

Jump Processes

Note Title

11/10/2005

We want to start to look at continuous-time processes.
Let's start with the fact that jump times for discrete-time Markov processes are geometric.

Q: How can we go from discrete to continuous with respect to the jump times.

Ξ is geometric(p); Ξ is position of first heads, where $P\{\Xi = k\} = p$.

$$P\{\Xi = k\} = (1-p)^{k-1} p \quad k \in \{1, 2, \dots\}$$

Note that

$$\begin{aligned} \mathbb{E}(e^{\lambda \xi}) &= \sum_{k=1}^{\infty} (1-p)^{k-1} e^{\lambda k} p \\ &= e^{\lambda} p \sum_{k=0}^{\infty} \{(1-p)e^{\lambda}\}^k \\ &= \frac{e^{\lambda} p}{1 - (1-p)e^{\lambda}} \approx \frac{p(1+\lambda\theta)}{1 - (1-p)(1+\lambda\theta)} \end{aligned}$$

$$\begin{aligned} &\approx \frac{p(1+\lambda\theta)}{\cancel{1-1+p} - (1-p)\lambda\theta} = \frac{1+\lambda\theta}{1 - \frac{1-p}{p}\lambda\theta} \end{aligned}$$

$$\approx (1+\lambda\theta) \left(1 + \frac{1-p}{p}\lambda\theta\right)$$

$$\approx 1 + \lambda\theta \left(1 + \frac{1-p}{p}\right) = 1 + \frac{\lambda\theta}{p}$$

$$\mathbb{E}(\lambda \xi) = \left. \frac{d}{d\lambda} \mathbb{E}(e^{\lambda \xi}) \right|_{\lambda=0} = \frac{\lambda}{p}$$

$$\Rightarrow \mathbb{E}(\xi) = \frac{1}{p}$$

This means that if $P(H) = p$, we expect to see a heads at about $1/p$ flips.

Now let's bias the coin. If $P(H) = 1/60$, we expect to see a heads after 60 flips.

If we flip the coin one every minute, we expect to see a heads after 1 hour. If $P(H) = 1/3600$, and we flip the coin once every second, we expect to see a heads after $\frac{3600 \text{ flips}}{\frac{3600 \text{ flips}}{\text{hour}}} = 1 \text{ hour}$.

In general, fix $\lambda > 0$, and for each $n \geq 0$, let \hat{X}_n be geometric(λ/n); \hat{X}_n is the # of flips needed for a coin (where $P(H) = \lambda/n$) to come up heads. If we flip the coin n times per hour, the total time until heads is

$$\bar{Z}_n \stackrel{\text{def}}{=} \frac{\widehat{Z}_n \text{ flips}}{n \text{ flips/hour}} = \frac{\widehat{Z}_n}{n} \text{ hours}$$

Note that

$$E(\bar{Z}_n) = \frac{1}{n} E(\widehat{Z}_n) = \frac{1}{n} \frac{1}{(2/n)} = 2.$$

More generally,

$$E(e^{r\theta \bar{Z}_n}) = E(e^{r\theta/n \widehat{Z}_n})$$

$$= \frac{e^{r\theta/n} 2/n}{1 - (1 - 2/n) e^{r\theta/n}}$$

$$= \frac{1 + r\theta/n}{n \{ 1 - (1 - 2/n)(1 + r\theta/n) \}}$$

$$= \frac{1 + r\theta/n}{n \{ 2/n - r\theta/n \}} \xrightarrow{n \rightarrow \infty} \frac{1}{2 - r\theta}$$

$$= \int_0^{\infty} e^{i\omega t} \underbrace{\lambda e^{-\lambda t}}_{\text{exponential } (\lambda)}$$

