$$

donc  $Z \in ]0, \frac{1}{2}[$

Bijection # 1

$$]0, \frac{1}{2}[ \rightarrow ]0, \frac{1}{2}[$$

$$x \mapsto z = \left| x - \frac{1}{2} \right| = \frac{1}{2} - x$$

$$x = \frac{1}{2} - z$$

$$\left| \frac{dx}{dz} \right| = |-1| = 1$$

$$g_1(z) = (a+1) \left( \frac{1}{2} - z \right)^a \times 1 = (a+1) \left( \frac{1}{2} - z \right)^a$$

Bijection # 2

$$]\frac{1}{2}, 1[ \rightarrow ]0, \frac{1}{2}[$$

$$x \mapsto z = \left| x - \frac{1}{2} \right| = x - \frac{1}{2}$$

$$x = \frac{1}{2} + z$$

$$\left| \frac{dx}{dz} \right| = |1| = 1$$

$$g_2(z) = (a+1) \left( \frac{1}{2} + z \right)^a \times 1$$

$$= (a+1) \left( z + \frac{1}{2} \right)^a$$

Donc la densité de Z est

$$g(z) = \begin{cases} (a+1) \left[ \left( \frac{1}{2} - z \right)^a + \left( \frac{1}{2} + z \right)^a \right] & z \in ]0, \frac{1}{2}[ \\ 0 & \text{sinon} \end{cases}$$

Files d'attente

A

Garsinet 1

B

Garsinet 2

C

Temps d'attente de C =  $\text{Inf}(\text{temps de service de A}, \text{temps de service de B})$

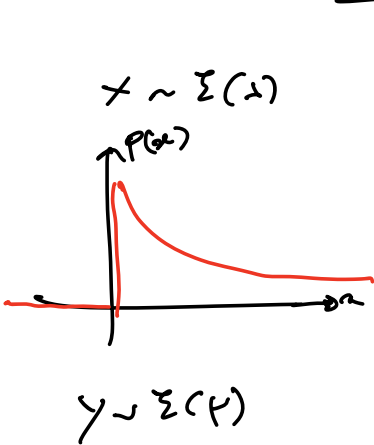
$T = \text{Inf}(X, Y)$

$E(T) ?$

$E[e^{iuT}]$

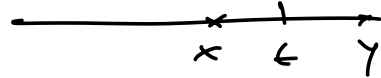
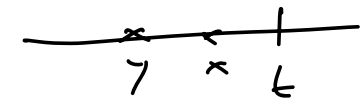
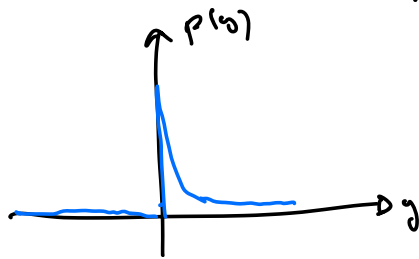
$E[e^{iu \text{Inf}(X, Y)}]$

$P(T < t)$



$$p(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$p(y) = \begin{cases} \mu e^{-\mu y} & y > 0 \\ 0 & y \leq 0 \end{cases}$$



Méthode 1

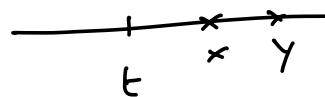
$$P(T < t) = P[\text{Inf}(X, Y) < t]$$

$$= P[ \underset{\text{ou}}{x < t, y < t} \text{ ou } \underset{\text{ou}}{x < t, y > t} \text{ ou } \underset{\text{ou}}{y < t, x > t} ]$$

Méthode 2

$$P(T < t) = 1 - P(T \geq t)$$

$$= 1 - P(x \geq t, y \geq t)$$

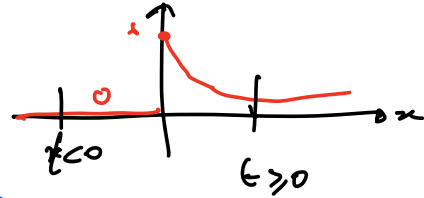


$$= 1 - \frac{P(X \geq t)}{1 - F_X(t)} \cdot \frac{P(Y \geq t)}{1 - F_Y(t)}$$

$$F_X(t) = P(X < t)$$

$$X \sim \mathcal{E}(\lambda)$$

$$p(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x < 0 \end{cases}$$



$$= \begin{cases} 0 & t < 0 \\ \int_0^t \lambda e^{-\lambda x} dx = \left[ -e^{-\lambda x} \right]_0^t = 1 - e^{-\lambda t} & t \geq 0 \end{cases}$$

$$P(T < t) = 1 - \frac{e^{-\lambda t}}{1 - F_X(t)} \cdot \frac{e^{-\mu t}}{1 - F_Y(t)} = 1 - e^{-(\lambda + \mu)t}$$

densité de T

$$p(t) = \begin{cases} (\lambda + \mu) e^{-(\lambda + \mu)t} & t > 0 \\ 0 & t < 0 \end{cases}$$

$$T \sim \mathcal{E} \quad E(T) = \frac{1}{\lambda + \mu}$$

Cours du 25/09/2023

indépendance

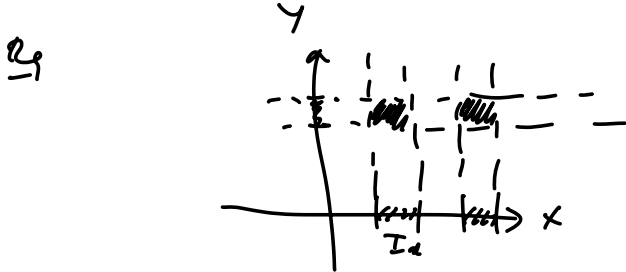
$$P_{i,j} = P_i \cdot P_j \quad \forall i, j //$$

$$\begin{aligned} P\left[ \underbrace{X \in \{x_1, x_2\}}_A, \underbrace{Y \in \{y_1\}}_B \right] &= P\left[ (X, Y) = (x_1, y_1) \text{ ou } (x_2, y_1) \right] \\ &= P_{x_1} \cdot P_{y_1} \\ &= P_{x_1} \cdot P_{x_1} \cdot P_{y_1} \\ &= \underbrace{(P_{x_1} + P_{x_2})}_{P_i} \cdot P_{y_1} \end{aligned}$$

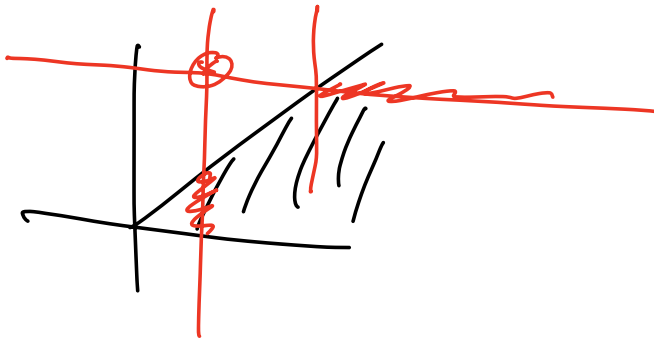
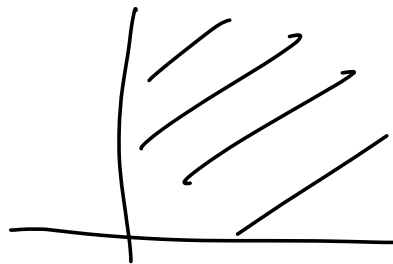
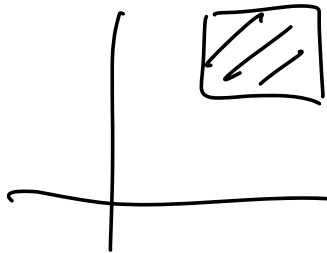
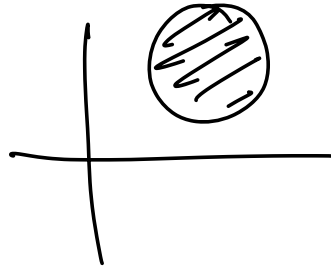
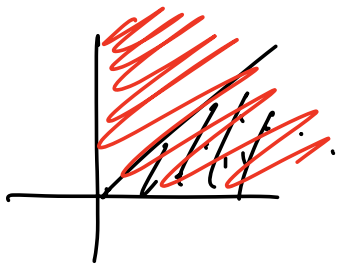
$$P[X \in (x_1, x_2)]$$

Cas continu

$$X \text{ et } Y \text{ ind. } \Leftrightarrow P(x, y) = \underbrace{P(x, \cdot)}_{x \in I_x} \times \underbrace{P(\cdot, y)}_{y \in I_y} \quad \forall x, y$$



le domaine de définition de  $(x, y)$  est une réunion de parties



Espérances mathématiques d'un couple  $(X, Y)$

$\mathbb{R}^2$

$$E[X^2]$$

$$\sum_i x_i^2 P[X=x_i]$$

$$\int x^2 P(x, \cdot) dx$$

à 2D

$$E[XY] \rightarrow \sum_{i,j} x_i y_j \underbrace{P[X=x_i, Y=y_j]}_{p_{ij}}$$

$$\rightarrow \iint xy \underbrace{p(x,y)}_{p(x,y)} dx dy$$

$$E[\alpha(X,Y)] \rightarrow \sum_{i,j} \alpha(x_i, y_j) p_{ij}$$

$$\forall \alpha \rightarrow \iint \alpha(x,y) p(x,y) dx dy$$

Propriété

$$E[cte] = \sum_{i,j} cte p_{ij} = cte$$

$$\rightarrow \iint cte p(x,y) dx dy = cte$$

$$E\left[XY - \frac{X^2}{Y^2}\right] = E[XY] - E\left[\frac{X^2}{Y^2}\right]$$

E est un opérateur linéaire

Définition covariante

$(X,Y)$  couple de va continus.

$$E[X] = \iint x p(x,y) dx dy = \int_x \left[ \int_y x p(x,y) dy \right] dx$$

$$= \int_x x \left[ \int_y p(x,y) dy \right] dx$$

Indépendance

si  $X$  et  $Y$  sont ind alors  $E[\alpha(X)\beta(Y)] = E[\alpha(X)]E[\beta(Y)]$   
 $\forall \alpha, \beta$

En effet (cas continu)

$$E[\alpha(X)\beta(Y)] = \iint \alpha(x)\beta(y) p(x,y) dx dy$$

$$= \iint \alpha(x)\beta(y) \underbrace{p(x,y)}_{p(x,y)p(y)} dx dy$$

$X$  et  $Y$  ind

$$= \left[ \int \alpha(x) p(x,y) dx \right] \times \left[ \int \beta(y) p(y) dy \right]$$

Exemple d'application

$$= E(\alpha(X)) E(\beta(Y))$$

si  $X$  et  $Y$  sont indépendantes, alors

$$E(XY) = E(X)E(Y)$$

Définition

$$\text{Cov}(X, Y) = E(XY) - E(X)E(Y)$$

s'appelle la covariance du couple  $(X, Y)$

Rq si  $X=Y$   $\text{Cov}(X, X) = \text{Var} X$

Matrice de covariance

$$M = \begin{pmatrix} \text{Var} X & \text{Cov}(X, Y) \\ \text{Cov}(X, Y) & \text{Var} Y \end{pmatrix}$$

$$V = \begin{bmatrix} X - E(X) \\ Y - E(Y) \end{bmatrix} \text{ vecteur de } \mathbb{R}^2$$

$$E[VV^T] = E \left[ \begin{pmatrix} X - E(X) & Y - E(Y) \\ Y - E(Y) & X - E(X) \end{pmatrix} \right]$$

$$= E \left[ \begin{pmatrix} (X - E(X))^2 & (X - E(X))(Y - E(Y)) \\ (Y - E(Y))(X - E(X)) & (Y - E(Y))^2 \end{pmatrix} \right]$$

$$= \begin{pmatrix} \text{Var} X & \text{Cov}(X, Y) \\ \text{Cov}(X, Y) & \text{Var} Y \end{pmatrix}$$

$\mathbb{R}^1$  Fonction caractéristique  $E[e^{i u X}] = \varphi_X(u)$

$\mathbb{R}^2$   $E[e^{i(u_1 X + u_2 Y)}] = \varphi_{X, Y}(u) \quad u = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}$

$\downarrow$

$(u_1, u_2) \begin{pmatrix} X \\ Y \end{pmatrix}$



$$\varphi_{X,Y}(u) = E\left( e^{i u^T \begin{pmatrix} X \\ Y \end{pmatrix}} \right)$$

Coefficient de corrélation       $\Gamma_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$        $\sigma_X = \sqrt{\text{Var} X}$   
 $\sigma_Y = \sqrt{\text{Var} Y}$

$$\Gamma_{10X,10Y} = \frac{\text{cov}(10X,10Y)}{\sqrt{\text{Var}(10X)} \sqrt{\text{Var}(10Y)}} = \frac{100 \text{cov}(X,Y)}{\sqrt{100 \text{Var} X} \sqrt{100 \text{Var} Y}} = \Gamma_{X,Y}$$

