

Introduction

Schedule:

- (I) Basic properties of continuous-time Markov Chains
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- (IV) Renewal theory
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1 Some basic aspects of continuous-time Markov Chains

Definition. A sequence of random variables is called a *stochastic process* or *process*. The process $X = (X_n)_{n \geq 1}$ is called a discrete-time Markov Chain with state space I if for all $x_0, x_1, \dots, x_n \in I$

$$\mathbb{P}(X_n = x_n | X_{n-1} = x_{n-1}, \dots, X_0 = x_0) = \mathbb{P}(X_n = x_n | X_{n-1} = x_{n-1}).$$

If $\mathbb{P}(X_{n+1} = y | X_n = x)$ is independent of n , the chain is called *time-homogeneous*. We then write $P = (P_{x,y})_{x,y \in I}$ for the *transition matrix* where $P_{x,y} = \mathbb{P}(X_1 = y | X_0 = x)$. The data associated to every time-homogeneous Markov Chain is the transition matrix P and the initial distribution μ , i.e $\mathbb{P}(X_0 = x_0) = \mu(x_0)$.

From now on:

- I denotes a countable (or finite) state space.
- $(\Omega, \mathcal{F}, \mathbb{P})$ is the probability space on which all the relevant random variables are defined.

Definition. $X = (X(t) : t \geq 0)$ is a (right-continuous) continuous-time random process with values in I if

- (a) for all $t \geq 0$, $X(t) = X_t$ is a random variable such that $X(t) : \Omega \rightarrow I$;
- (b) for all $\omega \in \Omega$, $t \mapsto X_t(\omega)$ is right-continuous (right-continuous sample path).
In our case this means for all $\omega \in \Omega$, for all $t \geq 0$, there exists $\varepsilon > 0$ (depending on ω, t) such that

$$X_t(\omega) = X_s(\omega) \quad \forall s \in [t, t + \varepsilon].$$

Fact. A right-continuous random process is defined by its finite-dimensional distributions

$$\mathbb{P}(X_{t_0}=i, X_{t_1}=i_1, \dots, X_{t_n}=i_{t_n}), \quad n \geq 0, \quad t_k \geq 0, \quad i_k \in I.$$

For every $\omega \in \Omega$, the path $t \mapsto X_t(\omega)$ of a right-continuous process stays constant for a while. So there are 3 possibilities:

- (i) The path makes infinitely many jumps overall but only finitely many in a given interval $[0, t]$.
- (ii) The path makes finitely many jumps & then gets absorbed in some state.
- (iii) The path makes infinitely jumps in a finite time interval. After the ‘explosion time’ ζ , the process starts up again.

Write $J_0 = 0, J_1, J_2, \dots$ for the jump times and S_1, S_2, \dots for the holding times, defined by

$$J_0 = 0, \quad J_{n+1} = \inf\{t \geq J_n : X_t \neq X_{J_n}\},$$

$$S_n = \begin{cases} J_n - J_{n-1} & J_{n-1} < \infty \\ \infty & \text{otherwise} \end{cases}.$$

By right-continuity, $S_n > 0$ for all n . If $J_{n+1} = \infty$ for some n , we define $X_\infty = X_{J_n}$ as the final value, otherwise X_∞ is not defined. The explosion time ζ is defined by

$$\zeta = \sup(J_n) = \sum_{n=1}^{\infty} S_n.$$

We are not going to consider what happens to a chain after explosion. We thus set $X_t = \infty$ for all $t \geq \zeta$ (adjoining a new state ‘ ∞ ’). We call such a chain *minimal*.

Definition. We define the *jump chain* Y_n of $(X_t)_{t \geq 0}$ by setting $Y_n = X_{J_n}$ for all n .

Definition. A right-continuous random process $X = (X_t)_{t \geq 0}$ has the Markov property (and is called a continuous-time markov chain) if for all $i_1, i_2, \dots, i_n \in I$ and $0 \leq t_1 < t_2 < \dots < t_n$,

$$\mathbb{P}(X_{t_n} = i_n | X_{t_{n-1}} = i_{n-1}, \dots, X_{t_0} = i_0) = \mathbb{P}(X_{t_n} = i_n | X_{t_0} = i_0).$$

Remark. For all $h > 0$, $Y_n = X(hn)$ defines a discrete-time Markov Chain.

Definition. The transition probabilities are $P_{ij}(s, t) = \mathbb{P}(X_t = j | X_s = i)$, $s \leq t$, $i, j \in I$. It is called *time-homogeneous* if it depends on $t - s$ only, i.e

$$P_{ij}(s, t) = P_{i,j}(0, t - s).$$

In this case we just write $P_{ij}(t - s)$. As in the case of discrete time, a (time-homogeneous) Markov process is characterised by

1. Its initial distribution $\lambda_i = \mathbb{P}(X_0 = i)$, $i \in I$;
2. Its *family of transition matrices* $(P(t))_{t \geq 0} = (P_{ij}(t))_{t \geq 0}$.

The family $(P(t))_{t \geq 0}$ is called the *transition subgroup* of the MC.

A (time-homogeneous) Markov process is characterised by

- its initial distribution;
- its transition subgroup $(P(t))_{t \geq 0}$

$$(P(t))_{t \geq 0} = (P(t))_{\substack{i, j \in I \\ t \geq 0}} = (\mathbb{P}(X_t = j | X_0 = i))_{\substack{i, j \in I \\ t \geq 0}}$$

It is easy to see that

- $P(0)$ is the identity
- $P(t)$ is a stochastic matrix for all t (i.e rows sum to 1)
- $P(t+s) = P(t)P(s) \forall s, t$ (Chapman-Kolmogorov equation)

$$\begin{aligned} P_{xz}(t+s) &= \mathbb{P}(X_{t+s} = z | X_0 = x) \\ &= \sum_{y \in I} \mathbb{P}(X_{t+s} = z | X_0 = x, X_t = y) \mathbb{P}(X_t = y | X_0 = x) \\ &= \sum_{y \in I} \mathbb{P}(X_s = z | X_0 = y) \mathbb{P}(X_t = y | X_0 = x) \\ &= \sum_{y \in I} P_{yz}(s) P_{xy}(t) = P_{x \cdot}(t) P_{\cdot z}(s) \end{aligned}$$

Holding times

Let X be a (right-continuous continuous-time time-homogeneous) Markov Chain on a countable state-space I .

Suppose X starts from $x \in I$. Question: how long does X stay in the state x ?

Definition. We call S_x the *holding time* at state x ($S_x > 0$ by right-continuity).

Let $s, t \geq 0$. Then

$$\begin{aligned} \mathbb{P}(S_x > t+s | S_x > s) &= \mathbb{P}(X_u = x \forall u \in [0, t+s] | X_u = x \forall u \in [0, s]) \\ &= \mathbb{P}(X_u = x \forall u \in [s, t+s] | X_u = x \forall u \in [0, s]) \\ &= \mathbb{P}(X_u = x \forall u \in [s, t+s] | X_s = x) \\ &= \mathbb{P}(X_u = x \forall u \in [0, t] | X_0 = x) \\ &= \mathbb{P}(S_x > t). \end{aligned}$$

Thus S_x has the memoryless property.

By the next theorem, we will get that S_x has the exponential distribution, say with parameter q_x .

Theorem 1.1 (Memoryless property). *Let S be a positive random variable. Then S has the memoryless property, i.e. $\mathbb{P}(S > t + s | S > s) = \mathbb{P}(S > t)$ for all $s, t \geq 0$ if and only if S has the exponential distribution.*

Proof. It is easy to see the exponential distribution is memoryless. So we prove the other direction. Set $F(t) = \mathbb{P}(S > t)$. Then $F(s + t) = F(s)F(t)$ for all $s, t \geq 0$.

Since S is a positive random variable, there exists $n \in \mathbb{N}$ large such that $F(1/n) = \mathbb{P}(S > 1/n) > 0$. Then $F(1) = F(1/n)^n > 0$. So we can set $F(1) = e^{-\lambda}$ for some $\lambda \geq 0$.

For $k \in \mathbb{N}$, $F(k) = F(1)^k = e^{-\lambda k}$. For p/q rational, $F(p/q) = F(1/q)^p = (F(1/q)^q)^{p/q} = F(1)^{p/q} = e^{-\lambda \frac{p}{q}}$.

For any $t \geq 0$, for any $r, s \in \mathbb{Q}$ such that $r \leq t \leq s$, since F is decreasing

$$e^{-\lambda s} = F(s) \leq F(t) \leq F(r) = e^{-\lambda r}.$$

So taking sequences of rationals approaching t , we have $F(t) = e^{-\lambda t}$. \square

Poisson Process'

We are now going to look at the simplest (and most important) example of continuous time Markov Chains - the Poisson process.

Definition. Suppose S_1, S_2, \dots are iid random variables with $S_1 \sim \text{Exp}(\lambda)$. Define the *jump times* $J_0 = 0, J_1 = S_1, J_n = S_1 + \dots + S_n$ for all n , and set $X_t = i$ if $J_i \leq t < J_{i+1}$. Then $I = \{0, 1, 2, \dots\}$ and note that X is right-continuous and increasing. X is called a *Poisson process* of parameter/intensity λ . We sometimes refer to the jump times $(J_i)_{i \geq 1}$ as the *points* of the Poisson process, then X = number of points in $[0, t]$.

Theorem 1.2 (Markov property). *Let $(X_t)_{t \geq 0}$ be a Poisson process of intensity λ . Then for all $s \geq 0$, the process $(X_{s+t} - X_s)_{t \geq 0}$ is also a Poisson process of intensity λ , and is independent of $(X_t)_{0 \leq t \leq s}$.*

Proof. Set $Y_t = X_{t+s} - X_s$ for all $t \geq 0$. Let $i \in \{0, 1, 2, \dots\}$ and condition on $\{X_s = i\}$. Then the jump times for the process Y are $J_{n+1} - s, J_{n+2} - s, \dots$ and the holding times are

$$\begin{aligned} T_1 &= J_{n+1} - s = S_{i+1} - (s - J_i) \\ T_2 &= S_{i+2} \\ T_3 &= S_{i+3} \\ &\vdots \end{aligned}$$

Since $\{X_s = i\} = \{J_i \leq s\} \cap \{s < J_{i+1}\} = \{J_i \leq s\} \cap \{S_{i+1} > s - J_i\}$, conditional on $\{X_s = i\}$, by the memoryless property of the exponential distribution (and

independence of S_{i+1} and J_i) we see that $T_1 \sim \text{Exp}(\lambda)$. Moreover the times J_j , $j \geq 2$ are independent of S_k , $k \leq i$ and hence independent of $(X_r)_{r \leq s}$, and they have iid $\text{Exp}(\lambda)$ distribution. Thus $((X_{s+t} - X_s))_{t \geq 0}$ is a Poisson process of parameter λ and is independent of $(X_t)_{0 \leq t \leq s}$. \square

Similar to this, one can show the Strong Markov property for a Poisson process of parameter λ . Recall a random variable $T \in [0, \infty]$ is called a *stopping time* if for all t , the event $\{T \leq t\}$ depends only on $(X_s)_{s \leq t}$.

