

# 10 Lamperti transformation


Def<sup>n</sup> A  $[0, \infty)$ -valued strong Markov process  
 $Y = \{Y_t : t \geq 0\}$  with probs  $\{P_x : x \geq 0\}$   
 is called a cts-state branching process  
 if its paths are a.s. right cts with left  
 limits and observes the branching property  
 as given in last lecture except  $y_1, y_2 \in [0, \infty)$


Another way of phrasing the br. property:

$$\forall \theta \geq 0 \quad \mathbb{E}_{x+y} \left[ e^{-\theta Y_t} \right]$$

$$x, y \geq 0$$

$$= \mathbb{E}_x \left( e^{-\theta Y_t} \right) \mathbb{E}_y \left( e^{-\theta Y_t} \right) \quad (H)$$

In particular  $\mathbb{E}_x \left( e^{-\theta Y_t} \right) = \mathbb{E}_{x/n} \left( e^{-\theta Y_t} \right)^n$  

(and so  $Y_t$  is an l.d. r.v.!) 

Introduce  $g(t, \theta, x) = -\log \mathbb{E}_x \left( e^{-\theta Y_t} \right)$

  $\Rightarrow$  for any integer  $m \geq 0$   $m = n \times \frac{m}{n}$   
 $= m \times 1$

on one hand  $g(t, \theta, m) = n g(t, \theta, m/n)$

on other hand  $g(t, \theta, m) = m g(t, \theta, 1)$

$\Rightarrow g(t, \theta, x) = x \underbrace{g(t, \theta, 1)}_{\substack{|| \\ u_t(\theta)}} \quad \text{for all } x \in \mathbb{Q}_{>0}$

By (†) we see that

$$E_{x+y}(e^{-\theta Y_t}) \leq E_x(e^{-\theta Y_t})$$

$$\Rightarrow g(t, \theta, x) \leq g(t, \theta, x+y)$$

$$\Rightarrow g(t, \theta, x-) \leq g(t, \theta, x+) \quad \leftarrow \text{limits defined by monotonicity}$$

now suppose  $x_n \downarrow x$   $x_n \in \mathbb{Q}_{>0}$   $y_n \uparrow x$

$$e^{-g(t, \theta, x_n)} = E_{x_n}(e^{-\theta Y_t}) = e^{-x_n u_t(\theta)} \xrightarrow[y_n \uparrow x]{x_n \downarrow x} e^{-x u_t(\theta)}$$

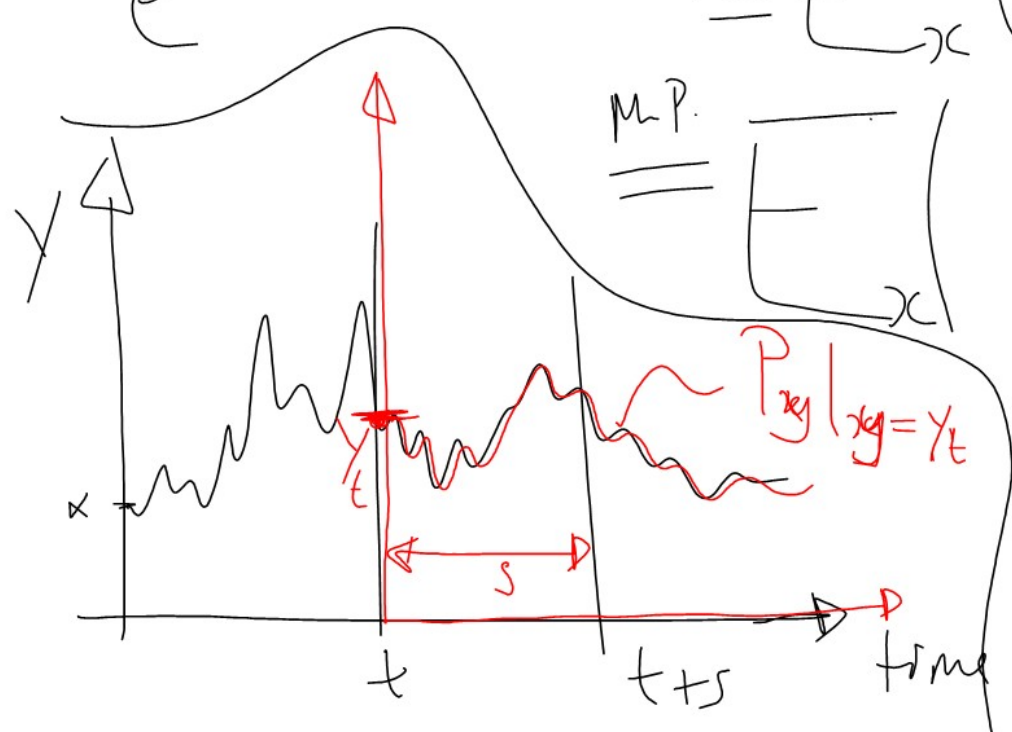
$$e^{-g(t, \theta, x_n)} \xrightarrow[y_n \uparrow x]{x_n \downarrow x} e^{-g(t, \theta, x+)} \quad \Rightarrow \quad g(t, \theta, x) = x u_t(\theta) \quad \forall x > 0$$