Rappel : Inégalité de CAUCHY-SCHWARTZ  
 $|\langle A, B \rangle| \leq \sqrt{\|A\|^2} \sqrt{\|B\|^2} = \|A\| \|B\|$

$$\|a\|^2 = \sum a_i^2$$

On démontre que si  $X$  et  $Y$  sont des variables aléatoires  
 $\langle X, Y \rangle = E(XY)$  définit un produit scalaire

Cauchy-Schwartz

$$|\langle X - E(X), Y - E(Y) \rangle| \leq \|X - E(X)\| \|Y - E(Y)\|$$

$$\leq \sqrt{E((X - E(X))^2)} \times \sqrt{E((Y - E(Y))^2)}$$

$\|X\|^2 = \langle X, X \rangle = E(X^2)$

$$\Gamma_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$$

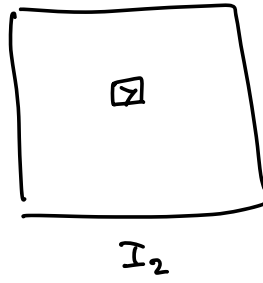
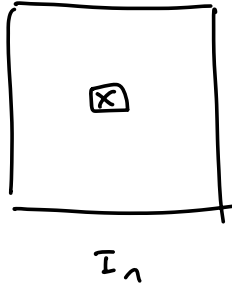
$$\Gamma_{X,Y}^2 = \frac{\text{cov}^2(X,Y)}{\sigma_X^2 \sigma_Y^2}$$

$$|\text{cov}(X,Y)| \leq \sqrt{\text{Var} X} \sqrt{\text{Var} Y}$$

d'où  $\frac{|\text{cov}(X,Y)|}{\sqrt{\sigma_X^2} \sqrt{\sigma_Y^2}} \leq 1$

$$\Gamma_{X,Y}^2 \leq 1 \iff -1 \leq \Gamma_{X,Y} \leq +1$$

$\Gamma_{X,Y} = \pm 1 \iff X$  et  $Y$  liés par une relation affine



$$\begin{aligned} r_{xy} &= \frac{\text{cov}(xy)}{\sigma_x \sigma_y} \\ &= \frac{E(xy) - E(x)E(y)}{\sqrt{E(x^2) - E^2(x)} \sqrt{E(y^2) - E^2(y)}} \end{aligned}$$

les 2 pixels  $x$  et  $y$  sont liés s'il n'y a pas de changement

les 2 pixels perdus s'il y a eu un changement  
d'où la règle

Détecter un changement si  $r_{xy}^2 \leq \text{seuil}$

↑  
↑  
fixé par l'utilisateur

$E(x)$  ?

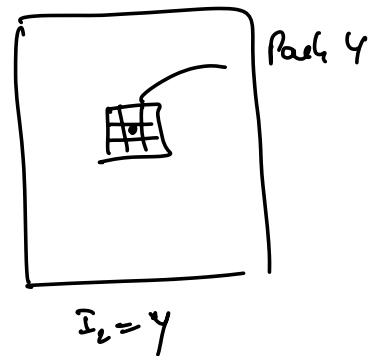
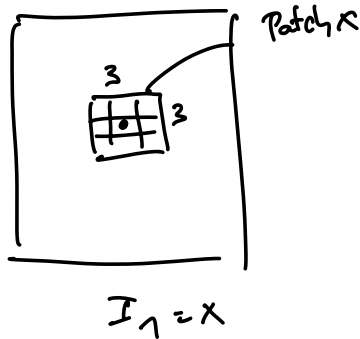
$E(y)$  ?

$E(x^2)$  ?

$E(y^2)$  ?

$E(xy)$  ?

$$\Rightarrow r_{xy} = \frac{E(xy) - E(x)E(y)}{\sqrt{E(x^2) - E^2(x)} \sqrt{E(y^2) - E^2(y)}}$$



$$E(x) \approx \frac{1}{9} \sum_{x_{ij} \in \text{Patch}_x} x_{ij}$$

$$E(y) \approx \frac{1}{9} \sum y_{ij}$$

$$E(x^2) \approx \frac{1}{9} \sum x_{ij}^2$$

$$E(y^2) \approx \frac{1}{9} \sum y_{ij}^2$$

$$E(xy) \approx \frac{1}{9} \sum x_{ij} y_{ij}$$

$$\text{Cov}(X, Y) = \underbrace{\frac{1}{n} \sum x_{ij} y_{ij}}_{x_{ij} y_{ij}} - \underbrace{\left( \frac{1}{n} \sum x_{ij} \right)}_{x_{ij}} \underbrace{\left( \frac{1}{n} \sum y_{ij} \right)}_{y_{ij}} = 0$$

Espérance conditionnelle

$$E[\alpha(x, y)] = \iint \alpha(x, y) \underbrace{p(x, y)}_{p(y|x) p(x, \cdot)} dx dy \quad \left| \begin{array}{l} p(y|x) = \frac{p(y, x)}{p(x, \cdot)} \end{array} \right.$$

$$= \int_x \left[ \int_y \alpha(x, y) p(y|x) p(x, \cdot) dy \right] dx$$

$$= \int_x p(x, \cdot) \left[ \int_y \alpha(x, y) p(y|x) dy \right] dx$$

$$E\left[ \int_y \alpha(x, y) p(y|x) dy \right] = E\left[ \int_y \alpha(x, y) p(y|x) dy \mid x \right]$$

$$E(\alpha(x)) = \int \alpha(x) p(x, \cdot) dx$$

$$E_x \left[ E\left( \int_y \alpha(x, y) p(y|x) dy \mid x \right) \right]$$

Exemple d'application

$$X \sim N(0, 1)$$

$$p(x, \cdot) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \quad x \in \mathbb{R}$$

$$Y \begin{cases} \rightarrow 1 & p \\ \rightarrow -1 & q = 1-p \end{cases}$$

Quelle est la loi de  $Z = XY$ ?

Fonction caractéristique de Z

$$\varphi_Z(u) = E[e^{iuZ}] = E[e^{iuXY}]$$

$$= E\left[ \int_x E\left( e^{iuxy} \mid y \right) \right]$$

TABLER

$$E[e^{iuy} | Y] = \varphi_X(uY)$$

$$= e^{-\frac{1}{2}u^2 Y^2}$$

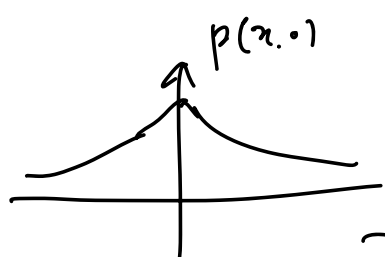
$$\varphi_Z(u) = E_Y \left[ e^{-\frac{u^2 Y^2}{2}} \right]$$

$$= e^{-\frac{u^2 (1)^2}{2}} P(Y=1) + e^{-\frac{u^2 (-1)^2}{2}} P(Y=-1)$$

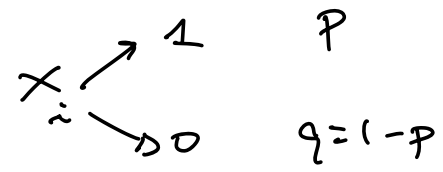
$$\varphi_Z(u) = e^{-u^2/2}$$

$$\Rightarrow Z \sim N(0,1)$$

$$\begin{aligned} X &\sim N(0,1) \\ \varphi_X(t) &= e^{i\mu t - \frac{\sigma^2 t^2}{2}} \\ &= e^{-\frac{t^2}{2}} \end{aligned}$$



Example 2



$$Y_N = \sum_{i=1}^N X_i$$

$$N \sim P(\lambda) \quad P(N=k) = \frac{\lambda^k}{k!} e^{-\lambda} \quad k \in \mathbb{N}$$

$$E(Y_N) = ?$$

Si  $N = n$  alors on sait que  $Y_n = \sum_{i=1}^n X_i \sim B(n, p)$

Table  $\left| \underline{E(Y_n) = np} \right|$

$$E[Y_N] = E \left[ \underbrace{E[Y_N | N]}_{np} \right]$$

$$= p \underbrace{E[N]}_{\lambda}$$

Espérance d'un loi de Poisson =  $\lambda$

$$= \boxed{\lambda p}$$

TD #2 du 25/09/2023

Rappel | Si  $X \sim N(m, \sigma^2)$  alors

$$Y = aX + b \sim N(\underbrace{am + b}_{E(Y)}, \underbrace{a^2 \sigma^2}_{\text{Var } Y})$$

$$\left[ Z = \frac{X - m}{\sigma} \sim N(0, 1) \right]$$

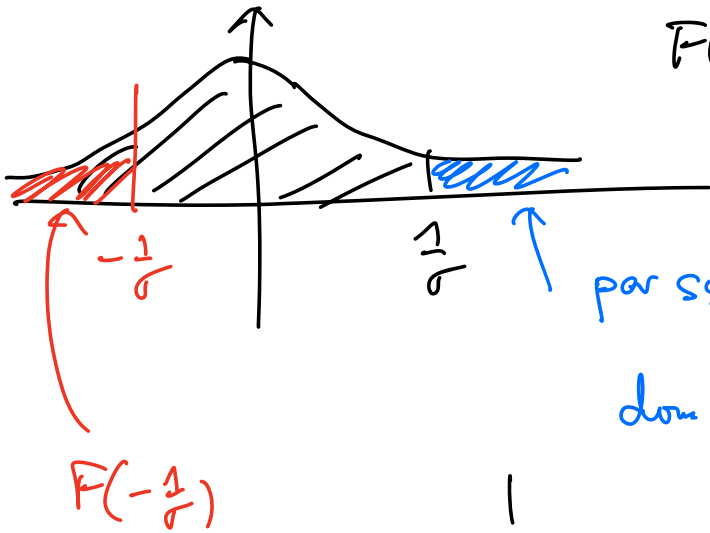
on centre et on réduit !!

Fonction de répartition de Z

$$P(Z < z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du$$

$$\int_{-\infty}^{\infty} = F(z)$$

normed f.m.  
cumulative distribution function

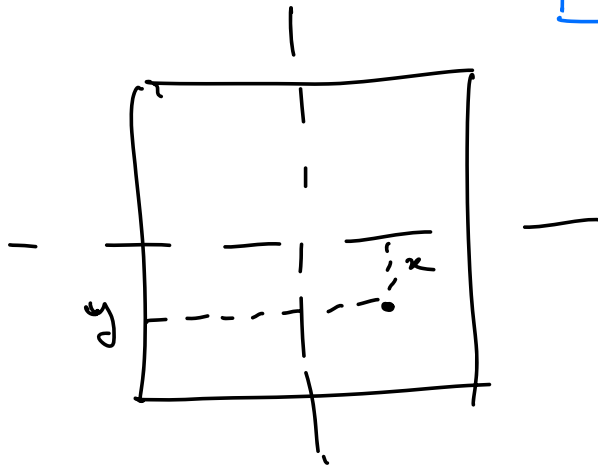


$$F\left(\frac{1}{\sigma}\right)$$

per symmetrie =  $1 - F\left(\frac{1}{\sigma}\right)$

damit

$$F\left(-\frac{1}{\sigma}\right) = 1 - F\left(\frac{1}{\sigma}\right)$$



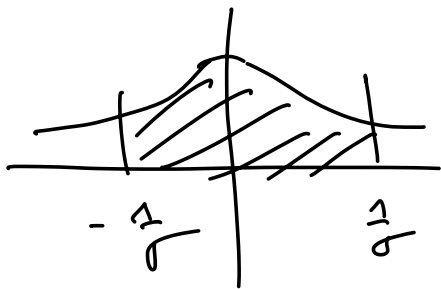
$$\begin{aligned}
 1) \quad q &= P[-1 \leq X \leq 1, -1 \leq Y \leq 1] \\
 &= P[-1 \leq X \leq 1] \times P[-1 \leq Y \leq 1] \\
 &\stackrel{\substack{\uparrow \\ \text{X und Y unabh.}}}{=} P\left[-\frac{1}{\sigma} \leq Z \leq \frac{1}{\sigma}\right] P\left[-\frac{1}{\sigma} < \frac{Y}{\sigma} < \frac{1}{\sigma}\right]
 \end{aligned}$$

Méthode 1

$$Z = \frac{X-0}{\sigma} \sim \mathcal{N}(0,1)$$

$$\text{donc } P(Z < z) = F(z)$$

$$= \left( \int_{-\frac{1}{\sigma}}^{\frac{1}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du \right) \times \left( F\left(\frac{1}{\sigma}\right) - F\left(-\frac{1}{\sigma}\right) \right)$$



$$F\left(\frac{1}{\sigma}\right) - F\left(-\frac{1}{\sigma}\right)$$

$$q = \left[ F\left(\frac{1}{\sigma}\right) - F\left(-\frac{1}{\sigma}\right) \right]^2$$

pour  $\sigma = \frac{1}{2}$

$$q = \left[ F(2) - F(-2) \right]^2$$

Méthode 2

$$P(-1 \leq X \leq 1) = \int_{-1}^{1} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{u^2}{2\sigma^2}} du$$

$$\begin{aligned} & \xrightarrow{v = \frac{u}{\sigma}} \int_{-\frac{1}{\sigma}}^{\frac{1}{\sigma}} \frac{1}{\sqrt{2\pi\cancel{\sigma^2}}} e^{-\frac{v^2}{2}} \cancel{\sigma} dv \\ & = \left[ F\left(\frac{1}{\sigma}\right) - F\left(-\frac{1}{\sigma}\right) \right] \end{aligned}$$

$$= \left[ F\left(\frac{1}{\sigma}\right) - F\left(-\frac{1}{\sigma}\right) \right]$$

$p =$  Probabilité que la flèche n'atteigne pas le carton.