Theorem 1.3 (Strong Markov property). *Let $(X_t)_{t \geq 0}$ be a Poisson process of parameter λ and T a stopping time. Then conditional on $T < \infty$, the process $(X_{T+t} - X_T)_{t \geq 0}$ is a Poisson process of parameter λ and independent of $(X_s)_{s \leq T}$.*

Theorem 1.4. Let $(X_t)_{t \geq 0}$ be an increasing right-continuous process taking values in $\{0, 1, 2, \dots\}$ with $X_0 = 0$. Let $\lambda > 0$. Then the following are equivalent

- (a) The holding times S_1, S_2, \dots are iid $\text{Exp}(\lambda)$ and the jump chain is given by $Y_n = n$ (i.e X is a poisson process of intensity λ)
- (b) (Infinitesimal def) X has independent increments and as $h \downarrow 0$ uniformly in t we have

$$\mathbb{P}(X_{t+h} - X_t = 1) = \lambda h + o(h),$$

$$\mathbb{P}(X_{t+h} - X_t = 0) = 1 - \lambda h + o(h).$$

- (c) X has independent and stationary increments and for all $t \geq 0$, $X_t \sim \text{Poi}(\lambda t)$.

Proof. First we show (a) \Rightarrow (b). If (a) holds, then by the Markov property, the increments are independent and stationary $((X_{t+s} - X_s)_{t \geq 0} \stackrel{d}{=} (X_t - X_0)_{t \geq 0})$. Using stationarity we have (uniformly in t) as $h \rightarrow 0$,

$$\mathbb{P}(X_{t+h} - X_t = 0) = \mathbb{P}(X_h = 0) = \mathbb{P}(S_1 > h) = e^{-\lambda h} = 1 - \lambda h + o(h),$$

$$\mathbb{P}(X_{t+h} - X_t \geq 1) = \mathbb{P}(X_h \geq 1) = \mathbb{P}(S_1 \leq h) = 1 - e^{-\lambda h} = \lambda h + o(h),$$

$$\begin{aligned} \mathbb{P}(X_{t+h} - X_t \geq 2) &= \mathbb{P}(X_h \geq 2) = \mathbb{P}(S_1 + S_2 \leq h) \\ &\leq \mathbb{P}(S_1 \leq h, S_2 \leq h) \\ &= \mathbb{P}(S_1 \leq h)^2 \\ &= (\lambda h + o(h))^2 = o(h). \end{aligned}$$

Now we show (b) \Rightarrow (c). If X satisfies (b), then $(X_{t+s} - X_s)_{t \geq 0}$ also satisfies (b). So X has independent and stationary increments. Now set $p_j(t) = \mathbb{P}(X_t = j)$. Then since increments are independent and X is increasing,

$$\begin{aligned} p_j(t+h) &= \mathbb{P}(X_{t+h} = j) = \sum_{i=0}^j \mathbb{P}(X_t = j-i) \mathbb{P}(X_{t+h} - X_t = i) \\ &= p_j(t)(1 - \lambda h + o(h)) + p_{j-1}(t)(\lambda h + o(h)) + o(h). \end{aligned}$$

Thus, $\frac{p_j(t+h) - p_j(t)}{h} = -\lambda p_j(t) + \lambda p_{j-1}(t) + o(1)$. Setting $s = t + h$, we get

$$\frac{p_j(s) - p_j(s-h)}{h} = -\lambda p_j(s-h) + \lambda p_{j-1}(s-h) + o(1).$$

In particular, $p_j(t)$ is continuous and differentiable with

$$p'_j(t) = -\lambda p_j(t) + \lambda p_{j-1}(t).$$

Differentiating

$$(e^{\lambda t} p(t))' = \lambda e^{\lambda t} p_j(t) + e^{\lambda t} p'_j(t) = \lambda e^{\lambda t} p_{j-1}(t).$$

For $j = 0$ we have $p_0(t + h) = p_0(t)(1 - \lambda h + o(h))$, i.e. $p'_0(t) = -\lambda p_0(t)$ so $p_0(t) = e^{-\lambda t}$. Thus

$$p'_1(t) = -\lambda p_1(t) + \lambda e^{-\lambda t}, \text{ i.e. } p_1(t) = \lambda t e^{-\lambda t}.$$

And by induction

$$p_k(t) = e^{-\lambda t} \frac{(\lambda t)^k}{k!},$$

i.e. $X_t \sim \text{Poi}(\lambda t)$.

Finally we show (c) \Rightarrow (a). We know X has independent stationary increments, We have for $t_1 \leq \dots \leq t_k$, $n_1 \leq \dots \leq n_k$,

$$\begin{aligned} & \mathbb{P}(X_{t_1} = n_1, \dots, X_{t_k} = n_k) \\ &= \mathbb{P}(X_{t_1} = n_1) \underbrace{\mathbb{P}(X_{t_2} - X_{t_1} = n_2 - n_1)}_{\sim \text{Poi}(\lambda(t_2 - t_1))} \dots \underbrace{\mathbb{P}(X_{t_k} - X_{t_{k-1}} = n_k - n_{k-1})}_{\sim \text{Poi}(\lambda(t_k - t_{k-1}))}. \end{aligned}$$

So (c) determines the finite-dimensional distributions (f.d.d) of a right-continuous process X , hence (c) determines X . So (c) \Rightarrow (a).

Question: can we show (a) \Rightarrow (c) directly? Indeed note

$$\begin{aligned} \mathbb{P}(X_t = n) &= \mathbb{P}(S_1 + \dots + S_n \leq t < S_1 + \dots + S_{n+1}) \\ &= \mathbb{P}(S_1 + \dots + S_n \leq t) - \mathbb{P}(S_1 + \dots + S_{n+1} \leq t) \\ &= \int_0^t \lambda e^{-\lambda x} \frac{(\lambda x)^{n-1}}{(n-1)!} dx - \int_0^t \lambda e^{-\lambda x} \frac{(\lambda x)^n}{n!} dx \\ &= e^{-\lambda t} \frac{(\lambda t)^n}{n!} \text{ (integration by parts).} \end{aligned}$$

□

Theorem 1.5 (Superposition). *Let X and Y be two independent Poisson processes with parameters λ and μ respectively. Then $(Z_t)_{t \geq 0} = (X_t + Y_t)_{t \geq 0}$ is a Poisson process with parameter $\lambda + \mu$.*

Proof. We use (c) from the previous theorem. So Z has stationary independent increments. Also $Z_t \sim \text{Poi}(\lambda t + \mu t)$. □

Theorem 1.6 (Thinning). *Let X be a Poisson process with parameter λ . Let $(Z_i)_{i \geq 1}$ be a sequence of iid Bernoulli(p) random variables. Let Y be a Poisson process with values in $\{0, \dots\}$ which jumps at time t if and only if X_t jumps at time t and $Z_{X_t} = 1$.*

In other words, we keep every point of X with probability p independently. Then Y is another Poisson process, with parameter λp and $X - Y$ is an independent Poisson process with parameter $\lambda(1 - p)$.

Proof. We shall use the infinitesimal definition. The independence of increments for Y is clear. Since $\mathbb{P}(X_{t+h} - X_t \geq 2) = o(h)$, we have

$$\mathbb{P}(Y_{t+h} - Y_t = 1) = p\mathbb{P}(X_{t+h} - X_t = 1) + o(h) = p\lambda h + o(h),$$

$$\begin{aligned}\mathbb{P}(Y_{t+h} - Y_t = 0) &= \mathbb{P}(X_{t+h} - X_t = 0) + (1-p)\mathbb{P}(X_{t+h} - X_t = 1) + o(h) \\ &= 1 - \lambda h + (1-p)(\lambda h + o(h)) + o(h) \\ &= 1 - \lambda p h + o(h).\end{aligned}$$

Hence Y is Poisson of parameter λp . Clearly $X - Y$ is a thinning of X with Bernoulli parameter $1 - p$, so $X - Y$ is Poisson of parameter $\lambda(1 - p)$.

Now we show Y and $X - Y$ are independent. It is enough to show that the f.d.d of Y and $X - Y$ are independent, i.e if $0 \leq t_1 \leq t_2 \leq \dots \leq t_k$, $n_1 \leq \dots \leq n_k$ and $m_1 \leq \dots \leq m_k$, then we want to prove

$$\begin{aligned}\mathbb{P}(Y_{t_1} = n_1, \dots, Y_{t_k} = n_k, X_{t_1} - Y_{t_1} = m_1, \dots, X_{t_k} - Y_{t_k} = m_k) \\ = \mathbb{P}(X_{t_1} = n_1, \dots, Y_{t_k} = n_k) \mathbb{P}(X_{t_1} - Y_{t_1} = m_1, \dots, X_{t_k} - Y_{t_k} = m_k).\end{aligned}$$

We will only show this for fixed t ($k = 1$) the general case follows similarly using independence of increments. We have

$$\begin{aligned}\mathbb{P}(Y_t = n, X_t - Y_t = m) &= \mathbb{P}(X_t = m + n, Y_t = n) \\ &= \mathbb{P}(X_t = m + n) \mathbb{P}(Y_t = n | X_t = m + n) \\ &= e^{-\lambda t} \frac{(\lambda t)^{m+n}}{(m+n)!} \binom{m+n}{n} p^n (1-p)^m \\ &= e^{-\lambda t p} \frac{(\lambda t p)^n}{n!} e^{-\lambda t(1-p)} \frac{(\lambda t(1-p))^m}{m!} \\ &= \mathbb{P}(X_t = n) \mathbb{P}(X_t - Y_t = m),\end{aligned}$$

as required. □

Theorem 1.7. *Let X be a Poisson Process. Conditional on the event $(X_t = n)$, the jump times J_1, J_2, \dots, J_n are distributed as the order statistics of n iid $U[0, t]$ random variables. That is, they have joint density*

$$f(t_1, \dots, t_n) = \frac{n!}{t^n} \mathbb{1}(0 \leq t_1 \leq \dots \leq t_n \leq t).$$

Proof. Since S_1, S_2, \dots are iid $\text{Exp}(\lambda)$, the joint density of (S_1, \dots, S_{n+1}) is

$$\lambda^{n+1} e^{-\lambda(S_1 + \dots + S_{n+1})} \mathbb{1}(S_i \geq 0 \text{ for all } i).$$

Then the jump times $J_1 = S_1, J_2 = S_1 + S_2, \dots, J_{n+1} = S_1 + \dots + S_{n+1}$ have joint density

$$g(t_1, \dots, t_{n+1}) = \lambda^{n+1} e^{-\lambda t_{n+1}} \mathbb{1}(0 \leq t_1 \leq t_2 \leq \dots \leq t_{n+1}).$$

(Noting the Jacobian of the transformation is 1.) Now take $A \subseteq \mathbb{R}^n$ so

$$\mathbb{P}((J_1, \dots, J_n) \in A | X_t = n) = \frac{\mathbb{P}((J_1, \dots, J_n) \in A | X_t = n)}{\mathbb{P}(X_t = n)}.$$

