

## Résumé intro 2

\* Distribution obtenue pour un mélange

$$f_X(x) = \int f_{X|\lambda}(x) f_\lambda(\lambda) d\lambda$$

• Ex But Généraliser  $Y \sim \text{Poi}(\lambda)$   $\begin{cases} E[Y] = \lambda \\ \text{Var}(Y) = \lambda \\ P_Y(t) = e^{t\lambda} t^{-1} \end{cases}$

$$\lambda \rightarrow \Lambda = \lambda \cdot \Theta$$

$$\text{Soit } \begin{cases} E[\Theta] = 1 \\ \text{Var}(\Theta) < \infty \\ P_\Theta(t) < \infty \end{cases}$$

$X$  tel que  $X|_\Theta \sim \text{Poi}(\lambda \cdot \Theta)$

$$E[X] = E[E[X|\Theta]] = E[\Theta X] = \lambda$$

$$\text{Var}(X) = E_\Theta[\text{Var}(X|\Theta)] + \text{Var}_\Theta(E[X|\Theta])$$

$$\text{Var}(X) = \lambda \text{Var}(\Theta) + \lambda^2 \text{Var}(\Theta)$$

$$P_X(t) = E_\Theta [E[t^X|\Theta]] = E_\Theta [e^{\lambda \Theta (t-1)}]$$

$$P_X(t) = M_\Theta(\lambda(t-1))$$

Exemple :

$$\Theta \sim \text{Gamma}(r, r)$$

$$E[X] = \lambda \quad \text{Var}(X) = \lambda + \frac{\lambda^2}{r} = \lambda \left(1 + \frac{1}{r}\right)$$

$$P_X(t) = M_\Theta(\lambda(t-1)) = \left( \frac{r}{r - \lambda(t-1)} \right)^r = \left( \frac{1}{1 - \frac{\lambda}{r}(t-1)} \right)^r$$

$$\frac{\lambda}{r} = \frac{1-q}{q} \rightarrow q = \frac{1}{1+\frac{\lambda}{r}} = \left( \frac{q}{q - (1-q)\frac{\lambda}{r}} \right)^r$$

$$\text{Or } r \rightarrow \infty \quad P_X(t) = e^{\lambda(t-1)}$$

## \* light et heavy tailed

Absolu :

light : tous  $\mathbb{E}[X^k] \exists$

heavy :  $\mathbb{E}[X^k] \exists$ , pour  $k \leq n$

$\hookrightarrow$  si fGH  $\exists$ , alors tous  $\mathbb{E}[X^k] \exists$

$\hookrightarrow$  si tout  $\mathbb{E}[X^k] \exists \xrightarrow{x} \text{fGH } \exists$

Relatif :

$$\lim_{x \rightarrow \infty} \frac{\bar{F}_X(x)}{\bar{F}_Y(x)} = \begin{cases} 0 & \text{Y plus lourd que X} \\ \infty & \text{X plus lourd que Y} \end{cases}$$

$$\lim_{x \rightarrow \infty} e^{rx} \bar{F}_X(x) = \lim_{x \rightarrow \infty} \frac{\bar{F}_X(x)}{e^{-rx}} = \lim_{x \rightarrow \infty} \frac{\bar{F}_X(x)}{\bar{F}_Z(x)} = 0 \text{ pour } Z \sim \text{Exp}(r > r_0)$$

$\hookrightarrow$  light

$$\lim_{x \rightarrow \infty} \frac{\bar{F}_X(x)}{e^{-rx}} = \lim_{x \rightarrow \infty} \frac{\bar{F}_X(x)}{\bar{F}_Z(x)} = \infty \rightarrow \text{heavy}$$

## \* fonction de mortalité

$$\cdot \quad \mu_x = \frac{f_x(x)}{\bar{f}_x(x)} \rightarrow \mu_x dx = \frac{\int_x^\infty f_x(x) dx}{\bar{f}_x(x)} = \frac{\mathbb{P}(x < X \leq x+dx)}{\mathbb{P}(X > x)}$$

$$= \mathbb{P}(x < X \leq x+dx | X > x)$$

$$\mu_x = \frac{f_x(x)}{\bar{f}_x(x)} = -\frac{\partial}{\partial x} \ln(\bar{f}_x(x))$$

$$\bar{f}_x(x) = e^{-\int_0^x \mu_x(t) dt}$$

$$\begin{aligned} f_x(x) &= -(\bar{f}_x(x))' = -\left[ e^{-\int_0^x \mu_x(t) dt} \right]' = -\left[ \left( -\int_0^x \mu_x(t) dt \right)' \right] e^{-\int_0^x \mu_x(t) dt} \\ &= -[-\mu_x(x)] e^{-\int_0^x \mu_x(t) dt} \end{aligned}$$

