

# JUMP PROCESSES :

DEF: Poisson Process  $\begin{cases} \rightarrow ① N_0 = 0 \text{ a.s.} \\ \rightarrow ② \text{Independent } \forall 0 \leq s \leq t < +\infty, N_t - N_s \perp\!\!\!\perp N_s - N_0. \\ \left( T_n - T_{n-1} \sim \text{Exp}(\lambda) \right) \end{cases}$

Increments:  $\rightarrow ③ \forall 0 \leq s \leq t < +\infty, N_t - N_s \sim D(d(t-s))$

1) Thm:  $M = \{M_t\}_{t \geq 0}$  defined by  $\forall t \geq 0, M_t = N_t - \lambda t$  (where  $N$  is a Poisson Process) is a martingale called "compensated Poisson Process".

PROOF:  $0 \leq s \leq t, E[M_t | \mathcal{F}_s] = E[N_t - N_s + M_s | \mathcal{F}_s] = E[N_t - N_s | \mathcal{F}_s] + E[M_s | \mathcal{F}_s]$

$\xrightarrow{N_s \text{ is } \mathcal{F}_s\text{-meas}} = E[N_t - N_s - \lambda(t-s) | \mathcal{F}_s] + M_s$

$= M_s - \lambda(t-s) + E[N_t - N_s | \mathcal{F}_s]$

$\xrightarrow{N_t - N_s \perp\!\!\!\perp \mathcal{F}_s} = M_s - \lambda(t-s) + \lambda(t-s) = M_s \quad \square$

Rmk:  $\{N_t\}_{t \geq 0}$  could not be a mg since, by def., it is "expected to ↑"

2) MG characterisation of the intensity: Let  $N$  be a jump process. Suppose  $\lambda = \{d_t\}_{t \geq 0}$  such that:

$N_{t \wedge T_n} - \int_0^{t \wedge T_n} \lambda_s ds$  is a MG. Then:  $\lambda$  is the intensity of  $N$ .

PROOF: Let  $t \geq 0$ , by the cst expectation of MG property:

$$E\left[N_{t \wedge T_n} - \int_0^{t \wedge T_n} \lambda_s ds\right] = 0 \text{ i.e. }$$

$$E\left[N_{t \wedge T_n}\right] = E\left[\int_0^{t \wedge T_n} \lambda_s ds\right] \text{ i.e. }$$

$$E\left[\int_0^t dN_s\right] = E\left[\int_0^{t \wedge T_n} \lambda_s ds\right]$$

According to the "MONOTONE CLASS THM" (cf. txtbook Brémaud), if we

can prove a result for such a process:  $C_s = \mathbb{1}_A \mathbb{1}_{(r,t]}(s)$  ( $A \in \mathcal{F}_r$ ,  $s \in (r,t]$ ), then the result is true for any predictable process.

So, using the fact that  $N_{t \wedge T_n} - \int_0^{t \wedge T_n} \lambda_s ds$  is a MG, we can write:  $\forall A \in \mathcal{F}_r$ ,  $\mathbb{E}[\mathbb{1}_A(N_{t \wedge T_n} - \int_0^{t \wedge T_n} \lambda_s ds)] = \mathbb{E}[\mathbb{1}_A(N_{r \wedge T_n} - \int_0^{r \wedge T_n} \lambda_s ds)]$  (eq. def of MG). So:  $\forall A \in \mathcal{F}_r$ ,

$$\mathbb{E}[\mathbb{1}_A(N_{t \wedge T_n} - N_{r \wedge T_n})] = \mathbb{E}[\mathbb{1}_A(\int_0^{t \wedge T_n} \lambda_s ds - \int_0^{r \wedge T_n} \lambda_s ds)]$$

i.e.  $\mathbb{E}[\mathbb{1}_A \int_r^{t \wedge T_n} dN_s] = \mathbb{E}[\mathbb{1}_A \int_{r \wedge T_n}^{t \wedge T_n} d_s ds]$

i.e.  $\mathbb{E}\left[\int_0^{t \wedge T_n} \mathbb{1}_A \mathbb{1}_{(r,t]}(s) dN_s\right] = \mathbb{E}\left[\int_0^{t \wedge T_n} \mathbb{1}_A \mathbb{1}_{(r,t]}(s) \lambda_s ds\right]$

i.e. (Monotone Class Thm from Bremaud's textbook)  $\mathbb{E}\left[\int_0^{t \wedge T_n} C_s dN_s\right] = \mathbb{E}\left[\int_0^{t \wedge T_n} C_s \lambda_s ds\right]$   
for any predictable (non-neg.) process  $C$ .  $\square$

3) Integration thm: Assume that  $N$  has intensity  $\lambda$ .