Note

$$\begin{aligned} & \mathbb{P}((J_1, \dots, J_n) \in A, X_t = n) \\ &= \mathbb{P}((J_1, \dots, J_n) \in A, J_n \leq t < J_{n+1}) \\ &= \int_{(t_1, \dots, t_{n+1}) \in A \times \mathbb{R}} g(t_1, \dots, t_n) \mathbb{1}(t_{n+1} \geq t \geq t_n) dt_1 \dots dt_{n+1} \\ &= \int_A \int_t^\infty \lambda^{n+1} e^{-\lambda t_{n+1}} \mathbb{1}(0 \leq t_1 \leq \dots \leq t_n \leq t) dt_{n+1} dt_1 \dots dt_n \\ &= \int_A \lambda^n e^{-\lambda t} \mathbb{1}(0 \leq t_1 \leq \dots \leq t_n \leq t) dt_1 \dots dt_n. \end{aligned}$$

Then we get

$$\mathbb{P}((J_1, \dots, J_n) \in A | X_t = n) = \int_A \frac{n!}{t^n} \mathbb{1}(0 \leq t_1 \leq \dots \leq t_n \leq t) dt_1 \dots dt_n.$$

As required. \square

Now we look at a generalisation of a Poisson Process: called a Birth Process. For a Poisson Process, the rate of going from i to $i+1$ is λ . For a Birth Process, this is q_i (can depend on i). More precisely:

Definition (Birth Process). For each i , let $S_i = \text{Exp}(q_i)$ with S_1, S_2, \dots independent. Set $J_i = S_1 + \dots + S_i$ and $X_t = i$ if $J_i \leq t < J_{i+1}$. Then X is called a *Birth Process*.

We have some special cases:

1. Simple birth process: when $q_i = \lambda i$ for $i = 1, 2, \dots$;
2. Poisson Process $q_i = \lambda$ for all i .

Motivation for Simple Birth Process (SBP): at time 0 there is only one ‘individual’ i.e $X_0 = 1$. Each individual has an exponential clock of parameter λ independently. Then if there are i individuals, the first clock rings after $\text{Exp}(\lambda i)$ time, and we jump from i to $i + 1$ individuals. Indeed, by the memoryless property, the process begins afresh after each jump.

Proposition 1.8. *Let $(T_k)_{k \geq 1}$ be a sequence of independent random variables with $T_K \sim \text{Exp}(q_k)$ and $\sum_k q_k < \infty$. Let $T = \inf_k T_k$. Then*

- (a) $T \sim \text{Exp}(\sum_k q_k)$
- (b) *The infimum is attained at a point T_K almost surely, and*

$$\mathbb{P}(K = n) = \frac{q_n}{\sum_k q_k}.$$

- (c) T and K are independent.

Proof. See example sheet. □

The main difference between a Poisson Process and a Birth Process is that there is the possibility of explosion in the Birth Process. Recall explosion occurs when $\zeta := \sum_n S_n < \infty$.

Proposition 1.9. *Let X be a Birth Process with rates q_i and $X_0 = 1$. Then*

1. *If $\sum_{i=1}^{\infty} \frac{1}{q_i} < \infty$, then X is explosive, i.e $\mathbb{P}(\zeta < \infty) = 1$;*
2. *If $\sum_{i=1}^{\infty} \frac{1}{q_i} = \infty$, then X is non-explosive, i.e $\mathbb{P}(\zeta = \infty) = 1$.*

Remark. This shows the SBP (as well as the PP) is non-explosive.

Proof.

1. If $\sum_n \frac{1}{q_n} < \infty$, then

$$\mathbb{E}[\zeta] = \mathbb{E} \left[\sum_n S_n \right] = \sum_n \mathbb{E} S_n = \sum_n \frac{1}{q_n} < \infty.$$

Where we have swapped summation and expectation by the MCT (monotone convergence theorem). Thus $\zeta = \sum_n S_n < \infty$ almost surely.

2. If $\sum_n \frac{1}{q_n} = \infty$, then $\prod_n \left(1 + \frac{1}{q_n}\right) \geq 1 + \sum_n \frac{1}{q_n} = \infty$. Then

$$\begin{aligned}
 \mathbb{E}[e^{-\zeta}] &= \mathbb{E}\left[e^{-\sum_{n=1}^{\infty} S_n}\right] \\
 &= \lim_{n \rightarrow \infty} \mathbb{E}\left[e^{-\sum_{i=1}^n S_i}\right] && \text{(MCT)} \\
 &= \lim_{n \rightarrow \infty} \prod_{i=1}^n \mathbb{E}[e^{-S_i}] && \text{(independence)} \\
 &\leq \lim_{n \rightarrow \infty} \prod_{i=1}^n \frac{1}{1 + 1/q_i} = 0.
 \end{aligned}$$

Since $e^{-\zeta} \geq 0$, since $\mathbb{E}(e^{-\zeta}) = 0$ we have $e^{-\zeta} = 0$ almsot surely, i.e $\mathbb{P}(\zeta = \infty) = 1$.

□

Theorem 1.10 (Markov Property). *Let X be a BP with parameters (q_i) . Conditional on $X_s = i$, the process $(X_{s+t})_{t \geq 0}$ is a birth process with rates $(q_j)_{j \geq i}$ starting from i , and independent of $(X_r)_{r \leq s}$.*

Proof. As in the Poisson Process case. \square

Theorem 1.11. *Let X be an increasing right-continuous process with values in $\{1, 2, \dots\} \cup \{\infty\}$. Let $0 \leq q_j < \infty$ for all $j \geq 0$. Then the following are equivalent:*

1. (jump chain/holding time definition) conditional on $X_s = i$, the holding times S_1, S_2, \dots are independent exponentials with rates q_i, q_{i+1}, \dots respectively and the jump chain is given $Y_n = i + n$ for all n .
2. (infinitesimal definition) for all $t, h \geq 0$, conditional on $X_t = i$, the process $(X_{t+h})_{h \geq 0}$ is independent of $(X_s)_{s \leq t}$ and as $h \rightarrow 0$, uniformly in t we have

$$\mathbb{P}(X_{t+h} = i | X_t = i) = 1 - q_i h + o(h),$$

$$\mathbb{P}(X_{t+h} = i + 1 | X_t = i) = q_i h + o(h).$$

3. (transition probability definition) for all $n = 0, 1, 2, \dots$ and all times $0 \leq t_0 \leq t_1 \leq \dots \leq t_{n+1}$, and all states i_0, i_1, \dots, i_{n+1} ,

$$\mathbb{P}(X_{t_{n+1}} = i_{n+1} | X_0 = i_0, \dots, X_{t_n} = i_n) = p_{i_n, i_{n+1}}(t_{n+1} - t_n),$$

where $(p_{ij}(t) : i, j = 0, 1, 2, \dots)$ is the unique solution to the equation (called Kolmogorov's forward equation)

$$p'_{ij}(t) = q_{j-1} p_{i, j-1}(t) - q_j p_{i, j}(t). \quad (*)$$

(as in the Poisson Process, $p_{ij}(t+h) = p_{i, j-1}(t) q_j h + p_{i, j}(t) (1 - q_j h) + o(h)$.)

Existence and uniqueness of a solution in (3) follow since for $i = j$ $p'_{i, i}(t) = -q_i p_{i, i}(t)$ and $p_{i, i}(0) = 1$, so $p_{i, i}(t) = e^{-q_i t}$. Then by induction, if the unique solution for $p_{i, j}(t)$ exists, then plug into (*) to see there exists a unique solution for $p_{i, j+1}(t)$.

Also note that we can write the equation in matrix form:

$$P'(t) = P(t)Q, \text{ where } Q = \begin{pmatrix} -q_1 & q_1 & 0 & \dots \\ 0 & -q_2 & q_2 & \dots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix}.$$

Q-matrix and construction of Markov Processes

Definition. $Q = (q_{ij})_{i, j \in I}$ is called a Q -matrix if

- (a) $-\infty < q_{ii} \leq 0$ for all $i \in I$;

(b) $0 \leq q_{ij} < \infty$ for all $i, j \in I$ with $i \neq j$;

(c) $\sum_{j \in I} q_{ij} = 0$ for all $i \in I$.

Write $q_i = -q_{ii} = \sum_{j \notin I} q_{ij}$ for all $i \in I$.

Given a Q -matrix Q , we define a jump matrix P as follows. For $x \neq y$ with $q_x \neq 0$, set $p_{xy} = \frac{q_{xy}}{q_x}$ and $p_{xx} = 0$. If $q_x = 0$, set $p_{xy} = \mathbb{1}(x = y)$.

Example.

$$Q = \begin{pmatrix} -1 & 1 & 0 \\ 1 & -2 & 1 \\ 2 & 1 & -3 \end{pmatrix} \implies P = \begin{pmatrix} 0 & 1 & 0 \\ 1/2 & 0 & 1/2 \\ 2/3 & 1/3 & 0 \end{pmatrix}.$$

Definition. Let Q be a Q -matrix and λ a probability measure on the state space I . Then a (minimal) random process X is a *Markov process* with initial distribution λ and infinitesimal generator Q if

- (a) The jump chain $Y_n = X_{J_n}$ is a discrete time Markov chain starting from $Y_0 \sim \lambda$ with transition matrix P .
- (b) Conditional on Y_0, Y_1, \dots, Y_n , the holding times S_1, \dots, S_{n+1} are independent with $S_i \sim \text{Exp}(q_{Y_{i-1}})$ for $i = 1, \dots, n+1$.

We write $X \sim \text{Markov}(\lambda, Q)$.

Example. Birth-Processes are $\text{Markov}(\lambda, Q)$ with $I = \mathbb{N}$ and

$$Q = \begin{pmatrix} -q_1 & q_1 & 0 & \dots \\ 0 & -q_2 & q_2 & \dots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix} \text{ and } P = \begin{pmatrix} 0 & 1 & 0 & \dots \\ 0 & 0 & 1 & \dots \\ \vdots & \ddots & \ddots & \ddots \end{pmatrix}.$$

And jump chain $Y_n = Y_0 + n$.

We have multiple constructions of a Markov(λ, Q) process:

Construction 1:

- $(Y_n)_{n \geq 1}$ is a discrete-time Markov chain, $Y_0 \sim \lambda$ & transition matrix P .
- $(T_i)_{i \geq 1}$ iid Exp(1) random variables, independent of Y and set $S_n = \frac{T_n}{q_{Y_{n-1}}}$ and $J_n = \sum_{i=1}^n S_i$ (this implies $S_n \sim \text{Exp}(q_{Y_{n-1}})$) and set $X_t = Y_n$ if $J_n \leq t < J_{n+1}$ and $X_t = \infty$ otherwise.