$$f_x(x) = \mu_x(x) e^{-\int_0^x \mu_x(t) dt}$$

.  $X$  est « light »  $\mu_x$  croissante

.  $X$  est « heavy »  $\mu_x$  décroissante

$$e_x(x) = \frac{f_x(x)}{\bar{f}_x(x)} \rightarrow \begin{cases} X \text{ light} & \text{si } e_x(\cdot) \text{ décroissante} \\ X \text{ heavy} & \text{si } e_x(\cdot) \text{ croissante} \end{cases}$$

$$e_x(x) = \frac{\int_x^\infty \bar{f}_x(x) dx}{\int_x^\infty \bar{f}_x(x) dx} = \frac{-\bar{f}_x(x)}{-\int_x^\infty \bar{f}_x(x) dx} = \frac{1}{M_x(x)}$$

	$\mathbb{E}[X^k]$	$\mu_x(x)$	$e_x(x)$
heavy	$\exists k \leq n$	décroissante	croissante
light	$\exists \forall k$	croissante	décroissante

$\mu_x(x)$  croissante (décroissante)  $\rightarrow e_x(x)$  décroissante (croissante)

$e_x(x)$  décroissante (croissante)  $\xrightarrow{x} \mu_x(x)$  croissante (décroissante)  
(pas nécessairement)

$$\bar{f}_x(x) = \frac{e_x(0)}{e_x(x)} e^{-\int_0^x \frac{1}{e_x(t)} dt}$$

Si on a  $e_x(\cdot)$  on peut retrouver  $\bar{f}_x(x)$

$$f_{x_e}(x) = \frac{\bar{f}_x(x)}{\mathbb{E}[X]} \quad x > 0$$

$$\bar{f}_{x_e}(x) = \frac{\int_x^\infty \bar{f}_x(y) dy}{\mathbb{E}[X]}$$

$$\mu_{x_e}(x) = \frac{\bar{f}_x(x)}{\mathbb{E}[X]} \cdot \frac{\mathbb{E}[X]}{\int_x^\infty \bar{f}_x(y) dy} = \frac{1}{e_x(x)}$$

$$\bar{f}_x(x) = \mathbb{E}[X] \cdot f_{x_e}(x), \quad f_{x_e}(x) = - \left( e^{-\int_0^x \frac{1}{e_x(t)} dt} \right)^1$$

$$\bar{f}_x(x) = \frac{e_x(0)}{e_x(x)} e^{-\int_0^x \frac{1}{e_x(t)} dt}$$

$$f_{x_e}(x) = \frac{1}{e_x(x)} e^{-\int_0^x \frac{1}{e_x(t)} dt}$$

## \* distribution冥ants de sinistre

.  $X \sim \text{Exp}(\lambda)$

$$\{X - a \mid X > a\} \rightarrow X \text{ sans m\'emoire}$$

Sum iid  $\sim \text{Erlang}(n, \lambda)$

pour simuler  $X^{(s)} = \frac{1}{\lambda} \ln(1 - U^{(s)})$

.  $X \sim \text{Erlang}(n, \lambda)$

$$Y = X_1 + \dots + X_n \quad X_i \sim \text{Exp}(\lambda)$$

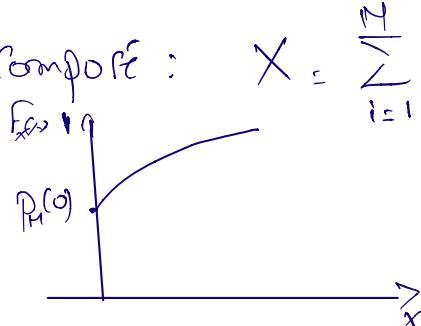
$$X^{(i)} = \frac{1}{\lambda} \ln(1 - U^{(i)})$$

$$Y = X_1 + X_2 + \dots + X_n = \frac{1}{\lambda} \ln \left( \prod_{i=1}^n (1 - U^{(i)}) \right)$$

$\ll \text{light tail} \gg, \mu_X \text{ croissante}$

\* le cas particulier de somme Compos\'e :  $X = \sum_{i=1}^M B_i$  o\`u  $M \sim \text{Bec}(q)$

$$M = \begin{cases} 1 & q \\ 0 & 1-q \end{cases}$$



$$f_X(x) = P_M(0) + P_M(1) f_B(x) = u$$

$$\frac{u - (1-q)}{q} = f_B(x)$$

$$\text{Var}_P(x) = \begin{cases} 0 & 1 < k \leq 1-q \\ \frac{\text{Var}(B)}{\frac{k - (1-q)}{q}} & k > 1-q \end{cases}$$