$= 1 -$  Probabilité que la flèche atteigne le carton

$$p = 1 - q$$

2)  $n$  tirés  
 $N \in \{0, \dots, n\}$  = nombre de flèche perdues

sur 1 tir  $P[\text{flèche perdue}] = p$

$P[\text{flèche non perdue}] = 1 - p$

si  $X_k$  nr le résultat au  $k^{\text{ème}}$  tir succès.

$X_k \rightarrow 1$   $p$   
 $\rightarrow 0$   $q = 1 - p$

$$N = \sum_{k=1}^n X_k$$

Rappel .

$$P[\text{k succès sur n expériences}] = P[Z = k]$$

$$Z \sim B(n, p)$$



nombre  
d'expériences

$p$   
probabilité  
de succès sur  
1 expérience

$$N \sim B(100, p) \quad p = 1 - q$$
$$E(N) \stackrel{\uparrow}{=} 100p$$

Table

Exo 1

$$Y | X=n \sim B(n, p)$$

$$\text{donc } P[Y=k | X=n] = \binom{n}{k} p^k q^{n-k}$$

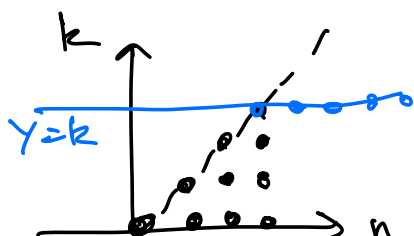
$$k \in \{0, \dots, n\}$$

$$X \sim P(\lambda) \text{ donc } P[X=k] = \frac{\lambda^k}{k!} e^{-\lambda}$$

$$k \in \mathbb{N}$$

1) loi de  $(X, Y)$

$$P[Y=k, X=n] = P(Y=k | X=n) P(X=n)$$



$$= \left[ \binom{n}{k} p^k q^{n-k} \frac{\lambda^n}{n!} e^{-\lambda} \right]$$

probabilités

$$\left. \begin{array}{l} k \in \mathbb{N} \\ k \leq n \end{array} \right\} \text{Domain}$$

2) Wirdy

$$P(Y=k) = \sum_n P(Y=k, X=n)$$

$$= \sum_{n=k}^{\infty} \frac{n!}{k!(n-k)!} p^k q^{n-k} \frac{e^{-n}}{n!}$$

$$= \frac{1}{k!} p^k e^{-1} \sum_{n=k}^{\infty} \frac{q^{n-k} 1^n}{(n-k)!}$$

$$= \frac{p^k}{k!} e^{-1} \sum_{m=0}^{\infty} \frac{q^m 1^{m+k}}{m!}$$

$$m = n - k$$

$$n = m + k$$

$$= \frac{1^k p^k e^{-1}}{k!} \sum_{m=0}^{\infty} \frac{(1q)^m}{m!}$$

$\underbrace{\hspace{10em}}_{e^{1q}}$

$$= \frac{(1p)^k}{k!} e^{-1(1-q)}$$

$$\boxed{Y \sim P(1p)}$$

Si  $p = \frac{1}{2}$

$Y \sim P\left(\frac{1}{2}\right)$

3) Calcul de  $E(XY)$

Méthode 1  $E(XY) = \sum_n \sum_k nk P[X=n, Y=k]$

$\binom{n}{k} p^k q^{n-k} \frac{\lambda^n}{n!} e^{-\lambda}$

$k \in \mathbb{N} \quad n \geq k$

$= \sum_{k=0}^{\infty} \sum_{n=k}^{\infty} \dots$

penible

Méthode 2  $E(XY) = E\left[ \underset{X}{E\left[ \underset{Y}{XY} \mid X=n \right]} \right]$   
 $= E\left[ X \frac{n}{X} E[Y \mid X=n] \right]$

$Y \mid X=n \sim B(n, p) \Rightarrow E[Y \mid X=n] = np$   
Table

$$= E\left[ \sum_{i=1}^n x_i^2 \mid X=n \right]$$

$$= p E[X^2]$$

$$X \sim P(1) \text{ donc } E(X^2) = \text{Var} X + E^2(X)$$

$$\text{car } \text{Var} X = E(X^2) - E^2(X) \quad \begin{array}{l} \downarrow \\ \textcircled{1} \end{array} \quad \begin{array}{l} \uparrow \\ \textcircled{2} \end{array}$$

$$p = \frac{1}{2} \text{ donc } E(X^2) = \frac{1}{2} \times (1+1^2)$$

$$= \frac{1(1+1)}{2}$$

4) a?

$$E[\alpha(X, Y)] = E[E(\alpha(X, Y) \mid X)]$$

$$\text{Cov}(X, Z) = E(XZ) - E(X)E(Z)$$

↓
↓

$$Z = X + aY$$

$$E \quad X \sim P(1) \Rightarrow E(X) = 1$$

$$Z = X + aY \Rightarrow E(Z) = \underbrace{E(X)}_1 + aE(Y)$$

↓

$$\text{car } Y \sim P(\lambda/2)$$

$$\text{donc } \begin{cases} E(X) = \lambda \\ E(Z) = \lambda + \frac{a\lambda}{2} \end{cases}$$

$$\begin{aligned} E(XZ) &= E(X^2 + aXY) \\ &= \underbrace{V_X}_{\lambda} + \underbrace{E(X^2)}_{\lambda^2} + a E(XY) \end{aligned}$$

vu à la question précédente

On cherche  $a$  /

$$\frac{\lambda(\lambda+1)}{2}$$

$$E(XZ) - E(X)E(Z) = 0$$

$$\cancel{\lambda} + \cancel{\lambda^2} + a \frac{\lambda(\lambda+1)}{2} - \lambda \left( \cancel{\lambda} + \frac{a}{2} \lambda \right) = 0$$

$$1 + \frac{a}{2} (\cancel{\lambda} + 1) - \frac{a}{2} \cancel{\lambda} = 0$$

$$\frac{a}{2} + 1 = 0$$

$$\boxed{a = -2}$$

Cours du 21/10/2023

2110

$$p(x) = \begin{cases} 2x & x \in ]0,1[ \\ 0 & \text{sinon} \end{cases}$$

loi de  $Y = \ln X$ ?  $\Leftrightarrow$

$x = e^y$

loi de Y

densité de Y

$$h(y) = \begin{cases} 2e^y & | e^y \\ 0 & \text{sinon} \end{cases}$$

$y \in ?$   
 $\frac{dx}{dy}$

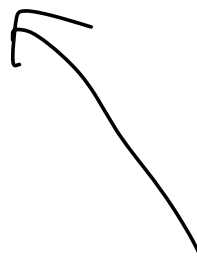
$$h(y) = 2e^{2y} \quad y \in ?$$

$x \in ]0,1[ \Rightarrow y = \ln x \in \mathbb{R} = ]-\infty, 0[$

$$h(y) = 2e^{2y} \quad ]-\infty, 0[ (y)$$

Preuve.

$$P\left(\begin{pmatrix} U \\ V \end{pmatrix} \in \Delta\right) = \iint_{\Delta} \pi(u,v) \, du \, dv$$



$$P\left(\begin{pmatrix} U \\ V \end{pmatrix} \in \Delta\right) = P\left(g\left(\begin{pmatrix} X \\ Y \end{pmatrix}\right) \in \Delta\right)$$

$$= P\left(\begin{pmatrix} X \\ Y \end{pmatrix} \in \bar{g}^{-1}(\Delta)\right)$$

!!!

$$= \iint_{\bar{g}^{-1}(\Delta)} p(x, y) dx dy$$

$$\left(\begin{pmatrix} U \\ V \end{pmatrix} = g\left(\begin{pmatrix} X \\ Y \end{pmatrix}\right)\right) \longrightarrow = \iint_{\Delta} p\left[\bar{g}^{-1}(u, v)\right] |\det(J)| du dv$$

$$J = \begin{pmatrix} \frac{\partial x}{\partial u} & \frac{\partial y}{\partial u} \\ \frac{\partial x}{\partial v} & \frac{\partial y}{\partial v} \end{pmatrix}$$

donc  $\pi(u, v) = p[\bar{g}^{-1}(u, v)] |\det(J)|$

Exemple 1

$$X \sim U(]0, 1[)$$

$$Y \sim U(]0, 1[)$$

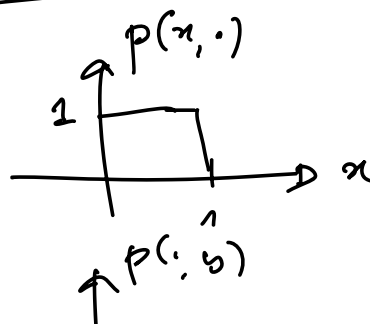
X et Y indépendants

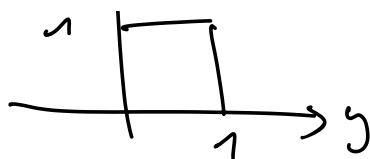
loi de  $\begin{pmatrix} T \\ U \end{pmatrix}$  ?

$$\begin{cases} T = X + Y \\ U = X \end{cases}$$

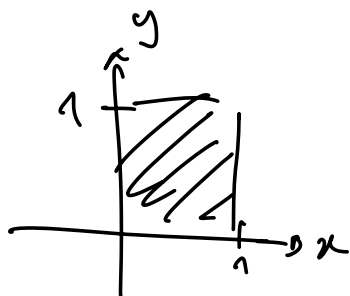
$$X \sim U(]0, 1[)$$

$$Y \sim U(]0, 1[)$$





$$X \text{ et } Y \text{ ind.} \Rightarrow p(x, y) = p(x, \cdot) \times p(\cdot, y)$$



$$= \begin{cases} 1 & \text{si } (x, y) \in ]0, 1[ \times ]0, 1[ \\ 0 & \text{sinon} \end{cases}$$

Densité de  $\begin{pmatrix} T \\ U \end{pmatrix} = \begin{pmatrix} X+Y \\ X \end{pmatrix} \Rightarrow$

$$\begin{cases} X = U \\ Y = T - U \end{cases}$$

donc le changement de variables est  
bijectif.

$$\pi(t, u) = 1 \times |\det(J)|$$

1 dans lequel j'ai remplacé  
 $(x, y)$  par  $(u, t-u)$

$$J = \begin{pmatrix} \frac{\partial x}{\partial t} & \frac{\partial y}{\partial t} \\ \frac{\partial x}{\partial u} & \frac{\partial y}{\partial u} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & -1 \end{pmatrix}$$

$$\det(J) = -1 \Rightarrow |\det(J)| = 1$$

$$\text{donc } \boxed{\pi(t, u) = 1 \times 1 \quad (t, u) \in \Delta}$$



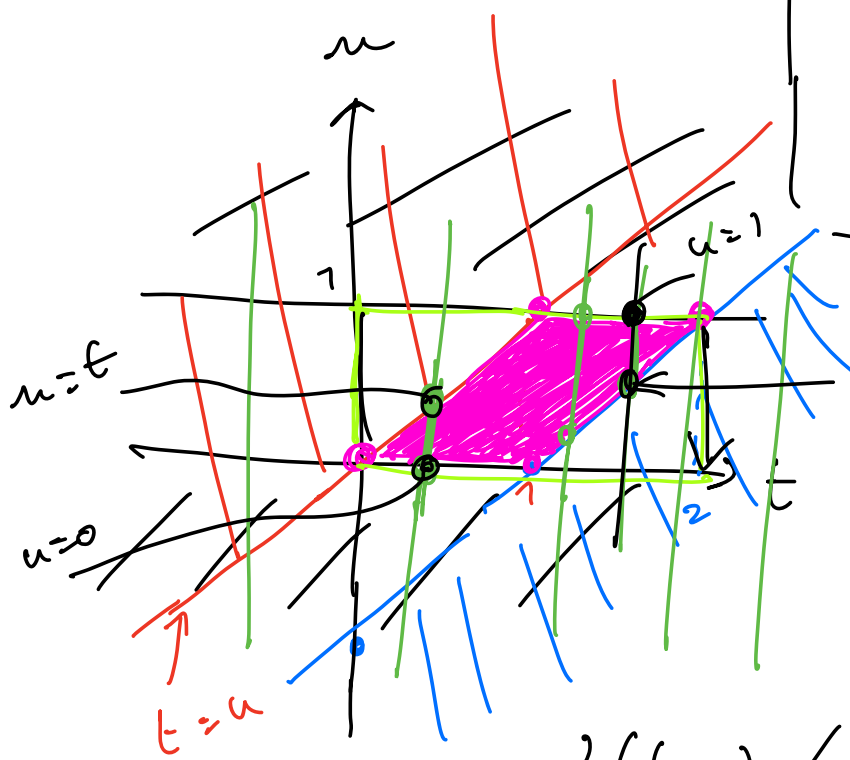
Recherche de  $\Delta$

$$\begin{cases} 0 < x < 1 \\ 0 < y < 1 \end{cases} \Leftrightarrow D$$

Domaine de  $(x, y)$

$$\begin{cases} 0 < u < 1 \\ 0 < t-u < 1 \end{cases}$$

$$\begin{cases} u > 0 \\ u < 1 \\ t > u \\ t < u+1 \end{cases}$$



Domaine de définition = parallélogramme

$$f(t, u) / \left. \begin{matrix} u \in ]0, 1[ \\ t > u \\ t < u+1 \end{matrix} \right\}$$