Let's look at this from a Markov process perspective. Consider



$$\text{ie } P_{\mu} = \begin{pmatrix} 1 - \lambda/\mu & \lambda/\mu \\ 0 & 1 \end{pmatrix}. \quad \star$$

$$\text{Set } \tau = \inf \{ n \geq 0 : X_n \neq X_0 \}.$$

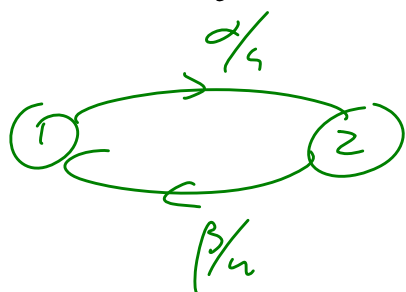
Then under \mathbb{P} , (ie start in ①), τ is geometric(λ/μ); $E_1(\tau) = \frac{\mu}{\lambda}$. In other words, we need to iterate the Markov chain $\frac{\mu}{\lambda}$ times before it jumps to ②. If we speed up the

Markov chain and run it once every $\frac{1}{n}$ th hour,
we expect it to jump to $\textcircled{2}$ at time

$$\frac{E_i[\tau]}{n} = \frac{\left(\frac{n}{\beta}\right) \text{ iterations}}{\frac{1}{n} \text{ iterations/hour}} = \frac{1}{\beta} \text{ hours.}$$

Let $\tilde{X}^{(n)}$ be Markov (\mathcal{S}, P_n) , where P_n is
as in \star . Set $X_t^{(n)} \stackrel{\text{def}}{=} \tilde{X}_{\lfloor nt \rfloor}^{(n)}$. Then in
time $t \in [1, 1+\epsilon]$ hour, we will have run $\tilde{X}^{(n)}$ for
 n iterations; i.e. $X^{(n)}$ should jump after about 1 hour.

Let's now go back to our favorite Markov chain



$$P_n = \begin{pmatrix} 1 - \alpha/n & \alpha/n \\ \beta/n & 1 - \beta/n \end{pmatrix}$$

$$= \mathbf{I} + \frac{1}{n} \underbrace{\begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix}}_Q$$

\hat{X}^n is Markov P_n

$$X_t^n = \tilde{X}_{\lfloor nt \rfloor}^n$$

$$\begin{aligned} \mathbb{P}_i \{ X_t^n = j \} &= \left(\mathbb{1} P_n^{\lfloor nt \rfloor} \right)_{ij} \\ &= \left\{ \left(I + \frac{1}{n} Q \right)^{\lfloor nt \rfloor} \right\}_{ij} \\ &= \left(\underbrace{\left\{ \left(I + \frac{1}{n} Q \right)^n \right\}}_{\approx e^Q} \right)^{\frac{\lfloor nt \rfloor}{n}} \approx e^{Qt} \end{aligned}$$

$$\xrightarrow{n \rightarrow \infty} \left(e^{Qt} \right)_{ij}$$

Recall that
$$e^{Qt} = \sum_{m=0}^{\infty} \frac{Q^m t^m}{m!}$$

converges; radius of convergence
for Taylor expansion of e^x is
 ∞ .

$$\text{Note: } (e^{Q(t+s)})_{ij} = (e^{Qt} e^{Qs})_{ij} = \sum_k (e^{Qt})_{ik} (e^{Qs})_{kj}$$

Chapman Kolmogorov

Infinitesimally, we have

$$P_{ij}\{X_T=j\} = (e^{Qt})_{ij} \approx (I + Qt + o(t))_{ij}$$

$$= \delta_{ij} + q_{ij}t + o(t)$$

$$\lim_{t \rightarrow 0} \frac{o(t)}{t} = 0$$

Also, note properties of $Q = \begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix}$

$$q_{ii} < 0$$

$$q_{ij} > 0 \text{ if } j \neq i$$

$$\sum_j q_{ij} = 0 \text{ for all } i$$

Let's make some general definitions

Definition A matrix $Q = (q_{ij}; i, j \in S)$ is the infinitesimal generator of a jump Markov chain if