Construction 2:

- Let $(T_n^y)_{n \geq 1, y \in I}$ be iid Exp(1) random variables
- $Y_0 \sim \lambda$ and inductively define Y_n, S_n : if $Y_n = x$ then for $y \neq x$ define $S_{n+1}^y = \frac{T_{n+1}^y}{q_{xy}} \sim \text{Exp}(q_{xy})$ and $S_{n+1} = \inf_{y \neq x} S_{n+1}^y \sim \text{Exp}\left(\sum_{y \neq x} q_{xy}\right)$, and if $S_{n+1} = S_{n+1}^Z$ for some random Z (since the infimum is attained), take $Y_{n+1} = Z$ (if $q_x > 0$). If $q_x = 0$ take $Y_{n+1} = x$.

(Proof of equivalence: see Example Sheet)

Construction 3:

- For $x \neq y$, let $(N_t^{x,y})$ be independent Poisson Processes with rates q_{xy} respectively. Let $Y_0 \sim \lambda$, $J_0 = 0$ and define inductively:

$$J_{n+1} = \inf\{t > J_n : N_t^{Y_n, y} \neq N_{J_n}^{Y_n, y} \text{ for some } y \neq Y_n\},$$

$$Y_{n+1} = \begin{cases} y & \text{if } J_{n+1} < \infty \text{ and } N_{J_{n+1}}^{Y_n, y} \neq N_{J_n}^{Y_n, y} \\ x & \text{if } J_{n+1} = \infty \end{cases}.$$

For a birth process, we characterised when explosion happens. In general, the next theorem gives a sufficient condition:

Theorem 1.12. *Let X be Markov(λ, Q) on I . Then $\mathbb{P}(\zeta = \infty) = 1$ (non-explosive) if any of the following hold:*

- (a) I is finite;
- (b) $\sup_{x \in I} q_x < \infty$;
- (c) $X_0 = x$ and x is recurrent for the jump chain Y .

Proof. Note that (a) \Rightarrow (b) so it is enough to show in the cases we have (b) or (c). If (b) holds, set $q = \sup_{x \in I} q_x < \infty$. Since $S_n = \frac{T_n}{q_{X_{n-1}}}$, $S_n \geq \frac{T_n}{q}$. Hence

$$\zeta = \sum_{n=1}^{\infty} S_n > \frac{1}{q} \sum_{n=1}^{\infty} T_n = \infty \text{ almost surely (SLLN),}$$

i.e $\mathbb{P}(\zeta = \infty) = 1$.

Now suppose (c) holds. Let $(N_i)_{i \in I}$ be the times when the jump chain Y visits x . By the SLLN,

$$\zeta \geq \sum_{i=1}^{\infty} S_{N_i+1} = \sum_{i=1}^{\infty} \frac{T_{N_i+1}}{q_{N_i}} = \frac{1}{q_x} \sum_{i=1}^{\infty} T_{N_i+1} = \infty \text{ almost surely,}$$

i.e $\mathbb{P}(\zeta = \infty) = 1$. □

Example. Suppose $I = \mathbb{Z}$, $q_{i,i+1} = q_{i,i-1} = 2^{|i|}$ for all i . Then $p_{i,i+1} = p_{i,i-1} = 1/2$ and the jump chain is the symmetric simple random walk on \mathbb{Z} , which is recurrent. Hence X is non-explosive.

Example. Suppose $I = \mathbb{Z}$, $q_{i,i+1} = 2^{|i|+1}$, $q_{i,i-1} = 2^{|i|}$ so $q_i = 2^{|i|} + 2^{|i|+1}$. Then the jump chain Y is a simple random walk with $1/3$ probability of moving towards 0 and $2/3$ probability of moving away from 0, hence is transient. We have

$$\mathbb{E}[\zeta] = \mathbb{E} \left[\sum_{n=1}^{\infty} S_n \right] = \sum_{j \in \mathbb{Z}} \mathbb{E} \left[\sum_{k=1}^{V_j} S_{N_k^j+1} \right],$$

where V_j is the total number of visits to j and N_k^j is the time of the k th visit to j . Hence

$$\sum_{j \in \mathbb{Z}} \mathbb{E} \left[\sum_{k=1}^{V_j} S_{N_k^j+1} \right] = \sum_{j \in \mathbb{Z}} \mathbb{E}[V_j] \mathbb{E}[S_{N_1^j+1}] = \sum_{j \in \mathbb{Z}} \mathbb{E}[V_j] \frac{1}{q_j} = \sum_{j \in \mathbb{Z}} \frac{1}{3 \cdot 2^{|j|}} \mathbb{E}V_j.$$

Since $\mathbb{E}V_j \leq 1 + \mathbb{E}_j V_j = 1 + \mathbb{E}_0 V_0 := C < \infty$ (transience) we have

$$\sum_{j \in \mathbb{Z}} \frac{1}{3 \cdot 2^{|j|}} \mathbb{E}V_j \leq \sum_{j \in \mathbb{Z}} \frac{C}{2 \cdot 2^{|j|}} < \infty.$$

So $\mathbb{E}[\zeta] < \infty$ and $\mathbb{P}(\zeta < \infty) = 1$, i.e explosive.

Theorem 1.13 (Strong Markov Property). *Let X be Markov(λ, Q) and let T be a stopping time. Then conditional on $T < \zeta$ and $X_T = x$, the process $(X_{T+t})_{t \geq 0}$ is Markov(δ_x, Q) and independent of $(X_s)_{s \leq T}$.*

Proof. Omitted (uses measure theory, see Norris (6.5)). □

Kolmogorov's forward & backward equations

We work on a countable state space I .

Theorem 1.14. *Let X be a minimal right-continuous process with values in a countable set I . Let Q be a Q -matrix with jump matrix P . Then the following are equivalent:*

(a) X is a continuous-time Markov chain with generator Q .

(b) For all $n \geq 0$, $0 \leq t_0 \leq \dots \leq t_{n+1}$, and all states $x_0, \dots, x_{n+1} \in I$,

$$\mathbb{P}(X_{t_{n+1}} = x_{n+1} | X_{t_n} = x_n, \dots, X_{t_0} = x_0) = p_{x_n x_{n+1}}(t_{n+1} - t_n).$$

Where $(P(t)) = (p_{xy}(t))$ is the minimal non-negative solution to the backward equation

$$P'(t) = QP(t), \text{ with } P(0) = I.$$

(Minimality means that if \tilde{P} is another non-negative solution, we have $p_{xy}(t) \leq \tilde{p}_{xy}(t)$ for all t and all $x, y \in I$.) In fact, if the chain is non-explosive, the solution is unique.

(c) $P(t)$ is the minimal non-negative solution to the forward equation

$$P'(t) = P(t)Q, \text{ with } P(0) = I.$$

Note. We shall skip the proof of the equivalence of (c) (see Norris (2.8)).

Proof. First we show (a) \Rightarrow (b). If $(J_n)_{n \geq 1}$ denote the jump times, then

$$\mathbb{P}_x(X_t = y, J_1 > t) = \mathbb{1}(x = y)e^{-q_x t}.$$

Integrating over the values of $J_1 \leq t$ and using independence of the jump chain, for $z \neq x$,

$$\begin{aligned} \mathbb{P}_x(X_t = y, J_1 \leq t, X_{J_1} = z) &= \int_0^t q_x e^{-q_x s} \frac{q_{xz}}{q_x} p_{zy}(t-s) ds \\ &= \int_0^t e^{-q_x s} q_{xz} p_{zy}(t-s) ds \end{aligned}$$

Summing over all $z \neq x$ (and by the MCT),

$$\mathbb{P}_x(X_t = y, J_1 \leq t) = \int_0^t \sum_{z \neq x} e^{-q_x s} q_{xz} p_{zy}(t-s) ds.$$

So

$$p_{xy}(t) = \mathbb{P}_x(X_t = y) = e^{-q_x t} \mathbb{1}(x = y) + \int_0^t \sum_{z \neq x} e^{-q_x s} q_{xz} p_{zy}(t-s) ds.$$

And by a substitution

$$e^{q_x t} p_{xy}(t) = \mathbb{1}(x = y) + \int_0^t \sum_{z \neq x} e^{q_x u} q_{xz} p_{zy}(u) du.$$

Hence $p_{xy}(t)$ is a continuous function in t , and hence

$$\sum_{z \neq x} e^{q_x u} q_{xz} p_{zy}(u)$$

is a series of continuous functions, and is also uniformly convergence (Weierstrass-M test), so continuous. Hence $e^{q_x t} p_{xy}(t)$ is differentiable with derivative

$$e^{q_x t} (q_x p_{xy}(t) + p'_{xy}(t)) = \sum_{z \neq x} e^{q_x t} q_{xz} p_{zy}(t).$$

Thus

$$p'_{xy}(t) = \sum_z q_{xz} p_{zy}(t) \implies P'(t) = QP(t).$$

Now we show minimality: let \tilde{P} be another non-negative solution of the backward equation. We will show $p_{xy}(t) \leq \tilde{p}_{xy}(t)$ for all x, y, t . As before,

$$\begin{aligned} \mathbb{P}_x(X_t = y, t < J_{n+1}) &= \mathbb{P}_x(X_t = y, J_1 > t) + \mathbb{P}_x(X_t = y, J_1 \leq t < J_{n+1}) \\ &= e^{-q_x t} \mathbb{1}(x = y) + \sum_{z \neq x} \int_0^t q_x e^{-q_x s} \frac{q_{xz}}{q_x} \mathbb{P}_z(X_{t-s} = y, t-s < J_n) ds. \end{aligned}$$

Now, as \tilde{P} satisfies the backward equation, we get as before (retracing previous steps)

$$\tilde{p}_{xy}(t) = e^{-q_x t} \mathbb{1}(x = y) + \sum_{z \neq x} \int_0^t e^{-q_x s} q_{xz} \tilde{p}_{zy}(t-s) ds. \quad (*)$$

Now we prove by induction that

$$\mathbb{P}_x(X_t = y, t < J_n) \leq \tilde{p}_{xy}(t) \text{ for all } n.$$

For $n = 1$,

$$e^{-q_x t} \mathbb{1}(x = y) \leq \tilde{p}_{xy}(t) \text{ by } (*).$$

Assume true for some $n \in \mathbb{N}$. Then for $n + 1$,

$$\mathbb{P}_x(X_t = y, t < J_{n+1}) \leq e^{-q_x t} \mathbb{1}(x = y) + \sum_{z \neq x} \int_0^t q_{xz} e^{-q_x s} \tilde{p}_{zy}(t-s) ds = \tilde{p}_{xy}(t).$$

So it holds for all n . Hence

$$\lim_{n \rightarrow \infty} \mathbb{P}_x(X_t = y, t < J_n) = \mathbb{P}_x(X_t = y, t < \zeta) \leq \tilde{p}_{xy}.$$

(Since $J_n \uparrow \zeta$.) Now by minimality,

$$p_{xy}(t) = \mathbb{P}_x(X_t = y) = \mathbb{P}_x(X_t = y, t < \zeta) \leq \tilde{p}_{xy}(t).$$

□

Finite state space:

Definition. If A is a finite-dimensional square matrix, its matrix exponential is given by

$$e^A = \sum_{k=0}^{\infty} \frac{A^k}{k!} = I + A + \frac{A^2}{2!} + \dots$$

Claim. For any $r \times r$ matrix A , the exponential e^A is an $r \times r$ matrix. If A_1 and A_2 commute, then $e^{A_1+A_2} = e^{A_1} e^{A_2}$.