We now can write  $E_x(e^{-\theta Y_t}) = e^{-x u_t(\theta)}$

$\forall x \geq 0$   
 $t \geq 0$   
 $\theta \geq 0$

Use the Markov property

$$e^{-x u_{t+s}(\theta)} = E_x(e^{-\theta Y_{t+s}}) = E_x(E(e^{-\theta Y_{t+s}} | \mathcal{F}_t))$$



$$= E_x(E_y(e^{-\theta Y_s}) | y = Y_t)$$

$$= E_x(e^{-Y_t u_s(\theta)})$$
  
$$e^{-u_t(u_s(\theta))x}$$

Y is a Markov Process

$$E_x(g(Y_{t+s}) | \{Y_u : u \leq t\})$$

$$= E_x(g(Y_{t+s}) | Y_t)$$

$$= E_y(g(Y_s)) | y = Y_t \quad \forall g \text{ cts and bounded}$$

$$u_{t+s}(\theta) = u_t(u_s(\theta)) \quad \forall t, s \geq 0$$

$$\theta \geq c$$

semi group property  
of Laplace exponent.

Strongly suggests we should try and  
look at

$$\frac{\partial u_t(\theta)}{\partial t} = \lim_{\Delta \downarrow 0} \frac{u_{t+\Delta}(\theta) - u_t(\theta)}{\Delta}$$



Theorem For  $\theta \geq 0$ , suppose  $u_t(\theta)$   
 is the Laplace exponent of a CSBP.  
 Then it is differentiable in  $t$  and satisfies

$$\frac{\partial u_t(\theta)}{\partial t} + \psi(u_t(\theta)) = 0, \quad u_0(\theta) = \theta$$

Where for  $\lambda \geq 0$

$$\psi(\lambda) = -q - a\lambda + \frac{1}{2}\sigma^2\lambda^2 + \int_{(0, \infty)} (e^{-\lambda x} - 1 + \lambda x \mathbb{1}_{(x < 1)}) \Pi(dx)$$

where  $q \geq 0$ ,  $a \in \mathbb{R}$ ,  $\sigma^2 \geq 0$  and  $\Pi$  is a measure  
 concentrated in  $(0, \infty)$  satisfying  $\int_{(0, \infty)} (1 \wedge x^2) \Pi(dx) < \infty$

Note that - the quantity  $\psi$  can be recognised as  $\psi(\lambda) = \log \mathbb{E}(e^{-\lambda X_t})$  where  $X$  is a spectrally positive Lévy process under  $\mathbb{P}$  OR a subordinator, killed independently at rate  $q \geq 0$ .

Indeed  $\psi$  is the Laplace exp. of - a SN LP or a -ve sub. (killed at rate  $q$ )

and so we have the picture we should keep in mind