- $q_{ii} < 0$ for all i and $q_{ij} > 0$ for $j \neq i$
- $\sum_j q_{ij} = 0$ for all i

Definition An S -valued stochastic process X is said to be a jump Markov process governed by Q if

- For each $\omega \in \Omega$, $t \mapsto X_t(\omega)$ is right-continuous with left-hand limits
- For $0 < t_1 < t_2 < t$ and $i_0, i_1, \dots, i_n, i \in S$ and $j \neq i$,

$$\mathbb{P}\{X_{t+\delta} = j \mid X_0 = i_0, \dots, X_{t_1} = i_1, \dots, X_t = i\} \\ = q_{ij} \delta + o(\delta)$$

where $\lim_{\delta \rightarrow 0} \frac{o(\delta)}{\delta} = 0$



While this infinitesimal definition is a bit unsettling,
note that the ODE $\dot{x}_t = f(x_t)$ means exactly that

$$X_{t+\delta} = X_t + f(X_t)\delta + o(\delta)$$

Note also that if $|S| < \infty$,

$$\mathbb{P}\{X_{t+\delta} = i \mid X_0 = i_0 \sim X_t = i\}$$

$$= 1 - \sum_{j \neq i} \mathbb{P}\{X_{t+\delta} = j \mid X_0 = i_0 \sim X_t = i, X_{t+\delta} = j\}$$

$$= 1 - \sum_{j \neq i} g_{ij}t + o(t)$$

$$\} g_{ii} + \sum_{j \neq i} g_{ij} = 0$$

$$= 1 + g_{ii}t + o(t)$$

$$\underbrace{g_{ii}}_{g_{ii} < 0}$$



Secondly, this definition is enough to pin down the law of X .

Claim If $|S| < \infty$, then for $0 = t_1 < t_2 \dots < t_n$ and $i_1, \dots, i_n \in S$,

$$\mathbb{P}_x \{ X_{t_1} = i_1, \dots, X_{t_n} = i_n \} = \left(e^{Q(t_1)} \right)_{i_1, i_1} \left(e^{Q(t_2 - t_1)} \right)_{i_1, i_2} \dots \left(e^{Q(t_n - t_{n-1})} \right)_{i_{n-1}, i_n} \quad \text{**}$$

PF Fix $0 = t_1 < t_2 \dots < t_n$ and $i_1, \dots, i_n \in S$. For $j \in S$ and $t > t_n$, define

$$f_j(t) = \mathbb{P}_x \{ X_t = j \mid X_{t_1} = i_1, \dots, X_{t_n} = i_n \}$$

Then

$$f_j(t + \delta) = \sum_i \mathbb{P}_x \{ X_{t+\delta} = j \mid X_t = i, X_{t_1} = i_1, \dots, X_{t_n} = i_n \}$$

$$\underbrace{\mathbb{P}_x \{ X_t = i \mid X_{t_1} = i_1, \dots, X_{t_n} = i_n \}}_{f_i(t)}$$

$$= f_j(t) + \sum_i f_i(t) g_{ij} \delta + o(\delta)$$

(use \star)

Thus

$$\dot{f}_j(t) = \sum_i f_i(t) g_{ij}$$

$$f_j(t_{n+}) = \delta_{1nj} \quad (\text{right-continuity})$$

Thus

$$f_j(t) = (e^{Q(t-t_n)})_{1nj}$$

ie

$$\mathbb{P}\{X_t = j \mid X_{t_n} = i, \sim X_{t_n} = 1_n\} = (e^{Q(t-t_n)})_{1nj}$$