Proof. Example Sheet. □

Proposition 1.15. Let Q be a Q -matrix on a finite set I and $P(t) = e^{tQ}$. Then

- (i) $P(t+s) = P(t)P(s)$ for all s, t ;
- (ii) $(P(t))_{t \geq 0}$ is the unique solution to the forward equation $P'(t) = P(t)Q$, $P(0) = I$;
- (iii) $(P(t))_{t \geq 0}$ is the unique solution to the backward equation $P'(t) = QP(t)$, $P(0) = I$;
- (iv) For $k = 0, 1, 2, \dots$, $\left(\frac{d}{dt}\right)^k P(t) \Big|_{t=0} = Q^k$.

Proof.

- (i) Since tQ and sQ commute, $\exp((t+s)Q) = \exp(tQ)\exp(sQ)$.
- (ii) The sum in e^{tQ} has infinite radius of convergence, hence we can differentiate term by term.
- (iii) Same as (ii).
- (iv) Same again.

Now we'll show uniqueness in (ii) and (iii). If \tilde{P} is another solution to the forward equation, $\tilde{P}'(t) = \tilde{P}(t)Q$, $\tilde{P}(0) = I$, then

$$\begin{aligned}\frac{d}{dt} \left(\tilde{P}(t)e^{-tQ} \right) &= \tilde{P}'(t)e^{-tQ} + \tilde{P}(t) (-Qe^{-tQ}) \\ &= \tilde{P}(t)Qe^{-tQ} - \tilde{P}(t)Qe^{-tQ} = 0\end{aligned}$$

So $\tilde{P}(t)e^{-tQ}$ is a constant matrix. Since $\tilde{P}(0) = I$, this implies $\tilde{P}(t) = e^{tQ}$. The same thing works for the backward equation. \square

Example. Let $Q = \begin{pmatrix} -2 & 1 & 1 \\ 1 & -1 & 0 \\ 2 & 1 & -3 \end{pmatrix}$. To find $p_{11}(t)$, we can diagonalise $Q = PDP^{-1}$ for a diagonal matrix

$$D = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix}$$

so

$$e^{tQ} = Pe^{tD}P^{-1} = P \begin{pmatrix} e^{t\lambda_1} & 0 & 0 \\ 0 & e^{t\lambda_2} & 0 \\ 0 & 0 & e^{t\lambda_3} \end{pmatrix} P^{-1}.$$

i.e $p_{11}(t) = ae^{t\lambda_1} + be^{t\lambda_2} + ce^{t\lambda_3}$, which we can solve by considering $p_{11}(0), p'_{11}(0), p''_{11}(0)$.

Theorem 1.16. *Let I be a finite state space and Q be a matrix. Then it is a Q -matrix iff $P(t) = e^{tQ}$ is a stochastic matrix for all t .*

Proof. For t sufficiently small, $p(t) = e^{tQ} = I + tQ + \mathcal{O}(t^2)$, so for all $x \neq y$, $q_{xy} \geq 0$ iff $p_{xy}(t) \geq 0$ for all t sufficiently small.

Since $P(t) = (P(t/n))^n$ for all n , we get $q_{xy} \geq 0$ for all $x \neq y$ iff $p_{xy}(t) \geq 0$ for all $t \geq 0$.

Assume now that Q is a Q -matrix, i.e. $\sum_y q_{xy} = 0$ for all x . Then $\sum_y (Q^n)_{xy} = \sum_y \sum_z (Q^{n-1})_{xz} Q_{zy} = \sum_z Q_{xz}^{n-1} \sum_y Q_{zy} = 0$. Hence $Q^n \mathbf{1} = Q^{n-1} Q \mathbf{1} = 0$ ($\mathbf{1}$ is vector with all entries 1). Hence, since

$$p_{xy}(t) = \delta_{xy} + \sum_{k=1}^{\infty} \frac{t^k}{k!} (Q^k)_{xy}$$

we have $\sum_y p_{xy}(t) = 1 + \sum_{k=1}^{\infty} \frac{t^k}{k!} \sum_y (Q^k)_{xy} = 1$. i.e $P(t)$ is a stochastic matrix.

Assume now that $P(t)$ is a stochastic matrix. Then as $Q = \left. \frac{d}{dt} P(t) \right|_{t=0}$, we have

$$\sum_y q_{xy} = \left. \frac{d}{dt} \sum_y p_{xy}(t) \right|_{t=0} = 0.$$

i.e Q is a Q -matrix. □

Theorem 1.17. *Let X be a right-continuous process with values in a finite set I , and let Q be a Q -matrix on I . Then the following are equivalent*

- (a) *The process X is Markov with generator Q (Markov(Q));*
- (b) *(infinitesimal definition) Conditional on $X_s = x$, the process $(X_{s+t})_{t \geq 0}$ is independent of $(X_r)_{r \leq s}$ and uniformly in t as $h \downarrow 0$, for all x, y*

$$\mathbb{P}(X_{t+h} = y | X_t = x) = \mathbb{1}(x = y) + q_{xy}h + o(h)$$

- (c) *For all $n \geq 0$, $0 \leq t_0 \leq \dots \leq t_n$ and all states x_0, \dots, x_n ,*

$$\mathbb{P}(X_{t_n} = x_n | X_{t_0} = x_0, \dots, X_{t_{n-1}} = x_{n-1}) = p_{x_{n-1}, x_n}(t_n - t_{n-1})$$

where $(p_{xy}(t))$ is the solution to the forward equation $P'(t) = P(t)Q$, $P(0) = I$.

Proof. We have already shown (a) \iff (b) (from countable setting), so it is enough to show (b) \iff (c).

First we show (c) \implies (b). $P(t) = e^{tQ}$ is the solution (as I is finite). As $t \downarrow 0$, $P(t) = I + tQ + \mathcal{O}(t^2)$. Thus for all $t > 0$ and as $h \downarrow 0$, $\forall x, y$,

$$\mathbb{P}(X_{t+h} = y | X_t = x) = \mathbb{P}(X_h = y | X_0 = x) = p_{xy}(h) = \delta_{xy} + hq_{xy} + o(h).$$

Now we show (b) \Rightarrow (c). We have

$$p_{xy}(t+h) = \sum_z p_{xz}(t)(\mathbb{1}(z=y) + q_{zy}h + o(h)).$$

So

$$\frac{p_{xy}(t+h) - p_{xy}(t)}{h} = \sum_z p_{xz}(t)q_{zy} + o(1).$$

As $h \downarrow 0$,

$$p'_{xy}(t) = \sum_z p_{xz}(t)q_{zy} = (P(t)Q)_{xy}.$$

□

Remark. To get the backward equation we could write

$$p_{xy}(t+h) = \sum_z p_{xz}(h)p_{zy}(t)$$

and continue similarly.

2 Qualitative Properties of Continuous Time Markov Chains

We have minimal chains, and countable state space.

Class Structure

Definition. For states $x, y \in I$, write $x \rightarrow y$ (“ x leads to y ”) if $\mathbb{P}_x(X_t = y \text{ for some } t \geq 0) > 0$. We write $x \leftrightarrow y$ (“ x communicates with y ”) if $x \rightarrow y$ and $y \rightarrow x$. Clearly this is an equivalence relation and we call the equivalence classes *communicating classes*. We define *irreducibility*, *closed class* and *absorbing states* exactly as in discrete Markov Chains.

Proposition 2.1. Let X be Markov(Q) with transition semigroup $(P(t))_{t \geq 0}$. For any 2 states $x, y \in I$, the following are equivalent

- (a) $x \rightarrow y$;
- (b) $x \rightarrow y$ for the jump chain;
- (c) $q_{x_0 x_1} \cdots q_{x_{n-1} x_n} > 0$ for some $x = x_0, x_1, \dots, x_{n-1}, x_n = y$;
- (d) $p_{xy}(t) > 0$ for all $t > 0$;
- (e) $p_{xy}(t) > 0$ for some $t > 0$.

Proof. Clearly (d) \Rightarrow (e) \Rightarrow (a) \Rightarrow (b). Now we show (b) \Rightarrow (c). Since $x \rightarrow y$ for the jump chain, there exist $x_0 = x, x_1, \dots, x_{n-1}, x_n = y \in I$ such that

$$p_{x_0 x_1} p_{x_1 x_2} \dots p_{x_{n-1} x_n} > 0.$$

Hence $q_{x_0 x_1} q_{x_1 x_2} \dots q_{x_{n-1} x_n}$ since $q_{xy}/q_x = p_{xy}$.

Now we show (c) \Rightarrow (d). For any 2 states w, z with $q_{wz} > 0$, and for any $t > 0$,

$$p_{wz}(t) \geq \mathbb{P}_w(J_1 \leq t, Y_1 = z, S_2 > t) = (1 - e^{-q_w t}) \frac{q_{wz}}{q_w} e^{-q_z t} > 0.$$

i.e $q_{wz} > 0$ implies $q_{wz}(t) > 0$ for all t . Hence if (c) holds, $p_{x_i x_{i+1}}(t) > 0$ for all t and all $0 \leq i \leq n-1$. Then $p_{xy}(t) = p_{x_0 x_1}(t/n) p_{x_1 x_2}(t/n) \dots p_{x_{n-1} x_n}(t/n) > 0$. \square

Hitting times

Definition. Let Y be the jump chain associated with X , and $A \subseteq I$. Set $T_A = \inf\{t > 0 : X_t \in A\}$, $H_A = \inf\{n \geq 0 : Y_n \in A\}$, $h_A(x) = \mathbb{P}_x(T_A < \infty)$ (hitting probability), $k_A(x) = \mathbb{E}_x T_A$ (mean hitting time).

Note. The hitting probability for X is the same as that for Y but the mean hitting times will differ in general.

Theorem 2.2. $(h_A(x))_{x \in I}$ and $(k_A(x))_{x \in I}$ are the minimal non-negative solutions to

$$\begin{cases} h_A(x) = 1 & \forall x \in A \\ Qh_A(x) = \sum_y q_{xy} h_A(y) = 0 & \forall x \notin A \end{cases}$$

and

$$\begin{cases} k_A(x) = 0 & \forall x \in A \\ Qk_A(x) = \sum_y q_{xy} k_A(y) = -1 & \forall x \notin A \end{cases}$$

respectively (assume $q_x > 0$ for all $x \notin A$).