Lois marginales de T et de U

$$\begin{cases} T = x+y \\ U = x \end{cases}$$

$U$  a la même loi que  $X$  donc  $U \sim U(]0,1[)$

Loi de  $T$

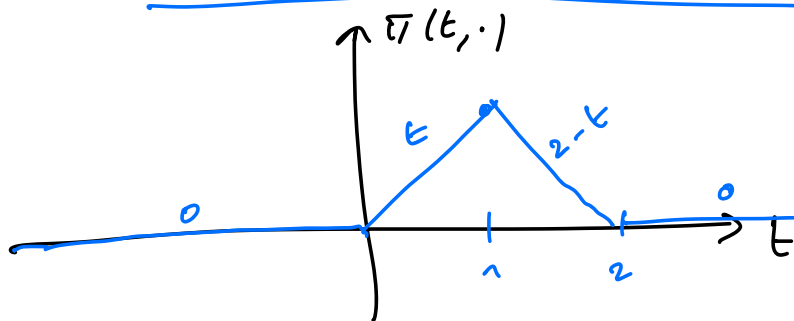
D'après la figure,  $T$  a des valeurs dans  $]0,2[$

La densité de  $T$  est

$$\begin{aligned} \pi(t, \cdot) &= \int \pi(t, u) du \\ &= \begin{cases} 0 & \text{si } t \notin ]0,2[ \\ \int_0^t \pi(t, u) du & t \in ]0,1[ \\ \int_{t-1}^2 \pi(t, u) du & t \in ]1,2[ \end{cases} \end{aligned}$$

donc

$$\pi(t, \cdot) = \begin{cases} 0 & t \notin ]0,2[ \\ t & t \in ]0,1[ \\ 2-t & t \in ]1,2[ \end{cases}$$



## Exemple 2

$$X \sim N(0,1)$$

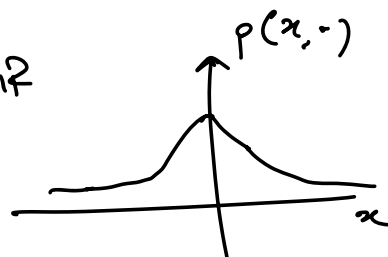
$$Y \sim N(0,1)$$

X et Y ind

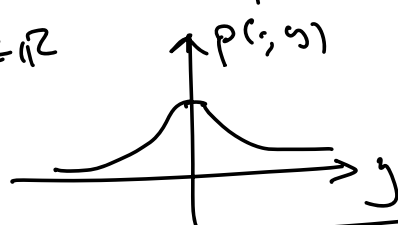
Quelle est la loi de  $\begin{pmatrix} R \\ \theta \end{pmatrix}$ ?

$$\begin{cases} X = R \cos \theta \\ Y = R \sin \theta \end{cases}$$

$$p(x, \cdot) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \quad x \in \mathbb{R}$$



$$p(\cdot, y) = \frac{1}{\sqrt{2\pi}} e^{-y^2/2} \quad y \in \mathbb{R}$$



$$X \text{ et } Y \text{ ind} \Rightarrow p(x, y) = \frac{1}{2\pi} e^{-\frac{1}{2}(x^2 + y^2)} \quad (x, y) \in \mathbb{R}^2$$

La densité de  $(R, \theta)$  est (application bijetive)

$$\pi(r, \theta) = \frac{1}{2\pi} \exp\left(-\frac{1}{2}(r^2 \cos^2 \theta + r^2 \sin^2 \theta)\right)$$

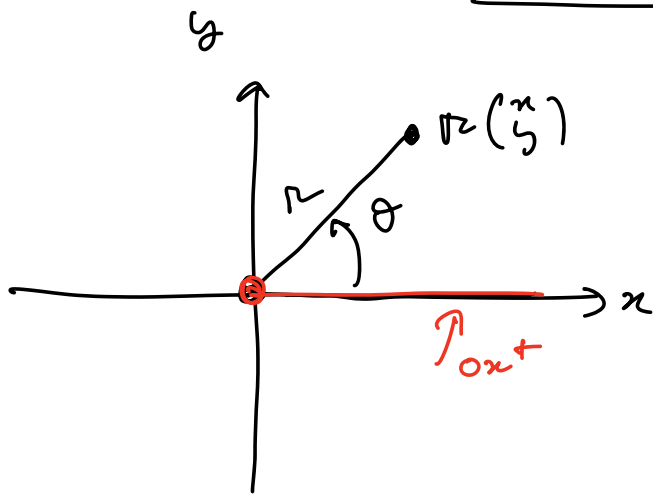
$$\times |\det(J)|$$

$$J = \begin{vmatrix} \frac{\partial x}{\partial r} & \frac{\partial y}{\partial r} \\ \frac{\partial x}{\partial \theta} & \frac{\partial y}{\partial \theta} \end{vmatrix} = \begin{vmatrix} \cos \theta & \sin \theta \\ -r \sin \theta & r \cos \theta \end{vmatrix}$$

$$\begin{aligned}x &= r \cos \theta \\ y &= r \sin \theta\end{aligned}$$

donc  $\det(J) = r \Rightarrow |\det(J)| = |r| = r$

donc  $\boxed{\pi(r, \theta) = \frac{r}{2\pi} e^{-\frac{r^2}{2}} \quad (r, \theta) \in ?}$



$$\begin{cases} x = r \cos \theta \\ y = r \sin \theta \end{cases}$$

$$\begin{cases} r = 0 \\ \theta \text{ quelconque} \end{cases} \Rightarrow \begin{cases} x = 0 \\ y = 0 \end{cases}$$

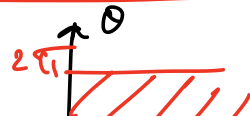
Le changement de variable est bijectif de

$$\mathbb{R}^2 \setminus \{(0,0)\} \text{ dans } ]0, +\infty[ \times [0, 2\pi[$$

Il est aussi bijectif de  $\mathbb{R}^2 \setminus \text{Ox}^+$  dans

$$]0, +\infty[ \times ]0, 2\pi[$$

$$\boxed{\pi(r, \theta) = \frac{r}{2\pi} e^{-\frac{r^2}{2}} \quad (r, \theta) \in ]0, +\infty[ \times ]0, 2\pi[}$$



Loi marginale de  $\theta$



$$\begin{aligned}
 \pi(\cdot, \theta) &= \int_0^{+\infty} \frac{z}{2\pi} e^{-z^2/2} dz \\
 &= \frac{1}{2\pi} \left[ -e^{-z^2/2} \right]_0^{+\infty} \\
 &= \begin{cases} \frac{1}{2\pi} & \theta \in ]0, 2\pi[ \\ 0 & \text{sinon} \end{cases}
 \end{aligned}$$

$$\theta \sim U(]0, 2\pi[)$$

Fonction caractéristique

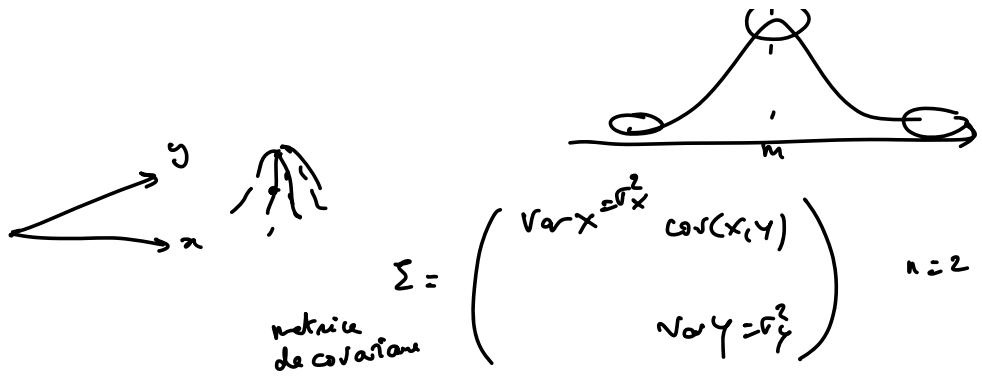
Loi de  $U = 2X + 3Y$  ?

$$\begin{aligned}
 \phi_U(t) &= E[e^{iUt}] = E[e^{i(2X+3Y)t}] \\
 &= E[e^{i2xt} e^{3iyt}] \\
 &\stackrel{x, y \text{ ind}}{=} E[e^{i2xt}] E[e^{3iyt}]
 \end{aligned}$$

$$= \phi_X(2t) \phi_Y(3t)$$

Loi normale à n dimensions.

$$\underline{n=1} \quad p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \quad x \in \mathbb{R}$$



$$\Sigma = (\text{Var } X) = (\sigma_x^2) \quad n=1$$

R9

$$\Sigma = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_n^2 \end{pmatrix} \quad \det(\Sigma) = \sigma_1^2 \times \dots \times \sigma_n^2$$

$$\sqrt{\det(\Sigma)} = \sqrt{\sigma_1^2 \dots \sigma_n^2}$$

$$\Sigma^{-1} = \begin{pmatrix} 1/\sigma_1^2 & 0 \\ 0 & 1/\sigma_n^2 \end{pmatrix}$$

$$\underline{(x_1 - m_1, \dots, x_n - m_n)} \Sigma^{-1} \begin{pmatrix} x_1 - m_1 \\ \vdots \\ x_n - m_n \end{pmatrix}$$

$$\begin{pmatrix} \frac{x_1 - m_1}{\sigma_1^2} \\ \vdots \\ \frac{x_n - m_n}{\sigma_n^2} \end{pmatrix}$$

$$\exp \left[ -\frac{1}{2} \left\{ \frac{(x_1 - m_1)^2}{\sigma_1^2} + \dots + \frac{(x_n - m_n)^2}{\sigma_n^2} \right\} \right] = \prod_{i=1}^n e^{-\frac{1}{2} \frac{(x_i - m_i)^2}{\sigma_i^2}}$$

$$P(x) = \frac{1}{(2\pi)^{n/2} \sqrt{\sigma_1^2 \dots \sigma_n^2}} \prod_{i=1}^n e^{-\frac{1}{2} \frac{(x_i - m_i)^2}{\sigma_i^2}}$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp - \frac{(x_i - m_i)^2}{2\sigma_i^2}$$

TD du 2/20/2023

$X \sim N(0,1)$   <sup>$E(X)$</sup>  donc  $p(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$   $x \in \mathbb{R}$   
 $Y \begin{cases} \rightarrow 1 & p \\ \rightarrow -1 & q=1 \end{cases}$   <sub>$Z \text{ var}$</sub>   $Z = XY$

Il est clair que  $Z$  est une variable continue à valeurs dans  $\mathbb{R}$   
 donc il faut déterminer sa densité de probabilité  $\pi(z)$ .