Repeated use of this result leads to the claim. ●

How to compute e^{Qt}

Explicitly compute e^{Qt} for our two-state chain

$$Q = \begin{pmatrix} -\alpha & \alpha \\ \beta & -\beta \end{pmatrix}$$

eigenvalues again

idea: $Q = U\Lambda U^{-1}$

Λ -diagonal matrix of eigenvalues

$$\Lambda = \text{diag}(\lambda_1, \lambda_2, \lambda_3)$$

$$e^{Qt} = U e^{\Lambda t} U^{-1}$$

$\longrightarrow = (e^{\lambda_1 t} \ e^{\lambda_2 t})$

linear sums of $e^{\lambda_1 t}$, $e^{\lambda_2 t}$

$$0 = \det \begin{pmatrix} \lambda + \alpha & -\alpha \\ -\beta & \lambda + \beta \end{pmatrix} = (\lambda + \alpha)(\lambda + \beta) - \alpha\beta$$

$$= \lambda^2 + (\alpha + \beta)\lambda = \lambda(\lambda + \alpha + \beta)$$

$$\lambda = 0, \quad \lambda = -(\alpha + \beta)$$

$Q\mathbf{1} = 0 \Rightarrow 0$ is an eigenvalue

$$g_u(t) = (e^{Qt})_{11} = c + d e^{-(\alpha + \beta)t}$$

$$g_u(0) = (\mathbf{I})_{11} = 1 \quad ; \quad g_u(0) = c + d$$

$$\dot{g}_u(0) = Q_{11} = -\alpha \quad ; \quad \dot{g}_u(0) = c - (\alpha + \beta)d \quad \rightarrow \text{like } u=1 \text{ calculation for discrete time}$$

$$\begin{aligned} 1 &= c + d \\ -\alpha &= c - (\alpha + \beta)d \end{aligned} \quad \Rightarrow \quad c = \frac{\beta}{1 + \alpha + \beta}$$

$$d = \frac{1 + \alpha}{1 + \alpha + \beta}$$

$$g_{11}(t) = \frac{\beta}{1+\alpha+\beta} + \frac{1+\alpha}{1+\alpha+\beta} e^{-(\alpha+\beta)t}$$

$$g_{12}(t) = 1 - g_{11}(t) = \frac{1+\alpha}{1+\alpha+\beta} - \frac{1+\alpha}{1+\alpha+\beta} e^{-(\alpha+\beta)t}$$

Similarly,

$$g_{22}(t) = \frac{\alpha}{1+\alpha+\beta} + \frac{1+\beta}{1+\alpha+\beta} e^{-(\alpha+\beta)t}$$

$$g_{21}(t) = \frac{1+\beta}{1+\alpha+\beta} - \frac{1+\beta}{1+\alpha+\beta} e^{-(\alpha+\beta)t}$$

$$e^{Qt} = \frac{1}{1+\alpha+\beta} \begin{pmatrix} \beta & 1+\alpha \\ 1+\beta & \alpha \end{pmatrix}$$

$$+ \frac{1}{1+\alpha+\beta} \begin{pmatrix} 1+\alpha & -(1+\alpha) \\ -(1+\beta) & 1+\beta \end{pmatrix} e^{-(\alpha+\beta)t}$$

Example: p. 65

$$Q = \begin{pmatrix} -2 & 1 & 1 \\ 1 & -1 & 0 \\ 2 & 1 & -3 \end{pmatrix}$$

Compute $(e^{Qt})_{ii}$,

$$\begin{aligned} 0 &= \det(\lambda I - Q) = \det \begin{pmatrix} \lambda + 2 & -1 & -1 \\ -1 & \lambda + 1 & 0 \\ -2 & -1 & \lambda + 3 \end{pmatrix} \\ &= \lambda(\lambda + 2)(\lambda + 4) \end{aligned}$$

$$f_{ii}(t) = (e^{Qt})_{ii} = a + be^{-2t} + ce^{-4t}$$

Also know that

$$f'_{ii}(t) = (Qe^{Qt})_{ii}$$

$$f''_{ii}(t) = (Q^2 e^{Qt})_{ii}$$

$$\begin{aligned} f''(0) = I'' = 1; & \quad f''(0) = a + b + c \\ f'(0) = Q'' = -2; & \quad f'(0) = -2b - 4c \\ f''(0) = (Q'')'' = 7; & \quad f''(0) = 4b - 16c \end{aligned}$$