Proof. The hitting probabilities are the same as those for the jump chain. Hence $h_A(x) = 1$ for all $x \in A$ and $h_A(x) = \sum_{y \neq x} p_{xy} h_A(y)$ for all $x \notin A$. Hence for all $x \notin A$

$$q_x h_A(x) = \sum_{y \neq x} h_A(y) q_{xy} \implies \sum_y h_A(y) q_{xy} = 0.$$

Clearly if $x \in A$, $T_A = 0$, so $k_A(x) = 0$. Let $x \notin A$. Then $J_1 \leq T_A$, and hence

$$\begin{aligned} k_A(x) &= \mathbb{E}_x T_A \\ &= \mathbb{E}_x J_1 + \mathbb{E}_x (T_A - J_1) \\ &= \mathbb{E}_x J_1 + \sum_{y \neq x} \mathbb{E}_x (T_A - J_1 | Y_1 = y) p_{xy} \\ &= \frac{1}{q_x} + \sum_{y \neq x} k_A(y) \frac{q_{xy}}{q_x}. \end{aligned}$$

Therefore

$$q_x k_A(x) = 1 + \sum_{y \neq x} q_{xy} k_A(y) \implies \sum_y q_{xy} k_A(y) = -1.$$

The minimality of solutions is as in the discrete chain. □

Recurrence and Transience

Definition. The state x is called *recurrent* for X if

$$\mathbb{P}(\{t : X_t = x\} \text{ is unbounded}) = 1.$$

The state x is called *transient* if

$$\mathbb{P}(\{t : X_t = x\} \text{ is unbounded}) = 0.$$

Remark. If X explodes with positive probability starting from x , i.e. $\mathbb{P}(\zeta < \infty) > 0$, then $\sup_t \{t : X_t = x\} \leq \zeta < \infty$ with positive probability so x cannot be recurrent.

Theorem 2.3. Let X be Markov(Q) with jump chain Y . Then

- (a) If x is recurrent for Y , then x is recurrent for X ;
- (b) If x is transient for Y , then x is transient for X ;
- (c) Every state is either recurrent or transient;
- (d) Recurrence and transience are class properties.

Proof. (a) & (b) will imply (c) & (d) through the results for the discrete chain. So we prove (a) and (b).

First we prove (a). Suppose x is recurrent for Y and $X_0 = x$. Then X is not explosive, i.e. $\mathbb{P}(\zeta = \infty) = 1$, so $J_n \rightarrow \infty$ with probability 1 (starting from x). Since $X_{J_n} = Y_n$ for all n , and Y visits x infinitely often with probability 1, $\{t : X_t = x\}$ is unbounded with probability 1.

Now we prove (b). If x is transient for Y , $q_x > 0$ (otherwise x is an absorbing state). Also, almost surely there is a last visit to x for Y , i.e.

$$N := \sup\{n : Y_n = x\} < \infty \text{ almost surely.}$$

Also, $J_{N+1} < \infty$ almost surely (as $q_x > 0$) and if $t \in \{s : X_s = x\}$, then $t \leq J_{N+1}$, i.e. $\sup\{s : X_s = x\} \leq J_{N+1} < \infty$ almost surely. \square

Like in the discrete-time chain, $\sum_{n \geq 1} p_{xx}(n) = \infty$ implies x is recurrent; and $\sum_{n \geq 1} p_{xx}(n) < \infty$ implies x is transient.

Theorem 2.4. x is recurrent for X if and only if $\int_0^\infty p_{xx}(t)dt = \infty$, and x is transient for X if and only if $\int_0^\infty p_{xx}(t)dt < \infty$.

Proof. If $q_{xx} = 0$, then x is absorbing, i.e. $p_{xx}(t) = 1$ for all t and $\int_0^\infty p_{xx}(t)dt = \infty$. Assume $q_x > 0$. Then

$$\begin{aligned} \int_0^\infty p_{xx}(t)dt &= \int_0^\infty \mathbb{E}[\mathbb{1}(X_t = x)]dt \\ &= \mathbb{E}_x \left[\int_0^\infty \mathbb{1}(X_t = x)dt \right] && \text{(Fubini)} \\ &= \mathbb{E}_x \left[\sum_{n=0}^\infty \mathbb{1}(Y_n = x) S_{n+1} \right] \\ &= \sum_{n=0}^\infty \mathbb{E}_x [\mathbb{1}(Y_n = x) S_{n+1}] && \text{(Fubini)} \\ &= \sum_{n=0}^\infty \mathbb{P}_x(Y_n = x) \mathbb{E}_x[S_{n+1} | Y_n = x] \\ &= \sum_{n=0}^\infty p_{xx}(n) \frac{1}{q_x}. \end{aligned}$$

\square

Invariant Distributions

Definition. For a discrete Markov Chain Y , π is an *invariant measure* for Y if $\pi P = \pi$. If in addition $\sum \pi_i = 1$, π is called a *invariant distribution*. Then if $Y_0 \sim \pi$, $Y_n \sim \pi$ for all $n \geq 1$.

Recall:

Theorem 2.5. If Y is a discrete time Markov Chain which is irreducible, recurrent and $x \in I$. Then

$$\nu^x(y) = \mathbb{E}_x \left[\sum_{n=0}^{H_x-1} \mathbb{1}(Y_n = y) \right] \text{ where } H_x = \inf\{n \geq 1 : Y_n = x\}.$$

Then $\nu^x(\cdot)$ is an invariant measure and $0 < \nu^x(y) \leq 1$ for all y , $\nu^x(x) = 1$.

Theorem 2.6. If Y is irreducible, λ is any invariant measure with $\lambda(x) = 1$, then

$$\lambda(y) \geq \nu^x(y) \text{ for all } y.$$

If Y is recurrent then $\lambda(y) = \nu^x(y)$ for all y .

Definition. Let $X \sim \text{Markov}(Q)$ and let λ be a measure. Then λ is called invariant/infinitesimally invariant if $\lambda Q = 0$.

Lemma 2.7. If $|I|$ is finite, then $\lambda Q = 0$ if and only if $\lambda P(s) = \lambda$ for all $s \geq 0$.

Proof. $P(s) = e^{sQ}$ since I is finite. If $\lambda Q = 0$, then

$$\lambda P(s) = \lambda e^{sQ} = \lambda \sum_{k=0}^{\infty} \frac{(sQ)^k}{k!} = I.$$

If $\lambda P(s) = \lambda$ for all s , then

$$\lambda Q = \lambda P'(0) = \left. \frac{d}{ds}(\lambda P(s)) \right|_{s=0} = \left. \frac{d}{ds} \lambda \right|_{s=0} = 0.$$

□

Lemma 2.8. Let X be $\text{Markov}(Q)$ and Y its jump chain. π is invariant for X if and only if μ defined by $\mu_x = q_x \pi_x$ is invariant for Y (i.e. $\pi Q = 0$ if and only if $\mu P = \mu$).

Proof. Since $q_x(p_{xy} - \delta_{xy}) = q_{xy}$,

$$\begin{aligned} (\pi Q)_y &= \sum_{x \in I} \pi_x q_{xy} = \sum_{x \in I} \pi_x q_x (p_{xy} - \delta_{xy}) \\ &= \sum_{x \in I} \mu_x (p_{xy} - \delta_{xy}) \\ &= \sum_x \mu_x p_{xy} - \mu_y \\ &= (\mu P)_y - \mu_y. \end{aligned}$$

□

Theorem 2.9. Let X be irreducible & recurrent, with generator Q . Then X has an invariant measure, which is unique up to scalar multiplication.

Proof. Assume $|I| > 1$. Then by irreducibility, $q_x > 0$ for all x . For Y , $\nu^x(y) = \mathbb{E}_x \left[\sum_{n=0}^{H_x-1} \mathbb{1}(Y_n = y) \right]$ where $H_x = \inf\{n \geq 1 : Y_n = x\}$ is an invariant measure as Y is irreducible & recurrent (since X is), hence ν^x is an invariant measure for Y which is unique up to scalar multiplication. By the previous lemma, $\frac{\nu^x(y)}{q_y}$ is an invariant measure for X , and also unique up to scalar multiplication. □

Definition. Let $T_x = \inf\{t \geq J_1 : X_t = x\}$ be the first return time to x .

Lemma 2.10. Assume $q_y > 0$. Define

$$\mu^x(y) = \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right].$$

Then $\mu^x(y) = \frac{\nu^x(y)}{q_y}$.

Proof.

$$\begin{aligned}
 \mu^x(y) &= \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right] \\
 &= \mathbb{E}_x \left[\sum_{n=0}^{H_x-1} \mathbb{1}(Y_n = y) S_{n+1} \right] \\
 &= \mathbb{E}_x \left[\sum_{n=0}^{\infty} S_{n+1} \mathbb{1}(Y_n = y, n \leq H_x - 1) \right] \\
 &= \sum_{n=0}^{\infty} \mathbb{E}_x [S_{n+1} | Y_n = y, n \leq H_x - 1] \mathbb{P}_x(Y_n = y, n \leq H_x - 1)
 \end{aligned}$$

Since $\{n < H_x\}^c = \{H_x \leq n\} \in \sigma\{Y_1, \dots, Y_n\}$ (i.e depends on Y_1, \dots, Y_n only) its a stopping time so the Strong Markov Property says

$$\begin{aligned}
 \mu^x(y) &= \sum_{n=0}^{\infty} \mathbb{E}_x [S_{n+1} | Y_n = y] \mathbb{P}_x(Y_n = y, n \leq H_x - 1) \\
 &= \sum_{n=0}^{\infty} \frac{1}{q_y} \mathbb{P}_x(Y_n = y, n \leq H_x - 1) \\
 &= \frac{1}{q_y} \sum_{n=0}^{\infty} \mathbb{E}_x [\mathbb{1}(Y_n = y, n \leq H_x - 1)] \\
 &= \frac{1}{q_y} \mathbb{E} \left[\sum_{n=0}^{\infty} \mathbb{1}(Y_n = y, n \leq H_x - 1) \right] \\
 &= \frac{1}{q_y} \mathbb{E}_x \left[\sum_{n=0}^{H_x-1} \mathbb{1}(Y_n = y) \right] \\
 &= \frac{\nu^x(y)}{q_y}.
 \end{aligned}$$

□

Definition. A recurrent state x is called *positive recurrent* if

$$m_x = \mathbb{E}_x T_x < \infty.$$

Otherwise, we call x *null recurrent*.

Theorem 2.11. Let $X \sim \text{Markov}(Q)$ be irreducible. Then the following are equivalent

- (a) Every state is positive recurrent;
- (b) Some state is positive recurrent;

(c) X is non-explosive and has an invariant distribution.

Also, when (c) holds, the invariant distribution λ is given by $\lambda(x) = \frac{1}{q_x m_x}$ for all x .

Proof. Clearly (a) \Rightarrow (b). Now we show (b) \Rightarrow (c). Assume without loss of generality that $q_x > 0$. Let x be a positive recurrent state. Then all states are recurrent, so Y is recurrent and the chain is non-explosive starting from any y . As Y is recurrent, ν^x is an invariant measure for Y . So $\mu^x = \frac{\nu^x}{q_y}$ (as defined previously) is an invariant measure for X . Also

$$\mu_x(y) = \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right],$$

so

$$\begin{aligned} \sum_{y \in I} \mu^x(y) &= \mathbb{E}_x \left[\int_0^{T_x} \sum_{y \in I} \mathbb{1}(X_t = y) dt \right] \\ &= \mathbb{E}_x T_x < \infty. \end{aligned}$$

So μ_x is normalisable, and $\frac{\mu_x}{\mathbb{E}_x T_x}$ is an invariant distribution for X .