$$\text{TuVar}_P(x) = \frac{1}{1-p} [\mathbb{E}(X \mathbf{1}_{\{X > \text{Var}_P(x)\}}] + \text{Var}_P(x) (f_X(\text{Var}_P(x)) - p)]$$

$$= \frac{1}{1-\kappa} \left[ \mathbb{E}(B \mathbb{1}_{\{B > \text{VaR}_\kappa(B)\}}) + \text{VaR}_\kappa(B) \left( f_X(\text{VaR}(B) - p) \right) \right]$$

$$\text{TVaR}_\kappa(x) = \begin{cases} \frac{1}{1-\kappa} \mathbb{E}[B] & \text{Si } \kappa \leq 1-q \\ \frac{1}{1-\kappa} \mathbb{E}[B \mathbb{1}_{\{B > \text{VaR}_\kappa(x)\}}] & \text{Sinon} \end{cases}$$

\* Somme n Poi Comp

$$S = X_1 + X_2 + \dots + X_n \quad X_i \sim \text{Pcomp}(\lambda_i, f_{B_i})$$

$$S \sim \text{Pcomp}(\sum \lambda_i, f_c) \quad \lambda_s = \sum_{i=s}^n \lambda_i$$

$$f_c(x) = \frac{\lambda_1}{\lambda_s} f_{B_1}(x) + \dots + \frac{\lambda_n}{\lambda_s} f_{B_n}(x)$$

\* les Somme Composée

$$X = \sum_i^M B_i$$

$$\mathbb{E}[X] = \mathbb{E}[M] \cdot \mathbb{E}[B]$$

$$\text{Var}(X) = \mathbb{E}[\text{Var}(B|M)] + \text{Var}(\mathbb{E}[B|M])$$

$$\text{Var}(X) = \mathbb{E}[M] \text{Var}(B) + \mathbb{E}^2[B] \text{Var}(M)$$

$$M_X(t) = \mathbb{E}_M \left[ \left( M_B(t) \right)^M \right] = P_M(M_B(t))$$

## \* Somme de n Composée

• Somme PComp( $\lambda_i, f_{B_i}$ )

$$S \sim PComp(\lambda_s, f_c)$$

•  $X_i \sim BiNeg(r_i, q, f_B)$        $B_1, B_2, \dots, B_n$

$$S \sim BiNeg(\sum r_i, q, f_B) \quad M = M_1 + M_2 + \dots + M_n$$

•  $X_i \sim BComp(n_i, q, f_B)$

$$S \sim BComp(\sum n_i, q, f_B)$$

## \* Approximation de $S = X_1 + \dots + X_n$

### 1) Normale

$$\mathbb{E}[T] = \mathbb{E}[S], \quad Var(S) = Var(T)$$

$$\frac{S_n - \mathbb{E}[S_n]}{\sigma_{S_n}} \rightarrow \mathcal{Z} \sim N(0,1)$$

$$T = \mu_s + \sigma_s \mathcal{Z}$$

$$f_S(x) \approx f_T(x)$$

$$Var_p(T) = \mu_s + \sigma_s Var_p(\mathcal{Z})$$

$$Var_p(x) \approx Var_p(T)$$

$$TVar_p(x) \approx TVar_p(T)$$

$$TVar_p(T) = \mu_s + \sigma_s TVar_p(\mathcal{Z})$$

## (2) Log Normal

$$\mathbb{E}[S] = \mathbb{E}[T] = e^{4 + \frac{\sigma^2}{2}}$$

$$\mathbb{E}[S^2] = \mathbb{E}[T^2] = e^{2u + 2\sigma^2}$$

$$\mathbb{P}(S > x) \approx \mathbb{P}(T > x) = 1 - \Phi\left(\frac{\ln(x) - 4}{\sigma}\right)$$

(3) Gamma translate  $T \sim \text{Gamma}(\alpha, \beta)$

$$x_0 + T$$

S: masse à zéro pas élevé

$$\mathbb{E}[S] = x_0 + \mathbb{E}[T]$$

$$\text{Var}(S) = \text{Var}(T)$$

$$\gamma(S) = \gamma(T)$$

$$\gamma(T) = \frac{\mathbb{E}[(T - \mathbb{E}[T])^3]}{(\text{Var}(T))^{3/2}}$$

$$\begin{aligned} \mathbb{E}[(T - \mathbb{E}[T])^3] &= \mathbb{E}\left[\sum_{i=0}^3 \binom{3}{i} T^i (\mathbb{E}[T])^{3-i}\right] \\ &= \mathbb{E}\left[-\left(\frac{\alpha}{\beta}\right)^3 + 3\left(\frac{\alpha}{\beta}\right)^2 T - 3T\left(\frac{\alpha}{\beta}\right) + T^3\right] \\ &= -\frac{\alpha^3}{\beta^3} + \frac{3\alpha^2}{\beta^3} - \frac{3\alpha(\alpha-1)}{\beta^3} + \frac{\alpha(\alpha-1)(\alpha-2)}{\beta^3} \\ &= \frac{-\alpha^3 + 3\alpha^2 - 3\alpha^2 + 2\alpha^2 + \alpha^3 - 3\alpha^2 + 2\alpha}{\beta^3} = \frac{2\alpha}{\beta^3} \end{aligned}$$