$$\Rightarrow f(t) = \frac{3}{8} + \frac{1}{4} e^{-2t} + \frac{3}{8} e^{-4t}$$

Our next calculation generalizes the approximation we used for the two-state jump Markov process

$$\text{Define } \bar{\delta}_i = -\delta_{ii} = \sum_{j \neq i} \delta_{ij}$$

Claim Assume $|S| < \infty$. For $N > \max_i \bar{\delta}_i$, let $\tilde{X}^{(N)}$ be Markov P_N , where $P_N = I + Q/N$.

Set $X_T^{(N)} = \tilde{X}_{\lfloor tN \rfloor}^{(N)}$; then the law of $X^{(N)}$ converges to ~~AA~~

Pf Note that

$$(P_N)_{ij} = \delta_{ij} + \delta_{ij}/N = \begin{cases} 1 + \delta_{ii}/N & \text{if } j=i \\ \delta_{ij}/N & \text{if } j \neq i \end{cases}$$

$$= \begin{cases} \frac{N - \bar{\delta}_i}{N} & \text{if } j=i \\ \delta_{ij}/N & \text{if } j \neq i \end{cases}$$

The requirement that $n > \sup_n \bar{g}_n$ ensures that P_n is indeed a transition matrix (note that $P_n \mathbb{1} = \mathbb{1} + \frac{Q\mathbb{1}}{N} = \mathbb{1} = \mathbb{1}$). Thus

$$\begin{aligned}
 P_n & \{ X_{t_1}^{(N)} = 1_1, X_{t_2}^{(N)} = 1_2 \sim X_{t_u}^{(N)} = 1_u \} \\
 & = P_n \{ \tilde{X}_{\lfloor Nt_1 \rfloor}^{(N)} = 1_1, \tilde{X}_{\lfloor Nt_2 \rfloor}^{(N)} = 1_2 \sim X_{\lfloor Nt_u \rfloor}^{(N)} = 1_u \} \\
 & = \left(P_n^{\lfloor Nt_1 \rfloor} \right)_{1,1_1} \left(P_n^{\lfloor Nt_2 \rfloor - \lfloor Nt_1 \rfloor} \right)_{1,1_2} \\
 & \sim \left(P_n^{\lfloor Nt_u \rfloor - \lfloor Nt_1 \rfloor} \right)_{1,1_u} \\
 & = \left(\left(I + \frac{Q}{N} \right)^{\lfloor Nt_1 \rfloor} \right)_{1,1_1} \left(\left(I + \frac{Q}{N} \right)^{\lfloor Nt_2 \rfloor - \lfloor Nt_1 \rfloor} \right)_{1,1_2} \\
 & \sim \left(I + \frac{Q}{N} \right)^{\lfloor Nt_u \rfloor - \lfloor Nt_1 \rfloor}
 \end{aligned}$$

$$\xrightarrow{n \rightarrow \infty} (e^{Qt_1})_{1,1}, (e^{Q(t_2-t_1)})_{1,1,2}$$

$$\sim (e^{Q(t_n-t_{n-1})})_{1,1,1,2}$$



Let's now look at $X^{(n)}$ in its own right,

Set $\tilde{\tau}_n = \inf\{u \geq 0: \tilde{X}_u^{(n)} \neq \tilde{X}_0^{(n)}\}$, and

$$\begin{aligned} \tau_n &= \inf\{t \geq 0: X_t^n \neq X_0\} = \inf\left\{\frac{k}{n}: X_{k/n}^n \neq X_0\right\} \\ &= \inf\left\{\frac{k}{n}: \tilde{X}_{k/n}^{(n)} \neq \tilde{X}_0^{(n)}\right\} = \frac{\tilde{\tau}_n}{n} \end{aligned}$$