Now we show (c) \Rightarrow (a). By a previous lemma, the measure $\beta(y) = \lambda(y)q_y$ is an invariant measure for Y . Since $\sum_{y \in I} \lambda(y) = 1$, $\lambda(x) > 0$ for some x . Since Y is irreducible, for any $y \in I$, $x \rightarrow y$, i.e. $p_{xy}(n) > 0$ for some n . As β is invariant for Y , $\beta P^n = \beta$. So

$$\lambda(y)q_y = \beta y = \sum_{z \in I} \beta_z p_{zy}(n) \geq \beta_x p_{xy}(n) = \lambda(x)q_x p_{xy}(n) > 0$$

so $\lambda(y) > 0$ for all y . Fix some $x \in I$. Then $\lambda(x) > 0$ so define $a^x(y) = \frac{\beta(y)}{\lambda(x)q_x}$ for all $y \in I$, which is invariant for Y as a scalar multiple of $\beta(y)$, and $a^x(x) = 1$. By the theorem for discrete-time chains $a^x(y) \geq \nu^x(y)$ for all $y \in I$, where $\nu^x(y) = \mathbb{E}_x \left[\sum_{n=0}^{H_x-1} \mathbb{1}(Y_n = y) \right]$ and where $H_x = \inf\{n \geq 1 : Y_n = x\}$.

Also if $\mu^x(y) = \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right]$ then $\mu^x(y) = \frac{\nu^x(y)}{q_y}$ and

$$\begin{aligned} \sum_{y \in I} \mu^x(y) &= \mathbb{E}_x \left[\int_0^{T_x} \sum_{y \in I} \mathbb{1}(X_t = y) dt \right] \\ &= \mathbb{E}_x T_x = m_x \quad (\text{as } X \text{ is non-explosive}) \end{aligned}$$

Then

$$\begin{aligned}
 \mu_x &= \sum_y \mu^x(y) = \sum_y \frac{\nu^x(y)}{q_y} \leq \sum_y \frac{a^x(y)}{q_y} \\
 &= \sum_y \frac{\beta(y)}{\lambda(x)q_x q_y} \\
 &= \sum_y \frac{\lambda(y)q_y}{\lambda(x)q_x q_y} \\
 &= \frac{1}{\lambda(x)q_x} \sum_y \lambda(y) \\
 &= \frac{\lambda(x)q_x}{<} \infty.
 \end{aligned}$$

Hence x is positive recurrent. As x was arbitrary this means all states are positive recurrent.

Also, if (c) holds, then X is recurrent, so Y is recurrent. Hence $a^x(y) = v^x(y)$ for all y . Therefore $m_x = \frac{1}{\lambda(x)q_x}$ as the previous inequality becomes equality. \square

Example. On \mathbb{Z}^+ , suppose $q_{i,i+1} = \lambda q_i$, $q_{i,i-1} = \mu q_i$ and $q_{ii} = -(\lambda + \mu)q_i$ and $q_{i,j} = 0$ for all other j (an example of a Birth & Death process). We have transition probabilities $p_{i,i+1} = \frac{\lambda}{\lambda + \mu}$ and $p_{i,i-1} = \frac{\mu}{\lambda + \mu}$. Then $(\lambda/\mu)^i$ is an invariant measure for Y . Then $\pi_i = \frac{1}{q_i}(\lambda/\mu)^i$ is invariant for X . So if $q_i = 2^i$ and $\lambda = \frac{3\mu}{2}$, then $\pi_i = (3/4)^i$ is invariant for X . Also $\sum_{i=0}^{\infty} \pi_x < \infty$ so X has an invariant distribution. Since $\lambda > \mu$, the chain is transient for Y and so is transient for X . If X were non-explosive then by the previous theorem it would be positive recurrent, hence X must be explosive.

Lemma 2.12. *Let X be a continuous-time Markov chain. Fix $t > 0$ and set $Z_n = X_{nt}$. Then $(Z_n)_{n=0}^{\infty}$ is a discrete-time Markov chain. Then x is recurrent for X if and only if x is recurrent for Z .*

Proof. Example Sheet. □

Theorem 2.13. *Let $X \sim \text{Markov}(Q)$ be recurrent, irreducible and λ be a measure. Then $\lambda Q = 0$ if and only if $\lambda P(s) = \lambda$ for all $s > 0$.*

Proof. Any measure λ such that $\lambda Q = 0$ is unique up to scalar multiplication (by a theorem proved previously).

Any measure λ such that $\lambda P(s) = \lambda$ for all s is unique up to scalar multiplication. Indeed, fix $s = 1$ so $\lambda P(1) = \lambda$. Then $(X_n)_{n=0}^{\infty}$ is a discrete time chain with transition matrix $P(1)$, and is irreducible, recurrent by the previous lemma. It also has λ as an invariant measure, hence unique (up to scalar multiplication).

So it is enough to show $\mu^x Q = 0$ and $\mu^x P(s) = \mu^x$ for all s where $\mu^x(y) = \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right]$.

Also $\mu^x(y) = \frac{\nu^x(y)}{q_y}$ and since X is recurrent, Y is recurrent so ν^x is an invariant measure for Y . So μ^x is an invariant measure for X , i.e $\mu^x Q = 0$.

Also, by the Strong Markov Property,

$$\mathbb{E}_x \left[\int_0^s \mathbb{1}(X_t = y) dt \right] = \mathbb{E}_x \left[\int_{T_x}^{T_x+s} \mathbb{1}(X_t = y) dt \right]. \quad (*)$$

Thus

$$\begin{aligned}
\mu^x(y) &= \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_t = y) dt \right] \\
&= \mathbb{E}_x \left[\int_0^s \mathbb{1}(X_t = y) dt \right] + \mathbb{E}_x \left[\int_s^{T_x} \mathbb{1}(X_t = y) dt \right] \\
&= \mathbb{E}_x \left[\int_{T_x}^{T_x+s} \mathbb{1}(X_t = y) dt \right] + \mathbb{E}_x \left[\int_s^{T_x} \mathbb{1}(X_t = y) dt \right] \\
&= \mathbb{E}_x \left[\int_s^{T_x+s} \mathbb{1}(X_t = y) dt \right] \\
&= \mathbb{E}_x \left[\int_0^\infty \mathbb{1}(X_{u+s} = y, u < T_x) du \right] \quad (\text{letting } t = u + s) \\
&= \int_0^\infty \mathbb{P}_x(X_{u+s} = y, u < T_x) du \\
&= \int_0^\infty \sum_{z \in I} \mathbb{P}_x(X_u = z, X_{u+s} = y, u < T_x) du \\
&= \sum_{z \in I} p_{zy}(s) \mathbb{E}_x \left[\int_0^{T_x} \mathbb{1}(X_u = z) dy \right] \\
&= \sum_{z \in I} \mu^x(z) p_{zy}.
\end{aligned}$$

i.e $\mu^x = \mu^x P(s)$. Since s was arbitrary, $\mu^x = \mu^x P(s)$ for all s . \square

Convergence to Equilibrium

Lemma 2.14. *For the semigroup $P(t)$ and all $t \geq 0$, $h \geq 0$,*

$$|p_{xy}(t+h) - p_{xy}(t)| \leq 1 - e^{-q_x h} \leq q_x h.$$

Proof.

$$\begin{aligned}
 |p_{xy}(t+h) - p_{xy}(t)| &= \left| \sum_z p_{xz}(h)p_{zy}(t) - p_{xy}(t) \right| \\
 &= \left| \underbrace{\sum_{z \neq x} p_{xz}(h)p_{zy}(t)}_{\in [0, 1-p_{xx}(h)]} - \underbrace{p_{xy}(t)(1-p_{xx}(h))}_{\in [0, 1-p_{xx}(h)]} \right| \\
 &\leq 1 - p_{xx}(h) \\
 &= \mathbb{P}_x(X(h) \neq x) \\
 &\leq \mathbb{P}_x(J_1 \leq h) \\
 &= 1 - e^{-q_x h}
 \end{aligned}$$

□

Theorem 2.15. *Let $X \sim \text{Markov}(Q)$ be irreducible, non-explosive, and let λ be an invariant distribution. Then for all $x, y \in I$, $p_{xy}(t) \rightarrow \lambda(y)$ as $t \rightarrow \infty$.*

Proof. Fix $\varepsilon > 0$. Fix $h > 0$ such that $q_x h < \varepsilon/2$. Consider the discrete time Markov Chain $(Z_n) = (X_{nh})_{n \geq 0}$. Then (Z_n) is irreducible and aperiodic ($p_{xy}(h) > 0$ for all x, y by irreducibility). As X is positive recurrent (non-explosive and has invariant distribution), $\lambda P(h) = \lambda$, so λ is an invariant distribution for Z_n .

By a discrete-time Markov Chain result, for all x, y , $p_{xy}(nh) \rightarrow \lambda(y)$ as $n \rightarrow \infty$. Hence there exists n_0 such that for all $n \geq n_0$, $|p_{xy}(nh) - \lambda(y)| < \varepsilon/2$. Let $t \geq n_0 h$. Then there exists $n \geq n_0$ such that $nh \leq t < (n+1)h$. So

$$|p_{xy}(t) - p_{xy}(nh)| \leq q_x(t - nh) \leq q_x h < \varepsilon/2.$$

Thus for all $n \geq n_0 h$,

$$|p_{xy}(t) - \lambda(y)| \leq |p_{xy}(t) - p_{xy}(nh)| + |p_{xy}(nh) - \lambda(y)| < \varepsilon.$$

□

Ergodic Theory

Theorem 2.16. *Let $X \sim \text{Markov}(\lambda, Q)$ be irreducible. Then*

$$\frac{1}{t} \int_0^t \mathbb{1}(X_s = x) ds \rightarrow \frac{1}{q_x m_x} \text{ as } t \rightarrow \infty \text{ almost surely.}$$

If X is positive recurrent \mathcal{E} π is the unique invariant distribution and $f : I \rightarrow \mathbb{R}$ is bounded, then

$$\frac{1}{t} \int_0^t f(X_s) ds \rightarrow \sum_{x \in I} f(x) \pi(x)$$

Proof. Not given.