Méthode 1

$$P[Z \in ]z, z+dz[) \approx \pi(z)dz$$

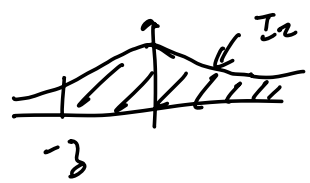
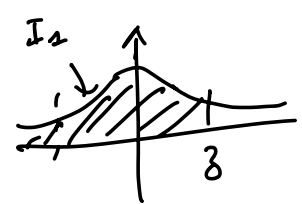
Méthode 2

(Fonctions de répartition)

$$P[Z < z] = P(XY < z)$$

$$\begin{aligned}
 P(Z < z) &= P(XY < z) \\
 &= P(X < z \text{ et } Y = 1 \text{ ou } -X < z \text{ et } Y = -1) \\
 &= P(X < z \text{ et } Y = 1) + P(-X < z \text{ et } Y = -1) \\
 &= P(X < z) P(Y = 1) + P(X > -z) P(Y = -1) \\
 &= \frac{1}{2} \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx + \frac{1}{2} \int_{-z}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\
 &= \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx
 \end{aligned}$$

*x et y i.d*



par symétrie  $I_1 = I_2$

$$\frac{dF(z)}{dz} = \pi(z) = \boxed{\frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}}$$

donc  $Z \sim N(0,1)$

Méthode 1

$$P[Z \in ]z, z+dz[ ] \approx \pi(z) dz$$

$$P[X \in ]z, z+dz[ ] = P[X \in ]z, z+dz[ ], Y=1$$

$$+ P[X \in ]z, z+dz[ ], Y=-1$$

$$= \underbrace{1/2}_{P(Y=1)} \underbrace{P(z) dz}_{\frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz}$$

$$+ \underbrace{1/2}_{P(Y=-1)} \underbrace{P(x \in ]z-dz, -z[ ])}_{\int_{-z-dz}^{-z} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx}$$

$$\approx \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

donc  $Z \sim N(0, 1)$

$\swarrow$   $Var(Z)$

$\uparrow$   $E(Z)$

2)  $Cov(X, Z)$

3)  $P(X+Z=0)$

$$Cov(X, Z) = E(XZ) - \underbrace{E(X)}_0 \underbrace{E(Z)}_0$$

$$\stackrel{Z=XY}{=} E(YX^2) = E(Y) \underbrace{E(X^2)}_1$$

$\uparrow$   $X \text{ et } Y \text{ ind.}$

$$Var X = E(X^2) - \underbrace{E(X)}_0^2$$

$$Y \begin{cases} \nearrow 1 & 1/2 \\ \searrow -1 & 1/2 \end{cases}$$

$$E(Y) = 1 \times \frac{1}{2} + (-1) \times \frac{1}{2} = 0$$

donc  $Cov(X, Z) = 0$

$$E(XZ) = E(E(XZ|X)) = E(X \underbrace{E(Z)}_0) = 0$$

$\uparrow$  espérance conditionnelle



$$= E \left[ \underbrace{E(xz|z)}_{zE(x)} \right] = E \left[ \underbrace{z \cdot 0}_0 \right] = 0$$

3)  $P[X+Z=0] = P[X+XY=0]$   
 $= P[X(1+Y)=0]$

$X \sim N(0,1)$  donc  $P(X=0)=0!!!$

$= P(1+Y=0) = \frac{1}{2}$

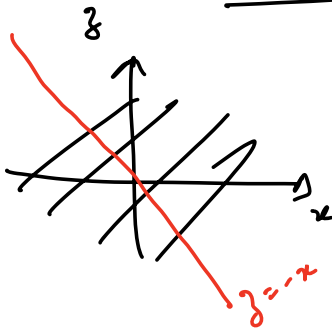
donc il y a une lien entre  $X$  et  $Z$   $\Rightarrow$  X et Z non indépendants

Pg: si  $X$  et  $Z$  étaient indépendants, alors  $\pi(x,z) = \pi(x)\pi(z)$

$P(X+Z=0) = P((X,Z) \in D, D = \{(x,z) / x+z=0\})$

$= \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$   
 $(x,z) \in \mathbb{R}^2$

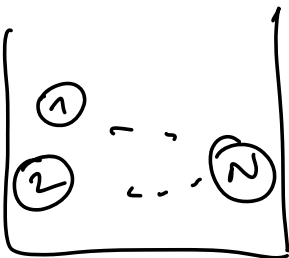
$= \iint_D \frac{1}{2\pi} e^{-x^2/2} e^{-z^2/2} dx dz = 0$



$X$  et  $Z$  ind  $\Rightarrow P(X+Z=0) = 0$

Contrepart

$P(X+Z=0) \neq 0 \Rightarrow X$  et  $Z$  non ind



2 tirages sans remise

$X_1$  = première boule

$X_2$  = seconde boule

1) lois de  $X_1$ ,  $X_2$  et de  $(X_1, X_2)$

2)  $\text{cov}(X_1, X_2)$

Loi de  $X_1$

$X_1$  est une va discrète à valeurs dans  $\{1, \dots, N\}$  avec

$$P[X_1 = k] = \frac{1}{N} \quad k \in \{1, \dots, N\}$$

Loi de  $X_2$

$X_2$  est une va discrète à valeurs dans  $\{1, \dots, N\}$  avec

$$P[X_2 = i] = P[(X_2=1, X_2=i) \text{ ou } \dots \text{ ou } (X_1=i-1, X_2=i) \text{ ou } (X_1=i, X_2=i) \\ \text{ou } (X_1=i+1, X_2=i) \text{ ou } \dots \text{ ou } (X_1=N, X_2=i)]$$

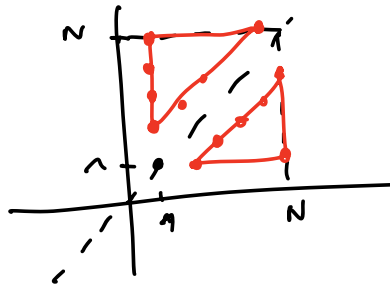
$$= \sum_{\substack{k \neq i \\ k=1, \dots, N}} P[X_1 = k, X_2 = i] \\ = \sum_{k=1, \dots, N, k \neq i} \underbrace{P[X_2 = i | X_1 = k]}_{\frac{1}{N-1}} \underbrace{P(X_1 = k)}_{\frac{1}{N}}$$

$$= (N-1) \times \frac{1}{N-1} \times \frac{1}{N} = \frac{1}{N}$$

$X_1$  et  $X_2$  suivent des lois uniformes sur  $\{1, \dots, N\}$ .

Loi de  $(X_1, X_2)$

$(X_1, X_2)$  est à valeurs dans  $\{(i, j), i=1, \dots, N, j=1, \dots, N, i \neq j\}$

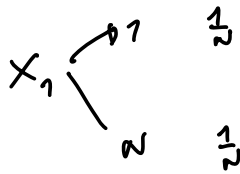


$$P[X_1 = i, X_2 = j] = \begin{cases} 0 & i = j \\ P(X_2 = j | X_1 = i) P(X_1 = i) & i \neq j \end{cases} \\ = \begin{cases} 0 & i = j \\ \frac{1}{N-1} \times \frac{1}{N} & i \neq j \end{cases}$$

$$\left| \begin{array}{l} \frac{1}{N(N-1)} \quad i \neq j \end{array} \right|$$

2) Covariance de  $(X_1, X_2)$

$$\text{cov}(X_1, X_2) = E[X_1 X_2] - E[X_1] E[X_2]$$



$$E(X_1) = 1 \times \frac{1}{2} + \dots + N \times \frac{1}{2} = \frac{1}{2} \sum_{i=1}^N i = \frac{1}{2} \frac{N(N+1)}{2} = \frac{N+1}{2}$$

$$E(X_2) = \frac{N+1}{2}$$

$$E(X_1 X_2) = \sum_i \sum_j x_i y_j P(X_1 = x_i, X_2 = y_j)$$

$$= \sum_{i=1}^N \sum_{j=1}^N i j \underbrace{P(X_1 = i, X_2 = j)}_{\substack{1 & i=j \\ N(N-1) & i \neq j}}$$

$$= \sum_{i \neq j} \frac{i j}{N(N-1)} = \frac{1}{N(N-1)} \left( \sum_{i \neq j} i j \right)$$

$$\sum_{i \neq j} i j = \sum_{i \neq j} i j - \sum_{i=1}^N i^2$$

$$\left( \frac{\sum_i i}{(1+2+\dots+N)} \right) \left( \frac{\sum_j j}{(1+\dots+N)} \right) - \frac{N(N+1)(2N+1)}{6}$$

$$\sum_{i \neq j} i j = (\sum_i i)(\sum_j j) - \sum_{i=1}^N i^2$$

$$= \left[ \frac{N(N+1)}{2} \right]^2 - \frac{N(N+1)(2N+1)}{6}$$

$$E(X_1 X_2) = \frac{1}{N(N-1)} \left[ \frac{N(N+1)^2}{4} - \frac{N(N+1)(2N+1)}{6} \right]$$

$$= \frac{N+1}{N-1} \left[ \frac{N(N+1)}{4} - \frac{2N+1}{6} \right]$$

$$\frac{3N^2 + 3N - 4N - 2}{12} = \frac{3N^2 - N - 2}{12} = \frac{(N-1)(3N+2)}{12}$$

$$= \frac{(N+1)(3N+2)}{12}$$

$$\text{cov}(x_1, x_2) = \frac{(N+1)(3N+2)}{12} - \left(\frac{N(N+1)}{2}\right)^2$$

$$= \dots$$

Cours du 8/10/2023

$n=1$   $\Sigma = (\sigma^2)$   $p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(x-m)^2}{2\sigma^2}\right] \quad x \in \mathbb{R}$

$n$   $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \quad m = \begin{pmatrix} m_1 \\ \vdots \\ m_n \end{pmatrix} \quad \begin{matrix} \xrightarrow{\Sigma} \\ \downarrow n \end{matrix}$

$X \sim N_n(m, \Sigma)$

$\Sigma$  symétrique définie positive

$$\Sigma^T = \Sigma$$

$$\Sigma \text{ positive} \Leftrightarrow x^T \Sigma x \geq 0 \quad \forall x \in \mathbb{R}^n$$

$$\Sigma \text{ définie} \Leftrightarrow x^T \Sigma x = 0 \Rightarrow x = 0$$

On va voir que  $m = \begin{pmatrix} E(x_1) \\ \vdots \\ E(x_n) \end{pmatrix}$  et  $\Sigma = \begin{pmatrix} \text{Var } x_1 & & \\ & \ddots & \\ & & \text{Var } x_n \end{pmatrix}$

$i$   $\left[ \begin{matrix} \text{Cov}(x_i, x_j) \\ \downarrow \\ \text{Var } x_i \end{matrix} \right]$

$$\phi(u) = E\left[e^{iu^T X}\right] = E\left[e^{i(u_1 x_1 + \dots + u_n x_n)}\right]$$

$$= \iiint \dots \int e^{i(u_1 x_1 + \dots + u_n x_n)} p(x_1, \dots, x_n) dx_1 \dots dx_n$$

$$= \dots = E \left[ e^{u_1 x_1 + \dots + u_n x_n} \right]$$

$$Q(u) = E \left[ e^{u^T x} \right] = E \left[ e^{u_1 x_1 + \dots + u_n x_n} \right]$$

$$\frac{\partial Q}{\partial u_1} = E \left[ e^{u^T x} x_1 \right]$$

$$\boxed{\frac{\partial Q}{\partial u_1} \Big|_{u=0} = E(x_1)}$$

$$\frac{\partial^2 Q}{\partial u_1 \partial u_2} \Big|_{u=0} = E \left[ e^{u^T x} x_1 x_2 \right] \Big|_{u=0} = E(x_1 x_2)$$

Conclusion s'  $x \sim N \left( \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 5 & 1 & 2 \\ 1 & 4 & 3 \\ 2 & 3 & 8 \end{pmatrix} \right)$

$$\Rightarrow \left\{ \begin{array}{l} E(x_1) = 1 \quad E(x_2) = 2 \quad E(x_3) = 3 \\ \text{Var}(x_1) = 5 \quad \text{Var}(x_2) = 4 \quad \text{Var}(x_3) = 8 \\ \text{Cov}(x_1, x_2) = 1 \quad \text{Cov}(x_1, x_3) = 2 \quad \text{Cov}(x_2, x_3) = 3 \end{array} \right.$$

Rq: n=1  $p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[ -\frac{(x-m)^2}{2\sigma^2} \right]$

$-q(x)$

$$\left\{ \begin{array}{l} q'(x) = +\frac{1}{2\sigma^2} 2(x-m) = \frac{x-m}{\sigma^2} \\ q''(x) = \frac{1}{\sigma^2} // \end{array} \right.$$

$$\exp(-2x^2 + x - 1)$$

$$q(x) = 2x^2 - x + 1$$

$$q'(x) = 4x - 1$$

$$q''(x) = 4 \Rightarrow \boxed{\sigma^2 = \frac{1}{4}}$$

pour avoir  $\mu$

$$4x - 1 = \frac{x - \mu}{\sigma^2} \stackrel{\uparrow}{=} 4(x - \mu)$$

$\sigma^2 = \frac{1}{4}$

$$-1 = -4\mu \Rightarrow \boxed{\mu = \frac{1}{4}}$$

en dimension  $n$   
 $x \in \mathbb{R}^n$

$$q'(x) = \begin{bmatrix} \frac{\partial q}{\partial x_1} \\ \frac{\partial q}{\partial x_2} \end{bmatrix}$$

$$q''(x) = \begin{bmatrix} \frac{\partial^2 q}{\partial x_1^2} & \frac{\partial^2 q}{\partial x_1 \partial x_2} & \dots & \frac{\partial^2 q}{\partial x_1 \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 q}{\partial x_n^2} \end{bmatrix}$$

On montre que

$$\boxed{q''(x) = \Sigma^{-1}}$$

$$q(x) = \frac{(x - \mu)^T \Sigma^{-1} (x - \mu)}{2}$$

$$\boxed{q'(x) = \Sigma^{-1} (x - \mu)}$$

$$p(x, y) \propto \exp\left(-x^2 - \frac{3}{2}y^2 - xy + 4x + 7y\right) \quad \mu? \quad \Sigma?$$

$$q(x, y) = x^2 + \frac{3}{2}y^2 + xy - 4x - 7y$$

$$q'' = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} = \Sigma^{-1}$$

$$\Sigma = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix}^{-1} = \frac{1}{5} \begin{pmatrix} 3 & -1 \\ -1 & 2 \end{pmatrix}$$

$$q'(x) = \begin{pmatrix} \frac{\partial q}{\partial x} = 2x + y - 4 \\ \frac{\partial q}{\partial y} = 3y + x - 7 \end{pmatrix} = \Sigma^{-1} \begin{pmatrix} x - m_1 \\ y - m_2 \end{pmatrix} = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} x - m_1 \\ y - m_2 \end{pmatrix}$$

$$\begin{cases} 2x + y - 4 = 2(x - m_1) + (y - m_2) \\ 3y + x - 7 = (x - m_1) + 3(y - m_2) \end{cases}$$

$$\text{d'où} \quad \begin{cases} -4 = -2m_1 - m_2 \\ -7 = -m_1 - 3m_2 \end{cases} \Rightarrow \begin{cases} m_1 = 1 \\ m_2 = 2 \end{cases}$$