We recall that $\tilde{\tau}_n$ & $\tilde{X}_{\tilde{\tau}_n}^{(n)}$ are independent, and

$\tilde{\tau}_n$ is geometric $(1-(P_n)_{11})$ and $\mathbb{P}_n\{\tilde{X}_{\tilde{\tau}_n}^{(n)} = j\} = \frac{(P_n)_{1j}}{1-(P_n)_{11}}$

Since $(P_n)_{11} = 1 + \beta/n$ and $(P_n)_{1j} = \beta_j/n$,

$$1-(P_n)_{11} = -\beta/n = \bar{\beta}/n$$

\tilde{T}_n is geometric $\bar{\delta}_n/n$ and $\mathbb{P}_i \{ \tilde{X}_{T_n}^{(n)} = j \} = \frac{\delta_n}{\bar{\delta}_n}$.

Since $T_n = \frac{\tilde{T}_n}{n}$, $T_n \rightarrow \text{exponential}(\bar{\delta}_0)$. Set

$$\Pi_{ij} = \begin{cases} \delta_{ij}/\bar{\delta}_i & \text{if } j \neq i, \bar{\delta}_i \neq 0 \\ 0 & \text{if } j = i, \bar{\delta}_i \neq 0 \\ 0 & \text{if } j \neq 1, \bar{\delta}_i = 0 \\ 1 & \text{if } j = 1, \bar{\delta}_i = 0 \end{cases} \left. \begin{array}{l} \\ \\ \\ \end{array} \right\} \begin{array}{l} \\ \\ \text{consistent;} \\ \text{if } \bar{\delta}_i = 0, \\ E[\text{waiting time}] \\ \approx \infty; \text{ process} \\ \text{stays at } i \end{array}$$

Jump Matrix

Lemma Let $\{\xi_1, \xi_2, \dots\}$ be iid exp(1).

Let $\{Y_n\}$ be Markov (\mathbb{Z}, Π) . Set

$$p_0 = 0$$

$$p_{n+1} = p_n + \frac{1}{\bar{\delta}_{Y_n}} \xi_{n+1}$$

Set

$$X_t \stackrel{\text{def}}{=} Y_u \quad \text{for } p_u \leq t < p_{u+1}.$$

If $\sup_n \bar{g}_n < \infty$, then $X^{(n)} \rightarrow X$.

PF Note that

$$\begin{aligned} \mathbb{P}\{p_{u+1} - p_u \geq t \mid Y_u = i\} &= \mathbb{P}\left\{\frac{1}{g} \sum_{u+1} \geq t\right\} \Big|_{g = \bar{g}_i} \\ &= \mathbb{P}\left\{\sum_{u+1} \geq t\bar{g}_i\right\} \Big|_{g = \bar{g}_i} = \int_{t\bar{g}_i}^{\infty} e^{-s} ds = e^{-t\bar{g}_i}; \end{aligned}$$

thus, conditional on $\{Y_u = i\}$, $T_{u+1} - T_u$ is $\text{exp}(\bar{g}_i)$.

We sort of know that $X^n \rightarrow X$, but let's be

more precise. Fix $n \geq \sup_n \bar{g}_n$. Define $p_0^{(n)} = 0$ and

$$p_{j+1}^{(n)} = \inf\{s \geq p_j^{(n)} : X_s^{(n)} \neq X_{p_j^{(n)}}^{(n)}\}$$

$$\mathbb{E} \left[\left(\prod_{j=1}^J \chi_{\left\{ X_{\rho_j^{(n)}}^{(n)} = 1_j \right\}} \exp \left[\underbrace{\lambda \Theta_j (\rho_j^{(n)} - \rho_{j-1}^{(n)})}_{\text{jump times}} \right] \right) \chi_{\left\{ X_0^{(n)} = 1_0 \right\}} \right]$$