$$\gamma(T) = \frac{2\alpha}{\beta^3} \cdot \left(\frac{\beta^3}{\alpha}\right)^{3/2} = \frac{2\alpha}{\beta^2} \cdot \frac{\beta^2}{\alpha^2} = \frac{2}{\alpha^2}$$

$$\alpha = \frac{u}{(\gamma(s))^2}, \quad \beta = \frac{2}{\sqrt{s} \sqrt{\text{Var}(s)}}, \quad x_0 = \mathbb{E}[S] - \frac{2\sqrt{\text{Var}(s)}}{\gamma(s)}$$

Si on a une masse élevée à zéro:  $S' = \{S | S > 0\}$

$$q = \mathbb{P}(S > 0) \text{ et } 1-q = \mathbb{P}(S=0)$$

$$\mathbb{P}(S \leq x) = \mathbb{P}(S=0) + \mathbb{P}(S>0) \mathbb{P}(S \leq x | S>0)$$

$$f_S(x) = 1 - q + q f_{S'}(x) \approx 1 - q + q \bar{f}_{\frac{x_0+\tau}{2}}(x)$$

$$\alpha = \frac{4}{(\sqrt{s})^2}, \quad \beta = \frac{2}{\sqrt{s} \sqrt{\text{Var}(s')}}, \quad x_0 = \mathbb{E}[S'] - \frac{2\sqrt{\text{Var}(s')}}{\sqrt{s'}}$$

## \* Proportion de prime

- (1)  $\rho(x) \leq \sup\{x\}$  surcharge
- (2)  $\rho(x) \geq \mathbb{E}[x] = \text{prime pur} + \text{marge}$  non-négative
- (3)  $\rho(x+c) = \rho(x) + c$  Invariance par translation
- (4)  $\rho(c) = c$  Constante
- (5)  $\rho(x+y) \leq \rho(x) + \rho(y)$  sous-additive
- (6)  $\rho(x+y) = \rho(x) + \rho(y)$  additive
- (7)  $\rho(cx) = c\rho(x)$  Homogénéité
- (8)  $\mathbb{P}(X \leq Y) = 1 \rightarrow \rho(x) \leq \rho(y)$  Monotonicité
- $X =_d Y \rightarrow \rho(X) = \rho(Y)$  Invariance

## \* Definition:

Coherente:

- |  |  |
|--|--|
| $\left\{ \begin{array}{l} \cdot \rho(x+c) = \rho(x) + c \\ \cdot \rho(cx) = c\rho(x) \\ \cdot \rho(x+y) \leq \rho(x) + \rho(y) \\ \cdot \forall X \leq Y \text{ avec prob 1} \rightarrow \rho(X) \leq \rho(Y) \end{array} \right.$ | Invariance par translation<br>Homogénéité<br>sous-additive<br>Monotonicité |
|--|--|

Convexe:  $\rho(x+c) = \rho(x) + c + x \leq y \text{ avec prob 1} \rightarrow \rho(x) \leq \rho(y)$   
 $+ \rho(\lambda x + (1-\lambda)y) \leq \lambda \rho(x) + (1-\lambda)\rho(y)$

Si  $\rho$  est convexe et positive homogène  $\rightarrow$  cohérente

## \* Principe et propriétés

- $P_1(x) = (1+\theta)\mathbb{E}[x]$
- $P_2(x) = \mathbb{E}[x] + \theta \text{Var}(x)$
- $P_3(x) = \mathbb{E}[x] + \theta \sigma_x$
- $P_4(x) = \text{VaR}_p(x)$
- $P_5(x) = \text{TVaR}_p(x)$
- $P_6(x) = \frac{1}{a} \ln(M_x(a))$
- $P_8(x) = \text{TVaR}_p(W_n) = \text{TVaR}_p\left(\frac{x_1 + x_2 + \dots + x_n}{n}\right)$

$$\frac{1}{n} \text{TVaR}_p(x_1 + x_2 + \dots + x_n) \leq \frac{1}{n} [\text{TVaR}_p(x_1) + \dots + \text{TVaR}_p(x_n)]$$

$$\frac{1}{n} \text{TVaR}_p(x_1 + \dots + x_n) \leq \text{TVaR}_p(x)$$