Then:  $\left(N_{t \wedge T_n} - \int_0^{t \wedge T_n} \lambda_s ds\right)_t$  is a MG,  $\forall n \geq 1$ .

(i.e.  $(N_t - \int_0^t \lambda_s ds)_t$  is a local MG)

PROOF: [USUALLY ASKED]

let  $n \geq 1$ ,  $N_{t \wedge T_n} \leq n$  .  $\begin{cases} \text{since } \int_0^t \lambda_s ds \leq \int_0^{T_n} \lambda_s ds = N_{t \wedge T_n} = N_t \leq n; \\ \text{if } t \geq T_n: N_{t \wedge T_n} = N_{T_n} = n. \end{cases}$

We have to prove that  $\mathbb{E}\left[\int_0^{t \wedge T_n} \lambda_s ds\right] < +\infty$ .

$$\bullet \quad \mathbb{E}\left[\int_0^{t \wedge T_n} dN_s\right] = \mathbb{E}\left[\int_0^{t \wedge T_n} 1 dN_s\right] = \mathbb{E}\left[\int_0^t 1_{\{s \leq T_n\}} dN_s\right]$$

↑ intensity of  $N$

by def of  $\int dN_s$

$$= \mathbb{E}\left[\sum_{k \geq 1} \mathbb{1}_{\{\tau_k \leq T_n\}} \cdot \mathbb{1}_{\{\tau_k \leq t\}}\right]$$

$$\begin{aligned} \{\tau_i\} &\rightarrow \quad \Rightarrow \\ &= \mathbb{E}\left[\sum_{k=1}^n \mathbb{1}_{\{\tau_k \leq T_n\}} \cdot \mathbb{1}_{\{\tau_k \leq t\}}\right] \\ &= \sum_{k=1}^n \mathbb{E}\left[\mathbb{1}_{\{\tau_k \leq T_n\}} \mathbb{1}_{\{\tau_k \leq t\}}\right] < +\infty \end{aligned}$$

$\rightarrow$   $\mathbb{E}$  is in  $L^1$ .

Now let's prove the property of the MG:

let  $M_t = N_t - \int_0^t dN_s$ . Let  $r \leq t$ ,

$$\begin{aligned} \mathbb{E}[M_{t \wedge T_n} | \mathcal{F}_r] &= \mathbb{E}[M_{t \wedge T_n} - M_{r \wedge T_n} + M_{r \wedge T_n} | \mathcal{F}_r] \\ &= M_{r \wedge T_n} + \boxed{\mathbb{E}\left[\int_{r \wedge T_n}^{t \wedge T_n} dN_s - \int_{r \wedge T_n}^{t \wedge T_n} dN_s | \mathcal{F}_r\right]} \\ &\quad \text{WE WANT TO PROVE IT'S } = 0. \end{aligned}$$

$$\mathbb{E}\left[\int_{r \wedge T_n}^{t \wedge T_n} dN_s | \mathcal{F}_r\right] = \mathbb{E}\left[\int_{r \wedge T_n}^{t \wedge T_n} dN_s | \mathcal{F}_r\right] \Leftrightarrow$$

$$\forall A \in \mathcal{F}_r, \quad \int_A \left( \int_{r \wedge T_n}^{t \wedge T_n} dN_s \right) dP = \int_A \left( \int_{r \wedge T_n}^{t \wedge T_n} dN_s \right) dP \Leftrightarrow$$

$$\forall A \in \mathcal{F}_r, \quad \int_{\Omega} \mathbb{1}_A(\dots) dP = \int_{\Omega} \mathbb{1}_A(\dots) dP \Leftrightarrow$$

$$\forall A \in \mathcal{F}_t, \quad \mathbb{E} \left[ \int_{r \wedge \tau_n}^{t \wedge \tau_n} \mathbb{1}_A dN_s \right] = \mathbb{E} \left[ \int_{r \wedge \tau_n}^{t \wedge \tau_n} \mathbb{1}_A \lambda_s ds \right] \Leftrightarrow$$

$$\forall A \in \mathcal{F}_t, \quad \mathbb{E} \left[ \int_0^t \mathbb{1}_A \mathbb{1}_{(r \wedge \tau_n, t \wedge \tau_n)}(s) dN_s \right] = \mathbb{E} \left[ \int_0^t \mathbb{1}_A \mathbb{1}_{(r \wedge \tau_n, t \wedge \tau_n)}(s) \lambda_s ds \right]$$

$$\Leftrightarrow \forall A \in \mathcal{F}_t, \quad \mathbb{E} \left[ \int_0^t \mathbb{1}_A \mathbb{1}_{(r, t]}(s) \mathbb{1}_{\{s \leq \tau_n\}} dN_s \right] = \mathbb{E} \left[ \int_0^t \mathbb{1}_A \mathbb{1}_{(r, t]}(s) \lambda_{\mathbb{1}_{\{s \leq \tau_n\}}} ds \right]$$