$$= \mathbb{E} \left[\mathbb{E} \left[\chi_{\left\{ X_{\rho_J^{(n)}}^{(n)} = 1_J \right\}} \exp \left[\lambda \Theta_J (\rho_J^{(n)} - \rho_{J-1}^{(n)}) \right] \middle| \mathcal{F}_{\rho_{J-1}^{(n)}} \right] \right]$$

$$\times \mathbb{E} \left[\prod_{j=0}^{J-1} \chi_{\left\{ X_{\rho_j^{(n)}}^{(n)} = 1_j \right\}} \exp \left[\lambda \Theta_j (\rho_j^{(n)} - \rho_{j-1}^{(n)}) \right] \chi_{\left\{ X_0^{(n)} = 1_0 \right\}} \right]$$

$$= \mathbb{E} \left[\prod_{j=0}^{J-1} \chi_{\left\{ X_{\rho_j^{(n)}}^{(n)} = 1_j \right\}} \frac{\exp \left[\lambda \Theta_j / \mu \right] \bar{\delta} X_{\rho_j^{(n)}}^{(n)}}{1 - \left((1 - \bar{\delta} X_{\rho_j^{(n)}}^{(n)}) e^{\lambda \Theta_j / \mu} \right)} \right]$$

$$\times \mathbb{E} \left[\prod_{j=0}^{J-1} \chi_{\left\{ X_{\rho_j^{(n)}}^{(n)} = 1_j \right\}} \exp \left[\lambda \Theta_j (\rho_j^{(n)} - \rho_{j-1}^{(n)}) \right] \chi_{\left\{ X_0^{(n)} = 1_0 \right\}} \right]$$

$$= \prod_{\lambda_0, \lambda_1} \prod_{\lambda_1, \lambda_2} \dots \prod_{\lambda_{J-1}, \lambda_J} \prod_{j=0}^{J-1} \frac{\exp(\lambda \Theta_j / \mu) \bar{\delta}_j}{1 - (1 - \bar{\delta}_j / \mu) e^{\lambda \Theta_j / \mu}}$$

$$\xrightarrow{\mu \rightarrow \infty} \prod_{\lambda_0, \lambda_1} \dots \prod_{\lambda_{J-1}, \lambda_J} \prod_{j=0}^{J-1} \frac{\bar{\delta}_j}{\bar{\delta}_j - \lambda \Theta_j}$$

$$= \mathbb{E} \left[\prod_{j=1}^J \left(\chi_{\{X_{j-1} = \lambda_j\}} \exp(\lambda \Theta_j (p_j - p_{j-1})) \right) \right]$$

$$\chi_{\{X_0 = \lambda_0\}} \bullet$$

Note: This construction does not require that $|S| < \infty$ or that $\sup_i \bar{\delta}_i < \infty$. Note, however, that we have not proved that X , thus constructed, satisfies the infinitesimal statement of \star . In general, our approximation of

characterization theorems work primarily when $|S| < \infty$.

When $|S| < \infty$, explosion can occur. If $\sup_n \bar{g}_n = \infty$, then we can have that

$$\zeta \stackrel{\text{def}}{=} \lim_{n \rightarrow \infty} \tau_n < \infty \quad \leftarrow \text{Explosion time}$$

which means that X hops more and more frequently as time approaches ζ . Thus $\lim_{t \rightarrow \zeta} X_t$ may fail to exist. Since our theory of Markov processes requires that the Markov process be defined on all time t not just a random subset, we can attach a new state \otimes to S & define

$$\hat{X}_t = \begin{cases} X_t & \text{if } t < \zeta \\ \otimes & \text{if } t \geq \zeta \end{cases}$$