Transformation affine  $y = Ax + B$

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$$A = \begin{pmatrix} \uparrow & & \\ p_1 & \dots & \\ \vdots & & \\ p_k & \dots & \\ \vdots & & \\ & \dots & \\ & & \vdots \\ & & p_n \end{pmatrix} \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$p \leq n$

$$\begin{aligned} \phi_y(u) &= E \left[ e^{iu^T y} \right] \\ &\stackrel{y = Ax + B}{=} E \left[ e^{iu^T (Ax + B)} \right] \\ &= e^{iu^T B} E \left[ e^{iu^T A x} \right] \end{aligned}$$

$\underbrace{e^{iu^T A x} e^{iu^T B}}_{\text{constants}}$

$$v^T = u^T A \quad \Leftrightarrow \quad \boxed{v = A^T u}$$

$$= e^{iu^T B} \phi_x(v)$$

$$= e^{i u^T B} \phi_X(A^T u)$$

$$X \sim N_n(m, \Sigma) \Rightarrow \phi_X(u) = \exp\left(i u^T m - \frac{1}{2} u^T \Sigma u\right)$$

$$\text{donc } \phi_Y(u) = e^{i u^T B} \exp\left(i u^T A m - \frac{1}{2} u^T A \Sigma A^T u\right)$$

$$= \exp\left[ i u^T \underbrace{(B + A m)}_{m_Y} - \frac{1}{2} u^T \underbrace{(A \Sigma A^T)}_{\Sigma_Y} u \right]$$

donc  $Y \sim N(Am + B, A \Sigma A^T)$  à la condition d'avoir  $A \Sigma A^T = M$  matrice symétrique définie positive

$M$  symétrique!

OUI

$$M^T = (A \Sigma A^T)^T = A \Sigma^T A^T = A \Sigma A^T = M$$

car  $\Sigma$  est la matrice de covariance d'un vecteur gaussien

$M$  positive?

OUI

$$x^T M x = \underbrace{x^T A}_{y^T} \Sigma \underbrace{A^T x}_y = y^T \Sigma y \geq 0$$

car  $\Sigma$  est positive

$M$  définie

$$x^T M x > 0 \Rightarrow y^T \Sigma y = 0 \text{ avec } y = A^T x$$

$$\Rightarrow y = A^T x = 0 \text{ car } \Sigma \text{ définie}$$

$$\text{il faut } \boxed{A^T x = 0 \Rightarrow x = 0}$$

il faut que  $A$  soit de rang  $p$  !!

$$X \sim N\left(\begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 4 & 1 & 2 \\ 1 & 5 & 3 \\ 2 & 3 & 7 \end{pmatrix}\right)$$

Quelle est la loi de  $Y = (2x_1 + x_2 - 3 \mid !)$



$$| \quad \quad \quad | \quad x_1 - x_3 + 1 \quad |$$

$$Y = AX + B \quad \text{avec} \quad A = \begin{pmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \end{pmatrix} \quad B = \begin{pmatrix} -3 \\ 1 \end{pmatrix}$$

$$s_1 A = \begin{pmatrix} 1 & 1 & 2 \\ -2 & -2 & -4 \end{pmatrix} \quad \text{rg} A = 1$$

$$\text{rg} A = 2$$

$$\text{donc } Y \sim N(Am + B, A \Sigma A^T)$$

$$Am + B = \begin{pmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \end{pmatrix} \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} + \begin{pmatrix} -3 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

$$A \Sigma A^T = \begin{pmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \end{pmatrix} \begin{pmatrix} 4 & 1 & 2 \\ 1 & 5 & 3 \\ 2 & 3 & 7 \end{pmatrix} \begin{pmatrix} 2 & 1 \\ 1 & 0 \\ 0 & -1 \end{pmatrix} = \dots$$

$$\text{Rg} \quad x_1 + x_2 + x_3 = \underbrace{(1 \quad 1 \quad 1)}_A \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

Lois marginales  $\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \sim N(\mu, \Sigma) \quad \mu = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} \quad \Sigma = \begin{pmatrix} 6 & 1 & 2 \\ 1 & 5 & 3 \\ 2 & 3 & 7 \end{pmatrix}$

Ce sont les lois de  $x_1, x_2, x_3, \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_3 \end{pmatrix} \begin{pmatrix} x_2 \\ x_3 \end{pmatrix}$

$$x_1 = \underbrace{(1 \quad 0 \quad 0)}_A \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

$$\text{rg} A = 1 \Rightarrow x_1 \sim N(1, 4)$$

$$\begin{pmatrix} x_1 \\ x_3 \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}}_A \underbrace{\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}}_{\mu}$$

$$\text{rg} A = 2 \Rightarrow \left( \begin{array}{c} X_1 \\ X_2 \\ X_3 \end{array} \right) \sim N \left( \begin{array}{c} \mu_1 \\ 1 \\ 3 \end{array} \right), \begin{pmatrix} 4 & 2 \\ 2 & 7 \end{pmatrix} \right)$$

### Indépendance

$$X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} \begin{matrix} X' \\ X'' \end{matrix}$$

$$X_2 \text{ ind de } \begin{pmatrix} X_2 \\ X_3 \end{pmatrix} ? \quad \text{Cas 1}$$

$$X_2 \text{ ind de } \begin{pmatrix} X_1 \\ X_3 \end{pmatrix} ? \quad \text{Cas 2}$$

$$\begin{pmatrix} X_2 \\ X_1 \\ X_3 \end{pmatrix} \begin{matrix} X' \\ X'' \end{matrix}$$

Cas 1 si  $X_1$  ind de  $\begin{pmatrix} X_2 \\ X_3 \end{pmatrix}$  alors

$$X_1 \text{ ind de } X_2 \Rightarrow \text{cov}(X_1, X_2) = 0$$

$$X_1 \text{ ind de } X_3 \Rightarrow \text{cov}(X_1, X_3) = 0$$

$$\text{donc } \Sigma = \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & a \\ 0 & a & \sigma_3^2 \end{pmatrix}$$

$$(x - \mu)^T \Sigma^{-1} (x - \mu) = (x_1 - \mu_1, x_2 - \mu_2, x_3 - \mu_3) \begin{pmatrix} \frac{1}{\sigma_1^2} & 0 & 0 \\ 0 & \left( \begin{array}{cc} \sigma_2^2 & a \\ a & \sigma_3^2 \end{array} \right)^{-1} \\ 0 & & \end{pmatrix}$$

$$= (x_1 - \mu_1, x_2 - \mu_2, x_3 - \mu_3) \begin{pmatrix} \frac{x_1 - \mu_1}{\sigma_1^2} \\ \left( \begin{array}{cc} \sigma_2^2 & a \\ a & \sigma_3^2 \end{array} \right)^{-1} \begin{pmatrix} x_2 - \mu_2 \\ x_3 - \mu_3 \end{pmatrix} \end{pmatrix} \times \begin{pmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \\ x_3 - \mu_3 \end{pmatrix}$$

$$= \frac{(x_1 - \mu_1)^2}{\sigma_1^2} + (x_2 - \mu_2, x_3 - \mu_3) \begin{pmatrix} \sigma_2^2 & a \\ a & \sigma_3^2 \end{pmatrix}^{-1} \begin{pmatrix} x_2 - \mu_2 \\ x_3 - \mu_3 \end{pmatrix}$$

$$\exp \left[ -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right] = \exp \left[ -\frac{1}{2\sigma_1^2} (x_1 - \mu_1)^2 \right] \times \exp \left[ -\frac{1}{2} (x'' - \mu'')^T (\Sigma'')^{-1} (x'' - \mu'') \right]$$

$$\Rightarrow p(x) = p(x', \cdot) \times p(\cdot, x'') \Rightarrow \boxed{x' \text{ et } x'' \text{ ind}}$$

Application:

$$X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 1/2 \\ 0 & 1 & 1/4 \\ 1/2 & 1/4 & 1 \end{pmatrix} \right)$$

$$\text{cov}(x_1, x_2) = 0 \Rightarrow x_1 \text{ et } x_2 \text{ ind}$$

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \text{ vect gaussien}$$

TD4 du 9/10/2023

○	$k e^{-\frac{x^2+y^2}{2}}$
$k e^{-\frac{x^2+y^2}{2}}$	○

Rappel  $\int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx = 1 \Rightarrow \int_{\mathbb{R}} e^{-x^2/2} dx = \sqrt{2\pi}$

i)  $\iint_{\mathbb{R}^2} f(x,y) dx dy = 1 \Rightarrow \iint_{(\mathbb{R}^+)^2 \cup (\mathbb{R}^-)^2} k e^{-\frac{x^2}{2}} e^{-\frac{y^2}{2}} dx dy = 2$

$$\Rightarrow 1 = k \left[ \int_0^{+\infty} \int_0^{+\infty} e^{-x^2/2} e^{-y^2/2} dx dy + \int_{-\infty}^0 \int_{-\infty}^0 e^{-x^2/2} e^{-y^2/2} dx dy \right]$$

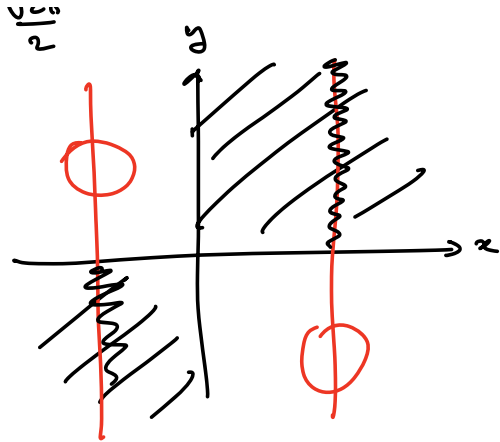
$$1 = 2k \left( \int_0^{+\infty} e^{-x^2/2} dx \right) \left( \int_0^{+\infty} e^{-y^2/2} dy \right)$$

$$\boxed{k = \frac{1}{\pi}}$$

2) Lois marginales de  $X$  et de  $Y$

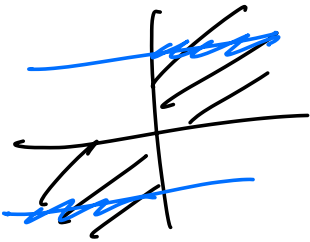
$$f(x, \cdot) = \int_{\mathbb{R}} f(x, y) dy$$

$$= \begin{cases} x \geq 0 & \int_0^{+\infty} \frac{1}{\pi} e^{-x^2/2} e^{-y^2/2} dy \\ x \leq 0 & \int_{-\infty}^0 \frac{1}{\pi} e^{-x^2/2} e^{-y^2/2} dy \end{cases}$$



donc

$$f(x, \cdot) = \begin{cases} \frac{1}{\pi} e^{-x^2/2} \frac{\sqrt{2\pi}}{2} & x \geq 0 \\ \frac{1}{\pi} e^{-x^2/2} \frac{\sqrt{2\pi}}{2} & x \leq 0 \end{cases}$$



donc

$$f(x, \cdot) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \quad x \in \mathbb{R}$$

$X \sim N(0, 1)$  donc  $E(X) = 0$   
 $\text{Var}(X) = 1$

De même

$$f(\cdot, y) = \begin{cases} y \geq 0 & \int_0^{+\infty} \frac{1}{\pi} e^{-x^2/2} e^{-y^2/2} dx \\ y \leq 0 & \int_{-\infty}^0 \frac{1}{\pi} e^{-x^2/2} e^{-y^2/2} dx \end{cases} \quad \text{in calcul}$$

$$Y \sim N(0, 1)$$

Remarque

$X \sim N(0, 1)$  et pourtant  $\begin{pmatrix} X \\ Y \end{pmatrix}$  n'est pas un vecteur gaussien!!  
 $Y \sim N(0, 1)$

3)  $\text{cov}(X, Y) = ?$  R<sub>s</sub>: On sait que  $X$  et  $Y$  ne sont pas indépendantes car le domaine de définition n'est pas  $\mathbb{R}^2$  !!

$$\text{COV}(X, Y) = E(XY) - E(X)E(Y) = E(XY)$$

$$E(XY) = \int_0^{+\infty} \int_0^{+\infty} + \int_{-\infty}^0 \int_{-\infty}^0 \frac{xy}{\pi} e^{-\frac{x^2}{2}} e^{-\frac{y^2}{2}} dx dy$$

$$= \frac{2}{\pi} \left( \int_0^{+\infty} x e^{-x^2/2} dx \right) \left( \int_0^{+\infty} y e^{-y^2/2} dy \right) = \boxed{\frac{2}{\pi}}$$

$$\left[ -e^{-x^2/2} \right]_0^{+\infty} = 1$$

4) Lois de Z = X+Y et U = X-Y ?