But the last equality is TRUE since the involved processes are positive & predictable; and  $\lambda$  is an intensity (so we can use the def of the stoch.  $\int$ ).  $\square$

4) Uniqueness theorem: Let  $N$  a jump process with intensities  $\lambda, \tilde{\lambda}$ . Then  $\lambda_t(w) = \tilde{\lambda}_t(w)$   $dP dN_t(w)$ -a.e.

PROOF: [NEVER HAS BEEN ASKED, AS OF TODAY]

$\lambda$  non-negative & predictable:

$$\mathbb{E} \left[ \int_0^t C_s dN_s \right] = \mathbb{E} \left[ \int_0^t C_s \lambda_s ds \right] \leq \mathbb{E} \left[ \int_0^t C_s \tilde{\lambda}_s ds \right] \quad \forall t \geq 0.$$

Let's fix  $t$ , we can define  $C_s = \mathbb{1}_{\{d_s > \tau_s\}} \mathbb{1}_{\{s \leq t\}}$ . It is non-neg. & predictable. So:

$$\underbrace{\mathbb{E} \left[ \int_0^{+\infty} \mathbb{1}_{\{d_s > \tau_s\}} \mathbb{1}_{\{s \leq t\}} \lambda_s ds \right]}_{C_s} = \mathbb{E} \left[ \int_0^{+\infty} \underbrace{\mathbb{1}_{\{d_s > \tau_s\}} \mathbb{1}_{\{s \leq t\}}}_{C_s} \tilde{\lambda}_s ds \right]$$

i.e.:

$$E\left[\int_0^{+\infty} \mathbb{1}_{\{d_s > \bar{d}_s\}} \mathbb{1}_{\{s \leq t\}} (d_s - \bar{d}_s) ds\right] = 0 \quad \text{so :}$$

$\mathbb{E}\left[\mathbb{1}_{\{d_s > \bar{d}_s\}}\right] = 0 \quad \text{from } dP_{d_s} ds$ . And we can do the same

$$\text{with } \mathbb{E}\left[\mathbb{1}_{\{d_s < \bar{d}_s\}}\right]. \text{ From } E\left[\int_0^t C_s dN_s\right] = E\left[\int_0^t C_s \mathbb{1}_{\{d_s < \bar{d}_s\}} ds\right]$$

we can say that  $dP dN_t = dP_t dt$  on non-neg-predictable processes.  $\square$

RMK:  $\lambda$  depends on  $P$  & on  $F$ :  $\lambda \mapsto \alpha(P, F)$  - intensity of  $N$ .

5) PROP: Let  $\{t_n\}_{n \geq 1}$  jump times,  $\lambda$  an intensity.

Then:  $\forall n \geq 1, \lambda_{[t_n]}(w) > 0 \quad \forall w \in \Omega$ .

PROOF: By definition of the intensity,

$$E\left[\int_0^{+\infty} C_t dN_t\right] = E\left[\int_0^{+\infty} C_t \mathbb{1}_t dt\right] \quad \forall C \text{ non-neg & pred.}$$

Take  $n \geq 1$ , and  $C_t = \mathbb{1}_{\{d_t = 0\}} \mathbb{1}_{\{[t_{n-1}; t_n]\}}$ .

Then:

• the left hand side is:  $E\left[\sum_{k \geq 1} C_{\tau_k} \mathbb{1}_{\{\tau_k < +\infty\}}\right] =$

$$E\left[\sum_{n \geq 1} \mathbb{1}_{\{d_{t_n} = 0\}} \mathbb{1}_{\{t_{n-1} < \tau_k \leq t_n\}}\right] = E\left[\sum_{n \geq 1} \mathbb{1}_{\{d_{t_n} = 0\}} \mathbb{1}_{\{\tau_k = t_n\}}\right]$$

$$= \mathbb{E} \left[ \mathbb{1}_{\{\lambda_{T_n} = 0\}} \right] = \mathbb{P}(\lambda_{T_n} = 0).$$