□

Note. The second limit can be justified by

$$\begin{aligned} \frac{1}{t} \int_0^t f(X_s) ds &= \frac{1}{t} \int_0^t \sum_{x \in I} f(x) \mathbb{1}(X_s = x) ds \\ &= \sum_{x \in I} f(x) \left(\frac{1}{t} \int_0^t \mathbb{1}(X_s = x) ds \right) \\ &\rightarrow \sum_{x \in I} f(x) \pi(x). \end{aligned}$$

Reversibility

Theorem 2.17. *Let $X \sim \text{Markov}(Q)$ be irreducible and non-explosive with invariant distribution π . Let $X_0 \sim \pi$. Fix $T > 0$ and set $\hat{X}_t = X_{T-t}$ for $0 \leq t \leq T$. Then $\hat{X} \sim \text{Markov}(\hat{Q})$ and has invariant distribution π where $\hat{q}_{xy} = \pi(y) \frac{q_{yx}}{\pi(x)}$. Also \hat{Q} is irreducible and non-explosive (i.e $Z \sim \text{Markov}(\hat{Q})$ is non-explosive).*

Proof. Note that \hat{Q} is indeed a Q -matrix: $\hat{q}_{xy} \geq 0$ for all x, y and $\sum_y \hat{q}_{xy} = \frac{1}{\pi(x)} \sum_y \pi(y) q_{yx} = \frac{1}{\pi(x)} (\pi Q)_x = 0$. Also \hat{Q} is irreducible (as Q is). Also $(\pi \hat{Q})_y = \sum_x \pi(x) \hat{q}_{xy} = \sum_x \pi(y) q_{yx} = 0$, so π is invariant for \hat{Q} .

Now, let $0 = t_0 \leq t_1 \leq \dots \leq t_n = T$, $x_1, \dots, x_n \in I$, let $s_i = t_i - t_{i-1}$. Then

$$\begin{aligned} \mathbb{P}(\hat{X}_{t_0} = x_0, \dots, \hat{X}_{t_n} = x_n) &= \mathbb{P}(X_0 = x_n, \dots, X_{T-t_1} = x_1, X_T = x_0) \\ &= \pi(x_n) p_{x_n x_{n-1}}(s_n) \dots p_{x_1 x_0}(s_1). \end{aligned}$$

Define $\hat{p}_{xy}(t) = \frac{\pi(y)}{\pi(x)} p_{yx}(t)$ so

$$\begin{aligned} \pi(x_n) p_{x_n x_{n-1}}(s_n) \dots p_{x_1 x_0}(s_1) &= \pi(x_n) \hat{p}_{x_{n-1} x_n}(s_n) \frac{\pi(x_{n-1})}{\pi(x_n)} \dots \hat{p}_{x_0 x_1}(s_1) \frac{\pi(x_0)}{\pi(x_1)} \\ &= \pi(x_0) \hat{p}_{x_0 x_1}(s_1) \dots \hat{p}_{x_{n-1} x_n}(s_n). \end{aligned}$$

So \hat{X} is Markov with transition semigroup $(\hat{P}(t))_{t \geq 0}$. Need to show that $\hat{P}(t)$ is the minimal non-negative solution to the Kolmogorov backward equation with \hat{Q} , that is $(\hat{P}(t))' = \hat{Q} \hat{P}(t)$.

Indeed,

$$\begin{aligned} \hat{p}'_{xy}(t) &= \frac{\pi(x)}{\pi(y)} p'_{yx}(t) \\ &= \frac{\pi(y)}{\pi(x)} \sum_z p_{yz}(t) q_{zx} && (\text{Kolmogorov forward eq for } P) \\ &= \frac{\pi(y)}{\pi(x)} \sum_z \frac{\pi(z)}{\pi(y)} \hat{p}_{zy}(t) q_{yx} \\ &= \frac{1}{\pi(x)} \sum_z \pi(x) \hat{q}_{xz} \hat{p}_{zy}(t) \\ &= (\hat{Q} \hat{P})_{xy}. \end{aligned}$$

Suppose R is another solution to the Kolmogorov forward equation: $R'(t) = \hat{Q} R(t)$. Then defining $\bar{R}_{xy}(t) = \frac{\pi(y)}{\pi(x)} R_{yx}(t)$ then as before \bar{R} satisfies $\bar{R}'(t) = \bar{R}(t) Q$. But we know that P is the minimal solution to this, so \hat{P} is minimal for the forward equation.

Now we show \hat{Q} is non-explosive. Indeed, X is irreducible and non-explosive with invariant distribution π , so X is (positive) recurrent. Hence $\pi P(t) = \pi$ for all t . Thus

$$\sum_y \hat{p}_{xy}(t) = \frac{1}{\pi(x)} \sum_y \pi(y) p_{yx}(t) = \frac{1}{\pi(x)} (\pi P(t))_x = \frac{1}{\pi(x)} \pi(x) = 1.$$

So if $Z \sim \text{Markov}(\hat{Q})$

$$1 = \sum_y \hat{p}_{xy}(t) = \sum_y \mathbb{P}_x(Z_t = y) = \sum_y \mathbb{P}_x(Z_t = y, t < \zeta) = \mathbb{P}_x(t < \zeta).$$

i.e $\mathbb{P}_x(\zeta > t) = 1$ for all t , so $\mathbb{P}_x(\zeta = \infty) = 1$, i.e non-explosive. □

Definition. Let $X \sim \text{Markov}(Q)$. It is called *reversible* if for all $T > 0$, $(X_t)_{0 \leq t \leq T}$ and $(X_{T-t})_{0 \leq t \leq T}$ have the same distribution.

Definition. A measure λ and a Q -matrix Q are said to be in *detailed balance* if for all x, y

$$\lambda(x)q_{xy} = \lambda(y)q_{yx}.$$

Lemma 2.18. If Q and λ are in detailed balance, then λ is invariant for Q (i.e $\lambda Q = 0$).

Proof.

$$(\lambda Q)_y = \sum_x \lambda(x)q_{xy} = \lambda(y) \sum_x q_{yx} = 0$$

□

Remark. To find an invariant measure, check the detailed balance equation as a first step.

Lemma 2.19. *Let $X \sim \text{Markov}(Q)$ be irreducible, non-explosive and π a distribution with $X_0 \sim \pi$. Then π and Q are in detailed balance if and only if $(X_t)_{t \geq 0}$ is reversible.*

Proof. X is reversible if and only if $Q = \hat{Q}$ and π is an invariant distribution, where $\hat{q}_{xy} = \frac{\pi(y)}{\pi(x)} q_{yx}$. This happens iff π and Q are in detailed balance. \square

Definition. A birth and death chain X is a continuous time Markov chain on $\mathbb{N} = \{0, 1, \dots\}$ where for $x \geq 1$ $q_{x,x-1} = \mu_x$, $q_{x,x+1} = \lambda_x$, q_{xy} for all other y ; and $q_{01} = \lambda_0$, $q_{0,y} = 0$ for all $y \neq 1$.

Lemma 2.20. *A measure π is an invariant measure for a birth and death chain if and only if it solves the detailed balance equation.*

Proof. We already have one direction. So we show that if π is invariant it satisfies the detailed balance equation. Indeed, let π be an invariant measure for Q , i.e $\pi Q = 0$. So for all $j \geq 1$,

$$\begin{aligned} (\pi Q)_j &= 0 = \pi_{j-1} q_{j-1,j} + \pi_j q_{j,j} + \pi_{j+1} q_{j+1,j} \\ &= \pi_{j-1} \lambda_{j-1} + \pi_{j+1} \mu_{j+1} - \pi_j (\lambda_j + \mu_j). \end{aligned}$$

So

$$\pi_{j+1} \mu_{j+1} - \pi_j \lambda_j = \pi_j \mu_j - \pi_{j-1} \lambda_{j-1}. \quad (*)$$

For $j = 1$ $(*)$ becomes $\pi_1 \mu_1 - \pi_0 \lambda_0 = 0$. So using induction and plugging in to the RHS of $(*)$ we get

$$\pi_{j+1} \mu_{j+1} = \pi_j \lambda_j.$$

As required. \square

3 Queueing Theory

Queues are processes which can be modelled as customers arriving at a server and then departing.

Q: what is the equilibrium queue length (including customers being served)?

Q: What is the busy period?

Q: Time spent by a customer in the queue/waiting-time (including the service time)?

We use M/G/K notation. The ‘M’ stands for “Markovian arrival” - customers arrive according to a Poisson process of rate λ . The ‘G’ stands for “general distribution” - it is the (iid) service time distribution, if ‘M’ is used instead of ‘G’ this represents $\text{Exp}(\mu)$ service times. The ‘K’ stands for the number of servers ($k = 1$ or ∞).

Let X_t be the queue length at time t (including the customers being served). Then $(X_t)_{t \geq 0}$ is a continuous time process on state space $I = \{0, 1, 2, \dots\}$. If we have a M/M/1 or M/M/ ∞ process, then $(X_t)_{t \geq 0}$ is Markov and in particular it's a birth & death chain with

$$\begin{aligned} \text{M/M/1: } & q_{i,i+1} = \lambda, \quad q_{i,i-1} = \mu \\ \text{M/M}/\infty: & q_{i,i+1} = \lambda, \quad q_{i,i-1} = i\mu \end{aligned}$$

M/M/1:

Theorem 3.1. *Let $\rho = \lambda/\mu$. Then the queue length X (for a M/M/1 process) is transient if and only if $\rho > 1$, recurrent if and only if $\rho \geq 1$ and positive recurrent if and only if $\rho < 1$. In the positive recurrent case, the invariant distribution is*

$$\pi(n) = (1 - \rho)\rho^n, \quad n = 0, 1, \dots$$

And if $\rho < 1$, and $X_0 \sim \pi$, then the wait time (including service time) for a customer that arrives at time t is $\text{Exp}(\mu - \lambda)$.

Proof. The jump chain Y is given by $p_{i,i+1} = \lambda/(\lambda + \mu)$ and $p_{i,i-1} = \mu/(\lambda + \mu)$. This is just a biased SRW on \mathbb{N} (with reflection at 0). Thus Y (and hence X) is transient if $\lambda > \mu$, and recurrent if $\lambda \leq \mu$.

It is non-explosive since $\sup_i q_i = (\lambda + \mu) < \infty$. Thus we have positive recurrence iff there is an invariant distribution. Since X is a birth & death chain, a measure is invariant iff it satisfies detailed balance. Thus $\pi(n)\lambda = \pi(n+1)\mu$, i.e. $\pi(n+1) = \pi(n)(\lambda/\mu)^{n+1}$. So π is normalisable iff $\lambda/\mu = \rho < 1$. When $\rho < 1$, $\pi(n) = (1 - \rho)\rho^n$ is an invariant distribution. So π is the distribution of a (shifted) geometric random variable, i.e. π is the distribution of $Z - 1$ where $Z \sim \text{Geo}(1 - \rho)$.

If $\rho < 1$ and $X_0 \sim \pi$ then $X_t \sim \pi$ (as X is recurrent, π invariant iff $\pi P(t) = \pi$ for all t). So the wait time W of a customer arriving at time t is $W = \sum_{i=1}^{X_t+1} T_i$ where $T_i \sim \text{Exp}(\mu)$ are iid and independent of X_t . As $X_t + 1 \sim \text{Geo}(1 - \rho)$ is independent of $(T_i)_{i \geq 1}$ we have $W \sim \text{Exp}(\mu(1 - \rho)) = \text{Exp}(\mu - \lambda)$ (by Example Sheet 1).

We have expected queue length at equilibrium

$$\mathbb{E}_\pi X_t = \mathbb{E}_\pi Z - 1 = \frac{1}{1 - \rho} - 1 = \frac{\rho}{1 - \rho} = \frac{\lambda}{\mu - \lambda}.$$

□