This is then a Markov process on $S \cup \{\otimes\}$

Now consider linear equations

$$u(u) = E_1 \left[\sum_{0 \leq j < \tilde{H}_n^*} \alpha^j c(\tilde{X}_j^{(u)}) + \alpha^{\tilde{H}_n^*} f(\tilde{X}_{\tilde{H}_n^*}^{(u)}) \right]$$

$\tilde{H}_n^* = \inf \{j \geq 0: \tilde{X}_j^{(u)} \in A\}$

$$= E_1 \left[\sum_{0 \leq j < H_n^*} \alpha^j c(X_{j/n}^{(u)}) + \alpha^{H_n^*} f(X_{\frac{H_n^*}{n}}^{(u)}) \right]$$

$H_n^* = \inf \{t \geq 0: X_t^{(u)} \in A\}$
 $= \inf \{k \frac{1}{n} \geq 0: X_{\frac{k}{n}}^{(u)} \in A\}$
 $= \frac{1}{n} \inf \{k \geq 0: \tilde{X}_k^{(u)} \in A\}$
 $= \frac{\tilde{H}_n^*}{n}$

satisfies

$$u = \alpha P_n u + c \quad \text{on } S \setminus A$$

$$u = f \quad \text{on } A.$$

Let's rescale; set $\alpha = e^{\beta/h}$; on $S \setminus A$

$$u_n(i) = \mathbb{E}_i \left[\sum_{0 \leq j < n^A} e^{\beta j/h} c(X_{j/h}^{(u)}) \frac{1}{h} + e^{\beta n^A/h} f(X_{\frac{n^A}{h}}^{(u)}) \right]$$

$$\approx \mathbb{E}_i \left[\int_0^{n^A} e^{\beta s} c(X_s) ds + e^{\beta n^A/h} f(X_{n^A/h}) \right]$$

We also have that on $S \setminus A$, $= u(i)$

$$u_n = e^{\beta/h} (I + Q/h) u_n + g/h$$

$$u_n \approx (1 + \beta/h) (I + Q/h) u_n + g/h$$

$$u_n \approx u_n + \frac{1}{h} \{ Q + \beta \} u_n + g/h$$

We thus expect that

$$Q u + \beta u + c = 0 \quad \text{on } S \setminus A$$

$$u = f \quad \text{on } A$$

Other calculations.

① Jump Processes are Strong Markov

② Communicating classes: $i \rightarrow j$ iff

$$f_{ii}^{(n)} f_{ij}^{(n)} - f_{ij}^{(n)} f_{ii}^{(n)} > 0 \text{ some } n, \sim \text{true}$$

(look at jumps)

③ Recurrence, transience, etc.

$$T = \inf \{ t > \hat{T} : X_t = X_0 \}$$

$$\hat{T} = \inf \{ t > 0 : X_t \neq X_0 \}$$

Stationary Distributions

A distribution π is stationary if $P\{X_t = i\} = \pi_i$ when

X is Markov(π, Q)

ie initial distribution π infinitesimal generator Q

$$\Leftrightarrow \pi e^{Qt} = \pi \quad \text{all } t \geq 0$$

$$\Leftrightarrow \pi Q = 0 \quad (\text{by differentiation})$$

Definition Distribution π is stationary if $\pi Q = 0$

Claim π is stationary iff $\mu_i = \frac{\pi_i g_i}{\sum_i \pi_i g_i}$ is

stationary for jump matrix Π

PA Set $\bar{\mu}_x = \sum_x \bar{\delta}_x$

$$\sum_n \bar{\mu}_n \bar{\pi}_{xy} = \sum_{x \neq y} \sum_x \bar{\delta}_x \frac{\delta_y}{\bar{\delta}_x}$$

0 if $x=y$

$$= \sum_{x \neq y} \sum_x \bar{\delta}_x \delta_y = (\sum_x \bar{\delta}_x)_y - \sum_x \bar{\delta}_x \delta_{xx}$$

$$= \sum_x \bar{\delta}_x = \bar{\mu}_y \bullet$$