• the right hand side is :

$$\begin{aligned} \mathbb{E} \left[ \int_0^{+\infty} \mathbb{1}_{\{\lambda_t = 0\}} \mathbb{1}_{\{(T_{n-1}, T_n]\}} d_t dt \right] &= \mathbb{E} \left[ \int_{T_{n-1}}^{T_n} \mathbb{1}_{\{\lambda_t = 0\}} d_t dt \right] \\ &= 0. \end{aligned}$$

$$\text{So } \mathbb{P}(\lambda_{T_n} = 0) = 0. \quad \square$$

# A NEW KIND OF JUMP PROCESSES: MARKED POINT PROCESSES

See the def + def of indexed process + def of intensity kernel.

Notation:

$$\int_0^t \int_E H(s, z) \mu(ds, dz) = \sum_{n=1}^{[t]} H(t_n, z_n) \mathbb{1}_{\{t_n \leq t\}}, \quad \forall t \geq 0.$$

↳ "Random measure"

6) Projection thm: Given  $(t_n, z_n)_{n \geq 1}$  with  $\lambda_t(dz)$ ; for any non-negative predictable & indexed  $(H_t)_{t \geq 0}$ :

$$\mathbb{E} \left[ \int_0^{+\infty} \int_E H(s, z) \lambda_s(ds, dz) \right] = \mathbb{E} \left[ \int_0^{+\infty} \int_E H(s, z) \lambda_s(dz) ds \right].$$

PROOF: It's enough to prove the result for

$$H_t(z) = C_t \mathbb{1}_A(z), \quad \forall A \in \mathcal{E}. \quad \text{So:}$$

$$\begin{aligned} \mathbb{E} \left[ \int_0^{+\infty} \int_E H(s, z) \mu(ds, dz) \right] &= \mathbb{E} \left[ \int_0^{+\infty} \int_E C_t \mathbb{1}_A(z) \mu(dt, dz) \right] \\ &= \mathbb{E} \left[ \int_0^{+\infty} \int_A C_t \mu(dt, dz) \right] \\ &\stackrel{\text{by the notation}}{=} \mathbb{E} \left[ \sum_{n=1}^{+\infty} C_{T_n} \mathbb{1}_A(z_n) \mathbb{1}_{\{T_n < +\infty\}} \right] \\ &\stackrel{\text{by def of the stochastic}}{=} \mathbb{E} \left[ \int_0^{+\infty} C_t dN_t(A) \right] \\ &\stackrel{\text{by def of } \lambda_t(A) \text{ being the intensity of } N_t(A).}{=} \mathbb{E} \left[ \int_0^{+\infty} C_t \lambda_t(A) dt \right] \end{aligned}$$

$H_t(z)$

IDEA OF THE PROOF: the thm is true for  $H$  of the form  $H_t(z) = C_t \mathbb{1}_A(z)$ , & then use Monotone Class Thm.

$$= \mathbb{E} \left[ \int_0^{+\infty} \int_A C_t \lambda_t(dz) dt \right] = \mathbb{E} \left[ \int_0^{+\infty} \int_E C_t \mathbb{1}_A(z) \lambda_t(dz) dt \right]$$

□

# CRAMER - LUNDBERG MODEL

1) Expected Surplus:  $\forall t \geq 0, E[R_t] = R_0 + ct - \frac{\lambda t}{\xi}$ .  

$$\left( (N_t) \sim \text{Poisson Process} \quad X \sim \exp(\xi) \right)$$

PROOF:  $E[R_t] = R_0 + ct - E\left[\sum_{n=1}^{N_t} x_n\right] = R_0 + ct - E\left[\sum_{n=1}^{\infty} \sum_{i=1}^n x_i \mathbb{1}_{\{N_t=n\}}\right]$

$$= R_0 + ct - \sum_{n=1}^{\infty} \sum_{i=1}^n E[x_i \mathbb{1}_{\{N_t=n\}}]$$

$$= R_0 + ct - E[X] \sum_{n=1}^{\infty} n P[N_t=n]$$

$$= R_0 + ct - E[X] \lambda t \quad \leftarrow E[N_t] = \lambda t$$

$$= R_0 + ct - \frac{\lambda t}{\xi} \quad \square \quad E[X] = \frac{1}{\xi} (X \sim \exp(\xi)).$$

2)  $\text{Var}(L_t) = \text{Var}\left(\sum_{n=1}^{N_t} x_n\right) = \mu_2 \cdot \lambda t$  where  $\mu_2 = E[X^2]$ .