Espérance conditionnelle

$$E(XY) = E[E(XY|X)]$$

Loi de Y|X

$$f(x,y) = \frac{1}{\pi} e^{-\frac{x^2+y^2}{2}}$$

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

$$(x,y) \in (\mathbb{R}^+)^2 \cup (\mathbb{R}^-)^2$$

donc

$$f(y|x) = \sqrt{\frac{2}{\pi}} e^{-y^2/2}$$

$$\text{si } x > 0 \quad f(y|x) = \sqrt{\frac{2}{\pi}} e^{-y^2/2} \quad y > 0$$

$$\text{si } x < 0 \quad f(y|x) = \sqrt{\frac{2}{\pi}} e^{-y^2/2} \quad y < 0$$

donc si  $x > 0$

$$E(Y|x) = \int_0^{+\infty} \sqrt{\frac{2}{\pi}} y e^{-y^2/2} dy$$

$$= \sqrt{\frac{2}{\pi}} \left[ -e^{-y^2/2} \right]_0^{+\infty}$$

$$= \sqrt{\frac{2}{\pi}} \quad x > 0$$

donc  $E(XY) = E[XE(Y|X)]$

$$= \int_0^{+\infty} x \cdot \sqrt{\frac{2}{\pi}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$+ \int_{-\infty}^0 x \sqrt{\frac{2}{\pi}} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$= \sqrt{\frac{2}{\pi}} \frac{1}{\sqrt{2\pi}} \left[ -e^{-x^2/2} \right]_0^{+\infty}$$

$$+ \sqrt{\frac{2}{\pi}} \frac{1}{\sqrt{2\pi}}$$

$$\left| \quad \quad \quad \right| = \boxed{\frac{2}{\pi}} \quad \left\{ \begin{array}{l} x > 0 \\ y > 0 \end{array} \right. \text{ ou } \left\{ \begin{array}{l} x < 0 \\ y < 0 \end{array} \right.$$

$$\left\{ \begin{array}{l} z = x + y \\ v = x - y \end{array} \right. \Leftrightarrow \boxed{\left\{ \begin{array}{l} x = \frac{1}{2}(z + v) \\ y = \frac{1}{2}(z - v) \end{array} \right.}$$

donc le changement de variables est bijectif

Jacobien  $\left| \begin{array}{cc} \frac{\partial x}{\partial z} & \frac{\partial y}{\partial z} \\ \frac{\partial x}{\partial v} & \frac{\partial y}{\partial v} \end{array} \right| = \left| \begin{array}{cc} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} \end{array} \right| = -\frac{1}{2}$

$$\boxed{|J| = \frac{1}{2}}$$

Densité de  $(z, v)$

$$\pi(z, v) = \frac{1}{\pi} \exp\left\{-\frac{1}{2}\left[\left(\frac{z+v}{2}\right)^2 + \left(\frac{z-v}{2}\right)^2\right]\right\} \times \frac{1}{2}$$

donc  $\boxed{\pi(z, v) = \frac{1}{2\pi} \exp\left(-\frac{z^2 + v^2}{4}\right)}$   $(z, v) \in ?$

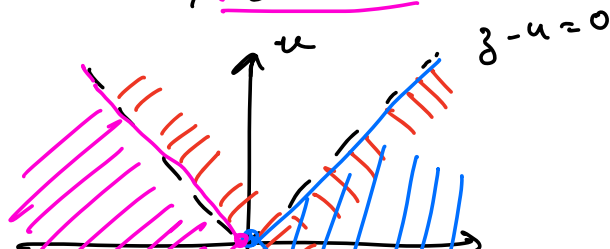
Domaine de  $(z, v)$

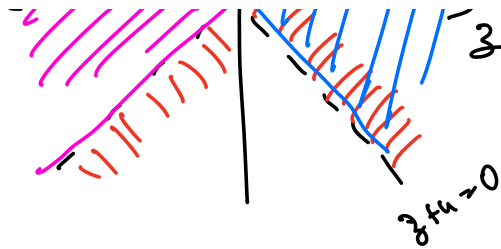
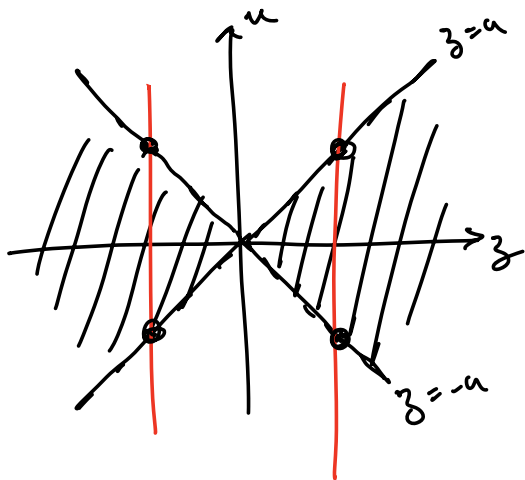
Domaine de  $(x, y)$   $\left\{ \begin{array}{l} x > 0 \\ y > 0 \end{array} \right. \Leftrightarrow \boxed{\left\{ \begin{array}{l} z + v > 0 \\ z - v > 0 \end{array} \right.}$

ou  $\left\{ \begin{array}{l} x < 0 \\ y < 0 \end{array} \right. \Leftrightarrow \boxed{\left\{ \begin{array}{l} z + v < 0 \\ z - v < 0 \end{array} \right.}$

$$x = \frac{z+v}{2}$$

$$y = \frac{z-v}{2}$$





Loi de Z

$$\pi(z_i \cdot) = \begin{cases} z > 0 & \int_{-z}^z \frac{1}{2\pi} e^{-\frac{z^2+u^2}{4}} du \\ z < 0 & \int_z^{-z} \frac{1}{2\pi} e^{-\frac{z^2+u^2}{4}} du \end{cases}$$

Dans les 2 cas

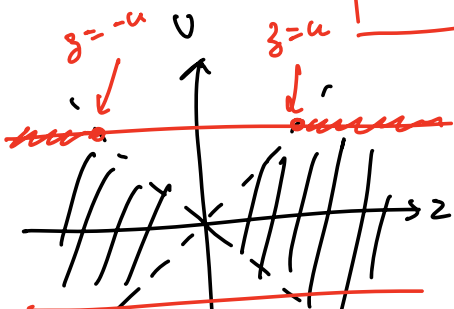
$$\pi(z_i \cdot) = \int_{-|z|}^{|z|} \frac{1}{2\pi} e^{-\frac{z^2+u^2}{4}} du$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{4}} \int_{-|z|}^{|z|} \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{4}} du$$

changement de variable  $v = \frac{u}{\sqrt{2}}$

$$\pi(z_i \cdot) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{4}} \int_{-\frac{|z|}{\sqrt{2}}}^{\frac{|z|}{\sqrt{2}}} \frac{1}{\sqrt{2\pi}} e^{-\frac{v^2}{2}} \sqrt{2} dv$$

$$\pi(z_i \cdot) = \frac{1}{\sqrt{\pi}} e^{-\frac{z^2}{4}} \left[ F\left(\frac{|z|}{\sqrt{2}}\right) - F\left(-\frac{|z|}{\sqrt{2}}\right) \right]$$

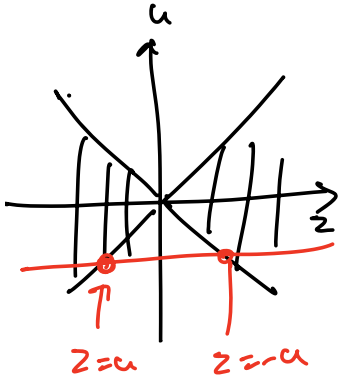


Loi de U

$$\text{si } u > 0 \quad \pi(\cdot, u) = \int_{-u}^{\infty} + \int_{-\infty}^u \frac{1}{2\pi} \exp\left(-\frac{z^2+u^2}{4}\right) dz$$



$$\pi(\cdot, u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/4} \int_{-\infty}^{-u} + \int_u^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-z^2/4} dz$$



$$\pi(\cdot, u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/4} \int_{-\frac{u}{\sqrt{2}}}^{-\frac{u}{\sqrt{2}}} + \int_{\frac{u}{\sqrt{2}}}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{v^2}{2}} \frac{1}{\sqrt{2}} dv$$

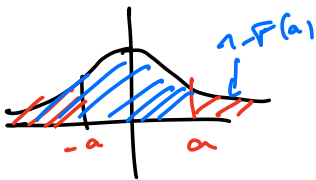
$v = \frac{z}{\sqrt{2}} \quad \frac{v^2}{2} = \frac{z^2}{4}$

donc  $\pi(\cdot, u) = \frac{1}{\sqrt{\pi}} e^{-u^2/4} \left[ F\left(-\frac{u}{\sqrt{2}}\right) + 1 - F\left(\frac{u}{\sqrt{2}}\right) \right]$   $u > 0$

si  $u < 0$

$$\pi(\cdot, u) = \int_{-\infty}^{-u} + \int_{-u}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2+u^2}{4}} dz$$

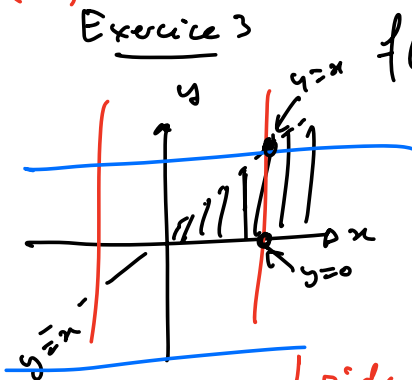
on change  $u$  en  $-u$



$F(-a) = 1 - F(a)$

$$\pi(\cdot, u) = \frac{1}{\sqrt{\pi}} e^{-u^2/4} \left( F\left(-\frac{|u|}{\sqrt{2}}\right) + 1 - F\left(\frac{|u|}{\sqrt{2}}\right) \right) \quad \forall u \in \mathbb{R}^?$$

Exercice 3



$$f(x, y) = \begin{cases} \theta^2 e^{-\theta x} & 0 < y < x \\ 0 & \text{sinon} \end{cases}$$

- 1) Lois marginales de  $X$  et de  $Y$
- 2) loi de  $Z = \frac{Y}{X}$

Loi de  $X$

$$f(x, \cdot) = \int_{\mathbb{R}^2} f(x, y) dy = \begin{cases} 0 & x \leq 0 \\ \int_0^x \theta^2 e^{-\theta x} dy & x > 0 \end{cases}$$

donc  $f(x, \cdot) = \begin{cases} \theta^2 x e^{-\theta x} & x > 0 \end{cases}$



$$\boxed{X \sim \Gamma(2, \theta)}$$

ln: de Y

$$f(x, y) = \begin{cases} 0 & y < 0 \\ \int_y^{+\infty} \underbrace{\theta^2 e^{-\theta x}}_{(-\theta e^{-\theta x})}' \Big|_y^{+\infty} = \theta e^{-\theta y} & y \geq 0 \end{cases}$$

donc  $f(x, y) = \begin{cases} 0 & y \leq 0 \\ \theta e^{-\theta y} & y > 0 \end{cases}$

$$\boxed{Y \sim \Gamma(1, \theta)}$$

copies du 16/10/2023

$$\begin{array}{l}
 X_n \begin{array}{l} \rightarrow 1 \\ \rightarrow 0 \end{array} \\
 P(X_n=1) = \frac{1}{n} \\
 P(X_n=0) = 1 - \frac{1}{n}
 \end{array}$$

$X_n \xrightarrow{L} X=0 ?$

$$\begin{aligned}
 \phi_n(t) = E[e^{itX_n}] &= \underbrace{e^{it \times 0}}_1 P(X_n=0) + e^{it \times 1} P(X_n=1) \\
 &= 1 - \underbrace{\frac{1}{n}}_0 + \underbrace{\frac{1}{n}}_{n \rightarrow \infty} e^{it}
 \end{aligned}$$

donc  $\phi_n(t) \rightarrow 1$   
 $n \rightarrow \infty$

$$\phi(t) = E[e^{itx}] \Big|_{x=0} = E[e^{itx_0}] = E(1) = 1$$

continue en  $t=0$

$\phi_n(t) \rightarrow \phi(t)$   
 $n \rightarrow \infty$   
 $\phi$  continue en  $t=0$

LEVY  
 $\Rightarrow$

$$X_n \xrightarrow[n \rightarrow \infty]{L} X=0$$

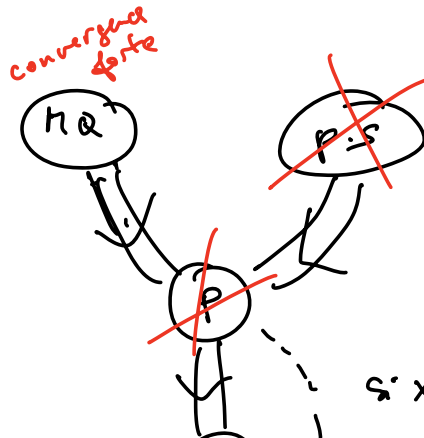
$X_n$	$\rightarrow$	1	$\frac{1}{n}$
	$\rightarrow$	0	$1 - \frac{1}{n}$
$X_n$	$\xrightarrow[n \rightarrow \infty]{M.Q.}$	$X=0$	?