PROOF:  $\text{Var}\left(\sum_{n=1}^{N_t} x_n\right) = E\left[\left(\sum_{n=1}^{N_t} x_n\right)^2\right] - E\left[\sum_{n=1}^{N_t} x_n\right]^2$

$$= E\left[\left(\sum_{n=1}^{N_t} x_n\right)^2\right] - \left(\frac{\lambda t}{\xi}\right)^2$$

$$E\left[\left(\sum_{n=1}^{N_t} x_n\right)^2\right] = \sum_{k \geq 1} E\left[\left(\sum_{n=1}^k x_n\right)^2 \mathbb{1}_{\{N_t=k\}}\right]$$

$$= \sum_{k \geq 1} E\left[\left(\sum_{n=1}^k x_n\right)^2\right] P[N_t=k] \quad \leftarrow N_t \perp\!\!\!\perp X_n$$

$$= \sum_{k \geq 1} P(N_t=k) \left[ \text{Var}\left(\sum_{n=1}^k x_n\right) + E\left[\sum_{n=1}^k x_n\right]^2 \right]$$

that's sum  $\sum_{n=1}^k$  (

$(x_n)_n$  iid

$$= \sum_{k \geq 1} P(N_t=k) \left[ \sum_{n=1}^k \text{Var}(x_n) + E\left[\sum_{n=1}^k x_n\right]^2 \right]$$

$\mu = E[X]$

$\mu_2 = E[X^2]$

$$= \sum_{k \geq 1} P(N_t=k) \left[ k \cdot (\mu_2 - \mu^2) + k^2 \mu^2 \right]$$

$$S_0 : \text{Var}\left(\sum_{n=1}^{N_t} X_n\right) = \sum_{k \geq 1} \mathbb{P}(N_t = k) \left[ k(\mu_2 - \mu^2) + k^2 \mu^2 \right] - \mu^2 (\Delta t)^2$$

$$\mathbb{E}[N_t] = \sum_k k \mathbb{P}(N_t = k) \quad \Rightarrow \quad \mathbb{E}[N_t] = \mu_2 \Delta t$$

$$\mathbb{E}[N_t^2] = \sum_k k^2 \mathbb{P}(N_t = k) \quad \Rightarrow \quad \mathbb{E}[N_t^2] = \mu_2 \Delta t + \cancel{\mu^2 (\Delta t)^2}$$

$$\mu_2^2 = \cancel{\mu_2 (\Delta t + \Delta t^2)} \quad \Rightarrow \quad \mu_2^2 = \mu_2 \Delta t + \cancel{\mu^2 (\Delta t + \Delta t^2)} - \cancel{\mu^2 (\Delta t)^2}$$

$$k^2 = k(k-1) + k \quad \Rightarrow \quad \mu_2^2 = \mu_2 \Delta t$$

$$S_0 : \text{Var}\left(\sum_{n=1}^{N_t} X_n\right) = \mu_2 \Delta t \quad \square$$

3)  $\mathbb{E}\left[e^{-r\sum_{i=1}^{N_t} X_i}\right] = e^{-\lambda t(M_x(r)-1)}$  with  $r \in \mathbb{R}$  and

$$M_x(r) = \mathbb{E}[e^{rX}] \quad (\text{Moment generating function}).$$

PROOF: see the slide 36/49.

4) Lemma 5.3: let  $r \in \mathbb{R}$ ,  $M_x(r) < +\infty$  and

$$\Theta(r) = \lambda(M_x(r)-1) - cr \quad \text{Then: } \left(e^{-rC_t - \Theta(r)t}\right)_{t \geq 0} \text{ is a Martingale, with } C_t = \mu + ct - \sum_{n=1}^{N_t} X_n.$$

PROOF: Fix  $0 \leq s \leq t$ .

$$\mathbb{E}\left[e^{-rC_t - \Theta(r)t} \mid \mathcal{F}_s\right] = \mathbb{E}\left[e^{-rC_t - \Theta(r)t + rC_s + \Theta(r)s} \mid \mathcal{F}_s\right]$$

$$= \mathbb{E} \left[ e^{-r(C_t - C_s)} \middle| \mathcal{F}_s \right] \cdot \underbrace{e^{-rC_s}}_{\mathcal{F}_s\text{-meas}} \cdot \underbrace{e^{-\lambda(M_X(r) - 1)t + crt}}_{\text{deterministic } t \in \mathbb{R}_+}$$

□

Let's study  $r \mapsto \theta(r)$ :