$$E[(X_n - x)^2] \Big|_{x=0} = E[X_n^2] = 1^2 \times \frac{1}{n} + 0^2 \times \left(1 - \frac{1}{n}\right)$$

$$= \frac{1}{n} \rightarrow 0 \quad n \rightarrow \infty$$

donc  $X_n \xrightarrow[n \rightarrow \infty]{M.Q.} X=0$

Comparison



si  $X_n \xrightarrow{L} X = \text{constante}$  alors  
 $0 \quad 1 \quad \infty$

(2)

$X_n \xrightarrow{p} X = \text{convergence}$

convergence  
faible

$$E[(\bar{X}_n - m)^2] = E\left[\left(\frac{1}{n} \sum_{k=1}^n X_k - m\right)^2\right]$$

$$\bar{X}_n = \frac{1}{n} \sum_{k=1}^n X_k \quad = \quad E\left[\left\{\frac{1}{n} \sum_{k=1}^n (X_k - m)\right\}^2\right]$$

$$m = \frac{1}{n} \sum_{k=1}^n m \quad = \quad \frac{1}{n^2} E\left[\sum_{k=1}^n (X_k - m) \sum_{l=1}^n (X_l - m)\right]$$

$$\left(\sum_{k=1}^n a_k\right)\left(\sum_{l=1}^n b_l\right) = \sum_{k=1}^n \sum_{l=1}^n a_k b_l$$

$$(a_1 + \dots + a_n)(b_1 + \dots + b_n) = a_1 b_1 + a_1 b_2 + \dots + a_n b_n$$

$$= \frac{1}{n^2} E\left[\sum_{k=1}^n \sum_{l=1}^n (X_k - m)(X_l - m)\right]$$

$$= \frac{1}{n^2} \sum_{k=1}^n \sum_{l=1}^n E[(X_k - m)(X_l - m)]$$

$$\begin{cases} \sigma^2 & k=l \\ 0 & k \neq l \end{cases}$$

si  $k \neq l$   $E[(X_k - m)(X_l - m)] = \text{cov}(X_k, X_l) = 0$

cov  $X_k$  et  $X_l$  ind

donc  $E[(\bar{X}_n - m)^2] = \frac{1}{n^2} \times n \sigma^2 = \left[\frac{\sigma^2}{n}\right] \xrightarrow[n \rightarrow +\infty]{\text{DO}}$

## Théorème de la limite centrale

$$\sum_{k=1}^n x_k \approx N(nm, n\sigma^2)$$

$\uparrow$   $E\left(\sum_{k=1}^n x_k\right) = \sum_{k=1}^n E(x_k) = nm$ 
                         
  $\uparrow$   $\text{Var}\left(\sum_{k=1}^n x_k\right) = \sum_{k=1}^n \text{Var} x_k = n\sigma^2$   
 $x_1, \dots, x_n \text{ ind}$

$$\frac{1}{n} \sum_{k=1}^n x_k \approx N\left(m, \frac{\sigma^2}{n}\right)$$

$$\text{Var}\left[\frac{1}{n} \sum_{k=1}^n x_k\right] = \frac{1}{n^2} \text{Var}\left(\sum_{k=1}^n x_k\right) = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}$$

$x_1, \dots, x_n \text{ ind}$

Propriété : Si  $X$  et  $Y$  sont des variables aléatoires indépendantes  
 alors  $\text{Var}(X+Y) = \text{Var} X + \text{Var} Y$

En effet

$$\begin{aligned} \text{Var}(X+Y) &= E((X+Y)^2) - (E(X+Y))^2 \\ &= E(X^2 + Y^2 + 2XY) - \underbrace{(E(X) + E(Y))^2}_{E^2(X) + E^2(Y) + 2E(X)E(Y)} \\ &= \underbrace{E(X^2) - E^2(X)}_{\text{Var} X} + \underbrace{E(Y^2) - E^2(Y)}_{\text{Var} Y} \\ &\quad + 2(E(XY) - E(X)E(Y)) \end{aligned}$$

$$\text{Var}(X+Y) = \text{Var} X + \text{Var} Y + 2 \text{cov}(X, Y)$$

Si  $X$  et  $Y$  ind  $\Rightarrow \text{cov}(X, Y) = 0 \Rightarrow \text{Var}(X+Y) = \text{Var} X + \text{Var} Y$   
CQFD

THE END!

TD du 16/10/2023

$X \sim N(0,1)$   $Y \sim N(0,1)$   $Z \sim N(0,1)$   
 $X, Y$  et  $Z$  indépendants

1) Loi de  $U = X+Y+Z$

Méthode 1

$$\begin{aligned} \varphi_U(t) &= E[e^{itU}] = E[e^{it(X+Y+Z)}] \\ &= E[e^{itX} e^{itY} e^{itZ}] \end{aligned}$$

$$\begin{aligned} &= \phi_X(t) \phi_Y(t) \phi_Z(t) \\ &\stackrel{X, Y, Z \text{ ind}}{=} e^{-t^2/2} \times e^{-t^2/2} \times e^{-t^2/2} \\ &= e^{-3t^2/2} \end{aligned}$$

qui est la fonction caractéristique d'une loi normale  $N(0, 3)$

donc  $U \sim N(0, 3)$

Rq:  $U = X+Y+Z$

Méthode 2

$$U = (1 \ 1 \ 1) \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

$$Z = A V + b$$

$$V = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

$$A = (1 \ 1 \ 1)$$

$$b = (0)$$

Rappel : Si  $V \sim N(m, \Sigma)$  alors  $AV + b \sim N(Am + b, A \Sigma A^T)$   
 $\text{rg} A = p$  (valeur de ligne)

$\text{rg} (1 \ 1 \ 1) = 1$   
 $\begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$  vecteur gaussien car  $X, Y, Z$  ind.  
 $N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}\right)$



$$U = A \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} + b \sim N\left(Am + b, A \Sigma A^T\right)$$

$$(1 \ 1 \ 1) \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} + 0 = 0$$

$$(1 \ 1 \ 1) \mathbb{I}_3 \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

3

donc  $U \sim N(0, 3)$

2) Montrer que  $V = X - Y$  et  $U = X + Y + Z$  sont des variables aléatoires indépendantes

Remarque

$$\begin{pmatrix} U \\ V \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & -1 & 0 \\ 1 & 1 & 1 \end{pmatrix}}_A \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

$\text{rg} A = 2$  donc  $\begin{pmatrix} U \\ V \end{pmatrix}$  est un vecteur gaussien (car transformation affine d'un vecteur gaussien)

donc  $\boxed{U \text{ et } V \text{ ind} \iff \text{cov}(U, V) = 0}$

$$\begin{pmatrix} U \\ V \end{pmatrix} = \begin{pmatrix} 1 & -1 & 0 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} \sim N_2 \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, A \Sigma A^T \right)$$

$\text{rg} \begin{pmatrix} 1 & -1 & 0 \\ 1 & 1 & 1 \end{pmatrix} = 2$ 
 $\uparrow$   
A m+b

Si  $V = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$  est un vecteur gaussien alors  $X, Y$  et  $Z$  sont des variables gaussiennes

La réciproque est fautive (voir TD4)

$$A \Sigma A^T = \begin{pmatrix} 1 & -1 & 0 \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ -1 & 1 \\ 0 & 1 \end{pmatrix}$$

$$= \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$$

donc  $\begin{pmatrix} U \\ V \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix} \right)$

$\begin{pmatrix} U \\ V \end{pmatrix}$  vecteur gaussien  
 $\text{cov}(U, V) = 0 \implies U \text{ et } V \text{ indépendants}$

Ex 03

$$X \sim N(0, 1)$$

$$Y \sim N(0, 1)$$

X et Y indépendants

$$\text{Choisir } M = \begin{pmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{pmatrix} \text{ et } n = \begin{pmatrix} n_1 \\ n_2 \end{pmatrix} \text{ tels que}$$

$$V = M \begin{pmatrix} X \\ Y \end{pmatrix} + n \sim N(m, \Sigma) \quad \text{et } \Sigma \text{ donné}$$

par exemple

$$n = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \quad \Sigma = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix}$$

si  $\text{rg} \Sigma = 2$ , on a  $V \sim N\left(n \begin{pmatrix} 0 \\ 0 \end{pmatrix} + n, M \Sigma \begin{pmatrix} X \\ Y \end{pmatrix} M^T\right)$

$$V \sim N\left(n, M M^T\right) \quad \text{car } \Sigma \begin{pmatrix} X \\ Y \end{pmatrix} = \mathbb{I}_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

si on veut  $V \sim N(m, \Sigma)$  il suffit de choisir  $n$  et  $M$

tels que

$$n = m \quad \left( = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \text{ pour l'exemple} \right)$$

$$M M^T = \Sigma \quad \left( \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \text{ pour l'exemple} \right)$$

$$\Sigma = P \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} P^T$$

matrice symétrique  
def  $> 0$  donc diagonalisable

$P, (\lambda_1, \lambda_2)$  sont fournis  
par la routine eig.m  
(sous matlab)



$$M = P \begin{pmatrix} \sqrt{\lambda_1} & 0 \\ 0 & \sqrt{\lambda_2} \end{pmatrix} P^T \quad \leftarrow$$

$$\begin{aligned} M M^T &= P \begin{pmatrix} \sqrt{\lambda_1} & 0 \\ 0 & \sqrt{\lambda_2} \end{pmatrix} P^T \underbrace{P \begin{pmatrix} \sqrt{\lambda_1} & 0 \\ 0 & \sqrt{\lambda_2} \end{pmatrix} P^T}_{I} \\ &= P \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} P^T = \Sigma \end{aligned}$$

Exo 6

$$X_j \sim P(\theta) \quad \theta = 2$$

1) Loi de  $S_n = \sum_{j=1}^n X_j$  ?

2)  $T_n = \frac{S_n - n}{\sqrt{n}}$

Théorème de la limite centrale  
En considérant  $T_n \xrightarrow{d} N(0,1)$ , montrer que

$$\lim_{n \rightarrow \infty} e^{-n} \sum_{k=0}^{n-1} \frac{n^k}{k!} = \frac{1}{2}$$

$$\frac{\overset{?}{S_n} - \overset{?}{n}}{\sqrt{\text{var } S_n}}$$

$n \rightarrow \infty$

$N(0,1)$

1) Fonction caractéristique

$$\begin{aligned} \phi_{S_n}(t) &= E\left(e^{itS_n}\right) = E\left[e^{it\sum_{j=1}^n X_j}\right] \\ &= E\left[\prod_{j=1}^n e^{itX_j}\right] \\ &= \prod_{j=1}^n \underbrace{E\left[e^{itX_j}\right]}_{\phi_{X_j}(t) = \exp\left[e^{it}-1\right]} \\ &\quad \begin{array}{l} \nearrow \\ x_1, \dots, x_n \text{ ind} \\ x_j \sim P(\lambda) \end{array} \\ &= \exp\left[n(e^{it}-1)\right] \end{aligned}$$

qui est la fonction caractéristique d'une loi de Poisson  $P(n)$

donc

$$S_n \sim P(n)$$

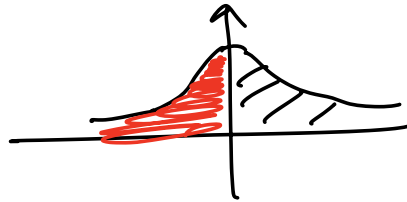
$$S_n = \sum_{j=1}^n X_j$$

$$E[S_n] = \sum_{j=1}^n \underbrace{E(X_j)}_n = n$$

$$\text{Var}[S_n] = \text{Var}\left(\sum_{j=1}^n X_j\right) \underset{x_1, \dots, x_n \text{ ind}}{=} \sum_{j=1}^n \underbrace{\text{Var}(X_j)}_1 = n$$

$$T_n = \frac{S_n - n}{\sqrt{n}} \xrightarrow[n \rightarrow +\infty]{} N(0,1)$$

$$P[T_n < 0] \xrightarrow[n \rightarrow +\infty]{} \int_{-\infty}^0 \frac{1}{\sqrt{2\pi}} e^{-u^2/2} du = \frac{1}{2}$$



$$\begin{aligned} P[T_n < 0] &= P[S_n < n] \\ &= P[S_n = 0, \text{ ou } 1, \text{ ou } \dots, \text{ ou } n-1] \\ &= \sum_{k=0}^{n-1} \underbrace{P[S_n = k]}_{S_n \sim P(n)} \end{aligned}$$

$$P[X=k] = \frac{n^k}{k!} e^{-n}$$

$k \in \mathbb{N}$   
Loi de Poisson  $P(\lambda)$

donc  $P[S_n = k] = \frac{n^k}{k!} e^{-n}$

$$\sum_{k=0}^{n-1} \left( \frac{n^k}{k!} e^{-n} \right) \xrightarrow[n \rightarrow +\infty]{} \frac{1}{2}$$

THE END!!